Evaluating Aviation Emission Inefficiencies and Reduction Challenges with Electric Flights

Based on an analysis of flights from 2019 in the Dutch and French airspaces

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***Abstract*—Inefficiencies in flight operations, like deviations and non-optimal flight speed or altitude, are directly linked to flight emission inefficiencies. Quantifying these emission inefficiencies and studying potential mitigation strategies is certainly beneficial for the sustainability of the aviation industry. In this paper, we analyze emission inefficiencies in Dutch and French airspaces using flight data from 2019. The emission inefficiency analysis quantifies the excess carbon emissions for each flight by comparing its emissions with a set of optimal alternative trajectories. We find that around 19% of excess emissions existed in 2019 within the airspace of interest. We also study the potential reduction of emissions by replacing short-range flights with electric aircraft. We propose a simple electric aircraft energy model and relate that to emissions in electric generations in different countries. We find that besides the significant increase in air traffic demand caused by the limited capacities of electric flights, the emissions caused by electricity generation cannot be neglected. Significant reductions can only be achieved when emissions caused by electricity generation are low, as is the case currently in France. However, more emissions can be indirectly generated if the electricity used to power the future electric aircraft is itself produced from high emission sources, as is the case currently in the Netherlands. The paper also provides further insights and recommendations on the data sources, research approach, and future research for aviation sustainability.**

***Keywords* —** flight emission; data analysis; emission inefficiencies; trajectory optimization; electric flight

I. Introduction

The impact of aviation on emissions and climate has become an increasing concern for the research community and the general public. This is partially due to the lack of action by the aviation industry policymakers over the past decades and partially the result of increased awareness of aviation climate impact. While new technology, like electric-powered flights and hydrogen-powered flights, are still years away, the current spotlight has been on *synthetic* aviation fuel. Furthermore, Synthetic aviation fuel is not always *sustainably* produced, and it does not directly reduce emission in flight operations.

Inefficiencies associated with excess fuel consumption are directly related to unnecessary emissions. Modeling and quantifying flight inefficiencies, as well as deriving related performance metrics, have been active areas of research over the past years [1], [2], [3]. Research [1] proposes comparing flight efficiencies using the actual trajectory and optimal reference trajectory. Study [2] makes use of aircraft surveillance data to provide cost-based indicators that represent flight inefficiencies. In the SESAR APACHE project [3], a set of new performance indicators, including distance-based and fuel-based indicators, are developed to evaluate flight inefficiencies.

A recent analysis conducted by EUROCONTROL [4] conducts a comprehensive study on fuel and emission inefficiencies. It finds that between 8% and 11% of inefficiencies exist in current flight operations in the EURTOCONTROL network. The study is performed based on all flights in the network, and the fuel inefficiencies are calculated using the reference fuel burn model, which is based on the 5th or 10th percentile of all fuel burn observed for a specific airport pair and aircraft type combination. The actual fuel burn is obtained based on the estimations from the tactical flow management system. Unlike the previously mentioned studies of [2], [3], The EUROCONTROL analysis [4] assumes the reference fuel burn based on the percentile of airport pairs. This creates larger errors for airspaces with structural inefficiencies, as all flights between two airports may fuel inefficiencies.

Besides analyzing and proposing ways to reduce these operational emission inefficiencies over Europe, electric-powered flights have been suggested as a novel and easy to implement approach to replace short-range flights [5]. However, the current energy density constraints of batteries limit the range and the passenger capacity of proposed electric aircraft designs [6]. In addition, not all types of electricity are generated equally. There is a large difference in terms of emissions caused by electricity generation [7]. All these facts must be considered when analyzing the electric flights's benefits for emissions.

In this study, we propose an optimization-based method that is similar to [3] for analyzing fuel and emission inefficiencies, which proposes an accurate reference for each flight. For each selected flight, we estimated the fuel consumption based on the open-source aircraft performance model (OpenAP) [8]. At the same time, we provide the reference trajectory using the optimal trajectory specifically generated for the selected flight. The excess fuel consumption and emissions are calculated for all flights and then aggregated for the entire region of interest.

The research is funded by the Dutch-Franco aviation sustainability collaboration initiative and specifically addresses flight operations between Dutch and French airspaces, which are also some of the busiest airspaces including free routing and non-free routing sectors.

The research objective is twofold. First, we want to quantify the total carbon emission and excess emissions created by inefficiencies for flights departing and arriving in the Netherlands and France, and Belgium, during 2019. Secondly, we want to focus on short-range flights (less than 500km) and study the potential emission reductions associated with prospective electric passenger aircraft.

The structure of the paper is organized as follows. Section II addresses the methodologies for obtainingflight operations' inefficiencies in the studied airspaces. Section III discusses the challenge of modeling and estimating emissions from newly emerging electric flights. Section IV provides the results and analysis. Finally, Sections V and VI describe the discussions, recommendations, and conclusion of this study.

II. Modeling Emission Inefficiency

In this section, we discuss the models and methods used for evaluating the fuel and emission inefficiencies of individual flights. We focus on the fuel and emission estimations based on data from the EUROCONTROL R&D dataset, as well as the qualification of inefficiencies that occur in each flight compared to an optimal reference trajectory.

