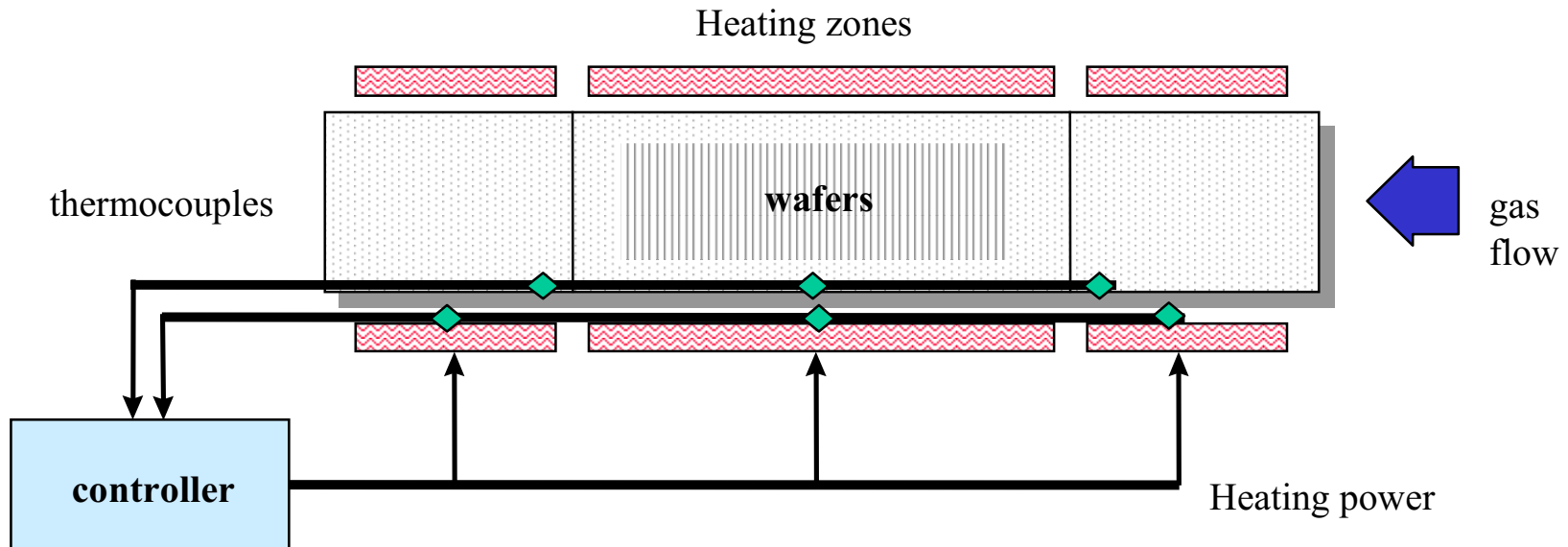


System Identification and Controller Design

- **Diffusion/CVD Furnace Temperature Control**



- **Objective:** Given temperature measurements determine heating power settings to achieve temperature uniformity and trajectory tracking (ramp-up/down)
- **Issues:** Modelling, coupling between “heating zones”, controller design and implementation, heating power constraints (saturation), disturbance rejection (gas flow, heat dissipation)
- **Design:** Input-Output system identification; hierarchical/2-DOF design using an H-infinity approach. Inner loop: Spike temperatures (near the heating element). Outer loop: Profile temperatures (inside the tube).

