DEPLOYMENT OF DYNAMIC NEURAL NETWORK OPTIMIZATION TO MINIMIZE HEAT RATE DURING RAMPING FOR COAL POWER PLANTS

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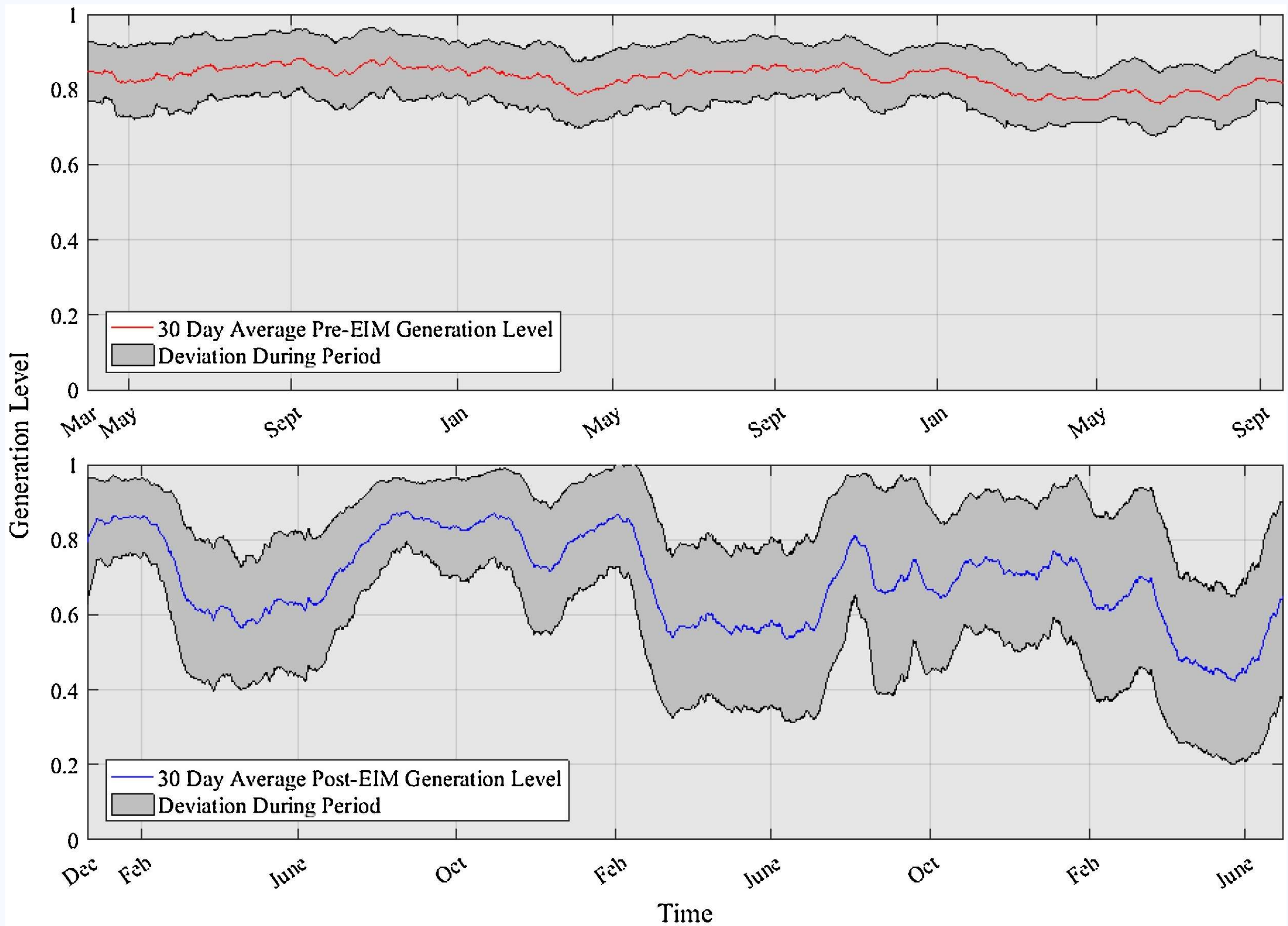
DISCLAIMER

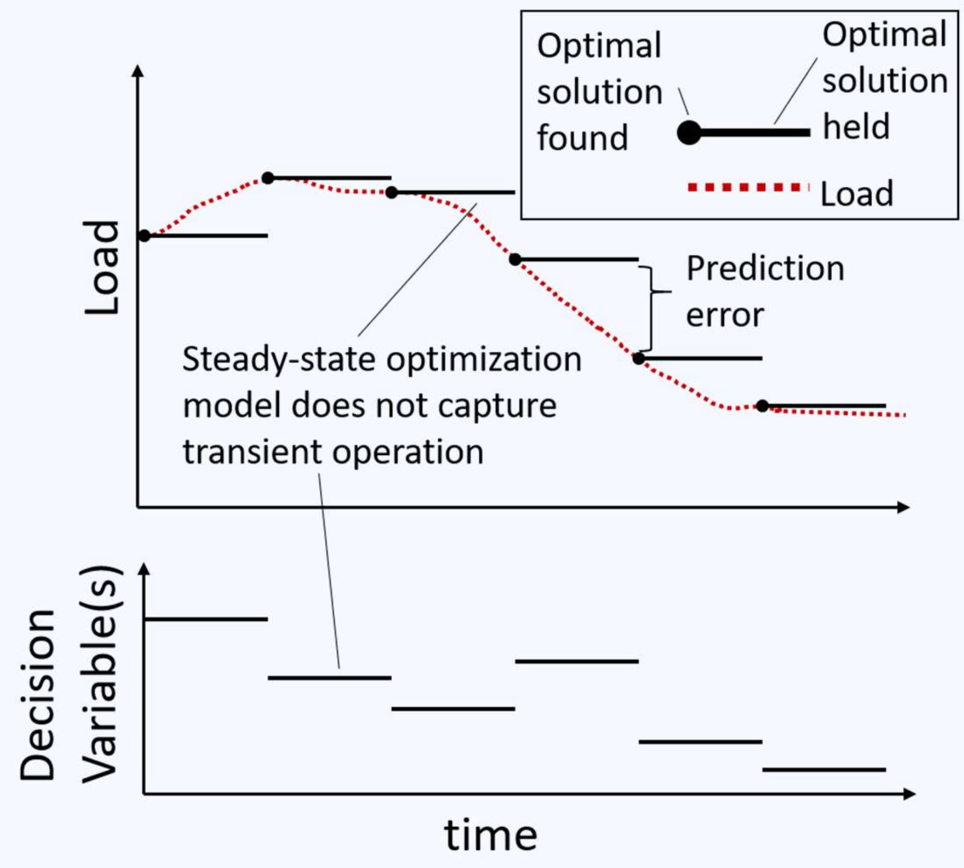
MOTIVATION

With the onset of renewables, some thermal plants are ramping much more



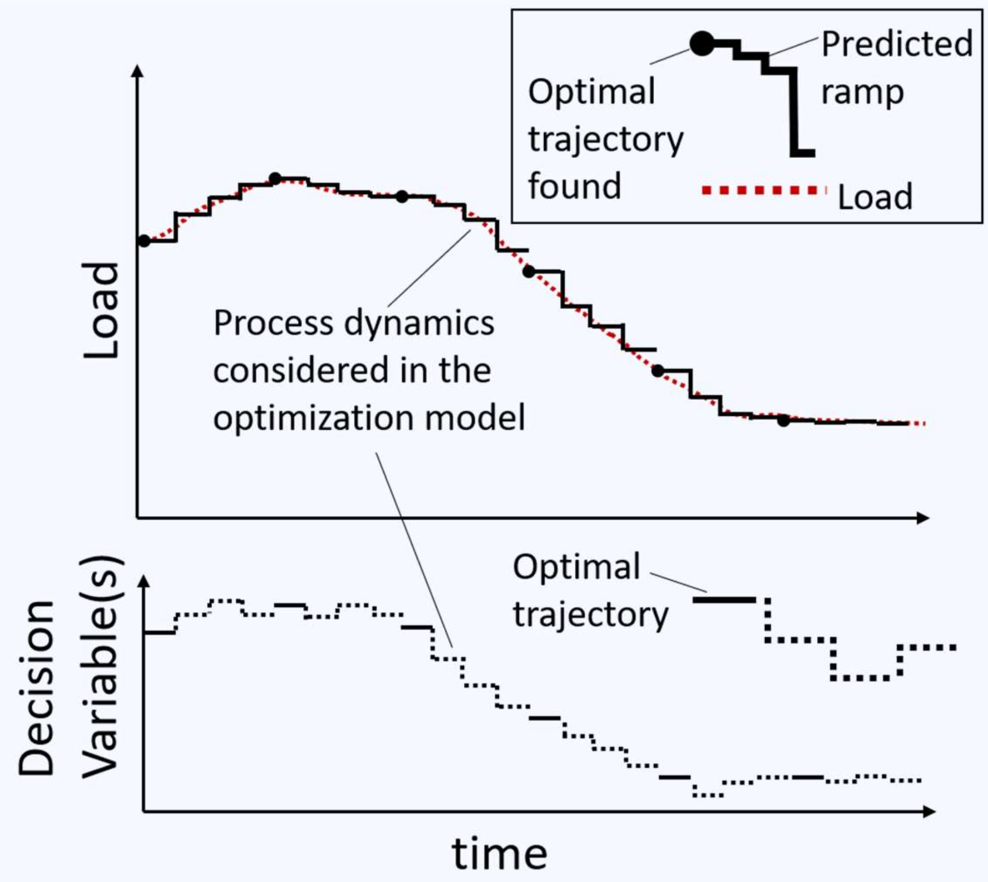
STEADY-STATE NEURAL NETWORK OPTIMIZATION (NNO)

