

Prediction of reactionary delay and cost using machine learning



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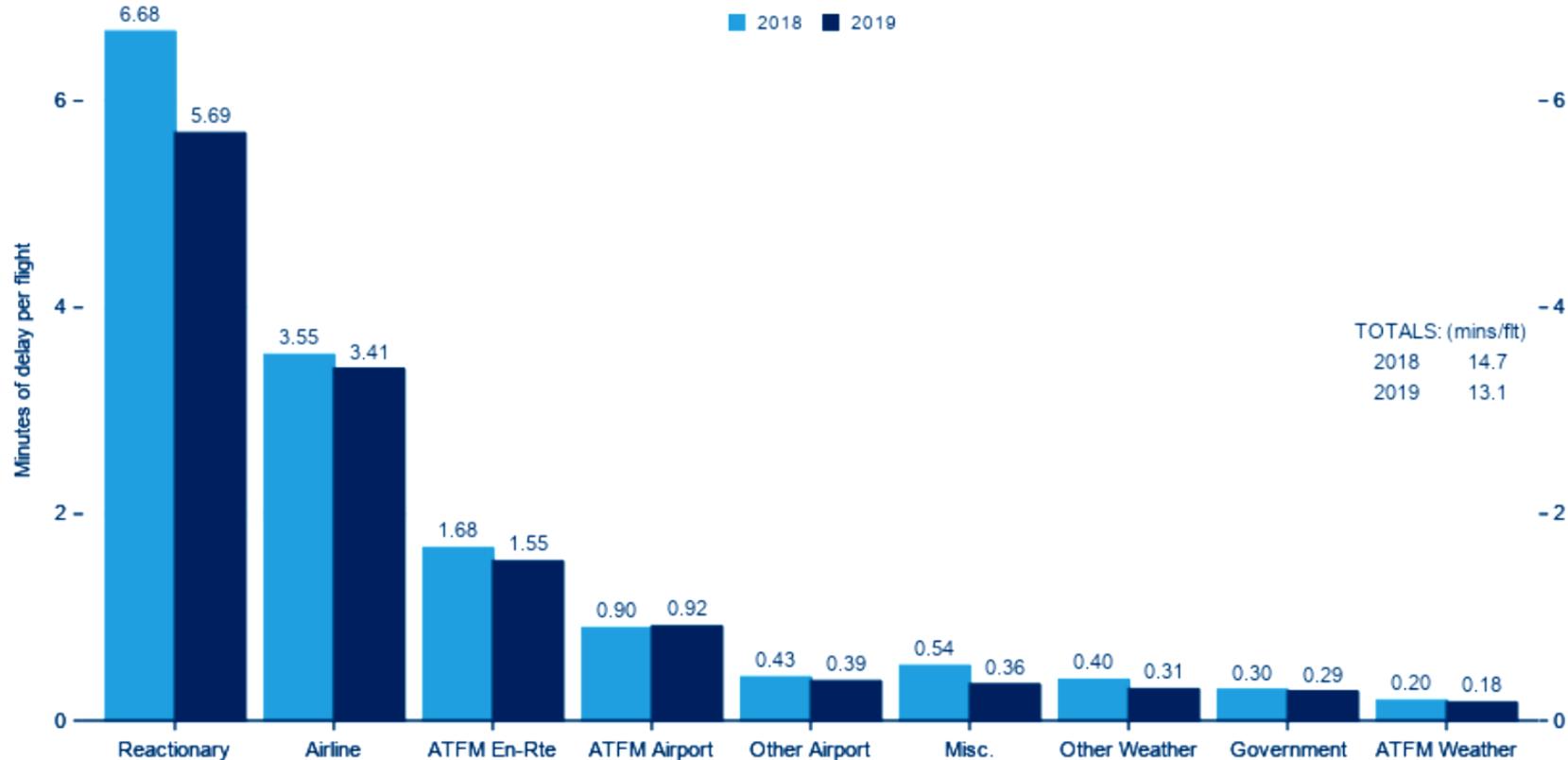
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- An overview on air traffic and delay
- Reactionary and rotational delay
- An approach to model reactionary delay using machine learning
- Dispatcher3 and Pilot3: two projects benefitting from this approach
- Future developments of the approach

Traffic and Average Delay per Flight Overview

All-causes, airline-reported delay: Main categories



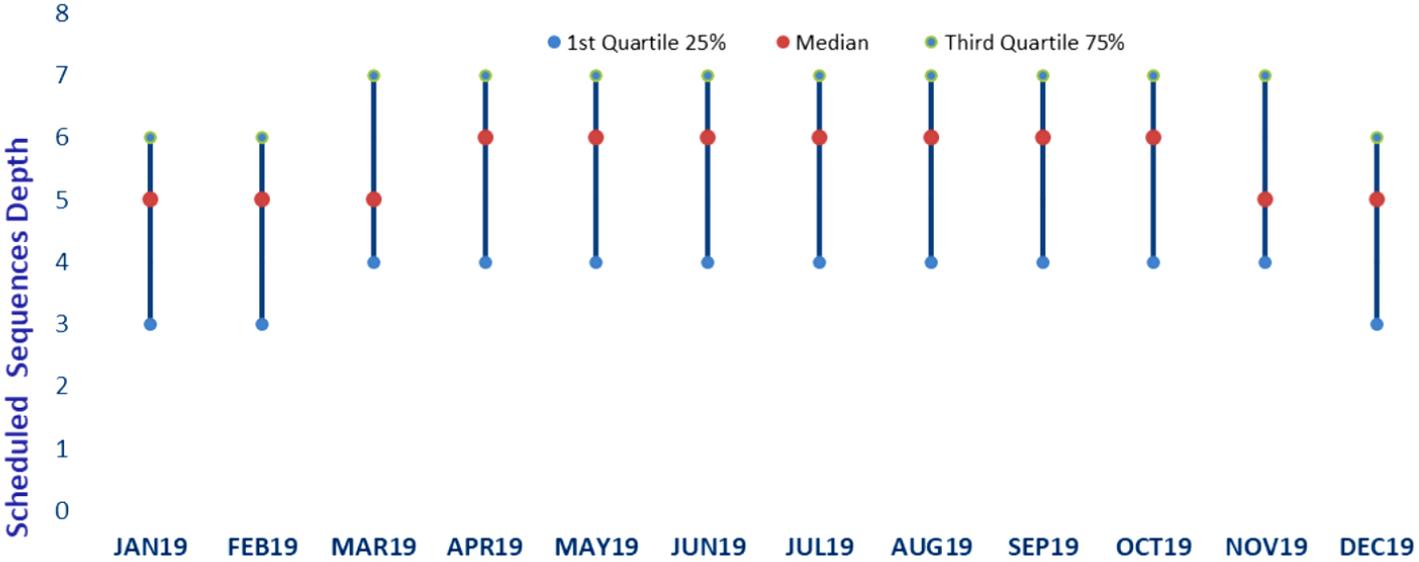
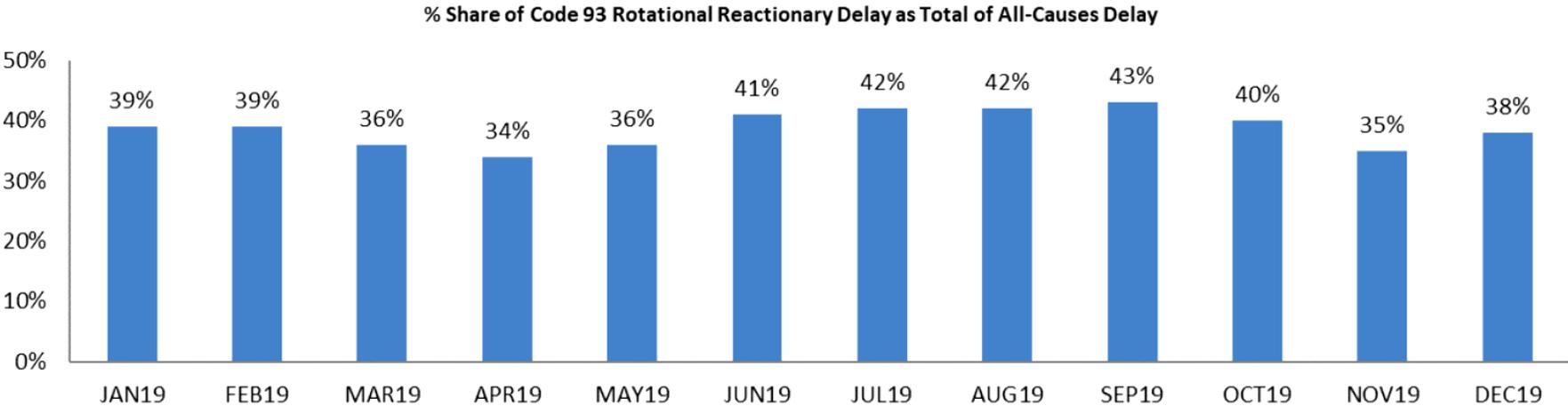
Based on CODA sample of 65.6% of commercial flights in the ECAC region in 2019

<https://www.eurocontrol.int/sites/default/files/2020-04/eurocontrol-coda-digest-annual-report-2019.pdf>

- **91 (RL):** Passenger or Load Connection, awaiting load or passengers from another flight. Protection of stranded passengers onto a new flight.
- **92 (RT):** Through Check-in error, passenger and baggage
- **93 (RA):** Aircraft rotation, late arrival of aircraft from another flight or previous sector
- **94 (RS):** Cabin crew rotation
- **95 (RC):** Crew rotation, awaiting crew from another flight (flight deck or entire crew)
- **96 (RO):** Operations control, rerouting, diversion, consolidation, aircraft change for reasons other than technical

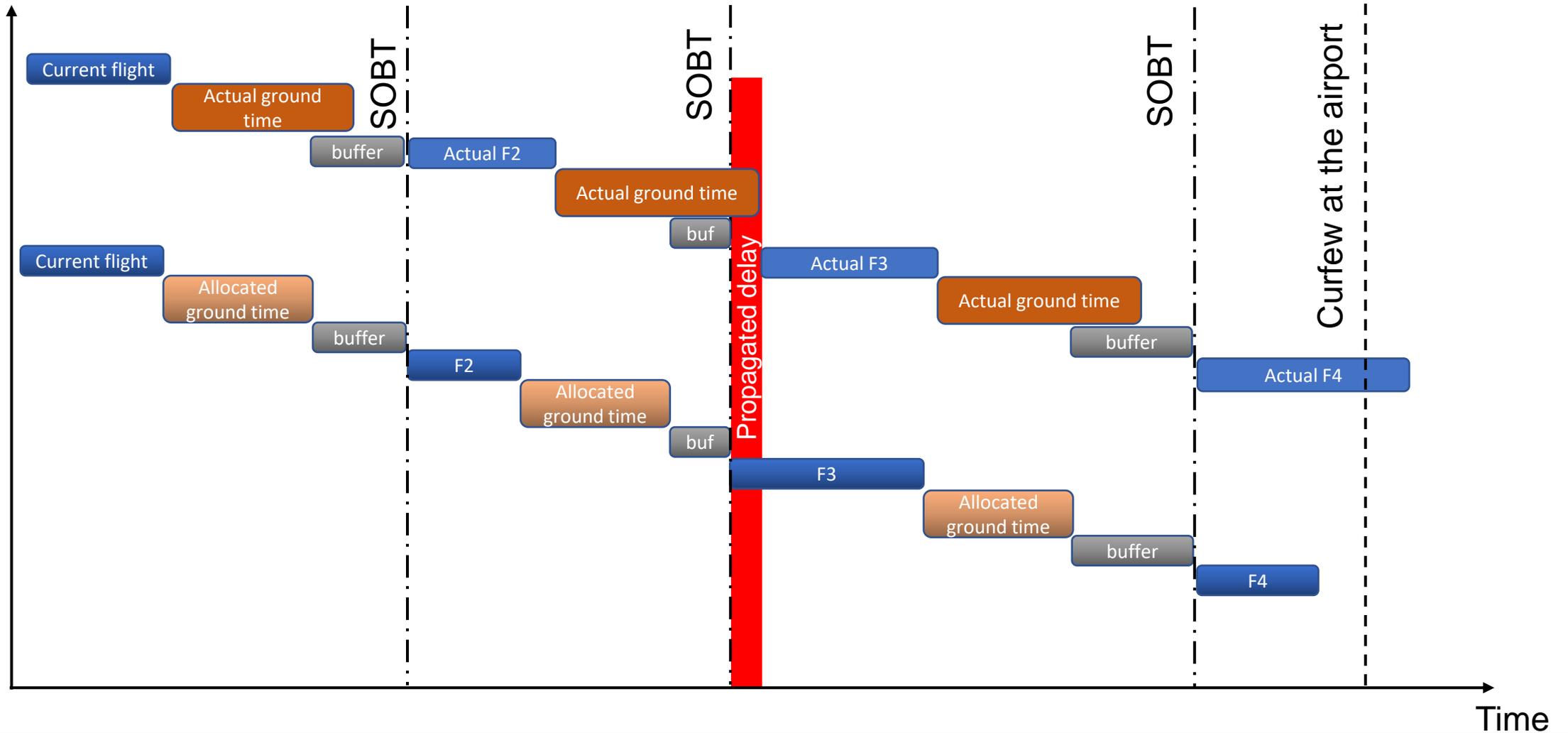
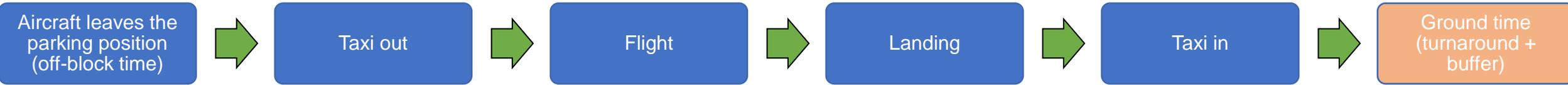
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Rotational reactionary delay

