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MITIGATION OF AVIATION'S CLIMATE IMPACT THROUGH ROBUST CLIMATE OPTIMIZED TRAJECTORIES IN INTRA-EUROPEAN AIRSPACE

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Abstract

Aircraft trajectories are currently flown and optimized to reduce operating costs, keeping engine CO_2-emissions from burnt fuel at a minimum by following fuel optimized routes under consideration of wind. However, research has shown that the location and time of non-CO_2 emissions such as NO_x, water vapor or the formation of contrail cirrus contribute to about two thirds of aviation's induced climate impact [1]. Consequently, one option to reduce this impact on a short time horizon is operational measures that aim to optimize aircraft trajectories with regard to climate impact by avoiding atmospheric regions that are especially sensitive to non-CO_2 emissions from aviation. For this purpose, the effects of individual emission species need to be quantified in order to assess the mitigation potential by climate-optimized routing. For this reason, multi-dimensional algorithmic climate change functions, which allow for the quantification of the climate impact of emissions, based on meteorological parameters which are available from weather forecast data is used. These algorithmic climate change functions are integrated into the cost functional of a trajectory planning algorithm which is based on an optimal control approach and applied in order to estimate climate optimized aircraft trajectories trading climate impact reduction against cost increase. Since the climate impact and therefore the algorithmic climate change functions are highly dependent on the prevailing atmospheric conditions, particularly the formation of contrail cirrus, weather prediction uncertainties are considered in order to determine robust eco-efficient trajectories. Within this study, the methodology and optimization applied to determine such a robust solution are presented and results are analyzed for an exemplary intra-European flight route.

Keywords: climate impact, non-CO_2 emissions, air traffic management, mitigation potential, eco-efficient trajectories, optimal control

1. Introduction

The environmental impact of aviation contributes to the overall anthropogenic climate change. Quantitatively, and based on the aviation sector prior to the Covid-19 pandemic, aviation was estimated to be responsible for approximately 5% of the global climate impact in terms of temperature change [1], [2], [3]. Operational, technological and regulatory options which may help to reduce this impact are thus subjects of ongoing research. In contrast to the effects of CO_2 emissions, the climate impact of non-CO_2 emissions is strongly dependent on location and time of emission [4]. Therefore, the concept of climate change functions (CCFs) which allows for the fast quantification of the climate impact of a unit emission as a function of location and time has been developed by Frömming et al. [5]. Based on these CCFs, the climate impact mitigation potential of climate optimized routing has been studied - e.g., Grewe et al. [6] and Lührs et al. [7] - indicating large climate impact mitigation potentials at low costs. The estimation of CCFs relies on complex climate chemistry model simulations which are very intensive in terms of computational effort and therefore not feasible in real time. In order to overcome this issue, within the European project ATM4E (Air Traffic Management for Environment), the concept of algorithmic climate change functions (aCCFs) has been proposed by Matthes et al. [8]. In contrast to CCFs, aCCFs allow for the quantification of aviation induced climate impact in real time and use meteorological data which are available from weather forecast services. The climate impact mitigation potential as well as the climate impact mitigation efficiencies (climate impact reduction per cost/fuel increase) in the European airspace have been estimated by Lührs et al. [9] for one case study day. The results show a climate impact mitigation potential of more than 70% associated with increased fuel burn of approximately 13%. Higher mitigation efficiencies occur for lower climate impact reductions, e.g., a 40% reduction of the climate impact can already be achieved with an additional fuel burn below 1% (Figure 1, left).

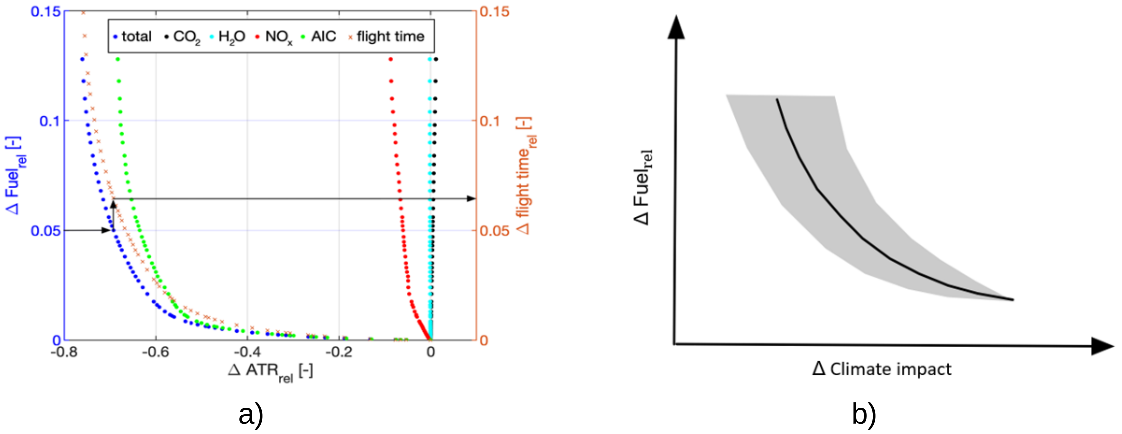

Figure 1 - Pareto front of climate impact and fuel consumption for different emission species and expected results including the consideration of uncertainties.
a. Pareto front showing relative climate mitigation potential and increase in fuel costs for most relevant routes in European Traffic [9].
b. expected interdependency range including uncertainties (grey shade).

These estimates are however in practice associated with uncertainties resulting e.g., from the weather forecast, uncertain aCCFs or uncertainties in the modeling of aircraft trajectories (see Figure 1, right). For the actual implementation of climate optimized routing, robust decisions despite uncertainties are required and consequently the estimation of climate optimized trajectories under consideration of uncertainties has been identified as one of the major goals of ATM4E's follow-up project FlyATM4E. Therefore, within this study, a methodology to consider these uncertainties when determining climate optimized aircraft trajectories and the associated climate impact mitigation potential is presented and applied to a European air traffic scenario assuming a free-route airspace.

