6-2022

Enhanced Methodology for Exploring Autonomy-enabled Multi-mode Regional Transportation

Daniel DeLaurentis

Hetal Rathore

Apoorv Maheshwari

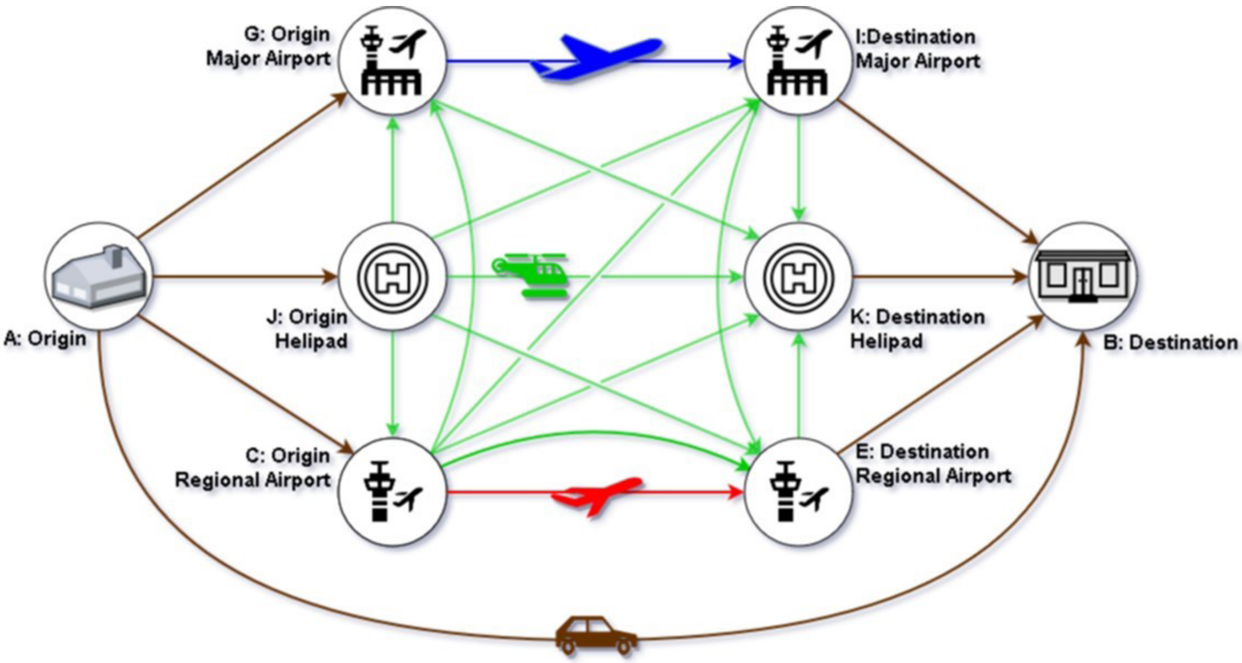
Recommended Citation

DeLaurentis, Daniel; Rathore, Hetal; and Maheshwari, Apoorv, "Enhanced Methodology for Exploring Autonomy-enabled Multi-mode Regional Transportation" (2022). *Center for Connected and Automated Transportation.* Paper 7.

http://dx.doi.org/10.5703/1288284317566

CENTER FOR CONNECTED AND
AUTOMATED TRANSPORTATION

Final Report #35
June 2022



Enhanced Methodology for Exploring Autonomy-enabled Multi-mode Regional Transportation

Daniel DeLaurentis
Hetal Rathore
Apoorv Maheshwari

PURDUE
UNIVERSITY

CENTER FOR CONNECTED
AND AUTOMATED
TRANSPORTATION

Report No. 35 **June 2022**
Project Start Date: 9/1/2019
Project End Date: 12/31/2020

Enhanced Methodology for Exploring Autonomy-enabled Multi-mode Regional Transportation

By
Daniel DeLaurentis
Hetal Rathore
Apoorv Maheshwari

Purdue University

ACKNOWLEDGEMENTS AND DISCLAIMER

Funding for this research was provided by the Center for Connected and Automated Transportation under Grant No. 69A3551747105 of the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Suggested APA Format Citation:

DeLaurentis, D., Rathore, H., Maheshwari, A. (2022). Enhanced Methodology for Exploring Autonomy-enabled Multi-mode Regional Transportation, CCAT Report #35, Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.

Contacts

For more information:

Samuel Labi
3000 Kent Ave., West Lafayette, IN
Phone: (765)494-5926
Email: labi@purdue.edu

Dan DeLaurentis
701 W. Stadium Ave.
West Lafayette, IN 47907-2045
Phone: (765) 494-0694
Email: ddelaure@purdue.edu

CCAT
University of Michigan Transportation Research Institute
2901 Baxter Road
Ann Arbor, MI 48152

uumtri-ccat@umich.edu
(734) 763-2498
www.ccat.umtri.umich.edu

CENTER FOR CONNECTED
AND AUTOMATED
TRANSPORTATION

Technical Report Documentation Page

1. Report No.
35

2. Government Accession No.
N/A

3. Recipient's Catalog No.
N/A

4. Title and Subtitle
Enhanced Methodology for Exploring Autonomy-enabled Multi-mode Regional Transportation

5. Report Date
June 2022

6. Performing Organization Code
N/A

7. Author(s)
Daniel DeLaurentis, Hetal Rathore, Apoorv Maheshwari

8. Performing Organization Report No.
N/A

9. Performing Organization Name and Address
Center for Connected and Automated Transportation
Purdue University, 550 Stadium Mall Drive, W. Lafayette, IN 47907;
and University of Michigan Ann Arbor, 2901 Baxter Road, Ann Arbor, MI 48109

10. Work Unit No.

11. Contract or Grant No.
Contract No. 69A3551747105

12. Sponsoring Agency Name and Address
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology
1200 New Jersey Avenue, SE, Washington, DC 20590

13. Type of Report and Period Covered
Final report, Sept 1 2019 - Dec 31 2020

14. Sponsoring Agency Code
OST-R

15. Supplementary Notes
Conducted under the U.S. DOT Office of the Assistant Secretary for Research and Technology's (OST-R) University Transportation Centers (UTC) program.

16. Abstract

Increasing the level of autonomy in both small aircraft and autos has the potential to generate greater efficiency and utility in multimodal regional transportation systems. In previous research, the PI and collaborators developed a computational analysis framework to assess the impact of aircraft technology advancement in electric propulsion and autonomy on the future of on-demand, regional air transportation system. A sensitivity analysis revealed increasing level of autonomy and an improved ride-sharing model (on the ground and in the air) could lead to significant increase in the total number of individuals who could afford this new mode of transportation. Activities in this CCAT project a) explored and then generated a model for for the autonomous automobile option to enhance the impact of autonomy at a multi-modal level b) explored options for a connectivity metrics that could well-capture the efficacy of different multi-modal architectures. Outcome models, analysis, and metrics were successfully developed and used to inform a larger research effort developing a computational model for a project under NASA sponsorship (in which the NASA Technical Monitor served as government partner on this CCAT project).

17. Key Words
Autonomous vehicles, Technology adoption, Connectivity

18. Distribution Statement
No restrictions.

19. Security Classif. (of this report)
Unclassified

20. Security Classif. (of this page)
Unclassified

21. No. of Pages
19

22. Price
Leave blank – not used

Form DOT F 1700.7 (8-72)
Reproduction of completed page authorized

Table of Contents

List of Figures

1. INTRODUCTION AND BACKGROUND

Increasing the level of autonomy in both small aircraft and autos has the potential to generate greater efficiency and utility in multimodal regional transportation systems. In previous research, this project's research team and collaborators developed a computational analysis framework to assess the impact of aircraft technology advancement in electric propulsion and autonomy on the future of on-demand, regional air transportation system. A sensitivity analysis revealed increasing level of autonomy and an improved ride-sharing model (on the ground and in the air) could lead to significant increase in the total number of individuals who could afford this new mode of transportation (Maheshwari, et.al., 2020). Thus, one goal of the CCAT project were designed to produce enhancements to this computational framework with models for the autonomous automobile option and thereby take a holistic approach to evaluate the impact of autonomy at a multi-modal level of operation. In addition, a second goal was established to explore options for a connectivity metrics that could well-capture the efficacy of different multi-modal architectures. Outcome models, analysis, and metrics were successfully developed and used to inform a larger research effort developing a computational model for a project under NASA sponsorship. These outcomes increased the research community's ability to characterize the impacts of differing levels of autonomy as well as the synergistic benefit of a ride-sharing economy in both air and ground modes.

