Improving Urban Sustainability of Transportation System with Shared Mobility

A Case Study for Ann Arbor

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Abstract

The current transportation sector in the United States is heavily relied on private automobile, consuming a large amount of fuel energy and producing a large quantity of greenhouse gases. Shared mobility, such as ridesharing and bikesharing, could potentially improve urban sustainability by decreasing the total vehicle-miles, saving fuel energy and reducing greenhouse gases. This research project utilized the real-world private vehicle trajectory data of the City of the Ann Arbor, identified the potential bike trips and sharable vehicle trips, and applied optimization model to obtain the sharing scenario with the maximum vehicle-miles avoidance. The results indicate that 1.06% of total-vehicle miles can be reduced by shared mobility, including 3,799 vehicle trips that could be replaced by bike trips. Shared mobility could reduce multiple types of tailpipe gas emissions (e.g., 536 tons of CO2). Although the sharing potential is low based on the results, it might be due to the limited vehicle data and the irregular travelling pattern of private vehicles. The ridesharing potential is sensitive to the passenger's time tolerance for dour of their trips and the number of potential bike trips is sensitive to the acceptable distance from trips' origins and destinations to the shared bike stations. Policies and incentives to encourage longer time tolerance for ridesharing. Also, more shared bike stations could be built in the future.

Key Words: Shared Mobility; Ridesharing; Bikesharing; Sustainability

Introduction

Current transportation system in the United States is heavily relied on private automobiles, which requires a large amount of fuel energy and emits a large amount of greenhouse gases. According to the U.S. Energy Information Administration (2015) and U.S. Environmental Protection Agency (2014), the transportation sector consumes about 28% of U.S. total energy and accounts for around 26% of greenhouse gases emissions. In addition, vehicular congestion is one of the greatest serious problems faced by many cities all around the world. For example, the costs of waste time and fuel caused by congestion are estimated to be US$ 60 billion in the 83 largest urban areas in the United States. Meanwhile, millions of deaths were caused by car accidents and outdoor air pollutions annually. (Santi et al., 2014) With the urbanization, economic development and population growth, the mobility demands in urban areas will probably keep increasing in the future. Therefore, improving sustainability and efficiency of transportation system has become one of the essential and central tasks for future urban sustainability.

Shared mobility, referring to mobility services that can be shared among different users, such as public transit, car-sharing, ride-sharing and bikesharing, has been recently discussed as way for future transportation mode. Car sharing is a service that offers short-term vehicle rentals, including one-way and round trip. Car sharing focuses on decreasing car ownership by temporarily providing cars to people when they need a car. It often requires participants to apply for a membership to use the shared vehicles. When people want to use a shared vehicle, they have to find nearby parking location where the shared cars park. However, there is no guarantee that those cars are always when the users are in need. They also need to drop off the rental cars at the designated parking lots near their destination and should find a way to finish the “last mile” (i.e., from the parking lot to their destination). These inconveniences often prevent people from participating car sharing activities (Shaheen and Cohen, 2013; Martin, 2011). Despite of the abovementioned inconveniences, the number of car-sharing users expands very quickly. For example, the number of users of car sharing companies, such as Car2Go and ZipCar, doubled every 1 to 2 years over the last decade (Fagnant, 2014). This may be because of the lower cost of car sharing compared to car ownership. In addition to the financial incentives, car sharing activities also brings out environmental benefit. For instance, car sharing is estimated to help reduce 0.84 tons CO_2 per household and an average of 27% of annual vehicle miles traveled (VMT) in the United States (Martin and Shaheen, 2011).

Ridesharing is more dynamic and real-time compared to car sharing (Santi, 2014). It essentially focuses on improving vehicle occupancy by filling empty seats in vehicles with riders that have closed origins and destinations. Ridesharing was first started as early as 20^{th} century and it could be a long-term transportation mode for decreasing total vehicle miles traveled, reducing greenhouse gas emissions, relieving road traffic and lowering travel cost (Handke & Jonuschat, 2012). Due to the recent emerging information and communication technology (ICT, e.g., personal positioning systems, smartphone and social media), and many new transportation networks companies (TNC, e.g., Uber, Lyft and Didi Chuxing), passengers are able to exchange information of their location and request in real time and have more opportunities to participate in ridesharing activities. The most important obstacles for potential ridesharing are the additional trips time (e.g., waiting time and trip delay), loss of privacy and uncomfortable feeling of sharing trips with strangers (Dueker et al., 1977; Teal, 1987). However, the financial incentives of low traveling cost and the involvement of social network reputation systems make people more willing to try ridesharing even with strangers nowadays (Finley, 2013; Zervas et al., 2014). Hence, ridesharing has become more popular during the recent years.

Either car sharing or ridesharing improve the efficiency of the transportation system by reducing car ownership, vehicle miles, and increasing vehicle occupancies. Therefore, these two kinds of vehicle-sharing modes have the potential to reduce total VMT and decrease the GHGs emissions, which is beneficial for achieving transportation sustainability.

