DATA DRIVEN AIRCRAFT TRAJECTORY PREDICTION RESEARCH

Project Acronym:	**[DART]**
Grant:	**[699299]**
Call:	**[H2020-SESAR-2015-1]**
Topic:	**[ER-2-2015]**
Consortium Coordinator:	**University of Piraeus Research Centre (UPRC)**

PROJECT DESCRIPTION

DART aimed at **high-fidelity aircraft trajectory prediction capabilities**, **exploring the potential of the rapidly maturing techniques** in complexity science and data science **for the ATM domain**, aiming to support the trajectory life-cycle at all stages efficiently.

Major research issues for DART were as follows:

- What are the **supporting data** required for robust and reliable trajectory predictions?
- What is the **potential of data-driven methods to improve our trajectory prediction** abilities?
- **How the complex nature of the ATM system could be mastered to reduce delays due to demand-capacity imbalances at the planning stage**?

Capturing the complexity of the ATM system using agent-based simulation and being able to devise trajectory prediction methods that take all the available and relevant information into account, DART developments addressed the **data-driven trajectory prediction** challenge and the challenge of **ATM network complexity** to resolve demand-capacity imbalances.

In both objectives, DART made a considerable leap from the classical model-based approaches.

Specifically, and with respect to the operational content considered, DART demonstrated how predictive analytics can **improve trajectory prediction in support of DCB processes at planning phase**, further reducing uncertainty and improving ATM operations and services provided.

From an AUs perspective, DART explored how to **compute the predicted trajectory** that an aircraft will fly during an operation day **without considering traffic**.

From ANSPs perspective, DART aimed to **study and determine the complexity to be considered in trajectories due to the influence of the surrounding traffic** at the planning phase, taking into account flight plans or the trajectory predictions made.

Specific research objectives the DART successfully achieved are as follows:

- Definition of **requirements for the input datasets** towards highly accurate data-driven trajectory prediction processes.
- Study of the **application of big-data techniques to trajectory related data gathering, filtering, storing, prioritization, indexing and segmentation** to support the generation of reliable and homogenous input datasets, supporting the comparison of trajectory predictors.
- Study of **different data-driven machine learning techniques to describe how a reliable trajectory prediction model will leverage them.**
- Provide a **formal description of the complexity network to support correlated multiple trajectory interactions** in the context of resolving the DCB problem.
- Study of the **application of agent-based models regarding the interactions of multiple correlated trajectories** considering complexity network effects.
- Description of **visualization techniques to enhance trajectory data management** capabilities.
- Exploration of **advanced visualization processes** for data-driven model algorithms formulation, tuning and validation, in the context of 4D trajectories.

In a nutshell:

DART explored and developed novel ***Machine Learning methods****,* which provide *the means to* ***make accurate predictions about individual trajectories*** *and to* ***effectively address complex phenomena due to trajectories interactions, reducing delays to resolve hotspots****, at the* ***planning phase of operations****.*

These capabilities, with the support of ***advanced visualization tools****, provide the* ***potential to advance stakeholders' collaborative decision making at planning phase of operations, contributing to ATM Master Plan strategic objectives****.*

Datasets *being managed* ***provide*** *the* ***uniform basis to compare different algorithms*** *and understand their potential, while future research activities can take further advantage of them and enrich them further.*

KEY RESULTS – QUANTIFIABLE PERFORMANCE BENEFITS

A. **Improvement in predictability** with respect to rational model-based trajectory prediction approaches.

Comparison between data-driven predictions versus flown trajectories, and data driven predictions versus Eurocontrol Network Manager pre-flight prediction show that data-driven methods can achieve high accuracy in predicting trajectories (D2.4). Visual analytics capabilities support these methods (D2.2).

