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A Trip-specific Model for Fuel Saving Estimation and Subsidy Policy Making of Carpooling Based on Empirical Data

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Abstract

As an eco-friendly and convenient transportation mode, mobile internet-based carpooling has achieved mushroom growth in many cities in recent years. Theoretical studies have verified that ridesharing is not only beneficial to drivers and passengers but particularly to the environment. Nevertheless, the exact impact of ridesharing on energy consumption and exhaust emission has been barely explored based on real carpooling data. In this study, using massive mobile internet based carpooling data offered by DiDi Company, a trip-specific model was initially proposed to study the intrinsic mechanism of carpooling services and then estimate the fuel savings of individual carpooling trip. According to the estimation results, delicacy subsidy strategies under the Personal Carbon Trading scheme were suggested to guarantee the moderation and equity in promoting carpooling services. The developed methodology was further tested in the case city of Beijing and associated results showed that ridesharing could be a feeder for public transit to support the commuting demands of workers living in suburban. More importantly, the fuel savings of ridesharing are considerable, every trip saving 1.23 liters on average, and the carbon subsidies are moderate, per trip reaching ¥5.38 with the strictest subsidy ceiling. From the spatial-temporal perspective, the Chaoyang district and the daily peak-hour period generate the largest number of both ridesharing orders and fuel savings. All the results demonstrate that the trip-specific model has the advantages of delicacy, reliability and accuracy, which could facilitate the estimation on the trip-specific fuel savings and the formulation of carpooling promotion strategies.

Key words: *Carpooling, Fuel savings, Trip-specific, Path length, Subsidies*

1. Introduction

1.1 Problem statement

Private car use accounts for the largest part of kilometers traveled across all travel modes in cities, e.g. more than 88% in Beijing (Zhang et al., 2017), making it one of the most important contributors to air pollution (Lau et al., 2008). Worldwide a variety of policy measures have been adopted to promote eco-friendly travel modes (e.g. public transport, biking and walking) and to discourage car usage (e.g. through parking charges and driving restrictions based on plate numbers). However, there are still numerous road users who are car-dependent, either by personal choices or being constrained by public transit circumstances (Mcintosh et al., 2014; Stiglic et al., 2018). Addressing the car-dependency and its related pollution problem has proved to be a challenging task for cities.

Ridesharing (carpooling and vanpooling), as a travel means of being more flexible than transit and less expensive than traditional car ownership, has been recognized as one of the solutions in mitigating the car-dependency problem. Carpools can consist of as few as two people, while vanpools carry six to fifteen commuters, with a van typically provided though a government- or employer-sponsored program (Cetin and Deakin, 2017). Studies have demonstrated that ridesharing plays an important role in reducing travel costs, fuel consumption, carbon emission, and traffic congestion (Morency, 2007; Caulfield, 2009; Minett and Pierce, 2010; Chan and Shaheen, 2012; Bachmann et al., 2018). It is not only beneficial to drivers and passengers but particularly to the environment. The International Energy Agency (2005) estimated that carpooling can reduce the number of kilometers traveled by 12.5%. This reduction will result a 7.7% reduction in fuel use, if one person was to be added to each commute. Another research conducted by Minett and Pearce (2011) shows that ridesharing service has a positive influence on cities' transportation energy consumption with at least saving 1.7–3.5 million liters of gasoline per year in San Francisco.

Nevertheless, despite the importance of ridesharing in addressing the most pressing transport problems, this travel mode is still not sufficiently used in practice. Focusing on the car owners, three major factors could underline the low ridesharing rate (Delhomme and Gheorghiu, 2016). The first is related to personal negative perception and attitudes towards public transport and ridesharing. The car owners who are reluctant to share their trips with strangers usually have highly preference to the comfort and convenience by driving alone and are more concerned about the personal privacy. At the same time, they express less positive views towards the other means of transportation and are less aware of transportation environment issues. The second factor lies in the traditional ride-matching systems that are not effective in linking drivers and passengers in terms of both travel time and travel routes, due to the lack of a database of sufficiently large numbers of participants as well as a dynamic efficient ride-matching algorithm (Wang, 2011). This makes it a challenge in finding appropriate carpooling partners to share their travel without jeopardizing the comfort and convenience that private travel would bring. The third factor is related to policy measures. In order to boost carpooling, a number of measures have been proposed worldwide, including financial incentives attributed to carpooling parking charges (Kingham et al., 2001; Vanoutrive et al. 2012) or directly allocated to carpooling trips (Delhomme and Gheorghiu, 2016). Alongside, the commonly-adopted policy, particularly in western industrialized countries, is High Occupancy Vehicle (HOV) lanes, which aim to improve travel time reliability and safety for passenger vehicles with or beyond required occupancy (e.g. two or three occupants). Nevertheless, both theoretical and empirical studies have shown that the supposed benefits of HOV lanes are often difficult to achieve (Wang, 2011), and the small travel time savings generated from the lanes do not provide a statistically significant carpooling incentive (Kwon and Varaiya, 2008). In sum, there is still a lack of consensus for the effective measures that best boost carpooling, particularly in developing countries, calling for further investigation into the methodologies that can assist governments in designing more efficient measures to promote the carpooling demand, which is of vital significance for the mitigation of environmental pollutants and the sustainable development of urban traffic.

With the rapid development of the mobile internet, location-based services (LBS) as well as the cloud computing technologies, the online carpooling systems have been built, accommodating more advanced ride-matching mechanism with on-demand and dynamic characteristics. The new systems provide an automated dynamic process of ride-matching (routing, scheduling and pricing) in real-time between drivers and passengers during very short time-windows or even on-route. They have lifted the traditional carpooling services to a significantly high level, attracting a growing number of people, particularly office workers, to find suitable carpoolers to travel along (Delhomme and Gheorghiu, 2016). This leads to increasing potential of carpooling as a practically effective travel alternative for car-dependents. Accordingly, massive raw data specific to very single carpooling trip recorded by online carpooling system offer us the possibility to conduct more delicate management. Thus, along with the technical development of carpooling services, if a data-driven methodology can be found that assists governments in designing more effective policy measures to further boost the growing carpooling demand, especially in cities with a population of a few million and a high car ownership rate (e.g. in dozens of world cities), the potential application and value of this approach will be immense. Especially they include: (1) promoting carpooling as a widely adopted travel alternative for current car-dependents particularly for car-commuters, and (2) reducing the number of single occupant vehicle users and thus mitigating a series of transport problems e.g. parking, congestion, energy consumption and emission. Considering the in transport sector financial incentive is easily accepted by people and frequently adopted by authorities, we would focus on formulating more reasonable and delicacy subsidy policy based on empirical carpooling data in this work.

1.2 Literature review

1.2.1 The related state-of-art of carpooling services

Carpooling can be conceptualized as an operation process where two or more people, with common or similar itineraries and schedules, share the use of a privately owned car for a trip (or part of a trip), and the passengers contribute to the driver's expenses (Ciari, 2012; Lu and Quadrifoglio, 2019). Both the drivers and the passenger(s) are considered as carpoolers. While conventional carpooling is not a new idea instituted temporarily during World War II to save fuel and resurrected in the 1970s to reduce air pollution emissions, traffic congestion, and energy consumption (Cetin and Deakin, 2017), the rapid development of transportation network companies (such as DiDi in China and Uber in America) have made the new carpooling services based on mobile internet popular again in many countries, especially in China. Therefore, many scholars have begun to revisit this old question.

Firstly, there is a rich of literature focusing on improving the operation mechanism of carpooling. Some scholars developed dynamic ride-matching algorithms by modelling the carpooling process as an optimization problem (Agatz et al., 2011; Amey, 2011; Herbawi and Weber, 2012; Stiglic et al., 2015). In these studies, the commonly-used optimal objective functions are to minimize the overall path length (Agatz et al., 2011; Stiglic et al., 2015), whereas Herbawi and Weber (2012) also considered additional objectives including minimizing the overall travel time and maximizing the number of ride-matches. On the other hand, Kamar and Horvitz (2009) and Wang et al. (2015) proposed heuristic approaches to explore the ridesharing formation process. In practice, a few matching agencies (e.g. DiDi company) have recently implemented the dynamic ride-matching algorithms in their smartphone-based application systems. The new systems provide an automated dynamic process of ride-matching in real-time between drivers and passengers. They satisfy on-demand requests and ensure that the carpooling participants would still be serviced even if their travel needs change unexpectedly (Levofsky and Greenberg, 2001). Apart from the analysis on matching algorithms and carpooling processes, there are also some studies conducting profound research on carpooling service pricing (Kamar and Horvitz, 2009; Kleiner et al., 2011; Nourinejad, 2016), retrieving and analyzing carpooling travel patterns (Cyndi et al., 2012; Xiao et al., 2016; Yongqi et al., 2018), and carpooling service management strategies (Wang, 2011; Vanoutrive et al., 2012; Delhomme and Gheorghiu, 2016).

1.2.2 Environmental impact of carpooling trips

Compared to the optimization and management carpooling services, the impact of online ridesharing on energy consumption and exhaust emission, however, has received less attention. The following work can represent the state-of-the-art of this line of research. Caulfield (2009) estimated the environmental benefits of ridesharing in terms of the reduction in both emission and vehicle kilometers travelled. The data from the 2006 Census of Ireland and the COPERT4[1] model were used to estimate the CO_2

[1] COPERT 4 is a software program which is developed as a European tool for the calculation of emissions from the road transport sector (Gkatzoflias et al., 2006).

emission saved by ridesharing. Jacobson and King (2009a) estimated the fuel savings that could be resulted from a predicted level of increases in ridesharing in the US. The authors considered the influence of incremental weight carried by each vehicle (in picking-up or dropping-off extra passengers during the trip) on carpooling's fuel consumptions. Guidotti et al. (2017) forecasted the potential economic and environmental impact of carpooling in Pisa and Florence, considering the number of private cars sold and the estimated carpooling usage rate. These three aforementioned studies focused on potential carpooling participants and conducted macroscopic analysis using traditional survey data, which only conducted a rough estimate for carpooling fuel using and were not true representative of the actual carpooling market. Recently, Yu et al. (2017) employed raw carpooling trip data to evaluate the direct environmental benefits of ridesharing as well as the indirect ones induced by possible car users' behavior changes, by means of life cycle analysis (LCA) and input-output (IO) analysis approaches, respectively. However, their work still only focused on the total energy savings and emission reductions achieved by the total carpooling trips, without examining the potential distinctions among each single trips, which is necessary to propose more effective and delicate promotion measures for carpooling services.

1.2.3 Subsidy policy making for transport sector

The financial incentive measures, such as target subsidies on public transport and tax exemption for electric vehicles, have been adopted by traffic authorities in worldwide countries to promote green traffic modes and reduce the carbon emission. For the same purpose, the subsidies strategy for promoting carpooling services has also been proposed by many scholars (Vanoutrive et al. 2012; Delhomme and Gheorghiu, 2016). However, the decision-makers could face two complex issues when seeking to make it more effective.

One is how to find the appropriate level of subsidies. Although carpooling can reduce the vehicle kilometers of travel, it is still the car-oriented traffic mode with lower occupancy comparing to the public transport. Wang (2011) argued that carpool subsidies can lead to unintended consequences such as the private cars' overuse and worse traffic congestion, while subsidizing transit and bicycles benefits the society more at less cost. Vanoutrive et al. (2012) agreed that carpooling as a commuting alternative can reduce the number of single occupant vehicle (SOV) users, however, they also emphasized the promotion of carpooling must not result in increased urban sprawl or lower levels of public transport or bicycle use. Therefore, it should be deliberate and moderate to determine the level of carpooling subsidies. On the other hand, how to allocate the subsidies among carpoolers fairly could be another challenge. The undifferentiated subsidies for the entirety or some segments of population have frequently been applied in many cities. Many scholars presented their worry about the equity of this kind of subsidy distribution (Iseki, 2016; Wang and Zhang, 2016; Guzman and Oviedo, 2018). To conduct more specific and equitable subsidy distribution, Yu et al. (2018) proposed a performance-based method constructed through data envelopment analysis to help governments allocate subsidies to individual offshore ferry routes, which is more easily implemented than the current policy. Fan et al. (2016) calculated the cost-effective carbon subsidy for hybrid electric vehicles based on a personal carbon trading (PCT) model using the Chinese market as the case study. Their sensitivity analyses showed that the change of fuel efficiency would have a distinct impact on the equilibrium carbon price and the cost-effective carbon subsidy. As a new market-oriented policy, PCT has been suggested as an effective measure in the transportation sector to influence travel choices and reduce emission at the individual level (Harwatt et al., 2011; McNamara and Caulfield, 2013; Li et al., 2016). Particularly, Aziz et al. (2015) argued that PCT studies in transportation sector were more representative and practicable considering that over 95% of the carbon was converted into CO2 when fossil fuels are consumed by private transportation. Li et al. (2017) further indicated that the PCT scheme was more capable of providing abatement certainties in transportation. Similarly, under the PCT scheme, it becomes possible to convert the trip-specific fuel savings into carbon allowance and then allocate them fairly among carpoolers.