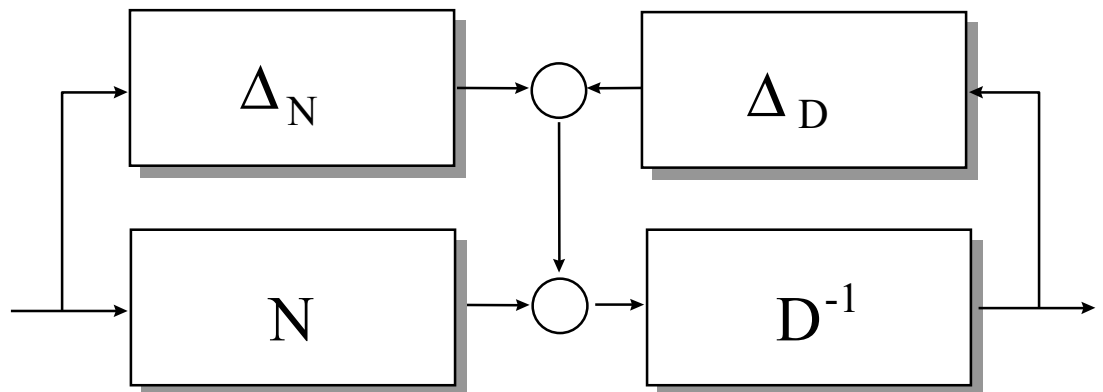
Modeling from Input-Output Data

- Should handle a great variety of furnace types (horizontal/vertical, 4-12 in diameter, different construction materials, #zones). Must be quick (key application is retrofits).
- Model itself rarely imposes any severe performance limitations (delays, RHP zeros).
- Need a reliable estimate of the achievable closed-loop bandwidth under modeling uncertainty constraints, to minimize controller evaluation and redesign iterations.
- Model (power-to-temperature) contains “slow” modes, near-integrators with respect to desired bandwidth.
- Model uncertainty is likely to be high at low frequencies (e.g., DC gain); getting a good estimate may require a lot of unnecessary effort and time.
- Approach: Identify a coprime factorization and estimate the coprime factor uncertainty (can handle large low frequency perturbations, even changes in unstable modes).
- Pros: Easy least squares problem; LS \Rightarrow white errors \sim white uncertainty blocks, all inputs/all outputs are “comparable” \Rightarrow scaling should not be necessary.
- Cons: Poor simulation/prediction models.

Interpretation:

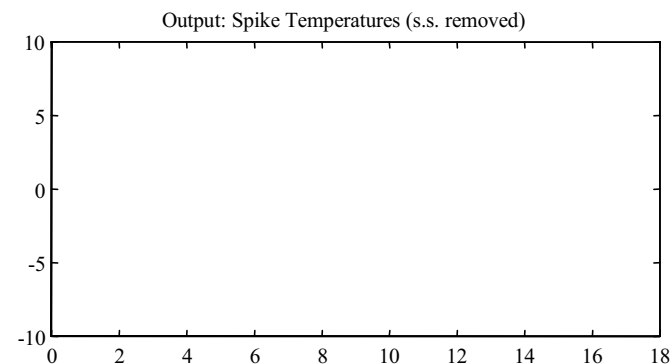
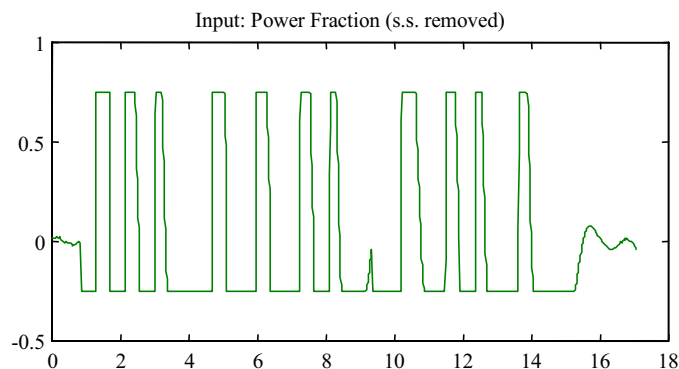
$\Delta_N \Rightarrow$ compl. sensitivity constraints,

$\Delta_D \Rightarrow$ sensitivity constraints



System Identification

- Identification structure: $\dot{x} = Ax + Bu = Fx + (B - LD)u + Ly; y = Cx + Du$
- Linear model regressors: $y = C(sI - F)^{-1}[\theta_1 u + \theta_2 y + \theta_4] + \theta_3 u$
Filtered I/O and initial conditions. The latter are important for data beginning in a transient or a non-zero steady-state. If ignored, significant errors are introduced, especially for short data-sets.
- Continuous time ID.
- Parameter estimation should contain regularization mechanisms to avoid problems because of low SNR/insufficient excitation.
- MISO identification may produce non-minimal models (usually not, especially after adjusting channel orders).
- Using all inputs and all outputs in the regressor is beneficial in reducing the order of the identified model but pole-zero structure may deteriorate; use guidance from first principles model.
- Typical I/O sequences shown; begin/end at steady-state minimizes FFT aliasing.



