

Pre-tactical advice using machine learning for Air Traffic Flow Management delay estimation

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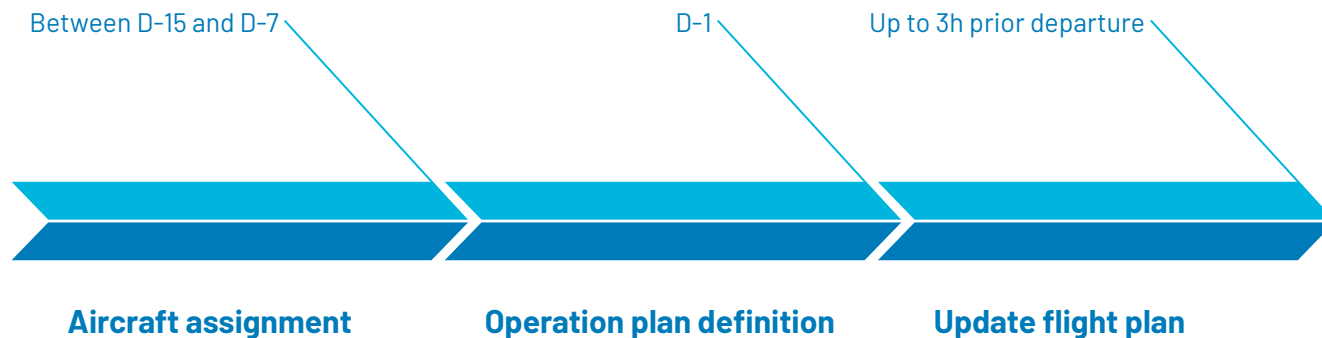
Outline

- ▶ Flight plans lifecycle
- ▶ Dispatcher3
- ▶ ATFM regulations
 - ▶ Analysis
 - ▶ Outcome of the system
- ▶ Data availability
- ▶ Methodology
- ▶ Evaluation
- ▶ Results
- ▶ Case study
- ▶ Conclusions
- ▶ Future development



Flight plans lifecycle

- ▶ Between D-15 and D-7: Aircraft assignment
- ▶ D-1 : Operation plan definition
- ▶ Up to 3 hours prior departure: Flight plans will be updated, and pre-tactical actions implementation



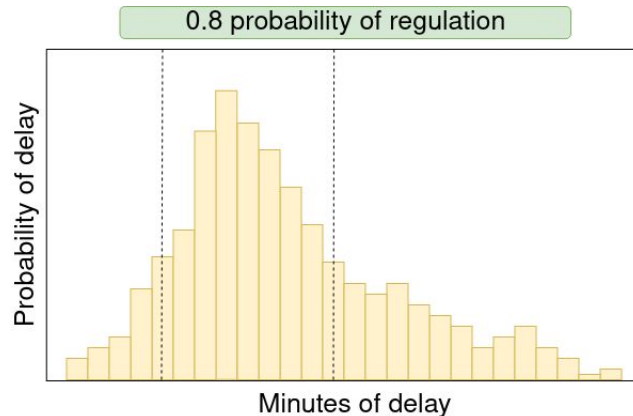
Dispatcher3

- ▶ Dispatcher3, a CleanSky 2 innovation action, uses machine learning techniques to support pre-departure processes
- ▶ Dispatcher3 is composed of three layers:
 - ▶ Data infrastructure
 - ▶ Predictive capabilities
 - ▶ Advice capabilities
- ▶ Flights might experience discrepancies between their plan and execution due to many factors
 - ▶ In particular, demand-capacity imbalances leading to ATFM regulations.
- ▶ Euro-centric approach
- ▶ We will focus on flights from Vueling

<https://dispatcher3.eu/>

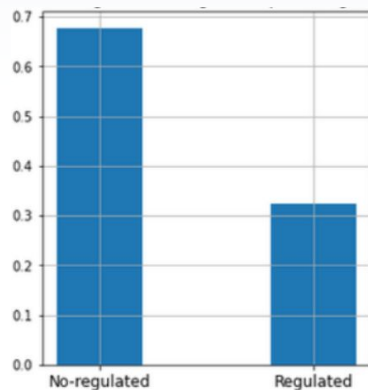
ATFM regulations

- ▶ Current work predicting ATFM regulations usually focuses on the network, or on specific OD pairs
- ▶ Early indication of potential disruptions at the flight level is important to plan and implement pre-tactical actions to minimise the potential propagation of these disruptions.

