Efficient Mobility Portfolio Schemes for Integrated, Intermodal, and Incentivized Shared Transportation

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A Research Report from the Pacific Southwest Region University Transportation Center

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This project studies the benefits of a smart mobility portfolio which is a trip planning system integrating multiple travel modes and including an incentive scheme. A smart mobility portfolio can provide time-dependent trip plans across multiple modes that include several options such as shared-cars, shared-rides, bikesharing, bus/rail transit and combinations of travel modes. research aims (1) to build an integrated, intermodal, and incentivized (3-Is) shared transportation system as a single platform by constructing a multi-layered transportation network that includes various travel modes layers (e.g., private vehicle mode and public transit mode) with a peer-to-peer (P2P) ridesharing system; (2) provide a smart mobility portfolio solution; and (3) study the benefits of a smart mobility portfolio. The modeling in this research demonstrates a reduction of total system vehicle-hour-traveled with a re-distribution of travel modes while keeping the total number of network passengers. In addition, this study makes a real-time mobile application to understand how the proposed method works by providing User Interfaces with Google maps. The app users provide their origin/destination and early departure time/latest arrival time, and then the app provides various travel options.		
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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

The PI R. Jayakrishnan, and two students, Ph.D. Candidates Daisik Nam and Sunghi An conducted this research titled, "Efficient Mobility Portfolio Schemes for Integrated, Intermodal, and Incentivized Shared Transportation" at the Institute of Transportation Studies at the University of California Irvine. The research took place from January 1, 2018 to June 30, 2020 and was funded by a grant from the California Department of Transportation (Caltrans) in the amount of $55,201.00. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

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Abstract

This project studies the benefits of a smart mobility portfolio which is a trip planning system integrating multiple travel modes and including an incentive scheme. A smart mobility portfolio can provide time-dependent trip plans across multiple modes that include several options such as shared-cars, shared-rides, bikesharing, bus/rail transit and combinations of travel modes. research aims to (1) build an integrated, intermodal, and incentivized (3-Is) shared transportation system as a single platform by constructing a multi-layered transportation network that includes various travel modes layers (e.g., private vehicle mode and public transit mode) with a peer-to-peer (P2P) ridesharing system; (2) provide a smart mobility portfolio solution; and (3) study the benefits of a smart mobility portfolio. The modeling in this research demonstrates a reduction of total system vehicle-hour-traveled with a re-distribution of travel modes while preserving the total number of network passengers. In addition, this study makes a real-time mobile application to understand how the proposed method works by providing User Interfaces with Google maps. The app users provide their origin/destination and early departure time/latest arrival time, and then the app provides various travel options.

Efficient Mobility Portfolio Schemes for Integrated, Intermodal, and Incentivized Shared Transportation

Executive Summary

Transportation supply has a distinctive characteristic that it is a service that cannot be stocked and transferred geographically and temporally. This is in sharp contrast with travel demand, which is distributed over time and space. In some popular areas such as the Los Angeles area, travel demand is so high at peak hours that existing infrastructure cannot serve the demand, resulting in traffic congestion. Under the given supply level, encouraging travelers to use efficient transportation modes (i.e., public transportation and ridesharing) can be a sustainable solution. The sharing economy in the transportation field and the advance of autonomous vehicle technologies can also help the efficient transportation system. Transportation operators can shed a bright light on the demand and behavior control side by leading people to shift to multi-modal ridesharing modes. We propose a smart mobility portfolio which finds an optimal mobility solution within the existing transportation system while preserving people's convenience. The proposed model is designed to promote ridership of efficient transportation modes, such as public transportation and ridesharing.

A smart mobility portfolio is a time-dependent trip plan across multiple modes that include travel options such as shared-cars, shared-rides, bikesharing, bus/rail transit, combinations of travel modes, and even shared autonomous vehicles. Transportation operators can provide a proper amount of incentives to the public who contribute to efficient transportation systems. Thus, this research aims (1) to build an integrated, intermodal, and incentivized shared (3-Is) transportation system as a single platform by constructing a multi-layered transportation network that includes various travel modes layers (e.g., private vehicle mode and public transit mode) with a peer-to-peer (P2P) ridesharing system; and (2) to provide a smart mobility portfolio solution; and (3) to study the benefits of a smart mobility portfolio.

We model a bi-level framework. Including the initialization process at the upper level, there are three different stages for the ridematching process to maximize the ridematching rate. In the upper model, we find the itinerary for better efficiency of the entire transportation system in terms of total travel time because the system devises the higher occupancy of vehicles and the lower number of vehicles in the system. Also, by introducing shared autonomous vehicle as a fleet, we find an optimal fleet number which maximized a fleet company's profit. As a result of the upper level, each 3-Is system participant has an optimal mobility portfolio that can have different travel options. The travel time and price of each travel option might differ according to travel modes and travel itineraries. This various quantity of travel options could be an issue in terms of fairness; thus, determining an appropriate amount of incentives can be important to the entire system. It is worth remembering the fact that some travelers should accept a longer

trip than the shortest path to improving the overall system's efficiency. The lower level calculates a proper amount of incentives that a system fairly compensates for an alternative's inconvenience to other travel options. This research designs the mathematical formulations for the incentive scheme and finds the optimal incentive amount to guarantee that all participants are satisfied.

By encouraging people to change their current travel behavior through the smart mobility portfolio platform, we find that the proposed portfolio can spread travelers over travel modes and attract more people to behave to improve transportation efficiency by promoting travelers to use higher efficient travel modes such as ridesharing and public transportation. Eventually, this research anticipates a reduction of total system vehicle-hour-traveled with a re-distribution of travel modes while keeping the total number of network passengers.

In addition, this study makes a real-time mobile application to understand how the proposed method works by providing User Interfaces with Google maps. The app users provide their origin/destination and early departure time/latest arrival time, and then the app provides various travel options.

Still certain limitations are inherent in this project. First is that we considered the availability of shared bikes only in the Downtown Los Angeles area only. This fact may affect the shared-bike usage results in our project study area. Another limitation is that we assumed that the private companies already have sufficient number of fleet vehicles; which means that the vehicle purchasing fee is not included. Finally, we assumed that it is not mandated that the fleet vehicles need to be returned to their depots. Thus, further research is required along such lines.

1. Introduction

Transportation supply has a distinctive characteristic that it is a service that cannot be stocked and transferred geographically and timely. This is in sharp contrast with travel demand, which is distributed over time and space. In some popular areas such as the Los Angeles area, demands are so high at peak hours that existing infrastructure cannot serve the demand, resulting in traffic congestion.

One of the major causes of congestion is the high volume of single-occupancy drivers. According to the latest 2017 National Household Travel Survey shows that almost 88% of commuters make their trip with a private vehicle. Even though there are public transportation systems in cities, the public transportation mode share ratio is too low. This imbalance happens because travelers want to maximize their travel comfort such as travel time, travel mode accessibility, travel cost and so on. This report also reveals that 1.18 of about 5 seats are used on average. It is noteworthy that most of these vehicles are parked until a commuter drives back to his/her home. Therefore, sharable resources (i.e., sharing empty seats in a car, public transit) are wasted. Due to these phenomena, traffic congestion has become even more chronic and the transportation system not efficiently utilized. Therefore, to improve the system conditions, it is necessary to find an optimal mobility solution within the existing transportation system while preserving people's convenience. Furthermore, efficient transportation modes, such as public transportation and ridesharing should be encouraged. In addition, autonomous and connected vehicles can mitigate traffic congestion to some extent by increasing the effective road capacity by virtue of lowered reaction time and other operating characteristics. However, congestion is still expected to be a pervasive problem in the future if we rely only upon improved vehicle performance. Even more exciting changes are to come that can tackle the ever-increasing traffic congestion, for which, we must, however, look beyond improved vehicle performance.

With the advent of sharing economy in the transportation field and the advance of autonomous vehicle technologies, transportation operators can shed a bright light on-demand behavior control side by leading people to shift to multi-modal ridesharing modes or change their current travel path. However, travelers are unlikely to follow the alternatives that may require travelers to yield their best route unless they are compensated in some way. Transportation operators can provide a proper amount of incentives to the public who contribute to efficient transportation systems. From the supply point of view, providing a ridesharing option can also improve the efficiency of the transportation system since higher vehicle occupancy can transport more travelers, in turn, relieving road congestion. Promoting ridership of public transportation can be a more efficient way to utilize existing transportation systems since public transportation is capable of transporting many travelers with low cost and emissions. However, the problem of accessibility to stations, also known as the last-mile problem, remains an issue. Flexible transportation options such as ridesharing and bikesharing can be active

feeders for public transportation services because these new options have higher accessibility to travelers' origin and destination. The private sector that now plays an increasing role as a component of urban transportation can augment public transportation accessibility. In other words, Transportation Network Companies (TNCs) and Mobility Service Providers (MSPs) can be complementary modes to the transit system by providing shared use of transportation capacity. This option requires a matching algorithm between drivers and riders. Institute of Transportation Studies, UC Irvine has been actively developing methodologies to envision a comprehensive multi-modal travel system as part of the UCConnect projects initiative. Moreover, autonomous vehicle technology can help foster not only transportation system change but also travel behavior change. Many pieces of research have been done to prove that shared autonomous vehicles can take the place of private vehicles or public transportations. Several cities are piloting the autonomous fleet vehicle program.

Implementing a comprehensive multi-modal shared travel system in an urban area is required to improve the performance of transportation systems as well as the efficiency of individuals' mobility. Therefore, this study proposes a smart mobility portfolio with an integrated, intermodal, and incentivized shared (3-Is) transportation system as a single platform that includes various travel modes (e.g., private vehicle mode and public transit mode) with a peer-to-peer (P2P) ridesharing system. This platform plays a role as a trip planner, which provides the best travel mobility portfolio satisfying both social and individual needs. Moreover, the shared autonomous vehicle as a fleet is also considered as one of the travel modes in this 3-Is transportation system. This integrated platform can identify various travel modes and recommends travelers with tailored information. The framework of the mobility portfolio is designed to search an optimal travel mode (i.e., can be a combination of travel modes with p2p ridesharing system) that minimize travel costs. Some travel modes might have a route consisting of multiple modes (i.e., ridesharing-transit-bikesharing). Some modes might suggest a detour from the users' original shortest path. To compensate for the loss of users' utility by giving up their primary mode and to encourage the use of alternative mode options, this research proposes an incentive scheme. Instead of forcing travelers to follow the suggested travel mode, the mobility portfolio attracts travelers to change their travel behavior by providing proper incentives. Individuals can choose one of the recommended options, which maximizes their utility.

We expect the proposed portfolio can spread travelers over travel modes and attract more people to behave to improve transportation efficiency by promoting travelers to use higher efficient travel modes such as ridesharing and public transportation. Eventually, this research anticipates a reduction of total system vehicle-hour-traveled with a re-distribution of travel modes while keeping the total number of network passengers. This paper is organized as follows. In section 2, we review previous research about shared transportation. In section 3, we introduce the integrated, intermodal, and incentivized shared (3-Is) transportation system and its operational algorithms for mobility portfolios. Section 4 will explain how we construct the

simulation environments such as a network, demands, and fare setting and evaluate the proposed system. A smart mobility portfolio mobile application will describe in Section 5. Finally, Section 6 discusses the importance of the findings and addresses an outlook for future research.

2. Literature review

In the 1990s, the concept of peer-to-peer ridesharing had emerged, with a focus on traditional ride sharing (i.e., carpooling). However, earlier studies were not very successful because of technological limitations at the time. The summary of earlier ridesharing projects and reasons for their failure is summarized in '2016 Promoting Peer-to-Peer ridesharing services as transit system feeder' report. In recent years, development in technologies - such as smartphone apps that contain information and communications technology (ICT) and payment systems, high-speed wireless networks - can help exchange information between person to person. In addition, with the growth and acceptance of the sharing economy and autonomous vehicles, ridesharing is receiving global attention. Ridesharing combining with such technologies (e.g., that is provided by mobile apps such as UberPool and Lyft Line apps) can help foster travel mode shift by exchanging information easier and faster. As ridesharing has drawn much interest in both industry and academic fields, many studies have been conducted and shown the potential of ridesharing system by reducing the traffic congestion impacts.

