PROMATCH

Model Reduction for Large Scale Dynamical Systems: **Glass as an application**

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Where innovation starts

Outline

- **Motivation**
- **Glass Manufacturing**
- **Parameter Uncertainty: Corrosion**
- **Problem Formulation**
- **Model Reduction – Strategy 1**
- **Model Reduction – Strategy 2**
- **Results**
- **Conclusion**

Motivation

- **Large Scale Systems (order ~ 10^6)**
- **Non-linear, multiphase-reactive fluid flow with parametric uncertainties**
- **Governed by Non-linear Navier-Stoke equations**
- **Modeled by Computational Fluid Dynamics (CFD) tools**
- **Need for computationally efficient models capturing process uncertainties**

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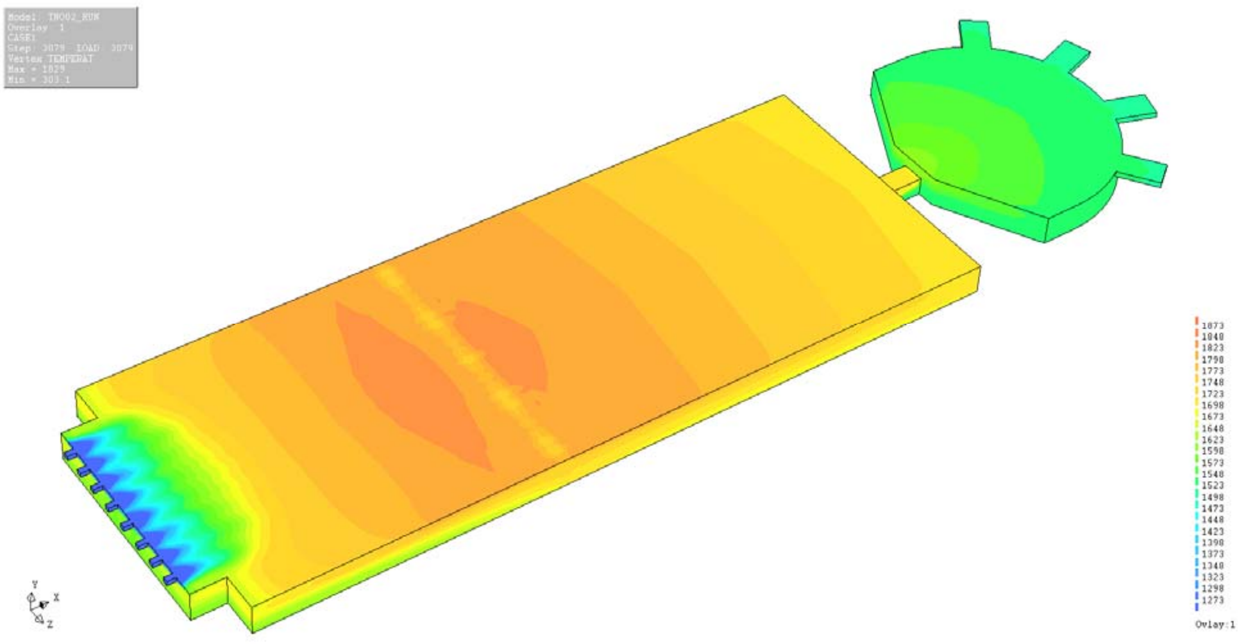
Application: Glass Manufacturing



