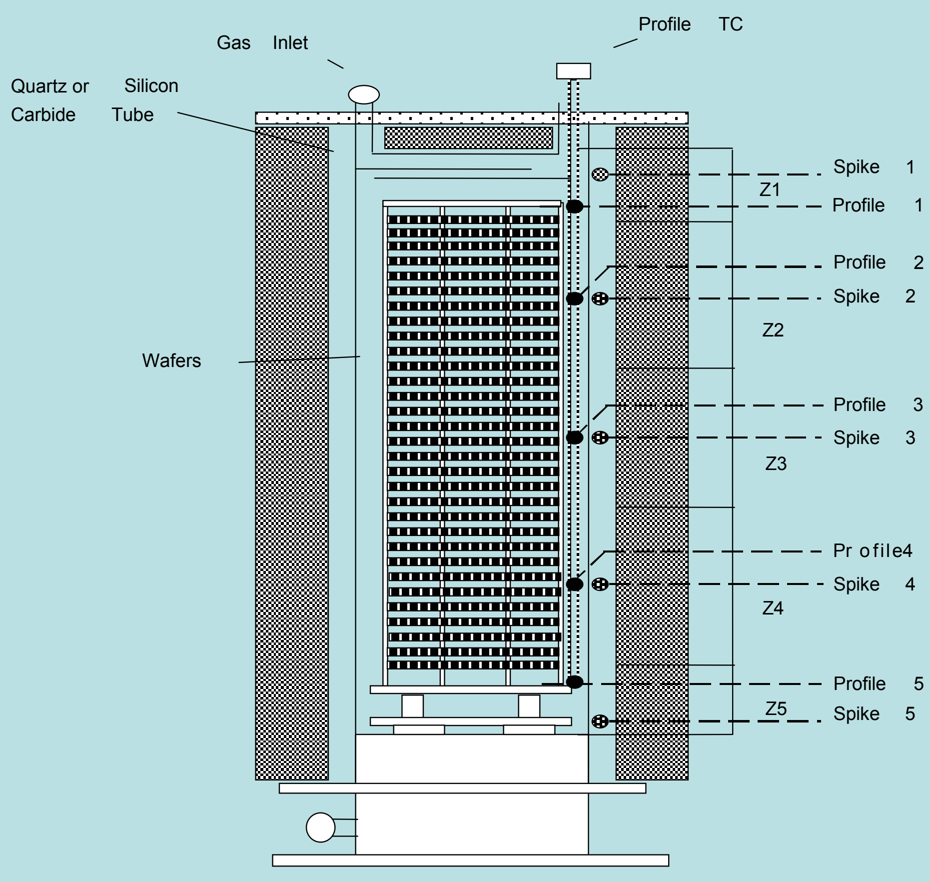
Nonlinear identification for diffusion/CVD furnaces

José-Job Flores-Godoy
Departamento de Física y Matemáticas
Universidad Iberoamericana
México City, D. F. MEXICO
job.flores@uia.mx

Kostas S. Tsakalis
Department of Elec. Eng.
Ira A. Fulton School of Engineering
Arizona State University
Tempe, AZ 85287-5706 USA
tsakalis@asu.edu

Kevin Stoddard
SSG EES Control Systems
Brooks Automation, Inc.
Phoenix, AZ, USA
kevin.stoddard@brooks.com



Main Result: Nonlinear Identification methods can provide "global" models with smooth transition between operating points, and with similar modeling errors as local linear models, suitable for controller design.

Experimental verification:

Vertical or horizontal furnaces, operating at atmospheric pressure or at low pressure.

Heat provided by electrical thermal elements

Temperatures measured by two sets of thermocouples,

- Spike TC near the heating element
- Profile TC inside reaction chamber

Simulation Test-Bed:

Partial Differential Equation model based on first principles

Model includes heat transfer due to radiation and convection

Model structure and parameterization

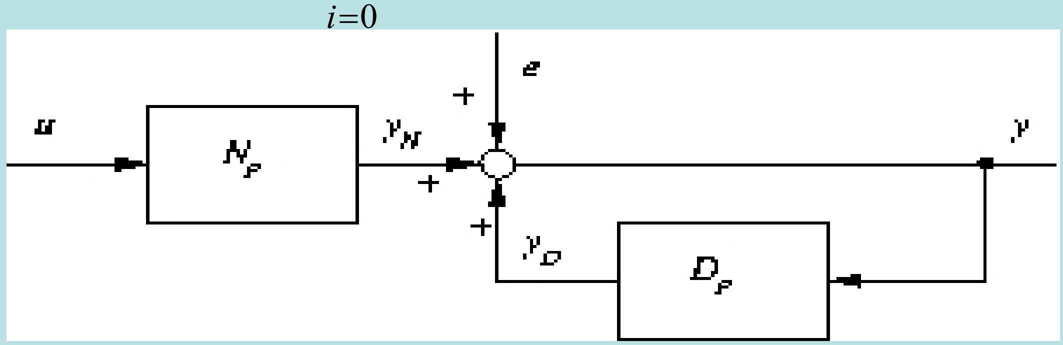
Nonlinear model structure:

