Learning-based Control for Deployment and Retrieval of a Spinning Tethered Satellite Formation System

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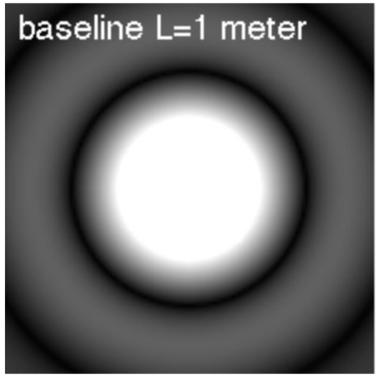
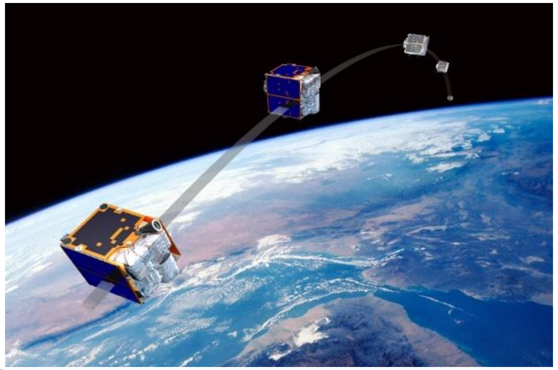
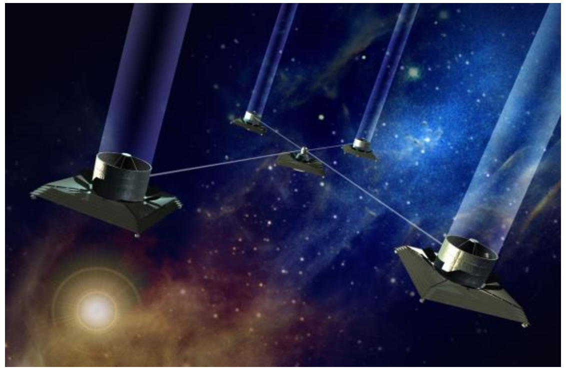
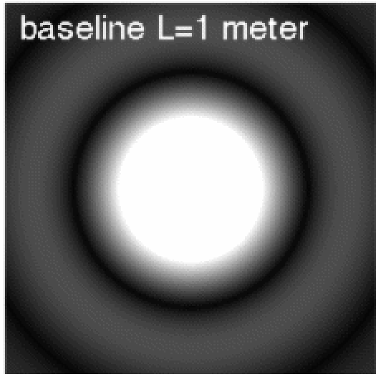
Space telescope with single aperture



Space exploration







Tethered Space telescope with synthetic aperture

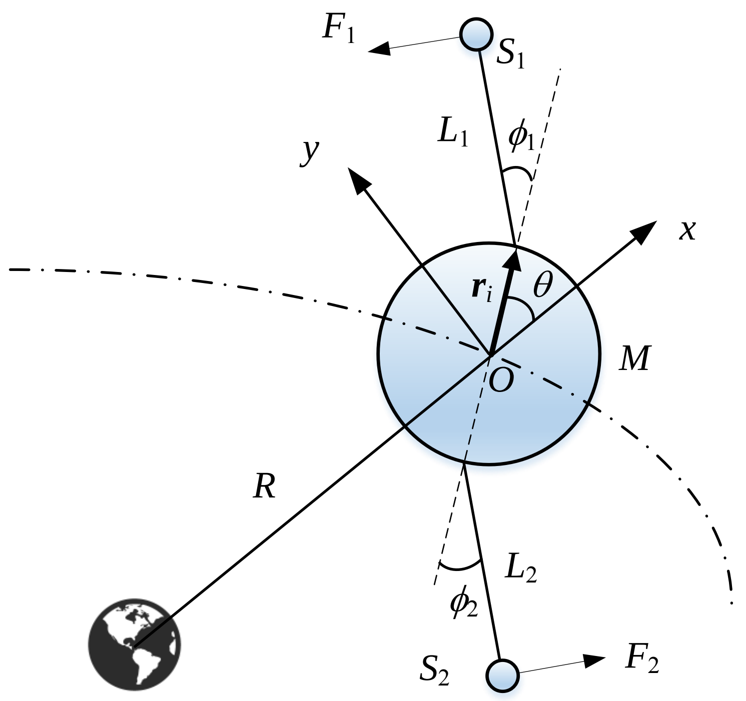
Focused Problems

- Attitude motions of tethers would be significantly affected due to deployment and retrieval of tethers. **Tangling motions** between the tethers and satellites may be generated and thereby destroy the system stability and safety.

- The system may have **asymmetric configurations** at initial due to perturbations, which is not good for keeping stability and should be considered.

- The system usually has **complex practical constraints**, such as the tether tension should not be too large to prevent cut-off of tethers. The control force should be kept in an acceptable range due to the limited maneuver ability of satellites, and so on.

- It is tough to compute control input online when the underlying control problem and the designed control law are complicated since the **onboard computing power of the satellites is limited**.



