

# **INTELLIGENT CONTROL**

## **ASSIGNMENT - 2**

*2018-2019 Spring*

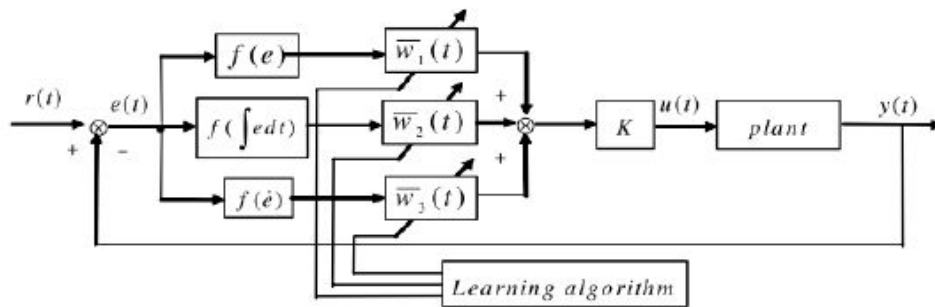
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# 1) Neuron Based Nonlinear PID Controller

PID controllers have been widely used in industrial applications mostly for linearized systems. Classical PID controllers are bad at nonlinearities of system model or model uncertainties. One of many approaches to overcome those issues is using “Neuron based nonlinear pid controller” which is offered by Wang and Yu.



*Fig 1. The neuron based nonlinear PID control system*

In this control method, weights of each neuron is updated for one loop. That means it is an ‘on-line’ algorithm.

Thus control signal can be expressed as below,

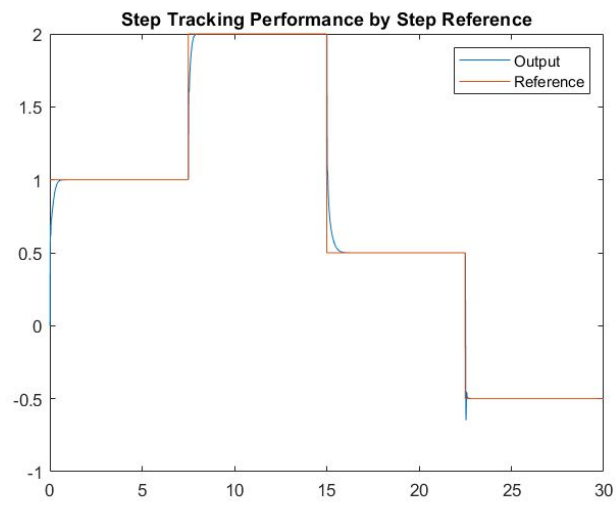
$$u(t) = f(e) * w_1 + f(\int e) * w_2 + f(e')$$

Where,

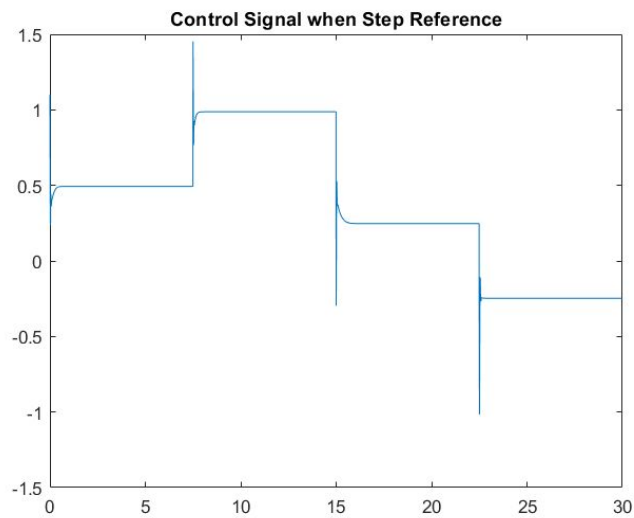
$$f(x, \alpha, \delta) = \begin{cases} \text{sign}(x) \cdot |x|^\alpha & \text{when } |x| > \delta, \\ \delta^{\alpha-1} x & \text{when } |x| \leq \delta, \end{cases}$$

This nonlinear function is coded in ‘nonl\_f.m’. The parameter  $\alpha$  is between (0,1). When  $\alpha = 1$  makes the nonlinear function linear.  $\delta$  is a small positive number applied to create a small linear area in this nonlinear function when  $x$  is around zero. For each of neuron has it is own alpha and  $\delta$  parameters.

