

Identifying the Sources of Flight Inefficiency from Historical Aircraft Trajectories

A set of distance- and fuel-based performance indicators for post-operational analysis

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Abstract—In this paper a set of new performance indicators (PIs) aiming to capture the environmental impact of aircraft operations is proposed. Its contribution is threefold: optimal trajectories are computed to compare them with historical trajectories and derive several flight efficiency PIs; a family of fuel-based PIs is proposed, where fuel is estimated only from surveillance trajectory datasets not requiring confidential data; and different PIs and variants are proposed aiming to decouple and to identify different sources of environmental inefficiencies, distinguishing those that could be attributed to the different layers of air traffic management (ATM), and those attributable to the airspace users (AUs). A case study is presented for two different days, where flight inefficiency was assessed with the proposed PIs for all traffic crossing the FABEC airspace during a 24h period. Main results show that average fuel inefficiencies that could be attributable to ATM are around 250 kg (7.8%) when a full free route without en-route charges scenario at maximum range operations is considered as reference for the optimal trajectories. AUs induced fuel inefficiencies (due to flying faster than the maximum range speed) have a mean around 100 kg (3%). It is also concluded that fuel inefficiencies in the vertical and horizontal trajectory domains have a similar contribution to the overall flight inefficiency. Yet, horizontal inefficiencies are higher at strategic level, while are negative at tactical level for the great majority of flights.

Keywords- *flight efficiency; ATM performance; post-ops; trajectory optimization; environmental impact; fuel estimation*

I. INTRODUCTION

Air traffic management (ATM) affects the environment, with more or less impact, depending on when, how far, how high, how fast and how efficiently aircraft can fly [1]. This influences how much fuel aircraft burn, the level of greenhouse and other gases emitted from their engines, and how much noise they emit. The environmental performance of aviation has improved significantly since the 1960s. Yet, with global traffic expected to increase in the following years, the challenge is meeting this expected growth while minimizing its environmental impact.

Several agencies and programs world-wide are setting ambitious environmental targets for future ATM paradigms, such as SESAR in Europe and NextGen in the United States. For example, one of the main political goals of SESAR 2020 in the

environment area is to contribute with a 10% of CO₂ reduction. This target supposes reducing burned fuel by 250 to 500 kg per flight by 2035, which corresponds to 0.8 to 1.6 tons of CO₂ emissions per flight [2]. Besides setting these ambitious targets, environmental performance (and ATM performance in general) shall be continuously monitored in order to identify areas of improvement; to validate new technological or procedural concepts or solutions; or to compare the actual measured performance against these high-level targets.

In this context, the International Civil Aviation Organization (ICAO) launched in 2003 a worldwide initiative to ensure that the future global ATM system is performance based [3,4]. Worldwide support to the ICAO initiative is also given by CANSO (Civil Air Navigation Services Organization) [5]. In line with these initiatives, current ATM performance assessment is addressed in Europe through the Single European Sky (SES) Performance Scheme, which establishes an agreed methodological framework for performance targeting, measuring, baselining and benchmarking in ATM [6]. In [7], a comprehensive review is given, comparing the performance frameworks proposed by ICAO, CANSO, the SES performance scheme, performance monitoring activities at Eurocontrol, and the SESAR 2020 performance framework; identifying over 150 performance indicators (PIs) for performance management and monitoring in 11 different key performance areas. Similarly, in NextGen numerous PIs have also been proposed to measure the performance of the program deployment [8,9].

This paper focus on PIs aiming to capture environmental inefficiencies from historical flight records coming from surveillance (and flight planning) datasets. Current indicators implemented by the SES performance scheme and CANSO, for instance, compare the trip distance of planned and actual routes with great circle distances (orthodromic trajectories). In this way, only the horizontal track of the trajectory is considered, neglecting the effects of vertical (and speed) flight inefficiencies on the environment. Furthermore, the best route (from an environment point of view) might be different from the orthodromic trajectory in realistic weather conditions (namely wind fields), in such a way a longer ground distance might represent a shorter air distance (taking advantage of tail wind). Furthermore, planned trajectories by airspace users (AUs) cannot either be taken as “reference” for the best

environmentally friendly flights, since AUs might prioritize shorter trip times at the expense of higher fuel consumption or, as reported in [10], longer routes to avoid some airspaces with higher en-route charges, for instance.

The contribution of this paper is threefold. First of all, optimal trajectories (from the environment point of view) are used as references to derive flight efficiency PIs, instead of using orthodromic or AU submitted trajectories.

Secondly, a wide family of PIs to measure fuel inefficiencies is proposed, aiming at better capturing the environmental impact of operations. The main challenge of this approach is the need for fuel consumption figures, which might be unavailable for most ATM performance monitoring agencies, at least to conduct generalized and/or recurrent assessments. Typical data sources for flown trajectories come from surveillance datasets, such as radar tracks or automatic dependent surveillance broadcast (ADS-B) records. Concerning planned trajectories, these are typically reconstructed from air traffic services (ATS) flight plans submitted by the AUs. In both cases, trajectory datasets basically contain aircraft 3D positions (and ground speed depending on the source) at given time stamps, and fuel must be inferred from this limited information.

Finally, we also propose several PIs with the objective to isolate and capture different sources or components of the environmental inefficiencies.

II. STATE OF THE ART AND LITERATURE REVIEW

Current PIs implemented by the SES performance scheme, CANSO and the FAA (Federal Aviation Administration) use orthodromic trajectories as reference trajectories to derive flight inefficiency indicators [7, 11]. Thus, trajectory inefficiencies in the vertical domain are not captured, and as commented before, an orthodromic trajectory is not necessarily optimal from a fuel consumption (and emissions) point of view.

