2021 Clean Space Industrial Days

AI-aided Guidance and Navigation for Dynamics Reconstruction of Uncooperative Spacecraft

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POLITECNICO MILANO 1863

DIPARTIMENTO DI SCIENZE E TECNOLOGIE AEROSPAZIALI

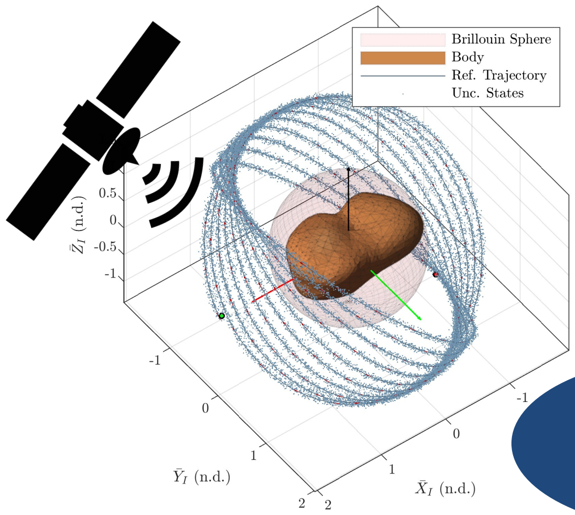
Advanced Space Technologies for Robotics and Astrodynamics

Outline

- Research Context & Motivation
- Research Objective and Methodology
- Neural Dynamics Learning & Navigation
- Neural-aided Guidance & Control
- Environment and External Agents Prediction
- Final remarks

Research Context & Motivation:
Proximity Operations and Relative Dynamics

Proximity Operations for debris removal



Exploration missions

- **Proximity Operations** allows daring mission objectives (close proximity with asteroids, planets, etc.)

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Challenging flight conditions due to **distances involved** and **uncertain environment**

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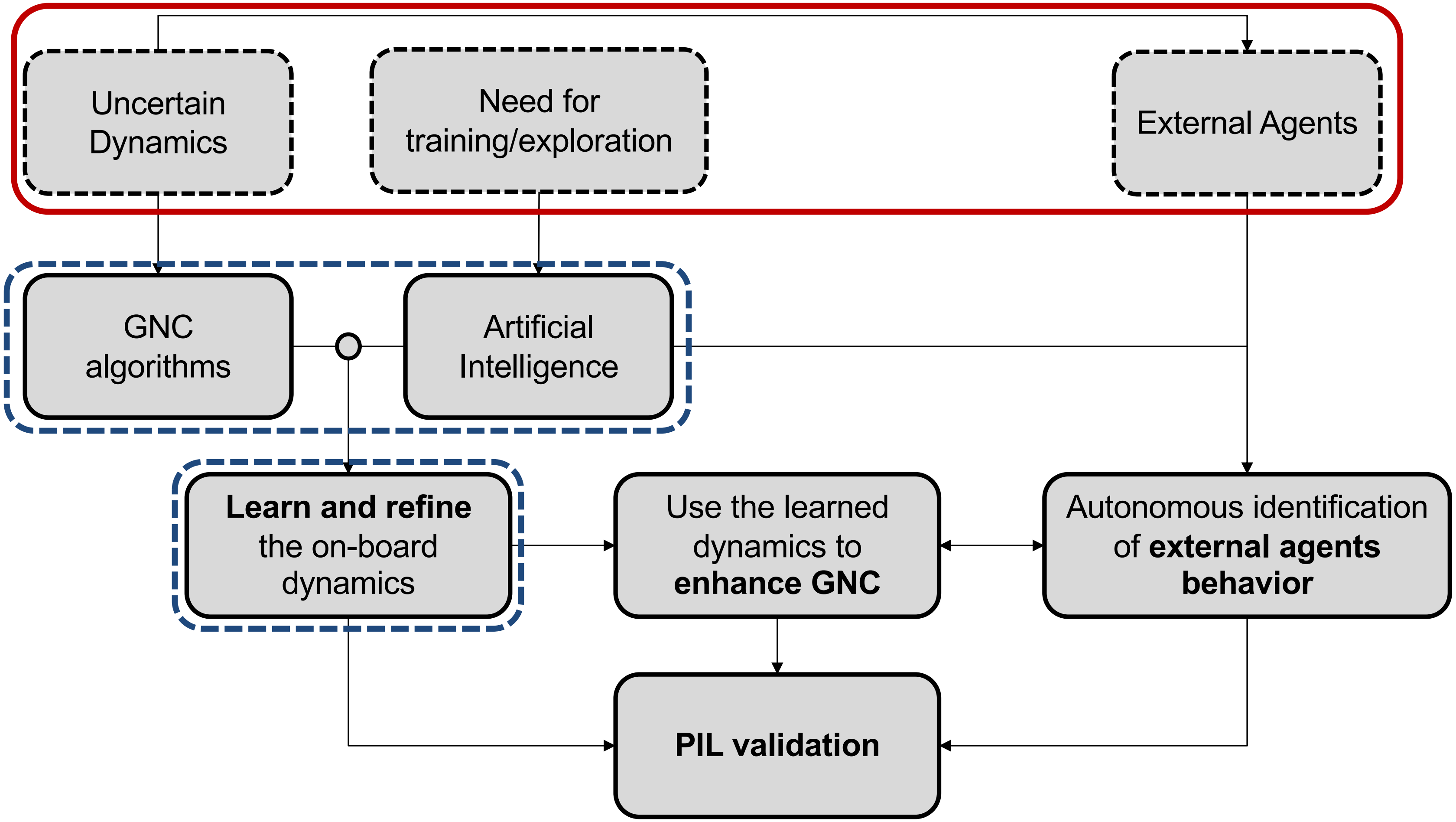
Need for accurate, flexible, adaptive and light GNC algorithm

Research Objectives

Research methods:

framework and drivers



Neural Dynamics Learning & Navigation:
Dynamics Reconstruction

Learn and refine the on-board dynamics

$$\dot{\mathbf{x}} = \boxed{\mathcal{N}(\mathbf{x}, \mathbf{u})} \qquad \dot{\mathbf{x}} = A\mathbf{x} + \boxed{\gamma(\mathbf{x}, \mathbf{u})} \qquad \mathbf{y} = A(\mathbf{x}) \cdot \boxed{\mathbf{C}}$$

The dynamics reconstruction can be performed in three ways:

1. **Neural Dynamics**: Fully encapsulated in a NN → very powerful when RNN are used, need rough initialization

2. **Neural Disturbance Reconstruction**: Analytical models refined with disturbance approximation output of the NN → robust due to Lyapunov convergence RBFNN when dealing with uncertain disturbance

3. **Neural Parameter Identification**: Parameter estimation of given analytical models → suitable when only parameters are uncertain

