Uncongested Mobility for All: A Proposal for an Area Wide Autonomous Taxi System in New Jersey

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ABSTRACT

This paper examines the feasibility of assembling a fleet of autonomous taxis (aTaxis) in the state of New Jersey to provide personalized, automated, direct, and demand-responsive transportation. Such aTaxis provide auto-like service where demand is diffuse in space and time while facilitating casual ridesharing to serve demand that happens to be correlated spatially and temporally. This casual ridesharing substantially improves transportation efficiency and eliminates congestion. A key component of this undertaking is the synthesis of the travel behavior of each of the roughly eight million individuals in New Jersey. This trip data can be used to inform a simulation of the servicing of travel demand. About two million trips are less than a mile and are readily served by walking and biking. The remaining thirty million trips are served by aTaxis. In the aTaxi system, a grid of quarter square mile pixels overlays New Jersey; each pixel contains an aTaxiStand to and from which passengers ride the aTaxi. Results show that denser locations during peak hours have substantial ridesharing potential that would correspondingly decongest roadways while delivering excellent mobility at reduced energy and environmental consequences.
MOTIVATION

In the realm of automated people movers, the Personal Rapid Transport (PRT) has been the prime focus of research as a personalized, automated, direct, and demand responsive form of transportation. However, PRTs are difficult to integrate in mass scale into existing transportation networks due to its dependence on an extensive dedicated guideway infrastructure. While PRT stations can readily be integrated in facilities that would embrace the premier accessibility and clientele connectivity afforded by them, it is cost prohibitive to place them underground and unsafe to place at-grade. Overhead is technologically feasible, but architecturally and societally unacceptable.

Autonomous vehicles, however, present a budding alternative to PRTs. They require no more than the existing road infrastructure to operate and can simply be integrated into current transportation networks. In addition, the technology offers safety and environmental advantages. With Google and most major car manufacturers expanding research on this technology, autonomous vehicles are on the verge of becoming a commercial reality. Utilizing these vehicles in a shared setting can lead to a system of autonomous taxis.

Consider an autonomous taxi (aTaxi) system consisting of automated vehicles operating from designated aTaxiStands located throughout New Jersey whereby aTaxis would travel between aTaxiStands using New Jersey's existing road and highway infrastructure. Since aTaxis are designed to operate automatically in traffic with human-operated vehicles while not requiring any change in the existing roadway infrastructure, such a system can readily begin to operate effectively with a single pair of aTaxiStands. Additional aTaxiStands can readily be built wherever there exists sufficient customer demand. As aTaxiStands are added, the mobility afforded grows more quickly, especially at first because of the network connectivity effects. A point of diminishing return will be so close to service for all, that service for all can be offered at a very small additional cost. Most importantly, the system has the opportunity to grow naturally or virally from austere beginnings to serve much if not all of New Jersey.

Assembling a fleet of autonomous vehicles that offer on-demand mobility between aTaxiStands conveniently located near all locations to and from where individual would travel in New Jersey may attract enough customers to take many, if not most cars off the roads – especially during times of congestion. If the demand is high and concentrated enough to allow for substantial casual sharing of aTaxi rides, then more human operated cars would be taken off congested roads than are being replaced by aTaxis. This reduces congestion, environmental impact and energy consumption.

TRIP SYNTHESIZER OVERVIEW

The most fundamental component of analyzing the potential of a statewide autonomous taxi system with ridesharing is high-resolution daily travel demand data that can inform the simulation. A comprehensive dataset requires spatial and temporal precision and accuracy. In this way, the precise 32 million daily trips of all 8 million people in New Jersey can be generated and analyzed. The methodology that produced this robust dataset used in this report was proposed by Talal Mufti in his Master’s thesis (2) and enhanced by Jingkang Gao (1) in his Senior thesis. Refer to these works for more details about the synthesizer.
Trip Synthesizing Process

The four fundamental steps for the generation of the dataset includes:

- creation of a population of individuals whose characteristics in aggregate resemble that of New Jersey,
- assignment of workplaces and schools (the “anchors”),
- assignment of activity patterns and specific trip ends,
- assignment of the arrival and departure times.

