arianeGROUP

AUTONOMOUS LAUNCHERS WITH NEXT GENERATION GNC

14th ESA Workshop on Avionics, Data, Control and Software Systems ~ ADCSS2020

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NEXT GENERATION LAUNCHERS

Ariane 6

Versatility

Reusability

Launch on demand

Smart Upper Stage

Space Logistics

Autonomous GNC

CALLISTO

Single launch

Main and auxiliary payloads

Dual launch

Config. 2 payloads

Heavy LEO missions

Large science satellites

LEO constellations

LEO Mega constellations

Single launch

Main and auxiliary payloads

Dual launch

Config

Heavy LEO miss

LEO tellations

LEO Mega constellations

NEW PARADIGM

SPACECRAFT NO MORE EFFORT FOR BEING QUALIFIED FOR ALL LAUNCHERS

GNC CHALLENGES - 1ST STAGE RETURN & LANDING

- Dissipate **energy**
- Minimize **consumption**
- Control **dispersions**
- Achieve **precision** landing

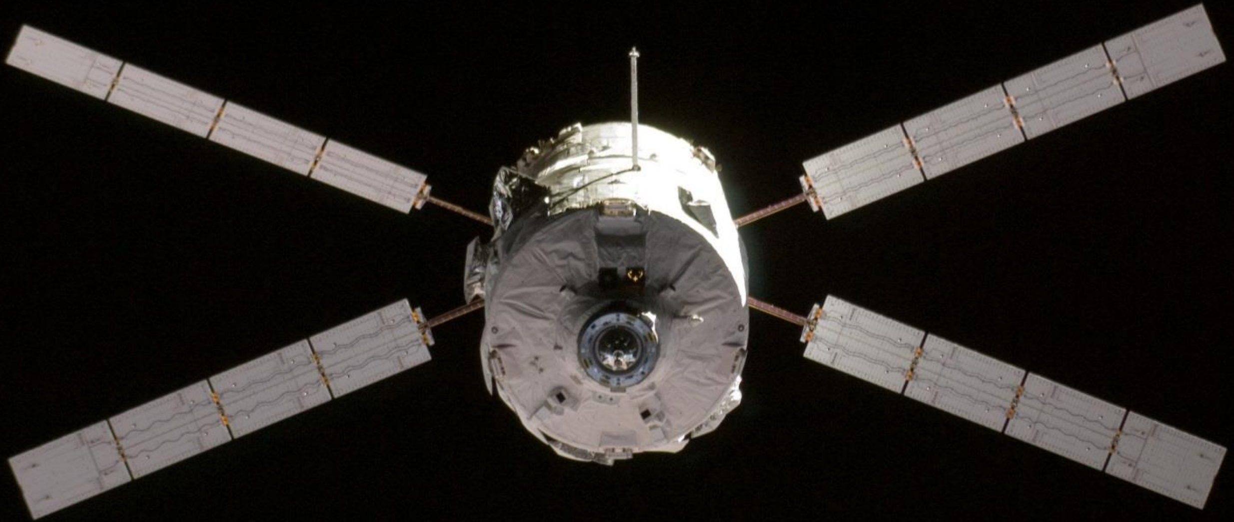
  with **low velocity**

  and **low maneuverability**

WHAT IS AUTONOMY ?

freedom, liberty, sovereignty, self-government, independence, self-rule, self-determination, self-sufficiency, home rule

AUTOMATED → AUTONOMOUS



BEYOND ATV

GNC AUTONOMY IN SPACE

Ability to succeed given complexity
Combination of knowledge based and learning capacities

LESS	MORE
Mission preparation	Perceive/Decide/Plan
Ground support	Learn
Constraining robustness	FDIR

WHY NOW ?