As the concept of ridesharing has revived, Furuhata et al., (2013) classified ridesharing activities into three groups: (a) Unorganized ridesharing which is happening by commitment between family members, colleagues, neighbors, and friends; (b) Organized ridesharing which is run by agencies with their own ride-matching process (i.e., '*Prearrangement*' is a key factor to match drivers and riders/passengers), and (c) Semi-organized ridesharing which is formed without prearrangement. Rather, this type of ridesharing service has meeting points and the matching process happens at the meeting places. For example, if a rider's destination and departure are similar (or same) to travel mode providers' (i.e., drivers) ones, then these people are matched. Although unorganized ridesharing has a long history, due to its inefficient communication methods, other types of ridesharing have gained more popularity.

By integrating characteristics of semi-organized and organized ridesharing systems, Agatz et al. (2012) stated that introducing meeting points between riders and drivers provided better matching solutions (including the reduction of travel time). Stiglic et al. (2015) conducted a study to investigate the benefits of meeting points for ridesharing. To do this, they assumed that the possible meeting locations are in a Euclidean plane to limit the number of feasible meeting points for rider. With the reduced meeting locations, they proposed a ridesharing matching problem considering a single driver and multi-riders and revealed that introducing the meeting locations may improve the matching rate results. Thus, finding proper meeting points is an important issue to improve the efficiency of ridesharing service. To find the optimal number of meeting points for riders, Aïvodji et al. (2016) have proposed algorithms based on the brute-force approach and heuristic approach. Their study found the reasonable size of pick-up and drop-off locations which is close to optimal. From a slightly different angle, Czioska et al. (2017) proposed a GIS-based ridesharing meeting point location identification algorithm,

considering existing and available facilities such as parking places, seating, shelter, and light. In their study, when the number of available meeting point increase, more people are matched with riders. Moreover, they assessed the relevance of the feasible meeting points on the side of safety (i.e., comfort) based on preferences from an online survey approach. The most significant characteristic of ridesharing with meeting points is that drivers are waiting at a commonplace and riders have to walk to that place. This means if the distance from riders' origin and meeting places are far (i.e., walking travel time is not acceptable for riders), then the matching process is not conducted. Thus, it may decrease the matching rate.

Many studies have developed various algorithms to improve the ridematching rate by providing a peer-to-peer (p2p) ridesharing system. As ridesharing became a p2p system, a trip time window information (i.e., departure time from origin and arrival time to destination) is another factor to be considered for a matching problem as well as a route. An initial stage of the p2p ridesharing studies and research suggested dynamic ridesharing (DRS) problem which mainly focuses on matching between a single driver who can serve a single rider's entire route from his/her origin to destination, considering their time window (Agatz et al., (2009), Agatz et al., (2011), Furuhata et al., (2013), Herbawi and Webber (2012), and Febbraro et al., (2013)). Ridematching problem can be expanded to one-to-many problem as follows: (a) By allowing transfer between drivers, as stated in Agatz et al., (2009), Herbawi and Weber (2011a), Herbawi and Weber (2011b), it becomes possible to match a single rider to multiple drivers; (b) Similarly, a driver can be arranged with multiple riders if the driver has enough time flexibility (Agatz et al., (2009), and Furuhata et al., (2013)). Further, as stated in Agatz et al., (2010), Masoud and Jayakrishnan (2017a), and Masoud and Jayakrishnan (2017b), ridematching problem can be formed as a many-to-many problem (i.e., multiple drivers could be arranged with multiple drivers). To reduce computational complexity, Masoud and Jayakrishnan (2017a) developed the ellipsoid spatiotemporal accessibility method (ESTAM) to limit a ridematching search area for both riders and drivers. Moreover, in their study, a dynamic programming (DP) algorithm had been applied to find the optimal matching rate.

In the real world, ridesharing systems operate with various travel modes such as mass transit (i.e., bus, metro, rail and so on), bike and even walking. There are many attempts to construct an integrated multi-modal network. In this network, riders have opportunities to hop between not only drivers but also different types of travel modes; and ridesharing can take a role as a public transportation feeder or an alternative transit mode. With the fixed scheduled public transit system, the route for a rider could be composed with links which are served by drivers and/or some parts of public transit lines (Agatz et al., (2009), Ma (2017), Lin et al. (2016), and Fahnenschreiber et al., (2016)). Furthermore, Masoud and Jayakrishnan (2017b) formulated a binary optimization problem to provide an optimal travel optimal itinerary for riders.

Additionally, the future availability of autonomous vehicles makes it possible to bring about a shared autonomous vehicle (SAV), and many projects are conducted to demonstrate the

benefits of SAV as a sustainable and road-friendly transportation alternative by increasing road capacities and speeds (Tientrakool et al., (2011), Zhang et al., (2015)). Based on scenarios, SAV shows its potential as a high-occupancy vehicle that can replace several single-drive cars (Fagnant et al., (2015), Llorca et al., (2017), Segal and Kockelman (2016), Gurumurthy and Kockelman (2018)). Considering shared autonomous vehicles as a fleet, Hyland and Mahmassani (2018) suggested optimization strategies to operate autonomous fleet vehicles dynamically to improve SAVs' performance efficiently by reducing empty miles and traveler wait times. With dynamic ridesharing (DRS), Fagnant and Kockelman (2018) demonstrated the SAVs may reduce network VMT (Farhan and Chen, 2018). Moreover, the authors addressed that SAVs could be a profitable travel mode for fleet operators.

Many researchers believe that providing incentives will contribute to changing travelers' behavior (E. T. Verhoef, Nijkamp, and Rietveld 1996; Roughgarden 2002; Boyce and Xiong 2004; Jahn, Mohring, and Schulz 2008; Zhou et al. 2009; Ben-elia and Ettema 2009; Ben-Elia, Tillema, and Ettema 2010; Bosch et al. 2011; H. Yang and Wang 2011; Y. M. Nie and Yin 2013; Hu et al. 2014; Djavadian et al. 2014; Kumar 2015). The relationship between toll and incentive can be likened to the "Carrot or Stick" idiom. Findings in psychology literature such as Ben-elia and Ettema (2009) and Ben-Elia, Tillema, and Ettema (2010) show that an incentive scheme brings about better outcomes than punishment (toll). They also showed that a reward scheme can be effectively used to manage travel demand from a survey test for "Spitsmijden" (Dutch for peak avoidance) in the Netherlands. They show that participants change their commuting schedules to avoid peak hours when they earn rewards. Ben-Elia, Tillema, and Ettema (2010) and Kumar (2015) analyze the behavioral changes from the "Yeti phone rewards".

On the whole, all the mentioned ridesharing studies and matching strategies aim to increase the matching ratio to enhance the performance of the transportation network by attracting people to use more shared-travel modes. It is noteworthy to mention that actual travel modes operate at the same time. If shared autonomous vehicles (SAVs) are introduced in the current transportation network, then SAVs will be floating the network spontaneously with the existing travel modes (e.g., personal vehicle, ridesharing trip mode, public transit lines, and bikes). However, previous studies do not consider such an integrated transportation network. Therefore, this study builds an integrated transportation system (including autonomous vehicles) based on the Los Angeles County network. Another challenge is the increase in computational complexity for the ridematching process because we have to search for all possible travel modes for riders. Thus, this study proposes a sequential peer-to-peer ridematching process with different operational algorithms to provide the optimal mobility portfolio for system participants. However, in reality (a) still a lot of people are depending on their current primary mode (which is a private vehicle) and (b) do not tend to give it up, thus it may be hard to shift all private vehicle demand to shared travel mode demand. Considering such limitations, this study proposes incentive strategies. Detailed explanations will be provided in the next section.

3. Methodology

3.1 Overview of smart mobility portfolio framework in 3-ls system

The overall process of the smart mobility portfolio is shown in Figure 1. As we can see in Figure 1, the smart mobility portfolio has a bi-level framework. Including the initialization process in the upper level, there are three different stages for the ridematching process and each stage utilizes a different participant set. At the first stage, the peer-to-peer ridesharing matching module searches available travel modes for each rider. In the next stage, a shared autonomous fleet vehicle (SAFV) service is introduced in the system to increase the matching rate by serving riders who are not matched in the previous stage. It is possible to apply SAFVs in the previous stage. However, in that case, the ridematching computation complexity increases extremely because SAFVs have a flexible route (i.e., which means that SAFVs routes depend on passengers who take that SAFVs). Moreover, if SAFVs are introduced in the early stage, it may cause more traffic congestion due to adding more vehicles on the roads. Therefore, this study runs the ridematching algorithm sequentially by applying different system participant groups at each stage. Once a route of each SAFV is fixed, then this study uses these SAFVs as a ridesharing mode to share the empty seats in autonomous fleet vehicles. Travel time of the Itineraries from the upper problem might differ from a user's current travel option, which could have longer travel time or shorter. The upper model finds the itinerary for better efficiency of the entire transportation system in terms of total travel time because the system devises the higher occupancy of vehicles and the lower number of vehicles in the system.

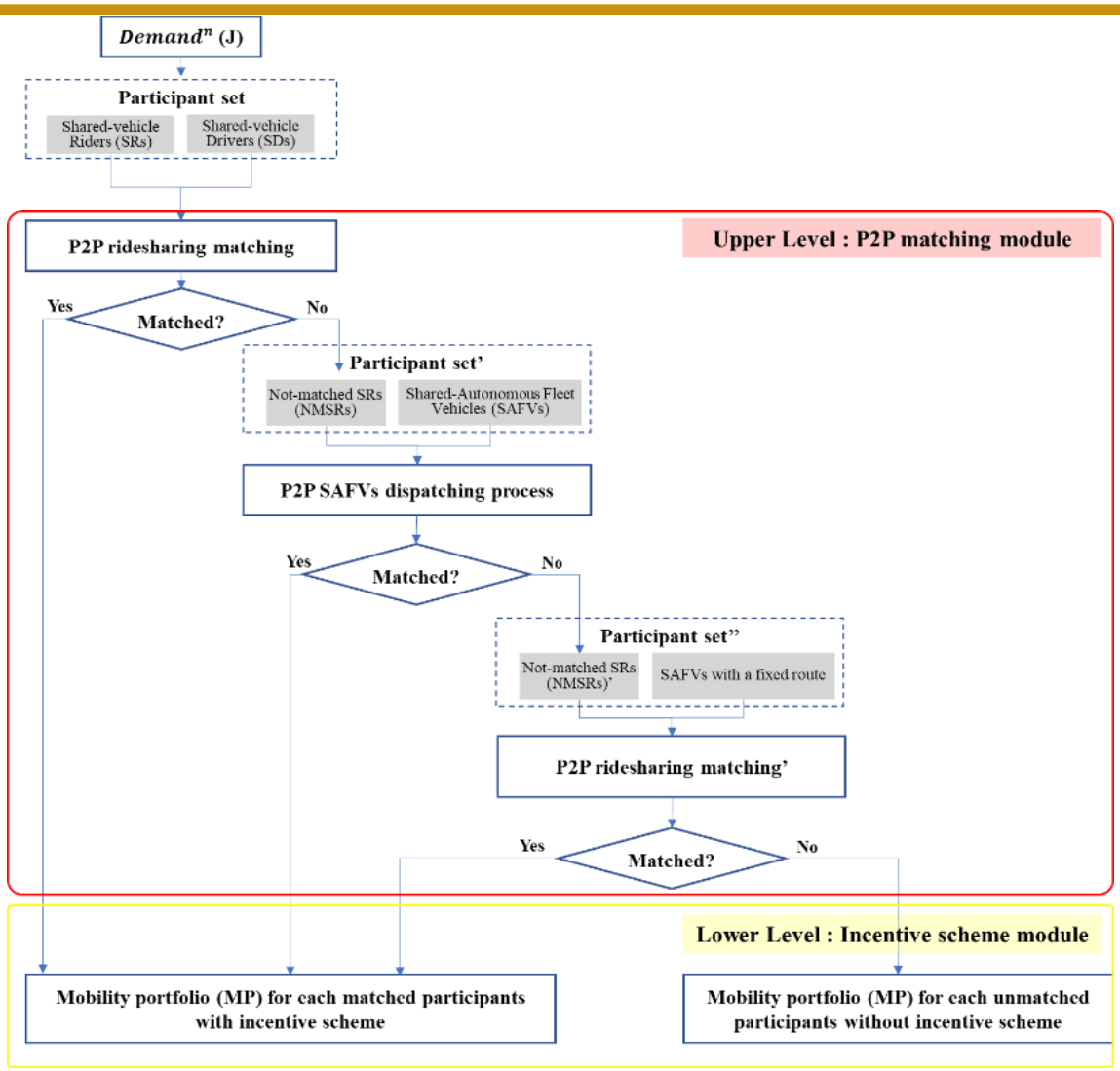


Figure 1. Smart mobility portfolio framework in 3-Is system

However, from the rider's point of view, a user is not likely to comply the itinerary if the matched itinerary brings longer travel time. Consequently, a user could not trust the recommendations of the Mobility Portfolio. The lower level estimates a proper amount of incentives to make the matched itinerary to be attractive by compensating the longer travel time. Also, if a user finds that other users' itinerary is better, an agent would also complain, thus the incentive problem should be carefully designed. We propose an incentive scheme to provide the best mode option for both two concerns:1) longer travel time than his/her current travel mode, and 2) longer travel time than other users.

