Aviation Global Demand Forecast Model Development and ISAAC Studies: UAS VTOL Cargo Study

Final Report

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EXECUTIVE SUMMARY

This report examines the potential market of cargo ODM operations in the Northern California area. The analysis presented describes how UAS VTOL cargo aircraft (called heron Cargo ODM) could be used in a dual-role purpose to carry cargo and passengers in a large metropolitan area. The purpose of this study is to provide NASA with insights on the potential market for cargo ODM operations. The analysis presented in the report uses various datasets including the American Community Survey (ACS), LODES data and the IHS International Transearch database. The following points provide a quick summary of the study findings.

1) Predicting cargo demand using electric VTOL vehicles presents a challenge due to the lack of cargo choice databases and the uncertainty of small package delivery information (i.e., commodity, value, etc.).
2) In this study, we use a combination of Transearch database and T-100 international data to make a first-order estimate cargo flows and hence potential ODM cargo demand in the Northern California area.
3) Neither Transearch, nor T-100-I include private warehouse-to-warehouse cargo flow information that could be relevant to estimate the cargo ODM demand. This adds significant uncertainty to the potential cargo flow estimations.
4) Market share analysis of cargo ODM operations in the Northern California region indicate that in the year 2033, between 877 to 2,357 daily cargo flights may be possible if the cost of ODM vehicle is modestly competitive with ground transportation modes.
5) The total CO_2 emissions of an air vehicle on a 50-mile trip are expected to be 20% less than those produced by a diesel-powered light heavy-duty truck.
6) The CO_2 emissions of an air vehicle on a per ton-kilometer are expected to be higher than those associated with ground vehicles. Using the Uber concept vehicle, the CO_2 emissions per ton-kilometer could be 5-7 higher than those associated with a medium, diesel powered vehicle.
7) The study provided some initial estimates of the impact of reducing the cost per passenger mile for passenger ODM users if ODM vehicle are used in the cargo role at off-peak passenger hours. The passenger demand function is very sensitive to ODM price and a 10% reduction in passenger ODM cost can have a significant effect in passenger demand in the region.

The following recommendations are suggested for follow-up studies of the cargo ODM concept.

1. In a follow-up study, we recommend the development of a detailed cargo choice model using the cost functions presented in Section 6 of the report. It is important to note that there is little publicly available data that explains the details on how customers select among shipping alternatives across commodities. In other words, there are macro-level databases like Transearch that aggregate cargo shipments across regions. Nevertheless, there is no data on the actual choices that customers considered before making a specific shipment. Such data will have to be derived synthetically in a follow-up study.
2. The hypothesis of the analysis is that people are the ultimate recipients of the cargo flowing into the area of interest. The population surrounding each landing site is used as a landing site "catchment" area. In a follow-up study we recommend that catchment areas for warehouses and retail space be considered as part of the distribution method.
3. In a follow-up study, consideration could be given to small regional airports as part of the cargo ODM network.
4. The landing site selection used a first-order, cost model based on net present value, to eliminate and reduce the number of landing sites in the study area. We recommend a more detail study to better understand the costs associated with typical ODM landing sites and their impact in landing fees and passenger and cargo demand.
5. The high-demand scenario presented in this study includes 2,357 daily cargo flights from various landing sites. These flights are assumed to be separated in time from passenger ODM flights. However, it is clear that if high priority cargo services are scheduled to meet 8-8:30 AM delivery times similar to today's parcel services, there will be an overlap of use of ODM

aircraft for cargo use with the morning peak hours of use by commuters. Such interaction requires a detailed simulator (similar to the simulation capabilities developed by Georgia Tech) with actual flight schedules.

6. More insight into the repositioning flights is needed to understand their impact in passenger ODM cost per mile and both passenger and cargo demands. The cost per passenger-mile for the ODM vehicle is very sensitive to the fraction of flights used to re-position vehicles across landing sites. This should be investigated in more detail.

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1 INTRODUCTION

The Aeronautics Research Mission Directorate (ARMD) at NASA Headquarters is responsible for establishing a strategic systems analysis capability focused on understanding the system-level impacts of NASA's programs, the potential for integrated solutions, and the development of high-leverage options for new investment and partnership.

To this end, ARMD's Portfolio Analysis Management Office (PAMO) has tasked the Systems Analysis and Concepts Directorate at NASA Langley to formalize, develop, and utilize, a framework that efficiently employs a variable fidelity analysis capability to aid in such assessments. The result, the Integrated Systems Analysis and Assessment Capability (ISAAC), allows PAMO, and hence ARMD, to rapidly and effectively respond to changing budgetary and/or technical targets.

This report contains preliminary analysis of ODM Cargo operations supplementing passenger ODM operations in the Northern California area. An ODM vehicle concept using four-seat ODM aircraft is used as cargo transportation system in seventeen counties in the San Francisco Bay Area.

The following tasks and deliverables are reported in this interim report analysis:

Task 1: The Contractor shall estimate the demand for cargo transportation that could reasonably be expected, given the costs compared to current alternatives and taking into account any additional utility. There may be a speed advantage, and delivery may be more reliable and flexible compared to using current methods.

Task 2: The Contractor shall assess the effects of the flown trajectories on existing air traffic and investigate the feasibility of planning trajectories to avoid most commercial air traffic.

Task 3: The Contractor shall determine the effect of cargo delivery missions on UAS VTOL aircraft fleet utilization, assess the feasibility of the cargo delivery concept, and determine the potential impact on passenger demand and operations for the UAS VTOL concept, previously explored in a previous task.

Task 4: The Contractor shall estimate the environmental impact of the UAS VTOL concept compared to using ground transportation. The Contractor shall compare the estimated total annual CO2 emissions of the UAS VTOL concept for cargo delivery for the region under study with current ground delivery methods.

Task 5: The Contractor shall deliver an analysis of the cargo demand for the UAS VTOL concept. The Contractor shall deliver an analysis of the impact cargo operations may have on UAS VTOL passenger operations (i.e., previous task). The Contractor shall deliver corresponding trajectory data (for cargo and updated passenger demand), along with airspace class boundary location data, major commercial air routes and airports locations, suitable for visualization in Google Earth (.kml format). The demand and trajectory data shall be suitable for use in an airspace simulation.

Deliverables: Virginia Tech document and deliver to NASA all methods and procedures generated under Task 1. This will include:

a) Methodology to estimate demand for cargo transportation given the costs compared to current alternatives

b) Methodology to estimate the effect of cargo delivery missions on UAS VTOL aircraft fleet utilization

c) Methodology to identify the environmental impact of the UAS VTOL concept compared to using ground transportation.

d) Trajectory data (for cargo and updated passenger demand)

The analysis presented leverages previous work done in the estimation of on-demand transportation services in the Silicon Valley area and to a lesser extend in the Washington DC area. In a previous study, we investigated the potential passenger commuting demand generated from 17 counties in the San Francisco Bay Area from strategically placed ODM vehicle landing sites. The ODM commuter demand was been estimated using conditional logit models and value-of-time analysis methods. The ODM estimates are linked to the performance of a four-seat, automated UAS VTOL vehicle. The same vehicle could be used in cargo operations transporting small-high value packages in metropolitan areas. This will improve the utilization of the vehicles and perhaps lower their overall life cycle cost. The passenger model employed national transportation survey data and origin-destination data to understand daily commuting patterns in the area.

Cargo demand is assumed to be responsive to socio-economic activities. However, the spatial component of the cargo delivery business in metropolitan areas is not as well documented in publicly available databases because some of the business is conducted by private companies. The United States Postal Service is the main carrier of packages to home addresses and business across United States. This study identifies potential cargo demand of an area (cargo demand generation step) with links to socio-economic activity. For example, if a zone (an area of interest of study) has known population, income characteristics, commercial retail space, etc., these variables can be used as surrogates to estimate potential cargo demand generated by each zone.

1.1 SCOPE OF THE STUDY

The ODM cargo concept complements the passenger application of advanced aircraft used for commuter travel. Northern California is the area of analysis selected for the study by NASA. The region is comprised of 17 counties which include Alameda, Contra Costa, Marin, Merced, Monterey, Napa, Sacramento, San Benito, San Francisco, San Joaquin, San Mateo, Santa Clara, Santa Cruz, Solano, Sonoma, Stanislaus and Yolo. Figure 1, shows the scope of counties in Northern California. According to U.S. Census Bureau, the Northern California metro areas like San Francisco and Sacramento have median household incomes of $185,290 and $170,170, respectively. The area of study includes 2,377 Census tracts shown in Figure 2. The demographic characteristics of the study area are summarized in Table 1. The study area includes more than 3 million people with 4.2 daily commuter work trips.

Table 1: Characteristics of Northern California Study Area for ODM Analysis

Item	Northern California
Area (square miles)	20,899
Number of Counties	17
Number of Census Tracts	2,377
Total Number of Commuters	4.2 million
Commuters making more than $100,000 per year	991,956
Origin-Destination Pairs with Jobs Greater or Equal to $100,000 Annually	132,088

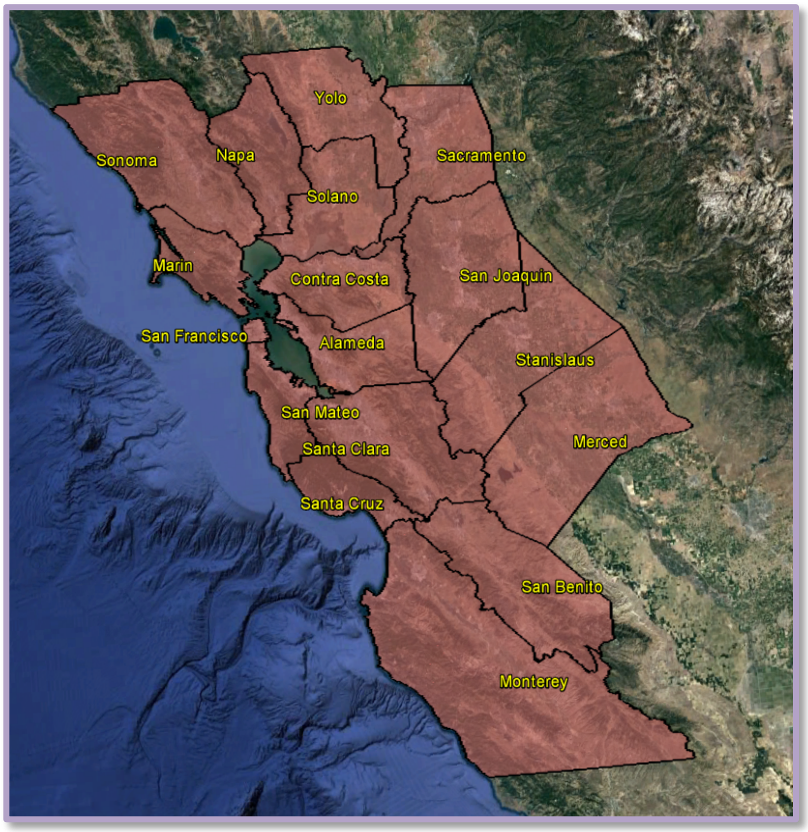

Figure 1: Scope of Counties in Northern California.

1.2 DATASETS USED IN THE STUDY

The main datasets used in the analysis are publicly available at the U.S. Census Bureau and a cargo-specific Transearch database. Some detail of the datasets employed in the study are briefly described below:

American Community Survey (ACS): This survey is done every year nationwide to help the communities in understanding and having the demographic, housing and socio-economic data. ACS has widely used by federal agencies, state and local agencies, non-governmental organizations, planners, educators, journalists and public.

Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES): This has been the main dataset of the analysis. Census Bureau and U.S. states partnered to develop this high-quality labor market information. It contains origin-destination jobs all the way down to the block level.

Transearch database: is a database that contains information on cargo shipments inside in the United States. The data is compiled by IHS International and includes shipments by mode, quantity and commodity types. The database is critical in this study to identify cargo flows inside and outside of the counties in the study area.

T-100I database: contains international cargo flows to and from US airports. The data was used to complement Transearch data to estimate cargo flows into major international airports in the study region.

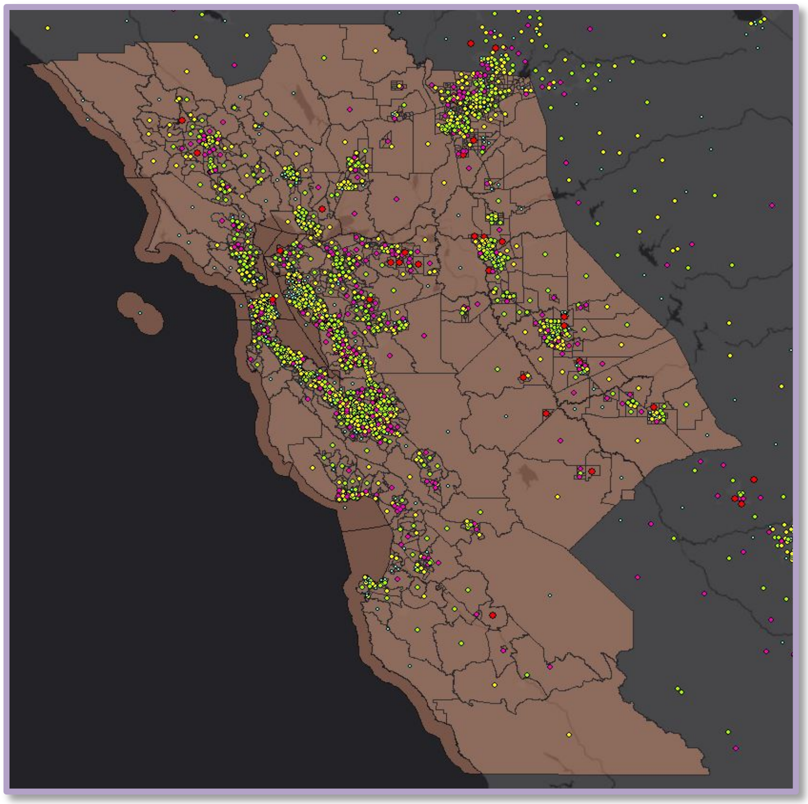

Figure 2: 2377 Tracts in Northern California. The Circles in this Plot Represent Tract Population Points According to US Census Bureau Data (year 2015).

2 ODM LANDING SITE REFINEMENT ANALYSIS

This section explains the refinement of the passenger ODM landing sites to accommodate the dual-role of the ODM vehicles: passenger and cargo use. In a companion study conducted by Virginia Tech for NASA Langley (Syed et al., 2017), we considered a range of scenarios offering passenger ODM service from 1,000 landing sites in the Northern California area. Table 2 shows all passenger scenarios considered in the companion study. For the landing site refinement analysis, we considered Scenario 1 as a starting point with 1,000 landing sites selected using a K-Means cluster analysis (Syed et al., 2017). Figure 3 shows 1,000 landing sites used in the passenger ODM study. The algorithm minimizes the distance between weighted population tract centroids, work locations and the ODM passenger landing sites. The number of ODM landing sites impact the intermodal distance between landing sites and the weighted Census tract centroids. Landing sites represent idealized locations near home residences and work locations to reduce intermodal times to each ODM landing site.

In this study, the landing sites selected for the passenger service were inspected and moved to areas where a landing site was considered feasible. Moreover, the number of landing sites was reduced from the original 1,000 sites to slightly less than 400, based on a first-order economic analysis. The following sections explain the rationale of moving the original passenger landing sites to serve in the cargo role as well.

Table 2: Passenger ODM Scenarios Modeled for Northern California (Source: Syed et al., 2017).

Scenario	Base Fare $15.00	Landing Fare $6.70	Auto Cost $0.54	Auto Cost $0.30	Ingress Time 5 minutes
1	X*	X		X	X
2	X*			X	X
3		X		X	X
4		X		X	X
5	X*	X	X		X
6	X*		X		X
7	X**	X	X		X
8	X**	X		X	X
9	X***			X	X

* $15 fare is charged to any ODM trip, additional passenger-mile cost applied

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

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

2.1 RELOCATION OF PASSENGER ODM LANDING SITES

This section explains the identification of warehouse and retail stores to serve passenger and cargo demand needs. The concept of operations is to use the ODM vehicle for passenger service during the peak hour times and during off-peak hour operations for cargo transportation. A process to identify the best landing sites for the dual-role of the ODM vehicle includes two steps: 1) identifying cargo warehouses and retail space with significant cargo flow activity; 2) down-selecting passenger landing sites sufficient passenger demand; and 3) identifying landing sites that best serve the dual-role. Using Google API, the cargo facility locations are extracted from publicly available data. Figure 4, shows 745 locations that have potential for ODM cargo operations. The facilities are selected because they represent warehouses, postal offices and large retailers. Figure 5 shows a composite map with 745 cargo sites identified and 1,000 ODM passenger landing sites selected in the previous study.

Most of the cargo facility locations are close to the first-order landing site locations. Of the 745 cargo facilities identified, 539 are within one statute mile of the original 1,000 passenger ODM landing sites used in the passenger ODM study (Syed et al., 2017). In this theory, co-location of landing sites near population, workplaces and cargo facilities will help expedite cargo movement from distribution or warehouse to stores which will be carried using trucks, mini-vans or even drones for last-mile delivery. Figure 6, shows a histogram with the distribution of cargo facilities based on distance from the original passenger ODM landing sites.

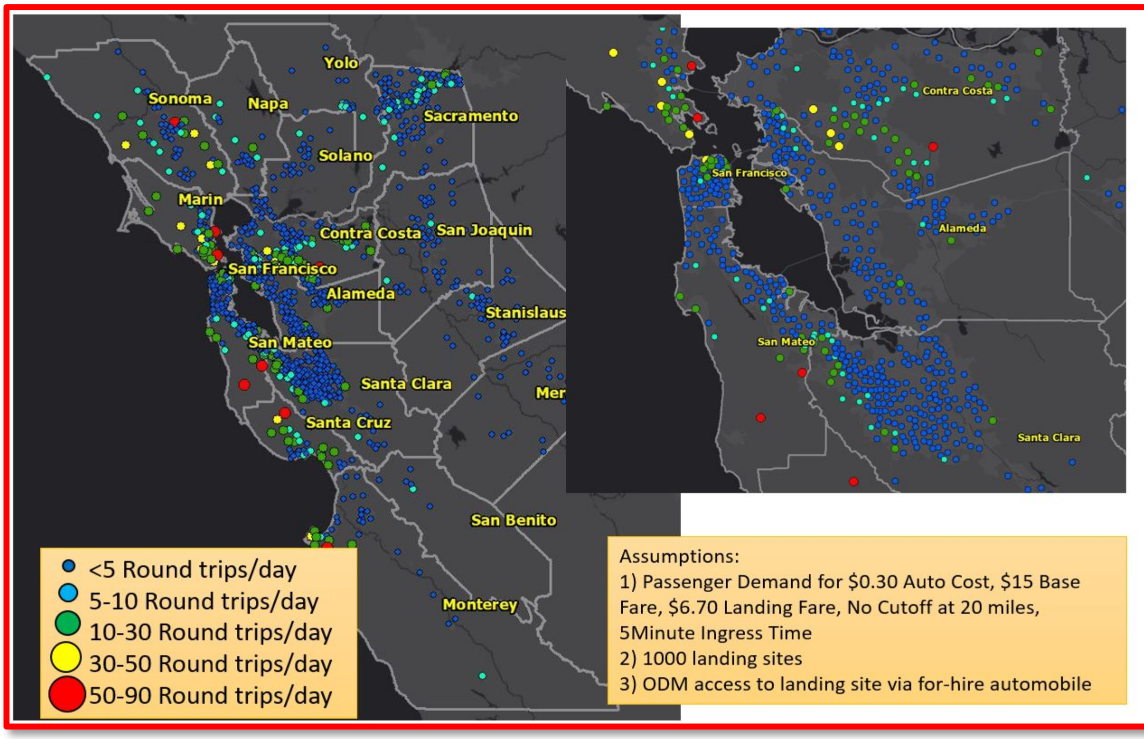

Figure 3: ODM Passenger Demand for Passenger Scenario 1 in Table 2.

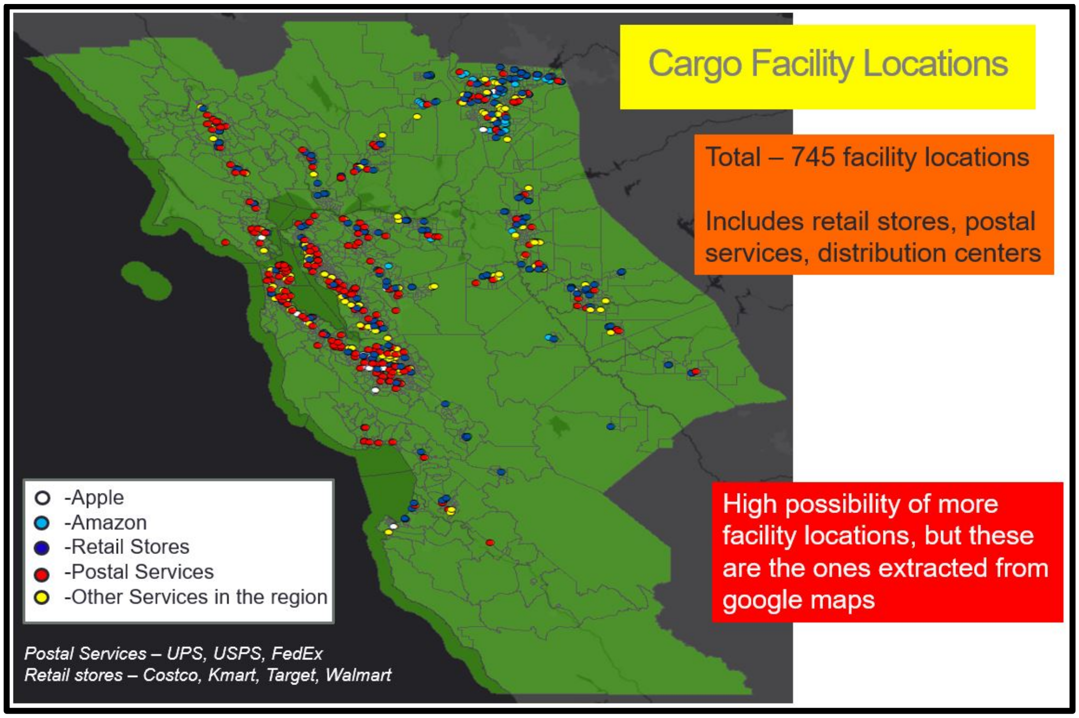

Figure 4: Cargo Facility Locations in Northern California Region.

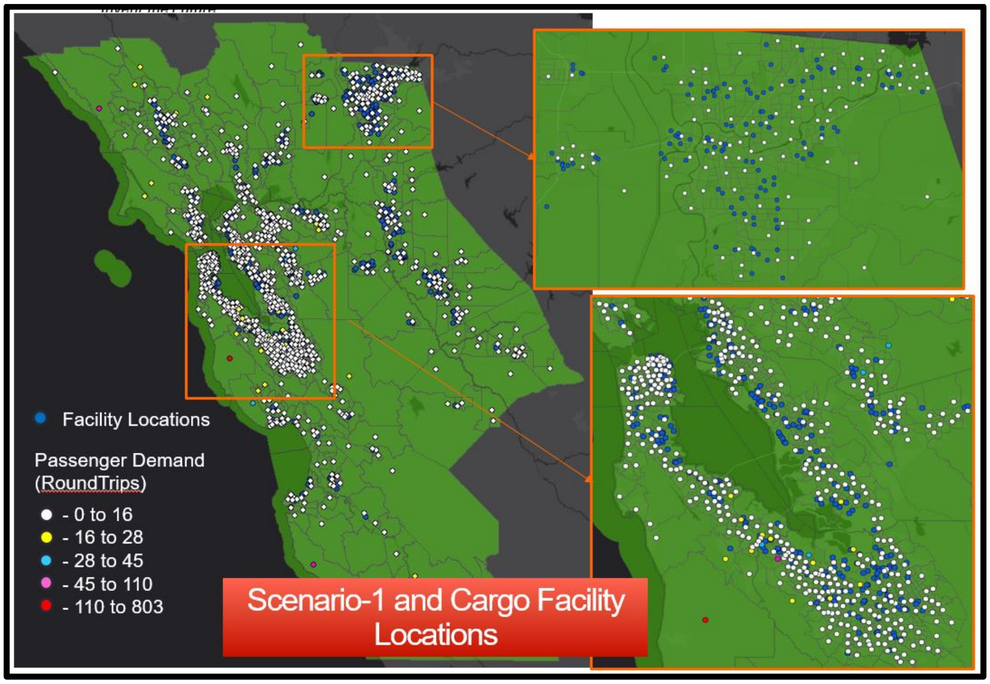

Figure 5: Visualization of Passenger Demand and Cargo Facility Locations within 5 Minutes of Ingress Time.

