

Supporting
European
Aviation



Prediction of propagation and evolution of delays with machine learning (ML)

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25/01/2021



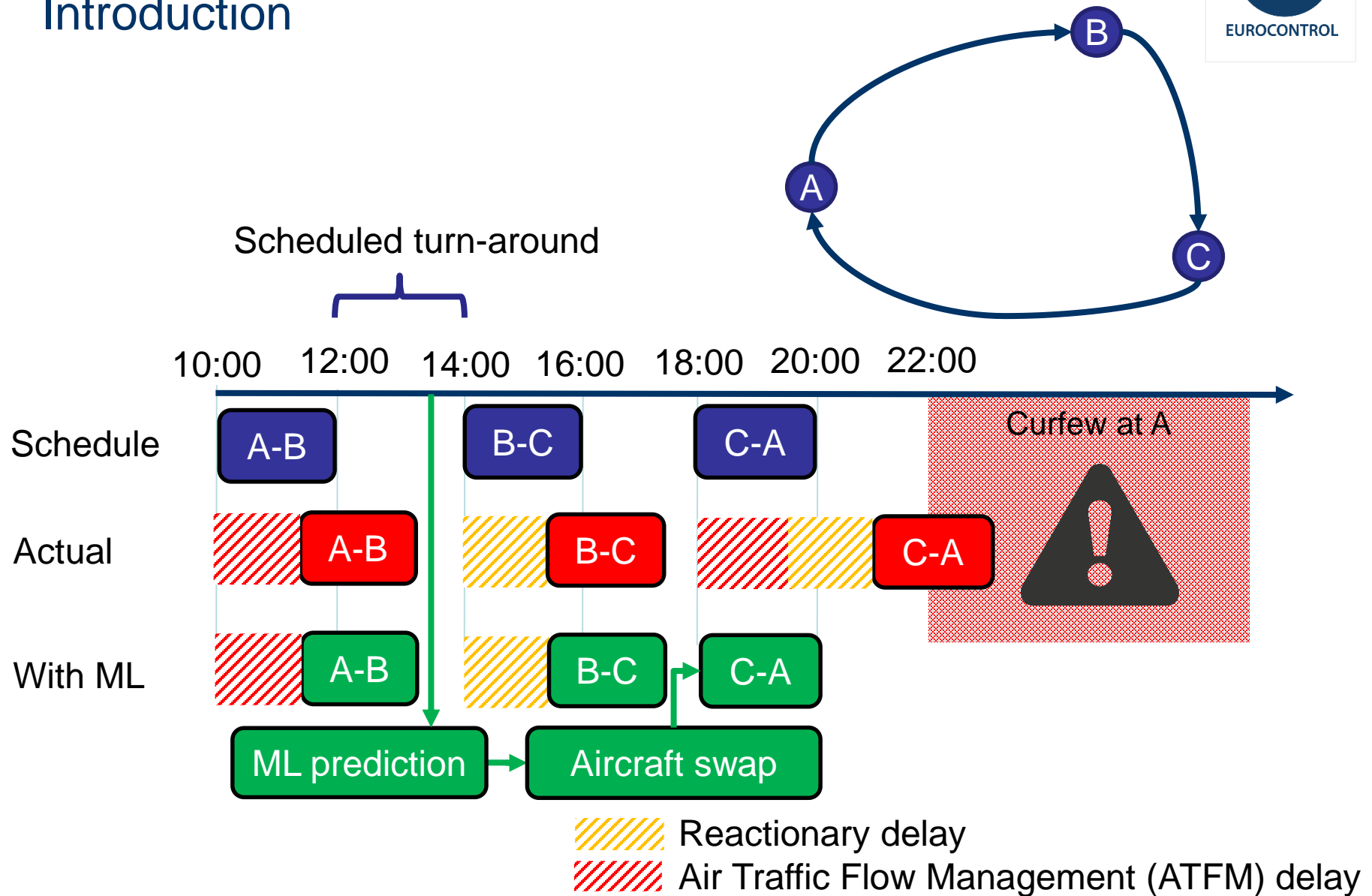
NETWORK
MANAGER



Outline

- Introduction
- Raw data
- Features
- Model
- Initial results
- Next steps
- Demo

