Boiler Health Monitoring Using a Hybrid First Principles-Artificial Intelligence Model

Award#:DE-FE0031768

PI: Debangsu Bhattacharyya[a]

Other Key Persons from WVU: Angan Mukherjee, Samuel Adeyemo, Katherine Reynolds, Vivek Saini

Co-PI: Daniel Purdy[b]

Other Key Persons from EPRI: Jonathan Parker, Kent Coleman, Tapasvi Lolla

Project partner: Southern Company (Contact: Chet Acharya)

[a] Department of Chemical and Biomedical Engineering, West Virginia University

[b] Electric Power Research Institute, Charlotte

2021 Crosscutting Research and Advanced Energy Systems Project Review Meeting

Sensors and Controls Program

Virtual

May 18, 2021

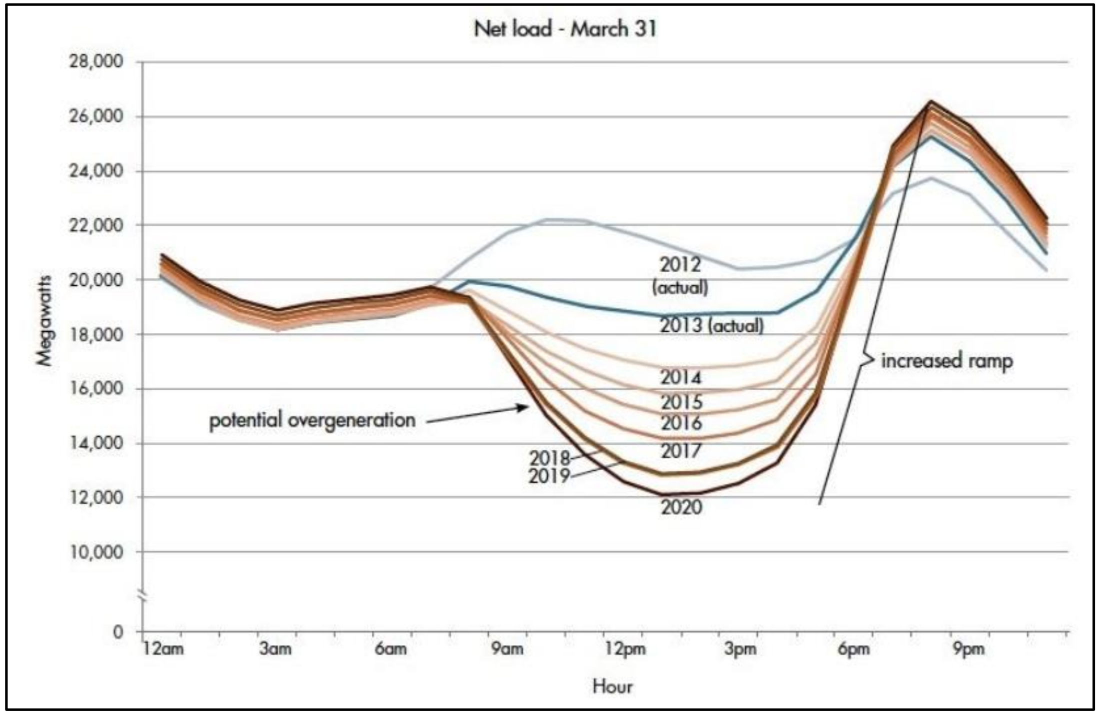
Outline

- **Motivation**
- **Our Approach**
- **Discussion on Tasks and Preliminary Results**
- **Conclusions**

Motivation: Flexible Operation and Extended Life

- **Renewable generation, demand response, and others require operational flexibility**
  - Lower minimum loads than considered in design
  - Faster startup times and ramp rates
- **Increased cycling operations are affecting:**
  - Equipment health and life expectancy
  - Plant downtime and operations & maintenance
  - Plant performance, efficiency, emissions
- **Flexible operation creates opportunities and challenges**
  - Flexible operation requires different, more complex consideration and tools
- **An on-line health monitoring tool can:**
  - Show the impacts of load-following
  - Help to schedule O&M more effectively
  - Help to develop process control strategies for improved flexibility

CAISO Duck Curve[1]



Net demand = Grid Demand – Renewable energy production

Source: www.caiso.com

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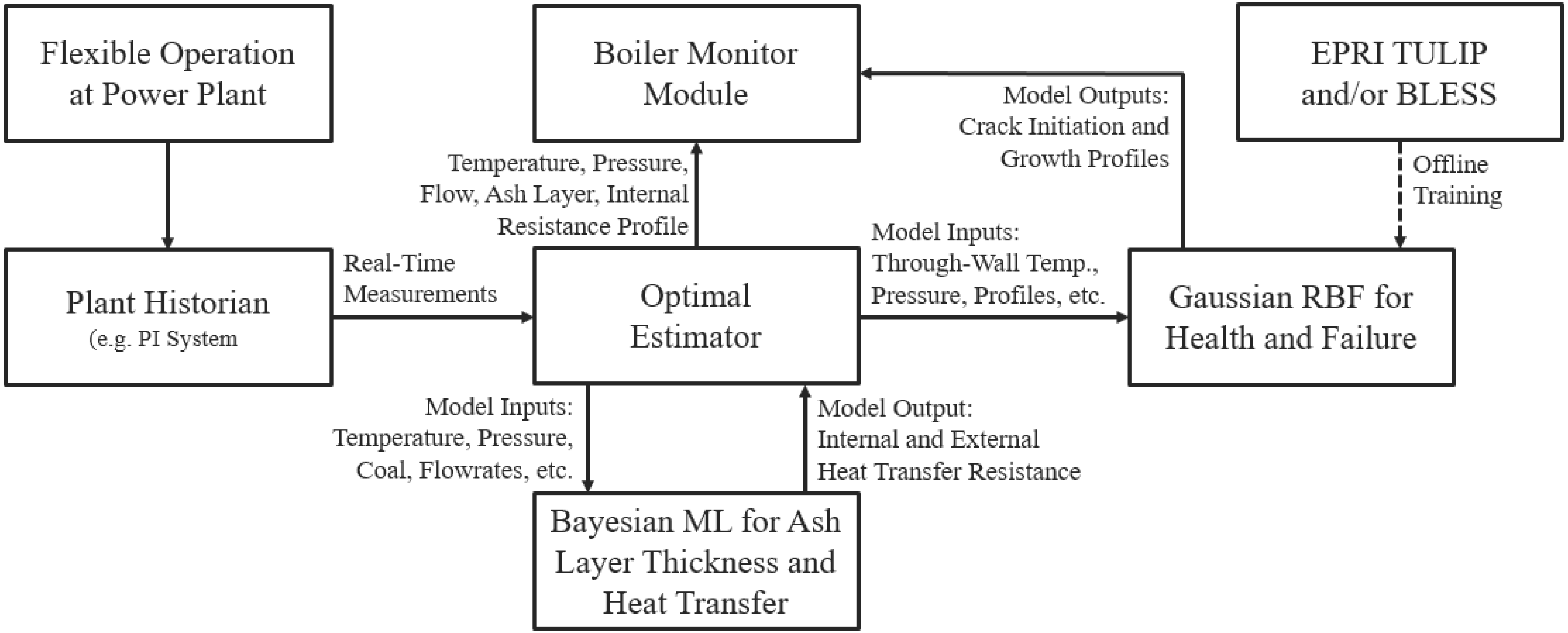
Our Approach: A Hybrid First-Principles-AI Based Approach

- **Advantages of first-principles and mechanistic models:**
  - Satisfies mass, momentum and energy balances
  - Can be predictive
  - Can provide spatial and temporal resolutions operational parameters
- **Disadvantages of first-principles model**
  - Can be difficult to develop for a number of complex phenomena in boilers
    - e.g., external fouling, internal deposit in boiler tubes
- **Advantages and Disadvantages of Artificial Intelligence (AI) models**
  - Complements first-principles models
- **This projects seeks to exploit the synergies of first-principles and AI models**
  - However, the complex phenomena of interest in boilers are uncertain and time-varying
  - Must take the measurements into account

End Goal is to Explore the Development of an On-line Health Monitoring Tool

Our Approach



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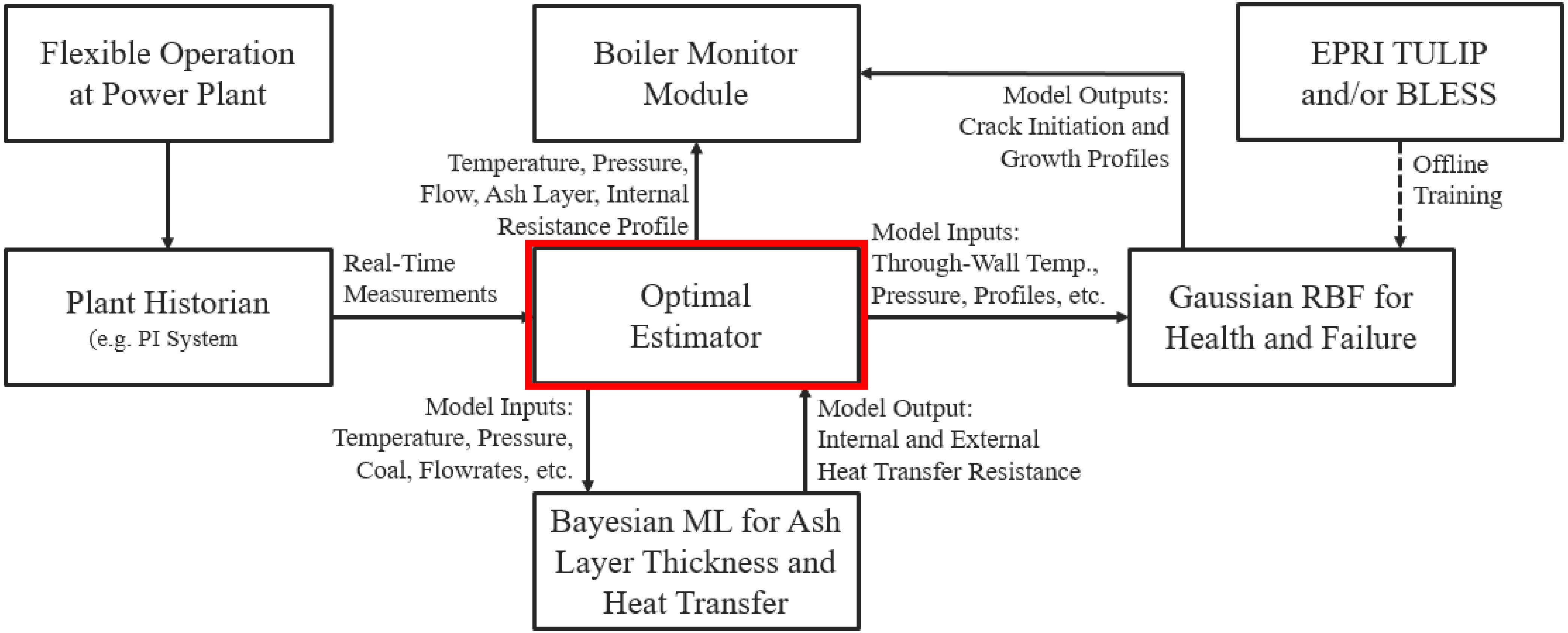
Project Objectives (Tasks)

- **Task 1.0 Project Management and Planning**

- **Task 2 – Hybrid Model Development, Validation, and Implementation at Plant A (mainly WVU)**
  - Subtask 2.1 – Plant Data Evaluation
  - Subtask 2.2 – Adapting the First-Principles Model to Plant A
  - Subtask 2.3 – Development and Validation of the Bayesian ML Model
  - Subtask 2.4 – Development and Validation of the Gaussian RBF Model
  - Subtask 2.5 – Modification and Implementation of the Optimal DAE Estimator
  - Subtask 2.6 – Evaluation and Testing of the Hybrid Model at Plant A

- **Task 3 – Validation and Integration of Hybrid Model at Plant A (mainly EPRI with Southern)**
  - Subtask 3.1 – Project Management
  - Subtask 3.2 – Initialize the Model with AUSC Steam Loop Exemplar
  - Subtask 3.3 – Collect a Snapshot of Southern Company Host Site Operation
  - Subtask 3.4 – Pilot Demonstration of Model
  - Subtask 3.5 – Enhance Software

