COLLABORATIVE TRAJECTORY PREDICTION SCENARIOS AND REQUIREMENTS SPECIFICATION

DART
Grant: 699299
Call: ER-2-2015
Topic: Data Science in ATM
Consortium coordinator: University of Piraeus Research Center
Edition date: 18 April 2017
Edition: [02.00.00]

Founding Members

EUROPEAN UNION EUROCONTROL

SESAR JOINT UNDERTAKING

Authoring & Approval

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Document History

Edition	Date	Status	Author	Justification
00.00.01	16/09/2016	First Draft	Lucía Meler Carcía	
00.05.00	18/11/2016	First Draft with	George Vouros	

		comments		
00.05.05	23/11/2016		Lucía Meler Carcía	First draft with all comments addressed and answered
00.08.00	01/12/2016	Second draft	George Vouros , Georgios Chalkiadakis, Konstantinos Blekas	Complete draft
00.01.00	16/12/2016	Final Document	George Vouros , Georgios Chalkiadakis, Konstantinos Blekas	Final document with all comments of reviewers addressed.
00.02.00	18/04/2017	Final Document	George Vouros	Final document with all comments from SJU addressed.

DART

DATA DRIVEN AIRCRAFT TRAJECTORY PREDICTION RESEARCH

This document is part of a project that has received funding from the SESAR Joint Undertaking under Grant Agreement No 699299 under European Union's Horizon 2020 research and innovation programme.

Abstract

This document describes the ATM Operational Contex and the trajectory prediction scenarios of the DART project according to the objectives established. As such, this document describes the overall operational context of research, and in particular ATM processes in the context of DCB. In addition, the deliverable includes a high level description of the operational scenarios proposed in WP2 and WP3 for validating the DART technical approach to data-driven trajectory prediction. The deliverable concludes with specifying concrete requirements for interactions among DART components and requirements for the visualization and visual analytics methods to be developed.[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.

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Executive Summary

This document details two aspects that are critical to developments in DART. The first is related to the ATM Operational Context assumed in DART; the second is the scope of the project, which considers a demand and capacity balancing application based on data-driven trajectory and traffic predictions. Demand and Capacity Balancing (DCB) is organised mainly in three phases, depending on the look-ahead time: strategic, planning and tactical. The project will focus exclusively on the planning phase (from days to hours prior the operation), aiming at improving the predictability of the traffic count within an airspace volume, and, therefore increasing the effectiveness demand and capacity balancing procedures.

This deliverable specifies also the trajectory evolution during the DCB process, which has a strong connection with trajectory prediction aimed in DART. Specifically, DART concerns planning at the pre-tactical phase, so a predicted trajectory will be considered as the Shared Business Trajectory, which is the one agreed by stakeholders of Air Traffic Flow Management (ATFM) services. Nowadays, one of the challenges is to be able to predict trajectories as accurately as possible, compared to the actual trajectory, taking into account factors such as weather, user preferences, ATM constrains (e.g., expected demand or airspace capacity).

Due to the fact that the requirements of both WP2 and WP3 are different, two types of scenarios have been designed. The first considers the airspace users' point of view. This first scenario aims at predicting a single trajectory, isolated from other trajectories, according to WP2 purposes. The second scenario assumes the Air Navigation Service Provider's (ANSP) point of view, in which a collaborative trajectory prediction problem needs to be solved, taking into account traffic, according to WP3 purposes. Therefore, the WP3 operational scenario should take into account multiple trajectories predicted by WP2, their interactions with respect to the DCB problems and foresee the regulations to be applied to these trajectories. The document offers a general overview of both scenarios taking into account the scope, characteristics, required data and potential performance metrics.

Finally, the document specifies interactions among the methods to be developed in WP2 and WP3, together with requirements from visualizations and visual analytics methods.

1 Introduction

1.1 Purpose and Scope

This deliverable reports on the scenario(s) for collaborative trajectory predictions, specifying geographical areas to be considered, actual states/stages to be considered when performing trajectory prediction, types of trajectory "interactions" and data to be considered. In conjunction to scenarios specification, the specification of requirements for the algorithms to be developed are reported and algorithms' evaluation criteria are specified.

1.2 Intended readership

This document is intended to be used by DART members.

1.3 Acronyms and Terminology

Term	Definition
ALS	Alert Service
ADP	ATFM Daily Plan
AIDL	Aircraft Intent Description Language
AIS	Aeronautical Information Services
ANM	ATFM Notification Message
ANS	Air Navigation Service
ANSP	Air Navigation Service Provider
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
ATC	Air Traffic Control
ATCO	Air Traffic Controller
AO	Airline Operator
AOP	Airport Operator
AU	Airspace User

BT	Business Trajectory
SBT	Shared Business Trajectory
RBT	Reference Business Trajectory
CDM	Collaborative Decision Making
CFMU	Central Flow Management Unit
CFS	Certificate on the Financial Statements
DCB	Demand and Capacity Balancing
DDSTP	Data Driven Single Trajectory Prediction
DMP	Data Management Plan
FIS	Flight Information Service
FMP	Flow Manager Position
GA	General Assembly
H	Humans
HEC	Hourly Entry Count
Horizon 2020	EU Research and Innovation programme implementing the Innovation Union, a Europe 2020 flagship initiative aimed at securing Europe's global competitiveness.
ICAO	International Civil Aviation Organisation
IPR	Intellectual Property Rights
KPI	Key Performance Indicator
NM	Network Manager
NOP	Network Operation Plan
OCC	Ocupancy
PMP	Project Management Plan
POPD	Protection of Personal Data
PRC	Performance Review Commission
RAD	Route Avaliabilty Document
TRL	Technology Readiness Level
SESAR	Single European Sky ATM Research Programme
SJU	SESAR Joint Undertaking (Agency of the European Commission)
SJU Work Programme	The programme which addresses all activities of the SESAR Joint Undertaking Agency.

SESAR Programme	The programme which defines the Research and Development activities and Projects for the SJU.
SSR	Secondary Surveillance Radar
WBS	Work Breakdown Structure
WP	Work Package

Table 1: Acronyms and Terminology

1.4 Relation to other Work Packages and Deliverables

This deliverable is related to the DART Data Management Plan (D1.1), and its subsequent developments, as D1.1 describes all data that the project will collect, exploit and generated. Thus, this deliverable serves as a first validation of the sufficiency and necessity of all the data sources described in D1.1. Concerning WP2, this deliverable specifies the operational context where trajectory predictions will be computed, thus specifying the scope and requirements from such computations. Finally, concerning WP3, this deliverable plays a crucial role, given that the problem formulation concerning collaborative prediction of trajectories, the DART approach towards it and computational methods to be chosen and further developments will be driven by it. Overall, this deliverable can serve as a basis to validating DART developments in subsequent project stages, towards application oriented research.

