Project 096 Future Transportation System Opportunities and Constraints

Georgia Institute of Technology

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- FAA Award Number: 13-C-AJFE-GIT-159
- Period of Performance: October 1, 2024, to September 30, 2025
- Tasks:
    1. Develop Background Scenarios
    2. Commercial Aviation
    3. Non-traditional Vehicle Scenarios
    4. Regional Passenger Demand Estimation
    5. Vehicle Technology Specific Scenarios
    6. Coordination with FAA
    7. Documentation

Project Funding Level

This research was funded by the Federal Aviation Administration (FAA) Office of Environment and Energy through ASCENT, the FAA Center of Excellence for Alternative Jet Fuels and the Environment, Project 096, through FAA Award Number 13-C-AJFE-GIT-159 under the supervision of Joshua Glottmann. Any opinions, findings, conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the FAA.

This project is funded at the following levels: Georgia Tech ($800,000). Georgia Tech has agreed to a total of $800,000 in matching funds for a two-year period of performance. This total includes salaries for the project director, research engineers, and graduate research assistants and for computing, financial, and administrative support, including meeting arrangements. The institute has also agreed to provide tuition remission for students whose tuition is paid via state funds.

Investigation Team

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Project Overview

The primary objective of this research project is to support the FAA in modeling and assessing the potential future evolution of the next generation aircraft fleet while supporting the FAA Office of Environment and Energy goals and objectives. Research under this project will consist of three integrated focus areas: (1) developing a set of harmonized scenarios investigating what the air transportation system will look like in 2050, 2075, or 2100, (2) modeling advanced aircraft technologies and advanced vehicles expected to enter the fleet through 2100, and (3) performing vehicle and fleet level assessments based on input from the FAA and the results of (1) and (2).

Task 1 – Develop Background Scenarios

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Objectives

The study will begin with a comprehensive literature review to provide an overview of the current state of the aviation industry and identify the challenges facing the sector. The research will also potentially include interviews with aviation experts, policymakers, and industry leaders to gain insights into the industry's current state and future direction. This review will be used to define macroeconomic and general technological advancements expected during this extended time horizon to 2100.

Research Approach

Literature Review

A review of the aviation sector's impacts on global carbon dioxide (CO_2) emissions is presented in the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) prepared by Working Group (WG)-III. The review emphasizes that around 65% of the sector's emissions are from international flights, with total emissions in 2018 adding to about 1 gigaton (Gt) of CO_2. The research focuses on the alarming acceleration of emission rates, which increased by 2.5% annually over the previous 20 years to almost 4% annually between 2010 and 2018. The study examines the net warming effects of aviation's CO_2 and non-CO_2 emissions, such as water vapor, soot, sulfur dioxide, and nitrogen oxides (NO_x).

Since net-zero emissions are a requisite for 1.5° scenarios, it calls for sweeping transformations in both technology and fuel types. It also asserts current technological advances, like blended wing body aircraft that could deliver about 10% fuel savings, will not be able to offset projected emissions growth due to their slow introduction into the market. The AR6 IPCC report also examines operational inefficiencies and potential improvements, including finding that better air traffic control could reduce emissions by 13% globally by the year 2050. It points to major uncertainties about non-CO_2 impacts of liquid hydrogen powered aircraft and suggests a move toward high-speed rail as a practical substitute for regional travel, which could significantly lower the demand for short-haul flights (Guivarch et al., 2022).

The process for generation of scenarios is a major component of the IPCC AR6 reports, involving collaboration between the IPCC's working groups to combine socio-economic storylines with environmental impacts. This comprehensive approach to scenario planning has been explained in the report, showing how socio-economic data are used with climate simulations to yield accurate and relevant policy scenarios (IPCC, 2023).

The report presents mid- to long-term projections through 2050 to illustrate how technology and infrastructure improvements could reduce aviation emissions, discusses hybrid modelling approaches used to project developments in the sector, and describes the top-down/bottom-up hybrid approach it uses which captures a wide range of drivers. It also rates potential mitigation pathways across three levels of concern based on a multidimensional feasibility framework that considers their transformative impact and feasibility, providing a systematic method for measuring the efficacy of different policymaking and technological approaches in addressing climate impacts from aviation (Lee et al., 2021).

To gain an understanding of how one of the models used by IPCC works, the Global Change Analysis Model (GCAM) was studied. GCAM integrates environmental, economic, and energy systems to forecast global future scenarios effectively. GCAM calculates transportation service demand using a sophisticated formula that includes variables such as per-capita gross domestic product (GDP), service price, population, and elasticity measures, which enables the prediction of future transportation needs under various socio-economic conditions.

More details in GCAM (discussing competition between different transportation subsectors, technology share, and time value of transport) also show how the model handles competition. The cost calculation method for alternative transportation technologies is also overly broad with respect to fuel price, vehicle fuel intensity factors, non-fuel costs and load factors (Joint Global Change Research Institute, 2024).

Another aviation model designed to quantify environmental and economic impacts of policies related to the emission reduction is the Aviation Emissions and Evaluation of Reduction Options Modelling System (AERO-MS). The AERO-MS is a framework built to provide a comprehensive quantitative system analysis of the present and future air transport system with special emphasis on assessing emissions from aircraft engines. The AERO-MS evaluates the downstream effect of policy change-related impact on supply-side costs, which in turn affects demand for air travel. The system evaluates global emissions under different emission mitigation scenarios, incorporating responses from all key stakeholders, including supply (airlines), demand (consumers), and policy sector (governments and manufacturers).

The AERO-MS has five linked modules: (1) the Unified Database, Airport Technology Model (ATEC), (2) Air Transportation Demand Module (ADEM), (3) Aviation Cost Module (ACOS), (4) Flights and Emissions Modules (FLEM), and (5) the Direct Economic Impacts Module (DECI). Together, these modules provide complementary perspectives on developments in the aviation system, with the DECI offering detailed assessments of volumes of air transport traffic, airline revenues and fleet and flight activity—all according to data from the other modules (European Commission, 2004).

The model organizes its analysis according to three scenarios: (1) the base scenario, which demonstrates what would happen in a business as usual global air transportation system, (2) the datum scenario, consisting of projections for technical and economic progress that continue with no policy changes, and (3) the forecast situation which inspects the impacts of various policy alternatives. The comparison of alternative mitigation policy measures against a common baseline enables the AERO-MS to provide high-resolution projections of future states, making the assessments applicable to real-world policy evaluation and subsequent efforts at mitigation with robust estimates.

In general, the AERO-MS is an important and necessary tool to better understand and predict the consequences of policy and technology changes in the aviation sector (European Union Aviation Safety Agency, 2009).

In addition to these models, trend projection is an important part of aviation forecasting. Trend projection is a process of making educated predictions of the future by using the known past as a basis. This approach necessitates in-depth knowledge of a large number of factors that affect the predicted outcomes. Trend projection should consider the consistency and variability of the main economic indicators, the technological advances, and the demographic changes.

To effectively project trends, the focus needs to dive into the inner structure and reasoning behind each variable. This requires examining how GDP, population, and technological advancement interacted with aviation demand in the past and how these can be projected to affect industry in the future under different conditions. For instance, when GDP is stable, air travel demand may be more predictably rising; whereas, when the economy is unstable, travel behavior can become more challenging to predict.

Apart from that, long-term forecasting should also take into consideration the probable occurrences of disturbances that can cause the trends to break. These disturbances might include, for instance, recent breakthroughs in aircraft technologies that would cut down the operation costs or new regulations that make flight operations difficult. In a like manner, there can be a massive geopolitical incident or a significant economic crisis that will highly affect the market conditions, which in turn would force changes in the trend projections. Besides, the forecast changes must be capable of bending if the baseline ideas turn out to be different than expected or if future circumstances exhibit unexpected behavioral changes. This versatility guarantees the survival of the methodology over time and its high predictive capability as to the strategic decisions of the aviation sector. The skill of recalibrating forecasts in the face of new developments or adaptations in the underlying assumptions is key for the accuracy and credibility of long-term aviation forecasts (Ashford et al., 2011).

Given the importance of trend projections, understanding the underlying assumptions in any forecast becomes important. The FAA forecast implements both optimistic and pessimistic scenarios to consider changes in national and global economic markets, which requires flexibility in bringing in the effects of various uncertainties that might impact the aviation sector, such as the economic recession or geopolitical conflicts (FAA, 2020).

The FAA's forecasting methodology is based on economic data and assumptions from IHS Markit® Economics. The data are divided into data, such as the Consumer Price Index (CPI) and unemployment rates, to form baseline, optimistic, and pessimistic economic scenarios. The scenarios typically do not consider factors such as recessions, changes in consumer behavior, and the overall economic effect of international conflicts.

Among the specific data sources utilized in the FAA forecast are the historical data from the Bureau of Labor Statistics (BLS) and Bureau of Economic Analysis (BEA) including forecasts from IHS Markit. These sources provide economic information that the FAA uses to make economic assumptions which, in turn, guides forecasts of future domestic aviation demands (FAA, 2023).

Milestones

- Examined the scenarios in the studies covered in Task 1 for how they include aviation and the emissions estimates.
- Identified how aviation is integrated into global change analysis models, including their links to the global economy and emissions impacts.

Major Accomplishments

The research team identified potential data sources for the development of very long-term trends. The IPCC scenarios are still a benchmark for climate analyses and therefore are useful in identifying the circumstances aviation will have to operate in. In addition, the scenarios for the 7th Assessment Cycle are currently under development. The research team therefore anticipates that this project will be able to assimilate data produced for this purpose.

Publications

None.

Outreach Efforts

- Presented at biannual ASCENT Advisory meetings.
- Participated in biweekly teleconferences with the FAA Technical Monitor.

Awards

None.

Student Involvement

Graduate students have been involved in the research of the background scenarios. This includes documentation and presentation of their findings. The students conducted research into how global change scenarios include or at least are connected to aviation-specific scenarios.

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Plans for Next Period

Consider opportunities to enrich the development efforts to connect aviation scenarios to high level global change scenarios including modeling efforts to cover a wide range of plausible outcomes of aviation sector scenarios.

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Task 2 – Commercial Aviation

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Objectives

This task includes the extension of existing commercial aviation forecasts with long-term trends to the year 2100. Additionally, this task will address potential vehicle and operational changes that could have larger scale effects on airline operating models. For example, reducing cruise Mach numbers to allow more efficient vehicles to operate could require significant airline schedule changes. A transition to smaller vehicle sizes and more direct service would also require significant route and schedule changes, which will also be among the potential changes to commercial aviation considered in this task.

Research Approach

The rapid technology estimation tools developed under prior PARTNER and ASCENT projects (Projects 010, 011, etc.) (FAA ASCENT, 2020) are being examined for how they could allow categorizing into smaller, well organized and tested components that can be used to quickly explore commercial aviation and emissions estimates for future years.

Enplanements and Passenger Flow Modeling

Using FAA T-100 All Carrier Segment Data (FAA, 2024) and the terminal area forecast (TAF) (FAA, 2024), the team developed a workflow to estimate current and future passenger volumes between airport pairs. The process includes:

- Extracting domestic segments from T-100 operations data.
- Reading TAF enplanements definitions across multiple subtypes (mainline, commuter, air taxi, United States (U.S.) and foreign international categories.
- Calculating base-year (2023) and forecast-year (2033) passengers for each airport.
- Applying TAF-derived growth factors to extrapolate future flows.
- Removing airport identifiers not included in the TAF dataset to ensure consistency.

A case study between Newark, New Jersey (Newark Liberty International Airport [EWR]) and Richmond, Virginia (Richmond International Airport [RIC]) was used in the monthly presentations to validate the methodology. Six airlines operated on the route in 2023, with passenger counts projected to grow from 74,968 in 2023 to 111,242 in 2033 based on TAF growth assumptions.

Terminal Area Forecast + Fleet Toolkit Integration

To support long-horizon commercial aviation analysis, the research team is loading the full 2024 TAF into a developing Fleet Toolkit built using existing libraries to handle user interaction. This includes:

- Airport metadata (i.e., location, region, identifiers)
- Enplanements
- Arrivals and departures (e.g., itinerant, local, civil, and military)
- Based aircraft counts
- Terminal Radar Approach Control activity levels

Initial visualizations and interactive components have been prototyped, demonstrating the ability to map traffic activity and airport operations using TAF data. These components will later support integrated CO_2 emissions and fuel-use projections.

Technology-Specific Fleet Evolution and Environmental Impact Assessment

Overview

In the initial part of this task the development of a route-level fleet evolution and environmental impact assessment framework designed to evaluate the long-term effects of emerging aircraft technologies across the U.S. domestic network. The framework models how advanced aircraft, such as the hybrid-electric aircraft (HEA), hydrogen-fueled aircraft, transonic truss-braced wing (TTBW) (Wells et al., 2024), and blended wing body (BWB) (Ahuja et al., 2024) configurations, propagate across origin–destination (OD) pairs as demand evolves over time. The methodology integrates forecasted operational activity, technology-specific performance models, survivorship behavior, and logistic adoption dynamics to quantify annual changes in fleet composition, fuel burn, and emissions through 2050.

