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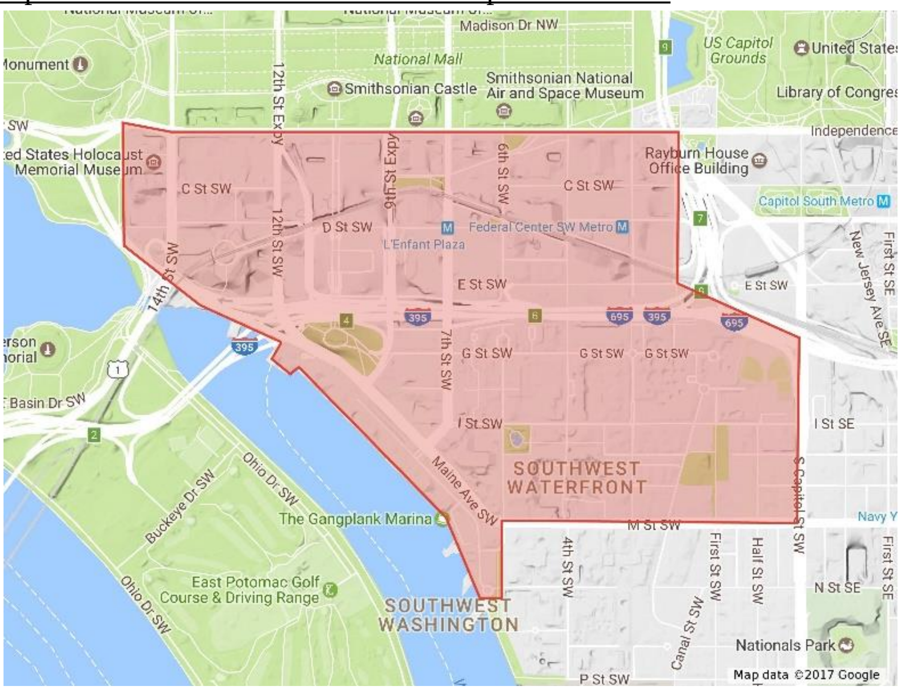
Nationwide Mobility Report
Professor Alain Kornhauser

Washington DC Mobility through Autonomous Taxis

Abstract

This paper analyses the impact of aTaxis on transit trips on the Southwest Business District (SWBID) in Washington DC. This it the region south of the National Mall, described by Figure 1 below, which gives a visual of the region analyzed, marked in red. We analyzed Professor Alain Kornhauser's and Kyle Marocchini's database of the billion daily trips using multiple mode split, ride sharing and visualization scripts. As a result, we were able to propose a solution for trips in the SWBID. Our final deductions showed a distinct opportunity for aTaxi deployment in the SWBID that would increase mobility, improve land use, and reduce congestion for this district. When aTaxis are implemented as an efficient means for transporting individuals to and from trip destinations, the current allocation of funding to existing transit systems may be redistributed to address a future shift to on-demand ridership on both roads and rails.

Figure 1: A Map of the Southwest Business Development District



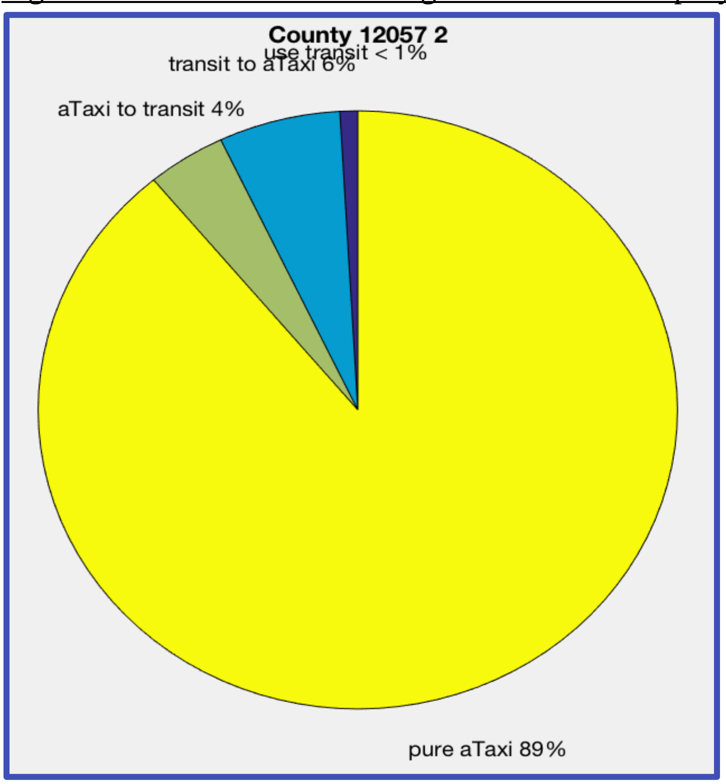
Within our region, we focused on the transit trips along the waterfront and the main corridor, M street.