1.5 Research Approach and Expected Results

WP3 Collaborative Trajectory Prediction is devoted to unveil the complexity to be considered in a trajectory prediction due to the influence of the surrounding traffic. Relying on the individual trajectory predictions provided by WP2, the application of reinforcement learning algorithms in an agent-based trajectory prediction framework will be studied in order to obtain improved predictions thanks to the consideration of ATM network effects.

According to task 3.1 entitled “Scenarios setup and specification of requirements”, the aim of this task is to setup the scenario(s) for collaborative trajectory predictions, specifying geographical areas to be considered, actual states/stages to be considered when performing trajectory prediction, co-occurring number of aircrafts, data to be considered. The task will produce, in conjunction to scenarios specification, the specification of requirements for the algorithms to be developed: Issues concerning features to be considered when describing recurring situations and contextual information, how to measure the “goodness” of trajectories depending on the context in which they occur, situations to be avoided when multiple aircrafts co-occur, and interactions among aircrafts’ trajectories, must be stated. Finally, algorithms’ evaluation criteria will be specified.

The objective is to understand if an agent-based model is capable of adapting the Data Driven Single Trajectory Prediction (DDSTP) in a way that its predictions can consider the effect of other trajectories, interacting (whatever this means) among themselves, also considering exogenous factors, such as weather updates, airspace changes or airline or ATC commands. The notion of Reinforcement Learning (RL) is to construct an intelligent platform that allows the adaptation of agents to unknown environments through learning and interaction. RL is a paradigm for learning sequential decision making tasks (e.g. trajectories), usually formulated as a Markov Decision Process (MDP). For an RL algorithm to be practical for trajectory prediction tasks using multiple data sources, it *ideally* must learn in very few samples. These are challenging issues that although they have been used for controlling unmanned vehicles, only a little work has been made for the prediction of agent's behavior in an environment taking into account behaviors of neighborhood agents: Thus, collaborative learning techniques must be developed. However, joint agents' decisions based on their interactions, their overall context and past experiences complicate computations, require communication and do not guarantee convergence given the dynamics of the overall context. Indeed, the predictions for any agent may change, while the predictions of others in its neighbourhood may also change at the same time.

Our goal in DART is to develop collaborative RL algorithms that will be trained in batch mode (i.e. offline) and will be applied to real-time prediction of trajectories of multiple aircrafts co-occurring in specific contexts, taking into account data from multiple sources, including single trajectory predictions, historic data concerning actual trajectories, while learning in very few samples.

Evaluation of results should obtain quantifiable assessments (metrics) of the methodologies and techniques applied in DART. For this purpose, several testing datasets will be identified at an initial stage as representative of a variety of operational scenarios (i.e., nominal operation conditions, high-density traffic, low-density traffic, varying weather conditions, etc.). These datasets will not be used for the training phase of the algorithms, and they will be used for testing every potential data science technique and assess its results independently of the training, and in a comparable way. The same process will be repeated with datasets that reflect the same operational scenarios, but that were used for training and modelling the system. Experimental results for every solution will be obtained separately and compared to each other, to gain deep understanding of solutions' performance.

The specific procedure for evaluating this set of scenarios will be, in every case, to replay them individually, comparing the predictions from DART with the later observed flights (this can be done as the datasets contain every snapshot of flight plan status, from planning phase to flight cancellation after landing, as well as the real flown trajectories), benchmarking the results with respect to other known and available trajectory predictors (i.e. FMS, flight planning tool or TP system).

2 ATM Operational Context

2.1 Air Navigation Services Organization

Air Navigation is the combination of procedures and techniques that make possible an aircraft to fly from an origin to a destination. It is formed by many services supporting this purpose. Each country has mainly the same organization of such services, following the ICAO rules for air navigation. [1] [2]

Air Navigation System is divided in three main services.

The first one is the **Aeronautical Information Service (AIS).** AIS is provided by Aeronautical Information Division to all users requesting it. AIS provides the necessary information so as to ensure that aeronautical operations are developed with safety, regularity, economy and efficiency. All the information is made public and distributed by the Air Navigation Service Provider of each country. [3]

Meteorological Services contribute towards the safety, regularity and efficiency of international air navigation by the provision of timely and accurate weather information. It will be apparent that aircrew must be able to access accurate weather information when planning their flight and given the changing nature of the earth's weather patterns this information will need to be updated as necessary, ensuring that a planned flight can be completed safely [4]. This is achieved by providing necessary meteorological information to aircraft operators, flight crew, air traffic services units and airport management through network of international communication systems which ensures close liaison between all stakeholders.

Air Traffic Management primarily consists of three distinct activities:

Airspace Service Management (ASM): The other activity in ATM is the Airspace Service Management (ASM). This service is responsible for airspace's planning and management. The main objective of this service is to allow safety, efficient and effective aircraft's operations (Sanz, Valdés, Nierto, Monge, & Comendador). The service works in these main aspects: to build an airspace structure, to maintain airways (aircraft's routes) and to coordinate civil and military activity

Air Traffic Control: It's the process by which aircrafts are safely separated as they fly and at the airports where they land and take off. Tower control at airports is a familiar concept regarding air traffic control, but aircrafts are also separated as they fly en route; Europe has many large Air Traffic Control Centres which guide aircrafts to and from terminal areas around airports [2].

Air Traffic Flow Management: It is an activity that is done before flights take place. Any aircraft using air traffic control, from a business aeroplane to an airliner, files a flight plan and sends it to a central repository. All flight plans for flying into, out of and within Europe are analysed and computed [3].

2.2 Air Traffic and Flow Capacity Management (ATFCM)

Europe has a complex airspace, where 30.000 aircrafts usually overfly its sky. Therefore, it is one of the airspaces with most activity in the world. ATFCM service appears in ninety's, where European airspace has a huge lack of capacity taken into account the growth of demand. For this reason, a service available to handle capacity and demand balancing appeared early in ninety's [5] [6] [7] .

The objective is to optimize traffic flows according to air traffic control capacity while enabling airlines to operate safe and efficient flights. Planning operations start as early as possible - sometimes more than one year in advance: Air traffic forecasts issued are consolidated by the aviation industry and the capacity plans issued by the Air Traffic Control Centers and airports. Also operational scenarios to anticipate specific events, which may cause congestion (such as sporting events, Christmas skiing or summer holiday traffic), are specified. Eventually, in case of an unforeseen event with major impact on traffic, a coordinated response to the crisis is organized.

Given that the objective is to protect ATC service of overload [7], this service is always looking for optimum traffic flow through a correct use of the capacity, guaranteed: safety, better use of capacity, equity, information sharing among stakeholders and fluency.

Coordination between actors in the system is necessary. The main actors involved are:

- Airline Operators (AO): Airlines must be informed of the regulations that are applied to their flights.
- Network Manager (NM): Central Position placed on Eurocontrol that is in charge of network monitoring in order to propose regulations to FMPs. Once these regulations are approved, these are applied to the flights affected.
- Flow Management Position (FMP): Local position placed at Airspace Control Centre (ACC) level that is in charge of network monitoring in order to approve the necessary regulations proposed by the NM.
- Airport Operators (AOP): Airports are the places where regulations are applied to specific flights. Operators must be informed of applied regulations to the flights while are still on the ground.

