

Improving air traffic control capacity planning with ML solutions

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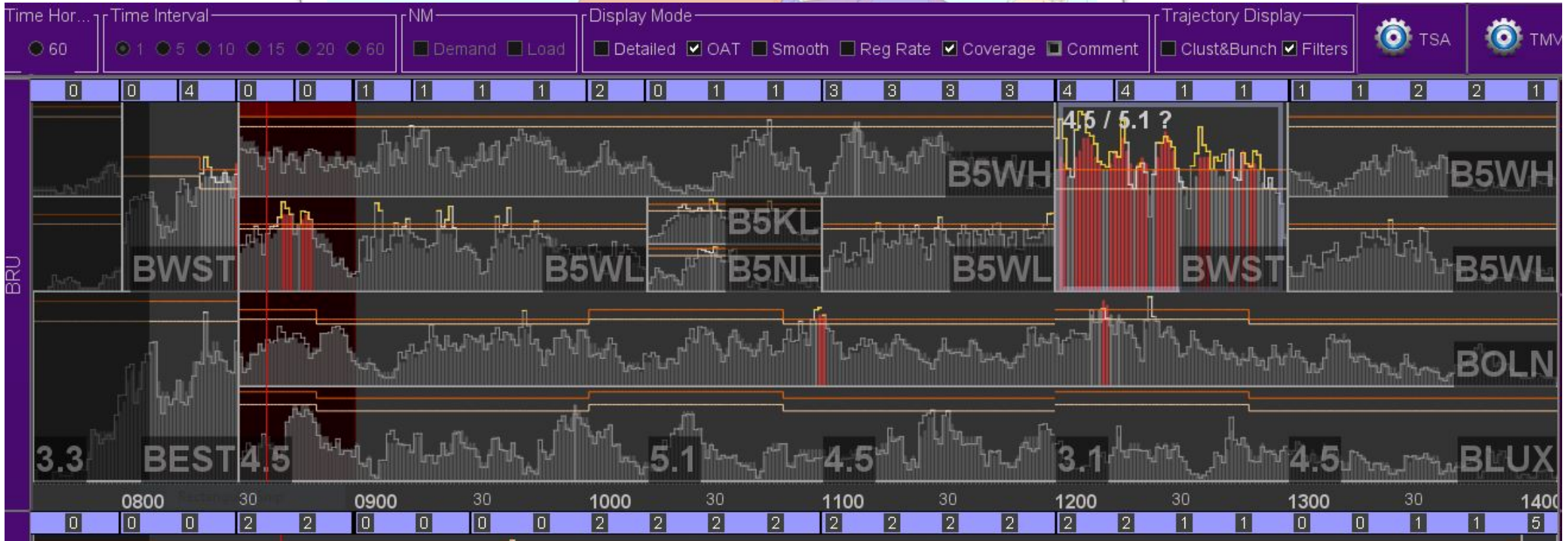
Supporting
European
Aviation



