Visual Analytics and Machine Learning for Air Traffic Management Performance Modelling

Preliminary Findings of the INTUIT Project and Prospects for Future Research

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

Laia Garrigó, Núria Alsina
Advanced Logistics Group
Barcelona, Spain

Natalia Adrienko, Gennady Andrienko
Fraunhofer IAIS
Sankt Augustin, Germany

Luca Piovano
Technical University of Madrid
Madrid, Spain

Thomas Blondiau
Transport & Mobility Leuven
Leuven, Belgium

***Abstract*—INTUIT is a SESAR 2020 Exploratory Research project which aims to explore the potential of visual analytics and machine learning techniques to improve our understanding of the trade-offs between ATM KPAs and identify cause-effect relationships between indicators at different scales. The ultimate goal is to provide ATM stakeholders with new decision support tools for ATM performance monitoring and management. This paper introduces the project and reports its initial results. We propose a set of research questions on ATM performance identified through a combination of desk research and consultation with ATM stakeholders, we assess the main data sources on ATM performance available at European level, and we map the research questions previously defined to the data sources that are most relevant for each question. To illustrate the role that visual analytics can play in addressing these questions, we present the preliminary results of an ongoing case study focused on analysing the spatio-temporal patterns of ATFM delays in the European network. We finish by outlining future research directions.**

Keywords-ATM performance modelling; visual analytics; machine learning; ATFM delay.

I. Introduction

Air Traffic Management (ATM) performance results from the complex interaction of interdependent policies and regulations, stakeholders, technologies and market conditions. Trade-offs arise not only between Key Performance Areas (KPAs), but also between stakeholders, as well as between short-term and long-term objectives. To effectively steer the performance of ATM operations, metrics and indicators must be capable of capturing the full range of economic, social and environmental impacts of the ATM system, both on the different stakeholders and society at large, at different temporal and geographical scales. Performance modelling techniques need to be able to grasp the interdependencies between different KPAs and Key Performance Indicators (KPIs) and allow the assessment of the possible future impacts of a range of policies and trends. The need for improved indicators and modelling methodologies has been acknowledged by the ATM stakeholders and the research community [1]. While a lot of effort has traditionally been devoted to the development of microscopic performance models, there is a lack of useful macro approaches able to translate local improvements or specific regulations into their impact on system-wide KPIs.

INTUIT (Interactive Toolset for Understanding Trade-offs in Air Traffic Management Performance - www.intuit-sesar.eu) is a project within SESAR Exploratory Research that aims to explore the potential of visual analytics and machine learning techniques to improve our understanding of the trade-offs between ATM KPAs; identify cause-effect relationships between indicators at different scales; and develop new decision support tools for ATM performance monitoring and management. In this paper, we present the preliminary findings of the project. Section II introduces the institutional context of ATM performance management in Europe. Section III reviews the state-of-the-art in ATM performance modelling. Section IV discusses the potential of visual analytics and machine learning to further the state-of-the-art in this field. Section V reports the main results of the first phase of the project, including a detailed assessment of the data sources on ATM performance available at European level and the research needs identified through a consultation process with different ATM stakeholders. Section VI describes a preliminary visual analytics exercise exploring different datasets related to Air Traffic Flow Management (ATFM) delay. Section VI summarizes the main results of the case study. Section VII concludes and outlines future research directions.

II. ATM Performance Management in Europe

A. Performance-Based Approach to ATM Decisions

The ongoing ATM modernization programmes, including the Single European Sky ATM Research (SESAR) Programme, build on the International Civil Aviation Organization (ICAO) Global ATM Operational Concept [2], one of whose cornerstones is performance orientation. ICAO defines a performance-based approach as one based on: (i) strong focus on desired/required results; (ii) informed decision-making, driven by the desired/required results; and (iii) reliance on facts and data for decision-making. A performance framework is intended to translate stakeholders' expectations into a shared set of values and priorities and be the basis for impact assessment, trade-off analysis and decision- making.