To address the above-mentioned limitations with respect to the development of more advanced methods to evaluate the impact of carpooling on energy consumption and exhaust emission as well as to design more effective policy measures based on the specific estimation results to assist governments in boosting carpooling, we will in this study propose a trip-specific model based on empirical carpooling data. Compared to the existing methods, the proposed technique will make significant contributions in the following aspects. (1) From the trip-specific perspective, the model estimates the fuel consumption of each single carpooling trip and its corresponding driving-alone trip (i.e. a trip if carpooling services are not available and both the driver and passengers would drive alone). The difference of the fuel consumption values of these two trips is used as the ceiling of the fuel savings for the specific trip. (2) In the process of calculating the fuel consumption, the specific path length and the impact of passengers' weight on fuel economy under various vehicle occupancy scenarios are initially taken into account. The model also distinguishes between secondary ridesharing trips (i.e. trips with two groups of passengers) and ordinary ridesharing trips (i.e. trips with only one group of passengers) based on the positional elements of carpooling participants. The former trips are more complex due to more kinds of vehicle occupancy scenarios, which are firstly divided into four saddle-sharing patterns in accordance with the carpooling service mechanism. (3) To develop more effective subsidy measures, the moderate-promotion and equitable-allocation two incentive principles are proposed. We take the socially acceptable subsidies for electric vehicles as the ceiling of the carpooling subsidies to embody the principle of moderate-promotion, and take every single carpooling trip's fuel savings as the measures of carbon subsidies amount based on the scheme of Personal Carbon Trading to guarantee fairness. According to the cost-effective method, a series of possible carpooling subsidies to promote carpooling services are presented with various pricing scenarios. (4) We also present the trip-specific method to calculate the impact of carpooling trips on fuel consumption of potential public transport users, which extends the application of proposed model to areas with different traffic statuses. The operation features of public transit are clarified and used to modify the traveling distance of carpooling. (5) By taking Beijing as the case city, the spatial-temporal distribution of energy savings of carpooling trips will be analyzed, and the pricing scenarios of the proposed subsidies will be discussed.

The rest of this paper is organized as follows. Section 2 describes the carpooling trip data, while Section 3 details the methodology of fuel saving estimation and subsidy strategy designing. The proposed method is tested in the case city of Beijing and the derived results are analyzed in Section 4. Finally, Section 5 ends this paper with major conclusion as well as discussion for future research.

2. Dataset and preliminary analysis

The carpooling trip data consists of a group of randomly sampled and anonymized carpooling order records obtained from a smartphone-based ridesharing application system named DiDi Hitch (DiDi, 2018), developed by DiDi Company. DiDi is the largest ride-hailing service company in China and one of the largest on-demand ride sourcing service platforms in the world (Shih, 2015). There are two types of carpooling dataset originally collected by DiDi Hitch, namely driver dataset and passenger dataset.

The driver dataset is comprised of detailed information on the origin and destination of drivers including a series of trip distances, as well as the trips timestamp. In the process of carpooling services, four types of trip distances are recorded in Fig.1. The order distance d_O (heavy arrow lines) denotes the trip distance of the passengers, i.e. the actual part of the carpooling service. The beginning distance d_B and ending distance d_E (solid arrow lines) are the driver's traveling distance from his/her origin to the picking up location of the passenger, and from the passenger getting off location to his/her destination, respectively. Besides, the route distance d_R (dotted arrow lines) represents the length of a driver's original trip route that he or she would have taken if driving alone. Note that all the traveling distances are the length of the optimal routes offered in real time by the AMAP (an online picture-based navigation program embedded in the DiDi Hitch), whose estimation is relatively accurate and will be directly utilized in this study. Unfortunately, this data need to be uploaded by drivers proactively, but some drivers could forget or dislike to upload it, which causes some drivers' data missing randomly. The passenger dataset focuses on passengers including the number of passengers as well as their trips' origin and destination. But in term of trip distance information, there is only the order distances in this dataset. This type of data is uploaded automatically and totally.

These two datasets are linked through the ID (identification) of the carpooling orders. Each record in the combined dataset represents a carpooling trip and its related information includes the ID of the trip, the number of the passengers, the origin and destination locations as well as timestamp of both the drivers and passengers, and the four types of trip distances. The locations are in the form of coordinates of latitude and longitude.

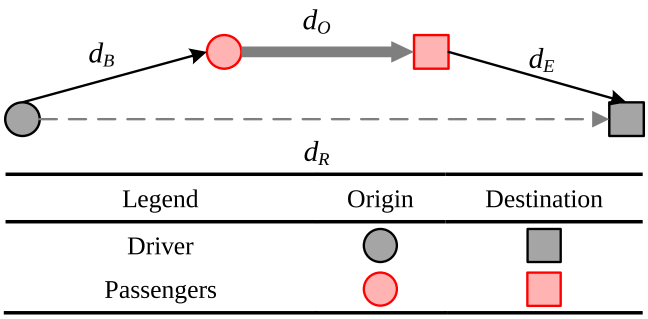


Fig.1 The travel pattern and recorded distance on one basic carpooling trip

The dataset used here contains records of 2,057,421 ridesharing orders including both the complete drive data and passenger data in December 2107 in Beijing. The sample ridesharing orders are fulfilled by 268,815 drivers, carrying about 2.57 million passengers and traveling 46 million kilometers, more than going around the earth 1100 times. During the 31 days of December 2017, only 3.3% of drivers undertook over one carpooling order per day on average, which implied the carpooling trips may be just the rigid demand for most carpooling drivers and they do not consider serving passengers as a job. Even without passengers, they would still fulfill commuting by cars.

Furthermore, it was noted from Fig.2 that the morning (7:00-9:00) and evening (17:00-19:00) traffic peak hours have significant impact on the distribution of the number of hourly orders. The orders among the rush hours account for 32% of the total orders throughout the day, which is much higher than the proportion of 20% for taxi trips during the same rush hour period (Yongqi et al., 2018). It demonstrates that ridesharing services play an important role in commuting travel. Moreover, from Fig.3, it was also observed that the order distances reach the peak of between 16 and 18 km, with the average as approximately 22 km and more than 85% of the distances being longer than 10 km. The order distances are much longer than the average distances of trips conducted by taxis or urban rail transit which are 9.9 km and 13.3 km respectively (BTI, 2016), but they are close to the average riding distance of suburban railways or city express (Rahman and Balijepalli, 2016). This implies that ridesharing services mainly satisfy the demand of mid- and long-distance trips and particularly make up the current shortage of suburban railway systems in Beijing.

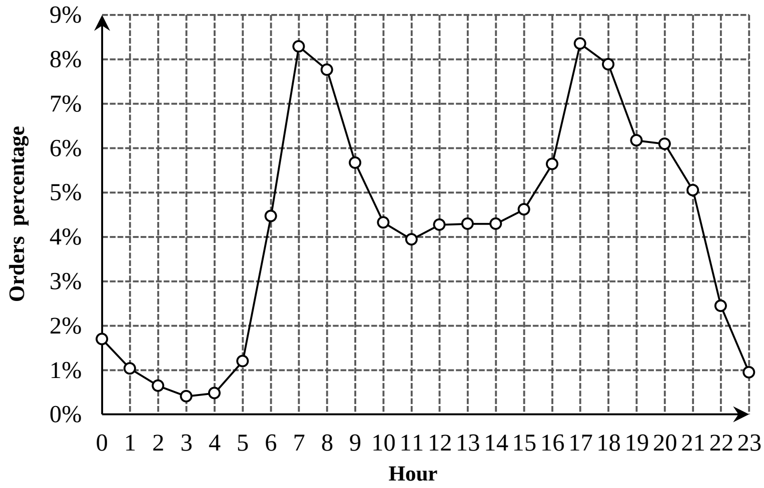


Fig.2 The carpooling orders hourly distribution in December

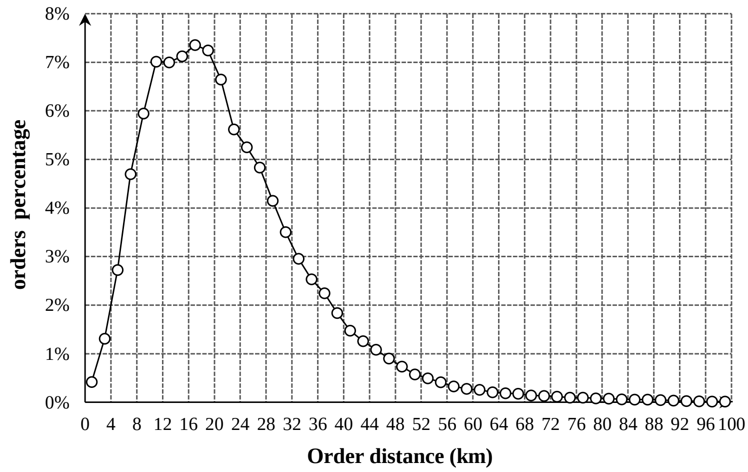


Fig.3 The carpooling orders distance distribution in December

3. Methodology

3.1 Determinants of carpooling fuel savings

Carpooling users may prefer to travel by cars even with higher expenditure, either because they pursue more convenience and comfort during the travel, or due to the fact that the cheaper public transport resources are unavailable for them. Therefore, the passengers' alternative travel modes would frequently shift to taxis or private cars if the ridesharing services are not available. In fact, most of the relevant studies analyzed carpooling's travel patterns and energy consumption by comparing the ridesharing trips with passengers using individual-service taxis or driving private cars alone (Jacobson and McLay, 2006; Jacobson and King, 2009 a, b; Cyndi et al., 2012; Xiao et al., 2016). On the other hand, the carpooling subsidy object should exclude the carpoolers who are potential green-passengers to guarantee the priority development of public transport or slow traffic. Therefore, the carpooling fuel savings estimation and carpooling encouragement policy making mainly focus on the potential car-users in this work. When regarding all carpoolers as potential car-users, in fact, what we estimated is the upper limits of carpooling's fuel savings. Specifically, the fuel saving FS in one particular carpooling trip can be defined as Eq.1, where FC^H and FC^R denote the fuel consumption of the hypothetic travel H by private cars and the fuel consumption during the ridesharing trip R in the real case, respectively. The fuel saving ratio FSR is defined as the ratio between FS and FC^R.

$$FS = FC^H - FC^R \ , \ FSR = FS \ / \ FC^R \tag{1}$$

In general, carpooling travel can save energy consumption by increasing the number of passengers per vehicle and reducing the number of vehicle kilometers needed to realize the desired passengers' trips. However, carpooling also increases the weight carried by each vehicle, and requires additional detour to pick-up the passengers, both of which increase fuel consumption. Jacobson and McLay (2006) and Jacobson and King (2009 a) stated that there exists a linear relationship between a change in vehicle weight and the corresponding change in fuel economy, FE (measured by the fuel consumption per hundred kilometer traveled) for that vehicle. Thus, the determinants of ridesharing on energy consumption are the fuel economy and person-kilometer traveled (PKT). Based on the two determinants and the specific carpooling trip dataset, a fuel consumption model is proposed in Eq.2. The subscript VOS represents the set of different vehicle occupancy scenarios which include the deadhead status of drivers (no-passenger travel status), carpooling status with different number of passenger groups, and passengers driving-alone status if ridesharing services are not available. The three scenarios are represented with the capital letters D, C and P, respectively, forming the scenario set $VOS=\{D, C, P\}$. Considering the weight contributed by the additional passengers with different vehicle occupancy scenarios, the vehicle fuel economy FE_{VOS} would be eroded to varying degrees, and the travel path length PL_{VOS} should be in one-to-one correspondence with the change of FE_{VOS}. Consequently, the quantity of the total fuel consumption FC during one trip is the sum of the fuel consumption in each vehicle occupancy scenario, which is further derived from the product of the specific fuel economy of the vehicle and the kilometers traveled in the corresponding scenario.

$$FC = \sum FE_{VOS} \times PL_{VOS} \tag{2}$$

For obtaining the amount of fuel savings for one carpooling trip, the fuel consumption FC^R for the ridesharing trip in a real case and FC^H for the corresponding driving-alone trip under a hypothetical scenario (without carpooling service) are calculated according to Eq.3 and Eq.4. Thereinto, the newly introduced subscript i represents the sequence of the orders in which the driver has picked-up different groups of passengers. If $i>1$, it means a driver takes more than one carpooling orders during one trip, namely multiple group passenger saddle-sharing in carpooling trips. In particular, when i=2, PL^R_{C1} and PL^R_{C2} are the paths length of the first group of passengers and the second group of passengers during carpooling trip respectively, while PL^H_{P1} and PL^H_{P2} are the paths length of the first group of passengers and the second group of passengers when passengers driving alone. Note that there may be several passengers placing one carpooling order, who are acquainted with each other and have similar origin and destination. The definitions of other subscripts D , C and P all stem from the set of VOS and have been illustrated above.

$$FC^{R} = FE_{D} \times PL_{D}^{R} + \sum FE_{Ci} \times PL_{Ci}^{R} \tag{3}$$

$$FC^{H} = FE_{D} \times PL_{D}^{H} + \sum FE_{Pi} \times PL_{Pi}^{H} \tag{4}$$

Two groups of data are needed to estimate fuel consumption: (1) real ridesharing travel data describing the itineraries of the carpooling trips, as introduced in Section 2; (2) passengers' weight data and corresponding fuel economy data retrieved from publicly available statistics, which characterize the average weight of each passenger in a vehicle and its impact on fuel economy. Under different vehicle occupancy scenarios, values of fuel economy can be estimated by searching the public data from "Notice on the accounting of average fuel consumption of Chinese passenger vehicle enterprises" released by Ministry of industry and information technology of China. The fuel economy of passenger cars produced during 2013~2015 is respectively 7.33, 7.22 and 7.04l/100km[2], the average of which is adopted as the value of FE , which is 7.20l/100km. Moreover, a parameter is defined to measure the number of additional gallons that are required to travel 100 miles for each additional pound, thus quantifying the linear relationship between a change in vehicle weight and the corresponding change in fuel consumption for that vehicle The value of this parameter for each vehicle was $R_{WF} = 8.70 \times 10^{-4}$ gal/100miles/lbs, reported by the US Environmental Protection Agency for model year 2015 vehicles (EPA, 2016). According to the user-portraits in carpooling travel survey reports, internet-based carpooling participants were mainly white-collar workers, whose ages distribute between 25-35 and sex ratio was in proximity to 1:1[3]. Furthermore, in the reference to the "Beijing National Physique Monitoring Communique in 2014" (GASC, 2015), the male and female average weight was approximate 75.5 and 58.9 kilograms respectively. All the above statistical data are supposed to remain unchanged in 2017. Hence, each additional passenger taking part in a carpooling trip would increase the weight of that car by 67.2kg. In this study, $R_{WF} = 0.3024$ l/100km/person is employed after unit conversion.

