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Citation for published version (APA):

Wattamwar, S. K., Weiland, S., & Backx, A. C. P. M. (2008). Identification of Low Dimensional Models for slow Geometric Parameter Variation in an Industrial Glass Manufacturing Process. In *Control Applications, 2008. CCA 2008. 17th IEEE International Conference on applications, 3-5-09-2008, San Antonio, Texas USA* Institute of Electrical and Electronics Engineers. <https://doi.org/10.1109/CCA.2008.4629689>

DOI:

[10.1109/CCA.2008.4629689](https://doi.org/10.1109/CCA.2008.4629689)

Document status and date:

Published: 01/01/2008

Document Version:

Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

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Identification of low dimensional models for slow geometric parameter variation in an Industrial Glass Manufacturing Process

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Abstract—In this paper we apply the method of Proper Orthogonal Decomposition (POD) to identify a lower dimensional model of a benchmark problem representing an Industrial Glass Manufacturing Process (IGMP). In particular, we identify a reduced model by identifying the mapping from process inputs to POD modal coefficients by a subspace identification method. Reduced models obtained from POD are not well equipped to capture the process behavior under time varying uncertain process parameters. For this reason we propose a novel hybrid detection scheme which approximates the process (benchmark CFD model) exhibiting non-smooth geometric parameter dependence (corrosion and wear) by using lower dimensional models. Given state or output information this detection mechanism detects the process parameter operation regime and suggests a computationally faster lower dimensional model as an approximate for real process.

I. INTRODUCTION

Industrial Processes involving fluid flows are usually modeled by Navier-Stoke's equations which are solved by some kind of spatial discretization. Due to this modeling approach they are referred to as Distributed Parameter Systems (DPS). Spatial discretization of Distributed Parameter Systems (DPS) is done by means of Finite Volume (FVM) or Finite Element methods (FEM) and Galerkin or Petro-Galerkin projection techniques and they are simulated in a Computational Fluid Dynamic (CFD) software environment. Although such discretizations approximate process behavior reasonably well, it leads to very high dimensional process models. Such process models can not easily be used for online plant optimization and control. Model Order Reduction (MOR) is therefore an important step before proceeding to control design [1]. The method of Proper Orthogonal Decomposition (POD) or Principle Component Analysis (PCA) is widely used for deriving lower dimensional models from the First Principle Model (FPM). The POD method searches for dominant patterns in the given process and defines an optimal, data-dependent basis, that is subsequently used as a projection space to infer reduced order models through Galerkin type of projections [2]. POD methods are empirical (data dependent) in nature and therefore these methods are susceptible to changes in process inputs and process parameters. Many processes show inherent non-linear dependence on process parameters. The reduced model obtained by POD techniques are not well equipped for

such processes exhibiting nonsmooth dependence on process parameters i.e. bifurcation type of behavior [3]. The problem becomes worse when the physical boundaries of the process domain becomes uncertain. It is shown in this paper how the POD basis becomes obsolete over time when the throat wall of the glass manufacturing furnace (a geometric parameter) wears out over time. This wearing out of a throat wall causes initiation of back-flow i.e inversion of the flow direction. This back-flow causes changes of critical process variable (Temperature, Pressure, Velocity...). Occurrence of back-flow is similar to bifurcation or trifurcation happening in many chemical processes exhibiting nonlinear parameter dependence.

This paper is organized in a few sections. The motivation - Industrial Glass Manufacturing Process (IGMP) is explained in the next section. A brief description of the POD technique is given in section III which is followed by a black-box type of system identification. We use a subspace identification technique coupled with POD modal coefficients to identify the low dimensional models. This is explained in the methodology section V along with the detection mechanism. Some results are presented in the section VI which is followed by future work and references.

II. INDUSTRIAL GLASS MANUFACTURING

Industrial Glass Manufacturing (IGM) is usually carried out in large furnaces which are very well designed in order to have a desired laminar flow pattern of the glass. A 2D view of a typical furnace is shown in Figure 1. The flow

Fig. 1: Industrial Glass Manufacturing

pattern of glass determines the residence time of the glass in the melting furnace which in turn determines the quality of the glass produced. The process is an example of very large scale integrated systems. Most of the process variables like temperature, velocity, pressure, viscosity are interacting

This work was supported by the European Union within the Marie-Curie Training Network PROMATCH under the grant number MRTN-CT-2004-512441.