1.1 Previous research

Aviation emissions play a substantial role in the anthropogenic climate change [10]. With an estimated contribution of approximately 5%, and a historic estimated growth rate of equally 5% [11], climate impact of aviation has become increasingly relevant. At the same time, global air transport is expected to grow at rates significantly higher than the annual increases in fuel efficiency. There is thus a risk that the relative contribution of aviation to anthropogenic emissions and the associated climate impact will increase, which is of particular importance due to the special effects of non-CO_2 emissions at high altitudes (formation of contrail cirrus or ozone). These emissions consist mainly of carbon dioxide (CO_2), nitrogen oxides (NO_x), water vapour (H_2O), soot and sulfate aerosols as well as contrails [2]. However, non-CO_2 emissions impact accounts for nearly two thirds of total climate impact of aviation, and is highly reliant on atmospheric conditions at the time and location of emission [2]. This geographical and temporal dependency has been previously analysed in research, e.g. in the

REACT4C project, in which the mitigation potential of climate-optimized flight routing as a measure to reduce aviation's climate impact was investigated [5]. In this study, the feasibility of adopting flight routes and altitudes leading to a reduced impact of emissions was assessed, and the global effects of such measures were estimated for the North Atlantic flight corridor. By using 4-D climate change functions to assess the climate impact, and combining them with traditional operating cost functions used by airlines, so-called Pareto-fronts could be calculated to determine not only climate-optimal but also cost-efficient flight routes. In the WeCare project conducted by the German Aerospace Centre (DLR) until 2017, the effects of non-CO_2 emissions and their atmospheric dependencies were investigated. In a feasibility study performed within the ATM4E project, a modelling chain of climate-optimized routing was developed and applied to the European Airspace, which introduced the concept of aCCFs [8], publishing initial estimates on mitigation potentials on individual trajectories and influence of individual physical climate metrics [12]. Mainly, the cost-benefit potential of climate-optimized flight trajectories, derived from tactical, weather-dependent optimization as well as strategic, climatological optimization of the flight altitude was addressed in order to determine which strategies are most suitable [9]. This analysis, and especially the estimation of eco-efficient trajectories, requires the aforementioned aCCFs which enable the quantification of the climate impact of emissions as a function of emission location and time. In the course of FlyATM4E, the aCCFs derived and revised from the previous research are used [7]. These functions are applied to estimate the climate impact of aviation's emissions, representing one part of the objective functions for the optimization models. They rely on mathematical algorithms that derive the climate impact directly from meteorological forecast data which is available at the flight planning stage. Goal of this study is the consideration of uncertainties resulting from (incomplete) representation of climate impact mechanisms and limited forecast quality by integration of forecast uncertainties into the trajectory optimization process.

1.2 Scope and structure of this study

The assessment of aviation's climate impact is typically performed by means of climate impact metrics such as average temperature response (ATR) with a specific time horizon. In this case we are applying a time horizon of 20 years over which the temperature response is integrated (ATR_{20}). Quantifying the climate impact per unit of emission, the aCCFs can be evaluated to indicate the sensitivity of specific areas of the atmosphere to these emissions depending on prevailing atmospheric conditions. This paper presents a methodology to assess uncertainties rising from climate impact estimation as well as weather prediction when computing climate optimized trajectories to characterize their robustness. As a case study to investigate the robustness of climate optimized trajectories, we calculate these trajectories for a single day of the selected air traffic sample using the correspondent meteorological forecast data to characterize the atmosphere. In order to determine continuous climate optimized routes, optimal control techniques are applied within the Trajectory Optimization Module (TOM) which has been developed jointly by DLR and TUHH for the computation of environmentally-optimized trajectories [7]. Within this study, the cost functional of the optimization is chosen as a weighted sum of the climate impact and the operating costs; the weighting factors are varied for each optimized trajectory in order to capture the full tradeoff between climate impact reduction and increase in costs. TOM has been designed as a deterministic trajectory optimization tool which optimizes a single trajectory per simulation run. Weather uncertainties are considered through the individual optimization of several ensemble weather prediction scenarios.

2. Methodology and Data

In order to achieve the aforementioned optimized trajectories under consideration of uncertainties, the following workflow is applied: Firstly, a reference trajectory for a selected origin-oestination pair is optimized with only operating costs as an objective function. This trajectory serves as a reference to quantify the relative changes of climate optimized trajectories when considering not only operating costs but also climate impact by introducing the aCCFs. The atmospheric conditions relevant for the identification of climate sensitive regions as well as the uncertainty in weather forecast are characterized by means of Ensemble Prediction System (EPS) forecasts acquired from the European Centre for Medium-Range Weather Forecast (ECMWF), specifically the re-analysis v5 (ERA-5) project [13].

2.1 Selection of flights & traffic scenario

The analysis performed is based on the commercial flight schedule of intra-ECAC flights of 2018, consisting of a total of 16,329 routes. This set of data was selected within the FlyATM4E project due to availability of a full European air traffic situation unaffected by Covid-19 pandemic, as the experienced reduced traffic scenario due to the pandemic is expected to recover back to pre-2019 levels [14][15]. Traffic data is acquired from the European flight plan collected by Sabre Market Intelligence Data base [16]. Within this study, aircraft trajectories are computed by an optimization tool with an optimal control approach – which requires large computational effort for each optimization. This circumstance raises the interest in finding ways of reducing the complexity of the optimization problem. The most direct approach is to reduce the number of trajectories to be optimized, which can be done by considering a reduced set of routes ranked in accordance to their overall relevance. The metric applied to determine the relevance of a trajectory is the total Available Seat Kilometre (ASK) offered on the connection throughout the year.

2.2 Complexity reduction

Applying the ASK as a relevance metric allows to initially contemplate a reduced set of trajectories, simplifying the optimization problem and allowing for a faster computation of trajectories. The ASK is used as a first indicator for the expected climate impact mitigation potential on a specific route, since a correlation between ASK, the amount of emissions, and hence climate impact, has been observed in previous research. The distribution of relative ASK is such, that the top 2,000 routes – equivalent to about 12% of the routes of the entire traffic sample - already account for about 60% of the total ASK as depicted in Figure 2. Consequently, considering only a subset of the most important routes is one very efficient first step towards a reduced flight route network for the optimization.