DART explored the exploitation of data-driven and hybrid (machine learning in combination to model-based) methods, exploiting raw surveillance data as well as Aircraft Intent inferred from raw surveillance data and reconstructed trajectories using a subset of independent Aircraft Intent variables: These include Reinforcement Learning methods, Random Forests, Hierarchical Agglomerative Clustering, Multi-Output Meta Estimators (MOME). These are presented in D2.3 and evaluated in D2.4. Here we emphasize on two very effective methods explored:

The first is a Hidden Markov Models (HMM) approach. This method exploits flight and meteorological information in order to define the spatio-temporal cubes that are the basis of 3D prediction, as well as airport and flow features, that can be calculated using raw radar data, for timestamp prediction. Airspace information is commonly used in both prediction cases. Figure 1 provides a visual overview of training and testing data for two routes used in evaluation, detailed in deliverable D2.4. Our evaluation on the trajectory dataset verified that this prediction system achieved horizontal and vertical accuracy of 7.692nmi and 1589.452ft, respectively. This shows that in many cases data-driven trajectory prediction can perform better than model-based trajectory prediction, but not in all cases.

Figure 1 – Training and test data for routes LEAL-LEBL and LEMD-LEIB.

Figure 2 provides a qualitative assessment in order to understand how predictions look like vs the actual trajectory flown.

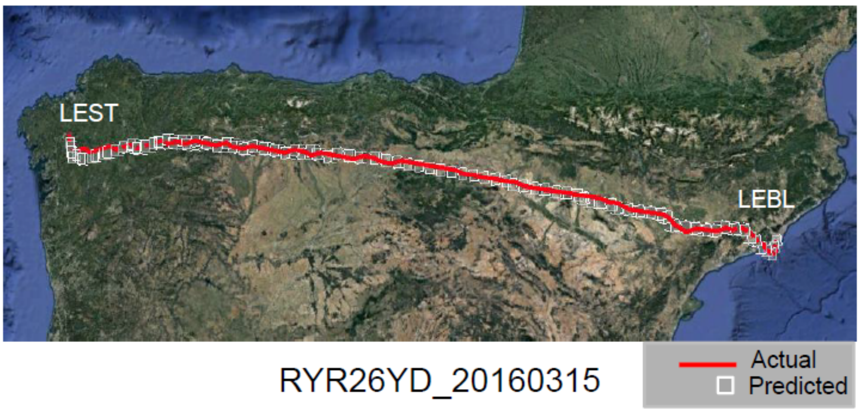

Figure 2– Qualitative assessment Actual vs Predicted.

Comparing our final results with the Estimated time of Arrival (ETA) values, Eurocontrol, Figure 3 illustrates RMSE values in minutes for each route between our predictions versus Eurocontrol's prediction. Figure 3 provides a close look to the results, focusing at the box plots rather than to outliers, where the median values are visible. From the results, we make the following observations:

1. HMM prediction yields better median scores on eight routes, while the Eurocontrol's ETA shows better median scores on two routes (LEBL-LEVX and LEBLLEZL).
2. The standard deviation values in Eurocontrol's ETAs are much larger, resulting in larger windows of predictability at arrival times.
3. Boxplots representing Eurocontrols's ETAs show extreme outliers.

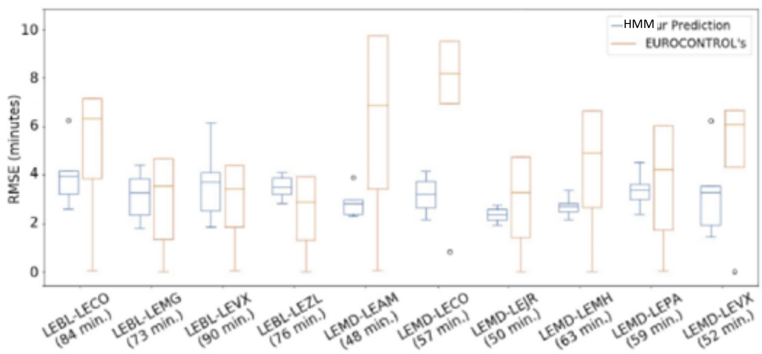

Figure 3 – HMM vs Eurocontrol ETA prediction – Zoom in.

The second, Multi-Stage approach, is a "constrained" method that makes use of the flight plan itself as the feature vector, testing its similarity with other tracks. The input vector for that method can include several other properties associated with any trajectory segment (e.g. weather variables, aircraft type, etc). So, a multi-stage approach comprising clustering, constructing a predictive model (e.g. HMM) representing each cluster, flight plan assignment to a cluster, refinement of prediction within the assigned cluster, has been designed and implemented, as shown in Figure 4.

