Energy 174 (2019) 503–508

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Environmental benefits of taxi ride sharing in Beijing

Hua Cai [a, b, *], Xi Wang [c], Peter Adriaens [d, e, f], Ming Xu [e, f, **]

[a] Industrial Engineering, Purdue University, West Lafayette, IN, 47907, United States
[b] Environmental and Ecological Engineering, Purdue University, West Lafayette, IN, 47907, United States
[c] IHS Markit, Southfield, MI, 48076, United States
[d] Ross School of Business, University of Michigan, Ann Arbor, MI, 48109, United States
[e] Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI 48109, United States
[f] School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, 48109, United States

A R T I C L E I N F O

Article history:
Received 27 October 2018
Received in revised form
21 February 2019
Accepted 23 February 2019
Available online 25 February 2019

Keywords:
Ride sharing
Energy saving
Emission reduction
Taxi

A B S T R A C T

Although ride sharing as a way to improve transportation efficiency is not new, the scale of ride sharing has historically been limited due to safety concerns and logistics challenges. Recent developments in information and communications technology (ICT) enable real-time sharing of individual geographical information, allow for easier participation in the "sharing economy", and present opportunities for implementing ride sharing at a large-scale. This research aims to quantify the environmental benefits of ride sharing using shared taxis in Beijing as a case study. Trip information extracted from vehicle trajectory data of 12,083 taxis in Beijing are used to evaluate the benefits of ride sharing. Our results show that: 1) only limited opportunity cost to the rider (i.e. tolerance of early departure or delayed arrival) can enable large-scale ride sharing; 2) at a tolerance level of 10 min, ride sharing can reduce fleet vehicle-miles-traveled (VMT) by 33%; and 3) if implemented for the entire taxi fleet, shared taxis can save 28.3 million gallons of gasoline and reduce 186 tons VOC, 199 tons NOx, 53 tons PM_{10}, 25 tons $PM_{2.5}$, and 2392 tons CO emissions annually.

1. Introduction

With over half of the global population living in urban areas, urban infrastructure is increasingly under pressure [1]. Vehicle transportation is a critical component of urban sustainability because it contributes significantly to energy consumption and emissions generation [2]. With accelerating economies and rising populations in urban centers, especially in developing countries, improving efficiencies in public transportation services and passenger automobile uses can provide more cost-effective and environmentally-friendly transportation solutions.

Sharing rides (combining two or more rider groups to travel together in the same car) as a way to reduce transportation energy consumption is not new. As early as the 19th century, the U.S. government has implemented policies to organize ride sharing (Car-Sharing Club) to conserve transportation fuel during World War II [3]. In addition to the societal benefits of reducing congestion, alleviating emissions, and conserving energy, ride sharing also offers benefits to the participants, including lowered travel (e.g., car ownership) cost, access to high occupancy vehicle (HOV) lanes, and elimination of the search for parking. However, due to the lack of attractive market mechanisms, difficulties of arrangement and logistics, and safety concerns (i.e. ride with strangers [3,4]), ride sharing has largely been constrained to families, friends, or colleagues, and is mostly prearranged (e.g., airport shuttles, vanpools) [5].

The recent developments in information and communications technologies (ICT), such as smartphones and various apps, have enabled users to exchange information in real-time and have facilitated participation in the "sharing economy", both on a technical and a social level. Technically, the availability of real-time rider travel information, such as trip origin, trip destination, and desired departure and arrival time, has made it possible to develop a dynamic ride sharing (a.k.a., real-time ride sharing) system which only requires a minimal amount of lead time to identify sharing matches. Additional riders can also be picked up and dropped off along the travel trajectory, instead of requiring the ride sharing

* Corresponding author. Industrial Engineering, Purdue University, West Lafayette, IN, 47907, United States.
** Corresponding author. School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, 48109, United States.
E-mail addresses: huacai@purdue.edu (H. Cai), mingxu@umich.edu (M. Xu).

https://doi.org/10.1016/j.energy.2019.02.166
0360-5442/

participants to have the same trip origins and/or destinations [6]. The involvement of social networks and reputation systems has helped build trust to share with strangers (e.g., Uber, Sidecar, Lyft, Airbnb) [7,8]. Therefore, ICT-enabled real-time ride sharing presents unprecedented opportunities to improve urban transportation efficiency. The technology and cyberinfrastructure for dynamic ride sharing at the large-scale is emerging. Several startup companies have already started to provide dynamic ride sharing services (e.g., Uberpool,[1] Split,[2] Lyft line[3]).