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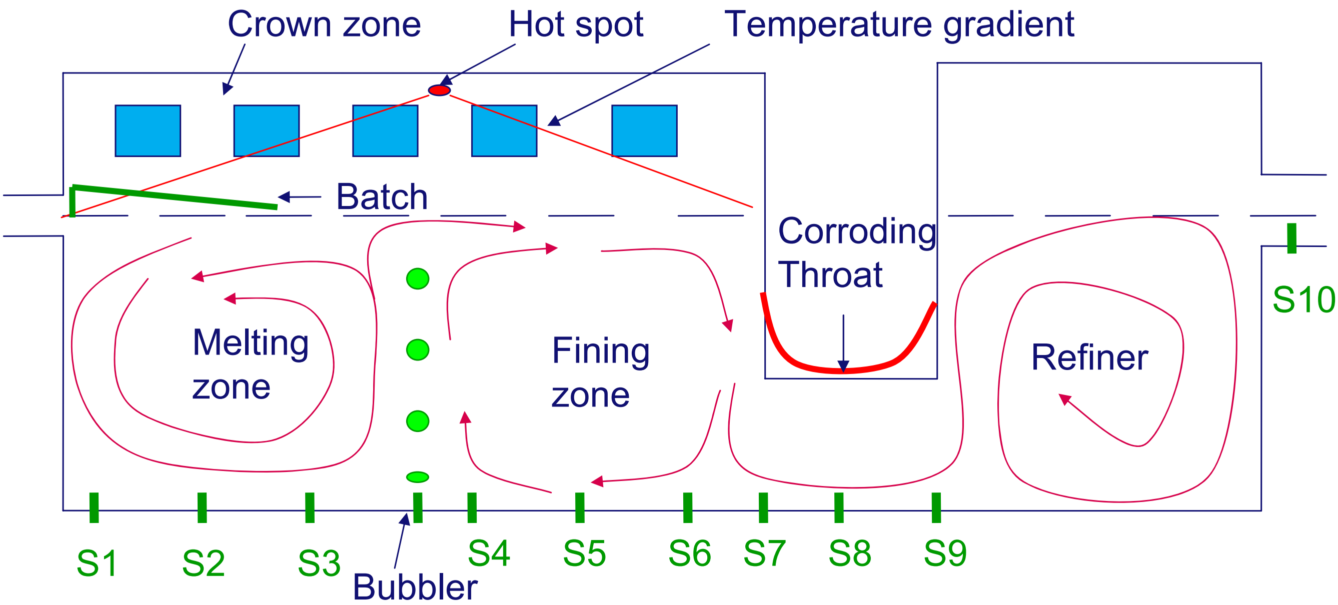
Benchmark: 2d Glass Tank

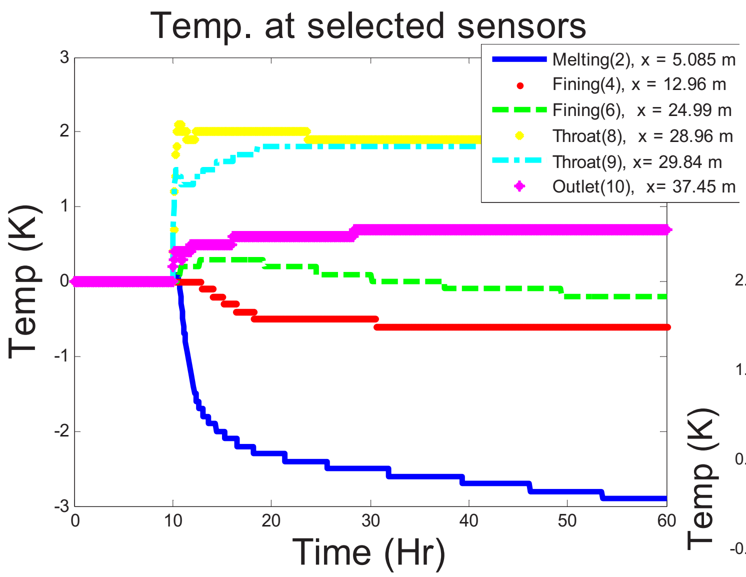


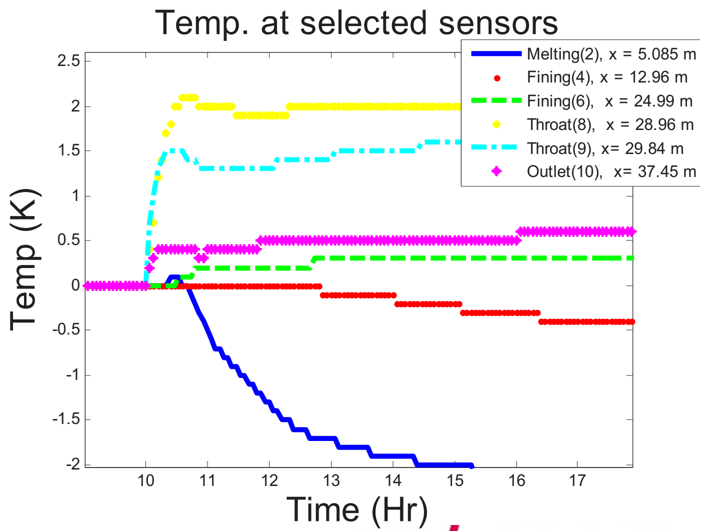
Characteristic Process Properties

- **Residence Time distribution (RTD) characterised as series combination of PFR and CSTR**
- **Time scale observations:**
  RTD response to glass pull rate/Color. change is 10-20 times slower than to changes in temperature (20 hr to days vs. 1/2hr to 2hr)