Steady-state neural network optimization has worked well in the past, but must be updated to include dynamics



DYNAMIC NEURAL NETWORK OPTIMIZATION (D-NNO)

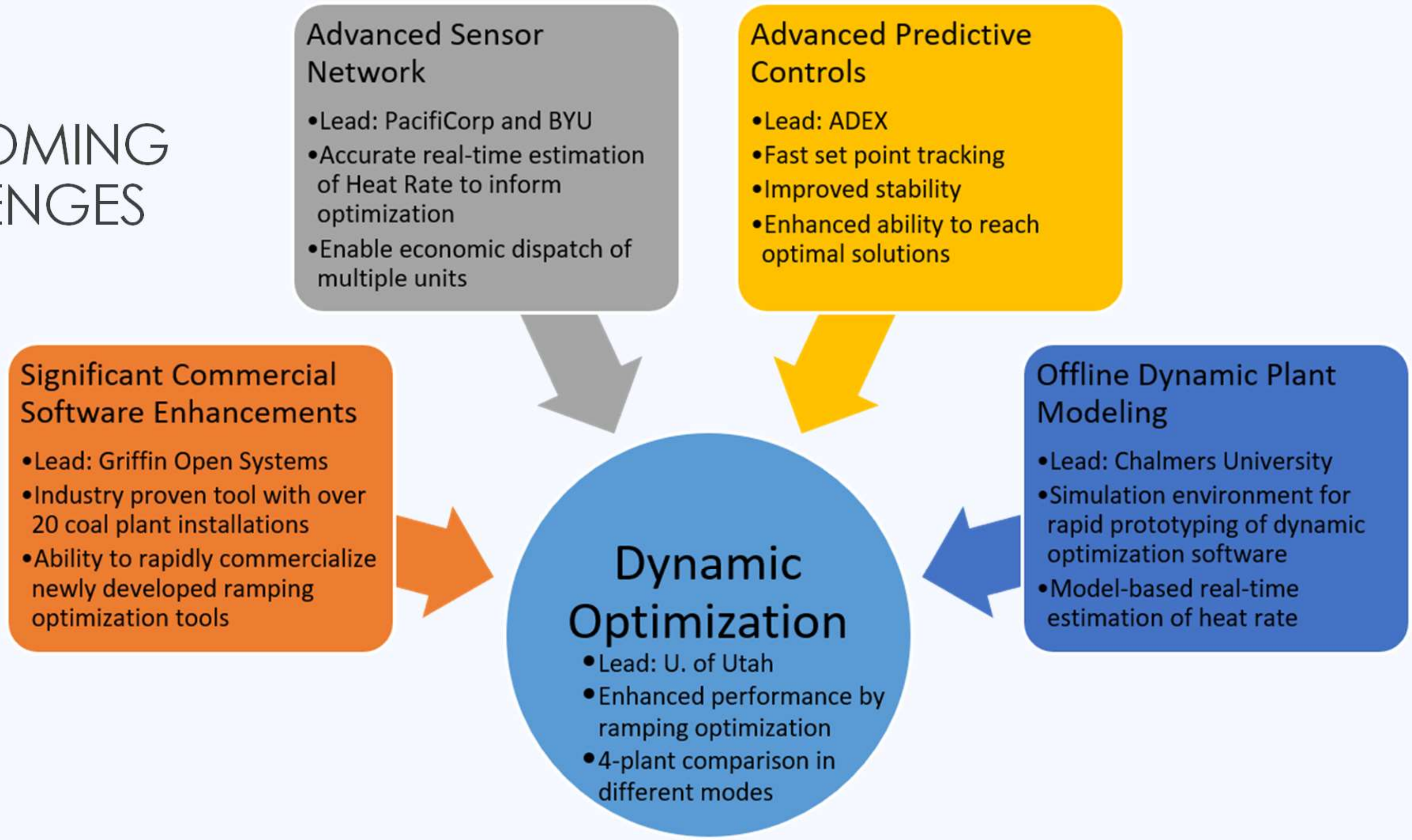
Dynamic neural network optimization could help a plant perform optimally, despite frequent ramping, by incorporating transient behavior in the plant and optimizing control move trajectories



KEY CHALLENGES

1. **There is no commercial D-NNO product on the market.**
2. **Dynamic ML-models are computationally intense.**
   1. Can we develop solution methodologies to keep up with real time?
3. **If we want to optimize it, we need to be able to accurately measure it.**
   1. Heat rate is difficult to measure / estimate in real time.
4. **Can we maintain set points in the short term (seconds, minutes) while optimizing over the longer term (minutes, hours)?**
5. **How do we prototype algorithms without upsetting the actual plant process?**

OVERCOMING CHALLENGES

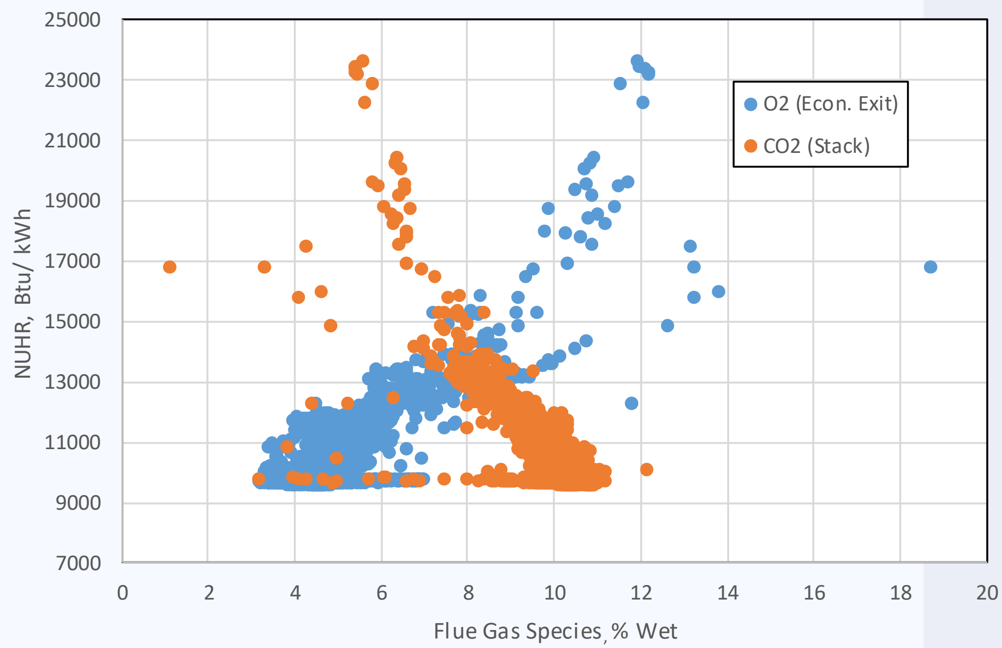


ADVANCED SENSOR NETWORK

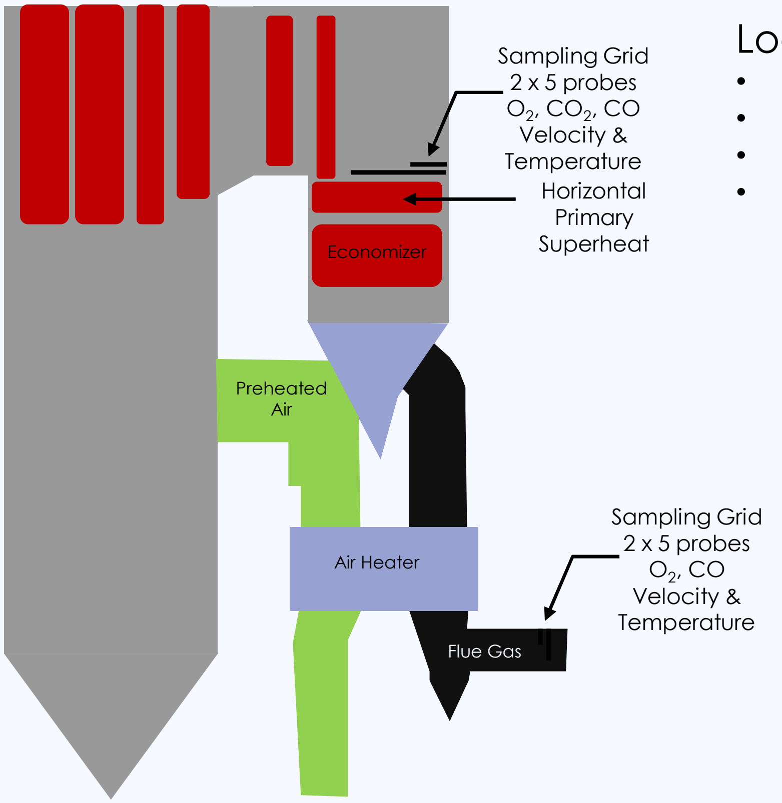
ASN OBJECTIVE

To measure/calculate the Net Unit Heat Rate (NUHR) in real time for PacifiCorp's Hunter, Unit 1 coal-fired boiler during dynamic load operation and report this value to the Dynamic Neural Network Optimization (DNNO) system.