Spinning tethered satellite formation (STSF)

$$\boldsymbol{R}_M = R\boldsymbol{e}_x, \quad \boldsymbol{R}_i = R\boldsymbol{e}_x + \boldsymbol{r}_i$$

$$\boldsymbol{v}_M = \dot{\boldsymbol{R}}_M = \Omega R\boldsymbol{e}_y, \quad \boldsymbol{v}_i = \dot{\boldsymbol{R}}_i = \Omega R\boldsymbol{e}_y + \dot{\boldsymbol{r}}_i$$

$$\Downarrow$$

$$T = \frac{1}{2} m_M \boldsymbol{v}_M \cdot \boldsymbol{v}_M + \frac{1}{2}\sum_{i=1}^{2} m_i \boldsymbol{v}_i \cdot \boldsymbol{v}_i + \frac{1}{2} J(\dot{\theta} + \omega)^2$$

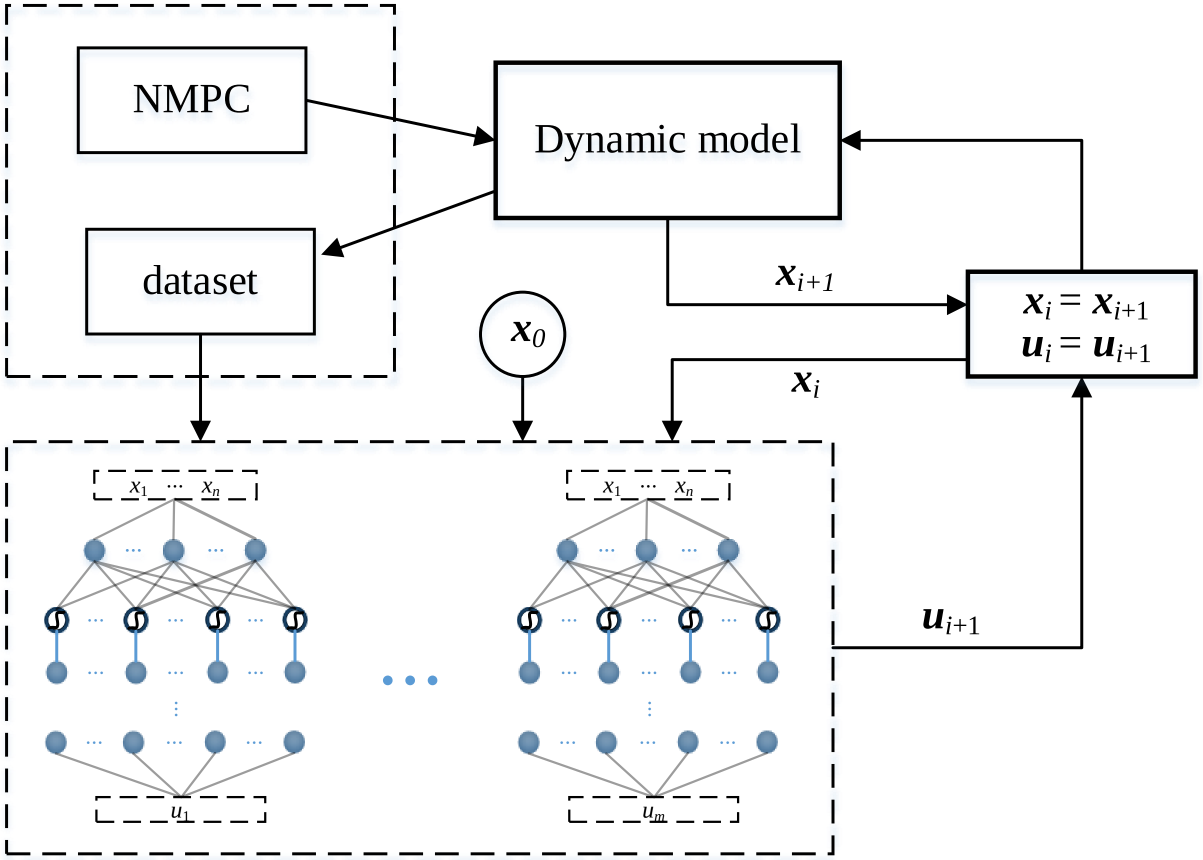
$$U = -\frac{\mu m_M}{|\boldsymbol{R}_M|} - \sum_{i=1}^{2}\frac{\mu m_i}{|\boldsymbol{R}_i|} = -\frac{\mu m_M}{R} - \sum_{i=1}^{2}\frac{\mu m_i}{|\boldsymbol{R}_M + \boldsymbol{r}_i|}$$

$$\frac{\mathrm{d}}{\mathrm{dt}}\left(\frac{\partial L}{\partial \dot{q}_j}\right) - \left(\frac{\partial L}{\partial q_j}\right) = Q_{q_j}, \quad j = 1, 2, 3, 4, 5$$

$$\Downarrow$$

$$\boldsymbol{M}\ddot{\boldsymbol{q}} + \boldsymbol{C}\dot{\boldsymbol{q}} + \boldsymbol{K} = \boldsymbol{F}$$

● Design concept



Flowchart of learning-based controller

a) Obtain dataset using NMPC;

b) Construct DNN based on dataset;

c) Input initial state x_0 to DNN to obtain control input quickly;

d) Achieve the control goal.