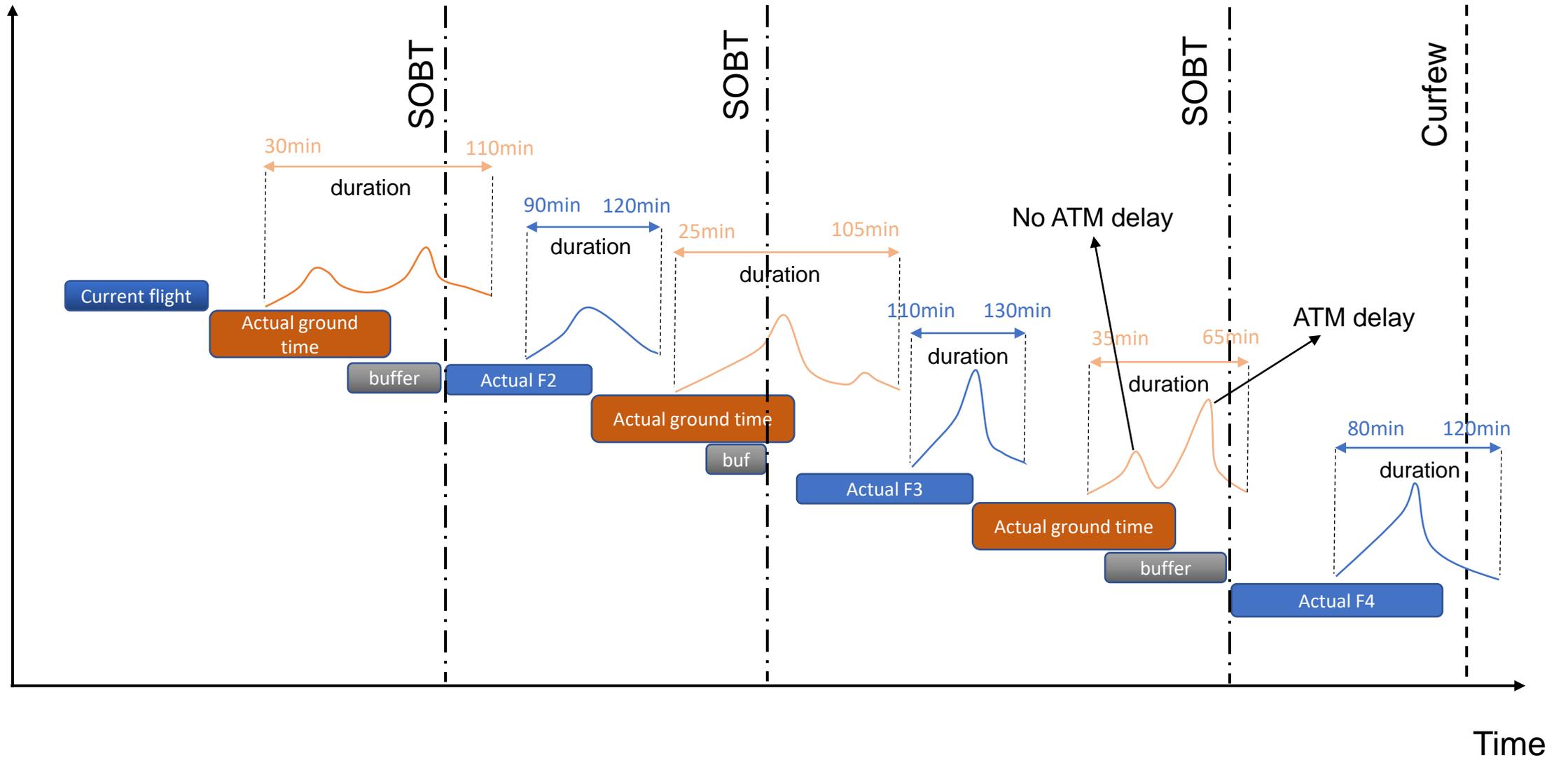


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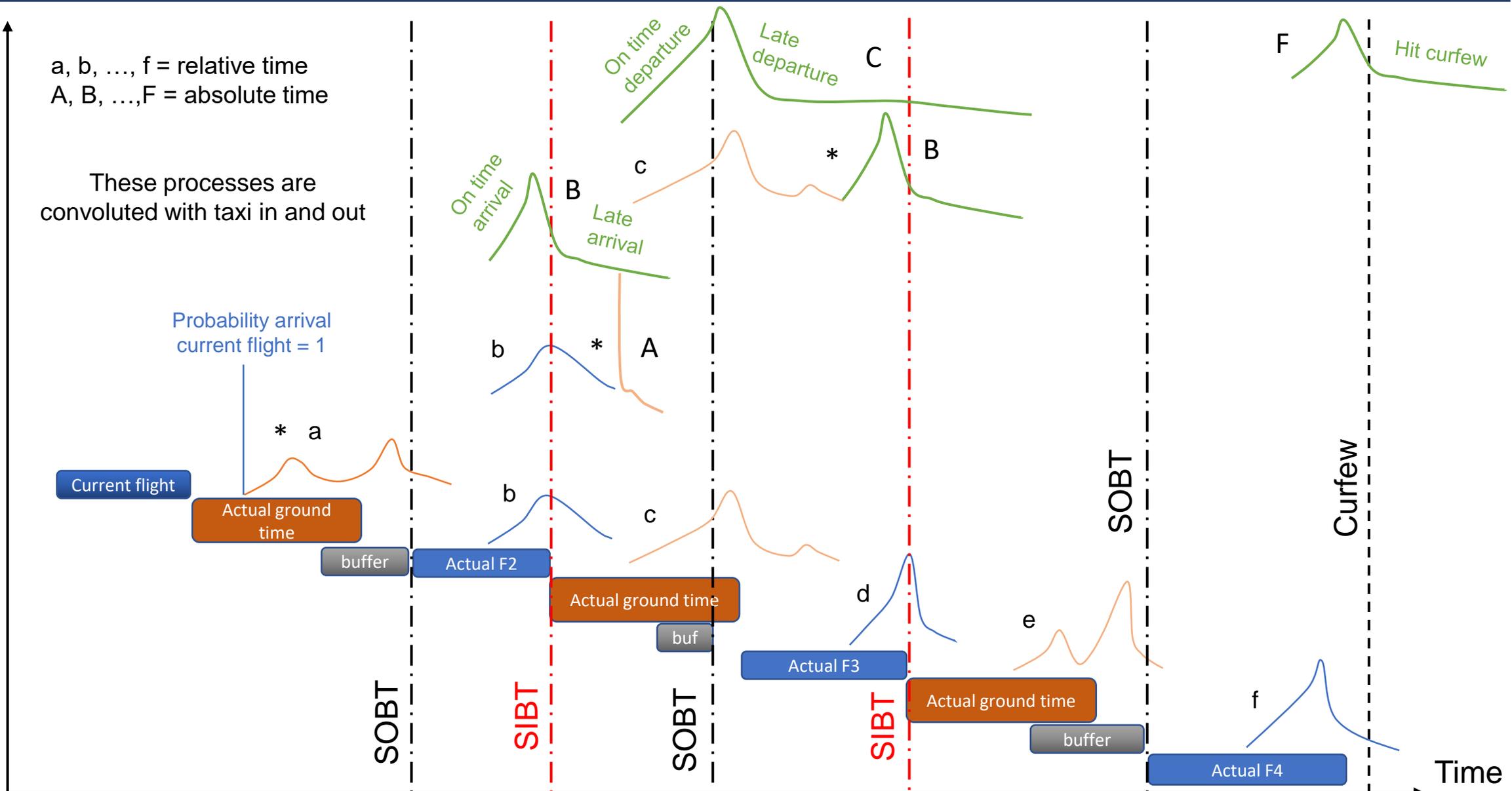
Aircrafts operations

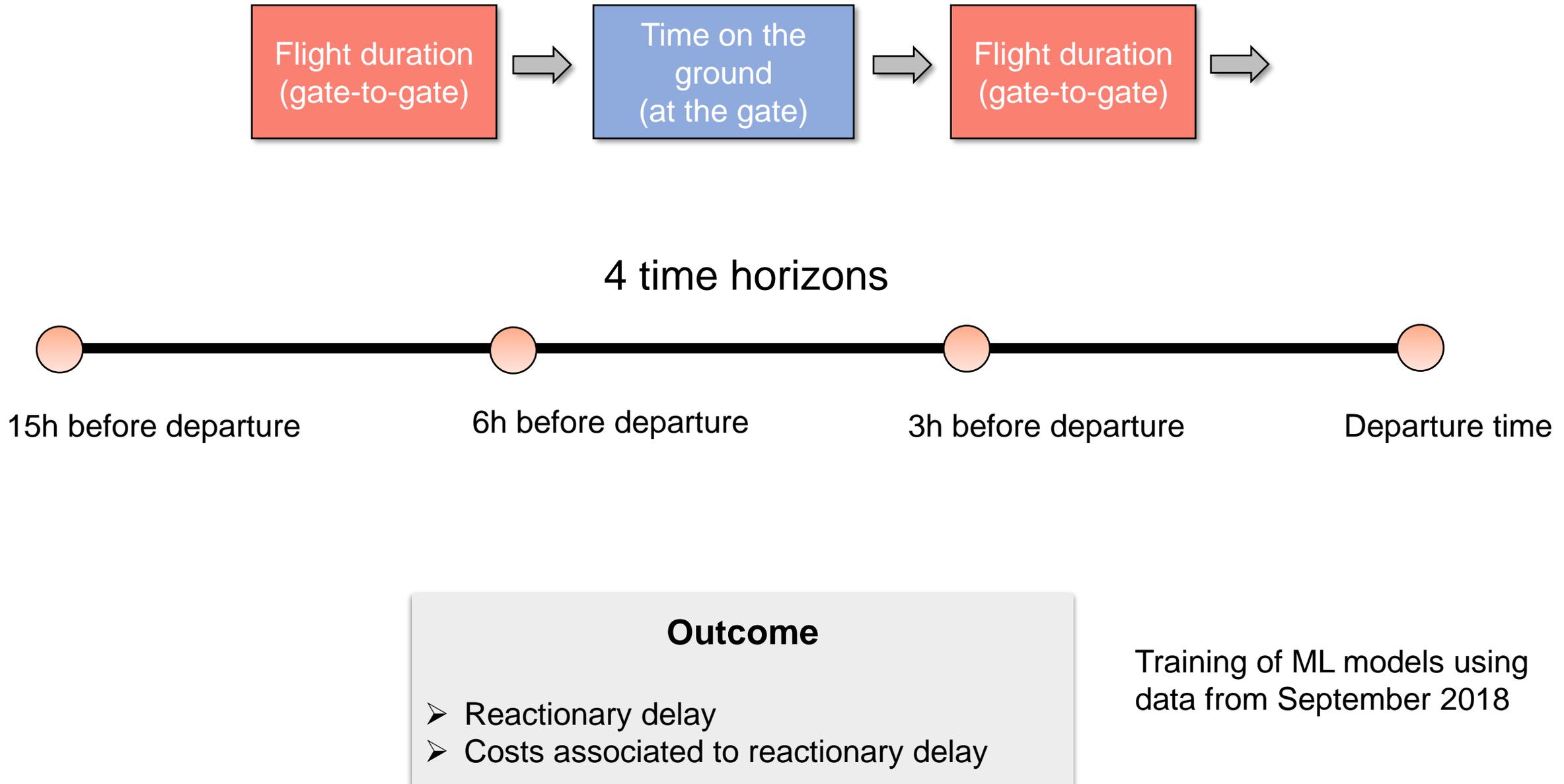


Aircrafts operations



Aircrafts operations





Selection of features for ML models

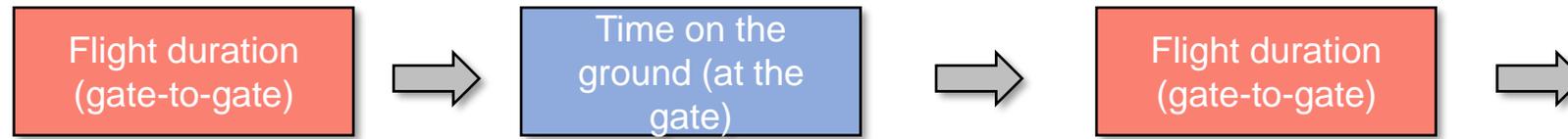
Static features	Dynamic features
Time_departure: morning, afternoon, evening	ATMAP score at departure airport
Airline_type: REG, LCC, FSC, Other	ATMAP score at arrival airport
Size airport departure: small, medium, big	Wind speed at departure airport
Size aircraft: low, medium, high, jumbo	Wind speed at arrival airport
Congestion at departure during the day of operations	Temperature at departure airport
Congestion at arrival during the day of operations	Temperature at arrival airport
Hub (yes/no)	Landing direction
Regulations (yes/no)	Average wind along trajectory
Great circle distance	Congestion_arrival: how many planes are landing in the hour of operations
Direction of flight (e.g., North-West, etc...)	Congestion_departure: how many planes are departing in the hour of operations
Size airport arrival: small, medium, big	

-  Features used in both ground and flight models
-  Features used in flight model only
-  Features used in ground model only

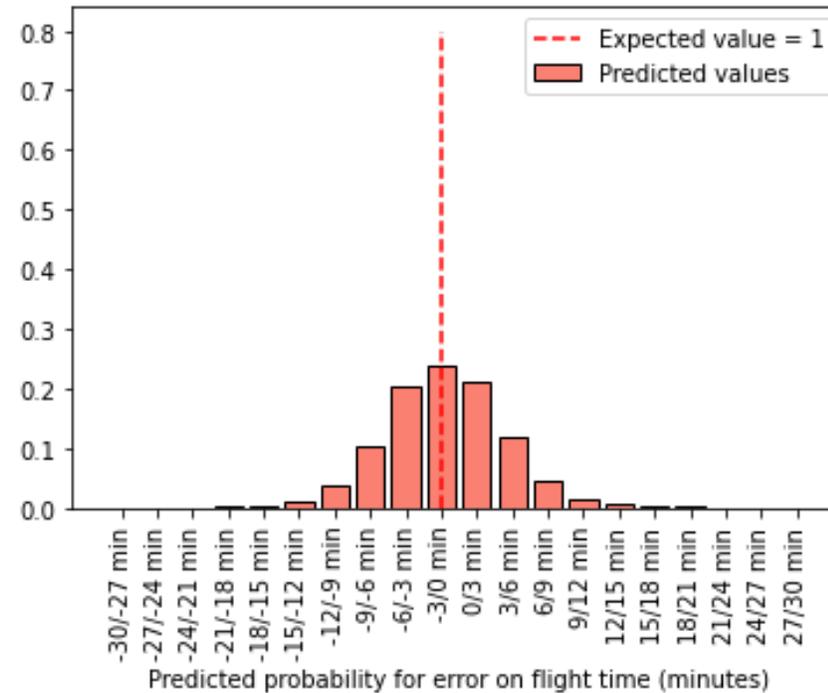
'Used' and 'potential' data

Data Source	Description
ADS-B (Automatic Dependent Surveillance–Broadcast)	Technology allowing to determine aircraft position via satellite navigation or other sensors. Data is periodically broadcasted enabling to track aircrafts
ERA5 (ECMWF (European Centre for Medium-Range Weather Forecasts) Reanalysis 5th Generation)	ERA5 provides hourly estimates of a large number of atmospheric, land and oceanic climate variables
Eurocontrol R&D	The archive contains a list of flights with key data for each flight; the airspace structure that applied at the time; filed and actual flight trajectory
Eurocontrol DDR (demand data repository)	'Extension' of R&D data containing more detailed information
METAR (Meteorological Aerodrome Report)	Weather information (current and historical) at the airports
SIGMET (Significant Meteorological Information)	A SIGMET provides information issued by a Meteorological Watch Office (MWO) concerning the occurrence or expected occurrence of en-route weather that may affect the safety of aircraft operations.
TAF (Terminal Aerodrome Forecasts)	Forecasts weather at the airports
FDM (Flight Data Monitoring)	FDM contains analyses on data generated by an aircraft in order to improve flight safety and increase overall operational efficiency

Modelling approach to predict flight duration

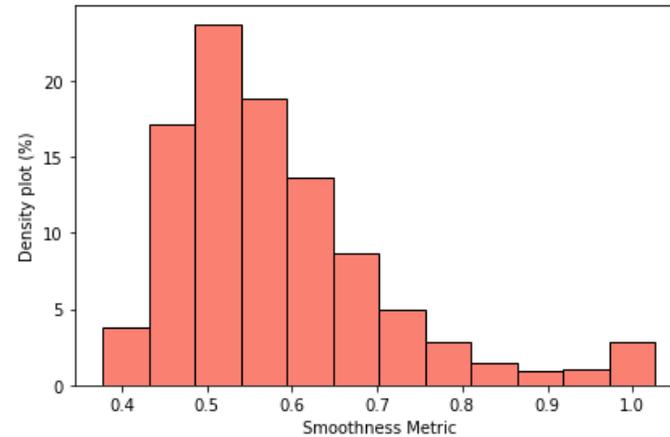
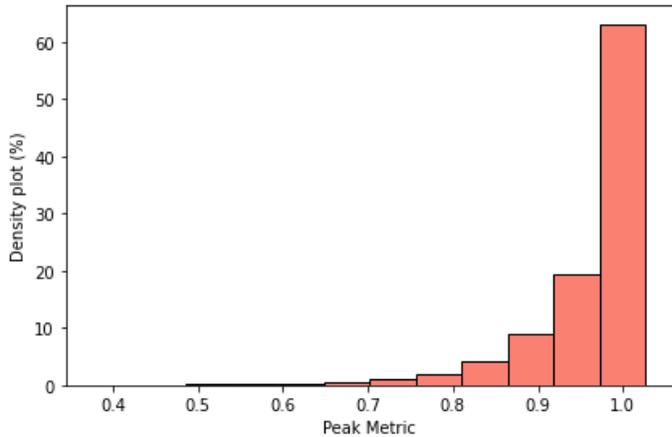


