DIAPasON: A Data-driven approach for Dynamic and Adaptative trajectory PredictiON

ENGAGE Thematic Challenge 2 Workshop

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José Manuel Cordero

SESAR
JOINT UNDERTAKING

Founding Members
EUROPEAN UNION EUROCONTROL

DIAPasON Project

DIAPasON: A **Data-driven** approach for **Dynamic** and **Adaptative** trajectory PredictiON

Objective: **Methodology for TP and traffic forecasting in pre-tactical phase**

- **Data-driven:** Outcomes based on data analysis and interpretation
- **Dynamic:** Adjusted to different planning horizons
- **Adaptative:** Enhanced iteratively with new tactical data

Validated in a Use Case (DCB) – **Combined trajectories, more than individual**

DIAPasON Consortium

CRIDA – *Operational, Data Management*

Deep Blue – *Scenario Definition, Validation*

ZenaByte – *Models, Machine Learning* (*Spin off University of Genova)*

DIAPasON Foundations

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Combining Probable Trajectories - Uncertainty Management

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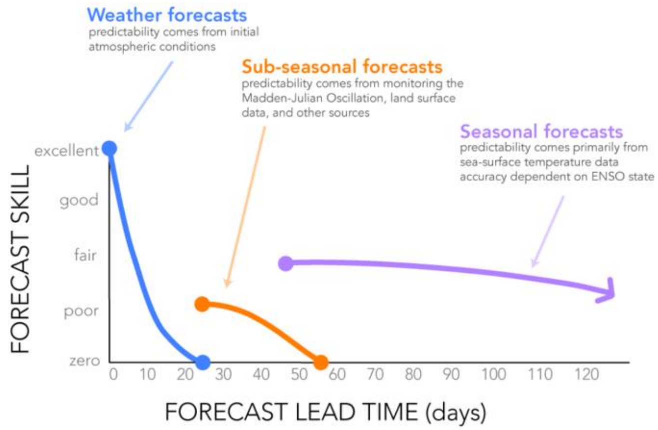
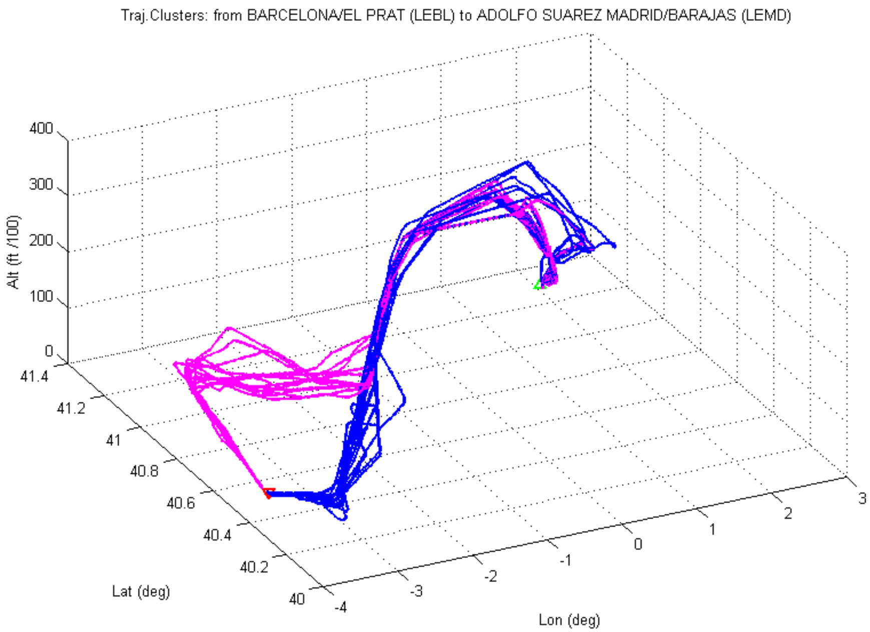
Individual/Multiple TP (with optimisation)

H2020 Datacron

Predicting Moving entities discrete events





Operational Context: TBO

TBO (**Trajectory-Based Operations**) approach 4D trajectories (TTO/TTA)

