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Robust climate-optimal flight planning toward identifying "win-win" solutions

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Abstract

Despite being a promising measure to mitigate non-CO_2 climate effects, climate-optimal flight planning is generally not cost-effective. However, aviation stakeholders can address this issue by implementing market-based instruments, which are currently lacking for non-CO_2 emissions. This study proposes a novel flight planning framework, which accounts for the cost of non-CO_2 emissions alongside CO_2 emissions in order to plan trajectories that mitigate both operational costs and climate effects. The costs of non-CO_2 species are quantified within the concept of equivalent CO_2 emissions. The prototype algorithmic climate change function is used to convert non-CO_2 emissions to equivalent CO_2 emissions by using average temperature response as a climate metric. This selection allows considering the location and weather dependencies of non-CO_2 species, as well as forecast-related uncertainty in conversion to equivalent CO_2 emissions. Simulate results demonstrates the effectiveness of the proposed in optimizing aircraft trajectories, yielding mitigation in both climate impact and operating cost.

1. Introduction

There was indeed a continuous increase in commercial air traffic up to the year 2019. However, a steep decrease in 2020 ended this trend due to the global COVID-19 pandemic (55% and 44% of flight movements declined in 2020 and 2021, respectively, compared to 2019 (EUROCONTROL, 2022[2]). This decline in air traffic is, however, temporary, and according to the latest estimation by International Air Transport Association (IATA), it will completely recover by 2024[7] and continue to grow by 1.2% annually. Among the critical challenges this growth poses is the aviation sector's contribution to global warming through CO_2 and non-CO_2 emissions, accounting for approximately 3 to 5% of total radiative forcing (RF).[8] The non-CO_2 climate effects, including NO_x-induced changes in the concentrations of ozone and methane, water vapor emissions, and the formation of persistent contrails as the most relevant species, are responsible for 66% of effective radiative forcing.[8] The aviation-induced non-CO_2 climate effects strongly depend on the atmospheric conditions at the time and location of emissions.[10] These dependencies offer opportunities to mitigate their climate effects with more efficient flight planning, i.e., avoiding areas with large climate impact.[19] In this respect, the preliminary step is identifying regions with significant climate effects, called climate-sensitive areas. Flight planning tools should then use such information to generate climate-friendly trajectories. Numerous studies in the literature have explored the feasibility of reducing the climate impact caused by non-CO_2 emissions by avoiding climate-sensitive regions (see[19] for a review). These studies have highlighted the existing trade-off between climate impact mitigation and operating cost. This is reasonable as aircraft will fly longer to re-route areas with significant climate effects, and thus, the operating costs increase (e.g., through an increase in flight time).[18]

The increase in the operating cost due to adopting climate-optimized routes is not favorable for aviation stakeholders. Thus, there is a need to compensate for the extra cost to incentivize airliners. Market-based instruments, such as taxes, charges, and marketable permits, are commonly favored for regulating international activities like aviation due to their potential to effectively accomplish climate goals at a lower cost.[12] Including additional costs through fees or taxes for aviation-induced climate impact would directly impact airlines' operating costs, prompting changes in current routing strategies and incentivizing the adoption of climate-optimized flight planning. Consequently, both climate impact and operational costs can be reduced, making climate-friendly trajectories cost-effective. Currently, under the EU ETS (European Union Emissions Trading System), aircraft operators are required to hold and surrender allowances for carbon dioxide emissions for all flights within the European Economic Area (EEA) from 2012.[15] While market-based instruments like emission trading schemes (ETS) include CO_2 emissions, they currently lack provisions for non-CO_2 emissions.[11,12] Several strategies have been proposed to quantify the costs of non-CO_2 emissions, which can be categorized under the concepts of climate-charged airspace and equivalent CO_2 emissions.[12] For climate-charged airspace,

