Dynamic Power Plant Modeling for Flexible Operations

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Motivation

Flexible Plant Operations



- Thermal power plants are required to operate more flexibly as renewable penetration increases
- Conventional plants were originally designed to operate at full load and **do not perform optimally during load-following**
 - Decreased efficiency (increased heat rate)
 - Leads to poor control
 - Increased environmental emissions (e.g., CO_2 , NO_x)
 - Increased equipment damage and O&M costs





R&D Objectives and Technical Approach



- R&D Objectives
 - Improve plant performance and reliability under flexible operations
- Technical Approach
 - Develop and validate high-fidelity dynamic power plant models
 - Develop plant-wide regulatory and supervisory **controls** and augment with **reinforcement learning**
 - Quantitatively assess flexible operation and control approaches
 - Develop creep and fatigue damage models for key equipment items
 - Assess and mitigate negative impacts of flexible operations on **plant health**





- Dynamic Power Plant Modeling
 - Process, Control, and Health
- Model Validation under Load-Following Operation
- Reinforcement Learning-Augmented Control Results
 - Main steam temperature control
 - NOx control in SCR unit
- Boiler Health Modeling Results
- Concluding Remarks and Future Work



Dynamic Power Plant Modeling



Overview



Plant Configuration – Major Equipment

- Plant-wide model
 - Supercritical pulverized coal (SCPC) system
 - Case B12A, NETL Cost and Performance Baseline*

• Equipment Models

- First-principles dynamic mass and energy balances
- Boiler System
 - Gas-side: combustion, radiation, convection
 - Water/steam-side: convection, volumetric and thermal holdups
 - Waterwall, Superheaters, Reheaters, Economizer
- Steam Cycle
 - Multistage Turbine: Sliding-pressure operation, efficiency calculations, moisture detection
 - Units with volumetric and thermal holdups: Condenser, Feedwater Heaters, Deaerator, ...
- Flue Gas Treatment
 - Selective catalytic reduction (SCR) for NOx control



* Case B12A, Cost and Performance Baseline for Fossil Energy Power Plants Study, Volume 1a: Bituminous Coal (PC) and Natural Gas to Electricity, Revision 3, National Energy Technology Laboratory, <u>www.netl.doe.gov</u>, DOE/NETL-2015/1723, July 6, 2015.

Dynamic Power Plant Modeling

Modeling Software and Physical Properties

Modeling Software

- Aspen Plus Dynamics $^{\mathbb{R}}$
 - Plant-wide model and controls
 - Equation-oriented, pressure-driven
- Aspen Custom Modeler® (ACM)
 - Equipment models
 - 1-2D Partial Differential Equations (PDEs)

• Physical Properties

- Flue Gas: PENG-ROB (Peng-Robinson Equation-of-State*)
- Water/Steam: IAPWS-95 Steam Tables**







Regulatory and Supervisory Controls



- Regulatory controls
 - ~30 proportional-integral-derivative (PID) control loops
 - Inventory controllers
 - 3-element drum level control
 - Two cascaded control loops
 - Drum level, main steam flow (FB), and feed water flow (FF)
 - Main steam temperature (MST) control
 - Two-stage attemperation
- Supervisory Controls
 - Coordinated Control System (CCS)
 - Boiler and turbine masters
 - Fixed- and sliding-pressure operation









Sarda, P., E. Hedrick, K. Reynolds, D. Bhattacharyya, S.E. Zitney, and B. Omell, "Development of a Dynamic Model and Control System for Load-Following Studies of Supercritical Pulverized Coal Power Plants," *Processes*, 6(11), 226, Nov. 2018.

Boiler Health Models

- Transient pressure and temperature profiles throughout the boiler
 - Superheaters and reheaters
 - 1D P/T profiles along length of tubes
 - Through-wall temperature profiles

Thermo-mechanical stresses

- Stress evolution over time
- Axial, radial, and tangential stresses, as well as equivalent (von Mises) stress
- SH/RH: Tube wall, header, header/wall junction
- Material dependent

• Creep and fatigue damage

- Load-following operation scenarios
- Estimated time to rupture (Creep high T)
- # of cycles until likely failure (Fatigue high ΔT)
 - Rainflow counting method
 - Effect of ramp rate







Tube Failures Source: Power Magazine



Superheater



Header Crack Source: Power Magazine







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Steady-State Parameter Estimation and Model Validation using Plant Data



