Visual Analytics of Flight Trajectories for Uncovering Decision Making Strategies

Gennady Andrienko, Natalia Andrienko, Georg Fuchs, Stefan Rüping
Fraunhofer Institute IAIS
Sankt Augustin, Germany

Jose Manuel Cordero Garcia
CRIDA (Reference Center for Research, Development and Innovation in ATM)
Madrid, Spain

David Scarlatti
Boeing Research & Development Europe, Madrid, Spain

George A Vouros
University of Piraeus, Piraeus, Greece

Ricardo Herranz, Rodrigo Marcos
Nommon Solutions and Technologies, Madrid, Spain

***Abstract*— In air traffic management and control, movement data describing actual and planned flights are used for planning, monitoring and post-operation analysis purposes with the goal of increased efficient utilization of air space capacities (in terms of delay reduction or flight efficiency), without compromising the safety of passengers and cargo, nor timeliness of flights.**

From flight data, it is possible to extract valuable information concerning preferences and decision making of airlines (e.g. route choice) and air traffic managers and controllers (e.g. flight re-routing or optimizing flight times), features whose understanding is intended as a key driver for bringing operational performance benefits.

In this paper, we propose a suite of visual analytics techniques for supporting assessment of flight data quality and data analysis workflows centred on revealing decision making preferences.

Keywords-visual analytics, trajectory analysis, route choice

I. Introduction

Aviation is a complex domain with a variety of different stakeholders such as airlines, airports, air traffic management services and of course, passengers. The different stakeholders have different preferences and, sometimes, conflicting interests. Understanding the driving factors of their decision making is essential for sustainable functioning of the overall system and resolving potential conflicts of interest. This knowledge is an enabler to enhanced predictability as key driver for improved operational performance, and also contributes to pave the way towards collaborative, performance-driven pre-tactical planning aiming for global optimum, which reconciles the stakeholders' individual goals.

Air traffic data contain latent information that can enable understanding of how the system works and uncovering decision making preferences. Visual analytics proved to be an appropriate instrument for supporting spatial decision making [1] and analysis of spatio-temporal [2] and movement data [3]. Visual analytics combines human and computational data processing through interactive visual interfaces, enabling understanding of large and complex data, sophisticated data analysis procedures, and informed decision making.

Flight data are collected by different agencies and vary in quality and resolution. Before trying to do any analysis, the quality of the data must be investigated. Purely computational methods often fail in detection of data problems due to high complexity of the data, while purely visual approaches are not able to handle huge amounts of data. Therefore, visual analytics approaches can be more suitable for this problem.

In this paper, we propose visual analytics techniques and workflows supporting, first, assessment of flight data quality and, second, data analysis aiming at revealing decision preferences of two types of stakeholders, airlines and air traffic management authorities. We study several typical decision making scenarios. Unlike prior publications [4][5][6], which were focused on description of data analysis methods, this paper focuses on application of the methods.

II. Related Word

A. *Visual data for spatial decision support and trajectory data analysis.*

Defined as the science of analytical reasoning facilitated by interactive visual interfaces [7], visual analytics tools are typically understood as technology products that can synthesize information from complex and dynamic data and in ways that directly support assessment, planning, and decision making in real-world settings from a wide range of application domains [8,9]. With regard to spatial decision making specifically, a number of recent advances highlight the utility of VA approaches and associated tools for decision making and tradeoff under uncertainty [10,11]. A particularly active sub-field of geo-spatial VA focusses on the analysis of movement data [1][12], with approaches ranging from trajectory-focussed analysis [3][4][5] to the capture and analysis of overall mobility patterns [13,14], trajectory interactions [15], and associated decision making processes [5,6,16] in complex transportation systems.

B. Visual analytics for air traffic tasks

Currently deployed and perspective software tools in the domain of air traffic management (ATM) support relatively simple queries and include rudimentary visualizations, such as maps showing individual movements and time histograms with aggregated flight data [17]. Nonetheless, a number of more advanced approaches have been proposed for various specific problems in air traffic analysis by visual analytics researches over recent years. Methods for detection of holding loops, missed approaches, and other aviation-specific patterns were implemented in a system integrating a moving object database with a visual analytics environment [18]. Albrecht et al. [19] calculate air traffic density and, considering aircraft separation constraints, assess the conflict probability and potentially underutilized air space. The traffic density and conflict probability are aggregated over different time scales to extract fluctuations and periodic air traffic patterns. Hurter et al. [20] propose a procedure for wind parameter extraction from the statistics of the speeds of planes that pass the same area at similar flight levels in different directions. Buchmüller et al. [21] describe techniques for studying the dynamics of landings at Zurich airport with the goal to detect cases of violating the rules that prohibit night-time landings from the north, which produce strong noise in populated regions. The detected violations can be examined in relation to weather conditions and air traffic intensity. Sophisticated domain-specific analyses can be done by applying clustering to interactively selected relevant parts of trajectories [5,6].