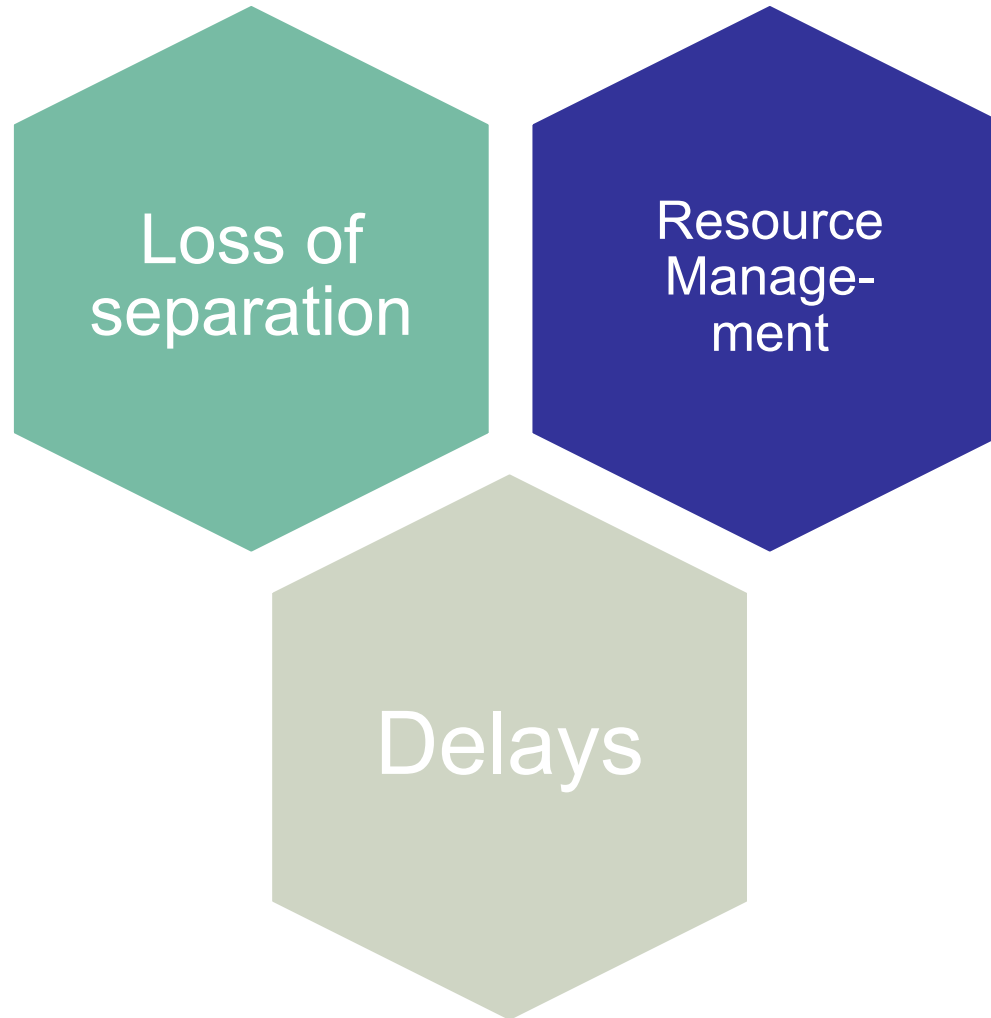
CONTEXT DEFINITION

AIR TRAFFIC FLOW & CAPACITY MANAGEMENT

iFMP (Integrated Flight Management Panel)