2.3 System and Temporal Scheme

ATFCM is organised in two levels. The NM is placed at the upper level and carries out four main functions:

- Route network design
- Central aeronautical frequency allocation for the European region
- Coordination of improvement of Secondary Surveillance Radar (SSR) code allocation
- Air Traffic Flow Management (ATFM)

NM tasks related with the capacity are delegated to Flow Manager Position (FMP).

The FMP is located at the Airspace Control Centre (ACC) level. A working position is established in an appropriate air traffic control unit to ensure the necessary interface with a central management unit on matters concerning the provision of the air traffic flow management service.

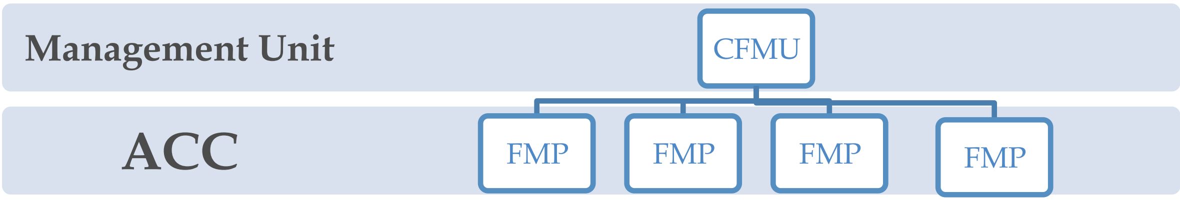

Figure 1 Framework of ATFCM service [5].

2.3.1 Temporal Scheme

The Demand and Capacity Balance (DCB) process is divided in three steps; each phase depends of the temporal horizon that will take place. Each phase has different objectives and results:

- Strategic Phase
- Planning Phase
- Tactical Phase

To obtain a good result of the service is necessary to have reliable information: FMP will have information of the capacity available and the expected demand will be the result of the Flight Plans presented.

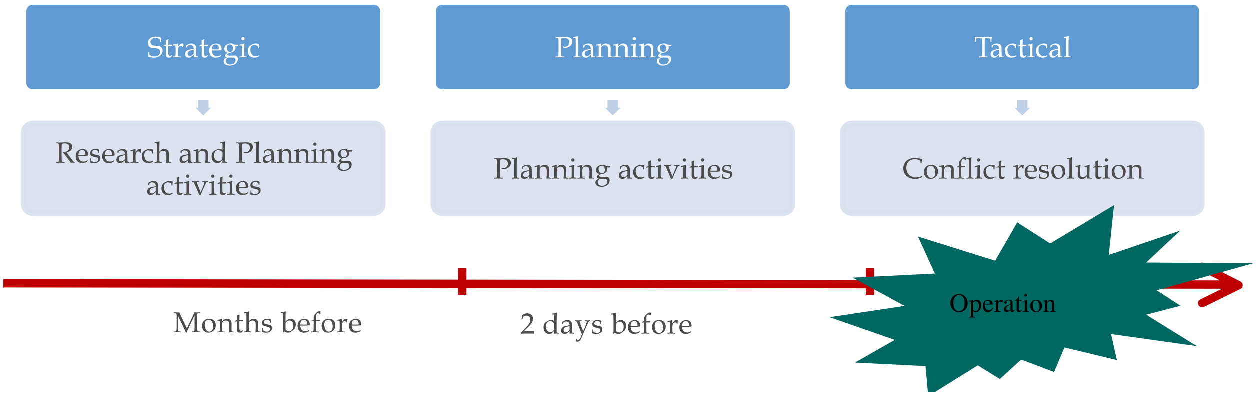

Figure 2 ATFCM Phases and Temporal Scheme

2.3.1.1 Strategic Phase

Strategic flow management takes place seven days or more, prior to the day of operations and includes research, planning and coordination activities through a Collaborative Decision Making (CDM) process. This phase comprises a continuous data collection with a review of procedures and measures directed towards an early identification of major demand / capacity imbalances (such as: axis management, air shows, major sport events, military exercises, etc.). The NM works with historical data and forecast demand[2]; in addition, airspace authorities inform about the capacity. When imbalances are identified, the NM is responsible for the overall coordination and execution of strategic ATFCM planning to optimize all available capacity and achieve performance targets. The output of this phase is the Route Availability Document (RAD), which is a document collecting all routes available for the operation day [8] [5].

2.3.1.2 Planning Phase

Pre-tactical flow management is applied during the six days prior to the day of operations and consists of planning and coordination activities. This phase studies the demand for the day of the operation, compares it with the predicted capacity on that day, and makes any necessary adjustments to the plan that was developed during the Strategic phase. At this phase, airlines send flight plans to the NM and FMP notify the NM about the available capacity; the NM crosses these two sources of information to detect problematic areas. The main objective of the pre-tactical phase is to optimise efficiency and balance demand and capacity through an effective organisation of resources (e.g., sector configuration management, use of scenarios, etc.) and the implementation of a wide range of appropriate ATFCM measures. The work methodology is based on a collaborative decision making (CDM) process between the stakeholders (e.g. the NM, FMPs, AOs). The output is the ATFCM Daily Plan (ADP) published via ATFCM Notification Message (ANM) / Network News and via the NOP portal [8].

2.3.1.3 Tactical Phase

Tactical flow management takes place on the day of operations and involves considering, in real time, those events that affect the ADP and make the necessary modifications to it. This phase aims at ensuring that the measures taken during the strategic and pre-tactical phases are the minimum required to solve the demand / capacity imbalances. The need to adjust the original plan may result from disturbances such as staffing problems, significant meteorological phenomena, crises and special events, unexpected limitations related to ground or air infrastructure, etc. and taking advantage of any opportunities that may arise. The provision of accurate information is of vital importance in this phase, since it permits short-term forecasts, given the impact of any event and maximises the existing capacity without jeopardising safety [8].

2.4 The Overall Process

During the development of the operation, NM acts as a link between the aircraft operator and the Air Traffic Services. Information flow can be established in the following way [5]:

- NM starts working with demand forecast, historical data and with capacity information from airspace authorities.

[2] NM works with historical data during strategic phase trying to detect possible hotspot in European airspace where demand will be higher than capacity. NM aims to infer the air traffic performance expected on the operation day based on past years. The output of this phase is a document (RAD) where NM sets out the routes available.