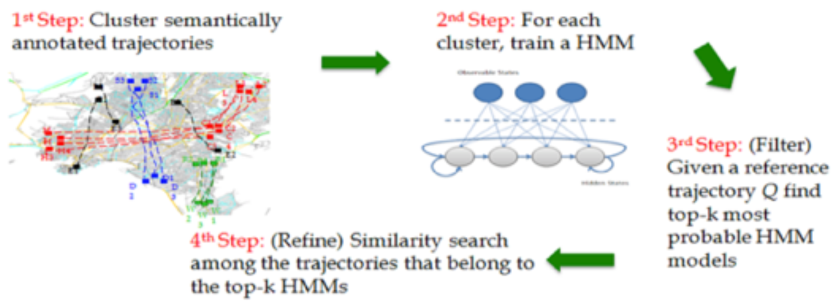

Figure 4 – Multi-Stage approach to Trajectory Prediction.

Compared to the "unconstrained" data-driven methods, e.g. the HMM approach, although not directly comparable, constrained trajectory prediction produces per-waypoint 3-D prediction errors consistently in the order of 2-3 km.

B. Improvement in airspace capacity management

Study of the application of agent-based models to the prediction of multiple correlated trajectories considering complexity network.

In the operational context of DART, results show that DART agent-based methods are capable to resolve all hotspots, while keeping the average delay for regulated flights at very low levels, regulating few flights with fairness. Visual analytics capabilities support these developments (D3.3).

It is important to stress that these methods introduce a novel paradigm for regulating individual flights, with the potential of the methods to incorporate stakeholders' constraints and preferences' on flight delays.

Although it is very difficult to make a direct comparison to the average delay reported by NM regulations, DART methods manage to keep the average delay for the regulated flights constant (with an average increase of 0.15 minutes compared to the NM regulations due to traffic), with an increase to the number of regulated flights by a factor of 1.13 compared to the number of flights regulated by the NM, while resolving all hotspots. A demanding case indicating differences between DART and NM solutions is provided in Figures 5 and 6.

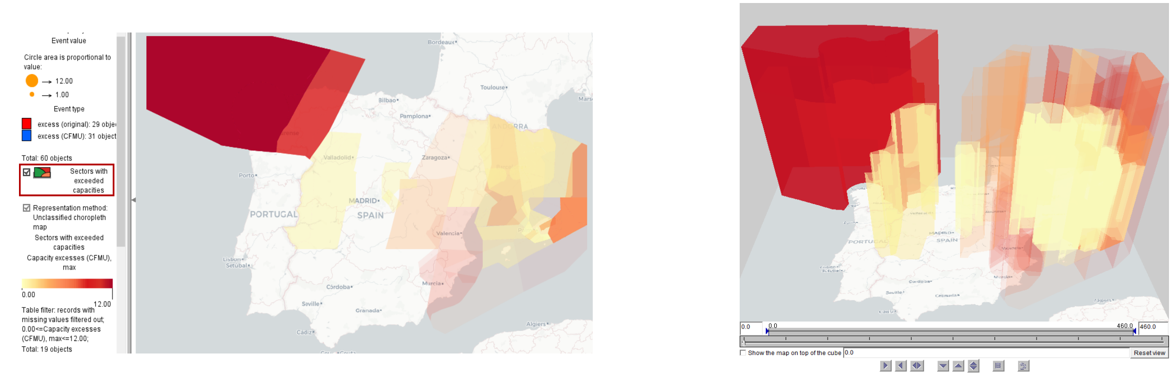

Figure 5 – The sectors whose capacities were exceeded by the NM-regulated flights. The colouring from yellow to red represents the maximal capacity excess, after the application of regulations in a demanding scenario (July 2, 2016).