Our Approach



Model and Estimation Approach

- **Dynamic, cross-flow, 2-D model of the superheater/reheater based on equations for the conservation of mass and energy**
- **Rigorous properties model and heat transfer calculations at each control volume**
- **Non-Linear DAE system**[2]

$$x_{k+1} = x_K + \int_{k\Delta t}^{(k+1)\Delta t} f(x(t), z(t)) + G\omega_{k+1}$$

$$g(x_{k+1}, z_{k+1}) + \Upsilon_{k+1} = 0$$

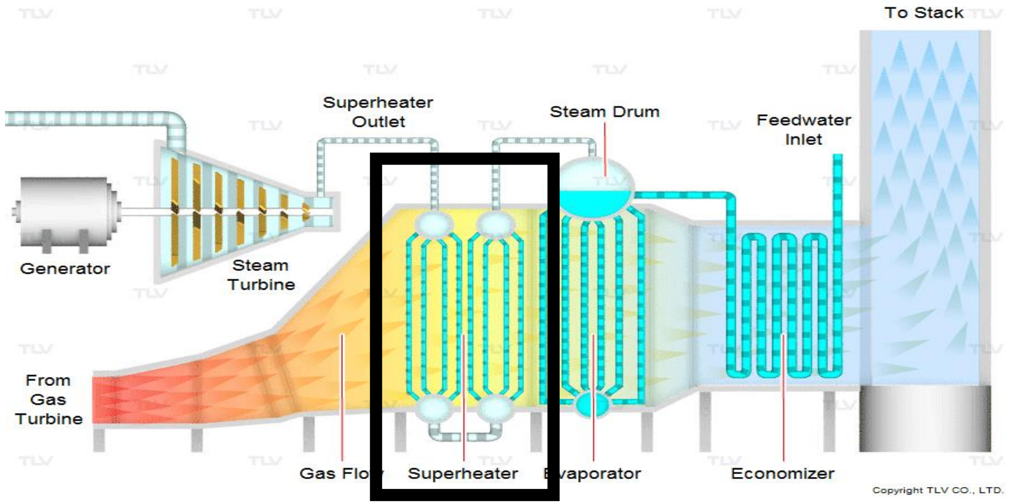
$$y_{k+1} = h(x_{k+1}, z_{k+1}) + v_{k+1}$$

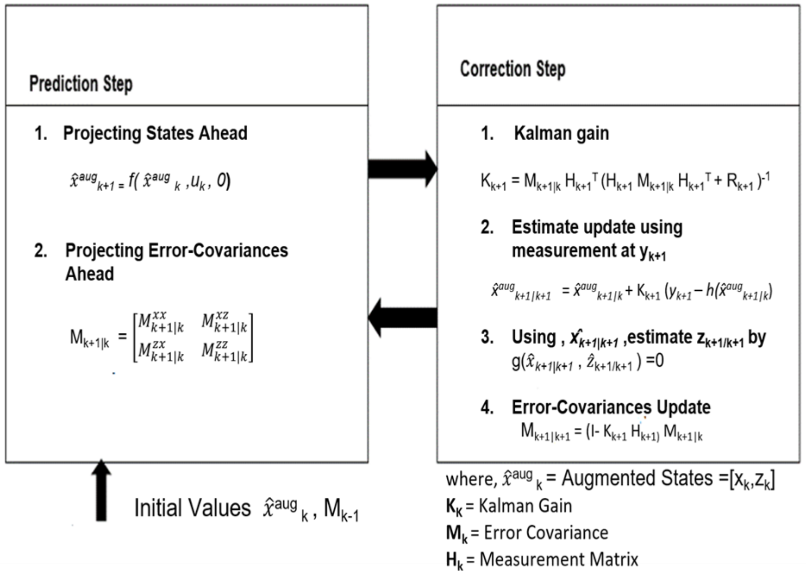
S.T. : $Ex^{aug}_{k+1} = b$

where: $\omega \sim N(0,Q)$, $v \sim N(0,R)$, $\Upsilon \sim N(0,W)$

$G \in R^{m \times m}$ - Process noise gain matrix

$E \in R^{l \times m+n}$ - equality constraints





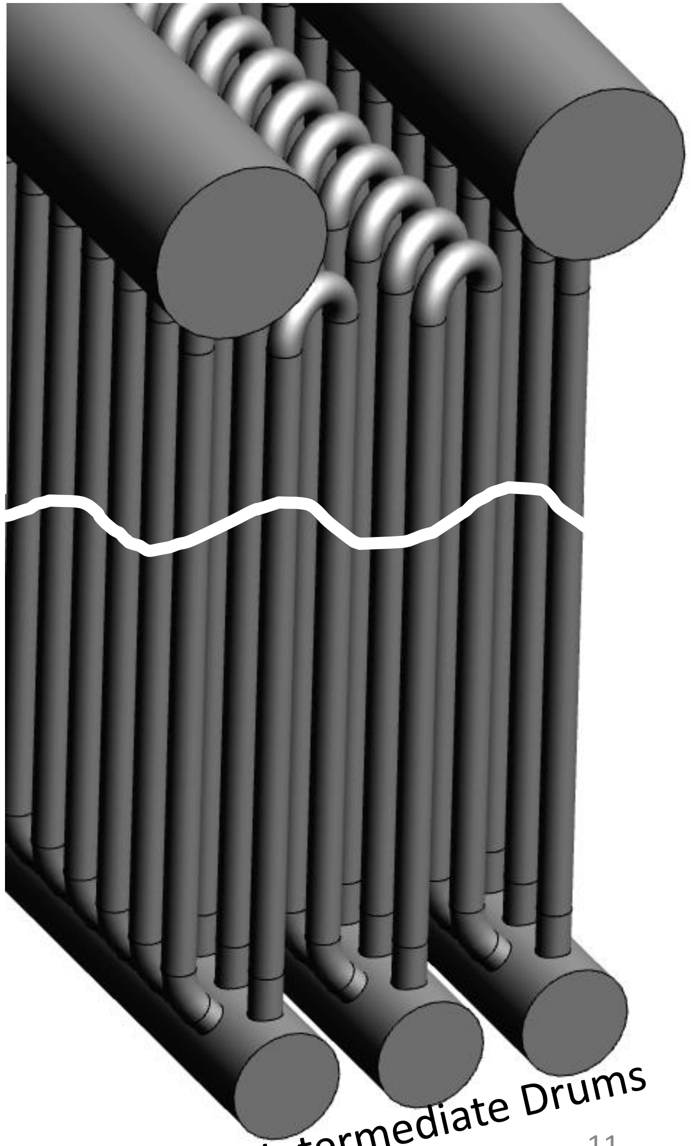
[1]**Waste Heat Recovery. Retrieved from https://www.tlv.com/global/ME/steam-theory/waste-heat-recovery.html**

[2] **P. Mobed, S. Munusamy, D. Bhattacharyya, and R. Rengaswamy, "State and parameter estimation in distributed constrained systems. 1. Extended Kalman filtering of a special class of differential-algebraic equation systems," Ind. Eng. Chem. Res., vol. 56, no. 1, pp. 206–215, 2017.**