1.1 Background and Literature Review: A Model for Autonomous Auto Mode Option

The first project goal was driven by the following Research Question:

Research Question 1: How to appropriately integrate the autonomous auto option in the existing computational framework and thereby improve the fidelity of the multimodal options in the model?

The current computational framework estimates the door-to-door travel time and operational cost associated with automobile, airline and proposed "regional air-taxi" modes of transportation with levels of autonomy enabled only in the regional air-taxi mode. The computational framework also performs calculations for a VTOL-based air-taxi service utilizing the existing publicly-owned helipads. Figure 1 shows the mode availability/breakdown and the trip network template for the computational analysis framework.

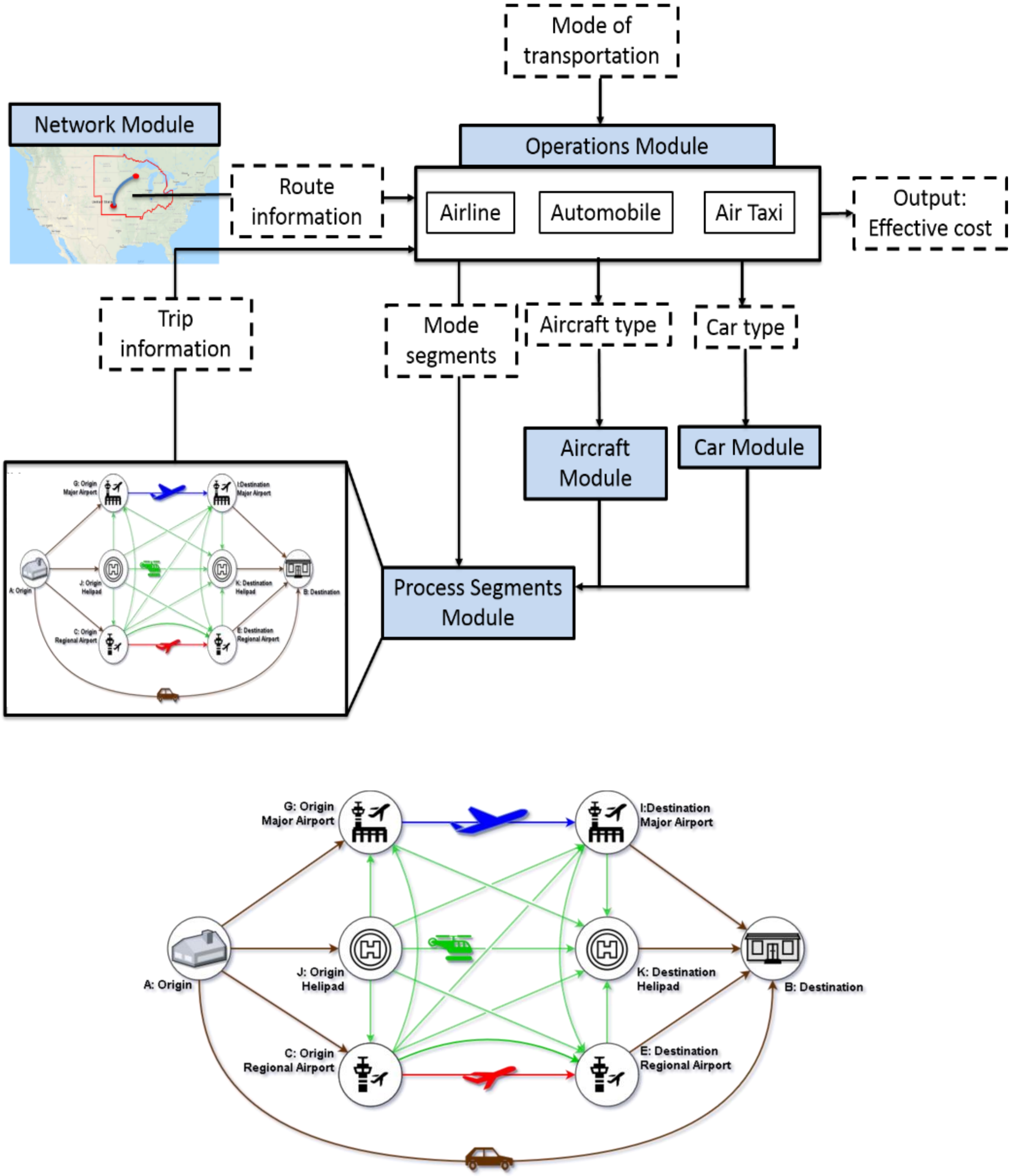


Figure 1.The regional air mobility computational analysis framework with mode breakdown (upper portion) and trip network template (lower portion)

For a given OD pair and mode of transportation, the computational framework identifies the trip-path and then calls the appropriate segment module to obtain the time and cost associated with the segment. The framework leverages Google Maps API and Rome2Rio API to acquire real-time information for the automobile and airline modules respectively. As an output, the framework combines the time and the cost associated with a given trip into a single metric – the effective cost (c_{eff}). The cost equivalent of the trip time is obtained using the product of trip time and an individual's hourly value of time. This metric enables us to compare different modes of transportation involving multi-segments taking into account both the trip time and cost. Roy, et.al. (2021) detail on the metric and the computational framework.

Our initial analysis identifies aircraft automation along with ride sharing as most significant enablers of the proposed "regional air taxi" mode of transportation. The automobile industry has also identified ridesharing (implemented by Uber, Lyft, and other Transportation Network Companies) and autonomous cars as disruptors that will shape the future of the automobile-based transportation. Thus, to ensure a holistic approach to transportation evaluation, we examined in this CCAT project the ample available literature in autonomous autos and attempted to understand how it could be leveraged for incorporation in our evolving computational framework.

1.2 Background and Literature Review: Connectivity Metric

The second project goal was driven by the following Research Question:

Research Question 2: How to define a connectivity metric that can capture the "connectedness" of a region with respect to different modes of transportation and trip distance? How to answer the question – "if I can afford the service, do I need the service?"

General Overview

A variety of connectivity metrics, or "Scores", are used to assess connectivity in a region for different transport modes. Examples including Walk Score (Carr, et.al., 2010), Transit Score and Bike Score (Dill 2004) were examined by the research team and their methodology studied in detail. For each of these scores, the concept of distance decay is used to ascribe a quantitative score to a certain region based on factors such as length of route, frequency of services, nearness to other nearby stops and amenities. These quantitative scores are then normalized to obtain a number between 0 – 100 to indicate how 'connected' a place is for that particular mode of transport.

In simplest terms, the distance decay effect states that as distance between two places increases, the interaction between them decreases. The farther away goods and services, the less likely people are to use it, therefore distance decay answers questions about where people are and what is available to them. This phenomenon is particularly evident in town and city centers. Many refer to this concept and related as "gravity model" when used to estimate demand for trips. Distance decay can be mathematically represented as an inverse-square law by the expression where *I* represents the interaction level and *d* represents the distance.

$$I = \frac{constant}{d^2}$$

It can take other forms such as negative exponential such as

$$I = constant * e^{-d}$$

An appropriate distance decay function is necessary for most forms of connectivity metric.

There are also a growing variety of "overall" transit scoring/rating systems. One prominent example if the AllTransit™ system (https://alltransit.cnt.org/). AllTransit is an overall transit score that looks at connectivity, access to jobs and frequency of service. According to their website, AllTransit increases our understanding of the value of transit by going beyond simple measures of "where transit exists" to nuanced interpretations of transit quality. AllTransit analyzes the social benefits of good transit service through the lenses of health, equity and economic opportunities. It mainly measures the six features in and around a region – transit quality, mobility, job access, economic growth, health benefits, transit equity. Such all-encompassing metrics were deemed outside the scope of our study.

Specific Overview (Synopsis of Four Sources from the Literature on Connectivity)

In this section, a summary of key points is provided from the four most relevant papers our team identified. These key points were used in shaping and identifying the factors we need to consider for the connectivity metric.