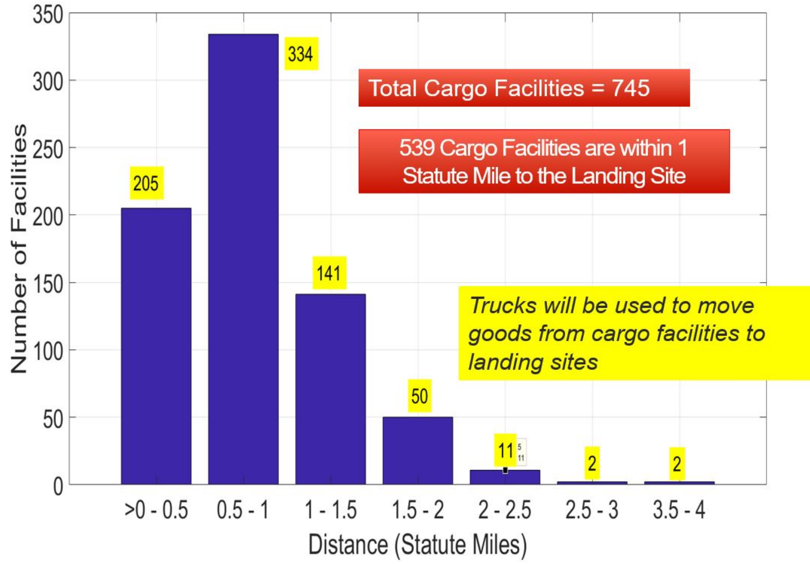

Figure 6: Distribution of Cargo Facilities Based on Distance from Passenger ODM Landing Sites.

The relevance in selecting Scenario 1 for this analysis is to eliminate passenger landing sites that are expected to have little demand. Scenario 1 represents an early ODM scenario with fares derived using a life cycle cost model with electric UAS vehicles priced at $750,000 dollars. For this analysis, the minimum passenger demand considered feasible for a landing site is 16 passenger roundtrips per day. This threshold was used to eliminate landing sites that generate little revenue in landing fees (set at $6.7 per landing operation in Scenario 1) and hence will be difficult to justify economically. Of the 1000 landing sites selected in the passenger ODM analysis, 362 sites have at least one associated cargo facility nearby (i.e., one-mile distance or less). Figure 7 illustrates the process to merge both sets. A landing site is moved to cargo facility location if the passenger demand is less than 16 roundtrips per day. As some of the landing sites are associated with more than one cargo facility, a K-means algorithm is used to relocate that landing site. Figure 7 illustrates how clusters 1 and 3 are landing sites associated with multiple cargo facilities and cluster 2 shows a single association. The landing sites in cluster 1 and 3 are relocated by *K*-means. This way equal importance is given to passenger and cargo demands in the selection of the final landing sites.

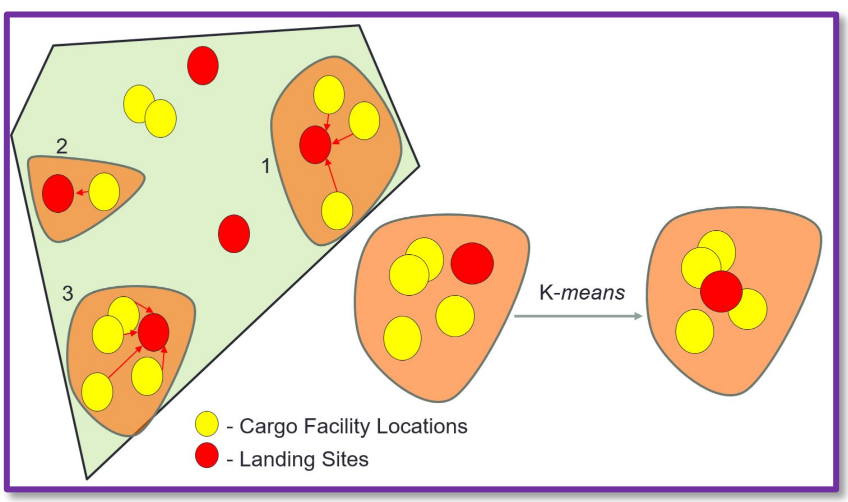

Figure 7: Relocation of Landing Sites.

2.2 TRIMMING OF LANDING SITES

The second step in the final selection of feasible landing sites for cargo ODM analysis considers the economic perspective of whether a vertiport is economically feasible. A rough net present value study was done to further identify a landing site has reasonable demand. For this analysis we did not consider landing sites with a passenger demand of less than six flight operations per hour. Landing sites whose passenger demand is less than the cutoff but are associated with a cargo facility location, are kept in the system. Further to understand the cost and area of land required at each landing site, FAA requirements are considered. The analysis includes determining the number of parking stalls and landing paths required at each vertiport system by doing capacity analysis based on passenger demand and cargo facility locations.

3 VTOL UAS AIRCRAFT CONCEPT AND COST MODEL

A Life Cycle Cost (LCC) model was developed to estimate the cost per passenger mile for each ODM vehicle operating in the study area. The LCC model was developed in STELLA Architect - a Systems Dynamics tool developed by High-Performance Systems (HPS, 2018). The LCC model has an interface created to facilitate making sensitivity runs of various ODM aircraft operational factors. The Systems Dynamics LCC model tracks aircraft costs over the life cycle of operations to estimate an hourly operating cost. The model considers the following cost categories:

- Facilities cost (hangar, office space and landing site)
- Periodic costs (engine, paint, refurbishing, avionics, mid-life inspection, etc.)
- Variable costs (fuel, oil, parts, miscellaneous, maintenance, etc.)
- Fixed costs (hull insurance, liability, maintenance software, property tax)
- Personnel costs (we assumed a pilot-less vehicle in the study)
- Training costs (initial, maintenance, recurrent training, etc.)
- Capital and amortization costs (percent resale value, interest rate, purchase cost)
- Airline administrative cost

Figure 8 shows the interface of the LCC model for a four-seat ODM vehicle powered by electric engines. In the life-cycle cost analysis, we assumed a 20-year life-cycle. Using a purchase cost of $750,000 per ODM aircraft, the LCC cost per hour is estimated to be $207 per hour. Appendix A shows the equations used in the life cycle cost model.

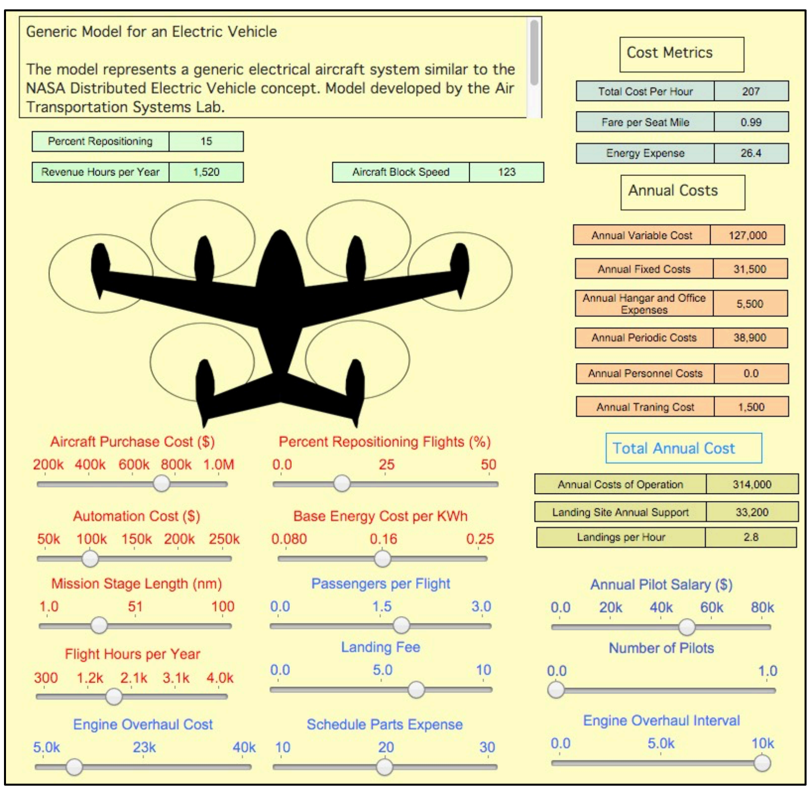

Figure 8: Life Cycle Cost Model User Interface for an ODM Vehicle Concept.

Table 3: Relevant Parameters for Passenger and Cargo ODM Vehicle Life Cycle Cost Model.

Parameter	**Value**	**Remarks**
Aircraft Baseline Cost ($)	800,000	Estimated for non-low boom aircraft (40 seats)
Aircraft Seats	4	
Pilot Salary ($)	50,000	25% benefits (zero cost for autonomous UAS VTOL operations)
Engine Overhaul Cost ($)	10,000 per engine	Electric engine (6 engines)
Engine Overhaul Interval	10,000	Time between engine overhauls
Flight Hours per Year (hr.)	1,000 to 3,000	Parametric analysis
Maintenance Man Hours per Flight Hour (hours)	0.40	Assumes a mature reliable vehicle
Load Factor per Flight (dim)	0.60	Fraction of number of seats occupied
Electric energy cost ($/kWhr)	0.16	California rates in 2017
Maintenance Labor Expense per Hour ($/hr)	50	Typical for GA aircraft maintenance
Modernization Time Interval (hr.)	3,000	
Modernization and Upgrades Cost (hr.)	12,000	Cabin renovation is estimated seperately
ODM Passenger/Cargo Service Provider Profit Margin (%)	10	Initial assumption

Figure 9 shows the cost per seat-mile for the ODM VTOL aircraft as a function of the number of hours flown. The plot show trends in cost per passenger mile when the number of hours of use of the aircraft increases from 1,000 to 3,000 hours per year. The results also show variations in passenger cost per mile as a function of the percent of repositioning flights. It is instructive to show that if cargo operations are conducted with the passenger ODM aircraft during off-peak hours, the cost per passenger mile is reduced for each passenger using the ODM vehicle during the commuting peak hours. The analysis is presented in Section 5 of the report. Figure 9 shows substantial changes in cost per passenger mile if the number of repositioning flights increases from 15% to 35%. A companion study by Georgia Tech of ODM vehicles flying in the San Francisco Bay area has made initial estimates of re-positioning flights using a simplified landing site network.

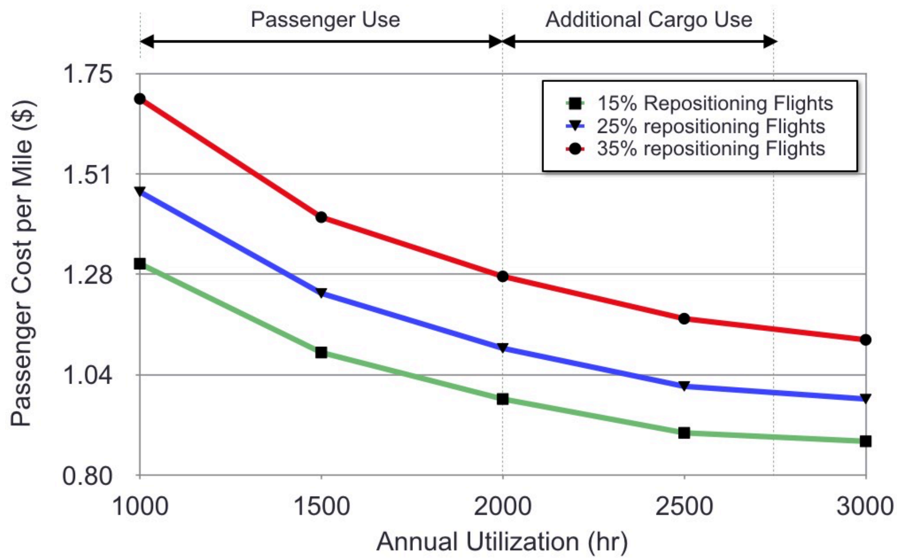

Figure 9: Estimated Life Cycle Cost Results for an all-Electric ODM Vehicle. Sensitivity with Respect to Annual Use of the ODM Vehicle.

4 POTENTIAL ODM CARGO DEMAND

Cargo demand in the Northern California region depends on many factors including the number of consumers of goods that are normally shipped by either ground or air modes. Consumers include industries, businesses, households, etc. The characteristics of consumers dictates the cargo demand generation (both productions and attractions) in the region. In this study, we have considered certain characteristics such as location of warehouses (for example: Walmart, Target, Walgreens etc.) in the area of interest as these warehouses would be critical components in a developed cargo ODM network. Another characteristic related to households is demographics. The cargo demand in the region is assumed to depend on demographics such as population, household income level, household size and location of industries. While most users prefer the cheapest delivery methods today (~70%), fast delivery services are more popular among the younger population. For example, a recent study suggests that 23% of the household surveyed in China, Germany and the United States prefer same-day delivery options for small packages (McKinsey, 2016). Similarly, the variety of goods transported using small packages is very diverse. High to moderate-price commodities delivered in small packages to landing site lockers or retailers from warehouses are some of the cargo delivery concepts for ODM vehicles.

4.1 POTENTIAL ODM CARGO DEMAND METHODOLOGY

Figure 10 shows a flowchart of the methodology used to predict potential ODM cargo demand in Northern California. The figure shows two databases used to generate cargo and freight flows in and out of the Northern California region: a) Transearch and b) International T-100 air freight data. Both datasets are identified in Figure 10 in blue color. The Transearch database includes details of tonnage, value and commodity types transported by air, ground (truck and rail) and ship into the study area. For this study we only use the air and truck modes of transportation in the Transearch database. Rail cargo is too bulky and has low value per unit weight to be a candidate for cargo ODM vehicles. ODM vehicles have limited internal volume and an 800-pound maximum payload capability. The Transearch data includes spatial information to estimate county-level attraction and production cargo flows. The T-100 International air freight data provides complementary information to Transearch by reporting air freight flows in and out of Northern California. The T-100 International data is airport specific and does not include details about commodity types or value of cargo. In this study we assume that most of the air freight shipments in the T-100 are valuable because they are being transported via cargo aircraft – a more expensive alternative to container ship transportation. The analysis still recognizes that even if a large fraction of the air shipments in the international T-100 air freight data arrive to large airports in the region, only a small fraction of them may be transported by ODM to the final destination points.

Three sub-models are identified in Figure 10 by three large red boxes: a) a cargo distribution model and b) a cargo flight generator model, and c) an ODM flight path generator model. The cargo distribution model handles three distinct cargo flow streams labeled Cargo Flow from Truck Mode, Cargo Flow from Air Mode and International Air Freight into Main Cargo Airports. These modules are shown in orange in Figure 10). The cargo distribution model handles the distribution of these flows into airports if the cargo arrives by air into the region. Similarly, the model handles the distribution of cargo from originating points inside the region (i.e., warehouses) to destination points (i.e., other counties). Finally, the model distributes the cargo flows to individual landing sites using population-weighted distribution factors.

The cargo flight generator estimates the number of flights at each landing site by ODM vehicles considering vehicle load carrying capacity, typical load factors and the landing site cargo flows produced by the cargo distribution model. The output of the ODM flight path generator model generates detailed flight tracks to be flown by cargo ODM vehicles considering airspace constraints that avoid runway approach and departure surfaces at major airports. The ODM flight generator constructs a network of routes in the study region, using the location of landing sites as waypoints to "anchor" these routes. The ODM flight generator uses a shortest path algorithm to identify the minimum travel distance route between an origin and a destination landing site. The ODM flight path generator produces files that can be visualized in Geographic Information System software and files in a format that can be used as input in the NASA ACES simulation model.

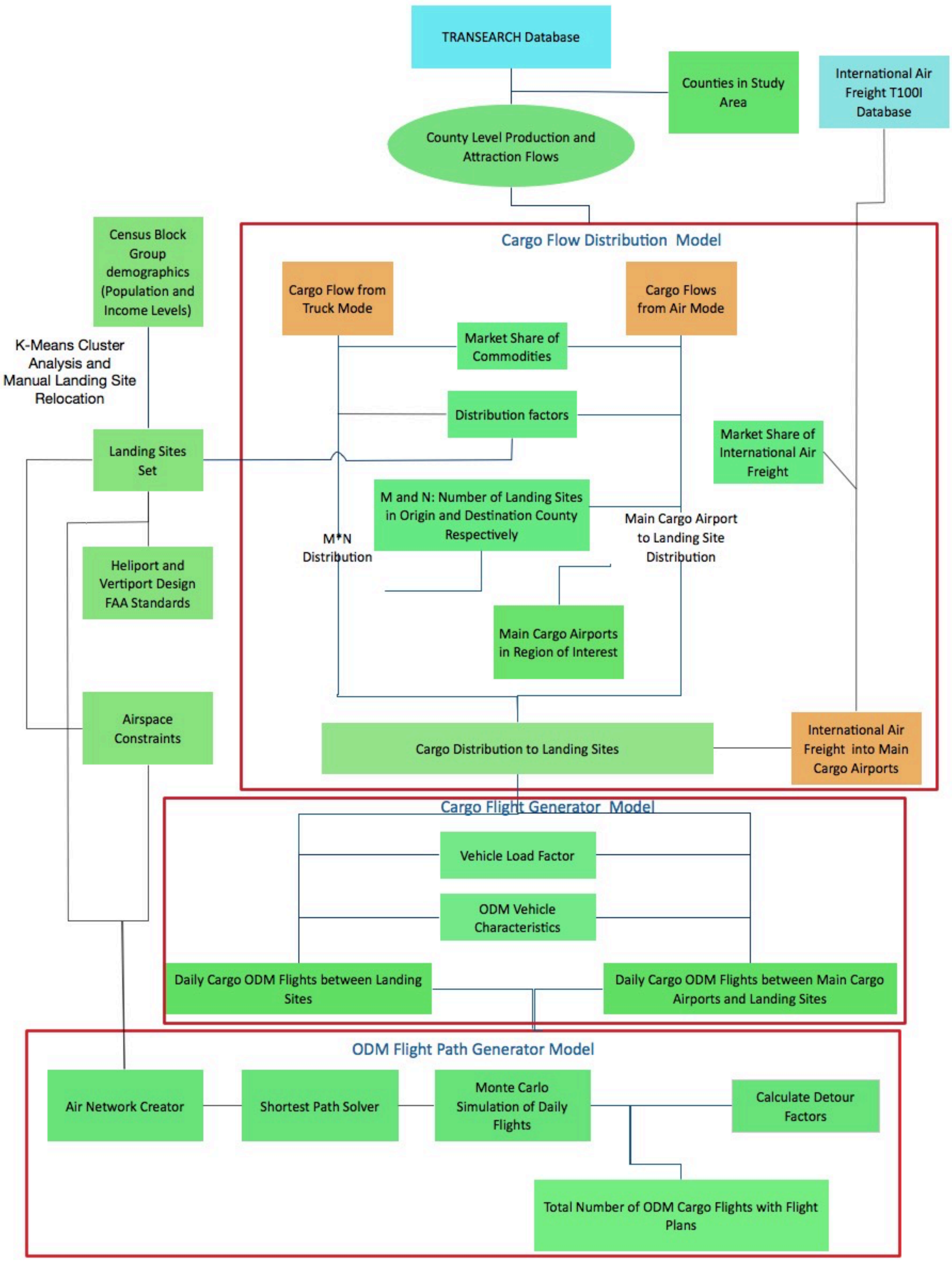

Figure 10: Potential Cargo ODM Demand Methodology Flowchart.

Figure 11 shows details in the analysis of "Truck" and "Air" mode flows contained in the Transearch database. Given the limited range of the ODM vehicle, Transearch cargo flows are divided into two branches for each of the two modes of transportation considered: a) internal flows and b) external flows. The internal flows are those that can be "flown" using an ODM vehicle because the distance between the origin and destination counties is less than the design range of the ODM aircraft. In this study we assumed a 150-nautical mile range. External flows are cargo shipments that originate at other regions in the United States located beyond the 150-nautical mile range of the ODM aircraft. For example, fish products from Maine are flown to Northern California via cargo aircraft and handled at one of six cargo airports designated in the area of interest. This particular shipment is handled as an external cargo flow labeled "air" mode in Figure 11. If the final destination of the shipment is San Mateo county, the closest cargo airport assigned to the shipment is San Francisco International Airport (SFO). From that airport, fish products will be distributed to the neighboring counties using distribution attraction factors based on population demographics. For example, the large population density of San Francisco Central Business District will "attract" more fish products than a sparsely populated area like Sonoma county. The process of estimating ODM cargo demand involves 10 steps according to Figure 10 and Figure 11 is explained in detail in the following section.

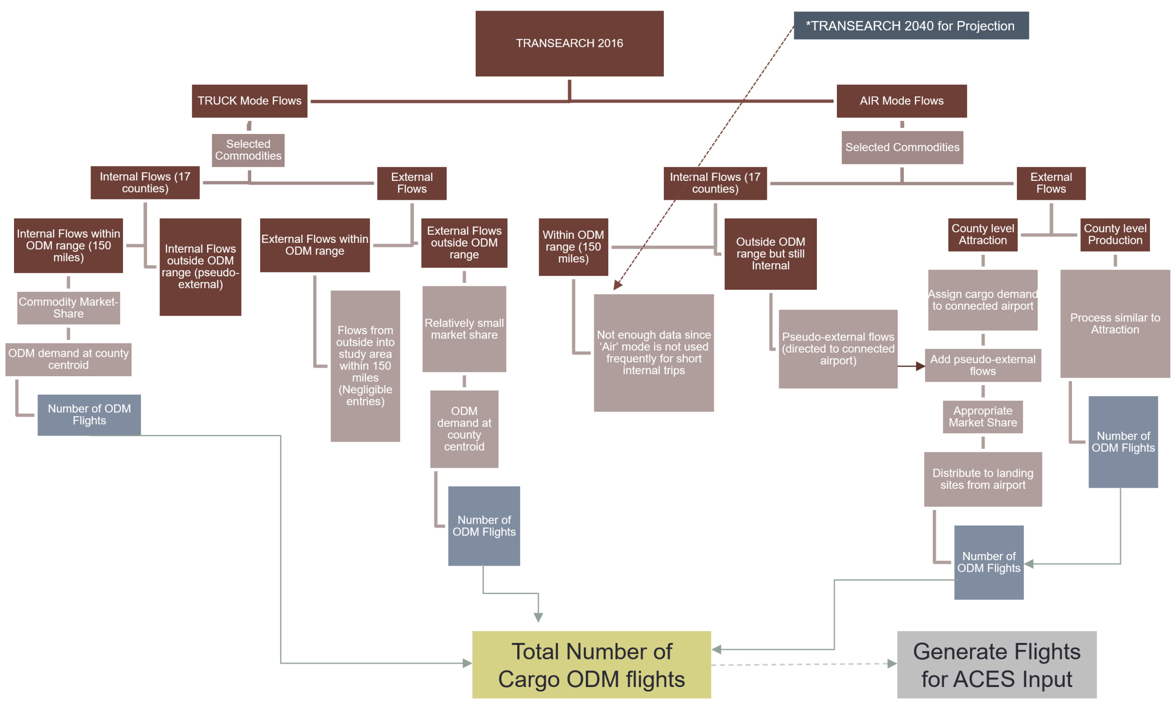

Figure 11: Handling of Various Cargo Flows in the Transearch Database.

