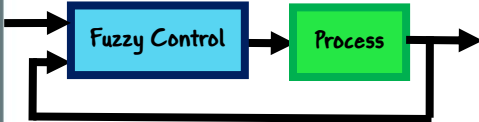



Intelligent Control





Fuzzy Control Systems

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Content

- ❖ Introduction
- ❖ Fuzzy Control of Linear systems
- ❖ Fuzzy Supervisory Control
- ❖ Design Example

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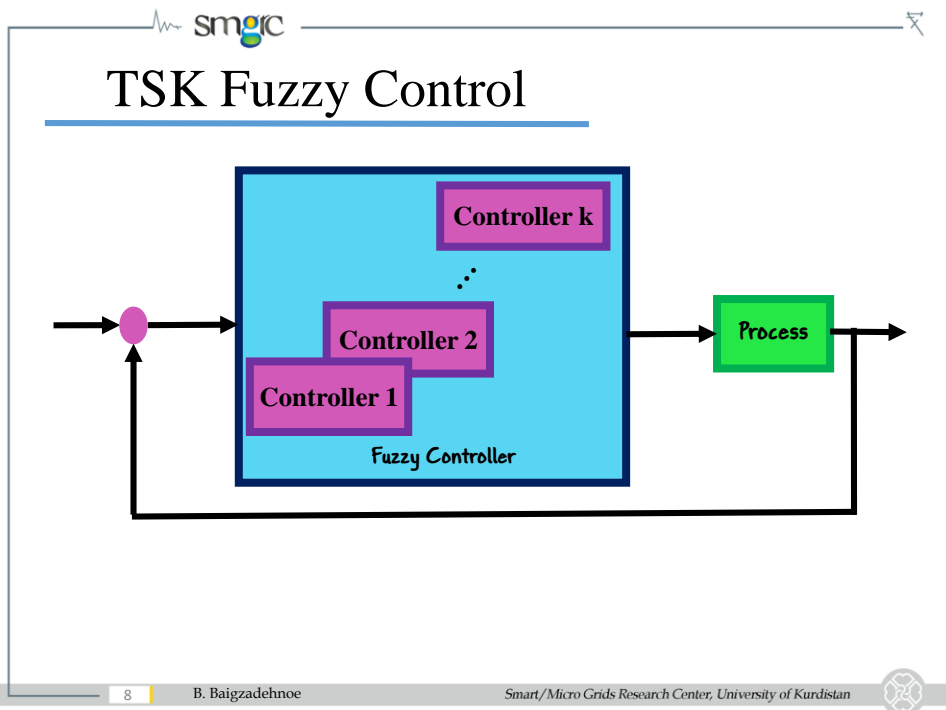
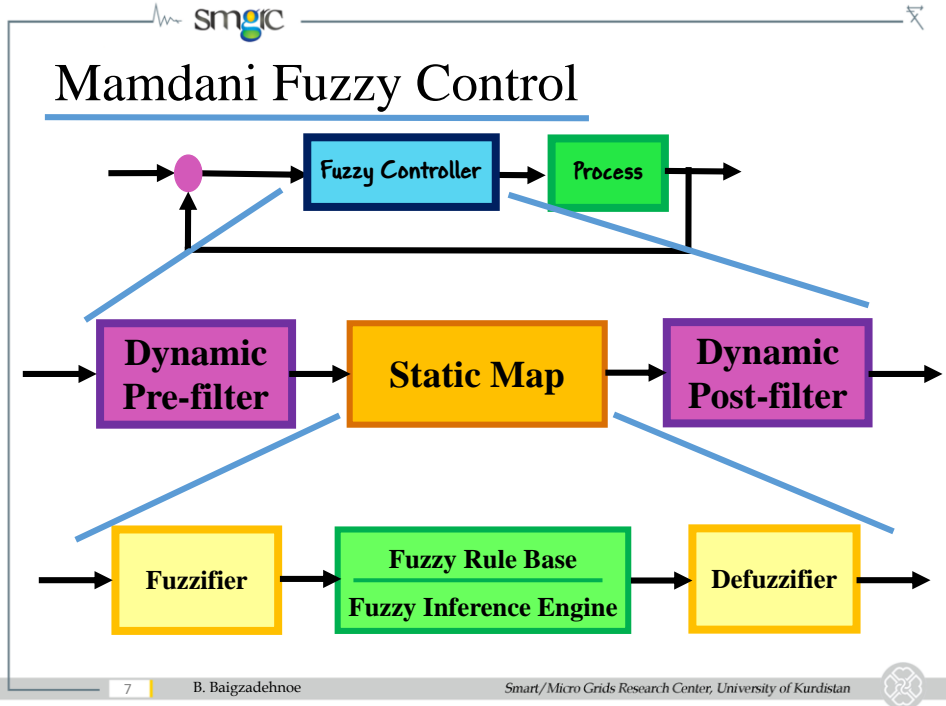


Definition of Fuzzy Control

- A *fuzzy controller* is a controller that includes a nonlinear mapping based on fuzzy if-then rules. In fact, a controller in which fuzzy logic is used in anyway, is known as a *fuzzy controller*.
- If fuzzy systems are directly used as controllers or controllers are designed based on the fuzzy model, then the resulting controllers are called *fuzzy controllers*.
- *Fuzzy control* is a methodology of intelligent control that mimics human thinking and reacting by using a multivalent fuzzy logic and elements of artificial intelligence.

Why Fuzzy Control?

- Efficiently incorporates human expert information
- Does not require a mathematical model of system
- Produces nonlinear controllers
- Easy and inexpensive to design
- Easy to understand



Stability of Fuzzy Control

Note: Although the rigorous mathematical framework of control systems *stability* theory in some way opposes the vagueness of fuzzy controller properties, *stability* remains a key issue in fuzzy controller design. The main criticism of fuzzy control is related to its lack of precise *stability* analysis. That is why efforts have been put into the investigation of various techniques that have a potential to solve the *stability* issue in fuzzy controlled systems.