The first step of the synthesizer is based on population and household demographics from the 2010 Decennial Census. The utilization of census data to inform the characteristics of the population is an incredibly precise method of simulating the actual population of New Jersey. Information is known at census block level which is the “smallest geographic unit used by the United States Census Bureau for tabulation of 100-percent data” (3). The great detail of the characteristics of the census blocks can be used to inform the features of the regions in the simulated system. In particular, distributions for factors such as age and salary can be created from census blocks and the synthesized residents of this census block will have characteristics drawn from this distribution.

After an individual is created, a traveler type of student, worker, or other is assigned based on age and regional attributes. In this way, the trip synthesizer generates demographic characteristics for each of the 8,791,894 individuals living in 118,654 census blocks that comprise New Jersey. In addition, out-of-state individuals who travel through New Jersey are generated in order to obtain a complete synthesis of daily trips. These individuals are assigned to the following buckets: Bucks County and westward, Philadelphia, New York, North of Bucks County in Pennsylvania, South of Philadelphia, Westchester County and eastward, Rockland County and rest of New York State, and International. Subsequently, the “anchor” activity of work or school is assigned stochastically based on an individual's attributes, region characteristics from census data, and distance from home.

Each individual's demographic signature is then used to generate the trip ends. In practice, the execution at this step fills in data around the home and anchor nodes. The specific name and address of each establishment visited during a trip are identified by selecting from the appropriate distributions.

The final step of the synthesizer assigns arrival and departure times, in seconds from midnight, for each trip. For each individual with a specific tour type, the synthesizer checks the types of the nodes (school, workplace, other) involved in the trip as well as other attributes such as the location of the trip within the daily tour schedule. Arrival time distributions and duration distributions for each type of trip are then used to randomly select precise departure times for each leg of the trip in a tour.

Multi-modal Adjustments

Autonomous taxis are not meant to usurp all modes of public transportation; rather, they are most effective when used in conjunction with robust and existing highly trafficked forms of public transportation. Practicality and efficiency dictate that a multi-modal form of transportation is utilized for longer trips or for trips along which robust travel modes already exist. For instance, commuters traveling to New York City for work might currently utilize a bimodal form of transportation. They take personal vehicles to train stations and then ride the train into New
York. Similarly, an aTaxi system should reflect the use of trains and other highly utilized existing transportation modes.

In this simulation, New Jersey Transit trains are an integral part of this system. To incorporate NJT, the dataset is modified so that all trips destined to New York City and Philadelphia are assumed to be taken on NJT. For a trip to a metropolitan area, the traveler departs the origin and travels to the closest train station to the origin (by walk or aTaxi); subsequently, the train takes this traveler to NYC or Philadelphia. Likewise, trips departing NYC and Philadelphia are taken on the train to the station nearest the destination. The subsequent leg from station to destination is satisfied by walking or aTaxi.

AUTONOMOUS TAXI SYSTEM DESIGN

With this robust demand dataset, transportation simulations can be performed quite accurately. The first step in developing an aTaxi system involves the placement of aTaxiStands, docking sites for travelers to access aTaxis. Accessibility is the prime feature of the system that provides it viability. Regardless of location, travelers should be able to simply walk a short distance to the nearest aTaxiStand and wait for an aTaxi to take them to their destination. A stipulation that all trip demand in New Jersey must be serviced will be imposed; hence, aTaxiStands must be pervasive.

Autonomous Taxi Stand Grid

Taking accessibility and full servicing into account, the simplest approach of determining the locations of the aTaxis will be to create an array of aTaxiStand locations that covers the entire state. Each of these aTaxiStands will have as many aTaxis as needed to service all tours originating from that pixel. The state was pixelated into square pixels, 0.5 miles on a side. In this way, no traveler would have to travel more than a quarter mile to satisfy his or her travel demand. In addition, this pixelation allows Manhattan distances to be conveniently utilized for distance calculations. Although, an ideal simulation would have current roadways underlie the process, Manhattan distances are preferred over Euclidean distances since it can account for some of the circuitry in roadways.

