The DART approach: Data-driven and agent-based modelling approaches for predicting trajectories

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DART
("ER-02-2015 - Data Science in ATM")

Operational Context

Overall Aim :

- Demonstrate how predictive analytics capability can **improve trajectory prediction in support of DCB processes at planning phase**, further reducing uncertainty and improving ATM operations and services provided.

- **Scenario 1** (AUs): aims to **compute the predicted trajectory** that an aircraft will fly during an operation day **without considering traffic**.

- **Scenario 2** (ANSPs): aims to **study and determine the complexity to be considered in trajectories due to the influence of the surrounding traffic**, at the planning phase, taking into account flight plans and/or individual trajectory predictions.

DART
(“ER-02-2015 - Data Science in ATM”)

DART explored and developed novel

Machine learning methods for single trajectory prediction and

agent-based machine learning methods accounting **for the complexity of the ATM network due to traffic**,

which either individually, or combined,

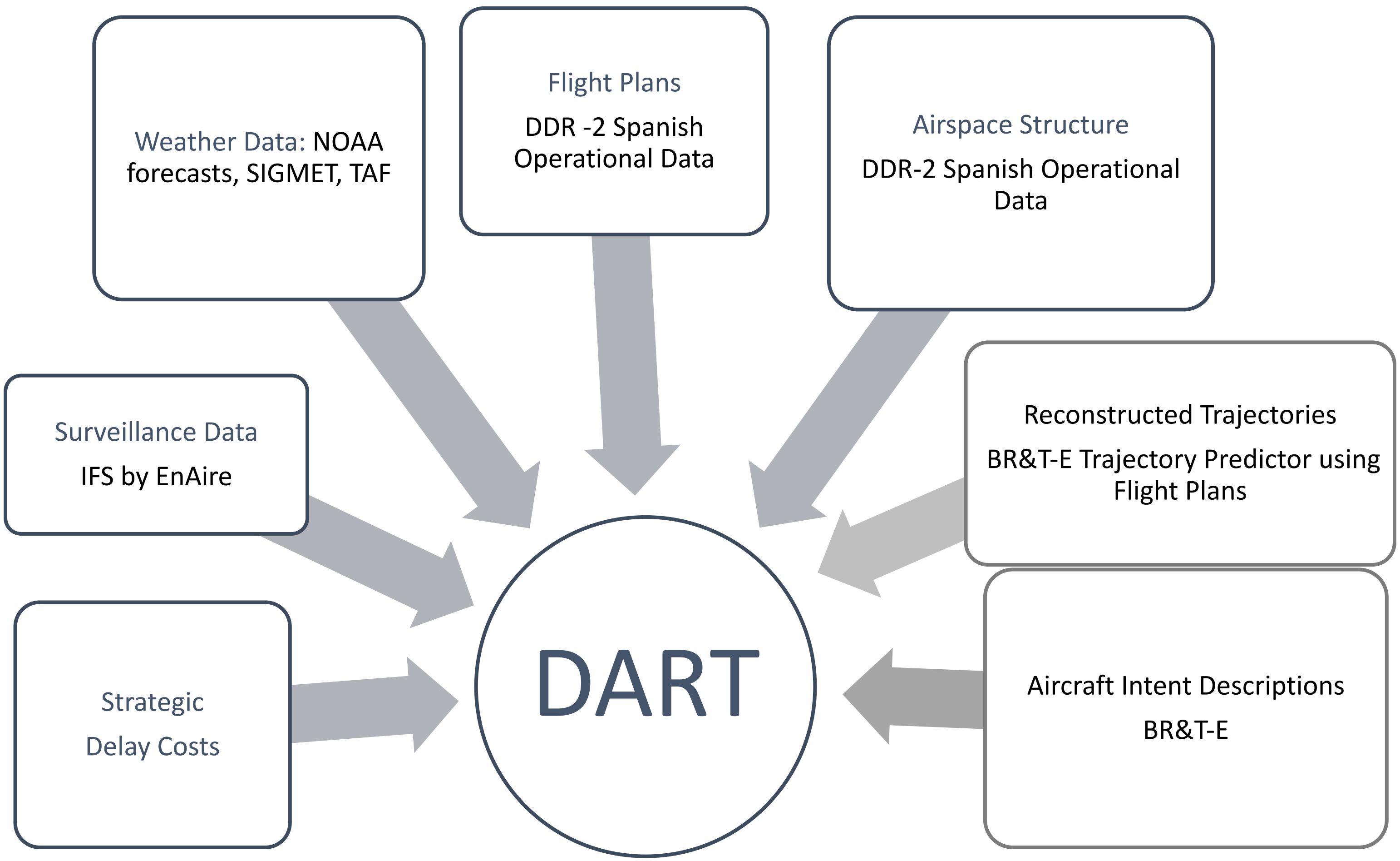
provide the means to **make accurate predictions about individual trajectories** and to **effectively reduce delays to resolve hotspots**,

at the **planning phase of operations**.

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

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

DART Data Sources



DART : Single Trajectory Prediction

Single Trajectory Prediction
Work Performed

Algorithms tested and validated:

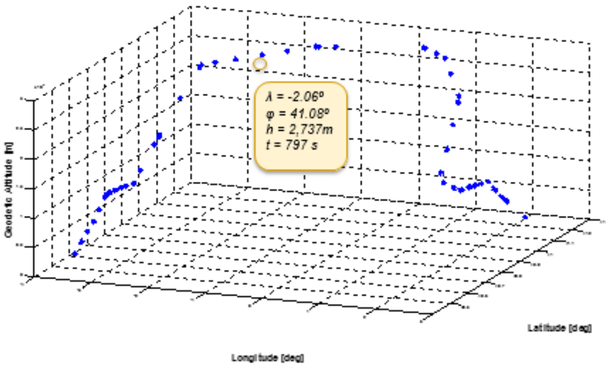
- Trajectory Prediction based on Raw Data
  - Hidden Markov Models

- Trajectory Prediction based on Raw Data and Flight Plan
  - Hybrid: Clustering + Predictors (e.g. HMMs)

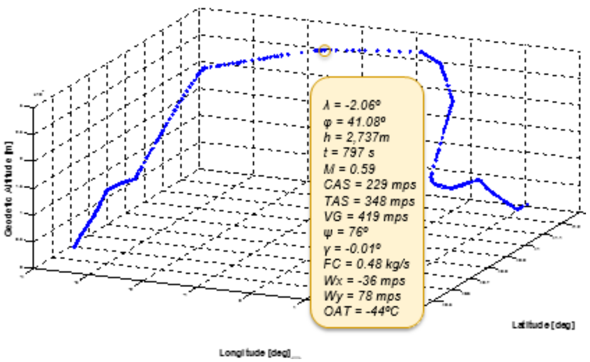
- Trajectory Prediction based on Tabular Aircraft Intent Descript
  - Hierarchic clustering (WARD method)
  - K-means
  - Random Forest (RF)
  - Multi-Output Meta Estimator (MOME)

