Deep learning and Gaussian process approach for optimal attitude control of a Two-CubeSat Virtual Telescope

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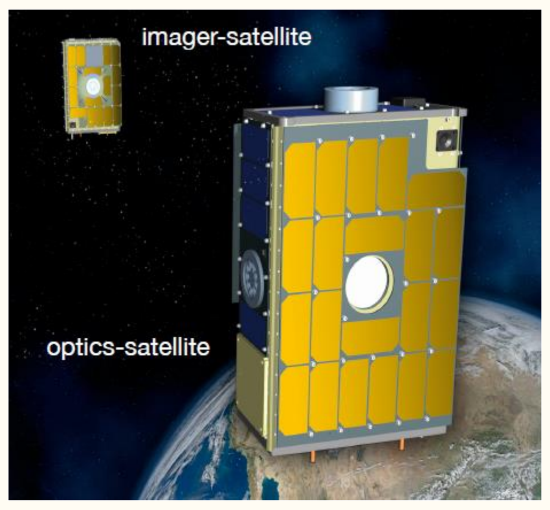
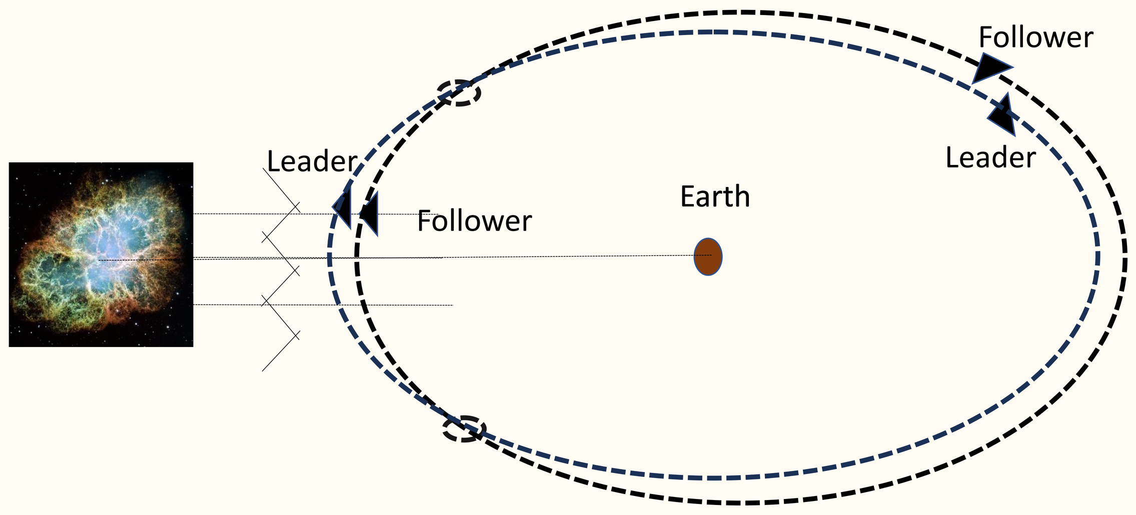
SSC19-WP2-24

Mission

- Virtual Telescope for X-ray Observations
- Attitude formation control with sub-arcsecond accuracy
- Highly eccentric geostationary orbit
- Approximately 1 hour observing the Crab Nebula

Orbit Design





Satellites' Dynamics Driven by Quaternions

$$\dot{\boldsymbol{q}}^{bI} = \frac{1}{2}E(\boldsymbol{q}^{bI})\boldsymbol{\omega}_b^{\ bI}$$

$$E(\boldsymbol{q}) = \begin{bmatrix} q_4\boldsymbol{I}_{3\times3} + [\boldsymbol{q}_{1:3}\times] \\ -\boldsymbol{q}_{1:3}^{\ T} \end{bmatrix}$$

$$\dot{\boldsymbol{\omega}}_b^{\ bI} = J^{-1}(-[\boldsymbol{\omega}_b^{\ bI}\times]J\boldsymbol{\omega}_b^{\ bI} + \boldsymbol{\tau})$$

$$\boldsymbol{\tau} = \boldsymbol{\tau}_{in} + \boldsymbol{\tau}_g + \boldsymbol{\tau}_d$$

$$\boldsymbol{\tau}_g = 3\frac{GM}{r^3}\boldsymbol{o}_3 \times \boldsymbol{I}_b\boldsymbol{o}_3$$

