Use of Monte Carlo Techniques in Robustness Evaluation of Different Temperature Control Methods of Heated Plates

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Problem Overview/Motivation

- Temperature control is important in many thermal processing systems
  - *The dynamic response of the system can change considerably depending on operating temperature, wafer types, and/or process conditions*
  - *Ideally one would like to get the exact same closed-loop temperature response (performance) despite these system variations (robustness)*
  - *One can achieve this by using real-time feedback control*

- In previous work, we used a simple example to compare three different control approaches in terms of their performance and robustness

- Performance bounds were calculated by ‘gridding’ the parameter space, which requires a large number of simulations

- In this work, robustness of the various controllers is evaluated using a Monte Carlo Simulation Technique
Overview

- Thermal Model of Lamp Heated Plate
- Process Variations and Robust Control
- Recap of Control Methods
- Monte Carlo Simulation Method
- Performance Evaluation using Monte Carlo Results
- Summary
Thermal Model of Lamp Heated Plate

- A tungsten-halogen lamp is shown heating a plate from below.
- The plate radiates, conducts, and convects heat to the walls and surroundings.
- The system can be divided into a number of control volumes and the heat equation can be written for the net rate of temperature change:

\[ \dot{T} = f(T, u), \quad y = g(T), \]

Dynamic System of Equations

Sensed Temperature

For each control volume, \( i \)

\[ m_i(T) \dot{T}_i = Q_i^r(T) + Q_i^c(T) + Q_i^v(T) + b_i u, \]

Thermal mass

Radiation

Conduction

Convection

Electrical Power In
The heat loss from the plate to the surroundings

\[ q_s = \varepsilon \sigma (T_s^4 - T_\infty^4) + h(T_s - T_\infty), \]

Effective emissivity \( \varepsilon \)
Effective heat transfer coefficient \( h \)

Effective emissivity for infinite parallel surfaces

\[ \varepsilon = \frac{1}{\frac{1}{\varepsilon_1} + \frac{1}{\varepsilon_2} - 1}. \]

Surface 1 \( \varepsilon_1 \)
Surface 2 \( \varepsilon_2 \)

We will look at control performance when these two parameters (\( \varepsilon \) and \( h \)) vary.
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Process Variations and Robust Control

- Plate emissivity can change in ways that are difficult to predict.
- Changes in gas flows or gas chemistry can change the heat losses.
- Changes can be “wafer-to-wafer” or during processing (dynamic).
- If you knew how the losses changed, you could tune the controller for a specific process condition.
- But often you cannot know about changes so the controller must be robust.
- Robustness here is defined as good performance for a wide range of process conditions.
The feedback controller is assumed to have no prior knowledge of these variations in the plant.

\[ q_s = \epsilon \sigma (T_s^4 - T_\infty^4) + h(T_s - T_\infty), \]

System Variations:

\[ 0.2 \leq \epsilon \leq 0.8 \]
\[ 5 \leq h \leq 100 \]
Dynamic System Variation

System Variations

\[ 0.2 \leq \epsilon \leq 0.8 \]
\[ 5 \leq h \leq 100 \]

Delay Time

First Order with Time Delay (FOTD) parameters for all systems

First order lag time

DC Gain

System is inherently faster with smaller DC gain at higher temperature due to non-linear radiant cooling.
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Gain-Scheduled PID Control

\[ C(s) = K_p + \frac{K_i}{s} + \frac{K_d s}{\tau_d s + 1}, \]

By trial-and-error we chose the gain values when $h=20\text{W/m}^2\text{K}$, $\varepsilon=0.2$

Simulated 2 C/s, 50 C ramp, $200 < T < 1150$ C

Performance measures:

- **Settling time**
  - *Time from end of ramp until sensor stays within 0.5 C*

- **Overshoot**
  - *How much response exceeds the reference in percent*

- **Repeatability**
  - *Range of settling times*

- **Noise accommodation**
  - *Effect of noise on control command*
Incorporate a mathematical model of the system directly into the controller.

Often referred to as Q-parameterization or Youla parameterization.

\[ C(s) = \frac{Q(s)}{1 - \hat{P}(s)Q(s)} \]

For stable \( P \), ALL stable controllers can be expressed in this form!

