## 2.5 ADDITIONAL ISSUES

### Refinement

- **State Estimation:**
  - Computation of state estimates based on the full nonlinear model (e.g., moving horizon estimation) instead of the linearized model. Again, this requires NLP (computationally much more expensive).
- **Input Computation:**
  - Repetition of linearization and input trajectory calculation for better linearized model ($\Longrightarrow$ better dynamic matrix).
  - Replace linearized model based prediction equation

$$\begin{aligned}\mathcal{X}(k+1|k) &= \mathcal{F}(x(k|k), u(k-1), d(k), w(k|k)) \\ &\quad + \mathcal{S}_k^{\mathcal{U}}(x(k|k), u(k-1), d(k), w(k|k))\Delta\mathcal{U}(k)\end{aligned}$$

  with nonlinear algebraic constraints obtained from discretization (e.g., orthogonal collocation). This requires NLP instead of QP in control computation, however.

### Alternatives

- **Gain scheduling:** separate model for different operating regimes.
- **Adaptive MPC:** recursive update of model parameters.

## 2.6 RECURSIVE PARAMETER ESTIMATION

### Adaptation via Recursive Parameter Identification

State space representation of general model structure for parametric identification is

$$\begin{aligned} X(k+1) &= \Phi(\theta)X(k) + ,_{u}(\theta)\Delta u(k) + ,_{d}(\theta)\Delta d(k) + ,_{e}(\theta)e(k) \\ \hat{y}(k) &= \Xi X(k) + \nu(k) \end{aligned}$$

- Initiation Step: Initial parameter estimate, $\theta_0^*$ is obtained using I/O data from PRBS tests.

$$\Downarrow$$

$$\begin{aligned} X(k+1) &= \Phi(\theta_0^*)X(k) + ,_{u}(\theta_0^*)\Delta u(k) + ,_{d}(\theta_0^*)\Delta d(k) + ,_{e}(\theta_0^*)e(k) \\ \hat{y}(k) &= \Xi X(k) + \nu(k) \end{aligned}$$