1. Extract the average flight time (take-off to landing) from data
2. Calculate the 'error' as (average flight time – actual flight time)
3. Predict this error as a discrete distribution with a classifier (problem of binning)



Classification model to predict the error as a difference with respect to the average flight duration

Classification model to predict the error as a difference with respect to the average flight duration

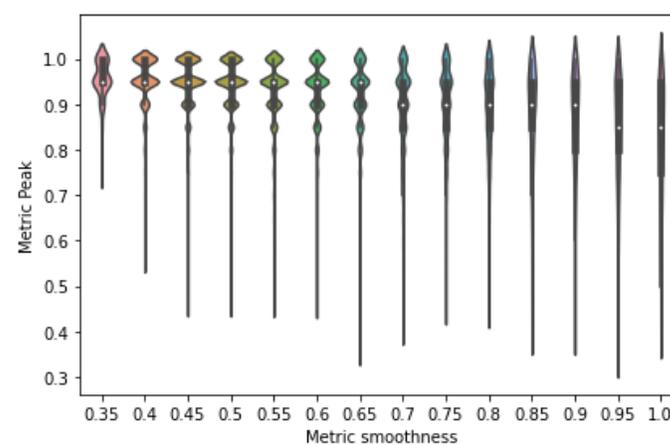
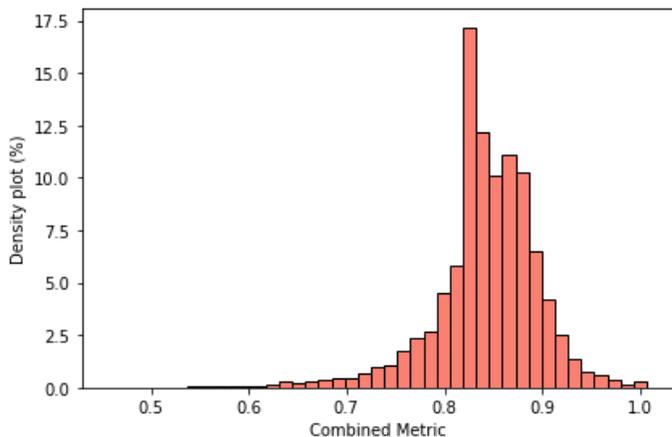


Peak metric

$$\left(1 - \frac{\text{distance in bins between predicted and expected peak values}}{\text{total number of bins}} \right)$$

Smoothness metric

$$\frac{\text{number of bins } (\neq 0)}{\text{total number of bins}}$$

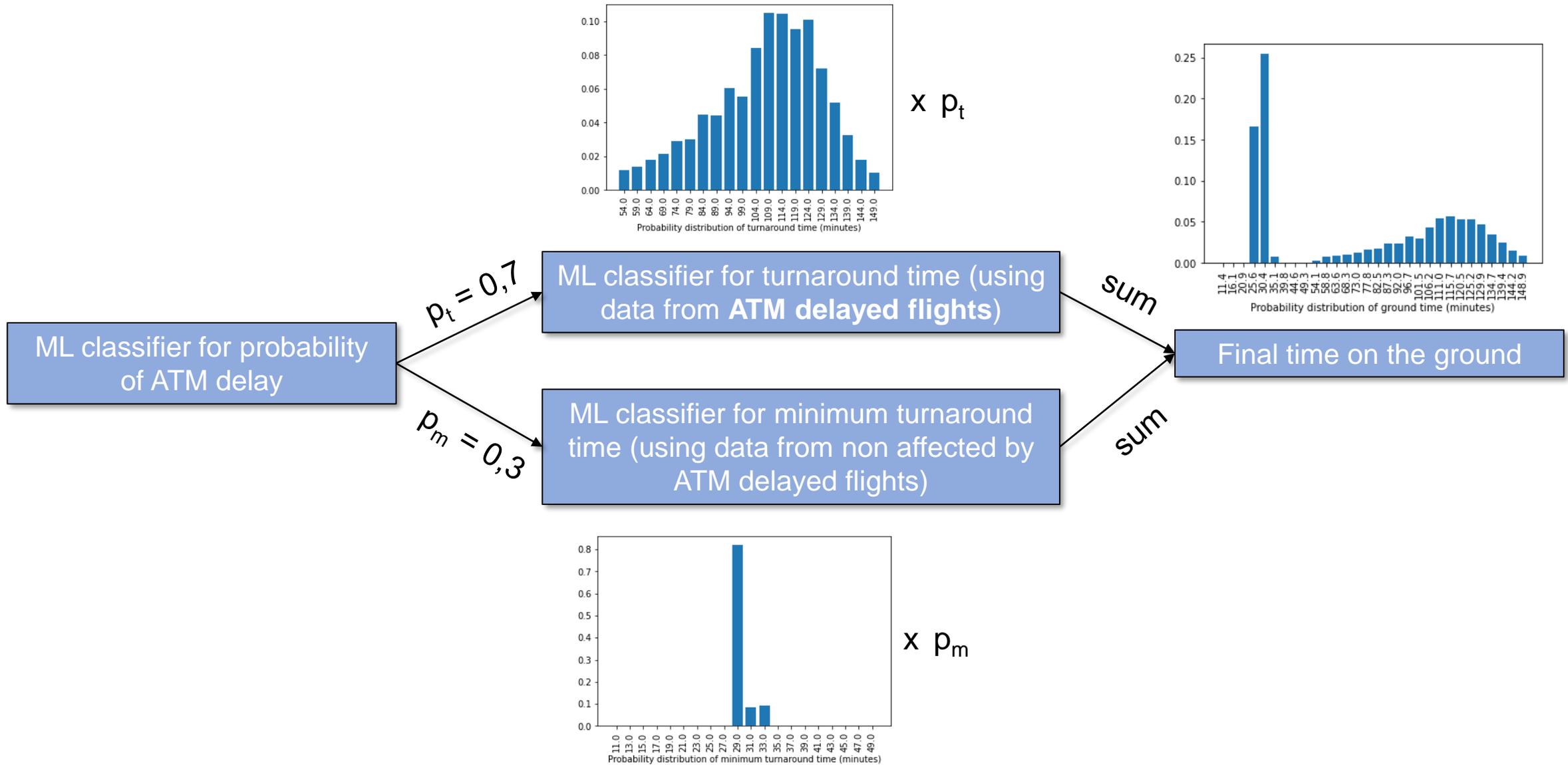


Combined metric

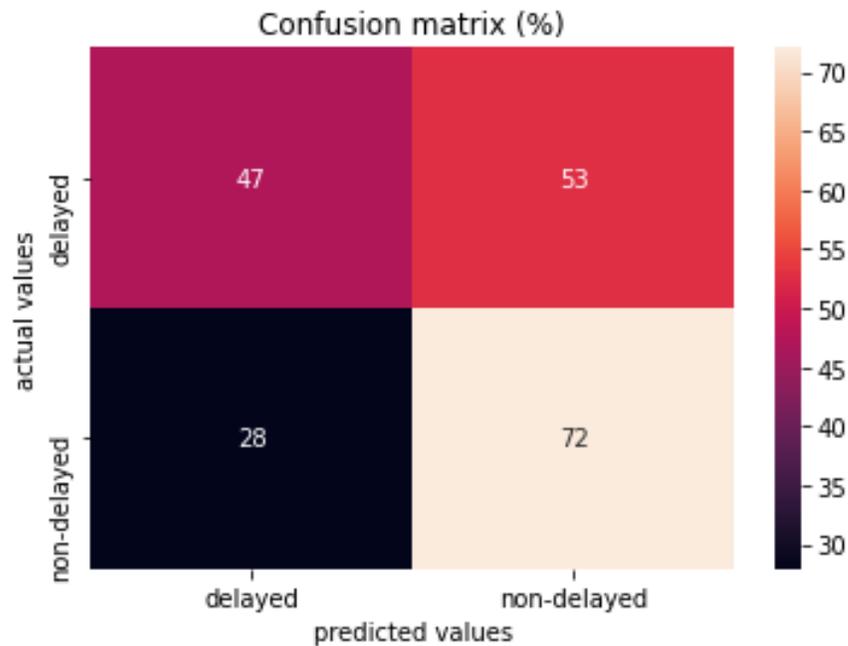
$$(\text{Peak metric} * w1) + (\text{Smoothness metric} * w2)$$

w1 = 0.75 if Peak metric > 0.5 otherwise w1 = 0.25
w2 = 0.25 if Peak metric < 0.5 otherwise w2 = 0.75

Modelling approach to predict ground time



ML classifier for probability of having ATM delay



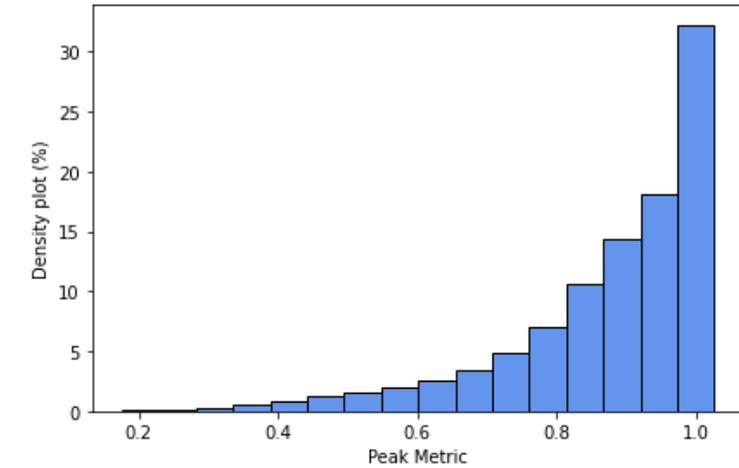
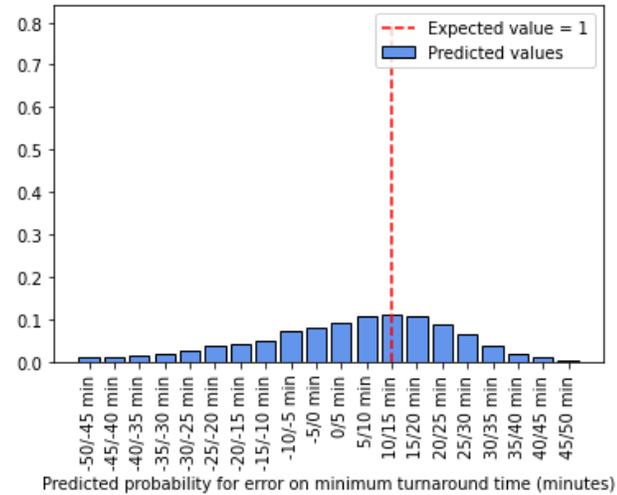
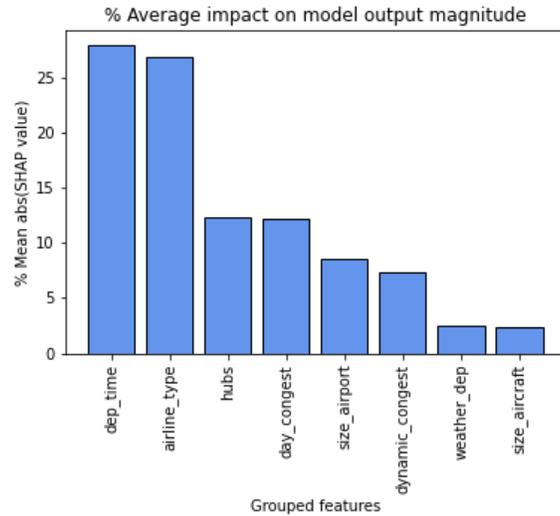
Balanced dataset

Example of output

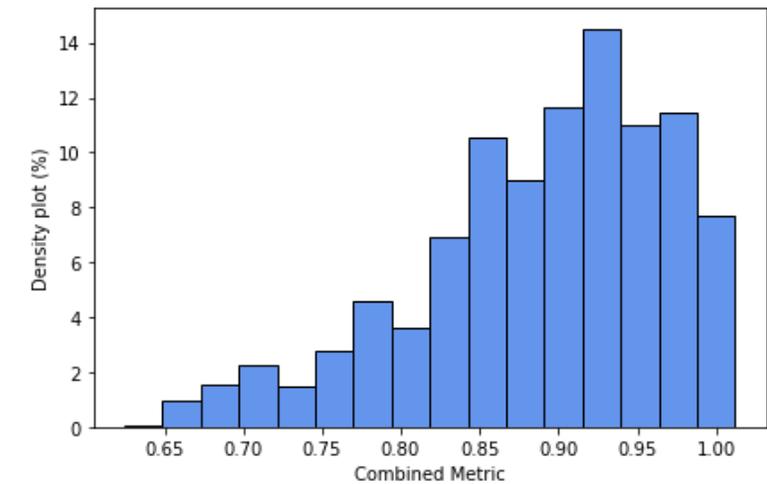
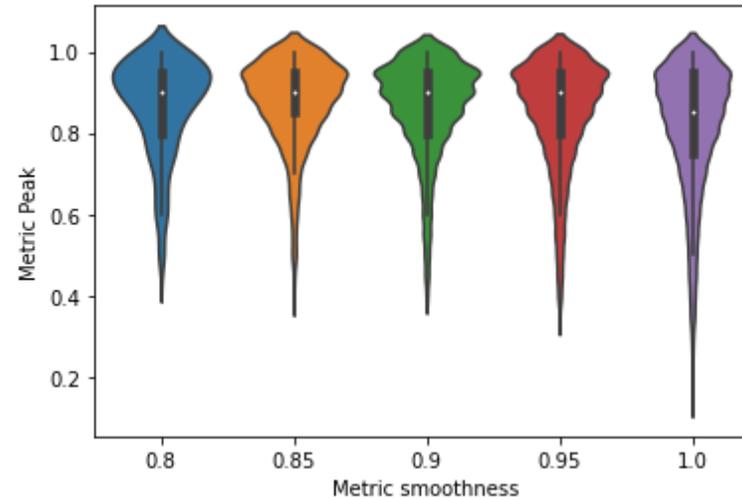
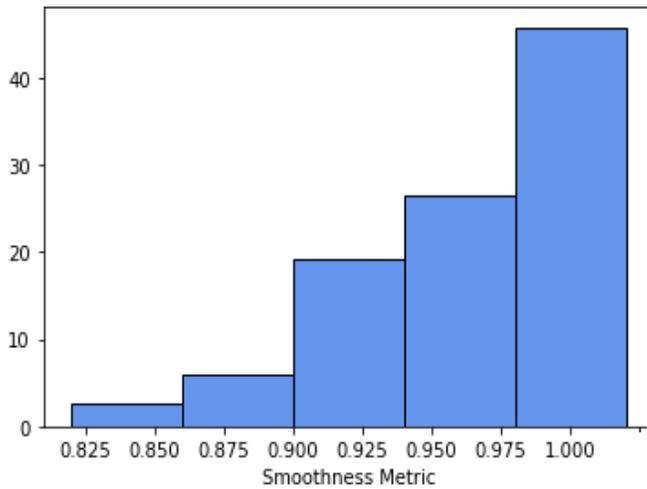
Probability ATM delay	Probability Non-delayed
0,6	0,4

Modelling approach to predict turnaround time (ATM delay)

Regression + classification models to characterise each prediction as a probability distribution