Eurocontrol proposes in [12] to assess (strategic) en-route vertical flight efficiency by analyzing the maximum altitude found in the flight plan, an approach that could lead to underestimations of the vertical flight inefficiency because there can be lower (non-optimal) cruise segments before or after the moment the maximum altitude is reached. Aiming to overcome this issue, NATS proposed a new metric called 3-Dimensional Inefficiency Score (3Di Score), where the reference trajectory is still based on the orthodromic track with an unimpeded climb phase to the AU requested flight level, followed by an unimpeded descent [13]. A similar approach is presented in [14], discussing on the different causes of flight inefficiency too. In both cases, Eurocontrol's Base for Aircraft Data (BADA) [15] was used to derive fuel figures, nominal speed schedules and nominal take-off weights.

Focusing in terminal operations, a harmonized vertical profile analysis algorithm, between the FAA and Eurocontrol, is reported in [16] to address vertical flight efficiency in climbs and descents, where level-off segments are identified. A similar approach was taken in [17]. There, efficiency was computed by comparing the fuel needed to fly the observed level segments to the scenario where these segments were removed. Fuel figures were roughly estimated with BADA tables.

The SESAR 2020 Performance Framework [1], in turn, proposes to directly measure fuel inefficiency, defining PIs such as FFFF1 (average fuel burn per flight); FFFF8 (average en-route horizontal deviation fuel burn); and FFFF9 (average en-route vertical deviation fuel burn). These PIs have the purpose to support the validation of certain SESAR solutions by comparing reference and solution scenarios. These scenarios, however, are in general simulated or synthesized (pre-operational assessments) and therefore, fuel figures are already an output of the simulation tools used for these validations.

Ref. [18] proposes some flight efficiency indicators aiming at measuring the fuel differences between the executed trajectories (i.e. post-operational analysis) and an optimal trajectory reference. A first indicator considers the vertical component of the flight on top of the orthodromic trajectory, similar to the 3Di Score. A second indicator optimizes only the vertical profile with maximum range conditions, while fixing the horizontal track of the historic trajectories. Finally, a third indicator takes the initial flight plan issued by the AU as optimal reference. Case studies, however, were restricted to only 45 illustrative flights in 6 different routes. BADA models were considered too, with some assumptions on the take-off mass based on BADA default tables.

Extending this previous work, in [19] fuel and aircraft mass are directly estimated from ADS-B records addressing the challenge to estimate fuel from the observed trajectory without requiring confidential or sensitive data from the AUs (such as the take-off mass of the aircraft, cost index, etc.). Some fuel figures are used to derive total AU cost-efficiency indicators and a case study with approximately 1500 trajectories is presented.

A similar approach is taken in [20], where the importance of this (optimal) reference trajectory is discussed when assessing different conceptual inefficiencies. Thus, by changing this reference, [20] decouples the contributions of the ATM strategic, pre-tactical and tactical layers to flight (in)efficiency.

As commented before, it is worth noting that inefficiencies for the AU are not necessarily the same inefficiencies for the environment, since AUs might wish to fly trajectories that are non-optimal, from a fuel consumption point of view [10, 21, 22].

The indicators proposed in this paper extend the SESAR 2020 indicators to their use in post-operational analysis, in line with [19], but focusing on the environmental inefficiencies. 4-dimensional (4D) weather optimal trajectories are used as reference to build these indicators and, by changing these references we are able to separate those inefficiencies that can be attributed to the different layers of ATM (in line with [20]); decoupling horizontal and vertical fuel inefficiencies; making an initial assessment of those inefficiencies attributable to the AU when cruising at speeds higher than the maximum range speed; and assessing results with different optimal references in order to change what is the *utopian* goal for maximum efficiency.

III. PROPOSED INDICATORS

Two families of PIs are proposed in this paper to assess inefficiencies from post-operational data: **distance-based** and **fuel-based** indicators. For each family, several PIs are defined, aiming to capture different sources of inefficiency.

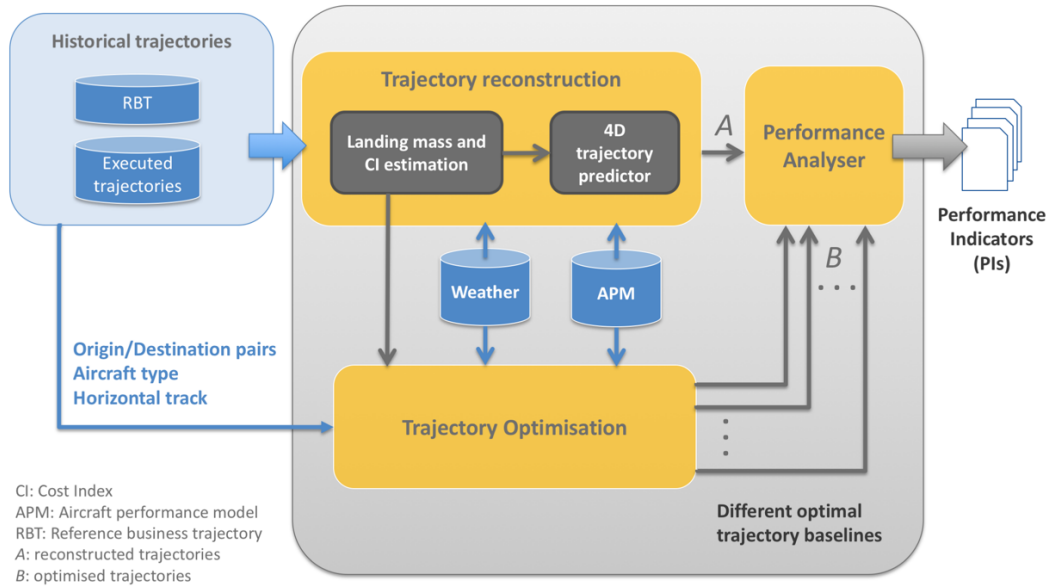


Figure 1 Methodology to compute the environmental Performance Indicators (PIs)

A. Overall Methodology

The methodology used to compute these indicators is illustrated in Fig. 1. Two types of historical trajectories are used. The nomenclature proposed in the SESAR trajectory based operations (TBO) concept has been adopted in this paper [23]:

- the RBT (reference business trajectory), which is the trajectory that has been agreed to fly by all concerned stakeholders after the negotiation process with the Network Manager, applying (if necessary) air traffic flow management (ATFM) regulations; and
- the executed RBT, or actual flown trajectory, which contains updates at tactical level on the RBT (if any), for instance due to air traffic control (ATC) interventions.

