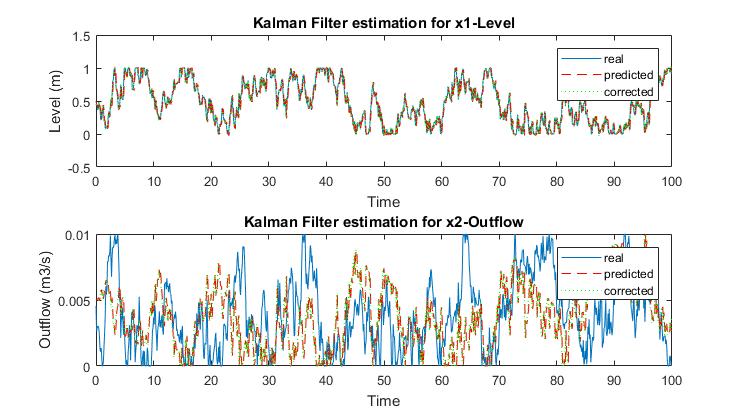
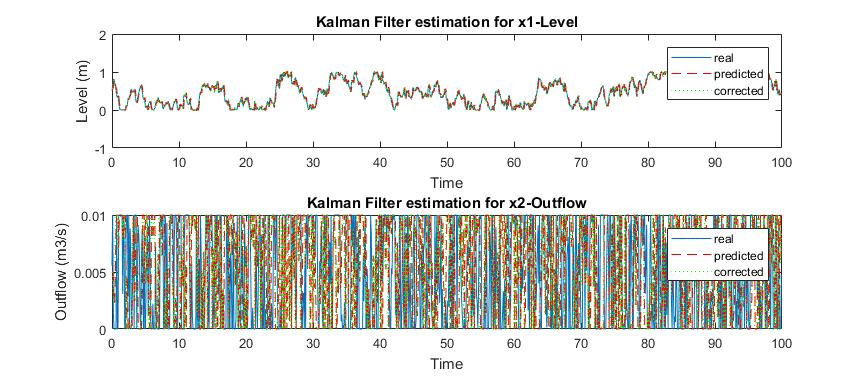
# Exercise 6.1

## Problem 6.1a.

When the process noise covariance matrix , the Kalman filter estimation of state variables are plotted as below



When , the Kalman filter estimation of state variables are plotted as below



The results shown that smaller measurement noise lead to better track of the state.

## Problem 6.1b.

The model from mass balance:

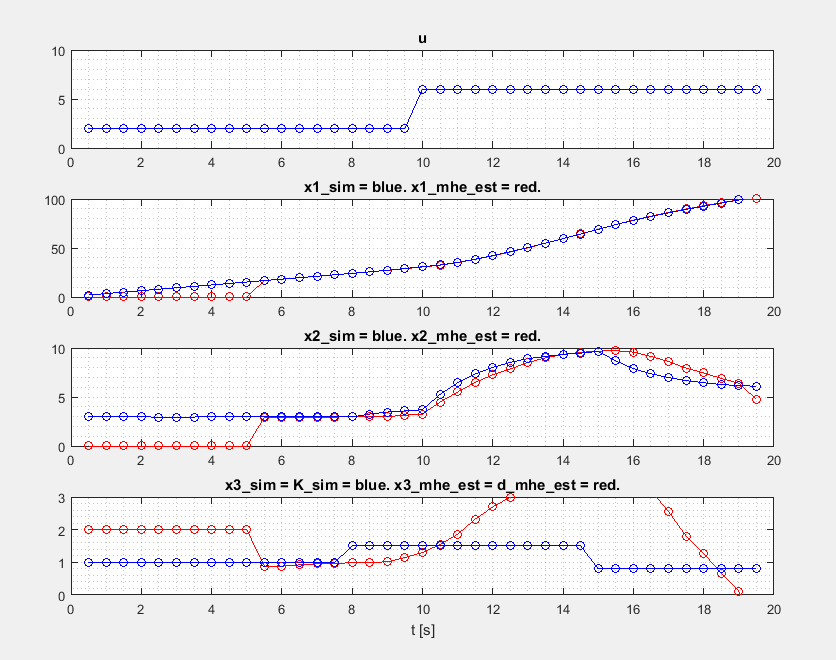
Let , , and

The continuous-time state space model with Kalman Filter for estimation can be written as below for:

The model is a nonlinear model.