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areas with large climate impact (a threshold needs to be defined in order to determine the severity), charges (e.g., in USD/km) are considered for the flights crossing the identified climate hotspots.[11] Within the latter concept, the non-CO_2 species are represented as equivalent CO_2 emissions using a climate metric. Then, existing environmental taxes of CO_2 emissions are applied to the determined equivalent CO_2 emissions. Conversion factors used in the literature are often constant and rely on climate response metrics like RF and GWP. For instance, in,[4] constant conversion factors based on GWP are used to convert non-CO_2 species' effects into equivalent CO_2 emissions. Then, the environmental taxes associated with CO_2 emissions based on the EU ETS certificate are used for the equivalent CO_2 emissions. However, considering only the amount of fuel consumed or CO_2 emitted in the flight planning process when using constant conversion factors may lead to a focus solely on reducing fuel consumption by flying at higher altitudes. Nevertheless, due to the weather and spatial dependency of non-CO_2 species, there is a risk of increasing their climate impact by flying in areas with higher climate sensitivity.[11] Therefore, it is required to derive time and spatial dependent conversion factors to capture the non-CO_2 climate effects more reliably when converting to equivalent CO_2 emissions. In addition, the strong dependency of non-CO_2 climate impacts on meteorological conditions leads to having an uncertain estimation of climate impact and, consequently, uncertain conversion factors, as the weather forecast is inevitably uncertainty. No recent study has considered the full location and weather dependency of non-CO_2 climate effects to plan climate-optimized aircraft trajectories cost-effectively. In addition, the effects of meteorological uncertainty have yet to be addressed in calculating equivalent CO_2 emissions.

This study will close these gaps by proposing a new framework for planning climate-optimal trajectories under meteorological uncertainty. We use version 1.0a of the algorithmic climate change function (aCCFs) to determine spatiotemporal dependent CO_2 equivalent conversion factors based on the average temperature response (ATR) as a climate metric.[1,9,21] Despite having better accuracy and flexibility compared to the concept of climate-charged airspace, one drawback that has been highlighted in the literature is the complexity of assessing the cost of equivalent CO_2 emissions as detailed information on the lateral path, altitude profile, speed schedule, weather data, fuel flow, and NO_x emissions per flight are required (see[11,12]). To cope with this challenge, we incorporate cost quantification of climate effects as a term in the objective function of the trajectory optimization problem. Therefore, the trajectory is optimized considering the cost of climate effects, in addition to costs of operation, including fuel burn and flight time. In this respect, the equivalent CO_2 emissions are dynamically calculated and optimized within the flight planning phase without requiring post-assessments. To consider weather forecast uncertainty in calculating climate impact and also climate impact cost quantification, we use an ensemble prediction system weather forecast, which provides n probable realization of meteorological conditions. The proposed flight planning problem is formulated within the context of robust optimal control theory, based on building trajectory ensemble introduced by.[5]

2. Cost-effective climate-optimal flight planning

This study explores the potentiality of reducing aviation-induced climate effects with flight planning at a reasonable operating cost. The approach generally used in the literature to model such an aircraft trajectory optimization problem is to consider a weighted sum of operating cost and climate impact as optimization objectives. However, these objectives are generally in conflict, implying that adopting optimized trajectories with a higher mitigation potential is only possible by accepting extra operating costs.[19] Such a cost increase may not be acceptable for aviation stakeholders. Therefore, a market-based mechanism for aviation-induced climate effects is needed to compensate for the additional cost of re-routing business-as-usual trajectories and a framework to incorporate such climate cost quantification into flight planning tools.[12] Our goal in this study is, therefore, to consider taxes for non-CO_2 species using the existing market-based measures of CO_2 emissions using the concept of equivalent CO_2 emissions and then formulating aircraft trajectory optimization problem to account for the taxes of emissions (CO_2 and non-CO_2) in order to deliver climate-optimal trajectories cost-effectively.

2.1 Equivalent CO_2 emissions

In order to quantify the cost of non-CO_2 species, we need first to convert them to equivalent CO_2 emissions. Such a conversion is generally done using a climate metric. In literature, metrics such as GWP and RF have been used (see, e.g.,[4,14]). However, these metrics relate the non-CO_2 emissions to CO_2 emissions through a constant factor. In this respect, the total equivalent CO_2 emissions is a linear function of fuel burn. Therefore, the optimizer tries to seek trajectories that reduce fuel consumption. Such an approach for conversion has been heavily criticized as the weather and spatial dependencies of non-CO_2 emissions are ignored, leading to inefficient cost quantification.[3] To this end, to avoid misguiding incentives, full dependencies on non-CO_2 climate effects need to be considered, which can be written