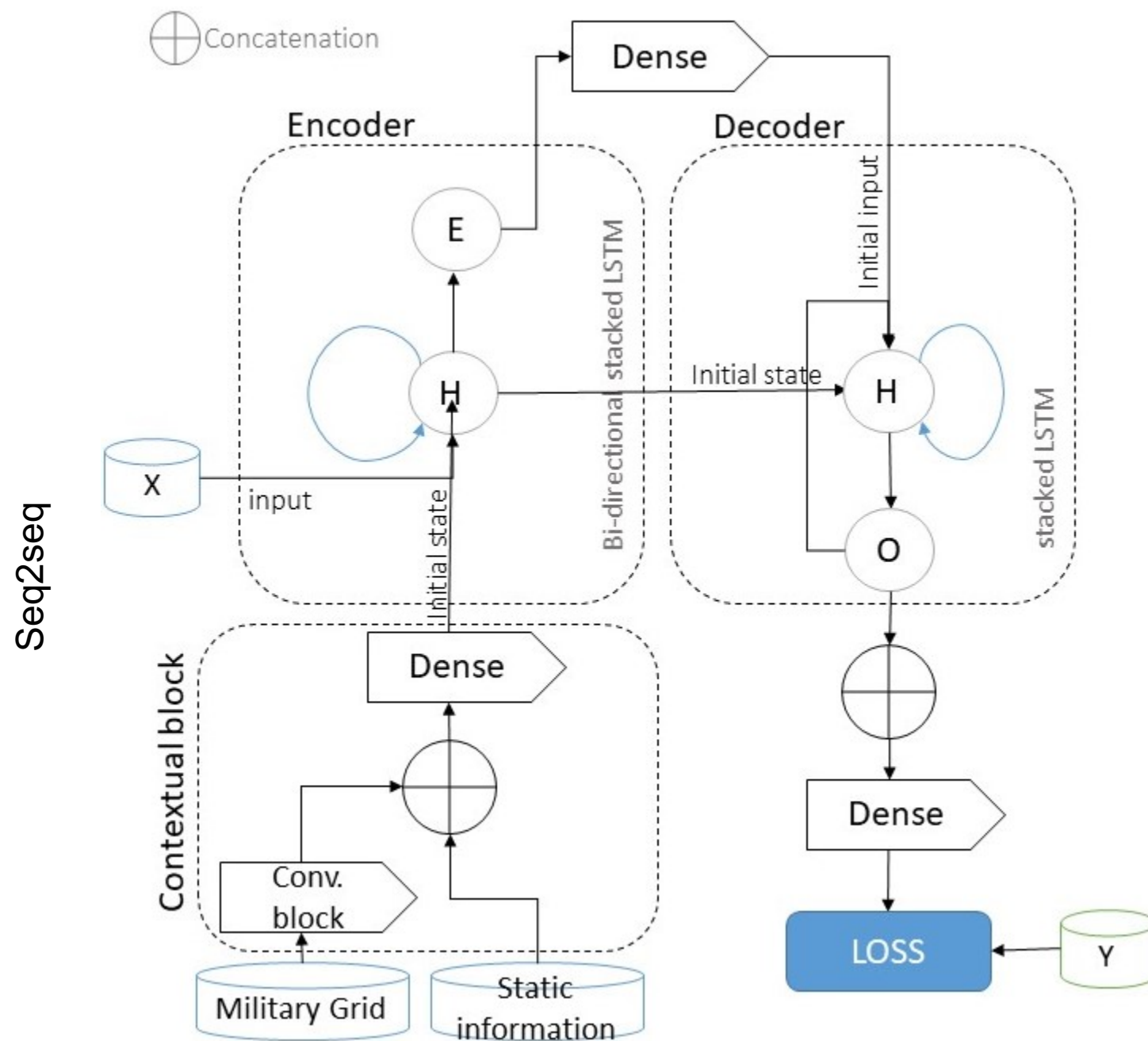


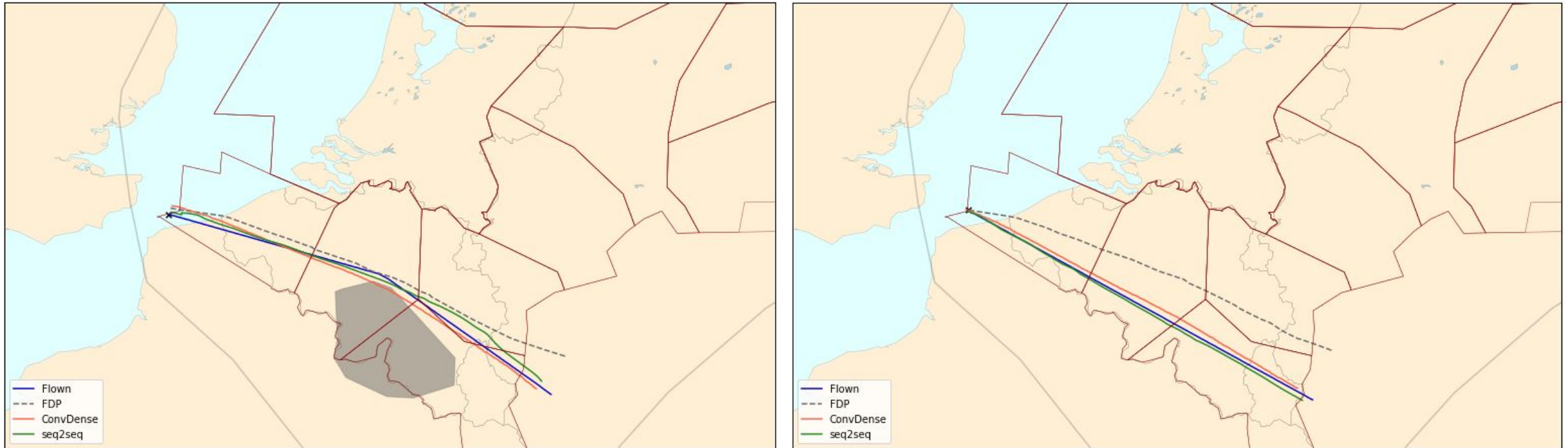
Effects of prediction errors



