Recent Progress on "Holistic" Control for Reactor Systems

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ASI Workshop on Advanced Reactors and the Need for Advanced Controls Argonne National Laboratory, July 12th, 2023







Outline

- Background and Problem Description
- Overview of Some Control Algorithms
- Case Studies
 - Economic Optimization of Flexible Power Operation
 - System Health Aware Control Methods
- Summary





Background





Context of this Work

- This work was performed under DOE's NEUP program under contract DE-NE0008975
- In collaboration with
 - Prof. Ben Lindley at UWisc and his staff and students Saeed Alhadrami, Una Baker, and Gabriel Soto; and
 - Prof. Jamie Coble at UTK and her students David Anderson, Matthew Scott, Richard Bisson
 - And Vivek Agarwhal (INL) and Ross Snuggerud (NuScale)
- Project Title: "Innovative Enhanced Automation Control Strategies for Multi-Unit SMRs"

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Problem Statement and Objectives

Objective of our Project

- Investigate methods for
 - Supervisory control for flexible power operation
 - "Tactical" control that integrates prognostics and health management into the control problem
 - "Strategic" control of multiple units at a single site.

Objective of this Workshop

- Discuss the problems, challenges, needs, and state of progress for
- "increased automation for realtime performance optimization and greater efficiency of operation and maintenance activities beyond traditional base load nuclear power."



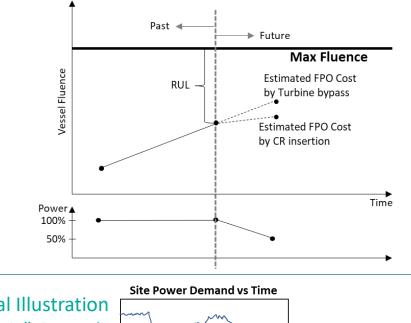
Problem Statement as Questions

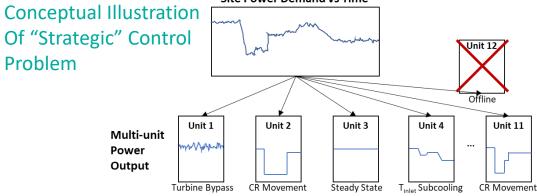
- How should I operate my reactor daily to maximize revenue?
- Subject to the constraints of

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- I need to make my outage window
- I do not want to "wear out" any components in my plant before my scheduled outage
- In addition there are the usual expected constraints related to operating envelope, regulatory requirements, environmental conditions

