

On Demand Mobility Commuter Aircraft Demand Estimation

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Abstract

On-Demand Mobility (ODM) is a concept to address congestion problems. Using an electric propulsion aircraft and vertical take-off with limited landing (VTOL) capabilities, the ODM concept offers on demand transportation service between designated landing sites at a fraction of driving time. The purpose of this research is to estimate the potential ODM demand and understand the challenges of introducing ODM using the Northern California region (including major cities like San Francisco, Sacramento, and San Jose) as an area of study and a second, less rigorous analysis for the Washington-Baltimore region. A conditional logit model was developed to estimate mode choice behavior and to estimate ODM demand; presenting automobile and public transportation as the two competing modes to ODM.

There are significant challenges associated with the service including ability to operate in bad weather, vehicle operating cost, siting and cost of landing sites, and overall public acceptance of small, remotely operated aircraft.

Nine scenarios were run varying the input for a base fare, landing fare, cost per-passenger-mile, auto operational costs, and ingress (waiting) times. The results yielded sensitivity of demand to all these parameters and especially showed a great difference in demand when auto costs were decreased from the standard American Automobile Association (AAA) cost per mile to a likely, future auto operating cost. The challenge that aerospace engineers face is designing an aircraft capable of achieving lower operational costs. The results showed that in order for the ODM to be a competitive mode, the cost per passenger-mile should be kept at \$1.

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General Audience Abstract

On-Demand Mobility (ODM) is a concept to address congestion problems. Using an electric propulsion aircraft, the ODM concept offers on demand transportation service between designated landing sites at a fraction of driving time; an “air taxi” or “air Uber” as coined by media outlets. The purpose of this research is to estimate the potential ODM demand and understand the challenges of introducing ODM using the Northern California region (including major cities like San Francisco, Sacramento, and San Jose) as an area of study and a second, less rigorous analysis for the Washington-Baltimore region. A model was developed to estimate mode choice behavior and to estimate ODM demand based on existing travel behavior and patterns in the Northern California region.

There are significant challenges associated with the service including ability to operate in bad weather, vehicle operating cost, siting and cost of landing sites, and overall public acceptance of small, remotely operated aircraft.

The results from the model yielded sensitivity of demand to these challenges and especially showed a great difference in demand as the cost of operating the car decreases in the future, making it a great competitor to the ODM concept. The major challenge that aerospace engineers face is designing an aircraft capable of achieving lower operational costs. The results showed that in order for the ODM to be a competitive mode, the cost per passenger-mile should be kept at \$1.

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Nomenclature

α_i : Logit model coefficients

AAA: American Automobile Association

ACS: American Community Survey

Census Block Group: Geographic area set by the United States Census Bureau; boundaries contain a population size between 600 and 3,000 people. Groups contain an average of 39 census blocks (the smallest geographic area defined by US Census Bureau) (US Census Bureau, 2010).

Census Tract: Geographic area set by the United States Census Bureau; boundaries contains a population size between 1,200 and 8,000 people, with an optimum size of 4,000 people (US Census Bureau, 2010)

CPI: Consumer Price Index

GCD: Great Circle Distance (statute miles)

IVT: In Vehicle Time (minutes)

LODES: Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics

NHTS: National Household Travel Survey

ODM: On Demand Mobility

OVT: Out of Vehicle Time (minutes)

P: Probability

TT: Total Travel Time (minutes)

TC: Travel Cost (2009 dollars)

VTOL: Vertical Takeoff and Landing

U: Utility of Travel

CHAPTER 1: INTRODUCTION

1.1 Urban Transportation

Current urban transportation problems include congestion, environmental degradation, and inhibited economic growth. According to the Federal Highway Administration (FHWA), weekday peak-period congestion has grown in intensity, duration, and extent in the past 20 years in the largest United States cities (see **Figure 1**). The reasons for road congestion include: limited road capacity and higher demands during longer peak periods of operation, weekend traffic delays in recreational areas, and capacity of roadways consumed by growth in traffic that become vulnerable to events such as traffic incidents, bad weather, and work zones (FHWA, 2017).

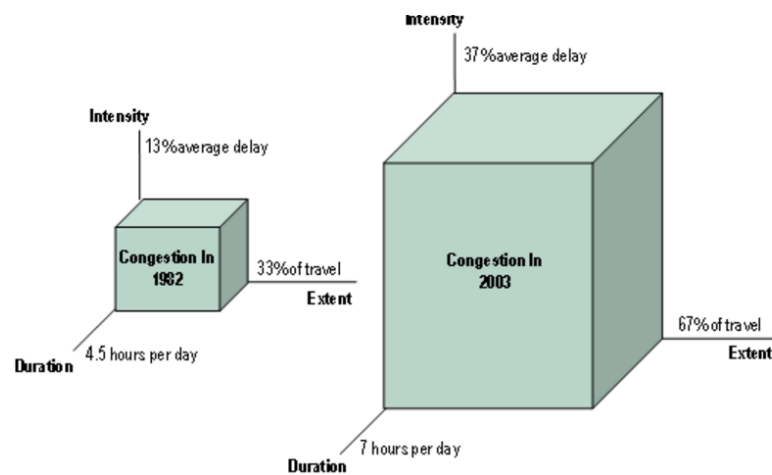


Figure 1: Weekday Peak-Period Congestion in the Largest US Cities (FHWA, 2017).

Existing transportation modes are faced with decision making to address near capacity issues for congestion. Solutions to improving congestion in road networks and solutions should expand far beyond increasing capacity.

Congestion impacts the environment with idling cars that pollute the atmosphere as well as noise pollution due to heavy congestion. To understand the impact of everyone using privately

owned vehicles, National Household Travel Survey (NHTS) data for the United States gives information about the market share of mode types used to access work (as an example).

According to the summary of travel trends report generated from the survey results of the NHTS for the United States, the following figure (**Figure 2**) depicts the access to work by mode:

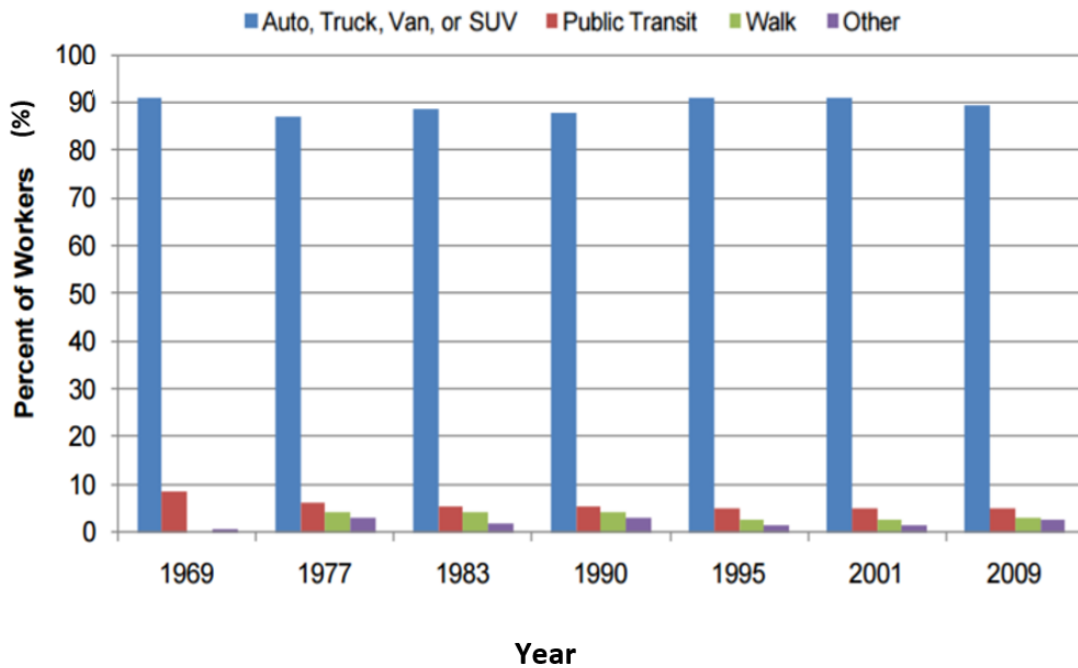


Figure 2: Distribution of Workers by Commuting Modes (Santos et al, 2011)

According to **Figure 2**, privately owned car dominates the market share for access to work with more than 87%. This contributes to environmental air pollution including emission of toxins such as nitrogen oxide, sulfur dioxide, and carbon dioxide (Hermes, 2012). Carbon dioxide constitutes the largest portion of greenhouse gas emissions coming from transportation (Grote, 2016). Almost 20% of the global carbon dioxide emissions come from fuel combustion from road traffic and a great amount of emissions can be attributed to idling time (Grote, 2016). More than half the world's population lives in an urban area (UNFPA, 2007). Urban road networks are constrained by the large number of vehicles that travel in smaller geographic areas

and contributes to greenhouse gas emissions. Millennials are increasingly making decisions to move away from private vehicle ownership, therefore, increasing urban growth as they choose to live in areas accessible by public transit systems or walking environments. Current solutions to reduce or eliminate traffic include offering incentives to carpool or use public transit as well as tax those who travel alone in a privately owned vehicle. Despite available public transit system, air quality and congestion issues are prevalent and there is a need for innovative transportation solutions.

From an economic perspective, congestion has shown to affect employment growth and productivity of workers (Sweet, 2014). Congestion has shown to hamper economic activity given limited mobility. Gridlock conditions in the urban environment contribute to greater travel costs (i.e. congestion pricing) and increased unreliability. Congestion reduces economic competitiveness; firms such as those meeting delivery times are burdened by commuting delays which in turn reduces the gross output in the system. Delays to commuters leads to slower employment growth as the delay per auto commuter per year is about 35 to 37 hours (Sweet, 2014). Urban congestion can decrease if other modes of transportation are introduced to enable access despite gridlock on roadways (Sweet, 2014).

1.2 On-Demand Mobility Concept

The On-Demand Mobility (ODM) concept is an effort by NASA to develop an innovative solution to transportation problems and improve mobility in urban regions. The concept offers transportation from an origin to a destination using a vertical takeoff-and landing (VTOL) aircraft that travels above the roadway network, reducing travel time than conventional modes. The aircraft is powered by distributed electrical propulsion and has a maximum range of 150-300 statute miles, depending on the vehicle used (Trani, 2015).

The concept has the ability to change urban travel by: reducing congestions on the roadway network, reducing the number of carbon emissions coming from vehicles, providing a faster and efficient mode compared to current alternatives, and providing better connectivity to areas not greatly accessible to public transit networks or a road network.

Currently, studies for this concept are being administered by other organizations; one such example is Uber which introduced the concept, “Uber Elevate.” The concept focuses on reducing urban congestion by providing an on demand aviation service with a focus on giving people back time in more important activities. Using the same vehicle characteristics, there is a hope to achieve affordable costs for everyone by scaled manufacturing, autonomous flight, decreased energy costs, and increased trip density (Uber, 2017). The demand studies conducted by Uber are for the Dallas, Texas and Dubai, United Arab Emirates.

1.3 Objective of the Study

The analysis presented in this study is a first order demand calculation that will predict the number of ODM users in the Northern California region and the Washington-Baltimore region. The contribution of this research is to further the study on how demand for these aircrafts should be computed and what considerations should be made with the limited data resources to capture the demand. After a detailed calculation, recommendations and considerations will be made for implementation of the new mode. The analysis was done with guidance from the NASA Langley Research Center; therefore some of the framework of the analysis is per their recommendation.

CHAPTER 2: DEMAND MODELING

2.1 Conditional Logit Model

A logit model is a tool used in binary choice models in which a decision maker's decision for an alternative from a finite set of mutually exclusive alternatives is predicted. The objective of a discrete choice model is to predict the behavior of a decision maker based on attributes of the decision maker and the attributes of the alternatives. In typical transportation studies, a logit model is used to predict behavior of individuals that need to make a decision from a set of options; specifically, predicting mode choice behavior. From that, transportation analysis can predict the market share of commuters using each of the alternatives (modes) given specific conditions. If a logit model is employed where attributes of the decision maker are accounted for, transportation analysis may be interested in identifying how characteristics of the decision maker are influential in how a decision maker makes a decision. For example, if the logit model was used to predict mode choice behavior, if income of the decision maker were taken into account, a decision maker who is from a higher income category would more likely value travel time savings when choosing an alternative (mode) than saving money on the travel (Koppelman, 2006).

Among the types of logit models that exist, the conditional logit model applies most to this analysis. The difference in a conditional logit model is that it is most appropriately used when the decision between alternatives is made as a function of the characteristics of the alternative (Hoffman, 1988); different from a multinomial logit model in which a decision is also considered based on the characteristic of the decision maker. For example, in the analysis presented in the paper, the decision maker's income or household size (parameters that are

commonly measured in transportation studies to predict mode choice behavior) is not included; rather the decision maker's choice is based off parameters relating to the travel.

In conditional logit modeling, there two primary equations: a utility equation and a probability equation. The model assumes that the decision to select among various transportation alternatives is calculated by maximizing a utility function (U), which depends on the mode alternative attributes. Each commuter traveler will choose the alternative that maximizes his or her utility. A generic utility equation would look like the following (Hoffman, 1988):

$$U_{ij} = (\alpha_a A_{ij}) + (\alpha_b B_{ij}) + \dots \quad (1)$$

Where:

U_{ij} = Utility function of the j th alternative for individual i

i = individual i

j = alternative j

A_{ij} = Characteristic of j th alternative for alternative i

α_a = Coefficient for corresponding characteristic

A generic probability equation (P) would then look like:

$$P_{ij} = \frac{\exp(U_{ij})}{\sum_{k=1}^J \exp(U_{ij})} \quad (2)$$

Where:

P_{ij} = Probability that individual i chooses alternative j

J = number of alternatives

The coefficients for the corresponding characteristics have two important components: sign and magnitude. The sign gives information about whether or not the decision maker (in this case, commuter) values or de-values that attribute. For example, travel time is generally de-valued; therefore, it is intuitively a negative coefficient. The magnitude gives information about the extent to which a decision maker values or de-values a characteristic of the attribute. For the purpose of this study, valuing or de-valuing will be known as a “utility” or “disutility.”

The following chapter will give further information of how a conditional logit model was used in the analysis.

2.2 Methodology of Demand Estimation

Demand will be estimated by means of the conditional logit model. The steps for the analysis are summarized in the following numerical list:

1. Determine a scope of study for demand analysis. In this project, the scope of study was defined by the NASA Langley Research Center
2. Determine what should be measured in an individual’s decision of choosing mode: in this analysis, total travel time and travel cost
3. Determine appropriate data sources to use for the analysis: calibration and application
4. Perform calibration using NHTS data as well as NHTS Add-On data which will give coefficients relating to the utility of total travel time and travel cost and then validate coefficients with literature review and value of time check.
5. Perform application to compute demand. Each data point used in the conditional logit model analysis consists of an origin tract number, destination tract number, and the

number of commuters travelling that origin-destination pair. Using this information, total travel time and travel cost for each mode (auto, public, and ODM) will be computed.

6. The utility equation for each mode (auto, public, and ODM) will be computed for each data point.
7. The probability equation for each mode will be computed for each data point
8. The LODES data volume of each origin-destination pair was used to get the final demand computations. Given the probabilities for each mode applicable to each origin-destination pair, we estimate the volume of travel by mode in the network for each model of transportation by simply multiplying the probabilities generated for each origin-destination pair by the volume on each origin-destination pair.
9. From the resulting demand, it was possible to determine the market share of each of the modes as a function of the distance between the origin and the destination pairs. Specifically the demand for the On Demand Electric aircraft. A variety of other information can be extracted from demand results including utilization of each of the landing sites and main demand regions for the ODM.

2.3 Scope of Study

In consultation with NASA, two large metropolitan areas in the country were selected for the study. The Northern California region was selected as the primary region of study comprising of 17 counties including the cities of Sacramento, Oakland, San Jose and San Francisco. The Northern California region includes 2,377 Census tracts covering 20,899 square miles and shown in **Figure 3**. These counties include:

- 1) Alameda

- 2) Contra Costa
- 3) Marin
- 4) Merced
- 5) Monterey
- 6) Napa
- 7) Sacramento
- 8) San Benito
- 9) San Francisco
- 10) San Joaquin
- 11) San Mateo
- 12) Santa Clara
- 13) Santa Cruz
- 14) Solano
- 15) Sonoma
- 16) Stanislaus
- 17) Yolo

A second region selected for a quick-study combines Washington, DC, Baltimore and the Northern Virginia region shown in **Figure 4**. This region comprises of 47 counties and 2,360 Census tracts. **Table 1** shows the characteristics of the two regions considered in this study. There are many similarities for the study areas including the number of commuters with Jobs making more than \$100,000 per year are. Due to its topography, the Washington-Baltimore region shows a more radial population distribution.



Figure 3: Study Area: Northern California Region Modeled

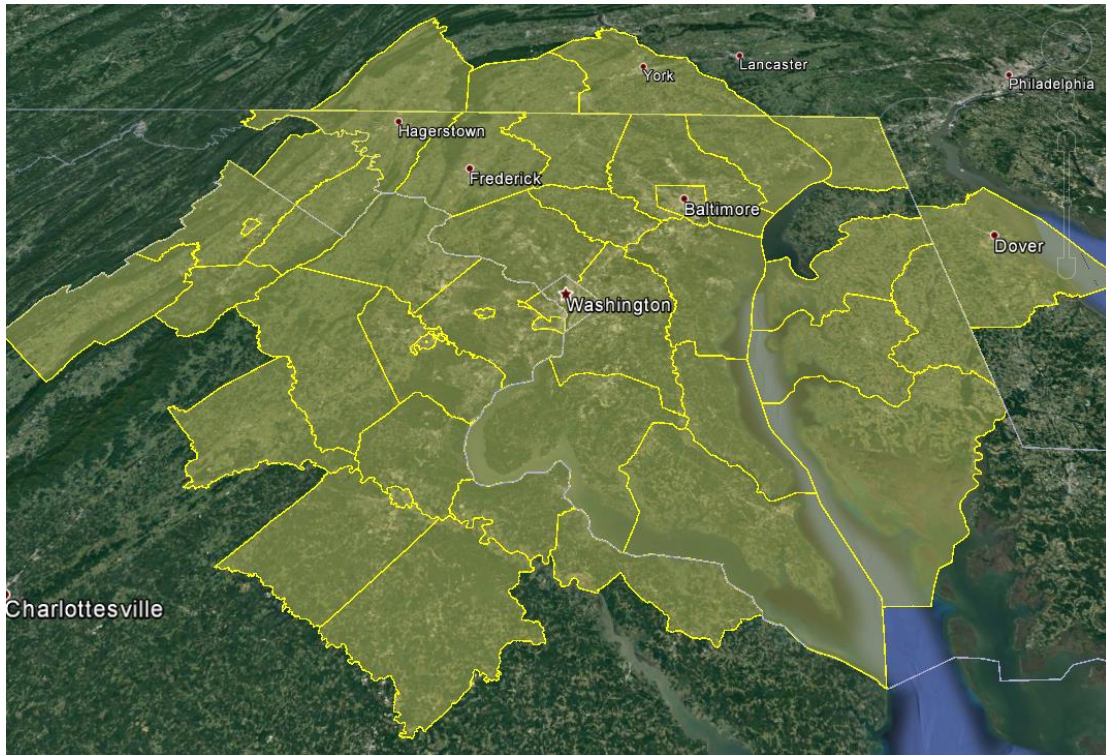


Figure 4: Study Area: Washington-Baltimore Region Modeled

Table 1: Characteristics of Metropolitan Areas Studied for ODM Analysis

Item	Northern California	Washington-Baltimore
Area (square miles)	20,899	18,193
Number of Counties	17	47
Number of Census Tracts	2,377	2,360
Total Number of Commuters	4.2 million	4.3 million
Commuters making more than \$100,000 per year	991,956	957,778
Origin-Destination Pairs with Jobs Greater or Equal than \$100,000 Annually	132,088	138,761

It is expected that first-adopters of the ODM mode are individuals belonging to high income classes. The Northern California region is a well-suited location of analysis given the average income of individuals living in the region, predominantly the Silicon Valley region. According to the United States Bureau of Labor Statistics, in 2015 the average annual wage in Silicon Valley was \$110,634 or 83% (\$50,167) above the average annual wage in the State of California (US BLS, 2016). Similarly, average annual wages in San Francisco are 60% (\$36,207) higher than those in the State of California.

Technology hubs situated in the Silicon Valley, employ many potential first-adopters of ODM technology. Corporations such as Google, Apple, Oracle and Tesla are companies involved in research and development of automated transportation technologies that could also develop applications in the aviation sector in the future. The Northern California region used in this study has 52 heliports available. Most of them are used by area hospitals and police services and hence are not suitable for commercial ODM operations. The Washington-Baltimore area has 105 heliports available. Like Northern California, most of heliports in the Washington-Baltimore area are used by hospitals and police and are not suitable for commercial ODM applications.

2.4 Data Sources Used

The details of the data sets are included in **Table 2**. The data sources are mainly public use data, therefore, due to privacy protocol, the information provided is aggregated. Though available readily, the aggregation of the data constrained the analysis; for example, the availability of income information for commuters was reported in ranges and has presented some issues when doing a demand analysis.

The data sources summarized in **Table 2** were used to build a conditional logit model to estimate ODM demand. The NHTS data (including Add-On data) was used for model calibration

and model application and for model verification. The American Community Survey (ACS) was used for model application and verification, and the LEHD Origin-Destination Employment Statistics (LODES) data was the main source to understand the distribution of commuter trips.

Table 2: Description of Data Sets Used in the Analysis

Datasets	Description
National Household Travel Survey (NHTS); 2009	<ul style="list-style-type: none"> • Comprehensive data set on travel and transportation patterns in the United States • Travel and transportation patterns for 24-hour period on daily trips • Data includes: <ul style="list-style-type: none"> ○ All trips ○ All modes ○ All purposes ○ All trip lengths ○ All areas of county (urban and rural) ○ Weights for each trip • Used for: <ul style="list-style-type: none"> ○ Understanding travel behavior ○ Understanding changes in travel behavior/characteristics over time ○ Travel behavior and demographics relationship
National Household Travel Survey: Add On Data, California; 2009	<ul style="list-style-type: none"> • States and Metropolitan Planning Organizations (MPO) from select states/metropolitan areas purchase samples of in state household travel survey • Origin-Destination geocodes provided for all trips
American Community Survey (ACS)	<ul style="list-style-type: none"> • Survey providing demographic and travel related information about individuals in the United States • Purpose to provide current demographic, social, economic, and housing estimates

**Longitudinal Employer-Household
Dynamics (LEHD) Origin-Destination
Employment Statistics (LODES)**

- Information about access to work:
 - Workplace Census Block Code
 - Home Census Block Code
 - Number of jobs associated with origin-destination pair
 - Number of jobs within age brackets
 - Number of jobs within income brackets
 - Number of jobs in various industry sectors
 - Data on which data was created

CHAPTER 3: CALIBRATION AND APPLICATION OF THE MODEL

3.1 Inputs to the Model

There are two parts to developing the model for this analysis: calibration and application. Calibration of a model involves generating coefficients based on travel survey data for the region of study; the coefficients are an input to the utility equation (Equation 1). Application involves using current trip distribution data and computing travel time and travel cost. The two variables are inputs to the utility equation; the utilities are further input into a probability equation, and finally producing demand results for analysis. A vital aspect of calibration and application is that the calculations for the calibration and application should be consistent. In other words, the method for computing “travel time” in the calibration should be consistent in the application of the model. More details of this process will be elaborated in the following sections.

A detailed calibrated model was produced using travel patterns and costs of the Northern California region. As per NASA Langley request, a brief, preliminary analysis was performed for Washington-Baltimore region using calibrated coefficients for Northern-California region.

3.1.1 Calibration

The calibration step involves generating coefficients denoted by the (α) shown in the generic utility equation (Equation 1). The output of the calibration are the coefficients corresponding to each of the variables. The coefficients multiplied by the corresponding variable contribute to the utility. The utility gives information of how much an individual is attracted to each of the modes of transportation. In this analysis, there are two main components used to compute the utility or perception of attractiveness of the decision maker of the mode: total travel time and total travel cost. Generally, in transportation studies, a distinction is made between in

vehicle time and out of vehicle time. In vehicle time is defined as time spent in the main mode of transportation; whereas out of vehicle time is the time spent getting to/from the main mode of transportation (intermodal time) and time spent waiting for the main mode of transportation. The distinction is made because a person will perceive out of vehicle times as a greater dis-utility than time spent in the vehicle. However, given the constraints of the data set provided and producing credible results, the distinction was not made; rather the two components merged to give a general “total travel time (minutes).”

In the calibration of the conditional logit model, survey data is most commonly used to find the magnitude and sign of the coefficients. Because the focal point of the analysis was the Northern California area, and the Washington-Baltimore area was added as a second, less rigorous analysis, all travel characteristics measured were specific to the Northern California (or greater San Francisco area as defined by NHTS). In this study, NHTS 2009 data for the greater San Francisco area was used to do the model calibration; therefore dollar amounts used in the analysis were reflective of 2009 dollars to maintain consistency. For calibration, auto and public transit entries were used to predict mode choice behavior as no current data exists for the new mode. The NHTS has information about commuting trips in the region of interest such as various components of travel time. Travel costs and aspects of total travel time are derived synthetically since no information was included in the survey data. Given the limitations of the available data, a conditional logit model was calibrated with total travel time (TT) and total travel cost (TC) for each mode for each origin-destination pair (i-j):

$$U_{ij}^{mode} = (\alpha_{TT} TT_{mode}) + (\alpha_{TC} TC_{mode}) \quad (3)$$

Because total travel time (minutes) and travel cost (2009 dollars) are computed for origin-destination pairs, the public NHTS data would have to include information for an origin-

destination pair. Because the public use data does not include “destination” information, the NHTS Add-On data was used to provide destination information for each survey entry. After filtering out any “bad” or “missing” data points, there were a total of 2,090 data points (2,025 auto entries, 65 public transit entries) from a pool of 11,000 that were provided. The following characteristics of the data points were filtered out:

- Missing information from data (mode, origin destination, so on)
- Mode not a form of “auto” or “public transit”
- Non-work entries (For consistency, we are capturing work related trips in LODES data)
- Same tract origin and destination (Inter-tract behavior was not modeled)

3.1.2 Application

In the application step there were four main components:

1. Compute total travel time (minutes) and travel cost (2009 dollars) for each mode for each origin-destination pair
2. Input the total travel time (minutes) and travel cost (2009 dollars) for each mode for each origin-destination pair into the utility equation. Therefore, for each origin-destination pair a utility is computed for auto, public, and ODM.
3. Input utility for each mode for each origin-destination pair to the probability equation to generate the probability of choosing each mode for each origin-destination pair. The generic probability equation was adapted for this analysis as follows:

$$P_{ij}^{mode} = \frac{\exp(U_{ij}^{mode})}{\sum_{k=1}^3 \exp(U_{ij}^{mode})} \quad (4)$$

Where:

P_{ij}^{mode} = Probability of choosing that mode for origin (i) – destination (j)

4. Multiply the probability values of each mode of each origin-destination pair by the current number of commuters of that origin-destination pair to generate demand for each of the modes for each origin-destination pair

The LODES data, a data set containing origin-destination information for commutes taken each day for work purpose trips as well as volume of trips on each origin-destination trip, was used in the application step. The LODES data includes trips (origin and destination) within the area of analysis of driving distances up to 300 miles. The distribution of trip distances are shown in **Figure 5. Table 3** describes specific distributions of the trips reported in the LODES data set. The distributions will be useful in understanding how much of the market share would be affected if there were to be a cutoff of “allowable” ODM trips at a specific distance. More information regarding this will be discussed in further sections. No inter-tract behavior was modeled; origin-destination pairs containing same tracts were removed from the analysis.