Step 1: Identification of ODM Cargo Competing Modes

The Transearch database includes fifteen transportation sub-modes categorized into five major mode groups. In the initial step, we segregated the data for two major modes of shipments namely 'Truck' and 'Air'. These two transportation modes account for 98.49% of the cargo shipment records in the Transearch 2016 database. All modes in the Transearch database are described in Figure 12.

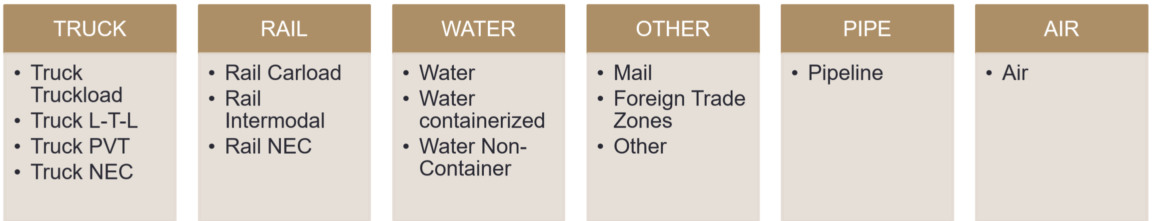

Figure 12: Mode Groups and Classification in the Transearch Database.

The characteristics of an ODM vehicle renders it to be considered as a competition (or complement) to only two mode groups in the Northern California region: 'Truck' and 'Air'. Therefore, the analysis breaks down the data for these two mode groups into internal and external flows. The Transearch database has thirty different commodity groups which could have some potential for ODM cargo shipments. These commodities were selected among 430+ commodities included in the Freight Analysis Framework database (FAF4) based on their value per unit weight. The FAF4 database was used earlier in the project before switching to the Transearch database. Transearch includes more detailed information compared to FAF4 and includes more than 700 commodity types. Figure 13 illustrates the final set of 30 commodities considered in the cargo ODM demand analysis.

Commodity Group	Commodity Name	Commodity Group	Commodity Name
1	Fresh Fish or Marine Products	16	MUSICAL INSTRUMENTS OR PARTS
2	Clothing and Apparel	17	SPORTING OR ATHLETIC GOODS
3	Paper Products	18	COSTUME JEWELRY OR NOVELTIES
4	DRUGS	19	SEMI-TRAILERS RETURNED EMPTY
5	COSMETICS,PERFUMES, ETC.	20	EMPTY EQUIPMENT, REVERSE ROUTE
6	Leather Products	21	MAIL AND EXPRESS TRAFFIC
7	ELECTRIC MEASURING INSTRMTS	22	OTHER CONTRACT TRAFFIC
8	PHONOGRAPH RECORDS	23	FREIGHT FORWARDER TRAFFIC
9	TELEPHONE OR TELEGRAPH EQUIPMENT	24	SHIPPER ASSOCIATION TRAFFIC
10	ELECTRONIC TUBES	25	FAK SHIPMENTS
11	SOLID STATE SEMICONDUCTS	26	MIXED SHIPMENTS, MULTI-STCC
12	MISC ELECTRONIC COMPONENTS	27	SMALL PACKAGED FREIGHT SHIPMENTS
13	Pharmaceutical Equipment	28	WAREHOUSE & DISTRIBUTION CENTER
14	JEWELRY, PRECIOUS METAL, ETC.	29	RAIL INTERMODAL DRAYAGE
15	SILVERWARE OR PLATED WARE	30	AIR FREIGHT DRAYAGE

Figure 13: Commodity Groups in Transearch Database Identified for Potential ODM Use.

Step 2: Commodity Value Analysis

All thirty commodity groups contained in the subset of the Transearch database were analyzed for their potential to be shipped via ODM sub-mode in the future. Different parameters were examined and calculated in the analysis for different mode groups. For 'Truck' mode, a new parameter was generated from given data called 'Value per Ton'. As the name suggests, this parameter predicts the shipment's value per English ton. Under same commodity group, different 'Value per Ton' numbers were tabulated. Using the mean and median of 'Value per Ton' associated with each commodity group, six commodity groups were selected as potential competitors to 'Truck' mode shipments and used in the analysis (see Table 3). The values of the six commodities considered range from $22,964 to $256,752 per ton ($10.4 to $116.7 per pound. Section 5 of the report highlights current parcel costs for various delivery methods to support some of the assumptions made later in this section about potential market share for ODM cargo shipments. For example, a five pound parcel shipped "next day air" (with delivery before 8:30 AM of the following day) over distances less than 150 miles costs $51 dollars on average.

Similarly, 'Air' mode commodity groups were analyzed but, from a different perspective. It is believed that shipments being flown into the region via 'Air' mode have a clearly defined 'urgency' factor associated with them i.e. the value of these shipments extends beyond their monetary value of the contents. There must be a value attached to the shipment generated by time constraint (overnight shipment) or nature of content (perishable). In order to quantify this criterion and estimate market shares in the parametric study, all commodity groups shipped via 'Air' mode in Transearch were analyzed to determine how often shipments of one commodity are shipped via 'Air' mode against other modes of transportation. Table 5 shows the top six commodity groups shipped more frequently via 'Air' mode in the Transearch database. The table shows that 99% of the mail and express traffic (in terms of tons) was shipped by 'Air'. Similarly, small packaged freight shipments were shipped by "Air".

Table 4: Selected Commodities for 'Truck' Mode. Values in the Table are Dollars per Ton.

Commodity	Mean ($)	Median ($)
Jewelry, Precious Metals etc.	190,515	193,562
Solid State Semiconductors	27,248	29,172
Electric Measuring Instruments	256,752	286,671
Pharmaceutical Equipment	27,350	14,761
Drugs	22,964	22,212
Telephone or Telegraph equipment	34,210	29,584
Phonograph Records	24,694	24,871

Table 5: Selected Commodities for 'Air' Mode.

Commodity	Percent of 'Air' mode entries
Small Packaged Freight Shipments	98
Mail and Express Traffic	99
Fish and Marine Products	92
Pharmaceutical Equipment	12
Drugs	11
Electric Measuring Instruments	5

Step 3: Internal and External Flow Analysis

The Transearch dataset offers some level of detail with respect to location of where the shipment originates and its delivery point. Transearch has county-level information for the study region (i.e., 17 counties in Northern California) and regional level information for areas outside the study region. The regions are defined as a collection of county Federal Information Processing Standard (FIPS) which together represent a Business Economic Area (BEA). The regional level information is coarser than the county level. Therefore, shipments originating in the study area have county-level information for origin and regional level for destination. The opposite is true for shipments originating outside the study area but having a destination inside the study area. For this study, the Transearch dataset was segregated into internal and external flows for both 'Truck' and 'Air' modes. 'Internal' flows are shipments having both origin and destination inside study region, whereas external flows are shipments having either origin or destination outside study region.

Step 4: Analysis of Internal/External Cargo Flows by Mode

In this step, internal and external flows are analyzed independently for both modes ('Truck' and 'Air'). For 'Truck' mode we adopted the following concept of operation rules:

a) Internal cargo flows for the 'Truck' mode, were divided into two categories based on the distance travelled: i) cargo flows with trips less than 150 miles and ii) cargo flows greater than or equal to 150 miles. The ODM vehicle range is assumed to be 150 miles and multi-legged trips were not considered. Internal flows within 150 miles are believed to have significant potential for ODM applications if the economics of the shipment via ODM can compete in price and speed with 'Truck' mode for selected high-value commodities. For internal cargo flows traveling more than 150 miles via truck were considered as pseudo-external flows as they will rely on the 'Truck' mode for a large portion of the trip. These flows were added to the external flows analysis.
b) It is unlikely that shifting shipments from the 'Truck' mode to relatively costlier ODM sub-mode for the final part of the trip. For this reason, we expect a very small market share for ODM sub-mode. Analysis estimated negligible number of flights which were ultimately removed from the analysis. The pseudo-external flows associated with internal flows by 'Truck' mode, were also eliminated because it is not plausible to shift cargo shipments to an ODM vehicle after they have travelled by truck over a large portion of the trip.

For the 'Air' mode we adopted the following concept of operation rules:

a) Similar segregation was applied to 'Air' mode shipments also, but with a modified perspective. The internal flows were separated into two categories based to trip distance. Transearch did not have enough records for internal shipments travelling less than 150 miles via 'Air' mode as expected. It is unlikely that traditional 'Air' mode would be selected for such short distances. The internal flows with travel distances greater than the ODM aircraft range (150 miles) were considered as pseudo-external flows and thereby added to the external flows.
b) The Transearch data methodology indicates that shipments under 'Air' mode were shipped from an airport nearest to the origin region to the airport nearest to the destination region. Further information on airport assignment is included in the following sections. External flows were divided into two categories namely attraction and production based on whether the shipment originates or ends in study region. The pseudo-external flows were added to external flows before proceeding for further analysis. Further investigation of the Transearch database shows that **international "Air' shipments** are not included in the Transearch database. A procedure to account for such trips is explained in Step 9 of this report.

Step 5: Airport Assignment Methodology

Our assumption is that commercial airports are the hubs for all the 'Air' cargo flowing in and out the study region. All shipments via 'Air' mode must go through a commercial airport that normally has cargo facilities. Using the domestic T-100 database from the Bureau of Transportation Statistics and reports from Caltrans on California air cargo studies, the top six commercial airports were chosen as potential cargo hubs for 'Air' mode shipments. These airports are shown in Figure 14. The figure shows that while the region encompasses seventeen counties, the number of cargo hub airports is more limited. There are large sections in the southern part of the study area without a cargo hub airport that can process 'Air' mode shipments contained in the Transearch data. According to domestic T-100 data, Monterey airport has few cargo flights per week but their share of cargo flows into the area are very small. After consultation with the NASA sponsor, such airports were ignored in this analysis. In a follow-up study, consideration could be given to small regional airports as part of the cargo ODM network.

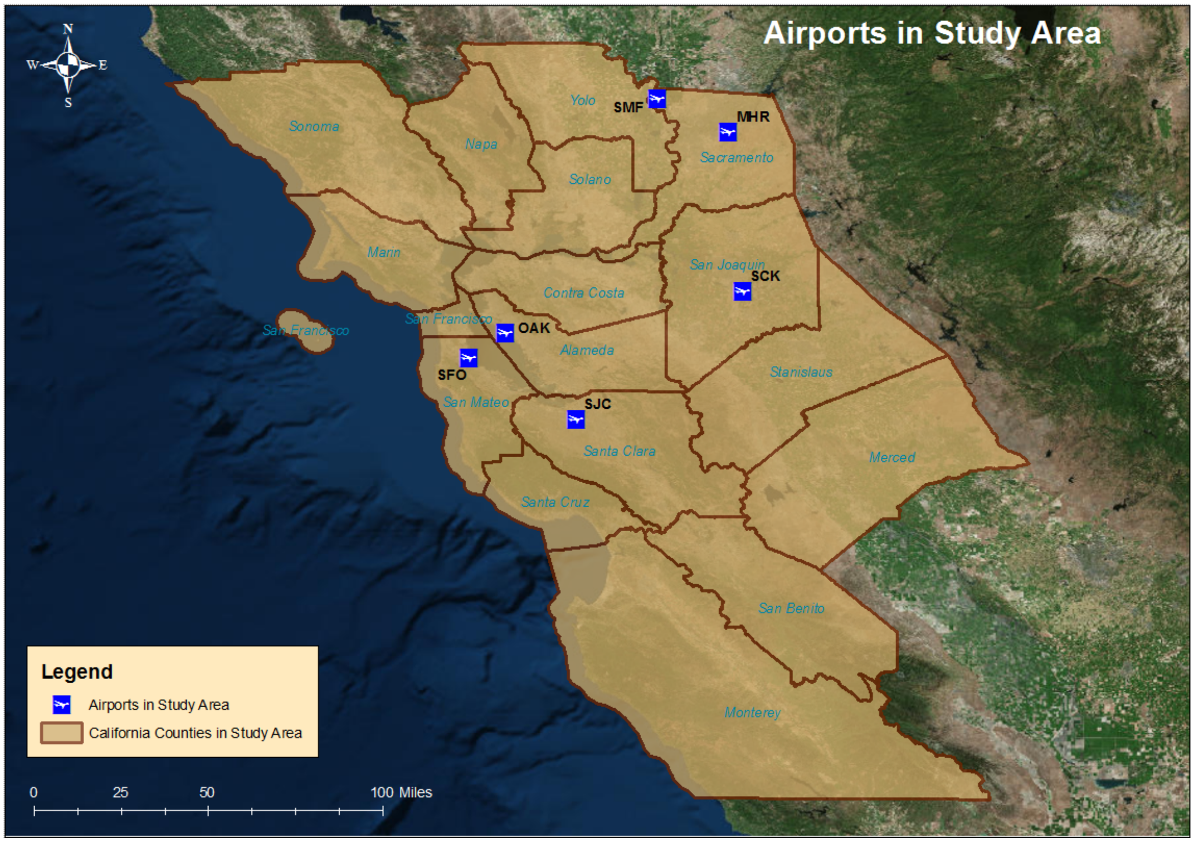

Figure 14: Selected Airports for Domestic Cargo Transfer in the Study Area.

The hub cargo airports were connected to counties via direct routes when possible or with the smallest detour to avoid commercial airport operations. For example, cargo ODM are subject to the same airspace operational restrictions used in the passenger ODM study (Syed et al., 2017). In that study, ODM aircraft avoid arrival and departure surfaces of runways at large commercial airports. Avoidance of the approach and departure surfaces will de-conflict ODM from commercial traffic (an assumption in the concept of operation of ODM vehicles) and more importantly, steer ODM aircraft away from wake turbulence effects of commercial operations.

Market Share Analysis

The ODM sub-mode is a concept whose potential cargo demand depends on the market share it can capture in future. This study does not involve the direct calculation of market share for the ODM sub-mode using a cargo choice model. Calibration of such model requires information that is not publicly available. Nevertheless, the effect of varying market share on final cargo ODM demand is estimated by parametric analysis. Different scenarios of market shares were developed from low to high demand to understand their influence on cargo ODM demand across the Northern California region. The initial market share for each commodity were selected with respect to the nature of commodity i.e. high priority shipments like 'Mail and Express Traffic' and perishable commodity like 'Fish and Marine Products' were assigned higher market share compared to others. Furthermore, the market share was varied parametrically according to the values shown in Table 7. In a follow-up study, we recommend the development of a first-order cargo choice model using the cost functions presented in Section 5 of the report. It is important to note that there is little publicly available data that explains the details on how customers select among shipping alternatives across commodities. In other words, there are macro-level databases like Transearch that aggregate cargo shipments across regions. Nevertheless, there is no data on the actual choices that customers or retailers considered before making a specific shipment. Such data will have to be derived synthetically in a follow-up study.

Table 6 shows the counties in Northern California and their assigned hub airports. The basis for the assignment is distance between population centroid of the county and location of airport. Every county is assigned the nearest hub cargo airport to its population centroid. Since there are fewer commercial airports receiving cargo compared to the number of counties, each commercial airport in the area is assigned to multiple counties. For example, Oakland Airport (OAK) is connected to four counties i.e. all the cargo (with six selected commodities) attracted or produced in these four counties shipped via 'Air' mode will move through OAK airport.

Market Share Analysis

The ODM sub-mode is a concept whose potential cargo demand depends on the market share it can capture in future. This study does not involve the direct calculation of market share for the ODM sub-mode using a cargo choice model. Calibration of such model requires information that is not publicly available. Nevertheless, the effect of varying market share on final cargo ODM demand is estimated by parametric analysis. Different scenarios of market shares were developed from low to high demand to understand their influence on cargo ODM demand across the Northern California region. The initial market share for each commodity were selected with respect to the nature of commodity i.e. high priority shipments like 'Mail and Express Traffic' and perishable commodity like 'Fish and Marine Products' were assigned higher market share compared to others. Furthermore, the market share was varied parametrically according to the values shown in Table 7. In a follow-up study, we recommend the development of a first-order cargo choice model using the cost functions presented in Section 5 of the report. It is important to note that there is little publicly available data that explains the details on how customers select among shipping alternatives across commodities. In other words, there are macro-level databases like Transearch that aggregate cargo shipments across regions. Nevertheless, there is no data on the actual choices that customers or retailers considered before making a specific shipment. Such data will have to be derived synthetically in a follow-up study.

Table 6: Northern California Counties and Connected Airports.

County	Airport ID
Alameda	OAK
Contra Costa	OAK
Marin	OAK
Merced	SCK
Monterey	SJC
Napa	OAK
Sacramento	MHR
San Benito	SJC
San Francisco	SFO

San Joaquin	SCK
San Mateo	SFO
Santa Clara	SJC
Santa Cruz	SJC
Solano	OAK
Sonoma	OAK
Stanislaus	SCK
Yolo	SMF

Table 7: Market Share Assumptions for ODM Cargo Scenarios Modeled.

Commodity	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	Percent Market Share from Truck (%)	Percent Market Share from Air (%)	Percent Market Share from Truck (%)	Percent Market Share from Air (%)	Percent Market Share from Truck (%)	Percent Market Share from Air (%)	Percent Market Share from Truck (%)	Percent Market Share from Air (%)
Fish and Marine products	-	5	-	5	-	2.5	-	2
Drugs	2.5	2.5	2.5	2.5	1.25	1.25	1	1
Pharmaceutical Equipment	2.5	2.5	2.5	2.5	1.25	1.25	1	1
Electric Measuring Instrument	5	2.5	2.5	2.5	1.25	1.25	1	1
Mail and Express Traffic	-	10	-	10	-	8	-	5
Small Freight Shipments	-	10	-	10	-	8	-	5
Solid State Semiconductors	5	-	2.5	-	1.25	-	1	-
Telephone Equipment	5	-	2.5	-	1.25	-	1	-
Jewelry and precious metals	2.5	-	2.5	-	1.25	-	1	-
International Air Freight		10.0		5.0		3.0		2.5

Landing Site Network

The landing site network used in this study consists 375 landing sites - 369 regular landing sites plus 6 commercial airports with dedicated facilities to land ODM aircraft. The landing sites were originally generated by k-means clustering. They were further modified for passenger demand according to Scenario 1 using the process described in Section 2 of this report. Thereafter, they were manually modified to locations near warehouses which are major cargo producers and attractors. Some landing site locations were modified in order to move them outside the approach and departure surfaces of runways at commercial airports. The final 375 landing sites that will serve both passenger and cargo are shown in Figure 15.

Cargo Distribution Methodology

The Transearch database is limited to county-level flows. The data does not contain information about flows inside each county. Therefore, to determine the cargo flows at the landing site network level a distribution methodology was developed. The initial step involved is the calculation of 'distribution factor' for each landing site in the study area. Using Census-2010 data at the block group level, we studied the demographics surrounding landing sites. It is assumed that ODM cargo demand at a landing site is proportional to the combined population of the surrounding area. For example, landing sites located in dense populated areas will receive or produce relatively more cargo than a landing site located in a sparsely populated area. Distribution centers can be a connected airport or a population centroid. The hypothesis of the analysis is that people are the ultimate recipients of the cargo flowing into the area of interest. The population surrounding each landing site is used as a landing site "catchment" area. In a follow-up study we recommend that catchment areas for warehouses and retail space be considered as part of the distribution method.

Step 7: Application of Appropriate Market Share

Using the respective market share values, cargo demand for ODM sub-mode at county level is calculated for each phase of analysis i.e. internal flows from 'Truck' mode travelling less than 150 miles and external flows (including pseudo-external) from 'Air' mode.

Step 8: Landing Site Cargo ODM flights Calculation

Certain ODM vehicle characteristics are assumed to calculate number of daily cargo ODM flights. Number of flights for cargo ODM involves separate analysis for 'Truck' and 'Air' mode which eventually adds up to find 'Total Number of Cargo ODM Flights' (on daily basis). The following ODM vehicle characteristics are assumed in this analysis: a) 800 lb. ODM vehicle capacity, b) 250 working days per year (with uniform demand) and 0.6-0.75 load factor of the ODM aircraft.

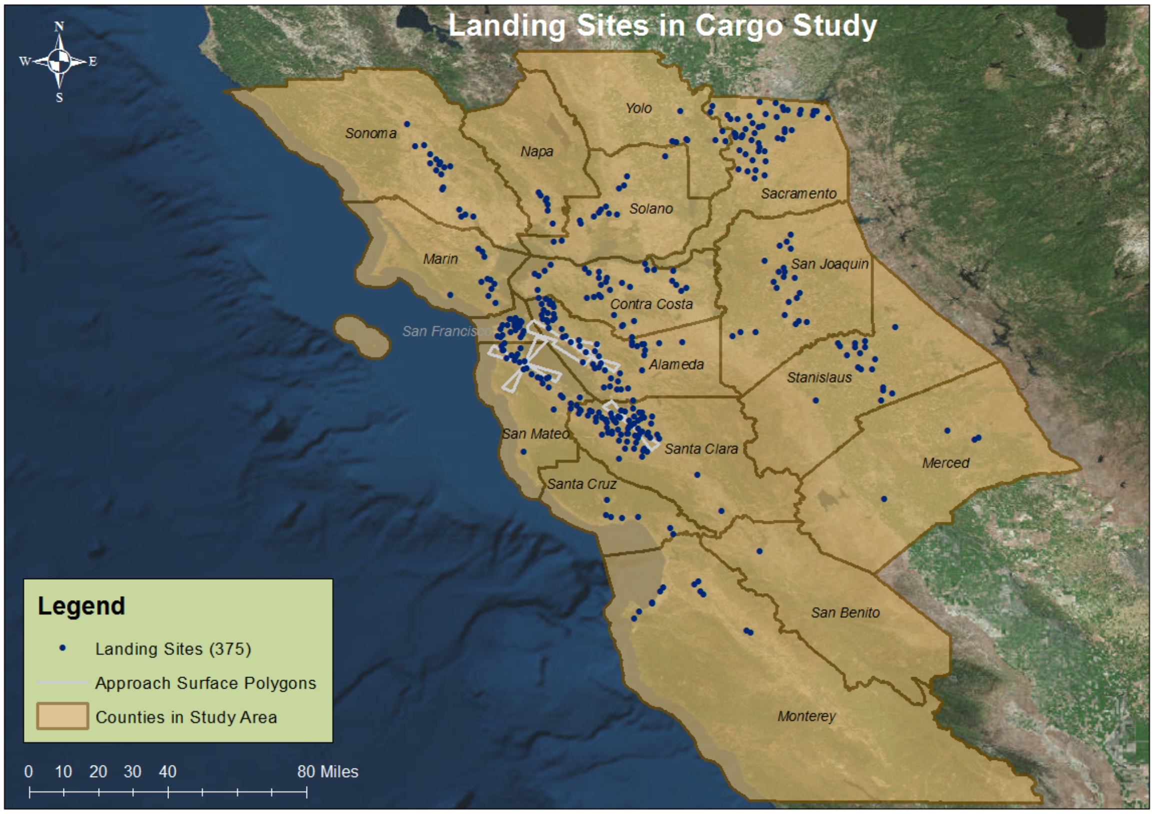

Figure 15: Landing Sites in Cargo Study

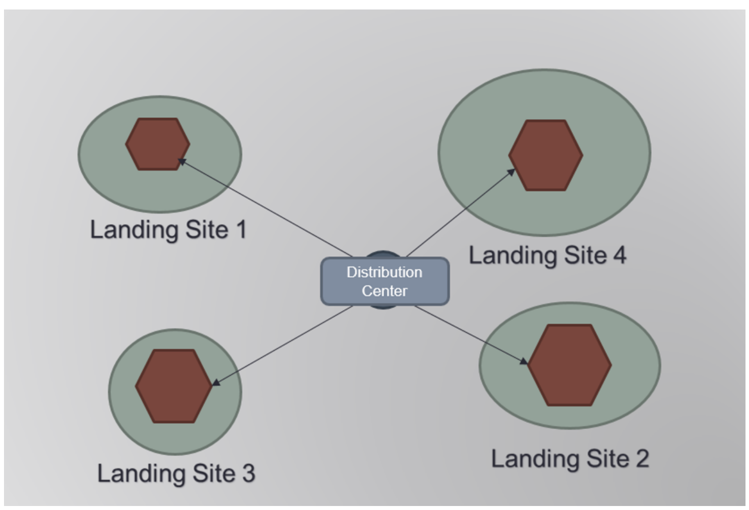

Figure 16: ODM Cargo Distribution Methodology.