The Data Set & How the Code Worked

Kornhauser and Marocchini had originally developed a base of data and code, founded on census data. The code took employer locations, schools, businesses, and residencies and created a day in the life of transportation across the entire United States. For the purposes of this project, we analyzed the trips originating in Washington with great circle distance between 0 and 10 miles. Marocchini and Kornhauser supplied a body of code and data respectively which was greatly helpful in defining this set of trips. After refactoring the code to produce more narrow results than originally designed, we obtained a file as described above. From there we pixelated the SWBID into 1000ft by 1000 foot squares, and divided the data into separate files. Each pixel had at least one file, which was based on Latitude and Longitude calculations. After pixelating the trips, we quickly broke down a density analysis of what were the existing transit demands and what were the estimates provided to us by the SWBID project brief.

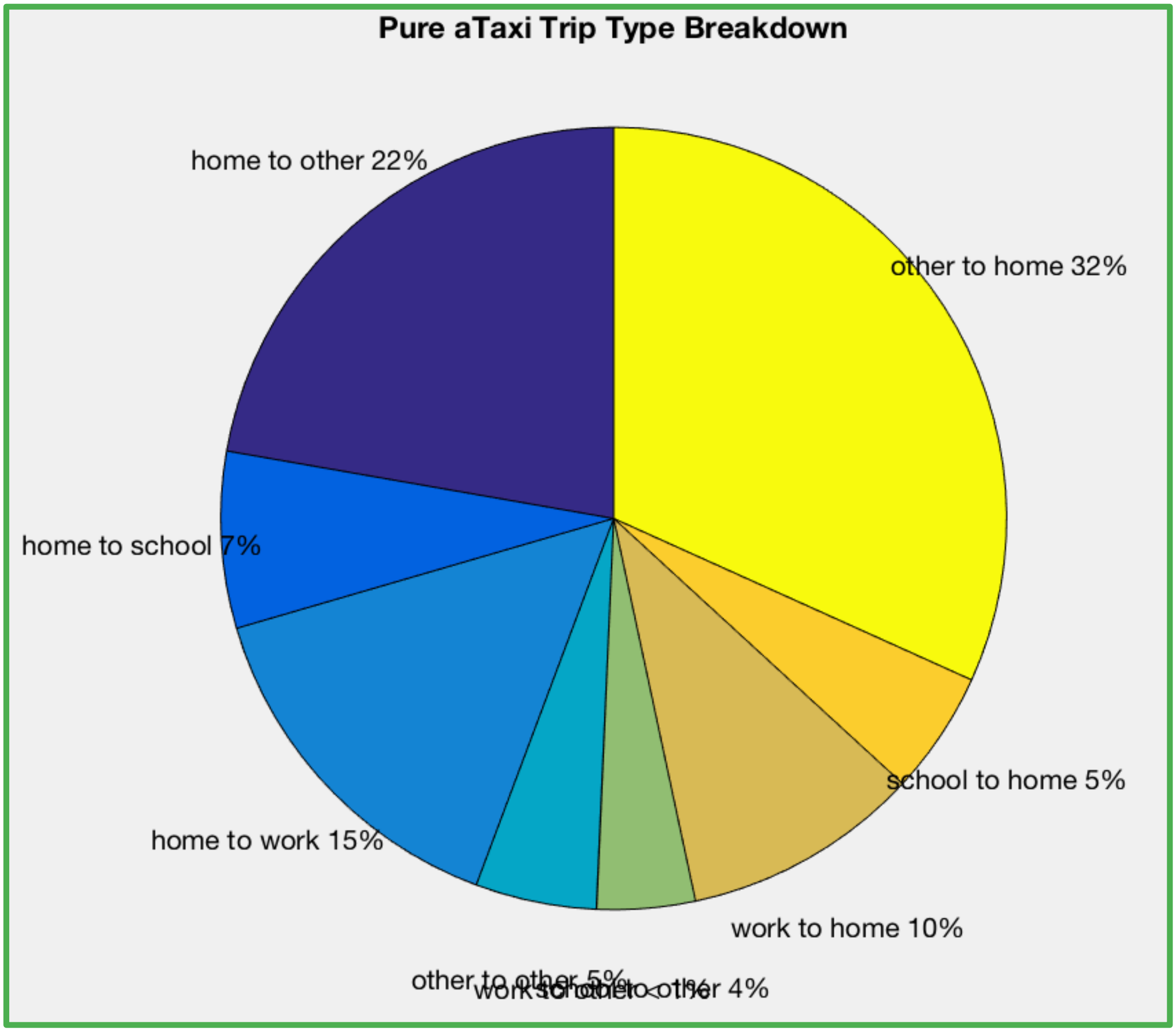
Using Matlab as the coding environment, we looped through all the pixelated files for each of the 1000ft regions and outputted a Matlab workspace for each file. Each contained all relevant information for each trip, including tour type, origin and destination identity, and information about destinations visited, with their location. Each trip served assumes that the traveler will wait up to 5 minutes before being picked up, and walk up to 1 minute over the whole trip (Walk speed assumed 3mph). In addition the trips were routed through the metro system, with station information taken from the Transit Oriented Development Database.