From tactical to strategical

- ATCOs progressively assuming a monitoring role, instead of a tactical CDR role

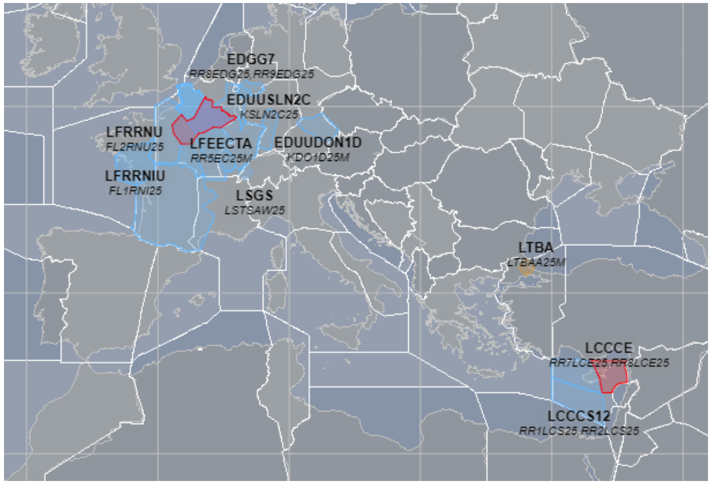
Overall traffic **predictability improvement as key driver** for improvements in:

- Enhanced Safety due to reduction in controller workload
- Increased airspace capacity due to a reduction in buffers
- Cost reduction (fuel/time)
- Reduction of Environmental impact (fuel, emissions, noise)
- Better service provided

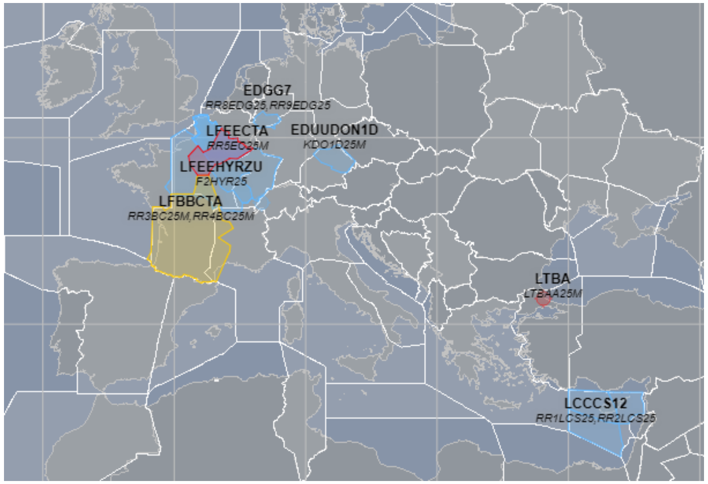
With this as final goal, TP can already bring benefits in this direction by managing uncertainty and putting in place suitable models and techniques (**Engage TC2**)

Uncertainty effects on Traffic

Forecast vs reality (from NOP; *any given day… in old normality*)



Expected



Actual

Are these patterns predictable?

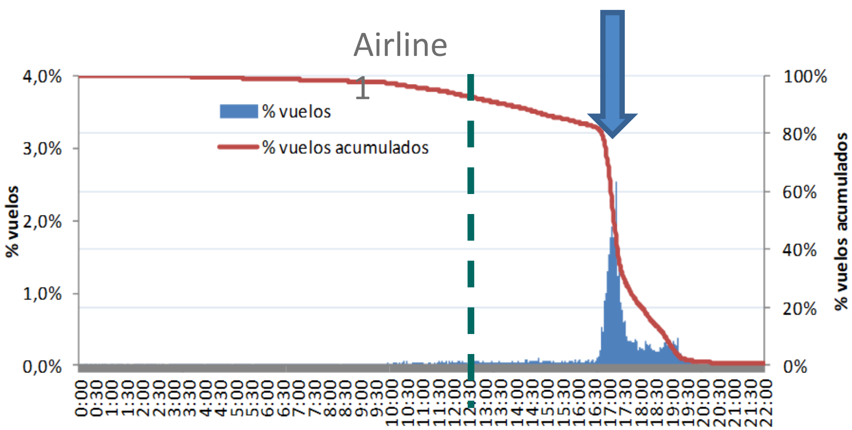
Data Characterization

Identification of patterns in data from different perspectives

Operational data from Spanish ATC Platform (SACTA/iTEC)

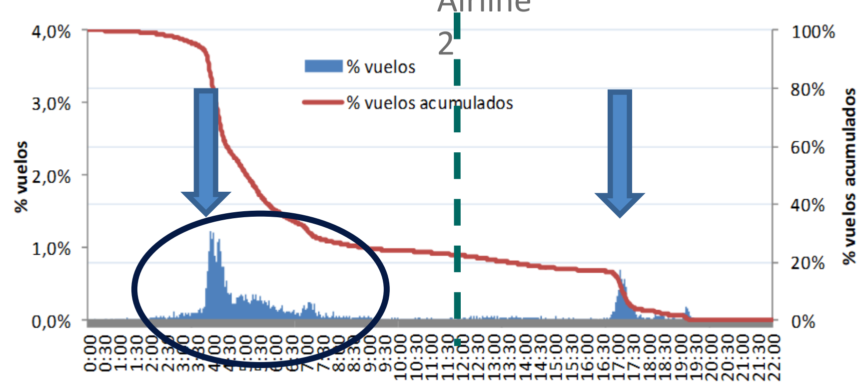
Flight Plan updates **in all phases** (including pretactical)