Methodology

Data Integration

The assessment integrates three main datasets: (1) base-year OD operations, aircraft families, and distances from the T-100 Domestic Segment dataset, (2) future airport-level operations from the FAA TAF covering 2024 to 2050, and (3) technology-specific fuel burn and emissions coefficients obtained from the Global and Regional Environmental Assessment Trade (GREAT)-Airport Noise Grid Integration Method (ANGIM) environmental modeling framework. Airport identifiers, which appear in mixed formats (FAA location identifiers, International Air Transport Association), were standardized to International Civil Aviation Organization (ICAO) codes to improve OD matching.

OD-Level Operational Forecasting

Future OD matrices are generated using an iterative Fratar algorithm in which airport-level growth factors, computed as the ratio of future to base-year departures are applied until row and column totals match TAF-provided values within a 0.6% convergence threshold. These OD forecasts replace historical GREAT inputs so that technology adoption is driven by realistic demand patterns. Each OD pair functions as a yearly control volume whose required operations must be met through a balance of surviving aircraft, replacements, and demand-driven growth. Survivorship curves determine how many aircraft remain in service, while logistic adoption parameters and seat-class distributions govern the entry of advanced technologies. Fuel burn and NO_x emissions for each aircraft family are evaluated using calibrated quadratic stage-length models, with coefficients sourced from National Aeronautics and Space Administration (NASA) system studies, FAA Continuous Lower Energy, Emissions and Noise (CLEEN) datasets, and reference aircraft calibrations, and route-year totals are obtained by multiplying intensity values by annual operations and stage length.

Output
The Interactive framework produces comprehensive annual outputs and projections for every domestic origin–destination pair, including route-level operations, distance flown, and technology penetration across conventional, TTBW, HEA, hydrogen fueled, and BWB aircraft from 2024 to 2050. Fuel burn and NO_x emissions are calculated for each technology category using quadratic stage-length models. Fleet turnover is tracked through survivors, replacements, and growth-driven additions, offering a clear view of how advanced technologies displace legacy aircraft over time. All results are delivered in multi-indexed tables indexed by year, origin ICAO, destination ICAO, and technology type, supporting integration with GREAT-ANGIM and FAA environmental assessments. Scenario-level summaries allow comparison across different adoption pathways and modeling assumptions, enabling long-range evaluation of fleet evolution, environmental impacts, and operational trends under alternative futures.

Units Management
Given the scope of the projects, datasets are sourced from multiple disciplines, which have different unit conventions when storing data. For one, it is not uncommon that datasets related to climate science use metric unit system whereas datasets related to U.S. aviation often employ imperial unit system. As the studies continue to expand, it is anticipated that an increasing number of datasets will be used. Thus, a unit conversion system was needed to provide a clean interface for defining and converting units.

To address this need, a proposed solution is the implementation of Pint, a Python® unit conversion library that enables arithmetic operations between numerical values and conversion to and from different units. In addition to conversion between common units, unit conversion for aviation-specific units, such as between available seat miles (ASM) and available seat kilometers (ASK), was also added to the library.

Milestone
Examine the scenarios in the studies covered in Task 1 for how these scenarios include aviation and the emissions estimates.

Major Accomplishments
The team made progress on establishing reference datasets like the well published forecasts. In addition, initial mockups of this capability have progressed to the prototyping phase.

Publications
None.

Outreach Efforts
- Presented at biannual ASCENT Advisory meetings.
- Participated in biweekly teleconferences with the FAA Technical Monitor.

Awards
None.

Student Involvement
The students have undergone training to familiarize themselves with the existing tools and their heritage.

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Plans for Next Period

Quickly move to a functional prototype so that its usefulness can be evaluated and expanded from there.

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Task 3 – Non-traditional Vehicle Scenarios

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Objective

Several new vehicles with capabilities that are completely different from conventional commercial airlines are expected to enter service and potentially become widely adopted. For this reason, traditional airline demand projections are not appropriate and are also not able to define future projections of these vehicles.

For example, intra-regional air travel in the U.S. is an economically challenging endeavor as the demand on any given route is minor compared to inter-regional travel which typically consists of flights to, from, and between large hub airports connecting these regions. Given the limited demand and shorter ranges, regional aircraft serving these intra-regional markets tend to be smaller, which leads to direct operating costs amortized over a smaller number of passenger seat-miles compared to larger aircraft. Regional aircraft usually have lower daily average utilization owing to the time spent on the ground in between flights. This increases the significance of fixed costs which are amortized over fewer passenger seat-miles. Short-range missions also result in more takeoffs and landings on average for each flight hour. Proportionally more time is thus spent during takeoff and climb, where power settings are high, and more takeoffs and landings are performed. This increases the wear and tear on the aircraft structure. All this tends to increase the maintenance costs and therefore the operating costs of regional air transportation.

The core of this research effort and its objective is to generate an optimized operational model to allow the construction of a potential future state of aviation where new types of mobility are enabled by highly efficient vehicles.

Research Approach

This task tries to connect the conventional commercial business models with new types of operation also supported by the results of Task 4.

Milestone

None. Not started yet.

Major Accomplishments
None. Not started yet.

Publications
None.

Outreach Efforts
None. Not started yet.

Awards
None.

Student Involvement
Student researchers will be involved in all aspects of this task.

Plans for Next Period
Determine the specific scope of this task in collaboration with FAA Technical Monitors.

Task 4 – Regional Passenger Demand Estimation
Georgia Institute of Technology

Objective
Regional aviation in the United States has seen a significant decline, with many routes left abandoned due to a multitude of challenges. The objective of this task is to assess the feasibility of revitalizing regional aviation by forecasting passenger demand using more advanced modeling techniques under various macroeconomic and energy price scenarios.

Research Approach
To model regional aviation demand effectively, this task was divided into two interconnected parts:

1. Creating scenarios to evaluate the impact of different effects on current aircraft configurations and estimate change of aviation demand from the baseline scenario, including:
    a. Operating cost breakdown
    b. Categorization and evaluation of impacts on direct operating costs (DOC)
    c. Technology impacts
    d. Energy impacts
    e. Operations impact
    f. Scenarios generation
2. Investigation and evaluation of demand models to:
    a. Explore forecasting methods, including statistical time-series methods such as auto-regressive integrated moving average (ARIMA) and machine learning/deep-learning techniques (ML/DL).
    b. Seek models that can incorporate both internal and external factors.

Modeling Techniques

Air travel demand forecasting is an important task for understanding and planning the future of any aviation system. The choice of an appropriate forecasting model is heavily dependent on the type of factors and goals of the forecast itself. In the case of modeling the demand for regional aviation, historical data are sparse. Additionally, regional aviation is influenced by advancements in technology and the fluctuation of energy prices. Recent advancements in ML and DL have motivated many researchers to explore the applicability of these techniques to aviation-related problems such as forecasting passenger demand (Zachariah et al., 2023). The ability of ML and DL to learn complex patterns and incorporate high-dimensional data offers the potential to create more accurate and robust forecasting models.
Figure 1 shows a breakdown of common techniques to forecast passenger demand.

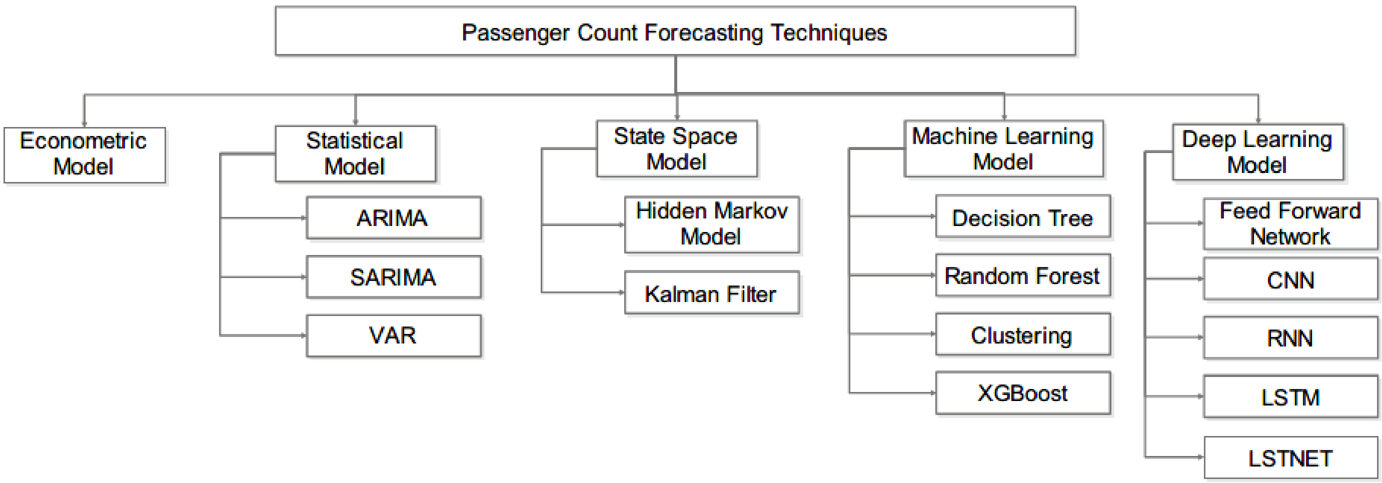


Figure 1. Aviation demand forecasting techniques.

Time-series forecasting is used to predict future trends based on historical data that are observed over regular intervals, much in an analogous way to econometric models. However, these models can be specifically designed to analyze and forecast data points ordered sequentially over time. A pure time-series forecasting method for aviation has increased challenges associated with the increased uncertainty and irregularity of air passenger movement. Two popular and well-known statistical time-series models are the ARIMA and seasonal auto-regressive integrated moving average (SARIMA) models. ARIMA and SARIMA both rely on linear assumptions between data points and thus limit their ability to accurately forecast high dimensional and nonlinear behavior as commonly found forecasting passenger demand. These models are typically used in hybridized models since alone, they often have poor performance at long time horizons (Kanavos et al., 2021).

ML provides a powerful framework for addressing the challenges of forecasting regional passenger demand. Unlike traditional models, ML techniques excel at identifying nonlinear relationships and dependencies between variables, making them more suitable to handle the complexity of factors influencing demand. Additionally, with the decrease in computational cost and increase of memory capacity, ML methods have already been utilized to solve real-world problems (Kanavos et al., 2021). Additionally, ML techniques are more flexible and adaptable to varying scenarios such as shifts in energy price or macroeconomic conditions. Most ML techniques work primarily with cross-sectional data but may be used in hybrid models to boost performance in forecasting by better relating macroeconomic factors to demand.

DL is a subcategory of ML that is based on iterative learning from the method's own error. DL is nonlinear by its very nature and, thus, is capable of modeling highly complex and nonlinear time-series data. Additionally, DL models can receive both time-series and cross-sectional data to capture patterns between variables automatically (Do et al., 2020). However, DL is much more computation intensive than ML methods and requires more resources and time to model with an additional tendency to overfit data. Long short-term memory (LSTM) models are a type of recurrent neural network (RNN) that solves many faults of RNN-based models: long-term dependency problem and vanishing gradient problem which occurs during backpropagation (Do et al., 2020). This allows the model to capture long-term effects on demand from factors such as population and GDP.

Hybrid models combine the strengths of multiple modeling approaches and balance each other's shortcomings. By integrating more traditional methods such as basic econometric or time-series methods (i.e., SARIMA) with more modern techniques like ML and DL, hybrid models can capture both simple and complex behaviors in the data. Hybrid models typically are a combination of statistical+ML, statistical+DL, and ML+DL. One side of the hybrid model can analyze the linear trends and seasonality while the ML or DL portion can account for the more complex relationships and interactions between diverse variables.

The performance of various forecasting techniques in predicting aviation demand varies significantly, as shown in Table 1. Hybrid models outperformed single method forecasting approaches. However, these models have primarily been evaluated for short- to medium-term forecasts. Although their effectiveness for long-term forecasting remains untested, their strong performance in shorter timeframes suggests they could be adapted successfully for long-term forecasting problems.

Table 1. Comparison of aviation demand models.

Model Description	Mean Absolute Percentage Errors (MAPE)
Random Forest (RF)	6.76%
Deep Neural Network	7.98%
Particle Swarm Optimization Support Vector Regression (PSO-SVR)	2.38%
Seasonal Auto-Regressive Integrated Moving Average (SARIMA)-SVR Passenger Traffic Volume	2.31%
Regression+SVM Model	5.07%
Long Short-Term Memory (LSTM)	4.00%

Model Description

The model type chosen to model demand will be an LSTM. LSTMs are composed of forget gates, input gates, output gates, and an internal state (cell memory). The vanilla LSTM cell is pictured in Figure 2.