This research assumes that a primary mode of all participants of this mobility portfolio system is a private vehicle. Considering a utility from a private vehicle, utilities from alternative modes may not be comparable because users might experience several transfers or waiting times which results in a decrease in users' utility by utilizing alternative modes. Therefore, for

alternative travel modes, an incentive scheme is necessary to give travel cost competitiveness compared to the travel costs of a private vehicle. Details of how to design incentives will be addressed in the next section.

3.2 Upper level – Peer-to-peer ridematching problem

3.2.1 Initialization

From information (trip information, time window information, and acceptable waiting time) given by users, in Step 0 (Figure 2), initially 3-Is system users are randomly fell into either (a) a shared-vehicle driver (SD) group (i.e., people who are willing to give up their primary mode (such as a personal vehicle) and use alternative modes) or (b) a shared-vehicle rider (SR) group (i.e., people who are willing to share their empty seats before finishing their trip).

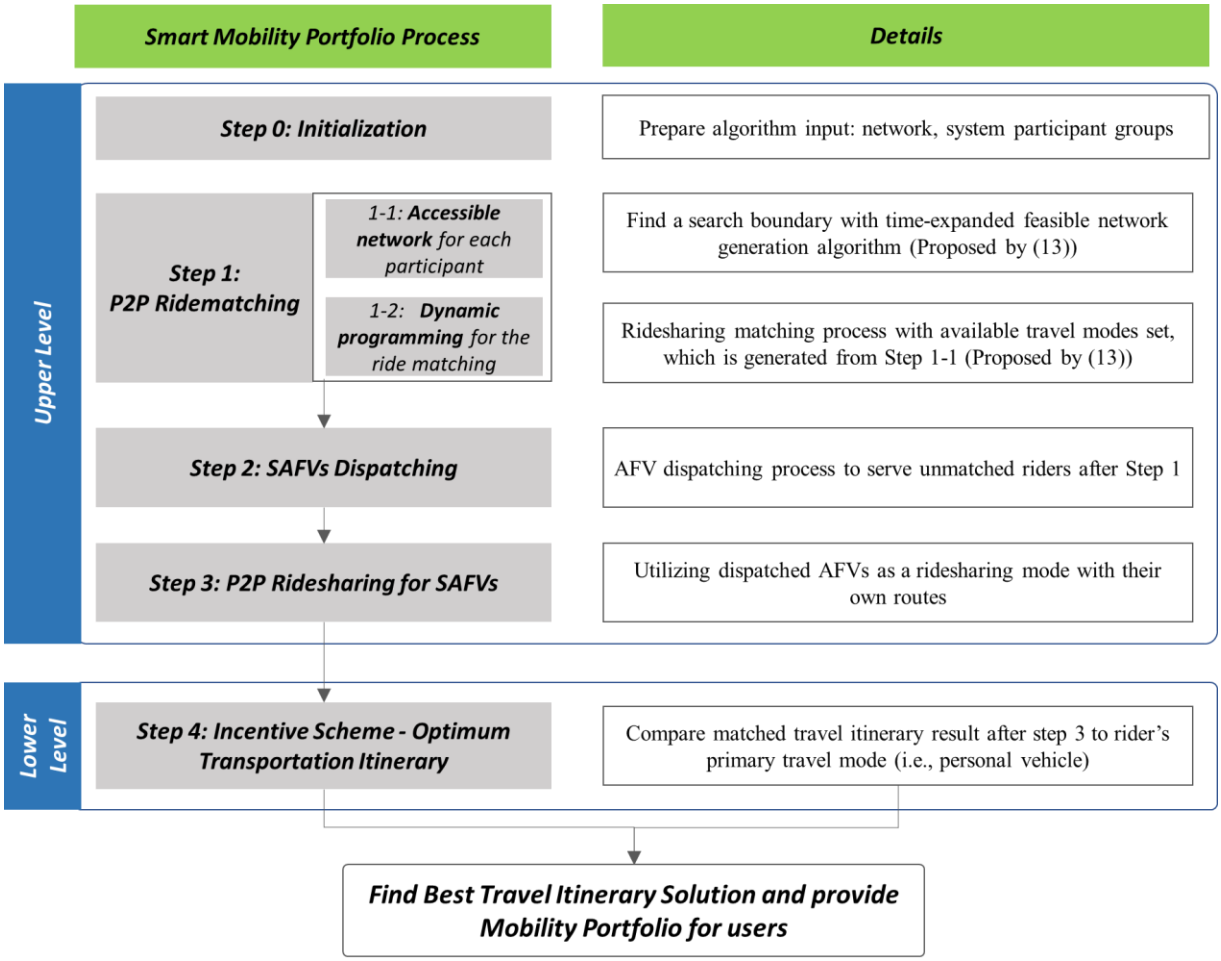


Figure 2. Detailed mobility portfolio flowchart

This study aims to utilize the integrated different travel modes (e.g., Bike-sharing, Transit, private vehicles, and autonomous vehicles) platform which would result in separate network sub-layers. This implies that we should consider various characteristics of each travel mode.

Thus, we implement a detailed network structure to capture all travel modes and then construct a multi-layered network. The multi-layered network means that travel mode which has different characteristic cannot share the other modes networks. Each network will be demonstrated in the next section. Figure 3 shows an example of the multi-layered network which will be used in this study. Black, red and green lines represent a vehicle, transit and bike network respectively, and dashed lines represent a transfer link which is a walking link. In this example, if a rider's trip is started from his origin (O) to destination (D), the rider's trip itinerary will be a sequence of travels such as 'walk to bike station', 'ride a bike', then 'transfer to transit', and 'take a ridesharing vehicle'.

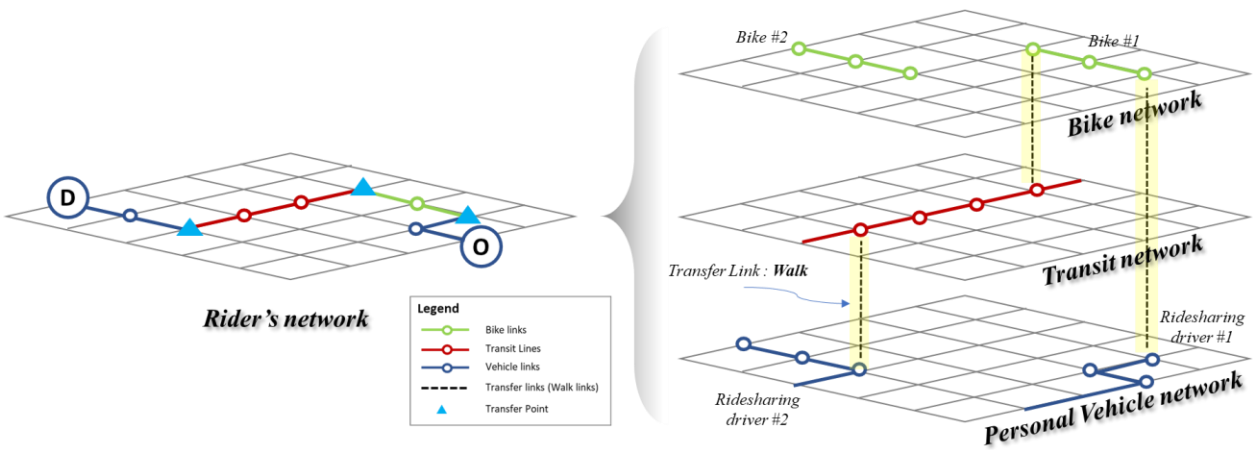


Figure 3. Multilayer Concept of an integrated intermodal network

3.2.2 Peer-to-Peer ridesharing matching module

In Step 1, the peer-to-peer (p2p) ridesharing process happens between shared-vehicle drivers (SDs) and shared-vehicle riders (SRs). The key factor of the ridesharing matching problem is to find drivers (or other travel modes) who can deliver a rider from his/her origin to destination. A shortest-path search algorithm is commonly used to match those drivers and riders. The benefit of this algorithm is computational speed is fast. However, once the size of a simulation and a network become large, the matching rate drops very quickly, because the algorithm restricts a search boundary to the shortest path of riders. Therefore, this study considers the ridesharing search boundary as not a single path but an area depending on their trip origin/destination and time window information. To find the search area, in Step 1 this study applied the ellipsoid-based spatiotemporal accessibility method (ESTAM) proposed by Masoud and Jayakrishnan (2017a). With the help of the method, we can not only increase the available travel region but also improve the matching process efficiency by reducing the travel mode search boundary from entire network to selected network. Thus, each shared-vehicle rider has a set of links which are reachable for the shared-vehicle drivers. With the pre-defined reduced network, in Step 2 the ridesharing matching module searches available travel modes for each rider. Masoud

and Jayakrishnan (2017a) proposed the dynamic programming (DP) algorithm. A detailed explanation can be found in (11). They formulated the ridematching rate maximization problem Eq (1). Eq (1.1)-(1.3) show riders' Origin-Destination demand and link volume; and Eq (1.4)-(1.6) shows drivers' Origin-Destination demand and link volume. Eq. (1.7)-(1.8) show is a travel time window constraint for riders and drivers.

$$Max \sum_{r \in R} z_r - \sum_{d \in D} \sum_{r \in R} \sum_{l \in L} W_l \, y_l^{rd} \tag{1}$$

subject to

$$\sum_{d \in D'} \sum_{\substack{l \in L: \\ s_i = OS_r(t_i, t_j) \in T_r}} y_l^{rd} - \sum_{d \in D'} \sum_{\substack{l \in L: \\ s_j = OS_r(t_i, t_j) \in T_r}} y_l^{rd} = 1 \qquad \forall\, r \in \mathrm{R} \tag{1.1}$$

Rider *r* leaves origin

$$\sum_{d \in D'} \sum_{\substack{l \in L: \\ s_j = DS_r(t_i, t_j) \in T_r}} y_l^{rd} - \sum_{d \in D'} \sum_{\substack{l \in L: \\ s_j = DS_r(t_i, t_j) \in T_r}} y_l^{rd} = 1 \qquad \forall\, r \in \mathrm{R} \tag{1.2}$$