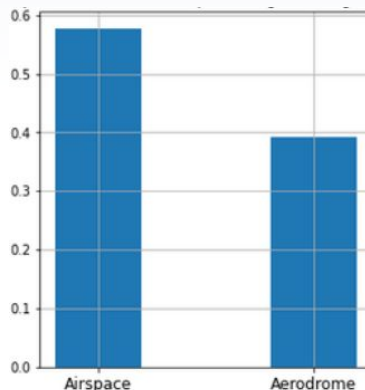


ATFM regulations - Analysis

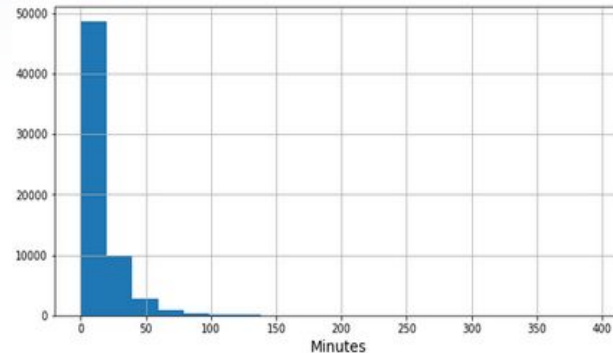
Non-regulated Vs Regulated



Type of delay

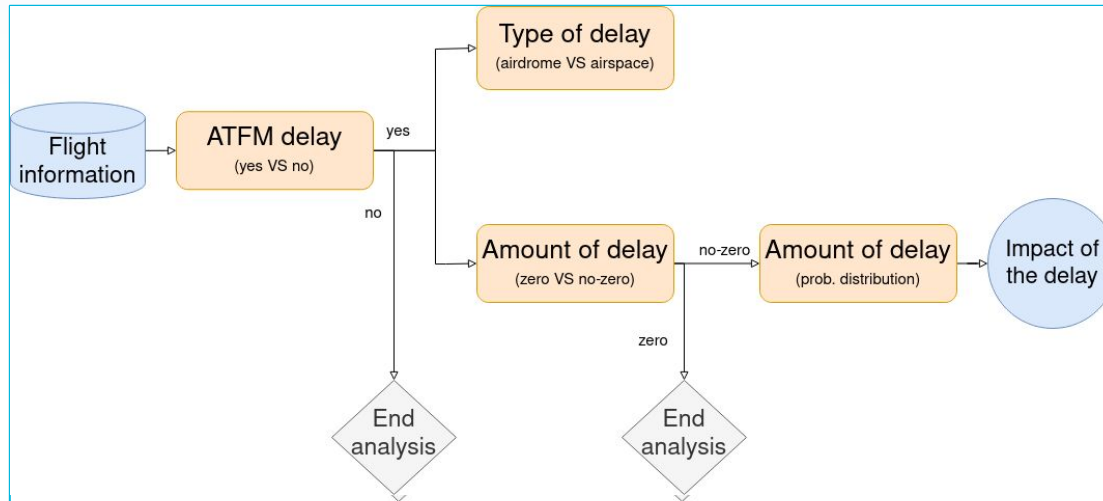


Distribution minutes of delay



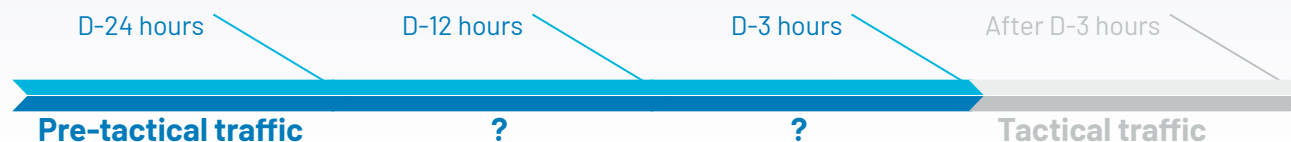
Outcome of the system

- ▶ Combination of machine learning models to create higher level interpretable predictions for D-1
 - ▷ Different levels of granularity
 - ▷ Take into account different scenarios (flexibility for D-1)