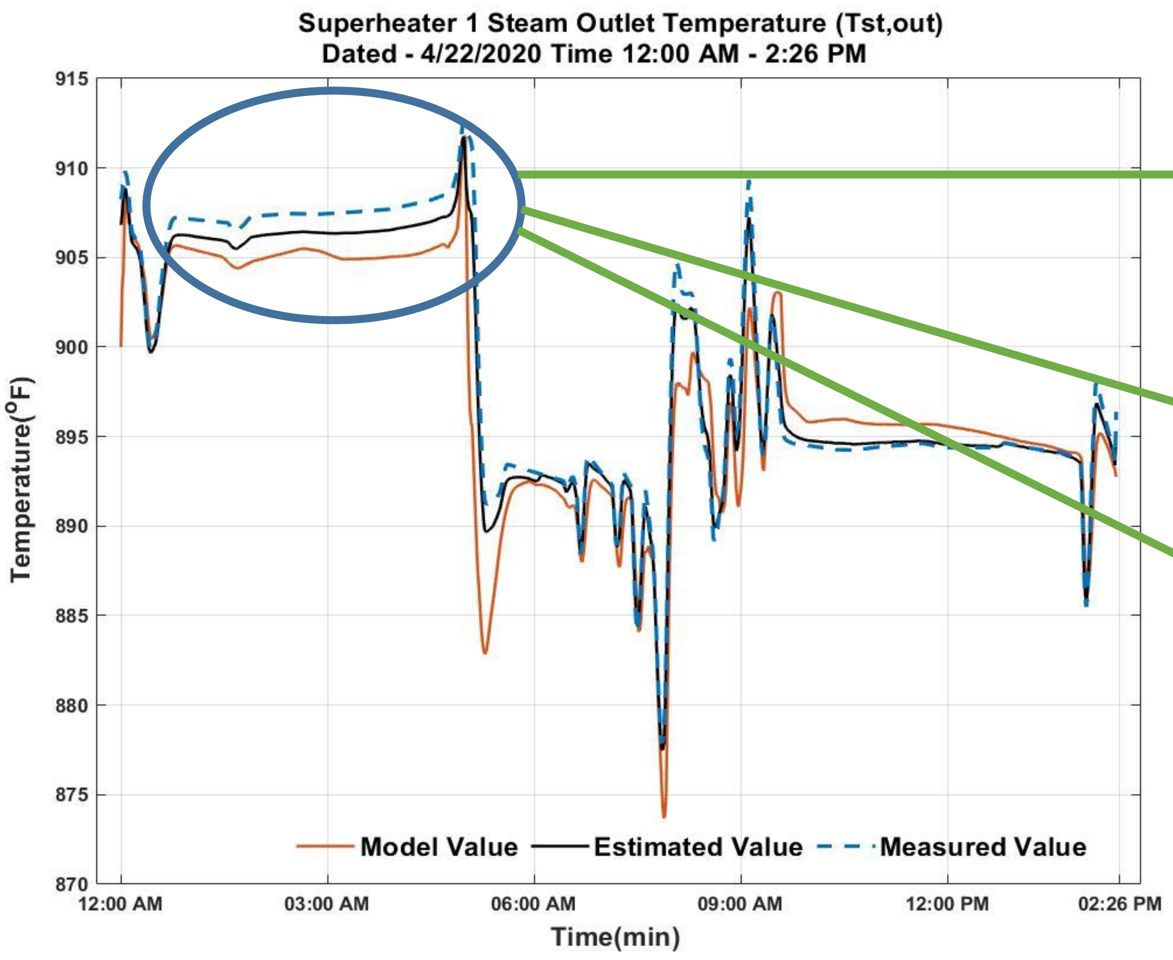
Input Data to WVU Hybrid Model: Plant B

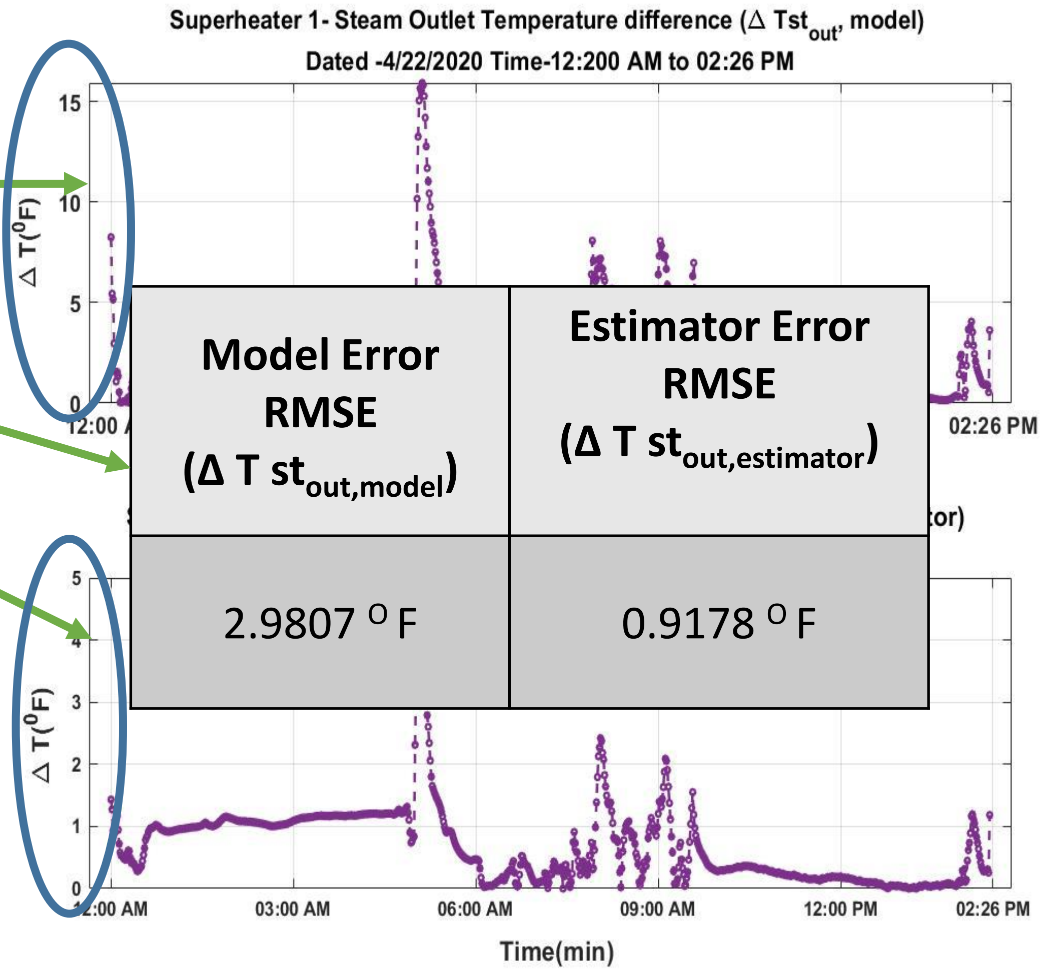
- **Known dataset to validate the model outputs**
- **HRSG Plant B has TCs installed on T91 superheater**
  - TCs installed on heat transfer surface of HRSG to watch the impact of duct burners
  - Gas and metal temperature both are measured and recorded
- **Configuration and initial datasets provided to WVU**
  - 74 tubes wide; six turns: two un-finned, four finned
    - T91 tubing with up to 350 μm oxide thickness measured
  - High spacial resolution on TCs: 3 elevations, 18 tubes across the width
    - Conventionally only inlet and outlet steam temperatures are recorded
- **We also have duct burner duty, steam outlet temperature, steam outlet pressure, unit load, etc.**
  - Provides a range of operating characteristics to feed into model

Excellent Example of Leveraged Utility Opportunities



Validation of Outlet Steam Temperature



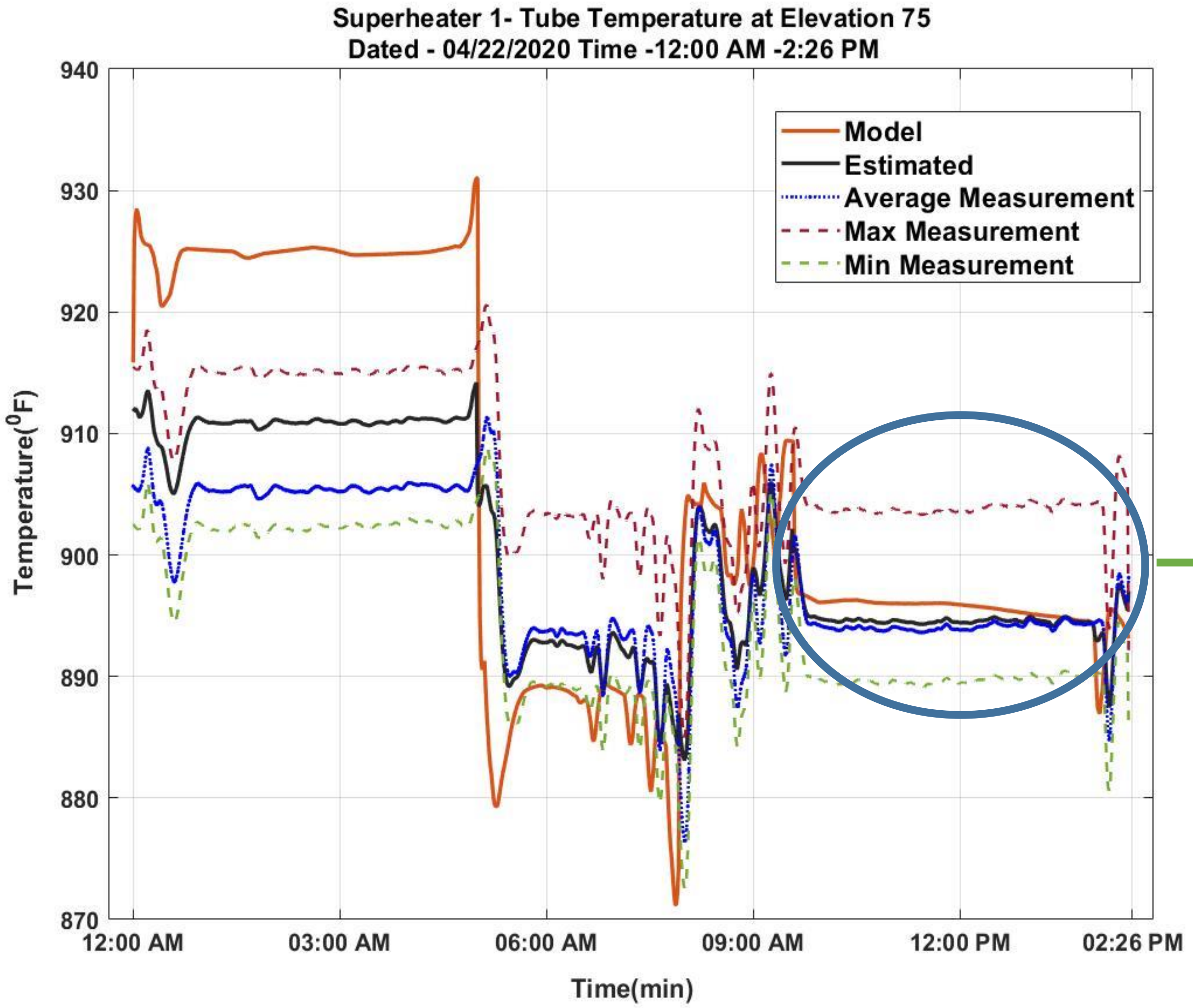


Model Error RMSE (Δ T $st_{out,model}$)	Estimator Error RMSE (Δ T $st_{out,estimator}$)
2.9807 ^{O} F	0.9178 ^{O} F

Initial T_o = 900^o F (near inlet steam value)

- Model Error (Δ T st $_{out}$, model)= Measured- Model
- Estimator Error (Δ T st $_{out}$, estimator)= Measured- Estimator

Validation of Tube Temperature

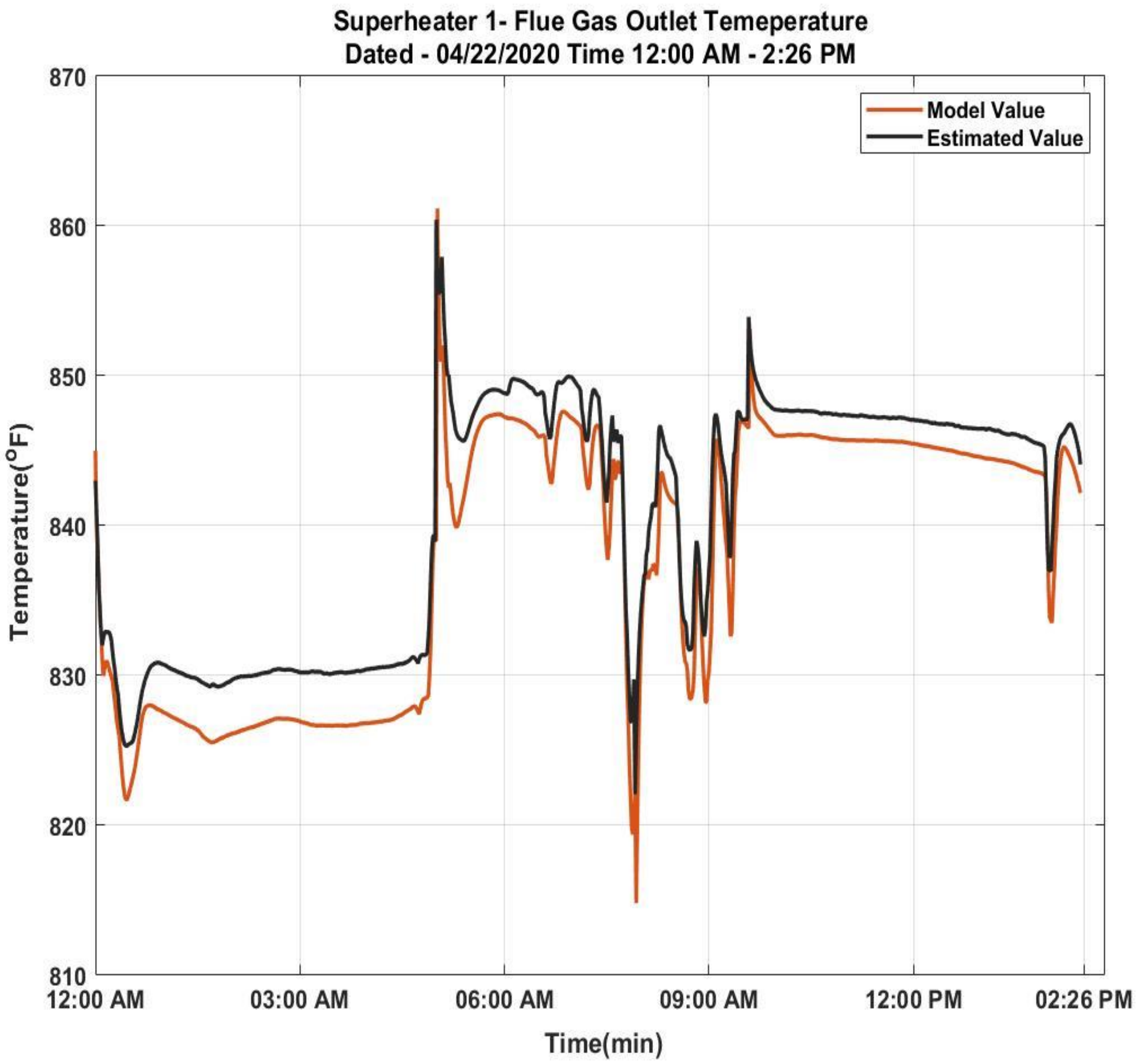


Model Error RMSE (Δ T $te_{75,model}$)	Estimator Error RMSE (Δ T $te_{75,estimator}$)
13.1460 ^{O} F	3.6051 ^{O} F

