Evaluating Transatlantic Flight Emissions and Inefficiencies Using Space-Based ADS-B Data

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***Abstract*—The increasing demand for global air travel has intensified the urgency to mitigate aviation's carbon emissions. Continuous monitoring of aircraft fuel efficiency and emissions has become an important task in aviation. One of the main challenges has been the lack of surveillance data for flights across oceans, specifically in the North Atlantic region, where numerous flights occur. Recently, space-based ADS-B data has been made available by new space companies like Spire Global, enabling flight surveillance for aircraft in remote regions, including transatlantic flights. In this study, we utilize several months of space-based ADS-B data from Spire, combined with ground-based ADS-B data from the OpenSky Network, to demonstrate increased accuracy in flight trajectory and emission estimations. We introduce the use of wind data to improve emission quantification. Utilizing these accurate trajectories, we quantify excess emissions by comparing actual flight paths with their optimal alternatives. Our approach provides a robust methodology that benefits future policy for carbon emissions assessments.**

keywords – ADS-B, Flight emissions, OpenSky, Spire Global

I. Introduction

The aviation sector is a significant contributor to global carbon emissions. Although advancements are being made in design optimization and the search for alternative fuels [1], operational improvements remain an important aspect to address for greener flights. Over the past year, research has focused on accurately assessing flight missions and discovering the potential for mitigation through operational optimizations.

Several research studies focus on assessing aviation emissions at an aggregated level to build emission inventories [2], [3], [4]. However, these studies often have to rely on lower-fidelity models that sometimes cannot capture variations in flights caused by different flight paths and speed profiles. They also fail to incorporate meteorological conditions into their analysis.

Since 2020, we have initiated a series of research studies that aim at accurately reconstructing flight trajectories using ADS-B data. This approach allows for the estimation of emissions from individual flight trajectories. In [5], the openly available ADS-B data gathered by the OpenSky network is used for the first time at the European level to assess aviation emissions. The study establishes a workflow that integrates large-scale open surveillance data with the open aircraft emission model, OpenAP, which can be effectively deployed to assess flight emissions. Currently, it supports 35 most common aircraft types and an additional 23 aircraft types through a similar aircraft type.

In a subsequent study [6], we propose a new methodology to interpolate long-range flights, where parts of the trajectories are not covered by ADS-B. This is particularly valuable for transatlantic flights, where only the beginning and end of a flight can be observed by ground-based ADS-B receivers from the OpenSky network. We also investigate the effect of wind and propose its integration with ADS-B trajectory data to provide a more accurate estimation of emissions.

Over the years, research into modeling and quantifying flight inefficiencies, along with the development of associated performance metrics, has gained momentum. The study [7], [8] suggests evaluating flight efficiencies by comparing the actual trajectory with an optimal reference trajectory. The study [9] employs aircraft surveillance data to generate cost-based indicators that quantify flight inefficiencies.

In our study [10], we explore ways to study inefficiencies in terms of excess emissions using open data and models. A fully open flight trajectory optimizer, TOP, is developed as an extension of OpenAP. These inefficiencies are identified as the differences between emissions from actual and optimal flight trajectories. One limitation is that wind conditions are not considered in the emission analysis.

There are three main challenges in flight emission analysis and inefficiency assessment: 1) limited coverage from ground-based ADS-B receivers; 2) the complexity of incorporating wind data into emission estimates; and 3) the computational speed required for optimal trajectory generation.

With the advent of space-based ADS-B, this paper focuses on merging space-based and ground-based aircraft surveillance data to offer a more accurate method for assessing flight emissions. We use a large dataset of transatlantic flights to demonstrate this approach. Additionally, we address uncertainties arising from the absence and availability of wind measurements. Specifically, we incorporate wind data from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 dataset to quantify the impact of upper-level wind components on emission analysis. Beyond quantifying carbon emissions, we also study and quantify flight inefficiencies by comparing them to fuel-optimal 4D trajectories that consider wind conditions.

The structure of the paper is organized as follows: Section II addresses the data sources of this study. Section III explains the process of data fusion to generate complete transatlantic trajectories. Section IV provides insights into how we perform the emission estimations with the enhanced flight trajectories and wind information. Section V explores the possibility of using the same trajectory data to study the emission inefficiencies. Finally, Sections VI and VII describe the discussions, recommendations, and conclusion of this study.

II. Data Sources

The data for this study originates from multiple sources, including space-based ADS-B information from Spire satellites, ground-based ADS-B information from the OpenSky Network, and reanalysis weather data from ECMWF ERA5. In total, we employ three months of data covering each March from 2020 to 2022 for the analysis presented in this paper.

Spire's Low Earth Multi-Use Receiver (LEMUR) satellites provide a network of space-based receivers that capture ADS-B data over remote areas, such as North Atlantic flight corridors. However, these satellites' low Earth orbit yields dynamic coverage. To augment this dataset, we retrieve historical information from the OpenSky Network, enhancing coverage at lower altitudes.

Fig. 1 illustrates OpenSky receiver coverage within the area of interest, which primarily encompasses continental and coastal regions. Atlantic coverage is notably absent, except around some islands outfitted with ADS-B receivers.

