

Advance Optimization Methods for NOx Reduction and Boiler Optimization

Neural Networks and Beyond

NOx Roundtable
Charlotte, North Carolina
January 23-24, 2006

Industry Challenges

- Asset life extended far beyond designed life
- Systems getting more complex
- Unit operations beyond design conditions
- Margins slimmer, markets more demanding
- Brain-drain is rampant

Traditional Tools

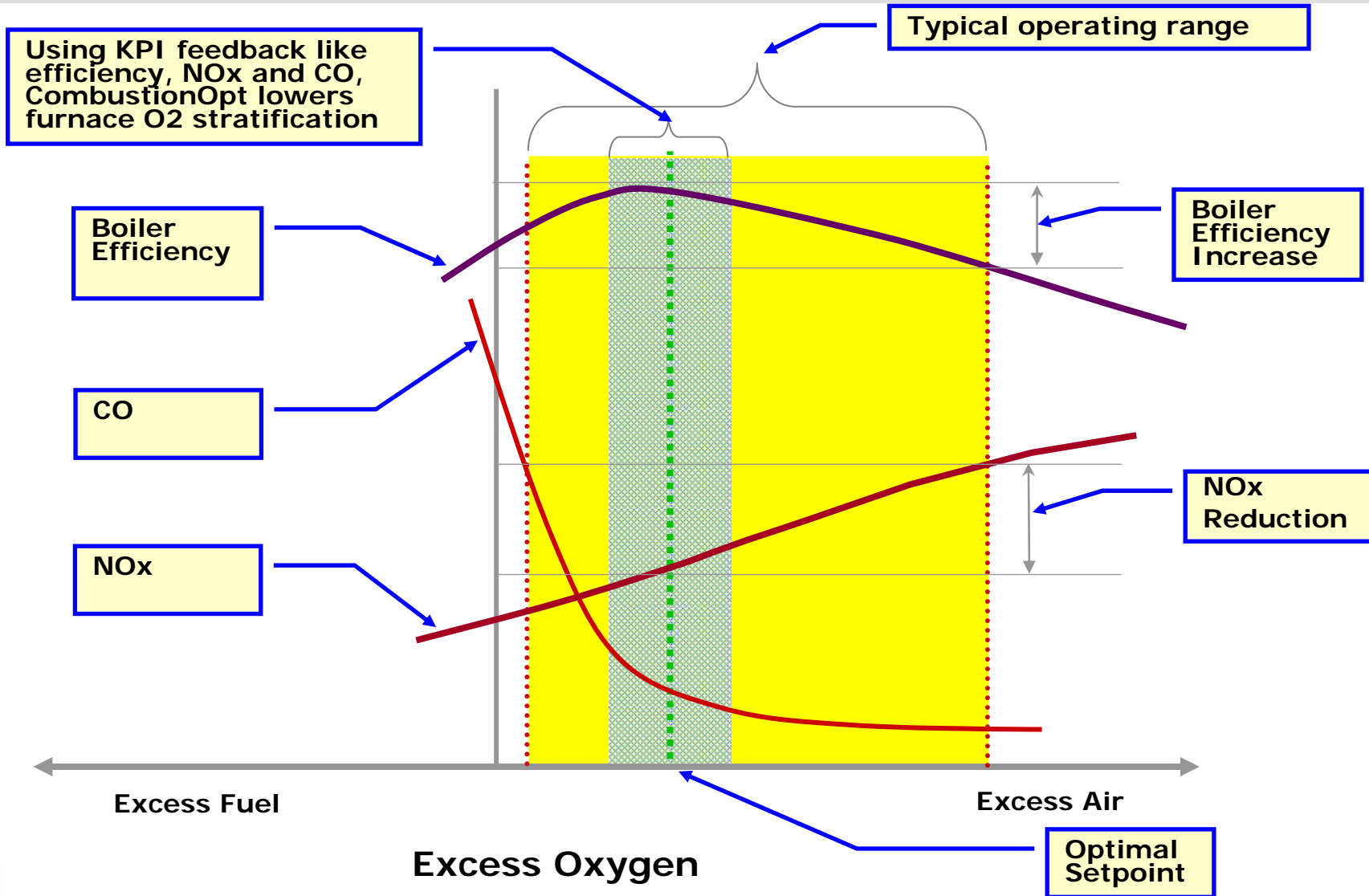
- **Systems:**
 - Instrumentation and Controls
 - Performance Monitoring
 - Advanced Sensors and Detectors
- **Infrastructures:**
 - Enterprise Resource Planning (ERP) Systems
 - Computerized Maintenance Management Systems (CMMS)
 - Historians and Portals
- **Methodologies:**
 - Six Sigma
 - Key Performance Indicators (KPI)
 - Earned Value Analysis (EVA)

Gaps

- Data
 - Too much of it and most of it is redundant
- Information
 - Lacks context and any understanding of implications
- Knowledge
 - Too late or too coarse-grained to be useful

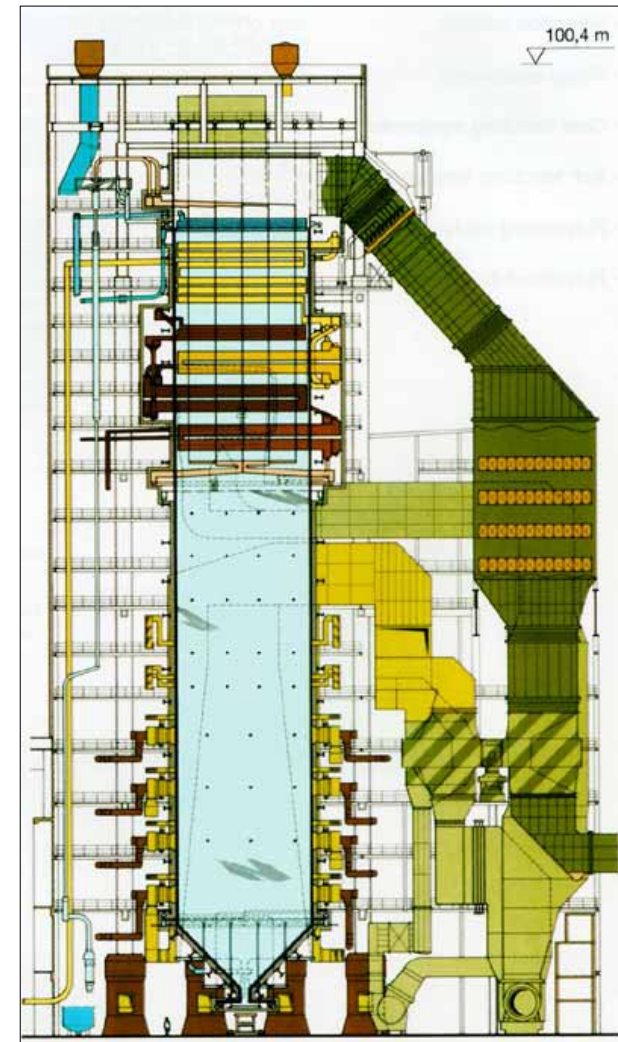
*Closing the gaps requires **real-time analytics!***

Combustion Optimization



Benefits of Neural Network Combustion Optimization

- Lower NO_x (5-25%) with 15% average
- Improved heat rate (0.25-1.5%)
- Better control of CO, LOI, and opacity
- Enhanced operator performance and more consistent operations
- Higher availability through advanced diagnostics
- Lower post-combustion operating costs
- Capital preservation (potential avoidance of SCR or SNCR)



The Evolution of Combustion Optimization Installations

- 1st Gen – Early 1980's
 - Design of Experiments in Advisory
 - 80+ Installed, None Still Running
- 2nd Gen – Early 1990's
 - Neural in Open-Loop (“Advisory” systems)
 - 40+ Installed, Few Still Running
- 3rd Gen –Mid 1990's
 - Neural in Closed-Loop
 - 40+ Installed, Half Still Running
- 4th Gen – Late 1990's
 - Neural Closed-Loop with On-Line Learning
 - 40+ Installed, All Still Running
- 5th Gen – Current
 - Multiple optimizers using different methods for different problems
 - Integration of the optimizers with one another and business objectives
 - Being currently demonstrated at several plants

Neural Network-Based Represents State-of-the-Art Combustion Optimization

- Insufficient direct feedback to control the combustion process better through conventional DCS methodology
- Highly non-linear and complex processes
- Process changes continuously based on burners, damper and mill issues
- Normal power plant equipment degradation and maintenance cycles and associated process changes
- Fuel changes, blending and fluctuations
- Changing and seasonal environmental regulations

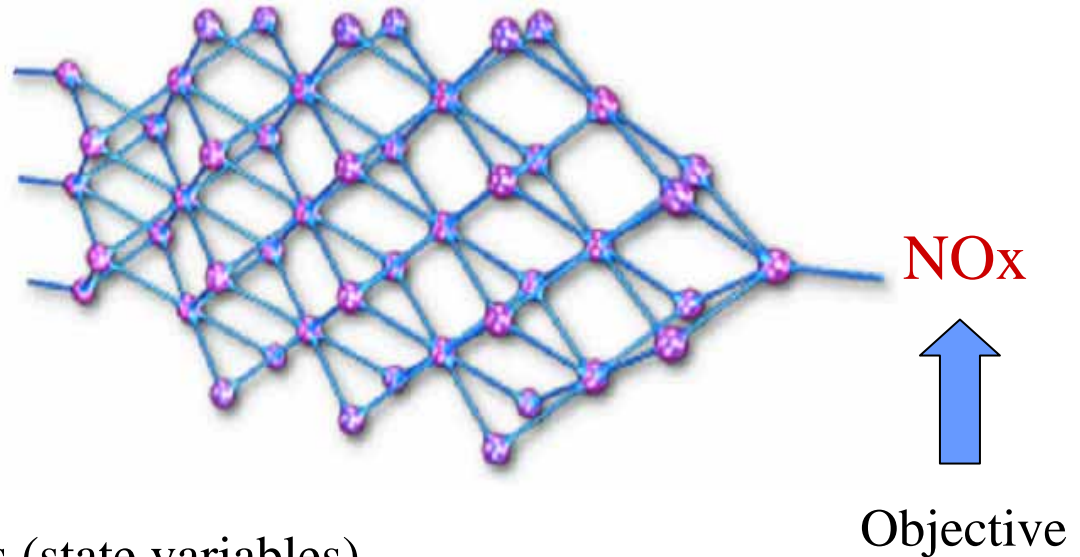
What is a Neural Network?

- Mathematical system that receives real-time operating data (inputs) and empirically learns through experience or experiment
- What is learned is the interrelationships between the input values and the objective function or goal
- Mathematical system emulates human's ability to recognize patterns and learn relationships from information received from input sensors
 - Biological NN: sight, hearing, touch, smell, & taste for human objectives
 - Artificial NN: state/manipulated variables for boiler performance objectives

Neural Networks As Applied to Combustion Optimization

Excess O_2
Ambient Conditions
Secondary Air Biases
Feeder Biases
Primary Air Biases

Controllable and
Non-Controllable Parameters (state variables)

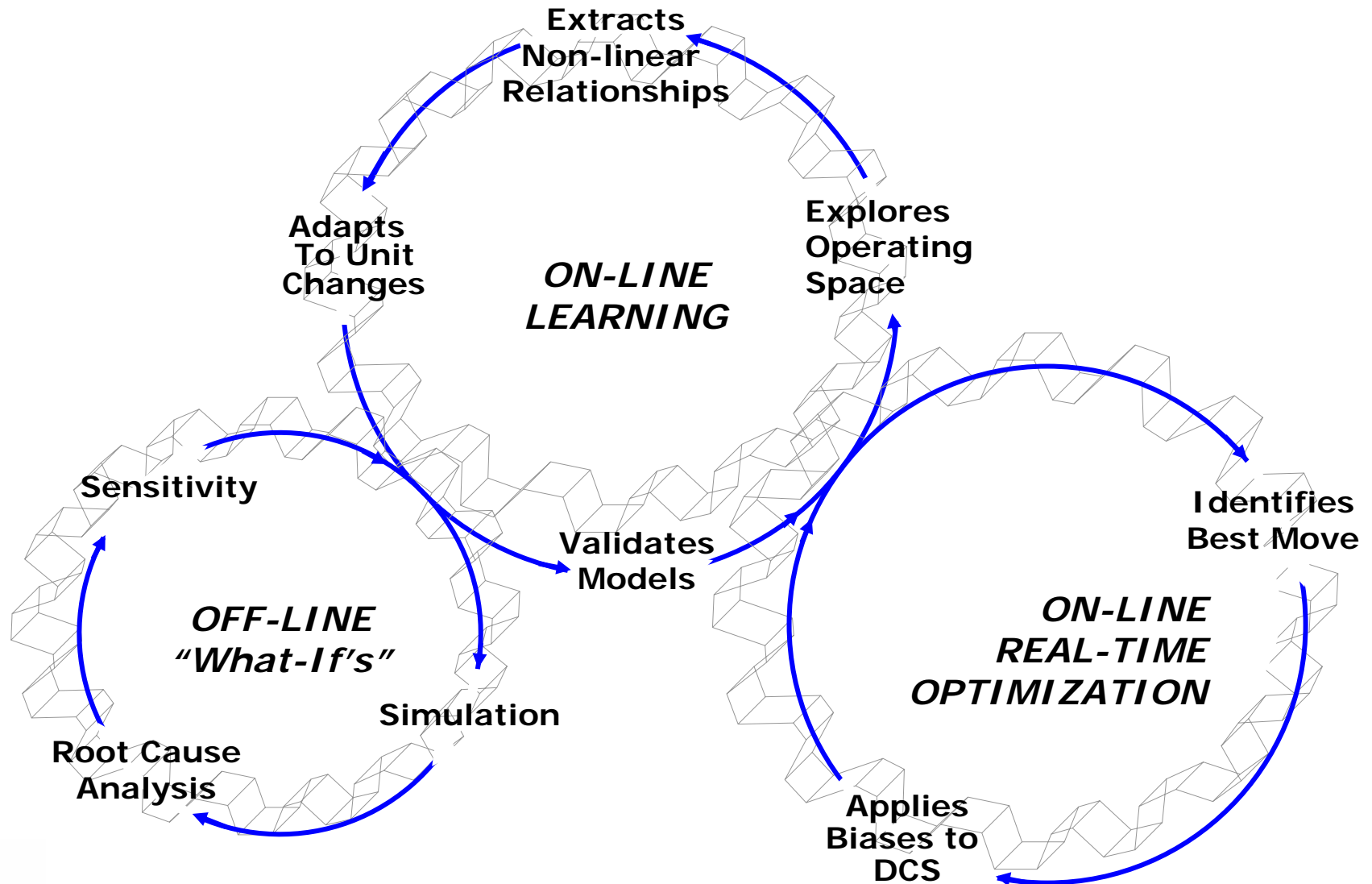


NO_x depends upon (O_2 , Ambient Conditions, Biases, etc.....)

How Does a Neural Network Train?

