The background of the slide features a dark, textured asteroid with several craters. Two spacecraft are visible: one in the upper right and another in the lower right, both with blue solar panels. A central spacecraft, the Hera probe, is shown in a yellow and black color scheme with a prominent circular antenna, positioned horizontally across the middle of the frame. The main title text is overlaid on this scene.

Embedded AI-based FDIR system for HERA mission

Presentation overview

1. HERA mission
2. FDIR system
3. AI approach compared to standard approaches
4. Embedding AI models into main flight computer
5. Future roadmap

HERA mission

- Planetary defense mission
- In cooperation with DART
- Goal is to characterize its impact



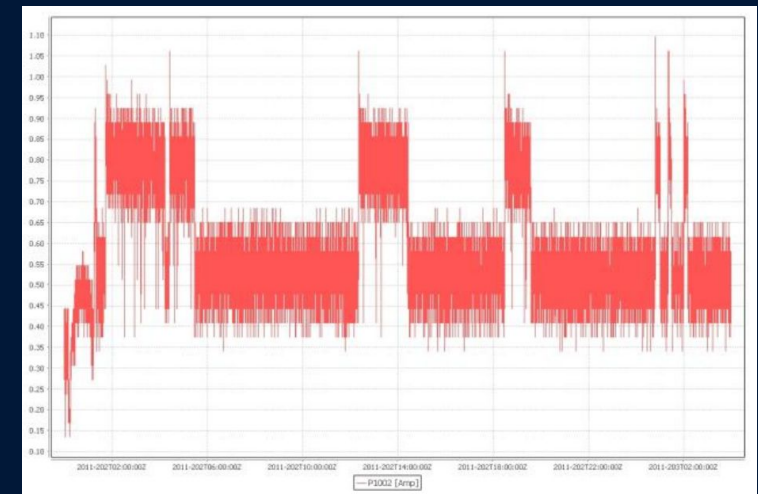
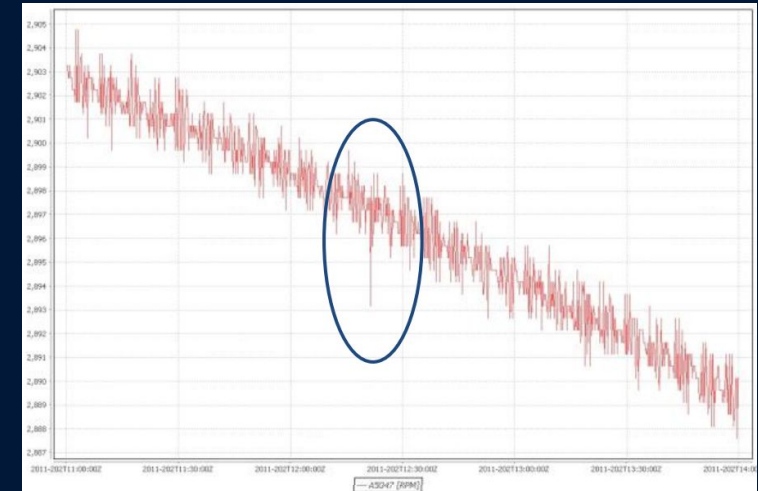
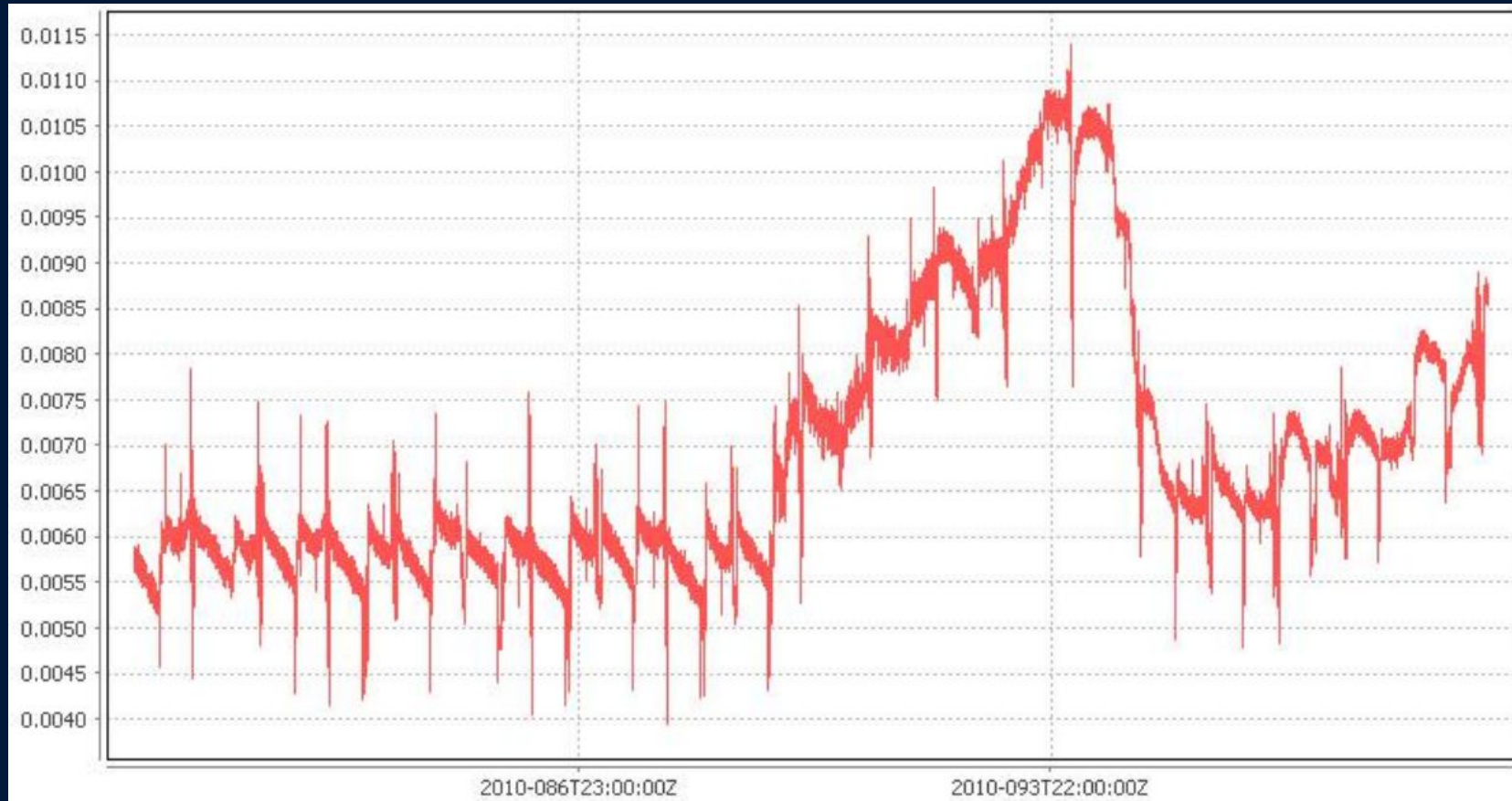
FDIR system