- **Each process phase is heterogeneous**
- **Residence time, temperature, pull/production rate, flow pattern, glass properties have interacting effects**
- Inputs: **Heat supply, stirring, bubbling, pressure, pull rate**
- Disturbances: **batch amount and composition**
- Control variables: **Temperature, Pressure, Flow**
- Constrains: **Variation in flow, Stability, Heat input**

Glass response to step change



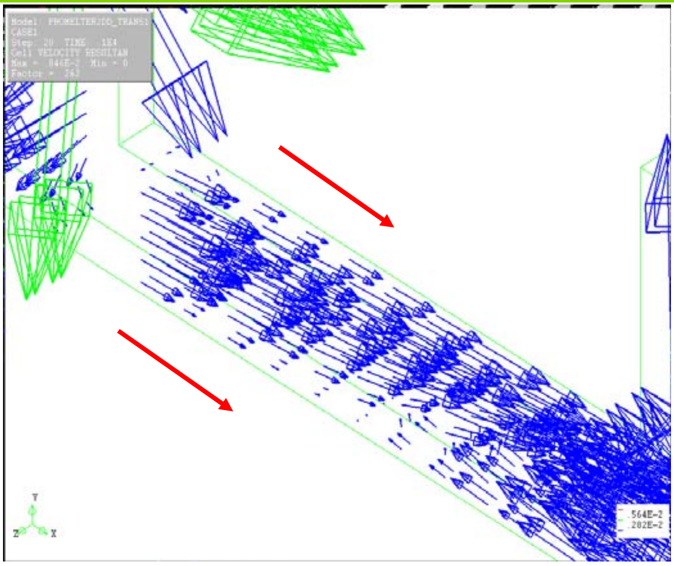


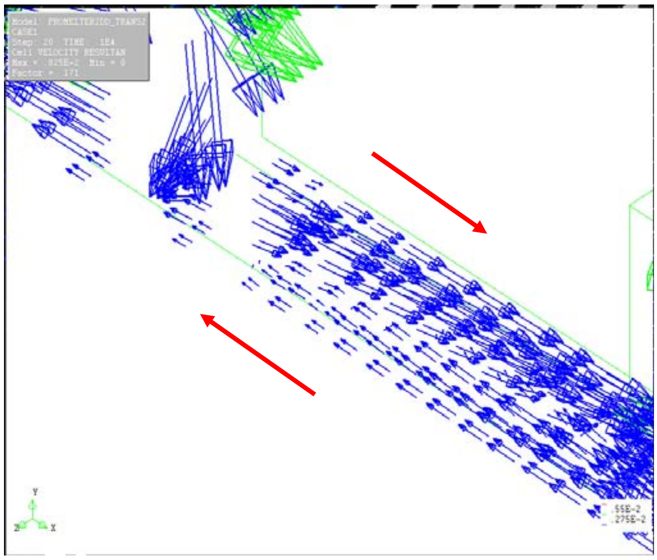
Some more challenges…

Industrial interest **(SCHOTT AG) includes capturing uncertain phenomena in model reduction framework like:**

- **Parameter varying phenomena (corrosion)**
- **Changing material properties (batch composition)**
- **Reaction kinetics at micro level**
- **Radiation effects**