B. *The Single European Sky Performance Scheme*

The Single European Sky (SES) initiative, launched in 2000 by the European Commission, aims to reform the architecture of the European ATM system through legislation [3]. One of the key features of SES II is the Performance Scheme, which seeks to enhance the performance of Air Navigation Services (ANS) in Europe through the adoption of performance targets for fixed reference periods of 3-5 years. These targets are set at both EU-wide and local level, and have been divided following four KPAs: Capacity, Environment, Cost Efficiency and Safety. Reference [4] develops a performance driven approach for operations focused on Reference Period 2 (RP2), which spans from 2015 to 2019. RP3 will develop the final stage of the SES Performance Scheme from 2020 until 2024. As it is supposed to encompass the enhancements and lessons learned from RP1 and RP2, little information is currently available on the targets or objectives of RP3, which are scheduled for 2018 according to the Industry Consultation Body (ICB). However, various related publications discuss the contents that RP3 should include [5]. One of these proposals is the inclusion of an indicator addressing the issue of KPAs interdependencies, which has not been formally analysed in the previous Reference Periods

C. *The SESAR Performance Framework*

On the technology side, the SES is supported by the SESAR Programme, which aims to provide advanced technologies and procedures with a view to modernising and optimising the future European ATM network. SESAR has developed its own Performance Framework which, as the SES Performance Scheme, also has its origins in the ICAO's Performance Framework [2]. However, while the SES Performance Scheme has been defined focusing on the performance of the operational ATM system as a whole, SESAR 2020 focuses on the definition of targets for the development of an appropriate operational concept to be measured in a validation environment. This leads to the use of different KPIs, although alignment with the SES II Performance Scheme is pursued as far as practicable.

III. ATM PERFORMANCE MODELLING: STATE-OF-THE-ART

There are two main approaches in the study of interdependencies between ATM KPAs: (i) approaches taking a macro-focus and (ii) approaches taking a micro-focus. Macroscopic studies typically consider performance trade-offs at a broad geographical scale and take into account multiple interdependencies between performance areas. These studies usually rely on simplified assumptions to be able to include multiple interdependencies. In contrast, microscopic studies typically focus on a few performance interdependencies, often through a case-study in a single (or a small number of) airspace sector(s).

Figure 1 illustrates the main interrelationships between the SES KPAs studied in the academic literature. Most of the analysed research focuses on capacity and cost-efficiency, and their interrelationship. The issues addressed by macroscopic research include the predictive accuracy of different modelling techniques, the description of network effects and the spillovers between airspace sectors. Microscopic studies focus rather on explaining the trade-offs through a more detailed representation of the underlying structural performance drivers. Several studies have addressed the optimization of Air Traffic Controller (ATCO) resources, such as through flexible rostering and optimal amount of ATCO staff. Another prominent research thread is the study of the external drivers of cost-efficiency: Grebensek and Magister [6], for example, have studied how cost-efficiency is affected by seasonal variations, while the Performance Review Unit (PRU) has analysed the influence of airspace complexity, traffic density and traffic variability [7]. There are also some studies which focus on the

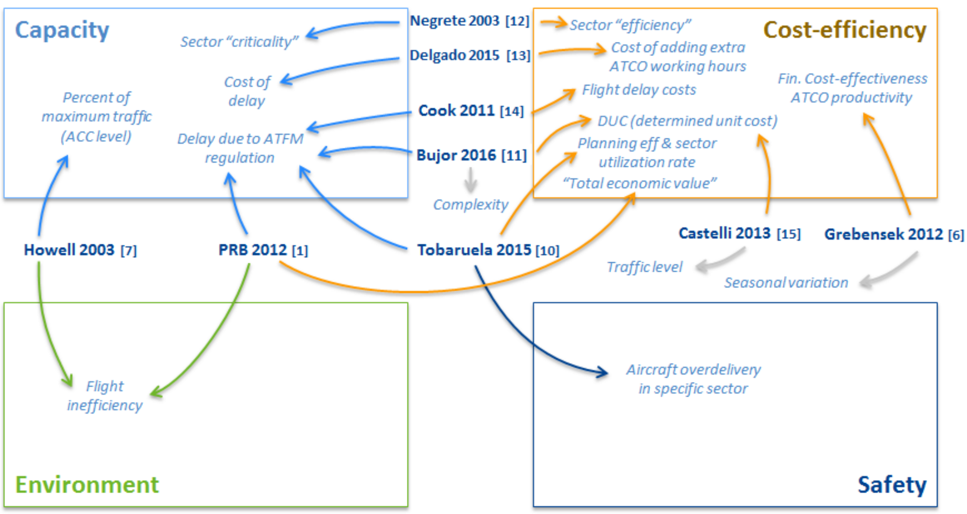

Figure 1. Main interrelationships between the SES KPAs analyzed in the academic literature

relationship between capacity and flight-efficiency: Howell *et al.* [8] make a study of route efficiency under three different traffic regimes; Reynolds [9] quantifies the importance of various sources of flight inefficiency. Safety performance and its interdependencies with other indicators have so far received less attention. The few attempts addressing safety mainly used overdeliveries (i.e., excess of flights entering a sector in one hour over the sector capacity) as a proxy indicator for safety.

