A path to take passengers from single to shared rides: a study on ridesplitting

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February 2020

Abstract

In the scenario of expanding ride-sourcing, ridesplitting still struggles to attract customers for everyday rides. However, most studies disregard passengers' willingness to hire ridesplitting while evaluating the service potential. Hence, we propose a simulation study to evaluate the impacts of willingness to share on driver availability and trip measurements, such as traveled times and distances. The investigation considered a simulated urban network based on data from Shenzhen, China. Results indicate that higher willingness to share increases the number of available drivers, whereas increases trip characteristics variability. In summary, reducing relative variability is a path to attract more passengers for ridesplitting services.

Keywords: Ride-sourcing; On-demand transportation; Simulation.

1 Introduction

Companies use mobile applications connected through the internet to match drivers to source rides. Due to the nature of their operations, these companies may be called Transportation Network Companies (TNCs), but the service itself might be called ride-sourcing (and other names in the literature), for instance [1]. Convenience, door-to-door rides, and low fares are some advantages of these services. Nowadays, the most notorious TNCs in the U.S. are Uber and Lyft, but many others operate around the globe as 99 (Brazil), Cabify (Spain, Portugal, and Latin America), DiDi (China), Ola (India).

Such transportation services operating in an on-demand framework sound promising to improve urban mobility and fight car ownership. Many TNCs offer, among the service options, shared rides (called ridesplitting), trying to match passengers in a single trip. 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 with door-to-door rides and no need to search for parking. In general, these services seem to have a positive impact on economic efficiency [2].

Due to the internet-based operations of TNCs, there are concerns over issues of data privacy and security [2]. Rogers [3] adds other social costs, such as diminished safety and lack of professional training. Several other concerns arise over ride-sourcing services, regarding their pricing policy [4, 5], and competition issues with taxis (and public transit) [1, 6, 7, 8]. Although appealing topics, they are outside the scope of this paper.

There has been a great effort to evaluate the benefits of ridesplitting. Santi et al. [9] used taxi data from New York to show the potential benefits of shared rides using shareability networks. Alonso-Mora et al. [4] improved the use of shareability networks to allow on-line vehicle-passenger matching. Martinez et al. [10] used an agent-based simulation to show potential fare and time savings for passengers without compromising driver revenues in Lisbon. Stiglic et al. [11] shows how ride-sharing services may benefit from drivers and passengers with higher flexibility in terms of departure time and detour allowance. One must acknowledge the efforts in improving taxis dispatching [12, 13, 14], and in modeling shared taxis [15, 16]. Other efforts aim ride-sharing systems [17, 18, 19, 20], pickup and delivery problems [21, 22], and, more specifically, dial-a-ride problems [23, 24, 25].

However, most of these studies disregard passengers' willingness to hire these shared rides. Li et al. [26], for instance, found that only 6-7% of travelers hired ridesplitting services, and 90% of them consist of rides shared by two passengers, at most. The remaining of the travelers preferred to ride alone. Some of the reasons pointed out as causes for the low adoption of ridesplitting services are travel time reliability and deviations/detours. Ridesplitting passengers would require considerable extra time to ensure on-time arrivals at destinations. Detours made passengers face longer travel times and lower speeds than ride-hailing options. Hence, although the potential of ridesplitting (and its peers) is high, passengers are reluctant to hire such service, compromising the envisioned benefits.

In face of such antitheses, how passengers' willingness to share poses as an obstacle to ridesplitting? To answer this question, we propose a simulation study to evaluate the impacts of willingness to share on driver availability and trip measurements, such as traveled times and distances. The investigation considered a simulated urban network based on Shenzhen, China. The traffic accounts for private vehicles and ride-sourcing vehicles. Computation of traveling speeds used a Macroscopic Fundamental Diagram (MFD) for the network [27].

This paper is structured as follows. Section 2 describes the simulation, its entities, and their interactions. Section 3 presents the key findings for this study. Finally, Section 4 shows some closing remarks and directions for further research.

2 Simulation Description

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, as shown in Table 1.

