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

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Problem Overview/Motivation

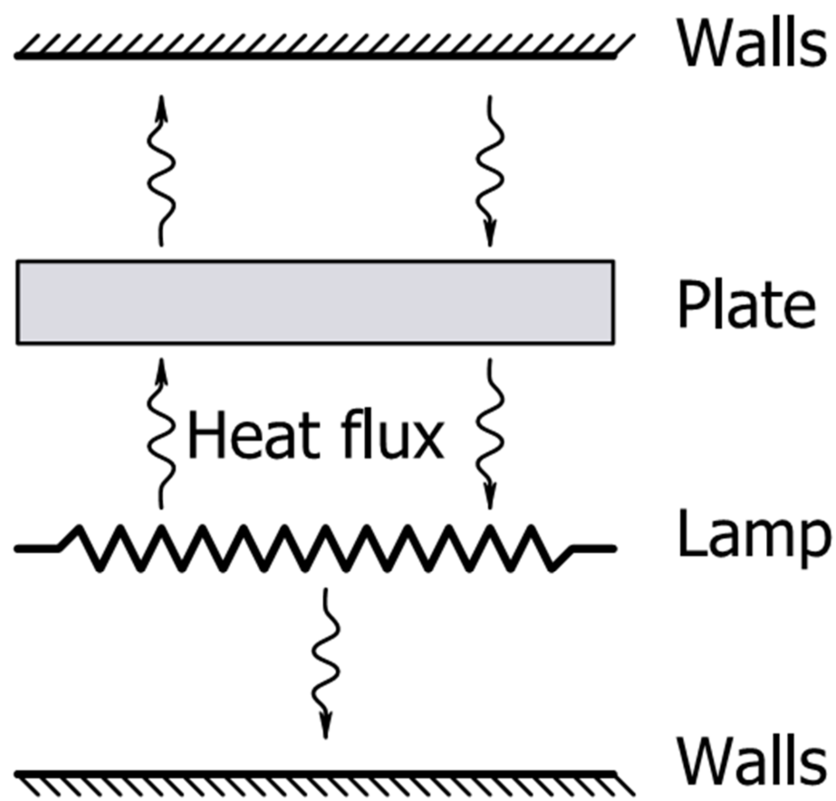
- Temperature control is important in many thermal processing systems
  - *The dynamic response of the system can change considerably depending on operating temperature, wafer types, and/or process conditions*
  - *Ideally one would like to get the exact same closed-loop temperature response (performance) 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:



$$\dot{T} = f(T, u),$$
Dynamic System of Equations

$$y = g(T),$$
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

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

Effective emissivity (ϵ) | Effective heat transfer coefficient (h)

Effective emissivity for infinite parallel surfaces

$$\epsilon = \frac{1}{\frac{1}{\epsilon_1} + \frac{1}{\epsilon_2} - 1}.$$

Surface 1 (ϵ_1) | Surface 2 (ϵ_2)

We will look at control performance when these two parameters (ε and *h*) vary.

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- ❑ **Process Variations and Robust Control**
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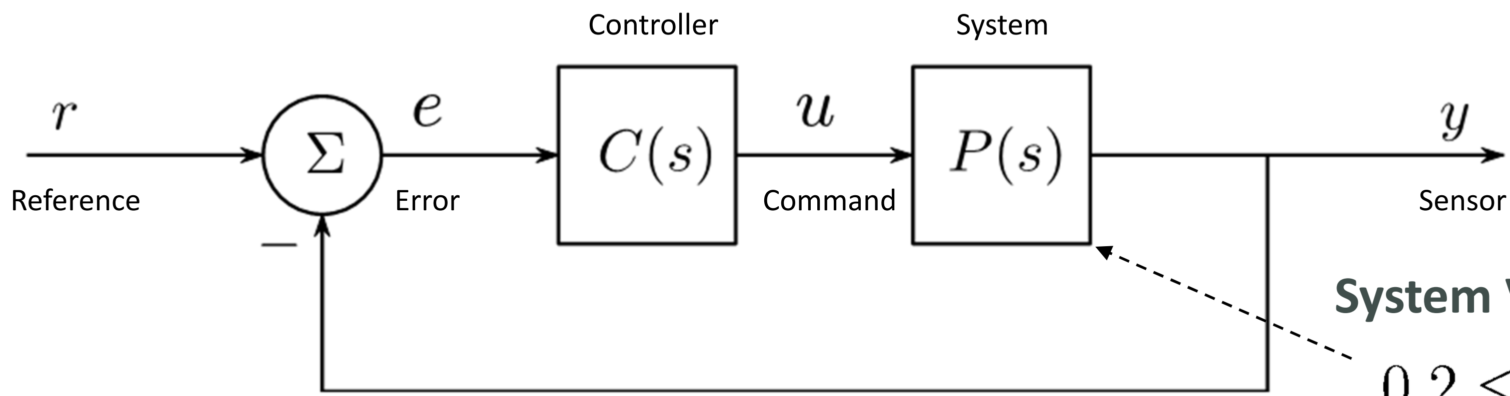
Process Variations and Robust Control

- 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



System Variations:

$$0.2 \le \epsilon \le 0.8$$
$$5 \le h \le 100$$

Heat loss from plate to surroundings:

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

Effective emissivity (ϵ)

Effective heat transfer coefficient (h)

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System Variations

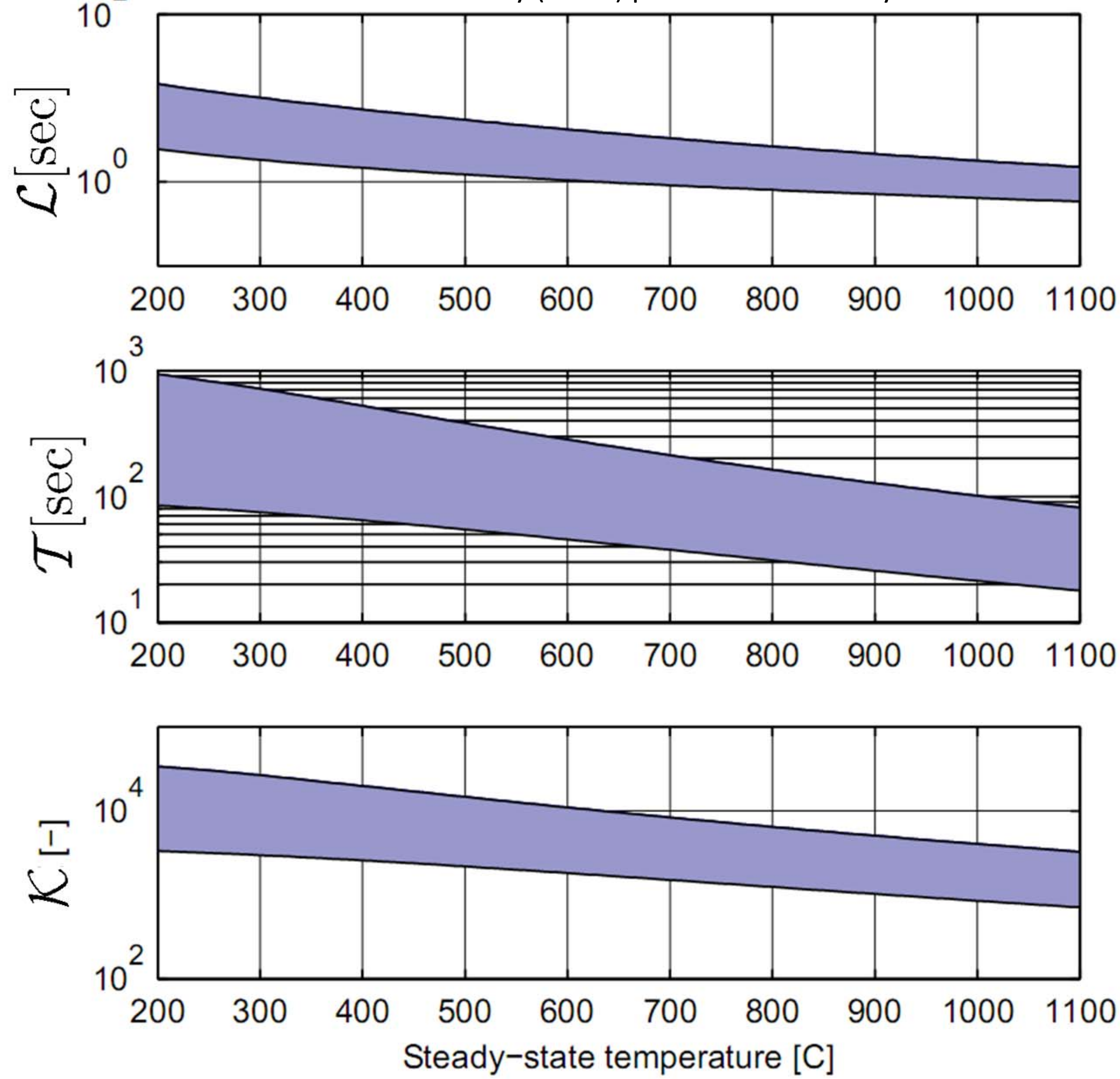
$$0.2 \le \epsilon \le 0.8$$
$$5 \le h \le 100$$