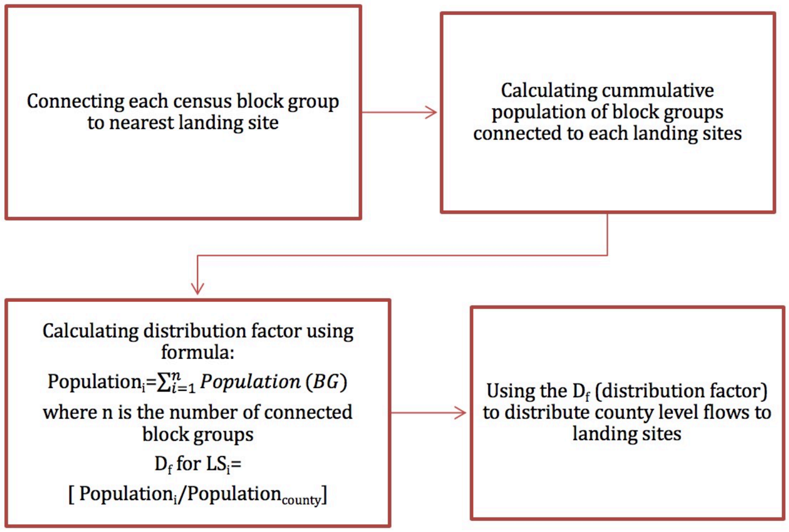

Figure 17: Distribution Factor Calculation Process.

Different load factors were assumed for commodities chosen in the analysis. A higher load factor was selected for commodities in the 'Truck' mode due to the slower transportation speeds of the 'Truck" mode. This implies that when ODM aircraft compete with trucks, there are greater opportunities to wait a longer period of time before the shipment and hence improve the chance to reach higher load factors. For commodities in the 'Air' mode, we expect lower load factors because ODM will compete with a faster mode of transportation.

Table 8 and Table 9 shows the assumed load factors for 'Truck' and "Air" modes, respectively. These assumptions should be studied more carefully in a follow-up study.

The county-level cargo demand follows a two-stage distribution model. Internal flows are first distributed using distribution factors in the origin county followed by distribution of the county share among landing sites in destination county. This generates a $m\ by\ n$ matrix where 'm' is number of landing sites at the origin county and 'n' is number of landing sites at the destination county.

The number of potential daily cargo ODM flights are determined between these landing site pairs using the assumptions stated above. In the next paragraphs we describe other assumptions in the assumed cargo ODM operational concept.

'Air' Mode Analysis

a) All the cargo attracted or produced at the county level is assumed to move through a hub cargo airport. The last-mile trip from and to the connected airport is the potential market for ODM sub-mode as it provides a time-advantage for shipments with delivery priority (e.g., next-day overnight). For this study we ran a parametric analysis of the potential cargo ODM demand assuming various market share values for each commodity. The cargo ODM demand is calculated after the application of a market share value to a commodity (see Table 7).
b) The cargo ODM demand is distributed from the cargo hub airport to individual landing sites based on distribution factor estimated based on population demographics.
c) The number of daily, cargo ODM flights is determined between airports and respective landing sites for each county in the study region.

Table 8: Load Factors for ‘Truck’ Mode Commodities.

Commodity	Load Factor (%)
Drugs	80
Pharmaceutical Equipment	80
Electric Measuring Instrument	80
Solid State Semiconductors	80
Telephone and Telegraph Equipment	80
Jewelry and precious metals	80

Table 9: Load Factors for 'Air' Mode Commodities.

Commodity	Load Factor (%)
Fish and Marine products	60
Drugs	60
Pharmaceutical Equipment	65
Electric Measuring Instrument	65
Mail and Express Traffic	50
Small Freight Shipments	50

Step 9: International Air Freight into the Region

The Transearch database does not account for two important additional cargo flows that could an important role in this analysis: a) international air cargo to and from the study area and b) internal cargo flows between private warehouses (e.g., Amazon shipments between warehouses). International cargo arriving or departing the study area is shipped by air using one of the few international airports in the study area. Using the T-100I (T-100 International data) we found the total international cargo inflows and outflows into four major airports: a) San Francisco International (SFO), b) Oakland (OAK), c) San Jose (SJC) and d) Sacramento (MHR). Figure 18 shows the freight leaving the region of interest via four international airports. Figure 19 shows the freight “entering” (inflow) the region of interest via four international airports. Both figures show that there is no significant international freight into Sacramento International. Both figures indicate that a large fraction of the international freight is routed through SFO. Figure 18 and Figure 19 demonstrate that in the year 2017, international air freight is well balanced between inflows and outflows at SFO International airports. SFO handles 94.4% of the total air freight arriving to the study area. Similarly, SFO handles 83% of the air freight departing the study area. For this reason, the results presented in this report considers SFO air freight as the only additional contribution to ODM cargo flights for now. It is important to recognize that international air freight statistics lack commodity type information. An important recommendation of the study is to investigate the types and value of commodities that make the bulk of international air freight shipments to and from this region. The proximity of Silicon Valley and the microprocessor industry, could boost the projections made in this analysis.

Figure 18: International Air Freight Arriving to the Region of Analysis (Cargo Inflows).

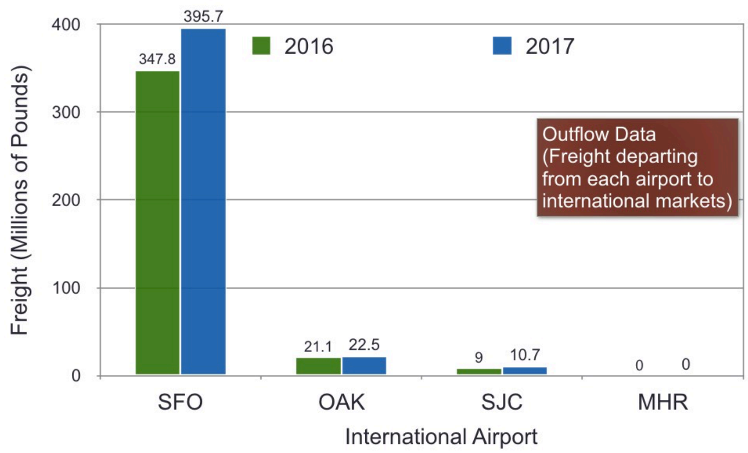

Figure 19: International Air Freight Arriving to the Region of Analysis (i.e., Outflows).

Step 10: Tally Flights at Each Landing Site.

The final step in the analysis consists of adding the number of daily, cargo ODM flights estimated in the procedure described in Steps 1-9 and generate flight tracks in ACES input format.

4.2 MODEL RESULTS

The steps described in Section 4.1 are applied to estimate ODM cargo flights for seventeen counties in the Northern California region. The ODM cargo demand is developed parametrically according to the market share assumptions presented in Table 10.

Table 10: Market Share Assumptions of ODM Cargo Scenarios Modeled.

Commodity	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	Percent Market Share from Truck (%)	Percent Market Share from Air (%)	Percent Market Share from Truck (%)	Percent Market Share from Air (%)	Percent Market Share from Truck (%)	Percent Market Share from Air (%)	Percent Market Share from Truck (%)	Percent Market Share from Air (%)

Fish and Marine products	-	5	-	5	-	2.5	-	2
Drugs	2.5	2.5	2.5	2.5	1.25	1.25	1	1
Pharmaceutical Equipment	2.5	2.5	2.5	2.5	1.25	1.25	1	1
Electric Measuring Instrument	5	2.5	2.5	2.5	1.25	1.25	1	1
Mail and Express Traffic	-	10	-	10	-	8	-	5
Small Freight Shipments	-	10	-	10	-	8	-	5
Solid State Semiconductors	5	-	2.5	-	1.25	-	1	-
Telephone Equipment	5	-	2.5	-	1.25	-	1	-
Jewelry and precious metals	2.5	-	2.5	-	1.25	-	1	-
International Air Freight		10.0		5.0		3.0		2.5

The results for the high market share scenario (called Scenario 1 in Table 10) are presented in Table 11 for the year 2033 when the cargo ODM services are expected to be 'mature'. The table contains detailed results by commodity and includes the daily tonnage shifted from 'Truck' and 'Air' to ODM and the number of daily ODM flights needed to transport the cargo shifted from 'Air' and 'Truck' modes. The results include additional ODM flights required to transport a small fraction (10%) of the international air freight shipments arriving to large cargo airports in the region. According to this scenario, in the year 2033, there is a potential demand for 1370 ODM cargo flights in the region associated with 9 commodities contained in the Transearch data. There could be an additional 1067 ODM cargo flights associated with international air freight (reported as the last row in Table 11). Overall, according to the market share assumptions made in Scenario 1, there could be 2,357 daily cargo ODM flights in the region. Note that small freight shipments account for almost 25% of the total ODM flights. Figure 20 shows the spatial distribution of ODM cargo flights in the Northern California region. The graphic shows prominently three airports (SFO, OAK and MHR) as having a substantial share of the cargo ODM flights. SFO receives 94.6% of the international air freight traffic. OAK receives a large share of the domestic "AIR" market due to its strategic proximity to six of the seventeen counties in the region. Domestic air cargo shipments are routed through Oakland International airport and then distributed to landing sites across six counties that represent the catchment area for the airport. Figure 21shows a summary of daily cargo ODM flights in the Northern California region for all four scenarios. The results vary from 2,357 flights for Scenario 1 to 877 daily flights for Scenario 4.

Table 11: Scenario 1 Results ODM Cargo Modeled (Year 2033 Demand).

Commodity	Value per Ton for Commodity ($ 2016)	Percent Market Share from Truck (%)	Percent Market Share from Air (%)	Daily Tonnage from Truck Market (US Tons)	Daily Tonnage from Air Market (US Tons)	Total Tonnage Carried by ODM Cargo (US Tons)	Rounded Daily ODM Flights

Fish and Marine products	7,580	0	5	0.0	1.2	1.2	5
Drugs	68,725	2.5	2.5	84.0	4.16	88.16	276
Electric Measuring Instrument	272,138	5	2.5	1.7	0.0	1.7	6
Pharmaceutical Equipment	45,799	2.5	2.5	32.1	7.3	39.4	128
Mail and Express Traffic	*	0	10	0.0	21.3	21.3	85
Small Freight Shipments	*	0	10	0.0	154.7	154.7	621
Telephone Equipment	35,608	5	0	7.6	0.0	7.6	24
Solid State Semiconductors	42,460	5	0	63.0	0.0	63.0	195
Jewelry and precious metals	255,900	2.5	0	0.1	0.0	0.1	1
International Air Cargo	*	0	10	0	295.5	295.5	1067

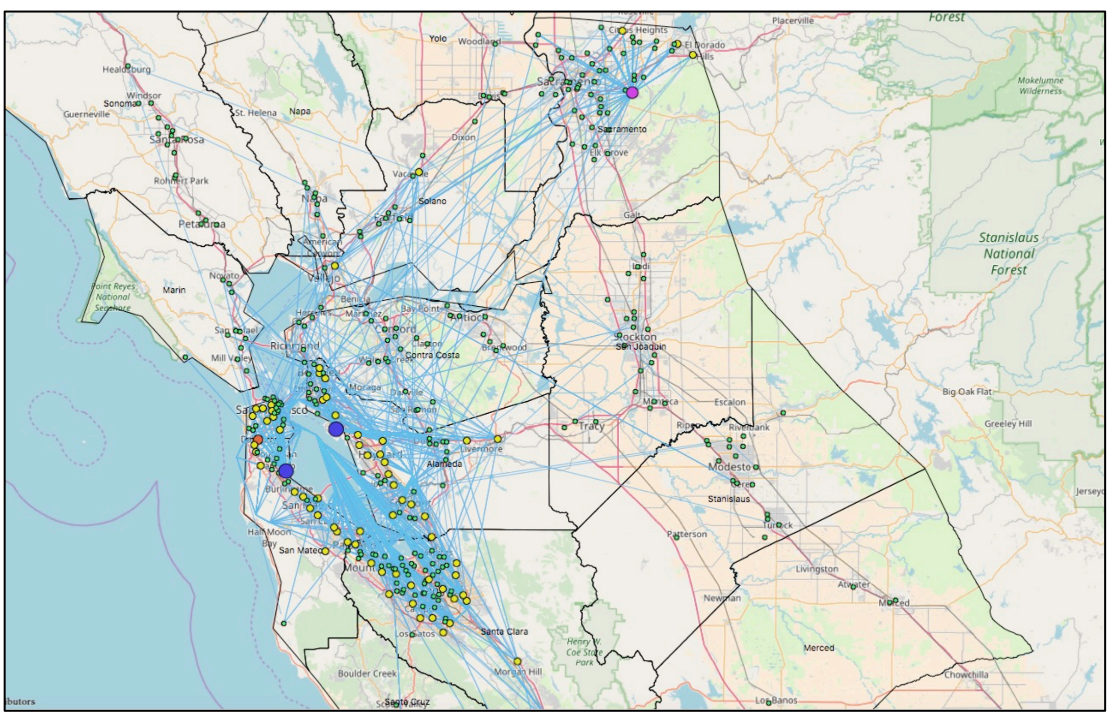

Figure 20: Spatial Distribution of ODM Cargo Flights (in blue) in Northern California for Scenario 1. The High-Demand Scenario Generated 2,357 Daily Cargo ODM Flights in the Region.

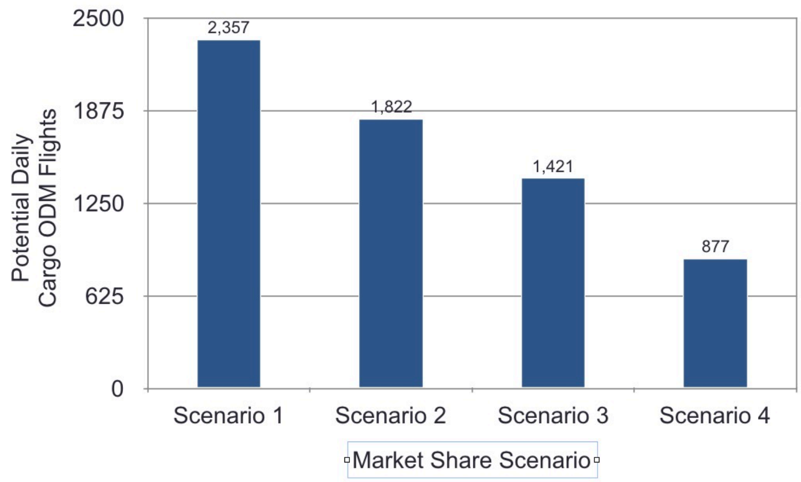

Figure 21: Summary of Potential Cargo ODM Flights in Northern California for Four Scenarios Studied.

4.3 EFFECT OF CARGO ODM OPERATIONS IN PASSENGER DEMAND

In this section we study the effect of cargo ODM flights on passenger ODM demand. Additional flights by eVTOL ODM aircraft, will increase the utilization of the ODM aircraft and hence reduce life cycle cost per mile for passengers using the same vehicles during peak-hour commuting periods. Figure 22 shows the effect of reducing ODM passenger fares by 5% and 10% for a passenger Scenario with 369 Landing Sites (i.e., airport landing sites were not considered in the passenger ODM service), $15 Base fare, $1.23 per passenger mile, $6.7 landing fee, $0.30 per mile car cost, 5-mile cutoff distance. Depending upon the assumptions made about the number of repositioning flights (see Figure 9) a 10% reduction in passenger ODM cost per mile may be achieve flying the vehicle an additional 500-750 hours per year. According to Figure 22, ODM passenger ridership could increase by 57% if the cost of the fare is reduced by 10%. The passenger ODM mode choice model is very sensitive to changes in cost because the average value of time for a rider in the Bay Area was found to be $32 per hour.

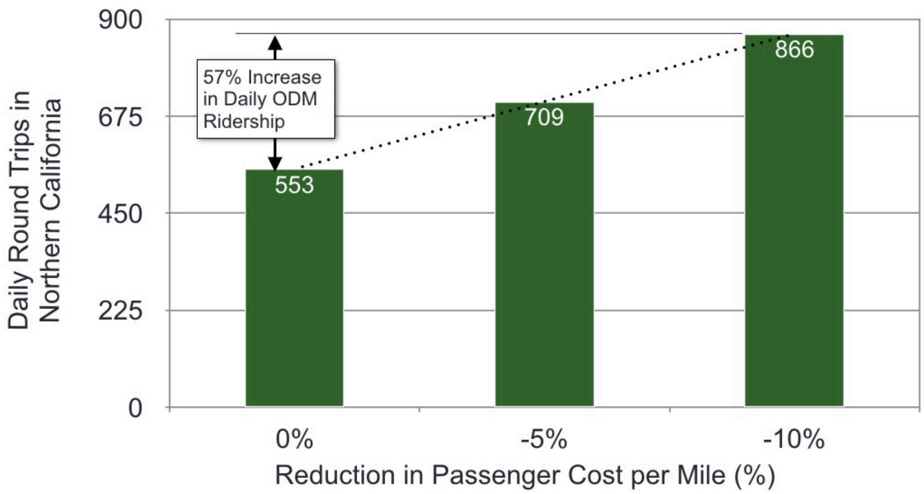

Figure 22: Parametric Effect of ODM Passenger Demand with Reduction in Cost per Passenger Mile. Assumptions: 369 Landing Sites, $15 Base fare, $1.23 per passenger mile, $6.7 landing fee, $0.30 per mile car cost, 5-mile Cutoff Distance.

Figure 23 shows the effect of reducing ODM passenger fares by 5% and 10% for a passenger Scenario with 369 Passenger Landing Sites, $20 for a trip up to 20 miles, $1.23 per mile beyond a 20-mile trip, $6.7 landing fee, $0.30 per mile car cost, 5-mile Cutoff Distance. Depending upon the assumptions made about the number of repositioning flights (see Figure 9) a 10% reduction in passenger ODM cost per mile may be achieve flying the vehicle an additional 500-750 hours per year. According to the figure, ODM passenger ridership could be increase by 86% if the cost of the fare is reduced by 10%.

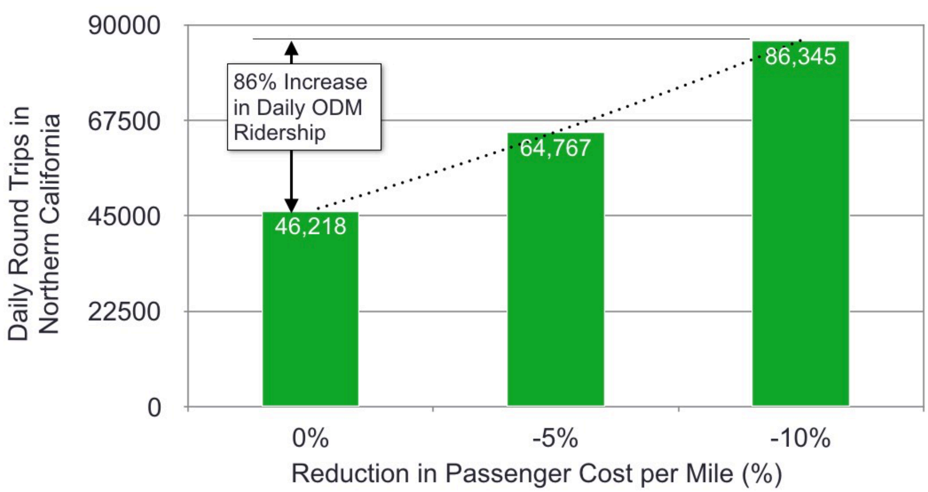

Figure 23: Parametric Effect of ODM Passenger Demand with Reduction in Cost per Passenger Mile. Assumptions: 369 Passenger Landing Sites, $20 for a trip up to 20 miles, $1.23 per mile beyond a 20-mile trip, $6.7 landing fee, $0.30 per mile car cost, 5-mile Cutoff Distance.

Northern California

5 CARGO COST FUNCTION ANALYSIS

To understand the potential cargo demand for the proposed ODM concept, we need to establish a baseline of current shipment costs as a function of weight and distance. The following section explains in detail the rates and cost function for a typical multi-national courier service company (FedEx). The analysis provides insight on the price point required by the UAS VTOL concept to compete with the existing courier service market. The analysis presented in this section could be used in a follow-up study for cargo ODM demand.

5.1 FEDEX STANDARD LIST RATE

Parcel shippers charge rates based on zones that represent distance ranges from origin to destination points. For example, FedEx shipments identify Zone 2 as shipments in the range of 0-150 miles anywhere within the contiguous U.S. Figure 24 and Figure 25 show the standard delivery rates for two scenarios: 1) First Overnight (8-8:30 A.M. next day), and 2) Priority Overnight (10:30 A.M. next day). The figures show linear equation models used to approximate the price charged as a function of parcel weight (in the x-axis).

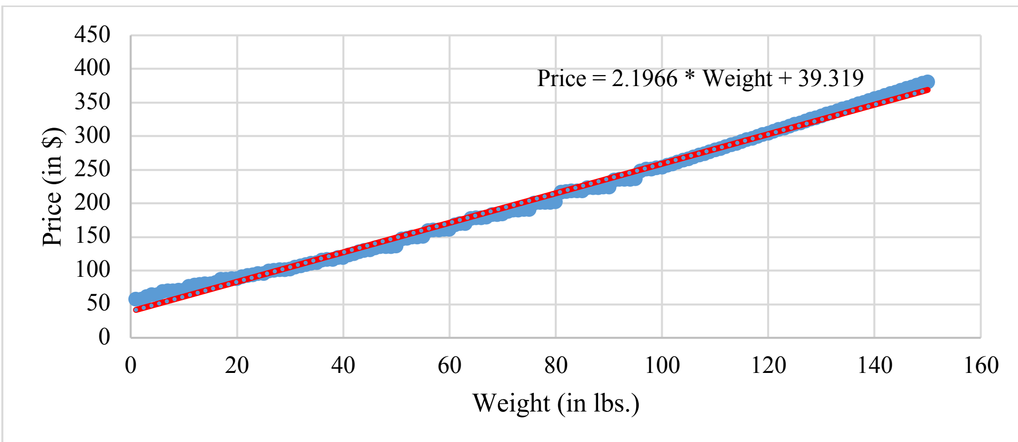

Figure 24: Cost Function with Respect to Weight for First Overnight (Delivery by 8-8:30 A.M. Next Day).