Corrosion: Occurrence of back-flow





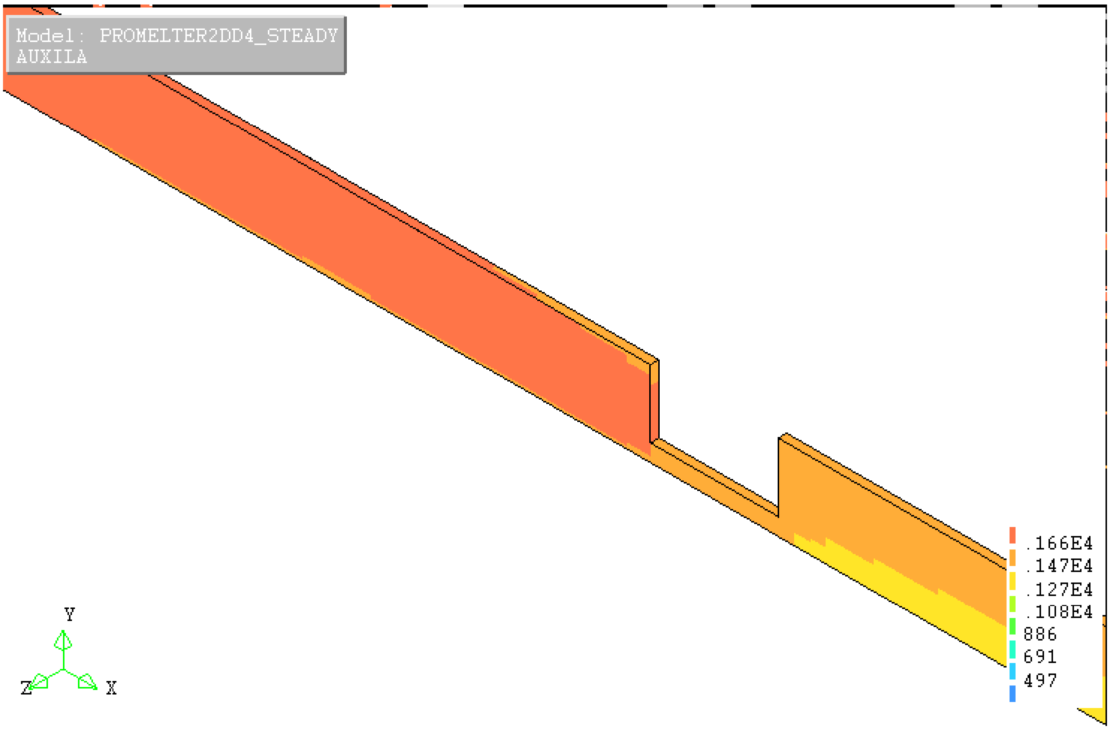
Below critical value (h^-)

Above critical value (h^+)