3.2 Calculation of path length

The calculation of travel path length with different vehicle occupancy scenarios is based on the operating mechanism of mobile internet-based carpooling services. In the operation process, the potential drivers and passengers of ridesharing need to first issue their itineraries on the carpooling application. The system then automatically matches the drivers and passengers with similar itineraries, and provides a series of carpooling selections for the participants. The highly matched carpooling trips will be

[2] http://www.miit.gov.cn/n1146290/n4388791/c6080976/content.html

[3] http://www.xinhuanet.com/fortune/2016-06/01/c_1118971732.htm

recommended to passengers first. If the drivers and passengers all agree on the plan, they make a deal and the passengers pay the trip fare once the carpooling trip has been realized. Of course, the trip fare is much lower than that of taxis or other types of online ride-hailing services. Throughout the course of carpooling travel, the carpooling service system plays a role as infomediary to achieve on-demand double-side matching. On the one hand, carpooling drivers offer passengers transport services while pursuing utility maximization, i.e. making the most profit at the least cost of extra time and other expenses. On the other hand, carpooling passengers usually take an initiative position in the supplier-customer relationship owing to the implicit customer-oriented service principle, in which drivers show great detour flexibility in order to pick-up and drop-off passengers.

In contrast with traditional ridesharing, detour flexibility is one of the important features for internet-based carpooling services. Detour is the increase in trip distances and time duration that drivers are willing to take in order to pick-up and drop-off passengers, and detour flexibility is the willingness of drivers to make a detour in order to have passengers for carpooling. Yongqi Dong et al. (2018) indicated that since internet-based ridesharing drivers are paid, they could detour further to pick-up or drop-off passengers than traditional hitchhike drivers. Considering the bucking effect of detour on carpooling's fuel savings, it is of great importance to clarify the specific detour distance on every carpooling trip. The concrete implication of traveling distances in ordinary carpooling travel record has been illustrated in section 2. In accordance with Fig.1, the detour distance in this trip can be determined in Eq.5, consisting of the driver' actual travel distance subtracted by the theoretical travel distance.

$$d_D = d_B + d_O + d_E - d_R \tag{5}$$

When a driver only receives one single order, i.e. the situation shown in Fig.1, the length of the travel paths with different vehicle occupancy scenarios can be computed based on Eq.6. In particular, the driving-alone distance of the passenger is equal to his/her ordered carpooling distance, as shown in the last formula of this equation.

$$PL_D^R = d_B + d_E \quad PL_C^R = d_O \quad PL_D^H = d_R \quad PL_P^H = d_O \tag{6}$$

Furthermore, if time limits do not constrain drivers, they may be able to successively provide rides to multiple groups of passengers during one single trip (Hosni et al., 2014). To calculate the travel distance in the multiple group case, the commonly adopted method is to classify the trips into different categories, and compute the travel distance for each category. The most relevant work includes the following two studies. Morency (2007) classified carpooling trips according to positional elements, i.e. the relative positions of the origin and destination of different passenger orders during one trip. Furuhata et al. (2013) further extended the previous research by analyzing how these different trip categories influence rideshare matching in general. The authors divided ridesharing trips into four patterns (Identical Ridesharing, Inclusive Ridesharing, Partial Ridesharing and Detour Ridesharing). Nevertheless, the partial ridesharing pattern (the passengers' trips are partially served by drivers and the drivers only providing passengers a carpooling service in the drivers' own routine trips rather than considering passengers' origins and destinations) does not exist in the current internet based carpooling services. Moreover, the proposed patterns failed to consider the scenario where the routes of two ridesharing orders are overlapping. To overcome the problems, in this study we will develop the new ridesharing patterns based on the actual process of the online ridesharing services according to the following three steps.

In the first step, to calculate the path length in the fuel consumption model, two assumptions are proposed based on the carpooling matching mechanism, customer-oriented service principles, and actual carpooling data: (1) drivers are willing to make a detour in order to accommodate the entire trips of the passengers. That is, passengers would be just picked-up at their origin and dropped-off at their own destination, and (2) all drivers are rational. If there are multiple orders during one carpooling trip, drivers will pick up the appropriate group of passengers according to their route own first to minimize the detour distance in the carpooling trip.

In the second step, the drivers and corresponding passenger groups as well as the positional elements are defined as follows. Let A as a driver, and the numbers 1 and 2 as the first and second orders (groups) of passengers, respectively. The driver and the two groups of passengers have their own origin and destination. Define Ori_i and Des_i (i=1, 2) as the origin and destination and U_i and V_i (i=1, 2) as the picking-up and dropping-off locations for the two passenger groups, respectively. According to the Assumption 1, the passengers' origins are very close to their picking-up locations, i.e. $Ori_i = U_i$; the same is true for the destination and dropping-off locations, i.e. $Des_i = V_i$. The saddle-sharing paths formed by the driver A and the two group of passengers are denoted as $P(A,1)$ and $P(A,2)$, respectively.

In the third step, based on the above assumptions and variable definitions, the ridesharing trips are classified into four patterns as illustrated in Fig. 4. In the following, we describe four patterns by schematic diagrams and explain the calculation of the path length.

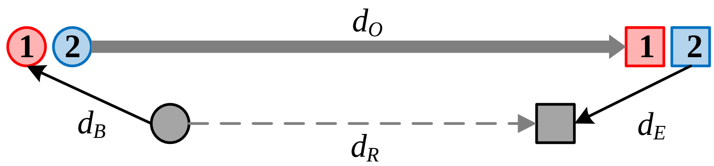
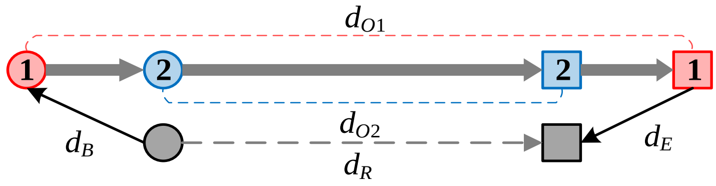
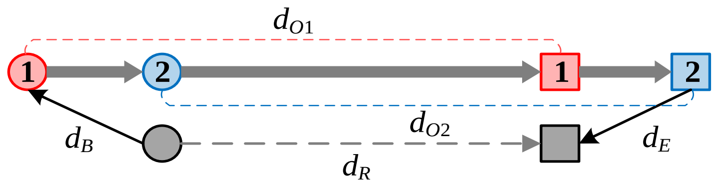
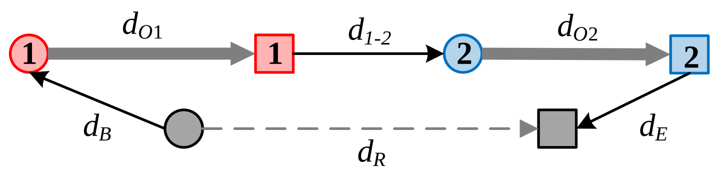
- Identical paths (pattern 1): both the origin and destination of the two groups of passengers are identical, namely $U_1 = U_2$ and $V_1 = V_2$. All the identical trips are implemented through saddle-sharing, and the calculation of the path length is equivalent to the formula in Eq.6 for the basic condition.

- Inclusive paths (pattern 2): the path of the group 2 is totally covered by the path of the passengers group 1, i.e. $U_2, V_2 \in P(A,1)$. There are three types of vehicle occupancy scenarios during the trip. The path length PL_D^R for the driver's deadhead status is up to the origin of the group 1, and the path length $PL_{C1,2}^R$ (the paths length when drivers carry the first and second group of passengers at the same time) for the saddle-sharing of the two groups is equal to the travel distance of the group 2. According to carpooling matching mechanism, the path length PL_{C1}^{R} in which only the group 1 takes carpooling is the difference in the travel distances between the group 1 and group 2. PL_{D}^{H} is the same as the one in the previous case, which is d_{R1}, namely the route distance in the first carpooling orders.

- Overlapping paths (pattern 3): a part of the path between the group 1 and group 2 is overlapping, i.e. $U_2 \in P(A,1)$, $V_1 \in P(A,2)$; $U_1 \notin P(A,2)$, $V_2 \notin P(A,1)$. Four types of vehicle occupancy scenarios are generated during this trip. The path length PL_{D}^{R} is determined by the origin of the group 1 and the destination of the group 2. Due to the lack of travel distance data that directly describe the path length of the overlapping trip, i.e. $PL_{C1,2}^{R}$ (or $d_{O1,2}$, namely the order distance under saddle-sharing scenarios), this variable is estimated based on the average of the two groups' own order distances d_{O1} and d_{O2} multiplied by the ratios $\tau_{O1,2}/\tau_{O1}$ and $\tau_{O1,2}/\tau_{O2}$ respectively. $\tau_{O1,2}$ is the travel duration of the overlapping trip, while τ_{O1} and τ_{O2}. are the total travel time of each of the two groups. The path length PL_{C1}^{R} and PL_{C2}^{R} are the difference between the two groups' own order distances and saddle-sharing distance $d_{O1,2}$, respectively. PL_{D}^{H} takes the longer one between d_{R1} and d_{R2}, which is closer to the path length when drivers traveling alone without passengers.

- Distinct paths (pattern 4): there is no overlapping between the paths of the two passenger groups, i.e. $P(A,1) \cup P(A,2) = \varnothing$. However, they share the same carpooling driver's trip. In fact, it is entirely separated carpooling orders accomplished by the same driver, and the calculation of the travel path length is analogous to that for the basic scenario of one driver with one group of passengers as described in Eq.6 other than the deadhead distance $d_{1\text{-}2}$ between V_1 and U_2, which happened when drivers seek the second group of passengers without the first group. The deadhead distance can be estimated by the product of straight-line distance from V_1 to U_2 and corresponding adjustment coefficient.

All the above-described four patterns can be distinguished and extracted from the carpooling trip data based on the timestamp and location sequences by which passengers get on or off the cars. Traditional matching agencies do not take these patterns into account, and they accomplish the matching process via proximity rather than exact locations. The positional deviations of locations between drivers and passengers as well as between different groups of passengers cause difficulties for drivers to make instantaneous decisions. This leads to less carpooling trips accomplished, since the additional detour time and travel costs incurred by the drivers are usually not paid by the passengers. However, with the advent of LBS , mobile technologies and GPS positioning, it becomes possible for the matching systems to timely and accurately know the exact positions of drivers and passengers (Levofsky Greenberg, 2001), generating much better matches in terms of both time and locations. This leads to more passengers and drivers participating in the carpooling services. In this paper, we only consider the most common case where a driver can offer rides to a maximum of two orders of passengers. Nevertheless, for the infrequent situations where more orders are served, the same principles can be applied as well. From the angle of practical application, the estimation of carpooling fuel savings was conducted based on a data-driven method. Except for the carpooling trips information, the other data are all available for public. Therefore, it is easy for carpooling companies or authorities to know the specific fuel savings of individual carpooling trip by this model. In addition, it should be noted that there is a potential deviation for using the order distance of passenger group 1 as actual order distance when the passenger group 2 cancel the order temporarily and the driver has went off the initial navigation route. However, the chance that a driver can receive the second order in one trip is very small and the DiDi service platform will punish the persons who have canceled the second-trip carpooling order through the negative reputation records. Therefore, the potential deviation about the path length would be very small and can be negligible in this study.