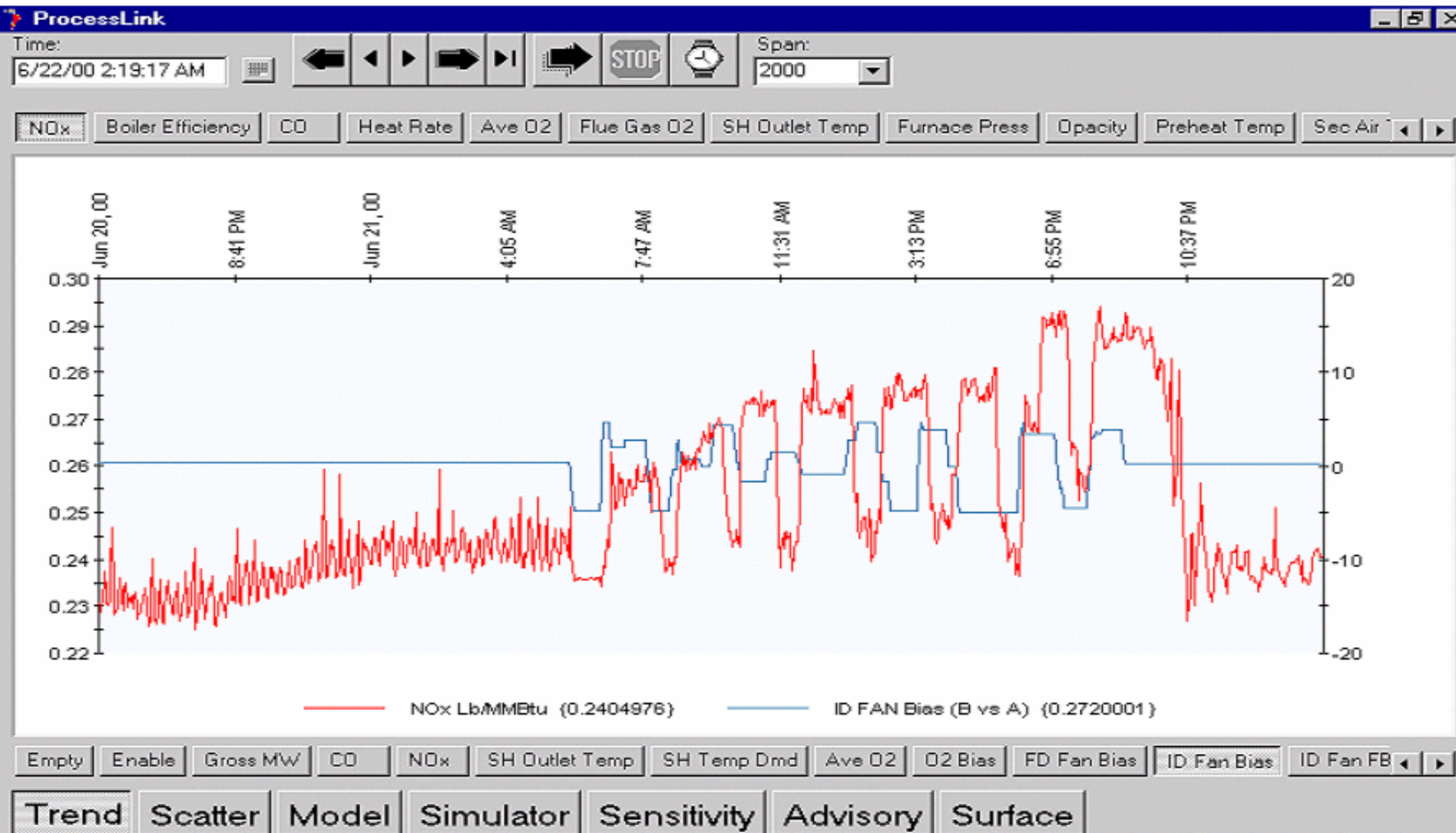
- Internal parameters (weights) are adjusted to minimize the error between actual data and the model predictions
- During training phase, error is calculated at each point in time and connection weights at each node adjusted using back propagation
- As the model's experience builds, so does model accuracy
- Statistical model validation is crucial for overcoming intrinsic ANN susceptibility to local minima/maxima

How On-line Learning Works



Automated Parametric Testing

Cause and Effect Relationships – Effect of ID Fan Bias (Blue) on NOx (Red)



Neural Network Model Development

Data Visualization indicates model accuracy

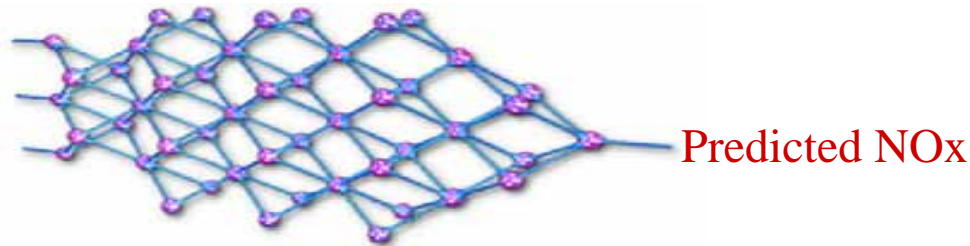


Neural Networks are Adaptive and Update Themselves Automatically

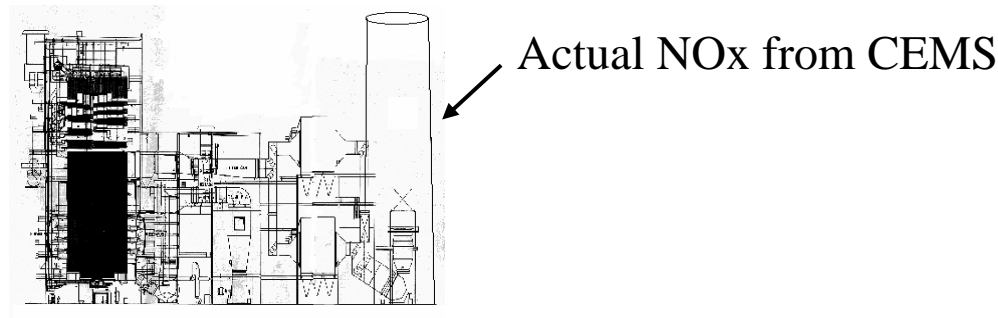
- Neural Nets continually update their regression coefficients (weights) using the most recent plant data

Model

Boiler state variables
Ambient Conditions
MVs (biases & trims)



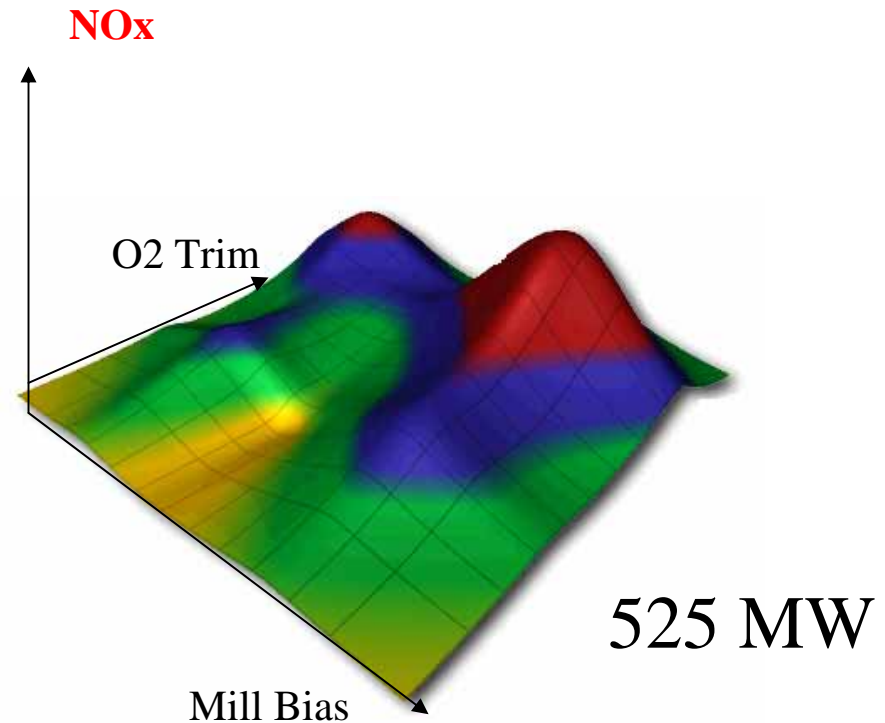
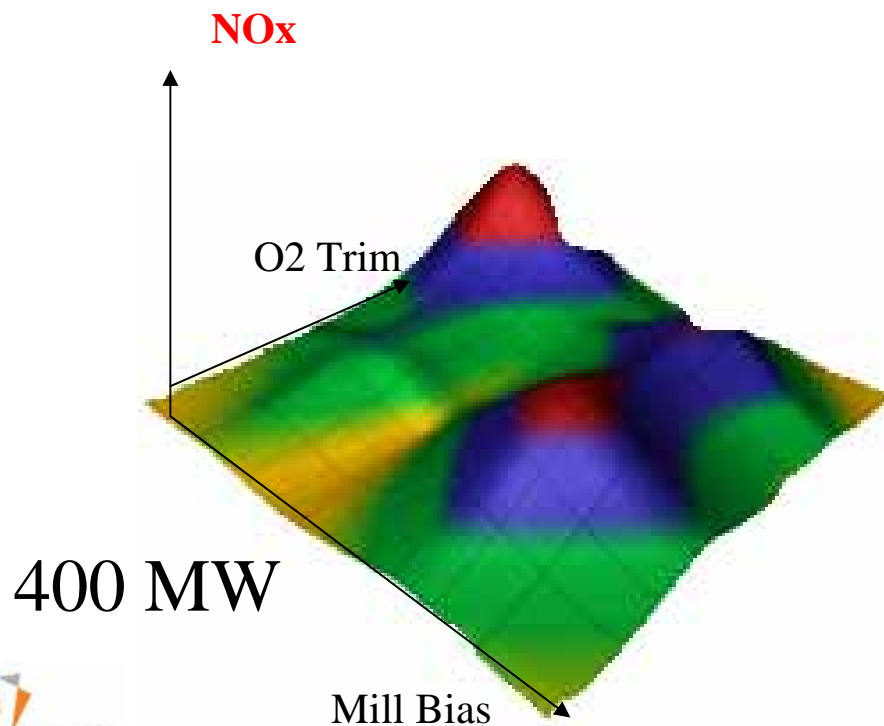
Plant



$$\text{Error} = \text{Actual NOx} - \text{Predicted NOx}$$

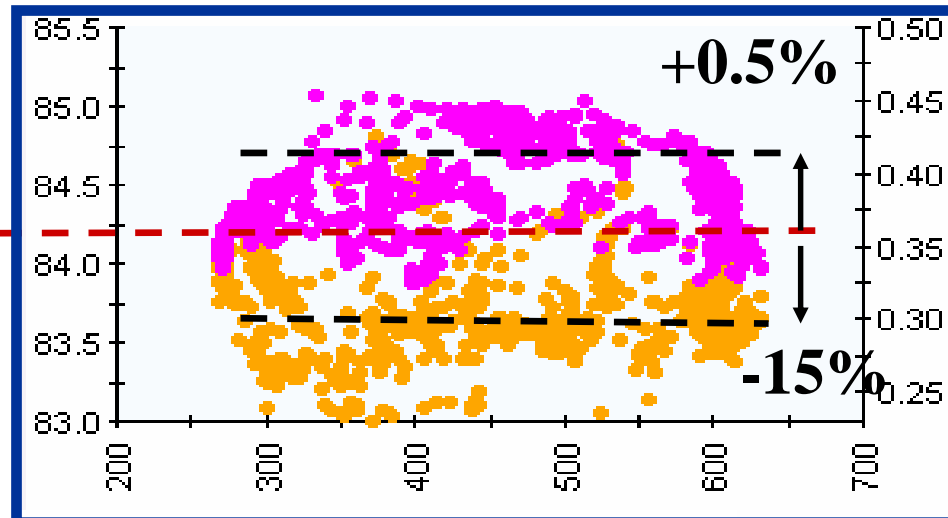
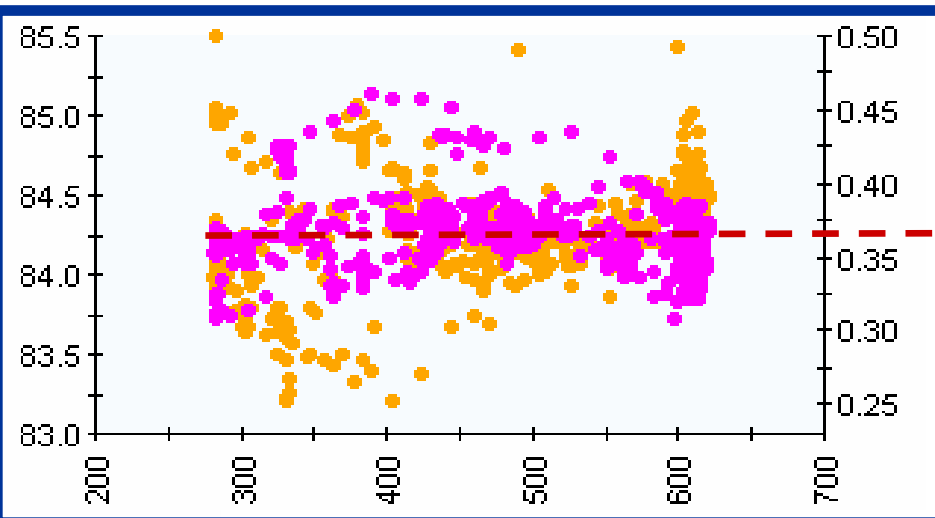
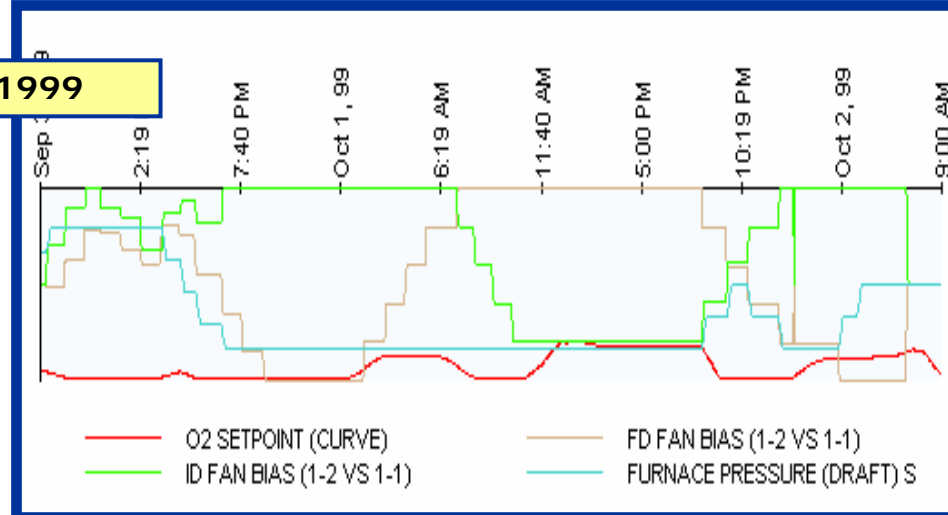
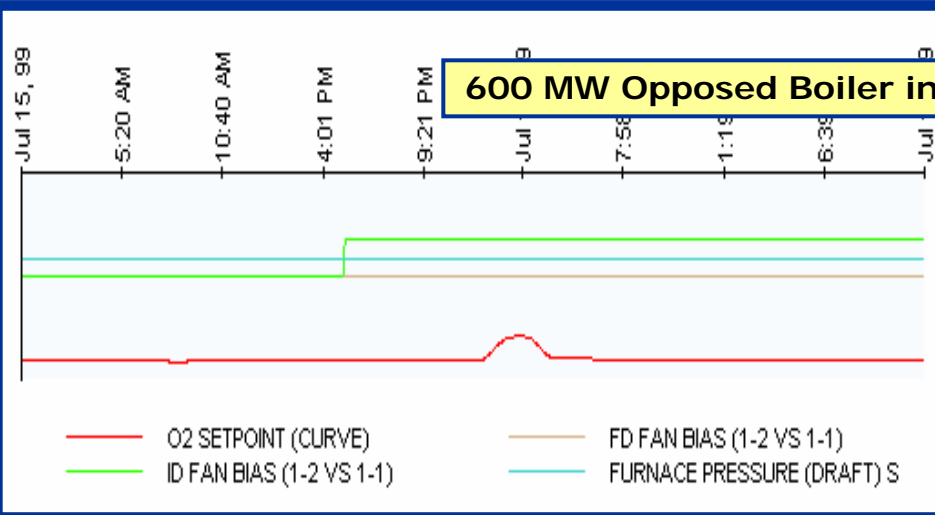
Combustion Optimization Response Surfaces