In order to reference these pixels, a coordinate system is necessary. Translation of the origin of the standard geographic coordinate system (0°, 0°) to a point south and west of the New Jersey boundary (-75.6E, 38.9°N) allows the integer value of any point in the new coordinate system to be defined as:

\[
\begin{align*}
    x_{coord} &= \text{int}(108.907 \times (\text{longitude} + 75.6)) \\
    y_{coord} &= \text{int}(138.2 \times (\text{latitude} - 38.9))
\end{align*}
\]

where 108.907 and 138.2 convert longitude and latitude units into half mile units.

These coordinates would now address some pixel in the array of New Jersey. Thus, by locating an aTaxiStand at the center of each pixel, any trip end within the pixel will be served by the aTaxiStand located at the center of the pixel. Thus, a simple coordinate transformation and integerization converts any trip end latitude and longitude into a pointer to a unique trip end aTaxiStand.
Rideshare Operational Parameters

With the aTaxiStands positioned, the daily trip simulation can occur. The rideshare process is meant to mirror a realistic transit and taxi system; hence, two operational parameters, departure delays (DD) and the number of common destinations (CD), are present. Departure delays are the period of waiting for additional passengers after an initial traveler enters an autonomous taxi. This is akin to a train that waits at a station for passengers prior to departing. As the departure delay increases, the ridesharing potential should increase as well.

The common destination measurement denotes the number of unique locations (pixels) an aTaxis can visit. Using the train analogy, this would be the number of stops a train would have along its path. A CD = 1 environment denotes the aTaxi can only go to one location and infinite shares to that one location are permitted. A CD = 2 environment indicates ridesharing to up to two destinations with infinite shares permitted, and so on. For conventions in this report, the CD = 0 environment is a special case in which no ridesharing is permitted. In this case, each individual travels in his or her own aTaxi. As the number of common destinations increase, the rideshare potential should also increase since it allows an aTaxi to collect travelers with a more diverse group of destinations. In this way, the departure delay and common destination parameters can be modulated to examine various ridesharing outcomes under different system parameters.

A crucial property to establish is the criteria for a rideshare. In this system, rideshare occurs when CD > 0. If CD > 0 and travelers arrive to a pixel within the departure delay with the exact same destination pixel, a ride will be shared. However, the system should be expanded so that when CD > 1, individuals who are heading to the same general area should be able to share a ride in order to minimize the number of cars on the road while adding only minimal inconvenience from the circuity.

In this report, a traveler is a person who arrives at an aTaxiStand seeking a ride and a passenger is an individual already in an aTaxi. For a new traveler to share a ride in an existing aTaxi, the insertion of the new traveler's destination should not cause the new aTaxi tour to deviate significantly from the direct trip from origin to destination for the new traveler or any of the passengers. If large deviations occurred and it took significantly longer to get to a destination via the aTaxi service, the system will not be utilized by travelers; people would simply use personal cars to make the direct trips to destinations. Hence, certain circuity criteria must exist to permit rideshare while minimizing the disutility associated with it. It was determined that 20% is a practical estimate of acceptable circuity for rideshare; hence, to share a ride, an additional trip in an aTaxi cannot increase the distance of any direct trip by more than 20%.