A. Fuel estimation

Fuel consumption can be estimated based on aircraft performance models. BADA (developed by EUROCONTROL) and OpenAP (developed by TU Delft) are two models commonly used in such air transport research. In this study, we choose the open-source OpenAP model for the estimation [8].

OpenAP currently supports the performance and emission models for the around 35 most common aircraft type codes. It can also model another additional 21 aircraft types through a similar aircraft type using synonyms, which estimate emissions using existing aircraft models in OpenAP. Table I shows the aircraft type codes that are supported by OpenAP and the percentage of flights in the airspaces for this study.

TABLE I
OpenAP aircraft types

support	typecode	flights
Full models	A19N A20N A21N A319 A320 A321 A332 A333 A343 A359 A388 B37M B38M B39M B3XM B734 B737 B738 B739 B744 B748 B752 B763 B772 B773 B77W B788 B789 C550 E145 E170 E190 E195 E75L GLF6	60%
Synonyms	C525 B77L B733 C25A E290 B762 MD11 A310 SU95 PC24 AT75 GLF5 C56X AT72 CRJ2 A306 B735 AT76 CRJ9 A124 LJ45	7%

The fuel flow model requires the flight states of speed, altitude, and vertical rate, which are all provided by the R&D dataset. However, the trajectories in this dataset have relatively low resolution. To ensure the consistency of fuel flow estimations, each trajectory is filtered and resampled into a trajectory of 15-second resolution before estimating the fuel and emissions. The processing, filtering, and resampling is performed with the traffic library [9]. The uncertainties in aircraft mass is also considered and described in detail in section II-C.

B. Fuel optimal reference trajectory

A set of emission optimal trajectories is generated for each flight to evaluate the emission inefficiency. The optimal trajectory is created using the open-source *OpenAP.top* trajectory optimizer [10]. The optimizer uses a non-linear optimal control approach to generate an optimal trajectory according to different cost functions, including both climate objectives and conventional cost index objectives. In this paper, we used the fuel optimal objective, which also minimizes for CO_2 emission. In the remainder of this section, we briefly explain the theory of this optimizer.

1) Optimal control problem: The optimal flight trajectory generation can be considered as an optimal control problem, where the best combination of parameters (such as position, speed, and altitude) over time need to be determined.

With the simplified point-mass aircraft performance model, the following flight states are considered:

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

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:

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

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

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

$$\frac{\mathrm{d}m}{\mathrm{d}t} = -\mathsf{ff}_t(m, v, h) \tag{6}$$

where v is the true airspeed, γ is the flight path angle, and ff is the fuel flow model that is dependent on the aircraft mass, speed, and altitude. w_x and w_y are wind speed components. True airspeed are calculated based on Mach number and altitude under the international standard atmosphere conditions:

$$\gamma = \tan^{-1}\left(\frac{\mathsf{vs}}{v}\right) \tag{7}$$

$$v = M a_0 \sqrt{\Gamma R T_h} \tag{8}$$

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 dynamic 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:

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

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:

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

is subject to the following constraints:

$$\dot{\mathbf{x}}_t = \mathbf{f}(\mathbf{x}_t, \mathbf{u}_t) \tag{11}$$

$$\mathbf{h}(\mathbf{x}_t, \mathbf{u}_t) < 0 \tag{12}$$

$$\mathbf{e}(t_0, t_f, \mathbf{x}_{t_0}, \mathbf{u}_{t_0}, \mathbf{x}_{t_f}, \mathbf{u}_{t_f}) = 0 \tag{13}$$

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.

2) Numerical approximations: 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 used by *OpenAP.top* is an open-source library called CasADi [11], a symbolic framework for numeric optimization. CasADi further utilizes the lower-level C code that invokes the Interior Point Optimizer (IPOPT) [12] to solve the non-linear programming problem.

The *OpenAP.top* optimizer can generate the global 4D flight from the initial climb to the final approach. Flight phases do not need to be explicitly expressed, which implies that the optimizer needs to generate the optimal climb, cruise, and descent automatically from the origin to the destination, considering the performance limit of the aircraft and wind conditions at different locations and altitudes.

3) Resulting optimal trajectory: Figure 1 shows an example of a flight and its optimal alternative from Amsterdam Airport Schiphol to Toulouse-Blagnac Airport. The red and green colors represent the actual flight and optimal trajectory, respectively.

The optimizer can consider real wind conditions. However, the analysis in this paper considers a large number of flights. To reduce computation load, wind information is not used for optimization. Hence, the ground track is equivalent to the great circle trajectory. We can observe a relatively large deviation from the optimal trajectory. This is one of the causes for potential fuel and emission inefficiencies.