The use of Performance Indicators, mainly oriented to SESAR KPAs, has also been addressed in several SESAR Exploratory Research projects, such as Predictability in ONBOARD [16], Punctuality in CASSIOPEIA [17] or Capacity in UTOPIA [18]. However, there is room for improvement addressing the interdependencies between ATM performance metrics and the definition of new ones, taking existing studies as a starting point.

IV. Visual Analytics and Machine Learning for ATM Performance Modelling: Challenges and Opportunities

The increasing availability of ATM data at different scales and recent advances in the fields of data science and data visualization open new opportunities to develop new ATM performance metrics and modelling techniques. INTUIT investigates how to exploit these opportunities in order to improve our understanding of ATM performance drivers and trade-offs.

Data science is a broad term that encompasses different techniques to extract knowledge and insights from data, including statistics, pattern discovery, and predictive analytics. Predictive analytics involves predicting unknown or future values of variables of interest from some metrics, and is typically based on machine learning algorithms that learn system properties from training datasets. Although different in nature, the problems approached with machine learning tools in other fields share some characteristics with ATM performance modelling. Example opportunities include the application of techniques of fuzzy classification to find further relationships between KPAs, extending the work done in [10]; the use of algorithms designed to deal with missing data in classification trees to work with missing or incomplete data in ATM systems; and the adaptation to ATM of classification techniques used for the development of early warning systems in other sectors (e.g., health [19]). These techniques will unveil correlations and possible cause-effect relationships between KPIs at intra and inter KPA level.

Visual analytics focuses on analytical reasoning facilitated by interactive visual interfaces. In the field of performance modelling, visual analytics techniques concern three main areas: discovery of relevant relationships between variables, trade-off evaluation, and uncertainty assessment. Existing tools usually rely on general-purpose approaches. Moreover, most KPI representation tools are limited to a mere visualization of values, without any analytical functionality supporting the exploration of interrelationships (see [20]). Interactive visualisations exploiting and reinforcing human perception could be coupled with analytical capabilities such as clustering, filtering or automatic event detection. Visual analytics represent an opportunity to extract interdependencies between ATM KPIs and KPAs, facilitating the interpretation of performance data and the understanding of complex relationships, improving the evaluation of policy alternatives in the face of multiple and conflicting objectives, and facilitating the communication between stakeholders and policy makers.

V. Preliminary Findings

The first stage of the INTUIT project has focused on the review of the available sources of ATM performance data at different scales. Each data source has been assessed on quantity, validity, integrity, quality, and spatial and temporal resolution. This assessment has allowed the identification of the information that can be extracted from each dataset, as well as the associated limitations. In parallel, a review of research papers and policy studies, together with a consultation with different ATM stakeholders represented in the project's Advisory Board, has led to the definition of a set of research challenges related to ATM performance.

A. ATM Performance Data Inventory: Quality Assessment

The available sources providing data on the performance of the European ATM system have been described and assessed on four main dimensions: (i) type of data provided, (ii) public availability, (iii) data exchange formats, and (iv) temporal and geographical scope and granularity. Figure 2 presents a visual guide to the information available from each source. These data sources can be classified into two main groups:

- High granularity data sources, which provide large amounts of low-processed data. They are useful to compute new metrics, typically at the cost of significant computing effort.
- Low granularity data sources, which provide highly processed and aggregated data. They contain relevant metrics that can be used without any processing.

The main high granularity data sources identified are depicted below:

- The Demand Data Repository (DDR2) [21] provides trajectories of individual flights in the European airspace. Although the geographical granularity is not the highest obtainable, it is sufficient for computing a wide range of metrics.
- Air Traffic Flow and Capacity Management (ATFCM) Statistics [22] consist of daily summaries of delays caused by ATFM regulations, useful for research on delay-capacity and its interdependencies.
- The Network Operations Portal (NOP) [23] provides two principal datasets: ATFCM Notification Messages (ANM), which contain information of regulations prior to the operation, useful for research on delay-capacity