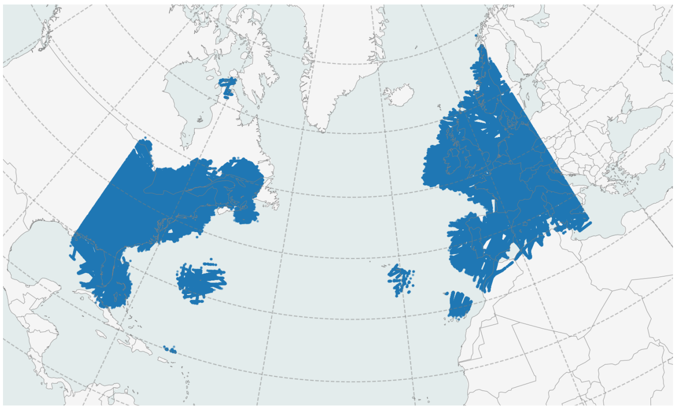

Figure 1. ADS-B coverage of OpenSky Network on 10 March 2021.

Fig. 2 depicts ADS-B coverage from Spire satellites. Here, we observe more extensive coverage over both land and ocean. However, the data appears less dense due to the satellites' rapid orbits and slower data downlink rates, compared to ground communications.

When we amalgamate both data sources, Fig. 3 reveals significantly enhanced aircraft surveillance coverage. This improved dataset enables high-resolution tracking of continental flights and comprehensive monitoring of oceanic flights. Utilizing a specialized data fusion algorithm, we construct complete flight trajectories.

Wind data from ECMWF is extensively employed in various studies. For data visualization completeness, we also present the 1-degree grid ERA5 wind coverage in Fig. 4. For subsequent calculations in this study, a grid with 0.25 degrees of resolution is utilized.

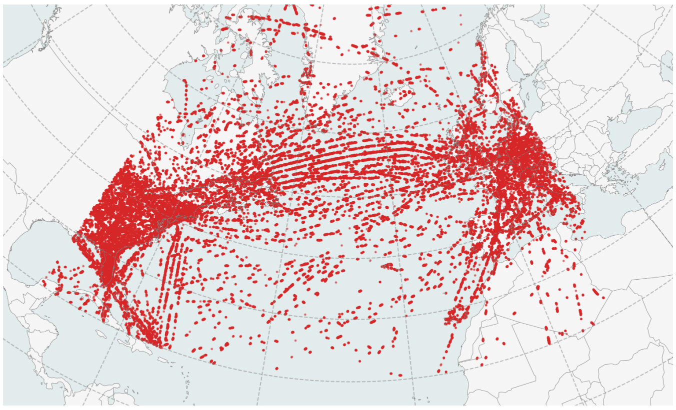

Figure. 2. ADS-B coverage from Spire satellites on 10 March 2021.

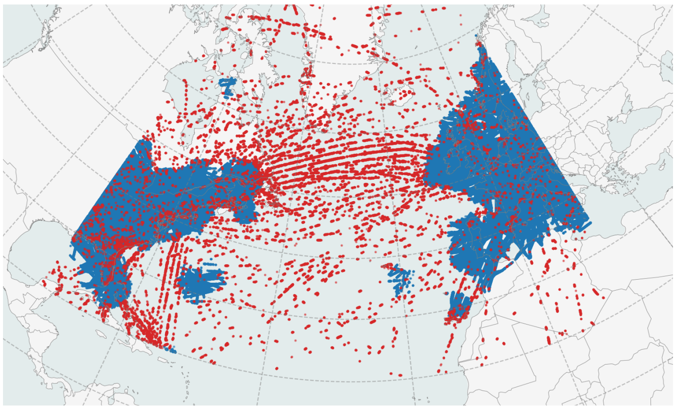

Figure 3. Combined ADS-B coverage from OpenSky and Spire on 10 March 2021.

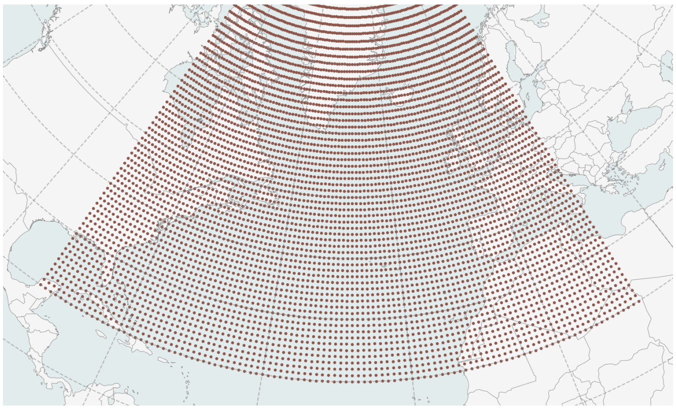

Figure 4. ERA5 wind coverage

For emission estimations involving wind, we employ a regular grid interpolator to determine wind components from the nearest wind grid point. This approach offers higher computational efficiency than interpolation methods while delivering comparable results.

In the excess emission analysis, we use wind data to generate optimal trajectories. The wind information is modeled by a second-order polynomial, enabling its use for gradient calculations in the non-linear optimal control optimizer, TOP, from OpenAP. In this context, a distinct polynomial model is constructed for each flight based on wind data near the great circle paths.