Trip distance and fuel must be estimated from these historical trajectory datasets, which typically contains only position and altitude reports at different time stamps (coming from surveillance or flight planning repositories). Distance estimation is straightforward, but fuel estimation is a complex issue and a trajectory reconstruction is needed before the PIs can be computed (A trajectories in Fig. 1). Several techniques are proposed in the literature, such as in [20, 24, 25], which require additionally an aircraft performance model (such as specific fuel consumption parameters and aerodynamic coefficients); and the historical weather conditions encountered by the flight.

These reconstructed trajectories are then compared with optimal trajectories specifically computed by an independent module (B trajectories in Fig. 1), which is also requiring from the same weather data and aircraft performance models. This trajectory optimization engine requires as well an estimation of

the landing mass for each flight, besides the origin/destination airports and aircraft type information, directly taken from the historical trajectory dataset. As it will be explained below, different optimization criteria and/or constraints can be configured in this module, leading consequently to different optimal trajectories as outputs of this module. For example, the optimal trajectory can be computed assuming a full free route airspace, or constrained to current ATS routes. It can be computed assuming maximum range operations (i.e. minimizing fuel), or by fixing the cost index (CI)¹ selected by the AU. In this case, the CI shall also be estimated, as depicted in Fig.1. Machine learning tools or model-based approaches similar to the mass estimation techniques cited above could be used.

Finally, this optimal trajectory can also be computed by fixing the horizontal track followed by the RBT or the executed trajectory, capturing in this way, only horizontal inefficiencies.

Regarding aircraft performance, Eurocontrol's BADA version 4.x is a good candidate, since it covers at present the 70% of aircraft types in the European Civil Aviation Conference (ECAC) area and provides more accurate fuel models than previous releases (modelling, for instance, the compressibility effects of the air in the aerodynamic drag)[15]. Concerning meteorology, historical wind fields and, to a lesser extent, temperature profiles, are required. This information is typically available in public data bases, such as the North-American National Oceanic and Atmospheric Administration (NOAA).

Wrapping up, by combining, on the one hand, the reconstruction of historical trajectories (A); and on the other hand, the different optimal trajectory references (B), a wide set

¹ The CI is a weighting parameter used by the AU at the flight planning stage that relates the cost of time with the cost of fuel. CI=0 implies fuel minimization (maximum range operations); while the higher the CI is, the more importance to reduce trip time is given, at the expense of burning more fuel.

The CI is manually entered into the flight management system of the aircraft by the pilot and affects not only the aircraft speed (higher CIs will lead to higher speeds), but also the vertical trajectory profile (higher CIs will lead to shallower climbs and lower cruise altitudes) [21].

of different PIs can be computed, capturing in this way, different sources and components of distance or fuel inefficiencies.

B. Capturing Inefficiencies due to Different ATM Layers

In line with [20], in this paper we will identify inefficiencies attributable to the **tactical** layer of the ATM; and those caused by the **strategic and/or pre-tactical (ATFM)** layer. In current operations, tactical inefficiencies mainly include path stretching from ATC (or vectoring); airborne holding; tactical altitude changes; level-offs; etc. Strategic inefficiencies might include the effects of following structured ATS routes; constraining the flight according to flight level allocation and orientation schemes; avoidance of no-fly (restricted/military) zones; observing restrictions in the flight planning such as the RAD (route availability document) in Europe; etc. Pre-tactical inefficiencies, in turn, might include pre-tactical re-routings or flight level capping (besides ATFM delay, which from an environmental point of view, has a negligible impact).

In the future TBO paradigm, however, the proposed methodology would allow to better decouple the sources of flight inefficiency across the whole trajectory life-cycle. Thus, tactical inefficiency indicators will capture the effects of updating and revising the RBT. By comparing the first submitted SBT (shared business trajectory) and the RBT we would be able to better isolate inefficiencies due to the pre-tactical phase (i.e. the negotiation phase with the Network Manager to solve demand and capacity imbalances). Then, by focusing on the first submitted SBT, we would be able to capture strategic inefficiencies plus all those attributable to the AU, when planning non-optimal trajectories (from the environment point of view).

In this context, it is worth noting that the inefficiencies in the first submitted SBT cannot all be attributed to the AU, since they might be forced to plan trajectories by using the ATS route network and/or observing the RAD, for instance. Yet, some inefficiencies originate indeed on some AUs decisions, such for example planning longer routes to save higher en-route charges [10], or avoid congestion [22]; or by simply flying at speeds higher than the minimum fuel speed [21].

C. Distance-based Performance Indicators

These indicators have the advantage that they are easier to compute if compared to fuel-based indicators. Yet, they cannot capture inefficiencies in the vertical domain of the trajectory. The indicators proposed here, however, represent already a step beyond current state-of-the-art methodologies used in post-operational contexts, which compare the actual/planned flown distances with the great circle distance between origin and destination airports². Instead, the actual/planned trip distance is compared with the distance measured on the optimal trajectory, which takes into account weather conditions and, in general, is different from the orthodromic trajectory.

Equations (1-3) mathematically express the three proposed PIs, which capture the horizontal track inefficiencies for a given flight. Then, several aggregate or statistical values can be provided, such as the total inefficiency; the mean or median

² More precisely, SES performance scheme indicators, exclude the segments of the trajectory within a 40NM radius around the origin and destination airports.

inefficiencies; the distribution quartiles, etc. ΔD_T is the Total route inefficiency (i.e. Distance inefficiency) caused by all ATM layers; ΔD_s captures only the inefficiencies due to the strategic (and pre-tactical) ATM layers; while ΔD_t captures the ATM inefficiencies in the horizontal track caused only to tactical interventions. D_e corresponds to the flown distance of the executed trajectory (i.e. the actual trip distance); D_{RBT} is the flown distance of the RBT (i.e. the planned trip distance); and D^* is the flown distance coming from the optimal trajectory for that particular flight (*B* trajectory in Fig. 1).

$$\Delta D_T = |D_e - D^*| \quad (1)$$

$$\Delta D_s = |D_{RBT} - D^*| \quad (2)$$

$$\Delta D_t = \Delta D_T - \Delta D_s \quad (3)$$

As commented before, weather conditions can move the optimal route from the shortest ground path between origin and destination airports. Thus, the actual flown distance might be eventually shorter than the optimal route, and for this reason the absolute value is taken to construct the ΔD_T and ΔD_s indicators. In other words, shortening a route beyond the optimal route distance will be also accounted as a (positive) route inefficiency.

