

Advanced Control of a Glass Cooling Forehearth

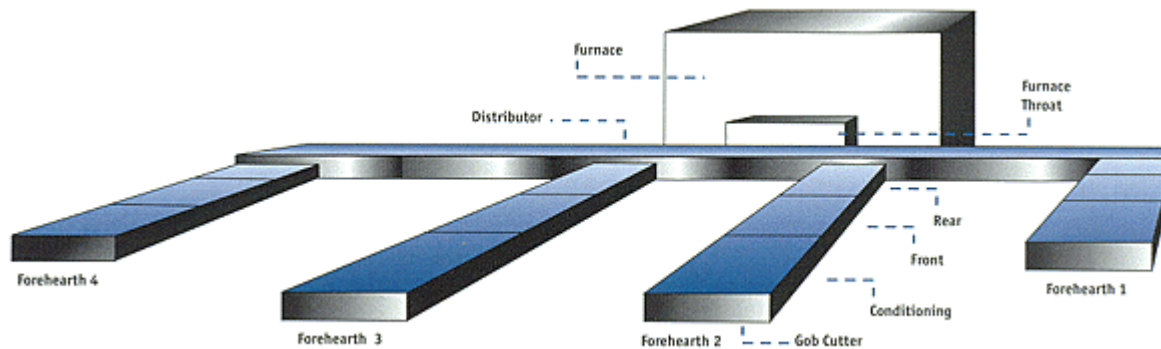


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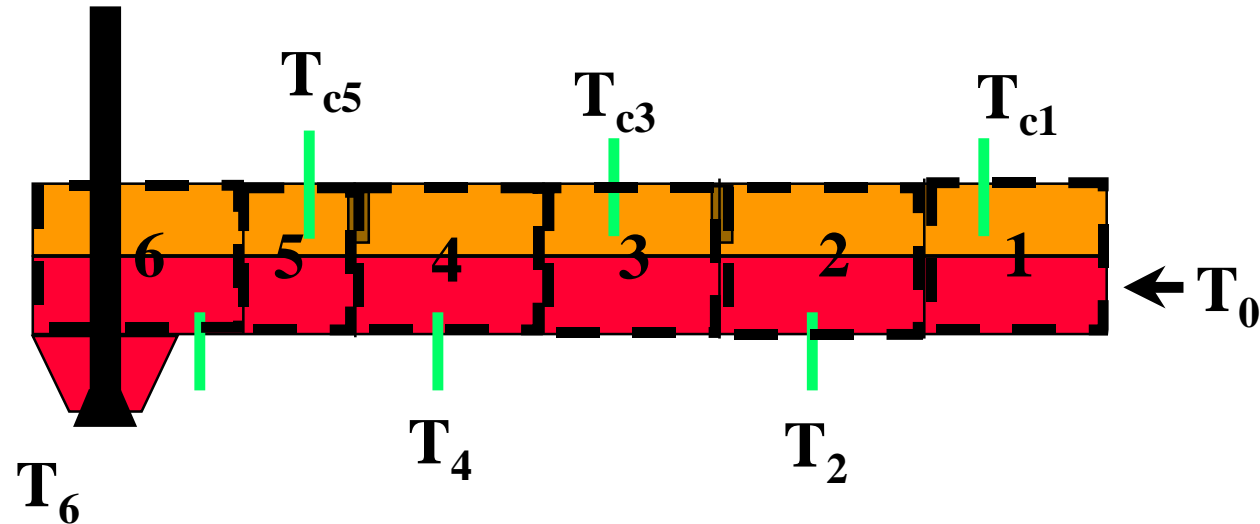
- **Motivation**

- ◆ Downstream product quality dependent on temperature
- ◆ Open-loop unstable process
- ◆ Requires tight regulation of temperature

Illustration source: (http://www.brainwave.com/industry/d3_furnace.html)