- Two days before operation, ATS units inform about the capacity that they could offer in the operation, as well as, they will have to inform about monitoring results. On the other hand, the aircraft operators send the flight plans to the NM. Once the NM had processed the information, the flight plans will be sent to ATS units.
- NM should use this information (capacity and demand) to accommodate the traffic and reach the objectives established. Then, they have to communicate the ATFM measures to the ATS units and the take-off time of the aircrafts is affected.
- The overall process needs a general coordination and a continuous information flow between aircraft operators and the NM. This coordination is necessary to guarantee the efficiency in the operation day, at real time (i.e. at any time instant).
- Operators receive the Calculated Time Of Take-off (CTOT) information and they have to notify about any change concerning the estimated off-block time.
- ATS units receive the information related to traffic, in terms of entry and exit time per flight and sector, and possible changes that can affect them.
- The group of affected ATS units provide necessary air traffic services for a specific flight with a CTOT. In this way, the forecasted entry time per flight and sector is obtained.

Next figure shows NM operational structure and the DCB process.

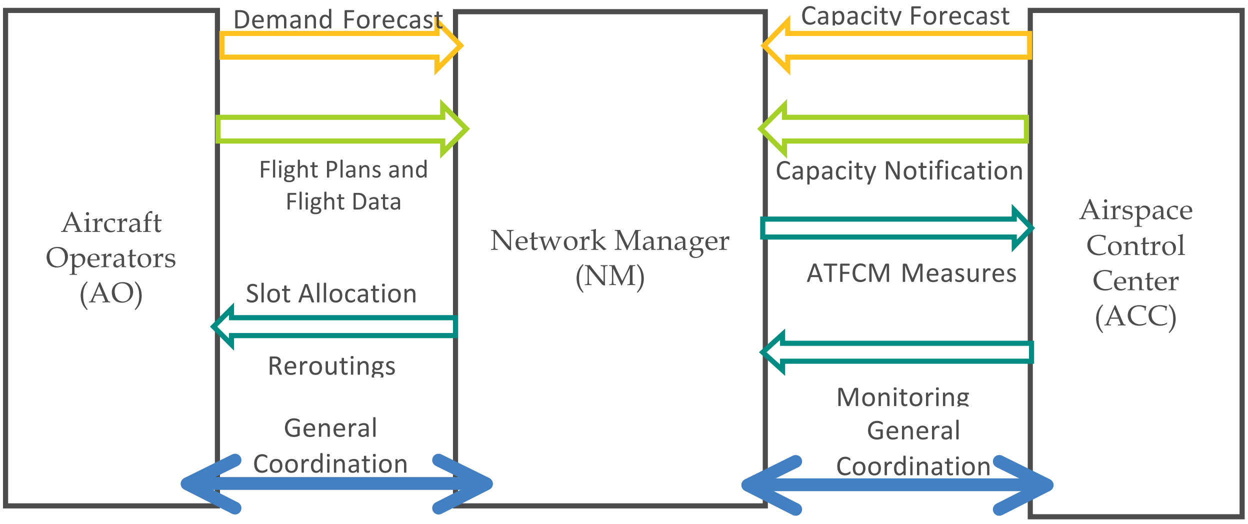

Figure 3 NM Operational Structure. Each arrow color denotes a phase of the DCB process: Yellow arrows are in the strategic phase, light green arrows are in the planning phase and dark green arrows are in the tactical phase [5] .

2.5 Trajectories in DCB

Currently, aircraft operators plan each flight in detail and then submit a less detailed flight to the relevant ACC and CFMU. The respective air traffic control units then compute these flight plans down to a detailed level in their respective prediction infrastructures.

2.5.1 Implementing 4D trajectories

The trajectory can be defined as the time evolution of the position of an aircraft. A typical trajectory is similar to the one shown in Figure 4. As ATFM is divided in three steps, trajectories inside DCB Process are divided in three phases as well (as shown in Figure 5 and explained in the next subsection). Thus, there is a predicted trajectory for each phase of the DCB process. The 4D trajectory concept requires that airspace users are able to agree the detailed 4D Business trajectory directly with the service providers involved in facilitating the flight in the specific airspaces concerned. Detailed positional information for the aircraft throughout the flight will be exchanged with all service providers on the route, as well as ascent and descent paths, and times will be agreed with departure and arrival airports in advance [9] [10].
Greater certainty about the position of every aircraft at any given moment will improve safety as well as planning of resources. More efficient resource planning implies more optimized use of the available capacity in airports and in the European sky.

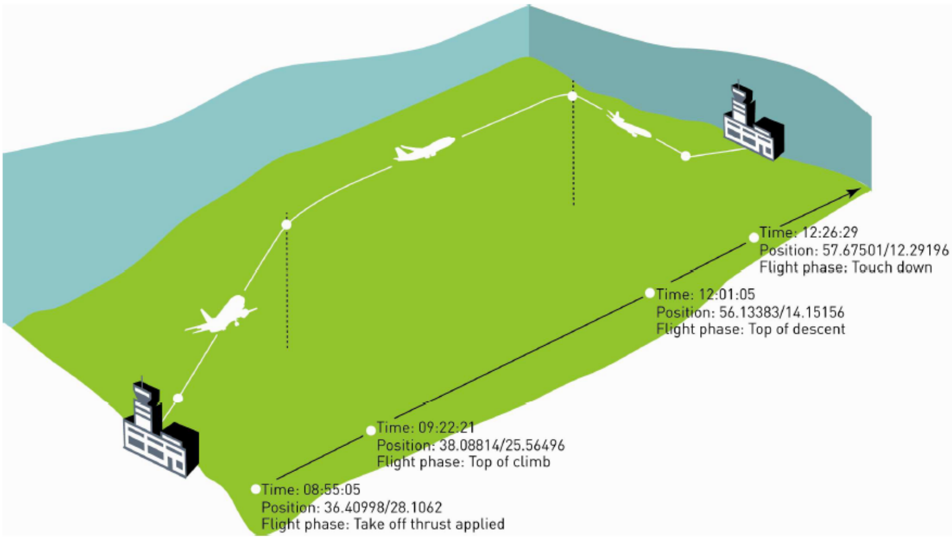

Figure 4 4D (three spatial dimensions plus time as a fourth dimension) trajectory of an aircraft [9].

2.5.2 Predicted Trajectory Evolution Process

There are three main steps that define the evolution of a predicted trajectory since the moment that an airline presents a prediction until the moment that the trajectory is eventually flown.

Business Development Phase takes place on the early stages of the trajectory prediction process. In this phase the airspace user gives its predicted trajectory. This trajectory is called Business Trajectory (BT), and represents the airspace user's intention. Typically, an airspace user submits the route that best fits its commercial strategy in terms of flown distance, fuel consumption and elapsed time.

