CEE 6620 Final Project Paper
Incentive Price for Meeting Points in On-demand Ridesharing Systems

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1 Introduction

Ridesharing has been an important topic in transportation studies recently. Ridesharing helps to reduce the number of vehicles on the road, which in turn reduces vehicular air pollution, and ridesharing can also save money for individual travelers [3]. The rapid increasing of ridesharing companies like Uber, Lyft and Didi has shown a huge potential in ridesharing systems.

Thus, both the academic and the industry have tried to come up with solutions to improve the ridesharing systems by increasing the shareability of on-demand services, especially in densely populated major cities. Two-person on-demand ridesharing is already a common practice. For example, Uber, the famous ridesharing company, has provided the "Uber Pool" option, of which the users may share the same vehicle with another party and pay a lower price. ridesharing services of three or more persons and even mini-bus services are also being experimented in some places, like the BRIDJ service in Boston.

The pricing issue is important in the ridesharing systems since passengers care about the price and the corresponding services they can get. Many research papers have focused on giving an appropriate pricing structure for the ridesharing systems [2]. However, there's only a few research papers and implementations considering the incentive price in the ridesharing systems. Using pricing strategies in vehicle rebalancing and extension of users' share-ability already have some real-world implementation. Uber has rolled out "Expressed Pool" in some cities, which is cheaper than Uber Pool with possibly longer delay time. After a user requested an "Express Pool", the app would take some time to search for other nearby users and instruct the user to wait for the vehicle at a designated pick-up point that should be close to but may not be the user's current location. Such incentive prices have also been used in other vehicle sharing systems. Citi Bike has came up with the 'Bike Angles' program [5], which gives people gift cards and free rides if people help them rebalance bikes.

Giving the incentives to passengers can make them walk to the same pick-up location or drop off at the same place, which saves a lot of time and travel distance since the detour and waiting time for vehicles take a relatively large proportion in total vehicle travel time, especially in urban areas of large cities like Manhattan, New York. These common pick-up or drop-off locations are also called meeting points and they have been studied for the offline ridesharing systems in the literature [7].

For this project, we are going to model the incentive price for meeting points in the on-demand ridesharing systems. Different passengers will take different incentives to walk to common pick-up and drop-off locations. The systems will have a trade-off between the time and distance savings by having common meeting points and the incentive prices paid to passengers. We try to model passengers behavior by building a “comfort zone” centered at an individual customer’s current position. The customer is assumed to be willing to go to any locations within the ”comfort zone” to board a shared on-demand vehicle. When multiple customers request a shared ride and such a ride meet all the constraints, we will let the customers to convene at a common pick-up point that lies within the overlap of their comfort zones. Customers can also take off the vehicle at the same drop-off points if the walking distance is ”comfortable” for them. The range of the comfort zone will depend on the incentives, the higher the incentive is, the larger the comfort zone is. The relationship between the incentive and the range of the ”comfort zone” should be heterogeneous across all passengers. The best way to reflect passengers’ behavior would be discrete choice model, but at this stage of the project, we will try to model this behavior by some simple distribution as a starting point.

The contribution of this project will be:

- Consider the benefits of meeting points in the on-demand ridesharing systems and combine with the incentive price.
- Propose the incentive price for the ridesharing systems to help improve the shareability of passengers and minimize the total travel time.

The rest of articles is organized as follows. Section 2 gives the literature reviews. The model formulations are contained in section 3. Section 4 displays the experiment results of our model. Section 5 recaps the main idea of this project and give a future directions for this research.

2 Literature Review

Ridesharing is such a hot topic that plentiful works have been done on ridesharing systems recent years. Furuhata et al. [4] gave a comprehensive review for current ridesharing research and pointed out the challenges and futures of ridesharing research. They presented a classification to understand the key aspects of existing ridesharing systems, which are dynamic real-time ridesharing, carpooling (commute), long-distance ride-match, one-shot ride-match, bulletin-board and flexible carpooling. This project will focus on the real-time ridesharing systems, which is also the hottest part in the recent ridesharing research.

