The Potential of Ride-pooling in VKT Reduction and its Environmental Implications

Abstract

Ride-pooling's contribution to VKT reduction and its associated environmental effects are not yet fully examined. We design a simulation with operational data from DiDi to model an ideal situation in which all riders are open to ride-pooling. We find that under our initial assumptions, with a buffer time of 60s, ride-pooling has the potential to reduce aggregate VKT by 8.21% as compared to standard ride-hailing mode in a mid-sized city, Haikou. This reduction in VKT is equivalent to a savings of 1,234,164 Liters in petroleum consumption and 3308 tons in carbon emissions annually. Additionally, our simulations indicate that the contribution of ride-pooling to VKT reduction is highly sensitive to buffer time and period of day. We further establish a decision model that aims to achieve a better balance between social benefits and riders' costs. We conclude that ride-pooling services, if implemented on a large scale, can substantially promote sustainable transportation.

Keywords: ride-pooling, GHG reduction, petroleum saving, Vehicle Kilometers Travelled, social welfare, urban sustainability

1. Introduction

Large-scale urbanization, rapid population increase, technological development, and diverse travel demand have exerted tremendous pressure on urban transport systems (Batty, 2008; Bettencourt et al., 2007; Bettencourt, 2013). Subway and bus systems provide efficient and concentrated transport to satisfy travelers' needs while enhancing urban sustainability. However, due to their limited and fixed-route service, they cannot fully cater to rising travel demand. Meanwhile, other options such as taxis provide flexible point-to-point service and are able to address a significant portion of our day-to-day travel demand. However, individualized point-to-point transportation services are far less environmentally friendly than mass transportation systems like buses and subways, and do little to reduce GHG (Greenhouse Gas) emissions or excessive petroleum consumption. Due to relatively low utilization1 and low capacity (many people ride alone), they may even aggravate these problems (Mitchell et al., 2010). Therefore, there is a great need for transportation solutions that both enhance environmental sustainability and satisfy demand for flexible point-to-point transportation services.

There is a growing body of literature illustrating that the ride-pooling made possible by digital ride-hailing platforms may be able to play this role: ride-pooling allows for flexible, personalized transportation services while significantly reducing VKT (Vehicle Kilometer Traveled) and therefore traffic emissions compared to traditional ride-hailing services without pooling (Litman, 2013; Yin et al., 2018; Wu et al., 2021). In this paper, ride-hailing mode refers to non-pooled ride-hailing, in which a rider hails a vehicle to take them to their destination, and the vehicle will not be shared with any other riders or make stops en route. Meanwhile, ride-pooling mode refers to the service mode in which a rider is willing to share a ride with others who have similar origin-destination (OD) pairs. In this mode, drivers serve more than one group of passengers at a time (Agatz et al. 2011; Zhang, 2020). With an increasing number of countries committed to mitigating climate change, it is important to investigate the potential of ride-pooling to reduce the carbon footprint of personalized point-to-point transportation services. Related policy measures that incentivize or mandate ride-pooling in e-hailing services may therefore have important implications for reducing carbon emissions of the transportation sector and achieving the sustainability goal. For example, the California Clean Miles Standard 2018 explicitly sets out to reduce the carbon footprint of ride-hailing services, and encourages ride-pooling as one of several measures to do so. The measure has been an important stimulus for studies on the environmental impacts of ride-pooling and electrification (California Air

[1] For example, taxies in New York City have an average idle time of 4.1 hours per 12-hour shift, or roughly a 33% idle rate (see Zhu and Prabhakar, 2017).

Resources Board, 2019; Wenzel et al. 2019; Jenn, 2020).

In order to develop similar policies elsewhere, an understanding of how different contexts may affect the benefits achieved through ride-pooling is necessary. Thus far, a few studies have investigated the VKT reduction potential of ride-pooling in megacities with high trip request density. Yet there are far fewer studies on smaller cities with relatively low trip request density and with no subway/rail system. As such cities account for a large portion of the world population, and the potential for ride-pooling is likely to be significantly different in these cities, studies that target such cities are necessary to better understand and regulate ride-hailing services. Furthermore, effective policymaking concerning ride-pooling strategy requires a nuanced understanding of all parties' benefits, costs, and optimization goals. Most of the existing literature on ride-pooling focuses only on benefits such as reductions in GHG emissions and petroleum consumption (Cai et al., 2019; Yu et al., 2017; Caulfield, 2009), which help to endorse emerging ride-pooling services but are not sufficient for guiding detailed policymaking where trade-offs to balance transportation needs and environmental sustainability are inevitable. Measuring the pros and cons of ride-pooling from multiple perspectives is of great practical significance for establishing a unified decision framework for ride-pooling policy.

Therefore, this paper endeavors to advance new knowledge on ride-pooling by answering three questions. First, to what extent can ride-pooling contribute to aggregate VKT reduction in mid-size cities with relatively low trip request density? We use actual operational data from the DiDi Chuxing GAIA Open Dataset Initiative as ride-sourcing demand. Simulations of standard ride-hailing mode and ride-pooling mode are based on all Didi trips recorded in Haikou between May 1st and June 30th of 2017 and apply the Shareability Network approach (Santi et al., 2014). Aggregate VKT are separately calculated for each mode by controlling scheduling efficiency to its respective optimal level, using the minimum path coverage condition of shareability networks.

The second question concerns the relationship between buffer time for pool-matching and aggregate VKT reduction. Aggregate VKT reduction improves as buffer time lengthens. DiDi uses 60 seconds as the default buffer time in its ride-pooling service, and many previous studies tend to assume this buffer time in their models (Santi et al., 2014; Yan et al., 2020). However, understanding how performance changes with buffer time can help policymakers and ride service operators optimize ride-pooling services to achieve different goals (e.g., maximum reduction in VKT, profit maximization). This paper examines VKT reduction for a range of buffer times, from 0 seconds (i.e., de-facto ride-hailing mode) to 120 seconds at 15-second intervals. This provides a detailed estimation of the empirical relationship between buffer time and

VKT reduction, providing a solid basis for evaluating the effects of ride-pooling under different buffer time conditions.

The third question concerns establishing an analytical framework to balance the benefits and costs induced by ride-pooling services. Ride-pooling services have been widely shown to contribute to urban sustainability by reducing aggregate VKT (Santi et al., 2014; Cai et al., 2019; Ning et al., 2020; Yan et al., 2020), but the longer waiting times experienced by riders also lower urban productivity. It is as yet unclear to policymakers how such services should be designed and regulated to maximize their merits. In this study, we propose a social welfare-oriented ride-pooling policy model to quantify the social costs and benefits of ride-pooling, allowing us to understand how social benefits, such as reduction in petroleum consumption and GHG emissions, can best be balanced against costs in the form of increased wait time for riders and hence loss of productivity.

2. Literature Review

With growing environmental concerns and the maturation of ride-pooling services, precise measurement of the potential contribution of ride-pooling to urban sustainability, including to transportation network efficiency and to the environment, is increasingly necessary. As shown in Appendix 1, a comprehensive review of recent simulation studies has demonstrated the potential for VKT reduction through ride-pooling. However, there are still major gaps in the existing literature on this topic.

Firstly, most of these previous studies are based on megacities with abundant populations, well-developed subway/rail networks, large built-up areas, and high density of transport demand.2 In such areas, ride-pooling agencies tend to have a larger pool, enabling better pool-matching between riders with similar OD pairs. They may therefore have better than average performance in VKT, GHG, and petroleum consumption reduction. In such megacity-based studies, Santi et al. (2014) reported that ride-pooling could reduce VKT by 30% in New York, Cai et al. (2019) estimated ride-pooling could contribute to a VKT reduction of up to 33% in Beijing if implemented for the entire taxi fleet, and Yan et al. (2020) concluded that ride-pooling could induce a 15.48% VKT reduction in Shanghai. On the contrary, insight into cities with low trip request density is limited. It is estimated that the trip request density of

[2] On a related field to ride-pooling and VKT reduction, a recent review paper, Pernestal and Kristofferson (2017), analyzed 26 simulation studies on the impact of driverless vehicles. They also examined VKT as one of the four impact measures. As shown in their review, most simulation studies on driverless vehicles also focused on large cities.

Uber in New York City was as high as 524/(day*km2) (Santi, 2014). In Chengdu and Xi'an, two of the most highly populated cities in China, trip demand levels reach 3144.7/(day*km^2) and 3225.06(day*km^2), respectively. Haikou's trip request density, by comparison, is only 26.82/(day*km^2), significantly lower than the aforementioned cities. Even though ride-pooling has the potential to significantly reduce VKT in megacities, it is unclear whether these outcomes will be consistent in cities like Haikou where trip request density is much lower. Thus, it is important to provide additional evidence to the literature that can help shed some light on these smaller cities.