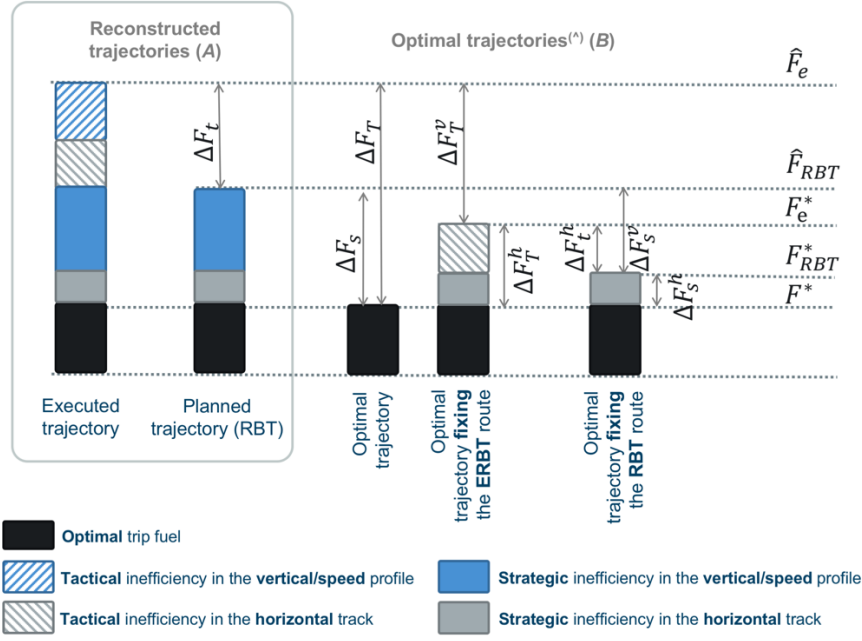
It should be noted that although ΔD_T and ΔD_s will always be zero or positive, ΔD_t can be negative since the ATM tactical layer (i.e. ATC instructions) might reduce the inefficiency of the executed trajectory if compared with the inefficiency measured over the RBT. In other words, ATC instructions, such as directs, might contribute to fly closer to the optimal trajectory.

D. Fuel-based Performance Indicators

In line with the *FEFF* indicators proposed in the SESAR 2020 Performance Framework [1], several fuel-based PIs are proposed here, aiming at a twofold objective. Firstly, to take into account the vertical (and speed) profiles of the trajectory when accounting for flight inefficiencies, aspects almost neglected with the distance-based indicators presented above. Secondly, fuel consumption provides a more direct proxy of CO₂ emissions, being the relation between fuel and CO₂ linear [26]; and consequently, directly matching with the high-level environmental aspirations of ICAO, SESAR and NexGen programs. Note that if an emissions model (other than CO₂) were available, these indicators could also be enhanced to derive more generic and comprehensive emissions figures.

It is worth noting that even if aircraft speed is not directly changed by any ATM constraint; changing the vertical profile of the trajectory (by enforcing, for instance, a given rate of climb, a sub-optimal cruise altitude, etc.) might indirectly change its speed profile too. For example, if an aircraft is cruising lower than its optimal altitude, the original planned speed (at the optimal altitude) will no longer be optimal for the new altitude. The AU will then probably change the planned speed to improve its operation at this new (and non-optimal) altitude. Similarly, any speed restriction imposed to the AU when planning or executing the trajectory will lead to a change in the vertical

They also show results in percentages of flight efficiency, taking into account the route length. Results are aggregated across several days.



(*)Different optimal trajectories can be generated by changing the optimisation objective and/or constraints

Figure 2. Breakdown of the different sources of fuel inefficiency

profile of the trajectory, especially affecting rates of climb and descent and even the selected cruise altitude. Thus, since vertical and speed profiles are intimately related, they are both considered at the same time and captured by the same indicator.

Nine fuel-based PIs are proposed in this paper, as expressed by Equations (4-12). Similar to the distance-based indicators, presented before, these indicators capture individual inefficiencies for each particular flight. Then, several aggregate or statistical values can be provided depending on the performance assessment characteristics and the desired granularity of the results.

$$\Delta F_T = \hat{F}_e - F^* \quad (4)$$

$$\Delta F_T^h = F_e^* - F^* \quad (5)$$

$$\Delta F_T^v = \Delta F_T - \Delta F_T^h \quad (6)$$

$$\Delta F_s = \hat{F}_{RBT} - F^* \quad (7)$$

$$\Delta F_s^h = F_{RBT}^* - F^* \quad (8)$$

$$\Delta F_s^v = \Delta F_s - \Delta F_s^h \quad (9)$$

$$\Delta F_t = \hat{F}_e - \hat{F}_{RBT} \quad (10)$$

$$\Delta F_t^h = F_e^* - F_{RBT}^* \quad (11)$$

$$\Delta F_t^v = \Delta F_t - \Delta F_t^h \quad (12)$$

ΔF_T is the Total fuel inefficiency caused by all ATM layers, computed as the difference of the estimated fuel of the executed trajectory (\hat{F}_e) and the fuel of the optimal trajectory for that particular flight (F^*). ΔF_T^h captures the fuel inefficiency due to all ATM layers only in the horizontal domain, regardless of how (in)efficient the vertical/speed trajectory profile was. This is achieved by comparing the fuel consumption of the best

trajectory one could fly if following the executed route (i.e., optimizing the vertical/speed profile while fixing as constraint in the optimization process the executed route, F_e^*); and the fuel consumption of the optimal 4D trajectory. ΔF_T^v , in turn, captures the fuel inefficiencies due to all ATM layers only in the vertical/speed domain, regardless of how (in)efficient the horizontal trajectory was.