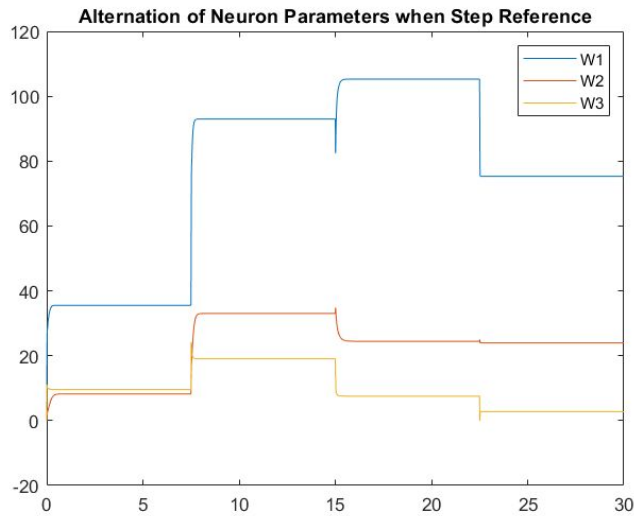
## 1.1 Step Reference Tracking Performance



*Fig 1.1.1 Unit Step Tracking*



*Fig 1.1.2 Control Signal for Unit Step Reference*

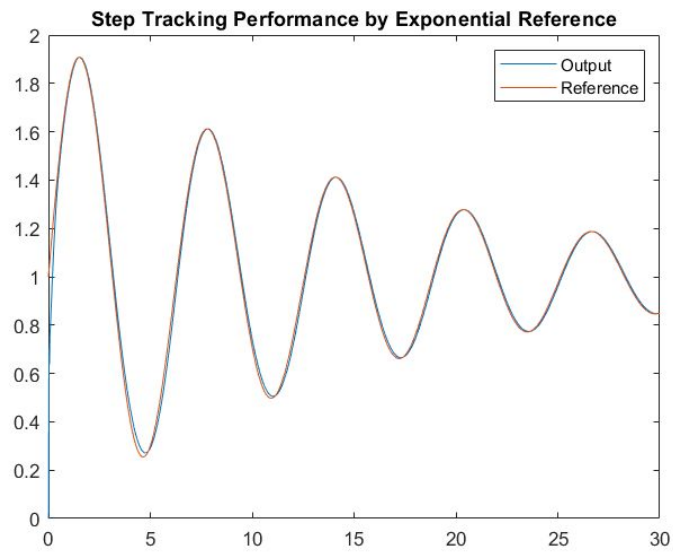


*Fig 1.1.3 Parameter Alternation for Unit Step Reference*

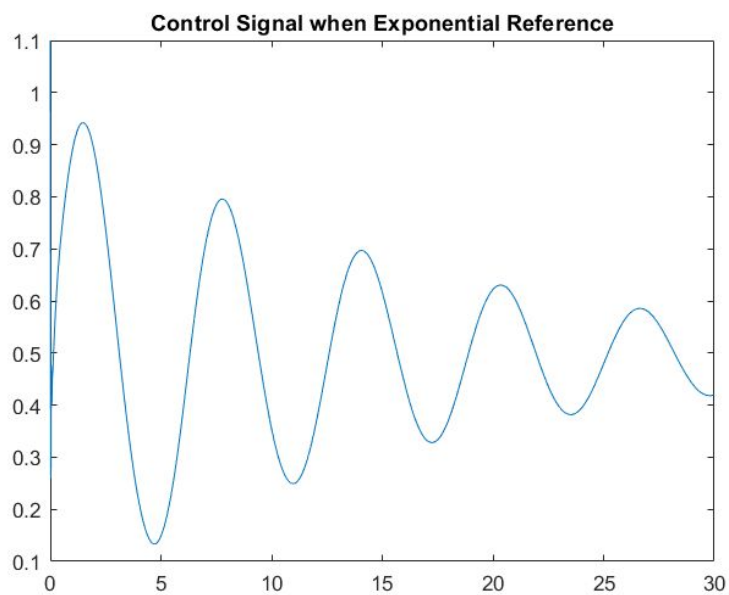
For unit step reference, controller has a remarkable performance. By the fig 1.1.2 change of control signal, it could be concluded that it reaches steady state slightly smoother for positive number references. But for references less than 0 such as -0.5, it reaches steady state with much more overshoot, that would make control signal worse and may harm the system.