Recently, Santi el al. [6] showed that up to 80% of the New York City taxi trips in Manhattan could be shared by two passengers with the increase in the travel time of a few minutes. They proposed the concept of the shareability network firstly to solve the matching problem between all passengers, which was also used in our project. Due to the limited capacity and intractable for the larger number of passengers, Alonso-Mora et al. [1] proposed a mathematical model for the real-time high-capacity ridesharing systems considering vehicle capacity up to 10. They showed the high-capacity ridesharing services can give a significant improvement in the urban transportation systems.

For the pricing issues in the ridesharing systems, Banerjee et al. [2] designed a general approximation framework for designing pricing policies in shared vehicle systems, but they didn't consider the how pricing influence the vehicle rebalancing and users' shareability and incentive price for users. The framework for pricing policies can't be solved optimally because the pricing is a continues variable and it's intractable to optimize the pricing in the large shared vehicle systems. In our project, we try to convert the pricing from a continues variable to a discrete variable by introducing the meeting points and optimize it by discrete optimization techniques.

For the meeting points in ridesharing systems, Stiglic et al. [7] investigated the potential benefits of introducing meeting points in the carpooling (commute) systems. We will use the mathematical formulation in this paper and consider the influence of incentive prices in the real-time ridesharing situation.

3 Problem Definition

The problem is for the on-demand ridesharing systems with a set of requests R in a certain time window ΔT, systems will give every passengers some incentives γ to walk to the common pick-up locations M. We make an assumption that the capacity of the vehicles is two and the number of vehicles is infinite, which means every passengers can finish their trips if they request a ride. Figure 1 shows an instance of this problem.

3.1 Model formulation

Let $G = (V, E)$ represent the road network. V is the set of predefined meeting points, which are all nodes in the road network. d_{ij} is the distance and T_{ij} is the travel time between any two points $i, j \in V$.

Let R be the set of all requests. Any request $r \in R$ has a request time t_r, an origin o_r, a destination d_r, a maximum delay time t_d^r, a maximum waiting time t_w^r, a walking distance W_r and a monetary incentive γ_r for him to walk to/from the meeting points.

We assume that $W_r = F(\gamma_r)$, where $F(\cdot)$ is a monotonous increasing and differentiable function. The maximum walking distance for each requester is

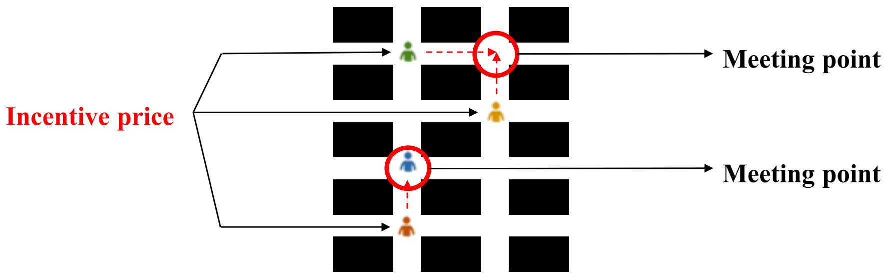

Figure 1: Instance of the problem. Red circle represents the common meeting points for these passengers and different passengers have different sensitivity to the incentive price. The blue passenger is unwilling to walk even if we give him a large incentive price.

W_r^{max}.

For each request $r \in R$, the set of feasible pick-up meeting points is $M_r^p := \{k \in V | d_k o_r \leq W_r^{max}\}$, and the set of feasible drop-off meeting points is $M_r^d := \{k \in V | d_{kd_r} \leq W_r^{max}\}$.

For each $m_r^p \in M_r^p$, $d_{o_r m_r^p}$ is the distance for request to walk to the meeting point. As $F(\cdot)$ is invertible, we can write $\gamma_r = F^{-1}(W_r)$. Thus, for each pick-up meeting point with distance $d_{o_r m_r^p}$, there will be a corresponding incentive pricing $\gamma_r^p = F^{-1}(d_{o_r m_r^p})$. The incentive pricing for each request is a strictly non-negative value, which means $\gamma_r^p = 0$ if $F^{-1}(d_{o_r m_r^p}) < 0$. Let T_r^p be the set of tuples (m_r^p, γ_r^p) for request r, where m_r^p is a pick-up meeting point for request r and γ_r^p is the corresponding incentive pricing for request r to walk to this meeting point.