Airline 1



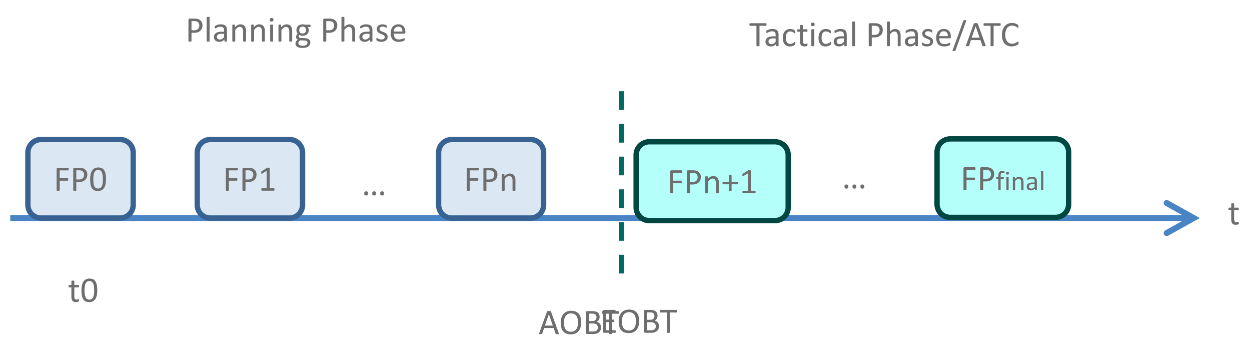
Time before departure

Airline 2



Time before departure

Data Characterization



- Is FP0 reliable enough to be used?
- If not, when?
- Which/How much is the difference between FP0 and FPn in path, and time?
- Is FP0 early enough to be used for planning purposes?
- *How can we use this information to enhance demand forecasting?*

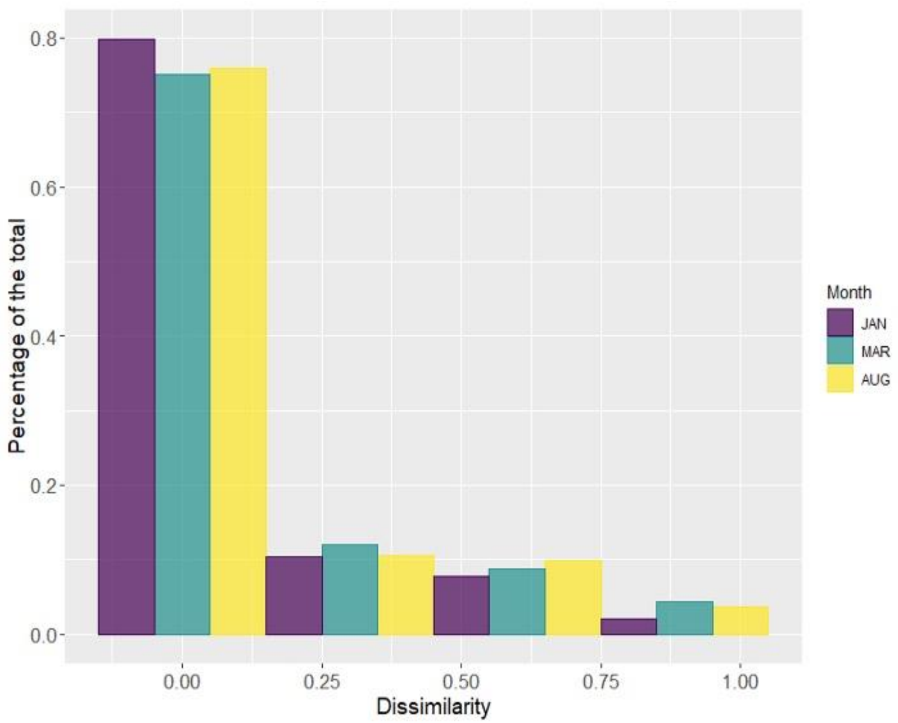
Data Characterization

Dissimilarity metric

$$\mathrm{d} = 1 - \left(\frac{common_{wp}}{\max(wp)}\right), \text{ where:}$$

- common wp: number of waypoints appearing in both the first and the last Flight Plan (intended as last before EOBT);
- max wp: maximum between the number of waypoints appearing in the first Flight Plan and the number of waypoints appearing in the last Flight Plan before EOBT

