Data-Driven

Aircraft Trajectory Prediction

Exploratory Research

Data science in ATM

The DART project

http://dart-research.eu/

Founding Members

DART

DATA-DRIVEN AIRCRAFT TRAJECTORY PREDICTION RESEARCH

Abstract

This paper presents challenges and opportunities regarding data-driven trajectory prediction research in the ATM domain: challenges and opportunities for exploiting disparate and heterogeneous data sources; challenges and opportunities towards increasing the capabilities of state-of-the-art methods for data-driven trajectory predictions to account for real-world and complex settings; and challenges and opportunities regarding the catalytic role information visualization and visual analytics can play in many phases of this research. In this context, the DART project positions itself as a key enabler towards the vision of the future ATM, contributing to a better understanding of how data-driven methods can increase our abilities to predict trajectories of aircrafts. [1]

[1] "The opinions expressed herein reflect the author's view only. Under no circumstances shall the SESAR Joint Undertaking be responsible for any use that may be made of the information contained herein."

Copyright 2017 DART

This document has been produced within the scope of the DART project.
The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members

EUROPEAN UNION EUROCONTROL

Table of Contents

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

Acronyms and Terminology

Term	Definition
ADS-B	Automatic Dependent Surveillance - Broadcast
AI	Aircraft Intent
ANS	Air Navigation Service
ANSP	Air Navigation Service Provider
AO	Airline Operator
ATC	Air Traffic Control
ATCO	Air Traffic Controller
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
AU	Airspace User
BADA	Base of Aircraft Data
BR&T-E	Boeing Research and Technology - Europe
CRIDA	Centro De Referentia Investigation, Desarrollo e Innovation ATM
DART	Data-driven AiRcraft Trajectory prediction research
DCB	Demand and Capacity Balancing
DDSTP	Data-Driven Single Trajectory Prediction
FMS	Flight Management System
FRHF	Fraunhofer-Gesellschaft zur Foerderung der Angewandten Forschung E.V.
HMM	Hidden Markov Model
H2020	Horizon 2020, EU Research and Innovation programme implementing the Innovation Union, a Europe 2020 flagship initiative aimed at securing Europe's global competitiveness.
METAR	Meteorological Aerodrome Report
NM	Network Manager
NOAA	National Oceanic and Atmospheric Administration
RL	Reinforcement Learning

Copyright 2017 DART

This document has been produced within the scope of the DART project. The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members

EUROPEAN UNION EUROCONTROL

SESAR	Single European Sky ATM Research Programme
SESAR Programme	The programme that defines the Research and Development activities and Projects for the SJU.
SIGMET	Significant Meteorological Information
SJU	SESAR Joint Undertaking (Agency of the European Commission)
SJU Work Programme	The programme that addresses all activities of the SESAR Joint Undertaking Agency.
TBO	Trajectory Based Operations
TP	Trajectory Predictor
UPRC	University of Piraeus Research Center

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

1 Introduction

The current Air Traffic Management (ATM) system worldwide has reached its limits in terms of predictability, efficiency and cost effectiveness. Nowadays, the ATM socio-technical system is based on an airspace management paradigm that leads to demand imbalances that cannot be dynamically adjusted. This entails higher air traffic controllers' workload, which, as a final result, determines the maximum ATM system capacity.

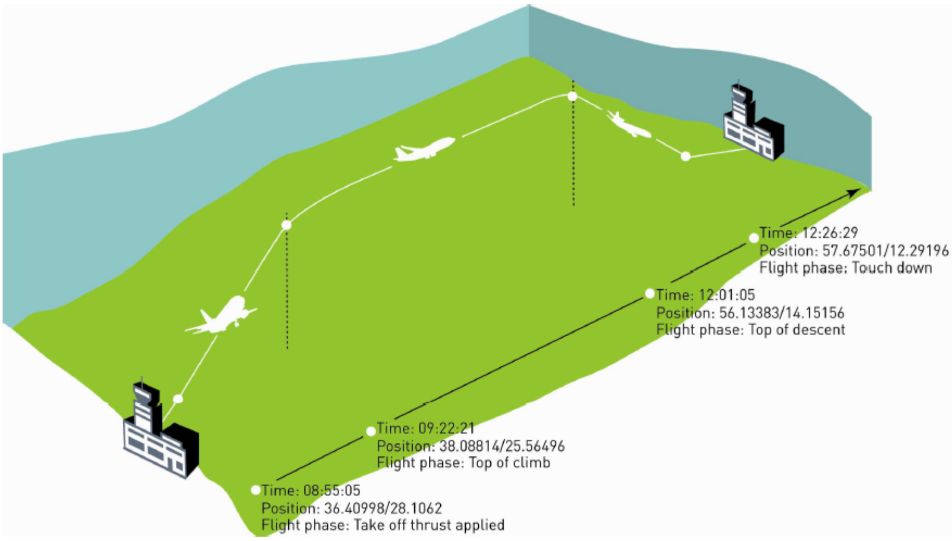

Figure 1 4D (three spatial dimensions plus time as a fourth dimension) trajectory of an aircraft (SESAR SJU)

With the aim of overcoming these ATM system drawbacks, different initiatives, dominated by SESAR in Europe [SESAR] and Next Gen in the US [NextGen], have promoted the transformation of the current environment towards a new *trajectory-based ATM paradigm*. This paradigm-shift changes the old-fashioned airspace management to the advanced concept of *Trajectory Based Operations* (TBO). In the future ATM system, the trajectory becomes the cornerstone upon which all the ATM capabilities will rely on. The trajectory life cycle describes the different stages from the trajectory planning, negotiation and agreement, to the trajectory execution, amendment and modification. The envisioned advanced decision support tools required for enabling future ATM capabilities will exploit trajectory information to provide optimized services to all ATM stakeholders (Airspace users (AUs), Air Navigation Service Providers (ANSPs), Air Traffic Control (ATC), etc.).

