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Pooling in Ridesharing using Meeting Points

Rakibul Hassan

Lecturer, Department of Civil Engineering, Presidency University, Dhaka, Bangladesh

***Abstract* - Ridesharing, a recent popular mode of transportation where two or more travelers following similar routes and schedules share a car to gain benefits in terms of monetary, comfort, door to door service etc. GPS technology, smartphones and ridesharing apps altogether have made it convenient and efficient for strangers to get matched in real-time for sharing a trip. In reality, this transportation mode is more of like on-demand taxi services. To attain more benefit in term of matching rate and distance savings, this paper introduces meeting point concept to motivate ride pooling or group sharing. To be more specific, meeting point is a common meet up point, to where riders might need to go by walking, from where driver can pick them up all at once given that riders and drivers meets time and distance feasibility. For this we propose time feasibility and distance feasibility conditions to find possible match lists. To find out the optimal match pairs or groups we introduce a mathematical optimization model that finds optimal groups on the fly. For implementing the whole framework, we take help of open source Python Programming language and Gurobi optimizer. We test our model with open source data sets of Chengdu city, China. The introduction of meeting points improves the matching rate and occupancy rate which implies meeting point opens the door for ride pooling with group matching.**

Keywords: Ridesharing, Pooling, Meeting Points, Grouping, Optimization.

I. INTRODUCTION

In recent years, the increased popularity of smart-phones and the rapid development of GPS, data repositories, and wireless communication technologies have led to the proliferation of smartphone-based dynamic ridesharing apps around the world[1]. This fact has also attracted industries to form traffic network companies (TNC) i.e. Uber, Lyft, Didi etc. The matching mechanism in a ride-sourcing market is different from that of traditional taxi market. In a traditional taxi market, the idle drivers cruise on the streets to search for waiting passengers, and the bilateral search frictions between idle drivers and waiting passengers has been studied for many years [2][3]. Whereas, in today's dynamic ridesharing program, the platform (mobile app run by TNCs) finds matching between riders and drivers using dynamic matching algorithm taking real-time location of riders and drivers, origin and destination of trips, flexible start time of trips as arguments [4]. Then rider is notified with the contact of matched driver to decide the pickup location through conversation.

Though shared mobility comes with many benefits, such as decreasing congestion and pollution levels and reducing transportation costs for both people and goods, but it also has challenges that are holding back widespread adoption. Three major challenges for agencies providing shared rides to passengers are designing attractive mechanisms, proper ride arrangement, and building trust among unknown passengers in online systems [5]. The success of ridesharing depends on stable matching and efficient pricing strategy. Due to limited driver supply, it's not always possible to match all the riders with drivers [6]. A study using Didi data for Chengdu city in November 2016 shows that the percentage of shared ride orders is only 6.2% of total orders, and the percentage of ride splitting trip hours among the total trip hours is 6.9%, which are both fairly low[7].

To tackle this issue, platform keeps some dedicated drivers to meet the ride demand as much as possible [8]. These drivers might need to be sent to a remote location for picking up matched riders which leads to rise in pickup time. If pickup time continues increasing, it might fall into wild goose chases as per the graph as below [9]. This wild goose chases can be solved through the implementation of maximum dispatch radius & surge pricing; they proved in their study. Regardless of multiple or single pickup, drivers usually need to pick up riders from their origin of trip.

This increases the detour/pickup time for the driver and first passenger (in multiple pick up case) in most cases. To avoid this extra detour time, riders sometimes walk to a meeting point from where driver can pick up all passengers at once with similar itinerary. Typically, these meeting points are located at popular places. But to promote increased matching and reduce individual trips, dynamic meeting point throughout the transportation network can be new chapter of exploration. In a recent research on Atlanta showed that carefully chosen meeting points can improve the ridesharing system performance in several aspects, i.e., percentage of matched riders, percentage of matched participants and mileage saving [10].

Previous studies have motivated us to explore field the ridesharing with meeting points. In our framework we consider all the passengers walk to meeting point within a reasonable walking distance. Drivers pick up all the passengers at once. For this rider will declare their willingness beforehand through the mobile app. To find our best matching groups/individuals we have proposed and mathematical optimization model in the subsequent section of this research paper.

The paper is organized as follows. In Section I, we have provided an overview of related literature and motivation. In Section II, we describe our problem and introduce notations. In Section III, we describe our group/individual matching strategy with meeting points. In Section IV, we describe our case study with Chengdu City dataset from Didi. Finally, in Section V, we summarize and discuss future research directions.

