智慧型控制及應用實驗室
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An Improved Neural Network Algorithm to Efficiently Track Various Trajectories of Robot Manipulator Arms

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Outlines

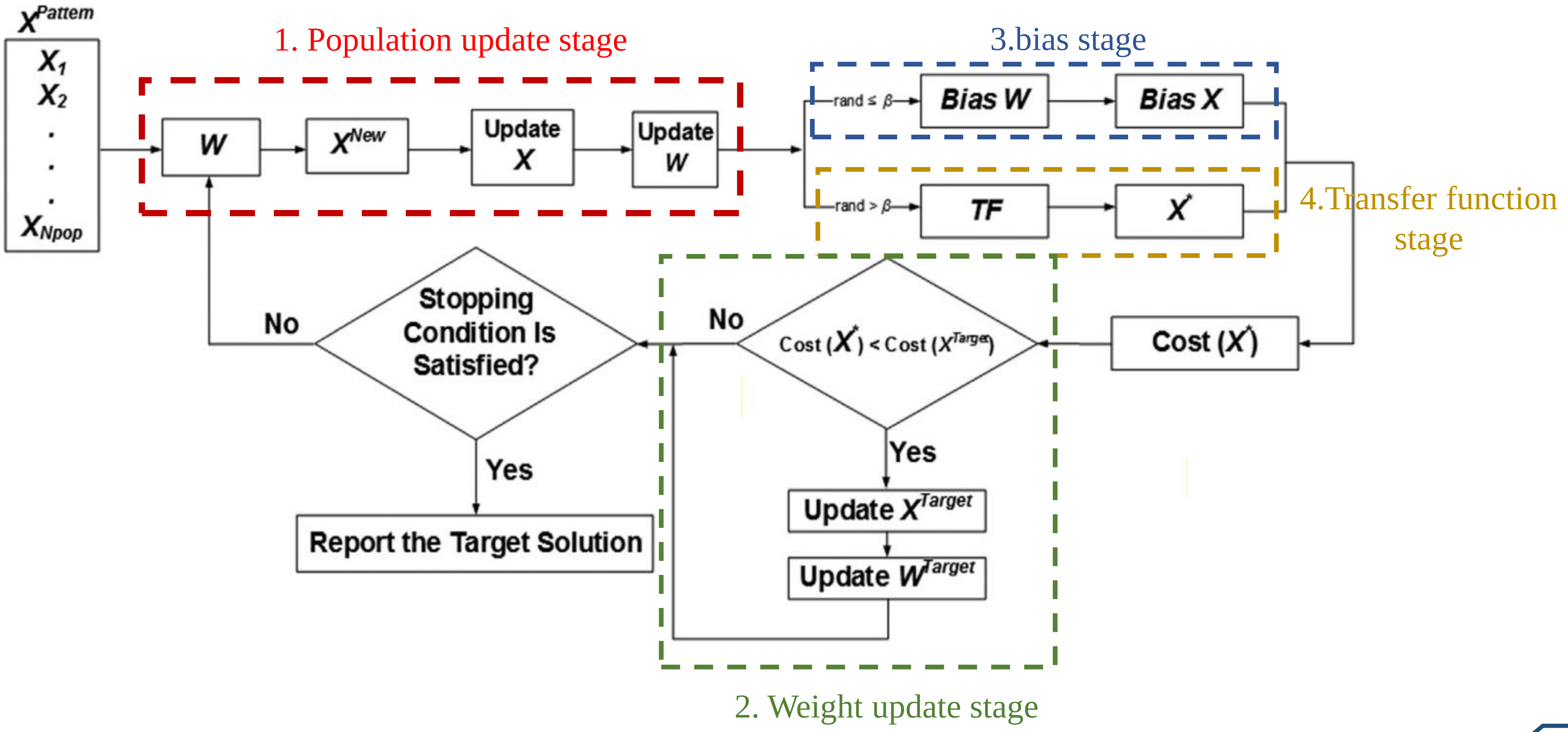
- Recap
- NNA Algorithm
- System modeling
- Experiment and Result
  - Comparison
  - Performance index
  - Robustness Experiment

Recap

- A new polynomial mutation is applied to promote the exploration manner of the original NNA without initial parameters.
- The new algorithm is introduced to obtain the optimal gains of the robot manipulator controller instead of conventional procedures of designer expertise.
- A new performance index is created to guarantee the decreasing of the settling time and the overshoot at the same time.
- The progress of the inspired procedure is confirmed against various trajectories and system parameter variations.

Recap

- **Neural Network algorithm**



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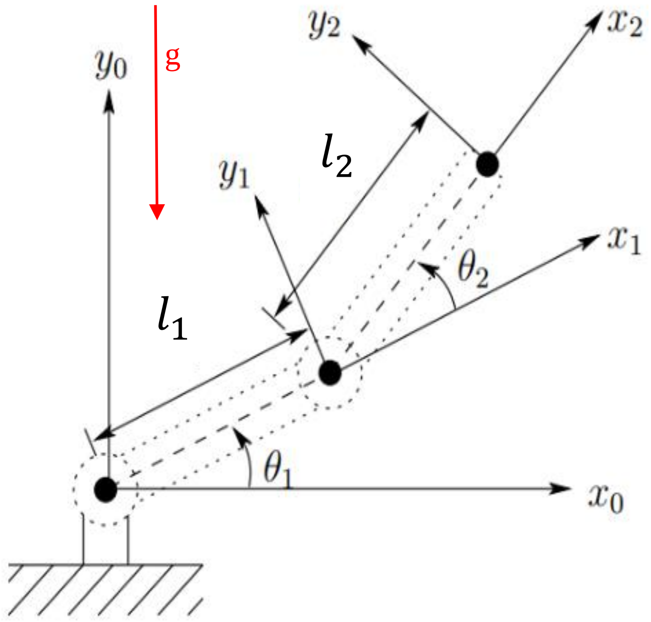
NNA Algorithm

- **Pseudocode of whole process**

Start MNNA
Simulate the manipulator including the chosen controller
Determine the performance function (J)
Select the best solution and the best weights
While t<Max iteration
    Carry out the steps of MNNA
    Simulate the manipulator including the chosen controller
    Obtain the performance function J
    Select the best fitness
END While
Stop

System modeling

- **System modeling**



Lagrange mechanics:

$$\tau = M(q)\ddot{q} + C(q,\dot{q}) + G(q)$$

Where

τ : *Torque vector*
$M(q)$: Inertia matrix
$C(q,\dot{q})$: Centrifugal and Coriolis effect
$G(q)$: Gravity

- Dynamic formulation:

$$\tau_1 = m_2 {l_2}^2(\ddot{\theta}_1 + \ddot{\theta}_2) + m_2 l_1 l_2 c_2(2\ddot{\theta}_1 + \ddot{\theta}_2)$$
$$+(m_1 + m_2){l_2}^2\ddot{\theta}_1 - m_2 l_1 l_2 s_2 {\dot{\theta}_2}^2$$
$$-2m_2 l_1 l_2 s_2 \dot{\theta}_1 \dot{\theta}_2 + m_2 l_2 g c_{12}$$
$$+(m_1 + m_2) l_1 g c_1$$
$$\tau_2 = m_2 {l_2}^2(\ddot{\theta}_1 + \ddot{\theta}_2) + m_2 l_1 l_2 c_2(\ddot{\theta}_1)$$
$$+m_2 l_1 l_2 c_2 {\dot{\theta}_1}^2 + m_2 l_1 g c_{12}$$

System modeling

Lagrange mechanics:

$$\boldsymbol{\tau_i = M(q_i)\ddot{q}_i + C(q_i,\dot{q}_i) + G(q_i)}$$

- Challenge of tuning controller for robotic manipulator: →Joints coupling

$$M(q_i) = \begin{bmatrix} m_2{l_2}^2 + (m_1+m_2){l_2}^2 + 2m_2l_1l_2c_2 & m_2{l_2}^2 + m_2l_1l_2c_2 \\ m_2{l_2}^2 + m_2l_1l_2c_2 & m_2{l_2}^2 \end{bmatrix}$$

$$C(q_i,\dot{q}_i) = \begin{bmatrix} -2m_2l_1l_2s_2\dot{q}_1\dot{q}_2 - m_2l_1l_2s_2{\dot{q}_2}^2 \\ m_2l_1l_2c_2{\dot{q}_1}^2 \end{bmatrix}$$

$$G(q_i) = \begin{bmatrix} m_2l_2gc_{12} + (m_1+m_2)l_1gc_1 \\ m_2l_1gc_{12} \end{bmatrix}$$

- **Control signal of the PID control**

$$\tau_i = K_{p,i}e_i + K_{I,i}\int e_i \cdot dt + K_{D,i}\frac{de_i}{dt}, \qquad i = 1,2$$

$$e_i = q_{d,i} - q_i$$

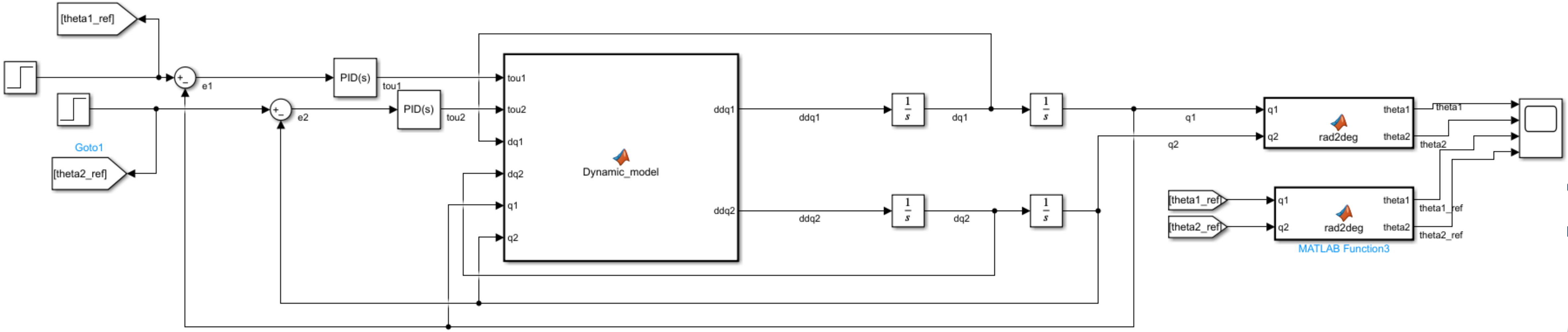
System modeling

$$\textbf{step1}:\ \tau[k] = K_p e[k] + K_d\left(\frac{e[k]-e[k-1]}{dt}\right) + K_i\sum_{j=0}^{k} e[j]\cdot dt$$

$$\textbf{step2}:\ \ddot{q}[k] = M^{-1}(q[k-1])(\tau[k] - C(q[k-1],\dot{q}[k-1]) - G(q[k-1]))$$

$$\textbf{step3}:\ \dot{q}[k] = \dot{q}[k-1] + \ddot{q}[k]\cdot dt$$

$$\textbf{step4}:\ q[k] = q[k-1] + \dot{q}[k]\cdot dt$$



Experiment and Result

- Robotic dynamic Parameter:

$$m_1 = m_2 = 0.1kg$$
$$l_1 = 0.8m \;\; l_2 = 0.4m$$
$$g = 9.81m/s^2$$

- Max iteration: 100

- Population size: 50

- Controller gain limit:

	Link1		Link2	
	min	max	min	max
K_p	0	250	0	250
K_I	0	1	0	1
K_D	0	20	0	10

- Compare subjects
  - GA-PID
  - PSO-PID
  - MNNA-PID

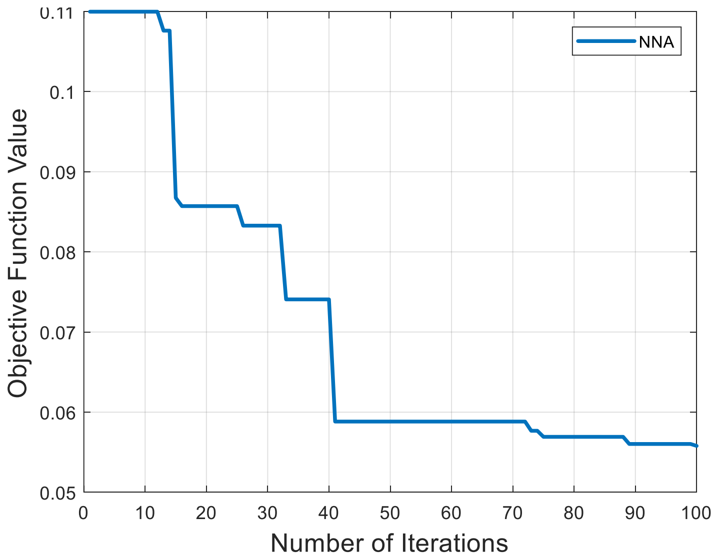
	Factors number	Tuning factor
GA-PID	4	Population size, iteration Crossover, mutation
PSO-PID	5	Population size, iteration C1,c2, w
MNNA-PID	2	Population size, iteration

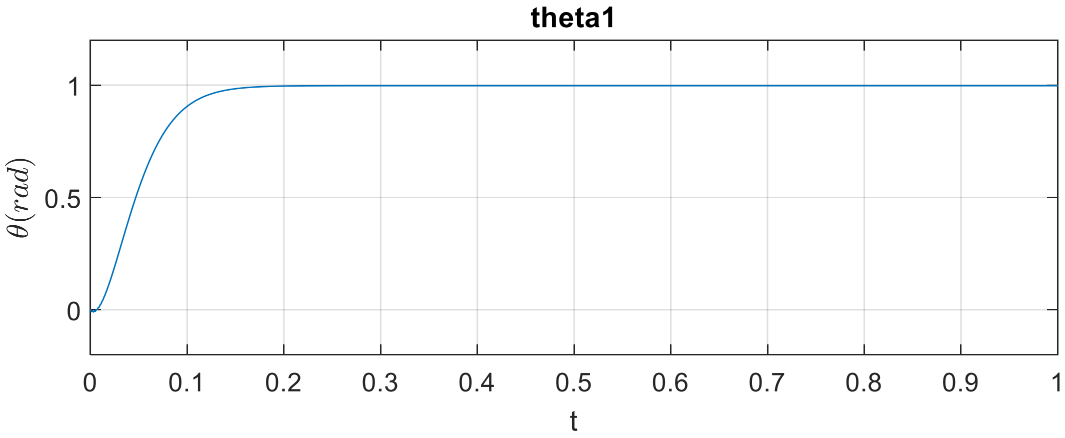
NNA result

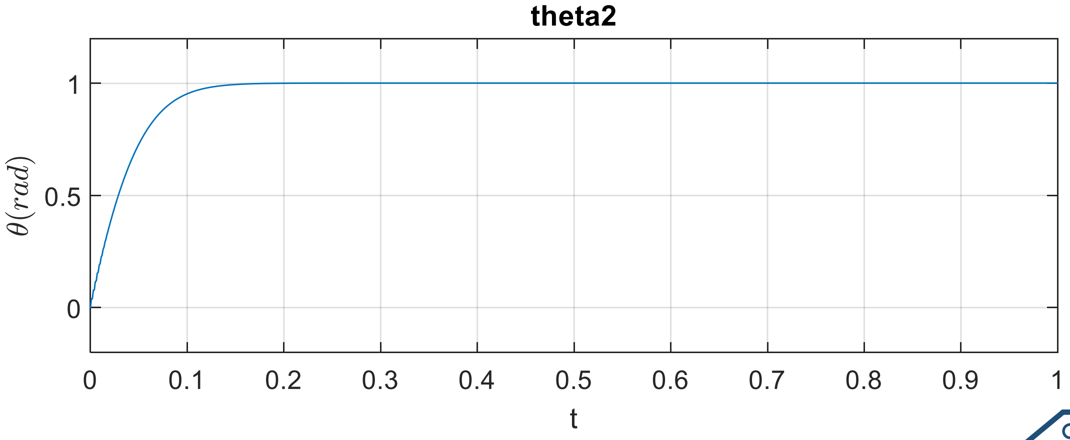
Tunning factor setting:
Max iteration: 100
Population size:50

Run: 1 Error: 0.055614 Elapsed_Time: 24.6562
============optimal solution==============

Link1	Link2
Kp1:250	Kp2:250
Ki1:0.41475	Ki2:0.59791
Kd1:13.4205	Kd2:8.8604







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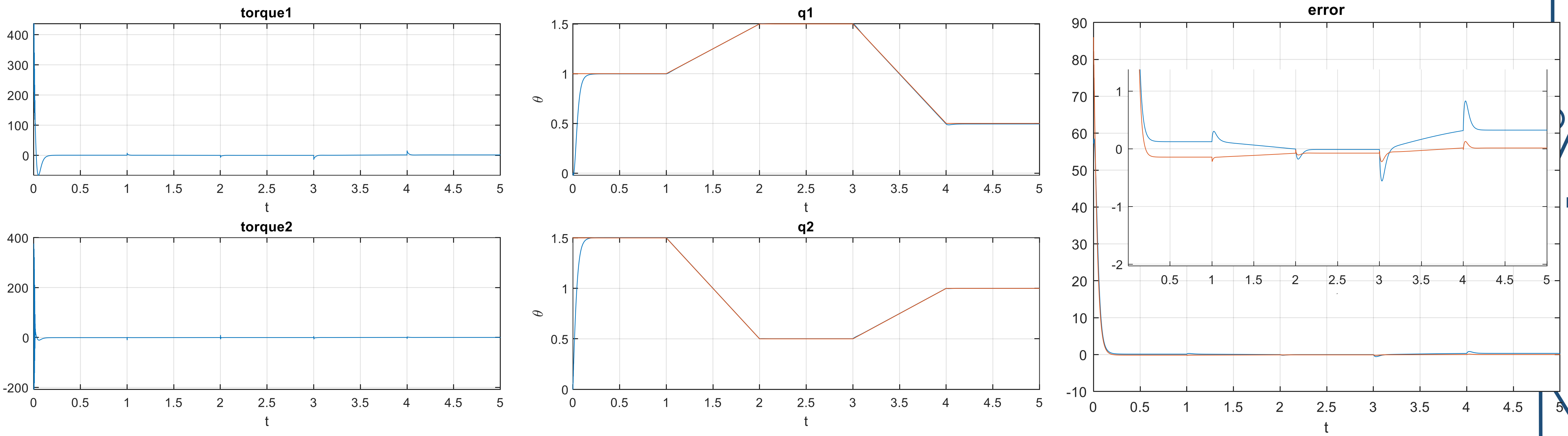
NNA result

