AEROBRAKING AT MARS: A Machine Learning Implementation

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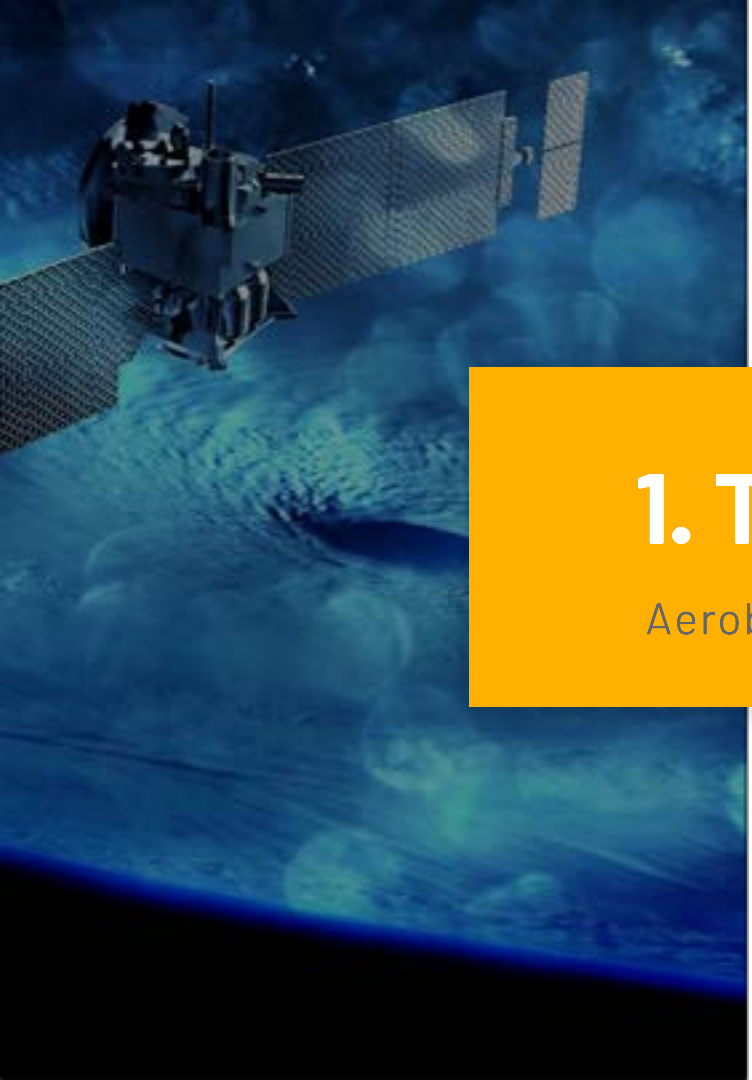


1. THE CONCEPT

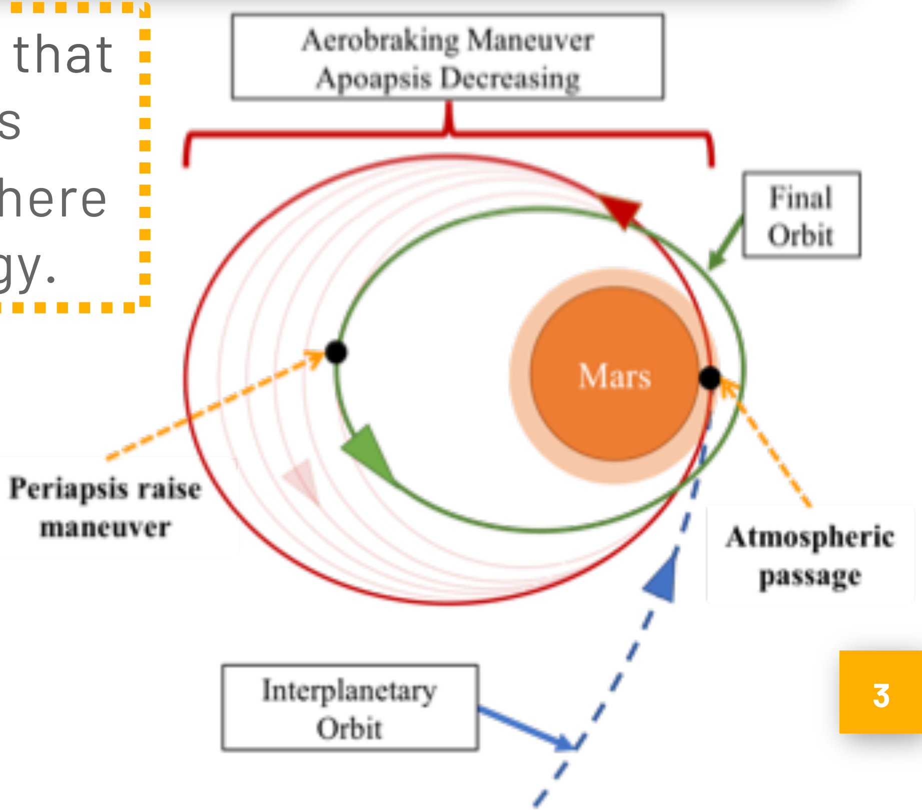
Aerobraking, Autonomy, Goal & Challenges

