Practice Final Exam – Simulation Results

ECEn 483/ ME 431

Winter 2023

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At the end of the exam, print this file and stable it to the handout portion of the exam.

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| --- | --- |
|  |  |
| Part I (25 pts) |  |
| Part II (25 pts) |  |
| Part III (25 pts) |  |
| Part IV (25 pts) |  |
| Total: (100 pts) |  |

# Part 1. Design models

1.2 Insert plot of the output of the simulation model with initial condition  and input directly below this line.

A picture containing chart

Description automatically generated

# Part 2. PID Control

2.4 Insert a plot that shows both and when is a square wave with magnitude degrees and frequency 0.1 Hz, and when using a PD controller.

\*\*\*would the first plot hurt me???\*\*\*

Chart, line chart

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Chart

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2.5 Insert a plot that shows both and when is a square wave with maginitude degrees and frequency 0.1 Hz, and when using a PID controller.

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Chart, line chart

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2.6 Insert the Python code for ctrlPID.py that implements PID control directly below this line.

import numpy as np

import rodMassParam as P

class ctrlPID:

    def \_\_init\_\_(self):

        tr = 0.1 #sec

        wn = 2.2/tr

        zeta = 0.707

        a1 = P.b/ (P.m \* P.ell\*\*2)

        b0 = 1.0 / (P.m \* P.ell\*\*2)

        a0 = P.k1 / (P.m \* P.ell\*\*2)

        self.kd = (2.0\*zeta\*wn - a1) / b0 #these are general equations and should work for all PD systems

        self.kp = (wn\*\*2 - a0) / b0

        self.ki = 1.0 #Integrator gain that I tune

        print("kd: ", self.kd, " kp: ", self.kp)

        #other needed parameters

        self.sigma = 0.005

        self.Ts = P.Ts

        self.beta = (2.0 \* self.sigma - P.Ts) / (2.0 \* self.sigma + P.Ts) #dirty derivative gain

        self.limit = P.tau\_max #his built in saturation function uses self.limit

        #variables and delayed variables for calculation

        self.thetadot = 0.0

        self.integrator = 0.0

        self.error\_d1 = 0.0

        self.theta\_d1 = 0.0 #delayed theta

    def update(self, theta\_r, y):

        theta = y#[0][0]

        error = theta\_r - theta

        #integrate on error

        #!do I need an anti-windup scheme?

        self.integrator = self.integrator + (P.Ts/2.0)\*(error + self.error\_d1)

        #compute derivative

        self.thetadot = self.beta\*self.thetadot + (1.0-self.beta) \* ((theta - self.theta\_d1) / P.Ts)

        tau\_tilde = self.kp \* error - self.kd \* self.thetadot + self.ki \* self.integrator

        #?no feedback linearized force as I did the Jacobian linearization earlier

        tau = self.saturate(tau\_tilde)

        #integrator anti windup just in case

        if self.ki != 0.0:

            self.integrator =  self.integrator + P.Ts/self.ki\*(tau - tau\_tilde) #?ie if it is saturating decrease the integrator

        #update delayed variables

        self.error\_d1 = error

        self.theta\_d1 = theta

        return tau

    def saturate(self, u):

        if abs(u) > self.limit:

            u = self.limit\*np.sign(u)

        return u

# Part 3. Observer based control

3.5. Insert a plot of the step response of the system for the complete observer based control.

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3.6 Insert a plot of the state estimation error.

Chart, line chart

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3.7 Insert a copy of ctrlObsv.py that implements the observer based controller directly below this line.

import numpy as np

import rodMassParam as P

import control as cnt

class ctrlObsv:

    def \_\_init\_\_(self):

        #tuning parameters

        tr = 0.1

        tr\_obs = tr/5.0 #this satisfies the 5x faster requirment

        zeta = 0.707

        wn = 2.2/tr

        wn\_obs = 2.2/tr\_obs

        integrator\_pole = -10.0 #make sure when I make the poly this is a positive value so it comes out negative in the left hand plane

        zeta\_obs = 0.707

        self.limit = P.tau\_max

        #State Space Matrices

        self.A = np.array([[0.0, 1.0],

                      [-P.k1/(P.m\*P.ell\*\*2), -P.b/(P.m\*P.ell\*\*2)]])

        self.B = np.array([[0.0],

                      [1/(P.m\*P.ell\*\*2)]])

        self.C = np.array([[1.0, 0.0]])

        self.D = np.array([[0.0]])