- Measurable relationship between flue gas composition and NUHR
- Calculate and report NUHR to D-NNO
- Provide raw composition data to D-NNO
- Provide a metric (NUHR) for evaluating success in real time



LOCATIONS OF ASN INSTALLATION



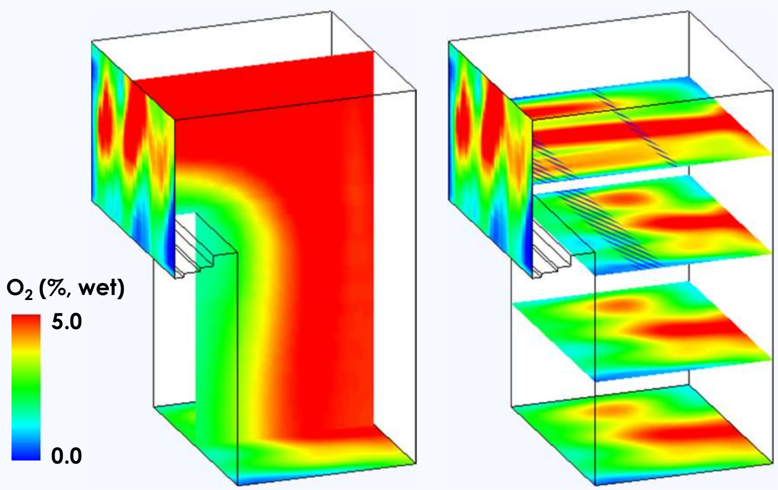
Location A

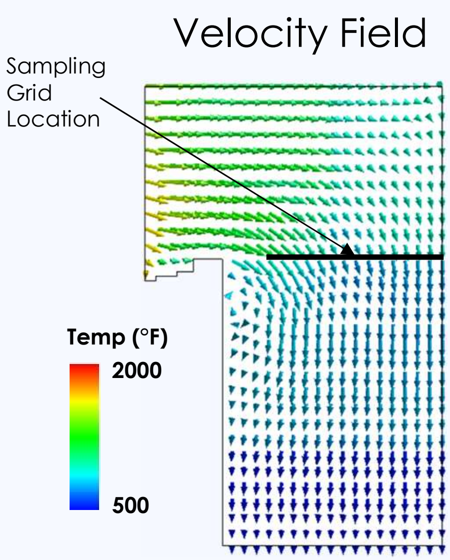
- Primary purpose is for performing combustion diagnostics
- Measurement of CO_2 is also included
- Probes exist at this location (only O_2 and CO)
- Are being upgraded to include measurement of:
  - Velocity
  - Temperature
  - CO_2

Location B

- Primary purpose is for quantifying air leakage through Ljungström air heater
- New installation with new duct penetrations
  - 2 ducts must be measured
  - Flow is separated into two air heaters and downstream ductwork

DIFFICULTY OF MEASURING COMPOSITION



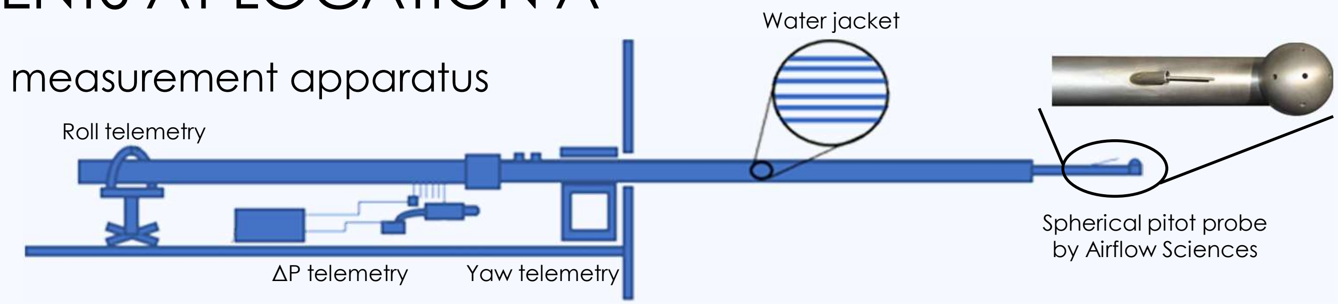


- Flue gas is expected to be stratified
  - Composition
  - Flow
  - Temperature
- To provide a measure of composition that is "representative", mass weighted averaging is necessary

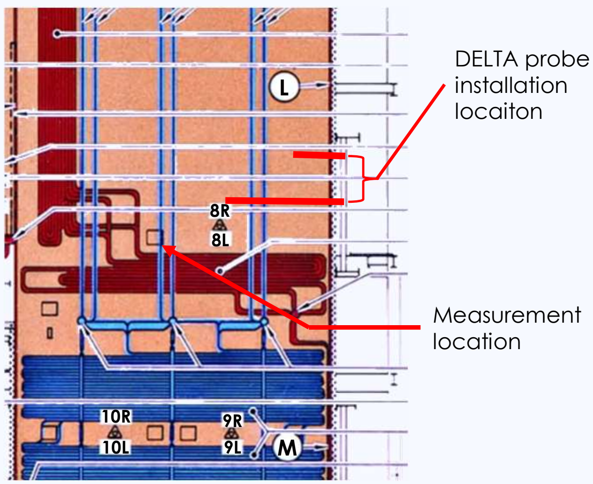
**These figures shows results from CFD modeling performed by REI for PacifiCorp's Hunter, Unit 3 under cooperative agreement DE-NT0005288*

MEASUREMENTS AT LOCATION A

Velocity measurement apparatus



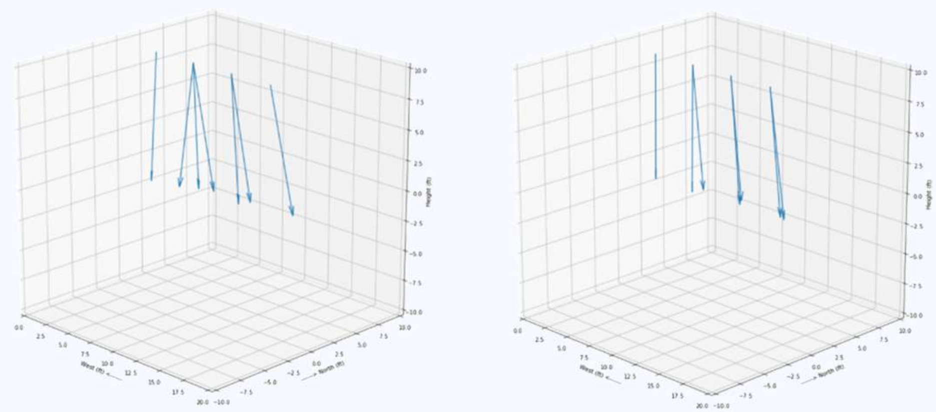
Velocity measurement Location



Measurement results

445 MW

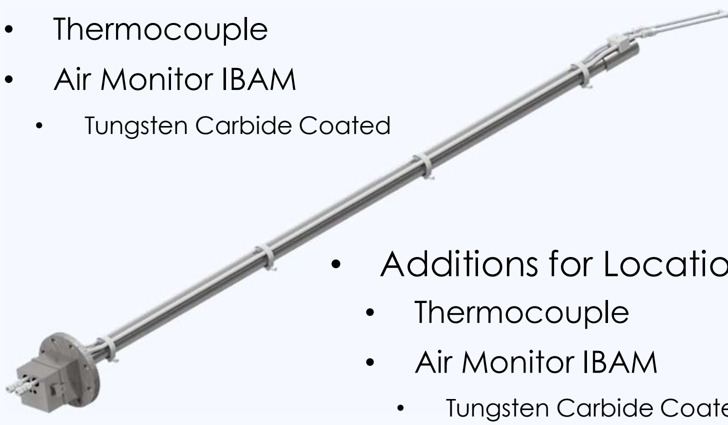
263 MW



HARDWARE SPECIFIED AND ORDERED

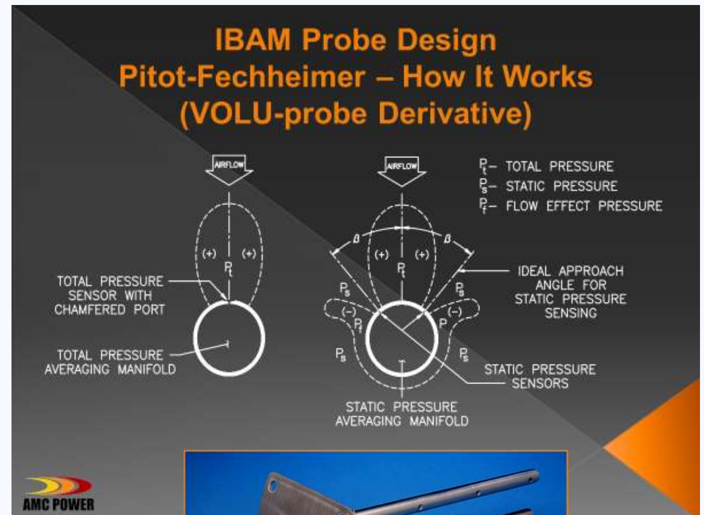
EES DELTA probe with IBAM

- Typical DELTA probe
  - Composition (O_2 & CO)
- Additions for Location A
  - Composition (CO_2)
  - Thermocouple
  - Air Monitor IBAM
    - Tungsten Carbide Coated