AEROBRAKING

Aerobraking is a maneuver that uses successive passes through the upper atmosphere to dissipate orbital energy.

Creation of drag is a function of velocity and flight-path angle

Propulsive maneuvers at apoapsis control velocity and flight-path angle



IMPORTANCE OF AEROBRAKING & AUTONOMY

Benefits and Costs

Massive propellant saving WRT single propulsive maneuver at the expense of risk caused by variability in atmospheric density (**heat rate & dynamic pressure**)

Successfully performed for three Mars missions:

- Mars Global Surveyor (1996)
- Mars Odyssey (2001)
- Mars Reconnaissance Orbiter (2005)

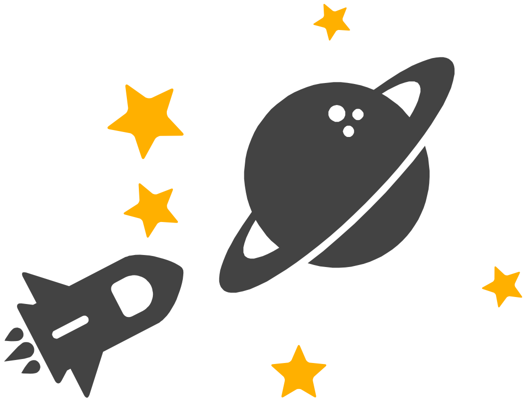
Importance of Autonomy

Ground cost, a team of engineers always-online, less aggressive conditions (more when orbital period decreases)

Previous efforts to address these issues with autonomy:

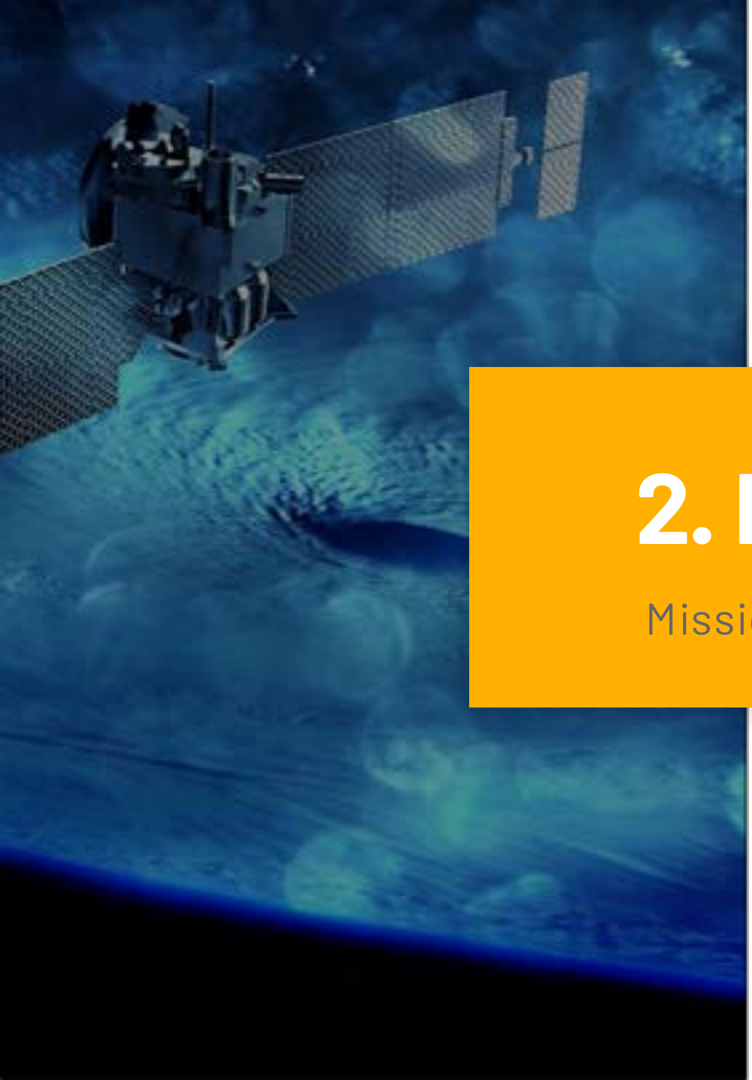
Aerobraking Autonomous Control (1999-2012)