Data availability

- ▶ Data challenges: Available traffic
 - ▶ Ideal pre-tactical traffic:



- ▶ Assumption:
 - ▶ Airline has access to pre-tactical traffic
 - ▶ Static pre-tactical traffic

- ▶ Datasets used:

Data source	Description
Eurocontrol DDR (ALLFT+)	'Extension' of R&D data containing more detailed information
METAR	Forecasted historical weather information at the airports

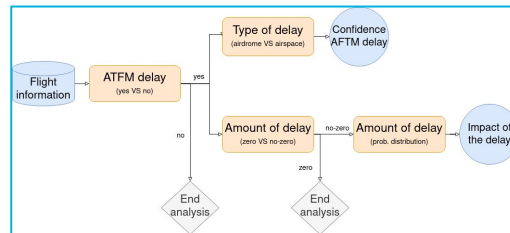
Methodology - Input features

Static features	Dynamic features
Time of departure (hourly discretization)	ATMAP score at departure/arrival airport (numerical)
Size departure airport (small, big, medium)	Temperature at departure/arrival airport (numerical)
Size arrival airport (small, big, medium)	Wind speed at departure/arrival airport (numerical)
	Visibility at departure/arrival airport (numerical)
	'Normalized' congestion at departure/arrival (in the day of operations)
	'Normalized' congestion at departure/arrival (within the hour of departure/arrival)
	Highest 'normalized' Occupancy Count (OC) within crossed sector
	Highest 'normalized' Entry Count (EC) within crossed sector

Methodology - Individual models

- ▶ Algorithms used for the individual models:

Models / Algorithms	
Probability ATFM delay (yes VS no)	Random Forest Classifier
Type of delay (airdrome VS airspace)	Decision Tree Classifier
Amount of delay (zero VS non-zero delay)	Decision Tree Classifier



Methodology - Confidence metric

- ▶ Visual higher level interpretable information easier to be processed by the duty-manager
- ▶ Predictions inside percentile(90) of TN (or TP) -> Model sure about the prediction
- ▶ Example:
 - ▶ Prediction prob. ATFM delay = 0.87 -> Model very sure about the need of a regulation
 - ▶ Prediction type of delay = 0.59 -> Uncertain prediction for aerodrome regulation
 - ▶ Prediction amount of delay = 0.17 -> Model sure about the delay is going to be zero

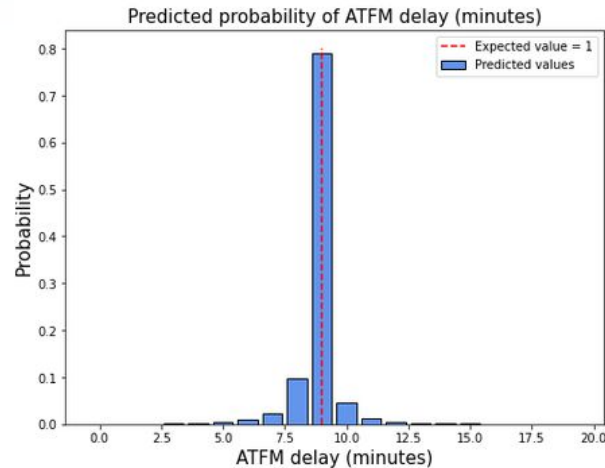
Prob. ATFM

Airdrome

Zero delay

Methodology – Delay distribution

- ▶ Machine learning models produce probabilistic outputs
- ▶ Distribution of delay to better assess the impact/severity of the expected delay
 - ▶ Regression: Estimate severity (exact minutes)
 - ▶ Classification: Estimate impact (uncertainty/spread possible delay)