From the fig 1.1.3, we can easily see the effect of  $\alpha$  parameter, which is equal to 1 for  $w_3$  parameter. It is a linear curve without exponential decays. This is suitable for feedforward gain. Because it directly empowering the error signal.

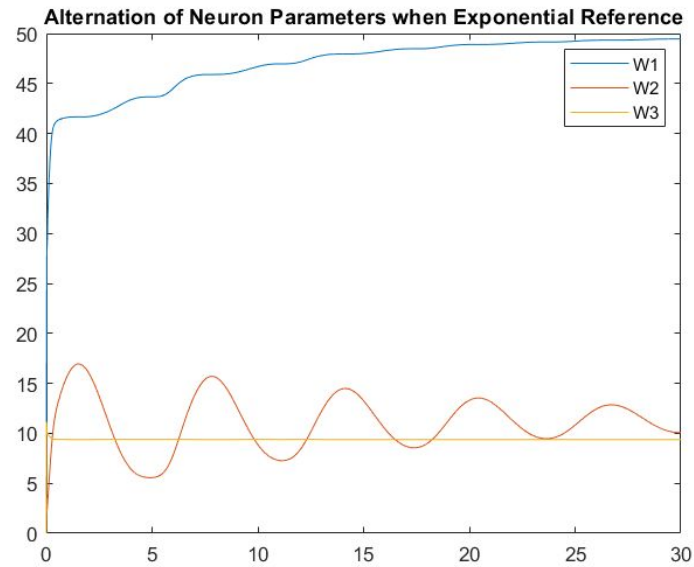
## 1.2 Exponential Reference Tracking Performance



*Fig 1.2.1 Exponential Reference Tracking*



*Fig 1.2.2 Control Signal for Exponential Reference*



*Fig 1.2.3 Parameter Alternation for Exponential Reference*

For exponential reference, controller has perfect performance. No steady state error occurred and settling time is nearly zero.

Final controller parameters are shown in table.1 .

	w1	w2	w3
Step Reference	75.2915	23.9515	2.7661
Exponential Reference	49.4569	10.0830	9.3797