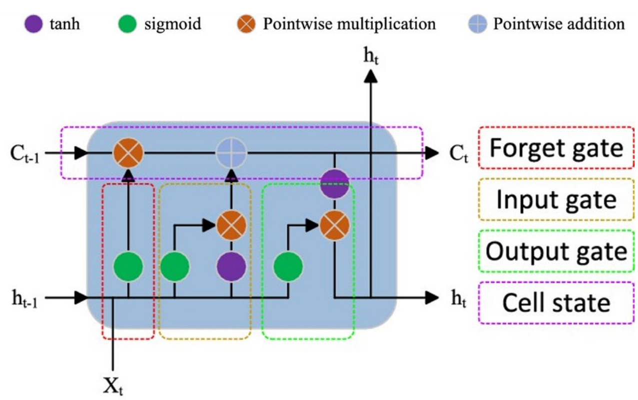


Figure 2. Long short-term memory cell (image from Dai et al. [2025]).

The structure of an LSTM as summarized by Abbasimehr et al. (2020):

X_t: The input value
h_{t-1} & h_t: The output value at time points t and $t-1$
C_{t-1} & C_t: The cell states at points t and $t-1$

The forget gate uses the current input (X_t) and previous output (h_{t-1}) to compute the information that will be stored in the cell state (C_{t-1}) using some activation function. Similar gating operations govern the update of new information and the generation of the output (h_t).

For this work, the demand model employs three LSTM layers, each with different hyperparameters and activation functions that are tuned with a large design of experiments. The LSTM's internal memory structure allows it to incorporate information across time horizons, which is essential in modeling long-term behavior.

Dataset Description

The model inputs consist of:

- Monthly domestic revenue passenger miles (RPM) in millions
- Real gross domestic product (RGDP) in trillions of 2024 USD
- Population in millions
- Crisis indicators (Boolean variables) for major disruptive events, including COVID-19, the September 11, 2001, attacks, and additional periods of significant financial distress

The dataset spans January 1990 through December 2024. RPM values are retrieved from the T-100 Segment dataset. Historical RGDP and population data are retrieved from the Federal Reserve Bank of St. Louis, Missouri. The first six months of these inputs are shown in Table 2.

Because future aviation demand depends strongly on past demand, the model incorporates lagged RPM values when generation predictions. This means the model's own prior output is used as an input in subsequent steps. In this way, the LSTM functions as an auto-regression model, using historical demand trends and economic indicators to forecast future domestic RPM.

The model needs dedicated training and validation datasets to evaluate forecasting performance. In typical time-series applications, the first ~70% of the data are used for training and the remaining ~30% for validation. However, the COVID-19 pandemic caused unprecedented disruptions in aviation demand that do not resemble any previous historical patterns. Using a traditional chronological split would prevent the model from learning COVID-related dynamics, which could lead to overly optimistic forecasting behavior.

Table 2. Sample of model inputs. RPM: revenue passenger miles, RGDP: real gross domestic product.

Date	RPM	RGDP	POPULATION	COVID	SEPT11	Financial Crisis
1/1/1990	25160794	12.85089	248.743	0	0	0
2/1/1990	24360423	12.85089	248.92	0	0	0
3/1/1990	29337299	12.85089	249.146	0	0	0
4/1/1990	27630792	12.89754	249.436	0	0	0
5/1/1990	27536900	12.89754	249.707	0	0	0
6/1/1990	29945449	12.89754	249.99	0	0	0

To address this, the historical dataset was divided into three disjoint training/validation segments, ensuring that the model encounters a mix of pre-crisis, crisis-adjacent, and post-crises behavior during training. A visual representation of the segments, as well as the deseasonalized trend of the domestic RPM is shown in Figure 3.

Training periods:
- 1990-2003
- 2005-2012
- 2018-2022

Validation periods:
- 2004
- 2013-2017
- 2023-2024

To ensure consistency across variables and to support stable model training, all input features were scaled prior to modeling. The RPM data are scaled relative to the first month's reported RPM value, which serves as a reference anchor. GDP and population inputs were scaled using a min-max normalization, allowing each feature to occupy a comparable numerical range despite significant differences in magnitude. This normalization process prevents any single variable from dominating the learning process solely because of its scale and facilitates more accurate interpretation of model performance.

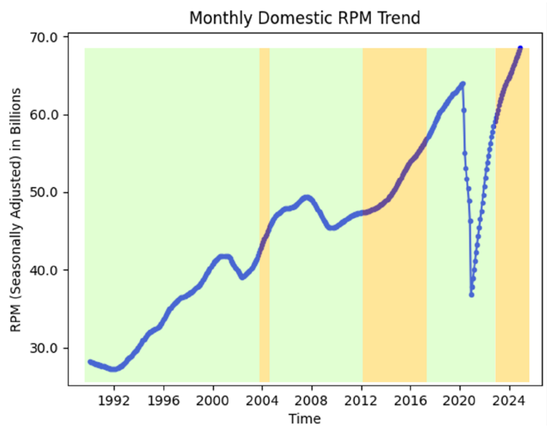


Figure 3. Training/validation segments on domestic revenue passenger miles (RPM).

Modeling Results and Validation

A backcasting approach on the historical data will be used to validate the selected forecasting model. Backcasting involves applying the model to the historical dataset, where actual results are already available. Backcasting is a widely used method for validating forecasting models, providing a benchmark for how well the model can replicate real-world outcomes. By comparing the model's predictions against these known values, performance parameters such as normalized root mean square error (NRMSE) and coefficient of determination (R^2) can be calculated. Additionally, the evaluation of the model's residuals will indicate if the trained model is overfitting on the data. These performance parameters quantitatively assess a model's accuracy, consistency, and ability to generalize, allowing for a more objective evaluation of the chosen model.

As mentioned beforehand, a large design of experiments was used to tune the hyperparameters of the model in order to achieve the best performance. Table 3 summarizes the top three cases with the highest NRMSE and R^2 values, while **Figure 4** shows their corresponding results graphically. In each plot, the dotted line represents the model's prediction on the validation set for that specific case.

Table 3. Top performing cases. NRMSE: normalized root mean square error, R^2: normalized root mean square error.

Case	Train NRMSE	Train R^2	Validation NMRSE	Test R^2
2126	0.0530	0.965	0.0602	0.939
1845	0.0396	0.981	0.0621	0.935
1032	0.0760	0.928	0.0664	0.926

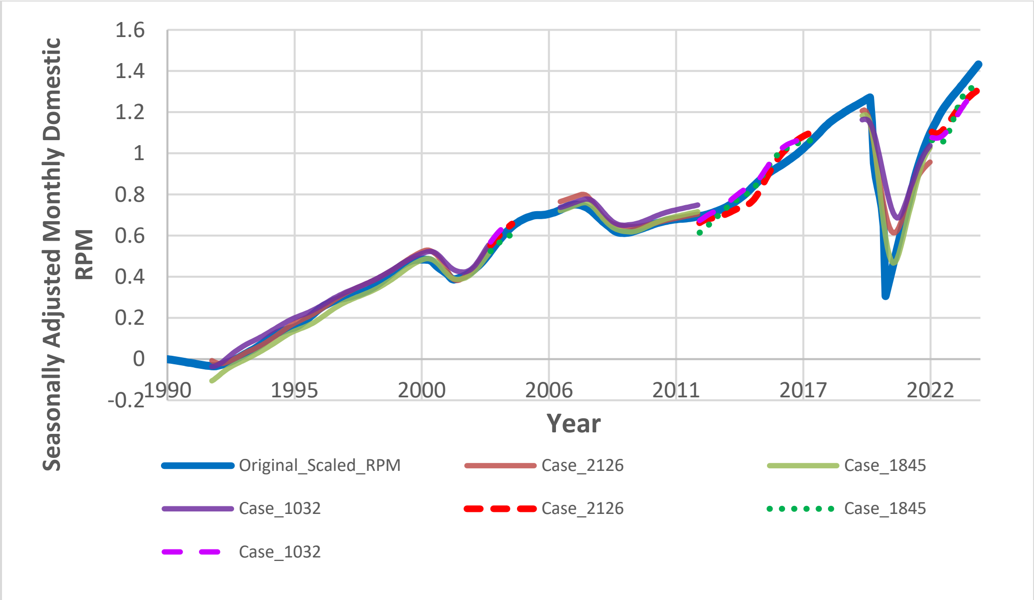


Figure 4. Model's performance on historical data.

It is important to note that for each training period, the model requires an initial sequence of historical observations to initialize its internal memory state before generating predictions. As a result, the first several timesteps of each training prediction window do not appear in Figure 4 and Figure 5. These initial values are used to "warm up" the LSTM's state and are not included in the reported performance metrics. Expanding this initialization window can improve the performance of the validation predictions for the tradeoff of less training data. For this disjointed training/validation segmented configuration, two years' worth of data were decided to be the ideal minimum before significant loss of data occurs. Also, recall that the y-axis (RPM) is scaled relative to first month's reported RPM value.

Figure 5 shows the training residuals of the model. Although the residuals may appear poor at first glance, much of this behavior is driven by the highly irregular demand patterns during the COVID-19 pandemic. This is especially apparent when examining the residuals over time as shown in the second subplot in Figure 5.

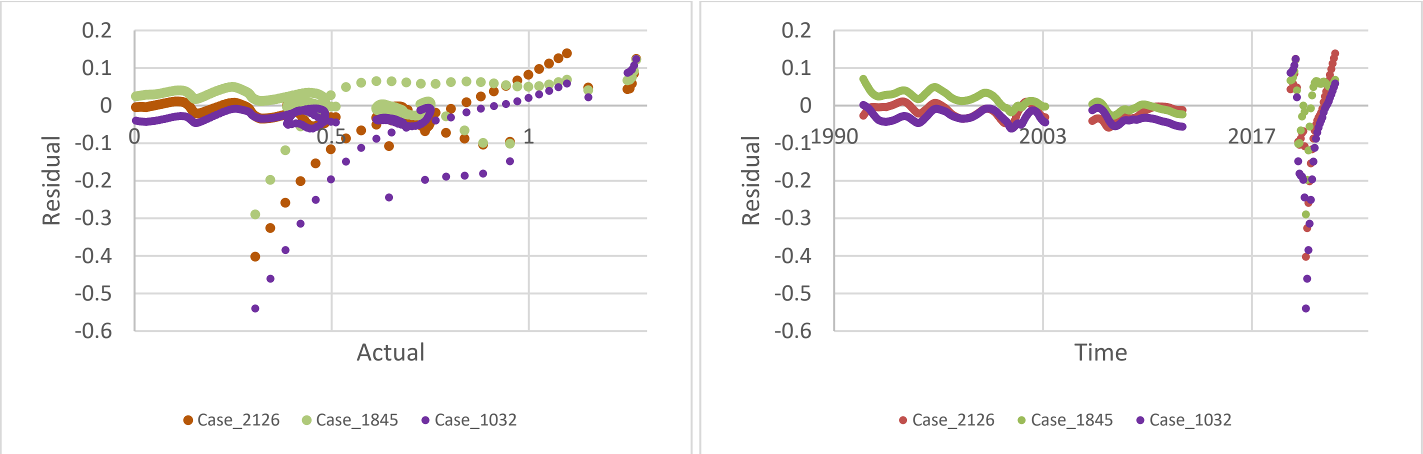


Figure 5. Training residual plots.

Model Forecast

Figure 6 shows the long-term forecasts generated from the top-performing model configurations. Up to 2045, the forecasts remained relatively consistent across all cases. Beyond this point, however, the projections begin to diverge substantially. The most optimistic case (Case 1845) predicts continued growth through the end of the century, while the more pessimistic case (Case 2126) shows demand flattening by approximately 2075. This widening spread reflects growing model uncertainty at long time-horizons and highlights the sensitivity of the LSTM to historical patterns that may not extend cleanly into the future.

Because these forecasts diverge so dramatically, it is challenging to select a single trajectory as the most representative. External benchmarks, such as the Boeing or Airbus market outlooks, can provide helpful reference points, but these industry forecasts only extend to 2044. Likewise, the FAA domestic market forecast terminates in 2045. Beyond this year, these existing forecasts offer little guidance for narrowing the model's long-term behavior.

To address this issue, future work may explore implementing a hybrid modeling architecture in order to stabilize long-range predictions. One potential approach would involve training one model exclusively on pre-COVID historical data to capture long-term structural trends. A second model will be trained to account for anomalous behavior related to COVID-19. Then, these two models will be combined to form a single predictive model capable of predicting other COVID-like events in the future. This hybrid approach will also have the benefit of allowing the model to retain more data in memory when making future predictions, which may lead to a more stabilized realistic forecast.

