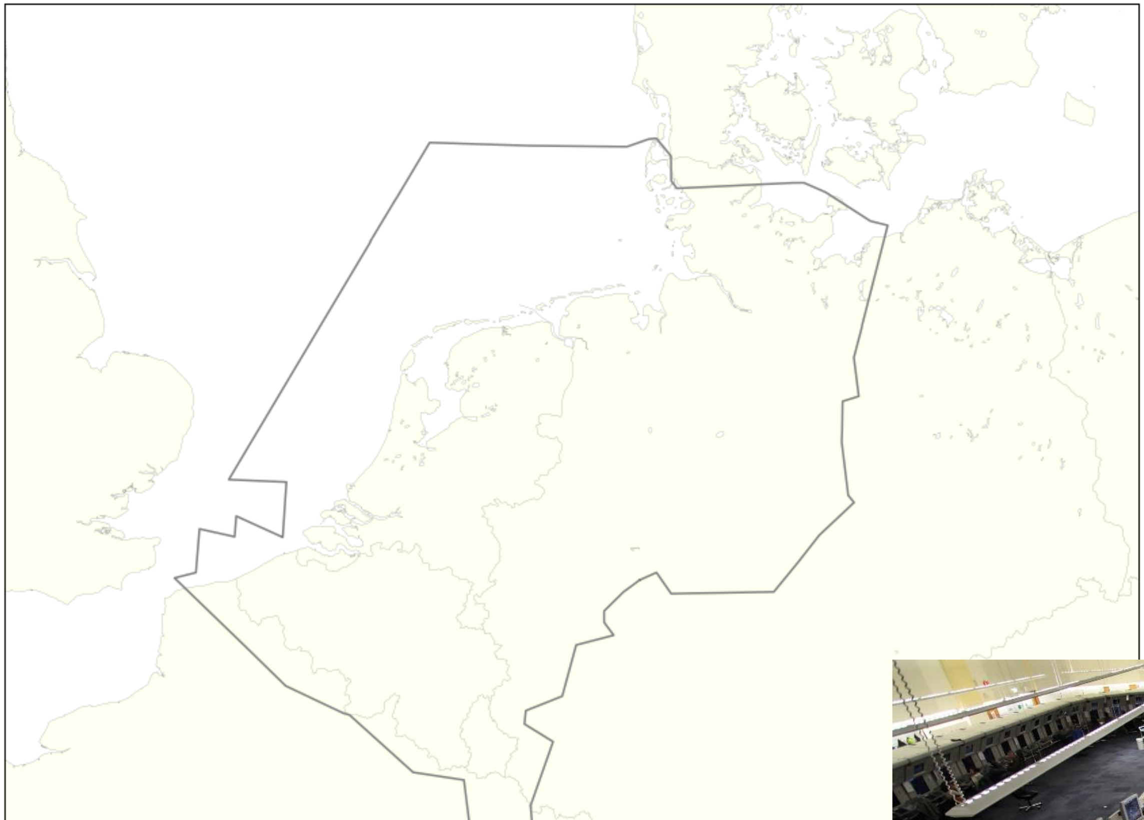
Predicting **flight routes** with a **deep neural network** in the Air Traffic Flow and Capacity Management system

Herbert Naessens, 11 October 2018

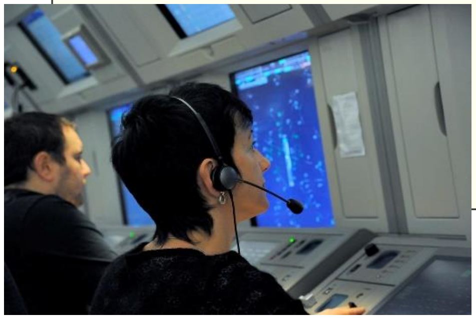
In this presentation

- Who is EUROCONTROL Maastricht UAC
- ATC to ATM, and the problem of predictability
- Rationale for a deep neural network
- Details of the implementation
- Integration in the operational system
- Real-life results

EUROCONTROL Maastricht Upper Area Control Centre



- Cross-border ATC
- Upper area
- > 1.8 million flights (5700 on peak day)
- Highest controller productivity
- Driven by innovation



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- https://www.youtube.com/watch?v=gBwwik4F2Og

Air Traffic Control to Air Traffic Management (ATC to ATM)

- Amount of traffic an air traffic controller can handle safely has a limit
- Traditional approach of splitting sectors in smaller pieces has reached limits