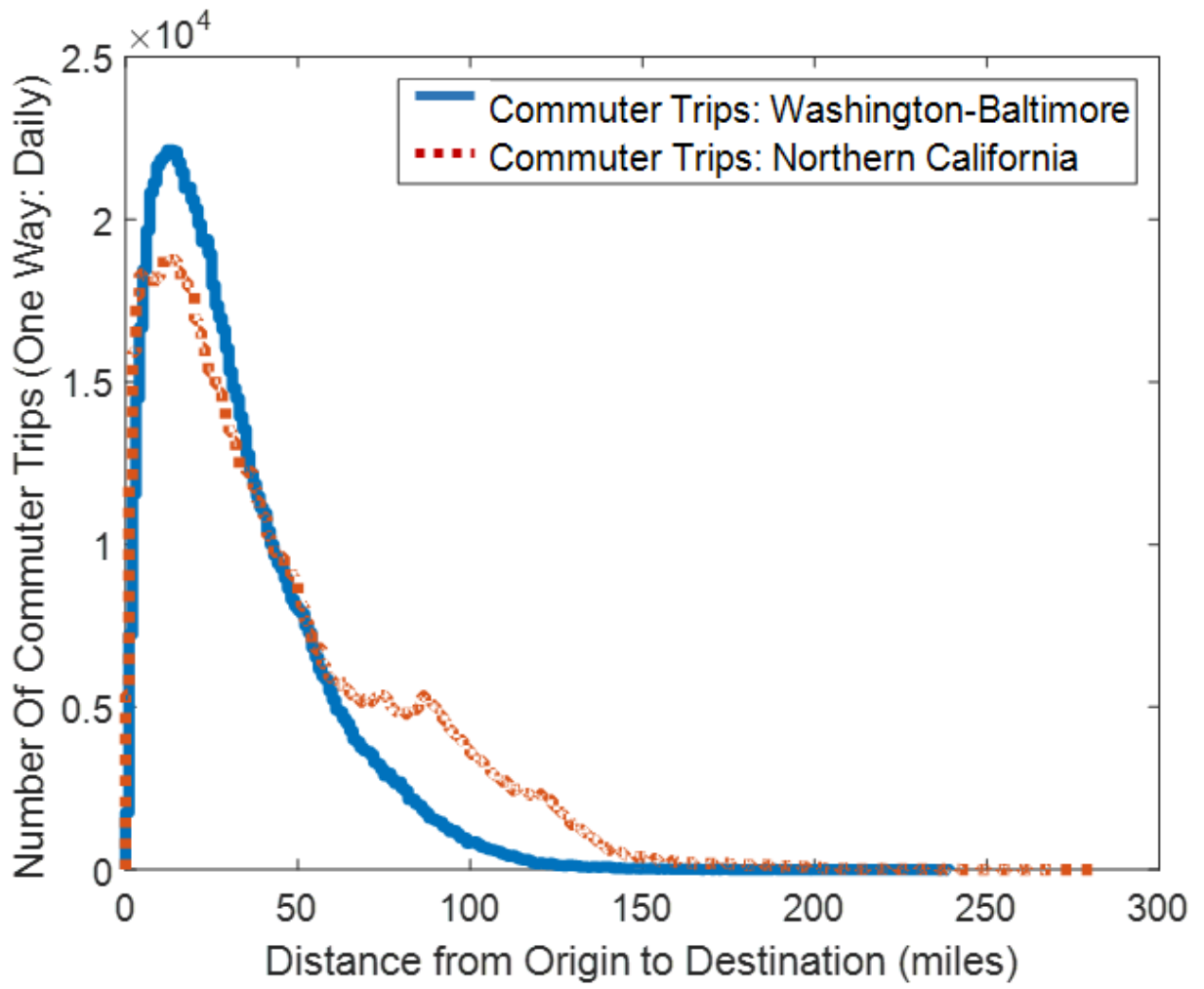


Figure 5: Distribution of Number of One-Way Daily Trips versus Distance: Washington-Baltimore and Northern California.

Table 3: Percentage of One-Way Daily Trips in Northern California and Washington-Baltimore Regions

Driving Distance (miles)	Percentage of Commuter Trips	
	Northern California Region	Washington - Baltimore Region
<= 10 miles	14.7	16.1
<=15 miles	23.4	27.6
<= 20 miles	31.7	38.5
<= 30 miles	45.9	57.4
>= 50 miles	34	19.4
Maximum Commuter Trip Distance Reported	281 miles	238 miles

The LODES data does not provide distinction of modes, therefore, the assumption made in this analysis was that these trips are actual auto trips performed and the equivalent transit and ODM trips total travel time and travel cost for those origin-destination pairs would be computed.

For each of the origin-destination pairs (1.08 million in the Northern California analysis area), a set of travel times (minutes) and travel costs (2009 dollars) were computed for each entry in the LODES dataset for each mode of transportation considered. As mentioned previously, the Northern California study was conducted at a high level of detail, the predominant travel characteristics are reflective of that region. As per NASA request, travel characteristics generated for Northern California were applied to the Washington-Baltimore analysis. The following shows the assumptions for each of the modes:

Converting Dollar Amounts: Dollar amounts were converted using the Consumer Price Index (CPI) to 2009 dollars for consistency.

Auto, In Vehicle Travel Time: The LODES data provides origin-destination information reported as census blocks. The census blocks were aggregated into census tracts (by US Census Bureau definition: one geographical unit larger than a census block) and the origins and destinations were found as the population centroid of those tracts. Auto travel times were generated from MapPoint data. MapPoint is a data source that gives information regarding driving distances and driving travel times between origin and destination. In the computation of auto travel times, MapPoint data took into account a general congestion index. There was no information provided in the LODES data set regarding time of day of travel; therefore, applying a congestion index specific to the time of day was not administered. The unit for auto travel times are in minutes.

Auto, Intermodal (Out of Vehicle) Time: An average value of 2.5 minutes was used. The time is inclusive of walking to the car from origin and walking from the parked car to the place of destination.

Auto Occupancy Rate: The value used in the analysis came from the NHTS 2009 of an average auto occupancy rate for a weekday, work related trip. The parameter is unit-less.

Auto AAA Cost: The American Automobile Association (AAA) cost per mile used reflects the average auto cost per mile (not differentiating between vehicle types). The AAA cost per mile was based off the 2016 average value and was then converted to 2009 dollars to maintain consistency throughout the model. The AAA cost includes the following:

- Fuel
- Maintenance
- Tires

- Insurance
- License, Registration, Taxes
- Depreciation
- Finance

Though individuals generally consider only the fuel aspect of the AAA cost in their perceived cost to drive, the calibration of the model produced credible coefficients under the assumption of including the entire AAA cost per mile. Some iterations of the model were run under the assumption of 30 cents per mile auto cost to account for the “perceived” auto cost; however, the calibration was not successful even after varying some of the inputs.

Some scenarios of the model were run to account for decrease in operating cost of the car in the future. This assumption in the model was 30 cents, results for which will be shown in the demand results section.

Auto Parking Cost: Based on parking rates in the region of analysis. Values are presented in 2009 dollars (Parking in America, 2010).

Auto Intermodal (Out of Vehicle) Cost: Given that there are no mode switches, the assumption is a \$0 cost.

Public Transit, In Vehicle Travel Time: Using the Map-point generated distances between origin and destination, the average speed for public transit of 23.5 mph was used to convert to a travel time. The average speed was generated from NHTS 2009 data for the greater San Francisco area. The unit is in minutes.

Public Transit, Intermodal (Out of Vehicle) Travel Time: Assumed a 2 mile access distance via auto to transportation stations for each origin-destination pair. Used an average auto speed of 27.5 mph from NHTS 2009 data for greater San Francisco area. The unit is in minutes.

Public Transit Parking Cost: Applied a 0.5 factor to the auto parking cost to account for average daily parking fares in the area

Public Transit, In Vehicle Costs: Based on analysis done by a previous Virginia Tech student, the student used public transit web sites and derived cost functions based on travel distance for each metropolitan area. The values are presented in 2009 dollars.

Number of ODM Landing Sites: A K-Means clustering algorithm was employed to identify the best placement of landing sites. Parametric runs were performed that varied the number of landing sites from 200 to 1000 as shown in the following figure:

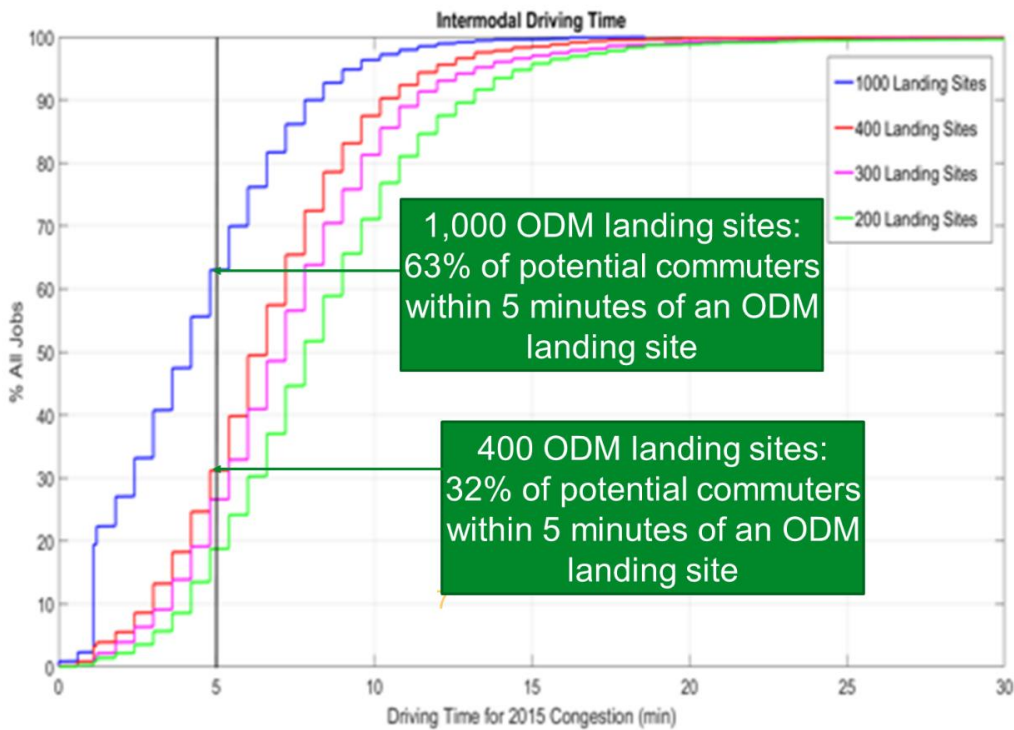


Figure 6: Parametric Analysis of Number of Landing Sites and Effect on Intermodal Driving Time

The idea was to minimize intermodal time spent to and from the landing site. Though intermodal time can get minimized by increasing the number of landing sites, there is a high cost associated with it. Land valuation in California is the highest out of all the contiguous states. Just as an example, in a rural area the \$7,700 compared to the national average of \$3,020 for 2015 (USDA, 2015). For this analysis, results were produced under the assumption of 1,000 landing sites.

ODM, In Vehicle Travel Time: After calculating the distances between the landing sites, flight profiles for the design aircraft were used to determine the in vehicle travel times. After an analysis of protected approach surfaces from existing airports, detour factors were determined for each origin-destination pair to evade the protected surfaces. The average detour factor was about 1.106 for Northern California and 1.099 for Washington-Baltimore (considering 1,000 landing sites for both analyses) (Maninder, 2017). The unit is in minutes.

ODM, Intermodal (Out of Vehicle) Time: The assumption was that access to a landing site would be provided via a ride sharing service (i.e. Uber) or walking. Based on transportation literature review, the maximum distance an individual will be willing to walk to a public transit station is 0.25 miles (El-Geneidy, 2014). Therefore, if the MapPoint distance calculated from the origin to the closest landing site (access distance) or the closest landing site to the destination (egress distance) is equal to or less than 0.25 miles, a walking travel time was incurred. Using an average walking speed of 3.1 mph (Carey, 2010), the walking distance was converted to a travel time. If either distance exceeded 0.25 miles, an Uber travel time (using auto speed of 27.5 mph) was used.

Additional intermodal time included wait time (ingress time) at the landing site and time getting out of the aircraft (egress time). The standard times for both parameters were 5 minutes. The unit is in minutes.

ODM, Intermodal (Out of Vehicle) Cost: The Uber cost was derived from the 2016 Uber cost model for San Francisco and converted to 2009 dollars. From guidance, there is a possibility for a “bundled fee” for taking the Uber to a landing site, however, given the limited amount of information, the bundled fee was applied to the minimum fee. As more information becomes available, the model can be more reflective of the actual cost model that will be implemented. If the access or egress distance was equal or below 0.25 miles, it was assumed the commuter walked; therefore incurring a \$0 cost.

ODM Cost Per Passenger-Mile: A life cycle cost model was employed to determine vehicle costs for the ODM aircraft. The following figure shows the interface used to administer the life cycle cost analysis:

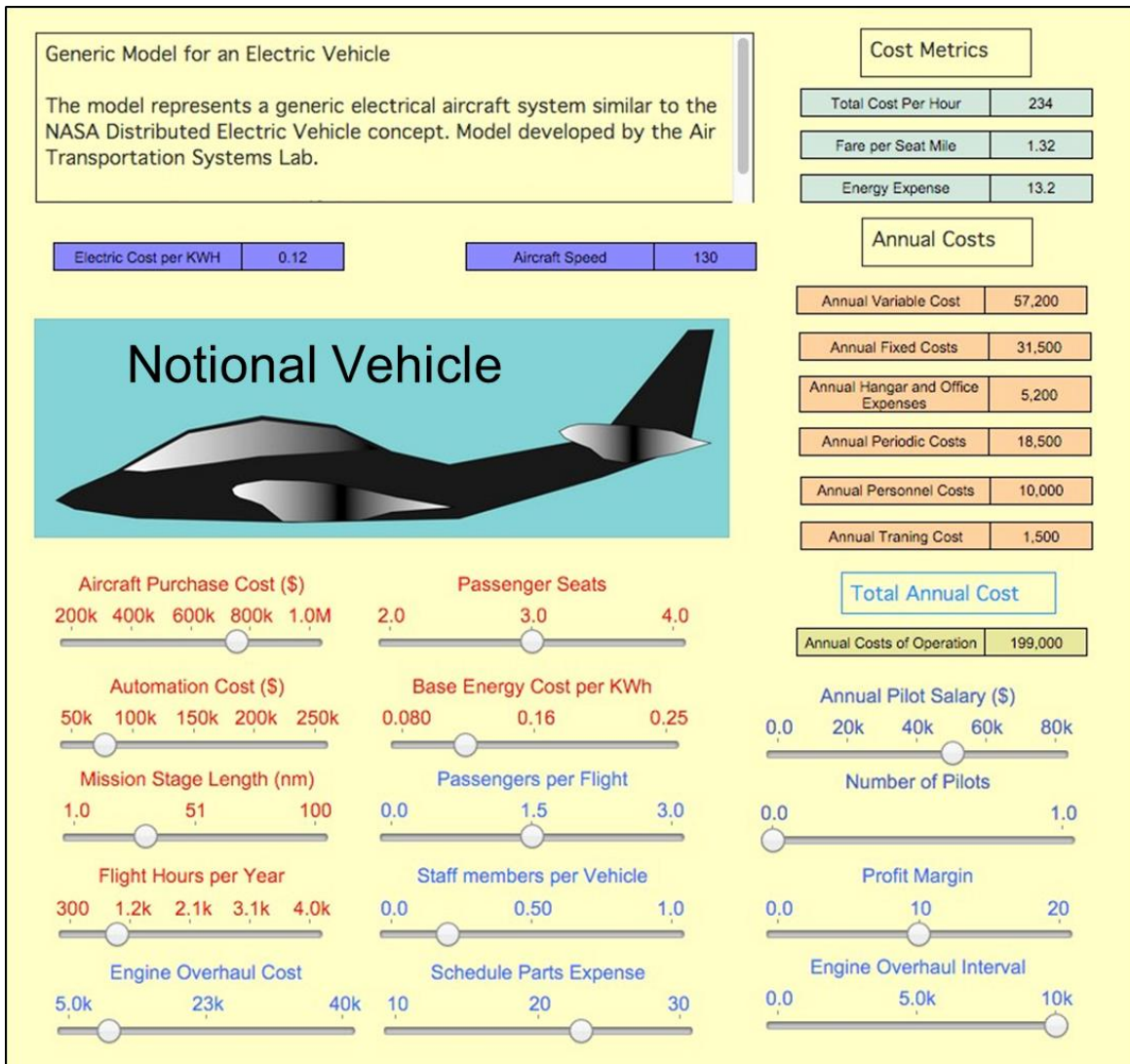


Figure 7: Stella Model Interface for Life Cycle Cost Model (Trani, 2016)

The model includes: facilities costs, periodic costs, variable costs, fixed costs, personnel costs, training costs, and capital and amortization costs (Trani, 2016). Based on pilotless, \$750,000 vehicle with a \$35,000 engine overhaul cost and an annual 1500 flight hours, the cost per passenger-mile would be \$1.23 (Trani, 2016). The landing fare was not included in the cost model; however, the predicted value would be about \$6.70. Additionally, a base fare of \$15 as a ticket to enter the ODM is a separate charge. The results section presents a variation of these metrics.

Table 4 consolidates the details of the inputs to the model.

Table 4: Summary of Assumptions in Model Application.

		Auto	Public Transit	On-Demand Electric
Travel Time (minutes)	In Vehicle Time	MapPoint data used to determine in distance and travel time from origin to destination	Assumed transit distance he same as MapPoint distance for "Auto" and converted to in vehicle time based on an average transit speed of 23.5 mph. The average was computed using NHTS 2009 data.	Distance between landing site closest to origin and landing site closest to destination and converted to a time using characteristics about the aircraft
	Intermodal (Out of Vehicle) Time	No data available about out of vehicle time for person taking personal vehicle; therefore assumption was 2.5 minutes	Average out of vehicle time in NHTS 2009 data: 22.66 minute	(Time spent getting to landing site from origin) + (time getting from landing site to destination) + (Ingress time at landing site) + (egress time at landing site) <u>To/From Landing Site:</u> Assume an Uber travel time to/from landing site (assumed same MapPoint data) if distance is greater than 0.25 miles; if less than or equal to, assumed a walking time using average walking speed of 3.1 mph <u>Ingress Time at Landing Site:</u> 5 minutes <u>Egress Time at Landing Site:</u> 5 minutes
Travel Cost (2009 dollars)	Intermodal Cost	\$0	Auto Cost To Transit Auto in vehicle cost equation: <u>Distance:</u> 2 mile distance to the transit station <u>Parking Cost:</u> \$9.38 and adding a 0.5 factor with the assumption that it is cheaper to park at a transit station	(Fee to/from Landing Site) + (In Vehicle Cost) <u>Fee to/From Landing Site:</u> If distance to/from landing site is less than or equal to 0.25 miles, assume the commuter walked, therefore \$0 cost incurred. If distance to/from landing site is greater than 0.25 miles, assume an Uber cost incurred: Uber Cost: Uber Base Fare (\$1.78) + Uber Service Fee (\$1.38) + Uber Per Minute (\$0.2) + Uber Per Mile (\$1.02) If the Uber cost is less than the minimum cost of \$9.40, then the minimum cost is incurred. In this analysis, because no further information is given regarding a "bundled fee" for taking Uber to and from the landing site, the assumption was that the minimum cost would be reduced by a factor of 0.5.
	In Vehicle Cost	(AAA cost per mile * miles traveled) + Parking Cost) ÷ (Auto Occupancy Rate) <u>AAA cost per mile:</u> \$0.54 per mile travelled <u>Parking Cost:</u> For average parking in the area of analysis, used a parking cost of \$9.38 <u>Auto Occupancy Rate:</u> NHTS 2009 data, the average occupancy rate for a weekday trip: 1.13	Base Fare + Variable Fare <u>Base Fare:</u> \$1.54 <u>Variable Fare:</u> \$0.087(In Vehicle Distance)	\$1.23 per passenger-mile is the baseline estimate Parametric studies were run with values of: \$1.63 \$1.48 \$1.00 \$0.75 \$6.70 Landing Fare \$15 Base Fare is the baseline estimate

3.2 Model Calibration

The coefficients generated from the runs are as follows:

Table 5: Calibrated Coefficients for Demand Analysis.

Parameter	Coefficient
Total Travel Time	-0.196
Travel Cost	-0.465

The method of validating these coefficients included a value of time check. The average wage in San Francisco area is \$34.97 last updated in May 2015. The equation to compute the value of time is as follows:

$$\frac{\alpha_{TT}}{\alpha_{TC}} \times \frac{60 \text{ min}}{1 \text{ hour}} \quad (5)$$

The unit breakdown of the equation is:

$$\frac{\alpha_{TT}/\text{min}}{\alpha_{TC}/\$} = \frac{\$}{\text{min}} \times \frac{60 \text{ min}}{1 \text{ hour}} = \frac{\$}{\text{hour}} \quad (6)$$

The value of time to \$25.29 (2009 dollars). In 2015 dollars, this would equate to \$27.94.

Compared to the average wage in San Francisco in 2015, this figure is roughly 79% of the value. Based on literature review, individuals will undervalue their value of time. In this case, this range based on the average wage would be (\$20.98-27.98) if we were to consider a perceived value of time between 60-80% of what the true value is; therefore, the coefficients meet the value of time check.

CHAPTER 4: RESULTS

4.1 Degrees of Freedom in Scenarios

The baseline assumptions were defined in the table of assumptions above, however the model was flexible to allow for various degrees of freedom of the inputs. The follows degrees of freedom are exercised in estimating results that are explained in the paragraphs following:

- With/without applying a cutoff for using ODM to 20 miles great circle distance (GCD)
- With/without a base fare of \$15 applied to in vehicle costs
- With/without a landing site cost of \$6.70
- Varying the in vehicle cost for ODM between \$1.63 and \$0.75 per passenger-mile, acknowledging that credible results obtained will be around a range of \$1.10 and higher
- Varying the “ingress time” (time waiting at the landing site) to increase to 7 and 9 minutes
- Auto costs of \$0.54 per mile and \$0.30 per mile

Based on guidance from NASA, the ODM concept would not be employed for short trips. The cut off distance varies per region; in this analysis, for distances shorter than 20 miles, the ODM aircraft should not be considered in the decision of mode choice (the model can relax such assumption). The results below show the market share percentage of ODM considering with and without a "20 mile cutoff."

Another consideration was including a \$15 base fare associated with the in vehicle cost. Current policies of on-demand ground transportation models such as Uber charge a minimum

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fare for most of their trips. Therefore, the scenarios highlight, additionally, with and without the inclusion of the \$15 base fare.

In a final run of the model, an alternate fare structure was suggested in which a base fare of \$15 and a landing fare of \$6.70 would be applied to trip distances up to 5 statute miles. Including 5 and above statute mile trip distances, the passenger would incur that base fare plus landing site cost and the cost per passenger-mile for any distances 5 statute miles and above.

In the analysis presented in the following section, we estimate realistic ODM cost per passenger-mile to be no less than \$1.10 per passenger-mile. The results shows that if ODM cost could be driven down to \$1.10 (a far reach goal in technology), the ODM market share could reach around 4.5% of the total commuter trips. This number assumes there are no additional landing site costs. A 4.5% of market share is equivalent to 180,000 one-way ODM trips per day. Such scenario would create large number of operations for some landing sites adding additional waiting time to a trip. Given the number of degrees of freedom, the scenarios run for the Northern California area include:

Table 6: Scenarios Presented in Results for Northern California

Scenarios	Cutoff 20 miles	Base Fare	Landing Fare \$6.70	Auto Cost \$0.54	Auto Cost \$0.30	Ingress Time 5 minutes	Ingress Time 7 minutes	Ingress Time 9 minutes
1		X	X		X	X	X	X
2		X			X	X	X	X
3			X		X	X	X	X
4	X		X		X	X	X	X
5		X	X	X		X	X	X
6		X		X		X	X	X
7 *		X	X	X		X	X	X
8 *		X	X		X	X	X	X
9**		X			X	X	X	X

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* = Alternative fare structure: \$15 fare buys a trip up to 5 statute miles, additional passenger-mile cost applied to commuter distances above 5 statute miles

** = Alternative fare structure: \$20 fare buys a trip up to 20 statute miles, additional passenger-mile cost applied to commuter distances above 20 statute miles

The results presented in the section are estimates made from the conditional logit model probabilities; therefore the results shown in the table reflect those values rounded to the tenth digit.

4.2 Demand Results for Northern California Region

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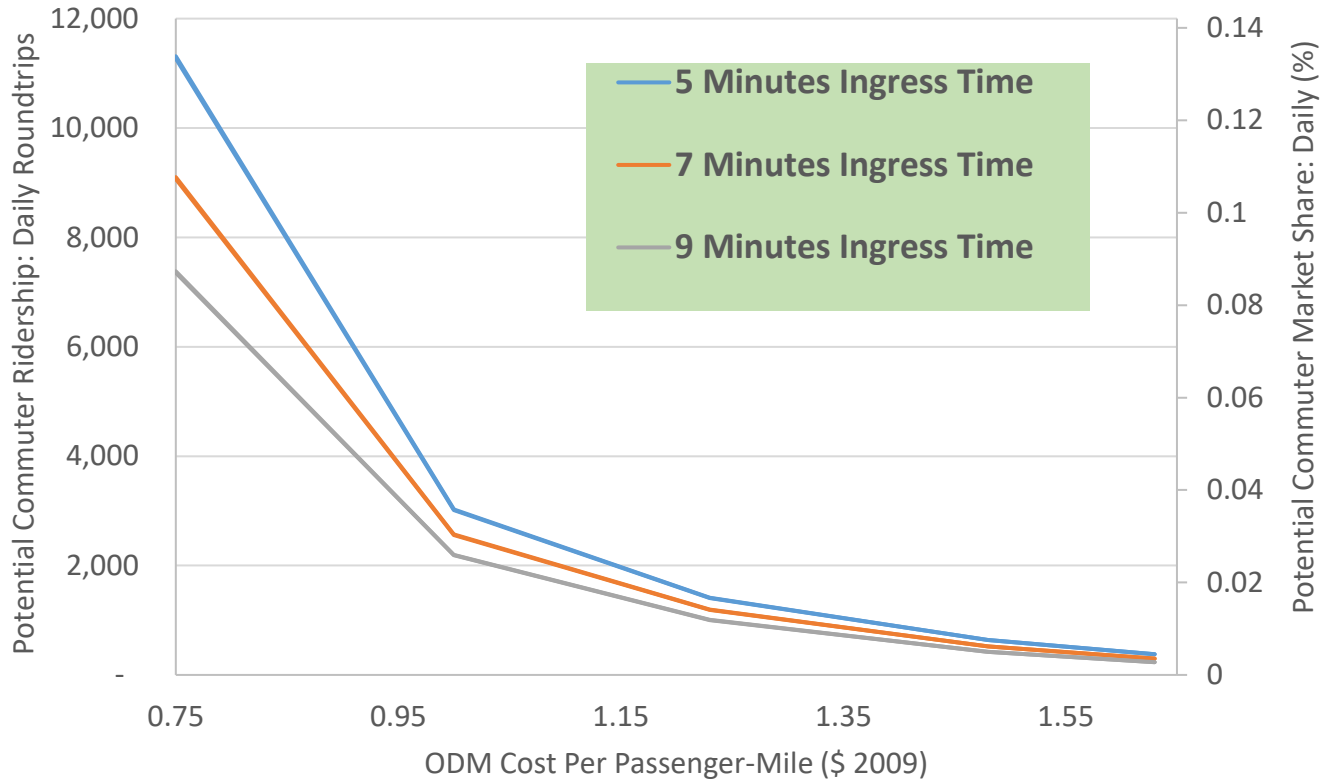


Figure 8: Scenario 1: Ridership and Market Share with \$0.30 Auto Cost, \$15 Base Fare, \$6.70 Landing Fare, No Cutoff at 20 miles, 5/7/9 Minute Ingress Time.