Similarly, ΔF_s and ΔF_t are the PIs capturing the **total** fuel inefficiency of, respectively, the strategic and tactical layers of the ATM; ΔF_s^h and ΔF_t^h are the PIs capturing the fuel inefficiency in the **horizontal** trajectory of, respectively, the strategic and tactical layers; and ΔF_s^v and ΔF_t^v are the PIs capturing the fuel inefficiency in the **vertical/speed** profiles of, respectively, the strategic and tactical layers.

As seen in (7-9) strategic inefficiencies can be computed by estimating the fuel consumption of the RBT trajectory (\hat{F}_{RBT}) and/or the fuel consumption of the best trajectory one could fly if following the RBT route (F_{RBT}^*), i.e., optimizing the vertical/speed profile while fixing as constraint the RBT route. Since the RBT is used for these indicators (and not the first submitted SBT), these indicators also capture the inefficiencies due to ATFM measures, if any (see the discussion in III.B).

Like with the distance-based PIs, some of the fuel-based indicators could take a negative value. Namely, ΔF_t , meaning that the estimated fuel of the executed trajectory is lower than the RBT estimated fuel (due to ATC interventions); ΔF_t^h , meaning that ATC interventions have brought the executed route closer to the optimal route; and ΔF_t^v , meaning that these tactical interventions have brought the executed vertical/speed profiles closer to the profiles of the optimal 4D trajectory.

Fig. 2 displays the breakdown of the fuel inefficiencies for the executed and the RBT (A trajectories depicted in Fig. 1),

along with their relation with the proposed PIs. Besides the fuel optimal trajectory, this figure also shows the two additional reference trajectories that are needed to construct some of the indicators presented above (B trajectories depicted in Fig. 1).

E. Main Assumptions and Limitations

The accuracy of the PIs will significantly depend on the quality and representativeness of historical trajectories. It is expected that radar tracks can provide the highest position accuracy and data reliability. ADS-B records could provide good results as well, as discussed in [19], although some trajectories might be incomplete due to poor ADS-B coverage. Eurocontrol's DDR2 database is also a possible alternative, although not as accurate as previous two, since tactical changes in the trajectory are only reflected when flight deviations from the filed flight plan exceed some pre-defined thresholds[27]. Thus, not all tactical interventions on the trajectory are captured in DDR2 files.

The quality of aircraft performance models is also an aspect to consider, especially for the fuel-based PIs. Yet, if the same models are used to estimate fuel consumption from historical tracks and to compute the optimal trajectories serving as reference (trajectories A and B in Fig. 1), model inaccuracies will be common and, to some extent, some error components could cancel in the final indicator, especially when it is expressed in relative terms. Nevertheless, a very important source of error in all these indicators will be in the estimation of the mass of the aircraft, which is required either to estimate fuel consumption from historical data, but also to generate optimal trajectories as seen in Fig. 1. Similarly, the error in the estimation of the CI from historical tracks (needed to construct some indicators as it will be seen below) will also affect the accuracy of these PIs.

The quality of the weather model will also affect the quality of the results. Moreover, differences between the models used to build the PIs (historical weather realizations) and the actual models used by AUs to plan their trajectories (weather forecasts) might lead to some additional inefficiencies in the indicators, which can be erroneously attributable to ATM. In this context, and as it will be seen in Section V.B, it is not always obvious to decouple the inefficiencies caused by the ATM and those inefficiencies that could be attributable to the AUs.

It is out of the scope of this paper to assess the sensitivity of the results to these different sources of error, which is a very necessary work to be done in the future in order to increase the maturity level of the proposed methodology.

IV. CASE STUDY SETUP

Two sets of 24h of historical flown and planned trajectories were analyzed. These correspond to July 28th 2016 (high demand) and February 20th 2017 (low demand). Historic trajectory data were extracted from Eurocontrol's DDR2 database using two different sources:

- a trajectory reconstruction based on the **last filed flight plan** submitted by the AU (DDR2 M1 file); and

- a trajectory reconstruction obtained from the correlation of different **surveillance** data coming from the Eurocontrol member states (DDR2 M3 file).

These sets of trajectories are, respectively referred as RBT and executed trajectory, according to the terminology used in this paper, although the full TBO concept has not yet been deployed in Europe.

The assessments shown in this paper considered all trajectories that had the origin and destination airports within the ECAC area and that crossed the FABEC³ airspace at some point within the 24h period assessed. Only turbojet aircraft were considered and any flight with a requested cruise flight level below FL195 was also discarded.

Input files were given in the *so6* format, which mainly contains the 3D coordinates of the trajectory at different timestamps, plus some basic information on the aircraft type, callsign and origin/destination airports. No other information on the trajectory is given, such as the speed, aircraft mass, CI (cost index) or fuel usage.

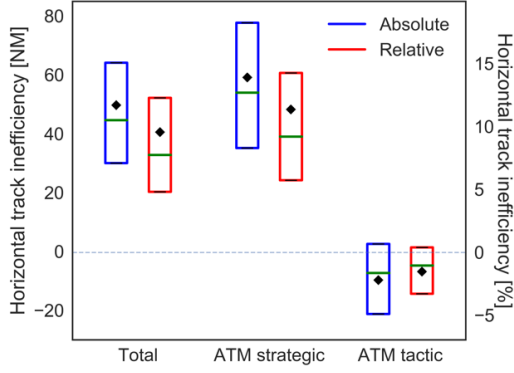
In order to construct all fuel-based PIs, an adaptation of the algorithm proposed in [24] was implemented to estimate the fuel consumption of the trajectories found in these DDR2 files. Briefly, this algorithm estimates the engine thrust that would be required to fit the observed trajectory acceleration and assuming an aircraft point-mass model. Once the thrust at each position (or segment) is known, the fuel flow can be computed by using an aircraft performance model. Eurocontrol's BADA version 4.1 was used in this paper. In order to estimate this thrust, the aerodynamic drag, the true airspeed, and the mass of the aircraft are needed. Regarding drag, the model given BADA v4.1 was taken. True airspeed was estimated from the recorded aircraft positions in the DDR2 file after applying a Savitzky-Golay filter and by using the historical wind fields taken from the GFS (global forecast service) models provided by the NOAA.