The performance of the 4 models in terms of 'combined metric' is **0,88**



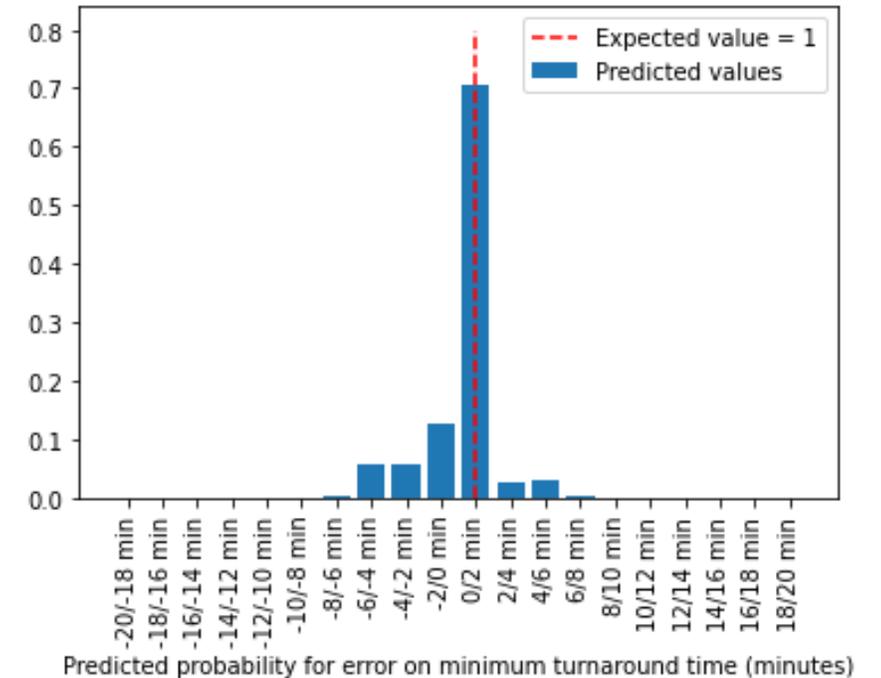
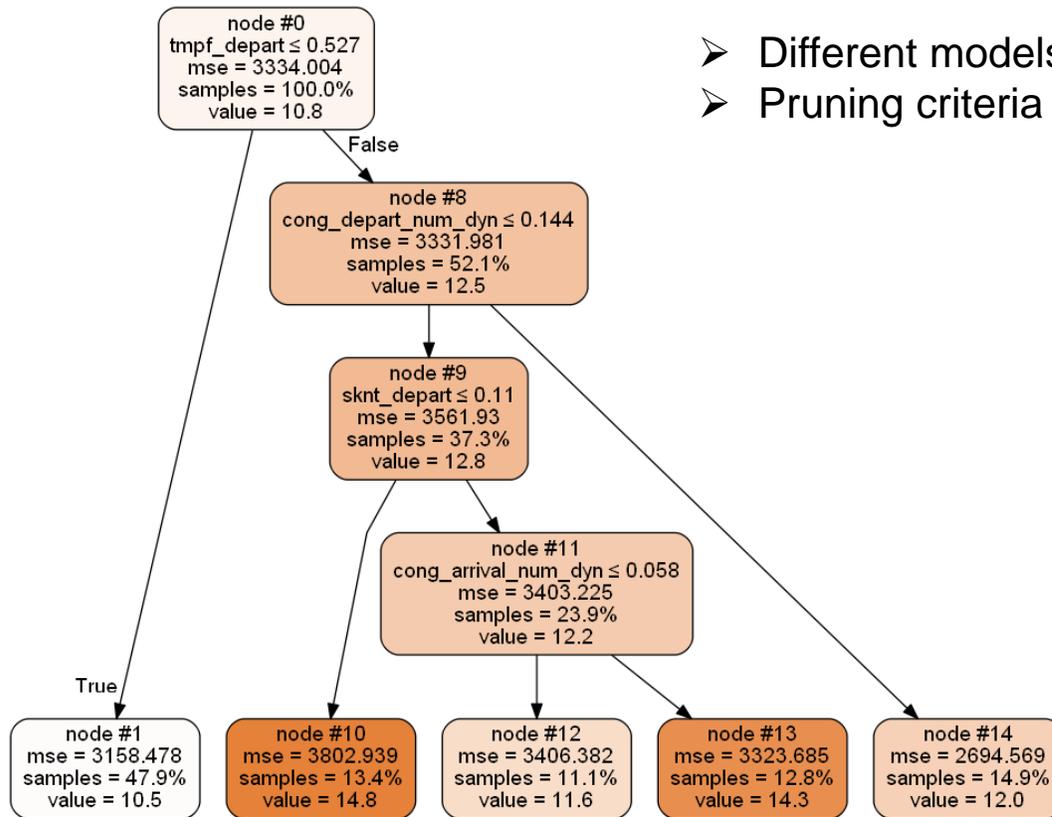
Modelling approach to predict minimum turnaround time

Regression decision tree for **labelling** the output as minimum turnaround time

Regression decision tree for 'clustering'/regrouping

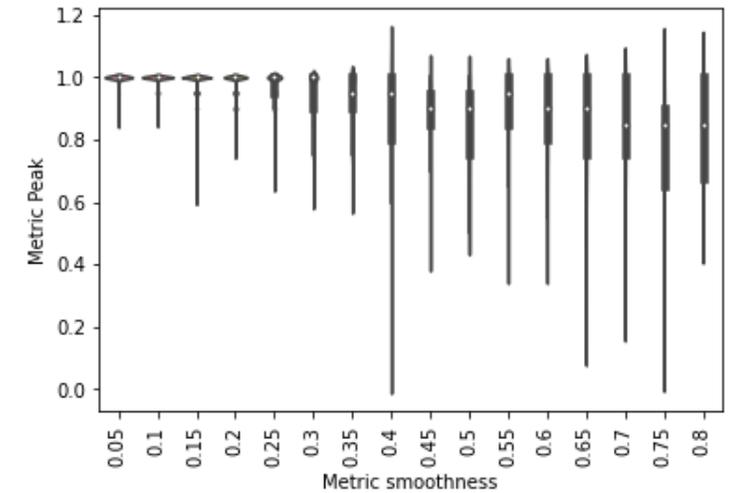
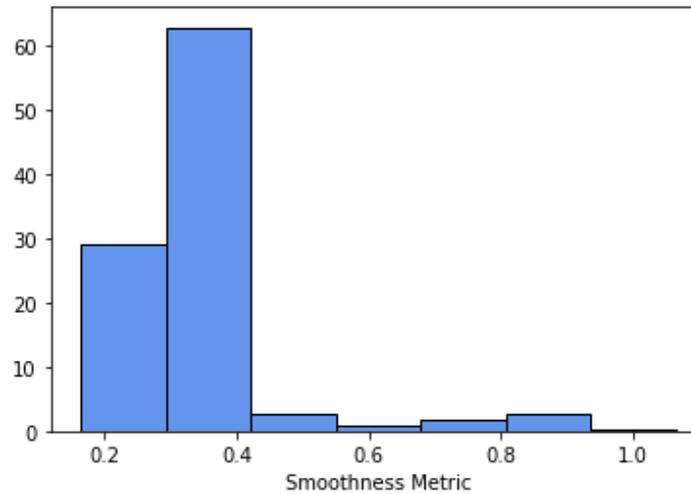
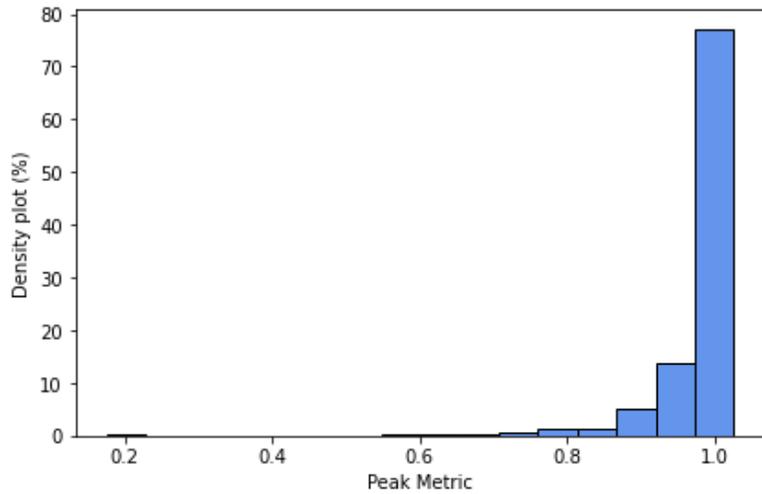
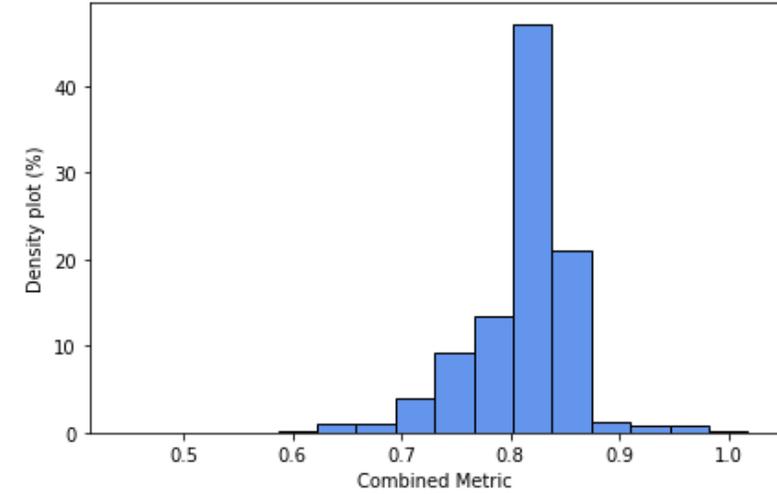
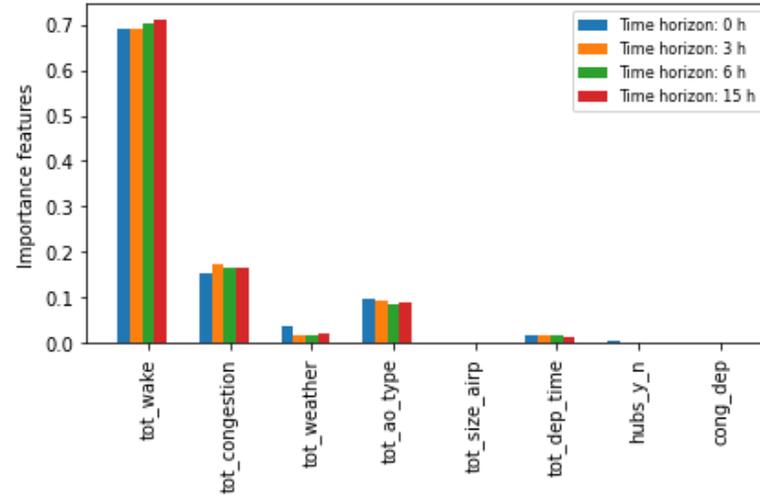
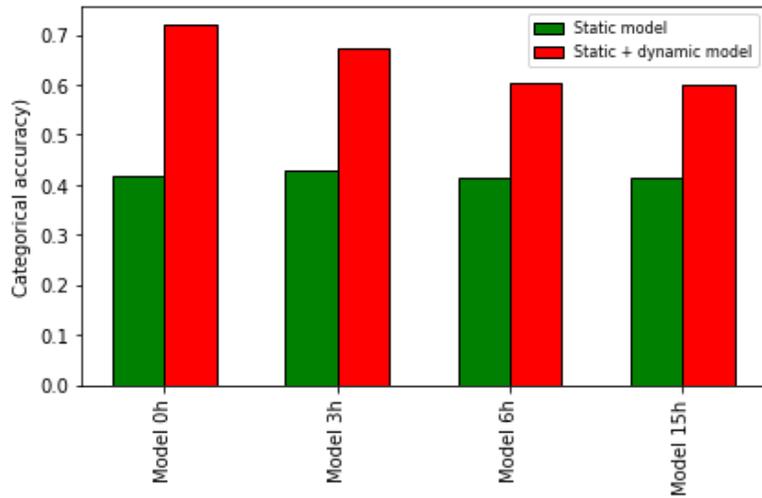
Classification ML model to characterize the error when predicting the output

- Different models for each wake size
- Pruning criteria



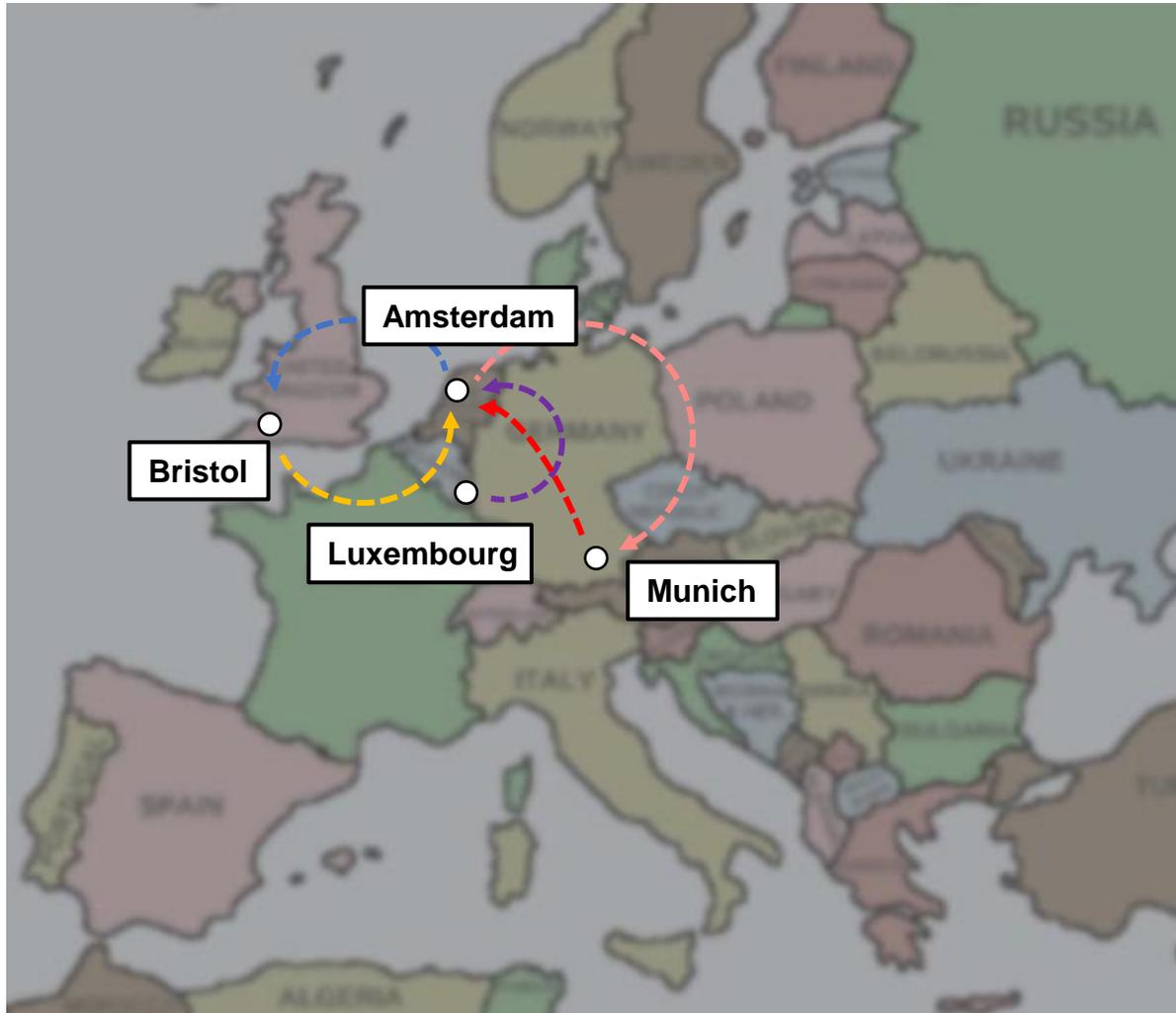
NB. Minimum turnaround time is calculated as 2% percentile of turnaround distributions