Content

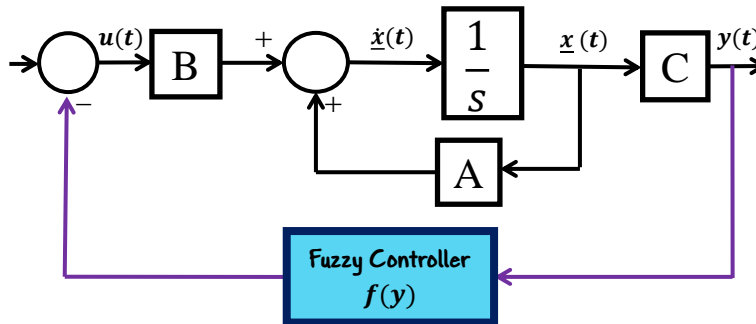
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- ❖ Design Example

Fuzzy Control system

Consider the following *LTI-SISO system* with the fuzzy control scheme:

$$\text{system: } \begin{cases} \dot{\underline{x}}(t) = A\underline{x}(t) + Bu(t) \\ y(t) = C\underline{x}(t) \end{cases}$$

$$\text{Controller: } \{u(t) = -f(y)\}$$



Fuzzy Control system

Proposition: Consider the following closed-loop control system

$$\text{system: } \begin{cases} \dot{\underline{x}}(t) = A\underline{x}(t) - Bf(y) \\ y(t) = C\underline{x}(t) \end{cases}$$

and suppose that

- all eigenvalues of A lie in the open left half of the complex plane
- the system is controllable and observable
- the transfer function of the system is strictly positive real.

If the nonlinear function f satisfies $f(0) = 0$ and

$$yf(y) \geq 0 \quad \text{for } \forall y \in \mathbb{R}$$

then the equilibrium point $x = 0$ of the closed-loop system is globally exponentially stable.



Fuzzy Control system

Theorem: Consider the fuzzy system from the $2N + 1$ fuzzy IF-THEN rules of the following form:

$$\text{IF } y \text{ is } A^l \text{ THEN } u \text{ is } B^l$$

In which $l = 1, 2, \dots, 2N + 1$ and the centers \bar{y}^l of fuzzy sets B^l are chosen such that

$$\bar{y}^l \begin{cases} \leq 0 & \text{for } l = 1, 2, \dots, N \\ = 0 & \text{for } l = N + 1 \\ \geq 0 & \text{for } l = N + 2, N + 3, \dots, 2N + 1 \end{cases}$$

If product inference engine, singleton fuzzifier, and center average defuzzifier are employed to construct fuzzy system; that is, the designed fuzzy system is

$$u = -f(y) = -\left(\sum_{l=1}^{2N+1} \bar{y}^l \mu_{A^l}(y) \right) / \left(\sum_{l=1}^{2N+1} \mu_{A^l}(y) \right)$$

, then the nonlinear function f satisfies $f(0) = 0$ and $yf(y) \geq 0$. (for $\forall y \in R$).



Optimal Fuzzy Control Scheme

Consider the following LTI SISO system:

$$\dot{\underline{x}}(t) = A\underline{x}(t) + B\underline{u}(t)$$

where $x \in R^n$ and $u \in R^m$, and that the performance criterion is the quadratic function:

$$J = \underline{x}^T(T)M\underline{x}(T) + \int_0^T [\underline{x}^T(t)Q\underline{x}(t) + \underline{u}^T(t)R\underline{u}(t)] dt$$

where the matrices $M \in R^{n \times n}$, $Q \in R^{n \times n}$ and $R \in R^{m \times m}$ symmetric and positive definite.



Optimal Fuzzy Control Scheme

Consider the following LTI SISO system:

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where the matrices $M \in R^{n \times n}$, $Q \in R^{n \times n}$ and $R \in R^{m \times m}$ symmetric and positive definite.



Optimal Fuzzy Control Scheme

Now, assume that the controller $\underline{u}(t) = [u_1, u_2, \dots, u_m]^T$ is a fuzzy system in the following form:

$$u_j = -f_j(\underline{x}) = \frac{\sum_{l_1=1}^{2N_1+1} \dots \sum_{l_n=1}^{2N_n+1} \bar{y}^{l_1 \dots l_n} \left[\prod_{i=1}^n \mu_{A_i^{l_i}}(x_i) \right]}{\sum_{l_1=1}^{2N_1+1} \dots \sum_{l_n=1}^{2N_n+1} \left[\prod_{i=1}^n \mu_{A_i^{l_i}}(x_i) \right]}$$

Define the fuzzy basis functions $b(t) = [b_1, b_2, \dots, b_N]^T$

$$b_l = \left(\prod_{i=1}^n \mu_{A_i^{l_i}}(x) \right) / \left(\sum_{l_1=1}^{2N_1+1} \dots \sum_{l_n=1}^{2N_n+1} \left(\prod_{i=1}^n \mu_{A_i^{l_i}}(x) \right) \right)$$

where $l = 1, 2, \dots, N$ and $N = \prod_{i=1}^n (2N_i + 1)$.



Optimal Fuzzy Control Scheme

Also, define the parameter matrix $\Theta \in R^{m \times N}$ as:

$$\Theta = \begin{bmatrix} \Theta_1^T \\ \Theta_2^T \\ \vdots \\ \Theta_m^T \end{bmatrix}$$

Where $\Theta_j^T \in R^{1 \times N}$ consists of the N parameters $\bar{y}^{l_1 \dots l_n}$. Using these notations, we can rewrite the fuzzy controller as:

$$\underline{u}(t) = \Theta b(x)$$

By using *Pontryagin Minimum Principle*, we can determine the optimal value of Θ .



Optimal Fuzzy Control Scheme

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By using *Pontryagin Minimum Principle*, we can determine the optimal value of Θ .