III. Data Fusion

The primary objective of this study is to identify an efficient method for merging sparse space-based ADS-B data with dense ground-based ADS-B data. Subsequently, we aim to provide filtered and properly resampled complete trajectories for subsequent analysis.

Utilizing the *traffic* library [11], we initially segment the trajectory data into multiple flights. This set comprises all flights within the region of interest, including intracontinental flights.

To pinpoint flights that have traversed the Atlantic Ocean, we first identify flights detected at latitudes between -45 degrees and -25 degrees, as well as at a maximum altitude of approximately 30,000 ft. This region is depicted in Fig. 5. We extract all relevant transponder codes (ICAO 24-bit addresses) from this region and subsequently filter out all corresponding flight data from the combined dataset, as shown in Fig. 6.

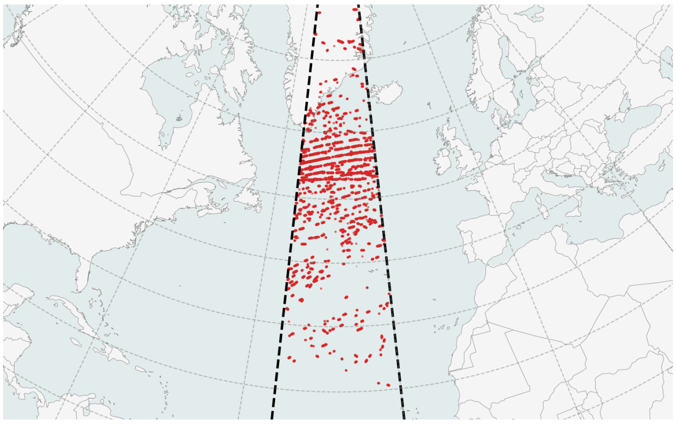

Figure 5. Filtering cross-Atlantic flights

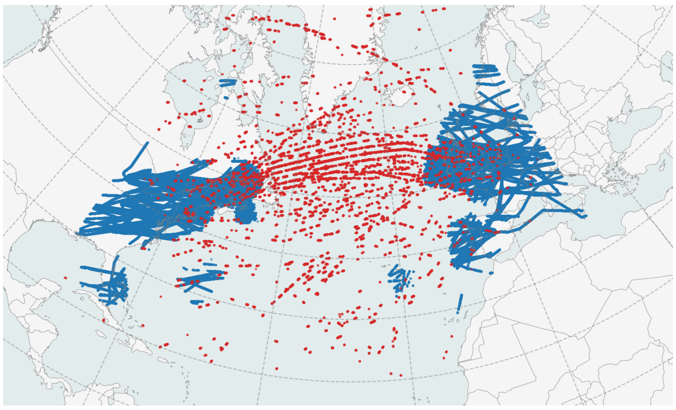

Figure 6. All cross-Atlantic flights

Lastly, to focus on flights from the beginning of the climb to the end of the descent, we ensure that only those with data below an altitude of 6000 ft are included. These trajectories are then filtered and resampled to a 15-second resolution for subsequent research steps. A final set of one-day trajectories is presented in Fig. 7, comprising approximately 200 complete flights, which only counts for the flights between the east coast of North America and Western Europe.

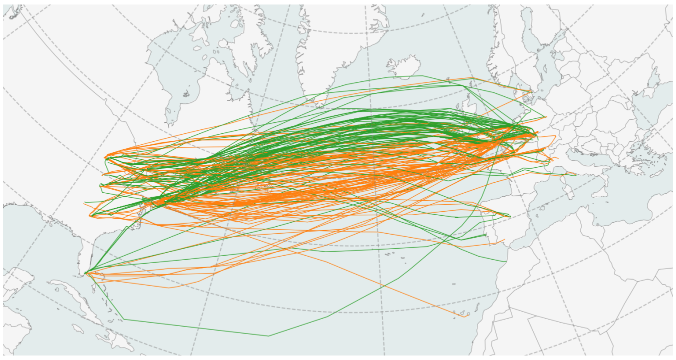

Figure 7. Full trajectories of around 200 cross-Atlantic flights, constructed based on the combined Spire and OpenSky data on 10 March 2021. The green trajectories represent eastbound flights, and the orange trajectories represent westbound flights.

These complete flights from all days in the dataset serve as the basis for subsequent emissions analysis and investigation into flight emission inefficiencies.

IV. Emission Analysis

The emission analysis primarily builds upon the methodology proposed in our previous work [6]. However, unlike in [6], where emissions are estimated solely based on ground speed, this study integrates weather data with ADS-B data for a more accurate wind approximation.

Utilizing the ground speed and approximated true airspeed, we estimate flight emissions using the OpenAP model [12]. This model incorporates multiple variables, such as aircraft mass, aircraft types, altitude, and speed, to estimate fuel consumption and emissions for each flight.

As the take-off masses of the aircraft are not available from the surveillance data, we treat them as an interval during the emission quantification process. For each flight, the initial mass is considered to fall between 70% and 90% of the maximum take-off weight for the corresponding aircraft type.

For each flight, two sets of total emissions are calculated. The first set is based on measured ground speed from ADS-B data and varying initial mass. The second set employs the approximated true airspeed, as previously mentioned.

Fig. 8 displays an example of an eastbound flight, with trajectory segments from Spire and OpenSky data labeled in red and blue, respectively. The direction and magnitude of the wind along the trajectory are also indicated.