Uncertainty Estimation

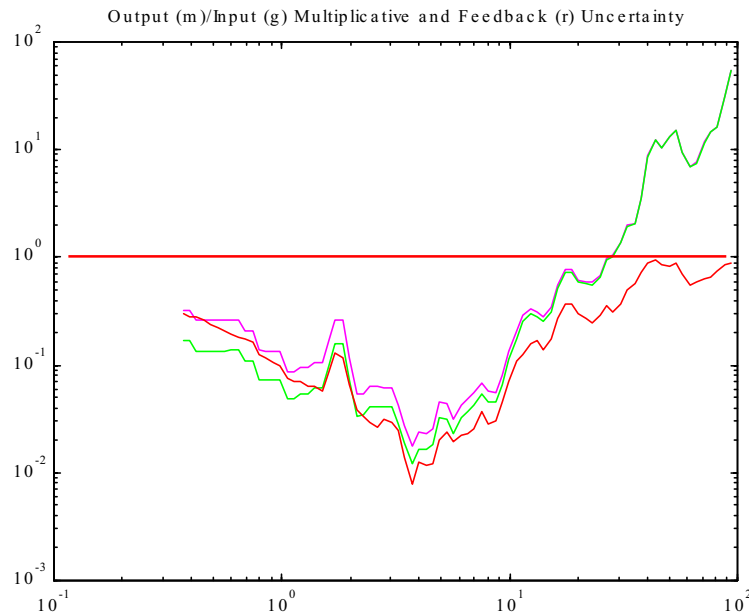
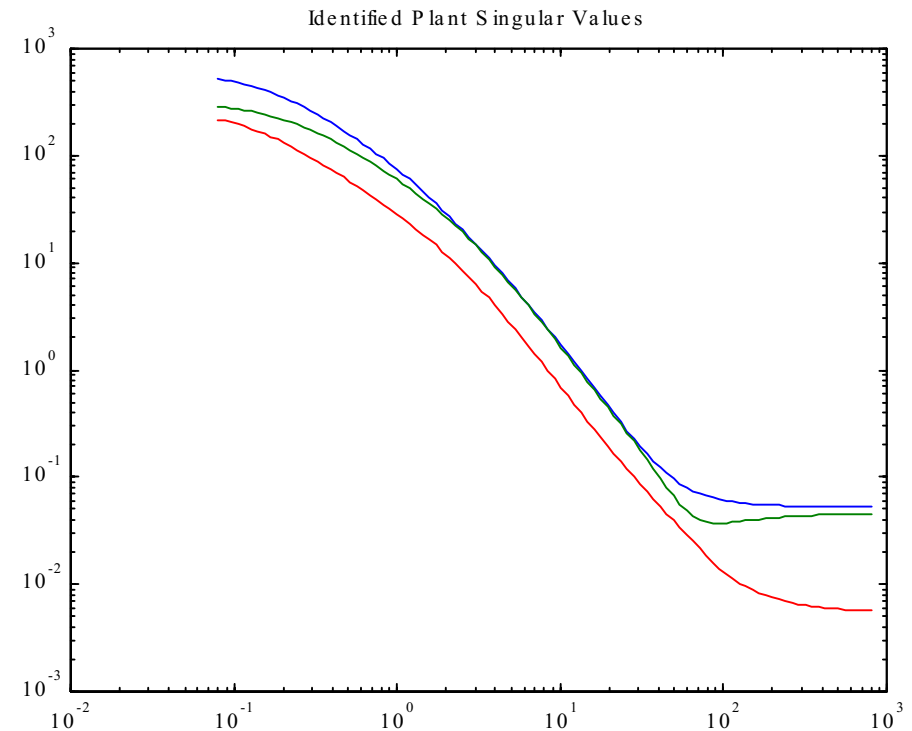
- Robust Stability Condition: $\sigma [C S D^{-1}] \sigma [\Delta_N] + \sigma [S D^{-1}] \sigma [\Delta_D] < 1$ (RSC)
- For square systems, write CS as $P^{-1}T$, define a target loop S&T (sensitivity and complementary sensitivity), and compute the “most favorable” uncertainty decomposition, minimizing the above left hand side, subject to $\Delta_N[u] + \Delta_D[y] = e$, the estimation error.
- A simple suboptimal solution can be computed in the frequency domain (via FFT’s) If the minimum value is less than one, a controller achieving the target S and T, is also expected to stabilize the actual system. (Pseudo-necessary condition for robust stability, Distance from 1 ~ “risk factor”).
- Guide to select a target loop and weights for an H-infinity controller design. Typical approach: select S&T roll-off rates at low and high frequencies from uncertainty data; then minimize S subject to T-constraints. Feasibility check: RSC less than one. Also, target loop must be achievable (RHP pole/zero constraints).
- A similar problem can be posed for the outer loop subsystem (profile temperature); here, the inner closed-loop TFM becomes a weight and additional terms appear with the contribution of an “effective” closed inner-loop uncertainty.
- Effective closed loop uncertainty estimate:

$$\delta_{M,e} < \{ \sigma [S D^{-1}] \sigma [C S] \sigma [T^{-1}] \sigma [\Delta_N] + \sigma [S D^{-1}] \sigma [\Delta_D] \} \alpha$$

$$\alpha = (1 - \sigma [C S D^{-1}] \sigma [\Delta_N] + \sigma [S D^{-1}] \sigma [\Delta_D])^{-1}$$

Inner Loop (Spike Subsystem) Modeling

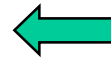
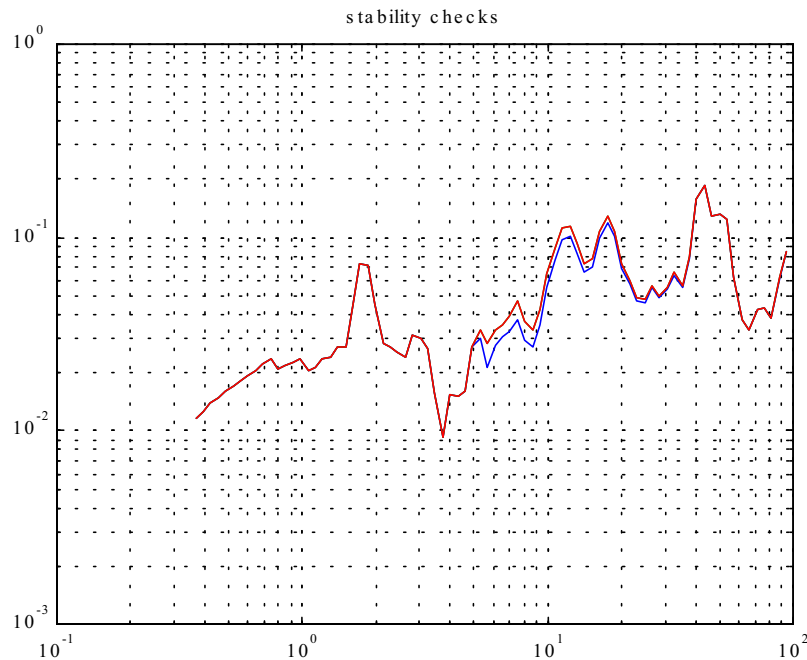
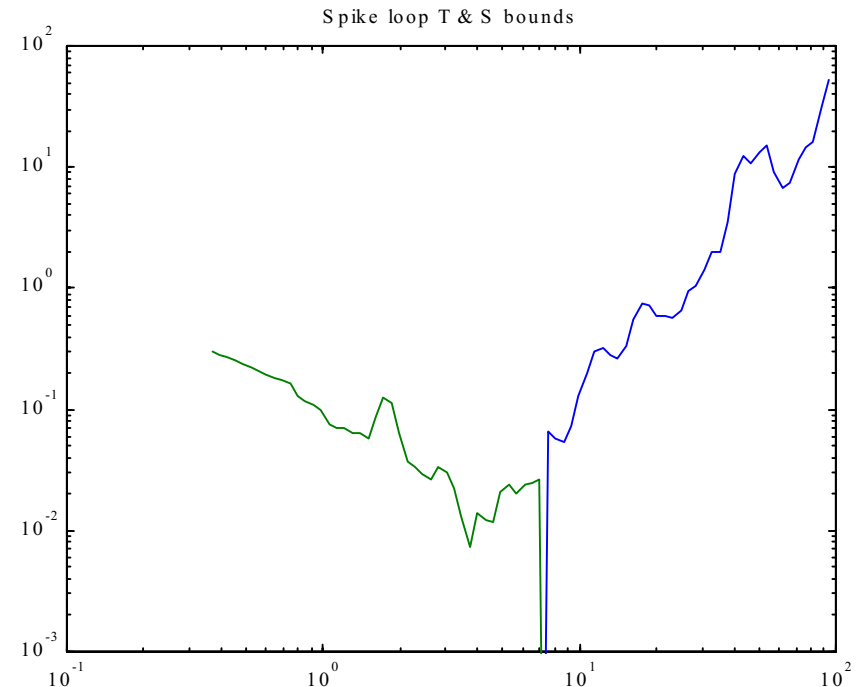
- Power to spike temperature. Very high and uncertain low frequency gain. (short data set, but sufficient to get a good model around the intended crossover $\sim 5\text{rad/min}$)
- slow poles, near-integral action with respect to desired closed loop bandwidth.