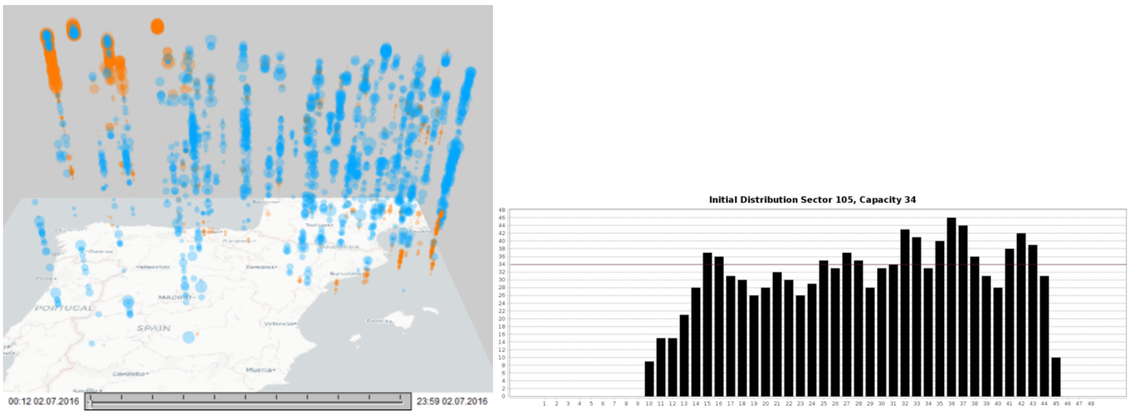

Figure 6 – The space-time cubes show the spatio-temporal distribution and intensity of the delays. The time axis is oriented upwards. Left: Delays due to NM regulations are indicated in blue and delays imposed by DART methods in orange. Right: Demand evolution in the most demanded sector northwest of Spain for the July 2, 2016 scenario, prior to applying any regulation.

C. **Interactive visualizations and visual analytics to support data-driven methods**

DART **designed, implemented and employed a suite of interactive visualization techniques integrated into a common framework** that facilitate the visual exploration and evaluation of trajectory data and associated context data, such as airspace sectorizations, in space and time (D1.5).

Visualization techniques have been **complemented by interactive filtering and clustering tools over spatial, temporal, and thematic attributes** (e.g., speed, altitude, a/c type, …) in the same framework to enable visual exploration and assessment of patterns, outliers, and spatio-temporal dynamics of user-specified subsets of trajectory data.

DART has **designed and tested visual analytics workflows supporting model development and evaluation** on the basis of the visualizations developed as their building blocks (D1.5, D2.2, D3.3):

- Linked comparative visualizations on 2D maps, 3D maps, and Space-Time cubes, and
- Linked comparative visualizations in the temporal domain, including linear and cyclic time frames; complemented by
- User-defined, interactive aggregation and comparison functions to enable analysis task-specific drilldowns in combination with the basic filtering and clustering methods provided.

Visual analysis methods and techniques developed in the context of DART for *Visual Exploration for Data Validation and Hypothesis Formulation,* as specified and detailed in deliverable D1.5 0, included two key aspects, namely, **the creation of a set of interactive visual interfaces that enable (1) identification of most common types of errors and omissions in data, and (2) exploration of cleaned data from multiple perspectives**, namely focusing on locations in air space, time moments and intervals, and trajectories of single and multiple inter-related aircraft.

The results are part of a more comprehensive suite of visualization techniques, interactive filtering, and coupled analysis tools developed and implemented over the course of the DART project: The underlying conceptual model is the Visual Analytics Loop (Figure 7). Most constituent visualizations are employed both for the exploratory and data curation phases of analysis, as well as during confirmatory analysis during algorithm design and evaluation.