AICHE 1999 Houston

Glass Cooling Forehearth



for $i = 1, 3, 5$

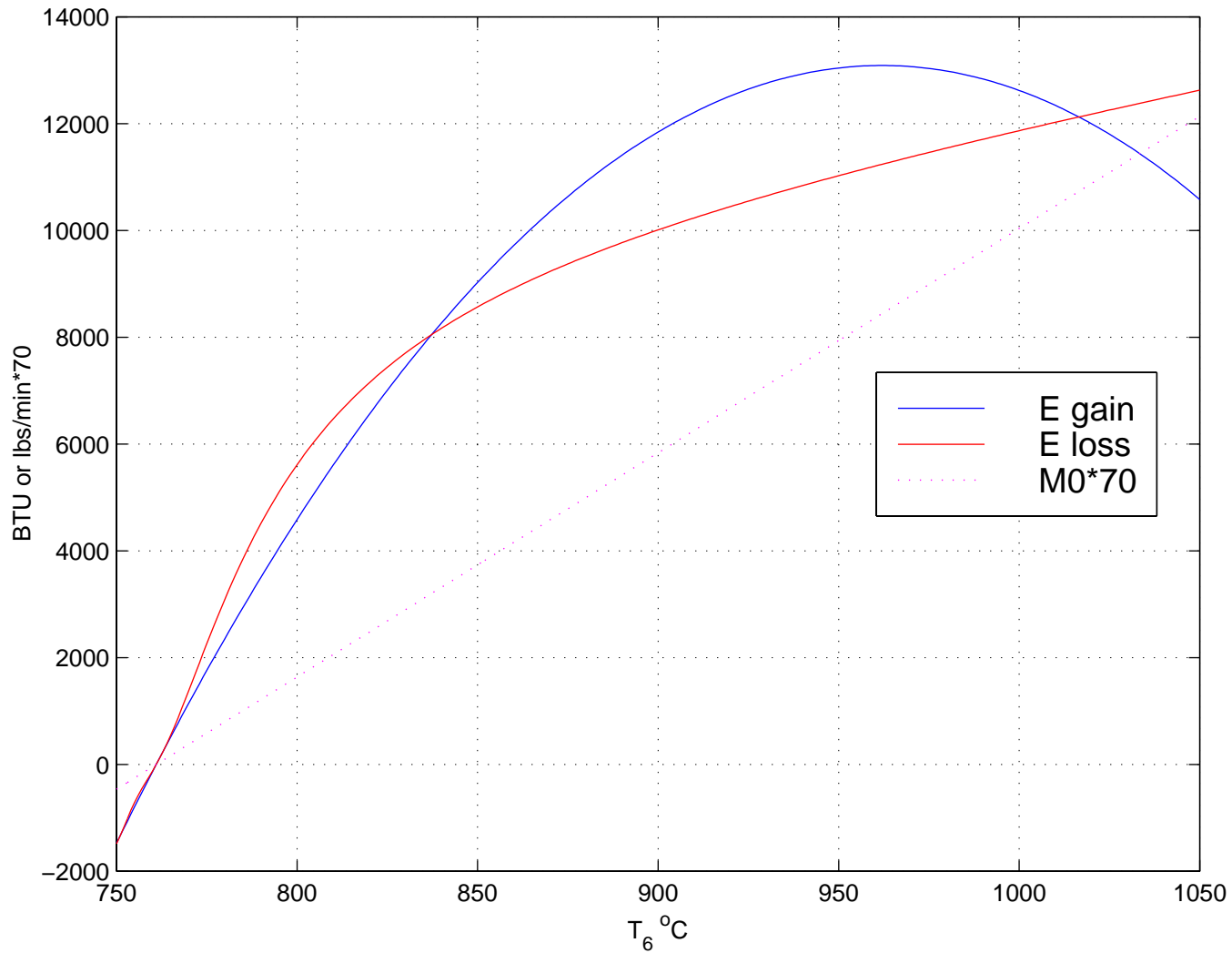
$$\rho C_p V \frac{dT_i}{dt} = MC_p (T_{i-1} - T_i) + U_c A_c (T_{c_i} - T_i) + U_s A_{s_i} (T_s - T_i)$$

for $i = 2, 4, 6$

$$\rho C_p V \frac{dT_i}{dt} = MC_p (T_{i-1} - T_i)$$

where $M = M_0 + \alpha(T_6 - T_R)$

Steady-State Energy Balance



Steady-States & Eigen Values

Zone Temp. °C	SS1	SS2	SS3
T1	581.8	979.6	1093.9
T2	581.8	979.6	1093.9
T3	501.8	850.5	1035.3
T4	501.8	850.5	1035.3
T5	763.1	837.2	1016.5
T6	763.1	837.2	1016.5

Eigen Values	SS1	SS2	SS3
1	-0.0119	-0.0673	-0.1732
2	-0.0104	0.0052	-0.0142
3	-0.0007	-0.0422 + 0.0257i	-0.1238 + 0.0609i
4	-0.0008	-0.0422 - 0.0257i	-0.1238 - 0.0609i
5	-0.0044 + 0.0074i	-0.0206 + 0.0263i	-0.0640 + 0.0612i
6	-0.0044 - 0.0074i	-0.0206 - 0.0263i	-0.0640 - 0.0612i