Optimal Fuzzy Control Scheme

Let \underline{x}^* and P^* ($t \in [0, T]$) be the (offline) solution of :

$$\begin{cases} \dot{\underline{x}} = A\underline{x} + 2(\alpha^2(\underline{x}) - \alpha(\underline{x}))BR^{-1}B^T P \\ \dot{P} = -2Q\underline{x} - A^T P - (2\alpha(\underline{x}) - 1) \frac{\partial \alpha(\underline{x})}{\partial \underline{x}} P^T BR^{-1}B^T P \end{cases}$$

where $\alpha(\underline{x}) = 0.5b^T(\underline{x}) \left(b(\underline{x})b^T(\underline{x}) \right)^{-1} b(\underline{x})$ and the initial conditions are $\underline{x}(0) = \underline{x}_0$ and $P(t) = 2M\underline{x}(T)$. Then, the optimal fuzzy controller parameters are:

$$\theta^* = -\frac{1}{2}R^{-1}B^T P^*(t)b^T(\underline{x}^*(t)) \left(b(\underline{x}^*(t))b^T(\underline{x}^*(t)) \right)^{-1}$$



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- ❖ Fuzzy Supervisory Control
- ❖ Design Example



Introduction

Most controllers in operation today have been developed using conventional control methods. There are, however, many situations where these controllers are not properly tuned and there is heuristic knowledge available on how to tune them while they are in operation. There is then the opportunity to utilize *fuzzy control* methods as the *supervisor* that tunes or coordinates the application of conventional controllers.

The *supervisor* can use any available data from the control system to characterize the system's current behavior so that it knows how to change the controller and ultimately achieve the desired specifications.



Introduction

The type of *heuristic knowledge* that is used in a *supervisor* may take one of the following two forms:

- Information from a *human control system operator* who observes the behavior of an existing control system (often a conventional control system) and knows how this controller should be tuned under various operating conditions.
- Information gathered by a *control engineer* who knows that under different operating conditions controller parameters should be tuned according to certain rules.



Types of Fuzzy Supervisory Control

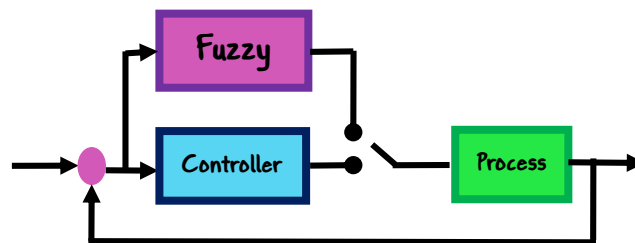
There are four types of fuzzy supervisory control:

- *Fuzzy replaces controller*
- *Fuzzy replaces operator*
- *Fuzzy adjusts control parameters*
- *Fuzzy adds to controller*



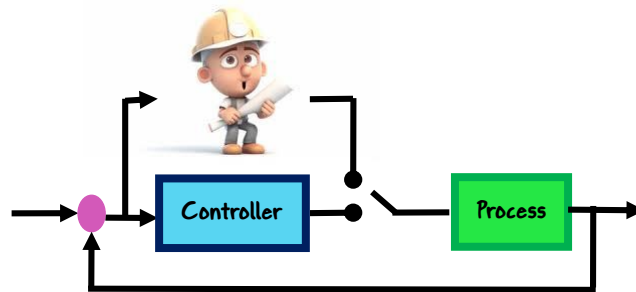
Fuzzy Replaced Controller

In this configuration, the operator may select between a high-level control strategy and conventional control loops.



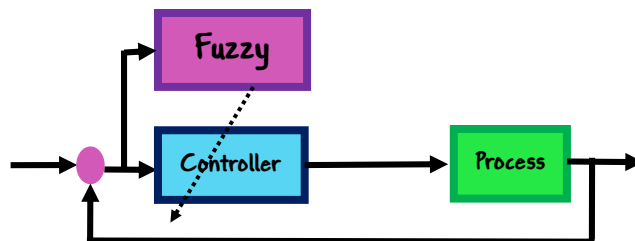
Fuzzy Replaced Operator

This configuration represents the original high level control idea, where manual control carried out by a human operator is replaced by automatic control



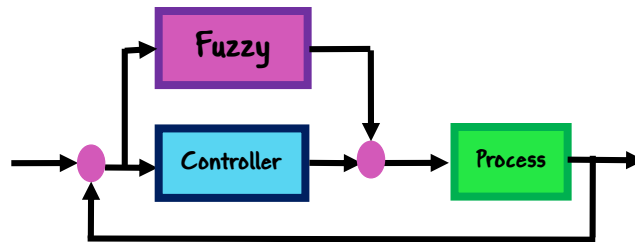
Fuzzy Adjusts Control Parameters

In this configuration, the high-level strategy adjusts the parameters of the conventional control loops.



Fuzzy adds to Controller

Normally, control systems based on controllers are capable of controlling the process when the operation is steady and close to normal conditions. However, if sudden changes occur, or if the process enters abnormal states, then this configuration may be applied to bring the process back to normal operation as fast as possible.



Fuzzy Systems

In order to design fuzzy supervisor, Mamdani fuzzy control with singleton fuzzifier, product inference engine and center average defuzzifier is usually employed. That is, the following formula:

$$\text{Parameter : } p = f(\underline{x}) = \frac{\sum_{l=1}^M \bar{p}^l \prod_{i=1}^n \mu_{A_i^l}(x_i)}{\sum_{l=1}^M \prod_{i=1}^n \mu_{A_i^l}(x_i)}$$

This parameter is usually the gain of controllers!



smgrc

Algorithm

Choose Inputs x_1, x_2, \dots, x_n and Output p

↓

Obtain Inputs Bounds $[x_{i,min}, x_{i,max}]$

↓

Select Membership Functions $\mu_{A_i^l}(x_i)$
(types and numbers)

↓

Construct Rules \bar{p}^l

$$\text{Parameter: } p = f(\underline{x}) = \frac{\sum_{l=1}^M \bar{p}^l \prod_{i=1}^n \mu_{A_i^l}(x_i)}{\sum_{l=1}^M \prod_{i=1}^n \mu_{A_i^l}(x_i)}$$

x_1
 x_2
 x_n

FLS

$\rightarrow p$

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Fuzzy Supervisory

$$p' = \frac{p - p_{min}}{p_{max} - p_{min}}$$

p or p'	\dot{e}							
	NB	NM	NS	Z	PS	PM	PB	
NB								
NM								
NS								
Z								
PS								
PM								
PB								