Evaluation - Individual models

Accuracy

Fraction of predictions right

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Recall

Proportion of positive samples correctly identified

$$Recall = \frac{TP}{TP+FN}$$

Precision

Proportion of positive identification correctly

$$Precision = \frac{TP}{TP+FP}$$

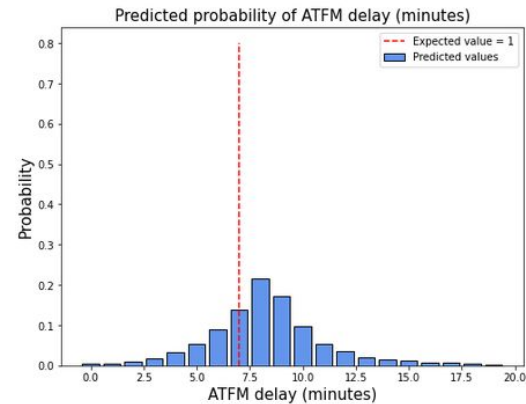
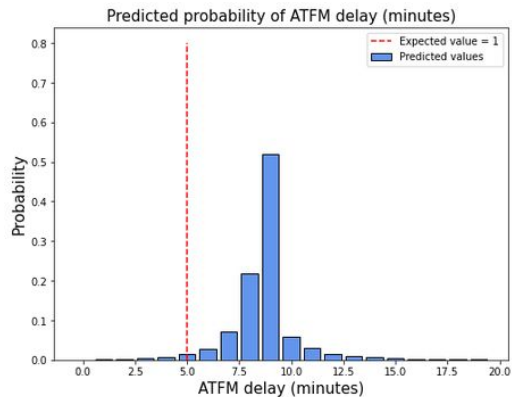
F1-score

Harmonic mean of the precision and recall

$$F1 \text{ score} = 2 \frac{Precision * Recall}{Precision + Recall}$$

Evaluation - Delay distribution

- ▶ How close is the prediction to the actual ATFM delay?
 - ▶ Compute the difference of minutes between ground-truth and the expected value from distribution
- ▶ How sure is the model about the expected delay?
 - ▶ Compute dispersion of predicted values
 - ▶ The more sure the model's prediction, the fewer bars will be present on the chart



Results - Individual models

Prob. ATFM delay (yes vs no)	
Accuracy	0.88
F1-score	0.87



Confusion matrix (%)

Actual values	Delayed	86	14
	Non-delayed	7.9	92
		Delayed	Non-delayed

Predicted values

Type of delay (Airdrome vs Airspace)	
Accuracy	0.87
F1-score	0.86



Confusion matrix (%)

Actual values	Airdrome	89	11
	Airspace	13	87
		Airdrome	Airspace

Predicted values

Amount of delay (zero vs non-zero delay)	
Accuracy	0.71
F1-score	0.66



Confusion matrix (%)

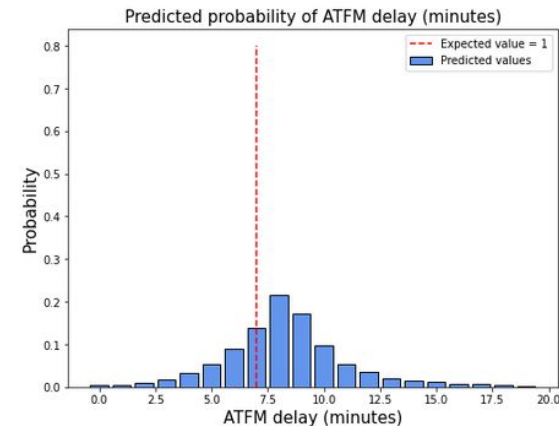
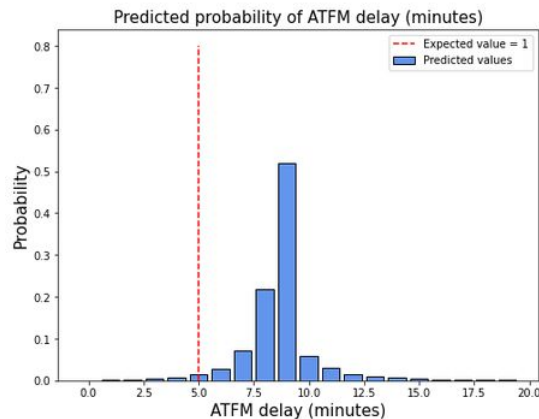
Actual values	Non-zero	77	13
	Zero	35	65
		Zero	Non-zero