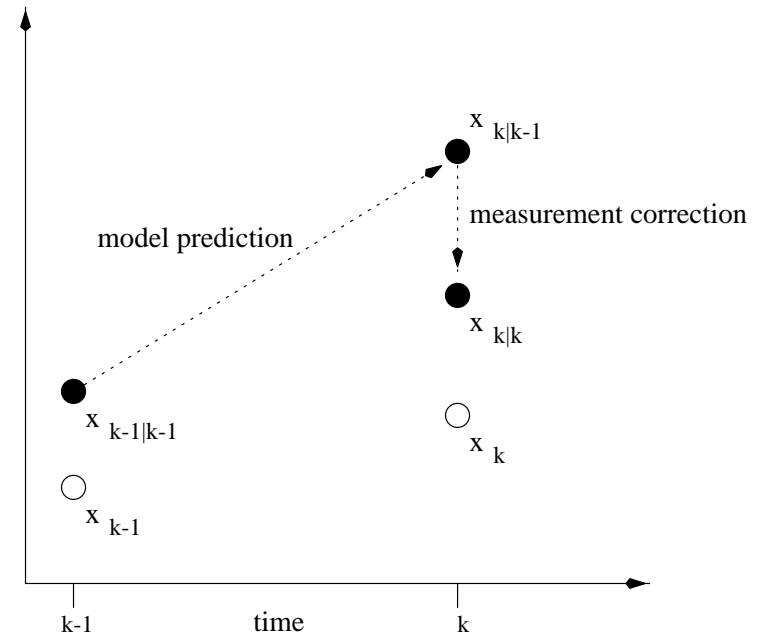
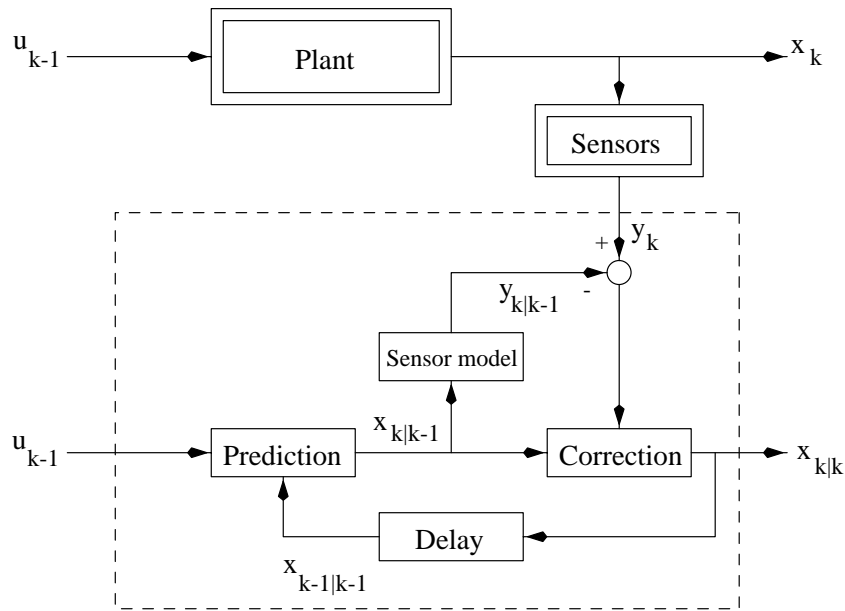
Control System Description

- Control of temperature in 3 zones of the forehearth $[T_2, T_4, T_6]$ by manipulating $[T_{c1}, T_{c3}, T_{c5}]$
- Need to operate at open-loop unstable steady state operating point
- Existence of model mismatch between plant and model in addition to unmeasured disturbances and measurement noise
- EKF based nonlinear MPC is used for state estimation and control
 - ◆ explicit handling of constraints
 - ◆ inferential control

Estimation and Control Strategy

- Extended Kalman filtering (EKF) is used to obtain current estimates of model states.
- Disturbances are modeled as integrated white noise states augmented to the original model.
- Nonlinear MPC algorithm uses EKF state estimates to predict future values of states and controlled outputs, which are then used to calculate the optimal manipulated variable action.
- Both the EKF and the nonlinear MPC algorithms are based on successive linearization of nonlinear model.