- VARIOUS TRAJECTORIES

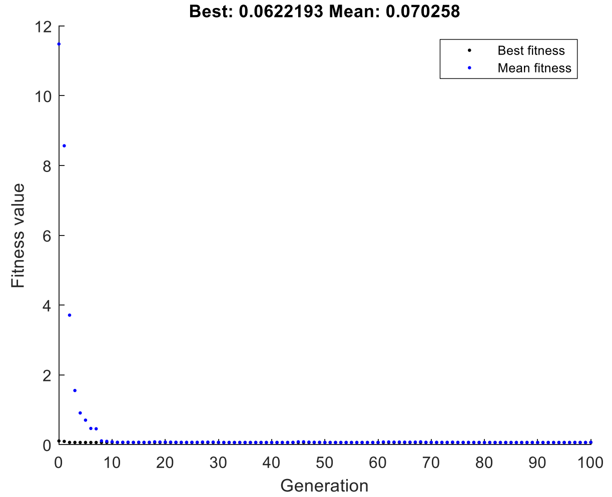


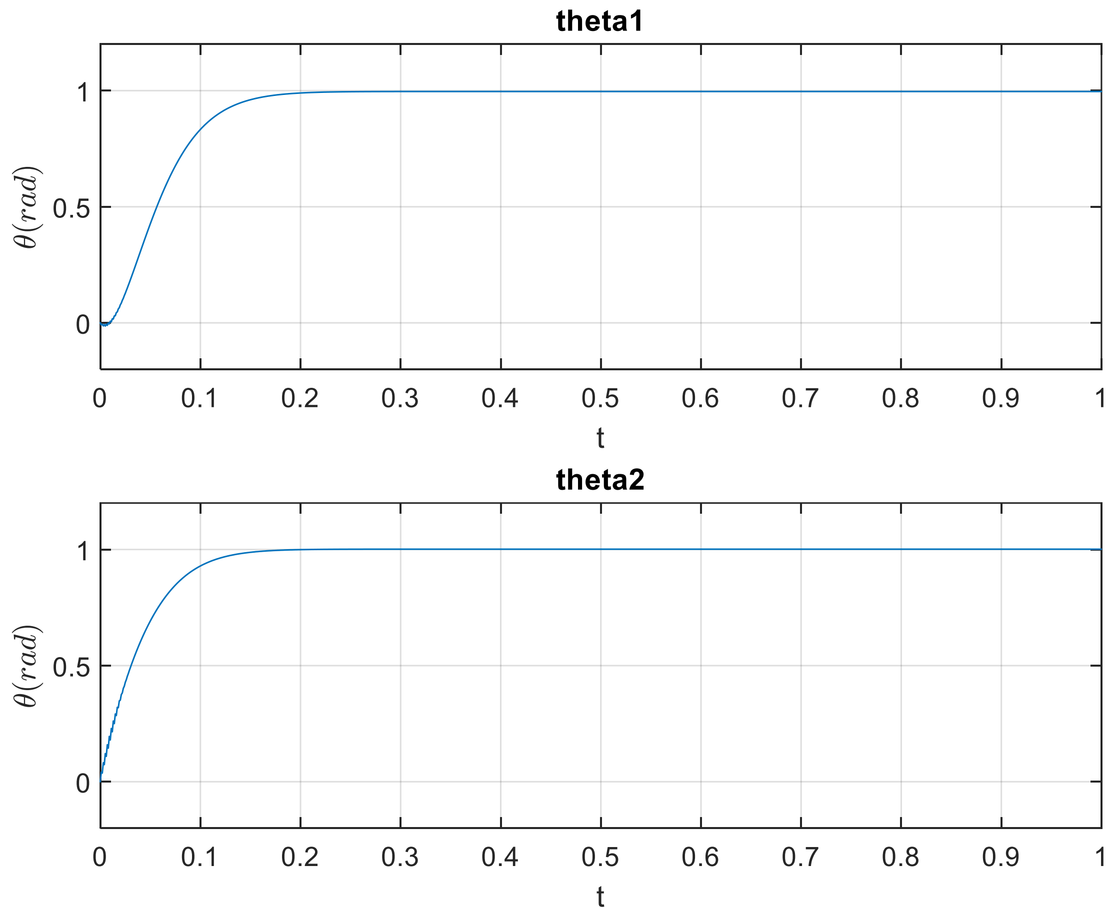
GA result

Tunning factor setting:
Max iteration: 100
Population size:50
Crossover: 0.8
Mutation: 0.1

Error: 0.058121   Elapsed Time: 23.9588
=========optimal solution=========

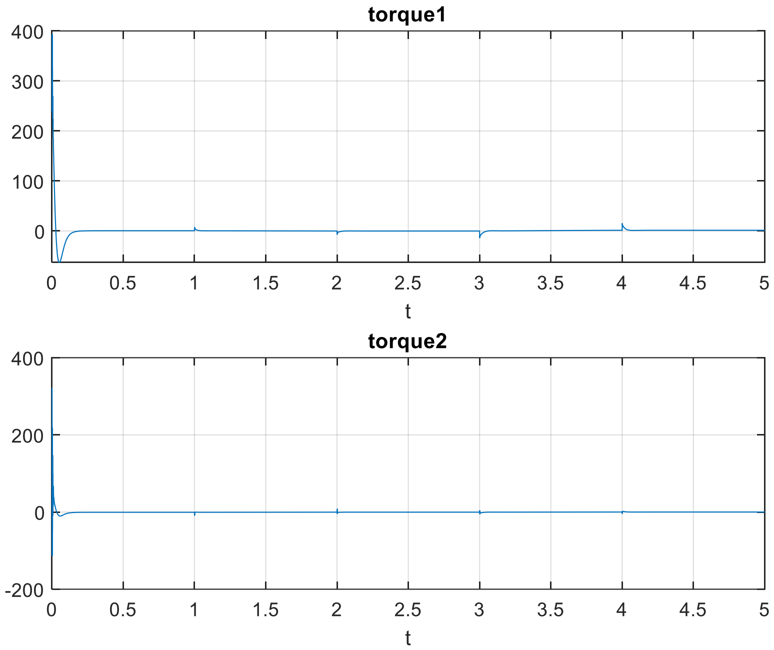
Link1	Link2
Kp1:193.8595	Kp2:223.0862
Ki1:1	Ki2:0.020764
Kd1:11.7447	Kd2:8.6229