Introduction



Raw data

- Enhanced Traffic Flow Management System (ETFMS) – **per flight and timestamp**. *Several events may trigger an update*
 - Departure airport ICAO code (e.g., LEBL)
 - Destination airport ICAO code (e.g., LEMD)
 - Airline (e.g., VLG)
 - Event that triggered the ETFMS update (e.g., Initial Flight Plan - IFP)
 - Flight state (e.g., Airborne – AA)
 - Air Traffic Flow Management (ATFM) delay (if any)
 - Off-block time - Estimated, targeted, calculated or actual
 - Landing time: Estimated, calculated and/or actual
 - Taxi-time
- Flight schedules – **per flight**
 - Scheduled off-block time (SOBT)
 - Scheduled in-block time (SIBT)

Features

(per flight and timestamp)

Legend:

Embedded features

One-hot encoded features

Periodic features (cos, sin)

Other features



- Departure airport ICAO code
- Destination airport ICAO code
- Aircraft type
- Airline
- Event that triggers the ETFMS update
- Flight state
- Hour of the day
- Day of the week
- Month of the year
- ATFM delay (if any)
- Taxi-in and Taxi-out times
- Time to SOBT
- Time to SIBT
- Scheduled block-time
- Estimated/calculated/actual (depending on flight state) block-time
- Scheduled turn-around
- Estimated/calculated/actual (depending on flight state) turn-around
- Departure delay (w.r.t to SOBT)
- Arrival delay (w.r.t to SIBT)
- Time from last update
- Time from Initial Flight Plan (IFP)
- Traffic volume of most penalising regulation (if any)
- Reason of the most penalising regulation (if any)
- ...

Model

Legend:



Input



Embedding



Concatenate



Feed-Forward Neural Network (FFNN)