For each $m_r^d \in M_r^d$, $\gamma_r^d = F^{-1}(d_{d_r m_r^d})$ is the corresponding incentive pricing for request r to be dropped off at the meeting point m_r^d. T_r^d is the set of tuples (m_r^d, γ_r^d) for request r with drop-off meeting points m_r^d.

Each request r can be picked up at his origin o_r or a meeting point in M_r^p and dropped off at his destination d_r or a meeting point M_r^d. Finally, we denote the service time at each meeting point $m \in V$ by τ_m, i.e., the time needed to get into and out of the vehicle at a pick-up or drop-off meeting point.

3.2 Definition of a feasible match

For any $r_i, r_j \in R$, there will be a feasible match between the two requests if the following constraints hold:

- $M_{r_i r_j}^p = M_{r_i}^p \cap M_{r_j}^p \neq \emptyset$ and $t_w^s \geq |(t_{r_i} + t_{o_{r_i} m^p}) - (t_{r_j} + t_{o_{r_j} m^p})|$, where $m^p \in M_{r_i r_j}^p$ and s is the request with minimum $(t_s + t_{o_s m^p})$, or $M_{r_i r_j}^d = M_{r_i}^d \cap M_{r_j}^d \neq \emptyset$[1].

[1] Two requests r_i and r_j should have at least one common meeting point for picking up or dropping off.

- $t_{o_{r_i}m^p} + t_{m^pm^d} + t_{m^dd_{r_i}} - t_{o_{r_i}d_{r_i}} \leq t_d^{r_i}$ and $t_{o_{r_j}m^p} + t_{m^pm^d} + t_{m^dd_{r_j}} - t_{o_{r_j}d_{r_j}} \leq t_d^{r_j}$, where $m^p \in M^p_{r_ir_j}$ and $m^d \in M^d_{r_ir_j}$ if requests r_i and r_j have both common pick-up and drop-off meeting points[2].

If there are more than one feasible trips, we will always choose the trip with more number of meeting points. If there exists more than one m^p for a feasible match r_i and r_j, we only consider the meeting point $m^p \in M^p_{r_ir_j}$ with minimum $|(t_{r_i} + t_{o_{r_i}m^p}) - (t_{r_j} + t_{o_{r_j}m^p})|$, which implies that the meeting point m^p has the minimum total waiting time for two requests. If there exists more than one m^d for a feasible match r_i and r_j, we choose the $m^d \in M^d_{r_ir_j}$ with minimum $(d_{m^dd_{r_i}} + d_{m^dd_{r_j}})$, which means the drop-off meeting point m^d will have minimum total walking distance for both requests, and also the minimum total incentives.

The first constraint assumes that we only consider the pair of requests with at least a common pick-up or drop-off meeting point, and the waiting time for both requests should not exceed the maximum waiting time $t_w^{r_i}$ and $t_w^{r_j}$. The second constraint ensures the delay for each request in this feasible match (r_i, r_j) should not exceed the maximum delay time $t_d^{r_i}$ and $t_d^{r_j}$.

Let $\sigma_{r_ir_j}$ represent the time saving for a feasible match (r_i, r_j) with both common pick-up and drop-off meeting points m^p and m^d. Then, we have [3]

$$\sigma_{r_ir_j} = 2\tau_m + t_{o_{r_i}d_{r_i}} + t_{o_{r_j}d_{r_j}} - t_{o_{r_i}m^p} - t_{o_{r_j}m^p} - t_{m^pm^d} - t_{m^dd_{r_i}} - t_{m^dd_{r_j}} \quad (1)$$

