



Leonardo Helicopters

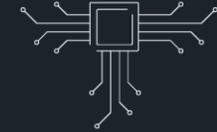
Effective Usage Monitoring through Machine Learning Approaches

EASA – Rotorcraft Structures Workshop

Dr. Andrea Baldi – Leonardo Helicopters

Cologne, February 18th 2025

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Electronics



Helicopters



Aircraft



Cyber & Security



Space



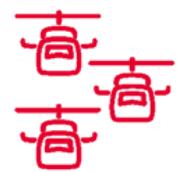
Aerostructures

SUMMARY

- ▶ **1** Context and Problem Statement
- 2 Dataset description
- 3 FCR through ML Algorithms
- 4 Application to Operative Fleets
- 5 Concluding Remarks



Context and Problem Statement

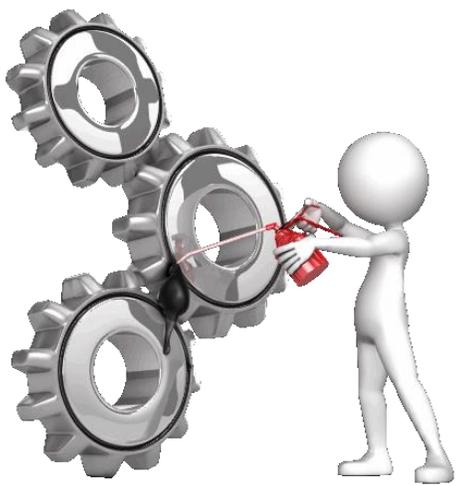
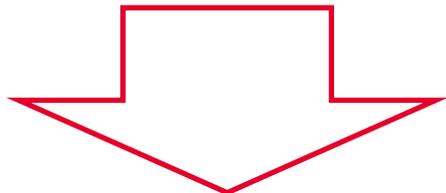


Helicopter Different Usages imply the definition of Diversified Maintenance Plans tailored to the actual usage of every specific fleet



Helicopter Maintenance Plans are usually defined based on Design Usage Assumptions that may differ from the actual operating scenario

Flight Condition Recognition (FCR) for an Effective Structural Usage Monitoring



Effective Maintenance Plans can be defined through a Periodical Validation of the Design Usage Assumptions with the following benefits:



Costs Reduction and Flight Safety Assurance



Customised and Flexible Maintenance Operations instead of Time-Based Maintenance (TBM)



Context and Problem Statement - LHD Proposal

Health and Usage Monitoring System (HUMS)

- Time-histories flight parameters

Data-driven Algorithms

- Trained on Load Survey Flights data

Multi-Strategy

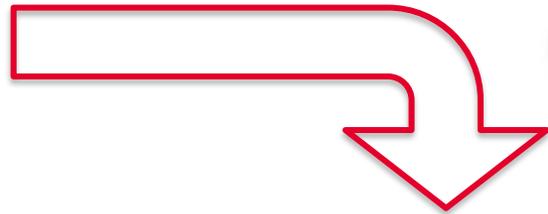
- 2 classification levels
- 2 strategies in the 1st Level



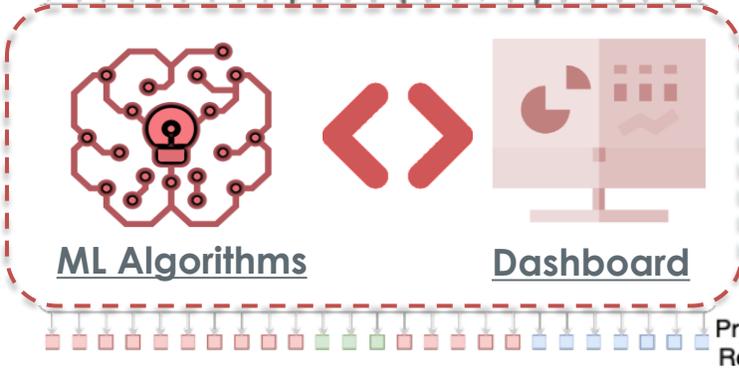
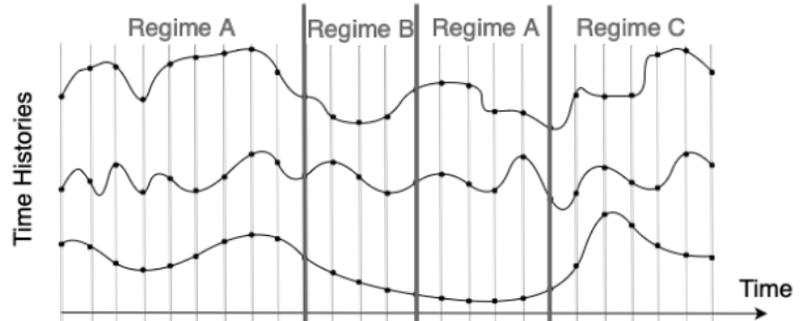
Flight Conditions Recognition (FCR)

Effective Structural Usage Monitoring

- Actual Usage Spectrum (AUS) vs Design Usage Spectrum (DUS)



Load Survey Flights



SUMMARY

① Context and Problem Statement

▶ ② **Dataset description**

③ FCR through ML Algorithms

④ Application to Operative Fleets

⑤ Concluding Remarks



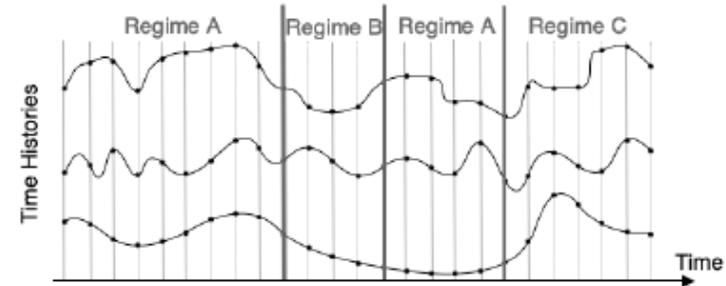
Dataset description

➤ Load Survey Flights: Time-series of 28 Flight Parameters & Labelled Regimes

- ✓ (2/3) of Dataset for Training (on partitioned manoeuvres) the Supervised ML Algorithm
- ✓ (1/3) of Dataset for Testing & Verifying (on full flights) the Supervised ML Algorithm



Category	# variables
Pilot Commands	4
Engines	6
Attitudes and Rates	6
Ground Speeds	2
Speeds and Accelerations	6
Environmental Conditions	4



