

Arrival flight efficiency in pre- and post-Covid-19 pandemics[☆]

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ABSTRACT

Covid-19 pandemic affected aviation severely, resulting in unprecedented reduction of air traffic. While aviation is slowly re-gaining traffic volumes, we use the opportunity to study the arrival performance in the Terminal Maneuvering Area (TMA) in non-congested scenarios.

Applying flight efficiency and environmental performance indicators (PIs) to the historical data of arrivals to Stockholm Arlanda and Gothenburg Landvetter airports, we discover noticeable inefficiencies, despite significant reduction of traffic intensity. We analyze the impact of such factors as weather and traffic intensity on arrival efficiency in isolated scenarios when only one factor dominates: isolated scenario with low traffic and isolated scenario with good weather conditions. Our analysis uncovers that weather has a stronger influence than traffic intensity on the vertical efficiency, while traffic intensity has stronger effect on the lateral efficiency. Impact of traffic intensity on the lateral efficiency might be explained by frequent hold-on patterns and flight trajectory extensions due to vectoring in high traffic conditions. Further investigation is needed to explain weather and vertical/lateral efficiency correlations, the conclusions might be country-specific.

1. Introduction

The Covid-19 pandemic has had a significant impact on the aviation industry due to travel restrictions and resulted in unprecedented reduction in air traffic worldwide (for Europe up to 88.2% in April [EUROCONTROL, 2020b](#) and 85.9% in May [EUROCONTROL, 2020a](#) 2020). Air traffic is still not completely recovered, daily flights over the first weeks of the year 2022 fulfill about 68% of 2019 levels ([EUROCONTROL, 2022](#)). Massively reduced revenues forced many airlines to lay off employees or declare bankruptcy. All aviation stakeholders got affected by the pandemic.

Apart from the negative effects of the pandemic, there are also some positive trends. According to [Le Quéré et al. \(2020\)](#) daily global CO₂ emissions decreased by 17% by early April 2020 compared with the mean 2019 levels. At their deepest point, emissions in individual countries decreased by 26% in average.

As outlined in one of the SESAR JU Digital Sky vodcasts ([SESAR JU, 2020](#)), during the pandemic time aviation community should be able to benefit from the unique opportunity to test the new operational concepts and initiatives in real non-congested scenarios. In this work,

we use the opportunity to study the arrival performance in TMA in non-congested scenarios.

This work is based on the conference paper ([Lemetti et al., 2020a](#)), where we compared operations in spring–summer 2020 against the same period in 2019 in Stockholm Arlanda airport, and perform a comprehensive analysis for these two periods. The contribution of this paper is as follows: we take one more airport into consideration, Gothenburg Landvetter airport; extend the period of investigation from spring–summer periods to the whole period of two years 2019 and 2020; improve the procedure of aircraft tracking data pre-processing; extend a range of weather metrics from 5 to 24; perform a Principal Component Analysis (PCA) to identify a subset of uncorrelated weather variables; add a new performance metric (Additional Distance in TMA) used for evaluation of horizontal flight efficiency; perform a trajectory clustering procedure for calculation of this metric; improve the methodology of Additional Fuel calculation.

Roadmap. The rest of the paper is organized as follows. In Section 2, we review the related work. In Section 3, we present the performance

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indicators for evaluation of arrival efficiency and list the impact factors we consider for investigation of the reasons for performance inefficiencies in TMA. In addition, we describe the methodology for estimating the Continuous Descent Operations (CDOs) profiles for the arrival flights. In Section 4 we describe the data and present our results for Stockholm Arlanda and Gothenburg Landvetter airports, and conclude in Section 5.

2. Related work

In this section, we review state of the art work on the evaluation of the flight efficiency and the impact of weather on ATM (Air Traffic Management).

2.1. Flight efficiency

Evaluation of flight efficiency, and in particular TMA performance, has been a topic of interest in recent years. International Civil Aviation Organization (ICAO) proposed a set of Key Performance Indicators (KPIs) to enable analysis of TMA performance (ICAO KPIs, 2020).

EUROCONTROL developed the methodology used by its Performance Review Unit (PRU) for the analysis of vertical flight efficiency (VFE) during climb and descent (EUROCONTROL, 2017). Performance Review Commission of EUROCONTROL made an assessment of ATM in Europe for the year 2019, where among other indicators reviewed flight inefficiency within TMA at the top 30 European airports, including Stockholm Arlanda airport (EUROCONTROL, 2019).

Pasutto et al. (2020) analyzed the factors affecting vertical efficiency in descent at the top 30 European airports. The paper reveals an increase of the vertical deviation with the horizontal deviation, and a dispersion of the vertical deviation for the same horizontal deviation. The analysis also reports a very significant disparity among airports, with some indicators ranging by a factor of 5 or more. Zanin (2020) evaluates the efficiency of flights landing at an airport using open large-scale data sets of aircraft trajectories. The author focuses on understanding the efficiency of different airspaces and on comparing them.