Table 7: Scenario 1: Ridership and Market Share with \$0.30 Auto Cost, \$15 Base Fare, \$6.70 Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	510	0.006	390	0.005	300	0.004
1.48	800	0.010	630	0.008	500	0.006
1.23	1,640	0.019	1,340	0.016	1,110	0.013
1.00	3,330	0.040	2,770	0.033	2,330	0.028
0.75	11,720	0.139	9,370	0.111	7,560	0.090

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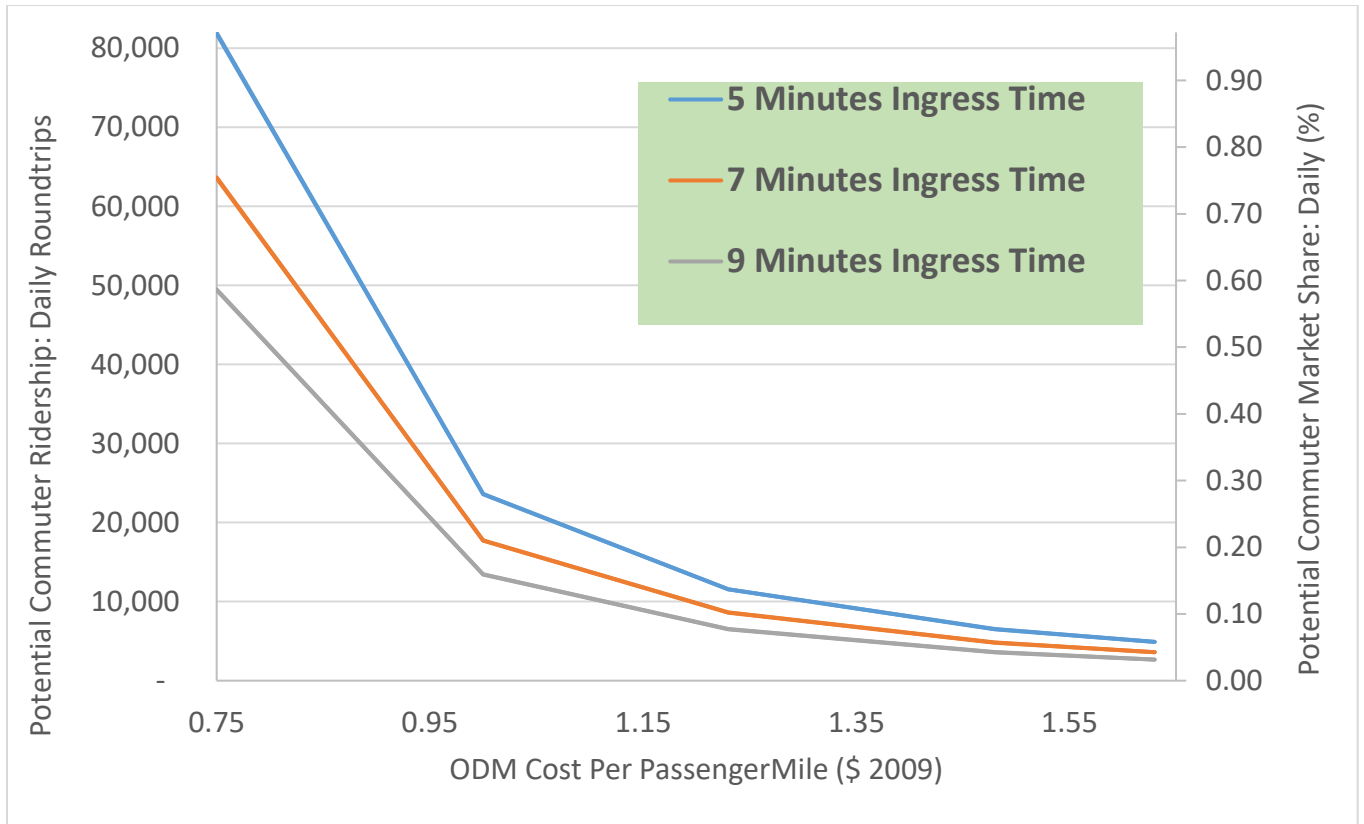


Figure 9: Scenario 2: Ridership and Market Share with \$0.30 Auto Cost, \$15 Base Fare, No Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Table 8: Scenario 2: Ridership and Market Share with \$0.30 Auto Cost, \$15 Base Fare, No Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	4,900	0.06	3,600	0.04	2,660	0.03
1.48	6,510	0.08	4,810	0.06	3,600	0.04
1.23	11,550	0.14	8,620	0.10	6,510	0.08
1.00	23,590	0.28	17,720	0.21	13,420	0.16
0.75	81,790	0.97	63,540	0.75	49,400	0.59

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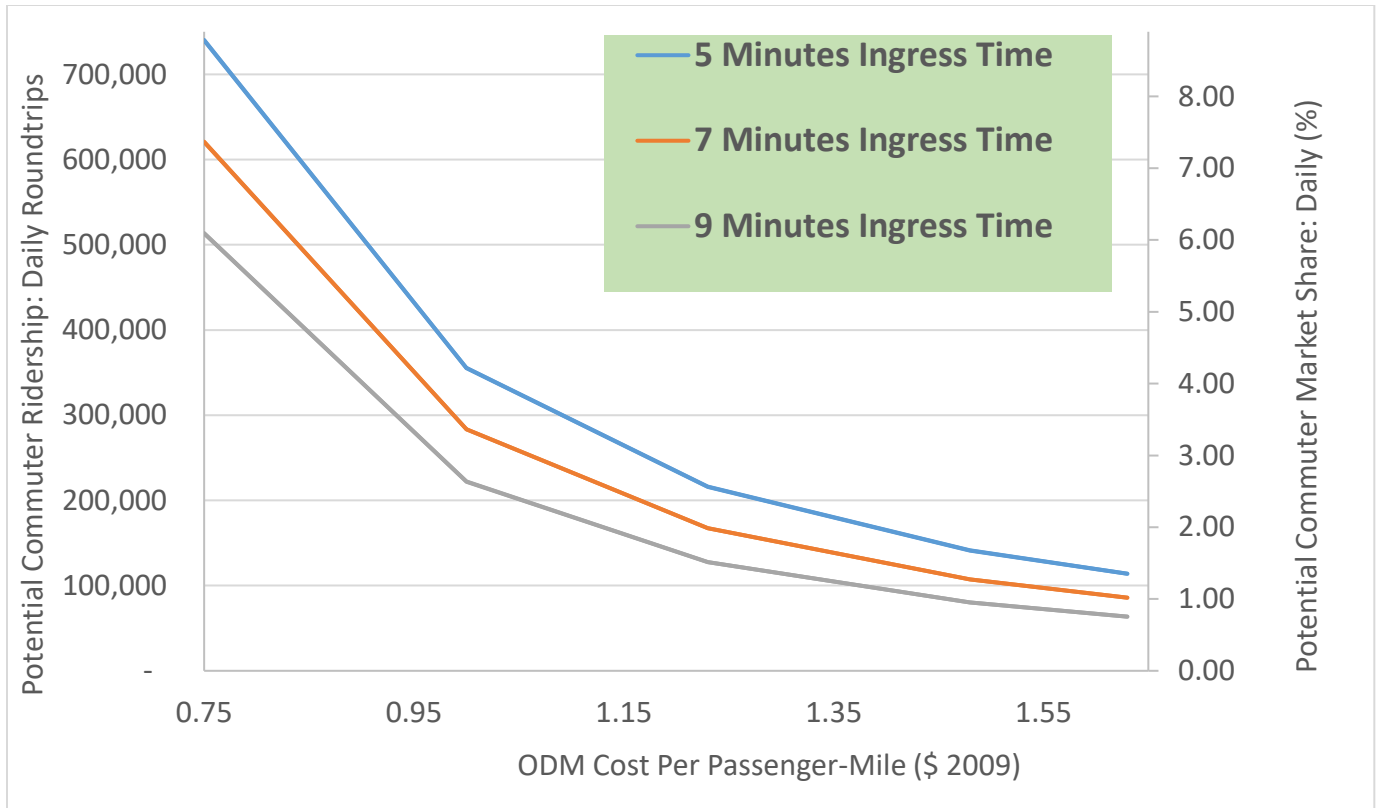


Figure 10: Scenario 3: Ridership and Market Share with \$0.30 Auto Cost, No Base Fare, \$6.70 Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Table 9: Scenario 3: Ridership and Market Share with \$0.30 Auto Cost, No Base Fare, \$6.70 Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	113,880	1.35	85,780	1.02	63,530	0.75
1.48	141,200	1.68	107,300	1.27	80,130	0.95
1.23	215,830	2.56	167,380	1.99	127,490	1.51
1.00	355,160	4.22	283,300	3.36	222,000	2.64
0.75	739,790	8.79	620,490	7.37	513,280	6.10

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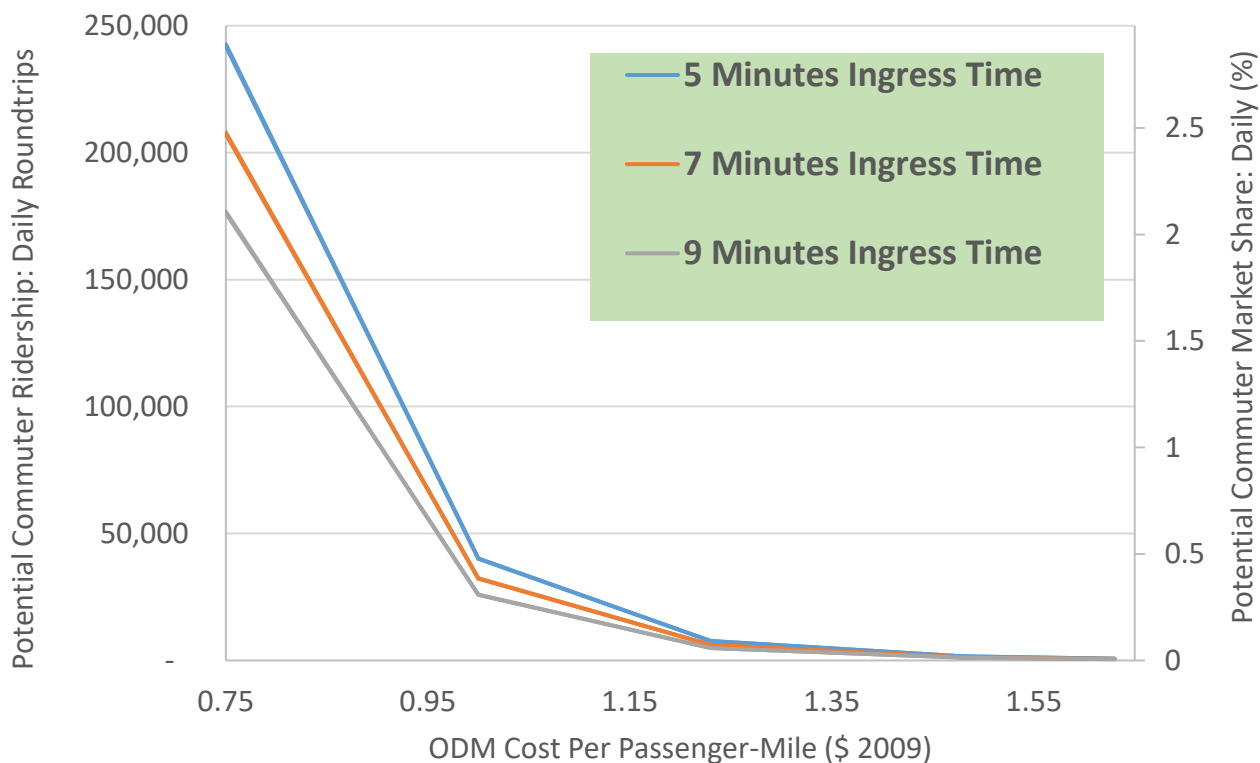


Figure 11: Scenario 4: Ridership and Market Share with \$0.30 Auto Cost, No Base Fare, \$6.70 Landing Fare, Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Table 10: Scenario 4: Ridership and Market Share with \$0.30 Auto Cost, No Base Fare, \$6.70 Landing Fare, Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	700	0.008	590	0.007	500	0.006
1.48	1,560	0.02	1,290	0.02	1,070	0.013
1.23	7,680	0.09	6,120	0.07	4,890	0.06
1.00	40,190	0.48	32,320	0.38	25,880	0.31
0.75	242,730	2.88	207,960	2.47	176,760	2.10

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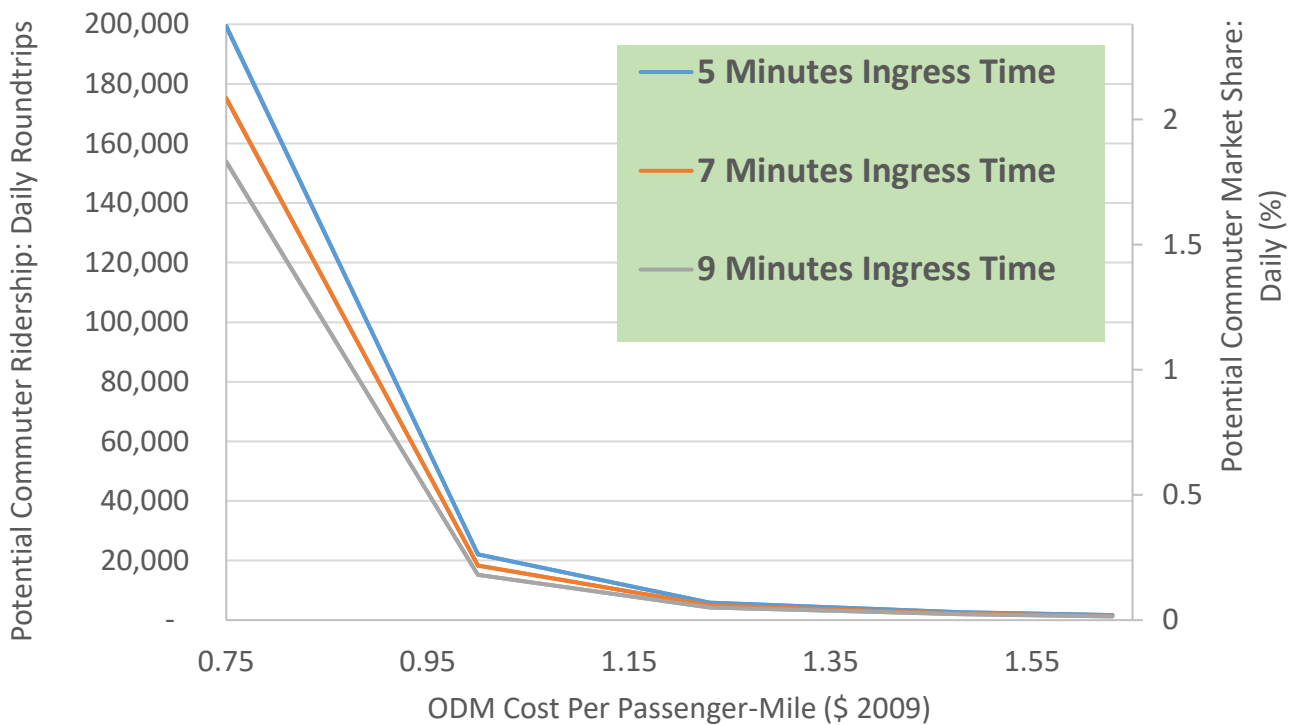


Figure 12: Scenario 5: Ridership and Market Share with \$0.54 Auto Cost, \$15 Base Fare, \$6.70 Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Table 11: Scenario 5: Ridership and Market Share with \$0.54 Auto Cost, \$15 Base Fare, \$6.70 Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	1,950	0.02	1,640	0.02	1,380	0.02
1.48	2,910	0.03	2,480	0.03	2,130	0.03
1.23	6,360	0.08	5,310	0.06	4,490	0.05
1.00	22,720	0.27	18,770	0.22	15,560	0.18
0.75	200,350	2.38	175,900	2.09	154,440	1.83

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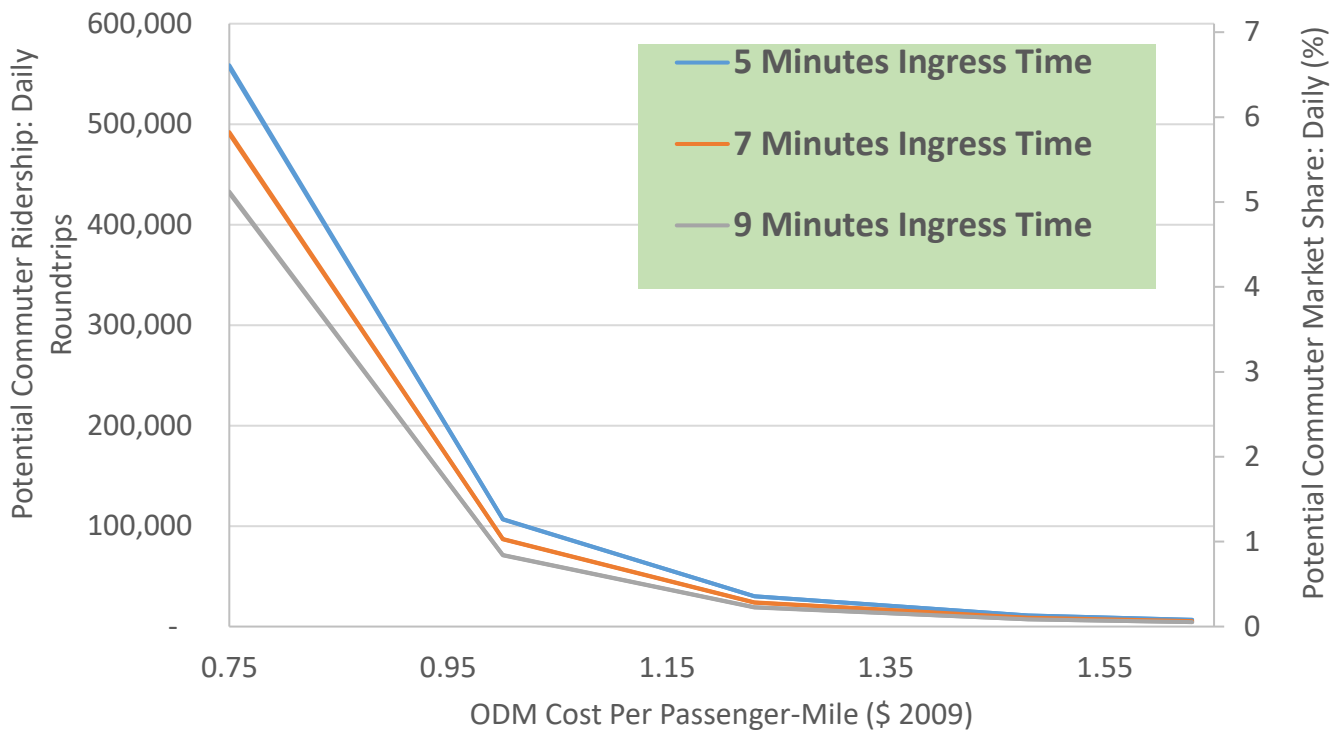


Figure 13: Scenario 6: Ridership and Market Share with \$0.54 Auto Cost, \$15 Base Fare, No Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Table 12: Scenario 6: Ridership and Market Share with \$0.54 Auto Cost, \$15 Base Fare, No Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	11,180	0.13	8,560	0.10	6,650	0.08
1.48	16,300	0.19	12,520	0.15	9,730	0.12
1.23	37,220	0.44	28,940	0.34	22,660	0.27
1.00	116,040	1.38	93,550	1.11	75,580	0.90
0.75	569,460	6.76	499,400	5.93	437,720	5.20

On Demand Mobility Commuter Aircraft Demand Estimation

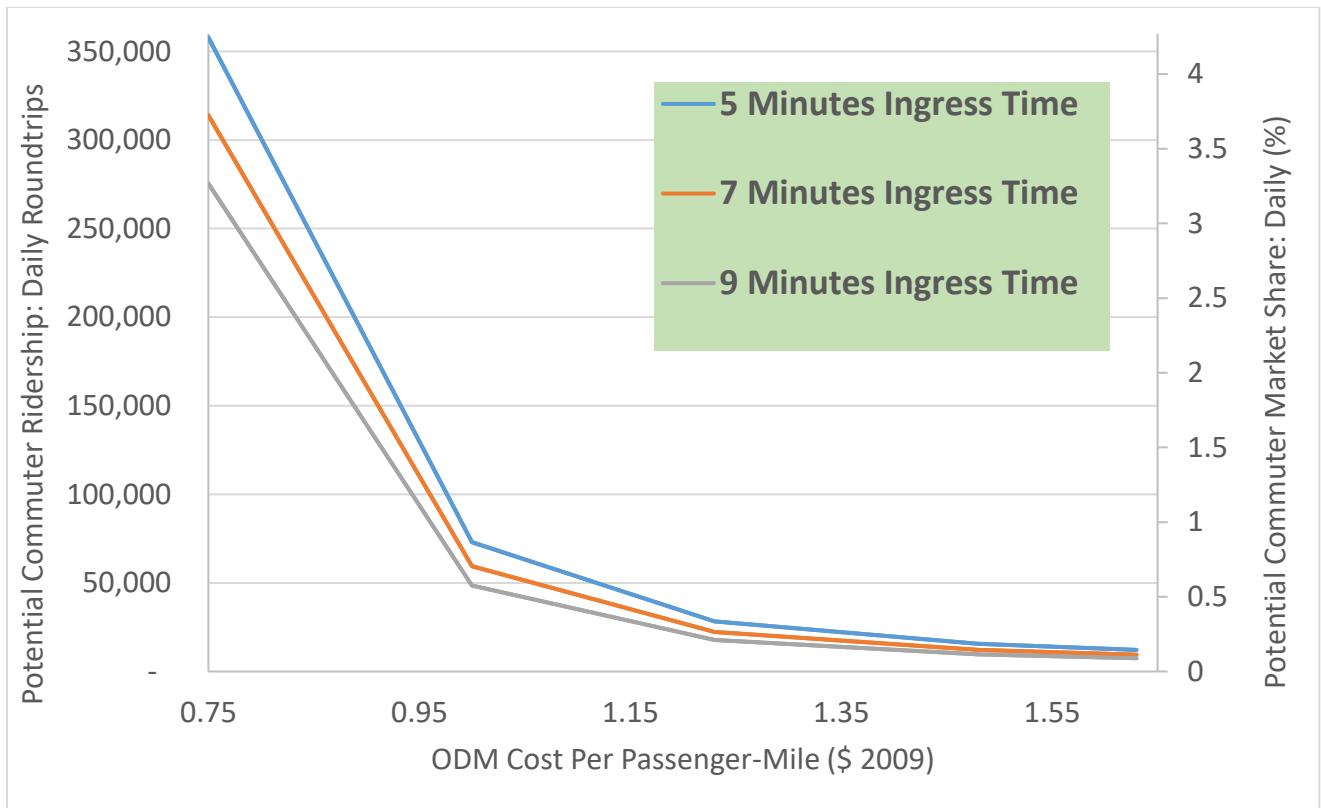


Figure 14: Scenario 7: Ridership and Market Share with \$0.54 Auto Cost, \$15 for Trips Less Than 5 Statute Miles, ODM Cost per Passenger-Mile for Additional Statute Miles Plus Landing Fare and \$15 Base Fee for Trips Greater Than or Equal to 5 Statute Miles , 5/7/9 Minute Ingress Time.

Table 13: Scenario 7.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	12,180	0.14	9,490	0.11	7,490	0.09
1.48	15,590	0.19	12,210	0.15	9,670	0.11
1.23	28,200	0.33	22,330	0.27	17,800	0.21
1.00	72,980	0.87	59,420	0.71	48,510	0.58
0.75	357,600	4.25	313,700	3.73	275,230	3.27

On Demand Mobility Commuter Aircraft Demand Estimation

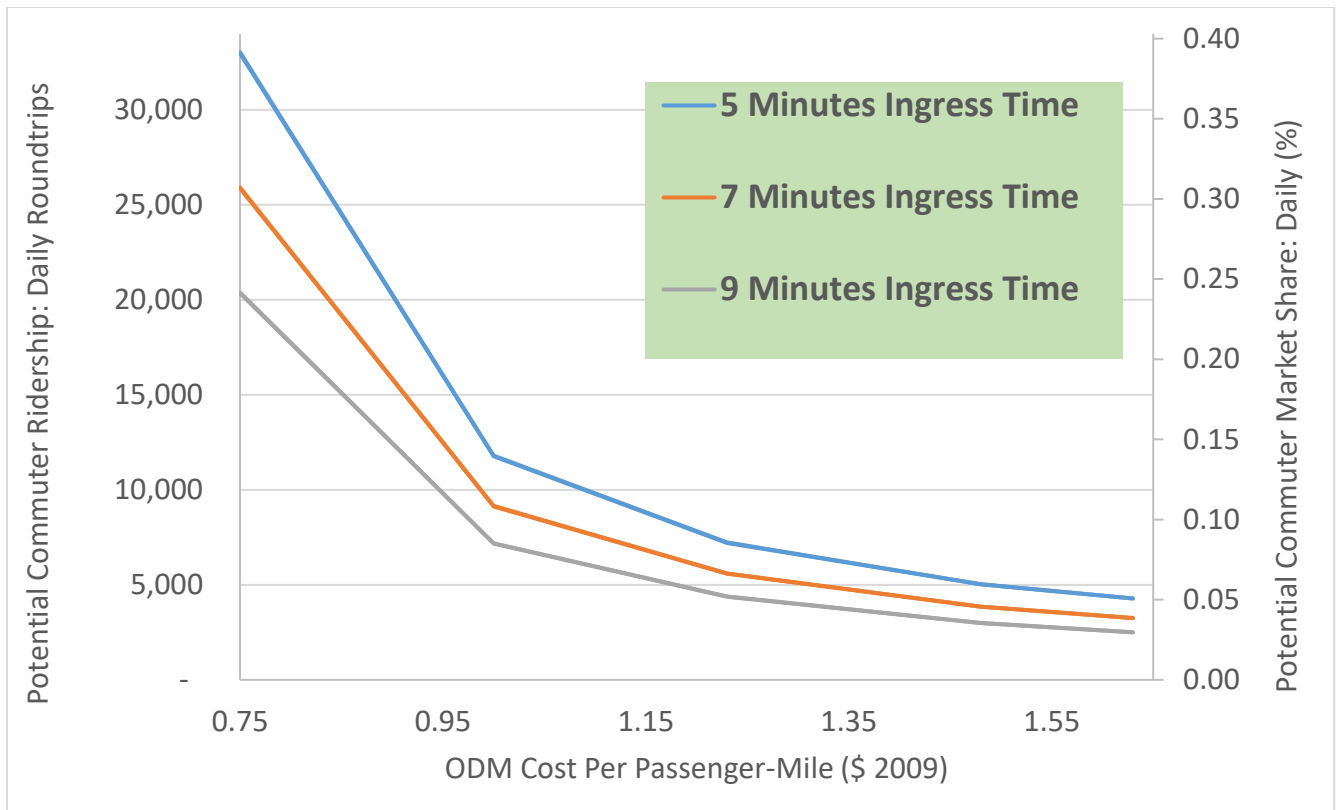


Figure 15: Scenario 8: Ridership and Market Share with \$0.30 Auto Cost, \$15 for Trips Less Than 5 Statute Miles, ODM Cost per Passenger-Mile for Additional Statute Miles Plus Landing Fare and \$15 Base Fee for Trips Greater Than or Equal to 5 Statute Miles, 5/7/9 Minute Ingress Time.