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

Delay Time

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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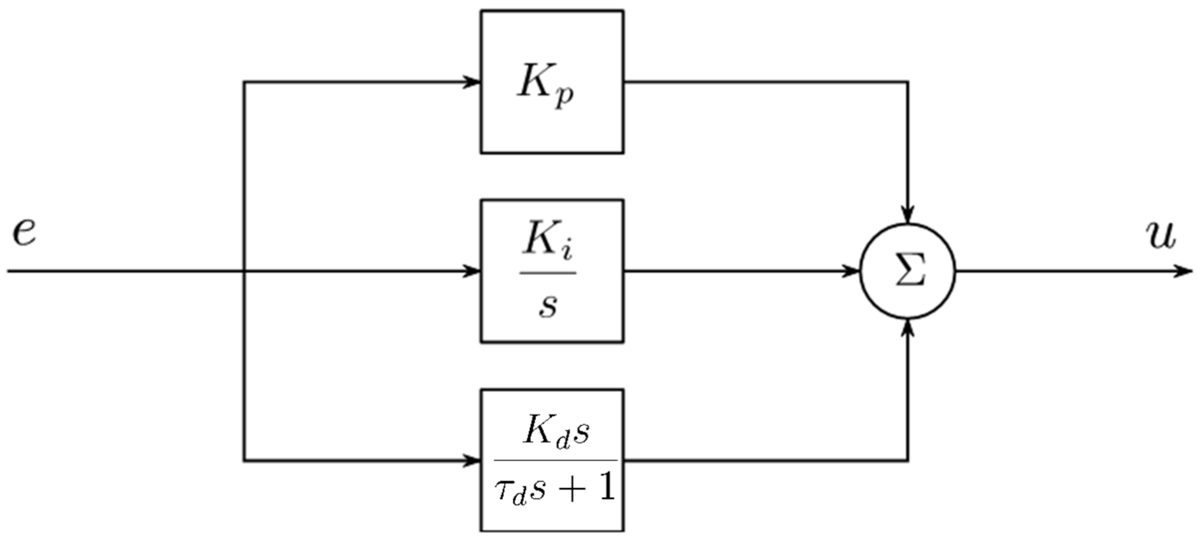
Gain-Scheduled PID Control

Proportional Gain — Integral Gain — Derivative Gain

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



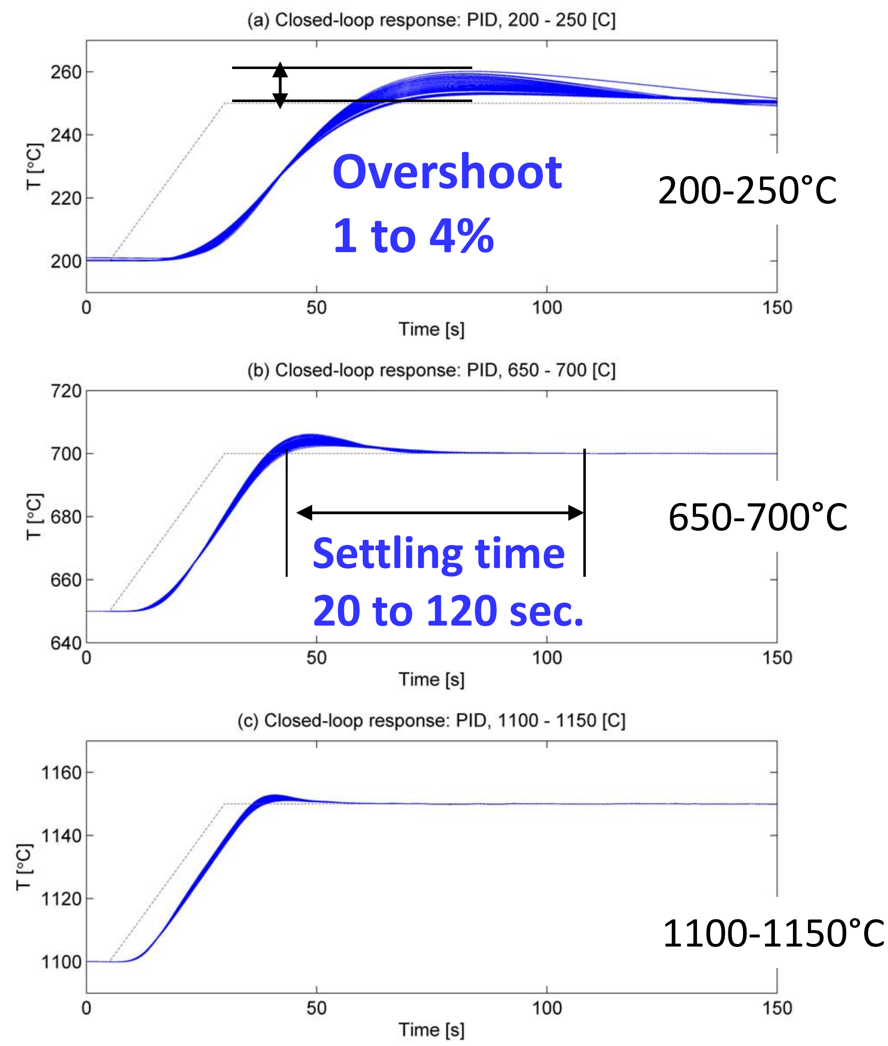
G. F. Franklin, J. D. Powell, and A. Emami-Naeini, *Feedback Control of Dynamic Systems*, 6th ed. Prentice-Hall, 2010.