Let $\gamma_{r_ir_j}$ denote the incentive pricing for a feasible match (r_i, r_j) with both common pick-up and drop-off meeting points m^p and m^d. Then we can find the corresponding $\gamma^p_{r_i}$ and $\gamma^p_{r_j}$ for in the set $T^p_{r_i}$ and $T^p_{r_j}$ with known pick-up meeting point m^p, the $\gamma^d_{r_i}$ and $\gamma^d_{r_j}$ can be got in the same way [4]. Thus, we have

$$\gamma_{r_ir_j} = \gamma^p_{r_i} + \gamma^p_{r_j} + \gamma^d_{r_i} + \gamma^d_{r_j} \quad (2)$$

3.3 Matching problem

After we define the feasible matching between two requests, we can build a shareability network $G_s = (V_s, E_s)$ with $V_s = R$ and $(r_i, r_j) \in E_s$ if there is a feasible matching between requests r_i and r_j. The weight of the edge would be $\alpha_e = \beta \cdot \sigma_{r_ir_j} - (1-\beta) \cdot \gamma_{r_ir_j}$, which is a weighted average savings of the trip and β is the weight of time saving. This is a maximum weight matching problem and can be solved by the blossom algorithm in polynomial time. Figure 2 shows an instance of the matching problem.

[2]This constraint can be different if requests r_i and r_j only have pick-up meeting points or drop-off meeting points.

[3]The mathematical formulation of $\sigma_{r_ir_j}$ can be different if requests r_i and r_j have only one common pick-up or drop-off meeting point.

[4]The incentive pricing $\gamma^p_{r_i}(\gamma^d_{r_i}) = \gamma^p_{r_j}(\gamma^d_{r_j}) = 0$ if requests r_i and r_j don't need have a feasible pick-up (drop-off) meeting point.

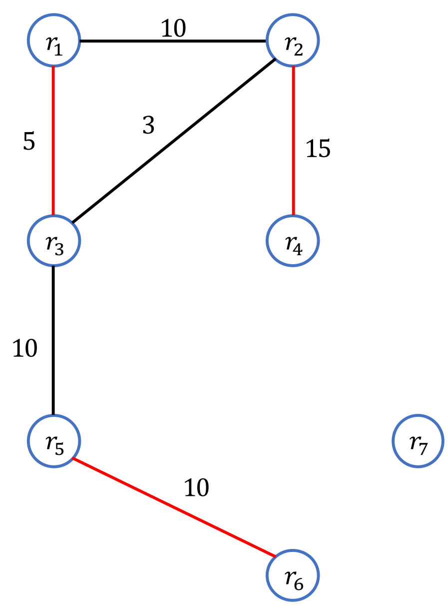

Figure 2: Instance of the maximum weight matching problem. There are 7 requests and r_7 can't share trips with any other requests. The maximum weight matching would be r_1 with r_3, r_2 with r_4 and r_5 with r_6, and the optimal value will be 30.

4 Experiments and results

4.1 Description of ride-sharing data sets

We use the Yellow Cab trip record data of Manhattan, New York for our experiments. The data was obtained from New York City Taxi and Limousine Commission[5]. Taxi and on-demand ridesharing applications provide similar service, so their demands should be comparable. Some of the data is polluted, and some cannot be used for this study. Any taxi trip that is missing origin or destination coordinates, which shows as 0, or does not originate or terminate in Manhattan is disregarded. After cleaning up the data, a valid taxi request is seen as a ridesharing request. We assign each request to the nearest road intersection, which is also the node in road network, and given that Manhattan has a very dense road network, it is a realistic assumption. All data that is used for the experiments comes from 2015-01-15. All experiments are run on a 2.9 GHz Intel Core i5 Processor with 8 GB memory using Python 3.6.

We obtained the Manhattan roadway information, including each roadway's geographical location and length, from Open Street Map. There are nearly 3000 nodes in the graph, which will serve as meeting points. Given that most

[5]http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml

roadways in Manhattan have a default speed limit of 25 mph, and that congestion and traffic signals will slow down traffic significantly, we assume that the average driving speed in the whole Manhattan network is 20 km/h, which is equivalent to 12.43 mph. We also set the walking speed in the whole network to be 5 km/h, which is the average human walking speed.