- Typical system has 20-40 inputs to predict each objective (NO_x, Efficiency, etc)
- Complex relationships – Output varies with time and input changes
- Example – Effects of Mill Biases and O₂ varies as load changes



Example of NOx and Efficiency Improvement

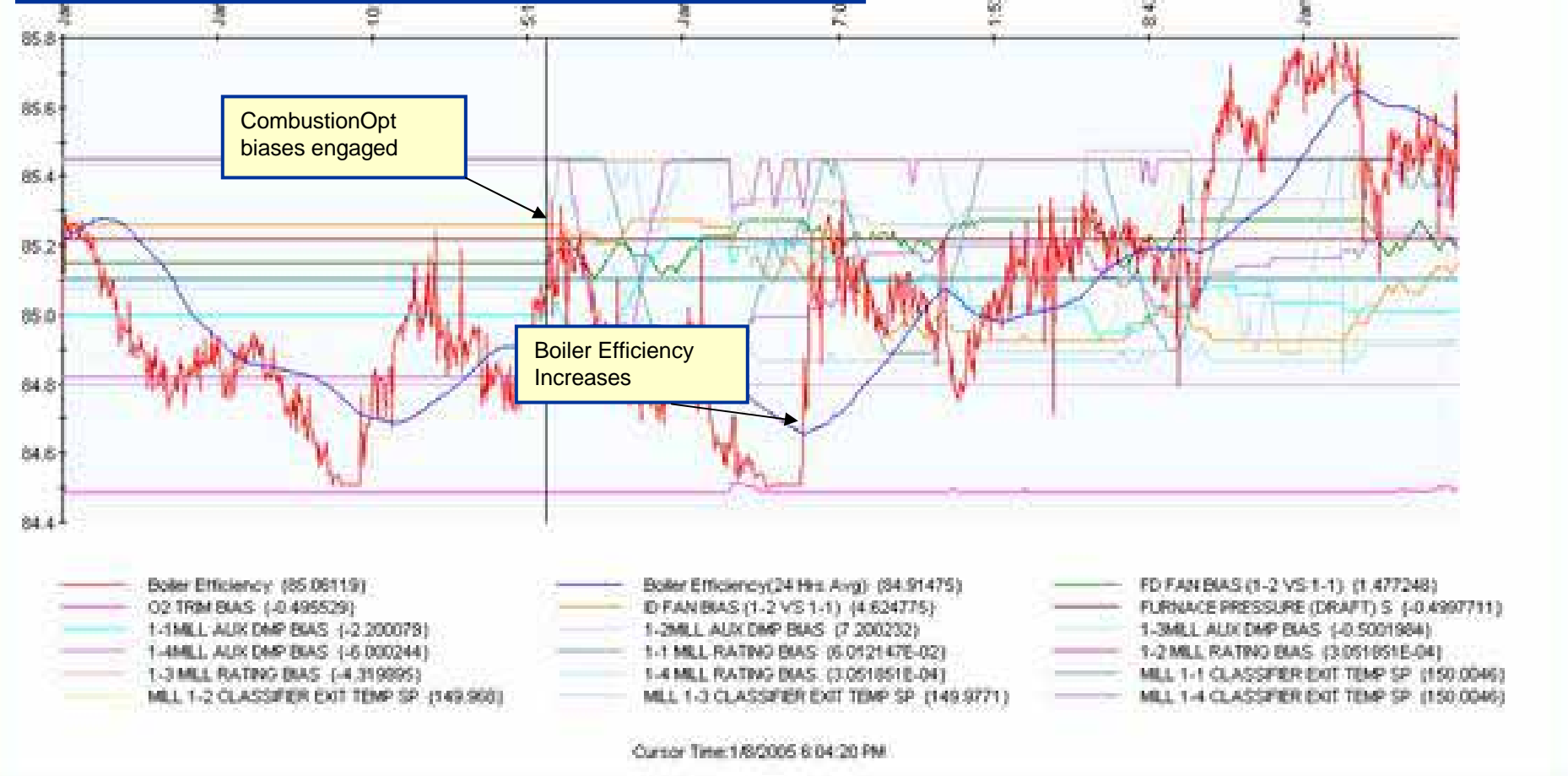
600 MW Opposed Boiler in 1999



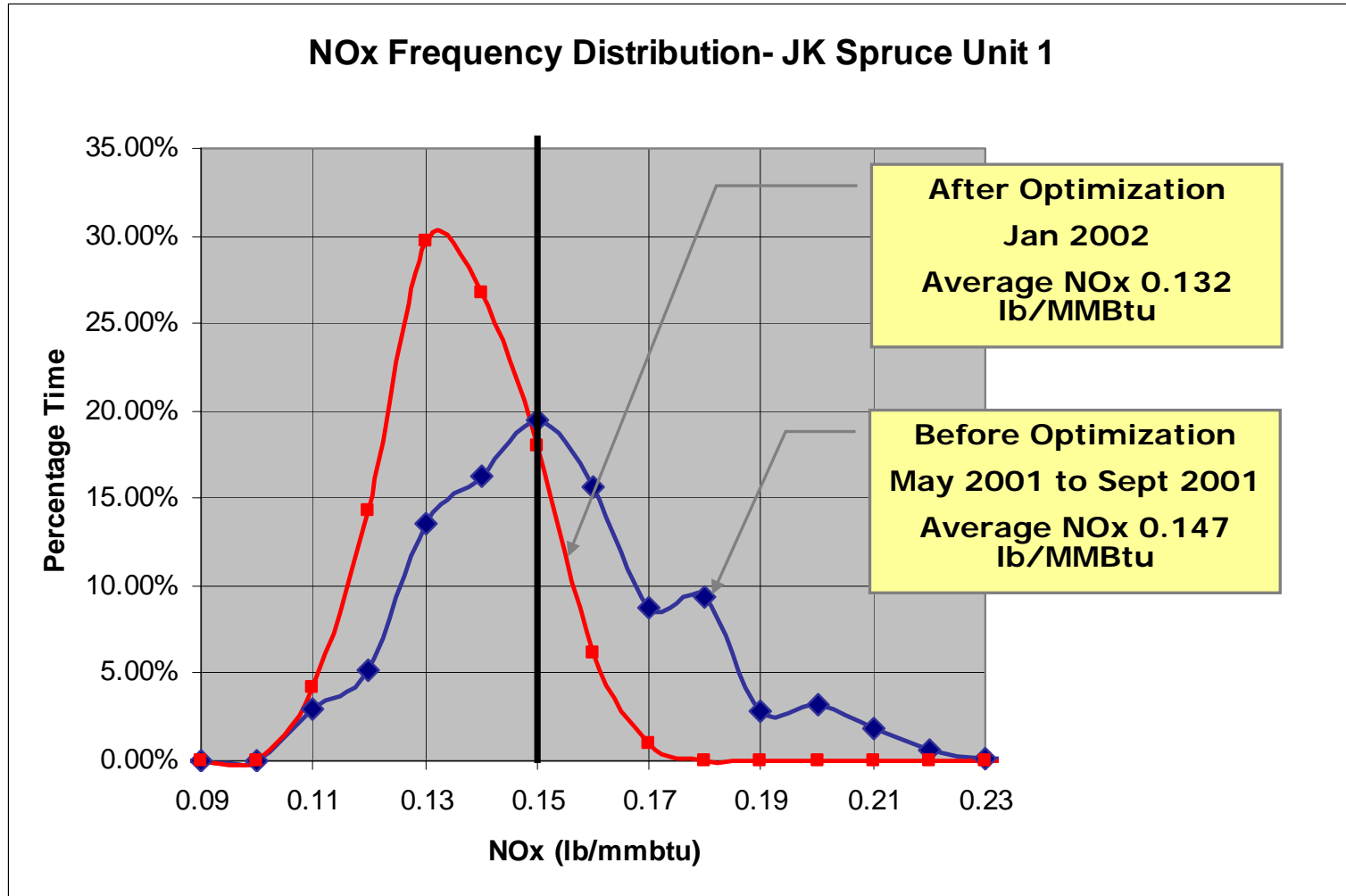
● Boiler Efficiency

● NOx

Same 600 MW Unit Five Years Later (1/1/05)



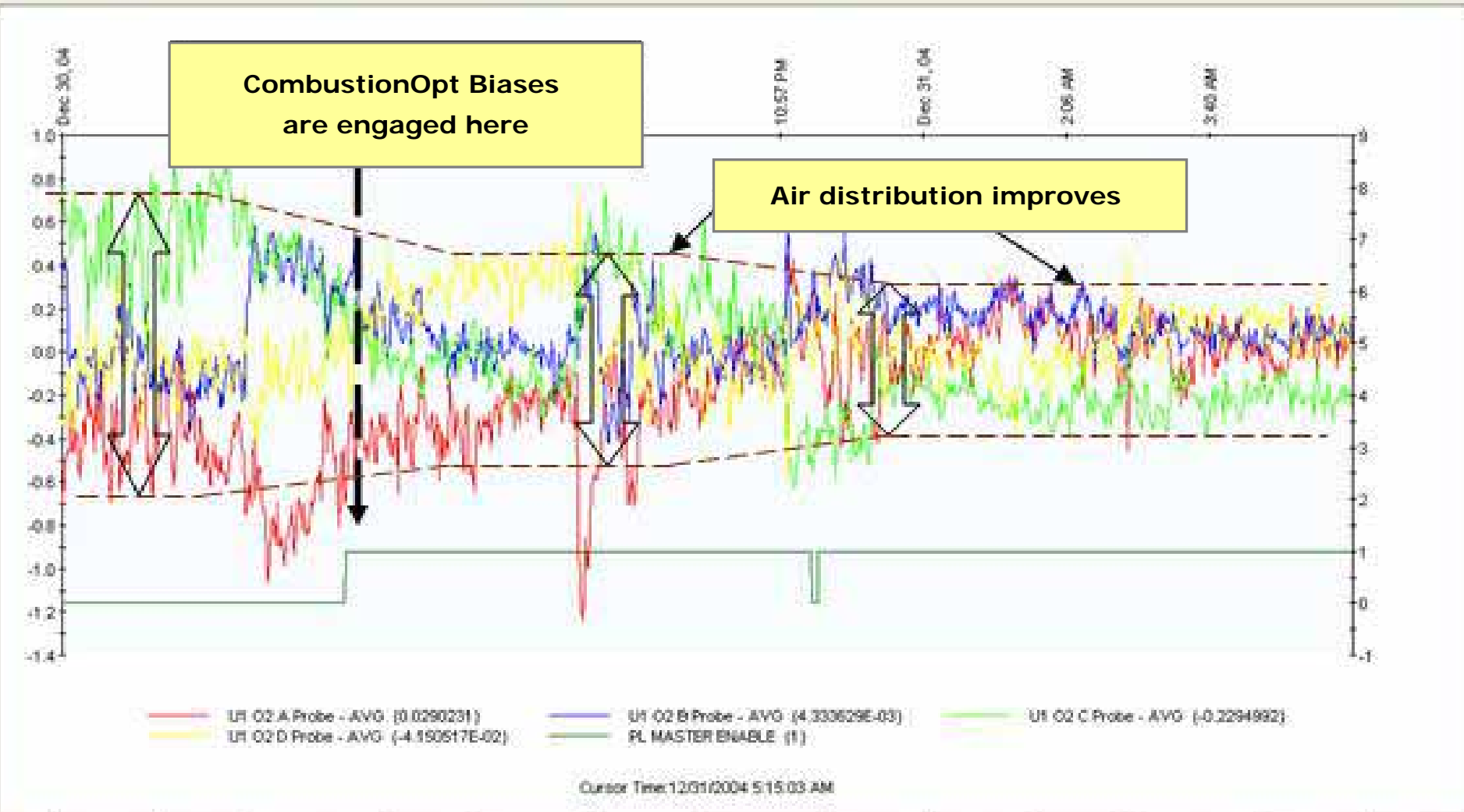
Effects of Combustion Optimization on 600 MW Coal-Fired Tangential Boiler



Key Driver is Better Distribution of O2

Time: 12/31/2004 05:15:03 AM
Boiler Efficiency NOx

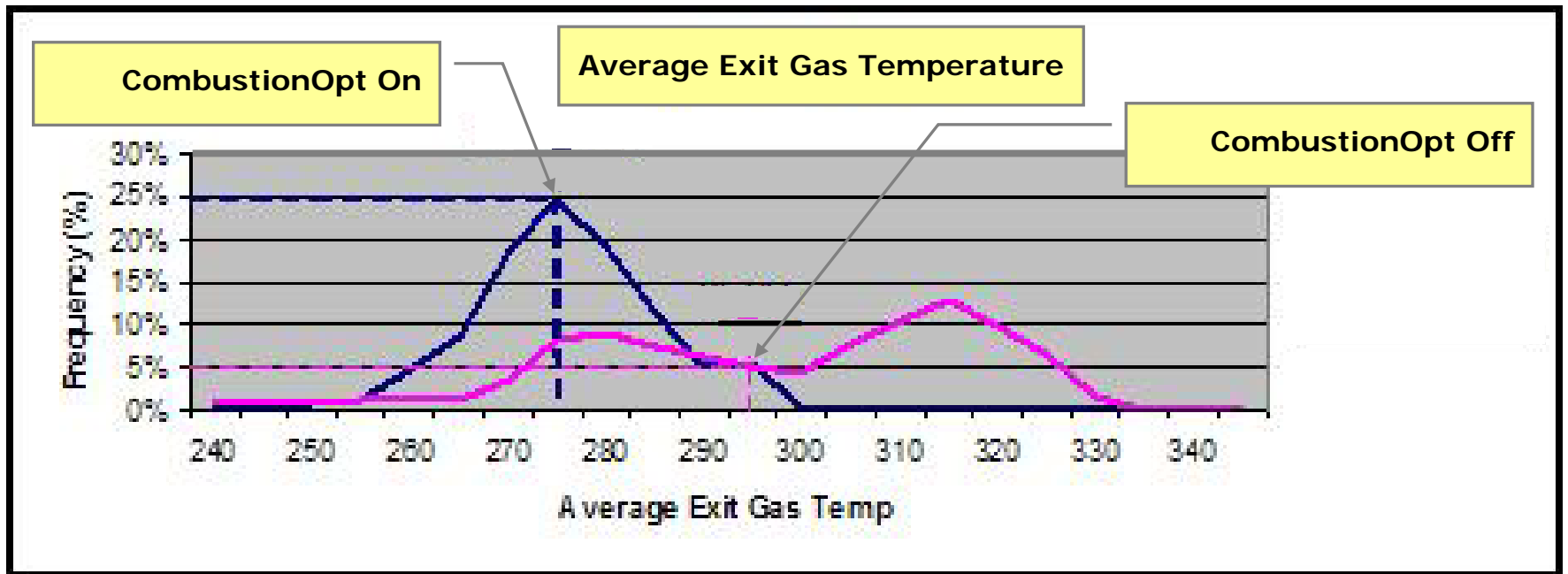
O2 Trim Bias FD Fan Bias ID Fan Bias ID Fan