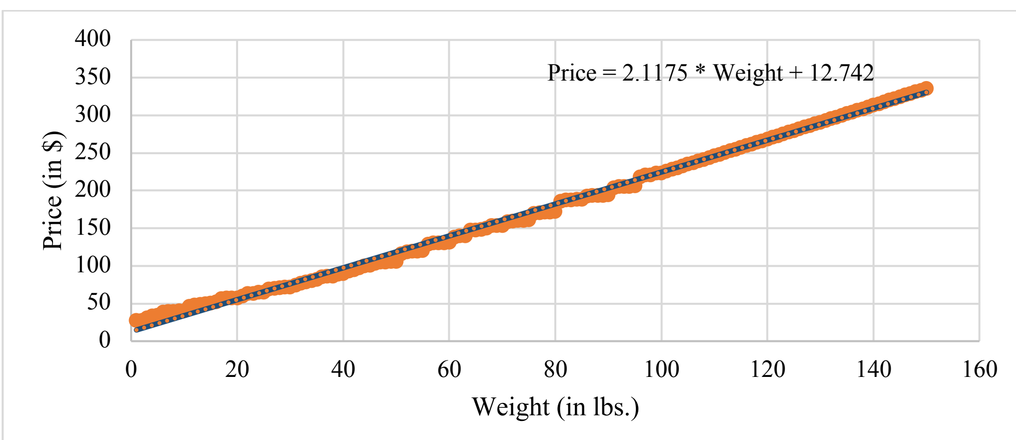

Figure 25: Cost Function with Respect to Weight for Priority Overnight (Delivery by 10:30 A.M. Next Day).

Figure 26 shows the shipment cost as a function of weight for two shipment priorities. The plot shows a linear relationship in cost savings as a function of weight. Light parcels (~3 lbs.) cost $13.5 per hour saved. Heavy parcels (~97 lbs.) cost $17 per hour saved. The justification of cargo ODM services could be made under the assumption that higher reliability in First Overnight deliveries could be made using an ODM aircraft compared to ground modes of transportation. Moreover, faster service is possible with the cargo ODM vehicle for such deliveries. This is a topic that will needs to be investigated in a follow-up study.

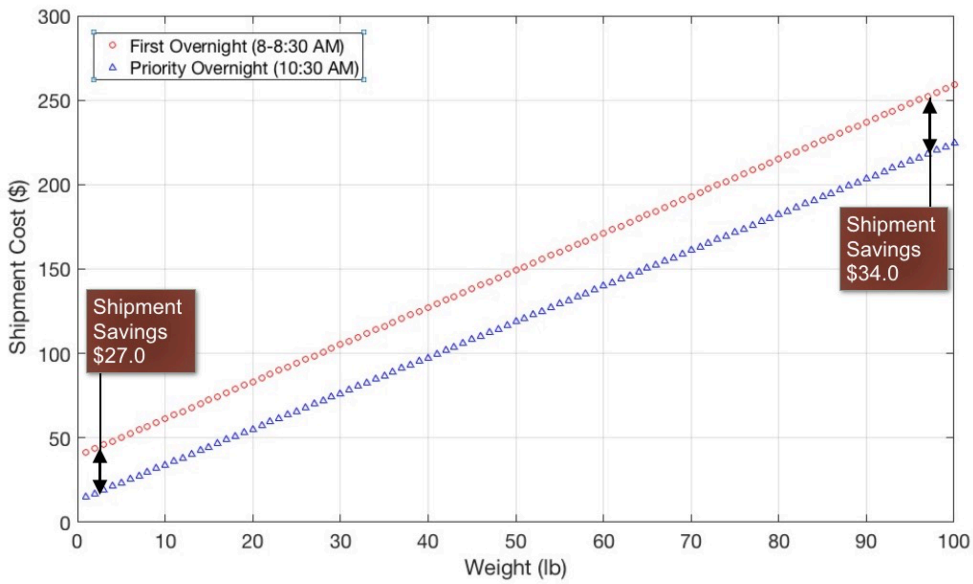

Figure 26: Approximate Shipment Costs for Two Shipment Priorities. Light Parcels Cost $13.5 per hour Saved. Heavy Parcels Cost $17 per Hour Saved.

5.2 U.S. PACKAGE RATES: FEDEX EXPRESS MULTI-WEIGHT

Table 12 lists the standard rate for multi-weight shipments for Zone 2 (0-150 miles anywhere within the contiguous U.S.). The rates for First Overnight, Priority Overnight and Standard Overnight are listed in the table. The differences in price are more pronounced compared to the smaller package rates. For example, sending a 200 lb. package and saving two hours results in $30 per hour additional fee. Granted, a 200 lb. package may be too large for an ODM aircraft.

Table 12: U.S. Package Rates: FedEx Express Multi-weight. Source: FedEx Standard List Shipping Rates.

Delivery Commitment	**8-8:30 A.M. Next Day**	**10:30 A.M. Next Day**	**3 P.M. Next Day**
Weight (in lbs.)	**First Overnight ($/lb.)**	**Priority Overnight ($/lb.)**	**Standard Overnight ($/lb.)**
100-499	2.54	2.24	2.06
500-999	2.52	2.22	2.04
1000-1999	2.50	2.20	2.02
2000+	2.48	2.18	2.00

Note:

1. For Zone 2 (0-150 miles) shipments.
2. A 15-lb. average minimum package weight for the shipment applies.
3. Multiply the per-pound rate by total shipment weight.

5.3 U.S. PACKAGE RATES: FREIGHT

Table 14 summarizes the freight rates for Zone 2 (0-150 miles anywhere within the contiguous U.S.) for FedEx shipments. This has only two categories: Overnight Freight and 1-Day Freight.

Table 13: U.S. Package Rates: FedEx Freight. Source: FedEx Standard List Shipping Rates.

Weight (in lbs.)	Overnight Freight ($/lb.)	1-Day Freight ($/lb.)
151-499	1.85	1.32
500-999	1.76	1.26
1000-1999	1.67	1.19
2000+	1.62	1.16
Minimum Charge	270.00	126.00

Table 14 lists the rates for same day freight. The reason for adding a separate table for the same day freight price rates is it has a more elaborate weight categorization process than Overnight Freight and 1-Day Freight.

Table 14: U.S. Package Rates: FedEx Same Day Freight. Source: FedEx Standard List Shipping Rates.

Weight (in lbs.)	Rate ($/lb.)
151-299	2.83
300- 499	2.25
500-999	2.12
1000-1999	1.78
2000+	1.73

Note:

1. For Zone 2 (0-150 miles) shipments.
2. Multiply the per-pound rate by total shipment weight.

5.4 FEDEX ONE RATE

FedEx One Rate, a flat rate pricing option, is available for qualifying FedEx Express U.S. shipments. FedEx One Rate pricing is an alternative to FedEx Standard List Rates, account-specific rates or FedEx Retail Rates. The table shows that users employing the faster First Overnight service by FedEx pay an additional $19 per hour for an earlier delivery service for a FedEx envelope, FedEx Pak or a FedEx Small Box. This information provides information on the willingness to pay for faster small parcel deliveries. A follow-up study could uses these relationships to further justify potential market share of the cargo ODM service in metropolitan areas.

Table 15: FedEx One Rate. Source: FedEx Standard List Shipping Rates.

Delivery Commitment	**8-8:30 A.M. Next Day**	**10:30 A.M. Next Day**	**3 P.M. Next Day**
Service	**First Overnight ($)**	**Priority Overnight ($)**	**Standard Overnight ($)**
Packing Type			
FedEx Envelope	66.80	28.80	23.90
FedEx Pak	73.10	35.10	29.35
FedEx Small Box	73.65	35.65	31.45
FedEx Medium Box	79.15	41.15	35.35
FedEx Large Box	83.85	45.85	41.15
FedEx Extra Large Box	92.50	54.50	46.65
FedEx Tube	92.50	54.50	46.65

Note:

1. For Zone 2 (0-150 miles) shipments.
2. To qualify for FedEx One Rate pricing, FedEx envelopes must weigh 10 lbs. or less, and FedEx paks, boxes and tubes must weigh 50 lbs. or less.

6 GREENHOUSE GASES EMISSIONS

In this section we estimate the environmental impact of the UAS VTOL concept compared to using traditional ground transportation modes to deliver small cargo packages. The analysis compares the estimated total annual CO_2 emissions of the UAS VTOL concept for cargo delivery for the region under study with current ground delivery methods. To estimate ground vehicle emissions, we use a mesoscopic emissions model used in California. The model and the results are described in the following sections.

6.1 EMISSIONS FACTOR (EMFAC) 2017

The EMFAC2017 is a mesoscopic emissions computer model. It is developed and used by California Air Resources Board (CARB) to assess emissions from on-road vehicles including cars, trucks, and buses operating in California. The model supports CARB's regulatory and air quality planning efforts to meet the Federal Highway Administration's transportation planning requirements. The United States Environmental Protection Agency (USEPA) approves EMFAC for use in State Implementation Plans and transportation conformity analyses.

6.2 METHODOLOGY

EMFAC2017 Project-Level Assessment (EMFAC2017-PL) is the EMFAC2017 tool designed to support project-level assessments. EMFAC2017-PL is triggered when EMFAC2017 is run under the Emission Rate mode. Using EMFAC-PL, emission rates are estimated based on user-specified, project-specific conditions: ambient outdoor temperature and relative humidity, vehicle speeds, vehicle classes, geographic location, and analysis period (month, season, annual average). EMFAC2017-PL provides emission rates by vehicle model year, or aggregated ones over model years for a vehicle class. It also provides emission rates by fuel type or emission rates aggregated over fuel types.

EMFAC2017 estimates emission rates for CO_2 for vehicles powered by gas and diesel (and electric for certain categories of vehicles). However, EMFAC2017 does not produce results for CO_2 emission rates for electric vehicles for the Running Exhaust (RUNEX) process type which is the major source of CO_2 (or any other Greenhouse gas). Moreover, EMFAC2017 has no inventory of Hybrid vehicles, some of which are common in today's package delivery fleet of multinational courier and package delivery companies like UPS, FedEx etc.

To calculate CO_2 Emission rates for such vehicles CARB provides with a "Documentation of California's Greenhouse Gas Inventory" which states that 427 grams of CO_2 is produced per kW-hr expenditure of energy in terms of electricity (generated from unspecified sources). This number is used in the study to manually calculate emission rates and emission profiles for hybrid/electric trucks and UAS VTOL.

6.3 VEHICLE CATEGORIES, SPECIFICATIONS & ENERGY CONSUMPTION

EMFAC2017 provides an inventory of vehicles defined based on their Gross Vehicle Weight Rating (GVWR). Common vehicles used in the package delivery fleet along with their specifications are listed in Table 16. The most common vehicles for ground delivery are the Light-Heavy Duty Truck 2 (LHDT2) model shown in the table. In California, FedEx and UPS have deployed hybrid gasoline/electric trucks recently. The cargo ODM vehicle used in this analysis is similar to the Uber eVTOL concept. The simulated energy consumption characteristics of the vehicle have been studied by Georgia Tech and are shown in Figure 27. The figure shows energy used is nearly linear with distance for typical mission profiles flown.

Table 16: Vehicle Categories and Specifications as per EMFAC2017.

EMFAC2017 Category	GVWR	Representative Vehicle		
		Name	Fuel	
Light Duty Truck 2 (LDT2)	< 6,000 lbs.	Ford Transit Connect	Gasoline	
Medium Duty Truck (MDV)	6,000 lbs. – 8,500 lbs.	Mercedes-Benz Sprinter	Gasoline/ Diesel	
Light-Heavy Duty Truck 2 (LHDT2)	10,001 lbs. – 14,000 lbs.	Workhorse E-GEN	Gasoline and Electric (Hybrid)	
		Navistar eSTAR	Electric – Battery Powered	

Note: Twice a year California Department of Motor Vehicles (DMV) shares a copy of their vehicle registration data with CARB in April called 'A' Cut and in October called 'B' Cut. EMFAC2017 uses the DMV 2016 'B' Cut as the main source of data for fleet characterization and uses the data from the 'A' Cut to incorporate the latest changes in the fleet as reported by the DMV in April 2017. LDT2, MDV and LHDT2 are characterized as per the 'B' Cut data.

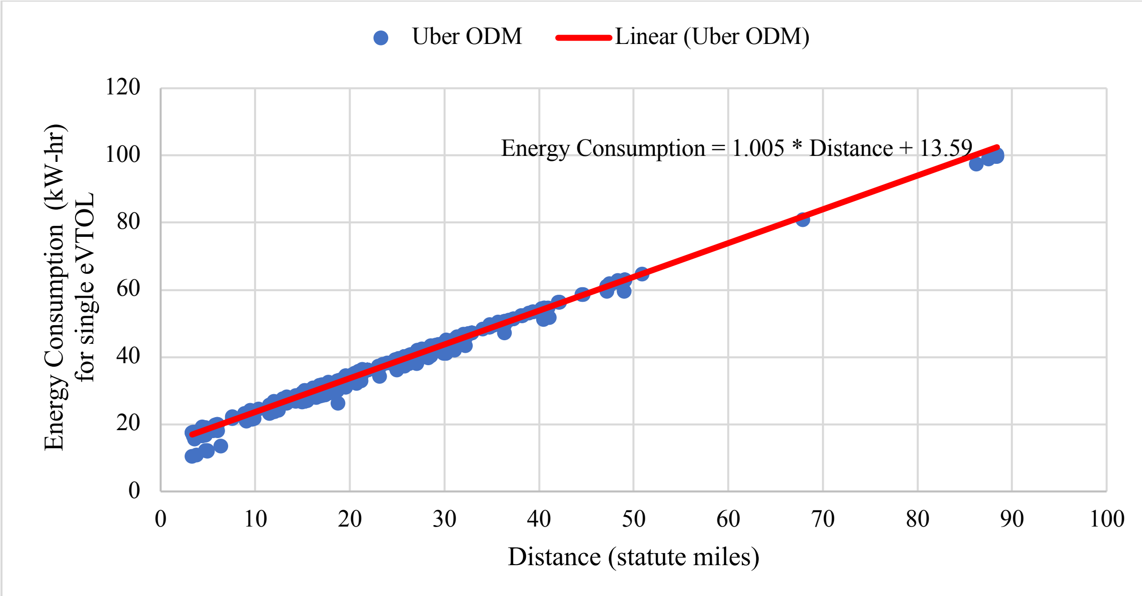

Figure 27: Energy Consumption Profiles for Uber ODM Cargo Concept.

6.4 SIMULATION PARAMETERS FOR EMFAC2017-PL

EMFAC2017- PL assessment requires a number of user inputs before the commencing simulation. The parameters and their respective values are shown in Table 17. The vehicle speed used in this analysis is typical of urban networks including the San Francisco Bay Area.

Table 17: User Defined Inputs for EMFAC2017-PL Model Simulation.

Parameters	**Input**
Average Speed	20 mph
Counties	17 counties in San Francisco Bay Area
Pollutants	CO_2
Process Type	Running Exhaust
Average Temperature	80 ◦F
Average Humidity	80%
Vehicle Categories	Light Duty Truck 2 (LDT2). Medium Duty Truck (MDV), Light-Heavy Duty Truck 2 (LHDT2)
Calendar Year	2016

6.5 CO_2 EMISSION PROFILE FOR DELIVERY TRUCKS: COUNTY-WISE COMPARISON

The CO_2 emission profiles generated by the EMFAC2017-PL assessment tool are presented in Figure 28-Figure 33. The figures show that according to this model, emission rates (in grams/vehicle-mile) vary from county to county in the study area due to topography and network characteristics. For example, counties with hilly terrain such as Santa Cruz and Sonoma counties, have higher emission rates compared to areas of relatively flat terrain like Alameda county. For further analysis we use the average of the emission rates reported for all seventeen counties since traffic loads were not collected in the study.

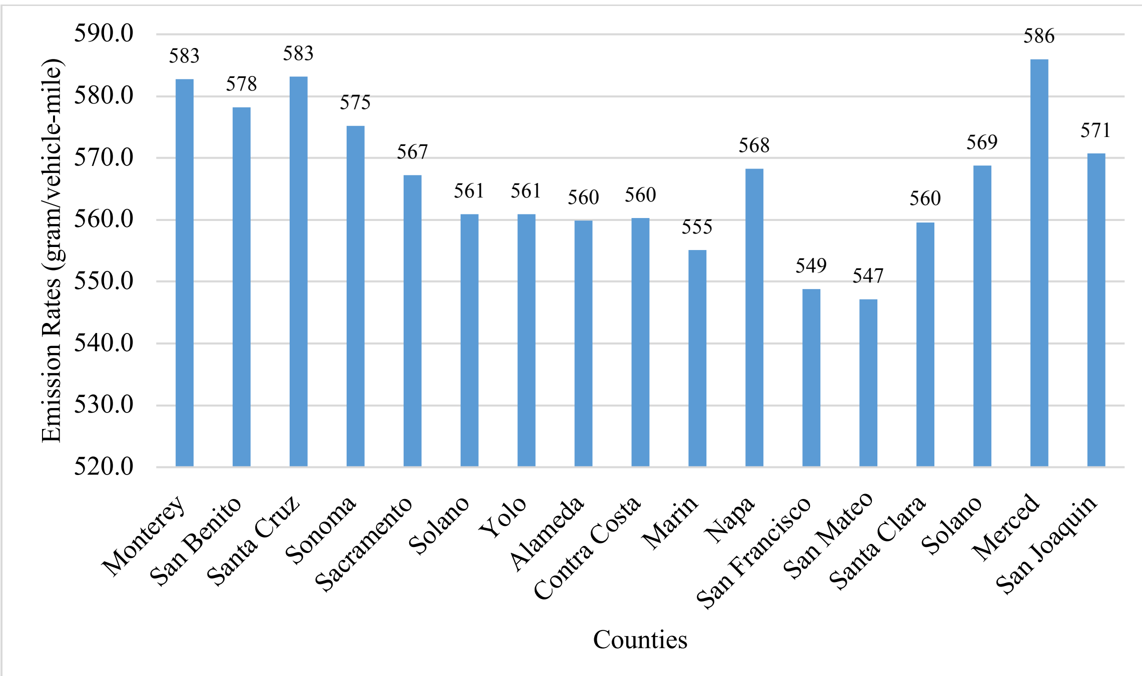

Figure 28: CO_2 Emission Rate for Light Duty Truck 2 fueled by Gasoline for Calendar Year 2016. 20 mph Average Speed. Gross Vehicle Weight Rating < 6,000 lb. Running Exhaust.

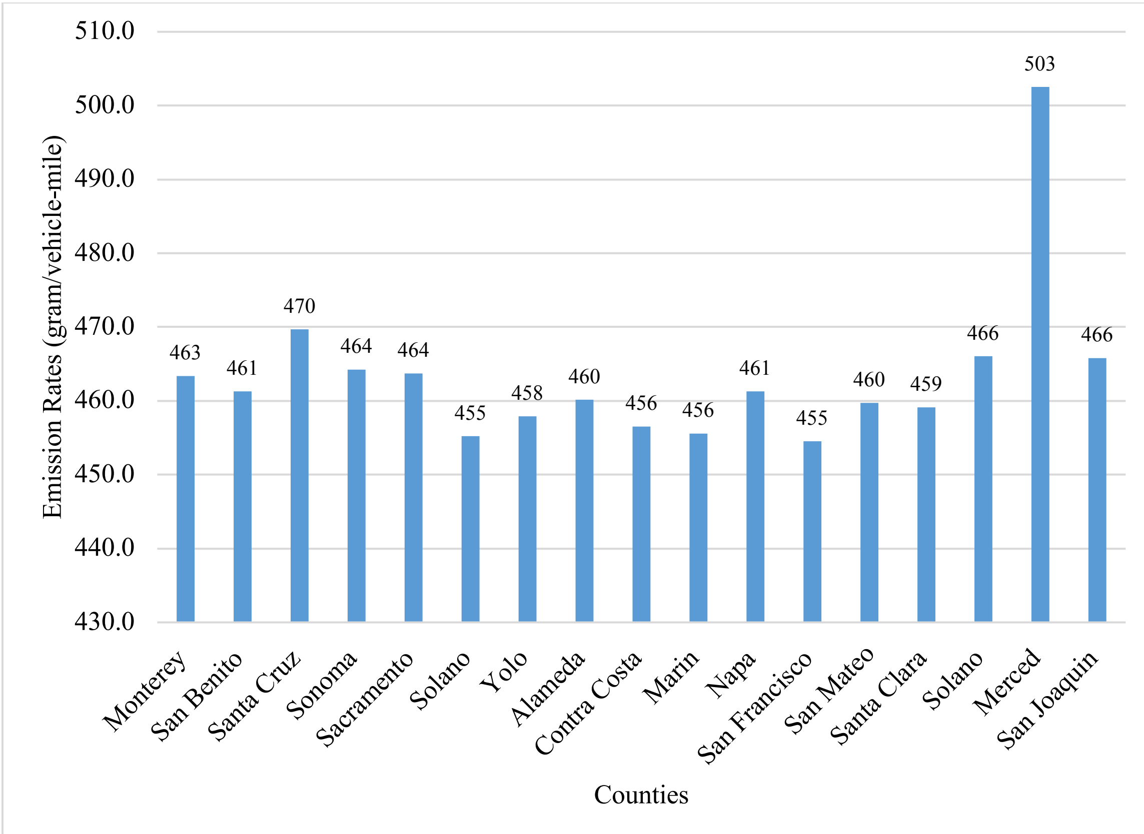

Figure 29: CO_2 Emission Rate for Light Duty Truck 2 fueled by Diesel for Calendar Year 2016. 20 mph Average Speed. Gross Vehicle Weight Rating < 6,000 lb. Running Exhaust.