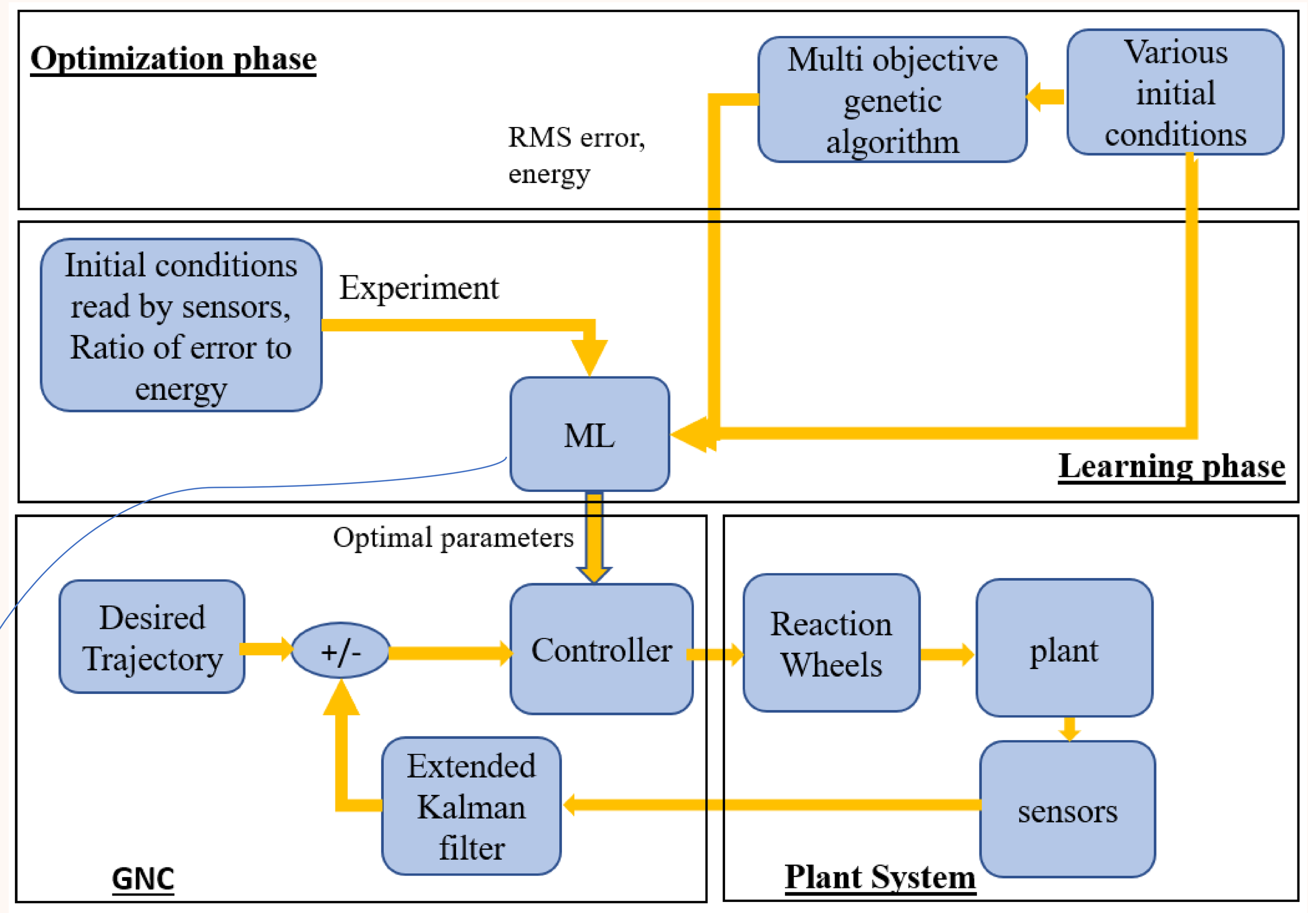
Satellites' Dynamics Driven by Euler Angles