Commuting in transit versus automobile neighborhoods (Cervero, R., & Gorham, R. (1995))

- Past work has shown mode choice to be more highly correlated with household income than any other sociodemographic factor or non-prize variable.
- When controlled for income differences, however, vehicle ownership levels exert a fairly modest influence on commuting choices
- Transit neighborhoods (where people travel chiefly by public transportation) by and large showed lower drive-alone modal shares and trip generation rates than did their automobile counterparts

Travel demand and the 3Ds – Density, Diversity and Design (Cervero, R., & Kockelman, K. (1997))

- Travel demand is a 'derived' demand in the sense that trips are made and distributed on the basis of the desire to reach places -i.e. their land uses, densities, design features can affect not only the number of trips generates, but also modes and routes of travel.
- While characteristics of origin-destination interchanges, like the relative prices and service qualities of competing modes, are known to affect travel demand, so are features of the trip ends (i.e. origins and destination) themselves.
- Characteristics of trip ends, and not just trip interchanges, influence travel behavior and cities.
- Macro-factors like density and the comparative cost of transit vs automobile travel, are the principal determinants of commuting choices. Control variables such as household incomes and travel distances, are measured on continuous ration scale and thus enjoy a predictive advantage.

How air transport connects the world – A new metric of air connectivity and its evolution between 1990 and 2012 (Allroggen, F., Wittman, M. D., & Malina, R. (2015))

- A connectivity metric is proposed, but is singularly focused on commercial air mode. Our assessment is that direct application to multi-modal regional context is not fruitful.
- The global connectivity index (CGI) for each airport is computed by summing the connection quality of each available flight connection weighted by the interaction potential, to which the connection provides access.
  1. First, on the link-quality level, they compute each connection's frequency and relative connective connectivity value as compared to (hypothetical) nonstop flights. The relative connectivity value is derived from flight duration and layover time and calibrated through observed routing data for US passengers.
  2. Second, on the link-quality level, they compute each connection's frequency and relative connectivity value as compared to (hypothetical) nonstop flights. The relative connectivity value is derived from flight duration and layover time and calibrated through observed routing data for US passengers.
  3. Third, on the destination-quality level, they model the interaction potential, to which each worldwide airport provides access. For this purpose, they use gridded wealth-adjusted population data and a distance decay function.

Air Connectivity – Why it matters and how to support growth (Morphet, H., & Bottini, C. (2014))

- If the objective of air connectivity analysis is to focus on passenger experience, then the analysis needs to consider entire door-to-door connectivity to travelers.
- Ideally, such a perspective would take into account how easy it is to get to an airport (surface access), how efficiently passengers can get onto their flight (landside and airside considerations inside the airport), and ultimately, to the destination of their choice.
- Affordability of the available options is usually an important part of such considerations.
- Comprehensive network connectivity assessment captures the following components
  - Direct connectivity: the level (number and quality) of connections offered from the assessed airport
  - Indirect connectivity: the level (number and quality) of reasonable connections offered from the assessed airport indirectly through other airports.
  - Hub connectivity: the level (number and quality) of reasonable indirect connections offered through the assessed airport.

2. METHODOLOGICAL APPROACH

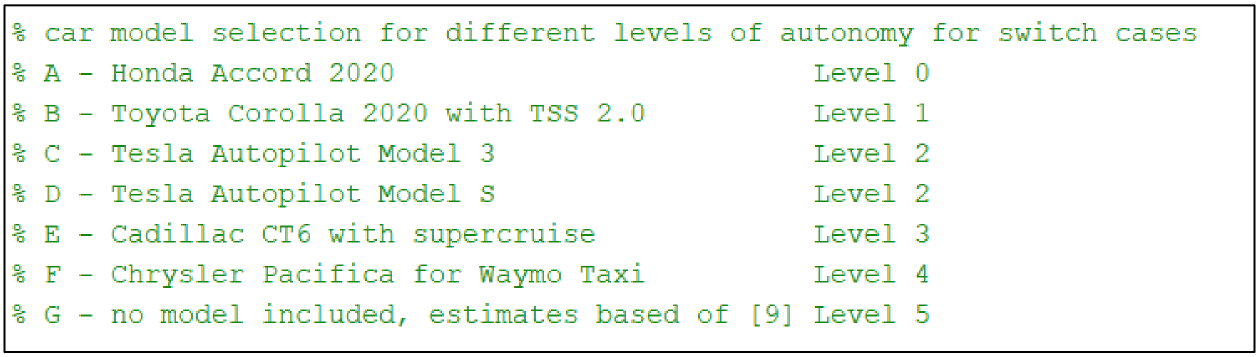
The research methodology for both project goals was the same: based on review of the relevant literature, and needs of the evolving computational model and guidance from the NASA government partner, develop a suitable model for autonomous auto cost (in the first case) and connectivity metric in the second case.

2.1 Autonomous Auto Model

The primary need for the autonomous auto mode is an estimate of the economic parameters as a function of autonomy level. The total cost for the autonomous auto mode is composed of the cost of operating the vehicle at a given autonomy level (*cost_oper*) and the cost of operating based on all other traveler and trip-related factors (*cost_time*). The total cost is then *cost_oper* + *cost_time*.

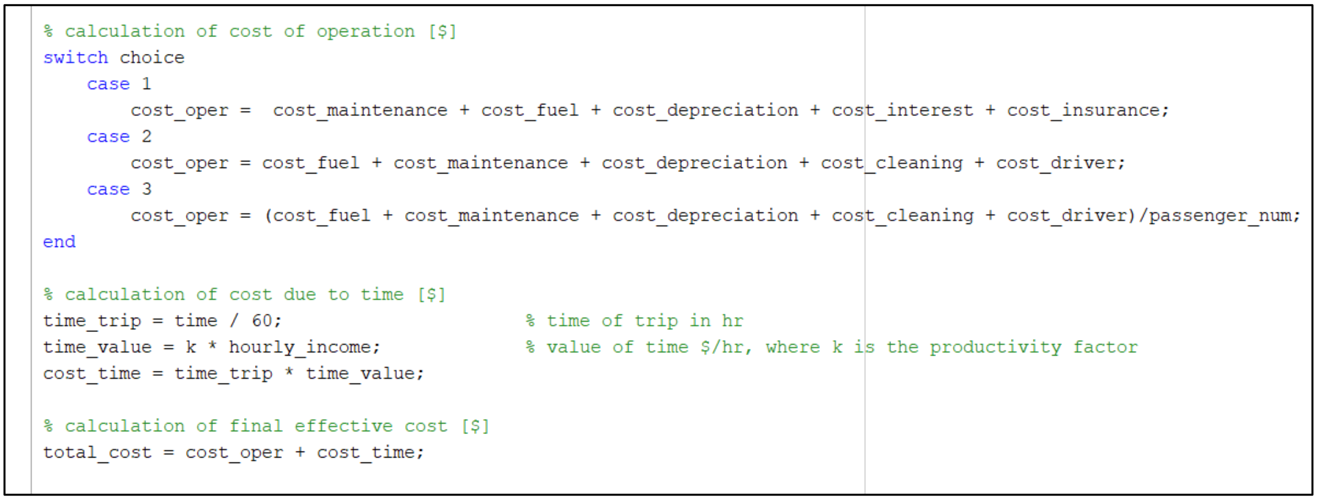
cost_time here is calculated in a standard way for all levels of autonomy and irrespective of a person is driving themselves, sharing with someone, or simply taking a taxi. It is the product of how a person values their time (time_value in $/hr - usually taken as their standard income, it's the monetary value they place on their time per hour) and the trip time: *cost_time* = *time_trip* * *time*_value

cost_oper is determined for different levels of autonomy (Levels - Low, mid, and high) and the variable 'choice'. The five SAE autonomy levels from 0 to 5 are used for this purpose, augmented by the following classifications: Low autonomy - SAE levels 0 and 1; Mid autonomy - SAE levels 2 and 3; High autonomy - SAE levels 4 and 5). Further, to get a real-world estimation of services, fuel costs and other variables such as - depreciation, interest, maintenance, and service charges, our team correlated these with vehicles that correspond to these SAE levels. The models for these vehicles are listed below as well.



```
% car model selection for different levels of autonomy for switch cases
% A - Honda Accord 2020                         Level 0
% B - Toyota Corolla 2020 with TSS 2.0          Level 1
% C - Tesla Autopilot Model 3                   Level 2
% D - Tesla Autopilot Model S                   Level 2
% E - Cadillac CT6 with supercruise             Level 3
% F - Chrysler Pacifica for Waymo Taxi          Level 4
% G - no model included, estimates based of [9] Level 5
```

