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Rosenthal, Dock S.

Publication Date

2015

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UNIVERSITY OF CALIFORNIA,
IRVINE

Estimating Auto Demand Diversion to Transit Caused by Bike-Sharing
Using Optimization Based on Value of Time

THESIS

submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Civil Engineering

by

Dock S. Rosenthal

Thesis Committee
Professor R. Jayakrishnan, Chair
Professor Will Recker
Associate Professor Wenlong Jin

2015

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ACKNOWLEDGMENTS

I would like to express my appreciation to Professor R. Jayakrishnan, my advisor, for all of his assistance brainstorming this topic and his guidance throughout the research process. His knowledge and expertise took my topic from a general interest into the complete paper presented here. Also the other members of my thesis committee Professor Will Recker and Professor Wenlong Jin who have tried their best to make me a more than just a competent transportation engineer throughout my education.

A thank you to my fellow students in the Transportation Systems and Transportation Studies program who have helped me learn tools essential to this thesis including Daisik Nam for his help with Google API and Jiang-Bo Yu for his help filtering through the SCAG data. This research would have dead-ended many times if not for the help of Neda Masoud who helped me over many hurdles during the formulation of the mathematical program and the constraints, with the utmost gratitude I thank her for all her time and advice.

Finally this research and my studies were made possible by a grant from UConnConnect and for that I am immensely grateful.

ABSTRACT OF THE THESIS

Estimating Auto Demand Diversion to Transit Caused by Bike-Sharing
Using Optimization Based on Value of Time

By

Dock S. Rosenthal

Master of Science in Civil Engineering

University of California, Irvine 2015

Professor R. Jayakrishnan, Chair

In 2015 bike-sharing has become a viable transportation mode in the urban core of many large cities worldwide. Notably lacking is research on the bike-sharing/transit connection. Bike-sharing provides an excellent solution to the “first-last mile” problem experienced by transit networks but data is difficult to collect due to the independent operation of each network. This thesis proposes an optimization algorithm of user mode choice based on minimizing cost. Required system characteristics for this optimization program are at least two bike-sharing market areas, transit links between the areas and a realistic potential for the vehicle network to become congested. The results show the optimal mode choice by Origin-Destination (OD) pair. This model was applied to trips from downtown Pasadena to downtown Los Angeles in California. These two areas are expected to have a bike-sharing system as soon as 2016 operated by the Los Angeles County Metropolitan Transportation Authority (METRO). Based on congestion from 1x to 4.25x the free-flow time, bike-sharing provides increasing value to commuters between these two areas. The simple parameters of this application including value-of-time and cost of use could be easily updated to reflect a deeper consideration of user cost.

Introduction

Bike and bike-sharing transportation networks are often viewed as operating entirely independent of the rest of the transportation system. It possesses obvious similarities with traditional biking but with key differences relating to parking, accessibility and security. There is ample research on multimodal bike-transit trips (Cheng & Liu, 2012; Flamm & Rivasplata, 2014; Flamm, Sutula, & Meenar, 2014; Hagelin & Datz, 2005; Martens, 2004) but little research on connecting bike-sharing and transit. The advantage of bike-sharing over biking is the elimination of some hindrances to cycling transit users (CTU). Of these, the biggest problems are bike storage at the station, bike storage on board the transit vehicle and bike accessibility at the egress end of the trip. Solving those issues would make traveling easier for cyclists and could make cycling more attractive to non-cyclists.

The literature of bike-sharing demand studies either retroactively develops regression models from the characteristics of the current users (Daddio, 2012; Schoner & Levinson, 2013) or estimates demand based on GIS characteristics and diversion rates from other modes (Gregerson et al., 2010; Krykewycz, Puchalsky, Rocks, Bonnette, & Jaskiewicz, 2010; Maurer, 2012). These studies incorporate transit as a variable in a regression model of bike-sharing demand but do not show how bike-sharing can influence transit demand. In one of the few studies combining bike-sharing and transit, Jäppinen, Toivonen, & Salonen (2013) find that shared bikes can reduce transit travel times by more than 10% in Helsinki, Finland.

Mathematical programming approaches such as proposed in this thesis can be used in order to optimize bike sharing fleet size or station location. They seem to be more

robust than the GIS based techniques discussed above, but it is unknown if there is a significant difference in the results of the two analyses that justifies the increased computation effort.

When evaluating a city's potential benefit from a new bike-sharing system, few studies have made attempts to ascertain the impact on the transit system from a predictive point of view. Providing insights towards such predictive analysis is an objective of this thesis that proposes a new optimization formulation based on user costs after summarizing the literature relating to *cyclist behavior*, *bike sharing – transit* and *optimization*. The formulation will minimize the cost to the users based on value of time for each transportation mode in the objective resulting in a number of new transit trips diverted from previous auto demand.

Literature Review

Cyclist Behavior

The traditional method of incorporating bicycles and transit has been “bikes-on-buses” (BOB). Hagelin & Datz (2005) focused on the different costs and benefits of various BOB measures in transit agencies nationwide. A majority of agencies reported that the bike racks had capacity limitations and 25% of commuters reported the racks often being full. Most bike racks can only hold 2-3 bikes, which allows only a limited number of spaces for BOB. That paper also reported that 72% of BOB users are commuting to work, with a very specific time frame, so if a bike rack is full, then the commuter could be late to work. While bike sharing also has capacity limitations

(parking/availability at the station), the issue of bringing a bike on board is eliminated by the ability to access a bike at either end of the transit trip.

Also of interest are the trip planning characteristics that are important to CTU. These factors are security from theft, guarantee of availability, flexibility to change plans and user cost (Krizek & Stonebraker, 2011). Krizek & Stonebraker found that *users* prefer bike-*on*-transit, riding to a station and boarding with their bike. Whereas, for *transit agencies*, bike-*to*-transit, riding and parking at the station, is the most cost effective, with the common method of racks on buses. Of primary concern to users was the security of leaving their bike at a station or relying on a shared bike later in their trip. Also related to cycling behavioral criteria are the findings of a user preference study for the Melbourne and Brisbane bike sharing systems that indicated users are more likely to use a bike-sharing if a station is within 250 meters of their work place (Fishman, Washington, Haworth, & Watson, 2015). The ability for users to walk a short distance to the station and perhaps check for availability before committing to the biking trip and forgoing an alternative results in a guarantee that the system will be available for use.

Another important factor that influences commuter choice is level of stress on bike routes (Franco, Campos, & Monteiro, 2014). Different types of bicycle facilities, such as bike lanes, can alleviate this disutility. While poor facilities are an impediment to any type of cycling a bike sharing station could be under utilized if its location is not incorporated with the existing bike facility network. Perceived self-image has also been shown to influence cycling behavior (Gatersleben & Appleton, 2007; Underwood, Handy, Paterniti, & Lee, 2014). Gatersleben & Appleton studied the perceptions of cyclists with non-cyclists. They found that many non-cyclists felt cycling was something

that “other people do” or that there were greater obstacles than the lack of bike facilities. Underwood et al. also found a similar conclusion with school children. They found that even though cycling is popular at a younger age many children cease riding as they age due to social perceptions and never begin again. These conclusions are important when attempting to force a mode shift, it is clear that removing structural barriers to cycling by improving safety and accessibility do not eliminate all the obstacles that people perceive towards cycling.

Bike Sharing - Transit

With an understanding of the types of structural and behavioral characteristics that influence biking it is now important to understand the ways to evaluate the travel decisions that are at the basis of multimodal trips. Common techniques to determine these preferences are stated and revealed preference surveys. In a Dutch study utility value ratios are found for a variety of factors such as main trip travel time, access travel time, egress travel time, various costs and base level utility of different single and multimodal trips. The results show the degree to which access and wait time have higher value than in vehicle time (Arentze & Molin, 2013).

Martin & Shaheen (2014) studied the relationship between an existing transit system and a new bike-sharing system by surveying the stated preference for using transit because of the implementation of bike-sharing. They found bike-sharing caused travelers to shift towards rail transit and away from bus transit in the more suburban Minneapolis while they shifted away from all modes of transit in the more urban city of Washington DC. They attribute this difference to the density of the DC bike sharing system where

bike trips can be more efficiently made than transit trips. In Minneapolis, the low density of the bike-sharing network does not allow for efficient bike trips and connections to transit are more desirable. This study suggests that in a relatively suburban city such as LA linking transit trips with bike sharing can increase the shift towards rail because the geographical size of the city makes biking long distances inefficient.

