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Towards Contrail Mitigation through Robust and Frugal AI-Driven Data Exploitation

Davide Di Giusto, Grégoire Boussu, Simon Alix,
Céline Reverdy, Mathieu Riou, Teodora Petrisor *

Thales, Research and Technology France,
1 avenue A. Fresnel, 91767, Palaiseau, France

Abstract. Condensation trails significantly contribute to aviation's impact on climate change. Their effective mitigation involves formulating accurate predictions of occurrence, introducing the relevant constraints in trajectory optimization and employing reliable verification strategies based on observations. Atmospheric data, expert knowledge and contrails observations can be leveraged for these purposes. However, several factors determine a limited prediction accuracy and high uncertainty bounds, including the difficulties in predicting contrails persistence, the complexity of trajectory optimization problems and the lack of labelled data for contrail verification. This paper gives an overview of our robust Artificial Intelligence methods aiming to tackle these challenges throughout the entire contrail mitigation chain.

1 Introduction

Aviation accounts for 1.9% of the anthropogenic carbon footprint[1], yet non-CO_2 effects were estimated between half and three times the CO_2 radiative forcing [2]. Among these, condensation trails (contrails) emerge as the predominant contributor, making their avoidance a major goal to achieve sustainable aviation operations. Contrails are the slender clouds trailing behind aircraft engines during flight, resulting from the mixing of humid jet exhaust with the cold ambient air. This process produces small ice particles that contribute significantly to the greenhouse effect (Figure 1 (a)).

While most contrails dissipate within ten minutes, the persistent ones can survive for several hours and spread to hundreds of kilometers. Largely responsible for the associated climate change effect, these persistent contrails are generated by only 2.2% of flights, opening to the perspective of an efficient mitigation by re-routing a limited amount of airplanes [1]. This operation requires the prediction of the regions where condensation trails will form, the modification of the flight trajectory to avoid these regions and, finally, the verification of the efficiency of the mitigation by analysing past predictions versus reality. Today this strategy is only nascent in Air Traffic Operations.

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[1] IPCC, Climate Change 2023: Synthesis report

[2] Lee et al, The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018, Atmos. Env. 2021

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Fig. 1: (a) Illustration of the green-house effect determined by the contrails; (b) Measurements of DRL A320 contrail by the NASA DC8 research aircraft [6]; (c) Satellite image showing contrails as dark blue lines, visible in the upper-half of the image.

Despite the thermodynamic Schmidt-Appleman criterion identifying the atmospheric regions where contrails are likely to form [2], numerical weather simulation still struggles to predict precise persistence localisation, i.e. in the Ice Super Saturated Regions (ISSRs) [3]. As for trajectory optimization, even if many different general methods exist to solve the problem, generating realistic paths efficiently remains a challenge under active research [4]. Finally, classical contrail detection algorithms struggle to achieve a low false detection alarm rate without loosing their efficiency [5], despite the abundance of sensors providing contrail observations (regular cameras, ground images such as whole-sky cameras, satellite or lidar). In particular, the limited availability of labelled data describing the contrails, as well as the difficulty in producing physically-plausible numerical representations of the phenomenon need to be tackled in order to develop robust detection or prediction methods.

A promising approach to face all these challenges is to combine domain knowledge such as physics, geometrical properties, network constraints with more classical data-driven AI, such as neural networks, in order to increase the frugality and the robustness of the solutions at all stages: before, during and after the flights. In this article we present an algorithmic overview of the research directions in contrail mitigation currently investigated in Thales based on hybrid-AI with reduced dependence of labelled data. We address the different sources of data in Section 2, contrail prediction solutions in Section 3.1, route optimisation strategies in Section 3.2 and AI-based contrail verification in Section 3.3.

2 Contrails sensing

AI for contrails mitigation requires data that can be provided by in-situ and remote measurements. In-situ measurements are operated through airborne sensor carried in close proximity of the contrails or the ISSRs by radiosondes or special aircraft (Figure 1 (b) [7]). Although these measurements directly sample local physical properties relevant to contrail modeling, obtaining extensive data sets is challenging. The IAGOS (In-service Aircraft for a Global Observing System) project addresses this issue by installing the sensors on commercial flights to

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sample the global atmospheric composition, but these measurements are constrained to the flight route of the aircraft and are sparse [8].