Estimation using EKF



EKF Equations

- Model prediction

$$\begin{bmatrix} \mathbf{x}_{k|k-1} \\ \mathbf{x}_{k|k-1}^w \end{bmatrix} = \begin{bmatrix} \mathbf{F}_{t_s}(\mathbf{x}_{k-1|k-1}, \mathbf{u}_{k-1}, \mathbf{C}^w \mathbf{x}_{k-1|k-1}^w) \\ \mathbf{A}^w \mathbf{x}_{k-1|k-1}^w \end{bmatrix}$$
$$\Sigma_{k|k-1} = \Phi_{k-1} \Sigma_{k-1|k-1} \Phi_{k-1}^T + \Gamma^w \mathbf{R}^w (\Gamma^w)^T$$

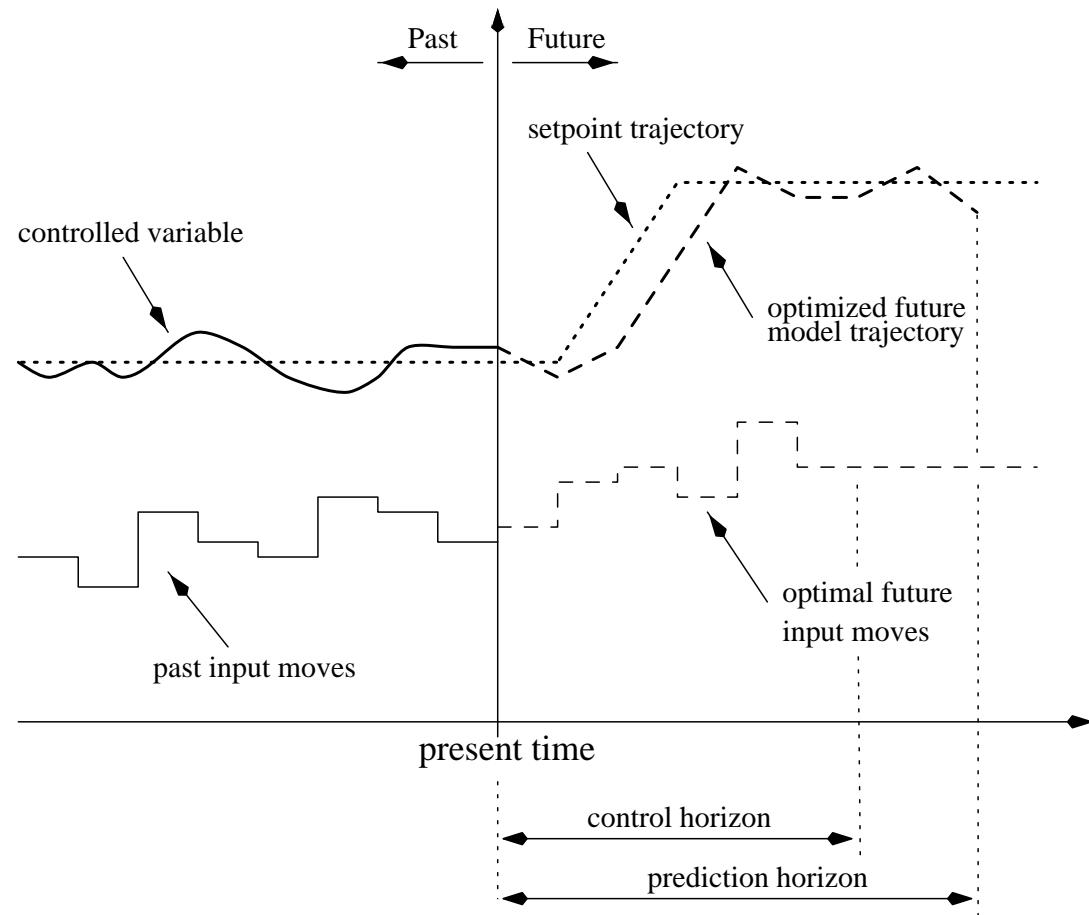
- Kalman filter gain and covariance

$$\mathbf{L}_k = \Sigma_{k|k-1} \mathbf{\Xi}_k^T (\mathbf{\Xi}_k \Sigma_{k|k-1} \mathbf{\Xi}_k^T + \mathbf{R}^v)^{-1}$$
$$\Sigma_{k|k} = (\mathbf{I} - \mathbf{L}_k \mathbf{\Xi}_k) \Sigma_{k|k-1}$$