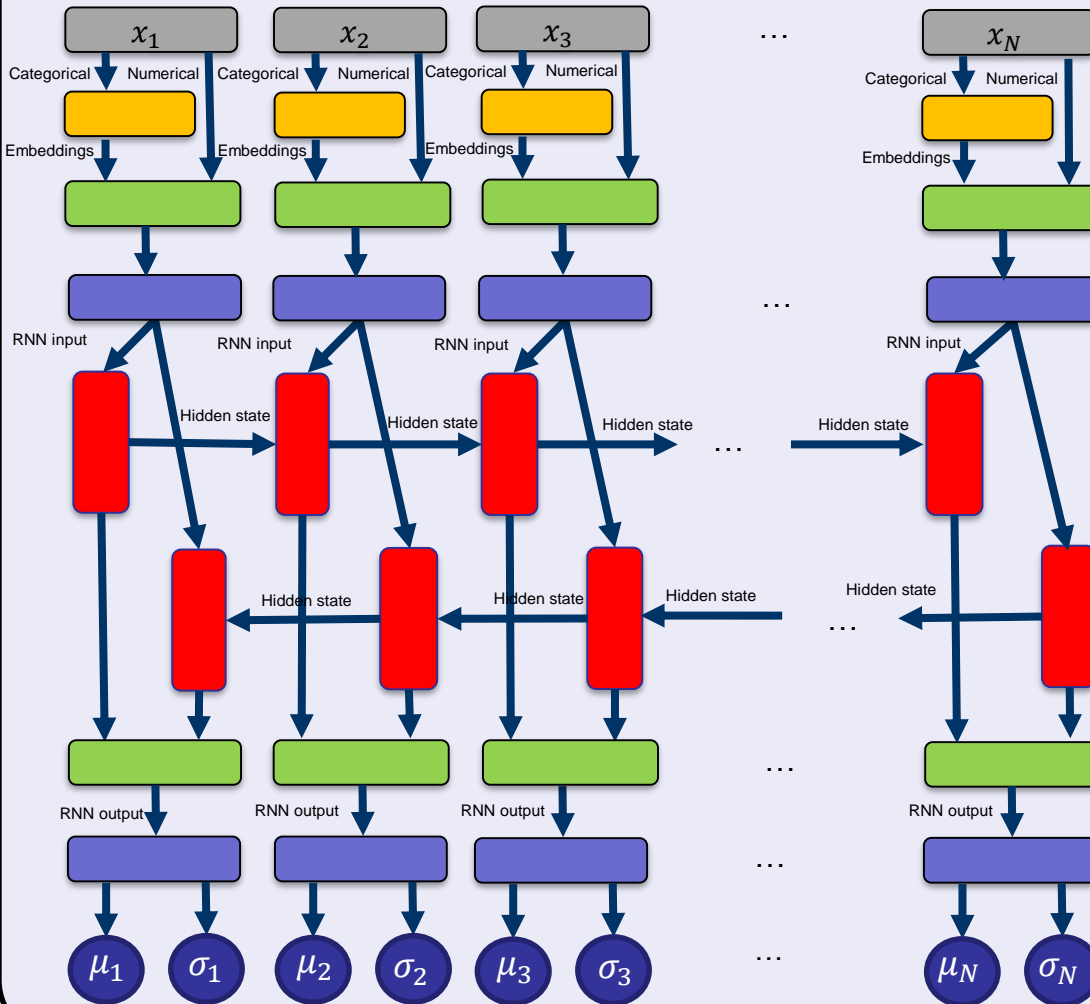


Recurrent Neural Network (RNN)