- **FDIR** = Fault Detection, Isolation and Recovery
- Spacecraft gathers a lot of data
- Impossible to send all data to Earth
- Autonomous health monitoring is necessary
- Autonomous timely reaction to failures is necessary

FDIR system

- Predefined nominal measurements ranges
- Out of Limits Alarms
- Simple, but not very good
- Correlations with other subsystems/operations are not considered
- Anomalies can be subtle and within nominal ranges - not detected

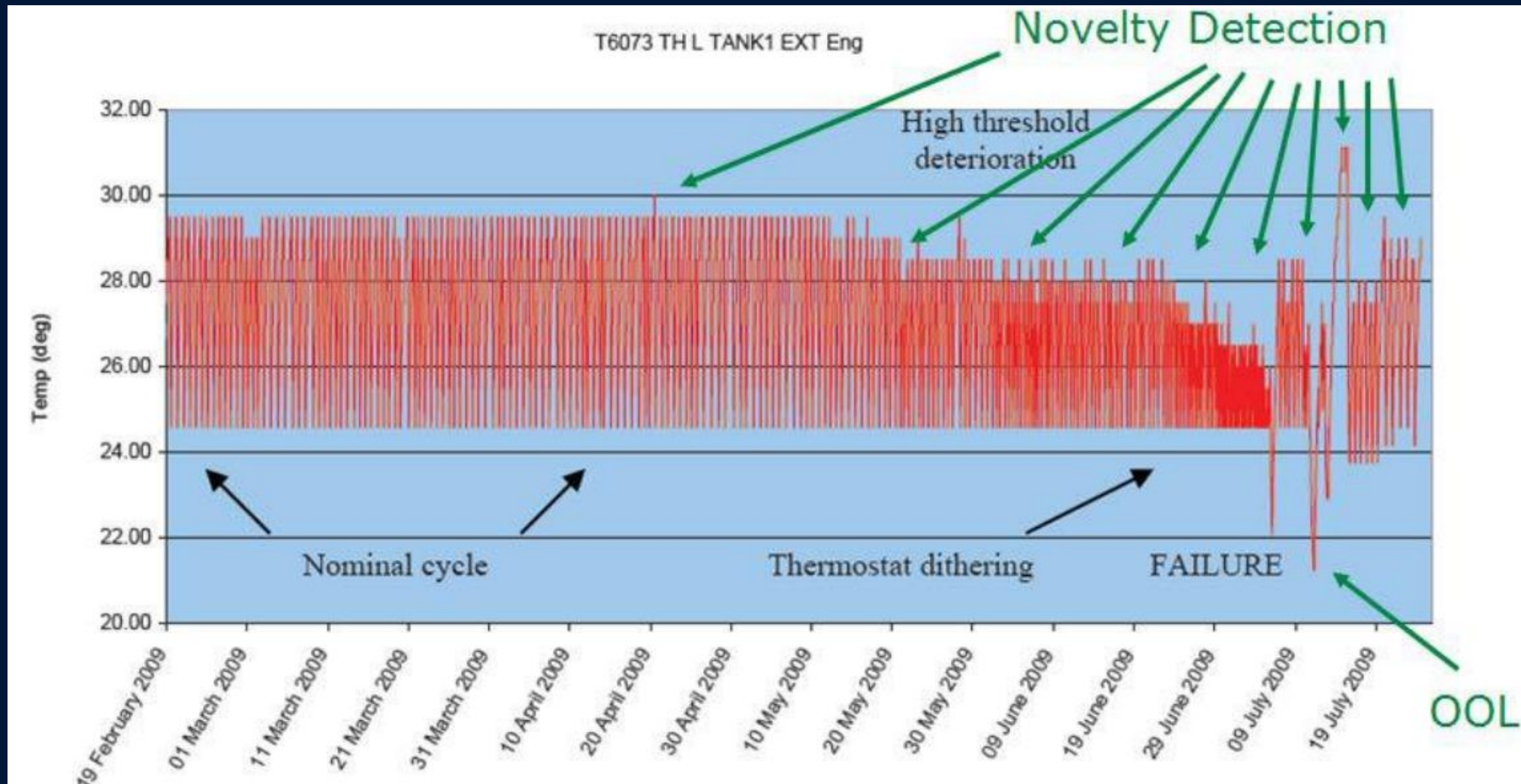
Anomalies examples

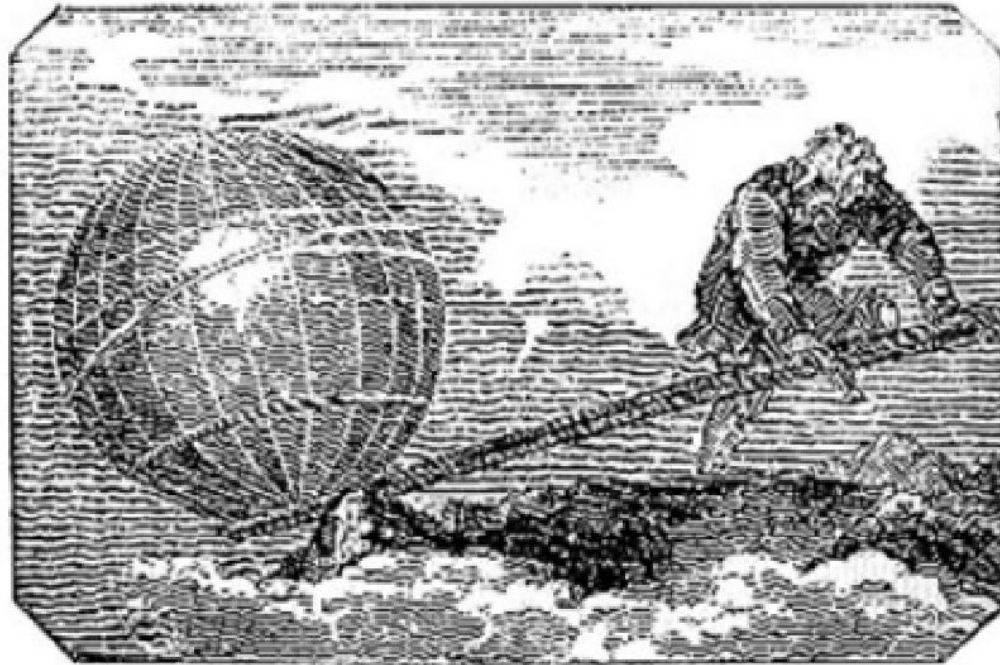


[1] Curing XMM-Newton's reaction wheel cage instability: the in-flight re-lubrication experience