4.2 Experiment with 30 seconds' data

The default batch time window of our study is 30 seconds. We used taxi data from 08:00:00 to 08:00:30. We used $\beta = \frac{1}{60}$ as the default β value, which implies the value of 1 minute is 1 dollar. The default maximum walking time and maximum delay of all requests are 300 seconds. The default delay caused by a pick-up or drop-off stop is set to be 60 seconds.

In that time window, there are 182 valid requests in total, among which we found 78 matched pairs. The matching rate is 85.71%. The average incentive is \$0.947 per request. A total of 24726 seconds of vehicle time were saved as a result of sharing.

As a breakdown, we found that 2 matches use both both pick-up and drop-off meeting points, 27 use pick-up meeting points only, 8 use drop-off meeting points only, and 41 do not use any meeting point.

As a comparison, we experimented with the same requests without allowing the use of meeting points. Each request can only be picked up or dropped off at the nearest nodes to its origin and destination. We found 70 matches. The matching rate is 76.92%. 21215 seconds of driving time were saved.

The results show that, for the time period we studied, the use of meeting points does not significantly raise the matching rate; however, it does significantly raise the system efficiency by saving an additional amount of vehicle time.

4.3 Effects of batching time window

In this subsection we discuss the effect of batching time window on the ride-sharing system. We experimented with five different lengths of time window, which are 30 seconds (the default value), 60 seconds, 90 seconds, 120 seconds and 150 seconds. The results are summarized in the following table and graphs.

Table 1: Effects of batching time window

Time window (s)	30	60	90	120	150
Number of valid requests	182	363	560	739	905
Number of matched pairs	78	161	261	360	434
Sharing rate (%)	85.71	88.71	93.21	94.72	95.91
Average incentive (\$/request)	0.947	1.130	1.333	1.407	1.422
Total saved time (s)	24726	62618	105818	146350	181768

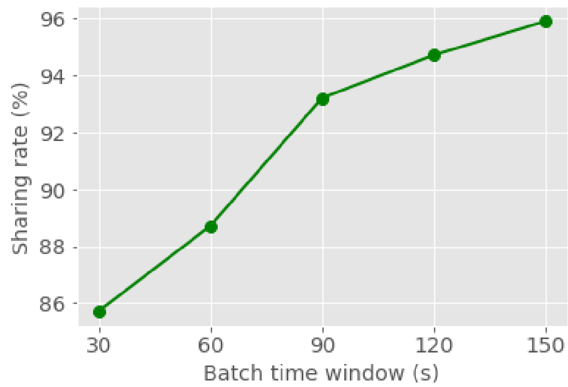

Figure 3: Sharing rates for different batch time windows

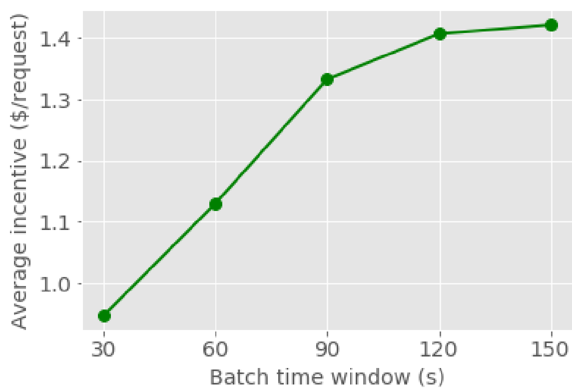

Figure 4: Average incentives for different batch time windows

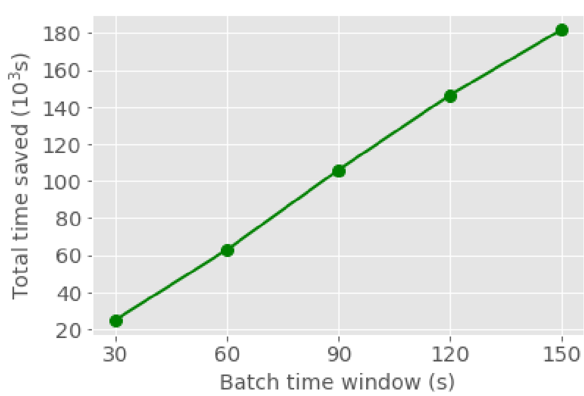

Figure 5: Total time saved for different batch time windows

With longer time window, there are more requests in the pool and the matching rate increases with it.

