Probabilistic Learning and Optimization for Real-time Flight Management with Safety and Environmental Constraints

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MOTIVATION

The climate crisis is changing aviation. Data analytics creates an opportunity to address this challenge.

We develop a workflow, using machine learning, data analytics, and relevant physics, to facilitate:

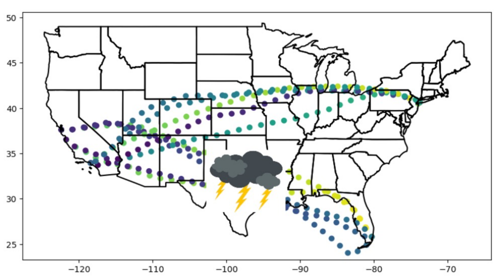
- ***Improved aviation safety***, in the face of weather or other airspace restrictions
- ***Sustainable aviation***, by minimizing emissions for manifested flights
- ***Operational efficiency of the NAS***, by introducing quick, safe, and environmentally-friendly flight replanning solutions

OUR PROBLEM STATEMENT

The day starts with an initial flight schedule manifest

Origin	Destination	Takeoff time	Arrival Time
SFO	MIA	14.25	19.61
SFO	MIA	2.2	7.9
SFO	MIA	14.2	19.8
SFO	MIA	1.48	7.23
SFO	MIA	2.86	8.38
LAX	JFK	8.65	13.91
LAX	JFK	14.45	19.31
LAX	JFK	6.41	11.3
LAX	JFK	0.55	5.43
LAX	JFK	6.5	11.73

But a bad weather system is aniticpated, intersecting flights. Flights must be replanned efficiently, safely, and with minimal emissions



$$\mathbf{x}^* = \underset{x}{\operatorname{argmin}}\, E(\alpha C + \beta F \mid W(t))$$

$$\text{subject to: } L_{i,j,k}(t) < A_{i,j,k}(t)\ \forall\, i, j, k, t$$

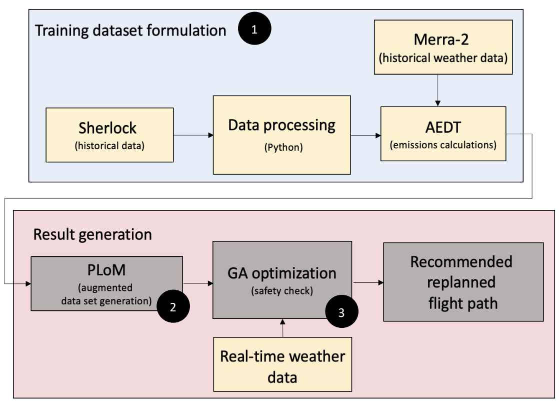
$$x_0' = x_0$$

$$x_f' = x_f$$

Find a new set of flight paths that minimize expected emissions, given observed weather

Ensure safety: load must be less than the capacity in each space/time grid.

Methods



There are 3 major components to the workflow: 1) formulating the training dataset, 2) generative probabilistic machine learning, 3) genetic algorithm optimization

References: See presentation, technical paper

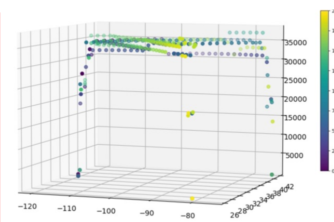
Model modules:

- Sherlock: source of flightpath data, which is then filtered using custom Python code
- AEDT: FAA-developed software which calculates fuel consumption and emissions, using NASA's Merra-2 weather data
- PLoM: generative probabilistic ML technique, used to solve the small data challenge by creating an augmented dataset from the training data while retaining inherent properties
- Genetic Algorithm Optimization: selects a set of optimal new paths, resolving safety constrains imposed by real-time weather
  - A GA is required because this is a non-convex and high-dimensional problem

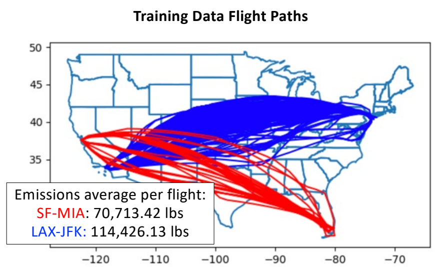
Key Assumptions:

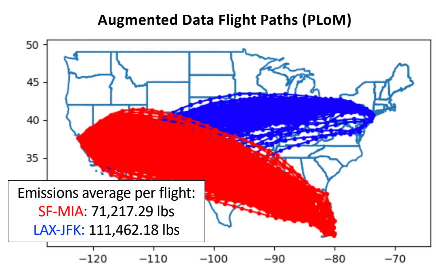
- Sherlock flights meet emissions and safety standards; therefore, flight paths hold approximate intrinsic information about future flights.
- Initial model considers only flights from LAX-JFK and SFO-MIA, chosen to simplify assumptions, while creating flight path intersections to implement safety constraints.
- Airspace capacity reduction due to weather is modeled by reducing the cell capacity to zero when weather is present.

Created a simplified safety model consisting of a 3D airspace grid over the contiguous United States with an allowable operating cell capacity.



Results and Discussion (Nicholas)





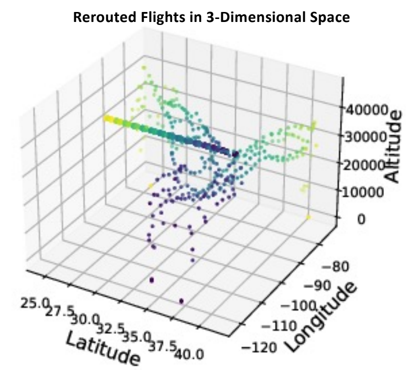
A large number of flight paths is needed for emissions optimization. A GA creates thousands of potential flight paths, and emissions computation using AEDT is too computationally expensive within the GA.

- The top figure shows the original training dataset of N=400 flight paths.
- The lower figure is the augmented flight path dataset produced by PLoM (N=1,000,000).

Example Updated Flight Manifest

	Origin	Destination	Takeoff time	Arrival Time
1	SFO	MIA	16.26	21.94
2	SFO	MIA	18.73	1.36
3	SFO	MIA	15.58	21.33
4	SFO	MIA	4.01	10.10
5	SFO	MIA	20.27	1.98
6	LAX	JFK	21.60	3.18
7	LAX	JFK	16.08	21.02
8	LAX	JFK	0.88	5.97
9	LAX	JFK	1.27	6.38
10	LAX	JFK	22.69	27.23

The right figure shows new flight paths for an optimization execution plotted, with markers color-coded by time-stamp.



- Results demonstrate successful execution of the workflow. Flights are rerouted, subject to airspace capacity constraints while minimizing the total emissions footprint.
- By rerouting aircraft prior to departure subject to known airspace capacity limitations, our algorithm can reduce enroute delays, improving the efficiency of the National Airspace System and reducing carbon emissions.