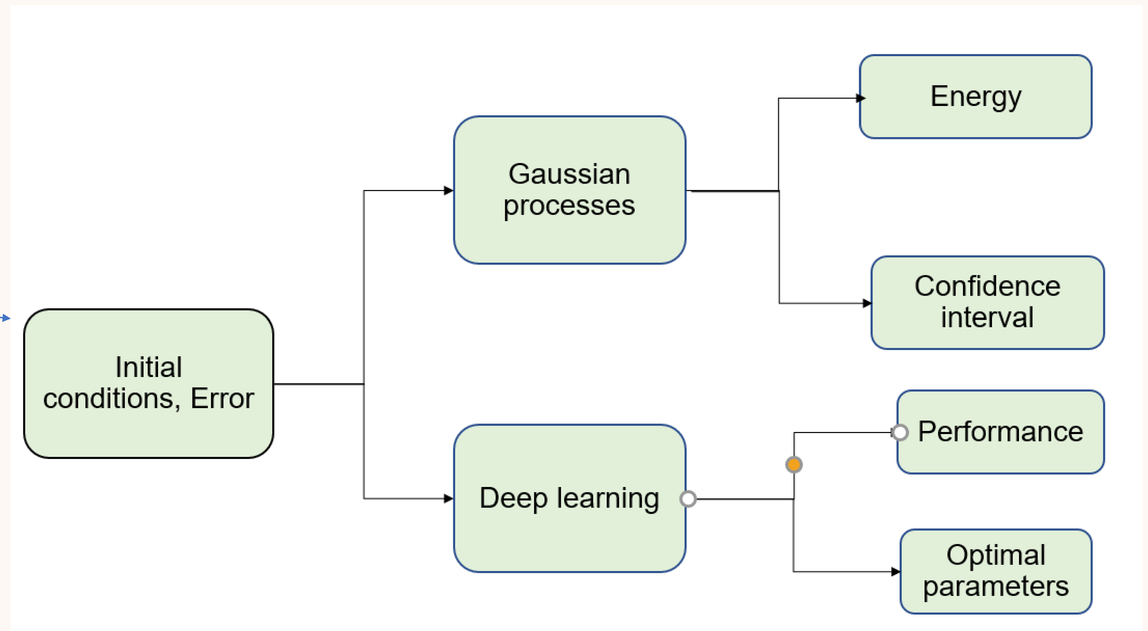
$$\dot{\boldsymbol{\omega}}_b^{\ bi} = \boldsymbol{M}\ddot{\theta} + \boldsymbol{G}(\dot{\theta}_1, \dot{\theta}_3, \dot{\theta}_2, \theta_1, \theta_3, \theta_2, \dot{f}) + \ddot{f}\,\boldsymbol{b}(\theta_1, \theta_3, \theta_2)$$

$$\boldsymbol{\omega}_b^{\ bi} = \begin{bmatrix} c_2c_3\dot{\theta}_1 + s_3\dot{\theta}_2 \\ -c_2s_3\dot{\theta}_1 + c_3\dot{\theta}_2 \\ s_2\dot{\theta}_1 + \dot{\theta}_3 \end{bmatrix} - \dot{f}\begin{bmatrix} s_1s_2c_3 \\ c_1c_3 - s_1s_2s_3 \\ -s_1c_2 \end{bmatrix}$$

$$\boldsymbol{\theta} = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix} \quad \boldsymbol{M} = \begin{bmatrix} c_2c_3 & s_3 & 0 \\ -c_2s_3 & c_3 & 0 \\ s_2 & 0 & 1 \end{bmatrix}$$