Despite these advances, there remain many analysis problems that have not yet been addressed in visual analytics research. Due to the complexity and various specifics of the aviation domain, it is important to do research in collaboration with domain experts [5, 17].

III. VALIDATING TRAJECTORY DATA QUALITY

Paper [4] considers a typology of problematic aspects of trajectory data quality and proposes visual analytics approaches to identify and, whenever possible, fix them. The key ideas of the approach are:

1. Consider the data structure. As trajectory data consist of flight identities, time stamps, positions and derived attributes such as calculated distances and speeds, it is necessary to address problems that may occur in each component of the data and in their combinations.

2. Support data transformations. The paper considers a full spectrum of potentially possible transformations between different types of spatio-temporal data such as events, trajectories, spatial time series, and spatial situations.

3. Take into account different types of problems: missing data, inconsistent sampling rates, precision errors, occasional and systematic errors in the data.

Figure 1. An example of problems with spatial coverage

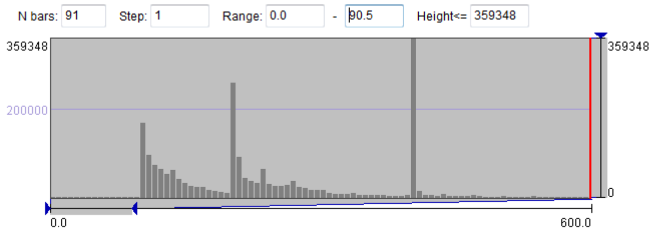

Figure 2. Variability of sampling rates in trajectories

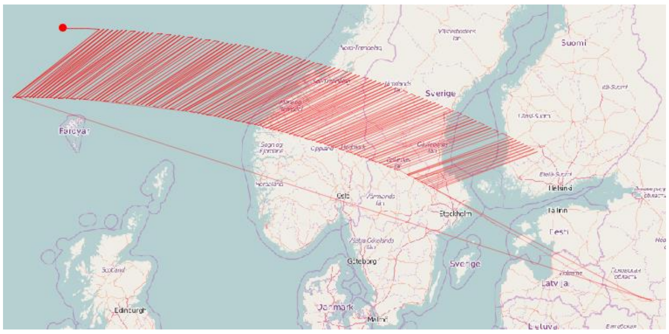

Figure 3. Duplicate flight identifiers

In the following subsections we shall illustrate some of such problems on examples of real data sets that we had access to in several projects.

A. Missing data, partial spatio-temporal data coverage

In some cases, identification of missing data can be performed through purely visual inspection. For example, Figure 1 demonstrates spatial coverage of one of data sets. Flights are drawn in a semi-transparent way. Respectively, darker colours reflect higher density of the flights. Some regions where we expect flights to be frequent appear as completely empty on the map. In other regions, the density of flights is lower than in neighbouring areas. Similar analysis in respect to time can be performed by inspecting time histograms with flight counts. Spatio-temporal omissions can be identified on a series of maps for different periods and/or on maps with localized temporal aggregates of trajectories presented by diagrams.

More sophisticated methods take into account historical density of flights for different days of weeks and times in different regions. After aggregating data over space and time and building dependency models, it is possible to identify cases when a number of flights in a data set substantially deviates from expected values for the given location and time interval. Such cases need to be inspected visually for checking if they represent real events that affected the traffic volume, occasional or systematic omissions in the data.

Many trajectory analysis methods assume that temporal resolution of position records is constant. Very often data sets do not comply to this requirement. Figure 2 presents an example of a data set that was composed from 3 different data sets with typical sampling rates of 15, 30 and 60 seconds, respectively.

B. *Duplicate identities*

Opposite to missing data, sometimes trajectory data sets contain duplicate records. This happens, for example, when files contain daily portions of the data extended by positions of flights that started before midnight but ended after the midnight. If a data base is assembled from such flights, it will contain many records with repeating combinations of flight identifier, time stamp, position and additional attributes. Such cases are easy to identify and fix by database queries.