In addition to vehicle sharing, bike sharing is another mode of shared mobility improving transportation sustainability. It has a history around 50 years and has become more popular and prevalent all around the world, especially Asia and Europe, since 2000 (Shaheen et al., 2010). The current bike sharing programs allow users to rent a shared bicycle from one docking station in a short term and users need to return these rental bikes to another station within the time limit to avoid paying the fines. There are several benefits of bike sharing, including mobile flexibility, emission reductions, body exercise involvement, congestion relief and fuel savings. It also provides individual with financial benefits since the cost of bike rental is low and it supports multi transportation connections (Shaheen et al., 2010). Therefore, bike sharing is another way to reduce congestions, emissions and fuel use in transportation sector and is good for urban sustainability as well.

Chen (2015) found that people living in high-density metropolitan areas and university towns are more willing to use ridesharing. In addition, Fishman et al. (2013) demonstrated that people from areas with higher employment rate, education level and lower average age would use shared bikes more often. Therefore, university towns become ideal places with high potential where people would like to use ridesharing service and shared bikes. Ann Arbor, MI, the home of University of Michigan, is one of the most famous university towns in the United States. Many car sharing companies (e.g., Zipcar), TNC (e.g., Uber and Lyft) have launched their business in Ann Arbor. Meanwhile, a university-funded bikesharing program, called Arborbike, has been providing its service in this city. There are 13 existing bike stations around the campus with one more coming soon. Therefore, the city of Ann Arbor becomes an ideal place to research the benefit of shared mobility taking the advantage of those infrastructure. In addition, the vehicle trajectory data is provided by University of Michigan Transportation Research Institute (UMTRI) Safety Pilot project, which can be used for evaluating the travel demand in this city and analyzing the potential for shared mobility.

This research aims to demonstrate the benefit of shared mobility (we focused on bikeshairng and vehicle sharing) for sustainability of urban transportation system. We selected the city of Ann Arbor as a demonstration example and analyzed more than 1 million vehicle trips data, evaluating the potential of vehicle sharing and bikesharing in this urban transportation system. We applied bike trips' identification algorithm and vehicle trips' matching algorithm on the original vehicle trips data. An optimization model was built to obtain the optimal sharing scenario for maximum VMT and GHGs reduction.

Literature review

The current literature about ride sharing mainly focused on three aspects of research, including developing algorithms for rides matching (Agatz et al., 2011; Fellows and Pitfield, 2000; Bicocchi and Mamei, 2014; Trasarti et al., 2011; He et al., 2012; Ma et al., 2014), assessing "shareability" oftrips (Cai, 2015), and optimizing sharing scenarios for specific purpose (Cai, 2015; Santi et al., 2014). The objectives of ride-sharing systems optimization mainly fall into three categories (Agatz et al., 2012):

(1) To minimize the total vehicle miles traveled (VMT) (Badacci et al, 2004; Calvo et al. 2004; Agatz et al., 2011; Amey, 2011) -- This objective is to achieve the maximum fuel efficiency and environmental benefit from the angle of the whole transportation system. The sharing scenario with maximum VMT reduction will be obtained under this objective. Because most VMT is avoided, it is also the best scenario for reducing GHGs emissions and saving fuel energy. This objective is critical for social sustainability because it reduces air pollutions and saves fuel most and it is beneficial for minimizing the total travel costs since least miles are driven.

(2) To minimize the total vehicle hours traveled (VHT) (Winter and Nittel, 2006) -- Vehicle hours traveled is a measure of transportation efficiency and congestions. This objective is to pursue the highest time efficiency of the whole transportation system. Traveling time is one of the most important factors when people choose their transportation mode.

Therefore, the shortest time sharing scenario will enhance the feasibility of ridesharing and more people may choose ridesharing because of its high efficiency.

(3) To maximize the number of ride sharing participants (Baldacci et al., 2004; Ghoseiri et al., 2011; Xing et al., 2009) – This objective maximizes the total number of ridesharing users. The ride sharing revenues are depends on the number of successful matches so this scenario may generate the highest profit for the ridesharing service providers. In addition, the prevalence and popularity of ridesharing will be increased in the long term with more and more people to participate ridesharing activities.

Despite of plenty of benefits provided by ridesharing, there are also some obstacles preventing the success of sharing multiple trips. The additional traveling time (e.g., travel delay and waiting time) requirement is one of the greatest challenges for ridesharing. Hence, most ride matching algorithms address this point by only allowing trips happening within a short time window to be shared. Santi et al. (2014) studied the shareability of taxi fleet in New York City and chose 10 minutes in his Oracle models, which assumed all the trips information were well known before matched. However, he used 1 minute as the time window in his Online models, which assumed that the travel demands were known a little ahead before happening. Cai (2015) studied the taxi fleet of Beijing, China and she focused on the time tolerance of participants, which means the maximum additional time that passengers can tolerate. Either early or late appearances of taxi at origins and arrival to destinations would induce the uncomfortable feeling of the participants. Only when the time differences between ride alone and ridesharing for both departure and arrival time are within the time tolerance, those trips are possible to be shared. They found that the percentage of shareable trips were sensitive to the time tolerance (Cai, 2015; Santi, 2014) and the percentage could be high (over 80%) when participants were willing to tolerate a long detour time. However, the taxi fleet could have a more regular traveling pattern where the trips' origins and destinations are densely distributed, making ridesharing among taxies easier. Therefore, it is important to investigate whether the shareability of private vehicle could also be as high as the taxi fleet.