NMPC controller

Optimal control model

State vector $\boldsymbol{x} = (x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10})^{\mathrm{T}} = (\theta, \phi_1, \phi_2, l_1, l_2, \dot{\theta}, \dot{\phi}_1, \dot{\phi}_2, \dot{l}_1, \dot{l}_2)^{\mathrm{T}}$

Control vector $\boldsymbol{u} = (u_1, u_2, u_3, u_4)^{\mathrm{T}} = (T_1, T_2, F_1, F_2)^{\mathrm{T}}$

State-space form $\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{u}, t)$

Moving horizon

Prediction horizon $T_P = N\sigma_t$

find $[t_{k+1}, t_{k+1} + T_p] \ni t \mapsto \{\boldsymbol{x}(t), \boldsymbol{u}(t)\}$

to minimize $f_J = \int_{t_{k+1}}^{t_{k+1}+T_p} f_F(\boldsymbol{x}, \boldsymbol{u}, t)\mathrm{d}t$

subject to $\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{u}, t)$

$\boldsymbol{x}(t_{k+1}) = \hat{\boldsymbol{x}}_{k+1}$

$u_L \le u_1, u_2, u_3, u_4 \le u_U$

Solving process

kth computation $[t_k, t_{k+1}]$ ⟷ $t_{k+1} = t_k + \sigma_t$

Sampling interval

NLP Problem

$$f_J \approx \sum_{i=1}^{N} \sum_{j=1}^{N_\tau} W_j^{(i)} f_F(\boldsymbol{x}_j^{(i)}, \boldsymbol{u}^{(i)})$$

$$\sum_{j=1}^{N_\tau+1} D_{ni} \boldsymbol{x}_j^{(i)} - \boldsymbol{f}(\boldsymbol{x}_n^{(i)}, \boldsymbol{u}^{(i)}, \tau_{i,n}) = 0$$

$$\boldsymbol{x}_1^{(k+1)} = \hat{\boldsymbol{x}}_{k+1}$$

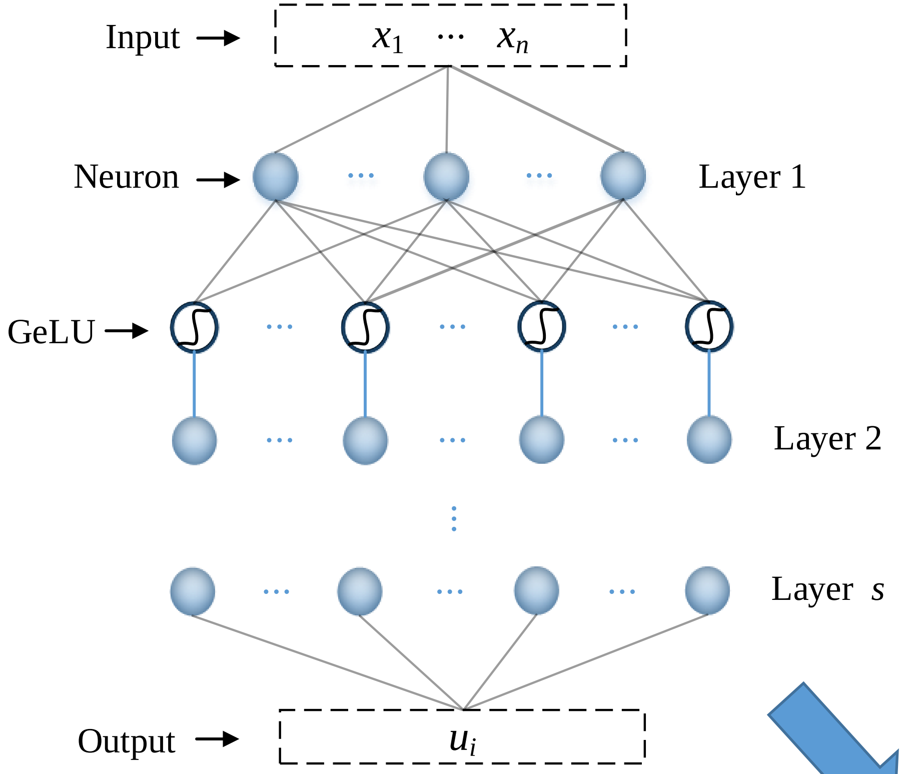
$$u_L \le (u_{i,j})_1, (u_{i,j})_2, (u_{i,j})_3, (u_{i,j})_4, \le u_U$$