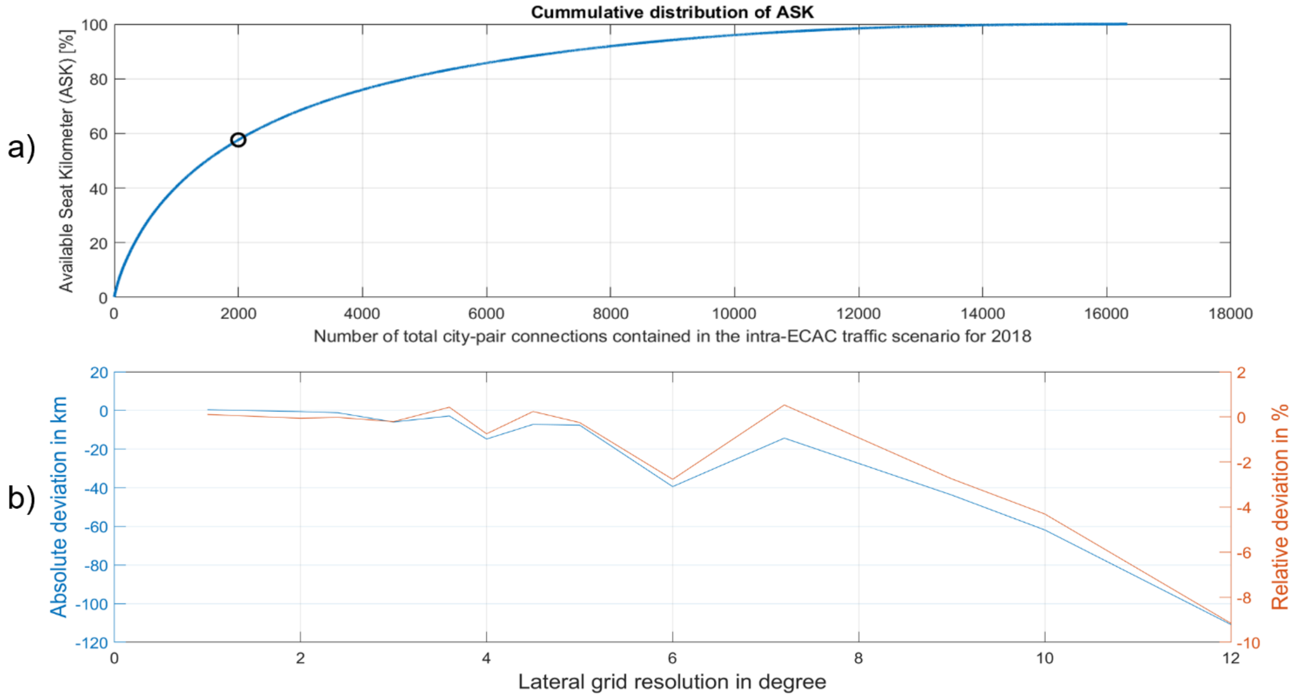

Figure 2: (a) Available Seat Kilometer as a function of city-pair connections contained in the traffic scenario. (b) Absolute and relative distance error of trajectories caused by the clustering of airports

Since the optimization of large sets of trajectories requires very high computational effort depending on the optimization approach, the route network is reduced by a clustering method to substantially reduce the complexity of the optimization problem. In this approach, first European airspace is divided into cells of a homogeneous grid. Then, airports within each grid cell are substituted by one fictitious airport located in the ASK-weighted centroid between the actual airports. Lastly, each city pair connection is assigned to the respective fictitious route between correspondent fictitious airports. This method reduces the complexity of the route network significantly, while still approximating major air traffic flows both in terms of traffic volume and location which are crucial for climate impact evaluation which strongly depends on the geographical distribution of the air traffic and the resulting emissions as depicted in **Figure 3**.

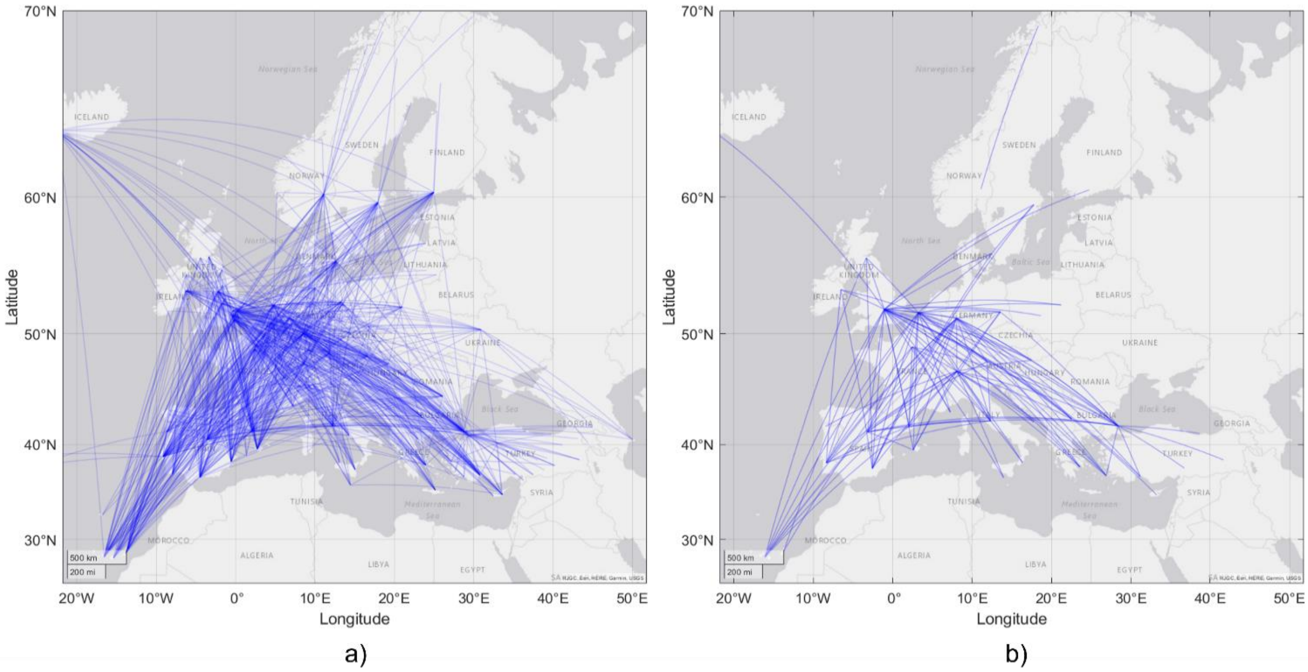

Figure 3 – *Route network complexity reduction of the 2000 most relevant flights of the traffic scenario by ASK.*
3.a *shows initial route network with real airport locations by relevance of ASK with a total of* $648{,}4 \times 10^{9}$ *ASK.*
3.b *Equivalent traffic scenario with 260 connections between ASK-weighted fictitious airports.*

A further simplification which reduces complexity and isolates an additional cause of uncertainty is the optimization of routes assuming one aircraft type for the entire traffic scenario. We assume that selecting the most representative aircraft from the traffic sample approximates the emissions of all aircraft. Evaluating the traffic sample of intra-ECAC flights, the most representative aircraft by ASK is an Airbus A320-214 with CFM56 engines, BADA designation A320-214(CFM56-5B4).

2.3 MET Data

Besides the traffic scenario considered, the prevailing meteorological conditions are of significant relevance for the calculation of environmental impact through aCCFs. Weather data is acquired through the ECMWF, specifically data from the EPS is used for the studies performed within FlyATM4E and retrieved from the ERA-5 dataset with a 0.5° horizontal resolution and highest available vertical resolution of 137 model levels [15]. EPS is a numerical weather prediction system which generates a certain number of individual forecasts, each representing a possible weather scenario which may develop based on the prevailing conditions at the time of forecast. Using EPS forecasts, meteorological uncertainties are considered in the trajectory optimization by individually calculating the optimal route for each ensemble member.