Estimation of the flight inefficiencies in terms of extra fuel burn calculated based on the algorithm proposed in Chatterji (2011) was considered in the scope of APACHE project (a SESAR 2020 exploratory research project), see Prats et al. (2018b,a), but mostly for en-route flight phase. Later (Prats et al., 2019) proposed a family of performance indicators to measure fuel inefficiencies.

In Ryerson et al. (2014) fuel consumption is evaluated for terminal areas with a Terminal Inefficiency metric based on the variation in terminal area fuel consumed across flights, reported by a major U.S. airline. Using this metric they quantify the additional fuel burn caused by ATM delay and terminal inefficiencies. Furthermore, in Fricke et al. (2015) and Wubben and Busink (2000), fuel savings of the CDOs with respect to conventional procedures are analyzed. A reduction in fuel consumption of around 25%–40% by flying CDOs was reported.

2.2. Weather impact

Weather conditions have a high impact on the performance of ATM, see, e.g., Borsky and Unterberger (2019). Within SESAR, new models for weather forecasts and their integration in planning problems, e.g., in trajectory planning, have been developed in several projects (IMET, 2013; FMP-MET, 2020-2022; PNOWWA, 2016-2018). The staple technique for capturing the uncertainty in weather predictions is retrieving probabilistic weather data from the Ensemble Prediction Systems (EPSs). An EPS quantifies weather uncertainty by generating a range of weather forecasts, referred to as members, which represent a sample of the possible states of the actual weather outcome (World Meteorological Organization, 2012).

Quantification of the impact of different weather phenomena on airport operation is reflected in many recent research activities. Schultz et al. (2018) used the ATMAP algorithm, published by Eurocontrol's PRU, which transforms the METAR data into the aggregated weather score weighting the different weather factors. They analyzed the correlation of the on-time performance of flight operations with the ATMAP score at major European airports. Inspired by the idea of ATMAP, in this work we propose similar aggregated weather factor, more simplistic, tailored to the needs of the arrival flight efficiency evaluation.

Impact of deep convection and thunderstorms is also subject to ongoing research, e.g. Steiner et al. (2010, 2014) and Song et al. (2009) investigated their implication both on the en-route flow management and on terminal area operations. Klein et al. (2009) used a high-level airport model to quantify the impact of weather forecast uncertainty on delay costs. Steiner (2015) discusses the crucial effect of accurate forecasts of high-impact winter weather for efficient management of airport and airline capacity and highlight the need of data sharing and integrated decision making between stakeholders. Recent works (Reitmann et al., 2019; Steinheimer et al., 2019; Hernández-Romero et al., 2022) confirmed the relevance and emphasized the importance of quantification and analysis of the weather impact on airport operation.

In Lemetti et al. (2019a,b, 2020b), the authors presented a detailed assessment of Stockholm Arlanda arrival performance, as well as investigated the impact of different factors influencing the efficiency of arrivals. High traffic volume was assumed in most of the considered scenarios, as the analysis was based on the historical flight data from the year 2018. In this paper, we are focusing on isolated scenarios with low traffic or good weather conditions.

3. Methodology

In this section, we present the PIs we use for comparative analysis of arrival efficiency in pre-pandemic and after-pandemic conditions. We also list the impact factors considered for investigation of the reasons for flight inefficiencies in TMA. In addition, we describe the methodology for estimating the CDO profiles for the arrival flights.

3.1. Performance indicators

To evaluate TMA performance, we use the following PIs: Additional Distance in TMA, Time Flown Level and Additional Fuel Burn.

3.1.1. Horizontal flight efficiency

The horizontal flight efficiency is assessed through the horizontal deviation from a reference trajectory, denoted as **Additional Distance**. We have considered as a reference an ideal trajectory, which encompasses both airspace and operations related inefficiencies (Pasutto et al., 2019, 2020). For that we cluster the trajectories in each of the two TMAs for each runway and for the whole time period of two years 2019–2020 using the methodology proposed in Pasutto et al. (2021), also applied in Hardell et al. (2021b) and Hardell et al. (2021a). Then a user-preferred route tree is constructed as defined in Polishchuk (2016). We identify the start of the reference trajectory as the point on the TMA border as the closest to each cluster centroid. The reference trajectory goes directly to the current interception point and altitude of the localizer, with a 2 NM straight segment before the Final Approach Point (FAP).

Fig. 1 shows the reference trajectories per arrival flow (cluster) in black, for two airports together with the actual arrival trajectories colored according to their relation to different clusters, for the whole period of the years 2019 and 2020 for runway 03 in Gothenburg Landvetter airport and runway 08 for Stockholm Arlanda airport. For statistical analysis we express Additional Distance in percentage to the corresponding reference trajectory distance.