Optimization Formulations

The optimization formulation for bike-sharing develops due to the problem of one way trips. Without rebalancing some stations will fill up and some will empty throughout the day. Some systems also have the problem of different modes used for access and return trips (Raviv & Kolka, 2013). Moving bikes around the system from stations with an excess to stations with a deficit solves the problem. The redistribution problem is similar to a single commodity pickup and delivery problem (1-PDP).

Contardo, Morency, & Rousseau (2012) formulate the objective as a minimization of unmet demand (the shortage and excess of bikes) at a state in the discretized time network. Unfortunately this solution algorithm is not applied to any real life network. Raviv & Kolka (2013) also approach the optimization as a 1-PDP, specifically as a closed loop inventory. Rather than focusing on the entire system, they focus on individual stations because in a well-operated system the unmet demand for parking or rentals is minimal, and therefore the spillover to other stations will be minimal as well. The station in question is not replenished before the end of the time step, so the only actions that can happen are a rider attempting to return with insufficient capacity or a rider attempting to rent without enough bikes. In such a situation, the station is assessed a penalty.

Shayarshad et al. also models the optimization based on the redistribution of empty bikes around the system but the objective function is a maximization of benefit to the company based on the costs of that redistribution. They do not compare their formulation with any other approaches but find a solution that gives the amount of bikes to be moved from station to station, in a two-origin, two-destination example (Sayarshad, Tavassoli, & Zhao, 2012). Martinez et al. also solves an optimization based on profit, explicitly revenue in this case but does not include redistribution operations in the optimization. Redistribution is simply included as a separate term for the time frame that is combined into the larger system. The model is applied to the city of Lisbon, Portugal using a discrete choice mode share model and p-median method for selecting station locations which is based on a minimum distance between stations and minimizing the maximum walking distance for users (Martinez, Caetano, Eiró, & Cruz, 2012).

Garcia-Palomeres et al. uses a GIS bases approach similar to those used in the demand studies above to compare two different approaches to locating bike stations, p-median as described above and maximizing coverage, where the stations are located to correspond with the highest demand areas. It is notable that they recognize the symbiotic relationship with transit and fix some bike-sharing stations at transit hubs (García-Palomares, Gutiérrez, & Latorre, 2012). Lin & Yang Ta-Hui (2011) also addresses the relationship with transit in their optimization approach. It is based on cost to the user and the operator (set up, bike lanes, unfulfilled demand). In their problem the costs are determined based upon the “candidate locations” for station locations meaning that the algorithm evaluates given locations but does not give any guidance about where to put them initially.

Chow & Sayarshad introduce an optimization approach to compare transit networks and bike sharing. They propose a symbiotic relationship between the two systems based upon shared commodities such as passengers, shared nodes or shared links. The formulation is a multi-objective optimization where the optimization includes the network in question and any other networks interacting with it. In a dual network example this can either be parasitic, where the guest benefits but the host degrades, or mutualistic, where both benefit. This is particularly appropriate in the “subsidy” problem where a guest network (bike-sharing) may wish to reach an optimal solution through minimized costs but the transit network stands to benefit through a sub-optimal formulation of the bike-sharing network. Specifically, bike-sharing will act as a feeder system to transit up to a certain size but will then start to shift trips towards biking when the size is larger. In that case the bike-sharing and transit systems should collaborate due to their shared commodities (commuters) (Chow & Sayarshad, 2014).

Summary

Improvements to bike facilities for existing CTU are well studied as are land use characteristics influencing bike-sharing ridership in cities with existing systems. Unfortunately those papers are based on current users and do not have any methodology to attract new users. Calculating bike-sharing demand based on diversion rates or station density might indicate some positive feedback to other modes of transit (such as bike-to-rail rather than bus-to-rail) but ultimately misses the goal of capturing new ridership. An area with high transit density is already well served and has little need for yet another mode choice. If biking is faster than transit then the bike-sharing system is introducing

new bike riders into the system. That is a laudable result but often takes riders out of the transit system rather than off the highways. This new optimization framework developed in this thesis deviates from the method of using simple diversion rates to find demand for bike-sharing and allows for real costs to be parameters.

Methodology

The formulation of Masoud & Jayakrishnan (n.d) uses decision variables to route vehicles and connect riders to vehicles in a point-to-point ridesharing system. That optimization finds trip-vehicle pairs by minimizing the total number of vehicles used. It is based on ridesharing where vehicles also need to be routed. In order to encompass a more diverse transportation network, including the option to bike and take transit, this formulation is expanded in this thesis to include a binary variable for bike trips and a binary variable for metro rail. As referenced above, bike-sharing routing has already been studied extensively so the routing functionality of the optimization was dropped. Instead the objective function in this model will minimize the user cost.

Similar to the formulation of Masoud & Jayakrishnan, link sets are made up of tuples consisting of time and station in the form $(t_0, t_0 + \Delta t, station, station)$. The general rule for these links is that the time will always increase by at least one Δt but can increase up to the end time of the interval. The stations do not have to change; these are the ‘waiting links.’ These links allow for a passenger to transfer from one mode to another such as bike to transit or vice versa. The super supply and super demand nodes that can churn out bikes instantaneously are an exception to this rule. The travel time to and from these ‘super’ nodes is zero so that bikes can be introduced without causing user delay. The cost of redistribution caused by those links can be ignored because it is a system cost and not a user cost.

The allowable link sets for bikes ($Links_b$), transit ($Links_m$), vehicles ($Links_{rv}$) and riders ($Links_r$) are made up as follows. The bike, transit and vehicle link sets all have dictionaries associated with the allowable origin-destination combinations and the

associated travel times. The travel times for these OD pairs are based on the free flow travel time for vehicles. For bikes, the travel times are based on the path between the two nodes that makes use of the available bike facilities either bike streets with sharrows (shared right of way) or bike lanes. It is important to note that this is usually not the most direct route between two nodes. The extra distance creates a built-in travel time penalty comparable to evaluating the accessibility or stress level between the OD pair by bike. Bikes are assigned to a specific origin station in order to limit the number of possible links for a certain bike. There are more than 30 nodes in the applied model discussed below. A bike with all OD combinations included as links would be unnecessarily complex. The methodology for restricting the bike links in the application case is discussed below. In a general application of this model bikes could be segregated in any reasonable manner to reduce the number of valid links per bike. In order to model the capacity limitations at each station a constraint of 20 bikes per station per time is included. Bikes cannot serve more than one rider at a time and must go back to the super demand node before they are redistributed.

Vehicle riders are not allowed to transfer to metro or bike and are much simpler to model. Each rider is assumed to have their own vehicle and can wait at their origin as long as they can still arrive on-time at their destination. Transit links are based on the transit schedule for each transit line included. Metro Links are taken from the schedule for the AM peak with headways of 6 minutes (rounded to 5 minutes to match time-steps in the model). There are no capacity constraints for the trains; they can serve any number of commuters traveling from the origin node to the destination node.

The rider links are constructed by combining any of the above links that connect a rider with their destination. That includes either a direct connection via auto or a transit trip with cycling as the access and egress mode. With the link sets constructed the optimization formulation is as follows.

Program

In this formulation there is only one decision variable used to route bikes in the system.

$$x_l^b = \begin{cases} 1 & \text{if bike } b \text{ is on link } l \\ 0 & \text{otherwise} \end{cases}$$

There are three decision variables used to assign trips to links for vehicle, bike and metro.

$$x_l^{rv} = \begin{cases} 1 & \text{if rider } r \text{ is assigned to vehicle } v \text{ on link } l \\ 0 & \text{otherwise} \end{cases}$$

$$x_l^{rb} = \begin{cases} 1 & \text{if rider } r \text{ is assigned to bike } b \text{ on link } l \\ 0 & \text{otherwise} \end{cases}$$

$$x_l^{rm} = \begin{cases} 1 & \text{if rider } r \text{ is assigned to metro } m \text{ on link } l \\ 0 & \text{otherwise} \end{cases}$$

The sets included in the program are:

- Riders – the commuters in the model
 - o TripSN – the start node associated with a commuter trip
 - o TripEN – the end node associated with a commuter trip
- B – set of bikes