Table 1: Atmospheric parameters acquired by the European Centre for Medium-Range Weather Forecast required for the evaluation of aCCFs

Parameter	Short name	Unit	ECMWF ERA5 Parameter ID
Temperature	T	[K]	130
Geopotential	Φ	[$m^2\ s^{-2}$]	129
Potential Vorticity	PV	[$10^{-6}K\ kg^{-1}\ m^2\ s^{-1}$]	60
Relative Humidity	r	[%]	157
Cloud-cover	cc	[-]	248
Logarithm of Surface pressure	$lnsp$	[-]	152
Top net thermal radiation	ttr	[$J\ m^{-2}$]	179
U component of wind	u	[$m\ s^{-1}$]	131
V component of wind	v	[$m\ s^{-1}$]	132

The investigated mission selected for this study is part of a larger set of selected days of the 2018 flight plan within ECAC. By avoiding singular weather scenarios with heavily regulated trajectories, a determination of deceptively high mitigation potential is prevented. For the selected day, trajectories are optimized considering static weather conditions at 12:00 UTC and 00:00 UTC. Since atmospheric phenomena are complex processes, a temporal interpolation of data could potentially lead to atmospheric conditions that are physically not plausible. However, the average duration of flights within the ECAC area is less than 2 hours. Hence, this simplification is expected to have a minor impact. Since the effects of non-CO_2 emissions have a strong dependency on time and location of emission, the flights considered in the traffic scenario of FlyATM4E are set for departure at four equidistant time points throughout the day, coinciding with EPS forecast broadcast times. Within this study, we focus on June 18th, 2018 at 00:00 UTC (bold red circle in Figure 4). The days considered for the studies within FlyATM4E are selected on the basis of present weather regulations. Weather regulations are an indicator for the atmospheric activity. By avoiding days with many regulations, we are actively avoiding atmospheric situations of high convection that could lead to an over-estimation of climate impact mitigation potential such as described in [12]. For this purpose, an upper threshold of 20 regulations per day was selected as a filtering approach.

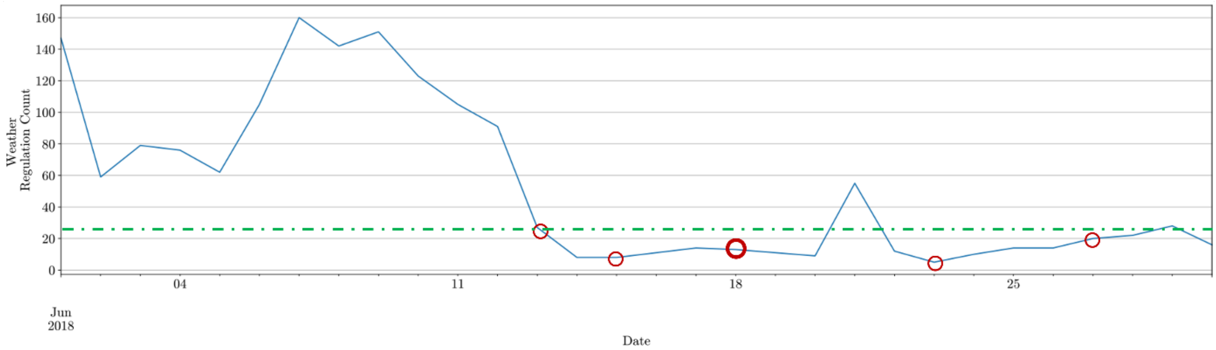

***Figure 4:** Weather regulations within Europe for the month of June 2018. Daily regulations are represented on the y-Axis, individual days on x-Axis. Five mostly evenly spaced days were selected considering an upper threshold of 20 regulations per day (dotted green line).*

2.4 Climate impact modelling

In this section the concept of aCCFs is illustrated. The aCCFs serve as the main metric to consider climate change when optimizing the lateral and vertical trajectory of aircraft. The main characteristic of the aCCFs is the fast quantification of climate impact of local aircraft induced emissions from burnt fuel as a function of atmospheric parameters, which are both location and time dependent. For this study, and oriented on FlyATM4E, the first complete, and consistent set of prototype aCCFs (aCCF-V1.1) is applied to quantify the average temperature response integrated over a time period of 20 years (ATR_{20}). The aCCFs applied within this study are based on the pulse emission scenario as described in Yin et al. [17], and then converted to a future scenario (F-ATR_{20}) by applying conversion factors and efficacies developed by Dietmüller et al. [18]. The efficacy parameters applied account for the effectiveness of non-CO_2 impact in terms of ATR when compared to CO_2. Uncertainties associated to climate impact estimation are included by means of so-called educated guess factors in the current version of aCCFs (V1.1) developed by Matthes et al. [19]. Based on the EPS forecast data, we evaluate the algorithmic climate change functions for CO_2 and non-CO_2 impacts on a specific day comprising impacts of nitrogen oxides (on ozone and methane), water vapor, and contrail cirrus. The aCCFs of individual species of emissions require the following parameters to be evaluated:

Table 2: Individual species of emissions considered within this study and required atmospheric parameters for the evaluation of aCCFs.

CO_2:	Fuel flow rate
NO_x - O_3:	Temperature, Geopotential
NO_x - CH_4:	Geopotential, Incoming solar radiation
H_2O:	Potential Vorticity
Contrail:	Outgoing longwave radiation, temperature, relative humidity

Since the uncertainty in regards of atmospheric conditions arises from the ten weather scenarios provided by the EPS forecasts, the variability between these scenarios is of interest. These scenarios provide a full description of the weather individually, and indicate the possible range of future weather scenarios. This range is illustrated in Figure 5 by evaluating the aCCF for contrail cirrus for the 18th of June 2018, 00:00 UTC. Figure 5a shows the mean value of contrail impact of all ensembles in western

Europe at latitudes between 35°N and 60°N. At a pressure level of 250hPa (~10228m) we observe contrail sensitive regions covering a large part of England, France and east-Europe. On Figure 5b the standard deviation of the ten ensemble members can be observed, with areas of small deviation in which contrails form in most of the forecasted weather scenarios highlighted in blue tones. Most interesting is the deviation, since it is an indicator of the potential robustness that can be achieved when optimizing trajectories. Large deviation values lead to higher uncertainties and thus raise the difficulty of achieving robust optimized trajectories for a variety of forecast scenarios.

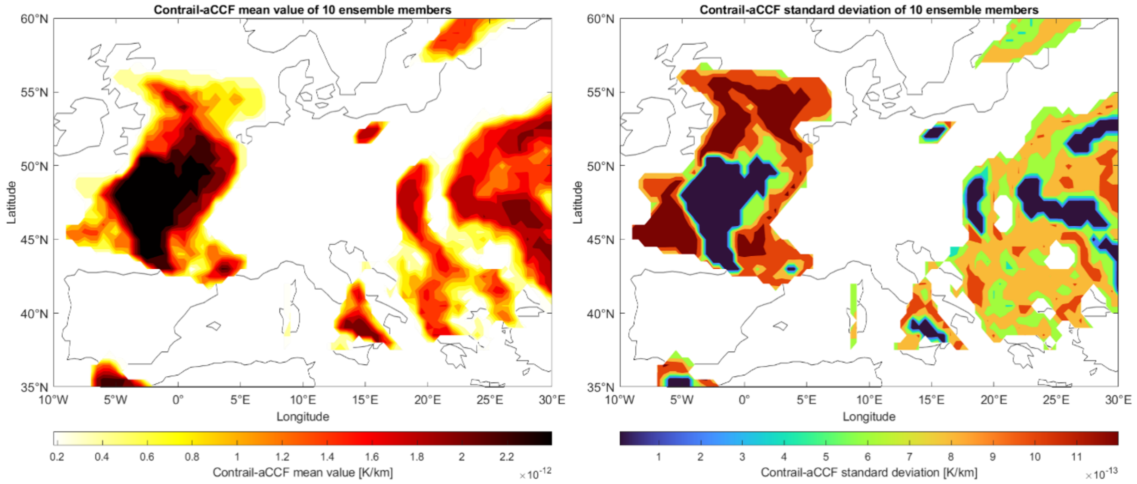

Figure 5: *a) mean value and b) standard deviation of Contrail algorithmic climate change function as a function of latitude and longitude for ten ensemble members on June 18th 2018 at 00:00 UTC at an altitude of 10228m (~250hPa). In a) dark areas highlight geographically intense climate impact by contrail formation. In b) deep blue areas highlight locations with low deviation of contrail formation impact.*

