Dedicated to innovation in aerospace

Final Approach Anomaly Detection

Machine Learning Anomaly Detection Based on FDM data
EASA SAFE 360, Brussel – 15 September 2022

Vincent de Vries

Motivation

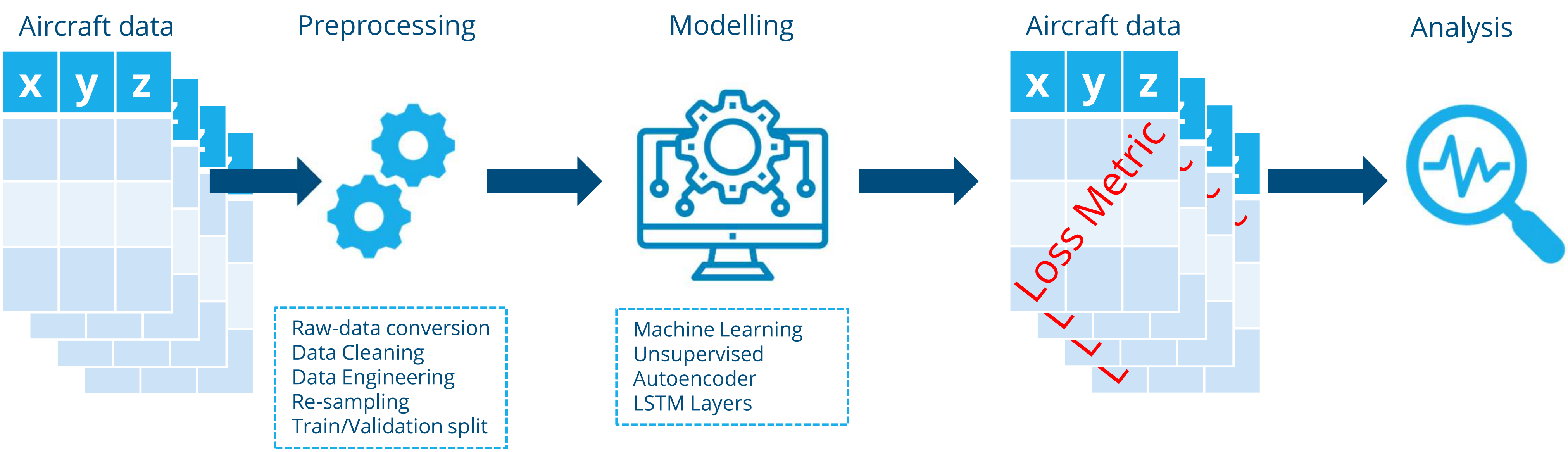
- Airlines monitor a large set of flight data in their Flight Data Monitoring (FDM) program to:
  - Identify, Quantify, Assess, and Address operational risks involved in the operation of commercial aircraft

- The current standard to detect events in the flight data are based on Boolean logic and pre-defined thresholds. Two drawabcks:
  - Only events that are known and have been specified can be detected
  - The detection of events relies on the threshold value being defined accordingly

?