DOI: 10.13009/EUCASS2023-632

in general form as follows:

$$\text{E-}^{eq}\text{CO}_2(t,\mathbf{l}) = \text{E-CO}_2 + \sum_{k\in K} {}^{eq}\text{CO}_2^k(t,\mathbf{l}) \cdot \text{E-}k(t,\mathbf{l}) + {}^{eq}\text{CO}_2^{\text{Cont.}}(t,\mathbf{l}) \cdot s(t,\mathbf{l}) \tag{1}$$

where t is the flight time, $\mathbf{l}$ is the atmospheric location of the flight (i.e., latitude, longitude, and altitude), E-${}^{eq}CO_2$ is the net equivalent CO_2 emissions, E-CO_2 is the CO_2 emissions, E-k is the volume of emissions and ${}^{eq}CO_2^k$ is the equivalent CO_2 conversion factor as a function of emission location and time corresponding to species k ($\in \{NO_x, H_2O\}$). s is the distance flown, and ${}^{eq}CO_2^{\text{Cont.}}$ is the equivalent CO_2 conversion factor for contrail-induced cloudiness as a function of emission location and time.

To consider such dependencies when converting non-CO_2 species to equivalent CO_2 emissions (i.e., E-${}^{eq}CO_2(t,\mathbf{l})$), the prototype aCCF is a suitable choice.[10] aCCFs quantify the climate effects of CO_2 emissions and the most important non-CO_2 species, such as NO_x emissions, water vapor emissions, and formation of persistent contrails by taking specific meteorological variables, such as geopotential and relative humidity, as inputs. The temperature change estimated using aCCFs is based on average temperature response as the climate metric. The implementation of these aCCFs has been recently released as an open-source Python library which can be accessed at DOI: 10.5281/zenodo.7074582. When using aCCFs, one needs to note that, depending on the application, metric parameters, such as emissions scenario, time horizon, and efficacy, need to be appropriately selected. Interested readers are referred to[1] for a detailed description of these parameters. In this study, we use the V1.0a of aCCFs with future emission scenarios integrated over 100 years time horizon to quantify climate effect using ATR. The formulation of the equivalent CO_2 emissions using aCCFs is presented in the Subsection 2.2.2 when defining the objective function.

As these aCCFs require weather information from inevitability uncertain weather forecasts in order to predict climate impact, they are associated with uncertainty. This, in turn, affects the reliability and effectiveness of the quantified cost. In order to account for such uncertainty in climate impact and cost quantification, we need to quantify meteorological uncertainty in the first step. In the meteorological community, the trend is toward using Ensemble Prediction Systems (EPS), generating probabilistic forecasts by running numerical weather prediction models with slightly different initial conditions or model configurations.[13] The individual model outputs are then combined to produce an ensemble forecast, which provides a range of possible outcomes (called ensemble members) to characterize forecast uncertainty. In this study, we use EPS weather information in order to quantify meteorological uncertainty, which is then incorporated into the trajectory optimization problem (in Section 2.2) to deliver robust solutions.

2.2 Trajectory optimization problem formulation

In this section, we present how to incorporate equivalent CO_2 emissions in flight planning in order to determine climate-optimal trajectories in the most cost-effective manner. In other words, we aim to determine a trajectory that minimizes the summation of operating costs and taxes to penalize aviation-induced climate impacts.

As previously mentioned, climate impact and, thus, equivalent CO_2 emissions are uncertain due to the inevitably uncertain weather forecast. In addition, meteorological uncertainty also affects aircraft performance variables as the components of wind and temperature are required for modeling the dynamical behavior of aircraft. To account for meteorological uncertainty in flight planning, we employ our recently developed methodology, which is based on the robust optimal control theory.[6,17] To formulate an aircraft trajectory optimization problem using optimal control theory, a set of constraints, known as dynamical constraints (or aircraft dynamical model), path constraints (e.g., flight envelope), and boundary constraints (e.g., coordinates of origin and destination airports) needs to be defined.[19] Additionally, flight planning objectives are defined as the performance index (or cost functional) of the optimal control problem in order to be minimized (or maximized) with control inputs (e.g., thrust and heading). In order to formulate the optimization problem, accounting for uncertainty, a characterization of uncertainty is required. For this purpose, we use an EPS to quantify meteorological uncertainty. Then, the aircraft dynamical model (point-mass model) is reformulated by defining some additional variables and imposing several path constraints in order to feasibly capture the impacts of uncertainty in wind and temperature on flight dynamical performance, such as flight time and fuel consumption. For integrating meteorological uncertainty, the reformulated dynamical aircraft model is expanded by the number of ensemble members. In the following, we briefly present some required formulations focusing on the aircraft dynamical model with uncertainty effects and objective function definition, including the monetary cost of non-CO_2 climate effects. Interested readers are referred to[17] for a detailed explanation of the proposed approach.