Figure 2 - Pie Chart Summarizing Breakdown of Trip Types



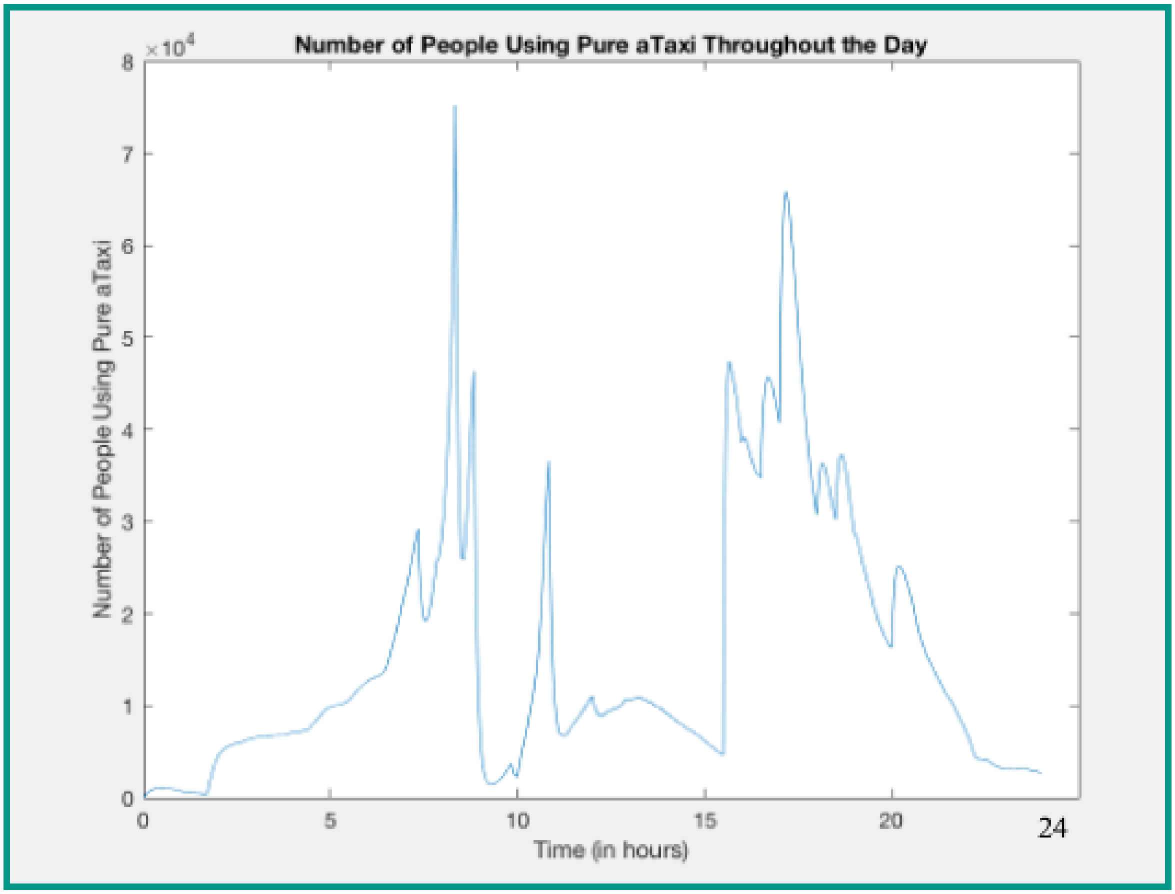
As a vestige of the previous code the above pie chart splits the transit trips into 3 categories, but it should be interpretted as 11% of trips utilize the existing transit network in some capacity. 89% of trips an be completely served by the aTaxi fleet, which shows the opportunity for aTaxi deployment