Predicted values

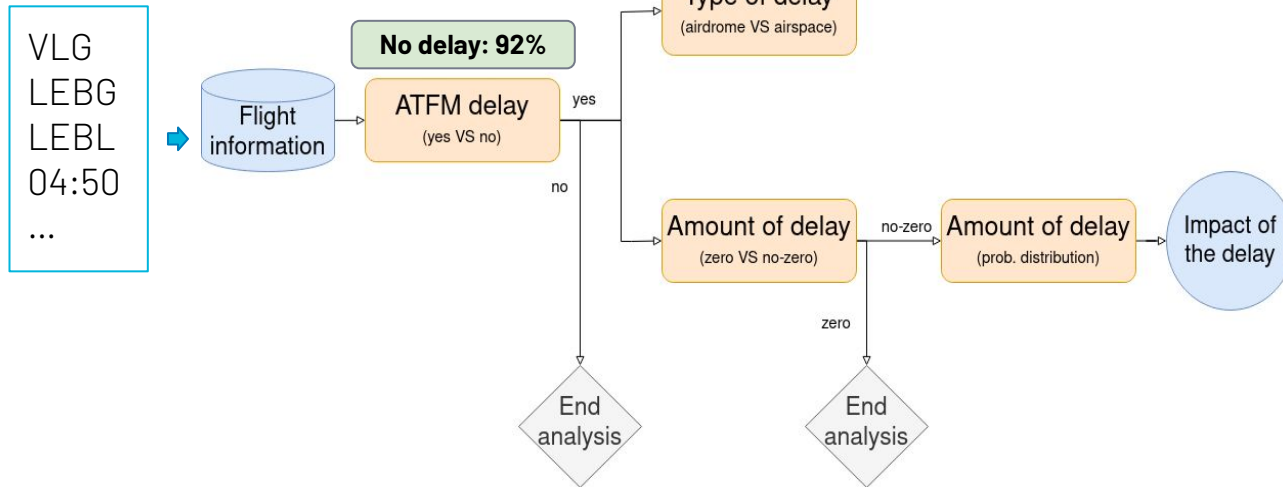


Results - Delay distribution

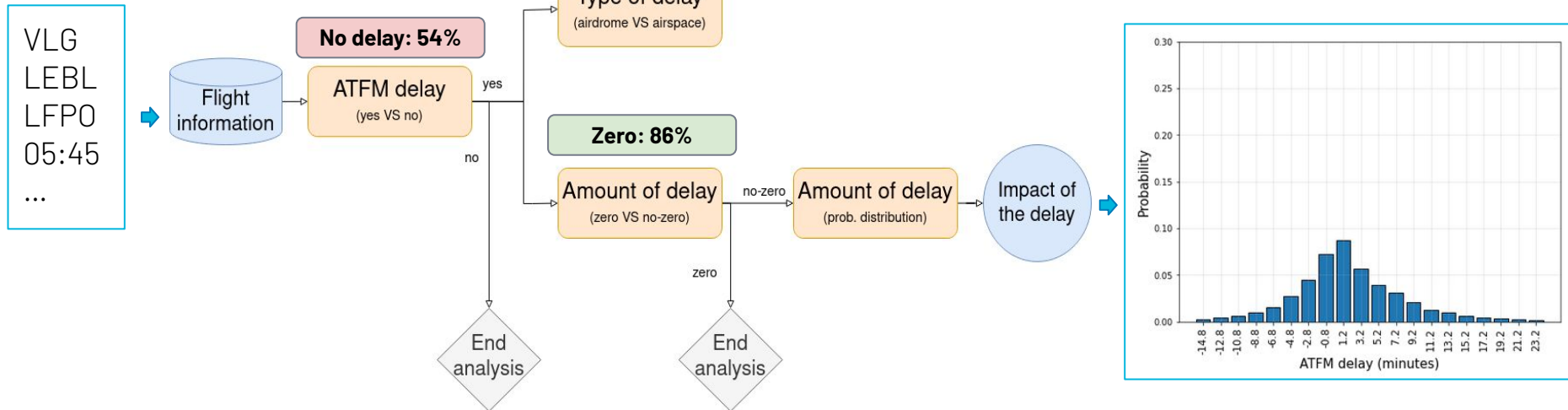
- ▶ Actual delay VS Predicted delay: 9,14 minutes
 - ▶ Mean difference between actual delay and expected value from the distribution
- ▶ Average dispersion of the prediction: 22,35 minutes