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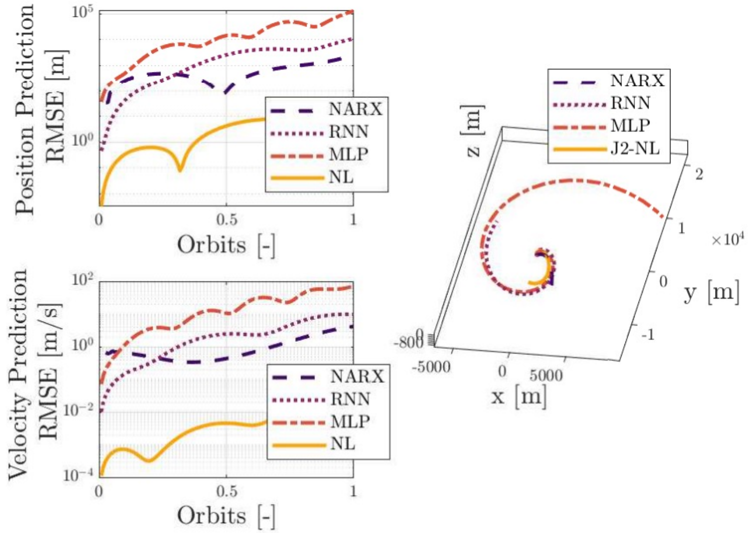
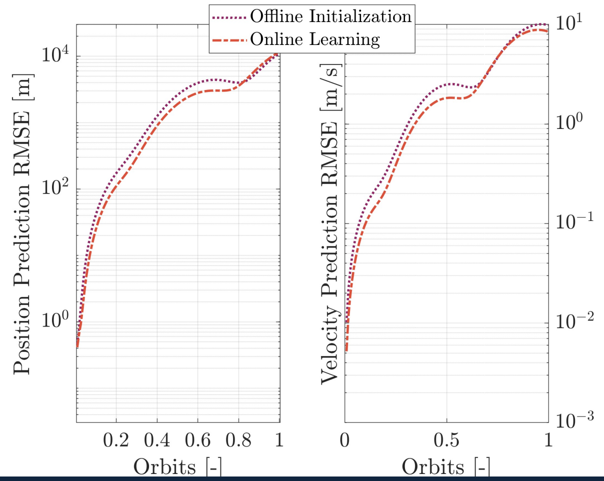
Neural Dynamics Learning & Navigation: Fully-Neural Dynamics



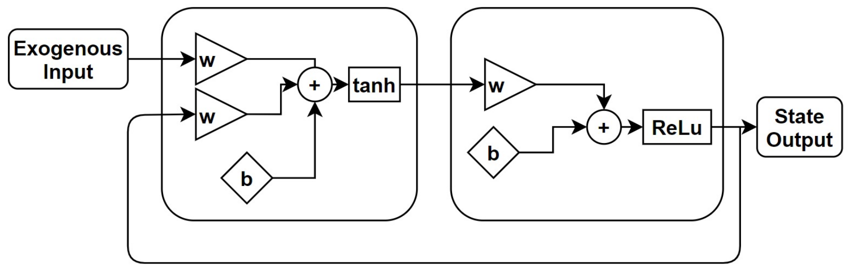


Neural Network is trained with supervised learning using **measurements** as training data:

$$\min_{\mathbf{w}} \sum_i ||\tilde{\mathcal{N}}_{T_s}(\mathbf{x},\mathbf{u},\mathbf{w}) - \mathbf{y}_{k+1}||^2$$

Online learning refines and **incrementally train** the network

Recurrent Neural Networks catches **temporal and secular behavior** → more suitable to fully encapsulate the dynamics



It explicitly recalls the **forced** dynamics

Neural Dynamics Learning & Navigation:
Dynamics Reconstruction

Learn and refine the on-board dynamics

$$\dot{\mathbf{x}} = \mathcal{N}(\mathbf{x}, \mathbf{u}) \qquad \boxed{\dot{\mathbf{x}} = A\mathbf{x} + \gamma(\mathbf{x}, \mathbf{u})} \qquad \mathbf{y} = A(\mathbf{x}) \cdot \mathbf{C}$$

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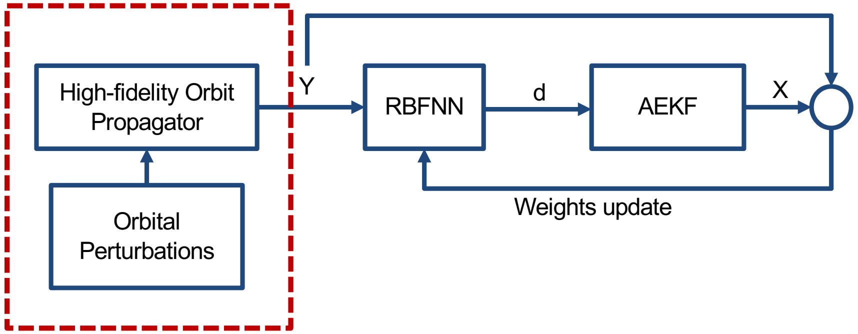
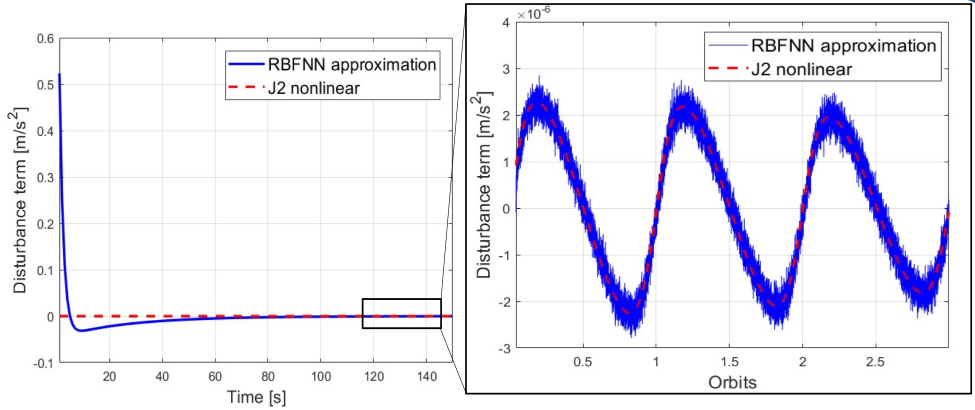
Neural Dynamics Learning & Navigation:
Disturbance Reconstruction

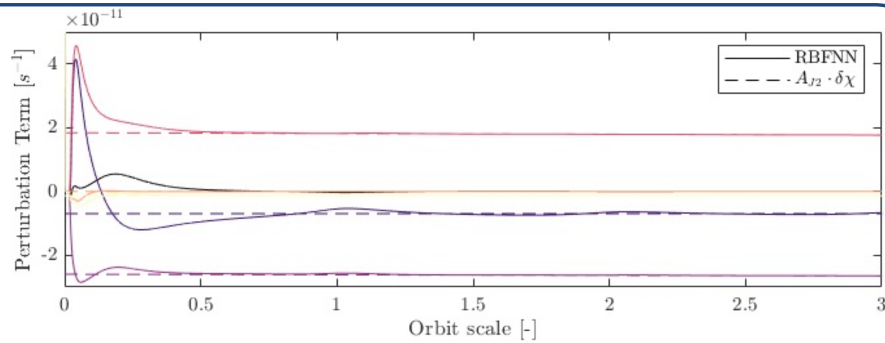


V. Pesce, **S. Silvestrini**, M. Lavagna, Radial Basis Function Neural Network aided Adaptive Extended Kalman Filter for Spacecraft Relative Navigation, Aerospace Science and Technology, vol. 96, 2020

