STATE OF CALIFORNIA • DEPARTMENT OF TRANSPORTATION
TECHNICAL REPORT DOCUMENTATION PAGE
TR0003 (REV 10/98)

1. REPORT NUMBER	2. GOVERNMENT ASSOCIATION NUMBER	3. RECIPIENT'S CATALOG NUMBER
CA16-2806		

4. TITLE AND SUBTITLE	5. REPORT DATE
Promoting Peer-to-Peer Ridesharing Services as Transit System Feeders	May 2016
	6. PERFORMING ORGANIZATION CODE

7. AUTHOR	8. PERFORMING ORGANIZATION REPORT NO.
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9. PERFORMING ORGANIZATION NAME AND ADDRESS	10. WORK UNIT NUMBER
The Institute of Transportation Studies, University of California, 4000 Anteater Instruction and Research Bldg (AIRB) Irvine, CA 92697	3762
	11. CONTRACT OR GRANT NUMBER
	65A0529 TO 025

12. SPONSORING AGENCY AND ADDRESS	13. TYPE OF REPORT AND PERIOD COVERED
University of California Center on Economic Competitiveness in Tranportation (UCCONNECT), UC Berkeley 2150 Shattack Avenue, Suite 300 Berkeley, CA 94704-5940	Final Report, March 1, 2015 - May 1, 2016
	14. SPONSORING AGENCY CODE
	Caltrans, DRISI

15. SUPPLEMENTARY NOTES

This project was a study of ridesharing's mode shift potential on transit. The goal of this study was to provide a real-time multi-hop Peer-to-peer (P2P) ridesharing mobile application along with accompanying analysis so that key insights could be gained on the potential that ridesharing services have in augmenting transit demand.

16. ABSTRACT

Peer-to-peer ridesharing is a recently emerging travel alternative that can help accomodate the growth in urban travel demand, and alleviate some of the current problems such as excessive vehicular emissions. Prior ridesharing projects suggest that the demand for ridesharing is usually shifted from transit, while its true benefits are obtained only if the demand shifts from private autos. This project studies the potential of efficient real-time ride-matching algorithms to augment demand for transit by reducing private auto use. The Los Angeles Metro red line is considered for a case study, since it has recently shown declining ridership. A mobile application with an innovative ride-matching algorithm is developed as a decision support tool that suggests transit-ridership and rideshare routes. The app also facilitates peer-to-peer communication of users via smart phones. For successful ride-sharing, strategically selecting locations for individuals to get on/off rideshare vehicles is crucial, along with the pricing structure for rides. These can be adjusted dynamically based on the feedback from the app-users. A parametric study of the application of real-time ride-matching algorithms using simulated demand in conjunction with the SCAG model for the selected study are is conducted.

17. KEY WORDS	18. DISTRIBUTION STATEMENT
Peer-to-peer (P2P) ridesharing, real-time multi-hop, LA Metro Ride Line, transit stations, first mile/last mile, trip origins, ITS UC Urvine,	The readers can freely refer to and distribute this report. If there are any questions, please contact one of the authors.

19. SECURITY CLASSIFICATION (of this report)	20. NUMBER OF PAGES	21. COST OF REPORT CHARGED
No security issues	40	Free for E-copy

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University of California Center on
Economic Competitiveness in Transportation

**Promoting Peer-to-Peer Ridesharing Services as
Transit System Feeders**

Draft Final Report on
Caltrans Task ID: 2806, Task Order: 25, Contract: 65A0529

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May 2016

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Abstract

Peer-to-peer ridesharing is a recently emerging travel alternative that can help accommodate the growth in urban travel demand, and alleviate some of the current problems such as excessive vehicular emissions. Prior ridesharing projects suggest that the demand for ridesharing is usually shifted from transit, while its true benefits are obtained only if the demand shifts from private autos. This project studies the potential of efficient real-time ride-matching algorithms to augment demand for transit by reducing private auto use. The Los Angeles Metro red line is considered for a case study, since it has recently shown declining ridership. A mobile application with an innovative ride-matching algorithm is developed as a decision support tool that suggests transit-rideshare and rideshare routes. The app also facilitates peer-to-peer communications of users via smart phones. For successful ride-sharing, strategically selecting locations for individuals to get on/off rideshare vehicles is crucial, along with the pricing structure for rides. These can be adjusted dynamically based on the feedback from the app-users. A parametric study of the application of real-time ride-matching algorithms using simulated demand in conjunction with the SCAG model for the selected study area is conducted.

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1 Introduction

One of the main issues faced by major cities in the US today is congestion. In addition to directly impacting travelers by increasing travel times and reducing travel time reliability, congestion leads to higher levels of Green House Gas (GHG) emissions which are damaging to people's health and the environment. One of the solutions as to how to reduce congestion is to eliminate vehicles from roads by putting individuals who are traveling along the same routes in the same vehicles.

Although carpooling has been around since the invention of cars, the nature of carpooling which requires making arrangements in advance of the travel and committing to those arrangements for a period of time, make it unattractive to many individuals. Dynamic ridesharing is a modernized form of carpooling that is on-demand, a one-time commitment, and does not require making arrangements far in advance of the trip.

In recent years, ridesharing (including carpooling) in the US has experienced a slight increase in mode share, reaching a mode share of 11% in 2008. Although this increase in ridesharing seems to be a step forward in the direction of a greener transportation system, this is not necessarily the case. The modal shift due to introduction of ridesharing is as important or more. The benefits of ridesharing depend tremendously on this model shift. The benefits would be high in terms of reducing congestion and GHG emissions if the demand is being shifted from private vehicles to rideshare systems, but may not be significant if the ridesharing demand is being shifted from transit. In addition, introduction of ridesharing can lead to emergence of more complex multi-modal alternatives, such as the transit-rideshare mode.

Study of the many government-funded ridesharing systems indicate that ridesharing systems, as they work today, are competitive to transit systems (Levofsky and Greenberg, 2001; Nelson Nygaard 2006). The goal of this project is to assess the potential of ridesharing in being a complement to the transit, feeding it instead of shifting demand away from it. We analyze the potential of such multi-modal travel using a parametric study with simulated demand based on the current Southern California Assosiation of Governments (SCAG) model of a selected area (LA Metro red Line catchment area), and develop an app using an advanced ride-matching algorithm.

The reason why we consider the LA Metro red line (Figure 1(a)) to study potential ride-share based demand augmentation is the noticeable reduction of ridership (shown in Figure 1(b)) in recent years. This indicates potential opportunities for additional demand-inducement strategies using rideshare options.

The success of a multi-modal transit-rideshare system can be considerably influenced by the architecture of the designed system, namely locations where the ridesharing service is offered, price of ridesharing, and the matching method used by the system. In this report, we elaborate on this system architecture, and show case the impact of such targeted architecture on transit ridership augmentation for the LA Metro red line.

2   Literature Review

Peer-to-peer ridesharing initially emerged in the US in 1990s. The earlier ridesharing projects where not very successful for a variety of reasons, including the difficulty of communication between peer riders and drivers, lack of incentives, and security and privacy concerns. Table 1 summarizes a number of ridesharing projects, and points out the reasons for their failure. The new wave of shared-mobility start-up companies have managed to get past the majority of obstacles faced by the previous generation of ridesharing systems, mainly thanks to new technologies that make communication between individuals seamless, promise security and privacy to users, and enable automatic online payments.
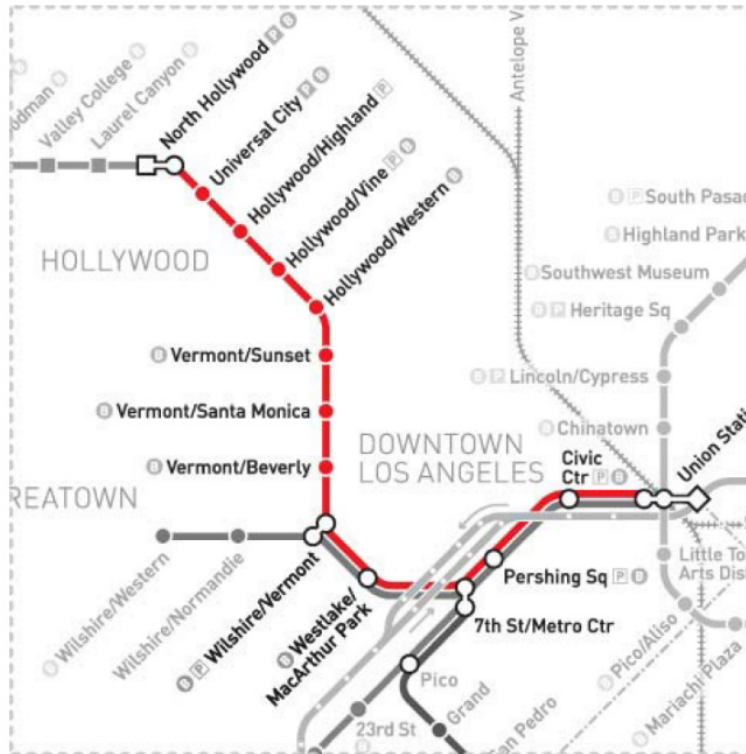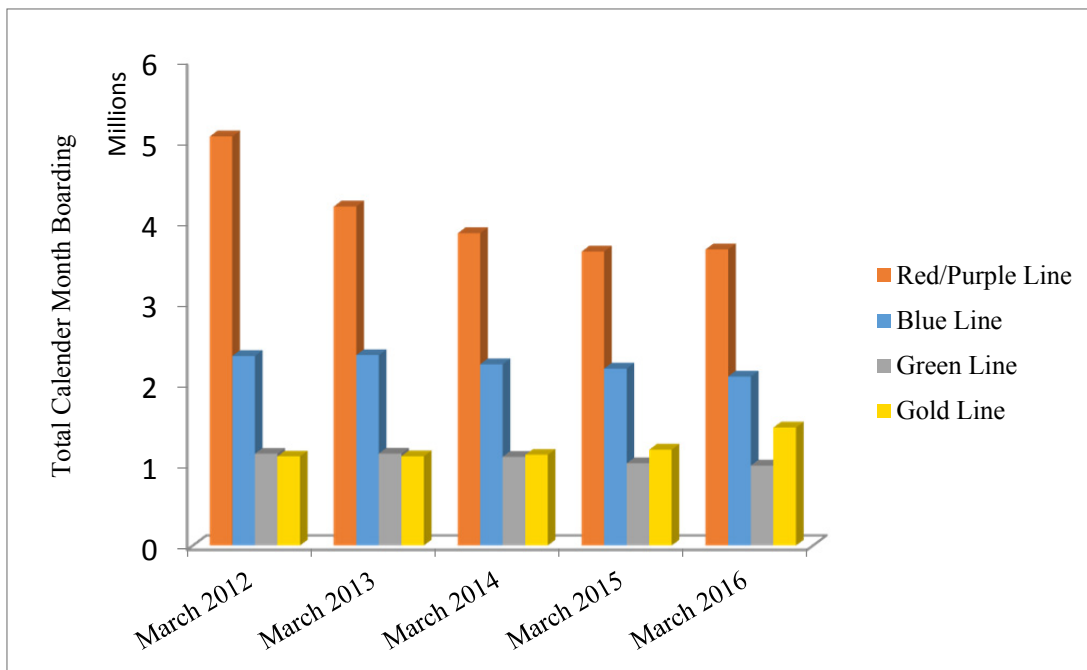
Figure 1(a) Los Angeles Metro red line

Figure 1(b) Ridership trends of LA metro

Figure 1. Case study area: Los Angeles Metro red line

One of the attractions of ridesharing/ridesoursing services, especially in densely populated cities, is access to on-demand transportation. Therefore, in order to be successful, a ridesharing company needs to match riders with drivers in real-time, while trying to maximize the number of served riders. This calls for a powerful, fast, yet flexible ride-matching algorithm.