In addition to the various objectives and matching algorithms, the datasets used in researching ridesharing are different as well. Amey (2011) used the travel survey data for the Massachusetts Institute of Technology (MIT) communities and her results indicated that ride sharing could reduce 6% to 19% of commute VMT. The survey data is appropriate for static ride sharing matching and is suitable for small scale research. Santi et al. (2014) and Cai (2015) evaluated sharing potential of taxi fleet in New York City, U.S. and Beijing, China, using vehicle trajectory data recorded by GPS devices. These vehicle trajectory data include trips' origins, destinations, starting and ending time. It can accurately represent the dynamic travel demands and is also suitable for larger scale ride sharing analysis. Other types of data, such as cell phone positioning records and geo-tagged tweets, are also used for this kind of research. However, these social media data are not in high granularity because it only records when the user is making a phone call or posting a tweet.

On the other hand, an increasing number of cities start implementing bike sharing programs and there is a growing number of literature discussing about these programs (Fishman, 2013;

García-Palomares et al., 2012). The first generation of bike sharing program was started in the 1960s in Amsterdam, Netherlands (Wang, 2010). Those bicycles were provided by government or public organizations and were almost free to use. However, due to the poor operation and lost problems, these programs were suspended. Recently, with more energy consumptions and GHGs emissions in the transportation sectors, people start to think reuse the bike, especially the bike sharing programs, to make the transportation systems more sustainable and environmental friendly. The second generation of bike sharing program was started in Copenhagen, Denmark in 1995. Nowadays, more and more cities around the world, such as Pairs, Barcelona, Montreal, Hangzhou and Washington D.C., have adopted their own bike sharing programs. Researchers started to think about how to plan the bike sharing system better in the real world. For example, García-Palomares et al. (2012) estimated the potential travel demands in different locations of central Madrid and applied the location – allocation algorithm in GIS software package to determine the optimal siting choices of bike stations with the objectives to minimize impedance and maximize coverage. Vogel et al., (2011) applied the data mining technologies on the real world public bike ride data to investigate the bike station activities, customer behavior and location factors. Based on those knowledge, they also conducted operations research for best locations of bike station choices. However, few of literature evaluate the potential of replacing vehicle trips with bike trips and address its importance in urban sustainability.

The key points to make a trip friendly to use shared bikes are the easy access for the users to shared bike stations and a short trip length (Fishamn et al., 2013; García-Palomares et al., 2012). On the other hand, a successful ridesharing that is beneficial for sustainability depends on two conditions. The first is that the length of combined route is less than the sum of separate ones so that the ridesharing will decrease the vehicle miles. Second, the total additional time of ridesharing should be within the time tolerance of each passenger. (Cai, 2015). Therefore, these factors should be considered to ensure the shared mobility is feasible in the reality.

Methods

Data

Data used in this research are from the University of Michigan Transportation Research Institute (UMTRI) Safety Pilot data from February 2012 to October 2013. These data were filtered according to the following criteria: (1) A random portion (between 3-8%) of each trip has been removed from the beginning and end of each trip. (2) Trips that are less than 2 minutes or 1 kilometer have been removed. After the data cleaning, there are 1,048,576 trip records in total. Each trip record includes information such as device ID, latitude and longitude of origins and destinations, starting and ending time, average speed, etc. The trip distance is calculated as the formulation of Manhattan distance, which measures the distance of two points (x_1, y_1) and (x_2, y_2) as $|x_1 - x_2| + |y_1 - y_2|$. The Manhattan distance better represents the locations' distances between two points in a road network (Cai, 2015).

Model

Bikesharing Identification

Fuller et al. (2011) conducted a survey program to investigate the prevalence of public bike sharing program, known as BIXI, in the city of Montreal. This survey made phone calls to 2,502 people to compare their usage of public bikes and the distance from one docking stations to their living places. The investigation found that people lived within 250 meters of a docking station had a higher potential to participate bike sharing programs. In addition, Jensen et al. (2010) extracted travel characteristics, such as speed and duration of bike trips, from the data obtained by the operator of Lyon's bike sharing programs. The results indicated that the average trip distance was around 2.5 km with an average duration of 15 minutes. In our research, if a vehicle trip fulfills the following two requirements at the same time, it will be identified as a potential bike trip: (1) Its origin and destination are both within 250 meters of one of the 13 public bike stations in the city of Ann Arbor; (2) The trip distance is no longer than 2.5 km. The framework of bikesharing identification is shown in figure 1.

