Space allocation for mutli-modal urban networks with ridesplitting services and public transportation

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Abstract

The surge of Mobility on Demand (MoD) is largely attributed to advancements in mobile internet and technology. Ridesourcing platforms, among other solution services, offer convenience and flexibility when it comes to pick-up/drop-off time and location, all while keeping prices within affordable ranges. Similarly, ridesplitting renders itself as an extension to ridesourcing where platform users agree to share their rides in return for a reduced fare yet a longer travel time. Despite the numerous advantages that sharing introduced to the platform operator by reducing the fleet size necessary to serve demand levels, or to the environment by mitigating emissions, e-hailing is still overall negatively impacting traffic performance in urban spaces. This is partially due to current tendency of users to favor solo over shared rides. This paper aims to use aggregate traffic flow models to put forward a network space redistribution policy that has the potential to alleviate urban congestion by inducing modal shifts towards more efficient modes. Accordingly, we investigate the new network split that minimizes the total passenger hours traveled for all network commuters in the event where shared rides are allowed to use underutilized bus lanes. As a result, the choice to share is associated with an inevitable additional detour distance but with a lower-than-anticipated trip time compared to standard scenarios where the totality of the fleet utilizes the same network space. Results show that the impact of this strategy extends beyond the mere improvement of the total travel time of all network users to the reduction of the detour distance incurred by sharing as more users opt for ridesplitting. Moreover, this strategy decreases total network accumulation and incentivizes e-hailing platforms to lower their fleet size without much disturbing bus operations.

Keywords

Ridesplitting, regulation, space allocation, detour time

1. Introduction

The rapid growth of ridesourcing systems evinces an increasing interest in personalized trips where users input their origins and destinations, and service providers assign them to convenient rides. These services, also interchangeably called e-hailing, are characterized by a single platform connecting both riders and drivers. It collects the totality of requested trip details to which it provides a feasible driver match from the operating fleet of available online vehicles. Another type of service fundamentally similar to ridesourcing is referred to as ridesplitting. In the latter, passengers grant their approval *a priori* to share their rides with other users of the system in return for an upfront decrease in fares to compensate for any inconvenience that sharing incurs. Ridesplitting has a myriad of advantages since it allows the same fleet of vehicles to accommodate a larger number of arriving requests while reducing the total travel distance [1].

Despite their success, the ubiquitous character of these platforms (Uber, Lyft, DiDi Chuxing, etc) raises particular concerns because they provide the same service structure in heterogeneous urban areas with diverse spatial configurations, various mode availabilities, mismatched public transport service levels, and different traffic intensities. Uber alone is available in more than 900 cities worldwide, with a total average trip count of around 18.7 million per day in 2020. Its revenue for this same year from the mobility segment alone summed up to $7.9 billion [2]. Other statistics from the United States showed that Transport Network Companies (TNCs) drastically amplified vehicle miles in 9 of the largest metropolitan areas in the country [3]. The scale of these numbers justifies the continuous effort to (i) set forth a framework that models the operation of ridesourcing services and (ii) unravel their influences on traffic externalities, Vehicle Kilometers Traveled (VKT), modal substitution and complimentary, long-term car ownership, and social welfare of drivers and riders [4, 5, 6]. Accordingly, a comprehensive understanding of the interactions between the previous factors helps decision-makers to adopt informed policies and actions to regulate the service of e-hailing platforms.

The type and extent of regulations are largely dependent on the expected outcomes that government aims to achieve. The multi-purpose intervention usually targets the fleet of vehicles by capping the number of registered drivers [7], or the cumulative time of driving empty [3]. Moreover, prompting TNCs to enact parking management strategies is efficient in reducing empty VKTs and subsequently mitigating congestion as demonstrated by a simulation study from a Chinese megacity [8]. The same results are reproduced under a static market equilibrium model where off-street parking spaces are utilized by TNCs to prevent on-street cruising [9, 10]. Another category of regulations involves policy-makers' attempt to maximize the social welfare of multiple stakeholders in the system by imposing a minimum driver wage, a maximum passenger fare, or by limiting commission rate which is the fraction of the total fare that is pocketed by the platform. Some of these policies are however not sustainable. In fact, the fare and fleet size values under social optimum are associated with a negative platform revenue in static modeling framework [11, 12].

To our knowledge, however, the assessment of incentive-based regulatory approaches rather than enforcement strategies is still deficient in the literature. Moreover, the majority of the previous models developed to study the efficiency of any regulation policy only account for stakeholders in direct affiliation with the platform without consideration of other transport network users. A quick review of available work on pooling in the context of e-hailing and carsharing validates the potential of trip sharing in mitigating congestion and reducing VKTs [4, 13]. We exploit these observations to put forward a regulation strategy that reconsiders space distribution in the network: by allowing shared TNCs to use dedicated bus lanes, we expect to achieve a new optimum that simultaneously reduces overall network delays and motivates e-hailing platforms to reduce their fleet size.

The remainder of this work is organized as follows. The next section describes the supply and demand sides of ridesplitting along with other major elements used in our model. The main findings and the sensitivity of our results to different demand levels and pricing schemes is displayed in the fourth section. The last part concludes on the optimal policy and advances future research considerations.

2. Model Formulation

The following section elaborates on the model that enables us to examine the redistribution of urban road space between different available transport modes. Given that ridesplitting services are central in our analysis, we start first by characterizing their foremost market properties. For simplicity, we assume a spatially homogeneous distribution of TNCs and passengers across the network. A single platform receives all requests, and its functionality is to arrange a proper vehicle-request match and dispatch but also to seize appropriate pooling opportunities when possible.