Data Characterization



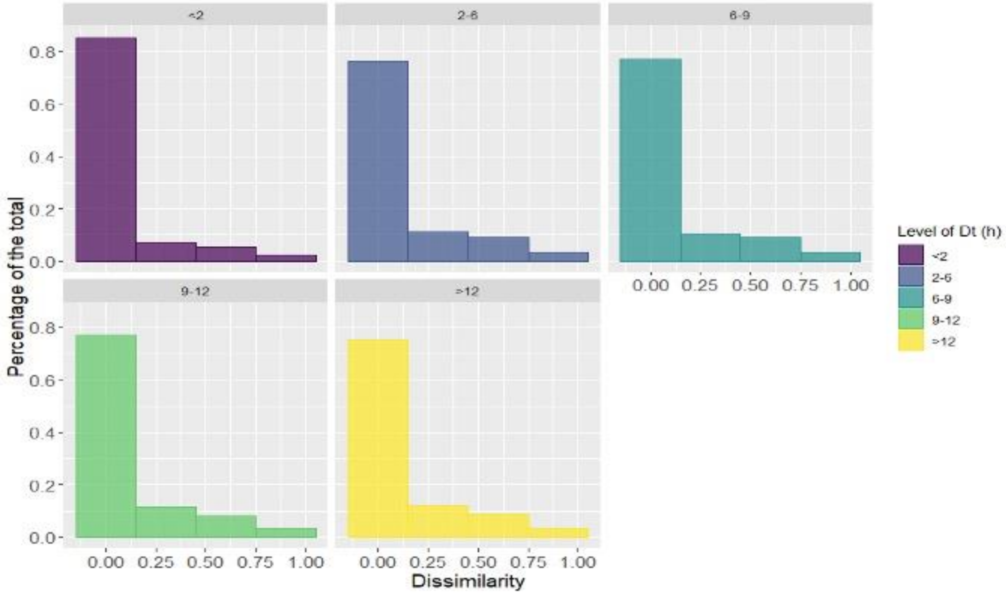
More than 70% of FP instances do not show difference in path

Only 10% of FP share less than 50% of waypoints between first and last record before OB

Most differences are thereby temporal

Data Characterization

DeltaT= Difference between EOBT of a FP record and timestamp of its corresponding first FP (anticipation)

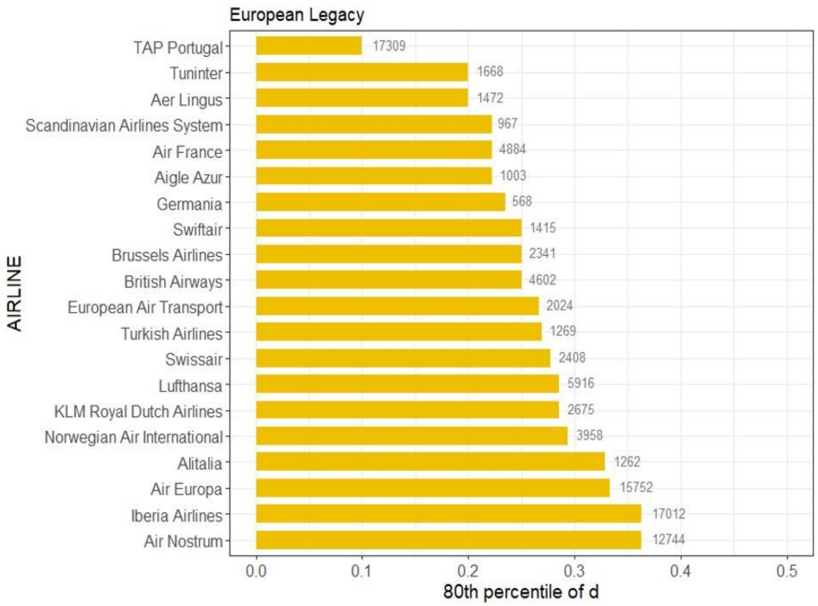


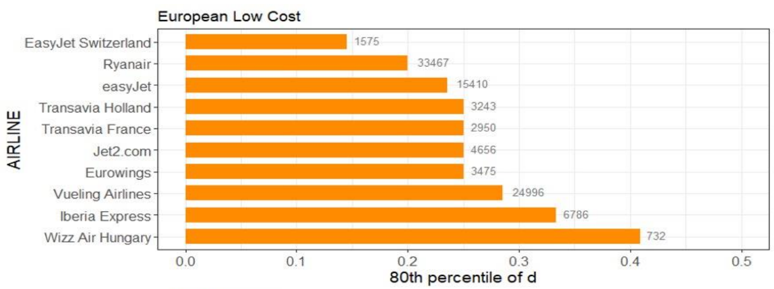
- Dissimilarity seems independent than Delta T (similar behaviour in terms of path change even if first FP issued quite early)
- Weather phenomena (at least linked to Airport data of weather-related regulations) don’t seem to directly impact dissimilarity

