# Anomalies Detection And Prognosis

## Status for Implementation on the Edge

DEFENCE AND SPACE

**F. Ales for ADAP & Airbus Team**

15 November 2023

ESTEC

AIRBUS

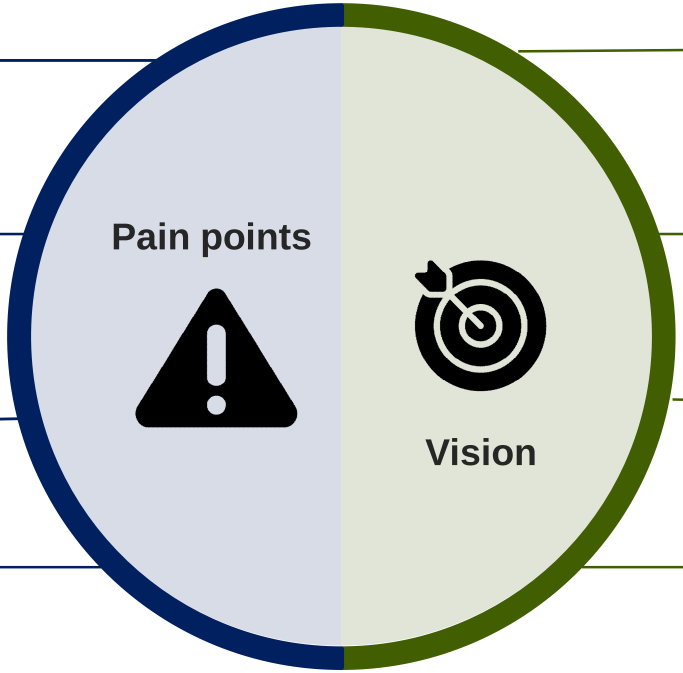
# Why AI-based FDIR?

Inefficient failure isolation leading to downtimes

Complex and expensive FDIR design

Expensive HW redundancy

Limited autonomy




Failures are detected and isolated before they become critical

**Simple** and **generic** FDIR

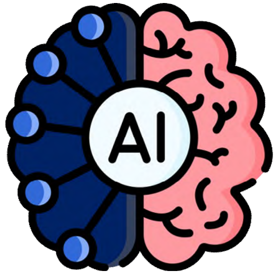
**Optimized** HW choices

Continuous operations and **higher autonomy**

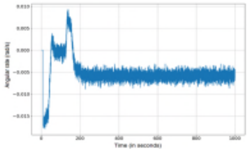
**Intelligent FDIR methods are crucial for enabling the future, i.e. for large satellite constellations based on COTS**

# Key Technology Enablers

AI methods (Machine/Deep Learning)

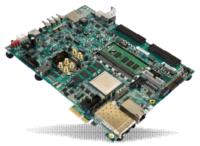



Modern on-board processing platforms



Generic data-driven technology applied to HK telemetry data

COTS hardware: Xilinx Zynq UltraScale+, Xilinx Versal…



Assumes little to no prior knowledge about the underlying system

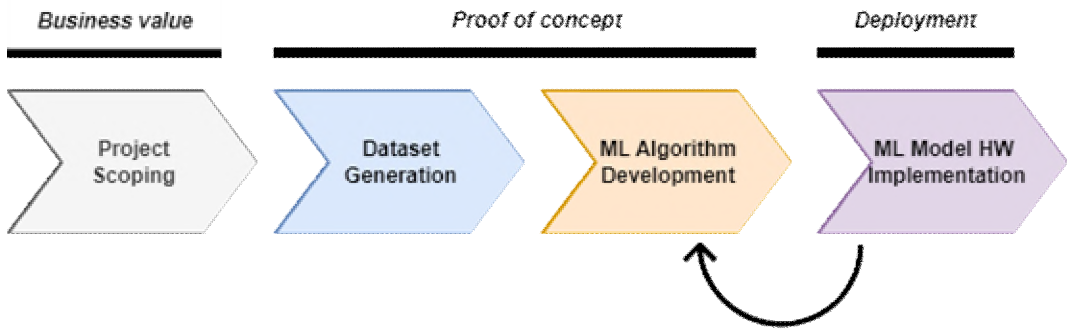
Deep learning processors to support accelerated processing (AI execution on the edge)