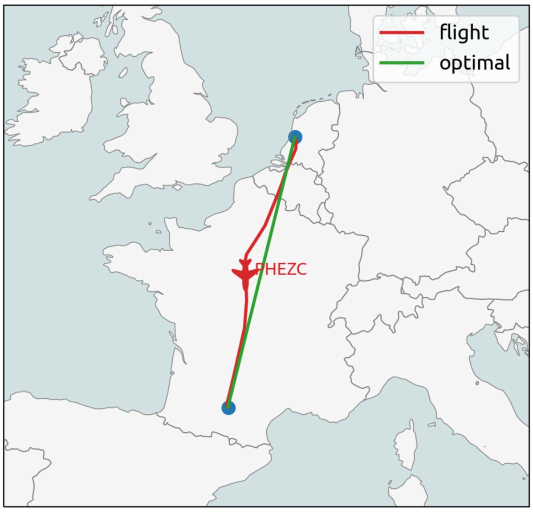

Fig. 1. Ground tracks of an example flight and optimal trajectory from EHAM airport to LFBO airport

The altitude and speed profiles of the optimal trajectory are dependent on the aircraft's takeoff mass. In Figure 2, we illustrate different optimal vertical profiles with different assumptions of takeoff mass. Based on these outputs, we can see that the altitude is most affected by the mass of the aircraft, while the speeds of these optimal trajectories are relatively similar.

The range of takeoff masses selected is intentionally the same as the ones earlier used for estimating the fuel and emissions. This provides convenient way to deal with uncertainties in both emission estimations and to compare the results with optimal alternative trajectories.

C. Dealing with uncertainty in aircraft mass

Take-off mass have a considerable impact on fuel consumption. For each aircraft, several sets of estimations are calculated based on different initial mass assumptions. In this study, six different initial mass values between 60% and 100% of the maximum takeoff weight are chosen for the estimations. In the later sections of this paper, we address how to choose the most likely mass based on the optimal trajectory.

The uncertainty of mass also affects the estimation of fuel consumption and emissions based on actual trajectories. Figure 3 shows

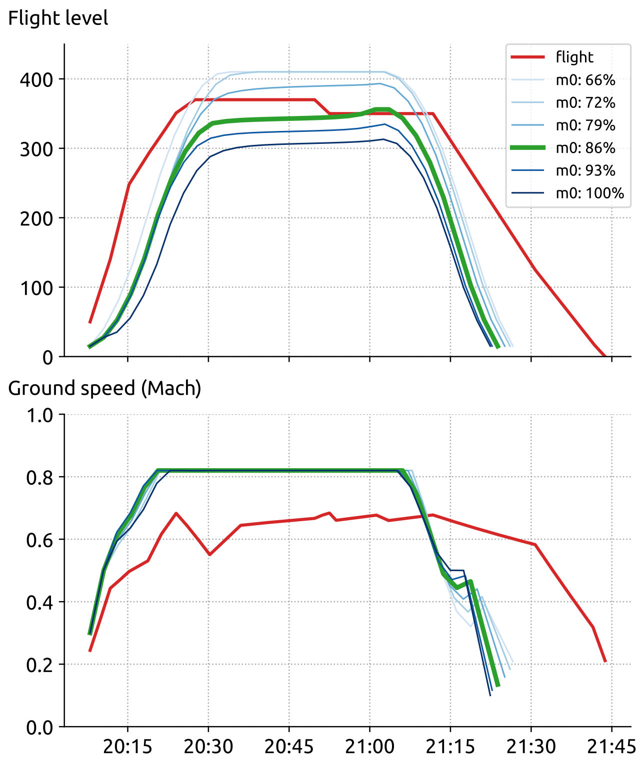

Fig. 2. Altitude and speed profiles of the example flight (red) and optimal trajectories with different takeoff mass (blue). The optimal trajectory in green is the one that has the closest flight level to the actual flight.

the difference in fuel consumption considering a range of aircraft take-off masses for this flown trajectory. The difference in fuel consumption is around 13% (2.6 tons versus 2.3 tons of fuel).

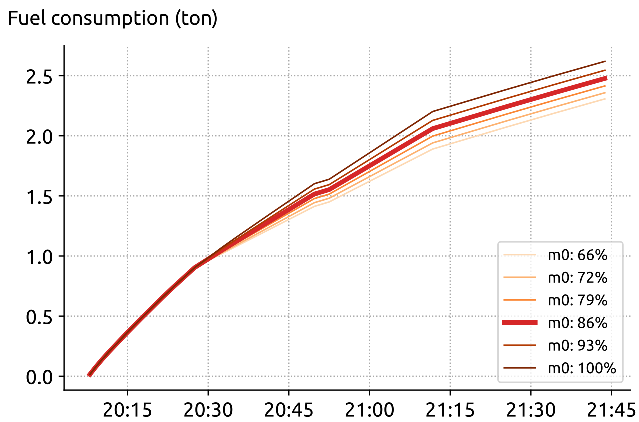

Fig. 3. Difference in fuel consumption due to different initial assumptions of aircraft takeoff mass. The variation of total fuel consumption is around 13% for this trajectory among different masses.

Figure 2 visualizes the influence of optimal trajectory due to different aircraft mass, from which we can see that mass affects mostly the optimal altitude of the aircraft based on these optimal trajectories. The same range of mass values is used for conducting the emission estimation. In this study, we chose the most likely optimal trajectory based on the closest altitude profiles among all different optimal alternatives. For the example flight, the selected optimal trajectory (86 % of takeoff mass) is marked in green in Figure 2, which corresponds to the fuel estimates marked with red color in Figure 3.

