Safety Monitoring in the Age of Big Data

From Description to Intervention

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Abstract— **The paper discusses how the increasing availability of large amount of digital data in ATM addresses the need for an approach that combines operational expertise, data analysis skills and information design. Big data pose both opportunities and challenges: by describing the big picture, they can provide fruitful insights into the ATM system that would be otherwise impossible to get, but they may as well remain opaque and merely overwhelming if a proper sense-making process is not put in place. Other industries have been taking advantage of big data for a long time with results that are hardly questionable. ATM is still exploring the methods and tools for the best exploitation of large data sets; the case of ASMT (Automatic Safety Monitoring Tool) well exemplifies the efforts in progress. The results from three previous studies based on ASMT are discussed in order to highlight the gap that exists when trying to transform ASMT-informed analysis into operationally relevant recommendations. A tentative solution proposed in the conclusive section focuses on the role of information design.**

Keywords- ASDG; ASMT; Safety Monitoring; Big Data; Data Analysis

I. INTRODUCTION

The structure of Air Traffic Management (ATM) as it is known today will undergo major changes both in Europe (the SESAR program) and in the USA (the NextGen programs). These initiatives aim to radically change the exiting transportation system, by intervening on technologies, procedures, role of human actors and organizational aspects.

One of the key innovation drivers of both SESAR and NextGen is the shift from a structured route network to a trajectory-based network, where users (i.e. single flights) will be able to fly their selected trajectory, instead of following a predetermined route grid (made of airways and crossing points) across the sky [1, 2]. Trajectory-based operations will increase the flexible use of the airspace, but they will not result in a totally unstructured airspace. It is reasonable to expect that most characteristics of the current situation (e.g. bottlenecks, main traffic flows and crossing points, boundary points, etc.) will also emerge in the future scenario, resulting in a different structure, probably a highly flexible and changing one.

The increase of the complexity degree will cause changes that will be hardly understood by relying on the analysis of single elements and will instead require the understanding of how all the new elements will interact together. Just few years ago, this challenge would have been impossible and baffled any attempt to address it. Today these changes happen in parallel to a scenario of radical technological innovation, where data have gone from scarce to super-abundant in nearly all fields of human activity. There are many reasons for such data explosion, the most obvious one being the introduction of new technologies and sensors, that can digitise information that was previously hard to capture and process. All these data give us unprecedented possibilities of understanding the system.

ATM makes no difference, as nowadays there is easy access to a vast amount of digital data, like radar data, FDP, controllers' input, system logs, etc. This makes it possible to do things that just few years ago could not be done: spot trends and patterns, prevent them from worsening, monitoring with the uttermost precision the performance of technical ATM systems, monitor Key Performance Indicators (KPI) of the whole system. Managed well, the data can unlock new opportunities and provide fresh insights into complex dynamic problems. But the overabundance of data also creates a host of new issues. ATM needs to develop new methods, techniques and tools for the analysis of these noisy data sets, if it is to succeed in extracting knowledge from these data.

At the present moment, the aviation community lacks disciplined methods to monitor the future airspace structure in quasi real time, especially as far as system-level emerging properties are concerned. The scenario envisioned by SESAR and NextGen entails a system with a bottom-up organisation (the flight structure emerges out of the single trajectories) and increased interconnections (less predefined boundary zones, information being shared by all the actors). Compared to the fixed route scenario, the structure and properties of the future aviation network system will emerge from the interactions among many elements, among which we may quote: users' decisions and actions (i.e. pilots and air traffic controllers), trajectory-based operations, organizational changes, and the temporary deployment of different arrays of resources/tools to

manage specific situations, weather and other environmental factors.

Two main issues can be identified in this scenario:

- The monitoring in quasi real-time of the system status, in particular by detecting and analyzing system level emerging properties, in order to inform tactical and planning adjustments.

- The analysis of the propagation of disturbances (i.e. delays, or technical malfunctions, or safety issues), to understand and predict the dynamics by which disturbances move across the airspace, and are absorbed or amplified.

Both issues will require the monitoring and understanding of system level phenomena, with the goal of understanding whether the emerging configuration is a "good order". While the proposed changes will most likely deliver a more flexible use of the airspace driven by users' requests, it cannot be assumed that the resulting order is going to be a "good" one under all the different performance criteria (e.g. efficiency, predictability and safety among the main ones).