Modelling approach to predict minimum turnaround time



The performance of the 4 models in terms of 'combined metric' is **0,79**

An experiment

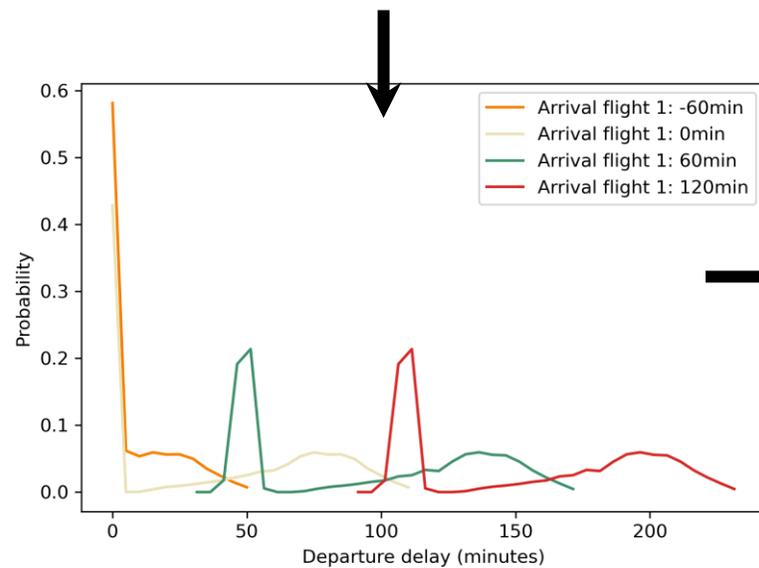
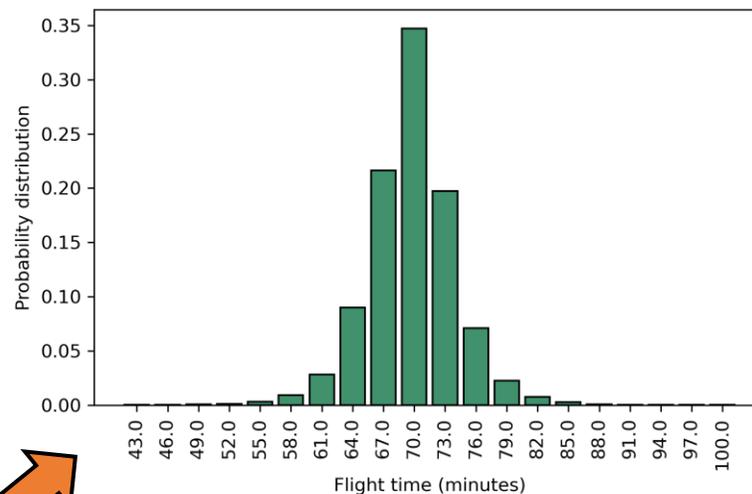
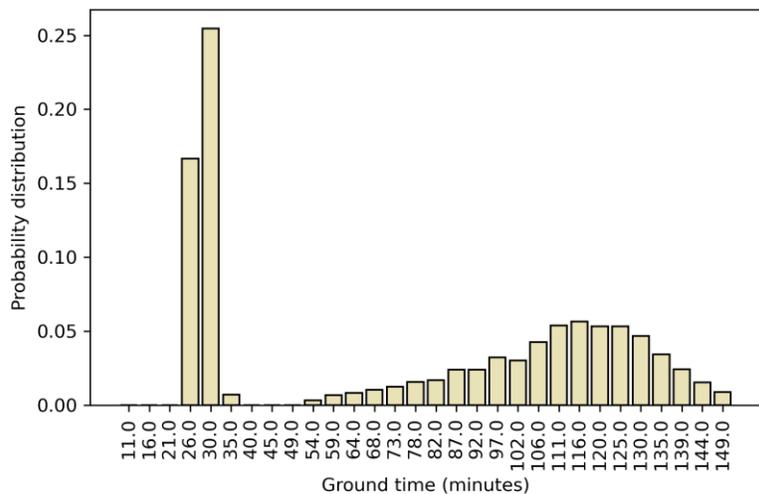


Origin	Destination	SOBT	SIBT
1. ELLX	EHAM	08:55am	10:00am
2. EHAM	EGGD	10:40am	11:50am
3. EGGD	EHAM	12:25pm	13:45pm
4. EHAM	EDDM	16:00pm	17:25pm
5. EDDM	EHAM	18:05pm	19:40pm

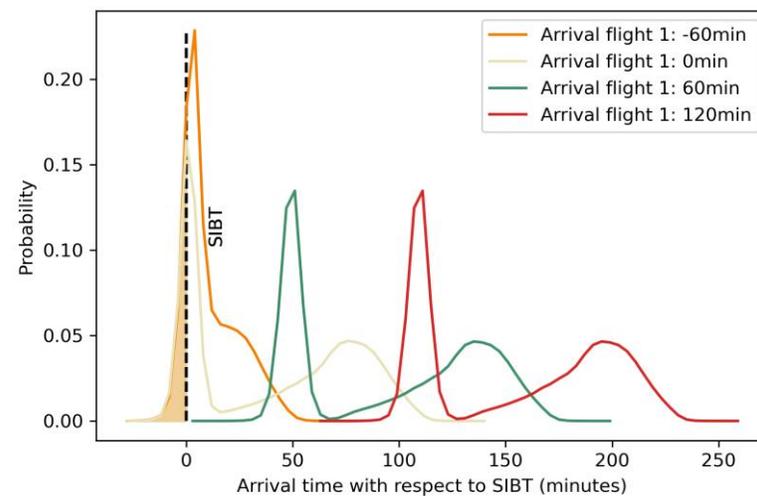
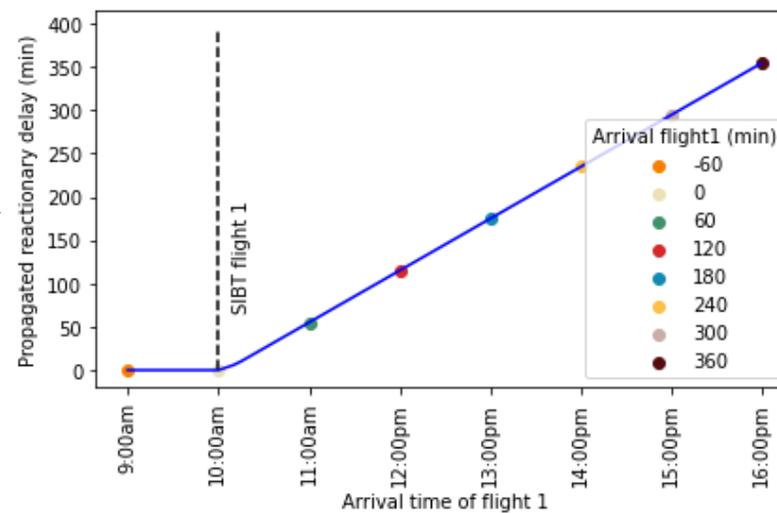


An experiment

Flight 2: Amsterdam - Bristol

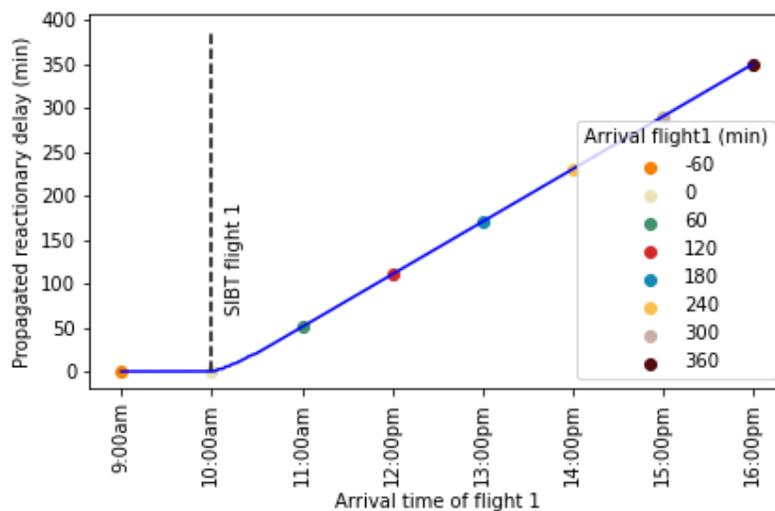
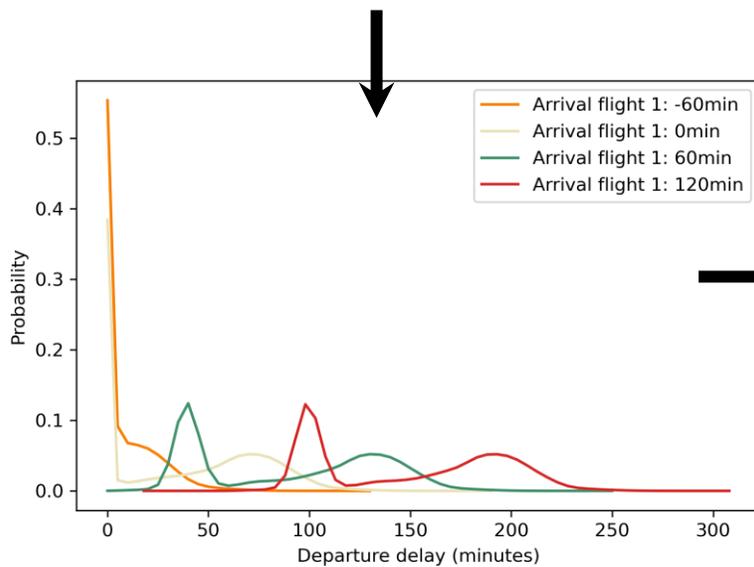
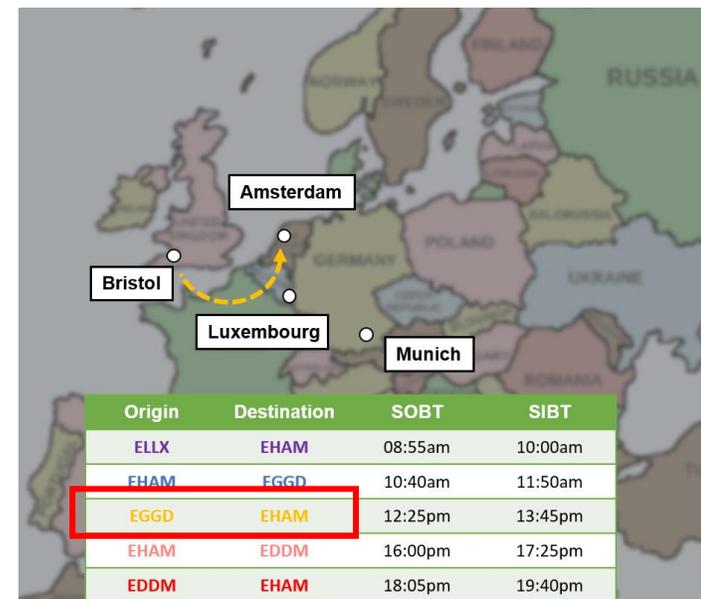
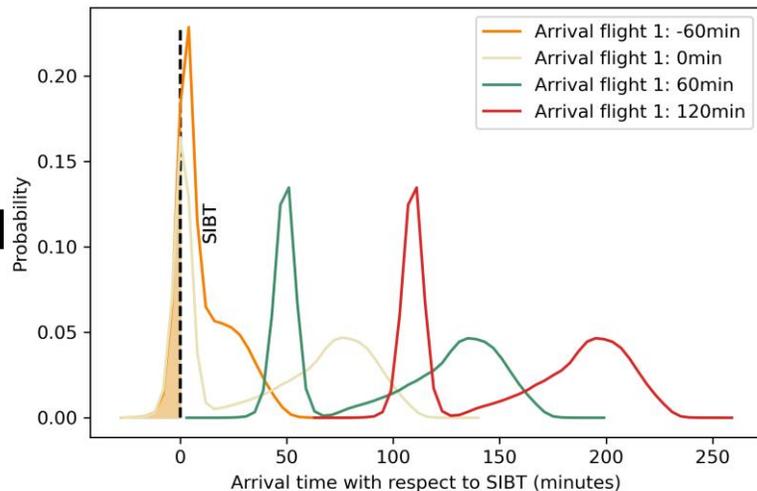
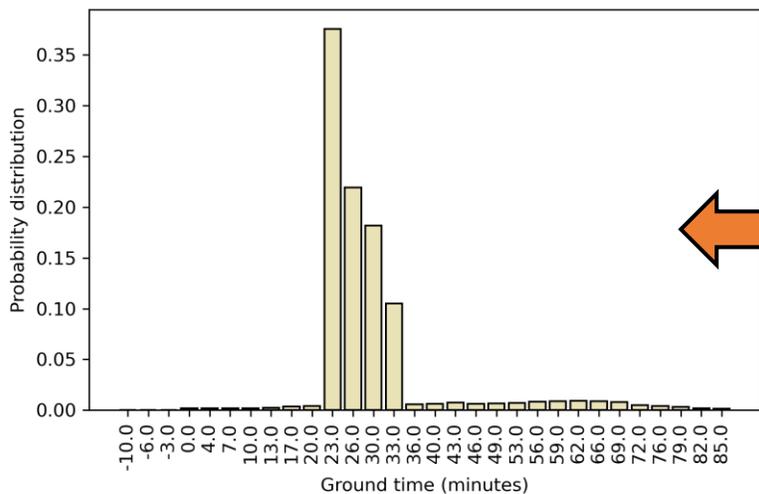