NEEDS

MEANS

CONTEXT

MEANS

LAUNCHER
AUTONOMOUS GNC

A REALITY

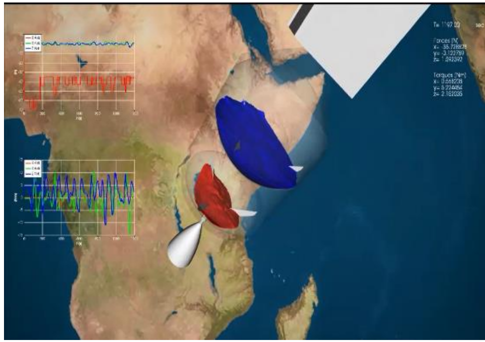
HARDWARE

SENSORS

ENGINES
SMART Upper Stage
&
PROMETHEUS

METHODS
INTELLIGENCE
&
LEARNING

CONCRETE ISSUES



LOADS

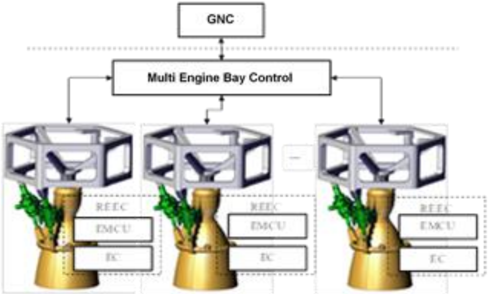
SAFEGUARD

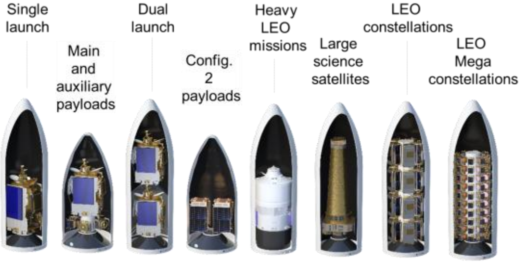
GNC TRENDS