Figure 3a - Pie Chart Summarizing Breakdown of Tour Types in Pure aTaxi Trips



The pure aTaxi trips mirror the public transit trips in terms of their tour type break down with the majority being other to home.

Figure 3b - Time Distribution of Pure aTaxi Riders



The number of aTaxis at each time throughout the day is almost a factor of 9 higher which corresponds to the 89% of trips going via the pure aTaxi mode. There is a very large and sharp peak in the morning at 8:00am for the work commute and then a smaller peak around 3:30pm when school let out and around 5:00pm for the end of the working day. This pattern is not entirely surprising given general rush hour stereotypes.

Velocity Assumptions

We made the following assumptions about the velocity of each mode to calculate travel and arrival times:

- 3 mph for Walks
- 30 mph for aTaxis
- 40 mph for Transit

Takeaways from Output

Our code provided a very rich dataset separating the trips in Washington into use transit only, and pure aTaxi trips, allowing us to break down the data into tour type and to take a look at the time distribution of each type of trip at every second of each day. Yet, because we constructed our code in Matlab, the run time was exceeding an hour for one file. Given more computing resources, faster run time, and better efficiency our Matlab code could output a very rich dataset on trips in the entire country, allowing us to break down the trips by tour type and potentially by most popular origins and destinations. However, due to the time constraints and limited scope of this competition, we did not consider a larger view.
The output of the code relied on a KD Tree search implementation graciously provided by Evan Wood and Elizabeth Haile. Run on our data set, the output was less rich, but still provided useful analyses. Although our code followed a similar logic methodology, the more lightweight Java environment as well as unlinking the trips and decreasing the information output meant that the new code ran in linearithmic rather than polynomial time.

Figure 4 - Average Distance and Travel Times For Each Mode Split

Trip Type	**Metric**	**Value**
Transit	Average Distance	1.49 miles
Transit	Average Travel Time	6.23 min
Transit to aTaxi	Average Distance	3.67 miles
Transit to aTaxi	Average Travel Time	6.08 min
aTaxi to Transit	Average Distance	3.77 miles
aTaxi to Transit	Average Travel Time	7.83 min

From Figure 4, the transit trips are on average more than half the distance of the transit to aTaxi or aTaxi to transit trips. The existence of aTaxi's makes these longer trips possible by solving the final mile problem and hence have a longer average distance. However, the travel time of these transit to aTaxi and aTaxi to transit trips is roughly comparable as it omits the slow (3mph) walking segment at one end and replaces it with a fast (30 mph) aTaxi segment.

Transit Utilization

From our analysis of the transit trips, we have been able to predict the number of trips and person miles travelled after the implementation of aTaxis. Thus, we have modeled the change in transit utilization from current levels aggregated from the National Transit Database to the predicted levels with aTaxis for the SWBID.

Figure 5 - Transit Utilization Tables: Passenger Miles Travelled

City	PMT Now*	PMT New	Multiplier
Washington D.C.	1,968,724,491	4,450,069,759	2.26

* The numbers in the "PMT Now" column are summations of PMT data found by visiting https://www.transit.dot.gov/ntd/transit-agency-profiles and entering the city of interest into the search field. After entering the city name, at least one option appears for each of the transit commissions in the city, each of which leads to a 2014 report of the data collected from the previous year for that commission. Refer to PMT data.

Figure 6 - Transit Utilization Tables: Unlinked Passenger Trips

City	Unlinked Trips Now*	Unlinked Trips New	Multiplier
Washington D.C.	411,323,792	1,001,410,715	2.43

* The numbers in the "Unlinked Trips Now" column are summations of unlinked trips data found by visiting https://www.transit.dot.gov/ntd/transit-agency-profiles and entering the city of interest into the search field. After entering the city name, at least one option appears for each of the transit commissions in the city, each of which leads to a 2014 report of the data collected from the previous year for that commission. Refer to unlinked trips data.