AW189



Number of maneuvers	> 5100
Number of flights	> 230

AW169



Number of maneuvers	> 5200
Number of flights	> 220

AW139

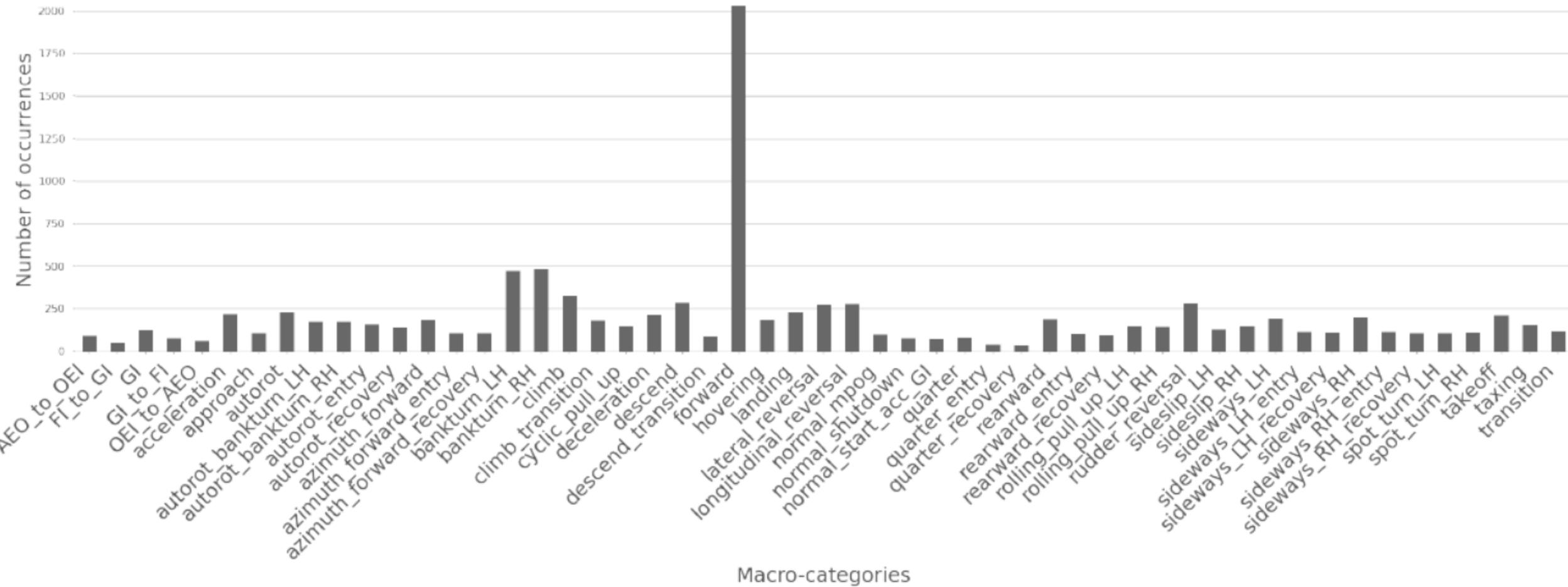


Number of maneuvers	> 8000
Number of flights	≈ 600



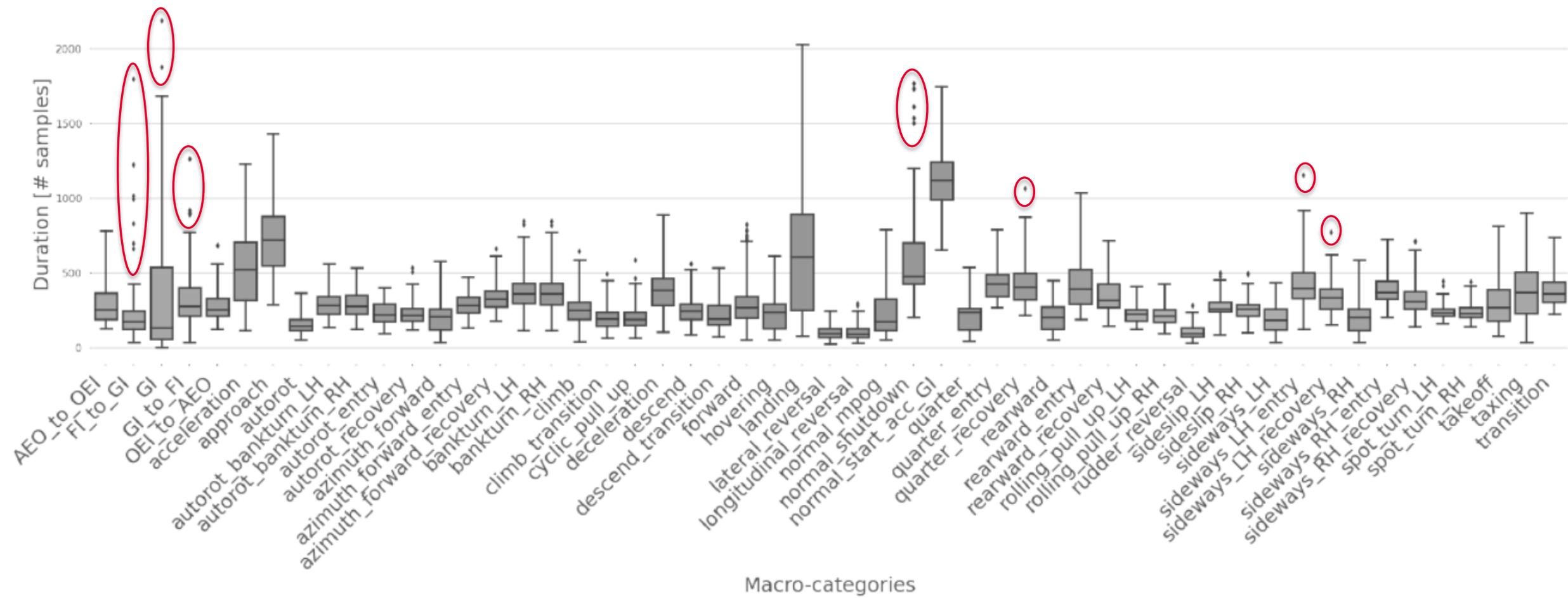
Dataset description - Exploratory Data Analysis and Pre-processing

➤ Unbalanced Dataset ➤ Over 300 standard flight regimes aggregated into 53 Macro-categories



Dataset description - Exploratory Data Analysis and Pre-processing

- Outliers removed from Training/Testing Dataset
- Non-uniform duration distribution of the **53 Macro-categories** ➤ Sliding Windows Approach