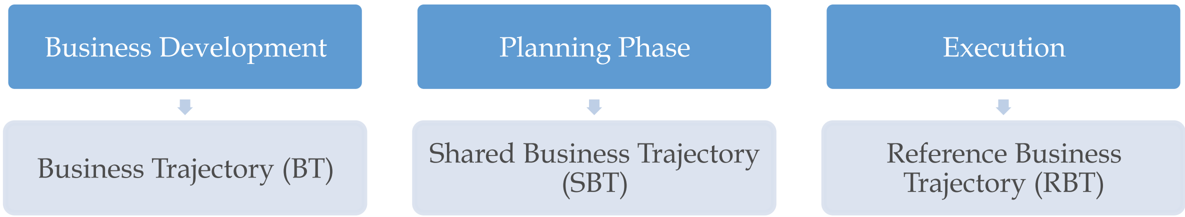

Figure 5 Evolution phases of a trajectory

During the **Planning Phase** the airspace users agree with ANSPs, airport operators, the airspace user's preferred trajectory, where the various constraints of airspace and airport capacity have been fully taken into account. Once agreed, the BT becomes the **Shared Business Trajectory (SBT)**, the trajectory that the airspace user agrees to fly and all the service providers agree to facilitate. From then on, all stakeholders will share information on this trajectory in real time.

The **Execution Phase** takes place in the day of operation. During this phase, the SBT evolves to Reference Business Trajectory (RBT), which is the final trajectory revised and authorized prediction that the airspace users have to adhere to when flown [10].

2.6 ATM Process Improvements

Trajectory prediction improvements can impact some of the key performance areas (KPA) of ATM system:

- **Predictability**: a comparison between the actual flight and the scheduled flight times, that basically represents the variability of flight duration due to unexpected events (e.g., [ICAO (2008), doc. 9882, Manual on Air Traffic Management System Requirements].
- **Safety**: In future ATM environment, every aircraft will report its position at regular time intervals. Enhanced automation capabilities on ground that leverage such surveillance data will increase situational awareness, and therefore, will reduce losses of separation minima [11].
- **Cost efficiency**: RBT represents the agreed trajectory that best fits airspace users' preferences considering all ATM constraints. The adherence to those predicted trajectories will lead to optimal routing and fuel usage. For instance, continuous ascent and descent paths usually require less fuel than the step-wise adjustments [10].
- **Environmental impact**: In turn, optimal routing and more efficient fuel usage will reduce CO_2 and NO_x emissions, and therefore, the impact on global climate change. In addition, trajectories could be compliant with local noise and pollution requirements [11].

2.7 DCB Tools

To maintain the balance between the demand and capacity, Eurocontrol has developed the ATFCM NM Human Machine Interface application. This tool provides a graphical interface for the Network Operations system, allowing users to display data and graphical information (such as routes, route attributes, airspaces, flight plan tracks, etc.) via map displays. This real time information enables Collaboration Decision-Making (CDM) between all partners.

There are different types of measures to monitor the demand evolution, although usually the two more-used indicators are Entry Counts and Occupancy.

- **Hourly Entry Count** (HEC) for a given sector is defined as the number of flights entering in the sector during a selected time period, referred as Hourly Entry Counting Period.
- This Hourly Entry Counting Period is defined as a picture of the entry traffic taken every time step value along an interval of fixed duration:
  - The Step value defines the time difference between two consecutive Hourly Entry Counting Periods.
  - The Duration value defines the time difference between start and end times of each Hourly Entry Counting Period.

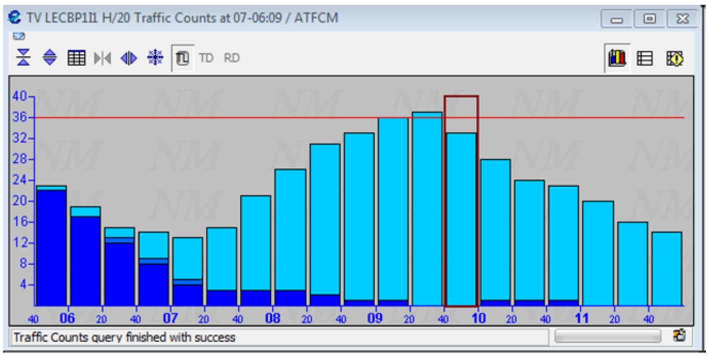

Figure 6 Entry Counts Indicator. In the graph, dark blue bar are flights that are flying in this moment, and clear blue bars are flights that are expected to entering in the sector. Y-axis represents the capacity of the sector and x-axis represents time [12].

For example, for a 20 min. step value and a 60 min. duration value, counts correspond to a picture taken every 20 min. with a duration of 60 min.

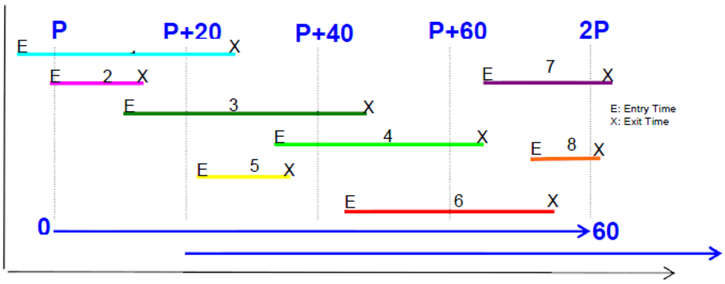

Figure 7 Hourly Entry-Counting Period-Step=20min., Duration=60 min [12].

The Hourly Entry Counts corresponding to the set of flights in Figure 7 at the different moments P with a 60/20 counting Period are:

- At P → HEC= 6 as {3,4,5,6}
- At P+20 → HEC= 6 as {4,5,6,7,8}

- At P+40 → HEC= 6 as {6,7,8}
- At P+60 → HEC= 6 as {7,8}

- **Occupancy** (OCC) for a given sector is defined as the number of flights inside the sector during a selected Occupancy Count Time period, referred as Occupancy Counting Period.

This Occupancy Counting Period is defined as a picture of the sector occupancy taken every time step value along an interval of fixed duration:

- The Step value defines the time difference between two consecutive Occupancy Counting Periods.
- The Duration value defines the time difference between start and end times of each Occupancy Counting Period.