➔ Delays have been increasing last couple of years

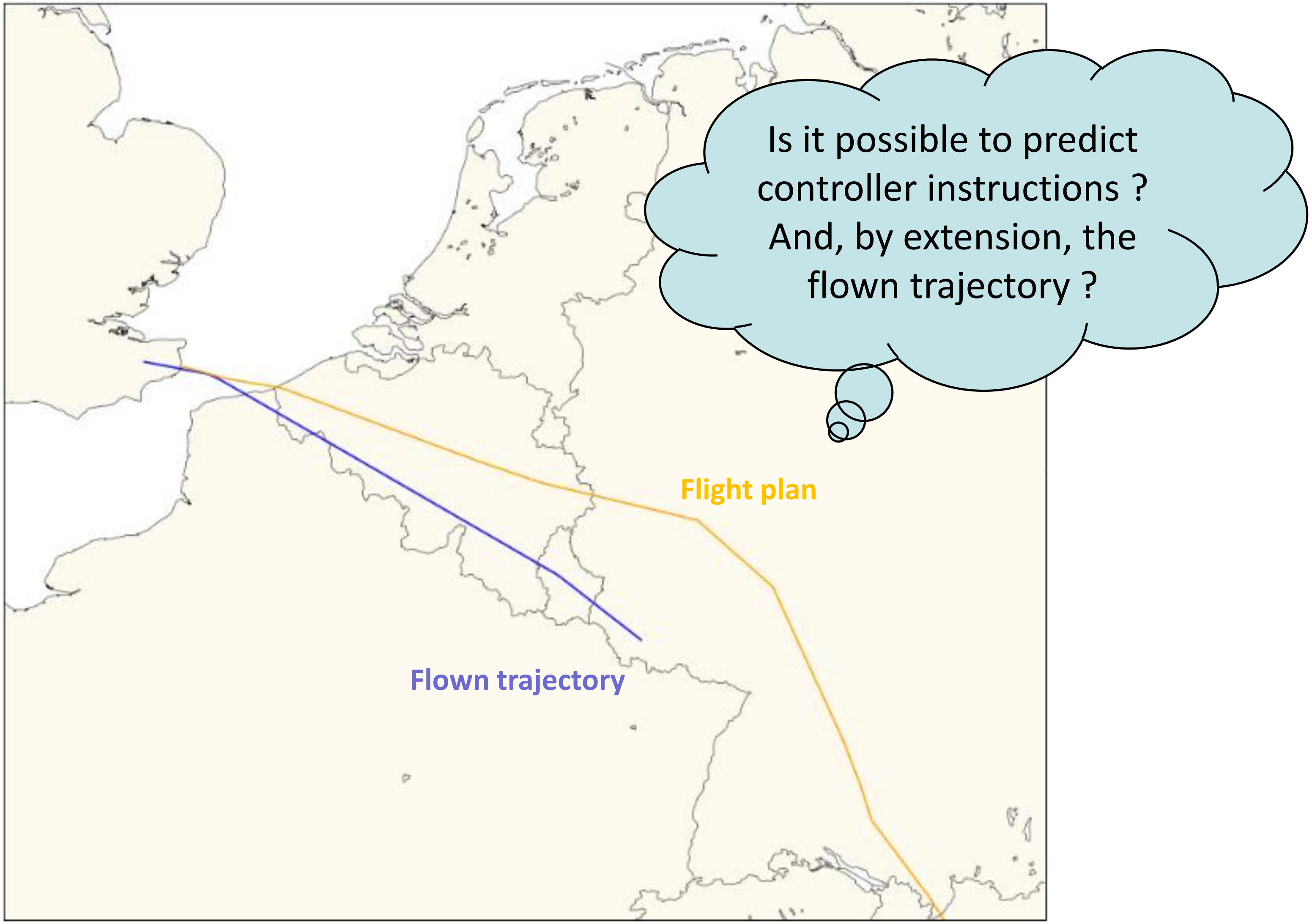
- **Vision**: avoid peaks in individual sectors by <u>proactive</u> traffic measures (*= Air Traffic Flow and Capacity Management*)
  - Sector workload prediction 3h-30min horizon from 'now time'
  - Detection of upcoming traffic clusters 30-10min horizon from 'now time'

- *But predictability degrades quickly when look-ahead is 10min or longer ...*

Challenges to predict traffic for MUAC

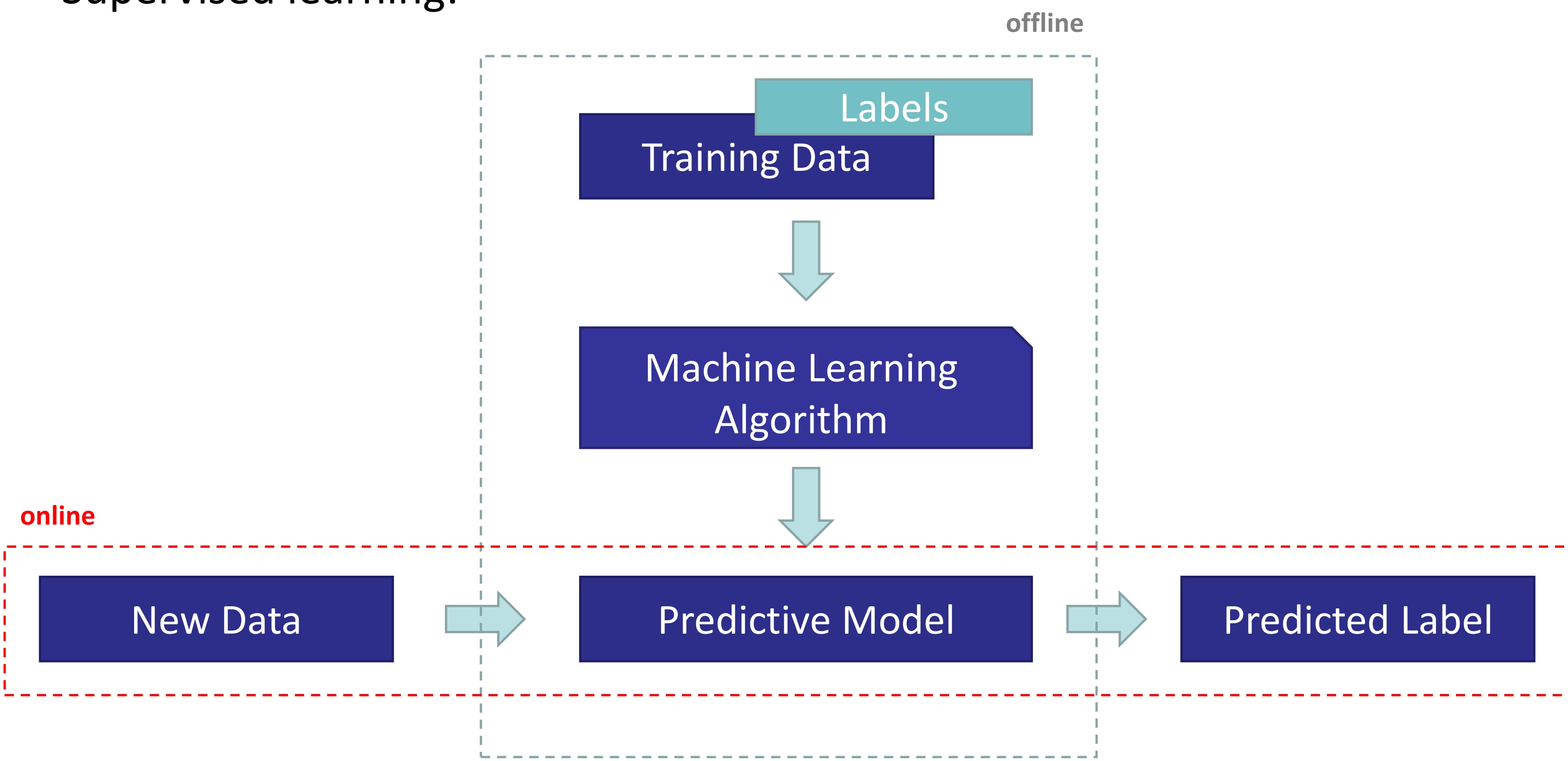
1. Flights not conforming to the route in the filed flight plan because air traffic controllers give permission to fly shorter routes (local & upstream)
2. Uncertainty of departure times at airports in the vicinity
3. Rate of climb/descent, ground speed

The problem


Is it possible to predict controller instructions ? And, by extension, the flown trajectory ?
Flight plan
Flown trajectory

Machine Learning

- Key enabler is availability of historical data
- Supervised learning:



Machine Learning Algorithms

- Several machine learning algorithms have been evaluated
  - Decision Trees
  - Random Forests
  - Kernel Support Vector Machines
  - K-Nearest Neighbours
  - Neural Networks

- Random forest with adequate pruning offered the best results out of the box.
- With lots of tuning, a deep neural network could surpass the results by a small margin.