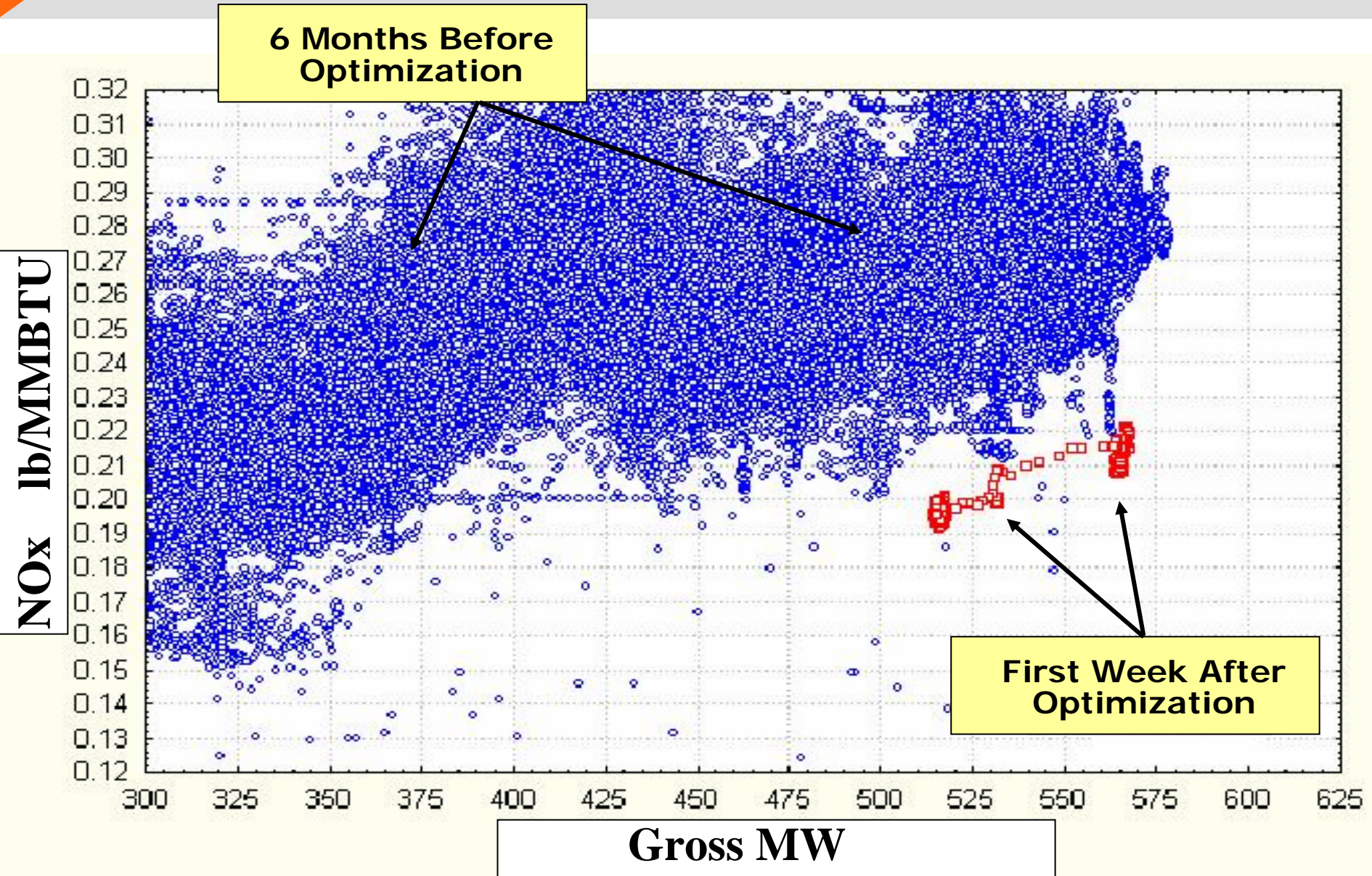
Empty Gross MW PL Enable Enable Switches Mill On/Off O2 Set Point Applied Biases O2 Trim Bias FD Fan Bias ID Fan Bias ID Fan Pos Furnace Pressure Aux Air Bias Fuel

Trend Scatter Model Simulator Sensitivity Advisory Surface Turbine Trend Turbine Scatter

Temperatures Affect NOx & Efficiency

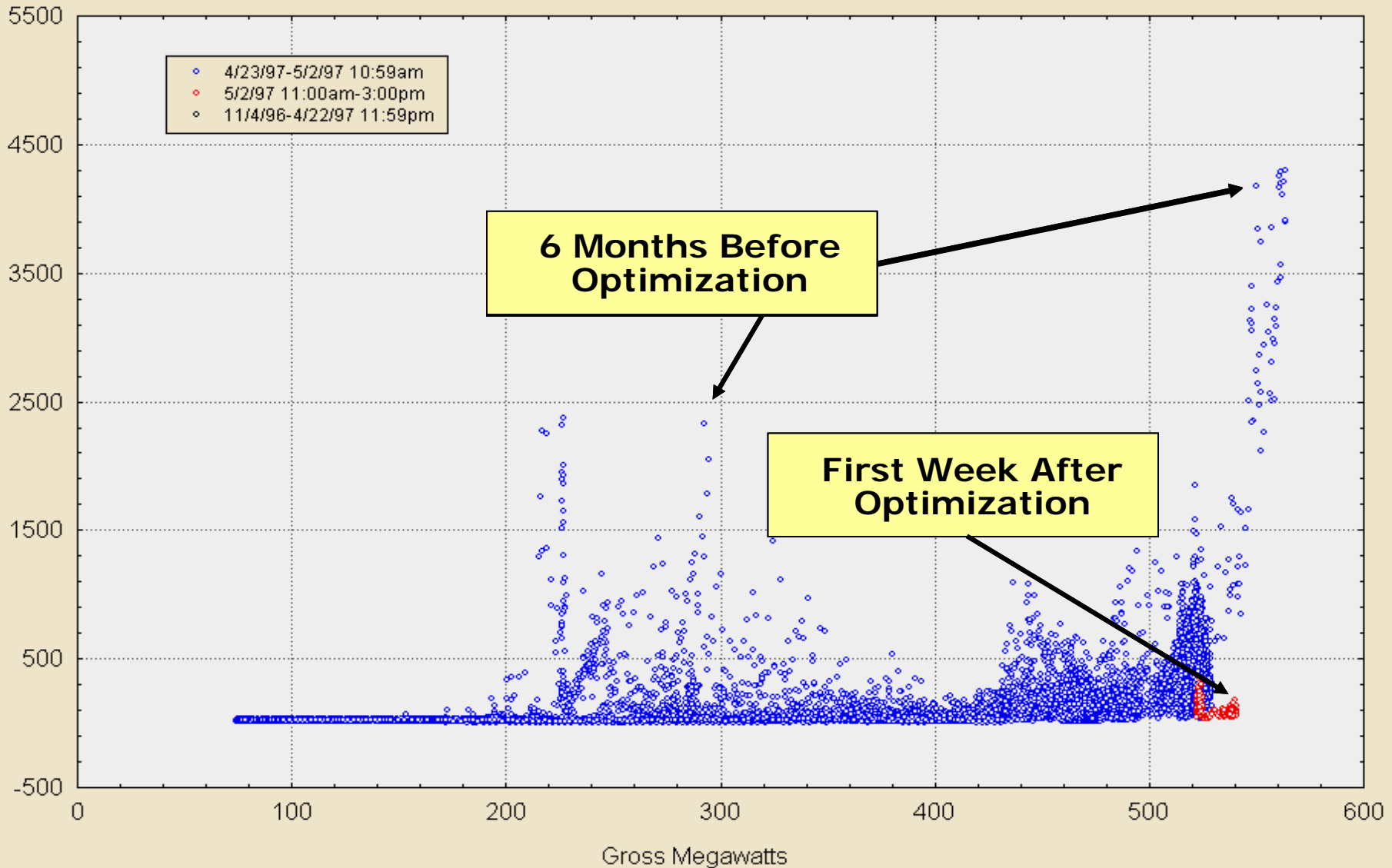


Impacts on NOx for 600 MW Oil/Gas-Fired Opposed Boiler

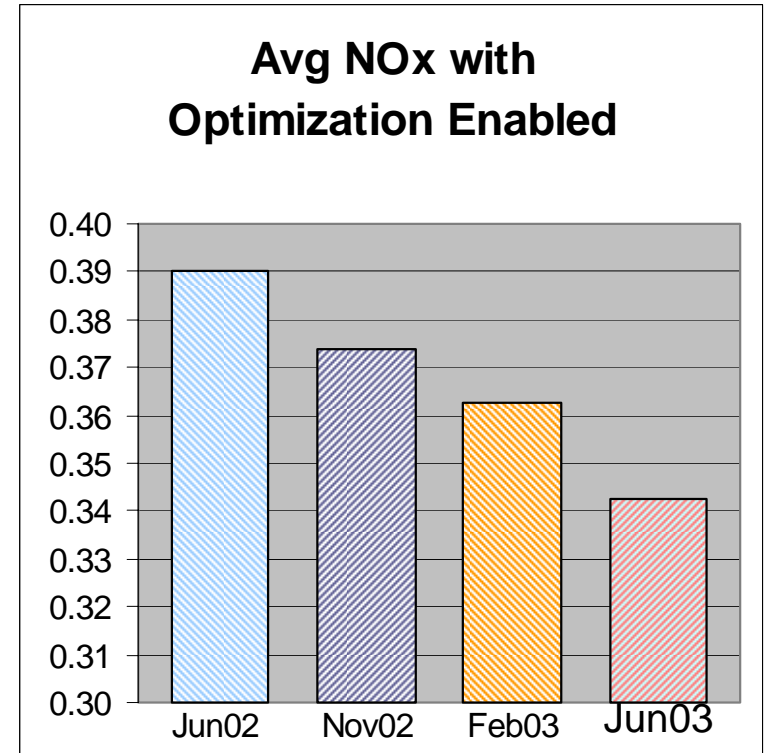
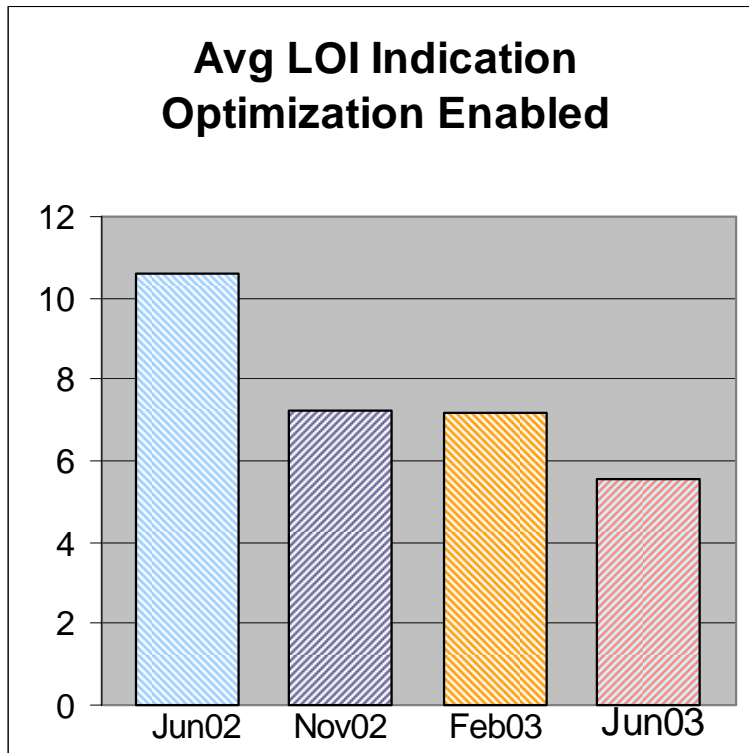


Impacts of Combustion Optimization on CO on Same Boiler Over Same Period

Gross vs CO Side A&B Average 4/23/97 - 5/2/97 3:00pm



Increasing LOI & NOx Reduction over One Year with In-Situ LOI Indicators



Recent Advances in Combustion Optimization

In recent year some newer techniques have evolved:

- Committees of models
- Automated design of experiments for normal operating conditions and AGC
- Easier means of implementing plant constraints in the optimization search
- Easier means of implementing objective profiles
- Improvements in data visualization
- Easier means of interfacing with DCS readily adopted

Key Recent Advances

- On-Line Learning
- Monetized tradeoffs between objectives
- Condition-based Optimization Profiles
- Scripting for any set of condition-based rules known to improve unit performance and/or avoid undesirable conditions
- Enhanced dynamic and discrete modeling enhancements

Unit 1: CombustionOpt Home

5/3/2005 02:00 PM

Optimization Advice

Recommended actions

- ! Enable Mill 4 PA
- ! Enable Mill 1 feeder speed
- ! Enable Mill 3 PA
- ! Enable Mill 5 PA
- ! Enable PA duct press
- ! Enable sleeve damper 1-3-2
- ! Enable Mill 3 outlet temperature

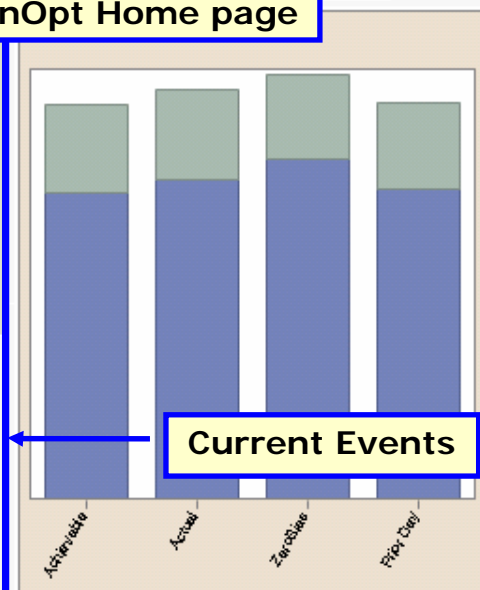
Cost Impact (\$/MWh)

Enable Mill 4 PA	\$0.04
Enable Mill 1 feeder speed	\$0.03
Enable Mill 3 PA	\$0.03
Enable Mill 5 PA	\$0.03
Enable PA duct press	\$0.03
Enable sleeve damper 1-3-2	\$0.03
Enable Mill 3 outlet temperature	\$0.03

The CombustionOpt Home page

Optimization Benchmarks

Optimization Benchmarks



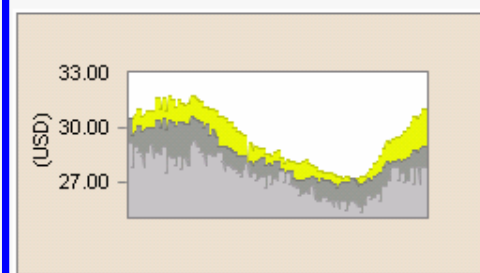
Current Events

Objectives for the most recent move

Details...