In practice, the match making between riders and drivers is mostly based on the origin and destination locations, i.e. a rider and a driver are matched if their origin and destination locations are both within a certain proximity of each other. An example of such ridesharing systems is Carma. This method of matching leaves out three main factors that if taken into consideration can substantially increase the number of served riders.

A ridesharing operator can increase the performance of a ridesharing system by using a ride-matching method than can: (1) prescribe the best possible route to drivers that can put them in spatiotemporal proximity of riders, (2) allow drivers to carry multiple riders, and (3) suggest multi-hop options to riders where riders can transfer between multiple drivers/modes of transportation. Most studies in the literature consider the simplest matching method which pairs a single rider with a single driver (Agatz et al., 2011). Not only does this approach lead to under-utilizing the limited supply in the network (drivers), but more importantly it does not allow for combining ridesharing with other modes of transportation, which is the purpose of this study. Similarly, ride-matching algorithms that allow each driver to carry multiple riders, but assume that riders start and end their trips in the same vehicle (Herbawi and Webber, 2012; Febbraro et al., 2013) cannot be used in a multi-modal setting.

The only ride-matching methods that can be used in a multi-modal setting are those that provide the possibility for riders to transfer between drivers. A driver in this context can be any mode of transportation, i.e. public transit, or private vehicles. Agatz et al. (2009) provide a mathematical formulation of a matching algorithm that allows for transfers, but do not discuss any solution methods to solve this problem. Masoud and Jayakrishnan (2015a) propose a decomposition algorithm to solve the matching problem with transfers to optimality. Their methodology, however, is suitable for problems in a rolling-horizon framework, and not for highly dynamic systems. Other studies that consider the possibility of transfers (Herbawi and Weber, 2011a and 2011b) use heuristic solutions. Masoud and Jayakrishnan (2015b) propose a dynamic programming (DP) algorithm that can solve the problem of ride-matching with transfers to

optimality in a matter of seconds. In addition, this algorithm allows for each driver to have multiple riders on board at each point in time, and optimally routes drivers to put them in spatiotemporal proximity of riders. Because of these nice properties, and the ability of the algorithm to provide optimal solutions in real-time, we use this DP algorithm for matching riders and drivers in this study.

In the rest of this report, we first provide a summary of the assumptions and requirements to use the DP algorithm proposed by Masoud and Jayakrishnan (2015b). We then discuss how different inputs of this algorithm can be generated using a combination of GIS-based and clustering methods. We run simulations to quantify the impact of promoting a multi-modal system composed of ridesharing and transit on transit ridership augmentation, and ridesharing demand. Next, we present the details of a mobile application developed to promote the transit-rideshare alternative. Finally, we discuss a set of survey questions that will be used in the next phase of the project to access the attractiveness of such system to users.

Table 1. History of ridesharing

Project name	time	location	location properties	technology	marketing	incentives	reasons of failure	suggestions
Bellevue Smart Traveler (Haselkorn et al., 1995)	Phase 1: 1993 Phase 2: 1995	Washington	dense employment location in the city's downtown area, where the majority of commuters travel	voice-activated matching service	-	-	lack of flexibility lack of convenience, Time consuming searching and confirming process, Lack of critical mass, Lack of awareness	Tangible incentives, Guaranteed ride home, Confirming rides one hour before the departure time, Prescreening process, Stations where people can meet
Los Angeles Smart Traveler (Giuliano et al., 1995)	1994	Los Angeles, California	-	kiosks	-	-	Lack of sense of security, No marketing, Ineffective technology (voice mail and waiting for return calls)	-
Coachella Valley Transaction Network (Levofsky and Greenberg, 2001)	1994	riverside, California	-	Kiosks	-	-	lack of interest	-
Sacramento Dynamic Ridesharing project (Kowshik et al. 1993)	1994	Sacramento, California	-	Email and cellphone number	-	-	Security concerns, Inadequate marketing, Lack of proper incentives	Pre-screening process, Fixed payment scheme
Seattle Smart Traveler (Dailey et al. 1999)	1996	Seattle, Washington	University of Washington (familiarity with communication techniques and schedule of classes)	-	Yes (toward the end)	-	-	Marketing
RideNow (Nelson Nygaard Consulting Associates and RideNow, Inc, 2006)	2005	Dublin/Pleasanton California	-	Phone	Yes	Free BART tickets, Guaranteed ride home	Cumbersome system, Short notification time frame than the 15 minutes	Sustained marketing, Parking spaces as an incentive where applicable, An easy-to-use system More lead time

Project name	time	location	location properties	technology	marketing	incentives	reasons of failure	suggestions
Goose Networks Co. (Heinrich, 2010)	-	San Francisco, California	For the employees of the Genentech Co.,	SMS texting		$4 per day commute incentive program	Competitive modes(the well-equipped busses offered by Genentech), Required a high level of customer service that was hard to sustain.	-
Avego (Heinrich, 2010; University College Cork (UCC) official student news)	2011	University Cork, Ireland	From Carrigaline to Cork (highly used, other modes not available)	iPhone app, Internet access	-	-	-	-
Go520 (Sate funded, by Avego) phase 1 (RTrip; O'Sullivan 2011)	2011	Washington	SR520 corridor ,a crowded corridor	Apps, internet-enabled cellphones	Yes	free gas cards, iPhone chargers, Avego credits,	Length of the pre-screening process	-
Go520 (Private funded, by Avego) phase 2 (RTrip; O'Sullivan 2011)	2011	Washington	Route connecting Capitol Hill in Seattle to Overlake in Radmond, where the Microsoft campus was located.	Apps, Internet-enabled cellphones.	-	Gas cards, gift cards, drawings, free Avego credits, Guaranteed Ride Home	-	involvement of TDMs and employers, to build the critical mass crowded corridors to build the critical mass
WeGo (Wego rideshare)	2013	California, San Francisco Bay area	-	-	-	Different incentives for different regions	-	-

3 Ridesharing System

In a ridesharing system, we have a set of riders who are looking for a ride, and a set of drivers who are willing to use the empty seats in their vehicles to carry passengers in exchange for a monetary compensation.

We define a set of locations in the network, where individuals can start and end their trips (called go-points), and riders can transfer between drivers (called transfer points). Lessons learnt from the failure of previous peer-to-peer ridesharing systems (Table 1) suggest that it is better for riders to be picked up/dropped off at pre-specified stations, than their homes (or the exact location where the trips start/end) for two reasons (Heinrich, 2010). First, these locations could be hard to find for drivers, causing missed rides. In addition, drivers could have difficulties in finding parking spots. Second, some drivers and riders would understandably be reluctant to reveal their home addresses to others.

Upon registering in the system, riders and drivers provide information on their origin and destination go-points, a travel time window bounded from below by their earliest departure times from their origin go-points and from above by their latest arrival times at their destination go-points, and a notification deadline by which they need to be informed whether they have been matched or not. Figure 2 displays a ridesharing instance.

Drivers are asked to provide the capacity of their vehicles, and riders have the option to specify the maximum number of transfers they are willing to make. For the purpose of this study, we assume each vehicle can carry four passengers, and that riders do not set a limit on the number of transfers (we later report the statistics on the number of transfers in our case study of LA).

When the notification deadline of a rider approaches, the ridesharing system solves a matching problem that includes the rider, and all the drivers whose travel time windows intersect with the travel time window of the rider. In the ridesharing instance in Figure 2, for example, all drivers are eligible to be included in the matching problem solved for the rider.
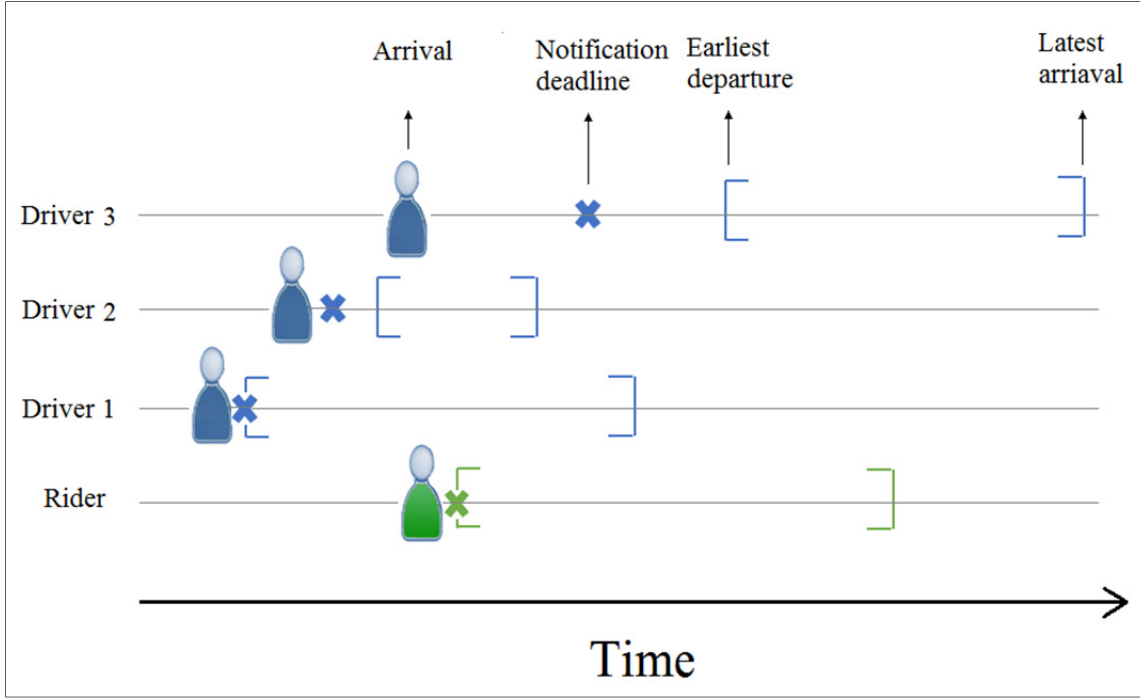
Figure 2. An example of a ridesharing instance

