



# **AI-4-GNC Airbus DS perspectives**

## **ADCSS**

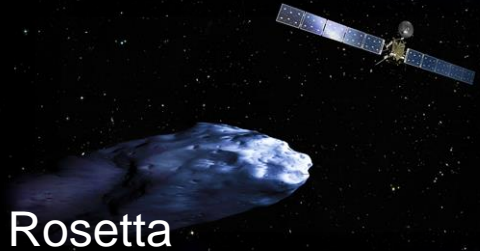
DEFENCE AND SPACE

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21 October 2020

**AIRBUS**

# Current challenges and limitations of GNC and the Functional Avionics chain

Today...



Rosetta



Solar Orbiter

- ✓ Safely and robustly delivered on challenging missions
- ✓ Partial autonomy and decision-making (large cost driver)



JUICE



ExoMars rover

Tomorrow...

Smarter and cheaper (**S&C**)



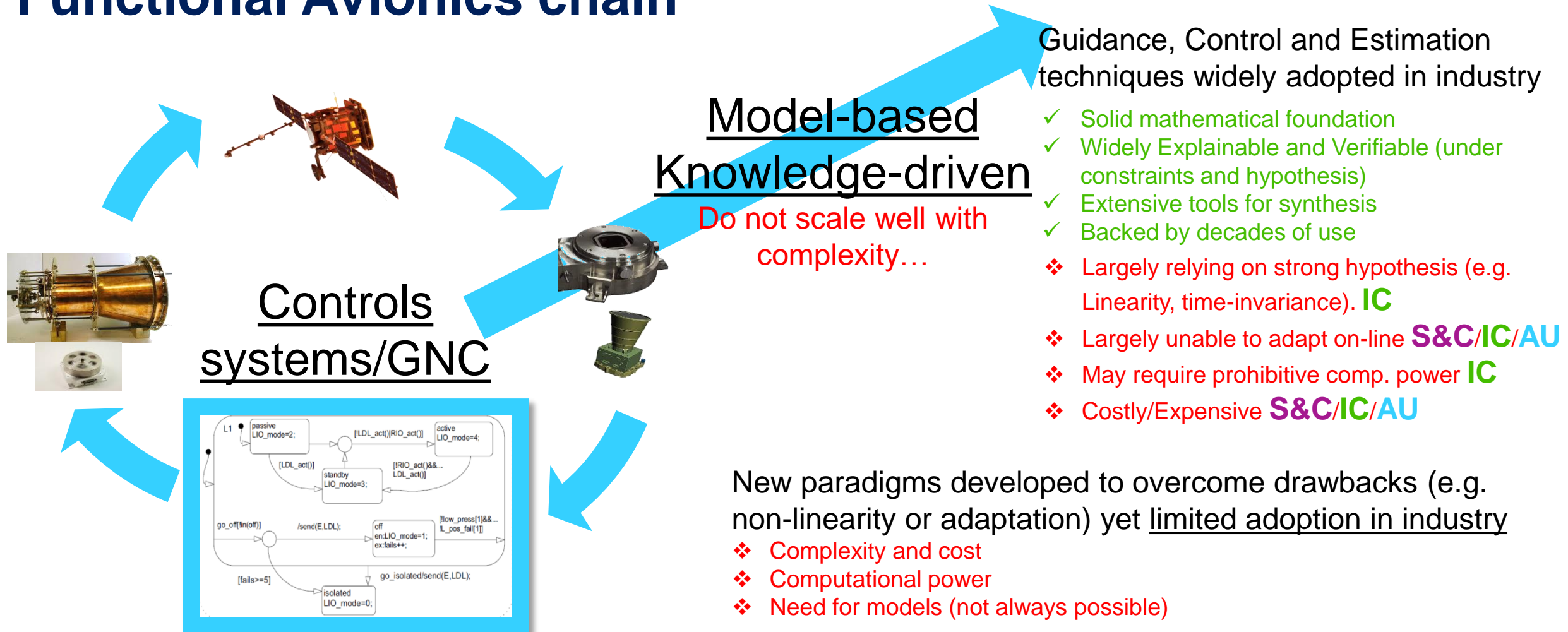
Autonomy (**AU**)

Increased complexity (**IC**)