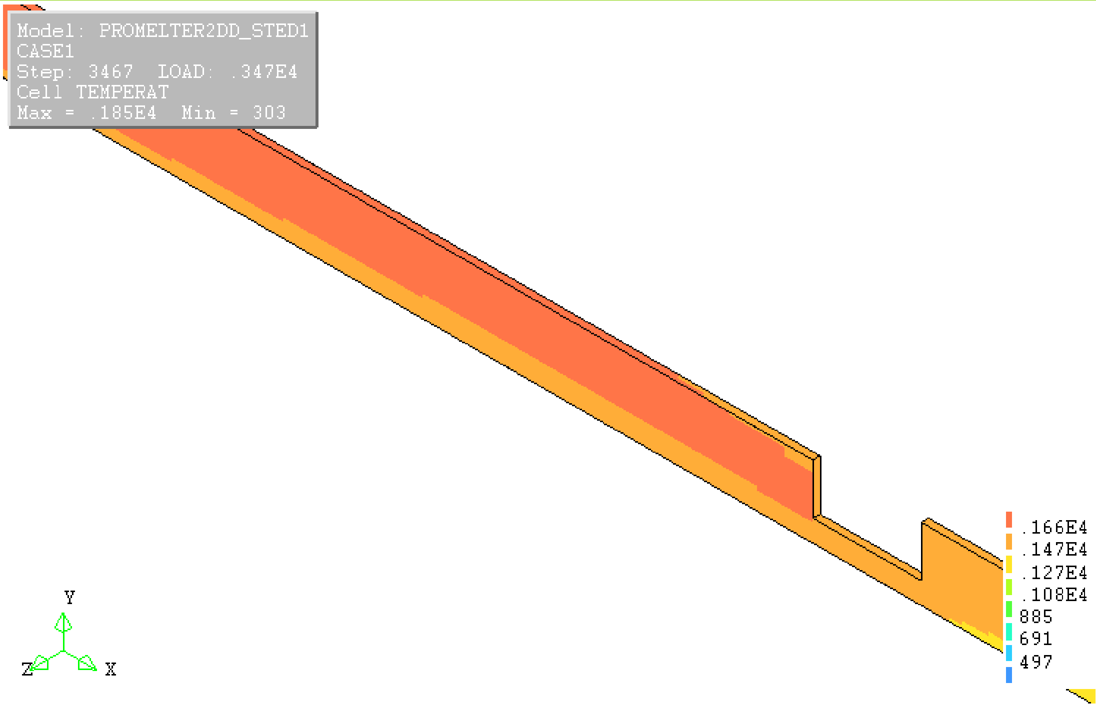
Bifurcation parameter window

$h^- < h^* < h^+ = 0.2m < h^* < 0.3\ m$

Temperature: No Corrosion, no back-flow



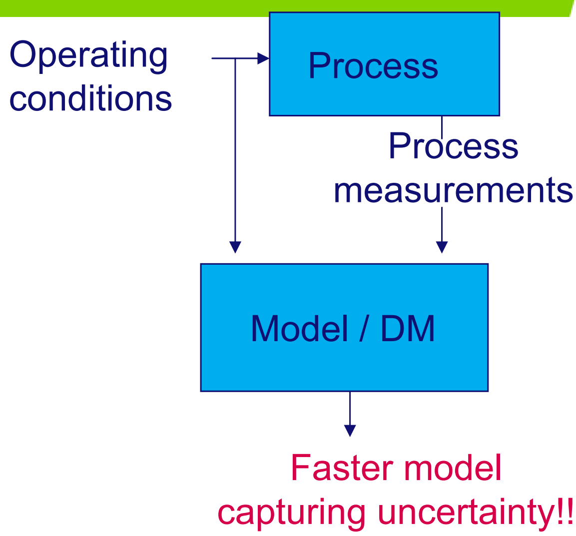
Temperature: With Corrosion, and back-flow



Problem statement

For any of the following systems-

$$\sum_{h_1} : f\left(x, y, z, T, Velocity, \ldots h = h_1\right)$$
$$\sum_{h_2} : f\left(x, y, z, T, Velocity, \ldots h = h_2\right)$$
$$\sum_{h_3} : f\left(x, y, z, T, Velocity, \ldots h = h_3\right)$$
.
.
$$\sum_{h_n} : f\left(x, y, z, T, Velocity, \ldots h = h_n\right)$$

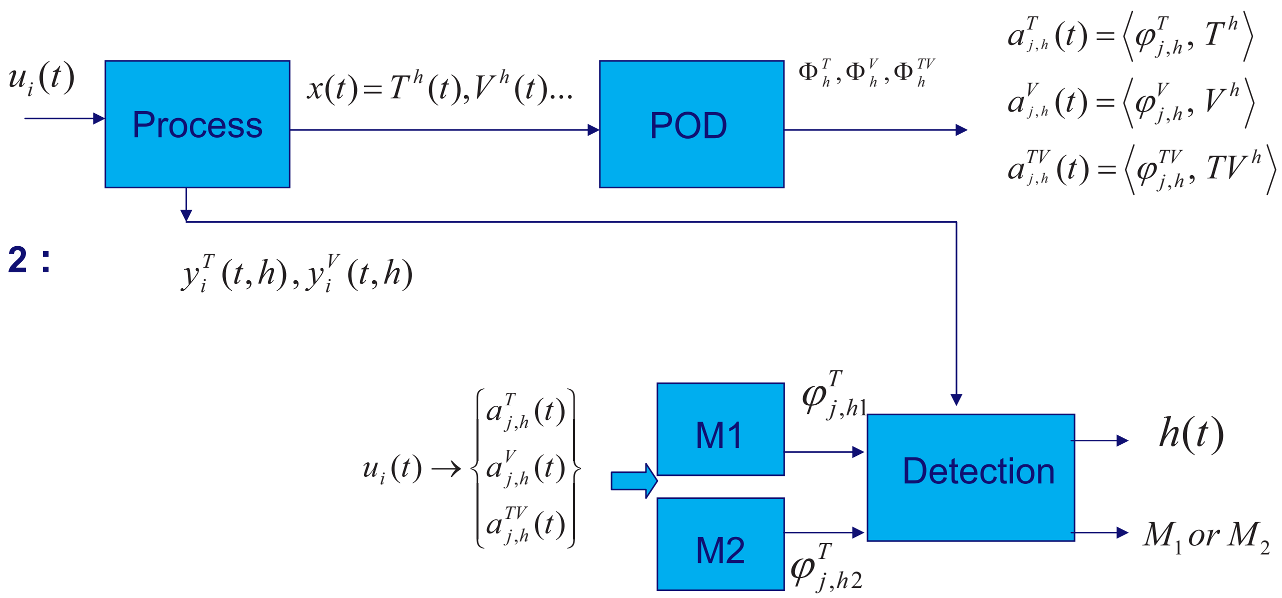


Q: Given few measurements and some system knowledge, can one find a reliable computationally efficient model under the influence of corrosion ?