Remote measurements include distant observations (ground, satellite, radar, lidar), which can be used to verify predictions. Radar and lidar systems are commonly utilized to optically characterize the atmospheric columns, allowing to infer local physical properties with some success [9]. Whole-sky ground imagers can capture very young contrails in both visible and infrared spectra albeit with limited geographical coverage (usually less than 100km). The dependence on meteorological phenomena or sun flares is quite high, requiring important calibration or otherwise processing. Networks of such cameras[3] are nevertheless very interesting to capture lower altitude contrails which may be missed by other sensors, e.g. satellite, in particular when they can instrument flight trajectories along heavy traffic corridors.

Satellites are among the most used sources of large-scale observations of contrails (Figure 1 (c)). Contrails are visible in the same infrared spectral bands as cirrus clouds and their ice particles content reveals them in brightness temperature differences (BTD) images. Therefore, color schemes combining all the relevant BTD channels[4] can be employed during preprocessing to enhance contrail observations and ease manual annotation for AI algorithms. These represent an effective mean to benchmark numerical predictions and mitigation strategies [3], but they may miss very young contrails. The detection problem in these images is quite difficult due to the degenerate dimensions of contrails[5] and the ambiguities with regular clouds.

To this end we are currently working on building a collocated dataset from ground imagers and European geostationary satellites. This necessary first step in using machine learning algorithms is considered in a frugal manner, aiming to take advantage of all the possible available annotated data sources, combined with few-shots/transfer learning.

3 AI in Green Aviation Operations

We aim to exploit data collected via in-situ and remote sensing through Artificial Intelligence to improve contrail mitigation along the whole Air Traffic Management pipeline. This includes the prediction of contrails for a given flight path, the optimization of the aircraft trajectory with regards to different indicators, and the verification of the adopted mitigation strategy through atmospheric observation.

3.1 Contrail prediction using Physics-informed AI

Given a flight path and the local weather conditions, the numerical prediction of persistent contrails strongly depends on the parameterisations of atmospheric

[3]For instance the FRIPON network: https://www.fripon.org

[4]e.g. the channels 12.0, 10.8 and 8.7μm of the European MSG satellite can be combined to yield the Ash-RGB colored image taken on 14/01/2024:09h05 in Figure 1 (c).

[5]Most contrails are sparse objects in the range of 2×40 pixels in an approx. MP image

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processes and the assessment of the ISSRs [2]. These could be learnt applying data assimilation techniques on in-situ and remote measurements. However, the latter typically consist of unlabelled proxies, while the former are labelled but very sparse in space and time.

Physics-Informed Neural Networks (PINNs) offer an ideal solution to obviate these limitations. PINNs (Figure 2 (a)) are neural networks that include both data and a physical principle in the learning framework, and have rapidly emerged as an alternative to classical numerical methods for Partial Differential Equations [10]. By incorporating physics laws as regularization, PINNs are less prone to overfitting the data, which makes them a more robust solution in the case of sparse or unlabelled measurements. Additionally, PINNs integrate physics equations as soft constraints and are thus less sensitive to model approximations. Both aspects represent an advantage that PINNs offer in the context of contrail mitigation and ISSR prediction. Finally, PINNs are extremely rapid at inference.

For these reasons, PINNs are being developed at Thales by combining in-situ and remote measurements together with suitable conservation principles. The short time to prediction of PINNs offers the possibility of ensemble predictions, facilitating the quantification of contrail risks across multiple trajectories.

3.2 Mitigation by trajectory optimization

While ISSRs prediction is an active field of studies, the idea of altering flight paths to avoid these locations becomes of great interest to mitigate the impact of aviation on climate. Thales develops the tool COHORT based on Path Planning as this approach proved to be efficient for trajectory optimization, among other methods listed in [4]. However, the application of general Path Planning algorithms for contrail mitigation raises several research questions. Firstly not only different climate impact indicators coexist[6], but also at this time, no aggregation of cost and climate impact indicator obtained consensus. As a consequence, our system will produce trajectories through a multi-objective optimization process, and the output Pareto front should then be considered as a support to decision (Figure 2 (b)). In this regard, our approach is close to the one in [11], whereas multi-criteria optimization was preferred in [12]. The second difficulty is linked with the dynamic nature of atmospheric state which dramatically increases the size of the solution space. To tackle this point and provide operators with moderate response times, we are considering to take advantage of massively parallel computation on GPU. Few such attempts were reported in literature. One of them is described in [13], but if the purpose is the same (significantly reducing the computation time), the parallel computation is applied on a different kind of algorithm. In future steps we will study the extension of COHORT library for dealing with the stochastic input data, as well as considering multi-flight optimization.