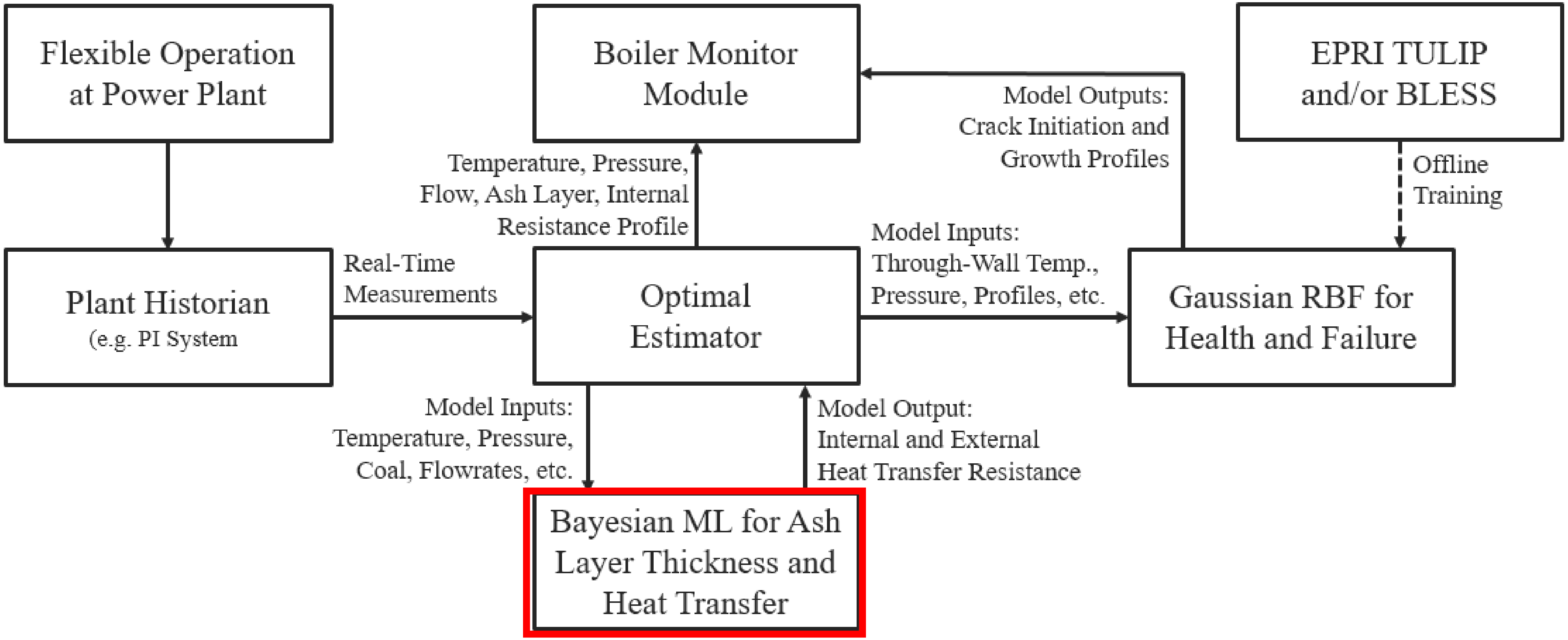
- Model Error (Δ T $te_{75,model}$)= Measured- Model
- Estimator Error (Δ T $te_{75,estimator}$)= Measured- Estimator

Prediction of Final Outlet Flue Gas Temperature from HPSH1

- **Physics-based model can be computationally expensive, but can accurately represent systems with reasonably known mechanisms and be instrumental in estimating variables that cannot be measured or measurements are unreliable**



Our Approach



Bayesian ML with Consideration of Colored Noise

Motivation

- Desired to obtain a data-driven model given input-output data
- Plant measurement comes with high noise with unknown characteristics. The model also has noise.
- Noises in different variables can be correlated.
- Thus, it is desired to estimate model parameters whose probability density function is 'close' to the truth.

Bayesian Inferencing

- Given a general nonlinear system

$$\dot{x} = f(x, u, \theta)$$

$$y = g(x)$$

- Bayes' rule

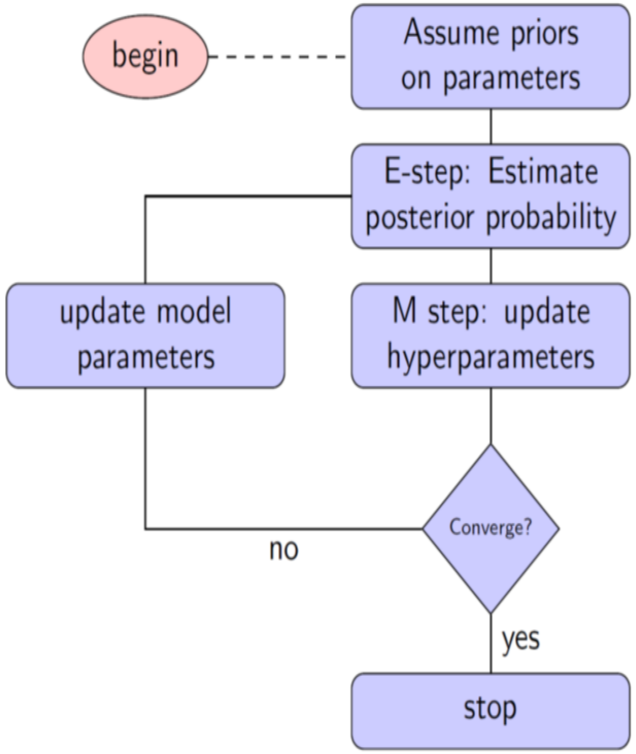
$$\pi(\theta|y) = \frac{l(y|\theta)p(\theta)}{m(y)}$$

where $m(y) = \int_{\Theta} l(y|\theta)p(\theta)d\theta$

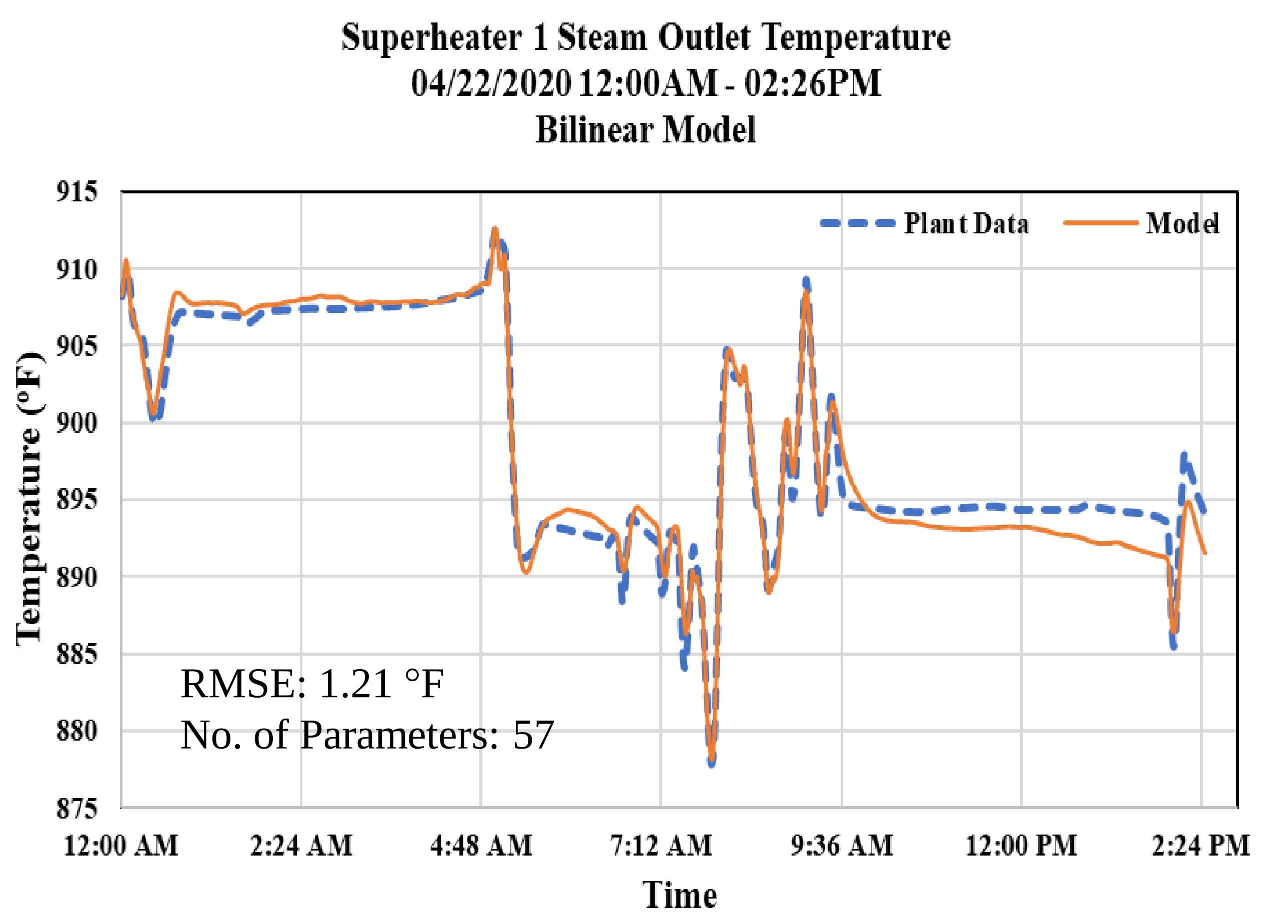
- Objective

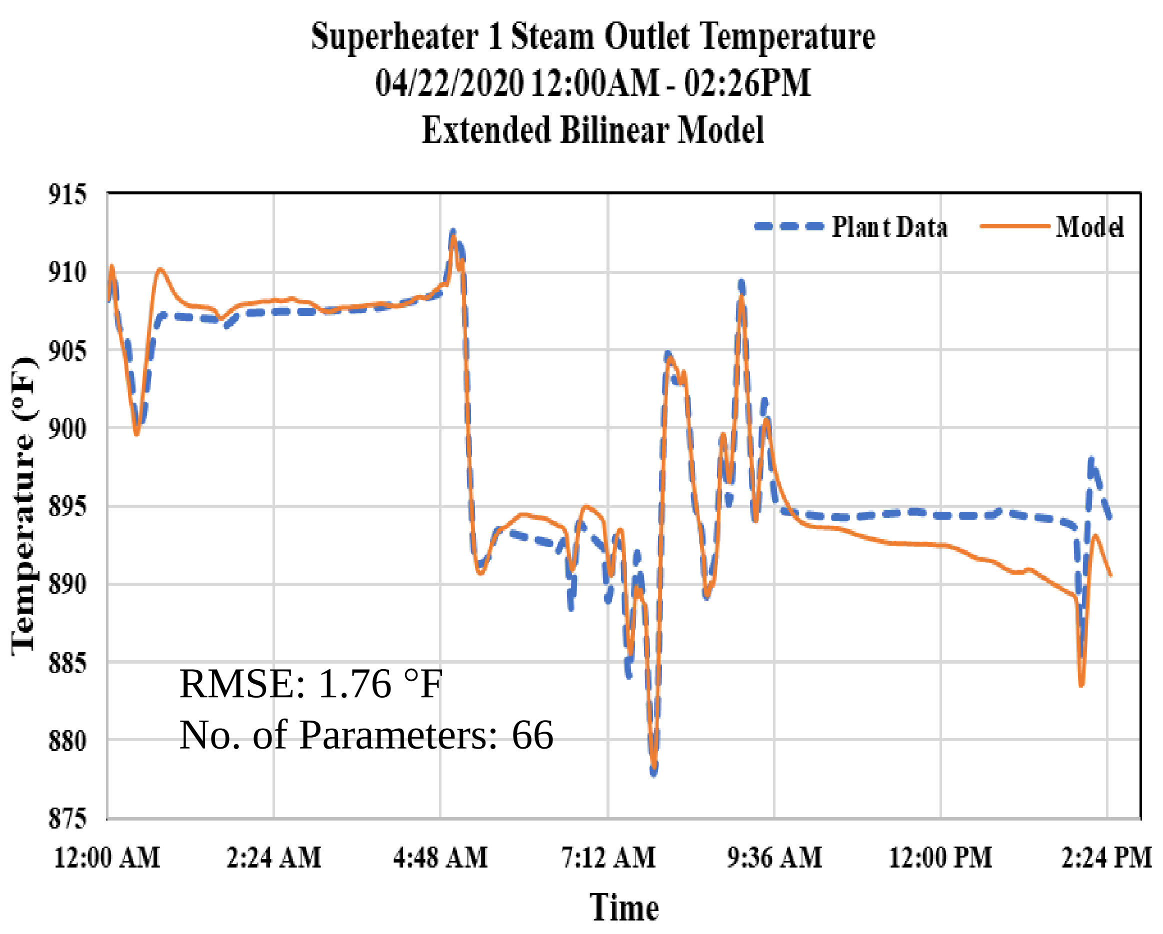
$$\hat{y}^*, \theta^* = \max_{\hat{y}, \theta} p(\hat{y}, \theta|y)$$