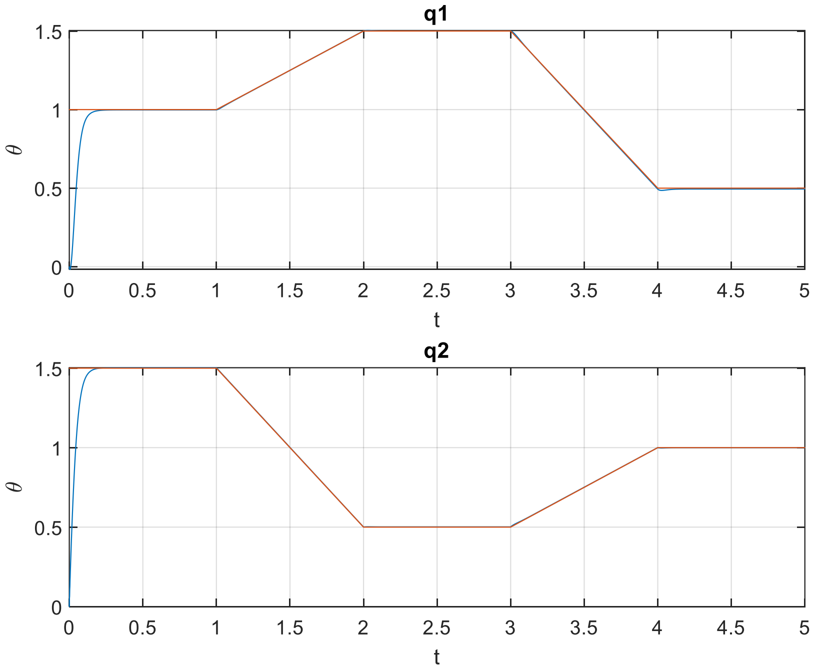


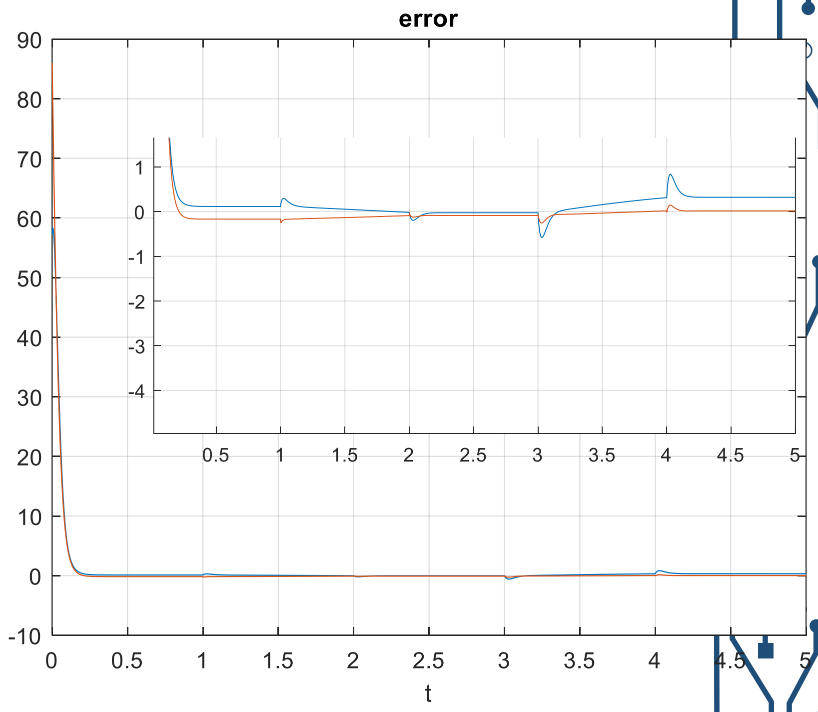


GA result

- VARIOUS TRAJECTORIES







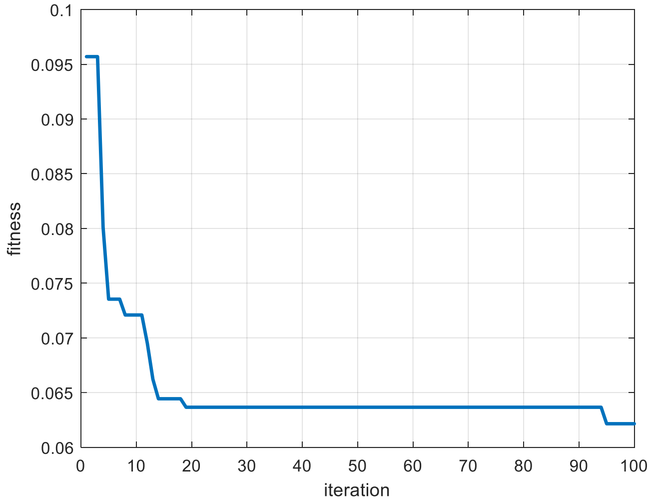
PSO result

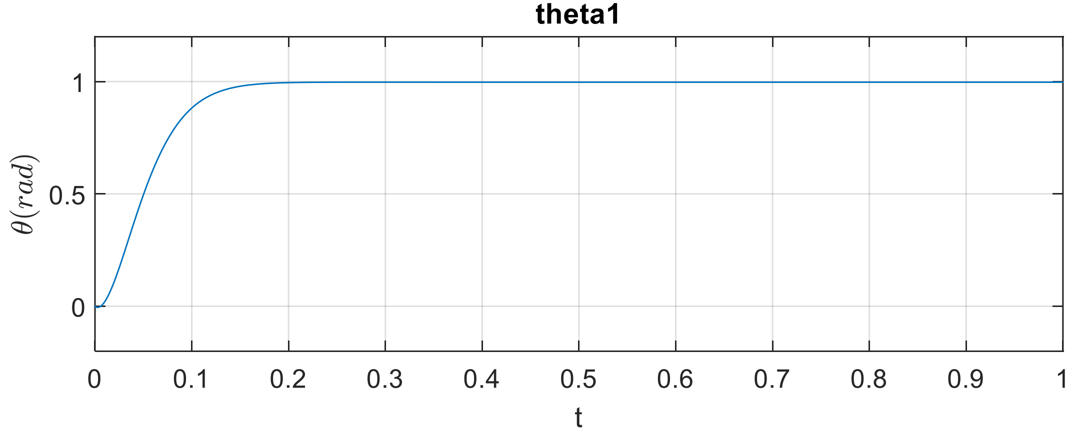
Tunning factor setting:
Max iteration: 100
Population size:50
Personal Learning Coefficient(c1): 1.5
Global Learning Coefficient(c2): 0.12
Inertia Weight Damping Ratio(w): 0.99

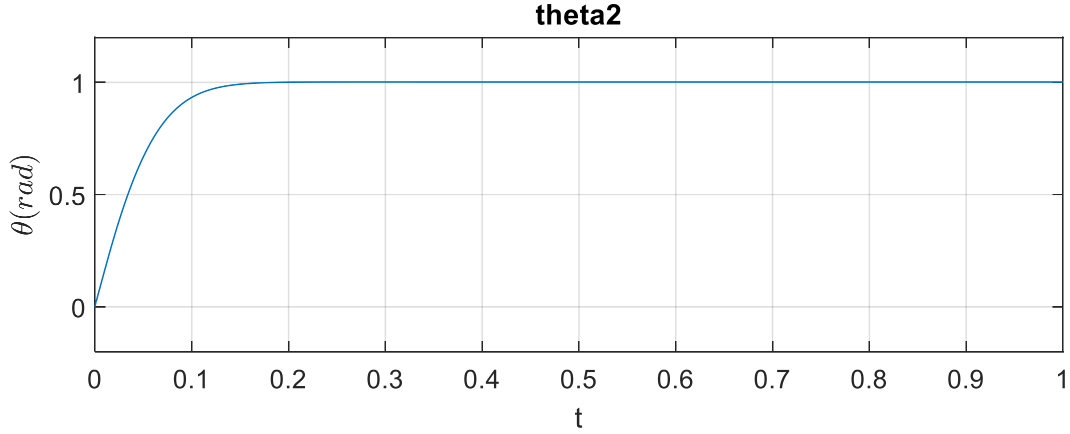
Error: 0.062151 Elapsed Time:23.7006

=============optimal solution============

Link1	Link2
Kp1:218.4591	Kp2:161.4128
Ki1:1	Ki2:0.94015
Kd1:12.492	Kd2:6.4216







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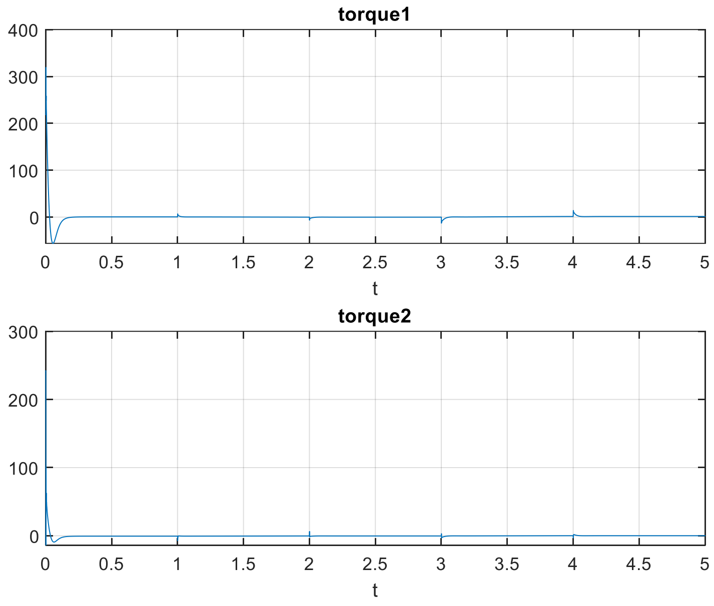
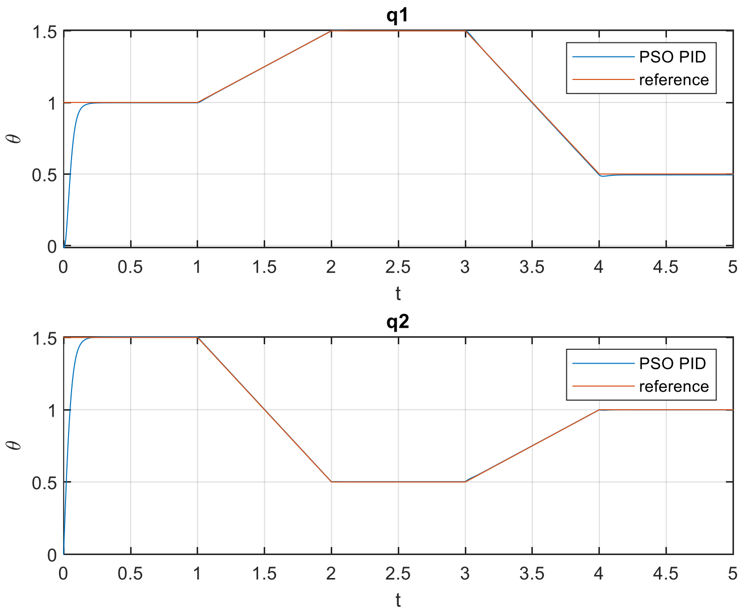
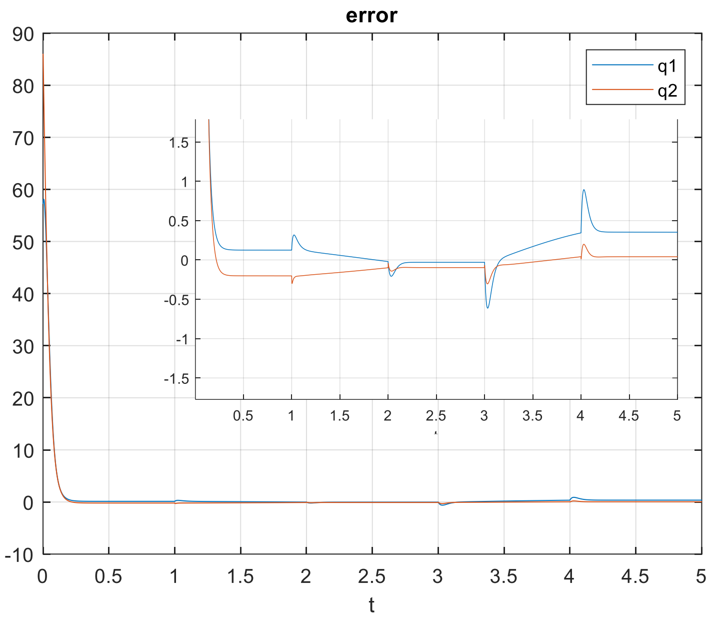
PSO result

- VARIOUS TRAJECTORIES







Comparison

		GA-PID	PSO-PID	NNA-PID
Controller Parameters	Link1	$K_P = 193.86$	$K_P = 218.45$	$K_P = 250$
		$K_I = 1$	$K_I = 1$	$K_I = 0.414$
		$K_D = 11.74$	$K_D = 12.492$	$K_D = 13.42$
	Link2	$K_P = 223.08$	$K_P = 161.41$	$K_P = 250$
		$K_I = 0.02$	$K_I = 0.94$	$K_I = 0.59791$
		$K_D = 8.62$	$K_D = 6.42$	$K_D = 8.8604$
J		0.05812	0.062151	0.055614