Rider *r* enter destination

$$\sum_{d \in D'} \sum_{\substack{t_i, s_i \\ l = (t_i, s_i, t, s) \in L}} y_l^{rd} = \sum_{d \in D'} \sum_{\substack{t_i, s_i \\ l = (t, s, t_j, s_j) \in L}} y_l^{rd} \qquad \forall\, r \in R, \forall\, t \in \mathrm{T_r},\ \mathrm{s} \in \mathrm{S}\{\mathrm{OS_r} \cup \mathrm{DS_r}\} \tag{1.3}$$

Rider *r* flow conservation

$$\sum_{\substack{l \in L: \\ s_i = OS_d(t_i, t_j) \in T_D}} x_l^d - \sum_{\substack{l \in L: \\ s_j = OS_d(t_i, t_j) \in T_D}} x_l^d = 1 \qquad \forall\, d \in D \tag{1.4}$$

Mobility provider d leaves origin

$$\sum_{\substack{l \in L: \\ s_j = DS_d(t_i, t_j) \in T_D}} x_l^d - \sum_{\substack{l \in L: \\ s_i = DS_d(t_i, t_j) \in T_D}} x_l^d = 1 \qquad \forall\, d \in D \tag{1.5}$$

Mobility provider *d* enters destination

$$\sum_{\substack{t_i, s_i \\ l = (t_i, s_i, t, s) \in L}} x_l^d = \sum_{\substack{t_i, s_i \\ l = (t, s, t_j, s_j) \in L}} x_l^d \qquad \forall\, d \in D, \forall\, t \in \mathrm{T_d},\ \mathrm{s} \in \mathrm{S}\{\mathrm{OS_d} \cup \mathrm{DS_d}\} \tag{1.6}$$

Mobility provider d flow conservation

$$\sum_{d \in D'} \sum_{l \in L} (t_j - t_i) y_l^{rd} \le T_r^{TB} \qquad \forall\, r \in R \tag{1.7}$$

Rider *r*'s travel time budget

$$\sum_{l \in L} (t_j - t_i) x_l^d \leq T_d^{TB} \qquad \forall\, d \in D \quad \text{Mode } d\text{'s travel time budget} \tag{1.8}$$

In their study, a shared-vehicle driver group and a single metro line (i.e., Redline) in the Los Angeles area are considered as mobility supplier for riders. In this study, we expend the mobility supplier by adopting all possible travel modes (including bikes, buses, metro rails, and even walking links for transferring), and then operate the ridematching process. Through this process, if a rider changes (i.e., transfer) his/her current mode to another mode, then the travel mode for 'transferring' is 'walk'. Travel modes which result from the matching process could be a set of single travel modes (i.e., using transit only, shared-vehicle only, bikesharing only, and so on) or a chain of travel modes (i.e., utilizing a shared-vehicle and then riding a bikesharing mode, and so on). After this process, some riders are matched with mobility suppliers. However, other riders are not. In the next section, we will describe how to serve these 'not-matched shared-vehicle riders (NMSRs)' with shared autonomous fleet vehicles.

3.2.3 Shared autonomous feet vehicle dispatching module

As briefly mentioned in 3.2.2, some riders may not be matched with the existing mobility suppliers because these suppliers are bound with their time window and fixed schedule and routes. Therefore, in this module, we introduce a shared autonomous fleet vehicle (SAFV) with a flexible route. To define the movement of SAFVs, we formulate the SAFVs dispatching problem. One thing to point out is that finding the optimal number of SAFVs is necessary to achieve a higher matching rate. This concept is general enough and can incorporate shared autonomous fleet vehicles from private mobility companies as well as from government (transportation planning) agencies, with appropriate parameters for maximizing the profit. Therefore, this research forms a profit maximization problem to find the optimal number of fleet vehicles and routes.

(1) Mathematical formulation

Let us start by defining several notations. Table 1 shows the important notations that will be used in our algorithm. The purpose of this module is to serve more people who are not matched in the previous step (Section 3.2.2) by providing a sharable travel mode, SAFVs. Thus, in this step, shared-vehicle riders who are not matched become the target group. This study called this group as a 'not matched shared-vehicle riders (NMSR)'. Each rider in the group still has a tuple trip information consisting of their origin and destination (O, D), and time window information such as 'departure time' from rider i's origin (DT_i), and 'arrival time' at rider i's destination (AT_i). Moreover, this study defines a variable, N_i^S as a node where SR i is sitting on location s; and a variable, $tt_{(a,b)}$ as travel time between node a and b. In the SAFV dispatching module, travel time for each rider on AFVs depends on fleets' route, r. Thus, a travel time variable for SRs can be represented as $tt^r_{(N_i^O, N_i^D)}$.

Table 1. Notations

	Notations		Notations
i	Shared-vehicle rider	DT_i	Departure time
j	Route	AT_i	Arrival time
NMSR	Not matched shared-vehicle riders	N_i^S	Node for a shared-vehicle rider i
(O, D)	Origin and Destination	$tt_{(a,b)}$	Travel time between node a and node b

To mathematically model the SAFV's dispatching problem, this study defines a decision variable, x_i^r, as a picked SR i who is riding a SAFV along with its route, r. The decision variable is used to capture that rider is on the SAFV's route, where indicator function Eq. (2) returns the value 1; otherwise, this function returns the value 0. Thus, the total number of SRs, M_r, who use the same SAFV and its route r can be calculated in Eq. (3).

$$x_i^r = \begin{cases} 1 & if\ SR\ i\ is\ matched\ with\ SAFV\ and\ its\ route\ r \\ 0 & otherwise \end{cases} \tag{2}$$

$$\sum_i x_i^r = N_r$$

$$where,\ N_r = the\ total\ number\ of\ Srs\ on\ the\ SAFV's\ route, r \tag{3}$$

Equation (4) describes the objective function of the problem which is to maximize the fleet operator's profit, P, by addressing the optimal number of the AFVs. (Table 2 shows variables for the function). As a profit maximization problem the profit, p_i^r, is composed of a time-based AFVs fleet fare and a pick-up cost. The first term is revenue by serving a rider i on an AFV's route r; (Eq. (4.4)) and the second term is a dead-mile travel cost for the SAFVs to pick-up the rider i (Eq. (4.5)).

$$Max\ P = \sum_j \left\{ \left(\sum_{i \in NMSR} p_i^r \cdot \varphi_j^r \right) \cdot \omega_j^r \right\}$$

$$= \sum_j \left\{ \left[\left(\sum_{i \in NMSR} (ST_i^r \cdot SF - IPT_i^r \cdot ITC) \cdot x_i^r \right) \cdot \varphi_j^r \right] \cdot \omega_j^r \right\} \tag{4}$$

subject to,

$$T_g^{D,r} + tt_{(N_g^D, N_i^O)}^r \leq DT_i \qquad \forall\ g, i\ \in NMSR \tag{4.1}$$

$$\varphi_j^r = \begin{cases} 1 & if\ M_r\ \geq 2 \\ 0 & otherwise \end{cases} \tag{4.2}$$

$$\omega_j^r = \begin{cases} 1 & if \sum_{i \in NMSR} p_i^r \leq 0 \\ 0 & otherwise \end{cases} \qquad \forall\, i,k \in NMSR \qquad (4.3)$$

where,

$$ST_i^r = tt^r_{(N_i^O, N_i^D)} \qquad \forall\, i \in NMSR \qquad (4.4)$$

$$IPT_i^r = tt^r_{(N_g^D, N_i^O)} \qquad \forall\, g,i \in NMSR \qquad (4.5)$$

* g : A rider who is served before SR i with the same AFV

$$** \; N_g^D = \begin{cases} Depot & if\ SR\ i\ is\ the\ first\ passenger\ on\ the\ AFVs \\ Destifation\ node\ of\ a\ rider\ g & otherwise \end{cases}$$

The set of constraints is shown in Eq. (4.1)-(4.3). The first constraint says that if a rider i is not the first passenger on the SAFVs, the term $T_g^{D,r}$ indicates a time when a rider g leaves his/her destination; otherwise $T_g^{D,r}$ become departure time for SAVFs from their own depot (and the departure time depends on the first passenger's departure time at his/her origin). The second and the third constrains address two assumptions that we made the above. There are pros and cons to those assumptions. The benefit is that, by restricting availability for the fleets with the closed time window, we could apply a brute force algorithm to search every possible SAFVs' route. Eq. (4) even makes it possible to simplify the search graph of the brute force algorithm. The downside is that because of these restrictions some SAFV routes are discarded so that it may happen to have shared-vehicle riders who are not matched after the whole simulation is done.

Table 2. Variables

	Variables
p_i^r	Profit from SR i on AFVs route r
ST_i^r	SR i travel time (i.e., between SR's origin and destination) via the AFVs' route r
SF	Autonomous fleet vehicle service fare
IPT_i^r	Dead mile travel time to pick-up the SR i on the route r
ITC	Dead mile travel cost

3.2.4 P2P Ridesharing with shared autonomous fleet vehicles module

One matter to consider is how to maximize the usage of the SAFVs. Specifically, even though a single SAFV can be shared with multiple passengers when a single passenger is riding the SAFV the rest of the seats in the fleet are wasted. Thus, this research revisits the DP algorithm to improve the efficiency of the SAFVs by operating them as a ridesharing mode to serve (still)

unmatched riders after the SAFVs module in Section 3.2.3. In this stage, only the SAFVs are considered as an available mode for riders and the SAFVs have a pre-defined route (i.e., means that the SAFVs cannot change their routs randomly). Firstly, a rider has his/her own accessible (reduced) network for a trip. Next, if some SAFVs pass this network and can deliver the rider to destination without conflicting with the rider's time window, then this rider is matched with the SAFVs.

3.3 Lower level – Mobility portfolio incentive problem

After completing the successive ridematching process, each participant in 3-Is system falls into two groups which are 'matched group' and 'unmatched group'. People in the 'matched group' have a more diverse mobility portfolio (Figure 1). For example, a matching result with multiple modes or drivers accompanies with additional waiting times for the connecting modes. Another case will be the increased travel time and miles for a driver. In the proposed system, matched drivers may experience a longer trip for a rider, so that his/her travel time may increase. The diverse travel options with longer travel times could incur users' unsatisfaction when the recommended travel time is worse than their current trip. A user might not trust the system if the proposed portfolio does not guarantee its shortest trip. In addition, if a user finds that his/her travel time is longer than other users', the user feels unfair for the recommended portfolio. These comparisons could deter a system from being reliable in that users lose their interest in the system. Thus, in the lower level, this study applies an incentive scheme to compensate for their inconvenience and to attract people to stay with the recommended travel itinerary from the system. (If matched participants have less travel time, compared to their usual travel time with personal vehicles, we consider that they already get benefits from our system. Thus, we do not provide an incentive scheme for them).

Each participant has an optimal mobility portfolio that can have different travel options. The travel time and price of each travel option might differ according to travel modes and travel itineraries. This various quantity of travel options could be an issue in terms of fairness. It is worth reminding the fact that some travelers should accept a longer trip that the shortest path to improving the overall system's efficiency. In this case how the system fairly compensates their inconvenience can an important issue. In other words, a system should fairly compensate for an alternative's inconvenience to other options by providing a proper amount of incentives. Thus, determining an appropriate amount of incentives can be important to the entire system. This research designs the mathematical formulations for the incentive scheme. The main research interest is to find the optimal incentive amount to guarantee that all participants satisfy. Detailed algorithms will be explained in the next section.

