A EUROPEAN STUDY TO IDENTIFY KEY OPERATIONAL PARAMETERS FOR ATFM ROUTING DECISIONS

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Abstract

The overall European Air Traffic Management aims for an efficient utilisation of ATM sub-systems like the European Air Traffic Management Network. Highly congested hub airports and controlled airspaces may lead to Demand-Capacity-Balancing issues during high demand periods. Air Traffic Flow Management as one of the European ATM domains resolves these issues with certain capacity balancing measures. Besides slot allocation, one frequently used measure is (lateral) re-routing, which often leads to less efficient trajectories resulting in additional CO2-emissions and costs for airspace users. Recent research suggests that the share of inefficient short-term re-routing measures could be reduced by high-quality predictions of future flight trajectories through Machine Learning methods. One essential requirement for the development of ML models is the optimal choice of input parameters. In this study, a structured analysis of an extensive set of flight plan data is conducted in order to identify key operational parameters for ATFM routing decisions. An extensive flight plan data sample covering three months in 2016 is parametrised and analysed to gather a sufficient data baseline. A set of representative Origin-Destination pairs with high demand rates are investigated in more detail. Results show that flights approaching large hub-airports have a higher chance of being re-routed resulting in a less efficient trajectory in terms of lateral ATS-efficiency. The parameters with the highest relevance on ATFM routing decisions were found to be lateral ATS-efficiency, demand along the individual sector profile as well as the weekday of departure for planned trajectories.

1. INTRODUCTION

The worldwide number of flights has grown from 2013 to 2018 over 20 % from 36.3 to 46.1 million [1]. With the increasing number of flights and growing competitive pressure, a demand for higher safety requirements and increased efficiency evolved. In order to satisfy these requirements, Air Traffic Flow Management (ATFM) was introduced in Europe, which takes over the function of strategic and tactical Demand-Capacity-Balancing (DCB) as part of flight planning and ATFM network management. In addition to delay allocation, a number of other ATFM measures play a central role. These include the selection and assignment of alternative lateral routes.

Alternative lateral routings often result in a decreased mission efficiency. This contributes to the fact that within the European Air Traffic Management Network (EATMN) the distance of flights is extended by an average of 6 % resulting in approx. 5 million tons of additional CO2 emissions and 2.5 billion € costs per year [2]. Besides the steadily growing number of flights per year in the European airspace (pre-Corona), the complex system of stakeholders and the limited resource of airspace create further complexity in route guidance. Compared to the US Air Traffic Management (ATM) system with one Air Traffic Control (ATC) organization, 21 control centers and one operating system, the European system actually consists of 47 Air Navigation Services Providers (ANSPs), 58 control centers and 22 operating systems.

Thus, the amount of en-route ATFM delay has doubled within one year from 2017 to 2018 [3]. This is an indication that European airspace is reaching its capacity limits. In order to avoid congestion of specific airspaces resulting in ATFM measures, a more precise demand prediction is needed. The German Air Navigation Service Provider (DFS) has addressed this fact at the NM User Forum 2019 as the most important task of the Upper Area Control Center Karlsruhe besides weather [4].

Since this is a complex problem with a high share of uncertainty, it is a suitable application area for Machine Learning (ML) and Deep Learning algorithms to lower these levels of uncertainty by elaborated demand predictions. One essential requirement for the development of ML models is an optimal choice of input parameters used for the prediction.

On the operational side, ATFM stakeholders may benefit from the findings in terms of being able for more robust traffic planning. Especially airlines may benefit from feedbacks on their operational flight plan trajectories regarding the ability to realize the individual route as filed. Due to time-related mission length with different flight routes, actual route predictions should have an impact on the cost index (CI) of a flight, which reflects the relationship of time-related flight costs to fuel costs. If there is a high probability, that a desired routing cannot be implemented like planned, airlines may be able to better compute their CI according to predicted flight routes. This study therefore contributes in a first step to a higher flight planning transparency also in terms of mission-related cost calculation.

Moreover ML-supported traffic predictions may enable the realization of an ATM-system with a higher automation level. Such functionality would support a more predictive network management, in which causal relationships e.g. between planned flight missions would be better reconciled on a higher level of automation.

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1.1. Related Work

Planned aircraft trajectories are generated on a high granular level based on the flight performance database, Eurocontrol's Base of Aircraft Data (BADA) [5]. On this basis Zhiyuan Shi et al. [6] developed a Long short-term memory (LSTM) network that predicts 4D trajectories. LSTM networks are recurrent neural networks that are used for sequential classification tasks. With this deep learning approach higher prediction accuracy is achieved compared to Markov models. The data basis is high-resolution trajectory data (3-4 data points per second) of the Automatic Dependent Surveillance-Broadcast (ADS-B).