Cartesian dynamics

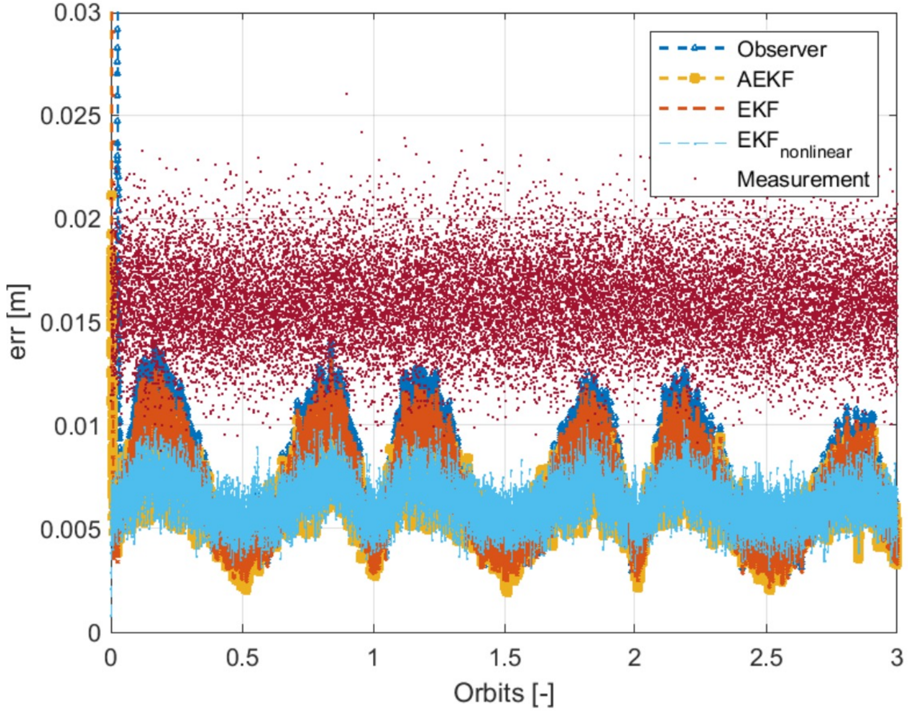


ROE dynamics



***ROE: Relative Orbital Elements**

Neural Dynamics Learning & Navigation:
Disturbance Reconstruction



Pros Adaptive EKF-RBFNN	Cons Adaptive EKF-RBFNN
Higher robustness when filter not tuned	Initial main learning process
Reconstructed perturbations term	Stability guaranteed under certain bounds
Better average accuracy	

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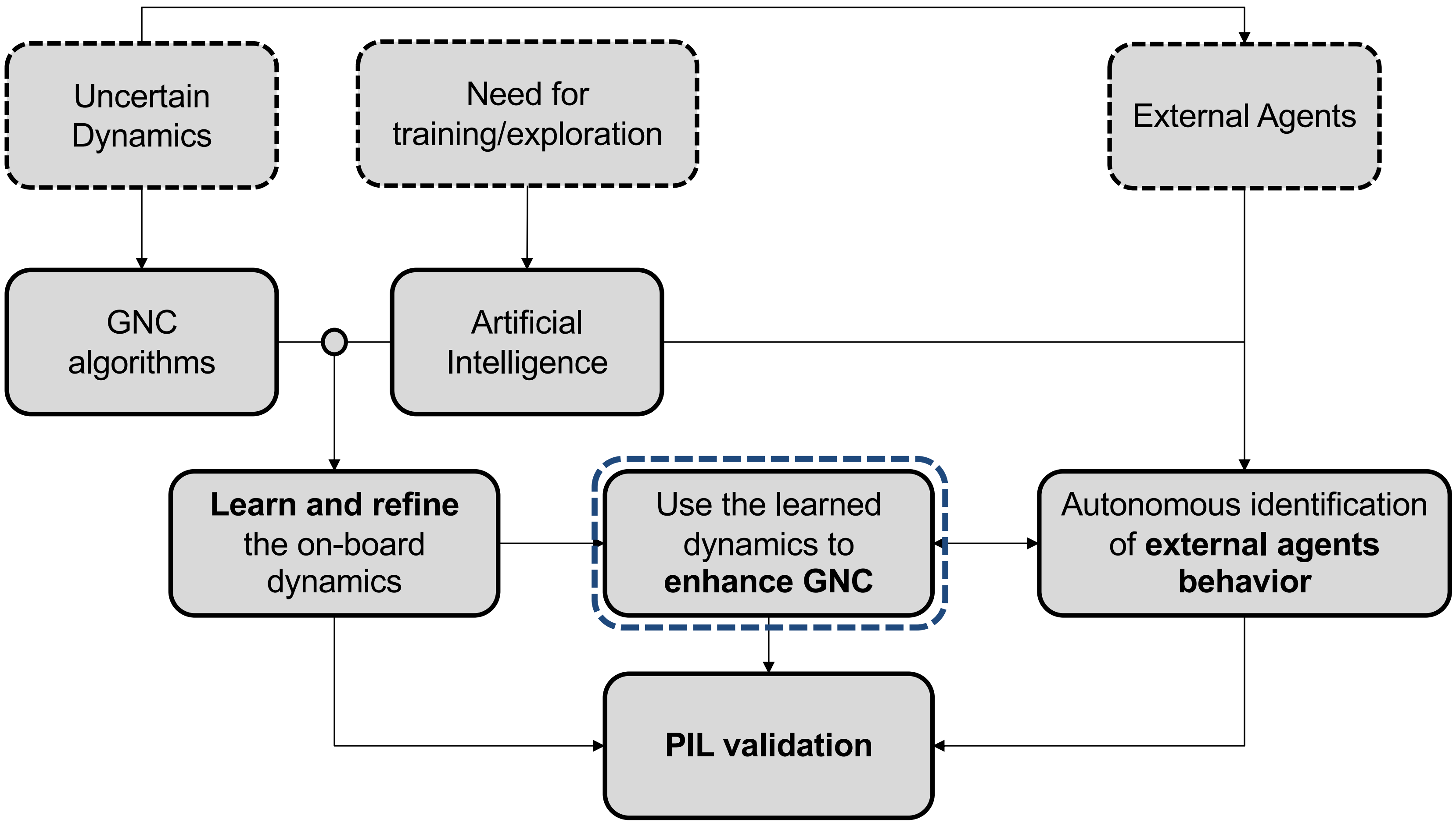
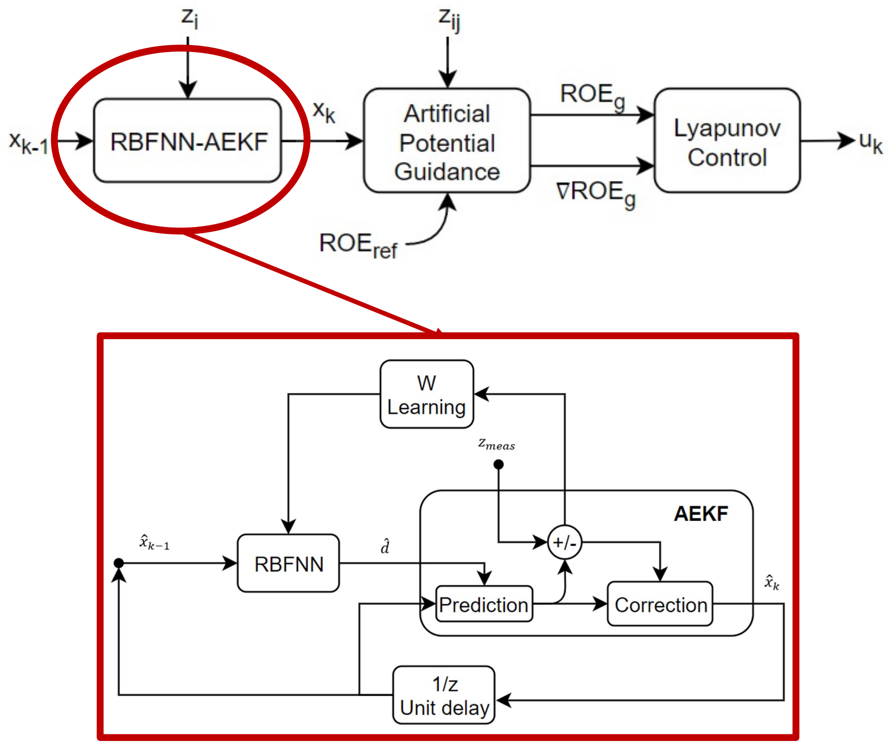
Research Objectives



Neural-aided Guidance & Control:
Radial Basis Function Neural Network - Artificial Potential Field

APF reconfiguration coupled with a **neural controller** based on **reconstructed relative dynamics**



The set of ROE to be achieved are called **reference state** and indicated as $\delta\chi_r$:

$$\Phi_a(\delta\chi) = \frac{1}{2}\xi_a\left\|\delta\chi_g - \delta\chi_r\right\|^2$$