GOAL AND CHALLENGES



Perform a complete and successful autonomous aerobraking campaign at Mars with a learning and adaptive behavior approach while:

1. Satisfying constraints on dynamic pressure and heat rate
2. Managing mission risk
3. Minimizing control effort and time of flight (**cost**)



2. PROBLEM FORMULATION

Mission Modeling, Reinforcement Learning and Interface

AEROBRAKING MISSION MODELING

Aerobraking mission: vary periapsis altitude to lower apoapsis altitude while satisfying constraints

r_{ao}

r_{pi}

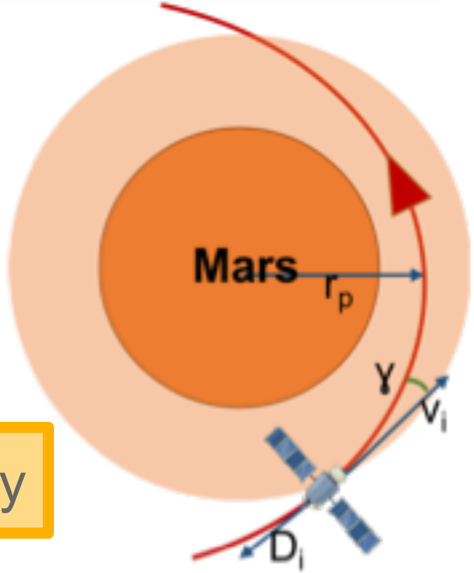
Keplerian Trajectory Simulator

v_i, fpa_i

Aeroassist Simulation

r_{ai}, dp_i, hr_i

Autonomy



REINFORCEMENT LEARNING

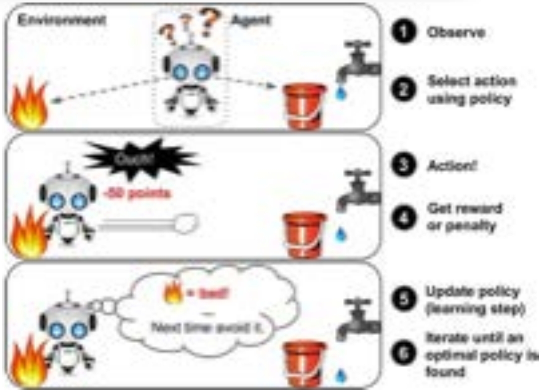
Tabular Q-Learning Algorithm with ε-greedy policy search

$$<S, A, P^{a}_{ss'}, R^{a}_{ss'}, \gamma>$$

S = apoapsis radius

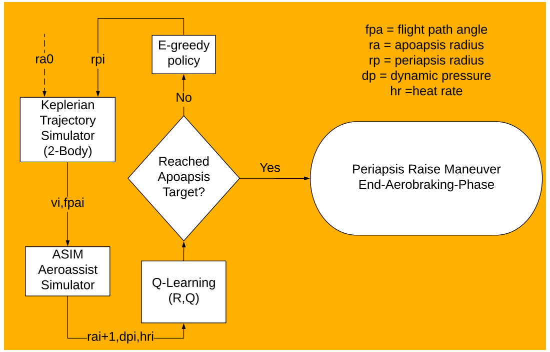
A = periapsis altitude

$R^{a}_{ss'}$ =reward built to minimize the aerobraking whole time.