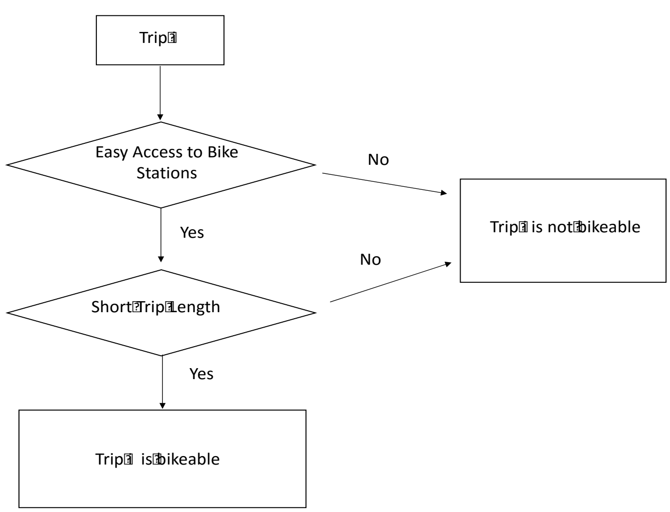


Figure 1. Framework of Bikesharing Identification

In our research, once a trip is identified as a potential shared bike trip, it would be removed from vehicle trips list. The rest of vehicle trips would be used for ride sharing matching and optimization for maximum vehicle-miles reduction.

Ridesharing Identification

The ridesharing identification algorithm used in this study is similar to that in Cai (2015). Two criteria, distance reduction and time tolerance, were applied to identify shareable trips. However, different way to store shareable trips information and a modified optimization model that could solve the “one hour limit” problem in Cai’s research (2015) and it will be discussed later.

In this study, we assumed that at most two trips can be shared because involving more trips will significantly increase computational intensity but only provide trivial ride sharing benefit. Also, it will make riders loss more of their privacy when sharing a trip with more strangers. For each trip i, we denoted its origin as O_i, destination D_i, starting time OT_i, ending time DT_i and average speed V_i. Only four types of possible sharing routes were considered in this study: O_i – O_j – D_i – D_j; O_i – O_j – D_j - D_i; O_j – O_i – D_i – D_j; and O_j – O_i – D_j – D_i. Routes without any overlap between two trips (e.g. O_i – D_i – O_j – D_j) were not considered.

Sharing two rides will induce detour of the original departure or arrival time. We assumed the two trips are driven on their original speeds in their individual parts and driven on their average speeds in the shared parts. The average speed of two trips i and j, is denoted as V_{ij}. In addition, extra loading time (e.g. pick up the second passenger) will be counted to the detour time and it is assumed to be fixed (one minute). Route O_i – O_j – D_j – D_i is used as an example to describe the process of time calculation:

$V_{ij} = (V_i + V_j)/2$

$OT_i' = OT_i$

$OT_j' = OT_i' + \text{distance } (O_i, O_j)/V_{ij} + \text{load time}$

$DT_j' = OT_j' + (DT_j - OT_j)$

$DT_i' = DT_j' + \text{distance } (D_i, D_j)/V_{ij} + \text{load time}$

Where distance (O_i, O_j) and distance (D_i, D_j) are the Manhattan distance between origins and destinations of trips i and j, respectively. one load time is added to the departure time of trip j because it assumes when the car arrived there are still some time to contact with the passenger in trip j and find him/her. Also, another load time is added to arrival time of trip i, assuming the time of passenger j getting off the car will induce the detour of the trip i.

The identification of sharable trips consists of two main criteria: (1) Distance criteria: the distance of shared route should be less than the sum of two individual trips; (2) Time criteria: the time detour for departure and arrival of each passenger should be less than time tolerance. We assumed either early or late detour will induce uncomfortable experience of each passenger. Figure 2 presents the frame work of identification process.