4.4 Effects of maximum walking time and maximum delay

We experimented with different values of maximum walking time and maximum delay for requests in the default time window. We found that those parameters have no significant affect on the matching rate. Large maximum times do result in an increase in the number of matches that involve at least one meeting point in average incentive and in the total time saved. However, those benefits are not significant, and the benefits do not grow linearly with the maximum times. The experiment results are summarized in the table and graph.

Table 2: Effects of maximum walking time and maximum delay

Max, walking time (s) and Max. delay (s)	300	420	600
Number of matches pairs	78	81	82
Number of matches that use meeting points	37	50	51
Average incentive ($/request)	0.947	1.310	1.406
Total time saved (s)	24726	27480	27064

4.5 Effects of pick-up and drop-off stop delays

We experimented with different pick-up and drop-off stop delays. According to Uber, a pick-up or drop-off stop will take 30 seconds in average. However, in a busy road network, like the one of Manhattan, these delays are usually longer than estimated. A stop for pick-up or drop-off will often cause the on-demand vehicle to be stopped by one or more traffic signals, which it could have passed freely without stopping. When the road network is congested, these delays also become longer. We experimented with four different lengths of pick-up and drop-off delay.

Table 3: Effects of pick-up and drop-off stop delays

Pick-up delay (s) and drop-off delay (s)	30	60	90	120
Number of matches pairs	77	78	74	65
Average incentive ($/request)	0.874	0.947	0.980	1.064
Total time saved (s)	24106	24726	25040	23269

We see that, with longer pick-up and drop-off delays, the sharing rate naturally drops. The extra time associated with making stops will make some

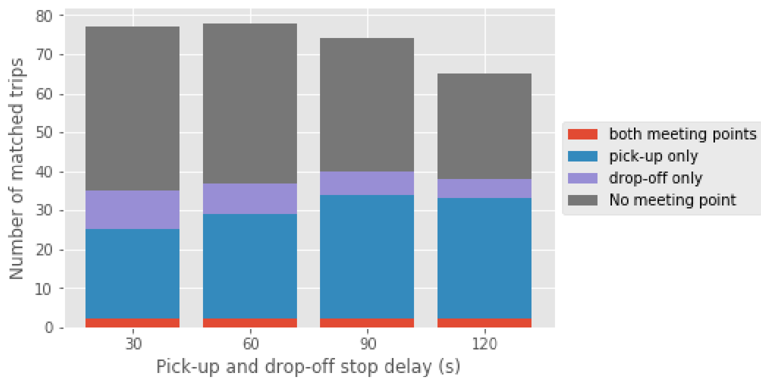

Figure 6: Use of meeting points in matches for different pick-up and drop-off stop delays

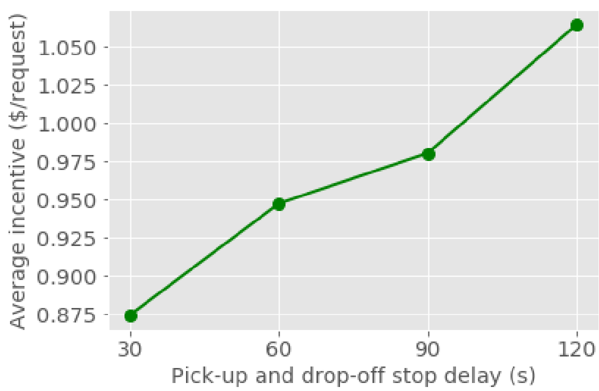

Figure 7: Average incentive for different pick-up and drop-off delays

matches unfeasible, because either the maximum delay or the maximum waiting time will be violated. Furthermore, more feasible matches use at least one meeting points as the delays increase en route. The traditional ride-sharing, which does not use any meeting point, costs additional time as it makes more stops than ride-sharing with meeting points. We conclude that the use of meeting points should be especially encouraged if congestion if expected.