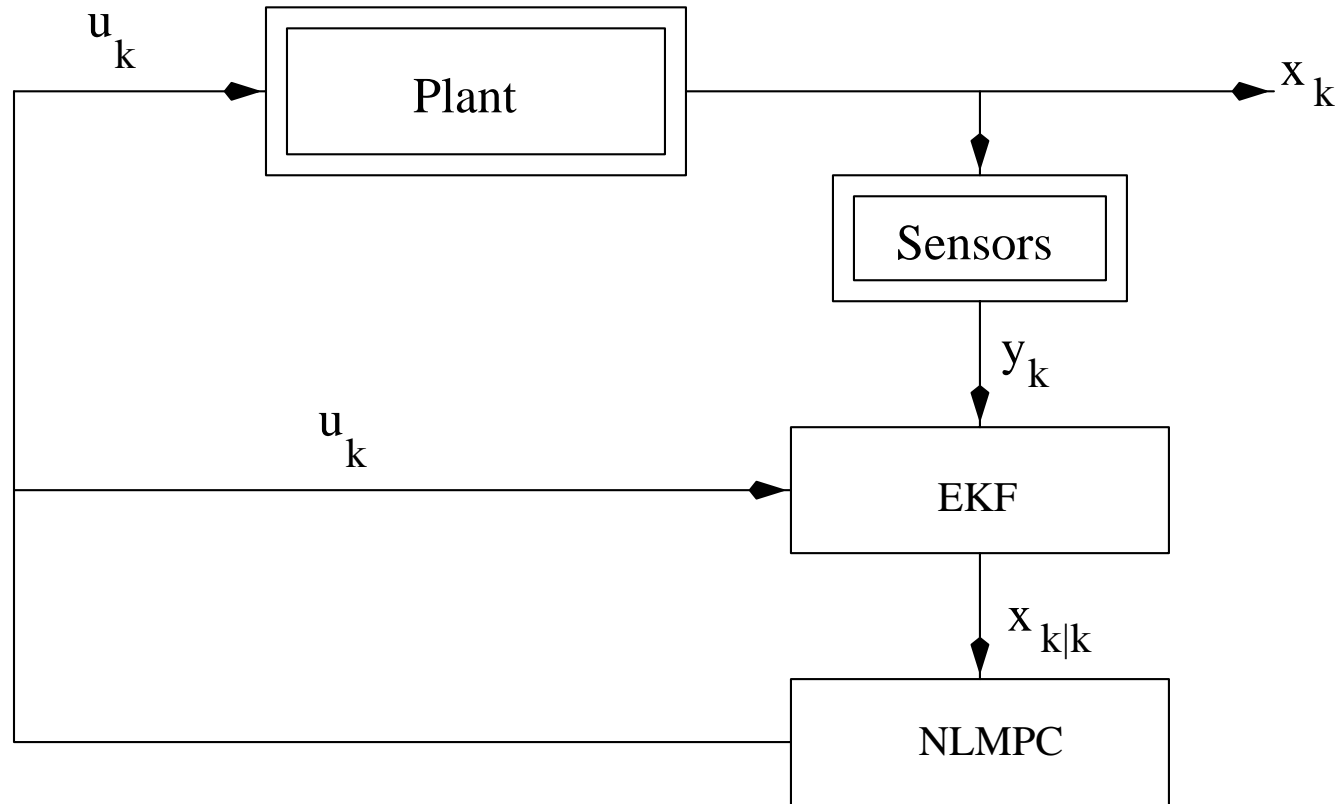
- Measurement correction

$$\begin{bmatrix} \mathbf{x}_{k|k} \\ \mathbf{x}_{k|k}^w \end{bmatrix} = \begin{bmatrix} \mathbf{x}_{k|k-1} \\ \mathbf{x}_{k|k-1}^w \end{bmatrix} + \mathbf{L}_k (y_k - \hat{y}_k)$$

MPC Strategy



Interaction of Estimation and Control



Results

- Setpoint tracking
- Parameter estimation
 - ◆ Viscosity parameter α
- Unmeasured disturbance
 - ◆ fluctuations in flow rate M_0
- Bias in heating circuit [T_{c1} , T_{c3} , T_{c5}]
- Bias in output measurements [T_2 , T_4 , T_6]
- Control parameters:
 - ◆ sample time 10 minutes
 - ◆ constraints on inputs 5 deg. C per 10 min
 - ◆ prediction horizon $P = 20$, control horizon $N = 3$, output weights Q 1:1:5, input weights R 1:1:1, Gaussian noise 0.1 deg. C

Summary

- A first principles model was developed and parameters were identified from plant data
- EKF based NLMPC was developed and tested in simulation studies
- Setpoint tracking and regulatory control in the presence of disturbances was achieved

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