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with each other. Due to this interacting nature the control of the furnace has to be done carefully. Usually pull rate (production rate), heat input and pressure valve positions are some of the control variables. Whereas variables of interest are temperature distribution and velocity profiles in the furnace. The product quality is determined by these two factors. The temperature maintained inside the furnace varies between 1400–1650 °C. The glass raw material enters from the left side (inlet) in the form of a batch blanket, it is melted by applying heat from the top. After circulating through the glass furnace for many hours glass passes through the throat and then leaves via the outlet. Based on the process operation there are roughly three regimes - glass melting (left side of hot spot), fining (on right side of hot-spot) to remove high concentration of dissolved gases from glass and refining (after throat) to remove all remaining nondissolved gases from the glass. The IGMP shows large variation in the time scales, from minutes to days. Process residence time shows combined behavior of an ideal Continuous Stirred Tank Reactor (CSTR) and an ideal Plug Flow Reactor (PFR). The transport of physical quantities in GMP can be approximated with reasonable accuracy by modeling it by a set of nonlinear Navier-Stokes equations of the form (1)

$$\frac{\partial(\rho\phi)}{\partial t} + \text{div}(\phi\rho v) = \text{div}(\Gamma \text{grad} \phi) + q_\phi \quad (1)$$

where ρ is mass density, v is velocity, div is divergence operator, Γ is diffusion coefficient, q_ϕ is source/sink term. when $\phi = 1$ we have continuity equation, for $\phi = v$ we have momentum equation and for $\phi = h$ we have energy balance equation. The source term brings the non-linearity. It is the term which gives contribution of physical effects like bubbling, boosting, reaction etc. Combination of different numerical schemes are used to obtain reliable simulation results. Some details about mathematical modeling of glass can be found in [4],[5],[6],[7]. Some more information about the CFD modeling software GTM-X can be found in [8]. Due to very high process temperature and due to the viscous nature of glass, the glass furnace is a hostile environment for sensor systems. Sensors are largely limited to temperature measurements in the bottom refractory of the melting furnace.

As 3 dimensional glass furnace model easily consist of $10^4 - 10^6$ finite elements. Simulating its steady and/or dynamic behavior takes days for a normal configured PC, it becomes very difficult to analyse its transient response to dynamic process changes. For this reason we are using an approximate 2D glass furnace which mimics the vertical cross section along the length of 3D glass furnace and it has only 2 grids cells in width direction. Currently we are trying to model the very slow geometric changes that take place in real 3D furnace in the form of throat or dam wall corrosion, Figure 1. This corrosion results into back-flow of molten glass from the working end to the melting furnace. Such back-flow behavior causes undesired changes in the temperature distribution in the fining and melting zone which ultimately leads to economic losses. For the 2D furnace we

observe this bifurcation behavior i.e the occurrence of back-flow somewhere between throat height of 0.2m (h^1) and 0.3m (h^2). Figure 2 shows back-flow results into completely different velocity pattern in throat section.

Fig. 2: Occurrence of back-flow

III. PROPER ORTHOGONAL DECOMPOSITION

One of the most promising and significant techniques for an efficient reduction of large-scale nonlinear systems in fluid dynamics is the method of Proper Orthogonal Decompositions (POD) also known as the Karhunen-Loève method [9]. The method is based on the observation that flow characteristics reveal coherent structures or *patterns* in many processes in fluid dynamics. This has led to the idea that the solutions of model equations may be approximated by considering a small number of dominant coherent structures (called *modes*) that are inferred in an *empirical* manner from measurements or simulated data.

Given an ensemble of K measurements $\mathbf{T}^k(\cdot)$, $k = 1, \dots, K$ with each measurement defined on some spatial domain Ω , the POD method amounts to assuming that each observation $\mathbf{T}^k$ belongs to a Hilbert space $\mathcal{H}$ of functions defined on Ω . With the inner product defined on $\mathcal{H}$, it then makes sense to call a collection $\{\varphi_j\}_{j=1}^\infty$ an *orthonormal basis* of $\mathcal{H}$ if any element, say $\mathbf{T} \in \mathcal{H}$, admits a representation

$$\mathbf{T}(x) = \sum_{j=1}^{\infty} a_j \varphi_j(x), \quad x \in \Omega.$$

Here, the a_j 's are referred to as the *coefficients* and the φ_j 's are the *modes* of the expansion. The truncated expansion