        #form augmented system

        A1 = np.vstack((np.hstack((self.A, np.zeros((np.size(self.A, 1),1)))),

                        np.hstack((-self.C, np.array([[0.0]]))) ))

        self.B1 = np.vstack((self.B, 0.0))

        #gain calculation

        des\_char\_poly = np.convolve([1, 2 \* zeta\*wn, wn\*\*2],

                                    [1, -integrator\_pole]) #!when is the integrator pole negative vs positive?

        des\_poles = np.roots(des\_char\_poly)

        # Compute the gains if the system is controllable

        if np.linalg.matrix\_rank(cnt.ctrb(A1, self.B1)) != 3:

            print("The system is not controllable")

        else:

            self.K1 = (cnt.place(A1, self.B1, des\_poles))

            self.K = self.K1[0][0:2]

            self.Ki = self.K1[0][2]

        print('K: ', self.K)

        print('ki: ', self.Ki)

        #print(des\_poles)

        #? I did the below because of 3.2, but then 3.3 immediately wants a disturbance observer?

        #observer design

        # des\_obs\_char\_poly = [1,2\*zeta\_obs\*wn\_obs, wn\_obs\*\*2]

        # des\_obs\_poles = np.roots(des\_obs\_char\_poly)

        # #compute the gains if the system is observable

        # if np.linalg.matrix\_rank(cnt.ctrb(self.A.T, self.C.T)) != 2:

        #     print("The system is not observable")

        # else:

        #     self.L = cnt.place(self.A.T, self.C.T, des\_obs\_poles).T

        # print('L.T: ', self.L.T)

        #?3.3 for disturbance observer

        #do this

        #augmented matrices for observer design

        self.A2 = np.concatenate((

                            np.concatenate((self.A, self.B), axis=1),

                            np.zeros((1, 3))),

                            axis=0)

        self.B2 = np.concatenate((self.B, np.zeros((1, 1))), axis=0)

        self.C2 = np.concatenate((self.C, np.zeros((1, 1))), axis=1)

        #disturbance observer design

        dist\_obs\_pole = -1.0 #same as above, both negative or both positive

        wn\_obs = 2.2/tr\_obs

        des\_obs\_char\_poly = np.convolve([1, 2\*zeta\_obs\*wn\_obs, wn\_obs\*\*2],

                                        [1.0, -dist\_obs\_pole]) #! should this pole input be negative or positive?

        des\_obs\_poles = np.roots(des\_obs\_char\_poly)

        #compute the gains if the system is observable

        if np.linalg.matrix\_rank(cnt.ctrb(self.A2.T, self.C2.T)) != 3:

            print("The system is not observable")

        else:

            self.L2 = cnt.acker(self.A2.T, self.C2.T, des\_obs\_poles).T

        print('L2: ', self.L2)

        print("\n")

        print('A2: ', self.A2)

        print("\n")

        print('B1: ', self.B1)

        print("\n")

        print("C2: ", self.C2)

        #variables to stay behind

        self.thetadot = 0.0 #estimated derivative of z

        self.theta\_d1 = 0.0 #z delayed by one sample

        self.integrator = 0.0

        self.error\_d1 = 0.0

        self.x\_hat = np.array([[0.0], #z\_hat\_0

                               [0.0]]) #zdot\_hat\_0

        self.Tau\_d1 = 0.0

        self.obs\_state = np.array([

            [0.0], #z\_hat

            [0.0], #zdot\_hat

            [0.0], # estimate of the disturbance

        ])

    def update(self, theta\_r, y):

        x\_hat, d\_hat = self.update\_observer(y)

        theta\_hat = x\_hat[0][0]

        error = theta\_r -theta\_hat

        #integrate the error

        self.integrator = self.integrator + (P.Ts/2.0)\*(error + self.error\_d1)

        self.error\_d1 = error #update the error

        #copmute the state feedback controller

        th\_eq = theta\_hat

        tau\_eq =  P.m\*P.g\*P.ell \* np.cos(th\_eq) + P.k1 \* th\_eq + P.k2 \* th\_eq\*\*3

        Tau\_tilde = -self.K @ x\_hat - self.Ki \* self.integrator - d\_hat

        tau = self.saturate(Tau\_tilde.item(0)+tau\_eq)