- Dynamic power plant model adapted to match industry partner plant
- Equipment sizing performed using plant design data
- Operating data obtained for steady-state and part-load operation
- Model parameters estimated where not available
 - Steam turbine isentropic head parameter estimated to match full-load power
- Model validated at steady-state full-load and part-load (~70%) operation

Full-Load	Error (Model - Plant)	
Economizer Inlet Temperature	-0.30%	
Gross Power Production	0.09%	
Main Steam Temperature	-0.12%	
Main Steam Pressure	-0.16%	
Main Steam Flow	-0.02%	
Coal Feed Rate	0.66%	
Boiler Feedwater Flow	0.00%	

Part-Load	Error (Model - Plant)
Economizer Inlet Temperature	0.01%
Gross Power Production	0.11%
Main Steam Temperature	0.00%
Main Steam Pressure	0.63%
Main Steam Flow	0.88%
Coal Feed Rate	-1.86%
Boiler Feedwater Flow	0.34%



Dynamic Model Validation using Plant Data



- Load-following operation
 - Ramp down from full load to part load ($\sim 70\%$) over 6 hours at ramp rate of ~ 0.5 MWe/min
 - Hold for 2 hrs
 - Ramp back up to full load over 4 hrs at ramp of ~ 0.75 MWe/min
- Data available from the plant is noisy and contains fluctuations
 - High frequency noise filtered out using low-pass Butterworth filter
 - 30-minute smoothing average filter applied
- Dynamic model simulated with mapped inputs from plant load-following data
 - Boiler feedwater flow
 - Coal flow
 - Feedwater heater outlet temperatures
 - Boundary temperatures and pressures
- Control of air feed via ratio with coal flow
- Regulatory control layer for maintaining boiler main steam temperature





- Model parameters estimated using full-load data remained unchanged for load-following case.
- Inlet coal conditions (moisture, HHV, composition) were not changed.
- Plant-model match for gross power and main steam temperature show good agreement throughout the entire load range.
- Model has a slightly higher pressure at part-load condition mainly because of mismatch in pressure drop profile across throttle valve. Going forward, throttle valve parameters will be estimated considering dynamic data.





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Main Steam Temperature Control Reinforcement Learning(RL)-Augmented PID Control



• Adaptive and retentive learning



- Q-learning for PID control parameters
- Episodic learning
 - Disturbance: Random ramped load changes
 - Input: BFW flow to Attemperator before FSH
 - Output: Main Steam Temperature
- State-action clustering
 - Retentive learning
 - Reduces computation time





Hedrick, E., K. Reynolds, P. Sarda, D. Bhattacharyya, S.E. Zitney, and B. Omell, "Development of a Reinforcement Learning-Based Control Strategy for Load Following in Supercritical Pulverized Coal (SCPC) Power Plants," *Clearwater Clean Energy Conf.*, Clearwater, FL, June 16-21 (2019).

Selective Catalytic Reduction (SCR) Control RL-Augmented Model Predictive Control



- SCR for NOx control is highly nonlinear time-varying system with time-delay
- SCR dynamic model is 1D heterogeneous plug flow reactor with detailed kinetics
- Reduced model is identified from dynamic SCR model of the form:

Treated Gas	MPC Model Variable	System Variable
SCP	u ₁	NH ₃ Flow (kmol/h)
	d ₁	Flue Gas Flow (kmol/h)
	d ₂	Flue Gas NO _x Flow (kmol/h)
	d ₃	Flue Gas Temperature (°C)
Gas Feed	У	Outlet NO _x (ppm)

• Identified model is used in a static linear Model Predictive Control (MPC)

• RL-augmented MPC

- Temporal-difference learning
- Learned parameters are MPC prediction (N_p) and control (N_c) horizons



• NO_x control under load-following



Controller	ISE	Ratio to FBAFF	
Feedback	2529	32	
Naïve RL-MPC	166	2.1	
FBAFF	79	1.0	
Static MPC	13	0.16	
RL-MPC Greedy	5	0.063	

ISE: Integral Square Error FBAFF: FeedBack-Augmented FeedForward (Industry Standard)



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Impact of Load-Following on Boiler Health Primary Superheater - Tubes



- Load ramped from 100% to 60% (5%/min)
- Boiler thermal profile depends on plant design and controls
- Temperature at inlet of Primary SH rises with reduction in load — possible location for damage



Boiler Thermal Profile



- ΔT between inner and outer tube wall is small
- Thermal stress does not add significantly to total stress (fatigue)
- However, higher temperature (+40°C) at 60% load increases **creep damage**
- **Relative rupture time** at 60% load reduced by 6X compared to full load

	PSH	
Load	100%	60%
Wall Surface Temperature [°C]	477.92	507.41
Equivalent Stress [MPa]	71.72	39.18
Relevant Rupture Time	1.00	0.16



* - "Water-tube boilers and auxiliary installations - Part 3: Design and calculation of pressure parts," British Standards Institution, London, UK, BS EN 12952-3:2001, May 2002.