Financial Analysis

While the previous section of our chapter focused on the ambitious parts of calculating and synthesizing all of this data, these last sections examine the bottom line impacts this type of model yields. Below we examine the change in operating expenses, fare revenue, and profits for the transit system.

Our first step was to go to the National Transit Database, a service offered by the Federal Transit Administration, a department of the US Department of Transportation. From there we collected two pieces of data for the city. The first was Operating expenses per vehicle mile (Train miles, not person miles). The second was Fare Revenue, and this was a total measure for the agency. We retrieved these data from the first available heavy rail system in a city, opting for light rail if no heavy rail measures were reported. From those two data points, and our own mileage data, we were able to create comprehensive data tables for each city outlining the financial impact of our model (essentially increasing ridership).

This data has a very poignant effect on the DC Metro looking for a financial forecast as aTaxis get deployed, provided a linked transit approach. More funds and creative pricing structures will be needed, and based on the industry's ability to deliver those services, it will either benefit financially from the prevalence of aTaxis, or be stunted by it.

This initial research is a start to allow us to at least ask some of these questions. With access to more data from the FTA, we might be able to test the assumption of whether operating expenses (which do only include the variable costs not the sunk capital costs) do vary linearly with such a large increase in ridership and a decrease in average trip length as shown in Figure 7a. However, this may be the first time that we have even been able to see estimates of the budgetary effects of aTaxis on transit and will hopefully be a starting point for future research.

Figure 7a - Average Trip Length Analysis

	Now*	New	Multiplier
Average Trip Length	5.39	5.15	0.96

* The number in the "Now" column is an average of the trip length data found by visiting https://www.transit.dot.gov/ntd/transit-agency-profiles and entering the city of interest into the search field. After entering the city name, at least one option appears for each of the transit commissions in the city, each of which leads to a 2014 report of the data collected from the previous year for that commission. Refer to trip length data.

Figure 7b - Current Average Unit Economic Effects In Per PMT and Per Trip

	Operating Expenses Now*	Fare Revenue Now	Profit Now
Per PMT	1.01	0.17	-0.83
Per Trip	5.42	0.94	-4.48

* The numbers in the "Operating Expenses Now" column are averages of the operating expenses data found by visiting https://www.transit.dot.gov/ntd/transit-agency-profiles and entering the city of interest into the search field. After entering the city name, at least one option appears for each of the transit commissions in the city, each of which leads to a 2014 report of the data collected from the previous year for that commission. Refer to operating expenses data.

Figure 7c - Change In Average Unit Economic Effects

	Now*	New	Multiplier
Operating Expenses Per Trip	5.42	5.18	0.96
Fare Revenue Per PMT	0.17	0.18	1.05

* The numbers in the "Now" column are averages of the operating expenses data found by visiting https://www.transit.dot.gov/ntd/transit-agency-profiles and entering the city of interest into the search field. After entering the city name, at least one option appears for each of the transit commissions in the city, each of which leads to a 2014 report of the data collected from the previous year for that commission. Refer to operating expenses and fare revenue data.

Figure 7a shows a 4% decrease in average trip length. Assuming that the operating expenses per PMT and revenue per trip remains the same as in the FTA database. In Figure 7b, we have worked back to give the current revenue per PMT and operating expenses per trip for reference.

In Figure 7c, the decrease in average trip length means the operating expenses per trip decreases by 4% while the revenue per PMT increases 5%. However, currently transit authorities are losing $0.83 per mile and $4.48 per trip so, despite this improvement in unit economics, the increased total number of trips and PMT means that losses on transit increase. Figures 7.20 and 7.22 show the aggregated financial effects on an individual city basis.

Figure 8a - Financial Impact Tables: Operating Expenses

City	Operating Expenses Per PMT Now*	Operating Expenses Now*	Operating Expenses New	Multiplier
Washington D.C.	0.63	1,240,296,429	2,803,543,948	2.26

* The numbers in the "Operating Expenses Per PMT Now" and "Operating Expenses Now" columns are the operating expenses data found by visiting https://www.transit.dot.gov/ntd/transit-agency-profiles and entering the city of interest into the search field. After entering the city name, at least one option appears for each of the transit commissions in the city, each of which leads to a 2014 report of the data collected from the previous year for that commission. Refer to operating expenses data.