Conceptual Illustration of "Tactical" Control Problem









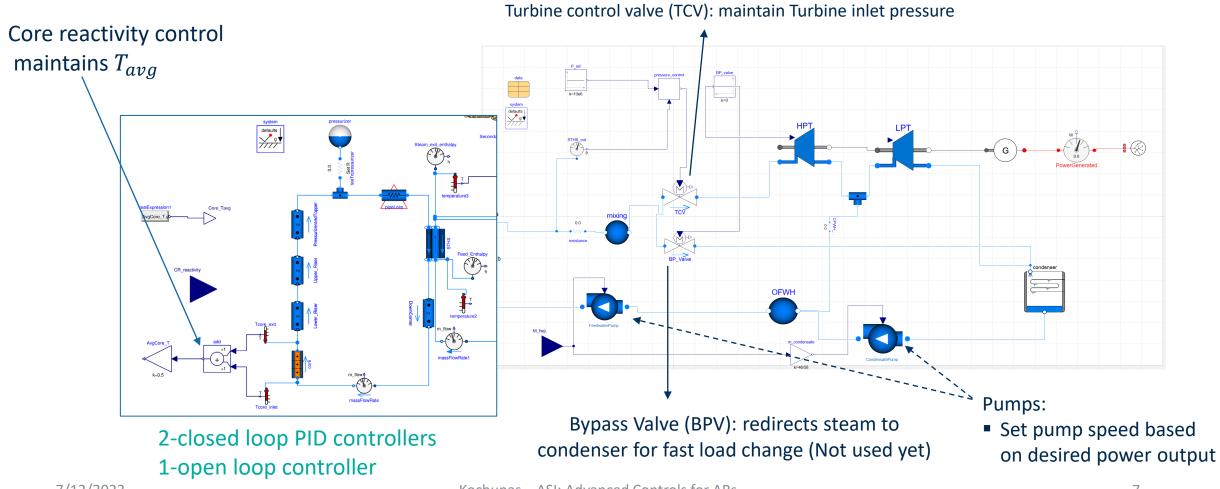
Overview of Some Control Algorithms

This relates to supervisory control





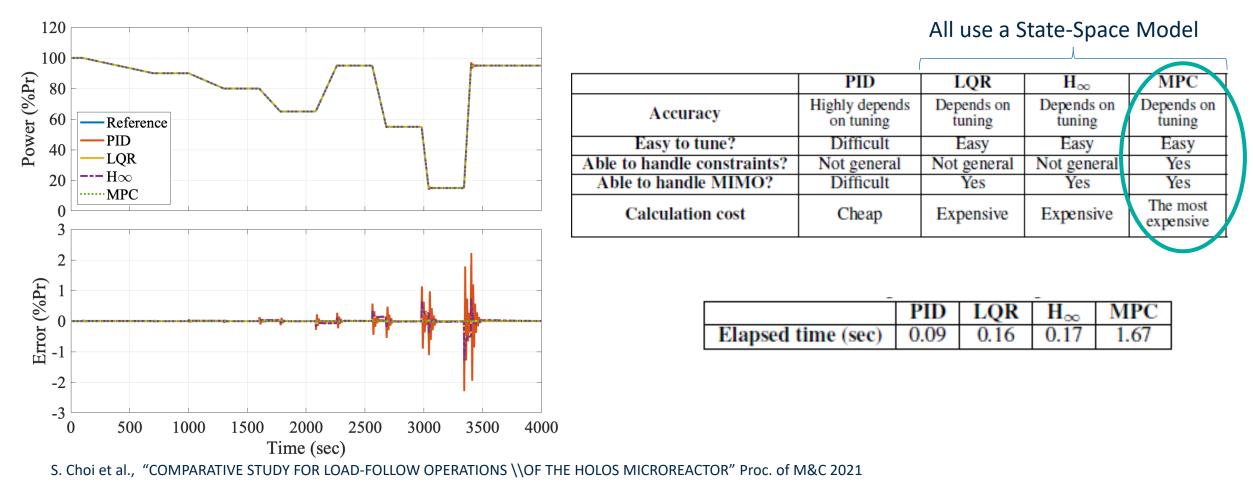
Load Follow Control for Simplified SMR Plant







Comparison of Control Algorithms







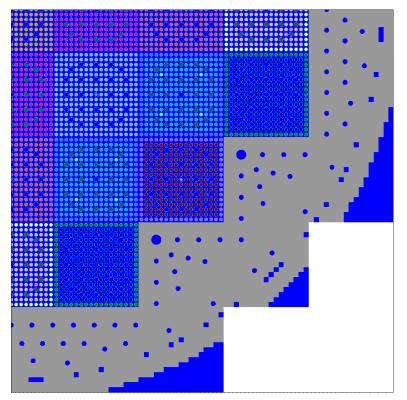
Supervisory Control with Model Predictive Control

Concept of Model Predictive Control PAST FUTURE **Reference/Command Governors Reference Trajectory Predicted Output** Constraints I MPC Measured Output Set point Predicted Control Input Past Control Input Reference State Observer Governor Estimated (Kalman Filter) State Modified **Prediction Horizon** Reference error Process **PID Controller Plant Process** Sensor Variable Control Sample Time (PV) k+1 k+2 k+p Action Measured PV For each Prediction Horizon solve **Closed-Loop Controller** optimization problem to **Minimize Cost Function**

Cost Function = Tracking Error + Control Action + Smoothness (variation in control input)







Applications

1. How do I do supervisory control that's "health-aware"?

2. How do I maximize revenue?

NuScale-SMR





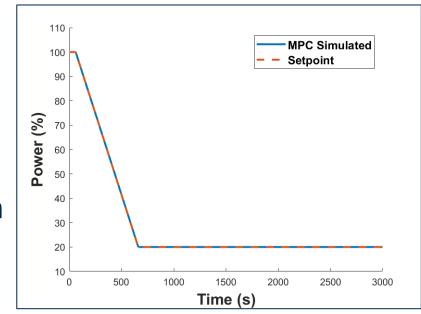
Health-aware MPC Description

 Basic Idea: Modify MPC cost function and statespace to have system/component "health" (remaining useful life)

> Cost Function = Tracking Error + Control Action + Smoothness (variation in control input) + Damage (decrement to RUL)

- Requires we be able to write a simple mathematical expression for damage accumulation
 - MPC cannot treat an arbitrarily large number of components explicitly
 - Need to reduce to some system-level remaining useful life (e.g. choose the limiting component for each prediction interval)