DOI: 10.13009/EUCASS2023-632

2.2.1 Aircraft dynamical model with uncertainty effects

An augmented dynamical model of aircraft that is constructed to capture the uncertainty effects corresponding to wind and temperature is given in the following:

$$\frac{\mathrm{d}}{\mathrm{d}s}\begin{bmatrix}\phi\\ \lambda\\ v_{tas}\\ m_1\\ \vdots\\ m_n\\ t_1\\ \vdots\\ t_n\end{bmatrix}=\begin{bmatrix}\cos(\psi)(R_M(\phi)+h)^{-1}\\ \sin(\psi)\Big((R_N(\phi)+h)\cos(\phi)\Big)^{-1}\\ d_v\\ -f_c(C_{T,1})v_{gs,1}^{-1}\\ \vdots\\ -f_c(C_{T,n})v_{gs,n}^{-1}\\ v_{gs,1}^{-1}\\ \vdots\\ v_{gs,n}^{-1}\end{bmatrix} \tag{2}$$

where ϕ, λ, and v_{tas} represent latitude, longitude, and true airspeed, respectively, while m_i and t_i denote the mass and time, both subject to uncertainty due to meteorological conditions. v_{gs} stands for groundspeed, ψ is the course, C_T is the thrust coefficient, and f_c is the fuel consumption rate. Note that the distance flown is selected as the independent variable instead of time (t) in order to reflect wind uncertainty in the groundspeed and, consequently, on flight time. The state and control variables in this representation are:

$$\begin{aligned}\mathbf{x}_a &= \begin{bmatrix}\phi & \lambda & v & m_1 & \cdots & m_n & t_1 & \cdots & t_n\end{bmatrix}^T\\ \mathbf{u}_a &= \begin{bmatrix}d_v & \psi & \chi_1 & \cdots & \chi_n & C_{T,1} & \cdots & C_{T,n}\end{bmatrix}^T.\end{aligned} \tag{3}$$

Notice that some state and control variables are considered once instead of being repeated n times. This is to obtain operationally feasible trajectories that start and end at specific geographical locations with fixed speed profiles satisfied by considering several equality and inequality boundary and path constraints (given in[17]).

2.2.2 Objective function modeling

The main focus of this study is on the objective function definition. Here, we interpret our goals of flight planning as mathematical expressions to be minimized. We aim to define an objective function, which includes the cost of operations and taxes of emitting CO_2 and non-CO_2 emissions. Notice that we refer to operating cost as the cost, excluding any taxes for emissions. To represent such a cost, we use the simple operating cost (SOC) metric, quantifying cost as a function of fuel and time in USD.[20] As for the cost of climate effects, we need to have a dynamic calculation of climate effects and conversion to equivalent CO_2 emissions. To this end, we define such a cost as a Lagrange term in the cost functional, allowing for evaluating and accumulating the cost over the whole optimization interval (i.e., flight duration). In the following, the proposed modeling of the performance index is given:

$$\begin{aligned}&\mathrm{J}: \text{Operating Cost (OC)} + \text{Climate Cost (CC)}\\ &\mathrm{OC}: \mathrm{C_t}\cdot\mathbb{E}\Big\{t(s_f)-t(0)\Big\}+\mathrm{C_f}\cdot\mathbb{E}\Big\{m(0)-m(s_f)\Big\} \qquad [\mathrm{USD}]\\ &\mathrm{CC}: \mathrm{C_{tax}}\cdot\mathbb{E}\Big\{\text{E-}^{eq}\mathrm{CO_2}(s,\mathbf{x}(s))\Big\}=\mathrm{C_{tax}}\cdot\mathbb{E}\Big\{\text{E-CO}_2\cdot\Big(1+\sum_{k\in K}\frac{\mathrm{ATR}_k^{100}(t,\mathbf{x},\mathbf{u})}{\mathrm{ATR}_{\mathrm{CO_2}}^{100}(t)}\Big)\Big\} \qquad [\mathrm{USD}]\end{aligned} \tag{4}$$