Ridesharing patterns	Ridesharing diagrams and path lengths calculation
Identical paths	 $PL_D^R = d_B + d_E$ $\quad PL_{C1}^R = PL_{C2}^R = d_O$ $PL_D^H = d_R$ $\quad PL_{P1}^H = PL_{P2}^H = d_O$
Inclusive paths	 $PL_D^R = d_B + d_E$ $\quad PL_{C1}^R = d_{O1} - d_{O2}$ $\quad PL_{C2}^R = PL_{C1,2}^R = d_{O2}$ $PL_D^H = d_R$ $\quad PL_{P1}^H = d_{O1}$ $\quad PL_{P2}^H = d_{O2}$
Overlapping paths	 $PL_D^R = d_{B1} + d_{E2}$ $\quad PL_{C1}^R = d_{O1} - d_{O1,2}$ $\quad PL_{C2}^R = d_{O2} - d_{O1,2}$ $PL_{C1,2}^R = d_{O1,2} = \frac{1}{2} \times \left(\frac{\tau_{O1,2}}{\tau_{O1}} \times d_{O1} + \frac{\tau_{O1,2}}{\tau_{O2}} \times d_{O2} \right)$ $PL_D^H = d_R$ $\quad PL_{P1}^H = d_{O1}$ $\quad PL_{P2}^H = d_{O2}$
Distinct paths	

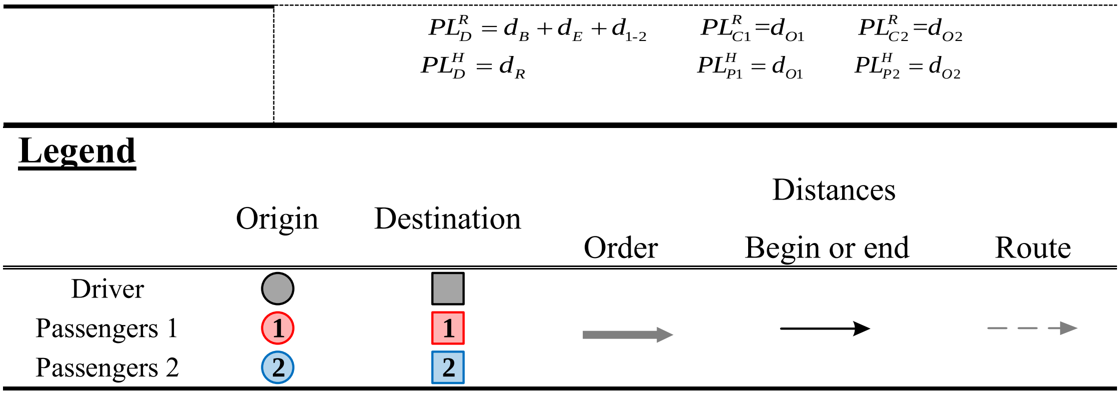


Fig.4 The positional elements of ridesharing patterns

3.3 Carpooling subsidy policy under personal carbon trading schemes

Through summarizing the previous studies about subsidy policy making in transport sector, two principles are proposed here to make more effective carpooling promotion measures. The first one, so-called moderate-promotion, is that the facilitation of carpooling should not result in increased urban sprawl or decreased usage rates of mass transit or other eco-friendly travel modes (e.g. biking and walking). The second, equitable-allocation, refers to subsidies allocation should be according to the environmental contributions from trip-specific perspective. According to above two incentive principles, the carbon-pricing under PCT was integrated into the calculation of travel costs to stimulate driving-alone passengers to participant in carpooling services. Considering the cost of both carbon permits and fuel consumption, the subsidy scheme is designed based on the cost-effective method, which has been widely adopted in the field of energy management. The typical examples using the cost-effective method include the optimal subsidies on a stove exchange program to reduce air pollution from wood combustion in southern Chile (Gómez et al., 2014), on promoting hybrid electric vehicles in the Chinese market (Fan et al., 2016), and on encouraging efficient room air conditioners in China (Guo et al. 2017). Based on this method, for a carpooling trip, the total cost of the carpooling users during the entire trip is denoted in the left side of Eq. 7, and the cost of these users when driving-alone is in the right. The cost-effective subsidy balancing the cost of the carpooling travel and single occupant travel meets the following conditions described in Eq.8. In these two equations, CF is the fare of carpooling services directly determined by the carpooling network platform, and CS is the carpooling subsidy that needs to be derived. λ denotes the carbon emission rate of gasoline and φ refers to the initial carbon allowance; both parameters are allocated to every vehicle owner on a per capita basis. Moreover, P_1 - P_4 represent a set of prices, including the carbon trading price (P_1), fuel price (P_2), private car purchase price (P_3), and parking charge price (P_4). Furthermore, SL is the service life of private cars and expressed in driving kilometers; while $PL_P^H \cdot P_3/SL$ is estimated as the depreciable cost for one trip conducted using a private car. Considering the moderate-promotion principle, the travel cost of carpooling should be higher than the fare by public transport (e.g. buses or subways), and the carpooling subsidy should be inferior to that for the public modes. This can be automatically guaranteed by the ultra-low ticket prices and huge subsidies for public transit in many cities, e.g. in Beijing. Furthermore, we take the socially acceptable subsidy EVS for EVs (electric vehicles) as the ceiling of the carpooling subsidies in practice in order to avoid the derived results leading to more car-oriented development and obstructing the development of green transport.

$$\left[\varphi-(FC^{R}-FC_{D}^{H})\lambda\right]P_{1}+CF-CS=(\varphi-FC_{P}^{H}\cdot\lambda)P_{1}+FC_{P}^{H}P_{2}+\frac{PL_{P}^{H}}{SL}P_{3}+P_{4} \tag{7}$$

$$CS=CF+FS\cdot\lambda P_{1}-FC_{P}^{H}P_{2}-\frac{PL_{P}^{H}}{SL}P_{3}-P_{4} \quad CS<EVS \tag{8}$$

Conducting delicate subsidies based on the trip-specific cost and emission abatement are supposed to effectively appeal to potential carpoolers and avoid inequitable allocation of subsidies among all carpooling trips. Note that the taxi fare (e.g. the average price as ¥30 for the riding distance of 10km in Beijing) is generally much higher than that of carpooling services in the real world, and thus taxis are not used as the comparable mode on the cost-effective method. Furthermore, the carpooling subsidy should be only made and paid to the potential car users to avoid reducing the split share of mass transit or other more eco-friendly means of transportation. However, it is hard to at present to survey the original travel modes of every carpooler. For facilitating the application, we can take the vehicle owners as the provisional incentive object at the beginning since the information of private vehicle's ownership is easier to gain. The car owners here refer to the carpooling users who have their own private cars, including both drivers and passengers who account for 77% of the current carpooling users according to the phone-based survey by Yu et al. (2017).

3.4 Estimation on carpooling fuel savings for potential public transport users

Although most of carpoolers would prefer to commute by private car or taxi, part of them have to use public transport in practice, especially in developing countries, considering the lower car ownership and the availability of public transportation systems. To expand the application of proposed model and consider various scenarios of travel mode transfers, the method to calculate the impact of every single carpooling trips on fuel consumption of potential public transport users was provided in the following.

$$FS_{B}=FC_{B}^{H}-FC^{R}\ ;\ \ FS_{M}=FC_{M}^{H}-FC^{R} \tag{9}$$

$$FC_{B}^{H}=FE_{D}\times PL_{D}^{H}+\sum_{i}FE_{P_{i}}^{B}\times PL_{P_{i}}^{B}\ \ ;\ \ FC_{M}^{H}=FE_{D}\times PL_{D}^{H}+\sum_{i}FE_{P_{i}}^{M}\times PL_{P_{i}}^{M} \tag{10}$$

According to the modeling process above, we still take the difference between the fuel consumption by taking bus FC_{B}^{H} (by taking metro FC_{M}^{H}) and the fuel consumption during the ridesharing trip FC^{R} as the fuel savings FS_{B} (FS_{M}). And the fuel economy coefficient and associated path length remain the two determinations of fuel consumption, shown in Eq.10. Due to lack of specific bus or metro route for every carpooling passenger, we take the modified order distance during carpooling trips as the path length traveled by public transport, considering two adjustment factors, detour conversion coefficients α_B , α_M , and distance to stations d_{BS} , d_{MS} , shown in Eq.11. The public transport system with fixed traveling routes may cause a detour comparing to flexible driving lines of cars. So, we take the ratio between the non-linear coefficient of bus network NL_B (or metro network NL_M) and the non-linear coefficient of road network NL_R as the conversion coefficient. For the bus or metro network, the non-linear coefficient is defined as the average ratio of operating route length to the Euclidean distance between origin station and destination station, while for the carpooling, we take the mean value of travel distance of every trip divided by associated Euclidean distance as its non-linear coefficient based on the empirical data. On the other hand, the public transport cannot provide door to door services like cars, thus users frequently need to go to the stations by walk or other modes, which can increase or reduce the original path length. Moreover, the potential walking distances to bus are different from the ones to metro stations. Yang et al. (2017) argued that the walking distance when using public transport could be simulated by gamma distribution, and the average walking distance to/from bus station and metro station is 0.73 km and 1.21 km, respectively, based on the survey sample in Beijing.

$$PL_{P_i}^B = \alpha_B(d_O \pm d_{BS}) \;\; ; \;\; PL_{P_i}^S = \alpha_M(d_O \pm d_{MS}) \;\; ; \;\; PL_D^H = d_R \tag{11}$$

$$\alpha_B = NL_B / NL_R \;\; ; \;\; \alpha_M = NL_M / NL_R \tag{12}$$

4. Results

4.1 Characteristics of fuel savings

4.1.1 Number of different types of carpooling trips

According to the trip-specific fuel saving estimation model presented in Section 3, every trip's fuel savings can be calculated. In this case study, we take the trips made during December, 2017 in Beijing (about 2 million orders in total) as the experimental data to present the basic statistical characteristics and spatial-temporal distribution patterns of the carpooling fuel savings.

According to the internal mechanism of carpooling services, there could be considerable differences of fuel savings between the common ridesharing trips that convey one group of passengers in one trip (one-trip-multi-passengers, for short OTMP) and the four types of saddle-sharing trips that serve two groups of passengers in one trip (one-trip-multi-passengers, for short OTMP). Thus, it is important to distinguish the different types of ridesharing travel based on the raw trip data. Two steps were taken for this purpose. The first step is to examine if only one group of passengers (OTOP) is present in a driver's trip record, or if two groups of passengers (OTMP) share the same trip of the driver. In the second step, if the trip is an OTMP, the sequence of the departure and arrival time and locations of the two carpooling orders as well as their relationship is analyzed, and the trip is further distinguished among the patterns of identical, inclusive, overlapping and distinct orders. Once the type of the trip is identified, the absolute fuel saving (*FS*) and fuel saving ratio (*FSR*) of the trip is computed based on Eq.1 to Eq.6 as well as the formulas described in Fig.4. The number of the ridesharing trips as well as the average fuel using, savings and saving ratios in each type were listed in Table 1.

Over all the carpooling trips in the carpooling data, about 95% of the trips only serve one group of passengers, leading to OTOP as the main ridesharing travel type. The types of overlapping orders (OTMPOL) and inclusive orders (OTMPIS) account for 3.6% and 1.4% of the total trips, respectively, being the major categories of the OTMP trips. For the remaining types of OTMP, the number of distinct orders (OTMPDT) is less than 500, and that of identical orders (OTMPID) is zero. These two types of trips were thus ignored in the following analysis.

Tab.1 Different carpooling pattern and average energy consumption in December

Pattern	number	Fuel using (liter per trip)	Fuel savings (liter per trip)	Saving ratio
OTOP	1851245	2.52	1.17	46.43%
OTMPOL	73559	3.44	2.36	68.60%
OTMPIS	28937	2.94	2.45	83.33%
OTMPDT	<500	/	/	/
OTMPID	0	/	/	/

4.1.2 Frequency distributions of fuel savings

In terms of the fuel savings, all the 1,953,741 carpooling trips (including OTOP, OTMPOL and OTMPIS) saved 2.41 million liters gasoline in total. All the three types of trips had considerable reduction in fuel consumption, with the average fuel savings (*FS*) from OTOP, OTMPOL and OTMPIS as 1.17, 2.36 and 2.45 (liters) and fuel saving ratios (*FSR*) as 46.43%, 68.60% and 83.33%, respectively. The fuel savings of OTMPOL and OTMPIS are both more than double of OTOP's fuel savings, reflecting the huge superiority of secondary ridesharing travel in energy savings. Moreover, there are also differences between OTMPOL and OTMPIS, with the deviations in the average fuel savings and saving ratios as 0.09 liters and 15%, respectively. This suggests that OTMPIS is more efficient than OTMPOL in fuel savings. Further investigation reveals that, the average driving-alone distances of drivers in both cases of OTMPIS and OTMPOL are almost equal (i.e. 29km), but the actual average travel distance of OTMPIS trips is 37km, much less than that for the OTMPOL trips (i.e. 45km), which show there is more detour in OTMPOL trips to reduce the fuel savings.

