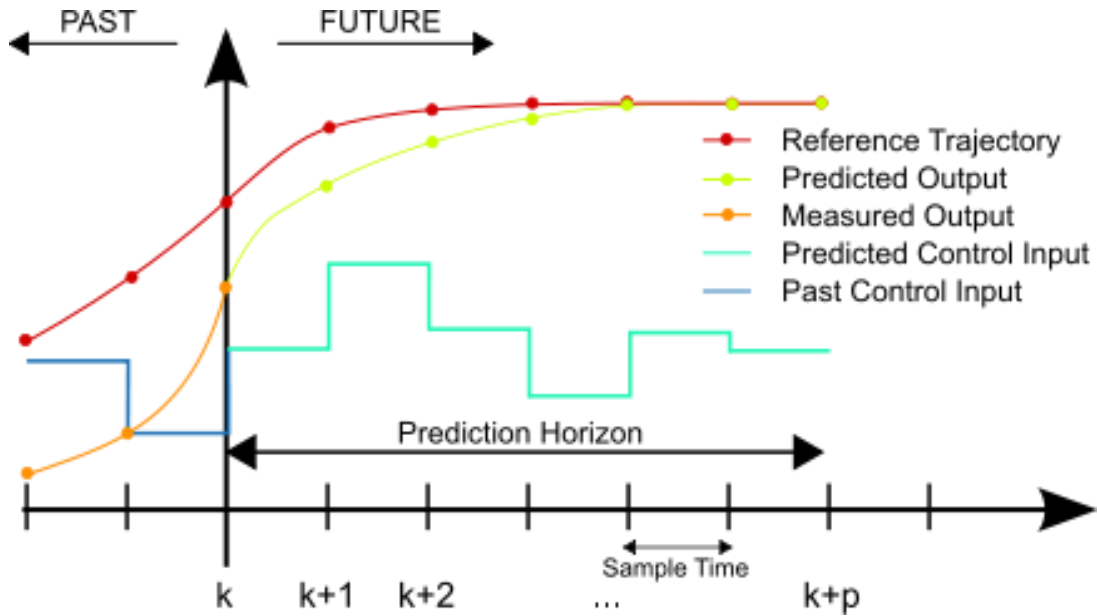
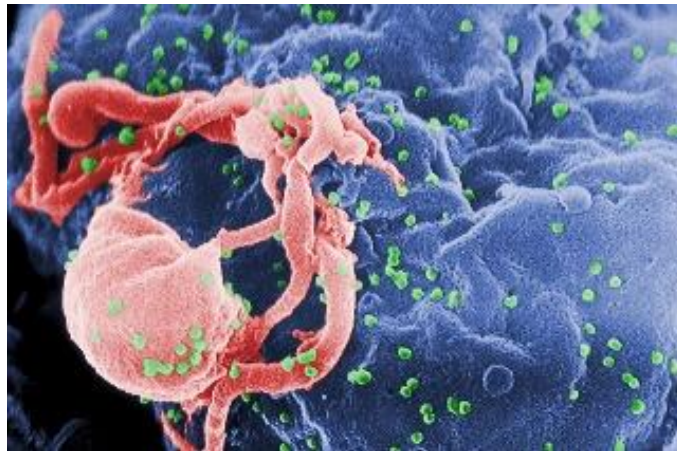


# Model Predictive Control



Source: Wikipedia



# Overview

- Model Predictive Control (MPC) – regulatory controls that use an explicit dynamic model of the response of process variables to changes in manipulated variables to calculate control “moves”
- Control moves are intended to force the process variables to follow a pre-specified trajectory from the current operating point to the target