Rationale for a deep neural network

- Random forest required disproportionate more computing resources if amount of training data and number of predictors increased

- The serialised model was much smaller with a neural network
important for scalability: training is done offline; the serialised model is deployed as adaptation data to the production environment

- Off-the-shelf libraries (TensorFlow)
  - high degree of customisability, e.g. custom cost functions
  - API integration with existing application code
    solution had to be integrated in EUROCAE ED-153 Software Assurance Level 4 (SWAL4) environment written in Java
  - offloading computations to GPU cards speeds up training

Target data to be predicted

- Intersection observed trajectory and the MUAC Area of Responsibility (AoR)

- Simplified to 4 points by iteratively applying the Douglas-Peucker algorithm
  For 99.6% of the flights, the lateral deviation does not exceed 5NM at any point along the trajectory. For 89%, the lateral deviation does not exceed 1NM

- Makes sense because flown route is typically result from ‘direct-to’ and ‘heading’ instructions, and controllers like to minimize the amount of instructions

Target data to be predicted

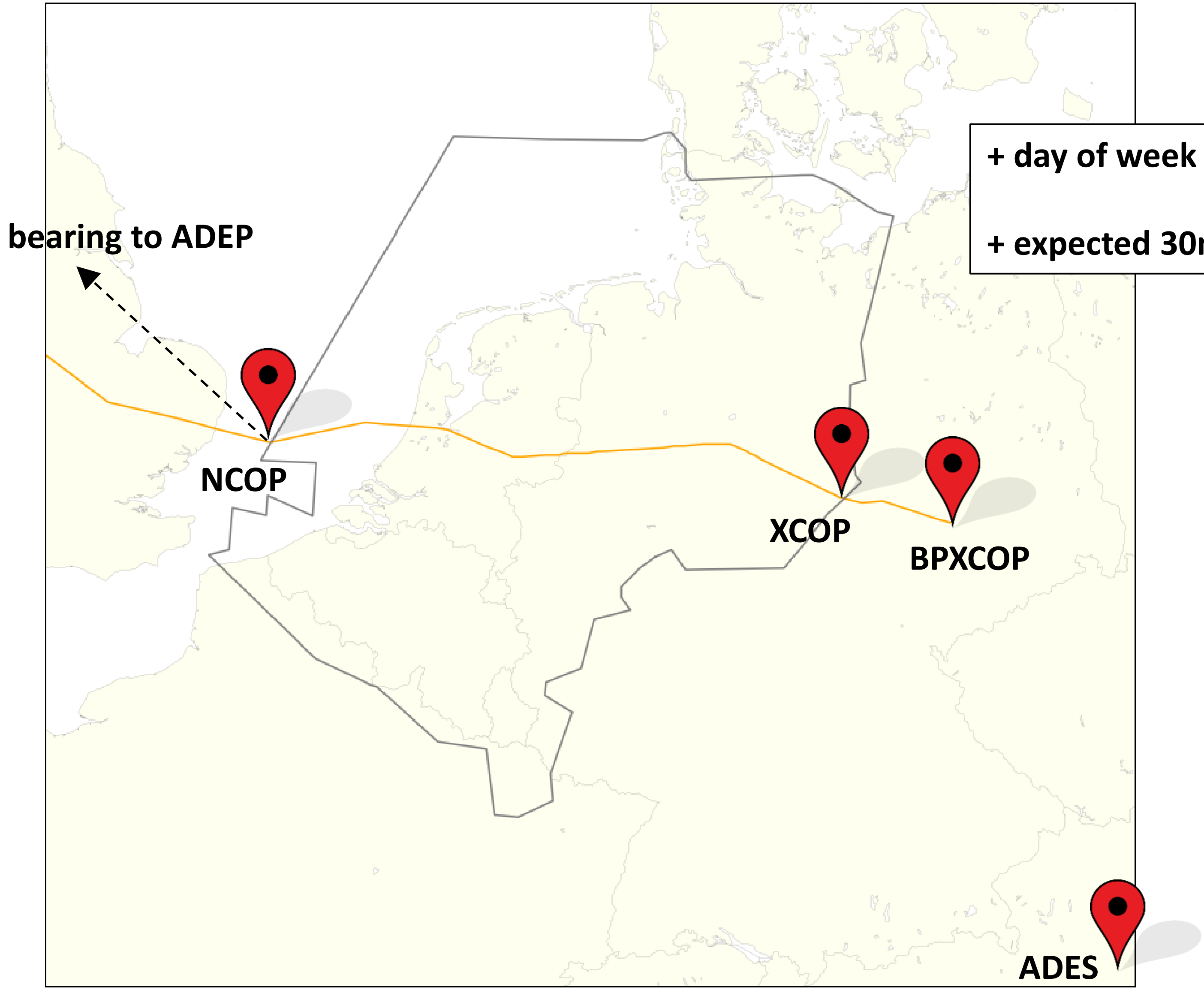
Transformation of target data to be predicted

Transformation of target data to be predicted

- The x/y coordinates of the 4 points are rotated and scaled.
  - NCOP-BPXCOP axis from filed plan → data known prior to prediction !
  - Coordinates on the new X-axis are scaled by 0.5

- normalization for the target data
- scaling along the new X-axis allows for a more optimal cost function
- generic sanity checking on the output data