        # self.Tau\_d1 = tau

        self.Tau\_d1 = Tau\_tilde

        return tau, x\_hat, d\_hat

    def update\_observer(self, y):

        # update the observer using RK4 integration

        F1 = self.observer\_f(self.obs\_state, y)

        F2 = self.observer\_f(self.obs\_state + P.Ts / 2 \* F1, y)

        F3 = self.observer\_f(self.obs\_state + P.Ts / 2 \* F2, y)

        F4 = self.observer\_f(self.obs\_state + P.Ts \* F3, y)

        self.obs\_state += P.Ts / 6 \* (F1 + 2 \* F2 + 2 \* F3 + F4)

        x\_hat = self.obs\_state[0:2]

        d\_hat = self.obs\_state[2][0]

        return x\_hat, d\_hat

    def observer\_f(self, x\_hat, y):

        #this is called in the update observer function for RK4

        # xhat = [z\_hat, zdot\_hat]

        # xhatdot = A\*(xhat-xe) + B\*(u-ue) + L(y-C\*xhat)

        #!is it always going to be B1 and A2 and C2 etc????

        xhat\_dot = self.A2 @ x\_hat\

                   + self.B1 \* (self.Tau\_d1)\

                   + self.L2 \* (y - self.C2 @ x\_hat)

        return xhat\_dot

    def saturate(self,u):

        if abs(u) > self.limit:

            u = self.limit\*np.sign(u)

        return u

# Part 4. Loopshaping

4.6 Insert the Bode plots for the original plant, the PID controlled plant, and the loopshaped controlled plant below this line.

Chart, line chart

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4.7 Insert simulation results for the loopshaping controller below this line.

Chart, line chart

Description automatically generated

4.8 Insert the file loopshapeRodMass.py for the controller below this line.

import rodMassParam as P

import matplotlib.pyplot as plt

from control import TransferFunction as tf

from control import tf, bode, margin, step\_response, mag2db

import numpy as np

import loopshape\_tools as ls

from ctrlPID import ctrlPID

PID = ctrlPID()

# Compute plant transfer functions

Plant = tf([1.0/(P.m \* P.ell\*\*2)],

           [1.0, P.b/(P.m \* P.ell\*\*2), P.k1 / (P.m \* P.ell\*\*2)]) #this comes from the plant

C\_pid = tf([(PID.kd+PID.kp\*PID.sigma),

            (PID.kp+PID.ki\*PID.sigma),

            PID.ki],

           [PID.sigma, 1, 0]) # this should be the same for every PID controller I believe

PLOT = True

#PLOT = False

dB\_flag = True

#######################################################################

#   Control Design

#######################################################################

C = C\_pid \* ls.lead(w=22.149,M=10.0) \* ls.lag(z=30.0, M =25.0) \* ls.lpf(p=100.0)

#lead is for phase margin, lag is for disturbances/tracking, lpf is for noise

###########################################################

# add a prefilter to eliminate the overshoot

###########################################################

F = F = tf(1, 1) \* ls.lpf(p=5.0)

##############################################

#  Convert Controller to State Space Equations if following method in 18.1.7

##############################################

C\_num = np.asarray(C.num[0])

C\_den = np.asarray(C.den[0])

F\_num = np.asarray(F.num[0])

F\_den = np.asarray(F.den[0])

if \_\_name\_\_ == "\_\_main\_\_":

    # calculate bode plot and gain and phase margin for just the plant dynamics

    #\*\*\*added by Jacob Child

    mag, phase, omega = bode(Plant, dB=True,

                             omega=np.logspace(-3, 5),

                             Plot=True, label="$P(s)$")

    gm, pm, Wcg, Wcp = margin(Plant \* C\_pid)

    #### Code added to find gammaN and gammaR and to plot the noise and tracking specifications

    #for the controller

    magCP, phaseCP, omegaCP = bode(Plant\*C\_pid, plot=False,

                            omega = [0.001, 100.0], dB=dB\_flag) #TODO fill out these omega's for gammaN and gammaR

    mag4Plt, phase4Plt, omega4Plt = bode(Plant\*C\_pid, plot=False,

                            omega = [0.02, 2000.0], dB=dB\_flag) #TODO fill out these omegas for the tracking and noise specifications