- Trajectory Prediction based on Aircraft Intent
  - Reinforcement Learning (RL)

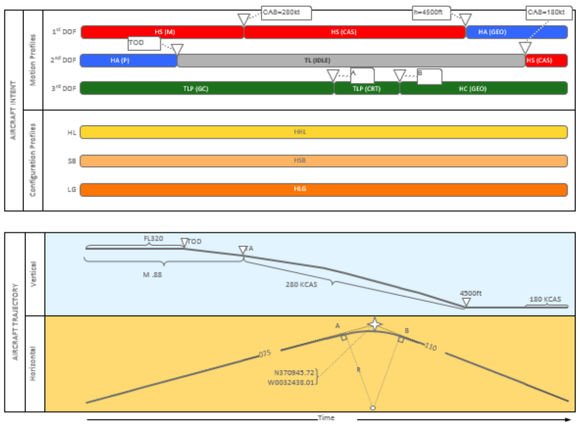
Raw Data



Enriched Data



Aircraft Intent



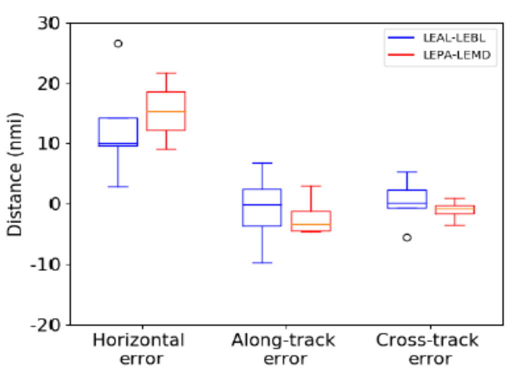
Single Trajectory Prediction Evaluation

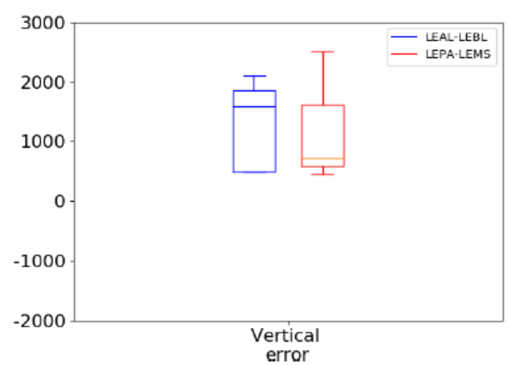
Results from Raw trajectory data based algorithms

Hidden Markov Models & Gradient Boost Machine Regression

TestCase#	Route#1	TrainingSetSize		TestSetSize		Route#2	TrainingSetSize		TestSetSize	
		#trjs	#pts	#trjs	#pts		#trjs	#pts	#trjs	#pts
1	LEAL-LEBL	1118	55116	200	9860	LEMD-LEIB	2572	125623	200	9769
2	LEAL-LEBL	1118	55116	19	937	LEMD-LEMH	1056	68141	19	1226
3	LEAL-LEBL	1118	55116	152	7493	LEPA-LEMD	5116	306128	152	9095
4	LEBL-LEMG	1704	127451	43	3216	LEMD-LEMH	1056	68141	43	2775
5	LEBL-LEMG	1704	127451	180	13463	LEPA-LEMD	5116	306128	180	10771
6	LEBL-LEZL	2404	183343	41	3127	LEMD-LEAM	1434	70128	41	2005
7	LEBL-LEZL	2404	183343	46	3508	LEMD-LEMH	1056	68141	46	2968
8	LEBL-LEZL	2404	183343	164	12508	LEMG-LEMD	1403	75408	164	8815
9	LEBL-LEZL	2404	183343	210	16016	LEPA-LEMD	5116	306128	210	12566
10	LEIB-LEBL	1360	53443	259	10178	LEPA-LEMD	5116	306128	259	15498
11	LEIB-LEBL	1360	53443	158	6209	LEPA-LEVC	1426	50467	158	5592
12	LEMG-LEBL	1563	114767	38	2790	LEMD-LEAM	1434	70128	38	1858
13	LEMG-LEBL	1563	114767	46	3378	LEMD-LEIB	2572	125623	46	2247
14	LEZL-LEBL	2380	186299	40	3131	LEMD-LEIB	2572	125623	40	1954

The mean value for the cross-track error and vertical error along the entire test trajectories in all route pairs is **7.692nmi** and **1589.452ft**

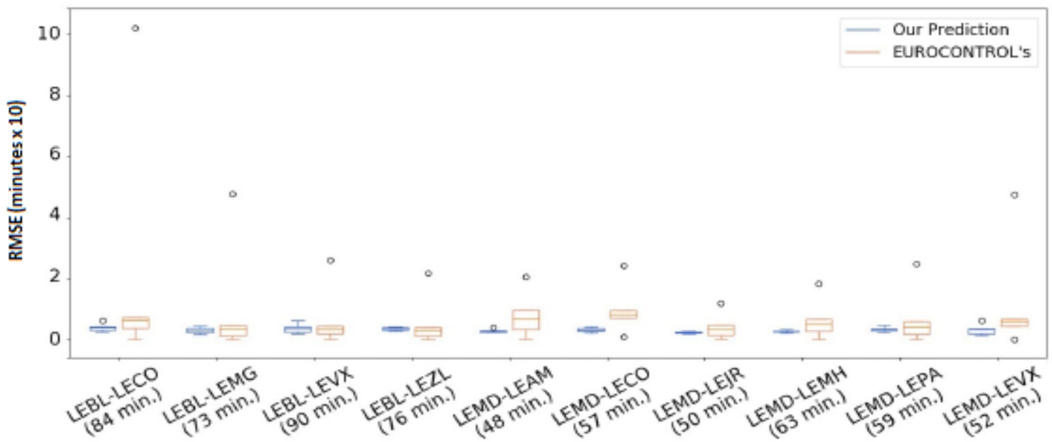


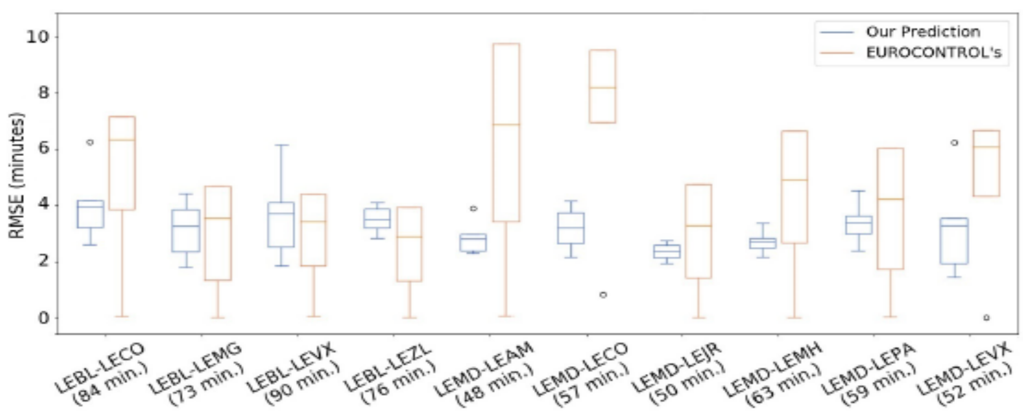


Single Trajectory Prediction Evaluation

Results from raw trajectory data based algorithms

ETA comparison with EC





Comparison of data driven and model based generated trajectories:

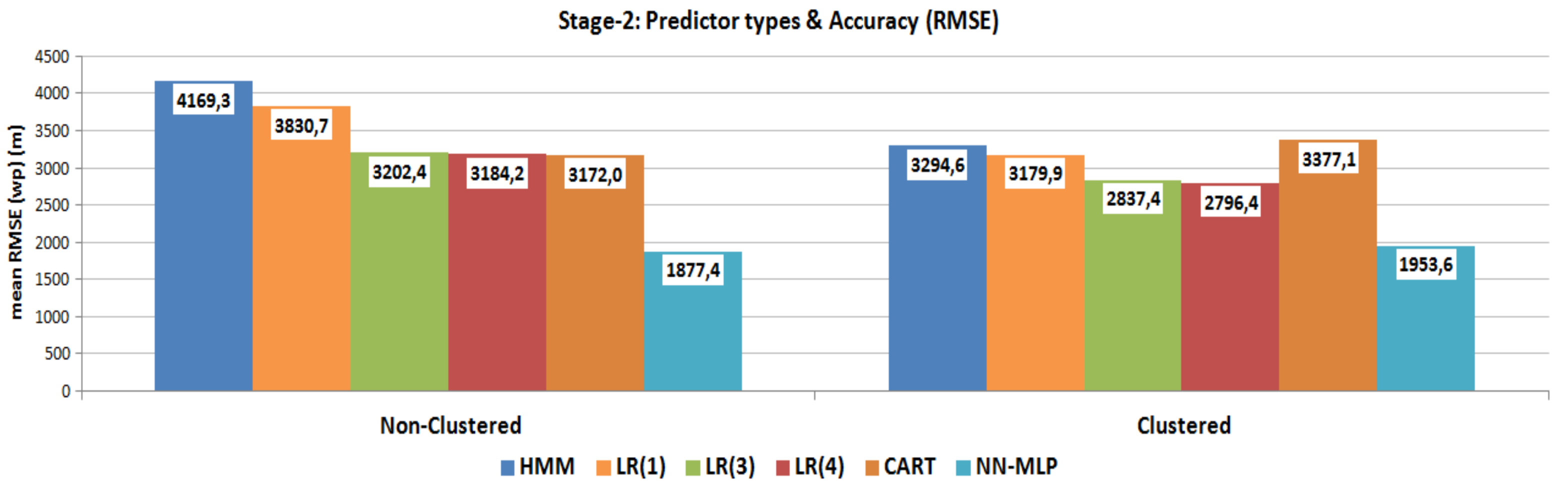
- Get from Eurocontrol DDR2 database 2016 and 2017 predicted trajectory data (CTFM, FTFM, RTFM)
- Extract model based CTFM trajectories (predictions) from the dataset
- Perform ETA and trajectory comparison between CFTM trajectories and HMM

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

Single Trajectory Prediction Evaluation

Results from hybrid clustering with flight plans as constraints.

TP Performance Summary: LEMD/LEBL, April 2016



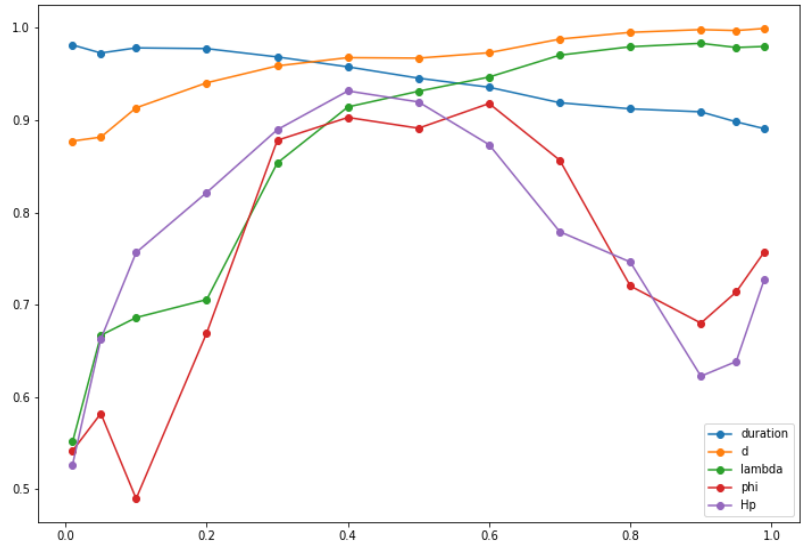
- Flight plans provide optimization constraints, i.e., ‘guidelines’ for the TP training
- They are also a realistic assumption about the intended (a priori) flight path
- Per-waypoint TP accuracy is in the order of 2-3 km (3-D RMSE), length-invariant

Single Trajectory Prediction Evaluation

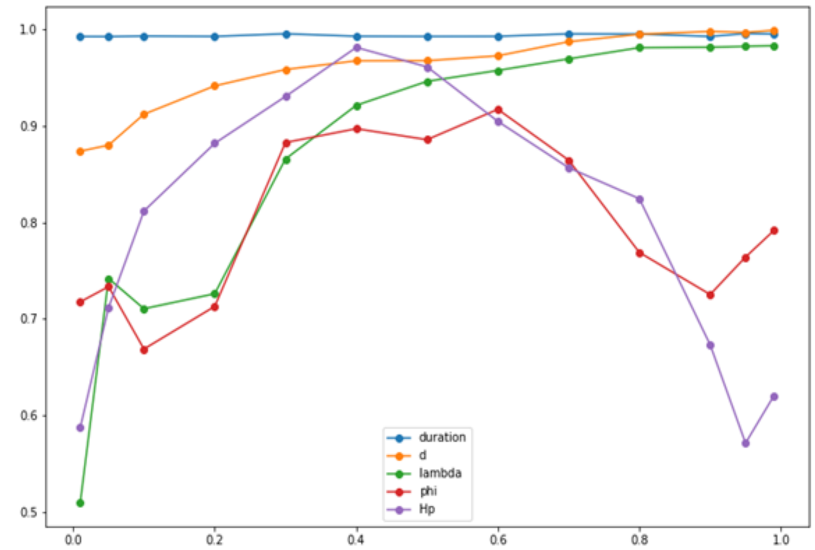
Results from Aircraft Intent data based algorithms

MOME, Random Forest

To validate the proposed methodology, we considered the route between Barcelona (BCN) and Madrid (MAD). The total number of flights taken into account have been 7609 (70% - 30%).