Time for FDIR design, implementation & testing can be reduced → cost savings

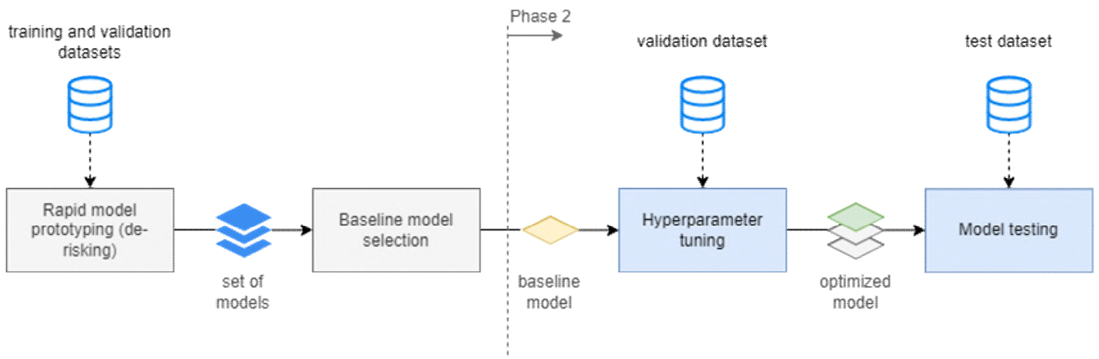
Dedicated frameworks to support model encoding onto HW (VitisAI, Matlab DLP, Xelera Silva)

# ML-based FDIR: Building blocks

- **Data**
  - High-quality representative data
  - Sources: simulation, test benches, in-flight data
  - Data characteristics
  - Data labelling
- **ML model(s)**
  - Learning paradigm
  - Model type and architecture
  - Model evaluation
- **Hardware implementation**
  - Target platform selection
  - AI inference development frameworks
  - Model adaptation
  - Model compilation and mapping to target platform




**Implementation workflow**

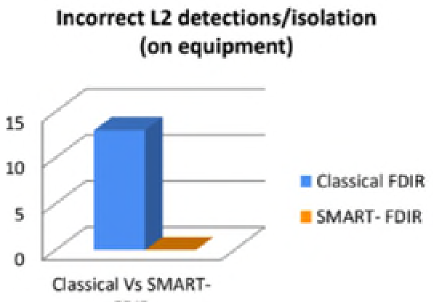


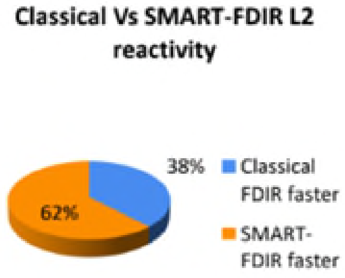

**Example of Model development workflow for ADAP**

# Airbus heritage on AI-based FDIR solutions

## Smart FDIR – Airbus R&T

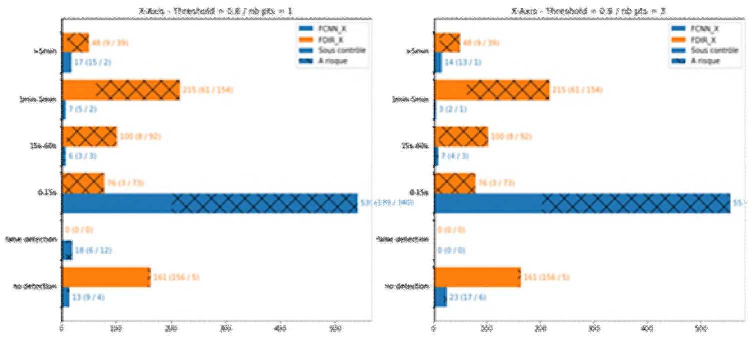
- First initiative for AI-based FDIR within Airbus
- Development of the MODISAN algorithm (MODificator DIScriminator Adversarial Networks)
- Excellent preliminary results on various simulated failures from AOCS (e.g. SOLO, GAIA or Aeolus)