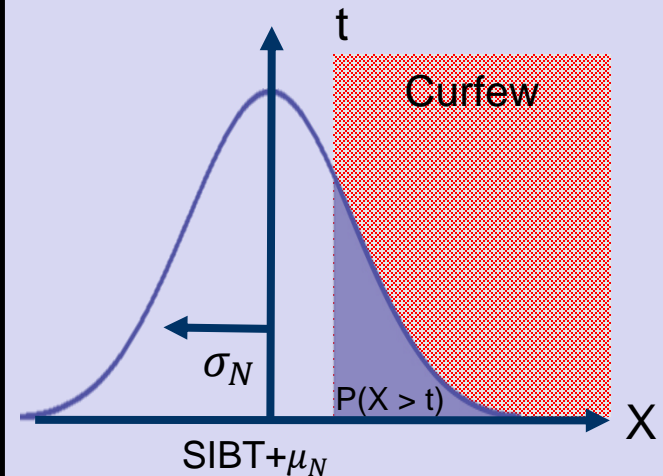


Output

1. Delay prediction and propagation with ML

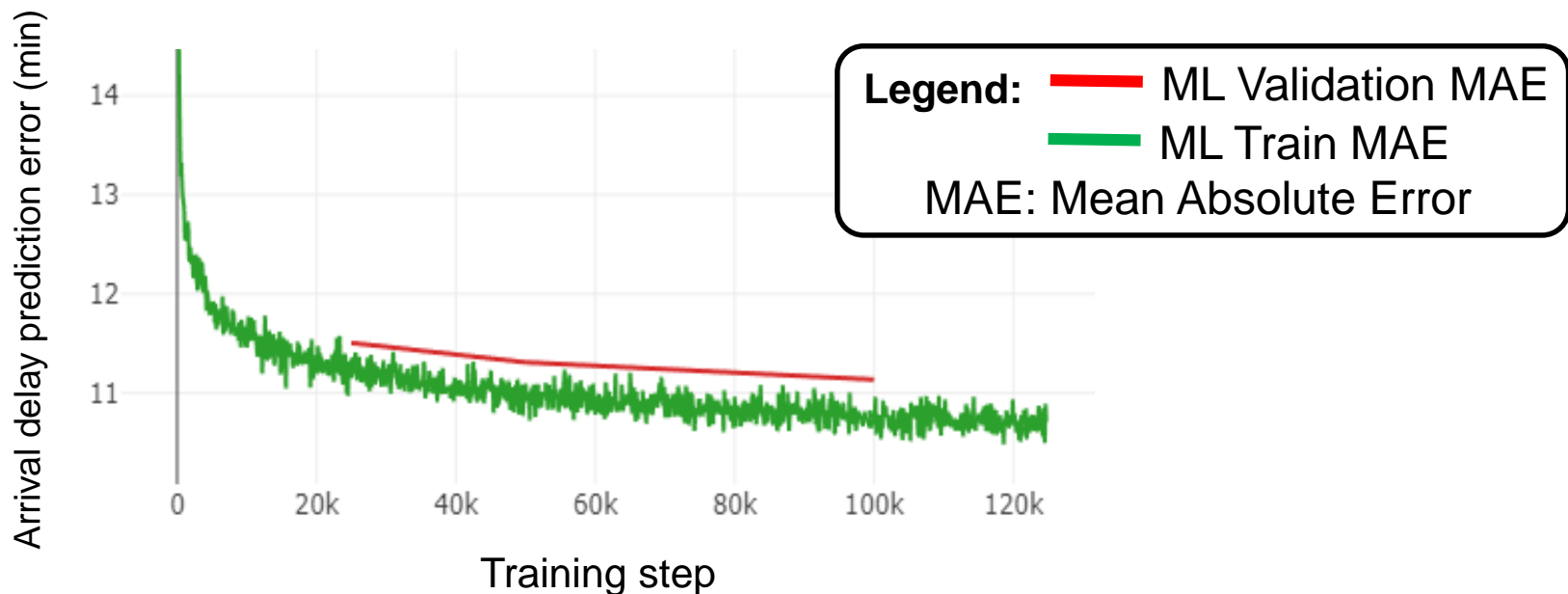


2. Curfew risk assessment



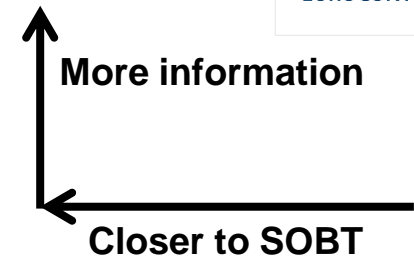
Initial results

- **2019** flight traffic – all aircraft that landed, at least once, at LFPO (Paris-Orly)
- 270 **random days** for train, 30 for **validation** and 60 for **testing**
- **24M** examples (sequences to train the RNN)
- **3 hours** training for **1 epoch** with a **batch size of 128** and **learning rate 1e-4**
- **Loss function** is the **negative log-likelihood**

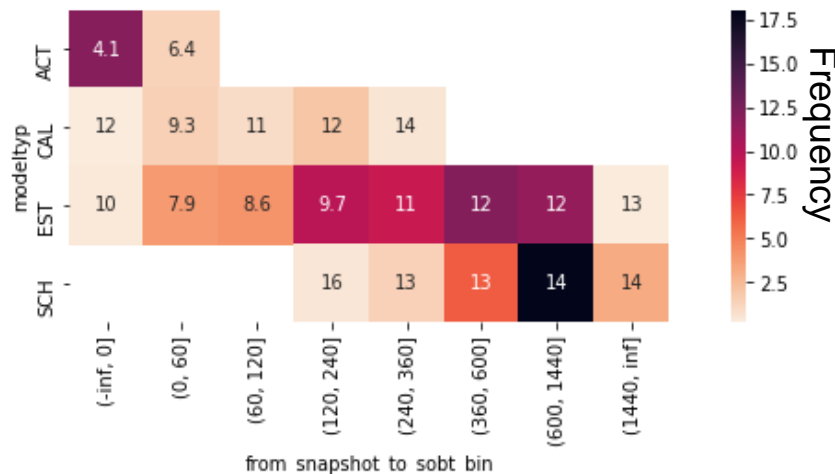


Initial results

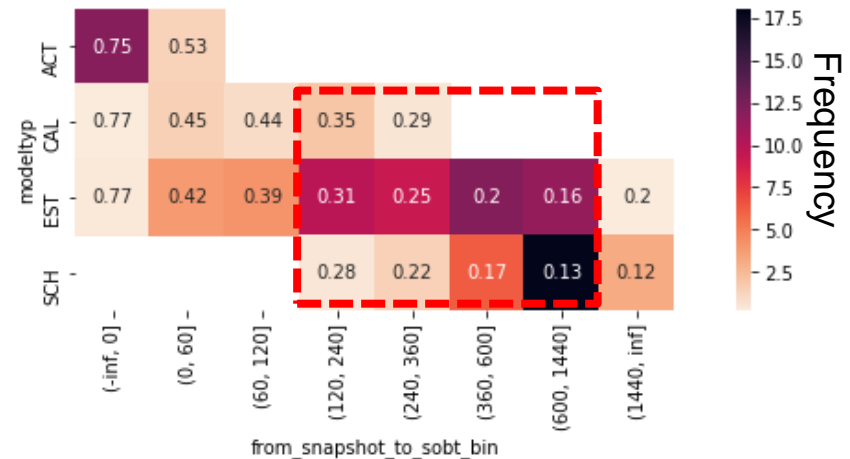
Machine Learning



Arrival delay prediction error (min)



Relative improvement (%)



SCH: Only the SOBT and SIBT are available

EST: The EOBT is available, in addition to SOBT and SIBT

CAL: The flight is **regulated**, CTOT is known, in addition to EOBT, SOBT and SIBT

ACT: The flight is supposed to be **airborne**, AOBT is available

Next steps (short-term)

- Weight of each sample (example) **inversely proportional** to its probability. Less frequent examples will have more importance
- **Analyse results** to identify in which situations the model *fails*
- **Deploy the model**

Thank you!