# Current challenges and limitations of GNC and the Functional Avionics chain



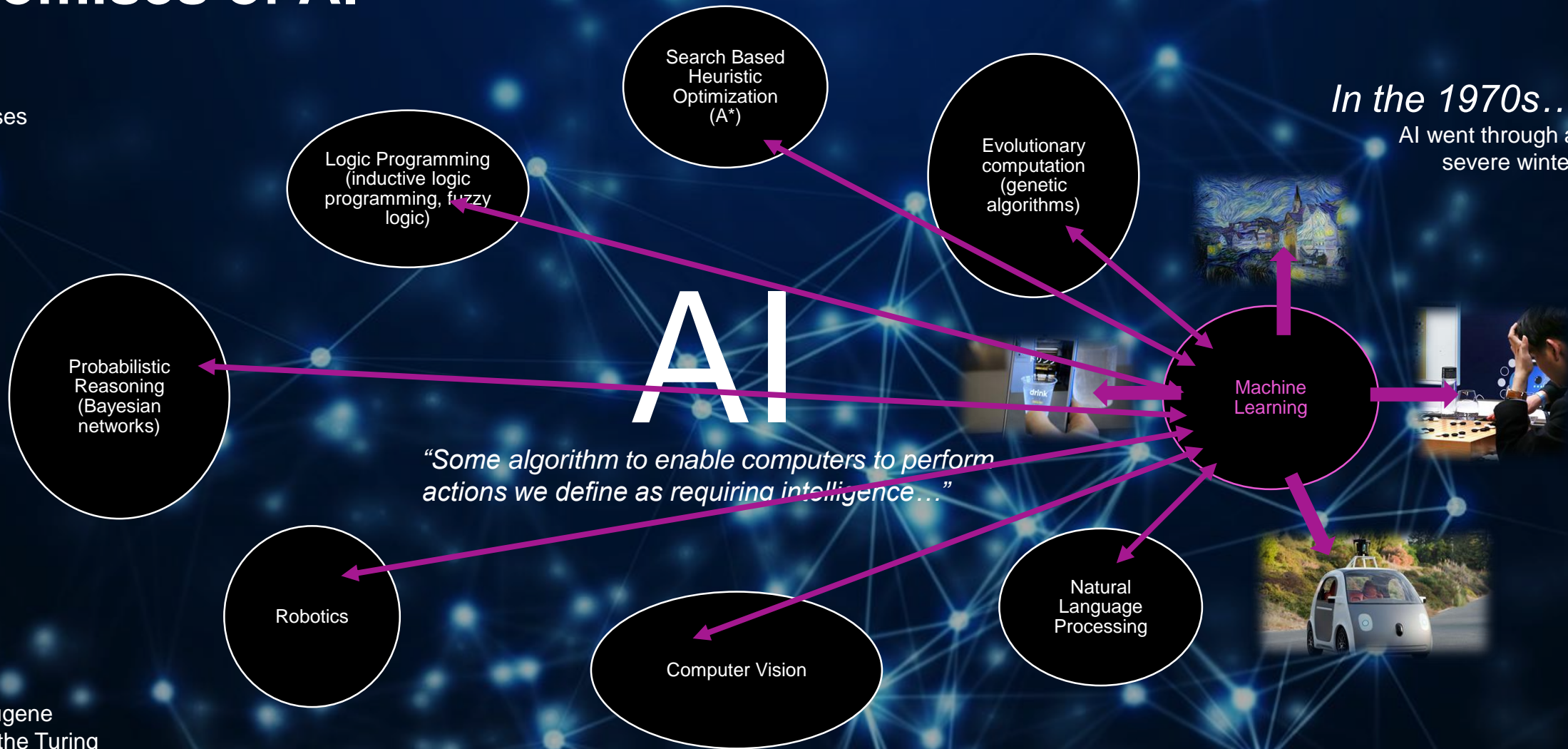
# The promises of AI

*In 1950...*

Allan Turing proposes  
the Turing test

*In the 1970s...*

AI went through a  
severe winter



*In 2014...*

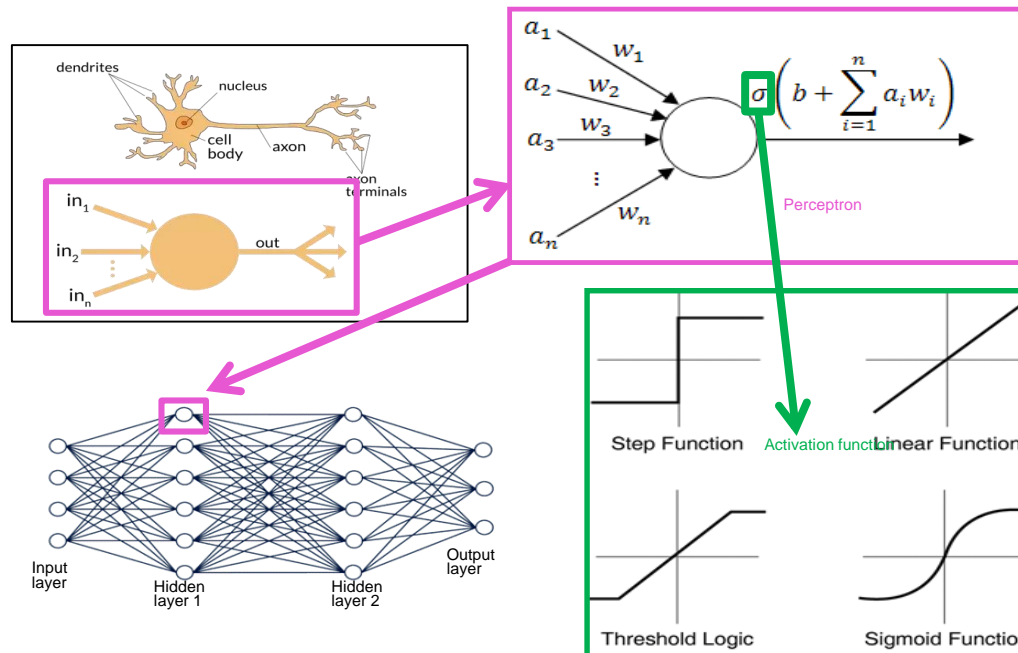
A chatbot called Eugene  
Goostman passes the Turing  
test