The deep learning algorithm developed by Herbert Naessens et al. [7] uses parameters of a planned trajectory in connection with data for the reservation of airspaces for military purposes to predict a 2D trajectory. The work focusses exclusively on the upper airspace controlled by EUROCONTROL Maastricht Upper Area Control Centre (UAC). The developed model is integrated into the 4D prediction logic of EUROCONTROL Maastricht UAC.

Yulin Liu et al. [8] have trained a deep learning network based on meteorological and trajectory data to generate 4D trajectories for flights between the airports in Houston (IAH) and Boston (BOS). Trajectories of 1342 flights from 2013 were used for training.

A paper by R. Kaidi et al. [9] also presents a model for trajectory prediction. This model should serve the purpose of automatic conflict detection and resolution between trajectories in the vertical plane. The developed model is limited to the simultaneous observation of a maximum of two aircraft for trajectory prediction.

Although some papers deal with trajectory prediction, these are either restricted to selected O-D pairs or to specific airspaces. The aim of this study is to take the whole European airspace into consideration.

1.2. General Approach

ATFM routing decisions can be implemented for various reasons, such as weather phenomena, military activities or congested ATC-sectors. This study focuses on the effects of congested ATC-sectors. In order to better understand their impact on ATFM routing decisions, a set of representative Origin-Destination (O-D) pairs with high demand rates is investigated (see fig. 1).

The O-D pairs are selected based on the different route characteristics. They differ with respect to their great circle distance and provide a good representation of a larger number of missions. The individual O-D pairs are described in more detail in ch. 3.1.

After analysing the selected O-D pairs, the whole dataset is investigated in order to compute correlations between defined trajectory parameters and less efficient, i.e. longer alternative routes. In a next step, a comparison is drawn to the most important parameters identified by an Extra Trees Classifier algorithm (Please refer to ch. 3). Identified key parameters for ATFM routing decisions will be used in future work for the development of Machine Learning models for airspace demand and trajectory prediction.

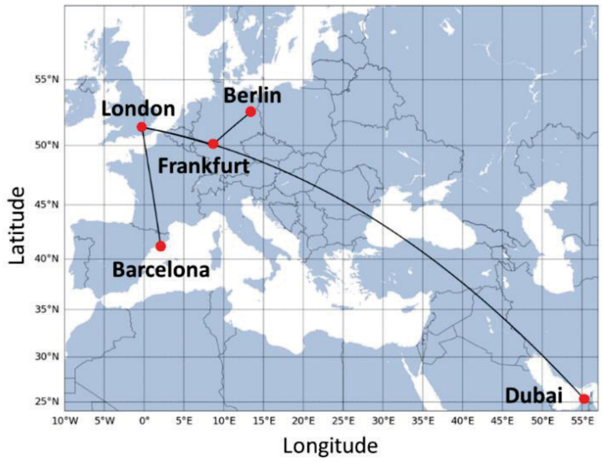

Figure 1. Analysed O-D pairs with different great circle distances.

1.3. Data Sources

The analysis is conducted for an extensive flight plan data sample covering 92 days in 2016 in the ECAC airspace with over 3 million flights. It is provided by the EUROCONTROL Demand Data Repository (DDR2) [10], which contains individual mission parameters as well as detailed 4-dimensional flight plan trajectory data. Flight plan and post-operational trajectories with a total of over 170 ATFM specific parameters per flight are evaluated, whereas relevant ones are identified and analysed in more detail for this study.

2. MODEL DEVELOPMENT

In a first step, the trajectories of both types are parametrized as a preprocessing step for the model in order to achieve better comparability. The following parameters are determined:

1) *Sectorprofile*: Mission-related ATC-sectors along the trajectories are computed, as well as the corresponding sector entry times. The result is a sequence of time dependent sectors for each trajectory, called sectorprofile (see fig. 2).

2) *Sector demand*: The planned and post-operational sector demand is derived as followed:

$$sector\ demand = \frac{flight\ entries\ per\ hour}{sector\ capacity} \tag{1}$$

For each sector in the *planned* sectorprofile the time dependent sector demand is added to the trajectory parameter list.