Finally, the aircraft mass at the destination airport was assumed to be the 90% of the maximum landing mass for that particular aircraft type, which is an educated guess based on the reported payload data, such as for example, the statistics provided by the European Low Fares Airline Association (ELFA). Then, a backwards integration was performed to derive the mass at the different points of the trajectory. In the future, this mass estimation could be improved by implementing mass estimation algorithms, such as those proposed in [25], or based in heuristics, as done for instance in [20].

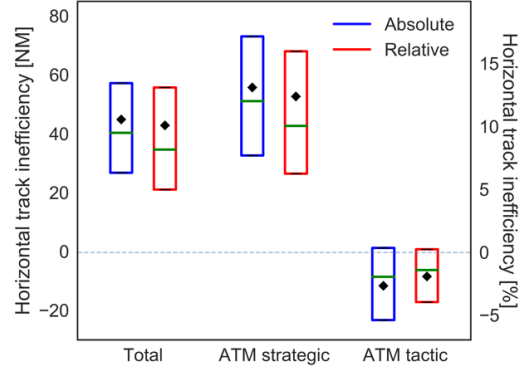
Regarding the different optimal trajectories needed to construct all proposed PIs (B trajectories in Fig. 1), DYNAMO was used [28]. This tool, developed by UPC, is a 4D trajectory prediction and optimization engine capable to rapidly compute trajectories using realistic and accurate weather and aircraft performance data. DYNAMO is based on an aircraft point-mass model and is highly flexible and configurable, allowing the user to specify a great variety of constraints and objective functions. DYNAMO's design allows for real-time applications and/or

³ FABEC is the functional airspace block (FAB) of central Europe, comprising the airspace of Belgium, France, Germany, Luxembourg, the

Netherlands and Switzerland. Traffic crossing FABEC roughly represents half of the overall traffic crossing the whole ECAC area.

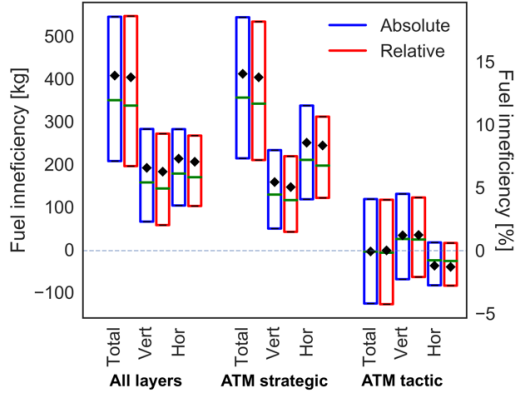


a) 24h FABEC on Jul 28th 2016

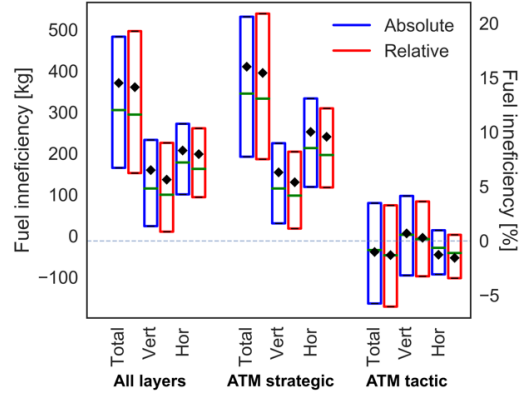


b) 24h FABEC on Feb 20th 2017

Figure 3: Distance-based flight inefficiencies for the two days of study (Optimal trajectory reference assuming a full free-route airspace, no en-route charges, flight level allocation and orientation schemes, and maximum range operations)



a) 24h FABEC on Jul 28th 2016



b) 24h FABEC on Feb 20th 2017

Figure 4: Fuel-based flight inefficiencies for the two days of study (Optimal trajectory reference assuming a full free-route airspace, no en-route charges, flight level allocation and orientation schemes, and maximum range operations)

TABLE I. RESULTS WITH DISTANCE-BASED INDICATORS

Performance Indicator ^a	Jul 28 th 2016				Feb 20 th 2017			
	Average		median		average		median	
	NM	%	NM	%	NM	%	NM	%
ΔD_T	50	9.6	45	7.7	45	10.1	40	8.2
ΔD_s	59	11.4	54	9.2	56	12.4	51	10.0
ΔD_t	-10	-1.5	-7	-1.1	-12	-1.9	-9	-1.4

TABLE II. RESULTS WITH FUEL-BASED INDICATORS

Performance Indicator ^a	Jul 28 th 2016				Feb 20 th 2017			
	Average		median		average		median	
	kg	%	kg	%	kg	%	kg	%
ΔF_T	408	13.8	350	11.5	371	14.1	305	11.6
ΔF_T^h	213	7.1	178	5.8	207	8.0	178	6.6
ΔF_T^p	192	6.3	157	4.9	160	5.6	115	4.2
ΔF_s	412	13.8	356	11.7	411	15.4	345	13.1
ΔF_s^h	251	8.4	210	6.8	252	9.6	213	7.9
ΔF_s^p	158	5.0	129	4.0	155	5.4	115	4.2
ΔF_t	-6	0.1	-7	-0.2	-40	-1.0	-36	-1.3
ΔF_t^h	-37	-1.1	-25	-0.8	-45	-1.3	-29	-1.0
ΔF_t^p	34	9.1	25	17.2	6	16.4	3	20.6

a. Optimal trajectory reference assuming a full free-route airspace, no en-route charges, flight level allocation and orientation schemes, and maximum range operations

when a large set of trajectories needs to be rapidly generated for simulation or benchmarking purposes, such as in this paper.