Furthermore, there are currently few studies that examine optimality in ride-pooling through a more holistic lens and take into consideration a range of economic and social factors such as different buffer time, income levels, petroleum prices and social carbon costs in their simulation models. As Ma et al. (2020) pointed out, previous research concerned primarily with reduction in system-wide VKT or travel time and failed to consider the many interest groups that are involved in ride-pooling. Excessive reduction in system-wide VKT, for example, may pass the costs onto passengers, who will need to wait longer or endure lengthier trips due to pooling. They therefore proposed a balanced strategy for ride-pooling services to explore the influence of several factors on carbon emissions and pool-matching rate. While their study provided some empirical evidence, it did not take into account the price (i.e., opportunity cost) that riders may pay in the form of long wait time for pool-matching. The current literature clearly indicates that ride-pooling has the potential to significantly reduce the VKT of ride-hailing services, but also suggests the complexity of considerations and variety of different approaches in determining the optimal pooling method.

To address such complexity, the majority of the literature thus far has relied on batch mode in ride-pooling simulations, where trip requests made within the same time-window are considered for pooling, but new trips are not allowed to join those that have already begun. In practice, the state-of-the-art algorithms used by ride-sourcing companies such as Didi and Uber for their continuous ride-pooling mode, where new trip requests can be matched with trips already on-route, utilize accurate real-time vehicle location and destination information to match new trip requests at any minute. This kind of rich dataset is generally not available to researchers. We have conducted a comprehensive literature review of all recent publications on ride-pooling, with their methodologies and major findings presented in Appendix 1. To the best of our knowledge, Zhang et al. (2014) is the only study that has developed a heuristic method for continuous mode simulation. However, their analysis is also possible only when detailed vehicle trajectory data is available. Furthermore, one weakness of their heuristic method for continuous mode is that the results are not necessarily optimal.

Given that their algorithm is based on estimation rather than actual calculations of optimality, it may allow for matching that does not in fact reduce aggregate VKT and thus may fail to produce optimal results. In contrast, the batch mode algorithm has the advantage of being able to calculate optimal matching under the specified conditions. Batch mode pooling in a real-world scenario also has the advantage of reducing uncertainty for riders, who will not face sudden additions to their estimated trip length and time part-way through their journeys.

3. Data and Method

3.1 Data

Data for this study were drawn from the Didi Chuxing GAIA Open Dataset Initiative. We collected detailed operational GPS trajectory data in Haikou city from May 1st to June 30th, 2017. Didi is the largest provider of online ride-sourcing services in China, and their trip dataset encompasses origin and destination coordinates, embarkment time, disembarkment time, and fees, among other variables. For this study, only data on origin and destination coordinates and embarkment time are necessary. The actual time of disembarkment or the actual trip distance are not needed for simulation because the ride-pooling mode will alter their disembarkemnt time and trip distance. Table 1 below illustrates the data extracted from the dataset for this study. During our study period, the average number of trips per day was 66,705, the maximum number was 108,044, and the minimum 52,078.

Feature	Example
Trip ID	17592719043682
Origin longitude	110.3665
Origin latitude	20.0059
Destination longitude	110.3645
Destination latitude	20.0353
Time of embarkment	2017-05-19 01:05:19

Table 2. Example of data extracted from The GAIA Open Dataset

We utilize the road network of Haikou city, available at OpenStreetMap (OSM), in our simulation. The map is presented in network format. Origin and destination of trip data is matched to the network with the closest node. Figure 1 demonstrates the road map and the urban area where most of the trip requests were generated.

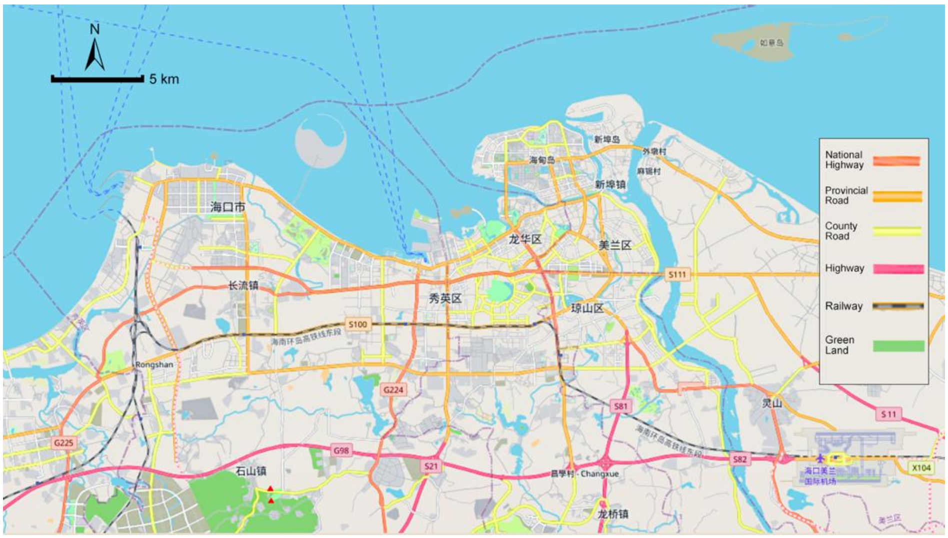


Figure 1 Road map of Haikou city. Source: OSM

3.2 Method Part I: Operation Simulation

In this section, we elaborate on the simulation experiment for the previously specified ride-hailing and ride-pooling modes. These simulations aim to compute aggregate VKT generated in each mode under a set of defined conditions (to be further clarified below) and then estimate the reduction in aggregate VKT under the ride-pooling mode. In the ride-hailing mode simulation, each trip request is satisfied by an exclusive ride-hailing vehicle in a real-time fashion. In ride-pooling mode, spatiotemporally distributed trip requests are collected and merged within pre-specified time windows, after which they are assigned to different vehicles. The details of the process are depicted in Figure 2 below:

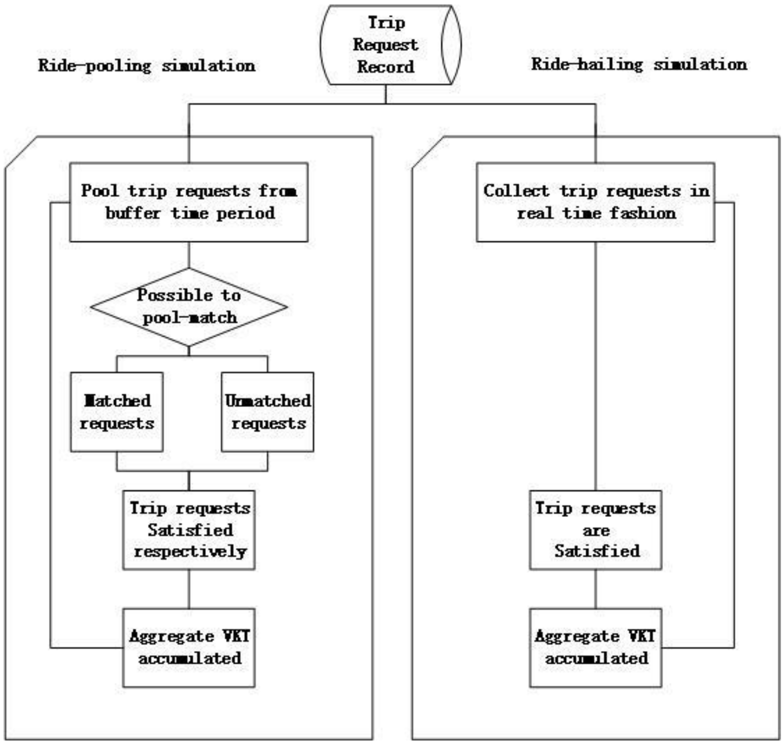


Figure. 2. Flow chart of simulation process

3.2.1 Description of key measurements and symbols

To facilitate the discussion, the key variables are summarized and defined as follows:

