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16. ABSTRACT
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The Los Angeles Metro’s Red and Gold line subway rail and the downtown bike-share system are included in the network for a case study. The study includes a simulation of the operation of the combined system that provides travel alternatives during morning peak hours for multiple riders. The results indicate that a multi-modal network would expand the coverage of public transit. Ridesharing and bike-sharing could both act as transit feeders when properly designed in the system. Increased travel demand from the system can induce the problem that pick-up and drop-off demand in the bike system is not evenly distributed in space and time, which implies that bike redistribution should be introduced. We also develop algorithms to improve service level and reduce unsatisfied bike demand.

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Designing a Transit-Feeder System Using Bikesharing and Peer-to-Peer Ridesharing

Final Report on
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Abstract

Peer-to-peer (P2P) ridesharing is a relatively new concept that aims at providing a sustainable method for transportation in urban areas. This research is on the second phase of a sequence of projects that follows the previously funded UCConnect project titled "Promoting Peer-to-Peer Ridesharing Services as Transit System Feeders". In this phase, the study constructs a multimodal network, which includes P2P ridesharing, transit and city bike-sharing. The research develops schemes to provide travel alternatives, routes and information across multiple modes in the network. In addition, we develop a mobile application that demonstrates the research in the context of Los Angeles, CA, by using a combination of subway transit lines, proposed P2P ridesharing, and bikesharing to provide multi-modal itineraries to users.

The Los Angeles Metro's Red and Gold line subway rail and the downtown bike-share system are included in the network for a case study. The study includes a simulation of the operation of the combined system that provides travel alternatives during morning peak hours for multiple riders. The results indicate that a multi-modal network would expand the coverage of public transit. Ridesharing and bike-sharing could both act as transit feeders when properly designed in the system.

Increased travel demand from the system can induce the problem that pick-up and drop-off demand in the bike system is not evenly distributed in space and time, which implies that bike redistribution should be introduced. We also develop algorithms to improve service level and reduce unsatisfied bike demand.

1. Introduction

Metropoles such as Los Angeles are encountering serious congestion issues due to high demand for transportation and limited capacity of the street networks. In such cities, public transportation plays a significant role in alleviating congestion on the street network. However, the problem of transporting people to and from public transport stations, also known as the last-mile problem, remains an issue. Commuters who would have otherwise used public transportation choose to drive their vehicles due to difficulty of access to public transportation stations.

Introducing sustainable transportation alternatives to provide access to public transportation allows the reduction of congestion and its side-effects. These alternatives include Peer-to-peer (P2P) rideshare, bike-share, walk, and transit. First, these alternatives encourage people to reduce the usage of personal vehicles, which would reduce greenhouse gas emissions. Second, mode combination allows for such sustainable modes to complement each other, overcoming the weaknesses of each one, were it to be used as the main mode of transportation. Last but not least, the combination of modes may reduce travel time and improve reliability. This research proposes a transit-feeder system that combines several modes of transportation to provide door-to-door transportation.

In P2P ridesharing, drivers who are traveling to perform activities use empty seats in their vehicles to transport passengers who have spatiotemporal proximity with them. The first phase of this sequence of project (in 2014-15) proposed a transit feeder system to improve transit ridership by connecting riders to transit using P2P Ridesharing. Their matching algorithm has a multi-hop property where a passenger can transfer between multiple vehicles/modes of transport. They also allow for each vehicle to carry multiple passengers at the same time. The system will take over the routing of drivers to place them in spatiotemporal proximity with passengers.

This research extends the previous project by integrating multiple shared mobility alternatives. In this study, bike sharing will also be integrated into the transit feeder system, along with P2P ridesharing, in an attempt to increase accessibility to transit stations and improve transit ridership. Biking has several advantages compared to normal vehicle usage: (i) it is not affected by the street traffic conditions, and (ii) while drivers' pre-specified schedules combined with the transit system's fixed routes and schedules constrain the potential for matches, the route and schedule of bikes are flexible, as long as bikes are available at stations. By guiding riders to walk some distances to the nearby bike stations and P2P ridesharing go-points and hence aggregating the demand (Stig et. al. 2015), the ride matching rate could increase.

Integrating multiple modes into the transit-feeder system is accompanied by certain challenges in terms of design and operational management, which this study attempts to address. First of all, we introduce a comprehensive multi-modal platform where each transportation alternative is allocated a separate layer in a multi-layer network. This multi-modal platform can be regarded as Supernetwork. A layer dedicated to a single mode of transportation can contain the mode's specific characteristics, reduce the computing time to find the shortest paths, and provide the basis for efficient management of network database (Liao et. al. 2010).

This research evaluates the proposed transit feeder system by applying it to the Los Angeles Metro Redline and bike-sharing program in downtown LA. The reason why we select this area is that ridership of Metro Red line has declined in the recent years (Masoud et. al. 2017). In addition, recently launched bike-sharing program in downtown LA has experienced low usage. The goal of the transit system feeder is to increase ridership of both.

Another component of the bikesharing system that should be taken into consideration is the redistribution of bicycles because our system might induce imbalances between bicycle supply and demand at the bike stations. Thus we design an interactive framework to redistribute bicycles. To this end, we propose an optimization problem to be solved periodically. The solution to this problem suggests how bicycles should be redistributed between bike stations to make them available where there is demand, using the available resources.

An important aspect of introducing bike and ridesharing in the transit-feeder system is the modal shift it can lead to. We attempt simulations in which individuals have to choose between the itinerary provided by the transit-feeder system and their personal vehicles to maximize their utility, which is a function of travel cost, time, and level of comfort. The results of these simulations can help shed light on the impact of introducing bikesharing in terms of the modal shift from automobile- and transit-only modes.

2. Related Research

2.1 Bikesharing program

In an attempt to expand the alternative transportation modes in the Los Angeles County, LA Metro is in the process of expanding the bikesharing programs. Metro bike system has been introduced to the Los Angeles downtown area since June 2016 and is planned to be service in Pasadena and Long Beach by July, 2017. Current locations of the bike stations in the LA downtown area, along with the red metro line and P2P ridesharing stations are displayed in Figure 2.1. In total, 61 bike stations are in operation. Three metro red line stations are located within the service area of the rideshare system. By providing connection modes with access information, our ride-matching system can attract more riders to Red line.

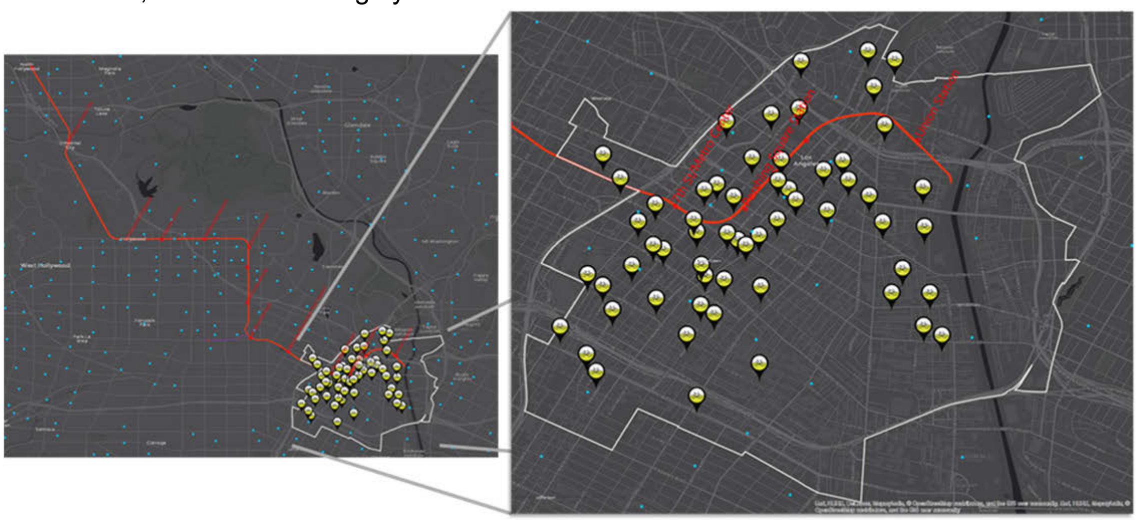


Figure 2.1 Distribution of bikesharing stations in LA downtown

Although the bikesharing program has been launched a year ago, it has experienced low ridership and there is a concern that it is unlikely to contribute to promoting transit ridership at the current usage levels. The open data policy of LA Metro Bikesharing program allows us to analyze operational conditions from June, 2016 to March in 2017. Figure 2.2 shows the trend of bike usage. The trend indicates that bike usage was increasing in the early months. One possible reason could be the launch promotions during that period. Between August and December of 2016, bike usage was experiencing a linearly dropping trend from around 800 bikes being used per day to about 200 per day – obviously a truly steep drop. Seasonal factors such as weather, temperature, and end-of-promotion may partially explain the decrease. Then the usage has been rebounding since late January 2017. Figure 2.3 shows the total bike usage in each quarter.

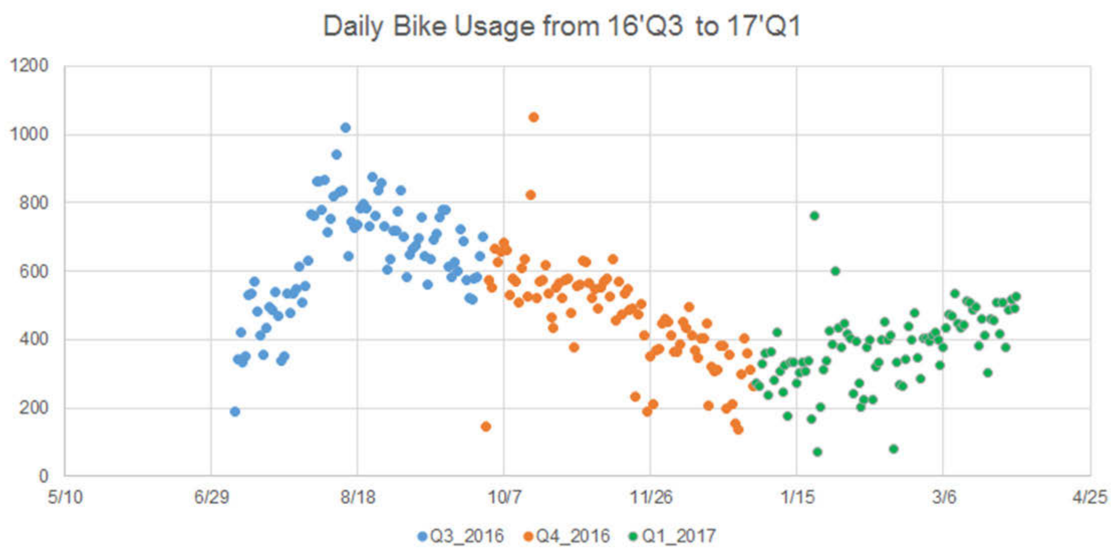
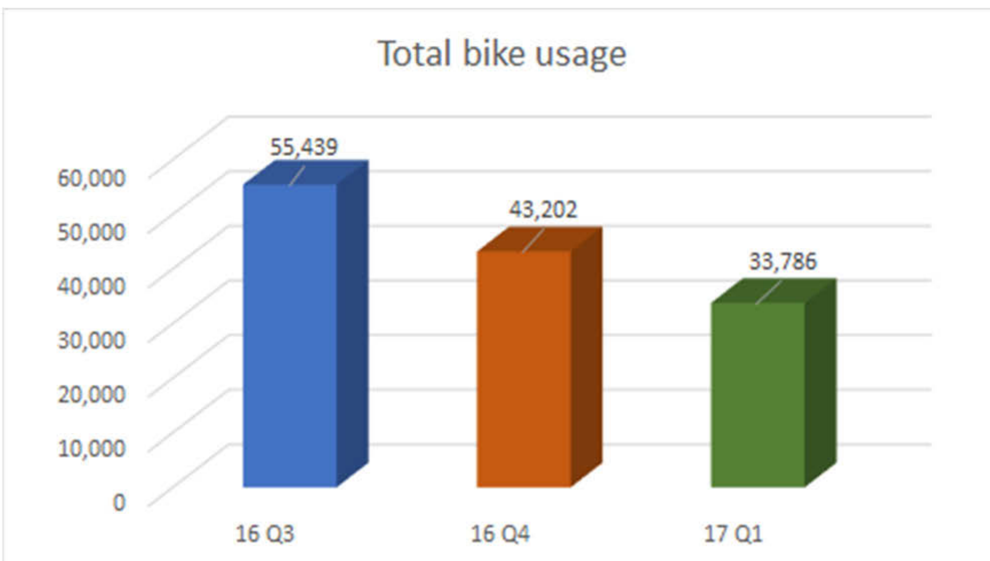


Figure 2.2 LA Metro bikesharing usage trend from July 2016 to March 2017

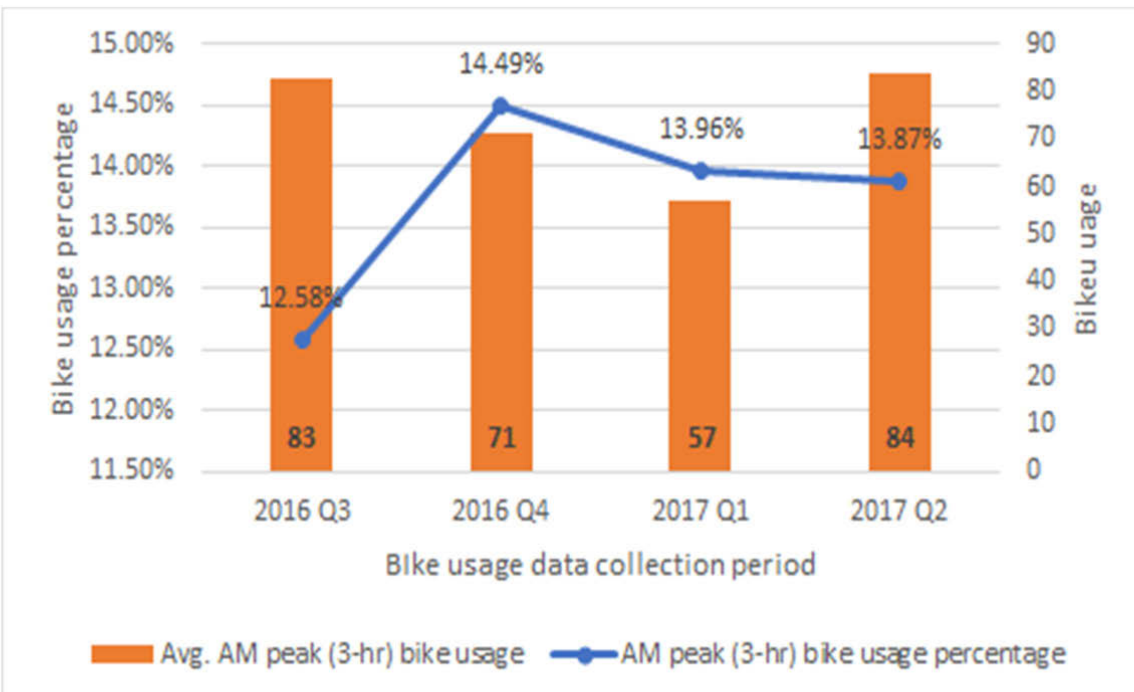


Quarter	Third Quarter, 2016	Fourth Quarter, 2016	First Quarter, 2017
Total Bike Usage	55,439	43,202	33,786

Figure 2.3 Total LA Metro bikesharing usage from 3Q, 2016 to 2Q, 2017

According to the LA metro bikesharing usage data, on average, about 410 bikes are used per day, and 57 bikes were being used in the morning peak hour on Wednesdays in first quarter, 2017 (Figure 2.4). Considering the number of bikesharing stations, only about one bike is used at each station in the morning pear hour, which is an alarmingly low rate of usage. Such low bike usage might be caused by several factors. First, the lack of awareness of the bikesharing system could be one of the reasons. Then, few travel planning systems provide the information on bikesharing as a travel mode, and thus there is low chance for travelers to get their travel route information with bikesharing and transfer option between travel modes such as autos and public transit..

In this project, the proposed ride-matching algorithm that connects different transit modes (e.g., personal vehicles, LA metro Red Line, and LA metro bikesharing) matches multiple riders and drivers in the same itinerary, and proposes multi-hop itineraries in real time. In addition, a smart-phone app is developed, so as to provide multi-modal ridesharing options. The smart-phone app will provide users with several ridesharing options when they enter their origin and destination into the app. By offering more information on ridesharing options with bikesharing resources, it is possible to encourage the use of LA metro and to promote metro red line ridership. Eventually, the multi-modal ridesharing system, provided by the smart-phone app, could play an important role as a transit feeder.



	2016 Q3	2016 Q4	2017 Q1
AM peak (3-hr) bike usage (%)	12.58%	14.49%	13.96%
Avg. Wednesday bike usage	660	497	410
Avg. AM peak (3-hr) bike (%)	83	71	57

Figure 2.4 LA Metro bikesharing usage in Wednesday average morning peak hour

2.2 Ridesharing and its matching algorithm

In the late 1990s, the concept of ridesharing emerged. Ine fact the notions of ridesharing existed in research as far back as the 1960s and 1970s in demand responsive transit (DRT) systems and several studies on taxi systems. True real-time ridesharing and possibilities of peer-to-peer communication were considered only by late 1990s. Some of the early research at UC Irvine is significant in the developments as well (Cortes and Jayakrishnan, 2002; Pages et al., 2006, Jung and Jayakrishnan, 2011). Unrelated to such research studies, implementation projects or similar systems were also underway; however, the initial ridesharing projects were not very successful due to several reasons, including the difficulty of communication between peer riders and drivers, lack of technologies, and the absence of incentives. Security and privacy issue was one of the biggest concerns. The summary of earlier ridesharing projects and reasons for their failure can be seen in the final report of the first phase of this sequence of projects, titled ‘2016 Promoting Peer-to-Peer ridesharing services as transit system feeders’ (Jayakrishnan et al, 2016).

Shared economy systems have been in wide-spread discussion since about 2010. Thanks to new technologies, the peer-to-peer ridesharing is now considered as a significant component of shared economy systems in transportation. One of the most significant features of ridesharing services, especially in densely populated cities, is providing on-demand transportation to users. Therefore, it is necessary to match riders with drivers in real-time, while trying to maximize the ride-share matching rate to serve large numbers of riders.

Referring to the earlier report ‘Promoting Peer-to-Peer ridesharing services as transit system feeders’ (Jayakrishnan et al., 2016), a ridesharing operator can increase the performance of the 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.

The simplest matching method which pairs a single rider with a single driver is used in many studies (Agatz et al., 2011). Similarly, Agatz et al. (2009) suggest ride-matching algorithms that allow each driver to carry multiple riders or multiple drivers can carry single/multiple riders, but Herbawi and Webber (2012) and Febbraro et al. (2013) assume that riders start and end their trips in the same vehicle which means that there is no connection between modes (e.g., car to car or car to transit). This assumption cannot be used in a multi-modal concept.

In a multi-modal setting, the possibility for riders to transfer between vehicles driven by different drivers should be considered in ride-matching. A “driver” in this context can conceptually refer to the vehicle control in any mode of transportation, i.e. public transit, or private vehicles. That is, In an analytical or network formulation, this means that a “driver” need not be a taxi or private driver operating their auto, but any vehicle such as a transit vehicle or a bike, A mathematical formulation of a matching algorithm that allows for transfers was introduced by Agatz et al., in 2009. To solve the matching problem with transfers to optimality, Masoud and Jayakrishnan (2015a) propose a decomposition algorithm. Their methodology, however, is suitable for problems in a rolling-horizon framework, but not for highly dynamic systems. Other studies that consider the possibility of transfers (Herbawi and

Weber, 2011a and 2011b) use a heuristic method to solve the problem. Stiglic et al. (2015) introduce a concept of meeting point in a ridesharing system, which is similar to those originally proposed at UC Irvine as part of the High-coverage point-to-point transit systems (Cortes and Jayakrishnan, 2002). With meeting points, rider can be picked up and dropped off at any points such as at their origin, destination, or meeting point.