3) *ATS-efficiency*: The ATS-efficiency represents the trajectory's lateral efficiency, calculated by the following formula:

$$\eta_{ATS} = \frac{trajectory\ distance}{great\ circle\ distance} \tag{2}$$

4) *Origin airport*

5) *Destination airport*

6) *Airline*

7) *Aircraft type*

8) *Weekday of departure*: The weekday of the departure is derived from the Estimated Off-Block Time parameter.

9) *Estimated Off-Block time* (EOBT)

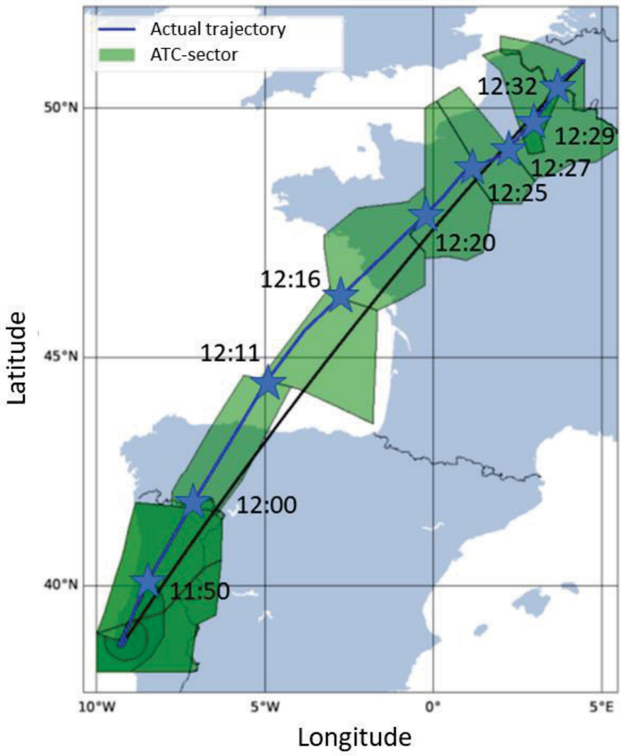

Figure 2. Example of a sectorprofile for a trajectory with intersected ATC-sectors and entry times. The black line describes the great circle.

The computed sectorprofiles for the planned as well as for the post-operational trajectories are compared for each flight. A flight is considered to be *"re-routed"*, if the sectorprofiles differ, meaning, that small deviations without sector change are not considered, since those routes do not represent a significant lateral shift of demand within the EATMN. Fig. 3 depicts trajectory and airspace data of a flight from Frankfurt (EDDF) to London (EGLL). Differences of the sector profiles related to the respective planned and post-operational trajectory are shown in red. The flight received a lateral *re-routing* in the airspaces of Belgium and Luxembourg and an adaptation of the vertical profile segment within the TMA of the arrival airport (EGLL).

ATFM-restricted flights with assigned alternative routes are classified into groups of flights with more and less efficient alternative routes depending on route lengths. The goal is to differentiate between different types of alternative routes based on capacity effects on the one side and on directs on the other side, which are generally requested by pilots during flight. This study focuses on less efficient (longer) routes.

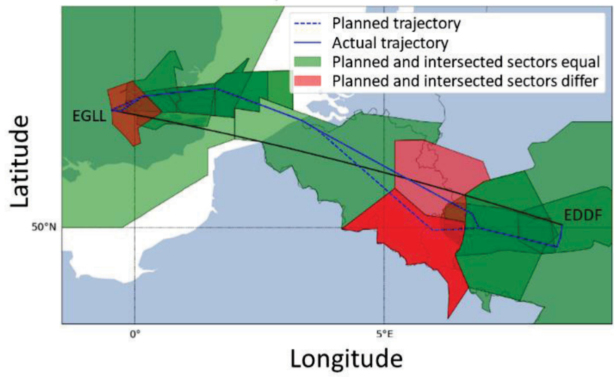

Figure 3. Example of a re-routing for a flight from Frankfurt airport to London Heathrow. The black line describes the great circle.

3. RESULTS

In this chapter results of the analysis for the four selected O-D pairs (see fig. 1) are presented. The correlation between trajectory parameters and less efficient alternative routes are compared to the most important parameters identified by an Extra Trees Classifier algorithm. An Extra Trees Classifier is a type of ensemble learning technique which aggregates the results of multiple de-correlated decision trees collected in a forest to output its classification result [11]. Finally, most relevant ATC-sectors involved in routing decisions are presented.

3.1. Origin-Destination Pairs

The considered O-D pairs vary in their great circle distance (GCD) as shown in table 1.