Linear in the parameters

ARX generalization. (e.g. Leontaritis 85)

$$\dot{x}(t) = Fx + \sum_{i=0}^{n_u} \theta_{1_i} f_i(u(t)) + \sum_{i=0}^{n_y} \theta_{2_i} g_i(y(t)),\ \theta_4 = x(t_0)$$

$$y(t) = Cx(t) + \sum_{i=0}^{n_d} \theta_{3_i} h_i(u(t))$$



Left factorization of the plant

$$y_k(t) = \Theta_k^{\mathrm{T}} W_k(t)$$

$$\Theta_k^{\mathrm{T}} = \begin{bmatrix} \vartheta_{k1}^{\mathrm{T}} & \vartheta_{k2}^{\mathrm{T}} & \vartheta_{k3}^{\mathrm{T}} & \vartheta_{k4}^{\mathrm{T}} \end{bmatrix}$$

$$W_k(t) = \begin{bmatrix} w_{k1}^{\mathrm{T}} & w_{k2}^{\mathrm{T}} & w_{k3}^{\mathrm{T}} & w_{k4}^{\mathrm{T}} \end{bmatrix}$$

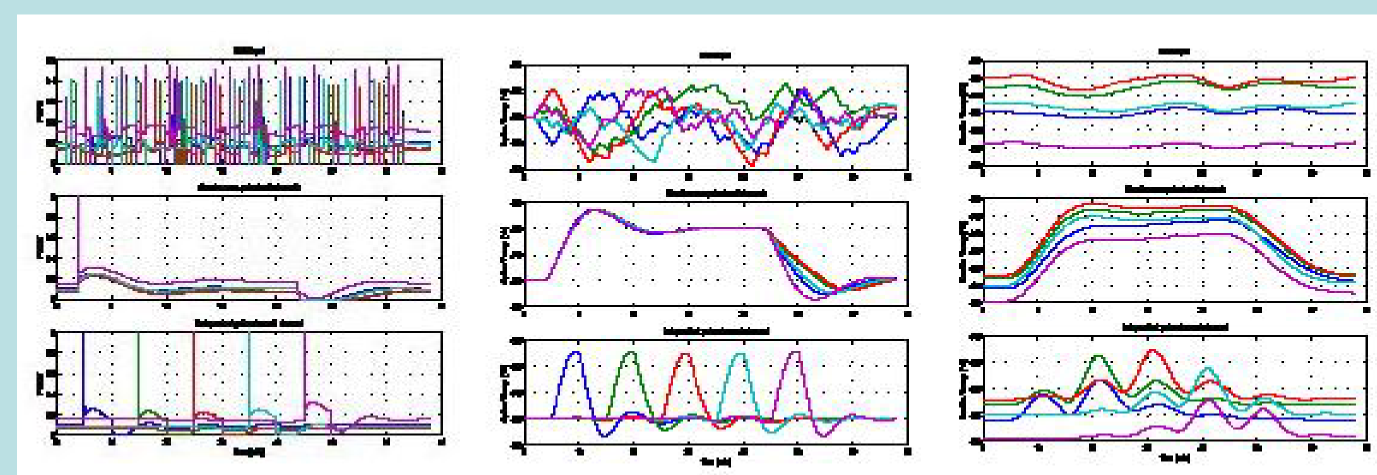
$$w_{k1} = \begin{bmatrix} H_k'\left(f_{1_1}(u_1)\right) \\ \vdots \\ H_k'\left(f_{1_p}(u_p)\right) \\ \vdots \\ H_k'\left(f_{f_{u1}}(u_1)\right) \\ \vdots \\ H_k'\left(f_{f_{up}}(u_p)\right) \end{bmatrix},\quad w_{k2} = \begin{bmatrix} H_k'\left(g_{1_1}(y_1)\right) \\ \vdots \\ H_k'\left(g_{1_q}(y_q)\right) \\ \vdots \\ H_k'\left(g_{g_{y_1}}(y_1)\right) \\ \vdots \\ H_k'\left(g_{g_{y_p}}(y_q)\right) \end{bmatrix},\quad w_{k3} = \begin{bmatrix} h_{1_1}(u_1) \\ \vdots \\ h_{1_p}(u_p) \\ \vdots \\ h_{h_{u1}}(u_p) \\ \vdots \\ h_{h_{up}}(u_p) \end{bmatrix},$$

$$w_{k4} = H^{\mathrm{T}}\left(C^{\mathrm{T}}\delta(t)\right)\ldots \quad \vartheta_{k4}^{\mathrm{T}} = x_{0_k}^{\mathrm{T}}$$

$$H_k'(\bullet) = \left(sI - F^{\mathrm{T}}\right)_k^{-1} c^{\mathrm{T}}(\bullet); \quad H^{\mathrm{T}}(\bullet) = \left(sI - F^{\mathrm{T}}\right)^{-1}$$