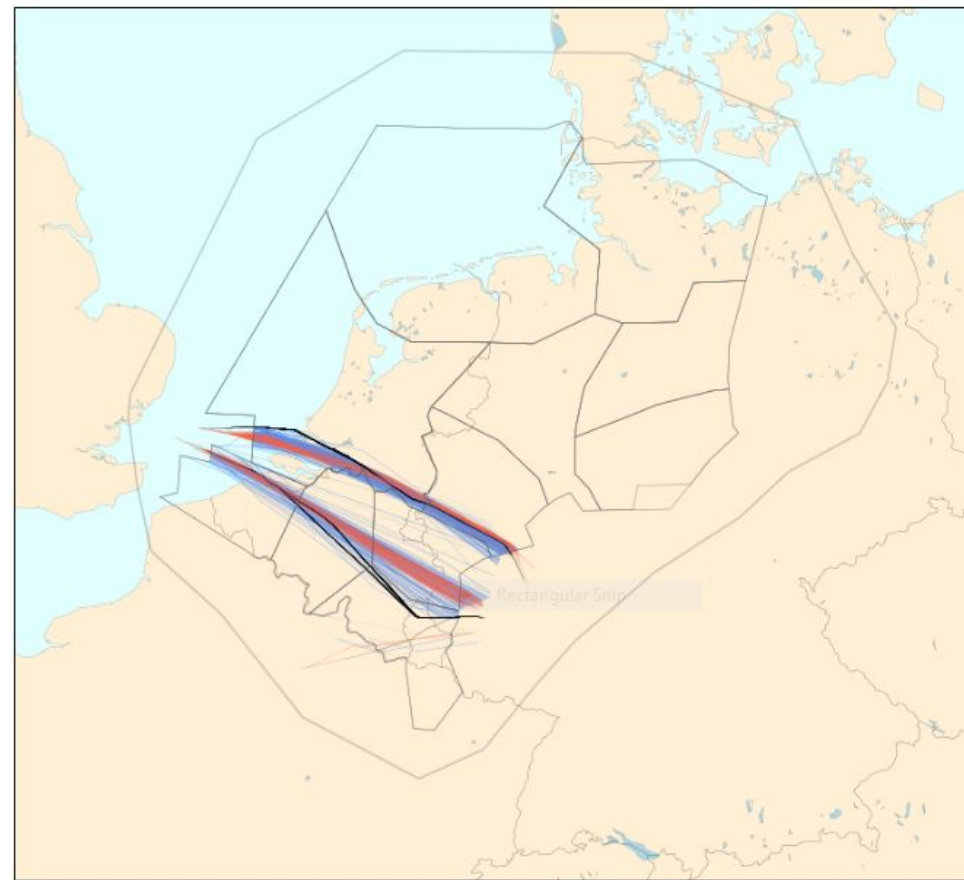
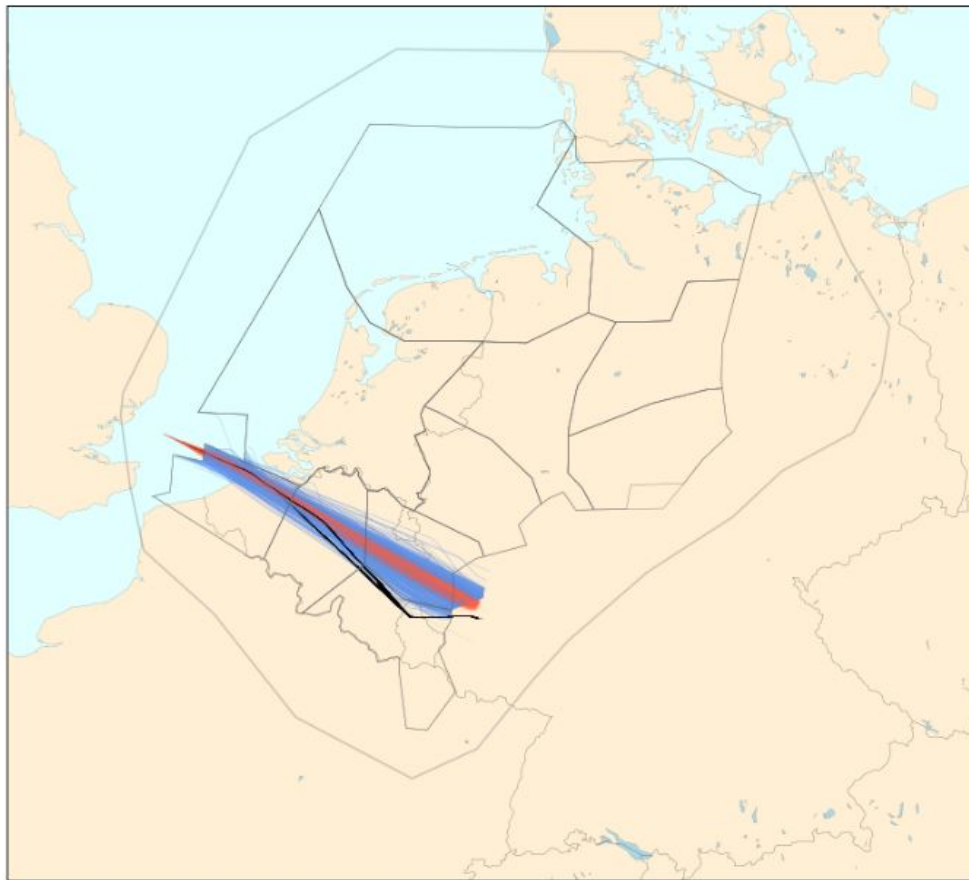
Solution Design