The Fig.5 describes the detailed frequency distributions of FS and FSR for the three types of trips, respectively, and large differences were observed. Firstly, the distributions of both FS and FSR are more centralized for OTOP, and the tail of the OTMPOL or OTMPIS curve is longer than that of OTOP, with the fuel savings at 90th -100th percentiles from OTOP spreading over 2.5-11.5 liters while those of OTMPOL and OTMPIS spanning 4.5-17 liters and 4.5-16 liters respectively. Secondly, there is a gap in the fuel savings' peak values between OTOP and OTMPOL/OTMPIS (See Fig.5a), where the peak for OTOP is between 0.5-1 liters accounting for 29.5% of all the OTOP orders, while the value for OTMPOL or OTMPIS is 1.5-2 liters making up 18% of all the corresponding trips. Similar peak gaps also exist in the distributions of *FSR* (See Fig.5b), demonstrating again that OTMPOL and OTMPIS are more efficient in energy savings. Both the above-observed differences demonstrate the importance of distinguishing the different types of carpooling trips and computing the fuel savings of the trips separately. Finally, it was noticed from Fig.5 (a) that, there exist a few negative fuel saving values particularly for OTOP, suggesting that the corresponding trips consume more fuel than the driving-alone cases. Further investigation reveals that, the average detour distance of the OTOP trips with the negative values is 13.49 km, nearly twice of the trips with positive saving values. This implies that inefficient route matching algorithms could be the main reason causing the abnormal phenomenon of fuel wastage for ridesharing travel.

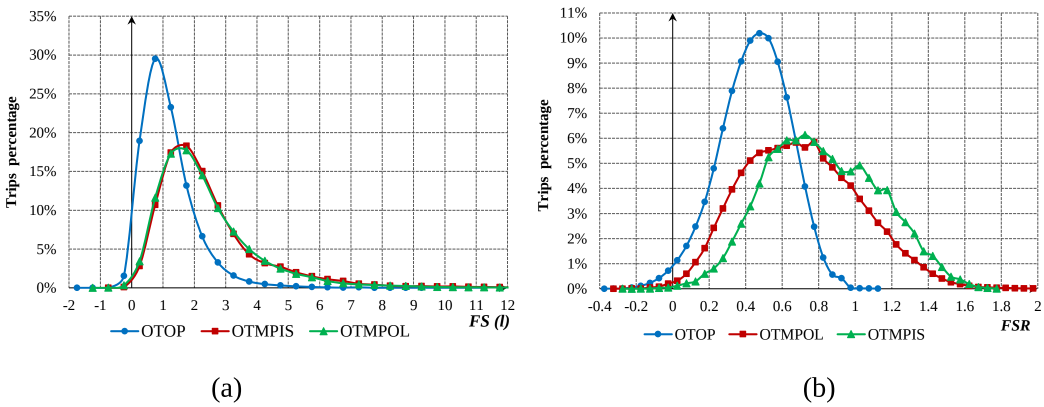


Fig.5 Frequency distribution of fuel savings (a) and fuel saving ratios (b)

4.1.3 Temporal and trip distance characteristics of fuel savings

Fig.6 shows the temporal distributions of carpooling fuel savings, indicating that the savings of OPOT reach peaks in the morning and evening rush hours, respectively. This is analogous to the hourly distribution of the number of carpooling orders depicted in Fig.2. In contrast, the saving distributions of OTMPIS and OTMPOL fluctuate over varied hours of the day, independent of the traffic conditions. The underlying reason could be that carpooling participants during rush hours are more constrained by the time needed to wait and take the second group of passengers, thus leading to OPOT as the most common type during commuting time.

The trip distance characteristics of the fuel savings are illustrated in fig.7, showing that the peak saving values of both OTOP and OTMPIS are at the distance of 20-24 km. In comparison, the distribution of OTMPOL is flatter, but its long-distance trips conserve more energy. Fig.8 further reveals the positive linear correlation between the trip distances and associate fuel savings for the three types of trips, and variations exist in the specific slopes and R-Square values, which are 0.059 and 0.811 for OTOP, 0.061 and 0.507 for OTMPOL, and 0.104 and 0.822, for OTMPIS, respectively. These three distributions indicate that, for trips with equal order distances, OTMPOL and OTMPIS trips save more fuel than OTOP on average, and the advantage becomes more obvious when the trip distances increasing. Thus, it is of more importance to encourage residents to accept secondary ridesharing and take long-distance carpooling when public transit is unavailable. In addition, the distribution of OTMPOL with lower R-Square value is more dispersed and has some exceptional dots. For the lower dots, as we mentioned above, OTMPOL trips having larger detour distance on average may cause considerable reduction on fuel savings and then make some trips with long distance yet have small amounts of fuel savings. As for the higher dots, namely those OTMPOL trips with short distance but large amounts of fuel savings, may be due to the situation that some well-matched routines among carpooling participants saved plenty of fuels beyond the average level.

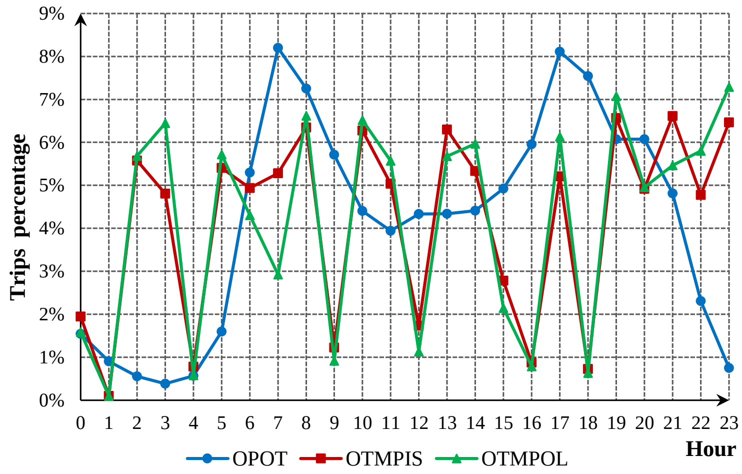


Fig.6 Hourly fuel savings distribution in December

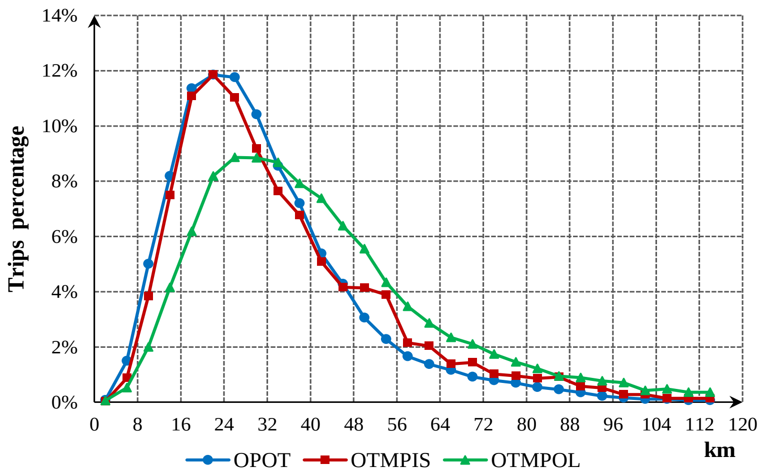


Fig.7 Fuel savings distribution in trip distance

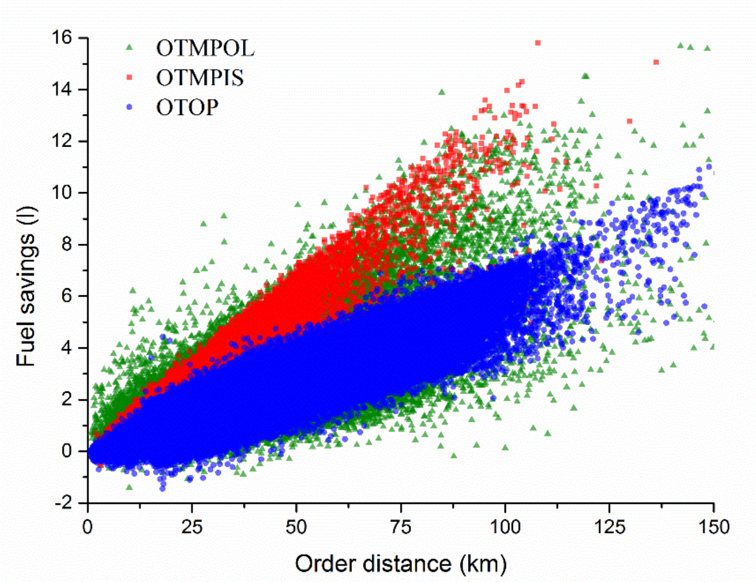


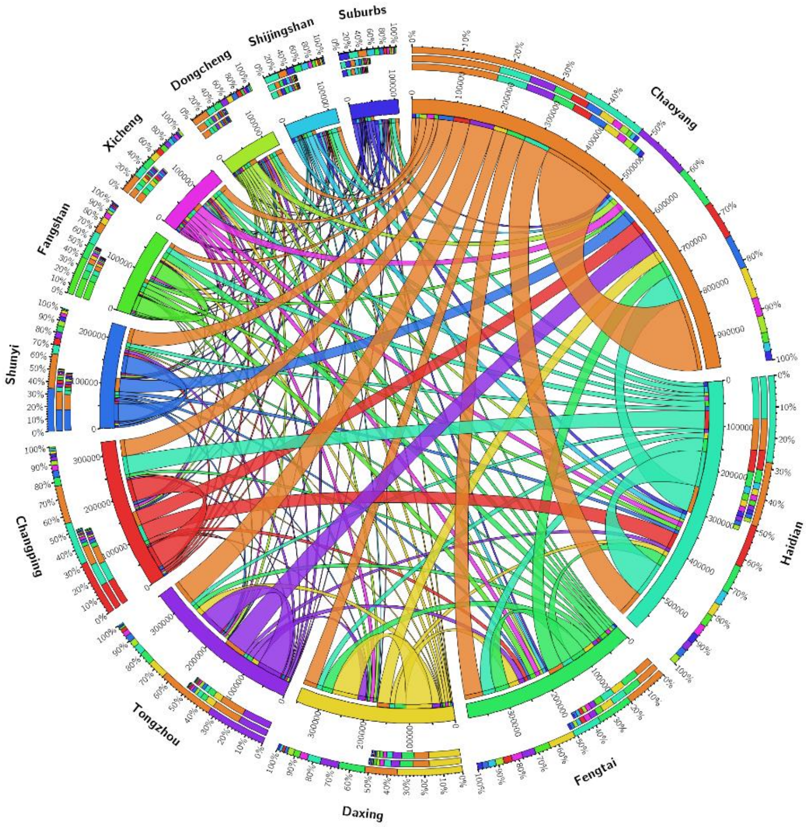
Fig.8 Relation between order distance and fuel savings for each carpooling trip

4.1.4 Origin and destination distributions of fuel savings

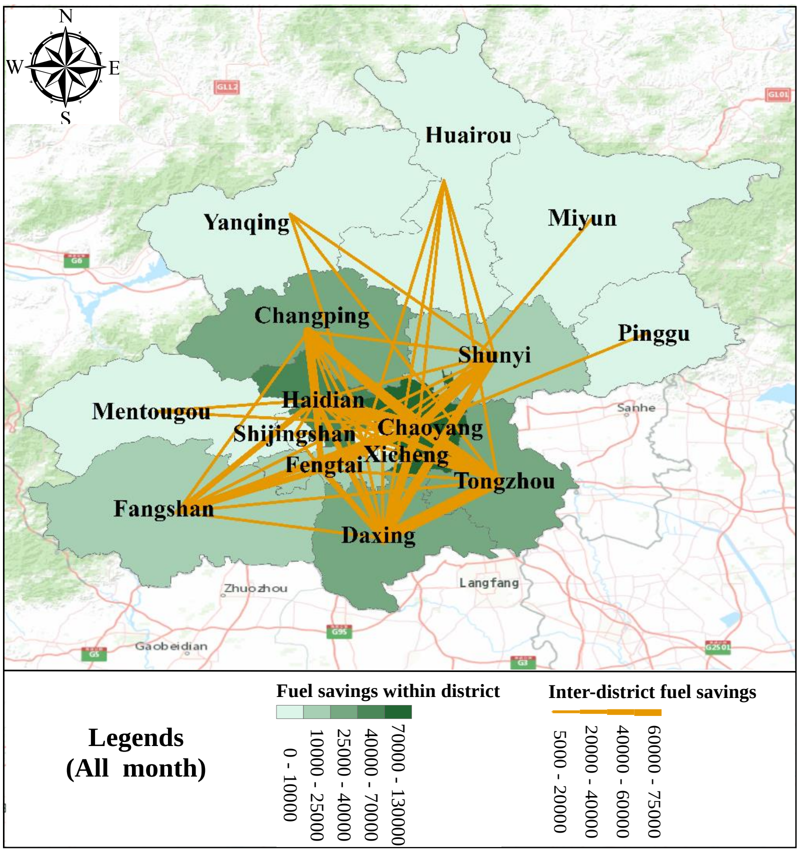
The origin and destination distributions of both the number of carpooling orders and the amount of fuel savings are examined among all district of Beijing. The total carpooling trip flows between and within the districts are portrayed in the circular Sankey diagram in Fig.9 (a). The proportion of the inter-district trips is overwhelmingly up to 70%, consistent with the long average distance of carpooling trips (i.e. 22km). For the majority of the districts, the amounts of generating and attracting ridesharing trips are balanced, but the numbers of the total carpooling trips differ. The Chaoyang district located in the city center accommodates the largest inflows and outflows of carpooling travel, accounting for a quarter of all the trips, presenting the largest ridesharing user base in Beijing. Moreover, Chaoyang is the largest destination of carpooling services from Haidian (if trips within districts are not considered) and Haidian also attracts the maximum ridesharing trips from Chaoyang, indicating the tight connection between two areas in terms of carpooling. Three districts at the suburb of the city, including Daxing, Tongzhou and Changping, each undertake over 300,000 ridesharing trips, indicating a high level of travel demand. In comparison, the districts further away from the city center (i.e. outer-suburbs), including Miyun, Huairou, Pinggu, Yanqing and Mentougou, namely the 'Suburbs' in Fig.9 (a), witness less ridesharing trips. This could be due to the overall lower level of travel demand as well as the overlong distance to the city center.