IPOPT Solver

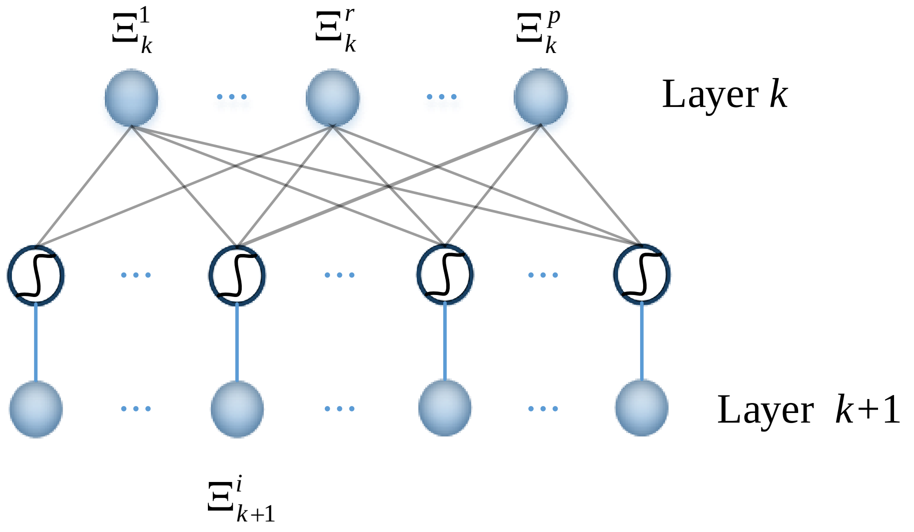
NMPC law → $[t_{k+1}, t_{k+2}]$

DNN method

- Deep neural network



An s-layer DNN



Relationship between two adjacent layers

Output

$$\Xi_{k+1}^i = f_{ac}^k(\Re_k^{i,1}\Xi_k^1 + \cdots + \Re_k^{i,r}\Xi_k^r + \cdots + \Re_k^{i,p}\Xi_k^p + B_k^i)$$

Weight: $\Re_k^{i,p}$; Bias: B_k^i

$$\mathrm{GeLU}(x) \approx 0.5x[1+\tanh(\sqrt{\frac{2}{\pi}}(x+0.0047715x^3))]$$

$$u_i = f_{DNN}(\boldsymbol{x})$$

Parameters setting

Table. 1 Physical parameters

Physical parameters	Values
Mass of main satellite	1×10^4 kg
Mass of sub-satellite	50 kg
Radius of main satellite	5 m
Orbital radius	6878 km

Table. 2 Control parameters

Control parameters	Values
Number of sampling intervals	20
Number of collocation points	4
Tether tension	[0.1, 10] N
Control force	[-0.5, 0.5] N

Table. 3 DNN parameters

DNN parameters	Values
Number of hidden layers	10
Number of neurons in hidden layers	256,128, 64, 64, 32, 32, 16, 16, 8, 5
Activation function of hidden layers	GeLU
Activation function of output layer	linear
Loss function	MSE
Optimizer	Adam
Batch size	256
Number of epochs	300
k-fold cross-validation method	$k = 6$

$$f_{FD} = 100(u_3^2 + u_4^2) + 500(x_2^2 + x_3^2) + 0.01[(x_4 - 100)^2 + (x_5 - 100)^2] + 100(x_9^2 + x_{10}^2)$$

$$f_{FR} = 100(u_3^2 + u_4^2) + 500(x_2^2 + x_3^2) + 0.01[(x_4 - 10)^2 + (x_5 - 10)^2] + 500(x_9^2 + x_{10}^2)$$

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Deployment Case

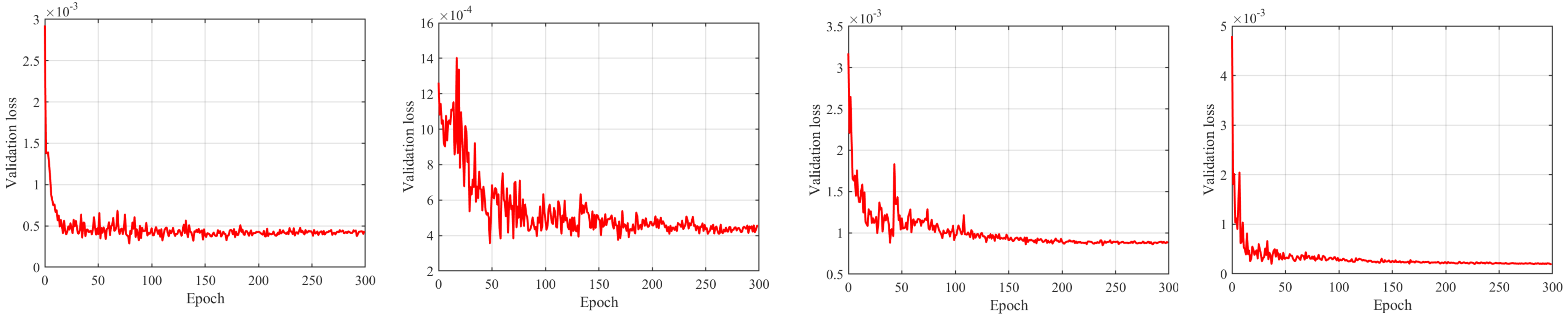
- Initial state

$$\boldsymbol{x}_0 = (\theta, \phi_1, \phi_2, l_1, l_2, \dot{\theta}, \dot{\phi}_1, \dot{\phi}_2, \dot{l}_1, \dot{l}_2)^{\mathrm{T}}$$
$$= (0,\ -30\,\text{deg},\ -30\,\text{deg},\ l_1,\ l_2,\ 0.02\ \text{rad/s},\ 0,\ 0,\ 0,\ 0)^{\mathrm{T}}$$

$$l_1 \in [2,12]\ \text{m},\quad l_2 \in [2,12]\ \text{m}$$

121 pairs of state-control data

$$\boldsymbol{u}_0 = (T_1, T_2, F_1, F_2)^{\mathrm{T}}$$
$$= (0.1,\ 0.1,\ 0,\ 0)^{\mathrm{T}}\ \text{N}$$