$$\mathbf{T}_n(x) = \sum_{j=1}^n a_j \varphi_j(x), \quad x \in \Omega$$

causes an approximation error $\|\mathbf{T} - \mathbf{T}_n\|$ in the norm of the Hilbert space. We will call $\{\varphi_j\}_{j=1}^\infty$ a *POD basis* of $\mathcal{H}$ whenever it is an orthonormal basis of $\mathcal{H}$ for which the *total approximation error* $\sum_{k=1}^K \|\mathbf{T}^k - \mathbf{T}_n^k\|$ is minimal for all truncation levels n . This is an *empirical basis* in the sense that every POD basis depends on the data ensemble.

Using variational calculus, the solution to this optimization problem amounts to finding the normalized eigenfunctions $\varphi_j \in \mathcal{H}$ of a positive semi-definite operator $R : \mathcal{H} \rightarrow \mathcal{H}$ that

is defined as

$$\langle \psi_1, R\psi_2 \rangle := \frac{1}{K} \sum_{k=1}^K \langle \psi_1, \mathbf{T}^k \rangle \cdot \langle \psi_2, \mathbf{T}^k \rangle$$

with $\psi_1, \psi_2 \in \mathcal{H}$. R is well defined in this manner and corresponds to a positive semi-definite matrix whenever $\mathcal{H}$ is finite dimensional. In that case, a POD basis is obtained from the normalized eigenvectors of R [2].

Subsequently, a Galerkin projection is used to obtain the reduced model as follows. Suppose that the system is governed by a PDE of the form

$$\frac{\partial T_n}{\partial t} = \mathcal{A}(T_n) + \mathcal{B}(u) + \mathcal{F}(T_n, u, d) \quad (2)$$

Let $\mathcal{H}_n$ denote an n dimensional subspace of $\mathcal{H}$ and let $P_n : \mathcal{H} \rightarrow \mathcal{H}_n$ and $I_n : \mathcal{H}_n \rightarrow \mathcal{H}$ denote the canonical projection and canonical injection maps. The reduced model is then given by

$$P_n \frac{\partial T_n}{\partial t} = P_n \mathcal{A}(T_n) + P_n \mathcal{B}(u) + P_n \mathcal{F}(T_n, u, d) \quad (3)$$

where $T_n(\cdot, t) = \mathbf{T}_n(t)$ belongs to $\mathcal{H}_n = P_n \mathcal{H}$ for all t . In the specific case of a POD basis, the finite dimensional subspace $\mathcal{H}_n = \text{span}(\varphi_1, \dots, \varphi_n)$ where the φ_j 's denote POD basis functions. In that case, (3) becomes an *ordinary differential equation* in the coefficients $a_j(t)$ in the expansion of T_n .

IV. SUBSPACE IDENTIFICATION TECHNIQUE

Subspace Identification (SI) techniques got a strong momentum in the beginning of 1990s. It has origin and interpretation in terms of geometry, system theory and linear algebra. As most of the modern control theory uses a state space description of the system, subspace methods become a most favored identification technique. Some standard references include [10],[11]. This method is quite well applied for many MIMO LTI systems. Advantages of subspace method over prediction error method are compared in [12] for many industrial application. A general linear discrete time-invariant state space system is given as (4)

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned} \quad (4)$$

where $x(k) \in \mathbb{R}^n$ is the state vector, $u(k) \in \mathbb{R}^{n_u}$ is input vector, $y(k) \in \mathbb{R}^{n_y}$ is the output vector. In subspace method the postulated model (4) is used to formulate 's' step ahead prediction (5),

$$y_k^{k+s-1}(k) = \mathcal{O}_s x(k) + \mathcal{T}_s u_k^{k+s-1}(k), \quad (5)$$

where $\mathcal{T}_s$ is a deterministic lower block triangular Toeplitz matrix and $\mathcal{O}_s$ is the observability matrix, $s \geq n$ and the state space model is observable when $\text{rank}(\mathcal{O}_s) = n$ for $k = 0, 1, \dots, K-1$ these equations in matrix form are (6)

$$Y_{0,s,K-1} = \mathcal{O}_s X_{0,K-1} + \mathcal{T}_s U_{0,s,K-1} \quad (6)$$

$X_{0,K-1}$ is state vector, $Y_{0,s,K-1}$ and $U_{0,s,K-1}$ are output and input Hankel matrices respectively.