DOI: 10.13009/EUCASS2023-632

for $k \in \{NO_x, H_2O, CO_2, \text{Cont.}\}$ where:

$$
\begin{aligned}
&\mathbb{E}\Big\{t(s_f) - t(0)\Big\} = \frac{1}{n}\sum_{i=1}^{n} t_i(s_f) - t_0 \\
&\mathbb{E}\Big\{m(0) - m(s_f)\Big\} = [m_0 - \frac{1}{n}\sum_{i=1}^{n} m_i(s_f)] \Big] \\
&\mathbb{E}\Big\{\text{E-CO}_2 \cdot \Big(1 + \sum_{k \in K} \frac{\text{ATR}_k^{100}(t, \mathbf{x}, \mathbf{u})}{\text{ATR}_{\text{CO}_2}^{100}(t)}\Big)\Big\} = \frac{1}{n}\sum_{i=1}^{n}\int_0^{s_f} 3.15 \cdot 10^{-3} \cdot |\dot{m}_i| \cdot \Big(1 + \frac{\text{aCCF}^i_{\text{NO}_x} \cdot |\dot{m}_i| \cdot \text{EI}^i_{\text{NO}_x}}{\text{aCCF}_{\text{CO}_2}} \\
&\qquad\qquad + \frac{\text{aCCF}^i_{\text{H}_2\text{O}} \cdot |\dot{m}_i|}{\text{aCCF}_{\text{CO}_2}} + \frac{\text{aCCF}^i_{\text{Cont.}}}{\text{aCCF}_{\text{CO}_2}}\Big) \cdot \text{ds}.
\end{aligned}
\tag{5}
$$

In Eq. (4), $C_t = 0.75$ [USD/s], $C_f = 0.51$ [USD/kg] are weighting parameters selected to represent the cost of operation (simply) in USD. C_{tax} [USD/T($^{eq}CO_2$)] is the tax for emitting equivalent CO_2 emissions. Notice that, as tax rates and pricing mechanisms are subject to change over time as governments and international bodies continue to refine and update their policies to address aviation emissions, we consider tax per tonnes of CO_2 equivalent emissions (C_{tax}) as user-defined parameters and for the case study in Section 3, we present the results by considering different tax penalties.

The defined objective function is based on cost, which includes costs of operations and climate impact. The objective is to determine an aircraft trajectory such that the defined objective function gets minimized. Depending on the severity of the climate effects, as will be shown in the next section, the operating cost without including the tax of emissions may no longer be the most cost-optimal routing strategy. In such cases, optimizing trajectory accounting for the cost of emissions can lead to identifying 'win-win' solutions, i.e., the cost of operations and climate effects are reduced.

3. Simulation results

In this section, we present the potentiality of the proposed methodology in planning cost-efficient climate-optimal aircraft trajectories. Let us consider a flight from Málaga to Geneva on June 18, 2018, at 1200 UTC. It is assumed that the aircraft is in the cruise phase at an altitude of 12 km. Meteorological information required for optimization is obtained from ERA5 reanalysis data products with ten ensemble members[1].

We start by solving a conventional approach to formulate a climate-optimal trajectory planning problem in which a weighted sum of operating cost and climate impact is considered as the optimization objective.[17,18] The operating cost here is the simple operating cost metric, excluding the cost of climate effects. Figure (1) shows the Pareto-frontier generated by varying the weighting parameters of climate impact in the objective function. It can be seen that climate impact mitigation is only possible by accepting increases in operating costs. In addition, relatively high uncertainty is seen in the resulting climate impact. This is mainly due to high variability among the ensemble members of relative humidity to determine areas favorable for generating persistent contrails, as highlighted in.[18] In terms of uncertainty in operating cost, the variability of wind components and temperature is relatively low, leading to negligible uncertainty in the calculation of flight time and fuel burn and, consequently, the operating cost assessed using the SOC metric.