# Problem 6.2

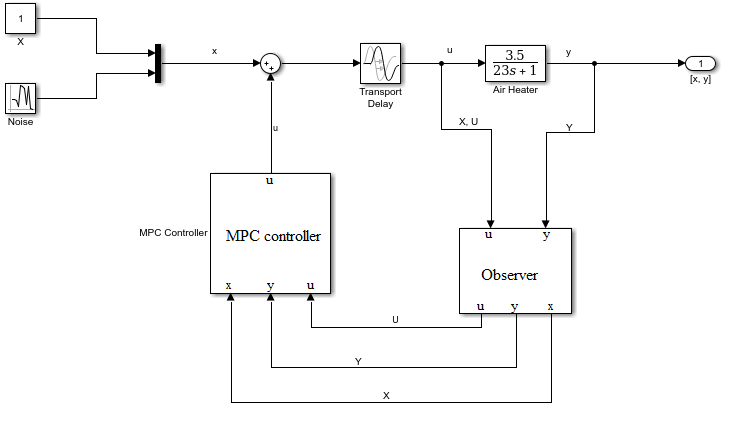
The estimation of K is not working as good as d estimation. The tracking of K is not good enough.



# Problem 6.3

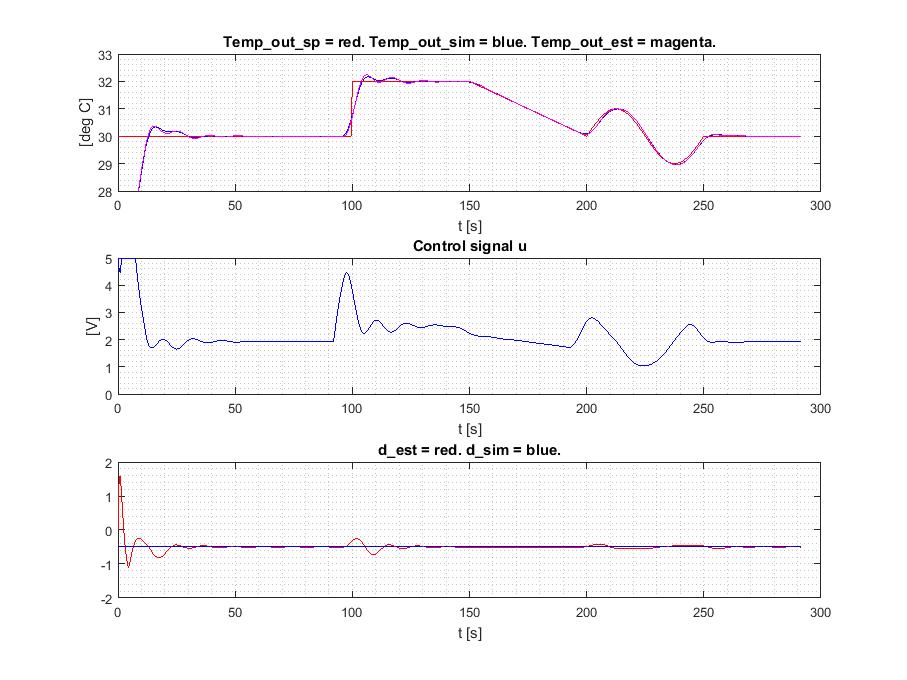
## Problem 6.3a

The interaction between the process simulator, observer and the MPC controller is illustrated as below.