Symbol	Definition	Notes
Δ	Buffer time for pool-matching trip requests	Default value sets to 60 seconds (Santi et al., 2014)
N	Number of trips in a batch	
O_i/D_i	Origin and destination of trip i	Represented as nearest OSM road network node
l_i	Distance of trip i in ride-hailing mode	$l_i = L(O_i, D_i)$, Km as unit
l_{ij}	Total distance of trip i, j after being pool-matched.	km as unit
$\Delta_i l_{ij}/\Delta_j l_{ij}$	Detour distance of i if pool-matched with j / Detour distance of j if pool-matched with i	km as unit
$DDRR$	Maximum detour distance restriction ratio	Default value is 20%
vc	Transition variable between VKT and mileage	Vehicle as unit
VKT_i	VKT of trip i in ride-hailing mode	$VKT_i = l_i vc$
VKT_{ij}	Total VKT of trips i, j after being pool-matched.	$VKT_{ij} = l_{ij} vc$
ΔVKT_{ij}	VKT saved by pool-matching trips i and j	$\Delta VKT_{ij} = VKT_{ij} - VKT_i - VKT_j$
v	Travel speed	According to weekly published Haikou average travel speeds of urban roads
t_{wait}	Maximum wait time the first rider is willing to tolerate for the assigned vehicle to pick him/her up.	Default value is 5min
t_{pick}	Maximum additional time the second rider is willing to wait for the assigned vehicle after picking up its first rider. This is only applicable in ride-pooling mode.	Default value is 5min.
x_{ij}	Decision variable on whether to match trip requests i and j	0-1 variable

Table 2. Explanation table of variables involved in simulation model

3.2.2 Assumptions

1. Vehicle travel speed is constant.
2. VKT of each vehicle is not limited to trip-related VKT. For example, in ride-hailing mode, if the vehicle/driver commits to trip A and B, the total VKT is not just limited to the sum of trip A and B's VKT, but also includes the empty-load VKT from the destination of trip A to the origin of trip B.[3]

[3] Deadhead kilometers at the beginning and end of the day (i.e., from the driver's home to the first trip, and

3. The coordination of the algorithmically-guided vehicles lead to vehicles being discharged from the system if no trip requests come up in a 30-minute period.
4. Rider embarkment and disembarkment are instantaneous, i.e., not affecting total travel time in the shareability network.[4]
5. As long as permitted by the pre-defined conditions, riders use ride-pooling instead of individual ride-hailing.
6. If a rider fails to be pool-matched under the specific conditions for ride-pooling mode, he/she switches to individual ride-hailing service instead of continuing to wait to be pool-matched.

3.2.3 Matching strategy

3.2.3.1 Objective for pool-matching strategy

The objective of the pool-matching strategy is to achieve maximum aggregate VKT reduction. Therefore, total VKT reduction is adopted as an objective function, as shown in Eq. (1).

$$\Delta VKT = \sum_{ij} -x_{ij}\Delta VKT_{ij} \quad (1)$$

3.2.3.2 Detour tolerance constraint

Under ride-pooling mode, we achieve the functionality of pool-matching by collecting batches of trip requests in real-time and merging them to the greatest extent possible under the given conditions. Our baseline model assumes a maximum of two trip requests per pool, given that most Didi vehicles in China have a 3-4 passenger capacity, and trip requests often involve more than one rider.[5]

from the last trip back to the driver's home) are not included, because data on driver's home addresses is not available. However, even if these deadhead kilometers are included in both ride-hailing and ride-pooling modes, they will be crossed out and hence do not affect the comparison of VKT between these two modes. (i.e., reduction in VKT).

[4] As the model already accounts for wait time (i.e., time that the passenger waits until the assigned vehicle arrives), and the vehicle is GPS-guided in arriving at the exact location where the passenger awaits, embarkment time is for the most part a matter of a few seconds. Occasionally, riders may arrive at the pick-up location after Didi vehicle has arrived, but the exact delay is hard to measure. We have to preclude this potential uncertainty through our assumption so as to make the simulation work. Meanwhile, disembarkment does not require the passenger to spend time on payment, because digital payment systems are the standard for Didi. Simply confirming arrival on one's phone triggers payment, and most passengers actually do so after disembarking.

[5] We also tested a scenario where we allow a maximum of three trip requests to be matched, with results briefly discussed in the Conclusion section. However, the three-trip scenario is likely to overestimate the

This section introduces the algorithm for merging trips. It is assumed there are N trips in a batch, (O_i, D_i), with $i = 1,2,\ldots,N$, denotes the origin and destination of the trip. For any two trips in the pool, i, j, there are four possible pick-and-drop routes:

$$D_{last} \to O_i \to O_j \to D_j \to D_i$$

$$D_{last} \to O_i \to O_j \to D_i \to D_j$$

$$D_{last} \to O_j \to O_i \to D_j \to D_i$$

$$D_{last} \to O_j \to O_i \to D_i \to D_j.$$

D_{last} denotes the disembarkment point of the previous trip request. Two trips can be shared if a route exists that connects all origins and destinations in any trip request, and each origin precedes the corresponding destination. For any candidate route from the four mentioned above, we calculate the total distance traveled as:

$$l_{pooling,k} = l_{1,k} + l_{2,k} + l_{3,k} + l_{4,k} \tag{2}$$

where $l_{1,k} + l_{2,k} + l_{3,k} + l_{4,k}$, reresents the tour distance of four sections of the tour. For route k, since riders are sensitive to pick-up wait time and detour time, we assume that under ride-pooling mode, the first rider to embark is willing to wait for 5 minutes at most. The second rider to embark is willing to wait for an additional 5 minutes at most, to allow the driver to pick up the other rider first. The constraints below should be satisfied:

$$\frac{l_{1,k}}{v} < t_{pick} = 5 \tag{3}$$

$$\frac{l_{2,k}}{v} < t_{wait} = 5 \tag{4}$$

Furthermore, riders also have limited patience for detours, as excessive detour distance can reduce riders' willingness to ride-pool. Lin et al. (2018) proposed an approach to measure riders' tolerance for detours called the Driver Detour Restriction (DDR). This approach ascertained the distance ratio between the length of original route and the length of detoured route to determine whether this route candidate

potential of ride-pooling for VKT reduction. A number of US-based studies find average occupancies of ride-hailing trips in different US regions range from 1.34 to 1.9 (CARB, 2019). A pool of three trips, assuming these numbers, would very likely to exceed the seat capacity of the standard Didi vehicle.

would be acceptable to the rider who agree to pool with others. Its original definition is as follows:

$$R_c = \begin{cases} accept,\ if\ \dfrac{MD - D_{free}}{MD} < DDRR \\ decline,\ if\ \dfrac{MD - D_{free}}{MD} \geq DDRR \end{cases} \tag{5}$$

where MD is the distance of the candidate route, D_{free} is the distance of the origin and destination locations of the driver and $DDRR$ stands for the *Detour Distance Restriction Ratio.* This restriction is adopted in our simulation. For both riders in the pool-matching pair, the maximum $DDRR$ is set to 0.2, meaning that if detour distance caused by pool-matching is no more than 20% of their original journey distance, riders can accept the pooled route. The constraints below should be satisfied in accepting a candidate route:

$$\Delta_j l_{ij} \leq 0.2 l_j \tag{6}$$

$$\Delta_i l_{ij} \leq 0.2 l_j \tag{7}$$

In which $\Delta_j l_{ij}$, $\Delta_i l_{ij}$ denote respectively the detour distance of rider i,j if their trip requests are merged. If any of the routes satisfy conditions (3)(4)(6)(7) simultaneously, trip requests i,j is seare selected for pool-matching, with binary decision variable $x_{ij} = 1$. In this case $VKT_{ij} = l_{ij} vc$. If routes do not satisfy all the conditions, they are denoted as $x_{ij} = 0$. It is crucial to note that: 1) To reduce strain on computational resources, the problem of optimization is confined to $i \leq j$, which does not influence the accuracy of unmatched trip requests as they are not regarded as self-merging (Ke et al., 2020). Specifically, the diagonal elements are 0s since a trip request cannot be pool-match with itself.

Since it is possible that merging decisions may conflict, for all potential pool-matching decisions with $x_{ij} = 1$, we calculate their VKT and compare this to the VKT generated if the trips were not merged. We denote $\Delta VKT_{ij} = VKT_{ij} - VKT_i - VKT_j$.

The integer programming model that aims at minimizing the aggregate VKT needed to accommodate all trips is given as below:

$$max \sum_{i,j,i \leq j} - x_{ij} \Delta VKT_{ij}$$

s.t.

$$\sum_{i} x_{ij} \leq 1, \forall j \in \{1,2,\ldots,N\} \tag{9}$$

$$\sum_{j} x_{ij} \leq 1, \forall i \in \{1,2,\ldots,N\} \tag{10}$$

$$(t_{wait} - \frac{l_{i,j,1,k}}{v})x_{ij} > 0 \tag{11}$$

$$(t_{pick} - \frac{l_{i,j,2,k}}{v})x_{ij} > 0 \tag{12}$$

$$(el_i - \Delta_i l_{i,j,n}) > 0 \tag{13}$$

$$(el_j - \Delta_j l_{i,j,n}) > 0 \tag{14}$$

This is where objective (8) seeks to minimize aggregate VKT induced by ride-pooling. Constraints (9) and (10) guarantee that each trip request can be pool-matched with at most one other trip request. If $x_{ij} = 1$, then trip requests i, j are successfully pool-matched, otherwise, they are not. Constraints (11) and (12) guarantee that wait time for pooled vehicles is within a reasonable range. Constraints (13) and (14) guarantee that the detour distance of both trip requests in a matched pair is less than 20% of their respective original trip distance.