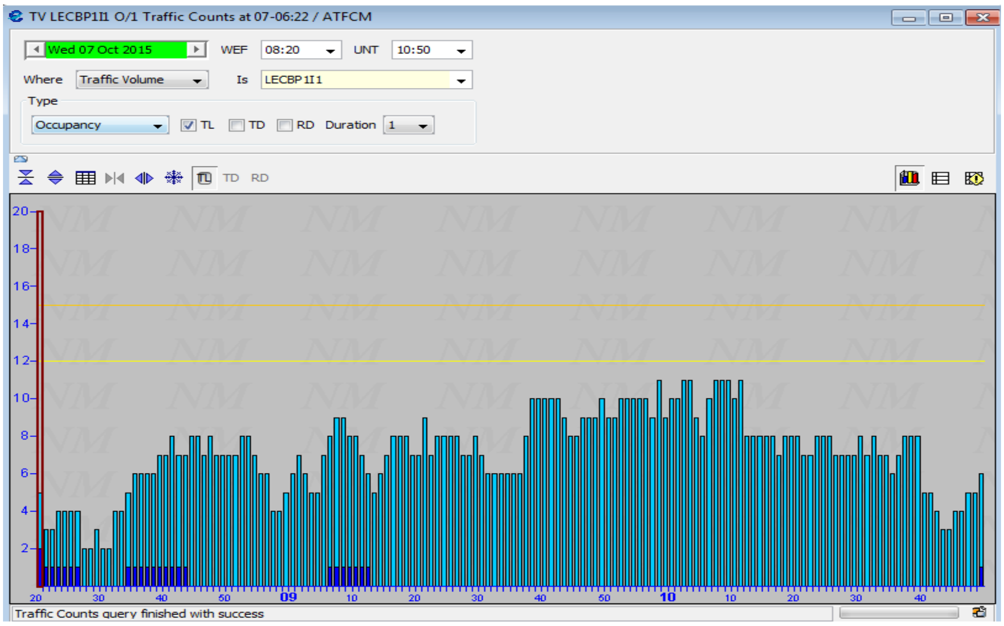

Figure 8 Occupancy Indicator. At the y-axis represents the occupancy count, and at x-axis represents time. Bars shows Occupancy counts, yellow line is sustainable threshold (12) and orange line is peak threshold (15). [12]

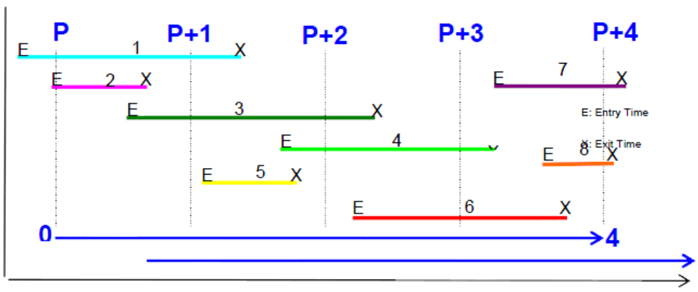

Figure 9NM Occupancy-Step=1min., Duration=1 min [12].

The Occupancy Counts corresponding to the set of flights at different moments P with a 1/1 counting Period are:

- At P → 1,2,3
- At P+1 → 1,3,4,5
- At P+2 → 3,4,6
- At P+3 → 4,6,7,8

3 WP2 and WP3 Scenarios

Two different scenarios are proposed, taking into account the requirements of WP2 and WP3. For each of them, below we define their scope, geographical areas to be considered and the necessary data sources.

There are the two scenarios proposed:

- WP2: Single Trajectory Prediction
- WP3: Collaborative Trajectory Prediction

3.1 WP2 Scenario: Single Trajectory Prediction

3.1.1 Objective

The objective of this scenario is to demonstrate how DART predictive analytics capability can improve trajectory prediction in support of DCB processes at planning phase. For a given flight plan, the objective is to compute the predicted trajectory that an aircraft will fly during an operation day.

This WP2 scenario concerns Spain and aims at analyzing and evaluating machine learning algorithms for trajectory prediction from an individual trajectory perspective (i.e. without considering traffic) and from the airspace users' point of view.

3.1.2 Operational Scenario Characteristics: Geographical area, roles, scope, data sources, evaluation metrics.

WP2 Operational Scenario assumes a DCB process at planning phase (i.e., during three days before operation). The scenario is developed in Spain, where the ANSP role is represented by CRIDA (local level). On the other hand, airspace users role are represented by Boeing Research & Technology – Europe (BR&T-E). The separation between aircraft is guaranteed, thus there won't be conflicts in the proposed scenario. Resolutions adopted by ATCO won't be part of the scope of this operational scenario. The scenario also assumes that there won't be any regulation applied by the NM.

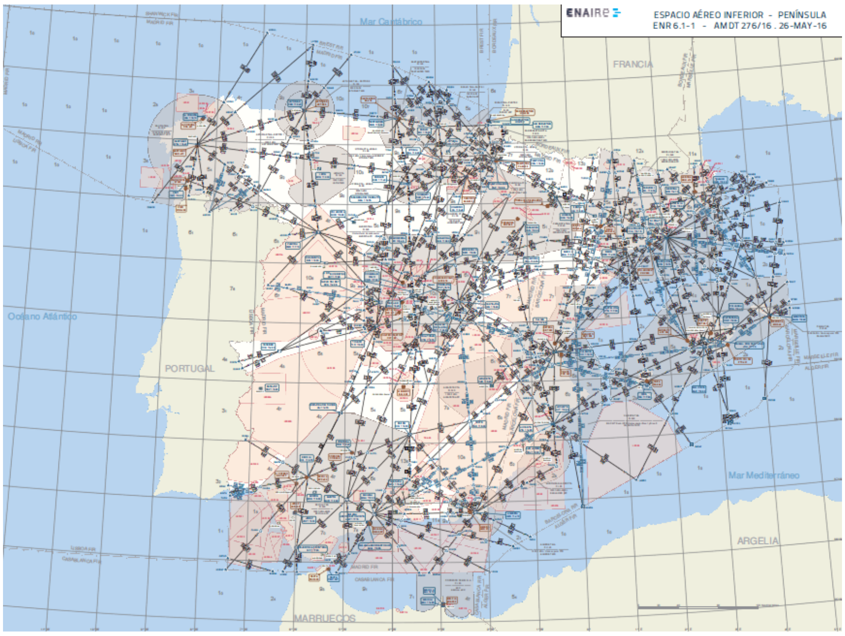

Figure 10 Geographical Area [3]

3.1.3 Data and Steps

The datasets available for this scenario are:

- Weather Data (METAR, NOAA, SIGMET y TAF).
- Demand: 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, a synthetically generated set of AI descriptions will be used during the initial stages of the project.
- Flight Plans: Used in order to know the flight intentions and predict trajectories based on that.
- Capacity: Sectorization information available from the day of operation (airspace configuration and airblocks).
- Radar Tracks (IFS).
- ADS-B data.
- Historical data (real flown trajectories, associated historical flight plans, and weather information at operation days).

As already pointed out before, testing datasets will be identified as representative of a variety of operational scenarios (i.e., nominal operation conditions, high-density traffic, low-density traffic, varying weather conditions, etc.). These datasets will not be used for the training phase of the algorithms, and they will be used for testing every potential data science technique and assess its results independently of the training, and in a comparable way. The same process will be repeated with datasets that reflect the same operational scenarios, but that were used for training and modelling the system. Experimental results for every solution will be obtained separately and compared to each other, to gain deep understanding of solutions' performance.