Table 14: Scenario 8.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	4,280	0.05	3,250	0.04	2,500	0.03
1.48	5,030	0.06	3,850	0.05	2,990	0.04
1.23	7,210	0.09	5,590	0.07	4,380	0.05
1.00	11,770	0.14	9,130	0.11	7,170	0.09
0.75	32,970	0.39	25,870	0.31	20,350	0.24

On Demand Mobility Commuter Aircraft Demand Estimation

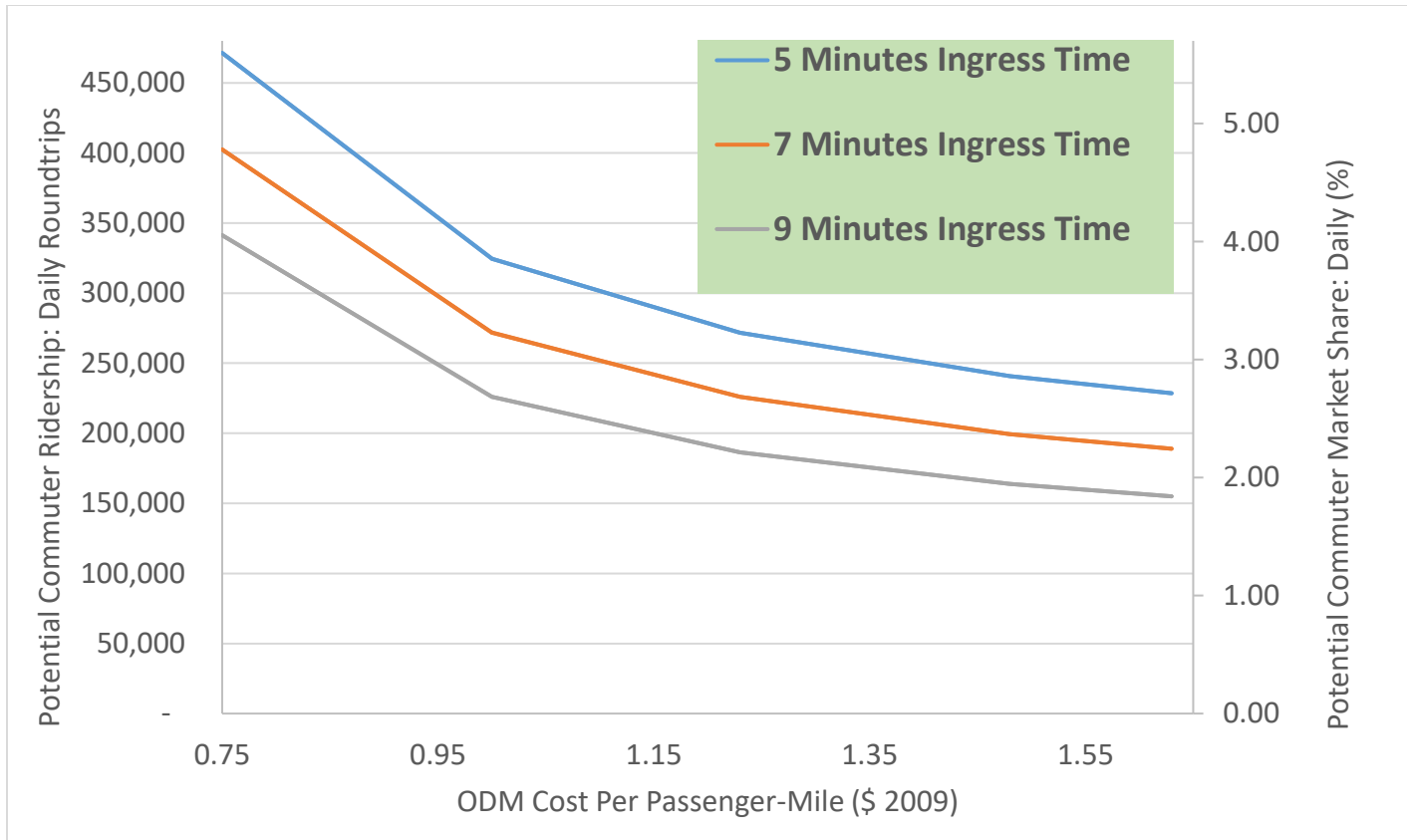


Figure 16: Scenario 9: Ridership and Market Share with \$0.30 Auto Cost, \$20 for Trips Less Than 20 Statute Miles, ODM Cost per Passenger-Mile for Additional Statute Miles and \$20 Base Fee for Trips Greater Than or Equal to 20 Statute Miles , 5/7/9 Minute Ingress

Table 15: Scenario 9

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	228,550	2.71	188,950	2.24	154,990	1.84
1.48	240,790	2.86	199,390	2.37	163,830	1.95
1.23	271,660	3.23	225,900	2.68	186,400	2.21
1.00	324,550	3.85	271,840	3.23	225,960	2.68
0.75	471,370	5.60	402,470	4.78	341,320	4.05

4.2.1 Northern California Results for Comparison

The scenarios that are likely to be predicted will be shown in the following chart for comparison assuming an ingress time of 5 minutes:

Table 16: Final Scenario Results Shown: Northern California

Scenarios	Cutoff 20 miles	Base Fare	Landing Fare \$6.70	Auto Cost \$0.54	Auto Cost \$0.30
1		X	X		X
5		X	X	X	
8 *		X	X		X
9**		X			X

* = Alternative fare structure: \$15 fare buys a trip up to 5 statute miles, additional passenger-mile cost applied to commuter distances above 5 statute miles

** = Alternative fare structure: \$20 fare buys a trip up to 20 statute miles, additional passenger-mile cost applied to commuter distances above 20 statute miles

The results presented in the section are estimates made from the conditional logit model probabilities; therefore the results shown in the table reflect those values rounded to the tenth digit.

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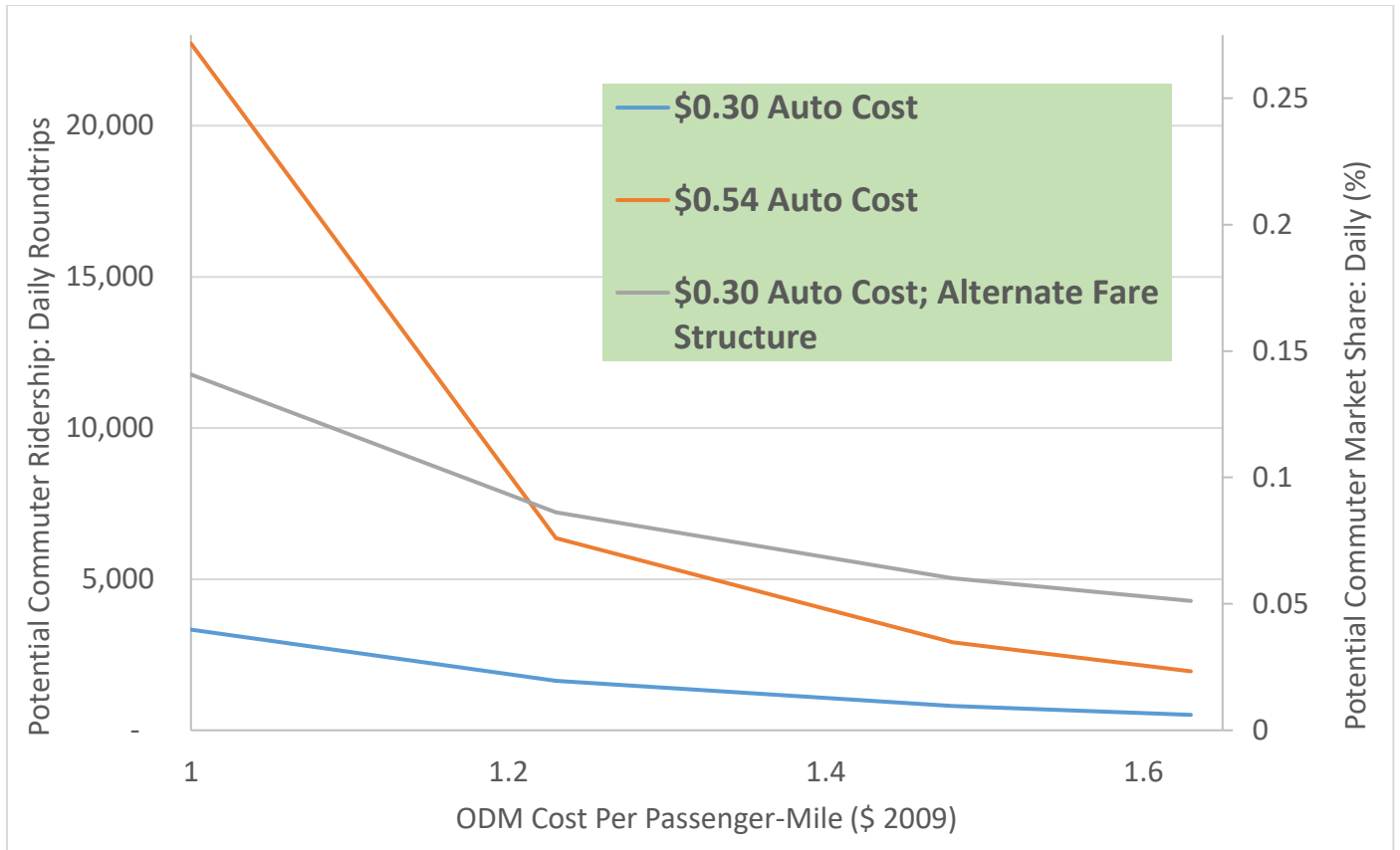


Figure 17: Final Results From Scenarios: Northern California. \$15 Base Fare. \$6.70 Landing Fare. 5 Minutes Ingress Time

Table 17: Final Results From Scenarios: Northern California. \$15 Base Fare. \$6.70 Landing Fare. 5 Minutes Ingress Time

Cost Per Passenger-Mile (\$ 2009)	\$0.30 Auto Cost		\$0.54 Auto Cost		\$0.30 Auto Cost (Alternative Fare Structure)	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	510	0.006	1,950	0.02	4,280	0.05
1.48	800	0.010	2,910	0.03	5,030	0.06
1.23	1,640	0.019	6,360	0.08	7,210	0.09
1.00	3,330	0.040	22,720	0.27	11,770	0.14

4.2.2 Northern California Landing Site Utilization

In Northern California, the following scenarios were run to obtain the following figures showing landing site utilization based on the demand results:

Table 18: Scenarios Run for Northern California Landing Site Utilization

Scenarios	Cutoff 20 miles	Base Fare \$15	Landing Fare \$6.70	Auto Cost\$0.54	Auto Cost \$0.30	Ingress Time 5 minutes	Ingress Time 7 minutes	Ingress Time 9 minutes
1		x	x	x		x		
2		x	x		x	x		

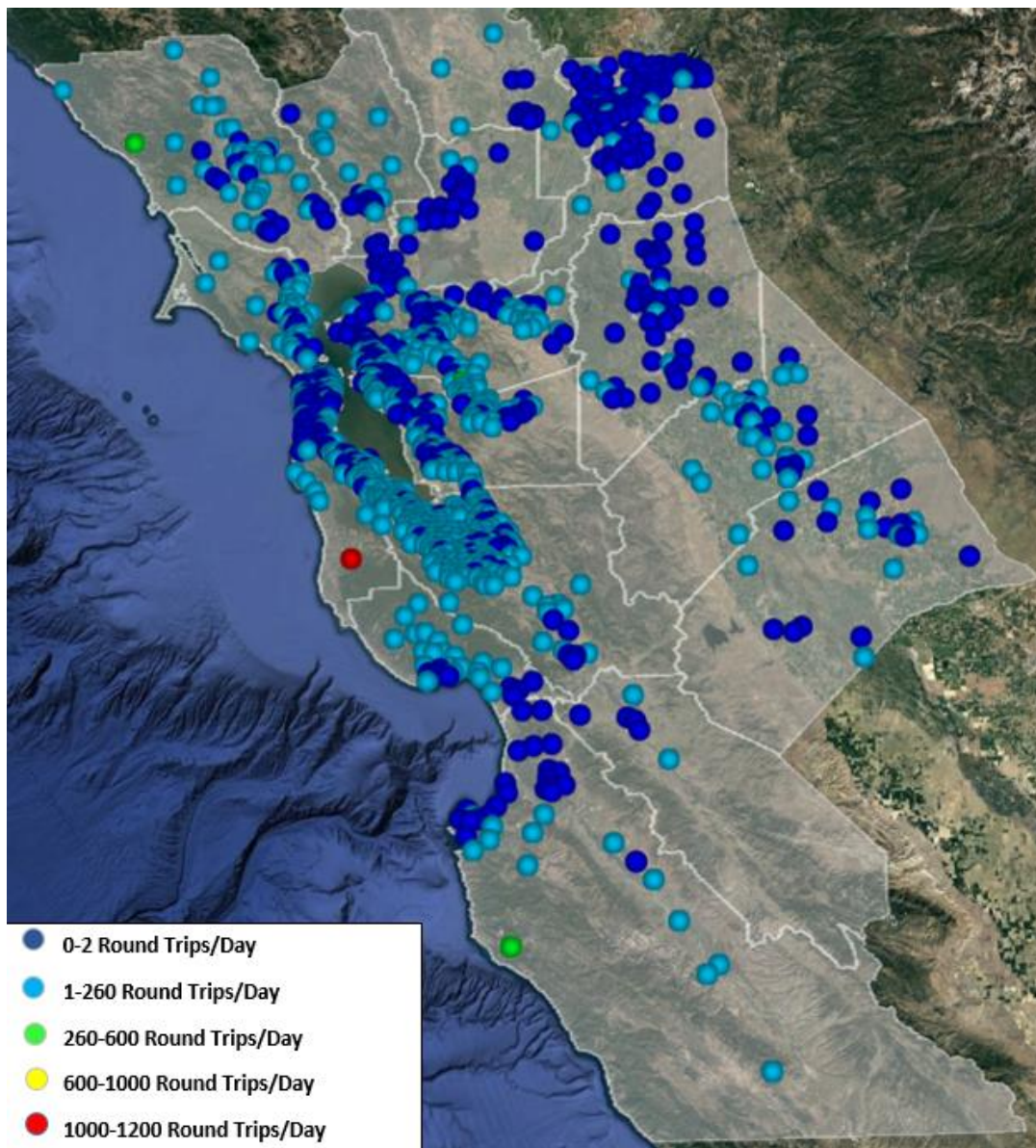


Figure 18: Scenario 1: Landing Site Utilization Northern California: \$0.54 Auto Cost, \$15 Base Fare, \$6.70 Landing Fare, No Cutoff at 20 miles, 5-Minute Ingres Time.

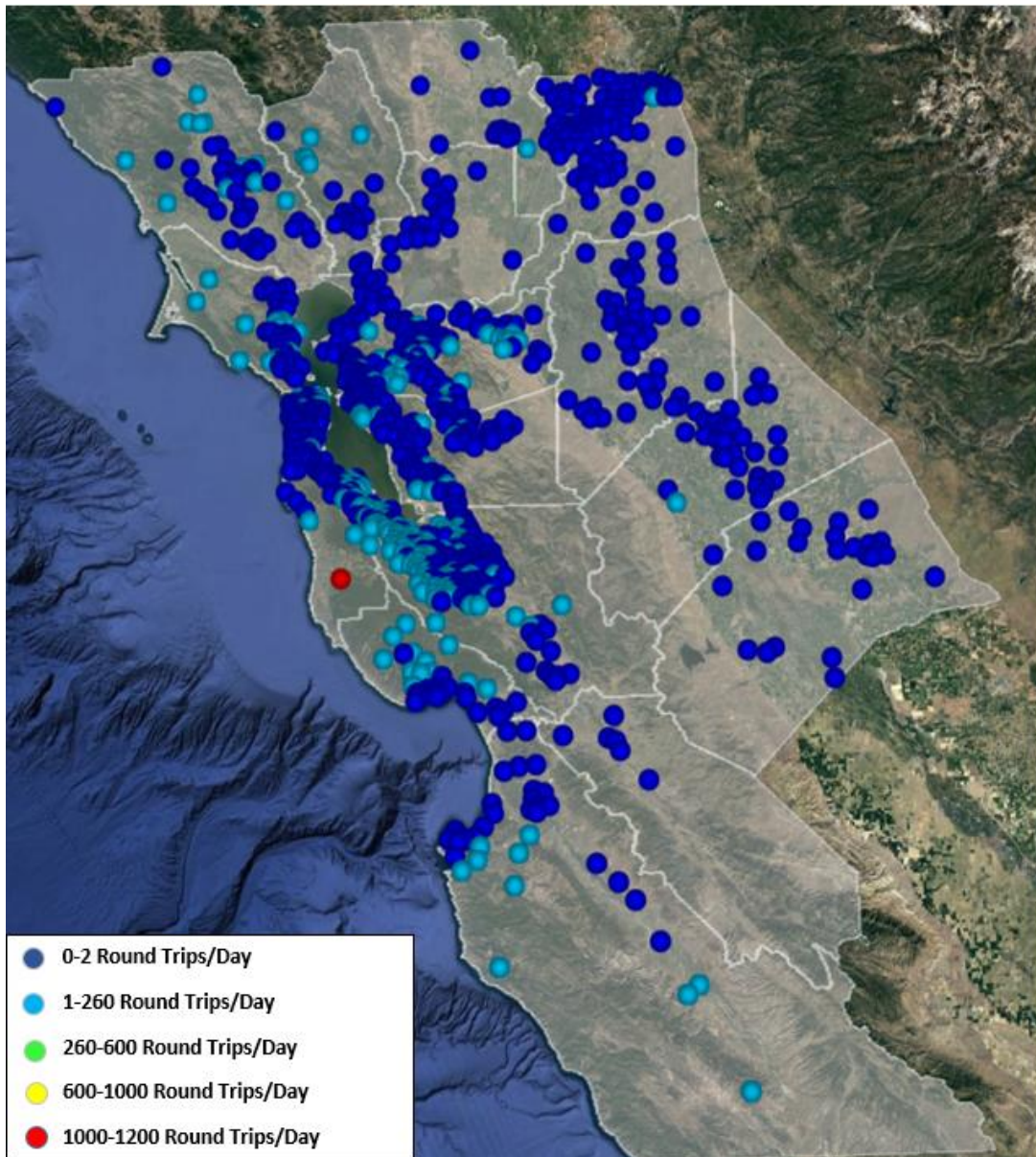


Figure 19: Scenario 2: Landing Site Utilization Northern California: \$0.30 Auto Cost, \$15 Base Fare, \$6.70 Landing Fare, No Cutoff at 20 miles, 5-Minute Ingres Time.

4.2.3 Northern California Results Discussion

Cost Per Passenger-Mile

Demand results show how sensitive the model is to the travel cost for ODM. Though the cost per passenger-mile is deemed reasonable starting at about \$1.10 per passenger-mile, the results for

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lower costs per passenger-mile were included in the analysis to anticipate a potential drop in cost in the future, if ever possible. Proposed aircraft design concepts show simplicity with little moving parts that would decrease maintenance and operational costs.

ODM cutoff

As stated, the cutoff distance is subjective depending on region of analysis. A cutoff of 20 miles was an idea borrowed from the Uber Elevate white paper and was recommended per NASA guidance. Uber employed the cutoff for taking the ODM as an arbitrary number applying specifically to the Dallas, Texas region. For the Dubai analysis, the cutoff was 10 miles.

In general, the cutoff is predicted to be about 5 miles in the future; however more scrutiny and study will be performed before deciding on an exact value.

Areas Most Suitable for ODM

Northern California includes mountainous terrain in which many individuals reside and lack better access to road or public transit networks. The demand results for landing site utilization shows a particular landing site having a high amount of traffic (see **Figure 18** and **Figure 19**). The area has been identified as a seemingly isolated region with mountainous terrain, however the area includes a population of 4,009 (ACS, 2009). The area does not have a good road network so a place of this level of isolation can be a good location for a landing site and advantageous location for the ODM to provide good access to destinations. Additionally, as early adopters of the ODM, individuals in the higher income ranges may prefer to live in more remote areas; therefore being able to afford the ODM mode.

4.3 Demand Results for Washington-Baltimore Region

In consultation with NASA, a first-order analysis was conducted for the Washington-Baltimore region. The analysis would not be a separately calibrated model based on Washington-Baltimore transportation patterns. Therefore, the calibrated model for the Northern California analysis was applied to obtain demand values for the Washington-Baltimore area to provide a crude, first order demand results. All other input parameters for Northern California were applied to the Washington-Baltimore.

Given the coarse analysis performed for the Washington-Baltimore area, the scenarios presented in **Table 19** are representative of the ODM demand expected in the Washington-Baltimore area.

Table 19: Scenarios for the Washington-Baltimore Area.

Scenarios	Cutoff 20 miles	Base Fare	Landing Fare \$6.70	Auto Cost\$0.54	Auto Cost \$0.30	Ingress Time 5 minutes	Ingress Time 7 minutes	Ingress Time 9 minutes
1		x	x		x	x	x	x
2*		x	x		x	x	x	x
3**		x			x	x	x	x

* = Alternative fare structure: \$15 fare buys a trip up to 5 statute miles, additional passenger-mile cost applied to commuter distances above 5 statute miles

** = Alternative fare structure: \$20 fare buys a trip up to 20 statute miles, additional passenger-mile cost applied to commuter distances above 20 statute miles

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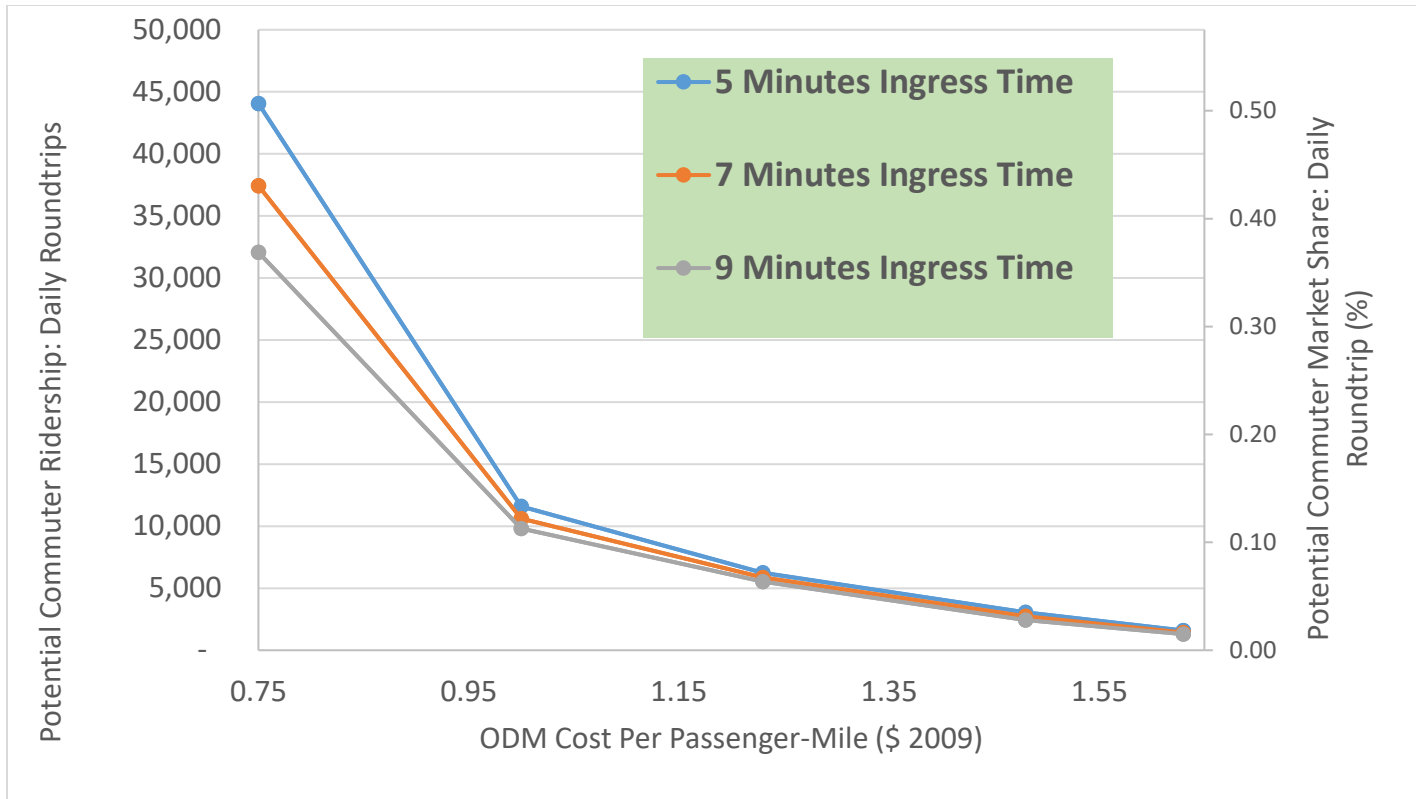


Figure 20: Scenario 1: Ridership and Market Share with \$0.30 Auto Cost, \$15 Base Fare, \$6.70 Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Table 20: Scenario 1: Ridership and Market Share with \$0.30 Auto Cost, \$15 Base Fare, \$6.70 Landing Fare, No Cutoff At 20 miles, 5/7/9 Minute Ingress Time.