An example will clarify this idea. Say that a new traveler (Traveler n with destination N) arrives at an aTaxiStand with one waiting aTaxi holding one passenger (Passenger p with destination P) where P ≠ N. If CD = 2, Traveler n still has the potential to share in this ride since the aTaxi can make trips to up to two distinct locations. In order to share the ride, the trip from origin to P to N to P must not eclipse the distance between both origin to N AND origin to P by more than 20%. In order for the trip to be shared in this example, the conditions that must be satisfied are:

\[
\min \{ \text{Distance}_{\text{origin-P-N}}, \text{Distance}_{\text{origin-N-P}} \} \leq 1.2 \times \text{Distance}_{\text{origin-P}} \\
\min \{ \text{Distance}_{\text{origin-P-N}}, \text{Distance}_{\text{origin-N-P}} \} \leq 1.2 \times \text{Distance}_{\text{origin-N}}
\]
Notice in the analysis that both permutations of the potential new aTaxi trip must be checked in order to determine whether rides are shared. That is, the order origin-N-P and origin-P-N must both be analyzed and checked for ridesharing opportunities. If no route satisfies the circuity conditions, the trip is not shared. In other cases, a simple approximation will determine the sharing of rides: when a unique potential destination is introduced by a traveler arriving to an aTaxi and the CD threshold has not been reached for the aTaxi, if the permutation that generates the shortest cumulative distance traveled by the aTaxi does not satisfy the circuity conditions, then no permutation will. If this shortest permutation does satisfy all the conditions, then the permutation is accepted as the new route and the aTaxi is shared. This heuristic can be readily applied to all simulations for all values of CD.

Trip Definitions
The dataset produces trips that are classified according to distance between the origin and destination pixel.

- Intrapixel Trips: Trips in which the origin and destination pixel are the same.
- Walk Trips: Trips in which the destination is one pixel away (N, NE, E, SE, S, SW, W, NW) from the source.
- aTaxi Trips: Trips which are more than 1 surrounding pixel away. These are the trips that are serviced by aTaxis.

Only the aTaxi trips are used in the rideshare analysis since there are the trips that will utilize an aTaxi.

Rideshare Methodology
The departure process for the aTaxis can be thought to function like a horizontal elevator. First, assume there are infinite empty aTaxis at an aTaxi Stand. A traveler will arrive at an aTaxi Stand at some time, oTime. All the vehicles set to depart prior to oTime will already have departed. There are then several cases to be considered:

- there are no existing aTaxis with passengers
- there are existing aTaxis with passengers
  - there is rideshare available in some aTaxi
  - there is no rideshare available in any aTaxi

In the first case, there are no existing aTaxis with passengers in the aTaxi Stand; hence, the traveler will enter an empty aTaxi. This traveler will enter the aTaxi at oTime. The aTaxi will then wait the departure_delay in order to wait for more potential passengers. If common_destinations = 0, then there will never be any ridesharing so the maximum occupancy for every aTaxi will be 1. If common_destinations > 0, infinite rideshares are permitted to common_destinations distinct locations. At depart_time = oTime + departure_delay, this vehicle departs.

In the second case, there are existing aTaxis with passengers that have some depart_time set by the each vehicle’s initial passenger. Therefore, a check of each aTaxi must be made to see whether the traveler's destination will permit a rideshare. The search will start at the top of the aTaxi Stand queue since the head of the queue contains the aTaxis that have the earliest
depart_time and it is in the traveler's interest to depart as early as possible. For each aTaxi, if any of the existing destinations of the passengers within that aTaxi match the traveler's destination, the ride is shared without it counting towards the common_destinations limit. If no current passenger is heading to the same location as the traveler and the common_destinations limit is reached, this aTaxi cannot share an additional ride and the next aTaxi is analyzed.

If the common_destinations limit has not been reached, then the circuity analysis is performed to see whether, after including this traveler's destination, some permutation of the new set of destinations will satisfy all the circuity conditions. If no permutation satisfies the circuity conditions, the ride cannot be shared and the next aTaxi in the queue is analyzed. However, after the first permutation that passes the circuity check is found, the traveler will enter this vehicle and share the ride. No changes to the depart_time will be made as only the oTime of the first entrant into an aTaxi determines that value.

In the case that the entire aTaxi queue has been searched and no rideshare opportunity is found, the traveler will enter a new aTaxi at oTime and wait the departure_delay in order to share rides with other potential passengers. The aTaxi departs at depart_time = oTime + departure_delay. This entire process occurs over the 24 hours until all travelers have been served by aTaxis.