The current literature on ride sharing mainly focuses on the development of efficient algorithms for rides matching and recommender systems [9–15]. Limited attention has been paid to quantifying the "share-ability" of travel demands at the city level, which is important to evaluate the feasibility and impacts of ride sharing and persuade investors and stakeholders to invest in and promote such systems [16]. This research aims to fill this gap to quantify the environmental benefits of ride sharing in urban cities, taking into account the heterogeneous individual travel demands.

Four types of data are currently used to study ride sharing: travel survey data, cellphone traces, geo-tagged social media data, and trip origin and destination data captured by GPS devices. Travel surveys are conducted in many countries at different scales to understand national or regional travel and transportation patterns. In the form of questionnaire or travel dairy, travel surveys collect information such as the travel purpose, transportation mode, travel distance etc. [17] For example, based on commuting survey data, Amey (2010) estimated that sharing rides can reduce commuting vehicle-miles-traveled (VMT) by 6%–19% for the Massachusetts Institute of Technology (MIT) communities [5]. Although travel survey data are best suited to serve the purpose of analyzing ride sharing at the small scale (e.g., commuting within the MIT community), the information provided by survey data is static and cannot be used to study dynamic ride sharing at the larger geographic scale. Mobile phone trace data are collected by mobile network carriers for billing and operational purposes. It records the date, time, phone number (anonymized) of each cellphone activity (making or receiving a phone call or text message), and the coordinates of the cellphone tower routing the communication [18]. Compared to travel survey data, mobile phone traces have a much larger sample size and a broader spatial and temporal coverage. In addition, because the data are routinely collected for business operation purposes, the data collection cost is low [19]. Geo-tagged social media data are publicly shared information (e.g., tweets, photos, and check-ins) on different social media sites (e.g., Twitter, Facebook, Google+, Flickr, and Foursquare) with location data associated (typically as GPS coordinates). Depending on each social media site's policy, large-scale social media data could be hard to obtain [20]. Most of the large-scale geo-tagged social media data used for research are streamed from Twitter API [21]. Using cellphone records and geo-tagged tweets, Cici et al. (2014) estimated that ride sharing with friends' friends can reduce the number of cars in a city by 31% [21]. However, cellphone traces and geo-tagged social media data have very coarse granularity because the geolocation data of a user are only recorded when the user makes a phone call or posts a tweet. Trips that occur between two consecutive phone calls or tweets cannot be captured and may lead to inaccurate travel demand inference. Trip origin and destination data captured by GPS devices are location data collected by GPS devices equipped on vehicles [22–26], bikes [27], or individuals [28,29]. Because the data are collected passively and do not require active participation of the user, in contrast to other types of data mentioned above, GPS traces normally have finer granularity both spatially (more accurate location information) and temporally (high frequency of sampling) [26]. Analyzing trip origins and destinations of taxi trips in New York City, Santi et al. (2014) concluded that sharing taxi trips can cut trip length by 40% or more [16], and Lokhandwala et al. (2018) showed that the average vehicle occupancy can be increased from 1.2 to 3 [6]. Trip origins and destinations data can more accurately describe the travel demand of each traveler and therefore can better support large-scale dynamic ride sharing analysis.

Beijing (China), a city which has been called out in the media and academic research for its severe air pollution [30] and congestion [31], may particularly benefit from ride sharing to reduce total trip length and vehicular emissions. Taxi sharing can be the first step to implement ride sharing at the urban scale. Beijing has around 66,000 taxis, which serve over 2 million trips a day and contribute 1.08 million tons CO_2 (7.2% of total transportation emission) each year based on 2012 data [32]. While some mobile phone apps (e.g., DiDi) are already in development to allow taxi sharing in Beijing [33], it is still unclear what the potential environmental benefits of taxi sharing are. To the best of our knowledge, there is only one study evaluated the environmental benefits of ride sharing in Beijing [34]. However, this study has a different scope, focusing on evaluating the environmental impacts of peer-to-peer car sharing trips from the perspective of transportation mode replacement, adoption of battery electric vehicles, and the potential changes of car ownership. Knowing the scale of trips that can be shared and the emissions that can be reduced through taxi sharing is critical to inform decision makers to design policies related to ridesharing.

Using real world trip origins and destinations extracted from the taxi trajectory data in Beijing, China as a case study, this research evaluates the environmental benefits of shared taxis (energy savings and emissions reduction of VOCs, NOx, PM_{10}, $PM_{2.5}$, and CO due to sharing). Although ride sharing using private vehicles may be different from shared taxi rides, the framework and methods developed in this research can be applied to private vehicles when trip origins and destinations using private vehicles become available at the large-scale. In addition, compared to ride sharing among private drivers, which requires more individual initiatives, shared taxi rides are more ready to be implemented. Compared to the existing literature, the unique contributions of this research are that (1) we proposed a framework to identify sharable trips and quantify the environmental benefits of ride sharing; (2) we analyzed the potential energy and emission reduction of taxi sharing in Beijing using real-world data; and (3) we evaluated the feasibility of ride sharing throughout the entire day, with different hourly travel demands.