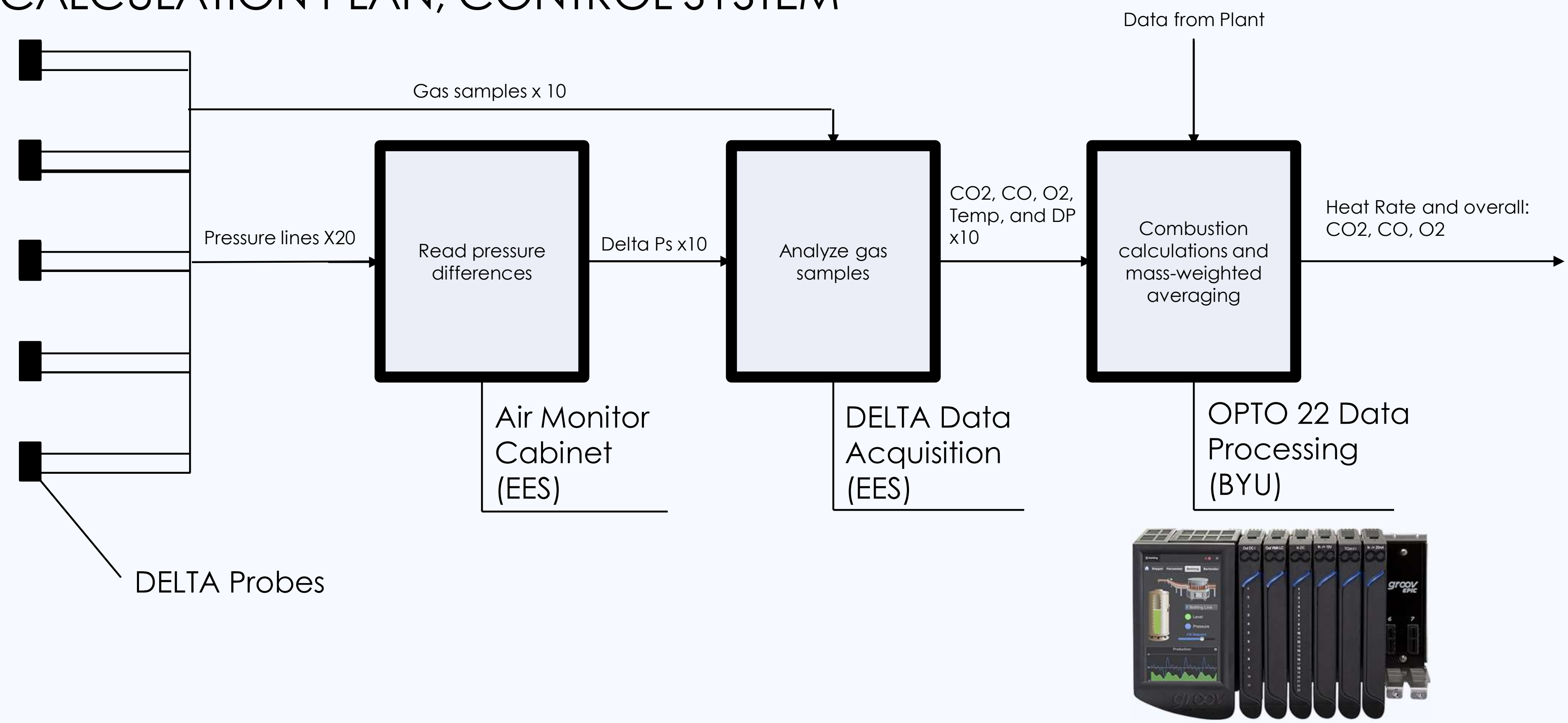


- Additions for Location B
  - Thermocouple
  - Air Monitor IBAM
    - Tungsten Carbide Coated

Air Monitor
Individual burner air measurement (IBAM) system



CALCULATION PLAN, CONTROL SYSTEM



CALCULATIONS

Flue Gas Composition $\xrightarrow{\text{Combustion Calcs}}$ Coal Composition $\xrightarrow{\text{Correlation}}$ Coal Heating Value $\xrightarrow{\text{Simple Calc}}$ NUHR