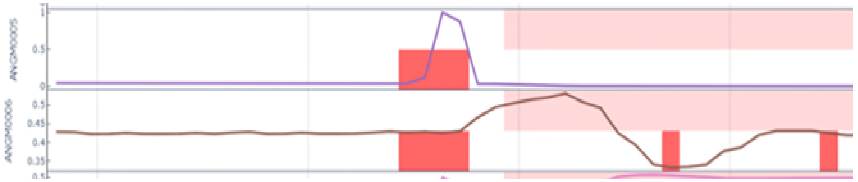

## MOBIA – CNES

- Exploration of different ML approaches (machine learning and deep learning) on simulation data and test bench data
- Use cases: frozen gyro and star tracker blinding
- Successful de-risking of neural networks as option for AI-based FDIR

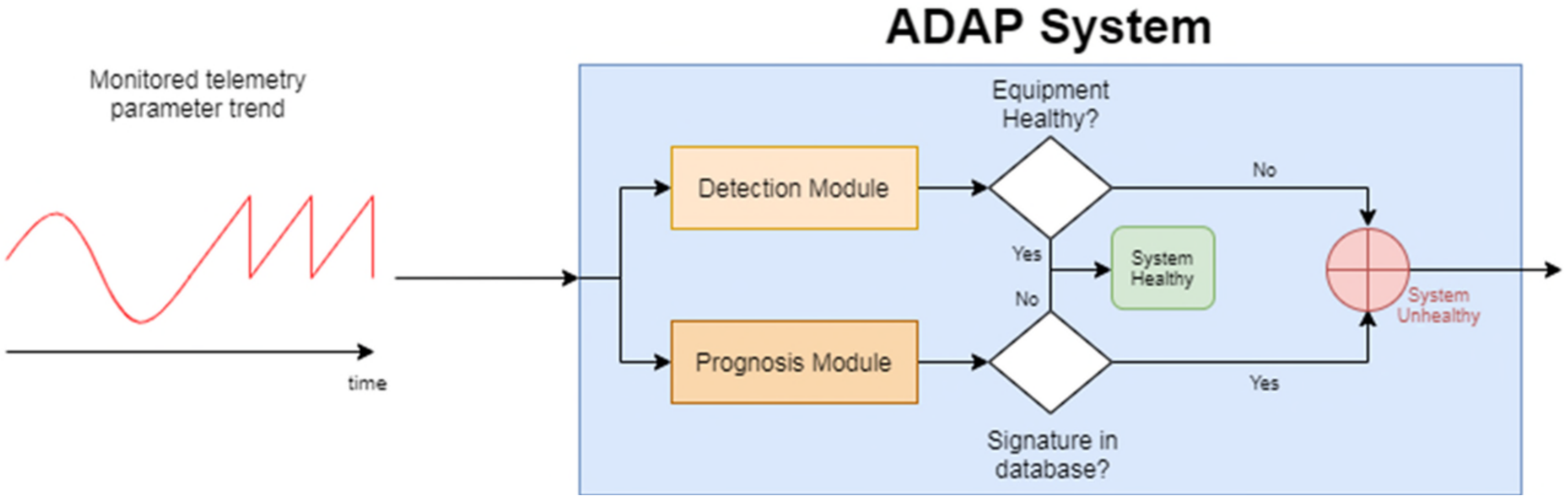


## ADAP – ESA (GSTP-304)

- Develop a ML-based failure detection and prognosis unit for TM processing:
  - In-orbit TM from a real satellite constellation
  - Three sub-systems tested with real flight anomalies (thermal, power, AOCS)
  - Deployment and validation of neural network models on CHICS OBC HW (ZUS+)
  - Demonstration scenario fully integrated with PUS & FDIR management
- Testing the use of the AI solution on constellation telemetry