- Reduce Fuel Cost by 0.06 \$
- Reduce NOx Cost by 0.79 \$
- Keep North O2 Average between 2.7 and 3.2
- Keep South O2 Average between 2.7 and 3.2

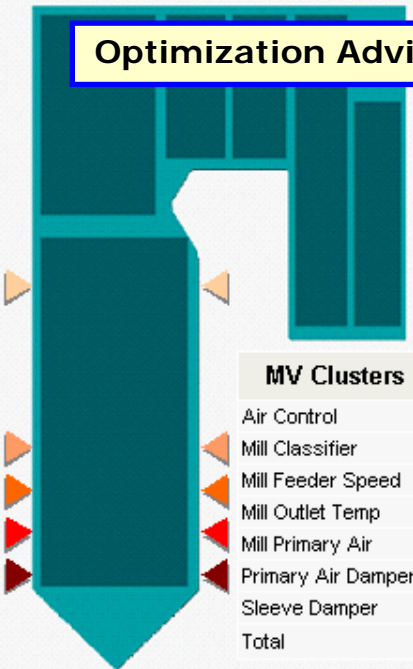
Potential benefits	\$/MWh
Fuel	0.91
NOx	0.18



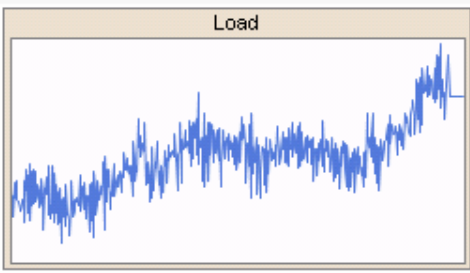
■ Benefits achieved (\$)

■ Potential additional benefits (\$)

Optimization Advice



MV Clusters	Enabled	Total
Air Control	2	3
Mill Classifier	3	3
Mill Feeder Speed	0	5
Mill Outlet Temp	4	5
Mill Primary Air	0	5
Primary Air Damper	1	2
Sleeve Damper	18	20
Total	28	43



Enhanced Dynamic and Discrete Modeling

- Both dynamic and discrete modeling techniques needed
- These capabilities needed to better address a variety of operating challenges:
 - Faster ramping
 - Burners and mills out-of-service
 - Anticipated changes in operating conditions
- Scripting functionality and a rules engine bolster these capabilities
- Greater flexibility and use of mathematical methods best suited to different problems provide a broader arsenal of tools to address combustion challenges

Monetized Objective Prioritization

- Important (where possible) to prioritize objectives and manage tradeoffs between them based on their monetary value
- Models of physical units (lb/mmBtu, Btu/kWh, etc.) require knowledge of process changes over time
- Costs of these units, however, are imposed externally by markets/contracts
- Physical units and monetary value address separately but brought together to prioritize and trades-off objectives

Combustion/SCR Optimization Challenges

- Must avoid problems associated with sub-stoichiometric combustion
 - Waterwall corrosion
 - Slagging
 - Increased LOI
- Exploit available fuel and air measurements
- SCRs increasingly operate year-round
- No automated control over AIG
- NH₃ instrumentation can be useful
- Objectives vary depending on market conditions



New On-Line Signals Becoming Available

- Flame scanner signals
- Tune-able Diode Laser NH₃ Signals
- New In-furnace TDL measurements

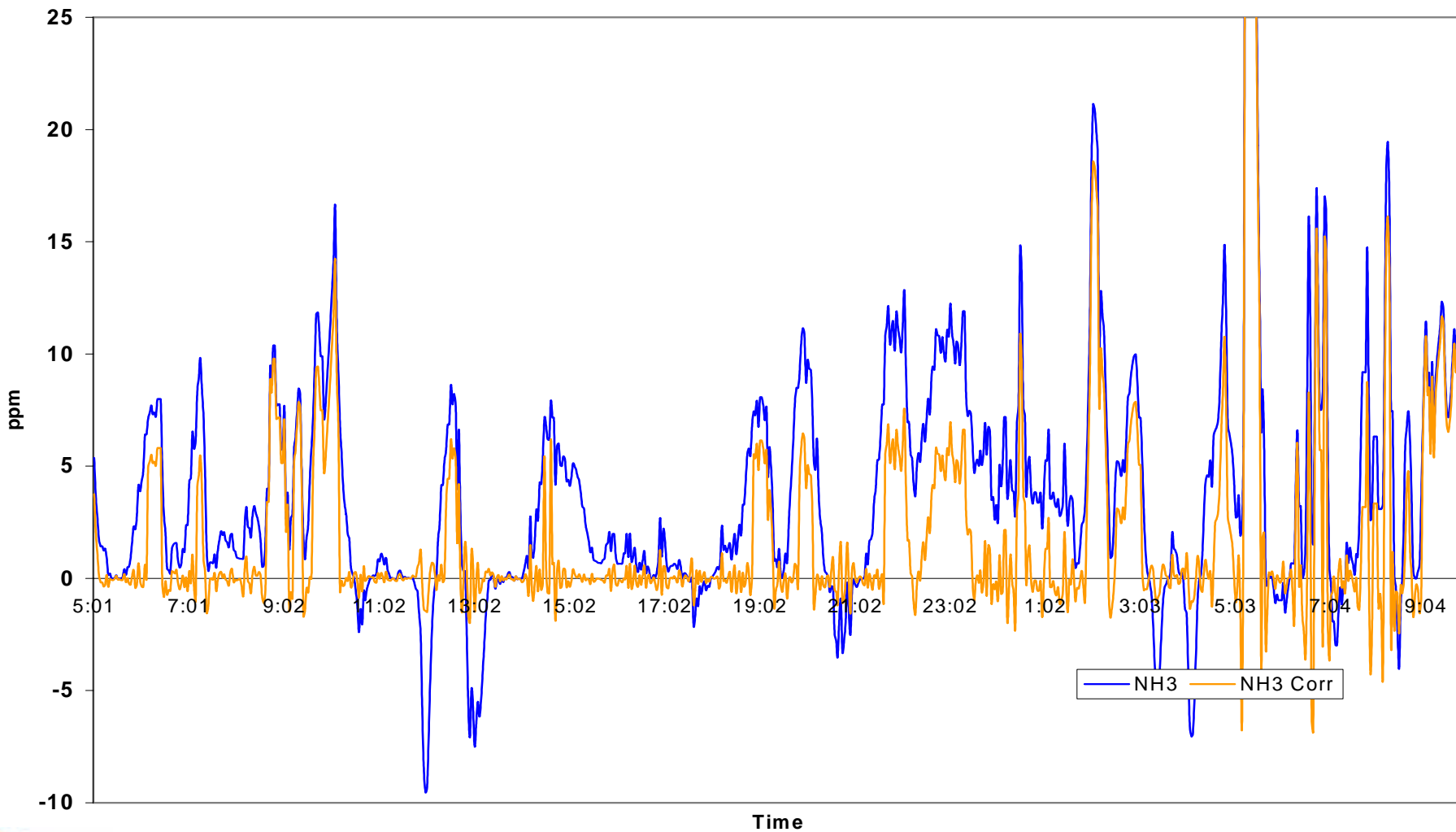


On-Line NH₃ Signal for Closed-Loop Optimization: CCPI Project at Baldwin

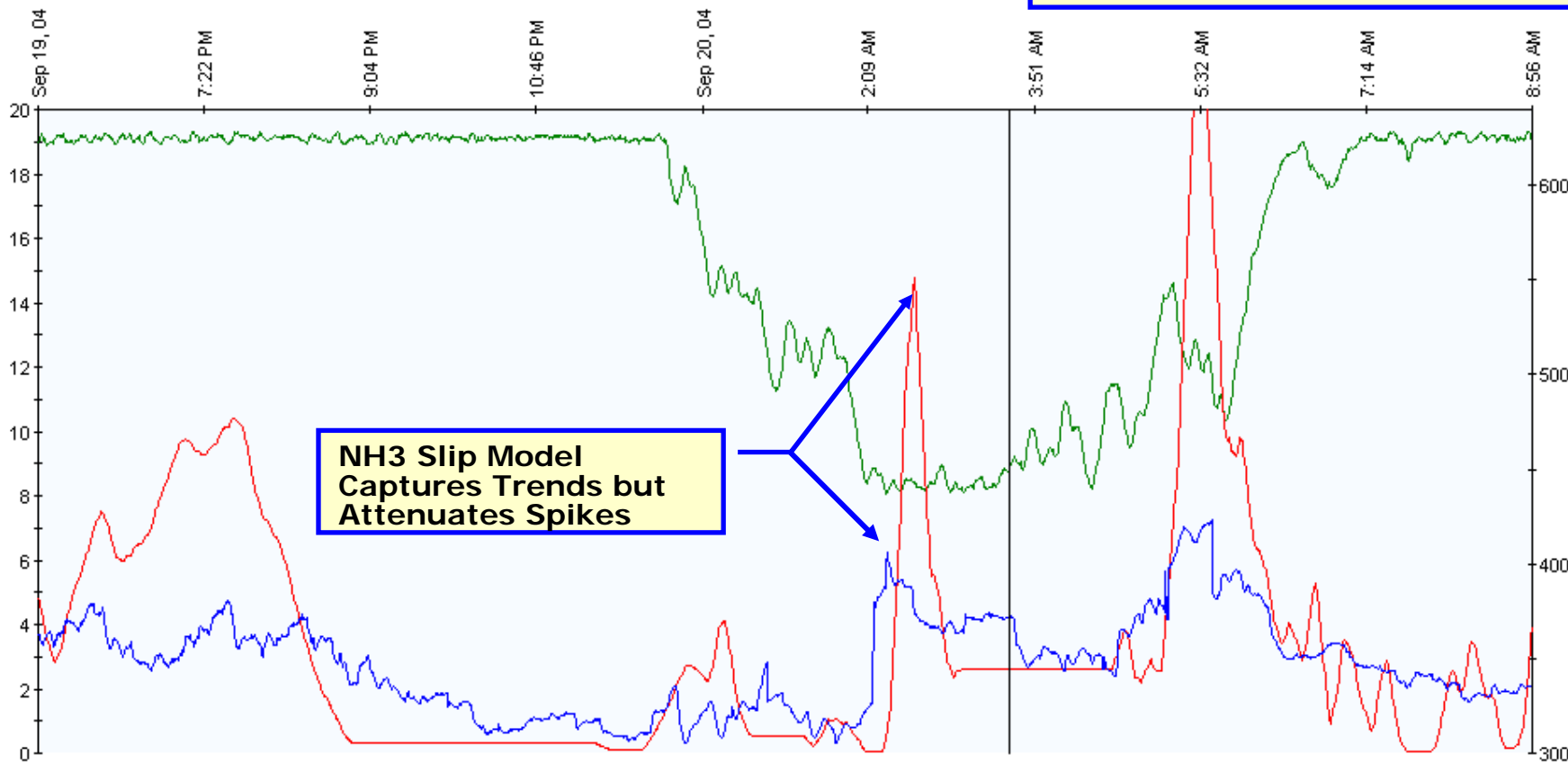
- Unisearch LASIR TDL Slip analyzer with 4 single traverse light paths on each unit, two per SCR section, just downstream of the SCR, above the air pre-heater.
- Installed 9/13/2004, began collecting data.
- Initial data showed surprisingly frequent and high levels of slip.
- Recent SCR Off base-lining has shown that some of the indicated slip frequency and magnitude is suspicious.
- The data collected were analyzed with the neural modeling available through CombustionOpt.
- Slip was successfully modeled as a function of CombustionOpt fuel and air bias variables.
- Work with Unisearch is on-going.

NH3 Slip at Baldwin 1 9/19 – 9/20

1AE Slip with Background Subtraction R=0.7



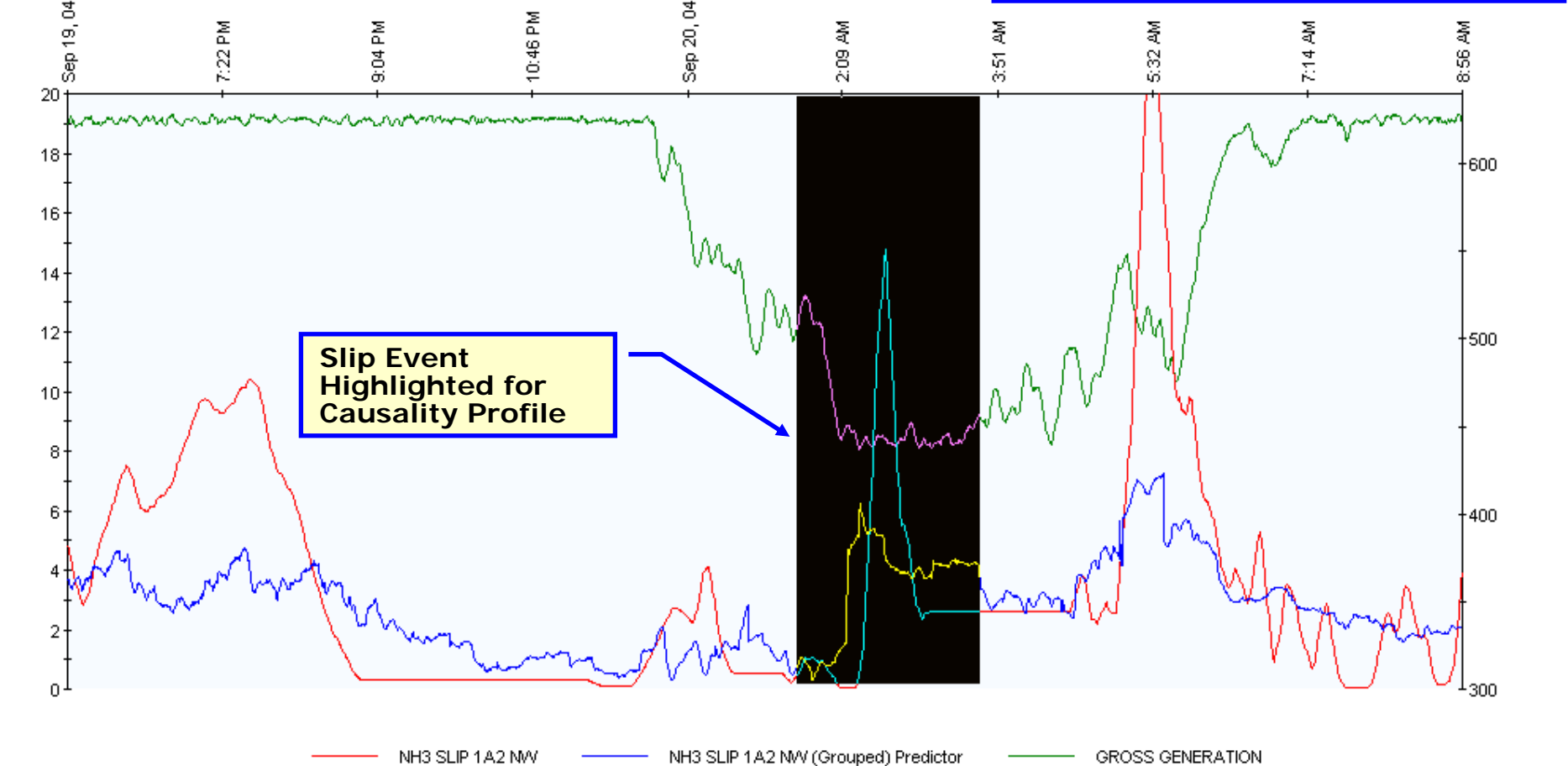
NH3 Slip Model with Closed-Loop Fuel and Air Biases as Inputs