Success of ridesharing systems depend on the matching rate between the riders and the drivers who can serve those riders, along with the possibility of transfers in real-time. To maximize the utility of ridesharing systems, a dynamic approach is introduced. Masoud and Jayakrishnan (2015b) propose a dynamic programming (DP) algorithm that can optimally solve the problem of ride-matching with transfers in a matter of seconds for reasonably sized problems with current computing capabilities. In this algorithm, each driver can serve multiple riders on board at each point in time, and drivers use optimal routes to place themselves in spatiotemporal proximity of riders. Stiglic et al., (2016) study the impact of different types of participant-flexibility on the performance of a single-driver, single-rider ridesharing system by introducing a dynamic ride-sharing system with the incentives. Masoud and jayakrishnan (2017) provide a mathematical model, the multi-hop Peer-to-Peer (P2P) dynamic ride-matching problem, as a binary program. To reduce the size of the problem and solve the ride-matching problem to optimality by means of solving multiple smaller problems, a decomposition algorithm is devised in their work.

A P2P ride-matching algorithm is central to the successful implementation of a ridesharing system. Due to the efficient properties of a P2P dynamic ridesharing system, and the ability of the algorithm to provide optimal solutions in real-time, we use this P2P Dynamic Programing (DP) algorithm for matching riders and drivers in this study. The study considers transfer possibilities in a multi-modal system that includes transit (i.e., LA Metro’s Red line) and the bike sharing system in LA downtown, as explained before.

2.3 Bike rebalancing

As described before, bike rebalancing is the issue for adding bikes to the ridesharing system, so as to adjust for the imbalances between the supply and demand for bikes that arise at bike stations at various times during operations. An effective and efficient rebalancing scheme needs to be deployed to avoid unsatisfied demand at bike stations and to control the total cost involved in repositioning the bikes, which may be done using, for example, bike re-distribution trucks or vans.

Bike rebalancing algorithms have been studied for some time. It is still drawing attention because the nature of complexity of this kind of NP-hard problem that are known not to allow polynomial-time computational solution algorithms. In the literature, the general form is the minimization of an objective function that is based on the total operating cost of rebalancing the system (typically, the travel cost or time). A depot of redistribution trucks is defined as a starting node for trucks and a truck should finish their journey at the depot as well.

The static bike rebalancing problem (SBRP) was introduced by Benchimol et al (2011). In SBRP, a set of bike stations are given. The aim is to restore the desired inventory level at each bike station at a minimum cost. Bike station revisit is allowed. The term ‘static’ refers to the situation that both the desired inventory level and the current number of bikes at each station are known in advance and do not change during the rebalancing procedure. Heuristic methods have been developed for this. Rainer-Harbach et al (2014), Papazek et al (2013), and Gaspero et al (2013) are all recent heuristic algorithms to solve SBRPs.

In contrast, a dynamic bike rebalancing problem considers the varying inventory level during the rebalancing period. The rebalancing in this case could be demand responsive. Dynamic rebalancing studies include Nair and Miller-Hooks (2011), Contardo et al (2012) and Chemla et al (2013).

In our situation, we are attempting to consider the problem in a relatively complete setting. The desired inventory level at each bike station is assumed to be known in advance. However, the number of bikes will be changing during the rebalancing period. Also, multiple vehicles would be introduced in this scheme. The objective function is to minimize the total route cost with respect to satisfying the demand at each station. In summary, we would form the problem as a multi-vehicle dynamic bike rebalancing problem (MDBRP). The detailed formulation of rebalancing will be discussed in Section 4.

3. Bikesharing and Ridesharing as Transit Feeders

3.1 Multi-modal ridesharing

3.1.1 Matching algorithm

In this project we devise a multi-hop and multi-modal ride-matching algorithm. The proposed algorithm provides a traveler with an itinerary with multiple potential connections, such as walk-ridesharing-transit-bike. This information provides travelers with door-to-door guidelines on how to combine several modes of transportation for their trips. The goal of the ride-matching algorithm is to find passengers' itineraries that can provide them with the highest utility, where utility is defined as a weighted combination of travel time, cost and mode preferences. Each passenger will be asked to provide the trip origin (SO) and the trip destination (SD), along with the earliest starting time (ES) and the latest arrival time (LA) of the trip.

Passengers are also encouraged to state their preferences about the maximum number of connections (between different modes of transportation, or different vehicles of the same mode), modes of transportation, and characteristics of the vehicles on which they travel. It is possible to even elicit preferences on the type of individuals with whom they may share rides. Based on user input and available modes of transportation, the system will devise itineraries within the travel time windows specified by passengers, and propose it to them.

The dynamic programming algorithm proposed in the first phase of the project has a multi-hop and flexible route property. This algorithm, however, only considers the combination of P2P ridesharing and transit. We reformulate the algorithm to include bike-sharing and walking to access the transit-feeder system. With algorithm enhancement and network expansion, the proposed method allows a rider's itinerary to include as many modes of transportation as desired. We redefine a network structure to efficiently manage multiple modes of transportation, and introduce methods to improve the matching rate and provide utility-maximizing itineraries to travelers.

To model the transit feeder system, we discretize the study time horizon into short time periods (5-minute periods in this study). Furthermore, we define locations in the network where travelers can start and end their trips, and/or transfer between transportation alternatives. Note that in this study we have several types of locations with different functionalities, elaborated in Table 3.1. The proposed algorithm has a node-link network structure. Let us define a node n_i to be a tuple of the time period (t_i) and the station (s_i), i.e., $n_i = (t_i, s_i)$. A link is denoted as (t_i, s_i, t_j, s_j), such that it can be interpreted as a trip that starts from station (s_i) at time (t_i) and ends at (s_j) at time (t_j). We define "go-points" that are pre-specified locations where riders can start or end a ride in a driver's vehicle, start or end a shared-bike ride, or transfer between modes.. A go-point (S_G) can be considered as a pre-specified meeting points in the network. Our research does not assume, however, that all riders start their journey from a go-point, as done in past research. The riders walk a certain distance between a go-point and their actual start/end points (S_O and S_D). This definition has advantages over the earlier schemes where only go-points were considered: 1) it reflects actual behavior of riders which can be extended to real mobile services, 2) it increases riders' route flexibility because they are not always restricted to one selected go-point, and 3) the ridesharing system can improve matching rate due to this flexibility.

3.1.2 Network expansion

In order to allow multi-modality, we introduce a super network concept which utilizes an independent layer for each mode and integrates all modes using connections across modes at mode-transfer stations. The locations (physical nodes in the network) are categorized into five types as Table 3.1: Go-points for ride-share vehicles (S_V), bikes (S_B), mode-connection points (S_C), and transit stations (S_T), as well as the riders' actual origin/destination locations (S_O and S_D). To promote transit ridership, we restrict that Go-points for bike are only connected to transit stations in this study.

Table 3. 1. Types of locations in the multi-modal shared-ride network

Station type	Symbol	Description
Go-points-Vehicles	S_V	Points where a rider starts/end their journey by taking a ridesharing vehicle $\forall\ S_V \in S_G$
Go-points-Bike	S_B	Points where a rider starts/end their journey by a bike-sharing $\forall S_B \in S_G$
Go-points-Connection points	S_C	Points where an individual can connect to other drivers or modes(bike, transit) $S_C \in S_V$, $S_C \in S_{B,}$ $\forall\ S_C \in S_G$
Go-points-Transit stations	S_T	Points where an individual can transfer to/from transit station $\forall\ S_T \in S_C$, $\forall\ S_T \in S_G$
Riders' Origin/Destination	S_O , S_D	Points where a rider starts/end their journey - it is connected to go-points by walk

A multimodal system implies that we should consider various characteristics of each mode. The complete network contains four different modes (P2P ridesharing, Bike-sharing, Transit, and riders), which would result in four separate network sub-layers. In Figure 3.1, the black, red and green lines represent the three different layers, and the blue lines represent the rider network. In this example, as a rider travels from his origin (O) to destination (D), the rider would walk to bike station, ride a bike, then transfer to transit, and then a ride-share vehicle will be in charge of his last mile. This ride matching can be accomplished through optimization on such a multimodal network, along the lines in Masoud and Jayakrishnan (2017).

P2P ridesharing network only contains the travel route of drivers, turn restrictions, penalties, and travel times of vehicles, since it is a vehicle-only network. The bike network would only represent availability of bikes, cost, and routes to nearby subway train stations. The transit network would have information about frequencies, route, and fare. The layer for each travel mode is independent, except for the connection points in terms of time and space. For riders, their travel can be accomplished through a certain combination of several modes. Furthermore, riders should walk to a nearby go-point from an actual origin point and from a go-point to an actual destination, where the origins and destinations are typically homes or work/shopping locations. For simplicity, we use a straight line for a walk link, though it can represent a separately found walk route.

Each connection go-point (S_C) is represented by separate tuples (t_i, s_i) corresponding to each mode because each mode has a different available time window. Our decomposed optimization algorithm for ride-matching in a rideshare system can optimize a multi-modal system in a similar fashion, essentially considering a bike or a transit vehicle as similar to a virtual "driver" in a ride-sharing system, as mentioned earlier.

The integrated multi-modal network improves efficiency in pre-processing, ride-matching and managing the database. The optimization algorithm includes multiple shortest path calculations in pre-processing and ride-matching. The multimodal network structure reduces computing time for shortest path calculations by restricting the number of node explorations from any node to only those of the associated mode, except at the connection nodes between the mode layers (mode transfer nodes). In terms of database management during path optimization, this network structure reduces searching time to find feasible drivers, as the user limits his/her preferences to only certain modes. The query process then searches for feasible drivers in only the preferred-mode set, which. is a relatively small database when compared to one that includes all modes.

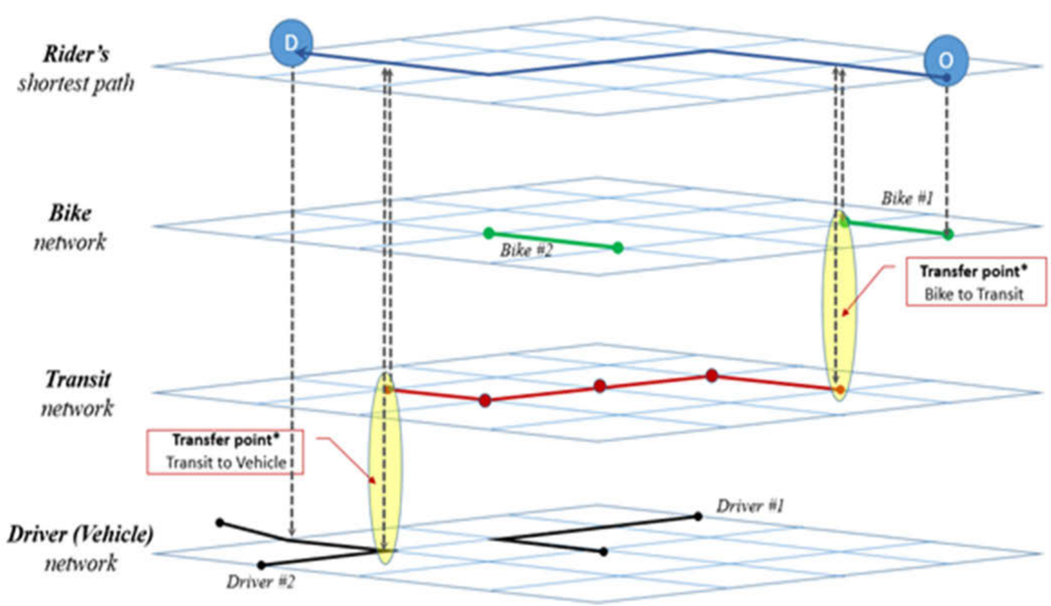
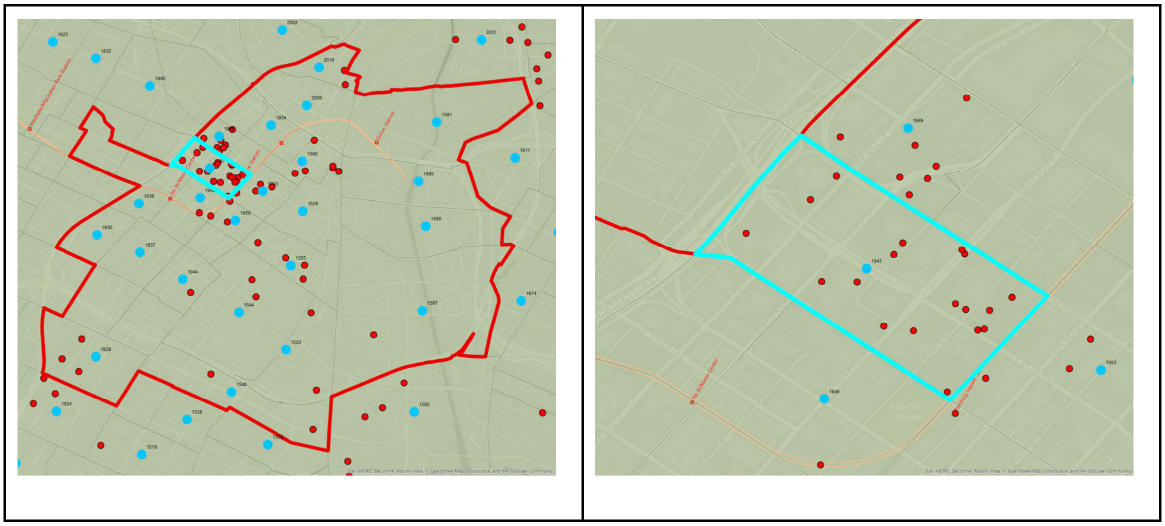


Figure 3.1 Multi-modal layers for the transit-feeder system.

3.1.3 Demand generation

The demand generation process is designed to reflect a realistic spatial distribution among the riders. As explained above, previous studies (Stiglic et al., 2015, Masoud et al., 2017, Masoud and Jayakrishnan, 2017) assume that riders' origin/destination are predefined locations as shown in blue dots in Figure 3.2. In reality, however, riders should access one of go-points by walking unless their starting/ending points are exactly at the go-points. We design our ride matching network to reflect the riders' actual starting/ending points. Instead of generating the demand at a representative point, we randomly disperse the travel demand to the associated transportation analysis zone (TAZ) as red dots in Figure 3.2. In other words, we take into account accessibility to/from a go-point.

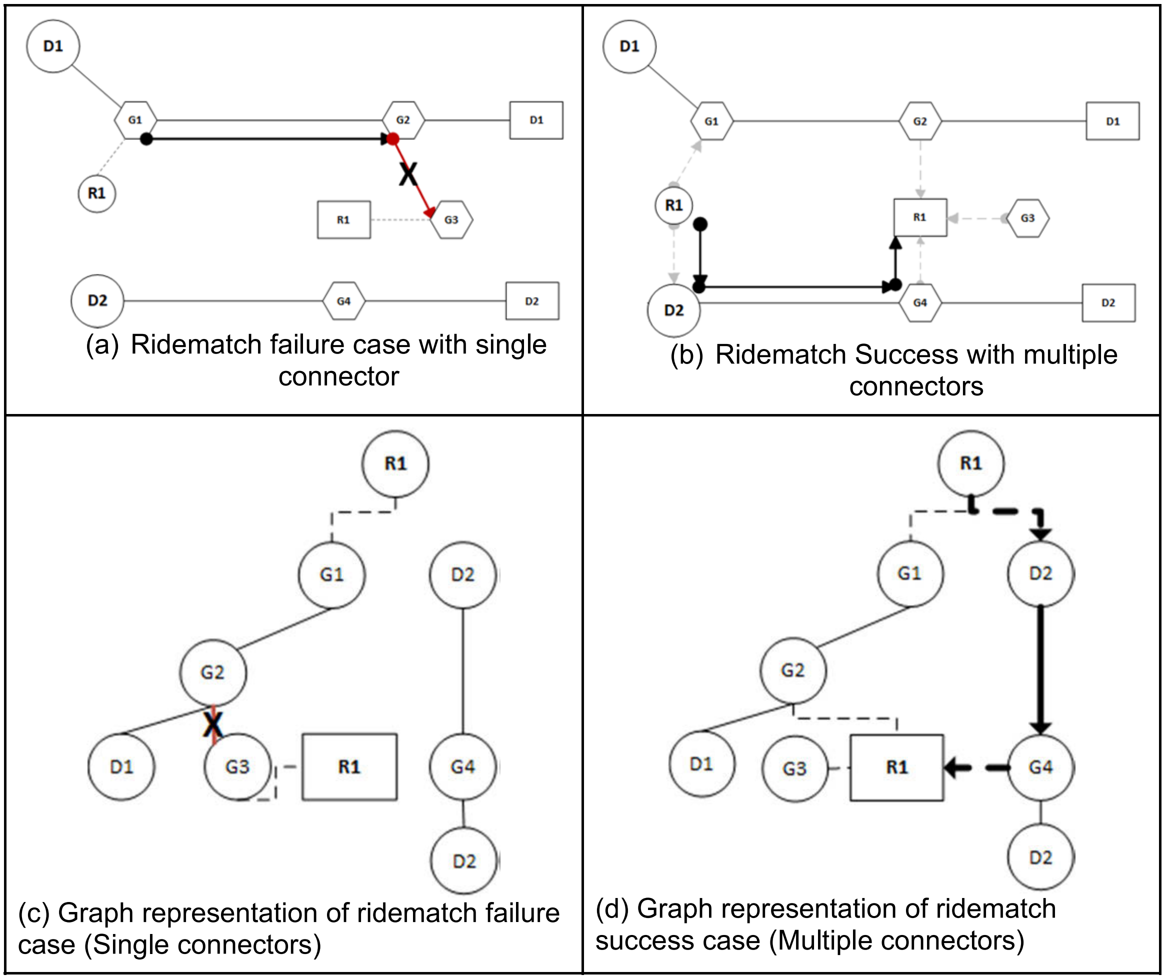


Note: blue dot: go-point, red dot: randomly generated riders' location

Figure 3.2 Example of demand generation

3.1.4 Dynamic connectors

To connect the randomly generated riders' Origin and Destination points to the network of go-points, we introduce dynamic walk links as connectors to the nearby go-points. They are indicated by the dashed line in Figure 3.3. We design the dynamic walk links to be connected to the nearest n go-points. These dynamic links are temporarily generated in our network when a rider requests a ride. After finishing the ride-matching process, the walk links are eliminated from the network for next process. This dynamic process allows for a simpler network structure for further processing.



(a) Ridematch failure case with single connector

(b) Ridematch Success with multiple connectors

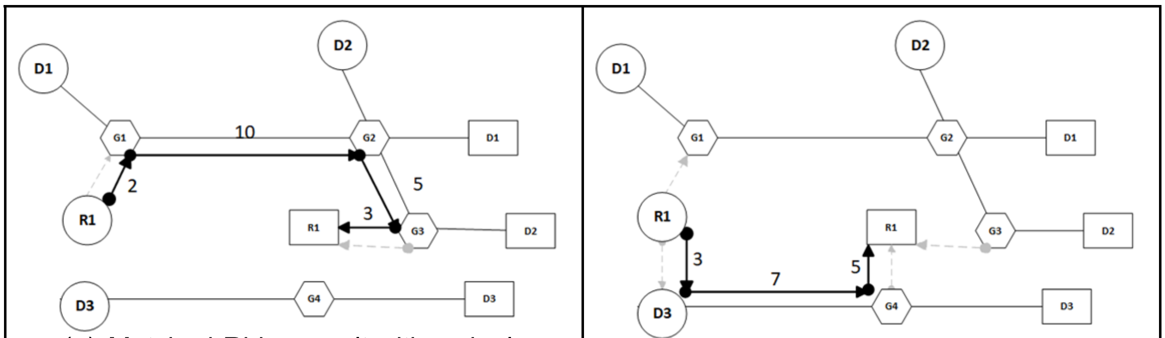
(c) Graph representation of ridematch failure case (Single connectors)

(d) Graph representation of ridematch success case (Multiple connectors)

Figure 3.3 Advantage of multiple connectors (improving matching rates)

Multiple dynamic connectors from an origin to go-points, and to a destination from go-points have the potential to increase matching rate as shown in Figure 3.3. Connecting a walk link to only one go-point has a limitation that the available drivers and possible routes are spatially restricted. Figure 3.3 (a) and (b) show an example of a ride-matching failure with a single connection. In the example, Rider 1's origin is R1 in a circle and his/her destination is R1 in a rectangle. Figure 3.3 (a) indicates that the rider's go-points are G1 for Origin and G3 for Destination. There are two drivers in the sample network. Driver 1 traverses D1-G1-G2-D1 and Driver 2 travels to D2 through G4. If there is no driver to the riders' solely connected go-point near his destination, the rider's trip cannot be matched. This problem could be solved if we find the second nearest go-point and search a route again. However, it is computationally expensive since the matching process should be repeated until the ride is matched. The concept of multiple connectors can solve this problem, as shown in Figure 3.3 (c) and 3.3(d), since the connected multiple links can include drivers/modes near multiple go-points. Although the connectors increase the computational time a little due to the increased network size, the better matching rate compensates for this.