The proposed transformation requires *high-fidelity aircraft trajectory prediction capabilities*, supporting the trajectory life cycle at all stages efficiently, towards realizing the TBO paradigm. Indeed, increasing the level of trajectory predictability is an essential driver for an effective deployment of this new concept. This is also evidenced by the fact that, improvements in trajectory prediction are fully aligned with FlightPath 2050 [FlightPath2050] goals, in particular with those

Copyright 2017 DART

This document has been produced within the scope of the DART project. The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members

EUROPEAN UNION EUROCONTROL

related to societal and market needs (with focus on improved, weather-independent arrival punctuality), protecting environment and energy supply, and ensuring safety and security.

The DART (Data-driven AiRcraft Trajectory prediction research) project has a clear view towards addressing the ATM system drawbacks via increasing aircraft trajectory prediction capabilities: The application of data science techniques in conjunction to agent-based modelling methods is expected to bring a significant breakthrough towards increasing trajectory prediction capabilities.

Data-driven techniques for trajectory prediction can lead to less computing-intensive processing than that required in classical model-based Trajectory Predictors (TP). To a greater extent than those TP, the expected advantage of data-driven TP is that they will allow more precise predictions by considering and learning appropriate models from *all* relevant, *actual* past data, taking also into consideration contextual features that affect the trajectories of aircrafts. The effect of this can be further increased by also considering the ATM network effect and thus being able to predict the effect that operational conditions and traffic have on individual trajectories: Modelling the ATM socio-technical system and predicting its behaviour based on operational constraints is thus a goal that need to be pursued.

DART aims to deliver understanding on the suitability of applying data-driven techniques for predicting single and multiple, correlated, aircraft trajectories. The whole approach is based on machine learning and agent-based modelling methods and removes the need of complex and computational intensive models: While computing needs could be high during the training of machine learning algorithms, the learned models are expected to be exploited more efficiently than model-based ones.

The outcomes of these techniques will be comparable thanks to the common dataset infrastructure developed in the project. In conjunction to that, DART has specified the operational scope of its research, aiming to provide clear, comprehensive and well-studied insights on the data-driven techniques to be studied, their suitability and limitations.

The structure of this paper is as follows: It first presents an overview of challenges and opportunities regarding data-driven trajectory prediction research. Specifically, the role and complexity of exploiting different data sources are presented in section 2, while section 3 presents the state of the art on data-driven trajectory prediction research, considering also the important role that information visualization and visual analytics can play in many phases of this research. Section 4 presents the DART specific objectives, approach and methodology, together with the DART operational context of research. Finally, the target outcomes of the exploratory research in DART and the expected impact of its results with respect to the vision for ATM, are summarized in Section 5.

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

2 Data Sources for Data-Driven Trajectory Prediction Research

Any data-driven process does, necessarily, require a sufficient amount of data to be at least feasible. Obviously, is not only an issue of how extensive any dataset can become, but what features it contains and how reliable data it contains: To mitigate potential pitfalls due to data imperfections and low quality, and in order to enrich datasets with additional features extracted from disparate sources, a data-driven process often implies exploiting a set of different sources that should be interlinked to get sufficient, comprehensive, coherent and meaningful datasets.

This problem is particularly difficult to be tackled in the ATM domain, where traditionally operational information is not openly shared among the different actors. Security and business interests are of course the most relevant reasons for that. In addition to that, what makes the construction of a comprehensive dataset through merging data from different sources rather complicated is the fact that data sources are segmented in different systems, serving different operational purposes. Surveillance data sources, flight plans (including updates), sector configurations, airport information, weather data sources, regulations, are just some of the data sources types that need to be considered in combination.

Orthogonally, data sources in ATM can be divided between data sources from service providers and data sources from airspace users. The first category comprises data from Network Manager, Air Navigation Services Providers, and Airports. All of these actors, parts of the ATM socio-technical system, aim to provide safe and efficient ATM services in their respective area of responsibility. The second category comprises data from airspace users (airlines) with different business models (such as network carriers, or low-cost carriers). Data sources in this category are much more heterogeneous than those in the first category, since their owners do not intend to share data with the other actors. As a conclusion, in any case, data are usually not shared, and when it happens, this is for purposes with limited operational focus: This results to high heterogeneity of data sources.

When it comes to a data-driven trajectory prediction approach, it is obvious that most of the data source types – such as those exemplified above - must be exploited in a combined way, as they do impact and contribute to information-rich views regarding the execution of actual trajectories.

A remarkable issue with ATM relevant data sources, beyond heterogeneity, which is challenging itself, is their variety in terms of quality: while operational surveillance data (IFS) are highly reliable, other surveillance data sources (e.g. ADS-B) may have different level of reliability. Flight plans provide a distinct case given that their nature is being quite generic: while the information included in them is updated often, they may not reflect all updates or significant events affecting a single trajectory. By combining and contrasting different data sources, quality issues can be mitigated towards providing high-quality datasets.

Copyright 2017 DART

This document has been produced within the scope of the DART project.
The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members
EUROPEAN UNION EUROCONTROL

3 Data-Driven Trajectory Prediction Research: Challenges and Opportunities

Current Trajectory Predictors (TPs) are based on deterministic formulations of the aircraft motion problem. Although there are sophisticated solutions that reach high levels of accuracy, all approaches rely on simplifications of the actual aircraft behaviour, which delivers appropriate results for a reasonable computational cost. TP outputs are generated based on a-priori knowledge of the flight plan, the expected command and control strategies released by the pilot or the Flight Management System (FMS), known as Aircraft Intent, a forecast of weather conditions affecting the trajectory, and a model of the aircraft performance. This model-based, or physics-based, approach is deterministic: it returns always the same trajectory prediction for identical inputs, without taking into consideration actual, past data.