4.6 Effects of β

In this subsection we study the effects of β on our ridesharing systems. As explained in the problem definition, β is used to calculate a weighted average savings of each feasible match by creating a monetary equivalent value of the time saved. In determining β, we must consider several factors that usually contribute to the "time value", which may include the driver's wage, fuel price, costs of vehicle maintenance, etc. β will also depend on the service provider's perception of the value of time, so it can sometimes be subjective. A bigger β means that time is valued more. We experimented with three different values of β.

We can see that, when time is valued more, more feasible matches involve the use of at least one meeting points because meeting points can help save more time. Meanwhile, the service provider is willing to give more incentives because, as time is valued more, the relative value of incentives diminishes. We also observe a general trend that, as β gets larger, the overall sharing rate increases.

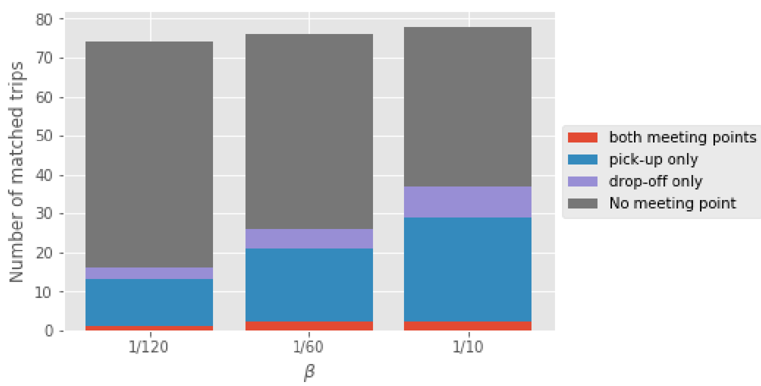

Figure 8: Use of meeting points in matches for different values of β

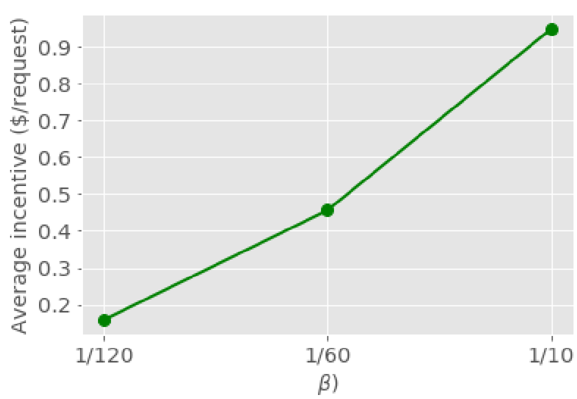

Figure 9: Average incentives for different values of β

4.7 Different time in a day

Finally, we experimented with ride-sharing demand data from different times in a day to check if our ride-sharing model is generalized enough. We experimented with five different hours in a day, with requests in the first 30 seconds of that hour. We conclude that our model is generally applicable to different times in a day. We did notice that, at 5 pm, the sharing rate is lower than in other times, but we believe that it is not the fault of our model, since four other times give consistent statistics. Stiglic et al. also noticed that the evening rush hours may have smaller rate of sharing than the morning rush hours do.

Table 4: Matching statistics of different times in a day

Time	8 am	9 am	12 am	5 pm	6 pm
Number of valid requests	182	181	153	125	187
Number of matches pairs	78	75	65	48	78
Sharing rate (%)	85.71	82.87	84.97	76.8	83.42

5 Concluding Remarks

This project considers the effects of meeting points with incentive prices in the on-demand ridesharing systems. The experiments results show that the sharing rate increases nearly 10% when we incentive users to walk to same pick-up locations or take off vehicles at the same drop-off locations. The total travel time saving also increases as we consider the meeting points with incentive prices for users.

For the future research directions, we can limit the number of vehicles in the system and consider the incentive prices in vehicle rebalancing. Moreover, this research can be extended to the high-capacity on-demand ridesharing systems which solved in [1].

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