A more complex situation happens when trajectories in different subsets of data have different sampling rates and/or different time offset. In such cases only a subset of all position records repeats, making detection and fixing more challenging.

Sometimes it happens that two or more trajectories have the same identifier by very different positions at the same time interval. Connecting consecutive points of such trajectories result in a zigzag or more complex shapes, see example in Figure 3. Such problems occur in flight trajectories data due to errors in manually entered data such as flight call signs. Identification and correction of such cases require computational processing for detecting candidate errors, visual inspection for understanding if errors are occasional or systematic and revealing the logic of the errors, and then computational methods for fixing the errors.

Similar zigzag patterns appear if data are integrated from multiple sources such as different radars. Paper [22] proposes an algorithm for identifying and fixing such problems.

IV. UNDERSTANDING DECISION MAKING

We describe three case studies, reflecting various operational environments and problems where decision policies are unknown a priori, and therefore can neither be predicted nor considered for planning purposes. This variety of scenarios illustrates the potential of these techniques.

In two of these cases we applied clustering of flight trajectories based on geometric similarity of the routes. The general approach is to use a density-based clustering algorithm with a special distance function that matches corresponding points and segments of trajectories according to their spatial proximity. The specifics of the case studies we undertook was that not all parts of trajectories might be relevant to the analysis

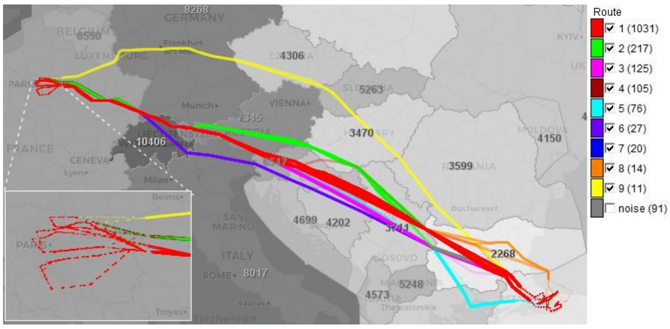

Figure 4. Trajectories according to flight plans have been clustered by route similarity to reveal the major fligh routes from Paris to Istanbul. The initial and final parts of the trajectories, which are represented by dashed lines, were disregarded in the clustering.

goals. Thus, in studying route choices, the initial and final parts of trajectories were irrelevant because these parts depend on the wind direction and not subject to choice by airlines. In studying the separation scheme of the approach routes to multiple airports of London, we needed to disregard the holding loops as inessential parts of the routes. To be able to apply clustering only to task-relevant parts of trajectories, we adapted the distance function so that it could account for results of interactive filtering of trajectory segments. The method is described in detail elsewhere [5].

A. *Revealing route choice criteria*

In this study, we wish to reveal the criteria used by airlines in choosing particular flight routes from many possible routes connecting a given origin-destination pair. This translates to a significant improvement in terms of predictability at pre-tactical phase (in particular for routes near local airspace boundaries, for which subtle route changes might imply the appearance or disappearance of hotspots), among other potential applications. As a representative example, we consider the flights from Paris to Istanbul. This example provides rich information for the study: there are many flights conducted by multiple airlines, which take diverse routes crossing the air spaces of different European countries whose navigation charges greatly vary. Some airlines may prefer such flight routes that minimize the navigation costs by avoiding expensive airspaces or travelling shorter distances across such airspaces. One of the questions in the study was to check if indeed some airlines are likely to have such preferences.

We apply our analysis to trajectories constructed from flight plans, because the route choices are made at the stage of planning. We use the plans of 1,717 flights performed during 5 months from January to May, 2016. Additionally, we use a dataset specifying the boundaries of the navigation charging zones in Europe and the unit rate in each. The map background in Fig. 4 represents the navigation rates by proportional darkness of shading. The labels show the exact values, in eurocents per mile. On top of this background, coloured lines represent the result of clustering of the trajectories by route similarity excluding the initial and final parts. On the bottom left, the area around Paris is enlarged; the initial parts of the trajectories are