Random Forest

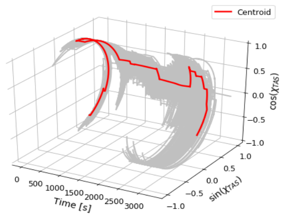


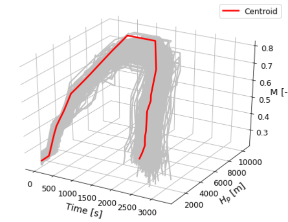
Multi Output Meta Estimator

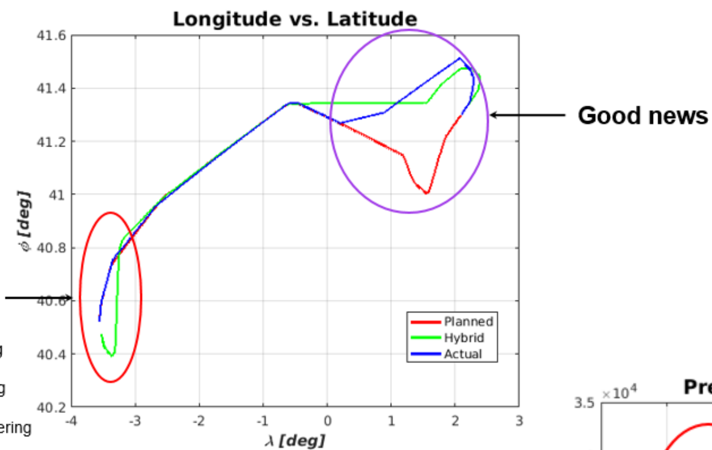
Single Trajectory Prediction Evaluation

Results from Aircraft Intent data based algorithms

Adding Clustering to RF

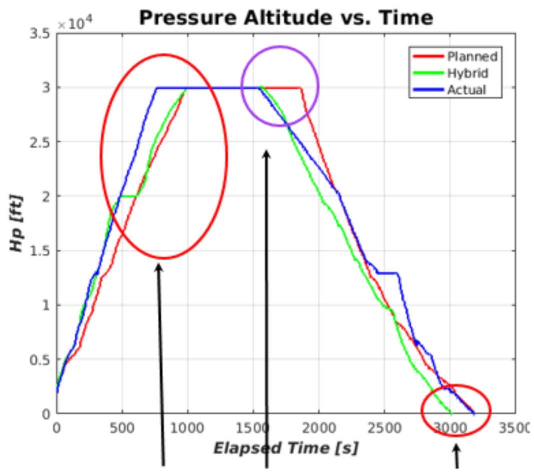


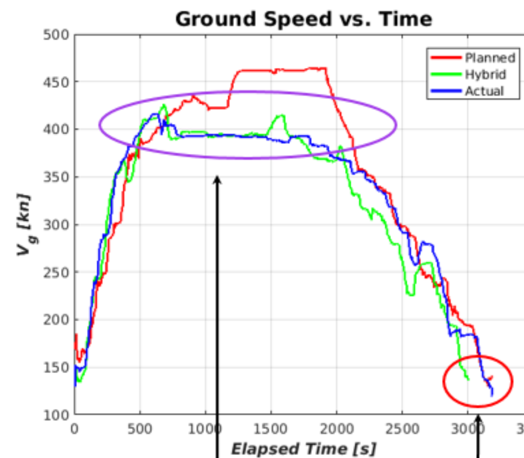




Bad news

1. Increase learning dataset
2. Review clustering process
3. Features engineering





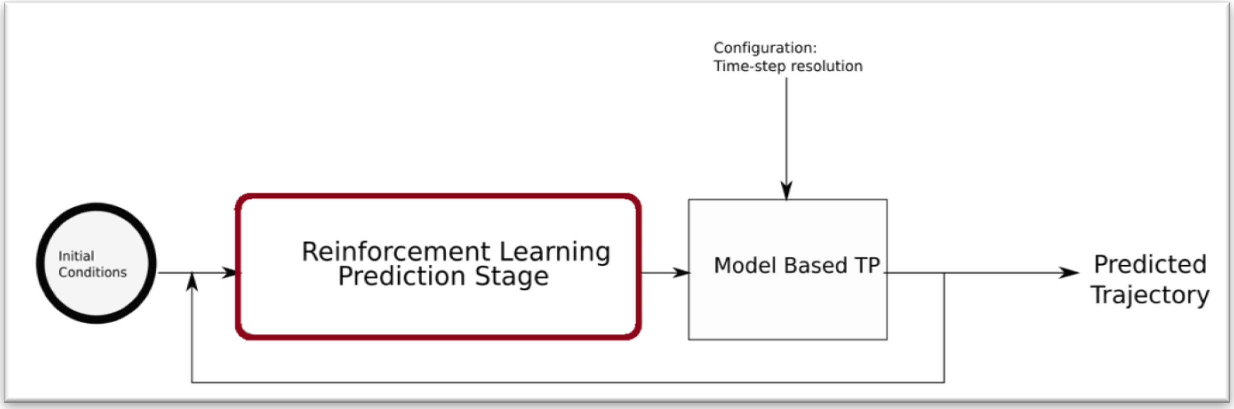
Bad news Good news Bad news Good news Bad news