Rideshare Assessment
An intuitive first metric to analyze rideshare potential is simple average vehicle occupancy. This is simply the average number of travelers in each aTaxi at departure (the total number of travelers over the number of aTaxis departed).

Although this gives us a fair indication of the shared ridership, it does not provide the entire picture. A true value for shared ridership potential accounts for the travel demand. Travel demand is better estimated as the distance that a traveler needs to travel to reach the destination. In particular, it is valuable to ascertain the number of miles saved as a result of the share.

\[
\text{True Average Vehicle Occupancy} = \frac{\text{Vehicle Miles Traveled}_{\text{No Share}}}{\text{Vehicle Miles Traveled}_{\text{Shared}}}
\]

Intuitively, this provides a better indication of the value of sharing rides. The vehicle miles travel under no sharing is simply the original travel demand of all travelers. In other words, these are the passenger miles originally demanded. Vehicle miles traveled with the share is the actual miles driven by the aTaxi on its path under the operational parameters. This ratio compares the effect of the share on the distance traveled by the vehicles. If this ratio is close to 1, very limited shared rides occurred or the sharing of rides did not effectively reduce the total vehicle miles traveled. Conversely, if this ratio is high, there could have been a greater number of shared rides or larger reduction in total vehicle miles traveled. This measure can also be thought of as a weighted vehicle occupancy. The weights in this case are the travel distances originally demanded. This True Average Vehicle Occupancy (AVO) will be the measure utilized throughout this report.

Benchmark
Average occupancy metrics for aTaxis are compared to those of cars for perspective. The National Household Travel Survey publishes a countrywide assessment that reports average vehicle occupancy as well as many other statistics. Since the 2010 Census informed the
1 synthesizer and all type of trips are considered in this system, the 2009 “All Purpose AVO” 
2 value of 1.67 will be used as a general benchmark to the system (4).
3 However, it is crucial to note that these survey values are inflated benchmarks. This 
4 inflation occurs as a result of chauffeuring – when individuals who have no demand for travel 
5 actually transport those with demand for travel. This causes vehicle occupancy numbers in the 
6 survey to be higher and not accurately reflect AVO due to actual travel demand. For example, if 
7 a parent were dropping a child off to practice, the survey would calculate a vehicle occupancy of 
8 2. However, the demand was generated from the child's need to travel to practice; hence, the true 
9 travel demand is 1.
10 In addition, this NHTS environment is different from the simulated demand environment. 
11 One key difference is that the synthesized travel demand does not include “trip correlations.”
12 These are changes in trip departure times and destinations which join trip utilities and increase 
13 ridesharing. For instance, having dinner together at a mutually agreed upon restaurant, shopping 
14 together, or recreating together are all major sources of ridesharing. The ridesharing values 
15 would be correspondingly higher for the aTaxi system if the travel demand had actually modeled 
16 this behavior. Although this NHTS environment is different from the simulation environment, 
17 the NHTS value still serves as a general benchmark with which the system's performance can be 
18 compared.
19
20 NEW JERSEY STATE SIMULATION RESULTS
21 New Jersey's features make it an excellent state to implement simulations. For instance, New 
22 Jersey is geographically varied with a mixture of open space and utilized space. New Jersey 
23 consists of mountainous regions in the northwest, coastal cities along the shoreline, and pine 
24 barrens in the southeast. Open space constitutes about 25% of the state. Therefore, this 
25 simulation can be checked for robustness across all major types of geography. Moreover, New 
26 Jersey's location and infrastructure make it quite accessible. It lies between New York and 
27 Philadelphia and proximity to these city centers induces greater traveling throughout New Jersey 
28 by both its residents and out-of-state residents. The expansiveness of the roadways such as I-95, 
29 Route 1, and the Garden State Parkway provides accessibility throughout the state. This allows 
30 more land to be utilized efficiently and gives rise to prime residential and recreational areas 
31 throughout the state. New Jersey is economically, educationally, and recreationally active; this 
32 activity translates into trips.
33
34 New Jersey Volume Analysis
35 To obtain a sense of time and location of the trips, cumulative trip distributions based on certain 
36 factors should be assessed. Specifically, the number of trips over time and the number of trips 
37 occurring by the order of highest ranked volume pixels should be observed. This will indicate 
38 how traveling is done over time and indicate the distribution of the trip origins. These are quite 
39 insightful since they can be used to inform the beginnings of an aTaxi system. For instance, the 
40 distribution by time indicates the times of the day aTaxi services would be most useful and the 
41 highest ranked volume pixel distribution indicates which aTaxiStands would have highest 
42 volumes.
43 Figure 1 shows the cumulative distribution of trips in New Jersey over the 86,400 
44 seconds of the day. The cumulative distribution graph displays the total percentage of trips that 
45 have been completed by some time. There is a jump from 7am to 8am which corresponds to the 
46 morning rush hour of school and work trips. This suggests that an aTaxi service during the 6am
to 9am rush period could have congestion reducing benefits since travel demand is high during that time period which, in turn, increases the likelihood of a rideshare arising. Smaller successive jumps can be seen in the period between 4pm and 7pm. These trips correspond to the waves of travelers leaving school and work during the afternoon and evening.