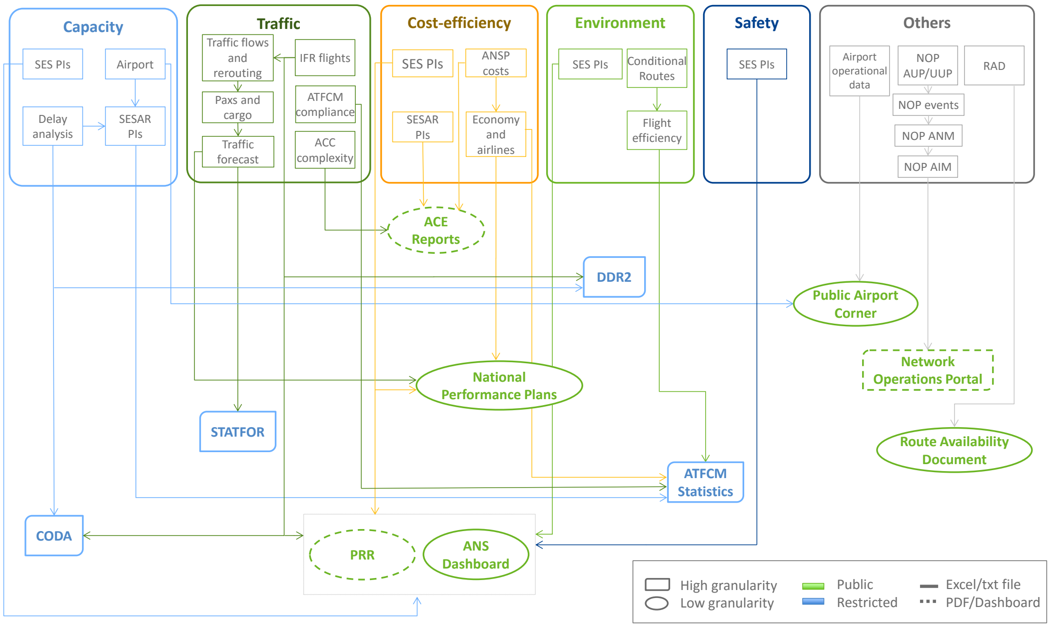

Figure 2. ATM Perfomance data map

and predictability; and European Airspace Use Plans (AUP) and their updates (UUP), which provide airspace restrictions and alternative routings due to military activity, essential for studies on civil-military cooperation.

- The Central Office for Delay Analysis (CODA) [24] gathers delay statistics reported by airlines, which are useful for the analysis of capacity-delay and the interdependencies with other areas. The provided data, however, are sometimes incomplete.
- EUROCONTROL's Statistics and Forecasts Service (STATFOR) [25] supplies actual and forecasted demand, useful for research on delay-capacity.

The main low granularity data sources identified are:

- ATM Cost-Effectiveness reports (ACE) [26] contain statistics and balance sheets of Air Navigation Service Providers' (ANSPs) costs and staffing, essential for any cost-efficiency analysis. The data are aggregated yearly and per ANSP.
- The Performance Review Reports (PRR) [27] provide statistics on the KPIs monitored since 1999. The data are aggregated yearly and per ANSP.
- The ANS Performance Monitoring Dashboard [28] gathers KPIs and PIs metrics for RP1 and RP2. The advantage with respect to the PRR is that data is easily exportable to structured formats, especially for RP2.
- Route Availability Documents (RAD) [29] present the route restrictions per AIRAC cycle, useful to study the interdependencies between airspace constraints and capacity/demand adjustment.
- The National Performance Plans (NPP) [30] provide the ANSP plans to comply with KPI objectives, allowing the computation of statistics on the accomplishment of the SES objectives. Data are currently only complete for RP1.
- The Public Airport Corner [31] provides static operational data of some European airports. Forecasted runway capacity can be used to analyse airport demand-capacity balance.

B. *Research Challenges*

The main research challenges that can be explored by applying visual analytics and machine learning techniques were identified through consultation with ATM stakeholders, including representatives of EASA, SJU, ANSPs, Network Manager and PRU. These research challenges are briefly depicted hereafter:

- ATM cost-efficiency has been the subject of abundant research ([14], [15], [32]), but there is room for improvement in specific areas. Under new operational paradigms, existing indicators may be suitable means to measure performance, but less appropriate for target setting. For example, using one indicator to aggregate flight-hours and airports movements may lead to a biased view of ATM output per ANSP [32]. The proposed approach would use machine learning techniques to calculate en-route and terminal KPIs and devise the most appropriate indicators for target setting.
- Further development of the calculation of the exact cost of the delay for an airline, which is highly nonlinear and depends on contextual and flight

characteristics [14], could improve the delay indicators used for target setting. Machine learning techniques could be used to compute the reactionary effects of delay, specially ATFM delay.