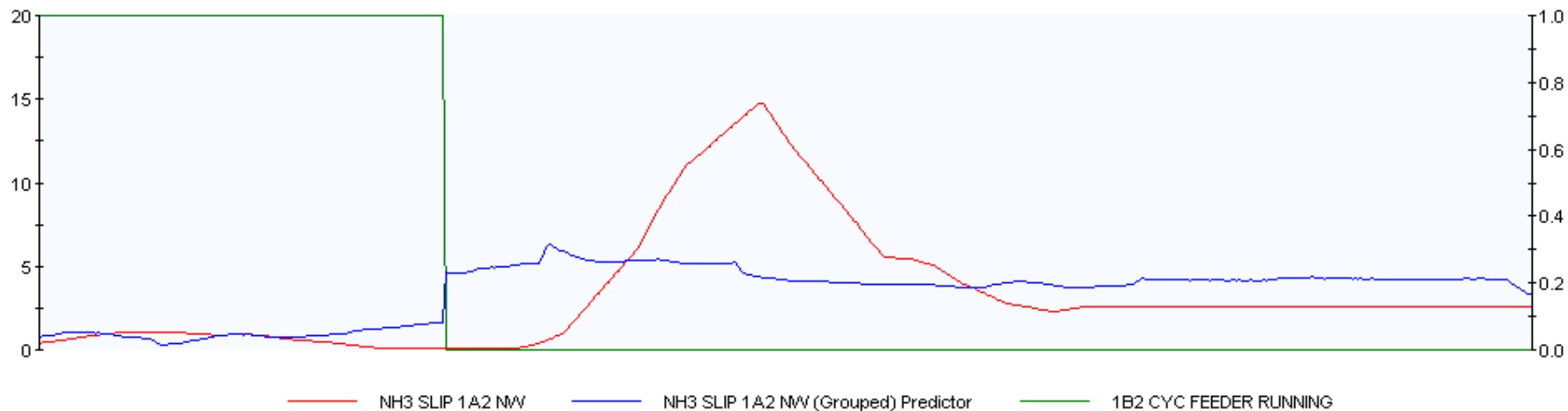
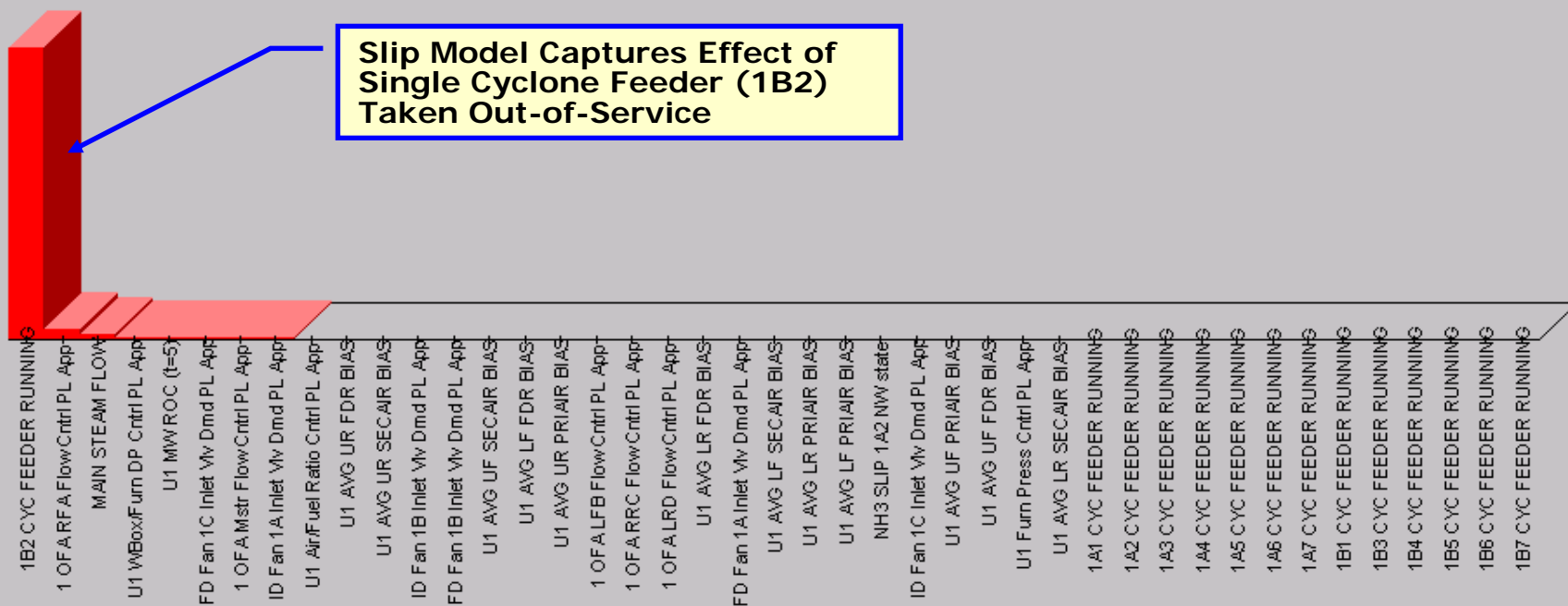


— NH3 SLIP 1A2 NW (2.604985)
 — NH3 SLIP 1A2 NW (Grouped) Predictor (4.258342)
 — GROSS GENERATION (449.271)

Cursor Time: 9/20/2004 3:35:41 AM

Causality on Slip Model with Closed-Loop Bias Inputs

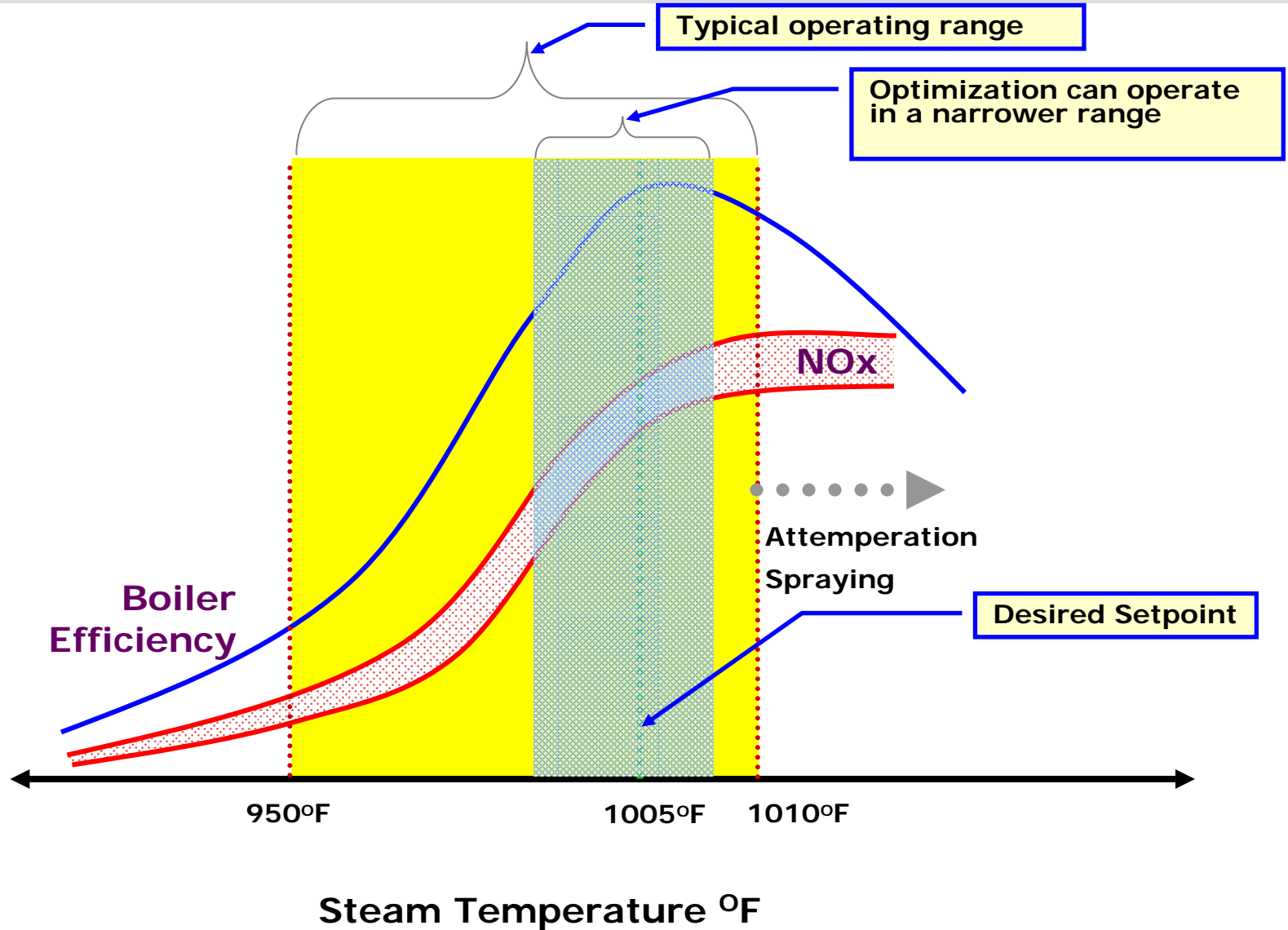




TDL Technology for In-Furnace Measurement of Key Combustion Constituents

- Same telecommunications-derived TDL technology has been adapted for in-furnace signals indication CO, O₂, CO₂, H₂O and temps
- Molecular measurements are temperature compensated
- Over \$50 million invested
- Complementarities with combustion optimization will be demonstrated at PRRP Rawhide
- Follow-on demonstration to demonstrated at CPS San Antonio Deely Unit 2

Optimization of Boiler Cleaning



Why Optimize Soot Cleaning?

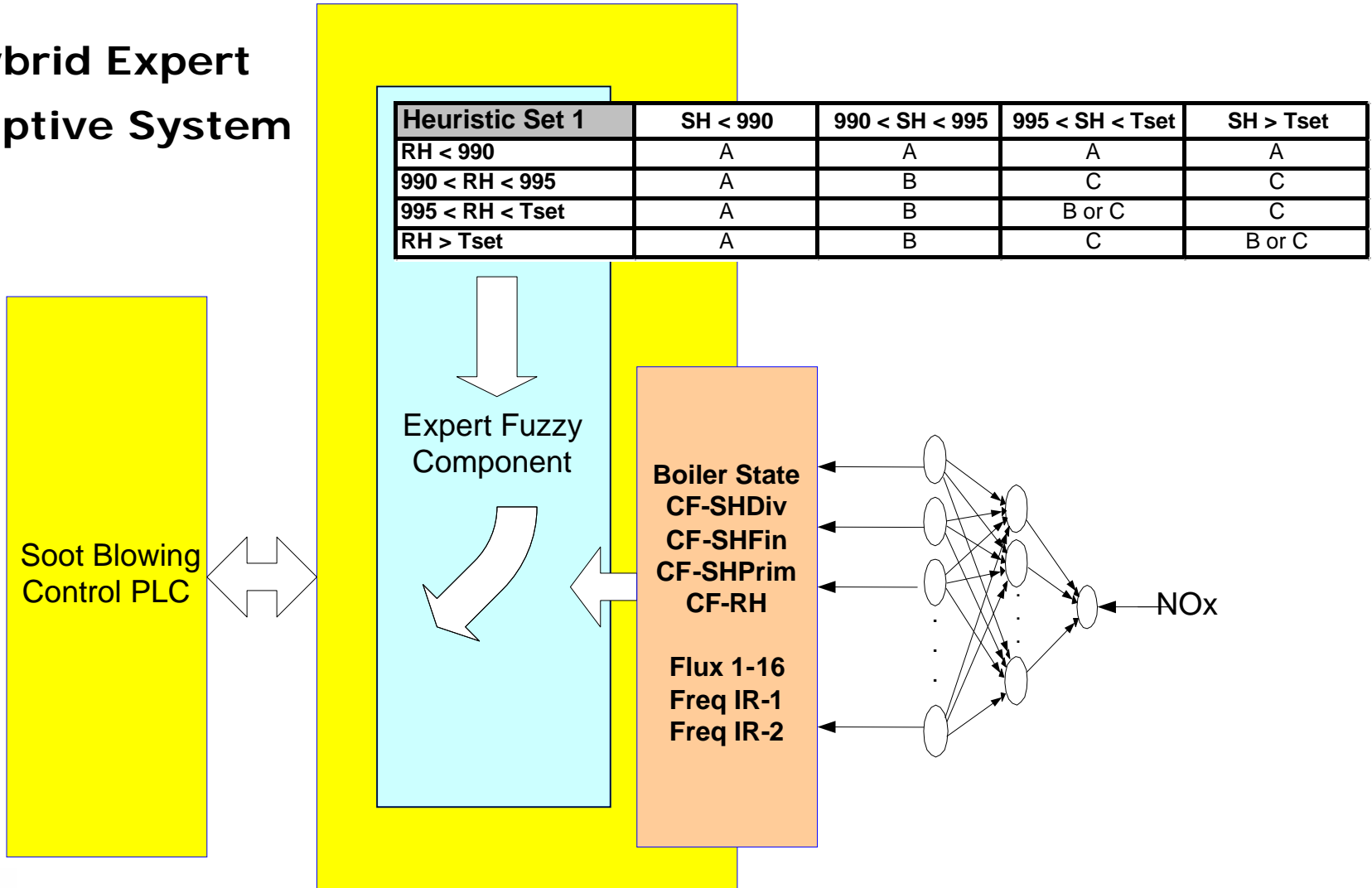
- Cleaning actions (or lack thereof) affect many plant parameters:
 - Slagging/fouling impacts heat transferability
 - Capacity: Steam and gas temperatures, spray flows, differential pressures, fan limits
 - Performance: Boiler efficiency, heat rate
 - Emissions: NO_x, Opacity, LOI, CO
 - Availability/Reliability: Waterwall/tube longevity, EFOR, equipment wear-and-tear
- Operational complexities:
 - Fuel and equipment variations
 - SCR/SNCR systems
 - LOI control objectives
- Bottom line economic impact - \$\$\$\$