It is also useful to understand the sources of the trips. There are 21,643 trip producing pixels in New Jersey. Figure 1 also indicates the cumulative distribution of trips by rank of the highest volume pixel. That is, pixels are ordered by the number of trips they produce and placed on the x axis. The cumulative percentage of trips is placed along the y axis. This graph suggests that the trip origins in New Jersey are quite dense since relatively few pixels are responsible for most of the trip production in the county. About 50% of trips in New Jersey come from the top 1,300 (~6.1%) trip producing pixels and about 95% come from the top 44% of pixels.

**New Jersey Rideshare Analysis**

Simulations for the True Average Vehicle Occupancy (AVO) for the system were conducted for the operational parameters of all combinations of CD = 0, 1, 2, 3, 4, 5 and DD = 0, 1, 2, 3, 4, 5. Figure 2 shows that as CD and DD increase, the AVO values increase. This matches the expectation since waiting longer for a rideshare or allowing a vehicle to visit more than one location could only allow more ridesharing to occur. It is also apparent that CD = 0 produces an AVO of 1 regardless of the DD. This was a system design and validates the functionality of the simulation.

The largest increases in AVO due to an increase in departure delay occur when DD is raised from 0 to 1. This should be expected because much of the rideshare pairing occurs between long trips and short trips since the structure of these tour types are more likely to satisfy circuity conditions. Since trips arrive very frequently, a short trip can almost immediately be paired with a longer trip and much ridesharing can be captured early (i.e. within the first minute). After the first minute, a greater number of passengers with varied destinations arrive to a greater number of waiting vehicles. Although these later minutes will allow more unfilled spaces in aTaxis with similar destinations to be filled, the “easy” pairing of a long trip and short trip will already have been exhausted by this time. Consequently, the first minute produces the greatest increase in ridesharing potential with ridesharing rates waning as departure delay is increased.
FIGURE 2 The NJ AVO plot shows that as CD and DD increases, AVO increases.

The largest increase in AVO due to CD increases occurs as CD goes from 1 to 2. This is logical because many short trips pair with long trips due to the circuity conditions. For instance, take two trips, one with a destination very close to the origin and one with a destination far from the origin. The circuity caused by the shorter trip would be so relatively short compared to the farther traveler's direct trip that the ride would likely be shared. In this way, the highest jump can be expected as the number of distinct locations increases from 1 to 2.