By combining all different pairs of estimates and optimal emissions, we can analyze the variations caused by different mass assumptions, and we can also provide an improved understanding of the uncertainties. Figure 4 shows the variation of excess between estimations and optimal trajectories due to different assumptions of takeoff mass.

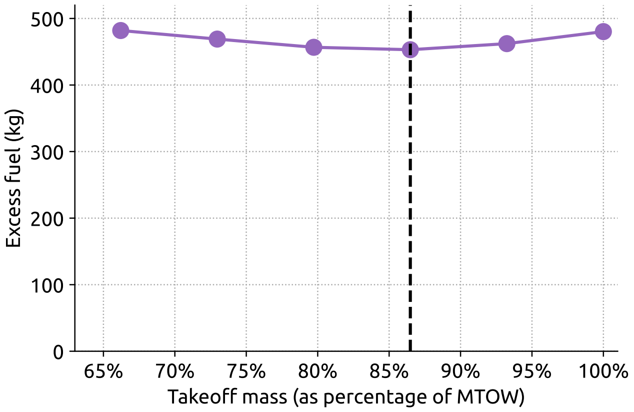

Fig. 4. Excess fuel estimated under different takeoff mass assumptions. The chosen mass from earlier figures, approximately 86% of maximum takeoff weight (MTOW), is marked in the dashed vertical line.

III. Impact of electric flights

In the second part of this study, we focus on short-range flights' emissions, which are flights with ranges of less than 500 kilometers. The city pairs and number of daily average flights for this analysis are shown in Figure 5. According to earlier studies [13], [14], these short-range flights have the most potential to be replaced by electric-powered airplanes. The recent development of all-electric flight tests by Eviation's Alice aircraft have demonstrated such capability with limited passenger capacities.

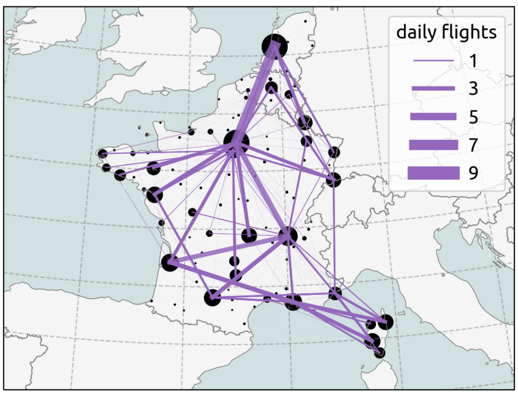

Fig. 5. City pairs with ranges of less than 500 kilometers. The thickness of the lines represent the number of average daily flight connections.

However, there are still two main constraints to achieving emission reductions through the replacement of the current fleet with a new all-electric fleet. Firstly, the energy density of the current battery limits both the passenger capacity and the flight range. Secondly, energy generation itself is not currently free from emissions in most countries. Hence, assessing the actual reduction in emissions provided by electric aircraft requires further investigation.

A. *Electric plane performance model*

The passenger capacity of current short-range regional, electric flights is quite limited currently. This study makes use of a reference aircraft, Eviation Alice, as the baseline for modeling the emission performance of electric flights.

Alice is designed and tested with a capacity of nine passengers. The maximum range is around 800 kilometers with zero payloads. When carrying all nine passengers, the range is significantly reduced. Since detailed performance is not available, we use the energy model shown in Table II as a base energy model for the electric aircraft, which is established on the empirical assumptions of this aircraft.

TABLE II
Reference energy model of electric flights in this study

parameter	Eviation Alice	simplified model
range	800 km	500 km
capacity	9 (max)	10
power	2×640 kW (max)	1000 kW (80%)
speed	400 km/h	320 km/h (80%)
trip energy		1600 kWh
energy / pax		170 kWh / pax
energy / pax / km		0.3 kWh / pax / km
sensitivity		± 0.1 kWh / pax / km

Several assumptions are made in our study to form a more realistic model for electric flights. First, the range is reduced to 500 kilometers from 900 kilometers based on a fully loaded aircraft. Furthermore, we assume 80% of the average power and speed during the trip. This is then used to estimate the total energy required per trip, as well as the energy required per passenger and kilometer.

B. *Estimation of carbon emissions*

Once we have the baseline energy model for potential future electric flights, we calculate the total energy required to theoretically replace all the short-range flights in the Dutch and French airspaces.

The energy requirement is then combined with the carbon emissions rate caused by energy generation from both countries. This provides indications on actual emissions for switching to electric flights, without considering the life-cycle of electric airplanes or batteries.

We approximate the number of total passengers based on the passenger capacity of current airliners provided by the OpenAP model. This way, we can estimate the number of electric power flights that are needed to replace total current short-range flight demand.

Once these results are obtained, we compare the difference in emissions between these future scenarios and the emissions we estimated earlier based on flight trajectories from the dataset. The entire process is shown in Figure 6.

Table II also provides an empirical sensitivity model, which we use to study the variations in the emissions caused by electrification of short-range flights. This will later be used in the sensitivity analysis for emission reduction caused by electrification in the future.