If a driver is matched with a rider, the part of the driver's route that is committed to the rider is fixed. Other parts of the driver's route, however, are flexible and can be optimized for the subsequent riders. Figure 3 displays an example of such a driver. The driver in this figure (shown in blue) is traveling from origin O to destination D. This driver has been matched with a rider, but his/her route from O to O′, and from the D′ to D can still be optimized to put the driver in spatiotemporal proximity of other riders that register at the system at a later point in time. In other words, this previously matched driver now enters the ride-matching problem as three separate drivers, one that travels from O to O′, one that travels from O′ to D′, and one that travels from D′ to D. The travel time window for each of these three drivers is determined based on the committed portion of the driver's route, and his/her original travel time window. Note that the capacity of the vehicle going from O′ to D′ has dropped by one unit.
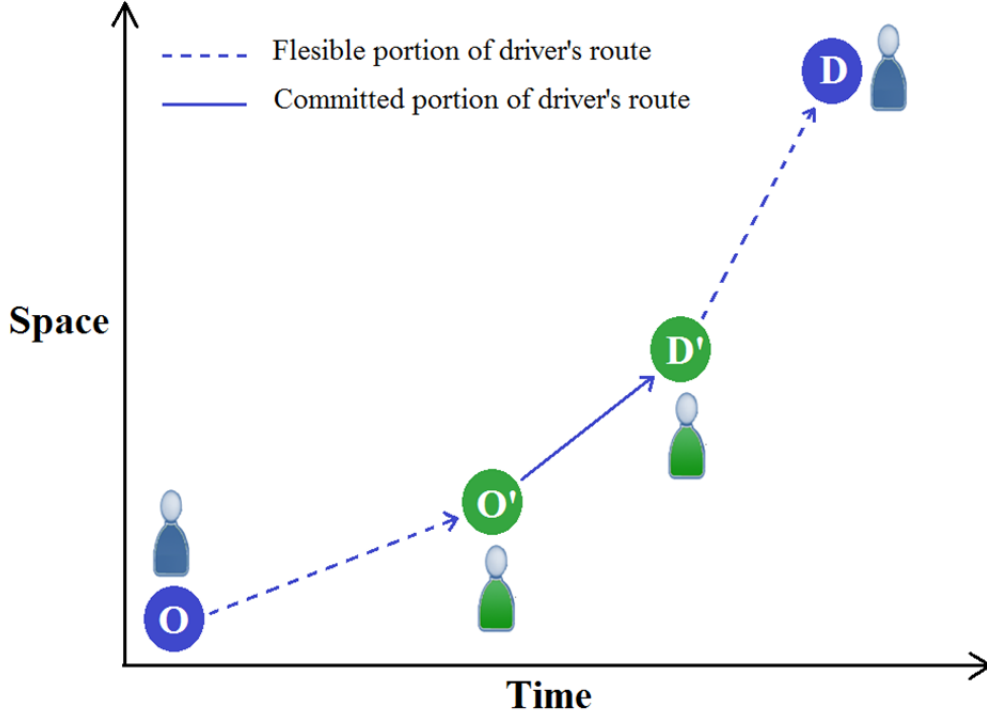
Figure 3. Partially fixed driver route

After determining drivers who are eligible to be included in a rider's matching problem, the system uses the DP algorithm to solve the matching problem, and announces to the rider within the matter of a few seconds (at most), whether the rider has been matched, and the itinerary of the rider is case of a successful match.

4 Dynamic Programming (DP) Algorithm

The DP algorithm tries to find a (multi-hop) path for a rider by optimally routing drivers. Transit lines can enter the model as inflexible drivers (since their routes and schedules are fixed and cannot be optimized).

The DP algorithm runs on a time expanded network. By introducing stations, we are in fact discretizing the two-dimensional continuous-space network into a set of one-dimensional discrete locations. In addition to that, we discretize the study time horizon into a set of time periods. We use 5-minute time periods in this study. In a network that is discretized in time and space, we denote a node $n_i = (t_i, s_i)$ as a tuple of time period and station, and a link as a tuple

(t_i, s_i, t_j, s_j). Such a link can be interpreted as a trip that starts at go-point s_i at time period t_i, and ends at go-point s_j at time period t_j.

For each rider, we identify the set of links that can be traveled both by the rider and at least one driver/transit line given the time constraints of the rider and drivers/transit line. Figure 4 shows an example of a time-expanded network for a rider. Nodes in this figure are shown as rectangles, and links as arcs connecting the nodes. In this example, the rider is starting his/her trip from go-point 5, and is traveling to go-point 12. The rider's earliest departure time from the origin go-point is the 3rd time period, and his/her latest arrival time at the destination go-point is the 39th time period. Drivers/transit lines that can potentially carry the rider on each link (i.e. leg of the trip) are noted next to the link.

The role of the DP algorithm is to search on this graph for the least expensive path (based on a cost function) that takes the rider from origin O to destination D, given the constraints posed by the rider (e.g. max number of transfers requested by the rider). The cost function we use in this study is sum of four components: (i) a distance-based fare, (ii) dollar value of travel time, (iii) dollar value of additional penalty for waiting time, and (iv) dollar value of penalty for transfers. We consider the default value of \$20/hr for value of time (VOT), \$0.25/mile distance-based fare, \$1.5 fare for use of transit, \$0.1 as the monetary equivalent of additional penalty for waiting for each time period (in addition to the value of time), and \$0.1 as the monetary equivalent of the penalty for each transfer. In section (), we perform sensitivity analysis over the VOT and the distance-based fare.
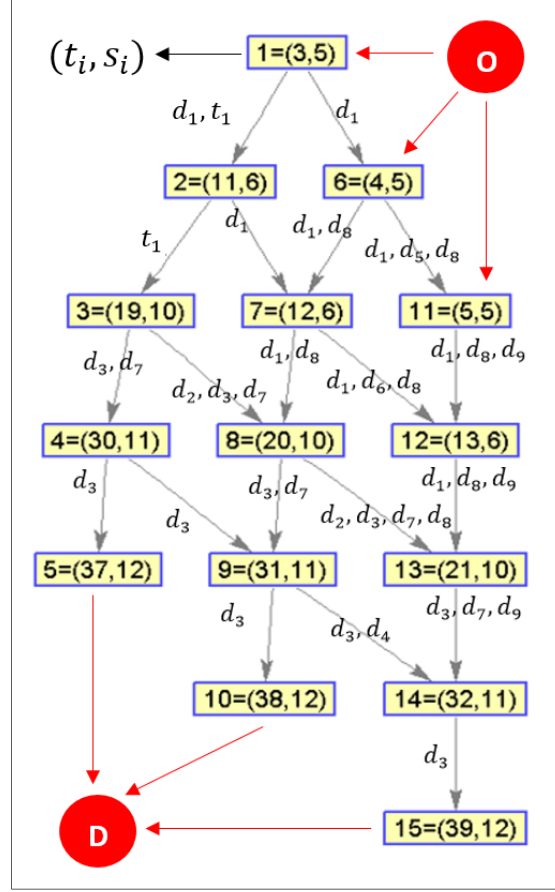
Figure 4. Time-expanded network

Two of the most important inputs to the DP algorithm are the set of stations and links. In the rest of this section, we elaborate on how we identify the set of stations and links in the LA network.

4.1 Stations

Stations are pre-specified locations in the transportation network where individuals can start and end their trips, and/or riders can transfer between drivers/transit. In this study, we have three types of stations listed in Table 2. In the rest of this section, we discuss the role of each type of station, and the methodology on how we identified them in the LA network.

Table 2. Types of stations

Station type	Symbol	Description
Go-points	S_G	Points where individuals can start/end their trips. Go-points are a subset of centroids in the LA County
Transfer points	S_T	Points were individuals can transfer between vehicles and/or transit. $S_T \in S_G$
Red line stations	S_R	LA metro red line stations. $S_R \in S_G, S_R \in S_T$

4.1.1 Go-points

In order to identify go-points, we used the auto trip tables in the LA County from the Southern California Association of Governments (SCAG) planning model. The SCAG region has a total of over 4000 TAZs (i.e. 16 million OD pairs). Our goal is to identify significant OD pairs in terms of level of demand, and use this information to identify the go- and transfer points in the network. For this purpose, we identified OD pairs in the SCAG trip tables with hourly trip rates higher than 10. We limited our analysis to auto demand only, because the focus of the study is to identify potential modal shift from drive-alone to rideshare and rideshare-transit alternatives. The SCAG trip tables used are listed below:

- Drive Alone
- SR2 HOV
- SR3 HOV
- SR2 Non-HOV
- SR3 Non-HOV

Figure 5 shows the origin and destinations of the OD pairs with auto demand higher than 10 per hour. We consider these origins and destinations as go-points.
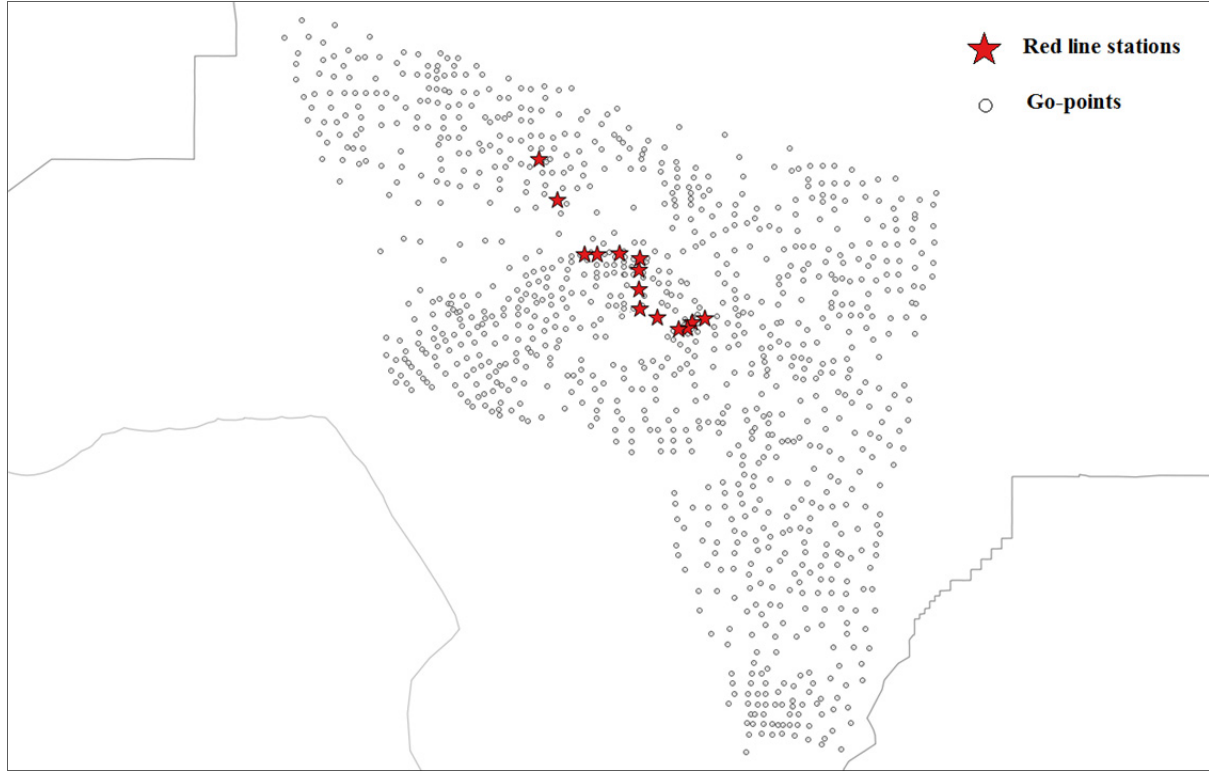
Figure 5. Go-points