# The promises of AI

AI => Machine Learning => (Mostly) Model-based =>

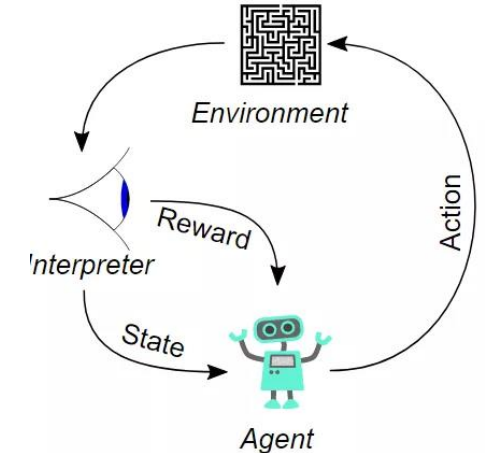
*“Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed...”* – Arthur Samuel. 1959

The great potential of ANNs as universal approximators...



Supervised/Unsupervised  
Reinforcement learning

The “generic”  
model learns with  
data...

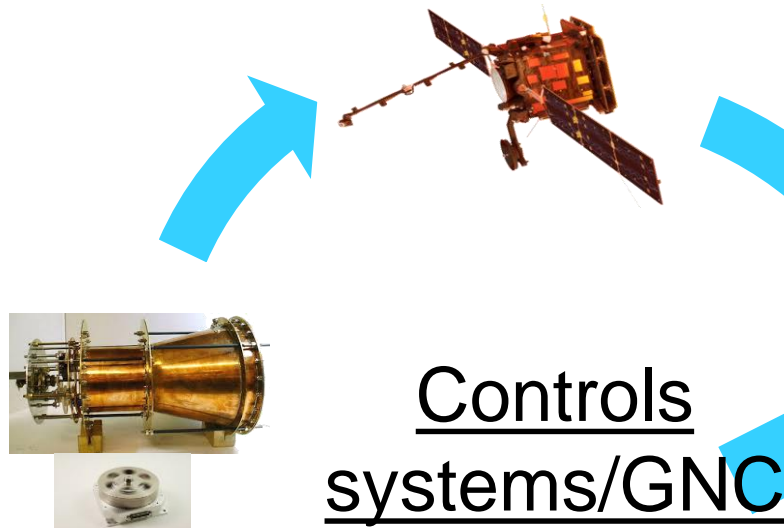


Potential of Neural Nets:

- ✓ Handling of extremely complex and high dimensional data (e.g. VBN or Decision-Making)
- ✓ Cheaper development processes
- ✓ Efficiently design taking into account non-ideal behaviour
- ✓ Mission enabler (HW and/or SW)
- ✓ Scalable on-line learning and/or adaptation for performance
- ❖ Explainability and Verification
- ❖ Generalisation outside training envelope/robustness
- ❖ Embeddability (for some applications)



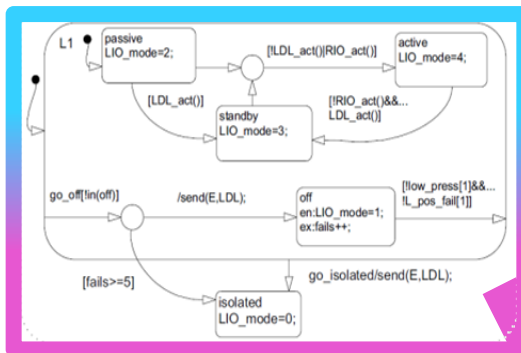
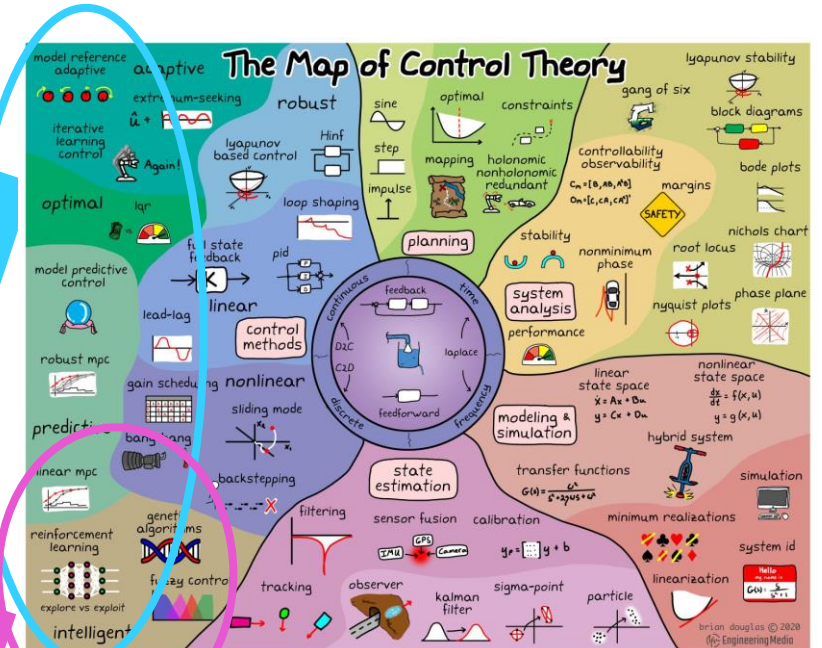
# Merging the two worlds (1)



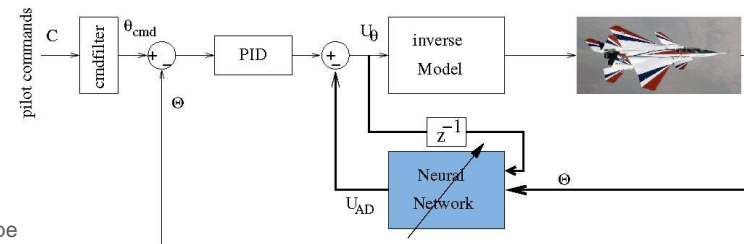
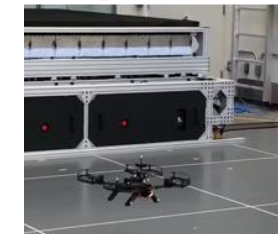
Model-based:  
Knowledge  
driven