Artificial intelligence framework





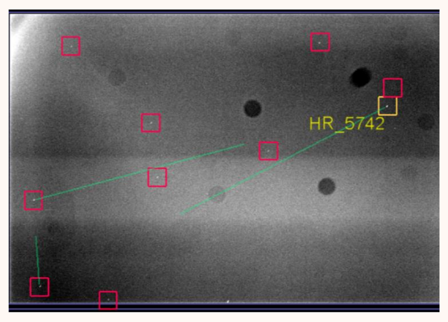
Sensors

Gyroscope

Sensing the angular velocity with noises included

Star Tracker

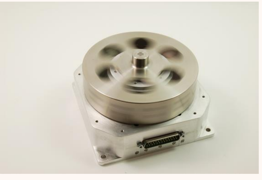
Sensing the angle of the satellites



Controllers

	Robust against dynamical disturbances	Linear vs Nonlinear	Computational complexity
Sliding Mode Controller	Guaranteed	Nonlinear	High
PD Controller	Not Guaranteed	Linear	Low
Anti Gravity Gradient Torque	None	None	Low

Actuator



Reaction wheels

Noise included in the model

Optimal Parameters

Initial quaternion	Initial angular velocity(rad/sec)	RMS Error(Rad), Energy (J)
[-0.4028 0.0776 -0.8484 0.3594]	[-0.0353 -0.0788 0.8009]	[0.21,0.38]

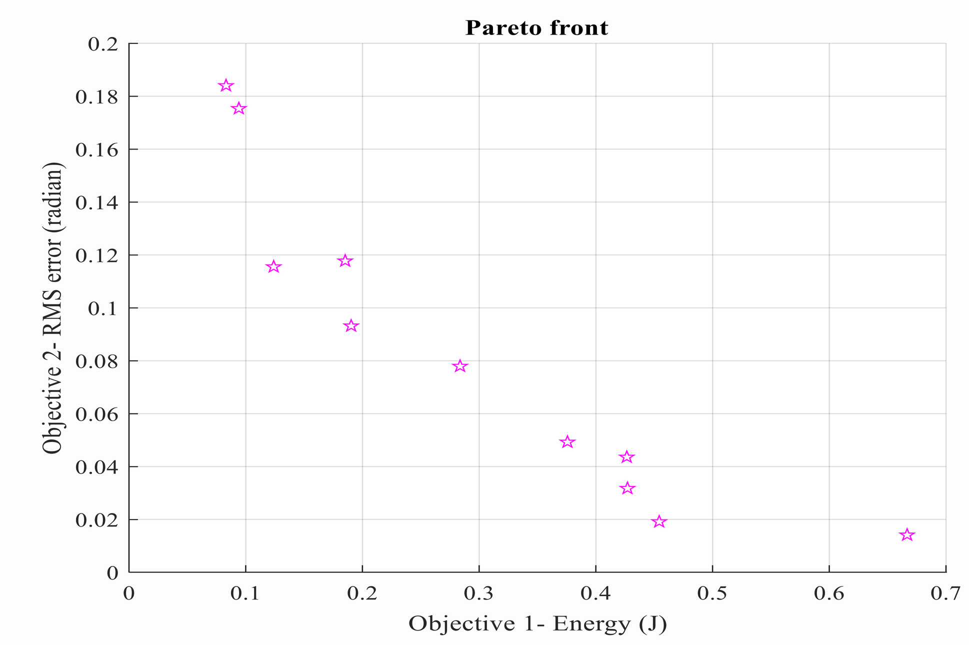
PD Controller parameters	Duration
$\begin{bmatrix} k_p \\ k_d \end{bmatrix} = \begin{bmatrix} 0.1208 \\ 0.3786 \end{bmatrix}$	0.4755 min