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	1,590	0.02	1,430	0.02	1,300	0.01
1.48	3,050	0.04	2,730	0.03	2,440	0.03
1.23	6,240	0.07	5,860	0.07	5,520	0.06
1.00	11,580	0.13	10,620	0.12	9,800	0.11
0.75	44,060	0.51	37,440	0.43	32,070	0.37

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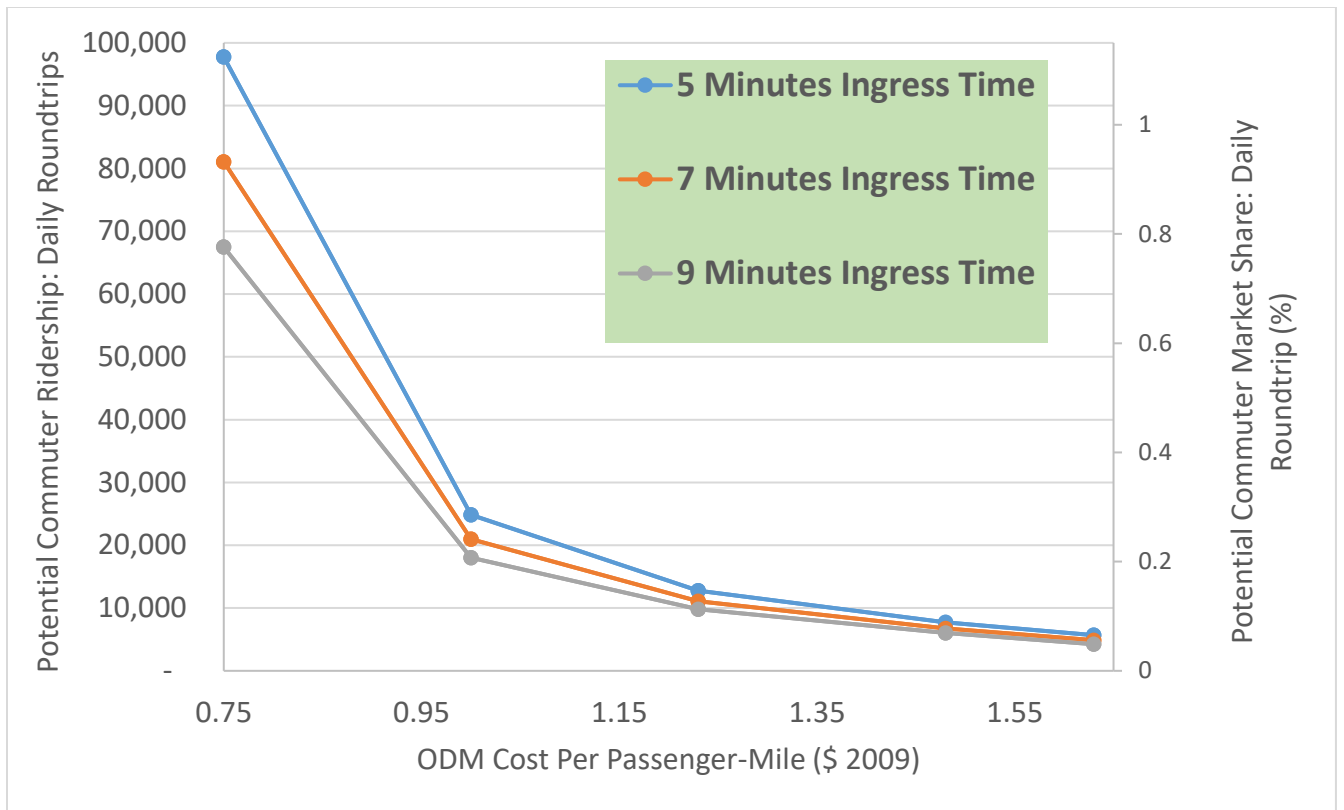


Figure 21: Scenario 2: Ridership and Market Share with \$0.30 Auto Cost, \$15 for Trips Less Than 5 Statute Miles, ODM Cost per Passenger-Mile for Additional Statute Miles Plus Landing Fare and \$15 Base Fee for Trips Greater Than or Equal to 5 Statute Miles, 5/7/9 Minute Ingress Time.

Table 21: Scenario 2

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	5,680	0.07	4,880	0.06	4,240	0.05
1.48	7,700	0.09	6,760	0.08	6,020	0.07
1.23	12,760	0.15	11,100	0.13	9,800	0.11
1.00	24,820	0.29	20,960	0.24	18,020	0.21
0.75	97,750	1.12	81,070	0.93	67,470	0.78

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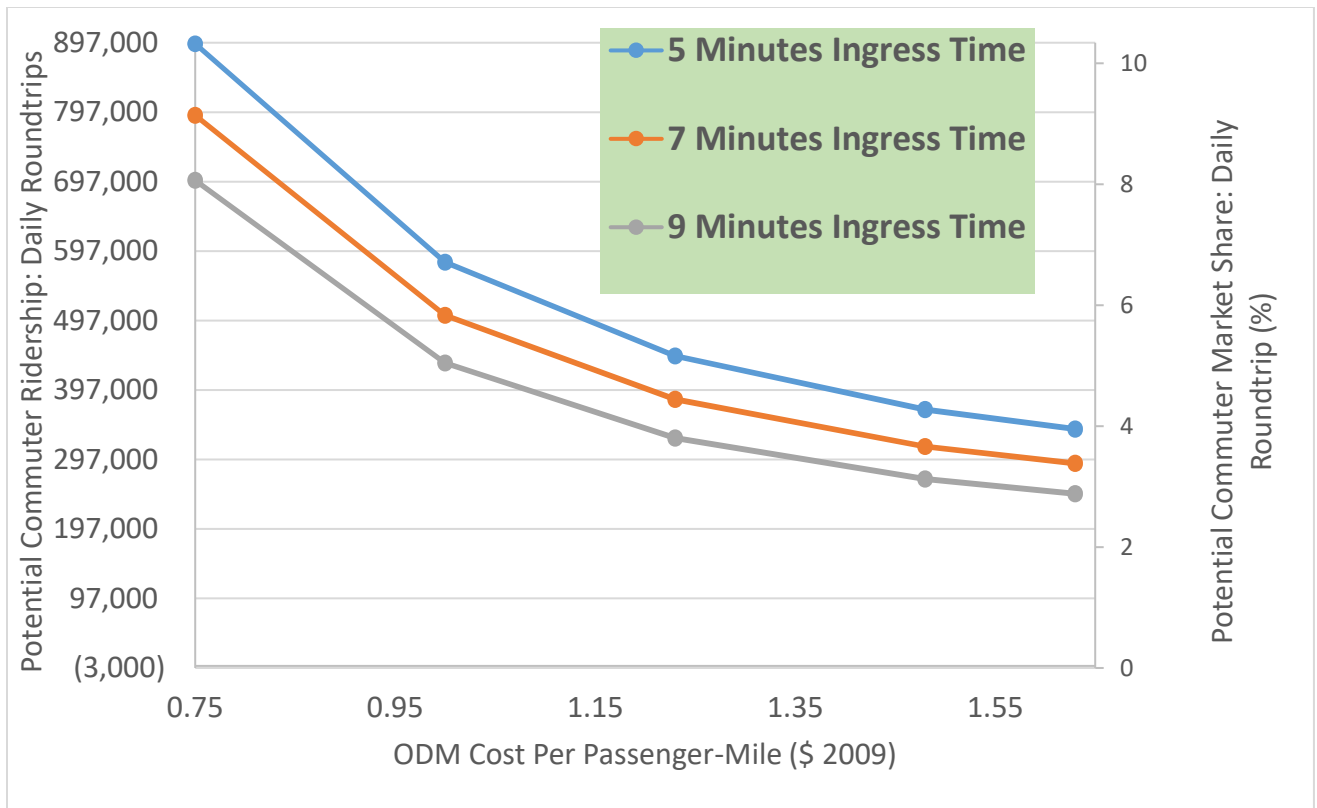


Figure 22: Scenario 3: Ridership and Market Share with \$0.30 Auto Cost, \$20 for Trips Less Than 20 Statute Miles, ODM Cost per Passenger-Mile for Additional Statute Miles Plus \$20 Base Fee for Trips Greater Than or Equal to 20 Statute Miles, 5/7/9 Minute Ingress Time.

Table 22: Scenario 3

Cost Per Passenger-Mile (\$ 2009)	5 Minutes Ingress Time		7 Minutes Ingress Time		9 Minutes Ingress Time	
	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)	Roundtrips Daily Ridership	Market share (%)
1.63	342,310	3.9	292,780	3.4	249,130	2.9
1.48	370,220	4.3	317,070	3.6	270,190	3.1
1.23	447,470	5.1	384,930	4.4	329,490	3.8
1.00	582,460	6.7	505,740	5.8	437,210	5.0
0.75	896,500	10.3	793,560	9.1	700,000	8.1

4.3.1 Washington-Baltimore Landing Site Utilization

In the Washington-Baltimore area, the following scenarios were run to obtain the following figures showing landing site utilization based on the demand results:

Table 23: Scenarios Run for Washington-Baltimore Landing Site Utilization

Scenarios	Cutoff 20 miles	Base Fare \$15	Landing Fare \$6.70	Auto Cost\$0.54	Auto Cost \$0.30	Ingress Time 5 minutes	Ingress Time 7 minutes	Ingress Time 9 minutes
1		X	X	X		X		
2		X	X		X	X		

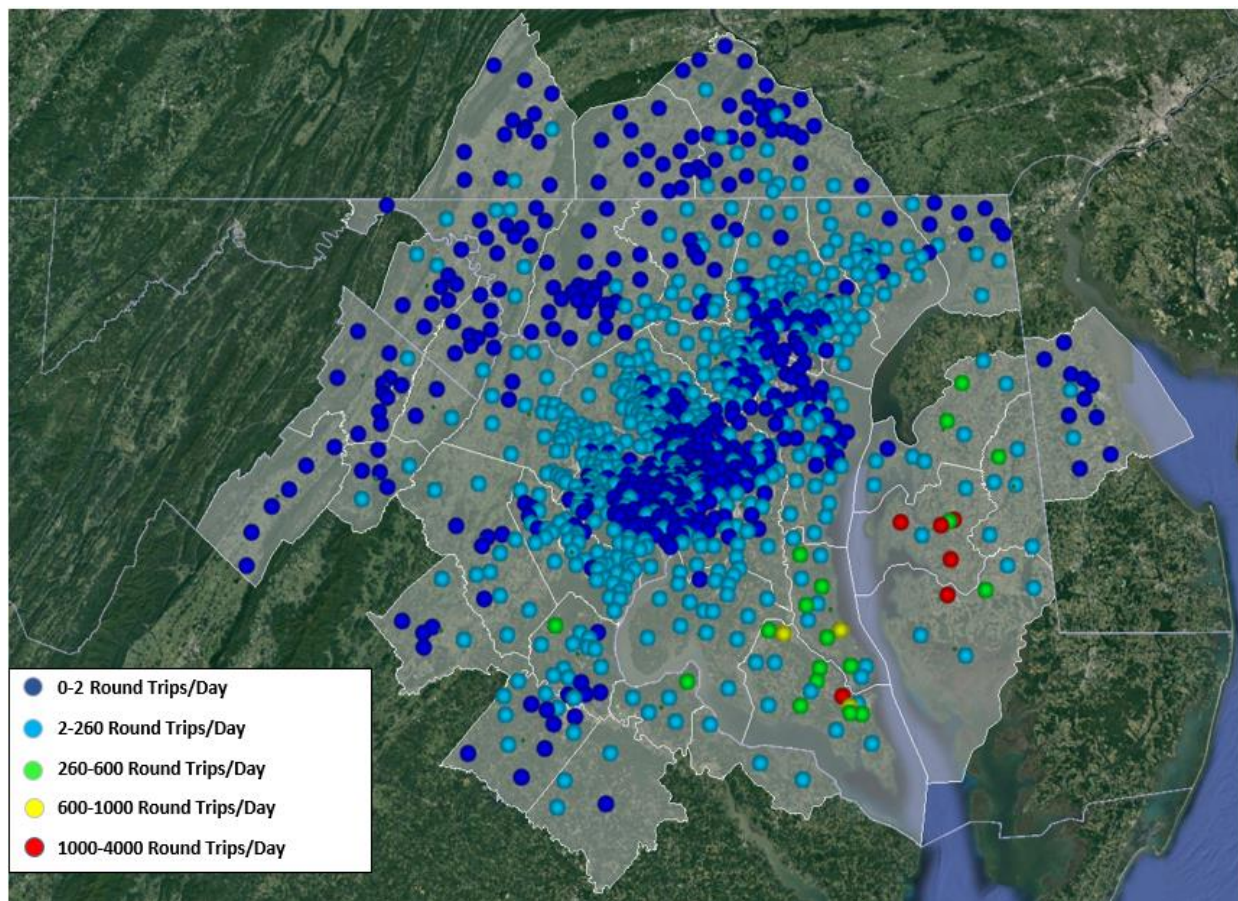


Figure 23: Scenario 1: Landing Site Utilization Washington-Baltimore: \$0.54 Auto Cost, \$15 Base Fare, No Landing Fare, No Cutoff at 20 miles, 5-Minute Ingress Time.

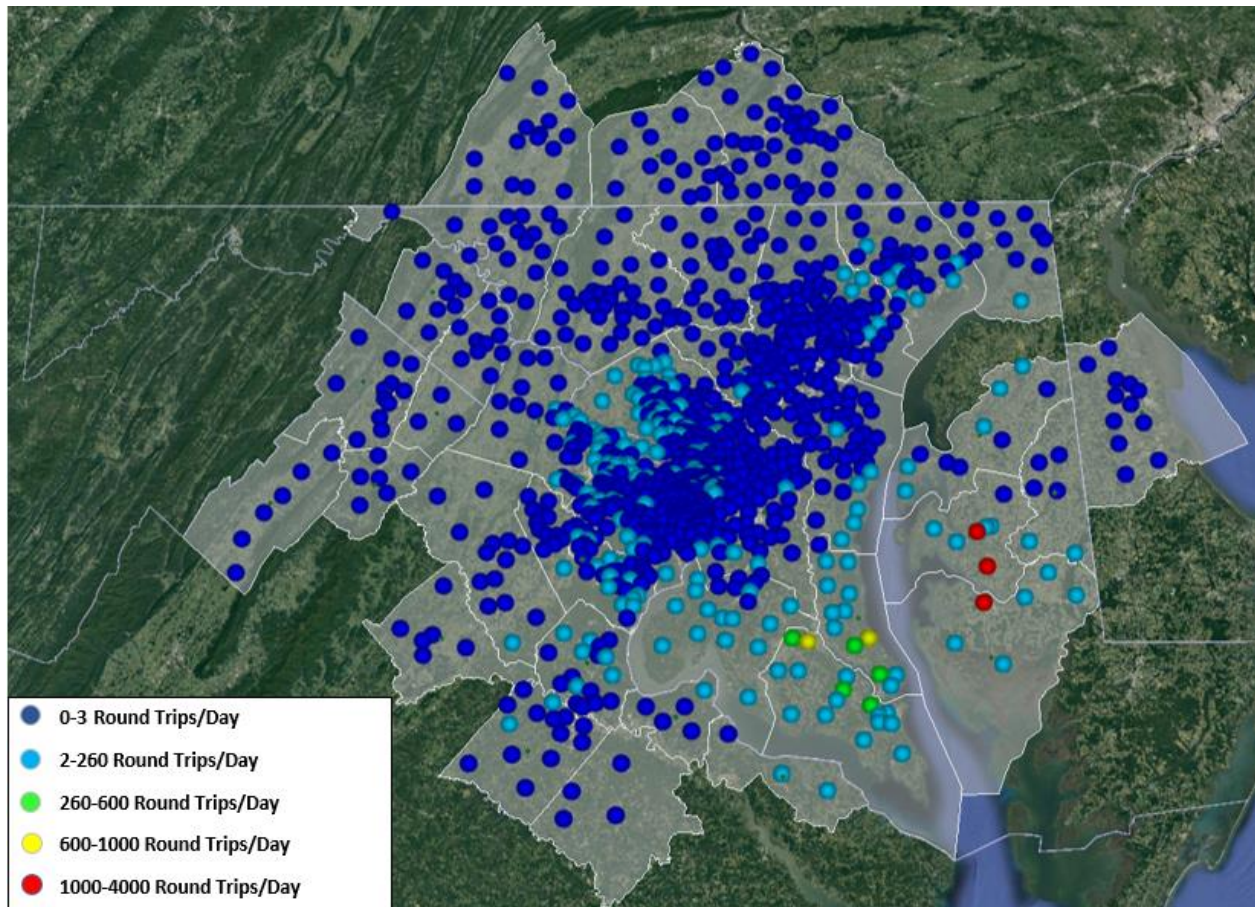


Figure 24: Scenario 2: Landing Site Utilization Washington-Baltimore: \$0.30 Auto Cost, \$15 Base Fare, No Landing Fare, No Cutoff at 20 miles, 5-Minute Ingres Time.

4.3.2 Washington-Baltimore Results Discussion

For the Washington-Baltimore area, the ODM demand is higher compared to the Northern California. The Washington-Baltimore area is not constrained topographically as Northern California and has less distribution of larger distance trips (see

Figure 5). This could explain a more concentrated demand in the Washington-Baltimore area. Furthermore, the calibration of the logit model was made using Northern California area parameters. This can introduce unwanted effects when applied to a different region. In a future analysis, a new re-calibration effort model should be performed specific to the region's travel patterns.

CHAPTER 5: RECOMMENDATIONS AND CONCLUSION

5.1 Conclusion

The preliminary results and considerations are subject to much uncertainty. The cost structure for the ODM concept is not concrete; therefore, the analysis considers many various factors that may contribute to the cost to a passenger. The preliminary results show that in order for the ODM concept to be a significant competitor to other modes, the ODM cost should be kept below \$1 per passenger mile. The cost for operating an automobile deemed to have a significant effect on the demand for the ODM. Considering a cost per passenger-mile of \$1, under the assumption of an auto cost of \$0.30, the demand for the ODM is 0.2%. Increasing the auto cost to the AAA cost per mile of \$0.54, the demand increases to 1.3%. The \$0.30 automobile cost per mile is probably a more realistic value as the current AAA cost per mile would be an over-estimate for future vehicles that are likely to take advantage of autonomous functions or electric technology. The AAA cost contains many different aspects of vehicle operation such as financing, maintenance, gas, and tires and most commuters do not perceive the hidden costs to operate a car aside from the direct operational costs.

Using a load factor of 0.6, 1% market share in Northern California represents about 40,000 commuters per day (4.2 million commuters reported in LODES and ACS). Servicing this demand with the load factor would give approximately 33,000 flights per day, not including dead-heading flights back to position. To put that in perspective, the Air Traffic Control Tower Operations Count from San Francisco Airport for April 2017 was 35,300 (Air Traffic Statistics, 2017).

Many companies that are looking at this concept have optimistic goals for achieving a low cost of operation for the ODM; however, the major challenge will be keeping vehicle

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acquisition and operational costs lower than typical small aircraft costs. Many companies prototyping the design of the aircraft have goals of achieving simplicity in the design and minimizing moving parts that may require heavy maintenance. Likely, a way to achieve lower vehicle acquisition and operational costs would be to produce them at high volumes and remove the pilot from operations (i.e. have autonomous functions for the aircraft).

Additionally, given the high land valuation in the Northern California area, achieving a high amount of landing sites to minimize intermodal time will be costly.

Weather considerations are vital in determining overall demand for the ODM concept. Very likely and based on evidence from existing chartered helicopter companies, commuters will choose not to take the mode in bad weather conditions. San Francisco Bay has 108 days with morning fog (14 days with heavy fog events with less than 0.25 mile visibility). The Washington-Baltimore area is prone to icing conditions.

Air traffic management would have to be considered to manage the large number of flights; therefore putting a great load on the facilities.

The analysis presented in the paper provides some demand calculations under various assumptions as well as recommendations and additional conditions; however, the concept is subject to more scrutiny before it can come into fruition.

5.2 Recommendations

Coefficients Based on Income and Travel Purpose

A distinction in how travel time and travel cost are valued exists depending on the income level. For example, an individual making a salary of over \$100k will value time savings more than travel cost savings. This would mean coefficients for these variables in the logit model

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would be differ depending on the income group. In the analysis presented in the report, the data sources did not have good enough data for defensible, income varied coefficients; therefore, the coefficients in the model presented were considered baseline coefficients that applied to the entire data set. A future run of the model would include coefficients generated based on income level of the individual

Full Public Acceptance

In the initial phases of this concept, the vehicle is expected to be operated with a pilot. As the system matures, the vehicle is expected to be autonomous or include easy enough interfaces for an individual to operate. In the analysis presented in this paper, there is no dis-utility assigned to an individual's perception for discomfort towards operating an autonomous vehicle in a small vehicle or travelling in a small vehicle altogether contributes to some dis-utility. According to a study sponsored by Boeing, 18.1% of Americans are anxious about flying and 12.6% are afraid to fly altogether. Disregarding the dis-utility for an individual because of the size of the ODM aircraft, there will be some decrease in demand because of generalized fear of flying. The model assumes a full public acceptance of flying in the ODM aircraft.

Weather

The model assumes clear weather conditions and full operational conditions. The Washington-Baltimore region is subject to greater IMC conditions than Northern California. In a statement made by the CEO of Blade (a charter flight service based in New York), individuals will generally cancel a flight service in one of the helicopters if weather conditions include precipitation.

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Wind routing is an additional consideration. Turbulence can cause dis-utility to an individual and the ODM aircrafts are very likely to be subject to them given the size. Wind routing based on optimal wind patterns would need to be taken into account.

Capacity Constraint on Landing Site

The demand values are subject to decrease given the capacity on each of the landing sites. There can be multiple take-off and landing points at a landing site but this increase in capacity comes at a cost and can potentially cause further delays that comes as a dis-utility to individuals.

Vertiport versus Vertipad

Consideration would have to be given to which of the landing sites would be simply “vertipads” (i.e. having a single takeoff and landing area) for smaller utilization landing sites or “vertiports” in which there are several takeoff and landing areas as well as charging stations.

Airspace Constraints

If high demand values occur as shown in some of the scenarios, the airspace, especially in high utilization corridors between high demand origin-destination pairs will encounter congestion that can add further travel time to a journey. In a future iteration of the model, there should be several iterations to determine the demand. For instance, in this scenario, high utilization origin-destination pairs can be further processed with additional travel times either by means of an assumed value or a change in the actual vehicle speed.

Closing Feedback Loop: Load Factor

The load factor in the assumptions is 0.6 (i.e. 2.4 passengers in a 4 seater aircraft). The load factor would vary depending on the demand on the ODM flights. This would then have to be re-inputted into the life cycle cost analysis that would increase the cost per passenger-mile.

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This would then drive down demand. The feedback loop would continue until a form of equilibrium is met.

Range of ODM Aircraft

In the analysis, there was no cutoff set for range of the aircraft. The range was assumed to be limitless. Based on literature review, the maximum range of the ODM aircrafts are anywhere from 150- 300 statute miles. In a future run of the model, there would be a design vehicle that would be used.

Proximity of Landing Sites to Residences

As per guidance from NASA, the access time to a landing site from a point of origin would ideally be 5 minutes walking distance. In order to achieve close proximity to residences, there would need to be acceptance of this for residential areas that are likely going to experience noise pollution as well as increased throughput on local streets.

CHAPTER 6: PAPERS

Alongside the thesis submitted, a paper was submitted for a presentation in the AIAA conference in Denver, CO on June 5th, 2017 titled “Preliminary Considerations for ODM Air Traffic Management Based on Analysis of Commuter Passenger Demand and Travel Patterns for the Silicon Valley Region of California.”

Additionally, a final report was submitted to the NASA Langley Research Center in July 2017 titled: “Aviation Global Demand Forecast Model Development and ISAAC Studies: On Demand Mobility Study.”

Throughout the course of the project, biweekly presentations were submitted to the NASA Langley Research Center that served to provide continual updates and, in turn, receive frequent feedback on all phases of the project.