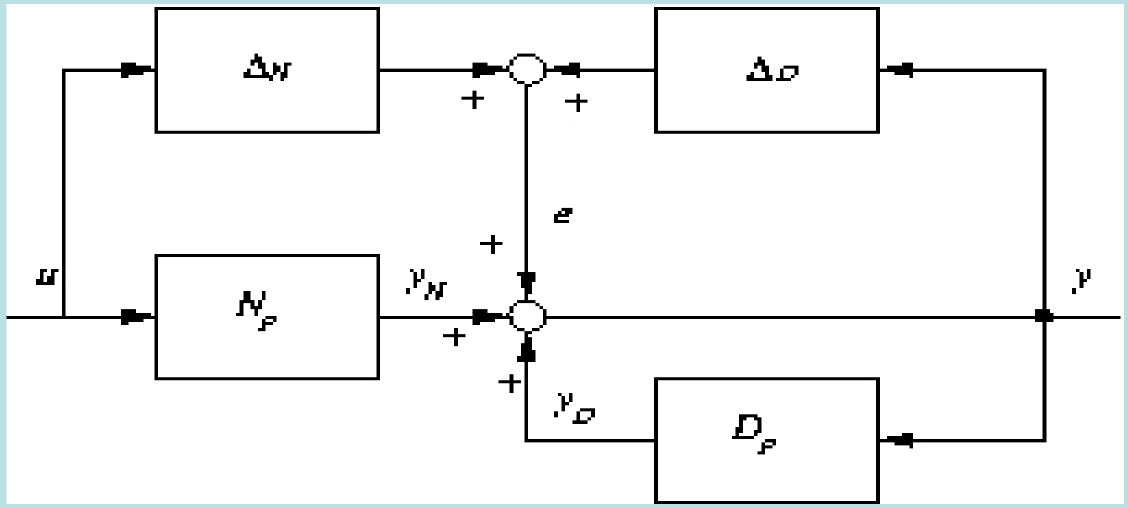
Typical Set of Experiments:

- Multiple Operating Points (50-100 degC separation)
- Random binary sequence excitation to provide mid-high frequency information
- Step tests to provide low frequency information



Typical Experiment: power, spike, profile

Identification structure



Least-squares problem for finding the unknown parameters

$$\min_{\Theta}\|e\|_2=\min_{\Theta}\left\{\sqrt{e^T(t)e(t)}\right\}$$

$$e=y(t)-\hat{y}(t),\quad \hat{y}(t)=W(t)\Theta$$

$$E_{LS}=\min_{\Theta}\|y(t)-W(t)\Theta\|_2$$

$$\min_{\Theta}\|H\Theta\|_2$$

$$s.t.:\|y(t)-W(t)\Theta\|_2\le(1+\rho)E_{LS}$$

Regularized parameter estimates

Uncertainty estimation

$$\min_{\delta_1,\delta_2}\left\{\bar{\sigma}\left(P^{-1}T(I-D_P)^{-1}\right)\delta_1+\bar{\sigma}\left(S(I-D_P)^{-1}\right)\delta_2\right\}$$

$$s.t.\begin{cases}\Delta_N(u)+\Delta_D(y)=e\\ \bar{\sigma}(\Delta_N)\le\delta_1,\ \bar{\sigma}(\Delta_D)\le\delta_2\end{cases}$$

$$[\delta_1\quad\delta_2]=\begin{cases}\begin{bmatrix}\dfrac{|S_e|}{|S_u|} & 0\end{bmatrix} & if\ \ell<1\\ \begin{bmatrix}0 & \dfrac{|S_e|}{|S_y|}\end{bmatrix} & if\ \ell>1\end{cases}\qquad \ell=\frac{|S_y|}{|S_u|}\frac{\bar{\sigma}(P^{-1})\bar{\sigma}(T)}{\bar{\sigma}(S)}$$

P: plant model, S_x: power spectrum of x
S: Sensitivity, T: Co-sensitivity

Uncertainty estimates:

- incremental gains
- translated to sensitivity and co-sensitivity bounds for loop-shaping controller design.
- Scheduled Controller design: Standard H-infinity design in MATLAB

$$\min\ \gamma:\sigma\begin{bmatrix}W_3T\\ W_1S\end{bmatrix}<\gamma$$

$$W_3=\sigma(P^{-1})\sigma((I-D_p)^{-1})\delta_1,\ W_1=\sigma((I-D_p)^{-1})\delta_2$$