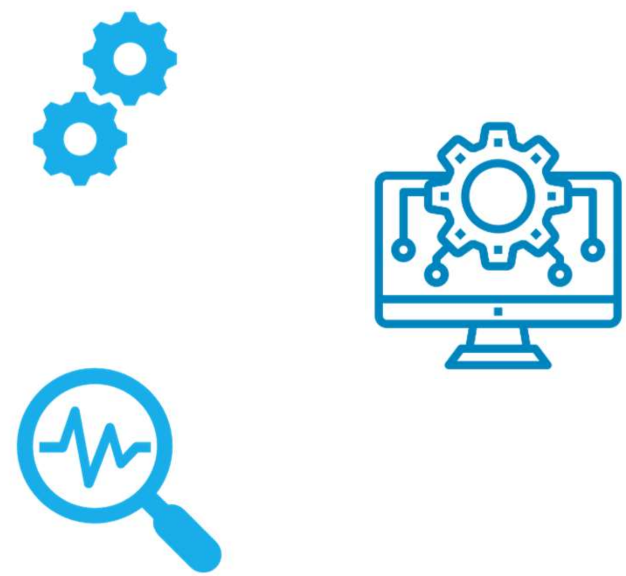
WHY

Methodology



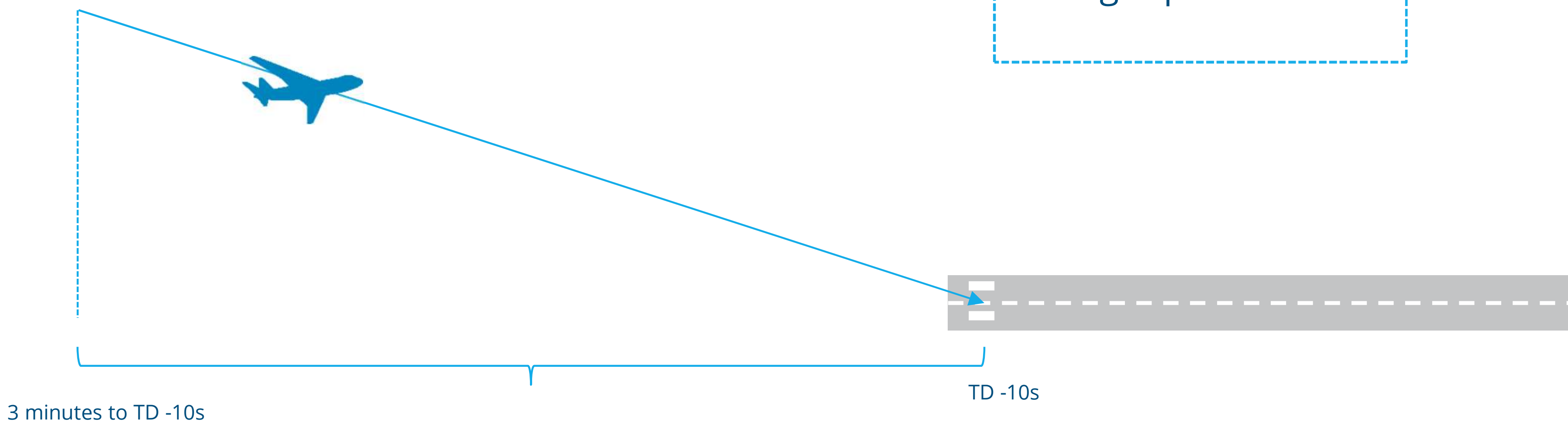
Method limits and caveats

- Use unsupervised Machine Learning to identify anomalous flights
  - No pre-defined events/training data necessary
  - The model considers all flight parameters simultanously
  - SME must analyse the model’s output and identify what was anomalous
  - The model wont specify the part of the flight that was anomalous



Case Study

Final Approach
Last 3 minutes
1Hz subsampled data
Narrow body a/c type
40,000+ flights
15 Flight parameters



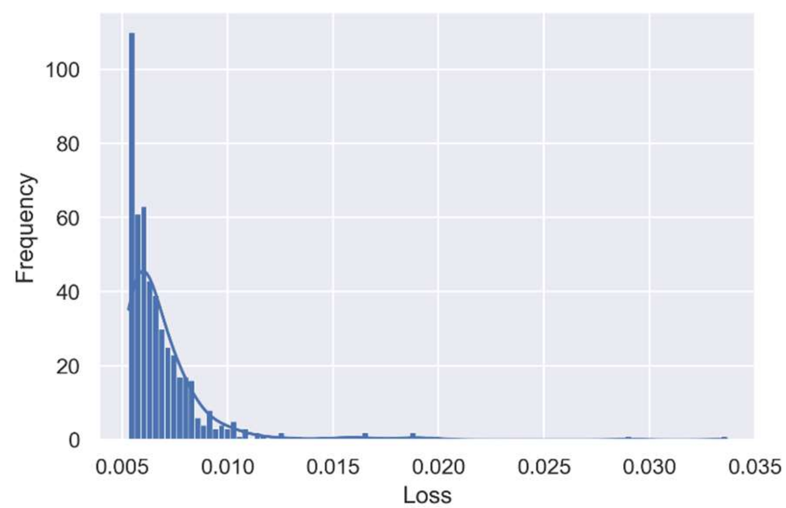
Scope & Parameter Selection

15 flight parameters selected as input that describe the state and trajectory of the aircraft