The variable called '*choice*' generates the following cases. Case 1 is when a person just drives their own vehicle (this could be any level of autonomy), Case 2 is when a person just hails a ride from a taxi service, and Case 3 is about sharing service such as Uber or Lyft. The following code snapshot illustrates the equations used to determine costs in these cases. For example, in Case 3, the variable *passenger_num* is used to split the cost based on how many passengers will be sharing that ride together. Case 2 includes a *cost_driver* which is based on the standard wage of drivers and Case 1 has *cost_insurance*.



```
% calculation of cost of operation [$]
switch choice
    case 1
        cost_oper =  cost_maintenance + cost_fuel + cost_depreciation + cost_interest + cost_insurance;
    case 2
        cost_oper = cost_fuel + cost_maintenance + cost_depreciation + cost_cleaning + cost_driver;
    case 3
        cost_oper = (cost_fuel + cost_maintenance + cost_depreciation + cost_cleaning + cost_driver)/passenger_num;
end

% calculation of cost due to time [$]
time_trip = time / 60;                      % time of trip in hr
time_value = k * hourly_income;             % value of time $/hr, where k is the productivity factor
cost_time = time_trip * time_value;

% calculation of final effective cost [$]
total_cost = cost_oper + cost_time;
```

Again, based on the level of autonomy (low, mid, and high corresponding to SAE levels 0 through 5), an actual existing model of the vehicle was used such as Cadillac CT6 which is classified as mid-level autonomy and SAE level 3. Purchase, fuel, and maintenance costs for a Cadillac CT6 were obtained from internet search. These values were then combined with costs such as interest, depreciation, and cost of cleaning (in case a taxi service was being used). In the end, *cost_oper* was a combination of *cost_fuel* + *cost_maintenance* + *cost_depreciation* + *cost_interest* + *cost_insurance*. The computer code implementation accounts for both autonomy levels and the variable '*choice*' depending on ride sharing status.

2.2 Connectivity Metric

Based on the literature review reported in Sect. 1.2, trip distance, frequency, affordability and interactivity emerge as prominent factors when defining connectivity of a particular region given a fixed set of transportation options. In pursuit of our goal of a connectivity metric suitable for a multi-modal regional setting with options for autonomous ground and air modes, we characterize these terms as follows:

- Distance and Frequency – actual distance between origin-destination pair and frequency of mode of transportation (transit score algorithm)
- Affordability – Economic feasibility of mode of travel vis-à-vis income and earning potential of traveler
- Interactivity / economic activity – nearness to job, commercial, retail, stores, restaurants, cultural activities (inspired by AllTransit score, described in Sect. 1.2)

Under these definitions, our research developed the following two candidate metrics.

Metric 1: An Aggregated Metric

The simple idea behind this metric is that the overall connectivity score is an appropriately weighted combination of a distance and frequency score, an affordability score, and an interactivity score. The distance and frequency score is based on Transit Score (via a transit score algorithm). The affordability score is based on monthly household income data and the proportion of it spent on daily commute or travel by an individual user in a particular region. The interactivity score is modeled on AllTransit score.

- Distance and Frequency score – This is based on the transit score methodology. A raw transit score for a location is computed by summing the value or routes for a location. Value of route is defined as the service level (frequency per week) multiplied by the mode weight (airline carriers/ low cost carriers is weighted 2X), air taxi (weighted 1.5X) and automobiles (weighted 1X)

$$raw\ transit\ score = \sum_{nearby\ routes} value\ of\ route$$

$$value\ of\ route = service\ level * mode\ weight * distance\ penalty$$

- Affordability score – To account for affordability and cost factors, the household income is compared with the amount of money spent on commuting and a 5-point rating system is used to award points. For example, if the cost for travel using a mode is equal to 5 percent or less of a person's monthly income/ budget then 5 points are awarded. For cost of mode less than or equal to 10 percent of a person's monthly income 4 points are awarded, so on and so forth, only 1 point is awarded after the 20 percent mark. This is very similar to how Walk Score is calculated where points are awarded based on a location's distance and after a 30-minute walk no more points are awarded (based on a distance decay function).
- Interactivity score – The All Transit metric is directly used as an interactivity score for a location since it contains information about job access, economic growth, health benefits, transit equity, transit quality and mobility for a specific location.
- Finally, the distance frequency, affordability and interactivity scores are combined to form a connectivity score for a given location. At this point we can assign a particular weight for these individual scores. For instance, if affordability is the most important factor is can be weighted at 100 -percent value, whereas frequency and distance might be less of a concern can be factored in at 75% (0.75 factor). A standardization and normalization process will have to be used at this stage to find a final cumulative connectivity value.

Metric 2: A Reachability Metric

This metric is based on the idea that connectedness is associated with how many people a person has access to and thus how connected they are in a given region. There are two perspectives on this topic. First, if a traveler has a certain trip budget, how far can they go (maximum distance) and how many people can they connect with? Second, if the traveler has a certain trip time constraint, how far can they go? Our second metric is based on the second perspective. For this idea, a budget for travel is assumed and this can be an approximate estimate obtained from the median household income or a person's individual income.

We then use the following formulas to estimate the maximum distance one can travel with a pre-defined travel budget. Several of these were already described in Section 2.1 and are largely standard in transportation mode characterization / demand analysis literature.

$$cost_{eff,i} = cost_{oper,i} + cost_{time,i}$$
$$cost_{time,i} = time_{trip,i} * time_{value}$$
$$cost_{eff} = cost_{oper} + time_{trip} * time_{value}$$
$$(\$) = \left(\frac{\$}{hr}\right) * (hr) + \left(\frac{\$}{hr}\right) * (hr)$$

Rearranging these equations and rewriting them, we get (1) and (2):

$$cost_{oper} = operating\ cost\ per\ unit\ time * travel\ time \tag{1}$$
$$cost_{time} = value\ of\ time\ * travel\ time \tag{2}$$

$$cost_{eff} = operating\ cost\ per\ unit\ time * travel\ time + value\ of\ time * travel\ time \tag{3}$$

$$travel\ time = \frac{cost_{eff}}{(operating\ cost\ per\ unit\ time + value\ of\ time)} \tag{4}$$

3. ANALYSIS AND RESULTS

The majority of the analysis in this project occurred for the illustration of sensitivities around the inclusion of an autonomous automobile mode using the methodology outlined in Section 2.1.

3.1 Autonomous Automobile Results

The following figures display the sensitivities for total cost per trip, the *cost_time*, and the *cost_oper* for a variety of cases using the formulation described in Section 2.1. The ‘choice’ variable indicates self-drive (choice 1), taxi (choice 2), ride-share (choice 3).