Power Maneuver



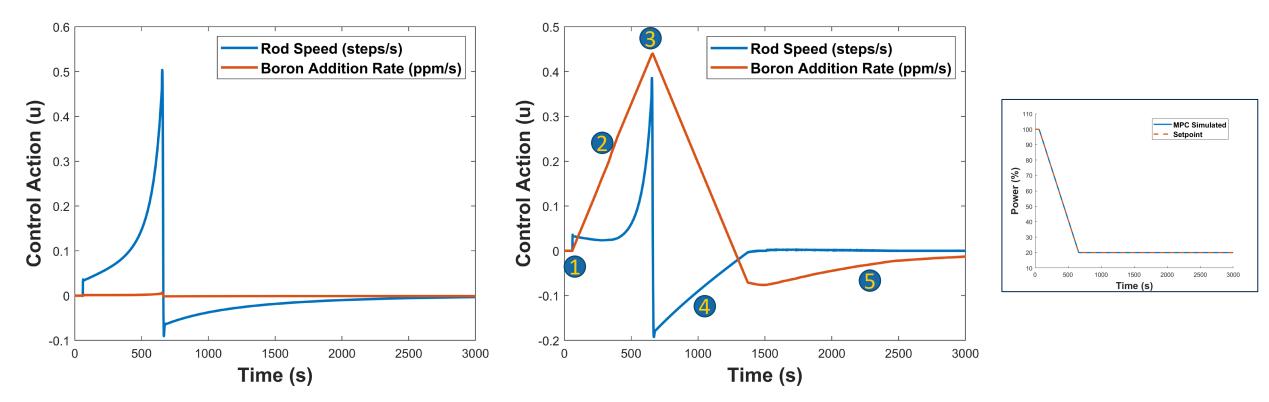
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Health-aware MPC Numerical Demonstration

Reactivity Control with No PHM Hypothetical PHM

(moving control rod is 200x worse than boron)



Basic Solution: Setup and solve a very complex optimization problem

 Cost of electricity Annual Average Throughout a day For Ancillary Services CAISO Daily Load Range with Average 2021

Strategic Control: Economic Optimization

Kochunas – ASI: Advanced Controls for ARs



- Spinning Reserves
- Regulation Up/Down

• De-regulated Market Revenues

- Etc.
- Two Dispatch Optimizations by Grid Operators
 - Day-ahead Market
 - Hourly Dispatch
 - Minimum Market Price is ~\$20/MWh

Alhadhrami, Soto, Lindley, "Dispatch Analysis of Flexible Power Operation with Multi-Unit SMRs" Recently published online in *Energy* https://doi.org/10.1016/j.energy.2023.128107

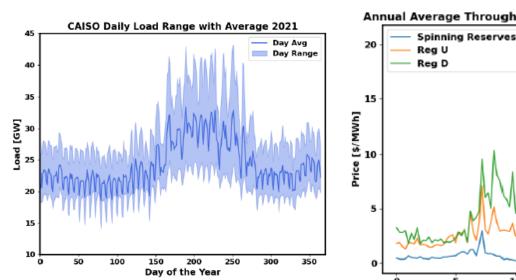


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Hour of the Day

15

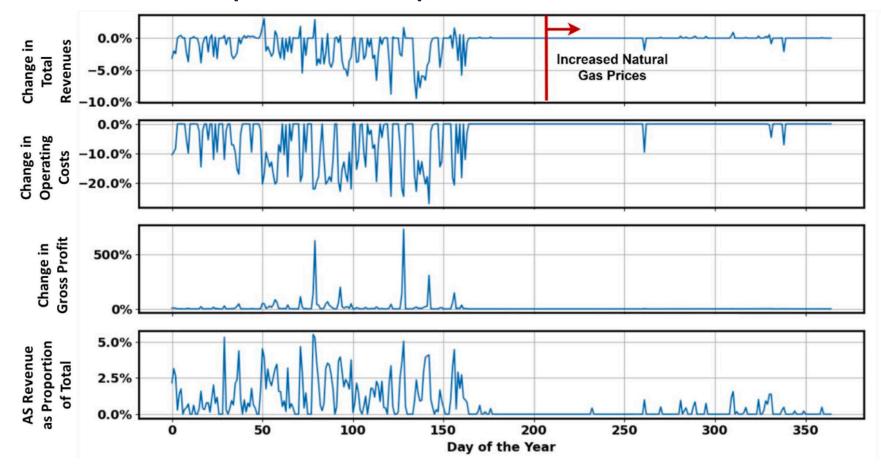
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Economic Dispatch Optimization Results