Control design becomes choice of \( Q \)

We choose \( Q \) such that the closed-loop transfer function is

\[ T_d(s) = \frac{\omega_d^2}{s^2 + 2\beta_d\omega_d s + \omega_d^2} \]

References for Q-parameterization Control Design

MBC Control – Performance

- Bandwidth of $T_d$ is only ‘tuning knob’:

$$T_d(s) = \frac{\omega_d^2}{s^2 + 2\beta_d\omega_ds + \omega_d^2}$$

The model used in the controller is not told how the model in the simulation is varying

Performance:

- Settling time
  - Fast settling: 10 to 25 sec.
- Overshoot
  - Very small: 0.05 to 0.15%
- Repeatability
  - Tight range in settling time & overshoot
- Noise accommodation
  - More sensitive to noise than PID
Performance Comparison: Settling Time

Settling time [sec]

Target temperature [°C]
Performance Comparison: Overshoot

![Graph showing Performance Comparison: Overshoot]
Performance Comparison: Noise Accommodation

![Graph showing performance comparison for noise accommodation between PID, LQG, and MBC methods. The graph plots noise reduction against target temperature.]
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Monte Carlo Simulation Method

- The term “Monte Carlo” is used to refer to a wide range of stochastic techniques meaning that they rely on random numbers and probability statistics to tackle problems.

- The term is coined after the casinos in the Principality of Monaco. Every game in a casino is a game of chance relying on random events: shuffling of cards, numbers on the dice, roulette wheel, etc.

- It is used in a variety of problems ranging from economics, communications, nuclear physics, and in control theory.

- Allows analysis of complex systems that are otherwise intractable analytically.
Monte Carlo Simulation Method

- Monte Carlo simulations are used to evaluate the performance robustness with respect to physical parameter variations when analytical approaches are difficult or not possible.

- The ranges of parameter variations (e.g. emissivity and heat transfer coefficient) are usually known.

- It is possible to map out the performance space with random selection of parameters within the allowable range and with given distributions using a pre-selected number of simulations.

- The advantage of this approach is that one can map out the performance space without simulating each parameter variation individually, which could take up considerably more simulations (e.g. 10 parameters using 5 values per parameter would require 9.76 million simulations, compared to for example 100 or 1000 Monte Carlo simulations where the parameters are varied randomly).
Each run of the Monte Carlo will produce different results depending on the seed.
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Heat transfer coefficient $h$:
Uniform distribution between 5 & 100

Emissivity $e$:
Normal distribution, mean=0.5, $\sigma=0.15$
Monte Carlo Results: PID Settling Time

\[ 5 \leq h \leq 100 \]

\[ 0.2 \leq \epsilon \leq 0.8 \]

Settling Time
Monte Carlo Results: MBC Settling Time

\[ 5 \leq h \leq 100 \]

\[ 0.2 \leq \epsilon \leq 0.8 \]

Settling Time
Comparison of Overshoot from Monte Carlo Simulations

![Graph showing comparison of overshoot from Monte Carlo simulations. The graph plots overshoot (%) against target temperature (°C). Different lines represent PID (original), PID (Monte Carlo), MBC (original), and MBC (Monte Carlo).]
Comparison of Settling Time from Monte Carlo Simulations

![Graph showing comparison of settling times for different control methods (PID and MBC) across various target temperatures. The graph indicates that MBC (Monte Carlo) has a faster settling time compared to PID (original) and MBC (original) across the range of target temperatures.]
Comparison of Noise Reduction from Monte Carlo Simulations

![Graph showing comparison of noise reduction from Monte Carlo simulations. The graph plots noise reduction against target temperature. The lines represent different controllers: PID (original), PID (Monte Carlo), MBC (original), and MBC (Monte Carlo).]
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Summary
In previous work, simulations were performed to compare the robustness & performance of different control methods for temperature control of plates.

The methods were compared with respect to:

- worst-case settling time,
- overshoot,
- robustness (repeatability),
- noise accommodation.

Performance bounds were calculated by ‘gridding’ the parameter space, which requires a large number of simulations.

In this work, robustness of the various controllers is evaluated using Monte Carlo Simulations, which requires a significantly smaller number of simulations.

The Monte Carlo simulation results compare well with the analytical gridding approach, and help to quickly identify trends and problem areas.

In addition, the Monte Carlo approach allows the user to be more specific about parameter variations by characterizing the random distribution.

These results were applied to real-time feedback control, but apply to other areas of AEC/APC as well, such as Fault Detection, Virtual Sensing, etc.