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$$\text{Parameter: } p = f(\underline{x}) = \frac{\sum_{l=1}^M \bar{p}^l \prod_{i=1}^n \mu_{A_i^l}(x_i)}{\sum_{l=1}^M \prod_{i=1}^n \mu_{A_i^l}(x_i)}$$

Fuzzy Supervisory

Calculate Inputs x_i

↓

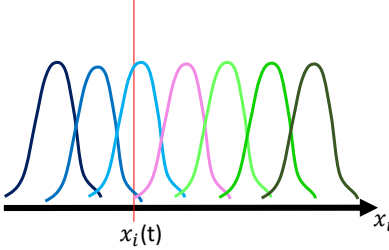
Obtain MF Values $\mu_{A_1^l}(x_i), \mu_{A_2^l}(x_i), \dots$

↓


Obtain \bar{y}^l Based on Rules


↓

Calculate Output



ONLINE

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$$\text{Parameter: } p = f(\underline{x}) = \frac{\sum_{l=1}^M \bar{p}^l \prod_{i=1}^n \mu_{A_i^l}(x_i)}{\sum_{l=1}^M \prod_{i=1}^n \mu_{A_i^l}(x_i)}$$


Fuzzy Supervisory

Number of Inputs: n
Number of Rules: $M=N_1 \times N_2 \times \dots \times N_n$

$$p = \frac{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \dots \sum_{i_n=1}^{N_n} \bar{p}^{i_1, i_2, \dots, i_n} \mu_{A_1^{i_1}}(x_1(t)) \mu_{A_2^{i_2}}(x_2(t)) \dots \mu_{A_n^{i_n}}(x_n(t))}{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \dots \sum_{i_n=1}^{N_n} \mu_{A_1^{i_1}}(x_1(t)) \mu_{A_2^{i_2}}(x_2(t)) \dots \mu_{A_n^{i_n}}(x_n(t))}$$

Number of Inputs: 2
Number of Rules: $M=N_1 \times N_2$

$$p = \frac{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \bar{p}^{i_1, i_2} \mu_{A_1^{i_1}}(e(t)) \mu_{A_2^{i_2}}(\dot{e}(t))}{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \mu_{A_1^{i_1}}(e(t)) \mu_{A_2^{i_2}}(\dot{e}(t))}$$

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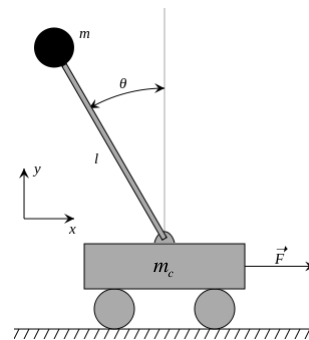
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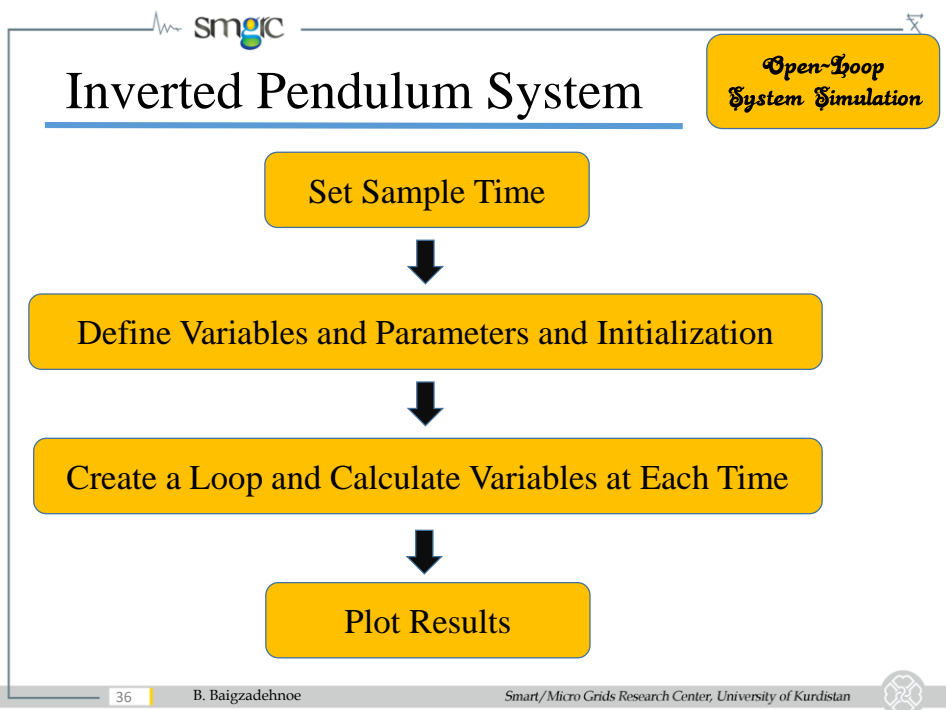
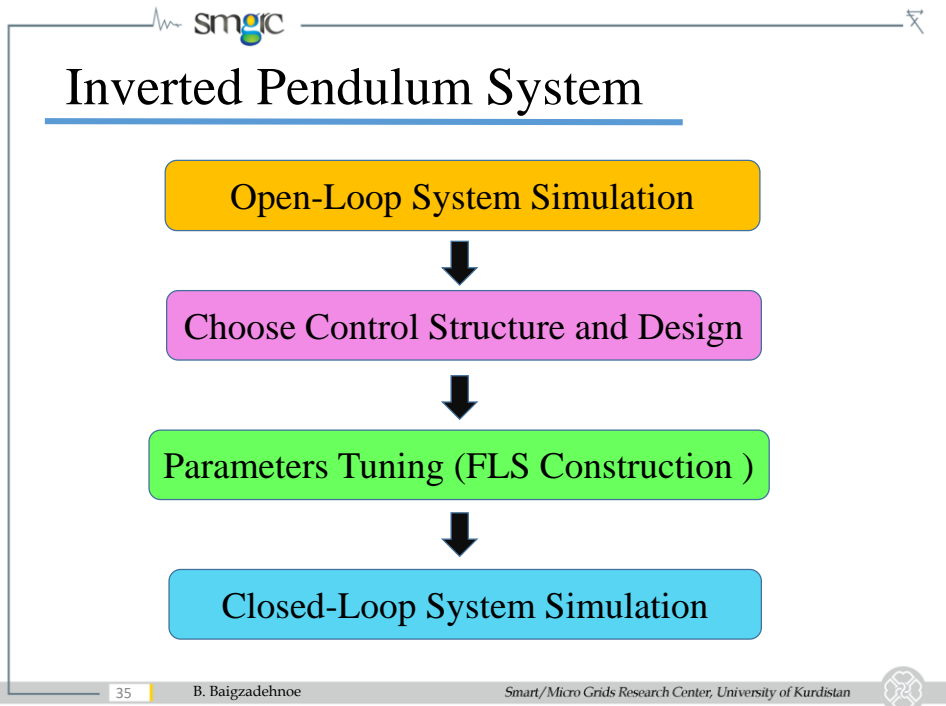