+

Data driven



Very few real life demonstrators

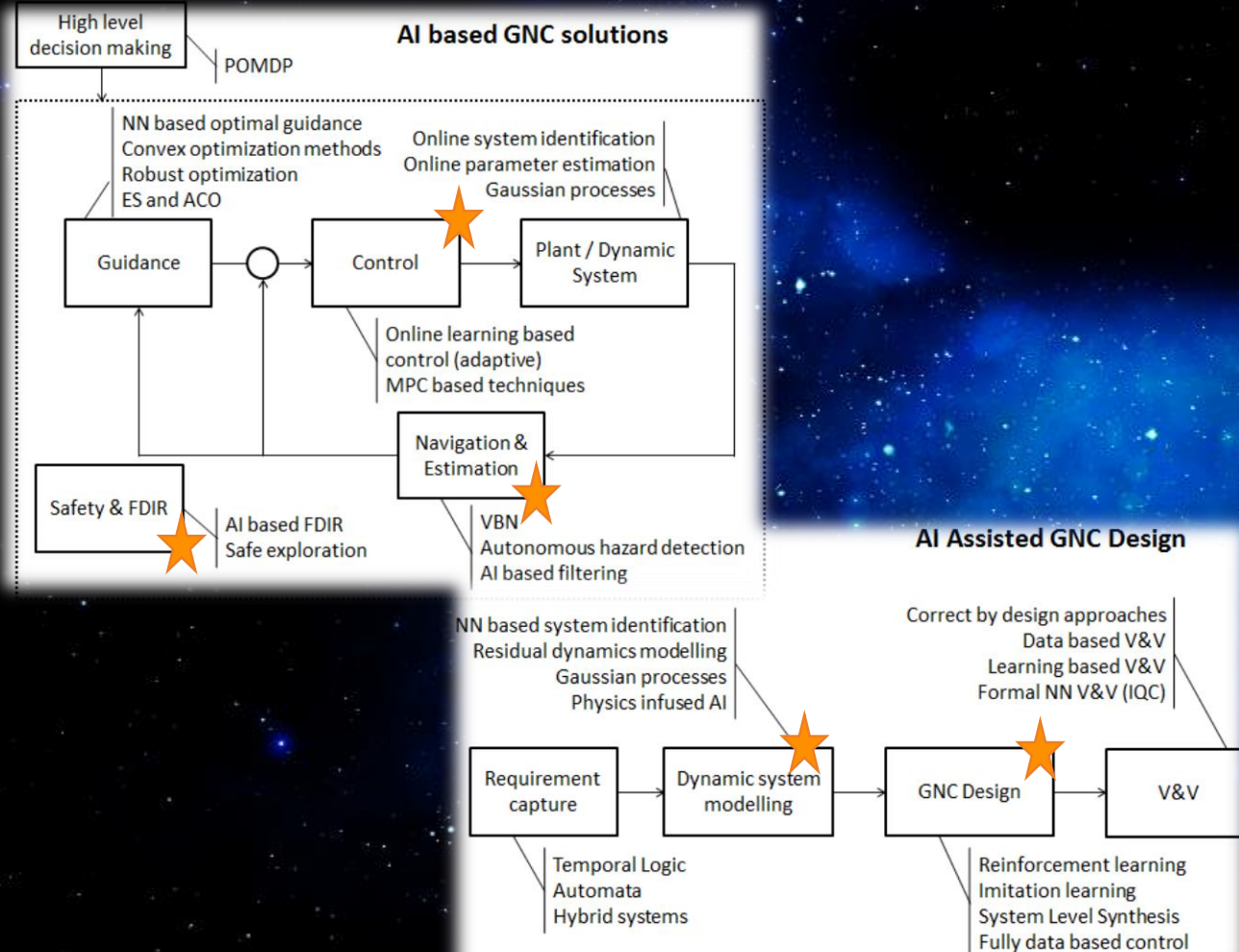


Only successful if...

- ✓ Generic
- ✓ Safe and Robust
- ✓ Efficient
- ✓ Verifiable solutions

# Merging the two worlds (2)

Tomorrow...