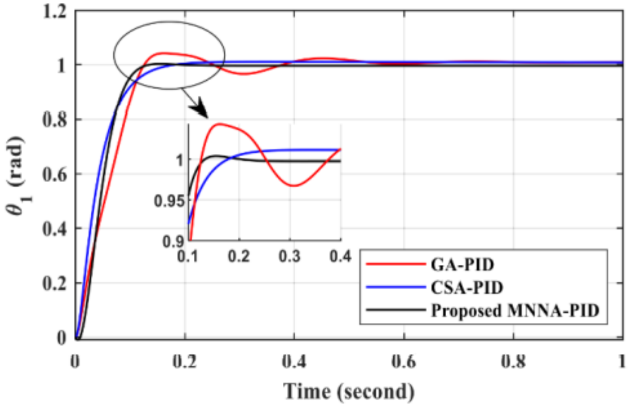


Figure 2 Link1 step response

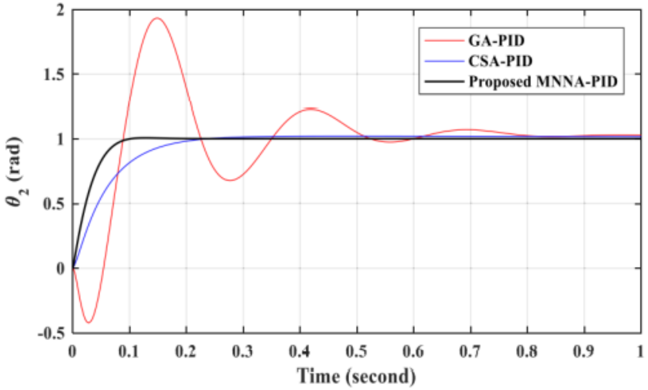
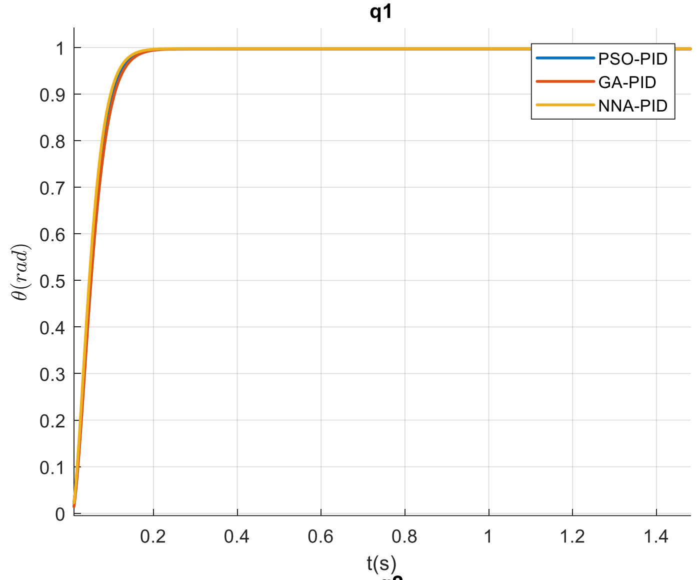
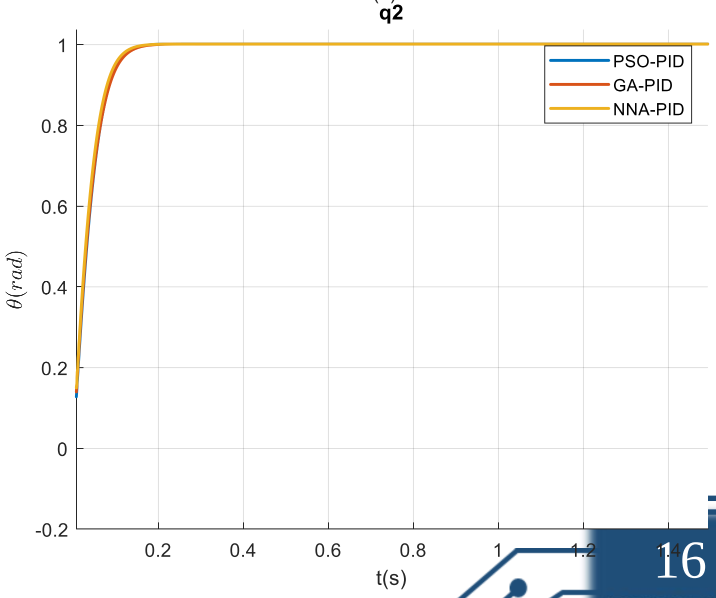
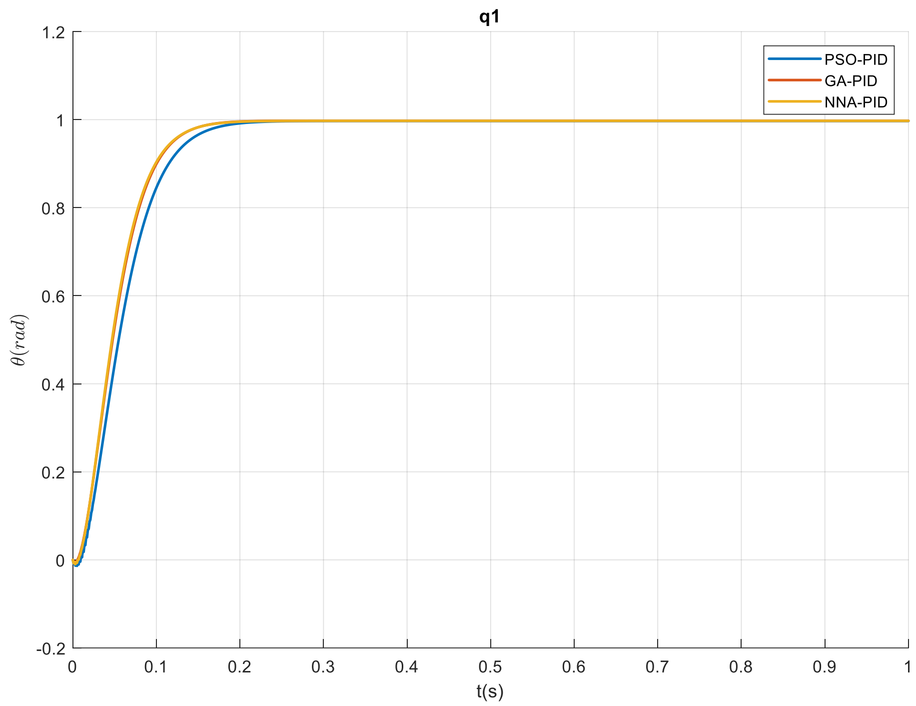