PID Control – Performance

- By trial-and-error we chose the gain values when h=20W/m^{2}K, ε=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*



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- 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

[10] D. C. Youla, J. J. Bongiorno Jr., and C. N. Lu, "Single-loop feedback-stabilization of linear multivariable dynamical plants," *Automatica*, vol. 10, no. 2, pp. 159 – 173, 1974.
[11] M. Morari and E. Zafiriou, *Robust Process Control*, 6th ed. Prentice-Hall, 1989.
[12] S. P. Boyd and C. H. Barratt, *Linear Controller Design: Limits of Performance*. Prenctic Hall, 1991.
[13] J. C. Doyle, B. F. Francis, and A. R. Tannenbaum, *Feedback Control Theory*. Macmillan Publishing Company, 1992.
[14] P. Dorato, *Analytic Feedback System Design: An Interpolation Approach*. Macmillan Publishing Company, 1994.

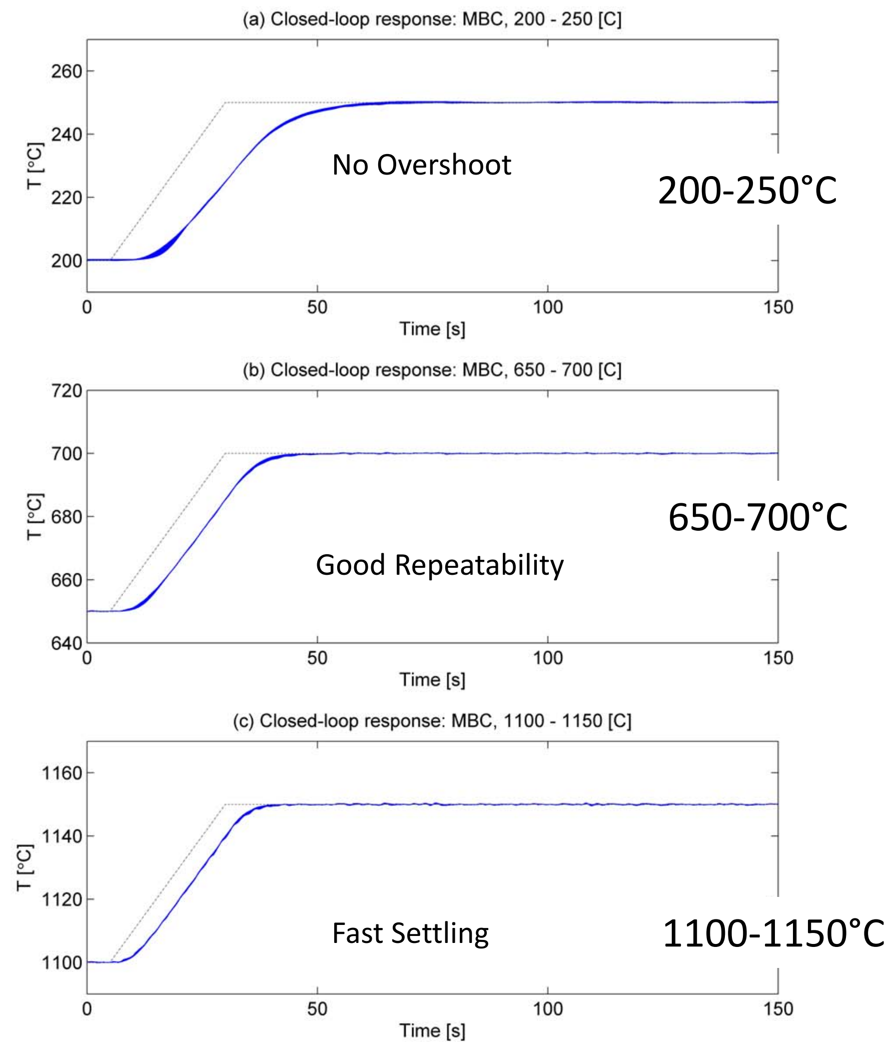
- Bandwidth of *Td* is only 'tuning knob':