2. Materials and methods

2.1. Data

Data used in this study are vehicle trajectory data for 12,083 taxis (18.3% of the taxi fleet) in Beijing from November 1 to December 1 in 2012, which is the latest dataset we have access to. This dataset represents a typical winter month in Beijing, which tends to have poorer air quality [35]. We did not observe any spatial coverage (e.g., where the taxis were distributed) or travel pattern (e.g., the densities of trip origin and destinations) bias during this period compared to a smaller dataset we have for a different period (March 2009). So we can consider the data as representative for taxi activities in Beijing. After data cleaning, the dataset includes a total of 894.5 million data points, covering 69.3 million miles of travel. Each

[1] https://get.uber.com/cl/uberpool/.
[2] http://split.us/.
[3] https://www.lyft.com/line.

data point includes a vehicle identification (ID) number, operation status (occupied by passengers, parked, or unoccupied), a time stamp when a data point is recorded, the geolocation of the taxi at the time of recording (longitude and latitude), GPS speed, GPS direction, and GPS status (whether the GPS device is functioning). The data were cleaned to remove scattered points that are outside of the main time span (November 1 to December 1, 2012), duplicate points, and points that are shown as invalid according to the GPS status information. Vehicles with less than 27 days of data during the period of November 1 to December 1 in 2012 (2% of the vehicles) are also removed from the dataset to preserve consistent time series information. The origins and destinations of passenger trips are identified based on the taxi operation status. Locations where the taxi operation status changes from other status (either parked or unoccupied) to occupied are identified as trip origins. Similarly, locations where the taxi operation status changes from occupied to other status are identified as trip destinations. For each pair of trip origins and destinations, the associated start- and end-time of the trip are known, as are trip duration, average speed, and trip distance. Trip distance is calculated as the summation of the Manhattan distances of each pair of consecutive points in the trip. The Manhattan distance, which measures the distance between two points (X_1, Y_1) and (X_2, Y_2) as $|X_1-X_2| + |Y_1-Y_2|$, can provide better estimates for the actual travel distance between two locations in a road network [36]. A total of 5.2 million occupied trips are extracted.

2.2. Shared rides matching analysis

In the shared rides matching analysis, we assumed that a maximum of two rider groups can share one taxi. This assumption is made because having more ride groups share a ride significantly complicates computation but only offers marginal ride sharing benefits [16,37]. The analysis includes two components: identification of all sharable trips (Section 2.2.1) and optimization of shared trips to maximize the total avoided VMT (Section 2.2.2).

2.2.1. Identification of all sharable trips

For each trip *i*, we know the trip origin (O_i), trip destination (D_i), trip distance (d_i), departure time from trip origin (t_O_i), and arrival time at destination (t_D_i). Trip *i* is considered as sharable with another trip (e.g., trip *j*) on two conditions: (1) the shared trip *ij* can reduce total travel distance, and (2) the time impact of trip departure and arrival for both passengers in trip *i* and trip *j* is tolerable (less than or equal to the predefined passenger tolerance θ). The selection of the tolerance level is explained in more detail later in this section.

Fig. 1 presents the framework for sharable trip identification. The candidate shared trip *ij* is identified as the route (R_{ij}) that can lead to the minimum shared trip distance (d_{ij}) among all possible routes. For sharing two trips, there are four possible routes: $O_i \rightarrow O_j \rightarrow D_i \rightarrow D_j$; $O_i \rightarrow O_j \rightarrow D_j \rightarrow D_i$; $O_j \rightarrow O_i \rightarrow D_i \rightarrow D_j$; and $O_j \rightarrow O_i \rightarrow D_j \rightarrow D_i$. We do not consider trips without overlap (e.g., $O_i \rightarrow D_i \rightarrow O_j \rightarrow D_j$) as sharable in this study. If the total distance of the candidate shared trip (d_{ij}, including the distance of picking up sharing passengers) is less than that of the two individual trips ($d_i + d_j$), the candidate shared trip *ij* passes the distance check. The trip time impact check examines whether the deviations of trip departure and arrival time are tolerable to passengers in both trips. The departure and arrival time of the shared trip are t_O_i', t_D_i', t_O_j', t_D_j' for passengers from trip *i* and trip *j*, respectively. We assume that both early departure and delayed arrival can equally cause inconvenience to the passengers.