Structured methods of monitoring the system status under all (or at least most of) these criteria need to be developed, to be able to intervene and possibly change in real time the relative priority of the above criteria. These methods should be able to cope with a large quantity of safety data and make sense of them from a systemic perspective.

II. BACKGROUND

A. The Need for Large Data Sets: the ICT and Retail Industry

Data have become super-abundant thanks to the explosion of digital technology. Organizations in every industry, in every part of the world, invest an increasing amount of money on systems for data collection and analysis. This huge amount of information enables organizations to do things that previously could have not been done like spot business trends, objectively monitor performance levels, anticipate market demands and so on.

Not all the industries are at the same maturity level when it comes to the ability to manage what is now called "big data". Information Communication Technologies (ICT) and retail industries, among the others, are at the forefront of the exploitation of big data, the first being centrally involved as producer in the digital data "explosion", the second valuing sales data as an asset of paramount importance since its very beginning [3]. Every significant Internet application to date has been backed by a specialized database like Google's web crawl and Amazon's database of products. For companies like these, data are "the next Intel inside", i.e. the real key-enabler of their business, as the software infrastructure needed to exploit them is largely commoditized [4]. Wal-Mart, one of the worldwide leading retailers, systematically studies its massive sales database (around 267 million transactions a day) to understand how to devise better pricing strategies, inventory control and advertising campaigns [5]. Companies using analytics achieve

a competitive advantage by informing their decision-making with insights based on the understanding of the market big picture and its dynamics. For example, analytics can unravel hidden correlations between variables, which can then be used to predict future behaviour [6]. A survey promoted by the MIT Sloan Management Review found out that: "[…] top performing organizations use analytics five times more than lower performers […] and twice as likely to use insights to guide day-to-day operations" [7].

Other industries have been starting a shift of focus on big data only in recent times. For example, User Experience (UX) practitioners have been relying for a long time on qualitative lab tests when assessing the usability of a website or any other digital tool. Only recently the UX industry has started a move to the integration of qualitative assessment with quantitative techniques like A/B testing, analysis of live website data and online usability studies which are based on the collection in quasi-real time of large sets of digital data [8]. In this case the driver behind this change is the opportunity to validate (or question) interface design on the base of insights derived by large sets of objective data gathered in a more natural context of use.

Similarly to the UX industry, ATM has just recently started to dedicate more attention to opportunities offered by analytics, especially when it comes to safety management. Whatever the industry – and ATM makes no difference - the biggest challenge in the age of analytics resides in not being overwhelmed by data and finding the best ways to obtain actable knowledge from them, a process that requires a combination of analytical and information design skills. Such a challenge is well reflected in the flourishing field of info-graphics and of information visualisation software like Tableau, Gapminder, or Google Public Data Explorer (the latter two based on the same technology).

B. Large Data Sets for ATM Safety Management: ASMT

The Commission Regulation (EC) No. 2096/2005 transposing ESARR3 into Common Requirements [9] defines the "Safety Monitoring principle": *methods should be in place to detect changes in systems or operations which may suggest any element is approaching a point at which acceptable standards of safety can no longer be met and corrective action should be taken*. To pursue these opportunities and comply with the regulatory requirements, EUROCONTROL has been actively investing in the development of Automatic Safety Data Gathering (ASDG) tools for more than ten years, and in particular it has developed and constantly upgraded the Automatic Safety Monitoring Tool (ASMT). ASMT has been designed to assist users in the collection and analysis of safety data, by constantly monitoring in quasi-real time radar tracks, flight plans and system alerts.

The Automatic Safety Monitoring Tool (ASMT) has been developed by the EUROCONTROL Experimental Centre, in co-operation with and on the basis of the requirements of the Maastricht Upper Area Control Centre (MUAC). The design was initiated in the 1996 and the first ASMT version was installed in MUAC in the 1999. More than 10 years of successive development and successful validation have led to

the current version of ASMT that EUROCONTROL HQ is currently supervising to reflect the requests and needs of a growing group of users. ASMT can now be considered as the most advanced tool for Automatic Safety Data Gathering (ASDG).

ASMT can be connected to the operational ATM system in an on line or off-line mode (it can be also connected to a simulation platform in the context of Real Time Simulation) to elaborate in quasi real-time data on radar tracks, flight plans and system alerts. It automatically detects operational and technical occurrences according to user-defined parameters. ASMT detects events through the computation of the current air traffic situation, continuously updated from the track and flight plan inputs.