Optimal Boiler Cleaning

- Optimizes boiler cleaning based on unit-specific objectives:
 - Improves emissions control (NO_x, opacity, CO)
 - Improves Heat Rate including Reheat & Superheat steam temperature control
 - Balances tradeoffs between furnace/backpass absorption
 - Reduces O&M costs by avoiding unnecessary boiler cleaning actions and reducing tube wear and thermal stressing
 - Compensates for off-design fuels and operations
 - Leverages existing soot cleaning instrumentation, models, equipment and control systems

How it Works

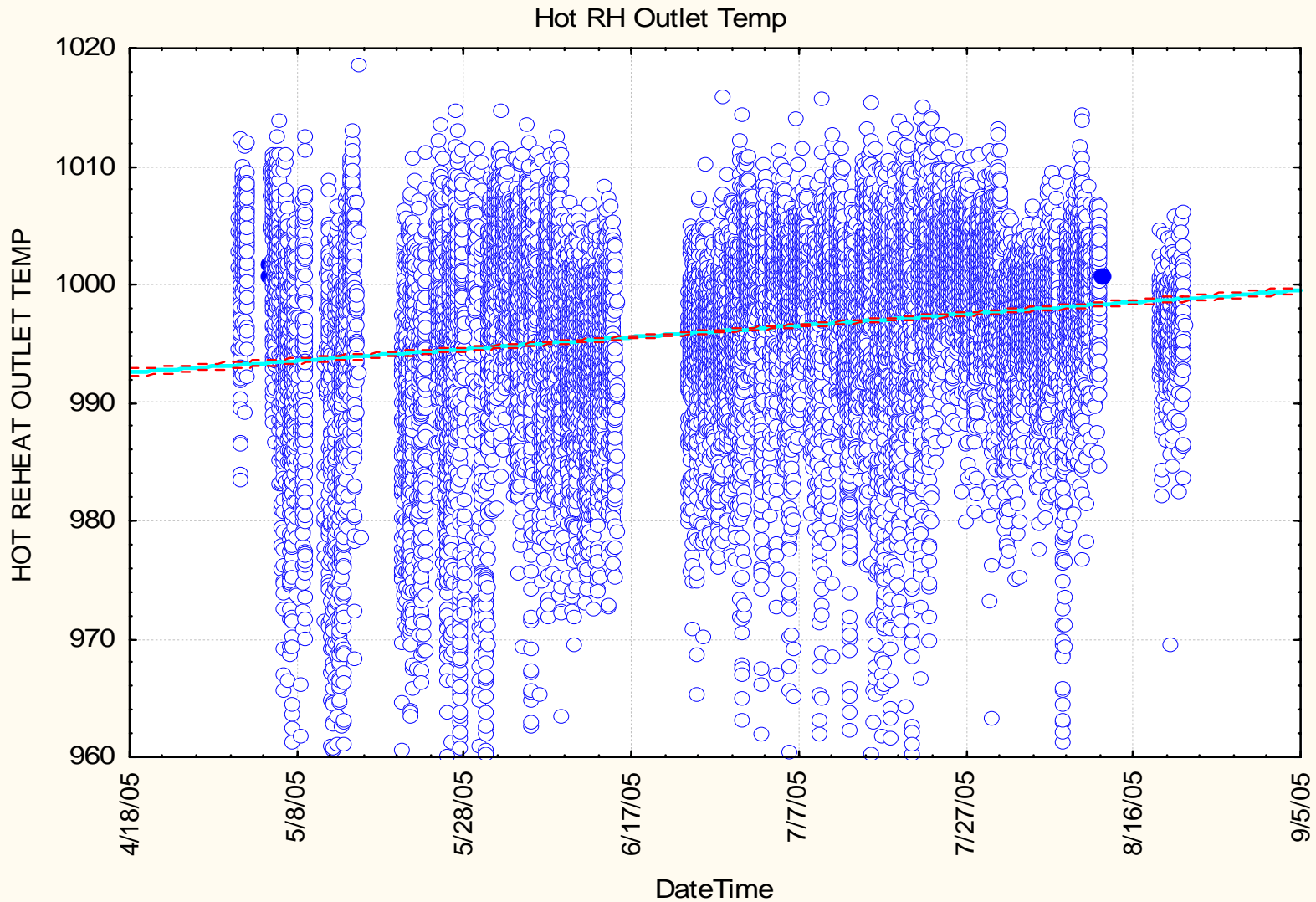
Hybrid Expert Adaptive System



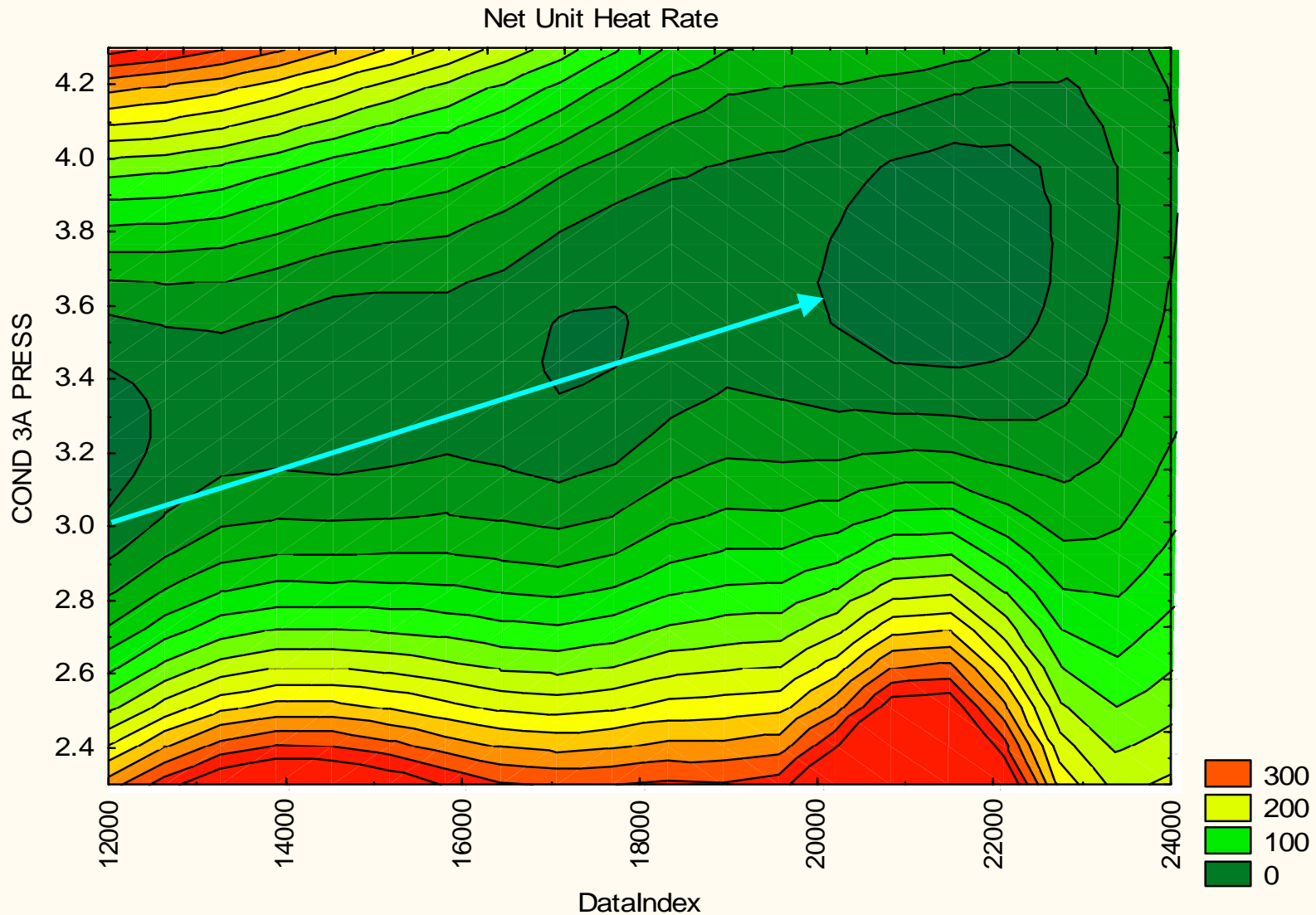
SootOpt at Baldwin Unit 3

- 630 MW, Base-Loaded, T-Fired
- SOFA, Low NOx Burners
- High variability in PRB coal
- Heat Flux Sensors and Water Cannons
- ASI PLC-based SB control system with locally intelligent controls
- PrecisionClean and standard IK's in convection pass
- Also thermocouples and FEGT
- Prevailing sootblowing guidelines:
 - ISB preset flux targets in the furnace, operators intervene
 - Operator initiated in the convection pass

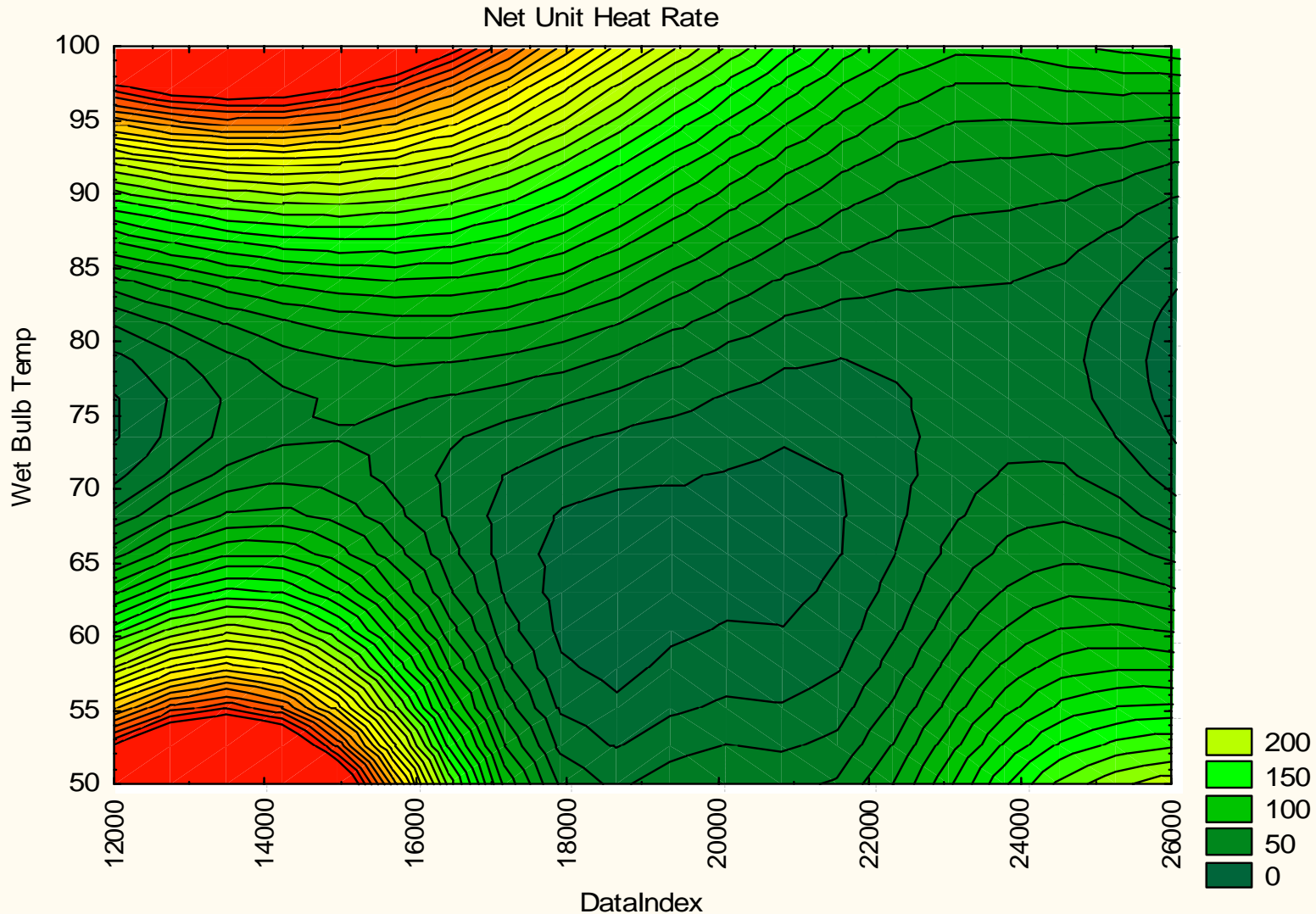
RH Temps



Heat Rate vs Cond Press over Time



Heat Rate vs Wet Bulb over Time



Action-Oriented Performance Optimization

- Identifies, analyses & takes or recommends actions to alleviate immediately controllable efficiency and capacity losses
- Single online model for performance monitoring & predictive simulations
- Uses actual data to determine realistically achievable efficiency & capacity targets and their impacts
- Distinguishes between actions that are immediately controllable vs. those that require an outage or de-rate
- Key Building Block for Availability Optimization

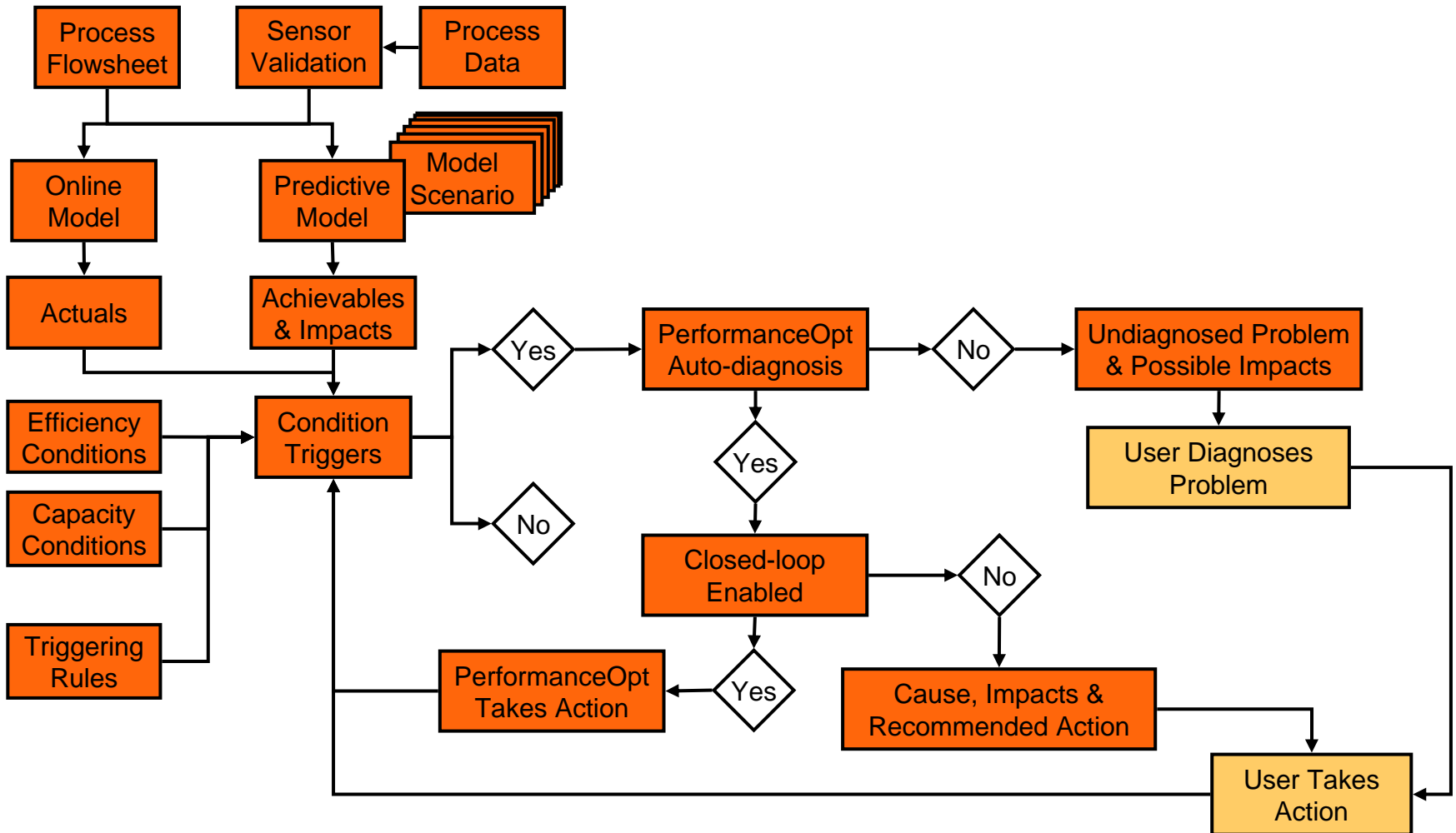
What's Needed for Action-Oriented Performance Optimization?