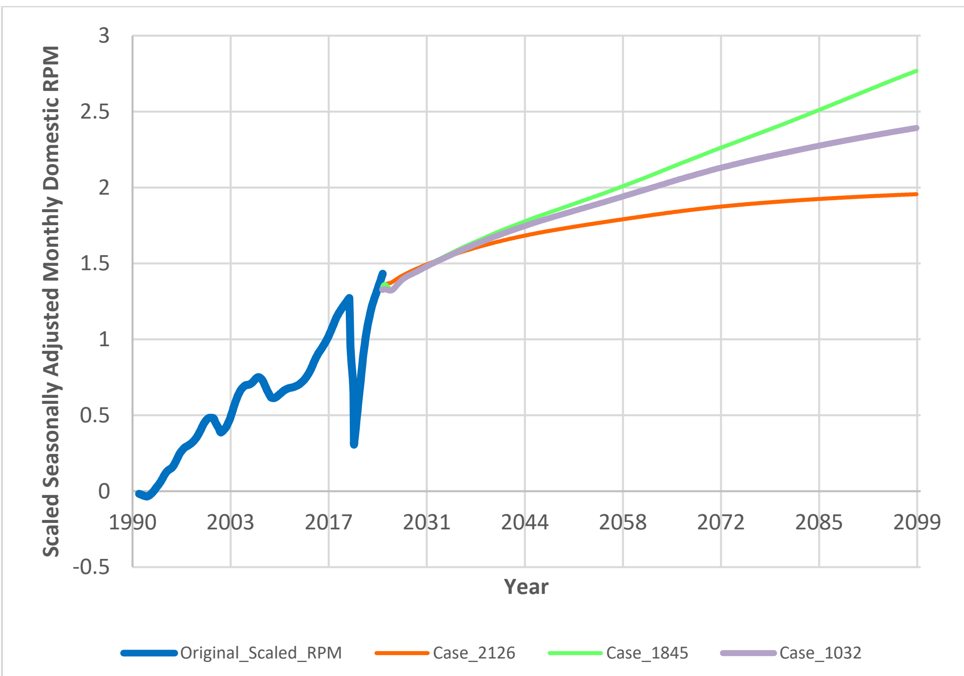


Figure 6. Model's forecasts of demand.

Scenario Analysis

Given the gradual change in commercial aviation to hub and spoke operations as well as other factors, the regional aviation sector has seen a decrease in attractivity which is estimated to be reversed given an introduction of technologies that can revitalize the sector with newer and more efficient configurations. These configurations may enable lower emissions and noise within urban areas. However, the inclusion of modern technologies that prompt new configurations makes it hard to predict what future configurations would be flown in 2050, 2075, and 2100. Therefore, there is a need to find a modeling approach for new emerging configurations.

Operating Cost Breakdown

To forecast different scenarios for future aviation demand, it is imperative to assess the pricing strategies that airlines use to generate “airfare” or “ticket prices” since it is one of the most important socio-economic factors behind air travel demand (Clark, 2017). The pricing system used by airlines currently is summarized in Revenue Management Systems (RMS), which enables airlines to maximize revenue by using multiple pricing strategies such as dynamic pricing, route-based pricing, and more. These pricing strategies are often a mix of three main pricing principles as laid out by Lesgourgues and Malavolti (2023):

- Cost-based pricing
- Demand-based pricing
- Service-based pricing

Cost-based pricing refers to a system of pricing in which the airline sets its prices equal to the marginal cost of producing an incremental unit of output. This practice is one of the theoretically optimal conditions of “perfectly competitive” markets. Demand-based pricing is based on consumers’ “willingness to pay,” as defined by the price–demand curve in each origin-destination market. Finally, service-based pricing refers to differences in the quality of services (and, in turn, in terms of the cost of providing these services) as a basis for pricing (Belobaba et al., 2009). For the scope of this task, the ASCENT Project 096 team will be using a cost-based model to derive the airfares set by the airlines in the future since other pricing principles require access to more data and more complex models that are not within the scope of this task. To use the cost-based pricing principle, our team will lay out a few assumptions such as a fixed marginal cost across all airlines which will in turn disregard pricing based on services and time of purchase of tickets.

The use of cost-based pricing principles causes us to investigate costs related to airline operations and more specifically direct operating cost, which is the cost related to the operations of the aircraft. The direct operating cost is usually expressed as a function of block hours to normalize the data collected from large and small fleets, long and short flights, and so on. To only consider the direct operating cost of airlines to predict future airfare, it is assumed that the indirect operating cost of airlines would not contribute to the airfare and thus is assumed to be constant. The direct operating cost can be further broken into two categories: (1) fixed direct operating cost and (2) variable direct operating cost. Fixed direct operating cost refers to operating cost components that are expenses directly tied to operating the aircraft but do not vary significantly with flight hours or distance flown. Variable operating cost refers to expenses directly tied to operating the aircraft and which vary with flight activity. Therefore, in order to further investigate the impact of effects on the direct operating cost, the focus is on the variable direct operating cost and the assumption that effects do not impact the fixed direct operating cost.

The literature review revealed that there are two main approaches to direct operating cost estimation. Both approach methodologies use historical data to a certain extent. The first approach, mean-based methodologies, use large datasets of reported direct operating cost broken down by component. The direct operating cost is categorized by aircraft category or by engine configuration and by using the mean of the cases selected from the datasets. The second approach uses historical data of the operating cost of certain aircraft, and performance and general data about the aircraft such as maximum takeoff weight to create a regression curve linking both variables and is thereby able to predict the direct operating cost of an aircraft given its general information.

For the task, our team will use the mean-based methodology to determine the direct operation cost breakdown by component for the respective aircraft categories within regional aviation as well as what might become part of regional aviation in the future due to effects.

When discussing effects that can impact the direct operating cost, the different advancements in other scientific fields as well as aviation that can directly decrease the cost associated with fuel, crew, and maintenance as defined in FAA (2024) are discussed.

Categorization and Evaluation of Impacts on DOC

The consideration of effects that can impact the future direct operating cost of aircraft is something that other research papers have tangentially explored (ICAO, 2022; Air Transport Action Group, 2021). ICAO (2022), for example, explores how different effects impact the CO_2 emissions of aircraft to meet future environmental aspirational goals. The report categorizes these effects into three main categories: (1) operations, (2) technologies, and (3) fuels. Operations effects are defined by opportunities for reducing costs and improving energy efficiency by improving the way existing aircraft operate. Technologies effects pertain to the development of evolutionary aircraft and engine technology such as incremental improvements of established architectures, development of novel aircraft concepts, and significant changes at the propulsion level. Fuels effects refer to the development of fuels and new energy carriers that can lead to decrease in fuel cost. Our team will use the same categorization to refer to the different impacts on the direct operating cost with a slight modification to the nomenclature referring to fuels, which will be rather referred to as energy, to better encapsulate a wider range of energy carriers that can be considered in the long future under the assumption that some future aircraft configurations may not rely on fuel to operate.

Technology Impacts

The technologies that have been considered have been carefully selected as potential implementations in future configurations of aircraft due to their impact on the performance of the aircraft as well as their readiness level.
The technologies are divided into the following categories:

- Aerodynamics and flight controls
  - Outboard Horizontal Stabilizers: Placing stabilizers further outboard leads to a 20% reduction in fuel consumption via improved trim efficiency (Dae & Nomenclature, n.d.)
  - Ducted Fans: Enclosed propellers increase airflow over the wing, practical during takeoff and landing operations (Jedamski et al., 2023)
- Operations and maintenance
  - Predictive Maintenance: Use of data and sensors to forecast component failures, reducing unplanned downtime and lowering maintenance costs by 25-30%
  - Simplified Vehicle Operations: Easier-to-fly designs lower pilot workload and training needs. Assuming reduction in pilot recurrent training time by 50% reduces crew cost by 1–41% annually.
- Powertrain efficiency
  - Hybrid Powertrain: Combines conventional and electric systems, leading to approximately 15% reduction in energy use (Zhang et al., 2018)
  - (Dae & Nomenclature, n.d.) Distributed Propulsion: Multiple small motors spread across the airframe improve efficiency, achieving up to 10% energy block reduction(Dae & Nomenclature, n.d.)
  - Electric Powertrain: Battery-powered electric motors drive propellers or ducted fans, reducing energy costs by up to 70% (Zhang et al., 2018)
- Structures and materials
  - Composite Technologies: Use of advanced composite materials yields in a weight reduction and savings of 2.8% (Cai et al., 2022)
  - Advanced Sandwich Composites: Lightweight layered materials contributing to 2.4% savings (Cai et al., 2022)
  - Out-of-Autoclave Composite Fabrication: Alternative to traditional curing processes with 0.2% improvement (Cai et al., 2022)
  - Lightweight Cabin Furnishings: Reduces interior weight, offering 0.5% savings (Cai et al., 2022)
  - Flexible Skins: Adaptive surfaces that reduce drag or support morphing wings; savings of 1.1% (Cai et al., 2022)
  - Variable-Camber Trailing-Edge Flap: Morphing flaps improve aerodynamics, saving 0.6% (Cai et al., 2022)
  - Natural Laminar Flow (NLF): Surface shaping that delays transition to turbulence, reducing drag and offering fuel block reduction of 10.8% (Cai et al., 2022); Catalano et al., 2020)

The infusion of technologies in future aircraft configurations would enable improvements in terms of performance. Given that certain technologies that have widely developed over the last century have reached their limits in terms of improvements, there is a need for a paradigm shift to enable more growth in the aviation industry. The technology sectors that would benefit the most from a paradigm shift would be the sectors that have a wide application of similar products such as the powertrain sector for which turbofans have been the standard choice despite their low efficiency compared to other powertrain configurations. One of the rapidly emerging technological advancements that could drive progress in the aerospace sector is the development of electric vehicles, which enables the use of electric powertrains in aircraft, resulting in higher efficiency and lower emissions. This is one of many examples of how a paradigm shift can impact future aircraft configuration, and thus, impact aviation demand.

Nine-passenger Aircraft Future Technology Selection

By 2050, the nine-passenger sub-fleet is expected to adopt key technologies that will reduce energy use and simplify operations. Battery-powered electric motors and ducted fans will enable short-range flights with up to a 75% reduction in energy costs. This move supports sustainable and low-cost operations. Electric propulsion will also slightly decrease the operating empty weight (OEW) by eliminating complex engine parts. Additionally, simpler vehicle operations from automation and fly-by-wire systems will reduce pilot workload and training hours by about 50%, leading to a 1 to 2% annual decrease in crew costs. Predictive maintenance driven by data analysis will further lower maintenance costs by optimizing parts replacement, minimizing aircraft downtime, and creating a more cost-effective and reliable operation.

By 2075, this same nine-passenger fleet is expected to benefit from further improvements in distributed electric propulsion and aerodynamic redesign. Distributed propulsion systems will enhance load distribution and thrust efficiency, resulting in an additional 10% reduction in energy use compared to earlier electric setups. Adding outboard horizontal stabilizers will improve aerodynamic stability and efficiency, contributing to a further 20% reduction in fuel or energy use. These aerodynamic and propulsion upgrades, along with the established predictive maintenance and electric powertrain technologies, will significantly cut direct operating costs, particularly energy and maintenance expenses, making the nine-passenger fleet a leading option for short-haul, low-cost regional travel by 2075.

19-passenger Aircraft Future Technology Selection:

For the 19-passenger sub-fleet, changes by 2050 will focus on enhancing both structure and propulsion. New composite technologies like sandwich structures (2.3%), out-of-autoclave fabrication (0.2%), and riblets (1.7%) will together provide about a 7% reduction in drag and weight, boosting overall efficiency. The introduction of hybrid-electric powertrains will lead to a notable 15% drop in energy costs. Natural laminar flow (8.7%) and reducing excrescence drag (0.3%) will also improve aerodynamic performance. Operationally, easier vehicle operations will reduce annual training hours by 50% resulting in a 2% decrease in crew costs, while predictive maintenance will cut maintenance expenses by up to 25%. Together, these technologies will improve the sub-fleet's energy efficiency, lower maintenance, and crew costs, and enhance lifecycle sustainability.

Looking ahead to 2075, the 19-passenger sub-fleet is set to reach even greater efficiency through electric propulsion and distributed systems, combined with outboard horizontal stabilizers. These technologies will collectively produce up to a 10% additional reduction in energy use and a 20% decrease in fuel consumption, making this sub-fleet a state-of-the-art hybrid-electric platform for medium-range routes in a sustainable way. A shift to single-pilot operations will decrease crew costs by 41%, marking a substantial change in operational economics. By 2075, these advancements in propulsion, aerodynamics, and operations will yield cumulative benefits across energy, crew, and maintenance costs, establishing the 19-passenger sub-fleet as a standard for efficient regional air travel well into the future.