Another advantage of dynamic links is to find shorter path for riders. The two sample networks in Figure 3.4 explain the reason. In here, we assume that there are three drivers:1) D1-G1-G2-D1, 2) D2-G2-G3-D2, and 3) D3-G4-D3. The left figure is the case when we connect only one walk link to the nearest station. Rider 1 will be guided to walk to G1 from the origin because the nearest go-point is go-point 1. She will then transfer to Driver 2 at go-point 2 (G2) and be dropped off at go-point 3. Total travel time of this itinerary is 20 minutes (5 min walk). In comparison, our proposed network structure, as shown in (b), can reduce the travel time to 15 minutes and no transfer although a rider should walk little longer (8 min). In here, three driver candidates can be considered for Rider 1.



(a) Matched-Rides result with a single connector(walk-G1-G2-walk)

(b) Matched-Rides results with multiple connectors(walk-D3-walk)

Figure 3.4 Advantages of multiple connectors (capability of finding shortest path)

3.2 System performance analysis

For a parametric study of the application of our ride matching system, we select the city of Los Angeles, as in our earlier study (Masoud et al., 2017) which developed a network based on the Southern California Association of Governments (SCAG) planning model. We enhanced that network to include multi-modal layers and the current bike-sharing stations in LA downtown as in Figure 3.5. Actual coordinates of the bike stations are collected and used to build the network. We used various data and actual travel time information such as the LA Metro time table, and the Google directions API for auto, bikes, and walk modes. Spatial connections between bike stations and transit stations are included in the network design step to efficiently improve accessibility to transit stations. Bike stations near transfer points (including metro stations) are selected as connection points.

Figure 3.5 Node-Link set and bike network expansion (Los Angeles region and the study area)

In the preprocessing step, participants (riders and drivers) are randomly selected from the vehicle Origin-Destination trip table of the SCAG demand model, as the interest is in finding how many vehicles will change their mode to our system. Then, as discussed in demand generation step, we randomly placed the selected-riders into the given TAZ, as shown in Figure 3.2. The demand in OD table is an aggregated level containing Origin ID, Destination ID, and volume. SCAG also provides with the geo-locations of each TAZ (both points and polygons). Points are generally located at the center of the associated polygon. A point and a related polygon are mapped by a key index. Using python programming and GIS libraries, all riders' Origin-Destinations are randomly generated and located.

Under the travel time budget which is the difference between the Earliest Start (ES) and the Latest Arrival (LA) times that are specified by any rider, the dynamic matching algorithm finds the multi-hop paths maximizing each rider's utility. To calculate this, we set the utility function as a linear combination of the rider's cost components: travel time, mile-based travel cost, transfer penalty, and bike-sharing cost. In this research, we use default values of \$20/hour 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 downtown LA, usage of bike is priced at \$1.5 by a half hour period. When a bike is used in our matching system, the bike must be returned to another bike station.

3.2.1 Metro rail stations accessibility

Reducing first/last mile for the transit ridership implies improvements of accessibility to transit stations. Improved accessibility to the Metro increases transit ridership. Walking is a main mode to access to rail stations (Hsiao et al. 1997, Owen, 2010, Moniruzzaman and Páez, 2012, and Chang and Lee, 2014). One of the main strategies to increase transit ridership is to provide increased accessibility to the Metro stations. Walking is a main mode to access to rail stations. Owen (2010) shows about 52% of Metro users in Los Angeles County are willing to walk to Metro stations. Furthermore, they tend to walk when their walking time is less than 10 minutes. Bus riding and Park-and-ride can also be a mode to Metro station, which are used by approximately 20 percent and 26 percent of travelers as an access mode, respectively. From the survey and GIS analysis by Owen (2010), bus and cars are used as an alternative mode to reach the metro station when walking distance is over 0.25 miles and walking time is greater than 5 minutes. This study shows the opportunity for P2P ridesharing and bikesharing to improve accessibility to the Metro stations.

We examine how the proposed system improves accessibility to the Metro red line subway rail stations in the morning peak. Assuming that riders only access the red line stations if the access time is less than 10 minutes, we find the possible catchment region from where riders are willing to use our system. To identify catchment areas, this study applies a network analysis with our multi-modal network. To measure improvements of the catchments region, we set access time to the Metro red line stations as an index. Access time to a metro station s is decomposed into access time by mode *m* from a go-point *i* to a metro station *s*, i.e.,$(tt_{i,\ s}^{m})$, and walking time to a go-point *i*, i.e.,(tt_{i}^{walk}), as in Eq (1). Here $tt_{i\ s}^{m}$ has three components: driving time from a go-point i to metro station s, denoted as $(tt_{inmode,i,s}^{m})$, waiting time for mode *m* at a go-point I, denoted as $(tt_{wait,i}^{m})$, and processing time for a mode at go-point I, denoted as $(tt_{process,i}^{m})$.

$$\text{Access Time}_s = tt_{i,\ s}^{m} + tt_{i}^{walk} \quad (1)$$
$$\text{where } tt_{i,\ s}^{m} = tt_{inmode,i,s}^{m} + tt_{wait,i}^{m} + tt_{process,i}^{m}$$

From our multi-modal network, in which the actual travel times during the morning peak hour is found from the Google Directions API, a Dijkstra shortest path search identifies all possible go-points where mode travel time $(tt_{inmode,i,s}^{m})$ is less than a certain limit (in minutes). Each mode layer has mode-specific characteristics such as average wait time $(tt_{wait,i}^{m})$ for the mode m at a go-point i, and processing time $(tt_{process,i}^{m})$ of a mode m at a go-point i as presented in Eq (1). Average wait time for transit is calculated as half of the average transit headway (i.e., 1/frequency), which technically assumes, implicitly, that the scheduled headways are generally uniform and that there is no substantial schedule variance. Waiting time for bikes is set to zero and the processing time for bike rental is assumed to be 2 minutes. Our network does not include actual walk links, thus we again utilized a private API (Google Directions) which provides walking level travel time and its geographic boundaries from a point.

Figure 3.6 (a) shows the accessible area to Red line stations, which indicates that our ridesharing system improves accessibility of Red Line stations in the Morning Peak. Red areas show the case where no feeder mode exists (except walking). Blue areas imply that more travelers can reach their nearest station by P2P ridesharing. We found the system to improve the area of accessibility to from 8.64 sq miles to 14.10 sq miles. The proposed method with bike-sharing also has the potential to improve accessibility to 15.64 square miles. An interesting fact is that the bike-sharing system in the downtown area has more potential to increase the red line's accessibility area than an autos-based ridesharing due to the fact that bikes are generally faster than such autos which may be stuck in downtown congestion.

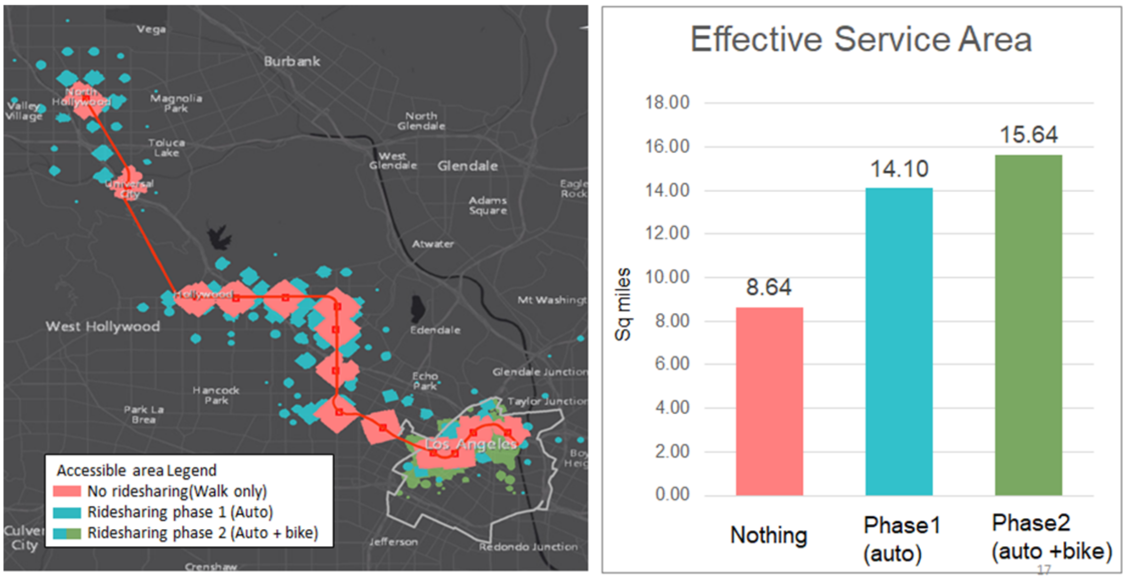


Figure 3.6 Accessibility improvement by P2P Ridesharing and Bikesharing

3.2.2 Demand Characteristics

Figure 3.7 and 3.8 are heat maps that demonstrate the origins and destinations of demand during the AM peak hour. The red color indicates high level of traffic demand in that region as origins or destinations. These heat maps are useful to develop a visual sense of the travel intensity (for travel by private vehicles).

Based on our study area, most of the demand originates from Santa Monica, Culver City, Hollywood, Burbank, Glendale and Pasadena. Each city has more than 3500 trips per square miles during morning peak. These cities have higher-population-density residential areas. The downtown area is of course a Central Business Center (CBD) and does not have the residential city characteristics. Therefore, this area does not have much traffic originating from there during the morning peak hour. The demand distributes intensively along the state highway 101 as several cities are located nearby.

The higher-demand destinations during the morning peak include Santa Monica, Beverly Hills, Hollywood, Burbank, Glendale, Pasadena, and downtown LA. As expected, the downtown area has considerable number of travelers as incoming population. They are naturally potential bike users for their trips' ending portions. Again, the demand is along state highway 101, and the Metro red line in a cross direction. Passengers with origins and destinations in Hollywood, and downtown LA is potential users of the Metro red line.

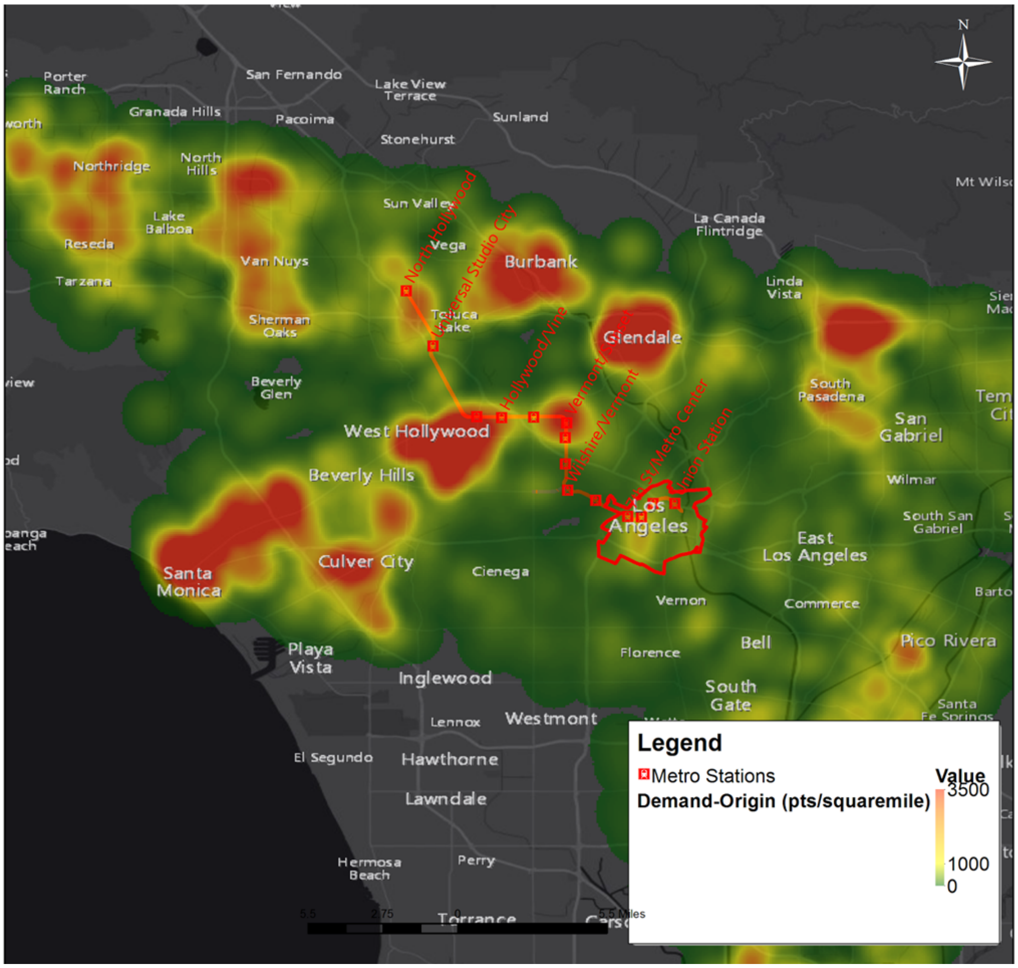


Figure 3.7. Spatial distribution of riders' origin

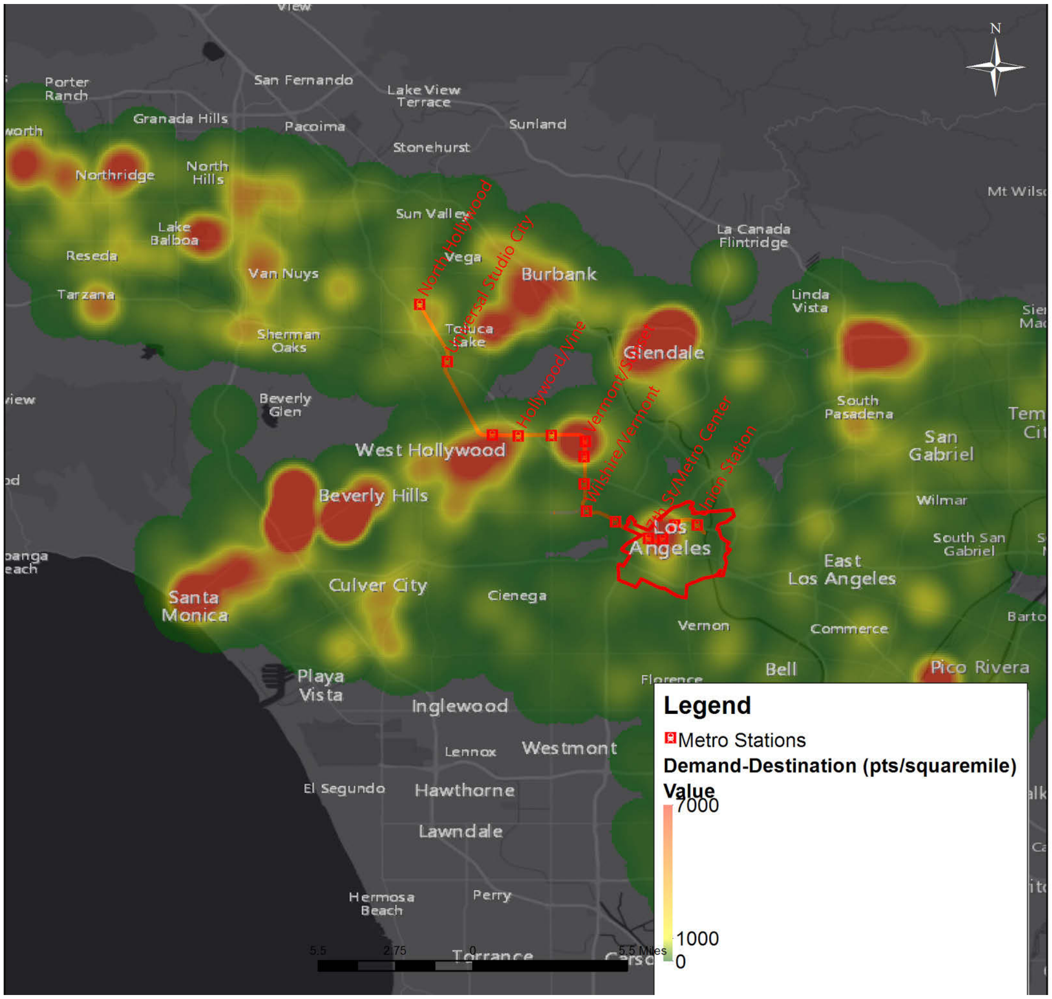


Figure 3.8. Spatial distribution of riders’ destination

3.2.3 Matching rates

Under the assumption that travelers will change their mode from personal autos, our simulation first changes the number of riders from 1000 to 4000, and increases the number of drivers gradually from 1000 to 10,000. The matching rate increases sharply at the beginning when we increase the number of drivers, as can be seen in Figure 3.9. Then the marginal matching rate decreases. When we increase the number of drivers from 1000 to 5000, the matching rate triples. However, when the number of drivers is twice that of the riders, the matching rate improves only slowly.

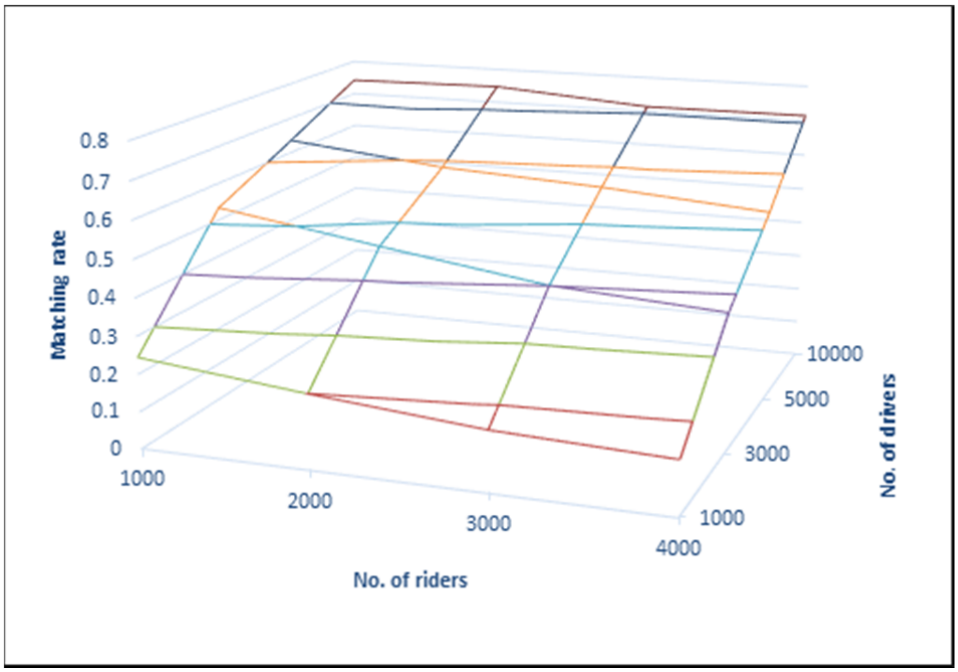


Figure 3.9 Parametric study for the impact of riders and drivers to matching rates

The general pattern is similar as in our Phase I (first-year) research which used only transit and the rideshare option, but we can recognize that matching rate in our study is significantly higher. The Figure indicates that in Phase II, with the same number of drivers and riders, more riders will be served than we found in Phase I. The most improvement happens with around 1000 riders and 5000 drivers. In Phase I, around 30% riders are served. However, with the Phase II algorithm, more than 60% are served. It can be seen that network expansion, addition of bike-sharing, and introduction of a multiple-layer network with dynamic walk connectors that we propose enable the riders to have more alternatives.