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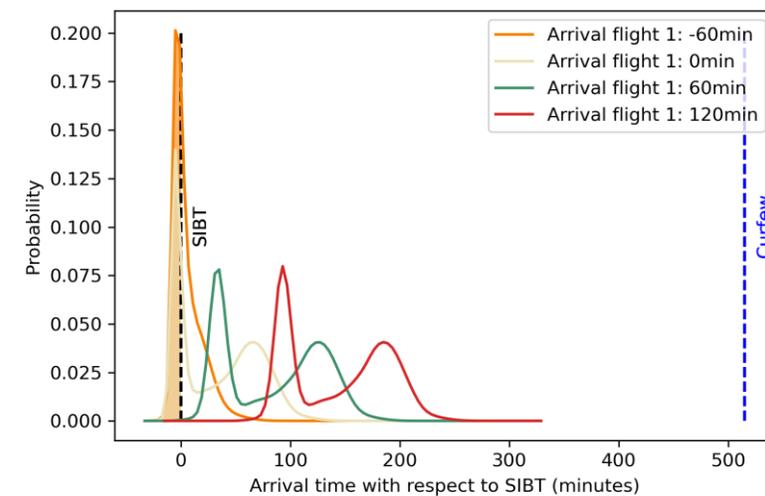
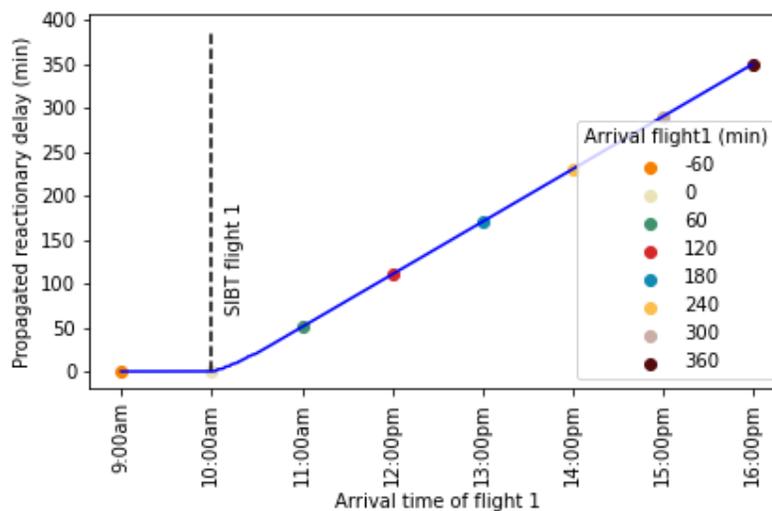
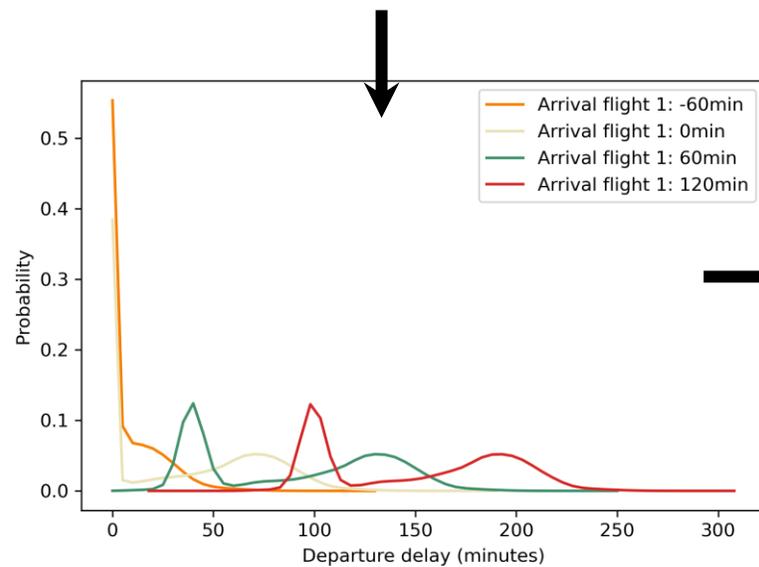
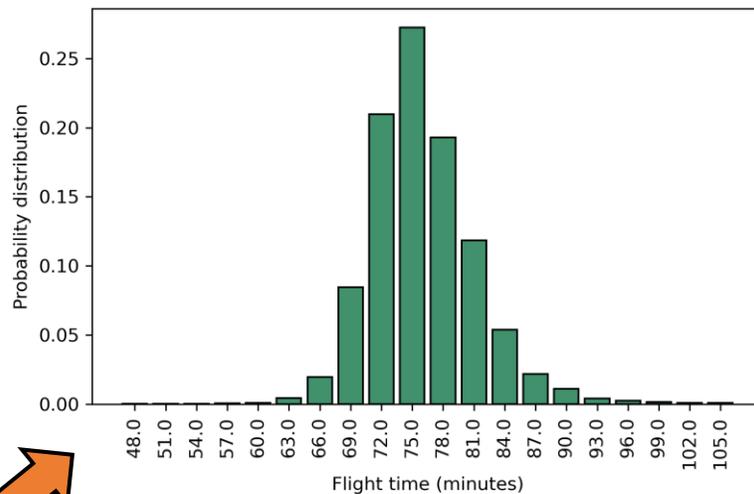
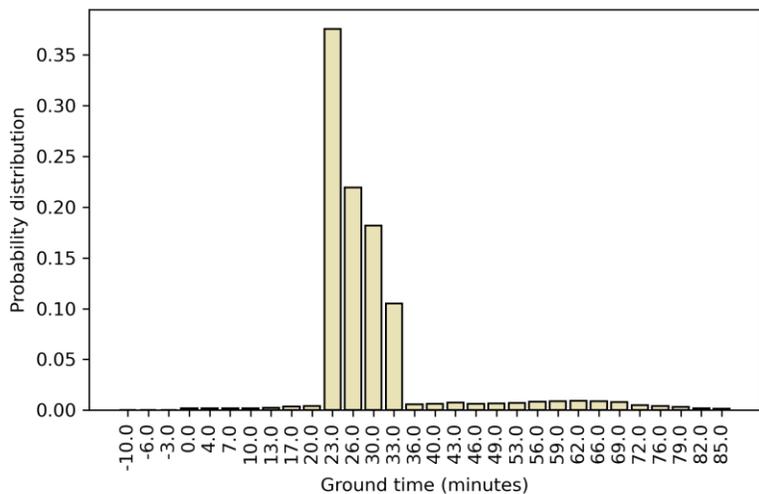
An experiment

Flight 3: Bristol – Amsterdam



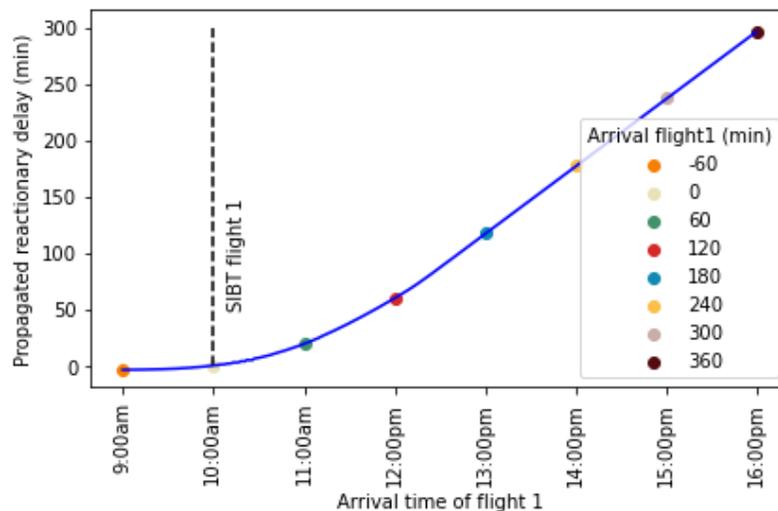
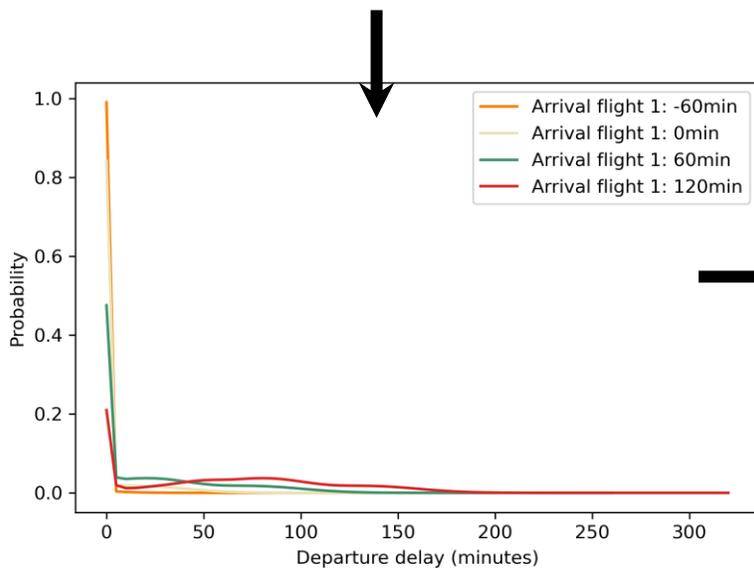
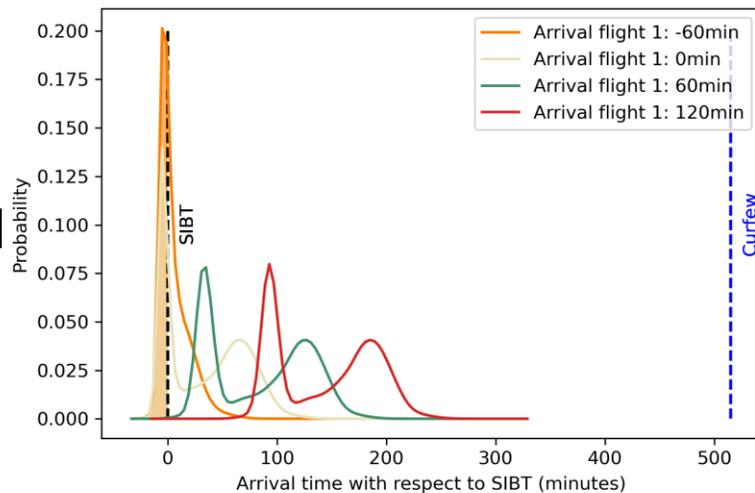
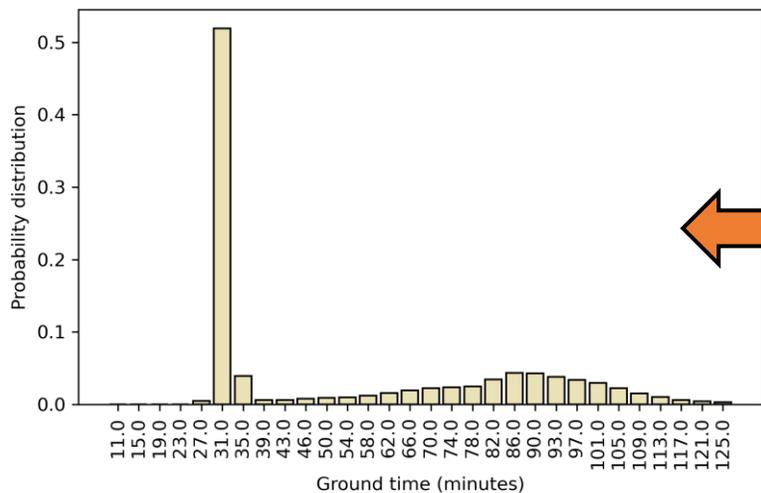
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Flight 3: Bristol – Amsterdam



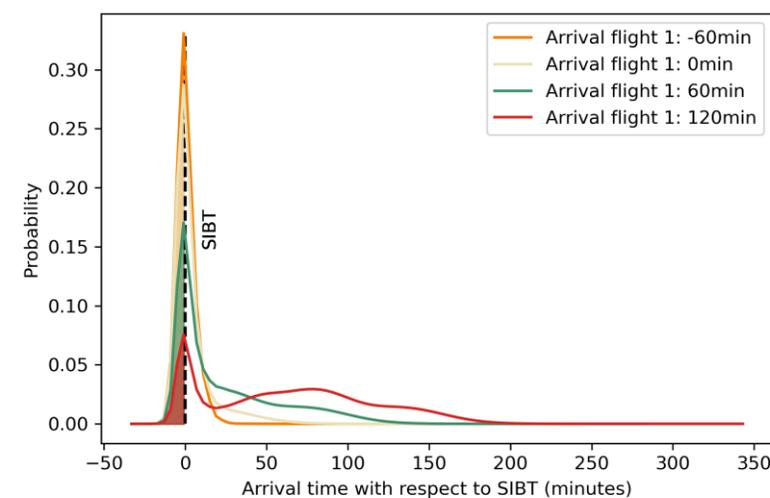
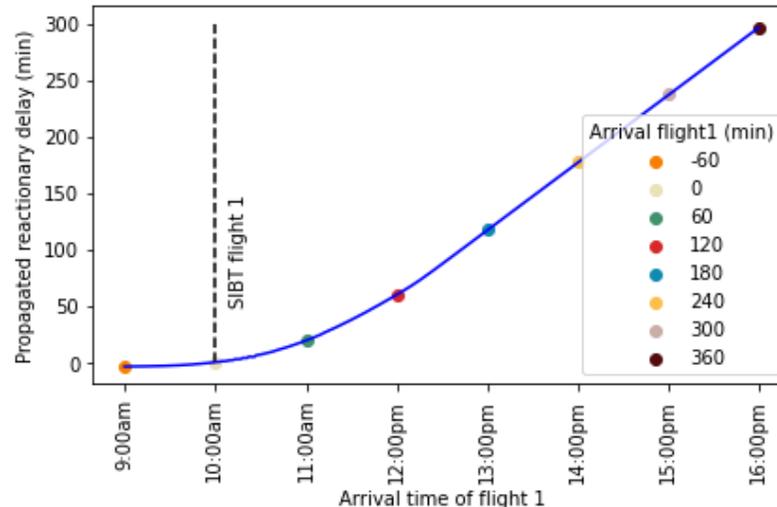
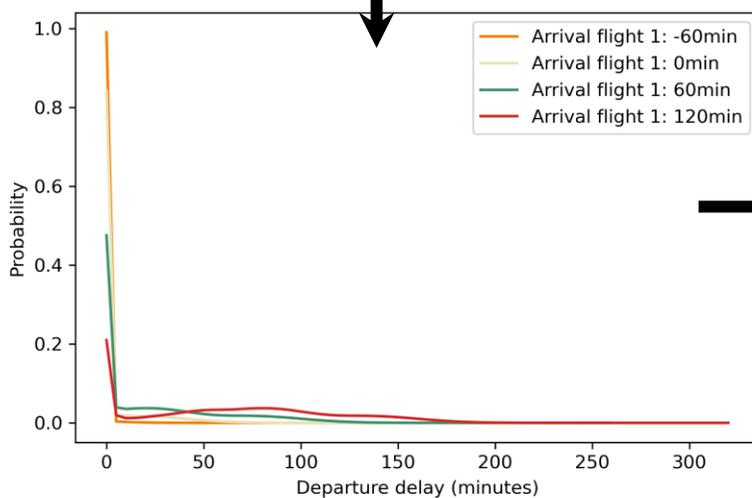
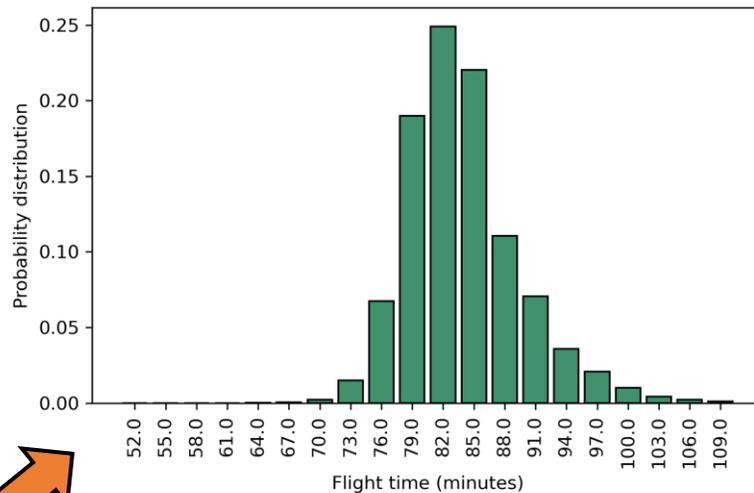
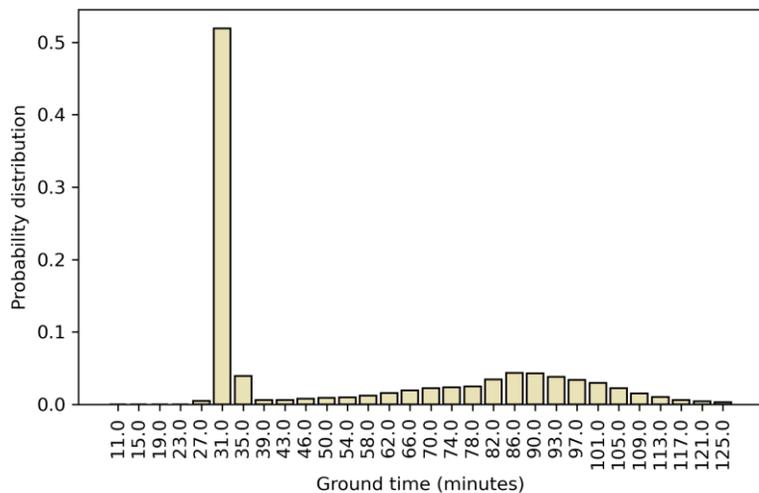
An experiment