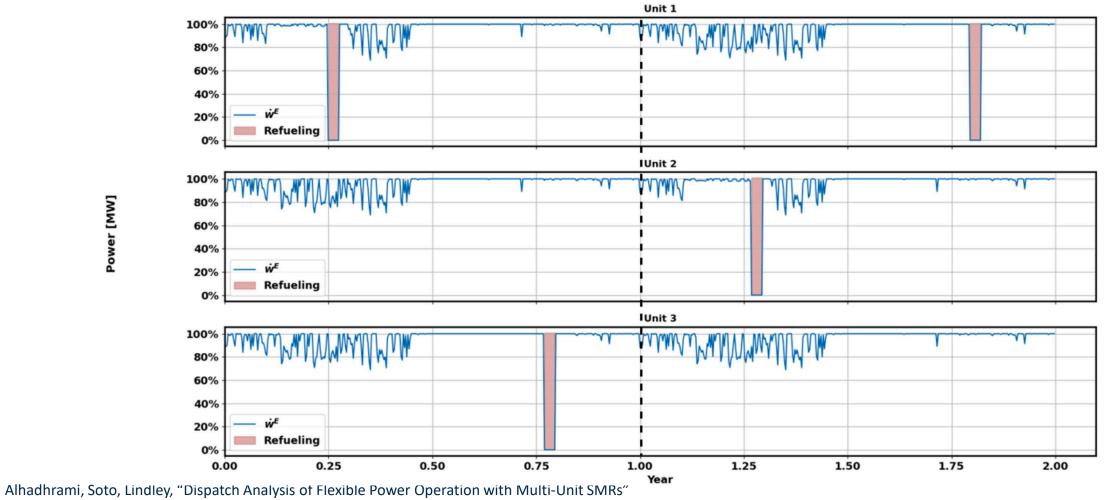


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Multi-Unit Site Optimization



Recently published online in Energy https://doi.org/10.1016/j.energy.2023.128107

Power [MW]





Summary





Summary and Future Work

- Some advancements
 - Demonstrated Model Predictive Control as supervisory control directly
 - Possibility to use as an "add-on" to PID system as a Command Governor
 - Demonstrated MPC can (rather easily) integrate prognostics for "health-aware" control
 - Studied Economic Optimization Problem for multi-unit SMR to see how much FPO can help revenues
 - We observed ancillary services do not provide significant revenue increases over baseload
- Some thoughts on Future work, needs, challenges
 - Integrate strategic/economic optimization with tactical control
 - Perform more realistic control problems
 - Consider more components or subsystems, more degradation modes for components, ncertainty in prognostics
 - Introduce noise
 - Evaluate robustness
 - Test as Command Governors
 - How good to prognostics models need to be?





Questions?





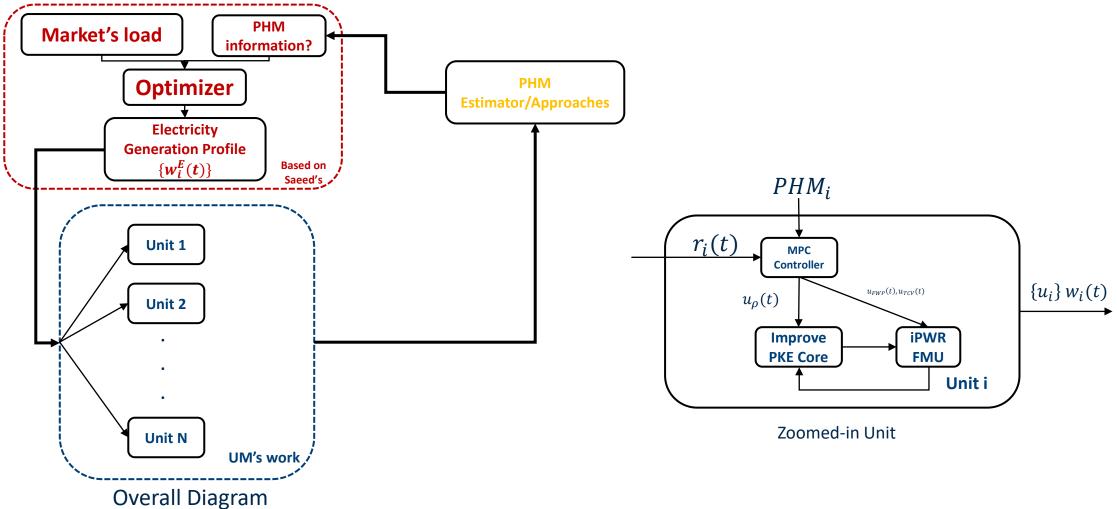
Backup

7/12/2023





Integrating Strategic & Tactical Controllers







100 (...