- Beyond controllable losses
 - Additionally identifies equipment/system problems at a much smaller grain-size i.e. closer to the source
 - Air Heater leakage
 - ID Fan amps
 - Feedwater Heater TTD
- Beyond performance curves and design data
 - Problems detected based on “achievable” values as opposed to “design” values
 - Helps differentiate between failed sensors and real process problems
 - Provides actionable advice for some of the problems it identifies

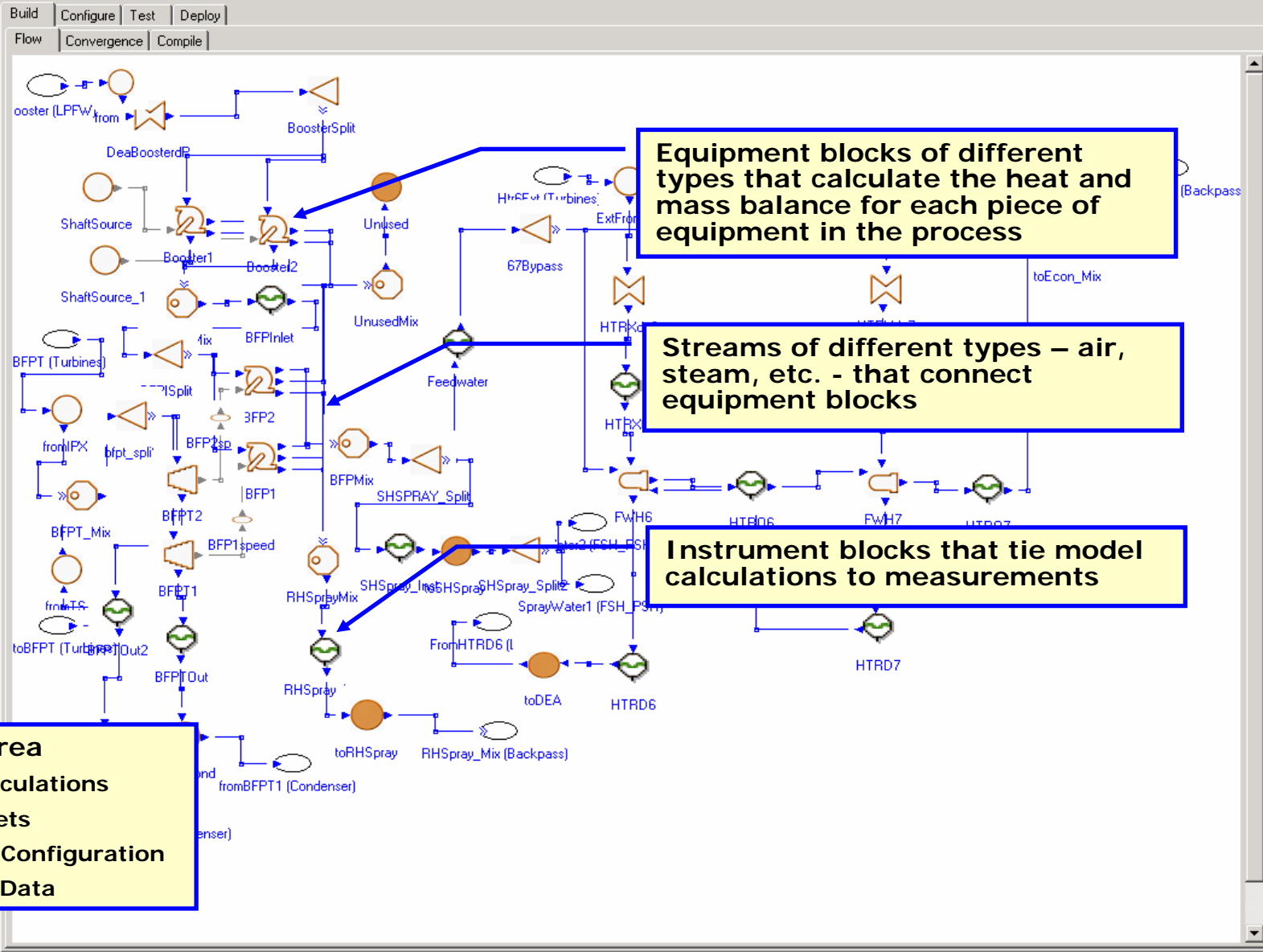
How Effective Performance Optimization is Accomplished

- Integrated boiler and steam cycle model
 - Rigorous mass and energy balance
 - Sophisticated sensor validation mechanisms
- Simultaneous, real-time on-line and what-if simulations
- Continuous determination of deviations from achievable
 - Achievable values based on current plant conditions
- Accurate model-based estimation of capacity as well as efficiency benefits

Performance Optimization Workflow



- PerformanceOpt Libraries
- Common Data
- Unit 1 MaintenanceOpt
- Unit 1 Advisor
- Unit 1 PerformanceOpt
- HotSpot
- Out-of-Service checks
- Triggers
- Libraries
- Calculations
- FlowSheets**
- Documents
- Toolbars
- Tasks and Services
- Roles



Equipment blocks of different types that calculate the heat and mass balance for each piece of equipment in the process

Streams of different types – air, steam, etc. - that connect equipment blocks

Instrument blocks that tie model calculations to measurements

Navigation Area

- Secondary Calculations
- Sub-Flow Sheets
- Table & Chart Configuration
- Specific Plant Data

Fundamental Building Block 1st Principle Models - Boiler

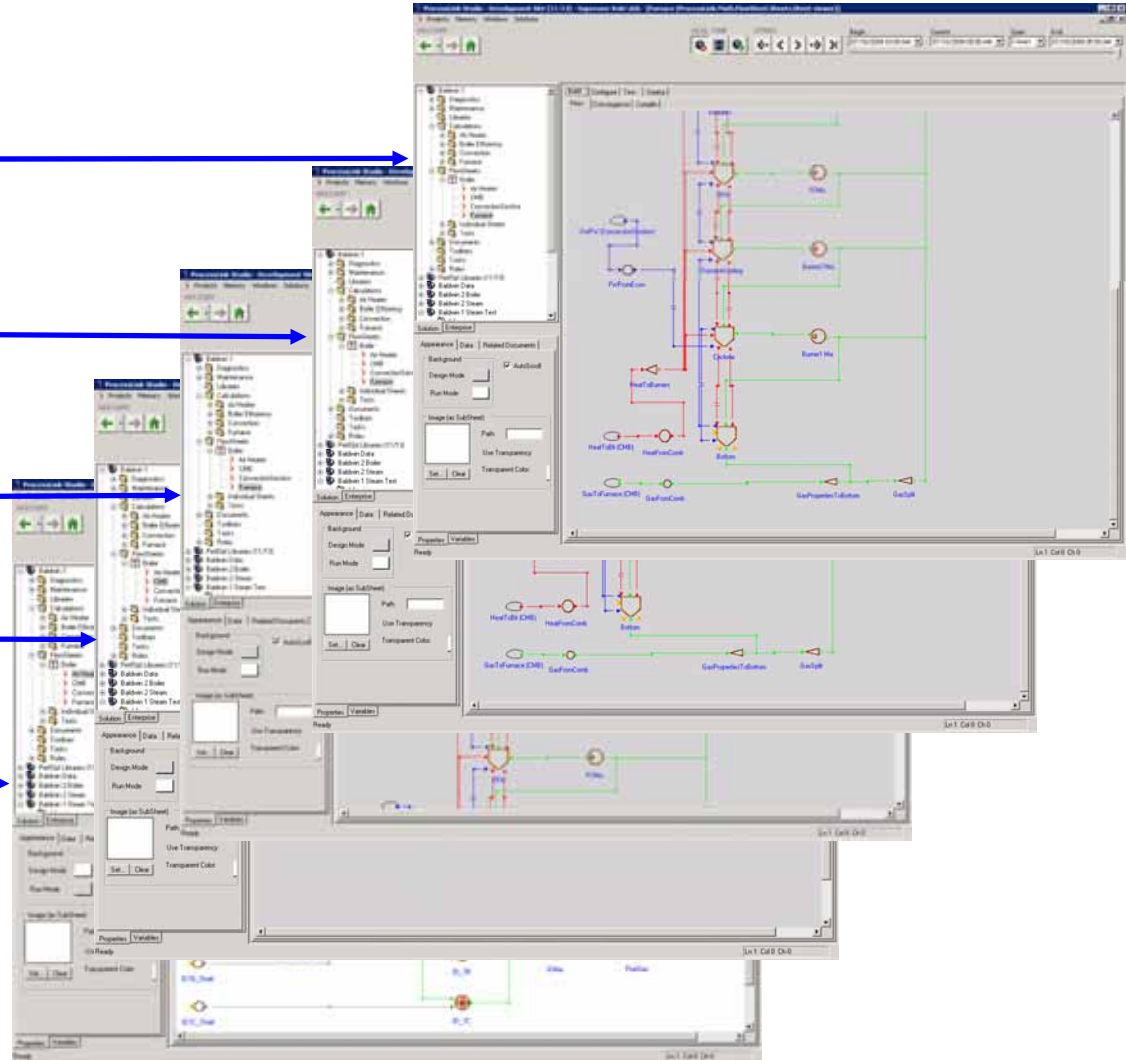
Boiler Convection Section

Boiler Furnace (Bottom)

Boiler Furnace (Top)

Boiler Combustor

Boiler Air Heater



Fundamental Building Block 1st Principle Models - Steam

Generator

FW HP Heater

BFW Turbine

BF Pump

Dearator

Feed Water Htr B

Feed Water Htr A

Condenser Pumps

Condenser

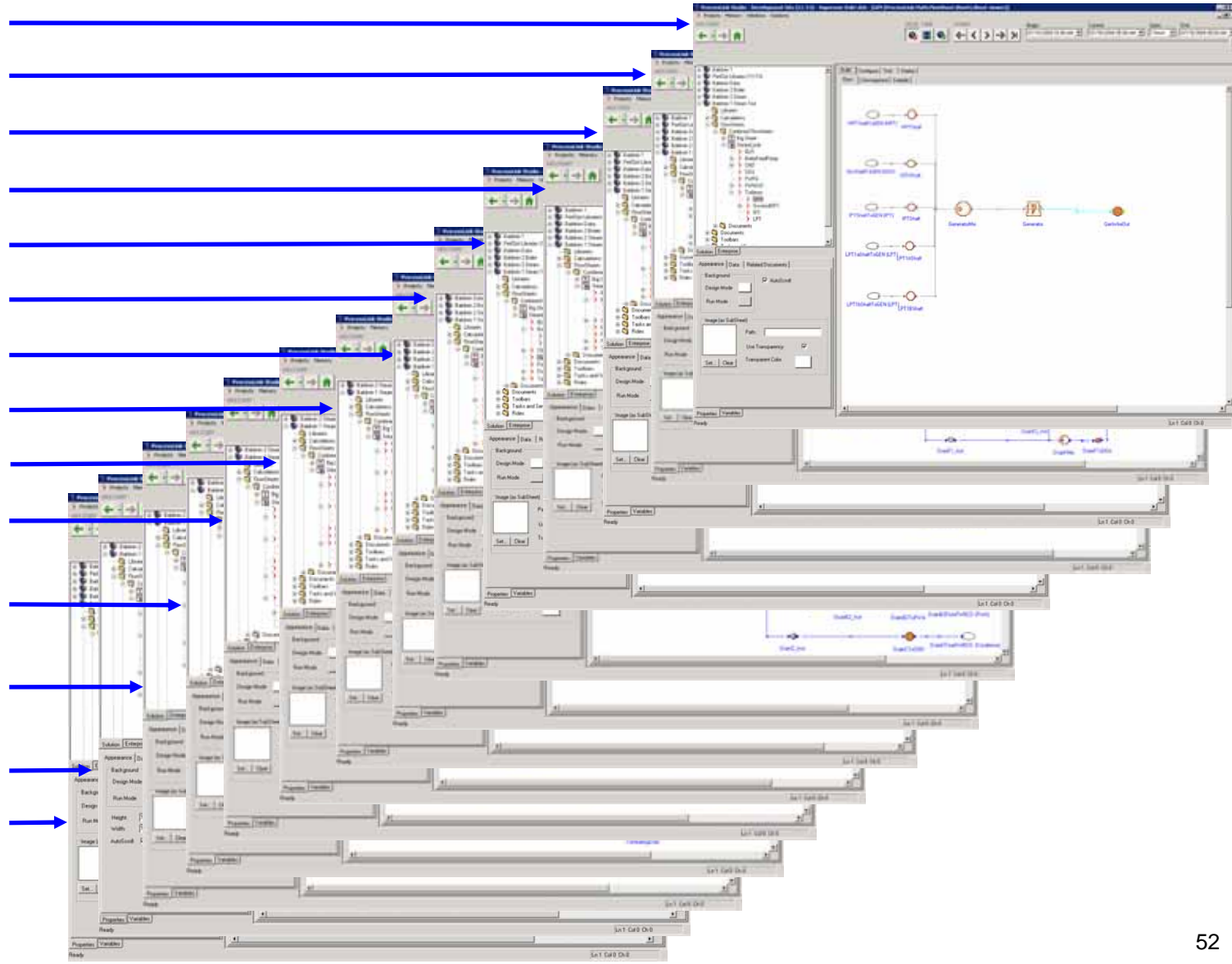
Low Pressure Turbine

Intermediate Pressure Turbine

High Pressure Turbine

Turbine Governor

Boiler



What's Needed for Plant Optimization

- **Enterprise Data Management**

- Integrate from any source
- Validate and replace if necessary
- Aggregate and manage calculations

- **Hybrid Modeling Methods**

- First-Principles: **When you know the math, write it**
- Rule-Based: **When experts have key knowledge, capture it**
- Machine Learning: **When not understood, learn it**

- **Integrated Optimization Engine**

- Coordinate local decisions based on global impact

- **Action-Centric Portals**

- Present actionable knowledge to the person that can act on it when it something can still be done, while allowing the user to drill-down all of the details upon which the knowledge is based