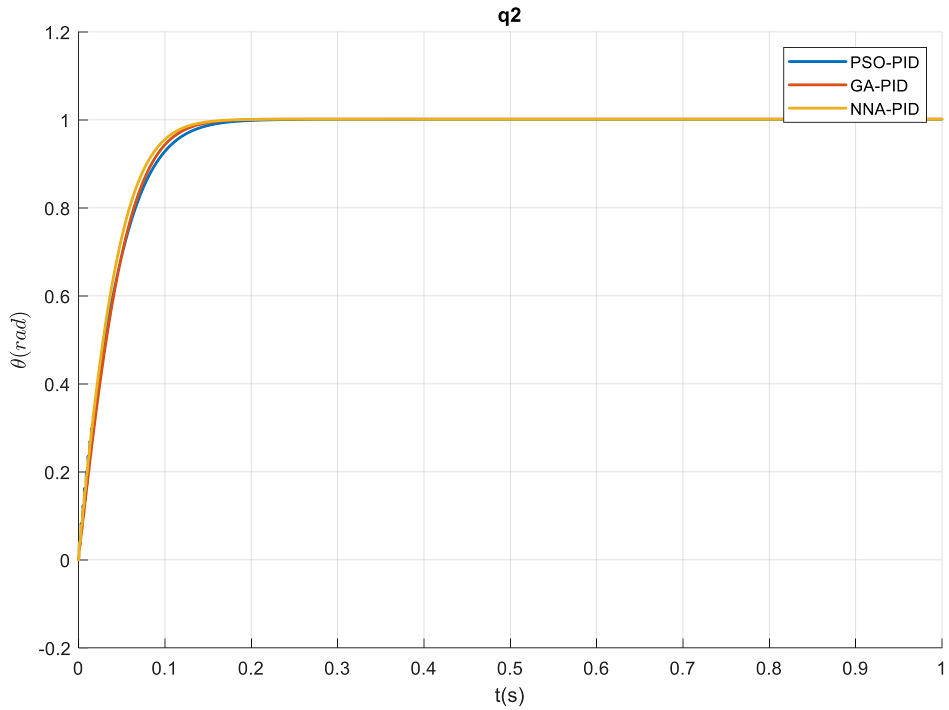
Figure 1 Link2 step response





Comparison

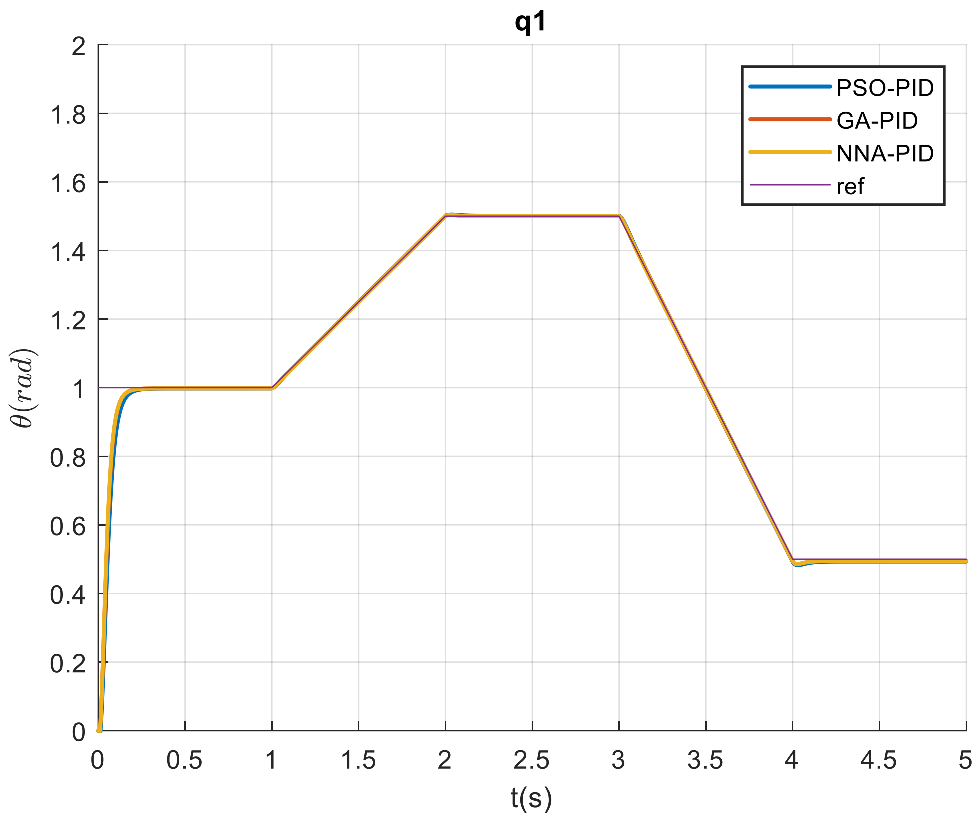


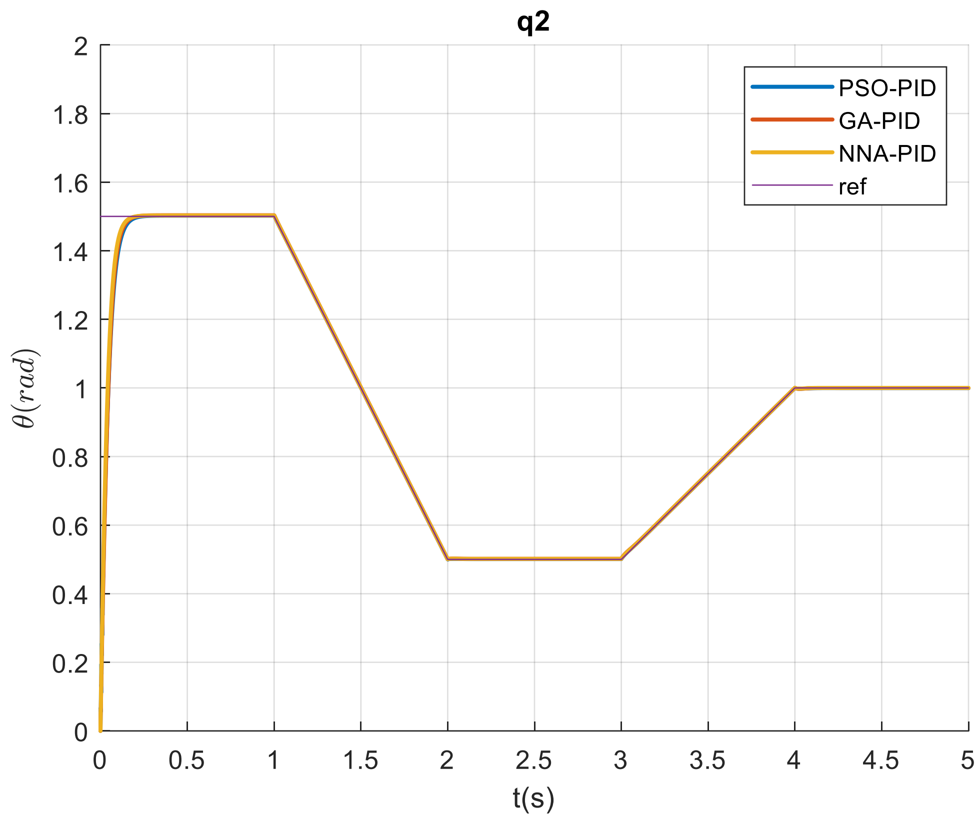


		GA-PID	PSO-PID	NNA-PID
Controller Parameters	Link1	$K_P = 494.94$	$K_P = 415.52$	$K_P = 497.45$
		$K_I = 0.995$	$K_I = 0.297$	$K_I = 0.0057$
		$K_D = 19.25$	$K_D = 18.02$	$K_D = 18.99$
	Link2	$K_P = 212.34$	$K_P = 112.80$	$K_P = 379.07$
		$K_I = 0.017$	$K_I = 0.187$	$K_I = 0.0307$
		$K_D = 6.58$	$K_D = 4.34$	$K_D = 10$
J		0.041568	0.050615	0.038131

Comparison

- VARIOUS TRAJECTORIES





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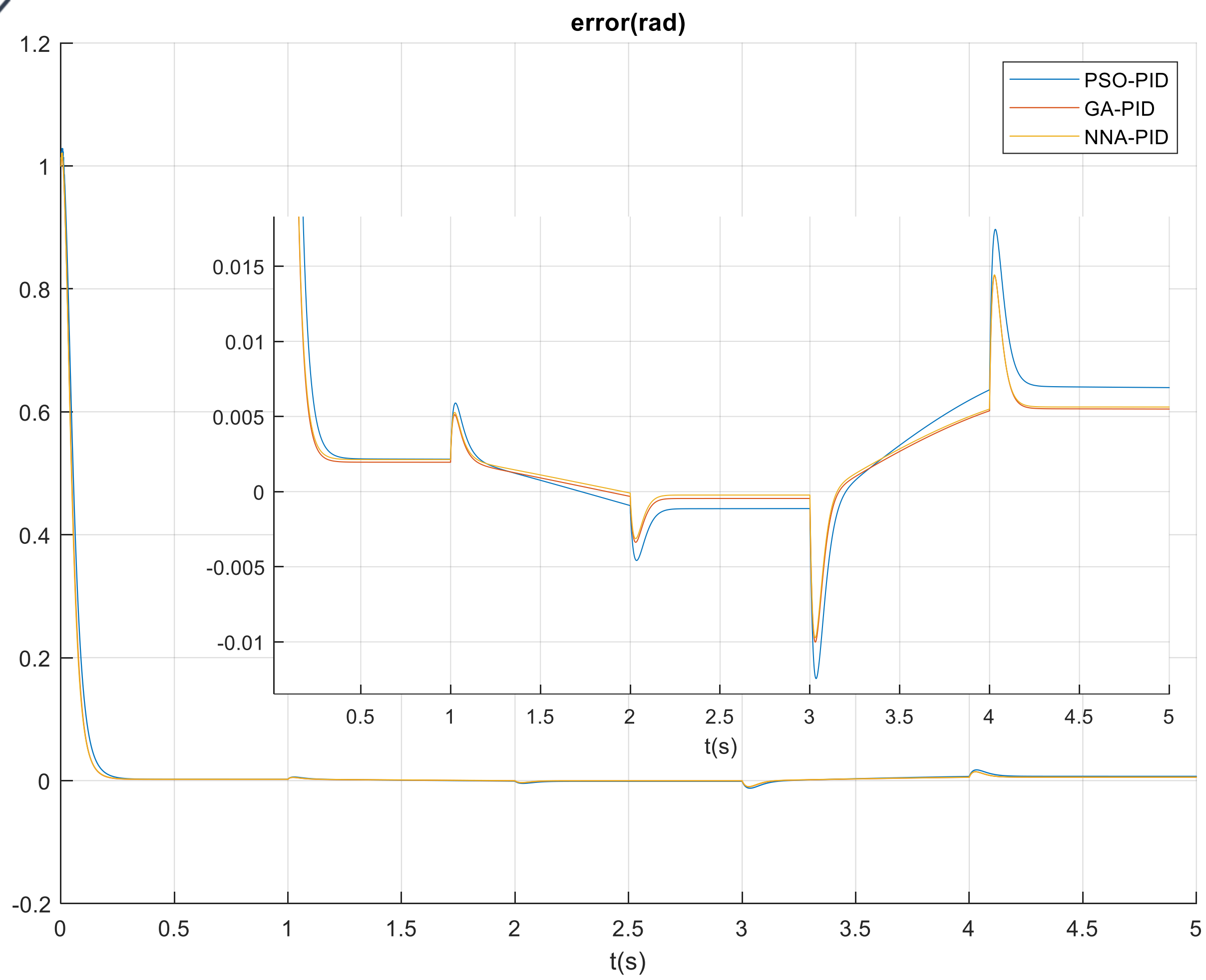
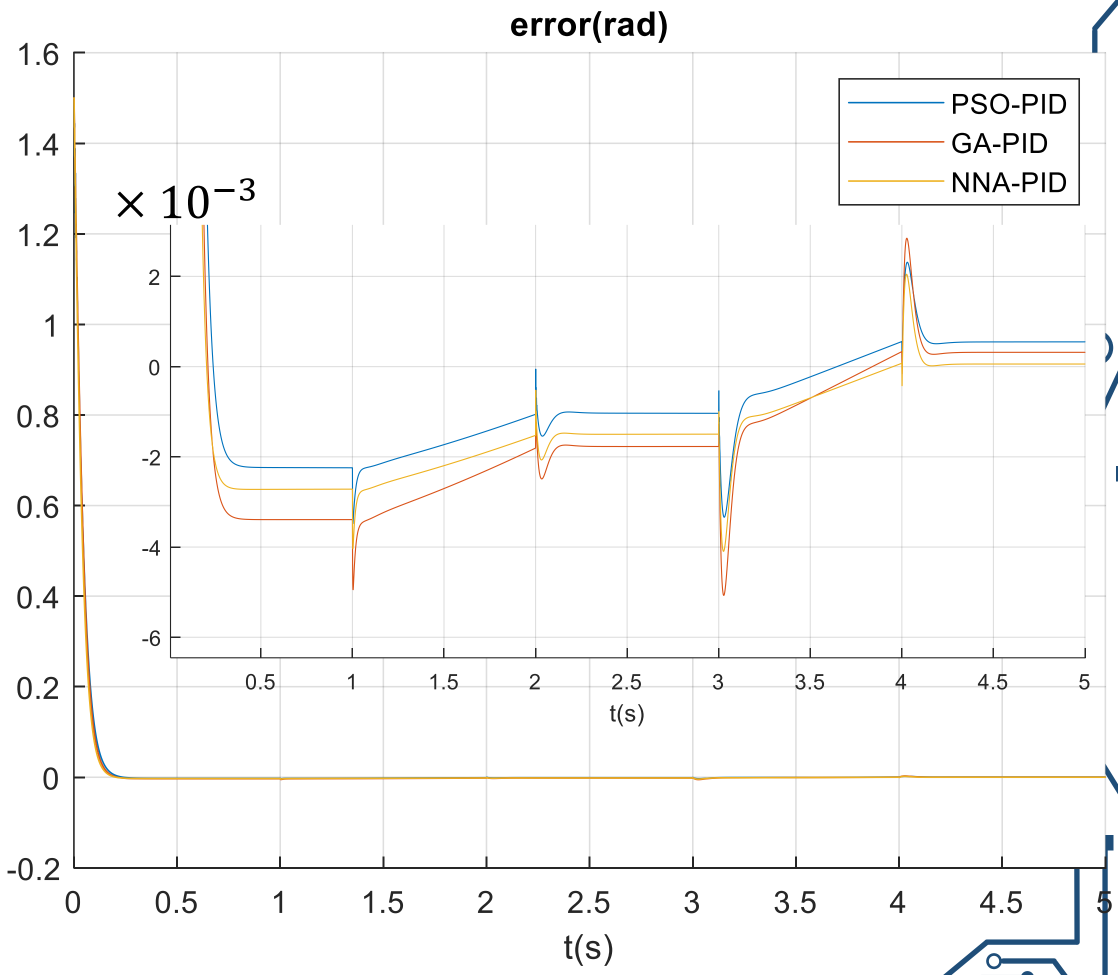
Comparison