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

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*



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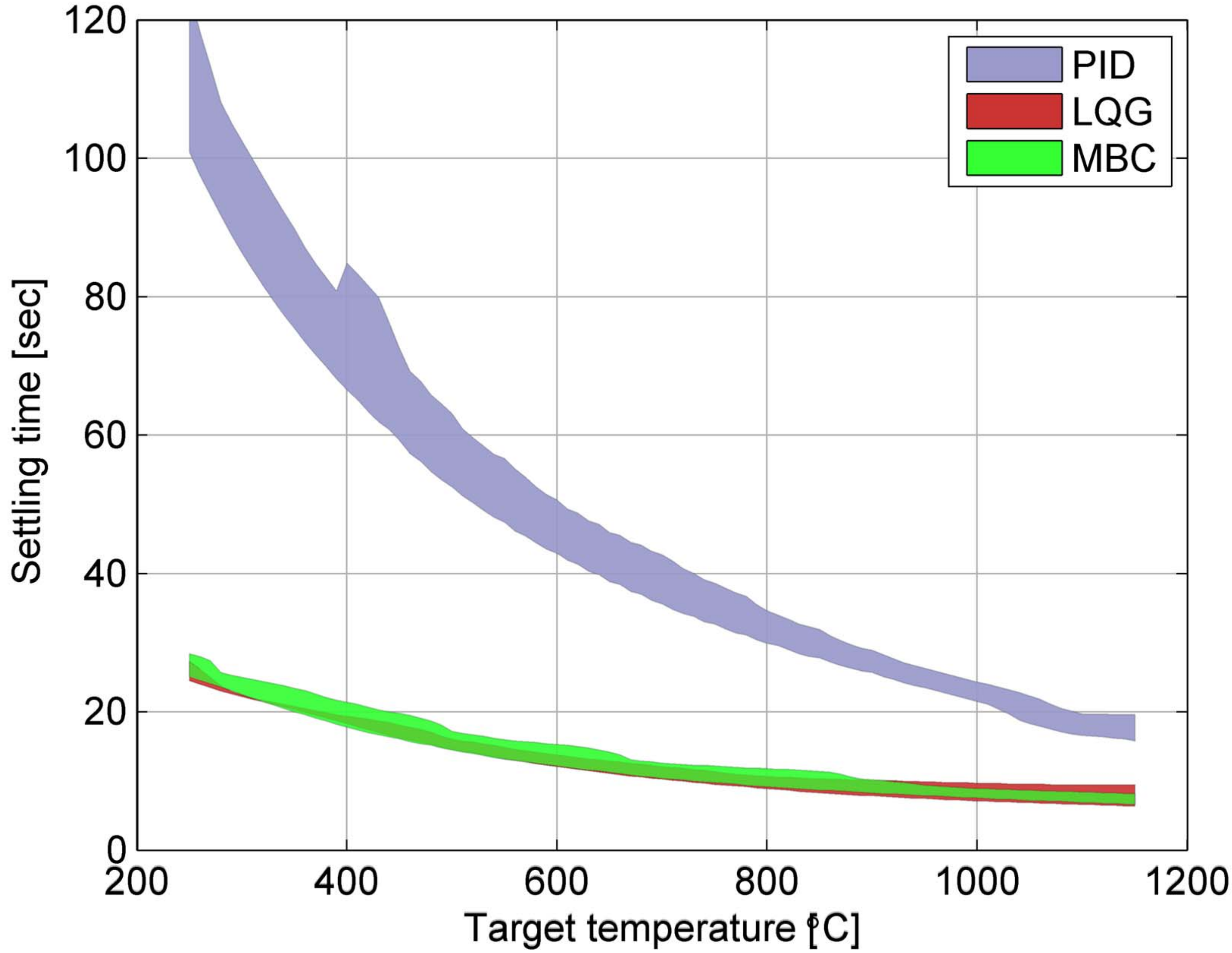
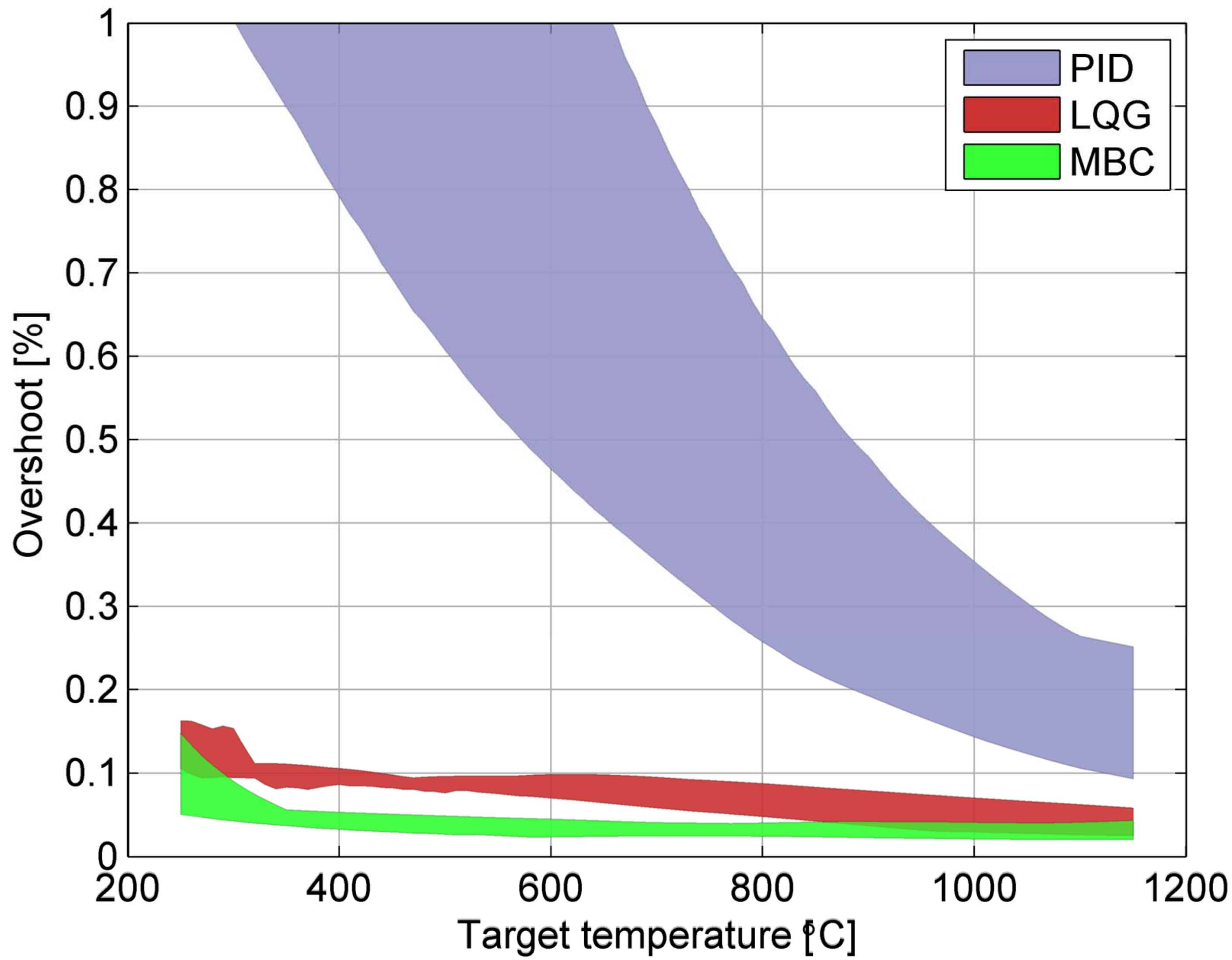
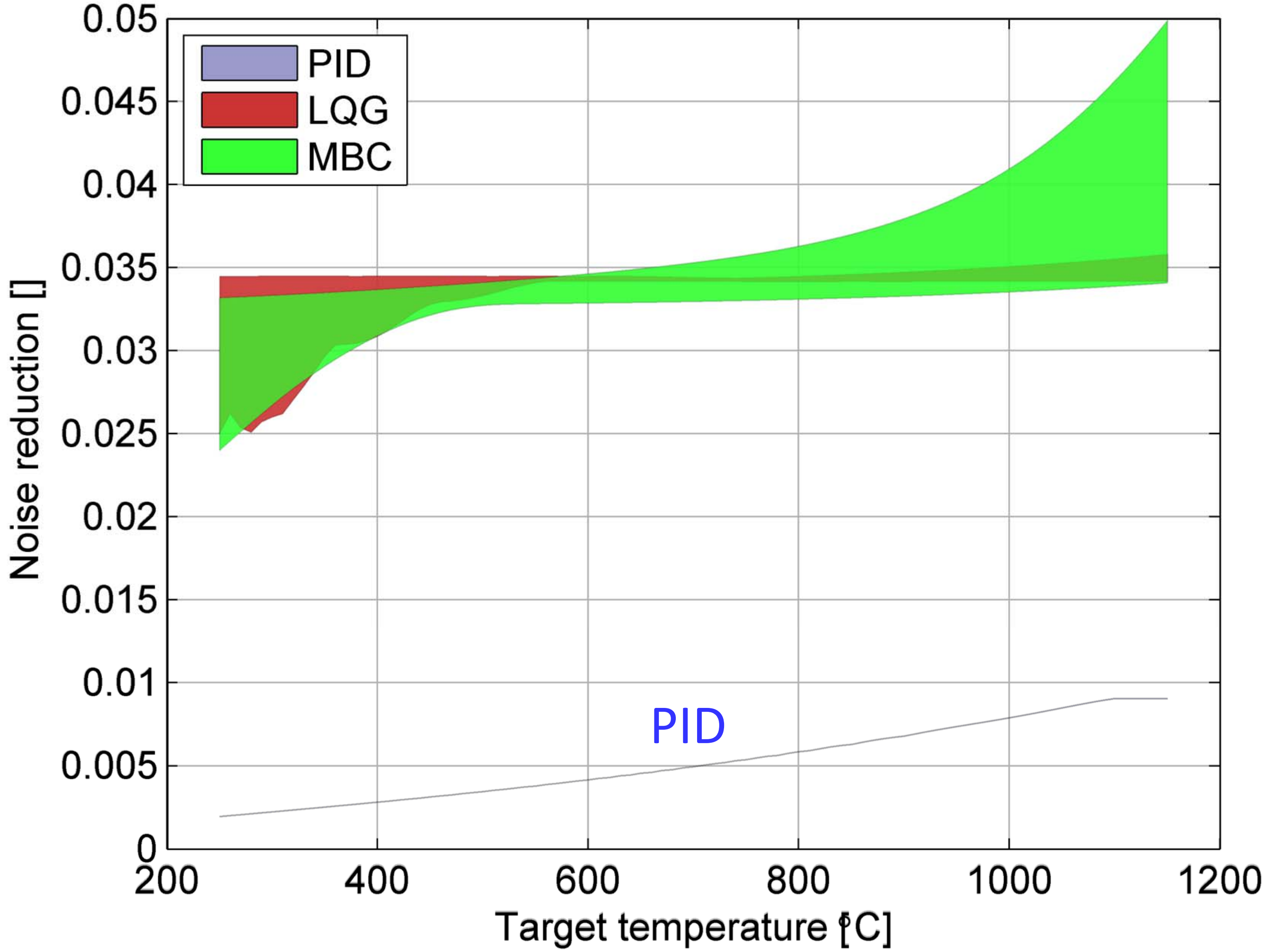
Performance Comparison: Settling Time