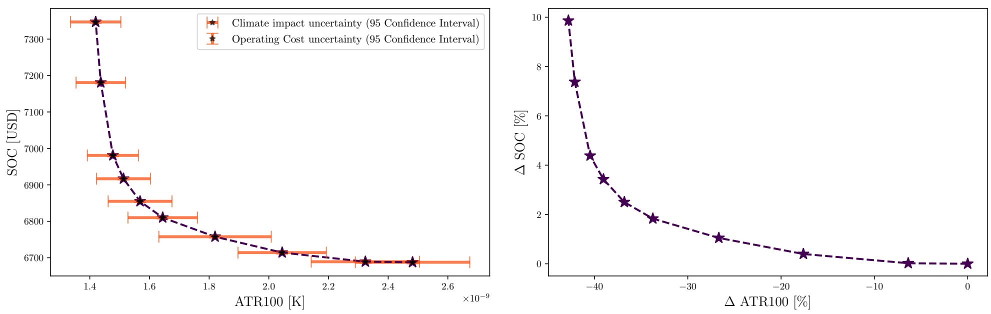

Figure 1: Pareto-frontiers (**LHS**: absolute values, **RHS**: relative values in percentage) obtained by penalizing the climate impact with different values. The objective function of the optimization is a weighted sum of SOC and ATR.

[1] Publicly available at DOI: 10.24381/cds.bd0915c6

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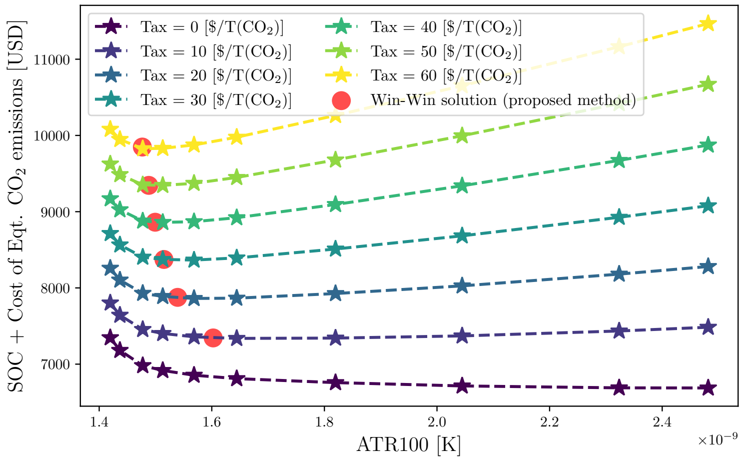

Figure 2: Pareto-frontier shown in Fig. (1) is regenerated by adding the cost of equivalent CO_2 emissions with different penalties in USD/T(CO_2).

Now let us assess the performance of the optimized trajectories (w.r.t. a weighted sum of climate effects and the operating cost) by considering taxes in USD per tonne of equivalent CO_2 emissions. The Pareto-frontier depicted in Fig. (2) shows that the cost-optimized trajectory is no longer the most cost-optimal routing option when the cost of resulting climate impact is considered. It can be seen that some routing options yield mitigation in both climate effects and cost, called "win-win" solutions. In literature, such a "win-win" analysis is performed only as an assessment of optimization w.r.t a weighted sum of climate impact and operating cost similar to what we have conducted so far (see[12,16]). In this respect, operationally speaking, the calculation of equivalent CO_2 emissions and cost quantification needs to be performed individually for each flight as post-assessments, which causes a recurring effort.[12] The Pareto-frontiers with uncertainty ranges on climate effects, and operating cost (which includes tax of emissions) is given in Fig. (3). Here, we conclude that uncertainty significantly increases when the cost of climate effects is considered in the operating cost. This is an important aspect (i.e., high dependency of non-CO_2 climate effects on weather conditions) that needs to be considered when planning market-based instruments for aviation-induced non-CO_2 climate effects.