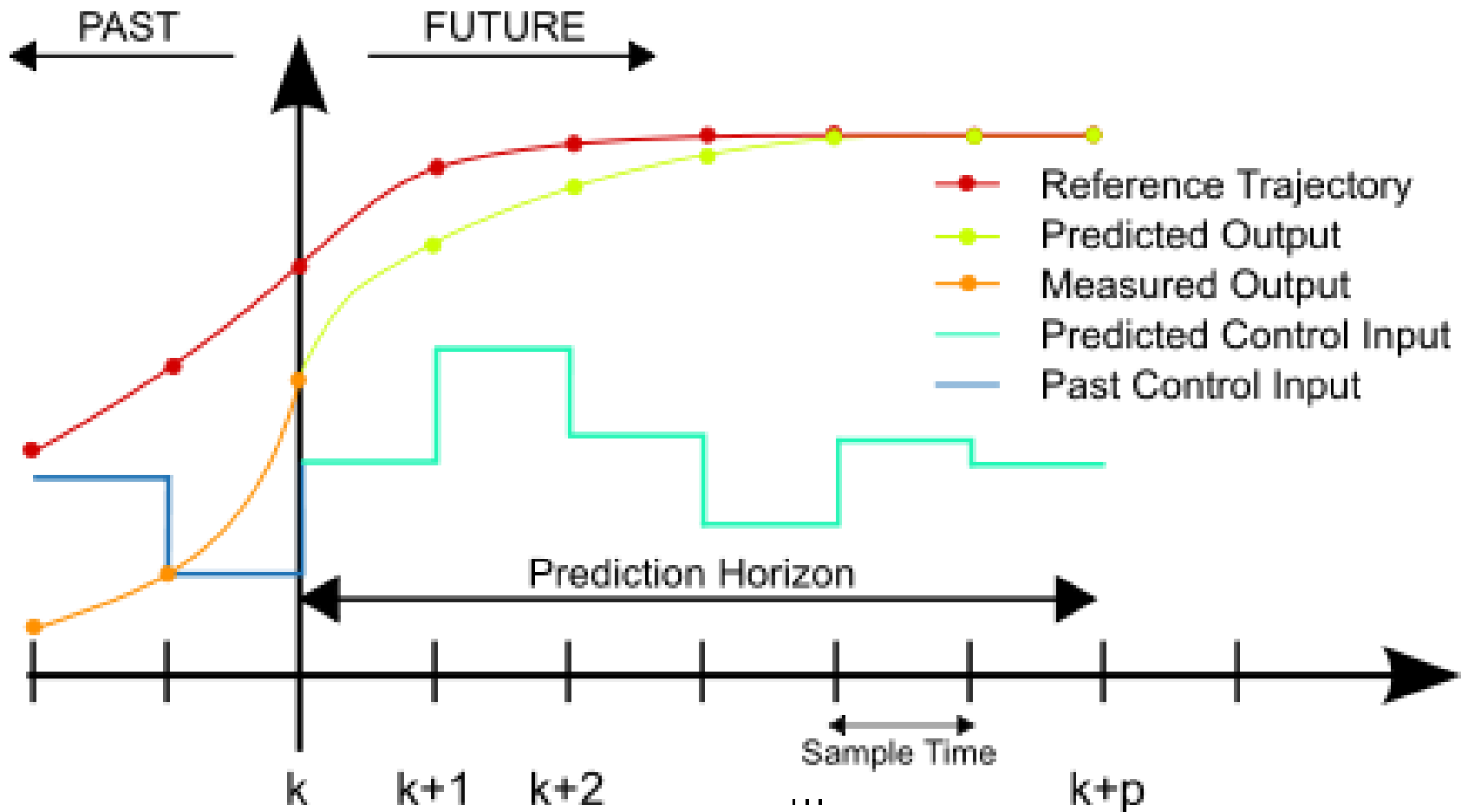
# MPC – model predictive control

- Optimal controller is based on minimizing error from trajectory
- Basic version uses linear model, but there are many possible models
- Corrections for unmeasured disturbances, model errors are included
- Treats multivariable control, feedforward control

# When Should Predictive Control be Used?

1. Processes are difficult to control with standard PID algorithm – long time constants, substantial time delays, inverse response, etc.
2. There is substantial dynamic interaction among controls, i.e., more than one manipulated variable has a significant effect on an important process variable.
3. Constraints (limits) on process variables and manipulated variables are important for normal control.

# MPC Overview



# General Characteristics

- Targets (set points) selected by real-time optimization software based on current operating and economic conditions
- Minimize square of deviations between predicted future outputs and specific reference trajectory to new targets
- Framework handles multiple input, multiple output (MIMO) control problems.

- Can include equality and inequality constraints on controlled and manipulated variables
- Solves a nonlinear programming problem at each sampling instant
- Disturbance is estimated by comparing the actual controlled variable with the model prediction
- Usually implements the first move out of  $M$  calculated moves

# Empirical Modeling

Consider a single input, single output process:



Where  $u$  and  $y$  are deviation variables (i.e. deviations from nominal steady-state values).