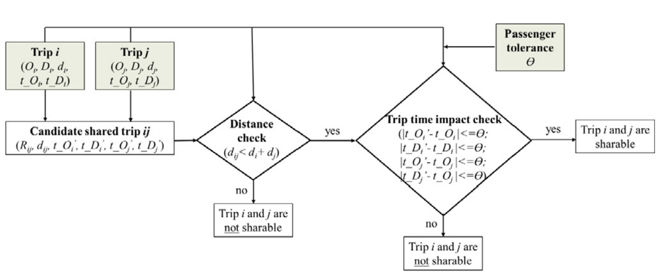

Fig. 1. Framework for sharable trip identification.

The passengers have a pre-specified tolerance level (Θ, in minutes), indicating their flexibility of the deviations of departure and arrival time caused by ride sharing. Only when the deviations of trip departure and arrival time for passengers in both trips are within the tolerance level, the candidate shared trip passes the trip time impact check. In this study, we assumed that all passengers have the same tolerance level and the tolerance level for deviating from original departure and arrival time (regardless of being early or late) is the same. The default tolerance level is 10 min, following Li et al. who reported that over 75% of the carpool participants they surveyed spent less than 10 min for carpool formation [38]. The impacts of different tolerance levels is examined in the sensitivity analysis in Section 3.2. This study also assumed a 1 min passenger loading/unloading time to account for the time required for the taxis to slow down, stop, and for the passengers to get on and off.

To calculate the departure and arrival time at each origin and destination locations for the shared trip, we assumed that the travel speed for the portion of the shared trip that deviates from the original trips to accommodate for ride sharing (e.g., pick up the second passenger) is the average of the travel speeds for the individual trips. We also assumed that ride sharing will not impact the traffic conditions for the portion of the shared trip that is identical with one of the original trips, because taxis are only a small portion of the overall traffic. Equations (1)–(7) present an example of travel time calculation for the route O_i - O_j - D_j - D_i.

$$\mathrm{v_i = d_i/} \tag{1}$$

$$\mathrm{v_j = d_j/(t\_D_j - t\_O_j)} \tag{2}$$

$$\mathrm{v_{ij} = (v_i + v_j)/2} \tag{3}$$

$$\mathrm{t\_O_i' = t\_O_i} \tag{4}$$

$$\mathrm{t\_O_j' = t\_O_i' + dist(O_i - O_j)/v_{ij}} \tag{5}$$

$$\mathrm{t\_D_j' = t\_O_j' + (t\_D_j - t\_O_j)} \tag{6}$$

$$\mathrm{t\_D_i' = t\_D_j' + dist(D_j - D_i)/v_{ij}} \tag{7}$$

where v_i, v_j, and v_{ij} are the average travel speed for individual trip *i*, individual trip *j*, and the deviated portion of shared trip ij; t_Oi', t_D_i', t_O_j', t_D_j' are the departure and arrival time in a shared trip for passengers from trip *i* and trip *j*, respectively; t_Oi, t_Di, t_Oj, t_Dj are the departure and arrival time for individual trip *i* and trip *j*, respectively; and $dist(Oi - Oj)$ and $dist(Dj - Di)$ are the distances between trip origin locations for the two shared trips and the distances between the trip destination locations for the two shared trips.

In the example route O_i - O_j - D_j - D_i, the trip distance of O_j - D_j is known from the information of the individual trip *j*, but the distance of O_i - O_j and D_j - D_i will need to be estimated. Trip travel distances are normally greater than the Manhattan distance between trip origins and destinations (Fig. 2) due to the required extra

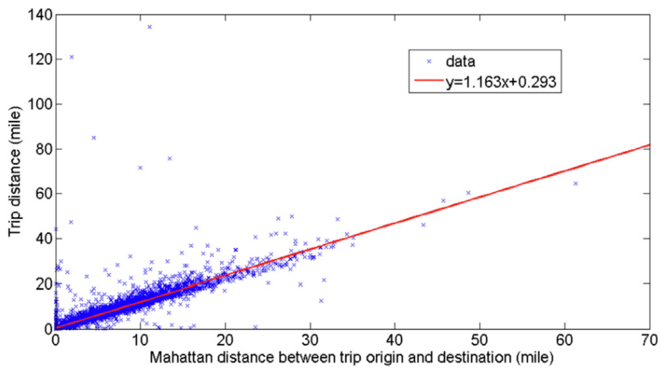

Fig. 2. Relationship between trip travel distance and Manhattan distance between trip origins and destinations ($R^2 = 0.775$ for the fitted line).

travel (e.g., extra distance traveled to get onto a highway or detour due to one-way streets). Therefore, we estimated trip travel distance in the portion of shared trip that deviates from the original trips (e.g., O_i - O_j and D_j - D_i) to accommodate for ride sharing based on the relationship observed in Fig. 2. For example,

$$\mathrm{dist}(O_i - O_j) = 1.163{*}\mathrm{MD}(O_i, O_j) + 0.293 \tag{8}$$

where $MD(O_i, O_j)$ is the Manhattan distance between point O_i and O_j. Although the large extreme values cause the R^2 of the fitting to be low, the actual trip distance of 80% of the trips is ±1 mile of the fitted value.