- “Raw” uncertainty data expressed as inverse S&T bounds ($|\text{fft}(e)|/|\text{fft}(u)|$, $|\text{fft}(e)|/|\text{fft}(y)|$) show asymptotic behavior.
- Notice the high uncertainty at low frequencies that should be removed by the high gain of the controller.

Spike Model Uncertainty

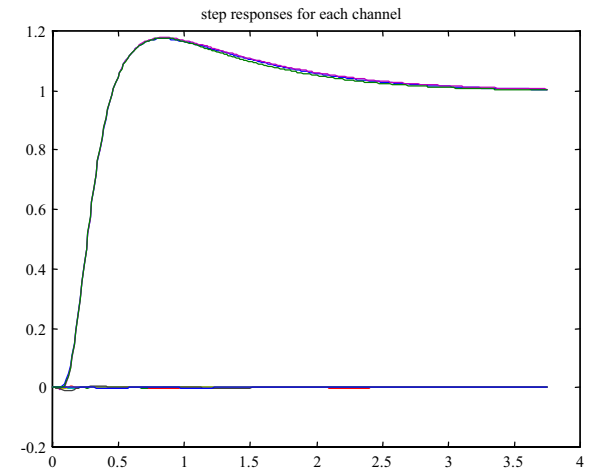
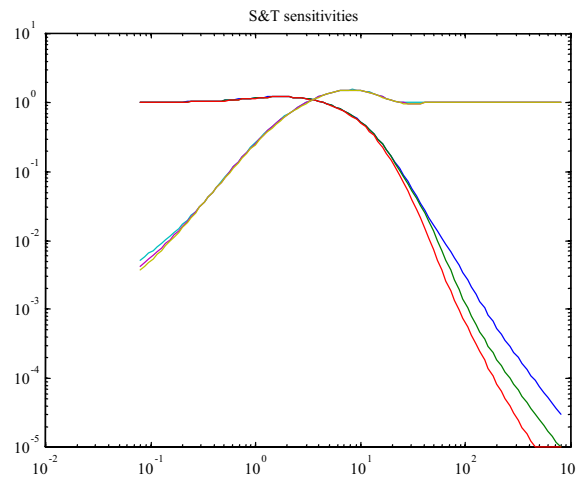
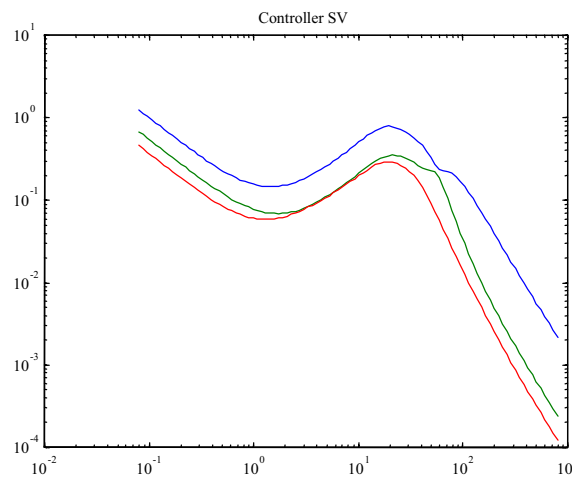
- After the split, the high frequency uncertainty is expressed as an inverse T constraint and the low frequency as an inverse S constraint.



- The selected target loop yields a fairly small RSC, indicating that the actual closed loop will match the nominal with a high degree of confidence.
- RHP zeros are very fast, almost a decade above the crossover, and should not present any problem in matching the target.