In this context, DYNAMO was used in a distributed manner embedded into a software and hardware architecture taking advantage of high performance computing concepts. Optimal trajectories computed in this paper also used BADA v4.1 and NOAA datasets.

V. RESULTS

This section presents some illustrative results assessing post-operational data with all the indicators proposed in section III and the case study described in section IV.

A. Flight Inefficiencies with Respect to Full Free-routing, no En-route Charges, Flight Levels and Cost Index Zero

For the following results, the optimal trajectory used as reference (B trajectories in Fig. 1) is computed assuming a full free-route airspace from origin to destination airports, imposing current flight level allocation and orientation schemes, assuming and airspace without en-route charges and imposing maximum range operations (i.e. setting the cost index to zero).

As commented in Section III, the proposed PIs are computed for each individual flight. This section presents, for each PI, the

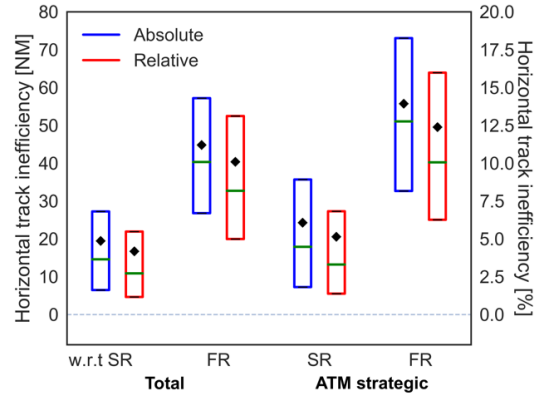
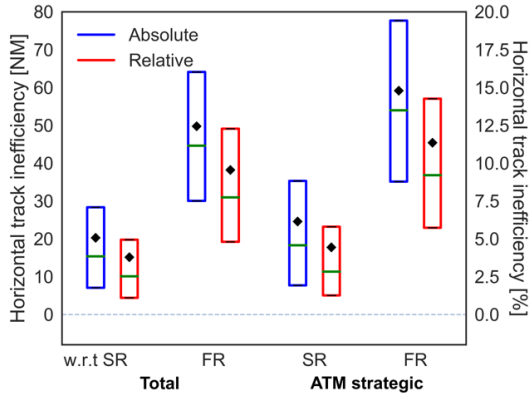


Figure 5: Distance-based flight inefficiencies for the two days of study using different references for the optimal trajectory (with CI=0)

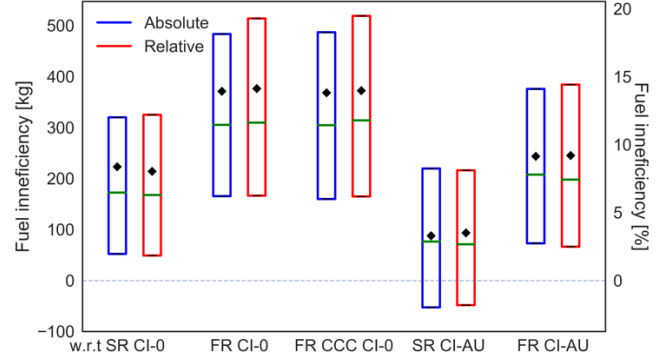
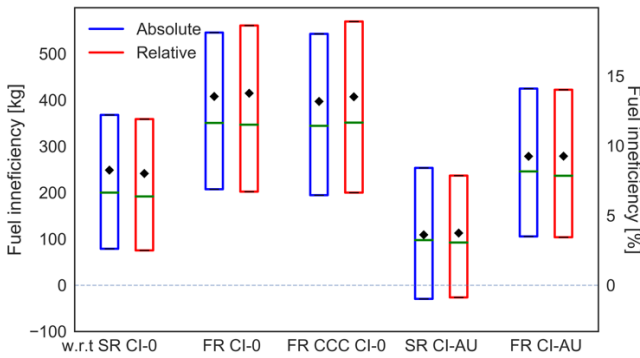


Figure 6: Total fuel-based flight inefficiencies for the two days of study using different references for the optimal trajectory

average, the median and the first and third quartiles of the two analyzed datasets. Among these statistical indicators the median, which lies at the midpoint of the frequency distribution of the observed values, will be taken for main analysis and comparison. The reason is because the median is more robust to both skewness and outliers (e.g. few flights with very high or low values of a particular indicator can easily increase or decrease the average value).

1) *Distance-based flight inefficiencies* are shown in Fig. 3 and Table I. The total inefficiency has a median around 42 NM (around 8% in relative terms if compared with the total route extension), mostly due to the strategic part of the ATM (the fact that airspace users are still forced to use a structured ATS en-route network). The average values are higher, due to the fact that few flights experience high route inefficiencies. We also observe how the tactical layer introduces, for most of the flights, a “negative inefficiency”, meaning that the ATC contributes to reduce route extension by short-cutting the planned trajectory. For this tactical layer, the inefficiency has a median around -8 NM (around -1.2% in relative terms).

2) *Fuel-based flight inefficiencies* are shown in Fig. 4 and Table II, using the nine fuel-based PIs. The total inefficiency has a median around 350 kg for the summer day and 305 kg for the winter one (around 11% in relative terms if compared with the total fuel burnt) mostly due to the strategic part of the ATM, as we already observed with the distance-based indicators.

The average values are higher than the median (around 400 kg, representing the 14% in relative terms), due to the fact that few flights experience high route inefficiencies. Here, the effects of ATC tactical interventions, which can lead to “negative inefficiencies”, are also observed: for the summer case study the median is -7 kg (0.2%) and for the winter case study the median is -36 kg (1.3%).

According to Fig. 4, strategic inefficiencies on the route (i.e. the effects of route restrictions, structured route networks, potential ATFM re-routings, etc.) are clearly above strategic inefficiencies on the vertical profile (i.e. the impossibility to fly at the optimal planned altitudes). At tactical level, however, we see that route inefficiencies are, in general, negative, meaning the ATC is actually shortcutting most of the flights, while we still have some positive (on average) vertical flight inefficiency. It is interesting to observe, however, that the tactical layer also contributes to reduce vertical fuel inefficiency of around the 40% of the flights.