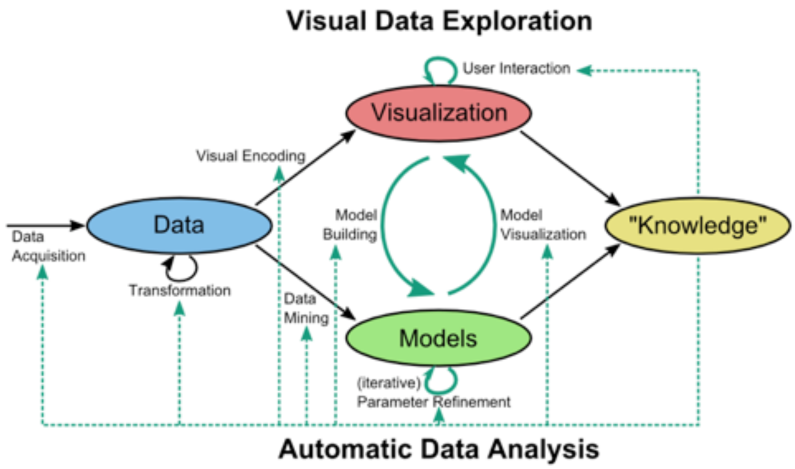

Figure 7: The Visual Analytics Loop followed by DART's Visual Analytics toolset.

DART expanded an existing set of standard visualization techniques, such as line plots and 2D map displays, by task-specific visualizations. These additions focus on the visual exploration of 3D aircraft trajectories (i.e., including the altitude and airspeed components): Examples from visualizations of sectorization schemes and aircraft trajectory data (e.g. actual tracks and flight plans) are shown in Figure 8.

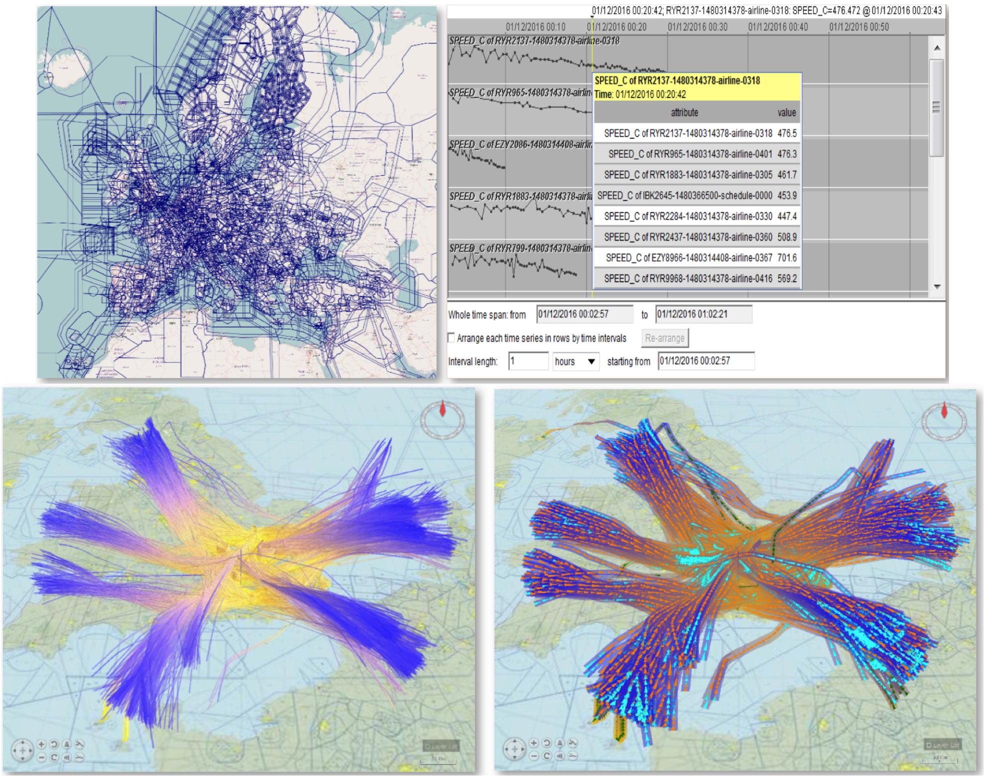

Figure 8: Tools for visual exploration of contextual data such as airspace sectorization schemes (top left) and various types of aircraft trajectory data such as actual tracks and flight plans (bottom row).

Visual-interactive exploration of aviation data sources, include

- Visualizations of sectorizations in 2D maps and 3D volumetric representations, as well as updated temporal displays for the visualization and analysis of temporal dynamics/cyclicity of airspace configuration schemes.