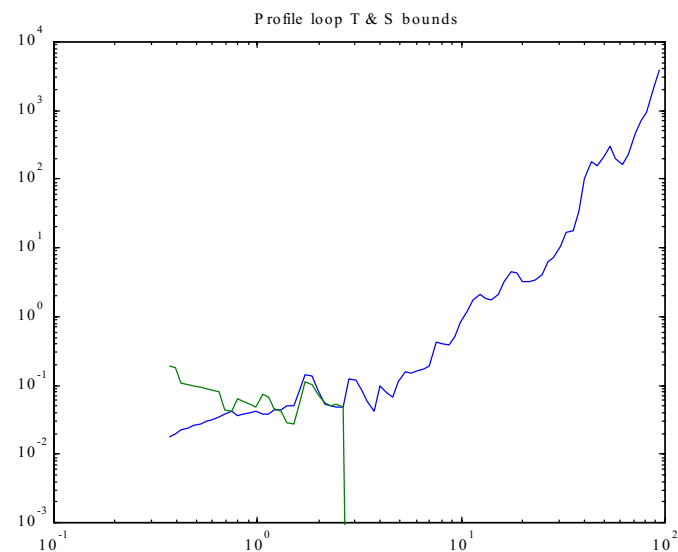
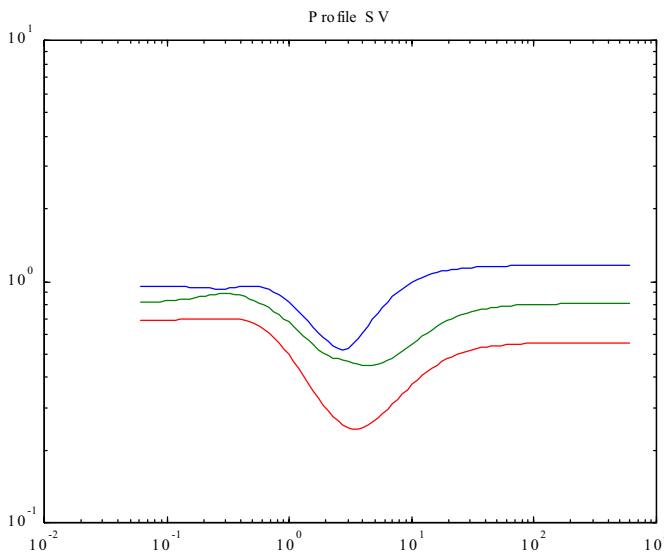
Spike Controller Design

- Using the selected target loop weights, an H-infinity controller is designed.
- The approach yields excellent matching properties with minimal iterations in the weight selection.
- Simple weights have the disadvantage of introducing irrelevant, but potentially harmful, very fast and slow modes in the controller. Slow-fast reductions are used to eliminate them before a general frequency-weighted balanced reduction.
- Small adjustments in the target loop do not require an iteration of the uncertainty split. The result is simply a little more conservative.