Currently ASMT gathers data on seven types of safety events. ASMT own modules detect four of these types: Proximity (e.g. separation minima infringements), Airspace Penetration, Altitude Deviation (e.g. level busts) and Rate of Closure. The recording of the three other types is triggered by system alerts, coming from the ATC system, e.g. the case of Safety Nets (Short Term Conflict Alert or Area Proximity Warning), or down-linked from aircraft, e.g. the case of ACAS-RA alert. For each detected occurrence, it stores the relevant data (shortly before, during and shortly after the event) into a database that can be later queried to extract the data or to review the occurrence in a dedicated replay window. More information on ASMT and on Automatic Safety Data Gathering can be found in [10-13].

The current major limitation of ASMT is certainly the sensitivity of the data being collected, especially as far as legal recording and human reporting are concerned. ASMT can be easily considered as a "big brother" tool, spying over the controller's shoulder and supporting a blame culture of punishment. Therefore, before starting implementing ASMT, fundamentals principles shall be put in place. These are, as a minimum, the policy to use ASMT, to analyze Safety Events with principles for Operational & Technical usage.

III. CASE STUDY: MAKING SENSE OF DATA COLLECTED BY ASMT

ASMT use should be mainly aimed to support safety management, through the provision of large data sets collected using objective criteria (as compared to subjective sources, like voluntary reporting). These data, when properly analyzed and interpreted, can inform decision-making processes. Provided that ASMT has been correctly set for data collection, the analysis and visualization are the most critical phases, because they are the interpretative activities that actually produce results and deliver them to the intended audience.

On the basis of our experience with ASMT [14-16], we maintain that ASMT requires its users to adopt a *data analyst perspective*, i.e. the ability to shift the attention focus from the dynamics of single events to the emerging statistical characteristics (e.g. distribution, trend etc.) of large data sets. This perspective is not part yet of the core operational competencies of the ATM community (being more the province of the research world) and should be developed to complement the *operational perspective* (i.e. detailed knowledge of a specific airspace, procedures, technical equipment being used, etc.), which currently plays a major role in safety analysis. More in detail:

- The *Data Analysis Perspective* is driven by analysis methods and techniques. It aims at a statistical characterization of the data set under analysis. Compared to current investigation processes, the attention focus shifts from the causes and dynamics of single events to the emerging statistical characteristics (e.g. distribution, trend etc.) of whole data set. Data analysis proceeds through iterative processing, till a clear characterization of the data set has been achieved.

- The *Operational Perspective* requires Safety and Operational expertise. This perspective currently plays a pivotal role in the investigation activities, but would require a change of paradigm to effectively contribute to safety monitoring activities carried out through Automatic Safety Data Gathering. Operational and Safety experts are currently performing case-based analyses, based on their domain knowledge and experience, with the aim of understanding specific events, and not abstract high-level properties. This is done by applying subjective knowledge of the work context on a (generally small) set of data. Their contribution to ASDG-informed activities should instead focus on the interpretation of large data sets, in order to "attach to the data an operational meaning", i.e. to read the data set and identify relevant ATM aspects therein. For instance, ATM experts should be able to interpret the clustering of events in some areas and describe a set of causes behind them, like the geometry of encounters in that area, or the Short Term Conflict Alert (STCA) parameterization, or maybe a technical issue. Likewise the expert should be able to superimpose her/his knowledge of the airspace structure to the event geographical distribution, e.g. see the event hotspot as stretched along a busy airway.

In brief terms, the data analyst perspective should focus on numbers and their emerging correlations and dependencies, while the operational perspective should focus on the meaning of events into a context.

The two perspectives can often push in divergent directions. The analysis perspective can churn out values and figures totally detached from the operational reality and make it impossible for experts to help with their interpretation. Very complex analysis techniques may too radically transform the data, often putting them in formats not familiar to operational experts. On the other hand, a too strong emphasis on operational knowledge may remain only at the surface level of what the data might tell, constraining the analysis only to some macro features and failing to extract additional results, often hard to appreciate at a first glance. The separation between the two perspectives often happens because they are mastered by different persons, who should find a shared working process in order to complement each other. The situation is even worse when the analysis and operational expertise reside in two different departments (or even organizations). Organizational

separation often engenders secrecy and blocks any coordination process.