Flight 4: Amsterdam - Munich



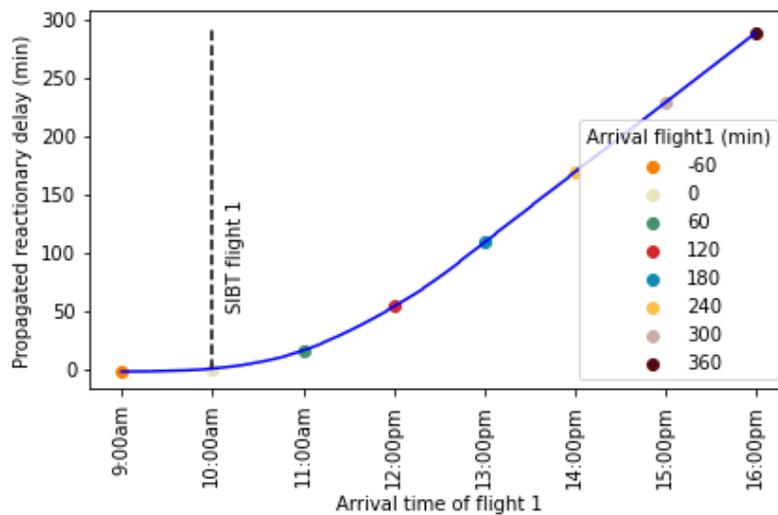
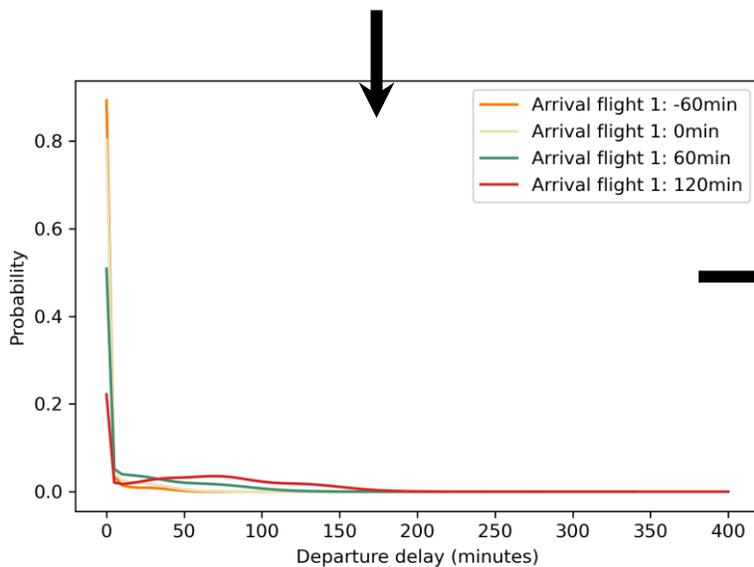
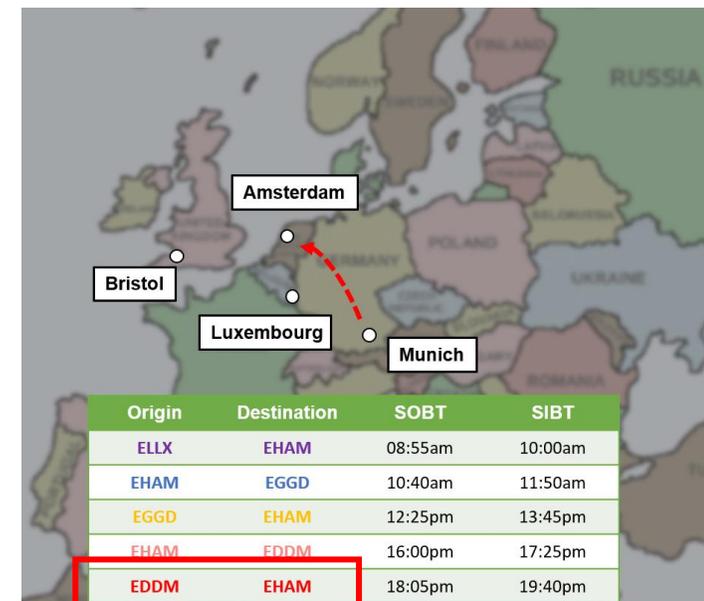
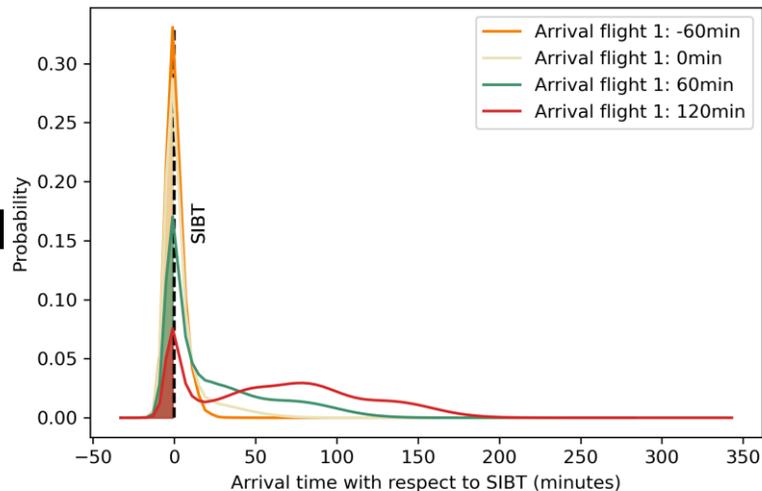
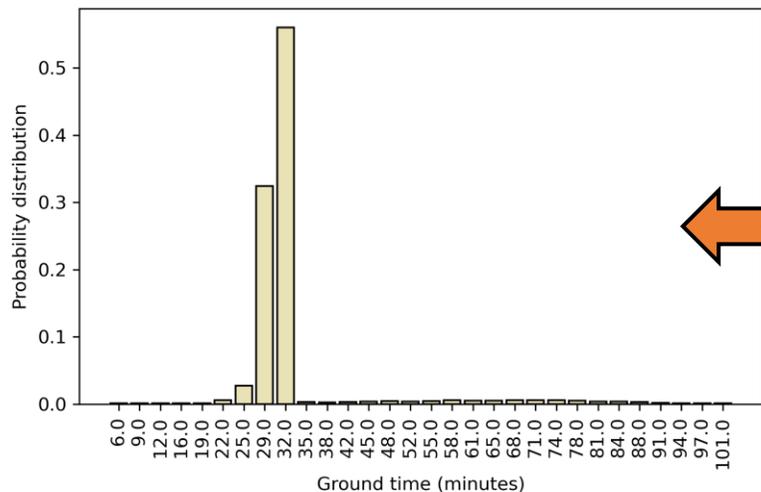
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Flight 4: Amsterdam - Munich



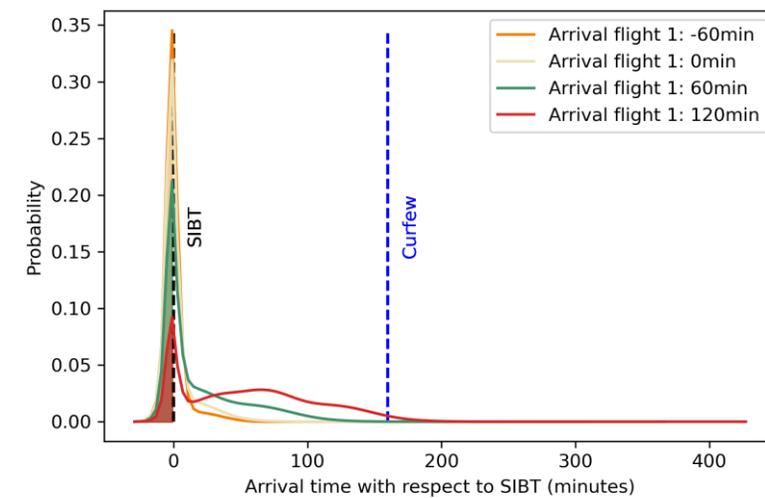
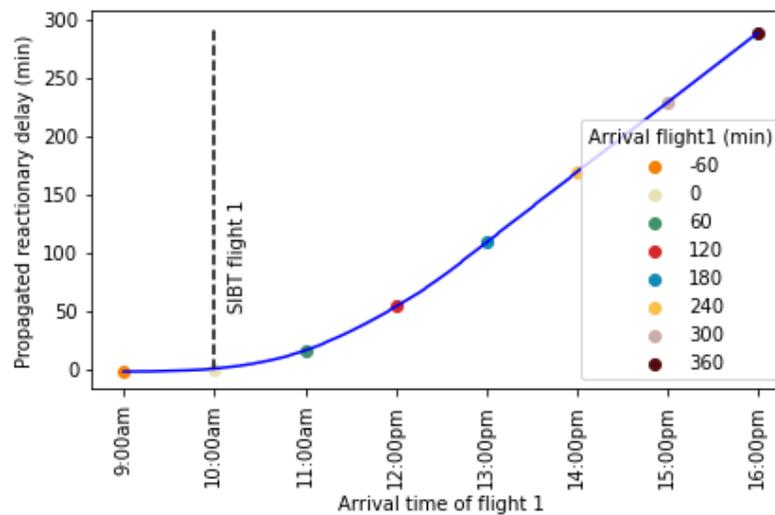
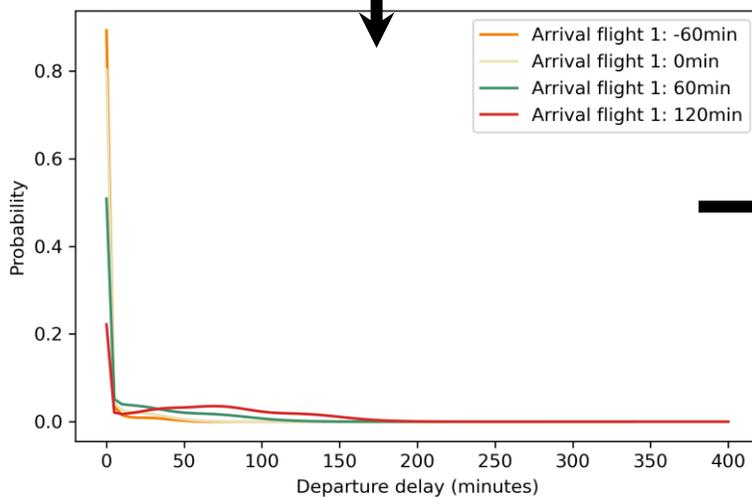
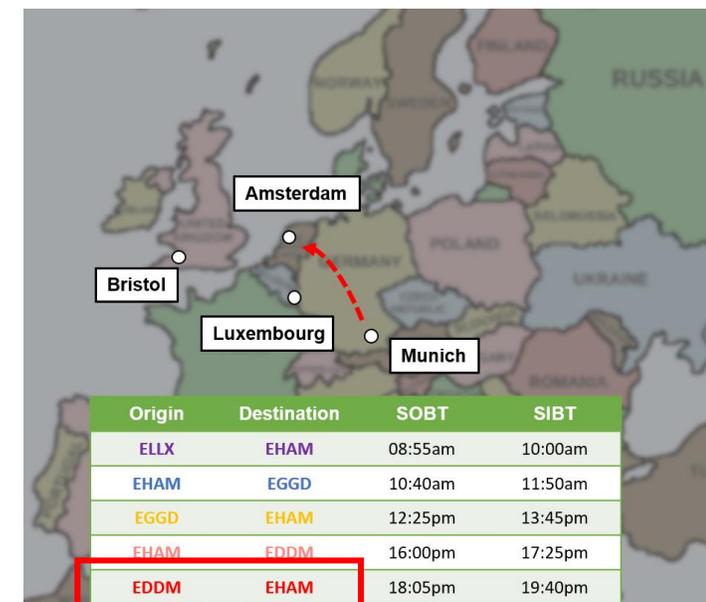
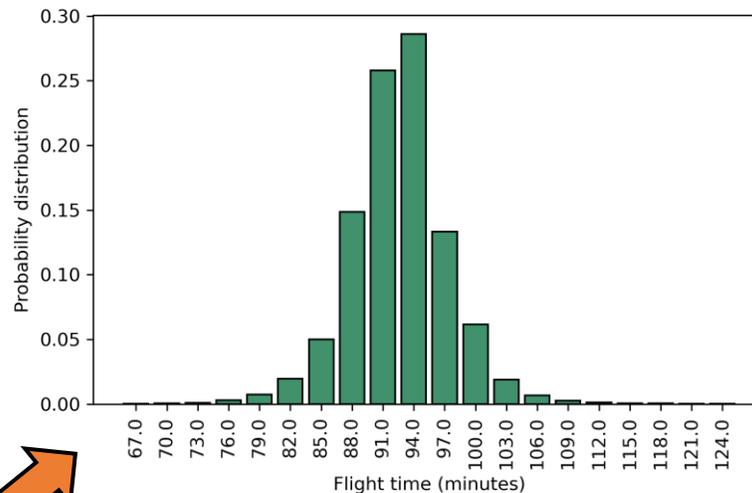
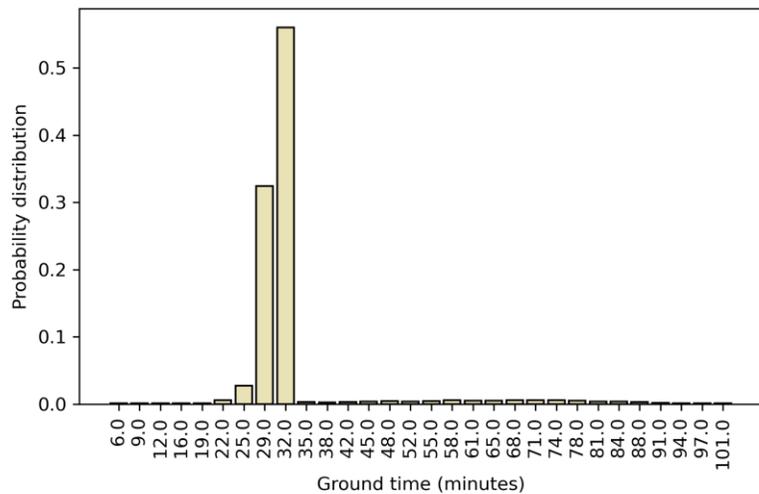
An experiment