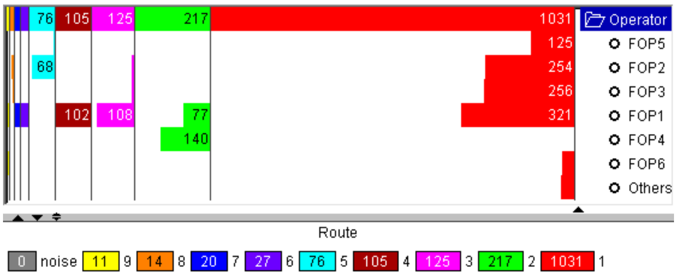

Figure 5. Route choices by 6 major flight operators labelled FOP1 to FOP6. The length of each coloured bar represents the frequency of using the corresponding route by the flight operator specified in the respective row of the graph. The topmost row corresponds to all operators in total..

shown in dashed lines. The lines are coloured according to their cluster membership. Through clustering, we have revealed 9 major routes. The most frequent was route 1 shown in red; it was used 1,031 times, i.e., in 60% of the flights. Route 2 (green) was used 217 times (12.6% flights), and the others were much less frequent.

It can be observed that the green route goes through cheaper airspaces than the other routes. This is the “cheapest” route among all, with the total navigation cost ranging from 434.9 to 492.8 euro, with the median 459.4 euro. The most popular route 1 costs from 472.2 to 547.3 euros, with the median 515.6 euros. Route 2 is the longest among all, except route 9 (yellow) that was taken only 11 times; however, the difference from route 1 is not dramatic, only about 12 km.

The graph in Fig. 5 shows how many times each of the 6 major flight operators (airlines) conducting flights from Paris to Istanbul chose each of the routes. The operators are labelled FOP1 to FOP6. It can be seen that FOP4 used only the cheapest route 2. This route was also occasionally used by FOP1, who conducted the largest number of flights (41.9% of all) but not by any other airline. Possibly, this route has disadvantages that overweigh the navigation cost saving. Apart from the path length difference, which is not very large, it may be lower flight levels or frequent deviations from the flight plans. Indeed, the flight levels on route 2 are lower than on route 1 by about 6 levels on the average and the difference between the third quartiles is 20. We have also calculated the deviations of the actual flights from the planned routes (i.e., the distances between the corresponding points in the planned and actual trajectories) and found that they are higher on route 2 than on route 1 by about 0.8 km on the average while the third quartiles differ by 3.2 km. Route 2 may also have other disadvantages that are not detectable from the available flight data.

Hence, we see that the navigation costs is not the main route choice criterion for most airlines, but it has high importance for some airlines.

Further details on analysis and modelling route choice preferences can be found in paper [23].

B. Exploring separation of airport approach routes

This case study was conducted using 5,045 trajectories of actual flights that arrived at 5 different airports of London during 4 days from December 1 to December 4, 2016. The goals were, first, to reconstruct the major approach routes, second, to determine which of them may be used simultaneously and, third, to study how the routes that can be used simultaneously are separated in the three-dimensional airspace, i.e., horizontally and vertically. Application of this analysis to TMA again allows the understanding of decision making policies allowing their modelling for further application.

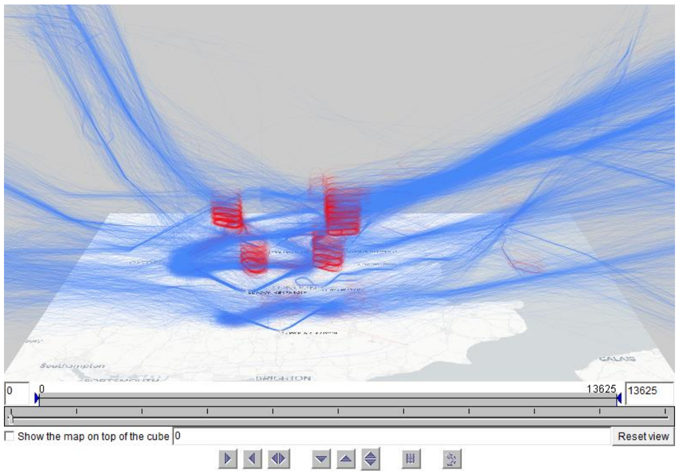

Figure 6. Holding loops in the trajectories of the flights arriving to London are marked in red.