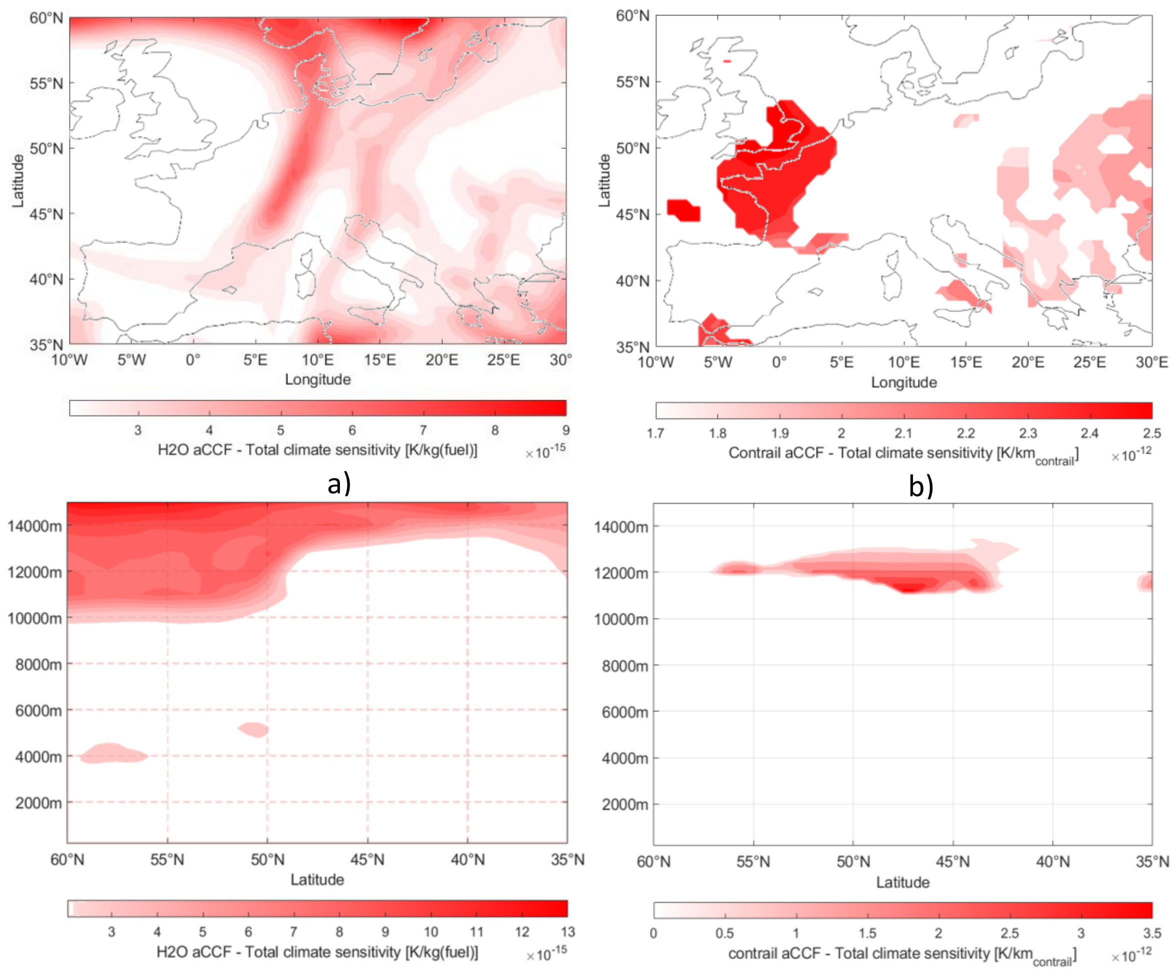

Figure 6: *Water vapor (a,c) and contrail (b,d) aCCFs as a function of latitude and longitude (a,b) at an altitude of 10228m (~250hPa), and latitude and altitude (c,d) at 2° W for June 18th 2018 at 00:00 UTC for a single ensemble member.*

2.5 Trajectory optimization

In this section the optimization methodology is briefly presented. In order to identify climate optimal trajectories, the TOM is used to calculate eco-efficient trajectories. Aircraft's motion is described as the temporal evolution of control variables (e.g., aircraft heading, thrust) and resulting state variables (e.g., position, mass, emissions). Optimized aircraft trajectories are determined by identifying a control input which minimizes a cost functional which may be defined as weighted sum of operating costs and climate impact. Additionally, dynamic constraints as well as control, state and path limitations can be set in order to specify the optimization problem. The continuous optimal control problem is then transformed into a nonlinear programming problem (NLP) and is finally solved using standard NLP solvers.

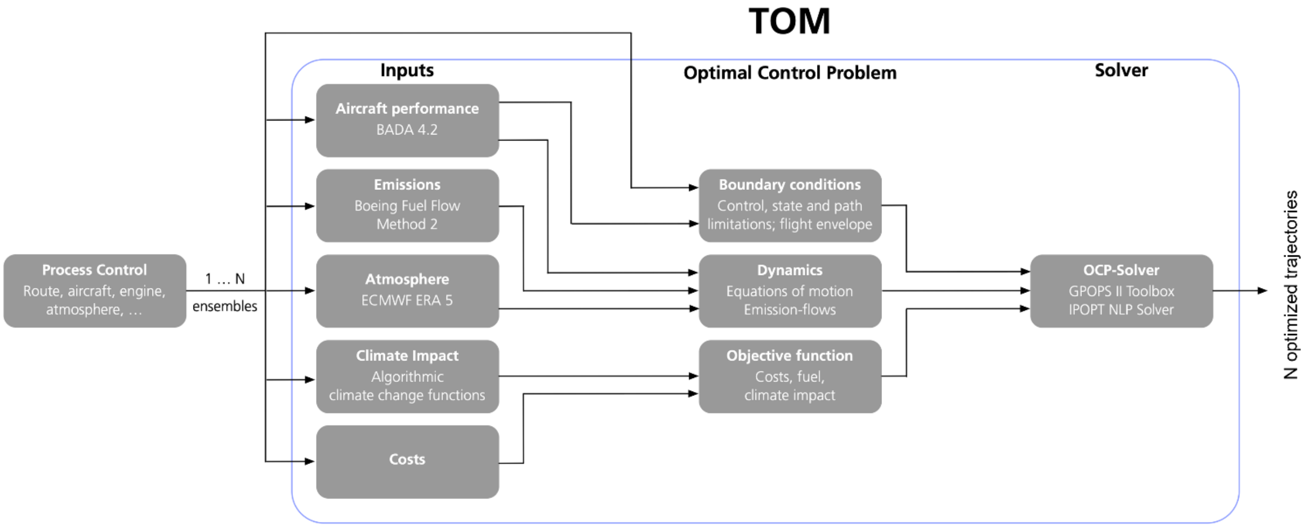

Figure 7: Updated flowchart of the Trajectory Optimization Module for the optimization of aircraft trajectories under a set of N ensemble members of weather forecast. Air traffic data from BADA [22], estimated fuel flow [23], atmospheric data, aCCFs and estimation of costs are necessary inputs for the optimization. Additionally, boundary conditions and dynamic constraints are applied and handed over to the solver.