2.1 Supply

2.1.1 Supply in ridesourcing markets

Any online operating vehicle belonging to the ridesourcing fleet is in one of the following states: (i) idling and waiting to be assigned, (ii) dispatching and on its way to pick up a request, (iii) in-service and dropping off a passenger. Under steady-state conditions, the influence of fleet size on network speed is usually disregarded assuming that its effect is negligible. Nevertheless, empirical evidence and simulation studies proved otherwise. The absence of any driver entry restrictions implies no limitations on fleet size particularly in scenarios where no regulations are involved. Consequently, the effect of a marginal increase in feet size extends beyond a decrease in speed to impact the service level of ridesourcing platforms.

Let d be the dispatched distance from a request origin to the nearest idle vehicle. We know that $d = d(I)$ is a decreasing function of the number of idle vehicles I such that $d' = \partial d/\partial I < 0$. We denote by v the speed of the network where a monopoly platform provides its service. $v = v(n)$ is a decreasing function of the total network accumulation $n = n_{pv} + N$ such that $v' = \partial v/\partial n < 0$, n_{pv} and N being the accumulation of private vehicles and fleet size respectively. Considering a short-term framework where no modal shift is involved and without loss of generality, we assume that the number of private vehicles remains constant in the network and hence $\partial v/\partial n = \partial v/\partial N$. The total number of operating vehicles N is hence given by:

$$N = I + Q\frac{d}{v} + Q\frac{\bar{l}}{v} \tag{1}$$

Where each term represents the three different states introduced in the previous paragraph. Q is the trip supply per unit time and $\bar{l}$ is the average trip length. d/v is the waiting time w of a request before being picked up by a vehicle. Assuming that the supply level remains constant, the partial derivative of w with respect to N is the following:

$$\frac{\partial w}{\partial N} = -\frac{dv'}{v^2} + \frac{d'\left(v'Q\left(\bar{l} + d\right) + v^2\right)}{v^2(Qd' + v)} \tag{2}$$

The change in waiting time with respect to the fleet size is non-monotonous. Assuming that vehicles enter the road and become directly available for service, Figure 1(a) displays the variation of waiting time as function of fleet size for the same trip supply level. As fleet size increases, more vehicles become available for pick-up and hence the waiting time of requests decreases progressively. However, a very high number of TNCs not only reduces network speed but also interferes with the platform own level of service. The assumption that the accumulation of private vehicles remains constant lessens this interference as we expect the waiting time to deteriorate further if we account for the effect of fleet size on the accumulation of private vehicles.

Moreover, limitless provision of vehicles in the network does not infinitely increase supply levels. In fact, the number of trips carried out by ridesourcing platforms displays an envelope (Figure 1(b)). This is because when we consider the influence of fleet size on speed, the partial derivative of Q with respect to fleet size is given by:

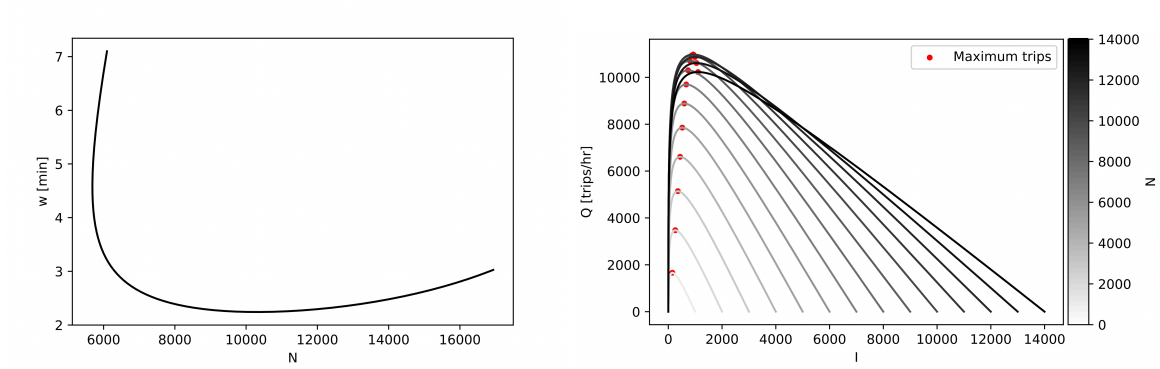
$$\frac{\partial Q}{\partial N} = \frac{v + v'(N - I)}{\bar{l} + d} \tag{3}$$

Eq.3 proves that when $v > v\ (N - I)$, system supply increases with fleet size. Conversely, this behavior changes when $v < v'(N - I)$. When $v = v'(N - I)$, the number of serviceable trips reaches a maximum beyond which supplying more vehicles affects the platform's own level of service. Again, the scenario presented here provides an upper bound on supply which will further decrease if the accumulation of other modes is accounted for. This interaction will be considered however in the remaining sections of this work.