EM Algorithm

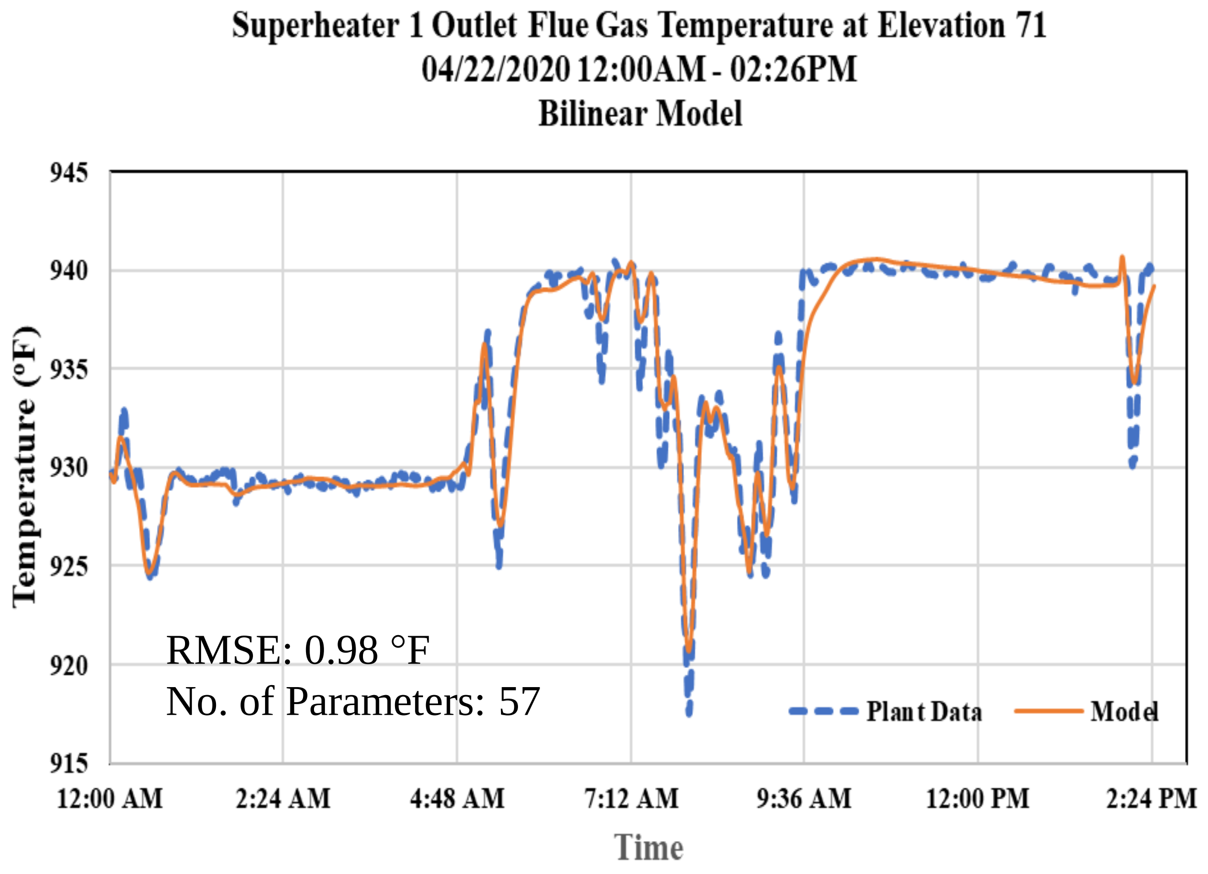


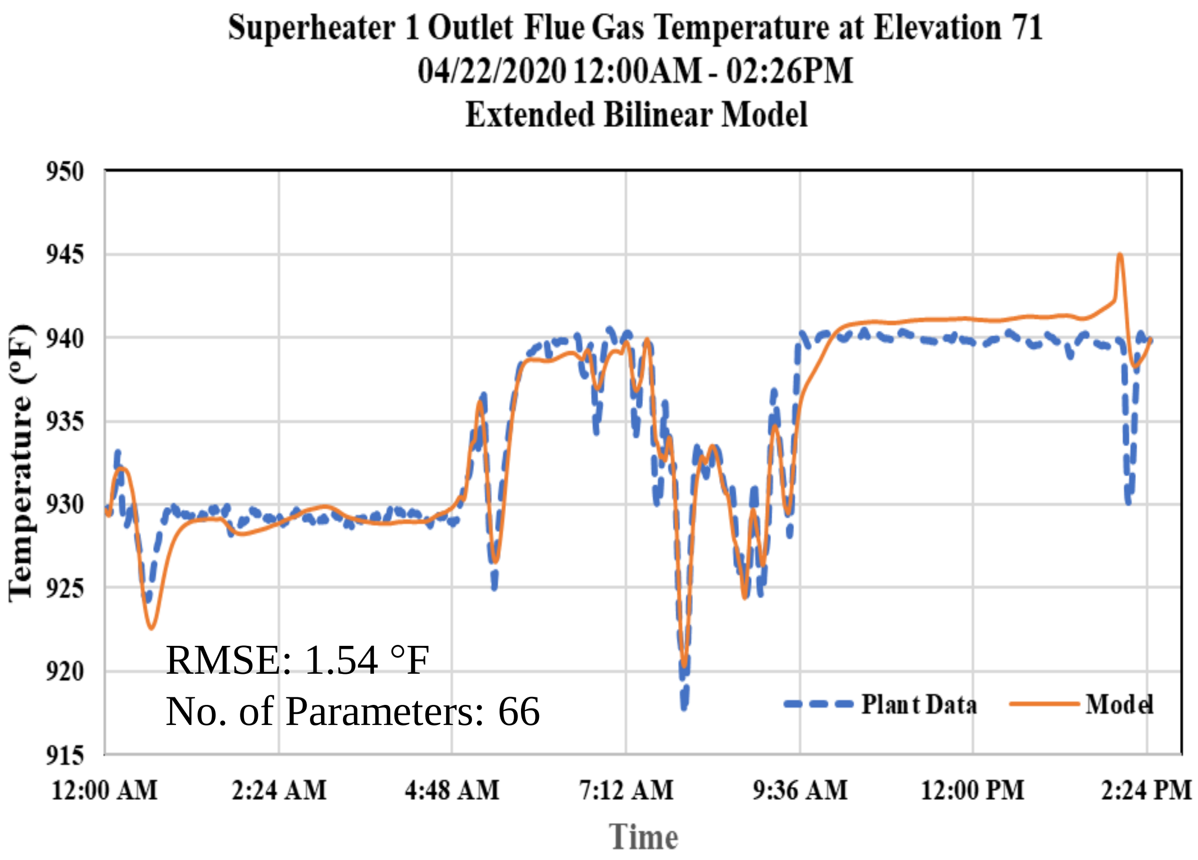
Validation of Steam Outlet Temperature





Validation of Flue Gas Temperature





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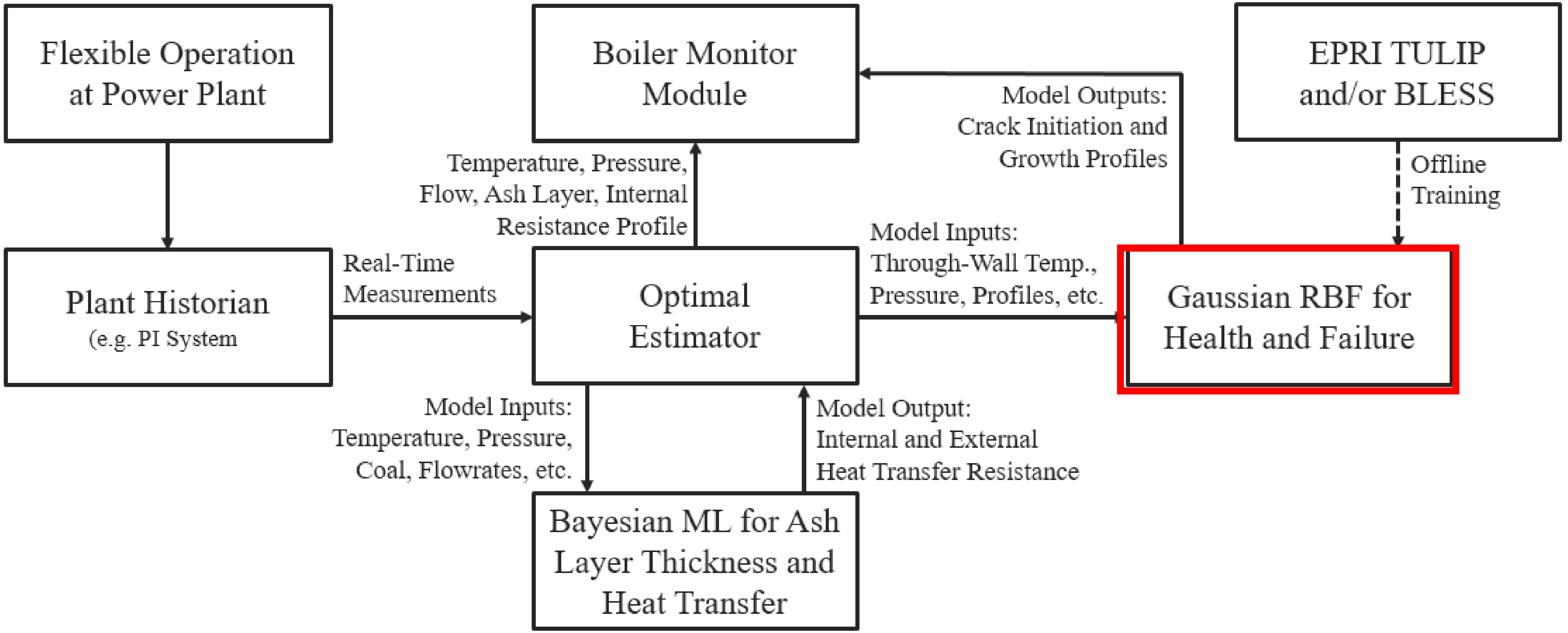


Dynamic and Probabilistic NN

Gaussian Radial Basis Function (RBF) Network

- Currently deterministic hybrid static-dynamic networks have been developed
- Efficient solution algorithms for these hybrid structures are being developed
- Algorithmic capabilities have been developed to impose physics constraints for the hybrid network

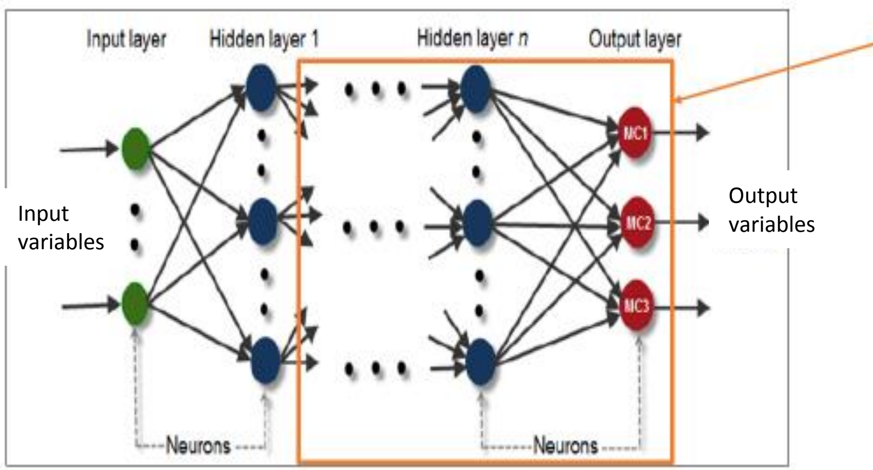
Model Inputs

- Inlet flue gas temperature (°F)
- Inlet steam temperature (°F)
- Inlet flue gas mass flow rate (Kg/hr)
- Inlet steam mass flow rate (Kg/hr)