50-passenger Aircraft Future Technology Selection

By 2050, the 50-passenger sub-fleet will combine electric propulsion, ducted fan systems, and predictive maintenance. It will adopt new technologies from smaller regional aircraft for larger-capacity operations. Battery-powered electric motors will make these aircraft ideal for short-haul routes, reducing energy costs by up to 35% compared to traditional regional jets or turboprops. Ducted fans will improve propulsive efficiency and slightly decrease OEW by eliminating heavy turbine assemblies. Furthermore, simpler vehicle operations and updated cockpit interfaces will lower pilot workload, cutting training hours by about 50% and reducing crew-related costs by 1 to 2% each year. The predictive maintenance systems, backed by constant data monitoring, will cut maintenance costs through improved component replacement and reduced downtime, enhancing overall fleet reliability and cost efficiency.

By 2075, the 50-passenger sub-fleet will become an extremely efficient regional platform powered by advanced electric powertrain technologies, distributed propulsion designs, and well-optimized flight deck layouts that ease pilot burden. The improved cockpit and dashboard systems will make flight management simpler, allowing one pilot to fly the aircraft safely and effectively while keeping operational backup through smart systems and streamlined controls. This change will lead to a 41% drop in crew costs, representing one of the biggest improvements in the fleet's operating economics. At the same time, innovations in distributed propulsion and next-generation energy storage will allow for another 10 to 15% reduction in energy use, further cutting DOC. When combined with ongoing progress in lightweight structures and predictive maintenance, the 50-passenger fleet will secure significant savings in energy, crew, and maintenance costs establishing itself as a leading example of efficient, sustainable, and economically improved regional air transport by 2075.

Future Aircraft Energy Consumption

The analysis starts with figuring out the power needed to keep the plane flying steadily. This depends on the aircraft's weight, speed, and how well it moves through the air. The lift-to-drag ratio and overall propulsive efficiency are key factors in determining the energy needed for a specific operating condition.

$$\eta_{propulsive} = \eta_{motor} \times \eta_{power_{converters}} \times \eta_{propeller} \quad \text{(Eq. 1)}$$

We calculate the overall propulsive efficiency by looking at how well the motor, power converters, and propeller work together. This shows how energy changes from electrical input to useful thrust.

$$P_{required} = \frac{Weight \times Velocity}{L/D \times \eta_{pr}} \quad \text{(Eq. 2)}$$

$$Energy\ Consumed_{kwh} = Power_{required} \times Energy\ Price \quad \text{(Eq. 3)}$$

Finally, we estimate the total energy consumption by multiplying the required power by the energy price. This helps us understand the operational energy cost for the chosen flight condition. It also allows us to compare different propulsion system setups or assess how improvements in efficiency affect energy spending.

Figure 7 outlines the future aircraft energy consumption and efficiency. Table 4 provides the physics-based modeling results compared to literature simulation results for energy consumption and the cost of energy per block hour use in validation of the electric model. Table 5 outlines the direct operating costs for fuel and oil, maintenance, and crew costs per block hour for the three passenger fleets evaluated. Table 6 provides a cost comparison for direct, indirect, and total operating costs for 2023, 2050, and 2075 for the three passenger fleets evaluated.

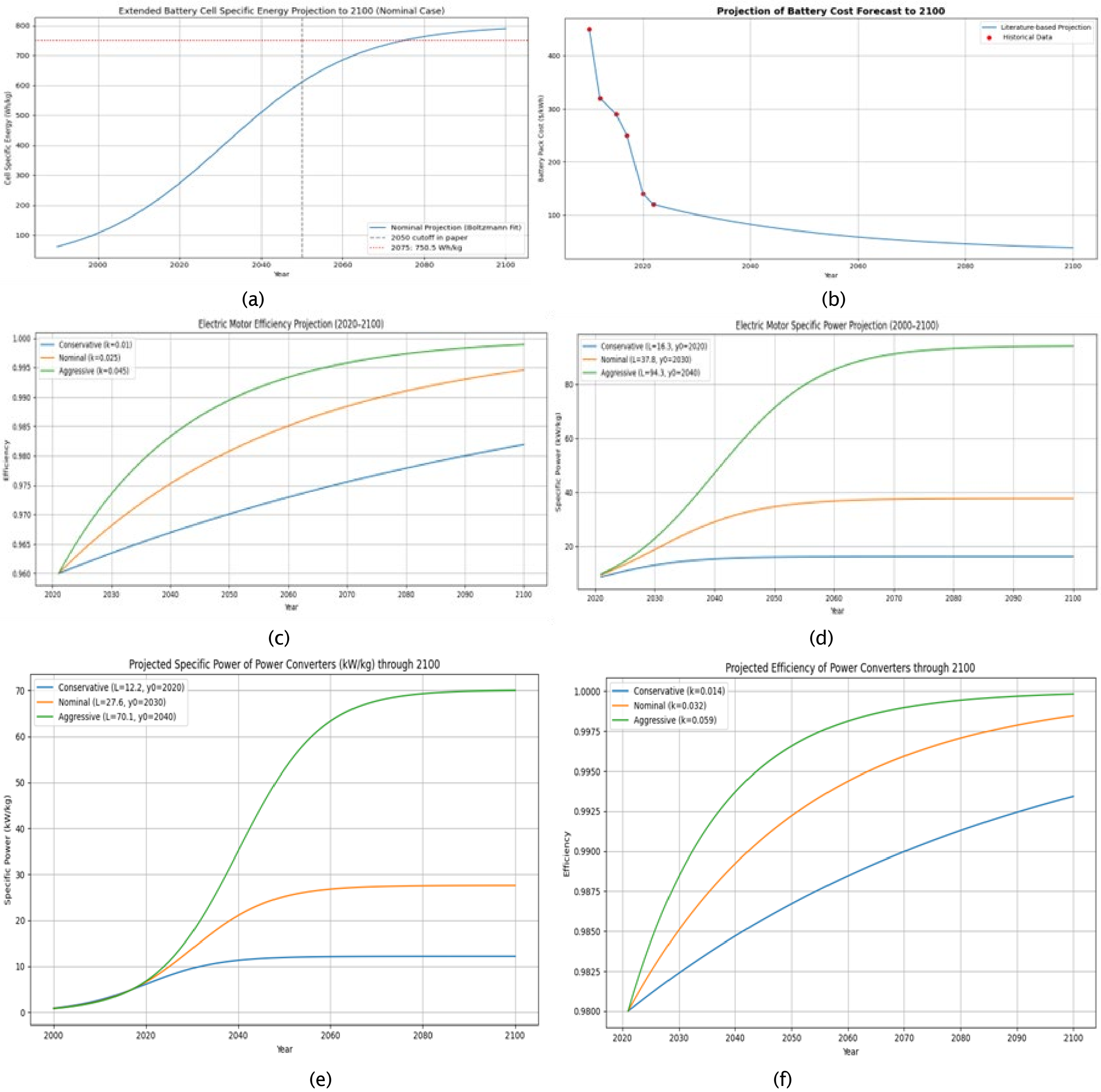


Figure 7. Future aircraft energy consumption and efficiency: (a) extended battery cell-specific energy (nominal case), (b) forecast of projection of battery costs, (c) future projection of electric motor efficiency, (d) future projection of electric motor-specific power, (e) projected specific power of power converters (kW/kg, and (f) projected efficiency of power converters through.

Table 4. Physics-based model results compared to literature simulation results.

Electric Model Validation	Physics Equations	Simulation Results
Energy Consumed per block hour (kwh)	356.2	367
Cost of Energy per block hour ($ 2023)	51	53

Table 5. Direct operating cost variable components for each sub-fleet per timeline.

Fleet	Cost Components	2023	2050	2075
9 pax: Cessna 208	Fuel and oil cost ($/BH)	227	42	32
	Maintenance cost per block hour ($/BH)	186	140	140
	Crew cost ($/BH)	116	133	112
19 pax: Cessna 408	Fuel and oil cost ($/BH)	776	534	319
	Maintenance cost per block hour ($/BH)	423	296	205
	Crew cost ($/BH)	177	173	104
50 pax: ATR 42-600	Fuel and oil cost ($/BH)	993	661	661
	Maintenance cost per block hour ($/BH)	627	439	439
	Crew cost ($/BH)	258	255	152

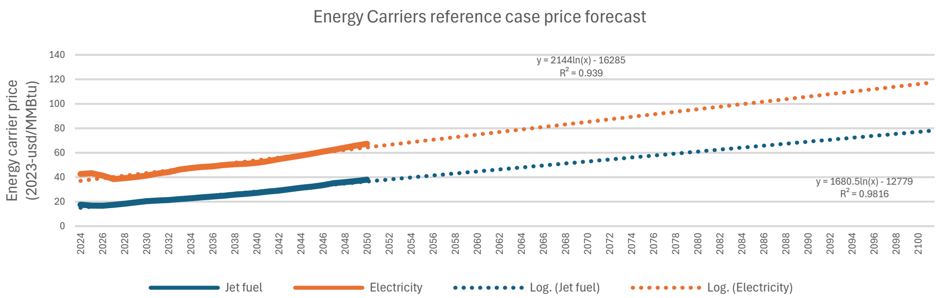
Table 6. Direct operating costs (DOC), indirect operating costs (IOC), and total operating costs (TOC) for each sub-fleet per timeline.

Fleet	Cost Components	2023	2050	2075
9 pax : Cessna 208	DOC	$ 649	$ 562	$ 558
	IOC	$ 649	$ 555	$ 555
	TOC	$ 1,298	$ 1,117	$ 1,113
19 pax : Cessna 408	DOC	$ 1,690	$ 1,472	$ 1,327
	IOC	$ 1,690	$ 1,457	$ 1,323
	TOC	$ 3,381	$ 2,929	$ 2,650
50 pax : ATR 42-500	DOC	$ 2,061	$ 1,871	$ 1,391
	IOC	$ 2,061	$ 1,856	$ 1,387
	TOC	$ 4,121	$ 3,727	$ 2,778

Energy Carriers: Jet-A, Electricity Forecast to 2100

The forecast of energy carrier prices was extended beyond the U.S. Energy Information Administration's (EIA) Annual Energy Outlook (AEO) 2050 projections by applying a time series regression model to the historical and projected data.

Using the EIA's long-term baseline as the foundation, the model extrapolated future trends in jet fuel and electricity prices through 2100. A logarithmic regression was selected to capture the diminishing rate of price increase over time, reflecting the stabilizing behavior observed in long-term energy markets. Figure 8 provides a reference case forecast for energy carriers for jet fuel and electricity.



$Fuel\ price = 1689.5\ ln(years) - 12779$ for jet fuel (2023-USD/MMBtu)
$Electricity\ price = 2144\ ln(years) - 16286$ for electricity (2023-USD/MMBtu)

Figure 8. Reference case price forecast for energy carriers.

The resulting fitted equations yielded high coefficients of determination ($R^2 = 0.9616$ and $R^2 = 0.939$, respectively), indicating strong model accuracy and goodness of fit. These metrics confirm that the extended forecast maintains statistical consistency with the EIA reference case, providing a credible outlook for long-term energy cost evolution.

Regional Market Demand Model Generation

The chosen demand model framework builds on a long history of research focused on modeling how travelers choose their modes of transportation. Traditionally, these models have used detailed utility-based methods, which evaluate the appeal of each transport option based on traveler characteristics like income, value of travel time, or trip purpose, along with specific attributes of the modes, such as cost, comfort, and service frequency. However, previous studies have shown that adjusting complex utility functions with many variables often requires a lot of survey data, which can be tough to gather. To solve this problem, the current model uses a simplified but effective approach based on the generalized cost of travel (GCT) (Roy et al., 2023). The GCT combines two main parts: (1) the monetary cost of a trip and (2) the opportunity cost of the time spent traveling. This provides a unified measure that reflects both the financial and time aspects of a traveler's decision-making.

$$GC_m = C_m + VT \times T_m \quad \text{(Eq. 4)}$$

$$U_{car} = \alpha \times GC_{car} + \epsilon \quad \text{(Eq. 5)}$$

$$U_{air} = \alpha \times GC_{air} + \beta + \epsilon \quad \text{(Eq. 6)}$$

This generalized cost approach allows for clear and data-efficient estimation of travel preferences while still being realistic compared to more complicated utility-based models. By using publicly available wage data from the U.S. Bureau of Labor Statistics, the model figures out the value of time by averaging the median hourly wages across the states of departure and arrival. When applied to comparison scenarios from 2008 and 2040, the GCT-based demand model shows its ability to measure how regional air mobility services affect traveler behavior (Justin et al., 2021).

$$P_{air} = \frac{1}{1+e^{\alpha\times(GC_{car}-GC_{air})-\beta}} \quad \text{(Eq. 7)}$$

Specifically, the decrease in GCT for air travel, resulting from shorter door-to-door times due to more regional airports, implies that air travel becomes more attractive and competitive compared to ground options. This ability to capture changing travel dynamics in a straightforward, understandable way makes the GCT-based demand model a strong choice for predicting future mobility patterns and evaluating the potential uptake of new air travel services.

Figure 9 outlines the Terminal Area Forecast for air, automobiles, and railways extended from 2040 to 2100. Figure 10 shows a diagram of the proposed framework to generate a future demand model.