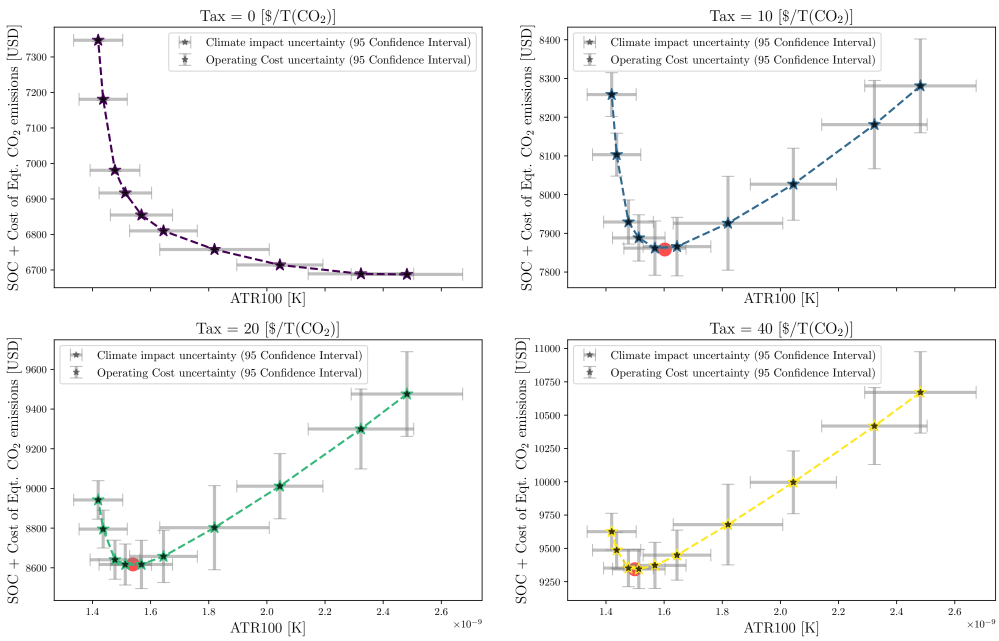

Figure 3: Pareto-frontiers depicted in Fig. (2) is shown for four different tax penalties with uncertainty ranges.

In the next simulations, we aim to explore the effectiveness of the formulated robust trajectory optimization (in Section 2.2) to find optimized trajectories yielding the identified "win-win" solution with only one-step optimiza-

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tion. Notice that we emphasize one-step optimization as there is no need to generate many alternative trajectories to determine "win-win" solutions within the assessment phase. In addition, the cost of climate impact is considered in the optimization step, meaning that the assessment of equivalent CO_2 emissions and cost quantification is no longer needed. Thus, this approach is operationally efficient and can be used by flight dispatchers in the flight planning phase. The red circles in Figs. (2, 3) is the result of optimizing the cost functional given in Eq. (4) by considering the taxes previously used for assessing the cost of climate effects. It can be seen that the previously found "win-win" solutions can be achieved with the proposed optimization using the tax considered for assessment (i.e., C_{tax} (in Eq. (4)) = Tax).

In order to analyze the results in more detail, Fig. (4) shows the obtained lateral paths and climate impact of individual species for three different routing options: 1) cost-optimal without considering tax for CO_2 equivalent emissions, 2) climate-optimal routing option, and 3) cost-optimal routing option using a tax of 40 [USD/T(CO_2)] for equivalent CO_2 emissions. It can be seen in Fig. (4a) that cases 2 and 3 are very similar. However, as expected, the deviation from case 1 (which is the cost-optimal routing option without considering tax) is smaller for case 3. Such deviations are to avoid warming contrails, dominating the net climate impact (see Fig. (4b)). For this scenario, we conclude that consideration of tax for non-CO_2 climate effects reduces both operating cost and climate impact at the same time.

4. Conclusion

This study explored the possibility of determining cost-beneficial climate-optimal trajectories by considering the cost of climate effects in the flight planning problem. For this purpose, the non-CO_2 species were converted to equivalent CO_2 emissions using aCCFs with ATR100 as a climate metric, which accounted for location and weather dependencies of non-CO_2 climate effects as well as meteorological uncertainty. Results showed that the cost-optimal scenarios, which exclude the cost of non-CO_2 climate effects, were no longer the most cost-friendly when penalizing the climate impact with taxes. For such cases, employing the proposed method enabled finding solutions that guaranteed mitigation of both the operating cost and climate effects, called "win-win" solutions. It is worth mentioning that the identified "win-win" depended on the tax penalties for climate impact. Due to uncertainty in meteorological variables, especially relative humidity, the estimated climate impacts were highly uncertain. This, in turn, led to relatively high uncertainty in the net operating cost when the cost of climate effects was included. Such a dependency of cost quantification on the meteorological variables needs to be considered when planning market-based instruments for aviation-induced climate effects.