- STATIONARITY
- MODULARITY
- ARCHITECTURE



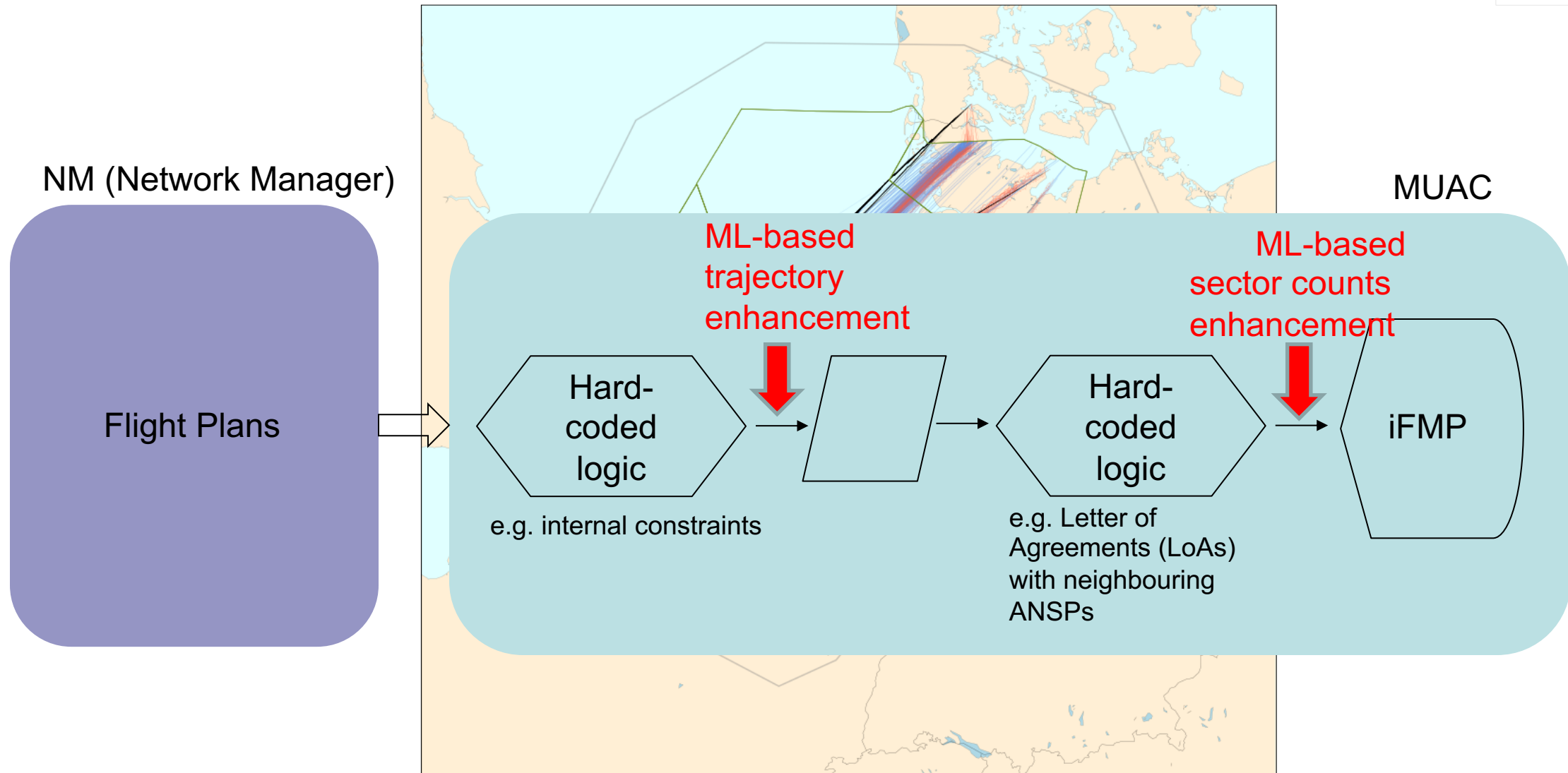


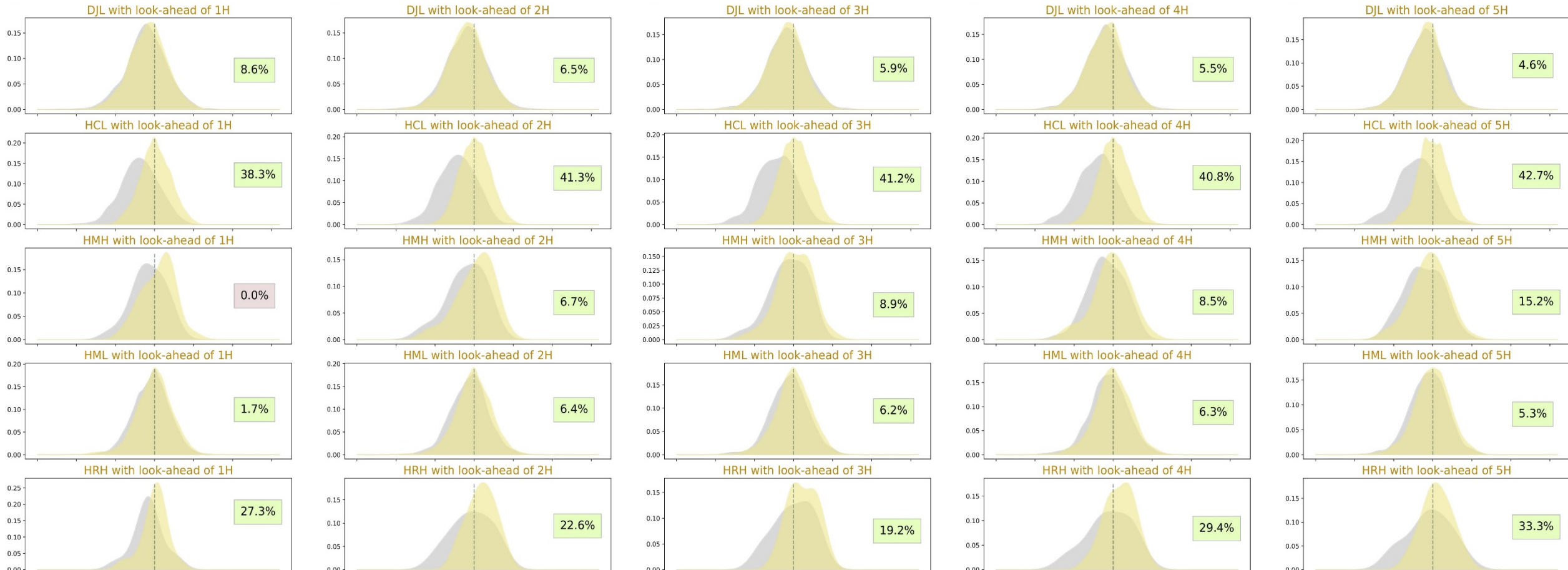
Example of a flight departing from Heathrow airport to Rome. Left panel displays a situation on the 19th of March 2019 where a military restriction was activated during the cruising of the flight - shown as a gray area. Both CONVDENSE (red) and SEQ2SEQ (green) successfully avoid the area, being closer to the real trajectory (blue) than the FDP prediction (gray dashes). Right