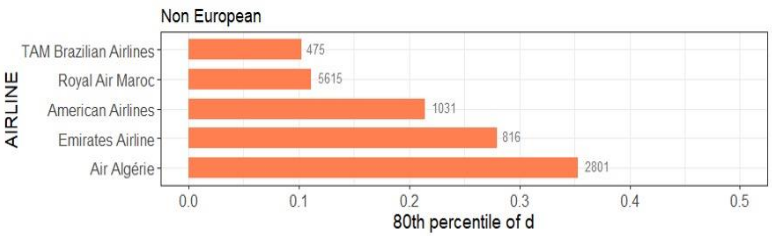
Data Characterization

Analysis per Airlines

- Percentile-80 used as representative value for airline representation in terms of dissimilarity
- Variability between individual Airlines, more than groups



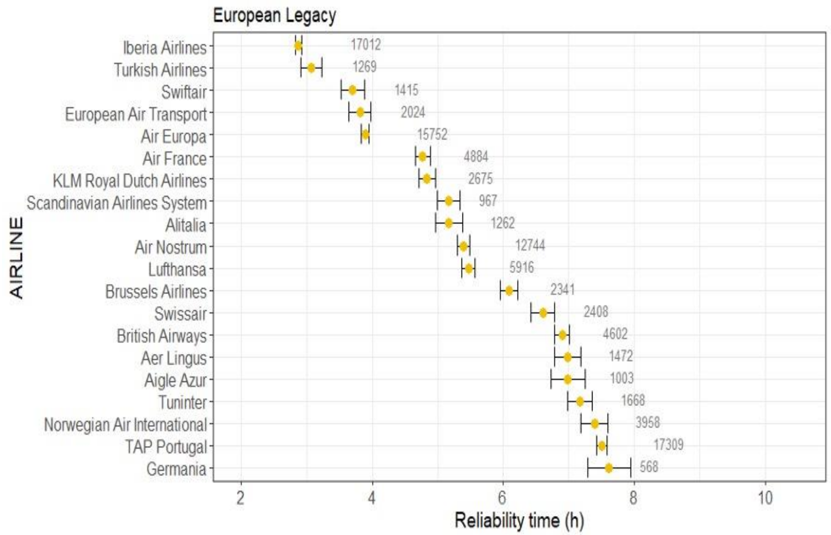


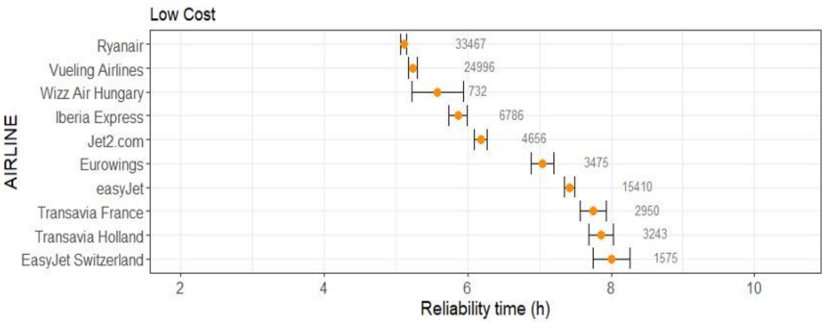


Data Characterization

Analysis per Airline: Reliability

- Average time at which issued FP becomes identical to the last FP before departure (includes a Confidence Interval based on variance and sample size)





- LCC in general issue reliable FP instances earlier than legacy carriers

Predictive Model

Prediction at different time horizons (diff to EOBT): 8h, 4h, 2h, 1h

For each time horizon:

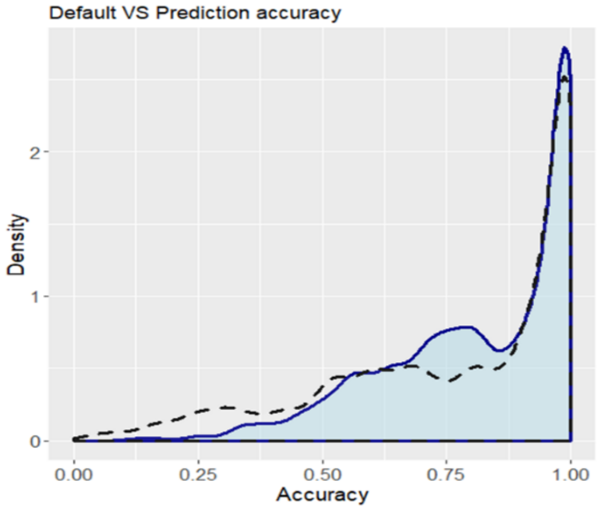
1. the current flight plan (the one in force) is compared with all the historical flight plans of the same flight at the same Δt, selecting all the past flights whose planned trajectories coincide with the current one.
2. if the current flight plan is not the first one recorded that day, also the previous flight plans are compared with the corresponding past ones, discarding from the previously selected single flights all the ones that do not match.
3. for all the selected single flights, the last-before-off-block-time planned trajectory is retrieved.
4. the predicted trajectory is taken as the most frequent one in this set.