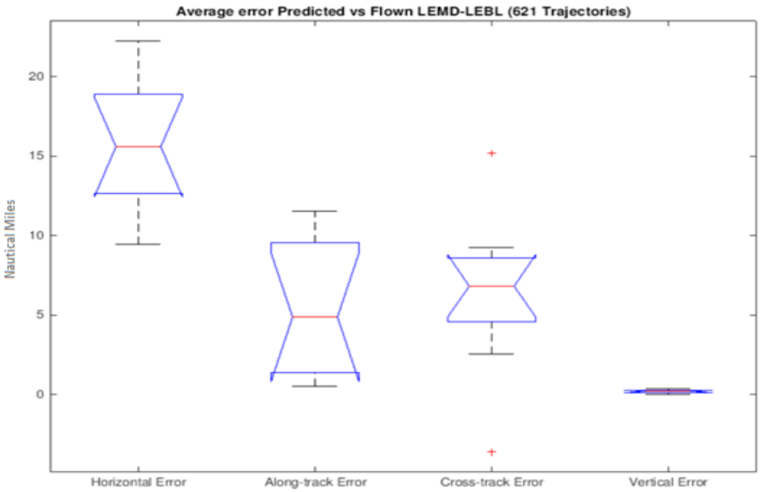
Single Trajectory Prediction Evaluation

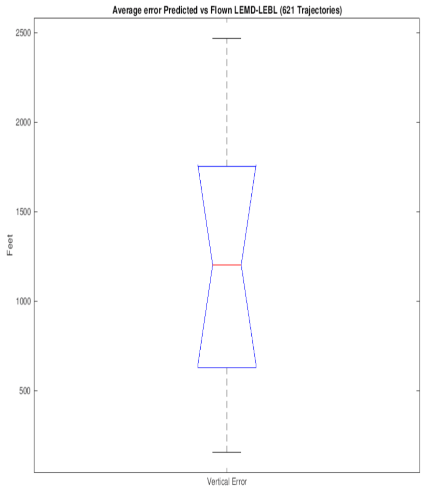
Results from Aircraft Intent data based algorithms

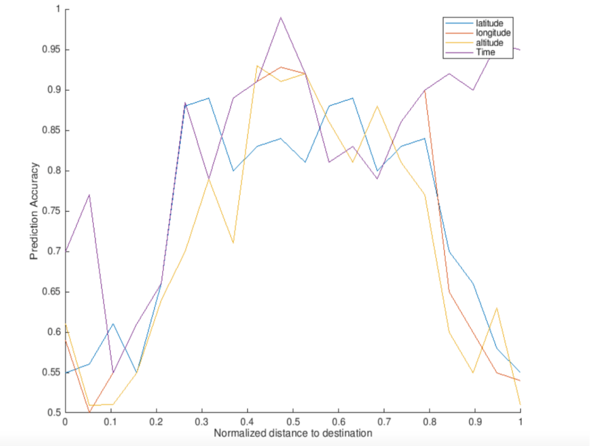
Reinforcement Learning

The learning dataset is composed by 3142 trajectories that produce over 158.600 instructions that are used to build the transition model of the Q-Learning algorithm. Validation is based on the route LEMD-LEBL



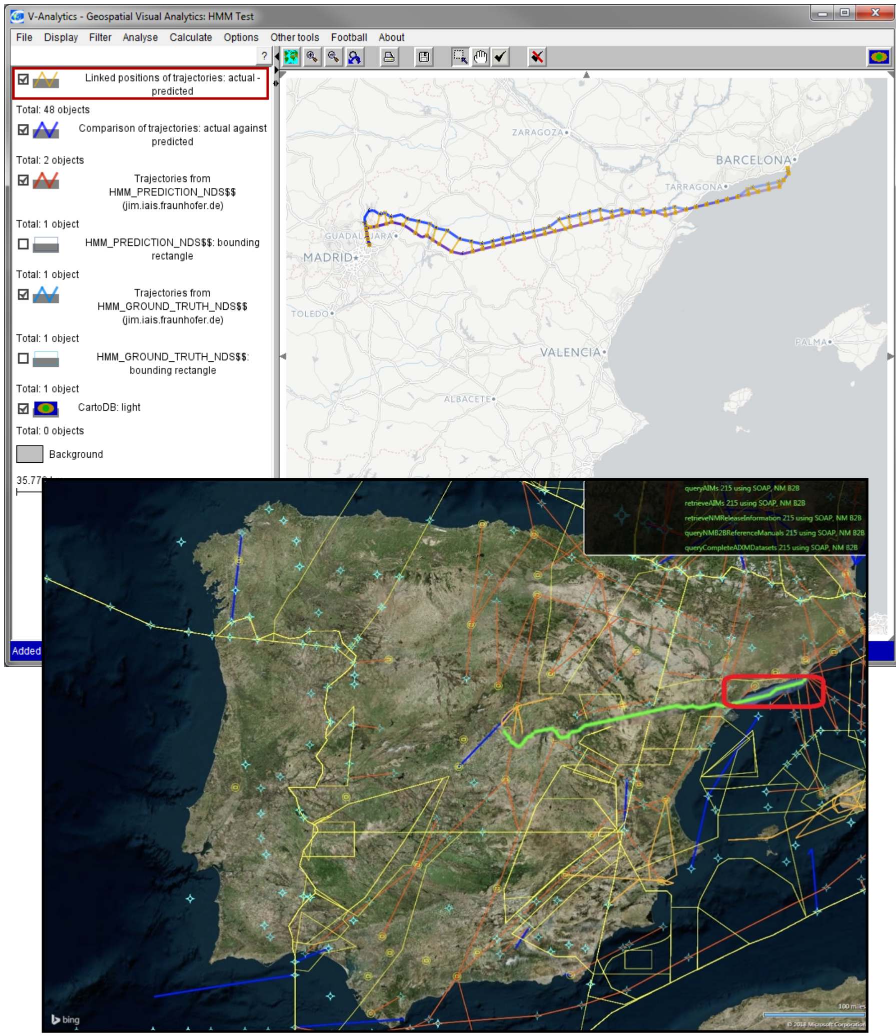


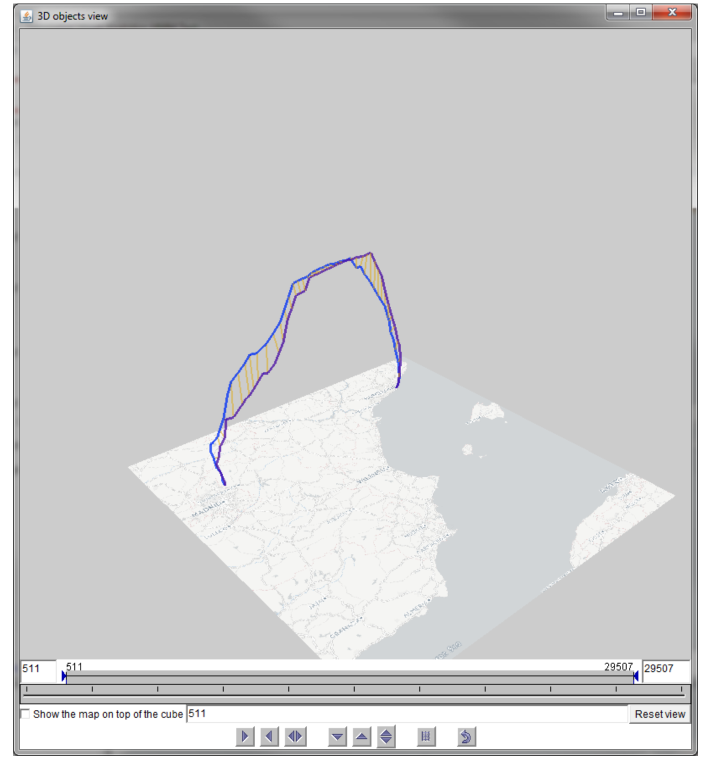




Single Trajectory Prediction Evaluation

Visual Analytics





Are data-driven TP's able to predict controller clearances to enter unavailable routes published in Route Availability Documents (RAD)?