Flight 5: Munich - Amsterdam



An experiment

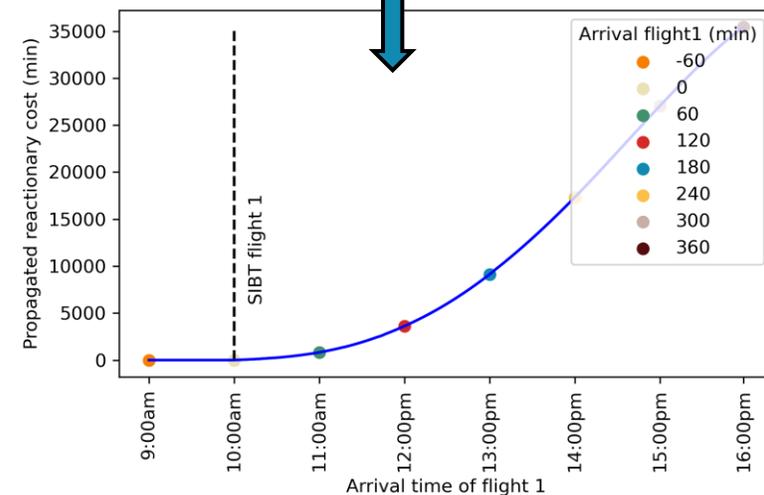
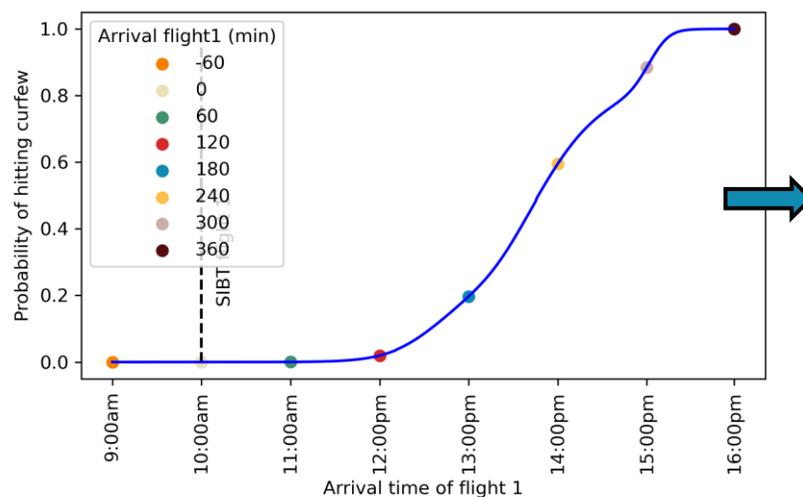
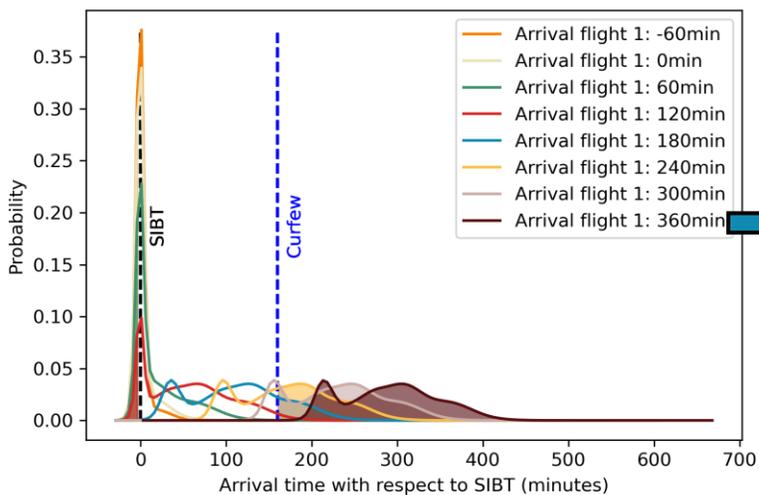
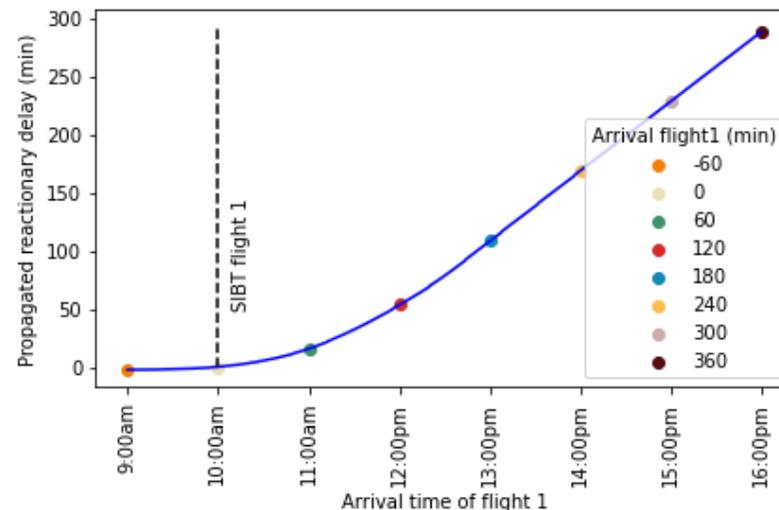
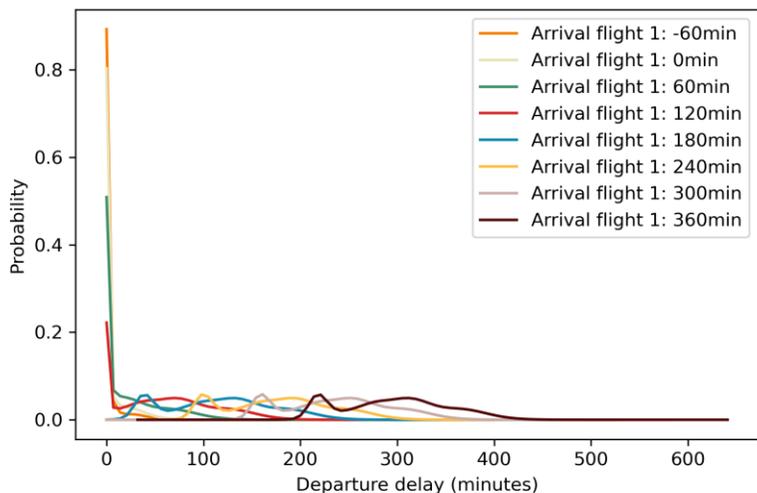
Flight 5: Munich - Amsterdam



An experiment

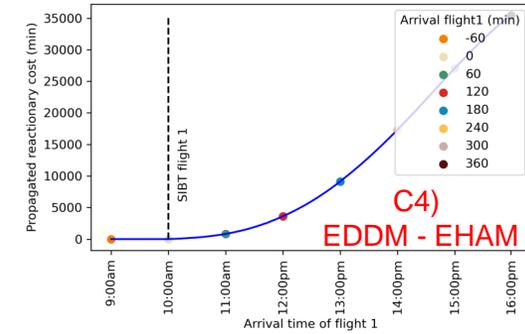
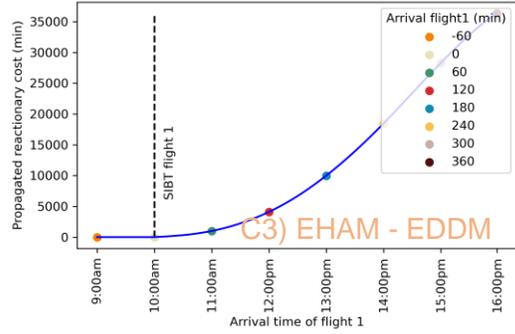
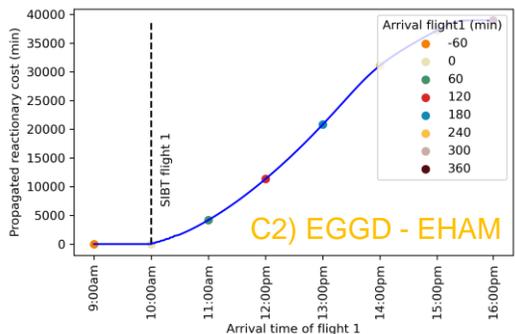
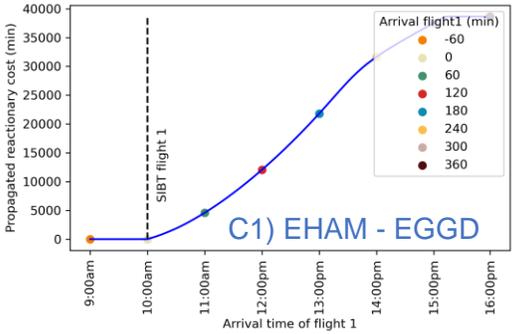
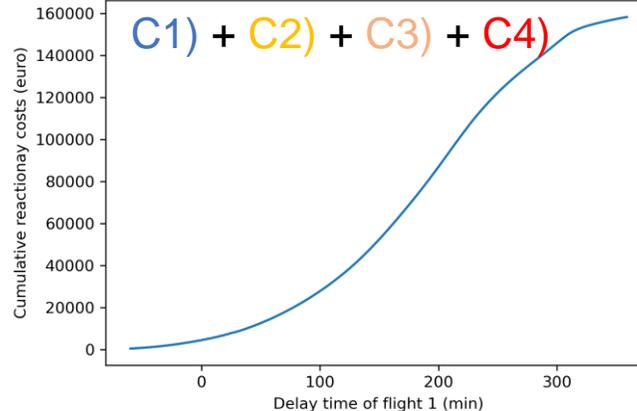
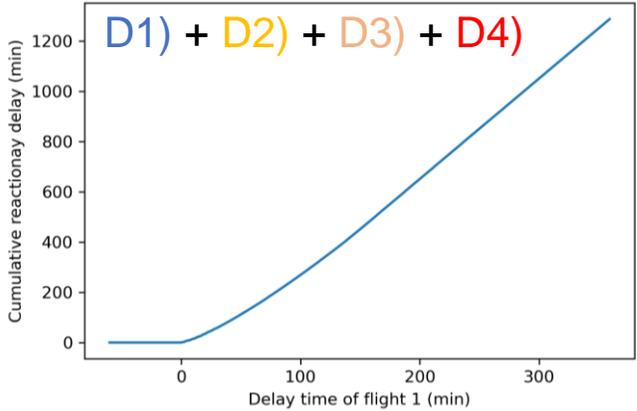
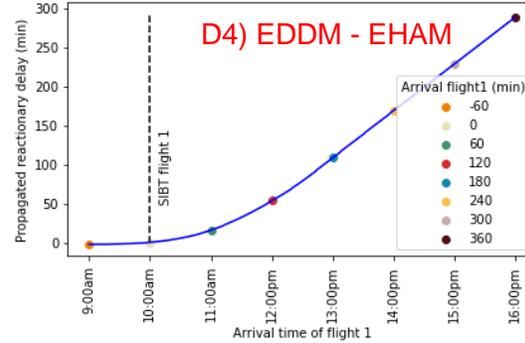
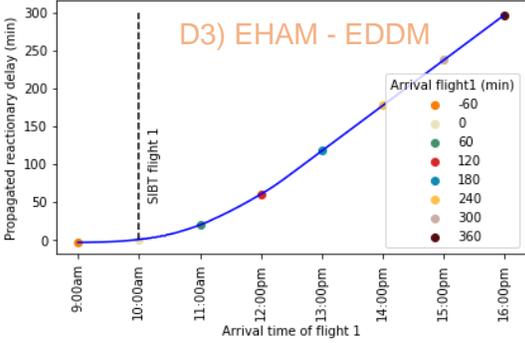
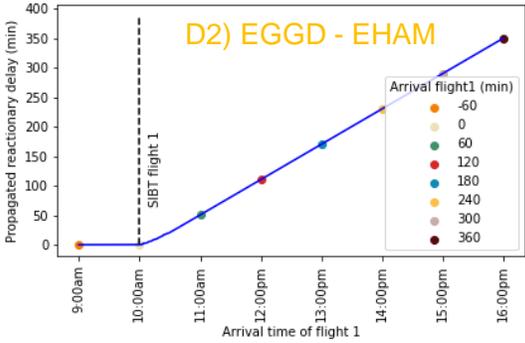
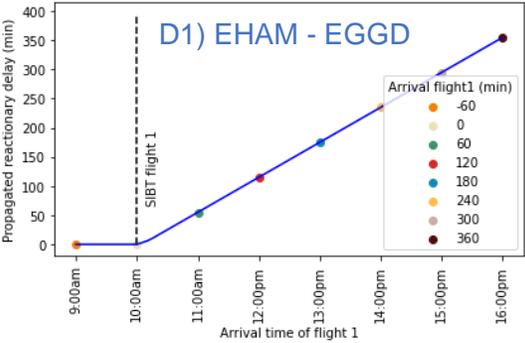
Flight 5: Munich - Amsterdam

Probability of hitting the curfew



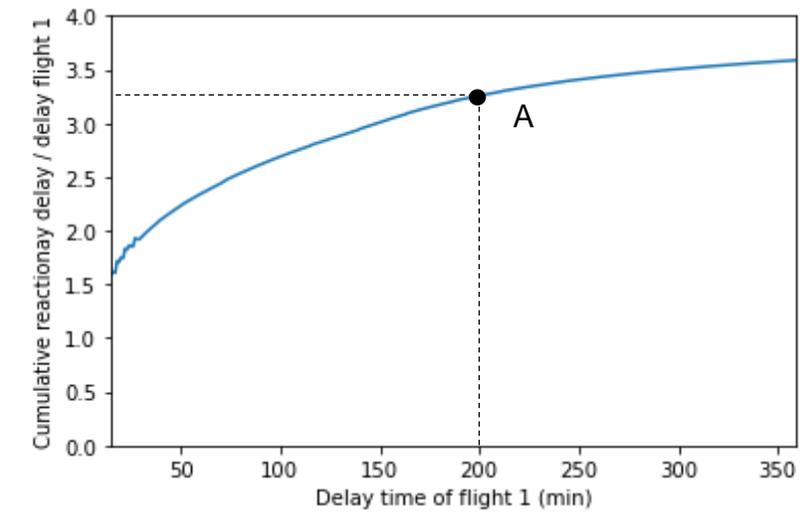
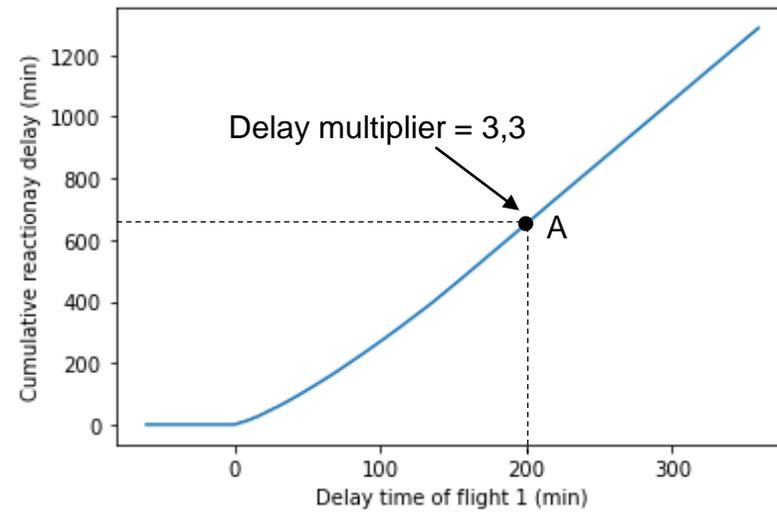
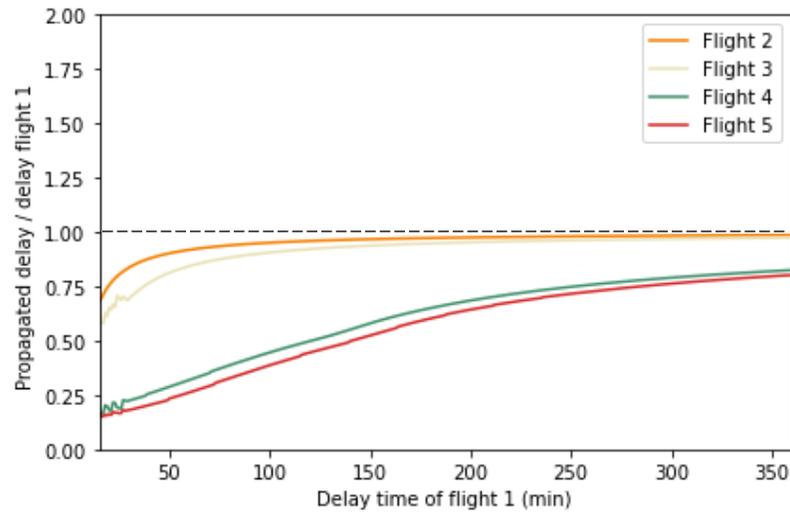
Cook, Andrew J., and Graham Tanner. "European airline delay cost reference values." (2011)

An overview on reactionary delay and costs



Cook, Andrew J., and Graham Tanner. "European airline delay cost reference values." (2011)

An overview on reactionary delay and costs



- Pilot3 will develop a software engine model for supporting crew decisions for civil aircraft.
- Pilot3 will integrate airlines flight policies and overall performance targets to select and rank the alternatives.
- The system does not only consider the flight but the whole network operations of the airline (for example, it will estimate the cost of reactionary delay).
- Pilot3 will allow the airline to select how to predict fields of interest: using airborne information, ground information, with analysis of data and heuristics or with machine learning predictors.

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Valentin Lago
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All Aviation Consulting

Jon Tugores

salient.

vueling

PILOT3

<https://pilot3.eu/>

- Dispatcher3 will develop a software prototype for the acquisition and preparation of historical flight data in order to give support to the optimisation of future flights providing predictive capabilities and advice to flight managers.
- Dispatcher3 focuses on activities prior to departure: dispatching and pilot advice on how to operate the flight.
- Dispatcher3 is composed of three layers: data infrastructure, predictive capabilities and advice capabilities.
- The predictive capabilities will be provided by the development of predictive models using machine learning algorithms for targeted airlines' KPIs.

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<https://dispatcher3.eu/>

- Progressively increase the amount of data for the training/validation steps
- Integrate with other data sources (e.g. TAF data) and increase the amount of features of the ML models
- Interpolation within the time horizons
- Create models for specific 'o/d pair' airports
- Extend the approach to the strategic level to improve the buffer assignment