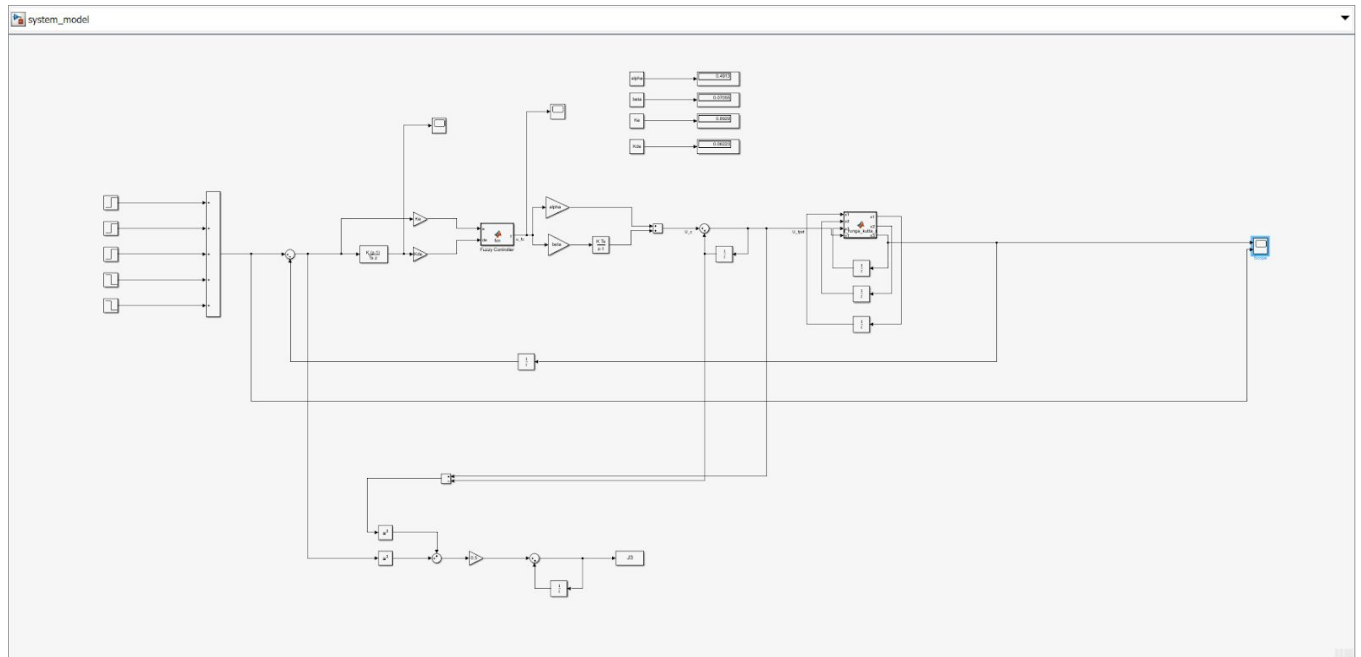
## 2) PID Type Fuzzy Controller

For this question, I created a simulink model of fuzzy PID. For fuzzy PID controller is implemented in a matlab function inside of simulink. After model is created the cost function,

$$J = \frac{1}{2} \sum_{n=1}^{\infty} [r_n - y_n]^2 + \frac{1}{2} \lambda \sum_{n=1}^{\infty} [u_n - u_{n-1}]^2$$

4 unknown parameters  $K_e$   $K_{de}$   $\alpha$   $\beta$  are optimized via 'optimtool' toolbox's multivariable genetic algorithm.

One of the challenges was creating the reference signal in simulink. To overcome this issue, reference signal is defined sum of 4 step function.



*Fig.2.1 Simulink Model of Fuzzy PID*

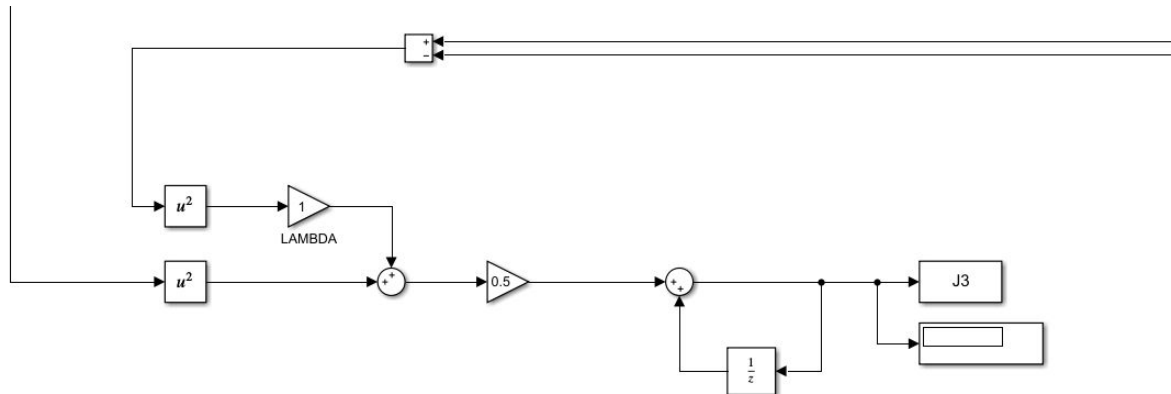
Runga-kutta model of CSTR model is created as below,





## 2.2 Fuzzy PID Controller Tuning with Genetic Algorithm

In the simulink file the cost function is modeled as in fig 2.2.2



*Fig 2.2.2 Cost Function in SIMULINK model*

In every step cost function is obtained simply by “sim(‘system\_model’)” command in the “cost.m’ matlab function file. This file is given into the genetic algorithm toolbox as a parameter. 4 different parameter is defined for fuzzy pid controller is tuned by every genetic algorithm training step. Control system and system output with reference is saved to workspace to plot later with ‘plot\_all.m’ file. General structure of optimtool toolbox for genetic algorithm is given in fig 2.2.3.