IV. Analysis

To analyze all the flights in 2019, flights with both departures and destinations in the Netherlands and France (and also Belgium) are extracted from the EUROCONTROL R&D dataset. We indicated earlier the flights in this dataset have a low resolution, hence the *traffic* library [9] is used to reconstruct and resample the flights with

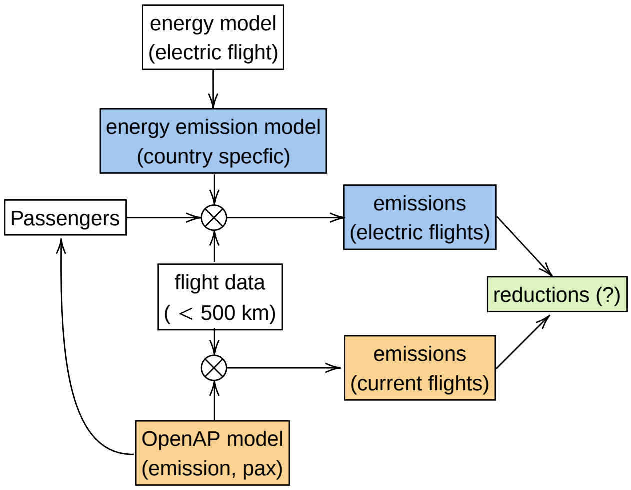

Fig. 6. The process of evaluating potential emission reductions with short-range electric flights

a 15-second resolution. This new subset of trajectory data then forms the basis of the analysis in the rest of this section.

A. Emission inefficiencies in current flight operations

For each flight in our research dataset, we compute the total fuel consumption, CO_2 emissions (linear to the fuel consumption), and inefficiencies based on the methods proposed earlier. Then, the total statistics are aggregated based on the four months of data included in the dataset. To obtain the estimations with the entire year of data, we extrapolate the aggregated results by a factor of three. The final emission inefficiency is found to be around 19%, which means that up to 19% of total emissions can be reduced if all flights can fly the most optimal trajectories.

TABLE III
EXCESS EMISSIONS FOR ALL THE FLIGHTS IN THE DUTCH, BELGIUM, AND FRENCH AIRSPACES DURING 2019

parameter	**4 months**	**full year**
number of flights	88,000	264,000 t
total fuel total excess fuel	160,000 t 31,000 t	479,000 t 93,000 t
total CO_2 total excess CO_2	502,000 t 97,000 t	1,510,000 t 291,000 t
CO_2 (<500 km) excess CO_2 (<500km)	104,000 t 28,000 t	1,500,000 t 291,000 t
CO_2 (>500 km) excess CO_2 (>500km)	398,000 t 70,000 t	1,190,000 t 209,000 t

We can normalize the fuel efficiencies for each flight using the following simple equation:

$$\eta = \frac{\mathtt{E}_{\mathtt{estimate}}}{\mathtt{E}_{\mathtt{optimal}}} \tag{14}$$

where $\mathtt{E}_{\mathtt{estimate}}$ is the total emissions estimated based on the actual flight, and $\mathtt{E}_{\mathtt{optimal}}$ is the emissions obtained from the optimal trajectory. With that, we visualize the efficiency for all the flights, aggregated by city pairs, in Figure 7.

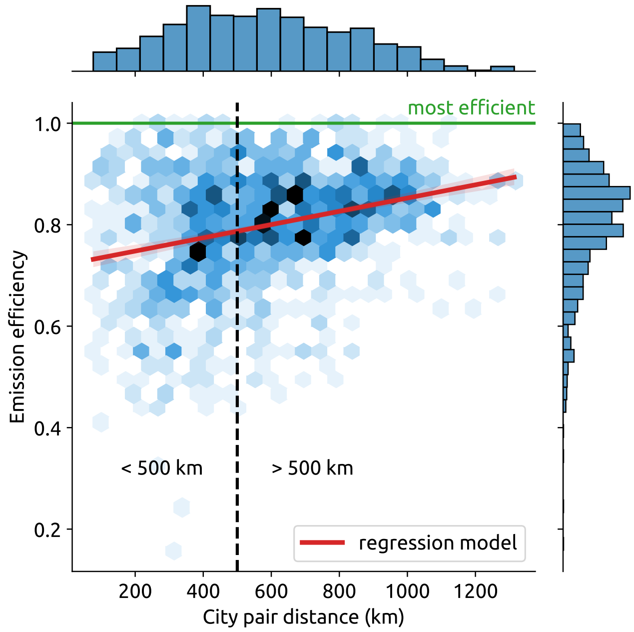

Fig. 7. Normalized fuel efficiencies among all flights in 2019 in the selected airspace, aggregated by pairs of origin and destination airports.

In this figure, the total trip fuel of all flights between each city pair is compared with the total fuel of all optimal trajectories. The green line shows the ones with the most efficient origin-detonation pairs. The red line shows a linear regression model. We can observe that the majority of the efficiency is only around 80% (or 20% of inefficiency). There is also more inefficiency among short-range flights, compared with the rest of the flights.