[2] New Telemetry Monitoring Paradigm with Novelty Detection

Anomalies examples





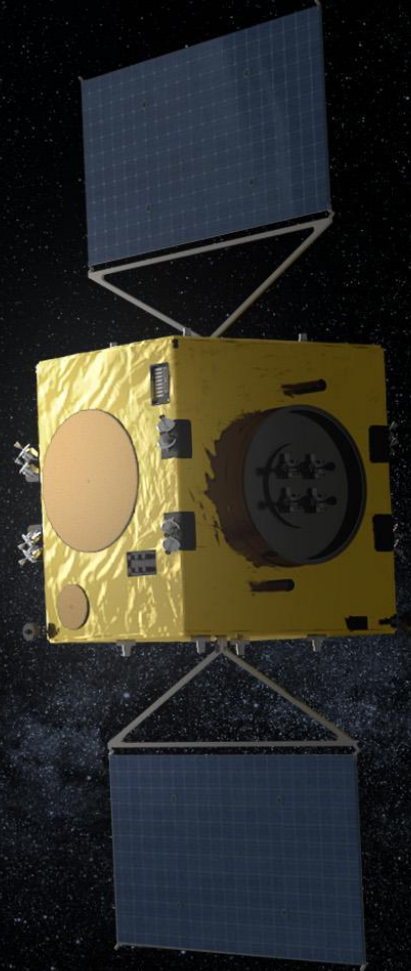
data

*“Give me ~~a lever and a place to stand~~