Plant Data

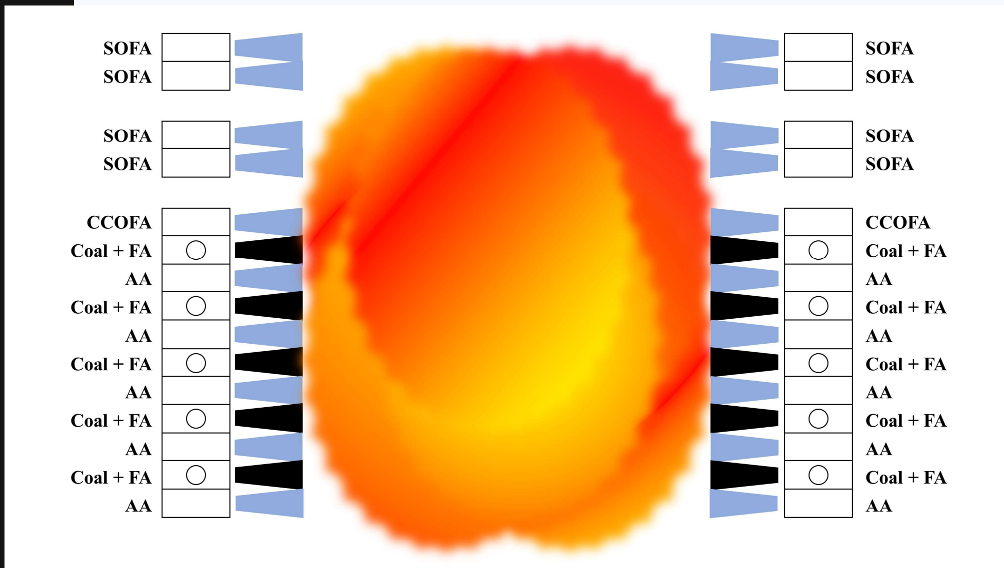
Plant Data

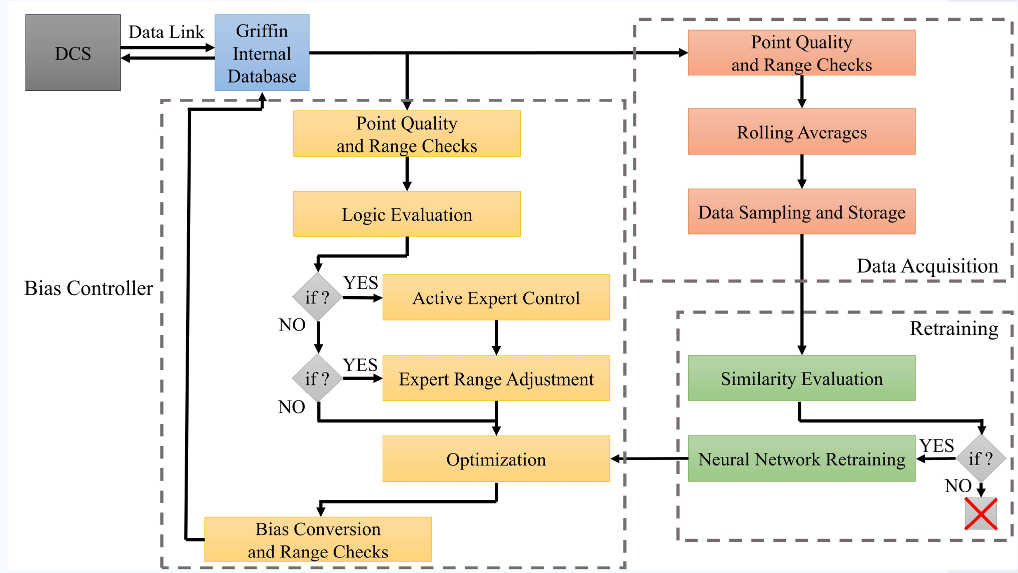
Coal Heating Value Correlations

Model	Model Form
Dulong [2], [3]	$\Delta H_c = aC + b\left(H - \frac{O}{8}\right) + cS$
Strache-Lant [2], [3], D'Huart [3],Boie [2], [3]	$\Delta H_c = aC + bH + cO + dS$
Steuer [2]	$\Delta H_c = a\left(C - \frac{3}{8}O\right) + bO + c\left(H - \frac{1}{16}O\right) + dS$
Seylor [2], [3]	$\Delta H_c = aC + bH + cO^2 + d$
Gumz [2], [3], Channiwala-Parikh [3]	$\Delta H_c = aC + bH + cN + dS + eO$
Dulong-Berthelot [2], [3]	$\Delta H_c = aC + bH - c(N + O - 1) + dS$
IGT [2], [3]	$\Delta H_c = aC + bH + c + d(O + N)$
VDI [2]	$\Delta H_c = aC + b\left(H - \frac{O}{8}\right) + cS + dH$
Mott-Spooner [3], [4]	$\Delta H_c = aC + bH + cO + dS \text{ for coals with } O < 15\%$
	$\Delta H_c = aC + bH + eO + fO^2 + gS \text{ for coals with } O > 15\%$
Given, et al. [4]	$\Delta H_c = aC + bH + cO + dS + e$

ALGORITHMIC DEVELOPMENTS

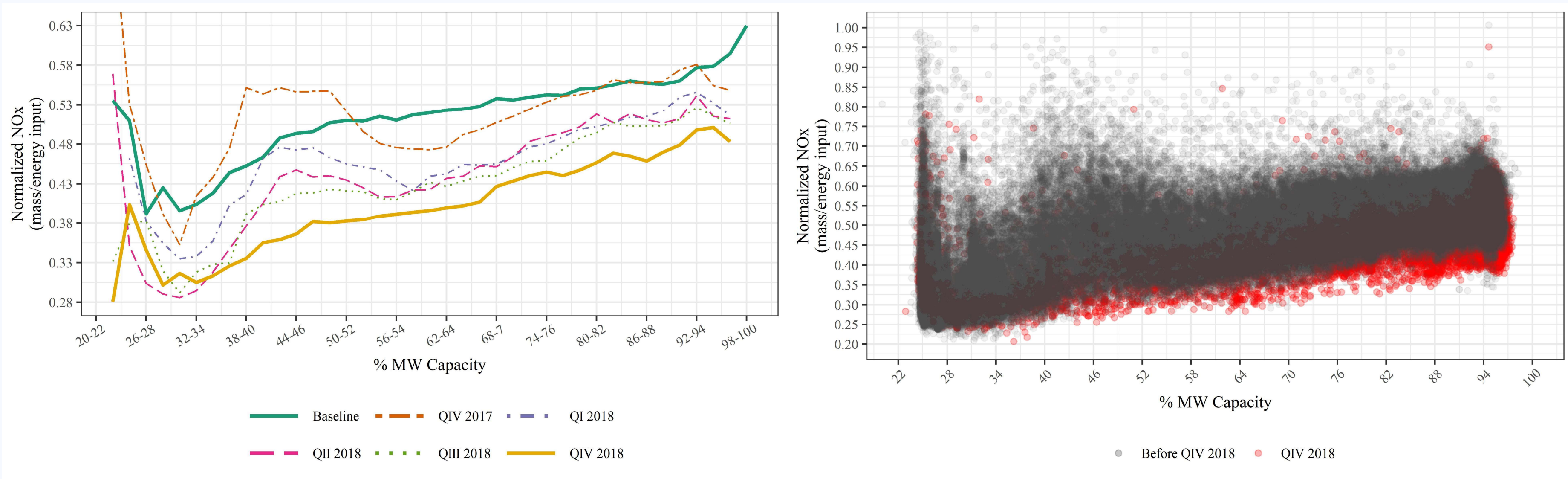
PAST NO_X PERFORMANCE RESULTS





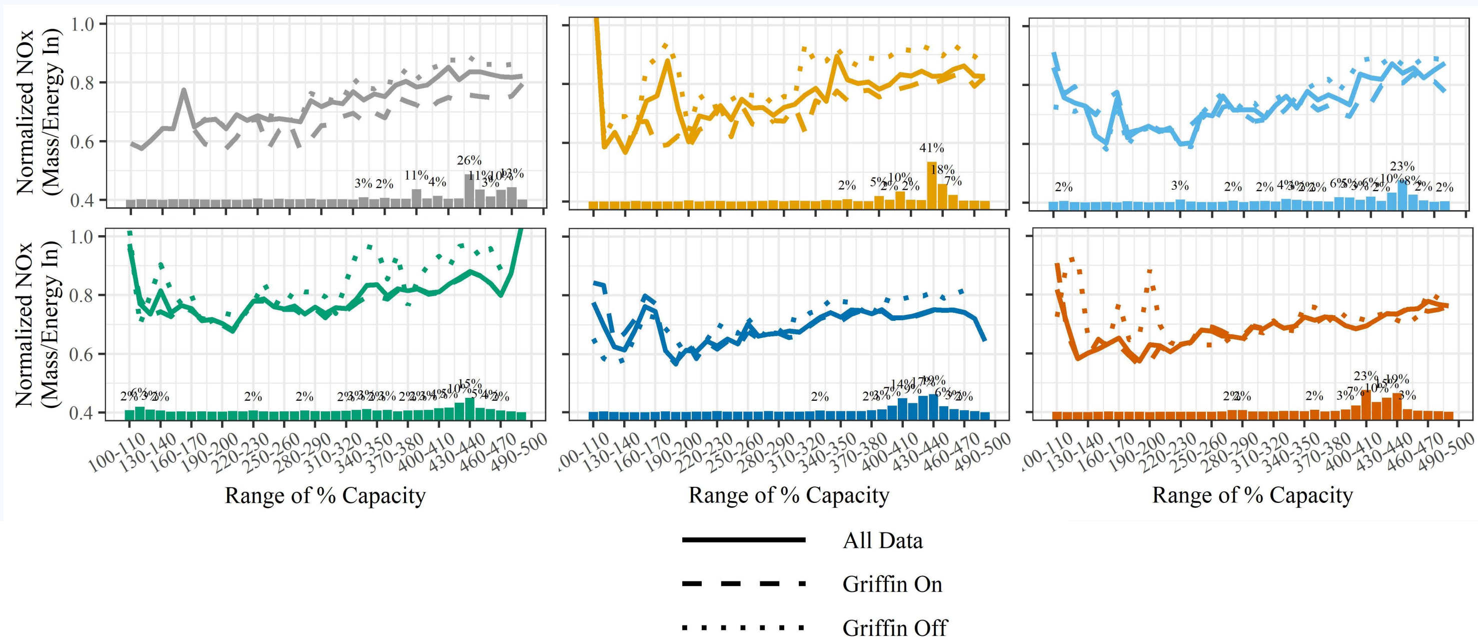
Previous projects with Griffin Open Systems, LLC. and The Griffin AI Toolkit™ focused on combustion optimization for NO_X emission rate reduction have been successful by optimizing air injection around the fireball in closed-loop. The developed combustion optimization system (COS) was self-learning and self-adapting, while also allowing incremental manual development.

PAST NO_X PERFORMANCE RESULTS



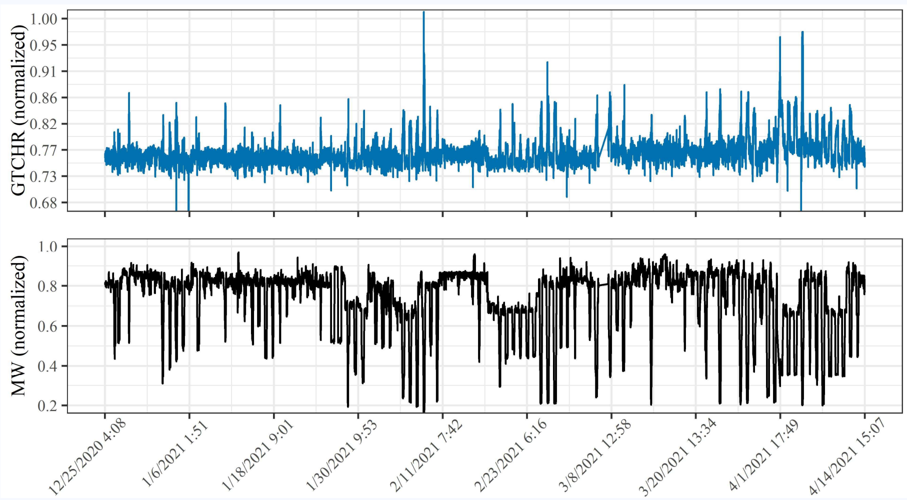
Significantly lower NO_x emission rates were observed throughout the project's duration on average with the self-learning and self-adapting process evident when comparing quarterly performance averages. NO_x emission rates lower than were recorded prior to implementation were also seen [1].