## Problem 6.3b

The script seems runs quite well, with the plot as a result as below. The control signal changes before setpoint changing, which indicates the power of predictive control.

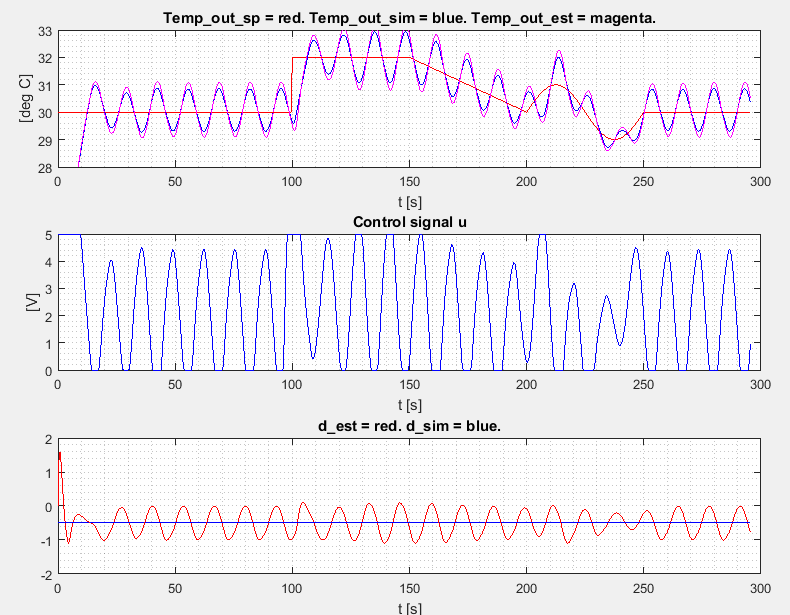


## Problem 6.3d

The changes of C\_e or C\_du do not affect the performance of the MPC system too much.

The simulation become slower when prediction horizon time increased, but the tracking of setpoint also getting better. For instance, t\_pred\_horizon was increased to 100, it took much more time to complete the simulation, but the output prediction was better.

A worse prediction (but faster) was obtained when the time prediction horizon was reduced to 4, see the result as bebow

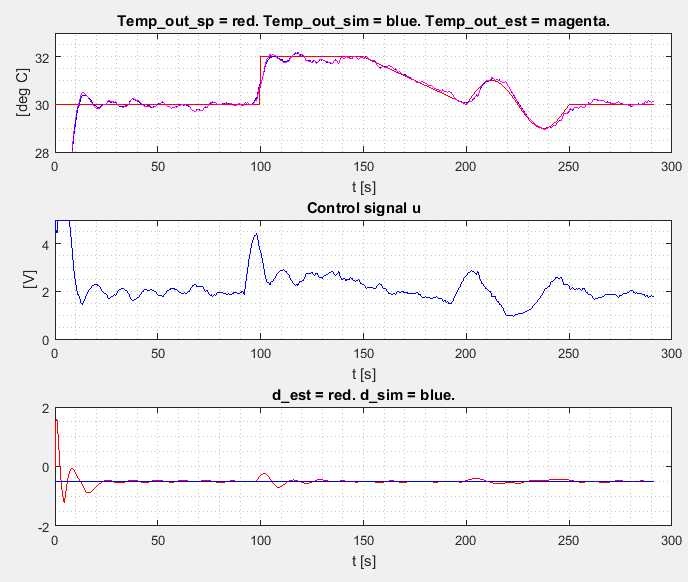


## Problem 6.3e

When I define a global variable gain\_init=3.5, and apply a dynamic gain with random error in the for loop:

gain = gain\_init + randn;

The results is shown in the following plot. It seems that MPC is still capable to perform predictive contril, although there is more noise than the original simulation.



## Problem 6.3f

I will try it later, using the same way to calculate Kalman gain as in Problem 6.1a.