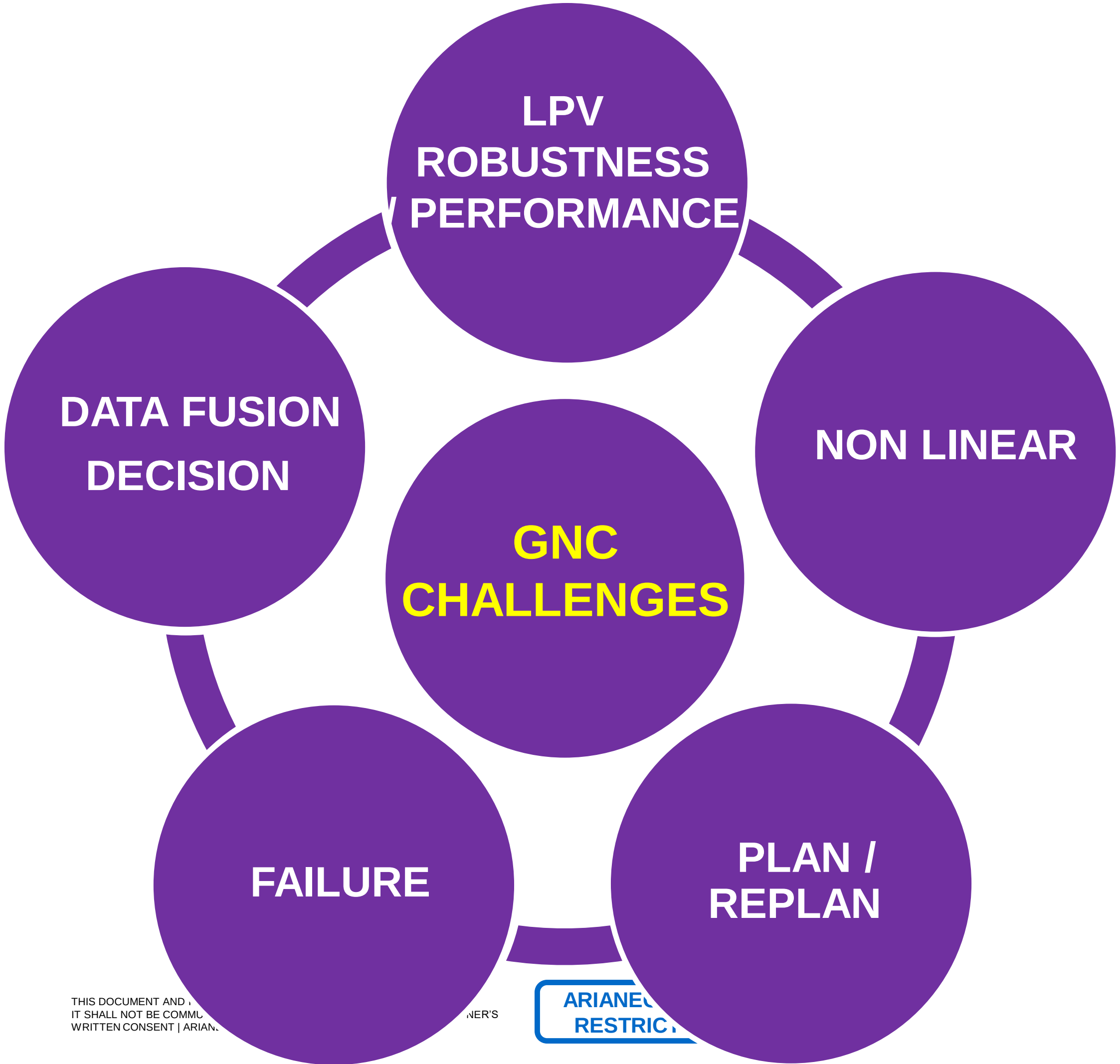
SLOSHING

REUSE

MISSION





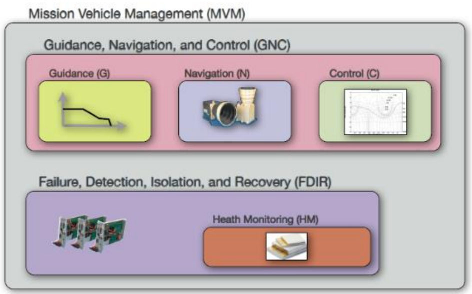

LPV
ROBUSTNESS
PERFORMANCE
NON LINEAR
PLAN /
REPLAN
FAILURE
DATA FUSION
DECISION
GNC
CHALLENGES

LEARN FROM LEARNING

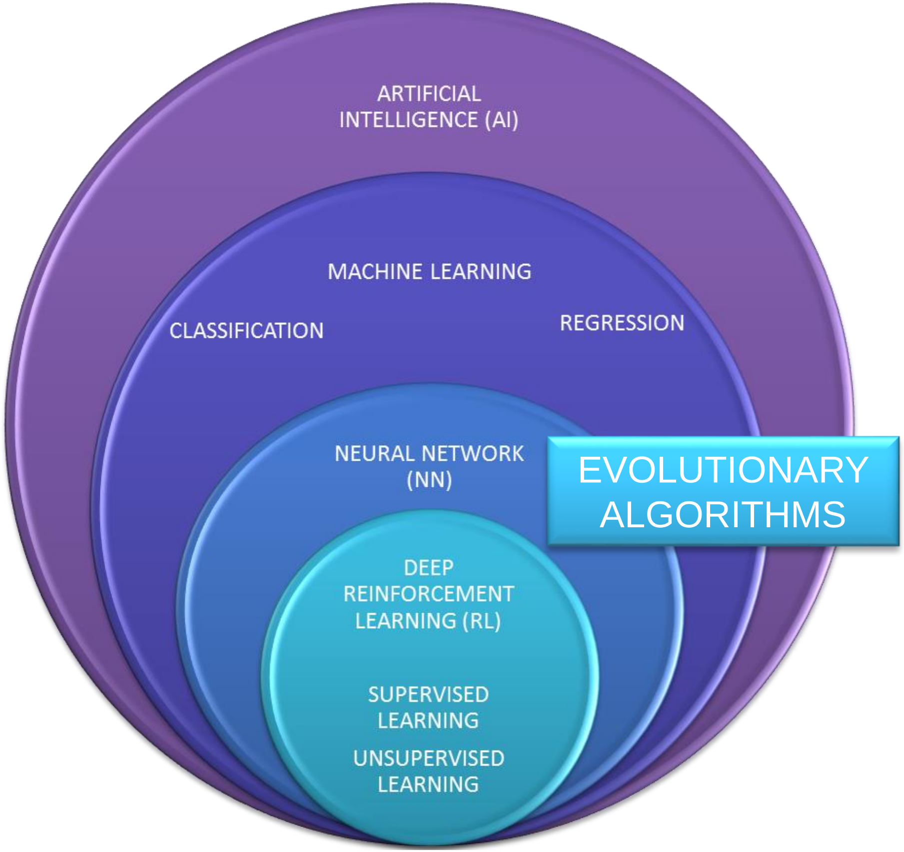
HOW TO USE AI TO DESIGN AND ANALYZE GNC SYSTEMS?