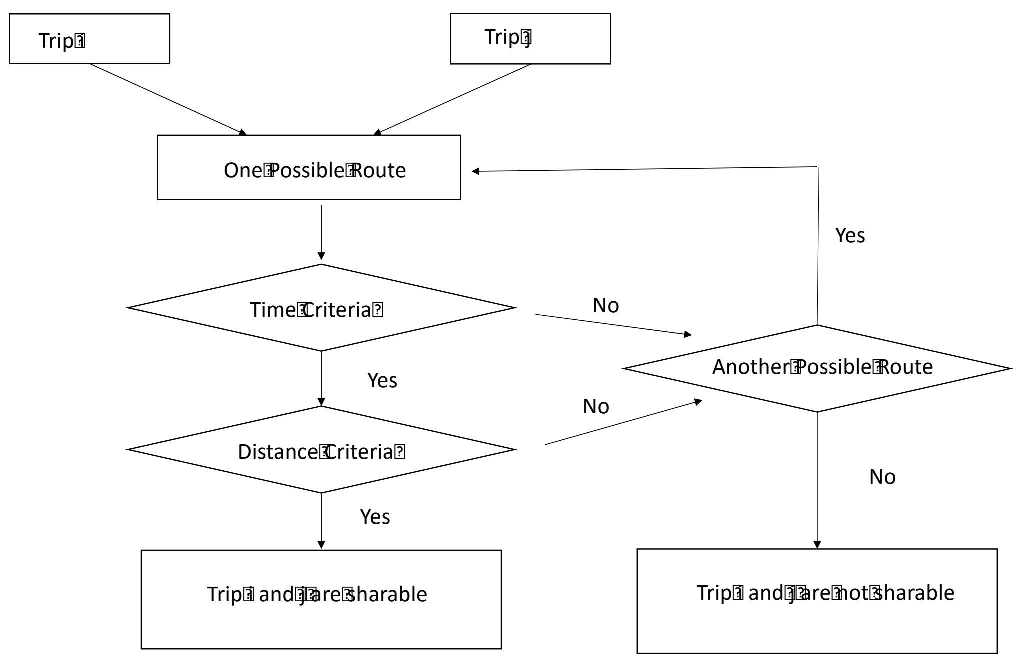


Figure 2. Framework of sharable trips identification

In Cai's research (2015), the shareability of trips are stored in a large matrix A, where A_{ij} equals to 1if trips i and j are sharable and equals to 0, otherwise. Therefore, if there are n trips in total, a n by n matrix is required to store the shareability information. It requires a large computer memory and makes the computation complicated. So she only used a portion of trips happening during one-hour at one time and did for every hour iteratively. This causes certain limitations. For example, trips happening at 7:59 am is not able to share with trips happening at 8:00 am, which does not make sense.

In order to solve this problem, we stored the data in another way in our research. If two trips are shareable, only trips' IDs and parameters that we may be interested in including in our objective functions are recorded. Each of these records is called a "sharing pattern".

i	j	C_1	…	C_m

where, i and j are the IDs of two sharable trips and C_1, …, C_m are coefficients that might be included in objective functions, such as VMT reduced or waiting time. In this study, we were aimed to obtain the maximum system-wide VMT reduction so only VMT reduction of each sharing pattern was recorded. Each of this pattern is called P_k, $k \in J$, where J is the set containing all the sharing patterns identified. Hence, if there are n sharing patterns in total, a matrix with size of n by (m+2) will be needed to store the information, which requires much less memory than that in Cai's research (2015).

Optimization

(1) Sharing matrix

Since each trip could only be shared with another trip for one time, if two patterns have same shareable trips included, only one of them can be selected. For instance, P_m contains trips 1 and 2, P_n contains trips 2 and 3, and P_s contains trips 1 and 3, these three patterns are conflicted with each other and only one pattern could be included in the optimal sharing scenario. Hence, we first formed a sharing matrix to represent the confliction among different patterns. Assuming there are t sharing patterns in total. A matrix would be a t by t matrix, and,

$$A_{ij} = \begin{cases} 1, if\ \ the\ pattern\ i\ and\ j\ contain\ same\ trips \\ 0, otherwise \end{cases}$$

(2) Decision Variable

$X = [x_1, x_2, \ldots, x_t]$, where

$$x_k = \begin{cases} 1, if\ \ Kth\ pattern\ is\ selected \\ 0, otherwise \end{cases}$$

(3) Constraints

At most one pattern can be selected among all other patterns having same one of the two components. Mathematically, the summation of decision variables of these patterns should be less or equal to 1.

(4) Objective Function

The objective function is to maximize the total VMT reduction, the coefficient $C= [c_1, c_2, \ldots, c_t]$ and c_k refers to the VMT reduction for the kth pattern.

(5) Generic Linear Programing Model

$$\text{Max } C^T X$$

s.t.

$$AX <= 1$$

$$X \text{ is binary}$$

Results

Vehicle-miles reduction

The total vehicle miles traveled by these recorded vehicles are 123,567,680 miles of the 1,048,576 trip records. Based on the identification of bikeable trips, there are 3,799 vehicle trips are potential to be replaced by shared bike trips. From the results of vehicle trips shareability identification, there are 81,924 possible sharing patterns. 59,396 patterns, which are 72.50% of total sharable trips, are selected in the optimal sharing scenario for achieving the maximum VMT reduction. The vehicle miles saved by bike sharing are 4,306 miles, and 1,301,029 miles by vehicles ride sharing. The total miles saved are 1,305,335 miles, accouting for 1.06% of the original vehicle miles. We also conducted an analysis only including the vehicle sharing in our system. The results indicate that 82,358 possible sharing patterns are identified and 59,696 patterns are selected in the optimal sharing scenario. The total miles saved are 1,301,441 miles, accounting for 1.05% of total vehicle miles traveled. Comparing these two results, the public bike sharing programs could potentially help avoid additional 3,894 vehicle miles.

Environmental benefits

Avoiding vehicle-miles means reducing tailpipe gas emissions. The amounts of tailpipe gas emissions are calculated based on the emission factors of these pollutants. In our study, we included the carbon dioxide (CO_2), hydrocarbon (HC), methane (CH_4), nitrous oxide (N_2O), nitrogen oxides (NOx), and carbon monoxide (CO). These atmospheric pollutants either have damage for human health or have contributions to global greenhouse effects. The emission factors are shown in the table 1 (EPA, 2010, 2014, 2015). Based on the vehicles miles saved and the emission factors, shared mobility, with bikesharing and ridesharing, could help reduce 536.493 tons of CO_2, 1.031 tons of HC, 0.023 tons of CH_4, 0.005 tons of N_2O, 0.731 tons of NO_x and 11.396 tons of CO during the time frame we studied, respectively. With bike sharing in the system, it can help reduce 534.892 tons of CO_2, 1.028 tons of HC, 0.023 tons of CH_4, 0.005 tons of N_2O, 0.729 tons of NO_x and 11.362 tons of CO respectively. The bikesharing provides some marginal benefits for emissions reduction even the improvement is small.