Plant Model

• 6-group PKE model with Xenon dynamics and two-region temperature model.

$$\frac{dn(t)}{dt} = \frac{\rho(t) - \beta}{\Lambda} n(t) + \sum_{i=1}^{6} \lambda_i C_i(t), \qquad \frac{dI(t)}{dt} = \gamma_I \Sigma_f v n(t) - \lambda_I I(t) \\
\frac{dC_i(t)}{dt} = \frac{\beta_i}{\Lambda} n(t) - \lambda_i C_i(t), i = 1 \dots 6. \\
6-\text{group PKE} \qquad \qquad \text{Xenon dynamics} \qquad \qquad \text{Merc}_r \frac{dI_f(t)}{dt} = qQ_0 \bar{n}(t) - K_{fc} (T_f(t) - T_c(t)) \\
\frac{m_f c_f \frac{dI_f(t)}{dt}}{dt} = qQ_0 \bar{n}(t) - K_{fc} (T_f(t) - T_c(t)) \\
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\frac{m_f c_f \frac{dI_f(t)}{dt}}{dt} = qQ_0 \bar{n}(t) - K_{fc} (T_f(t) - T_c(t)) - M_f c_f(t) \\
\frac{m_f c_f \frac{dI_f(t)}{dt}}{dt} = qQ_0 \bar{n}(t) - K_{fc} (T_f(t) - T_c(t)) \\
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\frac{m_f c_f \frac{dI_f(t)}{dt}}{dt} = qQ_0 \bar{n}(t) - K_{fc}$$

• The total reactivity $\rho(t)$ is the sum of the external reactivity and the reactivity feedback from xenon concentration and temperature

$$\begin{aligned} \rho(t) &= \rho_f(t) + \rho_c(t) + \rho_X(t) + \rho_{in}(t) \\ &= \alpha_f \left(T_f(t) - T_f(0) \right) + \alpha_c \left(T_c(t) - T_f(0) \right) - \frac{\sigma_X}{v \Sigma_f} (X(t) - X(0)) + \rho_{in}(t) \end{aligned}$$

Control inputs adjust the external reactivity

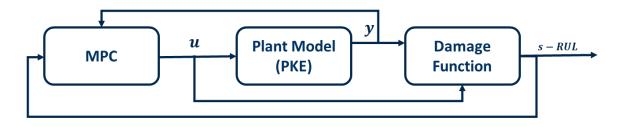
$$\frac{d\rho_{in}}{dt} = \sum_{i} a_{i}u_{i}$$





MPC Model

- MPC controller is adaptive
 - State-space model is obtained by linearizing nonlinear model adaptively.
 - Control input-- u_{cr} control rod speed and u_b boron concentration addition rate
- PHM-informed MPC