For the operational knowledge to effectively inform the safety monitoring process, actions should be taken to simplify the presentation of analysis results. For instance, visual design principles should be applied to geographical representations, in order to avoid the visual clutter that may be engendered by the display of a large number of events. When the data set dimension scales up, the "opacity" of the big picture increases. Operational perspective can easily make sense of a single occurrence but, if not supported by proper visualization, it struggles when interpreting large sets of data, as events superimpose in time, mask each other and get mixed with background noise. For this reason, to build a bridge between the two perspectives, in previous projects we successfully introduced a third perspective:

- The *Information Design Perspective*, i.e. the ability to conceive, prepare and present information in ways people can use it with efficiency and effectiveness. This third strand builds on the understanding of the most relevant features of a data set, in order to devise a graphical representation that eases the comparison among them, be it a geographical comparison or a time comparison. As well posed by Edward Tufte: "At the heart of quantitative reasoning is a single question: Compared to what? [Graphical representations] answer directly by visually enforcing comparisons of changes, of the differences among objects, of the scope of alternatives." [17]

Two examples of ASMT usage can better exemplify the process of turning the information into knowledge. In the first example the operational perspective took a leading role in framing the results, whilst in the second one the accent was more on the capability of the data analysis to make significant relationships emerge.

A. The Operational Perspective

The first example is the use of ASMT at the ENAV (the Italian Air Navigation Service Provider) Experimental Centre to support the Multi Radar Tracking (MRT) tuning and the STCA performance monitoring [14]. In both cases, the approach consisted in:

- Data gathering: collection of a significant amount of event (i.e. double tracks and STCA alerts) by properly setting ASMT for recording.

- Validation: validation of the collected data by finding and eliminating false positives.

- Data analysis: descriptive statistics was applied to the data collected, to analyze the distribution in relation to geography (latitude, longitude and Flight Level bands), time, horizontal and vertical separation and other relevant criteria (e.g. for STCA events conflict geometry, rate of closure etc.).

- Information visualization: intuitive graphs and charts were designed and draw to visualize the results, in order to support the interpretation by operational experts.

- Discussion with operational experts: the analysis results were presented to experts and discussed with them to identify relevant patterns and regularities in the data and construct hypotheses on the underlying causes.

- Analysis refinement: further data analyses were often required to verify hypotheses or to collect a richer data set on specific geographical areas or in specific hours.

In this case the process was mainly driven by operational experts who were giving sense to the data collected.

The analysis and information design were quite simple. Basically the results consisted in calculating different distributions of STCA and double tracks events with respect to characteristics like geography, Flight Level (FL) bands, duration, horizontal and vertical separation, time to infringement, horizontal and vertical rate of closure and so on. The representations used were mostly maps, tables and bar charts. Figure 1 is the geographical distribution of double tracks events recorded in the Italian airspace in a period of 3 weeks, while Figure 2 shows the distribution of STCA events recorded in 2 weeks.
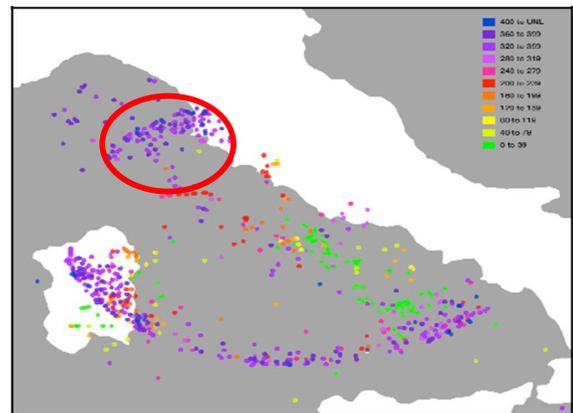
Figure 1. Geographical distribution of double tracks events in the Rome Flight Information Region (FIR), color coded for FL bands (three weeks of recording).
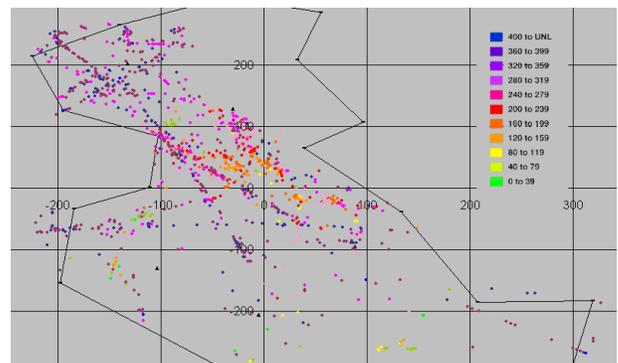
Figure 2. Geographical distribution of STCA events in the Rome FIR, colour coded for FL bands (two weeks of recording).