ICAO-Codes	**O-D pair**	**GCD** [NM]
EDDF - EDDT	Frankfurt am Main – Berlin Tegel	235
EDDF - EGLL	Frankfurt am Main – London Heathrow	353
EGKK - LEBL	London Gatwick – Barcelona El Prat	603
OMDB - EGLL	Dubai Intl – London Heathrow	3.004

TAB 1. Great circle distances for analysed O-D pairs.

The O-D pairs are selected based on the different route characteristics. Frankfurt - Berlin is a frequently flown route in domestic German airspace. Due to its function as a spoke-hub connection, the route serves as a feeder for medium and long-haul flights. With a great circle distance of 235 NM it is the shortest of the considered connections.

Frankfurt/Main Intl. and London Heathrow are among the largest airport hubs in Europe and are frequently used as hub-hub connections. There are also many direct connections, as both cities are home to important institutions from the financial and economic sectors. The spatial granularity of ATC-sectors on that route is high leading to a multitude of possible sector profiles.

The route between London and Barcelona is a hub-hub connection, similar to the Frankfurt - London route. The great circle distance is longer with 603 NM. Both airports experienced a steady growth in passenger volume in recent years.

Dubai Intl. is the most frequented of the considered airports. For Europe, the airport is an important hub for connections to Asia. The route London - Dubai is an intercontinental connection leading through a large part of European airspace and thus a multitude of ATC-sectors are intersected. This, in conjunction with the long distance (3.004 NM), allows a high number of possible sector profiles to be selected.

In fig. 4 longer, shorter and non-routed flights are shown for both directions each over the course of three months covered by the dataset. With the exception of London – Dubai there is a tendency towards a lower number of flights with a longer great circle distance. There is also an increasing percentage share of longer routed flights (shown in red) with shorter GCD evident. Looking at the O-D pairs London - Barcelona and London - Dubai, it can be seen that there are more flights to London on these routes than in the opposite direction. The higher frequented directions are more relevant in route planning for airlines. Flights arriving in London have a higher chance of receiving an extended route. The reason is the high congestion in the vicinity of London Heathrow. The results suggest a correlation between the O-D pair parameter and longer re-routed flights.

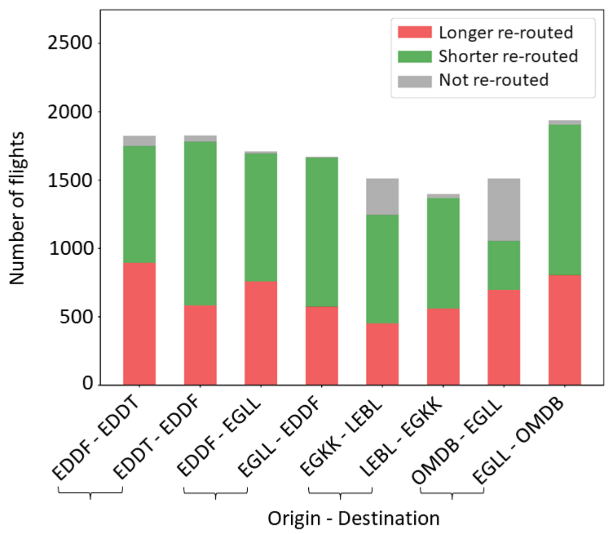

Figure 4. The number of longer, shorter and not re-routed flights for both directions of the four analysed O-D pairs for the whole dataset covering three months in 2016. O-D pairs are sorted from left to right by increasing GCD.

3.2. Representative O-D: Frankfurt – London

As a representative O-D pair, Frankfurt - London is investigated in more detail. Figure 5 shows the planned and actually flown trajectories for the route Frankfurt - London Heathrow (top) and London Heathrow - Frankfurt (bottom).

There are three planned main routes for EDDF - EGLL. One leads through Dutch airspace, one through Luxembourg and Belgian airspace and the third through Luxembourg and French airspace. The two less efficient routes are not exactly flown in reality. All flights deviate towards the great circle resulting in distance reduction. This is especially true for the Belgian and German airspace. Flown trajectories close to the great circle spread over a large area. Some flights received a longer re-routing in the English Channel area, indicating congested airspaces. In London, the trajectories lead beyond the destination airport London Heathrow. This is assumed to be due to the runway direction, city noise regulations and a congested airport.

In the direction London - Frankfurt, two main planned routes emerge, one near the great circle through Belgian airspace and one through the Netherland airspace. As seen in the opposite direction, some aircrafts received a less efficient re-routing in the area around London and the English Channel, indicating congested airspaces in this area. As indicated also in the opposite flight direction, flights fly by the arrival airport (EDDF) due to defined arrival procedures and operational runway directions and noise constraints.