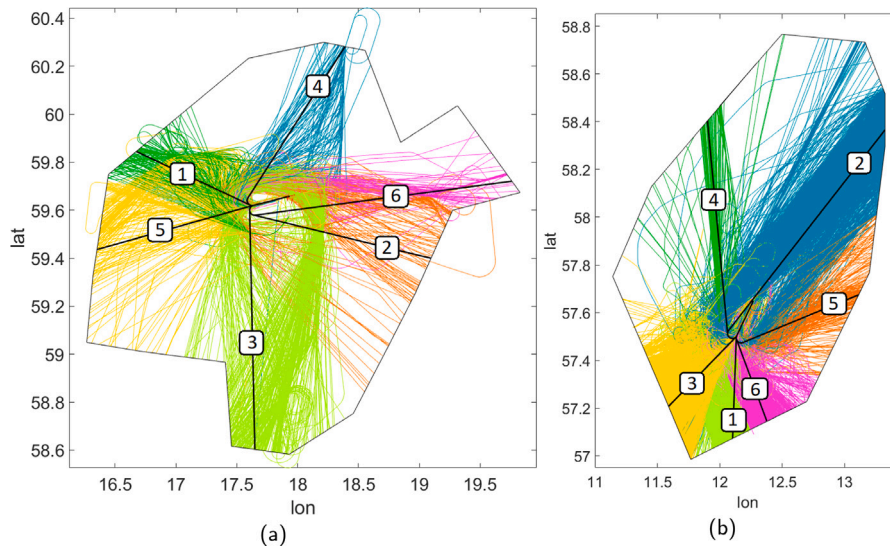


Fig. 1. Horizontal reference trajectories (black lines) and the actual arrival trajectories colored by cluster, for Stockholm Arlanda runway 08 (a) and Gothenburg Landvetter runway 03 (b).

3.1.2. Vertical flight efficiency

CDOs enable the execution of a flight profile optimized to the operating capability of the aircraft, resulting in optimal continuous engine-idle descents (without using speed-breaks). Vertical inefficiencies during the descent phase result from the inability of flights to follow CDOs. When the aircraft levels at intermediate altitudes before landing, the descent is considered to be vertically inefficient. The **Time Flown Level** is calculated using the technique proposed by EUROCONTROL in EUROCONTROL (2017) with small changes. We identify the point of the trajectory in which the aircraft enters the TMA and use it as a starting point for the calculations (instead of the Top of Descent (ToD), which may lie outside of TMA). A level segment is detected when the aircraft is flying with the vertical speed below the certain threshold. We use the value of 300 ft per minute for this threshold, the minimum time duration of the level flight is considered 30 s, and these 30 s are subtracted from each level duration as suggested in EUROCONTROL (2017). We do not consider as level the flight under 1000 ft, corresponding to the final approach. We calculate Time Flown Level in percentage to total time spent in TMA.

3.1.3. Additional fuel burn

Fuel-based PIs capture inefficiencies on tactical ATM layer in vertical domain as explained in Prats et al. (2019). The objective is to generate a set of CDO trajectories (using the methodology described in Section 3.3), calculate the fuel consumption for those, and compare against the fuel consumption of the actual trajectories. We calculate Additional Fuel Burn in percentage to the corresponding CDO trajectory fuel burn.

3.2. Impact factors

In this work, we examine the influence of traffic intensity and different weather conditions on the arrival flight performance within TMA.

3.2.1. Traffic impact factor

We analyze flight efficiency during the descent and consider the number of arriving aircraft. The normalized number of arrivals per hour is used as a measure of traffic intensity. We investigate an isolated scenario of flight performance in good weather conditions. Assuming the isolated scenario with no influence of weather, we take into account

only traffic intensity. To avoid the influence of outliers and overfitting in regression analysis, we introduce Traffic Impact Factor (TIF) (Lemetti et al., 2020b,a). We calculate TIF by discretizing the traffic intensity into 10 bins based on quantiles, that is we use values 0, 0.1, ..., 1 as cut points for binning.

3.2.2. Weather impact factor

To quantify the impact of weather, we consider the following 24 weather metrics: u- and v- components of the 10 m and 100 m wind, wind gust, convective available potential energy (CAPE), convective precipitation, K index, convective snowfall, convective snowfall rate water equivalent, large scale snowfall, large scale snowfall rate water equivalent, snowfall, total column cloud ice water, total column cloud liquid water, total column rain water, total column snow water, total column water, total precipitation, low cloud cover, medium cloud cover, high cloud cover, total cloud cover, cloud base height (for the detailed description of each weather variables, please refer to ECMWF, 2020).

First, we investigate an isolated scenario with low traffic flight performance. Assuming traffic intensity does not influence the flight efficiency in this scenario, we use Weather Impact Factor (WIF), developed in Lemetti et al. (2020a), as a unified weather condition metric. We aim to include all available weather data, that is as many weather metrics as possible. To identify a smaller number of uncorrelated variables we use the classical tool of PCA setting the variance of the input that is supposed to be explained by the generated components to 95%. As the initial features we take all 24 weather metrics with the granularity of one hour. To avoid negative correlation between the initial features and negative weights in the principal components, we substitute u- and v- components of wind by calculated wind speed, perform a unity-based normalization (scaling to [0, 1]) of the cloud base height (*cbh*) term and substitute it by $1 - cbh$. Before applying PCA we standardize all features.