Operational experts were able, by looking at Figure 1, to detect a possible problematic area over Elba Island (circled in the figure). The array of double tracks was first attributed to a nearby military area, thus to military traffic. But this hypothesis was discarded by closely inspecting each event, as involved aircraft were civil ones. A second hypothesis pointed to maintenance work to an Eastern radar site. The operational experts indicated the area as a good candidate for a follow-up recording period, in order to monitor these events and verify the maintenance hypothesis.

Operational experts were also able to make sense of the results shown in Figure 2. At first, a different FL bands distribution was expected. The STCA algorithm in use was known to over-react to vertical movements, so the large majority of alerts was expected to go off in FL with high density of climbs/descents. Instead the data set was showing a clear peak in high FL (see Figure 3).
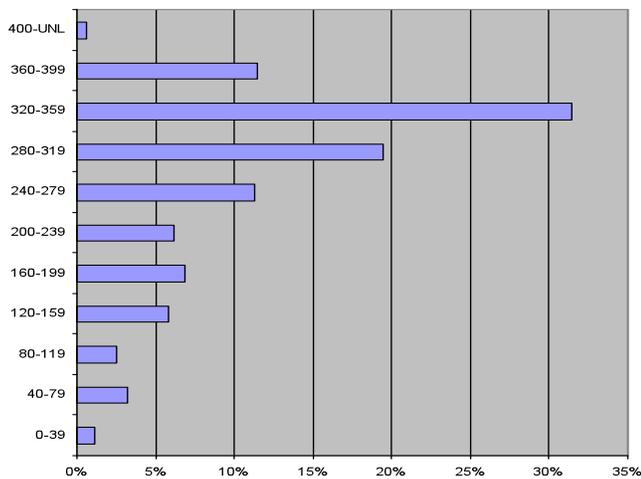
Figure 3. STCA events distribution (percentage by FL bands).

During the discussion, an hypothesis to account for the FL bands distribution was outlined. These STCA alerts might be engendered by the interaction among small movements on the Mode C, high horizontal speed and head-on trajectory geometry (which results in an even higher relative speed). In other words, the high horizontal speed might combine with small vertical movements (e.g. Mode C jumps) to trigger STCA alerts. This hypothesis was later confirmed by drilling a subset of data and producing a bar chart in which the number of STCA events per vertical distance for STCA with vertical rate of closure equal to zero is shown (Figure 4).
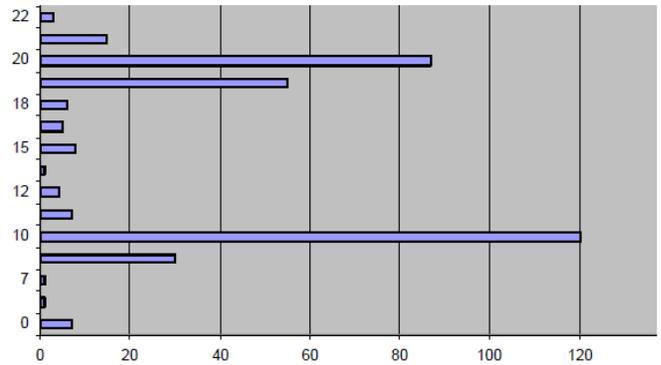
Figure 4. Number of STCA events per vertical distance (hundreds of feet), for STCA with zero vertical rate of closure. Difference above 2.200 feet not shown.

Again, the process of addressing the right question, i.e. understanding what to look for, was driven by operational expertise. As a consequence of the analysis presented above, an improvement action was defined as to enlarge the Mode C tolerability buffer, so that small Mode C jumps would not activate STCA alerts.

B. The Data Analysis Perspective

The second example is about using ASMT to understand the properties of STCA alerts at a system level, either by network analysis [15] or by analysis of hotspots areas dynamics [16].

In this case the approach consisted of the following steps:

- Data gathering: acquisition of 3 different sample sets delivered by the Italian service provider ENAV and the British one, NATS.

- Validation: events were systematically searched to find potential false positives and to verify that parameters and filters already in place had been working as expected.

- Data analysis: the data were plotted on the map corresponding to the area in which the events were collected, in order to outline hotspots.

- Analysis refinement: follow-up analyses were performed to analyze some of the interesting features emerging from the first round of analyses.

- Results visualization: data were graphically represented on a map, using scatter plots [15] or density lines [16].