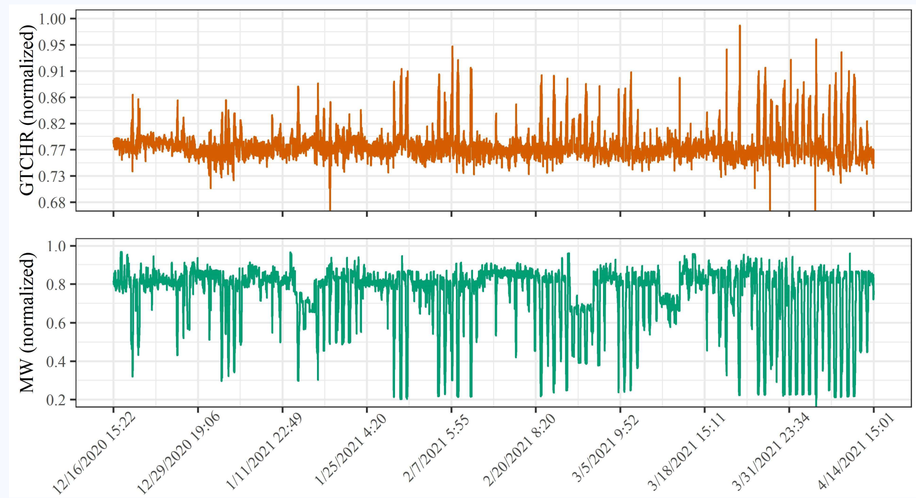
CURRENT PROJECT PROGRESS



The system's capabilities have been demonstrated at the current project plant site. In-lieu of reliable real-time heat rate values, NO_x has been the optimization target with improvements observed during each project quarter with the COS active relative to inactive.

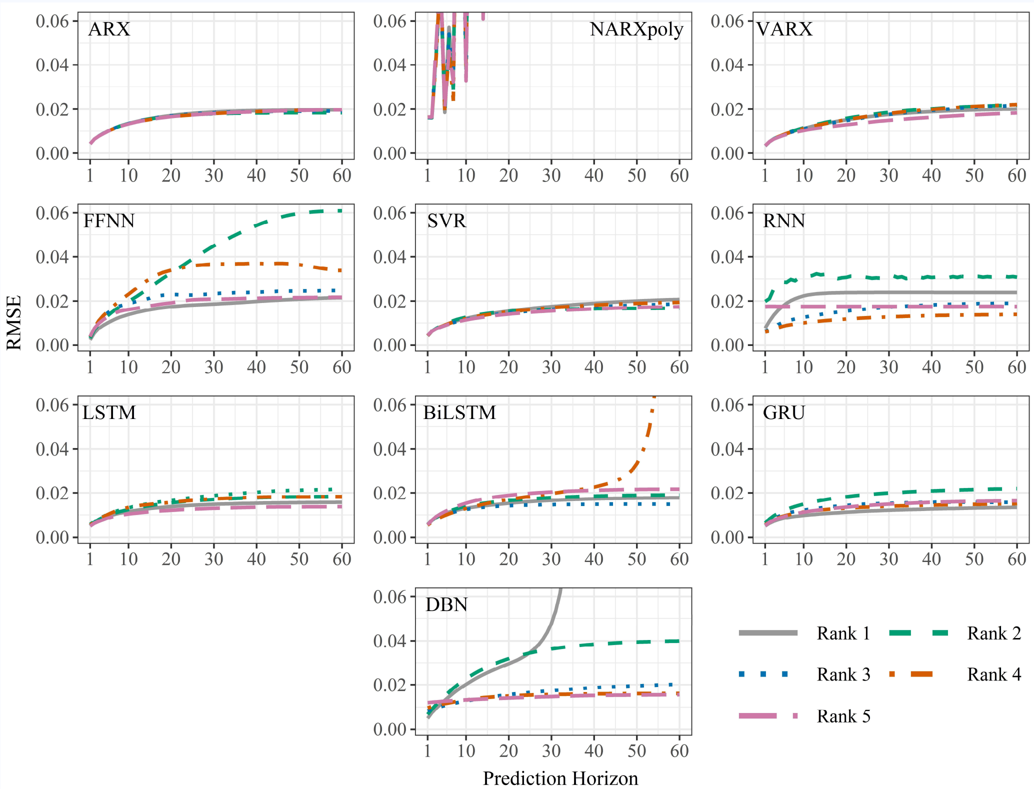
CURRENT PROJECT PROGRESS

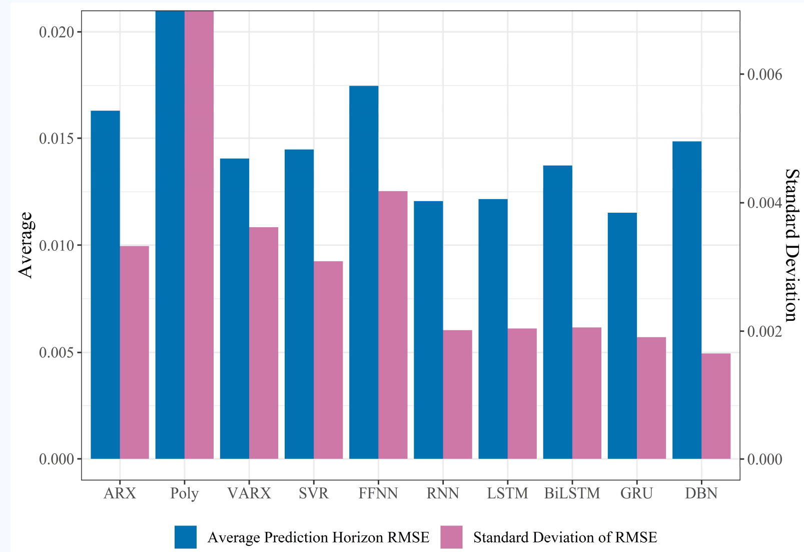




To complement the advanced sensor network, real-time heat rate values have been estimated on each unit within The Griffin AI Toolkit, based in mass and heat balances around the turbine cycle. This system is currently collecting estimated gross and net turbine cycle heat rate (GTCHR and NTCHR, respectively) to inform dynamic neural network model building and later optimization. Boiler efficiency will also be estimated using a similar methodology.

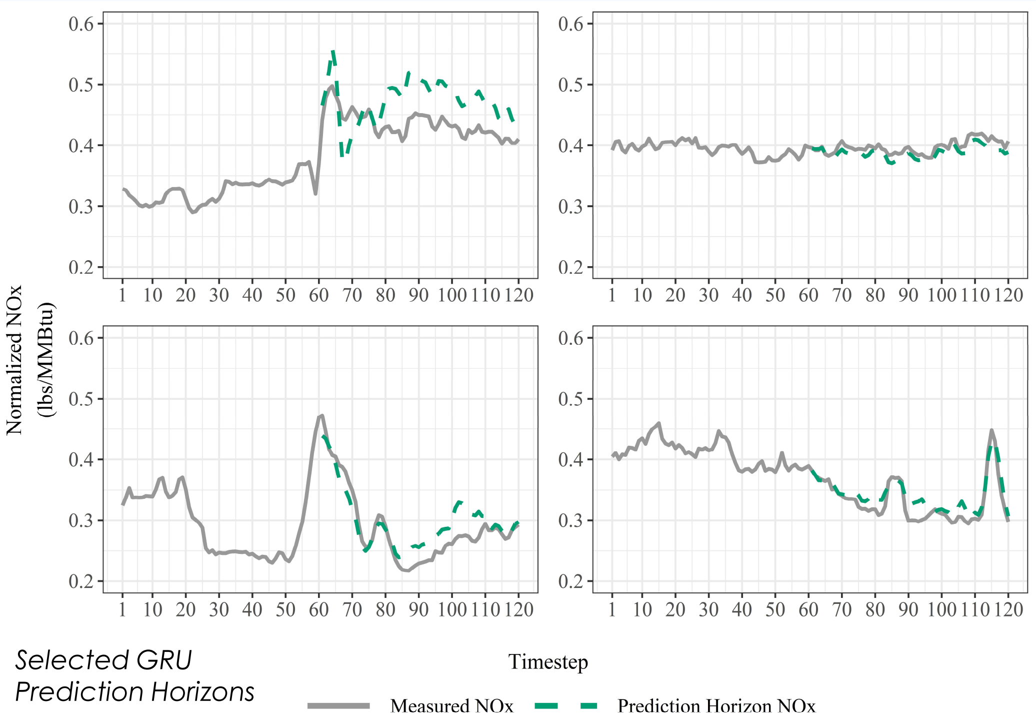
CURRENT PROJECT PROGRESS



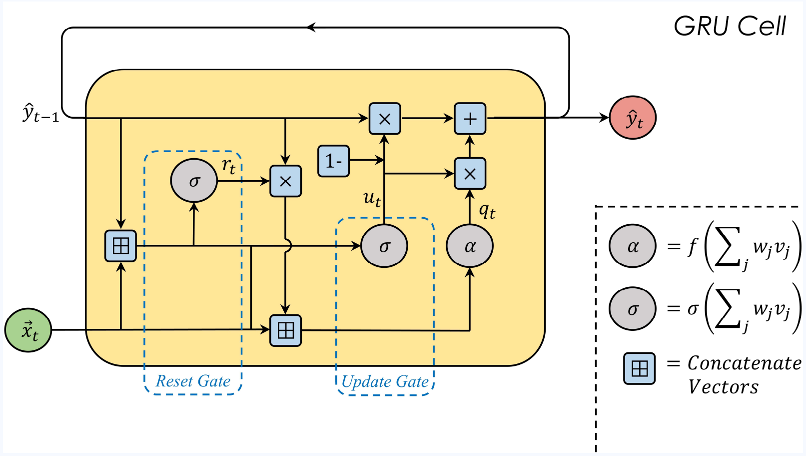


A selection of 10 dynamic data-driven modeling methods were analyzed for their ability to represent the combustion process. Each was used to predict NO_x emission rate over a sixty-step time horizon.