Model structure for the simulation test-bed

Power-Spike NL model

$$\dot{x} = Fx + \theta_{1_1} u + \theta_{1_2} u^{(2)} + \theta_{1_3} u^{(3)} + \theta_{1_4} u^{(4)} + \theta_{2_1} y + \theta_{2_2} y^{(2)} + \theta_{2_3} y^{(3)} + \theta_{2_4} y^{(4)}$$

$$y = Cx + \theta_{3_0}$$

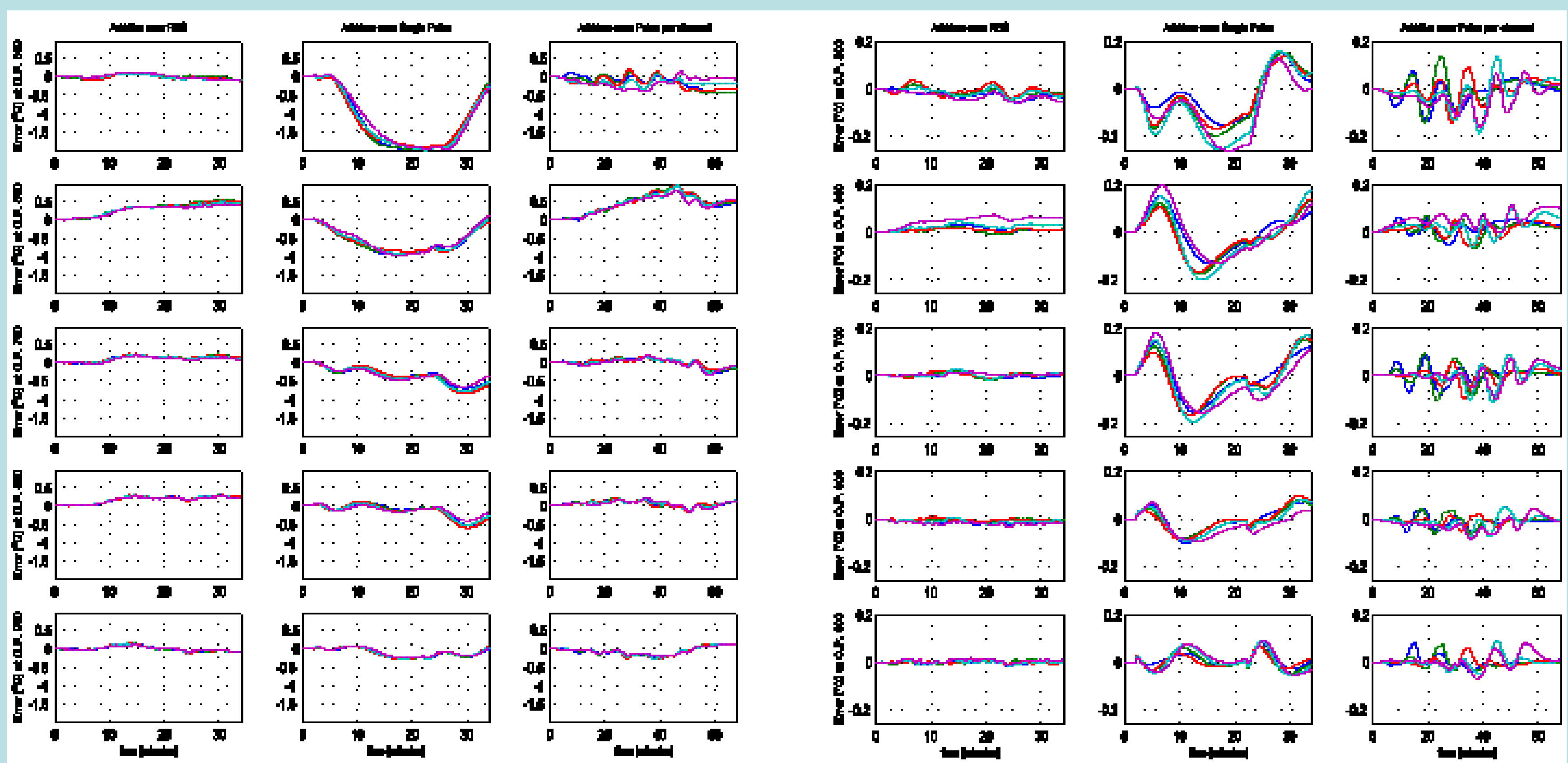
Spike-Profile NL model

$$\dot{x} = Fx + \theta_{1_1} u + \theta_{1_4} u^{(4)} + \theta_{2_1} y + \theta_{2_4} y^{(4)}$$