2.1.2 Supply in ridesplitting markets

The formulation of supply in the existence of pooling must account for additional states [12]. Vehicles are either dispatched to perform a solo trip s or a pooled trip p. The main difference lies in the fact that half as many vehicles are required to perform a pooled trip. This is achieved however at the expense of an additional detour distance incurred as drivers are expected to change their routes for this purpose. If Q^s and Q^p are trip request rates for solo and pooled rides respectively, and Δl_d is the driver detour, then the number of TNCs under steady-state conditions is given by:

Figure 1: (a) Variation of waiting time with fleet size, (b) Variation of supply with fleet size



$$N = I + \left(Q^s + \frac{1}{2}Q^p\right)\frac{d}{v} + Q^s\frac{\bar{l}}{v} + \frac{1}{2}Q^p\left(\frac{\bar{l} + \Delta l_d}{v}\right) \quad (4)$$

Compared to Eq.1, the four terms in Eq.4 represent vehicles that are: (i) idling, (ii) dispatching, (iii) occupied with one passenger, and (iv) occupied with at least one passenger. Clearly, ridesplitting market has the ability to serve more trips with the same fleet size compared to ridesourcing one. Nevertheless, the detour distance is a crucial factor in determining the potential and efficiency of pooling. A proper investigation of the different interactions between Δl_d and trip service level is hence required.

2.2 Demand in ridesplitting markets

We start first by assuming that all commuters in the network perform their trips by one of the available modes: private vehicles pv, bus b, solo e-hailing rides s, and pooled e-hailing rides p such that $M = \{pv, b, s, p\}$. We restrict the mode choice however between solo and pooled rides as the purpose of this study is not to evaluate long-term interactions between available modes but to induce a short-term behavioral shift among e-hailing users that potentially benefits all network users.

Let F^s and F^p be the average trip fare for solo and pooled rides, β_1 and β_2 the monetary value of time for the direct and detour trip portion respectively, Δl_p the average passenger detour distance. We denote by C^m the generalized cost of mode m, $m \in M_e = \{s, p\}$ and $M_e \subset M$, the cost expression C^s and C^p are given by:

$$C^s = F^s + \beta_1\frac{\bar{l}}{v} \quad (5)$$

$$C^p = F^p + \beta_1\frac{\bar{l}}{v} + \beta_2\frac{\Delta l_p}{v} \quad (6)$$

Using a binary logit model, we can estimate the fraction of passengers willing to share their rides f^p as follows:

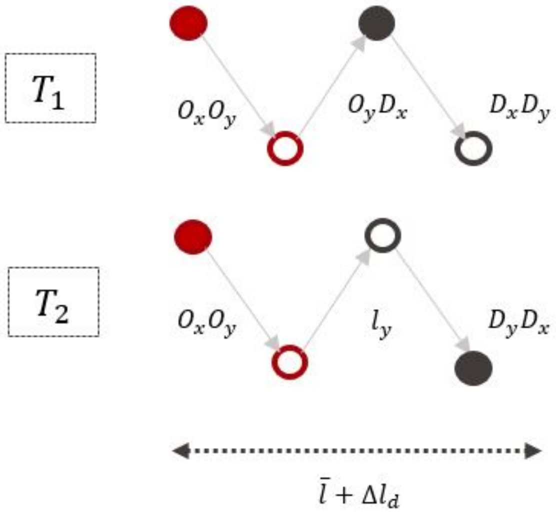
$$f^p = \frac{\exp(-\kappa C^p)}{\exp(-\kappa C^p) + \exp(-\kappa C^s)} \quad (7)$$

Where κ is the scale parameter which is usually an exogenous constant inferred from the characteristics of the population under consideration. Notice that the waiting time is dropped from the equations of the generalized cost. Even if this average waiting time of pooled passengers is larger than that of solo riders, this difference is neglected for reasons that we expand on in the next section.

2.3 Detour distance in ridesplitting platforms

Before elaborating on the different factors influencing driver and passenger detour distances, we start by concisely delineating what both terms stand for. We call passenger detour the additional distance traveled by users due to the pick-up or the drop-off of another passenger. Similarly, we refer to driver detour the difference between the total pooled trip length and the average direct OD trip of the passengers involved in pooling. Generally, high detour distances impair pooling and prevent the operator from deriving benefits from such systems. The following section resorts to simulated data to analyze specific cases where pooling benefits are more tangible.

Figure 2: Different pooled trip combinations



For this purpose, we use the set of taxi trips generated from real data in the Chinese city of Shenzhen to simulate the set of pooling requests that arrives to the platform [8]. In the scenario where two requests are allowed to share their rides, enumeration of the possible trip combinations is straightforward. If x and y are the first and second passengers to be picked up with origin nodes O_X and O_Y, and destination nodes D_X and D_Y, and l_Y is the distance O_YD_Y, then the resulting trip possibilities include but are not limited to T_1 and T_2 (Figure 2). The possibilities are in fact much larger in dynamic ridesplitting [14] but we limit our analysis to the static case. Given that the platform's objective is to minimize the total distance traveled by drivers performing a pooled trip and assuming that n_{pas} is the set of passengers willing to share their rides, we formulate the linear assignment problem as follows:

$$\min_z \quad \sum_i \sum_j c_{ij}\, z_{ij} \tag{8a}$$

$$s.t. \quad \sum_k (z_{ik} + z_{ki}) = 1 \qquad \forall i \in n_{pas} \tag{8b}$$

$$z \in \{0,\ 1\} \tag{8c}$$

$$Where\ c_{ij} = \begin{cases} min\left(O_iO_j + O_jD_i + D_iD_j, O_iO_j + l_j + D_jD_i\right) & i \neq j \\ \infty & i = j \end{cases} \tag{9}$$

Eq.8a summarizes the platform's objective to minimize the total traveled distance of pooled trips. c_{ij} is the total distance traveled by drivers in case they picked up passenger i before j. It is chosen to be the minimum over the two possible trips T_1 and T_2 as shown by Eq.9. z_{ij} is a binary variable indicating whether passenger i is matched to passenger j and picked up before i. To make sure all requests in a pooling batch are assigned to another request, we set c_{ij} to infinity when $i = j$. Eq.8b ensures that every request is matched exactly once to another request in the pooling set and Eq.8c constrains z to be a binary variable. We note that we do not include any constraint with regard to the maximum allowable detour as our goal is to capture the demand intensity for which pooling becomes attractive. In other words, when the detour distance is extremely high, requests automatically opt for solo trips.