An AVO value of 2 indicates that the total miles traveled by the aTaxi is half the amount that would have been traveled in an environment where each individual rides in a separate vehicle. In addition to indicating higher capacity utilization of vehicles, high values of AVO indicate significant vehicle mile savings associated with ridesharing. Even at reasonable (DD, CD) pairs, trip miles can be halved. For instance at (2, 3), the system produces an AVO of 2.07. The maximum AVO achieved in the feasible parameter set is 2.93 at (DD, CD) = (5, 5). In this situation, the vehicle miles traveled can be cut by two-thirds! See Table 1 for a complete table of values.

It is interesting to note that in at DD = 0, various CD parameters have AVOs noticeably above 1. This indicates that two travelers arrived at the aTaxiStand at the same time, immediately (since there is no departure delay) determined that rideshare was feasible between them, and then shared that ride. There is typically very low probability that two riders arrive at the exact same location at the exact same second but this phenomenon occurs with noticeable frequency due to the New Jersey train station adjustments. According to the simulation, the train makes arrivals at set schedules so all the individuals who depart at a given train stop exit the train at the same time. This time then becomes all of their origin times for the next leg of the trip.
Hence, they are all eligible for ridesharing at the same moment. Although doing this with a zero second delay is not entirely realistic, this feature captures the ridesharing potential at sites such
as train stations where a mass of travelers seeks rides immediately. This is precisely where ridesharing is most impactful.

### TABLE 1 NJ State True Average Vehicle Occupancy

<table>
<thead>
<tr>
<th></th>
<th>CD = 0</th>
<th>CD = 1</th>
<th>CD = 2</th>
<th>CD = 3</th>
<th>CD = 4</th>
<th>CD = 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>DD = 0</td>
<td>1.00</td>
<td>1.00</td>
<td>1.05</td>
<td>1.06</td>
<td>1.06</td>
<td>1.06</td>
</tr>
<tr>
<td>DD = 1</td>
<td>1.00</td>
<td>1.04</td>
<td>1.59</td>
<td>1.81</td>
<td>1.90</td>
<td>1.94</td>
</tr>
<tr>
<td>DD = 2</td>
<td>1.00</td>
<td>1.06</td>
<td>1.73</td>
<td>2.07</td>
<td>2.23</td>
<td>2.30</td>
</tr>
<tr>
<td>DD = 3</td>
<td>1.00</td>
<td>1.07</td>
<td>1.82</td>
<td>2.23</td>
<td>2.45</td>
<td>2.56</td>
</tr>
<tr>
<td>DD = 4</td>
<td>1.00</td>
<td>1.08</td>
<td>1.88</td>
<td>2.35</td>
<td>2.62</td>
<td>2.76</td>
</tr>
<tr>
<td>DD = 5</td>
<td>1.00</td>
<td>1.10</td>
<td>1.92</td>
<td>2.45</td>
<td>2.76</td>
<td>2.93</td>
</tr>
</tbody>
</table>

AVO ranged from 1.00 at (DD, CD) = (0, 0) to 2.93 at (DD, CD) = (5, 5). This indicates that the number of miles driven without any sharing would be almost 3 times as high the number of miles driven in the simulation. If the parameters are tightened, performance is still greater than the NHTS reported 1.67 AVO. At tighter parameters, performance persists. For example, at (DD, CD) = (1, 3) AVO is 1.81 and at (DD, CD) = (2, 2) AVO is 1.73.

### Spatial Breakdown

The rideshare figures can be stratified spatially as well to identify the rideshare potential of different regions of New Jersey. Table 2 displays the AVO values of Salem County and Hudson County. Salem County is a sparsely populated rural county. The values are lower across all operational parameter sets compared to NJ state values in Table 1.

On the opposite end of the spectrum are the AVO values of Hudson County, the most densely populated county in New Jersey. AVO values are significantly higher than New Jersey State values. In fact, under some operational parameters such as (DD, CD) = (5, 5), it doubles the AVO value of the sparsely populated Salem County.