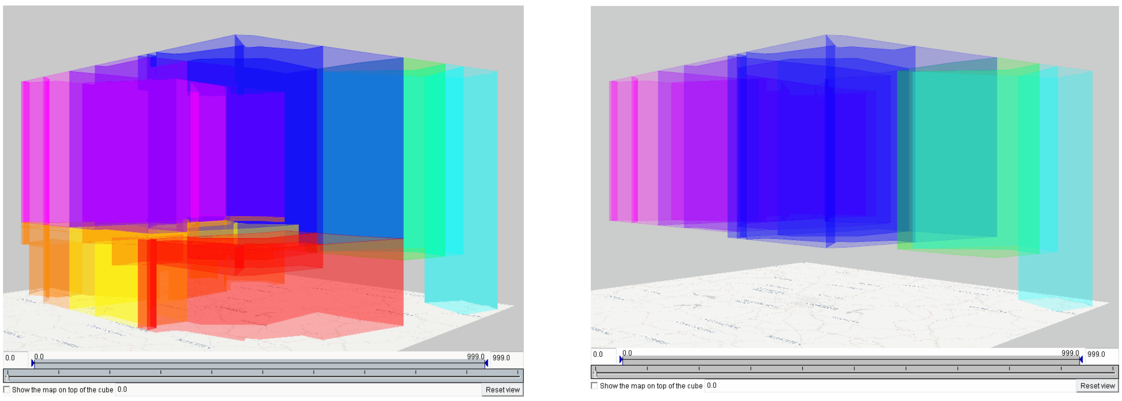

Figure 9 – 3D visualizations of two different configurations the LECM sector. Since sectorizations are 3D constructs comprised of several airblocks, a 2D map cannot always convey all relevant information. Here, two configurations vary in the inclusion of airblocks defining the lower airspace, which does not however change their 2D boundary.

- Visualizations that provide support for checking surveillance data coverage gaps in space and time.

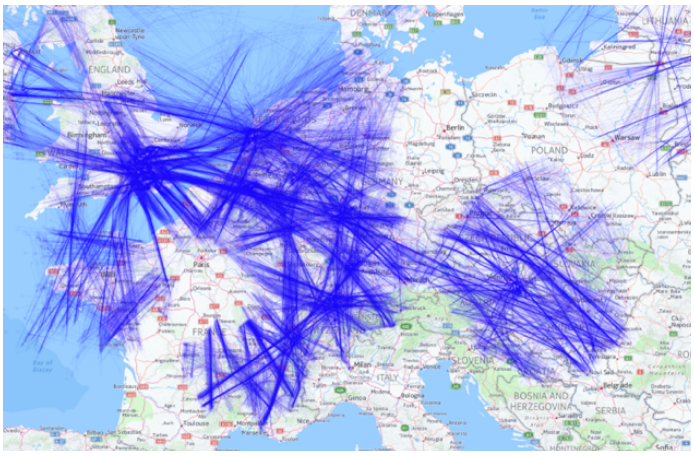

Figure 10 – Visual exploration of spatial data coverage: spatial gaps in aircraft tracks from a surveillance data set missing a number of stations.

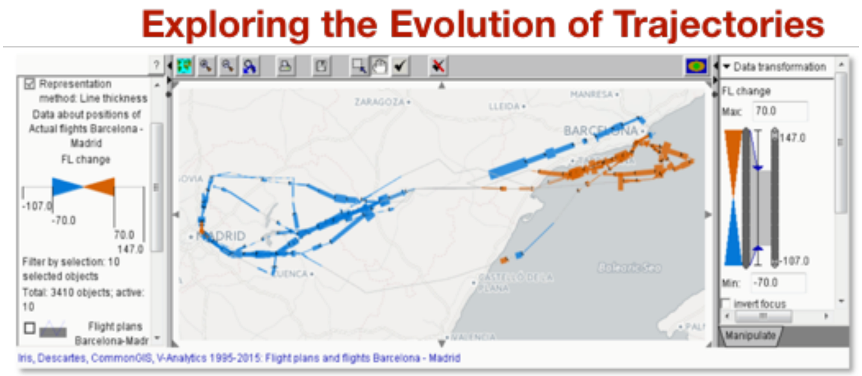

Figure 11 – Visual exploration of flight dynamics for flights between Barcelona and Madrid: integrated display of 2D trajectory shapes with flight level changes. Orange color encodes increases of flight levels (climbing), while blue indicates descend. The line thickness encodes the absolute change between to subsequent aircraft positions.