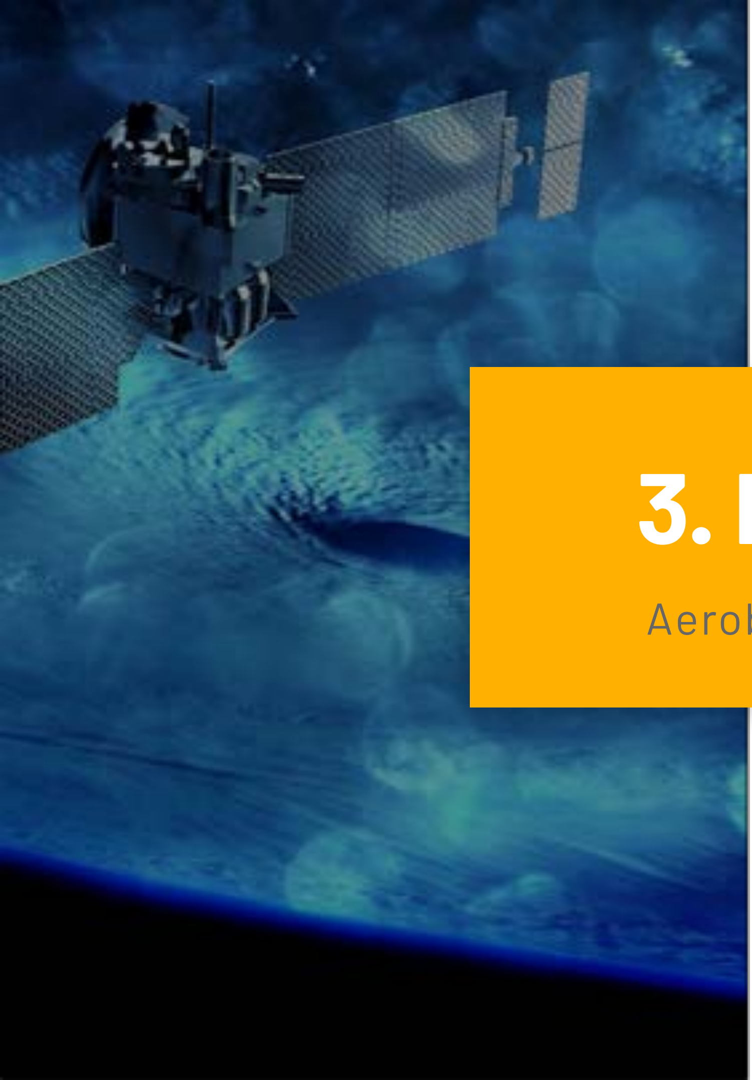


“ **Reinforcement learning is learning what to do...so as to maximize a numerical reward signal. (Sutton)**

INTERFACE BETWEEN MISSION AND RL



A trained policy chooses when perform a trim maneuver to minimize the aerobraking time and to avoid the violating constraints.