[6]Global Warming Potential (GTP), Average Temperature Response (ATR), Radiative Forcing (RF) to name a few

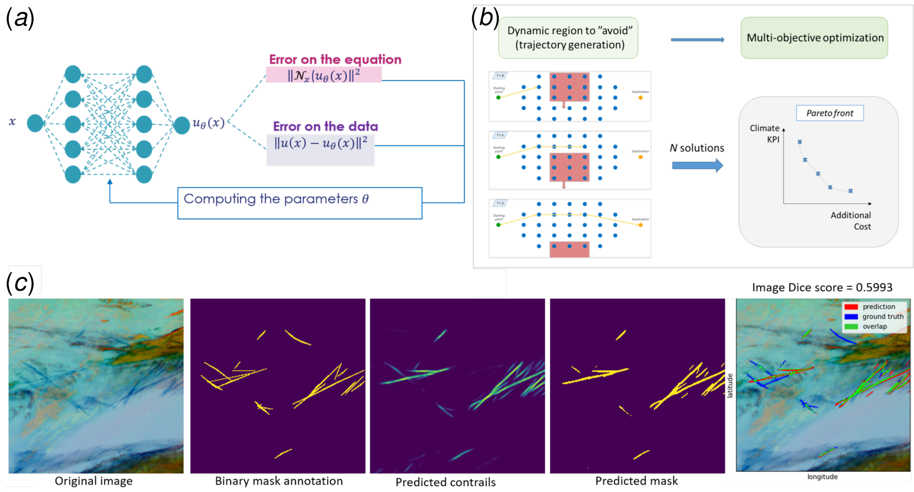

Fig. 2: (a) Physics informed neural network; (b) From trajectory generation to multi-objective optimization; (c) Qualitative inference results on one annotated European satellite image with a neural network trained on the GOES-16 dataset.

3.3 Contrail verification through imagery

We are currently also developing contrail classification and detection algorithms using two sources of data: ground cameras in spherical geometry and satellite images from the European weather satellite, Eumetsat[7]. The key idea is to limit the amount of needed labelled data through transfer learning as well as novel AI algorithms, such as geometric deep learning. These enforce knowledge about the symmetries present in an image directly in the model structure, allowing for a drastic reduction of trainable parameters [14] while being more data-frugal. Moreover, they work directly in the native geometry of the cameras (e.g. spherical), thus limiting the effects of projection distortions. Automatically detecting images containing at least one contrail, via neural classifiers could thus be a first screening step before tracking persistent contrails in satellite with more elaborated segmentation algorithms.

Geostationary satellites are gaining traction in the AI community through the Open Contrails labelled dataset [15], containing more than 20.000 annotated GOES-16 images, covering North America. For global contrail verification, a very interesting research avenue is combining training on this dataset with Eumetsat or Himawari data in order to cover other regions of the globe. In Figure 2 (c) we present a preliminary result showing the good detection capability of a neural network trained solely with GOES-16 images and tested on Eumetsat MSG ones[8]. Despite the differences in temporal and spatial resolution between

[7]https://view.eumetsat.int/productviewer?v=default

[8]This result is not to be interpreted in a statistical sense, the DICE score refers to the displayed image only. We do not currently have enough annotated images for statistical tests.

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the two sensors this result highlights the potential for transfer/few-shot learning, drastically reducing the need for labels on the MSG images.

4 Conclusions

In this article, we provided an overview of the research directions investigated in Thales for building robust AI solutions to mitigate contrails throughout the entire pipeline: prediction, trajectory optimisation and contrail verification. These include Physics-Informed Neural Networks, multi-objective optimization approaches, and robust-by-design Deep Learning. By leveraging the frugality and interpretability of these techniques we aim to speed up the introduction of contrail mitigation into sustainable Air Traffic Operations.

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