Private Vehicles may enter and leave the system. Waiting Passengers are the entities that were not served yet by a ride-sourcing vehicle. They can hire either ridesplitting or ride-hailing services. Once inside the vehicle, waiting passengers become traveling passengers.

The central entity of the simulation is the ride-sourcing vehicle, which is responsible for

Table 1: Nomenclature of tuple elements for each entity.

Entity	Notation	Description
PV	i	Identification
	at_i^{pv}	Arrival time
	o_i^{pv}	Origin
	d_i^{pv}	Destination
	rd_i^{pv}	Remaining distance
WP	j	Identification
	at_j^{wp}	Arrival time
	o_j^{wp}	Origin
	d_j^{wp}	Destination
	wts_j^{wp}	Willingness to share
	dr_j^{wp}	Assigned driver ID
TP	j	Identification
	pt_j^{tp}	Pick-up time
	o_j^{tp}	Origin
	d_j^{tp}	Destination
	wts_j^{tp}	Willingness to share
	dr_j^{tp}	Assigned driver ID
	dt_j^{tp}	Distance traveled
RSV	k	Identification
	l_k^{RSV}	Last known location
	cd_k^{RSV}	Current destination
	rd_k^{RSV}	Remaining distance to the current destination
	np_k^{RSV}	Number of passengers inside the vehicle
	p_k^{RSV}	ID of assigned passengers

picking-up and delivering passengers according to their preferences. They also may assume different states depending on their current activity (Fig. 1A).

A Macroscopic Fundamental Diagram (MFD) represents the traffic congestion and computes the average speeds in the network as a function of the accumulation of private vehicles and ride-sourcing vehicles. The MFD used on Shenzhen is an approximation based on the free-flow speeds obtained in Ji et al. [28], and the MFD for Yokohama, Japan, found in Geroliminis and Daganzo [27]. We assumed that congestion is homogeneous in the region. Eq. [1] shows the accumulation-speed relationship.

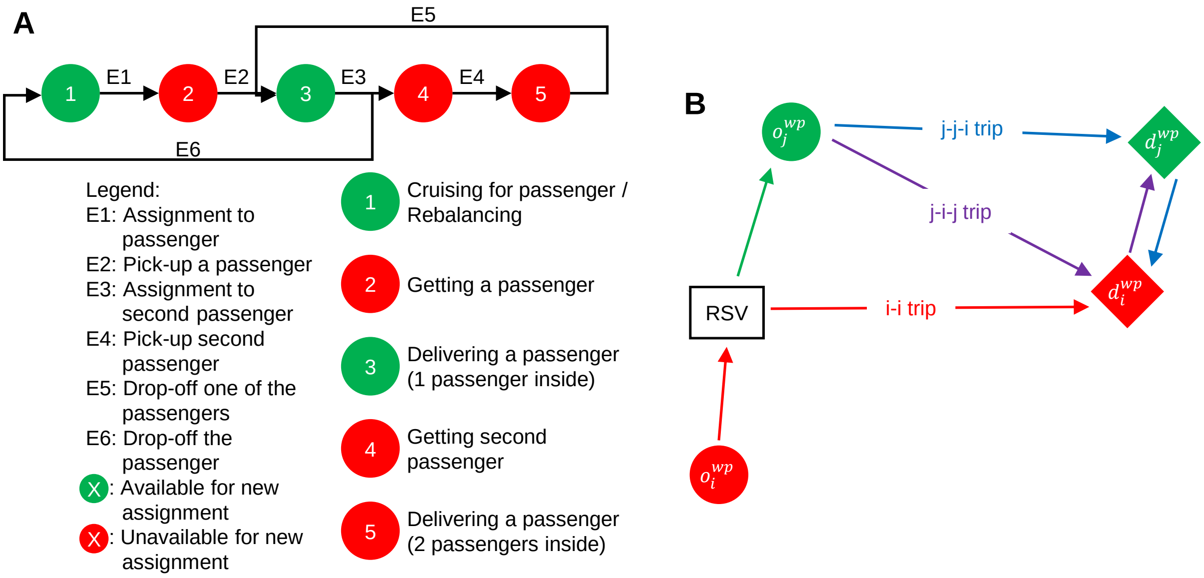

Figure 1: (A) RSV activity flow framework. (B) E-hailing and ridesplitting trip scheme. The 'i-i' trip refers to an e-hailing trip from o_i^{tp} to d_i^{tp}. The 'jji' trip refers to a ridesplitting trip that will deliver passenger j first, and then passenger i. The 'j-i-j' trip refers to a ridesplitting trip that will deliver passenger i, and then passenger j.