Figure 3: (a) Driver detour ratio, (b) Passenger detour ratio

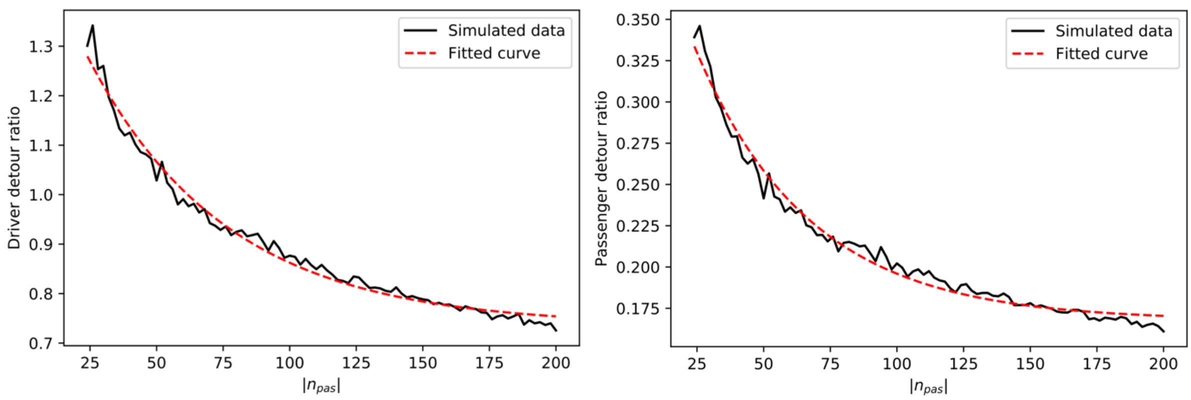


Figure 3 shows the ratio of the average passenger and driver detour divided by the mean trip length as functions of the batch size of pooling passengers. The batch size $|n_{pas}|$ is a proxy for pool demand intensity and time during which platform accumulates requests before running a pool matching algorithm. Evidently, as more and more passengers are willing to share their rides, the efficiency of pooled trips increases, namely because of savings in driver traveled distances and reduction in passenger detours. For very low batch size, pooling is unattractive as no distance savings are expected and an excessive passenger detour is unavoidable. The empirical fitted curves that we derive from the previous results provide aggregate relationships between passenger detour, driver detour, and pooled demand intensity that are useful for the remaining of our work. In instances where the pooling demand is suppressed, a different fit is used to better predict the results when $|n_{pas}|$ approaches zero. Overall, these relationships provide insight on how incentivizing trip sharing through optimal space allocation policies reciprocally induces higher pooled trips.

2.4 Aggregate traffic flow for mutli-network approach

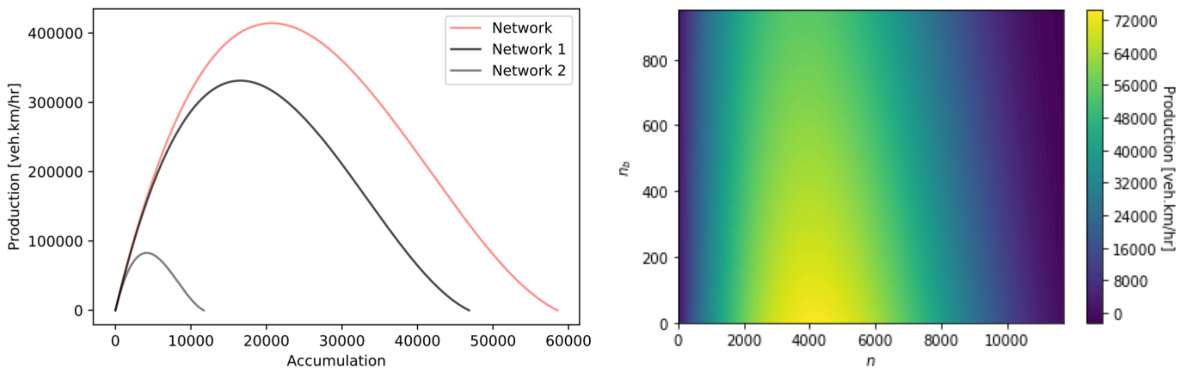
In the model we presented, the space-mean speed is a crucial element to evaluate the average trip time for solo and pooled trips. To estimate its value, we resort to aggregate traffic flow models using a production function P where $P(n) = vn$. Defining a production MFD *a priori* for the total network makes it possible to compute speed if accumulation values are known.

In order to incentivize passengers to share their rides, regulators might decide to allow pooled vehicles to use dedicated bus lanes where speed is expected to be higher than the remaining part of the network. We define $1 - \alpha$ to initially be the fraction of the network exclusively dedicated to buses that we denote by network 2. When the proposed incentive is implemented, the space usage becomes as follows:

- Network 1: Fraction of the total network space utilized by: (i) private vehicles, (ii) idle TNCs, (iii) dispatched TNCs, and (iv) solo rides.
- Network 2: Space of the total network utilized by buses and pooled rides.