In this case, the process was driven by the application of advanced analysis techniques and methods (network analysis in the first case, density calculation in the second case), in order to identify patterns, regularities and outliers in the data set. The key operation here was the processing of the data set by means of quantitative calculations, to identify properties that could not be seen at a first glance by operational and safety experts. While in the first case the patterns were identified by the "eye of the expert", here they emerged because of quantitative processing.

In the first study, analysis methods derived from complex systems theory (i.e. network analysis) were used to assist in the understanding, monitoring and management of the performance of ATM systems. Network analysis applied to STCA events showed that they were more coupled than ATM experts expected. More specifically it was found that 808 aircraft of the 1513 of the sample (53%) were involved in an STCA that involved only two aircraft, while 705 aircraft (47%) were involved in sub-networks of STCAs with more than only another aircraft. This result was quite unexpected because it indicates that in roughly half of the cases STCAs do not occur in isolation but rather they are clustered. This also indicates that the resolution of an STCA very often triggers another STCA. A more rigorous account of STCA network distribution by nodes (i.e. aircraft involved) is given in Table I.

TABLE I.   DISTRIBUTION OF STCA NETWORKS BY NUMBER OF AIRCRAFT INVOLVED

STCA network distribution by size											
Size	3	4	5	6	7	8	9	10	11	13	15	17
Frequency	94	32	17	8	4	4	4	1	1	1	1	1

Further analysis on the range of FL of STCA networks, revealed other system properties: for example, bigger networks span across many different FL, thus indicating that STCA can propagate through different flight phases (Figure 5).
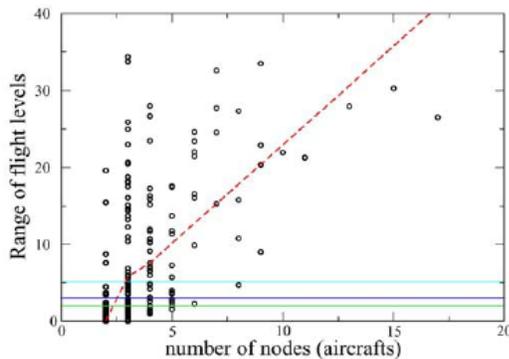
Figure 5. Delta FL for each subnetwork of aircraft. The red line shows the average Delta FL (smoother LOWESS) as a function of the number of nodes. The green line is the median Delta FL value for the whole data set, the blueone is the 75th percentile, the light blue one the 95th percentile.

The results of this study were almost exclusively driven by statistical analysis. The focus was more on the interpretation of abstract concepts like the mean number of network nodes and edges, in order to describe the STCA network configurations. For instance, the time threshold after which a network was terminated (i.e. two STCA were considered as being not related) was set to 50 minutes on the basis of purely statistical reasons (the distribution of the time distance between two alerts), while operational considerations indicating different thresholds (shorter ones) were not used to inform the analysis.

The second study aimed to identify the potential relationships between STCA high-density areas. As already mentioned, the first step was the localization of the STCA events (Figure 6). However, the intrinsic inhomogeneity displayed by the map of safety events hindered the detection of high-density areas, i.e. hotspots. In other words, the visual layout did not easily allowed any interpretative process. To overcome this problem, density estimation was proposed as an intuitive, powerful solution to the problem of hotspot detection and definition. This required the use of an analysis technique, i.e. kernel density estimation, and of a more elaborated information design (Figure 7). The transformation from Figure 6 to Figure 7 is not merely visual but, most importantly, of an informative nature.
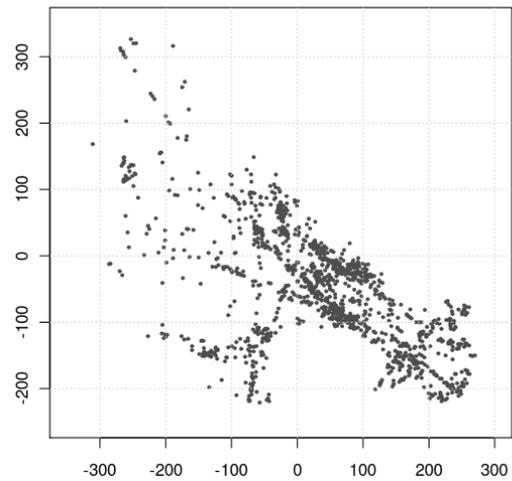
Figure 6. STCA events plotted on X-Y map.
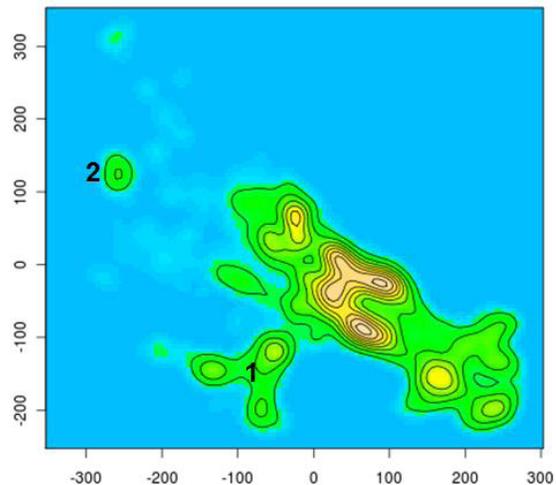
Figure 7. STCA density map (hotspot "1" identified as merging point, and "2" as a crossing point).