3.2.4 Effectiveness on transit demand and bike usage

Increasing metro rail and bike usage among those who use autos is our main research interest. A series of simulations is designed to understand how the usage numbers change when we increase the number of riders and drivers. We expect the number of Metro rail and bike users to also linearly increase when the number of total participants increases linearly. The usage results are shown in Figure 3.10 and 3.11.

First, for metro users (Figure 3.10), we could observe an approximately linear trend when we increase the number of participants. Out of the entire simulation sample (224,196 individuals), not all have access to the Metro line (i.e., origins and destinations are far away from metro stations). Out of all individuals in the much larger area, around 8400 individuals are potential metro users (since only the Metro red line is included in this study, and it covers only a small portion of the area). For a sampled 4000-rider case, there are about 150 potential metro users, and 5 of them are matched with a metro usage (3.3%). When the rider-to-driver ratio is high, the algorithm tends to match more people with metro rail. Therefore, designing a proper proportion of rider/driver ratio would help the usage of metro transit.

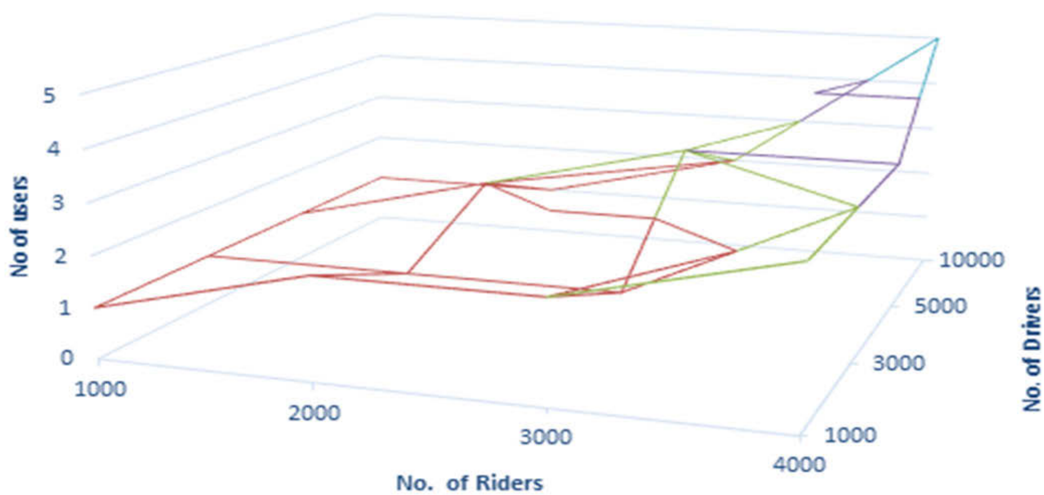


Figure 3.10. Number of Metro users in our system according to increasing participants

For bike users (Figure 3.11), the situation is similar. The trend is approximately linear when the total number of participants increases. Since the study only considers bike as a transit feeder, it does not include bike-only usage for temporary travel within the downtown region. In the 4000-rider case, 75 riders have either the origin or the destination located in the downtown area. We identify this group of people as potential bike users. Among 75 riders, 1 was matched with a bike (1.4%). If we include bike-only travel, we will however see higher bike usage rate for the downtown area.

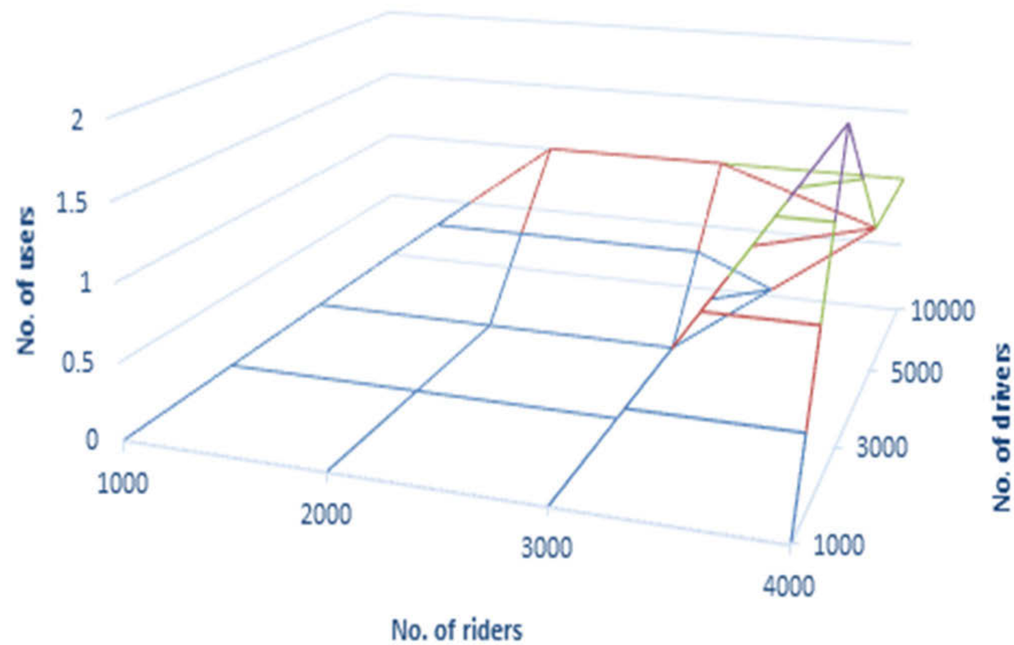


Figure 3.11. Number of Bike users in our system according to increasing participants

3.2.5. Analysis of number of transfers

Masoud et al. (2017) suggested that either too large or too small a number of drivers would result in low number of transfers. The reason is that with large number of drivers, most of the passengers can be served by single matching, and with extremely small number of drivers, the service rate would be low.

Figure 3.12 shows that in the 6000 riders case, 4987 riders have been served. 4329 riders (86.8%) riders are served without any transfer. Only less than 14% riders experience at least one transfer. 10.6% has one transfer. 2.2% has 2 transfers. Only 18 riders (0.36%) has 3 or more transfers. The maximum transfer could be 5.

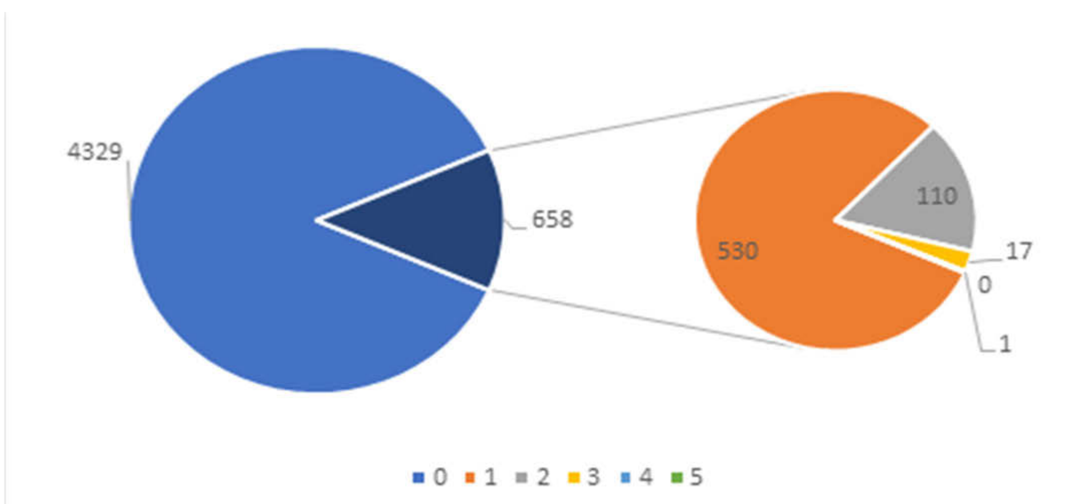


Figure 3.12 Details about number of transfers for 6000 riders

Figue 3.13 shows the number of transfers with the change of rider/ driver combinations. If the number of riders/drivers increases as a linear trend, the average number of transfers will also decrease also in an approximately linear manner. Therefore, number of participating drivers determines the average number of transfers at a high extent.

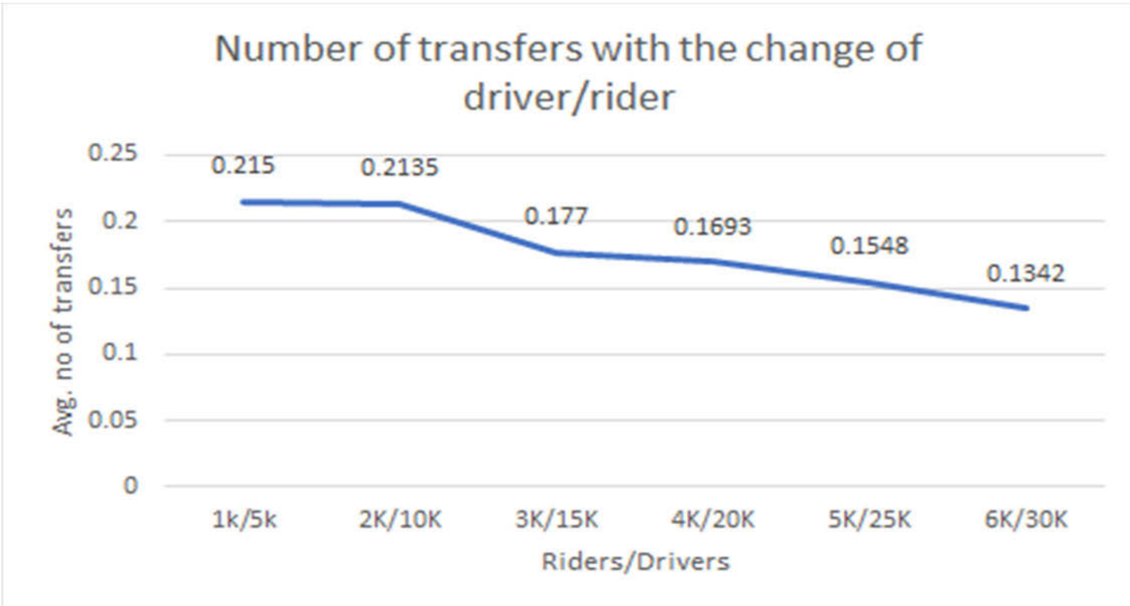


Figure 3.13 Details about number of transfers according to the number of participants

The result suggests that to avoid high level of transfers, the system needs to have sufficient supply of drivers.

4. Bike Rebalancing

4.1 Introduction and Overview

Bike rebalancing in this study is defined as an operation or a series of operations that allows service vans to pick up and drop off bikes among bike stations to maintain a certain level of service for bikers. This type of operation is also known as bike-repositioning or bike-redistributing. Recently, many cities have proposed regulations to allow and constrain private bike sharing services which renders the bike sharing and rebalancing operations to be more profit-oriented than equity/public good-oriented as well. Considering the cost involved in repositioning bikes to address demand-supply imbalances, there is a need to have a bike rebalancing algorithm that can be quickly and effectively implemented and easily interpreted by operators.

In the previous sections, we have assumed that there is no situation where a traveler would encounter a depleted or fully-racked bike station. This section, we study whether this assumption is valid under the current operational budget. That is, we consider whether the existing bike-rebalancing strategy can handle extra demand from the newly added ridesharing services, and if not, what the cost would be, to accommodate it. If the assumption made about bike-rebalancing is invalid, it is necessary to adjust the other parts of the model to produce a coherent result. Pickup and drop-off demand are treated as exogenous and the model will test if a strategy can handle such pickup and drop-off demands. Important factors and constraints include redistribution truck capacity, bike station capacity, and collaborative operations among multiple redistribution trucks.

The bike rebalancing problem is so far known to be NP-hard and thus without a polynomial time computation algorithm to solve (Ting and Liao, 2013). Thus it is challenging to formulate and optimize with a predefined objective function. However, any solution is relatively easy to evaluate. It is particularly so in this dynamic case, where one effective way to evaluate would be simulation.

Three major contributions in the proposed solutions are: (1) the solution algorithm works on a solution set of bike-station-pair instead of individual bike stations by realizing the essence of the problem, namely that routing can be studied as a series of *station pairs* rather than individual stations. This realization not only eases the analysis and model tractability but also significantly reduces the computational effort in large-scale cases and improved interpretability of the algorithm. (2) the “dynamic-static-dynamic” procedure significantly eases the complexity of the issue and allows convenient route visualization. (3) A validation data set is used to adjust the hyper-parameters to avoid the model overfitting issue that is commonly omitted in bike rebalancing literature.

After the initialization process where a highway/bikeway network is converted to a station-to-station network by skimming, the algorithm follows three general steps. First, the problem is converted from dynamic to static using a discounting-based method. Applying a discounting factor to convert a dynamic inventory problem to a static one is not an uncommon practice under uncertain demand (Ravindran, et al., 1987). The discounted total demand allows evaluating the “urgency gap” between any two bike station pairs, conveniently scaled by the van travel cost. In addition, a bicriteria problem -- reducing operation cost and maintaining bike station inventory levels simultaneously – can be immediately incorporated within the objective function. For example, suppose a discounted demand for station *i* is -7 bikes with respect to its predefined target stock while the station *j* is +8 with respect to its target stock. Then the urgency gap for delivering bikes from station *j* to *i* would be proportional to the 15 (assuming a linear cost function). This gap can be further scaled using impedance between the two stations so that the higher the cost to deliver, the less likely the station pairs is selected. In actual operation, such discounting can be practiced at any decision point, and the weighting and the demand can be relaxed to be adaptive to real-time information.

The second step randomly groups bike stations pairs to form the basis of van service routings. In this case study, we used an enumeration approach for top-ranked bike station pairs in terms of the "desire" to be served and the travel cost, thanks to the limited problem scale and the short study period (7-8am). When the problem scale is large, a heuristic method is recommended to reduce computational effort.

The third step "converts" the problem back to a dynamic one through simulation for determining the feasibility of the service routing strategy given the limited bike station and truck capacities. The actual dynamic demand is used instead of the discounted one in this case. Relatively detailed variables of routing and scheduling such as the specific numbers of bikes to drop off and pick up are also determined in this step. The result generates a new dynamic inventory profile so that the system service level can be evaluated. Figure 4.1 illustrates this process. The "feedback" arrow from the third step to the first step represents the process of system service evaluation and hyper-parameter tuning where parameters such as discounting factors, optimal number of vans, target inventories, impedance weighting (relative to the urgency gap) are adjusted.

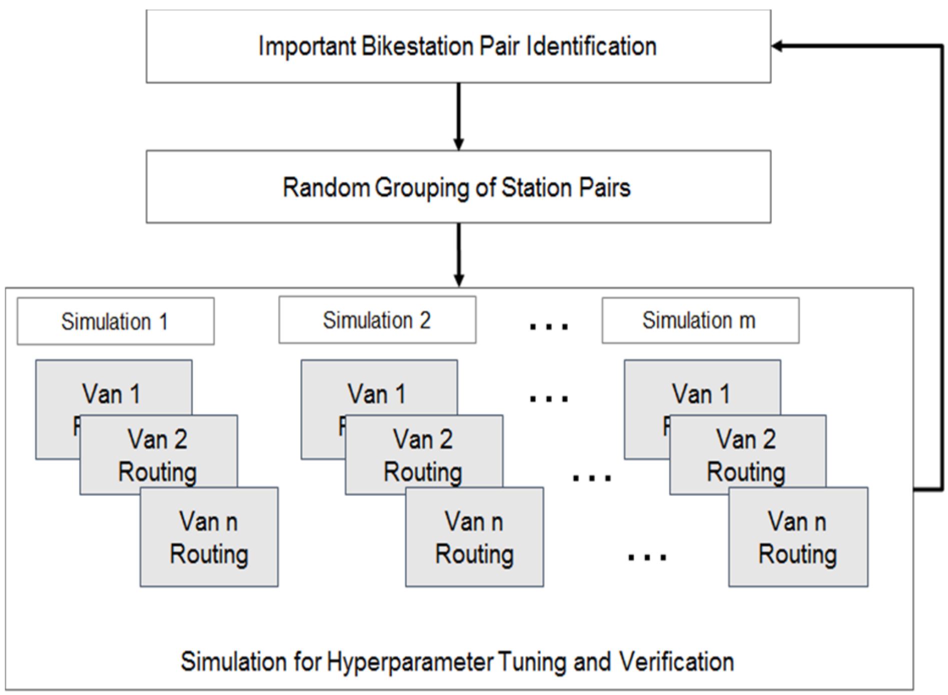


FIGURE 4.1 Conceptual Explanation of the Heuristic Solution Algorithm

Note that, in the estimation process, though specifying parameters such as discounting factors and impedance scalers with respect to individual stations and/or time steps might significantly improve the objective function, it may lead to a model overfitting issue. That is, the estimated parameters would fit well with the data of the study day but not data from other days that have different bike pick-up and drop-off patterns. Therefore, we use the data from 2017 April to validate the estimated model, and adjust if necessary to achieve a balance between reducing the objective function of the study day and reducing the objective function of the validating day.

4.2 Problem Formulation

In this section, the dynamic bike rebalancing problem described in the previous section is represented mathematically. Using the objective function along with the constraints, it prepares the next section to propose algorithm to improve the system. The underlying assumption is that the decision maker/operator's (subjective) goal would be to minimize this objective function. Although the objective function is linear, some of the constraints are either nonlinear or integer.

Since the travel time is treated to be stationary in this case study, a highway network can be degenerated by skimming to a G={V, A} where V is the set of vertices that represent depot ({0}) and bike stations ({1,2,3,...,n}). Directional arc set A contains every two vertices that have an attribute of travel cost for a bike redistribution van to travel on.

The objective function aims at minimizing general cost of truck operation and demand service, which can be formulated as

$$min \sum_{\tau=1}^{T}[\sum_{k=1}^{K} C^{TK}{}_{\tau k} + \sum_{j=1}^{J} C^{U}(S_{\tau j}))]$$

where $C^{TK}{}_{\tau k}$ is the operation cost of the van k during τin the study period $[0, T]$. Operation cost is a combination of staff cost, fuel consumption, maintenance, and management. When $C^{TK}{}_{\tau k} = 0$ the operator focuses solely on maximizing service level without considering operation cost. $S_{\tau j}$ is the unserved demand -- when negative, it is number of users who encounter empty station while positive means the number of users for the fully racked. $C_j^U(\cdot)$ converts unserved demand to the cost/penalty due to unserved demand. For example, C^U in the case study is defined as a linear function of S where $C_j^U(S) = \beta_1 S^2$ when $S < 0$, while $C_j^U(S) = \beta_2 S$ when $S > 0$. β_1 is a scaler that converts number of bikes to the same unit of truck operation cost. Consider the truck operation cost in the case study is mileage, β_2 is a scalar that converts number of bikes to the same unit of truck operation cost. In this case study, $\beta_1 = \beta_2 = 1.2$. β_1 and β_2 are subjective to the operator's goal and preference.

Below is the list of variables used in the formulation.

$tt_{ijk\tau}$ the travel time for truck k driving from i to j departing at the beginning of time interval τ

σ_τ: the time length of the time duration for time step τ

$p_{kij\tau}$: is the proportion of cost for serving j from i during time interval $\tau$with with respective to $tt_{ijk\tau}$

$s_{kij\tau}$: the number of bikes the van k is going to pick up/drop off driving from i to j arriving at time τ. When positive, it is dropping off; when negative, it is picking up.