Optimization Tool  
File Help

### Problem Setup and Results

Solver: **gamultiobj** - Multiobjective optimization using Genetic Algorithm

Problem

Fitness function:

Number of variables:

Constraints:

Linear inequalities: A:  b:

Linear equalities: Aeq:  beq:

Bounds: Lower:  Upper:

Nonlinear constraint function:

Run solver and view results

☐ Use random states from previous run

Current iteration:

Objective function value: 0.12065360197413878  
Optimization terminated: Stop requested;

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Optimization running.  
Pause requested.  
Stop requested.  
Objective function value: 6.055721785314567  
Optimization terminated: Stop requested;

### Options

**Population**

Population type: **Double vector**

Population size: ☒ Use default: 50 for five or fewer variables, otherwise 200  
☐ Specify:

Creation function: **Constraint dependent**

Initial population: ☒ Use default: []  
☐ Specify:

Initial scores: ☒ Use default: []  
☐ Specify:

Initial range: ☒ Use default: [-10;10]  
☐ Specify:

**Selection**

Selection function: **Tournament**

Tournament size: ☒ Use default: 2  
☐ Specify:

**Reproduction**

Crossover fraction: ☒ Use default: 0.8  
☐ Specify:

**Mutation**

Mutation function: **Constraint dependent**

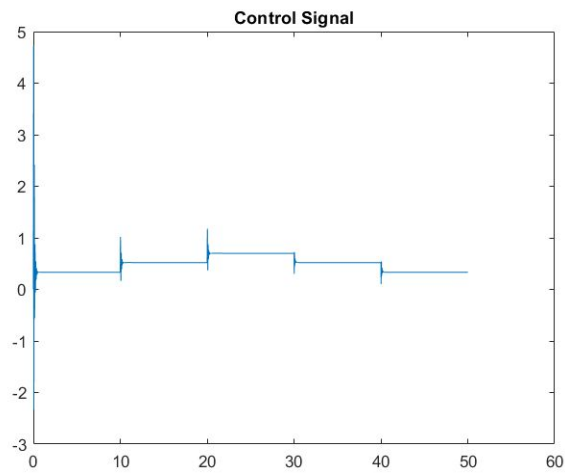
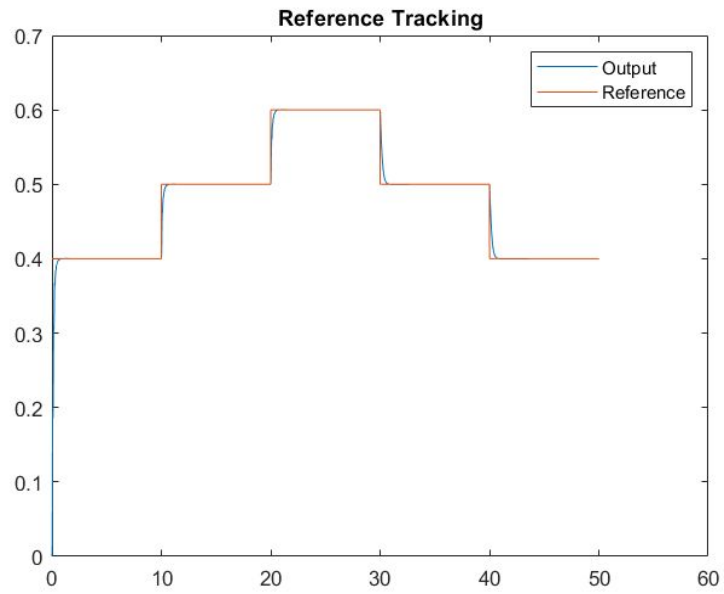
**Crossover**