SUMMARY

① Context and Problem Statement

② Dataset description

▶ ③ **FCR through ML Algorithms**

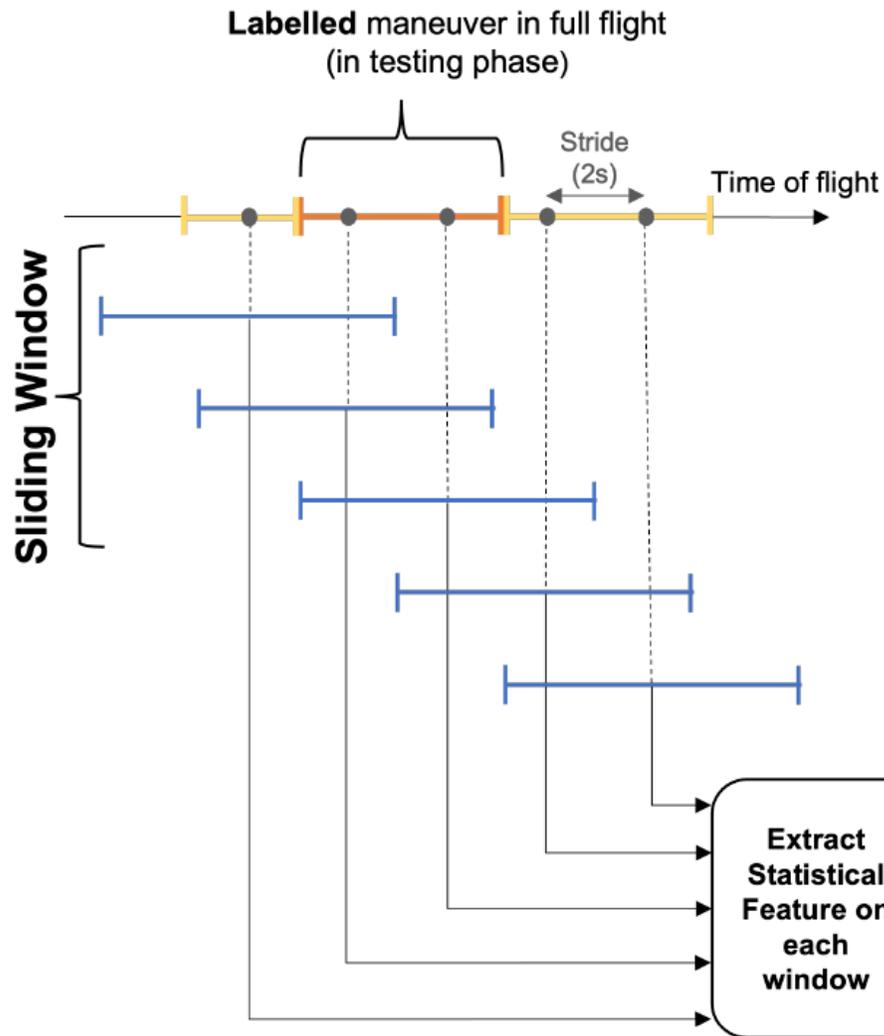
④ Application to Operative Fleets

⑤ Concluding Remarks



FCR through ML Algorithms - Design phase/Sliding Windows Approach

➤ Single Sliding Window



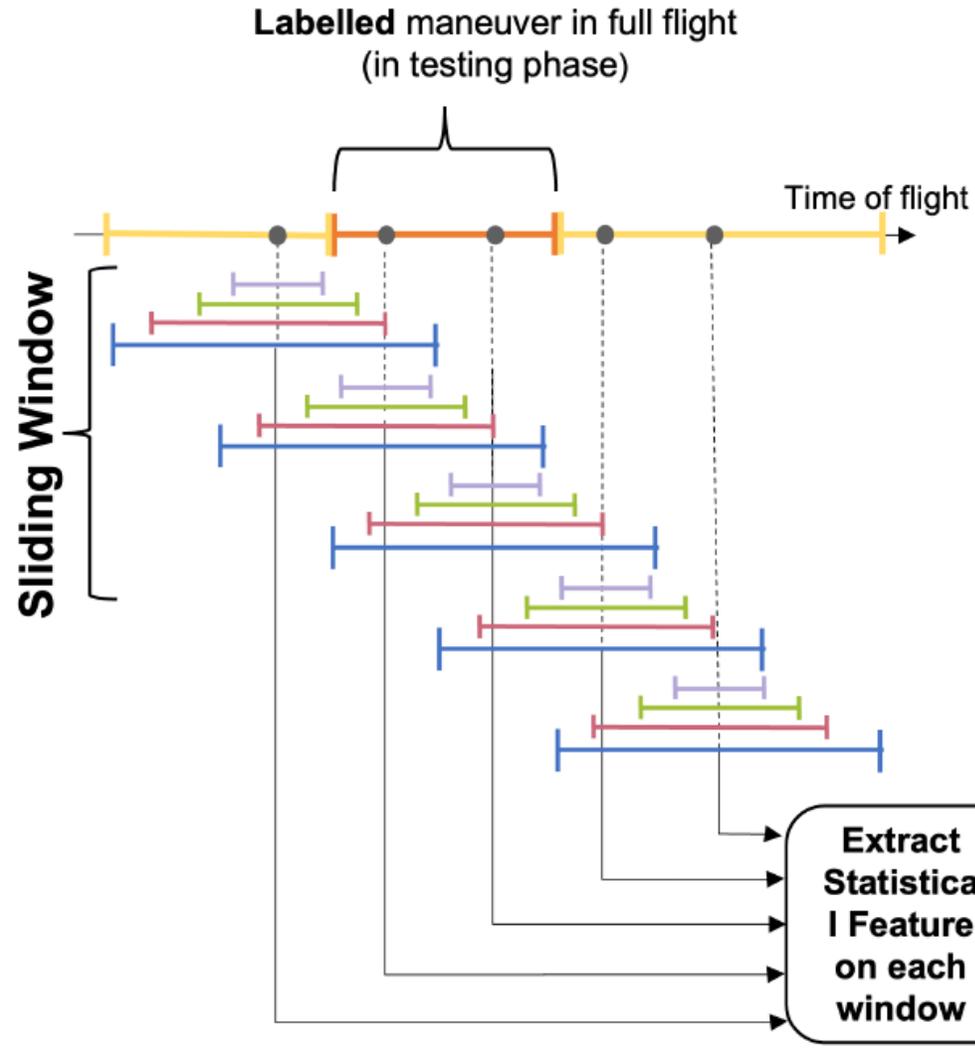
Sliding Windows

- Starting/ending points of each flight regime are a priori unknown in real flight operations
- A Sliding Window Approach has been applied to extract from each window **statistical features (MEAN, STD, MIN, MAX)**
- A properly Trained Random Forest Model has been designed and implemented to obtain the prediction for each time-step



FCR through ML Algorithms - Design phase/Sliding Windows Approach

Multiple Sliding Windows & Supervisor Model



Windows Sizes

- To address the problem of manoeuvres with different duration, 4 windows sizes are defined: **8s, 16s, 32s and 64s**
- The predictions obtained in these 4 different scenarios are then summarized in a **final prediction by means of a Supervisor Model** (i.e. a simple Logistic Regression)

FCR through ML Algorithms - The Single Strategy Approach: 1st Strategy

➤ 1st Strategy for the 1st classification Level (Fully Data-Driven Approach)

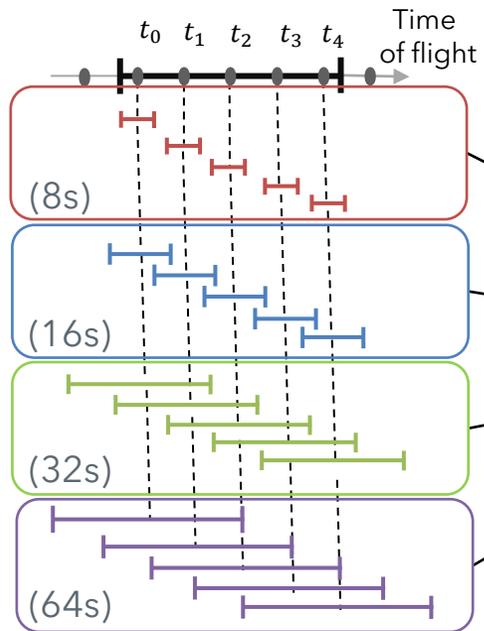


1

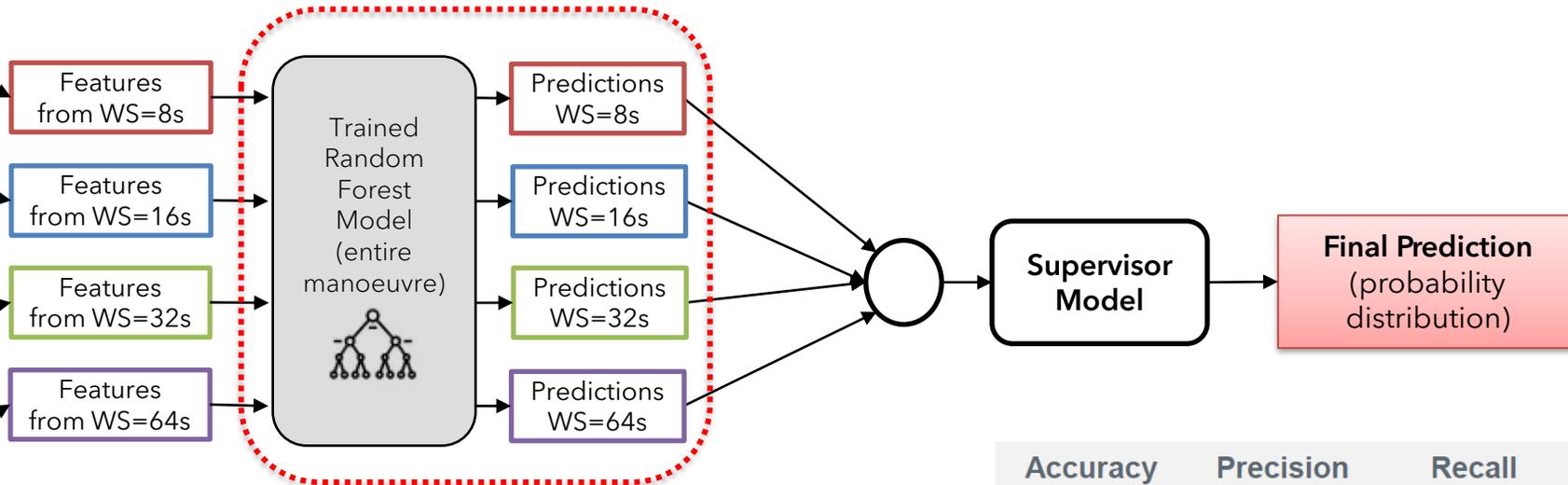
Entire-manoevres Approach

Random Forest Model Trained on statistical features extracted from the entire manoeuvres

Sliding Windows



Statistical features:
(MEAN, STD, MIN, MAX)



	Accuracy	Precision	Recall	F-1 score
WS = 8s	0.72	0.81	0.64	0.63
WS = 16s	0.83	0.85	0.78	0.78
WS = 32s	0.87	0.85	0.83	0.83
WS = 64s	0.73	0.72	0.65	0.63
Supervisor	96%	94%	95%	94%



FCR through ML Algorithms - The Single Strategy Approach: 2nd Strategy

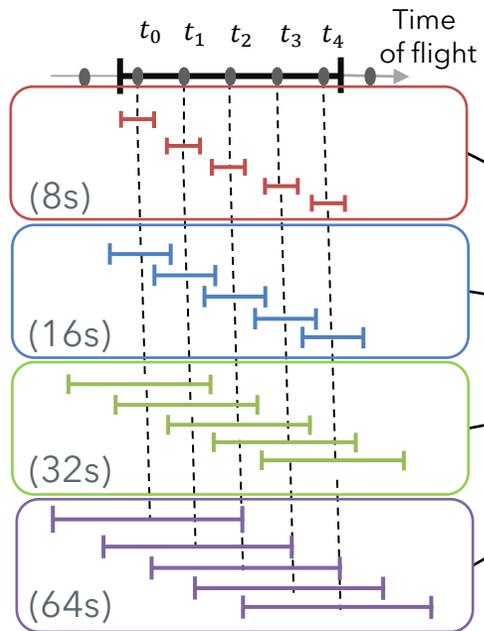
➤ 2nd Strategy for the 1st classification Level (Fully Data-Driven Approach)