- Nodes – set of all nodes
 - o $Depo_o$ – Super Supply Node
 - o $Depo_d$ – Super demand Node
- T1 – set of discretized time steps
- M – set of transit lines
- Links
 - o $Links_b$ – set of allowed links for each bike in B
 - o $Links_m$ – set of allowed links for each transit line in M
 - o $Links_r$ – set of allowed links for each rider in Riders
 - o $Links_{rv}$ – set of allowed links for the vehicle of each rider in Riders
 - o $Links_{rb}$ – intersection of $Links_r$ and $Links_b$ for each rider in Riders and each bike in B
 - o $Links_{rm}$ – intersection of $Links_r$ and $Links_m$ for each rider in Riders and transit line in M

The objective takes the sum of the trips assigned to vehicles multiplied by the travel time (first term), the sum of riders on bikes on links where the nodes change, which is the cost of biking in the system (second term), the sum of trips assigned to bikes where the station is the same which is the cost of waiting time (third term), the sum of trips assigned to metro which is the cost of using metro (fourth term). The coefficient of any term may be adjusted to incorporate a cost for value of time or flat rate for using the mode (as in transit).

$$\begin{aligned}
& \sum_{r \in Riders} \sum_{\substack{(t1,t2,i,j) \in Links_{rv} \\ i \neq j}} (t2 - t1) * x_l^{rv} + \sum_{b \in B} \sum_{\substack{(t1,t2,i,j) \in Links_b \\ i \neq j}} (t2 - t1) * x_l^b \\
& + \sum_{r \in Riders} \sum_{b \in B} \sum_{\substack{(t1,t2,i,j) \in Links_{rb} \\ i=j}} (t2 - t1) * x_l^{rb} \\
& + \sum_{r \in Riders} \sum_{m \in M} \sum_{\substack{(t1,t2,i,j) \in Links_{rm} \\ i \neq j}} (t2 - t1) * x_l^{rm}
\end{aligned}$$

The first constraint says that riders assigned to bikes on a link cannot exceed the number of bikes on a link.

$$(1) \quad \sum_{r \in Riders} x_l^{rb} \leq x_l^b \quad \forall b \in B: (t_1, t_2, i, j) \in Links_{rb}$$

The second constraint makes bikes exit their link at the end of the link, this does not mean that they must exit their station just that they must transfer to another link.

$$(2) \quad \sum_{i \in Nodes} \sum_{\substack{t1 \in T1 \\ Links(t1,t2,i,j)}} x_l^b = \sum_{n \in Nodes} \sum_{\substack{t3 \in T1 \\ Links(t2,t3,j,n)}} x_l^b$$

$$\forall b \in B, t2 \in T1, j \in Nodes: \neq depo_o \text{ or } depo_d$$

The next four constraints ensure (3) that the rider is considered from the beginning of the interval so she/he cannot sit idle to avoid violating bike-station capacity constraints, (4) there is only 1 mode and 1 link assigned for the start of the trip, (5) only 1 mode and 1 link assigned for the end of the trip and (6) that the flow going into a node equals the flow going out.

$$\begin{aligned}
 (3) \quad & \sum_{\substack{(t_1, t_2, i, j) \in Links_{rv} \\ i = TripSN \\ t_1 = 0}} x_l^{rv} - \sum_{\substack{(t_1, t_2, i, j) \in Links_{rv} \\ j = TripSN}} x_l^{rv} \\
 & + \sum_{b \in B} \left[\sum_{\substack{(t_1, t_2, i, j) \in Links_{rb} \\ i = TripSN \\ t_1 = 0}} x_l^{rb} - \sum_{\substack{(t_1, t_2, i, j) \in Links_{rb} \\ j = TripSN}} x_l^{rb} \right] \\
 & + \sum_{m \in M} \left[\sum_{\substack{(t_1, t_2, i, j) \in Links_{rm} \\ i = TripSN \\ t_1 = 0}} x_l^{rm} - \sum_{\substack{(t_1, t_2, i, j) \in Links_{rm} \\ j = TripSN}} x_l^{rm} \right] = 1 \\
 & \forall r \in Riders
 \end{aligned}$$

$$\begin{aligned}
(4) \quad & \sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rv} \\ i = \text{TripSN}}} x_l^{rv} - \sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rv} \\ j = \text{TripSN}}} x_l^{rv} \\
& + \sum_{b \in B} \left[\sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rb} \\ i = \text{TripSN}}} x_l^{rb} - \sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rb} \\ j = \text{TripSN}}} x_l^{rb} \right] \\
& + \sum_{m \in M} \left[\sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rm} \\ i = \text{TripSN}}} x_l^{rm} - \sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rm} \\ j = \text{TripSN}}} x_l^{rm} \right] = 1
\end{aligned}$$

$$\begin{aligned}
(5) \quad & \sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rv} \\ j = \text{TripEN}}} x_l^{rv} + \sum_{b \in B} \sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rb} \\ j = \text{TripEN}}} x_l^{rb} + \sum_{m \in M} \sum_{\substack{(t_1, t_2, i, j) \in \text{Links}_{rm} \\ j = \text{TripEN}}} x_l^{rm} \\
& = 1
\end{aligned}$$

$\forall r \in \text{Riders}$

$$\begin{aligned}
(6) \quad & \sum_{i \in \text{Nodes}} \sum_{\substack{t_1 \in T1 \\ (t_1, t_2, i, j) \in \text{Links}_{rv}}} x_l^{rv} + \sum_{b \in B} \sum_{i \in \text{Nodes}} \sum_{\substack{t_1 \in T1 \\ (t_1, t_2, i, j) \in \text{Links}_{rb}}} x_l^{rb} \\
& + \sum_{m \in M} \sum_{i \in \text{Nodes}} \sum_{\substack{t_1 \in T1 \\ (t_1, t_2, i, j) \in \text{Links}_{rm}}} x_l^{rm} \\
& = \sum_{n \in \text{Nodes}} \sum_{\substack{t_3 \in T1 \\ (t_2, t_3, j, n) \in \text{Links}_{rv}}} x_l^{rv} + \sum_{b \in B} \sum_{n \in \text{Nodes}} \sum_{\substack{t_3 \in T1 \\ (t_2, t_3, j, n) \in \text{Links}_{rb}}} x_l^{rb} \\
& + \sum_{m \in M} \sum_{n \in \text{Nodes}} \sum_{\substack{t_3 \in T1 \\ (t_2, t_3, j, n) \in \text{Links}_{rm}}} x_l^{rm}
\end{aligned}$$

$\forall r \in \text{Riders}, t_2 \in T1, j \in \text{Nodes} : j \neq \text{TripSN}, j \neq \text{TripEN}$

The station capacity constraint for the bikes is (6), it restricts the number of bikes at a station in any time interval to at most 20 bikes. The first two terms are the difference between the bikes coming into a station and the bikes exiting a station before time t , the next two terms are the difference between bikes coming into a station and exiting a station at time t .

$$\begin{aligned}
(7) \quad & \sum_{b \in B} \sum_{\substack{t_1 \in T1 \\ t_1 \leq t_2}} \sum_{\substack{t_2 \in T1 \\ t_2 < t}} \sum_{\substack{i \in Nodes \\ (t_1, t_2, i, s) \in Links_b}} x_l^b - \sum_{b \in B} \sum_{\substack{t_1 \in T1 \\ t_1 \leq t}} \sum_{\substack{t_2 \in T1 \\ t_2 < t}} \sum_{\substack{i \in Nodes \\ (t_1, t_2, s, i) \in Links_b}} x_l^b \\
& + \sum_{b \in B} \sum_{\substack{t_j \in T1 \\ t_j \leq t}} \sum_{\substack{i \in Nodes \\ (t_j, t, i, s) \in Links_b}} x_l^b - \sum_{b \in B} \sum_{\substack{t_j \in T1 \\ t_j \leq t}} \sum_{\substack{i \in Nodes \\ (t_j, t, s, i) \in Links_b}} x_l^b \leq 20
\end{aligned}$$

$$\forall s \in Nodes, t \in T1: s \neq depo_o \& s \neq depo_d$$

Constraint (8) restricts the total capacity of bikes in the system, for every time interval (t_1, t) the total number of bikes cannot exceed 1100.

$$(8) \quad \sum_{b \in B} \sum_{\substack{(t_1, t, i, j) \in Links_b \\ t_1 \leq t}} x_l^b \leq 1100 \quad \forall t \in T1$$

$$(9) \quad \sum_{\substack{(t_1, t_2, i, j) \in Links_b \\ j \in Nodes \neq depo_o \\ i = depo_d}} x_l^b = 0 \quad \forall b \in B, b \neq b_{dummy}$$

$$(10) \quad \sum_{\substack{(t_1, t_2, i, j) \in Links_b \\ j = depo_o \\ i = depo_d}} x_l^b = 1 \quad \forall b \in B, b \neq b_{dummy}$$

Constraints (9) and (10) restrict the action of bikes into and out of the super supply and super demand nodes. Importantly, constraint (10) only allows a bike to be redistributed once in an interval from the super demand node.