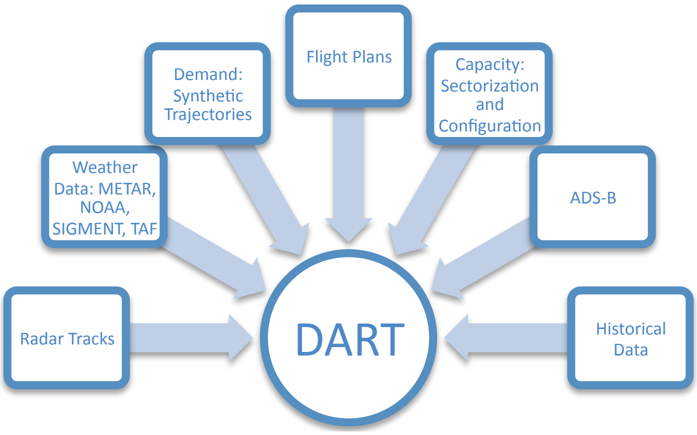

Figure 11 Data required for WP2 Scenario.

Steps

- Trajectory reconstruction based on surveillance data. This process requires the application of inference techniques to obtain the complete state vector that represents the aircraft state at any time, based on information concerning weather conditions and the aircraft performance.

- Description of the AI that best represents the flown trajectory. This is a semantic representation of the trajectory. The AI is considered as a model of guidance modes that univocally lead to a trajectory once applied to the aircraft in the presence of the wind, atmosphere conditions and operational context. An AI instance is formed by a chronologically ordered sequence of events and guidance laws that univocally describe a trajectory [Aircraft Intent Description Language (AIDL) Specification v1.3 Revision r1 (MAR/31/2008)]. Dedicated model-based trajectory predictors can compute a unique trajectory from a well-formed AI instance.

- Application of machine learning algorithms to aircraft trajectory prediction. Based on the set of reconstructed trajectories, the algorithm will be able to predict a trajectory thanks to the knowledge gained from the training set that will additionally include all datasets required by the WP2 scenario (Figure 11). Although the reconstructed trajectories provide detailed information about the evolution with time of all aircraft state variables, initially the algorithms will exploit those related to speed, altitude and lateral profiles.

- Application of machine learning algorithms to AI prediction. Due to the fact that AI is a compressed manner of representing a trajectory and includes semantic information that potentially could help the prediction process, it is planned to assess a hybrid approach in which an AI instance will be predicted as intermediate stage previous to obtain a prediction. Due to the fact that the process of inferring the associated AI to a trajectory requires additional effort, this approach will be explored using a set of AI synthetically generated trajectories (i.e., the generated AI instances will not correspond to actual trajectories). The outcome of the machine learning algorithms will be an AI instance that will require from a dedicated trajectory computation infrastructure to obtain the related predicted trajectory.

3.1.4 Metrics

- Accuracy of the predicted trajectory compared to the actual flown trajectory
- Performance of the prediction (time needed to calculate a single trajectory)
- Improvement in predictability with respect to rational model-based trajectory prediction approaches.

3.2 WP3 Scenario: Collaborative Predicted Trajectory

3.2.1 Objectives

The scenario objective is to demonstrate how DART predictive analytics capability can help in trajectory forecasting when demand exceeds sectors' capacity. Thus, WP3 scenario aims to study and determine the complexity to be considered in a trajectory prediction due to the influence of the surrounding traffic.

This scenario shows ANSP's point of view, and aims to compute and evaluate collaborative trajectory predictions.

3.2.2 Operational Scenario Characteristics

The operational scenario in WP3 concerns the planning phase during the DCB process (three days before operation). The scenario develops in Spain, where the ANSP roll is represented by CRIDA (local level). On the other hand, airspace users role are represented by Boeing. The separation between aircrafts is guaranteed; therefore, the scenario does not consider conflicts: Resolutions adopted by ATCO won't be part of the scope in the operational scenario WP3.

In this case, regulations of type C (i.e. delays) will be applied to the WP2 trajectories due to the imbalance between demand and capacity, so DART will have to recalculate and obtain the final trajectories taken into account surrounding traffic.

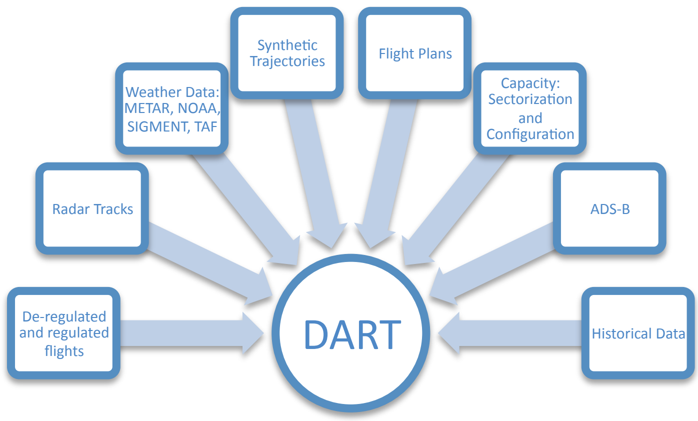

Figure 12 Data required for WP3 Scenario

3.2.3 Data and Step

The data involved in this scenario is:

- Weather Data (METAR, NOAA, SIGMET y TAF)
- Demand: Synthetic Trajectories (training and testing)
- WP2 output: Predicted Trajectories
- Flight Plans: Plans associated with the trajectories predicted from WP2 (those that may be regulated).
- Deregulated and regulated flights.
- Capacity: Sectorization information available at operation day (configurations and airblocks)
- Radar Tracks (IFS)
- ADS-B data
- Historical data (real flown trajectories, regulation applied and historical flight plans, airspace configurations and weather information at operation days)

As in the trajectory prediction scenario, testing datasets will be identified as representative of a variety of operational scenarios (i.e., nominal operation conditions, high-density traffic, low-density traffic, etc.). These datasets will not be used for the training phase of the algorithms, and they will be used for testing every potential data science technique and assess its results independently of the training, and in a comparable way. The same process will be repeated with datasets that reflect the same operational scenarios, but that were used for training and modelling the system. Experimental results for every solution will be obtained separately and compared to each other, to gain deep understanding of solutions' performance.

Steps

For a given historical data package (flight plans, sectorization, radar tracks, synthetic trajectories, regulated and deregulated flights) DART will study and develop a learning method, aiming to predict how to solve an imbalance between sectors' demand and capacity taking into account regulations applied in past situations.

- WP3 Scenario will consider mostly demand and capacity balance per sector (DCB): This will result to regulating flights. Other options may be examined, such as rerouting flights, taken into account cost and operational constraints.
- DCB imbalance prediction. The first step is to focus on learning on demand and capacity imbalance due to a lack of capacity. It will be necessary to apply algorithms to fulfill two main objectives: firstly, how to detect a DCB imbalance per sector and secondly, how to solve the problem. Using historical data of airspace configuration and de-conflicted flights, it is possible to learn how to resolve DCB problems. Towards the second objective it will be necessary to focus on how to predict regulated trajectories. For this purpose a package of datasets about predicted and past trajectories, airspace configurations for predicted and past trajectories, de-conflicted and deregulated past flights, is necessary.
- Application of machine learning algorithms to DCB problems (per sector) prediction and resolution. DART will recalculate WP2 trajectories taking into account interactions among trajectories (i.e. traffic conditions), airspace configuration and regulations. Thus, WP3 will consider all trajectories predicted in a joint manner.
- Collaborative trajectory prediction. The final output will be the most appropriate trajectory that aircraft must finally follow (RBT), jointly with others. The output will be a single trajectory prediction per flight, which will be a refinement of the one already provided by WP2, predicting regulations to be imposed (i.e delays) and/or rerouting possibilities.