Flight Parameter	Unit
Ground Speed	kts
Calibrated Airspeed (CAS)	kts
Vertical Speed	ft/min
Lateral, Longitudinal, Normal Acceleration	g
Pitch and Roll Attiude	Deg
Angle of Attack (AOA)	deg
Glide Slope Deviation	DDM
Localizer Deviation	DDM
Radio Altitude	ft
True Heading	deg
N1 Actual Engine 1 and 2	%RPM

Model Output

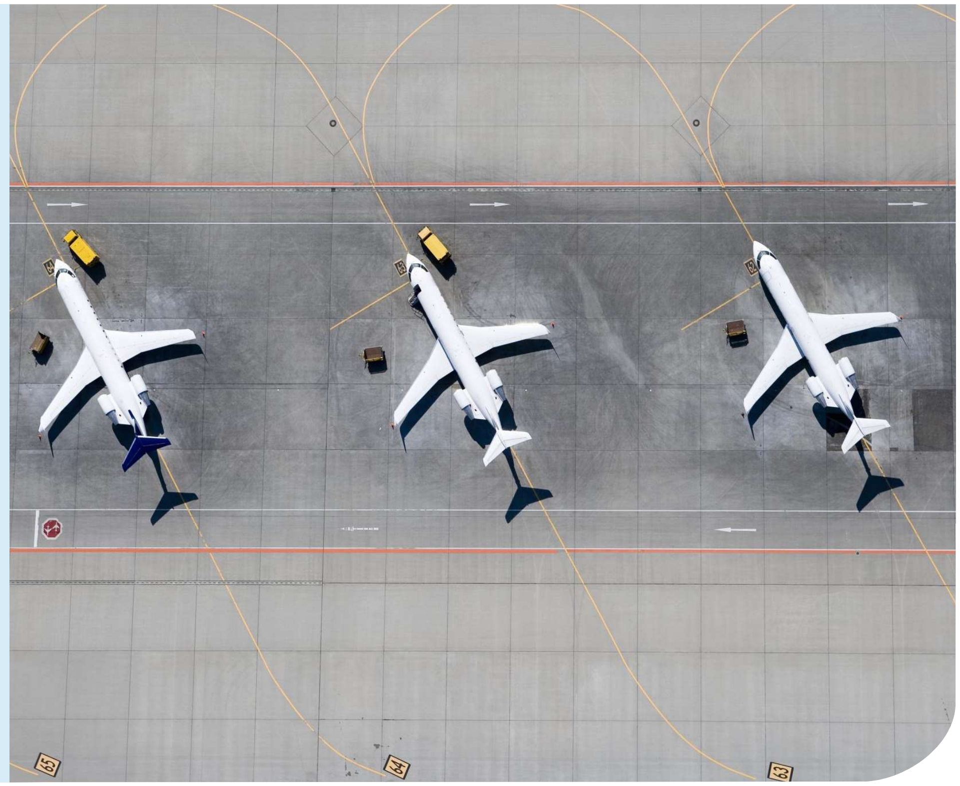
- Each flight gets a loss metric. Higher loss = more anomalous
- Experts need to determine whether those flights are indeed anomalous
- Experts need to determine where the anomality occurred during the flight