# Design of the ADAP (ML-based FDIR) system




**High-level architecture of the ADAP system**

- Module to encapsulate **anomaly detection ML model**
- Module to encapsulate **anomaly prognosis ML model**

**<u>Features</u>**

- Execution on flight representative hardware platform
- Monitor potentially hundreds to thousands of TM parameters
- Design for integration with the spacecraft OBSW
  - Access to system observables and high-frequency parameters
  - PUS based TM/TC Interface
- Detection of anomalous behavior followed by processing logic for appropriate recovery action

# Use cases of the ADAP project

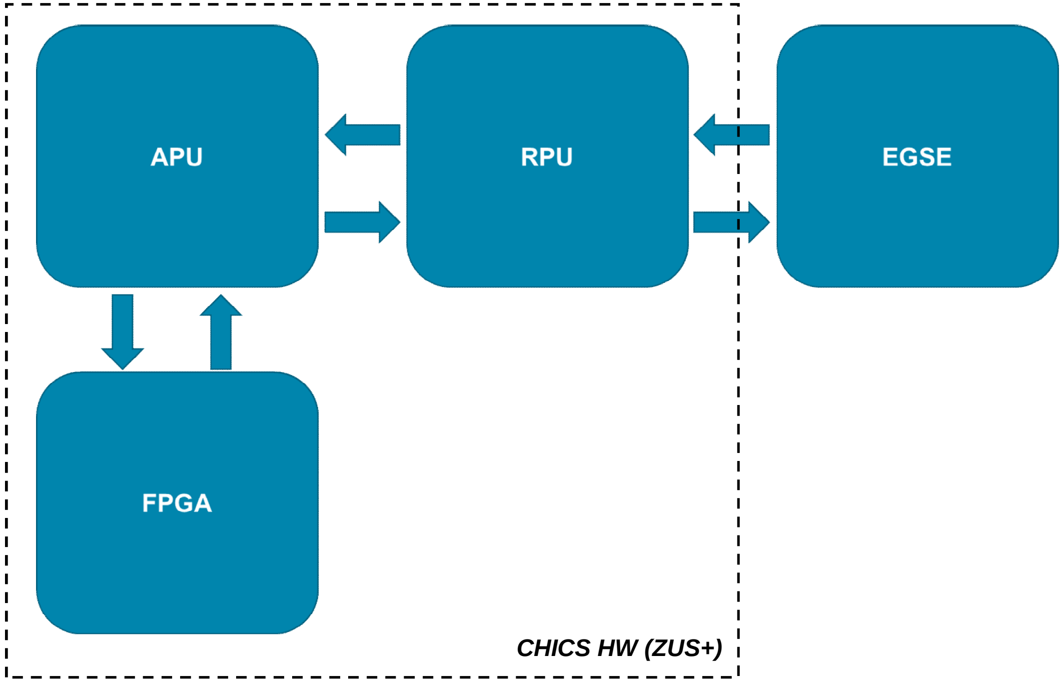
- Constellation of 4 satellites (20 years of TM, for a total of 2 TB of nominal + anomalous TM)
- Investigate different frameworks and development workflows (incl. HW porting)
- Test AI-FDIR reaction time Vs. classical FDIR reaction time
- Train the model with the TM of one satellite to detect anomalies on one of the twin satellites
- Use the anomaly prognosis module to predict systematic anomalies on the same satellite
- Use the anomaly prognosis module to predict systematic anomalies on the constellation

| Subsystem | Description | ADAP use-case | Dataset for TVT |
|---|---|---|---|
| Thermal sub-system | Unit temperature sudden increase with high gradient until the unit is damaged | Anomaly Detection | Real Nominal TM<br>Real Anomaly TM |
| Electrical Power sub-system | Solar Array power generation drop (typical case: space debris hitting SA) | Anomaly Detection | Real Nominal TM<br>Real Anomaly TM<br>Failure Injected in Nominal TM to test eclipse |
| AOCS sub-system | Sensor perturbation injecting noise in the attitude estimation, propagating the disturbance to the pointing error. | Anomaly Detection<br>Anomaly Prognosis | Real Nominal TM<br>Real Anomaly TM |