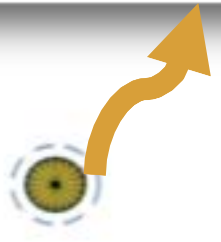
3. RESULTS

Aerobraking Simulation, Constraints & Corridor, Learning

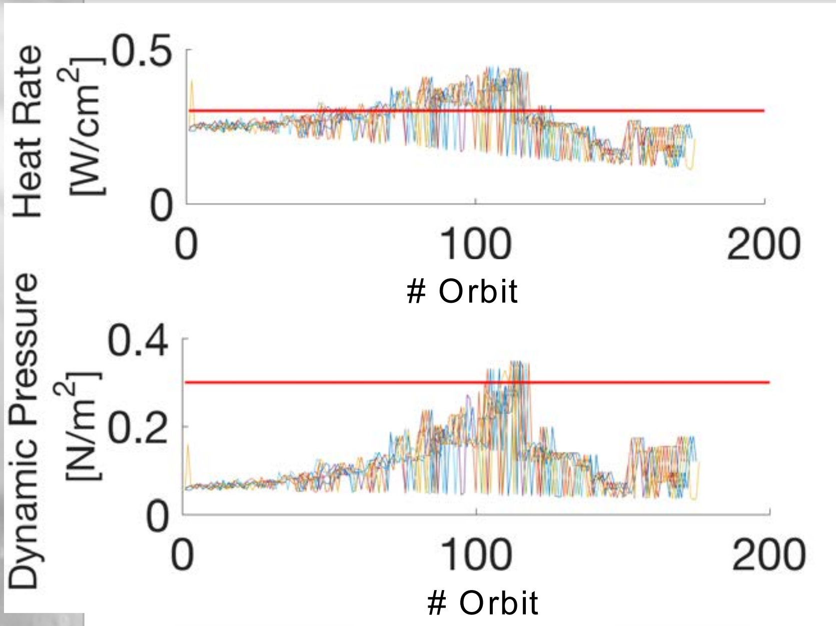
AEROBRAKING SIMULATION

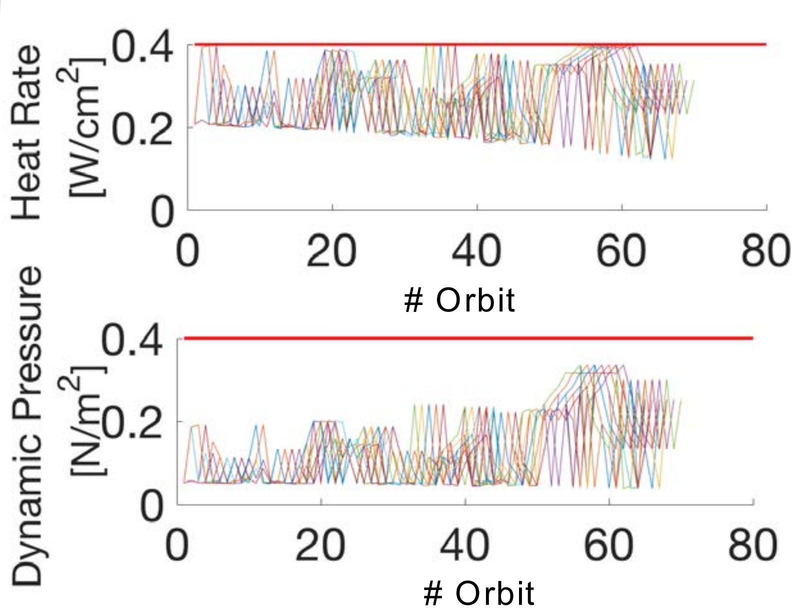
Apoapsis radius from 200,000 km to 5,000 km