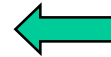
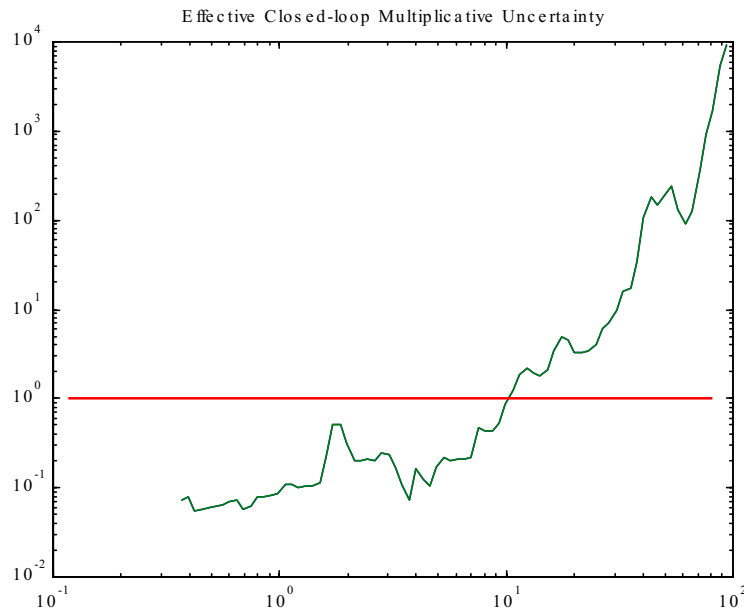
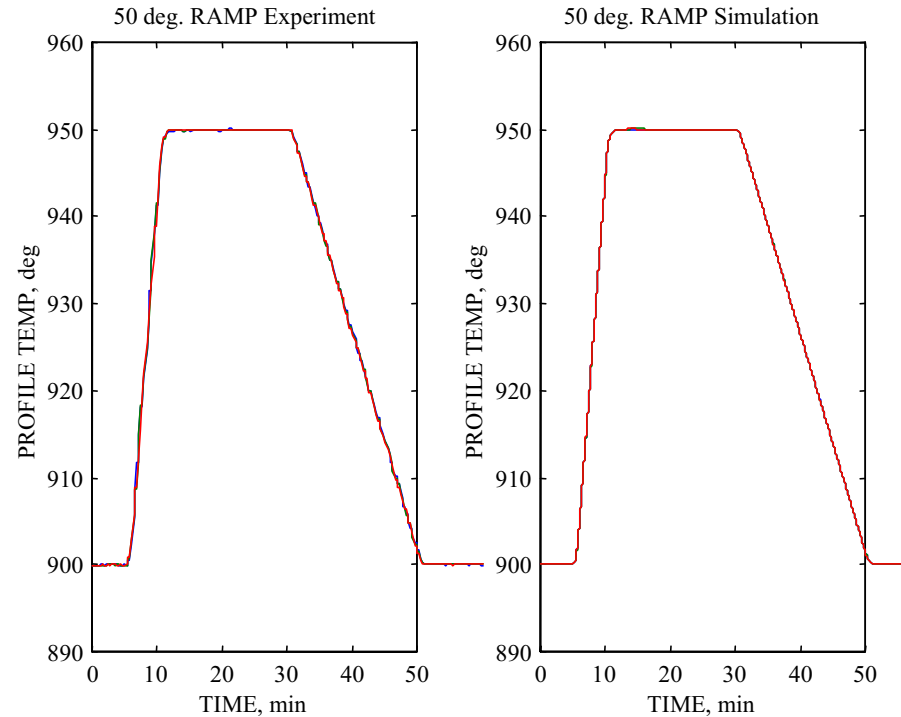
Outer Loop (Profile Subsystem)

- The profile subsystem (spike to profile temperatures) is identified in a similar manner.
- The uncertainty split is based on the combined effects of the modeling error in the profile subsystem, the nominal inner closed-loop, and the effective inner closed-loop uncertainty.
- Again, the uncertainty guides the selection of the outer loop S&T.
- Notice that, by design, the inner-loop uncertainty approaches zero at DC.
- Profile models are usually benign (stable and minimum phase) but may contain slow modes. More complicated sensitivity targets are needed to avoid direct cancellation of such modes, but this has the undesirable by-product of introducing an overshoot in the closed loop response (thus requiring some form of reference pre-filtering)