Furthermore, for WIF calculation we use the following algorithm. First, we normalize all principal component to fit into the range from 0 to 1. Then we sum them up and group the resulting numeric values into 10 bins, discretizing the results by quantiles to obtain the unified WIF score. As the correlation matrix of the initial pre-processed features shows either no correlation, or positive correlation between metrics, we can claim that sum of the principal components reflects 'bad weather intensity'. The fact that PCA components are uncorrelated guarantees that we do not take into account the same weather phenomena twice.

3.3. Generation of the CDO profiles

We calculate the shortest-path CDO trajectories for all aircraft arrivals to TMA, using the given entry conditions, with the goal to use them as a reference for calculation of the fuel-related PIs. We use the reference trajectory of the corresponding cluster as the horizontal track for the CDO.

We model the performance of the descent profiles using Base of Aircraft Data (BADA) v4.2 (EUROCONTROL, 2014) and consider an idle thrust descent without using speedbrakes, utilizing the BADA idle rating model. We calculate the engine idle thrust and drag at every timestamp, starting from the lowest altitude and calculating backwards, and feed it into the Total Energy Model (TEM) (Eq. (1)). We use the aircraft-specific speed profile designed according to the speed schedule formulas provided in BADA, which we convert from calibrated airspeed (CAS) to true airspeed (TAS). The speed profile is based on keeping a constant CAS (or Mach number at higher altitudes) during different altitude intervals. From the TEM, we obtain the vertical speed (dh/dt) at every timestamp. By calculating the vertical speed along the trajectory, we obtain the full vertical profile of the reference CDOs. We do not allow our vertical reference trajectories to cross the TMA border at a higher altitude than the cruise altitude for the flight, thus, we may have an initial level flight segment for flights that have a low cruise altitude. From the historical Opensky data we derive the CAS at TMA entry and use that speed as the initial TMA entry speed for the reference CDO.

For the aircraft mass, we consider 90% of the maximum landing weight for each aircraft type, specified in BADA. Since the decrease in mass due to the consumption of fuel is very small during the descent, we assume that the mass stays constant along the descent.

$$(Th - D) \cdot V_{TAS} = m \cdot g_0 \cdot \frac{dh}{dt} + m \cdot V_{TAS} \cdot \frac{dV_{TAS}}{dt} \quad (1)$$

Here, Th is the thrust force, D is the drag force, V_{TAS} is the true airspeed, m is the aircraft mass and g_0 is the gravitational acceleration.

Weather data described in Section 4.1 is used to obtain historical data on temperature and wind at different altitudes and positions, which we use to imitate the prevailing atmospheric conditions and for conversion between ground speed (GS) to TAS. We use linear interpolation in time, position and altitude to obtain the desired atmospheric value from the discretized historical data.

3.4. Fuel consumption

We calculate the fuel consumption according to the formula provided in the BADA manual (Eq. (2)).

$$F = \delta \cdot \theta^{\frac{1}{2}} \cdot m \cdot g_0 \cdot a_0 \cdot L_{HV}^{-1} \cdot C_F \quad (2)$$

Here, δ is the pressure ratio, θ is the temperature ratio, m is the reference mass, g_0 is the gravitational acceleration, a_0 is the speed of sound at sea level, L_{HV}^{-1} is the fuel lower heating value and C_F is the fuel coefficient.

For the actual trajectories (and for initial parts of the reference CDOs that contain a level flight segment), we use the TEM as a reference for calculating the thrust, obtaining the temperature and wind conditions at different pressure altitudes from historical weather data (see Section 4.1). Then we use the thrust to obtain the thrust coefficient. To ensure the calculated thrust stays within the feasible limits, we use BADA formulas for calculating the thrust at the maximum climb rating and idle rating, which bound the calculated thrust from below and above.

Next, we calculate the fuel coefficient from the thrust coefficient and input it to the formula for the fuel flow calculation in Eq. (2). We do not take into account the effects of deploying flaps and landing gear, which will generate more drag and increase the fuel consumption.

For the reference CDO trajectories, we calculate the idle thrust fuel coefficient for the current altitude and speed and use it in Eq. (2) to

calculate the fuel flow. After having obtained the fuel flow at every timestamp, we can calculate the total fuel consumption along the trajectory.

4. Experimental evaluation

This section describes the data used in this work and presents the results of the data analysis we perform to study the impact of traffic intensity and weather on arrival performance at Stockholm Arlanda and Gothenburg Landvetter airports. We investigate the period of two years 2019 and 2020 to compare flight efficiency in high and low traffic conditions.

4.1. Data

In this work, we use multiple sources of historical data related to the performance of Stockholm Arlanda and Gothenburg Landvetter airports during the years 2019 and 2020.