II. PROBLEM DESCRIPTION AND NOTATIONS

2.1 Framework Description

To illustrate our modelling framework, two situations of ridesharing have been illustrated in Figure 1. In the left side of the figure, one driver picks up one rider from rider's location. And in the right side, one driver picks up two passengers at a common pickup point and drop them off them one by one. This common pickup point is referred as meeting point in our study. The dashed circle around the meeting point in the right-hand side of Figure 1 is drawn by with radius equal to the maximum walking distance a rider is willing. That means if any rider willing to join meeting point is within this boundary, he will go the meeting point.

In our framework, we consider that the platform has all the information regarding origin, destination, time schedule, willingness to join meeting point, role etc. for each rider and driver beforehand. This consideration is realistic from recent form of ridesharing. We assume at most one pickup by one driver per trip for convenience at the early stage of this study which will be extended in future.

Line graph at the bottom of Figure 1 depicts the time budget for a representative rider in our framework. Here, a rider usually announces a trip bit earlier than his earliest departure time, e_i. And he/she is also constrained by maximum allowable waiting time f_i before being picked up by a matched driver. Sum of earliest departure time and maximum waiting time give latest departure time from origin location of rider.

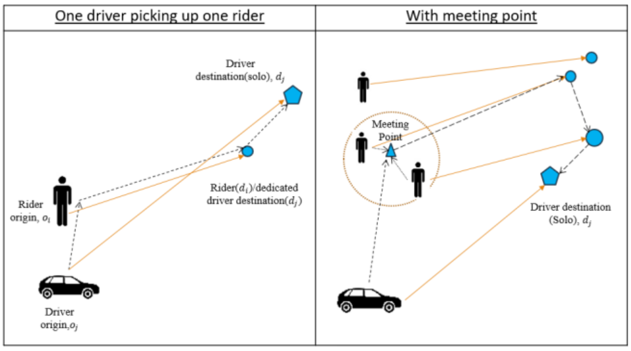
One driver picking up one rider
With meeting point
Driver destination(solo), d_j
Rider origin, o_i
Rider(d_i)/dedicated driver destination(d_j)
Driver origin,o_j
Meeting Point
Driver destination (Solo), d_j

Figure 1: Schematic representation of ridesharing with or without meeting point

Furthermore, a rider also has a target time to reach his destination. Similarly, a driver has earliest departure time and maximum allowable trip time. If a driver picks up multiple passengers from a meeting point than he drops the passengers one by one following shortest path to his destination.

2.2 Notations and feasibility condition of matching

Before introducing our mathematical model, following are the notations used for this study.

$o_i, d_i \approx$ origin and destination rider $i \in R$ respectively

$o_j, d_j \approx$ origin and destination driver $j \in D$ respectively

$e_i, e_j \approx$ earliest departure time of a rider $i \in R$ and driver $j \in D$ respectively

$d_{o_j,d_j} \approx$ distance between origin o_j and destination d_j of a driver $j \in D$

$t_{o_j,o_i} \approx$ travel time/pickup time from driver's origin o_j to riders' origin o_i

$f_i \approx$ maximum waiting time of a rider $i \in R$ before being picked up after successfully matched

$\sigma_{ij} \approx$ distance saving, for a matched trip between rider $i \in R$ and driver $j \in D$

For a match between driver and rider(s) to be feasible, two feasibility criteria are to be satisfied at the first place. One is time feasibility and another is distance feasibility. For single driver match with single rider case, two main time feasibility conditions are to be met i.e. (i) driver should be able to pick-up matched rider between a time window of rider's earliest departure time and time point that rider is willing to wait max till being picked up, (ii) sum of pickup time, trip time and drivers last mile should be less than driver's maximum time budget for the trip. But for the dedicated driver's number (ii) condition is not applicable. On the other hand, for matching a single driver with single/multiple rider(s) in a meeting point, an implied time window is calculated in the first place. This implied common time window at meeting point $k \in K$ corresponding to a rider group $g \subset R$ is represented by $[e_g^k, l_g^k]$, where e_g^k maximum of summation of walk time and earliest departure time for all riders in the group and e_g^k maximum summation of walk time, earliest departure time and maximum wait time for all riders in the group. Implied time window is only feasible if $e_g^k < l_g^k$. And for match to be feasible with a driver, summation of earliest departure time of the driver and pickup time at the meeting point $k \in K$ should lie within the time window as mentioned earlier

Distance feasibility means the distance saving should be no-zero, where distance saving is referred as the difference between sum of individual trip distance and distance for the shared trip. Distances saving for two cases are follows.

$$\sigma_{ji} = d_{o_j,d_j} + d_{o_i,d_i} - (d_{o_j,o_i} + d_{o_i,d_i} + d_{d_i,d_j})$$

$$\sigma_{jg} = d_{o_j,d_j} + \sum_{i \in g} d_{o_i,d_i} - \sum_{i \in g} d_{o_i,k} - (d_{o_j,k} + d_{k,d_i} + \sum_{i,n \in g} d_{d_i,d_n} + d_{d_n,d_j})$$

III. STRATEGY OF MATCHING IN GROUPS

3.1 Representation of match list

Before go into optimal matching, we want to visualize the feasible match list. To do that, we take the help of simple bipartite graph. In this study, bipartite graph has been formed between two disjoint sets of drivers and riders' group, where each connecting edge joining these two sets indicates a feasible match. The rider group can be consisted of single or multiple riders. A simple bipartite graph between one driver and two riders has been shown as below in Figure 2.