Although the use of the concept of Aircraft Intent [Lopez-Leones et al., 2007] together with very precise aircraft performance models such as BADA [BADA] (Base of Aircraft Data) has helped to improve the prediction accuracy, the model-based approach requires a set of input data that typically are not precisely known (i.e. initial aircraft weight, pilot/FMS flight modes, are some of these). In addition, accuracy varies depending on the intended prediction horizon (look-ahead time).

The outcome of these recent efforts provide promising results in terms of accuracy prediction [Yue et al., 2012], however *there is still a lack of a global vision on how to apply data-driven approaches to real ATM scenarios, and what the expected improvement will be. The disparity of the datasets used for validating different methods makes difficult to compare the proposed approaches, and therefore, prevents from extending the applicability of data-driven techniques to more realistic and complex scenarios.*

Therefore, data-driven trajectory prediction is an area of research where improvements with consequent benefits supporting the Trajectory Based Operations (TBO) paradigm can and should emerge.

Another strong limitation of state-of-the-art trajectory prediction methods is that the proposed data-driven approaches are limited to individual trajectory predictions. Indeed, the trajectories are predicted one-by-one based on the information related to the individual flights, ignoring the expected traffic at the prediction time lapse. Hence proposed methods disregard contextual aspects and their effects on the individual trajectory predictions. Consequently, the network effect resulting from the interactions of multiple trajectories is not considered at all, which may lead to huge prediction inaccuracies. *The complex nature of the ATM system impacts the trajectory predictions in many different manners. Capturing aspects of that complexity and being able to devise prediction methods that take the relevant information into account will improve the trajectory prediction process: This is a considerable leap from the classical model-based approaches*.

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

Closely related, highly correlated to the above, and with immense importance to create opportunities for synergy between human analysts and computer methods, Visual Analytics [Thomas et al., 2005] provide appropriate visual interfaces to all stages of computational analysis, from data pre-processing and exploration to pattern search and model building. It therefore facilitates the inclusion of the human domain expert's tacit knowledge and his capabilities for reasoning and intuition into the analysis process. In the ATM domain, the combination of large but imperfect data from different sources, and the idiosyncrasies or "hidden rules" underlying complex, intertwined planning and operation processes, particularly emphasize this need for human participation on all stages of data-driven trajectory prediction and ultimately, trajectory based operations: From the exploration of data sources and datasets to be exploited, to ensure its quality as training data; to visual inspection of exceptional situations within complex and varying operational contexts across multiple heterogeneous sources; to the visual inspection, tuning and validation of prediction models; and finally, to the evaluation/validation of prediction results with respect to contextual and operational conditions.

3.1 Single and Collaborative Trajectory Predictions State of the Art

Single Trajectory Prediction refers to the process of predicting an individual trajectory without considering contextual features: Tactical interventions released by ATC to ensure safe operations, and other flights influencing the plan and actual trajectory of any flight are not considered at all.

Current state of the art techniques enable predictions based on the exploitation of historical trajectory data. Those data may be obtained from surveillance systems (e.g., radar or ADS-B tracks) or directly from the aircraft (e.g., Quick Access Records).

Recent efforts in the field of aircraft trajectory prediction have explored the application of statistical analysis and machine learning techniques to capture non-deterministic influences concerning aircraft trajectory prediction. Linear regression models [Hamed et al., 2013] [Kun et al., 2008] and neural networks [Le Fablec et al., 1999] [Taoya et al., 2003], have returned successful outcomes for improving the trajectory prediction accuracy on the vertical plane and for traffic flow forecasting. Generalized Linear Models [de Leege et al., 2013] have been applied for the trajectory prediction in arrival management scenarios and multiple-linear regression [Tastambekov et al., 2014] [Hong et al., 2015] for predicting estimated times of arrival. Most of these approaches require as input dataset surveillance data, only: as already mentioned, additional data sources may be exploited in a combined way, providing a coherent view of the ATM system state at any time, towards improving the predictability of individual trajectories.

Towards exploiting different data sources, Ayhan [Ayhan et al., 2016] proposes a method that exploits aircraft trajectories modelled in space and time by using a set of spatiotemporal data cubes. Airspace is represented in 4D joint data cubes consisting of aircraft's motion parameters (i.e., latitude, longitude, altitude, and time) enriched by weather conditions. This approach computes the most likely sequence of states derived by a Hidden Markov Model (HMM) trained over historical surveillance and weather conditions data. The algorithm computes the maximal probability of the optimal state sequence, which is best aligned with the observation sequence of the aircraft trajectory.

In addition to weather data, by using information about air traffic control (ATC) regulations and flight plans, it is possible to design an Aircraft Intent inference process as a discrete optimization problem, whose cost function uses both spatial and temporal information. In such an approach, the trajectory

Copyright 2017 DART

This document has been produced within the scope of the DART project.
The utilisation and release of this document is subject to the conditions
of the Grant Agreement no.699299 within the H2020 Framework
Programme, and the Consortium Agreement signed by partners.

Founding Members
EUROPEAN UNION EUROCONTROL

can be computed thanks to an intent-based hybrid estimation algorithm (e.g., the residual-mean Interacting Multiple Model [Yepes et al., 2007]). For instance, using ADS-B messages the likelihood of possible flight modes can be obtained, and then, the most probable mode can be selected. The trajectory is determined by a sequence of the most probable flight modes computed, leading to a solvable aircraft motion problem. The mathematical resolution of such a problem can provide the predicted trajectory.