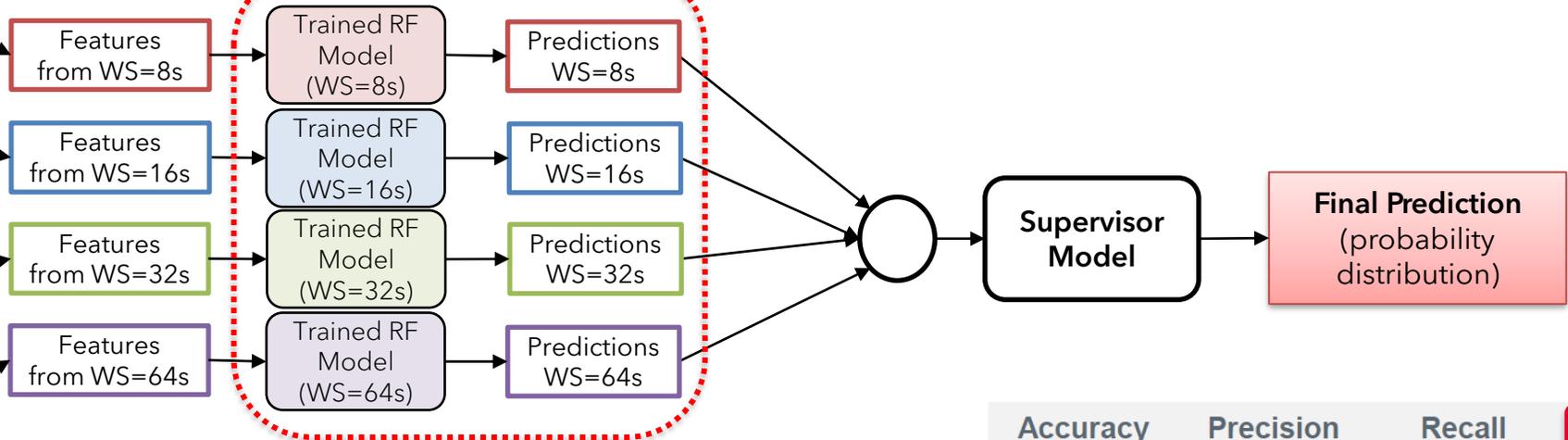
2 Sliced-maneuvres Approach

Multiple RF Models Trained on sliced manoeuvres partitioned from full-flights

Sliding Windows



Statistical features:
(MEAN, STD, MIN, MAX)



	Accuracy	Precision	Recall	F-1 score
WS = 8s	0.89	0.89	0.86	0.88
WS = 16s	0.91	0.91	0.89	0.90
WS = 32s	0.85	0.87	0.83	0.85
WS = 64s	0.72	0.72	0.62	0.70
Supervisor	96%	96%	95%	96%

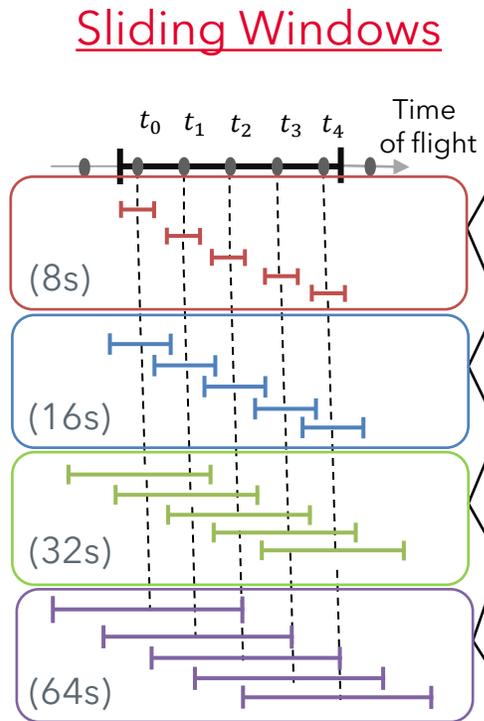


FCR through ML Algorithms - Optimised Multi-strategy Approach: 1st & 2nd Strategies

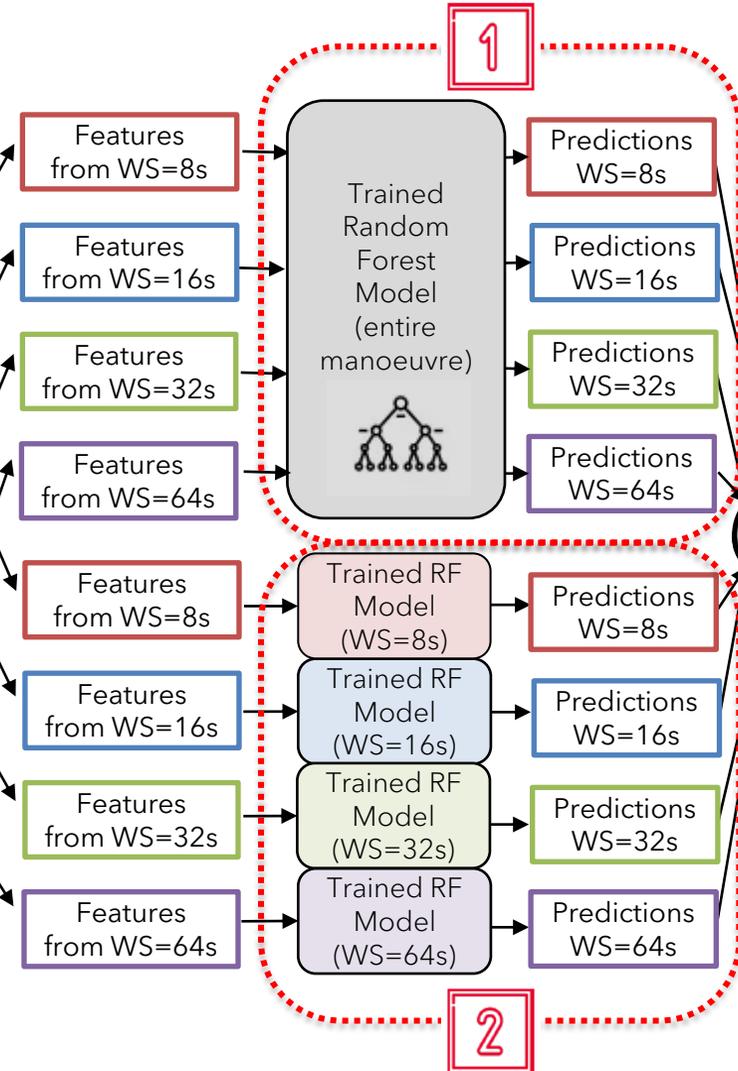
➤ 1st & 2nd Strategies implemented in parallel for the 1st classification Level



n.3 Patents granted



Statistical features:
(MEAN, STD, MIN, MAX)



Supervisor Model

Final Prediction
(probability distribution)



Dashboard
Manoeuvres Classification

1	Supervisor	96%	94%	95%	94%
2	Supervisor	96%	96%	95%	96%
1 + 2	Supervisor	97%	97%	96%	97%

	Accuracy	Precision	Recall	F-1 score
1	96%	94%	95%	94%
2	96%	96%	95%	96%
1 + 2	97%	97%	96%	97%



FCR through ML Algorithms - Design phase/Macro-categories vs Usage Spectrum

➤ Dataset rebalancing through Aggregation

✓ Dataset rebalancing procedure to improve the performance of Supervised ML algorithm



- FCR @ 1st Classification Level: Fully Data-driven approach for the recognition of the **53 Macro-categories**
- FCR @ 2nd Classification Level: Data- & Model-driven approaches to recognise usage spectrum regimes

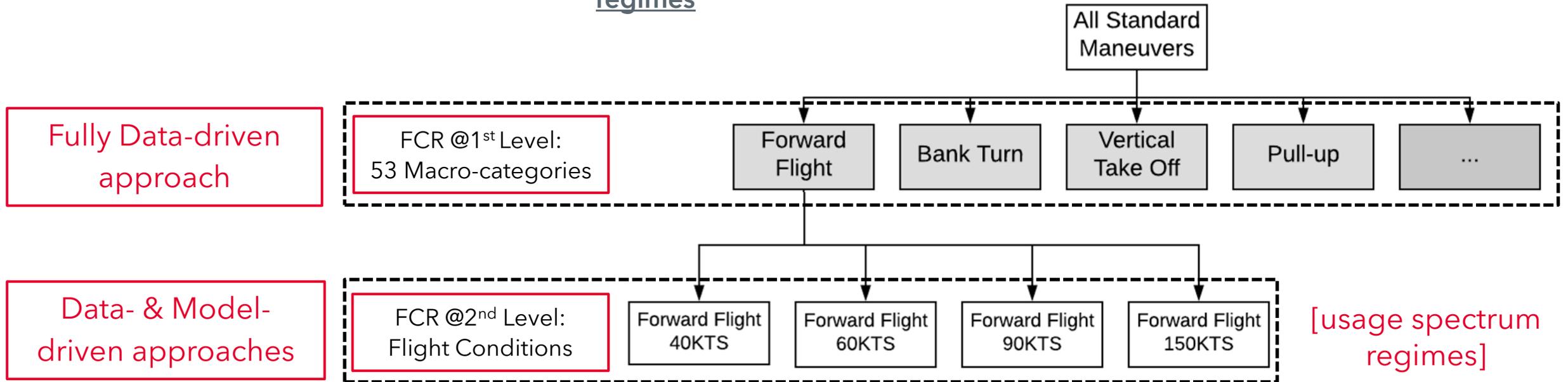


1st Classification Level (Macro-regimes)

Strategy 1

Strategy 2

2nd Classification Level (Spectrum regimes)