$$y = Cx + \theta_{3_0} + \theta_{3_1} u + \theta_{3_4} u^{(4)}$$

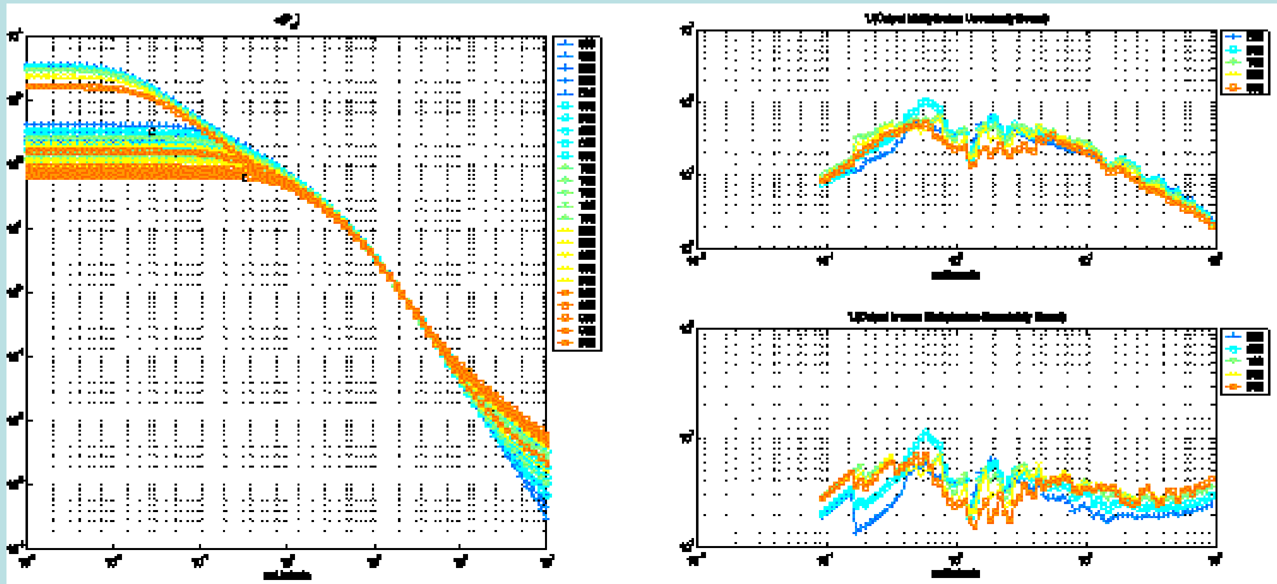
- Data from 5 sets of experiments From 500 to 900 C
- Nonlinear Model
    - 605 of Spike Parameters
    - 255 Profile Parameters
- Linear, scheduled model 5 operating points
    - 650 Spike Parameters
    - 300 Profile Parameters