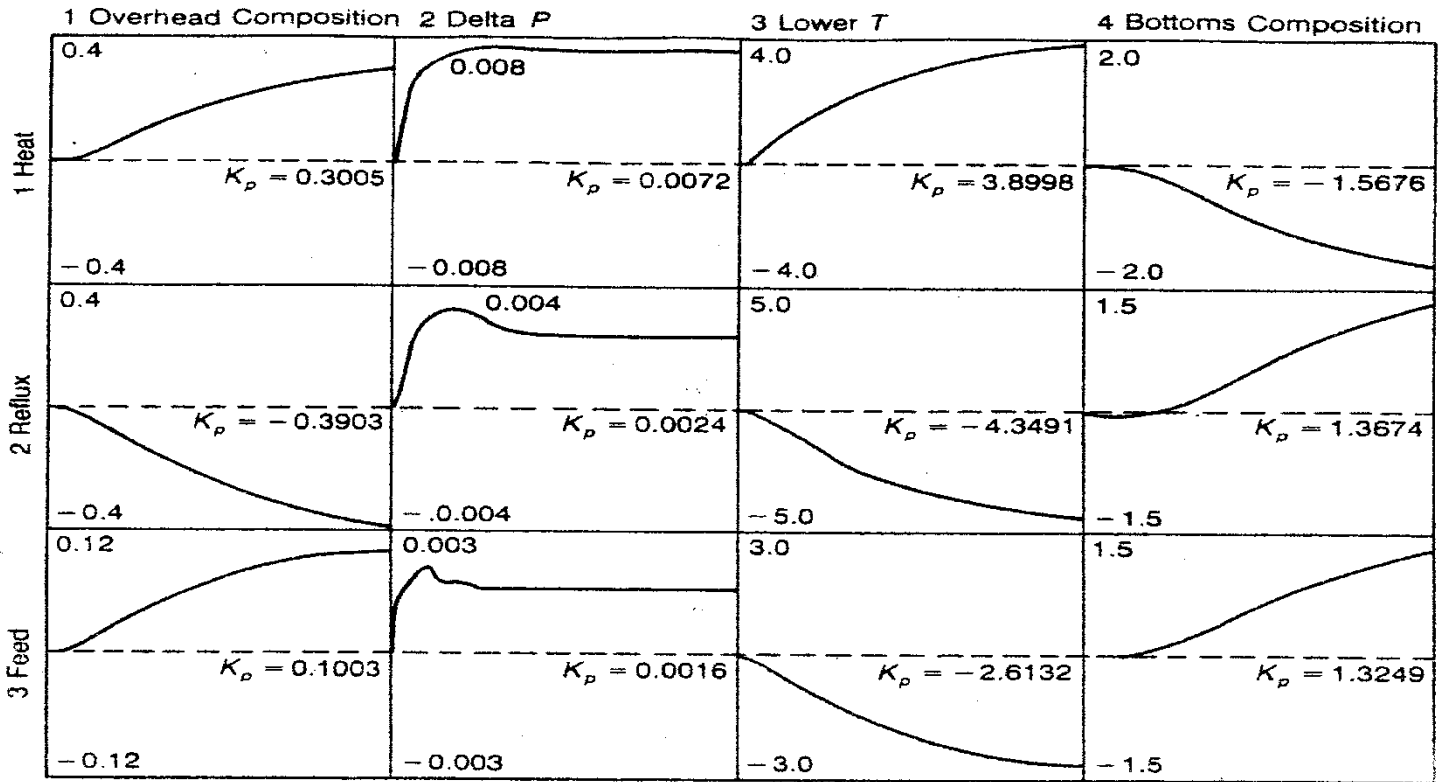
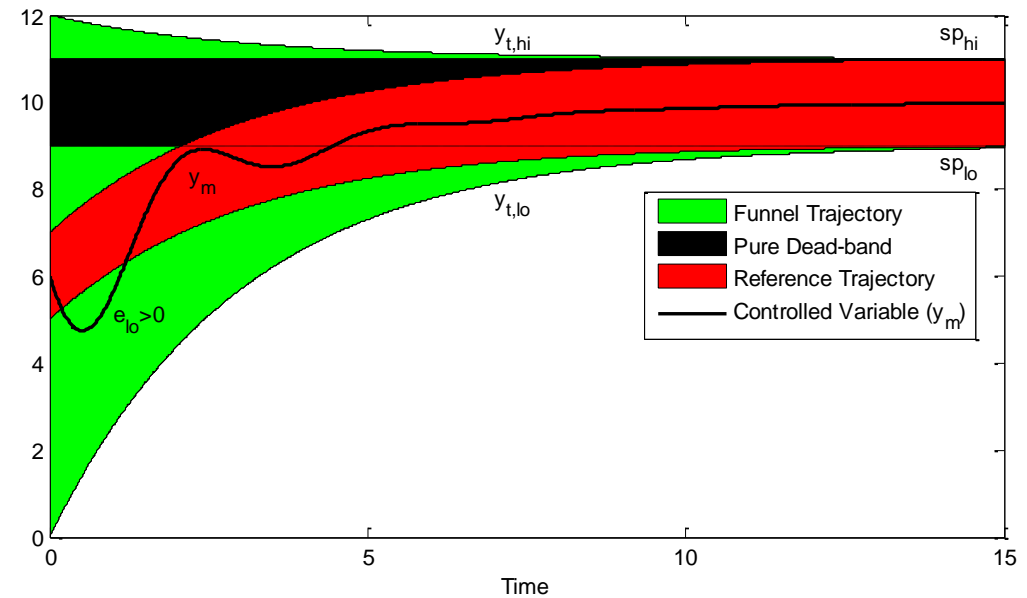