3.2.3.3 Other specifications

Scheduling efficiency control

Scheduling efficiency is an important control factor in simulation scenarios. Given that empty-load sections are also included in the simulation, it is necessary to control scheduling efficiency in both scenarios to eliminate biases as much as possible. In this paper, we use a shareability network to maintain scheduling efficiency.

Santi et al. (2014) first introduced the concept of a "shareability network" to address the ride-sourcing problem, providing researchers with a simple, static, and efficient modeling method. This approach converts a traditional vehicle sharing problem, with distinctive temporal-spatial dimensions, to a problem solvable by a static graph. Vazifeh et al (2018) applied this approach to a dynamic ride-sourcing minimum fleet problem and reported robust results on vehicle reduction. We adapt this approach to control the scheduling efficiencies of ride-hailing and ride-pooling to the same level for comparison. The simulations in both the ride-pooling and ride-hailing scenarios are operated under the minimum fleet conditions derived from this approach, so that differences in scheduling plans should not bias our results.

The method of constructing a vehicle shareability network in our simulation was as follows. We began by analyzing data in the GAIA Open Dataset and extracting rows of trip request information. Then we initialized the shareability network as a DAG (directed acyclic graph). Node $n_i \in N$ represents the i^{th} trip ('trip' here refers to trips after pool-matching and merging). With all trips represented as nodes in G, directed edges (n_i, n_j) are added into G i.f.f.

$$t_{i,end} - t_{j,start} \leq t_{wait} \tag{15}$$

$t_{i,end}$ is the disembarkment time for the ith trip request, $t_{i,start}$ is the embarkment time for the jth trip request. The inequality means that after finishing the i^{th} trip request, the vehicle must fulfill the j^{th} trip request while the time consumed cannot exceed the maximum tolerance t_{wait} If two trip requests can be satisfied by the same vehicle, we link the corresponding nodes in the shareability network with a directed edge. If a group of nodes is weakly viable by a path, this means that all the trip requests represented by these nodes can be satisfied by the same vehicle, which is called a dispatch. To facilitate a feasible dispatch, the model finds the minimum path coverage of the shareability network.

Figure.3 illustrates an example Shareability network. Nodes A to F represent 6 different trips, and nodes are mutually linked according to their viability. Figure 2(a) is the original shareability network, Figure 2(b) is a minimum path coverage, indicating that at least two vehicles are necessary to satisfy all trip demand. This dispatch is the most efficient one.

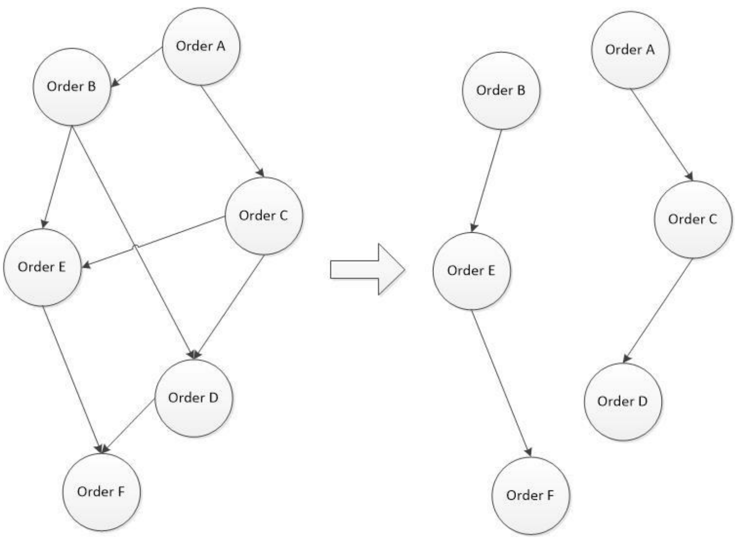


Figure.3 (a). Shareability network; (b) its minimum path coverage in a ride-pooling scenario

3.2.3.4 Method of aggregate VKT calculation

Let $S_1 = \{(i,j)|x_{ij} = 1\}$ denotes the set of trips successfully pool-matched, and $S_2 = \{(i,j)|x_{ij} = 1\}$ denotes the set of trips not pool-matched. Represented with pool-matching decision table, the total VKT induced by this batch of trips in their operational section is:

$$VKT_{operation} = \sum_{(i,j)\in S_1} VKT_{ij} + \sum_{(i,j)\in S_2} VKT_{ij} \tag{16}$$

Represented by the shareability network defined above, (16) can also be formulated

$$VKT_{operation} = \sum_{n\in N} VKT_n \tag{17}$$

where VKT_{n_i} is the VKT generated by the trip represented as node n_i in the network.

After this batch of trips, the fleet moves on to serve next batch. During this process, empty-load VKT, denoted as VKT_{empty_load}, is induced. The VKT generated in their empty-load sections by this batch of trips are:

$$VKT_{empty\_load} = \sum_{(n_i,n_j)\in E} VKT_{n_i,n_j} \tag{18}$$

This step can ensure the deadhead kilometers between trips are considered in our model. Therefore, the total VKT generated by this batch of trips is:

$$VKT_{batch} = VKT_{operation} + VKT_{empty\_load} \tag{19}$$

Aggregate VKT is the sum of the VKT of all the batches:

$$VKT_{aggregate} = \sum_{batch} VKT_{batch} \tag{20}$$

3.3 Method Part II: Ride-pooling Policy Model Development

A central problem for policymakers is balancing individual and social benefits and costs. If a matching algorithm prioritizes environmental benefits (aggregate VKT reduction in this case), individual riders may have to accept longer waiting times for pool-matching. As riders have limited tolerance, riders may be frustrated by excessive time loss and society may experience productivity loss even though the matching produces significant environmental benefits.

This section elaborates on a social welfare-oriented ride-pooling policy model (SW-oriented RPM) to address this problem. It offers an approach to balance benefits (fuel savings and reduction in carbon emissions) and costs (riders' time losses) of ride-pooling, thereby contributing to better policymaking in this field. Second, it involves several influential factors and integrates them into a single decision-making framework, enhancing the model's generalizability and providing an intuitive understanding of how these factors affect the balancing of different interests. Third, the model provides a guide for setting optimal buffer time for pool-matching under various scenarios, a practical problem faced in real-life ride-pooling service. Given the assumption that all riders are willing to ride-pool as much as possible within the model constraints, the implications of ride fee discounts for encouraging ride-pooling is not considered in our model.

3.3.1 Description of key measurement and symbols

Symbol	Definition	Unit	Note
FCE	Petroleum consumption Efficiency	L/100km	Default value as 9.06
CE	Carbon emission per litre petroleum	Kg/L	Default value as 2.68
CP	Carbon pricing	$/ton	Default value as 80
Ds	Density of petroleum	Kg/L	Default value as 0.8
FF	Petroleum fee	$/ton	Default value as 6870
Ω	All trip requests		$\Omega = \{i \mid trip\ i\ emerge\ from\ May\ 1st\ to\ Jun\ 30t$
w_i	Total waiting time of trip request i	s	Total waiting time of a trip request comprises buffer time and connection time, $i \in \Omega$
$VRR(\Delta, period)$	Mean VKT reduction rate	%	W It is a function of buffer time 'Δ' and periods of day '$period$'

Table 3. Explanation table of variables involved in SW-oriented RPM

3.3.2 Time cost function $TC(w)$

Waiting for transport vehicles can impose opportunity costs on riders. Such disutilities may lead to rider dissatisfaction (Suck et al., 1997). Furthermore, extra wait time for individuals may cumulatively reduce the productivity of the whole society. For simplicity's sake, we measure the time cost of ride-pooling as follows,

$$TC(w) = aw \tag{21}$$

where w symbolizes riders' wait time in ride-pooling mode and α symbols riders' economic loss per second, calculated using the average income level in Haikou city in 2017. This measure merely calculates loss in terms of monetary (opportunity) costs.