and I will ~~move the earth.~~”*

Archimedes

design AI for you

HERA AI FDIR



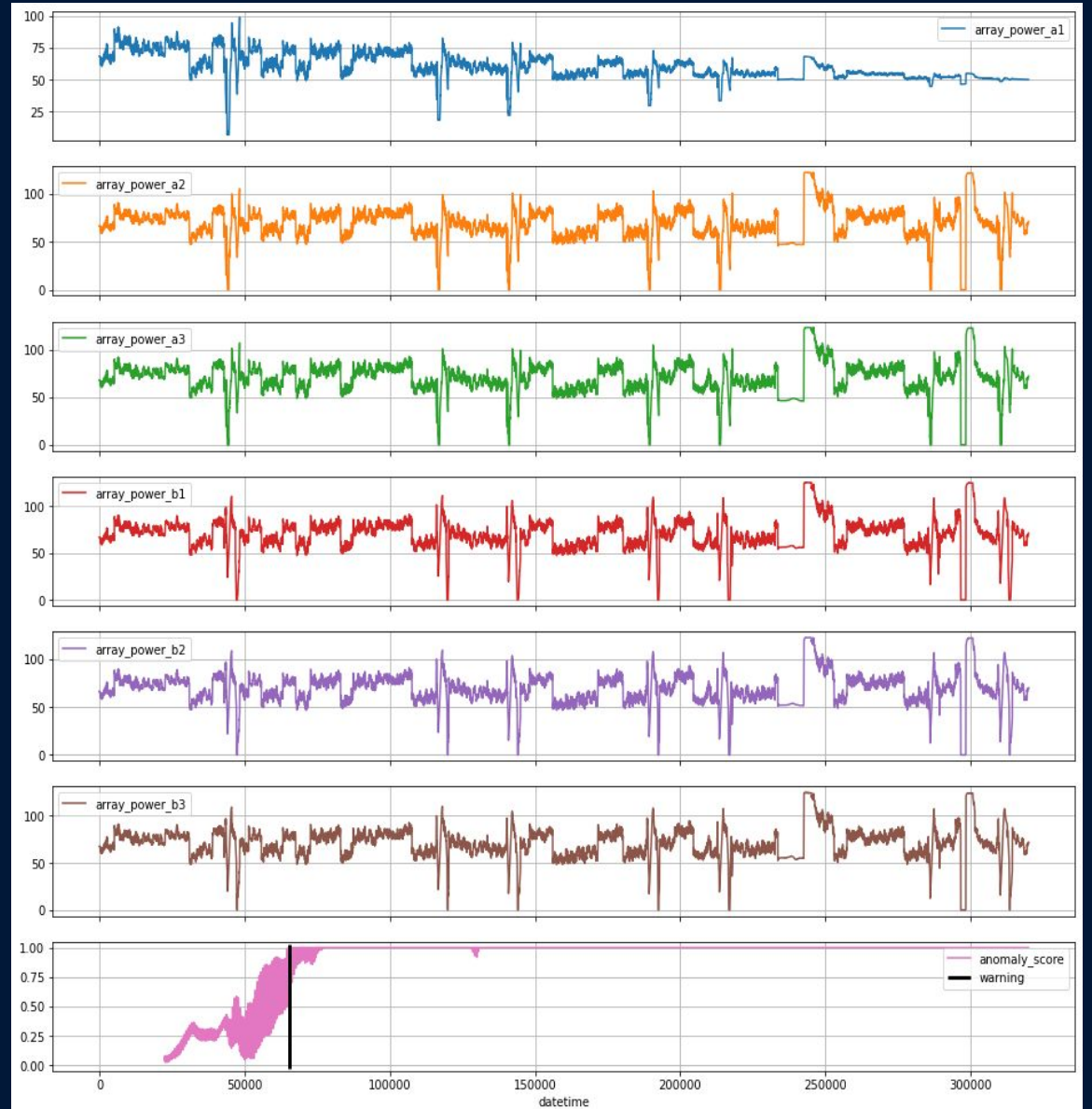
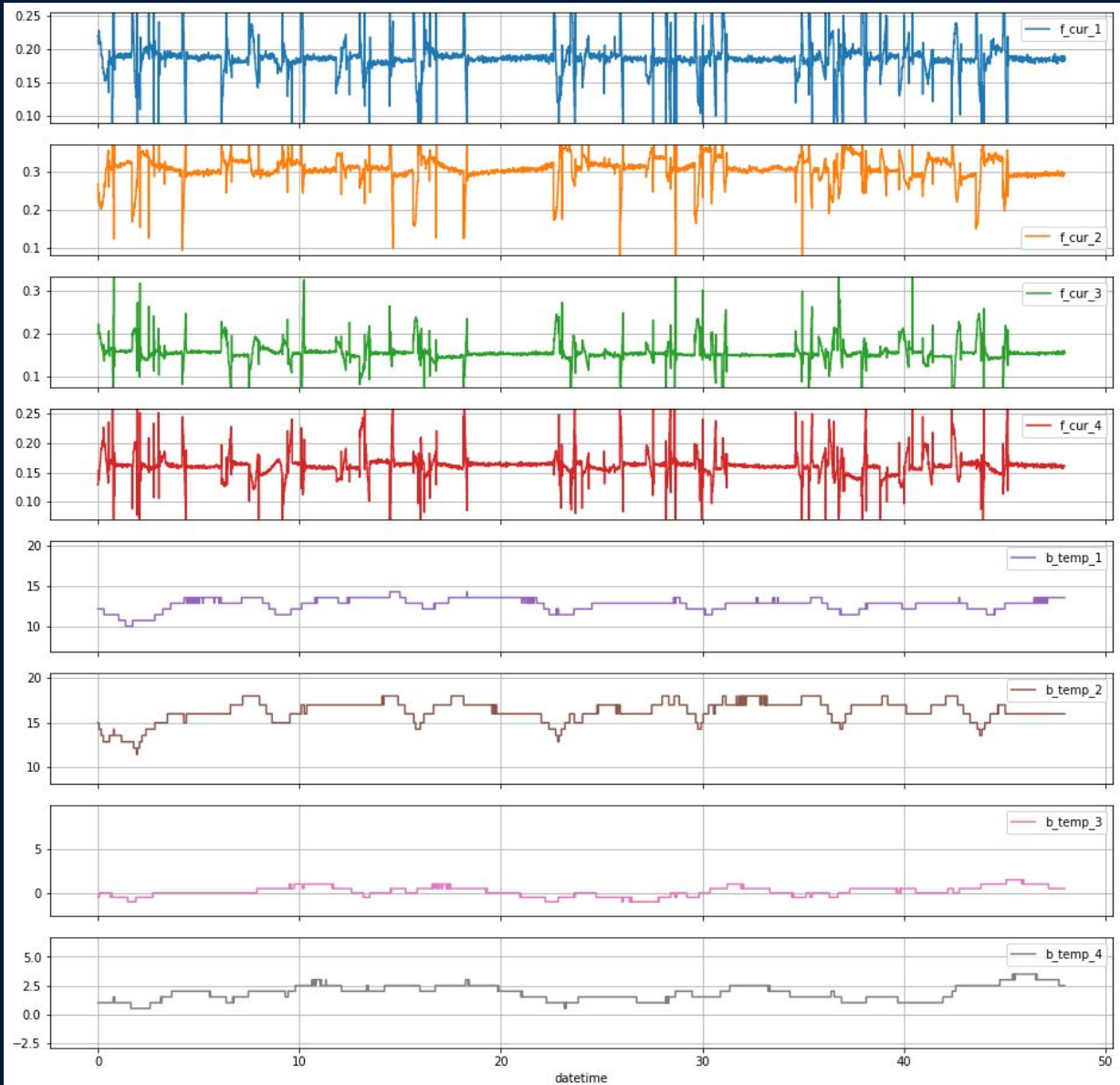
Training approaches

