

# Demand Modeling for Advanced Air Mobility

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# Contents

- 1 Introduction
- 2 Related Work
- 3 Methodology
- 4 Results
- 5 Conclusion
- 6 References

- Urbanization increases congestion and environmental issues.
- Advanced Air Mobility (AAM) emerges as a sustainable alternative.
- Research focuses on Tennessee's employment-based trip data.
- Key aspects:
  - Cost, time, and risk assessments.
  - Generalized Cost of Trip (GCT) modeling.

- Clustering techniques for air taxi station placement.[1]
- Deep learning for UAM demand forecasting.[2]
- Fare modeling and landing site feasibility studies.[3]

- Four-step travel demand model:
  - Trip generation
  - Trip distribution
  - Mode choice (focus of this study)
  - Route choice (out of scope)

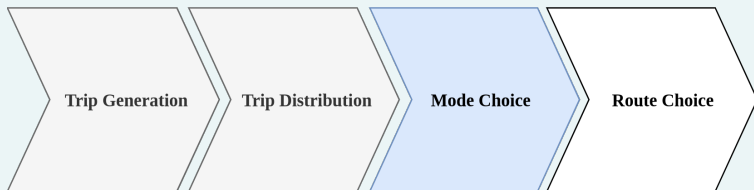


Figure: Four Step Model for travel demand modeling

- Tennessee as the focal region:
  - Strategic for AAM innovation.
  - Data collected at census tract level.
- Trip demand assumptions:
  - Ground trips start and end at census tract centroids.
  - AAM trips involve multimodal connections via airports.

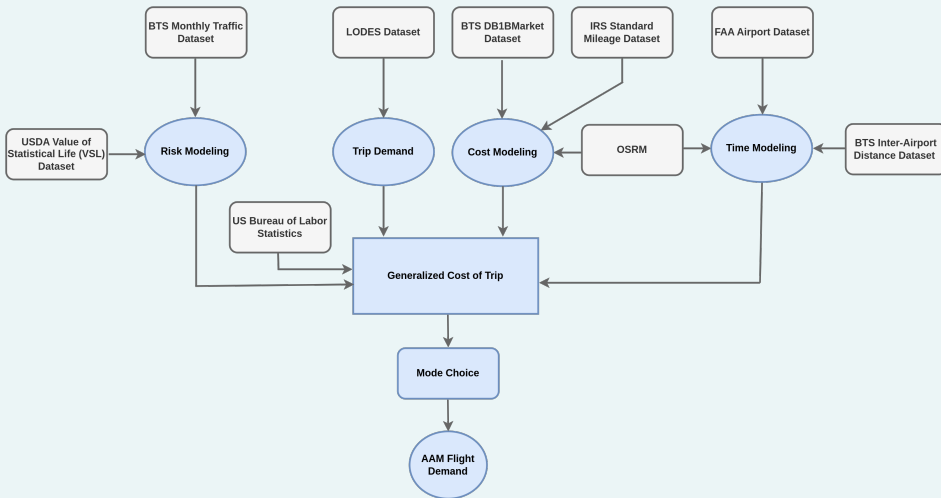


Figure: Approach for AAM demand modeling

Table: Datasets Used in the Research

Name	Details
BTS Monthly Traffic Dataset	Number of fatalities during Transportation
USDA VSL Dataset	Monetary equivalent of reducing one death in population
LODES Dataset	OD pairs in employment basis
BTS DB1BMarket Dataset	Ticket Price for the airlines
IRS Standard Mileage Dataset	Standard Mileage Rates(cents/miles)
FAA Airport Dataset	Block time of the flights
BTS Inter-Airport Distance Dataset	Distance between the airports
Open Source Routing Machine (OSRM)	Distance and Time of Ground transportation
US Bureau of Labor Statistics	Median hourly wages

## Cost Modeling( $C_m$ ):

- Ground transportation: IRS mileage rates.
- Air travel: Regression on DOT market data.

## Time Modeling( $T_m$ ):

- Ground transport: OSRM driving times.
- AAM: Flight times modeled using FAA data.

## Risk Modeling( $R_m$ ):

- Ground travel risk higher than air travel.
- Calculated using NSC data and VSL metrics.

# Risk and Generalized Cost Modeling

## Generalized Cost of Trip (GCT):

$$GCT_m = -C_m - W * T_m - R_m \quad (1)$$

where

- $m$  is mode of transportation either ground or AAM
- $W$  is average median hourly wage of origin and destination census tracts

## Utility for Trip (U):

$$\begin{aligned} U_G &= GCT_G + \epsilon; \\ U_{AAM} &= GCT_{AAM} + \epsilon \end{aligned} \quad (2)$$

where

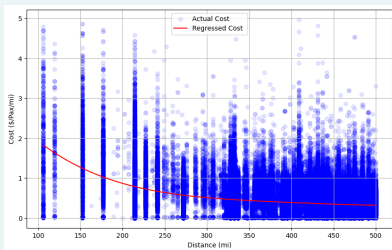
- $\epsilon$  is the error associated

## Mode Choice:

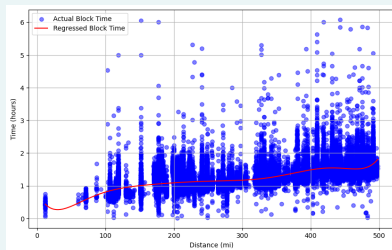
$$P_{AAM} = \frac{1}{1 + e^{(U_G - U_{AAM})}} \quad (3)$$
$$P_{AAM} = \frac{1}{1 + e^{(GCT_G - GCT_{AAM})}}$$