Techniques that have been applied to predict the Aircraft Intent include the work presented in [Yang et al., 2015]: This work proposes a two-stage process to obtain an inferred estimation of the Aircraft Intent. The first stage is devoted to identify the associated intent model, while the second one computes the specific intent based on the identified model. The intent modelling is formulated as an online trajectory-clustering problem where the intended routes are represented by dynamically updated cluster centroids extracted from radar tracks without flight plan correlations. Contrary, the intent identification is implemented with a probabilistic scheme incorporating multiple flight attributes. Although the results of the proposed approach are promising based on the verification with real radar trajectory and flight attributes data of 34 days collected from Chengdu terminal area, some important directions need to be further addressed. For example, the outliers in the clustering procedure should be investigated from the perspective of an air traffic controller.

However, in most cases, the literature only provides examples of machine learning algorithms and data analytics methods applied to reduced flight phases, focusing on specific state variables. For instance regression methods have been applied to predict the speed intent during climbs with highly promising results [Alligier et al., 2015a]. These results are based on the capability of predicting accurately the aircraft mass, which is unknown to ground-based automation tools. Usually, this kind of information is only accessible to airlines (i.e., data owners), and therefore, it needs to be estimated, if hybrid trajectory prediction approaches are to be used [Alligier et al., 2015b].

As already said above, the network effect resulting from the interactions of multiple trajectories is not considered at all in any of the methods proposed for predicting single trajectories: Corresponding features of multiple trajectories, together with contextual information (e.g. operational conditions and constraints) may impact greatly the prediction accuracy. By capturing and modelling aspects of the complex nature of the ATM system we can further improve the trajectory prediction process: There are promising methods from the multi-agents systems community towards modelling and decision-making in such complex systems [Guestrin et al., 2002][Kok et al., 2006][Vouros 2017].

3.2 Visual Analytics State of the Art

Obviously, the trajectory based operations paradigm implies exploiting data revolving around the notion of trajectory, which falls into the domain of spatio-temporal data analysis [Andrienko et al., 2013]. Noteworthy techniques of spatio-temporal data analysis, like aggregation, segmentation or clustering, can be found to be applied to a variety of different data types. For example, Tominski et al. [Tominski et al., 2012] visualize features of road traffic in a 3D visualization stacking trajectories as color-coded attribute bands on the map and on top of each other. Amongst others, Andrienko et al. [Andrienko et al., 2007] propose also the use of Space-Time Cubes [Kapler et al., 2005] to display the temporal evolution of a trajectory, and clustering to identify common patterns. Both, single trajectories [Ware et al., 2006] and sets of trajectories [Guo et al., 2011] can be visually explored.

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

It is often also desired to analyze other features along trajectories. Worner et al [Worner et al., 2012] for instance investigate for instance the speed feature of public transportation vehicles. Dykes et al. [Dykes et al., 2003] explore the design space detecting patterns and external influence factors to movement. The visual analysis of vessel movement is described by Willems et al. [Willems et al., 2009] with a focus on the visual representation of the speed of objects. Exploration of weather as a complex contextual dimension of movement is addressed through an interactive tool proposed by Lundblad et al. [Lundblad et al., 2009].

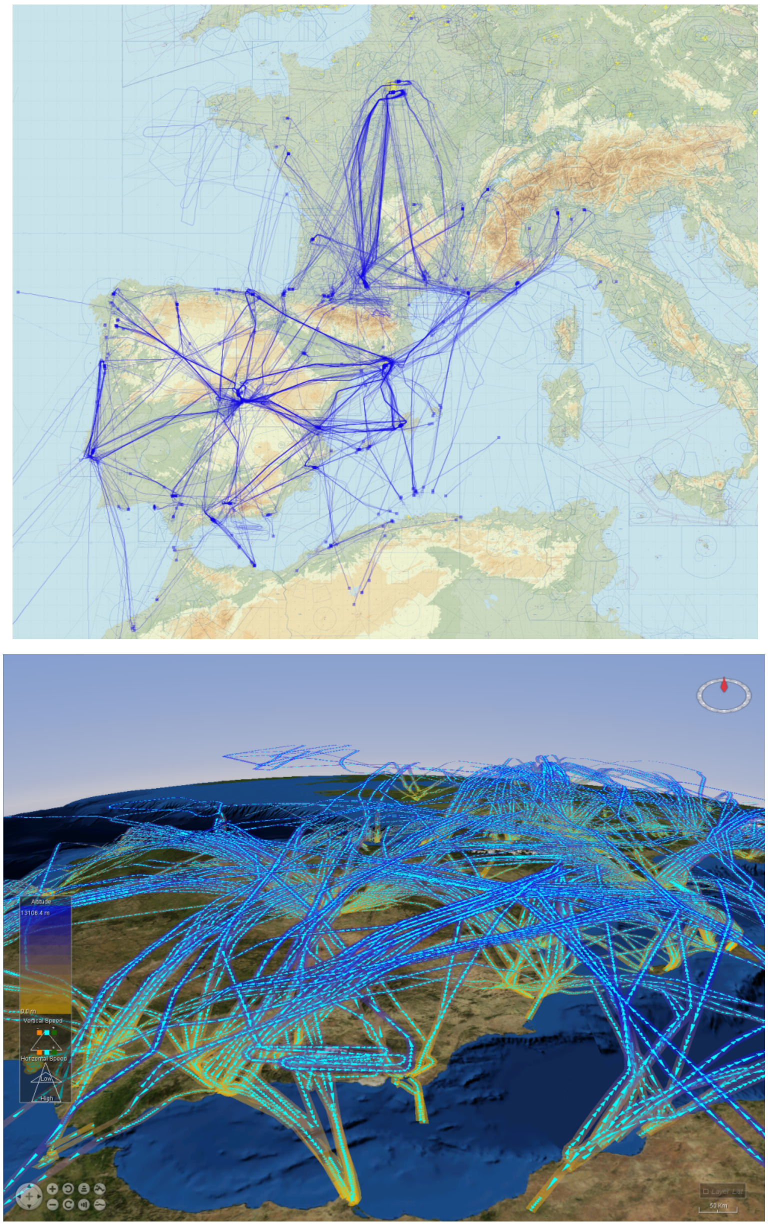

Figure 2 Visualization FlightAware surveillance data of short- and mid-haul flights for one day (December 1st, 2016) in 2D (top) and 3D (bottom). Images are provided by Fraunhofer Institute IAIS .