Once the previous step has processed the ride-match, the next step finds the optimum incentives that minimize envy among users and for their current travel mode. There are three objectives in the incentivizing function. The first objective focuses on envy behavior (e_{ij}) of traveler i to other travelers j, and the constraints sets consist of OD path travel time ($t_{k,i}^{od\tau}$) and

its price ($\pi_i^{od\tau}$) at an agent level. An agent measures envy by comparing the allocations with others' if and only if the agents belong to the same origin and their destinations group. The individual envy comparisons and cumulative sum of envy affect the total maximum envy, but our mathematical programming procedure solves the problem to minimize the total maximum envy. The second objective deals with the behavior where an agent feels envious when his/her travel option is not the shortest path (e_{is}). This objective function considers the limitation of envy comparisons in peer to peer communication. For example, some OD-time pairs in an optimized system might travel options not having the actual shortest path. The third object is a budget constraint for an OD-time pair. The optimization is to minimize all three objectives with parameters α, β, and γ. In our study, we evenly set the parameter to 1/3.

$$\text{Min obj} = \alpha \sum_{i \in I} \max_{i \neq j} \{e_{ij}\} + \beta \mathrm{e}_{is} + \gamma B^{od\tau} \tag{5}$$

subject to:

$$e_{ij} \geq -\theta_i \left(t_{k,j}^{od\tau} - t_{k,i}^{od\tau}\right) + \left(\pi_j^{od\tau} - \pi_i^{od\tau}\right) \qquad \forall\, i, \mathrm{j} \in I^{rs}, \mathrm{i} \neq j, \forall\, \mathrm{rs}\tau \tag{5.1}$$

$$e_{is} \geq -\theta_i \left(t_{k,s}^{od\tau} - t_{k,i}^{od\tau}\right) + \left(\pi_s^{od\tau} - \pi_i^{od\tau}\right) \qquad \forall\, i \in I,\ \forall\, \mathrm{od}\tau \tag{5.2}$$

$$e_{ij} \geq 0 \qquad \forall\, i \in I,\ \forall\, \mathrm{od}\tau \tag{5.3}$$

$$0 \geq \pi_i^{od\tau} \geq \pi_{max}^{od\tau} \qquad \forall\, i \in I,\ \forall\, \mathrm{od}\tau \tag{5.4}$$

$$\theta_i t_{k,i}^{od\tau} - \pi_i^{od\tau} \geq 0 \qquad \forall\, i \in I,\ \forall\, \mathrm{od}\tau \tag{5.5}$$

$$\sum_{i \in I^{od}} \pi_i^{od\tau} = B^{od\tau} \qquad \forall\, \mathrm{od}\tau \tag{5.6}$$

$$\mathrm{t}_{od\tau}^{*} \in \max_{t_{od\tau}} \sum_i -t_{k,i}^{od\tau} \theta_i \qquad \forall\, \mathrm{od}\tau \tag{5.7}$$

where, $t_{k,i}^{od\tau}$ is path travel time of an option k in a portfolio for Origin (o) and Destination (d) for user i. $t_{k,j}^{od\tau}$ in Eq (5.1) is the travel time of the other agent j. Similarly, $\pi_i^{od\tau}$ is the pricing for agent i and $\pi_j^{od\tau}$ is for the comparison target (agent j). The system manager can regulate incentive $\pi_i^{od\tau}$ to be less than his/her perceived travel time $\theta_i t_{k,i}^{od\tau}$, which might prevent an agent from abused behavior. Eq 5.7 indicates an allocation efficiency, which is a necessary condition to minimize total envy. It implies that agents having a higher valuation to time are matched to a shorter path. Similarly, agents who are less sensitive to travel time are matched to a longer path.

The proposed heuristic utilizes a local comparison property, which the local objective set for each OD-time pair is independent. In this manner, the decomposition method solves the complete problem efficiently. With the given path travel time and volume from the prior steps, this problem becomes a simpler linear optimization problem. We choose constraints (Eq 5.1-5.5) that are related to the envy minimization for an OD pair, as Eq (5.6).

4. Simulation study on '3-Is' Smart mobility portfolio efficiency

4.1 Simulation environment

This section describes our simulations to analyze the number of people who change their mode (i.e., a personal vehicle) to alternative modes that result from the peer-to-peer ridematching process. The simulation environment is as follows:

1. The smart mobility portfolio simulation is an agent-based simulation and is for a subscription-based ridesharing system (i.e., the system knows all participants' trip information and time window information).
2. We refer to the Southern California Association of Governments (SCAG) demand model.
3. The morning peak hour period is selected as the simulation time period.
4. Travel demand is randomly divided into two groups (i.e., SR and SD groups).
5. For the system participants, each participant starts and ends in the predefined TAZs, so-called as a go-points.
6. The simulation has a discretized time horizon with 5-minute time intervals.
7. All autonomous vehicle fleets dispatched from their own depot and operate within a certain region.
8. Buses and metro rails are simulated with a real-time schedule.
9. A sufficient number of bikes are provided at each station (i.e., means that a station does not have a capacity issue) so that any riders who arrive at any bikesharing stations can use a bike for his/her trip.

The User Interface (UI) follows the process which is shown in Figure 4. First of all, a user provides his/her personal profile and basic preferences. Then, just like in common route planning applications such as Google directions, a user enters their destination as an address, or as a place name that could be a selectable Point of Interest (POI). If the user has specific departure time and late arrival time windows, he/she can specify that information (Simulation environment rule 1). Based on the provided information, the main server finds possible alternatives matching the user's preferences. The alternatives are refined by the time window criteria. They are chosen among the system optimum routes which are already calculated by transportation models and stored in a server or in the cloud. If the user selects and drives along the suggested path with a detour, the driver earns some rewards (incentives).

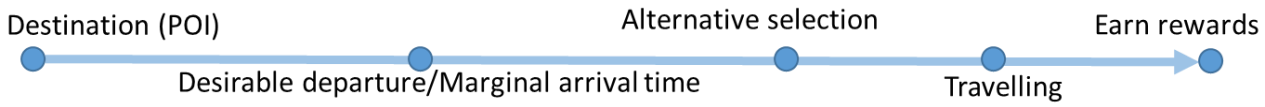


Figure 4. Regional User Interface flow of a reward-based trip planning system

4.2 Modeling of '3-Is' transportation network

4.2.1 Study area selection

Los Angeles is notorious for its poor quality of traffic, especially in morning/evening peak hours. One of the major causes of congestion in this city is that a large number of 'drive-alone' commuters. Furthermore, the portion of the usage of public transportations is relatively small. To improve the efficiency of the transportation system, the first priority is to reduce the potential vehicle demand by increasing the average occupancy of vehicles. The second strategy is to increase transit ridership by providing increased accessibility to transit stations. Our proposed scheme devises an integrated transportation system that multiple modes cooperate to provide better accessibility and mobility. The integrated transportation system includes various travel modes: 1) public transportation, 2) peer to peer (P2P), and 3) bikesharing. Public transportation modes provide better mobility in a congested area such as Downtown Los Angeles (DTLA) but it has accessibility problems. A peer-to-peer (p2p) ridesharing system can play an important role in improving the accessibility to the public transit (i.e., bikesharing station, bus station, and metro station).

Our research area the Downtown Los Angeles (DTLA) to the City of Los Angeles, Pasadena, and Long Beach to conduct a comprehensive analysis of integrated, intermodal and incentivized shared (3-Is) transportation network. One reason is that, according to the Southern California Association of Governments (SCAG) travel demand model, travel demands from the Pasadena area and Long Beach area have an immense influence on traffic congestion in Los Angeles Area; Another reason is that, even though the city suffers from chronic traffic congestion, it has various transportation modes such as LA Metro Railways, Buses, Vehicles, and Bikesharing as shown in Figure 5.

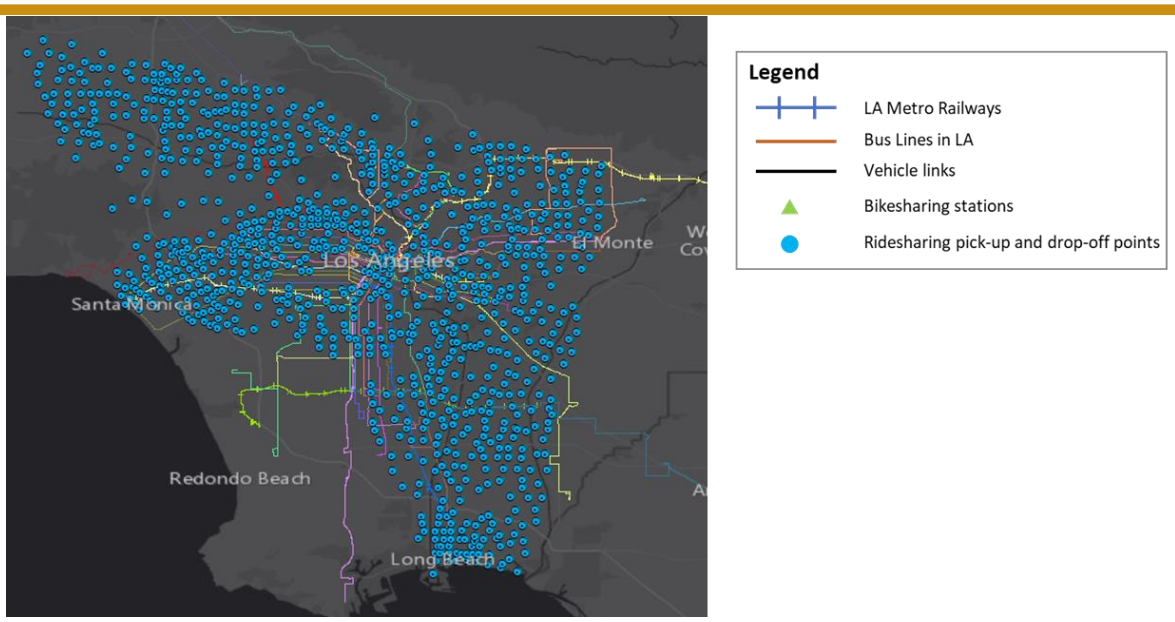


Figure 5. Network components of the study area (City of Los Angeles)

4.2.2 Urban transportation network selection

Considering 3-Is transportation system, this research focuses on designing a system to integrate travel modes in the study area. Moreover, an autonomous fleet vehicle system is introduced to support the shared-transportation network. The mobility portfolio takes advantage from a combination of multiple modes and connections among those modes. Table 3 lists the mode layers and their relevant data sources.

Table 3. Link type and data source of each mode layer

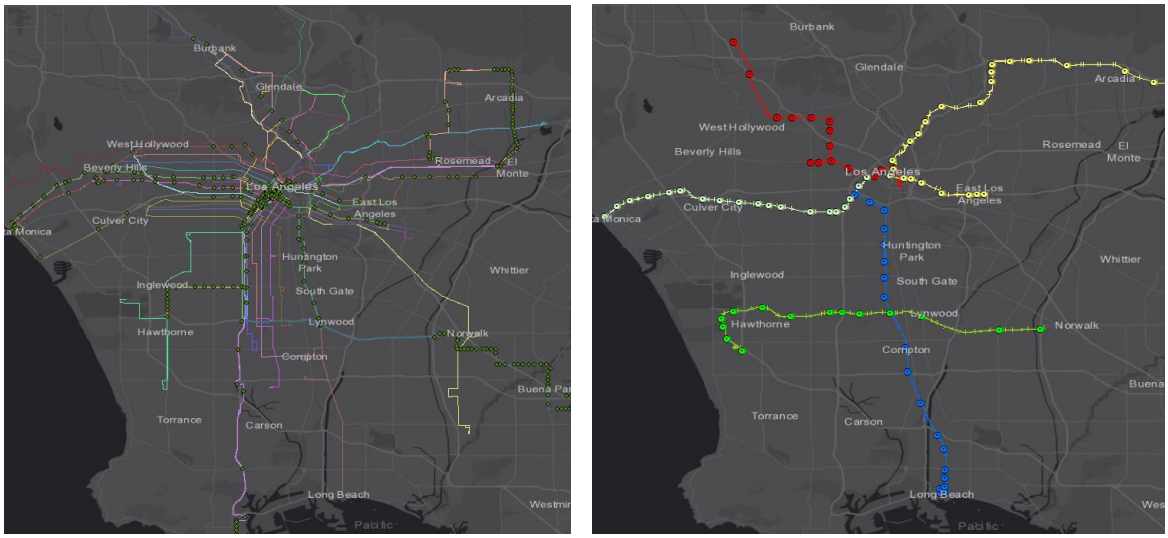
Network Type	Link type	Data source
Private vehicle	Highway links	SCAG travel demand model
Autonomous vehicle fleet	Highway links	-
Bus	Bus lines	GTFS
Metro rail	Metro lines	GTFS
Bike	Highway links + Bike lanes	LA Metro Bikesharing
Walk	Walk links	-

The basis network of the integrated and intermodal network is a personal vehicle's network (i.e., Highway links (Table 3)). With the help of SCAG demand model, this study creates a network for personal vehicles with 998 Traffic Analysis Zones (TAZs) nodes. In this study, we call the TAZ nodes as a go-point. Shared-ride driver (i.e., ridesharing system participants) will use this network with their vehicle. Los Angeles Metro has launched the metro bikeshare system in

Downtown Los Angeles (DTLA) since July 2016. Six Metro Rail lines operate in Los Angeles County. All Metro rail lines are originated or pass through downtown LA. In addition, 45 LA Metro Bus lines are operated in this area, including rapid bus lines and local bus lines. Compared to the size of bus network links and personal vehicle network links, this study selects the rapid bus lines. In this research, 1,512 transit/vehicle nodes are selected as our go-points. Detailed definitions of each network (including the walk network and the autonomous fleet vehicle network) will be presented in the next section.