The resulting optimal control problem which is defined by the cost functional, the dynamic constraints as well as the limitations of control-, state-, path-, and event-vectors, is solved using the MATLAB optimal control Toolbox GPOPS II [24]. GPOPS II relies on a direct approach and transforms the original continuous optimal control problem into a discrete nonlinear programming problem (NLP), which is then processed by the NLP solver IPOPT [25].

2.5.1 Objective function

In order to generate Pareto fronts which describe the trade-off between climate impact and operating costs, the weighted sum of climate impact (ATR) and simple operating costs are used to express the objective function. Both parameters are normalized with respect to the previously determined reference values corresponding to the minimum cost trajectory (ATR_{ref}, $m_{fuel,ref}$). By temporally integrating the product of aCCFs (see section 2.4) and the associated emission flow $\dot{m}_i$ for CO_2, NO_x and H_2O - or the true airspeed (TAS) for contrail cirrus formation - we obtain the total climate impact.

$$\boldsymbol{J} = c_{\text{SOC}} \cdot \underbrace{SOC\left(m_0 - m_f, t_f - t_0\right)}_{\text{Simple operating costs}} \cdot SOC_{\text{ref}}^{-1} + \ldots$$

$$\ldots c_{\text{ATR}} \cdot \underbrace{\int_{t_0}^{t_f} (\text{aCCF}_{\text{CO}_2} + \text{aCCF}_{\text{H}_2\text{O}}) \cdot \text{FF} + (\text{aCCF}_{\text{O}_3} + \text{aCCF}_{\text{CH}_4}) \cdot \text{EI}_{\text{NO}_\text{x}} \cdot \text{FF} + \text{aCCF}_{\text{Contrails}} \cdot v_{\text{TAS}}\, \text{d}t}_{\text{ATR}} \cdot \text{ATR}_{\text{ref}}^{-1} \quad (1)$$

$$c_{SOC} + c_{ATR} = 1 \text{ with } c_{SOC}, c_{ATR} \in [0,1] \quad (2)$$

For the generation of Pareto fronts the weighting of climate impact and SOC are varied. When optimizing towards the minimum climate impact c_{ATR} is set to 1, and when optimizing towards minimum operating costs c_{SOC} is set to 1. Originally, TOM has been designed as a deterministic trajectory optimization tool which creates a single trajectory output per simulation without considering uncertainties. In the previous version of TOM, the process control script has been used for the definition of the aircraft/engine combination, the route, the weather situation as well as additional boundary conditions. In order to consider EPS weather forecasts which enable the consideration of uncertainties originating from the weather forecast within TOM, the process control has been adapted. In the updated version of TOM, instead of once, the trajectory optimization is performed *N* times. Using a different ensemble member (1 … *N*) at every loop results in *N* optimized trajectories (one per ensemble member) which can then be further evaluated and compared with each other in terms of congruence. A very similar shape of all *N* trajectories for a specific route indicates a robust solution whereas deviating trajectories may indicate solutions which are not robust.

3. Results

The results for the selected reference day for the case study are characterized and climate optimized trajectories and corresponding Pareto fronts for different ensemble predictions are presented. Finally, ensembles are consolidated to assess the robustness of the mitigation potential observed for this study.

3.1 Single Route analysis – Spanish Riviera (CG) – London (FG)

Considering both climate impact and economic aspects in the optimization of trajectories, 50 Pareto-optimal trajectory variations for a single route and each ensemble of the selected traffic sample have been calculated. This is achieved by systematically varying the weighting factors c_{ATR} and c_{SOC} according to Equations (1) and (2). Here, we optimize the most relevant route in terms of ASK from our fictitious network depicted in Figure 8 for the 18th of June 2018 at 00:00 UTC at an average cruise altitude. The lateral path of the minimum cost trajectory (black) and orthodrome (blue) are depicted including the wind situation (left) and the total climate sensitivity (right) at an average cruise altitude. The minimum cost trajectory (black, c_{fuel} = 1) shows a shift westward when compared to the orthodrome (blue) mainly to benefit from the existing tailwinds over the Bay of Biscay between Spain and France. A warming contrail area characterized by a high climate sensitivity is crossed at about 47°N / 2°W (see Figure 8b). Since we are considering night-time conditions, contrails have exclusively warming effects as opposed to day-time contrails which can have both warming and cooling effects.

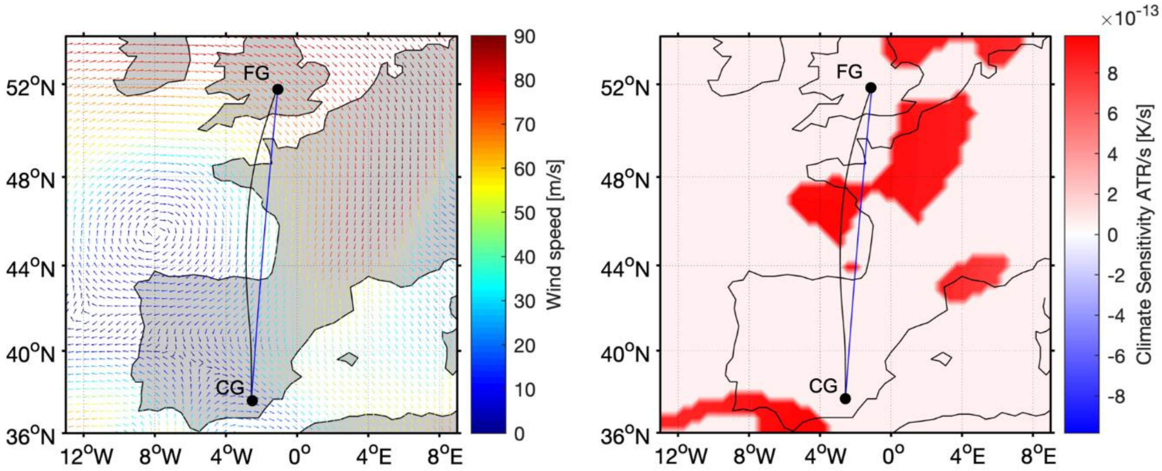

Figure 8: Optimized trajectories for the fictitious route with highest ASK volume. The lateral path of the minimum cost trajectory (black) and orthodrome (blue) are illustrated including the wind situation (left) and the total climate sensitivity (right) at an average cruising altitude of 9,918 m.