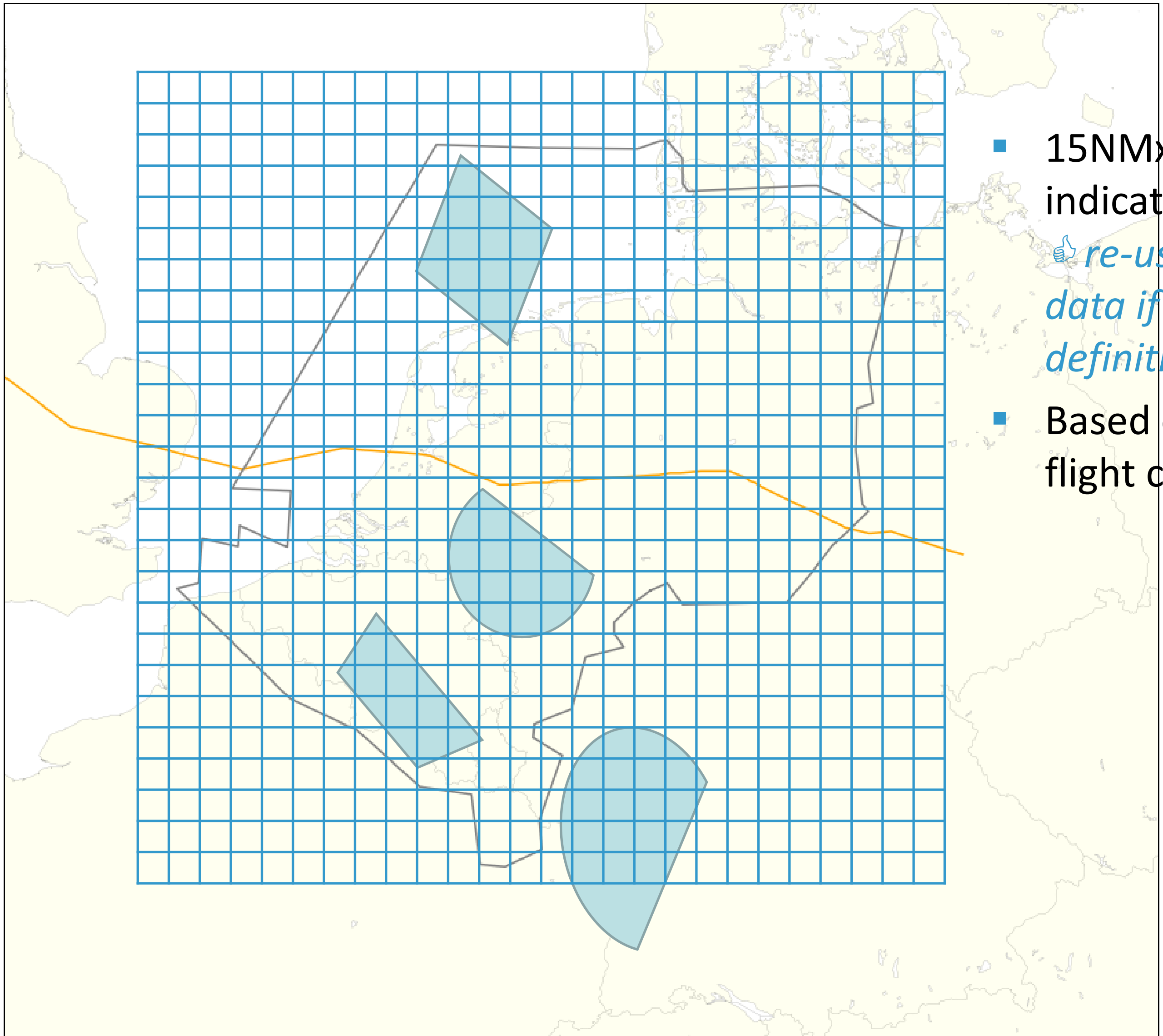
Predictors : flight plan data



+ day of week

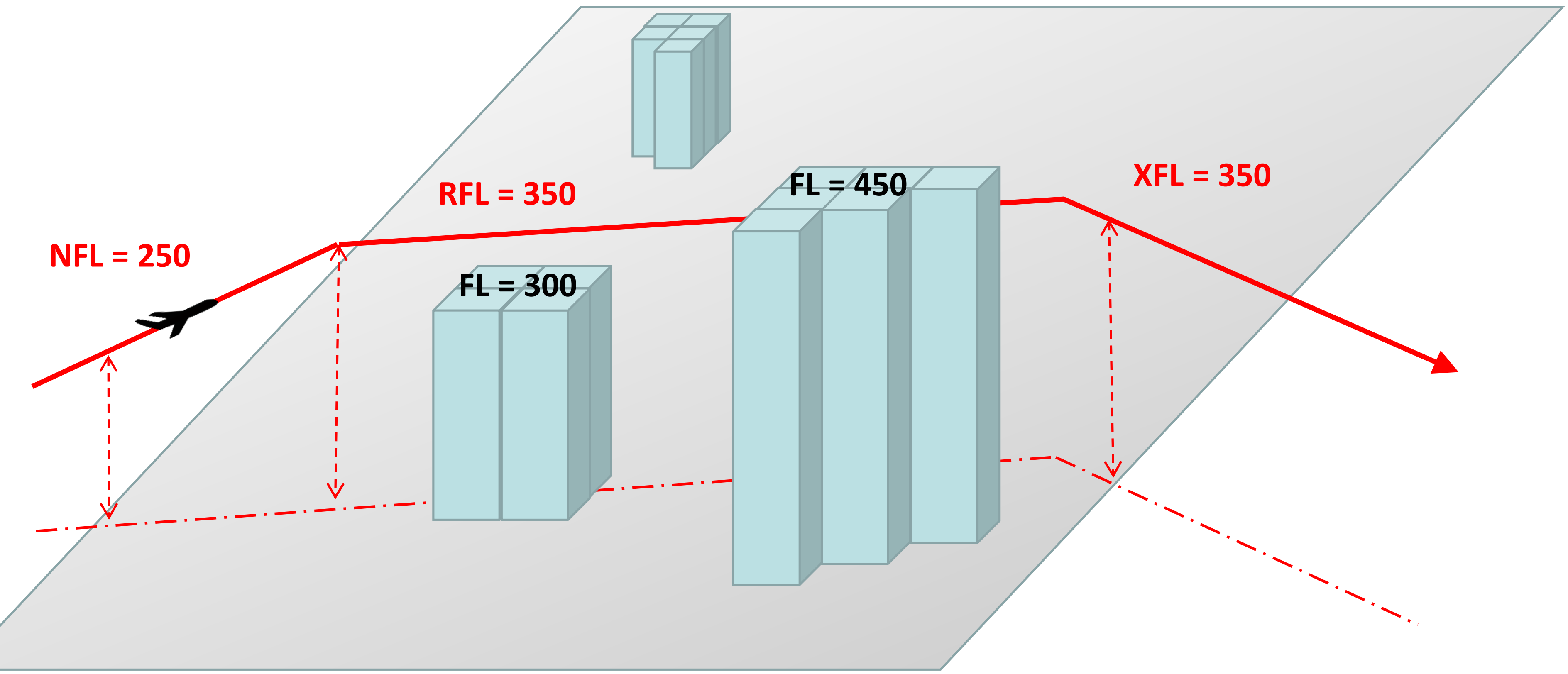
+ expected 30min entry interval

Predictors : military areas



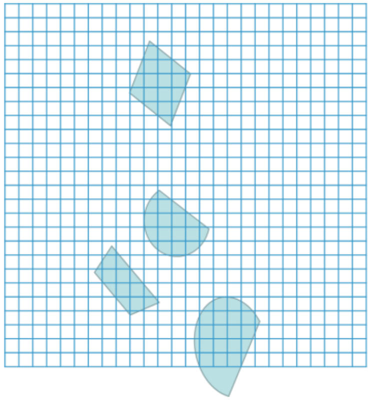
- 15NMx15NM grid cells, indicating upper reserved FL
  👍 *re-usability of old training data if names or geographic definitions change*
- Based on theoretical time flight could reach cell

Predictors : military areas

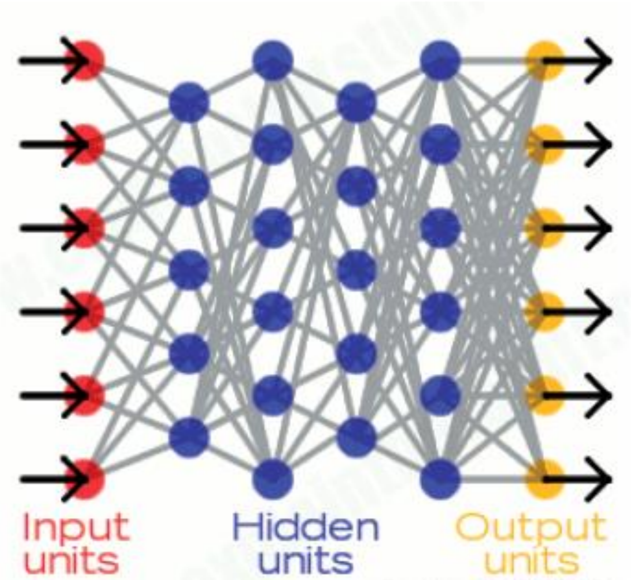


Neural network

NCOP
XCOP
BPXCOP
ADEP
Bearing to ADES
Day of week
Entry time interval
NFL
RFL
XFL



+ noise

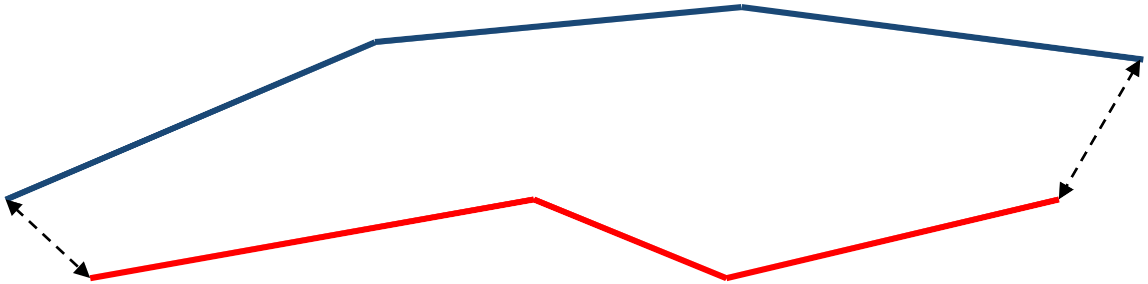


3 hidden layers of 170 units with ELU activation
dropout for regularisation

Cost function