4.2.3 Los Angeles bus lines network

We constructed a bus line network in Los Angeles county over general transit feed specification (GTFS) data which contains routes, bus stop information, and schedules. As mention above, this study considered rapid bus lines so that only 11 rapid bus lines were selected in Figure 6 (a). To promote commuter to use shared-transportation systems, we pick the morning peak period bus network (i.e., 7:00 am to 9:00 am) and schedules.



(a) Los Angeles Metro Bus network (b) Los Angeles Metro Rail network

Figure 6. Los Angeles Metro network

4.2.4 Los Angeles metro rail lines network

LA metro rails operate 6 lines in Los Angeles County. Figure 6 (b) shows all 6 metro lines. Each rail line has its own route and schedule. This study collected this information from the LA metro office website. Similar to the bus network, we followed the morning peak period metro rail network for analysis.

4.2.5 Los Angeles bikesharing network

Figure 7 (a) is all bikesharing network in Downtown Los Angeles (DTLA), Santa Monica, and Long Beach area. As shown in the figure, bikesharing stations in DTLA are located at the center of the

study area and close to other public transit lines. Therefore, this study chose the bikesharing station in DTLA (Figure 7 (b)). One characteristic of the bikesharing network is that a bike from one bikesharing station can reach any bikesharing stations so that it is necessary to generate links that connect from one bike station to other bike stations. However, this network increases calculation complexity. Thus, this study analyzed bikesharing trip data which have released from the LA metro bike and found bikesharing demand origin-destination pattern at each bike station. With this preprocessing, we filtered accessible bikesharing stations from each station and generated bikesharing network. To operate bikesharing system and promote usage of it in 3-Is system, we assume that there are a sufficient number of bikes and no capacity issues at each station. In this study, 70 bike stations are operating.

(a) Bikeshare network in Los Angeles County *(b) Bikesharing network in DTLA*

Figure 7. Bikesharing network in Los Angeles County

4.2.6 Walk-link (Connected link)

As this study proposes the multi-modal transportation system, the above modes (including private vehicle network) should be connected. In order to enhance the connectivity of the network and enable to transfer, we built virtual walk links to connect different type of travel networks. Transfer between travel modes could happen in several cases: (1) transfer from TAZ nodes to any public transit network nodes, (2) transfer from one bus line to other bus line (or one rail line to other rail line), (3) transfer from a bus to other transit mode (metro, bike, or AV fleet) or vice versa. To generate walk links, we search adjacent nodes within 0.1 miles from each node to provide not only reasonable walk distance, but to minimize the transferring cost for passengers. If selected nodes belong to different types of networks compared to the pivot node, then we created links between those nodes for the walk network.

4.2.7 Autonomous fleet vehicle network

As the study region (Figure 5) is large, it is hard to serve all commuters from one single depot for shared autonomous fleet vehicles. Therefore, this study selectively chooses the upper and middle parts of the study region for a SAFVs system in both areas. To run regional SAFVs services, each area has its own fleet depot and fleets are running only within the region. Figure 8 shows the boundaries of regional SAFVs services.

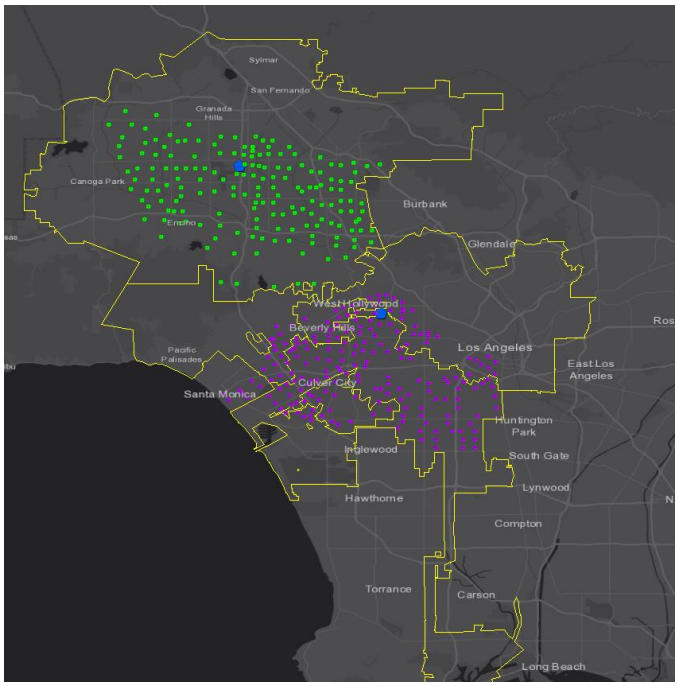


Figure 8. Regional autonomous fleet vehicle service area

Based on the selected study area, the multilayered network is designed by considering model efficiency and computation complexity for a simulation study. Moreover, the network is implemented on a mobile application, which plays an important role in trap planner for finding the best trip itineraries for users and to evaluate the proposed algorithm.

4.3 Simulation scenario setting

Based on the SCAG demand model, overall 224,196 system participants are generated in 3-Is system. During the morning peak period, 5,000 out of the entire demand are randomly selected as riders. Similarly, 30,000 people are also randomly selected as drivers. As introducing the successive ridematching algorithm process, a different type of matching method is applied at each step. To evaluate the performance of the proposed framework, we set three different scenarios as shown in Table 4.

Table 4. Simulation scenario setting

	P2P ridesharing matching module	SAFVs dispatching module	P2P ridesharing module with SAFVs
Scenario 1	√	X	X
Scenario 2	√	√	X
Scenario 3	√	√	√

4.3.1 Autonomous vehicle fleet fare

Referring to the earlier study (Masoud et al., 2017), the value of time (VOT) for SRs set at $20/hr, $1.6/5-min for a time-based fare. For the behavior of SAFVs, this study considered a default value of $10/h for the dead-mile travel time which is corresponding to the $0.8/5-min cost. Moreover, this study estimates a time-based service fare for SAFVs based on the Uber cost scheme. The application of Programmable Interfaces (APIs) which is provided by Uber help us to understand how the uber price is estimated in our research scope as shown in Figure 5. Using the Uber APIs we calculate the fare based on both travel time. The average uber service fare is $3.3 per 5 minutes. The highest and the lowest fares are $2.8 and $3.8, respectively. According to basic statistics (minimum, average, and maximum), we decide to use the average uber service cost as a SAFVs fare and analyze the impact of a service cost on maximizing the SAVF profit.

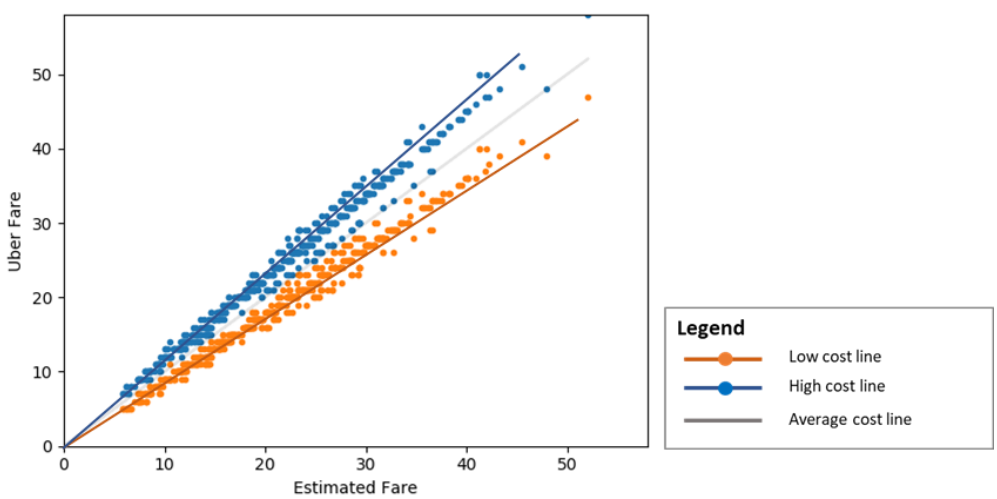


Figure 9. Estimated AFVs fare from Uber price

4.4 Simulation results

4.4.1 Matching rate

In this section, we describe simulations to analyze the number of people who change their mode (i.e., a personal vehicle) to shared transportation modes. We compare the matching rate

at each module. Figure 10 shows the overall matching rate results in the matching process. In Scenario 1, 3,514 out of 5,000 riders are matched with shared-vehicle drivers and other travel modes (e.g., public transit, bikesharing, and walk), which is 70.28% matching rate. In the next scenario, 254 riders are served by autonomous fleet vehicles (AFVs), so that the cumulated number of matched riders becomes 3,768 which is 75.36% out of the entire riders. In the final scenario, 2 riders use AFVs while sharing empty seats with other passengers. After finishing the entire process, the 3,770 riders use shared transportation modes, thus 75.40% riders are matched. A detailed explanation will be shown in the next sections.

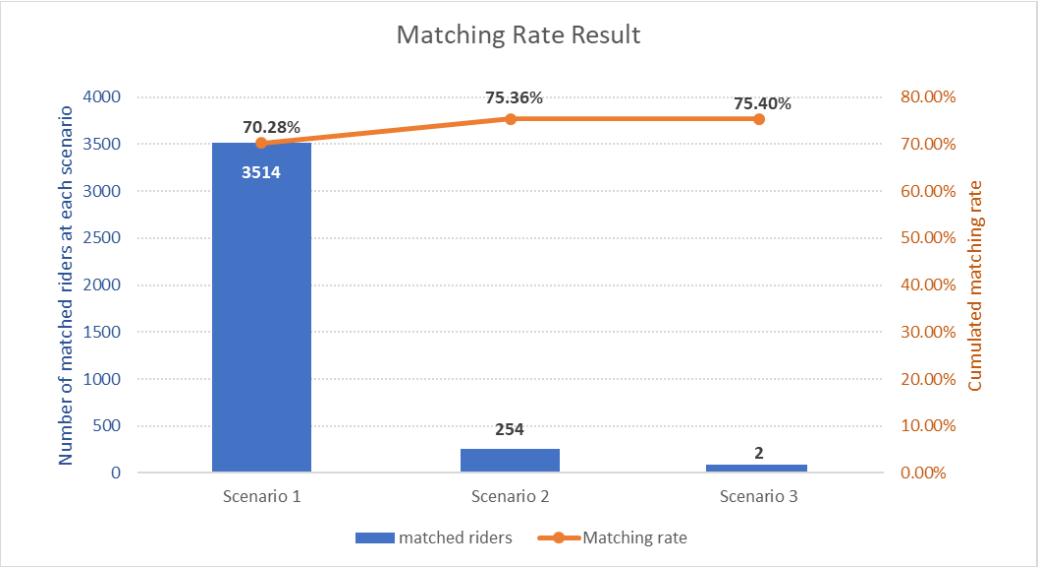


Figure 10. Matching rate result

(1) Shared-Travel Mode Usage in scenario 1

Referring to Table 5, the sum of the shared transit mode users (i.e., 5,207) is higher than the actual matched-rider (i.e., 3,514). The result shows the riders can not only use a single travel mode but also do 'transfer' to complete their trip by hopping travel modes. According to the simulation results, a rider (e.g., #15438) is matched with a single shared-vehicle driver (e.g., #218134). A rider (e.g., #15630) is matched with a driver (e.g., #64814) at first, and then this rider uses a metro rail and takes a walk to finish his/her trip. Moreover, a rider (e.g., #178954) uses a bike firstly and then takes a walk to his/her destination. As shown in Table 5, the number of riders who use the 'walk link' is 825. Therefore, we find that the riders using the suggested mobility portfolio have a better option than driving him/herself. Corresponding to the high number of walking link demand (transferring), an additional 224 number of people use public transit. This study proves that the proposed p2p ridematching algorithm in 3-Is system can promote the ridership of public transit. However, only 55 riders use a bikesharing mode for

commuting. This is because we only consider bike stations which are located in Downtown Los Angeles (DTLA). The size of the DTLA has less than one-tenth of the size of the study area, thus the bikesharing network may not large enough to cover all system participants' commuting routes.