Only when the shared-trip candidate passes both the distance and the trip time impact checks, the two trips are identified as sharable. In this component, we identify all sharable trips that meet above criteria. The outputs of this component are two ‘n × n’ matrices A and S, whereby n represents the total number of trips. Matrix A is the trip share-ability matrix where A_{ij} equals to 1 if trips i and j are sharable and equals to 0 otherwise. Matrix S is the travel saving matrix where S_{ij} equals to the VMT that can be saved by sharing trip i and j if A_{ij} is 1, and equals to 0 otherwise.

2.2.2. Optimization

This component optimizes the selection of shared-ride pairs to maximize total VMT reduction benefits.

The objective function is to max $\sum_j \sum_i L_{ij} \times S_{ij}$ (9)

Subject to:

$$\sum_i L_{ij} \le 1 \tag{10}$$

$$\sum_j L_{ij} \le 1 \tag{11}$$

$$L_{ij} \le A_{ij} \tag{12}$$

$$L_{ij} \ge 0 \tag{13}$$

where L_{ij} is the binary decision variable which equals to 1 when trip i and j are selected for sharing and equals to 0 otherwise.

2.3. Emission factors

To calculate the emission reduction gained from ride sharing, the following well-to-wheel emission factors for gasoline vehicles are used: 0.28 g/mile for volatile organic compounds (VOCs), 0.3 g/mile for nitrogen oxide (NOx), 0.08 g/mile for particulate matter with diameters of 10 μm or less (PM_{10}), 0.038 g/mile for particulate matter with diameters of 2.5 μm or less ($PM_{2.5}$), and 3.6 g/mile for carbon monoxide (CO) [39]. The pump-to-wheel fuel economy of gasoline vehicles of 23.5 mile/gallon is used to calculate the energy saving [39].

3. Results and discussions

3.1. Sharing benefits

Regardless of the variations in the total number of trips accrued during each day, the ride sharing benefits (miles saved and trips shared) are relatively stable (Fig. 3a). On average, about 77% of the trips can be shared, leading to 33% of the total VMT saved. This can be translated into saving 77,454 gallons of gasoline per day. The day-to-day variances of hourly sharing benefits are also relatively small, regardless of weekdays and weekends. These results indicate that the travel patterns of taxi riders in Beijing offer consistent high share-ability. Based on the average daily VMT saved, we then calculated the daily criteria emissions that are reduced due to ride sharing (Fig. 3b). Scaling up to the entire taxi fleet (66,000 taxis), assuming the sharing benefits per VMT remaining the same, shared taxis can reduce 186 tons of VOC, 199 tons of NOx, 53 of tons PM_{10}, 25 tons of $PM_{2.5}$, and 2392 tons of CO emissions annually. Based on the annual on-road vehicle emissions estimated for Beijing [40], shared taxi trips can reduce total vehicular NO_x, PM_{10}, and CO

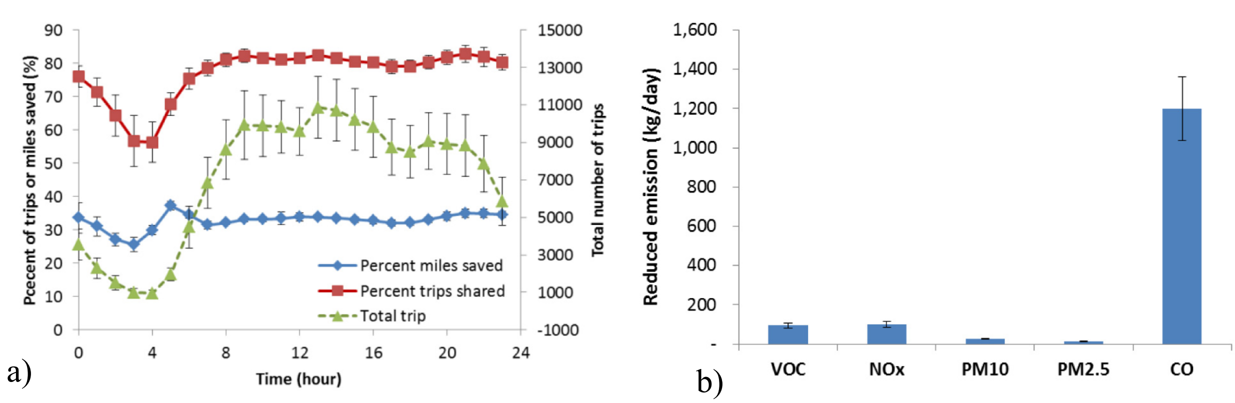

Fig. 3. Ride sharing benefits through door-to-door sharing. a) Hourly percentage trip VMT saved (primary axis) and shared trip percentages (primary axis) compared to the number of total trips (secondary axis). b) Daily avoided criteria pollutants.