Calculating the gradient:

$$\nabla_{\delta\chi_g} = \xi_a(\delta\chi_g - \delta\chi_r)$$

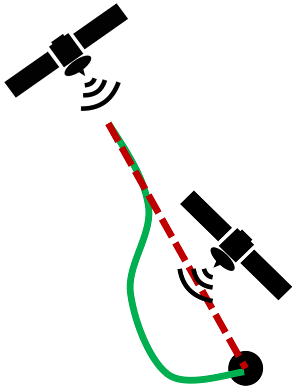
The repulsive potential is useful to calculate the trajectory in presence of other satellites, **avoiding collision between agents**.

$$\Phi_{r_{ij}} = \begin{cases} \frac{1}{2}\xi_r e^{-\frac{d_{ij}^2}{\eta}} = \frac{1}{2}\xi_r e^{-\frac{\left\|\boldsymbol{x_i}-\boldsymbol{x_j}\right\|^2}{\eta}} & \text{if } d_{ij} < d_{lim}, \\ 0 & \text{if } d_{ij} > d_{lim} \end{cases}$$

The gradient of the potential is calculated using the chain-rule, which involves the coordinate transformation from Cartesian state X to ROE:

$$\nabla_{\delta\chi_g}\Phi_{r_{ij}} = -\frac{\xi_r}{\eta}e^{-\frac{d_{ij}^2}{\eta}} \cdot (\boldsymbol{X_i} - \boldsymbol{X_j}) \cdot J_{\delta\chi}^{X}$$

Neural-aided Guidance & Control:
Radial Basis Function Neural Network - Artificial Potential Field



The output of the artificial potential guidance is a set of ROE, which may differ from the target reference ones. **Feedback control law** to guarantee that the **forced guidance dynamics** is followed.

$$\delta\dot{\chi}_{\mathbf{g}} = -\nabla\Phi_{glb} + (\mathbf{A_k} + \mathbf{A_{J2}})\cdot\delta\chi$$

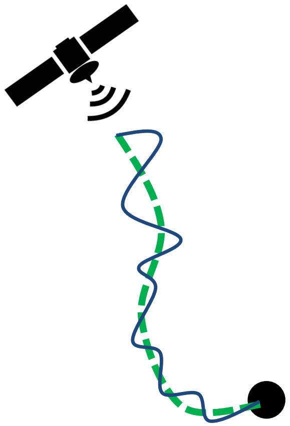
Control Lyapunov function (CLF):

$$\dot{V} = \left(\delta\chi_g - \delta\chi\right)^T \cdot \left[-\left(\nabla\Phi_a + \nabla\Phi_r + \gamma(\delta\chi) + B\mathbf{u}\right)\right]$$

The following control law is derived:

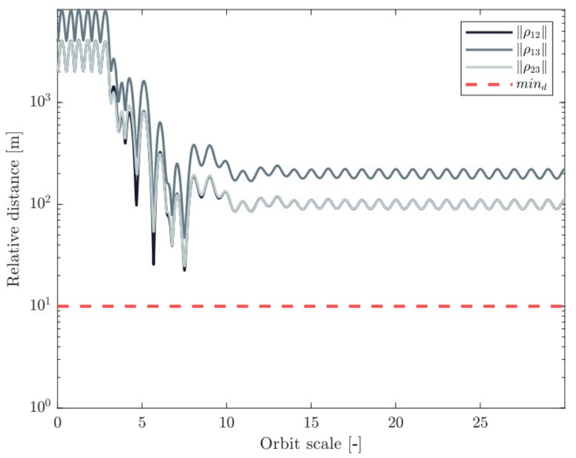
Neural Approximation

$$\mathbf{u} = \mathbf{B}^{-1}\left[\left(\delta\chi_g - \delta\chi\right) - \left(\nabla\Phi_a + \nabla\Phi_r\right) - \gamma(\delta\chi)\right]$$

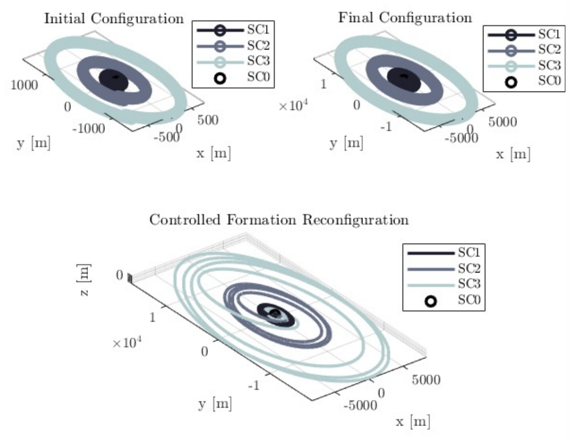


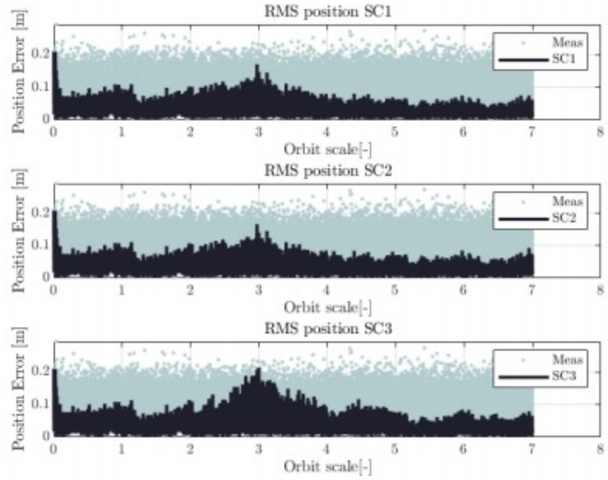
The repulsive potential relies on **mutual relative position**, hence a distributed architecture.

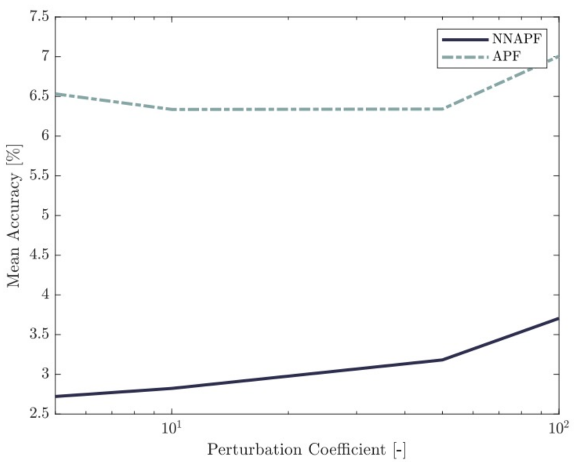
Neural-aided Guidance & Control:
Radial Basis Function Neural Network - Artificial Potential Field Numerical Results



Relative distance **safe** thanks to collision avoidance repulsive contribution







The **higher the perturbation** the better RBFNN-APF performs with respect to APF

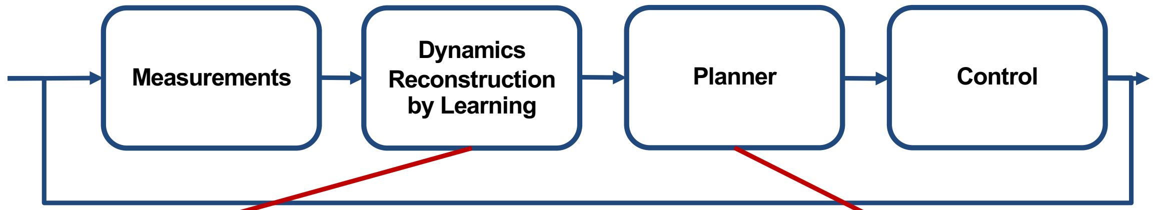
PROS RBFNN-APF	CONS RBFNN-APF
Better control accuracy	Δv < 10 m/s Slightly higher control wrt APF (~ 5%)
Better estimation accuracy	

S. Silvestrini, M. Lavagna, Neural-aided GNC Reconfiguration Algorithm for Distributed Space System: Development and PIL test, Advances in Space Research, vol. 67, 5, 1490-1505, 2021

Neural-aided Guidance & Control

Model-based Reinforcement Learning for Maneuver Planning: Architecture

Use the learned dynamics to **enhance GNC**



Dynamics Reconstruction

- $\dot{x} = N(x, u, w)$
- $\dot{x} = f(x, u) + N(x, u, w)$
- $\dot{x} = N(x, u, w) \cdot C$

Model predictive control (MPC) - like → **optimization** + **closed-loop**

Plan through $\dot{x} = f(x, u)$ for N_s steps → Execute first control action

Cost function: quadratic in **target state distance + control effort**

$$J(x_k, u_k) = (x_{k+N} - x_k^*)^T \hat{S} (x_{k+N} - x_k^*) + \sum_{i=1}^{N-1} (x_{k+i} - x_k^*)^T S (x_{k+i} - x_k^*) + \sum_{i=0}^{N-1} u_{k+1}^T R u_{k+1}$$

Subject to **dynamics** and **thrust constraint**.