Predictive Model

Accuracy compared with using the FP in force (*noted as default*)

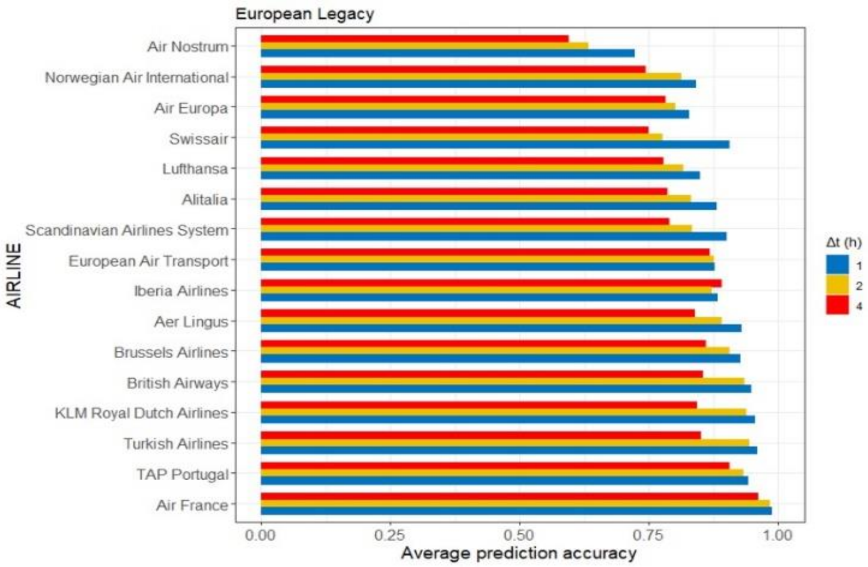
SPRING	8h	4h	2h	1h
average ***default*** accuracy	76%	75%	82%	86%
average ***prediction*** accuracy	82%	82%	85%	87%

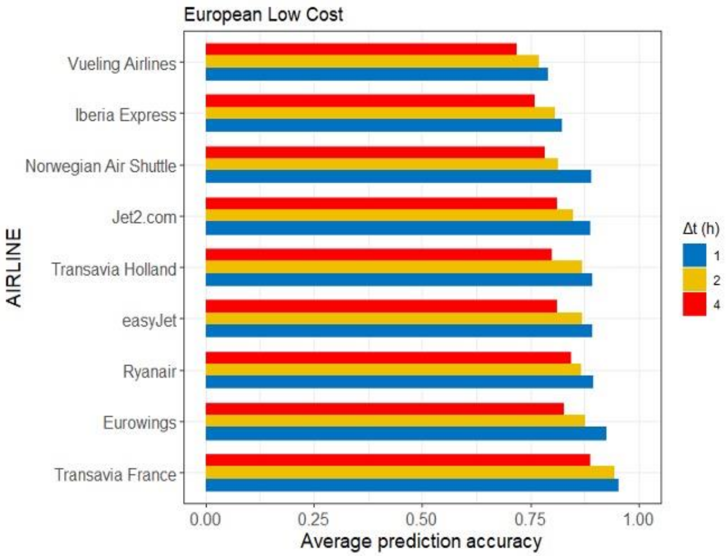
SUMMER	8h	4h	2h	1h
average ***default*** accuracy	88%	76%	83%	88%
average ***prediction*** accuracy	92%	85%	87%	90%