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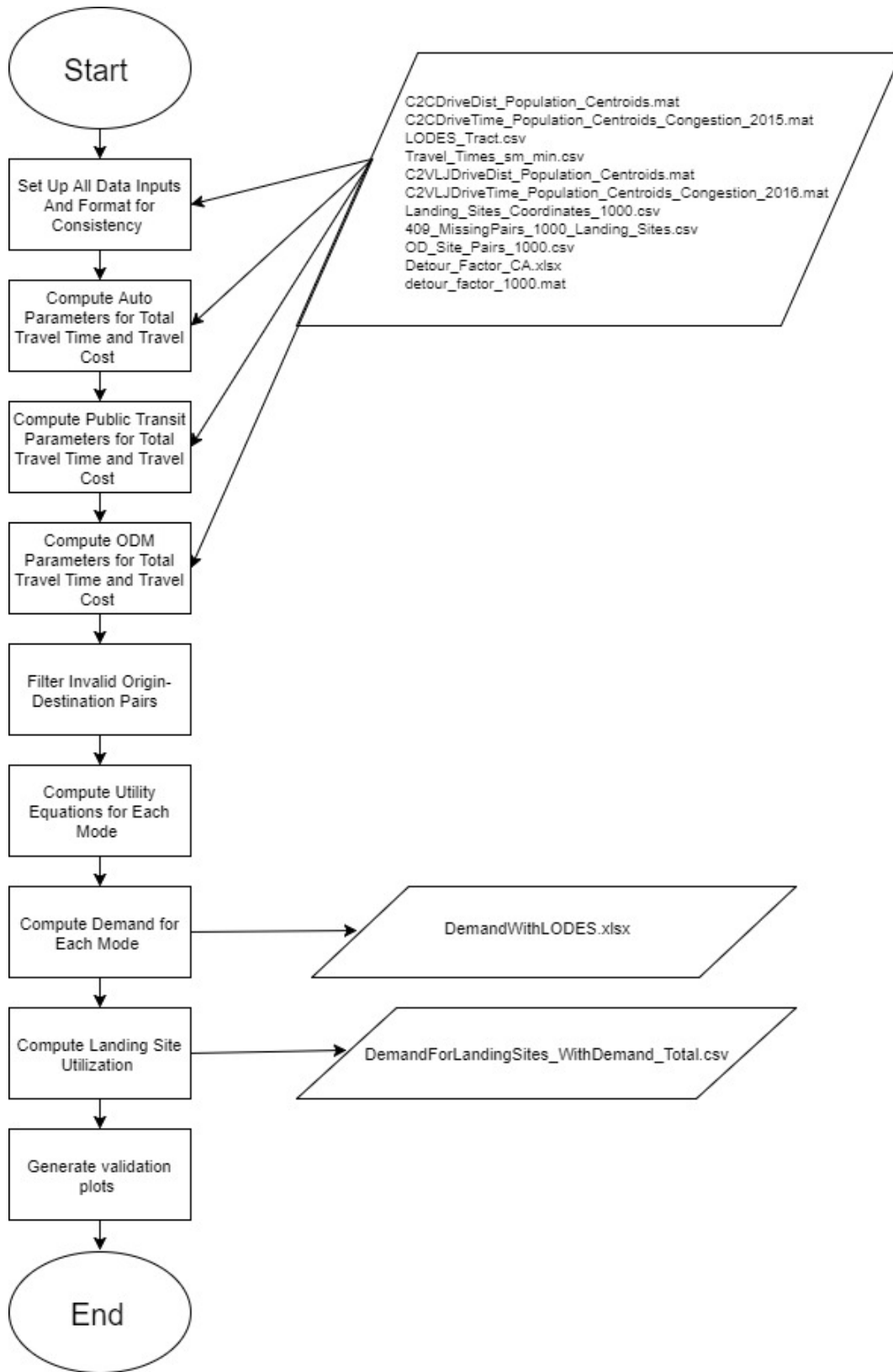
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APPENDIX A – FLOWCHART OF WORK



APPENDIX B – SOURCE CODE

Main Conditional Logit Model Application Script

```
clear all;
close all;
clc;

%This variable will be used when wishing to evaluate for Auto and Public
%parameters (that is done in recalibration)

Exclude_ODM_Recalibration = 0; % Use 1 to only run for Auto and Public

%% Loading Data
%Import the Excel sheet with information pertaining to LODES data
%Column 1: Home Tract INDICES
%Column 2: Work Tract INDICES

ImportTractPairIndices = importdata('.\Input\LODES_Tract_Pairs.csv');
LODES_Origin_Destination = ImportTractPairIndices.data;

%Import the Excel sheet that containing actual tract to tract O-D pairs
%with number of jobs and number of job with earnings over 40K/year
%Column 1: Home Tract GEOID
%Column 2: Work Tract GEOID
%Column 3: Number of Jobs
%Column 4: Number of Jobs >$40k

ImportOriginDestinationJobs = importdata('.\Input\LODES_Tract.csv');
LODES_Origin_Destination_AllInformation = ImportOriginDestinationJobs.data;

TotalNumberJobs = sum(LODES_Origin_Destination_AllInformation(:,3));
TotalHighIncomeJobs = sum(LODES_Origin_Destination_AllInformation(:,4));

%Load data with drive time between population centroids
load '.\Input\C2CDriveTime_Population_Centroids_Congestion_2015.mat';

%Convert the drive times to minutes
DriveTime_Minutes_Centroids = C2CDriveTime_Population_Centroids_Congestion .* 60;

%Load data with drive distance between population centroids
%(miles)
load '.\Input\C2CDriveDist_Population_Centroids.mat';

%Import the spreadsheet for flight profiles giving information of Travel Distance (Statute Miles) and Travel
Time (Minutes)
FlightProfileDistanceAndTravelTime = importdata('.\Input\Travel_Times_sm_min.csv');

%Import the distances between home and nearest ODM landing site
load '.\Input\1000landinganalysis\ODM_1000_3_16_2017\C2VLJDriveDist_Population_Centroids.mat'

%Import the driving time between home and ODM landing site
load '.\Input\1000landinganalysis\ODM_1000_3_16_2017\C2VLJDriveTime_Population_Centroids_Congestion_2016.mat'

%Import the coordinates for landing sites
%State
%ID
%Latitude
%Longitude

Coordinates1000LandingSites = importdata('.\Input\1000landinganalysis\Landing_Sites_Coordinates_1000.csv');
Coordinates1000LandingSites = Coordinates1000LandingSites.data(:,2:3);

%Import the 409 Tract Centroids that are manually assigned a landing site
%and distance
%Column 1: Tract Number
%Column 2: GEOID of Tract
%Column 3: Tract Longitude
%Column 4: Tract Latitude
%Column 5: Corresponding landing site number
%Column 6: Landing site longitude
%Column 7: Landing site latitude
%Column 8: Population
%Column 9: Distance (statute miles)
```

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```
Missing409Pairs1000LandingSites =
importdata('.\Input\1000landinganalysis\409_MissingPairs_1000_Landing_Sites.csv');
Missing409Pairs1000LandingSites = Missing409Pairs1000LandingSites.data;

%Import file showing assigned landing sites to each tract (1968). There are
%a total of 2386 tracts; however, 9 are removed from the analysis
%altogether :(

OD_LandingSite_AssignedTractCentroid = importdata('.\Input\1000landinganalysis\OD_Site_Pairs_1000.csv');
OD_LandingSite_AssignedTractCentroid = OD_LandingSite_AssignedTractCentroid.data;

%Import detour factors for each route
DetourFactorEachRoute = importdata('.\Input\DetourFactors\Detour_Factor_CA.xlsx');
DetourFactorEachRoute = DetourFactorEachRoute.data.xl1000;

    %Used Columns: Column 1 = Home Landing Site
    %                Column 4 = Work Landing Site
    %                Column 9 = Detour Factor
    %NOTE: Column 9 (Detour Factor) will actually be removed because there
    %were errors found in the original data file, therefore the following
    %will be used for detour factors for the 1000 landing site analysis

    load '.\Input\DetourFactors\detour_factor_1000.mat'

DetourFactorEachRoute_Home = DetourFactorEachRoute(:,1);
DetourFactorEachRoute_Work = DetourFactorEachRoute(:,4);
DetourFactorEachRoute = detour_factor;

%% A Few Constants
%Inflation Array to convert dollar amount equivalents in each year compared to 2009
%[DollarAmount2010 DollarAmount2011 DollarAmount2012 DollarAmount2013
%DollarAmount 2014 DollarAmount2015 DollarAmount2016]

CPIConversionFrom2009 = [1.02 1.05 1.07 1.09 1.10 1.10 1.12];

NumberODData_LODES = length(LODES_Origin_Desination);

NumberOfTracts = length(C2CDriveDist_Population_Centroids);

%% Computing Auto Parameters

%In Vehicle Time-Auto-----

Origin_Destination_Home = LODES_Origin_Desination(:,1);
Origin_Destination_Work = LODES_Origin_Desination(:,2);
linear_idx = sub2ind(size(DriveTime_Minutes_Centroids), Origin_Destination_Home, Origin_Destination_Work);
InVehicleTimeAuto = DriveTime_Minutes_Centroids(linear_idx);

%Out of Vehicle Time-----

OVTAuto = ones(NumberODData_LODES,1) * 2.5;

%Travel Cost-----

AAAacostpermile = 0.592 / CPIConversionFrom2009(5); %In units of dollars from 2009

AutoOccupancyRate = 1.13; %The units are in person miles/vehicle miles
ParkingCost       = 9.38; %dollars

%The Interstate Tolls Cost is based on July 1, 2016 rates for Golden Gate
%Toll Rates (2 axles/motorcycles FasTrack Toll: $6.50) http://goldengatebridge.org/tolls\_traffic/toll\_rates.php

%Antioch Bridge = $5
%Benicia-Martinez Bridge = $5
% Carquinez Bridge = $5
% Dumbarton Bridge = $5
% Richmond-San Rafael Bridge = $5
% San Francisco-Oakland Bay Bridge = $6
% San Mateo-Hayward Bridge = $5

InterstateTollsCost = 0; %dollars

%In Vehicle Distance
```

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```
Origin_Destination_Home = LODES_Origin_Desination(:,1);
Origin_Destination_Work = LODES_Origin_Desination(:,2);
linear_idx = sub2ind(size(C2CDriveDist_Population_Centroids), Origin_Destination_Home,
Origin_Destination_Work);
InVehicleMilesTraveledAuto = C2CDriveDist_Population_Centroids(linear_idx);

AutoCost_DistanceMiles = InVehicleMilesTraveledAuto * AAAcostpermile ;

%Total Auto Travel Cost door to door
TravelCost_Auto = ((AutoCost_DistanceMiles) + (ParkingCost+InterstateTollsCost)) / AutoOccupancyRate;

%Auto Cost For Just Driving (Used in plotting)
AutoInVehicleCost = AutoCost_DistanceMiles / AutoOccupancyRate; % For plotting

%% Computing Public Transportation Parameters

%In Vehicle Time-----
%Equating the same in vehicle distance as in vehicle distance for auto
%since we do not have better information at the moment

    InVehicleMilesTraveledPublic = InVehicleMilesTraveledAuto;

    AvgAutoSpeedSanFran = 27.5;
    AvgPublicSpeedSanFran = 23.5;    %Original Speed from average NHTS entries is 23.5 mph

    InVehicleTimePublic = (InVehicleMilesTraveledPublic / AvgPublicSpeedSanFran) * 60; % Use average speed
according to Davide's thesis

%Out of Vehicle
%Time-----

%Total OVT For Public
% OVTPublic = PublicAutoTravelTime + OVT_WaitTimeStation_Public + OVT_StationToWork_Public;
    % Intermodal time used by Davide. See thesis.
    OVTPublic = ones(NumberODData_LODES,1) * 22.66;

%Travel Cost-----
%The equation to compute public transportation cost is: Transit Cost =
%Base Fare+Variable Fare + Auto Cost for Driving to/from Transit

%The base fare that will be used is $1.54 (2009 Dollars)
    BaseFare_Public = 1.54;

% To compute auto cost for driving to/from transit we will be using the same
% equation as previously for auto users: (AAA cost per mile+parkingcost_interstatetoll)/(AutoOccupancyRate)
% The parameter that would be changed in this case would be the parameter
% (AAA cost per mile) because the distances will be different.
%Use the 2 mile distance to get to transit as defined earlier:
    DistancefromHometoStationPublic = 2; %miles

    AutoCostToPublic_DistanceMiles = DistancefromHometoStationPublic * AAAcostpermile;
    AutoCostPortionofTravelCostPublic = (AutoCostToPublic_DistanceMiles + ((ParkingCost +
InterstateTollsCost) * 0.5)) / AutoOccupancyRate;

%Computing the total cost of taking transit door to door
    TravelCost_Public = BaseFare_Public + AutoCostPortionofTravelCostPublic + (0.087 *
InVehicleMilesTraveledPublic);

%Computing the cost of taking transit just in vehicle
    PublicInVehicleCost = TravelCost_Public - AutoCostPortionofTravelCostPublic; % For plotting

%% Computing ODM Parameters

%Out of Vehicle
%Time-----

%Use the Out of Vehicle Time constant as stated above in the "constants"
%section:

%There are several parameters that come into play to compute the OVT for
%ODM
%(1) Home to Airport----> Auto (Intermodal)
%(2) Ingress/Egress @ Airport ---> (Wait Time)
%(3) Airport to Work ----> Auto (Intermodal)

%Assign a Landing Site to Each Tract

    ODMLandSites_Assigned = [OD_LandingSite_AssignedTractCentroid; Missing409Pairs1000LandingSites(:, [1
5])];
```

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```
ODMLandSites_Assigned = sortrows (ODMLandSites_Assigned);

ODMLandSites_Unassigned = (1:NumberOfTracts)';
ODMLandSites_Unassigned = setdiff(ODMLandSites_Unassigned, ODMLandSites_Assigned(:,1));
Matrix (1:9,1) = 1001; %To prevent the nan from causing issues later, just assign it to a landing
site of 1001 for INVALID
% ODMLandSites_Unassigned = [ODMLandSites_Unassigned nan(9,1)];
ODMLandSites_Unassigned = [ODMLandSites_Unassigned Matrix];

ODMLandingSiteUsedForEachTract = [ODMLandSites_Assigned; ODMLandSites_Unassigned];
ODMLandingSiteUsedForEachTract = sortrows (ODMLandingSiteUsedForEachTract);
ODMLandingSiteUsedForEachTract = ODMLandingSiteUsedForEachTract(:,2);

%Find the ODM Landing Site used from home to nearest landing site

HomeTractNumber = LODES_Origin_Desination(:,1);
ODMLandingUsedInAnalysis_Home = ODMLandingSiteUsedForEachTract (HomeTractNumber);

%Find the ODM Landing Site used to access each work place

WorkTractNumber = LODES_Origin_Desination(:,2);
ODMLandingUsedInAnalysis_Work = ODMLandingSiteUsedForEachTract (WorkTractNumber);
[row_findisanwork, col_findisanwork] = find(isnan(ODMLandingUsedInAnalysis_Work));
[row_findisanhome, col_findisanhome] = find(isnan(ODMLandingUsedInAnalysis_Home));

%Consolidate information about which landing sites were used for each O-D
%pair
ODMLandingUsedInAnalysis = [ODMLandingUsedInAnalysis_Home ODMLandingUsedInAnalysis_Work];

%-----
%Find distances for the Tracts that have an assigned landing site
PopulationCentroidToODMLandingDistance = abs(C2VLJDriveDist_Population_Centroids);
PopulationCentroidToODMLandingDistance_ShortestAssigned =
zeros (length (PopulationCentroidToODMLandingDistance),1);

for shortdistancedetermine = 1: length(PopulationCentroidToODMLandingDistance)
PopulationCentroidToODMLandingDistance_ShortestAssigned (shortdistancedetermine) = min
(PopulationCentroidToODMLandingDistance (shortdistancedetermine,:));
end

% Find the 999 entries:
Find999ForShortDistanceAssignedODM =
(PopulationCentroidToODMLandingDistance_ShortestAssigned ~= 999);

% Get resultant matrix
PopulationCentroidToODMLandingDistance_ShortestAssigned =
PopulationCentroidToODMLandingDistance_ShortestAssigned (Find999ForShortDistanceAssignedODM);
PopulationCentroidToODMLandingDistance_ShortestAssigned =
[OD_LandingSite_AssignedTractCentroid(:,1) PopulationCentroidToODMLandingDistance_ShortestAssigned];

%Find distances for Tracts that have manually been assigned a landing site

PopulationCentroidToODMLandingDistance_ShortestManual =
[Missing409Pairs1000LandingSites(:,1) Missing409Pairs1000LandingSites(:,9)];

%Create a matrix for 9 tracts that don't have a landing site
PopulationCentroidToODMLandingDistance_ShortestUnAssigned = ODMLandSites_Unassigned;

%Culimmate all the information about shortest distance to the landing sites
PopulationCentroidToODMLandingDistance_Shortest =
[PopulationCentroidToODMLandingDistance_ShortestAssigned;
PopulationCentroidToODMLandingDistance_ShortestManual;
PopulationCentroidToODMLandingDistance_ShortestUnAssigned];
PopulationCentroidToODMLandingDistance_Shortest = sortrows
(PopulationCentroidToODMLandingDistance_Shortest);
PopulationCentroidToODMLandingDistance_Shortest =
PopulationCentroidToODMLandingDistance_Shortest(:,2);

%Find times for the Tracts that have an assigned landing site
```

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```

        PopulationCentroidToODMLandingTime = abs(C2VLJDriveTime_Population_Centroids_Congestion .*
60);
        PopulationCentroidToODMLandingTime_ShortestAssigned =
zeros(length(PopulationCentroidToODMLandingTime),1);

        for shorttimedetermine = 1:length(PopulationCentroidToODMLandingDistance)
            PopulationCentroidToODMLandingTime_ShortestAssigned(shorttimedetermine) = min
(PopulationCentroidToODMLandingTime(shorttimedetermine,:));
        end

        % Find the 999 entries:
        Find999ForShortTimeAssignedODM =
(PopulationCentroidToODMLandingTime_ShortestAssigned ~= (999*60));

        % Get resultant matrix
        PopulationCentroidToODMLandingTime_ShortestAssigned =
PopulationCentroidToODMLandingTime_ShortestAssigned(Find999ForShortTimeAssignedODM);
        PopulationCentroidToODMLandingTime_ShortestAssigned =
[OD_LandingSite_AssignedTractCentroid(:,1) PopulationCentroidToODMLandingTime_ShortestAssigned];

        %Find times for Tracts that have manually been assigned a landing site
        %Based on assumption of 3.1 mph walking speeds (assume for
        %these distances people will walk)
        WalkingSpeed = 3.1 /60; %miles/min

        Missing409Pairs1000LandingSites_DistanceconvertedToTime =
Missing409Pairs1000LandingSites(:,9) / WalkingSpeed;

        PopulationCentroidToODMLandingTime_ShortestManual = [Missing409Pairs1000LandingSites(:,1)
Missing409Pairs1000LandingSites_DistanceconvertedToTime];

        %Create a matrix for 9 tracts that don't have a landing site
        PopulationCentroidToODMLandingTime_ShortestUnAssigned = ODMLandSites_Unassigned;

        %Culminate all the information about shortest times to the landing sites
        PopulationCentroidToODMLandingTime_Shortest =
[PopulationCentroidToODMLandingTime_ShortestAssigned; PopulationCentroidToODMLandingTime_ShortestManual;
PopulationCentroidToODMLandingTime_ShortestUnAssigned];
        PopulationCentroidToODMLandingTime_Shortest = sortrows
(PopulationCentroidToODMLandingTime_Shortest);
        PopulationCentroidToODMLandingTime_Shortest =
PopulationCentroidToODMLandingTime_Shortest(:,2);

        %-----
%Find the time for the distance to landing site from home (OVTODM-->Home To
%Airport)

        HomeTractNumber = LODES_Origin_Desination(:,1);
        ODMIntermodalTravelTime_HomeToAirport = PopulationCentroidToODMLandingTime_Shortest(HomeTractNumber);
        ODMIntermodalDistance_HometoAirport = PopulationCentroidToODMLandingDistance_Shortest(HomeTractNumber);

%Find the time for the distance from the landing site to work (OVTODM-->Airport to Work)

        WorkTractNumber = LODES_Origin_Desination(:,2);
        ODMIntermodalTravelTime_AirportToWork = PopulationCentroidToODMLandingTime_Shortest(WorkTractNumber);
        ODMIntermodalDistance_AirportToWork = PopulationCentroidToODMLandingDistance_Shortest(WorkTractNumber);

        % ODMIntermodalTravelTime_HomeToAirport = zeros(NumberODData_LODES,1);
        % ODMIntermodalTravelTime_AirportToWork = zeros(NumberODData_LODES,1);

        AverageWalkingSpeed = 3.1; %miles per hour
        AverageWalkingSpeed = AverageWalkingSpeed / 60; %miles per minute

tic

        for i= 1: NumberODData_LODES
            if ODMIntermodalDistance_HometoAirport(i) <= 0.25
                ODMIntermodalTravelTime_HomeToAirport(i) = (ODMIntermodalDistance_HometoAirport(i)) ./
(AverageWalkingSpeed);

            else
                ODMIntermodalTravelTime_HomeToAirport(i) = ODMIntermodalTravelTime_HomeToAirport(i);
            end
        end
    
```

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```

        if ODMIntermodalDistance_AirportToWork (i) <= 0.25
            ODMIntermodalTravelTime_AirportToWork (i) = (ODMIntermodalDistance_AirportToWork (i)) ./
(AverageWalkingSpeed);
        else
            ODMIntermodalTravelTime_AirportToWork (i) = ODMIntermodalTravelTime_AirportToWork (i);
        end
    end

end

toc

    ODMIntermodalTravelTime = ODMIntermodalTravelTime_HomeToAirport +
ODMIntermodalTravelTime_AirportToWork;

%Ingress and Egress Time AT Landing Site

    ODMIngressTime = 5; %minutes
    ODMEgressTime = 5; %minutes

%Total Out of Vehicle Time for ODM
    OVTODM = ODMIntermodalTravelTime + ODMIngressTime + ODMEgressTime;

%In Vehicle Time: ODM -----
%Determine what the in vehicle time is between landing sites

    %Find coordinates matched to each landing site

        %Working with ODM Detour factors, we have specific ones depending
        %on the route

        Detour_Home_ForConcat = DetourFactorEachRoute_Home * 10000;
        Detour_Total_Concat = Detour_Home_ForConcat + DetourFactorEachRoute_Work;

        ODMLandingUsedInAnalysis_Home_ForConcat = ODMLandingUsedInAnalysis_Home * 10000;
        ODMLandingUsedInAnalysis_Total_ForConcat = ODMLandingUsedInAnalysis_Home_ForConcat +
ODMLandingUsedInAnalysis_Work;

        [Logical_Detour, Location_Detour] = ismember (ODMLandingUsedInAnalysis_Total_ForConcat,
Detour_Total_Concat);

        AverageDetourFactor = mean(DetourFactorEachRoute);

        %If the route is not assigned a detour factor location, assign it the mean
        %detour factor

        ArtificialLocationNoDetour = (length(DetourFactorEachRoute)) + 1;

        for detourfactorcheck = 1: length(Location_Detour)
            if Location_Detour (detourfactorcheck) == 0
                Location_Detour (detourfactorcheck) = ArtificialLocationNoDetour;
            else
                Location_Detour (detourfactorcheck) = Location_Detour (detourfactorcheck);
            end
        end

        DetourFactorEachRoute = [DetourFactorEachRoute; AverageDetourFactor]; %Making the last element of the
matrix, the average to account for pairs with no detour reported

        %Assign detour factors to each route
        ODM_Detour_Factor = DetourFactorEachRoute (Location_Detour);

        Latitudes = Coordinates1000LandingSites(:,2);
        Latitudes = [Latitudes; 0]; % We are adding a zero to account for those tracts that are located on
water

        Longitudes = Coordinates1000LandingSites(:,1);
        Longitudes = [Longitudes; 0]; %We are adding a zero to account for those tracts that are located on
water

        LatsUsedHome = Latitudes (ODMLandingUsedInAnalysis_Home);
        LongsUsedHome = Longitudes (ODMLandingUsedInAnalysis_Home);

        LatsUsedWork = Latitudes (ODMLandingUsedInAnalysis_Work);
        LongsUsedWork = Longitudes (ODMLandingUsedInAnalysis_Work);

        ComputingInVehicleDistanceODM = distance (LatsUsedHome, LongsUsedHome, LatsUsedWork, LongsUsedWork);

```

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```

InVehicleMilesTraveledODM      = deg2sm(ComputingInVehicleDistanceODM);
InVehicleMilesTraveledODM     = ODM_Detour_Factor .* InVehicleMilesTraveledODM ;

InVehicleTimeODM = (interpl(FlightProfileDistanceAndTravelTime(:,1),
FlightProfileDistanceAndTravelTime(:,2), InVehicleMilesTraveledODM));

%Travel Cost-----
%There are two portions of travel cost needed to consider for the ODM
%vehicle:
%(1) Intermodal Travel Cost to and from the airport
%     (1a) Walking to landing site
%     (2a) Taking Uber to landing site
%(2) Travel Cost in ODM vehicle

% TRAVEL COST IN ODM VEHICLE
ODM_LandingCost = 6.70; %6.70
ODM_InVehicle_Base_Cost = 15; %2009 Dollars
ODM_InVehicle_Base_Cost = ODM_InVehicle_Base_Cost + ODM_LandingCost;
ODM_Cost_Per_Seat_Mile = 1.23; %2009 Dollars

ODMInVehicleCost = ODM_InVehicle_Base_Cost + ODM_Cost_Per_Seat_Mile.* InVehicleMilesTraveledODM;

% INTERMODAL TRAVEL COST TO AND FROM THE AIRPORT

Uber_BaseFare      = 1.78; %2009 Dollars--Converted from ($2) 2016 dollars
Uber_PerMinute     = 0.2; %2009 Dollars--Converted from ($0.22) 2016 dollars
Uber_PerMile       = 1.02; %2009 Dollars--Converted from ($1.15) 2016 dollars
Uber_ServiceFee    = 1.38; %2009 Dollars--Converted from ($1.55) 2016 dollars
Uber_MinimumFare   = 9.40/2; %2009 Dollars--Converted from ($10.55) 2016 dollars

TravelCostODM_UberPerMinute = zeros(NumberODData_LODES,1);
TravelCostODM_UberPerMile   = zeros(NumberODData_LODES,1);
TravelCost_ODM_UberComponent_HometoAirport = zeros(NumberODData_LODES,1);

tic

for i= 1: NumberODData_LODES
    if ODMIntermodalDistance_HometoAirport (i) <= 0.25
        TravelCostODM_UberPerMinute(i) = 0;
        TravelCostODM_UberPerMile(i)   = 0;
        TravelCost_ODM_UberComponent_HometoAirport(i) = 0;
    else
        TravelCostODM_UberPerMinute(i) = ODMIntermodalTravelTime_HomeToAirport(i) * Uber_PerMinute;
        TravelCostODM_UberPerMile(i)   = (ODMIntermodalDistance_HometoAirport(i)) .* Uber_PerMile;
        TravelCost_ODM_UberComponent_HometoAirport(i) = Uber_BaseFare + Uber_ServiceFee +
TravelCostODM_UberPerMinute(i) + TravelCostODM_UberPerMile(i);

        if TravelCost_ODM_UberComponent_HometoAirport (i) < Uber_MinimumFare
            TravelCost_ODM_UberComponent_HometoAirport (i) = Uber_MinimumFare;
        else
            TravelCost_ODM_UberComponent_HometoAirport (i) = Uber_BaseFare + Uber_ServiceFee +
TravelCostODM_UberPerMinute(i) + TravelCostODM_UberPerMile(i);
        end
    end
end

toc

TravelCostODMIntermodal_HometoAirport = 1.5 * TravelCost_ODM_UberComponent_HometoAirport ; %The 1.5 is to
account for surge pricing

TravelCostODM_UberPerMinute2 = zeros(NumberODData_LODES,1);
TravelCostODM_UberPerMile2   = zeros(NumberODData_LODES,1);
TravelCost_ODM_UberComponent_AirporttoWork = zeros(NumberODData_LODES,1);

tic

for i= 1: NumberODData_LODES

```


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```
if ODMIntermodalDistance_AirportToWork (i) <= 0.25
    TravelCostODM_UberPerMinute2(i) = 0;
    TravelCostODM_UberPerMile2(i) = 0;
    TravelCost_ODM_UberComponent_AirporttoWork(i) = 0;
else
    TravelCostODM_UberPerMinute2(i) = ODMIntermodalTravelTime_AirportToWork(i) * Uber_PerMinute;
    TravelCostODM_UberPerMile2(i) = (ODMIntermodalDistance_AirportToWork(i)) .* Uber_PerMile;
    TravelCost_ODM_UberComponent_AirporttoWork(i) = Uber_BaseFare + Uber_ServiceFee +
    TravelCostODM_UberPerMinute2(i) + TravelCostODM_UberPerMile2(i);

    if TravelCost_ODM_UberComponent_AirporttoWork (i) < Uber_MinimumFare
        TravelCost_ODM_UberComponent_AirporttoWork (i) = Uber_MinimumFare;
    else
        TravelCost_ODM_UberComponent_AirporttoWork (i) = Uber_BaseFare + Uber_ServiceFee +
    TravelCostODM_UberPerMinute2(i) + TravelCostODM_UberPerMile2(i);
    end
end
end
end

toc

TravelCostODMIntermodal_AirportToWork = 1.5 * TravelCost_ODM_UberComponent_AirporttoWork; %The 1.5 is to
account for surge pricing

%Computing the total cost
    TravelCost_ODM = TravelCostODMIntermodal_HometoAirport + TravelCostODMIntermodal_AirportToWork +
    ODMInVehicleCost;

%% Filtering process

% Remove OD pairs with same Origin/Destination
    Valid_OD_Pairs_Tract2Tract = LODES_Origin_Desination(:,1) ~= LODES_Origin_Desination(:,2);
    disp(['Invalid Tract2Tract OD Pairs: ', num2str(sum(Valid_OD_Pairs_Tract2Tract == 0))]);

% Remove OD Pairs where there is no drivng distance between tract and landing site
    Valid_OD_Pairs_Tract2LandingSite = ODMLandingUsedInAnalysis_Home ~= 1001 &
    ODMLandingUsedInAnalysis_Work~= 1001;
    disp(['Invalid Tract2Landing OD Pairs: ', num2str(sum(Valid_OD_Pairs_Tract2LandingSite == 0))]);