- Most correct cost function would be lateral distance between the position on the predicted route and the position on the real route at equivalent progression times.
  ➔ difficult from a practical perspective

- Pragmatic:
  - Distances at entry and exit
  - Area of polygon / L



Training data

- Flow from UK to south / south-east
- ~10% of all traffic, suffers heavily from route deviations
- 15 January 2015 – 20 March 2018   (more than 362.000 flights)

- Incremental training with 2.600.000 batches of 1000 random samples

- *Neural network has also been trained on all flows (> 3.5 million flights), but is not yet in operational use due to integration issue legacy system*

Example prediction

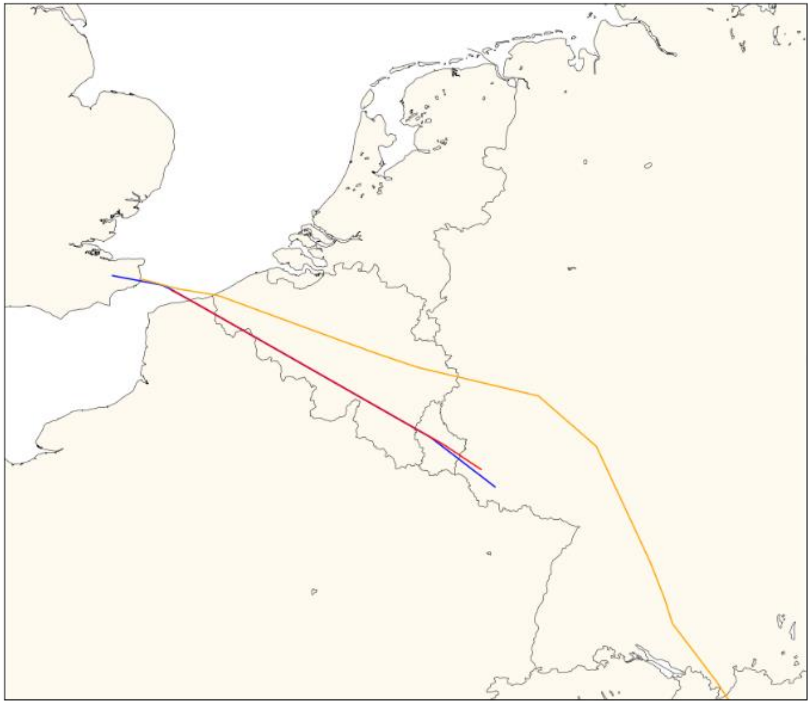


Figure 2: prediction (red) for flight of figure 1 (blue)