MACHINE LEARNING

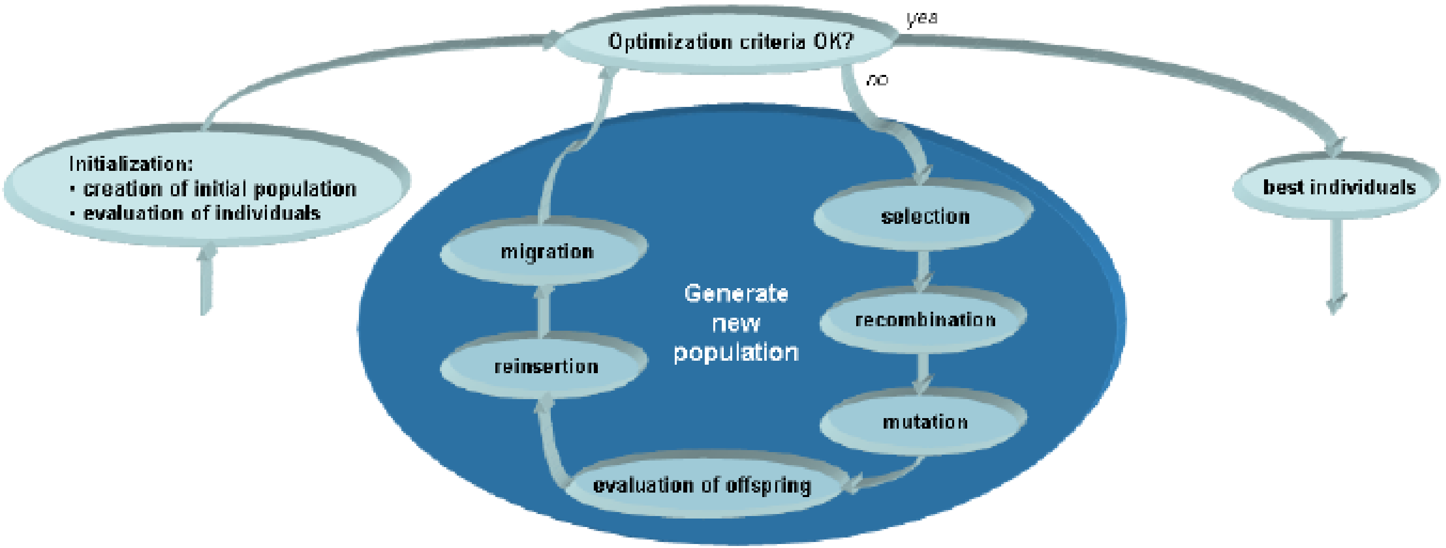
- NEED DEDICATED GPU CCOMPUTERS
- DATA ANALYSIS
- GNC
  - ADAPTIVE/ NON LINEAR CONTROL
  - ESTIMATION
  - PLANIFICATION
- MODELING/FDIR
  - MULTI ENGINE BAY
- SPECIFICATION/VALIDATION