%Remove OD Pairs where same landing site

    Valid_OD_Pairs_Tract_SameLandingSite = ODMLandingUsedInAnalysis_Home ~= ODMLandingUsedInAnalysis_Work;

    disp(['Invalid SameLandingSite: ', num2str(sum(Valid_OD_Pairs_Tract_SameLandingSite == 0))]);

% Set valid OD pairs
    Valid_OD_Pairs = Valid_OD_Pairs_Tract2Tract & Valid_OD_Pairs_Tract2LandingSite &
    Valid_OD_Pairs_Tract_SameLandingSite;

    disp(['Invalid OD Pairs: ', num2str(sum(Valid_OD_Pairs == 0))]);

%% Summing Up the Travel Times
    TotalTravelTimeAuto = InVehicleTimeAuto + OVTAuto;
    TotalTravelTimePublic = InVehicleTimePublic + OVTPublic;
    if Exclude_ODM_Recalibration == 0
        TotalTravelTimeODM = InVehicleTimeODM + OVTODM;
    end

%% Utility Computations

%The Utility Function equation for each mode is as follows:
%U=coeffTC*TC+coeffTT*TT

%Input the coefficients
    TC_Coefficient = -.465;
    TT_Coefficient = -.196;

%Auto-----

%For computation of utility WITHOUT Income Groups coefficients
    UtilitiesAutoMatrixWithOUTIncomeGroups = (TT_Coefficient * TotalTravelTimeAuto) + (TC_Coefficient *
    TravelCost_Auto);
    if any(isnan(UtilitiesAutoMatrixWithOUTIncomeGroups))
        error('ERROR: NaN found in UtilitiesAutoMatrixWithOUTIncomeGroups!');
```

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```
end

%Public-----
%For computation of utility WITHOUT Income Groups coefficients
UtilitiesPublicMatrixWithOUTIncomeGroups = (TT_Coefficient * TotalTravelTimePublic) + (TC_Coefficient *
TravelCost_Public);
if any(isnan(UtilitiesPublicMatrixWithOUTIncomeGroups))
    error('ERROR: NaN found in UtilitiesPublicMatrixWithOUTIncomeGroups!');
end

% ODM -----
%For computation of utility for ODM without Income Groups coefficients and
%using Uber
if Exclude_ODM_Recalibration == 0
    UtilitiesODMMatrixWithOUTIncomeGroups = (TT_Coefficient * TotalTravelTimeODM) + (TC_Coefficient *
TravelCost_ODM);
%     if any(isnan(UtilitiesODMMatrixWithOUTIncomeGroups))
%         error('ERROR: NaN found in UtilitiesODMMatrixWithOUTIncomeGroups!');
%     end
end

% Only keep valid OD pairs
UtilitiesAutoMatrixWithOUTIncomeGroups = UtilitiesAutoMatrixWithOUTIncomeGroups(Valid_OD_Pairs);
UtilitiesPublicMatrixWithOUTIncomeGroups = UtilitiesPublicMatrixWithOUTIncomeGroups(Valid_OD_Pairs);

if Exclude_ODM_Recalibration == 0
    UtilitiesODMMatrixWithOUTIncomeGroups = UtilitiesODMMatrixWithOUTIncomeGroups(Valid_OD_Pairs);
end

%For ODM, we want to only keep the valid in vehicle distances.
if Exclude_ODM_Recalibration == 0
    InVehicleMilesTraveledODMForValidPairs = InVehicleMilesTraveledODM(Valid_OD_Pairs);
end

%% Computing Probability

%We are making a distinction in computing the denominator of
%including/excluding ODM--- for purpose of recalibration
if Exclude_ODM_Recalibration == 0
    ShortDistance_ODM = find(InVehicleMilesTraveledODMForValidPairs <= 0);
    LongerDistance_ODM = find(InVehicleMilesTraveledODMForValidPairs > 0);
end

if Exclude_ODM_Recalibration == 0
    Denominator = exp(UtilitiesAutoMatrixWithOUTIncomeGroups) +
exp(UtilitiesPublicMatrixWithOUTIncomeGroups) + exp(UtilitiesODMMatrixWithOUTIncomeGroups);
    Denominator(ShortDistance_ODM) = exp(UtilitiesAutoMatrixWithOUTIncomeGroups(ShortDistance_ODM)) +
exp(UtilitiesPublicMatrixWithOUTIncomeGroups(ShortDistance_ODM));
else
    Denominator = exp(UtilitiesAutoMatrixWithOUTIncomeGroups) +
exp(UtilitiesPublicMatrixWithOUTIncomeGroups);
end

%Compute the probability of ODM-- the first check is to ensure that the
%calibration "switch is on." Then the second check is to set the
%probability equal to zero for any entries where the in vehicle miles is
%equal to or less than 5.

if Exclude_ODM_Recalibration == 0
    ProbabilityODMMatrixWithOUTIncomeWithUber = exp(UtilitiesODMMatrixWithOUTIncomeGroups) ./
Denominator;
    ProbabilityODMMatrixWithOUTIncomeWithUber(ShortDistance_ODM) = 0;
end

%Compute the other two probabilities
ProbabilityAutoMatrixWithOUTIncomeWithUber = exp(UtilitiesAutoMatrixWithOUTIncomeGroups) ./
Denominator;

ProbabilityPublicMatrixWithOUTIncomeWithUber = exp(UtilitiesPublicMatrixWithOUTIncomeGroups) ./
Denominator;

%All probabilities should be equal to 1-- if not, find them
%NOTE: When Matlab computes exponents sometimes there is a very minor
%error, so some values cannot be PERFECTLY 1.
if Exclude_ODM_Recalibration == 0
```

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```
ProbabilityCheck= ProbabilityODMMatrixWithOUTIncomeWithUber +
ProbabilityAutoMatrixWithOUTIncomeWithUber + ProbabilityPublicMatrixWithOUTIncomeWithUber;
disp(['Invalid Probability: ', num2str(sum( abs(ProbabilityCheck-1)> .0001 ))]);

else
    ProbabilityCheck = ProbabilityAutoMatrixWithOUTIncomeWithUber +
ProbabilityPublicMatrixWithOUTIncomeWithUber;
    disp(['Invalid Probability: ', num2str(sum( abs(ProbabilityCheck-1)> .0001 ))]);
end

%If there are any bad probabilities, find them!
FindBadProbability = find(abs(ProbabilityCheck-1)> .0001);

%% Model Test
OVTAuto_Test = 2.5; % minutes
OVTPublic_Test = 22.6600; % minutes

InVehicleTimeAuto_Test = 1:100;
TravelCost_Auto_Test = 1:100;
TotalTravelTimeAuto_Test = InVehicleTimeAuto_Test + OVTAuto_Test;

InVehicleTimePublic_Test = (1:100) * 2;
TravelCost_Public_Test = (1:100) * 0.5;
TotalTravelTimePublic_Test = InVehicleTimePublic_Test + OVTPublic_Test;

UtilitiesAuto_Test = (TT_Coefficient * TotalTravelTimeAuto_Test) + (TC_Coefficient *
TravelCost_Auto_Test);
UtilitiesPublic_Test = (TT_Coefficient * TotalTravelTimePublic_Test) + (TC_Coefficient *
TravelCost_Public_Test);

ProbabilityAuto_Test = exp(UtilitiesAuto_Test) ./ (exp(UtilitiesAuto_Test) +
exp(UtilitiesPublic_Test));
ProbabilityPublic_Test = exp(UtilitiesPublic_Test) ./ (exp(UtilitiesAuto_Test) +
exp(UtilitiesPublic_Test));

figure ('Name','Probability Test');
plot(1:100, ProbabilityAuto_Test, '-b','DisplayName', 'ProbabilityAutoTest');
hold on;
plot(1:100, ProbabilityPublic_Test, '-r', 'DisplayName', 'ProbabilityPublicTest');
% xlabel('Driving Distance From Origin-Destination(miles)')
ylabel('Probability')
title('Model Test: Probability Test')
legend ('show')

%% Compute Demand

%Calculate the Demand for Each Mode
DemandForAuto = ProbabilityAutoMatrixWithOUTIncomeWithUber .*
LODES_Origin_Destination_AllInformation(Valid_OD_Pairs,3);
DemandForPublic = ProbabilityPublicMatrixWithOUTIncomeWithUber .*
LODES_Origin_Destination_AllInformation(Valid_OD_Pairs,3);
if Exclude_ODM Recalibration == 0
    DemandForODM = ProbabilityODMMatrixWithOUTIncomeWithUber .*
LODES_Origin_Destination_AllInformation(Valid_OD_Pairs,3);
end

% Find the utilization of each of the landing sites without demand
if Exclude_ODM Recalibration == 0
    UtilizationLandingSites_ValidLandingSites_Origin = ODMLandingUsedInAnalysis_Home (Valid_OD_Pairs) ;
    UtilizationLandingSites_ValidLandingSites_Destination = ODMLandingUsedInAnalysis_Work (Valid_OD_Pairs);
    UtilizationLandingSites_ValidLandingSites_Joined = [UtilizationLandingSites_ValidLandingSites_Origin
UtilizationLandingSites_ValidLandingSites_Destination];

    UniqueODMLandingSites_OriginDestination = unique( UtilizationLandingSites_ValidLandingSites_Joined );
    CountOfUtilizationOfEachLandingSite_WithoutDemand =
[UniqueODMLandingSites_OriginDestination,histc( UtilizationLandingSites_ValidLandingSites_Joined(:,UniqueODMLa
ndingSites_OriginDestination))];
% figure;
% histogram(UniqueODMLandingSites_Origin)

% Find the utilization of each of the landing sites with demand
%Column 1: Origin/Destination Landing Site
%Column 2: Demand for that origin/destination landing site
CountOfUtilizationOfEachLandingSite_WithDemand_Origin =
[UtilizationLandingSites_ValidLandingSites_Origin DemandForODM] ;
CountOfUtilizationOfEachLandingSite_WithDemand_Destination =
[UtilizationLandingSites_ValidLandingSites_Destination DemandForODM] ;
```

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%Column 1/2: Origin/Destination Landing Site
%Column 3: Demand for that Origin-Destination Landing Site Pair
%Roundtrip
TotalDemandOrigin_DestODM = CountOfUtilizationOfEachLandingSite_WithDemand_Destination(:,2) +
CountOfUtilizationOfEachLandingSite_WithDemand_Origin(:,2);
OutputOriginDestinationODMAndDemand = [UtilizationLandingSites_ValidLandingSites_Origin
UtilizationLandingSites_ValidLandingSites_Destination TotalDemandOrigin_DestODM];

%
[UniqueValueLS_Home,~,LocationUniqueValueLS_Home] =
unique(CountOfUtilizationOfEachLandingSite_WithDemand_Origin(:,1));
UtilizationofLandingSite_WithDemand_Origin = [UniqueValueLS_Home,
accumarray(LocationUniqueValueLS_Home,CountOfUtilizationOfEachLandingSite_WithDemand_Origin(:,2))];

[UniqueValueLS_Work,~,LocationUniqueValueLS_Work] =
unique(CountOfUtilizationOfEachLandingSite_WithDemand_Destination(:,1));
UtilizationofLandingSite_WithDemand_Destination = [UniqueValueLS_Work,
accumarray(LocationUniqueValueLS_Work,CountOfUtilizationOfEachLandingSite_WithDemand_Destination(:,2))];

SumofDemandofLandingSites = UtilizationofLandingSite_WithDemand_Origin(:,2) +
UtilizationofLandingSite_WithDemand_Destination(:,2);

%Put it all together
DemandForLandingSites_WithDemand_LandingSitesIncluded =
[UtilizationofLandingSite_WithDemand_Destination(:,1) SumofDemandofLandingSites];

% Do check to make sure the landing site demand computation is
% correct

IncorrectLandingSite = find (UtilizationofLandingSite_WithDemand_Origin(:,1) ~=
UtilizationofLandingSite_WithDemand_Destination(:,1));
disp(['Incorrect Landing Site Information For Demand: ', num2str(sum(IncorrectLandingSite > 0))]);

%Find Landing Sites Not Included
LandingSiteNumbers = [1:length(Coordinates1000LandingSites)];

LandingSitesNotIncluded_Logical = ~ismember(LandingSiteNumbers,
UtilizationofLandingSite_WithDemand_Destination(:,1) );
LandingSitesNotIncluded = LandingSiteNumbers (LandingSitesNotIncluded_Logical);

LengthLandingSitesNotIncluded = length (LandingSitesNotIncluded);

DemandAssociatedWithLandingSitesNotIncluded = zeros (LengthLandingSitesNotIncluded,1);

DemandForLandingSites_WithDemand_LandingSitesNotIncluded = [LandingSitesNotIncluded
DemandAssociatedWithLandingSitesNotIncluded];

%Consolidate both pieces of information
DemandForLandingSites_WithDemand_Total = [DemandForLandingSites_WithDemand_LandingSitesIncluded;
DemandForLandingSites_WithDemand_LandingSitesNotIncluded];

[values,order] = sortrows (DemandForLandingSites_WithDemand_Total(:,1) );

DemandForLandingSites_WithDemand_Total = DemandForLandingSites_WithDemand_Total (order,:);

%Write to an Excel sheet
FilenameForDemandForLandingSites='.\Output\DemandForLandingSites_WithDemand_Total.csv';
csvwrite (FilenameForDemandForLandingSites,DemandForLandingSites_WithDemand_Total)

end

% Find the door to door driving distances that belong to each travel distance range
InVehicleMilesTraveledAuto_Less10 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 10;
InVehicleMilesTraveledAuto_10ToLess20 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 10 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 20;
InVehicleMilesTraveledAuto_20ToLess30 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 20 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 30;
InVehicleMilesTraveledAuto_30ToLess40 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 30 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 40;
InVehicleMilesTraveledAuto_40ToLess50 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 40 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 50;
InVehicleMilesTraveledAuto_50ToLess60 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 50 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 60;
InVehicleMilesTraveledAuto_60ToLess70 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 60 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 70;
InVehicleMilesTraveledAuto_70ToLess80 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 70 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 80;

```

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InVehicleMilesTraveledAuto_80ToLess90 = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 80 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 90;
InVehicleMilesTraveledAuto_90ToLess100= InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 90 &
InVehicleMilesTraveledAuto(Valid_OD_Pairs) < 100;
InVehicleMilesTraveledAuto_100Plus    = InVehicleMilesTraveledAuto(Valid_OD_Pairs) >= 100;

%Get the demand for that corresponding driving distance for Auto
DemandAutoLess10    = DemandForAuto(InVehicleMilesTraveledAuto_Less10);
DemandAuto10ToLess20 = DemandForAuto(InVehicleMilesTraveledAuto_10ToLess20);
DemandAuto20ToLess30 = DemandForAuto(InVehicleMilesTraveledAuto_20ToLess30);
DemandAuto30ToLess40 = DemandForAuto(InVehicleMilesTraveledAuto_30ToLess40);
DemandAuto40ToLess50 = DemandForAuto(InVehicleMilesTraveledAuto_40ToLess50);
DemandAuto50ToLess60 = DemandForAuto(InVehicleMilesTraveledAuto_50ToLess60);
DemandAuto60ToLess70 = DemandForAuto(InVehicleMilesTraveledAuto_60ToLess70);
DemandAuto70ToLess80 = DemandForAuto(InVehicleMilesTraveledAuto_70ToLess80);
DemandAuto80ToLess90 = DemandForAuto(InVehicleMilesTraveledAuto_80ToLess90);
DemandAuto90ToLess100= DemandForAuto(InVehicleMilesTraveledAuto_90ToLess100);
DemandAuto100Plus    = DemandForAuto(InVehicleMilesTraveledAuto_100Plus );

%Get the demand for that corresponding driving distance for Public
DemandPublicLess10    = DemandForPublic(InVehicleMilesTraveledAuto_Less10);
DemandPublic10ToLess20 = DemandForPublic(InVehicleMilesTraveledAuto_10ToLess20);
DemandPublic20ToLess30 = DemandForPublic(InVehicleMilesTraveledAuto_20ToLess30);
DemandPublic30ToLess40 = DemandForPublic(InVehicleMilesTraveledAuto_30ToLess40);
DemandPublic40ToLess50 = DemandForPublic(InVehicleMilesTraveledAuto_40ToLess50);
DemandPublic50ToLess60 = DemandForPublic(InVehicleMilesTraveledAuto_50ToLess60);
DemandPublic60ToLess70 = DemandForPublic(InVehicleMilesTraveledAuto_60ToLess70);
DemandPublic70ToLess80 = DemandForPublic(InVehicleMilesTraveledAuto_70ToLess80);
DemandPublic80ToLess90 = DemandForPublic(InVehicleMilesTraveledAuto_80ToLess90);
DemandPublic90ToLess100= DemandForPublic(InVehicleMilesTraveledAuto_90ToLess100);
DemandPublic100Plus    = DemandForPublic(InVehicleMilesTraveledAuto_100Plus );

%Get the demand for that corresponding driving distance for Public
if Exclude_ODM_Recalibration == 0
    DemandODMLess10    = DemandForODM(InVehicleMilesTraveledAuto_Less10);
    DemandODM10ToLess20 = DemandForODM(InVehicleMilesTraveledAuto_10ToLess20);
    DemandODM20ToLess30 = DemandForODM(InVehicleMilesTraveledAuto_20ToLess30);
    DemandODM30ToLess40 = DemandForODM(InVehicleMilesTraveledAuto_30ToLess40);
    DemandODM40ToLess50 = DemandForODM(InVehicleMilesTraveledAuto_40ToLess50);
    DemandODM50ToLess60 = DemandForODM(InVehicleMilesTraveledAuto_50ToLess60);
    DemandODM60ToLess70 = DemandForODM(InVehicleMilesTraveledAuto_60ToLess70);
    DemandODM70ToLess80 = DemandForODM(InVehicleMilesTraveledAuto_70ToLess80);
    DemandODM80ToLess90 = DemandForODM(InVehicleMilesTraveledAuto_80ToLess90);
    DemandODM90ToLess100= DemandForODM(InVehicleMilesTraveledAuto_90ToLess100);
    DemandODM100Plus    = DemandForODM(InVehicleMilesTraveledAuto_100Plus );

end

%Have a different directory
mkdir('Output');

%Sum up all the demands for ODM and then write it to Excel Sheet
if Exclude_ODM_Recalibration == 0

    DemandODMLess10Sum    = sum(DemandODMLess10);
    DemandODM10ToLess20Sum = sum(DemandODM10ToLess20);
    DemandODM20ToLess30Sum = sum(DemandODM20ToLess30);
    DemandODM30ToLess40Sum = sum(DemandODM30ToLess40);
    DemandODM40ToLess50Sum = nansum(DemandODM40ToLess50);
    DemandODM50ToLess60Sum = nansum(DemandODM50ToLess60);
    DemandODM60ToLess70Sum = nansum(DemandODM60ToLess70);
    DemandODM70ToLess80Sum = nansum(DemandODM70ToLess80);
    DemandODM80ToLess90Sum = nansum(DemandODM80ToLess90);
    DemandODM90ToLess100Sum= nansum(DemandODM90ToLess100);
    DemandODM100PlusSum    = nansum(DemandODM100Plus);

    DemandODMSumArray = [DemandODMLess10Sum DemandODM10ToLess20Sum DemandODM20ToLess30Sum
    DemandODM30ToLess40Sum DemandODM40ToLess50Sum DemandODM50ToLess60Sum DemandODM60ToLess70Sum
    DemandODM70ToLess80Sum DemandODM80ToLess90Sum DemandODM90ToLess100Sum DemandODM100PlusSum];
    DemandODMSumArray = transpose(DemandODMSumArray);

    filename='.\Output\DemandWithLODES.xlsx';
    xlswrite(filename,DemandODMSumArray,'D2:D12')

end

%Sum all the demands for Auto and write to Excel Sheet
DemandAutoLess10Sum    = sum(DemandAutoLess10);
```

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DemandAuto10ToLess20Sum = sum(DemandAuto10ToLess20);
DemandAuto20ToLess30Sum = sum(DemandAuto20ToLess30);
DemandAuto30ToLess40Sum = sum(DemandAuto30ToLess40);
DemandAuto40ToLess50Sum = nansum(DemandAuto40ToLess50);
DemandAuto50ToLess60Sum = nansum(DemandAuto50ToLess60);
DemandAuto60ToLess70Sum = nansum(DemandAuto60ToLess70);
DemandAuto70ToLess80Sum = nansum(DemandAuto70ToLess80);
DemandAuto80ToLess90Sum = nansum(DemandAuto80ToLess90);
DemandAuto90ToLess100Sum= nansum(DemandAuto90ToLess100);
DemandAuto100PlusSum    = nansum(DemandAuto100Plus);

DemandAutoSumArray= [DemandAutoLess10Sum DemandAuto10ToLess20Sum DemandAuto20ToLess30Sum
DemandAuto30ToLess40Sum DemandAuto40ToLess50Sum DemandAuto50ToLess60Sum DemandAuto60ToLess70Sum
DemandAuto70ToLess80Sum DemandAuto80ToLess90Sum DemandAuto90ToLess100Sum DemandAuto100PlusSum];
DemandAutoSumArray= transpose(DemandAutoSumArray);

filename='.\Output\DemandWithLODES.xlsx';
xlswrite(filename,DemandAutoSumArray,'B2:B12')

%Sum all the demands for Public and write to Excel Sheet
DemandPublicLess10Sum    = sum(DemandPublicLess10);
DemandPublic10ToLess20Sum = sum(DemandPublic10ToLess20);
DemandPublic20ToLess30Sum = sum(DemandPublic20ToLess30);
DemandPublic30ToLess40Sum = sum(DemandPublic30ToLess40);
DemandPublic40ToLess50Sum = nansum(DemandPublic40ToLess50);
DemandPublic50ToLess60Sum = nansum(DemandPublic50ToLess60);
DemandPublic60ToLess70Sum = nansum(DemandPublic60ToLess70);
DemandPublic70ToLess80Sum = nansum(DemandPublic70ToLess80);
DemandPublic80ToLess90Sum = nansum(DemandPublic80ToLess90);
DemandPublic90ToLess100Sum= nansum(DemandPublic90ToLess100);
DemandPublic100PlusSum   = nansum(DemandPublic100Plus);

DemandPublicSumArray = [DemandPublicLess10Sum DemandPublic10ToLess20Sum DemandPublic20ToLess30Sum
DemandPublic30ToLess40Sum DemandPublic40ToLess50Sum DemandPublic50ToLess60Sum DemandPublic60ToLess70Sum
DemandPublic70ToLess80Sum DemandPublic80ToLess90Sum DemandPublic90ToLess100Sum DemandPublic100PlusSum];
DemandPublicSumArray = transpose(DemandPublicSumArray);

filename='.\Output\DemandWithLODES.xlsx';
xlswrite(filename,DemandPublicSumArray,'C2:C12')

%% Travel Time and Travel Cost Savings
%All time and cost savings will be against taking an automobile for the
%same driving distance from origin to destination.

%Total Travel Time Savings
if Exclude_ODM_Recalibration == 0
    ODM_Time_SavingsTotal = TotalTravelTimeAuto - TotalTravelTimeODM;
end
    Public_Time_SavingsTotal = TotalTravelTimeAuto - TotalTravelTimePublic;

%In Vehicle Travel Time Savings
if Exclude_ODM_Recalibration == 0
    ODM_Time_Savings_InVehicleTime = InVehicleTimeAuto - InVehicleTimeODM;
end
    Public_Time_Savings_InVehicleTime = InVehicleTimeAuto - InVehicleTimePublic;

%Out of Vehicle Travel Time Savings
if Exclude_ODM_Recalibration == 0
    ODM_Time_Savings_OutVehicleTime = OVTAuto - OVTODM;
end
    Public_Time_Savings_OutVehicleTime = OVTAuto - OVTPublic;

%Additional Cost Using ODM
if Exclude_ODM_Recalibration == 0
    AdditionalCostForODM = TravelCost_ODM - TravelCost_Auto;
end

%% Validation Plots
    if Exclude_ODM_Recalibration == 0
        cols = 2;
    else
        cols = 1;
    end
end
```

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```
%-----  
%  
% Generate a plot for Auto for Probability against Driving Distance  
figure('Name','Driving Distance Between Origin and Destination vs. Probability');  
  
subplot(2,cols,1);  
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), ProbabilityAutoMatrixWithOUTIncomeWithUber, '.')  
xlabel('Driving Distance between Origin and Destination (miles)')  
ylabel('Probability')  
title('Driving Distance Between Origin and Destination vs. Probability: Auto')  
% xlim([0 50])  
% ylim([0 150])  
grid on  
  
subplot(2,cols,2);  
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), ProbabilityPublicMatrixWithOUTIncomeWithUber, '.')  
xlabel('Driving Distance between Origin and Destination (miles)')  
ylabel('Probability')  
title('Driving Distance Between Origin and Destination vs. Probability: Public')  
% xlim([0 50])  
% ylim([0 150])  
grid on  
  
if Exclude_ODM_Recalibration == 0  
    subplot(2,cols,3);  
    plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), ProbabilityODMMatrixWithOUTIncomeWithUber, '.')  
    xlabel('Driving Distance between Origin and Destination (miles)')  
    ylabel('Probability')  
    title('Driving Distance Between Origin and Destination vs. Probability: ODM')  
    % xlim([0 50])  
    % ylim([0 150])  
    grid on  
end  
%-----  
  
% Generate a plot for Auto for Travel Time against Travel Cost  
figure('Name','Total Travel Time (min) vs. Travel Cost (2009 dollars)');  
  
if Exclude_ODM_Recalibration == 0  
    max_TC = max([max(TravelCost_Auto(Valid_OD_Pairs)), max(TravelCost_Public(Valid_OD_Pairs)),  
max(TravelCost_ODM(Valid_OD_Pairs))]);  
else  
    max_TC = max([max(TravelCost_Auto(Valid_OD_Pairs)), max(TravelCost_Public(Valid_OD_Pairs))]);  
end  
  
if Exclude_ODM_Recalibration == 0  
    max_TT = max([max(TotalTravelTimeAuto(Valid_OD_Pairs)), max(TotalTravelTimePublic(Valid_OD_Pairs)),  
max(TotalTravelTimeODM(Valid_OD_Pairs))]);  
else  
    max_TT = max([max(TotalTravelTimeAuto(Valid_OD_Pairs)), max(TotalTravelTimePublic(Valid_OD_Pairs))]);  
end  
  
subplot(2,cols,1);  
plot(TotalTravelTimeAuto(Valid_OD_Pairs), TravelCost_Auto(Valid_OD_Pairs), '.')  
xlabel('Total Travel Time (min)')  
ylabel('Travel Cost (2009 dollars)')  
title('Total Travel Time (min) vs. Travel Cost (2009 dollars): Auto')  
xlim([0 max_TT])  
ylim([0 max_TC])  
grid on  
  