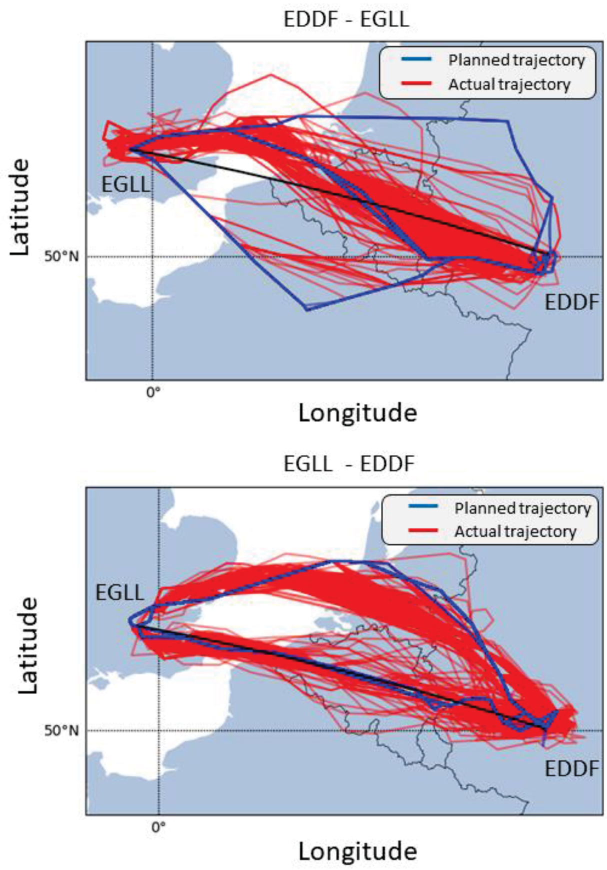

Figure 5. Planned (blue) and post-operational (red) trajectories for flights from Frankfurt airport to London Heathrow (top) and in the opposite direction (bottom). The whole dataset was analysed covering three months in 2016.

The ATS-efficiency, as described in ch. 2., is a measure for the lateral route efficiency. When looking at the probability density distribution of ATS-efficiency for Frankfurt - London, it is noticeable that mainly the planned route (X) through Luxembourg and Belgian airspace is used (see fig. 6). Longer re-routed flights show very different ATS-efficiency values, whereby two specific routes seem to be selected regularly (1)(2). Shorter re-routed flights run along similar corridors (3). It can be concluded that shorter re-routed flights often follow a similar path, while longer re-routed flights are diverted in different ways. This is an indication of multiple small and overloaded airspaces.

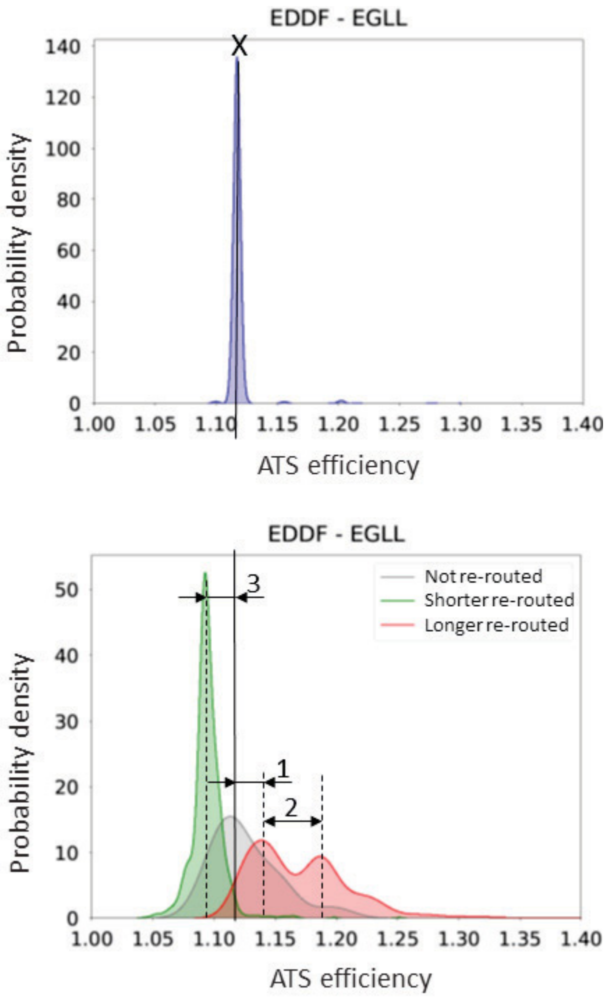

Figure 6. The probability density function of the ATS-efficiency is plotted for planned (blue) as well as for shorter (green), longer (red) and not re-routed (grey) flights for the direction Frankfurt airport to London Heathrow.