FCR through ML Algorithms - Performance for Load Survey Flights

 <p>AW189</p>	 <p>PREDICTION ACCURACY ON PARTITIONED MANEUVERS</p> <p>98.5%</p> <p>(HUMS Family)</p>	<p>PREDICTION ACCURACY ON <u>FULL FLIGHTS</u> at 1st Classification Level</p> <p>97.3%</p>
 <p>AW139</p>	 <p>PREDICTION ACCURACY ON PARTITIONED MANEUVERS</p> <p>96.8%</p> <p>(HUMS LH)</p>	<p>PREDICTION ACCURACY ON <u>FULL FLIGHTS</u> at 1st Classification Level</p> <p>96.4%</p>
 <p>AW169</p>	 <p>PREDICTION ACCURACY ON PARTITIONED MANEUVERS</p> <p>98.5%</p> <p>(HUMS Family)</p>	<p>PREDICTION ACCURACY ON <u>FULL FLIGHTS</u> at 1st Classification Level</p> <p>97.3%</p>



SUMMARY

① Context and Problem Statement

② Dataset description

③ FCR through ML Algorithms

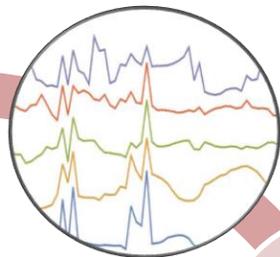
▶ ④ **Application to Operative Fleets**

⑤ Concluding Remarks



Application to Operative Fleets - End-to-end flight data analysis process

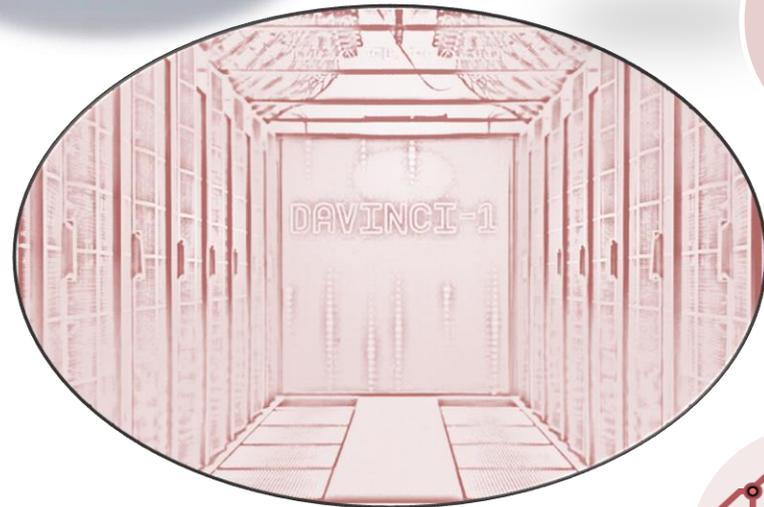
- Usage Monitoring of operative Helicopters Fleets through HUMS



- Verification & Validation of the Time history of the flight parameters recorded by HUMS - Ongoing



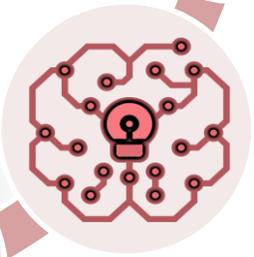
- Pipeline designed for Data acquisition and Data Lake ingestion



- Data Lake population

Effective Structural Usage Monitoring

Flight Condition Recognition (FCR)



- Verification & Validation of Output of the ML-FCR algorithm for real flight - Ongoing



- Dashboard





Application to Operative Fleets - Results and Discussion

➤ Dashboard

- The Dashboard allows visualizing the results of the ML-FCR Algorithm in terms of classified manoeuvres both in Detailed and Aggregated way through **3 Environments**

Flight Explorer

Flight
Research data by determining a flight



- Visualize a single flight and explore how it was segmented in terms of recognised manoeuvres
- Access to the individual recognised manoeuvre to verify the trends of the characteristics flight parameters
- Visualize useful information: %-of-time and occurrences of the recognised flight regimes

Helicopter Explorer

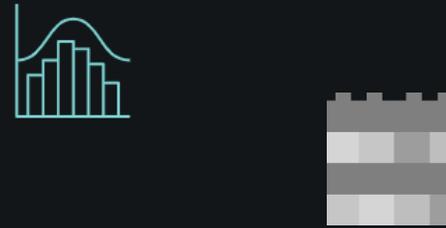
Helicopter
Research data by determining a helicopter



- Explore how a generic helicopter has been used across several different flights
- Visualize the total time spent by the considered helicopter in each recognised manoeuvres
- Visualize useful information: %-of-time and occurrences of the recognised flight regimes

Fleet Explorer

Fleet
Research data by determining a fleet



- Explore how a generic helicopter fleet has been used across several different flights
- Visualize the total time spent by the considered fleet in each recognised manoeuvres
- Visualize useful information: %-of-time and occurrences of the recognised flight regimes





Application to Operative Fleets - Results and Discussion

Dashboard - Flight Explorer: Flight Segmentation Visualizer - 1st Classification Level



Macro-categories

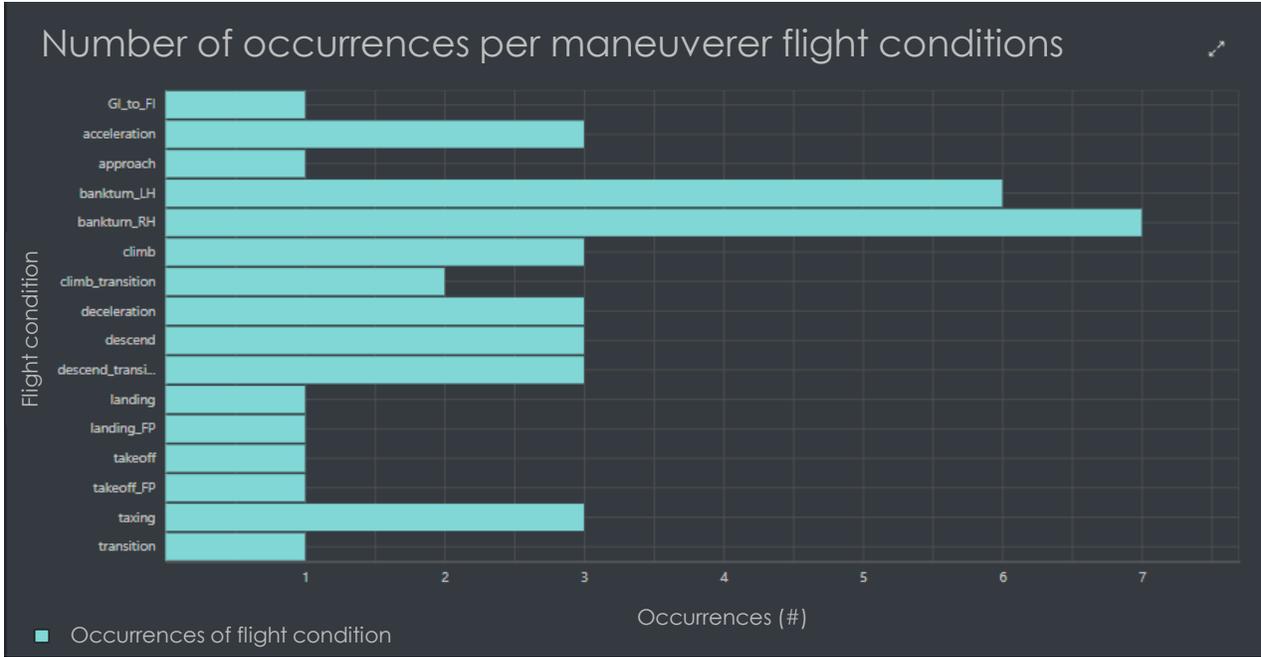
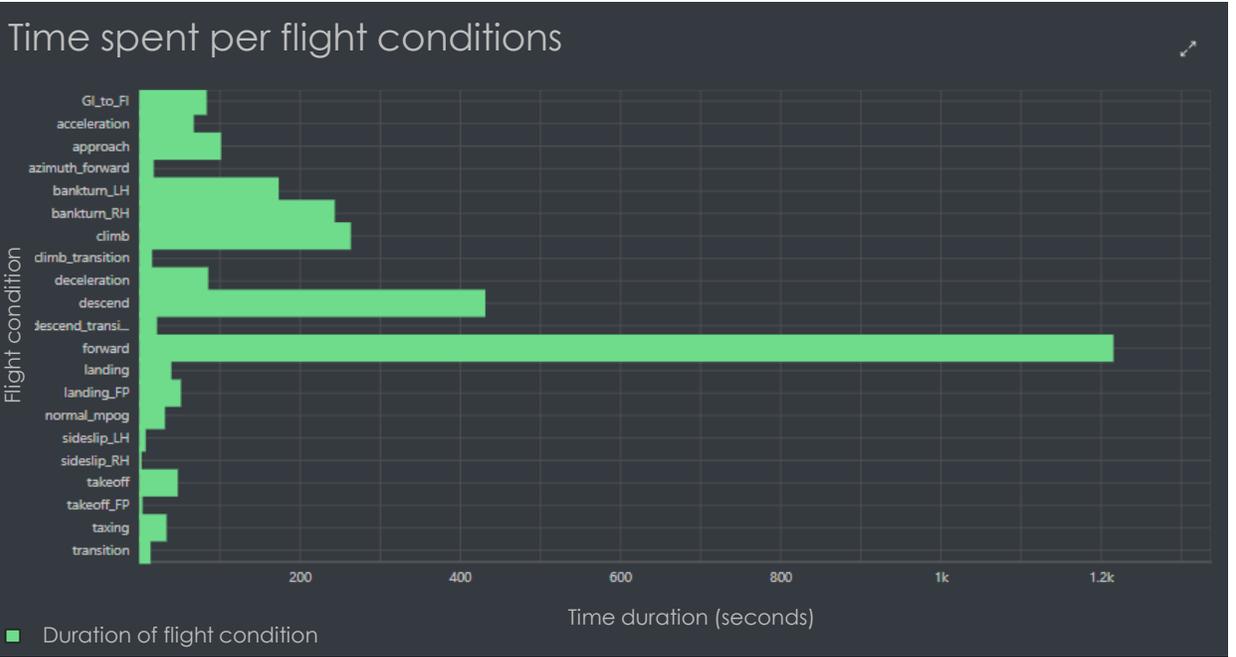