$Capa_k$: capacity of van k

CP_i: capacity of station i

$g_{mi\tau}$: the number of bikes dropped off by users at station i from station m at time interval τ

$f_{ij\tau}$: the number of bikes picked up by users at station i to station j at time interval τ

$I_{i\tau}$: the inventory at bike station i at the beginning of the time interval τ
$L_{k\tau}$: the number of bikes on the van k at time interval τ

$\xi_{ki\tau}$: dummy variable indicating whether the van k is at station i at time step τ. 1 yes, 0 no.

Constraints:

$I_{i\tau} + \sum_j g_{ji\tau} - \sum_j f_{ij\tau} + \sum_{kij} s_{kij\tau} = I_{i,\tau+1}$ #Bike station inventory conservation

$s_{kij\tau} < min\{Capa_k, CP_j - I_{j\tau}\}$ if $s_{kij\tau} \geq 0$ #the number of bikes dropped off at station j should be equal or less than the slack on the van k as well as the empty racks at station j.

$-s_{kij\tau} < min\{Capa_k - I_{k\tau}, I_{j\tau}\}$ if $s_{kij\tau} < 0$ #the number of bikes picked up should be less than the slack capacity in this van (or else no place to put the bikes) as well as the how much the bikestation j can "offer".

$C_k^{TK} = \sum_{ij}[tt_{ijk\tau} + \theta(\sigma_\tau - p_{kij\tau} tt_{kij\tau})] + \sigma_\tau c^{staff}$ # service time includes fixed time + unfixed time (depending on how many bikes being dropped off and picked up at the given station j).

$\sum_i \xi_{ki\tau} = 1$ #a van can only appear at a station one at a time

$\xi_{ki\tau_m} + \xi_{kj\tau_n} = 0$ if $\tau_n - \tau_m < TT_{ij}, \forall i, j, i \neq j$ #sure van won't be able to serve another station before it actually arrives

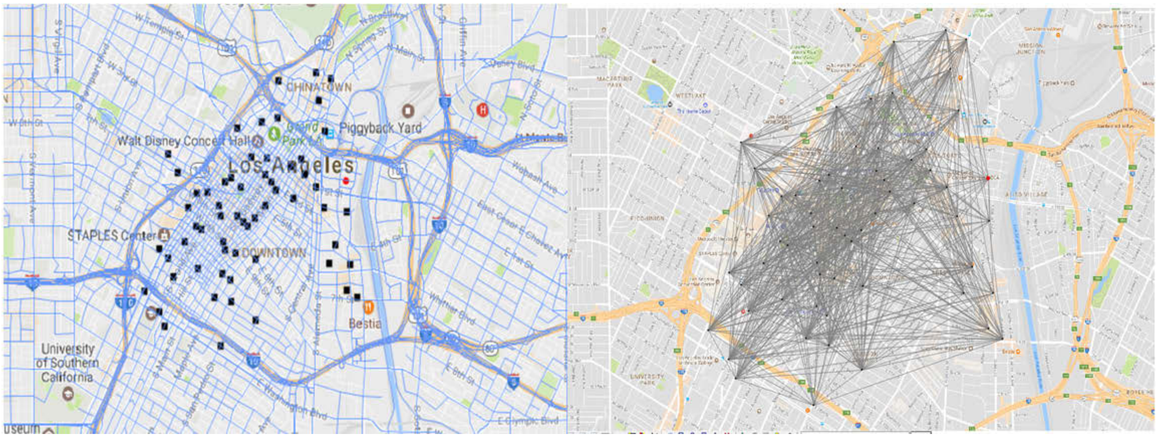
Note that a van's departure time from a station (or depot) is rounded to the nearest beginning of a time interval. This means that the simulation time step should be set small enough compared to the between-station travel times so as to avoid the situation where a van departs from the origin station and arrives at the destination station in the same time step. Another detailed but important setting in this case study is the fixed travel times, which can be extended to incorporate dynamics in a future study.

4.3 Solution Algorithm

As described in the beginning of the section 4, the proposed heuristic solution algorithm contains three main steps: converting the dynamic problem to a static one, bike station pair assignment, and simulation (converting back to dynamic problem). The results are fed back to the first step's assumptions about operation cost and demand gaps to test for consistency. The following subsection describes these steps in more detail.

4.3.1 Procedure

The initialization process (before the first step) prepares information for the later steps. First, at a given decision time point, critical bike station pairs are identified based on two criteria. The first criterion is the gradient of the inventory gaps between the pick-up station and a drop-off station. The second criterion is the travel impedance between these two pairs. To take into account the dynamic demand for each station (assumed known, based on historical data), a discounting method is used. Since the travel cost on the roadway network (Figure 4.2 Left) is assumed fixed, the network is simplified to a station-to-station network (Figure 4.2 Right) by skimming the impedance the roadway network.



Note: The red node represents the depot.

FIGURE 4.2 Left: Highway network of LADOT 2016 Travel Demand Forecasting Model (light blue); Right: the station-to-station network skimmed from the LADOT highway network.

Figure 4.3 shows a part of the skim matrices for the bike stations for illustrative purposes.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42
1	0.0	4.6	5.8	5.0	14.7	13.9	27.9	21.6	5.9	12.1	23.1	31.3	21.9	16.4	21.7	23.6	14.4	19.5	15.2	19.1	9.2	4.1	9.9	9.4	2.3	33.7	37.2	13.0	10.6	24.3	24.2	14.4	13.5	29.6	12.0	7.6	7.3	29.3	10.4	15.3	20.9	34.6
2	4.6	0.0	6.4	7.4	10.4	14.6	26.9	20.2	4.7	9.7	21.4	28.3	19.9	17.3	20.5	24.8	12.6	19.9	12.9	17.5	5.2	5.3	5.6	9.1	6.2	30.0	33.1	10.1	15.1	21.9	20.4	13.8	13.4	26.0	14.2	3.8	11.6	25.4	6.3	14.3	20.7	30.5
3	5.8	6.4	0.0	10.8	16.1	19.6	22.1	15.9	10.5	16.1	27.7	26.3	16.4	11.0	26.6	18.5	8.9	13.9	10.0	13.4	7.4	1.7	11.5	14.6	8.0	29.7	33.7	8.7	14.6	19.0	26.5	8.5	19.0	25.4	7.9	6.2	12.0	25.6	8.4	20.3	26.3	31.2
4	5.0	7.4	10.8	0.0	14.9	9.1	32.9	26.5	4.6	9.9	19.4	35.6	26.6	21.2	17.7	28.4	19.1	24.4	19.8	23.9	12.6	9.1	10.7	5.5	3.0	37.3	40.3	17.3	9.4	28.9	22.9	19.3	9.1	33.4	16.6	11.1	5.8	32.7	13.7	11.4	16.3	37.8
5	14.7	10.4	16.1	14.9	0.0	16.5	31.6	24.8	10.2	7.4	16.3	28.3	23.6	25.8	16.6	33.2	18.1	27.6	17.4	22.5	9.6	15.5	4.9	11.9	15.5	26.9	28.4	14.1	24.1	24.2	10.5	20.9	14.3	24.1	24.0	10.2	20.5	22.2	9.4	12.6	19.2	26.1
6	13.9	14.6	19.6	9.1	16.5	0.0	41.3	34.7	9.9	9.1	12.1	42.3	34.5	30.3	9.9	37.5	27.1	33.4	27.5	32.1	19.1	17.9	14.6	5.6	12.1	42.6	44.7	24.5	15.1	36.4	20.3	28.0	2.3	39.2	25.7	18.1	12.6	37.9	20.0	5.4	7.4	42.3
7	27.9	26.9	22.1	32.9	31.6	41.3	0.0	6.9	31.6	35.7	47.2	13.6	8.2	14.2	46.7	13.1	14.3	10.9	14.5	9.4	23.2	23.8	29.1	35.9	30.1	21.6	27.1	17.8	35.2	9.0	41.0	13.6	40.3	18.0	19.7	23.7	33.5	20.9	22.8	40.9	47.5	25.4
8	21.6	20.2	15.9	26.5	24.8	34.7	6.9	0.0	24.9	28.8	40.3	13.1	2.5	10.6	39.9	13.4	7.6	8.5	7.6	2.6	16.3	17.6	22.3	29.2	23.9	19.7	25.0	10.9	29.8	5.4	34.4	7.7	33.6	15.4	15.2	16.9	27.7	17.5	16.0	34.1	40.7	22.9
9	5.9	4.7	10.5	4.6	10.2	9.9	31.6	24.9	0.0	6.2	17.4	32.6	24.6	21.5	16.2	28.9	17.3	24.3	17.6	22.2	9.3	9.0	6.2	4.4	5.7	33.6	36.3	14.6	14.0	26.5	18.7	18.4	8.8	29.8	17.7	8.2	10.3	28.9	10.3	9.8	16.0	33.7
10	12.1	9.7	16.1	9.9	7.4	9.1	35.7	28.8	6.2	0.0	11.8	34.5	28.1	27.0	11.1	34.5	21.4	29.6	21.2	26.2	12.5	14.8	6.7	5.1	11.7	34.0	35.8	18.0	19.1	29.4	13.1	23.2	6.8	30.8	23.7	12.0	15.6	29.3	13.0	5.6	12.4	33.4
11	23.1	21.4	27.7	19.4	16.3	12.1	47.2	40.3	17.4	11.8	0.0	44.6	39.4	38.7	2.5	46.2	33.0	41.3	32.7	37.8	24.0	26.3	18.1	13.9	22.1	42.6	43.2	29.4	27.0	40.4	12.9	35.0	10.7	40.2	35.1	23.7	24.3	38.0	24.4	8.0	7.1	41.1
12	31.3	28.3	26.3	35.6	28.3	42.3	13.6	13.1	32.6	34.5	44.6	0.0	11.1	23.6	44.9	25.6	17.5	21.4	16.3	14.4	23.3	27.7	27.9	36.7	33.5	8.3	13.7	18.3	40.9	7.9	35.3	19.7	40.6	5.9	27.9	24.5	38.2	9.2	22.3	40.1	46.9	12.3
13	21.9	19.9	16.4	26.6	23.6	34.5	8.2	2.5	24.6	28.1	39.4	11.1	0.0	12.6	39.1	15.9	7.5	10.8	7.0	3.3	15.7	17.9	21.4	28.9	24.2	17.3	22.6	10.1	30.6	3.2	32.8	8.8	33.2	13.0	16.8	16.4	28.3	15.0	15.1	33.4	40.2	20.4
14	16.4	17.3	11.0	21.2	25.8	30.3	14.2	10.6	21.5	27.0	38.7	23.6	12.6	0.0	37.6	7.5	9.5	3.5	11.1	9.5	16.2	12.5	21.7	25.5	18.2	29.7	34.7	13.1	21.5	15.8	36.2	5.8	29.8	25.2	5.6	15.7	20.3	26.8	16.6	31.3	37.2	32.4
15	21.7	20.5	26.6	17.7	16.6	9.9	46.7	39.9	16.2	11.1	2.5	44.9	39.1	37.6	0.0	45.1	32.4	40.4	32.3	37.3	23.5	25.1	17.7	12.4	20.5	43.3	44.2	29.0	24.9	40.3	14.7	34.2	8.8	40.7	33.8	23.1	22.3	38.7	24.0	6.4	4.7	42.0
16	23.6	24.8	18.5	28.4	33.2	37.5	13.1	13.4	28.9	34.5	46.2	25.6	15.9	7.5	45.1	0.0	15.9	5.8	17.2	13.8	23.5	20.0	29.2	32.9	25.3	32.9	38.3	19.9	27.1	18.7	43.6	12.4	37.2	28.7	11.9	23.2	26.7	30.9	23.8	38.7	44.5	36.2
17	14.4	12.6	8.9	19.1	18.1	27.1	14.3	7.6	17.3	21.4	33.0	17.5	7.5	9.5	32.4	15.9	0.0	10.1	1.6	5.0	9.0	10.5	15.0	21.7	16.7	21.8	26.4	4.1	23.4	10.1	28.2	3.8	26.0	17.3	11.4	9.4	20.9	18.2	8.8	26.5	33.2	23.9
18	19.5	19.9	13.9	24.4	27.6	33.4	10.9	8.5	24.3	29.6	41.3	21.4	10.8	3.5	40.4	5.8	10.1	0.0	11.4	8.2	18.0	15.5	23.8	28.5	21.4	28.1	33.4	14.1	25.0	13.9	38.0	6.7	32.8	23.8	9.1	17.9	23.8	25.7	18.2	34.1	40.2	31.2
19	15.2	12.9	10.0	19.8	17.4	27.5	14.5	7.6	17.6	21.2	32.7	16.3	7.0	11.1	32.3	17.2	1.6	11.4	0.0	5.1	8.8	11.4	14.7	21.9	17.4	20.3	24.8	3.4	24.6	9.1	27.3	5.3	26.2	15.8	13.0	9.5	21.9	16.6	8.4	26.5	33.3	22.3
20	19.1	17.5	13.4	23.9	22.5	32.1	9.4	2.6	22.2	26.2	37.8	14.4	3.3	9.5	37.3	13.8	5.0	8.2	5.1	0.0	13.8	15.0	19.7	26.6	21.3	20.2	25.3	8.4	27.5	6.5	32.2	5.5	31.0	15.7	13.5	14.3	25.3	17.4	13.4	31.5	38.1	23.0
21	9.2	5.2	7.4	12.6	9.6	19.1	23.2	16.3	9.3	12.5	24.0	23.3	15.7	16.2	23.5	23.5	9.0	18.0	8.8	13.8	0.0	7.5	6.0	13.5	11.1	24.8	28.0	5.5	19.8	17.3	20.1	11.3	17.7	20.8	14.8	1.6	16.4	20.2	1.2	17.8	24.6	25.5
22	4.1	5.3	1.7	9.1	15.5	17.9	23.8	17.6	9.0	14.8	26.3	27.7	17.9	12.5	25.1	20.0	10.5	15.5	11.4	15.0	7.5	0.0	10.7	13.0	6.3	30.8	34.6	9.8	13.3	20.5	25.7	10.2	17.3	26.5	8.9	6.1	10.5	26.6	8.6	18.8	24.7	32.1
23	9.9	5.6	11.5	10.7	4.9	14.6	29.1	22.3	6.2	6.7	18.1	27.9	21.4	21.7	17.7	29.2	15.0	23.8	14.7	19.7	6.0	10.7	0.0	9.2	10.8	28.0	30.3	11.4	19.7	22.7	15.0	17.2	12.8	24.6	19.4	6.0	16.1	23.3	6.3	12.3	19.1	27.9
24	9.4	9.1	14.6	5.5	11.9	5.6	35.9	29.2	4.4	5.1	13.9	36.7	28.9	25.5	12.4	32.9	21.7	28.5	21.9	26.6	13.5	13.0	9.2	0.0	8.1	37.2	39.5	18.9	14.3	30.7	18.1	22.7	4.4	33.6	21.4	12.5	10.9	32.4	14.4	6.0	11.8	37.0
25	2.3	6.2	8.0	3.0	15.5	12.1	30.1	23.9	5.7	11.7	22.1	33.5	24.2	18.2	20.5	25.3	16.7	21.4	17.4	21.3	11.1	6.3	10.8	8.1	0.0	35.9	39.2	15.2	9.0	26.6	24.4	16.6	12.0	31.8	13.6	9.6	5.4	31.4	12.3	14.2	19.3	36.6
26	33.7	30.0	29.7	37.3	26.9	42.6	21.6	19.7	33.6	34.0	42.6	8.3	17.3	29.7	43.3	32.9	21.8	28.1	20.3	20.2	24.8	30.8	28.0	37.2	35.9	0.0	5.5	21.1	44.1	14.3	31.7	24.9	40.7	4.5	33.1	26.3	41.0	4.8	23.6	39.5	46.1	4.1
27	37.2	33.1	33.7	40.3	28.4	44.7	27.1	25.0	36.3	35.8	43.2	13.7	22.6	34.7	44.2	38.3	26.4	33.4	24.8	25.3	28.0	34.6	30.3	39.5	39.2	5.5	0.0	25.1	47.7	19.6	31.4	29.6	42.6	9.6	37.7	29.6	44.5	8.2	26.8	41.0	47.4	2.6
28	13.0	10.1	8.7	17.3	14.1	24.5	17.8	10.9	14.6	18.0	29.4	18.3	10.1	13.1	29.0	19.9	4.1	14.1	3.4	8.4	5.5	9.8	11.4	18.9	15.2	21.1	25.1	0.0	23.1	11.8	24.1	7.5	23.2	16.8	13.7	6.4	20.1	16.9	5.0	23.3	30.1	22.5
29	10.6	15.1	14.6	9.4	24.1	15.1	35.2	29.8	14.0	19.1	27.0	40.9	30.6	21.5	24.9	27.1	23.4	25.0	24.6	27.5	19.8	13.3	19.7	14.3	9.0	44.1	47.7	23.1	0.0	33.5	32.2	22.1	16.3	39.8	15.9	18.2	3.7	39.8	21.0	19.4	22.1	45.2

FIGURE 4.3 Service Van inter-station skim matrix for AM peak

The urgency gap is calculated based on the following formulation.

$$G_{ij} = \frac{(I_j^{\ d} - \Lambda_{j\tau}) - (I_j^{\ d} - \Lambda_{j\tau})}{\alpha \cdot tt_{ij}}$$

where $I_j^{\ d}$ is the discounted inventory for station j. Λ_{jt} is the target inventory for j at time τ (in this study, we assume constant inventory target throughout the AM peak period). α scales travel time tt_{ij} as impedance to be weighted for obtaining the gradient.

To consider future demand (with respect to the moment the strategy is being considered), a discounting method is used so that the weight is distributed in a way that the more into the future of a pickup or drop off the less weight it affects the urgency gap. This concept is formulated for station *i* as

$$D_i^{\ d} = \sum_{\tau} \frac{D_i^{\ \tau}}{(1 + r)^{\tau}}$$

where r is a parameter that puts more weight on the future demand when closer to 0 and requires calibration and operation objectives.