System Identification (SI) by a subspace method is carried out in two steps in all the algorithms. First step always performs the (weighted) projection of the row space of the above mentioned Hankel matrices. From this projection the observability matrix $\mathcal{O}_s$ and/or an estimate $\hat{X}_{0,K-1}$ can be retrieved [12]. In the second step, the system matrices A, B, C, D and Q, S, R (when stochastic part is modeled as well) are determined.

Now we can find $\mathcal{O}_s X_{0,K-1}$ by orthogonal projection by projecting the row space of $Y_{0,s,K-1}$ onto the $U_{0,s,K-1}^\perp$, where

$$U_{0,s,K-1}^\perp = I_k - U_{0,s,K-1}^T (U_{0,s,K-1} U_{0,s,K-1}^T)^{-1} U_{0,s,K-1} \quad (7)$$

with the property,

$$U_{0,s,K-1} U_{0,s,K-1}^\perp = 0 \quad (8)$$

This leads to

$$Y_{0,s,K-1} U_{0,s,K-1}^\perp = \mathcal{O}_s X_{0,K-1} U_{0,s,K-1}^\perp \quad (9)$$

Eq. (9) show that each column of $Y_{0,s,K-1} U_{0,s,K-1}^\perp$ is linear combination of the columns of $\mathcal{O}_s$, i.e. the column space of $Y_{0,s,K-1} U_{0,s,K-1}^\perp$ is contained in column space of $\mathcal{O}_s$. This is the first step of the all the subspace method numerical algorithms, now starts the second step. Here we have 2 classes. With the Singular Value Decomposition (SVD),

$$Y_{0,s,K-1} U_{0,s,K-1}^\perp = (U_1 \ U_2) \begin{pmatrix} S_1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} V_1^T \\ V_2^T \end{pmatrix} \quad (10)$$

$$\text{rank}(Y_{0,s,K-1} U_{0,s,K-1}^\perp) = n_x \quad (11)$$

$$\mathcal{O}_s = U_1 S_1^{1/2} \quad (12)$$

$$X_{0,K-1} U_{0,s,K-1}^\perp = S_1^{1/2} V_1^T \quad (13)$$

Left singular vectors contain information about observability $\mathcal{O}_s$, where as right singular vectors contain info about states $X_{0,K-1}$. State space matrices A and C can be determined from it. Algorithms like *N4SID* and *CVA* uses estimate of states whereas *MOESP*, *IV-4SID* uses extended observability matrix. Once state space matrices A & C are determined, matrices B & D can be determined by solving parameter estimation problem.

V. METHODOLOGY

In this section we explain the methodology for identifying smaller dimensional, computationally faster models which can approximate the original non-linear, complex, very large process model showing non-smooth geometric parameter dependence. Furthermore this section will explain how to detect the operation regime of the geometric parameter (i.e.

below or above bifurcation value) from the obtained reduced model and some process measurements. In this paper a 2D benchmark CFD problem is considered as the original process.

The problem can be formulated as for a given process,

$$x \in \Omega, \quad \Sigma : \dot{x} = f(x, u, h), \quad (14)$$

identify the model $\tilde{\Sigma}$, such that the norm of the error between the solution of original CFD model and reduced identified model is minimum and is given by,

$$\min \sum_{k=0}^K \|T(spx, spy, k, h) - \tilde{T}(spx, spy, k, h)\|_2^2 \quad (15)$$

Where,

$spx :=$ spatial co-ordinate in x-direction,

$spy :=$ spatial co-ordinate in y-direction, $h :=$ value of bifurcation parameter (geometric parameter - throat height),

$T(spx, spy, k, h) :=$ the solution of the real process i.e. CFD model (Σ),

$\tilde{T}(spx, spy, k, h) :=$ the solution of the identified model in reduced space ($\tilde{\Sigma}$),

Solution to the problem can be found by using Proper Orthogonal Decomposition (POD) as a chosen method for Model Order Reduction (MOR), Subspace Identification (SI) to find state space matrices and Dynamic Detection Mechanism (DDM) to represent the geometric parameter variation in the process. This is explained below in detail.