Inverted Pendulum System

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \frac{g \sin(x_1) - \frac{mlx_2^2 \cos(x_1) \sin(x_1)}{m_c + m}}{l \left(\frac{4}{3} - \frac{m(\cos(x_1))^2}{m_c + m} \right)} + \frac{\frac{\cos(x_1)}{m_c + m}}{l \left(\frac{4}{3} - \frac{m(\cos(x_1))^2}{m_c + m} \right)} u \end{cases}$$

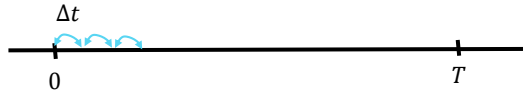
Objective:
Tracking step type reference





Inverted Pendulum System

```
T=5;
dt=0.001;
sample=T/dt+1; Time
```



```
g=9.8;
mc=1;
m=0.1;
l=0.5 Define Parameters
```

```
x1=zeros(1,sample);
x2=zeros(1,sample);
%*****
u=zeros(1,sample);
%*****
x1(1,1)=0.3;
x2(1,1)=0.3; Define Variables
```

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Inverted Pendulum System

```
for t=2:sample Loop
x1(1,t) = (x2(1,t-1) * dt + x1(1,t-1) );
x2(1,t) = (1 / (1 * (4/3 - m * (cos(x1(1,t-1))) ^ 2) / (mc+m)))
* ((cos(x1(1,t-1))) / (mc+m)) * u(1,t) + g * sin(x1(1,t-1)) -
(m * l * ((x2(1,t-1)) ^ 2) * cos(x1(1,t-1)) * sin(x1(1,t-1))) / (mc+m) )
* dt + x2(1,t-1) ;
end
```

$$\dot{x}(t) = \lim_{\Delta t \rightarrow 0} \frac{x(t) - x(t - \Delta t)}{\Delta t} = f(x)$$

$$\Rightarrow x(t) = (f(x(t - \Delta t))) \Delta t + x(t - \Delta t)$$

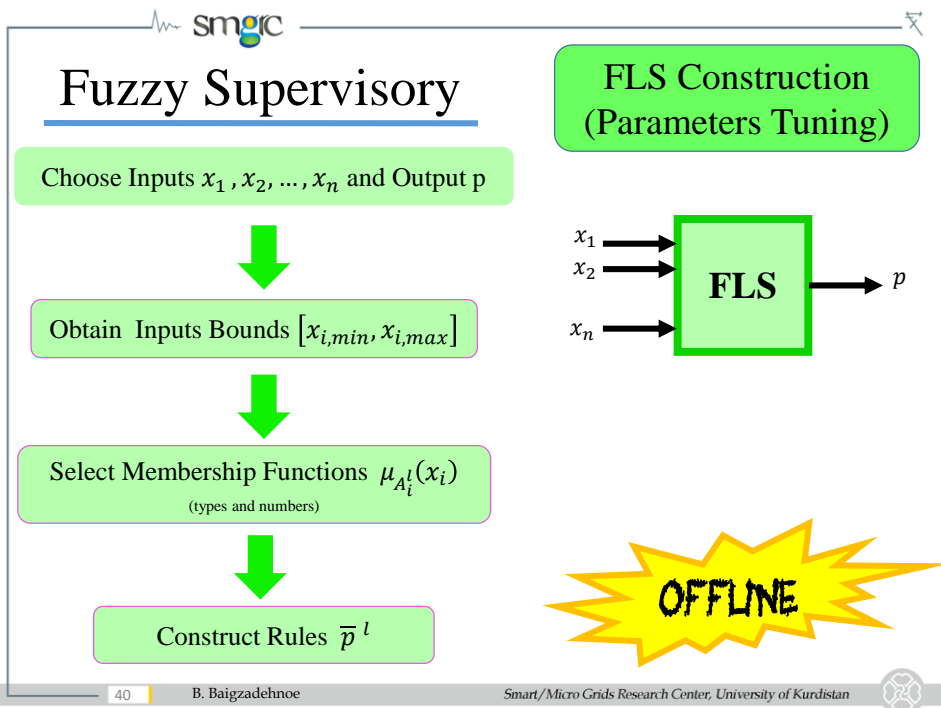
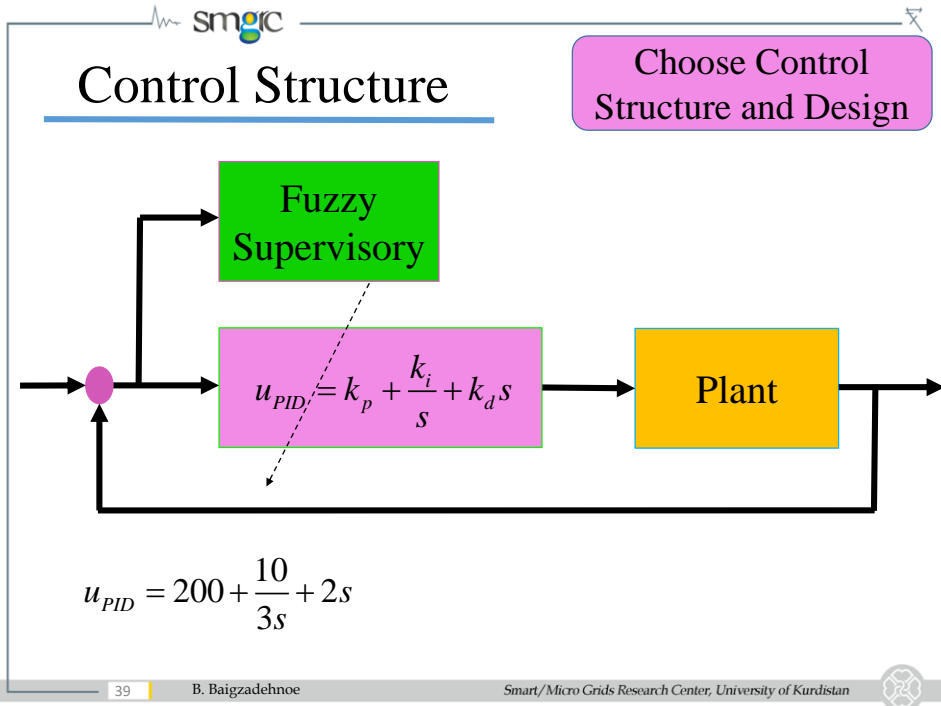
$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \frac{g \sin(x_1) - \frac{m l x_2^2 \cos(x_1) \sin(x_1)}{m_c + m}}{l \left(\frac{4}{3} - \frac{m (\cos(x_1))^2}{m_c + m} \right)} + \frac{\cos(x_1)}{m_c + m} u \end{cases}$$