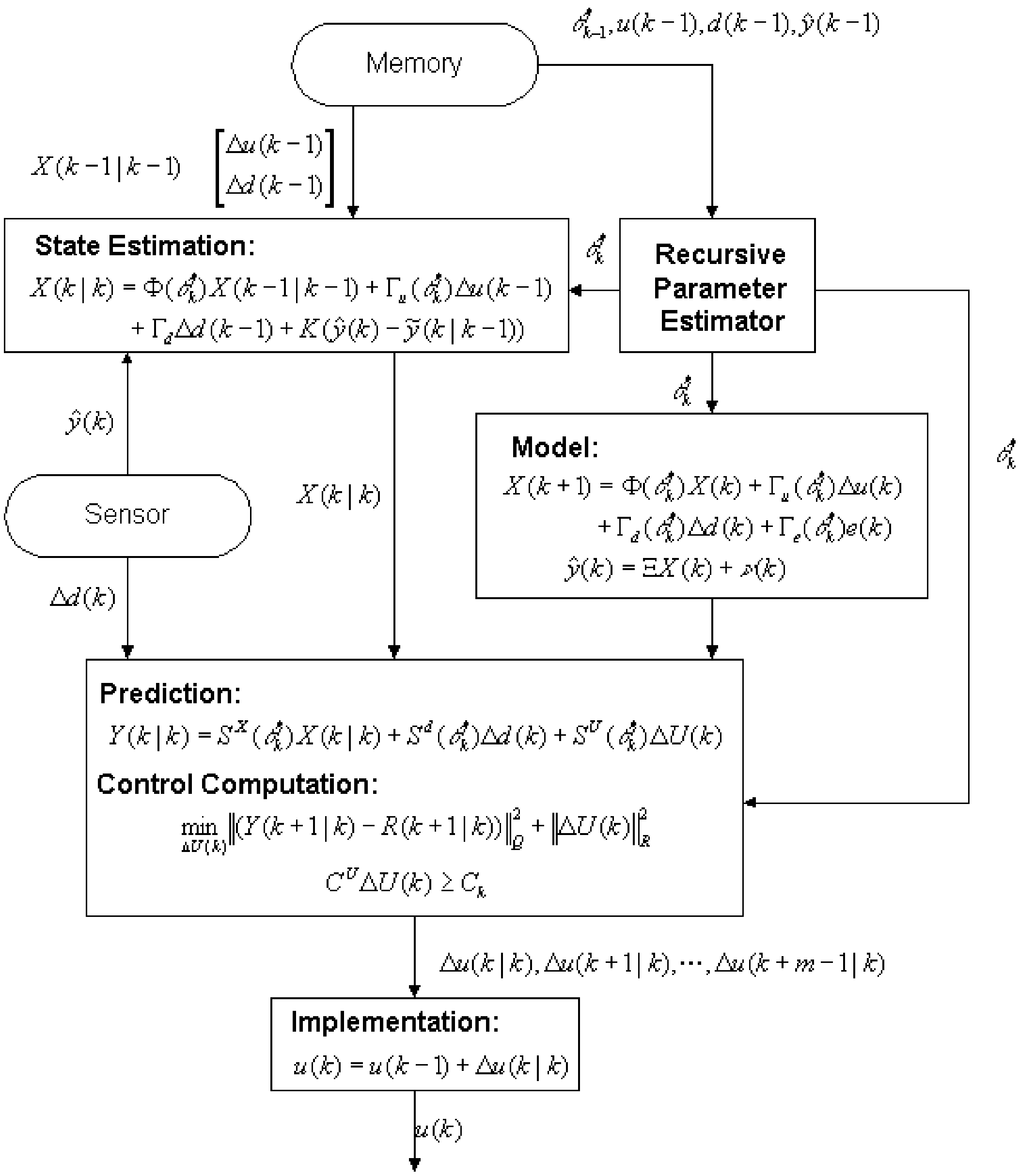
- $k$th Sampling time: Given $(k-1)$th parameter estimate $\theta_{k-1}^*$, $\theta_k^*$ is obtained using $\theta_{k-1}^*, u(k-1), d(k-1), \hat{y}(k-1)$.

$$\Downarrow$$

$$\begin{aligned} X(k+1) &= \Phi(\theta_k^*)X(k) + ,_{u}(\theta_k^*)\Delta u(k) + ,_{d}(\theta_k^*)\Delta d(k) + ,_{e}(\theta_k^*)e(k) \\ \hat{y}(k) &= \Xi X(k) + \nu(k) \end{aligned}$$

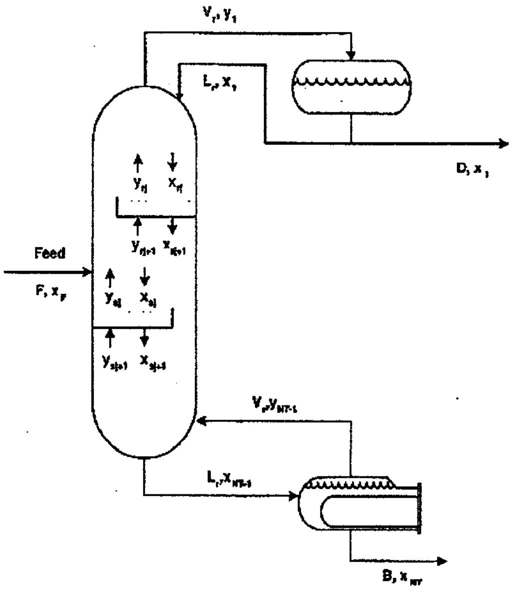
## 2.7 ADAPTIVE MPC FORMULATION

### Overview



# 2.8 EXAMPLE: BINARY DISTILLATION COLUMN

## Problem Description



$x, y$: liquid and vapor compositions.

$D, B$: overhead and bottom products.

$L, V$: liquid and vapor flow rate.

$F, x_F$: feed and feed composition.

$q$: feed quality.

$H$: liquid holdup.

$K$: vapor-liquid equilibrium constant.

Control objective: regulation of overhead and bottom compositions $x_1, x_{N_T}$