Model Outputs

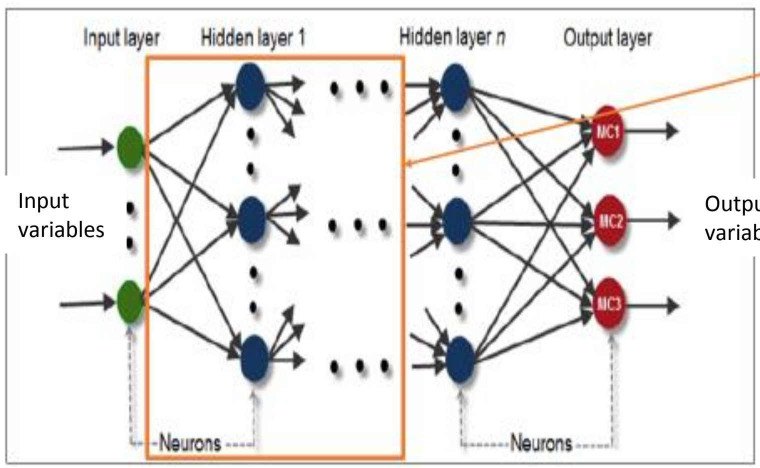
- Outlet flue gas temperature (G71) (°F)
- Outlet steam temperature (°F)
- Tube temperature (E75) (°F)

Hammerstein-Type Network



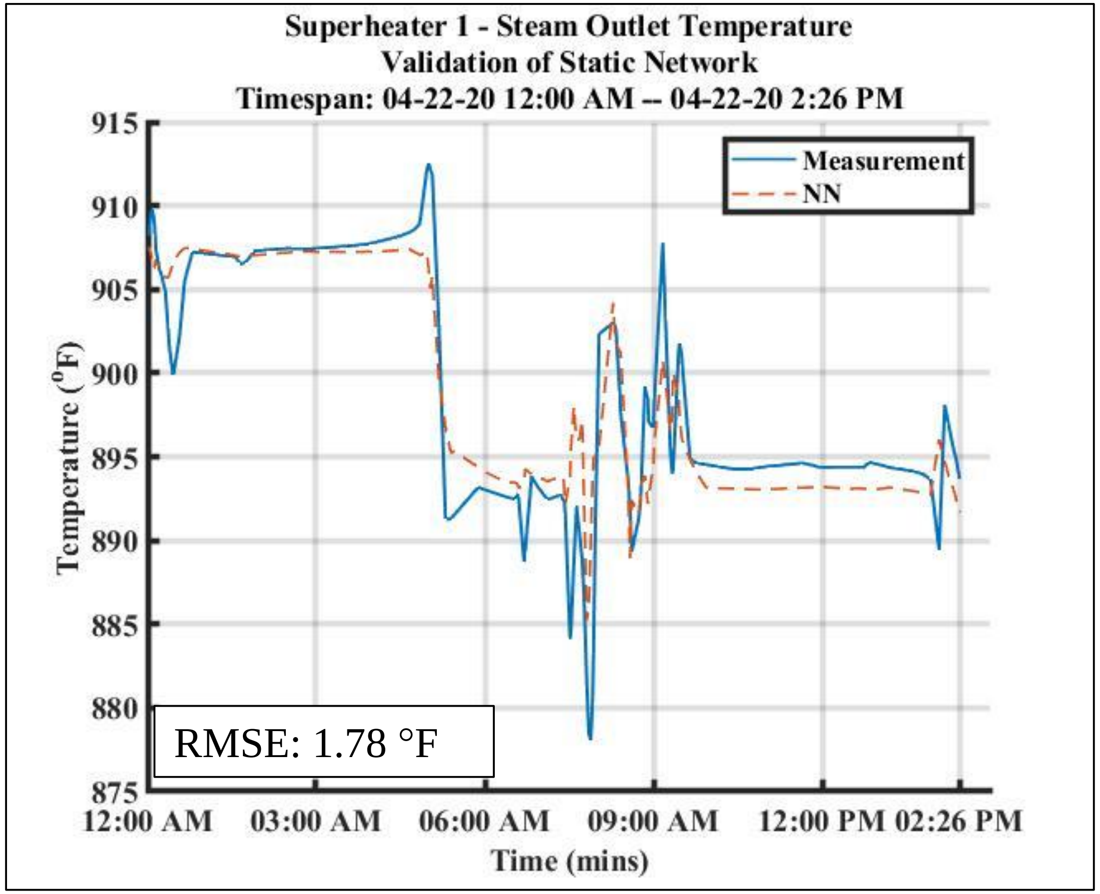
Hammerstein-type Network (non-linear static network followed by non-linear dynamic network)

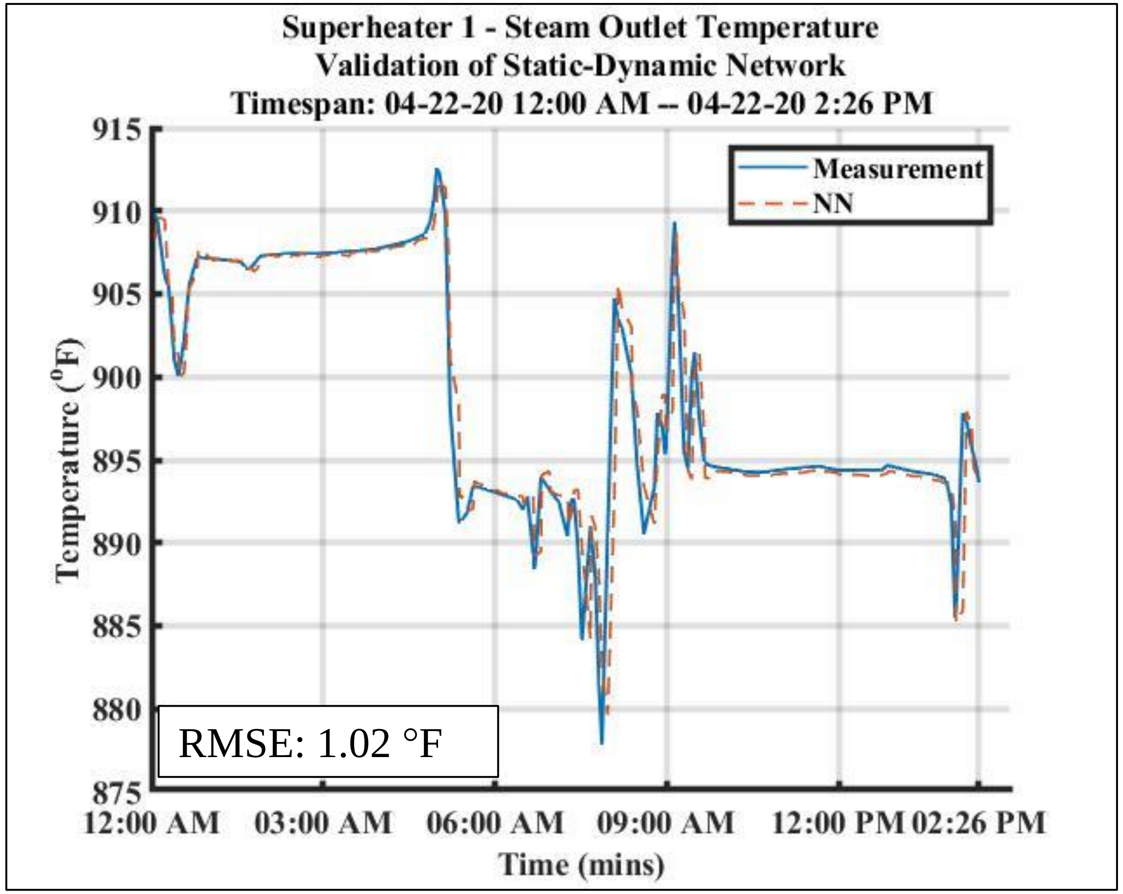
Wiener-Type Network



Wiener-type Network (non-linear dynamic network followed by non-linear static network)

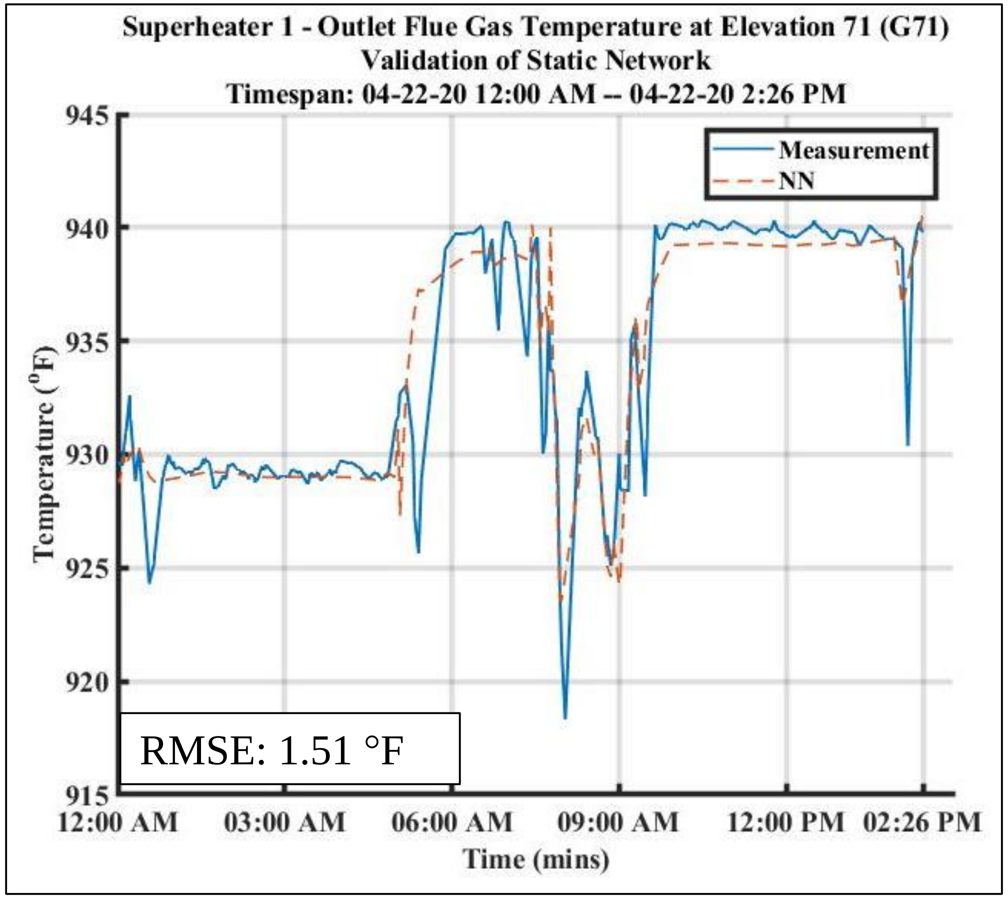
Hybrid Static-Dynamic NN vs Static NN

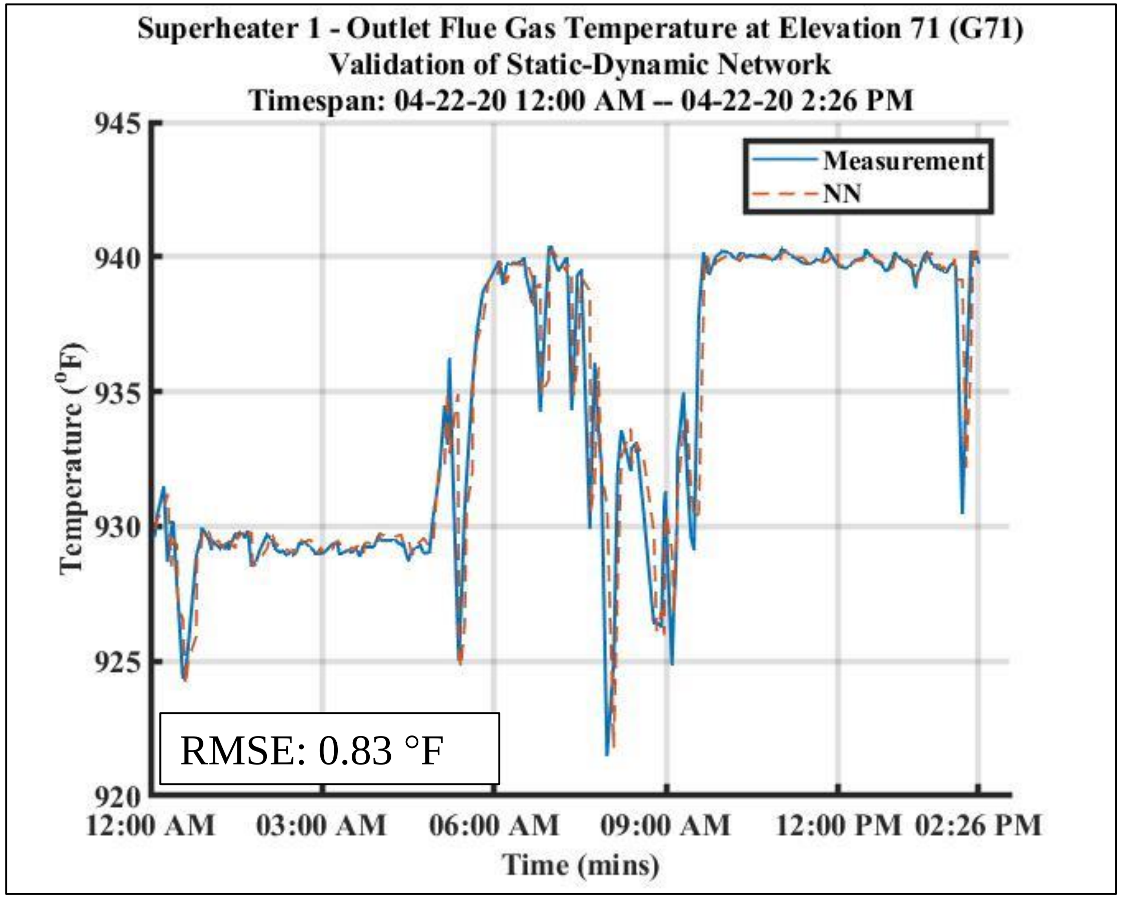




- **The hybrid static-dynamic network provides a better fit especially for over/undershoots as compared to the pure static network.**
- **Predicting these over/undershoots correctly is important for health analysis since they may damage the equipment items.**