Smarter and cheaper (**S&C**)

Autonomy (**AU**)

Increased complexity (**IC**)



# Current efforts...

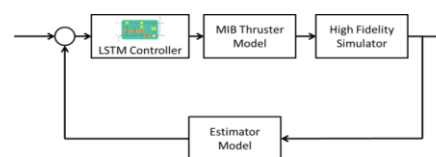
## SMART-FDIR & Fly SMART-FDIR IOD

- **Objectives/Value:** Cheaper FDIR design + higher autonomy and availability of the spacecraft
- **Achievements:** In-house algorithm tailored for unsupervised anomaly detection + isolation. First go on embedding the NNs
- **Main conclusions:** Increased Some use cases may be embeddable in future HW (Leon4).



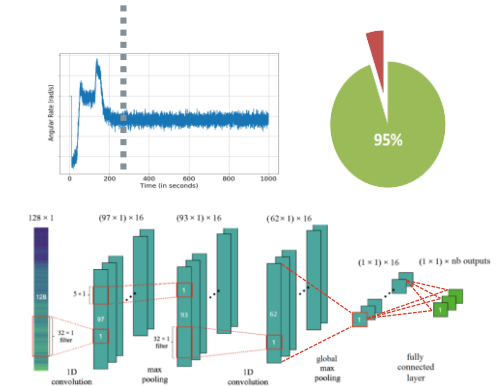
## GNC-v.AI

- **Objective/Value:** Algorithms “learnt” by the NNs through interaction on the simulator. Cheaper algorithm design with potential performance improvement
- **Achievements:** First initiatives exploring RL as a GNC algorithm development approach. PG and ES techniques explored. GYM-like env. available
- **Main conclusions:** Domain randomisation successful in achieving robustness to different uncertainties. Unable to beat human design performance



## Supervised Learning for GYR-frozen use case in Telecommunication satellites

- **Objectives/Value:** Address classical FDIR design limitation on a “tricky” GYR failure mode
- **Achievements:** CNN trained as a very effective monitor with 95% detections and Zero false triggering
- **Main conclusions:** Supervised methods are very powerful for specific FDIR challenges

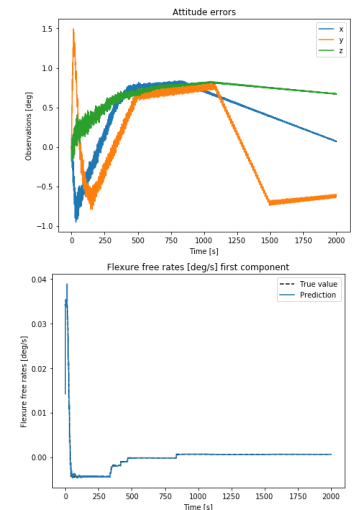


## Extension of GNC-v.AI – Deep Estimation

Supervised learning for advanced estimation:  
**RNN based flexure-free angular rates estimation**  
for highly flexible spacecraft (JUICE, SoI...).

$$\begin{bmatrix} \underline{v}^I \\ \underline{\omega}^I \end{bmatrix}_{\text{flex-free}} = \begin{pmatrix} m\mathbf{I}_3 & \mathbf{0} \\ \mathbf{0} & \mathbf{J}_{\text{CoM}} \end{pmatrix}^{-1} \begin{bmatrix} m\underline{\dot{v}} + \underline{\Gamma}\underline{\dot{\eta}} \\ \mathbf{J}\underline{\dot{\omega}} + \underline{\delta}\underline{\dot{\eta}} \end{bmatrix}_{\text{CoM}}$$

- Classical solution (e.g. LKF or EKF) never attempted due to model complexity => so far only flexure filters are used
- Early results show **better accuracy than linear filters**