- Duplicated IDs, inspection of outliers or suspicious values in data (e.g. speed or altitude profiles) are further facilitated via appropriate visualizations combined with filtering.
- Techniques and visualization guidelines for supporting the use of relevance-aware clustering in visual exploration and analysis of movement data: This includes summarization of trajectory clusters and visual representation of the clusters in the context of the original data with visual distinction between relevant and non-relevant parts. At a high level of abstraction, the proposed approach supports an analytical workflow that consists of (1) selecting task-relevant parts of trajectories, (2) filter-aware clustering of the trajectories by the similarity of their relevant parts, and (3) exploiting the clustering results in subsequent analysis with the help of interactive visual displays.

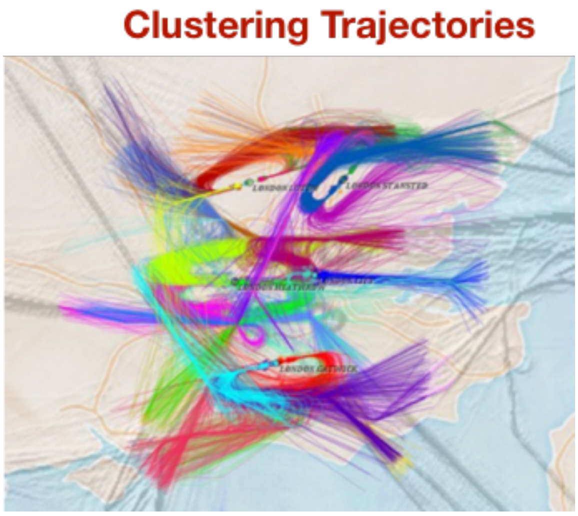

Figure 12 – 34 clusters representing the main approaches to the airports of London represented by coloring of the relevant parts of the trajectories, while a density surface summarizes irrelevant trajectory parts (here: cruise phases, holding patterns).

Implementations of the presented approaches have been integrated into a broader visual analytics framework comprising visualization techniques, interactive filtering, and coupled analysis tools. The framework's design follows a well-defined structure of interrelated principal data types and transformations between these types. These are presented in detail in deliverable D1.5.

CONTRIBUTIONS TO THE DIGITAL EUROPEAN SKY

DART explored data-driven and agent-based centred transformations regarding the future growth and diversity of air traffic towards safety and efficiency. Specifically, it explored how and at which degree these technologies can increase predictability of trajectory evolution and capacity management, further increasing the levels of automation in air traffic management (ATM) and air traffic service provision in all types of airspace, considering scenarios with no specific constraints or requirements.

A key result of DART is that, while it is envisaged that aviation infrastructure will be more data intensive, DART investigated thoroughly and expanded our understanding of how data-driven and agent-based machine learning techniques can be exploited to design an ATM system that is smarter and safer by analysing and learning from the ATM environment.

Project Deliverables

D1.1: DART- **Data Management Plan**, ed. 00.01.03, CRIDA, 27 Oct 2016, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D1.2: DART- **Data Transaction Pipeline Description**, ed. 00.01.00, CRIDA, 25 Nov 2016, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D1.3: DART- **DART Data Pool**, ed. 00.01.01, CRIDA, 15 Jan 2018, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D1.4: DART- **Synthetic Data Package**, ed. 01.00.00, BR&T-E, 02 May 2018, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D1.5: DART- **Visualization exploration report**, ed. 01.00.00. FRHF, 18 May 2018, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D2.1: DART- **Initial Set of Data-Driven Trajectory Prediction Algorithms**, ed. 02.00.00, BR&T-E, 02 Feb 2017.