Validation loss of the DNNs for u_1---u_4

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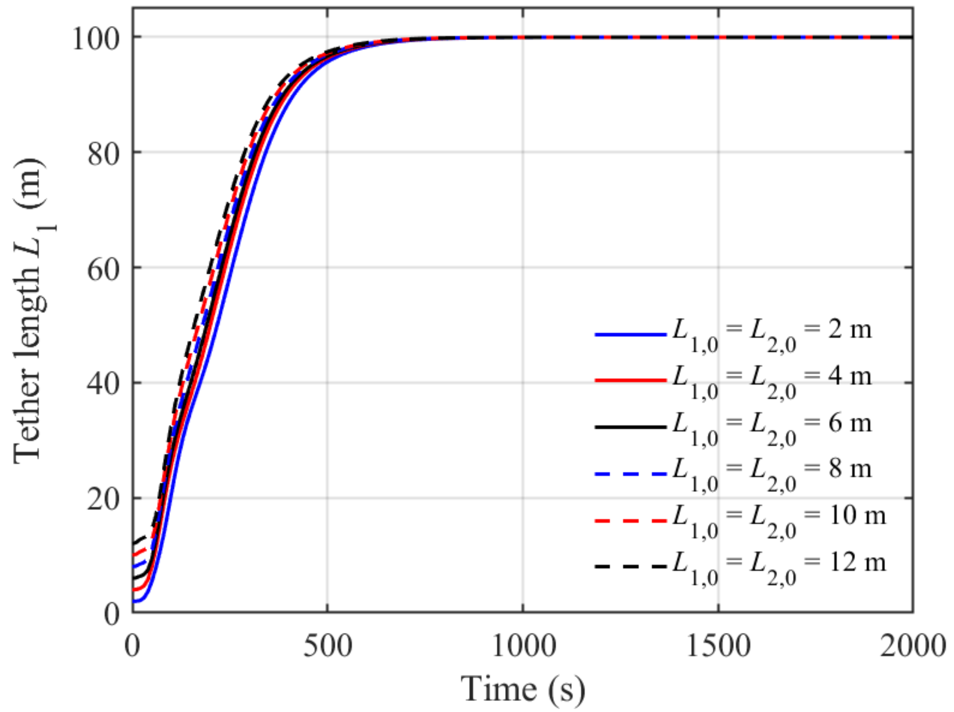
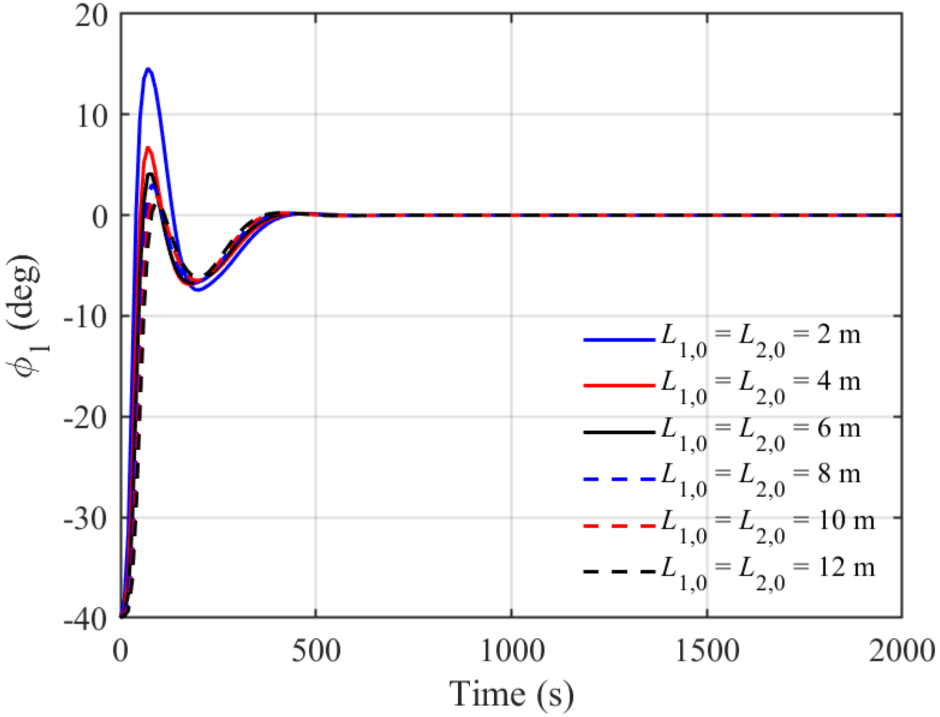
Deployment Case