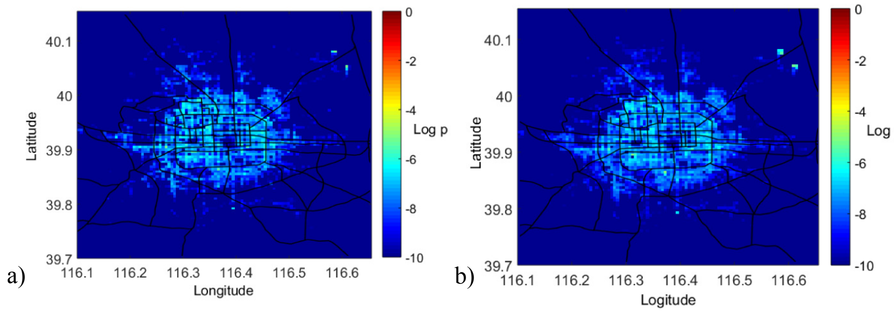

Fig. 4. Spatial distribution of the origins (a) and destinations (b) of the sharable trips in the inner city of Beijing.

emissions by 0.24%, 1.4%, and 0.28%, respectively. It should be noted that these benefits occur annually. Given that taxis only represent 1.2% of the total vehicles in Beijing, this emission reduction is significant [41]. The annual energy saving is 28.3 million gallon gasolines. Ride sharing, if implemented at the large-scale, can potentially be a more effective policy than the current one-day-a-week driving restriction scheme (depending on the last digit of the license plate, each vehicle is restricted from traveling in the city on one specific day each week) in reducing total vehicle VMT, energy use, and pollution [42,43]. The spatial distribution of the sharable trips are concentrated in the inner city (within the fifth ring) and the airport (Fig. 4). Within the inner city, the travel demand is quite dispersed and no particular region dominates the sharable trips as either trip origin or destination, indicating that a taxi sharing approach would be widely applicable in the city.

It should be noted that the emission reductions in this study are based on average emission factors. It is well known that driving conditions (e.g., travel speed and acceleration) and ambient environment (e.g., cold or hot weather which results the use of heating and air conditioning in the vehicle) affect vehicular emissions [44,45]. More detailed modeling of emissions considering these factors can improve this analysis. Additionally, other factors which may lead to higher or lower ride sharing benefits should also be further investigated in future research. First, spillover effects have not been considered in this research. Shared taxis free taxi capacities and reduce per-person taxi fares, which may motivate more people to take taxis. If these additional taxi riders are switched over from private vehicle drivers, the environmental benefits of ride sharing is potentially increased by reducing the number of private vehicles on the road, and by increasing average vehicle occupancy rate. On the other hand, however, if these additional taxi riders are diverted from users of the public transit systems, the environmental benefits of ride sharing can be undermined as a result of the spillover effect [46]. Additionally, when scaling up the emissions reduction of ride shares from the sampled taxis to the entire fleet, we assumed that the percent of VMT that can be saved remains constant. We did not take into account that, with increased numbers of vehicles and travel demand, the ride sharing benefits may increase due to economies of scale. The relationship of ride-sharing benefits and the total number of riders needs to be further explored.

3.2. Impact of tolerance to trip time deviation

Sharing benefits are most sensitive to the tolerance level of trip time change (Θ) due to ride sharing. We conducted a sensitivity analysis by using different Θ to identify the sharable trips and then calculate the VMT savings. The results show that the tolerance required from riders to enable ride sharing is less than 10 min

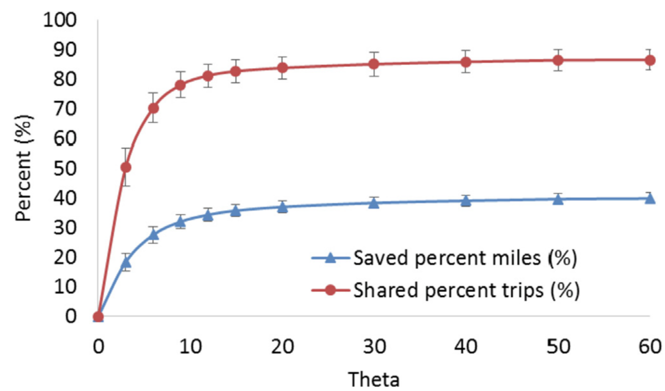

Fig. 5. The impact of rider's tolerance level of trip time change (theta, in minutes) to ride sharing benefits.