The use of density estimation and the related representation allowed to achieved two different kinds of results:

- The detection of isolines of constant density, which are the key ingredient for the definition of hotspots. The possibility to appreciate the different densities of STCA could be taken as a starting point to define the hotspot boundaries in a quantitative manner.

- A visualization with a higher degree of intelligibility for the ATM experts, who were then enabled to match

the information with their operational expertise. For example a first interpretation of the density map consisted in the recognition of hotspots 1 and 2 (in Figure 7) as a "merging" and "crossing" point respectively.

It is worth noting, that the statistics used to process the data produced results that the operational knowledge alone would have never been capable of. Most noticeably, these results often opened up unexpected research directions, by showing data from a totally different perspective. For instance, the movement of density isolines in time pointed at the characterization of safety hotspots not only in terms of topology or other geographical characteristics, but also for their temporal evolution. Such an analysis could potentially identify the main axes of propagation of safety events clusters, to render a description of the anisotropy of the aviation system and outline the main directions in which safety events clusters selectively move.

The two works just cited were targeting long-term research goals, so the operational interpretation was not actively sought. This is especially true for the first case study, while in the second case some resources were devoted to drawing a more user-friendly representation, in order to gather a first light feedback (not elaborated further). However, in both cases most of the efforts was on finding the "right statistics" or calculation method. A full session with safety and operational experts would be required at this stage to get their feedback, interpret the results and define additional analyses. The goal would be to close the loop between analysis and operational needs and eventually define improvement actions. For this to happen, the current visualization should be made more user-friendly and easy to interpret by operational experts.

IV. DISCUSSION: THE GAP BETWEEN DESCRIPTION AND APPLICATION

The cases presented above provide a good example of the insights that can be acquired by analyzing data collected by ASDG tools. The key issue to be addressed is the same faced by the other domains: avoid being overwhelmed by data and find the best ways to obtain actable knowledge from them. If only the operational perspective is applied, the risk is to remain at a superficial level, by appreciating only macro-features that may be more apparent than of real operational relevance. If only data analysis is pursued, the risk is to obtain a very detailed numerical characterisation of the data set without any clue on how to operationally interpret these figures.

These two risks are both related to the challenge of obtaining actable knowledge out of the data, which is how to provide a good description that can inform the definition of improvement actions. As far as ASDG is concerned, currently the ATM community seems to be mostly concerned with the description pole. There are quite a few quantitative methods to process safety and performance data, such as the Aerospace Performance Factor [18], or the Risk Analysis Tool [19]. Other methods exist to calculate the complexity of a given airspace area [20, 21]. However, structured methods are still to be developed to address both purposes: description and intervention. This knowledge gap can be represented as in Figure 8, where the operational and the data analysis perspectives are mapped with their descriptive and applicative power.
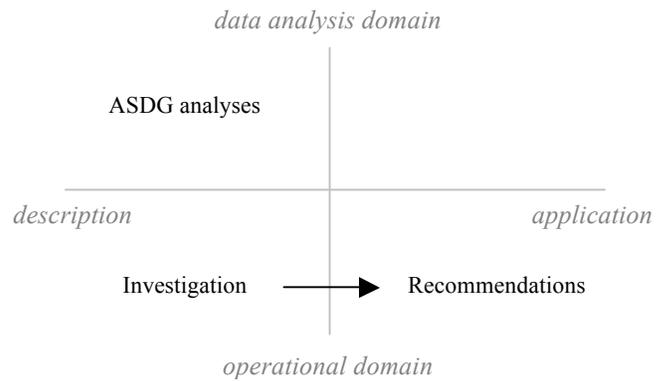
Figure 8. The knowledge gap in the data analysis perspective, with the *application* part of the graph still to be filled in.