4.1.2 Transfer points

Transfer points are stations where individuals can transfer between ridesharing vehicles and/or the LA Metro red line stations. We select a subset of go-points that fulfil two criteria as transfer points. Transfer points should be distributed in the network such that (i) they are located closer to go-points with higher levels of demand, and (ii) they are distributed in the network as evenly as possible. Toward this end, we use Algorithm 1 to determine the set of transfer stations.

The algorithms starts by initializing the set of transfer points by the set of red line stations. An additional 40 number of transfer points are picked from the set of go-points and added to the set of transfer points, one at a time, in an iterative process. We experimented with the number of transfer points and came to the conclusion that 40 transfer points provide a nice balance between the number of transfer points (too many transfer points increase the running time of the algorithm), and the degree of network coverage (too few transfer points can cause in-sufficient network coverage).

At each iteration, the algorithm selects the go-point with the lowest person-travel distance required for travel from the rest of the go-points. The selected go-point requires the least effort for other individuals traveling to it for a transfer, and therefore is set as a transfer point. In order to ensure that transfer points are not too close to each other, the algorithm then eliminates from the set of go-points the stations within 4 miles distance from the newly selected transfer point.

The algorithm then moves forward to the next iteration where the next transfer point is selected. The algorithm stops when the set of the remaining go-points becomes empty, or the limit of 40 transfer points (besides the red line stations) is reached. Figure 6 displays the three set of stations in the network.

Algorithm 1. Identifying transfer stations

$S_T = S_R$
$S'_G = S_G \setminus S_R$
For $s \in S_R$
    $del = \{k \in S_G : d_{s,k} \leq 2 \text{ miles}\}$
    $S_G = S_G \setminus del$
End For
Set $Done \leftarrow 0$
For $t = 40$
    While $Done = 0$
        For $s \in S'_G$
            $NS = argmin_{i \in S'_G}\{w^{*1}_{i,s} \times d^{*2}_{i,s}\}$
            $S_T = S_T \cup NS$
            $del = \{k \in S'_G : d_{NS,k} \leq 3.5 \text{ miles}\}$
            $S'_G = S'_G \setminus del$
            If $S'_G = \emptyset$
                $Done \leftarrow 1$
            End IF
        End For
    End While
End For
* 1 $w_{i,s}$: travel demand from station i to station s
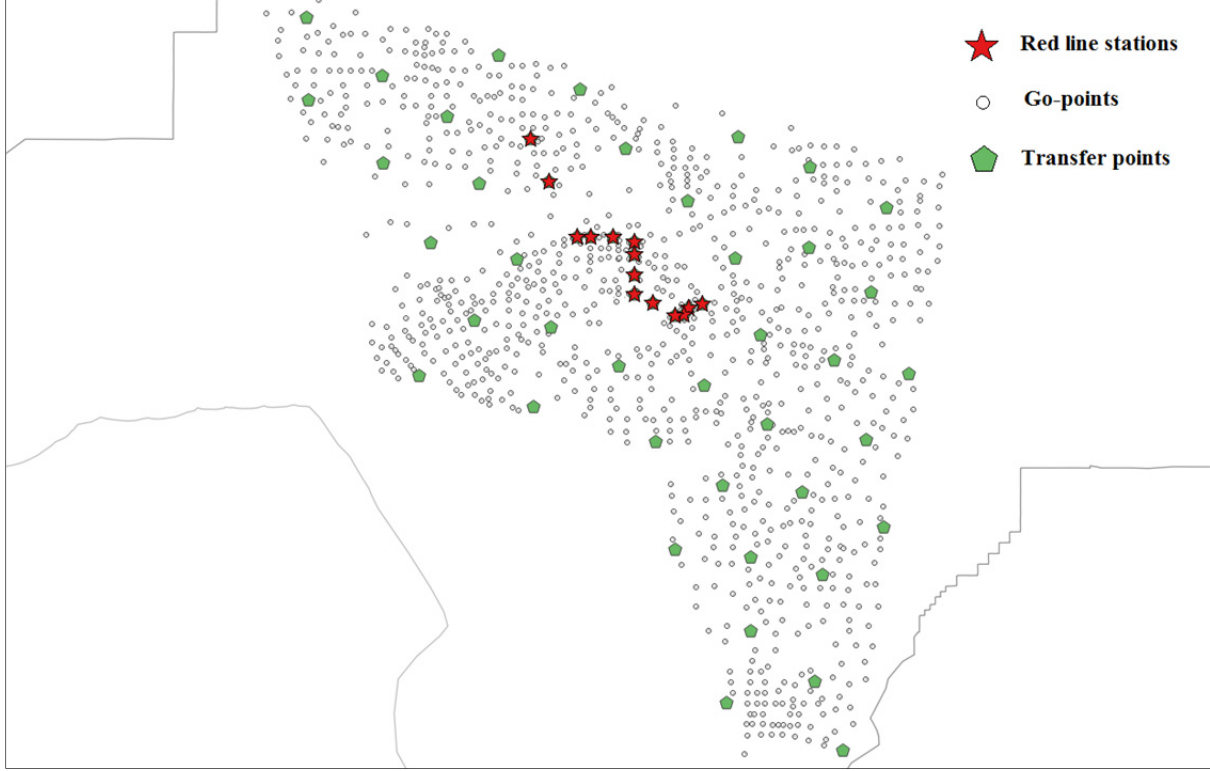* 2 $d_{i,s}$: travel distance from station i to station s

Figure 6. Transfer points

4.2 Link Sets

We introduce three l ink sets that connect different types of stations (i.e. go-points, transfer points, and red line stations) in the network. Figure 7 demonstrates the three families of link sets. The first link set displayed in Figure 7(a) connects transfer points to each other. The second link set (Figure 7(b)) connects go-points to their corresponding transfer points identified in Algorithm 1. Figure 7(c) demonstrates the third link set that connects red line stations to their nearby go-points. This link set connects each of the go-points confined within a 2.5 mile radius of at least one of the red line stations to the red line stations within their 2.5 miles radius.

Each go-point in the network is connected to at least one transfer point (link sets 2 and 3). In addition, all transfer points are connected to each other (link set 1). This indicates that there is a path between any two go-points in the network. Link set number 2 implies that the shortest path of a rider who is traveling between two go-points (that are not are not within 2.5 miles radius of the red line) includes traveling to the transfer point corresponding to the origin go-point; next, traveling from this transfer point to the transfer point corresponding to the destination go-point;

and finally traveling from there to the destination go-point itself. Another implication of link set 2 is that since all go-points corresponding to the same transfer point are connected to each other, if a rider needs to make a short trip between two such go-points, no transfers are required.

For practical reasons, it is assumed that transfers for trips that originate from or are destined to go-points within a 2.5 radius of the red line stations are limited to the metro red line stations only. Hence, link set 3 connects such go-points to red line stations directly. This link set is appropriate to use, because we wish to promote the rideshare-transit option. In the contrary, if the goal was for ridesharing to replace transit, we could introduce links that connect such go-points to each other, rather than to transit stations.

5 Ridesharing as transit feeder

In this section, we study the modal shift from drive-alone to rideshare and rideshare-transit alternatives using simulations. Simulations are done for the morning peak hour in LA. Origin-destination trip tables used in simulations are obtained from the SCAG planning model, and spread throughout the three-hour morning peak period based on a uniform distribution.

For each simulation run, we randomly select our set of riders and drivers. In all simulation runs, we use 1,000 riders. We change the number of drivers from 1,000 to 80,000 in order to study the impact of rider to driver ratio on the matching rate.

As mentioned in section 4, we use default values of $20/hr for value of time, and $0.25 for each mile of ridesharing. In addition, we consider a $0.1 penalty for each transfer, and for each time period of waiting in transfers.

In each simulation run, we serve the 1,000 riders on a first-come, first-served basis, using the DP algorithm. Note that the DP algorithm finds the min-cost path for riders based on the cost function defined in section 4. Whether this path is more favorable to the rider compared to an outside option (which we consider to be drive-alone in this study) in looked at afterwards. In other words, even though we use a cost function in the DP algorithm, the output of the algorithm that indicates whether a rider can be served or not only depends on whether his/her trip has spatiotemporal proximity with trips of drivers/red line. We then study in section 6, what percentage of the riders that can be theoretically served based on the spatiotemporal

characteristics of their trips, can be served in practice taking into consideration the cost of the trip and the cost of the competing alternative (e.g. drive-alone).
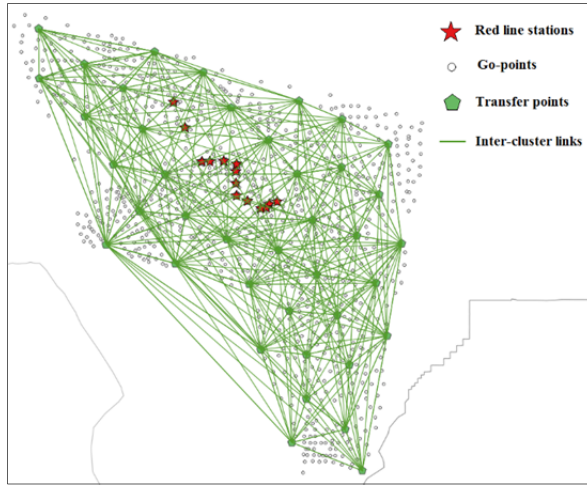