For the purpose of this study, we use the 3D-MFD obtained by [15]. Figure 4(a) shows the production MFDs for a given network as well as that of the two resulting subnetworks when $\alpha = 0.8$. Clearly, the shape of the two functions changes with α. Moreover, the production function for network 2 is reflective of scenarios with no buses. To compute vehicle speed in the existence of buses, an adjustment is introduced to take into account the fact that buses make frequent stops that possibly hinder vehicle movements [15, 16, 17]. Figure 4(b) shows these interactions using a 3D-vMFD where vehicle production decreases in the presence of buses.

Figure 4: (a) Production MFD, (b) 3D-vMFD



2.5 Network model for ridesplitting markets

If Q^{pv}, Q^{b}, and Q^{rs} are the total demand for private vehicles, buses, and e-hailing rides respectively, we consider that demand is inelastic in the short-run. The available choice is hence whether e-hailing users opt for solo or pooled trips. The main factors dictating this choice are speeds in network 1 and 2. The accumulation in both networks is dependent on the fraction of pooling versus non pooling passengers as TNCs make different use of space depending on the type of trip they are assigned to. For a given α, the stationary state requires solving a system of non-linear equations defined by Eq.10. We refer to speed in network 1 and 2 by $v_1 = v_1(n_1,\alpha)$ and $v_2 = v_2(n_2,n_b,\alpha)$ respectively, where n_1, n_2, and n_b are the accumulation in network 1 and 2 and the number of operating buses. Their values are dependent on the demand for solo and pooled rides which implicitly influences private vehicle accumulation. Concurrently, the choice of whether to pool or not is a direct outcome of the two network speeds but also of the detour distance. A high number of pooling trips entails a small passenger and driver detour, but a lower speed in network 2 which itself influences the choice for pooling.

$$n_1 = I + \left(Q^s + \frac{1}{2}Q^p\right)\frac{d}{v_1} + Q^{pv}\frac{\bar{l}}{v_1} + Q^s\left(\frac{\bar{l}}{v_1}\right) \tag{20a}$$

$$n_2 = \frac{1}{2}Q^p\left(\frac{\bar{l} + \Delta l_d(Q^p)}{v_2}\right) \tag{30b}$$

$$I = d^{-1}(\tau \cdot v_1) \tag{10c}$$

$$C^s = F^s + \beta_1\frac{\bar{l}}{v_1} \tag{10d}$$

$$C^p = F^p + \beta_1\frac{\bar{l}}{v_2} + \beta_2\frac{\Delta l_p(Q^p)}{v_2} \tag{10e}$$

$$Q^p = Q^{rs}f^p \tag{10f}$$

Eq.10a and 10b compute the vehicle accumulation in network 1 and 2 respectively. They take into account exclusive usage of space as defined by the suggested policy. The average trip length $\bar{l}$ for private vehicles and solo trips is presumably similar. Defining τ to be the target waiting time that e-hailing platform wants to sustain to guarantee a certain level of service, Eq.10c returns the number of idle vehicles required to maintain τ. The inclusion of idling and dispatched vehicles in our model is crucial given that their influence on network speed is sometimes detrimental. Eq.10d and 10e summarize the modifications introduced to the generalized cost functions such that users who opt for pooling travels for a distance $\bar{l} + \Delta l_p$ with a speed v_2 compared to solo users who travel for a distance $\bar{l}$ with a speed v_1. Note that cases where $\bar{l}/v_1 \geq (\bar{l} + \Delta l_p(Q^p))/v_2$ are possible using the previous formulation. Consequently, the rationale behind having different βs in this case is to ensure that the sharing inconvenience is still accounted for in the model. Moreover, we do not include the waiting time in the generalized cost because on one hand, when the demand for pooling is high, origins of passengers are very close such that the additional waiting time incurred by the second passenger is minimal. On the other hand, when the pooling demand intensity is low, having a high detour ratio is sufficient to reinforce solo ride as a more favorable option. Finally, Eq.10f gives the demand for solo and pooled rides based on a binary logit choice model.

2.6 Optimal allocation policy

In this part, we elaborate on the optimal space allocation ratio under the suggested policy. The objective is to determine the network fraction split that minimizes the total Passenger Hours Travelled (PHT) for all network users. Because possible delays for bus users are accounted for in the objective function, it is necessary to provide assumptions on the number and speed of buses n_b and v_b. Assuming that public transport operators aim to maintain an average occupancy $\bar{o}$ at any point in time, then the number of operating buses is given by:

$$n_b = \frac{Q_b \overline{l_b}}{\bar{o}\overline{v_b}} \tag{11}$$

Where $\overline{l_b}$ is the average trip length of bus users usually greater than $\bar{l}$ and $\overline{v_b}$ is the average bus speed. The actual speed however is retrieved from the 3D-vMFD that we elaborated on in the previous section. It is equal to the speed of vehicles in network 2 but should be reduced to consider the additional dwell time of buses at different stops in the network. If the average spacing between successive bus stops is $\bar{s}$ and t_d is the dwell time at stops, then the speed of bus is $v_b = \gamma(v_2)$ such that γ is computed using the following equation:

$$\gamma(v_2) = \frac{1}{1 + v_2 \frac{t_d}{\bar{s}}} \tag{12}$$

Because v_2 is itself function of α, n_2, and n_b, this entails that the value of speed is dependent on these three variables such that $v_b = v_b(n_2, n_b, \alpha)$. Eq.13 below summarizes the objective of the regulator to minimize delays for all network users by modifying the space share α given to network 1.