3.3.3 Utility function

The utility function for social welfare, U, is equivalent to the sum of the positive utility from the reduction in petroleum consumption and carbon emissions and the negative utility from riders' time loss due to waiting for ride pooling. Intuitively, we define it as follows.

$$U = U_{petroleum} + U_{carbon} - U_{waiting} \tag{22}$$

$U_{petroleum}$, U_{carbon}, $U_{waiting}$ are defined as

$$U_{petroleum} = VRR(\Delta, period) \sum_{i \in \Omega} VKT_i * FC * Ds * FF \tag{23}$$

$$U_{carbon} = VRR(\Delta, period) \sum_{i \in \Omega} VKT_i * FC * CE * CP \tag{24}$$

$$U_{waiting} = \sum_{i \in \Omega} TC(w_i) \tag{25}$$

Specifically, $U_{petroleum}$ represents utility of reduced petroleum consumption, U_{carbon} represents the utility of reduced carbon emissions, and $U_{waiting}$ represents the (negative) utility of riders' time loss due to waiting for pool-matching and vehicle arrival. Note that total waiting time comprises buffer time and connection time. Buffer time Δ is a determining factor in the SW-oriented RPM and will be assigned a designated value. Longer buffer time theoretically enables more pooling and therefore greater VKT reduction and larger savings on petroleum consumption and carbon emissions. Connection time is a variable that describes the necessary travel time for the assigned vehicle to pick up the riders, which will be calculated dynamically based on our pool-matching algorithm. For reference, the average connection time was 3.07 minutes in ride-pooling mode and 2.2 minutes in ride-hailing mode based on our simulations.

4. Result

4.1 Ride-pooling's impact on aggregate VKT reduction

Under our pre-defined conditions, we conduct simulations for both ride-pooling mode and ride-hailing mode and compare their aggregate VKT. Figure 4 displays the daily results. The blue line indicates aggregate VKT in ride-hailing mode; the orange line indicates aggregate VKT in ride-pooling mode. We find that while aggregate VKT generated by both modes vary periodically, proportionate VKT reduction is relatively stable at around 8.21%, except on several abnormal days. The simulation results suggest that ride-pooling's performance in lowering aggregate VKT is significant. Note that our simulated aggregate VKT results include both VKT generated during trips and those during empty-load periods.

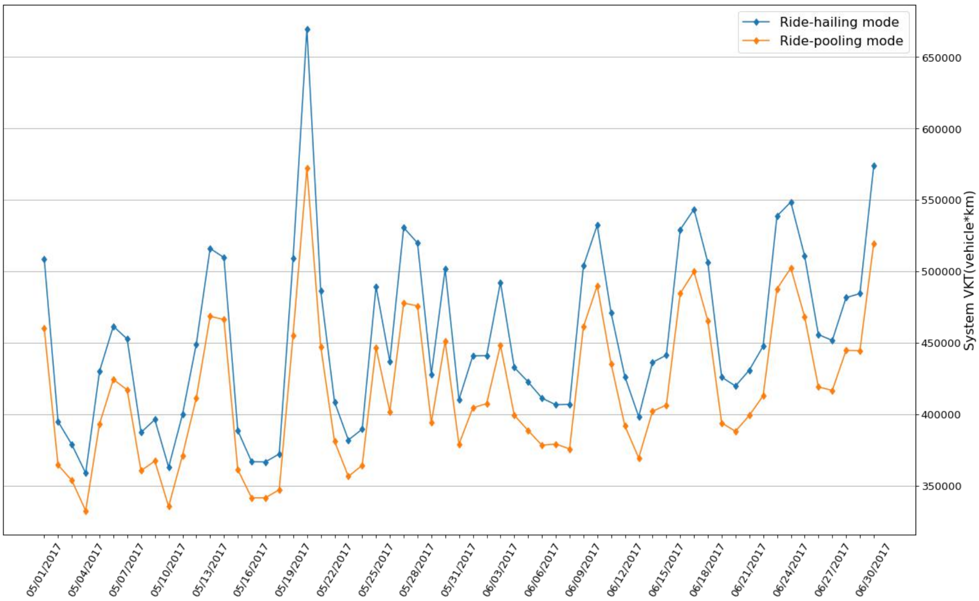


Figure.4 Aggregate VKT generated on daily basis

4.2 Ride-pooling's contribution to energy savings and GHG emission reduction

One benefit generated by reduction in aggregate VKT is reduced petroleum usage. Figure 5 displays the daily petroleum savings generated by ride-pooling. It is shown that ride-pooling mode, compared to standard ride-hailing mode, could reduce petroleum consumption by an average of 3,372L per day in Haikou city.

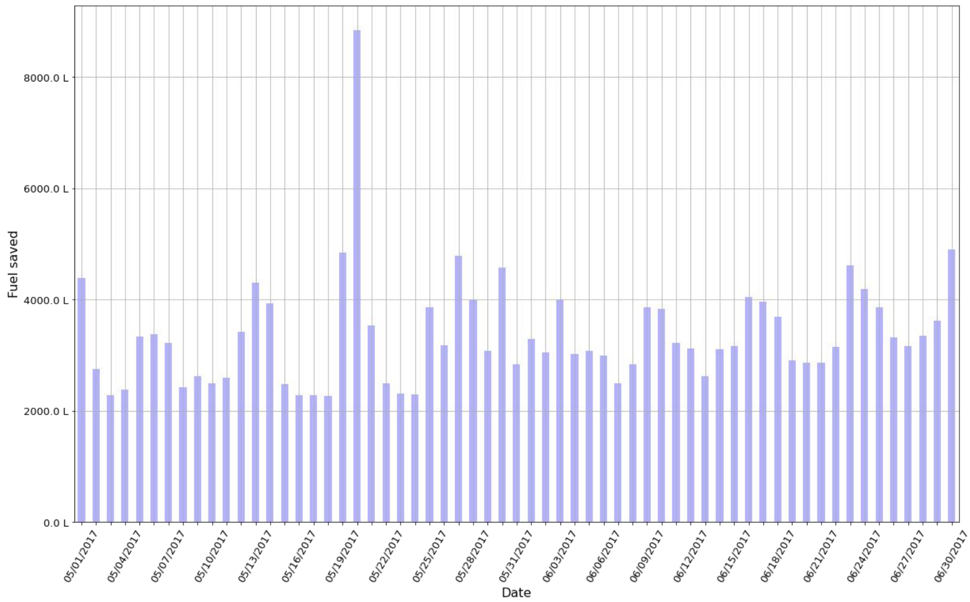


Figure 5 Daily savings in petroleum consumption

A decrease in petroleum consumption brings with it environmental benefits and promotes sustainability as it reduces GHG (Greenhouse Gases, mainly carbon dioxide) emissions. High GHG emissions pose a major threat to environmental sustainability globally, contributing to the escalation of the greenhouse effect and threatening global ecological security.

Kolbe et al. (2019) define a method of measuring automobile GHG emissions:

$$C = \sum_{i=1}^{N} \frac{L_i R}{E} \tag{26}$$

Where N is the fleet size, L_i is the mileage of vehicle i, E is the petroleum consumption rate (unit by L/km), and R is the GHG produced by each liter of petroleum when fully burnt.

Since DiDi restricts operating vehicle models, we can calculate GHG emissions accordingly. The results show that 1,234,163.80 L of petroleum can be saved each year through ride-pooling, corresponding to 3,307.56 tons of carbon emissions.

4.3 Empirical relationship between buffer time and aggregate VKT reduction

Our previous ride-pooling simulation was based on collecting all trips in batches at 60-second intervals (i.e., buffer time). This allows TNCs and riders to fully exploit the potential for pooling any collected trips within the same batch. Theoretically, longer buffer time increases pool-matching potentials and thus allows for larger aggregate VKT reduction. However, this trend may be non-linear. Thus, we further simulate VKT reductions based on different buffer times. We conduct such simulations for a sample of 14 days (May 1st -14th), which should be sufficient to provide robust estimates of the mean and standard deviation of VKT reduction for each buffer time.

Figure 6 demonstrates the relationship between buffer times and VKT reduction rates. The dark blue dots represent the mean VKT reduction rate at each buffer time (i.e., 0s, 15s, 30s…) and the light blue area indicates a region of two standard deviations from the means.