Neural-aided Guidance & Control

Model-based Reinforcement Learning Algorithm

Use the learned dynamics to **enhance GNC**

Initialize NN model $\tilde{N}(x_k, u_k, w_0)$

Collect Measurements
$D = \{(x_k, u_k, x_{k+1})\}$

Train by supervised learning
$x_{k+1} = \tilde{N}(x_k, u_k, w_k)$

Constrained Optimization

for N_s time steps

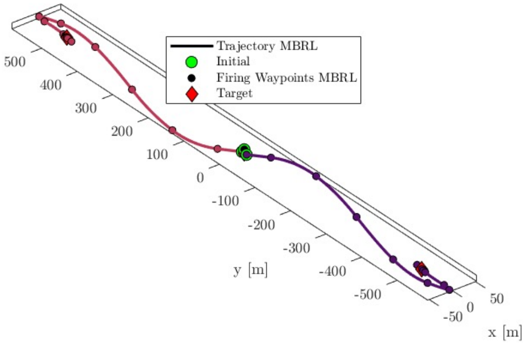
Execution of first control action u_k

Actuators

S. Silvestrini, M. Lavagna, Neural-based Predictive Control and Relative Trajectory Identification Algorithms for Relative Spacecraft Maneuvers, Journal of Guidance, Control and Dynamics, 2020

Neural-aided Guidance & Control

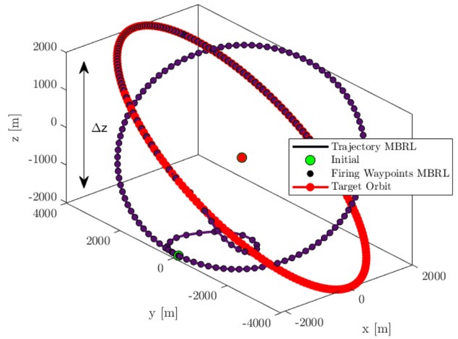
Model-based Reinforcement Learning Numerical Results

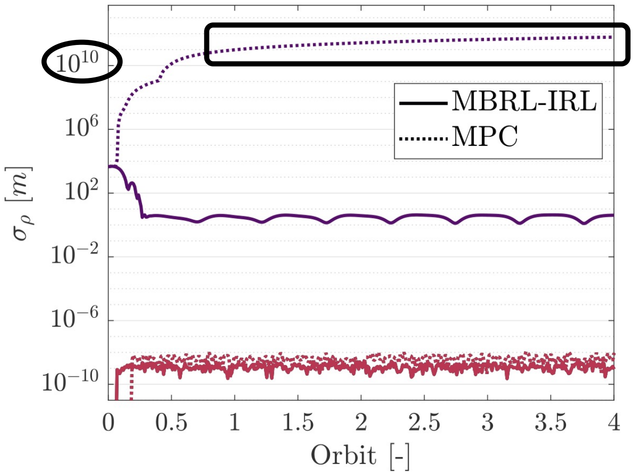


Planar:

Lower Δv ~ 10% for MBRL

Lower TOF for MBRL





Large formation Out-of-Plane:

MBRL successful/ MPC fails

PROS MBRL	CONS MBRL
Lower Δv	Initial learning process
Lower TOF (free variable)	Excellent performance with offline initialization
It manages non-modelled environment	Recurrent Neural Networks lacks implementation support

S. Silvestrini, M. Lavagna, Neural-based Predictive Control and Relative Trajectory Identification Algorithms for Relative Spacecraft Maneuvers, Journal of Guidance, Control and Dynamics, 2020

Research Objectives

Advanced Space Technologies for Robotics and Astrodynamics
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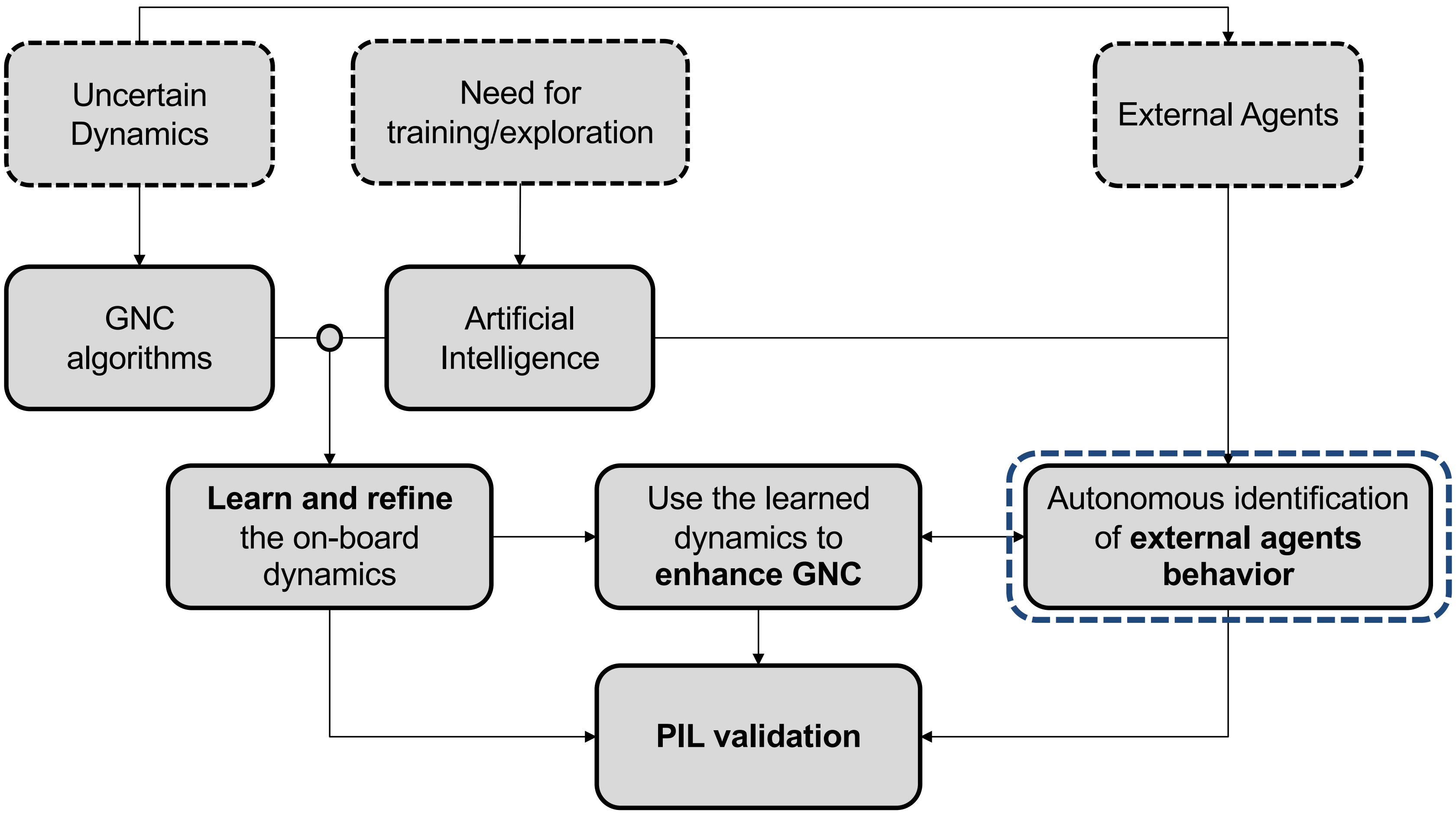