Crossover function: **Intermediate**

Ratio: ☒ Use default: 1.0

*Fig 2.2.3 MATLAB Genetic Algorithm Toolbox Overview,*

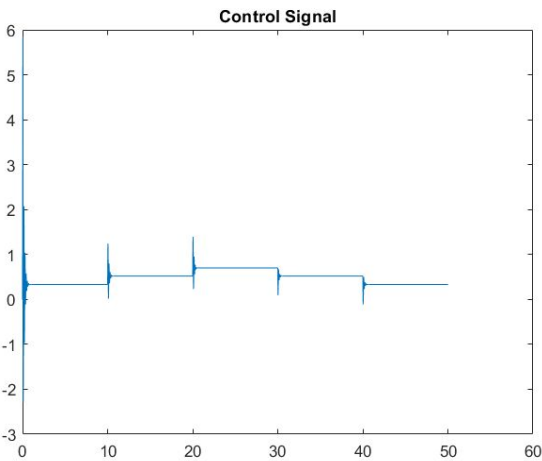
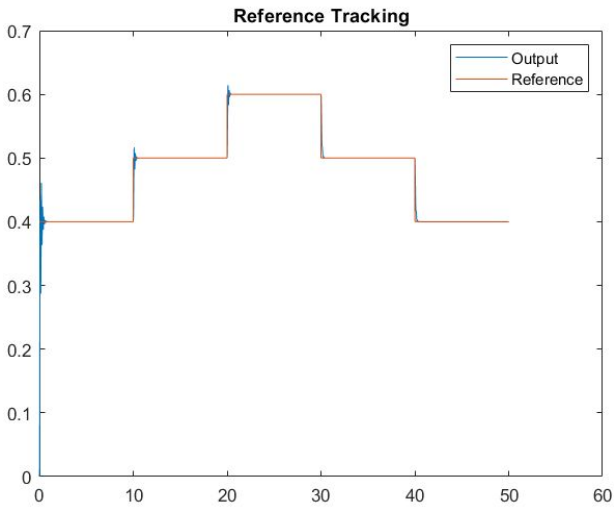
**For  $\lambda = 0.1$  ,**



$\alpha$	0.7910
$\beta$	0.7523
$K_e$	0.9409

$K_{de}$	0.1269
Cost	7.0176

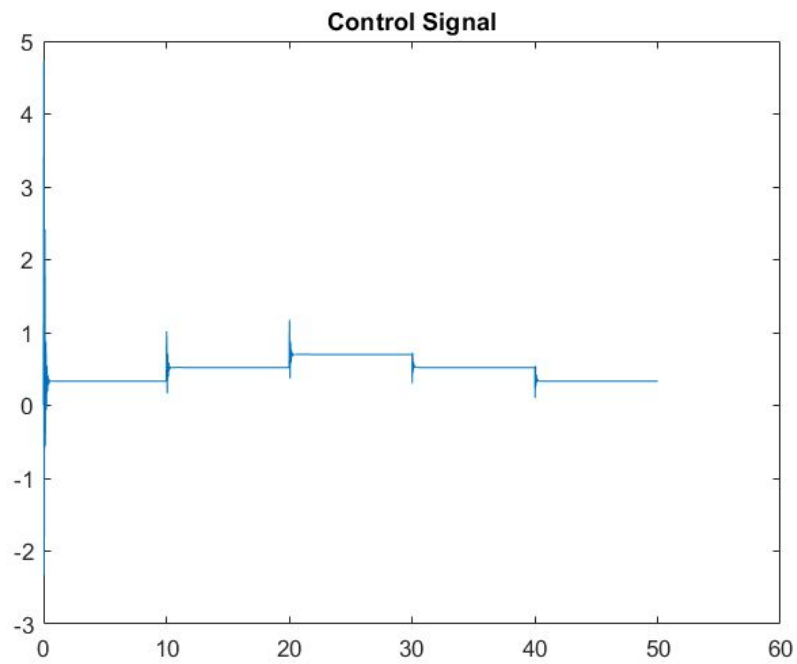
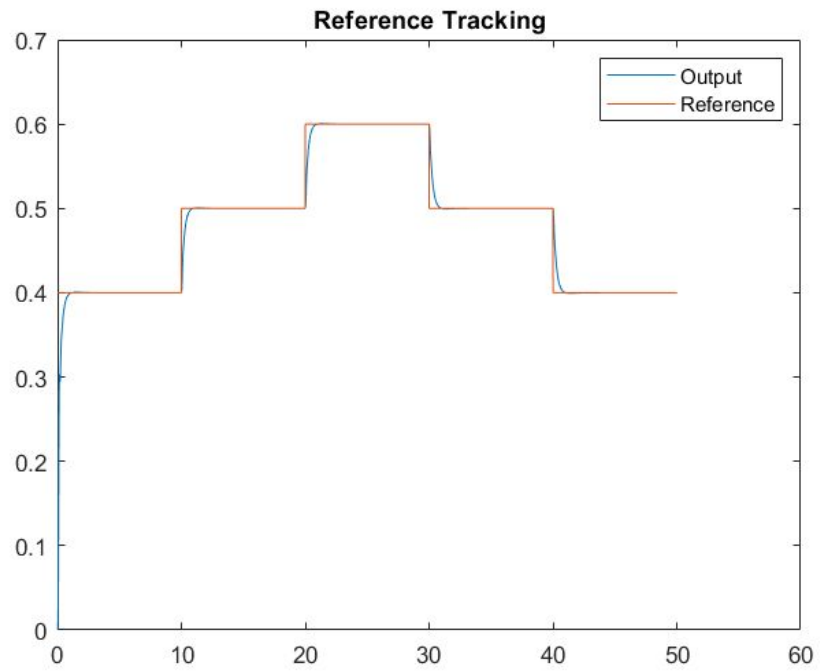
For  $\lambda = 0.5$  ,