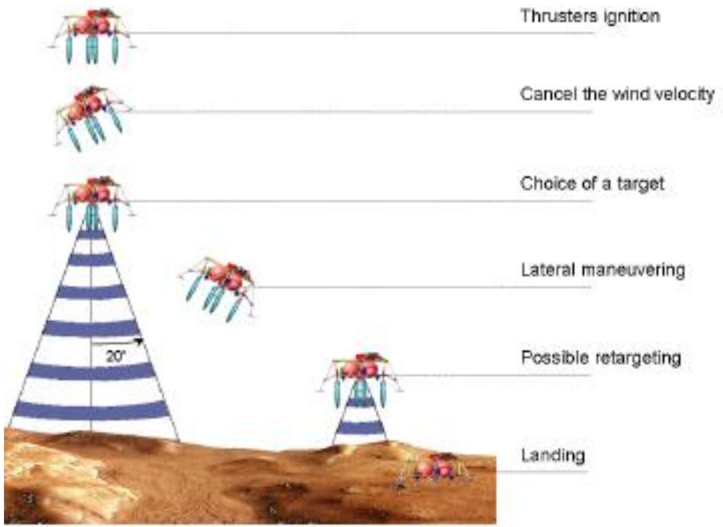
MACHINE LEARNING FOR GNC



GENETIC ALGORITHM EXAMPLE FOR LANDING GUIDANCE



NN TRAINED BY GA



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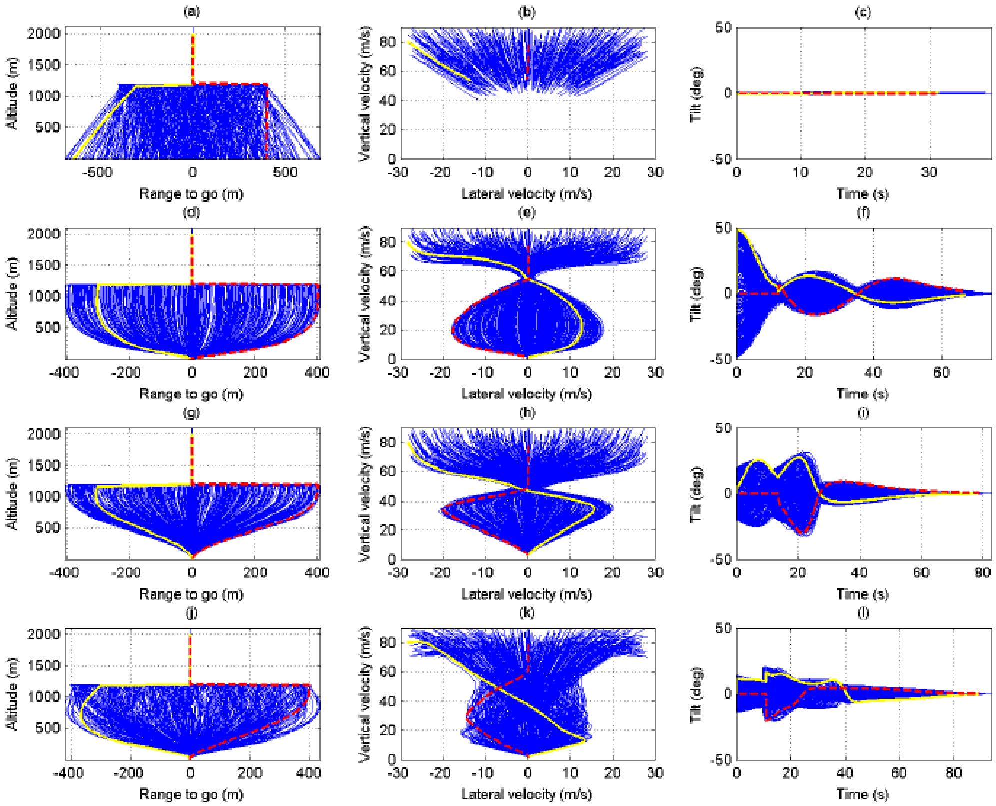
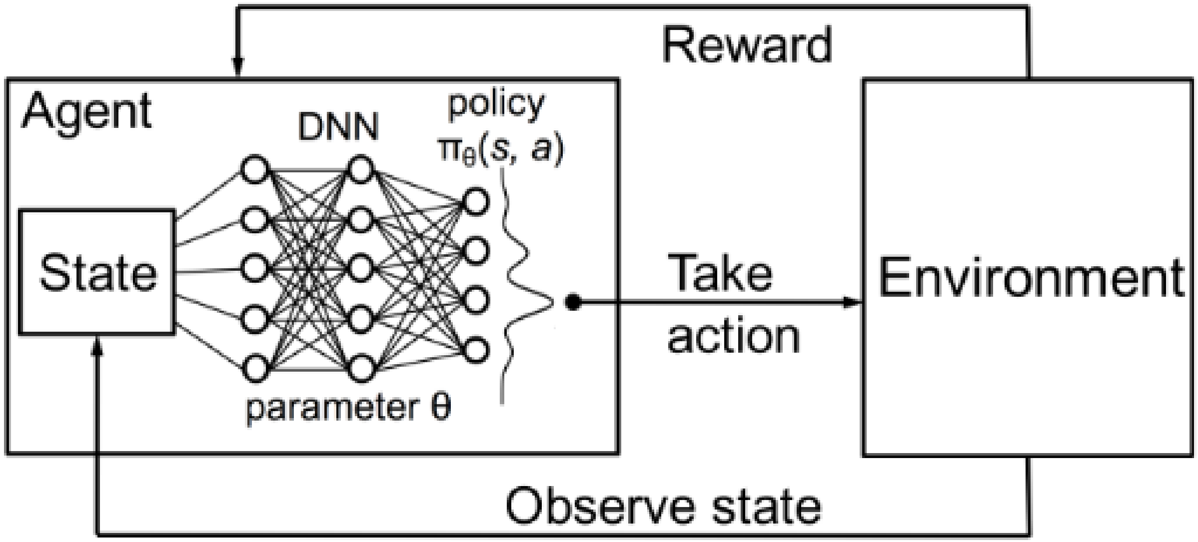