- Supervised learning:
 - a model is trained on labeled data to classify anomalies based on previous encounters
- Unsupervised learning:
 - a model is trained on unlabeled data to automatically detect anomalies (e.g., 1% of the most suspicious events)

Training approaches

- Semi-supervised learning:
 - a model is trained solely on nominal data to effectively identify new anomalies that may arise

Data



AI architecture

- One model for each subsystem
- Siamese Convolutional Encoder + Outlier detector
- KNN OD for outlier detection
- Other tested approaches included using:
 - Convolutional encoder, convolutional variational encoder, LSTM, isolation forests, one class SVM, reconstruction error, etc.

AI architecture

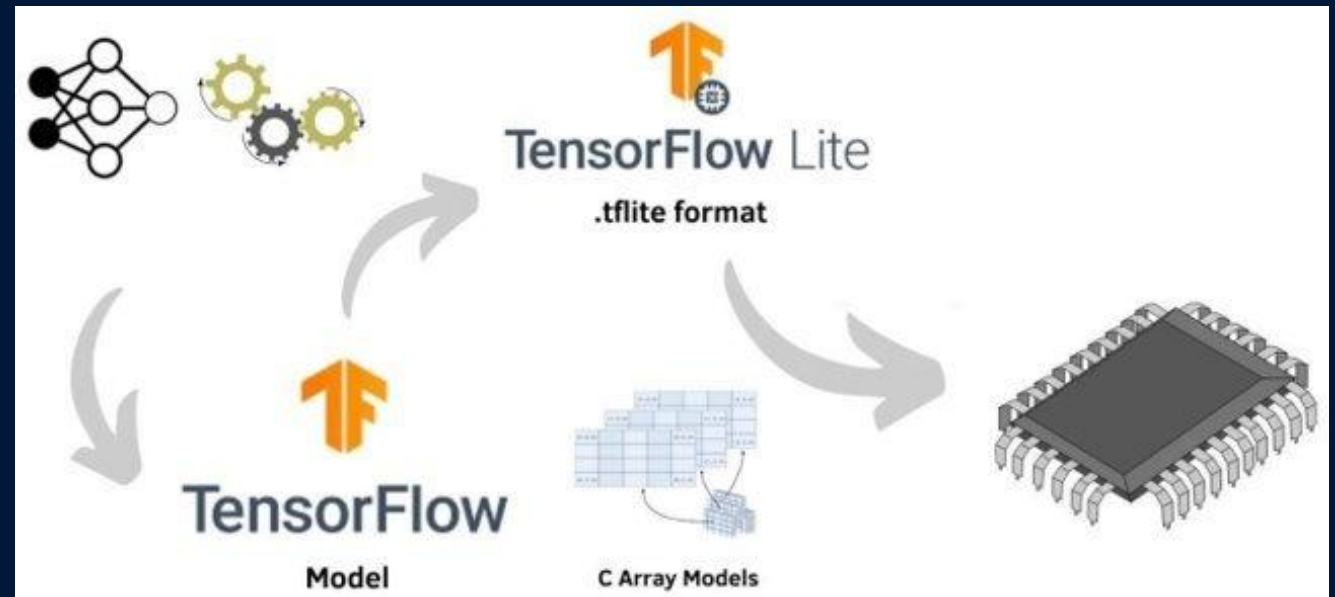
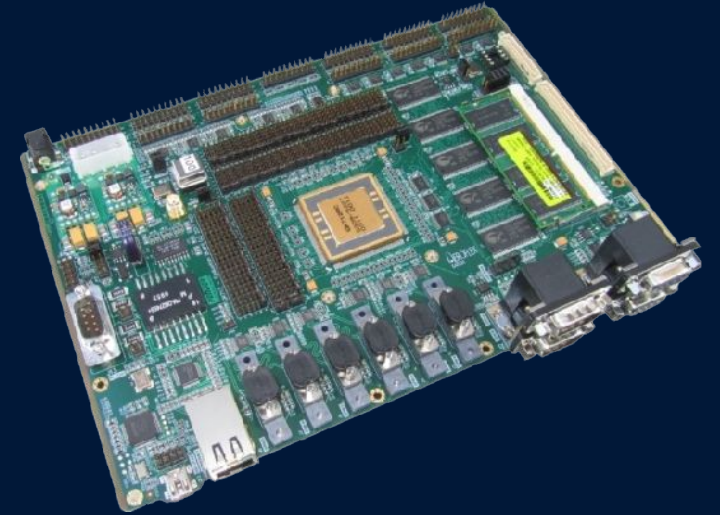
- All approaches tested using XMM and MEX data with artificial anomalies

Encoder	Detector	Precision	Recall	F1 Score
Conv. AE	KNN	0.840	0.808	0.824
Conv. AE	I-forest	0.742	0.723	0.733
Conv. AE	Recon. error	0.766	0.764	0.765
Var. conv. AE	Recon. error	0.895	0.895	0.895
Siamese conv. AE	KNN	0.995	0.995	0.995
Siamese LSTM	KNN	0.994	0.994	0.994