Here, driver d_1 has three feasible matches with two riders r_1 and r_2. The value in parentheses (2,7) associated with first edge between d_1 and r_1 represents matched number of participants $\upsilon_{jg} = 2$ and distance saving $\sigma_{jg} = 7$ units. Similarly, for the third edge, the matched number of participants $\upsilon_{jg} = 3$ and distance saving of $\sigma_{jg} = 10$ units. We consider each node on the right-hand side as a rider group which might be consisted of single or multiple passengers. All the feasible match list is found satisfying the time and distance feasibility conditions discussed in the previous chapter within an interval in consideration.

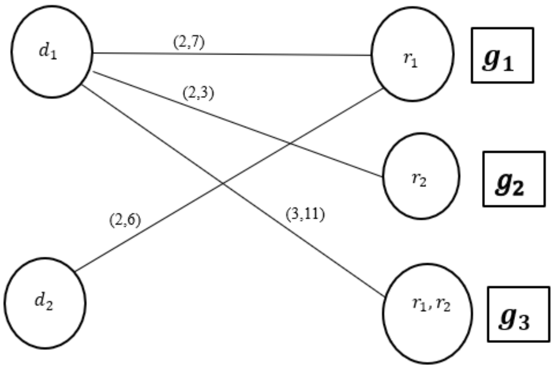

Figure 2: Feasible match representation for simple case

3.2 Optimization to find optimal match list

To find the best matches from feasible match list, we introduce two MILP optimization problem, one (z_1) to maximize the number of matched participants υ_{jg} and another (z_2) to maximize system wide distance saving σ_{jg} as below.

$$\max\ z_1 = \sum_{jg \in E} \upsilon_{jg} x_{jg}$$

subject to

$$\sum_{j \in D} x_{jg} \le 1 \qquad \forall g \in G$$

$$\sum_{g \in G} x_{jg} \le 1 \qquad \forall j \in D$$

$$\sum_{g \in G} \sum_{j \in D} x_{jg} \delta_g^i \le 1 \qquad \forall i \in R$$

$$\text{where, } x_{jg} \in \{0,1\} \ \& \ G \subset R$$

$$\text{And parameter } \delta_g^i = \begin{cases} 1 \text{ passsenger } i \text{ belongs to group } g \in G \\ 0 \text{ passsenger } i \text{ doesnt belong to group } g \in G \end{cases}$$

$$\max\ z_2 = \sum_{jg \in E} \sigma_{jg} x_{jg}$$

subject to

$$\sum_{j \in D} x_{jg} \le 1 \qquad \forall g \in G$$

$$\sum_{g \in G} x_{jg} \le 1 \qquad \forall j \in D$$

$$\sum_{g \in G} \sum_{j \in D} x_{jg} \delta_g^i \le 1 \qquad \forall i \in R$$

$$\text{where, } x_{jg} \in \{0,1\} \ \& \ G \subset R$$

$$\text{And parameter } \delta_g^i = \begin{cases} 1 \text{ passsenger } i \text{ belongs to group } g \in G \\ 0 \text{ passsenger } i \text{ doesnt belong to group } g \in G \end{cases}$$

In the above formulation, x_{jg} is a binary variable which takes value 1 if driver j is optimally matched with rider group g otherwise x_{jg} will take the value zero. The first two constraints in the both formulations guarantee that a rider group can be matched with only one driver and a driver can be matched with only one unique rider group respectively. And the third constraints ensure that one rider can be appeared only once in any group out of all groups matched optimally. The optimal match list from the first formulation doesn't ensure the optimality of the second optimization problem. To tackle this issue, we take the help from combined multi-objective optimization[11].

The two objectives are summed upon giving each a weight α and β respectively, where $\alpha + \beta = 1$. Changing the weights, we can check the sensitivity on objective function.

Combined optimization model turns into: $\max \ \alpha z_1 + \beta z_2 = \alpha \sum_{jg \in E} \upsilon_{jg} x_{jg} + \beta \sum_{jg \in E} \sigma_{jg} x_{jg}$ subject to the same constraints as discussed earlier above. To simulate the real-world scenario, rolling horizon strategy has been used in this research and also the planning horizon has been split into equal intervals, Δt. At each interval match lists are found satisfying both time and distance feasibility conditions and optimal match are found by using the combined optimization problem discussed above.