Figure 20.8. Individual step-response models for a distillation column with three inputs and four outputs. Each model represents the step response for 120 minutes. Reference: Hokanson and Gerstle (1992).

# MPC Target Trajectories

- Target Trajectories
  - Funnel Trajectory
  - Pure dead-band
  - Reference Trajectory
- Response Target
- Response Speed
- Near-term vs. Long-term objectives



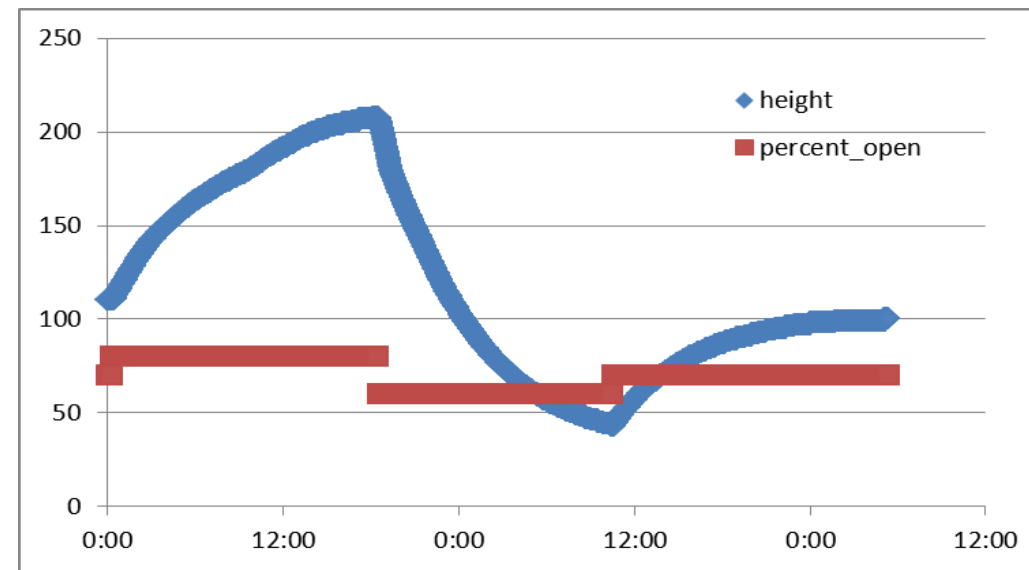
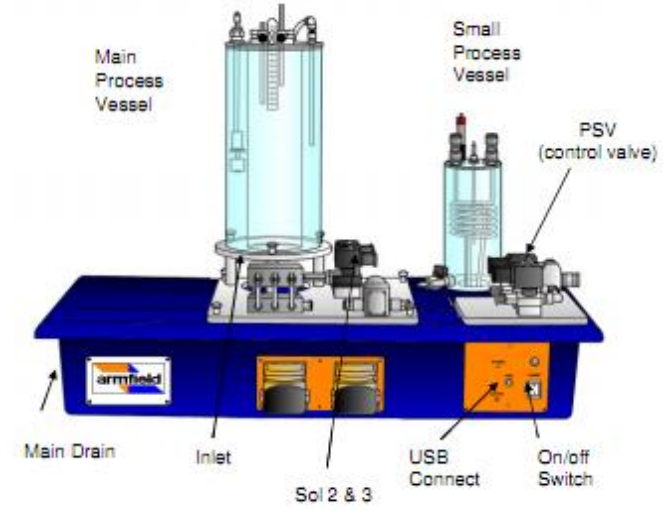
# Control of a Gravity Drained Tank