CURRENT PROJECT PROGRESS



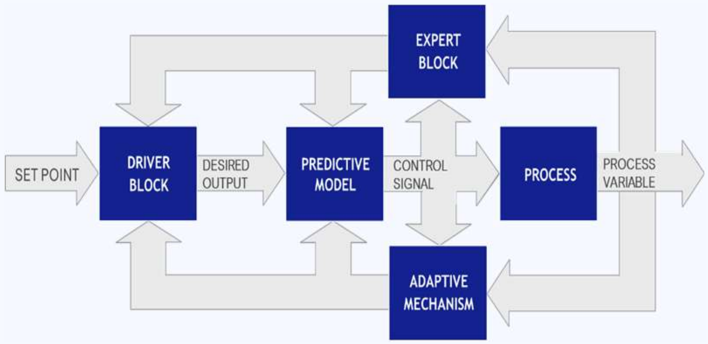
Selected GRU Prediction Horizons

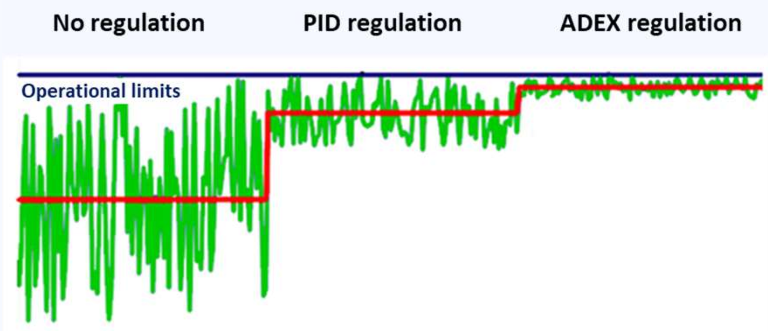


The Gated Recurrent Unit (GRU) neural network was identified to provide the most accurate and stable prediction of NOx emission rates across the time horizon. Long-Short Term Memory (LSTM), Support Vector Regression (SVR), and Vector Autoregression (VAR) also exhibited satisfactory performance [2].

ADVANCED CONTROL

ADEX – ADAPTIVE PREDICTIVE CONTROL





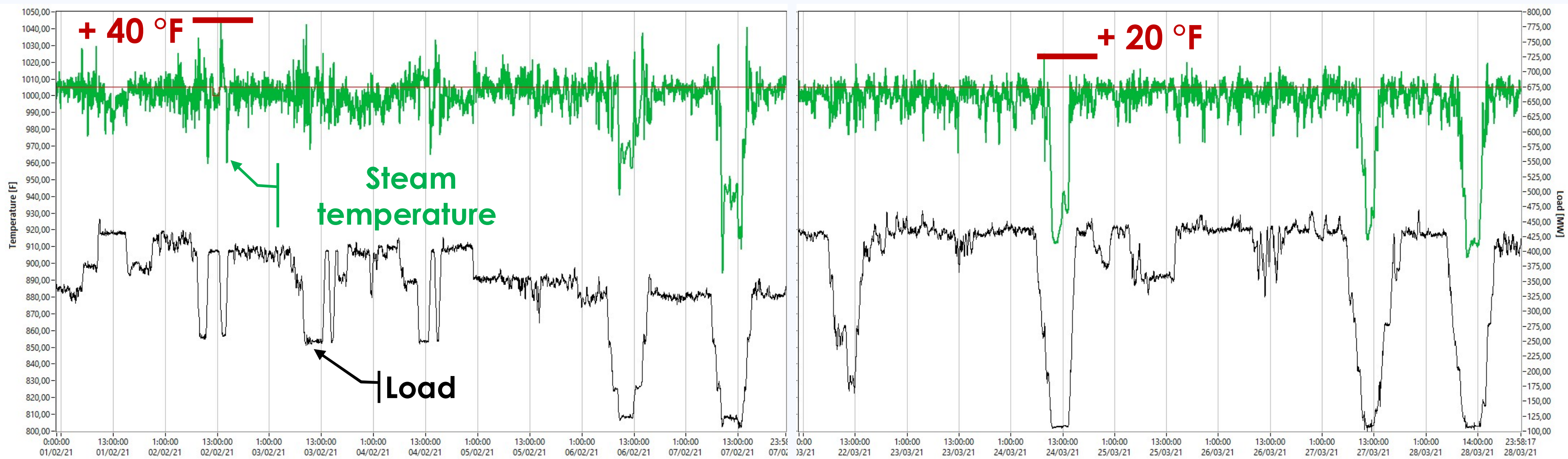
ADEX is a self-tuning AI platform used to ensure real-time control precision. Self-tuning AI manages controllers for enhanced control over the full load range. A predictive model incorporates real-time model predictions. An expert block enables knowledge of process dynamics to influence control decision within various operating domains and accounts for multi-variable interactions

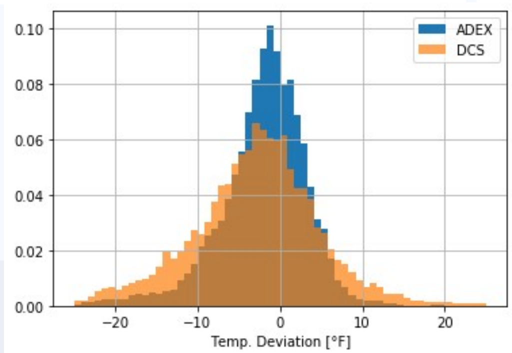
Project status:

Superheater steam temp ✓ → Reheater steam temp ✓ → Power / Pressure → Emissions → Drum level

CURRENT PROJECT PROGRESS

One-week DCS control system | One-week ADEX control





DCS
Average Temp: 1002 °F
Std. Dev: 8 °F

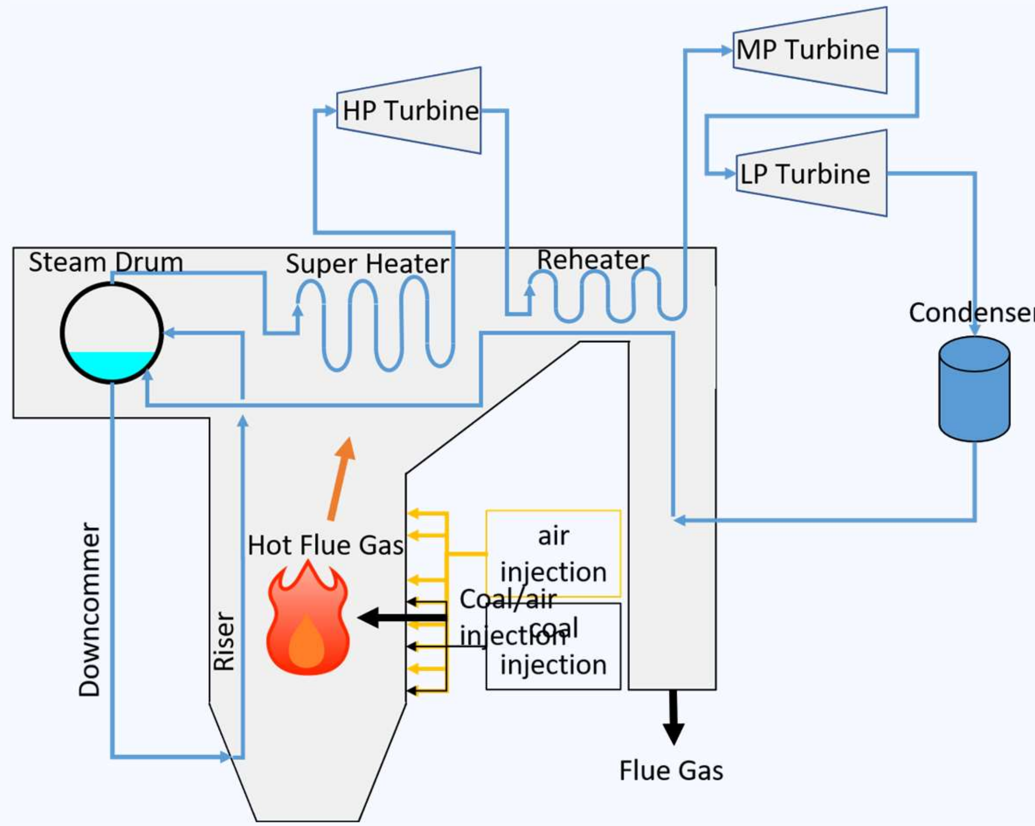
ADEX
Average Temp: 1003 °F
Std. Dev: 5 °F