An interesting property of movement data is the different restrictions that apply to the analyzed objects. Road traffic for instance, has to follow roads and obey speed limits. By contrast, air traffic is

Copyright 2017 DART

This document has been produced within the scope of the DART project. The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members
EUROPEAN UNION EUROCONTROL

subject to numerous regulations and flight rules. With growing numbers of flights every day, keeping track of and understanding air traffic for security and regulatory reasons, a lot of research interest is present in the topic. For the analysis of multiples of trajectories, Hurter et al. [Hurter et al., 2009] presented a comprehensive framework that allows the user to visualize a limited set of features interactively, supported by extensive brushing- and linking capabilities. Klein et al. [Klein et al., 2014] build upon the aforementioned solution and claim to furthermore be able to visually identify pattern changes in flight trajectories both locally and globally. Buschmann et al. [Buschmann et al., 2014] present another 2D/3D approach to the visualization of massive aircraft trajectories and provide responsive techniques for filtering, aggregation and mapping of attributes. Vrotzou et al. [Vrotzou et al., 2015] introduce a method that combines 3D visualization of trajectories combined with a regionalization-based trajectory segmentation approach that facilitates both geometric simplification and classification into different flight phases, simultaneously. Another approach by Albrecht et al. [Albrecht et al., 2012] abstracts from single trajectories to density maps of air traffic, also making it possible to show path conflict probabilities in a density map.

As predictions always incorporate uncertainty about the results, several approaches to uncertainty visualization have been proposed. Kinkeldey et al. [Kinkeldey et al., 2014] apply pixel noise to the edges of a grid to encode degree of uncertainty. Cedilnik et al. [Cedilnik et al., 2000] use the edges of a procedural grid to display uncertainty by applying distortion - the more uniform the grid is, the less uncertain the underlying data are. By contrast, Buchmüller at al. [Buchmueller et al., 2015] examine different encodings applied to grid cells of aggregated individual trajectory predictions, as well as interactions to support exploration.

© – 2017 – DART Consortium.

All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

4 The DART Project

4.1 Project Objectives

The main research objective of the DART (Data-driven AiRcraft Trajectory prediction research) project is to explore the application of advanced data-driven techniques to the aircraft trajectory prediction problem, accounting also for the complexity of ATM network effects. As part of this objective DART emphasizes the role that visualization techniques can have in facilitating trajectory predictions.

To achieve this high-level main research objective, and according to the issues identified in the previous sections of this article, the following specific research objectives have been defined:

- Definition of requirements for the input datasets to be exploited. The requirements will target to increasing the trajectory prediction accuracy.
- Study of big data techniques to trajectory-related data gathering, filtering, storing, indexing or segmentation to support the generation of reliable and homogenous input datasets.
- Study of different data-driven machine learning techniques to describe how a reliable trajectory prediction model will leverage different datasets.
- Formal description of the complexity network of the ATM socio-technical system, to support correlated, multiple trajectory predictions.
- Study of the application of agent-based models to the prediction of multiple correlated trajectories, considering the ATM complexity network.
- 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.

The main goal of DART is to deliver understanding on the suitability of applying data-driven techniques for predicting single and multiple correlated aircraft trajectories. The outcomes of these techniques will be comparable to any such method, thanks to the common dataset infrastructure developed in the project.

Therefore, DART addresses challenges towards producing high-quality and extensive datasets from well-known data sources with operational origin, exploiting as many features as possible –extracted from data sources- in combination, towards increasing prediction accuracy and efficiency. Doing so, DART provides unique datasets for training and testing different data-driven approaches for trajectory prediction. These datasets comprise several years of data, paving the way to the research objectives that DART pursues.

4.2 Approach and Methodology

Copyright 2017 DART

This document has been produced within the scope of the DART project. The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members

EUROPEAN UNION EUROCONTROL

As already said, the variety and heterogeneity of the data sources adds high complexity to the data fusion process.

The DART project explores alternatives for developing extensible datasets, gathering inputs from disparate data sources that are expected to provide valuable information to the data-driven trajectory prediction process.

In general, the data-driven approach followed by DART consists of two – rather standard – phases: supervised learning phase and learned/operational phase. During the former, the system learns how to associate and classify the available data with the information related to trajectories. During the latter, once the system has trained, the learned model is evaluated for aircraft trajectory prediction in real-world conditions.

Since not every attribute in the datasets may be potentially and equally significant in terms of predicting aircraft trajectories, the important features to be used by the underlying machine learning algorithms must be identified and extracted from the datasets. The feature subsets may be different for different learning algorithms. Timing information is key to align different sets of features together assuring unified datasets for training and testing of methods. However, timing information may not be directly available in some of the data sources: this may be derived by data analysis methods, while alternative ways to interlink data from different sources are examined.

DART evaluates different kinds of supervised-learning algorithms: Hidden Markov Models, Kernel-based distance metrics and advanced machine learning models, and ensembles for non-linear regression. Algorithm parameters are steered through interactive visual interfaces that support examination of data quality, impact of parameters, allowing also exploration of derived patterns from multiple perspectives (locations/areas in space, time moments and intervals, trajectories of aircraft and their clusters, events such as interrupted landings, etc.).

The expected outcome of this learning process is a Data-Driven Single Trajectory Predictor (DDSTP). A set of scenarios have been defined to validate the DDSTP against different model-based TPs (e.g., FMS, flight planning tool, TP prototypes).