The operating costs increased in each city by, 2.26 times (Just a multiplication by the greater PMT). As operating costs per PMT scale linearly with PMT, Washington and the SWBID will need solutions to cover their increased ridership.

Figure 8b - Financial Impact Tables: Fare Revenue

City	Average Fare Revenue Now*	Fare Revenue Now*	Fare Revenue New	Multiplier
Washington D.C.	1.44	593,323,968	1,444,509,145	2.43

* The numbers in the "Average Fare Revenue Now" and "Revenue Now" columns are the fare revenue data found by visiting https://www.transit.dot.gov/ntd/transit-agency-profiles and entering the city of interest into the search field. After entering the city name, at least one option appears for each of the transit commissions in the city, each of which leads to a 2014 report of the data collected from the previous year for that commission. Refer to fare revenue data.

The operating costs increased in the city by, 2.43 times. As fare revenue scales linearly with the number of trips, DC can expect an increase in revenues that outpace unit costs, but lag behind the overall increase in costs. Again, this is largely due to the existing losses of our public transit systems.

Figure 8c- Financial Impact Tables: Profits

City	Profits Now*	Profits New	Profits Percentage Change
Washington D.C.	-646,972,461	-1,359,034,803	-110.06

* The numbers in the "Profits Now" column are the profits in each city found by summing the "Operating Expenses Now" column and the "Revenue Now" column.

Simply to wrap up the question of financing, Washington Metro Profits decrease by 10% under the above assumptions. An increase in volume in our city's metro leads to higher losses that outpace our current revenue, as the Metro currently loses money on every passenger.

Ride-Sharing Analysis

The aTaxi end of the transit to aTaxi and aTaxi to transit mode splits are an ideal opportunity for ridesharing. This is because, as train unload numerous passengers at the same time, you can load an aTaxi that satisfies common destination and circuity constraints with a minimal departure delay. Below Figures 9 and 10 illustrate especially the times where ride sharing can happen.

Figure 9 - Cumulative Departure of aTaxis Serving Transit to aTaxi Trips throughout the Day