# ML-based FDIR on the edge – implementation

## Implementation key highlights

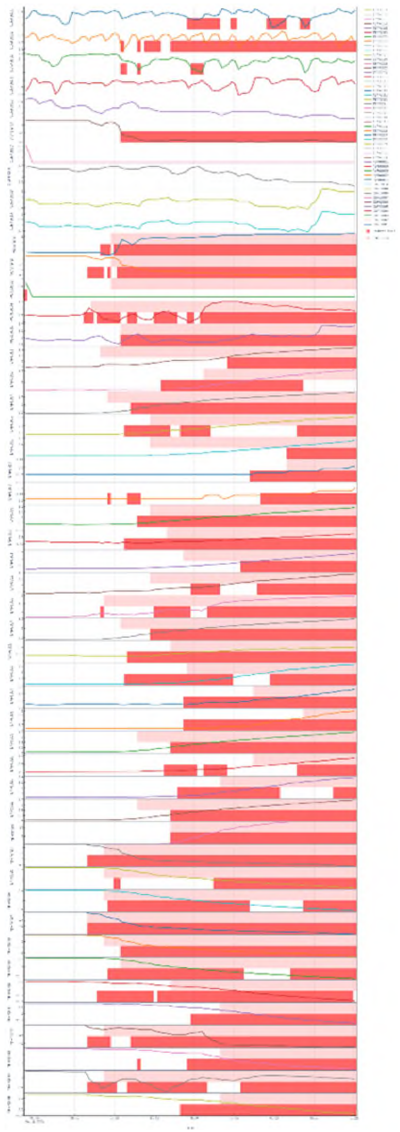
- Xilinx DPU processor
- ADAP neural networks orchestration from RPU (i.e. memory management)
  - > 100 parameters monitored
- Dedicated IP deployed on FPGA
- Neural network acceleration
- Data is sent and received via Python API to simulate communication from/to OBSW
- PUS IF to command the ADAP system
- EGSE for real-time data output and evaluation




| Item | DSPs | Block RAM tiles | LUTs (CLB/ALUT) |
|---|---|---|---|
| Available | 2520 | 912 | 274080 |
| Used by 3 AI-FDIR models + IF to OBSW | 1029 | 378 | 144475 |
| Used (%) | **41%** | **41%** | **53%** |