Particularly useful for "very unpredictable" flights

Predictive Model



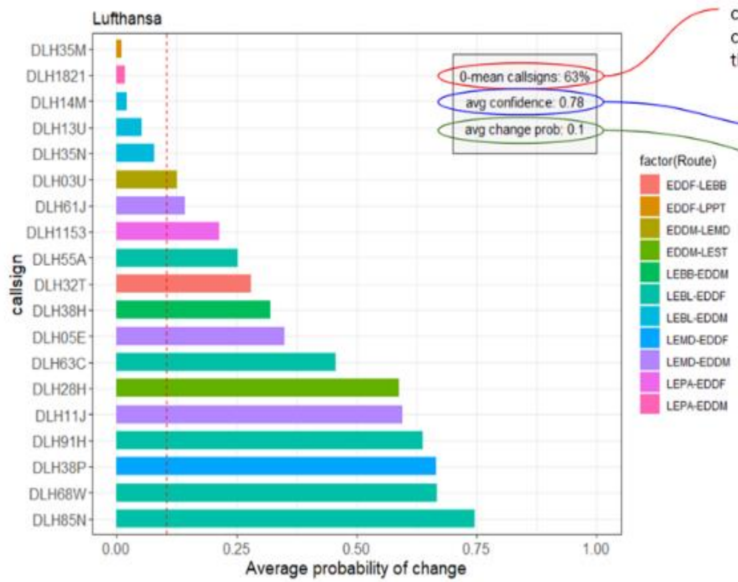


- In most of the airlines the prediction accuracy increases as Δt decreases.
- The prediction reaches a similar level of accuracy in for all the airlines, apparently without any bias.
- The level of accuracy is, on average, over 80% for the great majority of airlines.

Predictive Model

Unpredictability of most airline is "systematic enough" to become predictable

It is possible to estimate the probability of change for every flight (and apply them in demand forecasting or a value for confidence of the forecast mix)



The percentage of airline's callsigns which have on average 0 probability of change (i.e., are never predicted to change in the data considered) and are therefore not reported in the graph

The average confidence of the predictions performed on the airline

The average probability of change for the airline's callsigns

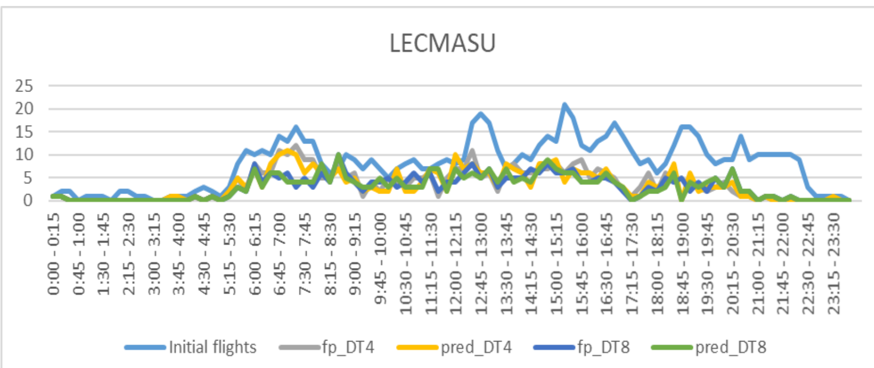
*Notice that the "default" predictions (i.e., when the model doesn't find any matching examplein the past) are excluded from the computation of these numbers

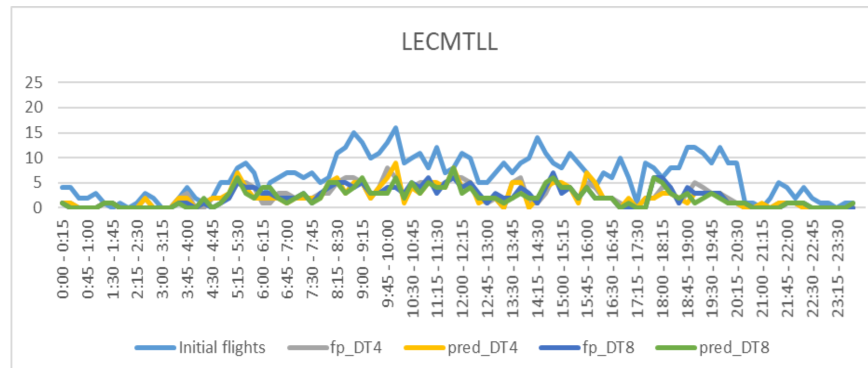
Application: DCB Use case

- Differences in occupancy counts per sectors between the real data in the planning phase and the output provided by an application of the predictive framework described
- Assumption: Vertical profile estimated to consider a 4D trajectory, en-route phase
- 6 days tested, from summer and winter season 2018 (June & November, respectively)
- 2 different en-route sectors (LECMTLL and LECMASU)
- 8h and 4h before operation

Application: DCB Use case

The forecast normally captures the trend of the occupancy counts, better in one sector (upper) than the other (lower, possibly due to flights in evolution)