where

- $P_{AAM}$  is Probability of selecting AAM

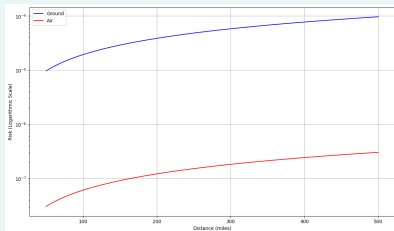


Cost Regression

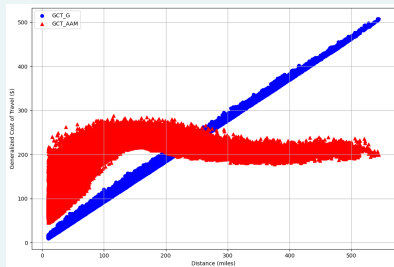


Block Time Regression

Figure: Regression Analysis



Risk Regression



GCT Regression

Figure: Regression Analysis

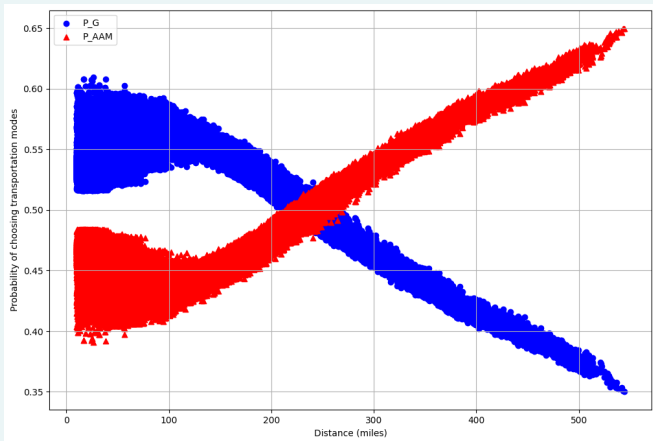


Figure: Probability of choosing transportation mode

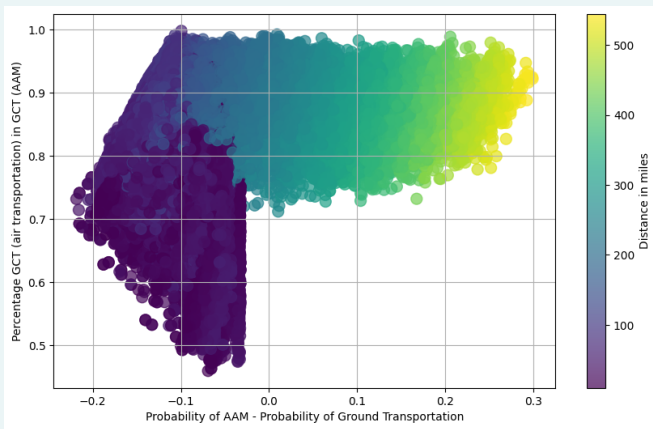
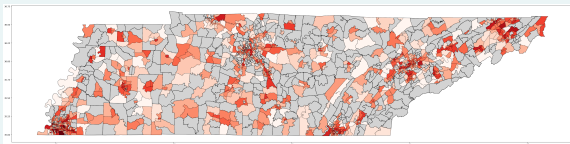


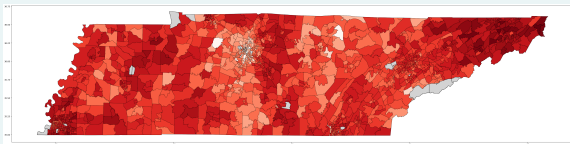
Figure: Percentage of  $GCT_A$  in  $GCT_{AAM}$  vs difference of  $P_G$  and  $P_{AAM}$

Table: Comparison of Trip Demand Features

Features	Sub-categories	All Trips (%)	AAM Trips (%)
Age	29 or younger	23.47	22.88
	30 - 54	53.28	53.34
	55 or Older	23.25	23.78
Earning	\$1250/month or less	23.51	26.59
	\$1251/month to \$3333/month	32.06	29.49
	Greater than \$3333/month	44.43	43.92
Industry	Goods Producing	16.91	10.89
	Trade, Transportation, and Utilities	21.61	33.75
	Other Services industry	61.48	55.36



Job part of OD pairs



Home part of OD pairs

Figure: Census Tracts for AAM OD pairs in Tennessee

- AAM viable for trips  $> 250$  miles and air-heavy GCT.
- Significant implications for urban and regional planning.
- Future work: Electric AAM aircraft cost modeling.

-  S. Rajendran and J. Zack, “Insights on strategic air taxi network infrastructure locations using an iterative constrained clustering approach,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 128, pp. 470–505, 2019.
-  F. Ahmed, M. A. Memon, K. Rajab, H. Alshahrani, M. E. Abdalla, A. Rajab, R. Houe, and A. Shaikh, “Demand prediction for urban air mobility using deep learning,” *PeerJ Computer Science*, vol. 10, p. e1946, 2024.
-  S. Tarafdar, M. Rimjha, N. Hinze, S. Hotle, and A. A. Trani, “Urban air mobility regional landing site feasibility and fare model analysis in the greater northern california region,” in *2019 Integrated Communications, Navigation and Surveillance Conference (ICNS)*, pp. 1–11, IEEE, 2019.

*Thank You*