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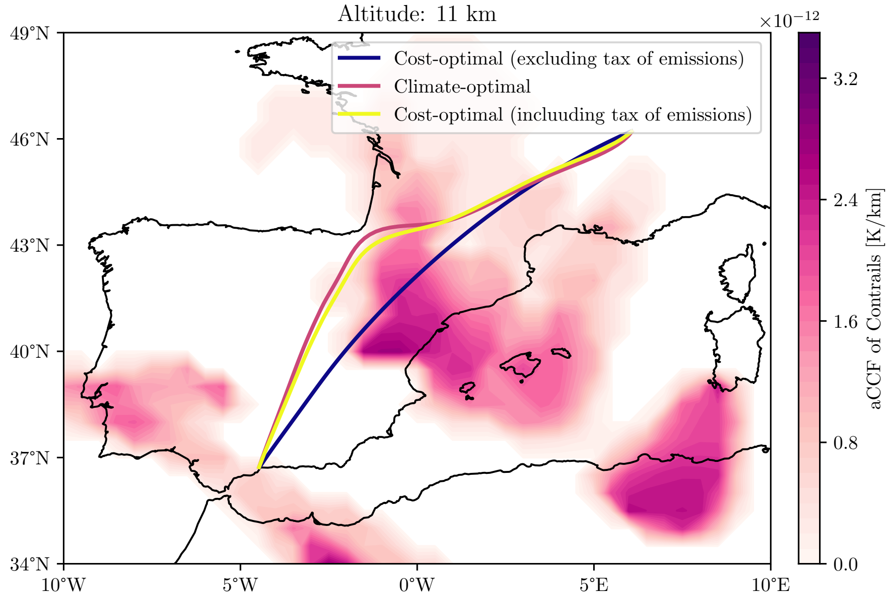
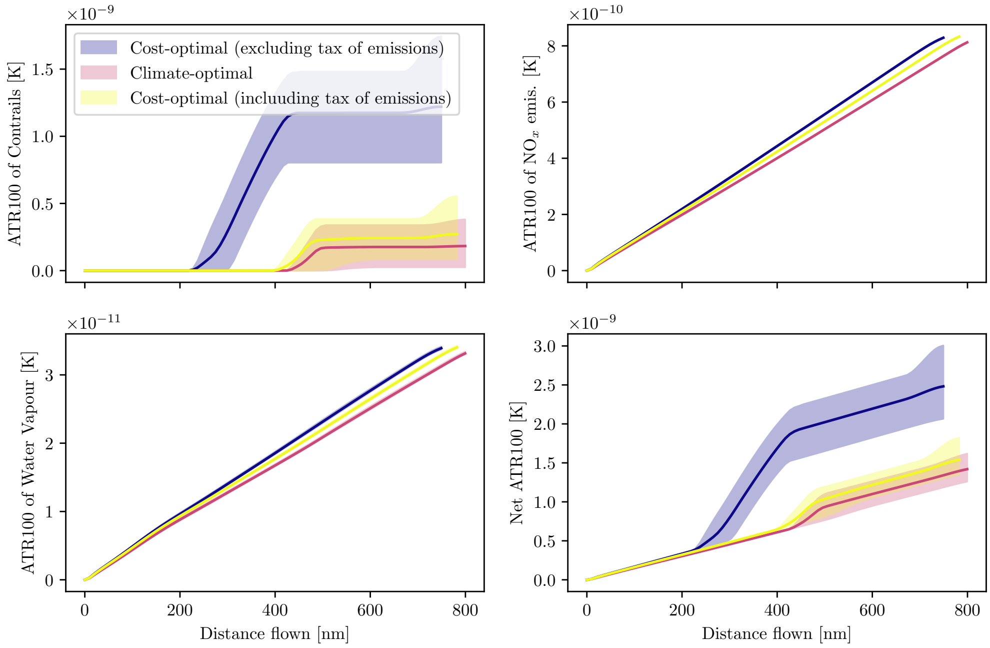


(a) Optimized lateral paths with the aCCF of contrails as color map.



(b) ATRs associated with each non- species and the net ATR (accumulated values along the route). Shaded areas illustrate uncertainty ranges due to uncertain meteorological conditions.

Figure 4: Results of optimization for different routing options.

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