Environment and External Agents Prediction: Collision Avoidance

Assuming only one agent is maneuvering and the rest following natural motion

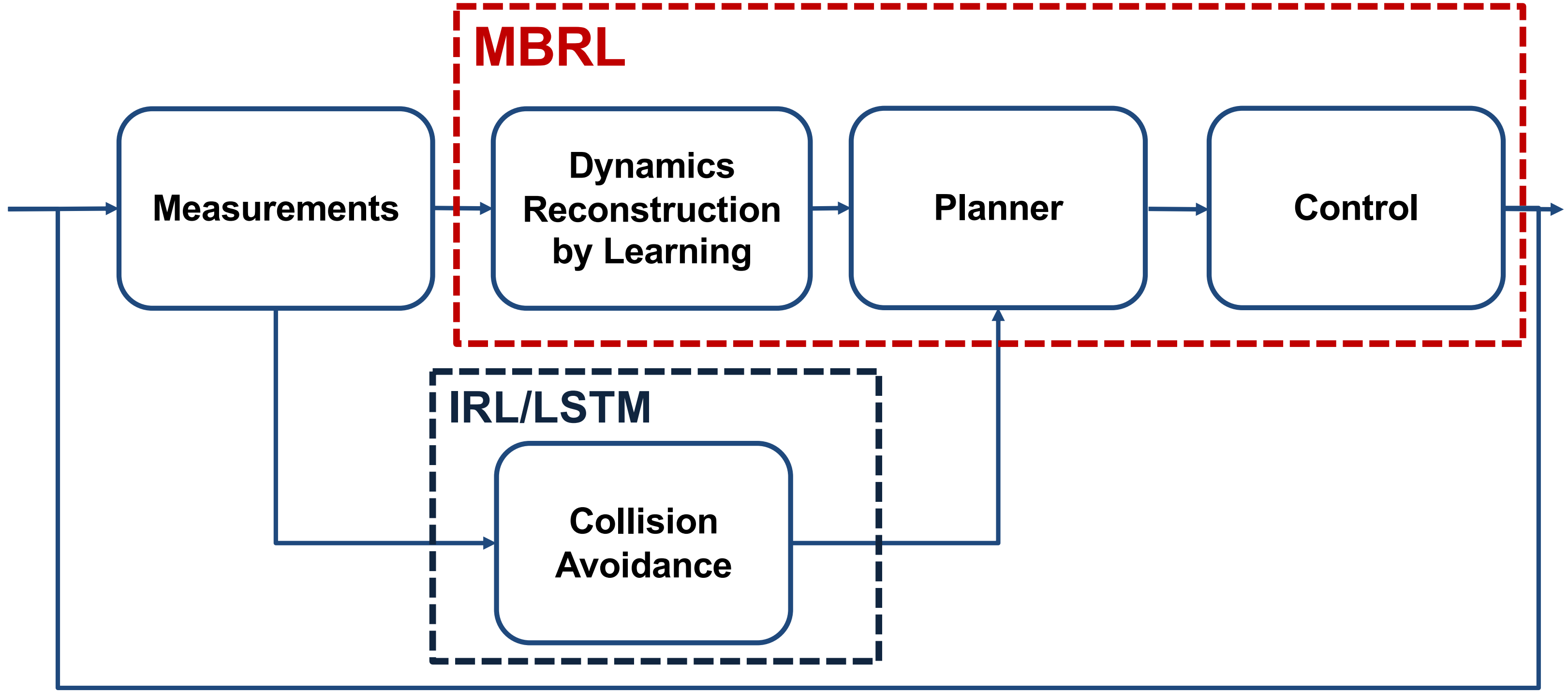
Reconfiguring distributed formation → each agent **plans maneuvers autonomously**
→ need to know what the other agents are doing

One critical task for distributed operation is to safely maneuver **avoiding collision between agents.**

Assuming evolution following natural motion → **too restrictive**

We need a technique to **predict neighboring agents future trajectory based only on past observations of relative positions**

Environment and External Agents Prediction:
Inverse Reinforcement Learning for Collision Avoidance: Algorithm



Autonomous identification of **external agents behavior**

MBRL: Model-based Reinforcement Learning
IRL: Inverse Reinforcement Learning
LSTM: Long Short-Term Memory

Environment and External Agents Prediction:
Inverse Reinforcement Learning for Collision Avoidance: Algorithm

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The concept of Inverse Reinforcement Learning is to **estimate a cost function** that delivers an **optimal trajectory compatible with an expert demonstrated trajectory.**

In this research, parametrize the cost function:

$$\mathbf{w} = [w_1, w_2, ..., w_f, w_T]^T, \quad \mu(\pi) = \begin{bmatrix} \sum_t^{T-1} \phi_1(\mathbf{x_t}, \mathbf{u_t}) \\ \sum_t^{T-1} \phi_2(\mathbf{x_t}, \mathbf{u_t}) \\ \dots \\ \sum_t^{T-1} \phi_f(\mathbf{x_t}, \mathbf{u_t}) \\ \phi_T(\mathbf{x_T}) \end{bmatrix}$$

Cumulative feature cost

$$\text{cost: } \mathcal{J} = \mathbf{w}^T \cdot \mu(\pi)$$

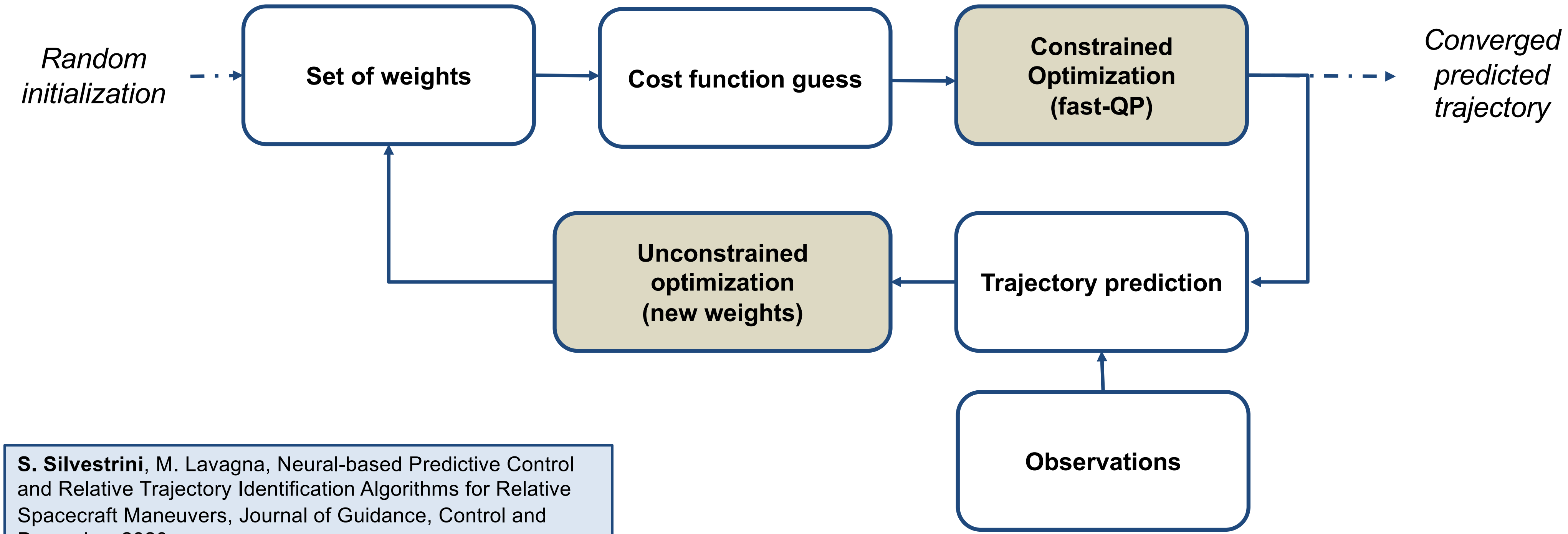
Cumulative **estimated** feature cost

Cumulative **observed** feature cost

Environment and External Agents Prediction:
Inverse Reinforcement Learning for Collision Avoidance: Algorithm