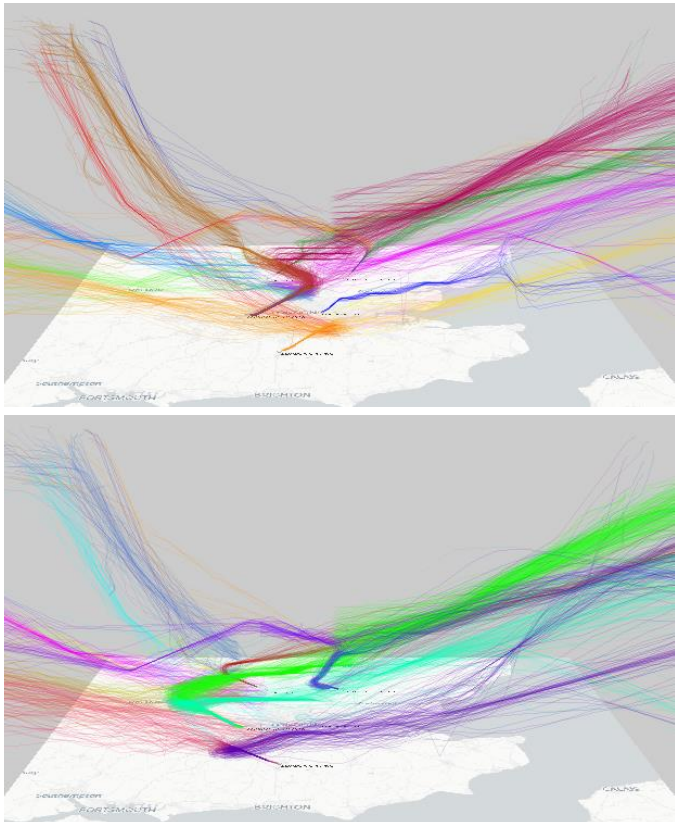

Figure 7. The routes that were used on the first day till 18:25 (top) and on the following days after the wind change (bottom).

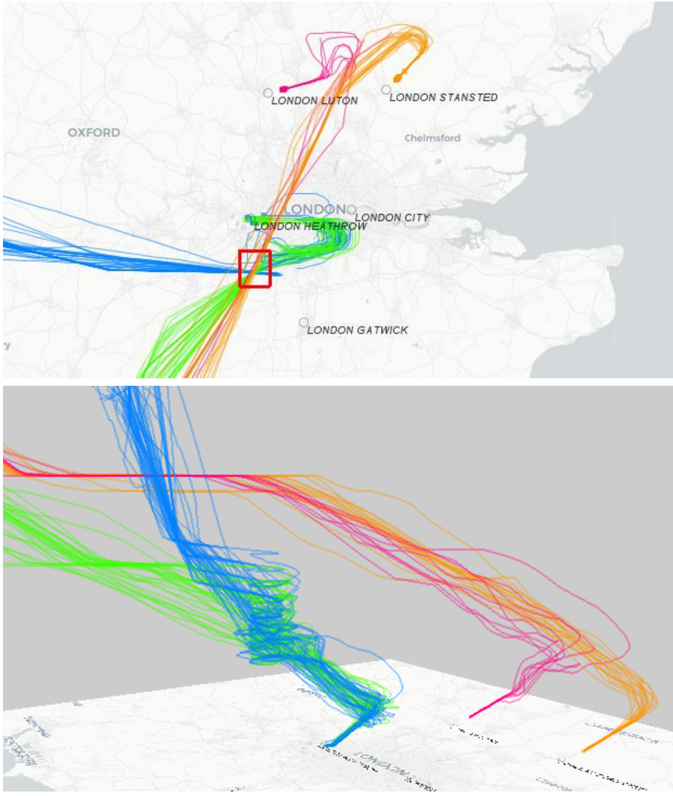

Figure 9. Investigation of the route separation.

Like in the previous case study, we used clustering of trajectories by route similarity to identify the major approach routes. A problem we had to deal with was the presence of holding loops in many trajectories (Fig. 6). It was necessary to filter the loops out so that they could not affect the clustering. We have found a combination of query conditions involving derived attributes of trajectory segments, such as sum of turns during 5 minutes, which allowed us to separate the loops from the main paths and filter them out [5].

By means of clustering, we have identified 34 distinct routes, 16 of which were used only on the first day out of four. A major change in the use of the routes happened at about 10AM on the second day, when the east-west component of the wind direction changed from the western to the eastern. This refers to all airports except Stansted, where the approach routes changed on the first day at about 18:25 in response to a change of the north-south component of the wind. This was due to the northeast-southwest orientation of the runway in Stansted while the other airports have the east-west orientation.