Three main planned routes (X) can be identified for the direction London - Frankfurt, but the one with the average ATS-efficiency between 1.1 and 1.3 is used most frequently (see fig. 7). The longer re-routed flights are assigned to two main routes (4). It can be concluded that flights with the highest ATS-efficiency 1.3 are rarely longer re-routed. The function of the ATS-efficiency for planned routes is reflected in the profile for shorter re-routed flights with a shift towards a lower value of ATS-efficiency (5)(6)(7). In this direction shorter re-routed flights are diverted in different ways, whereas longer re-routed flights tend to follow a similar path.

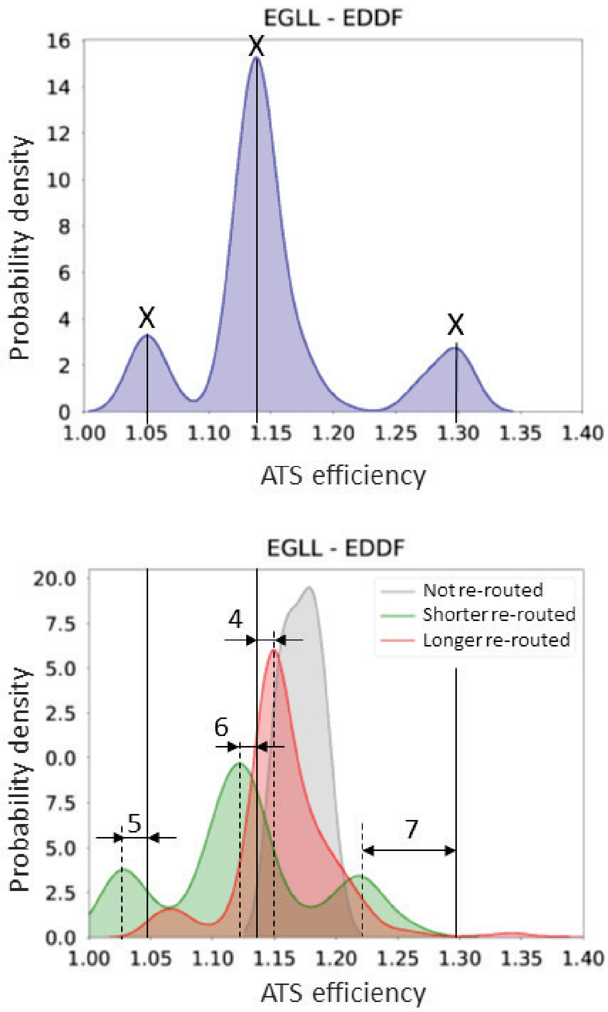

Figure 7. The probability density function of the ATS-efficiency is plotted for planned (blue) as well as for shorter (green), longer (red) and not re-routed (grey) flights for the direction London Heathrow to Frankfurt airport.

It can be concluded, that the high congestion at the destination airports as well as in ATC-sectors across the English Channel plays a major role in ATFM routing decisions. In addition, the high number of requested directs have a significant impact on the flown trajectory and the resulting ATS-efficiency.

3.3. Parameter correlation

The Pearson correlation coefficients for considered trajectory parameters are calculated for the whole dataset as a measurement for linear correlation (see fig. 8). It is a statistical value, describing the relationship between two quantities and ranges from -1 to +1. It can be used to evaluate different parameters as input for Machine Learning models [12].

The arrival airport as an input variable seems to have the highest impact on the fact, if a trajectory will be affected by routing decisions resulting in a less efficient trajectory. This is due to congested arrival airspaces. It was previously detected that trajectories often lead beyond certain destination airports due to runway directions, resulting in a longer flight distance. This also seems to contribute to the high correlation coefficient besides en-route re-routings on which this study focuses.

The airline itself also represents an important input parameter. Differences in flight planning constitute one possible reason, the location of the individual hub also has an influence. Differences in the size and business models may have an influence.

The departure airport seems to be less relevant than the arrival airport regarding routing decisions. It can be concluded that flights with congested arrival airports are more likely to receive a longer route than flights with congested departure airports.