Table 1. Emission Factors of different atmospheric pollutants

Emission Factors (g/mile)	
CO_2	411
HC	0.79
CH4	0.0173
N_2O	0.0036
NO_x	0.56
CO	8.73

Sensitivity analysis

Because the vehicle sharing potential is affected by the level of passengers' time tolerance (Cai, 2015; Santi et al., 2014), so the time tolerance is a key variable in our research and we conducted sensitivity analysis of this variable. The figure 2 shows the relationship between sharing patterns (log-transformed) and the time tolerance. According to this figure, the sharing pattern is positively related to the passengers' time tolerance. It makes senses that when passengers are willing to wait more time, more trips could be shared with each other. Particularly, when the time tolerance is low, one additional minute will lead to serval magnitude increases. For example, when the time tolerance increases from 1 minute to 2 minutes, 2 magnitudes are increased.

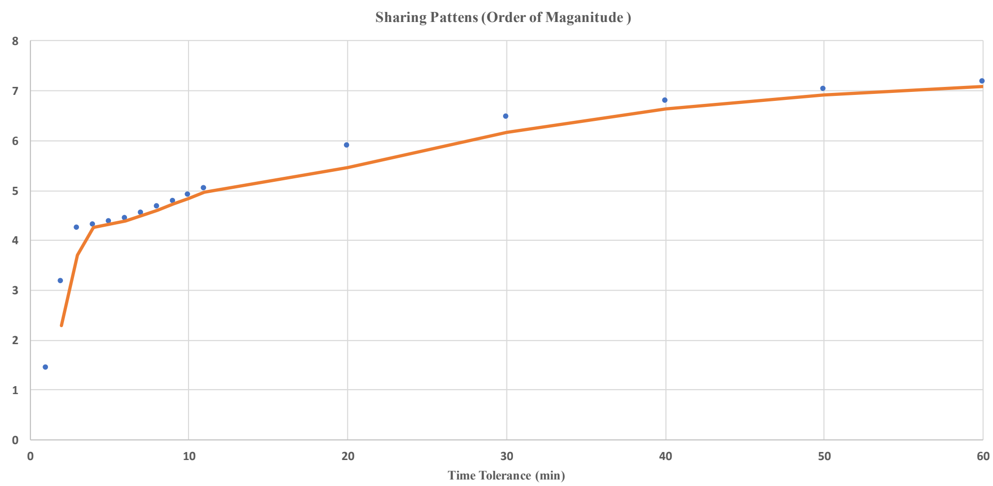
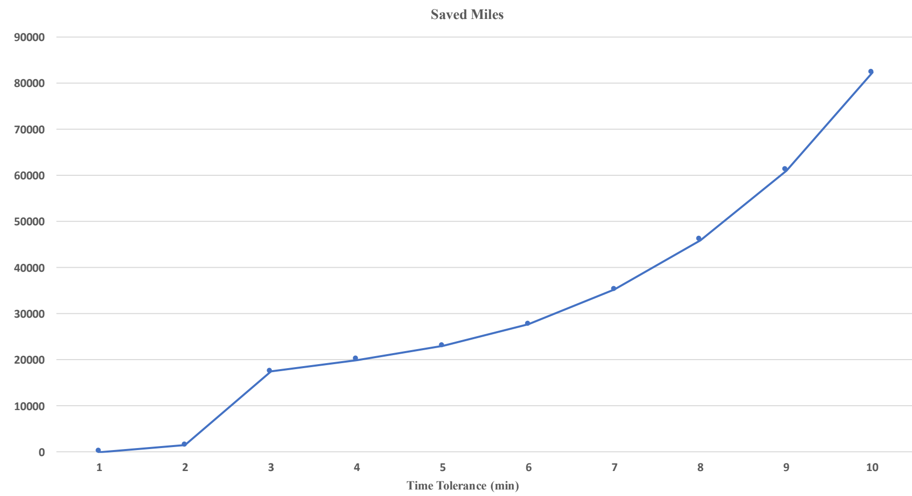


Figure 2. Sensitivity Analysis: Sharing Patterns VS. Time Tolerance

Because of the computational limitation, we only have the sensitivity analysis of optimization from 1 minutes to 10 minutes. The relationship between total saved miles and the time tolerance is presented in figure 3. The saved miles are also positively corresponding to the time tolerance and it is because that more trips are shareable. There is an obvious jump between 2 minutes and 3 minutes which means a large amount of saved miles will be created by this 1 additional waiting time. It is similar to the results of sensitivity analysis of sharing patterns, when the time tolerance is low, additional waiting time is critical for additional vehicle-miles reduction.