- The trade-off between ANSP cost-efficiency (ATM navigation costs) and environmental cost-efficiency (fuel costs) in the presence of unit rate variability between ANSPs [15] could be further developed. Visual analytics would be used to get insights into the effect of having different unit rates.
- There is also room for improvement regarding the study of ATCO workload as defined in ACE reports, in order to better understand its dependencies with other areas such as: (i) capacity, by studying how overdeliveries or traffic demand-capacity imbalance lead to an increase of sector complexity, (ii) uncertainty, by uncovering systematic relationships between volatility of demand and complexity patterns; and (iii) airspace complexity, by exploring the ATCO workload differences between lower and upper airspace for instance.
- Another research area is the development of decision-making tools for representing relationships in ATM operational performance. This could be implemented as an enhancement of the PRU Dashboard developed by EUROCONTROL [28]. Visual analytics could be used to disaggregate the data by sectors and show their evolution over different time-scales. The tool could provide insights into the relationship between local decisions made in real-time operations and overall performance indicators, which are calculated ex-post.
- The implementation of new KPIs has also been proposed. A new predictability KPI could compare the forecasted demand with the actual demand, using analytics and big data methodologies to improve ATM predictability. Another KPI could be developed in order to reflect the effect of the ATM system in constraining air traffic. Another line of research would be modifying KPIs to include airport operations performance. Finally, new metrics to measure safety in a significant way could be considered. Visual analytics here plays an important role to find patterns in data that can be translated into meaningful new metrics.
- The trade-off between safety and other performance areas should be further developed. The optimization of capacity, cost-efficiency and environment imposed by the Performance Scheme target-setting could lead to minor safety deficiencies [10].
- There is also a strong interest in the development of research questions related with uncertainty, such as studying the impact of on ground processes on gate-to-gate predictability. These relationships could be measured with machine learning methods such as Bayesian networks.

C. Mapping Data Sources and Research Questions

Table I maps the ATM performance data sources described in section V-A to the research threads identified in section V-B.

Cost-efficiency related data would include flight plans and actual trajectories, which can be obtained from DDR2 [21]. ANSP and airline costs can be gathered from ACE reports [26] and from the International Air Transport Association (IATA) [33], respectively. Fuel burn values could be obtained from the Base of Aircraft Data (BADA) [34] or Lufthansa Integrated Dispatch Operation (LIDO) [35] databases, while Route per State Overflown (RSO) distance tool [36] would provide the required data in terms of route options/distances.

Post-operational ATCO workload data is accessible via DDR2. However, planning data to study different temporal scales is not easily accessible, as it is sensitive information for ANSPs. Only limited subsets of planning data can usually be gathered, which limits the scope of the research.

For the development of improved dashboards and decision-making tools, it would be crucial to gather the KPI raw data used by the PRU to compute the results presented in the ANS Performance Monitoring Dashboard [28]. Flight plans, trajectories, staffing and theoretical throughput of sectors is provided by DDR2, but collaboration of certain ANSPs would be necessary to study staff planning in order to model capacity as a statistical variable.

TABLE I. MAPPING BETWEEN PROPOSED RESEARCH THREADS AND PERFORMANCE DATA SOURCES

	Threads					
Data sources	***Cost-efficiency***	***ATCO workload***	***Decision-making tools***	***New KPIs***	***Safety trade-offs***	***Uncertainty***
ANSPs		X	X	X	X	X
DDR2	X	X	X	X	X	X
PRU	X		X	X	X	X
RSO Distance Tool	X			X		
BADA / LIDO	X			X		X
IATA / ICAO	X			X		
ACE	X			X		
Network Manager				X	X	
EASA				X	X	
CODA				X		X
Daily Summaries			X	X		
National AIPs				X	X	

The definition of the new KPIs proposed in section V-B would require access to the CODA database [24] and Daily Summaries from ATFM Statistics [22] for delay analysis and to national Aeronautical Information Publications (AIPs) to consider ATM procedures.

The study of safety drivers and interdependencies would additionally require information about ATM procedures compliance and safety events.

VI. Case Study: Visual Analytics for ATFM Delay Analysis

A. *Scope and Objectives*

The proposed case study includes the development of several visualizations of ATFM delay and regulation statistics time series, with two main objectives:

- Explore the DDR2 and ATFM Statistics datasets and devise methods for aggregating data with different geographical references and temporal granularity.
- Gain understanding of spatio-temporal patterns of regulated flights and identify network bottlenecks.

The datasets used consist of:

- Spatial references obtained from DDR2: airports, navigation points, and traffic volumes.
- ATFM statistics during AIRAC 1604 (31/03/2016-27/04/2016) obtained from Daily Summaries: daily regulated flights per departure airport; daily regulated flights per destination airport; and regulations applied, number of regulated flights and cause of regulations, according to Network Manager regulation causes [37].