panel shows how both algorithms manage to capture direct clearance opportunities as there was no military restriction on the 15th March of 2019 in that region.



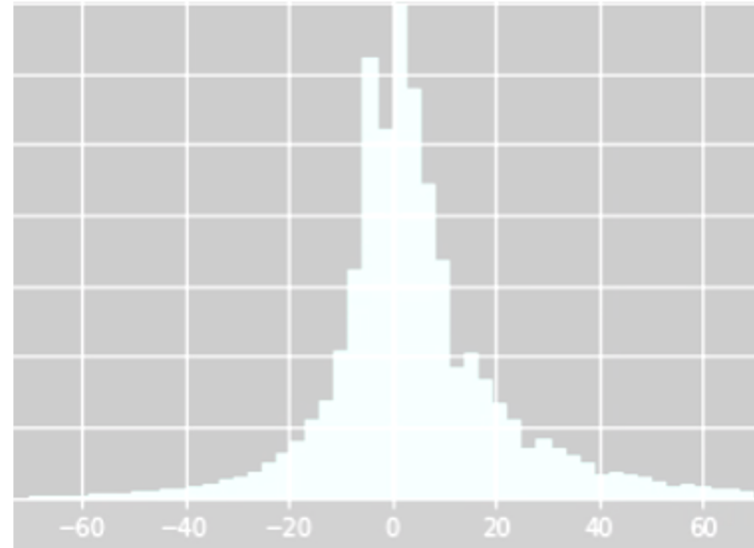
Example of a flight departing from Frankfurt airport to Heathrow. Left panel displays trajectories from the 19th of March 2019 until the 24th of April 2019. Right panel shows trajectories posterior to the 24th of April 2019, with the apparition of a new route due to restrictive measures from NM (new flows).