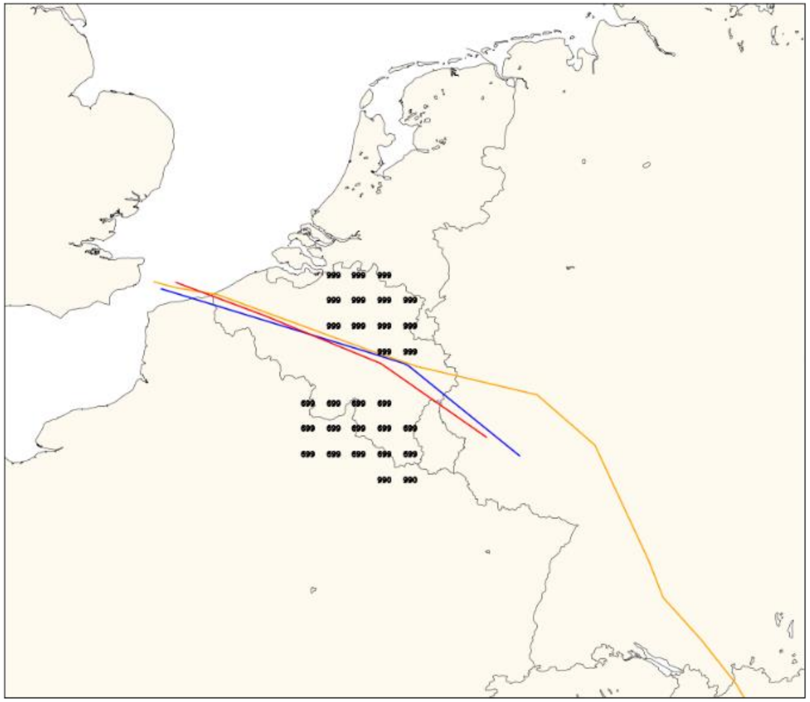
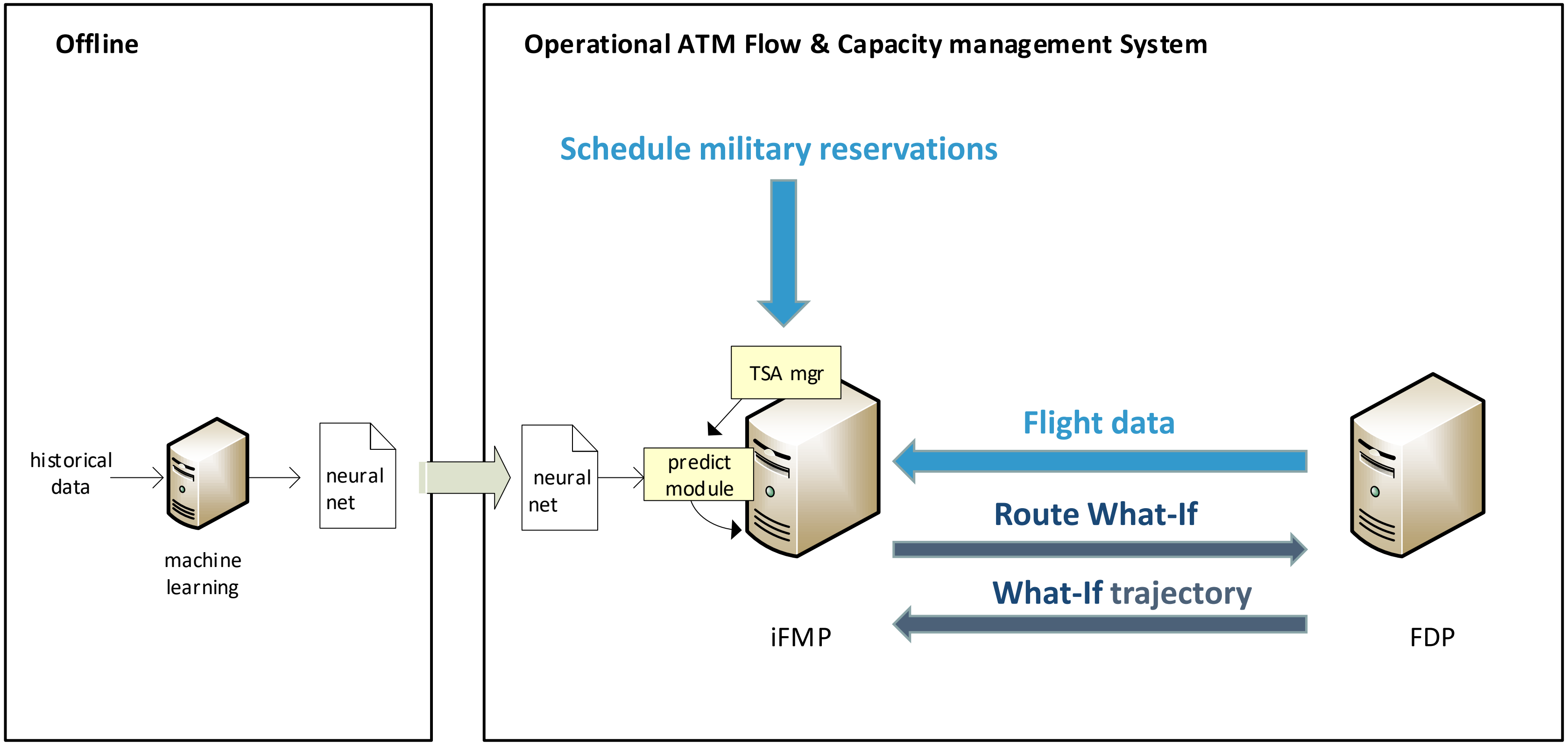