Application of the Model

Metro, the Los Angeles County transportation authority, has plans to implement a bike-sharing program starting with a pilot in 2016 in the area of Downtown LA and expanding in various phases throughout the county. Pasadena is included in Phase 2 of the expansion. The application of this model is perfect due to the Gold Line, a light-rail, that links these two areas.

Demand data was pulled from the Southern California Association of Governments (SCAG) Traffic Analysis Zones (TAZ) in the area around the Gold line from Downtown Pasadena to Union Station. There are 65 bike-sharing stations in Downtown LA and 33 in Pasadena. With 32 and 14 TAZ respectively the ratio of BSS to TAZ is approximately 2:1. However, these BSS are not evenly distributed within the TAZ, some TAZ are well covered and others only have access to one station. The stations were aggregated due to the redundancy of service created by the high density in certain TAZ.

Aggregating BSS

The most important information about the location of the bike sharing stations is the distance from Union Station (LA) or Del Mar Station (Pasadena). Those two stations were selected as the points of transfer between the bike sharing network and the transit line. That distance gives the travel time between the nodes and the feasible window when a trip can take place. Stations were aggregated based on each TAZ. If a certain station was centrally located within the TAZ it was selected as representative. Otherwise stations were selected based on which would serve a greater percentage of the TAZ and the area as a whole. The aggregated stations are shown in the Figure 1 and Figure 2 below. The stations that were not included are small black dots. Stations 2, 13 and 37 are not shown because they had a demand of less than 0.5 trips for the period.

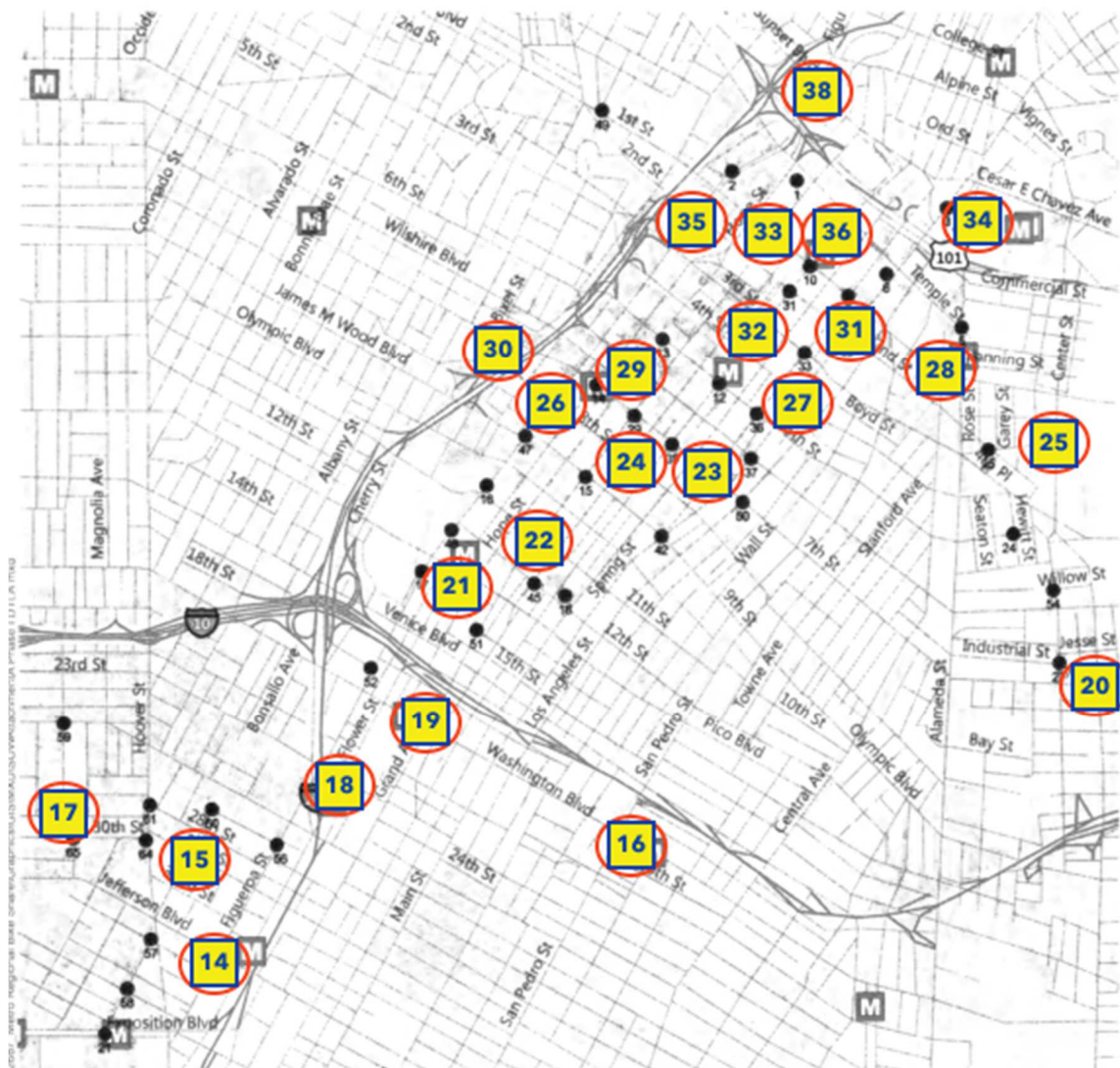


Figure 1: Aggregated Stations LA (RFP No. PS11357 Metro, 2014)

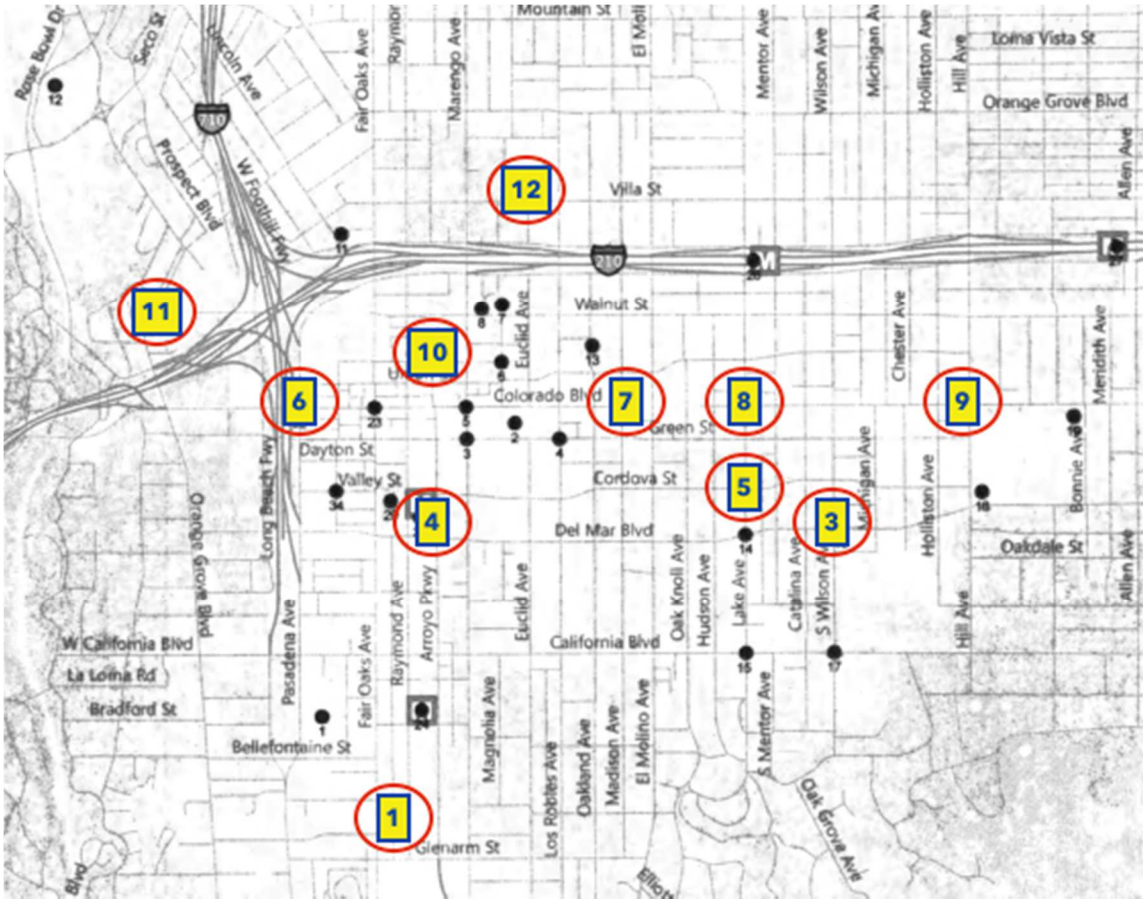


Figure 2: Aggregated Stations Pasadena (RFP No. PS11357 Metro, 2014)