Knowing when each route was used, we could investigate the groups of the routes that were used simultaneously. Figure 7 shows the routes that were used on the first day till 18:25 (top) and the routes that were used after 10:00 on the second day, i.e., after the wind change. Using the 3D representation of the trajectories, we observe that the routes coming to the same airport from different sides join in their final parts.

Some routes going to different airports intersect or overlap on the 2D map. To investigate whether they are separated

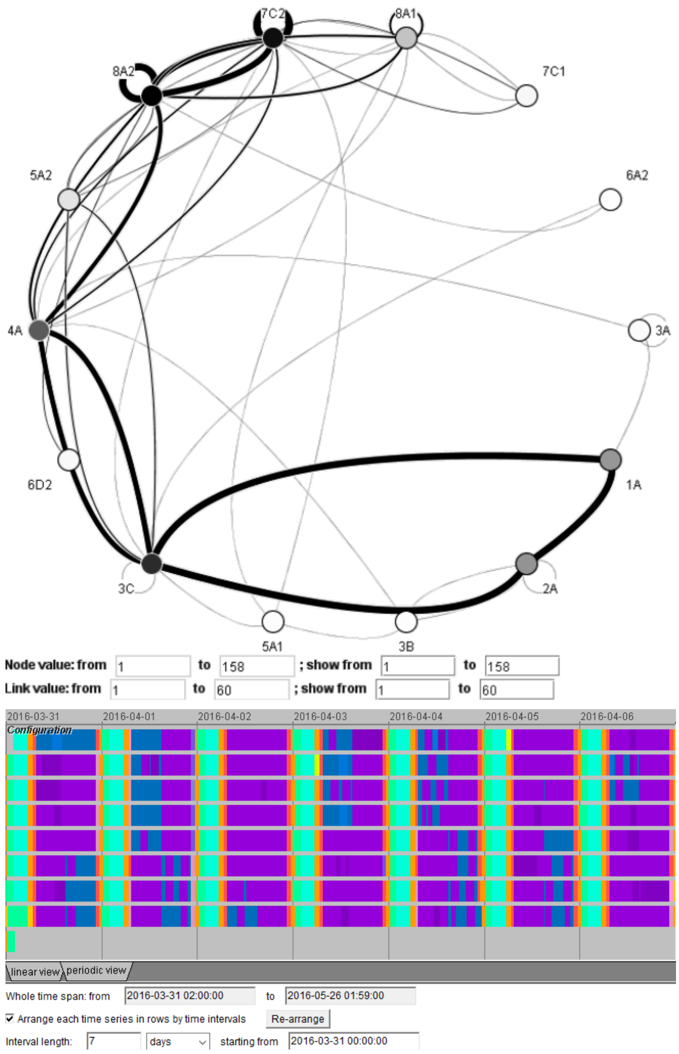

Figure 8. Top: A state transition graph shows changes of airspace configurations in one region during a month. Bottom: The configurations are represented by differently coloured bar segments in a periodic time view. The rows correspond to time intervals of one week length.

vertically, we repeatedly applied a spatial filter for selecting various groups of intersecting and overlapping routes. An example is shown in Fig. 8. The filter (Fig. 8, top) selects two partly overlapping routes ending at Luton and Stansted (pink and orange, respectively) that apparently intersect two routes ending at Heathrow. In a 3D view (Fig. 8, bottom), we see that the former two routes overlap also in the vertical dimension but there is no intersection with the routes to Heathrow due to differences in the flight levels. Our interactive investigation shows that it is a general pattern: where segments of different routes overlap in the horizontal dimension, their altitude ranges overlap as well, and routes intersecting in 2D are separated vertically. Hence, relevance-aware clustering of trajectories and interactive exploration with the use of temporal and spatial filters and a combination of a geographic map and a 3D view helped us to understand how air traffic services organise and manage a huge number of flights following diverse routes within a small densely packed air space.