Similarly, the distributions of ridesharing fuel savings between and within districts are also uneven, as shown in Fig.9 (b). It should be noted that we only drawn the key flows whose fuel savings are over 5000 liters for better presentation. Trips related to Chaoyang conserve the largest amount of fuel savings, which is about one million liters, e.g. five times the total savings produced from the five outer-suburb districts.

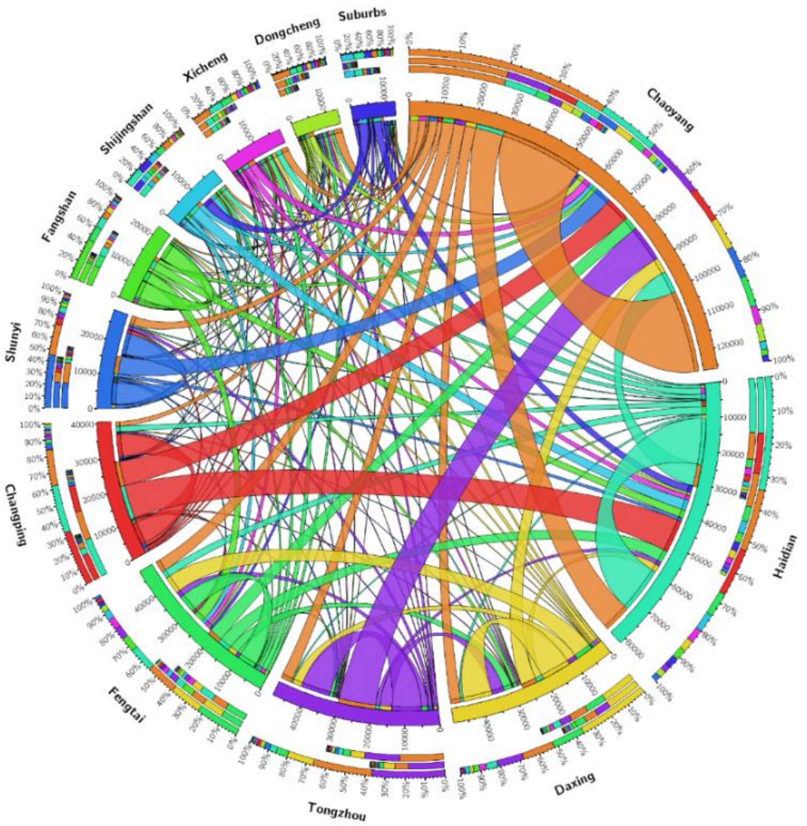
Nevertheless, although these outer-suburb districts undertake less carpooling trips, due to the longer distances of the trips, these areas save more energy than districts in the suburb of the city, e.g. Dongcheng, Xicheng and Shijingshan. Moreover, among the fuel savings of inter-district trips, the savings between Chaoyang and Haidian are dominant, but the savings between Chaoyang or Haidian and other districts in the inner urban areas also account for a large part.



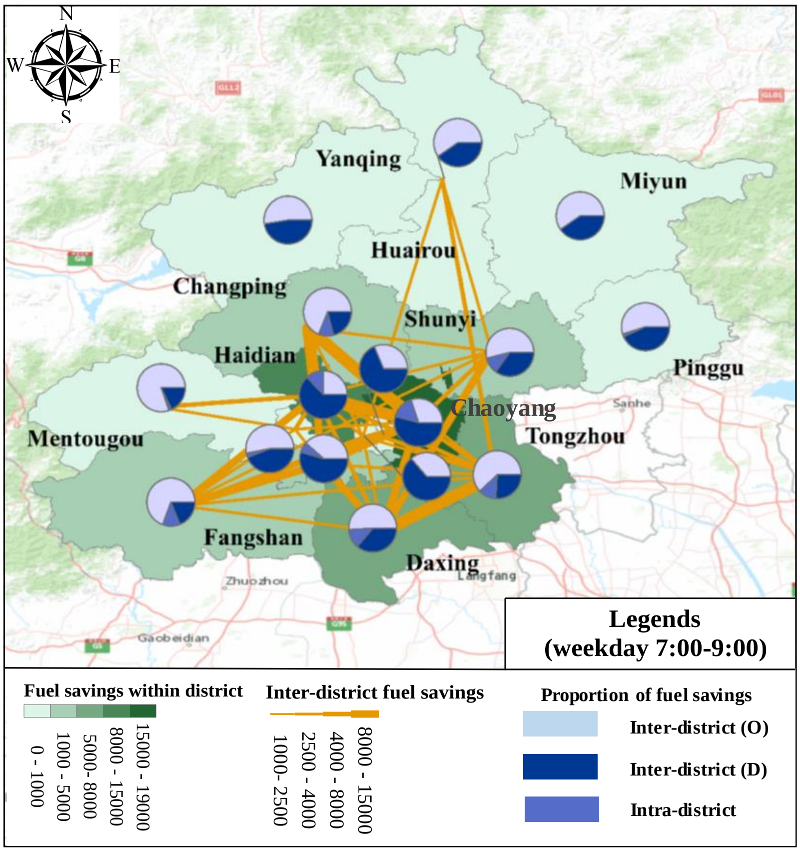
(a) OD distribution of total carpooling orders in December



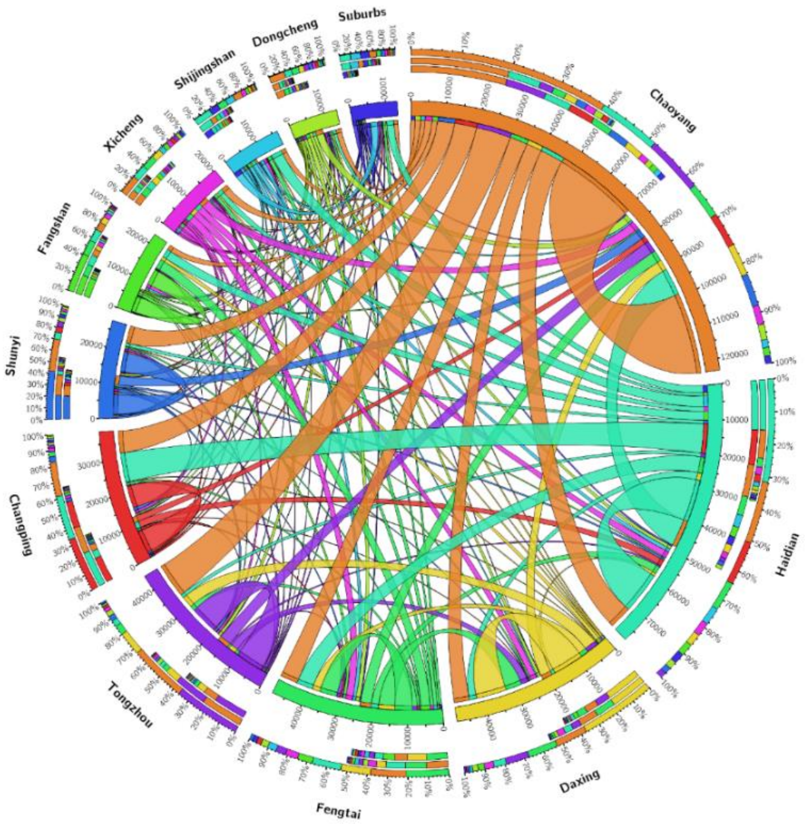
(b) Fuel savings distribution among districts and within district



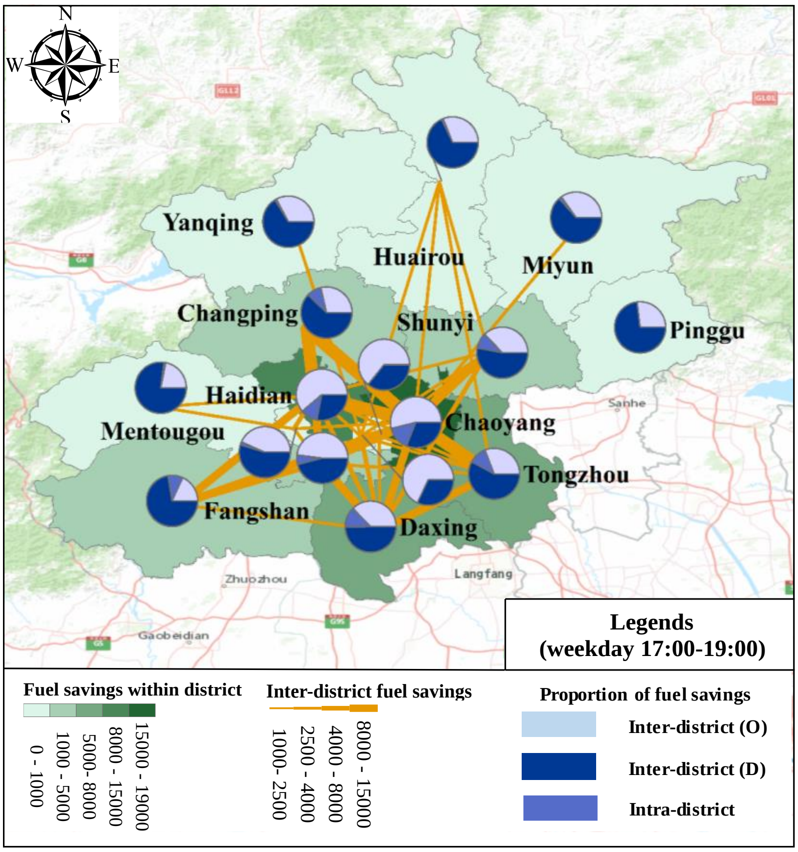
(c) OD distribution of carpooling orders during morning peak hours



(d) Fuel savings distribution during morning peak hours



(e) OD distribution of carpooling orders during evening peak hours



(f) Fuel savings distribution during evening peak hours

Fig.9 The distribution of order numbers and fuel savings in total month and during peak hours

4.1.5 Commuting attributes of fuel savings

To explore the commuting attributes of carpooling travel and fuel savings, trip records during the morning and evening peak hours (7:00-9:00 and 17:00-19:00 respectively) are extracted. The OD distributions of the trips are visualized in Fig.9 (c) and (e), while the fuel saving maps only with the key flows over 1000 liters in Fig.9 (d) and (f), respectively. In December 2017, there are 21 workdays, leading to the total rushing hours as 84. In Fig.9 (c) and (e), it is noted that, for most of the districts during the morning rush hours, the amounts of generating and attracting trips are not balanced any more. If not considering the intra-districts carpooling trips, the ratio between carpooling trips generation and attraction is respectively 62% in Chaoyang and 46% in Haidian. In contrast, the suburb and outer-suburb areas generate more carpooling trips, the proportion accounting for their inter-district trips even over 70% in Changping, Tongzhou, Fangshan and Mentougou. Regarding the trips during the evening rush hours, they exhibit exactly opposite OD distribution patterns to the ones in the morning rush hours. This fully embodies the phenomenon of home-work location separation in Beijing, in which Chaoyang and Haidian provide more job opportunities while the suburb and outer-suburb areas accommodate more homes. This leads to the travel connection during rush hours between Chaoyang and Haidian not being the strongest one any more, while the OD pairs of Chaoyang-Tongzhou or Haidian-Changping dominate the carpooling commuting travel. Furthermore, to verify the important role of carpooling service in commute, we collected and ranked the quantity of employment in each district of Beijing from the Beijing Statistical Yearbook in 20177. At the same time, we also ranked the number of carpooling trips to each district within morning rush hours and then explored the specific relationships between these two rankings. It should be noted that we excluded the suburban districts and the inner districts including Dongcheng and Xicheng from the rankings since their special locations (outermost and innermost of cities) presumably cause the local commuters' traveling distance unfitting for (over or under) the required carpooling service distance. Analysis results showed that there is an obvious linear relationship between local employment and carpooling trips within peak hours (R-Square up to 0.837), proving commuting was an important driver for carpooling trips when the driving distance is suitable for travel mode.