Results of the system with initial symmetric configurations

4 Numerical cases

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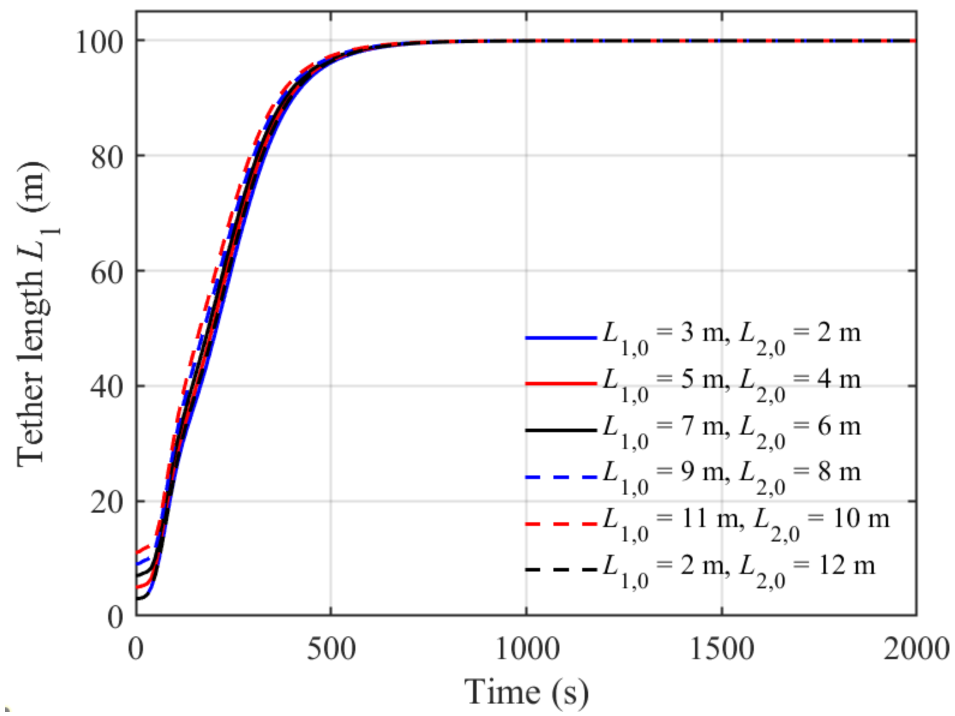
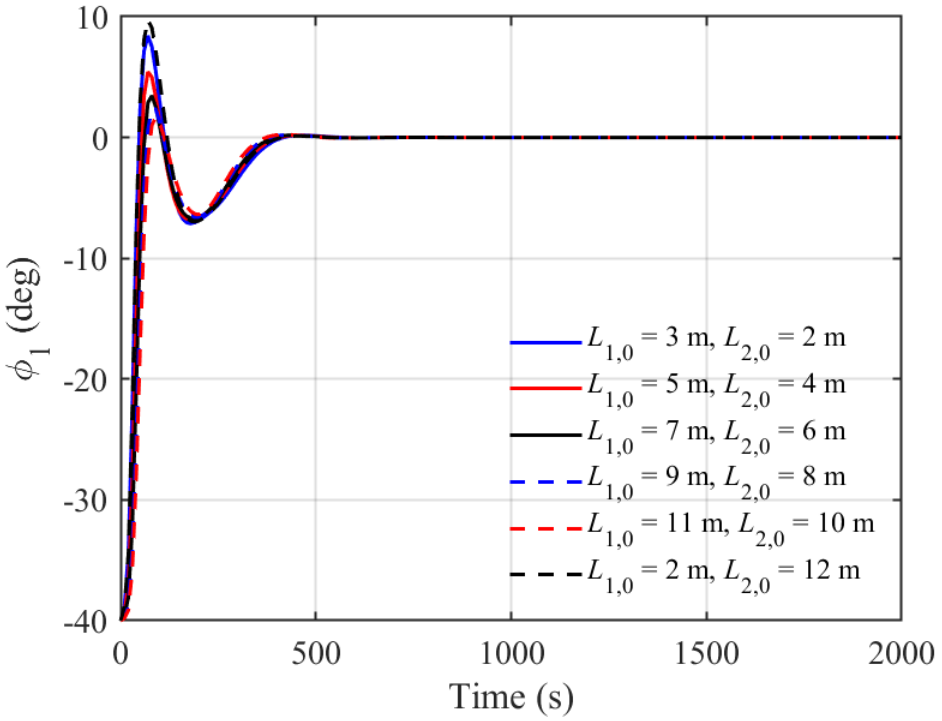
Deployment Case





Results of the system with initial asymmetric configurations

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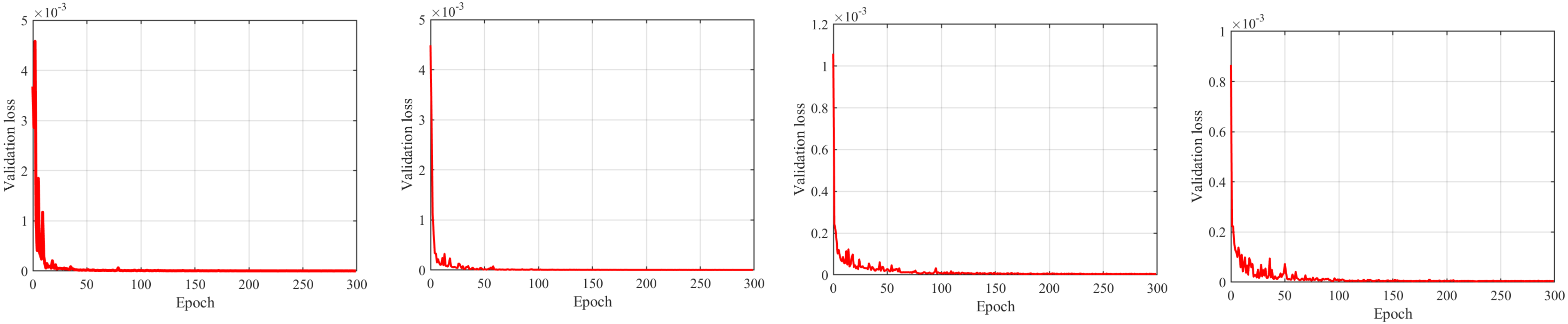
Retrieval Case