Case study - No ATFM delay

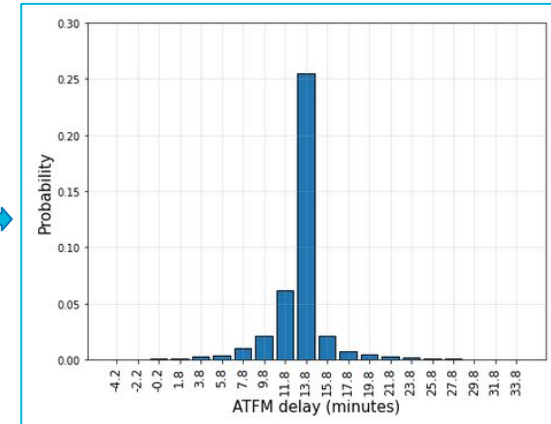
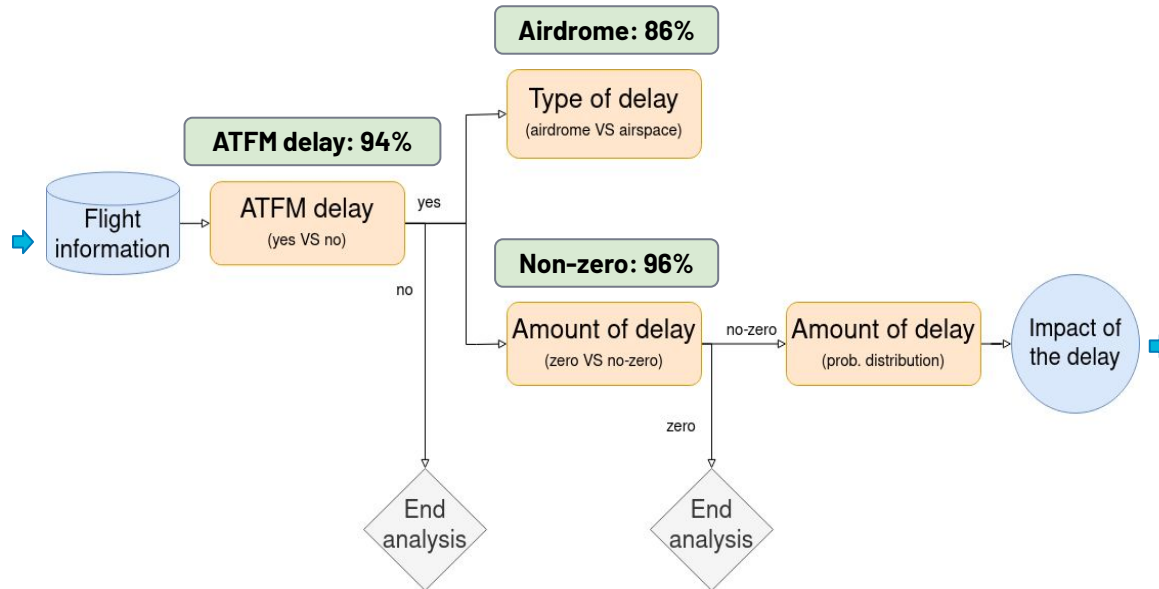