Application to Operative Fleets - Results and Discussion

Dashboard - Flight Explorer @ 1st Classification Level

- Duration of flight conditions and Manoeuvres counting

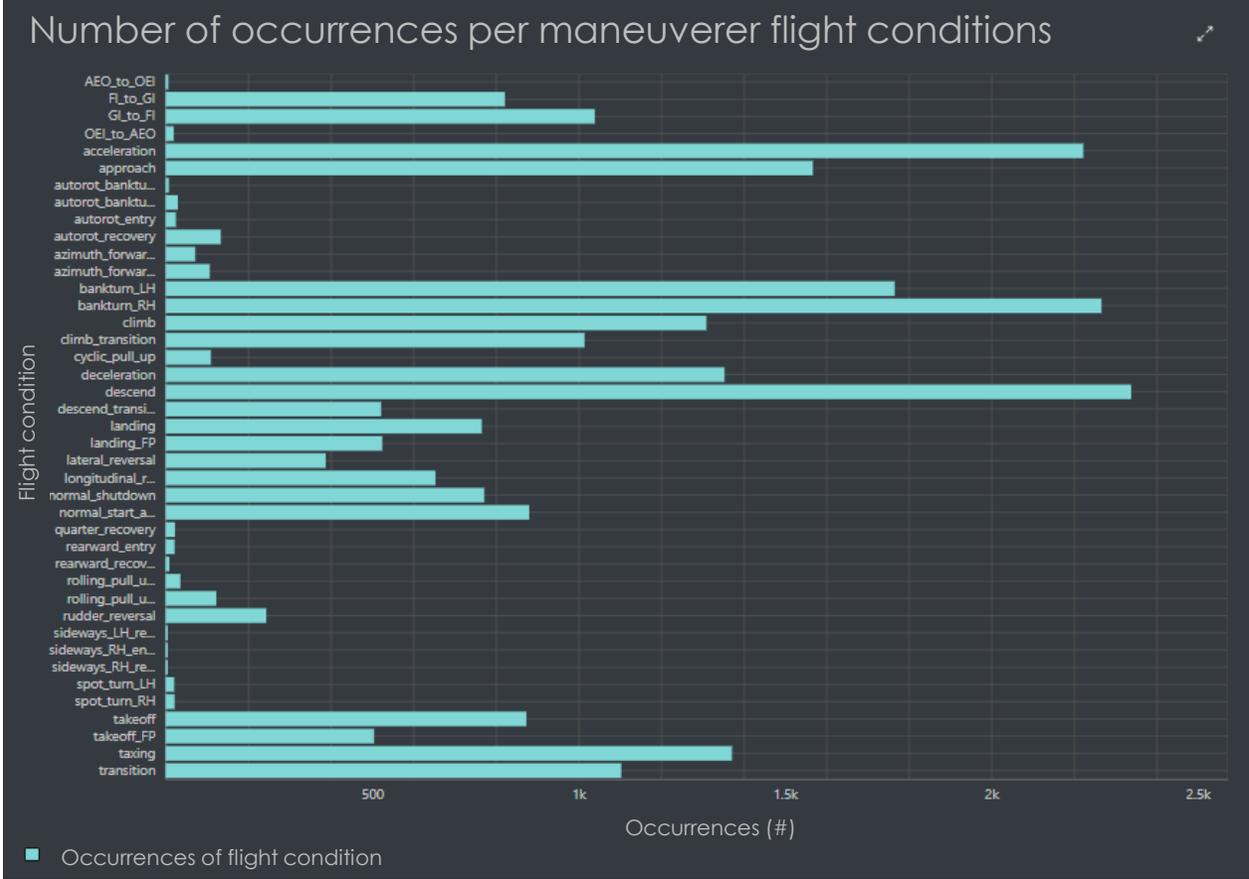
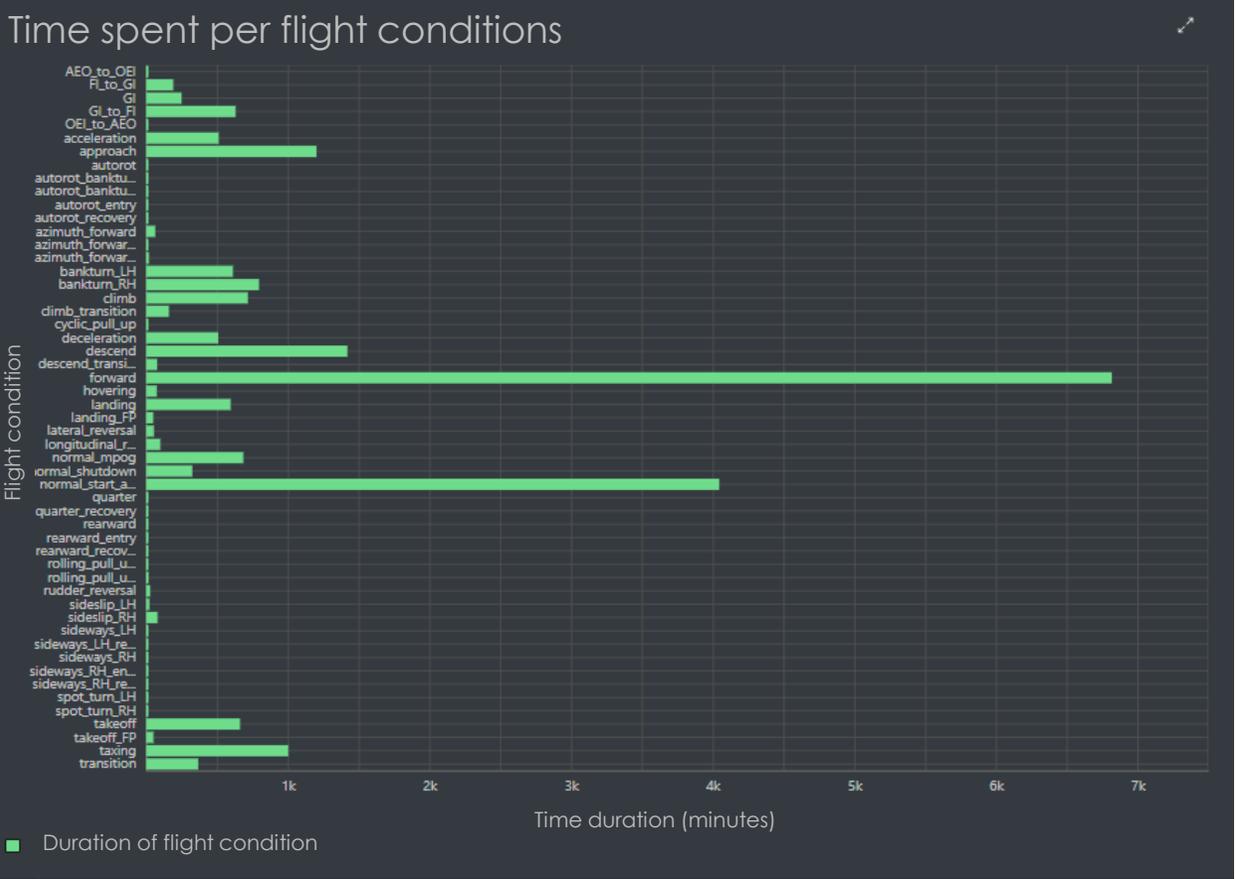