The lateral path of the minimum climate impact trajectory is not shown separately, since it only deviates slightly from the minimum cost trajectory. Since the lateral expansion of contrails is generally higher than the vertical one, the optimizer avoids contrail-sensitive regions by changing the vertical profile of the trajectory. This deviation consequently causes a lower cost increase when compared to a lateral avoidance. Furthermore, the prevailing headwinds also have an impact on the vertical profile, causing a dip from about 11,000 m at t/t_f = 0.2 and an ascend back to almost 12,000 m to decrease flight time in regions with headwind.

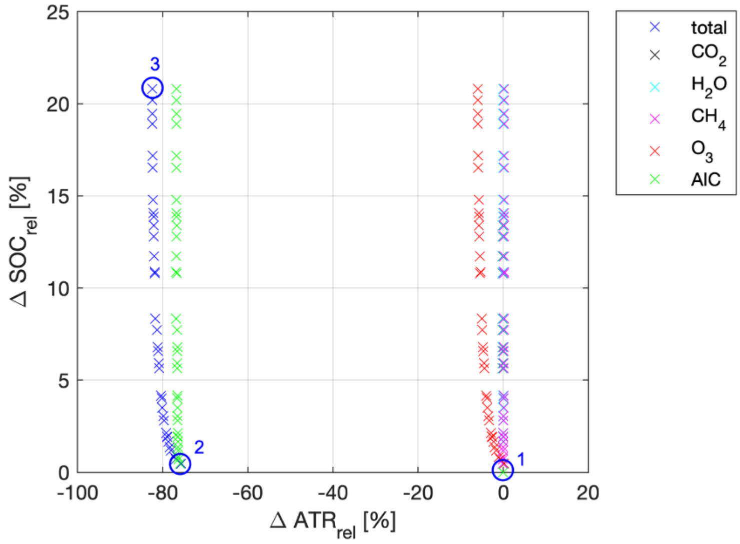

Figure 9: Pareto front for the 18th of June 2018, 00:00 UTC. 50 different parameter combinations of c_{ATR} and c_{SOC} are applied to generate the pareto front. Highlighted blue circles show 1) a cost optimal solution, 2) a high mitigation efficiency solution and 3) a climate optimal solution.

The parameter sweep for the Pareto front shown in Figure 9 ranges from cost optimal to climate optimal routes. The presence of contrails is the main contributor to the shape and total mitigation potential observed in the Pareto front. Since avoiding the contrail-sensitive region vertically has little economic consequences, a large reduction in relative ATR can be achieved at minimal cost increase as highlighted by Point 2 in Figure 9. A total relative climate impact mitigation potential of 82% can be achieved when compared to a reference trajectory optimized for minimal costs. Figure 10 depicts the corresponding vertical profiles to the highlighted points from Figure 9.

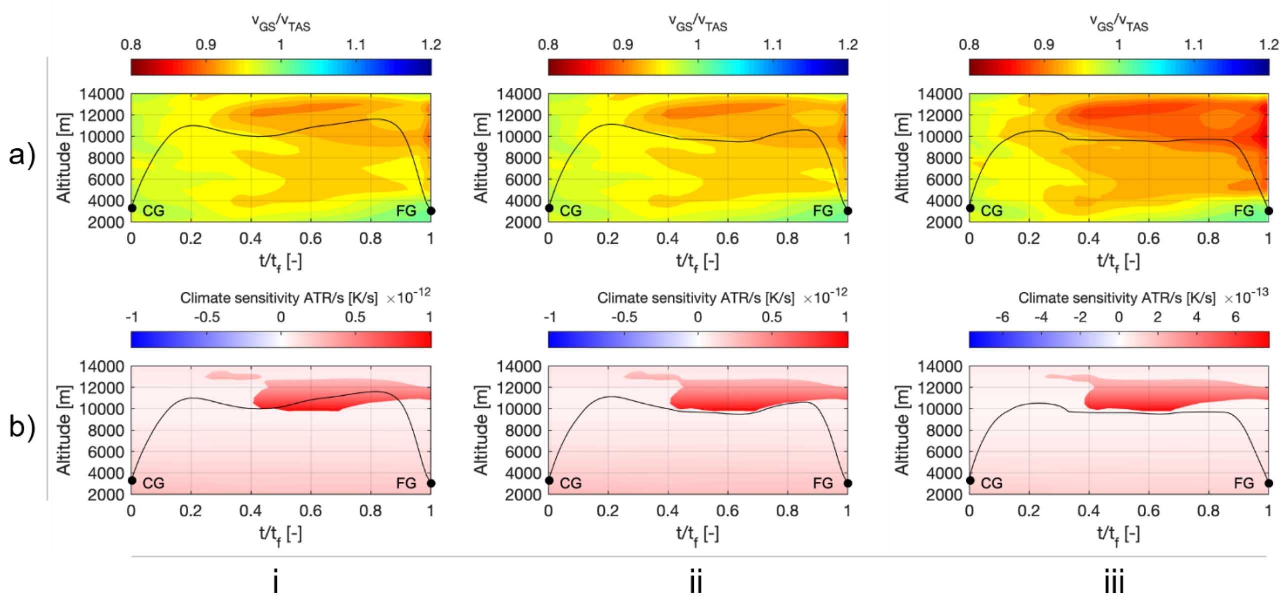

Figure 10: Vertical profiles of a) wind and b) contrail-aCCFs along the cross section of the lateral path are shown for minimum cost case (i), a point of high mitigation efficiency along the relative flight time t/t_f (ii) and the minimum climate impact case (iii).

The wind situation for the vertical trajectories is indicated as a ratio between ground speed v_{GS} and true airspeed v_{TAS}. Values greater than one indicate tailwind areas, values smaller than one indicate headwind areas. When observing the climate optimal case (Figure 10 iii), a lower routing at $t/t_f = 0.4$ is visible which is caused by both the field of headwind and the contrail-sensitive area ahead compared to Figure 10 i. The cost optimal case (i) ascends into a higher altitude at about $t/t_f = 0.6$ and the cost optimal trajectory crosses contrail-sensitive areas in favor of reduced headwinds. By increasing the weighting of the climate impact in the objective function of the optimization by a value increment of c_{clim}, the trajectory is shifted to reduced altitudes successively. The lateral path remains almost unchanged and is therefore not shown in Figure 10. For c_{ATR} = 1, the minimum climate impact trajectory is obtained, which has a reduced mean altitude of 9,155m instead of 9,918m for the minimum cost trajectory. As a consequence of the reduced altitude, the fuel burn shows a slight increase, see Figure 11a. However, it is possible to avoid the strong warming region at t/t_f = 0.6 - 0.8 caused by a contrail-sensitive area completely (see Figure 10b). Due to a large contrail-sensitive area the total climate impact mitigation potential is dominated by the influence of contrails.