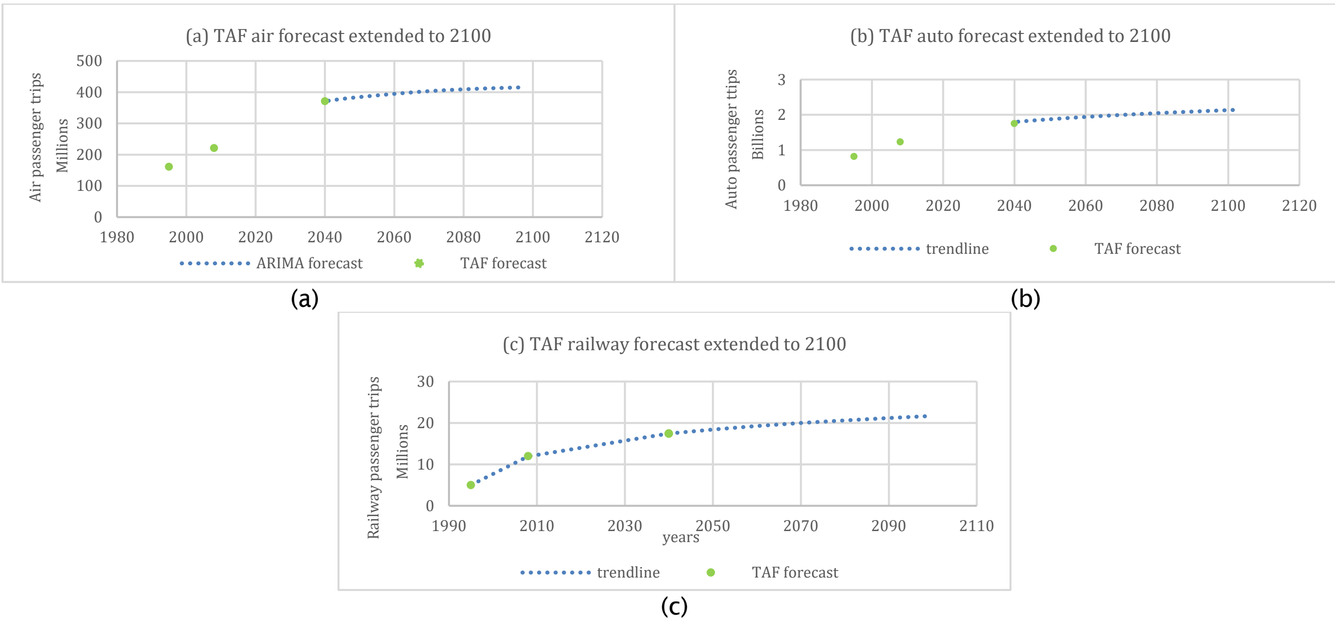


Figure 9. Annual passenger trips forecast extended from 2040 to 2100 for three modes of transportation (a) air, (b) business automobile, and (c) passenger railway.

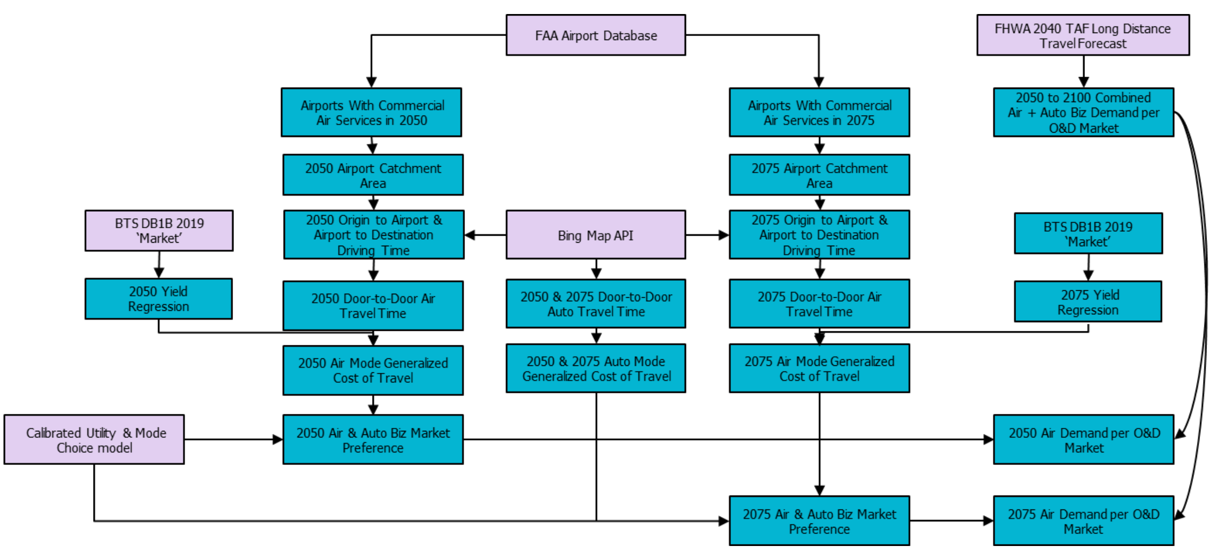


Figure 10. Proposed framework to generate a future demand model.

Milestones

- Created demand model and demand forecasts.
- Investigated use cases of various forecasting models.
- Evaluated different operating cost prediction methodologies.

- Examined the technologies to evaluate their impact on operating cost for scenarios generation.
- Generated surrogates of aircraft costs with respect to flow distance for each sub-fleet and timeline
- Generated an approach for scenarios based on traveler demand elasticities.
- Identified and prepared the required datasets for the demand model framework.

Major Accomplishments
None.

Publications
None.

Outreach Efforts
None.

Awards
None.

Student Involvement
Graduate students are actively participating in research.

Plans for Next Period
Continued Model Evaluation
As discussed previously, a modeling method was selected and evaluated. However, further improvement is still warranted. During the writing of this report, it has become apparent that a hybrid modeling architecture might offer a more effective way to handle the structural disruptions introduced by COVID-19 data. This may become especially useful in stabilizing long-term forecasts.

Modeling Modes of Transportation
For the mode of choice modeling, the next steps include implementation of a railway model that depicts future plans envisioned by the federal railway administration which include high speed railways between megaregions in the US mainland as well as a complete modeling of the rail network using a generalized cost of travel mode. Coupling the railway model with the already developed Air and Automobile models will enable direct analysis of traveler preferences for 2050 and 2075 given the introduction of novel technologies using a fleet assignment and scheduling module predict future demand for different airports as well as the needed infrastructure to handle these novel aircrafts in the United States.

Scenario Generation
The mean-based methodology will be used to generate a direct operating cost breakdown for the respective aircraft categories that is to be assessed. A range of impacts from the different technologies on the aircraft performances will be created, which will then be used to generate the scenarios.

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Task 5 – Vehicle Technology Specific Scenarios

Georgia Institute of Technology

Objectives

This task aims to capture the implications of vehicle-specific technology and their potentially required infrastructure changes. This is intended to cover the adoption of electric or fuel cell aircraft as well as the potential large-scale adoption of sustainable aviation fuel and hydrogen vehicles. Combined with the results of Tasks 1, 2, 3, and 4, this will define combined scenarios that bring the various aspects of demand, operational changes, and new vehicle-specific changes together in new scenarios for aviation.

This year we developed an analytical dashboard for evaluating ground charging infrastructure requirements across the U.S. domestic airport network. The tool addresses a gap in existing aviation infrastructure planning: how to size and deploy charging systems for HEA as this technology moves toward commercial deployment.

The dashboard uses actual operational data—flight schedules, turnaround times, and route-level energy consumption—to estimate charging demand at individual airports. Rather than relying on simplified assumptions about average daily usage, we model charging requirements at the hourly level using January 2023 on-time performance data matched with physics-based energy consumption estimates for turboprop and turbofan routes.

Research Approach

- Narrow down the potential options in coordination with the FAA and industry.
- Perform initial tests of how the vehicle technologies intersect with the overall modeling framework.
- Study and estimate the infrastructure needed to generate the required electricity using renewable energy, particularly wind and solar energy. One of the scenarios currently being developed is if majority of the passenger's

transportation part of commercial aviation is flown by hybrid-electric aircraft. For this scenario, it is reasonable to assume additional infrastructure would be required to supply sufficient electrical energy to charge the aircraft.

Data Integration
We work with three primary data sources. The Bureau of Transportation Statistics T-100 dataset provides route-level traffic volumes and operational patterns. FAA Aerospace Forecast domestic RPM projections scale these baseline figures through 2045. On-time performance records give us actual arrival and departure timestamps, which we use to construct realistic charging schedules rather than assuming uniform distribution throughout the day.

Energy consumption per route comes from surrogate models that account for distance, payload, and aircraft market (turboprop vs. turbofan). These models estimate both fuel burn and electrical energy requirements under hybrid-electric operation. The key assumption—that all charging occurs at departure airports—simplifies the analysis but captures the dominant infrastructure burden. Destination charging would redistribute demand but not eliminate it.

Charging Window Calculations
A critical parameter is the usable charging window. Aircraft do not arrive and immediately plug in, nor do they charge until the instant of pushback. We define the usable turnaround time as:

$$Usable\,TAT = Actual\,TAT \times (1 - \alpha) \qquad \text{(Eq. 8)}$$

where α represents non-charging buffer time (default 0.20, or 20% of turnaround). This accounts for deplaning, servicing, boarding, and the practical reality that chargers are not connected for the full ground time.

Required charging power follows directly:

$$P\_required = Energy\_needed\,/\,Usable\_time \qquad \text{(Eq. 9)}$$

This gives us the minimum charger rating needed to replenish the battery within available time. Flights where this exceeds installed charger capacity are flagged as infeasible under current operational constraints.

Charging Model
The dashboard implements both a simplified linear charging model and a more realistic constant current-constant voltage (CC-CV) model. The linear model assumes constant power delivery throughout the charging session—charge delivered is simply power multiplied by time. This works for rough estimates but overstates charging capability.

The CC-CV model reflects actual lithium-ion battery behavior. It charges at constant current until reaching approximately 80% state of charge, then transitions to constant voltage with declining current. This transition matters: a charger rated at 600 kW delivers 600 kW through most of the charge cycle but tapers off as the battery approaches full. Our implementation uses HEA battery specifications (396 kWh total capacity, 317 kWh usable from 20-100% state of charge) and shows that the CC-CV physics can reduce effective charging by 15-40% compared to linear assumptions for longer sessions.

Dashboard Structure
The tool comprises six analytical pages, each addressing various aspects of infrastructure planning:

Page 1: Route Explorer provides an interactive map for examining individual origin-destination pairs. Users select airports to view route distance, traffic volume, aircraft types, and per-mission energy requirements (see Figure 11). Growth projections through 2045 are displayed based on FAA domestic RPM forecasts. This is useful for understanding specific route characteristics and identifying high-priority corridors.