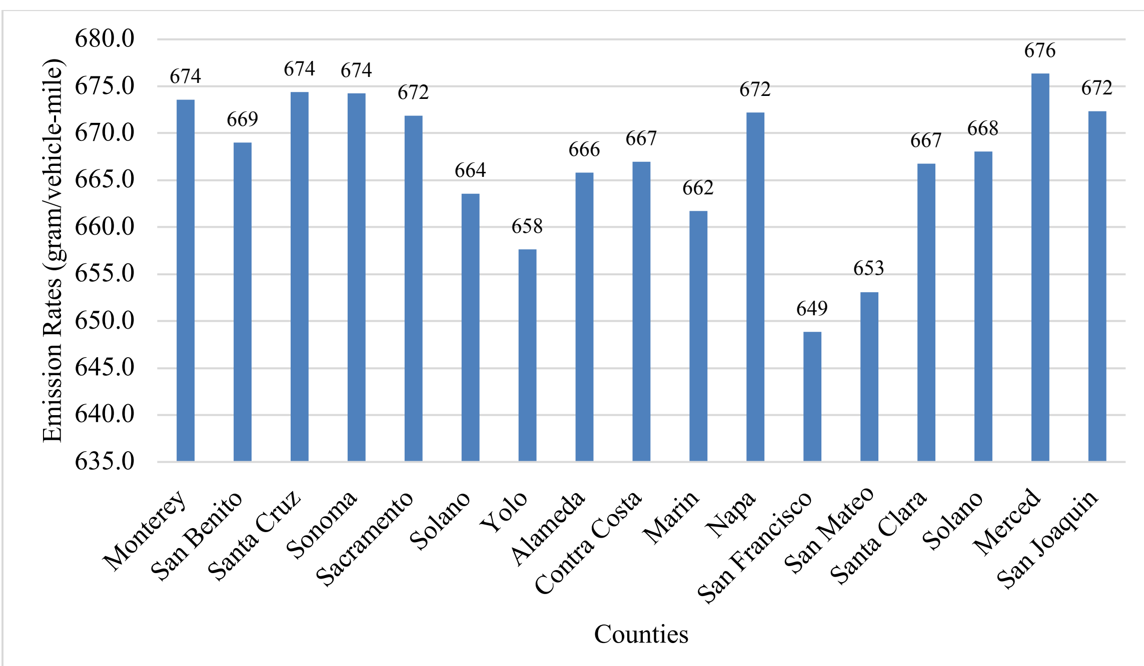

Figure 30: CO_2 Emission Rate for Medium Duty Truck fueled by Gasoline for Calendar Year 2016. 20 mph Average Speed. Gross Vehicle Weight Rating 6,001-8,500 lb. Running Exhaust

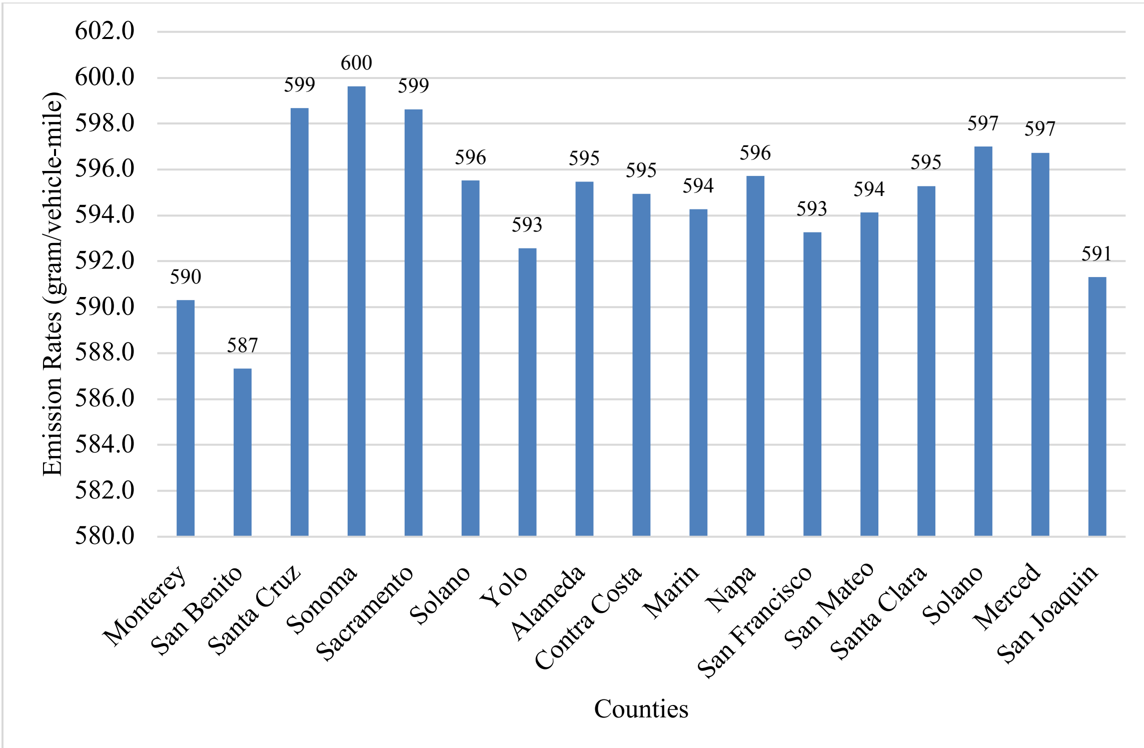

Figure 31: CO_2 Emission Rate for Medium Duty Truck fueled by Diesel for Calendar Year 2016. 20 mph Average Speed. Gross Vehicle Weight Rating 6,000-8,500 lb. Running Exhaust.

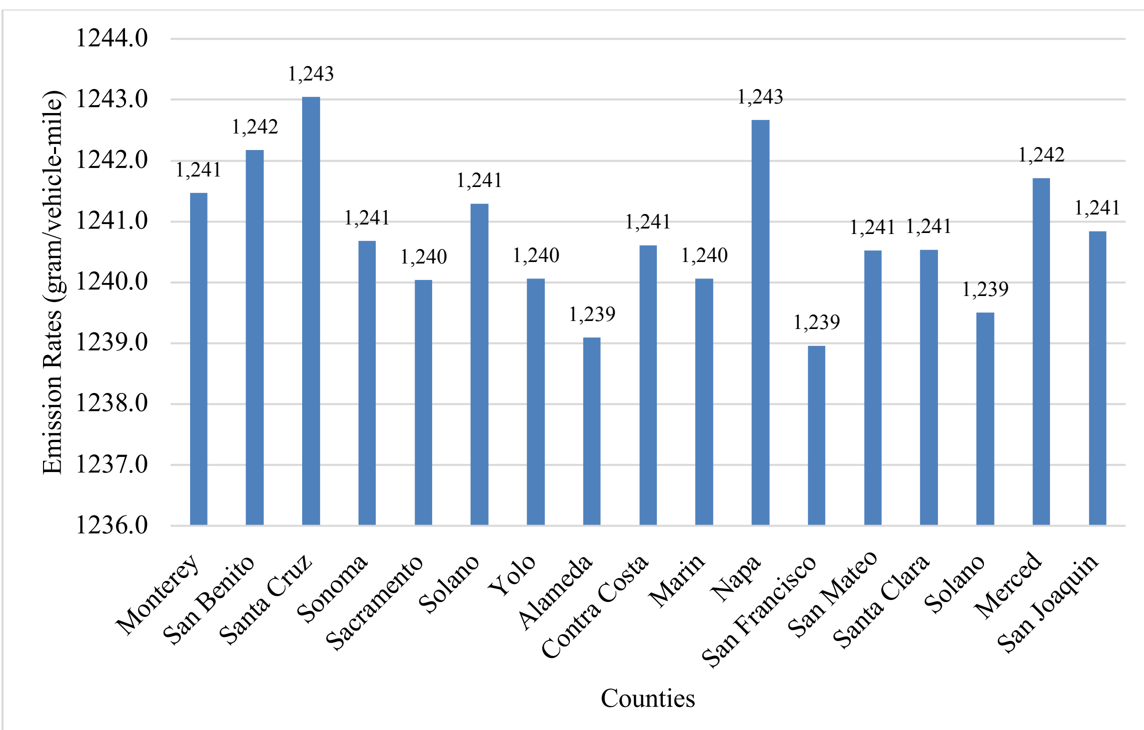

Figure 32: CO_2 Emission Rate for Light-Heavy Duty Truck 2 fueled by Gasoline for Calendar Year 2016. 20 mph Average Speed. Gross Vehicle Weight Rating 10,001-14,000 lb. Running Exhaust.

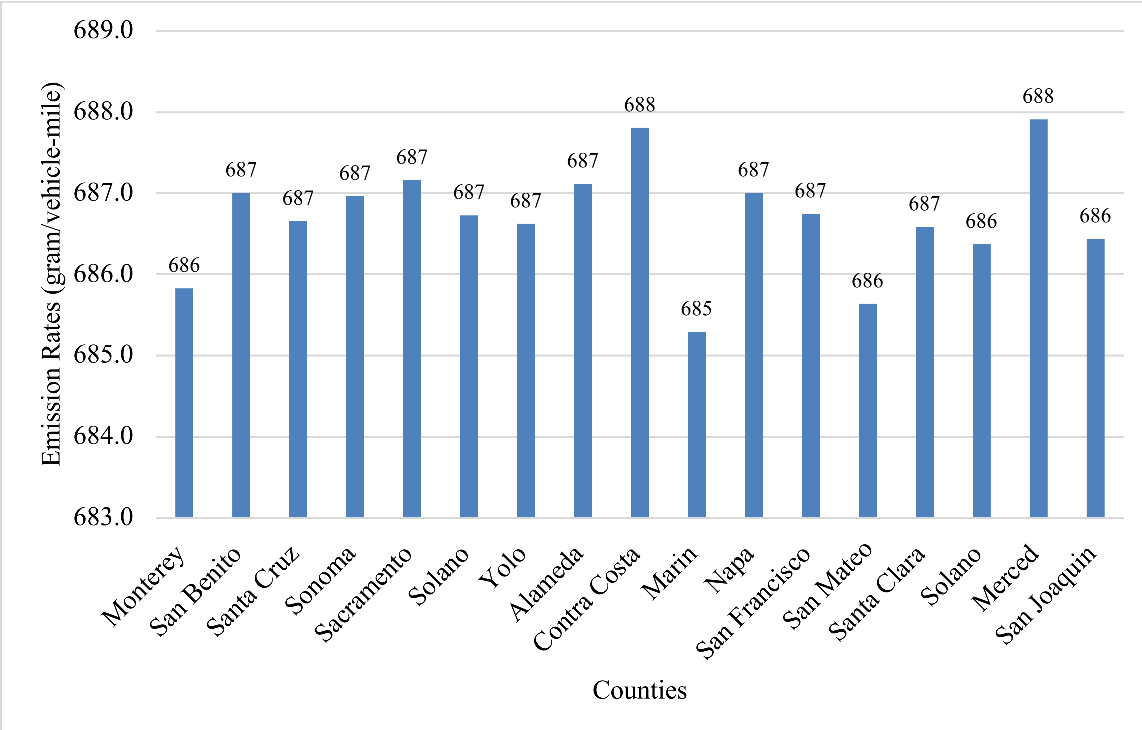

Figure 33: CO_2 Emission Rate for Light-Heavy Duty Truck 2 fueled by Diesel for Calendar Year 2016. 20 mph Average Speed. Gross Vehicle Weight Rating 10,001-14,000 lb. Running Exhaust.

6.6 SAMPLE ENERGY USE CALCULATION FOR ELECTRIC VEHICLES

A typical Electric Light-Heavy Duty Truck like the Navistar eSTAR (Table 16) utilizes an 80-kWhr lithium-ion battery improve fuel economy. The vehicle has a maximum range of 100 miles. The following assumptions are made before carrying out the calculations:

1. Vehicle travels the entire distance that defines its mileage
2. Vehicle uses up the entire fuel/ battery electricity to cover the distance

CO_2 emitted per unit activity = 427 grams/ kW-hr (according to "Documentation of California's Greenhouse Gas Inventory')
Battery = 80 kW-hr (Lithium-ion)
Mileage = 100 miles
Average CO_2 Emission Rate = (427 * 80)/ 100 grams/vehicle-mile = 341.6 grams/vehicle-mile

For the Uber ODM Cargo Concept VTOL, the sample calculation are as follows,

Trip Distance = 20 nm ≈ 23 statute miles
Average Power consumption = 26.7 kW-hr
Average CO_2 Emission for a 20 nm trip = (26.7 * 427) grams = 11,417 grams

Average CO_2 Emission Rate = (11,417 / 23) grams/vehicle-mile = 496 grams/vehicle-mile

Conversion: 1 nautical mile = 1.15078 statute mile

6.7 CO_2 EMISSION PROFILE FOR UBER ODM CARGO CONCEPT VTOL

The equivalent CO_2 emission profiles for the Uber ODM Concept VTOL for a single trip are shown in Figure 34-Figure 36 using two emission metrics: 1) grams, and 2) grams/vehicle-mile. The figures show the equivalent emissions produced using the stated 427 grams/ kW-hr. applicable in California.

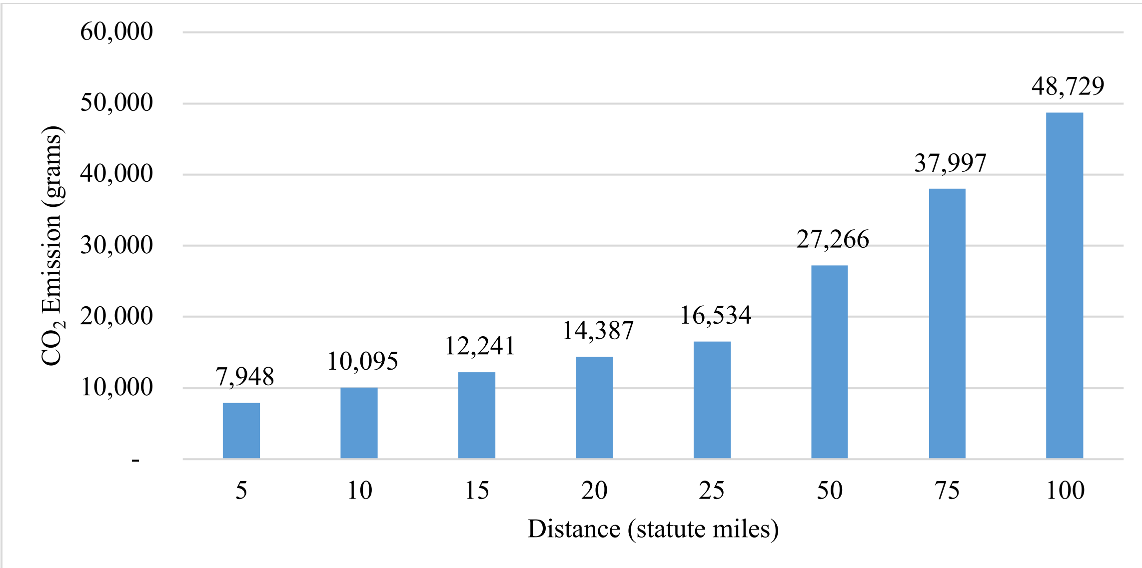

Figure 34: CO_2 Emissions for a Single Uber ODM Concept VTOL for a Single Trip.

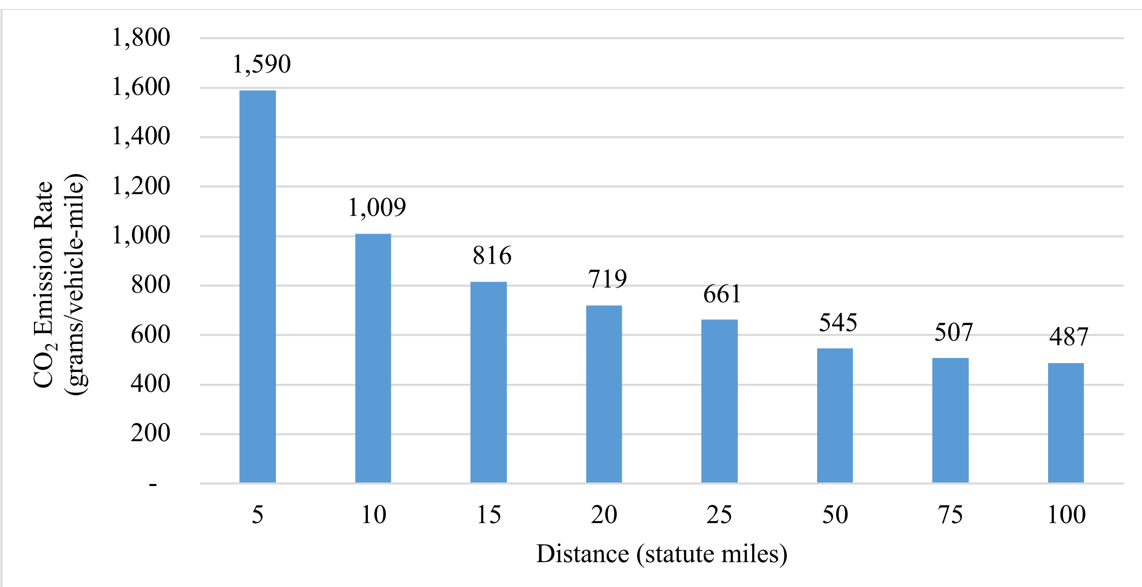

Figure 35: CO_2 Emission Rates for a Single Uber ODM Concept VTOL for a Single Trip.

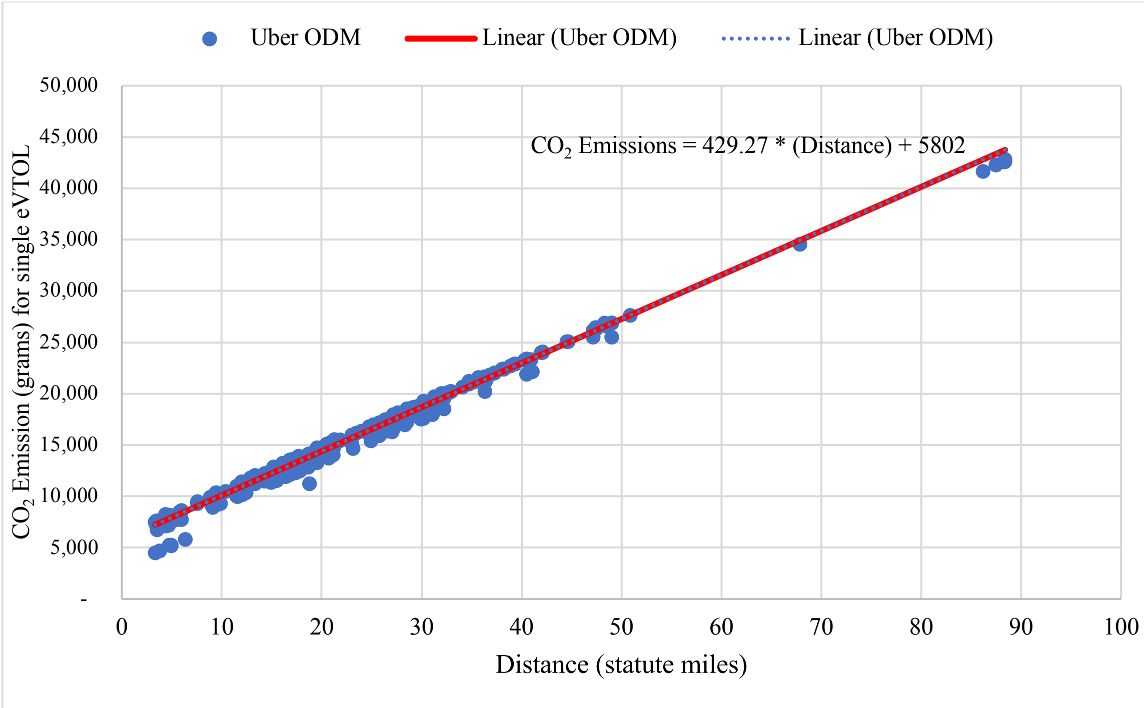

Figure 36: CO_2 Emission Profile for an Uber ODM Cargo Concept VTOL for a Single Trip.

Note: Energy profile data provided by Georgia Tech (Figure 27) which was converted to CO_2 Emission Profiles using 427 grams to kW-hr consumption of each VTOL over distance (statute miles).

6.8 COMPARISON OF CO_2 EMISSION PROFILES FOR LIGHT-HEAVY DUTY VEHICLE 2 (LHDT2) AND VTOL

In this section we present emission profiles for four ground delivery vehicles including the Light Duty Truck 2 (LDT2) and Medium Duty Truck (MDV) and compare them with the Uber ODM Cargo Concept VTOL aircraft. The CO_2 emission profiles for all are provided in Figure 37-Figure 44. Several figures show differences in trip distance ranging from 5 to 100 statute miles. In the analysis we made the following modeling assumptions.

1. All emissions calculated and stated are for a single Light-Heavy Duty truck/VTOL.
2. All emissions are calculated based on a single trip.
3. Average speed for Light-Heavy Duty Truck is 20 mph.
4. Gross Vehicle Weight Rating for Light-Heavy Duty Truck: 10,001-14,000 lbs.
5. Emissions calculated for Running Exhaust process type.
6. Emissions due to last mile delivery for VTOL is not considered.
7. Hybrid vehicles use a combination of Gas and Electricity.

The results show that for a 50-mile trip, the Uber ODM Cargo Concept VTOL produces 24% fewer total CO_2 emissions (in grams) compared to a Diesel Light Heavy-Duty truck and 18% more total CO_2 emissions compared to a Gasoline-Hybrid Light Heavy-Duty truck. On a 100-mile journey, the Uber ODM Cargo Concept VTOL produces 41% fewer total CO_2 emissions (in grams) compared to a Diesel Light Heavy-Duty truck and 8% more total CO_2 emissions compared to a Gasoline-Hybrid Light Heavy-Duty truck.

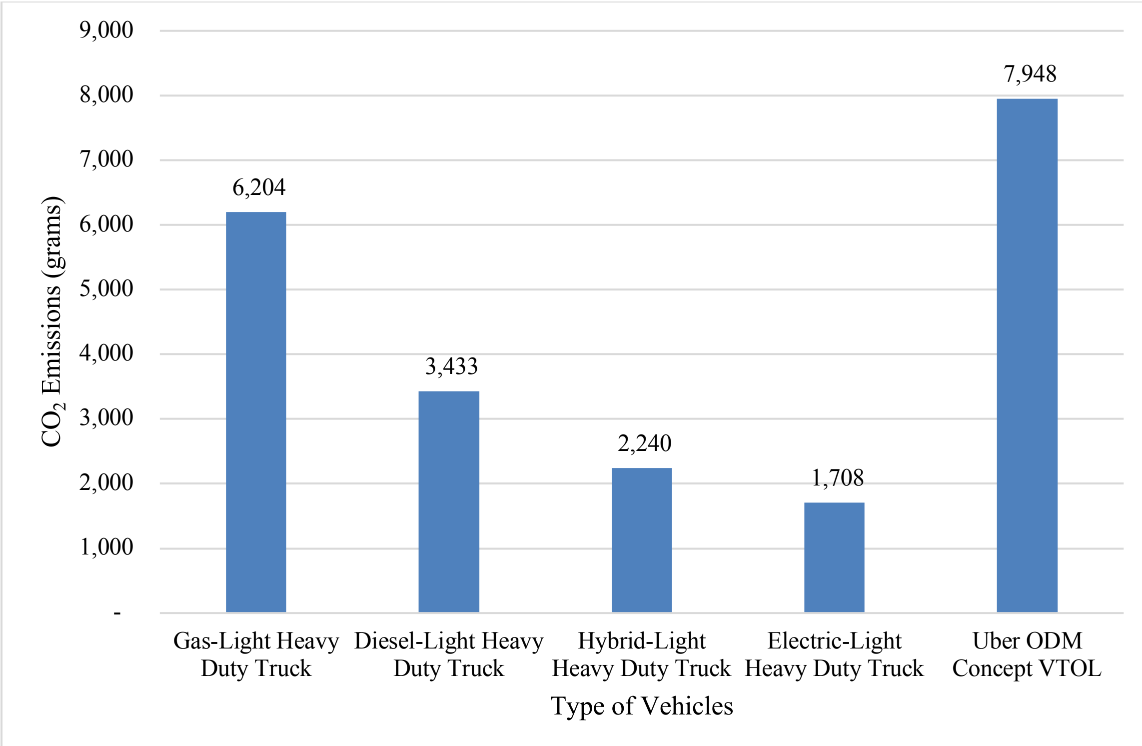

Figure 37: CO_2 Emissions for Light-Heavy Duty Trucks and ODM Cargo Vehicle for a 5-statute mile Trip.