Table 5. Number of matched riders on each travel mode of Scenario 1

	Overall Matched riders	Shared Travel Mode Usage			
		Shared-vehicle drivers	Bus and Metro rail	Bikesharing	Walk
Number of riders	3,514	4,760	224	55	825

(2) Autonomous Fleet Vehicle and Shared Autonomous Fleet Vehicle Usage (in scenario 2 & 3)

From the previous module, we observe that 1,486 riders are not matched and they still have some opportunities to be served by the autonomous fleet vehicles. As shown in Figure 5, there are two AFV service areas: (a) the upper area and (b) the lower area. 43 fleet vehicles and 58 fleet vehicles are dispatched from the upper and the lower areas, respectively. In the second scenario, 125 riders use fleets in the upper region, so that on average there are 2.9 passengers on each fleet; in the lower region, 58 fleets serve 129 riders and each fleet has 2.22 passengers.

With the fixed route, AFVs are introduced in the third scenario as the ridesharing mode in the third module. Among the remaining riders (i.e., who are not matched in Scenario 1 and 2), one passenger is matched at each region. For example, in Scenario 2, the AFV (#14) which runs in the upper area is matched with three passengers (e.g., riders - #54458, #99575, and #185937) and its path is a sequence of nodes as follows: depot (node #2221) – node #528 – node #562 – #node 556 – #node 554 – #node556 – #node544. A rider (#122438) who has a path (such as #node 562 – #node 556 – #node 554) shares the AFV (#14)'s route without conflicting his/her time window. For another example, in the lower area, the AFV (#1) has two passengers (e.g., riders - #41124, and #75224) and its route is composed of a sequence of nodes as follows: depot (node #2222) - #node 949 – #node 945 – #node 949 – #node 966 – #node 970 – #node 969 – #node 935 – #node 930. A rider (#78928) who has a route (such as #node 970 – #node 969) shares the AFV (#1)'s empty seats.

In the simulation, the fleet service company earns $1,010.4 and $1,577.2 after finishing Scenario 2. When the whole simulation process is completed, the fleet company get additional costs, $11.2 and $11.2, respectively. Thus, the total amount of the profit that the fleet company earns is $2,610 in the morning peak hour per day.

In summary, after finishing the first scenario, 70.28% of riders (i.e., 3,514 out of 5,000) are being served, and in the second and the third scenarios, 5.12% of riders (i.e., 256 out of 5,000) use the AFVs. The total number of riders who use shared-transportation mode is 3,770.

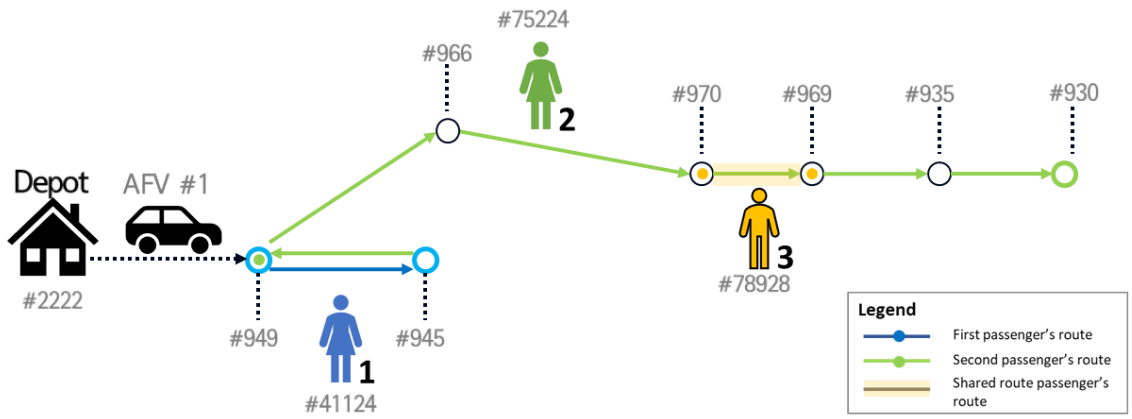


Figure 11. Example of Autonomous fleet vehicle #1 route

4.4.2 Shared-mobility system efficiency test

This study evaluates the performance of the simulations results from the smart mobility portfolio framework with (a) the total number of loaded personal vehicles on the roads and (b) vehicle-hour-traveled (VHT). Even though more than 224K people commute within the study area, we assess the efficiency of the system only considering people who are participating in the shared-mobility system.

(1) Total Number of Vehicles Operating on the Study Area

In order to assess the number of shared-mobility system participants (i.e., 30,000 shared-vehicle drivers and 5,000 shared-vehicle riders), a total of 35,000 people exit in the system (i.e., No scenario case). If none of the riders are matched to the drivers, they use their personal vehicles. With the peer-to-peer ridesharing algorithm, 4,343 shared-vehicle drivers cover 3,380 number of riders in Scenario 1. This means that unmatched 1,620 number of riders need to drive themselves for commuting. Therefore, in this scenario, 31,620 vehicles are entering the network. In the second scenario, autonomous fleets serve 254 riders with a size of 101, so that the total 31,467 number of vehicles are running in the system. In the last scenario, an additional two riders share the empty seats in fleets. Eventually, only 31,475 number of vehicles are utilizing in the shared-mobility system. Table 6 shows the system participants' trip status in each scenario and the total number of loaded vehicles on the roads; Figure 12 shows the ratio of the reduced vehicles on the network.

(2) Reduced Vehicle-Hour-Traveled

As shown in Table 6 and Figure 12, we observe that the sum of the vehicles on the roads is reduced. However, due to introducing the AFVs service in our system, the total VHT could be increasing. Therefore, this study analyzes the value of VHT in each Scenario.

Table 6. Comparisons of the total number of loaded vehicles on the network

	System Participating type	Trip type		Loaded Vehicle	Total Loaded Vehicle
		Solo Trip	Shared Trip		
No Scenario	Driver	30,000	0	30,000	35,000
	Rider	5,000	0	5,000	
	AFVs	0	0	0	
Scenario 1 (with the p2p ridesharing)	Driver	25,657	4,343	30,000	31,620
	Rider	1,620	3,380	1,620	
	AFVs	0	0	0	
Scenario 2 (Scenario 1 + AFVs)	Driver	2,5657	4,343	30,000	31,467
	Rider	1,366	3,634	1,366	
	AFVs	0	101	101	
Scenario 3 (Scenario 2 + with the p2p AFVs ridesharing)	Driver	25,657	4,343	30,000	31,475
	Rider	1,364	3,636	1,364	
	AFVs	0	101	101	

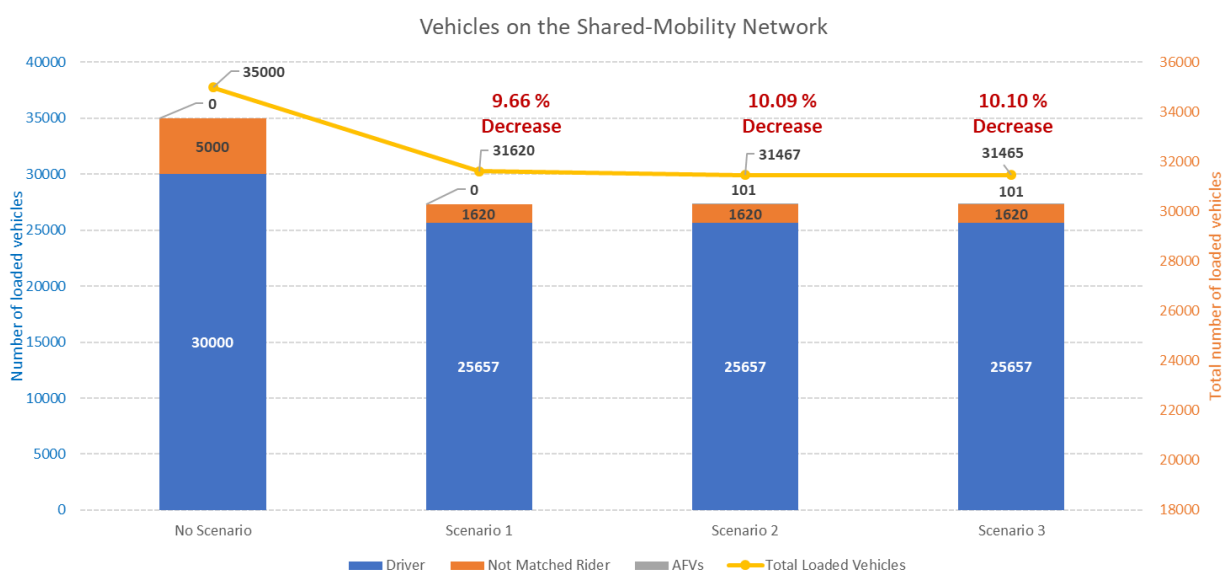


Figure 12. The ratio of reduced vehicles on the network by scenarios

When none of the shared travel modes is applied, the total amount of vehicle-hour-traveled is 1,503,165. Once the smart mobility portfolio is given to the people in this system, we find that the VHT is reduced. Table 7 shows that after the first scenario, the VHT is dropped about 3.14%; after completing the whole scenario, the VHT is slightly increased due to the AFVs. Overall, in our system, the total VHT is decreased by 3.01%.

Table 7. Effectiveness on the network by scenarios

	Vehicle type		No Scenario	Scenario 1	Scenario 2 & 3
Vehicle-Hour-Traveled	Personal Vehicle	Drivers	1,503,165	1,436,144	1,436,144
		Not matched riders	0	19,881	17,326
	AFVs	Driverless	0	0	4,726
Total VHT			1,503,165	1,456,025	1,458,196
The ratio of reduced VHT			-	3.14%	3.01%

In summary, simulation results show that the matching rate is improved with the 3-Is network as the results from the smart mobility portfolio framework. Also, the peer-to-peer ridesharing service can promote the usage of public transit. As introducing the autonomous fleet vehicle, the matching rate is increasing by serving unserved riders. In addition, the total number of vehicles on the roads is reduced so that we can infer that the proposed system could improve the system better; and overall VHT is also decreasing.

4.4.3 Incentives and Required budget

In this section, we examine the optimum incentives for the Mobility portfolio estimated from the prior step. Initially, we assume the homogeneous VOT at $20/hour. The results of the prior step indicate that 45 riders among 5,000 riders experience longer travel time than their original travel time for driving. The maximum travel time increase is 15 minutes. Most of the riders have a similar travel time with driving within 5 minutes gaps. 418 riders have significantly faster travel time. We assume that travel time and incentives only affect the riders' choice behavior.