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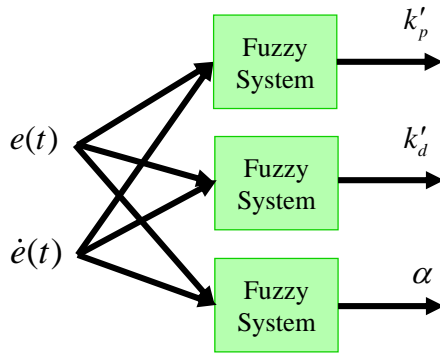
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Tuning Parameters

Choose Inputs x_1, x_2, \dots, x_n and Output p



$$p = \frac{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \bar{p}^{i_1 \cdot i_2} \mu_{A_1^{i_1}}(e(t)) \mu_{A_2^{i_2}}(\dot{e}(t))}{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \mu_{A_1^{i_1}}(e(t)) \mu_{A_2^{i_2}}(\dot{e}(t))}$$



Tuning Parameters

Choose Inputs x_1, x_2, \dots, x_n and Output p

$$k'_p = \frac{k_p - k_{p,\min}}{k_{p,\max} - k_{p,\min}}$$

$$k'_d = \frac{k_d - k_{d,\min}}{k_{d,\max} - k_{d,\min}}$$

$$\alpha = \frac{T_i}{T_d}$$

Fuzzy System Output

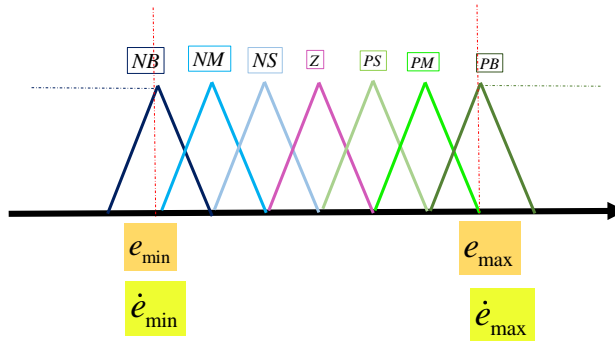
$$K[e(t) + \frac{1}{T_i} \int_{\tau=0}^t e(\tau) d\tau + T_d \frac{d}{dt} e(t)]$$



Input Membership Functions

Obtain Inputs Bounds
[$x_{i,min}, x_{i,max}$]

Select Membership Functions $\mu_{A_i^l}(x_i)$



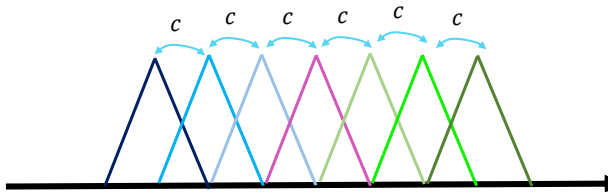
Input Membership Functions

```

e_max=0.3;
e_min=-0.3;
%*****
%*****MF e
ai=e_min;
af=e_max;
ne=7;
eff=ai:0.001:af;
c=(af-(ai))/(ne-1);
for i=1:ne
    mu(i,:)=trimf(eff,[ai+(i-2)*c ai+(i-1)*c ai+i*c]);
end
    
```

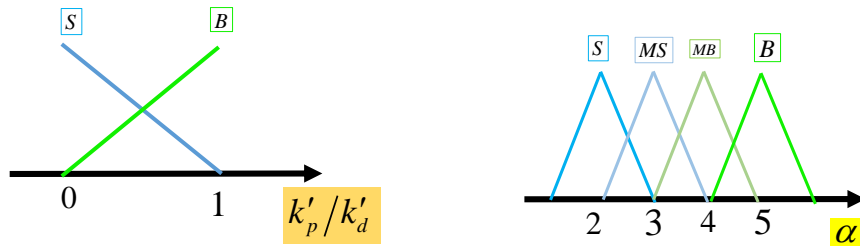
Obtain Inputs Bounds
[$x_{i,min}, x_{i,max}$]