B. Uncertainties considering the varying mass assumptions

In the earlier section, we analyze the effect of variation among emission estimations due to different assumptions of masses with one example flight. To further demonstrate the aggregated results, Figure 8 shows the distributions for all flights in the dataset. The top plot shows the distributions of estimated CO_2 emissions per flight, and the bottom plot shows the distributions of excess CO_2 emissions per flight. Green and red dashed lines represent low and high takeoff mass assumptions. Black solid lines show the default results based on vertical profile matching.

We can see a large variety of emissions exists among all flights. The distributions do not change much based on different aircraft mass assumptions. The difference in excess CO_2 caused by the different mass assumptions is found to be around 30,000 tons. The following Table IV shows the lower and upper bound for the total emissions and excess emissions.

TABLE IV
UNCERTAINTIES CAUSED BY TAKEOFF MASS (4-MONTH)

parameter	**lower bound**	**upper bound**
total CO_2 total excess CO_2	490,000 t 90,000 t	510,000 t 120,000 t
excess CO_2 (>500 km) excess CO_2 (<500 km)	27,000 t 63,000 t	31,000 t 89,000 t

Compared to the previous Table III, we can see that the previously obtained total inefficiency (19%) is at the lower bound of the ineffi-

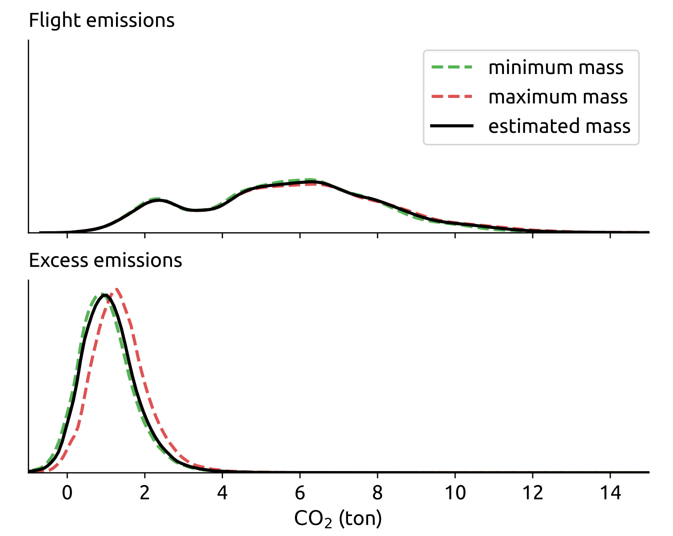

Fig. 8. Estimation of emissions and excess emissions considering different mass assumptions.

ciency level. Hence, we can infer that the real emission inefficiency might be even higher.

C. Emission reductions with electric powered flights

Based on the performance model from Table II and the process shown in Figure 6, we estimate the total number of electric flights required for replacing the current short-range flights in the regions of interest. Figure 9 reveals the number of flights and passengers that were carried during March, June, September, and December of 2019.

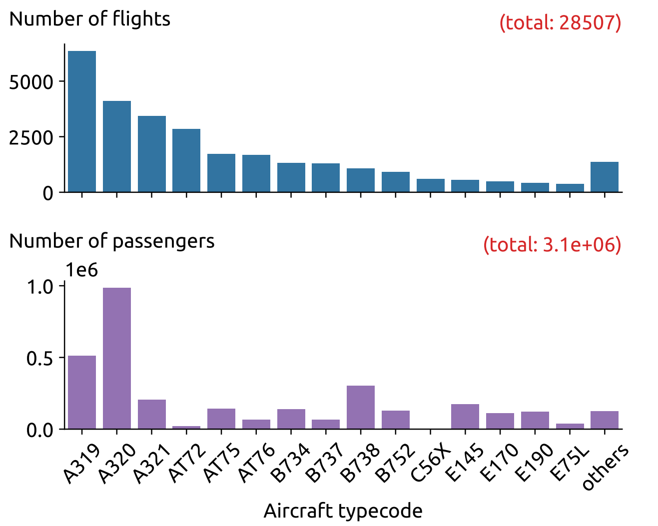

Fig. 9. Number of flights and passengers for the four months of data in 2019

Figure 9 demonstrates the challenge of replacing current passenger flights (average capacity >100 passengers) with electric aircraft that have very limited passenger capacities. This results in a much higher density of air traffic in the airspaces, which can disrupt current operations and further calls for a very high level of automation in air traffic control.

Another commonly ignored factor we want to study is the emissions caused by the generation of electricity. Figure 10 shows the carbon emissions for electricity production among most of the western and southern European countries [7]. Among these countries, France, the Netherlands, and Belgium are used for evaluating the potential emission reduction of electric flights.