The loss metric distribution of the 500 most anomalous flights

ML Model Evaluation

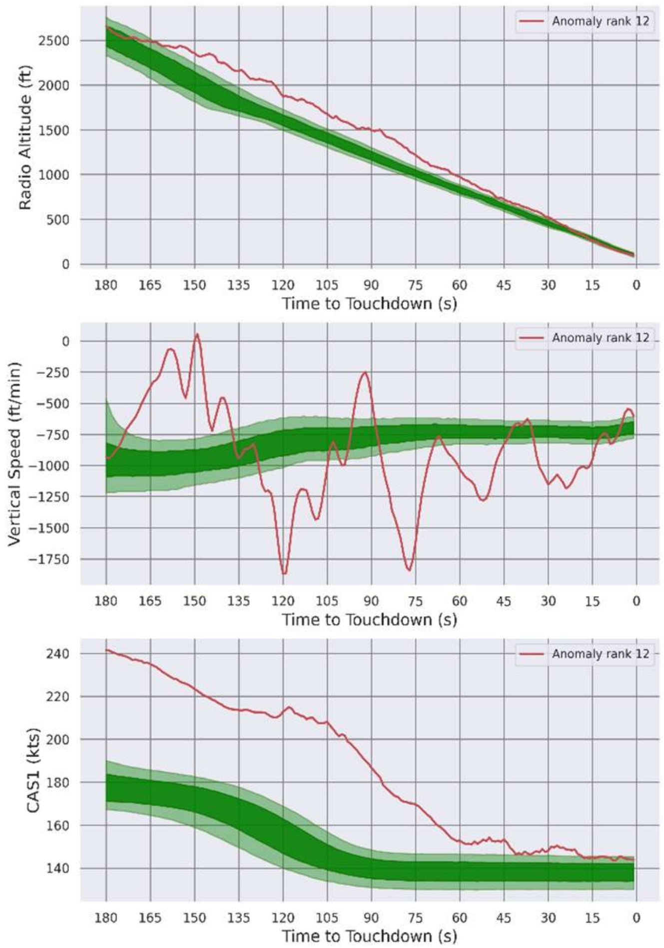
- Examples of anomalous flights identified by the ML model:
  – Flight 1: Unstable Approach
  – Flight 2: Stabilized Approach



Unstable Approach

Analysis

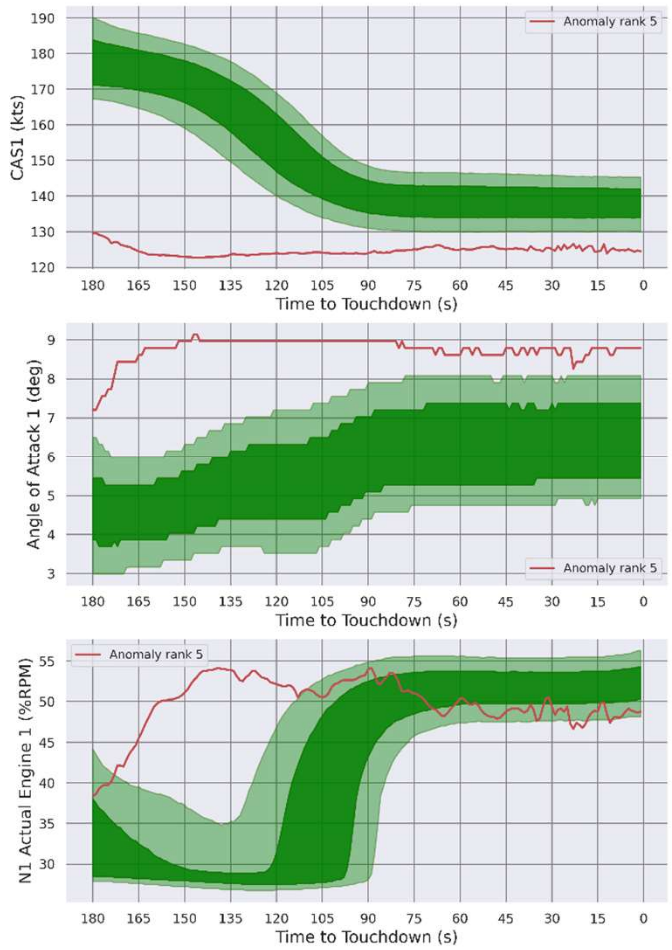
- Fluctuating Vertical Speed
  - At both unstable approach gates the Vertical Speed exceeds -1000ft/min
- High CAS throughout most of the interval



Stable Approach

Analysis

- Constant low speed
- Final thrust settings attained at the start of the observed interval
- High angle of attack