Figure 6. Training of the "low tilt" neural guidance with genetic algorithms. (a, b, c) Position evolution, velocity evolution and commanded tilt of the vehicle after 1 generation. (d, e, f) Position evolution, velocity evolution and commanded tilt of the vehicle after 50 generations. (g, h, i) Position evolution, velocity evolution and commanded tilt of the vehicle after 300 generations. (j, k, l) Position evolution, velocity evolution and commanded tilt of the vehicle after 600 generations.

REINFORCEMENT LEARNING GENERAL PRINCIPLE



LINK WITH CONTROL THEORY

RL	Control
Agent	Controller (K)
Environment	Controlled system (simulator G)
Action	Control signal (U)
State/Observations	State (X) /Measurements (Y)

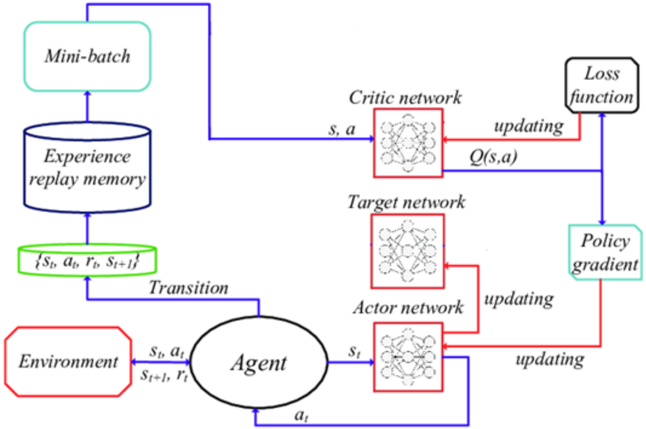
The most important feature distinguishing RL from other types of learning is that it uses information that **evaluates in real time the actions taken** rather than instructs by giving the correct actions.