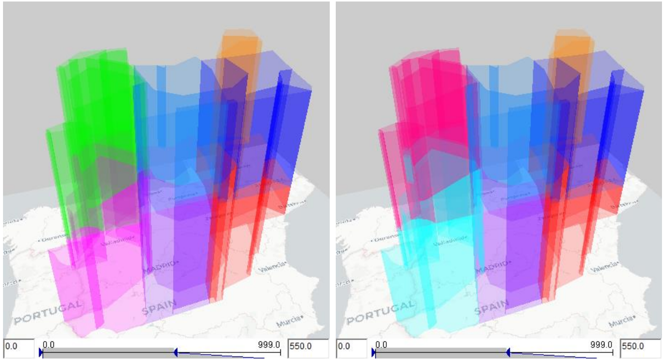

Figure 10. Two configurations with the same number of sectors differ only in the vertical division of the sub-region on the west.

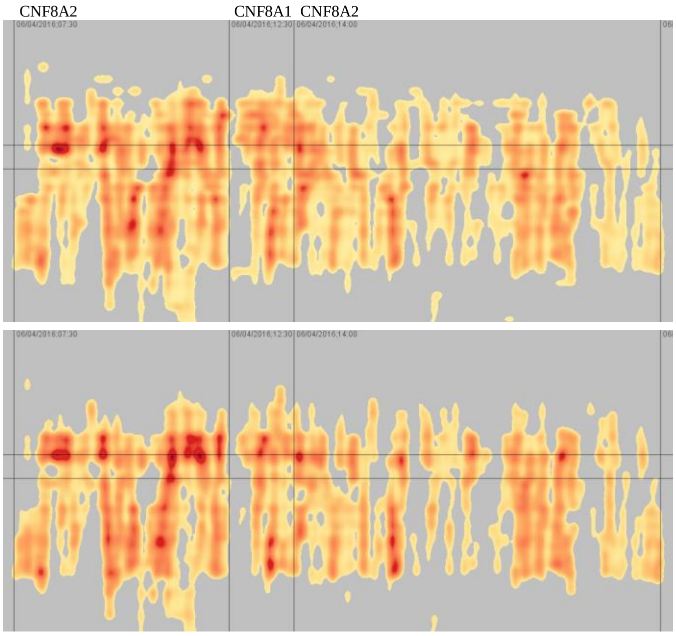

Figure 11. The horizontal and vertical dimensions of the graph represent the time and flight level, respectively. The vertical lines mark the times 07:30, 12:30, 14:00, and 22:30. The horizontal lines mark the flight levels 325 and 345. The shading shows the variation of the traffic intensity in the western sub-region; top: all trajectory segments; bottom: segments where the flight level changed with respect to the previous position.

C. Understanding airspace configuration choices

A sector configuration is a particular division of an airspace region into sectors, such that each sector is managed by a specific number of air traffic controllers (typically two, Executive and Planning Controllers). The number of active sectors depends, on the one hand, on the expected traffic features (such as number of flights within a time interval and their associated complexity/workload given the traffic complexity) and, on the other hand, on the available number of controllers for that given shift (which depends on the strategical demand forecast, which diverges from actual flights for a set of reason).

On the other hand, often there are multiple ways to divide a region into a given number of sectors. The choice of a particular division depends on the flight routes within the region.

Sector configurations schedule is continuously refined as getting closer to operation, when the available flight plan information is progressively refined. The flight plan information available the day before operation, while is sure to change in tactical phase, already allows to prepare a schedule of sector configurations for the next shifts.

Ideally, configurations should be chosen so that the demand for the use of the airspace in each sector does not exceed the sector capacity, while making efficient and balanced use of resources (controllers). In reality, demand-capacity imbalances happen quite often for a set of reasons (deviations of actual flights from flight plans, weather conditions, etc…), causing flight regulations and delays. In search for predictive models that might support enhanced pre-tactical planning (able to forecast deviations), researchers would like to understand how configuration choices are made by airspace managers. They would also like to find a way to predict which configuration will be used at each time moment during the day of operation, considering uncertainty caused by operational factors in search for a more accurate sector configuration schedule in the day before operation (or earlier), allowing better management of demand-capacity imbalances. However, it is unclear what features should be used for building a predictive model. We utilised visual analytics approaches to gain understanding of the configuration system, patterns of change, and probable reasons for preferring one configuration over another. We performed interactive visual exploration of configurations used in several regions.