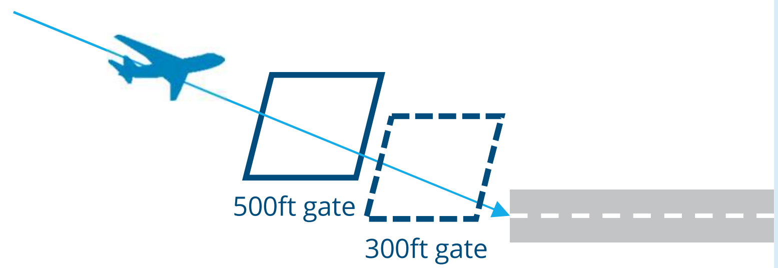


Comparison between ML and Threshold based approach

Stable approach criteria applied to the 500 most anomalous flights according to the ML model:

- Vertical speed <1000 ft
- V_{APP} >= -5 kts and <=10 kts
- GS deviation < 1 dot
- LOC deviation <0.5 dot
- Landing flaps selected
- Gear down selected

Note: 3 consecutive seconds/data points necessary

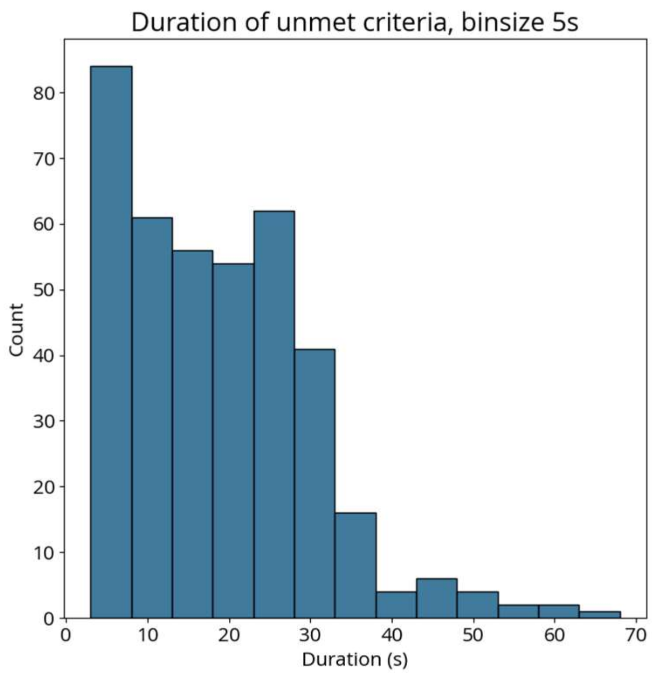


Unstable Approach Comparison

Criteria	500ft Gate	300ft Gate
Vapp	364	321
LOC	30	24
vs	29	22
GS	24	9
Gear	0	0
Flaps	0	0
Total	447	376

Note: some flights exceeded multiple criteria

***120** flights were not unstable*



Duration of instabilities in 500ft gate unstable set

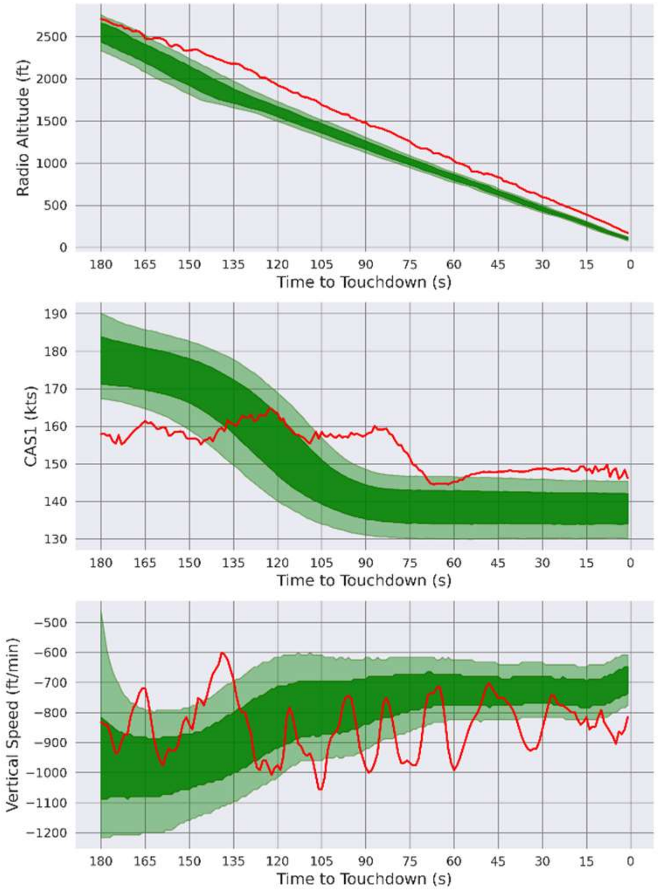
Model Evaluation

- The model was able to detect different types of anomalous approaches without labeled data
- Not all anomalies were non-compliant to stable approach criteria
- Anomalies such as unstable approaches were picked up by the model.
- Some hot&high approaches were detected by the model as well, which can be a precursor for a unstable approach