Therefore, discounted inventory of station i at the initial time step is

$$I_i^d = I_i + D_i^{\ d}$$

Intuitively, a van does not solely determine the urgency of a station pair two be served t

The resultant gap matrix is shown partially in Figure 4.4 for illustrative purposes. The urgency of a bike pair to be served is marked and ranked as red. As can see, Pair 11-15, Pair 33-19, and Pair 33-17 are urgent to be served among other bike station pairs.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.000	17.627	19.720	0.000	11.692	17.854	0.000	0.000	0.000	0.000	0.000	0.000	14.676	15.431	24.789
2	-0.929	0.000	0.000	-14.865	0.000	0.000	-8.196	-7.900	-38.236	-11.406	-13.207	-3.867	0.000	0.000	0.000
3	-3.654	0.000	0.000	-15.376	0.000	0.000	-11.040	-11.227	-29.821	-11.399	-13.498	-5.879	0.000	0.000	0.000
4	-4.304	14.865	15.376	0.000	11.959	22.115	0.000	0.000	0.000	0.000	0.000	0.000	13.607	13.914	27.625
5	-1.521	0.000	0.000	-11.959	0.000	0.000	-8.376	-8.050	-28.622	-14.437	-16.116	-4.712	0.000	0.000	0.000
6	-3.693	0.000	0.000	-22.115	0.000	0.000	-10.840	-10.645	-35.879	-20.365	-24.768	-7.325	0.000	0.000	0.000
7	2.459	8.196	11.040	0.000	8.376	10.840	0.000	0.000	0.000	0.000	0.000	0.000	23.657	16.895	17.325
8	-0.625	7.900	11.227	0.000	8.050	10.645	0.000	0.000	0.000	0.000	0.000	0.000	34.691	17.287	17.638
9	-0.788	38.236	29.821	0.000	28.622	35.879	0.000	0.000	0.000	0.000	0.000	0.000	23.679	24.002	40.489
10	-8.464	11.406	11.399	0.000	14.437	20.365	0.000	0.000	0.000	0.000	0.000	0.000	12.207	11.316	32.741
11	-0.564	13.207	13.498	0.000	16.116	24.768	0.000	0.000	0.000	0.000	0.000	0.000	14.321	13.504	74.539
12	-2.106	3.867	5.879	0.000	4.712	7.325	0.000	0.000	0.000	0.000	0.000	0.000	14.202	8.760	14.374
13	-0.271	0.000	0.000	-13.607	0.000	0.000	-23.657	-34.691	-23.679	-12.207	-14.321	-14.202	0.000	0.000	0.000
14	-0.265	0.000	0.000	-13.914	0.000	0.000	-16.895	-17.287	-24.002	-11.316	-13.504	-8.760	0.000	0.000	0.000
15	-6.571	0.000	0.000	-27.625	0.000	0.000	-17.325	-17.638	-40.489	-32.741	-74.539	-14.374	0.000	0.000	0.000
16	-1.117	9.834	13.544	0.000	9.331	12.452	0.000	0.000	0.000	0.000	0.000	0.000	19.102	24.830	18.618
17	1.772	0.000	0.000	-14.949	0.000	0.000	-17.172	-20.606	-26.954	-12.972	-14.844	-10.441	0.000	0.000	0.000
18	1.821	0.000	0.000	-17.938	0.000	0.000	-26.334	-27.203	-27.562	-15.329	-16.901	-14.425	0.000	0.000	0.000
19	-1.181	0.000	0.000	-24.397	0.000	0.000	-28.332	-35.636	-36.978	-22.358	-22.492	-21.381	0.000	0.000	0.000
20	-4.650	0.000	0.000	-15.932	0.000	0.000	-24.692	-38.226	-26.500	-14.145	-15.898	-14.642	0.000	0.000	0.000
21	-0.942	8.219	10.431	0.000	7.665	10.627	0.000	0.000	0.000	0.000	0.000	0.000	11.981	10.370	19.552
22	-0.210	28.110	48.906	0.000	18.527	22.491	0.000	0.000	0.000	0.000	0.000	0.000	22.763	25.318	28.756
23	-0.483	0.000	0.000	-20.340	0.000	0.000	-12.718	-13.037	-44.030	-23.010	-20.409	-8.828	0.000	0.000	0.000
24	-9.622	7.528	8.530	0.000	7.939	19.862	0.000	0.000	0.000	0.000	0.000	0.000	9.572	9.014	27.409
25	-6.940	0.000	0.000	-38.751	0.000	0.000	-13.978	-14.251	-48.723	-20.188	-20.245	-9.472	0.000	0.000	0.000
26	-1.825	2.626	4.405	0.000	3.629	6.341	0.000	0.000	0.000	0.000	0.000	0.000	10.061	6.703	13.674
27	-3.000	7.026	8.627	0.000	8.403	10.101	0.000	0.000	0.000	0.000	0.000	0.000	14.315	10.632	17.466
28	-1.363	4.815	8.309	0.000	5.306	8.572	0.000	0.000	0.000	0.000	0.000	0.000	13.345	10.277	16.883
29	-6.904	18.156	20.928	0.000	15.440	24.987	0.000	0.000	0.000	0.000	0.000	0.000	18.014	20.133	29.313
30	-1.577	0.000	0.000	-13.119	0.000	0.000	-22.773	-25.630	-22.889	-11.972	-14.176	-16.643	0.000	0.000	0.000
31	3.873	3.915	5.329	0.000	6.701	9.826	0.000	0.000	0.000	0.000	0.000	0.000	8.011	6.665	23.901
32	0.074	31.015	41.809	0.000	26.471	27.232	0.000	0.000	0.000	0.000	0.000	0.000	47.311	54.498	32.991
33	-2.272	11.036	11.584	0.000	11.902	37.841	0.000	0.000	0.000	0.000	0.000	0.000	12.038	11.613	37.857
34	-5.967	7.025	9.017	0.000	8.202	10.062	0.000	0.000	0.000	0.000	0.000	0.000	17.390	11.527	17.493
35	1.298	0.000	0.000	-20.936	0.000	0.000	-19.360	-20.120	-31.426	-16.516	-17.860	-12.223	0.000	0.000	0.000
36	-0.131	0.000	0.000	-19.501	0.000	0.000	-13.709	-14.469	-38.304	-17.257	-17.588	-9.074	0.000	0.000	0.000
37	-3.570	13.165	15.681	0.000	11.062	20.020	0.000	0.000	0.000	0.000	0.000	0.000	13.884	14.996	25.514

	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1	0.000	16.767	19.696	27.323	17.461	0.000	0.000	20.706	0.000	42.180	0.000	0.000	0.000	0.000
2	-9.834	0.000	0.000	0.000	0.000	-8.219	-28.110	0.000	-7.528	0.000	-2.626	-7.026	-4.815	-18.156
3	-13.544	0.000	0.000	0.000	0.000	-10.431	-48.906	0.000	-8.530	0.000	-4.405	-8.627	-8.309	-20.928
4	0.000	14.949	17.938	24.397	15.932	0.000	0.000	20.340	0.000	38.751	0.000	0.000	0.000	0.000
5	-9.331	0.000	0.000	0.000	0.000	-7.665	-18.527	0.000	-7.939	0.000	-3.629	-8.403	-5.306	-15.440
6	-12.452	0.000	0.000	0.000	0.000	-10.627	-22.491	0.000	-19.862	0.000	-6.341	-10.101	-8.572	-24.987
7	0.000	17.172	26.334	28.332	24.692	0.000	0.000	12.718	0.000	13.978	0.000	0.000	0.000	0.000
8	0.000	20.606	27.203	35.636	38.226	0.000	0.000	13.037	0.000	14.251	0.000	0.000	0.000	0.000
9	0.000	26.954	27.562	36.978	26.500	0.000	0.000	44.030	0.000	48.723	0.000	0.000	0.000	0.000
10	0.000	12.972	15.329	22.358	14.145	0.000	0.000	23.010	0.000	20.188	0.000	0.000	0.000	0.000
11	0.000	14.844	16.901	22.492	15.898	0.000	0.000	20.409	0.000	20.245	0.000	0.000	0.000	0.000
12	0.000	10.441	14.425	21.381	14.642	0.000	0.000	8.828	0.000	9.472	0.000	0.000	0.000	0.000
13	-19.102	0.000	0.000	0.000	0.000	-11.981	-22.763	0.000	-9.572	0.000	-10.061	-14.315	-13.345	-18.014
14	-24.830	0.000	0.000	0.000	0.000	-10.370	-25.318	0.000	-9.014	0.000	-6.703	-10.632	-10.277	-20.133
15	-18.618	0.000	0.000	0.000	0.000	-19.552	-28.756	0.000	-27.409	0.000	-13.674	-17.466	-16.883	-29.313
16	0.000	17.986	37.233	27.670	22.485	0.000	0.000	13.931	0.000	16.508	0.000	0.000	0.000	0.000
17	-17.986	0.000	0.000	0.000	0.000	-14.077	-27.936	0.000	-10.061	0.000	-8.085	-12.431	-17.818	-19.593
18	-37.233	0.000	0.000	0.000	0.000	-15.544	-29.041	0.000	-13.128	0.000	-11.486	-15.084	-16.344	-23.590
19	-27.670	0.000	0.000	0.000	0.000	-28.316	-39.353	0.000	-19.214	0.000	-17.921	-21.489	-40.294	-27.865
20	-22.485	0.000	0.000	0.000	0.000	-14.802	-26.747	0.000	-11.489	0.000	-11.094	-15.117	-17.096	-20.492
21	0.000	14.077	15.544	28.316	14.802	0.000	0.000	17.746	0.000	15.835	0.000	0.000	0.000	0.000
22	0.000	27.936	29.041	39.353	26.747	0.000	0.000	28.421	0.000	38.873	0.000	0.000	0.000	0.000
23	-13.931	0.000	0.000	0.000	0.000	-17.746	-28.421	0.000	-15.803	0.000	-7.642	-12.068	-12.119	-21.843
24	0.000	10.061	13.128	19.214	11.489	0.000	0.000	15.803	0.000	19.385	0.000	0.000	0.000	0.000
25	-16.508	0.000	0.000	0.000	0.000	-15.835	-38.873	0.000	-19.385	0.000	-8.130	-11.954	-12.603	-34.059
26	0.000	8.085	11.486	17.921	11.094	0.000	0.000	7.642	0.000	8.130	0.000	0.000	0.000	0.000
27	0.000	12.431	15.084	21.489	15.117	0.000	0.000	12.068	0.000	11.954	0.000	0.000	0.000	0.000
28	0.000	17.818	16.344	40.294	17.096	0.000	0.000	12.119	0.000	12.603	0.000	0.000	0.000	0.000
29	0.000	19.593	23.590	27.865	20.492	0.000	0.000	21.843	0.000	34.059	0.000	0.000	0.000	0.000
30	-17.721	0.000	0.000	0.000	0.000	-11.489	-21.408	0.000	-9.330	0.000	-11.072	-15.352	-12.485	-17.296
31	0.000	7.800	10.497	16.200	9.472	0.000	0.000	11.165	0.000	10.487	0.000	0.000	0.000	0.000
32	0.000	65.604	59.902	74.471	61.276	0.000	0.000	34.144	0.000	36.756	0.000	0.000	0.000	0.000
33	0.000	12.688	15.358	21.089	13.870	0.000	0.000	18.454	0.000	21.240	0.000	0.000	0.000	0.000
34	0.000	14.139	16.862	25.506	17.839	0.000	0.000	12.473	0.000	12.448	0.000	0.000	0.000	0.000
35	-26.387	0.000	0.000	0.000	0.000	-16.398	-36.596	0.000	-14.498	0.000	-10.166	-13.777	-15.848	-28.639
36	-15.221	0.000	0.000	0.000	0.000	-28.349	-35.927	0.000	-13.282	0.000	-7.568	-11.924	-15.029	-22.284
37	0.000	15.101	18.895	23.972	16.233	0.000	0.000	17.738	0.000	32.168	0.000	0.000	0.000	0.000

Note: The red cell indicates how urgent a bike station needs to be served. This is before being scaled by the impedance.

FIGURE 4.4 Urgency Gap Matrices.

The desire line analysis is visualized in Figure 4.5

FIGURE 4.5. Left: The top 30 Inter-zonal gradients (evaluated based on inventory gap and impedance); Right: All the non-zero inter-zonal gradients (The thickness represent the values).

One possibility can arise in the situations such as, for example, when a van picks up bikes sequentially at two bike stations and drops off bikes at a third station. This situation occurs because when there’s a major gap between the third one and the combination of one and two (but one of them). Moreover, the second station is favorably along the path from the first one to the third one. Although due to the limitation of van capacity, this situation happens less, it is possible to consider when using a hierarchical clustering method where not only the demand gap of individual station pairs are measured but also gap between clusters. For example, in a three-station (A, B, C) scenario, instead of only measuring gap of {A, B}, {A, C}, and (B, C}, we can also measure {A, {B, C}), {{A, B}, C}, {B, {A, C}}. As we see, for larger problems, clustering methods should be used that take into account the spatial impedance among stations.

The second and third step can be seen as an algorithm to aid the vans in picking up bikes in a strategic way for two objectives -- maintain stocks to be close with stations' target inventory and reduce travel time as much as possible. A challenge is to avoid a multiple-van scenario where collaboration is needed. The study clusters the bike stations into different regions which are adjusted over time when the vans' locations change. The clustering criterion is based on the skim matrices, though other criteria can be incorporated, such as the number of bike station urgently needing service.

Two important advantages of using simulation are: (1) many constraints such as the capacities of bike stations and vans in the formulation section are nearly trivial. (2) Finding an optimal solution can be viewed as a learning process by the operator and therefore, easier to present and adopt.

The operation cost for rebalancing is mainly composed of staffing cost, mileage/fuel cost, and vehicle maintenance. This study considers the number of staff and operation mileage as the proxies for staffing cost and fuel consumption. Vehicle maintenance cost is treated as a long term cost and considered not significant in any one-day operation.

TABLE 4.1 Van Cost Table

Vans in Operation	1	2	3	5	7	9
Staff Cost ($)	15.65	31.30	46.95	78.25	109.55	140.85
VMT (Miles)	3.72	5.44	12.31	19.57	26.63	38.33
Total Bikes Served	16	31	44	69	77	92

This rebalancing process can also be seen as an ordering procedure of pick-up and drop-off stations with collaboration among vans based on the two criteria (i.e., travel cost and urgency). Since the routing is obtained through random combination in which bike station pairs with high urgency scores are more likely to be chosen, the collaborative one that renders lower cost can be naturally selected without explicitly being designated.

Converting a dynamic problem into a static one needs to allow for a static index that contains information about the prioritization so that a van attempts to serve urgent bike pairs earlier. This information is captured by the urgency weighted by the distance with a parameter α which can be tuned during operation. An operator can increase or decrease the relative weight of distance with respect to urgency.

4.3.2 Parameter Estimation

Due to the nonlinear nature of the problem, a grid-search method is used for parameter estimation on the discounting factor, impedance scaler, number of trucks, and target inventory. Table 4.2 shows some results.

TABLE 4.2 Sensitivity Test for 1 truck for urgency gap served per mile

$r \setminus \alpha$	0.25	0.5	0.75	1.0	1.25
0.001	1.490	1.490	***1.490***	1.490	1.490
0.01	1.427	1.427	1.428	1.427	1.425
0.50	1.344	1.345	1.345	1.346	1.349
1.00	1.356	1.356	1.356	1.357	1,358

Note: The bold and italic cell indicates a relatively ideal fine-tuned value

TABLE 4.3 Sensitivity Test for 2 trucks urgency gap served per mile

$r \setminus \alpha$	0.25	0.5	0.75	1.0	1.25
0.01	0.015	0.011	0.015	0.023	0.011
0.50	0.015	0.010	0.013	0.021	0.213
1.00	0.013	0.018	0.018	0.018	0.017
2.00	0.023	0.023	0.023	***0.024***	0.024

Note: The bold and italic cell indicates a relatively ideal fine-tuned value

TABLE 4.4 Sensitivity Test for 3 trucks urgency gap served per mile.

$r \setminus \alpha$	0.25	0.5	0.75	1.0	1.25
0.50	0.007	0.009	0.008	0.008	0.006
1.00	0.011	0.007	0.010	0.011	0.012
2.00	***0.012***	0.012	0.011	0.008	0.010
4.00	0.009	0.011	0.007	0.010	0.011

Note: The bold and italic cell indicates a relatively ideal fine-tuned value

As can be seen in the Table 4.2 – 4.4, when we increase the number of service vans, discounting factor r should be increased, in order to achieve better routing strategy. That is, when there are more vans, there is less need to consider “future demand” and more focus on the present inventory. Also note that the objective function is non-monotonous, implying that a stochastic searching mechanism might be beneficial to avoid being “trapped” in local optima. However, we did observe a general “stochastic monotonicity” in the fine-tuning region.

The results show that the current demand can be handled by one to two vans. According to LA Metro staff, they are currently (at least in 2017 Q3 to 2016 Q2) dispatching three vans simultaneously serving the downtown area during AM and PM peak hours. This suggests that there exists a cost reduction opportunity from implementing more advanced bike redistribution strategies such as proposed here. This may be more significant in the future, if the bikeshare usage is significantly higher and several more redistributions vans are in operation.

Owing to the hyperparameter tuning, the model might run the risk of being overfitted to one particular data set. The 2017 Spring data set is used for validation. The result (Figure 4.6) shows no overfitting issue for the estimated parameters.

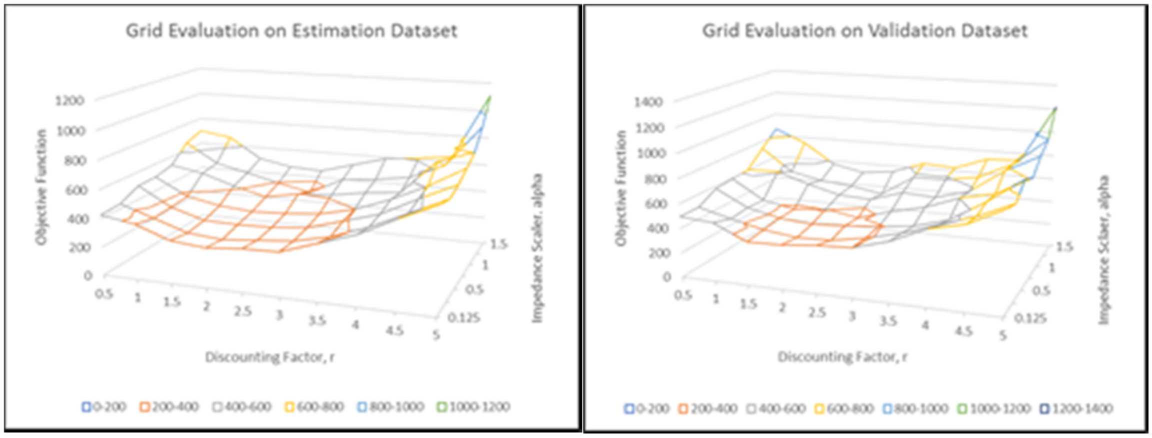


FIGURE 4.6 Checking for overfitting of the estimated models in 3-van operation simulation

4.4 Results and Discussion

4.4.1 Results Analysis

We imported the newly induced demand from the P2P service by adding the additional pick-up and drop-off demand to the 2016 Sep. 17 conditions. Note that the algorithm is so set that the pickup/delivery van has no need to return to the depot by the end of the delivery.

Table 4.5 shows the top 9 station pairs based on two criteria: demand gap and impedance (van travel time). The inter-station travel time is obtained from skimming SCAG highway network. Travel times for regular workday from Google API are used to validate the result.

TABLE 4.5 Station Pair Identification

No	Pair_ID	Impedance	UrgencyGap	UrgencyScore
1	24-0	3.8118	20.5033	5.3788
2	30-35	2.5959	12.6080	4.8567
3	21-2	2.9370	9.6106	3.3875
4	27-18	5.6020	13.0247	2.3249
5	49-38	3.3680	7.5643	2.2458
6	10-14	4.1261	9.0276	2.1879
7	48-56	5.8379	10.0661	1.7242
8	41-26	4.2764	7.2555	1.6966
9	12-7	4.1512	6.9648	1.6777

Figure 4.7 shows the static routing optimization strategy given 1, 2, 3, 5, 7, 9 vans. Redistribution vans operating under current (though tuned) parameter settings for discounting and weighing over distance and “inventory gap” still show a tendency to avoid central areas where congestion is significant. Therefore, further weighting might be needed to adjust if serving transit hub is more of priority (though it might lead to a suboptimal solution for the rebalancing problem). We applied the same method to study the impact of various number of trucks (1,3,5,7). Currently, Metro is typically designating 3 vans for peak hours with exceptions when demand is particularly irregular.