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

Ride-sourcing vehicles perform different activities. Fig. 1A shows how they change their states during the simulation according to the activities they perform. Their routes follow the shortest path (Floyd-Warshall algorithm). When evaluating a ridesplitting match (a vehicle with one passenger matches with a second passenger), two types of trip schemes arise. Fig. 1B illustrates both types of trips ('j-i-j' and 'j-j-i' trips) and direct route ('i-i' trip).

Matching waiting passengers and ride-sourcing vehicles requires a few conditions fulfilled. Waiting passengers cannot wait more than 1 minute for an assignment. The ride-sourcing vehicle must be less than 10 minutes far from the passenger (Δ) at the moment of the assignment. If a passenger cannot find a driver, it will then drive a private vehicle (in this way, the total number of completed passenger trips is the same across all simulations). Finally, the closest ride-sourcing vehicle that fulfills all requirements is assigned to the passenger. Note that we do not claim that this is an optimized assignment process.

Performing ridesplitting must fulfill other conditions. Firstly, both passengers must be willing to share their rides. Secondly, the waiting time conditions to match a waiting passenger apply (Eq. [2]). In the 'j-i-j' trip from Fig. 1B, it is not allowed to add more than maximum relative detour (Ω) to the traveling passenger's trip distance. Thus, the detour of picking-up the waiting passenger 'j' must be acceptable for the traveling passenger 'i' (Eq. [3]); the same applies to passenger 'j' (Eq. [4]). Finally, for the other pick-drop sequence ('j-j-i' trip in Fig. 1B), the detour of picking-up and delivering passenger 'j' must be acceptable for passenger 'i' (Eq. [5]). Note that, in this sequence, there is no detour for passenger 'j'. The simulation considers the distance between two points ($p(\cdot,\cdot)$), the distance traveled by a traveling passenger ($td(\cdot)$), and current speed ($v(t_{clock})$) to compute the conditions of Eqs. [2–5]. If both ridesplitting trips ('j-i-j' and 'j-j-i') are possible, the simulation always chooses the shortest one.

$$p(l_k^{RSV}, o_j^{wp}) \leq v(t_{clock}) \cdot \Delta \tag{2}$$

$$td(i) + p(l_k^{RSV}, o_j^{wp}) + p(o_j^{wp}, d_i^{tp}) \leq p(o_i^{tp}, d_i^{tp}) \cdot (1+\Omega) \tag{3}$$

$$p(o_j^{wp}, d_i^{tp}) + p(d_i^{tp}, d_j^{wp}) \leq p(o_j^{wp}, d_j^{wp}) \cdot (1+\Omega) \tag{4}$$

$$td(i) + p(l_k^{RSV}, o_j^{wp}) + p(o_j^{wp}, d_j^{wp}) + p(d_j^{wp}, d_i^{tp}) \leq p(o_i^{tp}, d_i^{tp}) \cdot (1+\Omega) \tag{5}$$

3 Computational Results

In this section, we present results of our simulations evaluating various willingness to share (from 0% to 90% every 30%), and different maximum detours (20% and 50% for relative detours and 1.5km and 6km for absolute detours) at a fixed operating fleet for ride-sourcing service. The analyses comprise the accessibility of ridesplitting and ride-sourcing services and trip characteristics.

Experiments used a simulated network based on Shenzhen's central area. The data comprises most of the Futian and the Luohu Districts in Shenzhen, the location of the Central Business District. Shenzhen is immediately north of Hong Kong, in the southern province of Guangdong. Due to a fast growth period, the population was close to 11 million in 2014 [28].

Fig. 2 compares the number of available vehicles for ride-hailing (single trips) and ridesplitting (shared trips) services under different willingness to share. Note that fewer vehicles are available to ride-hailing than ridesplitting. Some compelling results raise when willingness to share is 90%. Approximately, one-third of the fleet is available for ridesplitting at the peak-hour. The benefits extend to ride-hailing as well, making vehicles available at the peak-hour.