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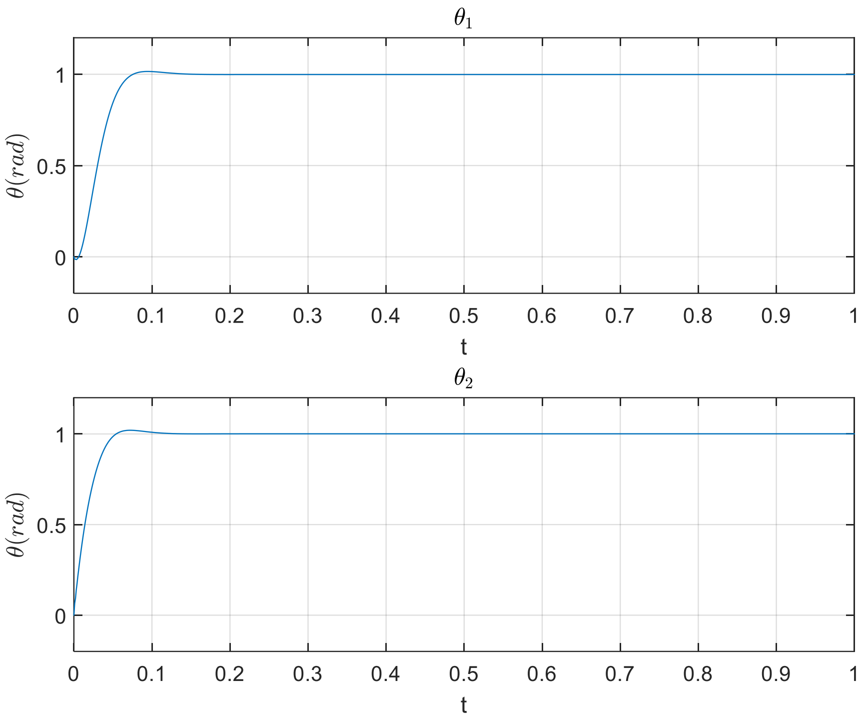
Performance index

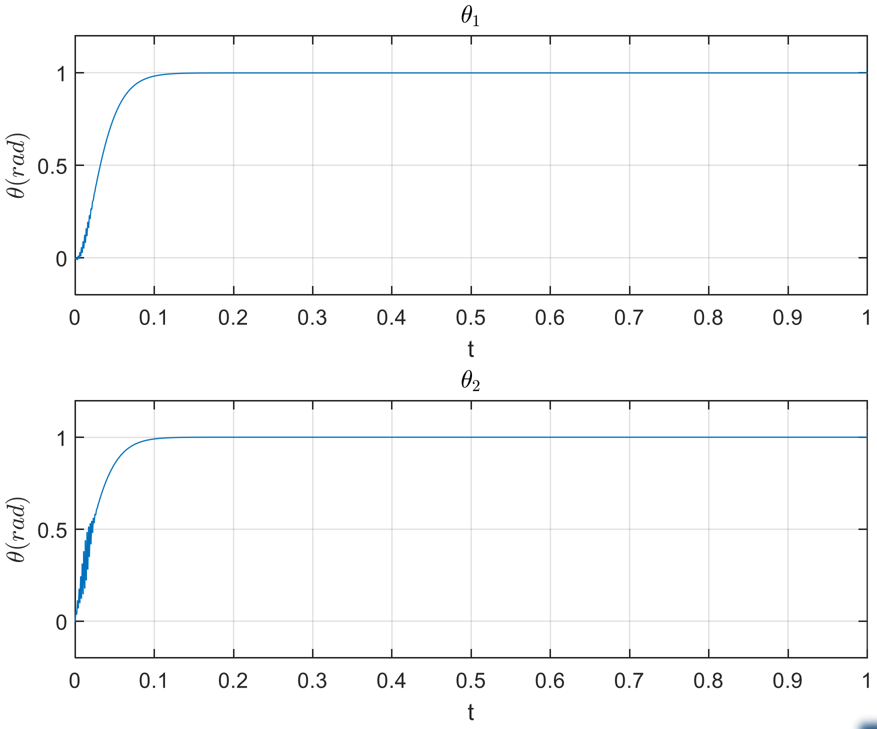
- **Performance index**
  Goal: decrease settling time 't_s' and maximum overshoot 'M_p'

$$J = \sum_{i=1}^{2}\left(1-e^{-\psi}\right)\left(M_{P,i}+E_{ss,i}\right)+e^{-\psi}\left(t_{s,i}-t_{r,i}\right)$$

$M_{P,i}$	Overshoot
$E_{ss,i}$	Steady-state error
$t_{s,i}$	settling time
$t_{r,i}$	rise time
$\psi(=0.7)$	weight constant



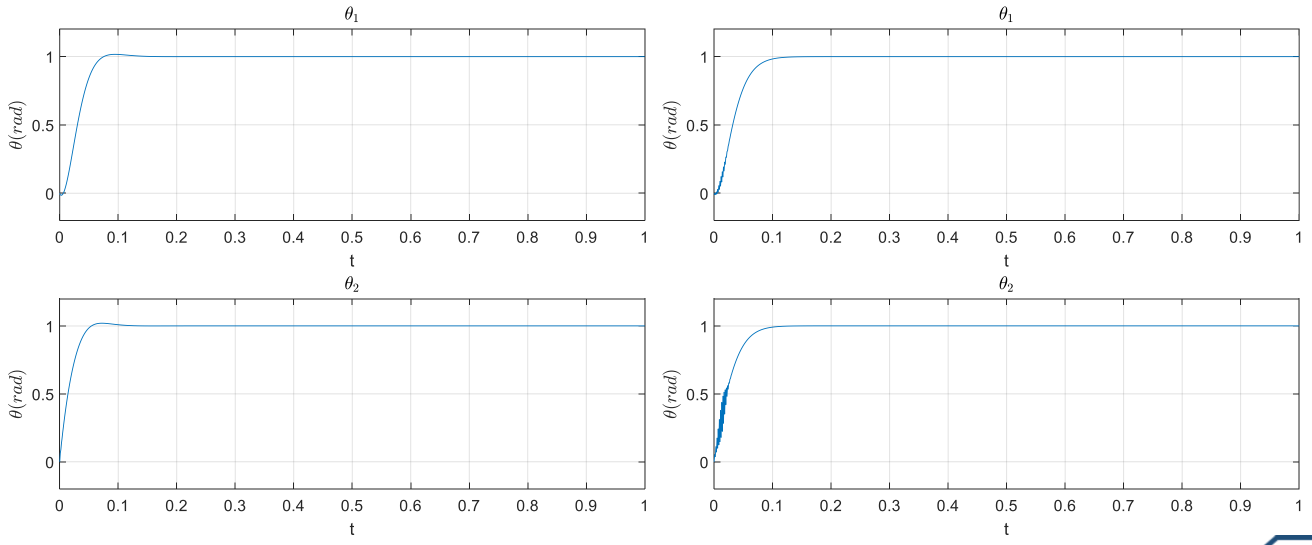
ψ =0 loss: 0.03989



ψ =1 loss: 0.028892

Performance index

	ψ =0		ψ = 1	
	Link1	Link2	Link1	Link2
RiseTime	**0.0409**	**0.0328**	0.0550	0.0541
SettlingTime	**0.0662**	**0.0462**	0.0962	0.0865
Overshoot	2.035%	1.939%	**0.021%**	**0.052%**
Steady-state error	0.0013	**0.0006**	**0.0012**	0.0009
Total loss	0.03989		**0.0289**	



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Performance index

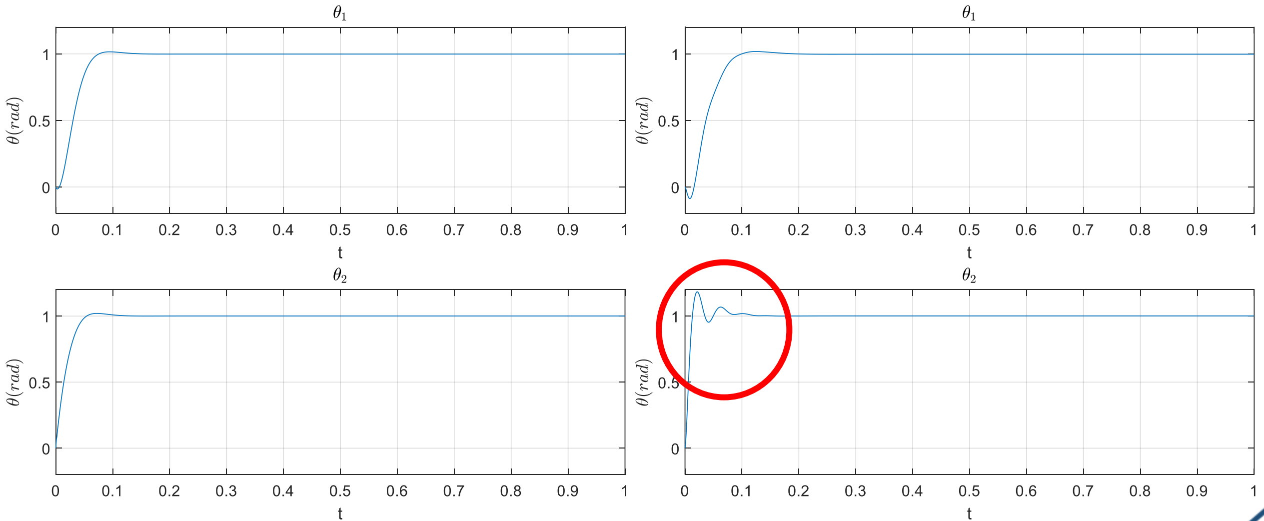
- **Performance index** $(let\ \psi = 0)$

Goal: decrease settling time 't_s' and maximum overshoot 'M_p' $\quad J = \sum_{i=1}^{2}(t_{s,i} \mp t_{r,i})$

	$(t_{s,i} - t_{r,i})$		$(t_{s,i} + t_{r,i})$	
	Link1	Link2	Link1	Link2
RiseTime	**0.0409**	0.0328	0.0518	**0.0091**
SettlingTime	**0.0662**	**0.0462**	0.0883	0.0779
Overshoot	2.035%	**1.939%**	**1.995%**	19.751%
Steady-state error	**0.0013**	**0.0006**	0.0025	0.0013

Why?