$\alpha$	0.7351
$\beta$	0.0933
$K_e$	0.9405

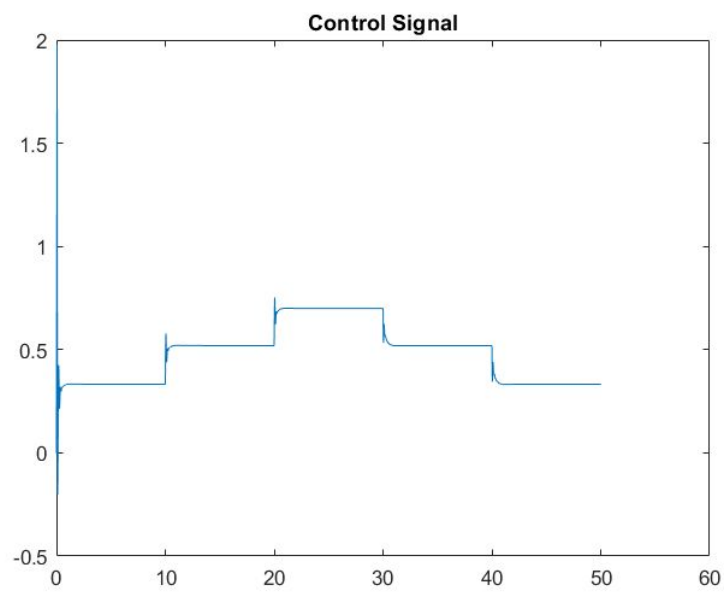
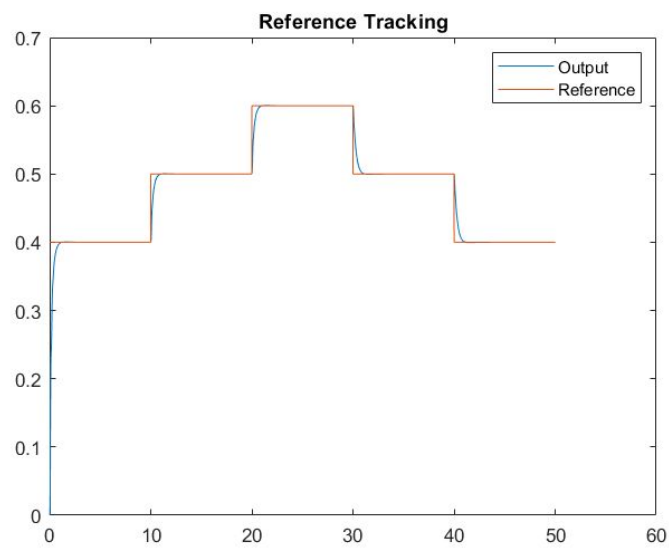
$K_{de}$	0.0535
Cost	5.6507