- Initial state

$$\boldsymbol{x}_0 = (\theta, \phi_1, \phi_2, l_1, l_2, \dot{\theta}, \dot{\phi}_1, \dot{\phi}_2, \dot{l}_1, \dot{l}_2)^{\mathrm{T}}$$
$$= (0,\ \phi_1, \phi_2,\ 100\ \mathrm{m},\ 100\ \mathrm{m},\ 0.02\ \mathrm{rad/s},\ 0,\ 0,\ 0,\ 0)^{\mathrm{T}}$$

$$\phi_1 \in [-30, -20]\ \mathrm{deg},\quad \phi_2 \in [-30, -20]\ \mathrm{deg}$$

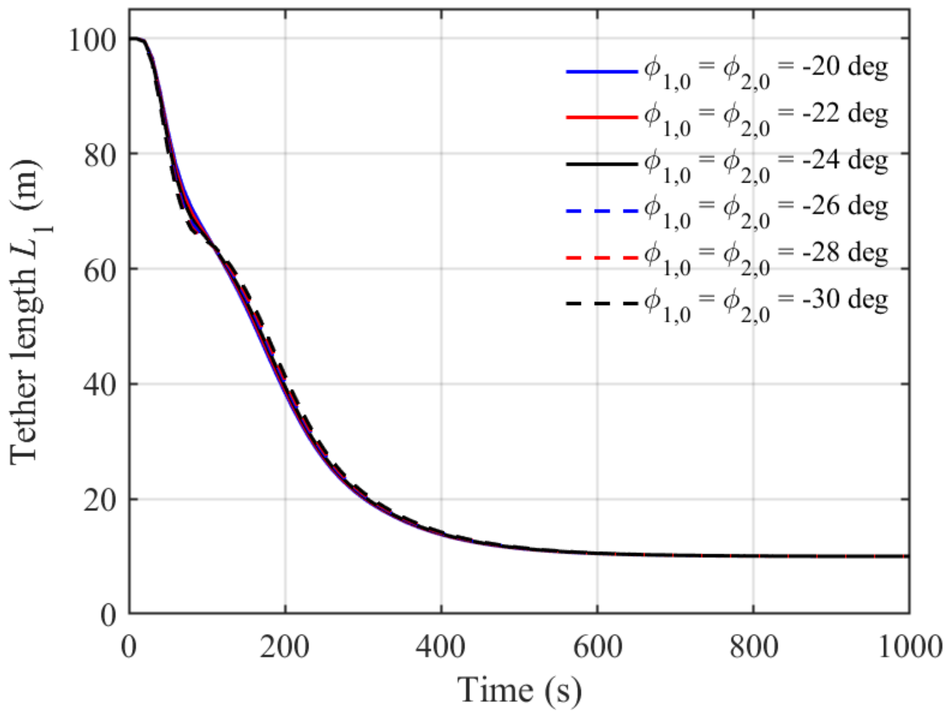
$$\boldsymbol{u}_0 = (T_1, T_2, F_1, F_2)^{\mathrm{T}}$$
$$= (2.8,\ 2.8,\ 0,\ 0)^{\mathrm{T}}\ \mathrm{N}$$