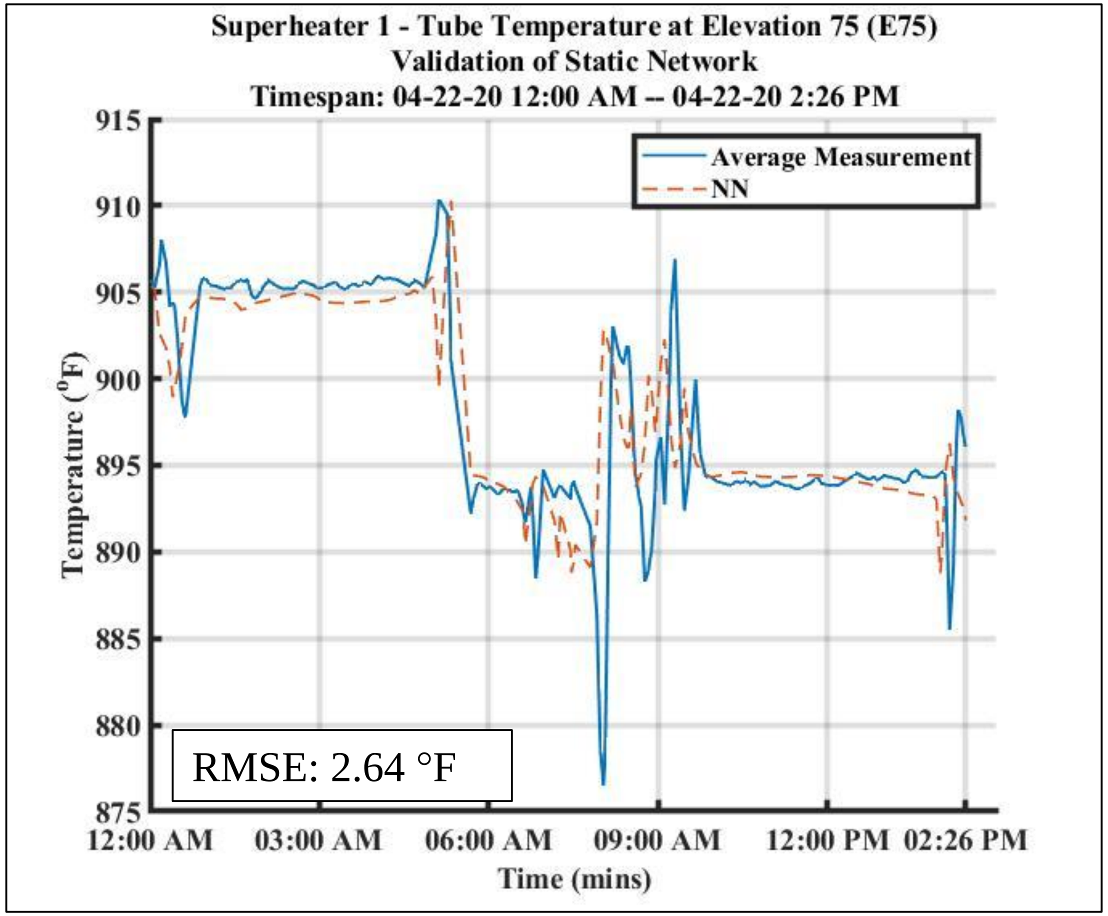
Hybrid Static-Dynamic NN vs Static NN

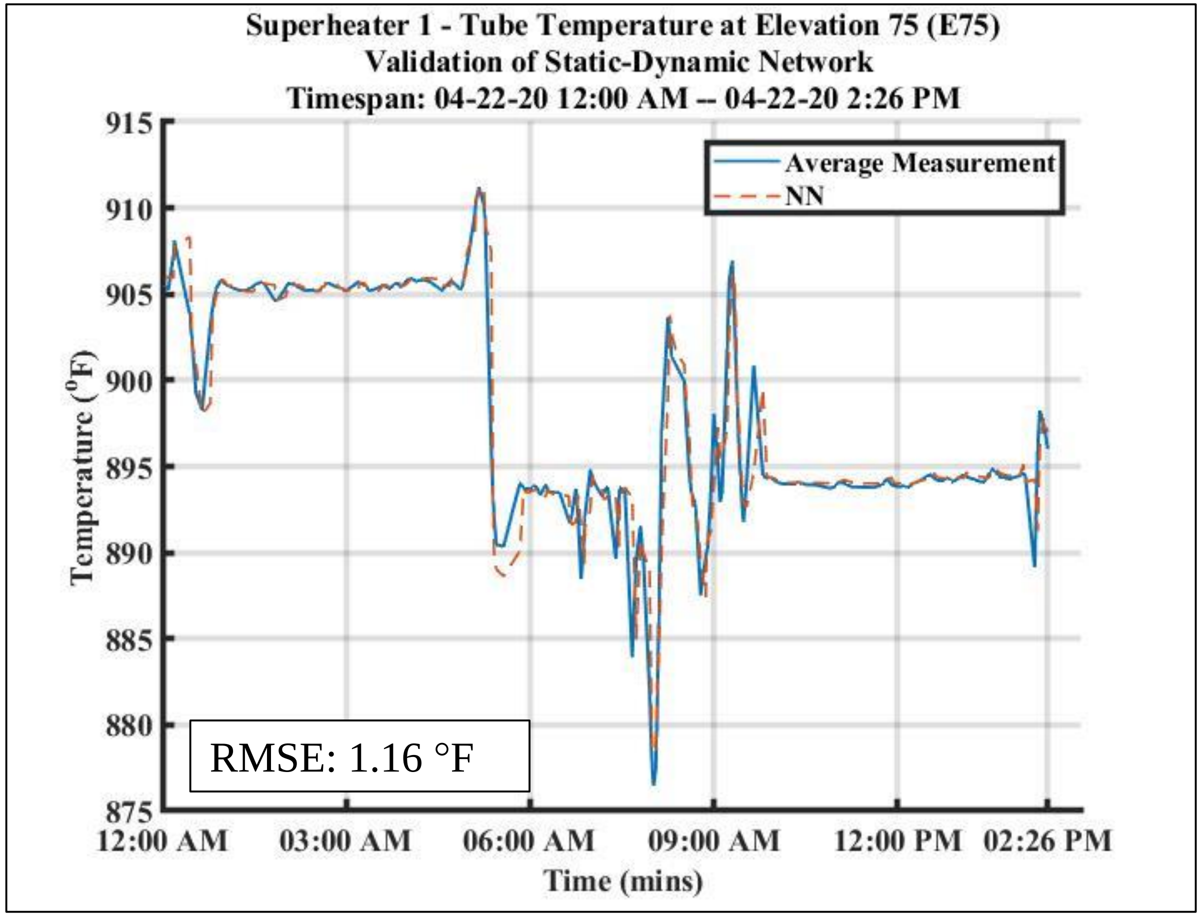




- **The hybrid static-dynamic network provides a significantly better fit as compared to the pure static network in validating the measured flue gas outlet temperature at Elevation 71 (G71).**

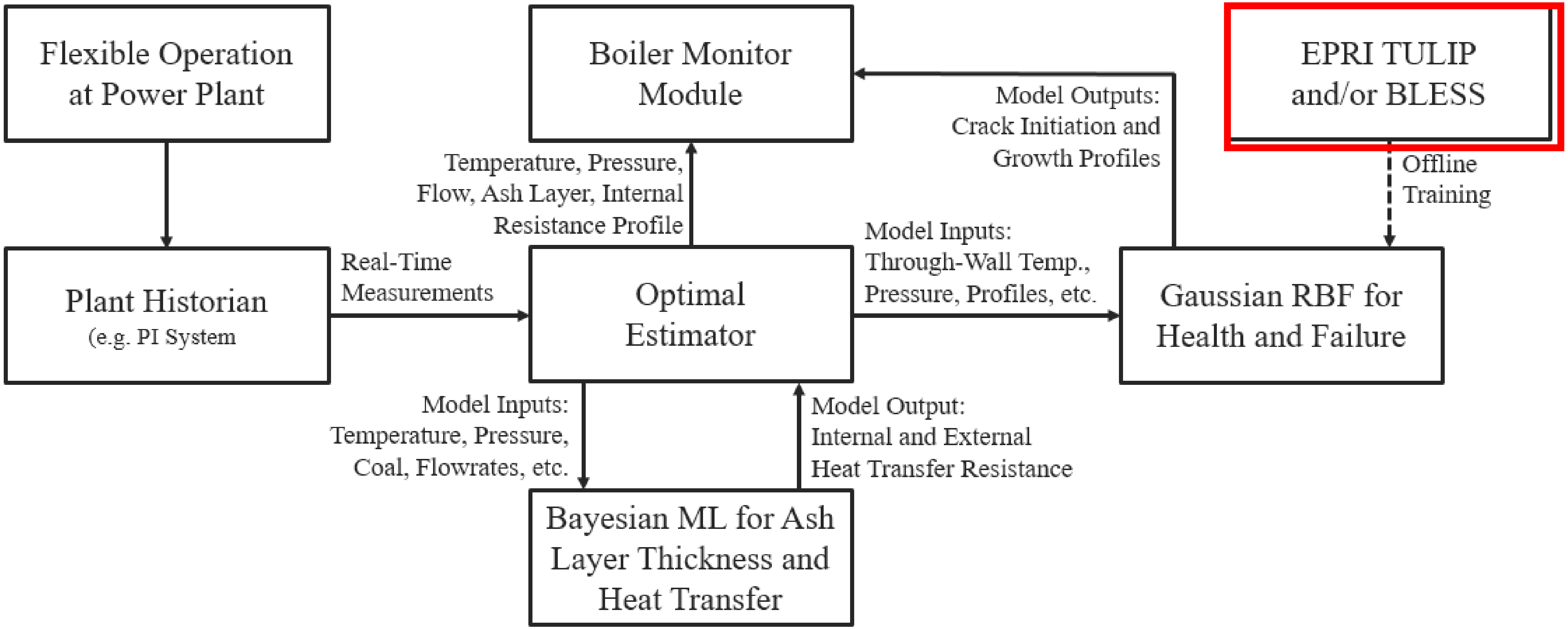
Hybrid Static-Dynamic NN vs Static NN





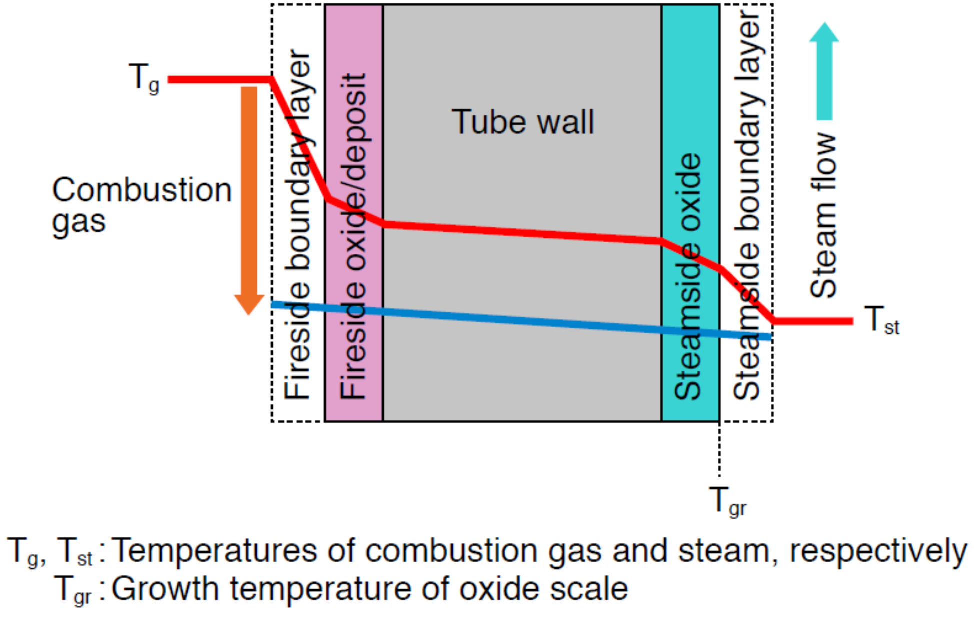
- **The hybrid static-dynamic network provides a significantly better fit as compared to the pure static network in validating the average tube temperature at Elevation 75 (E75).**