A lower impact on the fact, if a trajectory will be affected by routing decisions resulting in a less efficient trajectory was found in the Estimated Off-Block Time, the aircraft type, the planned ATS-efficiency as well as the weekday of departure. It should be noted, that the Pearson correlation coefficient only represents linear correlations. As the ATFM network is complex, it is assumed that non-linear relationships exist. Therefore, the most important parameters for extended alternative routes compared to planned routes were identified using an Extra Trees Classifier algorithm.

3.4. Extra trees classifier

An Extra Trees Classifier algorithm [13] was used in order to evaluate the feature importance based on the Gini Impurity [14]. The Gini Impurity is used for different decision trees in the Extra Trees Classifier algorithm as mathematical criteria to split the data for the classification task. It was shown that the planned ATS-efficiency had the highest impact on routing decisions (see fig. 9). This contradicts the results of the correlation coefficients, whereby the planned ATS-efficiency had a lower value. The combination with other parameters seems to provide a relevant information gain. In addition to the planned ATS-efficiency and the weekday of departure, the planned demand of various ATC-sectors is highly relevant for ATFM routing decisions.

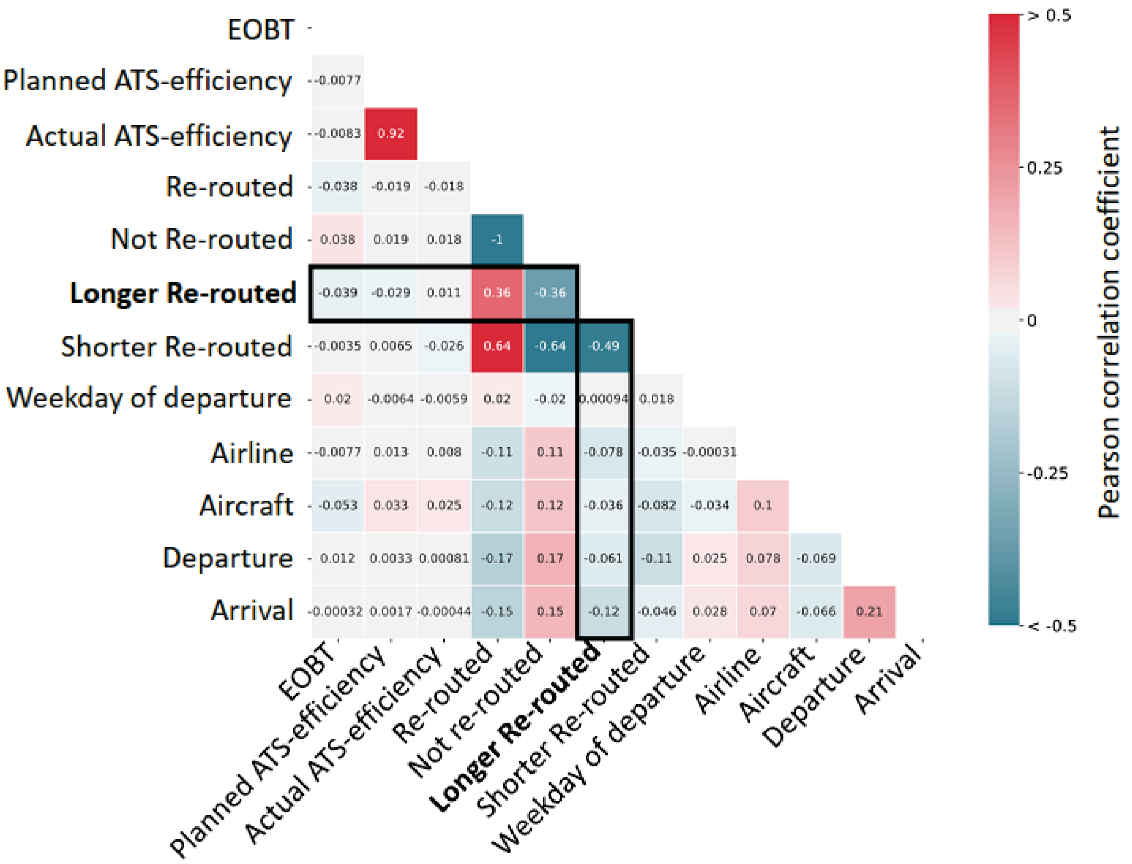

Figure 8. The Pearson correlation coeffients for combinations of mission-related parameters derived from flight plan-trajectories.

Fig. 10 presents these most relevant ATC-sectors in terms of ATFM routing decisions. The northern German airspace and ATC-sectors across the English Channel were found to be most significant on routing decisions. This coincides with the findings from the observation of the trajectories for the O-D pair Frankfurt - London. In the airspace above the English Channel a large number of “directs” and increased alternative routes are observed. ATC-sectors in these areas appear to be heavily congested.