Anomalous/Not unstable

Analysis

- Slightly above glide slope
- Slightly faster than usual after 105 seconds
- Fluctuating Vertical Speed



Conclusion

- ML is able to detect flights that can be considered as anomalous
- Not a replacement for FDM but an add-on to enable the detection of unmonitored events and a method for detecting new events.
- Manual validation by an SME is essential to determine if the flight was anomalous and relevant for safety.
- These are first results, a lot of different preprocessing and modelling approaches could applied.

Next steps

- Anomality classification with ML
- Different Parameters for better performance/ possibility of detecting other types of anomalies
- Cross checking of anomalies with detected FDM events. If a event was detected, the anomaly does not have to be investigated

NEXT
STEPS

Dedicated to innovation in aerospace

Royal NLR - Netherlands Aerospace Centre

V.J.F. (Vincent) de Vries

R&D Engineer

p) +31 88 511 30 32 / +31614721360

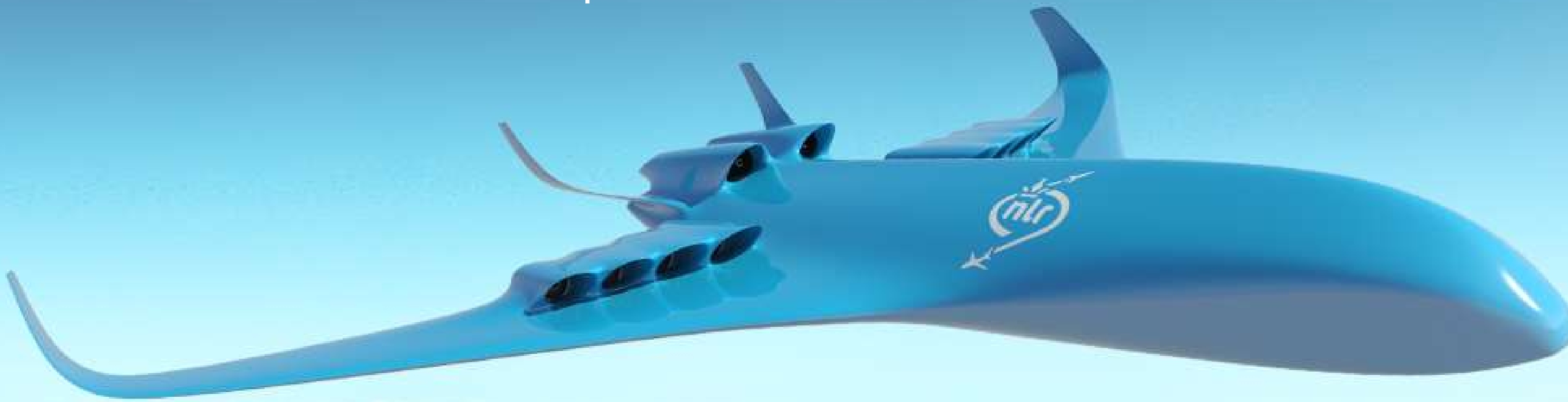
e) vincent.de.vries@nlr.nl

i) www.nlr.org

Dedicated to innovation in aerospace

Fully engaged

NLR - Netherlands Aerospace Centre



Anthony Fokkerweg 2
1059 CM Amsterdam
The Netherlands

p) **+31 88 511 31 13**
e) **info@nlr.nl** i) **www.nlr.org**

Voorsterweg 31
8316 PR Marknesse
The Netherlands

p) **+31 88 511 44 44**
e) **info@nlr.nl** i) **www.nlr.org**