Predicted trajectories are used in a collaborative trajectory prediction scenario as part of a prediction loop using Reinforcement Learning (RL) algorithms. The objective of this scenario is to understand if an agent-based model is capable of adapting the DDSTP in a way that its predictions can consider the effect of other trajectories, i.e., other flights, and potential exogenous factors, focusing on traffic and contextual features affecting trajectories, thus accounting for the ATM complexity network effects. Reinforcement learning techniques allow agents in such a socio-technical system to learn and adapt to new situations online, depending on their action capabilities.

Our goal in DART is to develop collaborative RL algorithms that will be applied to multiple co-occurring predicted trajectories, taking into account data from multiple sources, while learning in very few samples.

To evaluate predictions made, several testing datasets have been identified, serving as representatives of a variety of operational scenarios (i.e., nominal operation conditions, high-density traffic, low-density traffic, bad weather). These datasets are not to be used for training the algorithms. They will be used only for assessing the predictability of each algorithm studied in a comparable way. The same process is repeated with datasets that reflect the same operational

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

scenarios, but that were used for training and modelling the system. Experimental results for every solution are obtained separately and compared to each other, to gain deep understanding of solutions' performance.

The specific procedure for evaluating each of the data-driven algorithms is to replay them individually, comparing the predictions from DART with the observed behaviour of flights, benchmarking the results with respect to other known and available trajectory predictors.

4.3 ATM Operational Context of Research

The DART operational scenarios for trajectory predictions assume that the process of predicting traffic happens at the planning phase (i.e., during three days before operation). The scenarios are developed in Spain, where the ANSP is represented by one of the project partners (CRIDA) at the local level. On the other hand, airspace users are represented by Boeing Research & Technology – Europe (BR&T-E). In the single trajectory prediction scenario the separation among aircrafts is guaranteed, thus the scenario considers that resolutions adopted by Air Traffic Control Operators are out of its scope. The scenario also assumes that there will not be any regulations applied by the Network Manager.

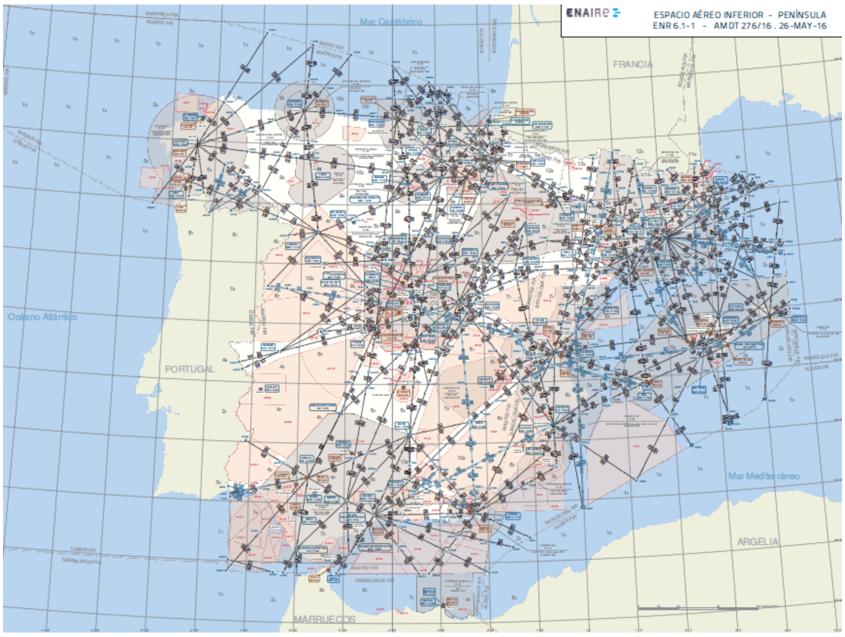

Figure 3 The Geographical Area considered in DART (ENAIRE)

Considering the ATM network effects and multiple trajectories prediction, the objective in DART is to demonstrate how predictive analytics capability can help in trajectory forecasting when demand exceeds sectors' capacity (i.e. the Demand and Capacity Balance (DCB) process). Doing so, DART aims to study and determine the complexity to be considered in a trajectory prediction due to the influence of the surrounding traffic.

Copyright 2017 DART

This document has been produced within the scope of the DART project. The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members
EUROPEAN UNION EUROCONTROL

Resolutions adopted by ATCO are not considered in this operational scenario, since it happens in the planning phase. The objective is to predict regulations of type C (i.e. delays) that will be applied to the trajectories, due to the imbalance between demand and capacity.

The datasets available for both scenarios include:

- Weather Data (METAR, NOAA, SIGMET)
- Reconstructed Trajectories obtained from surveillance data, and the associated Aircraft Intent (AI) descriptions. In order to facilitate the process of training and validating the algorithms, an enhanced set of AI descriptions will be used during the initial stages of the project.
- Flight Plans providing the flight intentions.
- Sectorization information available from the day of operation (airspace configuration and airblocks)
- Radar Tracks (IFS) of actual trajectories
- Historical data (real flown trajectories, associated historical flight plans, and weather information at operation days)

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

5 Target Outcomes and Expected Impact

Trajectory prediction capabilities are at the core of the most advanced decision support systems required in the future trajectory-based operations' environment. Predictions are used at strategic level, when designing the airspace structure and planning the traffic flow, and at tactical level for conflict detection and resolution, traffic management and even collision avoidance.

Data science is being pervasively applied to many businesses today; it is easy to find many success stories in which the application of modern big-data technologies boost developments that were out of the mind of anybody a few years ago. It has even made room for provoking proposals like the now famous from Anderson, Chris: "The end of theory: The Data Deluge Makes the Scientific Method Obsolete." Wired magazine 16.7 (2008): 16-07.