B. *Approach and Methodology*

Two types of spatio-temporal representation have been developed: (i) time-series of the number of regulated flights and ATFM delay in bar diagrams classified by causes, and (ii) time-series represented according to their spatial reference (airport, navigation point, traffic volume).

With this last technique, several metrics were represented:

- Number of regulated flights incoming or outgoing from each airport.
- Difference between incoming and outgoing regulated flights at each airport.
- Spatio-temporal aggregation of regulations: total number of regulated flights during the day for each reference location (airport, navigation point, sector).
- Difference between the number of flights regulated at each airport due to Aerodrome capacity and the sum of regulated incoming and outgoing flights. This metric represents the number of the flights that were regulated due to factors external to the airport.

C. *Results*

1) *Daily Series of Regulations and Delayed Flights*

Figure 3 presents the general statistics of regulation events and affected flights. By exploring these representations, the following outliers were identified:

- Two major (31/03 and 27/04) and one minor (09/04) disruptions caused by "ATC industrial action" (dark blue) in France and Italy, respectively.
- Special events (01/04 - 03/04) related to ATC system maintenance and upgrade (in magenta).
- Bad weather events (12/04 - 13/04 and 26/04 - 27/04, in blue).

Together with these punctual events, it can also be observed continuous delay due to "Aerodrome capacity" (light red) and "ATC capacity" (yellow) with peaks during weekends.

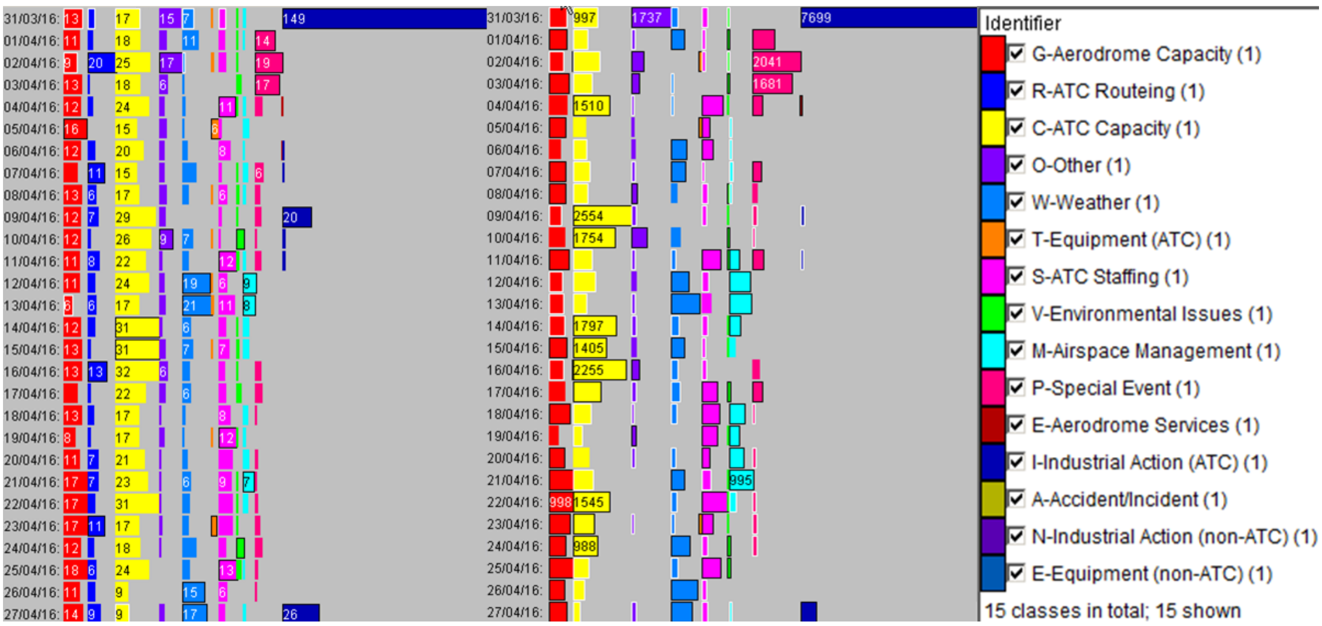

Figure 3. Dynamics of the number of regulation events (left) and regulated flights (center) by regulation causes represented by different colors and dates (vertical dimension). The legend on the right shows the correspondence between the colors and the causes.