    #Tracking and noise specifications

    ls.spec\_tracking(gamma=0.1\*1.0/mag4Plt[0], omega=0.02, flag=dB\_flag)

    ls.spec\_noise(gamma=0.1\*mag4Plt[1], omega=2000.0, flag=dB\_flag)

    print("MagCP: ", magCP)

    print("for original C\_pid system:")

    #It will spit out absolute magnitude, so I will not need to convert

    print(" pm: ", pm, " Wcp: ", Wcp, "gm: ", gm, " Wcg: ", Wcg)

    print("gammaR = ", 1.0/magCP[0])

    print("gammaN = ", magCP[1])

    # calculate bode plot and gain and phase margin for original PID \* plant dynamics

    mag, phase, omega = bode(Plant \* C\_pid, dB=True,

                             omega=np.logspace(-3, 5),

                             Plot=True, label="$P(s)C\_{pid}(s)$")

    gm, pm, Wcg, Wcp = margin(Plant \* C\_pid)

    print("for original C\_pid system:")

    if dB\_flag is True:

        print(" pm: ", pm, " Wcp: ", Wcp, "gm: ", mag2db(gm), " Wcg: ", Wcg)

    elif dB\_flag is False:

        print(" pm: ", pm, " Wcp: ", Wcp, "gm: ", gm, " Wcg: ", Wcg)

    #########################################

    #   Define Design Specifications

    #########################################

    # plot the effect of adding the new compensator terms

    mag, phase, omega = bode(Plant \* C, dB=dB\_flag,

                             omega=np.logspace(-4, 5),

                             plot=True, label="$P(s)C\_{final}(s)$")

    gm, pm, Wcg, Wcp = margin(Plant \* C)

    print("for final P\*C:")

    if dB\_flag is True:

        print(" pm: ", pm, " Wcp: ", Wcp, "gm: ", mag2db(gm), " Wcg: ", Wcg)

    elif dB\_flag is False:

        print(" pm: ", pm, " Wcp: ", Wcp, "gm: ", gm, " Wcg: ", Wcg)

    plt.figure(1)

    fig = plt.gcf()

    fig.axes[0].legend()

    ############################################

    # now check the closed-loop response with prefilter

    ############################################

    # Closed loop transfer function from R to Y - no prefilter

    CLOSED\_R\_to\_Y = (Plant \* C / (1.0 + Plant \* C))

    # Closed loop transfer function from R to Y - with prefilter

    CLOSED\_R\_to\_Y\_with\_F = (F \* Plant \* C / (1.0 + Plant \* C))

    # Closed loop transfer function from R to U - no prefilter

    CLOSED\_R\_to\_U = (C / (1.0 + Plant \* C))

    # Closed loop transfer function from R to U - with prefilter

    CLOSED\_R\_to\_U\_with\_F = (F \* C / (1.0 + Plant \* C))

    fig = plt.figure(2)

    plt.clf()

    plt.grid(True)

    mag, phase, omega = bode(CLOSED\_R\_to\_Y, dB=dB\_flag, plot=True,

                             color=[0, 0, 1], label='closed-loop $\\frac{Y}{R}$ - no pre-filter')

    mag, phase, omega = bode(CLOSED\_R\_to\_Y\_with\_F, dB=dB\_flag, plot=True,

                             color=[0, 1, 0], label='closed-loop $\\frac{Y}{R}$ - with pre-filter')

    fig.axes[0].set\_title('Closed-Loop Bode Plot')

    fig.axes[0].legend()

    plt.figure(4)

    plt.clf()

    plt.subplot(211), plt.grid(True)

    T = np.linspace(0, 2, 100)

    \_, yout\_no\_F = step\_response(CLOSED\_R\_to\_Y, T)

    \_, yout\_F = step\_response(CLOSED\_R\_to\_Y\_with\_F, T)

    plt.plot(T, yout\_no\_F, 'b', label='response without prefilter')

    plt.plot(T, yout\_F, 'g', label='response with prefilter')

    plt.legend()

    plt.ylabel('Step Response')

    plt.subplot(212), plt.grid(True)

    \_, Uout\_no\_F = step\_response(CLOSED\_R\_to\_U, T)

    \_, Uout\_F = step\_response(CLOSED\_R\_to\_U\_with\_F, T)

    plt.plot(T, Uout\_no\_F, color='b', label='control effort without prefilter')

    plt.plot(T, Uout\_F, color='g', label='control effort with prefilter')

    plt.ylabel('Control Effort')

    plt.legend()

    plt.show()