Dynamic solver

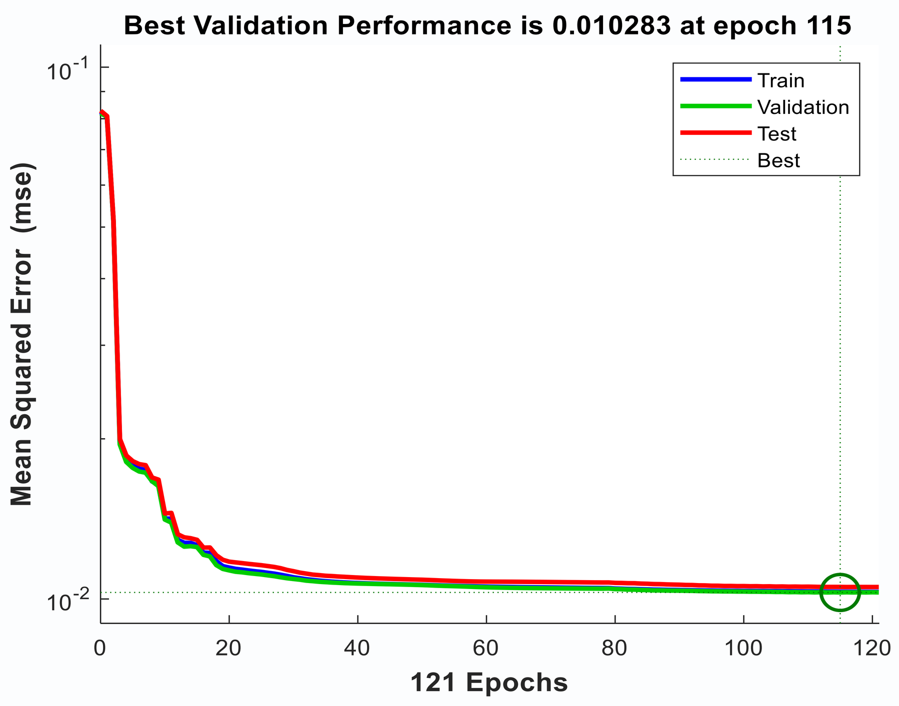
PD controllers' parameters	Maximum amount of time steps	The time of solving the equations
$\begin{bmatrix} kp \\ kd \end{bmatrix} = \begin{bmatrix} 3 \\ 3 \end{bmatrix}$	T=0.09s	T=11.2s
$\begin{bmatrix} kp \\ kd \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$	T=0.14s	T=7.14s
$\begin{bmatrix} kp \\ kd \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$	T=0.3s	T=3.42s
$\begin{bmatrix} kp \\ kd \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$	T=0.65s	T=1.74s
$\begin{bmatrix} kp \\ kd \end{bmatrix} = \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix}$	T=2s	T=0.6s

Optimization

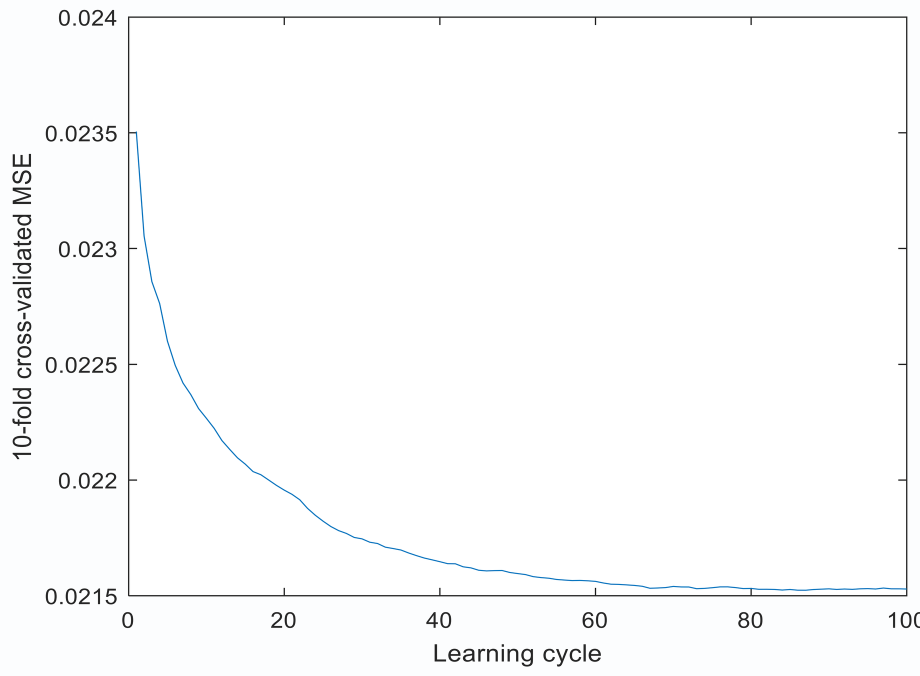
Multi –objective genetic algorithm



Neural network



Decision trees



Result