Case study - No ATFM delay



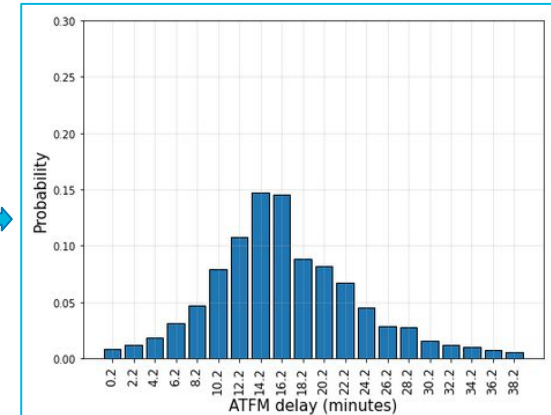
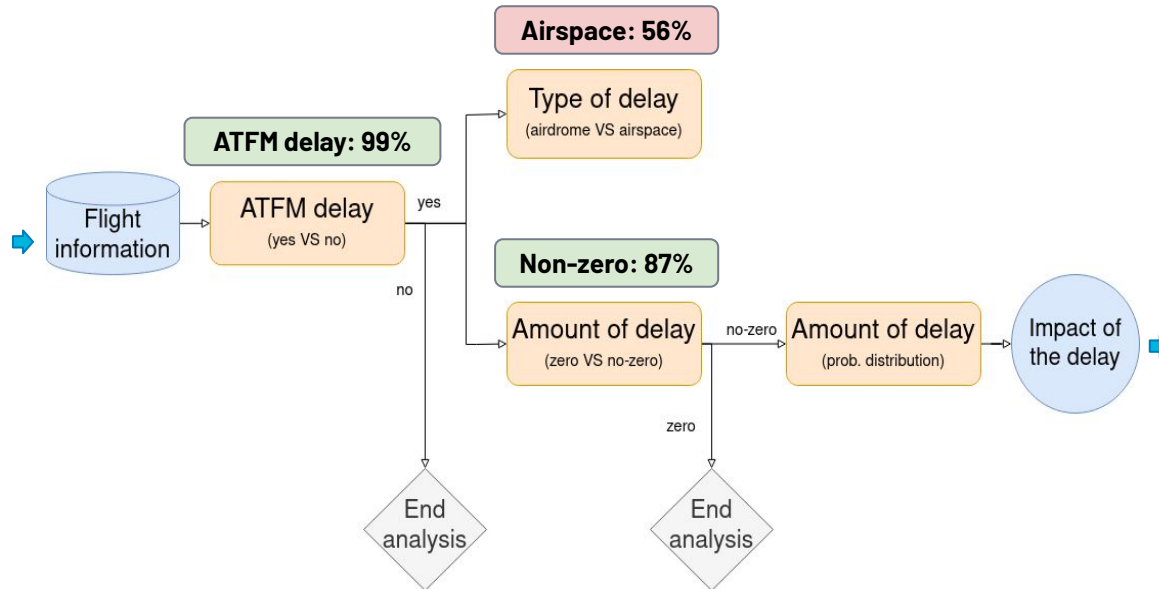
Case study - ATFM delay

VLG
LIQR
LFPO
08:24
...



Case study - ATFM delay

VLG
LEBL
EDDM
10:32
...



Conclusions

Benefits:

- ▶ Models can be used to identify ATFM regulation pre-tactically
- ▶ Individual models between 70% and 90% accuracy
- ▶ Impact/severity can be assessed with distribution of possible delay (mean error of 9 minutes with dispersion of 22 minutes)
- ▶ Models can be improved even further

Drawbacks:

- ▶ Assumed airlines have access to network information (M1 traffic)
- ▶ Assumed a static pre-tactical flight plan has been defined for each flight
- ▶ The less accurate individual model is the zero VS non-zero delay



Future development

- ▶ Feature selection analysis (e.g PCA, SHAP values)
- ▶ Fine-tune less accurate models
- ▶ Release predictions according to specific time horizons
- ▶ Integrate other data sources (e.g. network weather information)
- ▶ Provide additional information about the network status
- ▶ Validate the proposed representation of the predicted information with experts in the field



THANKS!

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