Performance Comparison: Overshoot



Performance Comparison: Noise Accommodation



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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

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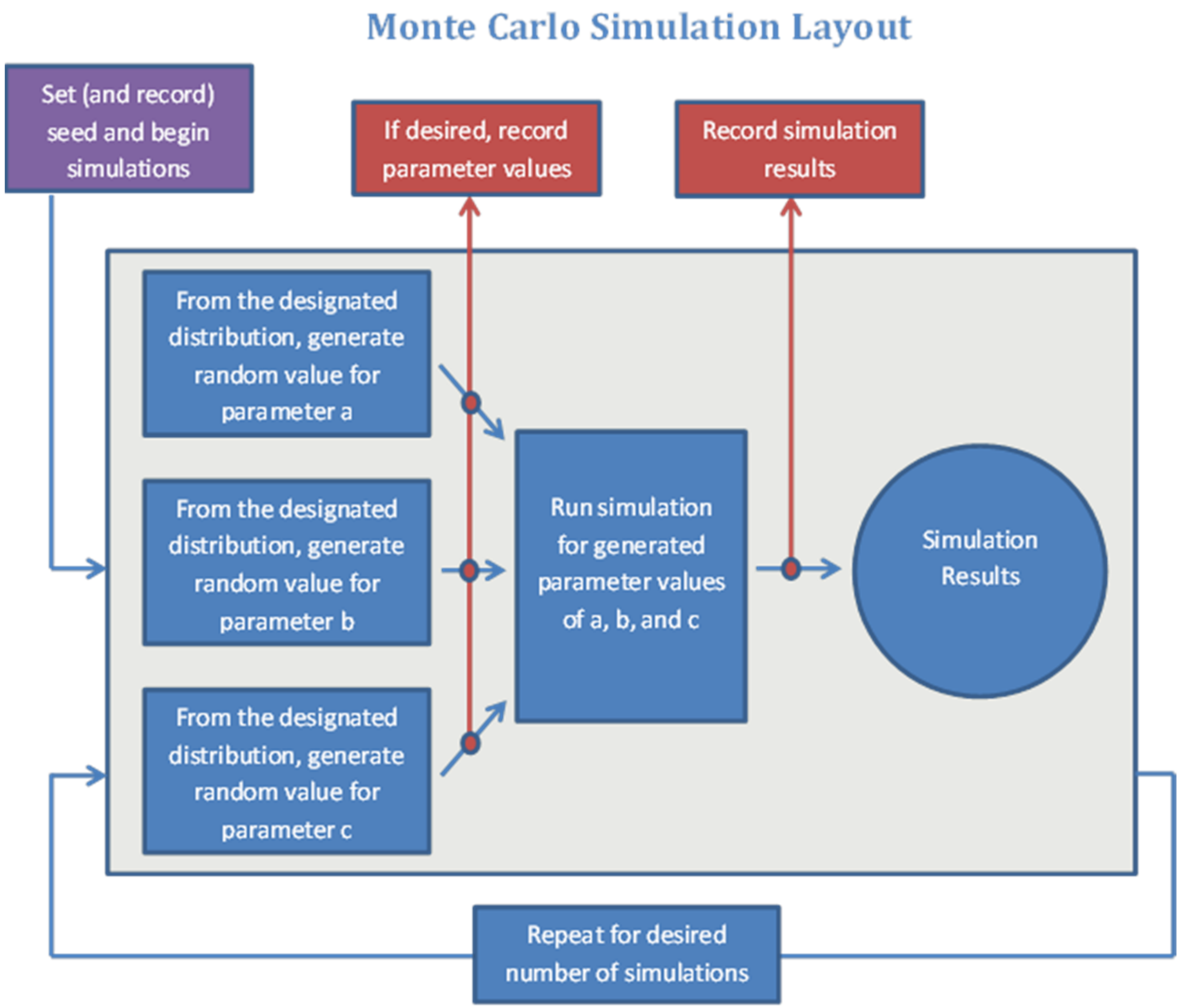
Monte Carlo Simulation Method

- 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)*

Monte Carlo Simulation Process



Each run of the Monte Carlo will produce different results depending on the seed.

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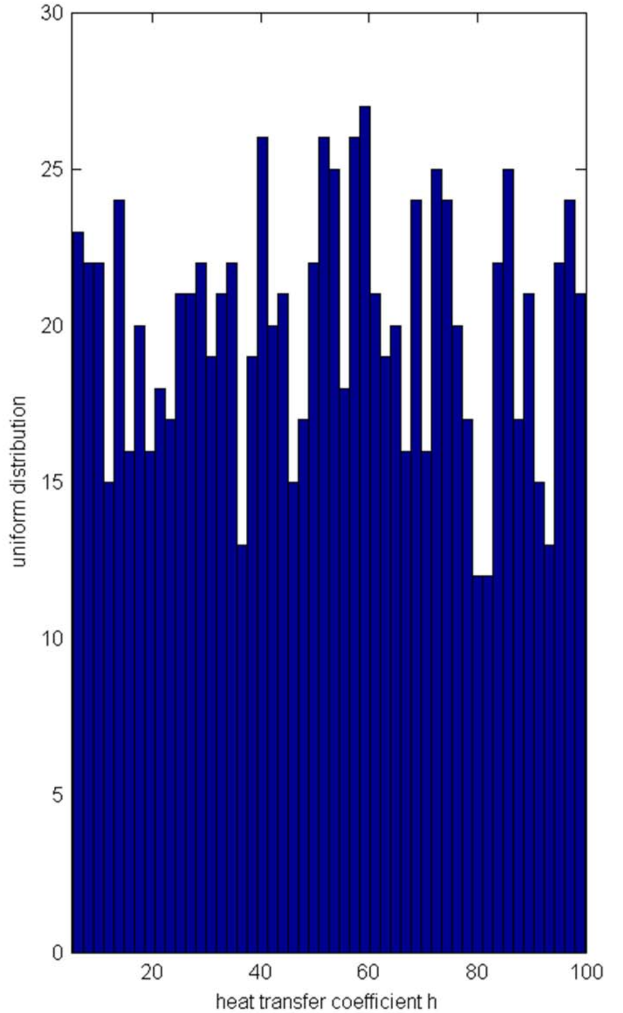
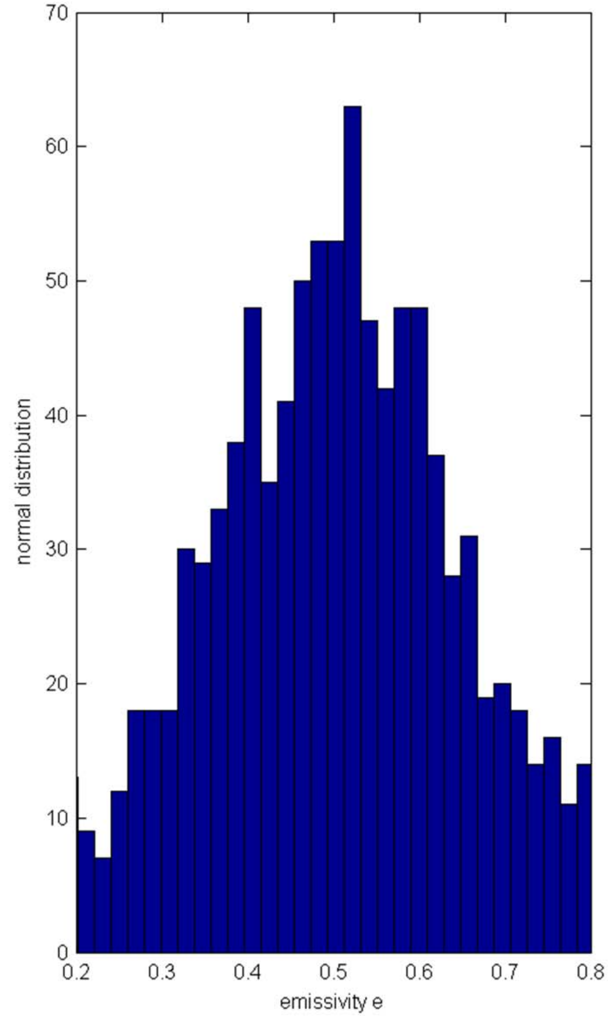
Parameter Distributions