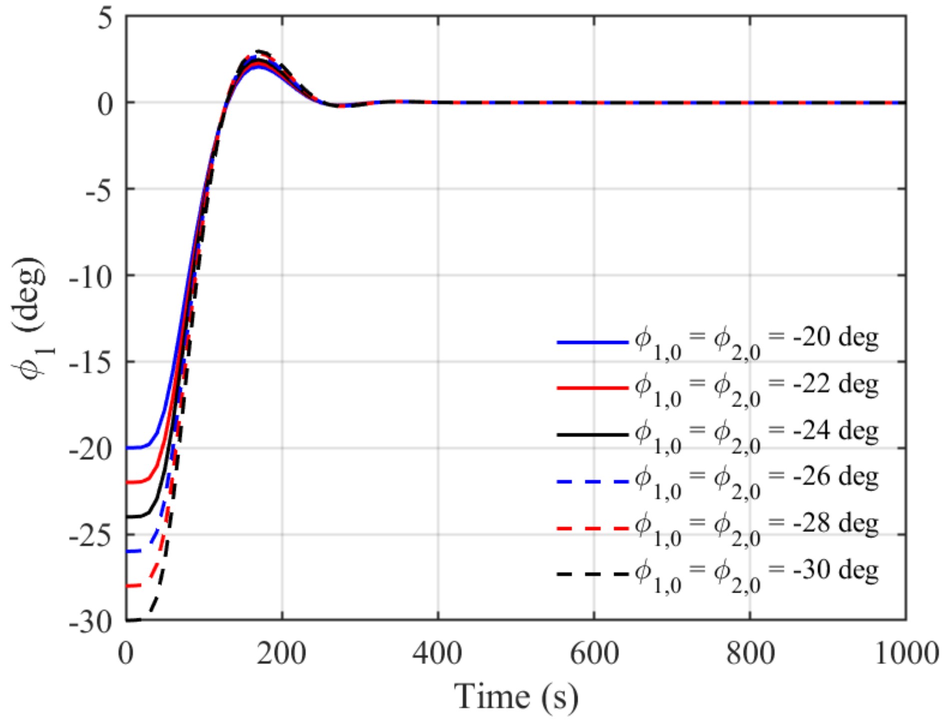


Validation loss of the DNNs for u_1---u_4

4 Numerical cases

Retrieval Case





Results of the system with initial symmetric configurations

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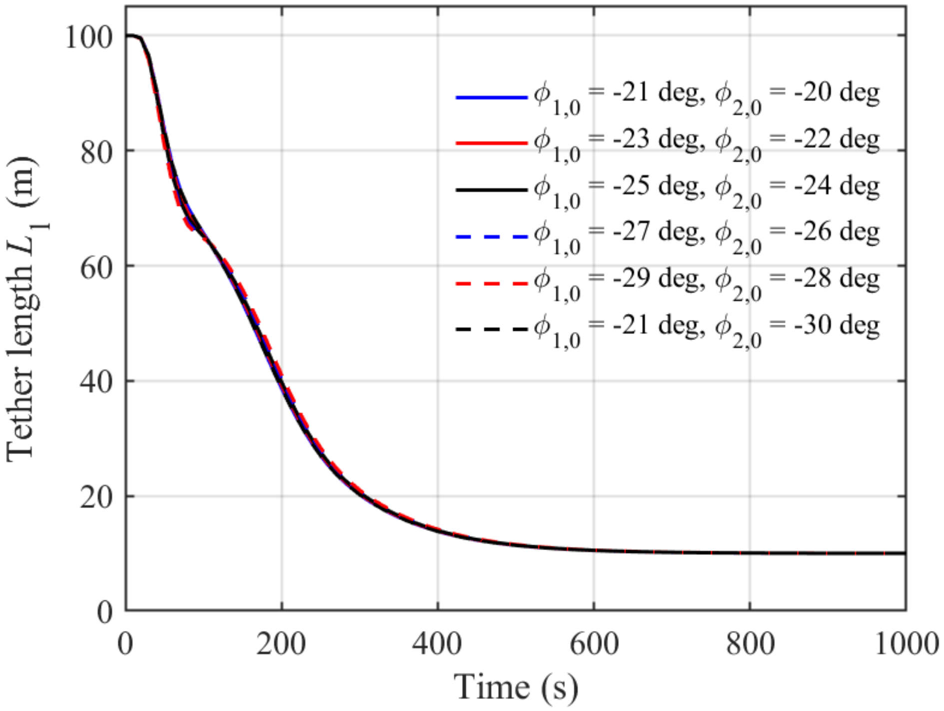
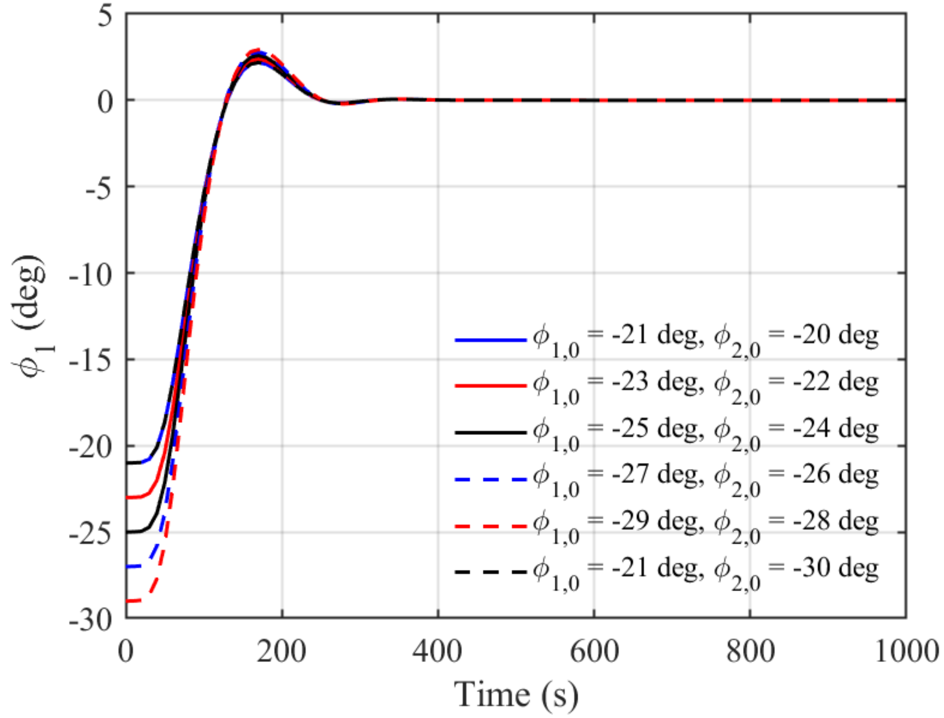
Retrieval Case





Results of the system with initial asymmetric configurations

5 Conclusions

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- The results show that the designed NMPC control law can well deal with the deployment and retrieval problems of the system with symmetric and asymmetric configurations and multiple constraints.

- The designed learning based controller can achieve the desired control goals using the DNNs obtained from the off-line dataset, which can greatly reduce the computational costs.

- In future work, a reinforcement learning-based controller is expected to be designed to achieve the quick deployment and retrieval control without the requirement of off-line pre-computed dataset.

Thank you!

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