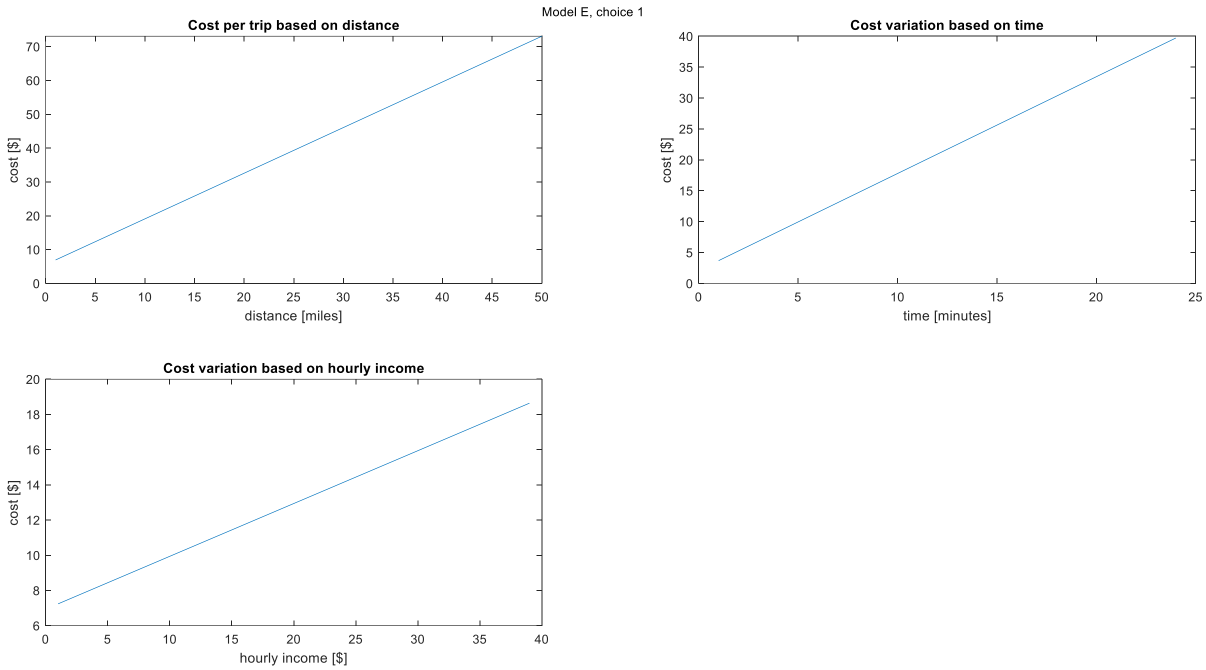


Figure 2.Case 1 (self-drive), Mid-Level of Autonomy

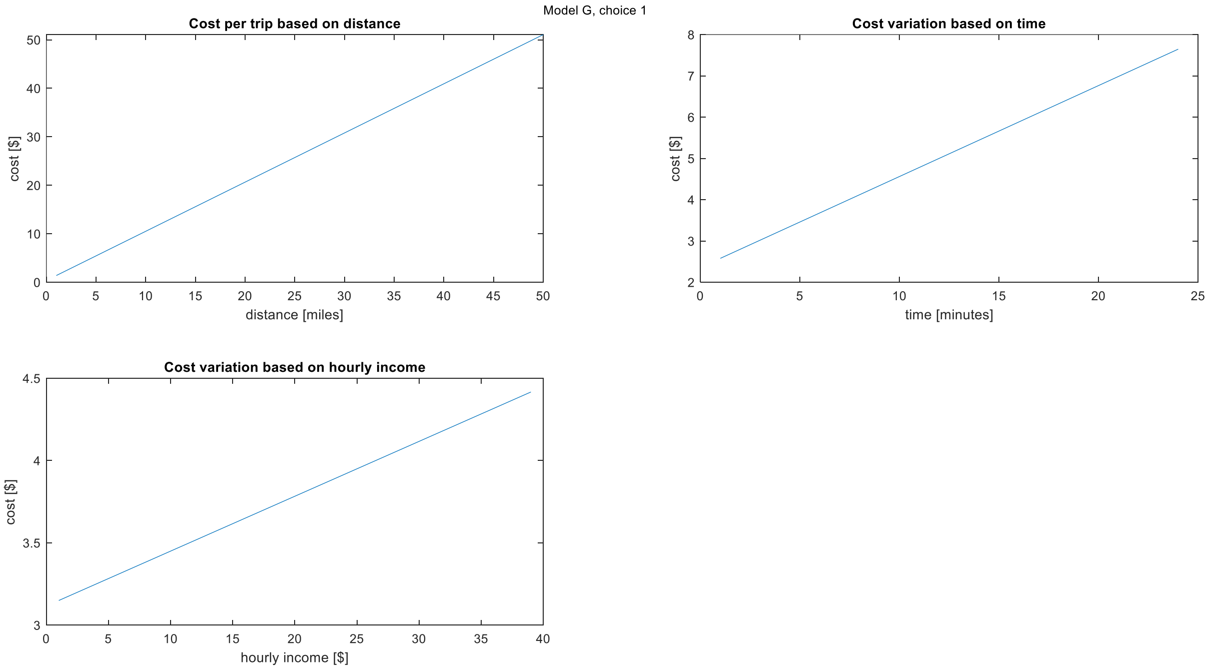


Figure 3.Case 1 (self-drive), High-Level of Autonomy

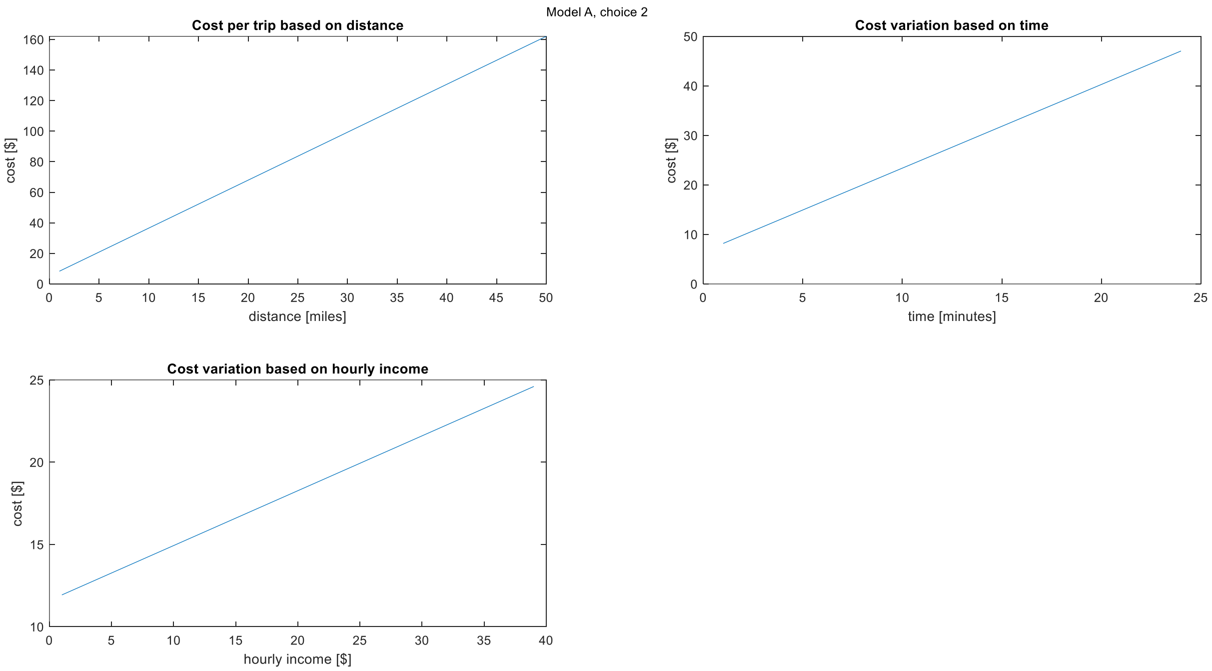


Figure 4.Case 2 (taxi), Low-Level of Autonomy

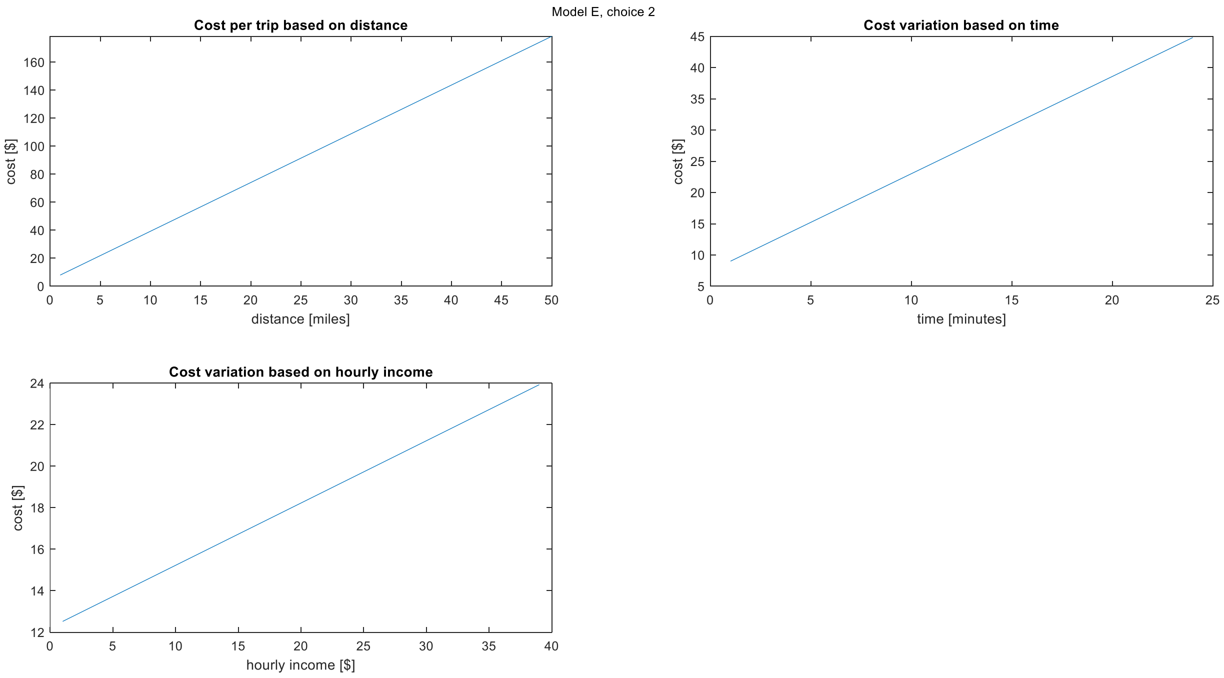


Figure 5.Case 2 (taxi), Mid-Level of Autonomy

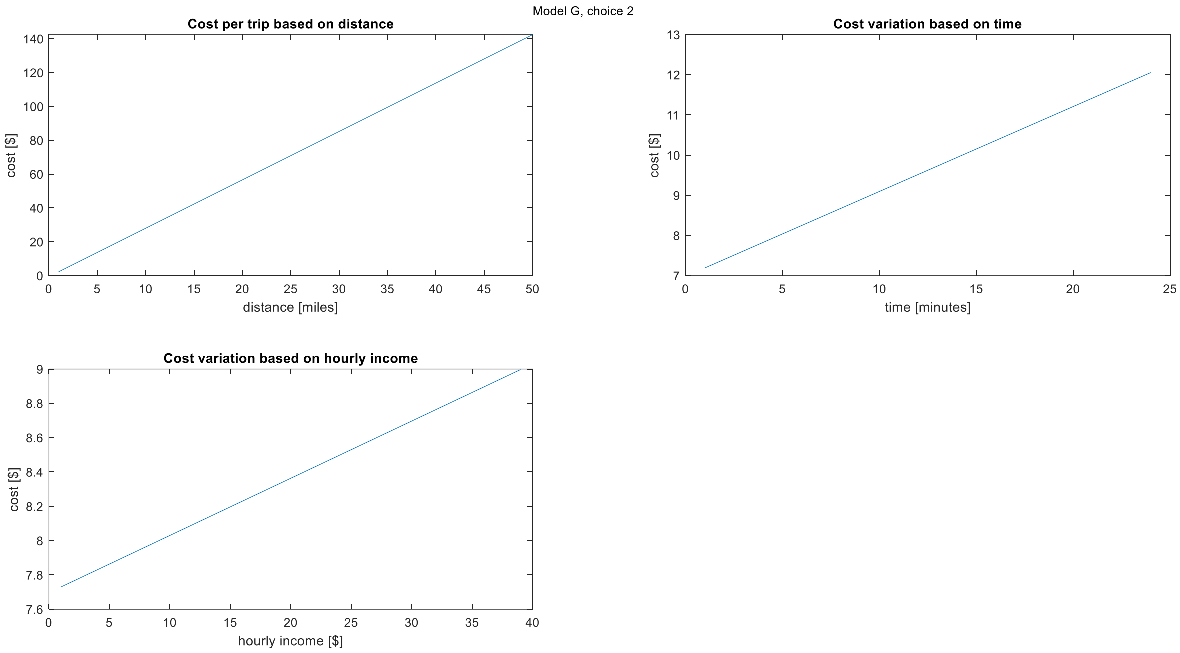


Figure 6. Case 2 (taxi), High-Level of Autonomy

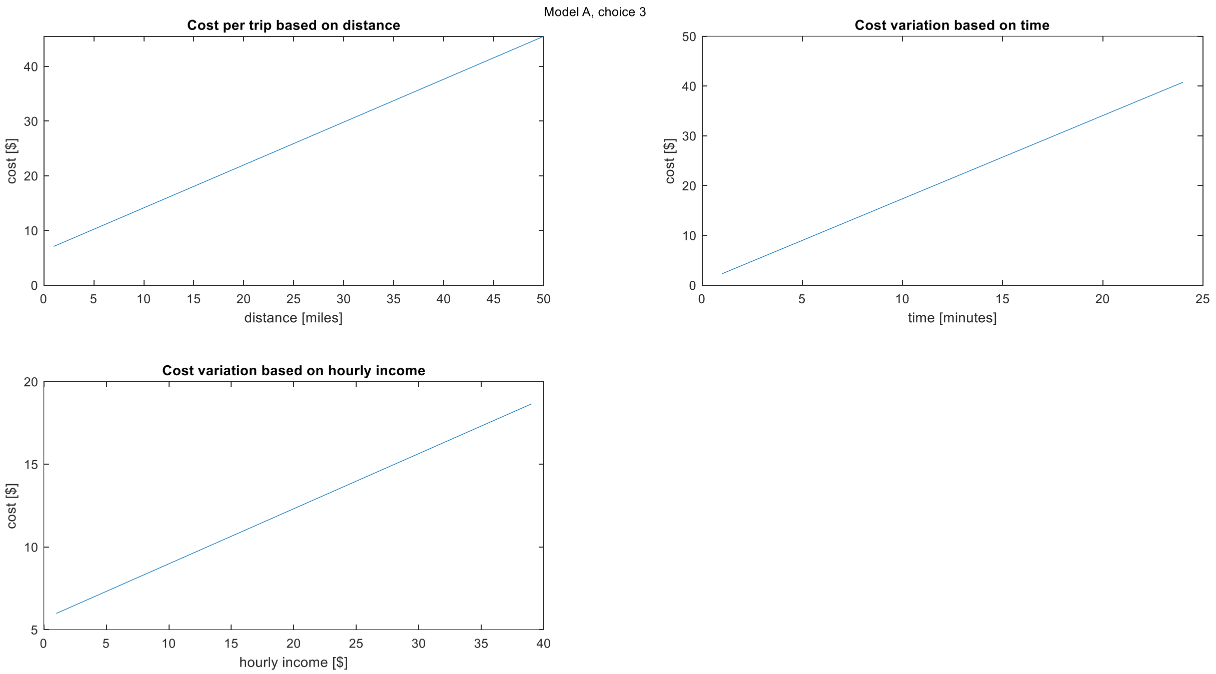


Figure 7. Case 3 (ride share 2-4 people), Low-Level of Autonomy

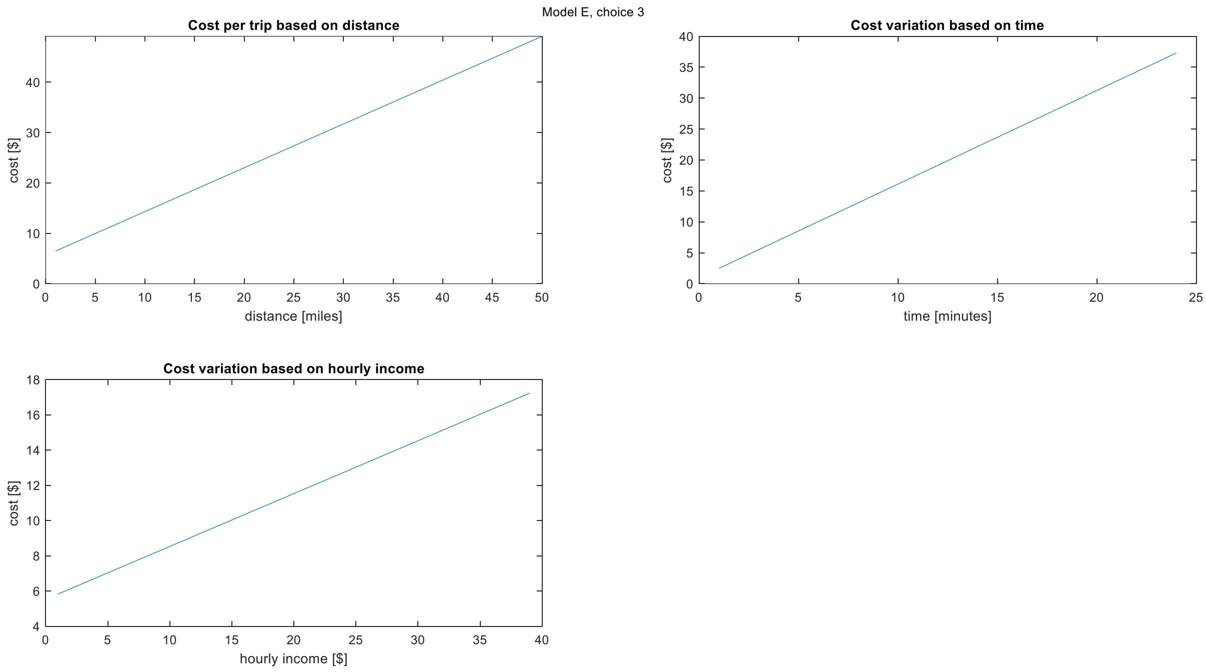


Figure 8. Case 3 (ride share 2-4 people), Mid-Level of Autonomy

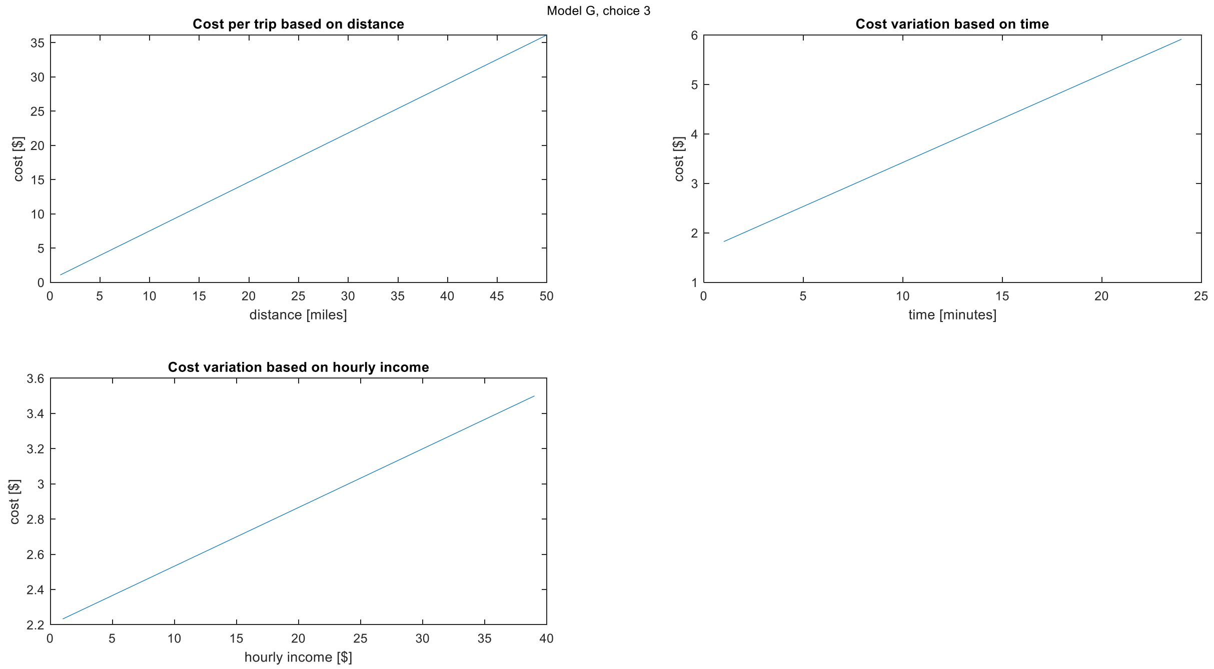


Figure 9. Case 3 (ride share 2-4 people), High-Level of Autonomy