Actions:

- Get from Eurocontrol NM B2B services AIXM information containing RAD's
- Extract unavailable routes from RAD matching the dates of data-driven predictions
- Visually check if data-driven TP predicts that the aircraft will enter a forbidden route in the RAD

Single Trajectory Prediction
Concluding Remarks

DART specifically focused on scalable methods to improve prediction accuracy

Results show that:

- There is a **trade-off** between prediction accuracy and scalability.

- Comparing the results and the complexity of the techniques, **clustering and Hidden Markov algorithms based in raw data and enriched trajectory or flight plans are the best performers** and the most promising.

- Although a lot of processing has been added in order to **learn from the complete AIDL instead from raw data**, **no improvement is shown** when comparing the results with the ones obtained in the HMM analysis or even regression methods.

- **Clustering methods are more suitable to be used in combination with other machine learning algorithms or even today's model-based operation systems.**

Single Trajectory Prediction
Concluding Remarks

Data-driven trajectory predictor models can that get better prediction than the state of the art model-based trajectory predictors, but not in all circumstances.

Hybrid Trajectory predictors, that combine clustering + data-driven (HMM) or model based trajectory predictors are the ones most promising.

All data-driven TP are trained by city-pair. **Training time and scaling factors is the main drawback of these methods.** However, computing power should be a limitation nowadays.

Future research should be focused on implementing an hybrid approach and detect WHEN and WHERE a data/driven TP outperforms model/based TP in order to integrate both.

DART Accounting for complexity due to traffic (towards resolving DCB problems)

DART Operational Context: Multiple Trajectories

- This operational scenario concerns **the planning phase during the DCB process** (i.e some days before operation).

- The separation between aircrafts is guaranteed; therefore**, the scenario does not consider conflicts: Resolutions adopted by ATCO are not part of the operational scenario**.
- In this case**, regulations of type C (i.e. ground delays)** are applied to trajectories due to **the imbalances between demand and capacity**, so as to recalculate and obtain the final trajectories taken into account **surrounding traffic**.

Multiple trajectories: Goal

Minimize the average ground delay per flight w.r.t. the number of flights with ground delay so as to resolve DCB problems at the planning stage.

In doing so, we aim to

- **distribute ground delays among flights without penalizing a small number of them**, and
- **utilize efficiently the airspace so as to have an even distribution of demand to sectors in different periods**.

Multiple trajectories: Approach

Formalize the DCB problem as a **multi-agent planning problem** and apply **multi-agent reinforcement learning methods (MARL)** to solve it.

Agents, representing **flights**, aim to coordinate their joint actions with respect to operational constraints on the use of airspace.

Agents **environment** comprises the airspace and other **interacting flights** comprising "**traffic**"

Each agent reconciles conflicting options (i.e. options creating hotspots) **jointly** with others and **decide about individual policies on delays**, while possessing no information about the preferences and payoffs of others.

Shifting to the TBO paradigm: Trajectory Abstraction Model for DCB

- Each flight is situated in some sector at all times
- Abstraction of flight trajectories
    - In space and time: time series of sectors crossed **with entry/exit time**

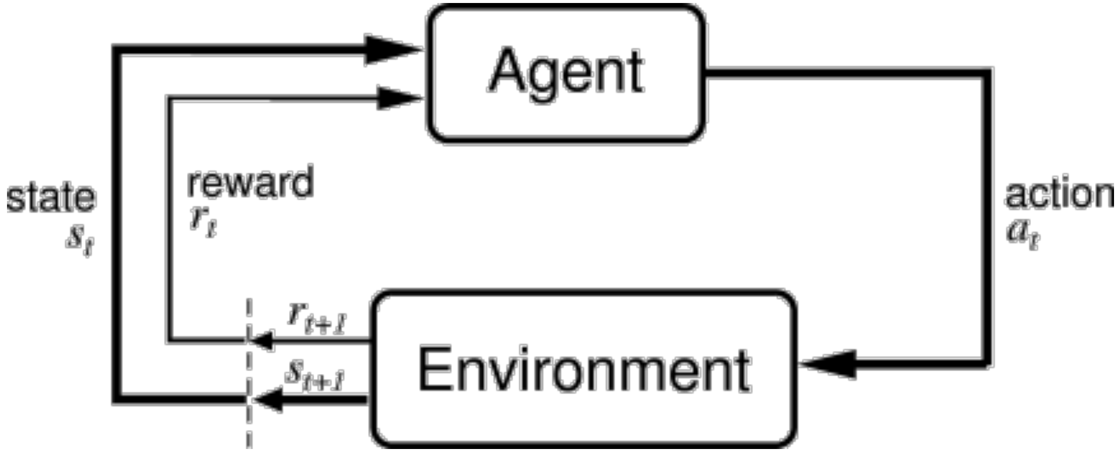
Sufficient for DCB operations

Original: … sect_x (eT,xT) sect_y (eT,xT) sect_z (eT,xT) sect_w (eT,xT) sect_v (eT,xT) ….
Delay : …. …. sect_x (eT',xT') sect_y (eT',xT') sect_z (eT',xT') sect_w (eT',xT') sect_v (eT',xT') …

eT: Entry Time in sector S & xT: Exit Time in sector S

- To accommodate delays: shift the entry/exit time per sector

Reinforcement Learning Primer



- Agent: A particular flight executed by a specific aircraft
- **Markov Decision Process**
  - State Space (delay, hotspots)
  - Action Space (adding or not delay at each time point)
  - Transition Model (State + Action = New States)
  - Reward Model (*f* (State) = Reward)
- **Goal: Optimal Action at every state (a policy)**

MDP Reward Model

$$Rwd_A(s^t_A, str^t_A) = \lambda_1 * C(str^t_A, s^t_A) + \lambda_2 * D(str^t_A, s^t_A)$$

$$C(str^t_A, s^t_A) = \begin{cases} \text{-TDC*81} & \text{if TDCs} > 0 \\ \text{PositiveReward} & \text{if TDC=0} \end{cases}$$

TDC: total duration in congestions/hotspots.