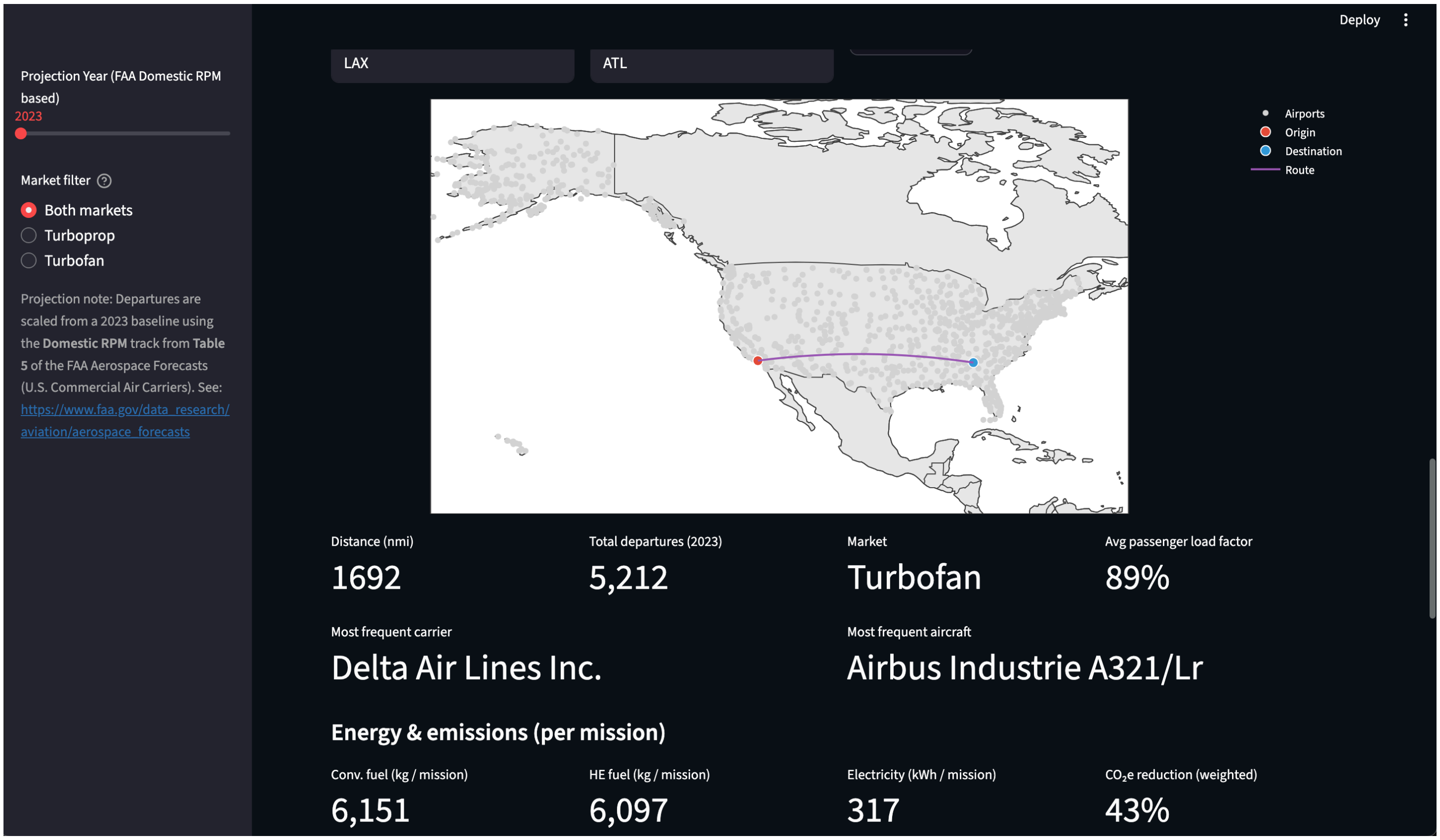

Figure 11. Tab 1 route explorer (from Los Angeles International Airport to Atlanta International Airport).

Page 2: Geographic Energy Demand maps total annual electricity consumption and average required energy per mission across airports (see Figure 12, Figure 13, and Figure 14). The visualizations help identify geographic clusters of charging demand and show which airports face the highest per-flight energy requirements. Filters allow focusing on airports above specified departure thresholds and separate analysis of turboprop versus turbofan markets.

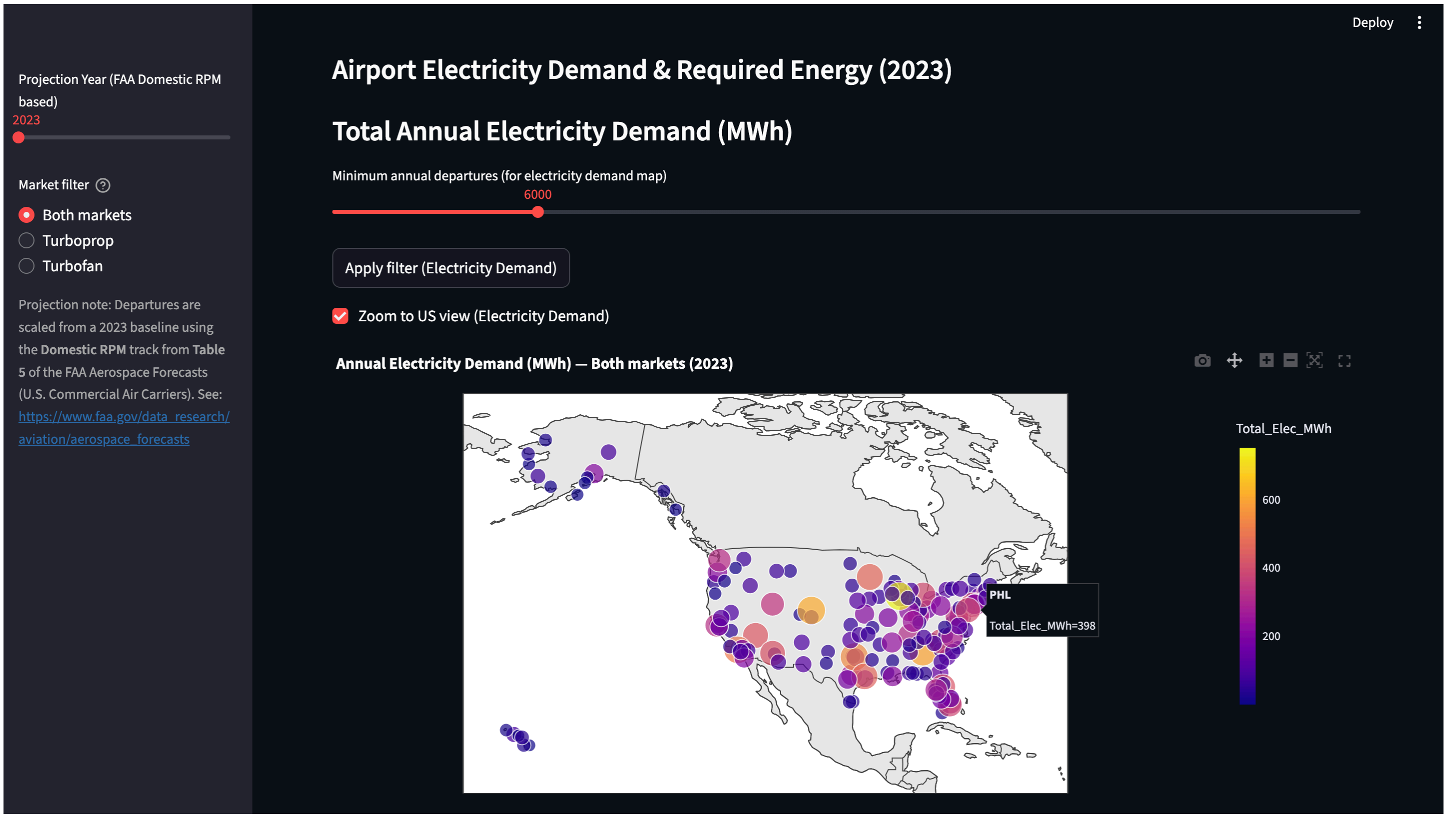

Figure 12. Tab 2 annual electricity demand by airport.

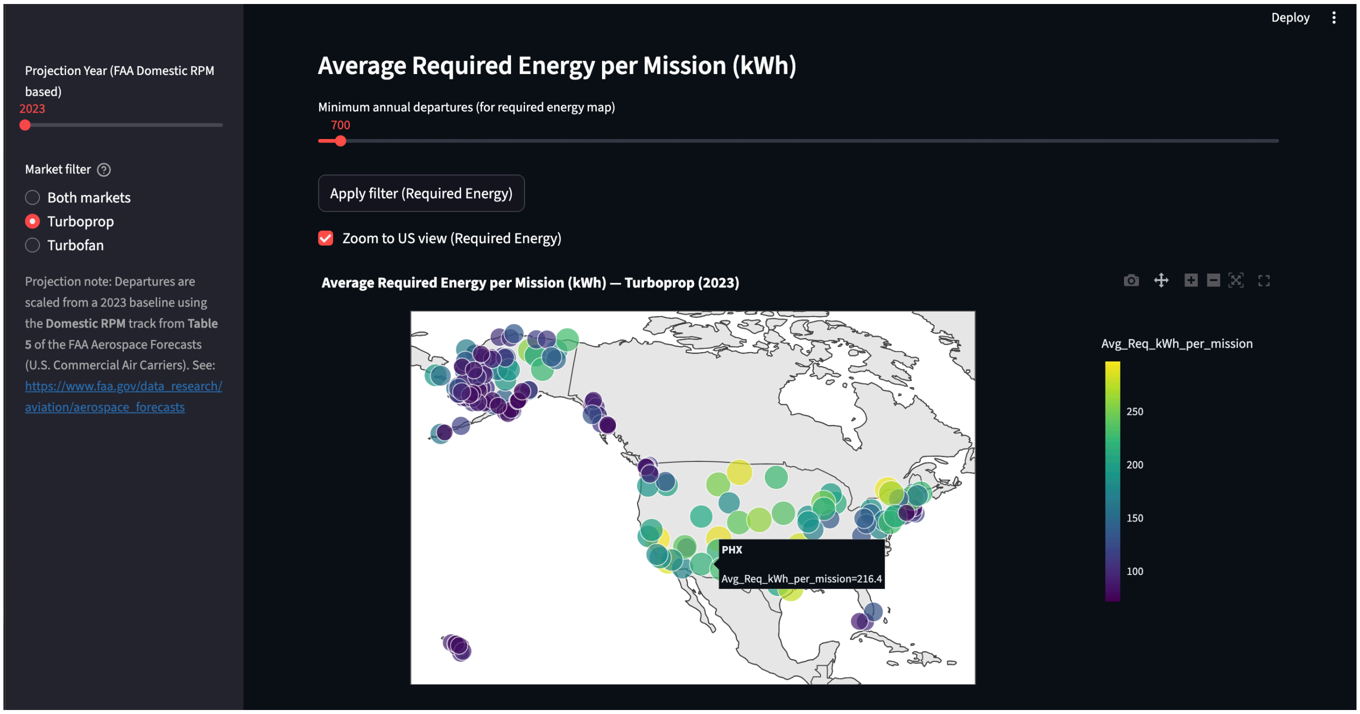

Figure 13. Tab 2 average electricity demand by airport (turboprop only).

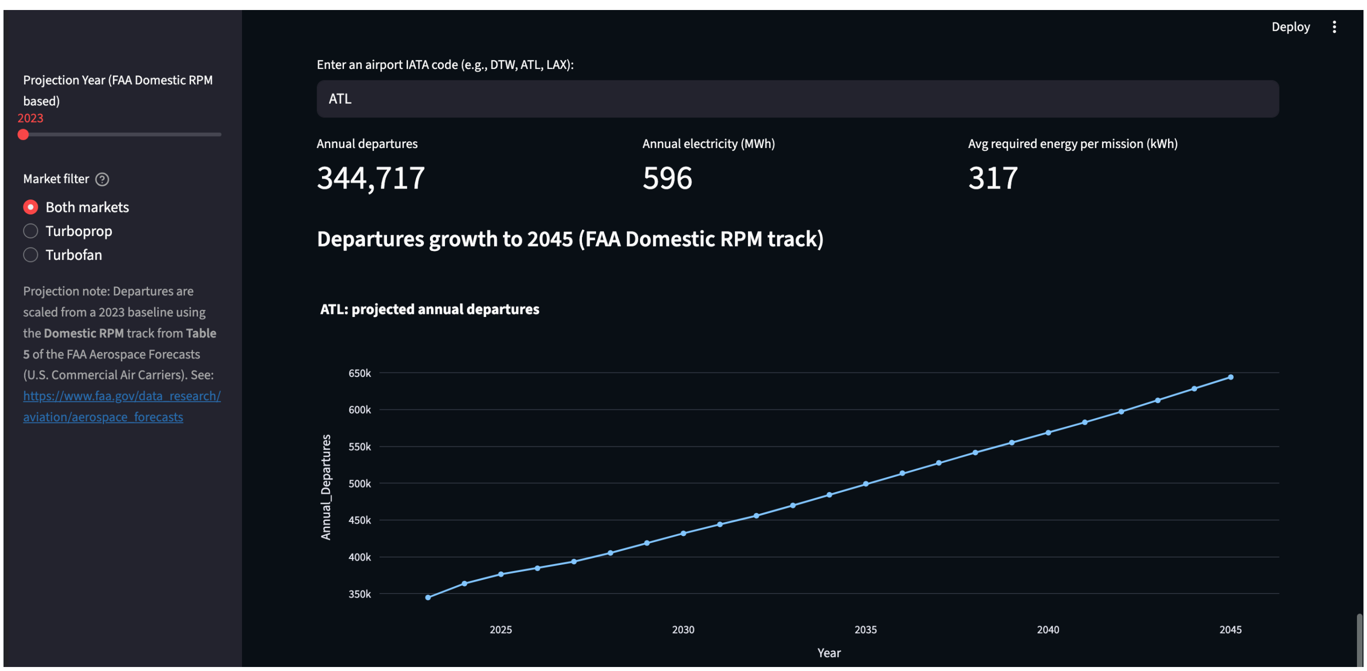

Figure 14. Tab 2 airport explorer (for Atlanta International Airport [AT]) displaying the projected departures growth to 2045 (Federal Aviation Administration [FAA] Domestic revenue passenger-mile [RPM] track).

Page 3: Charge Availability vs. Requirement compares what can be delivered (charger power × turnaround time) against what is needed (mission energy requirement) on a per-airport basis. This reveals where standard turnaround times are sufficient for charging and where they are not. The analysis is parametric in charger rating, allowing quick assessment of how increasing charger power affects feasibility.