For the input sequence $\{u(k)\}_{k=1}^K$, the glass furnace simulation model is excited. The snapshots of the temperature $\{T(k)\}_{k=1}^K$ (see POD details in section III) are collected as

$$T_{snap} = [T(1) \dots T(K)],$$

where $T(k)$ is temperature snapshot at time instance 'k'. From this snapshot sequence optimal POD basis ϕ_j and corresponding modal coefficients are determined (see section III). After getting the POD basis ϕ_j which represent the spatial pattern and modal coefficients $a_i(t)$ which characterize temporal evolution from the snapshot matrix we proceed to the model identification by the subspace method. By using the subspace method a mapping (state space matrices A,B,C,D) is found between the process inputs and first few POD modal coefficients corresponding to the dominant gain directions [13]. *This process is repeated for two models;* which correspond to two throat heights $h = 0.2$ i.e model M1 and $h = 0.3$ i.e. model M2. The general strategy is shown in Figure 3. The figure shows that the above said approach can be used for identifying the map between system inputs and velocity modal coefficients a_j^V or for multi-variable a_j^{TV} modal coefficients, which can be obtained by stacking temperature and velocity snapshots together. More on multidimensional/multivariable POD can be found in [14].

The identified model in general state space format is given by

Step1:

Step 2:

SI:

Fig. 3: Overall Strategy

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ \hat{a}_i(k) &= C_{a_i} x(k) \end{aligned} \quad (16)$$

We can reconstruct the estimated or reconstructed outputs from the estimated POD modal coefficients as

$$\hat{y}_i(k) = C\Phi_n C_{a_i} x(k) = C_T x(k) \quad (17)$$

The last part of the strategy mentioned is the Dynamic Detection Mechanism (DDM) which is residual between either of the identified models, i.e. M1 or M2 with process (CFD software) at any time. DDM is shown in Figure 4.

Fig. 4: Dynamic Detection Mechanism

Both identified models represent the two extreme cases-back-flow or no-back-flow.

Let's denote 1 : M1 i.e no back-flow, 2 : M2 i.e back-flow, and i : sensor index, then we have residuals (error) at any time at some sensor location as,

$$\varepsilon_i(t) = \|(y_i(k) - \hat{y}_i^1(k))\|_2^2 - \|(y_i(k) - \hat{y}_i^2(k))\|_2^2. \quad (18)$$

Where, $y_i(k)$ is real process output, $\hat{y}_i^1(k)$ and $\hat{y}_i^2(k)$ are outputs of the identified model M1 and M2 respectively. Now we define $Y := \{y_i(k)\}_{i=1}^{n_y}$ as a set of all outputs and we further define a set of sensor positions (all sensors are located in the bottom wall of glass furnace, i.e. the same

y-axis position and different x-axis position). The set of sensors is given by $\{S_i\}_{i=1}^{n_y}$. Where $n_y = 4$, and the four sensors at those locations are [Figure 1],
 $S6 = Y(x = \text{before left end of the throat})$,
 $S7 = Y(x = \text{left end of the throat})$,
 $S8 = Y(x = \text{middle of the throat})$,
 $S9 = Y(x = \text{right end of the throat})$.

Sensors at location $S1$ to $S5$ are located in the melting and fining section which are far from the throat section, and hence are not of interest in this work. We now proceed by defining residuals at the above sensor locations as defined in (18). We can now confirm occurrence of the back-flow and make a decision about choice of identified model. If all elements of set $\{\varepsilon_i(t)\}_{S6}^{S9} > 0$: we are in regime 2 i.e we have *back-flow* and if all elements of set $\{\varepsilon_i(t)\}_{S6}^{S9} < 0$: we are in regime 1 i.e we have *no back-flow*. After confirming the regime we can select the correct subspace identified (reduced) model from either of the models. Occurrence of back-flow first starts at right hand side of throat (side close to the working end) and then it proceeds to the left side i.e. towards the inlet. As we are interested in occurrence of back-flow at left hand side entrance of throat (side close to fining section, $S7$) [Figure 1] we have certain range of throat height $h^1 < h^* < h^2$ such that at certain critical height h^* we observe back-flow at the left end of the throat i.e. at $S7$. As the corrosion phenomenon is very slow (timescale of years), occurrence of back-flow is very slow process. From this process knowledge we can predict its occurrence if each element of above mentioned set of residual starts changing their sign from negative to positive, one after another. In short, we are identifying reduced models corresponding to corrosion or no corrosion case and comparing both of them at every time instance with real process. Model which gives small error represents the real process.