IV. NUMERICAL STUDY

For simulating the ride-matching framework discussed earlier, we used Python programming language 3.6 and GUROBI (8.1) optimizer. All the scenarios are experimented on a 3.40 GHz i7-4470 CPU Windows 10 PC with 16GB RAM. The optimization program's solution was optimal as per GUROBI optimizer each time.

4.1 Data Description

We conducted our using the data from the DiDi GAIA Initiative, DiDi's open data project (DiDiChuxing, 2017). The project shares the complete ride trajectory and order data of DiDi Express and DiDi Premier, two of DiDiChuxing's core ride sourcing services, in the city of Chengdu, China, from November 1st to November 30th, 2016. The trajectory dataset contains fields such as anonymous driver ID, order ID, timestamp, longitude, and latitude, with an average sampling interval of 3 s. The order dataset includes fields such as order ID, start and end timestamps, pick-up and drop-off locations.

4.2 Sensitivity test

We have done some sensitivity test by varying meeting point. Firstly, we investigate how meeting point affects percentage of matched riders. Percentage matched is defined as number of participants matched divided by total number of participants in input. We have plotted percentage matched against number of meeting points in Figure 3. From the plot, it is obvious that increase of meeting point increases percentage matched participants with some deviation. This deviation is due to the random generation of location of meeting points.

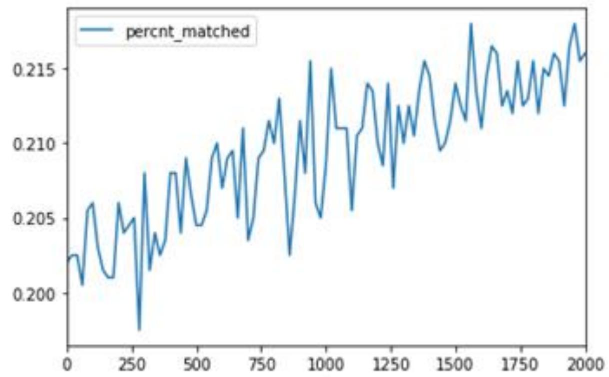

Figure 3: Percentage matched vs meeting points number

Secondly, we further investigated how meeting points affects occupancy rate where occupancy rate is defined to be the average number of participants per trip. Similar to the percentage matched versus number of meeting points, we also plot another graph of occupancy rate versus number of meeting points.

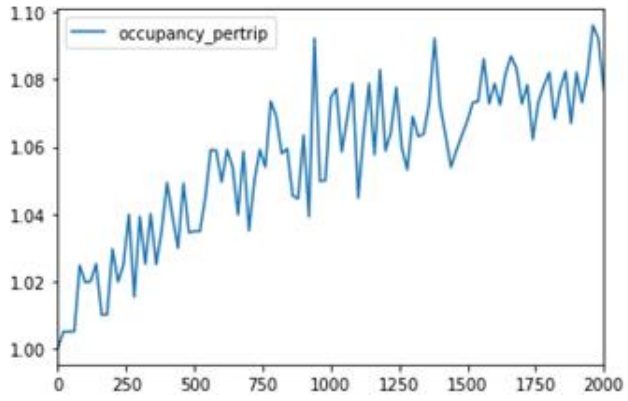

Figure 4: Occupancy rate vs meeting points number

This graph is also intuitive here as well since meeting points allows group matching giving rise to occupancy rate. Initially with the increase of number of meeting points occupancy rate also increases. With further increase in meeting points occupancy rate increase stabilizes slowly.

V. CONCLUSION AND FURTURE DIRECTION

Meeting point opens the door for group matching and system wide extra distance savings. From the numerical case study, we can summarize that increase in number of meeting point improves some performance matrices i.e. percent matched participant, occupancy rate. But if we keep on increasing these parameters infinitely, the performance measures become stable showing no further improvement after some point or at the end.

With some positive outputs, we also want to discuss our limitations here. First of all, we didn't consider the whole dataset availed at Didi GAIA for our numerical study. Since distribution of origin and destination will affect the result, but we hope that the pattern might be similar since our data has been randomly sampled from the whole dataset. Another limitation is that, distances were assumed to be Euclidean which is not exact from the realistic point of view. Furthermore, location of meeting points was randomly generated randomly based on uniform distribution which might not be uniform for that city.

In our future research intend to improve and extend the proposed modelling frameworks addressing the limitations discussed earlier. We also want to look into better estimation of meeting point location based on the spatial temporal distribution of historic demand data using some machine learning tool.

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AUTHOR'S BIOGRAPHY

Rakibul Hassan has been working as a Lecturer in the Department of Civil Engineering Presidency University, Dhaka, Bangladesh.

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