$$\min_{\alpha} \quad PHT(\alpha) = Q^{pv} \frac{\bar{l}}{v_1} + Q^s \frac{\bar{l}}{v_1} + Q^p \left(\frac{\bar{l} + \Delta l_p(Q^p)}{v_2} \right) + Q^b \frac{\bar{l}_b}{v_b} \tag{13}$$

Each term in Eq.13 computes the PHT for different modes by taking into account the appropriate speed, demand levels, and traveled distance as defined by Eq.10. This ensures that (i) demand split between solo and pooled rides is computed according to users' choice, (ii) speed in every network is the result of the sharing fraction and of the fleet size, and (iii) the passenger detour time is decreasing with demand intensity but increasing with speed.

The bus demand and subsequently the number of operating buses in the network is an exogenous variable. The speed of buses however is a direct outcome of the number of vehicles in network 2 and the value of α. Therefore, although Q^b is inelastic, it influences the speed in network 2 which is a major element in determining the total PHT of bus users in the objective function.

To examine the usefulness of the proposed allocation policy, we define a benchmark scenario where dedicated lanes are exclusively used by buses and the remainder of the network is jointly utilized by private vehicles and TNCs. For this purpose, Eq.10 and 13 are modified where v_2 is replaced by v_1 and n_2 is now embedded in n_1. We note that solving Eq.10 for some values of α returns solutions in the hypercongested regime. We will however limit our analysis to solutions located in the uncongested regime.

3. Results

3.1 Performance of allocation strategy

In this section, we resort to a numerical example to elucidate how the main variables of our model change under the proposed network allocation strategy where pool passengers are allowed to use dedicated bus lanes (dbl). We refer to this scenario as dbl + pool, and to benchmark one as dbl. Table 1 displays the values of parameters used to generate the results.

With regard to the dispatched distance, we compute it based on closest vehicle assignment such that $d(I) = 0.63\sqrt{A/I}$ where A is the network area [18]. The production-MFD function follows a third degree polynomial where the critical accumulation of the whole network is 20690 veh, the jam accumulation is 58540 veh, and the free flow speed is equal to 40 km/hr. The passenger and driver detour ratios are computed according to the graph generated from empirical data in the previous section. In order to provide a map from Q^p to $|n_{pas}|$, we define a batching time window w_b which is the period during which platforms await pooling requests to accumulate before performing a pool matching round.

Table 1: Default parameter values for numerical example

Parameter		Value	Unit
Value of time for direct trips	β_1	30	\$/hr
Value of time for detour	β_2	40	\$/hr
Solo ride fare	F^s	6	\$
Pooling ride fare	F^p	5.1	\$
Average vehicle trip length	$\bar{l}$	3.86	km
Average bus trip length	$\overline{l_b}$	5.4	km
Demand for private vehicles	Q^{pv}	64000	pax/hr
Demand for buses	Q^b	20000	pax/hr
Demand for e-hailing	Q^{rs}	16000	pax/hr
Average spacing between bus stops	$\bar{s}$	0.6	km
Dwell time	t_d	30	sec
Average bus speed	$\overline{v_b}$	18	km/hr
Batching time window	w_b	60	sec
Binary logit scale parameter	κ	1	-
Platform target waiting time	τ	2	min
Network area	A	107	km^2

Figure 5: (a) Variation of PHT with $1 - \alpha$, (b) Variation of accumulation and fleet size with $1 - \alpha$