VI. RESULTS AND DISCUSSION

Simulation experiments were performed on the 2D glass furnace model for two different throat heights for a time horizon of 60 hr. The data was extracted and imported in MATLAB environment for carrying out POD and subspace identification. As identified models are tremendously fast (> 1000 times faster than the CFD simulation), the computational performance of the identified models is not compared with the original CFD models. The lower dimensional maps were identified for single input - *glass pull rate/production rate* and three outputs which are first three POD modal coefficients corresponding to dominant singular values. Figure 5 shows process input profile (left) and temporal evolution of the mean temperature in the glass furnace for the two states of the real process (two different CFD models), each corresponding to case - before and after corrosion. The input perturbation was simply $\pm 10\%$ with sampling rate of 8 min.

The average temperature plot shows that both the CFD models (throat height(h_1) = 0.2) & (throat height(h_2) = 0.3) show similar temporal profile with very small differences. But based on this observation we should not con-

Fig. 5: Left: Process input Right: Average temp. profile

clude that the two process conditions are same. Rather the difference between the two process conditions (i.e two CFD models) is dominant only near the throat section, which can not be observed in this mean temperature profile. The first POD basis function for the temperature (which is similar to steady state of the process), is similar for both CFD models but there is significant difference in the first POD basis function for velocity. This is observed due to the process directionality to velocity, which results into inversion of the flow direction. Figure 6 confirms the observation related to the velocity POD basis, which shows that near throat section i.e. around $x = 29m$ we have visually observable difference.

Fig. 6: Comparison between first velocity basis function. Left: $h = 0.2$, Right: $h = 0.3$

Reduced models were identified by the strategy as explained in section V. As in reality we can measure *temperature* only at a few locations in the bottom of the furnace, the state space description between process inputs and the POD modal coefficients for temperature were identified only. Identification of the map between POD modal coefficients for velocity or for multi-variable modal coefficient is not done in this work. Moreover, as we are interested in the reconstructed outputs (eq. 17), the parameter fit of the identified models to the given data is not shown anywhere. We have,

$S6$ at $x = 25m$, i.e. $3m$ left of the throat entrance

$S7$ at $x = 28m$, i.e. at the throat entrance

$S8$ at $x = 29m$, i.e. at the middle of the throat

$S9$ at $x = 30m$, i.e. right end of the throat

Figure 7 compares the performance of the original and the

Fig. 7: (a) Temp. at S6. (b) Temp. at S7

Fig. 8: (a) Temp. at S8. (b) Temp. at S9

identified model at (S_6) & at (S_7), while Figure 8 shows the same at sensor (S_8) & at (S_9).

Both identified models show a good performance match with the true process (CFD models). They capture the process dynamics well. From the plots it is also clear that the process is non-linear and it does not have a same gain for perturbation in $\pm$ input directions. Moreover due to the distributed nature of the process we see different performance quality of identified models at each sensor locations. At S_6 the identified model is faster than the real process. The reason for this mismatch at S_6 stems from the turbulent region which is observed at S_6 where as most of the regions in the glass furnace show comparatively laminar (no turbulence) flow. From these results it is clear that we can use the dynamic detection mechanism mentioned in section V to approximate the process behavior with lower dimensional and computationally fast models under the influence of a corroding throat wall. We can also use the residual criteria mentioned in (18) to predict the occurrence of back-flow before it happens. The throat height can be determined based on a few measurements. Although here we have considered only two discrete cases, the method can be applied to slow and continuous geometric parameter change, but probably we will need more subspace identified models to cover the whole domain of throat variation.

VII. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

We conclude this paper with the remark that for a slow geometric parameter variation one can use the mentioned hybrid type of detection mechanism which employs subspace method with POD to identify lower dimensional models which are computationally faster than the CFD simulations. While implementing the strategy mentioned in section V one needs to take care of a proper excitation signal and a corresponding collection of snapshots such that POD captures the interesting dynamics. The suggested detection mechanism is easy to implement and can be used to detect the uncertain value of bifurcating parameter (throat height). This detection mechanism can predict the occurrence of back-flow in advance as well.

B. Future Works

Immediate extension to the current research in near future could be the system identification for MIMO case, derivation of a better mathematical framework for the switching mechanism, implementation of a parameter dependent Luenberger observer to observe the geometric parameter variation and model identification in a closed loop setting. Other tasks required to carry out above said future work is to create an interface between MATLAB and GTM-X (CFD) software.

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