DART aims to present to the ATM community an understanding on what can be achieved today in trajectory prediction by using data-driven and agent-based modelling techniques. It is expected that data-driven techniques help to improve the performance and accuracy of predictions by complementing classical model-based prediction approaches, while agent-modelling techniques can further enhance our abilities to predict trajectories, also accounting for real-world complex phenomena. These improved predictions will enable advanced collaborative decision making processes, which finally will lead to more efficient and effective ATM procedures.

The final goal for ATM community in this case is the improvement in predictability, which is usually considered as one of the main (if not the principal) ATM performance drivers. By increasing predictability uncertainty can be considerably reduced; capacity buffers can be reduced, thus decreasing values of unused capacity and increasing effective capacity allocation; arrival punctuality can be improved, thus enhancing airport operations and reducing both primary and reactionary delays. In addition to these, improvements in flight efficiency (caused by a more likely adherence to the agreed trajectory) and in safety can be expected.

These are particularly compliant with the vision expressed in Flightpath 2050 [FlightPath2050] report of the High Level Group on Aviation Research of the European Commission. The report sets highly ambitious goals, focusing on meeting societal and market needs, maintaining and extending industrial leadership, protecting the environment and the energy supply, ensuring safety and security, and prioritising research, testing capabilities and education.

Flightpath 2050 clearly sets that the passenger experience will be paramount. It sets specific goals in this context. Two of these goals are outstanding in terms of enhanced predictability:

- 90% of travellers within Europe are able to complete their journey, door-to-door within 4 hours. Passenger and freight are able to transfer seamlessly between transport modes to reach the final destination smoothly, predictably and on-time.
- Flights arrive within 1 minute of the planned arrival time regardless of weather conditions. The transport system is resilient against disruptive events and is capable of automatically and

Copyright 2017 DART

This document has been produced within the scope of the DART project. The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members

EUROPEAN UNION EUROCONTROL

dynamically reconfiguring the journey within the network to meet the needs of the traveller if disruption occurs. Special mission flights can be completed in the majority of weather, atmospheric conditions and operational environments.

Predictability is a key enabler for reaching the aforementioned objectives, with direct influence in other important aspects. The DART project fully aligns its activities in this direction, paving the way to the future of ATM.

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

References

[Albrecht et al., 2012] Albrecht, G. H.; Lee, H. T. & Pang, A. Visual Analysis of Air Traffic Data Using Aircraft Density and Conflict Probability. Infotech@ Aerospace 2012, 2012.

[Alligier et al., 2015a] Alligier, R., Gianazza D., and Durand N., "Machine learning applied to airspeed prediction during climb." ATM seminar 2015, 11th USA/EUROPE Air Traffic Management R&D Seminar, 2015.

[Alligier et al., 2015b] Alligier, R., Gianazza D., and Durand N., "Machine learning and mass estimation methods for ground-based aircraft climb prediction." IEEE Transactions on Intelligent Transportation Systems 16.6: 3138-3149, 2015.

[Andrienko et al., 2007] Andrienko, G.; Andrienko, N. & Wrobel, S. Visual Analytics Tools for Analysis of Movement Data. SIGKDD Explor. Newsl., ACM, 9(2), 38-46 , 2007.

[Andrienko et al., 2013] Andrienko, G.; Andrienko, N.; Bak, P.; Keim, D. A. & Wrobel, S. Visual Analytics of Movement. Springer, 2013.

[Ayhan et al., 2016] Ayhan, S., and Hanan S., "Aircraft trajectory prediction made easy with predictive analytics." Proc. of the 22nd Intl'Conf. on Knowledge Discovery and Data Mining, 2016.

[BADA] “https://www.eurocontrol.int/services/bada,” [Online].

[Buchmueller et al., 2015] J.Buchmuller, H.Janetzko, G.Andrienko, N.Andrienko, G.Fuchs, and D.A.Keim. Visual Analytics for Exploring Local Impact of Air Traffic. Compurter Graphics Forum, vol. 34(3), pp.181-190, 2015.

[Buschmann et al., 2014] Buschmann, S.; Trapp, M. & Döllner, J. Real-Time Animated Visualization of Massive Air-Traffic Trajectories. Proceedings of CyberWorlds 2014, IEEE Computer Society , 172-181, 2014.

[Cedilnik et al., 2000] Cedilnik, A. & Rheingans, P. Procedural annotation of uncertain information. Visualization 2000. Proceedings, 77-84, 2000.

[de Leege et al., 2013] de Leege, M. van Paassen and M. Mulder, A Machine Learning Approach to Trajectory Prediction, 2013.

[Dykes et al., 2003] Dykes, J. A. & Mountain, D. M. Seeking structure in records of spatio-temporal behaviour: visualization issues, efforts and applications. Computational Statistics & Data Analysis, Elsevier, 43(4), 581-603, 2003.

[FlightPath2050] “Flightpath 2050,” European Commission - Europa. Online. Available: http://ec.europa.eu/transport/modes/air/doc/flightpath2050.pdf.

[Guestrin et al., 2002] Guestrin G. and et al., “Coordinated Reinforcement Learning.,” ICML, 2002.

Copyright 2017 DART

This document has been produced within the scope of the DART project.
The utilisation and release of this document is subject to the conditions
of the Grant Agreement no.699299 within the H2020 Framework
Programme, and the Consortium Agreement signed by partners.

Founding Members

EUROPEAN UNION EUROCONTROL

[Guo et al., 2011] Guo, H.; Wang, Z.; Yu, B.; Zhao, H. & Yuan, X. TripVista: Triple perspective visual trajectory analytics and its application on microscopic traffic data at a road intersection. Pacific Visualization Symposium (PacificVis), 2011 IEEE, 2011, 163-170, 2011.

[Hamed et al., 2013] Hamed M. G. and et al., “Statistical prediction of aircraft trajectory: regression methods vs point-mass model.,” in ATM 2013, 10th USA/Europe Air Traffic Management Research and Development Seminar ,13 Jun. 2013.