A. Examples of Eastbound and Westbound Flights

Fig. 9 presents an eastbound example flight from KMIA to LFPG. Tailwinds along the trajectory can be observed. The lower plot displays CO_2 emission rates along the trajectory, with confidence intervals representing uncertainty due to

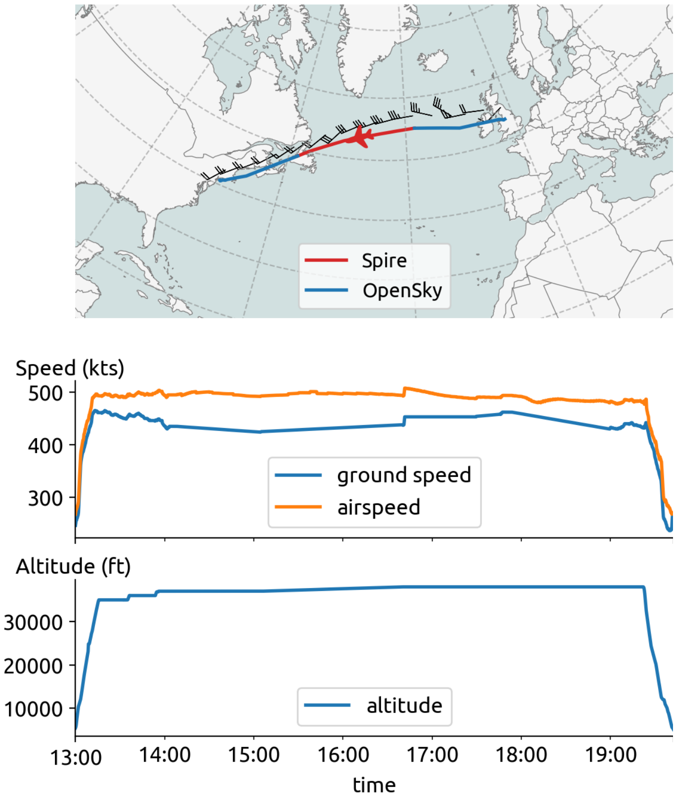

Figure 8. An example flight trajectory combining both space-based and ground-based ADS-B data

