Dynamic Distillation Modeling and Control

Over 40,000 distillation columns in the U.S. consume 40-60% of the total energy in the petrochemical industry and 6% of the total U.S. energy usage. Reducing distillation energy usage would have a major impact on energy independence, greenhouse gas emissions, and give a competitive advantage to any manufacturer that is better able to implement improvements.

Your task is to design a control system for a binary (cyclohexane / n-heptane) distillation column and maintain the distillate composition above 0.95 mole fraction C_6H_{12} and the bottoms composition below 0.05 mole fraction C_6H_{12}. If the distillate composition is above 0.95, it indicates that energy was wasted to exceed the target specification limit. If the distillate composition is too low, energy is also wasted because the product must be recycled through the distillation column. In order to meet the target specifications, the reflux ratio and bottoms flow (fraction of feed) can be changed.

A distillation column is a highly coupled system that leads to interacting controllers. Some useful techniques for designing the control system are:

- Empirical model fitting of a Multiple Input Multiple Output (MIMO) System
- Relative Gain Array (RGA) analysis to determine best pairing of Manipulated and Controlled Variables
- Derivation of a first principles model

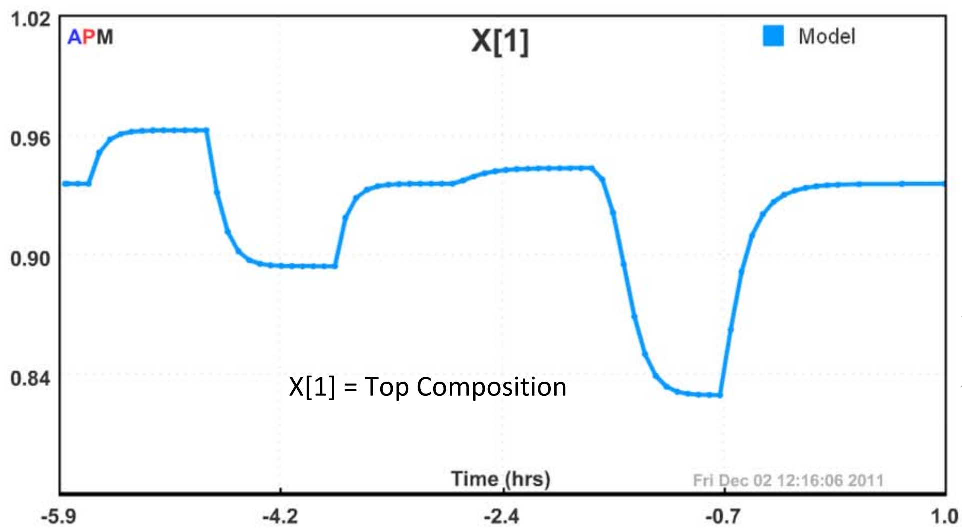
The appendices provide some assistance in designing and one of three control systems:

1. Non-interacting PID controllers
2. Interacting PID controllers (feedforward information from other controller)
3. Nonlinear Control (NLC)

Your task is to evaluate the three control systems to determine which will provide the best performance for feed disturbances of both flow and composition.

Appendix A: Calculate transfer functions for the distillation column model response and put model into the form

$$\begin{bmatrix} X[1] \\ X[32] \end{bmatrix} = \begin{bmatrix} \dfrac{K_{p,11}}{\tau_{p,11}s+1} & \dfrac{K_{p,12}}{\tau_{p,12}s+1} \\ \dfrac{K_{p,21}}{\tau_{p,21}s+1} & \dfrac{K_{p,22}}{\tau_{p,22}s+1} \end{bmatrix} \begin{bmatrix} RR \\ FBOT \end{bmatrix} =$$