- Lab Experiment #1
- Material Balance

$$\frac{\partial m}{\partial t} = \dot{m}_{in} - \dot{m}_{out}$$

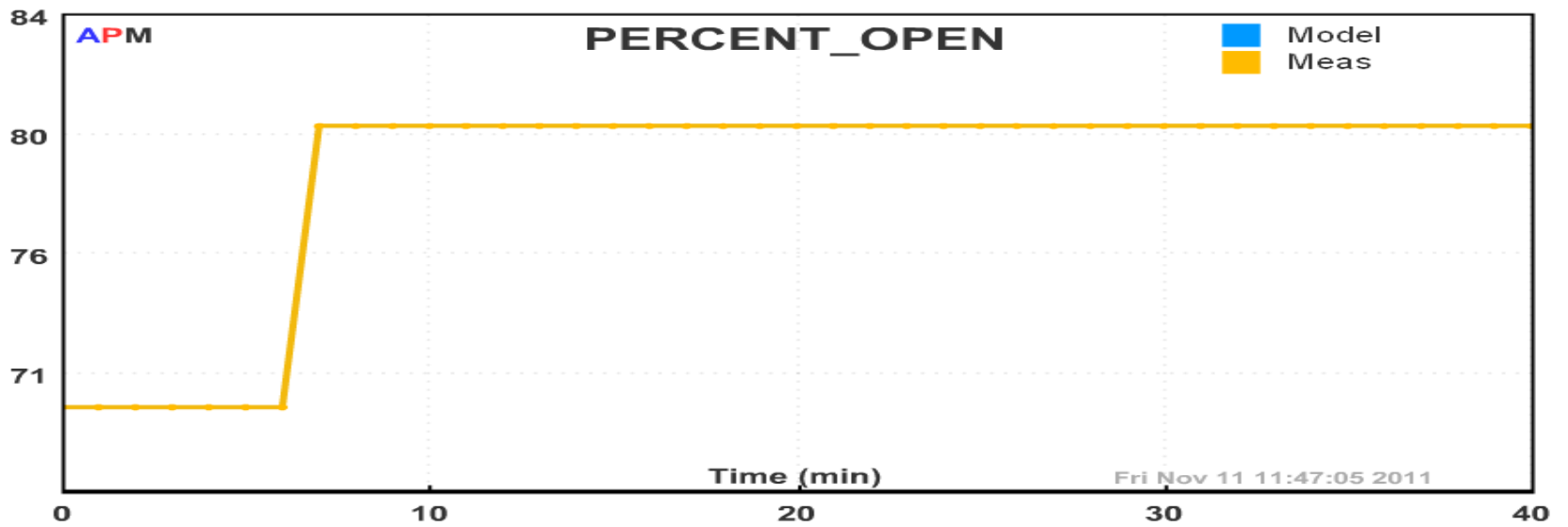
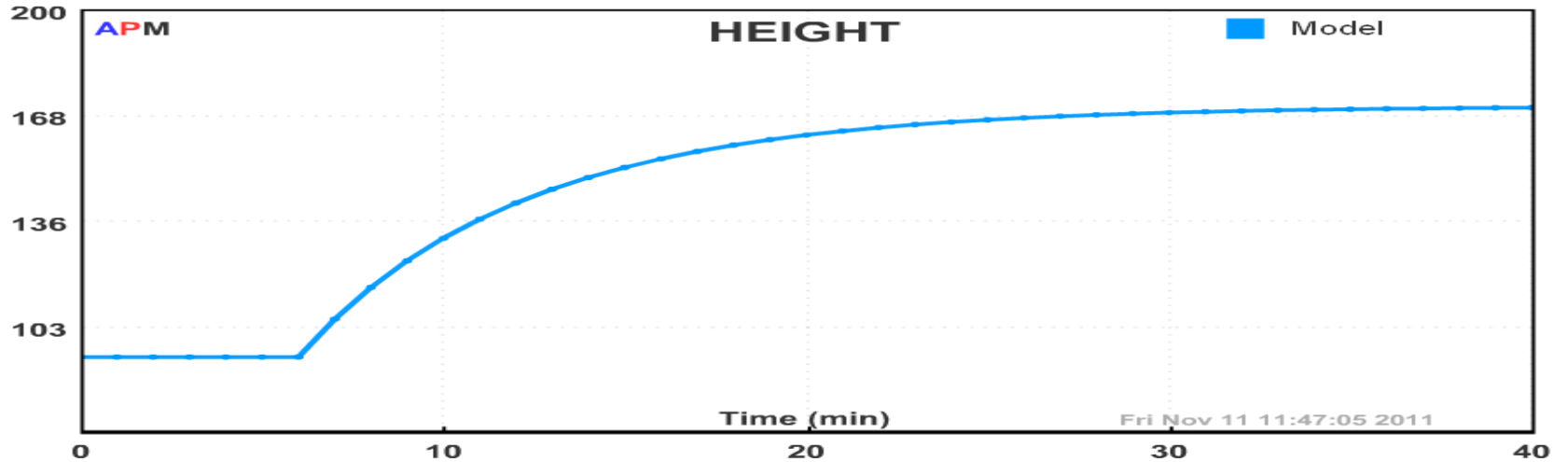
$$\rho A \frac{\partial h}{\partial t} = \rho (\dot{V}_{in} - \dot{V}_{out})$$