**HW footprint from all ML models of ADAP**

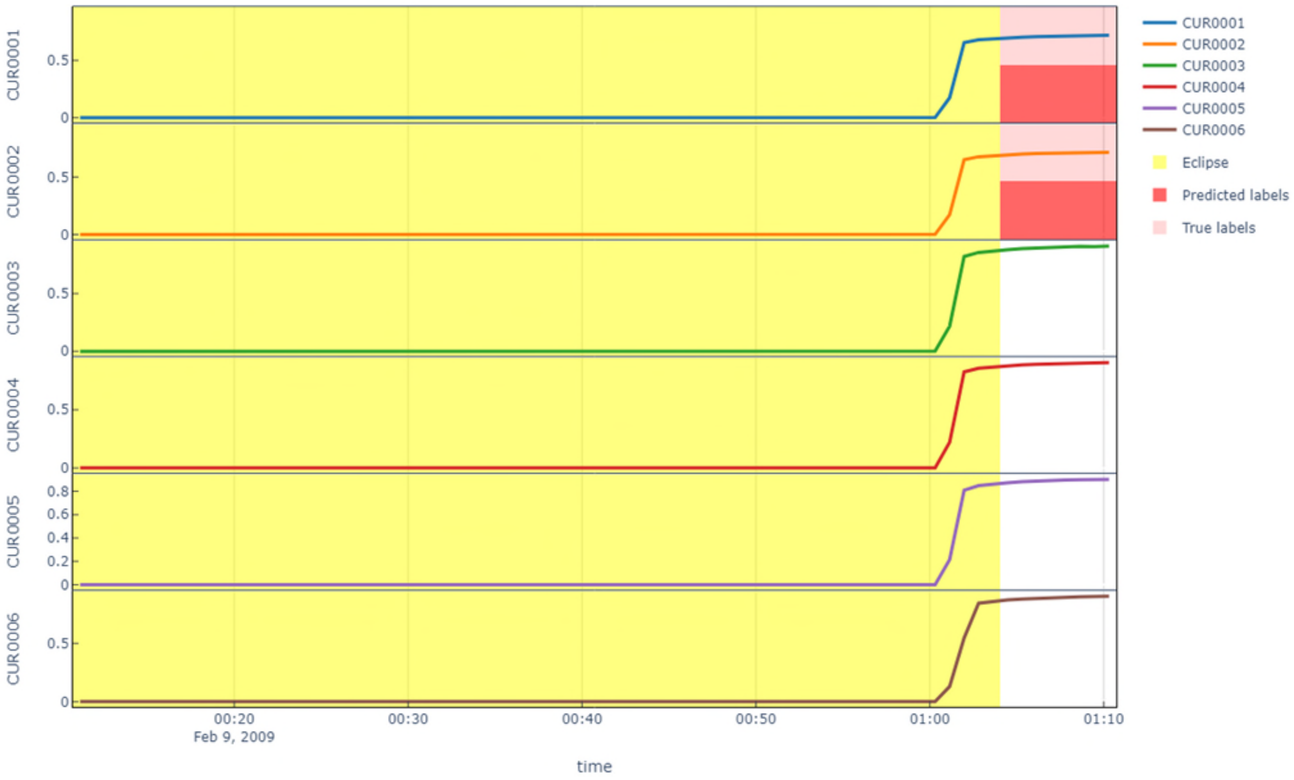
# Summary of ADAP results – Thermal sub-system



**Achievements**:

- ✓ Capable of detecting the failure well ahead of the classical FDIR at unit level (isolation on channel):
  - Anomaly signature detected in area originally marked as nominal by the operator
- ✓ Up to 49 thermal channels monitored simultaneously
- ✓ (Very) high metric scores
- ✓ Model ported deployed on HW (parallel execution with other use case)
  - Developed dedicated IP → could be deployed directly on FPGA without need of processor
- ✓ Capable of detecting failures in other satellite of the constellation