A: Full Model (CFD) + Model Reduction (POD) + System Identification + Dynamic Detection Mechanism/LPV approximation

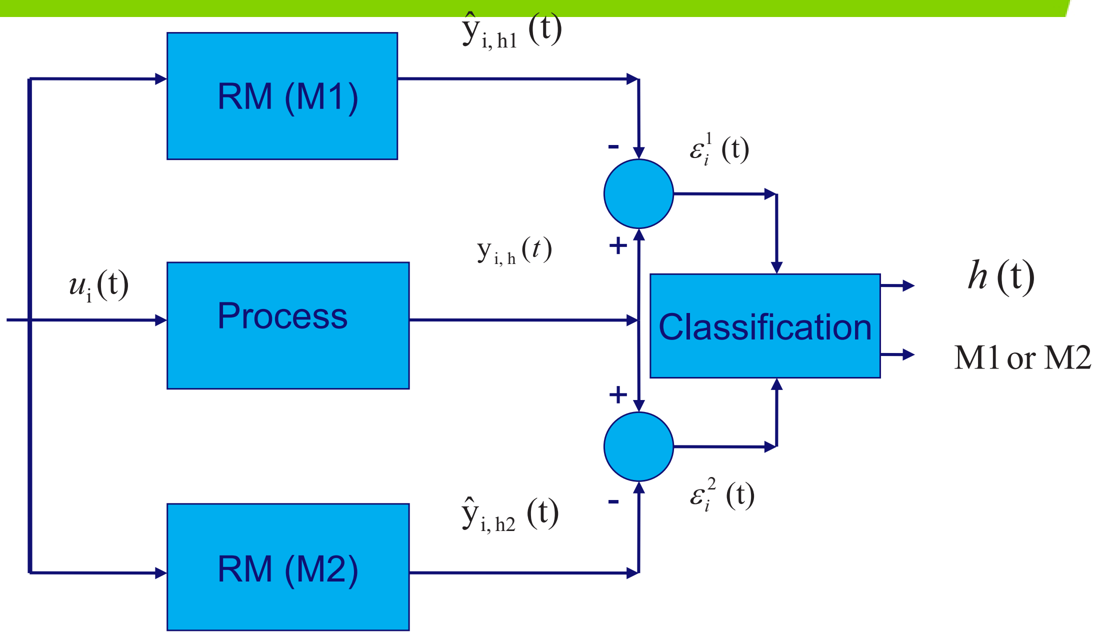
Model Reduction Strategy – 1, Hybrid Detection