### TABLE 2 Comparison of Salem County and Hudson County AVO

<table>
<thead>
<tr>
<th>Salem County - True Average Vehicle Occupancy</th>
<th>Hudson County - True Average Vehicle Occupancy</th>
</tr>
</thead>
<tbody>
<tr>
<td>DD = 0</td>
<td>CD = 0</td>
</tr>
<tr>
<td>-------</td>
<td>--------</td>
</tr>
<tr>
<td>1.00</td>
<td>1.02</td>
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<tr>
<td>1.00</td>
<td>1.02</td>
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<td>1.00</td>
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</tbody>
</table>

This analysis indicates that particular regions of New Jersey would benefit more from an institution of aTaxis. These regions would serve as better candidates for initial aTaxi deployment as well.

### Temporal Breakdown

In addition to analyzing the trips with spatial stratification, trips can be analyzed temporally as well. Figure 3 displays the hourly AVO values over 24 hours. Trips in the morning and evening exhibit higher rideshare potential across all parameter sets. For instance, the AVO of (DD, CD) = (2, 3) of NJ all day is 2.07, yet in the morning between 7am and 8am, it is almost 2.25. In the evening, between 3pm and 6pm, the AVO reaches 2.3.
Another interesting behavior is that the CD = 1 exhibits rather high values for the morning hours. At CD = 1, the vehicles are permitted to travel to only one location. Even with this limitation, CD = 1 produces a bulge in the graph from 6am to 9am which indicates that many people go to the same destinations at similar times. Currently, these individuals drive separately in the morning. Taking advantage of this shared AM ridership could significantly reduce congestion in the mornings.

CONCLUSION
There is significant rideshare potential in New Jersey along with the opportunity to reduce vehicle miles traveled with the institution of an autonomous taxi system. This analysis can begin to suggest optimal parameter sets for aTaxiStand operations. Since both metrics experience diminishing returns as the values increase, it is important to select parameters (CD and DD) that extract as much value as possible where there are high rates and then proceed in tuning the parameters once the diminishing of the rates begins to occur. The parameter set should also produce values that exceed the national values in order make the system more competitive with current transportation modes.

Moreover, the simulation indicates that rideshare opportunities vary spatially and temporally. For instance, shared rides opportunities are abundant at different locations throughout New Jersey. Certain pixels such as train stations will have a substantial potential for rideshare due to the regular mass influx of people seeking to travel. In addition, shared ride opportunities are not static throughout the day. Greater rideshare potential and vehicle miles saved potential exist during certain portions of the day. This delivers important insight because it can inform the beginnings of an aTaxi system. Serving high potential areas at high potential times will allow the system to reduce congestion at heavily trafficked regions during high
volume time. Taking advantage of the spatial and temporal variations in ridesharing is key in
allowing this system to be even further optimized and utilized.

**Improvements to Methodology**

Several changes could be made to improve both the framework of the aTaxi system and the
implementation simulation. Currently, the optimum rideshare match does not always occur
when rideshare is identified since the first aTaxi that passes the criteria is simply used as the
rideshare vehicle. This causes the suboptimal pairing phenomenon in which long trips are paired
with short trips which subsequently lowers AVO values. Ideally, a long trip will be matched with
a long trip and a short trip will be matched with a short trip.

More realistic features can be added to this framework. Perhaps travelers can be picked
up from intermediate location between two nodes. Perhaps a new traveler can be picked up from
a destination of one of the current passengers. Perhaps trains to locations other than just New
York City or Philadelphia can be utilized. These are all adjustments that would make for a more
realistic system.

**Outlook**

Autonomous vehicles and an aTaxi system are attractive since the only primary
implementation cost is technology. Unlike other modes of transportation that require an
infrastructure investment, autonomous vehicles use existing guideways. Although technological,
legal, and financial barriers do exist, the convenience, safety, mobility, and utility that
autonomous vehicles confer make the adoption of such a transformative technology inevitable.
With the advent of autonomous taxis, vehicles will shift from the “ultimate driving machine” to
the “ultimate riding machine.”

**REFERENCES**

[1] Gao, J. *A Disaggregate Transportation Demand Model for the Analysis of an Autonomous