3.2 Climate impact mitigation under uncertainty

Taking into consideration the same route as previously presented, in this section we include results for the optimization of the trajectory for a set of ten scenarios to consider the uncertainty related to weather variability. Individual Pareto fronts are combined for all ensemble members (Figure 11b). The previously shown results for the single route example were computed on the basis of a single ensemble member of the EPS forecast. Here, we further analyze the influence of the whole set of ten ensemble members to assess the impact of uncertainty in the weather prediction on the solutions generated with TOM. For this we have optimized the same route individually for each of the ensemble members, which renders ten different Pareto-fronts. We determine maxima, minima and mean values for each parameter combination with shifting weights on climate and cost penalty (Figure 11c). Finally, the mean impact of individual emission species is analyzed per route. Higher climate impact mitigation efficiencies (climate impact reduction per cost increase) are obtained at low fuel penalties; e.g., a fuel penalty of 5% may already lead to a climate impact reduction of about 80% on average (for the given route, time and aircraft). The large mitigation potential caused by the area of strong contrail-sensitivity (see Figure 10) is responsible for the distinctive shape of the Pareto front. The individual contribution of species indicates that the climate impact reduction for the investigated weather scenario and route is dominated by the reduction of the contrail climate impact followed by the reduction in relative ATR of NO_x (Figure 11d). CO_2 and H_2O impact contributions show only minor impacts on the total impact Pareto front. The main weather scenario considered in this study shows a high potential for contrail formation which dominates the mitigation potential and thus the shape and quantitative characteristics of the Pareto front. However, mitigation potentials and efficiencies may evolve differently for distinct weather situations (ensemble members) as shown in Figure 11.

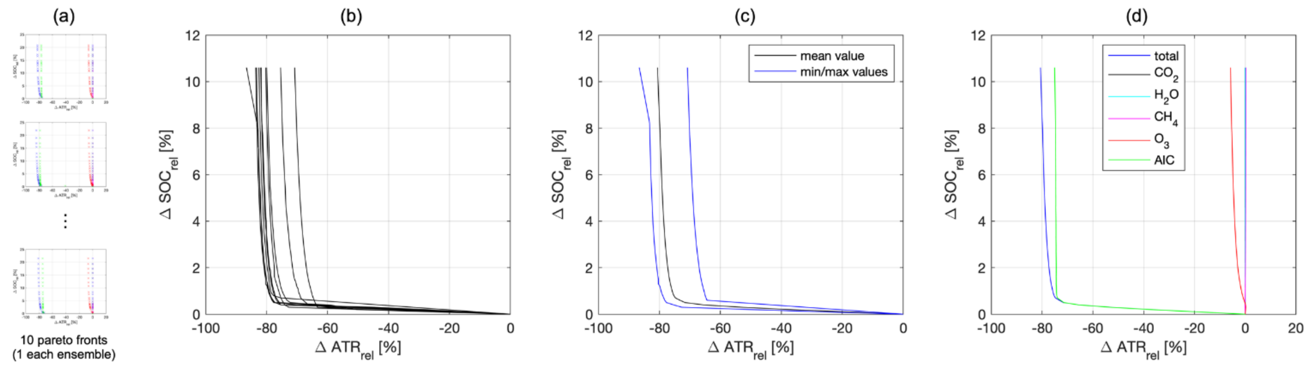

Figure 11: Pareto fronts of the fictitious route for 18th of June 2018 at 00:00 UTC.
a. Pareto fronts for individual emission species for each ensemble member.
b. Pareto fronts for total mitigation potential for each ensemble member.
c. Averaged Pareto front (black) for all weather situations as well as maxima and minima of mitigation potentials (blue).
d. Averaged Pareto front for all weather situations and contribution of individual species of emission.

Pareto fronts for each ensemble member serve as input for the aggregated results. From this set of ensembles, eight Pareto-fronts show a similar correlation between relative changes of ATR and SOC, while in two cases we can observe 10% lower relative mitigation potential for the same SOCs, see Figure 11.b. The overall distinctive shape due to contrail-forming regions yields a high gradient at very low increases of SOCs, which rapidly converge to the maximum mitigation potential achieved once the contrail region is avoided completely.

4. Summary

Our results achieved within this study are in line with previous research in terms of mitigation potential when considering a single route case and weather scenario. Assuming a free-route airspace, we optimized aircraft trajectories with regard to climate impact as well as simplified operating costs (SOC). Climate impact is considered by avoiding atmospheric regions that show a particular sensitivity to non-CO_2 emissions, such as contrail cirrus. In order to assess this sensitivity, algorithmic climate change functions are applied to measure the climate impact per unit emission of burnt fuel based on atmospheric conditions and applying a future-ATR metric on a time horizon of 20 years. Previous research has identified the necessity of integrating the uncertainties both climate impact prediction and weather forecasts are afflicted with. For this purpose, and to assess the robustness of eco-efficient trajectories, EPS-forecast data from the ERA-5 dataset provided by ECMWF with a set of 10 ensemble members is considered. By taking into account different predicted atmospheric scenarios predicted and evaluating optimized trajectories individually for each ensemble prediction, the robustness of the solutions is determined. The main aspect of the assessment being the assurance of climate impact mitigation despite uncertainties which are an inherent aspect of climate science and weather prediction. The single route analysis is based on a fictitious route network to consider most relevant routes in terms of ASK. Geographic distribution of traffic volume and emissions are considered for a set of 10 ensemble members from the operational forecast data set of the ECMWF. Performing a parameter study varying the weighting of climate impact and simple operating costs allows to generate Pareto fronts to assess the climate impact mitigation efficiency. By generating these Pareto fronts for each forecasted weather scenario, we obtain a spread of Pareto fronts which is analyzed to assess the robustness of trajectories obtained by the trajectory optimization module. The smaller the spread across Pareto fronts, the higher is the robustness of the solutions. For this study and the considered weather scenario each optimized route could still show mitigation potential for each ensemble with an average relative impact mitigation in the range of 80% climate impact reduction with a fuel penalty of about 5% in presence of strong contrail-sensitive regions. The difference in climate impact mitigation for the best- and worst-case ensembles stayed within a relative ATR difference of $\Delta\mathrm{ATR}_{\mathrm{rel}} = 0.18$. A re-evaluation of trajectories which are optimized for one ensemble member using the weather conditions and associated climate impacts (aCCFs) of another ensemble member could be subject of further research. In a similar way, comparing the performance of the trajectories for one ensemble member using the weather conditions of the reanalysis data, is expected to show the robustness of the forecasted trajectory performance by an additional hindcast analysis. This procedure would answer the question to what extent fuel consumption and climate impact vary under different weather conditions (e.g., reanalysis or different ensemble), and if the trajectory was optimized and planned assuming one specific ensemble member and to what extent they may vary.

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6. Copyright Statement

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8. Data Availability Statement

The data presented in this study is available on reasonable request from the corresponding author.

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