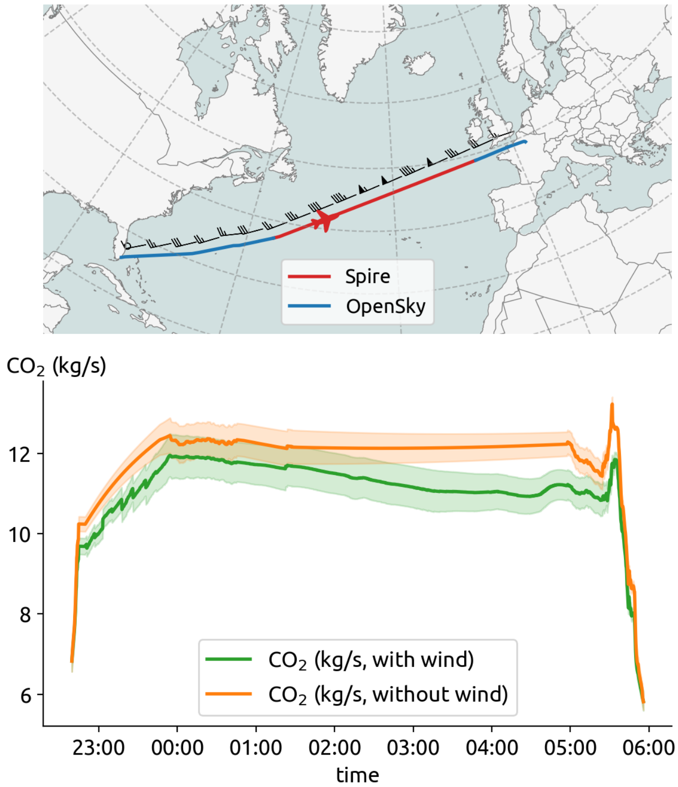

Figure 9. An eastbound flight from KMIA to LFPG

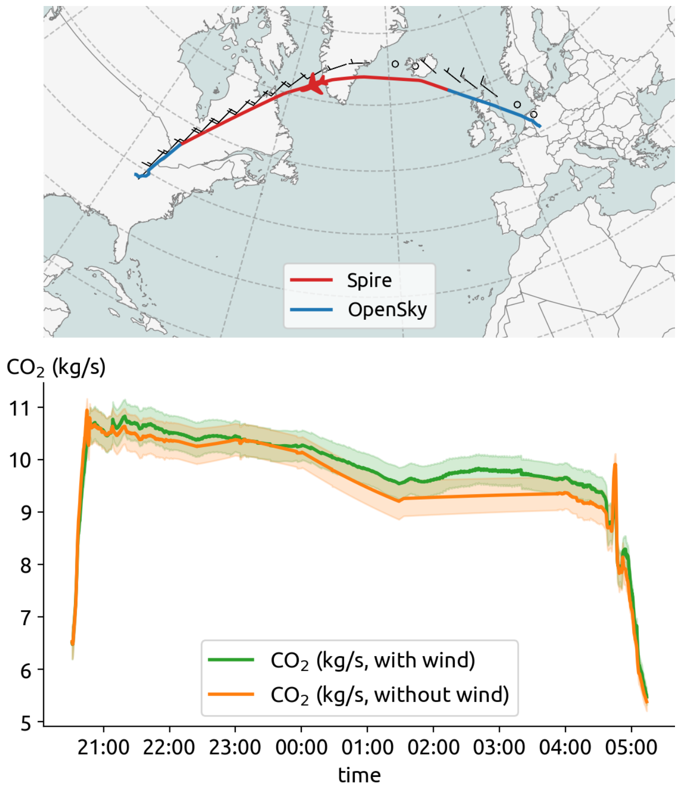

Figure 10. A westbound flight from EDDK to KSDF

varying take-off weight assumptions. In this case, emissions estimated under true airspeed conditions are lower than those based on ground speed. Total emissions are approximately 290 and 310 tons, respectively. The difference of 20 tons constitutes around 6.5% of the total emissions for this flight, which is quite a significant error.

In Fig. 10, a westbound example flight is depicted. Here, emissions estimated with wind are higher than those based on ground speed. The difference is minimal at the flight's commencement due to calm winds but increases later due to stronger headwinds.

B. Aggregated Emission Analysis

A comprehensive analysis is conducted on a dataset of 21,674 complete flight trajectories, comprising 10,940 eastbound and 10,734 westbound flights. This dataset spans flights from March in three consecutive years, from 2020 to 2022, offering a robust evaluation of emission estimations considering the influence of wind on ADS-B trajectories.

Fig. 11 illustrates the difference in CO_2 emission estimates when using ground speed and true airspeed. Negative values indicate that emissions estimated with airspeed are lower than those with ground speed. For eastward flights, average CO_2 emissions can be overestimated by about 10 tons, with a variation of up to 1.5 tons depending on the assumed take-off mass. This constitutes approximately 5% of the total carbon emissions per flight. Conversely, for westbound flights, emissions tend to be underestimated by around 6 tons.

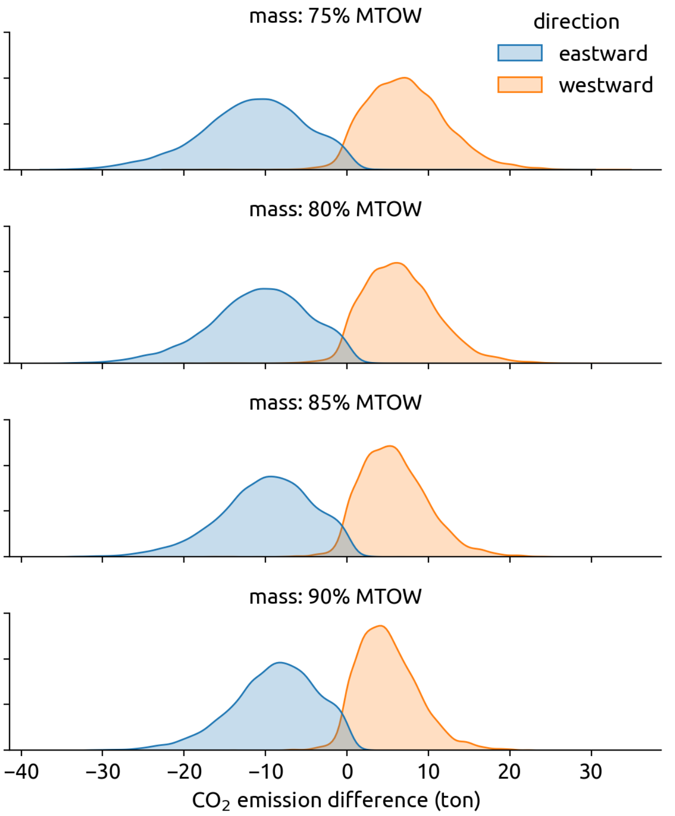

Figure 11. Differences in CO_2 calculations when considering wind. The results include all flights for the months of March from 2020 to 2022.

This figure also reveals the overall impact of different take-off mass assumptions on emission estimates. Higher assumptions generally yield smaller wind-induced differences. However, the significance of over- and underestimation for eastward and westward flights remains consistent across different mass assumptions.

V. Inefficiency Analysis

The inefficiency analysis focuses on examining excess carbon emissions caused by suboptimality in all flights. For each flown trajectory, we construct its optimal alternative considering a 3D wind field and the time at the start of the flight. Inefficiency is then quantified as the additional emissions from the optimal trajectory compared to the flown one.

To handle uncertainties in take-off mass, we adopt a strategy similar to previous emissions analyses for mass initialization. Optimal trajectories are constructed using different initial masses ranging from 70% to 90% of the maximum take-off mass.

When wind is factored in, optimizing a complete trajectory, which includes climb, cruise, and descent, becomes noticeably slower than without wind consideration. To simplify the computational effort, only the optimal cruise trajectory, assuming the same origin and destination, is generated for comparison in this study. We note this is a simplification made to improve the computation speed for optimal trajectory generation.

A. Generation of Optimal Trajectory

The optimal trajectory is generated using the open-source *OpenAP.top* trajectory optimizer [13]. This optimizer employs a non-linear optimal control approach to create the best trajectory based on various cost functions, including fuel, cost index, and other climate metrics. In this study, we opt for the fuel-efficient objective, which is synonymous with emission efficiency.