From these sensitivities, ridesharing with an autonomous taxi would be the most feasible in terms of cost based upon both value for time and operational costs. However, the real test of this conclusion must occur within the full computational framework. At present, we have not been able to incorporate this autonomous auto model into the framework because of insufficient information for validating the estimates, especially as compared to the other mode models and datasets for demand used in the framework. We mention this topic in Sections 4 and 5 below.

3.2 Connectivity Metric Example Result

The following is a simple analysis illustrating the computations for Metric 2. In this test case, the travel budget (effective cost) is \$ 100 and the mode of transportation is a car. In this case, the individual values their time at \$ 40/hour and the operating cost of the vehicle is \$20 per hour. Also, the speed of the vehicle is 30 miles per hour. Using this information and substituting in equations (3) and (4) from Sect. 2.2, we can get the travel time.

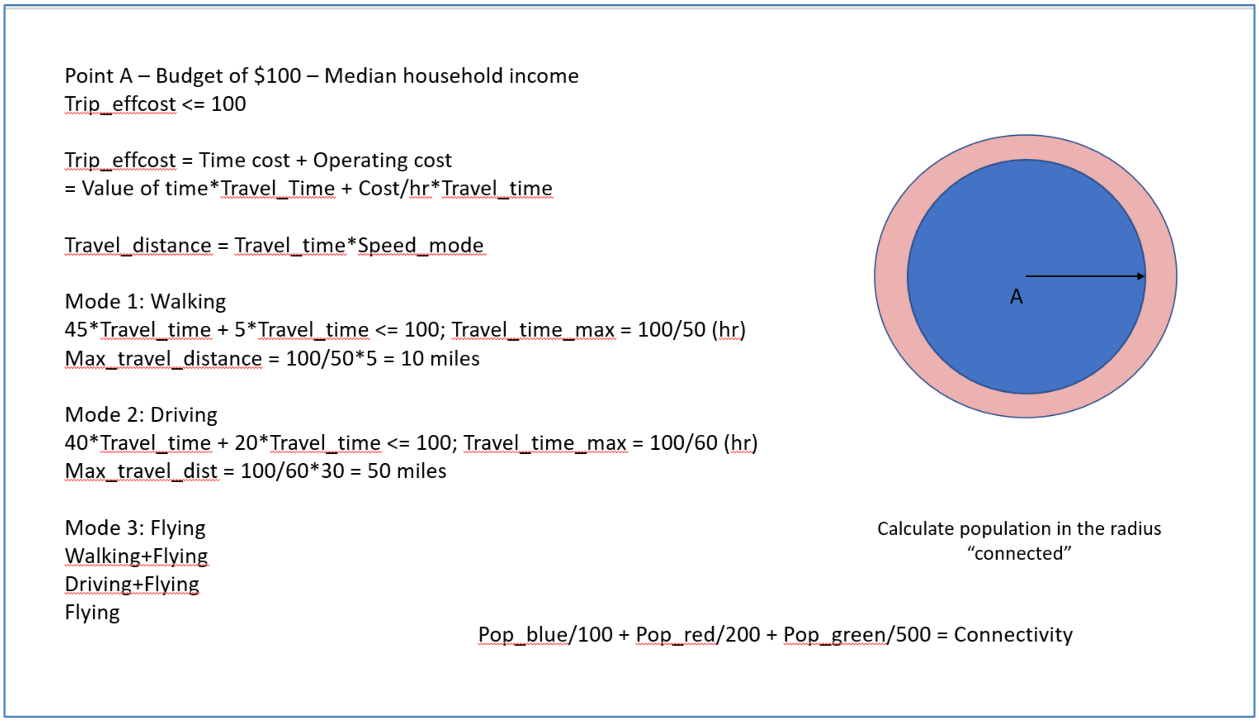
$$travel\ time = \frac{\$\,100}{(\frac{\$20}{hr}+\frac{\$40}{hr})} = \frac{100}{60}hr$$

Using this travel time, we can then calculate the maximum travel distance a person can travel given their budget.

$$\max\ travel\ time = \ travel\ time * speed\ mode$$

$$\max travel\ time = \frac{100}{60}hr * \frac{30\ miles}{hr} = 50\ miles$$

We then consider a 50-mile circular radius around the location (say point A) and anticipate the population contained within that circular region by using a map tool and a population request API. With the population density information, we then use an appropriate distance decay function to find a connectivity metric for that location. Figure 10 illustrates this computation and the notion of a reachable distance from Point A.