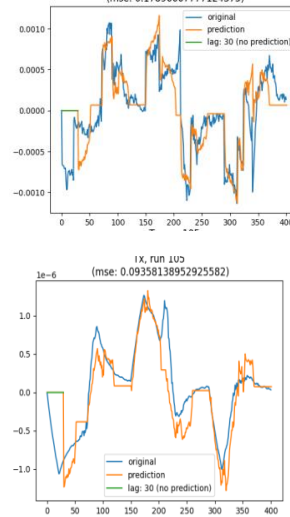




# Current efforts...

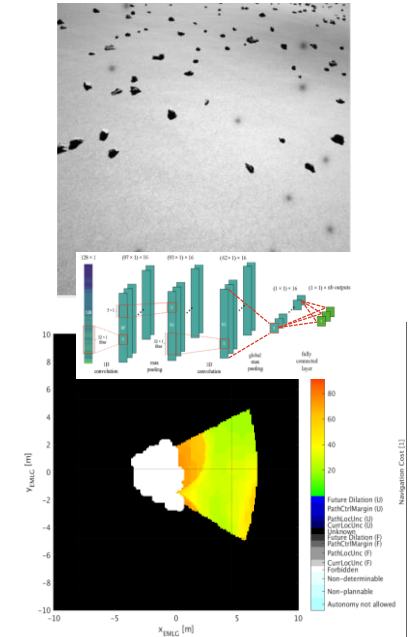
## Sloshing meta-Modelling

- **Objective/Value:** meta-model of the Sloshing phenomenon in the context of “agile” missions, in order to speed up verification and increase the pointing stability.
- **Achievements:** Promising open-loop predictions have been achieved. Best results encountered for the moment using time spanned MLP.
- **Conclusions/Issues:** Method good enough to capture/approximate fundamental behaviour in open loop. Close-loop validation ongoing



## FARNAV

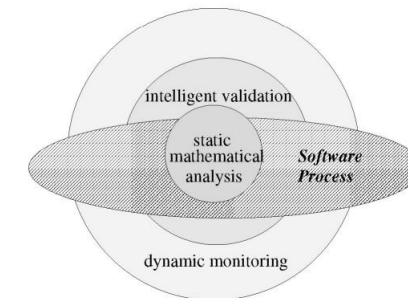
- **Objective/Value:** achieve Fast And Robust NAVigation maps against noise, motion blur or other camera defects for continuous drive. Leverage CNNs robustness to image artefacts and semantic extraction power to produce navigation maps significantly faster
- **Achievements:** Imitation learning/supervised framework setup and relevant dataset specification and generation process ongoing
- **Conclusion/Issues:** study just started



## Study on Verification of AI for GNC

- **Objective/Value:** Start tackling the problem of verification of AI-augmented solutions in AOCS/GNC
- **Achievements:**
  - Reviewed V&V of AI applied to other engineering fields (automotive/aviation)
  - Reviewed V&V formal methods from control/formal verification
  - Reviewed V&V statistical/probabilistic methods
  - Reviewed metrics to quantify safety/robustness for AI

- **Conclusions (so far):**
  - Significant efforts in V&V of AI can be leveraged from other fields
  - Both formal (with severe limitations) and statistical/probabilistic guarantees approaches exist
  - The techniques are still in their infancy, almost never used in industrial examples
  - Run time assurance is an interesting concept to



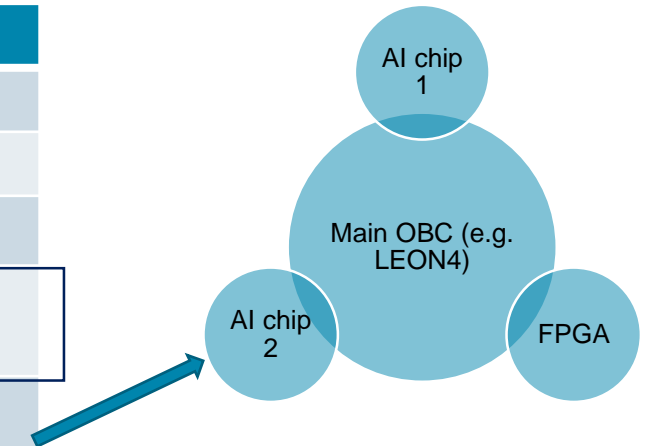
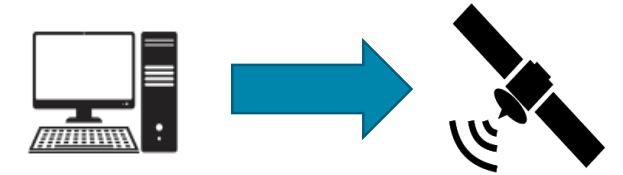
Multi-layered V&V approach for AI-augmented systems

# AI in the FA chain... Future challenges

Challenge: Tensorflow Model representation → Specialised Space-grade HW executable representation