Formulating the optimal flight trajectory is treated as an optimal control problem, where the ideal combination of parameters such as position, speed, and altitude must be determined at each time interval.

Considering a simplified point-mass aircraft performance model, the following flight states are involved in this control process:

$$\mathbf{x}_t = [x_t, y_t, h_t, m_t] \tag{1}$$

where (x, y), h, and m are the position, altitude, and mass of the aircraft. The control states include:

$$\mathbf{u}_t = [M_t, \mathsf{vs}_t, \psi_t] \tag{2}$$

where M, vs, and ψ are Mach number, vertical rate, and heading of the aircraft. The dynamic, or evolution, of the states, can be defined by the following ordinary differential equations:

$$\frac{\mathrm{d}x}{\mathrm{d}t} = v_t \sin(\psi_t)\cos(\gamma_t) + w_{x,t} \tag{3}$$

$$\frac{\mathrm{d}y}{\mathrm{d}t} = v_t \cos(\psi_t)\cos(\gamma_t) + w_{y,t} \tag{4}$$

$$\frac{\mathrm{d}h}{\mathrm{d}t} = \mathsf{vs}_t \tag{5}$$

$$\frac{\mathrm{d}m}{\mathrm{d}t} = -\mathsf{ff}_t(m_t, v_t, h_t) \tag{6}$$

where v_t is the true airspeed, γ_t is the flight path angle, and ff_t is the fuel flow model that is dependent on the aircraft mass, speed, and altitude. $w_{x,t}$ and $w_{y,t}$ are wind speed components. True airspeed is calculated based on Mach number (M) and altitude (h) assuming the international standard atmosphere (ISA) conditions:

$$\gamma_t = \tan^{-1}\left(\frac{\mathsf{vs}_t}{v_t}\right) \tag{7}$$

$$v_t = M_t a_0 \sqrt{\Gamma R T_{h_t}} \tag{8}$$

where a_0 is the speed of sound constant at sea level, Γ is the ratio of specific heat, R is the gas constant for air, and T_h is the air temperature at altitude h.

Knowing states, controls, and the dynamics of an optimal control system, the next task is to formulate the problem in a way that can be solved by non-linear programming that consists of a set of constraints and an objective function. The generalized form of an objective function (J) can be expressed as:

$$J(\mathbf{x}, \mathbf{u}, t_0, t_f) := E(t_0, t_f, \mathbf{x}_{t_0}, \mathbf{x}_{t_f}) + \int_{t_0}^{t_f} L(\mathbf{x}_t, \mathbf{u}_t, t)\mathrm{d}t \quad (9)$$

where $E(\cdot)$ and $L(\cdot)$ are the Mayer and Lagrangian terms. They correspond to the cost at the endpoints, as well as the cost along the trajectory, respectively. The minimization of the objective function is:

$$\min_{\mathbf{x}_t, \mathbf{u}_t} J(\mathbf{x}, \mathbf{u}, t_0, t_f); \quad t_0 < t < t_f \quad (10)$$

is subject to the following constraints:

$$\dot{\mathbf{x}}_t = \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t) \quad (11)$$
$$\mathbf{h}(\mathbf{x}_t, \mathbf{u}_t) < 0 \quad (12)$$
$$\mathbf{e}(t_0, t_f, \mathbf{x}_{t_0}, \mathbf{u}_{t_0}, \mathbf{x}_{t_f}, \mathbf{u}_{t_f}) = 0 \quad (13)$$

where $\dot{\mathbf{x}}$ is the first-order dynamic constraint represented by the earlier system equations, $\mathbf{h}(\cdot)$ represents the path constraints, and $\mathbf{e}(\cdot)$ represents the conditions at endpoints.

The solution for such an optimal control problem can be computed numerically. The direct collocation approach from *OpenAP.top* discretizes the continuous problem into segments that consist of a predefined number of time intervals. Within each interval, the states are approximated using polynomials at collocation points in each time interval.

Finally, a numeric solver is adopted to derive the optimal control states (and related flight states). The numerical solver is an open-source library called CasADi [14], a symbolic framework for numeric optimization.

Fig. 12 illustrates a real-world flight alongside its optimal trajectories under varying initial mass assumptions.

B. Aggregated Inefficiency Analysis

The analysis of inefficiencies demands elevated computational resources due to the necessity of generating optimal trajectories. Optimizations for all trajectories over a three-month period, taking into account wind conditions and varying initial masses, are performed on a high-performance computing node and completed in approximately 30 hours.

Fig. 13 presents the reasonable differences between the optimal and estimated emissions from flown trajectories with corresponding initial masses. In this figure, it is evident that there is a wide range of emission inefficiencies, which can reach up to 25 tons of CO_2 per flight. Different initial mass assumptions exert only a minor influence on the overall emission inefficiency distribution.

However, a noteworthy number of optimal trajectories result in greater emissions than their estimated counterparts from actual flights. This has significant implications for trajectory optimization, which will be discussed in the subsequent section.