81 is the average strategic delay cost per minute (in Euros) in Europe when 92% of the flights do not have delays

$$D(str^t_A, s^t_A) = -TotalDelay * StrategicDelayCost(AircraftType)$$

MARL Algorithms solving the MDP

- **Independent Learners Approach**:
  - Each agent (flight) is **self-interested and learns by itself to resolve the DCB problem**, by measuring its own reward after each decision

- **Cooperative approaches among interacting agents**:
  - Sparse Cooperative Q-Learning - Agent-Based Decomposition- **Edge Based Update**
  - Sparse Cooperative Q-Learning - Agent-Based Decomposition- **Agent Based Update**

  - Each agent is **to resolve the DCB problem** jointly with peers in a coordination graph (agents connected represent **interacting trajectories**), by measuring its own reward after each decision

Evaluation of multi-agent algorithms to resolve DCB problems

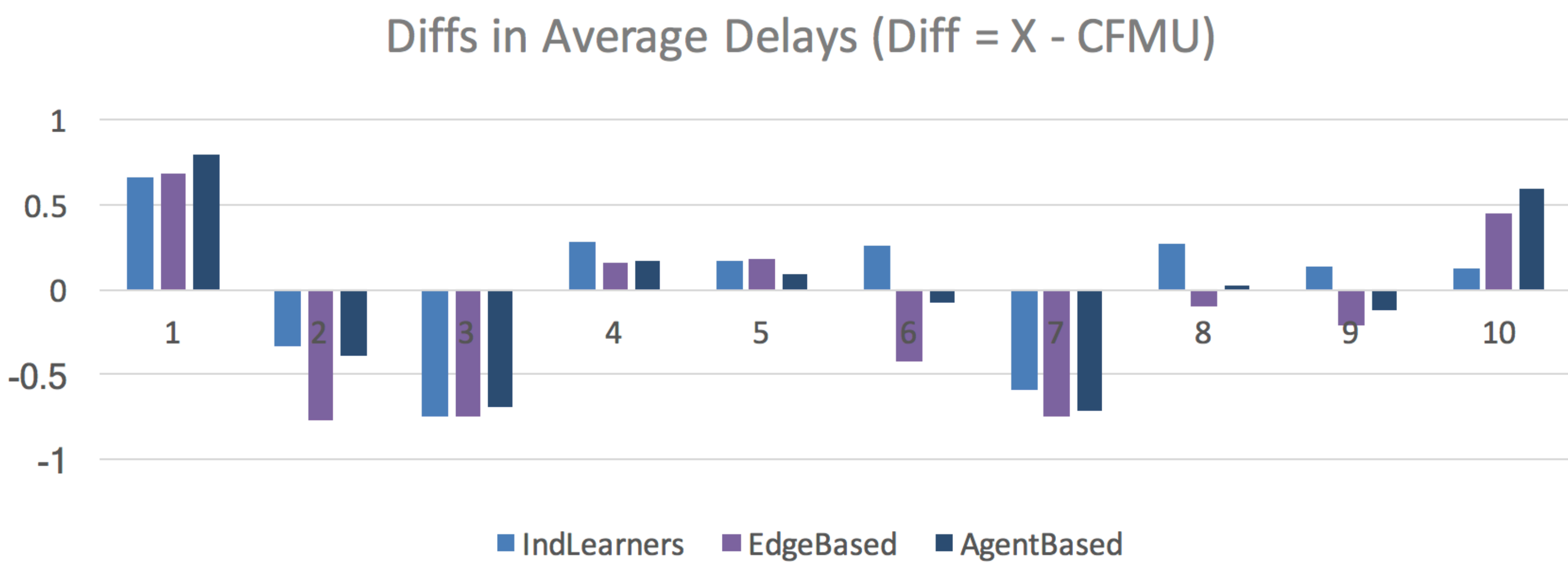
Evaluation Cases

- **10 evaluation cases of varying difficulty**, by inspecting problem parameters in conjunction to the average delay **considering CFMU reported regulations**.
- Each case corresponds to a specific day of 2016 above Spain
- Difficulty has been determined by means of
  - the **number of flights** involved,
  - the **average number of interacting flights per flight** (which is translated to the average degree for each agent in the coordination graph, connecting that agent with its peers),
  - the **maximum delay imposed to flights** for that day to resolve DCB problems **according to CFMU data**,
  - the **average delay for all regulated flights according to CFMU data**, and
  - the **number of hotspots** in relation to the **number of flights participating in hotspots**.