Why?



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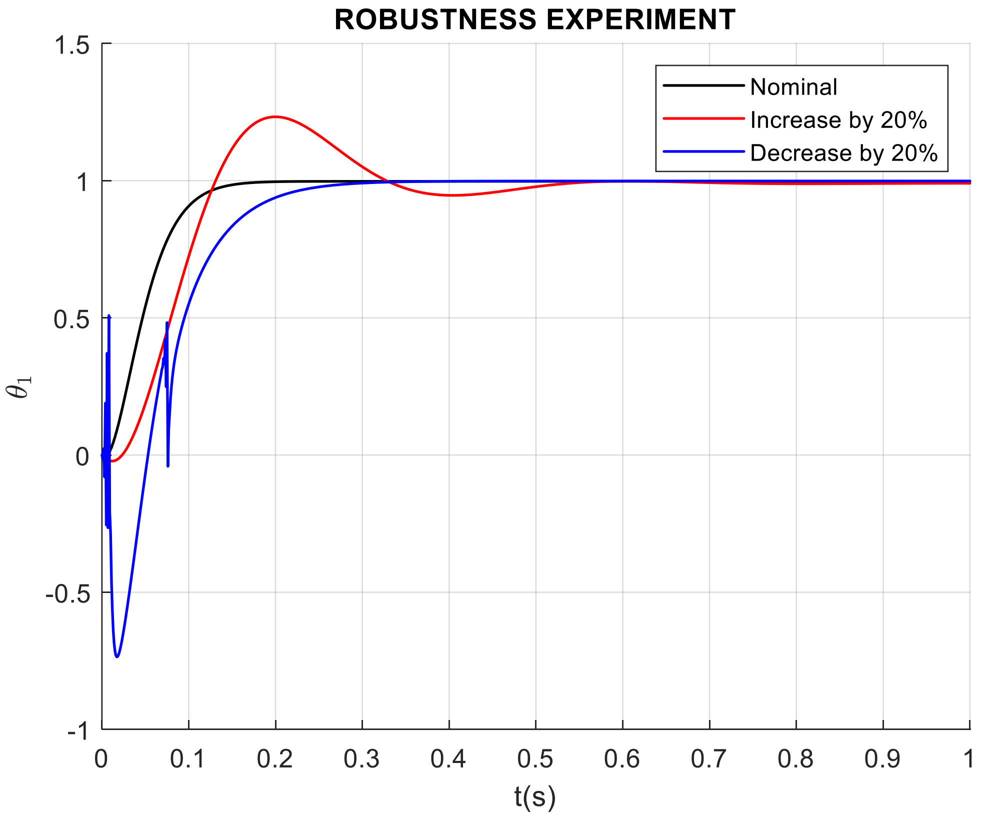
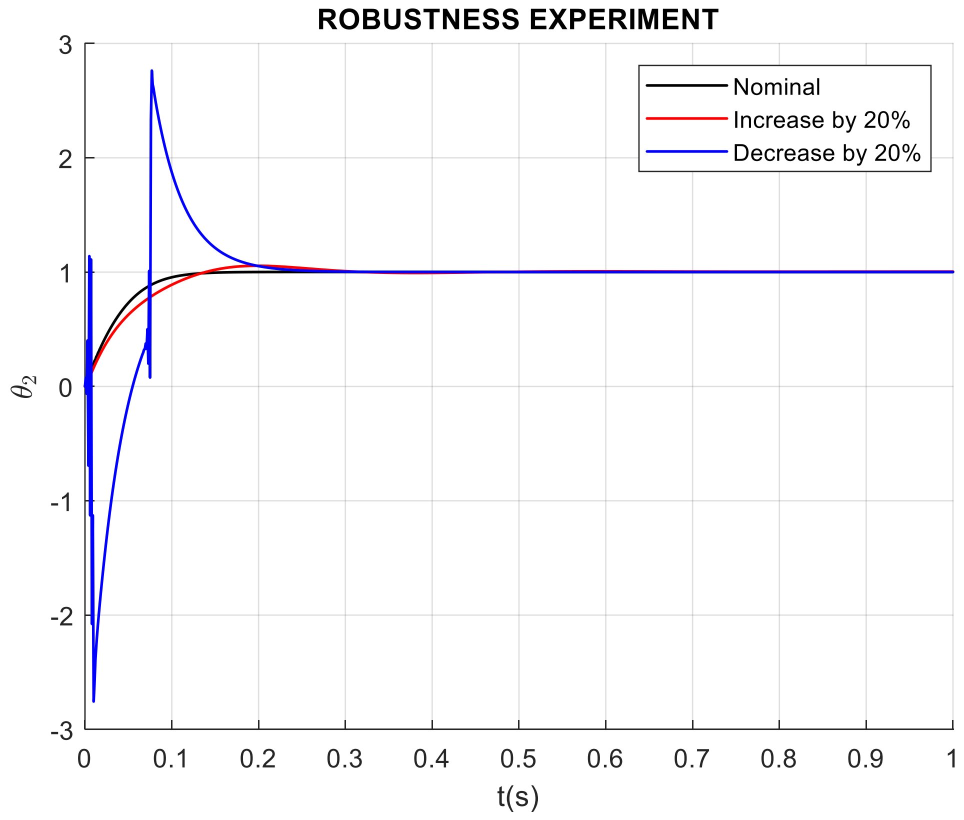
Robustness Experiment

- Making uncertainty in masses and lengths of the robotic arms by ±20%





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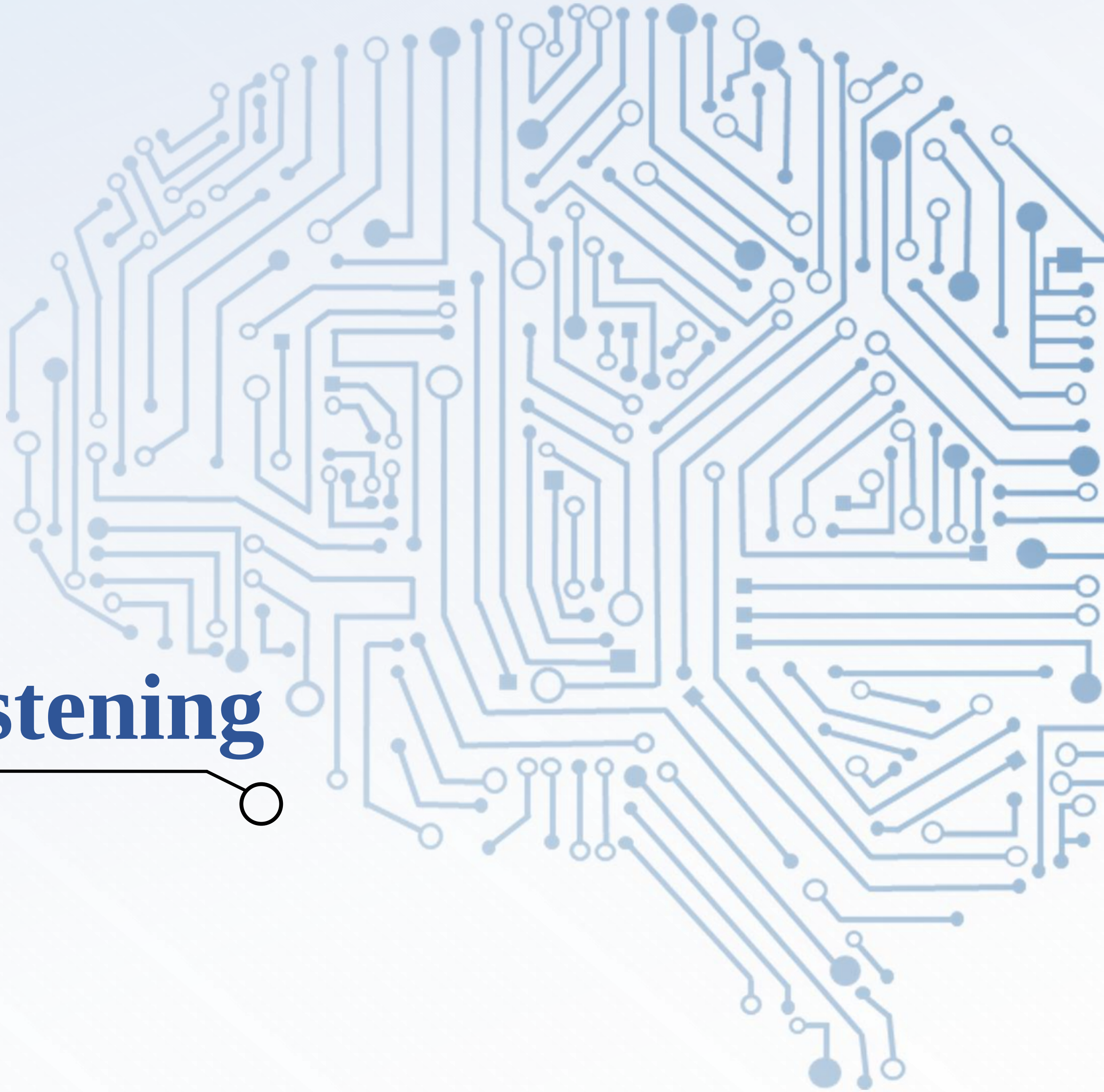

Thanks for Your Listening