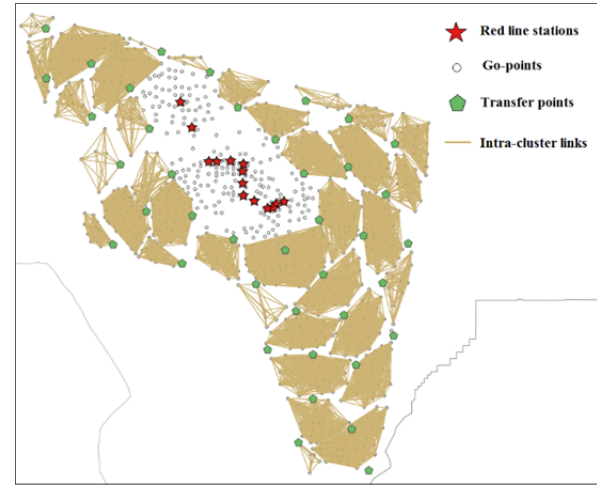Figure 7(a) Link set 1: Links connecting transfer points to each other

Figure 7(b) Link set 2: Links connecting go-points to their corresponding transfer points
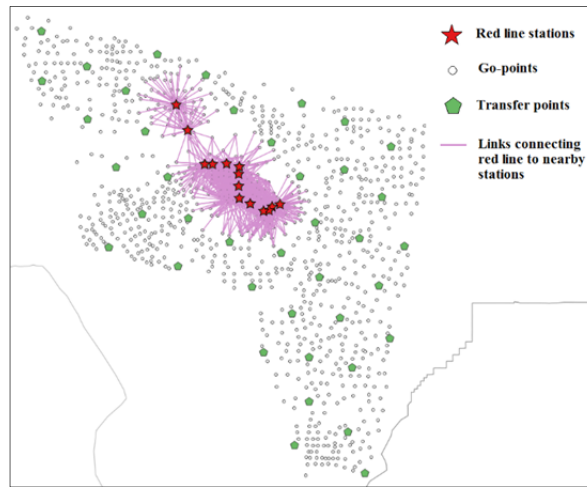

Figure 7(c) Link set 3: Links connecting red line stations to the nearby go-points

Figure 7. Link sets

5.1   Matching rate

In order to study the impact of number of drivers on the matching rate, we ran a set of simulations. All simulation runs include 1,000 riders, while the number of drivers are changed from 1,000 to 80,000 in different runs. Other parameter values in all simulations are default values. Results are displayed in Figure 8.

Figure 8(a) displays the percentage of served riders as a function of number of drivers. As intuition suggests, the percentage of served rider requests increases with the number of drivers. Percentage of served riders, however, grows with number of drivers at a rate slower than linear. For example, with 5,000 increase in the number of drivers (going from 5,000 to 10,000 drivers), we witness a 22% increase in the percentage of served rider. However, in order to experience another 22% increase in the percentage of served riders, we have to have a 10,000 increase in the number drivers (going from 10,000 to 20,000 drivers).

Figure 8(b) displays the number of served riders and matched drivers as a function of number of drivers in the system. This figure sheds light on the performance of the system under different levels of supply (i.e. number of drivers). When the number of drivers is the lowest, the number of matched riders and drivers is about the same, implying that most trips are being served without transfers (this conclusion is confirmed by looking at the number of transfers for each level of supply in Figure 10, as we will discuss in the following section). At such low level of supply, the number of drivers is too small for multi-hop routes to be formed for riders. Up to a certain level (20,000 drivers), the number of matched riders and drivers increases with the number of drivers in the system. The higher number of matched drivers compared to served riders in supply levels below 20,000 drivers suggests that multi-hop routes are being formed, as confirmed by Figure 10. Finally, when the supply level becomes really large, and most of the demand is being served, there is no need for more costly multi-hop routes anymore, and the number of matched riders and drivers start to converge again.

Figure 9 shows the percentage of riders who use the transit-rideshare option. As this figure suggests, this percentage reaches its peak at around 20,000 drivers, and remains stable after a small drop afterwards, following the same trend witnessed in Figure 8(b). Although in the first glance it might seem like the percentage of individuals using ridesharing as a means to connect to transit is not significant, it should be noted that the trip tables used for simulations are drive-alone trip tables, and the individuals using the transit-rideshare option are actually increasing the current level of transit ridership. Furthermore, keep in mind that having as little as 1.7% of drive-alone trips switch to transit would translate to a considerable increase in transit ridership. According to SCAG trip tables, 750,000 single occupancy vehicles travel during the morning peak hours in LA County in a working day. This adds up to a total of about 12,500 additional

trips, just by the Metro red line. This number of trips distributed evenly between the roughly 50 Metro red lines during the morning peak hour indicates an additional 250 passengers in each train.
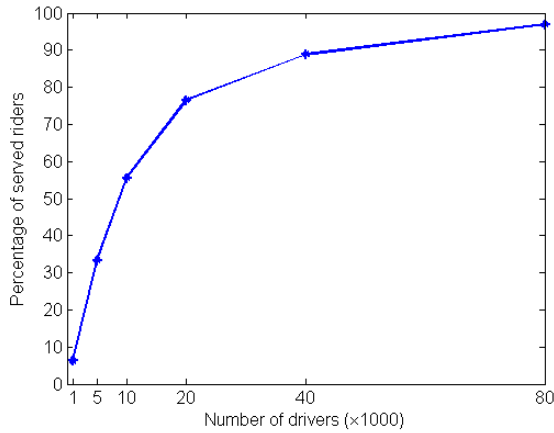

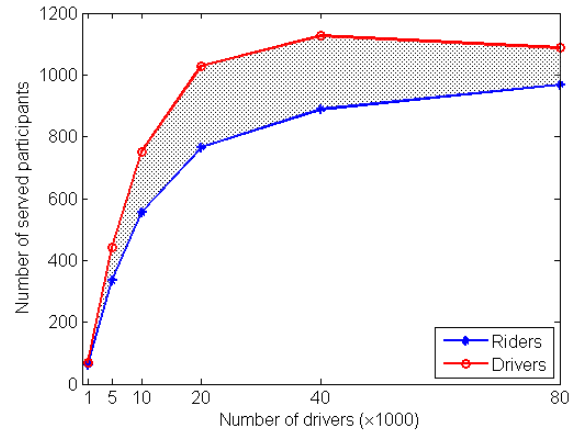Figure 8(a) Percentage of served riders

Figure 8(b) Number of served riders and matched drivers

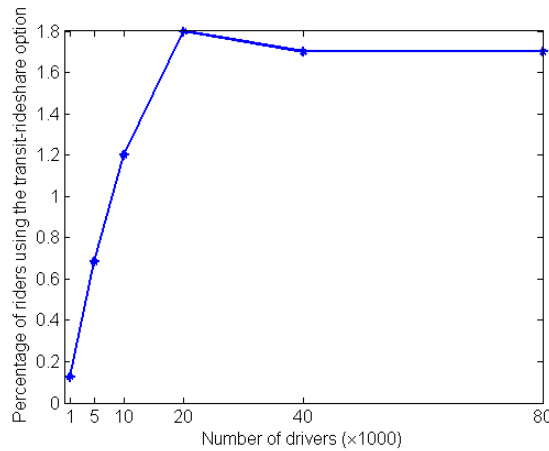Figure 8. Matching rate as a function of number drivers

Figure 9. Percentage of riders using ridesharing as transit-feeder

Figure 10 shows the OD pairs that could potentially use the transit-rideshare alternative. Links in this figure connect such OD pairs. It is interesting to note that the OD pairs that could use the red line are limited to those with both origin and destination locations in the vicinity of the red line stations. Assuming such results can be replicated for other Metro lines, since the entire Metro system offers a good coverage of the LA County, a considerable modes hare for the transit-rideshare alternative could be speculated.

5.2 System performance

Performance of the proposed system is partially a function of the matching rate, covered in section 5.1. However, measures of quality of service, such as number of transfers by riders, and the average occupancy of vehicles are additional good metrics to assess system performance.

Figure 11 demonstrates the number of transfers under different levels of supply. This figure suggests that when the number of drivers is too low or too high, transfers are very limited, and most riders can be served with zero transfers. However, in the middle ranges more transfers are required. As discussed in the previous section, at very low supply levels there are not enough drivers in the system to form multi-hop routes, and at very high supply levels almost all rides can be served without any transfers, and therefore an overwhelming number of trips end up being single-hop. In the middle ranges, however, transfers are necessary to obtain higher matching rates (as shown in Figure 8(b)). A look at figure 11 reveals that even in the middle ranges most riders experience zero transfers, with a few percentage experiencing 1 transfer. The maximum number of transfers ever witnessed was 3.