Select Membership Functions $\mu_{A_i^l}(x_i)$



Output Membership Functions

Construct Rules \bar{p}^l

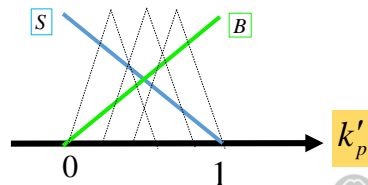


Fuzzy Rules

Construct Rules \bar{p}^l

		\dot{e}							
		NB	NM	NS	Z	PS	PM	PB	
e	NB	B	B	B	B	B	B	B	
	NM	S	B	B	B	B	B	S	
	NS	S	S	B	B	B	S	S	
	Z	S	S	S	B	S	S	S	
	PS	S	S	B	B	B	S	S	
	PM	S	B	B	B	B	B	S	
	PB	B	B	B	B	B	B	B	

$$k'_p(t) = \frac{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} k'_{p,i_1,i_2} \mu_{A_{i_1}}(e(t)) \mu_{A_{i_2}}(\dot{e}(t))}{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \mu_{A_{i_1}}(e(t)) \mu_{A_{i_2}}(\dot{e}(t))}$$



Fuzzy Rules

Construct Rules \bar{p}^l

```
R_kpf=[1 1 1 1 1 1 1;
        0 1 1 1 1 1 0;
        0 0 1 1 1 0 0;
        0 0 0 1 0 0 0;
        0 0 1 1 1 0 0;
        0 1 1 1 1 1 0;
        1 1 1 1 1 1 1];
```

		\dot{e}						
		NB	NM	NS	Z	PS	PM	PB
e	NB	B	B	B	B	B	B	B
	NM	S	B	B	B	B	B	S
	NS	S	S	B	B	B	S	S
	Z	S	S	S	B	S	S	S
	PS	S	S	B	B	B	S	S
	PM	S	B	B	B	B	B	S
	PB	B	B	B	B	B	B	B



Fuzzy Rules

Construct Rules \bar{p}^l

		\dot{e}						
		NB	NM	NS	Z	PS	PM	PB
e	NB	S	S	S	S	S	S	S
	NM	B	B	S	S	S	B	B
	NS	B	B	B	S	B	B	B
	Z	B	B	B	B	B	B	B
	PS	B	B	B	S	B	B	B
	PM	B	B	S	S	S	B	B
	PB	S	S	S	S	S	S	S



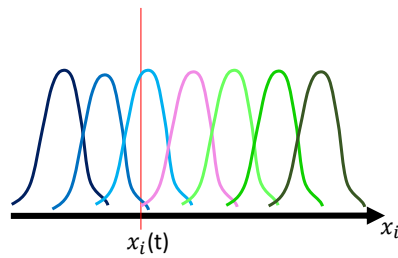
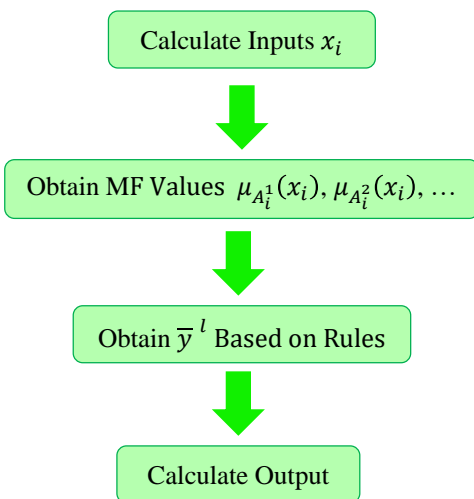
Fuzzy Rules

Construct Rules \bar{p}^l

α		\dot{e}						
		NB	NM	NS	Z	PS	PM	PB
e	NB	S	S	S	S	S	S	S
	NM	MS	MS	S	S	S	MS	MS
	NS	MB	MS	MS	S	MS	MS	MB
	Z	B	MB	MS	MS	MS	MB	B
	PS	MB	MS	MS	S	MS	MS	MB
	PM	MS	MS	S	S	S	MS	MS
	PB	S	S	S	S	S	S	S



Fuzzy Supervisory



$e(t)$ & $\dot{e}(t)$ Membership Functions Values

Calculate Inputs
 $e(t), \dot{e}(t)$

$$ef(1, t) = x1r(1, t-1) - x1f(1, t-1);$$

$$edf(1, t) = -x2f(1, t-1);$$

$$eif(1, t) = ef(1, t) * dt + eif(1, t-1);$$

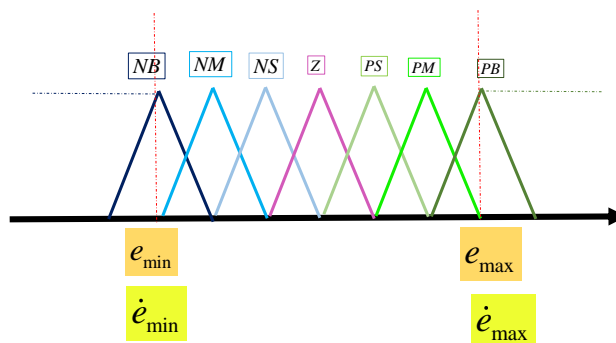


$e(t)$ & $\dot{e}(t)$ Membership Functions Values

Obtain MF Values

$$\mu_{A_e^1}(e(t)), \mu_{A_e^2}(e(t)), \dots, \mu_{A_e^7}(e(t))$$

$$\mu_{A_{\dot{e}}^1}(\dot{e}(t)), \mu_{A_{\dot{e}}^2}(\dot{e}(t)), \dots, \mu_{A_{\dot{e}}^7}(\dot{e}(t))$$



$e(t)$ & $\dot{e}(t)$ Membership Functions Values

Obtain MF Values

$$\mu_{A_e^1}(e(t)), \mu_{A_e^2}(e(t)), \dots, \mu_{A_e^7}(e(t))$$

$$\mu_{A_e^1}(\dot{e}(t)), \mu_{A_e^2}(\dot{e}(t)), \dots, \mu_{A_e^7}(\dot{e}(t))$$

```

ee=ef(1,t-1);
eed=edf(1,t-1);
%*****
if ee>e_max
    ee=e_max;
end
if ee<e_min
    ee=e_min;
end