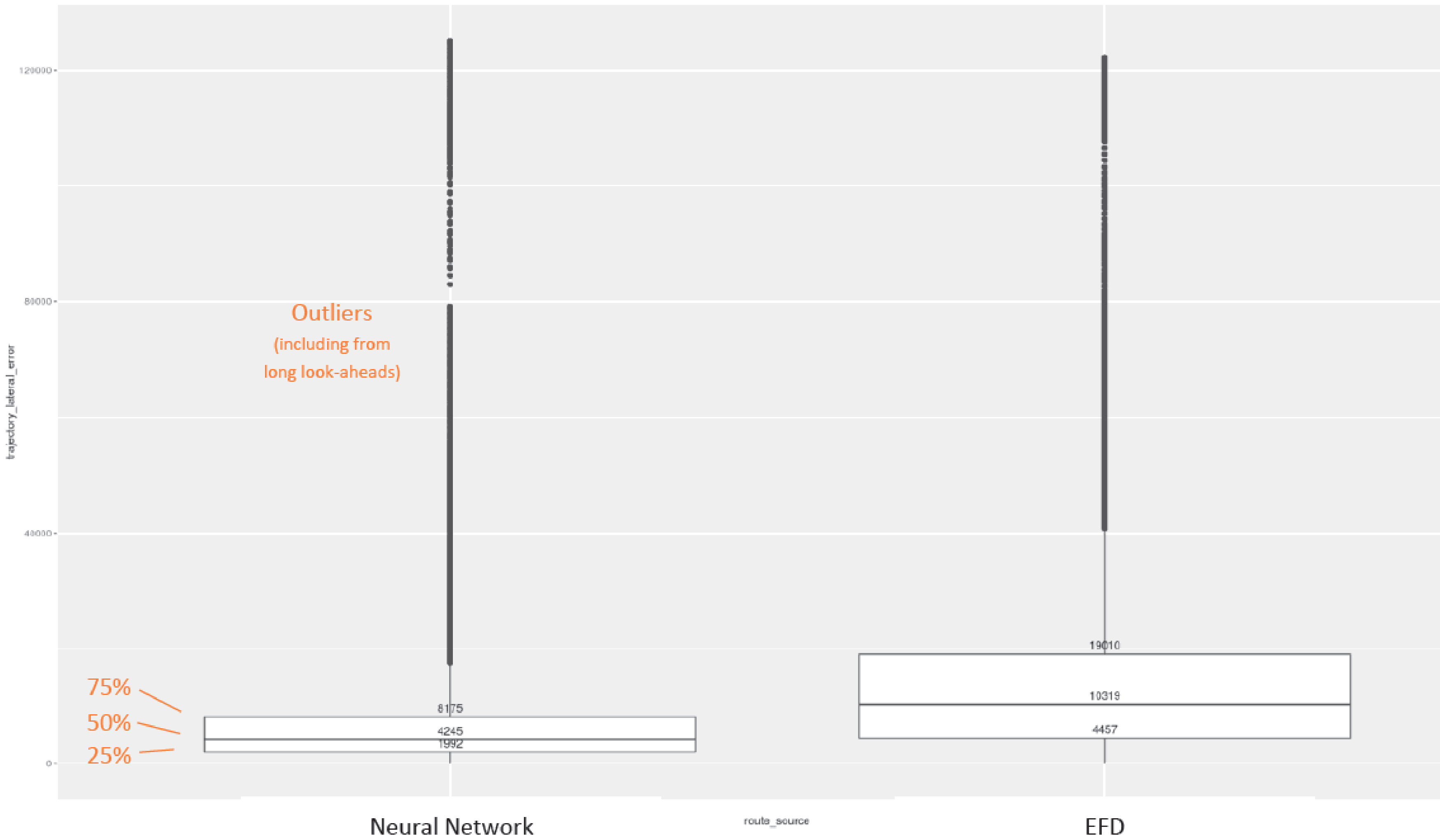
Figure 3: prediction for flight with active military areas