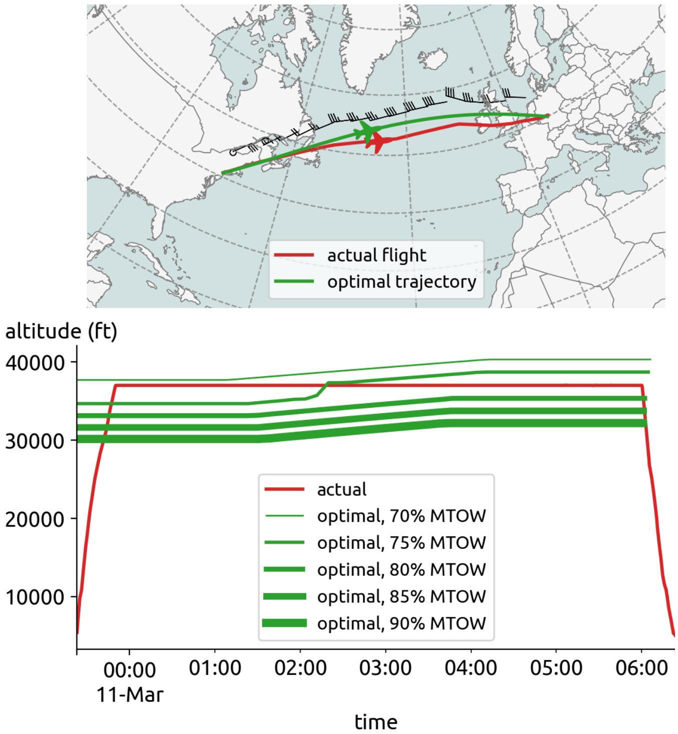

Figure 12. An example of an actual trajectory (in red) and its optimal alternatives, depending on the initial mass

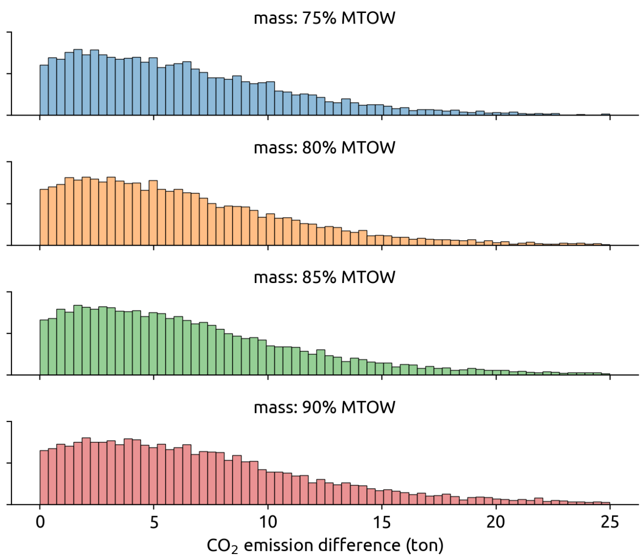

Figure 13. The discrepancy in CO_2 emissions between optimal trajectories and estimations from actual flights. Note that there are also negative values, visualized in Fig. 14.

VI. Discussions

A. Space-based ADS-B Data

The first part of this paper focuses on maximizing the utility of space-based ADS-B data for trajectory-based analyses. Although our primary focus is on emission analysis, this data can also be employed for other research areas, such as efficiency and safety in oceanic airspace.

Space-based surveillance systems offer unparalleled coverage across global airspaces. However, they come with limitations. Compared to ground-based ADS-B data, the data rate from space-based systems is significantly lower due to the limited communication downlink capacity of satellites. Additionally, ADS-B observations are often provided in patches, influenced by the dynamic orbits of the satellites.

As more satellites are deployed and integrated with ground-based ADS-B systems, these challenges are likely to be mitigated. In this study, we have developed a workflow using the *traffic* library to aggregate data, segment flight legs, filter outliers, and resample trajectories at a fine resolution for in-depth analyses.

B. Complete Trajectories

It is important to note that our analysis does not encompass all transatlantic flights. We have restricted our focus to flights departing and arriving at the east coast of North America and Europe, based on a bounding box defined between longitudes of -90 and 15 degrees.

The construction of full trajectories excludes flights that lack observations below 6000 ft during either ascent or descent, regardless of whether the data is ground or space-based. In cases where a flight is not observed by Spire satellites, it is reconstructed using only OpenSky data. The oceanic segment is interpolated based on available data at the beginning and end of the flight.

C. Emissions Variability Due to Wind Components

This study aims to analyze emission variations in eastbound and westbound flights considering wind components. Eastbound flights generally exhibit reduced emissions due to tailwinds (up to around -20%), while westbound flights tend to show increased emissions (up to around 10%) due to headwinds.

We have performed this analysis considering different initial masses, revealing that the variability in total emissions is consistent across mass assumptions. In this study, ERA5 wind data was used, although wind data from Spire satellites could further enhance the analysis.

D. Policy Implications

The rationale behind this study is to provide a more accurate method for quantifying individual flight emissions, aiming to inform future policy decisions. The incorporation of space-based ADS-B and upper wind components into emission models could substantially influence policy recommendations and corporate carbon emission strategies.

E. Limitation of Emission Inefficiency Analysis

The emission inefficiency in this paper should be considered as a preliminary study, as we do observe anomalies in the final results. Previously, we have shown the statistics of inefficiencies in Figure 13, which is observed in the majority of the flights.