Impact of Load-Following on Boiler Health Primary Superheater - Header



- Stresses in **superheater headers** are higher than in tubes due to thicker walls and larger through-wall temperature differences, so **fatigue damage** is of more concern
- Stress used in a fatigue cycle calculation (rainflow counting using ASTM E1049)*
- Ramp rate affects number of allowable cycles



- Load ramped from 100% to 60% at Time=1 hr and then back up to 100% at Time = 3 hr
- Two different ramp rates: 3%/min, 5%/min

Ramp Rate [%/min]	3	5
Δσ _{Tresca} [MPa]	212	256
Relative # of Cycles	1	0.14



* - "Water-tube boilers and auxiliary installations - Part 3: Design and calculation of pressure parts," British Standards Institution, London, UK, BS EN 12952-3:2001, May 2002.

Concluding Remarks and Future Work



- Developed first-principles dynamic power plant model with controls and health models
- Validated dynamic power plant model using industrial load-following data
- Demonstrated reinforcement learning-augmented control
 - RL-augmented PID control improved main steam temperature control by reducing maximum temperature deviation by 50% during load ramp
 - RL-augmented MPC improved NOx control for highly nonlinear SCR process with time-delay
- Studied impact of load-following on boiler health with focus on primary SH
 - Tube rupture times due to creep damage are impacted by low load operation
 - Fatigue damage and number of allowable cycles for thick-walled headers are greatly affected by ramp rate
- Future work
 - Adaptive NMPC strategies to maximize efficiency with health/damage constraints during load-following



Upcoming Presentations and Publications



Presentations

- Hedrick, E., K. Reynolds, D. Bhattacharyya, S.E. Zitney, and B. Omell, "Development of Algorithms for Reinforcement Learning Augmented Model Predictive Control," *AIChE 2021 Annual Meeting*, Boston, MA, November 7-12 (2021).
- Hedrick, E., K. Reynolds, D. Bhattacharyya, S.E. Zitney, and B. Omell, "Nonlinear Predictive Control of an Industrial Selective Catalytic Reduction Unit with Time-Varying Time Delay," *AIChE 2021 Annual Meeting*, Boston, MA, November 7-12 (2021).
- Hedrick, E., K. Reynolds, S. Hong, D. Bhattacharyya, S.E. Zitney, and B. Omell, "Advanced Model Predictive Control for Reducing Equipment Damage in a Supercritical Pulverized Coal Fired Power Plant during Load-Following Operation," *AIChE 2021 Annual Meeting*, Boston, MA, November 7-12 (2021).
- Reynolds, K., E. Hedrick, B. Omell, S.E. Zitney, D. Bhattacharyya, "Dynamic Optimization of the Operational Trajectory of a Supercritical Pulverized Coal-Fired Boiler under Load-Following with Consideration of Boiler Health," *AIChE 2021 Annual Meeting*, Boston, MA, November 7-12 (2021).
- Reynolds, K., E. Hedrick, B. Omell, S.E. Zitney, D. Bhattacharyya, "Health Monitoring of an Industrial Supercritical Pulverized Coal Boiler," *AIChE 2021 Annual Meeting*, Boston, MA, November 7-12 (2021).

Publications

- Hedrick, E., K. Reynolds, D. Bhattacharyya, S.E. Zitney, and B. Omell, "Reinforcement Learning for Online Adaptation of Model Predictive Controllers: Application to a Selective Catalytic Reduction Unit," In Preparation.
- Reynolds, K., E. Hedrick, B. Omell, S.E. Zitney, D. Bhattacharyya, "Dynamic Data Reconciliation, Parameter Estimation, and Health Analysis of a Supercritical Pulverized Coal Boiler Under Load-Following Operation," In Preparation.



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