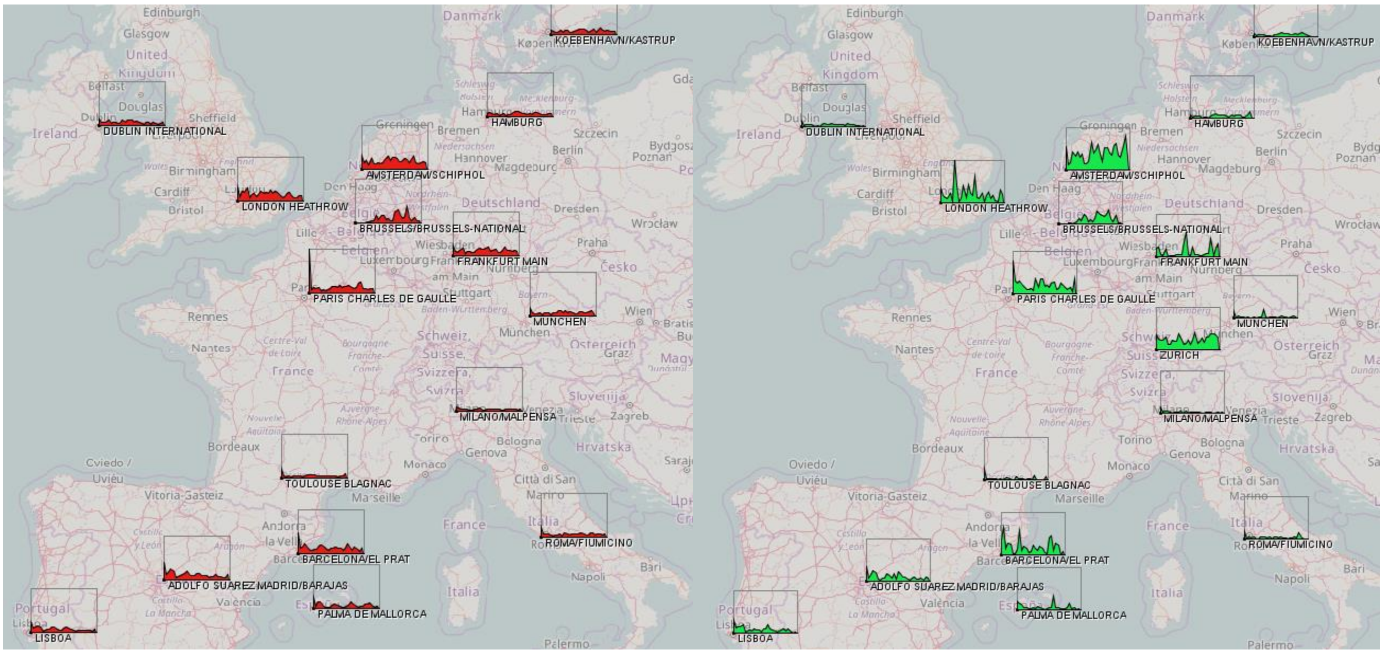

Figure 4. Time series of the daily counts of the regulated flights at the airports of departure (red, left) and destination (green, right).

2) Temporal Series of Airport Incoming and Outgoing Regulated Flights

Figure 4 presents the time series of the daily counts of regulated flights at the airports of departure and destination, respectively. For departing flights, we can observe peaks in France and Spain during the industrial action on 31/03, as well as permanent high values in Amsterdam, Frankfurt, Paris, Munich and London Heathrow. Spanish and Portuguese airports present weekly patterns with peaks on weekends. For arriving flights, the most prominent pattern is the high values in both Heathrow and Amsterdam airports. The Southwest airports in Spain and Portugal once again present weekly patterns with weekend peaks. It is to be noted that here only most important airports are shown. Delayed flights dataset has smaller number of arrival airports (124) than departing (150 airports). This is because, at low density airports, is usual that arriving flights are not subjected to regulations.

Figure 5 shows the time series of the difference between the number of outgoing and incoming regulated flights. It is observed that both Istanbul and Thessaloniki airports appear in green (more regulated incoming flights) while Athens and the rest of Turkish airports appear in red (more regulated outgoing flights). This finding suggests that flights arriving at these major airports have higher probability of being delayed than those departing from the same airports.

3) External Impact on Airports Figures

In order to relate regulation events to the time series of the regulated flights departing or arriving at the airports, a spatio-temporal aggregation of the regulations has been performed, assigning a number of regulated flights per day to each reference location (airport, navigation point, sector). The objective is to assess the impact of the regulations at the airport level. For this purpose, we use a metric defined as the difference between the sum of the regulated incoming and outgoing flights and the number of flights affected by a regulation assigned to the airport ("Aerodrome capacity"). This metric represents the number of flights that were regulated due to external factors and departed or arrived at that airport, providing insights of the external impact of regulations on each airport.