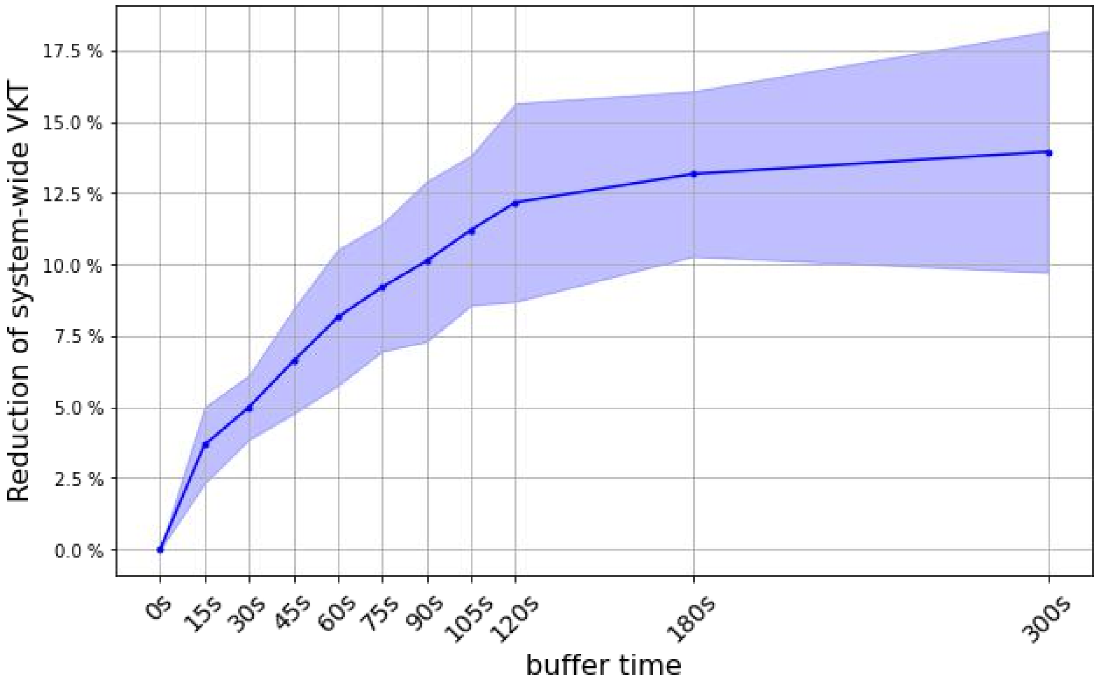
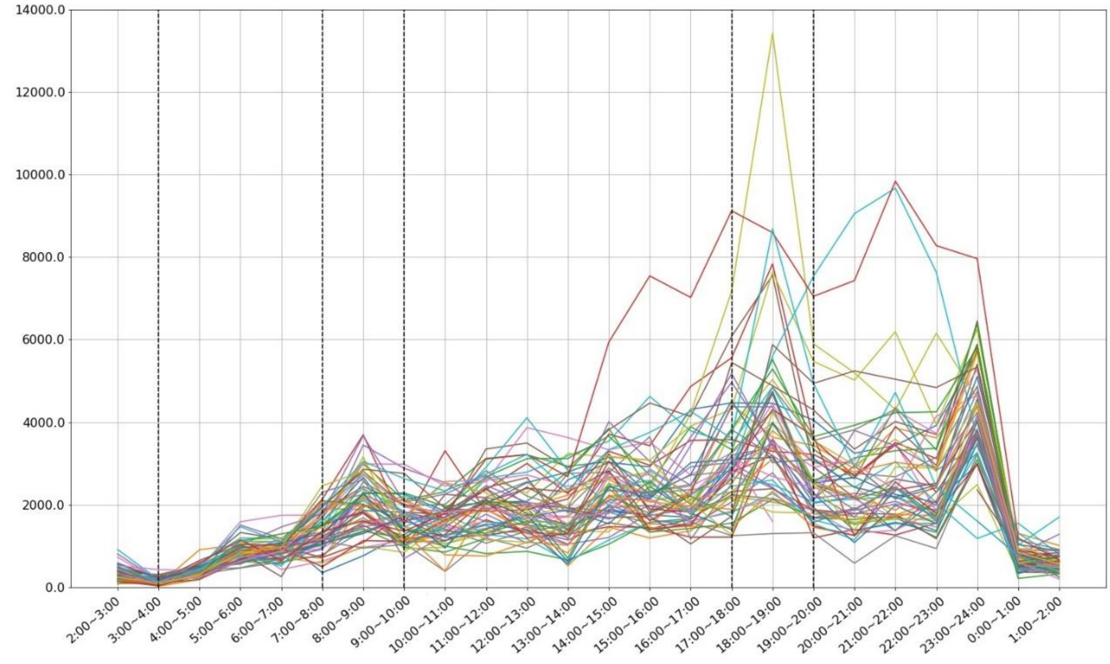
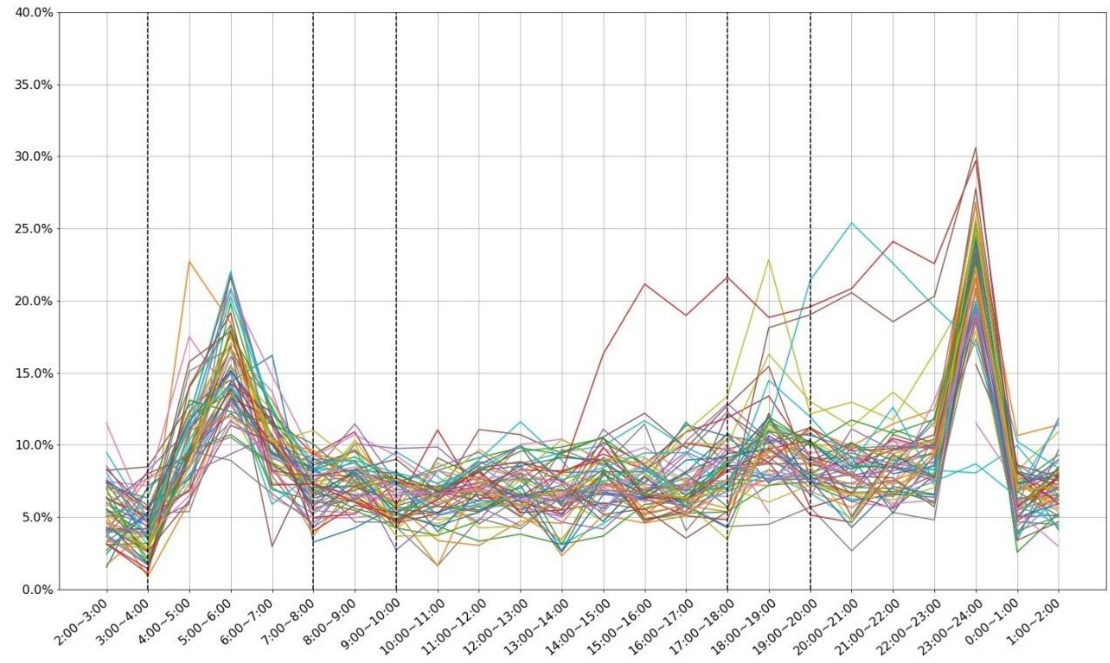


Figure.6 Buffer time vs. percentage of aggregate VKT reduction. As buffer time increases, percentage of aggregate VKT reduction grows with approximate logarithmic rate

Furthermore, ride-pooling at different periods of day is also likely to demonstrate different levels of VKT reduction due to the varying intra-day demand. Wang et al. (2021) have demonstrated this phenomenon. Using 60 seconds as the default buffer time, we also examine the intra-day temporal heterogeneity in VKT reduction effects; that is, how VKT reduction from ride-pooling may vary at different times of day.



(a)



(b)

Figure.7 (a) hourly reduced aggregate VKT (unit by vehicle*km); (b) hourly reduced aggregate VKT percentage. Vertical black dash lines separate the day into five distinct periods.

Figure 7(a) and 7(b) displays the temporal variation in VKT reduction effects. Both Figures contain 61 lines, which represent the 61 days from May 1st to Jun 30th. The X axis indicates the 24 hours of a day. The Y axis in Figure 7(a) represents absolute reduction in VKT and the Y axis in Figure 7(b) represents proportionate reduction in VKT. Based on the patterns illustrated in Figure 7, we roughly divide a day into five periods: early morning (4 am~7 am), AM peak (7 am~9 am), midday (9 am~5 pm), PM peak (5 pm~7 pm), and evening (7 pm~4 am). As the figures show, early morning exhibits only a small VKT reduction in terms of absolute volume since few people are traveling so early. However, interestingly, this period demonstrates a high percentage reduction in VKT. The same pattern also emerges during the evening period, when the volume reduction in VKT is average, but the percentage reduction is disproportionately high. This may be because in the early morning or evening, trips tend to share more similarities in terms of their origin and destination areas. For example, riders tend to travel from home to workplace or other points of interest (POIs) in the morning and from the workplace or entertainment venues to home in the evening. Therefore, it is more likely that riders' routes overlap and that they can share a vehicle during these periods. The AM peak and PM peak witness a moderate rise in both absolute and proportionate reduction in VKT, and the midday period remains at around the average level. Finally, there is a sudden spike in both absolute and proportionate VKT reduction from 11 p.m. to 12 a.m., followed by a significant decline after midnight. Our data show that there is indeed a substantive increase in Didi trip requests between 11pm and 12am, which we suspect is due to the standard closing time of commercial venues in Haikou city at 11pm. Moreover, during this late evening hour, people will be hailing Didi and taxis to go from a few commercial venues to residential areas, and thus they tend to have similar O-D pairs, making ride-pooling highly efficient. After midnight, most of these trip requests have been fulfilled and the efficiency of ride-pooling drops again. In sum, the many variations in VKT reduction over the course of the day suggest the necessity of considering differences in periods of the day in calculating the benefits of ride-pooling. They also serve as the basis for proposing a dynamic buffer time scheme that adjusts according to intra-day variations in travel demand in order to achieve the optimum societal benefits from ride-pooling.