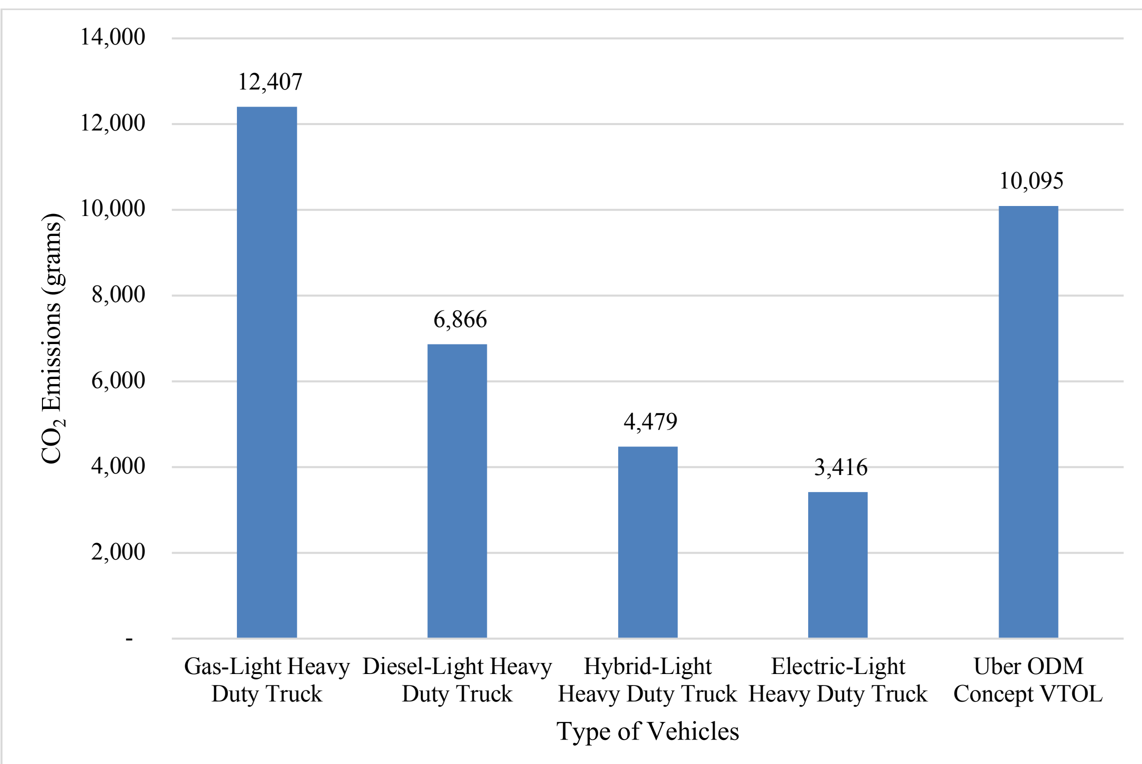

Figure 38: CO_2 Emissions for Light-Heavy Duty Trucks and ODM Cargo Vehicle for a 10-statute mile Trip.

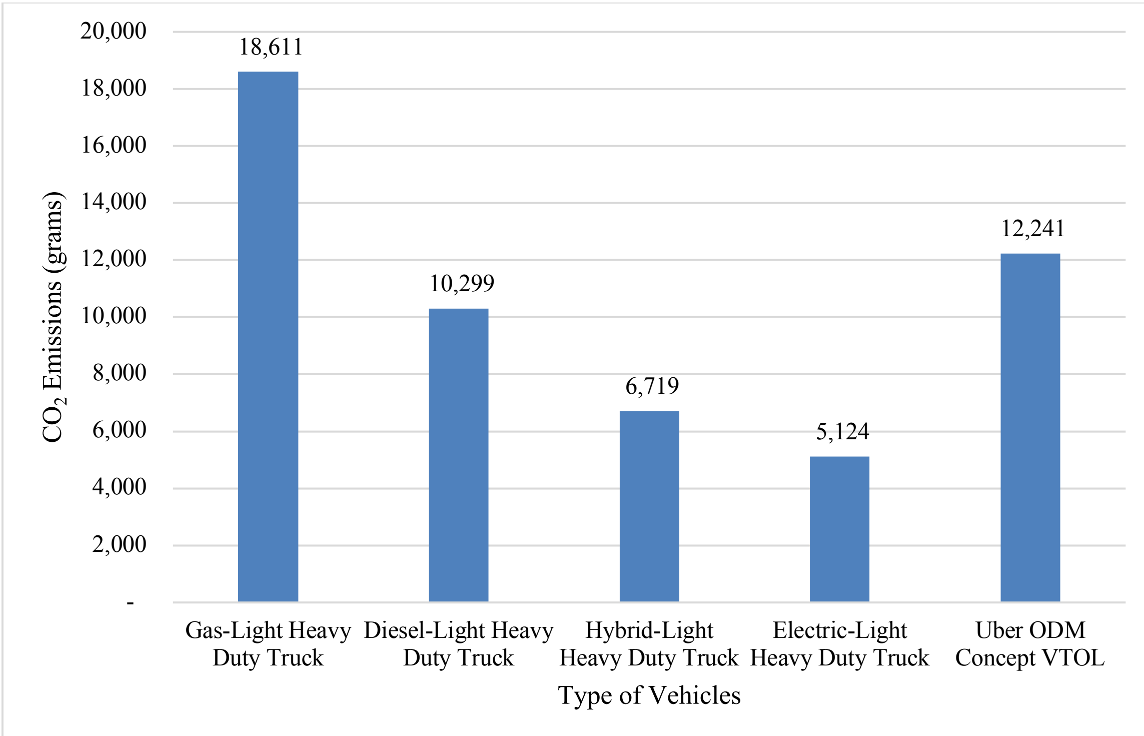

Figure 39: CO_2 Emissions for Light-Heavy Duty Trucks and ODM Cargo Vehicle for a 15-statute mile Trip.

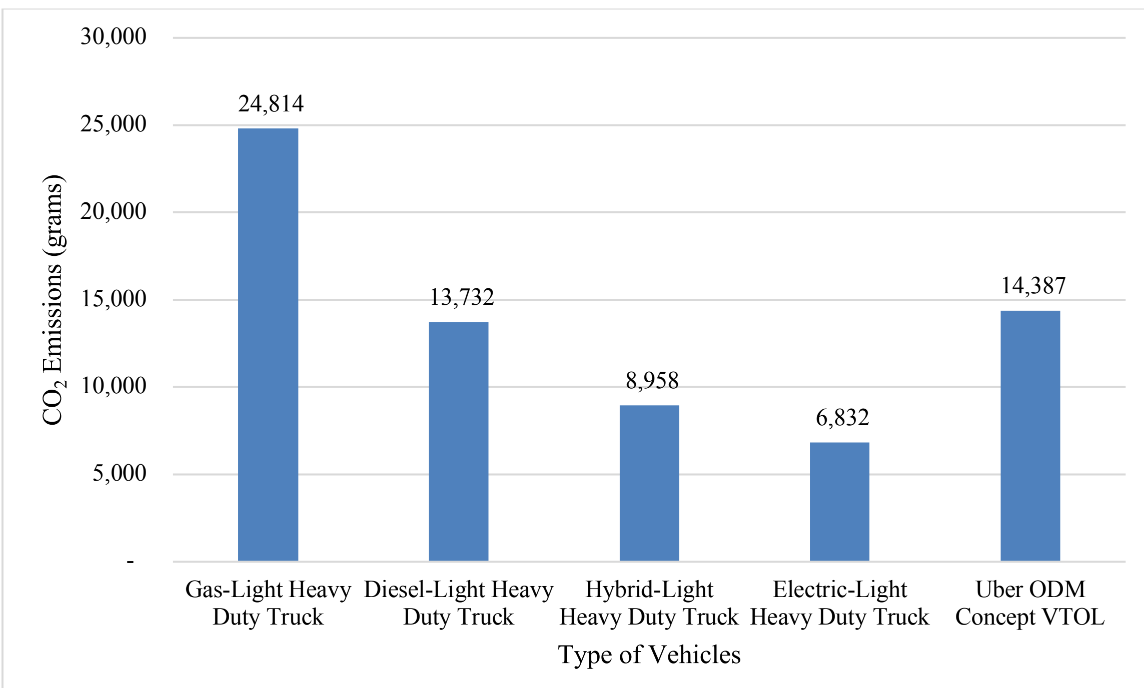

Figure 40: CO_2 Emissions for Light-Heavy Duty Trucks and ODM Cargo Vehicle for a 20-statute mile Trip.

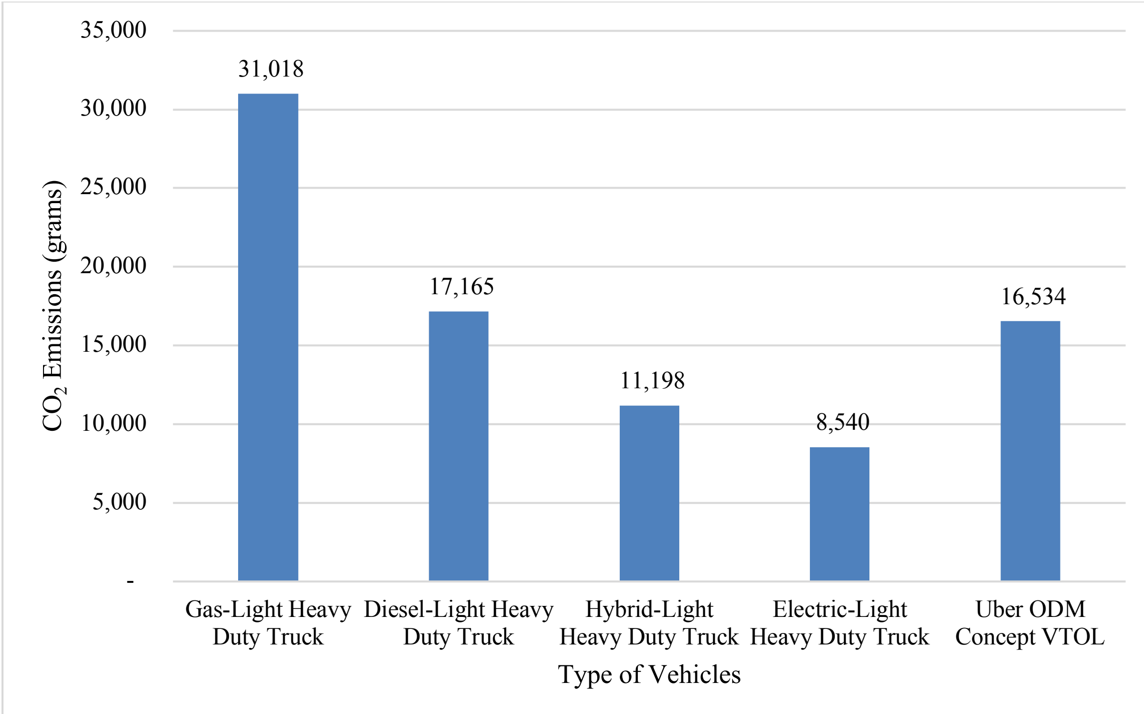

Figure 41: CO_2 Emissions for Light-Heavy Duty Trucks and ODM Cargo Vehicle for a 25-statute mile Trip.

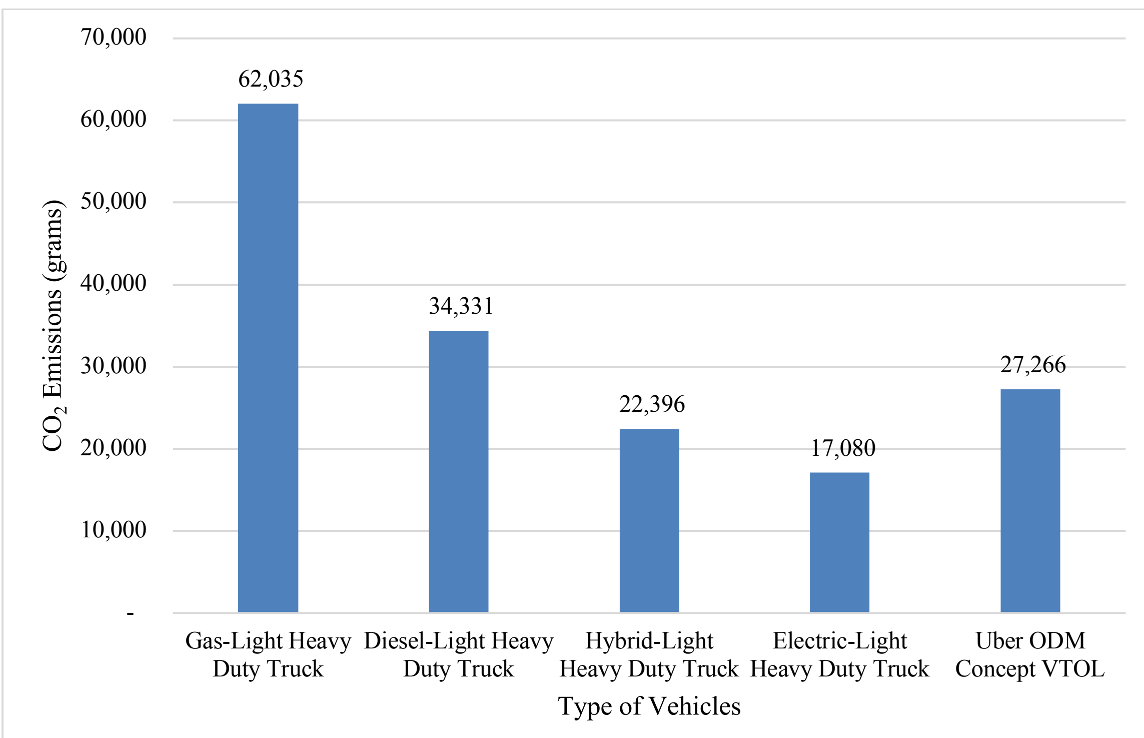

Figure 42: CO_2 Emissions for Light-Heavy Duty Trucks and ODM Cargo Vehicle for a 50-statute mile Trip.

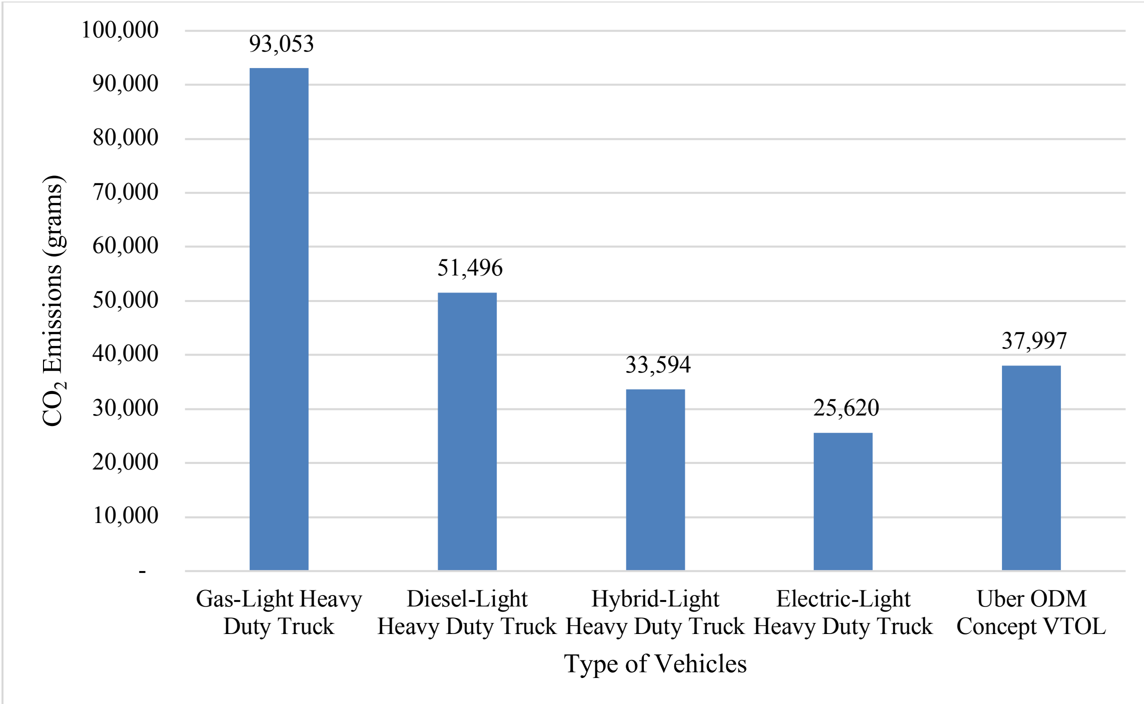

Figure 43: CO_2 Emissions for Light-Heavy Duty Trucks and ODM Cargo Vehicle for a 75-statute mile Trip.

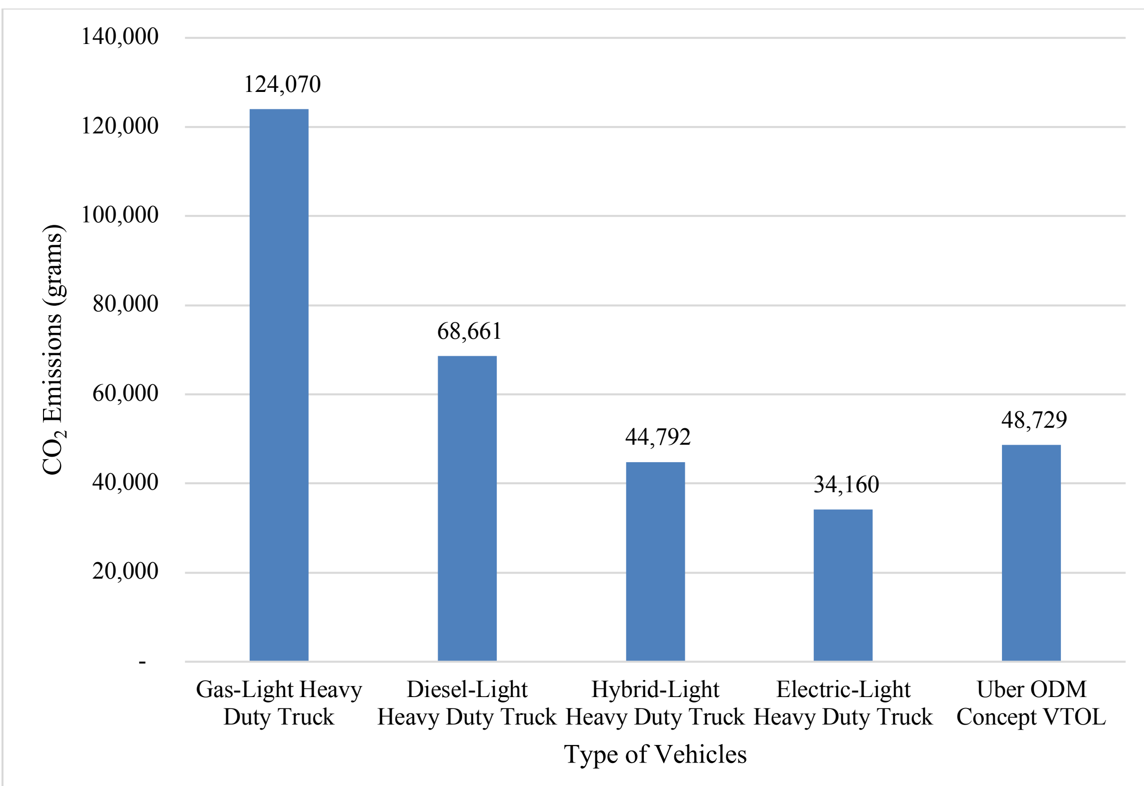

Figure 44: CO_2 Emissions for Light-Heavy Duty Trucks and ODM Cargo Vehicle for a 100-statute mile Trip.

6.9 CO_2 PER TON-KM DATA

This section provides an insight into the characteristic CO_2 emissions of a vehicle (both truck and VTOL) in terms of grams per ton-km. This metric is used contrast the emissions accounting for individual payloads for a truck which are significantly higher than the VTOL aircraft. Estimation of CO_2 emissions in terms of CO_2 per ton-km (CPK) provides another metric to compare the vehicles performance considering that California has more strict rules in terms of pollution and their environmental impacts. Table 18 summarizes the payload capacity of each vehicle along with the average load factor and other factors required to calculate CPK.

Table 18: Data for CPK Calculation

Type of Vehicle	Fuel	Payload in lbs. (metric tons)	Distance in Statute Miles (km)	Average Load Factor	CO_2 Emissions (grams)
Light- Heavy Duty Truck	Gasoline	5,100 (2.3)	20 (32.2)	0.6	24,814
Light- Heavy Duty Truck	Diesel	5,100 (2.3)	20 (32.2)	0.6	13,732
Light- Heavy Duty Truck	Hybrid (Gasoline-Electric)	5,100 (2.3)	20 (32.2)	0.6	8,958
Light- Heavy Duty Truck	All-Electric	5,100 (2.3)	20 (32.2)	0.6	6,832
Uber ODM Concept	All-Electric	800 (0.4)	20 (32.2)	0.6	14,387

The following shows a sample computation used in the analysis.

Vehicle Type: Light-Heavy Duty Truck 2
Fuel: Gas
Distance = 20 statute miles = 32.2 kilometers
Load factor = 0.8
Maximum Payload = 5,100 lbs. = 2.3 metric-tons
CO_2 emissions for a trip of 20 statute miles = 24,814 grams
CO_2 per ton-km = 24,814/ (32.2 * 0.8 * 2.3) grams/ton-km = 417 grams/ton-km

Conversion: 1 statute mile = 1.609344 kilometers
1 lb. = 0.000453592 metric-ton

Note: All calculations are for a single trip.

6.10 COMPARISON OF CO_2 PER TON-KM PROFILES FOR CARGO-DELIVERY TRUCKS AND VTOL

Figure 45 summarizes the CO_2 emissions per ton-km for four ground vehicles and compared to the Uber ODM Concept for a 20-mile (32.2 km) trip distance. This distance is similar to the average distance flown by cargo ODM aircraft according to the ODM flight generator. The distance accounts for an average detour factor of 6.1% for cargo flights. An average load factor of 0.6 is considered for all the vehicles since the cargo delivery is limited volumetrically. Emissions for the last mile delivery for VTOL is not considered in the figure. All emissions are calculated based on a single trip.

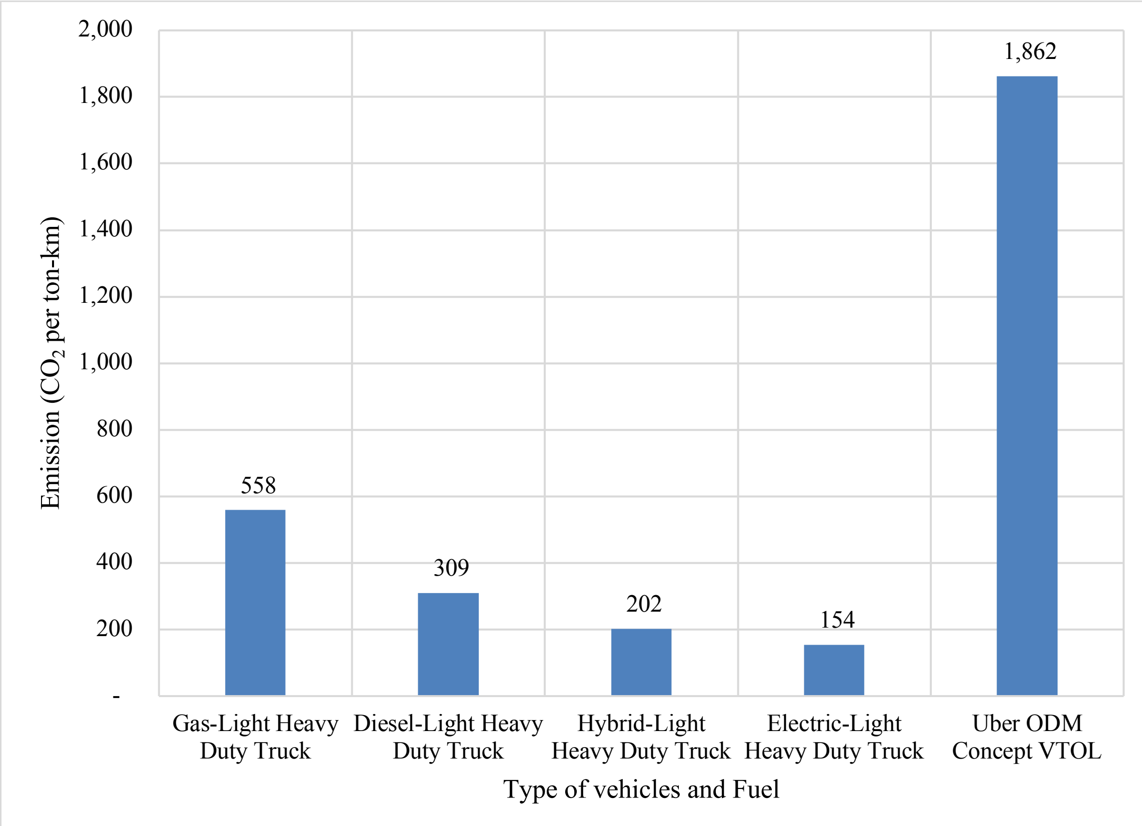

Figure 45: CO_2 per ton-km Emission Profile for a 20-statute mile Trip. 20 mph Average Speed. Running Exhaust.