One of the complaints raised in Li et al. [26] for passengers' refusal to hire ridesplitting is travel time reliability. Most of the literature evaluating ride-sourcing services considers maximum detours in minutes [4, 9, 10], usually. However, we can observe in Fig. 3 how the trip characteristics change for different maximum detours. Indeed, traveled distances and times experience higher variability when more passengers hire ridesplitting services for both methods of maximum detour computation. In the case that the TNC wants to increase the chances of matching ridesplitting passengers through enlarging detours, variability is increased.

On the other hand, the column on the left-hand side of Fig. 4 reveals that the methods for computing maximum detours have a low impact on the chances of matching. However, short trips experience longer detours than themselves, for cases with fixed maximum detours. Thus, the detour policy is more significant than the willingness-to-share to determine the deviation

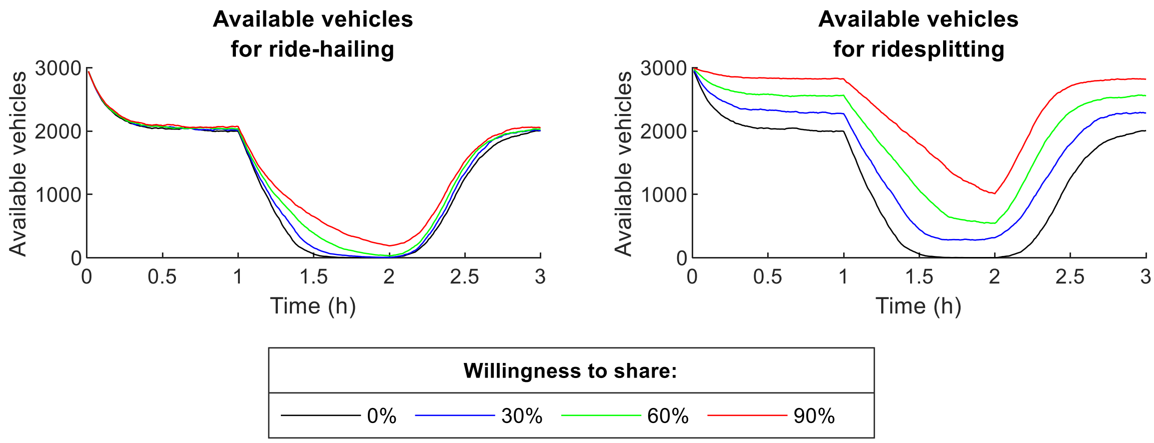

Figure 2: Timely vehicle availability for ride-sourcing services under different willingness to share.

from a passenger's original path. In general, the moment users' willingness to share rises, it also becomes easier to match them, increasing matching 'efficiency' (in terms of the fraction of matches from the pool of passengers). In this direction, the higher 'efficiency' may compensate the possible issues from limiting detours (to improve travel time reliability).

Previous results indicate that a change in the maximum detour computation during the matching process might be influential in improving travel time reliability while maintaining the number of matched trips. Recall that the matching algorithm searches for the closest available vehicle, and, thus, is not an optimization algorithm *per se* aiming to maximize the number of matched trips nor minimize traveled distances.

4 Final Considerations

Ridesplitting shows the potential to improve urban mobility but struggles to convince users to adopt it for their daily activities. In this scenario, we investigated how passengers' attitude towards such service poses a challenge to obtain the envisioned benefits. The paper aimed to evaluate the impacts of willingness to share on driver availability and trip measurements, such as traveled times and distances. The investigation considered a simulated urban network based on data from Shenzhen, China. Four entities compose the simulation. Their interactions replicate those from a ride-sourcing service that allows for ridesplitting within a congested network with private vehicles.