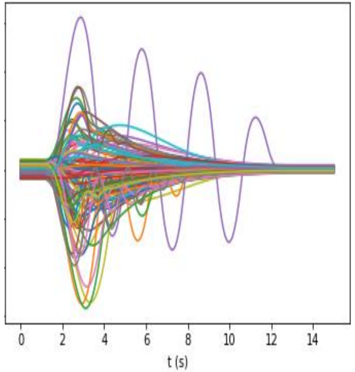
KERAS-RL ALGORITHMS

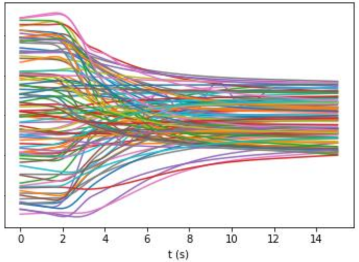
As of today, the following algorithms have been implemented:

- [x] Deep Q Learning (DQN) [1], [2]
- [x] Double DQN [3]
- [x] Deep Deterministic Policy Gradient (DDPG) [4]
- [x] Continuous DQN (CDQN or NAF) [6]
- [x] Cross-Entropy Method (CEM) [7], [8]
- [x] Dueling network DQN (Dueling DQN) [9]
- [x] Deep SARSA [10]
- [ ] Asynchronous Advantage Actor-Critic (A3C) [5]
- [ ] Proximal Policy Optimization Algorithms (PPO) [11]

NON LINEAR CONTROL – QUICK WINS EXAMPLE

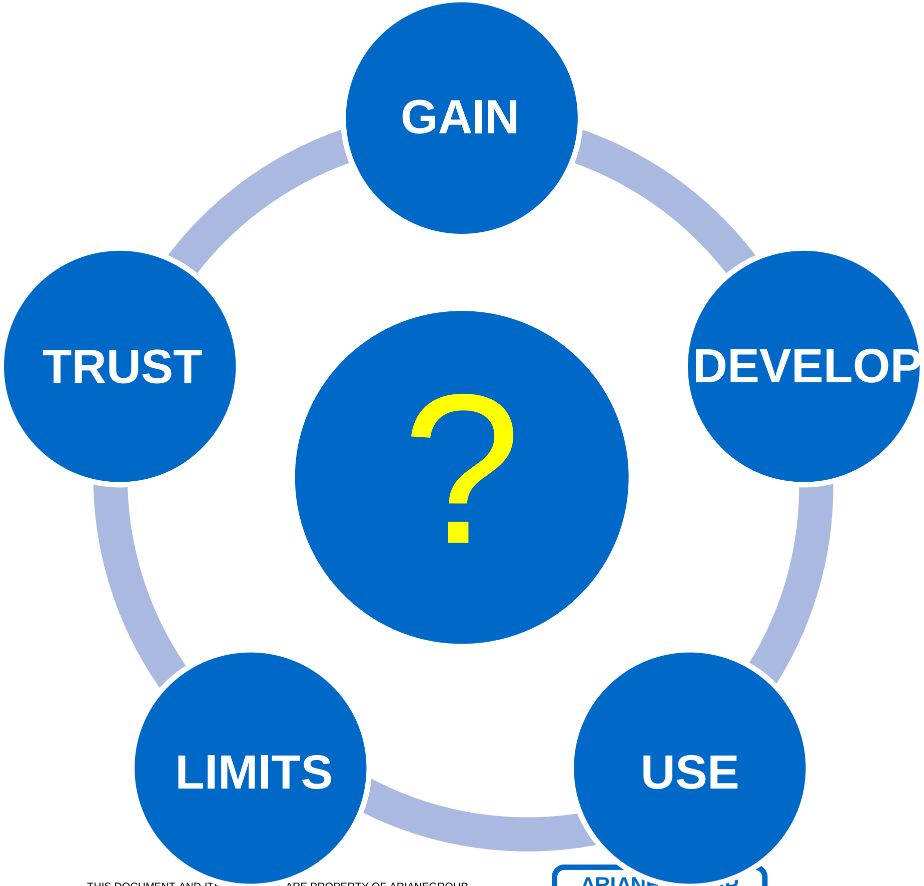






Acknowledgments for AIRBUS group fruitful exchanges

WE SHALL USE ALL NEW TECHNOLOGIES



AND USE THEM WELL