4.1.1. Aircraft tracking information

For the historical flight trajectories we use the OpenSky Network Database (OpenSky Network, 2021; Schäfer et al., 2014). We use aircraft state vectors for every second of the trajectories inside TMA. A set of methods has been chained to perform a general cleaning of the trajectories:

- Determine incorrect latitude or longitude (more than 0.1 degree distance from the previous record), fix all incorrect latitudes and longitudes using linear interpolation between the correct values
- Substitute fluctuations in altitude (more than 300 meters up and more than 600 meters down) with the previous value
- Use Gaussian filter to smooth the altitude
- Remove the trajectories for which latitude, longitude or altitude could not be fixed by means of the previous steps
- Remove the flights that go too far from the TMA border (more than 0.5 degree of latitude or longitude)
- Remove the trajectories that are incomplete within TMA and do not reach the runway (last altitude is larger than 600 m)
- Remove the trajectories, which start from the altitude lower than 600 meters (departure and arrival at the same airport, mostly helicopters)
- Remove the trajectories, which represent the landings too far from the runway (detected visually)
- Remove the trajectories, representing the go around within TMA (detected visually)

In addition, we removed the trajectories with the following callsigns (representing mostly non-commercial flights):

- Consisting of only letters
- Consisting of only digits
- Shorter than four symbols
- Starting with DFL (Babcock Scandinavian Air Ambulance)
- Starting with SVF (Swedish Armed Forces)
- Starting with HMF (Swedish Maritime Administration)

Flightradar24 (FlightRadar24, 2020) is a Swedish Internet-based service that shows real-time commercial aircraft flight tracking information on a map. We use this data source for some additional investigation of flight inefficiency during the specific days.

4.1.2. Aircraft performance data

We use BADA version 4.2 (EUROCONTROL, 2014) for CDO trajectory generation and fuel consumption calculation. For the aircraft types which are not available in BADA, we replace them with a type similar in performance and size.

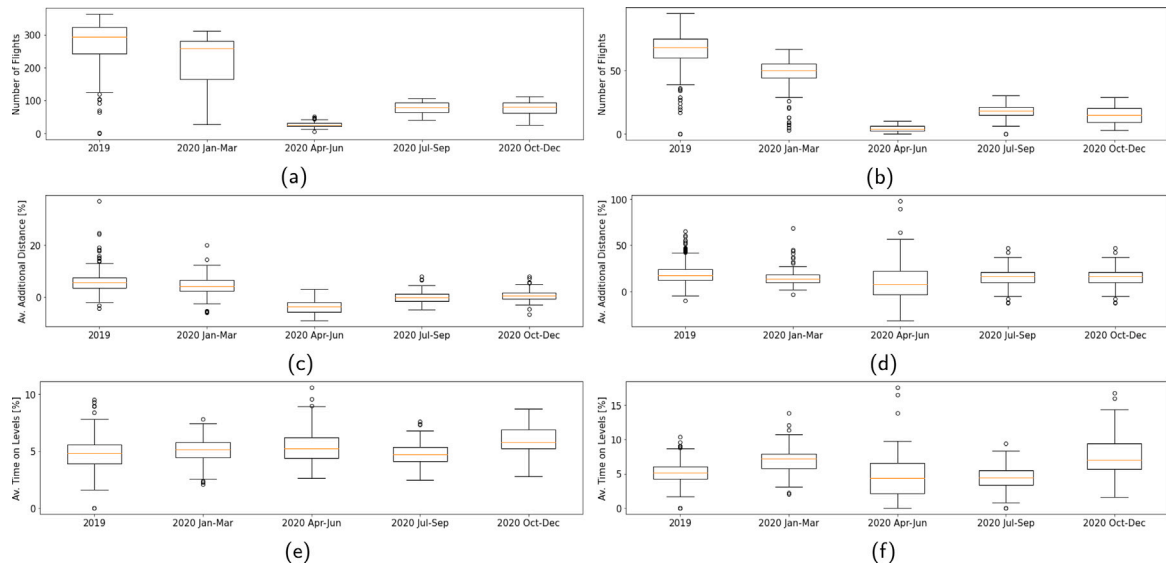


Fig. 2. Number of arrival flights (a, b), Average Additional Distance in TMA (c, d) and Average Time Flown Level (e, f) at Stockholm Arlanda and Gothenburg Landvetter airports for the years 2019 and 2020.

4.1.3. Weather data

The source of historical weather data in this paper is (ECMWF, 2020) ERA5 reanalysis dataset provided via the C3S Data Store in form of NetCDF files with 0.25° granularity and temporal granularity of one hour. The data is used for evaluation of weather impact on flight efficiency as well as for fuel consumption and CDO calculations.

Airports record current weather conditions in the form of Meteorological Aerodrome Reports (METARs). Historical METARs data is accessible at different publicly available web sources, e.g. OGIMET (2020). We use METARs data to get more precise information about the weather on the specific days.

4.2. Principal component analysis

For performing a PCA (see Section 3.2.2), we consider the observations for the whole two years period 2019–2020. PCA results in 7 principal components for both Stockholm Arlanda and Gothenburg Landvetter airports. These principal components become the contributing factors (terms) in WIF calculation.

4.3. Analysis of flight efficiency

Fig. 2(a, b) illustrates the dramatic decrease of the number of flights in April–June 2020, in comparison to January–March 2020 and to all months under consideration in the year 2019, in both airports of consideration, with slight recover in July–September 2020. We can observe some PIs following the same trend in April–June 2020 (see Average Additional Distance boxplots in Fig. 2(c, d)). Other PIs contrariwise do not clearly respond to the traffic reduction (see Average Time Flown Level plots in Fig. 2(e, f)), which might imply other factors to be more significant for these PIs.