Heat transfer coefficient *h*:
Uniform distribution between 5 & 100



Emissivity *e*:
Normal distribution, mean=0.5, σ=0.15

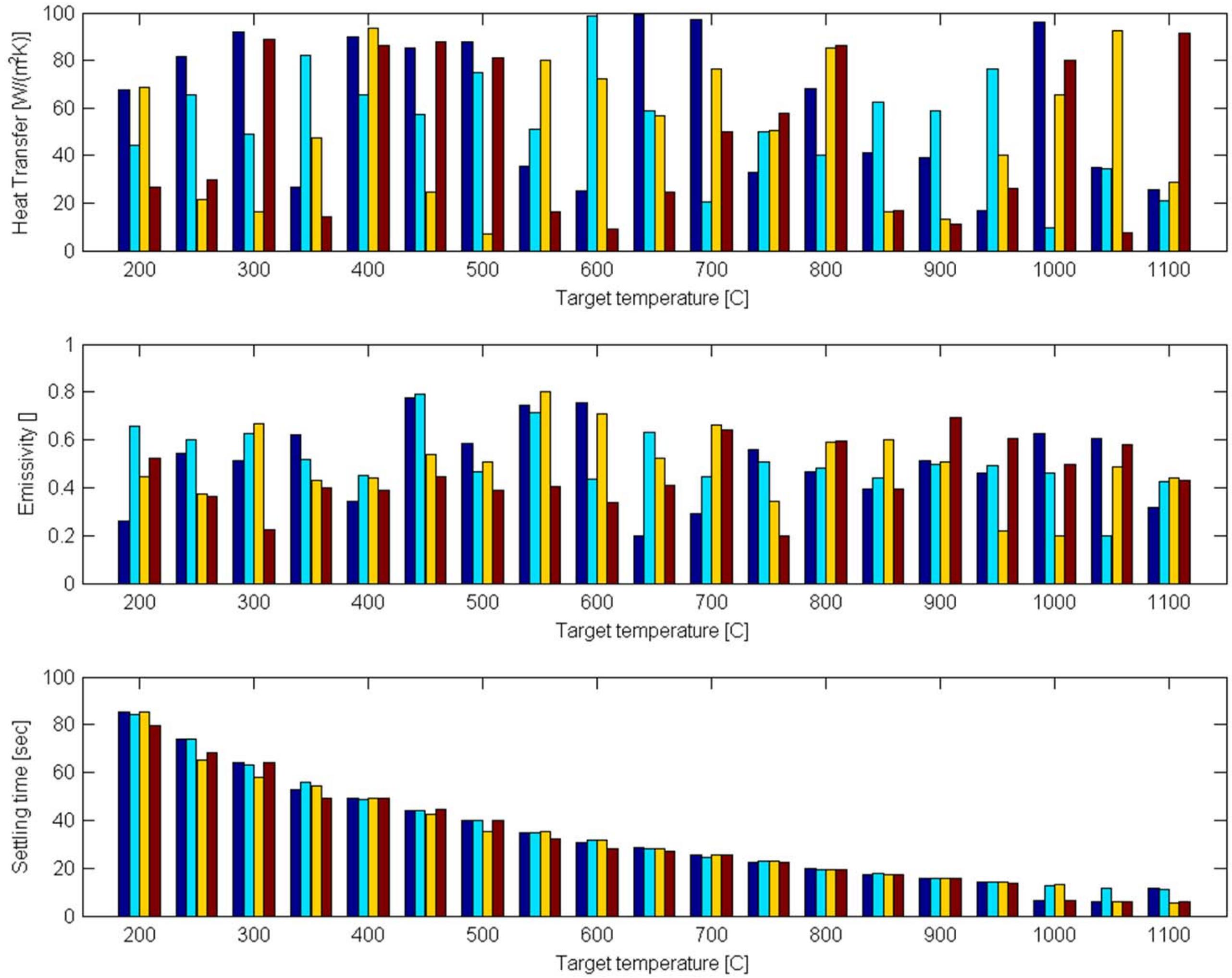


Monte Carlo Results: PID Settling Time

$5 \leq h \leq 100$

$0.2 \leq \epsilon \leq 0.8$

Settling Time



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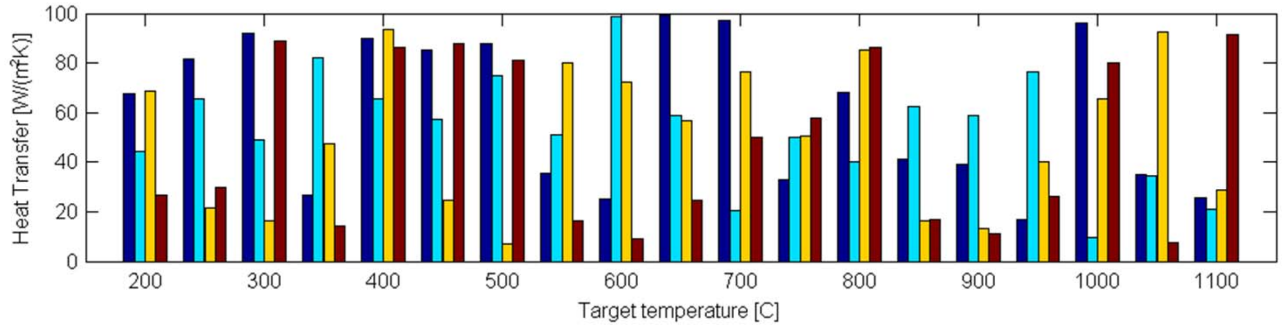
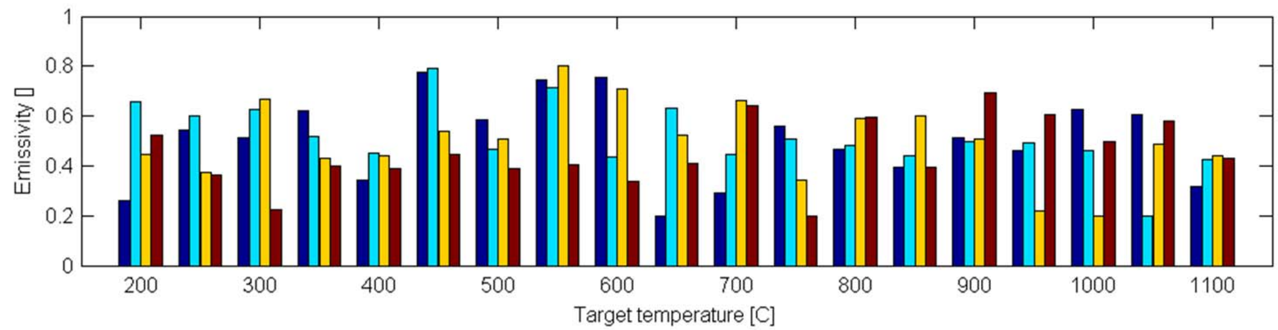
Monte Carlo Results: MBC Settling Time