Determining demand

Cambridge Systematics (CS) developed a bike sketch plan for Metro LA to model the change in bike trips resulting from improved bike facilities such as parking and bike only lanes (Cambridge Systematics & Associates, 2014). The plan assumes driving costs at \$0.6 per mile, biking cost at \$0.08 per mile and health benefits of biking at \$1.50 per mile. They use an average cycling work trip of 3.9 miles. Diversion rates from a new bike-sharing system are 60% from auto and 17% from active modes such as walking or riding a personal bike. However, these bike trip characteristics are based on a single mode of travel, so not all of this information is directly applicable. This model studies the

induced transit demand from bike-sharing in a multimodal trip framework not the potential of bike-sharing alone to divert auto trips. The information used was the cost of driving, the monetary health benefit of biking and the average trip length (used to inform which transit stations would be accessible by bike).

Other bike-sharing demand predictions, such as in New York City, use constant adoption factors based on user class, such as resident or tourist (Department for City Planning New York, 2009). The Philadelphia and Seattle demand models use GIS land use characteristics to determine areas of high ridership potential but these models are based on bike-sharing as an unlinked mode (Gregerson et al., 2011; Krykewycz et al., 2010). Assuming that the characteristics of *multimodal bike-transit* rider are the same or similar to a *bike-only* rider may be reasonable, but there is no way to validate that without ridership data that is unavailable at this time.

This paper proposes a parametric study of the sensitivity of auto demand to congestion delay. Utilizing the auto demand from SCAG and the coverage of the BSS to determine riders could benefit from linking bike-sharing and transit rather than applying a regression model created from data outside of Los Angeles. The time period for the demand is the 7-8 AM peak. Adjusting the value of time costs and the fixed or per-mile costs of each mode (car, bike, train) resulted in different values of modal shift from auto to bike/transit. Demand was assigned from the TAZ within the downtown areas using the aggregated bike sharing stations determined above. The feasible walking distance for each station is a circle extending $\frac{1}{4}$ mile. Each station covers between 1 and 4 TAZ's. The demand assigned from each TAZ was determined using the ratio of the covered area

to the total TAZ area. The TAZ and station were linked by proximity. Only a couple stations had demand from multiple TAZ.

Feasible Links

Bike travel times range from 1 to 3 times that of auto travel times for local trips. The ratio is significantly higher over long distances but feasible bike trips will not exceed 5 miles, the maximum distance a user could travel in the 30 minutes of “free time” provided by the LA bike sharing system at 10mph. The distance between LA and Pasadena is approximately 11 miles, which significantly exceeds not only a possible bike-sharing trip but also a reasonable bike-only commute trip. However, nearly all of the bike-sharing stations in Downtown and all of the bike-sharing stations in Pasadena can access a Gold line station within the trip window provided by the bike-sharing system.

The maximum distance from a bike-sharing station to any Gold line station in Pasadena is 1.5 miles. In the downtown Pasadena area, Lake, Allen and Del Mar stations are all accessible. Del Mar station was selected as the only hub in order to simplify the model, resulting in a maximum biking distance of 2.5 miles over mostly flat terrain on bike friendly streets.

In downtown LA the maximum distance to Union station, where the Gold line can be accessed is 4.6 miles (from Expo Park/USC station). While there are numerous public transit options that can access Union Station from Expo Park it requires multiple transfers, in that one must take the Expo line and transfer to the Purple line a trip time of about 25 minutes. A trip all the way to Del Mar station takes a full hour, approximately equal to the bike/Gold Line commuting time. In Washington DC, bike-sharing diverted

trips from the transit system indicating that there is some greater utility to use bike-sharing over transit for short access trips (Martin & Shaheen, 2014). Furthermore competition between bike-sharing and transit is not the focus of this paper, rather the possibility of attracting drivers to use the transit system through bike-sharing.

Considering those alternative transit access modes would result in too many feasible links, therefore the model was applied considering only 1 transit line, the Gold line, connecting the two bike-sharing areas. Other transit connections, such as bus, are not included.

The total number of nodes (the aggregated bike sharing stations) in the system is 40, including two nodes for super supply and super demand. However, not all of those node pairs had a demand over 0.5 trips, the threshold for inclusion. This model also excludes any intra-area trips within Pasadena or within Downtown. Some OD pairs exceed the time window of 1 hour during the period of investigation (morning peak, 7-8 am). Any BSS-Transit trip that exceeds 60 minutes is defined as infeasible and not included in the link set. Since the transit travel time is 20min from Pasadena to LA this results in a maximum feasible bike travel time of 40 minutes total (access and egress). 40 minutes corresponds to a distance of 4 miles at a speed of 10mph a reasonable distance for a “bike only” trip based on the information from CS. It is unknown how the behavior of linked cyclists matches with that of bike-only commuters but it is reasonable to assume it is similar. Also the application is only encompassing trips *from* Pasadena *to* Downtown and not in the other direction. There are approximately twice the trips from Pasadena than to Pasadena (602 compared to 265). The only way this decision changes the model is the total number of bikes at a station at a time. The way this model is constructed, that would not change the availability of bikes for commuters, rather only

the frequency at which they are removed from the station (or redistributed). The cost of redistribution is not a user cost, and so can be ignored in this formulation.

Redistribution occurs between time steps which allowed the total number of feasible links for each bike to be reduced by only allowing trips between specific OD pairs. For example stations 1-12 are in Pasadena. Technically any bike can be assigned to any origin out of those 12 stations but that results in hundreds of nodes for each bike. Since the demand between OD pairs is known, bikes were assigned to a certain node based on the demand, e. g., Bike #1 can only start from Node #3. Node 3 has a demand of 43 trips in the morning peak so it was assigned the highest number of bikes in Pasadena whereas Node 11 has a demand of 8 so it was assigned the lowest. The total trip table for Pasadena is shown in table 1 and for Los Angeles in table 2.

Table 1: Demand From Pasadena by BSS

Node	Trip Freq.
3	42
7	42
5	32
1	31
12	31
9	29
6	22
8	15
10	12
11	8

Table 2: Demand From LA by BSS

Node	Trip Freq.
32	70
31	38
29	33
27	32
26	19
33	19
23	18
36	16
20	11
28	11
22	7
21	6
25	6
30	6
24	5
38	5
14	4
19	3
18	2
16	1

To create a problem where different parameters could be efficiently tested, another subset was cut out of the Nodes. Nodes 3,5,7,9 & 12 are the highest Origin demand points in Pasadena and also provide a good geographic distribution of stations; they are shown in figure 3. Nodes 20, 23, 31& 32 provide distribution, but they however do not reflect the highest trip Destination demand points, and are shown in figure 4.