Further in this section, we present the results of the experimental evaluation in the isolated scenarios when one of the impact factors, such as traffic intensity or weather conditions, may be disregarded. In addition, we perform a fine-grained evaluation of the vertical efficiency and fuel consumption in low-traffic scenarios.

4.4. Analysis of flight efficiency within TMA in an isolated scenario with low traffic

To analyze the weather impact and to determine which PI is more affected by weather, we investigate an isolated non-congested scenario.

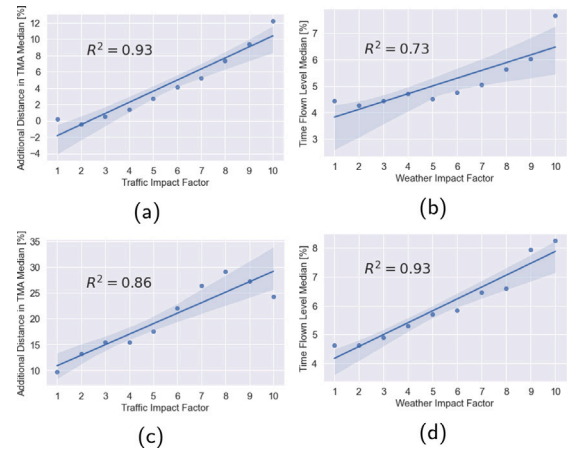


Fig. 3. Regression of Additional Distance median values onto the TIF (a) and Time Flown Level median values onto the WIF (b) at Stockholm Arlanda airport, regression of Additional Distance median values onto the TIF (c) and Time Flown Level median values onto the WIF (d) at Gothenburg Landvetter airport.

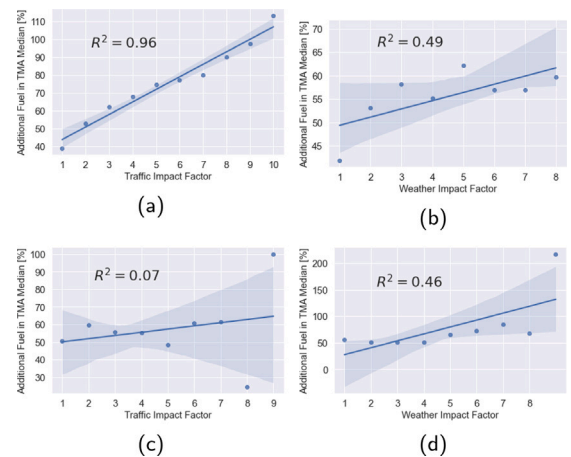


Fig. 4. Regression of Additional Fuel Burn median values onto the TIF (a) and onto the WIF (b) at Stockholm Arlanda airport, regression of Additional Fuel Burn median values onto the TIF (c) and onto the WIF (d) at Gothenburg Landvetter airport.

Table 1
Statistics coefficients for Stockholm Arlanda airport.

PI	Factor	R^2	Pearson's r	Spearman's ρ
Time Flown Level	TIF	0.63	0.79	0.77
Time Flown Level	WIF	0.73	0.85	0.95
Additional Distance	TIF	0.93	0.97	0.99
Additional Distance	WIF	0.18	0.43	0.38
Additional Fuel	TIF	0.96	0.98	0.9(9)
Additional Fuel	WIF	0.49	0.7	0.67

Table 2
Statistics coefficients for Gothenburg Landvetter airport.

PI	Factor	R^2	Pearson's r	Spearman's ρ
Time Flown Level	TIF	0.13	0.37	0.3
Time Flown Level	WIF	0.93	0.97	0.99
Additional Distance	TIF	0.86	0.92	0.92
Additional Distance	WIF	0.18	0.42	0.38
Additional Fuel	TIF	0.07	0.26	0.3
Additional Fuel	WIF	0.46	0.68	0.82

For the two-years time period 2019–2020, we exclude from the consideration 10% of the most busy hours (for Arlanda it corresponds to more than 11 flights per hour, and for Landvetter — more than 3 flights per hour). We apply methodology developed in [Lemetti et al. \(2020b\)](#). Regressing the medians of our PIs onto WIF values we notice significantly stronger correlation ($R^2 = 0.73$ for Arlanda and $R^2 = 0.93$ for Landvetter) for vertical efficiency (see [Fig. 3\(b, d\)](#)). Additional Distance shows moderate/low correlation with WIF ($R^2 = 0.63$ for Arlanda and $R^2 = 0.13$ for Landvetter).

Coefficient of determination together with Pearson and Spearman's rank correlation coefficients for all PI-impact factor pairs are presented in [Tables 1 and 2](#). Spearman's rank correlation coefficient values confirm the monotonic relationship between our PIs and impact factors and Pearson coefficient values confirm the positive correlation of the PIs with impact factors in all the considered cases.