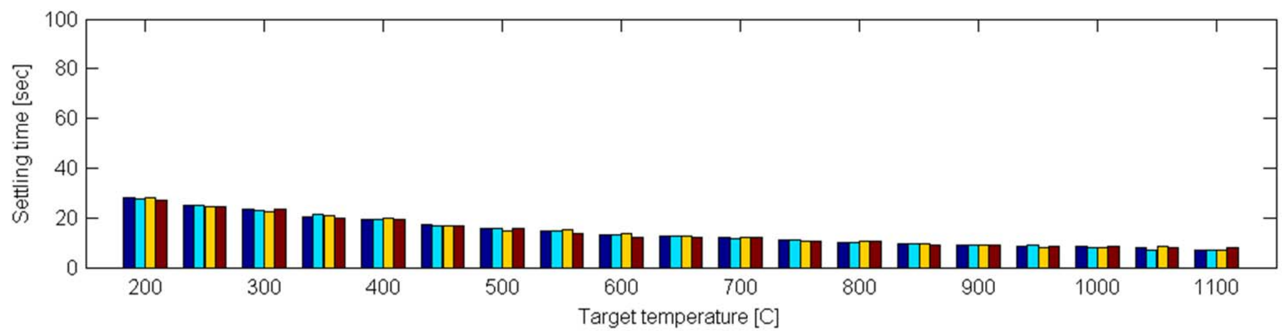
$$5 \leq h \leq 100$$



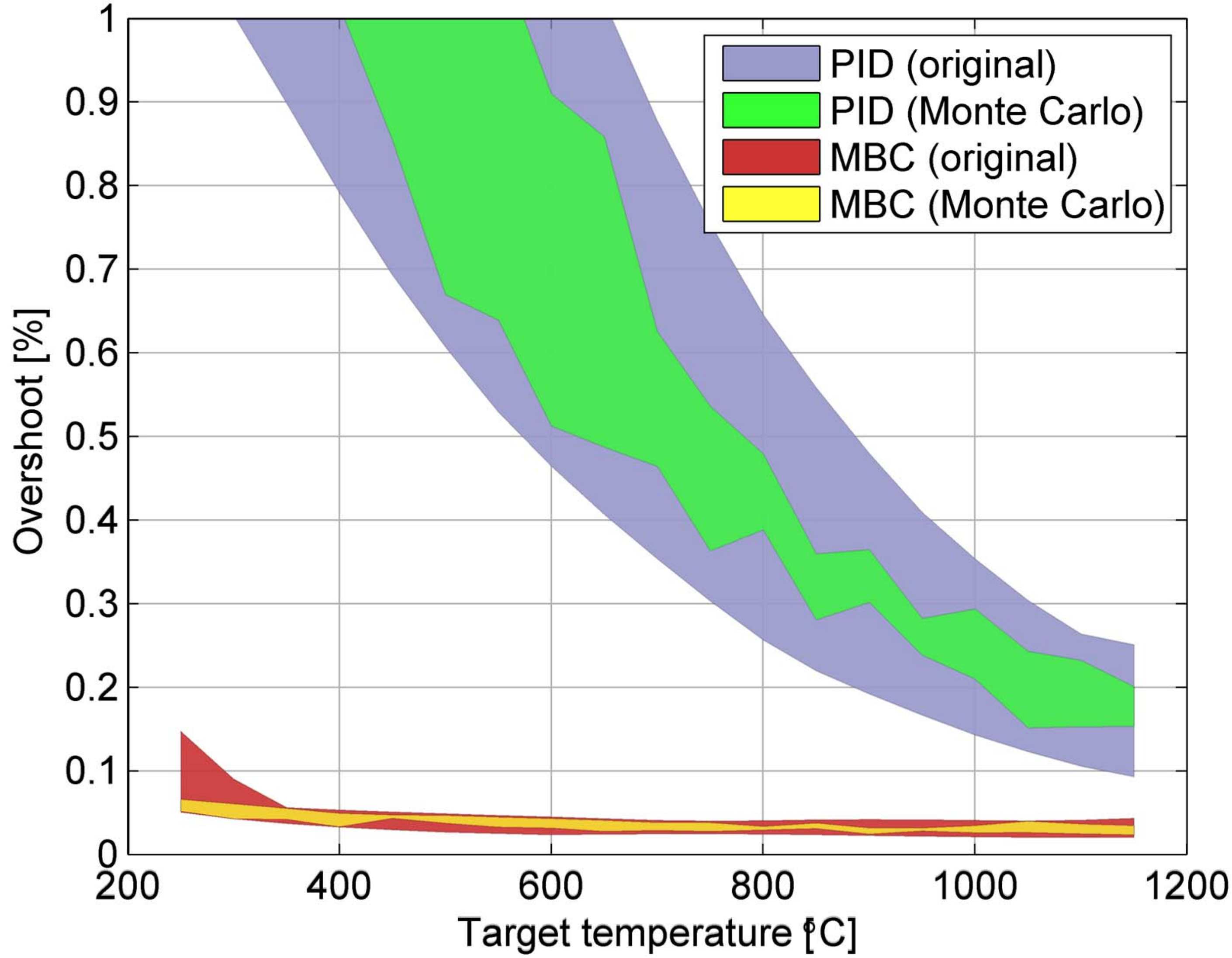
$$0.2 \leq \epsilon \leq 0.8$$



Settling Time



Comparison of Overshoot from Monte Carlo Simulations



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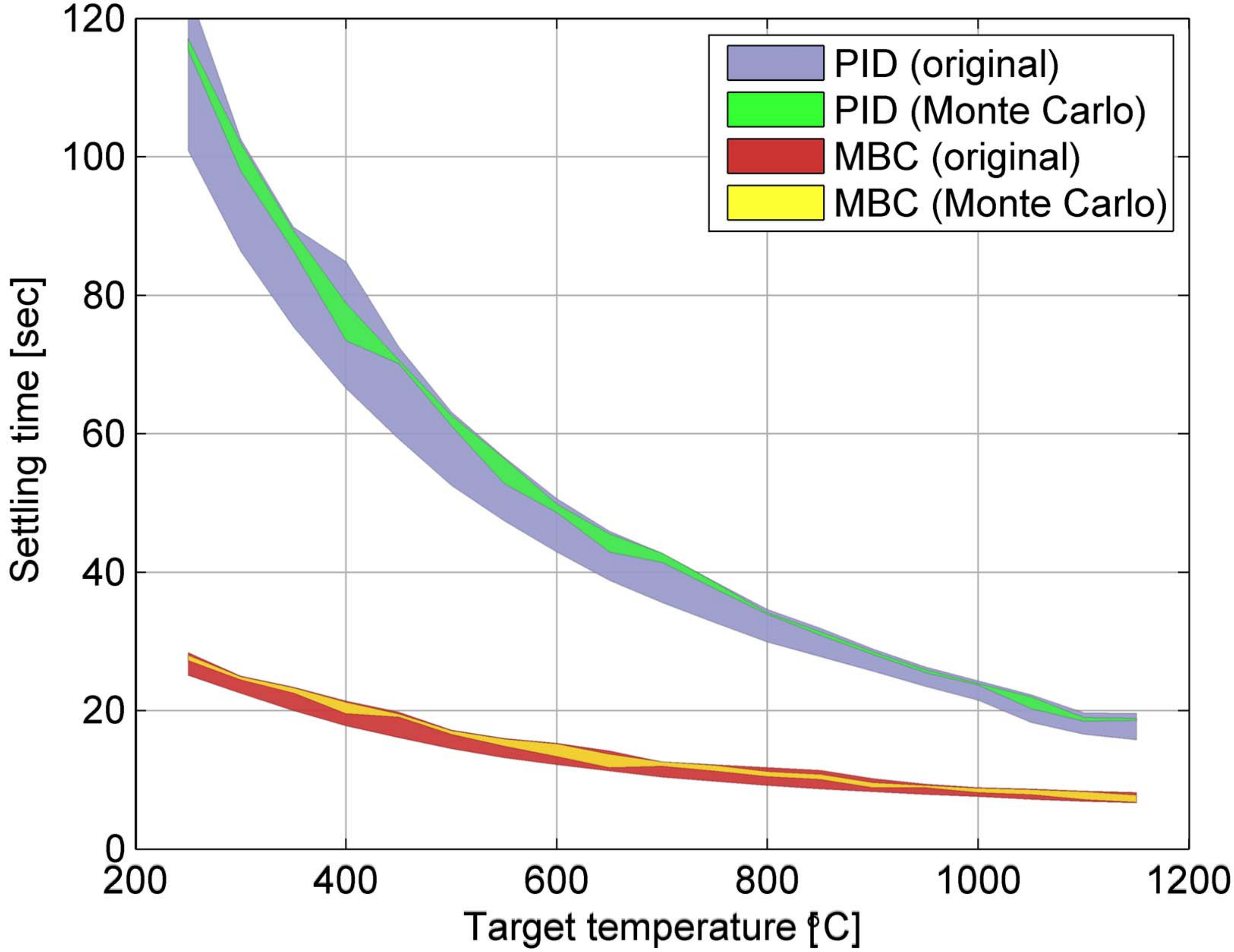