Improvement
+ 1 °F
- 3 °F

OFFLINE MODELING FOR PROTOTYPING

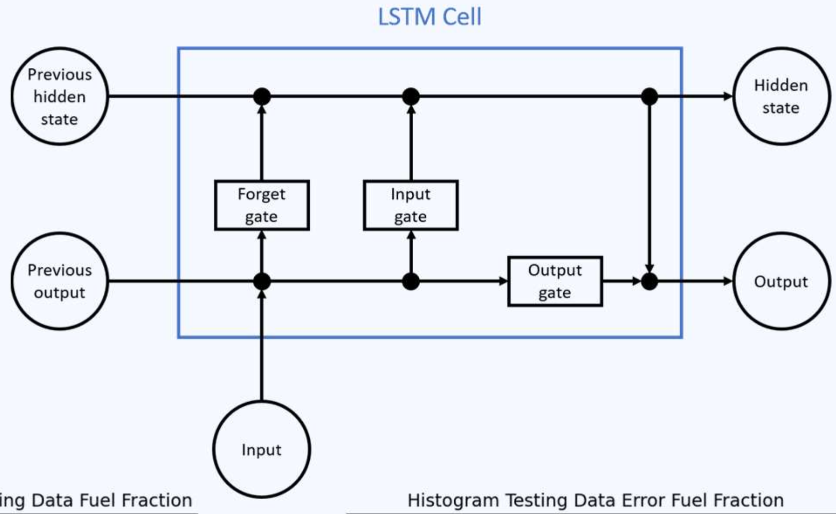
DYNAMIC MODEL

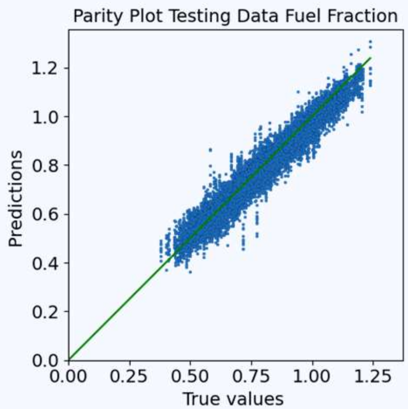
- Dynamic model created of boil, turbines, and super-/re-heater
- Simplified reaction chemistry in boiler
- Three types of thermal inertia:
  - Flue gas (very short timescale)
  - Pipes (medium timescale)
  - Refractory brick (long timescale)
- Boiler discretized spatially and temporally
- Performance tuned to existing boiler specifications to within 4% deviation

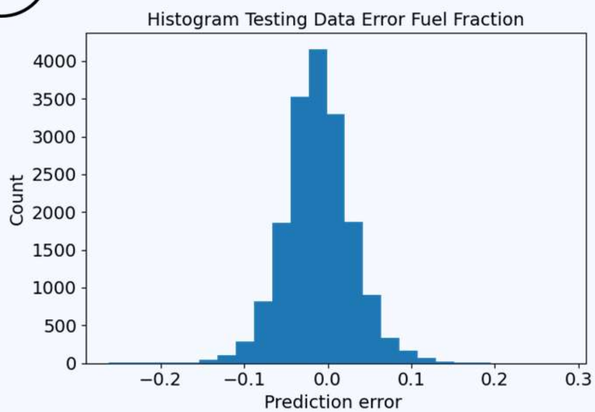


MACHINE LEARNING – LONG SHORT-TERM MEMORY

- Long short-term memory (LSTM) proved accurate at data-driven dynamic modeling of simulated plant
- High prediction accuracy 10-minutes into the future, using:
  - Current system state
  - System history
  - Future system inputs
- Machine Learning Model used for Model Predictive Control (MPC) of boiler

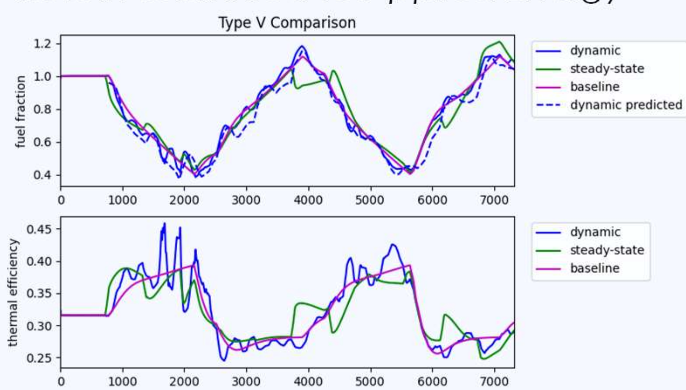


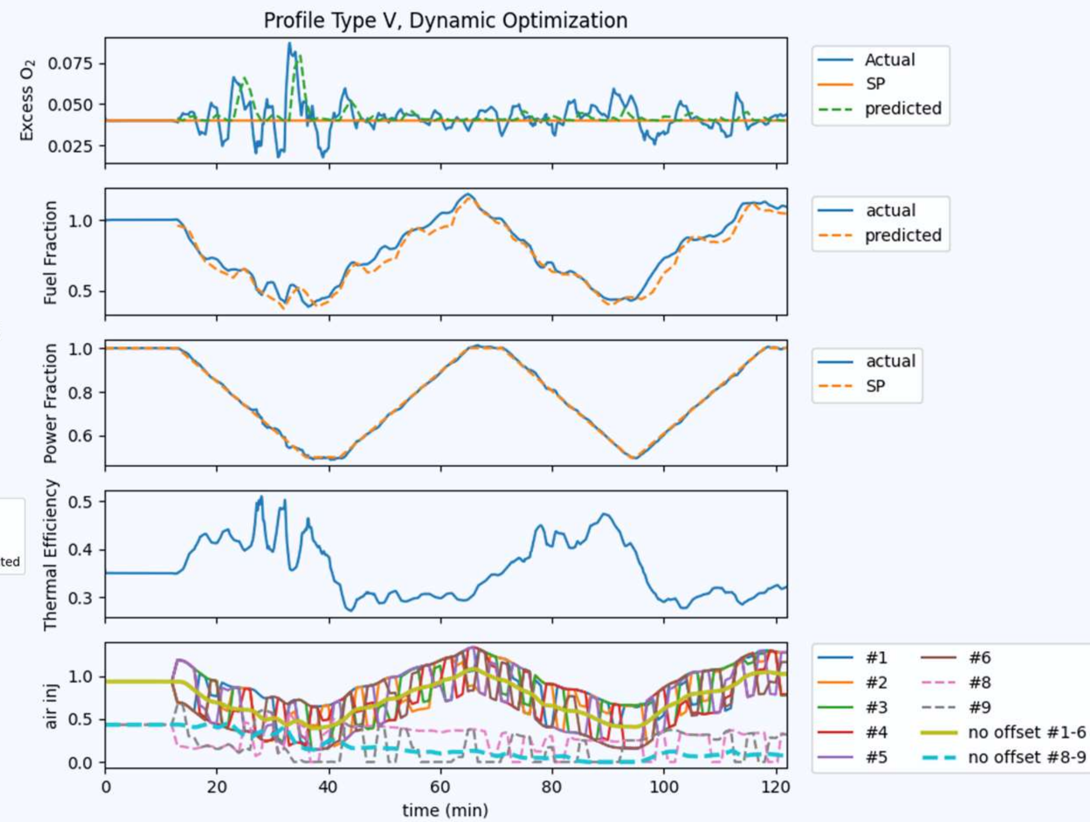




MACHINE LEARNING-BASED DYNAMIC OPTIMIZATION RESULTS

- Proof of concept for Dynamic Neural Network-based optimization (D-NNO)
- Up to 4.58% improvement of Dynamic over Steady-state Optimization
- Results submitted to *Applied Energy*





CONCLUSIONS

- Because of increased ramping, dynamic optimization is needed
- We need better accuracy in heat rate estimation to improve D-NNO results
- Most promising dynamic models are:
  - Long short-term memory (LSTM)
  - Gated-recurrent unit (GRU)
- In simulation studies, D-NNO is definitively better than Steady-State NNO
- Going forward, focus on:
  - Accurate dynamic ML models trained on best possible transient heat rate data
  - Handing algorithmic developments "over the fence"
  - Coordinating short-term control objectives with longer-term optimization objectives
  - Developing a commercial D-NNO product

ACKNOWLEDGEMENTS

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- Thank you to PacifiCorp Energy and the Hunter Power Plant for their support and collaboration as the host site.

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