4.5. Analysis of flight efficiency within TMA in an isolated scenario with good weather conditions

Next, we investigate an isolated scenario with good weather conditions. Again, for the whole periods of investigation 2019–2020, we exclude from the consideration all the hours, when weather metrics exceed (or is below for cloud base height) at least one of the following thresholds: wind gust ≤ 25 knots, cloud base height ≥ 200 feet, low cloud cover < 1 , CAPE ≤ 150 J/kg. The threshold values for the definition of the hazardous types of different weather phenomena are selected as specified in [Taszarek et al. \(2020\)](#). Regression of Additional Distance in TMA medians onto the TIF confirms that traffic intensity significantly influences this PI ($R^2 = 0.93$ for Arlanda and $R^2 = 0.86$ for Landvetter, see [Fig. 3\(a, c\)](#)). Regression of Time Flown Level medians expectedly shows weak correlation ($R^2 = 0.18$ for Arlanda and $R^2 = 0.18$ for Landvetter).

4.6. Analysis of flight efficiency in terms of fuel burn

Calculation of the fuel consumption requires the data of high granularity and is a computationally expensive task. We calculate this PI for the two months: October 2019 and April 2020, representing scenarios of high and low traffic load at both airports.

Regressing Additional Fuel Burn medians onto WIF values, we observe moderate correlation for both airports ($R^2 = 0.49$ for Arlanda and $R^2 = 0.46$ for Landvetter, see [Fig. 4\(b, d\)](#)). However, regression of this PI onto the traffic factor gives different results for Arlanda and Landvetter: Additional Fuel Burn strongly correlates with TIF in Arlanda ($R^2 = 0.96$), but does not correlate for Landvetter ($R^2 = 0.07$), see [Fig. 4\(a, c\)](#).

4.7. Fine-grained analysis of flight inefficiency within TMA in low traffic conditions

To examine the vertical efficiency further and get a better understanding of what are the sources of inefficiencies inside TMA, we perform a fine-grained evaluation of flight efficiency within Stockholm Arlanda Airport TMA during the particular days. We choose two days with high values of the Average Time Flown Level PI: April 12 and May 4 of the year 2020. [Fig. 5\(a, b\)](#) shows the actual vertical profiles and their corresponding estimated CDO profiles for the chosen days. We observe that the aircraft start to descend earlier and fly significantly lower and often longer than recommended by CDO trajectories. Some of them have long levels at the low altitudes.

Next, applying the methodology similar to the one proposed in [Pasutto et al. \(2020\)](#), we differentiate between the inefficiencies in lower and upper parts of the TMA. For that we split the trajectories as shown in [Fig. 5\(c, d\)](#) with the different colored parts representing inefficiencies below and over the FL65. Calculating average deviation for lower and upper parts of the trajectories, we observe higher deviations from the CDOs in the upper parts of the flights with median value of 1103 m on April 12 and 1099 m on May 4. For the altitudes below FL65 the median values are 559 m and 492 m correspondingly.

The results of comparison of the fuel consumption for the actual aircraft trajectories against the fuel consumption estimated for the CDO profiles, show that there are noticeable inefficiencies, despite the low traffic volume ([Figs. 6 and 7](#)). For April 12, the estimated additional fuel burn is 1416 kgs (42%), and for May 5–1444 kgs (41%).

Very high values of the fuel consumption for the aircraft 4 and 5 in [Fig. 7](#), could possibly be explained by the weather influence. According to historical METARs from [OGIMET \(2020\)](#), cumulonimbus (CB) clouds were present in the area of Stockholm TMA, at the time of arrival of the two flights. By performing a playback of the flights around Stockholm TMA at FlightRadar24 website ([FlightRadar24, 2020](#)), we can see that all arriving flights on May 4, 2020, landed on runway 01L, while aircraft 4 and 5 landed on runway 26 ([Fig. 8](#)). Following the flight paths of the two flights, we can guess that the two flights initially were heading towards runway 01L, but were diverted to runway 26 because of the bad weather conditions, i.e. CB clouds present in the final approach path to runway 01L. The diversion is clearly visible for SAS88R, while SAS58E is flying a right-hand circuit, instead of approaching the final from the south, which is the typical way of approaching runway 26 coming from the southern parts of the TMA, and we can suppose that the aircraft was deliberately diverted out of the certain parts of the TMA by the air traffic controller.

5. Conclusions

In this work, we used the opportunity provided by the Covid-19 pandemic situation to evaluate TMA performance in an isolated scenario with low traffic in Stockholm Arlanda and Gothenburg Landvetter airports. We revealed that the horizontal flight efficiency has improved after April 2020 in response to the reduction of the traffic volumes, while vertical flight efficiency did not follow the trend. In particular, we discovered noticeable vertical inefficiencies on two days in 2020 (in low-traffic scenario) in Stockholm Arlanda airport, and evaluated the associated environmental effect, which corresponds to up to 42% extra fuel burned.