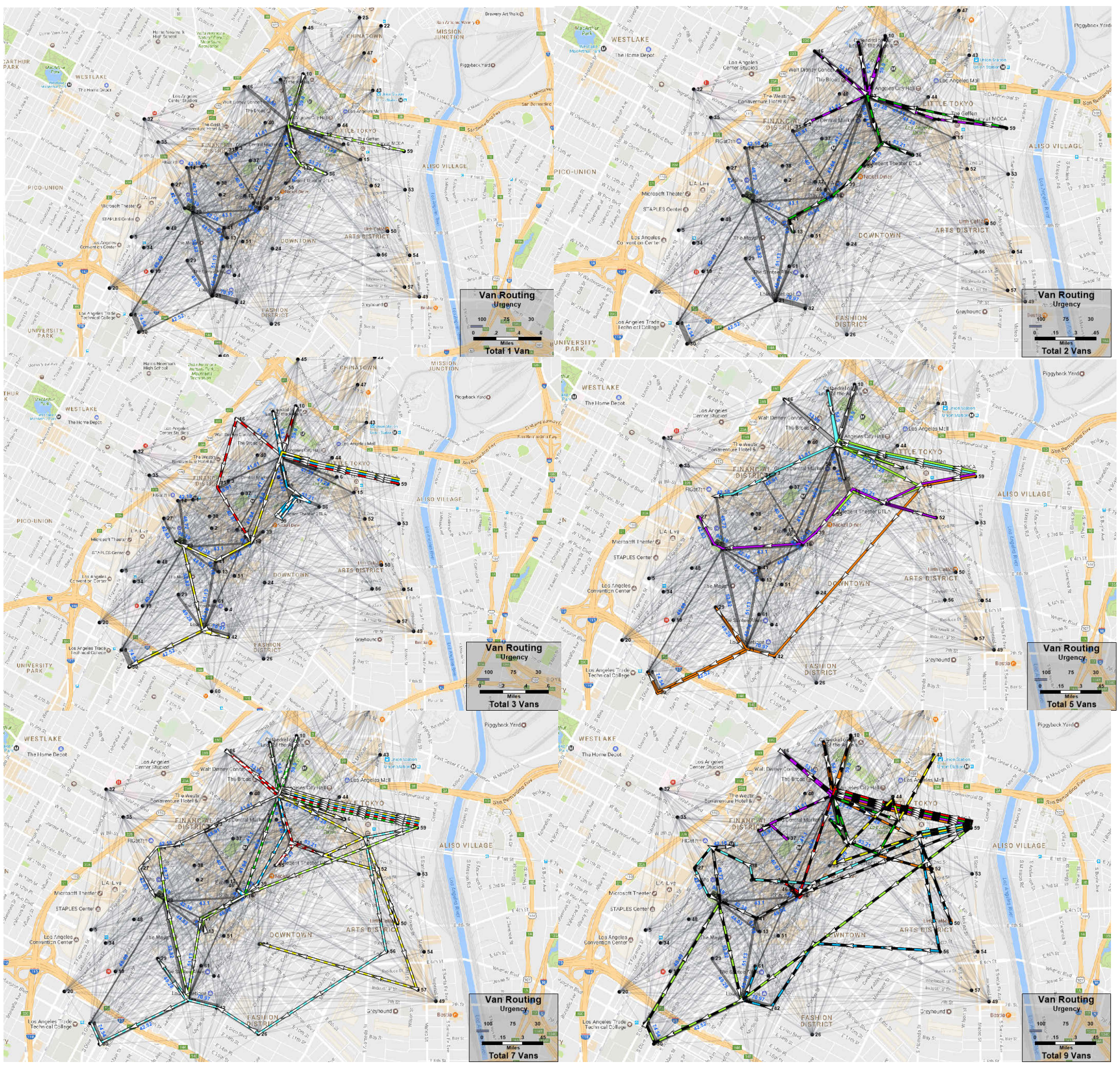


FIGURE 4.7 Van Routing (Total of 1, 2, 3, 5, 7, 9 Vans)

Below is an example 3-van scenario with 0.9 weight on inventory gap (and 0.1 weight on impedance). Below are the station sequence for each truck (P for pick-up station, D for drop-off station) and the total number of bikes served.

- Van 1: 10 (P)-14 (D)-21(P)-2(D)-15(P)-17(D): 35 Bikes
- Van 2: 39(P)-32(D)-54(P)-22(D)-27(P)-18(D): 27 Bikes
- Van 3: 49(P)-38(D)-60(P)-57(D)-36(P)-27(D): 33 BIkes

Figure 4.8 shows one example of individual van. Note that the dotted line indicates that it reaches 8:00am simulation termination before the van actually arrives at the destination station.

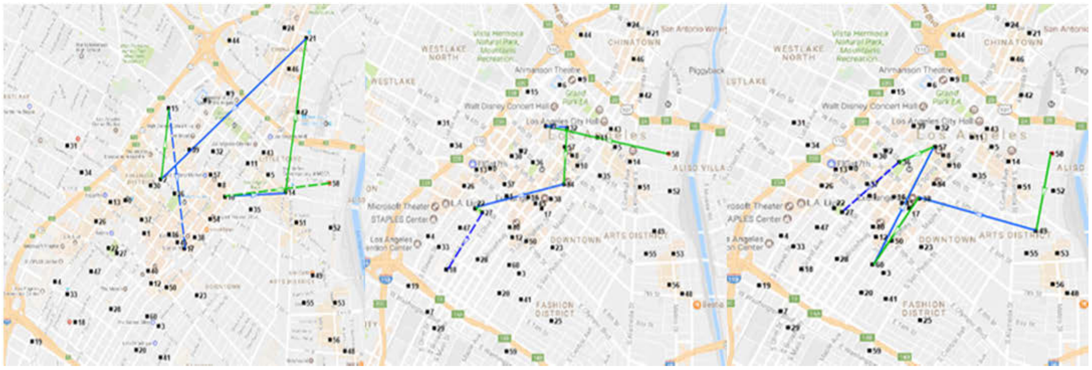


FIGURE 4.8 (a) Van 1 Trajectory; (b) Van 2 Trajectory; (c) Van 3 Trajectory

Based on the above analysis, it is seen that the current 2-van service is sufficient and only needs rerouting to accommodate the extra demand from the newly added ridesharing services. That is, marginal increase caused by ridesharing may not require change of the current service vans, provided an adjusted strategy is used, as proposed here.

Relationships among the spatial demand distribution, the number of bike stations, and the number of vans in service need to be studied. Online algorithms for the direct use by the operator may be a potential direction of study. Future study on vehicle routing for various numbers of stations is also desirable.

The data collection procedure and measurements are confirmed to be consistent with those during September to December of 2016. The result shows minor overfitting and therefore, the parameters are adjusted (with the compromise of minor increasing of the final objective function) to achieve a balance between the reducing the evaluated objective function for the training dataset as well as the validation dataset.

4.4.2 Why The Proposed Solution Algorithm Is More Efficient And Tractable

The essential action of bike redistribution is to pick up some bikes from one or several stations and to drop off at other bike station(s) then the van drives to another station to pick to iterate the process. The proposed algorithm starts from this observation and builds a solution set on the sequence of station pairs rather than that of individual stations to significantly reduce the computational effort and output performance. A more mathematical way to illustrate this is that the proposed algorithm converts a "$n!$" problem (where n being the number of stations) to a problem that is about $\frac{n}{2}!$. Below shows the corresponding graph which presents a significantly larger gap when n gradually increases.

4.4.3 Future Extension

The algorithm can be improved through more refined simulation that considers more details during operation. An actual day-to-day learning process using the algorithm would also be beneficial for understanding the prescriptive power of the algorithm. During the progress of our study, the Los Angeles Metro has been expanding the bike sharing stations to locations near the Port of Los Angeles, City of the Pasadena, and Venice. The impact of the bikeshare program in the City of Santa Monica would be also interesting to consider and be integrated into the proposed P2P analysis framework. In addition, one might be curious of the possible scenario where a van would pick up (drop off) consecutively at two or more stations and drop off (pick up) afterwards. This requires clustering using the proposed method, as mentioned above. That is, the algorithm requires clustering the stations and creating “super stations” to run simulation. This will significantly increase the computational effort. In this study, this scenario is not considered, though it is possible that during the simulation, a van would be able to serve a station “along with way.”

It will certainly be useful to work directly with the LA Metro bike redistribution operators and decision makers to test the validity and effectiveness of the proposed algorithms and further fine tune the parameters.

5. Mode Shift Study

5.1 Demand Model Overview

This study utilizes Southern California Association of Governments (SCAG) RTP 2016 regional travel demand forecasting model by using 2016 Scenario 3 as the base year. Ridesharing, transit, and bikeshare are modeled as one holistic system due to the model's resolution limit. Because of this, the model can predict the modal shift from drive alone to an "augmented transit system" but it is not clear what the distribution among the modes involved within that augmented transit system is, i.e., among transit, transit-rideshare, transit-bikeshare, and transit-rideshare-bikeshare. Figure 5.1 shows Tier 2 Traffic Analysis Zones (TAZs), the highway network, and the transit network near the downtown LA area which are used by SCAG RTP 2016 travel demand forecasting model.

(a) Tier 2 TAZ setup (b) Highway network setup (c) Transit network setup

FIGURE 5.1 SCAG 16 RTP travel demand forecasting model setup near the downtown LA

5.2 Incorporating P2P and Bike Share Service

Since the SCAG RTP model has no explicit consideration of services such as Transit Network Companies (TNCs) and ride share, some indirect adjustment is needed to act as the proxy of these emerging business models. We first added a non-motorized mode (i.e., bikeshare) along with its travel cost attributes in downtown area to reflect the bikesharing service. Then we adjusted the 87 Tier 1 TAZ pairs (914 Tier 2 TAZ pairs) for access and egress from urban rail and commuter rail service. Then we re-skimmed the network to obtain the accessibility index for mode at the end, and a partial model run was conducted from trip distribution, mode split, and PA-to-OD steps by assuming new total trip changes during the day (which means that we may lose or gain more trips during certain periods). The next section presents the results from the SCAG RTP 2016 model run. The modification is based on the project's need and SCAG, as they state, takes no responsibility for any of the results.

Below shows a summary of the adjusted parameters for SCAG model to consider P2P from a regional level perspective.

- Adjusting non-motorized travel cost only in downtown areas to reflect the addition of bikeshare services
- Adjusting 87 Tier 1 TAZ pairs (i.e., 914 Tier 2 TAZs) for access and egress from urban rail and commuter rail (Union Station)
- Adjusting both walk skims and access/egress urban and commuter rail in downtown
- Model run on the trip distribution, mode split, PA-to-OD steps on the last (5th) iteration of the SCAG model.

5.3 Results and Discussion

Due to the large number of TAZs, we picked two TAZ pairs as examples and then present a general change of trend in the overall study area. The comparison of OD pair 0920-1947 is shown in Figure 5.2. UR stands for Urban Rail and CR stands for Commuter Rail. Both rideshare and bikeshare are incorporated in this example.

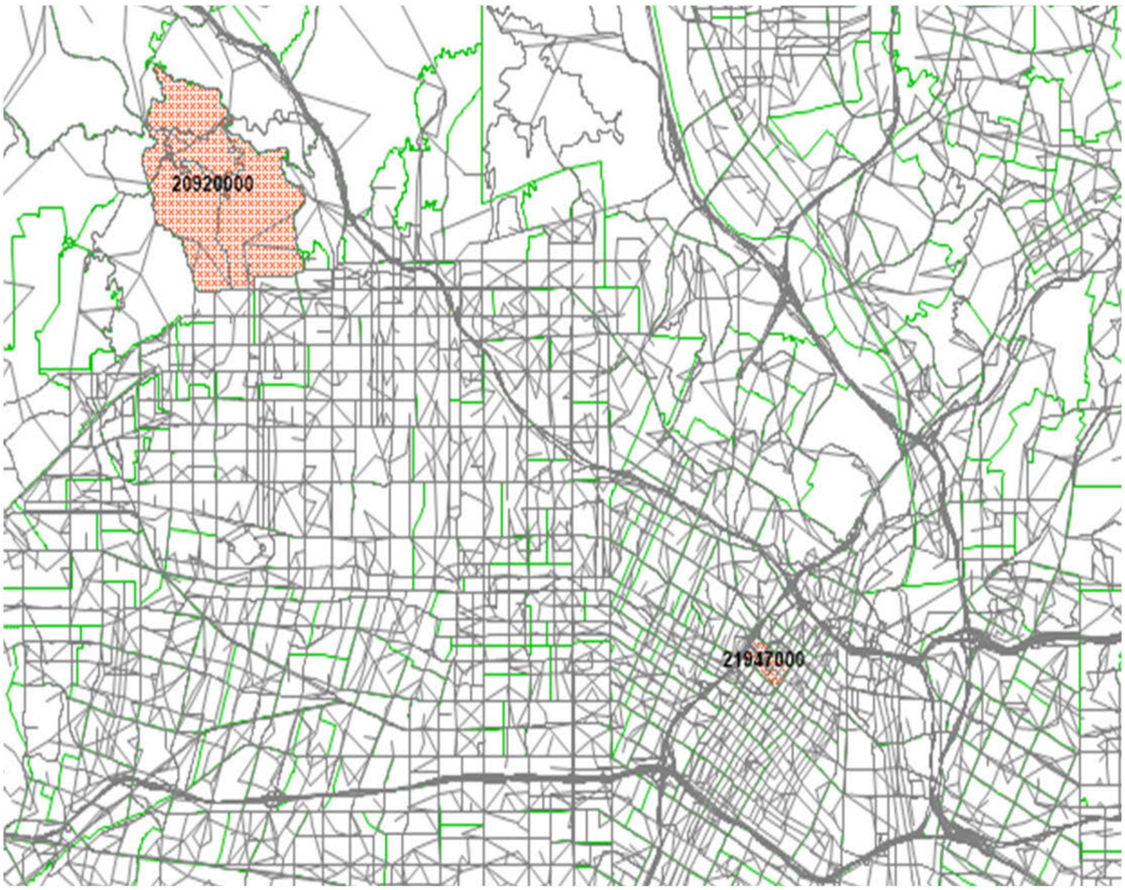


FIGURE 5.2 Location of Origin (0920) and Destination (1947)

TABLE 5.1 The before-after analysis of mode distribution for OD pair 0920-1947.

	Origin (Tier1)	Destination (Tier 2)	Acc UR or CR	Egr UR or CR	Other
AFTER	920	1947	19.0834	2739.5225	0.0972
BEFORE	920	1947	16.3315	2688.3430	0.0717

Figure 5.3 shows another (TAZ 1008 to TAZ 1947).

FIGURE 5. 3 Location of Origin (0920) and Destination (1947)

TABLE 5.2 The before-after analysis of mode distribution for OD pair 1008-1947.

	Origin (Tier1)	Destination (Tier 2)	Acc UR or CR	Egr UR or CR	Other
AFTER	1008	1947	95.4936	2739.5225	2.2389
BEFORE	1008	1947	82.3542	2715.3430	2.3176

Note that the cost of a given OD pair also influences the trips of other OD pairs in scenarios where P2P has significant influence on the system performance. Thus the elasticity or sensitivity to pricing is worth further exploration.

Table 5.3 shows the AM peak hours (6AM-9AM) passenger trips arriving within downtown Los Angeles. As can be seen, the change is not significant when we integrate only the P2P service with the Metro Red Line. This finding is consistent with the finding from the section 3. We suggest a broader network integration in the future study.

TABLE 5.3 AM peak passenger trips arriving within DTLA

Mode	Base	Bikesharing Only	Ridesharing Only	Bikesharing + Ridesharing
Drive-Alone	93,519	-17	-113	-136
Drive 2+	27,927	0	-25	-32
Rail	12,609+4,798	15	144	179
Other Transit Modes	10,198	15	-6	-5

The reduced travel cost produces moderate mode shift. In total, more trips are shown to shift from highway (auto) trips to transit and active transportation. In transit submodes, rapid bus is shown to receive a reduced demand. This could be because of the reduced cost to access to rail (UR and CR) from using the newly enhanced ride-sharing and bike share services.

6. Mobile Application

6.1 Overview

Information technology (IT) such as a mobile application provides an opportunity to attract more people to participate in ridesharing systems because mobile apps provide easier accessibility to the system. When many travelers are unfamiliar with an integrated-modes transit feeder concept, a mobile application can help them understand how it works and how their travel can be optimized. We design the mobile application in which a user gets the matched connections after simply inputting their origin/destination, early departure time and latest arrival time. The user Interface of the app smoothly guides users in finding his/her route. After a user chooses a proposed route, he/she can also easily follow the guidance from the mobile phone. Furthermore, this mobile application can collect a massive dataset to analyze travelers' behavior, subject to privacy settings and regulations. From this dataset which includes revealed preferences, the system designer or policy maker can redesign their ride-matching strategies as well. Table 6.1 summarizes the benefits of mobile the application.

Table 6.1. Benefits of Mobile application for P2P Ridesharing and Bikesharing

- Ease of Use
    - Improved access for new transportation service
    - Reducing the nervousness about a new ridesharing system concept.
    - Visualization of multi-modal options

- Data collection and analysis
    - Collecting real-time data for planning to increase transit ridership
    - Analysis of users' travel behavior
    - Spatial usage pattern such as hot-spots and frequently used go-points
    - Connection to a web-based survey
    - Field survey application
    - Integration of public/private transportation supply

In addition to the developed components in the precursor Phase-I (2015-16) project, this task involves integrating the bikesharing program in the mobile application. The mobile application developed in the first phase of the project includes the Metro red line and the P2P ridesharing stations, and can provide itineraries that include a combination of these alternatives. In this task, we added the bikesharing stations located in downtown LA to the mobile app. To improve visualization of the matched routes, we redesigned the mobile application so as to indicate the options more intuitively by showing specific icons for each mode and to provide more detailed information. The details of the modifications will be addressed in the next section.

6.2 Application Design

Figure 6.1 is a general overview of our mobile application. We call this application "***DeepRides***" because the app takes advantages of multiple modal layers including transit, auto, and bike, and is thus "deeper" in its analysis of the "rides". Furthermore it is capable of expanding travel modes to all possible shared mobility options for work envisaged for the following project in the sequence (Phase 3 research in 2017-18). We have designed all activities on digital maps. The map system is powered by Google maps. Based on this information, the algorithm in our server finds available drivers in the Driver Database and matches drivers by network database using our advanced matching algorithm. It also checks bike availability by parsing the LA metro bikesharing system data.

The ***DeepRides*** server is also designed to collect alternatives' travel time and cost information from third-party agents like rideshare or ride-hailing companies (such as Uber/Lyft) or Transit agencies,. A rider can make a decision based on their preferred mode as well. For the purpose of any data collection through comprehensive surveys, respondents will be asked to give answers to a short satisfaction questionnaire, on pushing the button on the ride-matching result screen. From the survey window, we can capture the traveler's preferences and important variables such as their willingness to pay. This app also guides travelers to respond to more detailed surveys if they are willing to do so.

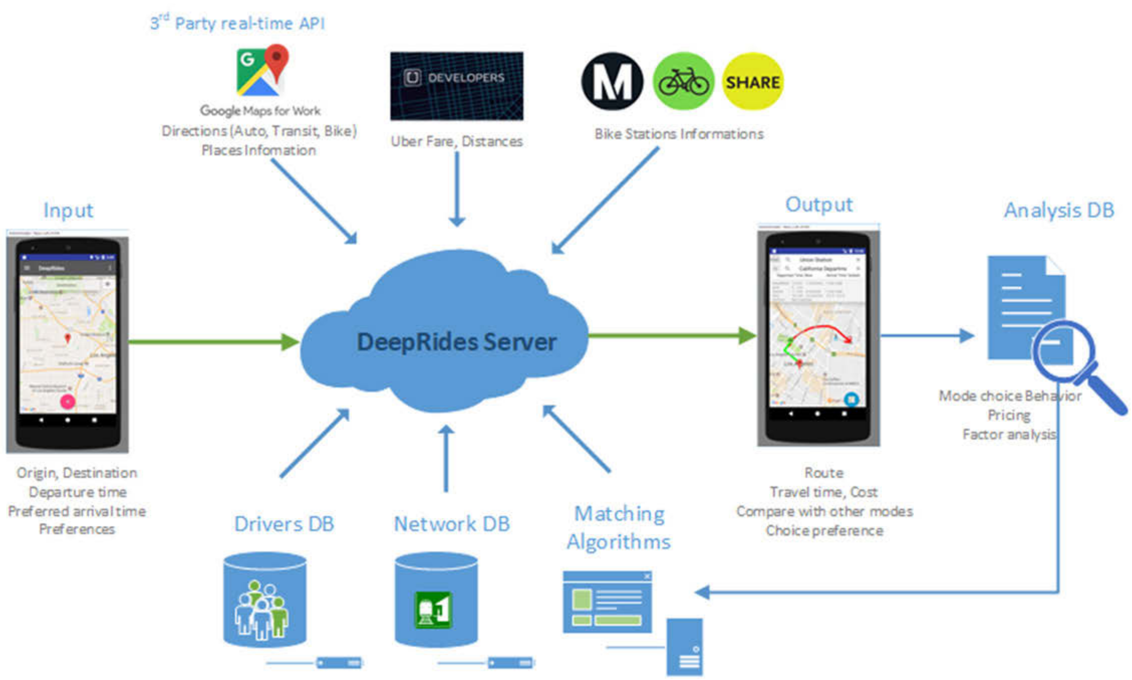


Figure 6.1 System overview of the mobile application (DeepRides)

We fully utilize several open source IDE and libraries to develop the mobile application, namely, Android Studio 2.3, Pycharm Studio, Python2.7, Tornado Server, MongoDB and Matlab 2016b. The number of drivers in our research scope is approximately two hundred thousand, for a morning period that we studied. Furthermore our algorithm inherently includes a large number of complex querying processes such as geo-spatial queries, and data-join, which requires high performance computing power. Multi-processor computation is used with rider and driver databases, for efficient and fast processing. Shared distribution and geo-index techniques in MongoDB enable fast processing of querying from our database. The core matching algorithm is coded in MATLab, and Python programming manages the database. In addition, Python enables the interaction between the MATLab engine (installed on the server) and the mobile application.