Integration in operational system

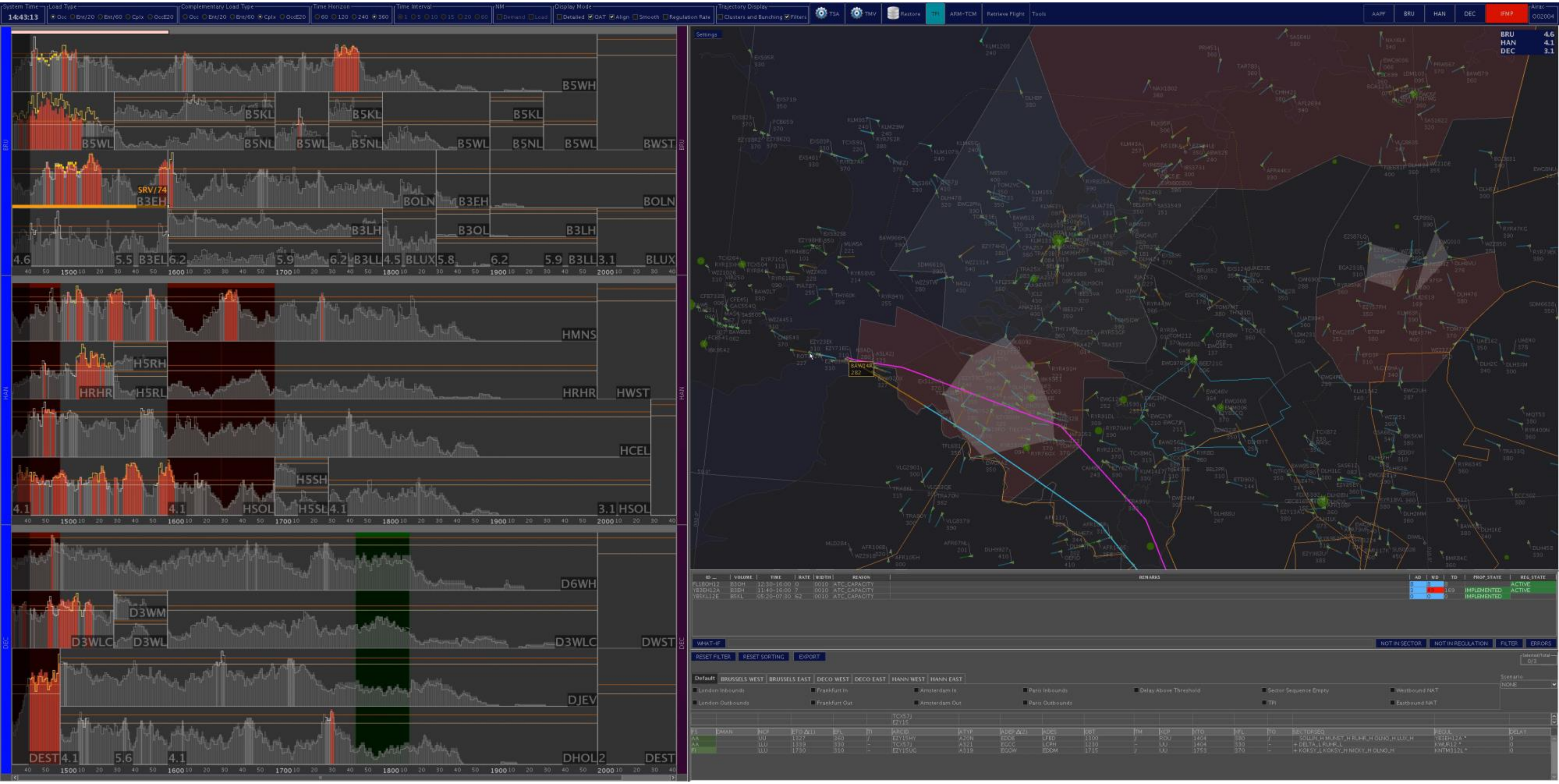


In operational use since January 2018

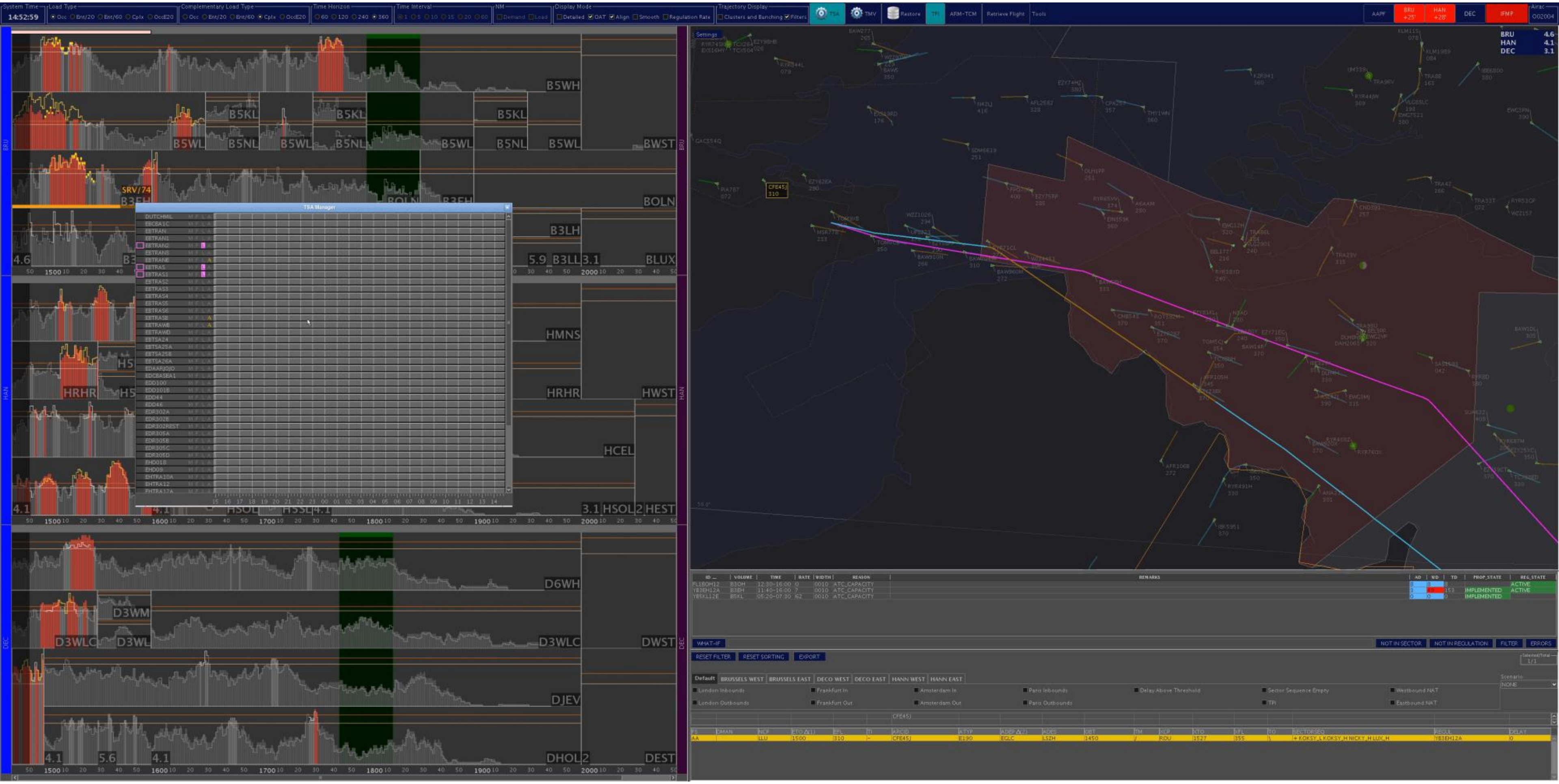
Real life results



Real life video



Real life video



Real life use case

- CFE53TK EGLC to LIML
- 27’ delay because included in regulation OLNO sector
- Neural network predicted that flight would <u>not</u> fly through OLNO but LUX
- Flight was excluded by FMP operator from regulation : no delay
- under study: exclude flights via NM B2B interface, enabling automation of this workflow


ANY
QUESTIONS
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