D2.2: DART- **Visual Interface for Algorithms Analysis**, ed. 02.01.00, FRHF, 29 Aug 2017, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D2.3: DART- **Enhanced Set of Data-Driven Trajectory Prediction Algorithms**, ed. 01.01.00, BR&T-E, 19 Feb 2018.

D2.4: DART- **Evaluation and Validation of Algorithms for Single Trajectory Prediction**, ed. 04.020.00, BR&T-E, 03 July 2018, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D3.1: DART- **Collaborative Trajectory Prediction Scenarios and Requirements Specification**, ed. 02.00.00, UPRC, 18 Apr 2017, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D3.2: DART-**Collaborative Trajectory Prediction Algorithm**, ed. 00.02.00, UPRC, 15 Mar 2018.

D3.3: DART- **Evaluation and Validation of the Collaborative Trajectory Prediction Algorithm**, ed. 02.00.00, UPRC, 16 May 2018, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D4.1: DART- **Project Management Plan**, ed. 02.05.00, UPRC, 19 Sept 2016, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D4.2: DART-**Dissemination Plan**, 02.00.00, BR&T-E, 26 Sept 2016, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D4.3: DART- **Project website, wiki, social media channels**, ed. 01.01.00, BR&T-E, 26 Oct 2016, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D4.4: DART- **Dissemination Report**, ed. 01.00.00, BR&T-E, 19 May 2018, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

D4.5: DART- **Project Results Final Report**, ed. 04.00.00, UPRC, 9 Jul 2018, available at http://dart-research.eu/2018/07/10/dart-final-deliverables

Project Publications

[1] **DART Facts Sheet:** http://dart-research.eu/wp-content/uploads/2017/01/DART_fc.pdf, 2016

[2] **DART White Paper:** http://dart-research.eu/2017/04/03/dart-white-paper/, 2017

[3] T.Kravaris, G.Vouros, C.Spatharis, K.Blekas, G.Chalkiadakis, J-M.Cordero Garcia "**Learning Policies for Resolving Demand-Capacity Imbalances during Pre-tactical Air Traffic**

Management”, 15th German Conference on Multiagent System Technologies, Leipzig, Germany, 2017.

[4] G Andrienko, N Andrienko, W Chen, R Maciejewski, Y Zhao. “**Visual Analytics of Mobility and Transportation: State of the Art and Further Research Directions.”** IEEE Transactions on Intelligent Transportation Systems, 2017.

[5] J-M Cordero Garcia et al on “**Integration of meteorological information in trajectory prediction (DART Project)**”, 1st “International Workshop on Meteorology and Air Traffic Management, hosted by University of Sevilla and funded by project TBO-MET, 2016.

[6] Gennady Andrienko, Natalia Andrienko, Georg Fuchs, Jose Manuel Cordero Garcia. **Clustering Trajectories by Relevant Parts for Air Traffic Analysis.** IEEE Transactions on Visualization and Computer Graphics, 2017.

[7] Boeing Research and Technology Europe filed a patent in the European Patent Office: Applicant: The Boeing Company Application title: "**Method and system for autonomously operating an aircraft**”, Filing date: 29th June 2017, Filing number: EP17382412.9

[8] E.C. Fernádez et al., **DART: A Machine-Learning Approach to Trajectory Prediction and Demand-Capacity Balancing**, SID 2017.

[9] G. Vouros et al., **Multiagent RL for Real-World Interdependent Congestion Problems**, accepted in SETN 2018 (Hellenic Artificial Intelligence Conference).

[10] C.Spatharis et al: **Multiagent Reinforcement Learning Methods for Resolving Demand-Capacity Imbalances**, DASC 2018.

[11] E. Casado, A. Muñoz: **Data-driven Aircraft Trajectory Predictions using Ensemble Meta-Estimators**, accepted in DASC 2018.

[12] WAC-2018 workshop: **DATA DRIVEN ATM: GOING DIGITAL** (in collaboration with COPTRA, BigData4ATM, UPM, datAcron).

[13] ICRAT 2018 Workshop on **Data Enhanced Trajectory Based Operations**, in collaboration with datAcron.