In overall design of ***DeepRides***, Application Programming Interfaces (APIs) play an important role for communication between the server and the various applications. ***DeepRides*** fully utilizes HTTP RESTful APIs, which enables an application and a server to dynamically interact by using a requesting form of a url type and responses of a json/xml type. Table 6.2 and Figure 6.2 show examples of a requesting url and its response. The main advantage of an HTTP RESTful API is that any internet-connected device can access the ***DeepRides*** server. We expect that the accessible app will increase the number of participants in our ride-matching system. This means that it is capable of attracting 3rd party participants such as from TNCs (Uber, Lyft and Carpool companies, for instance).

After our mobile application requests a matched ride, the ride-matching engine on the server finds the optimal matching results. In addition, the server provides travel time and cost for other modes to help the user select a reasonable alternative. In our study, the alternative modes are private vehicle, public transportation only, Uber, and Carpool. The information is obtained via commercial Open API (Google directions for Car and Transit, Uber, and Carpool).

Table 6.2. Examples of HTTP Open API requesting ride-matching

Function	Request Url
Ride match	http://address/routes/SLat/SLng/ELat/ELng/EarlyD/lateA/OType/DType/OID/DID/APIkey
Near go-points list	http://address/gopoint/SLat/SLng/APIkey
Preference setting	http://address/preference/String/APIkey
Travel history	http://address/travelhistory/APIkey

Figure 6.2. Sample results of trip-matching through an HTTP API request

6.3 Mobile application UI

Figure 6.3 and 6.4 indicate the user interfaces (UI) of ***DeepRides***. This application is developed from a rider's point of view, i.e. the drivers' trips are encoded in the app, although it is straightforward to extend the app to accept driver trips as input as well.

For a convenient UI, we have designed all activities on digital maps. The map is powered by *Google maps* and *Google Place Autocomplete*. By dragging a map on a screen, a user can simply register his/her destination by checking address (a). Users can also search their itinerary by pushing the direction button (pink button on the screen) and input their Origin and Destination on the input box (b). For user convenience and accurate place information, we utilized *Google Place Autocomplete*. As can be seen (c), suggested words help a user easily find his/her place. Since there are many places with the same place name existing in other regions, we restrict the *Autocomplete* searching coverage to only our research-scope area. It is also possible to set the departure time and the arrival time by using a clock UI.

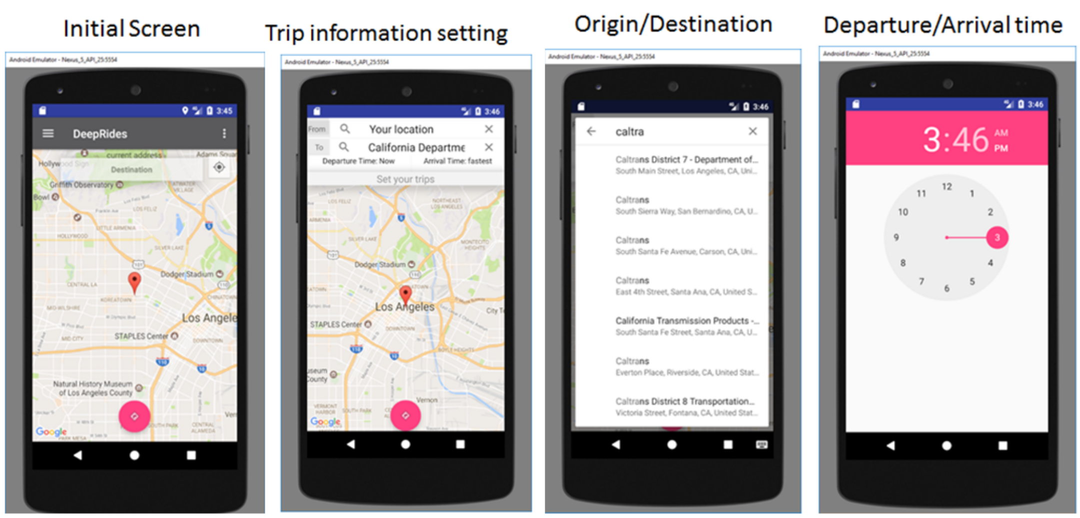


Figure 6.3 User Interfaces for user input

Fig 6.4 shows the user interface with the matched results. Each mode has a different icon and route color for distinctive visualization. When a rider pushes the mode icon, he/she can see their approximate arrival time to each go-point. A rider can check their detailed route information and location by enlarging the screen. The app provides not only matching results but also travel time and cost information on the mode alternatives. From this information, participants can realize that our matched results are attractive. For example, when a rider asks rider-matching from Hollywood to California District 7 in LA downtown, ***DeepRides*** shows the route that has walk, ride-share, Redline, and Bikesharing. That is, 1) walk to the near go-point and use a rideshring 2) transfer to Red line at Hollywood/Vine station, 3) get off the train at the Civic Center station and ride a bike to the destination. It takes 31 minutes, which is only 1 minute slower than a vehicle trip. It is faster and cheaper than Uber in this particular case (based on the data we accessed for the particular time; thus it is not to be generalized). Furthermore, matching result says that it is faster than using purely the transit mode.

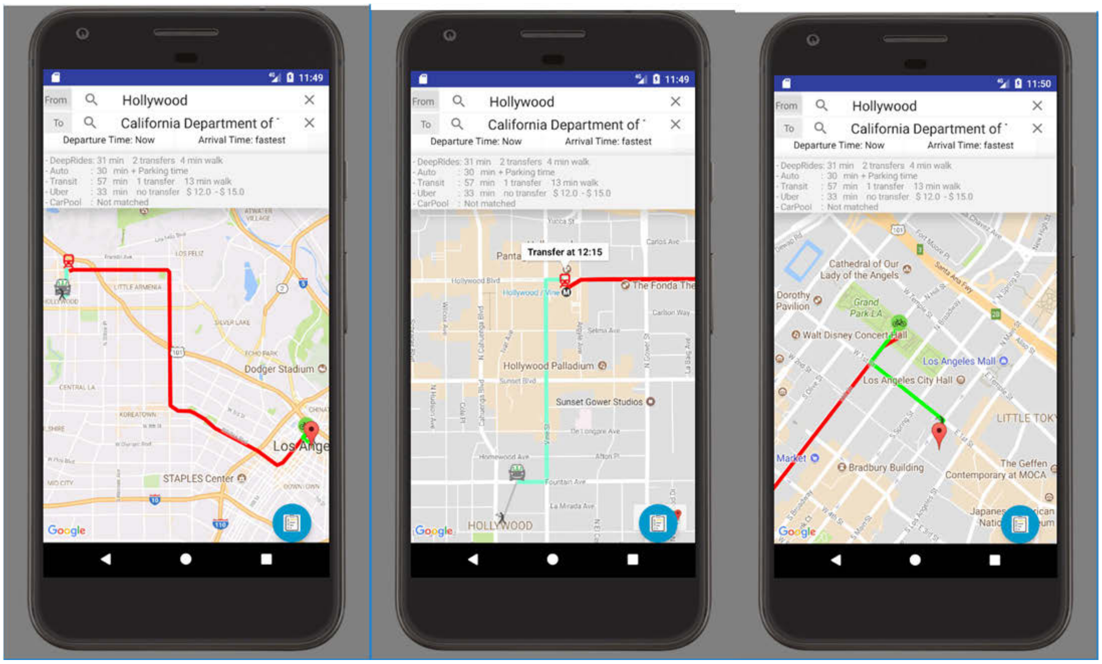


Figure 6.4 User Interfaces for matched results

The mobile app is capable of collecting riders' preferences about our ride-matching system from the short survey screen. A user can go to this screen by pushing a blue survey button activated after route matching. Figure 6.5 shows the survey screen. A user is asked to show their preference toward the matched-result and their willingness to pay (WTP) for the service. Since the previous screen provides price information for other modes, we expect that a user can give their opinion about the price properly. Mode choice preference under the given conditions can be collected from the last question. With this survey data, the route results will be sent to the ***DeepRides*** server so that we can analyze the behavior of the participants in detail.

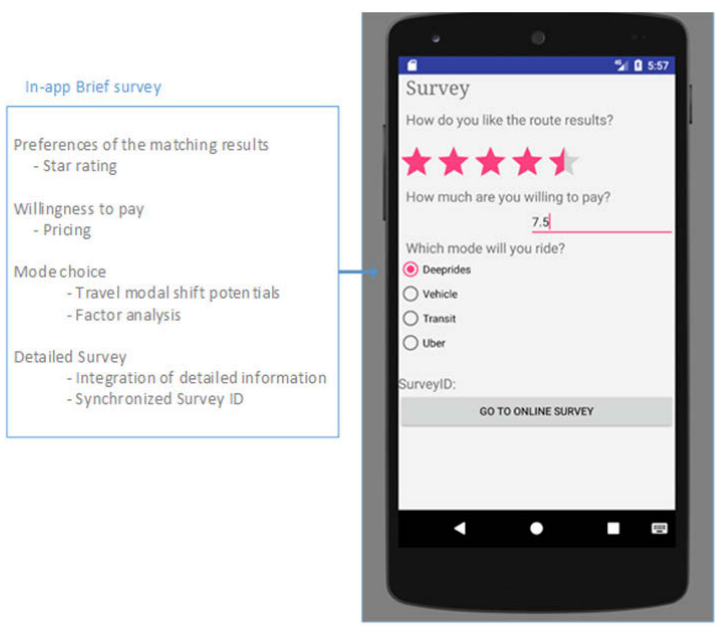


Figure 6.5 Survey screen of DeepRides app

7. Survey design

As the P2P ridesharing system is a travel that is largely not experienced by travellrs at this time, it is important to know how users accept the proposed system. In order to conduct a user acceptance study, we have prepared a set of survey questions for conducting a field survey. Based on discussions with Caltrans, the survey is scheduled to be conducted in conjunction with the subsequent UCConnect research on a fully integrated system that includes bus transit as well as other shared-mobility options, during 2017-18. We however describe the expected survey details here.

This survey is modified from a plan for a survey that was initially prepared during the first phase of this sequence of projects, during 2015-16. The bikesharing system is now added to the transit-ridesharing alternative that was initially considered in phase-I. Therefore, this survey also includes questions regarding bikesharing and is designed for individuals who use the LA Metro red line, the LA bike share system, or the public parking lot near LA Metro red line. In the rest of this section, we present the detailed survey plan, survey screening, and a possible analysis methodology.

7.1 Survey Plan

7.1.1 Field Survey Area

- Survey period
  - The survey is conducted during three days Tuesday through Thursday in morning peak hour (7:00 - 9:00 am) and evening peak hour (4:30 - 6:30 pm).

- Survey area
  - LA Metro red line user: the survey for the LA metro red line users is conducted on the red line.
  - LA public parking lot user: the survey for the parking is conducted at the public parking lots near red line stations.
  - LA bikesharing program user: In the morning peak hour, the survey for the LA bikesharing program user is conducted at the Union station west portal bike station and 1st & central bike station. In the evening peak hour, the survey for the bikesharing user is conducted at the Main & 1st bike station and Broadway & 3rd bike station.

Table 7.1 Target number of Survey respondents

	LA red line station	Bike station	Parking lot	Total
target number	50	50	50	150

7.1.2 Survey Method

During the survey, a smart-phone (or a tablet) 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 their trip, and will choose the best travel mode among alternatives and will be asked follow up questions on their opinion on the ridesharing cost, and the ease of working with the app. The mobile survey instrument is connected with the QuestionPro survey program. The survey results are submitted directly to a secure server, QuestionPro data collection set.

The survey for the P2P ridesharing system as a transit feeder contains 20 questions including some open-ended questions for which the respondents can provide commentary. The survey is offered in English, and is designed to take about 15 minutes to complete. Obviously this means that many busy travelers may need to be asked to take the survey after their busy travel period, if a field survey needs to be done. One option in this case is to conduct the survey in person at their leisure, after the travel or during a trip in a car or transit vehicle. Parking lot surveys after the trip are also possible. Initially, however, the survey can be done on the internet, with users who are not on their trip at the time, though corrections for biases will also be needed in this case. The initial target is to collect at least 50 completed survey result from each survey area. The survey data will be analyzed to see the mode choice pattern among given travel alternatives.

7.2 Screening Questions

The survey is composed of four parts: (1) Testing and feedback on the App described in section 6; (2) Screening questions on the P2P ridesharing system; (3) Current travel status; (4) Socio demographic information. The screening questions are designed to assess their mode choice behavior with sociodemographic information. Participants will be asked to try the app and requested to answer the following questions within four categories.

Table 7.2 Overview of screening questions

Category	Elements
. Testing and feedback on App	Mode choice, ridesharing cost, ease of working with the app,
. Screening questions on P2P ridesharing system	Necessary incentive, distance between origin/destination and red line station, proper mode to red line station, checks on whether the user wants to transfer or not when using the p2p ridesharing system, preference to be a driver or rider in the p2p ridesharing system
. Current travel status	Travel mode, mode choice reason, travel distance, travel time, number of transfer
. Socio demographic information	employment status, trip purpose, household income, number of cars available, number of people in household

7.3 Analysis Methodology

During the survey, respondents will be asked to choose the most preferable mode from among the proposed travel modes based on characteristics such as time, cost, and socio-economic characteristics. It is possible to conduct a predictive analysis based on the respondents' choices collected in the survey. To examine the discrete choice behavior, So and Kuhfeld (1995) indicates generalized logit model, conditional logit model and mixed logit model as possible statistical techniques for this kind of a survey. We provide below some possible models of this kind, so as to detail the possible candidate analysis methodologies which are well-known the transportation field. We however also suspect that the validity of the calibrated models would be questionable when such discrete choice models are built from data on stated preference to alternatives that are not experienced fully by the respondents yet. Alternative methods such as conjoint analysis that is more prevalent in consumer behavior analysis for business and marketing may also be relevant, though not used extensively the transportation user behavior studies. This will be further explored in the third phase of this sequence of projects on shared travel, during 2017-18.

7.3.1 Multinomial discrete choice model

Consider an individual choosing from among m alternatives in a choice set. Let Π_{jk} denote the probability that individual j chooses alternative k, let X_j represent the characteristics of individual j, and let Z_{jk} be the characteristics of the kth alternative for individual j (So and Kuhfeld (1995)).

(1) Generalized logit model

In a generalized logit model, each individual is considered as the unit of analysis, and characteristics of each individual is regarded as explanatory variables. The explanatory variable which consists of its own characteristics is assumed to be constant over other alternatives. The probability of the individual *j* to choose alternative *k* is:

$$\Pi_{jk} = \frac{exp(\beta_k^{'} X_j)}{\sum_{l=1}^{m} exp(\beta_l^{'} X_j)}$$

$\beta_1, \ldots, \beta_m$ are *m* vectors of unknown regression parameters. The last set of coefficients (that is, β_m) is to be null (=0) value because the coefficients β_k represent the effects of the X variables on the probability of choosing the *k*th alternative over the last alternative. To conduct the goodness of fit test such a model, (*m*-1) sets of regression coefficients are needed.

(2) Conditional logit model

In a conditional logit model, it is assumed that explanatory variables (Z) for each alternative has different values, but the impact of a unit of Z is assumed to be constant across alternatives. In this model, the probability of the individual *j* to choose alternative *k* is:

$$\Pi_{jk} = \frac{exp(\theta^{'} Z_{jk})}{\sum_{l=1}^{m} exp(\theta^{'} Z_{jl})}$$

θ is a single vector of regression coefficient. It is possible to derive the impact of each variable on the choice probabilities by exploring the difference of its values across the alternatives.

(3) Mixed logit model

So and Kuhfeld (1995) state that in a mixed logit model, both the characteristics of the individual and the alternatives are considered at the same time. The choice probability is:

$$\Pi_{jk} = \frac{exp(\beta_k^{'} X_j + \theta^{'} Z_{jk})}{\sum_{l=1}^{m} exp(\beta_l^{'} X_j + \theta^{'} Z_{jl})}$$

$\beta_1, \ldots, \beta_{m-1}$ and $\beta_m \equiv 0$ are the alternative-specific coefficients and θ is the set of global coefficients.

7.4 Limitations

There are some limitations to the generalizability of the data. The first limitation is that survey areas are limited at certain spots and place. Location bias, therefore, is possible since participants are not chosen randomly. The bias ensure from the fact that an individual's decision to choose their travel mode may be related to their travel purpose; however in this research, we only consider a commute trip and non-commute trip. Such considerations, as well as the specific methodology (standard discrete choice models vs alternatives such as conjoint analysis, as mentioned above) are left for further research during the survey phase of the subsequent project in 2017-18.

8. Conclusion

This project introduces schemes to study sustainable transportation alternatives that provide access to public transportation. We design a transit feeder system by matching a ride to P2P ridesharing, bike-sharing, walk, and transit. Green transportation modes in the system can be mutually beneficial in terms of improving ridership, saving cost and increasing mobility. Following our earlier study (Phase 1 research in 2015-16), we further proposed schemes to integrate multiple transportation modes and methods to increase ride-matching rates.

The proposed system is tested in LA County. Target modes are metro red line subway rail in the, Metro bike-sharing program in Downtown LA, walk, and P2P ridesharing. Geographical analysis for accessibility indicates that both P2P ridesharing and bike-sharing enlarge the catchment area of the red line stations. In the morning peak, bikes are more effective in Downtown LA because bikes are generally not affected by downtown street congestion. The parametric study indicates that our system generally improves matching rates when we compare it to our earlier results on only the rideshare system being a feeder to transit (from Phase 1).

The insights gained from our parametric study include the following. First, the matching rate is determined by the riders-to-drivers ratio. The rate increases sharply at first and then remains relatively stable when the number of drivers is more than two times that of riders. Besides, both P2P ridesharing and shared bikes are used as transit feeders by some riders. The usage would increase linearly when the availability of drivers and bikes increases. One limitation, which is also a future research topic, is that this study only included travel demand from vehicle demands. In other words, this study focused on the rideshare matching potential from vehicle demands, and not the total travel demand (vehicle and transit). In future research, transit demand data could be included to study the potential improvements and mode shift.

In addition, we propose a heuristic search algorithm to resolve the bike-rebalancing problem. The case study result demonstrates the algorithm's practicality and effectiveness. The core of the algorithm evolved from two key concepts. The first is to view the element of the solution set as bike station pairs rather than individual stations, and the second is the parameter estimation and validation procedure using the concept of unsupervised learning. Dynamic bike rebalancing problem with uncertain demand is challenging using conventional programming-based method because routing, operation cost, dynamic demand, and specific number of bikes to pick up and drop off are highly intertwined. We proposed a ready-to-implement alternative to solve the rebalancing problem with high model interpretability and tractability. The proposed methodology was tested in our research area (Downtown LA). We are interested in extending the study to the upcoming scenarios where additional service vans are dispatched near the Port of Los Angeles, City of the Pasadena, and Venice. Integrating the LA Metro bike redistribution with that in the City of Santa Monica may also be beneficial for both cities and worth examining.

Finally, a large component of the existing transit system , namely the bus system, needs to be incorporated into or studies to fully determine the full breadth of possibilities offered by the new shared-mobility alternatives in achieving green and sustainable transportation. This is expected to be a focus in our further research during the subsequent phase-III of the sequence of projects, in 2017-18.

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