Figure 12 displays the most frequently used transfer points. This figure has been created based on the simulation results for a ridesharing system with 20,000 number of drivers, since such a system was shown to have the highest number of transfers. This figure suggest that the most important transfer points coincide with some of the red line stations, which implies good decision making in determining the station locations by Metro. This figure can also be a guide in revising the transfer points in our models.
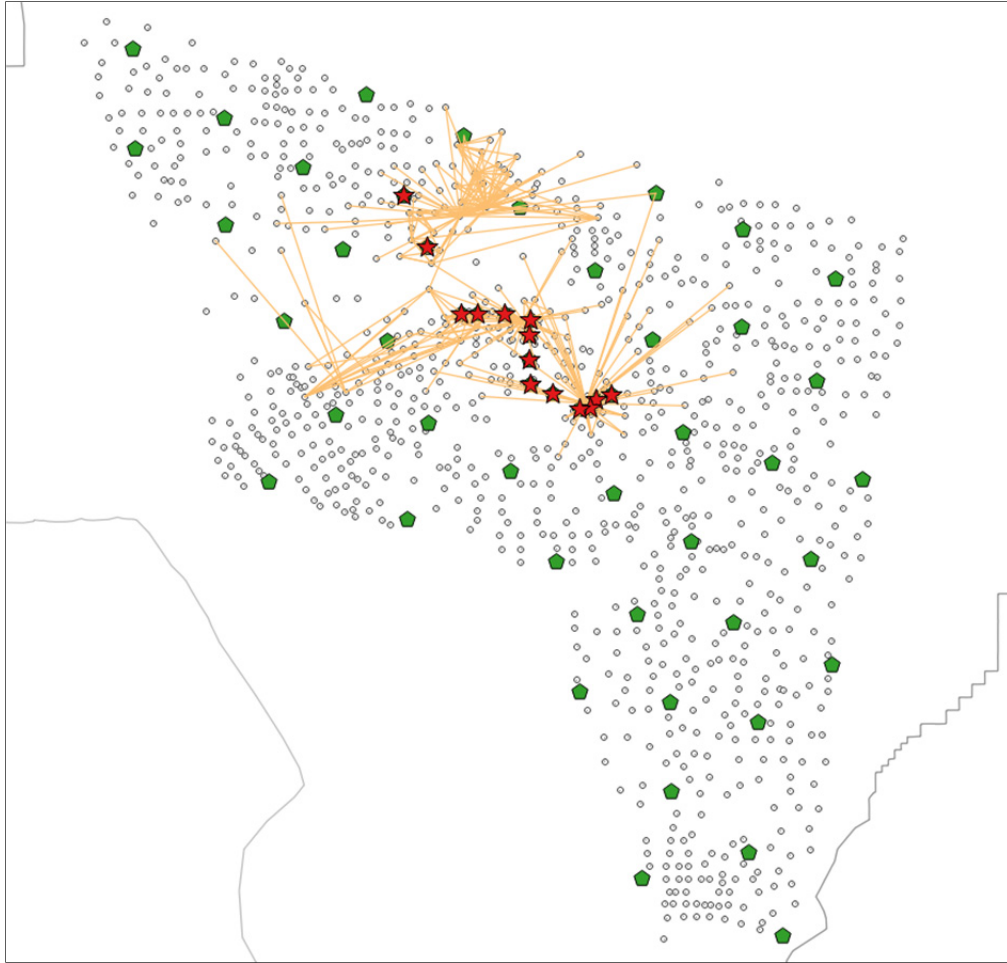
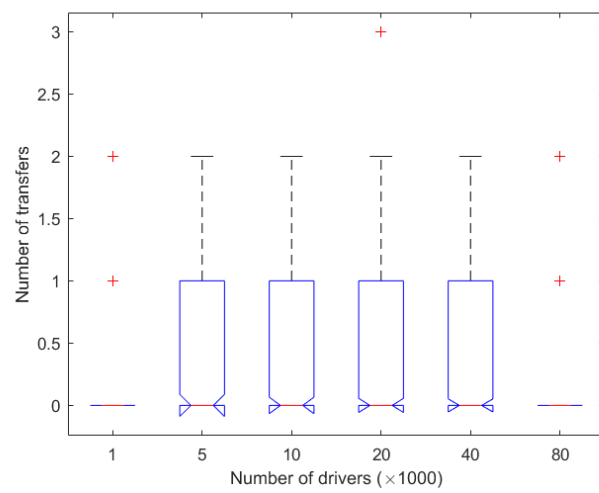Figure 10. OD pairs that use the LA Metro red line
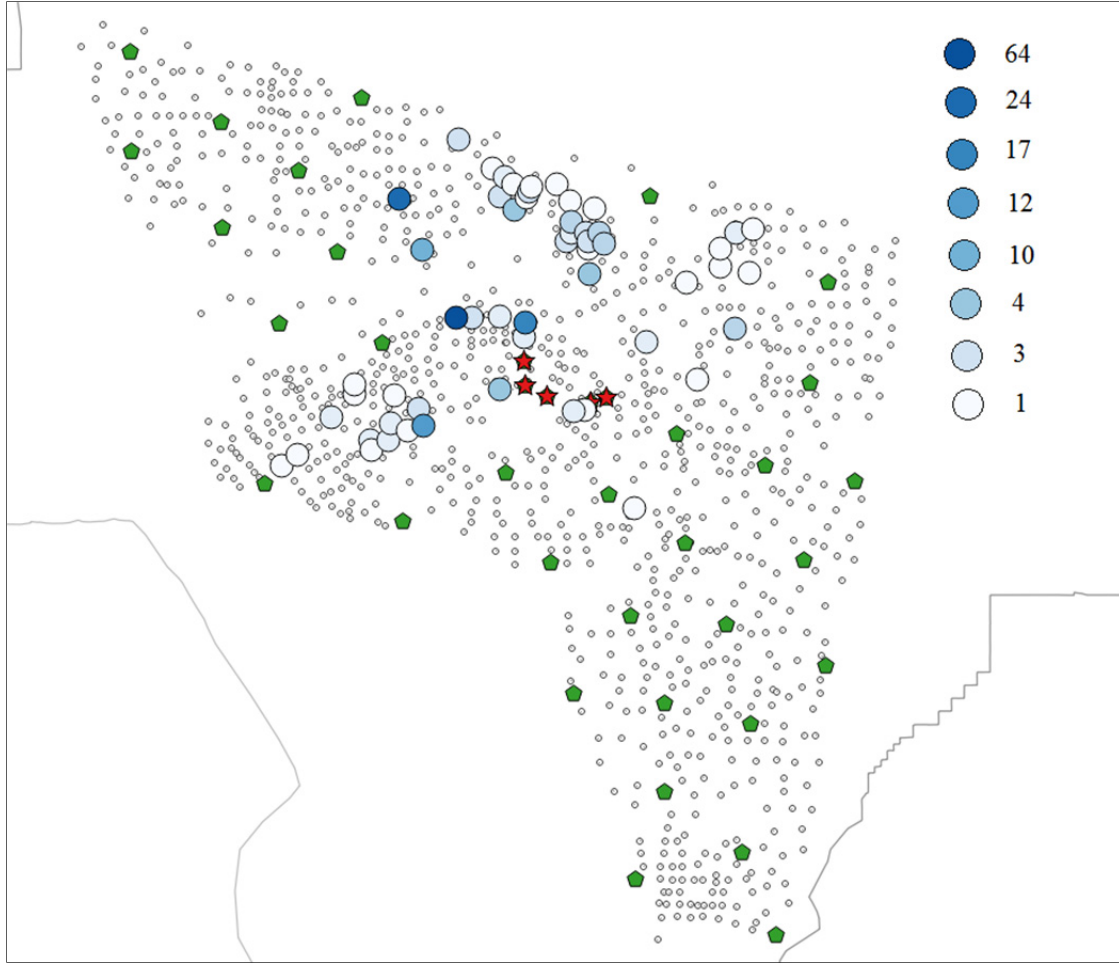

Figure 11. Number of transfers

Figure 12. Most frequently used transfer points

Figure 13 shows the average vehicle occupancy as a function of supply level. This figure suggests that the average occupancy of vehicles decreases as the number of drivers in the system increases, which is intuitive, since at lower levels of supply riders are more probable to share the limited resources. The maximum vehicle occupancy, however, follows the previously observed trend of initially experiencing a rise, followed by a decline. Notice that the minimum vehicle occupancy is always higher than 2, since each matched driver carries at least one rider. At the maximum occupancy of 5, the vehicle capacity is being fully utilized (e.g. the vehicle is carrying the driver and 4 riders).

6 Pricing

We consider a very simple pricing scheme of distance-based fares for riders. If a rider uses the rideshare-transit option, for the part of his/her route that is covered by transit, the per-mile fare will be replaced with a fixed transit fare of $1.75. This fare is what riders actually have to pay to the system, and is different from the cost function that is used by the DP algorithm to find the optimal path for riders. As discussed in the previous sections, this cost function is assumed to be a linear combination of four components, all converted into dollar amounts:
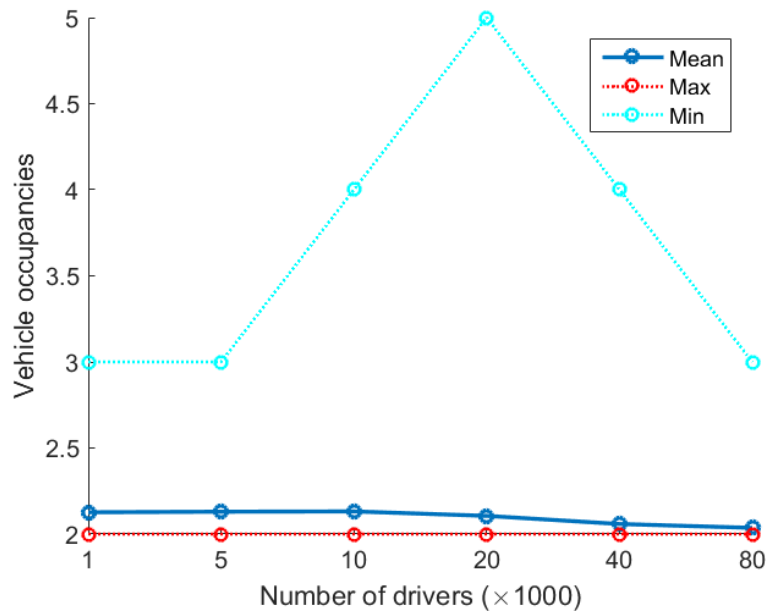

Figure 13. Average vehicle occupancies

1. Per mile fare charged (in dollars)
2. Monetary value of the travel time, computed as the production of the travel time (in hours), and value of time (VOT, in dollars per hour)
3. Penalty per transfer, which is assumed to be 10 cents
4. Penalty for each time period of waiting during transfers, which is assumed to be 10 cents for each time period (of 5 minutes). Note that this is in addition to the VOT cost.

The DP algorithm uses the aforementioned cost matrix to find the optimal route for each rider. Note that whether the algorithm finds a route for a rider does not depend on the composition of

this cost function. After computing the best route for a rider using the DP algorithm, we compare the cost of this route with that of the of drive-alone mode, assuming that if not participating in the ridesharing system a rider travels using a private car through his/her shortest path. The cost of the drive-alone option is calculated as sum of the monetary expense of the trip (which is considered to be $0.56/mile) and the value of the rider's time spent on the trip. Note that components 3 and 4 that were used to estimate the ridesharing cost do not apply to the drive-alone alternative, due to the unnecessity of making transfers.

The matching rates reported in section 5.1 were only based on the spatiotemporal coverage of riders' trips by drivers/Metro red line, and were independent of the trip cost. In reality, the cost of ridesharing could end up being higher than the cost of the alternative mode of drive-alone. Figure 14(a) shows the percentage of served riders in systems with different number of drivers, under different distance-based fares and VOT values. The matching rates shown in this figure are obtained by running the DP algorithm, and therefore are not dependent on the distance-based fares and VOT values.

Figure 14(b) shows the percentage of riders who can be matched, but will choose not to use the ridesharing system due to its higher cost. This figure suggests that for a given distance-based fee, the percentage of riders who reject the ridesharing option increases with VOT. This result is intuitive, since the rideshare alternative typically has a higher travel time. For a given VOT, a higher distance-based fare results in a higher rejection rate, since the monetary cost of ridesharing starts approaching the cost of the drive-alone alternative.