4.4 Scenario analysis using SW-oriented RPM

This section explores how TNCs can determine optimal buffer time for ride-pooling services under different scenarios based on the SW-oriented RPM. Period of day, petroleum price, carbon emission cost, and regional income level (i.e., riders' time costs) are tested at different levels to analyze their influence on optimal buffer time. The optimal buffer time $\widehat{\Delta}$ based on social welfare maximization is calculated using the equation

$$\widehat{\Delta} = arg\max_{\Delta} U(\Delta) \tag{27}$$

Scenario 1. Period of day analysis

As illustrated above, different periods of the day correspond to different levels of demand. Morning peak and evening peak periods are likely to generate many riders, concentrated in direction (commuters). This makes pool-matching easier and leads to better performance in aggregate VKT reduction. During off-peak hours, when trip demand is less concentrated temporally and spatially, ride-pooling is likely to have worse performance in aggregate VKT reduction. The relationship between periods of day and optimal buffer time for social welfare maximization is shown in Figure 8(a) below.

Scenario 2. Petroleum price analysis

Petroleum price directly determines the economic benefits of ride-pooling. Reduced aggregate VKT in ride-pooling mode reduces petroleum consumption and hence petroleum costs. The higher the price of petroleum, the more significant the economic benefit of ride-pooling. In our simulation, we consider scenarios with different petroleum prices from low to high, and calculate their corresponding optimal buffer time. The relationship is shown in Figure 8(b). For reference, petroleum prices in 2017 were around 6870 CNY/ton. It is shown that petroleum price is a significant determinant of optimal buffer time. The empirical relationship is roughly linear.

Scenario 3. Carbon emission governance cost analysis

Social Carbon Cost (SCC) is a popular tool used in climate change policy, particularly in determining regulatory policies involving GHG emissions. Nordhaus et al. (2017) proposed a specific means of calculating SCC as well as an estimate of its value. SCC was estimated at around USD 31.2/ton (with 1USD:6.4CNY, 199.68CNY/ton) in 2015 and is projected to reach USD102.5/ton by 2050. Similar to petroleum price, SCC influences the social welfare of ride-pooling. Greater VKT reduction in ride-pooling mode means a larger reduction in carbon emissions, hence reducing SCC. In our simulation, we consider scenarios with different levels of SCC and examine how they are related to the optimal buffer time for social welfare maximization. Figure 8(c) shows that SCC consistently increases optimal buffer time. With an increase in SCC from 200 CNY/ton to 2,000 CNY/ton, optimal buffer time increases by 12 seconds.

Scenario 4. Regional income level analysis

Regional income level is an essential factor affecting the wait time riders are willing to tolerate in ride-pooling mode.[6] Higher regional income level means riders are less patient in waiting to be pool-matched. Our simulation explores different levels of regional income from 40,000 CNY/year to 120,000 CNY/year at intervals of 10,000 CNY/year, and estimates the corresponding optimal buffer times. The relationship between regional income level and optimal buffer time are shown in Figure 8(d) below. As shown in the figure, optimal buffer time for ride-pooling decreases as regional income level increases. However, this relationship is not linear. In the range between 40,000 CNY/year and 70,000 CNY/year, optimal buffer time decreases rapidly as regional income level rises. From 70,000 CNY/year to 120,000 CNY/year, the rate of decline in optimal buffer time in response to a higher income slows down substantially. Although this scenario focuses on on-demand ride-pooling services, it may also have relevance for understanding how riders with different income levels are able to tolerate waiting in other situations, such as waiting for public transit.

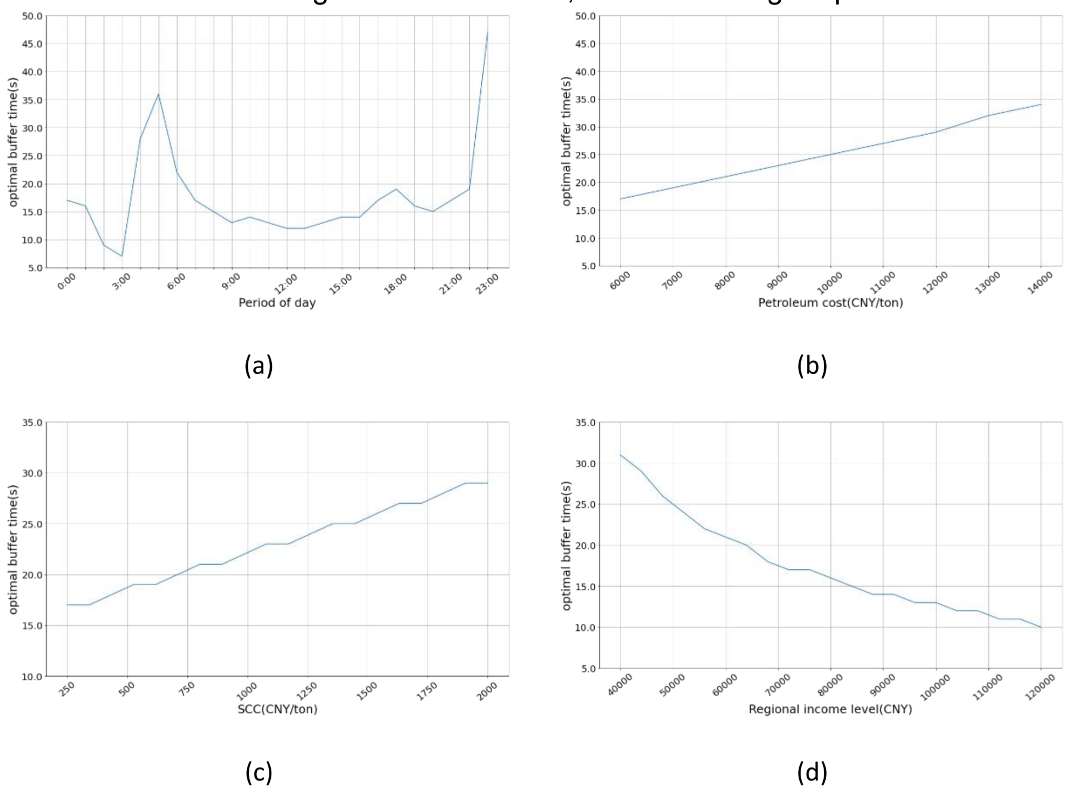


Figure.8 (a) Relationship between periods of day and optimal buffer time (b) Relationship between petroleum price and optimal buffer time; (c) Relationship between SCC level and optimal buffer time; (d) Relationship between regional income level and optimal buffer time

5. Conclusion, discussion, and policy implications

This paper estimates the reduction in aggregate VKT potentially generated by large-scale ride-pooling service and analyzes the balance of social benefits and costs under different conditions. The results can enrich our understanding of the potential benefits of ride-pooling service in medium-sized cities where trip request density is typically lower, hence make an important addition to the literature that has been only focusing on megacities so far.

Our results show that ride-pooling can significantly reduce aggregate VKT in a medium-sized city. Under the default conditions of the model, ride-pooling reduces aggregate VKT by 8.21% compared to standard ride-hailing and commensurately reduces petroleum consumption and GHG emissions. Moreover, altering buffer time in ride-pooling mode from the standard 60 seconds, which is widely adopted in ride-pooling practice and in empirical research, can significantly enhance the VKT reduction effects of ride-pooling. In our default model, adding another 60 seconds to buffer time can increase the aggregate VKT reduction from the estimated 8.21% to around 12%. However, increasing buffer time is not always going to incur better, or socially optimum, solution, especially when other model conditions may also be affected (e.g., longer buffer time increases riders' opportunity costs). Therefore, we propose a SW-oriented RPM to provide a unified framework to measure and balance several major potential benefits and costs induced by ride-pooling service. Our result shows that, despite varying periods of day, petroleum prices, carbon emission costs, and regional income levels (within a reasonable range), optimal buffer time consistently falls between 15 seconds and 30 seconds, suggesting the strong viability of the ride-pooling market, as this buffer time is rather short for riders. Regulations and incentives thus should be proactively considered to increase the proportion of people who pool their rides.

