# Exploring the Dynamics of Reinforcement Learning in Aerospace Control

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## JRC ISIA

#### Autonomous agents

Process optimization

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- Autonomous agents
- Process optimization

## AI4Green

- Process optimization
- Energy efficiency and cost reduction



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## What test system?



#### Requirements

- Mechatronic system
- Multiple inputs / Multiple outputs
- Non-linear system
- System model can be derived



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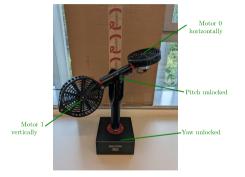


Figure: Aero 2 system (https://quanser.com)

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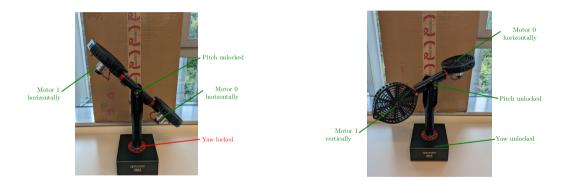


Figure: 1 degree-of-freedom (DOF) - Pitch control (one input  $u = u_0 = -u_1$ , one output  $y = \Theta$ )

Figure: 2 DOF - Yaw and Pitch control (two inputs, two outputs)



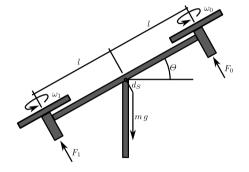


Figure: 1 DOF - Pitch control (one input  $u = u_0 = -u_1$ , one output  $y = \Theta$ )

- 1 DOF configuration, controlled variable y: pitch-angle, manipulated variable u: fan voltage (u<sub>0</sub> = -u<sub>1</sub> = u)
- Thrusters:  $F_i \approx k \cdot u_i$

Beam:

$$\frac{d\Theta}{dt} = \omega$$

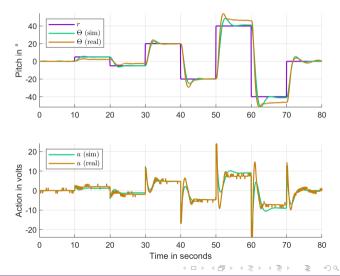
$$J_{p}\frac{d\omega}{dt} = \underbrace{(F_{0} - F_{1})I}_{2 k \mu I} - D_{p}\omega - mg d_{S} \sin(\Theta)$$

Baseline



## Model Predictive Control

- works well in simulation
- steady state deviation on real system, depending on angle
- Can we obtain similar results via Reinforcement Learning?





Problem Formulation

Orient the beam to a desired angle (r) by applying a voltage (u and -u) to the motors.



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- Action: Voltage applied to the motors (u)
- **State**: Distance to the desired angle  $(\Delta = \Theta r)$  and the current angular velocity  $(\omega = \dot{\Theta})$
- **Reward**: Negative absolute distance to the desired angle  $(-|\Delta|)$



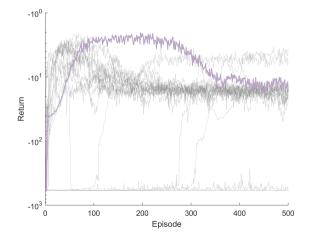
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- Agent: Proximal Policy Optimization (PPO)

# RL Training Runs (constant r)





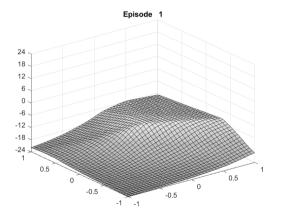
## **Configurations:**

- 20 runs
- $ightarrow r = 10^{\circ}$
- Episode length = 60s

Sample time = 0.1s

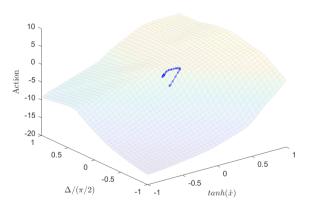
# **Result:** Max(Return) = -2.13 $|-2.13| \cdot \frac{180}{\pi} = 0.64^{\circ}$



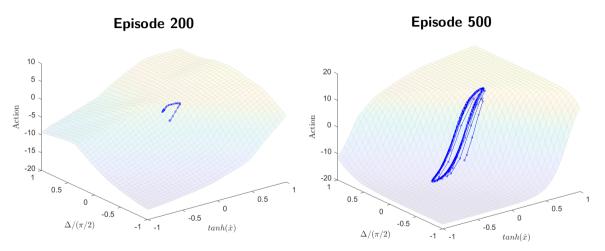




Episode 200



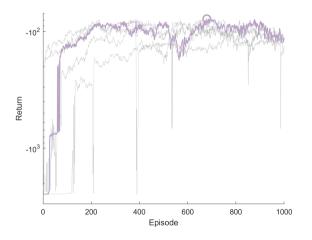




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# RL Training Runs (dynamic r)



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## **Configurations:**

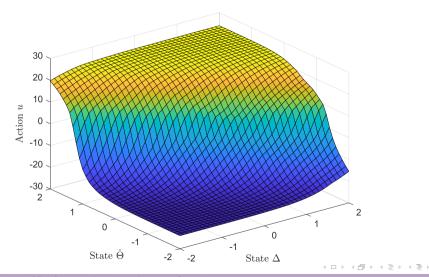
- 5 runs
- $\blacktriangleright r = [0, -5, 5, 20, -20, 40, -40]$
- r changes every 10s
- Episode length = 80s
- ▶ Sample time = 0.1s

## **Result:**

max(Return) = -77.93
$$\frac{|-77.93|}{800} \cdot \frac{180}{\pi} = 5.6^{\circ}$$

# Policy Evaluation (dynamic r)

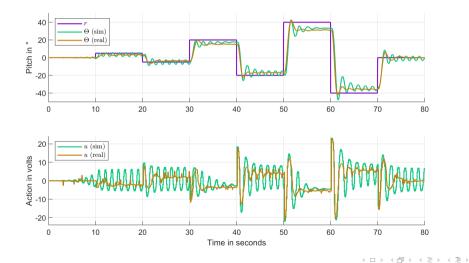




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Test Runs





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## Results

Using RL we can achieve a similar performance as with the MPC controller.

## Outlook

- Detailed comparison to well established controller like MPC
- Adaptations in state space
- Extension to 2 DOF system