B. Flight Inefficiencies with Different Optimal References

In this section, the same PIs presented before are computed again but changing the objective function and/or optimization constraints when computing the optimal trajectory references (B trajectories in Fig. 1). Five different optimal trajectory references have been analyzed:

1. assuming a full free-route airspace, current flight level allocation and orientation schemes, and maximum range operations (CI=0), which is the case presented in previous section IV.B (FR CI-0);
2. assuming a full free-route airspace, continuous cruise climbs, and CI=0 (FR CCC CI-0);
3. assuming a full free-route airspace, current flight level allocation and orientation schemes, and using the CI estimated from the executed trajectory (FR CI-AU);
4. constraining the trajectory to the current structured ATS en-route network, current flight level allocation and orientation schemes, and CI=0 (SR CI-0); and
5. constraining the trajectory to the current structured ATS en-route network, current flight level allocation and orientation schemes, and using the CI estimated from the executed trajectory (SR CI-AU).

For all previous five baselines, the optimal trajectory was computed assuming no en-route charges.

1) *Distance-based flight inefficiencies* are shown in Fig. 5, where two of the previously defined trajectory references are compared: FR CI-0 and SR CI-0. The results for the two days of study are very similar. The ATM strategic environmental inefficiency goes from a median of around 52 NM (10%), if a full free-route case is considered, to a median of only 18 NM (3%) when the optimal trajectories are restricted to follow current ATS routes. This clearly shows the impact that this structured route network has on the trip distance.

Yet, even if the optimal trajectory is constrained to ATS routes, some distance inefficiency is still observed. This might be caused by the AUs not planning their trajectories by using the best route sequence in the network, or when AUs want to avoid higher en-route charges [10] or areas typically congested [22]. It should be noted that part of these inefficiencies can also be caused by differences between the weather (and aircraft performance) model used when computing the optimal trajectories (see Fig. 1), and those used by the AU when planning their trajectories.

The total inefficiency values show even smaller figures due to the ATC tactical layer, which helps in general to reduce these inefficiencies as discussed in previous section.

2) *Total fuel-based flight inefficiencies* are shown in Fig. 6, where the five previously defined trajectory references are compared. As expected (and already noticed in Fig. 5), inefficiencies for the cases where the optimal trajectory is constrained to ATS routes (SR CI-0 and SR CI-AU) are lower if compared with the references assuming full free-route operations. For maximum range operations (CI=0) the median of the total inefficiency goes from 350 kg (11%) to around 200 kg (6.3%) for the summer day (a similar trend is observed for the winter day).

Interestingly, allowing for continuous cruise climbs does not practically change the inefficiency values, meaning that for these Case Studies the benefits of flying continuous cruise climbs are negligible, providing the aircraft can fly at their optimal (constant) cruise altitudes, which is not always the case as observed before.

The SR CI-0, FR CI-0 and FR CCC CI-0 references all three consider that the optimal trajectory is flown at maximum range operations (CI=0), since this is the operational condition that minimizes fuel consumption. Yet, the decision to fly slower or faster mainly resides on the AU, who selects the best cruising speeds (i.e. the CI) according to their cost-break down structure and business models. For this reason, it would be unfair to attribute to the ATM system all the environmental inefficiencies commented so far, since some of these inefficiencies are a consequence of the AU flying faster than the minimum fuel consumption speed.

This is what SR CI-AU and FR CI-AU references try to capture. As observed in Fig. 6, the inefficiencies that could be attributable to ATM go down to approximately 250 kg (7.8%) if a full free-route scenario is considered for the reference trajectories (instead of 350 kg – 11%), or 97 kg (3.0%) if the structured route network is considered (instead of 200 kg – 6.3%). In other words, AU's induced fuel inefficiencies (due to flying faster than the maximum range speed) have an average inefficiency around 100 kg (representing approximately a 3%).

Like in previous case, inefficiencies captured by the SR CI-AU indicator are explained by discrepancies between the optimization tool used here, and those used by the AU at the moment of planning their flights, which could have different nature: different weather forecasts, an inappropriate mass and/or CI estimation trajectory reconstruction tool, or different aircraft performance models (see Fig. 1). As commented before, however, they could also be as consequence of the AU planning consciously or unconsciously a non-optimal route.

VI. CONCLUSION

A performance-driven air traffic management (ATM) is central to ATM modernization programs worldwide. Besides the effort that is still required to harmonize some of the existing performance frameworks, there is also a need to further enhance the existing processes, outcomes, and performance indicators (PIs). An important contribution of this paper is that state-of-the-art fuel-based PIs used in pre-operational validation exercises have been extended for post-operational analysis, assessing in this way performance from historical surveillance data and submitted flight plans databases.

In this context, this paper has shown how advanced parameter estimation and trajectory optimization techniques can be used to build advanced PIs aiming to capture the environmental impact of aircraft trajectories, in terms of distance and fuel inefficiencies. A trajectory optimization process can result in different outcomes, depending on how the optimization objective(s) and optimization constraints are configured. Exploiting this idea, and using different input trajectories taken at different stages of the trajectory life-cycle several different indicators are built. It has been shown how the proposed methodology can be used to separate the different sources of flight inefficiency, either at trajectory level (vertical/horizontal inefficiency) or by capturing the contribution of different ATM layers separately.

The proposed distance-based PIs are easier to compute, but cannot capture all components of the flight inefficiency, although they already represent a step beyond current state-of-

the-art indicators for post-operational analysis. The proposed fuel-based PIs, in turn, are subject to several uncertainty sources, such as uncertainty in the weather data, aircraft performance, estimation of mass, estimation of the cost index, etc. Further work is necessary to quantify and characterize these sources of error and assess the PIs sensitivity to these errors.

In the next years, the advent of new methodologies and tools based on the combination of data science, machine learning and model-based simulations will be a key enabler to further improve the ideas presented in this paper.

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