Our results indicate that, on the one hand, a higher willingness to share increases the number of available drivers for ride-sourcing services, in general. On the other hand, it may increase trip characteristics variability. One could point a trade-off between limiting detours (which decreases relative variation on traveled distances) and maximizing matching 'efficiency'. However, 'efficiency' does not drop as considerably as variability (in relative terms), suggesting that TNCs may try to improve travel time reliability as a path to attract more passengers for ridesplitting

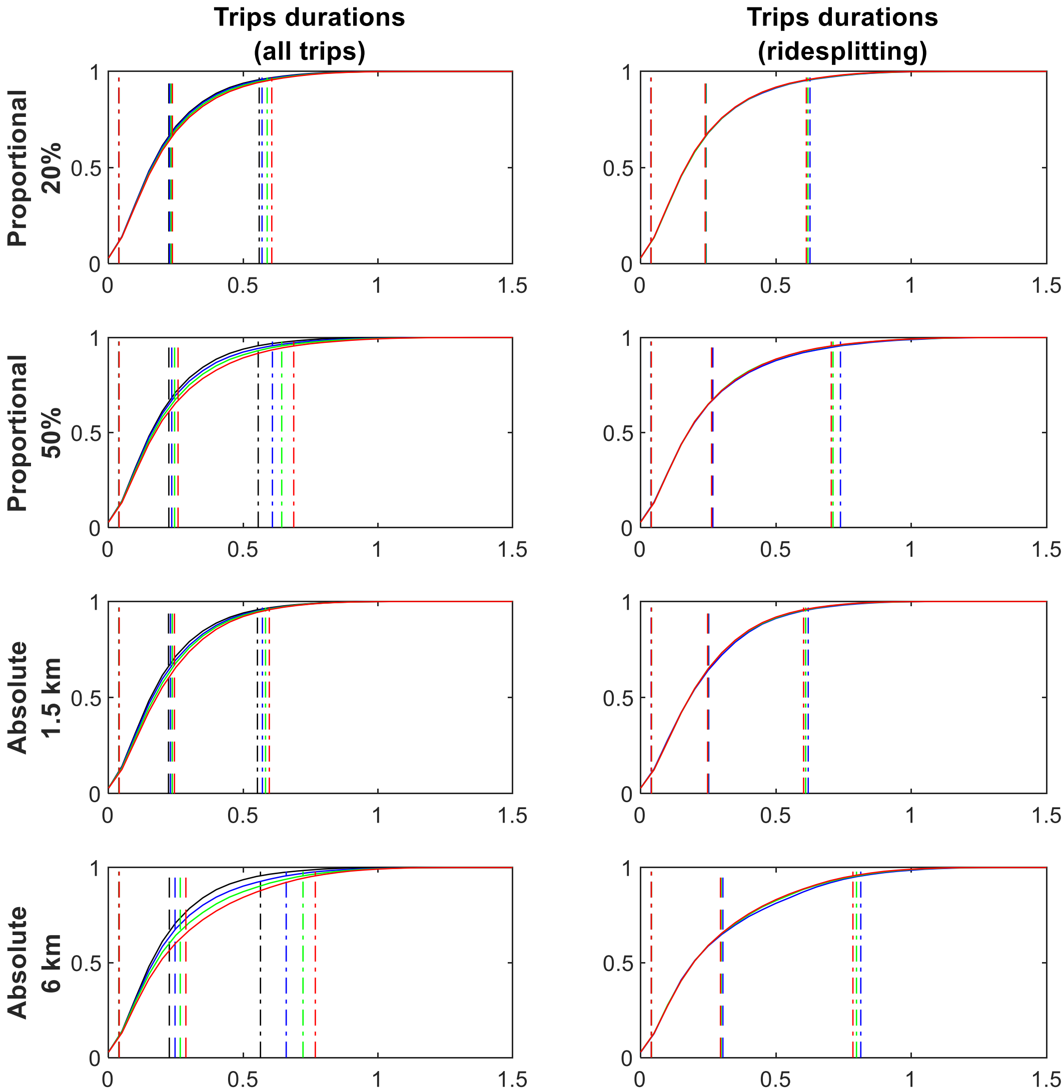

Figure 3: Statistical analysis on trip characteristics for different detours allowances.