Figure 3. Sensitivity Analysis: Saved Miles VS. Time Tolerance



In addition to sensitivity analysis of vehicle sharing, we also conducted sensitivity analysis of bikesharing. The key factor of possible bikeable trip is the distances between trip's origin and destination to bike sharing stations. The number of sharable bike trips is correlated to the distance from bike stations. The fastest increases are achieved when the allowable distance increases from 250 meters to 500 meters.

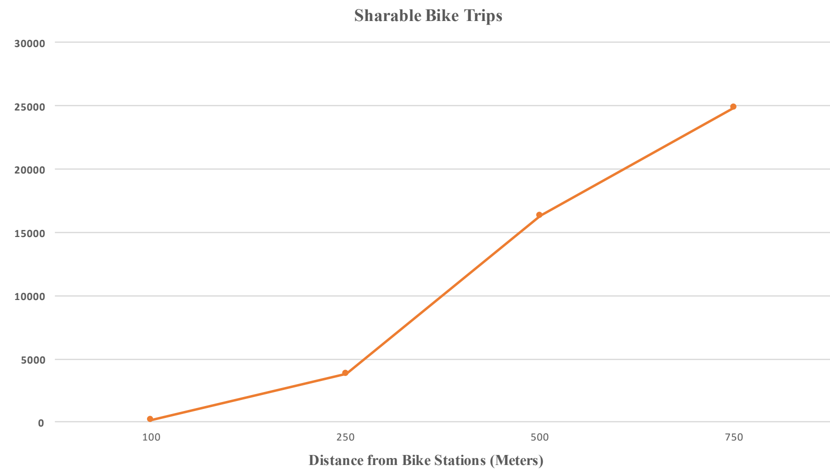


Figure 4. Sensitivity Analysis: Sharable Bike Trips VS. Distance from Bike Stations

Conclusion & Future Research

This research project utilized real-world vehicle trajectory data to evaluate the potential benefit of shared mobility in one specific transportation system in the city of Ann Arbor. The shared mobility could help avoid 1.06% of total vehicle-miles and reduce multiple types of tailpipe gas emissions. The ridesharing potential is sensitive to the passenger's time tolerance for dour of their trips and the number of potential bike trips is sensitive to the acceptable distance from trips' origins and destinations to the shared bike stations. Policies and incentives to encourage longer time tolerance for ride sharing should be implemented to promote ride sharing. Although the sharability of trips are relatively low compared to some previous research (Cai 2015; Santi et al., 2014; Chen, 2015), the shared mobility with bikesharing and ridesharing, could also have contributions to the urban sustainability. In addition, there are several reasons leading to the low sharing potential: (1) The vehicle data collected were sparse. Only 3,000 private vehicles' data were recorded while Ann Arbor has a population over 100,000 and vehicle ownership per capita in Michigan is around 0.9. Therefore, only a small portion of vehicles were studied and some sharing opportunities might be missed. (2) The vehicle data were generated from private vehicles while the previous studies were focused on taxi fleet (Cai, 2015; Santi et al., 2014), which would have similar travel patterns among these trips. For example, more taxi trips might happen close to the commercial centers and transit center during the peak hours. Hence, taxi trips might be easier to be shared than private cars.

For the future research, more vehicle trajectory data could be collected or the vehicles that within a small community could be researched. It might increase the sharability since those trips might share similar travel patterns, spatially and temporally. Seasonal effects would also be considered in the future research when studying the shared bike trips. Because in the bad weather, such as snowing, people may be not willing to use the bike for their trips. In addition, some advanced optimization models are worth trying in the future, such as spatial–temporal network model. These models can combine the trips matching and optimization into the same part, which might outperform the model we used in this research.

Reference

Agatz N., Erera A., Savelsbergh M., Wang X., 2012, Optimization for dynamic ride-sharing: A review. European Journal of Operational Research. 223(2):295-303.

Agatz, N., Erera, A., Savelsbergh, M., Wang, X., 2011. Dynamic ride-sharing: a simulation study in metro atlanta. Transportation Reserch Part B, Methodological 45 (9), 1450–1464.

Amey, A., 2011. Proposed Methodology for Estimating Rideshare Viability Within an Organization: Application to the MIT Community, Transportation Research Board Annual Meeting 2011, Paper 11-2585.

Baldacci, R., Maniezzo, V., Mingozzi, A., 2004. An exact method for the car pooling problem based on lagrangean column generation. Operations Research 52 (3), 422–439.

Bicocchi N, Mamei M, 201, Investigating ride sharing opportunities through mobility data analysis. Pervasive and Mobile Computing. 14(0):83-94.

Cai, H., 2015, Big Data for Urban Sustainability, University of Michigan at Ann Arbor.

Calvo, R.W., de Luigi, F., Haastrup, P., Maniezzo, V., 2004. A distributed geographic information system for the daily car pooling problem. Computers & Operations Research 31 (13), 2263–2278.

Chen, T. D., 2015, Management of a Shared, Autonomous, Electric Vehicle Fleet: Vehicle Choice, Charging Infrastructure & Pricing Strategies, The University of Texas at Austin.