- **Step 1 (for h_1=0.2, h_2=0.3)**



- **Step 2 :**

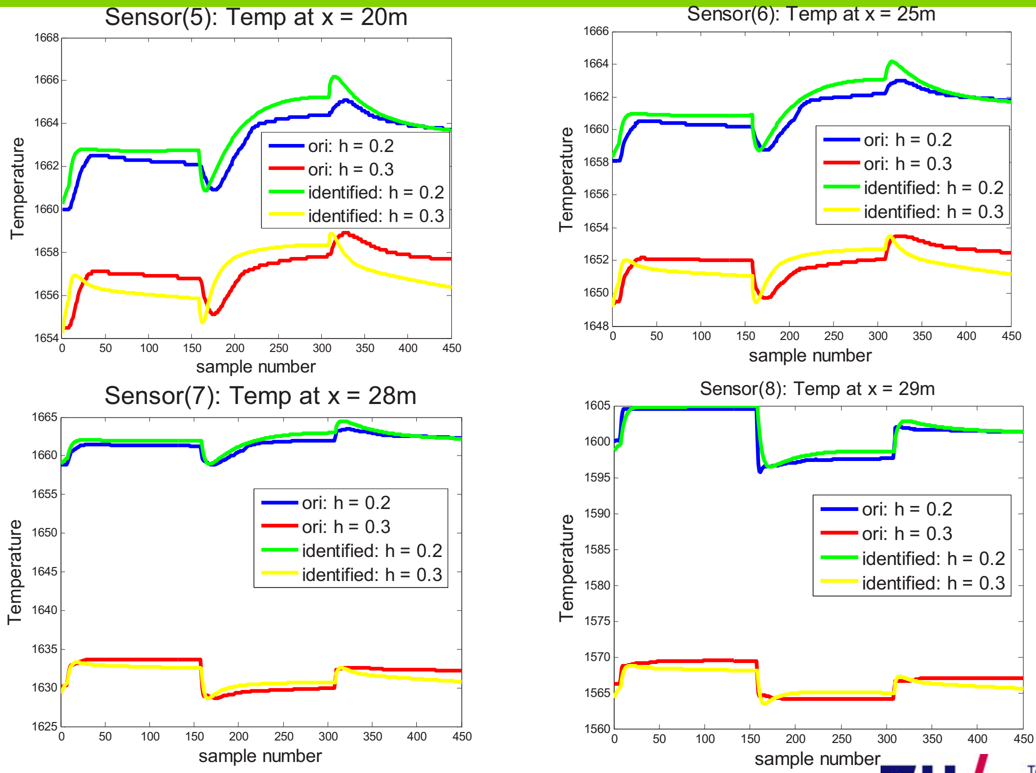
Detection Mechanism



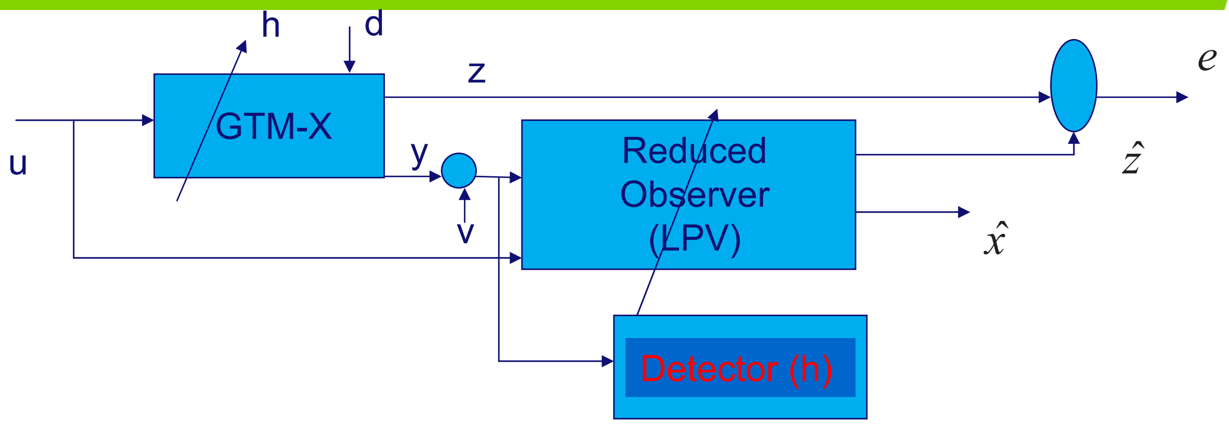
Assumption : Process bifurcation parameter is above or below critical value.

Disadvantage: For small difference and substantial noise presence can lead to wrong result.

Results: Strategy 1, Detection



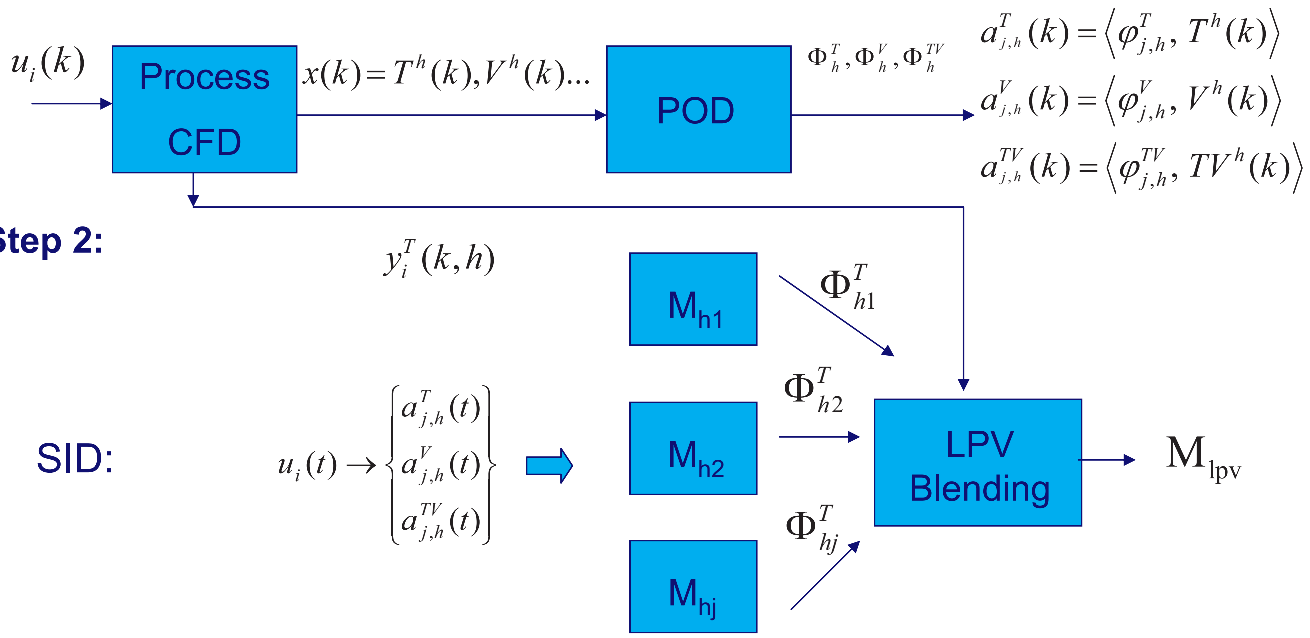
Strategy 2: LPV SID model/Observer



Detector (h): A dynamic or static map to detect the throat height from knowledge of plant (GTM-X) outputs