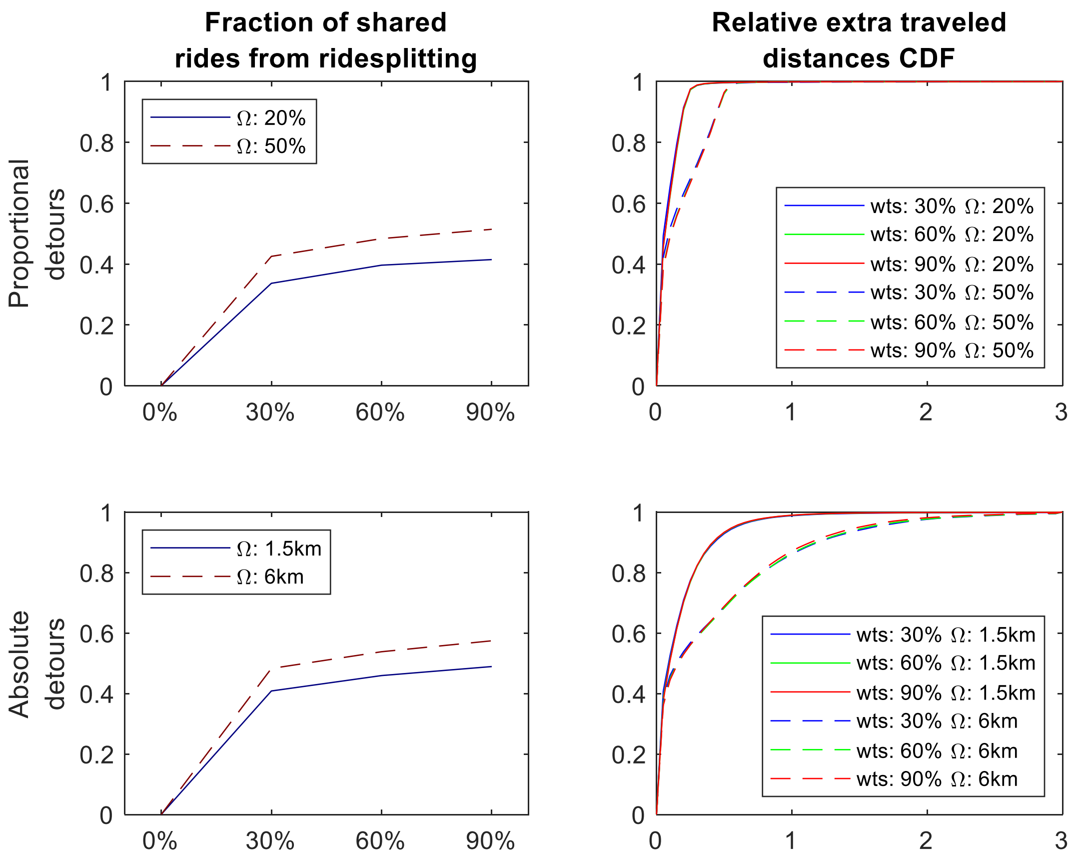

Figure 4: Matching efficiency and extra traveled distances.

services.