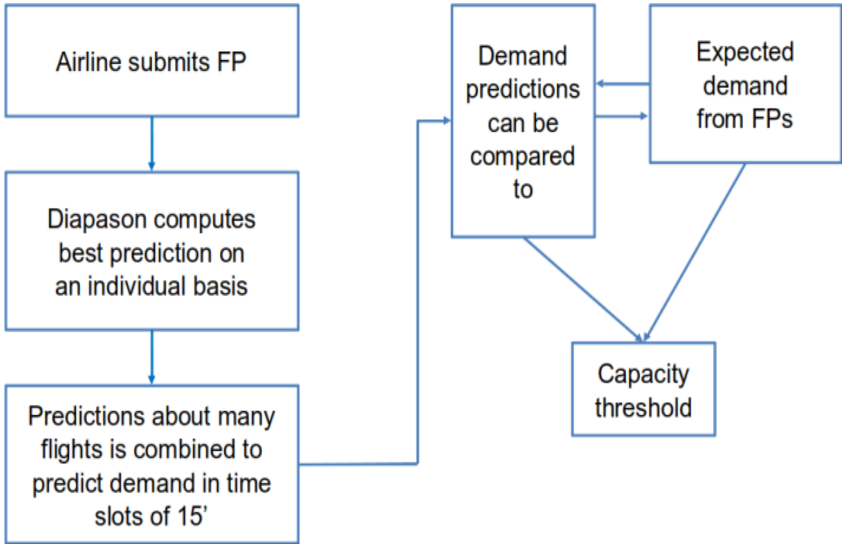
Application to be further refined

Application: DCB Use case

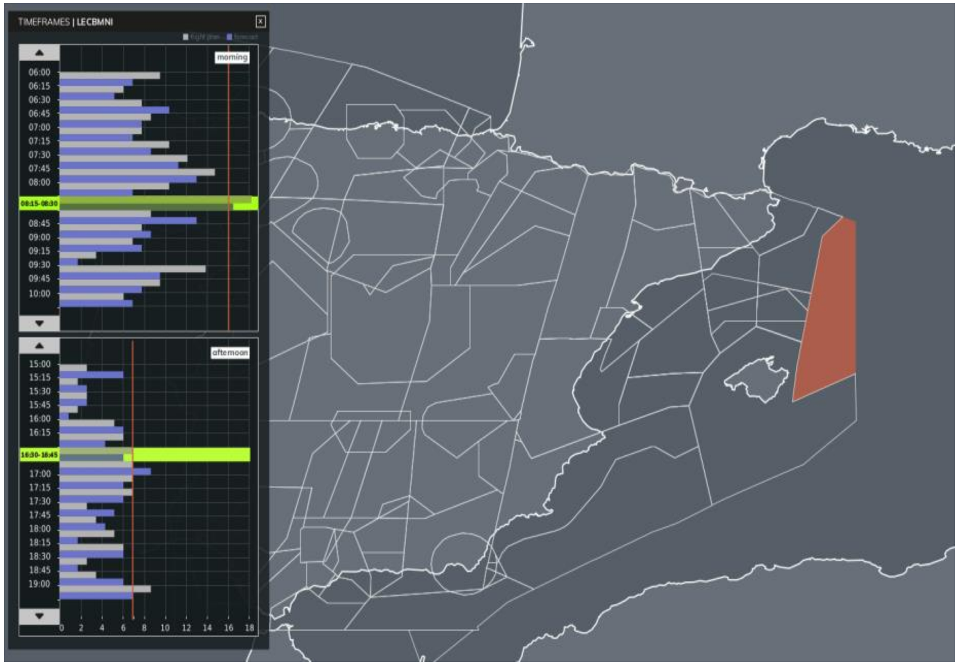
Interviews on application on such capabilities

- Giovanni Lenti, EUROCONTROL, Head of Network Operations Services.
- Debora Palombi, ENAV, Head of Network Manager Unit.
- Patricia Ruiz-Martino, ENAIRE, ATCO and former Head of En-route Operations Unit

How DIAPasON predictions could be integrated in the Strategic planning process at NM level?



Application: DCB Use case Mock-up



FP (white) and Diapason prediction (blue) 4 hours before EOBT for flight #3229838 LIRF – LEBL.

Same as for flight #3229078 LEMD – LEMH.

Conclussions

- The project has obtained a Trajectory Prediction framework considered to be data-driven, dynamic, adaptive, and Airspace User oriented.
- Data-driven characterization of demand in pre-tactical phase demonstrates the potential for trajectory prediction application of the repetitive features of traffic within ATM domain – availability of data in this stage is an enabling factor for this
    - Especially using pre-tactical data brings additional benefits
- Airlines show different behaviours, that the presented framework is able to capture and update in a tactical manner for this application.
- The model significantly enhances the prediction accuracy for “very variable” flights, while for very regular flights the default choice and the prediction are usually the same.
- Refinement for specific applications would be necessary in order to obtain the maximum benefit of the predictive features of demand. In particular, extension to vertical profile information in the considered application

Thank you very much for your attention!

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