7   Mobile application

The emergence of smartphones enables us to easily access various transportation information services using mobile applications. This has brought significant opportunities to enhance mobility services in the transportation field. Mobile applications can play a pivotal role in promoting public transportation by fostering multimodal synchronizations. The ridesharing application designed in this project is capable of facilitating interactions between riders and drivers under location-based services, making it easy for riders to inquire about their trips in real-time.
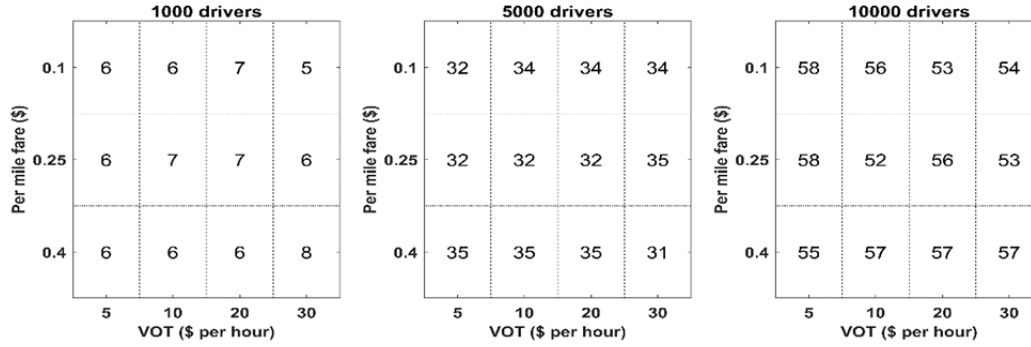
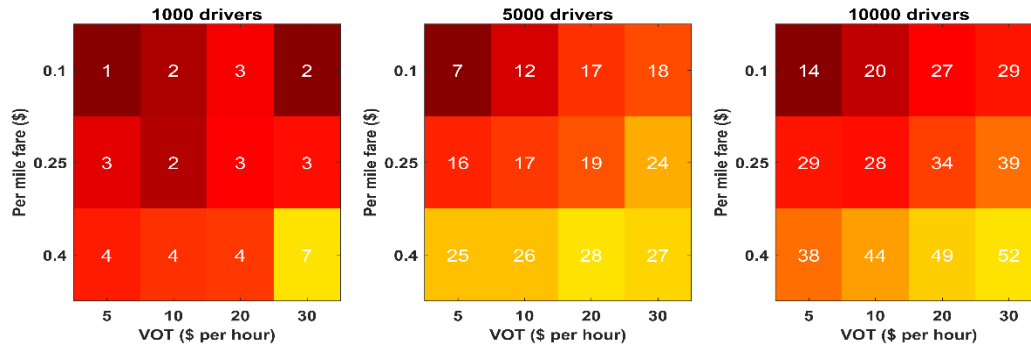Figure 14(a) Mathcing rates based on spatiotemporal compatiblity of trips

Figure 14(b) Percentage of riders who do not use the rideshare alternative despite a match

Figure 14. Impact of value of time and distance-based fare on the riders' approval rate of proposed matches

The data architecture of the mobile application is designed to handle multiple data sources. Specifically, the design includes a four-layer data structure that could integrate transit and rideshare modes, although the flexible structure of the design makes the framework capable of integrating additional modes of transportation, such as bikesharing.

Figure 15 demonstrates the four layers of data structure. The bottom layer consists of map data that can be used as background location information. This map layer is powered by Google maps API, which enables us to get an up-to-date map service. The second layer is a static layer, and consists of network data (e.g. nodes and links). The third layer contains transient dynamic information about timetable of the LA Metro red line and ridesharing go-points. The second and third datasets are stored in a database on a server. The fourth layer is highly dynamic; it collects drivers' current routes and riders' travel needs in real-time. Both static and dynamic layers are used when the engine processes the DP algorithm to match drivers and riders. This four-layer data structure is also used to visualize itineraries of matched rider in the mobile application.
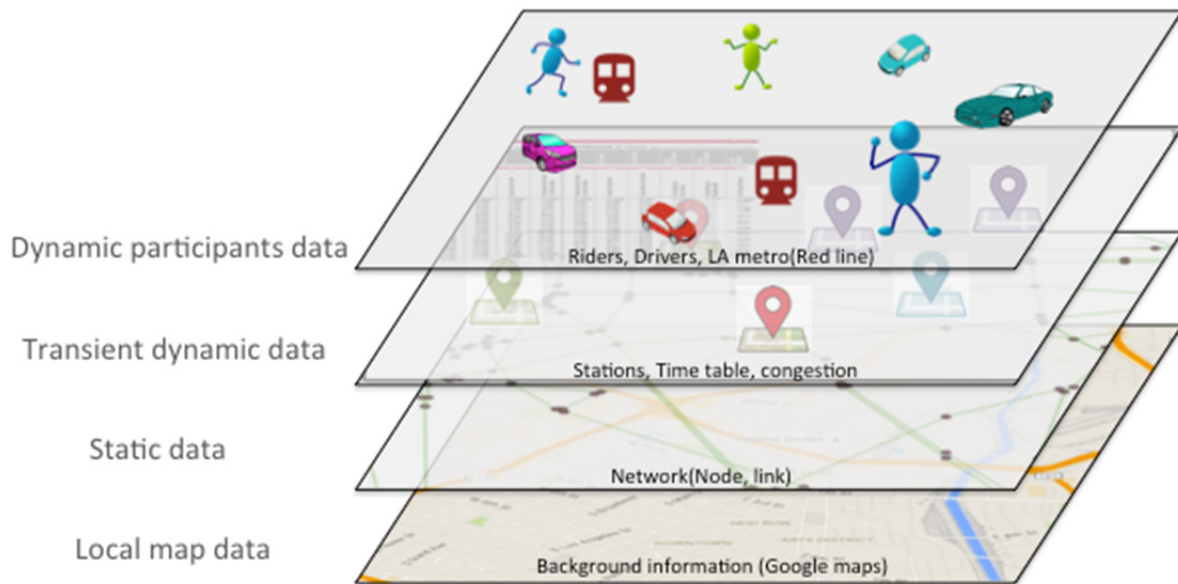
Figure 15. Layer configuration of the Mobile application

The mobile application is developed using various developing tools: MATLab, Python 2.7, MongoDB 3.2, and Android Studio 2.0. The core matching algorithm is coded in the MATLab. Python programming manages the database. In addition, Python enables the interaction between the MATLab engine (installed on the server) and the mobile application.

The communication between the server and the mobile application is processed through the HTTP RESTful API. From this http-based API, the mobile application transmits the dynamic data, such as users' ride request information, to the server. The ride-matching engine on the server finds the optimal matching and the corresponding rider and driver itineraries. The server then sends the matching results to the mobile application. HTTP RESTful API waits for the server to send out the results. The type of results can be defined in a specific format (json or xml). The mobile app then visualizes the results on the digital map in a device. This application is developed from a rider's point of view, i.e. drivers' trips are encoded in the app, although it is straightforward to extend the app to accept driver trips as input as well.

Figure 16 displays the overall design of the mobile application. To increase users' convenience, we make an effort to minimize user activities in the mobile application. The key principal is to present the results, requiring minimal touching actions from users. In this mobile app, users can obtain their matched route results within 3 actions. In the initial screen (activity #1), a user can swipe the map to find his/her destination. After the destination is set, the app will ask about the

origin and late arrival time, as shown in the activity #2 (we assume that the moment a user requests a ride, is also the notification deadline for the trip, as well as the trip's earliest departure time). Once the results are presented to the rider, he/she has to accept/reject the proposed ride (activity #3).
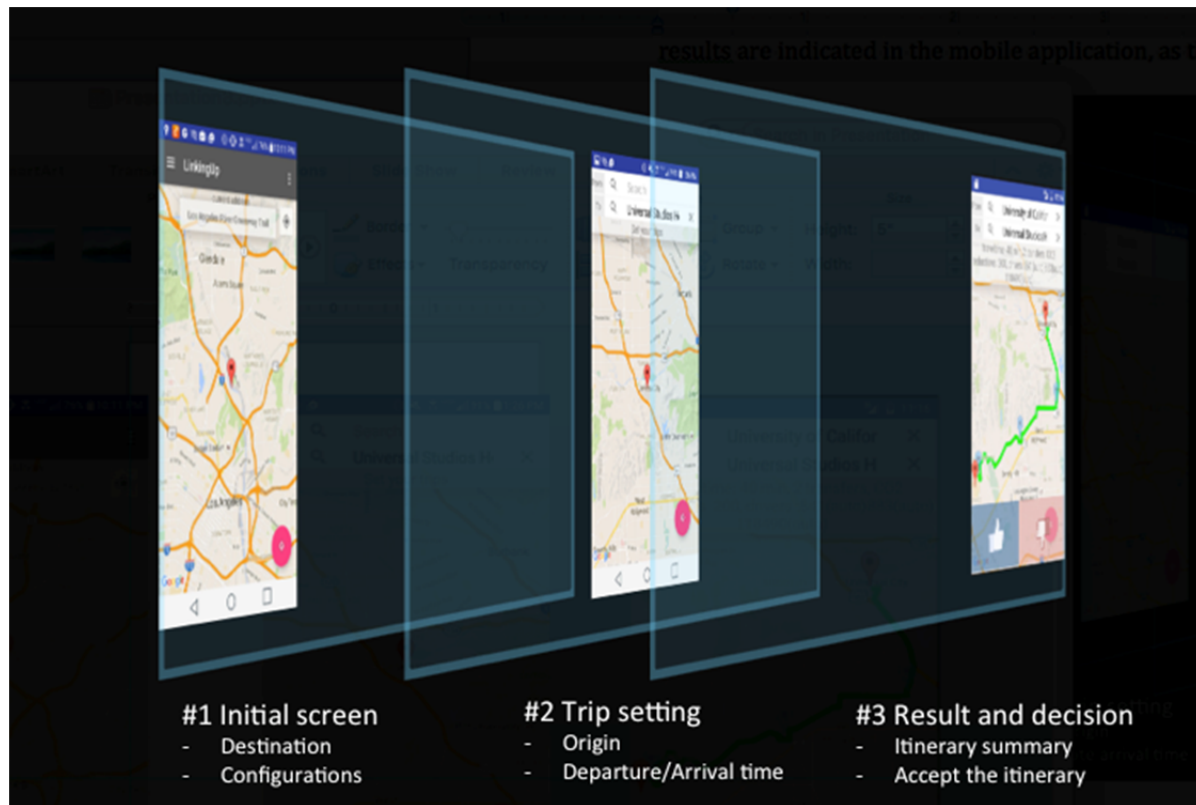

Figure 16. Mobile application user interface design

Setting user's trip information can also be done on the trip preferences screen, as shown in Figure 17. In addition, a user can find his/her trip history and favorites trips on the preference screen. Finding an origin/a destination can be done in two alternate ways. Firstly, a location flag is always shown at the center of the screen. Users can set their destination by swiping their touch screen and locating the flag to their destination. Alternatively, users can use a textbox which is connected to Google place autocomplete service API. This API matches and suggests on full words as a user types. If all inputs are entered and a user touches the direction icon, the matched results are shown. The two alternate ways of registering a trip are displayed in figure 17.