Figure 45 shows that the CPK metric for Light-Heavy Duty Trucks stays constant for the Running Exhaust process type given the basic assumption that the vehicles travel at a constant speed of 20 mph. Figure 46 shows the decreasing trend in CO_2 emissions per ton-km for the Uber ODM Cargo Concept VTOL. Using the CPK metric, it is clear that the Uber ODM Cargo Concept VTOL aircraft is significantly less efficient than ground transportation vehicles. This is expected given the large energy requirements of powered flight and the low payload capacity of the vehicle.

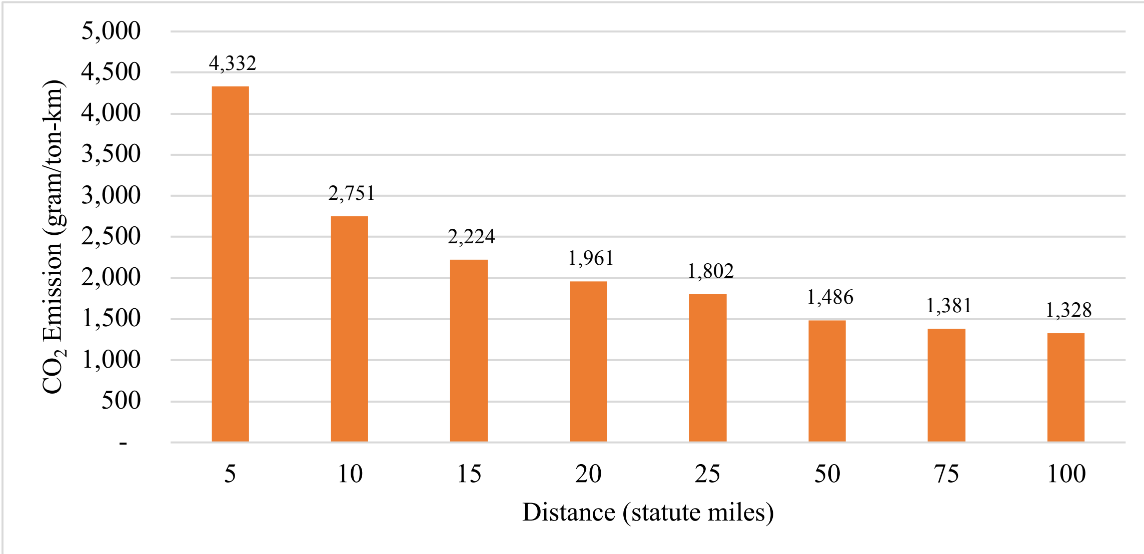

Figure 46: CO_2 per ton-km for Uber ODM Concept VTOL with Respect to Distance.

Figure 47 summarizes the CO_2 per ton-km comparison profiles for a vehicle mix since a single type vehicle is not used for delivery in California (or any other state). Table 19 provides data on the basic specifications of the vehicles (including the Uber ODM Concept VTOL).

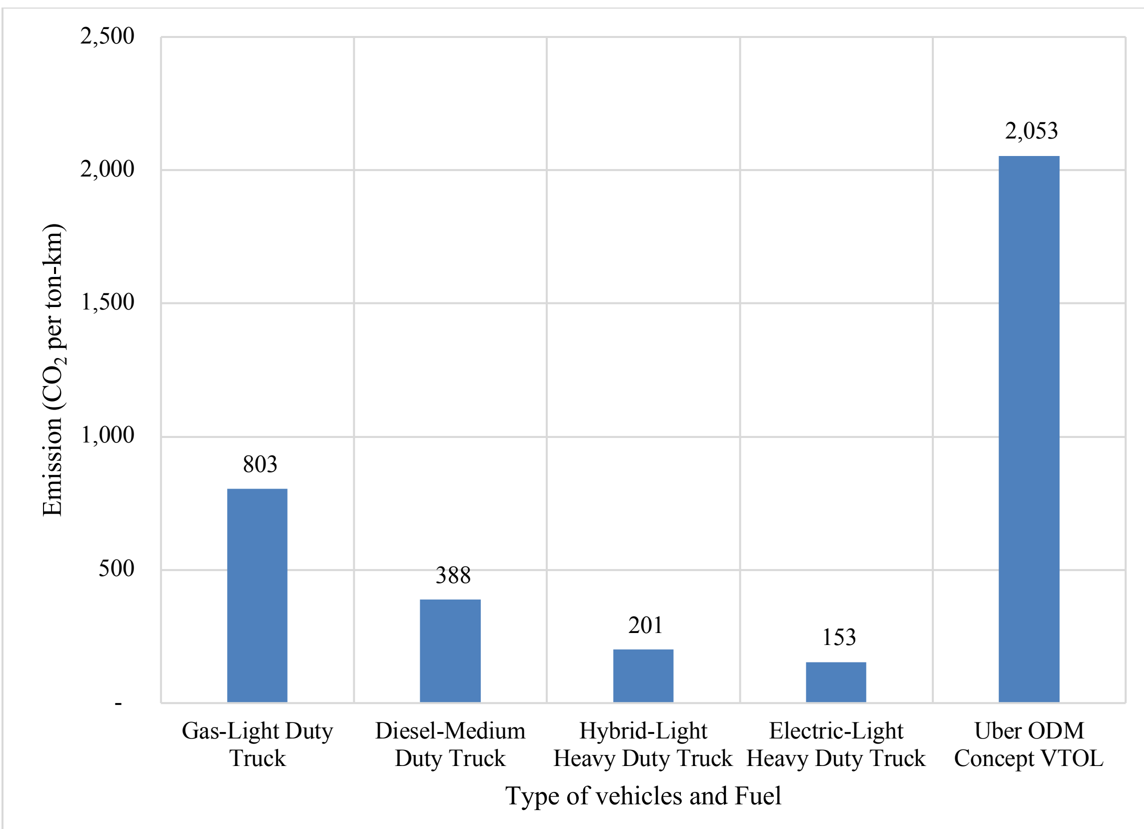

Figure 47: CO_2 per ton-km Comparison for a Vehicle Mix. 20 Statute Miles Distance. 20 mph Average Speed. Running Exhaust.

Table 19: Data for Vehicle Mix to Calculate CO_2 per ton-km

Type of Vehicle	**GVWR (lbs.)**	**Fuel**	**Payload in lbs. (metric ton)**	**Distance in Statute Miles (km)**	**Average Load Factor**	**CO_2 Emission (grams)**	**Representative Vehicle**
Light Duty Truck 2 (LDT2)	<6,000	Gas	1,610 (0.7)	20 (32.2)	0.6	11,331	
Medium Duty Truck (MDV)	6,000-8,500	Diesel	3,501 (1.6)	20 (32.2)	0.6	11,894	
Light-Heavy Duty Truck 2 (LHDT2)	10,001-14,000	Hybrid (Gas & Electricity)	5,100 (2.3)	20 (32.2)	0.6	8,958	
Light-Heavy Duty Truck 2 (LHDT2	10,001-14,000	All-Electric	5,100 (2.3)	20 (32.2)	0.6	6,832	
Uber ODM Cargo Concept VTOL		All-Electric	800 (0.4)	20 (32.2)	0.6	14,387	

7 STUDY FINDINGS AND RECOMMENDATIONS

1. Predicting cargo demand using electric VTOL vehicles presents a challenge due to the lack of cargo choice databases and the uncertainty of small package delivery information (i.e., commodity, value, etc.).
2. The combination of Transearch database and T-100 international data provide a first-order estimate of cargo flows into the study area. Neither Transearch, nor T-100-I include private warehouse-to-warehouse cargo flow information that could be relevant to estimate the cargo ODM demand.
3. Market share analysis of cargo ODM operations in the Northern California region indicate that in the year 2033, between 877 to 2,357 daily cargo flights may be possible if the cost of ODM vehicle is modestly competitive with ground transportation modes.
4. The total CO_2 emissions of an air vehicle on a 50-mile trip are expected to be 20% less than those produced by a diesel-powered light heavy-duty truck.
5. The CO_2 emissions of an air vehicle on a per ton-kilometer are expected to be higher than those associated with ground vehicles. Using the Uber concept vehicle, the CO_2 emissions per ton-kilometer could be 5-7 higher than those associated with a medium, diesel powered vehicle.
6. The study provided some initial estimates of the impact of reducing the cost per passenger mile for passenger ODM users if ODM vehicle are used in the cargo role at off-peak passenger hours. The passenger demand function is very sensitive to ODM price and a 10% reduction in passenger ODM cost can have a significant effect in passenger demand in the region.
7. The study provided some initial estimates of the impact of reducing the cost per passenger mile for passenger ODM users if ODM vehicle are used in the cargo role at off-peak passenger hours. The passenger demand function is very sensitive to ODM price and a 10% reduction in passenger ODM cost can have a significant effect in passenger demand in the region.

The following recommendations are suggested for follow-up studies of the cargo ODM concept.

7. In a follow-up study, we recommend the development of a detailed cargo choice model using the cost functions presented in Section 6 of the report. It is important to note that there is little publicly available data that explains the details on how customers select among shipping alternatives across commodities. In other words, there are macro-level databases like Transearch that aggregate cargo shipments across regions. Nevertheless, there is no data on the actual choices that customers considered before making a specific shipment. Such data will have to be derived synthetically in a follow-up study.
8. The hypothesis of the analysis is that people are the ultimate recipients of the cargo flowing into the area of interest. The population surrounding each landing site is used as a landing site "catchment" area. In a follow-up study we recommend that catchment areas for warehouses and retail space be considered as part of the distribution method.
9. In a follow-up study, consideration could be given to small regional airports as part of the cargo ODM network.
10. The landing site selection used a first-order, cost model based on net present value, to eliminate and reduce the number of landing sites in the study area. We recommend a more detail study to better understand the costs associated with typical ODM landing sites and their impact in landing fees and passenger and cargo demand.
11. The high-demand scenario presented in this study includes 2,357 daily cargo flights from various landing sites. These flights are assumed to be separated in time from passenger ODM flights. However, it is clear that if high priority cargo services are scheduled to meet 8-8:30 AM delivery times similar to today's parcel services, there will be an overlap of use of ODM aircraft for cargo use with the morning peak hours of use by commuters. Such interaction requires a detailed simulator (similar to the simulation capabilities developed by Georgia Tech) with actual flight schedules.

12. More insight into the repositioning flights is needed to understand their impact in passenger ODM cost per mile and both passenger and cargo demands. The cost per passenger-mile for the ODM vehicle is very sensitive to the fraction of flights used to re-position vehicles across landing sites. This should be investigated in more detail.

REFERENCES

1. Syed, N., Rye, M.; Ade, M.; Trani, A.A.; Hinze, N.; Swingle, H.; Smith, J.; Marien, T.; Dollyhigh, S., ODM Commuter Aircraft Demand Estimation, 17th AIAA Aviation Technology, Integration, and Operations Conference, 2017, 2017, 17th AIAA Aviation Technology, Integration, and Operations Conference, 2017.
2. Bureau of Transportation Statistics, 2017.
3. McKinsey and Company, Parcel delivery: The future of last mile, 2016. Available at: https://www.mckinsey.com/~/media/mckinsey/industries/travel%20transport%20and%20logistics/our%20insights/how%20customer%20demands%20are%20reshaping%20last%20mile%20delivery/parcel_delivery_the_future_of_last_mile.ashx
4. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions
5. Traffic Congestion Costs Americans $124 Billion A Year
6. https://www.forbes.com/sites/federicoguerrini/2014/10/14/traffic-congestion-costs-americans-124-billion-a-year-report-says/#a25e434c107a
7. Freight Facts and Figure 2015, BTS and US Department of Transportation
8. Five Lesser-Known Amazon Services That Can Save You Time and Money
9. https://lifehacker.com/5927127/five-lesser-known-amazon-services-that-can-save-you-time-and-money
10. Walmart To Go vs AmazonFresh: Who Deserves Your Grocery Order?
11. https://www.fool.com/investing/general/2014/02/05/walmart-to-go-vs-amazonfresh-who-deserves-your-gro.aspx
12. Instacart vs Google Express vs Amazon Prime Fresh
13. http://www.businessinsider.com/instacart-vs-google-express-vs-amazon-prime-fresh-2016-3/#whereas-amazon-fresh-is-only-available-in-select-zip-codes-in-seattle-philadelphia-new-york-new-jersey-and-northern-and-southern-california-2
14. eBay Is Launching A Same-Day Shipping Service Called eBay Now
15. https://techcrunch.com/2012/08/05/ebay-is-launching-a-same-day-shipping-service-called-ebay-now/
16. US Transportation Infrastructure Investment
17. https://data.oecd.org/transport/infrastructure-investment.htm
18. Frank S. Koppelman and Chandra Bhat, 2006 “A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models”.

APPENDIX A – LIFE CYCLE MODEL EQUATIONS FOR CARGO ODM VTOL VEHICLE

Top-Level Model:

Cumulative_Amortization_Cost(t) = Cumulative_Amortization_Cost(t - dt) + (Annual_LandingSite_and_Amortization_Cost) * dt

INIT Cumulative_Amortization_Cost = 0

INFLOWS:

Annual_LandingSite_and_Amortization_Cost = Monthly_Payment*12+Landing_Site_Annual_Support

Cumulative_Costs(t) = Cumulative_Costs(t - dt) + (Annual_Costs_of_Operation) * dt

INIT Cumulative_Costs = 0

INFLOWS:

Annual_Costs_of_Operation = Annual_LandingSite_and_Amortization_Cost+Annual_Fixed_Costs+Annual_Hangar_and_Office_Expenses+Annual_Periodic_Costs+Annual_Traning_Cost+Annual_Variable_Cost+Annual_Personnel_Costs

Cumulative_Fixed_Costs(t) = Cumulative_Fixed_Costs(t - dt) + (Annual_Fixed_Costs) * dt

INIT Cumulative_Fixed_Costs = 0

INFLOWS:

Annual_Fixed_Costs = Hull_Insurance+Liability_Insurance+Maintenance_Software_Programs+Miscellaneous_Service+Property_Tax

Cumulative_Hangar_and_Office_Expenses(t) = Cumulative_Hangar_and_Office_Expenses(t - dt) + (Annual_Hangar_and_Office_Expenses) * dt

INIT Cumulative_Hangar_and_Office_Expenses = 0

INFLOWS:

Annual_Hangar_and_Office_Expenses = Hangar_and_Office_Lease_Space+Miscellaneous_Office_Expense

Cumulative_Periodic_Costs(t) = Cumulative_Periodic_Costs(t - dt) + (Annual_Periodic_Costs) * dt

INIT Cumulative_Periodic_Costs = 0

INFLOWS:

Annual_Periodic_Costs = Annual_Engine_Overhaul_Cost+Annual_Midlife_Cost+Annual_Modernisation_Costs+Annual_Paint_Cost+Annual_Refurbishing_Cost

Cumulative_Personnel_Cost(t) = Cumulative_Personnel_Cost(t - dt) + (Annual_Personnel_Costs) * dt

INIT Cumulative_Personnel_Cost = 0

INFLOWS:

Annual_Personnel_Costs = Personnel_Benefits+Pilots_Salaries+Annual_Staff_Cost_per_Aircraft

Cumulative_Training_Cost(t) = Cumulative_Training_Cost(t - dt) + (Annual_Traning_Cost) * dt

INIT Cumulative_Training_Cost = Total_Initial_Training_Cost

INFLOWS:

Annual_Traning_Cost = Recurrent_Maintenance_Training+Recurrent_Pilot_Training*Pilots_per_Aircraft

Cumulative_Variable_Cost(t) = Cumulative_Variable_Cost(t - dt) + (Annual_Variable_Cost) * dt

INIT Cumulative_Variable_Cost = 0

INFLOWS:

Annual_Variable_Cost = Flight_Hours_per_Year*Total_Variable_Costs_per_Hour

Total_Hours_Flown(t) = Total_Hours_Flown(t - dt) + (Annual_Hours) * dt

INIT Total_Hours_Flown = 0

INFLOWS:

Annual_Hours = Flight_Hours_per_Year

Aircraft_Baseline_Cost = 750000

Aircraft_Block_Speed = GRAPH(Mission_Stage_Length)

(0.0, 75.0), (25.0, 120.0), (50.0, 136.2), (75.0, 148.2), (100.0, 155.0), (125.0, 160.0), (150.0, 160.0)

Aircraft_Paint = 20000

Aircraft_PAX_Seats = 3

Aircraft_Purchase_Price = Aircraft_Baseline_Cost+Automation_Cost

Annual_Engine_Overhaul_Cost = Engine_Overhaul_Cost*Number_of_Engines*Flight_Hours_per_Year/Engine_Overhaul_Interval

Annual_Midlife_Cost = MidLife_Engine_Section_Inspection_Cost*Number_of_Engines*Flight_Hours_per_Year/Engine_Overhaul_Interval

Annual_Modernisation_Costs = Modernisation_and_Upgrades*Flight_Hours_per_Year/Modernisation_Time_INterval

Annual_Paint_Cost = Aircraft_Paint*Flight_Hours_per_Year/Paint_and_Refurbishing_Interval

Annual_Pilot_Salary = 50000

Annual_Refurbishing_Cost = Interior_Refurbishing*Flight_Hours_per_Year/Paint_and_Refurbishing_Interval

Annual_Staff_Cost_per_Aircraft = Staff_Salaries

Automation_Cost = IF(Number_of_Pilots=0) THEN Automation_Cost_Base ELSE 0

Automation_Cost_Base = 75000

Base_Energy_Cost_per_KWh = 0.12

Cost_Per_Mile = Revenue_Required_Per_Hour/Aircraft_Block_Speed

Crews_vs_Vehicle_Flight_Hours_Function = GRAPH(Flight_Hours_per_Year)

(0, 1.125), (300, 1.125), (600, 1.125), (900, 1.125), (1200, 1.125), (1500, 1.125), (1800, 1.125), (2100, 1.125), (2400, 2.250), (2700, 2.250), (3000, 2.250)

Deadhead_Hours = Flight_Hours_per_Year*Percent_Repositioning/100

Electric_Consumption_per_Hour = GRAPH(Mission_Stage_Length)

(0.0, 250.0), (10.0, 190.0), (20.0, 170.0), (30.0, 160.0), (40.0, 153.0), (50.0, 150.0), (60.0, 150.0), (70.0, 150.0), (80.0, 150.0), (90.0, 150.0), (100.0, 150.0)

Electric_Cost_per_KWH = Base_Energy_Cost_per_KWh

Energy_Consumption_per_Hour = Electric_Consumption_per_Hour

Energy_Cost_Fraction_of_Total_Cost = Energy_Expense/(Revenue_Required_Per_Hour+1e-6)

Energy_Cost_Fraction_Var_Cost = Energy_Expense/(Total_Variable_Costs_per_Hour+1e-6)

Energy_Expense = Energy_Consumption_per_Hour*Electric_Cost_per_KWH

Engine_Overhaul_Cost = 10000

Engine_Overhaul_Interval = 10000

Fare_per_Seat_Mile = Cost_Per_Mile/(Load_Factor*Aircraft_PAX_Seats)

Flight_Hours_per_Year = 1000

Hangar_and_Office_Lease_Space = 4000

Hull_Insurance = 5000

Initial_Maintenance_Training = 1000

Initial_Pilot_Training = 2000

Interest_Rate = 0.06

Interior_Refurbishing = 10000

Landing_Fee = 6.7

Landing_Site_Annual_Support = Landing_Fee*Flight_Hours_per_Year*Landings_per_Hour

Landings_per_Hour = 60/(Mission_Stage_Length/Aircraft_Block_Speed*60+Turnaround_Time)

Liability_Insurance = IF Number_of_Pilots=0 THEN 20000 ELSE 7500

Life_Cycle_Time = 15

Load_Factor = Passengers_per_Flight/Aircraft_PAX_Seats

Loaded_Salary_of_Staff_Member = 50000

Loan_Amount = Aircraft_Purchase_Price-Resale_Value

Maintenance_Cost_per_Hour = Annual_Engine_Overhaul_Cost/Flight_Hours_per_Year+Maintenance_Hours_per_Flight_Hour*Maintenance_Labor_Expense_per_Hour+Schedule_Parts_Expense

Maintenance_Hours_per_Flight_Hour = IF (Automation_Cost = 0) THEN 0.40 ELSE 0.50

Maintenance_Labor_Expense_per_Hour = 50

Maintenance_Software_Programs = 2000

MidLife_Engine_Section_Inspection_Cost = 3000

Miscellaneous_Office_Expense = 1500

Miscellaneous_Service = 2000

Miscellaneous_Trip_Expenses = 0

Mission_Stage_Length = 30

Modernisation_and_Upgrades = 12000

Modernisation_Time_INterval = 3000

Monthly_Payment = -PMT(Interest_Rate/12,Payments,Loan_Amount,0)

Non_Revenue_Trips = Deadhead_Hours/Time_per_Flight

Number_of_Engines = 6

Number_of_Pilots = 1

Paint_and_Refurbishing_Interval = 3000

Passengers_per_Aircraft_per_Year = Revenue_Trips_per_Year*Load_Factor*Aircraft_PAX_Seats

Passengers_per_Flight = 1.5

Payments = Life_Cycle_Time*12

Percent_Repositioning = 15

Percent_Resale_Value = 0.10

Percent_Salaries_to_Benefits = .25

Personnel_Benefits = Annual_Pilot_Salary*Percent_Salaries_to_Benefits*Pilots_per_Aircraft

Pilots_per_Aircraft = Number_of_Pilots*Crews_vs_Vehicle_Flight_Hours_Function

Pilots_Salaries = Annual_Pilot_Salary*Pilots_per_Aircraft

Profit_Margin = 10

Property_Tax = 2500

Recurrent_Maintenance_Training = 1500

Recurrent_Pilot_Training = 1500

Resale_Value = Aircraft_Purchase_Price*Percent_Resale_Value

Revenue_Hours_LC = Total_Hours_Flown*Revenue_Hours_per_Year/Flight_Hours_per_Year

Revenue_Hours_per_Year = Flight_Hours_per_Year-Deadhead_Hours

Revenue_Required_Per_Hour = (1+Profit_Margin/100)*Total_Cost_Per_Hour

Revenue_Trips_per_Year = Revenue_Hours_per_Year/Time_per_Flight

Schedule_Parts_Expense = 20

Staff_members_per_Vehicle = 0.2

Staff_Salaries = Loaded_Salary_of_Staff_Member*Staff_members_per_Vehicle

Time_per_Flight = Mission_Stage_Length/Aircraft_Block_Speed

Total_Cost_Per_Hour = Cumulative_Costs/(Revenue_Hours_LC+1e-5)

Total_Initial_Training_Cost = Initial_Pilot_Training*Pilots_per_Aircraft+Initial_Maintenance_Training

Total_Variable_Costs_per_Hour = Energy_Expense+Maintenance_Hours_per_Flight_Hour*Maintenance_Labor_Expense_per_Hour+Miscellaneous_Trip_Expenses+Schedule_Parts_Expense

Turnaround_Time = 7

{ The model has 102 (102) variables (array expansion in parens).

In 1 Modules with 8 Sectors.

Stocks: 9 (9) Flows: 9 (9) Converters: 84 (84)

Constants: 41 (41) Equations: 52 (52) Graphicals: 3 (3)

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