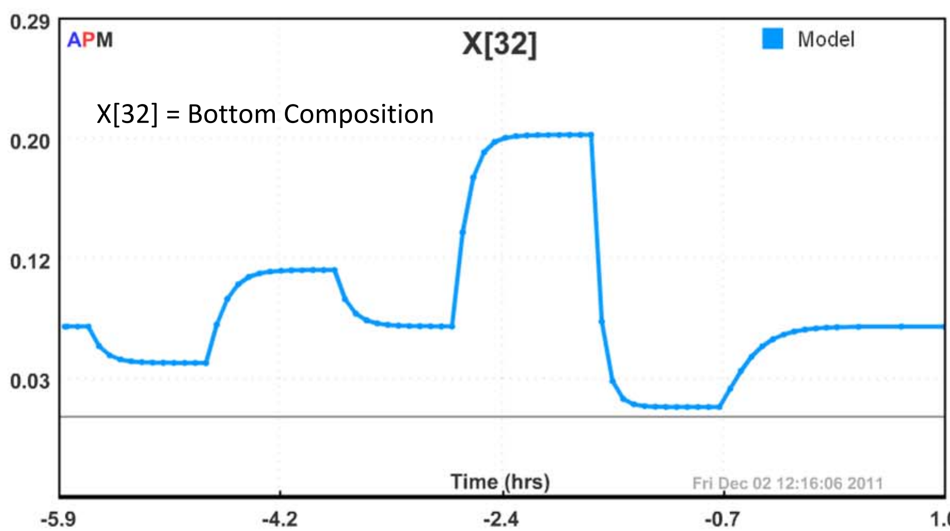


$K_{p,11}=$

$K_{p,12}=$

$\tau_{p,11}=$

$\tau_{p,12}=$

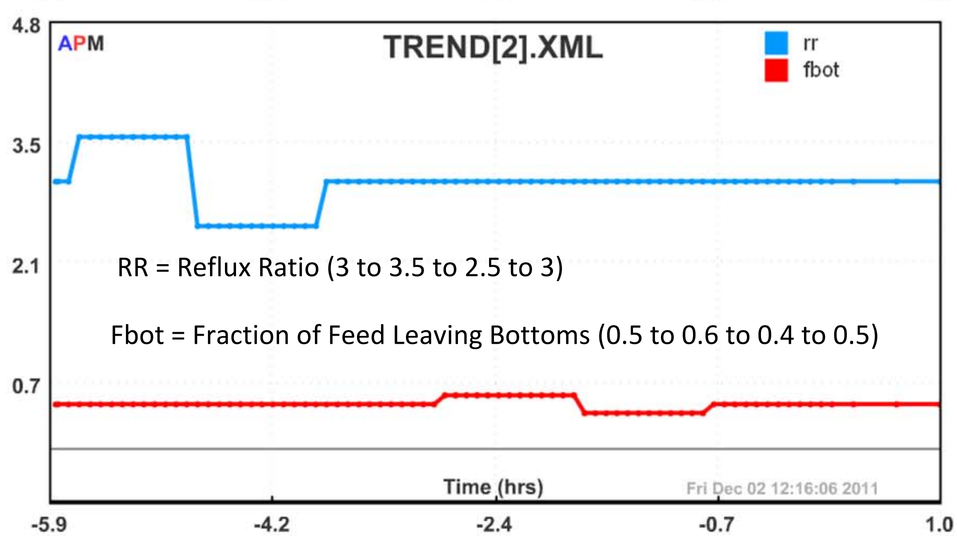


$K_{p,21}=$

$K_{p,22}=$

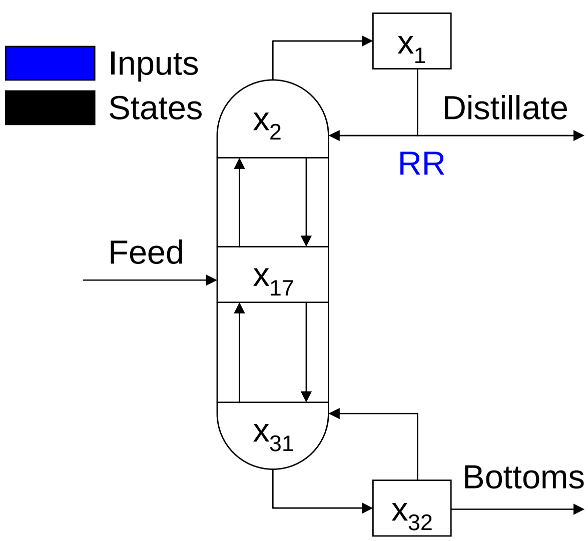
$\tau_{p,21}=$

$\tau_{p,22}=$



Appendix B – Derivation of a single tray model for the distillation column:

- Two Components
- Constant Relative Volatility
- Constant Tray Molar Holdup
- Liquid Feed at the Bubble Point
- 30 Trays, Reboiler, and Condenser
- Manipulated Variables
  - RR – Reflux Ratio
  - FBOT – Fraction of Feed Leaving at Bottoms Product
- Controlled Variables
  - x[1] – Light component composition in overhead product
  - x[32] – Light component composition in bottoms product



Appendix C - Using Relative Gain Array (RGA) analysis, suggest best pairing options for the MVs (RR and FBOT) and CVs (X[1] and X[32]). The steady state gains at a nominal operating condition are provided below.