Point A – Budget of $100 – Median household income
Trip_effcost <= 100

Trip_effcost = Time cost + Operating cost
= Value of time*Travel_Time + Cost/hr*Travel_time

Travel_distance = Travel_time*Speed_mode

Mode 1: Walking
45*Travel_time + 5*Travel_time <= 100; Travel_time_max = 100/50 (hr)
Max_travel_distance = 100/50*5 = 10 miles

Mode 2: Driving
40*Travel_time + 20*Travel_time <= 100; Travel_time_max = 100/60 (hr)
Max_travel_dist = 100/60*30 = 50 miles

Mode 3: Flying
Walking+Flying
Driving+Flying
Flying

Calculate population in the radius
"connected"

Pop_blue/100 + Pop_red/200 + Pop_green/500 = Connectivity

Figure 10. Illustration of Metric 2 for a specific case

More extensive work on this idea of a connectivity metric, in the end, was not warranted as assessed by our CCAT project team and our NASA collaboration partner, especially in light of the utility and needs of our computational framework for regional air mobility.

4. DISCUSSION AND IMPLICATIONS

4.1 Why this CCAT project added value to our collaboration with govt. partner at NASA

While the specific autonomous auto model and connectivity metrics developed in this CCAT work have not been deployed in our NASA sponsored computational model for advanced aerial mobility, the CCAT project was instrumental in the maturation of the models we have since deployed in that project. The synergy we anticipated for this CCAT project with NASA sponsor was in fact achieved. On numerous occasions, when we shared on our ongoing CCAT results with our NASA project technical monitor (and our CCAT project government partner) Dr. Michael Patterson, a vigorous discussion took place on both the merits of the particular finding but also more broadly on the scope of our computational framework. As an example, we carefully decided to invest more time in our models for weather and emissions versus greater fidelity of autonomy in modes competing with the air mode in our regional and urban settings. This decision was supported by the model and sensitivities our CCAT project generated in regard to the autonomous automobile option and the likely limits on We have continued to work with NASA and Dr. Patterson and feel that CCAT collaborations may grow with NASA (and related) communities in advanced regional/urban transportation systems.

5. LIMITATIONS AND FUTURE RESEARCH

Several of the limitations were addressed in the previous sections of this final report. However, two particular areas of limitation/need-for-further-work relate strongly to our broader research (and really that of the entire community studying multi-modal (air ground) regional transportation with potential for autonomous operations).

Our first research goal, developing of a useful model for autonomous automobile mode for our computational framework intended to study regional mobility exposed the substantial difficulty in arriving at a broadly applicable but significantly detailed performance and cost profile. Such detailed vehicle performance modeling in the aircraft realm may affect the actual mission profile such as climb and takeoff performances and may accordingly affect the range credit and flight time information incorporated in this study. On the auto side, there is wide variety of potential capabilities that could be addressed by autonomy but their actual implementation may be delayed due to policy constraints. It is hard to predict the future! Finally, in both air and ground vehicles, the true impact of adverse weather on the performance / safety of the systems is still understudied, including in our work. But this is a definite need in the future, and not too-distance future for sure.

Our second research goal, on connectivity metrics. Remains immature both at conclusion of this CCAT activity as well as for our larger NASA work. In particular, most state-of-the-art approaches do not provide specific connection between the travel origin–destination pairs and the actual demand. Even though it may make economic sense to use a regional air taxi as an alternate mode of transportation for some individuals given their value of time, these individuals in the population may not intend to travel on routes to be served by the regional air taxi operators. In essence, the assessment of connectivity in the aggregate will never be the same as in the particular individual cases that make up the aggregate. How bad such connectivity metrics are is unknown, especially in our case of regional and urban transportation envision both advanced aircraft and surface vehicles.

6. CONCLUDING COMMENTS

The key contribution in this work was the enhanced development of a computational framework capable of quantifying the impact of technological advancements, especially, autonomy on the future mobility for both ground and air modes of transportation. The work contributed to ongoing efforts with government collaborator at NASA and aligned well with the following CCAT research thrusts:

- **Enabling Technology:** By identifying the potential features of proposed new modes of regional transportation, enabled by levels of autonomy technology, this work helped to characterize the economic attractiveness for application of these advanced technologies.
- **Policy and Planning**: The work used sensitivity studies to evaluate the impact of different technologies on the regional and total mobility, which are crucial for future policy and planning. The enhanced computational framework is now better equipped to evaluate the impact of infrastructure investment and vehicle technology (air and auto) on the mobility. Future developments on the connectivity metric will also provide the policy makers a quick quantification of a region’s transportation standing.
- **Modeling and Implementation:** The enhanced computational framework improved modeling and implementing new technology solutions, but also this CCAT project exposed areas in need of significant further research.

7. OUTPUTS, OUTCOMES, AND IMPACTS

7.1 List of research outputs (publications, conference papers, and presentations)

No publications resulted from this CCAT project. However, as documented in the earlier sections of the report, the project influenced and enhanced our larger NASA-sponsored research.

7.2 Outcomes

Outcome models, analysis, and metrics were successfully developed and used to inform a larger research effort developing a computational model for a project under NASA sponsorship (in which the NASA Technical Monitor happily served as government partner on this CCAT project). The literature reviews conducted for both research goals in this project have been accessed by other students in Dr. DeLaurentis' group.

7.3 Impacts

While the specific autonomous auto model and connectivity metrics developed in this CCAT work have not been deployed in our NASA sponsored computational model for advanced aerial mobility, the CCAT project was instrumental in the maturation of the models we have since deployed in that project. Further, the two graduate students who participated in this project (Apoorv Maheshwari and Hetal Rathore) earned valuable research experience. Now completed with his PhD., Dr. Maheshwari is no working for a company in the autonomous and connected transportation R&D sector and his experience in the CCAT project gave him a wider exposure than the NASA project experienced afforded. Ms. Rathore matured tremendously through the course of her participation

7.4 Tech Transfer

No new technologies were created during this project. However, the two wonderful graduate students who worked on the project (identified in Sect. 7.3) helped to transfer the learning in the CCAT (and their related project experiences) through their internal (Purdue symposia, etc.) and external conference and meeting presentations.

8. REFERENCES

Allroggen, F., Wittman, M. D., & Malina, R. (2015). How air transport connects the world–A new metric of air connectivity and its evolution between 1990 and 2012. Transportation Research Part E: Logistics and Transportation Review, 80, 184-201.

Carr, L.J., Dunsiger, S.I. and Marcus, B.H., (2010). Walk score™ as a global estimate of neighborhood walkability. American journal of preventive medicine, 39(5), pp.460-463.

Cervero, R., & Gorham, R. (1995). Commuting in transit versus automobile neighborhoods. *Journal of the American planning Association*, *61*(2), 210-225.

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation research part D: Transport and environment*, *2*(3), 199-219.

Dill, J., (2004), January. Measuring network connectivity for bicycling and walking. In 83rd Annual Meeting of the Transportation Research Board, Washington, DC (pp. 11-15).

Maheshwari, A., Mudumba, S., Sells, B., E., DeLaurentis, D., A., and Crossley, W. A., (2020) Identifying and Analyzing Operations Limits for Passenger-Carrying Urban Air Mobility Missions. In Proceedings of the AIAA Aviation Forum (p. 2913). DOI: 10.2514/6.2020-2913

Mishra, S., Welch, T.F. and Jha, M.K., (2012). Performance indicators for public transit connectivity in multi-modal transportation networks. Transportation Research Part A: Policy and Practice, 46(7), pp.1066-1085.

Morphet, H., & Bottini, C. (2014). Air connectivity: Why it matters and how to support growth. Connectivity and Growth. PricewaterhouseCoopers, London, 11-29.

Roy, S., Maheshwari, A., DeLaurentis ,D., & Crossley, W., (2021). Future regional air mobility analysis using conventional, electric, and autonomous vehicles. AIAA Journal of Air Transportation, 29:3, pp. 113-126.