$$A \frac{\partial h}{\partial t} = \dot{V}_{in} - \dot{V}_{out}$$



Source: Lee Jacobsen / James Memmott

# Step Response



# Parameter Estimation

$$\text{Min}(h_{\text{meas}} - h_{\text{model}})$$

$$A \frac{\partial h}{\partial t} = c_1(\% \text{Open}) - c_2 \sqrt{h}$$

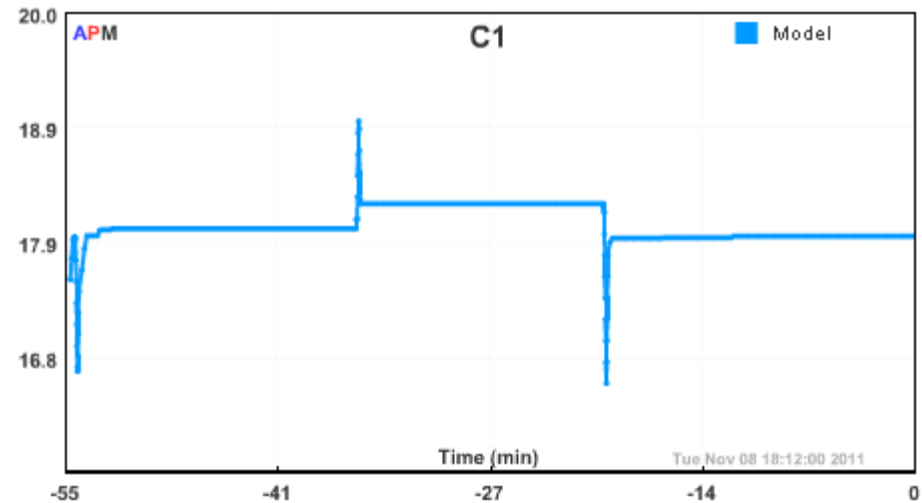
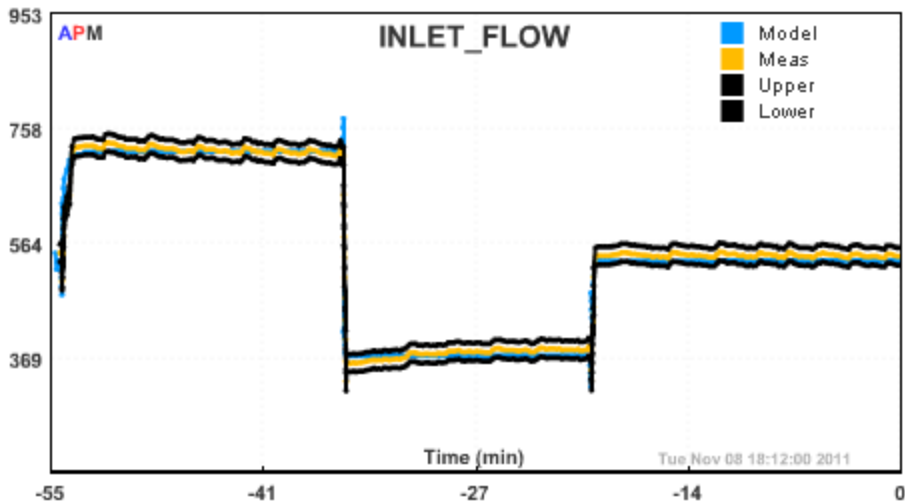