In the aspect of fuel savings, about 23% of the total savings are derived from the peak hour period. Moreover, there are also variations in fuel savings among different pairs of districts as shown in Fig.9 (d) and (f), with the common home-work location pairs of Chaoyang-Tongzhou and Haidian-Changping presenting the largest amounts of savings (i.e. 6% and 4% of total fuel savings during peak hours respectively). It is interesting to find some of northern outer-suburb areas, like Yanqing, Huairou and Miyun, have more fuel savings during evening peak hours than morning peak hours, yet with similar carpooling orders. According to the spatial distribution of carpooling trips, presumably because the relative looser commuting time allows more workers to offer secondary carpooling services during evening peak hours, which can cause a higher proportion of commuters from northern outer-suburb areas shared their carpooling trips with more than one groups of passengers after work and then save more energy.

4.2 Scenarios of carpooling subsidies

The settings of the parameters in making carbon subsidies are as follows. Regarding the carbon trading price P_1 , different values have been adopted in the literature. For instance, P_1 was set between ¥50 and ¥2500 per ton of CO_2 (Bristow et al., 2010), in the assessment of whether the different prices in this range were critical to the acceptability of PCT in the survey. In Raux et al. (2015), P_1 was set as approximately ¥1, ¥3, ¥5, or ¥7 per liter of gasoline to represent various trade-off scenarios for the survey participants. At present, the carbon price under the system of Corporate Carbon Trading (CCT) in China is at a lower level than it is in developed countries. For example, the highest carbon price is only ¥51.58 per ton of CO_2 on February 16th, 2018 in Beijing[4], equivalent to approximate ¥0.15 per liter of gasoline if one liter of gasoline combustion generates 3kg CO_2. Combining the existing literatures with the future development trend in China, the four prices of ¥0.5, ¥1, ¥3, ¥5 per liter of gasoline are taken as the feasible carbon pricing levels in this study. In terms of the fuel price P_2 , the average price (gasoline, 92#) in 2017 in Beijing[5] is adopted, which is ¥6.5. With respect to the depreciable cost, the average private car price P_3 is set as

[4] http://www.tanjiaoyi.com/article-23842-1.html
[5] http://www.chyxx.com/industry/201711/586283.html

¥155,000[6] with the corresponding usage life about 0.3 million kilometers. For the parking charge P_4 , it is set based on a round commuting trip between home and work locations for a typical white-collar worker. In the light of the concept of “Parking necessarily paid” in Beijing, the parking charge is ¥150~¥450 per month in residential areas and ¥10~¥30 per day in working places. Thus, the range of P_4 for one trip is specified between ¥7.5 and ¥22.5. Lastly, for the electric vehicle subsidy EVS , the subsidies in 2017 in Beijing[7] are respective ¥20000, ¥36000, ¥44000, depending on the different categories of endurance mileages of the vehicles. Assuming the service life of EVs is 0.15 million kilometers, so the subsidies on EVS are about ¥0.13, ¥0.24, ¥0.29 per kilometer. In fact, the government needs to pay more implicitly since the payable vehicle purchase tax is exempted for electric vehicles. A summary of all the above-described parameters and their corresponding settings is given in Table 2.

Tab.2 Parameters used in the carpooling subsidy model

Parameters	Definition	Value
P_1	Carbon trading price	¥0.5, ¥1, ¥3, ¥5/ liter
P_2	Gasoline price	¥6.5
P_3	Average private cars price	¥155,000
P_4	Parking charge	¥7.5- ¥22.5
SL	Average service life of private cars	300000 kilometers
EVS	Electric vehicle subsidy	¥0.13, ¥0.24, ¥0.29/km
CS	Carpooling subsidy	/

Based on all the parameters, a series of subsidies only for OTOP trips, represented with ¥/km (Yuan per person-kilometer traveled), were derived under the diverse carbon prices and parking charges. The average of the subsidies is ranged from 0.09 ¥/km to 0.5 ¥/km, as presented in Tab.3. Note that the average subsidy is reckoned after excluding the negative values (See Eq.8) that represent that the cost of carpooling services is too low to require extra incentives. Furthermore, taking the relatively mature subsidy policy of 0.13 ¥/km - 0.29 ¥/km for electric vehicles as the constraint condition, the feasibility evaluation is conducted and visualized by the gradation of the background color in Tab.3. The darker the color, the lower the carpooling subsidy is. When the carpooling subsidies increase from the bottom right to the top left, the color changes from darkness to lightness. When the carbon price is 0.5 ¥ and parking charge is 15 ¥ or when these two variables are 3 ¥ and 20 ¥, respectively, the subsidy for carpooling is 0.13 ¥/km, which just meets the strictest ceiling limit. Considering carbon price still at a lower level in China, we took the former scenario as an example and the associated frequency distribution of all the carpooling subsidies was described in Fig.10. The average value of the carpooling subsidies is 5.38 ¥ and 90% of the passengers can gain subsidies of 0-10 ¥. Excluding the negative values, the sum of the subsidies reaches

[6] http://www.chyxx.com/industry/201711/580313.html
[7] http://www.bjcz.gov.cn/zwxx/tztg/t20160414_602511.htm

7 million ¥in December, which is much less than the fiscal subsidies on bus that is 8.37 billion ¥in the entire year of 2015 in Beijing[8].

Tab.3 Carpooling subsidies under different pricing scenarios

Carpooling subsidy (¥/km)		Carbon price (¥)			
		5.0	3.0	1.0	0.5
Parking charge (¥)	7.5	0.50	0.43	0.36	0.34
	10.0	0.41	0.34	0.27	0.24
	15.0	0.27	0.21	0.15	0.13
	20.0	0.18	0.13	0.09	0.09
	22.5	0.15	0.11	0.10	0.10

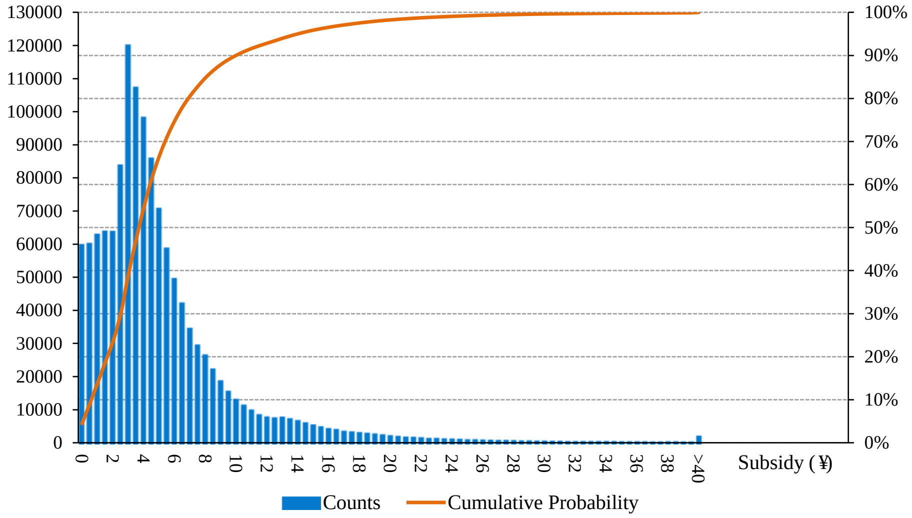


Fig.10 Frequency distribution of carpooling subsidies when P_1=0.5 and P_4=15

According to Fan et al. (2016), a certain amount of trial and error would help find the rational level of subsidies. However, these trial and error procedures would incur high administrative costs as the carpooling services standards change. Therefore, the calculated carpooling subsidy level could be taken as the benchmark for policy making and subsidy allocation. A series of feasible subsidies are made under various pricing scenarios, which can be selectively adopted by authorities combined local conditions. With the prerequisite of moderate-promotion for carpooling services, these funds will be able to effectively boost private car users to take carpooling, thus reduce fuel using and carbon emission from road traffic.

4.3 Carpooling's fuel savings considering all alternative traffic modes

As for the people who used to take public transport including bus and metro, the impact of shifting to carpooling on fuel consumptions was also estimated based on Eq.9 to Eq.12. The detour conversion coefficients of bus and metro are taken 1.2 and 1.0,

8 http://www.jt12345.com/article-45451-1.html

respectively, according to the traffic network structure in Beijing. For measuring the fuel using with carbon emission, the fuel economy of bus and metro is adopted as 1.6 liter/person•km and 0.4 liter/person•km, referring to the emission factors of various traffic tools in Beijing estimated by Yang et al. (2017). Without the specific information about positional relationship between carpoolers and public transport stations, it is assumed the origin points of carpoolers distributes uniformly around the stations. Hence, the impact of walking distances in every direction to stations on the path length by bus or metro would be canceled each other out, which is neglected in this case study. By dividing carpooling trips into common carpooling trip (OTOP) and two kinds of secondary carpooling trips (OTMPOL and OTMPIS), the distributions of average fuel savings (or wastes) for potential bus users and metro users are shown in Fig.11.

Evidently, the environment benefits of carpooling services are sharply shrank and even turn into bad side comparing to the green transport tools with high passenger capacity. Only about 50% carpooling trips of former bus users and 10% carpooling trips of former metro users can still save fuel, and with a tiny quantity. Similarly, the distributions of OTOP are more centralized, however, the gaps in the fuel savings' peak values between OTOP and OTMPOL/OTMPIS are not observable any more. For carpoolers used to take metro, the secondary carpooling patterns even cause more fuel wastes than OTOP trips, which may be due to the fuel consumption of cars are more sensitive to the increase of passengers.

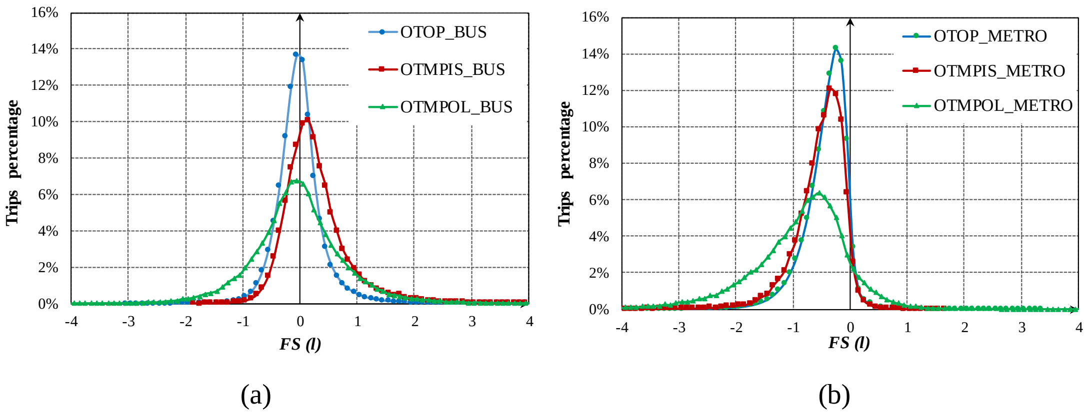


Fig.11 Distribution of carpooling fuel savings for potential bus users (a) and metro users (b)

According to the results of 1063 app-based questionnaires about carpoolers in Beijing conducted by DiDi company (see Fig.12), only 3.4% of respondents would cancel their trips if ridesharing is not available, which proves that the emerging carpooling services basically have not triggered extra travel demand. Moreover, 47.5% of carpoolers surveyed used to be green travelers, most of whom would take public transport including metro and bus, and 45.1% was car-dependent, in which the ride-haling services have been an important alternative for conventional taxi. All above numbers indicate that carpooling services not only effectively alleviate operation pressure of public transport, but also reduce the driving distance and fuel using form private car or taxi. The trip-specific model is adopted to calculate the fuel consumption of all travel modes, shown in Table 4.

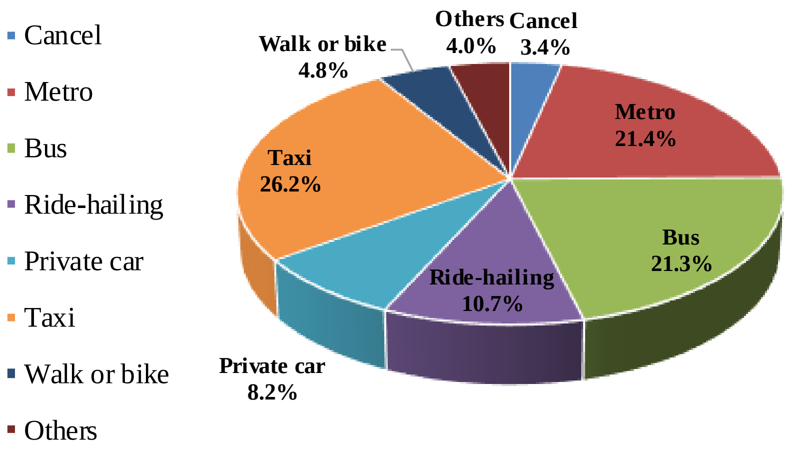


Fig.12 Survey results on carpoolers' alternative travel modes without carpooling services

Obviously, the carpoolers who used to be car-users contribute most of fuel savings due to sharing free saddles, who should be the key target group to promote carpooling services. Meanwhile, the public transport modes and the slow traffic present a huge advantage of energy utilization. If carpoolers' original travel modes are in line with these survey results, comparing to the assumption that all carpoolers are potential car-users, the average fuel saving of one carpooling trip would be reduced to 0.32 l, and the quantity of subsidies only focusing on car-owners would be less than ¥600 thousand in December, 2017.