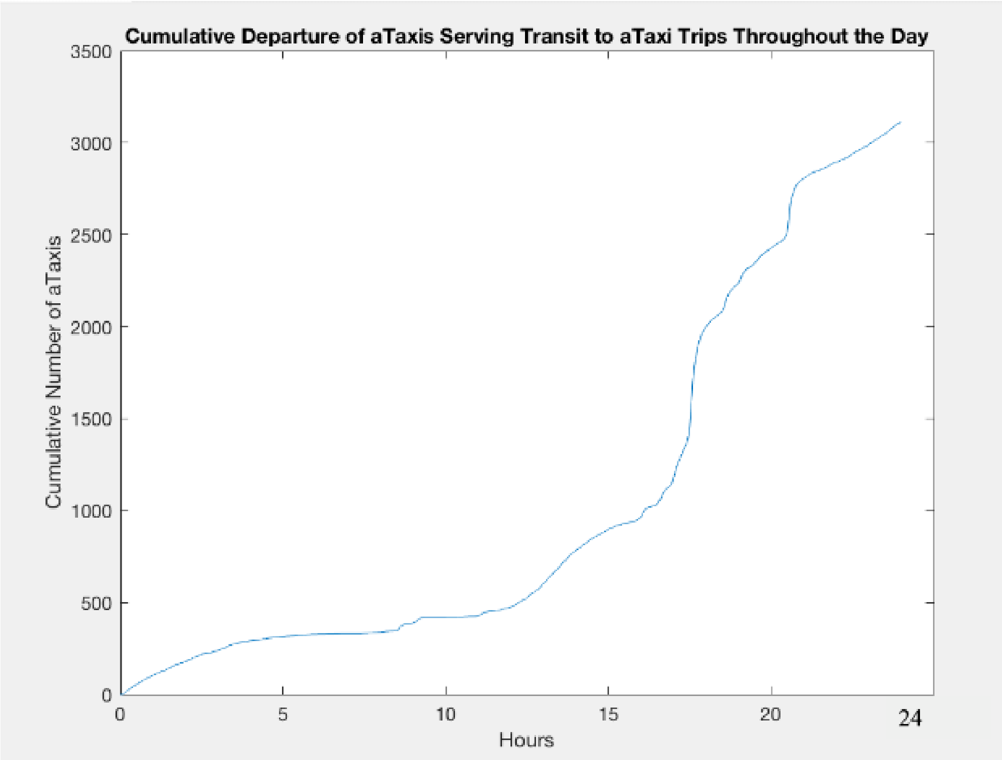
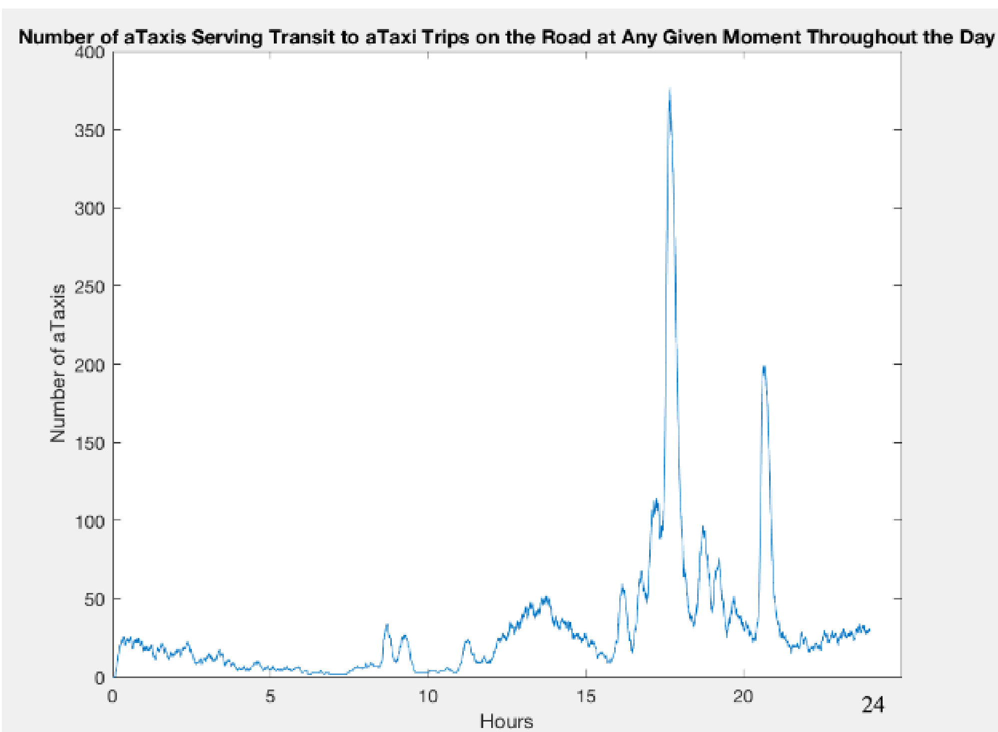


Figure 10 - Number of aTaxis Serving Mixed Mode Trips on the Road at Every Moment



There is a major rise in Figures 9 and 10 around 5:30pm after work and then again at 8:30pm after dinner out as was shown in the analysis of transit to aTaxi trips in Figure 3b. From Figure 9, the minimum fleet size assuming there is no empty vehicle repositioning is 3,119. From Figure 10, we can see that the maximum number of aTaxis required is 379 at 5:30pm. This corresponds to the minimum fleet size if empty vehicle repositioning was fully optimized.

Figure 11 - Number of aTaxis Serving Transit to aTaxi Trips Vs Number of Occupants per Departing Vehicle