PERIAPSIS



CONSTRAINTS AND CORRIDOR

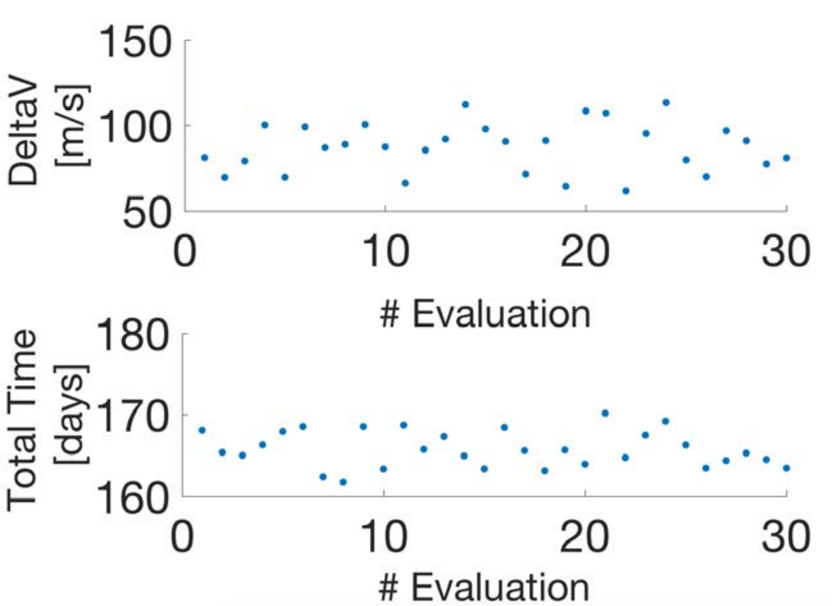


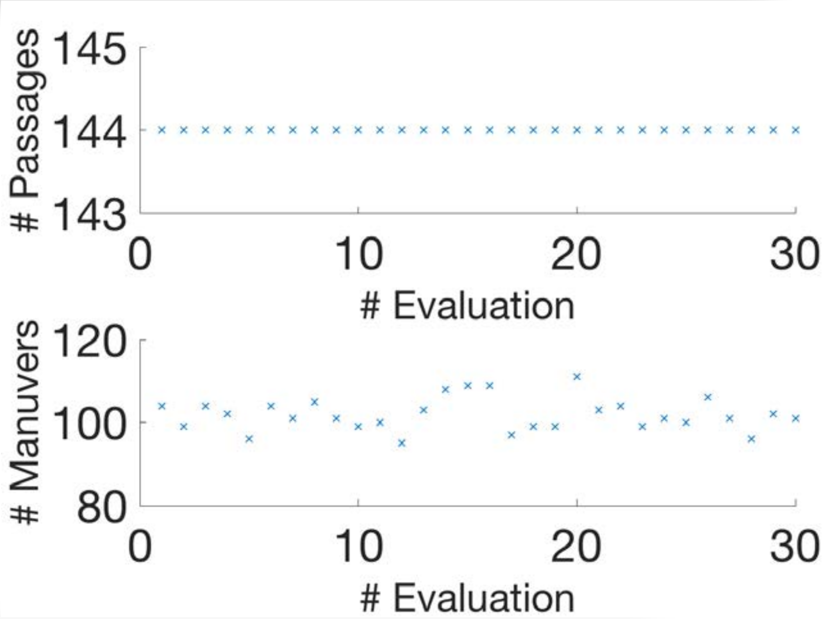


NOT TRAINED MACHINE

TRAINED MACHINE

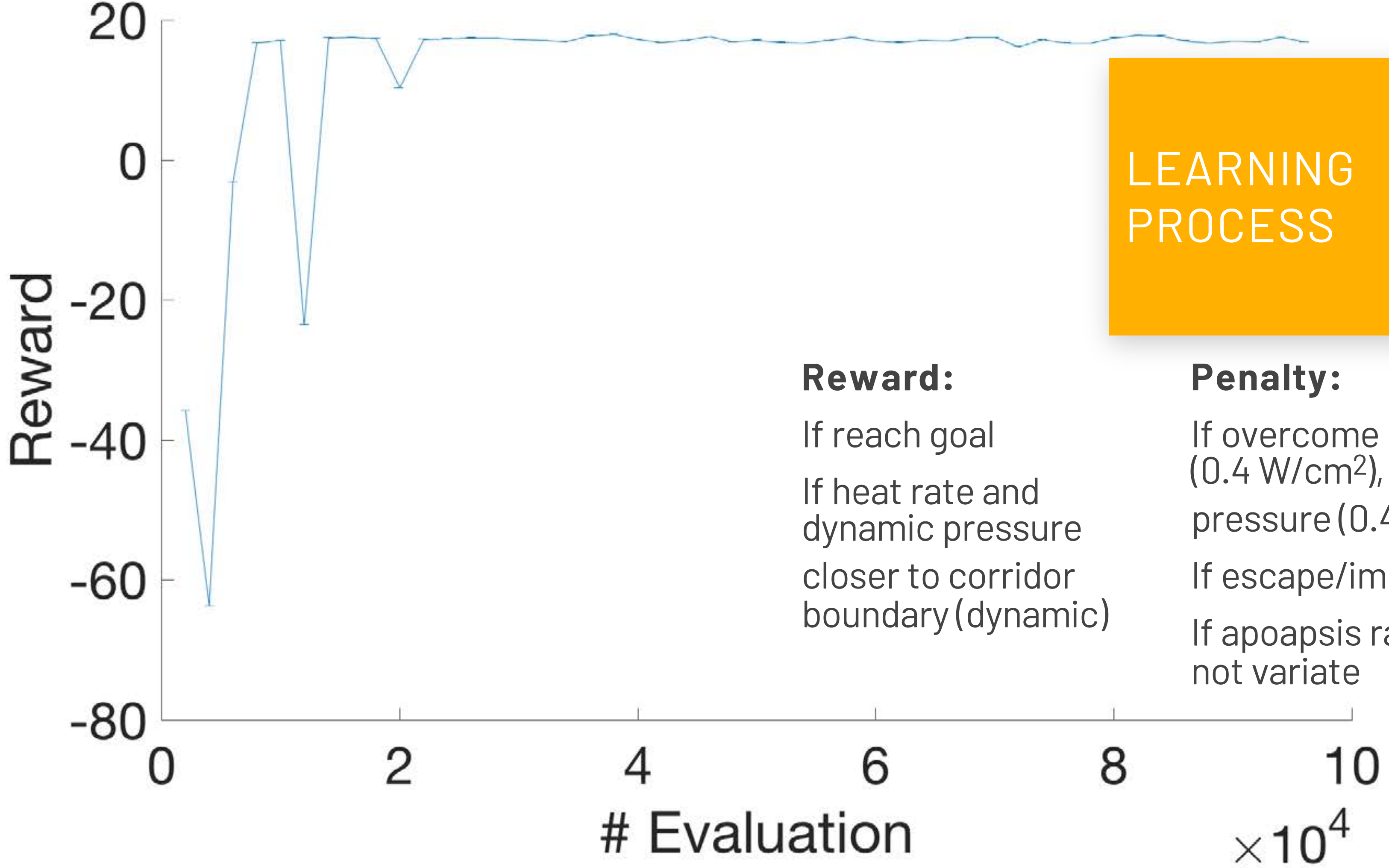
RESULTS DELTA-V AND TOTAL TIME





REWARD FUNCTION DECREASES ONLY TOTAL TIME

LEARNING PROCESS



Reward:

If reach goal

If heat rate and dynamic pressure closer to corridor boundary (dynamic)

Penalty:

If overcome heat rate (0.4 W/cm^2), dynamic pressure (0.4 N/m^2)

If escape/impact

If apoapsis radius does not variate

THANKS!

Any questions?

You can find me at:

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MISSION DESIGN CHARACTERISTICS

Small Satellite

Mass: 110 kg

Drag Area: 10 m^2

C_D: 1.2

Keplerian Trajectory Simulator (2-bodies)

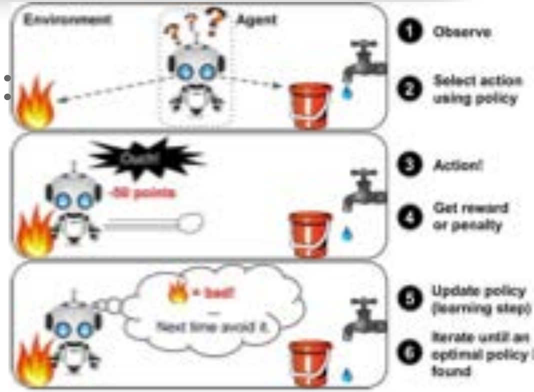
$$\ddot{r} - r\dot{\vartheta}^2 = -\frac{\mu}{r}$$

Aeroassist Simulator

3 DOF equations of motion. Numeric simulation integrated using a forth order Runge-Kutta scheme.

Density model: Mars-Gram 2010

REINFORCEMENT LEARNING



Markov Decision Process (stochastic):

<S, A,P $^{a}_{ss'}$, R $^{a}_{ss'}$, γ >

S = state space (apoapsis radius)

A = action space (periapsis altitude)

P $^{a}_{ss}$ ==probability of getting into s′ after a from s

R $^{a}_{ss'}$ =expected reward from s to s′ after a

Find policy π^* through iteration Bellman eq.

$$Q^*(s,a) = \sum_{s' \in S} P_{ss'}^{\pi(s)}\left[R_{ss'}^{a} + \gamma max_{a'} Q^*(s',a')\right]$$

MDP

STATE SPACE

Apoapsis radius

From 4000 to 400000 km.

981 states.

ACTION SPACE

Periapsis altitude

From 105 to 127 km.

147 states.

REWARD FUNCTION

Reward:

Reach goal.

If closer to corridor boundary (dynamic).

Penalty:

Overcome heat rate (0.4 W/cm^2), dynamic pressure (0.4 N/m^2).

Escape/Impact.

If apoapsis radius does not variate.

Q-LEARNING ALGORITHM

Algorithm 5: Q-Learning	Complexity
Input: MDP $\setminus \{\mathcal{P}, \mathcal{R}\}, \alpha, \epsilon$	
Output: π	
$\boldsymbol{\theta} \leftarrow$ Initialize arbitrarily	
$\langle s, a \rangle \leftarrow \langle s_0, \pi^{\epsilon}(s_0) \rangle$	
while *time left* **do**	
Take action a and receive reward r and next state s'	
$Q^{+}(s, a) \leftarrow r + \gamma \max_{a'} Q(s', a')$	$\mathcal{O}(n\|\mathcal{A}\|)$
$\delta \leftarrow Q^{+}(s, a) - Q(s, a)$	
$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha \delta \phi(s, a)$	$\mathcal{O}(n)$
$\langle s, a \rangle \leftarrow \langle s', \pi^{\epsilon}(s') \rangle$	$\mathcal{O}(n\|\mathcal{A}\|)$
return π greedy w.r.t. Q	

Off-policy and model free algorithm

ε-GREEDY POLICY SEARCH

ε-greedy policy spans between exploration and exploitation:

- With probability 1- ε, uses the greedy action:

$$a_i = \arg\max_a \hat{Q}(s_i, a)$$

- With probability ε, play random action.