(Fig. 5). For example, as long as the riders can tolerate a trip departure or arrival time change of 3 min, 47% of the trips can be included in ride sharing, and save 17% of the VMT. Although the total number of trips vary significantly throughout the day, the trip time change tolerance has very similar impacts on the sharing results regardless of trip starting time (as indicated by the small error bars in Fig. 5).

4. Conclusion

In summary, using the shared taxi case study in Beijing as an example, we analyzed the environmental benefits of ride sharing. Shared taxis can provide stable sharing benefits in total VMT, energy, and emissions reduction, regardless of the travel volume and daily travel pattern variations. With a rider's tolerance level at 10 min, ride sharing can reduce fleet VMT by 33%. If implemented for the entire taxi fleet, shared taxis can save 28.3 million gallons of gasoline and reduce 186 tons VOC, 199 tons NOx, 53 tons PM_{10}, 25 tons $PM_{2.5}$, and 2392 tons CO emissions annually. Although the sharing benefits significantly depend on riders' tolerance level to trip time deviation, not much tolerance is required to gain significant ride sharing benefits.

Acknowledgement

This material is based upon work partially supported by the Department of Energy under Award Number DE-PI0000012. HC thanks the support of the Dow Sustainability Fellows Program.

References

[1] United Nations. World urbanization prospects: the 2014 revision. United

Nations, Department of Economic and Social Affairs, Population Division; 2014.
[2] Bilgen S. Structure and environmental impact of global energy consumption. Renew Sustain Energy Rev 2014;38:890–902.
[3] Furuhata M, et al. Ridesharing: the state-of-the-art and future directions. Transp Res Part B Methodol 2013;57(0):28–46.
[4] Li B, et al. The Share-a-Ride Problem: people and parcels sharing taxis. Eur J Oper Res 2014;238(1):31–40.
[5] Amey AM. Real-time ridesharing: exploring the opportunities and challenges of designing a technology-based rideshare trial for the MIT community. Boston: Department of Urban Studies and Planning and Department of Civil and Environmental Engineering; 2010. Massachusetts Institute Of Technology.
[6] Lokhandwala M, Cai H. Dynamic ride sharing using traditional taxis and shared autonomous taxis: a case study of NYC. Transport Res C Emerg Technol 2018;97:45–60.
[7] Finley K. Trust in the sharing economy: an exploratory study. The University of Warwick; 2013.
[8] Zervas G, Proserpio Davide, Byers John. The rise of the sharing economy: estimating the impact of Airbnb on the hotel industry. Boston University School of Management; 2015.
[9] Agatz N, et al. Optimization for dynamic ride-sharing: a review. Eur J Oper Res 2012;223(2):295–303.
[10] Fellows NT, Pitfield DE. An economic and operational evaluation of urban car-sharing. Transport Res Transport Environ 2000;5(1):1–10.
[11] Bicocchi N, Mamei M. Investigating ride sharing opportunities through mobility data analysis. Pervasive Mob Comput 2014;14(0):83–94.
[12] Trasarti R, et al. Mining mobility user profiles for car pooling. In: Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining. San Diego, California, USA: ACM; 2011. p. 1190–8.
[13] He W, et al. Mining regular routes from GPS data for ridesharing recommendations. In: Proceedings of the ACM SIGKDD international workshop on urban computing. Beijing, China: ACM; 2012. p. 79–86.
[14] Ma S, Zheng Y, Wolfson O. Real-time city-scale taxi ridesharing. knowledge and data engineering. IEEE Transactions on; 2014. PP(99): pp. 1–1.
[15] Masoud N, Jayakrishnan R. A real-time algorithm to solve the peer-to-peer ride-matching problem in a flexible ridesharing system. Transp Res Part B Methodol 2017;106:218–36.
[16] Santi P, et al. Quantifying the benefits of vehicle pooling with shareability networks. Proc Natl Acad Sci Unit States Am 2014;111(37):13290–4.
[17] U.S. Department of Transportation Federal Highway Administration. National Household Travel Survey User's Guide (version 2). 2011. U.S. Department of Transportation Federal Highway Administration; 2009.
[18] Marta C, González CAH, Barabási Albert-László. Understanding individual human mobility patterns. Nature 2008;453:779–82.