Tab.4 Potential fuel using of original travel modes and actual fuel saving

Travel modes	Car or taxi	Bus	Metro	Walk or bike
Trips (10^3)	927.8	438.2	440.3	98.8
Fuel using (10^3 l)	1515.2	189.3	47.3	0
Fuel saving (10^3 l)	1087.1	1.5	-183.6	-245.2

4.4 Advantages of the trip-specific model

Built on the massive real ridesharing data, the trip-specific model proposed in this work has the advantages of delicacy, reliability and accuracy in estimating fuel savings and designing promotion strategies, which can be utilized by worldwide decision-makers for better managing the carpooling industries. First, the delicacy is manifest by the fact that the energy saving calculation and carpooling promotion subsidizing are based on individual trips rather than aggregation over all the trips. It is important to focus on each individual trips since the numerical volatility across the trips is drastic in both fuel savings and subsidies. Taking the OTOP trips as an example, while the average of all the fuel savings is 1.17l, the averages of the savings over 0-10th percentiles and 90-100th percentiles of the trips are 0.13l and 3.05l, respectively, with the latter value being 20 times the former one. Moreover, the standard deviation and the variation coefficient of the fuel savings are 0.87l and 74%. Similar levels of volatility are also observed among the individual subsidies. Only with the trip-specific model, can optimal promotion policy be put into practice that are more objective, trip sensitive, and unbiased to carpoolers.

The second advantage is reliability, which is stemmed from the data source and model building process. The data include the actual carpooling trip records and the authoritative statistical data; both types of data are collected in the same or similar periods. The distances of the carpooling trips are estimated by online navigation applications, leading to the estimated results very close to the length of the actual routes. In terms of the model building process, the carpooling trips are divided into the types of OTOP and four additional patterns of OTMPs; each type has its own distinct frequency distributions and specific computation methods for fuel savings. This guarantees the reliability of this model. Moreover, by taking the subsidies on electric vehicles as the cap, a series of reasonable pricing scenarios built on the cost-effective method can be more socially acceptable.

The previously described two advantages of delicacy and reliability would inevitably lead to the third advantage of this model, i.e. accuracy. The fuel savings of every trip, which are estimated by the sum of the products between the route length and the corresponding fuel economy under diverse vehicle occupancy scenarios, have considered all the significant factors influencing the fuel usage. Particularly, a comprehensive method has been developed for the route length calculation of each pattern of the OTMP trips, as shown in Fig.4.

Last but not least, although we take carpooling trips within Beijing in China as case study, the trip-specific fuel savings estimation model and associated quantitative carbon subsidies measures proposed are of universal significance. Firstly, the mobile internet based carpooling services offered by DiDi Company have similar operation mechanism that is on-demand, real-time and location-based to the other worldwide transportation network companies. All these ridesharing platforms can record the specific itineraries of carpooling participants, which can be extracted to accurately estimate the fuel savings. Secondly, the financial incentive has been adopted extensively by authorities to promote green transportation, and considerable scholars argued that PCT is an effective measure in the transportation sector to reduce emission. The quantitative carbon subsidies based on PCT scheme have a solid base to be easily implemented and accord with the prevailing trend of urban sustainable development. Thirdly, the capability of estimating the carpooling’s fuel savings for all alternative traffic modes makes this model more comprehensive, which can be applied to different urban conditions with different split rates of travel modes. Thus, this methodology proposed in this study can be adopted as a reference by the other countries’ decision-makers considering their local conditions.

Comparing the performance between this model and the existing online or traditional off-line carpooling fuel saving computation methods, Tab.5 lists a set of key indexes regarding the aspects of delicacy, reliability and accuracy. From this table, the differences are noted and the innovation and stringency of the model proposed in this study are demonstrated.

Tab.5 The comparison of trip-specific models with previous works

Works	Delicacy		Reliability		Accuracy		Typical results (per trip)	
	Trip-specific	Aggregate analysis	Data source	Model principle	Influence factors	Route length	Average Distance traveled	Average fuel savings
Caulfield (2009)		√	Census data	COPERT 4	VKT and factors in software	RP survey	9.75 km	1.25 l
Jacobson and King (2009a)		√	publicly available statistics	Difference between driving-alone and ridesharing	VKT, PKT,FE	General survey	15.88 km	3.5-3.8 l
Bruck et al. (2017)		√	Shifts data from a pilot case	VKT×FE	VKT	Shortest paths for direct-route and tree-route	/	0.93 l
Guidotti et al. (2017)		√	publicly available statistics	VKT×FE	VKT	Navigation distances	8.16 km	0.49 l
Yu et al. (2017)		√	Raw data and statistical data	Direct impact: LCA Indirect impact: IO	PKT, Travel mode share	Residential trip survey	17.70 km	5.02 l
This paper (2018)	√		Raw data and statistical data	Trips-specific models considering saddle-sharing trips	VKT, PKT,FE	Reprocessing navigation distances	22.50 km	1.23 l

5. Conclusion and discussion

The potential of fuel savings and other advantages from increased ridesharing in noncommercial passenger vehicles has been theoretically proved (Noland et al., 2006; Chan and Shaheen, 2012), which is regarded as one of the mitigation roadmaps for cities to control energy consumption and reduce pollutions emission of urban traffic. However, practically the energy savings can be offset by the demand to travel additional distances to pick-up passengers. This raise a further demand for deeply investigating the exact carpooling travel mechanism and its associated fuel-saving patterns. On the other hand, there is still a lack of effective measures to promote carpooling to the car-dependent people. Therefore, it is necessary to assist governments in designing more efficient carpooling strategies to mitigate the congestions and pollutions of urban road traffic. Owing to the emergence of internet-based carpooling services and big data technologies, it becomes possible to study energy consumption from individual points of views and implement delicate promotion measures with lower costs. Based on the massive carpooling trip data provided by the largest ridesharing service platform in China, this study has unraveled the internal mechanism of mobile internet based carpooling trips and the distribution of carpooling trips and fuel savings. Particularly, it has developed a trip-specific model for fuel saving estimation and carpooling subsidy designing for carbon emission reduction. In comparison with the existing methods, the model proposed in this paper has the advantages of delicacy, reliability and accuracy; based on this model a number of important findings have been made as follows.

(1) On average, the fuel savings of a carpooling trip is 1.23 liters, accounting for 47% of the fuel consumed when passengers drive alone, and the annual fuel savings reach 36 million liters. There is a positive relationship between the amount of fuel savings and the number of passenger groups as well as the travel distances of the trips. It is thus of much significance to encourage current carpoolers to accept secondary ridesharing and take long-distance carpooling, which can reduce more energy consumption and make the promotion subsidies more effective.

(2) The common carpooling trips with one group of passengers are the main ridesharing travel type, accounting for 95% of all the trips; the remaining 5% belongs to saddle-sharing patterns mainly including the overlapping orders and inclusive orders. The average fuel savings of a one-trip-multi-passengers trip are more than double those of a one-trip-one-passengers trip, reflecting the huge superiority of secondary ridesharing travel in energy savings. Moreover, one of the saddle-sharing patterns, “inclusive” orders, is more efficient in fuel savings than the other, “overlapping” orders. In addition, the fuel saving frequency distributions of secondary carpooling trips are flatter with longer tails (See Fig. 5), demonstrating larger variations in fuel savings among the trips and embodying the necessity of extracting each individual secondary carpooling trip and managing them separately. Furthermore, the fluctuation of the saddle-sharing trips over various hours of the day (See Fig. 6) suggests that the saddle-sharing trips happen more frequently for non-commuting trips than for commuting trips.

(3) In the majority districts of Beijing, the amounts of generating and attracting ridesharing trips are balanced, but the numbers of the total carpooling trips differ. The Chaoyang district in downtown has the largest number of carpooling orders and generates the largest amount of fuel savings. The further a district is from the city center, the less the number of carpooling orders, and the smaller the amount of fuel savings. In addition, the separation of the common home and work locations reflected from the carpooling trips is clearly demonstrated, and the trips during the morning and evening peak hours exhibit converse origin-destination distribution patterns between these home and work locations. The carpooling trips during rush hours contribute about 23% of the total fuel savings.

(4) Under a set of diverse carbon prices and parking charges, the average of the derived subsidies is distributed from 0.09 ¥/km to 0.5 ¥/km. In particular, when the subsidy meets the strictest ceiling limit of 0.13 ¥/km, the average subsidy per trip is ¥5.38 and the annual subsidy sums up as ¥157 million, which is much lower than the practical fiscal subsidies for public transport in Beijing. With the prerequisite of moderate development for carpooling services, these funds could effectively encourage more original car users to participate in carpooling in a fair way.

(5) When compared to green transport with high passenger capacity, the previous environment benefits of carpooling is sharply shrank and even turned into bad side. Beyond 90% carpooling trips would waste fuel in contrast to taking metro. Moreover, nearly half of carpoolers surveyed was car-dependent, in which the ride-haling services have developed to be an important alternative for conventional taxis. If the estimation of carpooling fuel savings consider all alternative traffic modes, the average fuel saving would be down to 0.32 l per trip, and the quantity of subsidies only focusing on car-owners would be less than ¥600 thousand.

(6) The number of carpooling orders during rush hours accounts for 30% of the total orders throughout the day, demonstrating the commuting features of the ridesharing trips. The average distance of ridesharing trips is approximately 22 kilometers and more than 85% of the trips are longer than 10 kilometers, suggesting that the ridesharing mode mainly serves mid- and long-distance trips. This may make up the current shortage of railway systems in the suburbs of Beijing.

This study can be regarded as a starting point with respect to the research and management on internet-based carpooling services and fuel savings. On the one hand, several limitations of this study should be considered. Firstly, although the carbon subsides could attract more car owners to be carpoolers, the supply/demand relationships in the market could be complicatedly associated with the other potential influencing factors, including insurance availability (Shaheen et al. 2016), trust and reputation (Salamanis et al. 2018), ride-matching efficiency (Furuhata et al. 2013), and so on. To achieve this industry's sustainable development, the authorities should make a distinction between social and economic regulations in moving forward. Cetin and Deakin (2017) argued that economic regulations such as fare controls and entry restrictions were not necessary for ride shares, while social regulations regarding safety and environmental performance are crucial to a healthy ridesharing industry. The government also should start collecting data on carpooling and make them available. This may help the insurance market react accordingly by adjusting prices to match risks in the carpool scenario (Wang, 2011). Additionally, some specific campaigns should be initiated and emphasize the environmental benefits from carpooling and the environmental threat human facing to arouse people's awareness of environmental protection. According to the findings of Delhomme and Gheorghiu (2016), the environmental attitudes of passengers play an important role in the decision to use carpooling. Secondly, there still is some difference between the navigation route and actual travel route in carpooling trips, especially in secondary carpooling trips. If the trajectory data of carpooling cars is provided, we can conduct more accurate estimation on fuel savings. Thirdly, it would better to validate the results of estimation on carpooling fuel savings by some practical experiments. Owning to the operational complexity, the validation study is beyond the scope of this study and suggested for the implementation stage in the next step.

On the other hand, there are more work lying ahead in the future development of the proposed method. Firstly, it is interesting to divide the carpooling trips into non-commuting as well as commuting trips and to study their impact on fuel savings separately. Secondly, in terms of promotion policy, the exact allocation of subsidies among the different groups of passengers still need to be investigated. Thirdly, some literatures argued that extreme weather, such as very high or low temperatures and heavy rainfall would reduce public transport ridership (Zhou et al., 2017; Miao et al., 2019). These original mass transit users may shift to taking more comfortable travel modes like carpooling. Actually, according to the annual data in 2017 from DiDi Company, the number of carpooling orders will have a slight increase (about 10%) in summer or winter mainly because of the impact of the unpleasant weather. We can seek to study the specific impact of weather on carpooling services by combining the carpooling data with associated weather data in following work. Lastly, at present, DiDi Company focus on introducing new energy vehicles into carpooling service and the total amount will be increased to 1 million over the next 5 years (DiDi, 2017). The fuel savings of the trips realized with the new energy vehicles, along with the optimal carpooling management policy, will be further explored based on the approach developed in this study.

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Conflicts of Interest

The authors declare that there is no conflict of interest in any aspect of the data collection, analysis, or the funding received regarding the publication of this paper.

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