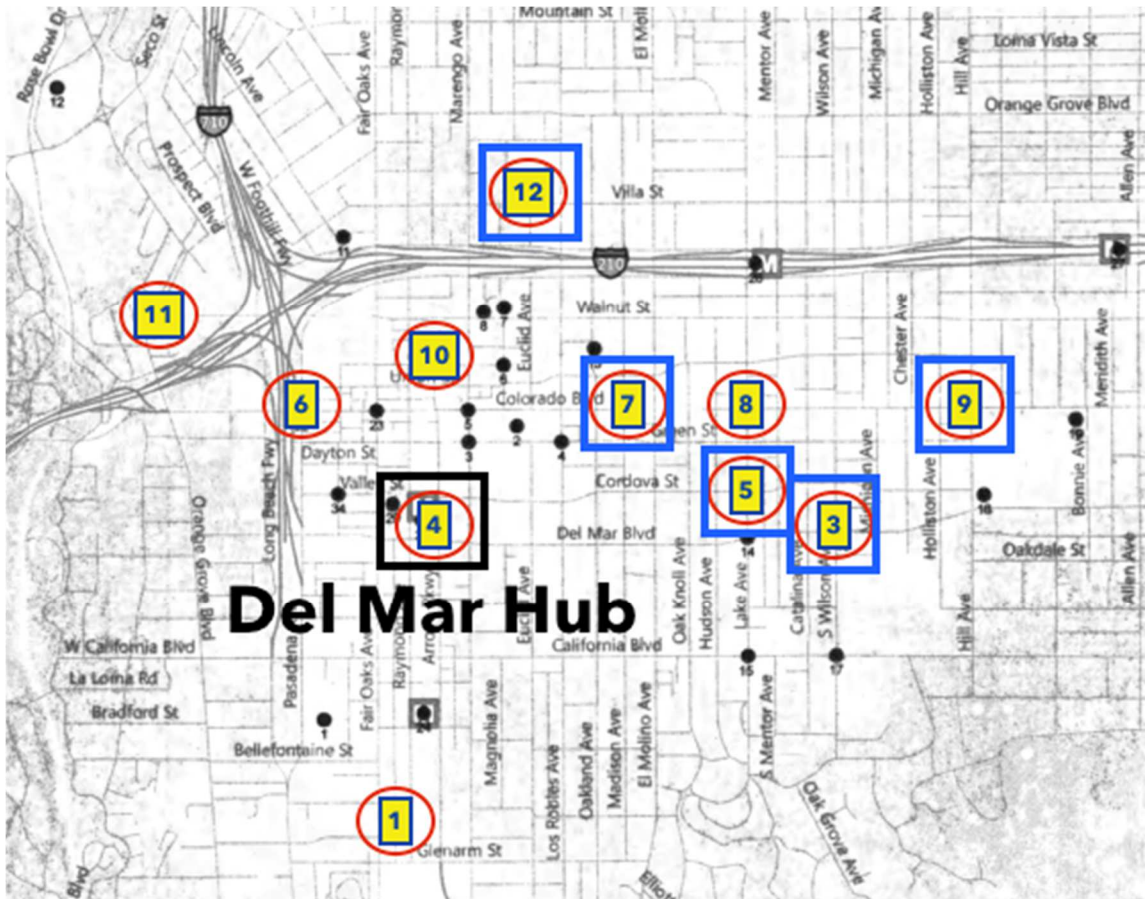


Figure 3: Selected Bike Sharing Stations Pasadena (RFP# PS11357 Metro, 2014)

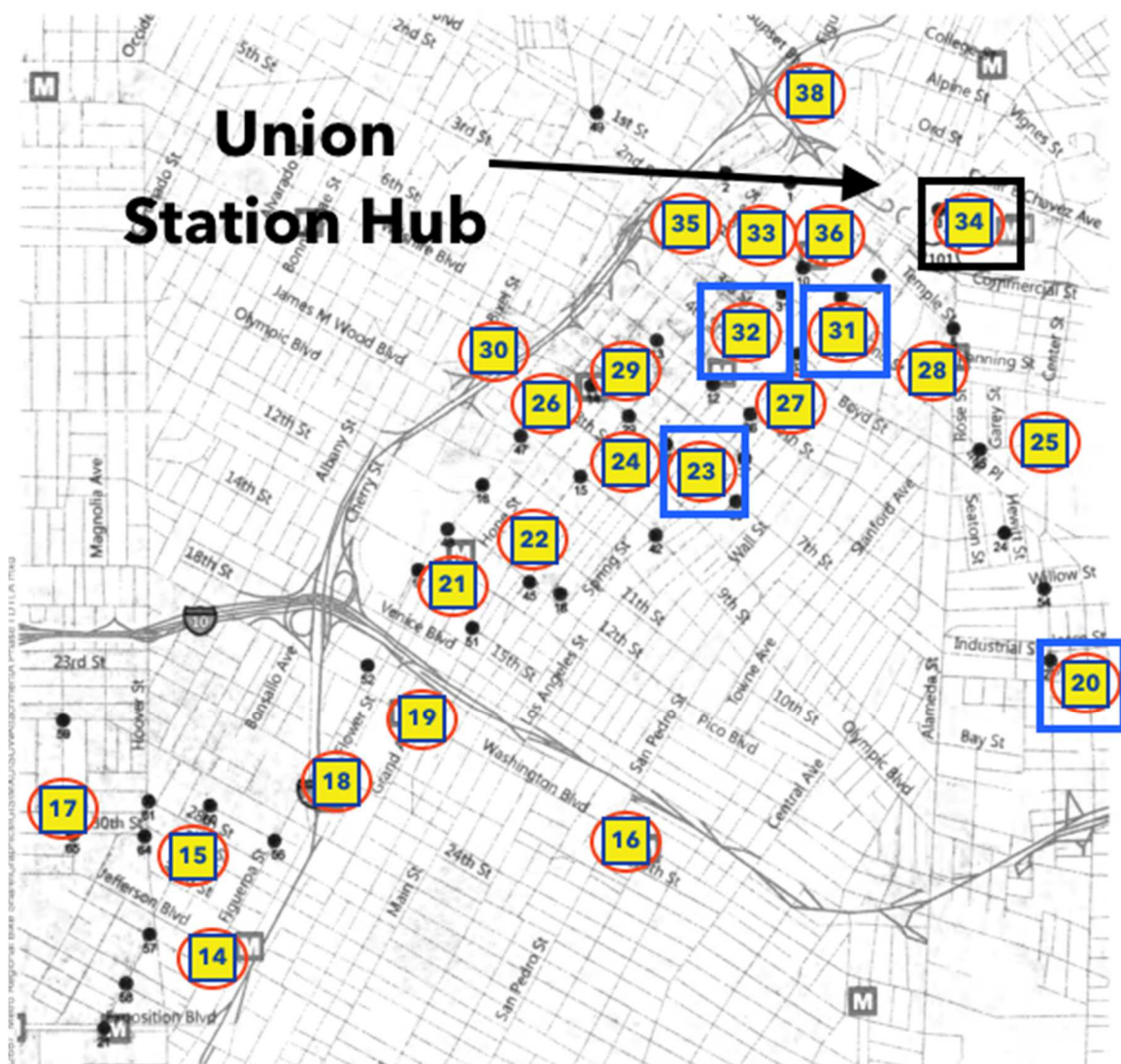


Figure 4: Selected Bike Sharing Stations LA (RFP No. PS11357 Metro, 2014)

Parameters

Based on the above information from the Cambridge systematics report, the cost of driving is \$0.6 per mile and biking has a net benefit of \$ -1.42 per mile. The user cost of bike-sharing is based on an access trip and a return trip, with trips not exceeding the

“free window” and used every work day for the year. The pricing for Metro bike share has not yet been published but based on the Citibike (NYC) annual subscription of \$149 (accessed in September 2015) and assuming use every workday with two trips a day results in a user cost of \$.30 per trip. The Gold line has a fixed fare but also the benefit of allowing for other activities while traveling. It is likely that there is some value of this benefit but it is not included here. Driving times during the morning peak from Pasadena to LA increase approximately 2.75 times that of the free flow travel time from around 24 minutes to 65 minutes (from Google Maps, October 2015).

The first case investigated is the free-flow travel time case. The second case is the congested peak hour travel time case. The auto travel time congestion multiplier (explained below) will be adjusted until no more trips are diverted to bike/transit. The results will provide an indication of how the perceived cost of driving effect diversion rates to bike/transit.

Solution Program

The algorithm was coded in AMPL (**A Mathematical Programming Language**). AMPL is a programming language intended for mathematical optimization. A free trial version of the compiler can be used for any problem with less than 300 variables. This research required much greater capacity and made use of an unlimited 30 day trial offered by AMPL. The language supports a variety of solvers; the solver used in this problem was IBM ILOG CPLEX or just CPLEX. CPLEX can solve linear and integer programs. For integer programs it uses a branch-and-cut approach, which starts by relaxing the integrality of the program and proceeds by adding “cutting planes” that restrict the feasible region until an integer solution is found. The branching comes from the non-

integer components of each solution, specifically for binary variables a zero or one option is branched from the non-integer root (IBM, 2010). Due to the branching approach memory can be an issue with large problems. In this problem, even with 60000 links, memory was not an issue but there are solver options that can be used to help for much larger problems. The program was run on a Mac Book Pro with 4 GB of memory.