However, there are still a significant number of flights that seem to produce more emissions with the optimal trajectory, shown as white bars in Figure 14. For different flights, the appearance of negative inefficiency can also depend on the initial mass. But at the aggregated level, the trends are similar.

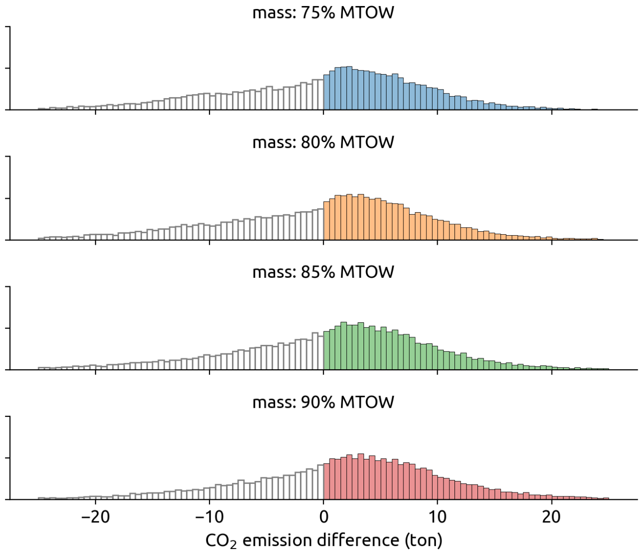

Figure 14. The emission inefficiencies estimated based on optimal trajectories. Negative inefficiencies are shown as white bars.

With some investigation, it seems the main issue lies with the optimization process when the wind field is considered. In the following Figure 15, the negative inefficiencies are mostly related to the westward flights. It is very likely that the optimizer failed to find more aggressive diverted flight paths with very strong headwinds, which occur due to jet streams.

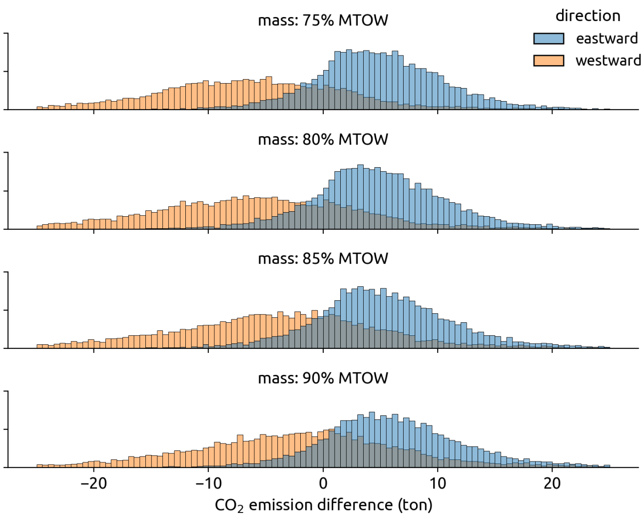

Figure 15. The inefficiencies grouped by the flight directions. The generation of optimal trajectories for westward flights seems to have failed.

To cope with this issue, we will need to revisit the construction and constraints in the TOP optimizer from OpenAP. Currently, only a 3D wind field can be considered in the optimization; for transatlantic flights, a 4D wind field should ideally be considered in future updates.

Another potential issue caused by the wind is the regularized polynomial model assumed for the wind field. The regularized model may not be able to capture the large changes in the wind due to jet streams, which in turn provides an overly smoothed wind model. As a realistic wind gradient is important for generating the optimal trajectory, this would also affect the optimizer and produce non-optimal flight trajectories.

The final approach to improving the convergence of the optimizer could consider the actual trajectory, instead of the great circle, as the initial condition. This is because many westbound trajectories have been observed to have large differences from the great circle due to strong headwinds. The change in the initial condition could potentially reduce the number of *locally optimal* trajectories.

VII. Conclusion

In this research, we bridged a gap in aviation emissions assessment by integrating both ground-based and space-based ADS-B data, specifically targeting transatlantic flights. This was complemented by the inclusion of ECMWF ERA5 wind data, introducing a new layer of precision into the emission estimation process. The overarching aim was to address gaps in surveillance coverage and meteorological data integration, thereby offering a more robust methodology for quantifying aviation emissions.

Our primary finding indicates that the fusion of ground-based and space-based ADS-B data significantly enhances the trajectories, and thus improves emissions estimates. This is particularly crucial for policymaking and corporate decision-making in aviation, as it provides a reliable foundation for emissions evaluations, especially for future aviation carbon offset programs. The study also reveals that wind conditions, often overlooked, play a critical role in emissions variability. In particular, eastbound flights generally show reduced emissions estimations with wind information, while westbound flights experience elevated emissions due to the influence of headwinds.

While the study brings several advancements, it also uncovers certain limitations, notably in the optimization algorithm for westward flights. Addressing these constraints and considering the integration of 4D wind data are essentially the next steps. Subsequent research may focus on refining optimization algorithms. In this study, we do not consider the North Atlantic Organized Track System that ensures the safety of flight operations. Thus, this optimal trajectory-based inefficiency approach shows only the theoretical emission inefficiency.

In summary, this research stands as a milestone in emissions assessment using open models and ADS-B data, offering a robust, comprehensive methodology at individual flight levels with potential policy implications on emission assessment.

Acknowledgement

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