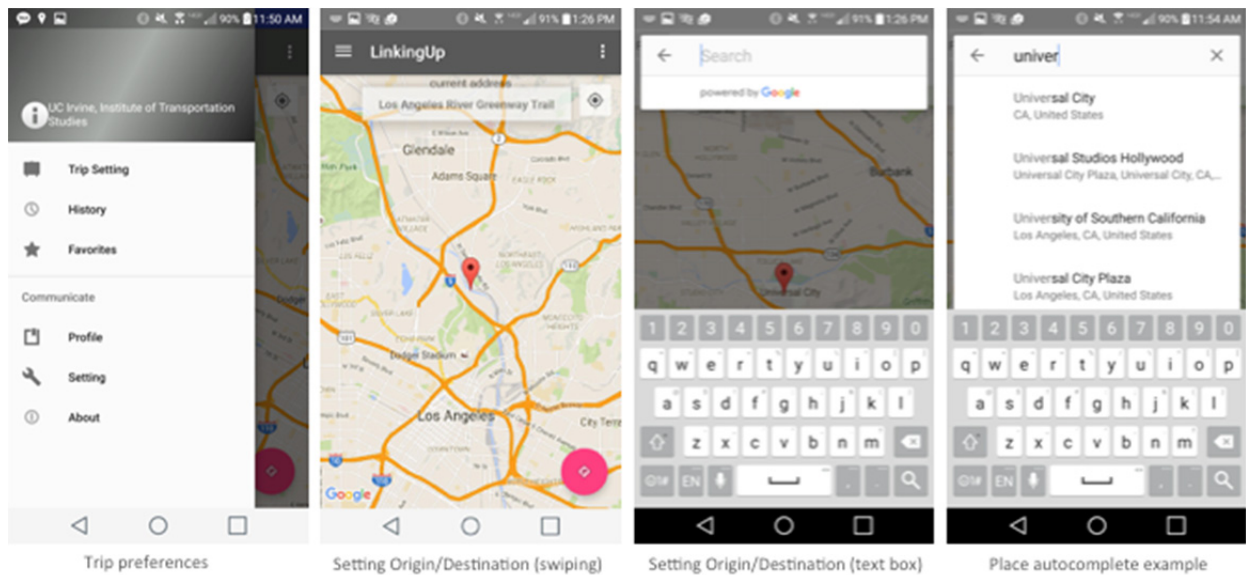| Trip preferences | Setting Origin/Destination (swiping) | Setting Origin/Destination (text box) | Place autocomplete example |

Figure 17. Trip preference and origin/destination setting

Figure 18 shows an example of an itinerary for a rider. The mobile application provides the itinerary summary in a pop-up text box. The itinerary includes travel time, number of drivers, and CO2 reductions to aid the user in making a decision. A route combination is visualized on the map, so the users can easily identify the place where they hop in and hop off. Finally, users have to touch the like or dislike icon on the screen. This user's preference is transmitted to the server with the itinerary information in order to analyze user behavior. This will allow us to improve the system to attract more people.
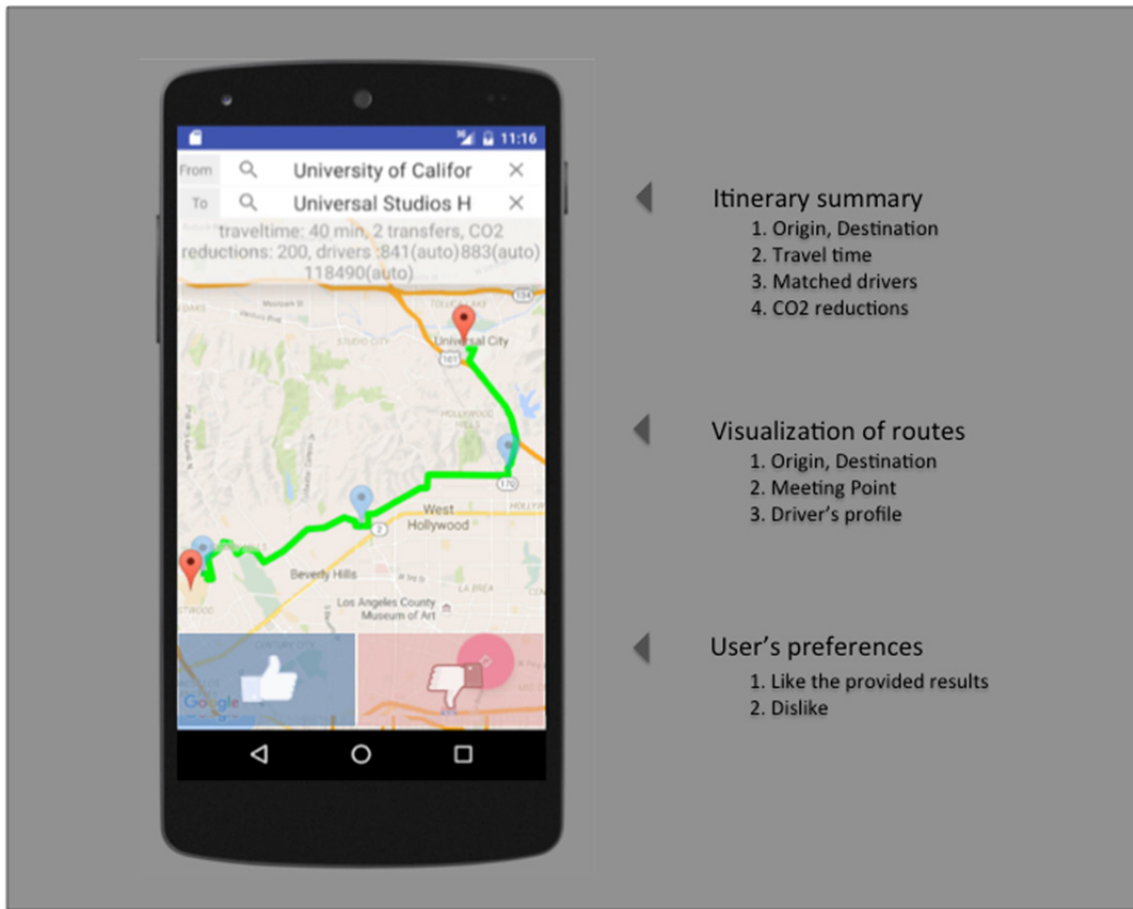
Figure 18 Screen example: matched results

8 Survey

In order to conduct a user acceptance study of the proposed system, we have prepared a set of survey questions. The survey is designed for individuals who use the LA Metro red line. During the survey, a smart phone programmed with the mobile application discussed in the previous section will be made available to the survey participants. Participants will be asked to try the app by requesting a trip, and will be asked follow up questions on their opinion on the location of go- and transfer points, ridesharing cost, and the ease of working with the app.

Considering the fact that the next phase of the project extends the existing work by adding bikesharing to the transit-rideshare alternative, we have delayed conducting the survey to the next phase, in order to include questions regarding bikesharing as well, and do a more

comprehensive study of the proposed system. In the rest of this section, we present the set of questions currently designed for the transit-rideshare alternative.

8.1 Screening questions

1- How far are your trip origin and destination away from the red line stations?

In case both the origin and destination stations were not within walking distance to the red line stations, proceed to the next question. Otherwise, the individual is not a good candidate for the survey.

2- How do you travel from your origin to the red line station of your choice, and from your destination red line station to your final destination?

Explain the transit-rideshare alternative in a few sentences.

3- Would you be interested in trying the app?

If yes, proceed to the remaining sections of the survey. Otherwise, finish the survey with question 4.

4- What are the reasons why you will not consider using such an app?

8.2 Feedback on the App

The survey participant will be presented with either the ridesharing app, or the website in which the app functionalities are imbedded. Survey takers either select their origin and destination stations from a set of pre-defined go-points on a map, or just type in the addresses. Furthermore, participants in the survey specify the latest time they have to arrive at their destination station. The app either finds an itinerary for individuals, or let them know that none exists. In the case of availability of an itinerary, app also gives individuals a quote on the price of the trip. The survey takers are then presented with the following questions.

5- How do you feel about the price of the proposed route? (very low, low, appropriate, high, very high)

If the answer was not "appropriate" proceed to question 6. Otherwise proceed to question 7.

6- At what price would you be willing to travel according to the proposed itinerary?

7- How does the travel time of the proposed itinerary compare to that of your current trip mode? (much lower, lower, the same, higher, much higher)

8- How do you feel about the distribution of go-points in the app (very bad, bad, neutral, good, very good)

If the answer is "bad" or "very bad" proceed to question 9. Otherwise, proceed to question 10.

9- What is the reason why you are not pleased with the distribution of stations? (too much walking, not accessible through walking, dangerous area, other)

10- Would you consider using ridesharing for your work commute trips? (Yes, No, NA)

11- Would you consider using ridesharing for your non-commute trips? (Yes, No)

8.3 Current travel status

12- How many one-way trips a day do you make on average?

13- For how many of these trips do you have a car available, and use the car for transportation?

14- For how many of these trips do you have a car available, and choose **NOT** to use the car for transportation?

15- What are the reasons for choosing not to use a car when available? Select as many as applicable (congestion, environmental concerns, cost of travel, other)

16- Do you commute to work on a regular basis (more than twice per week)? (Yes, No, NA)

17- How do you commute to work? Select as many as applicable (public transit, walk, bicycle, personal vehicle, carpool, other, NA)

18- What is your major mode of transportation, i.e. larger portion of your trips (rail/bus, commuter rail, personal vehicle, bicycle, walking, carpool, transportation network companies such as Uber and Lyft)

19- If you do not use rail/bus, what is the reason? Select as many as applicable (not accessible, not comfortable, lack of privacy, high transfer time, high travel time, lack of punctuality)

20- If you use rail/bus, what is the reason? Select as many as applicable (suitable price, punctuality, travel time, free to perform other tasks, comfortable, other)

21- If you are using public transit, how do you pay for it? (purchase monthly/annual bus pass, receive bus passes from your company, pay on a daily basis)

22- What is your current monthly expenditure on public transportation? (less than 50, 50-100,100-200, over 200)

23- What is your family's monthly out of pocket expenditure on personal vehicles (ignoring lease costs if applicable)? (less than 100, 100-200, 200-300, over 300)

8.4 Socio demographic info

24- Gender (M, F, NA)

25- Age (Less than 25, 25-35, 35-45, higher than 45)

26- To what degree are you employed? (student, part time employee, full time employee, unemployed)

9 Conclusion

In this project, we proposed a system architecture that included strategically selecting a set of go-points for ridesharing, and a pricing scheme, to promote ridesharing as a solution for the last mile problem faced by transit agencies. We used the LA Metro red line as a case study, and showed that there exists a range of distance-based ridesharing fares for which people would prefer ridesharing to driving alone. In addition, we showed that for trips with both origin and destination close to the Metro red line, ridesharing can in fact be used to feed transit. Finally, we developed a user-friendly mobile application that can suggest rideshare and/or transit-rideshare routes to passengers using a few simple actions from the user's part.

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