Positive u—rod insertion or boron

concentration addition

• Hypothetical RUL Model

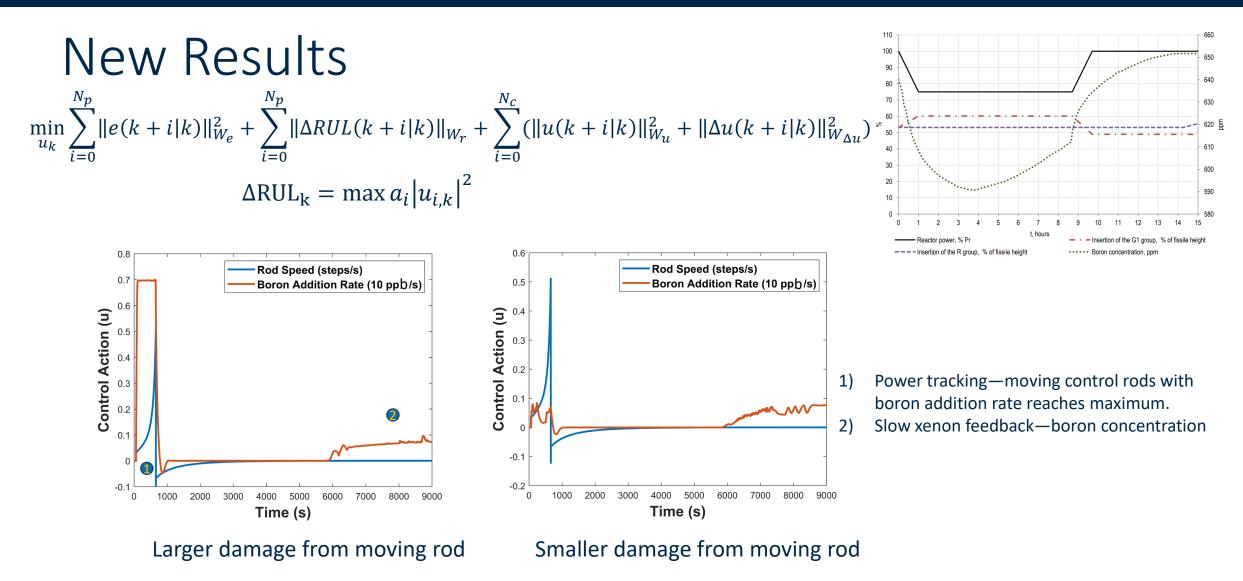
$$RUL_{k+1} = RUL_k - \sum_i b_i u_i^2(k)$$
$$\Delta RUL = -\sum_i b_i u_i^2(k)$$

• Objective function for MPC

$$\min_{u_k} \sum_{i=0}^{N_p} \|e(k+i|k)\|_{W_e}^2 + \sum_{i=0}^{N_p} \|\Delta RUL(k+i|k)\|_{W_r} + \sum_{i=0}^{N_c} (\|u(k+i|k)\|_{W_u}^2 + \|\Delta u(k+i|k)\|_{W_{\Delta u}}^2)$$







Maximum boron concentration addition rate 25ppm/hr—based on OECD FPO report¹



Sensitivities on Reduced Order Model Parameters

- Even though observer may correct some degree of error, MPC still needs to have a reasonable ROM for accurate and stable simulation results
- Control drum differential worth and β_i have larger sensitivities than other parameters
- ROM parameters may have pretty large margin (30%)
- Standard MPC causes large error since it cannot predict time-varying component

	Tracking difference (%)		Control cost	
Description	RMS	Max	Velocity	Acceleration
			(deg/s)	(deg/s ²)
3D core simulation	0.027	0.234	2.22E-02	5.55E-03
2D core simulation (Base case)	0.017	0.170	2.03E-02	5.10E-03
Standard MPC	0.180	1.196	1.81E-02	2.03E-03
Position-dependent drum worth	0.019	0.166	2.03E-02	5.26E-03
Drum worth -60%	0.106	0.790	9.95E-02	<u>1.93E-01</u>
Drum worth –30%	0.022	0.326	2.04E-02	7.54E-03
Drum worth +30%	0.031	0.172	2.03E-02	4.49E-03
Drum worth +60%	0.049	0.226	2.02E-02	4.06E-03
$\beta_i - 30\%$	0.020	0.145	2.02E-02	4.29E-03
β_i +30%	0.019	<u>0.267</u>	2.03E-02	6.31E-03
$\lambda_i - 30\%$	0.021	0.176	2.05E-02	5.66E-03
λ_i +30%	0.016	0.165	2.04E-02	4.79E-03
Λ -30%	0.017	0.170	2.03E-02	5.10E-03
Λ +30%	0.017	0.170	2.03E-02	5.10E-03
α_f, α_m -30%	0.030	0.221	2.03E-02	5.10E-03
α_f, α_m +30%	0.019	0.170	2.03E-02	5.11E-03
$c_{p,f}, c_{p,m}, c_{p,c} - 30\%$	0.020	0.171	2.03E-02	5.10E-03
$c_{p,f}, c_{p,m}, c_{p,c}$ +30%	0.022	0.192	2.03E-02	5.10E-03
Ramp rate 5%/min	0.012	0.097	1.23E-02	1.65E-03
Ramp rate 10%/min	0.014	0.112	1.52E-02	2.78E-03
Ramp rate 30%/min	0.021	0.384	2.59E-02	8.29E-03
Power 100%→140%→100%	0.015	0.140	8.14E-03	1.21E-03





Adaptive MPC vs. Standard MPC

- Ignoring time-varying elements in standard MPC may degrade accuracy
- Successive linearization in adaptive MPC can consider these nonlinearity in ROM