Dueker KJ, Bair BO, Levin IP, 1977, Ride sharing: Psychological factors. Transp Engrg J 103:685–692.

Fagnant, D. J., 2014, "The Future of Fully Automated Vehicles: Opportunities for Vehicle- and Ride-Sharing, with Cost and Emission Ssavings," The University of Texas at Austin.

Fellows NT, Pitfield DE, 2000, An economic and operational evaluation of urban car-sharing. Transportation Research Part D: Transport and Environment. 5(1):1-10.

Finley K, 2013, Trust in the Sharing Economy: An Exploratory Study: The University of Warwick.

Fishman, E., Washington, S., & Haworth, N., 2013, Bike share: a synthesis of the literature. Transport reviews, 33(2), 148-165.

Fuller, D., Gauvin, L., Kestens, Y., Daniel, M., Fournier, M., Morency, P., & Drouin, L., 2011, Use of a new public bicycle share program in Montreal, Canada. American Journal of Preventive Medicine, 41(1), 80–83. doi: 10.1016/j.amepre.2011.03.002

García-Palomares, J. C., Gutiérrez, J., & Latorre, M, 2012, Optimizing the location of stations in bike-sharing programs: a GIS approach. Applied Geography, 35(1), 235-246.

Ghoseiri, K., Haghani, A., Hamedi, M., 2011. Real-time rideshare matching problem. University of Maryland, Department of Civil and Environmental Engineering, UMD-2009-05.

Handke, V., & Jonuschat, H., 2012, Flexible ridesharing: new opportunities and service concepts for sustainable mobility. Springer Science & Business Media.

He W, Li D, Zhang T, An L, Guo M, Chen G, 2012, Mining regular routes from GPS data for ridesharing recommendations. Proceedings of the ACM SIGKDD International Workshop on Urban Computing; Beijing, China. 2346510: ACM. p. 79-86.

Jensen, P., Rouquier, J.-B., Ovtracht, N., & Robardet, C., 2010, Characterizing the speed and paths of shared bicycle use in Lyon. Transportation Research Part D, 15(8), 522–524. doi: 10.1016/j.trd. 2010.07.002

Martin, E. W., and Shaheen, S. A., 2011, "Greenhouse Gas Emission Impacts of Carsharing in North America," IEEE Transactions on Intelligent Transportation Systems, 12(4) pp. 1074-1086.

Ma S, Zheng Y, Wolfson O. Real-Time City-Scale Taxi Ridesharing, 2014, Knowledge and Data Engineering, IEEE Transactions on;PP(99):1-.

Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S. H., & Ratti, C., 2014, Quantifying the benefits of vehicle pooling with shareability networks. Proceedings of the National Academy of Sciences, 111(37), 13290-13294.

Shaheen, S., and Cohen, A., 2013, "Innovative Mobility Carsharing Outlook. Transportation Sustainability Research Center," University of California at Berkeley.

Shaheen, S., Guzman, S., & Zhang, H., 2010, Bikesharing in Europe, the Americas, and Asia. Transportation Research Record: Journal of the Transportation Research Board, 2143, 159–167. doi: 10.3141/2143-20.

Teal RF, 1987, Carpooling: Who, how and why. Transp Res A 21(3):203–214.

Trasarti R, Pinelli F, Nanni M, Giannotti F, 2011, Mining mobility user profiles for car pooling. Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining; San Diego, California, USA. 2020591: ACM. p. 1190-8.

U.S. Environmental Protection Agency, 2010, National Vehicle and Fuel Emissions Laboratory, personal communication.

U.S. Energy Information Administration, 2015, Monthly energy review.

U.S. Environmental Protection Agency, 2014, Sources of greenhouse gases emissions.

U.S. Environmental Protection Agency, 2015, Emission Factors for Greenhouse Gas Inventories.

U.S. Environmental Protection Agency, 2014, Greenhouse Gas Emissions from a Typical Passenger Vehicle.

Vogel, P., Greiser, T., & Mattfeld, D. C., 2011, Understanding bike-sharing systems using data mining: Exploring activity patterns. Procedia-Social and Behavioral Sciences, 20, 514-523.

Wang, S., Zhang, J., Liu, L., & Duan, Z. Y. (2010, August). Bike-Sharing-A new public transportation mode: State of the practice & prospects. In Emergency Management and Management Sciences (ICEMMS), 2010 IEEE International Conference on (pp. 222-225). IEEE.

Winter, S., Nittel, S., 2006. Ad-hoc shared-ride trip planning by mobile geosensor networks. International Journal of Geographic Information Science 00 (00), 1–21.

Xing, X., Warden, T., Nicolai, T., Herzog, O., 2009. Smize: a spontaneous ride-sharing system for individual urban transit. In: Proceedings of the 7th German Conference on Multiagent System Technologies, MATES'09. Springer-Verlag, Berlin Heidelberg, pp. 165–176.

Zervas, G., Proserpio, D., & Byers, J. W., 2014, The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. Journal of Marketing Research.