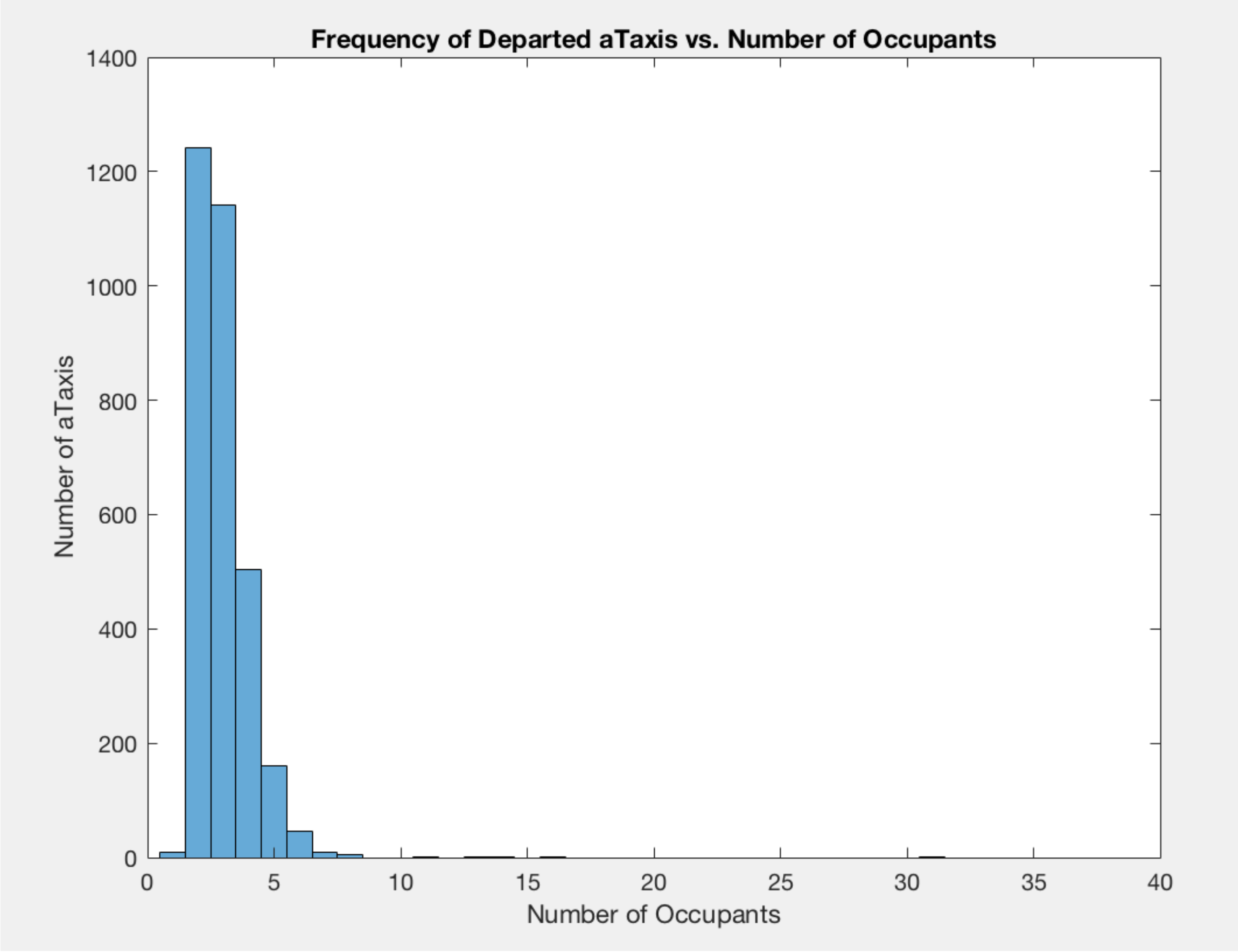


Figure 10 shows the number of aTaxis against the number of occupants when the vehicle departs. It seems odd that the number of aTaxi departing with 2 occupants is so much greater than the number departing with 1 occupant. However, we double checked the values to verify. One potential explanation is that, as many transit passengers are arriving at exactly the same location, it is rare for a single passenger to not have at least one other passenger present that meets the circuity and common destination constraints. What is clear is that, with an AVO of 2.95, there is significant ride-sharing potential.

The ride-sharing analysis was sadly left until the end and as we came close to exceeding the time constraint on this project but, in future research, this ride-sharing code (or even other more data rich version we have developed, see Code Appendix) could be run for all of the aTaxis serving transit to aTaxi and aTaxi to transit modes in a larger scope.

Conclusions

This project focused on creating mode split, purpose split, time of day, trip length distributions and ride-sharing analysis for transit trips in the SWBID. We showed that Pure aTaxi trips are the most used mode of travel. We found that the most frequent travel purposes are “Home to other” and “Other to home”. We investigated the time of day and distance distributions for transit, transit to aTaxi and aTaxi to transit modes with impacts on fleet size and repositioning strategies for aTaxis. We conducted an initial investigation, which provides a clear starting point for future research, into the ride-sharing potential for the transit to aTaxi trips in Washington DC determining its minimum fleet size and determining, with an AVO of 2.95, there is significant ride-sharing potential.

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