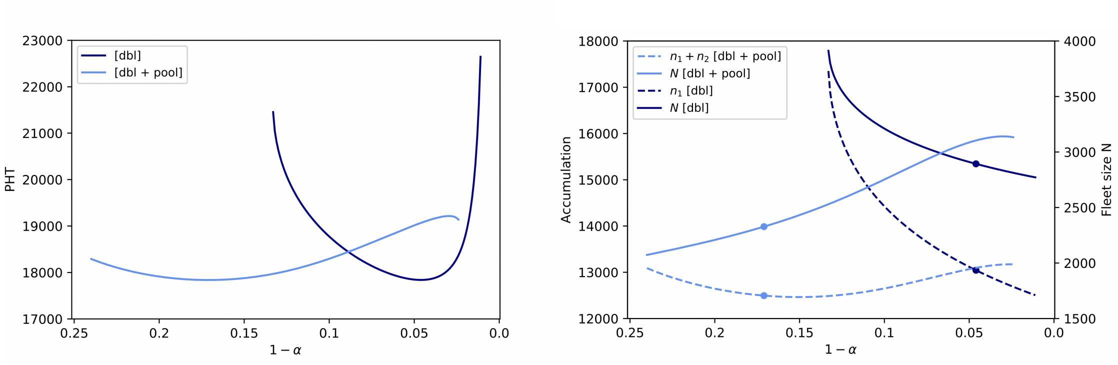


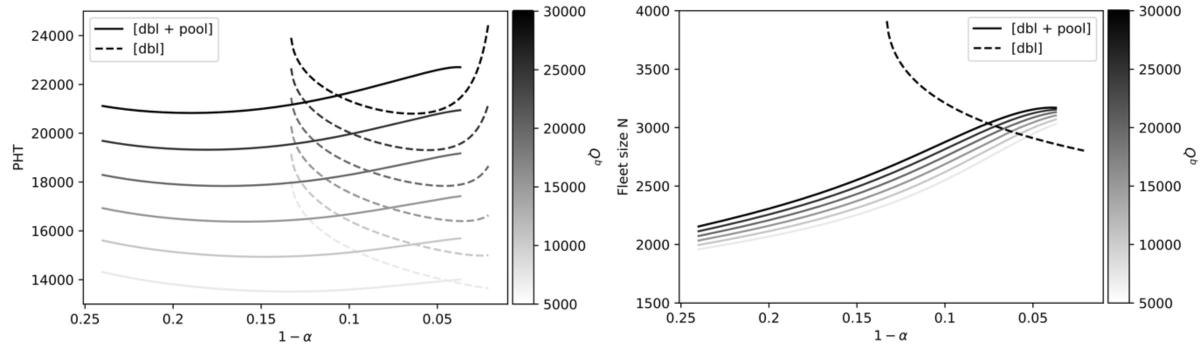
Figure 5 displays the PHT along with the fleet size and total network accumulation for the dbl + pool and dbl scenario with the point that minimizes PHT occurring for α^* equal to 0.829 and 0.954 respectively. The values of PHT at these two points are approximately the same. Because the individual PHTs of bus and private vehicle users constitute a significant fraction of the total PHT, we particularly investigate their variations with α. In the two scenarios presented, the PHT of private vehicle users achieves its maximum for the lowest α over which the solution is defined. Contrarily, bus PHT is worst when the space attributed to network 2 is the lowest. The values of PHT in between the two extrema are additionally dictated by the interaction with TNCs. As α increases in the dbl + pool case, Q^s increases as well up to a point where the influence of solo TNCs on v_1 overrides the network capacity increase. For the dbl case, the decrease in fleet size and private vehicle accumulation is a dominant factor up until the dbl optimum. Beyond this point, the operation of buses is significantly impaired.

However, discrepancies exist when we look at the accumulation and the fleet size at the two optimal points. In the dbl + pool case, given the attractiveness of pooling for low values of α, a significant portion of the fleet size is using network 2. Because pooled trips require less vehicles to serve them, the fleet size is lower in dbl + pool in spite of the fact that (i) more vehicles are needed to serve solo trips since the speed in network 1 is reduced for relatively small α, and (ii) a large value of Q^p reduces detour distance but further disrupts flow in network 2. In the dbl case, Q^p and Q^s vary much less with α given that no privilege is involved. Pooling becomes more attractive of an option when travel time in the only available network space is reduced and the additional detour time incurred becomes more tolerable.

3.2 Influence of bus demand on solution

The concurrent use of space by TNCs and buses in network 2 causes inevitable delays for both modes. The proposed policy compensates for this delay by allocating a larger space for network 2. Nevertheless, since buses carry more passengers compared to pooled trips, the marginal increase of PHT with n_2 is more consequential for buses than for the fraction of TNCs already utilizing network 2. It is necessary hence to investigate the demand levels for buses up to which our policy continues to be beneficial when compared to the benchmark scenario. Figure 6(a) shows that for a given bus demand, the value of dbl + pool minimum PHT continues to be approximately equal to that of dbl, with the latter being slightly higher than the former when bus demand is large enough. Despite this, fleet size at optimum is always lower in the dbl + pool scenario regardless of the bus demand indicating that platform operators are always motivated to reduce fleet size under our policy (Figure 6(b)).

Figure 6: (a) Variation of PHT with $1-\alpha$, (b) Variation of fleet size with $1-\alpha$ for various bus demand levels



3.3 Influence of price discount on solution

Besides travel time, the pooling discount factor is a major determinant of users' choice to share their rides. Since the intervention of the regulator is restricted to changing α, we assess in this part how optimal values of α vary with the pooling discount factor set by the platform operator. On one hand, a low discount factor implies a larger Q^p, and a lower α^* and N. A high discount factor on the other hand means that the platform is not encouraging sharing. In this case, both α^* and N increase, and the benefits derived from policy enactment are limited (Figure 7). This is anticipated because, provided that the operator is a revenue maximizer, the objectives of the two stakeholders do not necessarily collide.

To better understand variations of the objective function away from optimal points for various discount factors, we look at the PHT values for every available mode $m \in M$ (Figure 8). Of a particular interest is the PHT for pooled rides which monotonically decreases with α for high a discount factor (and hence a low discount) as more users shift to solo rides. Nevertheless, for low discount factors, PHT rises at the beginning despite the reduction in network 2 capacity as some users continue to share their rides given the price gap between solo and pool trips. For $\alpha > 0.86$ and a discount factor of 0.5, the PHT of pool decreases again as travel time on network 2 notably grows. Q^p does not completely vanish however for low discount factors and hence disturbances to bus operations remain significant. This is due to a small fraction of demand that continues to pool albeit the deterioration of speed and the high detour distance in network 2.

3.4 Influence of target time on solution

Lastly, we considered in our model that the target waiting time is an exogenous variable that e-hailing platforms aim to guarantee. Here, we assess how α^* and PHT change with τ. A lengthy waiting time replicates the case of an inefficient service where the number of dispatching vehicles is very high which leads to a speed deterioration in network 1. A low value of τ explores solutions in the efficient regime where the dispatched distance is small and hence the fleet size necessary to serve a given demand level decreases (Figure 9(b)). A moderately low waiting time is also beneficial to the entire network because it decreases PHT as shown in Figure 9(a).