Spike Additive Error

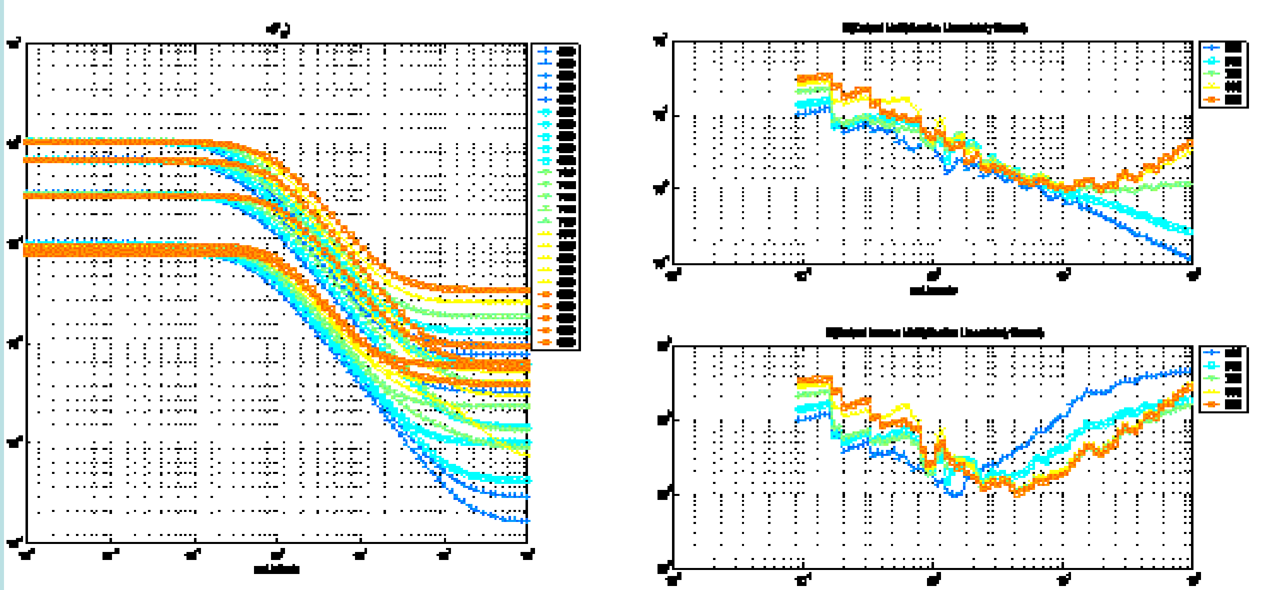


Profile Additive Error

Simulation test-bed model



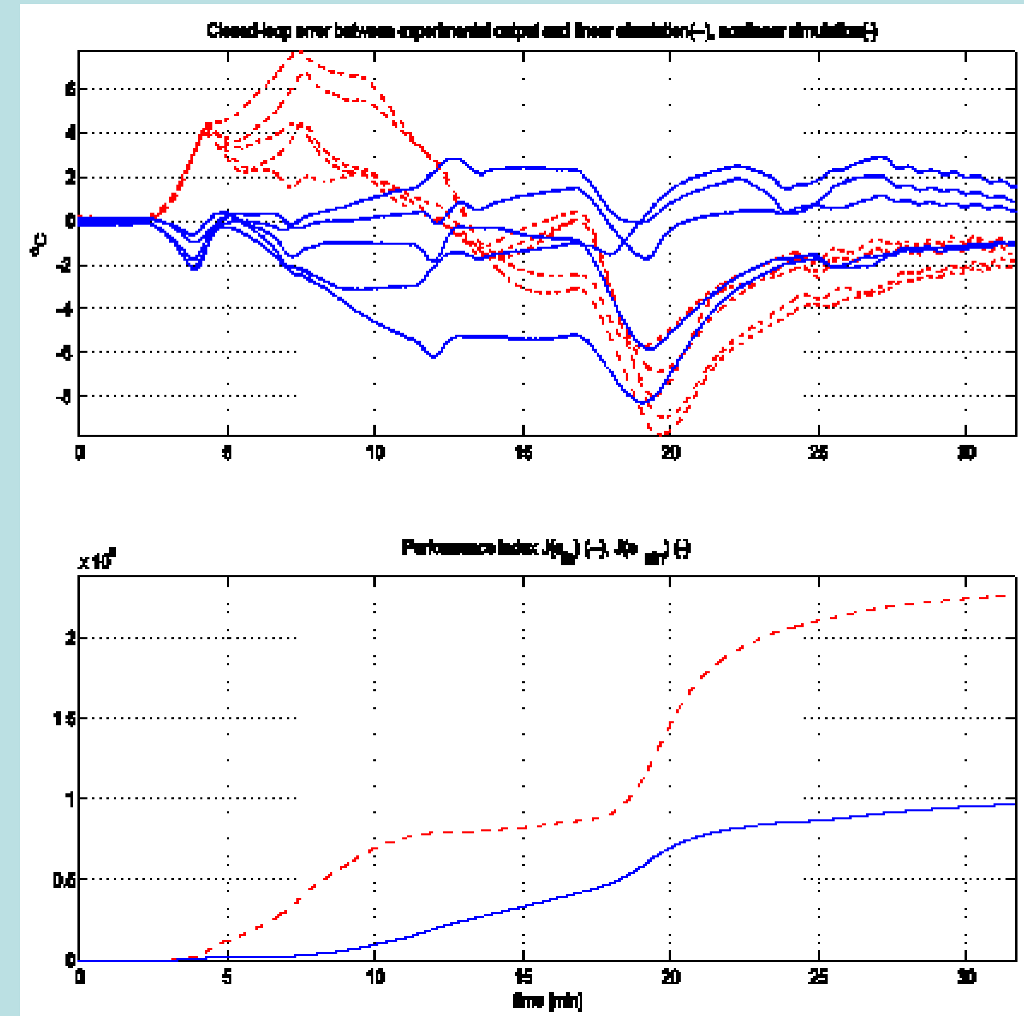
Power-Spike Model



Spike-Profile Model

Singular values
Linearized model

Uncertainty Estimates
as Sens./Co-Sens. bounds
(=> feasibility of controller design)



Comparison between the closed-loop differences :

- •PDE model and the linear, scheduled plant (red);
- •PDE model and nonlinear plant (blue)
- •Reference signal: ramp from 500 to 800, 20deg/min.
- •Closed-loop with a gain-scheduled H-infinity controller
- •details: [Flores-Godoy 02]

Modeling Example:
Thermco Minibrute 5in horizontal 3 zones

Power-Spike NL model

$$\dot{x} = Fx + \theta_{1_1} u + \theta_{1_2} u^{(2)} + \theta_{1_3} u^{(3)} + \theta_{2_1} y + \theta_{2_2} y^{(2)} + \theta_{2_3} y^{(3)}$$