Strategy 2: LPV SID model/Observer

- **Step 1:**



- **Step 2:**

LPV Identification - Spline based

RO-LPV can be considered as weighted blend of Reduced Order models

$$
\begin{aligned}
y(t) = {} & \alpha_1(w)[\hat{G}_1^1(q)u_1(t) + \ldots + \hat{G}_m^1(q)u_m(t)] \\
& + \alpha_2(w)[\hat{G}_1^2(q)u_1(t) + \ldots + \hat{G}_m^2(q)u_m(t)] \\
& + \alpha_3(w)[\hat{G}_1^3(q)u_1(t) + \ldots + \hat{G}_m^3(q)u_m(t)] + v(t)
\end{aligned}
$$

Where w is the scheduling parameter and the weightings α_i are parameterized as cubic splines

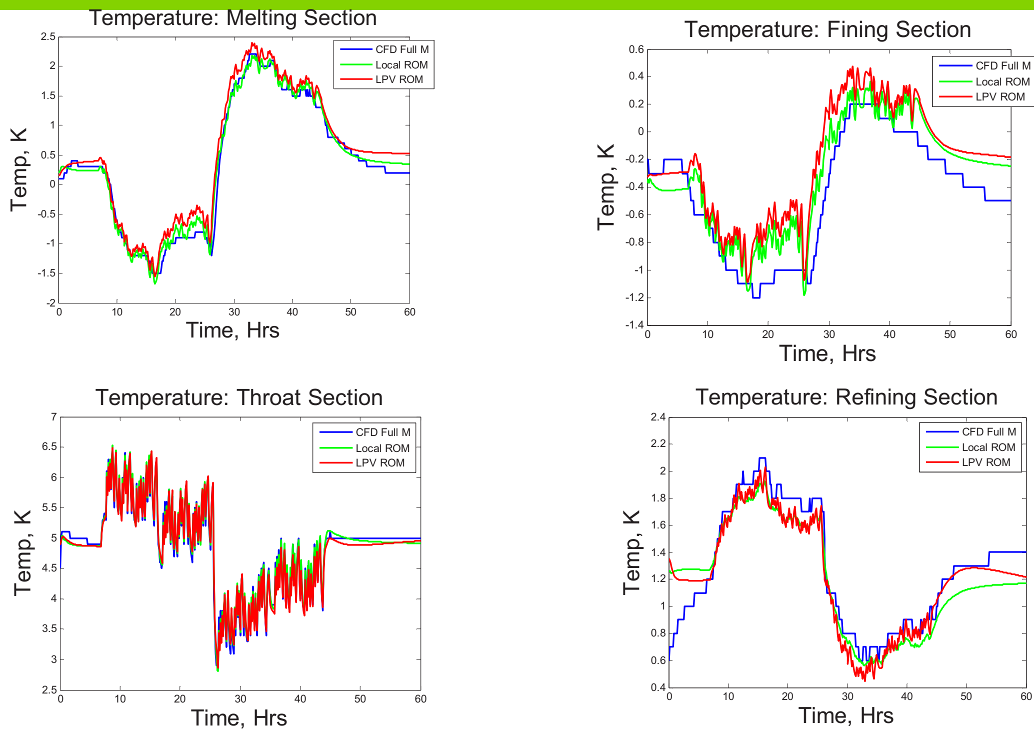
$$
\alpha_1(w) = \beta_1^1 + \beta_2^1 w + \sum_{j=2}^{m-1} \beta_{j+1}^1 |w - k_j|^3
$$

LPV identification ≈ Spline parameter Identification

Use least square for parameter identification

Ref. Zhu, Y. IFAC 2008

Results: Strategy 2, RO-LPV



Conclusions

- **Computationally efficient model can be obtained for Large Scale Dynamical Systems in easy way. These models can be used for online control and optimization purpose.**
- **Process uncertainty can be incorporated in the model reduction framework.**
- **Nonlinear identification and exploitation of distributed nature of the process in model reduction can be very useful!**

Thank You!!