Autonomous identification of **external agents behavior**

In this research a nested optimization is developed:



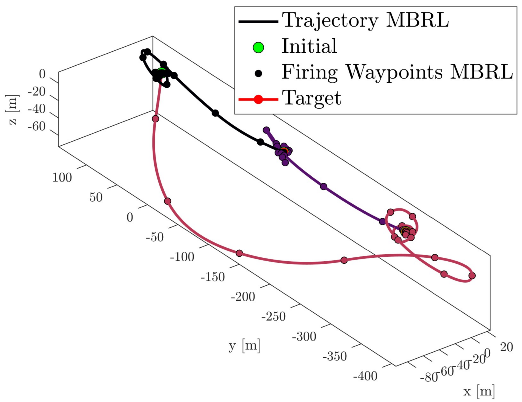
S. Silvestrini, M. Lavagna, Neural-based Predictive Control and Relative Trajectory Identification Algorithms for Relative Spacecraft Maneuvers, Journal of Guidance, Control and Dynamics, 2020

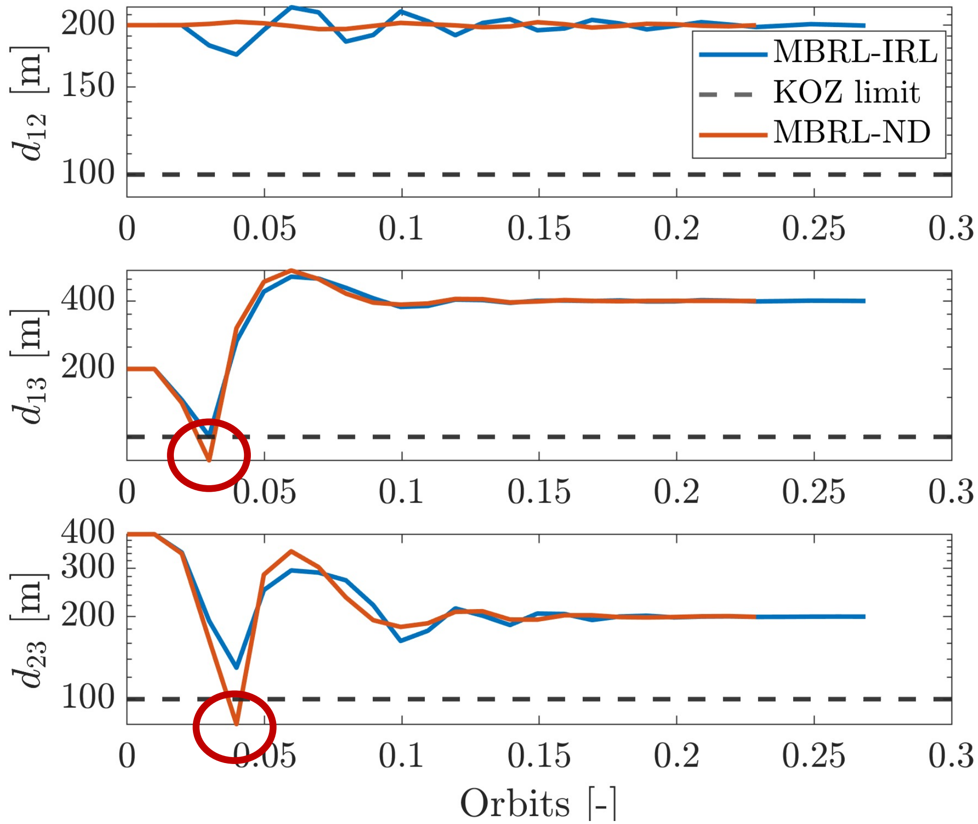
Environment and External Agents Prediction:
Numerical Results

Challenging test case:
Swap the along track positions separated by 200 m.

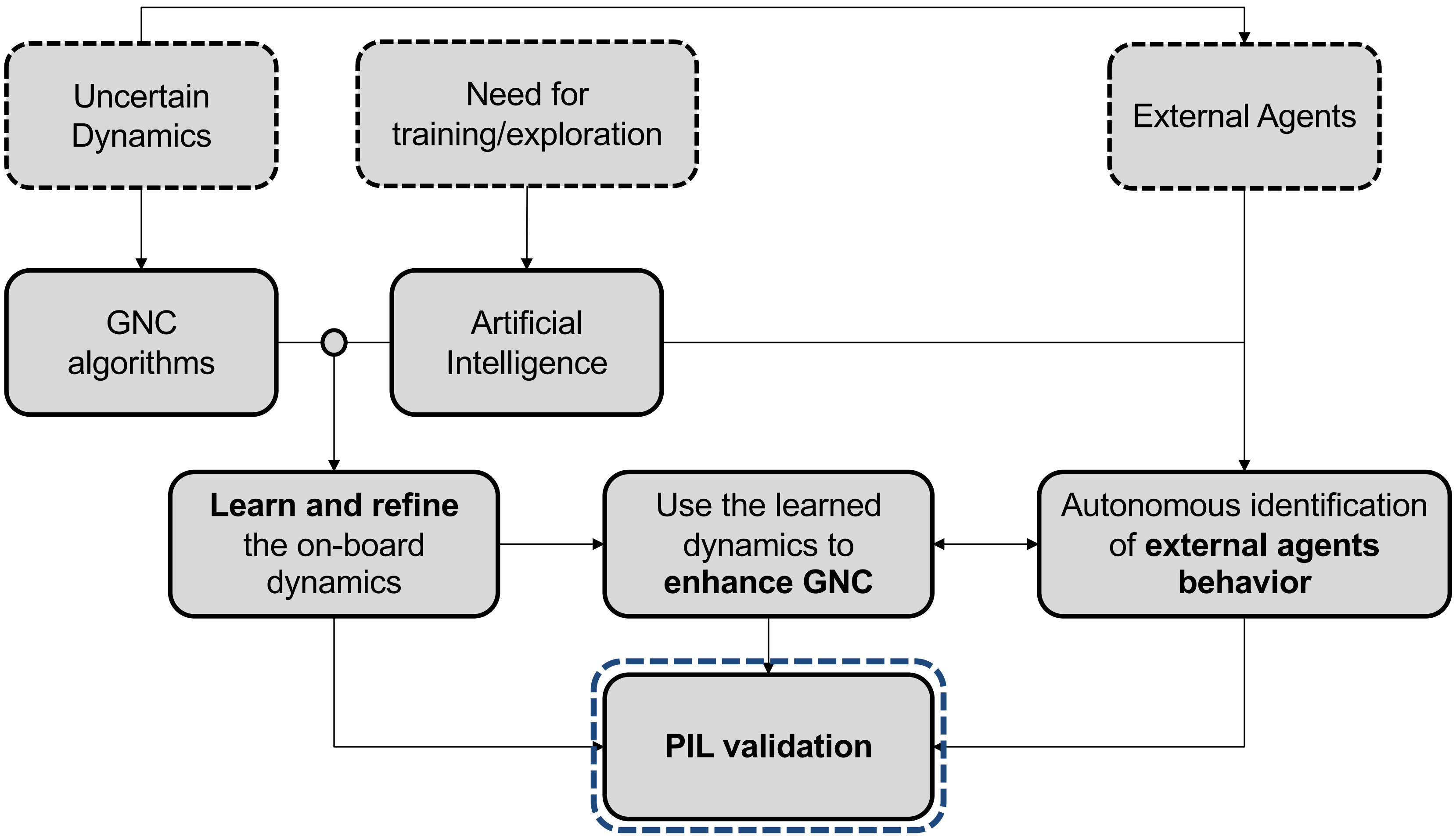
The relative distance between the satellites **falls below the Keep-Out-Zone limit (100 m)**, when predicting neighboring trajectories using natural dynamics.