We investigated the impact of weather on TMA performance, and confirmed that weather conditions have a significant impact on vertical flight efficiency. Weaker correlation between weather conditions and horizontal flight efficiency might be country-specific, since, for example, convective weather is relatively rare event in our study area. We also evaluated an isolated scenario with good weather conditions and concluded that traffic intensity has a strong impact on TMA performance but influences mostly the lateral efficiency. Strong correlation between traffic intensity and horizontal flight efficiency

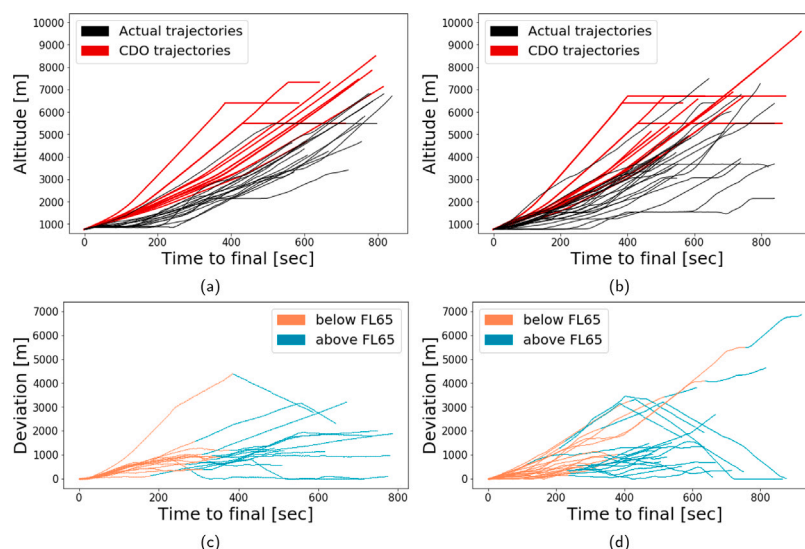


Fig. 5. Vertical profiles of the arrival flights in Stockholm Arlanda airport TMA together with CDOs on April 12 (a) and May 4 (b) of the year 2020. Vertical deviations from CDOs on April 12 (c) and May 4 (d) of the year 2020.

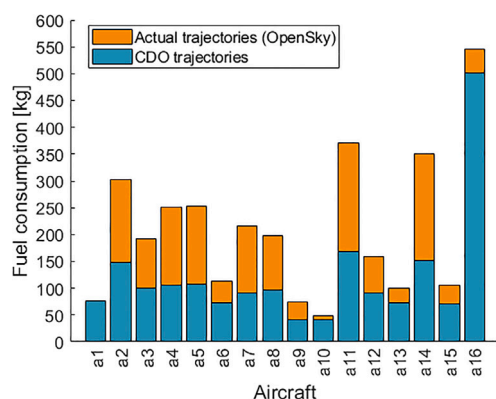


Fig. 6. Comparison of the fuel consumption for the actual aircraft trajectories against the CDOs, for 16 arrivals within Arlanda TMA on April 12, 2020.

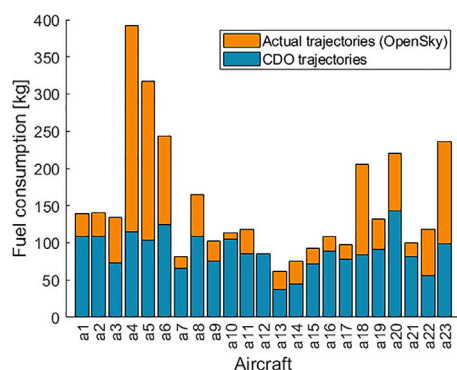


Fig. 7. Comparison of the fuel consumption for the actual aircraft trajectories against the CDOs, for 23 arrivals within Arlanda TMA on May 4, 2020.

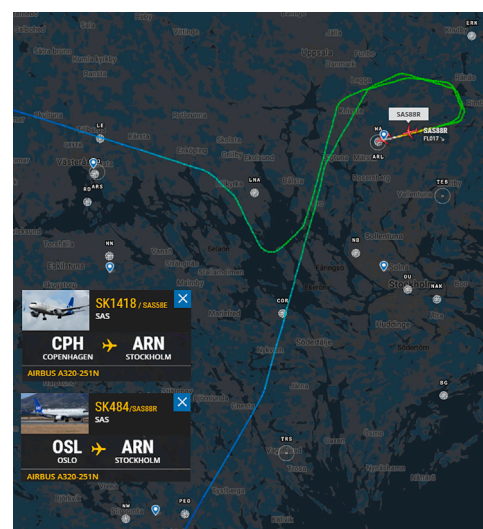


Fig. 8. Aircraft trajectories for the flights SAS88R and SAS58E on May 4, 2020.

traffic situation for Stockholm Arlanda airport. The results for the Gothenburg Landvetter airport does not show correlation of Additional Fuel Burn with traffic intensity. That can be explained by lower volumes of the traffic in this airport, as well as smaller TMA.

The results of this work contribute to the understanding of sources of flight inefficiency within TMA, and give an incite towards optimization activities in the corresponding areas.

CRedit authorship contribution statement

Anastasia Lemetti: Methodology, Data curation, Software, Formal analysis, Writing – original draft. **Henrik Hardell:** Methodology, Software, Writing – original draft. **Tatiana Polishchuk:** Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

might be caused by frequent trajectory extensions due to hold-ons or vectoring in high traffic conditions.

For Additional Fuel Burn in TMA, we observe moderate correlation with weather conditions at both airports, and strong correlation with

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