% Generate a plot for Public for Travel Time against Travel Cost  
subplot(2,cols,2);  
plot(TotalTravelTimePublic(Valid_OD_Pairs), TravelCost_Public(Valid_OD_Pairs), '.')  
xlabel('Total Travel Time (min)')  
ylabel('Travel Cost (2009 dollars)')  
title('Total Travel Time (min) vs. Travel Cost (2009 dollars): Public')  
xlim([0 max_TT])  
ylim([0 max_TC])  
grid on
```

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```
% Generate a plot for ODM for Travel Time against Travel Cost
if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    plot(TotalTravelTimeODM(Valid_OD_Pairs), TravelCost_ODM(Valid_OD_Pairs), '.')
    xlabel('Total Travel Time (min)')
    ylabel('Travel Cost (2009 dollars)')
    title('Total Travel Time (min) vs. Travel Cost (2009 dollars): ODM')
    xlim([0 max_TT])
    ylim([0 max_TC])
    grid on
end
%-----

% Generate a plot for Auto for IV Travel Time against IV Distance
figure('Name','InVehicle Travel Time (min) vs. InVehicle Distance (miles)');

if Exclude_ODM_Recalibration == 0
    y_max = max([max(InVehicleTimeAuto(Valid_OD_Pairs)), max(InVehicleTimePublic(Valid_OD_Pairs)),
max(InVehicleTimeODM(Valid_OD_Pairs))]);
else
    y_max = max([max(InVehicleTimeAuto(Valid_OD_Pairs)), max(InVehicleTimePublic(Valid_OD_Pairs))]);
end

if Exclude_ODM_Recalibration == 0
    max_IVD = max([max(InVehicleMilesTraveledAuto(Valid_OD_Pairs)),
max(InVehicleMilesTraveledPublic(Valid_OD_Pairs)), max(InVehicleMilesTraveledODM(Valid_OD_Pairs))]);
else
    max_IVD = max([max(InVehicleMilesTraveledAuto(Valid_OD_Pairs)),
max(InVehicleMilesTraveledPublic(Valid_OD_Pairs))]);
end

subplot(2,cols,1);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), InVehicleTimeAuto(Valid_OD_Pairs), '.')
xlabel('InVehicle Distance (miles)')
ylabel('InVehicle Travel Time (min)')
title('InVehicle Travel Time (min) vs. InVehicle Distance (miles): Auto')
xlim([0 max_IVD])
ylim([0 y_max])
grid on

% Generate a plot for Public for IV Travel Time against IV Distance
subplot(2,cols,2);
plot(InVehicleMilesTraveledPublic(Valid_OD_Pairs), InVehicleTimePublic(Valid_OD_Pairs), '.')
xlabel('InVehicle Distance (miles)')
ylabel('InVehicle Travel Time (min)')
title('InVehicle Travel Time (min) vs. InVehicle Distance (miles): Public')
xlim([0 max_IVD])
ylim([0 y_max])
grid on

% Generate a plot for ODM for IV Travel Time against IV Distance
if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    plot(InVehicleMilesTraveledODM(Valid_OD_Pairs), InVehicleTimeODM(Valid_OD_Pairs), '.')
    xlabel('InVehicle Distance (miles)')
    ylabel('InVehicle Travel Time (min)')
    title('InVehicle Travel Time (min) vs. InVehicle Distance (miles): ODM')
    xlim([0 max_IVD])
    ylim([0 y_max])
    grid on
end
%-----

% Generate a plot for Auto for IV Travel Cost against IV Distance
figure('Name','InVehicle Travel Cost (2009 dollars) vs. InVehicle Distance (miles)');

if Exclude_ODM_Recalibration == 0
    y_max = max([max(AutoInVehicleCost(Valid_OD_Pairs)), max(PublicInVehicleCost(Valid_OD_Pairs)),
max(ODMInVehicleCost(Valid_OD_Pairs))]);
else
    y_max = max([max(AutoInVehicleCost(Valid_OD_Pairs)), max(PublicInVehicleCost(Valid_OD_Pairs))]);
end

subplot(2,cols,1);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), AutoInVehicleCost(Valid_OD_Pairs), '.')
```


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```
xlabel('InVehicle Distance (miles)')
ylabel('InVehicle Travel Cost (2009 dollars)')
title('InVehicle Travel Cost (2009 dollars) vs. InVehicle Distance (miles): Auto')
xlim([0 max_IVD])
ylim([0 y_max])
grid on

% Generate a plot for Public for IV Travel Time against IV Travel Cost
subplot(2,cols,2);
plot(InVehicleMilesTraveledPublic(Valid_OD_Pairs), PublicInVehicleCost(Valid_OD_Pairs), '.')
xlabel('InVehicle Distance (miles)')
ylabel('InVehicle Travel Cost (2009 dollars)')
title('InVehicle Travel Cost (2009 dollars) vs. InVehicle Distance (miles): Public')
xlim([0 max_IVD])
ylim([0 y_max])
grid on

% Generate a plot for ODM for IV Travel Time against IV Travel Cost
if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    plot(InVehicleMilesTraveledODM(Valid_OD_Pairs), ODMInVehicleCost(Valid_OD_Pairs), '.')
    xlabel('InVehicle Distance (miles)')
    ylabel('InVehicle Travel Cost (2009 dollars)')
    title('InVehicle Travel Cost (2009 dollars) vs. InVehicle Distance (miles): ODM')
    xlim([0 max_IVD])
    ylim([0 y_max])
    grid on
end
%-----

% Generate a plot for Auto for Travel Distance against Travel Cost
figure('Name','Driving Distance Between Origin and Destination vs. Travel Cost (2009 Dollars)');

if Exclude_ODM_Recalibration == 0
    y_max = max([max(TravelCost_Auto(Valid_OD_Pairs)), max(TravelCost_Public(Valid_OD_Pairs)),
max(TravelCost_ODM(Valid_OD_Pairs))]);
else
    y_max = max([max(TravelCost_Auto(Valid_OD_Pairs)), max(TravelCost_Public(Valid_OD_Pairs))]);
end

subplot(2,cols,1);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TravelCost_Auto(Valid_OD_Pairs), '.')
xlabel('Driving Distance between Origin and Destination (miles)')
ylabel('Travel Cost (2009 dollars)')
title('Driving Distance Between Origin and Destination vs. Travel Cost (2009 Dollars): Auto')
xlim([0 max(InVehicleMilesTraveledAuto)])
ylim([0 y_max])
grid on

% Generate a plot for Public for Travel Distance against Travel Cost
subplot(2,cols,2);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TravelCost_Public(Valid_OD_Pairs), '.')
xlabel('Driving Distance between Origin and Destination (miles)')
ylabel('Travel Cost (2009 dollars)')
title('Driving Distance Between Origin and Destination vs. Travel Cost (2009 Dollars): Public')
xlim([0 max(InVehicleMilesTraveledAuto)])
ylim([0 y_max])
grid on

% Generate a plot for ODM for Travel Distance against Travel Cost
if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TravelCost_ODM(Valid_OD_Pairs), '.')
    xlabel('Driving Distance between Origin and Destination (miles)')
    ylabel('Travel Cost (2009 dollars)')
    title('Driving Distance Between Origin and Destination vs. Travel Cost (2009 Dollars): ODM')
    xlim([0 max(InVehicleMilesTraveledAuto)])
    ylim([0 y_max])
    grid on
end
%-----

% Generate a plot for Auto for Travel Distance against Demand
figure('Name','Driving Distance From Origin-Destination vs. Demand');

if Exclude_ODM_Recalibration == 0
    y_max = max([max(DemandForAuto), max(DemandForPublic), max(DemandForODM)]);
else
    y_max = max([max(DemandForAuto), max(DemandForPublic)]);
end
```

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```
end

subplot(2,cols,1);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), DemandForAuto, '.')
xlabel('Driving Distance From Origin-Destination(miles)')
ylabel('Demand For Auto (Number Of Jobs)')
title('Driving Distance From Origin-Destination vs. Demand For Auto')
xlim([0 max(InVehicleMilesTraveledAuto)])
ylim([0 y_max])
grid on

% Generate a plot for Public for Travel Distance against Travel Cost
subplot(2,cols,2);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), DemandForPublic, '.')
xlabel('Driving Distance From Origin-Destination(miles)')
ylabel('Demand For Public (Number Of Jobs)')
title('Driving Distance From Origin-Destination vs. Demand For Public')
xlim([0 max(InVehicleMilesTraveledAuto)])
ylim([0 y_max])
grid on

% Generate a plot for ODM for Travel Distance against Travel Cost
if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), DemandForODM, '.')
    xlabel('Driving Distance From Origin-Destination(miles)')
    ylabel('Demand For ODM (Number Of Jobs)')
    title('Driving Distance From Origin-Destination vs. Demand For ODM')
    xlim([0 max(InVehicleMilesTraveledAuto)])
    ylim([0 y_max])
    grid on
end

%-----
% Generate a plot for Auto for Travel Distance against Travel Time
figure('Name','Driving Distance Between Origin and Destination vs. Total Travel Time');

if Exclude_ODM_Recalibration == 0
    y_max = max([max(TotalTravelTimeAuto(Valid_OD_Pairs)), max(TotalTravelTimePublic(Valid_OD_Pairs)),
max(TotalTravelTimeODM(Valid_OD_Pairs))]);
else
    y_max = max([max(TotalTravelTimeAuto(Valid_OD_Pairs)), max(TotalTravelTimePublic(Valid_OD_Pairs))]);
end

subplot(2,cols,1);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TotalTravelTimeAuto(Valid_OD_Pairs), '.')
xlabel('Driving Distance between Origin and Destination (miles)')
ylabel('Total Travel Time(min)')
title('Driving Distance Between Origin and Destination vs. Total Travel Time: Auto')
xlim([0 max(InVehicleMilesTraveledAuto)])
ylim([0 y_max])
grid on

% Generate a plot for Public for Travel Distance against Travel Time
subplot(2,cols,2);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TotalTravelTimePublic(Valid_OD_Pairs), '.')
xlabel('Driving Distance between Origin and Destination (miles)')
ylabel('Total Travel Time(min)')
title('Driving Distance Between Origin and Destination vs. Total Travel Time: Public')
xlim([0 max(InVehicleMilesTraveledAuto)])
ylim([0 y_max])
grid on

% Generate a plot for ODM for Travel Distance against Travel Time
if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TotalTravelTimeODM(Valid_OD_Pairs), '.')
    xlabel('Driving Distance between Origin and Destination (miles)')
    ylabel('Total Travel Time(min)')
    title('Driving Distance Between Origin and Destination vs. Total Travel Time: ODM')
    xlim([0 max_IVD])
    ylim([0 y_max])
    grid on
end

%-----
% Generate a plot for Total Average Speed over Distance
figure('Name','Driving Distance Between Origin and Destination vs. Total Average Speed');
```

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```
TotalAverageSpeed_Auto = (InVehicleMilesTraveledAuto(Valid_OD_Pairs) ./ TotalTravelTimeAuto(Valid_OD_Pairs))
* 60; % mph
TotalAverageSpeed_Public = (InVehicleMilesTraveledAuto(Valid_OD_Pairs) ./
TotalTravelTimePublic(Valid_OD_Pairs)) * 60; % mph

if Exclude_ODM_Recalibration == 0
    TotalAverageSpeed_ODM = (InVehicleMilesTraveledODM(Valid_OD_Pairs) ./ TotalTravelTimeODM(Valid_OD_Pairs)) *
60; % mph

    y_max = max([max(TotalAverageSpeed_Auto), max(TotalAverageSpeed_Public), max(TotalAverageSpeed_ODM)]);
else
    y_max = max([max(TotalAverageSpeed_Auto), max(TotalAverageSpeed_Public)]);
end

subplot(2,cols,1);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TotalAverageSpeed_Auto, '.')
xlabel('Driving Distance between Origin and Destination (miles)')
ylabel('Total Average Speed (mph)')
title('Driving Distance Between Origin and Destination vs. Total Average Speed: Auto')
xlim([0 max(InVehicleMilesTraveledAuto)])
ylim([0 y_max])
grid on

% Generate a plot for Public for Travel Distance against Travel Time
subplot(2,cols,2);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TotalAverageSpeed_Public, '.')
xlabel('Driving Distance between Origin and Destination (miles)')
ylabel('Total Average Speed (mph)')
title('Driving Distance Between Origin and Destination vs. Total Average Speed: Public')
xlim([0 max(InVehicleMilesTraveledAuto)])
ylim([0 y_max])
grid on

% Generate a plot for ODM for Travel Distance against Travel Time
if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), TotalAverageSpeed_ODM, '.')
    xlabel('Driving Distance between Origin and Destination (miles)')
    ylabel('Total Average Speed (mph)')
    title('Driving Distance Between Origin and Destination vs. Total Average Speed: ODM')
    xlim([0 max(InVehicleMilesTraveledAuto)])
    ylim([0 y_max])
    grid on
end

%-----

% Generate a plot for Auto for IV Average Speed against IV Distance
figure('Name','InVehicle Average Speed (mph) vs. InVehicle Distance (miles)');

InVehicleAverageSpeed_Auto = (InVehicleMilesTraveledAuto(Valid_OD_Pairs) ./
InVehicleTimeAuto(Valid_OD_Pairs)) * 60; % mph
InVehicleAverageSpeed_Public = (InVehicleMilesTraveledAuto(Valid_OD_Pairs) ./
InVehicleTimePublic(Valid_OD_Pairs)) * 60; % mph

if Exclude_ODM_Recalibration == 0
    InVehicleAverageSpeed_ODM = (InVehicleMilesTraveledODM(Valid_OD_Pairs) ./ InVehicleTimeODM(Valid_OD_Pairs))
* 60; % mph

    y_max = max([max(InVehicleAverageSpeed_Auto), max(InVehicleAverageSpeed_Public),
max(InVehicleAverageSpeed_ODM)]);
else
    y_max = max([max(InVehicleAverageSpeed_Auto), max(InVehicleAverageSpeed_Public)]);
end

subplot(2,cols,1);
plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), InVehicleAverageSpeed_Auto, '.')
xlabel('InVehicle Distance (miles)')
ylabel('InVehicle Average Speed (mph)')
title('InVehicle Average Speed (mph) vs. InVehicle Distance (miles): Auto')
xlim([0 max_IVD])
ylim([0 y_max])
grid on

% Generate a plot for Public for IV Travel Time against IV Travel Cost
subplot(2,cols,2);
plot(InVehicleMilesTraveledPublic(Valid_OD_Pairs), InVehicleAverageSpeed_Public, '.')
xlabel('InVehicle Distance (miles)')
ylabel('InVehicle Average Speed (mph)')
```

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```
title('InVehicle Average Speed (mph) vs. InVehicle Distance (miles): Public')
xlim([0 max_IVD])
ylim([0 y_max])
grid on

% Generate a plot for ODM for IV Travel Time against IV Travel Cost
if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    plot(InVehicleMilesTraveledODM(Valid_OD_Pairs), InVehicleAverageSpeed_ODM, '.')
    xlabel('InVehicle Distance (miles)')
    ylabel('InVehicle Average Speed (mph)')
    title('InVehicle Average Speed (mph) vs. InVehicle Distance (miles): ODM')
    xlim([0 max_IVD])
    ylim([0 y_max])
    grid on
end

%BAR graph for demand
boundaries = 0:2:300;

[n,edges,bin] = histcounts(InVehicleMilesTraveledAuto(Valid_OD_Pairs), boundaries);

total_Auto = 0;
total_Public = 0;
if Exclude_ODM_Recalibration == 0
    total_ODM = 0;
end

final_y_Auto = zeros(length(n),1);
final_y_Public = zeros(length(n),1);
if Exclude_ODM_Recalibration == 0
    final_y_ODM = zeros(length(n),1);
end

for tea = 1:1:length(n)

    k = find(bin == tea);

    for j = 1:length(k)
        total_Auto = total_Auto + DemandForAuto(k(j));
        total_Public = total_Public + DemandForPublic(k(j));
        if Exclude_ODM_Recalibration == 0
            total_ODM = total_ODM + DemandForODM(k(j));
        end
    end

    final_y_Auto(tea) = total_Auto;
    final_y_Public(tea) = total_Public;
    if Exclude_ODM_Recalibration == 0
        final_y_ODM(tea) = total_ODM;
    end

    total_Auto = 0;
    total_Public = 0;
    if Exclude_ODM_Recalibration == 0
        total_ODM = 0;
    end
end

final_x = boundaries(2:end);

figure('Name','Demand vs. Driving Distance From Origin-Destination');

if Exclude_ODM_Recalibration == 0
    y_max = max([max(final_y_Auto), max(final_y_Public), max(final_y_ODM)]);
else
    y_max = max([max(final_y_Auto), max(final_y_Public)]);
end

subplot(2,cols,1);
bar(final_x, final_y_Auto)
xlabel('Driving Distance From Origin-Destination(miles)')
ylabel('Demand for Auto (Number of Jobs)')
title('Demand For Auto vs. Driving Distance From Origin-Destination')
ylim([0 y_max])
grid on

subplot(2,cols,2);
bar(final_x, final_y_Public)
```

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```

xlabel('Driving Distance From Origin-Destination(miles)')
ylabel('Demand for Public (Number of Jobs)')
title('Demand For Public vs. Driving Distance From Origin-Destination')
ylim([0 y_max])
grid on

if Exclude_ODM_Recalibration == 0
    subplot(2,cols,3);
    bar(final_x, final_y_ODM)
    xlabel('Driving Distance From Origin-Destination(miles)')
    ylabel('Demand for ODM (Number of Jobs)')
    title('Demand For ODM vs. Driving Distance From Origin-Destination')
    ylim([0 y_max])
    grid on
end

% Marketshare stacked bar (with Demand)-----
if Exclude_ODM_Recalibration == 0
    Denominator = final_y_Auto + final_y_Public + final_y_ODM;
    ODM_Marketshare = final_y_ODM ./ Denominator;
else
    Denominator = final_y_Auto + final_y_Public;
end

Auto_Marketshare = final_y_Auto ./ Denominator;
Public_Marketshare = final_y_Public ./ Denominator;

figure;
if Exclude_ODM_Recalibration == 0
    bar(final_x, [Auto_Marketshare Public_Marketshare ODM_Marketshare], 'stacked')
    legend('Auto', 'Public', 'ODM')
else
    bar(final_x, [Auto_Marketshare Public_Marketshare], 'stacked')
    legend('Auto', 'Public')
end

xlabel('Driving Distance From Origin-Destination(miles)')
ylabel('Marketshare')
title('Marketshare vs. Driving Distance From Origin-Destination')
xlim([0 150])
ylim([0 1])
grid on

clearvars n edges bin k tea j

% % Marketshare stacked bar (with Probabilities)-----
% boundaries1 = 0:2:300;
%
% [n,edges,bin] = histcounts(InVehicleMilesTraveledAuto(Valid_OD_Pairs), boundaries1);
%
% total_Auto_P = 0;
% total_Public_P = 0;
% if Exclude_ODM_Recalibration == 0
%     total_ODM_P = 0;
% end
%
% final_y_Auto_P = zeros(length(n),1);
% final_y_Public_P = zeros(length(n),1);
% if Exclude_ODM_Recalibration == 0
%     final_y_ODM_P = zeros(length(n),1);
% end
%
% for tea = 1:length(n)
%
%     k = find(bin == tea);
%
%     for j = 1:length(k)
%         total_Auto_P = total_Auto_P + ProbabilityAutoMatrixWithOUTIncomeWithUber(k(j));
%         total_Public_P = total_Public_P + ProbabilityPublicMatrixWithOUTIncomeWithUber(k(j));
%         if Exclude_ODM_Recalibration == 0
%             total_ODM_P = total_ODM_P + ProbabilityODMMatrixWithOUTIncomeWithUber(k(j));
%         end
%     end
%
%     final_y_Auto_P(tea) = total_Auto_P;
%     final_y_Public_P(tea) = total_Public_P;
%     if Exclude_ODM_Recalibration == 0
%         final_y_ODM_P(tea) = total_ODM_P;
%     end
% end

```

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```

%
% total_Auto_P = 0;
% total_Public_P = 0;
% if Exclude_ODM_Recalibration == 0
%     total_ODM_P = 0;
% end
%
% end
%
% final_x = boundaries1(2:end);
%
% if Exclude_ODM_Recalibration == 0
%     Denominator = final_y_Auto_P + final_y_Public_P + final_y_ODM_P;
%     ODM_Marketshare = final_y_ODM_P ./ Denominator;
% else
%     Denominator = final_y_Auto_P + final_y_Public_P;
% end
%
% Auto_Marketshare = final_y_Auto_P ./ Denominator;
% Public_Marketshare = final_y_Public_P ./ Denominator;
%
% figure;
% if Exclude_ODM_Recalibration == 0
%     bar(final_x, [Auto_Marketshare Public_Marketshare ODM_Marketshare], 'stacked')
%     legend('Auto', 'Public', 'ODM')
% else
%     bar(final_x, [Auto_Marketshare Public_Marketshare], 'stacked')
%     legend('Auto', 'Public')
% end
%
% xlabel('Driving Distance From Origin-Destination(miles)')
% ylabel('Probability Marketshare')
% title('Probability Marketshare vs. Driving Distance From Origin-Destination')
% xlim([0 150])
% ylim([0 1])
% grid on
%

% Generate a plot showing travel time savings over the driving
% distances
% -----

figure('Name','Total Travel Time Savings (min) vs. Driving Distance From Origin-Destination(miles)');

if Exclude_ODM_Recalibration == 0
    y_max = max([max(Public_Time_SavingsTotal(Valid_OD_Pairs)),
max(ODM_Time_SavingsTotal(Valid_OD_Pairs))]);
    y_min = min([min(Public_Time_SavingsTotal(Valid_OD_Pairs)),
min(ODM_Time_SavingsTotal(Valid_OD_Pairs))]);
else
    y_max = max((Public_Time_SavingsTotal(Valid_OD_Pairs)));
    y_min = min((Public_Time_SavingsTotal(Valid_OD_Pairs)));
end

subplot(2,cols,1);
plot(InVehicleMilesTraveledPublic(Valid_OD_Pairs),Public_Time_SavingsTotal(Valid_OD_Pairs) , '.')
xlabel('Driving Distance From Origin-Destination(miles)')
ylabel('Total Travel Time Savings (min)')
title('Total Travel Time Savings vs. Driving Distance From Origin-Destination: Public')
%
xlim([-100 500])
ylim([y_min y_max])
grid on

if Exclude_ODM_Recalibration == 0
    subplot(2,cols,2);
plot(InVehicleMilesTraveledPublic(Valid_OD_Pairs), ODM_Time_SavingsTotal(Valid_OD_Pairs), '.')
xlabel('Driving Distance From Origin-Destination(miles)')
ylabel('Total Travel Time Savings (min)')
title('Total Travel Time Savings vs. Driving Distance From Origin-Destination: ODM')
%
xlim([-100 500])
ylim([y_min y_max])
grid on
end
end

```

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```
% Generate a plot showing in vehicle travel time savings over the driving distances

figure('Name','In Vehicle Travel Time Savings (min) vs. Driving Distance From Origin-
Destination(miles)');

if Exclude_ODM_Recalibration == 0
    y_max = max([max(Public_Time_Savings_InVehicleTime(Valid_OD_Pairs)),
max(ODM_Time_Savings_InVehicleTime(Valid_OD_Pairs))]);
    y_min = min([min(Public_Time_Savings_InVehicleTime(Valid_OD_Pairs)),
min(ODM_Time_Savings_InVehicleTime(Valid_OD_Pairs))]);
else
    y_max = max((Public_Time_Savings_InVehicleTime(Valid_OD_Pairs)));
    y_min = min((Public_Time_Savings_InVehicleTime(Valid_OD_Pairs)));
end

subplot(2,cols,1);

plot(InVehicleMilesTraveledPublic(Valid_OD_Pairs),Public_Time_Savings_InVehicleTime(Valid_OD_Pairs) , '.')
    xlabel('Driving Distance From Origin-Destination(miles)')
    ylabel('In Vehicle Travel Time Savings (min)')
    title('In Vehicle Travel Time Savings vs. Driving Distance From Origin-Destination: Public')
%
    xlim([-100 500])
    ylim([y_min y_max])
    grid on

if Exclude_ODM_Recalibration == 0
    subplot(2,cols,2);
    plot(InVehicleMilesTraveledPublic(Valid_OD_Pairs), ODM_Time_Savings_InVehicleTime(Valid_OD_Pairs),
'.')

    xlabel('Driving Distance From Origin-Destination(miles)')
    ylabel('In Vehicle Travel Time Savings (min)')
    title('In Vehicle Travel Time Savings vs. Driving Distance From Origin-Destination: ODM')
%
    xlim([-100 500])
    ylim([y_min y_max])
    grid on
end

% Generate a plot showing out of vehicle travel time savings over the driving distances
if Exclude_ODM_Recalibration == 0
    figure('Name','Out of Vehicle Travel Time Savings (min) vs. Driving Distance From Origin-
Destination(miles)');

    y_max = max([max(Public_Time_Savings_OutVehicleTime(Valid_OD_Pairs)),
max(ODM_Time_Savings_OutVehicleTime(Valid_OD_Pairs))]);
    y_min = min([min(Public_Time_Savings_OutVehicleTime(Valid_OD_Pairs)),
min(ODM_Time_Savings_OutVehicleTime(Valid_OD_Pairs))]);
else
    y_max = max((Public_Time_Savings_OutVehicleTime(Valid_OD_Pairs)));
    y_min = min((Public_Time_Savings_OutVehicleTime(Valid_OD_Pairs)));
end

if Exclude_ODM_Recalibration == 0;
    subplot(2,cols,1);

plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs),Public_Time_Savings_OutVehicleTime(Valid_OD_Pairs) , '.')
    xlabel('Driving Distance From Origin-Destination(miles)')
    ylabel('Out of Vehicle Travel Time Savings (min)')
    title('Out of Vehicle Travel Time Savings vs. Driving Distance From Origin-Destination: Public')
%
    xlim([-100 500])
    ylim([y_min y_max])
    grid on
end

if Exclude_ODM_Recalibration == 0
    subplot(2,cols,2);
    plot(InVehicleMilesTraveledAuto(Valid_OD_Pairs), ODM_Time_Savings_OutVehicleTime(Valid_OD_Pairs),
'.')

    xlabel('Driving Distance From Origin-Destination(miles)')
    ylabel('Out of Vehicle Travel Time Savings (min)')
    title('Out of Vehicle Travel Time Savings vs. Driving Distance From Origin-Destination: ODM')
```

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```
%           xlim([-100 500])
           ylim([y_min y_max])
           grid on
end

% Generate a plot showing additional costs over the driving distances
if Exclude_ODM_Recalibration == 0;

    figure('Name','Additional Costs (2009$) vs. Driving Distance From Origin-Destination(miles)');

    plot(InVehicleMilesTraveledPublic(Valid_OD_Pairs), AdditionalCostForODM(Valid_OD_Pairs), '.')
    xlabel('Driving Distance From Origin-Destination(miles)')
    ylabel('Additional Costs (2009 Dollars)')
    title('Additional Cost for Using ODM vs. Driving Distance From Origin-Destination')
    grid on
end

% Show histogram of Distances reported in LODES: ALL
figure ('Name','Histogram of Distances in LODES Data: All')
histogram(InVehicleMilesTraveledAuto)
title('Histogram of Distances in LODES Data')
ylabel('Number Of Entries in LODES')
xlabel('Distance from Origin to Destination (miles)')
hold on
% plot([15 15], [20000 0], 'r', 'Linewidth',3)
```