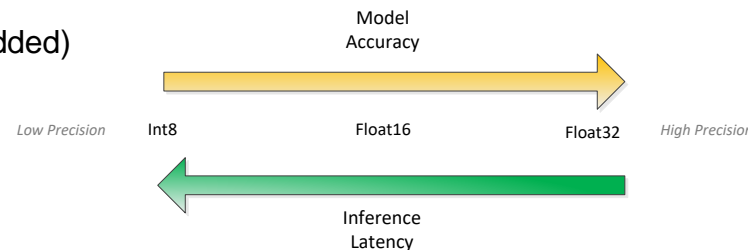
Different “Edge” Inference HW options considered:

Device Type	Remarks
GPU	Primarily for cloud training. Not space-grade.
FPGA	Fast. Low power. Payload? Future?
Dedicated AI Chip	Fastest. Low power. Not space-grade. Payload? Future?
Traditional Microprocessor (e.g. SPARC LEONx)	Not ideal, but space-grade and <b>fastest path to flight for platform application</b> . “Safest” according to existing ECSS standards.
Combination of options above	More plausible long term solution. Traditional CPU with AI chips/FPGA co-processors



## • Important considerations for embedding DNNs:

- ✓ Validation of model conversion (prototype == embedded)
  - After optimisation: Quantisation, Pruning
- ✓ Build/Integration: Compiling & Linking with OBS
- ✓ Software Budget:
  - Memory (~Millions of parameters)
  - CPU Latency (Inference time based on FLOPS/MIPS)



- ✓ Verification
  - Code metrics & Code complexity analysis
  - Unit testing (boundary, coverage, floating point robustness)
- ✓ Qualification & Licensing
  - 3rd party tools (maths library, conversion tool)
- ✓ Observability (trainable NN parameters as datapool parameters)

# Conclusions

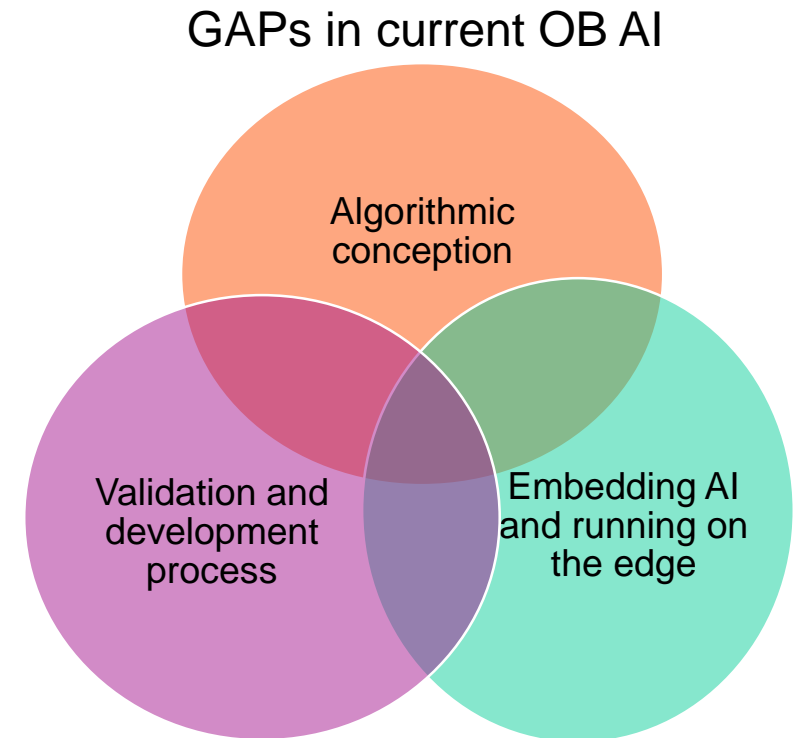
Controls theory will be stretched to overcome its current limitations and deliver for the challenges of tomorrow

AI and in particular ML offers promising solutions to the above but...  
It must remain compatible to current safety/robustness

First interesting Proofs of Concept developed with some further advanced  
The Functional Avionics chain (e.g. SMART-FDIR). OBSW embedability  
And SMART FA process outlined... but work to do!

The field of Controls/GNC shall and cannot walk alone in this adventure!  
Algos + SW + HW intimately related. We need a truly FA joint effort!

In Orbit Demonstrators to play an important role in adoption of AI for  
Technical and non-technical reasons





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# Thank you

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