[Hong et al., 2015] Hong S. and Lee K., “Trajectory Prediction for Vectored Area Navigation Arrivals.,” Journal of Aerospace Information Systems, 2015.

[Hurter et al., 2009] Hurter, C.; Tissoires, B. & Conversy, S. FromDaDy: Spreading Aircraft Trajectories Across Views to Support Iterative Queries. IEEE Transactions on Visualization and Computer Graphics, IEEE Educational Activities Department, 15(6), 1017-1024, 2009.

[Kapler et al., 2005] Kapler, T. & Wright, W. GeoTime information visualization. Information Visualization, SAGE Publications, 4(2), 136-146, 2005.

[Kinkeldey et al., 2014] Kinkeldey, C.; Mason, J.; Klippel, A. & Schiewe, J. Evaluation of noise annotation lines: using noise to represent thematic uncertainty in maps. Cartography and Geographic Information Science, 41(5), 430-439, 2014.

[Klein et al., 2014] Klein, T. R.; van der Zwan, M. & Telea, A. Dynamic Multiscale Visualization of Flight Data. VISAPP (1), 104-114, 2014.

[Kok et al., 2006] Kok J.R. and Vlassis N., “Collaborative multiagent reinforcement learning by payoff propagation,” JMLR, 2006.

[Kun et al., 2008] Kun W. and Wei P., “A 4-D trajectory prediction model based on radar data.,” in Control Conference, 2008. CCC 2008. 27th Chinese Control Conference, 16 Jul. 2008.

[Le Fablec et al., 1999] Le Fablec Y. and Alliot J.-M. , “Using Neural Networks to Predict Aircraft Trajectories.,” in IC-AI, 1999.

[Lopez-Leones et al., 2007]J. Lopez-Leones, M. Vilaplana, E. Gallo, F. Navarro and C. Querejeta, “The Aircraft Intent Description Language: A key enabler for air-ground synchronization in Trajectory-Based Operations,” in Digital Avionics Systems Conference, DASC '07. IEEE/A., 2007.

[Lundbladet al., 2009] Lundblad, P.; Eurenius, O. & Heldring, T. Interactive visualization of weather and ship data. Information Visualisation, 2009 13th International Conference, 379-386, 2009.

[NextGen] NextGen, https://www.faa.gov/nextgen/

[SESAR2020] SESAR 2020, http://www.sesarju.eu/

[Taoya et al., 2003] Cheng, Taoya, D. Cui and Cheng P., “Data mining for air traffic flow forecasting: a hybrid model of neural network and statistical analysis.,” in Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE 12 Oct. 2003: 211-21, 2003.

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions.

[Tastambekov et al., 2014] Tastambekov K. and et al, “Aircraft trajectory forecasting using local functional regression in Sobolev space”, Transportation research part C: emerging technologies, vol. 39, pp. 1-22, 2014.

[Thomas et al., 2005] Thomas J. J. and Cook K. A., Illuminating the path:[the research and development agenda for visual analytics]. IEEE Computer Society, 2005.

[Tominski et al., 2012] Tominski, C.; Schumann, H.; Andrienko, G. & Andrienko, N. Stacking-based visualization of trajectory attribute data. Visualization and Computer Graphics, IEEE Transactions on, IEEE, 18(12), 2565-2574, 2012.

[Vouros 2017] Vouros G., “Learning Conventions via Social Reinforcement Learning in Complex and Open Settings”, to appear in Proc. of AAMAS 2017, Sao Paulo. Brazil, 2017.

[Vrotzou et al., 2015] Katerina Vrotsou, Halldor Janetzko, Carlo Navarra, Georg Fuchs, David Spretke, Florian Mansmann, Natalia Andrienko, and Gennady Andrienko. SimpliFly: A Methodology for Simplification and Thematic Enhancement of Trajectories. IEEE Transactions on Visualization and Computer Graphics, vol. 21(1), pp.107-121, 2015.

[Ware et al., 2006] Ware, C., A. R. P. M. & Wiley, D. Visualizing the Underwater Behavior of Humpback Whales. IEEE Computer Graphics and Applications, 26(4), 14-18, 2006.

[Willems et al., 2009] Willems, N.; Van De Wetering, H. & Van Wijk, J. J., Visualization of vessel movements. Computer Graphics Forum, 28(3), 959-966, 2009.

[Yang et al., 2015] Yang, Y., Zhang, J., and Cai K., "Terminal-area aircraft intent inference approach based on online trajectory clustering." The Scientific World Journal, 2015.

[Yepes et al., 2007] Yepes, J. L., Hwang I., and Rotea M., "New algorithms for aircraft intent inference and trajectory prediction." Journal of guidance, control, and dynamics 30.2: 370-382, 2007

[Yue et al., 2012] Yue S. , Cheng P. and Mu C. , “An improved trajectory prediction algorithm based on trajectory data mining for air traffic management,” in Information and Automation (ICIA), 2012 International Conference, 6 Jun., 2012.

Copyright 2017 DART

This document has been produced within the scope of the DART project.
The utilisation and release of this document is subject to the conditions of the Grant Agreement no.699299 within the H2020 Framework Programme, and the Consortium Agreement signed by partners.

Founding Members

EUROPEAN UNION EUROCONTROL

The DART consortium

University of Piraeus Research Center (UPRC)	
Boeing Research and Technology Europe (BR&TE)	
Centro De Referentia Investigation, Desarrollo E Innovation ATM (CRIDA)	
Fraunhofer-Gesellschaft zur Foerderung der Angewandten Forschung E.V (FRHF)	

DART website: http://dart-research.eu/

Contact Information:

Prof. George Vouros, Project Coordinator,
University of Piraeus
Email: georgev@unipi.gr
Tel: + 30 210 4142552

Founding Members

© – 2017 – DART Consortium.
All rights reserved. Licensed to the SESAR Joint Undertaking under conditions