$$y = Cx$$

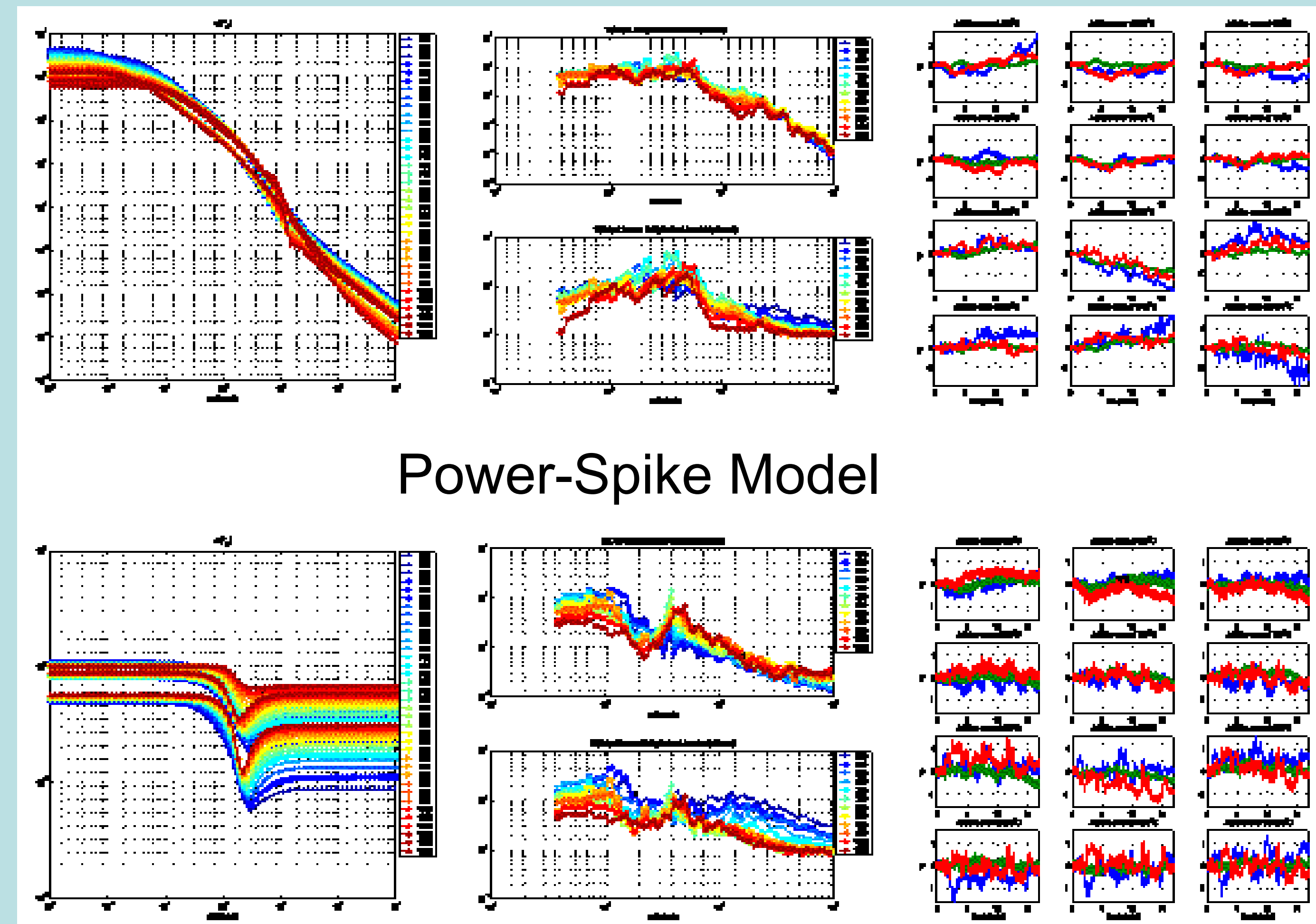
Spike-Profile NL model

$$\dot{x} = Fx + \theta_{1_1} u + \theta_{1_2} u^{(2)} + \theta_{2_1} y + \theta_{2_2} y^{(2)} + \theta_{2_3} y^{(3)} + \theta_{2_4} y^{(4)}$$

$$y = Cx + \theta_{3_1} u + \theta_{3_2} u^{(2)}$$

Identification Experiments:
12 Experiments (RBS signal) at operating points from 550 to 1050 C
[Tsakalis 99]

Controller Design Feasibility:
Similar to local linear models
10 rad/min spike loop bandwidth
2-4 rad/min profile loop bandwidth
[Tsakalis 99]



Power-Spike Model

Spike-Profile Model

Singular values of Linearized model

Uncertainty Estimates

Additive errors

Example: Vertical Furnace 5 zones

Power-Spike NL model

$$\dot{x} = Fx + \theta_{1_1} u + \theta_{1_2} u^{(2)} + \theta_{2_1} y + \theta_{2_2} y^{(2)}$$