Page 4: Required Charging Rate calculates the minimum charger power needed at each airport given typical turnaround times and energy requirements. This inverts the usual question: instead of asking "can we charge with 300 kW chargers," it asks "what charger power do we actually need here?" The answers vary substantially by airport due to differences in typical route distances and turnaround times.

Page 5: Charging Facility Sizing performs date-aware analysis using individual flight records (see Figure 15 and Figure 16). This is the most detailed method. We track each flight's charging session from arrival through departure, accounting for actual timestamps and calculating hourly load profiles and port concurrency. The analysis supports two scenarios:

- Power-based sizing*:* Determines charger count from peak hourly load divided by charger rating and diversity factor. Different charger ratings yield different port counts.
- Make-up charging scenario*:* Assumes each flight occupies a port for its entire usable turnaround window, regardless of charger power. Required ports equal the peak number of simultaneous charging sessions. This is conservative but reflects operational realities where aircraft positions are fixed.

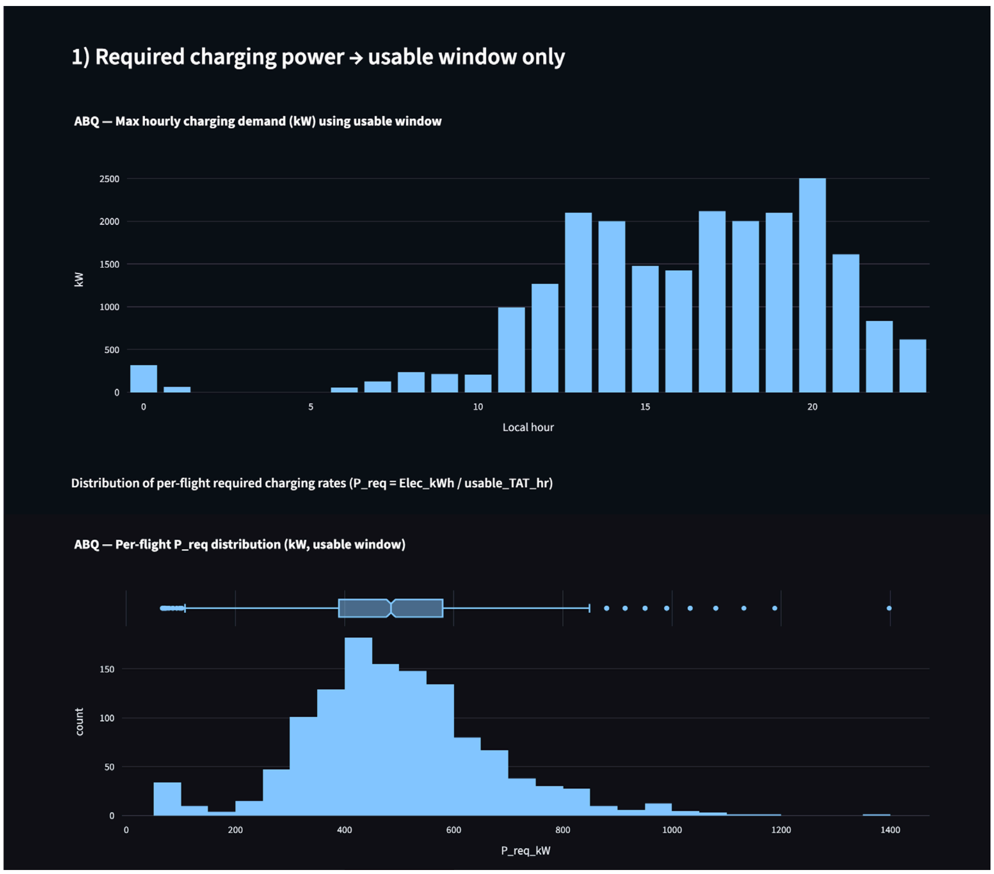

Figure 15. Tab 5 scenario 1 (for Albuquerque International Sunport [ABQ]).

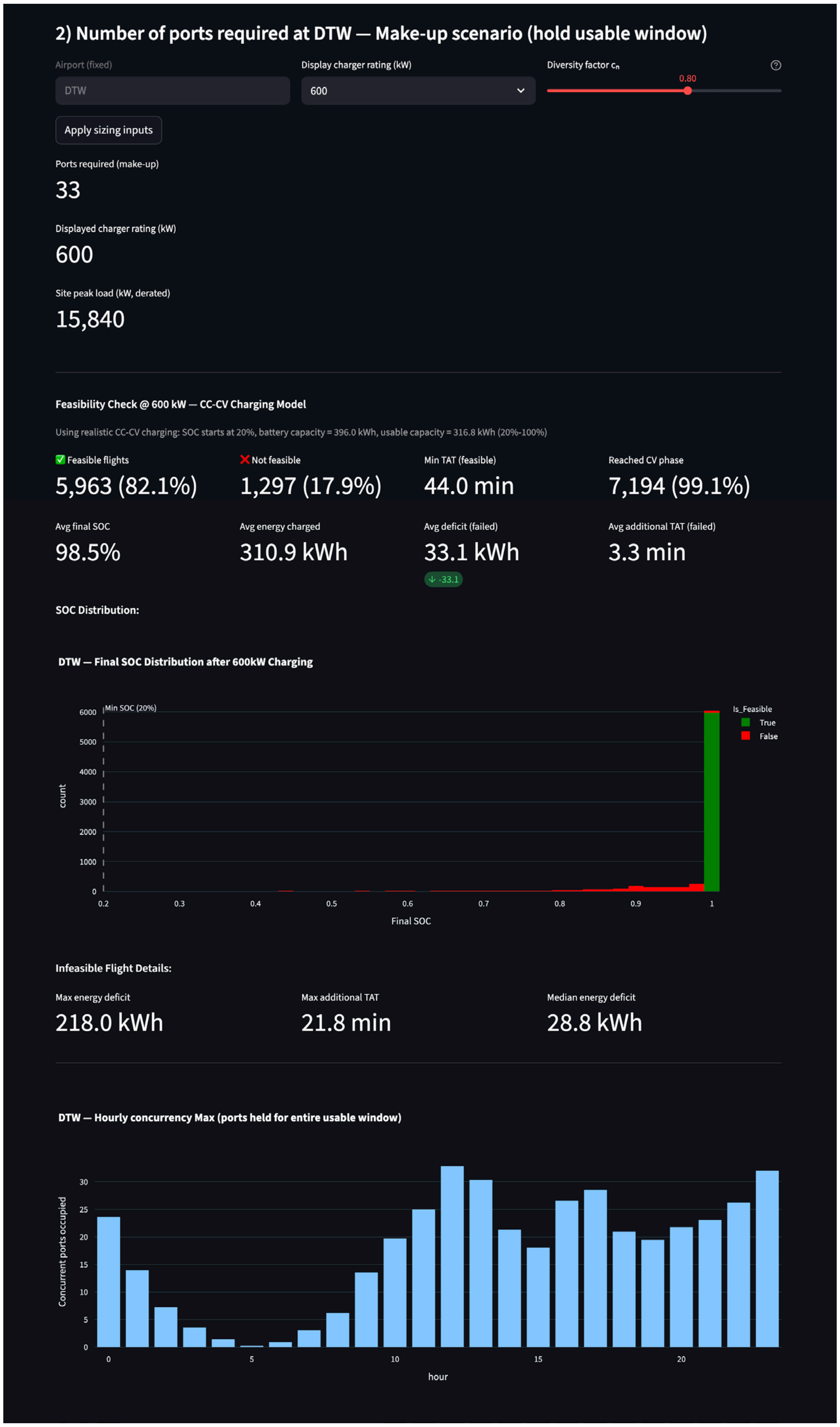

Figure 16. Tab 5 scenario 2 (for Detroit Metropolitan Wayne County Airport [DTW]).

The per-flight analysis also includes feasibility assessment. For each flight and charger rating, we compare energy that can be delivered against energy required. Infeasible flights are those that cannot fully charge within available time. The dashboard reports not just feasibility rates but also the additional turnaround time needed to make infeasible flights feasible. This quantifies the operational impact: if 15% of flights need an extra 25 minutes of ground time on average, which has real implications for schedule design and aircraft utilization.

Milestone

Identified the specific technologies and scenarios that will be covered under this task in collaboration with the FAA.

Key Capabilities and Findings

The dashboard reveals several important patterns. First, required charging rates vary more by typical route structure than by absolute traffic volume. An airport handling many short routes might need only 150-300 kW chargers, while one serving longer turbofan routes might require 600+ kW even with comparable departure counts. We have extended the charger rating range to 1,200 kW to capture potential future high-power installations.

Second, turnaround time is often the binding constraint, not charger power. Increasing charger power from 300 to 600 kW helps, but if typical turnaround times are 40-50 minutes, even 600 kW is not enough for longer routes. Some route-airport combinations are fundamentally infeasible without operational changes—longer ground times, mid-route charging, or reduced payload.

Third, the CC-CV charging physics matter for accurate planning. Linear models consistently overestimate charging capability. For an airport where the CC-CV model shows 85% flight feasibility at 450 kW, a linear model might show 95% feasibility—a difference of hundreds of missed flights per year. Infrastructure sized based on linear assumptions will underperform.

Fourth, hourly demand profiles are not uniform. Morning and evening banks at hub airports create sharp peaks in charging load. Schedule-aware analysis shows these peaks can be 2-3× higher than assumptions based on spreading daily energy evenly across hours. This affects both the number of chargers needed and the electrical service capacity required from the grid.

Applications and Limitations

We have used the dashboard internally for several analyses. One examined Atlanta (ATL) in detail, showing that with 300 kW chargers approximately 60-70% of turboprop flights are feasible under current turnaround constraints, but this drops substantially for turbofan operations. Increasing to 600 kW improves feasibility but still leaves 20-30% of flights requiring operational adjustments.

Another analysis compared schedule-aware versus averaged facility sizing across top 20 airports by electricity demand. Schedule-aware methods consistently require 15-25% more chargers due to actual peaking patterns versus smoothed averages. This is not a flaw in either method, it reflects the difference between detailed operational realism and simplified planning estimates.

The tool has clear limitations. It assumes all charging occurs at departure airports, ignoring potential destination charging that could reduce departure-side infrastructure needs. It uses January 2023 schedules, which may not represent seasonal variations or post-pandemic traffic patterns. The energy consumption models are surrogate estimates, not actual aircraft performance data. Battery specifications assume a single standardized HEA design, when in reality different manufacturers will have different battery systems.

The FAA RPM scaling is a rough projection method. It assumes traffic growth scales all routes proportionally, when in reality growth patterns will vary by region and route type. The 20% non-charging buffer is based on judgment rather than time-motion studies of actual ground operations. These assumptions are defensible for system-level planning but would need refinement for actual infrastructure deployment.

Major Accomplishments

These vehicle-specific analyses will be integrated with the conventional aviation and the long-term scenarios from Tasks 1, 2, and 3. The goal is to show how certain technologies could help or hinder the adoption of certain types of vehicles.

The dashboard provides a data-driven foundation for evaluating HEA charging infrastructure needs. It translates abstract questions about electrification feasibility into concrete engineering requirements: how many chargers, what power ratings, what electrical service, at which airports. The analysis shows that universal answers do not exist—requirements vary substantially by location, route mix, and operational constraints.

The tool's value is not in providing definitive answers but in enabling systematic evaluation of alternatives. How does feasibility change at 450 vs. 600 kW? What happens if we accept 10% infeasible flights? Which airports should be prioritized? These are answerable questions, and the dashboard provides the analytical framework to answer them with realistic operational constraints and physics-based charging models.

Publications

None.

Outreach Efforts

None.

Awards

None.

Student Involvement

The graduate students that are part of this project will conduct most of this research under faculty supervision and with feedback from project management and other stakeholders.

Plans for Next Period

Consider specific technologies to enable new types of vehicles to be commercially and environmentally successful based on the results of Task 3.

Future Development

Several extensions would add value. Integration with grid capacity data would help identify locations where electrical infrastructure may be limiting. Weather impacts on charging (temperature effects on battery performance) are not currently modeled. Economic analysis—capital costs, electricity costs, revenue impacts of extended turnarounds—would help prioritize investments.

The per-flight analysis could be extended beyond single airports to network-wide assessment, though computational costs increase substantially. Machine learning models might identify patterns in which flights are most likely to face charging constraints, helping prioritize operational solutions. Integration with aircraft scheduling optimization could explore how modifying turnaround times or aircraft rotations might improve charging feasibility.

We are also considering support for mixed charger deployments—a hub might have both 300 kW chargers for short routes and 600+ kW chargers for longer flights. This would require matching flights to charger types, adding complexity but reflecting probable real-world deployments.

As hybrid electric aircraft move from concept to certification to entry into service, infrastructure planning needs to move in parallel. This dashboard represents one approach to that planning—imperfect, assumption-dependent, but grounded in real schedules and honest physics.