Application to Operative Fleets - Results and Discussion

Dashboard - Helicopter Explorer @1st Classification Level

- Duration of flight conditions and Manoeuvres counting

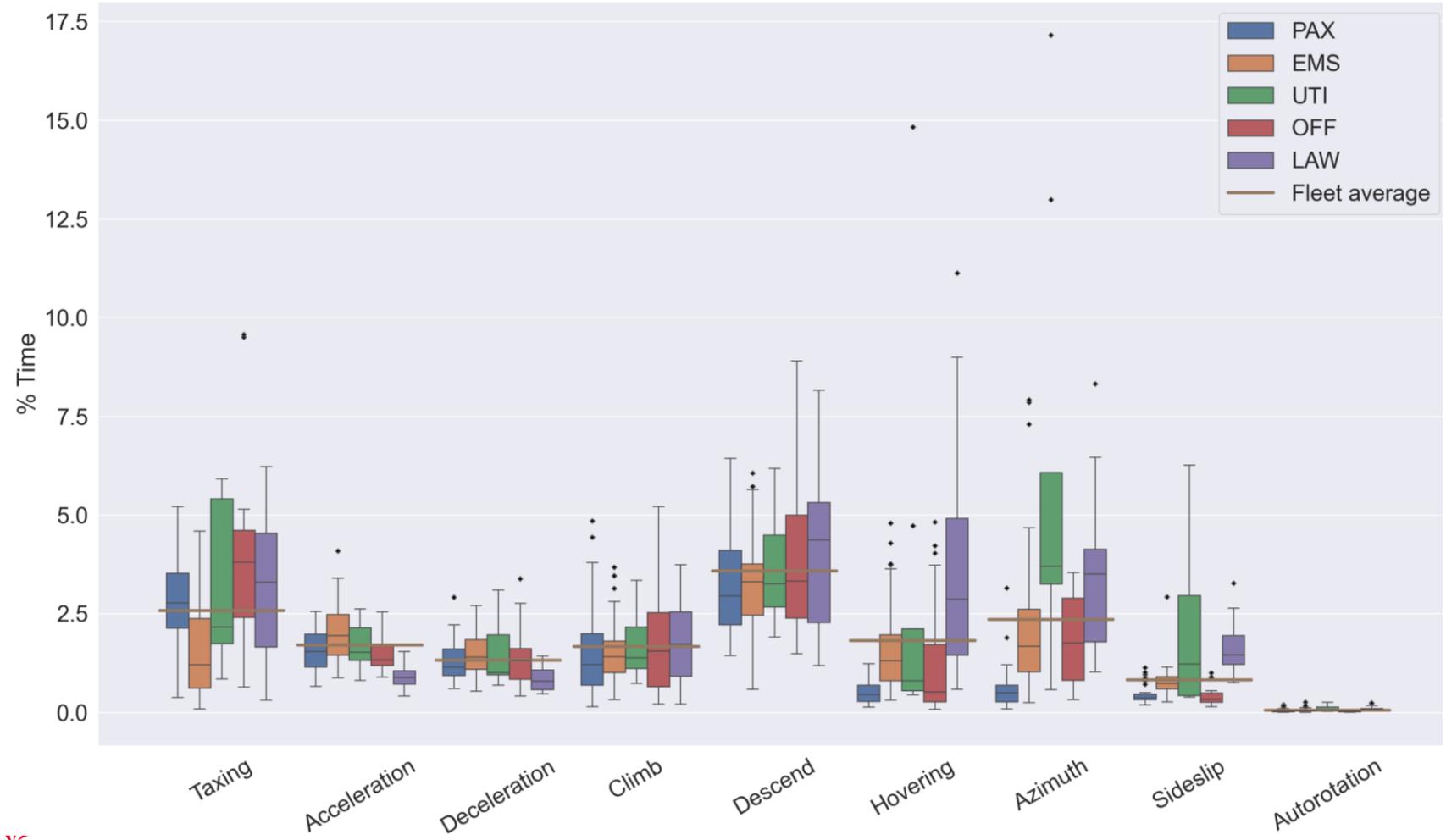




Application to Operative Fleets - Results and Discussion

➤ Dashboard - Fleet Explorer @1st Classification Level

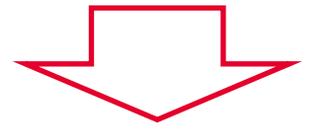
○ Mission comparison - Flight Conditions (% Time)



○ Clustering of typical mission profiles of an operative fleet of a specific helicopter model



○ Actual Usage Spectrum (AUS)
VS
Design Usage Spectrum (DUS)



○ Effective Structural Usage Monitoring

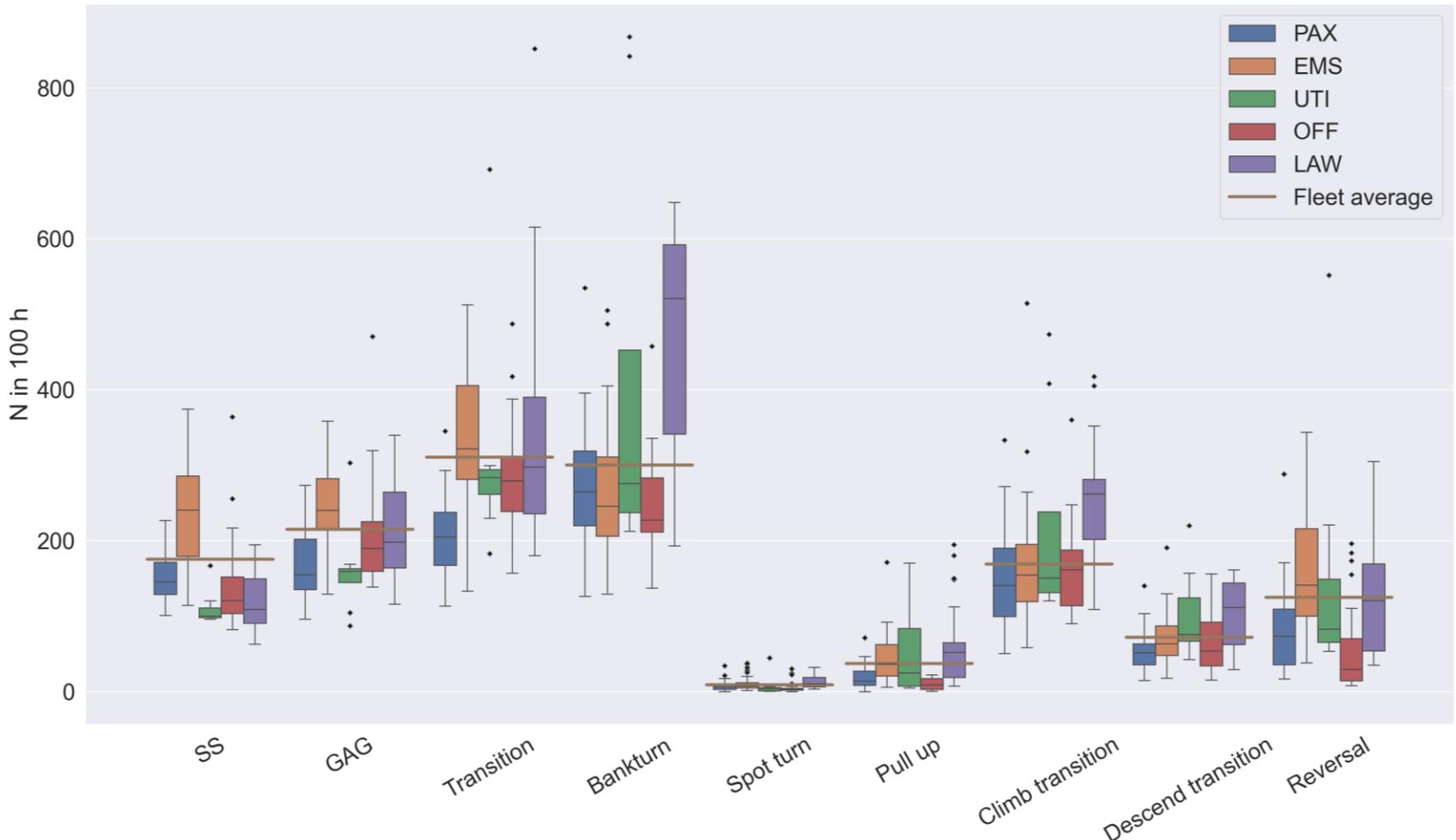




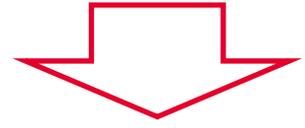
Application to Operative Fleets - Results and Discussion