MBRL planner with an impulsive trajectory identification algorithm, such as IRL, allows a **safe reconfiguration.**



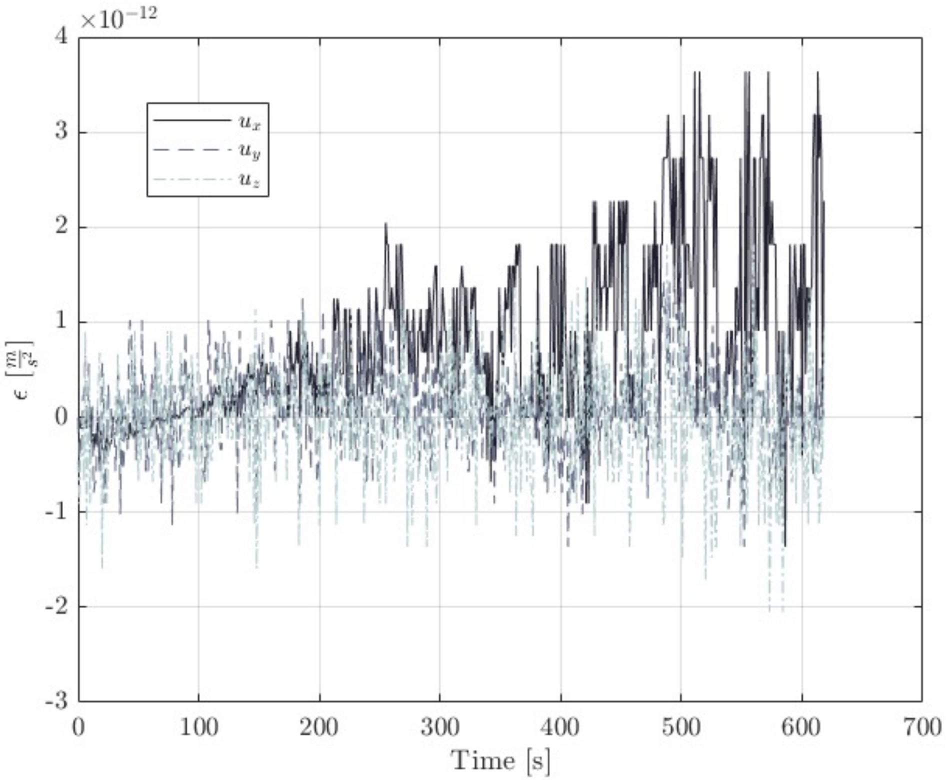


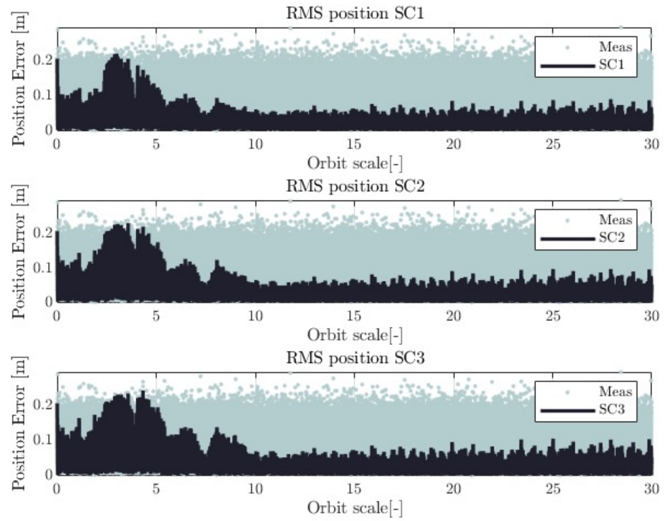
Research Objectives



PIL Validation:
Test Results TI LAUNCHXL-F28379D

Discrepancy between CPU output and PIL module output in the order of 10^{-12} m/s^2





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PIL validation

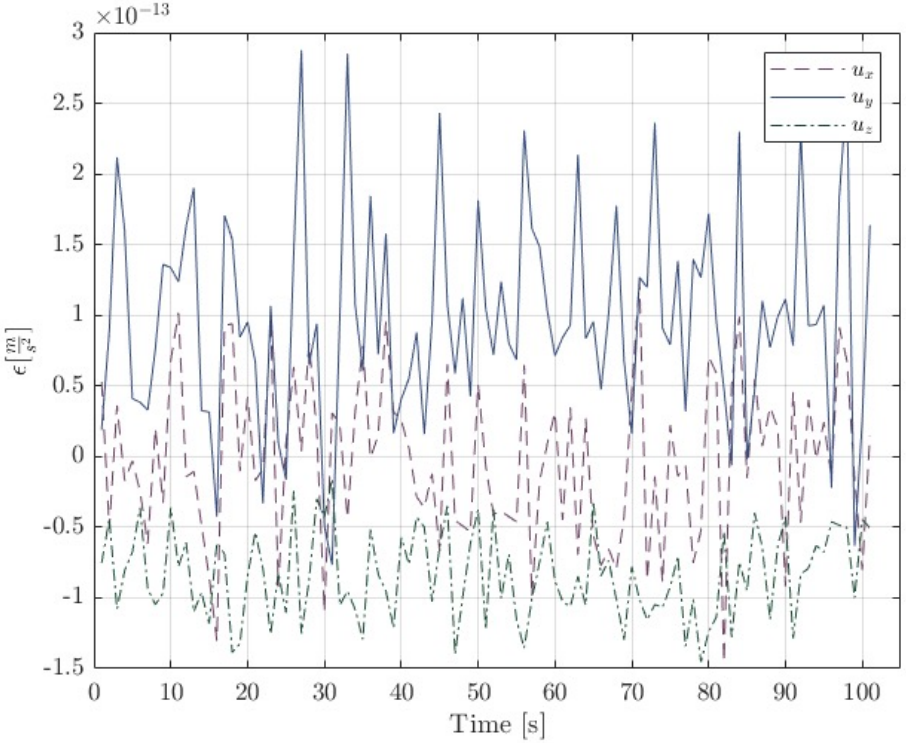
Elapsed times of execution: Runner Profiler

Routine	Avg [ms]	Max [ms]
ANN-learning	0.89	0.90
Navigation	0.81	0.82
Guidance	0.32	0.32
Control	0.28	0.33

PIL Validation:
Test Results BeagleBoneBlack

PIL validation

MBRL and MPC for IRL requires **double** precision. Discrepancy between CPU output and PIL module output in the order of 10^{-13} m/s^2



On-board **resource utilization**:

qp: ~ 0.3 % for MBRL running 1/60 Hz
sqp: ~ 0.5 % for MBRL running 1/60 Hz

Percentage of CPU time assigned to a task. Computed by dividing task execution time by sample time.

Elapsed times of execution: Runner Profiler
MBRL sample time is 60 s.

Routine	Avg [ms]	Max [ms]
ANN-learning	0.89	0.90
MBRL (qp)	191.10	272.20
MBRL (sqp)	290.10	337.10

Thank you for your attention.
Questions?