This research has two major implications. *First*, we contend that while past studies have demonstrated significant VKT reduction effects from ride-pooling in megacities like NYC, Shanghai, and Chengdu, the performance of ride-pooling in mid-sized cities, like Haikou in our study, are much lower. While cases in megacities report reductions of 30% to 40% in aggregate VKT, our simulation suggests that the potential for VKT reduction in Haikou is only 8.21% under our defined default conditions. Therefore, it is reasonable to caution policymakers that ride-pooling's effects for reducing aggregate VKT are not universal across cities with different situations. To evaluate this effect and make appropriate policies, transport planners and TNCs should consider the exact background in which ride-pooling services operate and conduct case-by-case analysis. In this regard, the analytical framework presented in this paper is highly generalizable. Second, from the perspective of overall utility or social welfare, the proposed SW-oriented RPM suggests that TNCs should consider adjusting buffer times according to a range of conditions including times of day, petroleum costs, SCC, and regional income levels. In particular, optimal buffer time should be altered dynamically based on the time of the day to achieve social welfare maximization. Moreover, our SW-oriented RPM framework can be extended to include additional considerations pertinent in practical scenarios, hence providing a more concrete basis for ride-pooling service design.

While this study makes important contributions to the literature, there are several areas that future research can aim to improve. First, the effectiveness of ride-pooling mode in lowering aggregate VKT is highly correlated with riders' travel patterns. Riders' travel patterns are affected by the distribution of urban functional areas, the built environment, and so on. For cities with denser built environment, such as Hong Kong, New York, and Tokyo, ride-pooling may lead to more significant VKT reduction. On the other hand, in cities with a smaller population, more dispersed urban form, and lower trip request density, VKT reduction effects are less manifest. Due to limitations in data availability, this paper is unable to test more cities with varying characteristics. However, our analytical framework can be directly applied to many cities. Once this same analysis is completed for a sufficient number of cities, we can then run a regression to examine how different urban forms and built environment characteristics may influence the performance of ride-pooling in terms of VKT reduction, thereby informing better urban design and urban planning. This would be an interesting direction for future research.

Second, our simulation uses batch mode, under which a new trip cannot be accepted until the completion of the current pooled trip. Another mode known as "continuous mode" allows the vehicle to take new orders during an ongoing pooled trip under certain circumstances. While continuous mode is currently being used in most ride-pooling platforms (e.g., UberPool, Didi *Pingche*), their algorithms utilize accurate real-time vehicle location and destination information to match new trip requests instantaneously. This kind of data are only accessible to these service providers. Due to this data limitation, most academic research uses batch mode for ride-pooling simulations. Zhang et al. (2014) is the only exception that explores the continuous mode ride-pooling simulation, but the heuristic method they use generally cannot guarantee the results are optimal. With real-time data on vehicle locations, destinations and trajectories provided to researchers, future research could more accurately investigate the potential for VKT reduction given continuous mode matching and compare the results with the optimal matching under batch mode.

Finally, due to lack of data on the exact number of passengers per trip request, we assume a maximum of two trip requests can be matched in each pool. Although this may slightly underestimate potential VKT reduction, we believe it is a reasonable assumption because a number of studies have found average occupancies of ride-hailing trips in different US regions range from 1.34 to 1.9 (CARB, 2019). A pool of three trips, assuming these numbers, would very likely to exceed the seat capacity of a standard Didi vehicle. In order to test the robustness of our results under the two-trip maximum assumption, we also examined the stronger assumption that allows a maximum of three trip requests to be pool-matched. Results show that only 5% of all trip requests have sufficiently aligned O-Ds to be matched into these larger pools of three trip requests. The resulting VKT reduction in the maximum three-trip requests scenario is 9.41%, meaning only 1.2% additional VKT reduction is achieved over the 8.21% reduction in a two-trip requests scenario. Therefore, the underestimation of potential VKT reduction due to our initial assumption of a maximum of two trip requests in any pool should be minor, even if each vehicle can have sufficient seat capacity to accommodate three trip requests. Nevertheless, with data on the exact passenger number of each requested trip, future research could provide more accurate estimates on VKT reduction.

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Appendix 1. Summary of literature on ride-pooling and VKT reduction

Source	Research objectives	Study Cities	Modelling or simulation method	Important technical details			Conclusions
				Support continuous mode?	Support capacity ≥ 3?	Optimality of the result?	
Agatz, N., Erera, A. L., Savelsbergh, M. W., & Wang, X. (2011). Dynamic ride-sharing: A simulation study in metro Atlanta. *Procedia-Social and Behavioral Sciences*, *17*, 532-550.	Minimize the aggregate VKT	Atlanta	The rolling horizon approach	NO	NO	NO	14~18% of reduction in aggregate VKT
Zhang, D., He, T., Liu, Y., Lin, S., & Stankovic, J. A. (2014). A carpooling recommendation system for taxicab services. *IEEE Transactions on Emerging Topics in Computing*, *2*(3), 254-266.	1) Minimize aggregate VKT 2) Minimize the aggregate travel time	Shenzhen	1) Distributed computation 2) Heuristic matching	YES	YES	NO	60% of reduction in the total mileage compared to its baseline
Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S. H., & Ratti, C. (2014). Quantifying the benefits of vehicle pooling with shareability networks. *Proceedings of the National Academy of Sciences*, *111*(37), 13290-13294.	1) Maximize the number of participants 2) Minimize aggregate VKT	New York	Graph's minimum path coverage	NO	NO	YES	40% reduction in fleet size and accumulative trip lengths
Yu, B., Ma, Y., Xue, M., Tang, B., Wang, B., Yan, J., & Wei, Y. M. (2017). Environmental benefits from ridesharing: A case of Beijing. *Applied energy*, *191*, 141-152.	Minimize aggregate VKT	Beijing	Not mentioned	Not mentioned	Not mentioned	Not mentioned	Energy consumption, CO2 emissions, and NOx emissions by 26.6 thousand tce, 46.2 thousand tons, and 235.7 tons, respectively in one year
Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., & Rus, D. (2017). On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *Proceedings of the National Academy of Sciences*, *114*(3), 462-467.	Minimize the aggregate travel time	New York	Linear Programming	NO	YES	NO	
Chen, M. H., Jauhri, A., & Shen, J. P. (2017, November). Data driven analysis of the potentials of dynamic ride pooling. In *Proceedings of the 10th ACM SIGSPATIAL Workshop on Computational Transportation Science* (pp. 7-12).	1) Minimize aggregate VKT 2) Minimize the fleet size	San Francisco New York Los Angeles	Greedy search algorithm	NO	YES	NO	Averagely around 18% reduction in VMT and 32% reduction in fleet size.

Xue, M., Yu, B., Du, Y., Wang, B., Tang, B., & Wei, Y. M. (2018). Possible emission reductions from ride-sourcing travel in a global megacity: the case of Beijing. *The Journal of Environment & Development*, *27*(2), 156-185.	Minimize aggregate VKT	Beijing	Not mentioned	Not mentioned	Not mention ed	Not mentioned	Cooperation strategy can achieve up to 85% CO_2 emission reduction and 88% NO_x reduction
Cai, H., Wang, X., Adriaens, P., & Xu, M. (2019). Environmental benefits of taxi ride sharing in Beijing. *Energy*, *174*, 503-508.	Minimize aggregate VKT	Beijing	Linear Programming	NO	NO	YES	Ridesharing can reduce VMT by 33%
Yan, L., Luo, X., Zhu, R., Santi, P., Wang, H., Wang, D., ... & Ratti, C. (2020). Quantifying and analyzing traffic emission reductions from ridesharing: A case study of Shanghai. *Transportation Research Part D: Transport and Environment*, *89*, 102629.	Minimize the aggregate travel time	Shanghai	Graph's minimum path coverage	NO	NO	YES	23% reduction in fuel consumption
Ma, N., Zeng, Z., Wang, Y., & Xu, J. (2021). Balanced strategy based on environment and user benefit-oriented carpooling service mode for commuting trips. *Transportation*, *48*(3).	Minimize aggregate VKT	Chengdu	1) Graph's minimum path coverage 2) Linear programming 3) GA algorithm	NO	YES	NO	Significant carbon emission reduction under several scenarios