Free Flow case

A Google search of “from Pasadena to Downtown Los Angeles” results in 2.7 miles of travel on Local roads and 8.9 on freeways or approximately 1:3. Assuming Local speeds are 35 mph and freeway speeds are 65 mph the average speed on during the trip is 54mph. The cost of driving can be expressed relative to time for this particular route as \$0.54/minute. Using the same process for cycling and a speed of 10 mph the benefit per minute is \$-0.24. A federal DOT report from 2011 suggests a valuation of travel time as \$23.90 per person-hour (Belenky, 2011). A 2015 report from Texas A&M Transportation Institute uses \$17.67 per person-hour (Schrunk, Eisele, Lomax, & Bak, 2015). Another report based on SR-91 in Orange County finds a RP (Reveled Preference) value of time of \$21.46 for the morning peak (Small, Winston, & Yan, 2005). Finally a report from Victoria Transportation Institute shows the values of time for various modes of transportation, freeway driving versus rail commuting versus bike commuting in Boston, MA (Litman & Doherty, 2013). It is clear that there is some flexibility in evaluating the perception of value of travel time; for this paper the value of \$21.46 is used due to the Small, Winston and Yan study being conducted in Southern California. The value of time

for the Metro rail and for bike-sharing is based on the ratio of values from the Litman & Doherty paper calculated with respect to \$21.46, the base value selected for this paper.

Table 3: Relationships to Auto Value of Time (for Boston, MA)

Mode	% of Auto Peak Value	% of Auto Off Peak Value
Auto Off Peak	39%	-
Rail Peak	165%	-
Rail Off Peak	-	298%
Bike Peak	249%	-
Bike Off Peak	-	497%

The objective function including these parameters:

$$\begin{aligned}
& \sum_{\text{vehicle links}} (0.54 + 0.14) * (t_2 - t_1) * x_l^{rv} \\
& + \sum_{\substack{i \neq j \\ \text{traveling bike links}}} [(0.70 - 0.24) * (t_2 - t_1) + 0.3] * x_l^{rb} \\
& + \sum_{\substack{i=j \\ \text{waiting bike links}}} 1.75 * (t_2 - t_1) * x_l^{rb} \\
& + \sum_{\text{rail links}} [0.42 * (t_2 - t_1) + 1.75] * x_l^{rm}
\end{aligned}$$

The solution results in all trips being assigned to auto (as expected) presumably due to the significantly faster travel times. The value of the objective function is \$1074.4 equating to an average trip cost of \$14.92 a standard value.

Congested Case

Following the same procedure as above and introducing new constants for value of time the objective function changes to that below.

$$\begin{aligned}
 & \sum_{\text{vehicle links}} (0.54 + 0.36) * 2.75 * (t_2 - t_1) * x_l^{rv} \\
 & + \sum_{\substack{i \neq j \\ \text{traveling bike links}}} [(0.90 - 0.24) * (t_2 - t_1) + 0.3] * x_l^{rb} \\
 & + \sum_{\substack{i=j \\ \text{waiting bike links}}} 2.25 * (t_2 - t_1) * x_l^{rb} \\
 & + \sum_{\text{rail links}} [0.59 * (t_2 - t_1) + 1.75] * x_l^{rm}
 \end{aligned}$$

The solution is \$2580 or an average cost of \$35.83 with about 74% of trips assigned to bike-sharing/transit and 26% assigned to auto. 18% of the bike-sharing transit trips have to wait for some portion of the trip. The result is reasonable given the value of time factors used in the formulation above. The per minute cost of driving plus the per minute value of time for drivers is \$0.9, higher than the per minute value of time plus the per minute benefit for bikers, \$0.66. When the auto travel times are low, as in the free flow case, driving is cheaper, when travel times increase biking becomes a better option.

In order to investigate the sensitivity of this result various congestion multipliers were used, 4.25x, 3.75x, 3.25x, 1.5x, 1.25x, 1.125x and 1.0625x the free-flow rate, replacing the value of 2.75x in the formulation above. The value 1.5 results in a nearly equal split of trips between bike and auto. With an increase in peak hour travel times of

4.25x all trips are assigned to bike/transit despite 40 riders having to wait at some point during the ride. 4.25x corresponds to an average travel time increase from 21.9 minutes to 93.1 minutes, probably unrealistically high. At a realistic travel time increase of 2.75x from 21.9 minutes to 60.2 minutes the OD split between bike/transit and auto is about 3:1. Complete results are tabulated in Table 4 and illustrated in Figure 5 and Figure 6.

Table 4: Influence of Congestion Multiplier on Number of Bike/Transit trips

Multiplier	Obj. Solution \$	Avg Cost \$	Rides on B	Rides wait	Rides in veh.
4.25	2880	40.00	72	40	0
3.75	2845.05	39.51	65	32	7
3.25	2751.85	38.22	53	17	19
2.75	2580	35.83	53	17	19
1.5	1943.1	26.99	33	0	39
1.25	1744.125	24.22	24	0	48
1.125	1595.96	22.17	3	0	69
1.0625	1510.875	20.98	0	0	72

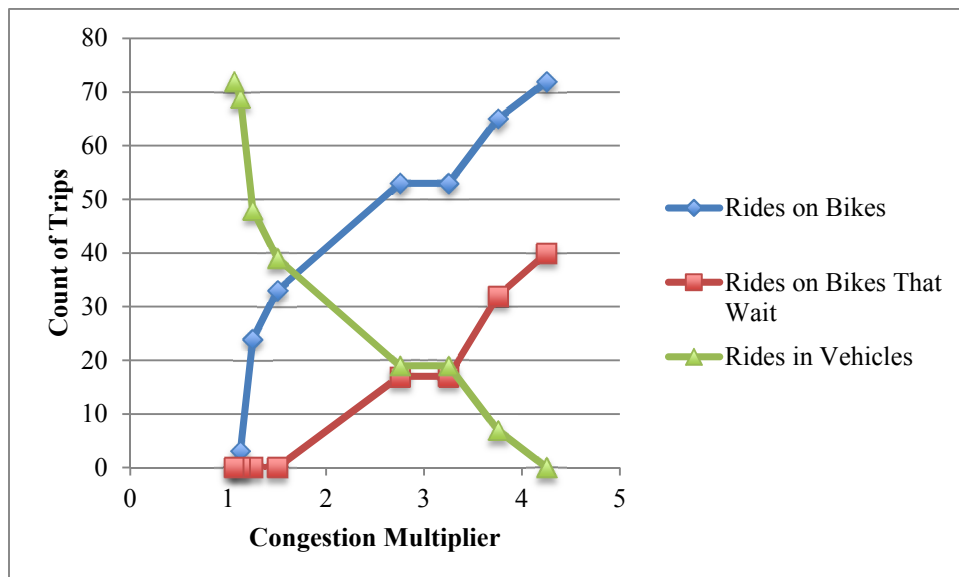


Figure 5: Chart of Trip Distribution versus Congestion Multiplier

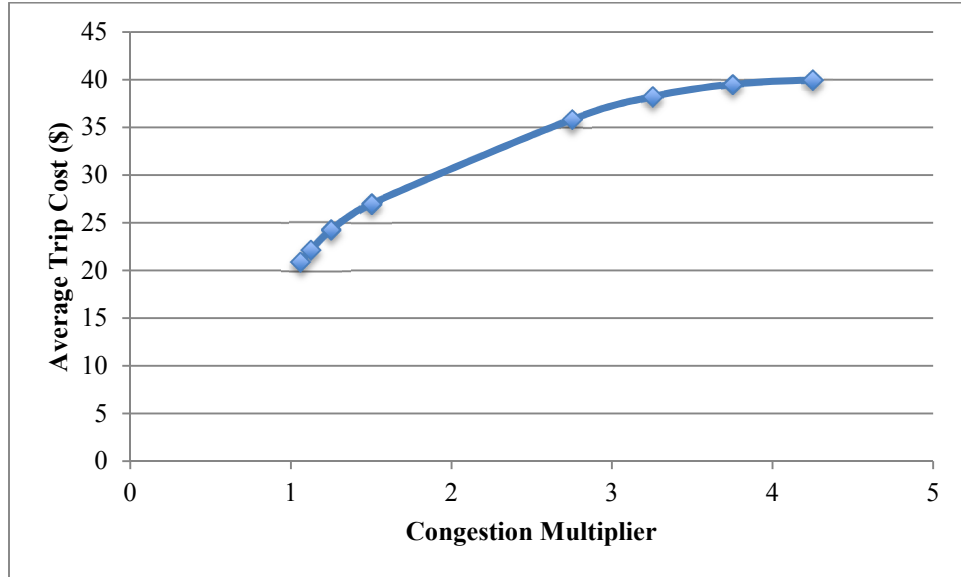


Figure 6: Chart of Average Trip Cost versus Congestion Multiplier

The results show that even at low congestion levels (1.25x) there is value for some OD pairs to switch modes to bike-sharing/transit. As mentioned above, the realistic range of congestion values ends at 2.75x but the higher values show the shape of the trip distribution. The number of auto trips decreases at every level from 1.0625x except between 2.75x and 3.25x. Likewise the number of bike-sharing trips increases at every level from 1.0625x except between 2.75x and 3.25x. This is probably due to the time steps used in the analysis and the rounding of travel times to the nearest five. The rounding results in clustering that would be dispersed if smaller time steps were used.