The proposed method estimates the amount of incentive-based on the three factors. The first factor is associated with peer to peer envy comparisons. In the result of the case study, however, the comparisons do not affect the incentive although there are some riders having the same OD-departure time. The main reason is that all riders in the same OD-time group have the same travel time because of the ridesharing module, which matches those riders to the same drivers if ridesharing vehicles have enough seats for them. The higher number of riders' cases at the same number of drivers will produce multiple MP combinations that have travel

time differences, then, the mathematical programming will utilize this peer to peer comparison factor.

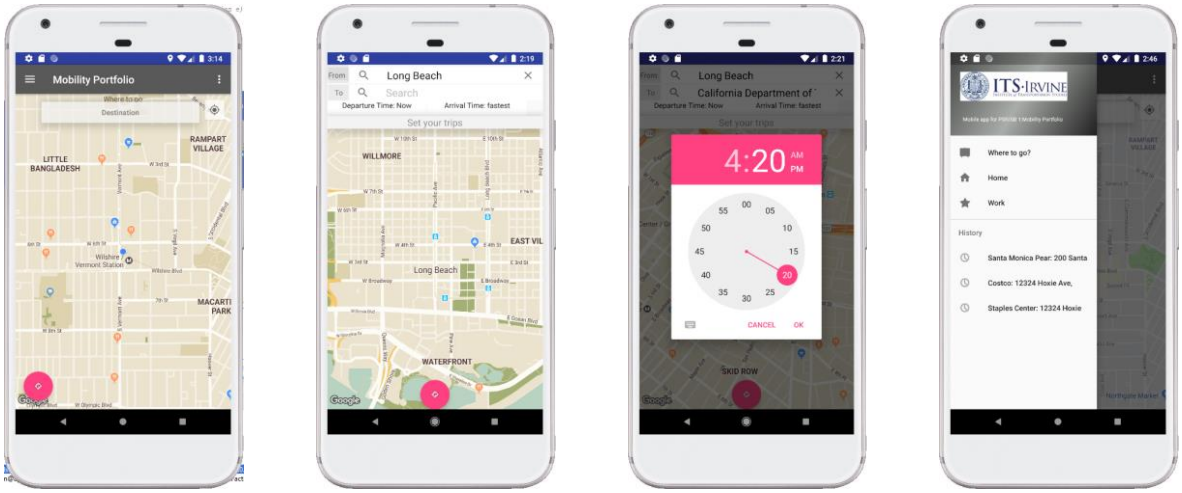
The travel time increases of MP and incentive budget constraints also affect the amount of incentives. Incentives might be effective to attract the potential riders to MP if an incentive lessens the generalized cost than his/her original travel mode (e.g. personal vehicle). In other words, an incentive scheme works efficiently if and only if the travel time of MP is higher than his/her original travel mode. In this manner, riders who have the similar ETA (Estimated Time of Arrival) or faster ETA do not get incentives. Travelers will select the because they have similar or better mobility services that their original travel mode. Since the third objective in our mathematical formulation is the required budget for incentives and we minimize the budget under the constraint, the amount of incentive and the budget are the results of the optimization problem. Table 8 shows the results of the required budgets for an incentive for each rider group.

Table 8. Required budget for incentives

Rider group by ETA	# of riders	Incentive budget ($)
Similar ETA	3,285	0.0
Increased ETA	45	96.7
Decreased ETA	418	0.0

5. Smart mobility portfolio mobile application

A real mobile application can help us understand how the proposed method works by providing User Interfaces. Figure 13 shows examples of User Interfaces. A participant indicates his/her trip information and preferences to the app, then the app communicates to a server with those inputs. The base interface is on digital maps (Google maps). A user can drag a flag for their destination or manually search his/her destination in the origin/destination box. The input box is connected to Google Place Autocomplete API so that a user can find his/her origin/destination with few words. A user can also define his/her early departure time and latest arrival time. For user's convenience, they can use their trip history or favorites for their journey.



Initial Screen | Trip Information Setting | Departure Time / Arrival Time | Trip History

Figure 13. User Interface of the mobile application

A cloud server in ITS, UCI receives a user's trip request and an engine in the server finds the best itineraries based on various data sources. The current application collects real-time traffic information from LA Metro Public Transportation, Bikesharing program, Uber, and Google traffic through Application Program Interfaces (APIs). Figure 14 shows an overview of the data flow of the mobile application.

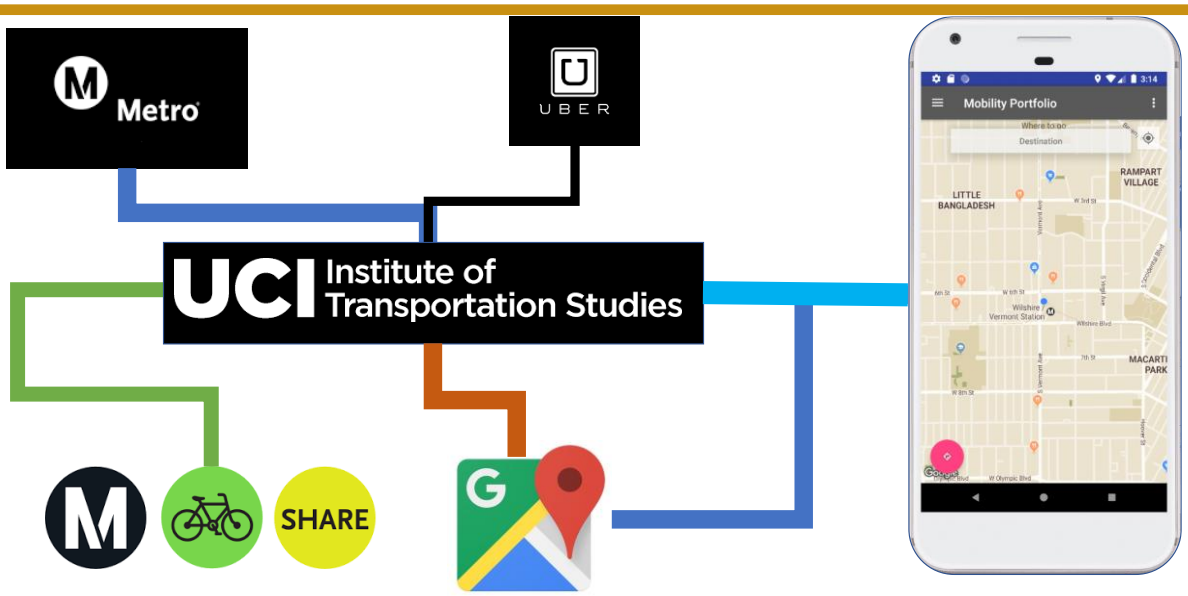
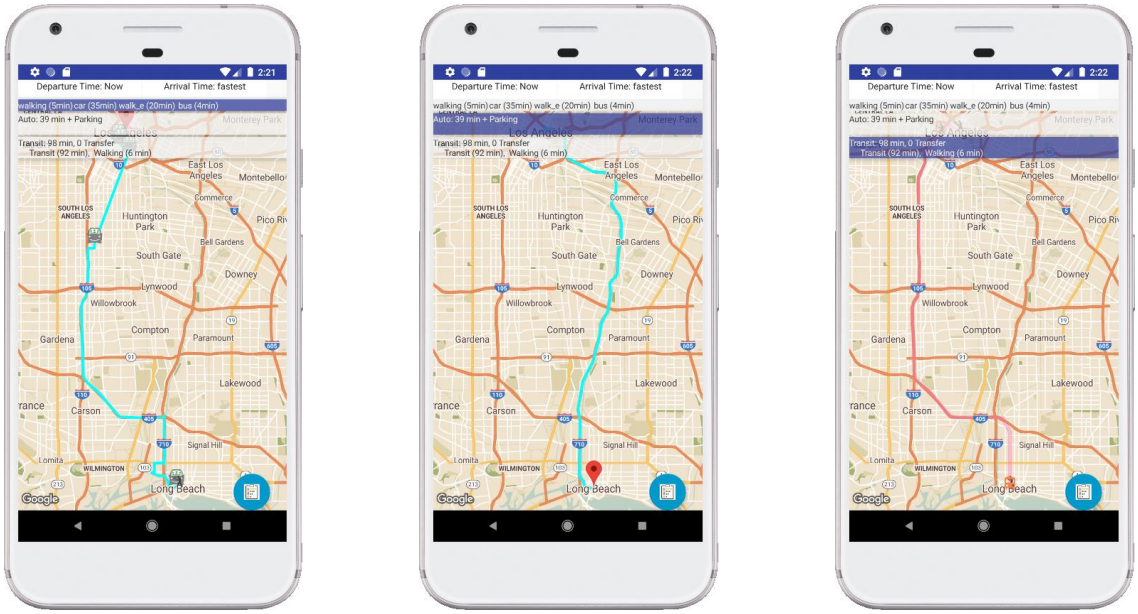


Figure 14. Overview of the data flow of the mobile application

The output of the mobile application includes travel options. As shown in Figure 15, the results show trip information about various travel options. Potential system participants will be asked for their feedback about the results in the following survey page. A user shows their mode preferences and these revealed preferences can be utilized to update the current model for a mobility portfolio.



Mobility Portfolio | Personal vehicle | Public Transportation

Figure 15. MP results on the mobile application

6. Conclusion

In this project, we proposed an Integrated, Intermodal, and Incentivized Shared (3-Is) Transportation system that included strategically constructing a multi-layered transportation network and a pricing scheme to attract people to use more shared transportation modes with a smart mobility portfolio. We considered various travel modes such as - mass transit lines in Los Angeles county, bikesharing, autonomous fleet vehicles, and private vehicles for a ridesharing case study. To facilitate the existing and potential travel modes in the study area, we proposed a sequential ridematching framework and provided the best mobility portfolio option for each rider by maximizing their utility. As a result of the ridematching process, we showed that the multi-modal network the ridesharing can, in fact, be used to carry people to other travel modes as a feeder. In addition, we observed a transfer between travel modes happens within a single trip. From a systemic point of view, the proposed mobility portfolio system with an incentive scheme can be a solution for the congestion issue faced by a transportation-related government agency while collaborating with private traffic agencies that provide autonomous fleet vehicles by maximizing their profits. We also proposed a method to estimate the proper incentives for users having longer travel time than their original travel mode (e.g., personal vehicle). The government might fund the incentive scheme for the improved efficiency of transportation systems or the private sector can support the scheme to attract more users to their system. We can even imagine a collaboration between the public and private sectors. For example, once the public sector identifies desirable travel options, business sectors in this system can use our proposed incentive scheme to attract travelers passing by their stores. In other words, for a traveler who has ample time to arrive at her destination and prefers to a coffee during longer trips, the incentive mechanism could possibly suggest alternative itineraries which maybe just a little longer but also comes with a reward in the form of a Starbucks gift card or credit.

Still some limitations lie in this project. First thing is that we considered bikes which are sitting in the Downtown Los Angeles area only. This fact may affect the usage of bikesharing in our project. Another limitation is that we assumed that the private companies already have sufficient number of fleets; which means that the vehicle purchasing fee is not counted. Finally, we assumed that for each fleet it is not mandatory to return its depot. Thus, further research is required along such lines.

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Data Management Plan

Products of Research

Describe the data that were collected and used for the study.

1. Data

a. Southern California Association of Government (SCAG) network

b. Transit data from GTFS Google.

c. LA Metro Bikesharing data

2. Software/Algorithms

a. Ride-matching algorithm

b. In-house optimization codes

Data Format and Content

Describe the format, or file type, of the data, and the contents of each file.

1. SCAG Network and demand Data. In TransCAD software format
2. Transit data. GTFS Format

Data Access and Sharing

The data and software are available on request from the PI.