As an example, the upper image in Fig. 9 shows the configurations that were used in one of the regions in Spain (namely, LECMCTAS) during one month. The configurations are denoted by labels starting with a digit showing the number of sectors in which the region is divided. Almost for each number of sectors, there are two or more variants, some of which are used quite rarely. The lower image shows the use of the different configurations over time. The configurations are represented by coloured segments of horizontal bars. The light colours correspond to small numbers of sectors and dark blue to dark purple colours to 7 and 8 sectors, respectively. The positions of the segments correspond to the times when the configurations were used. The rows correspond to time intervals of one week length. The temporal bar graph shows that the changes of the configurations happen quite periodically. The configurations with small numbers of sectors are used in nights, when the air traffic is low. The configurations with 7 and 8 sectors are usually used from 07:30 till 22:30.

While the choices between configurations differing in the number of sectors can be explained by differences in the traffic volume, the reasons for choosing between configuration variants with the same number of sectors are not obvious. To understand how configurations differ from each other, we used a 3D view as shown in Fig. 10. The example in Fig. 10 shows two configurations in which the region is divided into 8 sectors, CNF8A1 on the left and CNF8A2 on the right. The sectors are represented by distinct colours. The configurations are almost identical, except the vertical division of the sub-region on the west. In CNF8A1, the sub-area is divided into two sectors at the flight level 325, and in CNF8A2 at the flight level 345. These two configurations are often used interchangeably during a day.

The density graph in Fig. 11, in which the horizontal dimension represents time and the vertical dimension flight level, shows the traffic intensity in the western sub-region in one day when CNF8A1 was used in time interval from 12:30 till 14:00 and CNF8A2 in the remaining time from 07:30 till 22:30. These times are marked in the graph by vertical lines. The horizontal lines mark the flight levels 325 and 345. The flight intensity is represented by shading from light yellow (low) to dark red (high). The upper image shows the temporal density of all trajectory positions within the western sub-region and the lower image shows the density of the positions where the flight level changed with respect to the previous positions.

A reasonable hypothesis for explaining the choice between different subdivisions would be that the traffic managers strive to balance the workload among the operators controlling different sectors, according to the behaviour of the specific traffic. Indeed, we see that the traffic intensity at the flight levels above 345 decreased after 12:30, and the division level was lowered from 345 to 325. However, after 14:00, when the division level returned to 345, there was no corresponding increase of traffic at the higher levels; so, our hypothesis would not be supported by this exclusive factor. Another possible decision rationale would be to choose such a division level that fewer flights have to cross this level while they are within the area. However, this hypothesis is not supported by the lower image in Fig. 11, where we see many intersections of both level 325 and level 345 at the time of using either of the two configurations. Hence, the vertical distribution of the flights does not explain the reasons for preferring one configuration over the other, and further investigation is needed. Domain expert suggest that the sector configuration change was motivated by controller workload, not always precisely represented by traffic counts or intensity. For this model, controller workload was not an input so this factor could only be taken into account indirectly through traffic.

V. Discussion and Conclusion

ATM existing information is often considered inaccurate in pre-tactical stages, as well as affected by certain quality flaws derived from its pure operational nature. This makes difficult its direct exploitation for data-driven analysis unless some quality checks and data curation strategies are put in place.

With them, existing data have the potential to improve knowledge and understanding of the existing system, revealing decision policies and patterns, from the different actors, that are useful tools when moving towards pre-tactical and even strategic operations planning for the different actors. Data-driven technologies have a great potential for this purposes. In particular, visual analytics have proven great potential to identify useful patterns and features with a reduced effort, in combination with a domain expert analyst.

This potential has been illustrated by three different cases corresponding to diverse operating environment and different data sources. The results have been discussed and validated with domain experts to ensure applicability to operational needs, in particular in terms of predictability. It is demonstrated the value of these technologies to identify decision criteria as key aspects of the system, able to feed predictive or analytic models applicable in planning phase. It is particularly highlighted the power of these techniques to derive results from spatio-temporal patterns. On the other hand, this paper also shows the capability in terms of assessment of data quality.

Several SESAR projects concluded that visual analytics is an important instrument for data analysis and modelling. The white paper [24] supports the use of visual analytics for performance modelling. Is to be highlighted that in some cases, as well as in data quality assessment, similar results can be achieved by means of non-visual techniques, but at a significantly higher cost of data preparation and analysis. Visual analytics techniques have proven as time-efficient for these purposes.

The improvement in data quality and reliability at planning stages that SESAR new concepts will deliver (i.e., by means of SBT/RBT and Trajectory-Based Operations) will only enhance the benefits demonstrated by reducing data uncertainty. However, current day data is already usable by this kind of techniques, delivering applicable results.

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