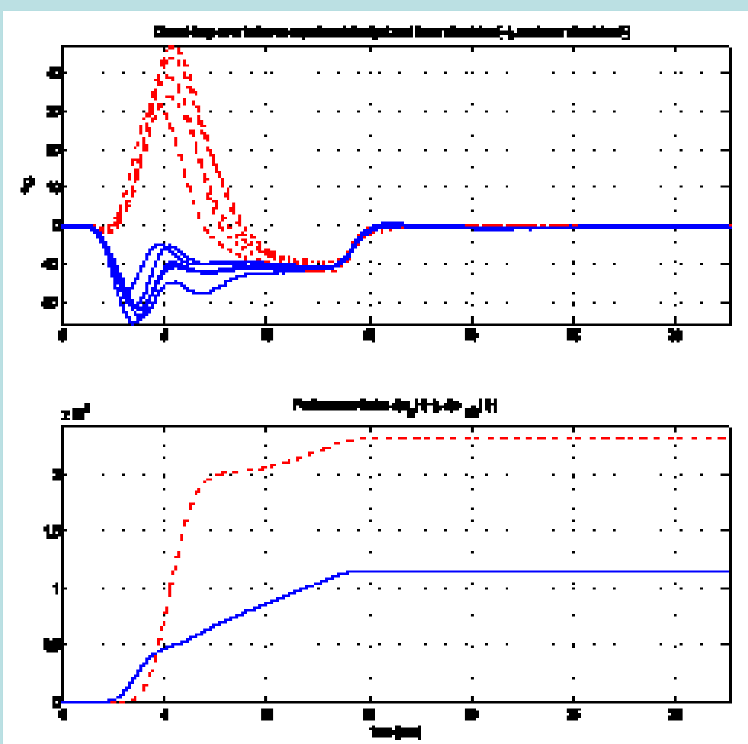
$$y = Cx$$

Spike-Profile NL model

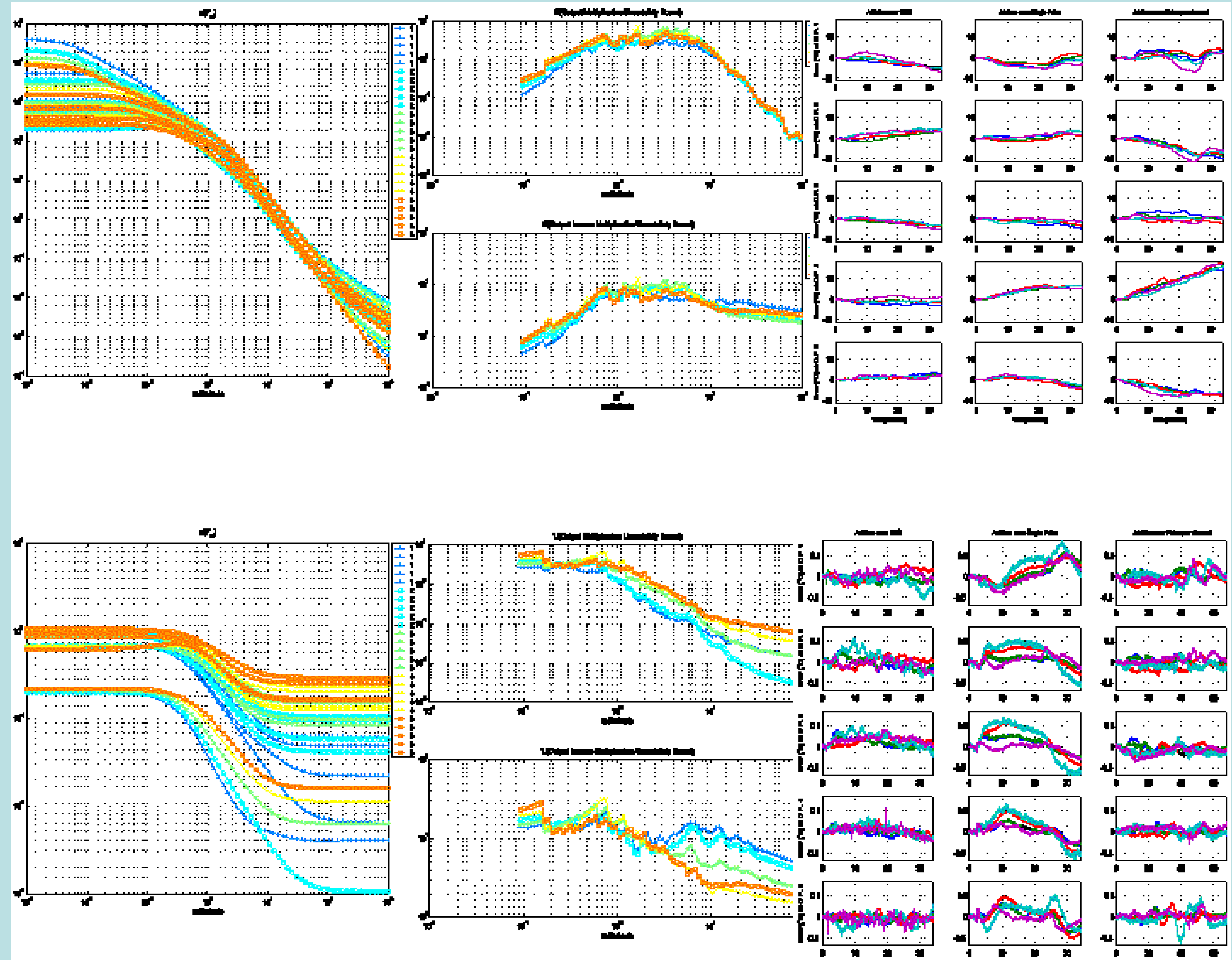
$$\dot{x} = Fx + \theta_{1_1} u + \theta_{1_2} u^{(2)} + \theta_{2_1} y +$$

$$+ \theta_{2_2} y^{(2)} + \theta_{2_3} y^{(3)} + \theta_{2_4} y^{(4)}$$

$$y = Cx + \theta_{3_1} u + \theta_{3_2} u^{(2)}$$



Closed-loop comparison between GS vs NL



Singular values of Linearized model

Uncertainty Estimates

Additive errors

Conclusions

- Generalization of linear modeling and uncertainty estimation techniques.
- Efficient parameter estimation via least-squares algorithms.
- Dynamic uncertainty estimates with incremental gain interpretation, suitable for robust controller design
- Controller design:
  - linearization-and-scheduling methods (well-established, [Tsakalis 99])
  - linear-parameter-varying methods (next phase [Packard 94, Rugh 2000, Gahinet 95])

References

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