Sector Occupancy Application

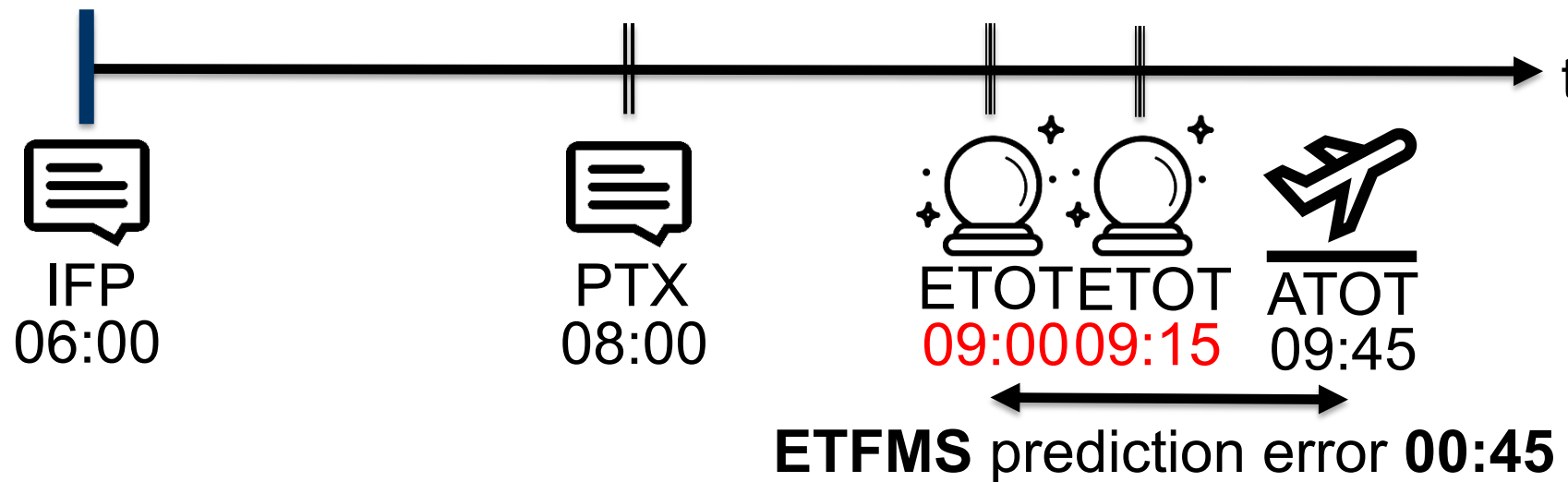




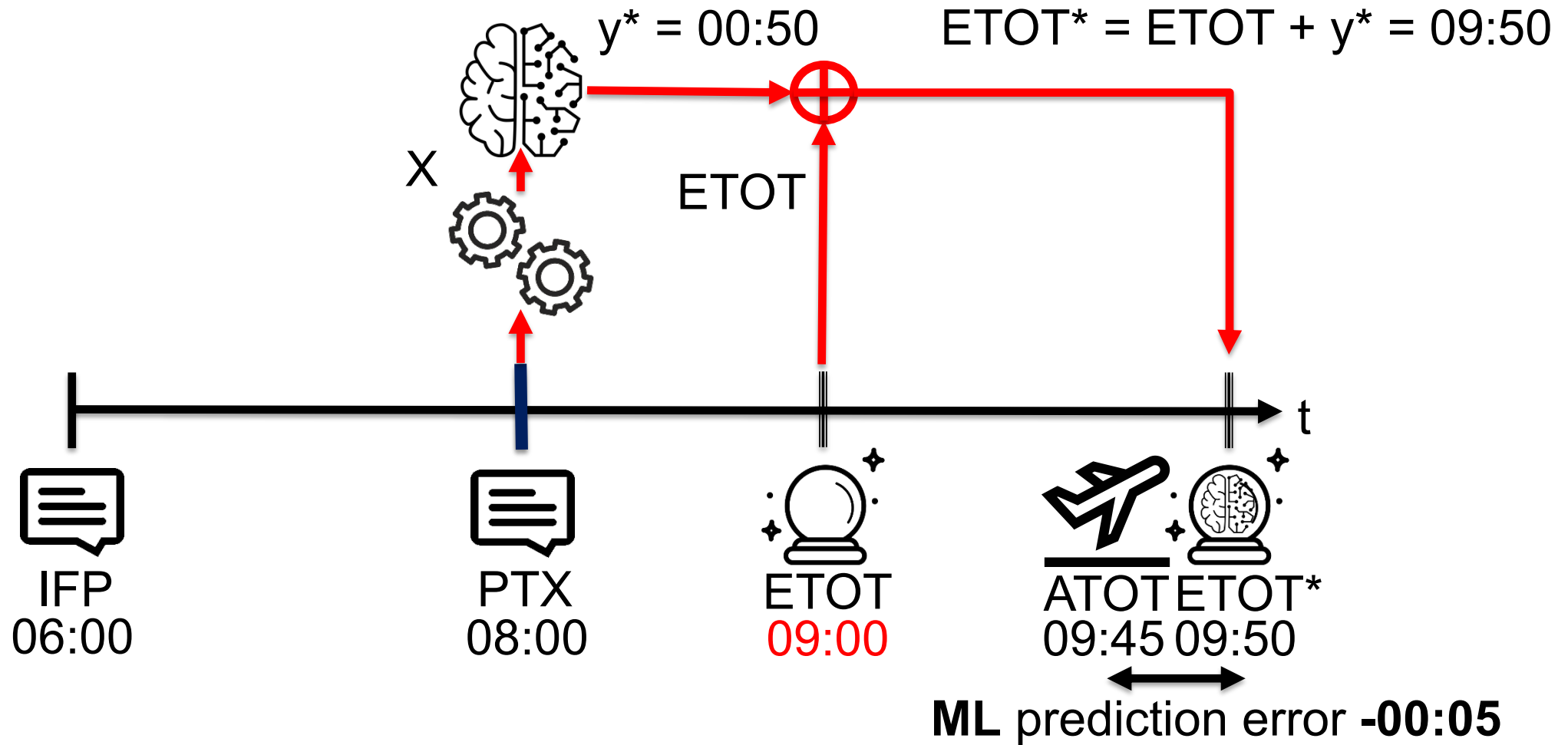
TAKE-OFF TIME PREDICTION



IFP: Initial Flight Plan
PTX: Periodic Transmission
ETOT: Estimated Take-off Time
ATOT: Actual Take-off Time
ETFMS: Enhanced Traffic Flow Management System



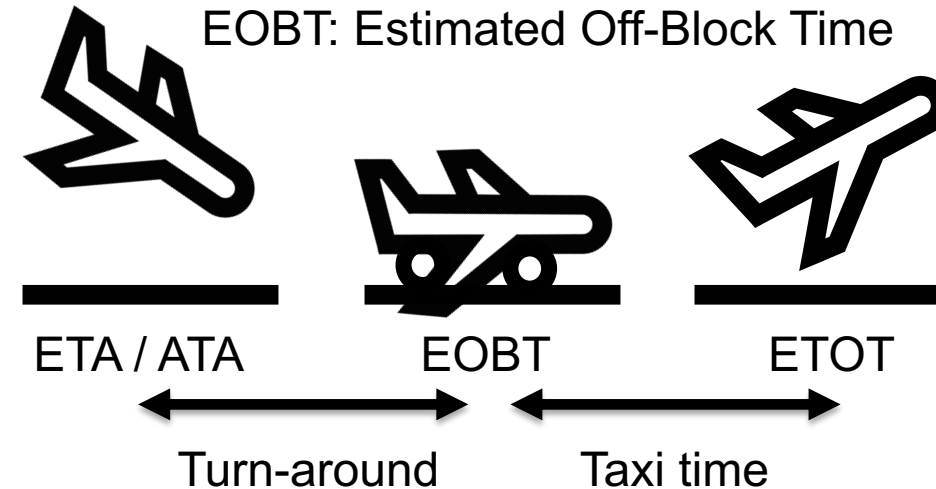
TAKE-OFF TIME PREDICTION



FEATURES



ETA: Estimated Time of Arrival
ATA: Actual Time of Arrival
EOBT: Estimated Off-Block Time



- **Flight-related features**

- Departure airport
- Destination airport
- Airline
- Time available to perform the turn-around
- ATFM delay assigned to the flight (if any)

- **Airport congestion features**

- Number of operations planned near ETOT

- **Airport delay state features**

- Distribution of delays in the last hour

- **Weather features**

- Temperature
- Visibility

- **Basic calendar features**

- Hour of the day
- Day of the week
- Month of the year

MODELS

Gradient Boosted Decision Trees (**GBDT**)

Microsoft
LightGBM

Each **example** corresponds to one **ETFMS message**

input shape = (batch size, # of features)