Profile Controller Design and Evaluation

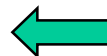
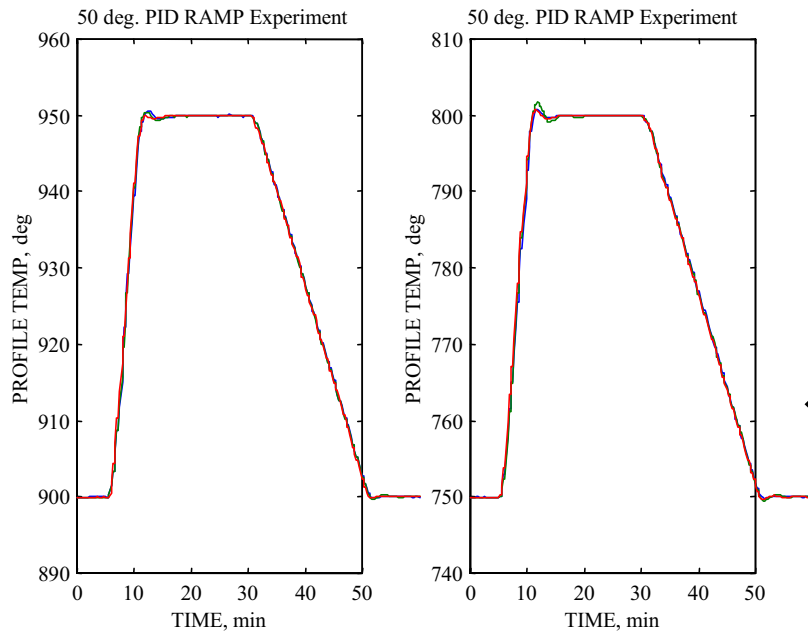
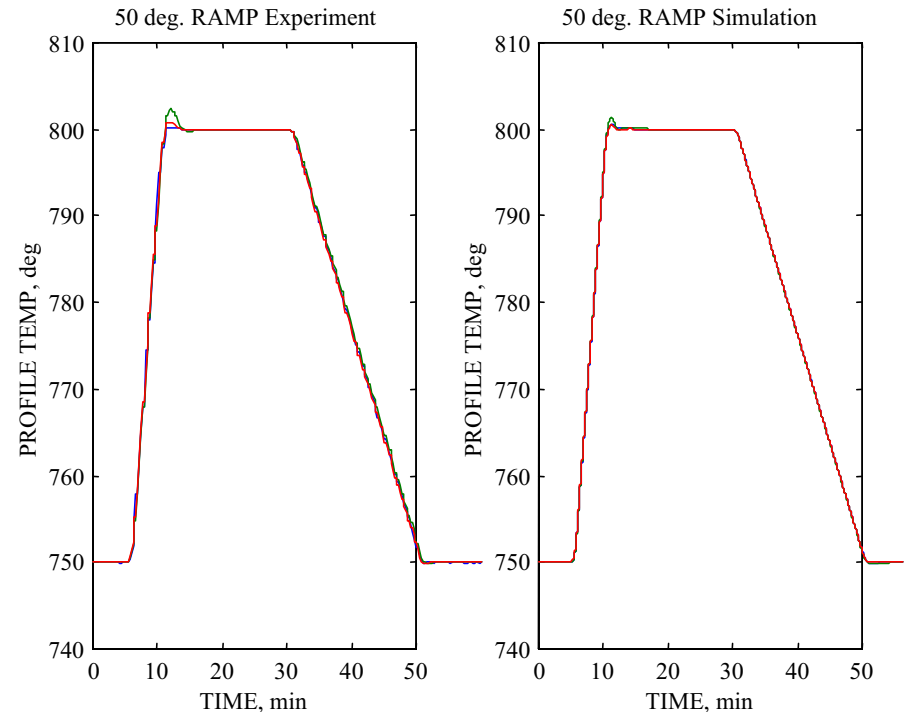
- The profile controller is designed for the combined profile/inner-loop system.
- After the necessary reduction, the controller is discretized and augmented with anti-windup mechanisms.
- Its implementation and test during a typical ramp-up/ramp-down operation shows excellent performance.



- The closed-loop behavior is also predictable (model simulation), as indicated by the effective closed loop uncertainty estimate.
- These estimates, however, become increasingly conservative with the number of hierarchical levels

Profile Controller Evaluation (cont.)

- At a different operating condition, the controller performance, naturally, deteriorates.
- This is predictable (simulation with the 750 deg. model), but the prediction quality also deteriorates.
- Still, the response is very good, even though it shows some overshoot.



- A similar approach can be taken to design a dual loop decoupled PID for the same system.
- The loop-shaping-based tuning [Grassi+ Tsakalis, CDC96] yields acceptable performance and, even, more graceful deterioration away from the modeled steady-state (less aggressive).
- However, it may not be suitable for all furnaces (more heating zones)

Conclusions

- **Methodology:**

- Integrated identification and controller design with control-oriented uncertainty estimation. Can handle integrating and, even, unstable plants. (Original motivation was the inverted pendulum experiment; has also been successfully applied to a ball-and-beam experiment.)
- Loop-shaping approach for controller design, compatible with the uncertainty estimates.
- Reasonably automated procedure with some rules-of-thumb tailored to the specific application (e.g., S-weight selection given a T-bandwidth).
- Quick design turn-around time. One-pass data-to-controller: 15min/3 zone-furnace, 30min/5 zone-furnace (Pentium 120). Typical first-time design: 1-5 hours. Most of the effort is spent on obtaining a reasonable identification model (excitation, SNR issues), while the controller design is “almost transparent.” Second-time designs (like-furnaces) rarely require any iterations.
- Works well with short data records (20 min identification + experiment set-up; one day typical retrofit installation).
- “Normal” cases require little user interaction (hence, expertise). Typical specs can be reduced down to a single number (bandwidth), which can often be determined automatically.

- **Application:**

- Reliable performance optimization and robustness with respect to the usual furnace maintenance operations. Over 200 controllers currently in operation, 20 types of furnaces, 10 different semiconductor industries.
- Improved control performance translates into better tool utilization and process results [Tucker et al 98], [Yelverton et al 97].