APMonitor		CV(1)	CV(2)	SV(1)	SV(2)	SV(3)	SV(4)	SV(5)	SV(6)	SV(7)	SV(8)
	Sensitivities	ss.x[1]	ss.x[32]	ss.x[2]	ss.x[5]	ss.x[10]	ss.x[15]	ss.x[20]	ss.x[25]	ss.x[30]	ss.x[31]
FV(1)	ss.feed	-4.204E-09	4.204E-09	-5.313E-09	-5.383E-09	-2.321E-09	8.049E-09	5.356E-09	6.675E-09	5.061E-09	4.792E-09
FV(2)	ss.x_feed	0.880362	1.11964	1.30545	2.42762	2.64995	1.80586	2.16519	3.25674	2.00723	1.55214
FV(3)	ss.alpha	0.446683	-0.446683	0.606380	0.889874	0.565205	0.095437	-0.178455	-0.702162	-0.689056	-0.574441
FV(4)	ss.atray	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FV(5)	ss.acond	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FV(6)	ss.areb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MV(1)	ss.rr	0.068707	-0.068707	0.101883	0.170145	0.121322	0.019434	-0.050178	-0.152264	-0.118547	-0.093852
MV(2)	ss.fbot	0.314140	1.42754	0.465825	0.866247	0.945584	0.644385	1.43757	3.39092	2.48516	1.95664

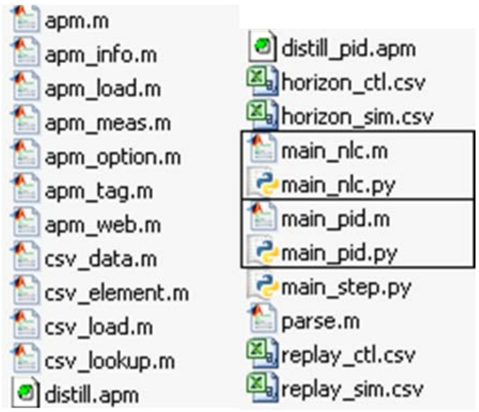
The RGA analysis can be completed by using the gains above or the gains from Part a)

$$\lambda_{11} = \lambda_{22} = \frac{1}{1 - \dfrac{K_{12}K_{21}}{K_{11}K_{22}}}$$

$$\lambda_{12} = \lambda_{21} = 1 - \lambda_{11}$$

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} =$$

Appendix D - Simulate a PID controller for the distillation column using files provided with this assignment (run **main_pid.py**). Adjust the PI controller tuning parameters to achieve acceptable set point and disturbance tracking. PI controller tuning can be adjusted by opening **distill_pid.apm** with a text editor and modifying the values of Kc_1, Kc_2, taui_1, and taui_2.

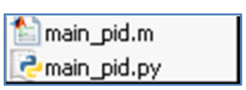


Edit  with a text editor to change the PID tuning parameters.


```
! pid tuning parameters for top composition control
kc_1   = 1/0.069   ! ~1/Kp1
taui_1 = 30        ! ~taup1
taud_1 = 0         !  0
sp_x[1] = 0.935

! pid tuning parameters for bottom composition control
kc_2   = 1/1.42    ! ~1/Kp2
taui_2 = 60        ! ~taup2
taud_2 = 0         !  0
sp_x[32] = 0.065
```

Run PID Control with either MATLAB or Python

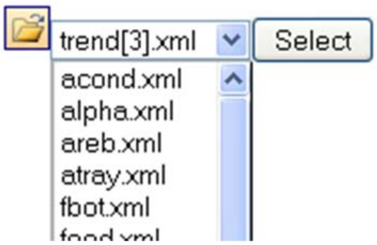


Adjust the PID equations in distill_pid.apm to make them interacting controllers (i.e. a feedforward element) that accounts for changes in the other controller. You'll want to copy distill_pid.apm into a new file so that you can compare the two controllers.

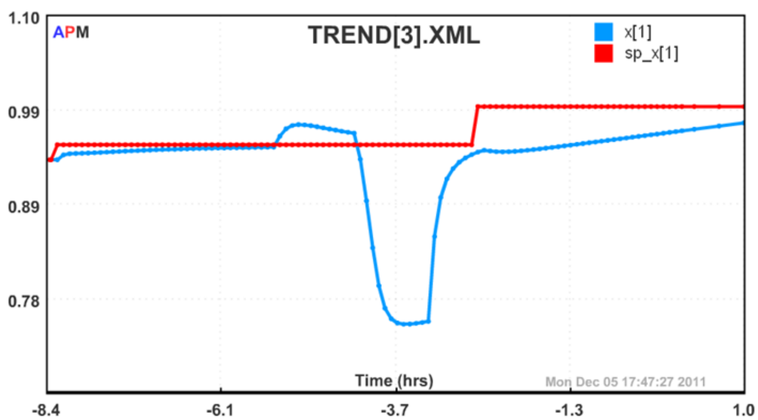
Appendix E - Compare the performance of the PID controller with Nonlinear Control.

Run Nonlinear Control with either MATLAB (**main_nlc.m**) or Python (**main_nlc.py**):

When the web-viewer starts, select custom trends **Trend[3]** or **Trend[4]** to view controller performance.



PID Control Performance for Distillate Composition Control (sample plots with disturbances and set point changes)



NLC Control Performance for Distillate Composition Control