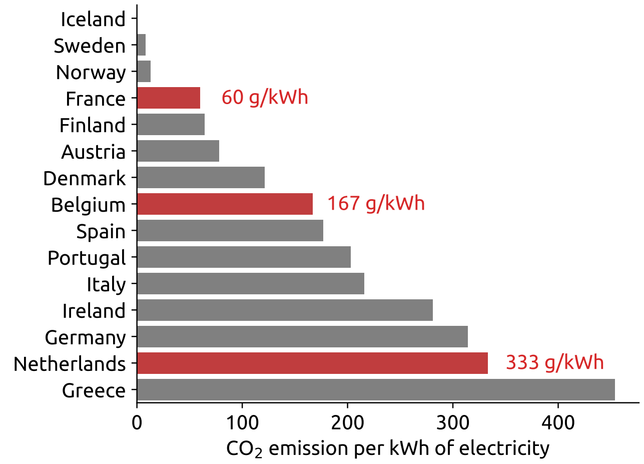

Fig. 10. CO_2 emissions caused by electricity generation in different countries

Table V offers the quantitative results of this analysis. We can conclude that, replacing all the flights with the electric flight based on our simplified model requires a new fleet of electric-power flights that is more than 10 times larger than the current fleet. The table also shows the comparison of emissions between current flights and emissions at energy production source for electric flights. The positive conclusion is that, with the energy emission rate of the French electricity matrix, there is a significant decrease in carbon emissions (around 80% of reduction). However, if the electricity is generated in the Netherlands where the energy matrix comes from more than 75% fossil sources, electrification will induce more carbon emissions from the aviation sector than emissions from all current jet fuel aircraft.

TABLE V
COMPARISON STUDY BETWEEN CURRENT JET FUEL AND POTENTIAL ELECTRIC FLIGHTS

	jet	**electric**
number of flights (avg. daily)	240	2,700
number of flights (4 months)	28,500	320,000
number of flights (est. yearly)	85,500	960,000
jet fuel CO_2 (yearly)	**310,000 t**	
electricity CO_2 - FR (yearly)		**67,000 t**
electricity CO_2 - BE (yearly)		**187,000 t**
electricity CO_2 - NL (yearly)		**370,000 t**

It is worth noting that this analysis considers the direct energy consumption, which does not account for the emissions' loss during transmission. However, we think this is a fair comparison since the excess emission caused by the production and transporting of jet fuel are also not included in our study and most other aviation emission studies.

D. Sensitivity of electric flight energy model

Previously, in Table II, we have specified the level of uncertainties in the energy rate for the electric flights. Figure 11 shows the impact of emissions if we also consider these levels of uncertainties.

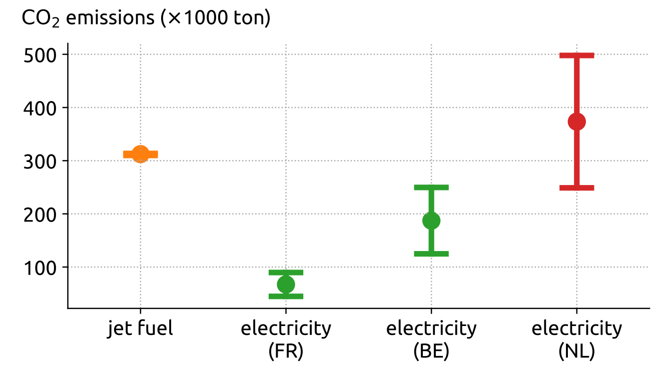

Fig. 11. CO_2 emission by jet aircraft and electric aircraft for short-range flights in Dutch and French airspaces

We observe that if all electricity used to power the electric aircraft is generated in France, then there is still a very large reduction in emissions even in the worst scenarios for passenger energy rate. This also confirms the importance of sustainable energy sources over largely fossil fuel-based electricity generation (like the Netherlands or Germany). The transition to sustainable aviation cannot be separated from the wider energy transition.

V. Discussions

This study addresses the emission inefficiency for flight operations over Dutch and French airspace and evaluates the potential of emission reduction with short-range electric flights. Both analyses are based on the EUROCONTROL R&D dataset from 2019, where the network operates at its peak capacity before the COVID-19 pandemic. In the section, we further elaborate on the limitations associated with some of the approaches proposed in the paper. We also give more insight into the models and analysis of the study.

A. Limitations

EUROCONTROL R&D dataset is a comprehensive dataset that contains all commercial flights over the network. However, several limitations exist that restrict the potential of this paper's analysis. First, only four months of data from each year are provided in the dataset, which is always March, June, September, and December. This limits the completeness of the dataset for this study, and results have to be extrapolated to obtain the yearly statistics.

The publication of this data also has a delay of two years, which makes the analyses of recent emissions impossible. Lastly, the resolution of the flight trajectories can be quite low. In some cases, only a few data points are available for flight trajectories. This certainly reduces the accuracy of estimations for some trajectories.

OpenAP is the aircraft performance model used for emission estimation, and it is also the base model for generating fuel-optimal trajectories. However, it is known that the model underestimates the emissions during the climbing phase of the flight. Hence, the actual emissions may be higher than the results presented in this paper. When the model is used to quantify the emission inefficiencies, the discrepancy is, fortunately, reduced. This is because both estimation and optimal trajectories obtained from the OpenAP consider fewer emissions during the climb. Hence, a large portion of the bias is likely to be canceled out.

OpenAP also has a limited number of aircraft models. In the original dataset, there are a number of aircraft types, which are not modeled by OpenAP and not included in the analysis of this study. These aircraft type codes are shown in Table VI. The actual emission would be higher if these aircraft types are considered. Most of these un-modelled aircraft are light jets, helicopters, turboprops.

TABLE VI
Aircraft typecodes occur in EUROCONTROL dataset but not modeled in OpenAP. Related flights are not included in the analysis.