[19] Calabrese F, et al. Understanding individual mobility patterns from urban sensing data: a mobile phone trace example. Transport Res C Emerg Technol 2013;26(0):301–13.
[20] Morstatter F, Pfeffer Jürgen, Liu Huan, Carley Kathleen M. Is the sample good enough? Comparing data from twitter's streaming API with twitter's firehose. ICWSM 2013. 2013. cs. SI.
[21] Cici B, et al. Assessing the potential of ride-sharing using mobile and social data: a tale of four cities. In: Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing. Seattle, Washington: ACM; 2014. p. 201–11.
[22] Tamor MA, Gearhart C, Soto C. A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation. Transport Res C Emerg Technol 2013;26:125–34.
[23] Jing Yuan, Y.Z., Chengyang Zhang, Wenlei Xie, Xing Xie, Guangzhong Sun, and Yan Huang. T-drive: driving directions based on taxi trajectories. in Proceedings of the 18th SIGSPATIAL international conference on advances in geographic information systems, GIS '10. 2010. New York, NY, USA: ACM.
[24] Pearre NS, et al. Electric vehicles: how much range is required for a day's driving? Transport Res C Emerg Technol 2011;19(6):1171–84.
[25] Dong J, Liu C, Lin Z. Charging infrastructure planning for promoting battery electric vehicles: an activity-based approach using multiday travel data. Transport Res C Emerg Technol 2014;38:44–55.
[26] Liang X, et al. The scaling of human mobility by taxis is exponential. Phys Stat Mech Appl 2012;391(5):2135–44.
[27] Hood J, Sall E, Charlton B. A GPS-based bicycle route choice model for San Francisco, California. Transportation Letters 2011;3(1):63–75.
[28] Zheng Y, et al. Mining interesting locations and travel sequences from GPS trajectories. In: Proceedings of international conference on world wild web (WWW 2009). Madrid Spain: ACM Press; 2009. p. 791–800.
[29] Yu Zheng QL, Chen Yukun, Xie Xing, Ma Wei-Ying. Understanding mobility based on GPS data. In: UbiComp'08. Seoul, Korea: ACM; 2008.
[30] Bloomberg. Beijing issues air pollution red alert for the first time. Bloomberg Business; 2015.
[31] Bowerman M. Thousands stuck in 50-lane traffic jam in beijing. USA Today; 2015.
[32] Wang Z, Chen F, Fujiyama T. Carbon emission from urban passenger transportation in Beijing. Transport Res Transport Environ 2015;41:217–27.
[33] Hua Times Jing. DiDi is testing for taxi ridesharing. 2015 (in Chinese).
[34] Yu B, et al. Environmental benefits from ridesharing: a case of Beijing. Appl Energy 2017;191:141–52.
[35] Young, R. Beijing Air Quality: PM2.5. Available from: http://www.young-0.com/airquality/.
[36] Shahid R, et al. Comparison of distance measures in spatial analytical modeling for health service planning. BMC Health Serv Res 2009;9. 200-200.
[37] Fagnant DJ, Kockelman KM. Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles. In: Proceedings of the 94th annual meeting of the transportation research board in Washington DC; 2015. January 2015.
[38] Li J, et al. *Who Chooses to Carpool and why?: Examination of Texas carpoolers.* Transportation research record. Journal of the Transportation Research Board 2007;2021:110–7.
[39] Huo H, Wu Y, Wang M. Total versus urban: well-to-wheels assessment of criteria pollutant emissions from various vehicle/fuel systems. Atmos Environ 2009;43(10):1796–804.
[40] Wu Y, et al. On-road vehicle emission control in beijing: past, present, and future. Environ Sci Technol 2011;45(1):147–53.
[41] Beijing Bureau of Statistics. Urban infrastructure and transportation information. 2014 [cited 2016 March 22, 2016]; Available from: http://www.bjstats.gov.cn/bjsq/csjs/.
[42] Wang L, Xu J, Qin P. Will a driving restriction policy reduce car trips?—the case study of Beijing, China. Transport Res Pol Pract 2014;67:279–90.
[43] Sun C, Zheng S, Wang R. Restricting driving for better traffic and clearer skies: did it work in Beijing? Transport Pol 2014;32:34–41.
[44] Ahn K, Rakha H, Trani A, Van Aerde M. Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels. J Transport Eng 2002;128(2):182–90.
[45] Van Mierlo J, et al. Driving style and traffic measures-influence on vehicle emissions and fuel consumption. Proc Inst Mech Eng - Part D J Automob Eng 2004;218(1):43–50.
[46] Font Vivanco D, Kemp R, van der Voet E. The relativity of eco-innovation: environmental rebound effects from past transport innovations in Europe. J Clean Prod 2015;101(0):71–85.