

Model Reduction for Parameter Sensitive Processes



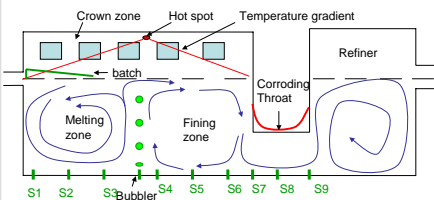
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Objective

Develop a methodology to approximate a high dimensional (order $\approx 10^6$) process model exhibiting strong parameter sensitivity by using reduced order models (order $\approx 10^1$).

Motivation

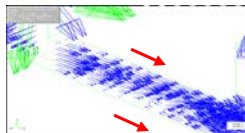
Industrial processes under certain operating conditions show extreme parameter sensitivity which is difficult to capture in a single reduced order model obtained by method of Proper Orthogonal Decompositions (POD) and Subspace Identification.

Industrial Application - Glass Manufacturing Process

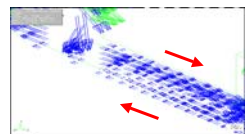


Problem

Corrosion of throat wall is a geometric parameter variation, which causes backflow in the glass, a kind of bifurcation behavior. This results into undesired process dynamics. A single reduced model obtained by POD does not capture the bifurcation, i.e. transition from no backflow to occurrence of the backflow.



a. Throat region, no back-flow

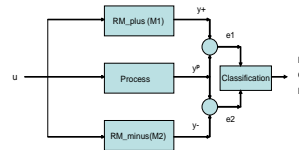


b. Throat region, presence of back-flow

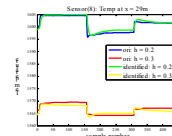
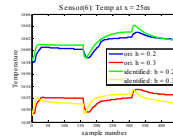


Proposed solutions

1. A **detection mechanism**, which is based on specific output error tells about the presence of backflow. Reduced order model M1 will approximate process without backflow while reduced order model M2 will approximate the process with backflow. Detection mechanism classifies the selection of reduced model for best approximation to the real process.



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

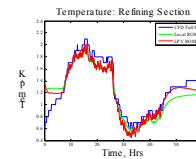
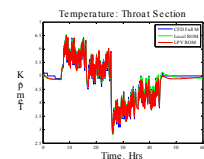
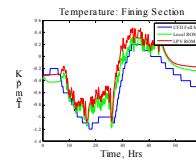
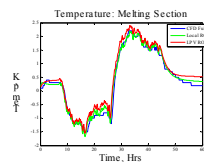


2. Reduced Order Linear Parameter Varying (RO-LPV) system

Corrosion of throat wall is a geometric parameter variation. If Reduced Order Model (ROM) is presented in transfer function form then RO-LPV output is linear combination of outputs of local ROM.

$$y_{lpv}(k) = \sum_{j=1}^M \sum_{l=1}^{n_{\alpha_j}} \alpha_j^l G_l^j(q) u_l(k)$$

and α_j^l are spline based weights



Acknowledgement

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Model Reduction for Large Scale Systems

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Objective

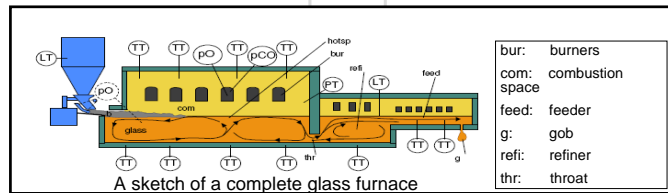
Developing generic model reduction methodologies to obtain computationally efficient, reliable, accurate dynamic process models from complex nonlinear models for fluid flow systems.

Glass manufacturing process

The temperature and flow distribution in glass melting tanks is described by the **Navier-Stokes Equations** which are solved using Computational Fluid Dynamic tools. This results in approximately 10^5 equations which leads to very slow computations.

Navier-Stokes Equations

- ❖ Mass Balance: $\frac{\partial \rho}{\partial t} = -\text{div } \rho v = 0$
- ❖ Energy Balance: $\frac{\partial (\rho C_p T)}{\partial t} = -\text{div}(\rho C_p T v) + \text{div}(\lambda \text{grad } T) + q$
- ❖ Moment Balance: $\frac{\partial (\rho v)}{\partial t} = -\text{div}(\rho v v) + \text{div}(\eta \text{grad } v) - \text{grad } P + \rho g$



Motivation

Glass manufacturing is an energy-intensive process. There is a need for fast and accurate models to be used in optimization and efficient control of glass manufacturing processes to improve glass quality and decrease environmental damage.

Method

Proper Orthogonal Decomposition + Subspace Identification

Approximate temperature by finite expansions

$$T(z, t) = \sum_{i=1}^N \alpha_i(t) \varphi_i$$

where,

- $\varphi_i(z)$ is dominant spatial basis function
- $\alpha_i(t)$ is dominant modal coefficient

Identify a map $u(t) \mapsto \alpha_i(t)$: SID Techniques

Leads to,

Full Model

Reduced Model

$$\frac{\partial T}{\partial t} = D(T(z, t)) \Rightarrow x(k+1) = Ax(k) + Bu(k)$$

$$\alpha(k) = C_1 x(k)$$

$$T(k) = C_2 \Phi \alpha(k)$$

Model Reduction Results