Figure 7: (a) Variation of PHT with $1-\alpha$, (b) Variation of fleet size with $1-\alpha$ for various pooling discount factor

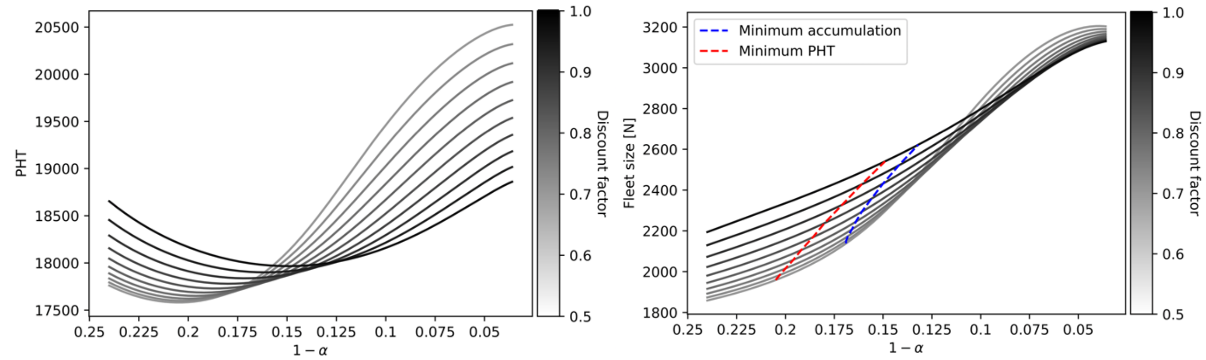


Figure 8: PHT for different modes with various pooling discount factor

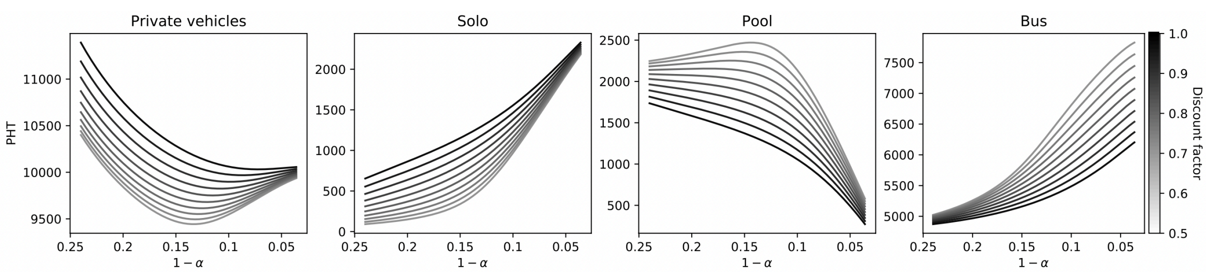
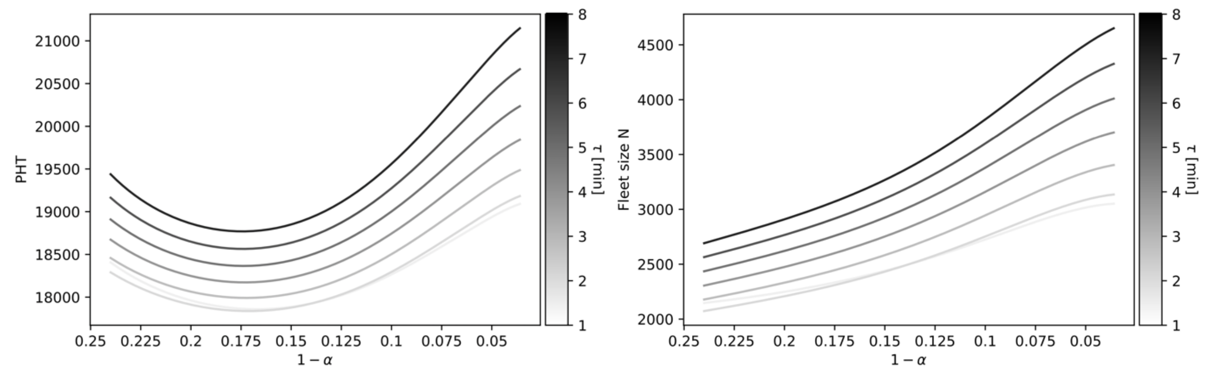


Figure 9: (a) Variation of PHT with $1-\alpha$, (b) Variation of fleet size with $1-\alpha$ for various target waiting time



4. Conclusion

This paper proposed a network allocation policy that encourages trip sharing in e-hailing markets by promising pool users of - on top of trip fare monetary discount - a privileged use of dedicated space where travel time is lower than the rest of the network. By considering overall delays of all commuters for different modes, results show that assigning a larger space to dedicated bus lanes and pool vehicles guarantees a lower PHT for scenarios where bus demands are not too large. It also incentivizes TNCs to reduce the fleet of vehicles because of an increase in the number of pooled trips.

F^{s}, F^{p}, and subsequently τ and Q^{rs} are all variables that, when subject to no regulations, are freely controlled by e-hailing platforms. These platforms will set the fare and provide a fleet size that maximizes their own revenues. Future research directions include integrating the objective of platform operators when investigating the optimal network split ratio, and to provide an optimal solution with a more comprehensive choice model that includes all modes.

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