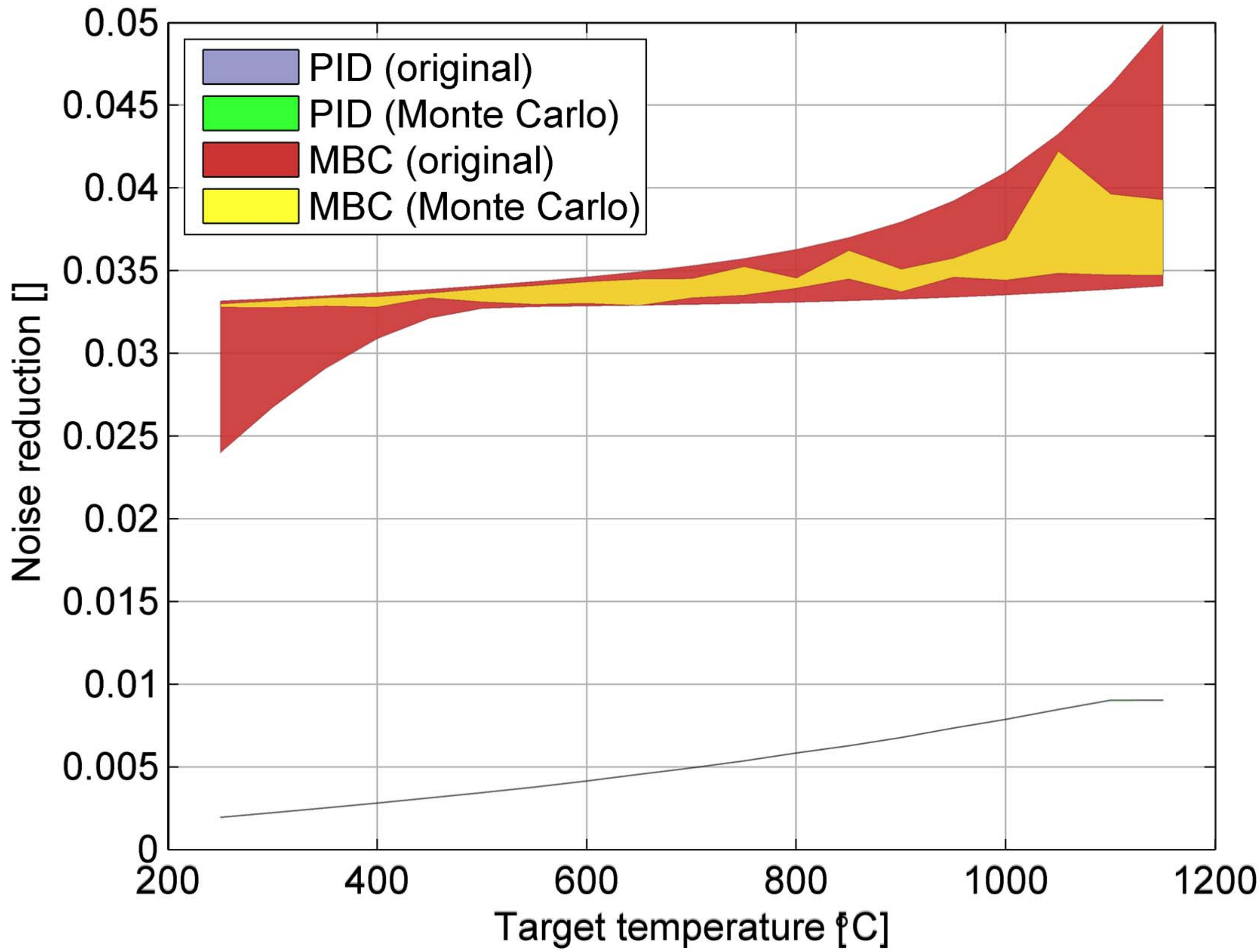
Comparison of Settling Time from Monte Carlo Simulations



Comparison of Noise Reduction from Monte Carlo Simulations



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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.**