Performance of some of the considered models

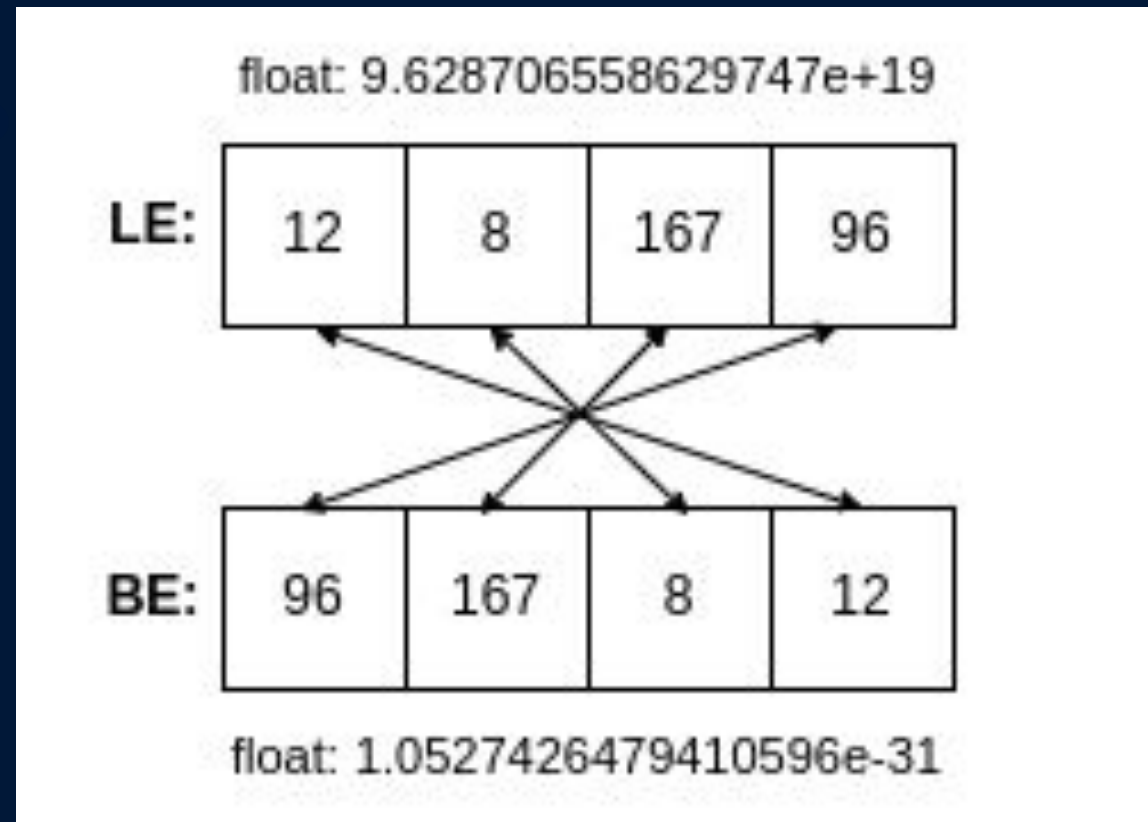
Embedding to HW

- Deploy to one core of Leon 3
- No OS, limited ROM and RAM
- Avoid affecting main flight computer
- Tensorflow for training encoders
- Tensorflow Lite For Microcontrollers for integration into C++



Embedding to HW

- Endianness incompatibility
- Underlying buffers byte swapping, updating models loading routines



Final results

- RAM – 20 kB
- ROM – 750 kB
- Prediction time – 75 milliseconds

Final results in detail

Component	Size
TFLM	
Baseline	11.62 KB
TFLM framework	211.27 KB
All TFLM ops	717.51 KB
Used TFLM ops	124.48 KB
Baseline + TFLM + used ops	347.36 KB
MODELS	
Encoder	62.13 KB
KNN code	1.34 KB
KNN data - 10,000 points	390.62 KB
INFERENCE CODE	
Main file	7.05 KB
Full inference code	745.03 KB

Action	Time
TFLM setup	39.75 ms
Passing data to interpreter	0.15 ms
Encoder inference	31.58 ms
KNN inference	43.59 ms
Full inference	75.32 ms

What next?

- Do more than just the FD part of FDIR
- Employing "Explainable AI" techniques to better understand the black-box algorithm's reasoning behind its decision
- Validation and verification of the software
- Shoot the thing into the space and pray it works

Thank you for attention