Recurrent Neural Network (**RNN**)



Keras

Each **example** includes the sequence of ETFMS messages for one **flight, from IFP to take-off**

input shape = (batch size, # of messages, # of features)

RESULTS

- Only flights **crossing MUAC airspace**
- **January of 2016 to December of 2018**
- 70-10-20 train-validation-test split

Metric	ETFMS	lightGBM	Benefit
MAE	13.84	10.40	25%
STD	21.54	17.48	19%
Q1	3.00	2.57	14%
Q2	7.23	5.95	18%
Q3	17.00	11.87	30%

Time to ETOT	ETFMS MAE	lightGBM MAE	Benefit
[0, 30)	6.34	5.12	19%
[30, 60)	10.18	8.21	19%
[60, 120)	14.02	10.0	28%
[120, 180)	15.09	10.64	30%
[180, 240)	16.19	11.51	29%
[240, 300)	17.63	12.40	30%
[300, 360)	18.70	12.98	31%

More details: Dalmau. R et al., (December 2019), *Improving the Predictability of Take-off Times with Machine Learning*, Proceedings of the 9th SESAR Innovation Days (SIDs), Vienna, Austria

POTENTIAL FUTURE WORK DIRECTIONS

- Include data specific from airlines
 - Crew schedules
 - Catering status
 - Boarding status
- Include data specific from airports
 - Gates utilization
 - Departures/Arrivals sequence
- Consider features capturing network effects
- ...