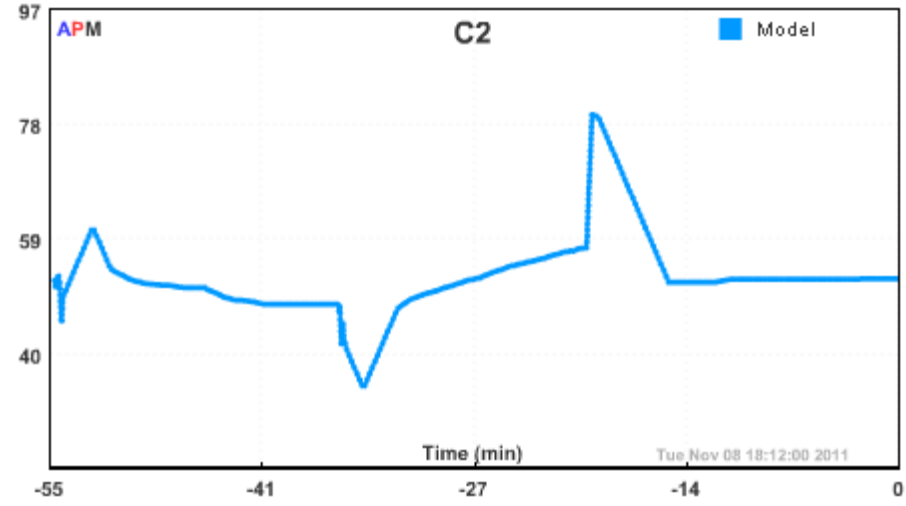
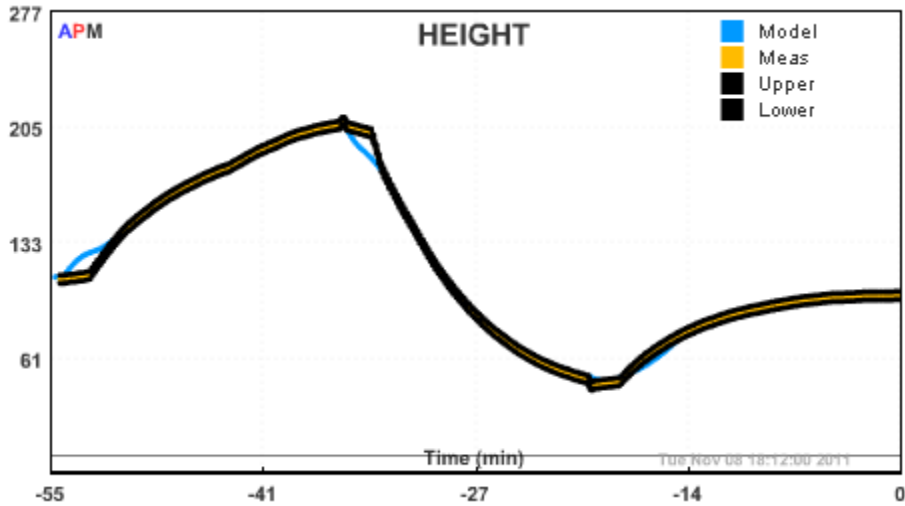
Can we use the Nonlinear Model in a controller?

#1 : Step Response

#2 : Estimate Parameters

#3 : Model Predictive Control

# Need Valve Dynamics?



# Need Valve Dynamics

$$A \frac{\partial h}{\partial t} = \dot{V}_{in} - \dot{V}_{out}$$

$$A \frac{\partial h}{\partial t} = c_1(\% Open) - c_2 \sqrt{h}$$