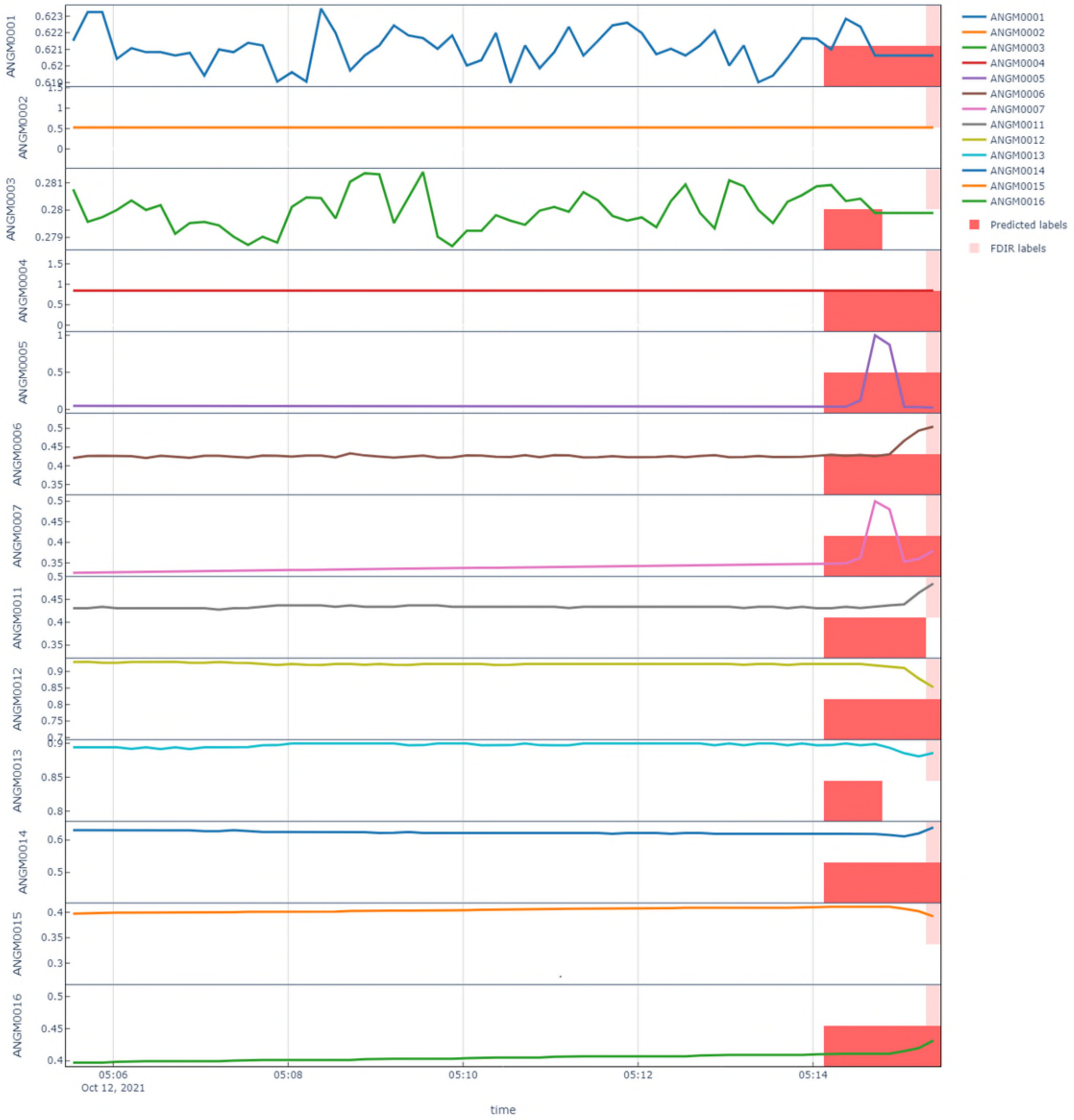
# Summary of ADAP results – EP sub-system




**Achievements**:

- ✓ Capable of detecting failures not observable with classical FDIR methods:
  - In sun-illumination
  - Coming out of eclipse
- ✓ Very high metric scores (>99% accuracy)
- ✓ Model ported on HW (parallel execution with other use case)
- ✓ Capable of detecting other anomalies in the electrical power system (due to DHS failure) in another satellite of the constellation

# Summary of ADAP results – AOCS sub-system




**Achievements**:

- ✓ Capable of detecting the failure well ahead of the classical FDIR at unit level (isolated in channel):
  - Anomaly signature detected in area originally marked as nominal by the operator
- ✓ Good metric scores (> 90% accuracy)
- ✓ Prognosis module capable or recognizing anomaly signature
- ✓ Model ported on HW (parallel execution of detection and prognosis module)
- X Bad data quality due to many data gaps and down-sampling of packets forwarded to ground
  - X Loss of performance when deployed on another satellite of the constellation

# Some Lessons Learned

Lessons Learned

**Dataset engineering**
Iterative effort between data and ML team to obtain the best quality data possible

**Model porting to HW**
Start iterating with HW team as early as possible to avoid framework incompatibilities

**Infrastructure to support rapid experimentation**
On-premise is good, cloud is better

**Standard evaluation metrics are not enough**
FDIR needs dedicated evaluation metric

**Drivers**
Check all vital drivers before starting development (interaction with ML accelerator, power measurement..)

**Documentation for ML accelerators**
Communicate early with ML accelerator vendors in case of lacking documentation

# Thank you

AIRBUS