Based on the results of the Extra Trees Classifier, it can be deduced that the lateral ATS-efficiency for the planned trajectory, the demand along the individual sector profile as well as the weekday of departure for planned trajectories are most relevant as input for machine learning models for demand prediction. The parameters EOBT, airline, aircraft type, departure and arrival airport could be considered additionally to achieve higher prediction accuracy. In doing so, a balance must be struck between additional information gain and the complexity of the model.

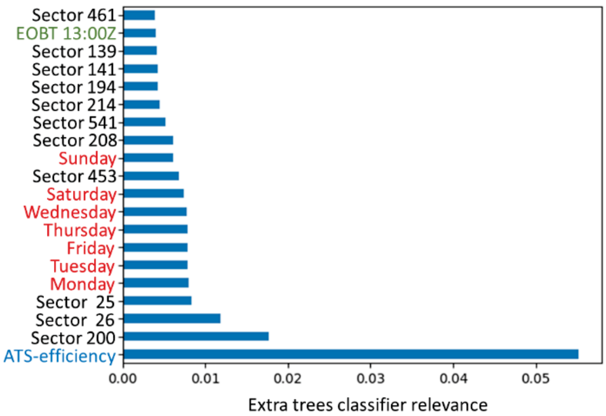

Figure 9. Relevance of trajectory features evaluated by an Extra Trees Classifier based on the Gini Impurity.

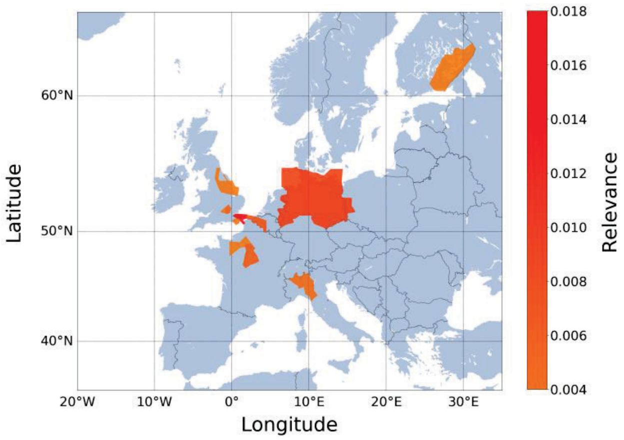

Figure 10. Most relevant ATC-sectors in terms of ATFM routing decisions. The northern German airspace and ATC-sectors across the English Channel were found to be most significant.

4. CONCLUSION AND OUTLOOK

In this study, an extensive flight plan data sample covering three months in 2016 was parametrised and analysed to gather a sufficient data baseline. Furthermore, a set of representative Origin-Destination (O-D) pairs on high-demand routes were investigated in more detail.

The correlation between selected trajectory parameters and less efficient post-operational routes was compared to most important parameters identified by an Extra Trees Classifier algorithm. The goal was to identify those parameters with high relevance for ATFM routing decisions. In this context, fig. 10 provides an indication of most affected airspaces regarding routing decisions.

Results show that flights approaching large hub-airports had a higher chance of receiving an alternative route resulting in a less efficient trajectory in terms of lateral ATS-efficiency. The reasons are congested ATC-sectors along the trajectory as well as near the airport. Furthermore, the high number of requested directs seem to have a significant impact on the actual trajectory and the resulting ATS-efficiency. These may be explained by an increasing competitive pressure between airlines.

The parameters with the highest relevance on ATFM routing decisions were found to be the lateral ATS-efficiency, the demand along the individual sector profile as well as the weekday of departure for planned trajectories. The latter ones are related to each other in terms of repetitive traffic load patterns, whereas the impact of lateral ATS-efficiency is of higher complexity. It is clear, that also pilot`s decisions play a role in this matter and it is therefore not totally transparent yet, if a mathematical approach like the one presented will be able to cover such impact systematically.

The northern German airspace and ATC-sectors across the English Channel were most significant in terms of ATFM routing decisions. These airspaces are highly congested during nominal demand conditions. The Identification of the key parameters for ATFM routing decisions will be used in future work for the development of Machine Learning models for airspace demand and flight trajectory prediction.

In future work, trajectory parametrisation could be performed using a grid instead of the ATC-sector network. This could provide a more detailed insight into ATFM routing decisions.

ACKNOWLEDGMENT

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