For  $\lambda = 1$  ,



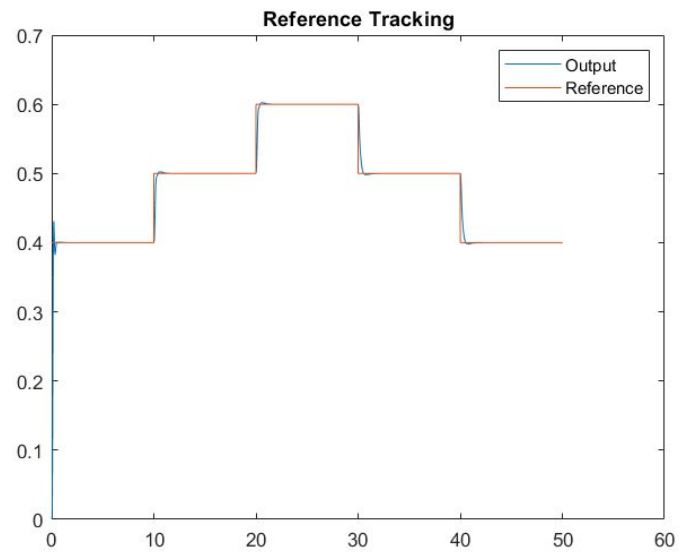
$\alpha$	0.6264
$\beta$	0.9855
$K_e$	0.2421
$K_{de}$	0.0519
Cost	9.9732

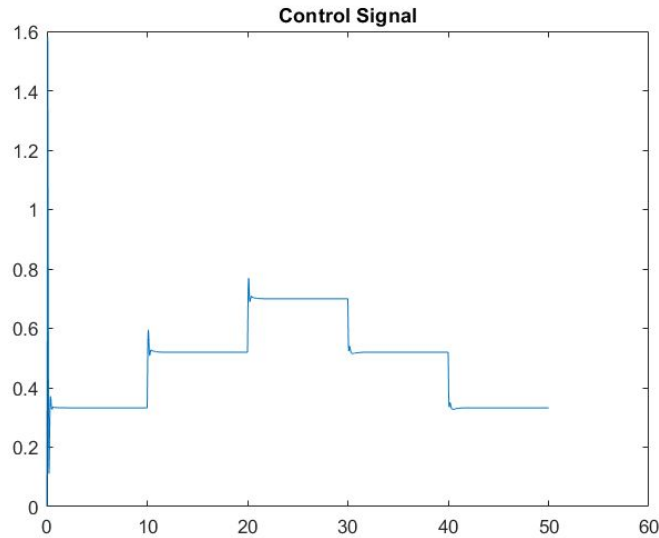
For  $\lambda = 10$  ,



$\alpha$	0.3023
$\beta$	0.5207
$K_e$	0.5508
$K_{de}$	0.1264
Cost	11.7173

For  $\lambda = 100$  ,





$\alpha$	0.1151
$\beta$	0.3562
$K_e$	0.6763
$K_{de}$	0.0981
Cost	12.2835

## Results

Through minimizing the cost function with genetic algorithm I achieved successful results. That was an expecting result because to minimize cost function we should have minimized two things tracking error and control effort. I could achieve better results by running the genetic algorithm longer since those results sufficiently good I decided to stop the algorithm.

I should also state that increasing  $\lambda$  increases the cost function and making finding right parameters harder. Because I already achieved good results by not punishing control effort that much. So that local minimas should have between minimal differences from our parameters. That is an expected phenomenon when optimizing with genetic algorithm. That algorithm totally randomly generating populations, which makes it stochastic process and finding sensitive local minimas hard sometimes.

**All codes and files included in the rar file .**