Figure 6 depicts the computed external impact on the airports. It is interesting to note that Istanbul airports have low values of external impact, which implies that most of their regulated flights are affected by airport regulations instead of external factors. Similar behaviour can be observed in major hubs such as Frankfurt and Munich. On the other hand, the airports of Heathrow, Amsterdam, Brussels, and Paris are continuously affected by external factors. Another observable pattern is weekly peaks (with highest amplitude on Saturdays) in several airports in Portugal and Spain.

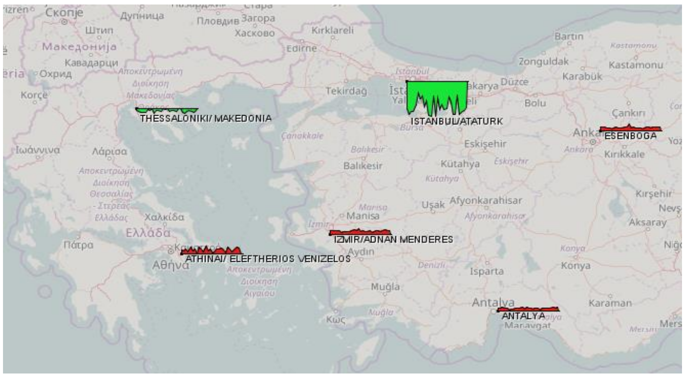

Figure 5. Differences between the counts of outgoing and incoming regulated flights. Positive differences (in red) depict prevalence of outgoing regulated flights; negative (in green), of incoming regulated flights.

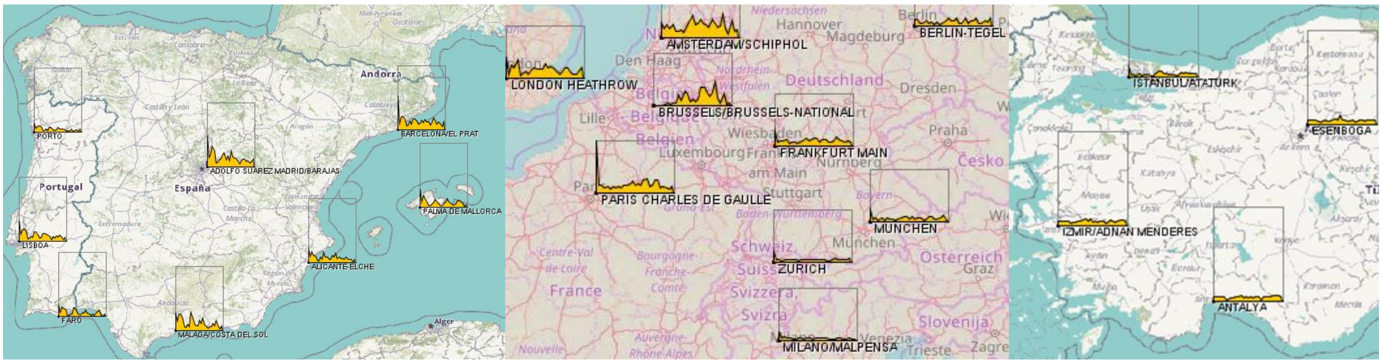

Figure 6. External impact on airports: time series of flights regulated elsewhere

VII. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we have reported the initial results of the INTUIT project. An extensive literature review, together with a consultation process with ATM stakeholders, has led to the identification of a set of research questions pertaining to ATM performance modelling. These research questions have been mapped with existing ATM performance datasets, which have been analysed regarding data quality and completeness. A case study including several visual analytics exercises has been carried out to start exploring some of these questions, in particular those related to ATFM delays.

The preliminary results of the case study show the potential of visual analytics techniques in assessing ATM performance. More specifically, visual analytics can be of great value to suggest specific hypotheses and patterns that can then be tested and characterized by means of data science techniques such as statistical analysis, pattern discovery, and predictive modelling. At the end of this process, visualization can again be of help to analyse and communicate in an intuitive way the results of such models.

In the subsequent stages of INTUIT, a subset of the research questions identified in this paper will be selected and investigated in depth. The selection of these research questions will be based on a combination of factors, including the relevance of the research question, the expected impact of the results, the availability of sufficient data, and the potential of visual analytics and machine learning techniques to provide new insights. The synergistic approach between visual analytics and machine learning techniques outlined herein is expected to contribute to advance the state-of-the-art in ATM performance modelling, and ultimately to set the basis for the development of improved tools for ATM performance monitoring and management.

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