The specific mode for each OD pair can be pulled from the results. There was never a case of an OD pair having a mode split between bike-sharing and auto because individual trips are assumed to originate at the specific bike-sharing station. A model, with more specific OD data, including the walking links in the optimization could show a mode split for TAZ between commuters with long walks and those with short ones. This

assumption is mitigated in this application by the reduction of total TAZ demand based on coverage of the bike-sharing station network as discussed above. The mode distribution by OD pair at a congestion level of 2.75x is shown in Table 5.

Table 5: Trip mode distribution at 2.75x Free Flow

Origins \ Destinations				
	20	23	31	32
3	1 auto	5 bike	5 bike	9 auto
5	1 auto	1 bike	3 bike	7 auto
7	1 bike	3 bike	5 bike	8 bike
9	1 bike	1 bike	4 bike	7 bike
12	1 auto	1 bike	3 bike	5 bike

Table 6 below is a presentation of the travel times adjusted by the magnification rate, the sum of bike travel times on either end of the transit trip, and the ratio of the in-vehicle time to the on-bike time. It is presented by increasing in-vehicle time for OD pairs. The first five rows of Table 6 correspond to the cells assigned to “auto” in Table 5. The distinguishing characteristics of these cells are low in-vehicle time and higher on-bike times resulting in lower ratios of vehicle-time to bike-time (2.75). Other OD pairs have the same ratio but it results from a greater difference in vehicle and bike times (see OD pairs 9-32 & 9-20).

Table 6: OD Characteristics

Origin	Destination	2.75x Adj	sum Bike	ratio
3	32	55	20	2.75
5	20	55	20	2.75
5	32	55	20	2.75
3	20	55	20	2.75
12	20	55	20	2.75
3	31	55	15	3.67
5	31	55	15	3.67
7	32	55	15	3.67
12	31	55	15	3.67
7	20	55	15	3.67
7	31	55	10	5.50
9	32	68.75	25	2.75
9	20	68.75	25	2.75
9	23	68.75	25	2.75
9	31	68.75	20	3.44
12	32	68.75	20	3.44
3	23	68.75	20	3.44
5	23	68.75	20	3.44
12	23	68.75	20	3.44
7	23	68.75	15	4.58

Evaluation of Algorithm

The algorithm speed was evaluated for an increasing number of links, shown in Figure 7. Algorithm computation time increases linearly for the trend line shown with a slope of about 0.38 seconds per 1000 links. The results calculated in this paper are for 9 OD nodes corresponding to about 20,000 links. At 60,000 links there are approximately 30 OD nodes. There is no relationship between nodes and links as some OD pairs have only a few trips, the comparison is only included for reference. The linear relationship implies that this problem can be scaled up without a prohibitively high increase in computation time.

It would be interesting to consider including other transit options such as bus. It cannot be solved in real-time but there is no advantage in generating a real-time solution because fleet assignment for bike-sharing is not included in this formulation. The computational results however, indicate that the formulation is computationally nimble enough to be used for other such interesting applications.

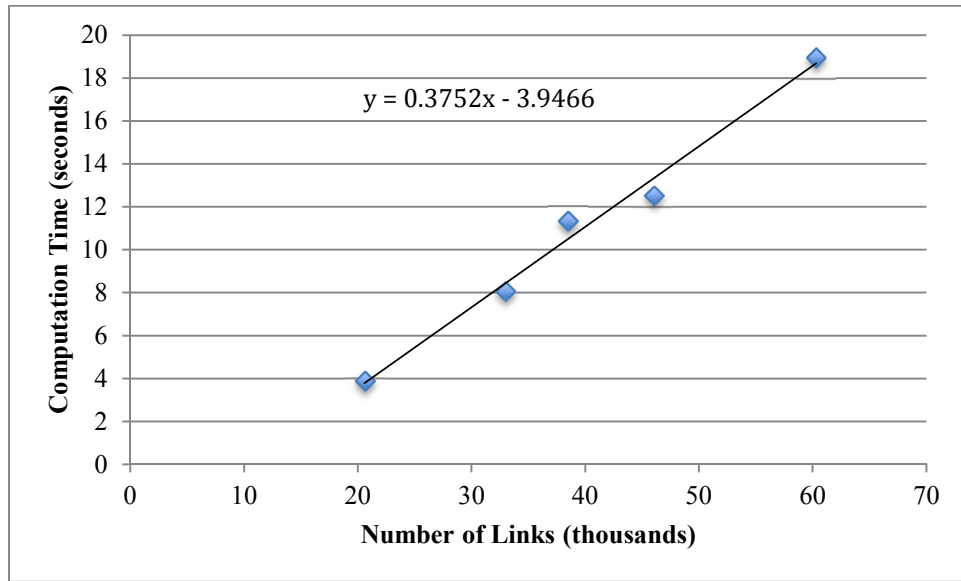


Figure 7: Computation Time versus Number of Links

Limitations & Application for Future Work

The results produced by the trial application show how an increased cost of driving pushed commuters toward bike-sharing. Essentially this is a mode choice optimization that does include any demographic data. A traditional mode choice Logit model has the advantage that it is linked to user preferences, however non-motorized transportation data is limited. Particularly for linked cycling-transit trips data is almost nonexistent. This is partially due to the difficulty in collecting data for linked trips. The

study of how transit service reductions affect the number of BOB in Flamm et al. (2014) is based on unlinked passenger trips because there is no way to track the CTU after they exit the bus. Metro LA plans to allow TAP cards (their quick payment system) to rent public bikes. If popular, there could be a large dataset in the near future that shows how public bikes are integrated into commuters trip chain. Regardless of the data, each city has a unique response to bike-sharing and it is difficult to apply one cities experience to another. The advantage of this model is that a rough value of time can be estimated based on average income of a region and all other parameters in the model can be derived from that value.

For the time being, this model is a best option to fill the gap and attempt to predict the usage of a new public bike system. It should be reiterated that there are many other possible modes that could have been included in the simple application of the model. Downtown LA is transit-rich and there are 3 other Metro Rail lines within the area of investigation (along with numerous bus lines). If all the possible options were included a solution to this model would not be feasible. This limitation could cause a problem in some applications where many transit lines are viable but in most cases the transit or bus lines to include should be obvious, and thus the dimensionality can be reduced. Also not included was park-and-ride options that could result in a trip chain of auto-transit-bike, again a trip made simpler by the bike-sharing network. In either case the only change is in the set of viable links for each rider and no change needs to be made in the program itself. The biggest omission in the study is not including trips from LA to Pasadena or intra-area bike-sharing trips. In real operations there would be some demand from those sources that would bring additional bikes to certain stations. This demand would change

how the bikes need to redistribute. It effects the operations cost for the vendor but not the mode choice of commuters and so was outside of this paper's scope. Another assumption was that the bike-sharing/transit links would not experience any congestion-related price increases or delay related to average travel speed. The utilization of bike facilities is currently not high enough to warrant considering delay from that portion of the trip chain. If transit does experience high utilization, this will not increase travel times but it could change how commuters value their transit experience. More research is needed to explore such factors.

A reverse application of this program could be used to find relative "average value of time" for the variables in the objective, if the mode split was known. That information could be valuable because "average value of time" can be a nebulous term for an economically diverse urban area. Another way to find a more representative value of time would be to narrow the scope of the optimization to one TAZ. This application would not result in meaningful mode split results since the solution would likely be all-auto or all-bike but could be used to investigate how the fixed cost parameters effect mode choice (for example a congestion charge zone that increases the cost of driving).

As more data about linked bike-sharing/transit trips becomes available this model can be modified to better reflect the real "value of time" difference between cyclists, strap-hangers and drivers. This paper connects bike-sharing to transit without the need for a massive survey campaign. It can be an asset to planners to get a rough estimate of how bike-sharing can be incorporated into a city's transit network.

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