References

1. Rayle, L., Dai, D., Chan, N., Cervero, R. & Shaheen, S. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy* **45,** 168–178 (2016).
2. Jin, S. T., Kong, H., Wu, R. & Sui, D. Z. Ridesourcing, the sharing economy, and the future of cities. *Cities* **76,** 96–104 (2018).
3. Rogers, B. The Social Costs of Uber. *The University of Chicago Law Review Online* **82,** Art. 6 (2017).
4. Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E. & Rus, D. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *Proceedings of the National Academy of Sciences USA* **114,** 462–467 (2017).
5. Vinayak, P. *et al.* Accounting for multi-dimensional dependencies among decision-makers within a generalized model framework: An application to understanding shared mobility service usage levels. *Transport Policy* **72,** 129–137 (2018).
6. Alemi, F., Circella, G., Handy, S. & Mokhtarian, P. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society* **13,** 88–104 (2018).
7. Zha, L., Yin, Y. & Yang, H. Economic analysis of ride-sourcing markets. *Transportation Research Part C* **71,** 249–266 (2016).
8. Contreras, S. D. & Paz, A. The effects of ride-hailing companies on the taxicab industry in Las Vegas, Nevada. *Transportation Research Part A* **115,** 63–70 (2018).
9. Santi, P. *et al.* Quantifying the benefits of vehicle pooling with shareability networks. *Proceedings of the National Academy of Sciences USA* **111,** 13290–13294 (2014).
10. Martinez, L. M., Correia, G. H. A. & Viegas, J. M. An agent-based simulation model to assess the impacts of introducing a shared-taxi system: an application to Lisbon (Portugal). *Journal of Advanced Transportation* **49,** 475–495 (2015).
11. Stiglic, M., Agatz, N., Savelsbergh, M. & Gradisar, M. Making dynamic ride-sharing work: The impact of driver and rider flexibility. *Transportation Research Part E* **91,** 190–207 (2016).
12. Lee, D.-H., Wang, H., Cheu, R. L. & Teo, S. H. A taxi dispatch system based on current demands and real-time traffic conditions. *Transportation Research Record: Journal of the Transportation Research Board* **1882,** 193–200 (2004).
13. Wong, K. I. & Bell, M. G. H. The Optimal Dispatching of Taxis under Congestion: a Rolling Horizon Approach. *Journal of Advanced Transportation* **40,** 203–220 (2006).
14. Ramezani, M. & Nourinejad, M. Dynamic modeling and control of taxi services in large-scale urban networks: A macroscopic approach. *Transportation Research Part C* **94,** 203–219 (2018).

15. Jung, J., Jayakrishnan, R & Park, J. Y. Dynamic Shared-Taxi Dispatch Algorithm with Hybrid-Simulated Annealing. *Computer-Aided Civil and Infrastructure Engineering* **31,** 275–291 (2016).

16. Hosni, H., Naoum-Sawaya, J. & Artail, H. The shared-taxi problem: Formulation and solution methods. *Transportation Research Part B* **70,** 303–318 (2014).

17. Nourinejad, M. & Roorda, M. J. Agent based model for dynamic ridesharing. *Transportation Research Part C* **64,** 117–132 (2016).

18. Long, J., Tan, W., Szeto, W. Y. & Li, Y. Ride-sharing with travel time uncertainty. *Transportation Research Part B* **118,** 143–171 (2018).

19. Furuhata, M. *et al.* Ridesharing: The state-of-the-art and future directions. *Transportation Research Part B* **57,** 28–46 (2013).

20. Agatz, N., Erera, A., Savelsbergh, M. & Wang, X. Optimization for dynamic ride-sharing: A review. *European Journal of Operational Research* **223,** 295–303 (2012).

21. Cortés, C. E., Matamala, M. & Contardo, C. The pickup and delivery problem with transfers: Formulation and branch-and-cut solution method. *European Journal of Operational Research* **200,** 711–724 (2010).

22. Berbeglia, G., Cordeau, J.-F. & Laporte, G. Dynamic pickup and delivery problems. *European Journal of Operational Research* **202,** 8–15 (2010).

23. Molenbruch, Y., Braekers, K. & Caris, A. Typology and literature review for dial-a-ride problems. *Annals of Operations Research* **259,** 295–325 (2017).

24. Masmoudi, M. A., Hosny, M., Demir, E., Genikomsakis, K. N. & Cheikhrouhou, N. The dial-a-ride problem with electric vehicles and battery swapping. *Transportation Research Part E* **118,** 392–420 (2018).

25. Ho, S. C. *et al.* A survey of dial-a-ride problems: Literature review and recent developments. *Transportation Research Part B* **111,** 395–421 (2018).

26. Li, W., Pu, Z., Li, Y. & Ban, X. J. Characterization of ridesplitting based on observed data: A case study of Chengdu, China. *Transportation Research Part C* **100,** 330–353 (2019).

27. Geroliminis, N. & Daganzo, C. F. Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. *Transportation Research Part B* **42,** 759–770 (2008).

28. Ji, Y., Luo, J. & Geroliminis, N. Empirical Observations of Congestion Propagation and Dynamic Partitioning with Probe Data for Large-Scale Systems. *Transportation Research Record: Journal of the Transportation Research Board* **2422,** 1–11 (2014).