A139	A338	A3ST	AN12	AS65	AT43	AT45	AT46	AT73	ATP
B190	B350	B462	B712	BE20	BE40	BE9L	C208	C25B	C25C
C25M	C310	C402	C425	C510	C55B	C650	C680	C68A	C750
CL30	CL35	CL60	CRJ7	CRJX	D228	D328	DA62	DH8D	E135
E35L	E50P	E545	E550	E55P	E75S	EA50	EC55	EC75	F100
F2TH	F406	F900	FA10	FA50	FA7X	FA8X	GL5T	GLEX	GLF4
H25B	H25C	HDJT	IL76	J328	JS32	LJ35	LJ40	LJ60	LJ75
P180	P68	PA46	PC12	PRM1	RJ1H	RJ85	SF34	SW3	SW4

The entire process of analysis is time-consuming and computationally expensive. This is because, for each trajectory, several estimates need to be computed under different takeoff mass assumptions. At the same time, multiple optimal trajectories under different initial mass assumptions need to be generated for each flight. The *OpenAP.top* optimizer is already quite efficient, taking tens of second to compute an optimal trajectory. However, there are around 88,000 flights and each with 6 optimal alternatives to generate, which requires 528,000 optimization runs to complete the analysis.

In the end, we had to rely on the TU Delft's DelftBlue supercomputer [15] to perform this calculation, which takes for more than 10 days for processing the entire dataset of 2019. Such computational complexity also prevents the use of real-time wind conditions and limits the analysis to only the Dutch and French airspaces in this study.

B. Insights on emission inefficiencies

It is worth pointing out the 19 % emission inefficiencies is the comparison with the absolute theoretically optimal trajectories. It is apparent that not all of can be completely mitigated.

For example, deviation due to convective weather or avoiding special use airspace (like military activities) is hard to avoid. This calls for better predictions of extreme weather and better integration of different airspace users. On the other hand, inefficiencies caused by a lack of capacities can be reduced, for example, with a high level of automation [16]. There are also inherent inefficiencies caused by routing planning and execution of the flights, which can be, and should be, mitigated in future flight operations.

To further analyze the causes of inefficiencies, more research should be conducted to associate the inefficiencies with flight plans, airspace capacity measures, convective weather data, and airspace restriction information. This will lead to futher understand how inefficiencies occur.

C. Less jargon and more transparency – the only pathway to sustainable aviation

Electric aircraft, in addition to synthetic aviation fuel and hydrogen aircraft, has been identified as one of the pathways to aviation sustainability. We constructed a simplified model to evaluate the potential benefit of introducing electric flights as the replacement for current short-range jet-fuel powered air travel, based on an existing electric aircraft model. It is worth noting that the simplified model used in the paper may differ from the electric aircraft real performance. However, it helps us to have a rudimentary comparison with currently jet fuel-powered aircraft.

The main insight provided is that aviation sustainability cannot be claimed without the context of the energy sources powering flight. It is often assumed that electric flight will lower emissions, but the source of the electricity determines whether this assumption becomes a reality. Especially, we must form a better understanding of the carbon budget when analyzing different approaches, including electrification, hydrogen, and synthetic aviation fuel. For example, a recent open model, CAST [17], addresses exactly such energy transition and carbon budget challenges for aviation. It places aviation in a global context to evaluate the actions required to achieve better sustainability.

The pathway to a truly sustainable aviation future, unfortunately, asks for the de-growth of air travel, at least in short term. For example, a limited number of short-range electric flights can be best combined with railway transport to avoid the saturation of airspace resources. On the one hand, this scenario can reduce air traffic management challenges, and at the same time, it reduces emissions by avoiding short-range air travel. In the longer term, new technology in batteries and more energy sources with low emissions is the only way that aviation can truly reach sustainability.

VI. Conclusion

In this paper, we used the flight trajectory data from 2019 and conducted studies on emission inefficiency and reduction for flight operations in Dutch, French, and Belgium airspaces. The emission inefficiency analysis focused on quantifying the excess carbon emissions by comparing flight emissions with an optimal alternative trajectory. The potential emission reduction focused on short-range flights with less than 500 km range, which have the potential to be replaced by the emerging electric aircraft. We conducted this part of the study by introducing a simplified electric aircraft emission model and calculated indirect emissions in electric generations.

The first main finding is that around 19% of excess emissions existed in the entire airspace containing the Netherlands, Belgium, and France. The second part of the study focused on the challenge of reducing emissions by replacing the current fleet with electric flights. In addition to the ten-fold increase in air traffic caused by the limited passenger capacity of electric flights, we found that the emission caused by electricity generation cannot be neglected in evaluating aviation emissions. We concluded that a significant reduction can be archived if the electricity is provided by France, while more total emissions are produced if the electricity is provided in the Netherlands.

This study focused primarily on the Dutch and French airspaces. However, the methodologies developed during the study, including the emission estimation, and optimal trajectory generations, are all openly accessible and can be extended to a broader scope. Follow-up studies can also focus on further identifying the causes of emission inefficiencies and studying the emission reductions caused by other sustainable alternatives.

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