The operational perspective has found disciplined ways of passing from description to application, by effectively delivering improvement recommendations as an outcome of investigations. The same movement is still to be designed in the data analysis perspective. A gap currently exists in how to translate ASDG-informed analysis into operationally relevant recommendations.

The tentative solution we explored in our previous works is to work on data visualisation to make sure operational and safety knowledge can be brought into play. In other words, we have been trying to increase the knowledge exchange between the data analysis and operational domains. The two domains should remain separate to ensure the benefits of both perspectives, but methods are needed to ensure that they complement each other in the analysis of big data. As discussed in the previous sections, this has been done mostly by introducing an information design perspective. As a side note, we should also mention how the operational domain may also profit from ASDG data, for instance by prioritising investigations with the use of automatic indexes, or even to stop some of them. The ESARR2 Risk of Collision may be one of these indexes [22] .

To better outline the process and the different contributions by data analysts and by operational experts, we may rely on the concepts of data, information and knowledge.

- *Data* are what is collected by ASDG tools like ASMT. They are factual events and raw numbers that quantitatively describe the different characteristics of the events. Examples of them are the number of STCA collected last month, or the horizontal rates of closure for all the losses of separation.

- Data are turned into *information* by undergoing statistical and mathematical transformations (e.g. sorting, distribution, correlation etc.). The aim is to create a structured *description* of what has been collected from the environment. This is the descriptive part of the process.

- Last, *information* has to be translated into *knowledge*, i.e. into a full-fledged understanding of the system dynamics and of the underlying causes. With the term *knowledge*, we mean information that makes sense to the people who will use it, i.e. operational and safety experts, because it can be used to derive improvement actions, to control the system, to predict future events.

In the case of investigations, our claim is that ATM experts can move from the *data* stage directly to the *knowledge* stage. This is due to the small amount of data to be processed and to the use of tools like narratives, which can efficiently summarize the event in a coherent manner. ASDG brings a drastic change of paradigm, for the main reason that the amount of collected data is so extensive that it cannot be understood by direct analysis, thus requiring dedicated effort to summarize it. This brings into play the data analysis perspective required to turn data into information.

Once at the information stage, the operational knowledge is needed to interpret the data and reach the knowledge stage. The contribution of information designers is required at this stage, to make information accessible to operational experts. The complexity of the information design can vary; nevertheless a visual elaboration to enable an understanding of the information is always performed. For example, a distribution table is a very simple way to elaborate data by sorting them, while a density map requires more transformations.

The above process of ASDG data analysis is mapped with the three perspectives' contribution in the following table.

TABLE II. THE ANALYSIS PROCESS OF ASDG DATA AND THE CONTRIBUTION OF THREE PERSPECTIVES.

	Operational expert	Data analyst	Information designer
Data		X	
Information			X
Knowledge	X		

Although the process is likely to be iterative (e.g. operational experts may request additional analyses, or a refinement of the visualisation), the above table well captures the main aspects in the sense-making process of large sets of data, at least as from our experience, showing the different competences that should be involved.

V. CONCLUDING REMARKS

The use of ASDG for safety monitoring represents a change of paradigm in ATM, and not only a mere refinement of current practices. In order to profit from the insights that these data may provide, it does not appear to be either viable, or methodologically correct, to solely return to the single-event level and analyze the data case by case. Such an approach might fail to appreciate emergent system properties or to highlight macro-level patterns, overly concentrating on single specific cases. Worse than that, the application of the investigation methods and tools to ASDG data might end up reinforcing the Big Brother concept, thus failing to acquire the support of Air Traffic Controllers for the implementation of such tools.

In order to exploit the full potentialities of ASDG for safety monitoring, a change of paradigm in the current analysis approach would be instead required, to develop methods and techniques for the assessment of the overall ATM system performance that are appropriate for the amount of data. As we have discussed in this paper, such a new paradigm is highly interdisciplinary and requires the contribution of competencies that have been traditionally outside of the ATM community. Furthermore, these new methods should also consider existing regulatory requirements [23], to feed input to current Key Performance Indicators (KPI) and proceed in the direction of an harmonised KPI set for Air Traffic Service Providers, thus adding a further layer (i.e. policy making and standardization) to an already complex issue.

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