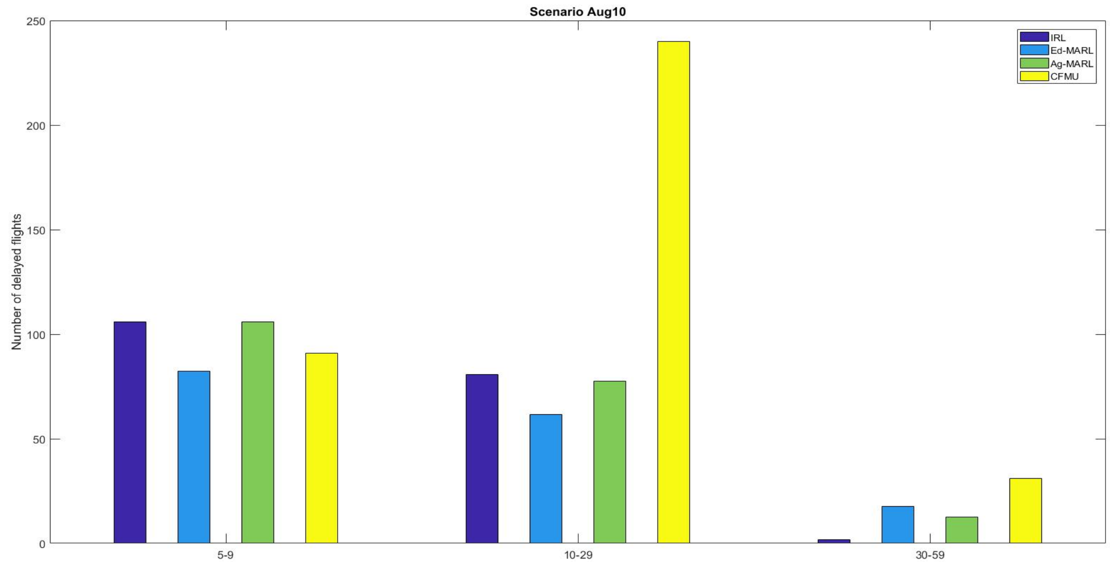
Evaluation Cases

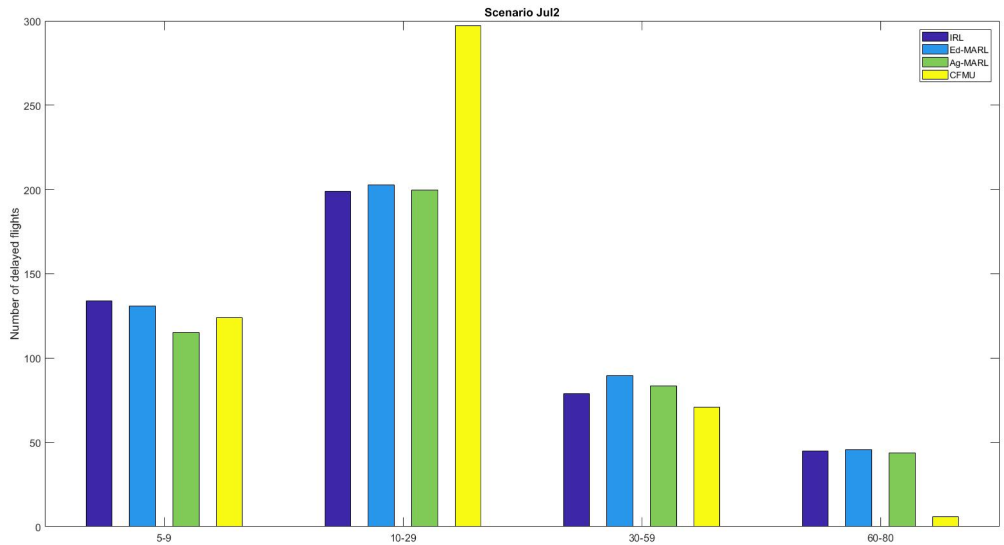
Evaluation case	Number of Flights (Agents)	Average Degree in Coordination Graph (non-zero min/max)	MaxDelay (CFMU data)	Average Delay (CFMU data)	Num of Regulated Flights (type C) (CFMU data)	Num of hotspots (Num of flights)
1: Aug4	5544	6.41 (17-120)	66	12.41	179	33 (853)
2: Aug7	5868	8.03 (23-121)	112	17.54	475	42 (1104)
3: Aug10	5500	5.92 (19-125)	59	15.37	402	27 (759)
4: Aug13	6000	10.89 (22-105)	147	16.02	434	53 (1460)
5: Jul2	5572	6.39 (29-107)	80	17.89	521	29 (778)
6: Jul10	5824	9.98 (21-175)	175	17.35	305	51 (1320)
7: Jul12	5408	5.84 (21-95)	95	18.55	281	28 (820)
8: Jun5	5348	6.77 (20-111)	84	14.99	162	32 (803)
9: Sep2	5498	5.41 (21-112)	88	13.95	165	27 (754)
10: Sep3	5788	5.24 (18-77)	61	14.41	297	26 (783)

Experimental Results



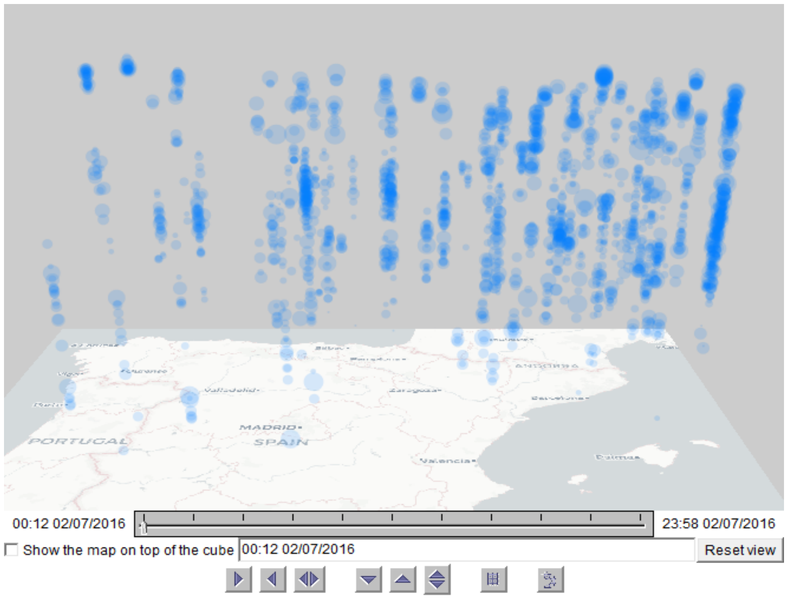
Experimental results

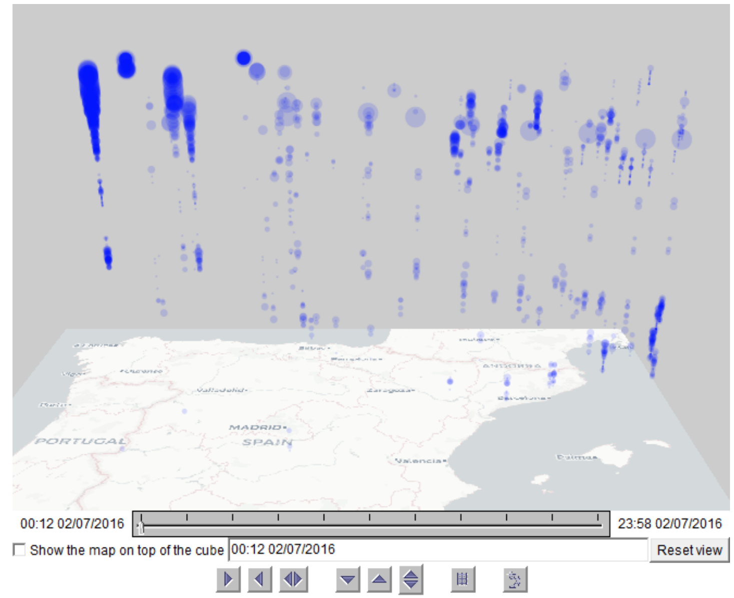




Visualizations of solutions

Visualizations of solutions





The space-time cubes show the spatio-temporal distribution of the delays. The time axis is oriented upwards.
From left to right: CFMU, EdgeBased.

Agent-Based Models for resolving DCB problems Concluding Remarks

- **Agent-based methods have the potential for resolving DCB problems very effectively** (i.e. with small average delays per flight and with zero hotspots, also considering cost indicators) and in computational **efficient ways**.
- **Agent-based methods provide** a **shift of paradigm** towards regulating flights, accounting for ATM network effects (in contrast to 1st come – 1st regulation model);
- This new paradigm inherently **enables to consider preferences regarding individual flights' delays**;
- While providing the means to **assess delays at the pre-tactical stage** to resolve all hotspots
- Contributing to **Increasing Predictability & Collaborative Decision Making.**

Thank you!

DART

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