➤ Dashboard - Fleet Explorer @1st Classification Level

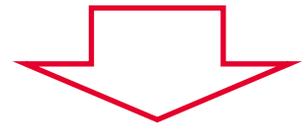
○ Mission comparison - Flight Conditions Occurrences (Num. Man. in 100h)



○ Clustering of typical mission profiles of an operative fleet of a specific helicopter model



○ Actual Usage Spectrum (AUS)
VS
Design Usage Spectrum (DUS)



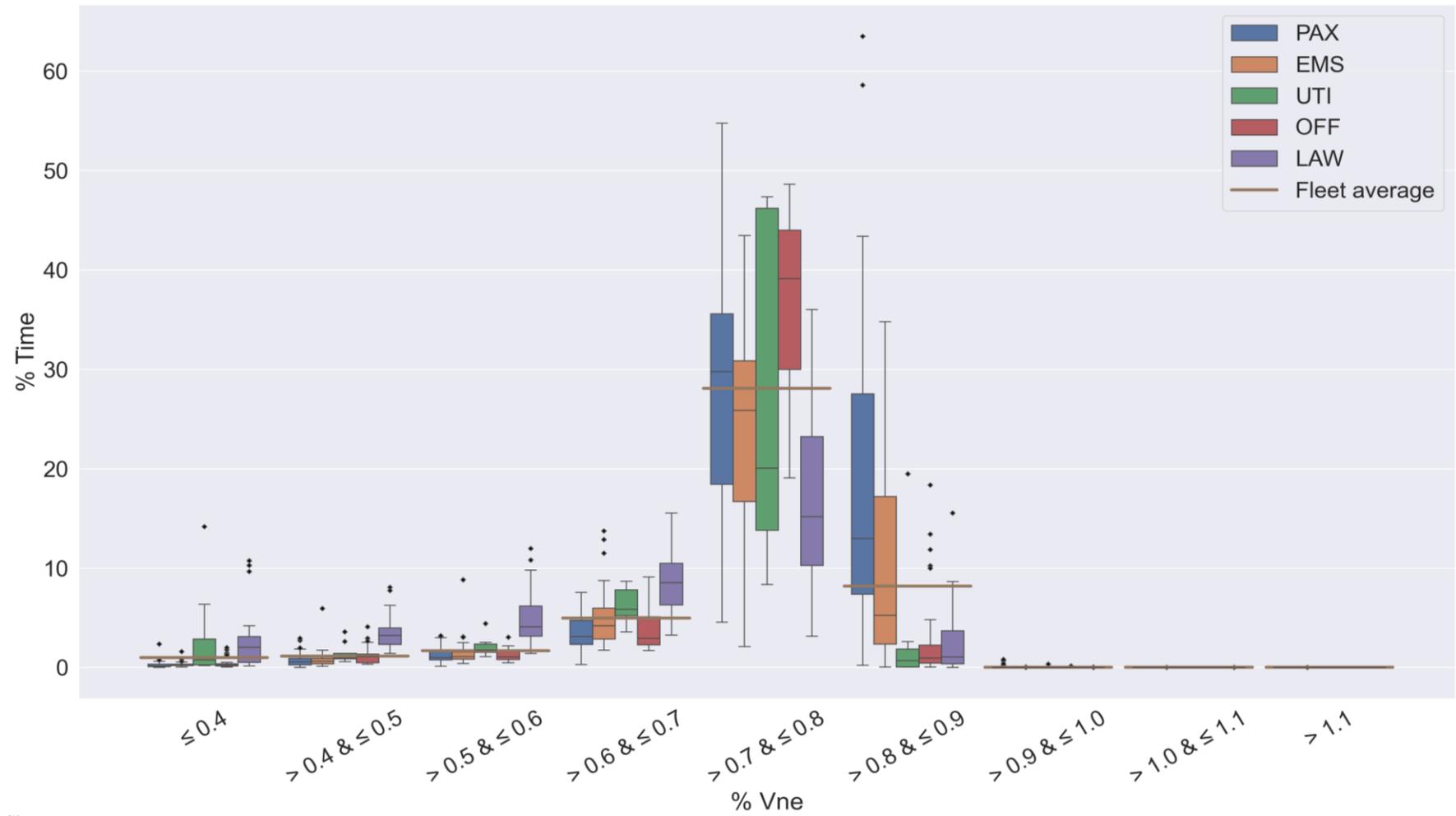
○ Effective Structural Usage Monitoring



Application to Operative Fleets - Results and Discussion

➤ Dashboard - Fleet Explorer @2nd Classification Level

○ Mission comparison - Forward Flight regimes (%Time)



- Actual Usage Spectrum (AUS) VS Design Usage Spectrum (DUS)
- Effective Structural Usage Monitoring

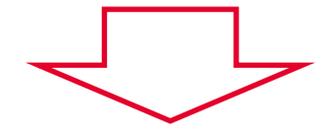
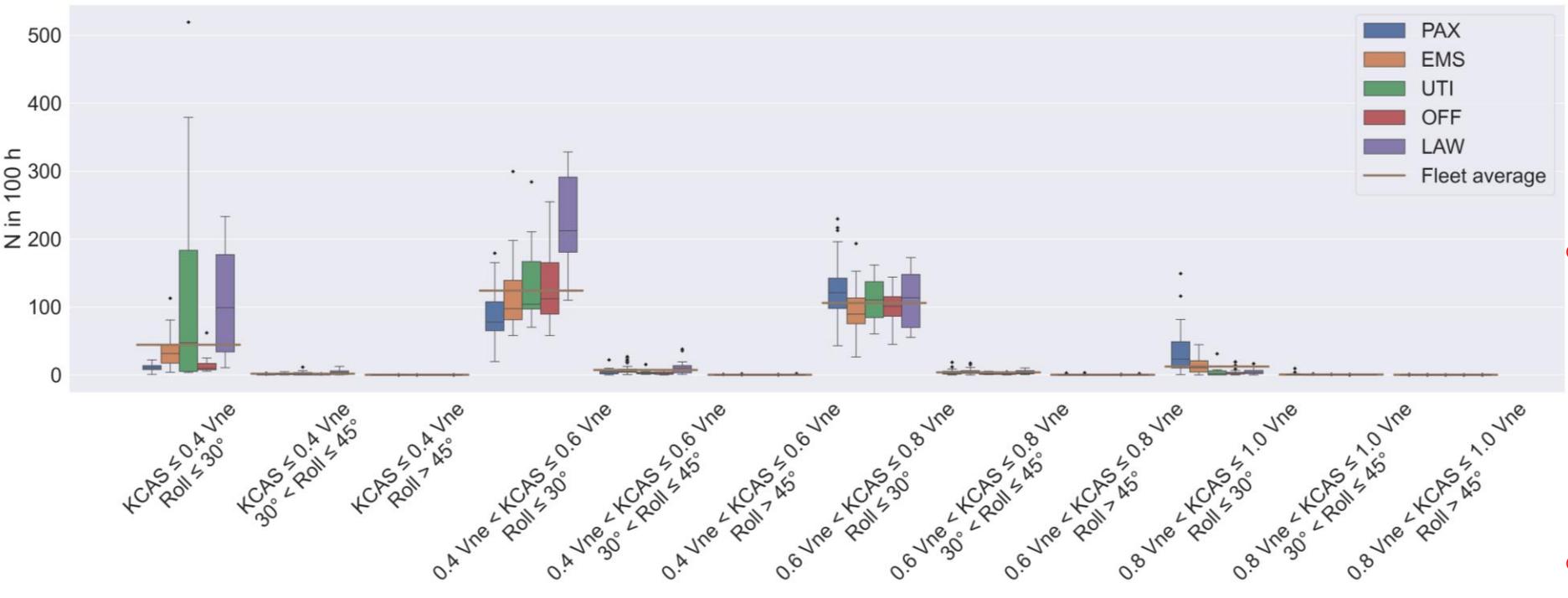




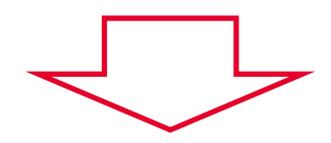
Application to Operative Fleets - Results and Discussion

➤ Dashboard - Fleet Explorer @2nd Classification Level

- Mission comparison - Bank Turns Occurrences (Num. Man. in 100h)



- Actual Usage Spectrum (AUS)
VS
Design Usage Spectrum (DUS)



- Effective Structural Usage Monitoring



SUMMARY

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▶ ⑤ **Concluding Remarks**



Concluding Remarks

The proposed Multi-Strategy ML-based approach is



- Robust
- Flexible (easily adaptable to different aircraft variants)
- Scalable (with the number of available measurements)
- Easily re-trainable (if more or different measurements are available)



Effectively addresses the FCR problem enabling an
Effective Structural Usage Monitoring



Customised and Flexible Maintenance Operations
instead of Time-Based Maintenance (TBM)



Maintenance Costs Reduction



Flight Safety Assurance





THANK YOU FOR YOUR ATTENTION

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