```



$e(t)$ & $\dot{e}(t)$ Membership Functions Values

Obtain MF Values

$$\mu_{A_e^1}(e(t)), \mu_{A_e^2}(e(t)), \dots, \mu_{A_e^7}(e(t))$$

$$\mu_{A_e^1}(\dot{e}(t)), \mu_{A_e^2}(\dot{e}(t)), \dots, \mu_{A_e^7}(\dot{e}(t))$$

```

finder_e=ee*ones(1,length(eff));
[mme,nee]=min(abs(ee-eff));

finder_ed=eed*ones(1,length(edff));
[mmed,need]=min(abs(eed-edff));

```



Calculate FLS Outputs Values

Calculate Output

```

accd=0; accn_kpf=0; accn_kdf=0; accn_alphaf=0

for i=1:ne
    for j=1:ned
        accd=accd+mu (i, nee) *mud (j, need) ;
        %*****kp
        accn_kpf=accn_kpf+R_kpf (i, j) *mu (i, nee) *mud (j, need) ;
        %*****kd
        accn_kdf=accn_kdf+R_kdf (i, j) *mu (i, nee) *mud (j, need) ;
        %*****alpha
        accn_alphaf=accn_alphaf+R_alphaf (i, j) *mu (i, nee) *mud (j, need) ;
    end
end

```

$$p = \frac{\sum_{i=1}^{N_1} \sum_{i_2=1}^{N_2} \bar{p}^{i, i_2} \mu_{A_1^i}(e(t)) \mu_{A_2^{i_2}}(\dot{e}(t))}{\sum_{i=1}^{N_1} \sum_{i_2=1}^{N_2} \mu_{A_1^i}(e(t)) \mu_{A_2^{i_2}}(\dot{e}(t))}$$

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Calculate FLS Outputs Values

Calculate Output

```

kpf (1, t) = (accn_kpf/accd) * (kp_max-kp_min) +kp_min;

kdf (1, t) = (accn_kdf/accd) * (kd_max-kd_min) +kd_min;

alphaf (1, t) = (accn_alphaf/accd) ;

```

$$p = \frac{\sum_{i=1}^{N_1} \sum_{i_2=1}^{N_2} \bar{p}^{i, i_2} \mu_{A_1^i}(e(t)) \mu_{A_2^{i_2}}(\dot{e}(t))}{\sum_{i=1}^{N_1} \sum_{i_2=1}^{N_2} \mu_{A_1^i}(e(t)) \mu_{A_2^{i_2}}(\dot{e}(t))}$$

$$k'_p = \frac{k_p - k_{p,\min}}{k_{p,\max} - k_{p,\min}}$$

$$k'_d = \frac{k_d - k_{d,\min}}{k_{d,\max} - k_{d,\min}}$$

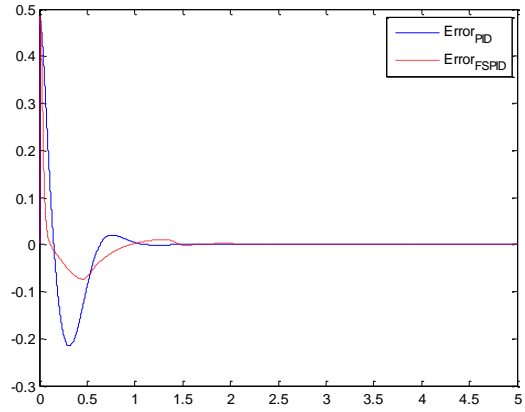
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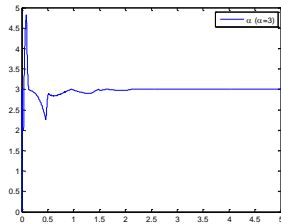
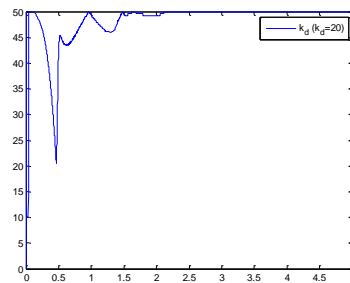
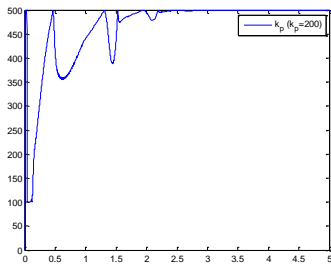
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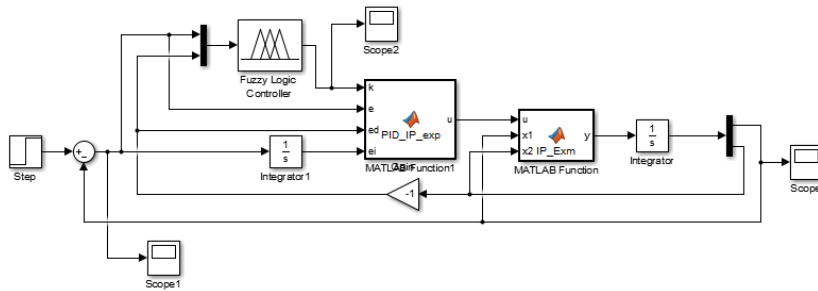
PID vs FSPID



PID vs FSPID



Fuzzy Supervisory with Toolbox



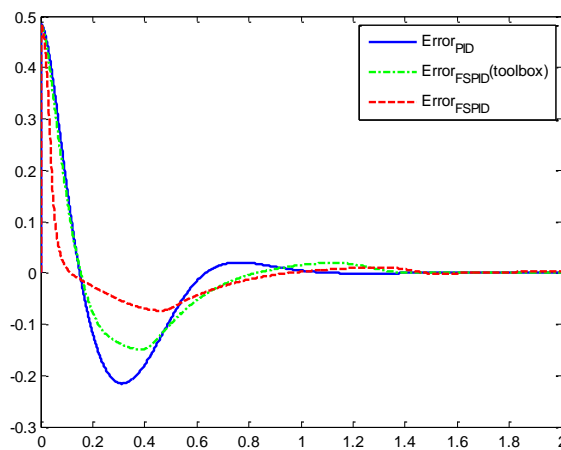
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Personal Code vs. Toolbox



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Thanks