3.2.4 Metrics

- Testing Phase: Accuracy of the predicted trajectories (compared with the real trajectories flown by aircrafts, as reported in historical data)
- Evaluation metrics over the prediction ability (computational time needed for multiple trajectories, depending also on sectorization information: Multiple settings should be examined of different complexity depending on number of flights and sectors considered)
- Information exploited for predictions made: single trajectory predictions, weather data, aircraft type, flight plan.
- Improvement in airspace capacity management given the WP2 and WP3 predicted trajectories.

3.3 Cost and Optimization Criteria for DCB

To enrich the DCB scenario considered in the context of WP3, and based on the results to be achieved for the DCB scenario specified above, DART partners aim also to further explore the application of further policies, in addition to applying delays to flights, for balancing demand and capacity per sector. The aim of this enriched scenario is to allow re-routings of trajectories in combination with delays, considering also the fuel cost imposed by these re-routings. Thus, in the DCB scenario, re-routings aim to reduce demand to specific sectors (reflecting ANSPs and NMs interests) without increasing considerably the fuel cost of flights (reflecting airlines interests).

This necessitates computing multi-objective optimizations:

The first objective is to satisfy the airline's interest to reduce fuel consumption, thus decreasing the cost of the solution and adhere to the flight plan. The second objective is to solve air traffic planning, trying to achieve a homogenous flow distribution, and consequently a demand and capacity balancing prior to operation. The best solution for the multi-objective function will be to minimize the cost of fuel consumption and at the same time, maximize the adherence between trajectory and flight plan, assuring demand and capacity balancing per sector.

4 DART Components' Interaction, Visualization and Visual Analytics Requirements.

This section specifies the requirements concerning the interaction of components developed by WP2 and WP3. The overall process is depicted in Figure 13 and explained below.

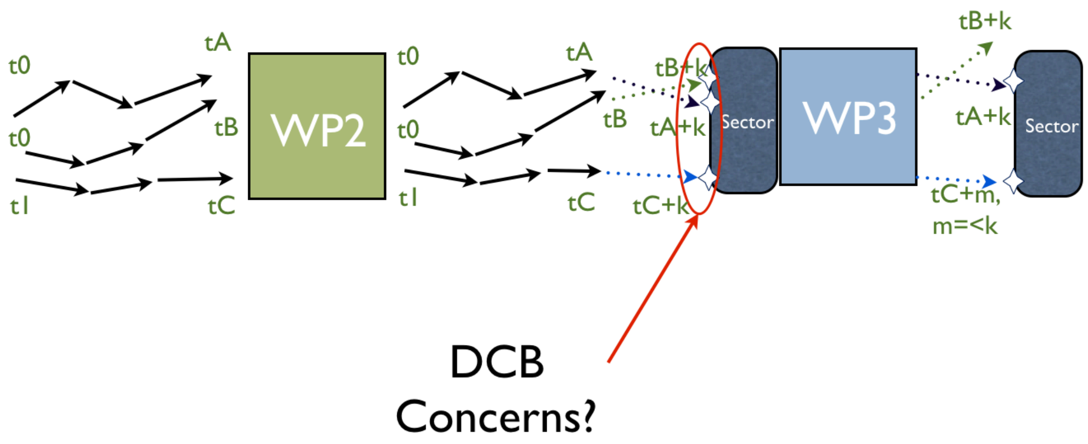

Figure 13 Interaction among WP2 and WP3 and demonstration of functionality to be provided.

Full trajectories will be predicted by WP2 in a nominal approach: one prediction per flight and in a stochastic feature, i.e. it is possible to have available probabilities on the predictive trajectories (this also depends on the machine learning algorithm to be used). The output of WP2 components are predicted trajectories, without considering traffic and thus, without considering any interactions among trajectories.

WP2 will also calculate the demand per sector, based on the single trajectory predictions it makes, and will provide the corresponding measurements per sector to WP3.

WP3 will address the balance between demand and capacity per sector (DCB) considering all trajectories predicted by WP2, in a joint manner, accounting for traffic effects: This will result to detecting DCB problems to be resolved. Computations by WP3 will result to regulating flights (e.g. flight C in Figure 13). Additionally, at later stages of the project other options will be examined, such as rerouting flights, taking into account fuel cost in conjunction to operational constraints (e.g. flight B in Figure 13).

The output of WP3 will be a single trajectory prediction per flight, which will be a refinement of the prediction already provided by WP2, predicting regulations to be imposed (i.e. delays) and/or rerouting possibilities, aiming to achieve a homogenous flow distribution, and consequently a demand and capacity balancing prior to operation.

WP2 will not consider any direct input from WP3, as the predictions computed by WP3 need to be taken into account towards constructing a new flight plan that will then be provided to WP2 towards refining the predictions and so on.

Concerning visualizations and visual analytics, these will be used for a comparative analysis of predictions generated by WP2 and WP3 methods and the actual trajectories and regulations recorded in the available data.

Visualizations shall support:

- Detection of deviations between predicted and real trajectories, towards tuning the prediction process.

- Detection of excessive demand events: spatial locations, time intervals, sector capacities, amounts of demand and amounts of demand excess.

- Detection of regulations caused by the excessive demand events: Affected flights and assigned delay durations.

- For a selected excessive demand event, detection of flights that collectively produced the demand, particularly, at what times they were expected to enter the affected sector. Flights that were regulated and coresponding regulations will be shown, together with the changes in the distribution of the times of entering the affected sector.

The visualization techniques should be able to show where and when the predictions made correspond well to the real trajectories and the regulations imposed to them, where and when there are discrepancies supporting sensitivity analysis in respect to algorithms parameters.

The main goal of Visual Analytics is to check the possibility to predict trajectories and regulations based on patterns existing in historical data. The expected result may be positive or negative. A positive result would mean that the historical data contain patterns that are suitable for the creation of predictive models, and these models can be used sufficiently well to make accurate predictions. A negative result would mean that trajectories and/or regulations are unpredictable, particularly, due to the absence of clear regular patterns in the historical data. Both results should be treated as valid.

If a positive result is obtained, then the validity of predictions will be validated by visualizing the similarities and dissimilarities between the real and predicted situations. The aviation domain experts will review the results and give their judgements concerning the dissimilarity tolerance threshold(s). In a case of a negative result, the validity of this result needs to be justified by visualizations providing evidence to the absence of regular patterns that could allow making reasonable predictions.

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