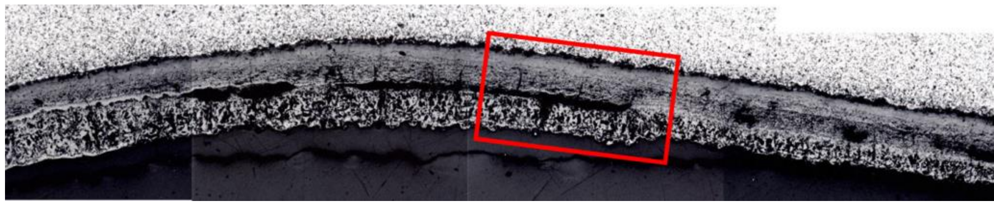
Our Approach



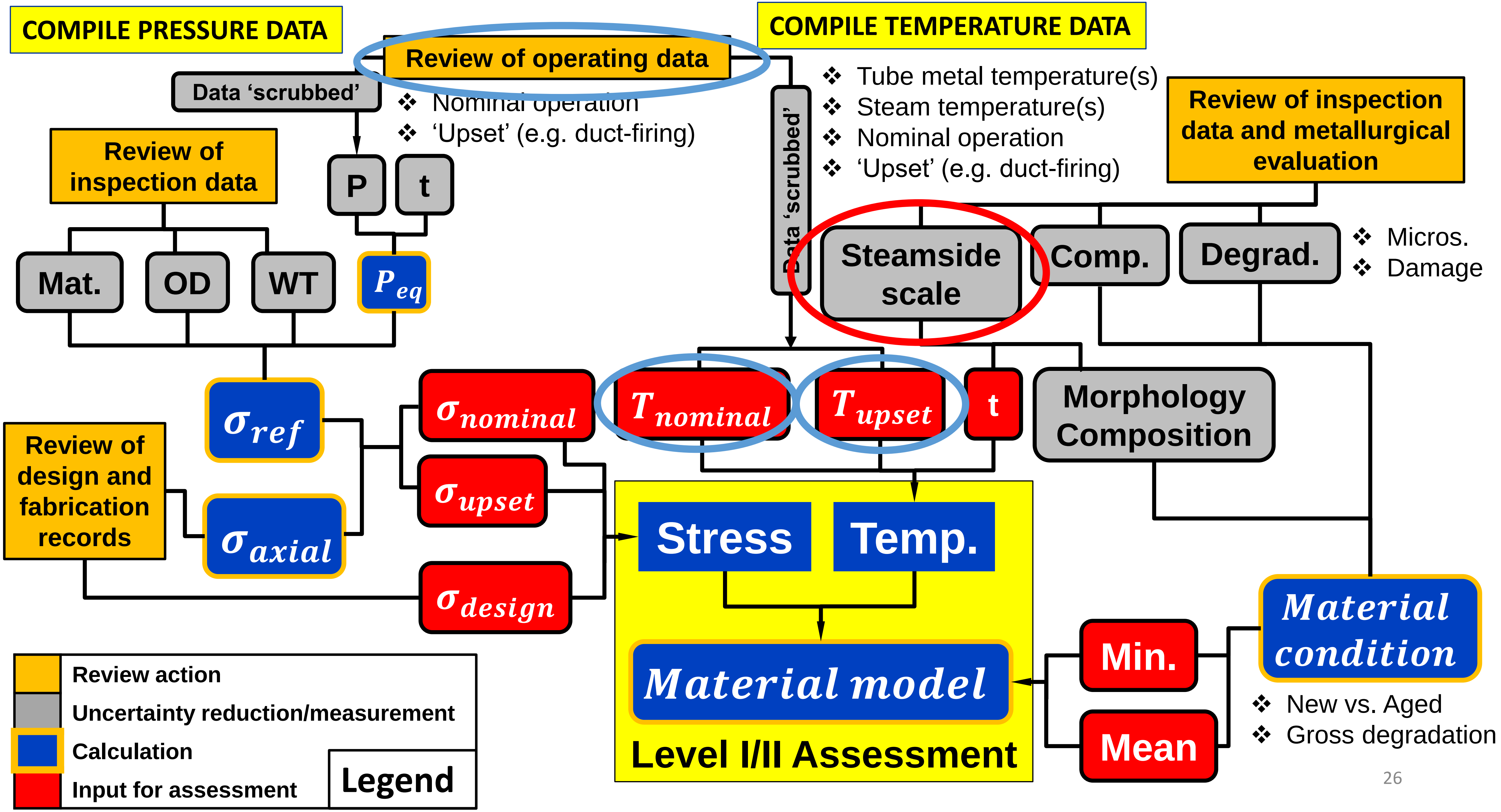
Boiler Tubes and Damage Mechanisms

- **Boiler tubes are fundamentally heat exchangers that run in the creep regime**
  - Creep is temperature-accelerated a damage mechanism leading to tube rupture after life is consumed
    - +25C/45F consumes creep life 6x faster; the same as +33% stress
    - +50C/90F consumes creep life 40x faster; the same as +140% stress
- **Tubes are exposed to internal and external surface degradation and wall loss**
  - Most critical is internal steam oxide growth
  - Complex, multi-phase constructions, up to about 0.5 mm (20 mils).
  - Oxides resist heat transfer, driving up metal temperature
  - Thickness can be measured periodically by UT from about 0.05 mm (2 mils) and greater during an outage





Interaction Between Damage Mechanisms Leads to Self-Acceleration

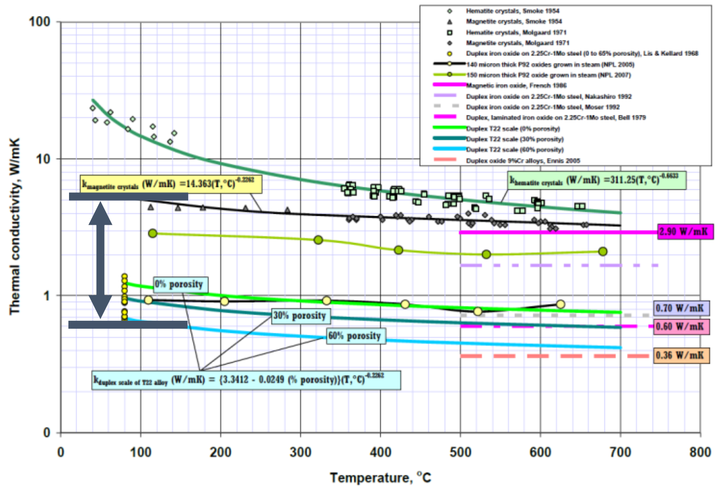


COMPILE PRESSURE DATA
Review of operating data
Data 'scrubbed'
❖ Nominal operation
❖ 'Upset' (e.g. duct-firing)
Review of inspection data
P
t
Mat.
OD
WT
P_{eq}
σ_{ref}
Review of design and fabrication records
σ_{axial}
$\sigma_{nominal}$
σ_{upset}
σ_{design}
COMPILE TEMPERATURE DATA
❖ Tube metal temperature(s)
❖ Steam temperature(s)
❖ Nominal operation
❖ 'Upset' (e.g. duct-firing)
Data 'scrubbed'
Review of inspection data and metallurgical evaluation
Steamside scale
Comp.
Degrad.
❖ Micros.
❖ Damage
$T_{nominal}$
T_{upset}
t
Morphology Composition
Stress
Temp.
Material model
Level I/II Assessment
Min.
Mean
Material condition
❖ New vs. Aged
❖ Gross degradation
Review action
Uncertainty reduction/measurement
Calculation
Input for assessment
Legend

Metal Oxides Thermal Conductivity

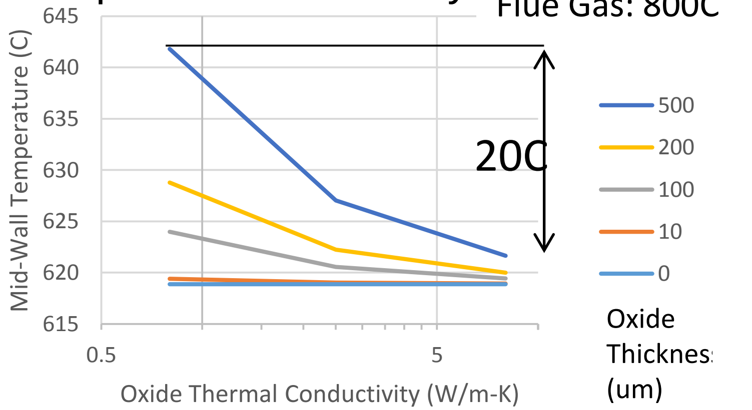
- **This research is aiming to reduce uncertainty in the impact of oxide growth on metal temperature**
  - Oxides change with time: thickness, porosity, spallation, and precent Fe_2O_3 vs. Fe_3O_4
  - Develop a better, more rigorous understanding of oxide thermal conductivity as it relates to morphology
- **Currently metal oxide thermal conductivity reported over one order of magnitude**
  - This results in a significant Δ20C in the prediction
    - Or about 5x life consumption
  - Leads to a need for experimental evaluation of ex-service boiler tubes

Literature Data:
Thermal Conductivity of Steel Oxides



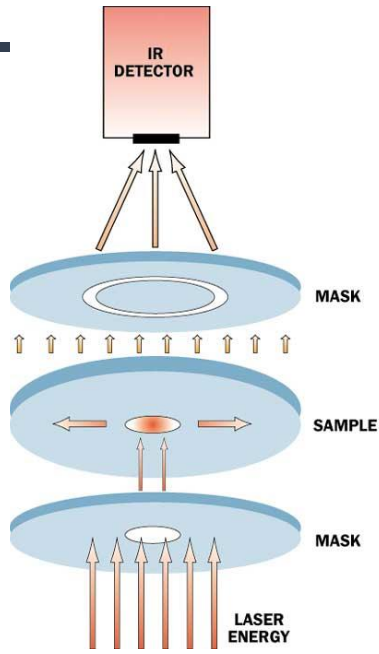
Theoretical Analysis:
Impact of Conductivity

Steam: 550C
Flue Gas: 800C



Measuring Thermal Conductivity of Oxides

- **EPRI pursuing two methods in parallel**
  - ASTM Standard test method E1461 Laser Flash
    - Works well for multi-layered structures like boiler tube + oxide
    - Can be run at elevated temperature
    - Preliminary results show the intense burst of energy does not cause oxide spallation
  - Water bath experiment at EPRI laboratory
    - Monitor heat flux through the specimen
    - Simpler setup for rapid, large area measurements

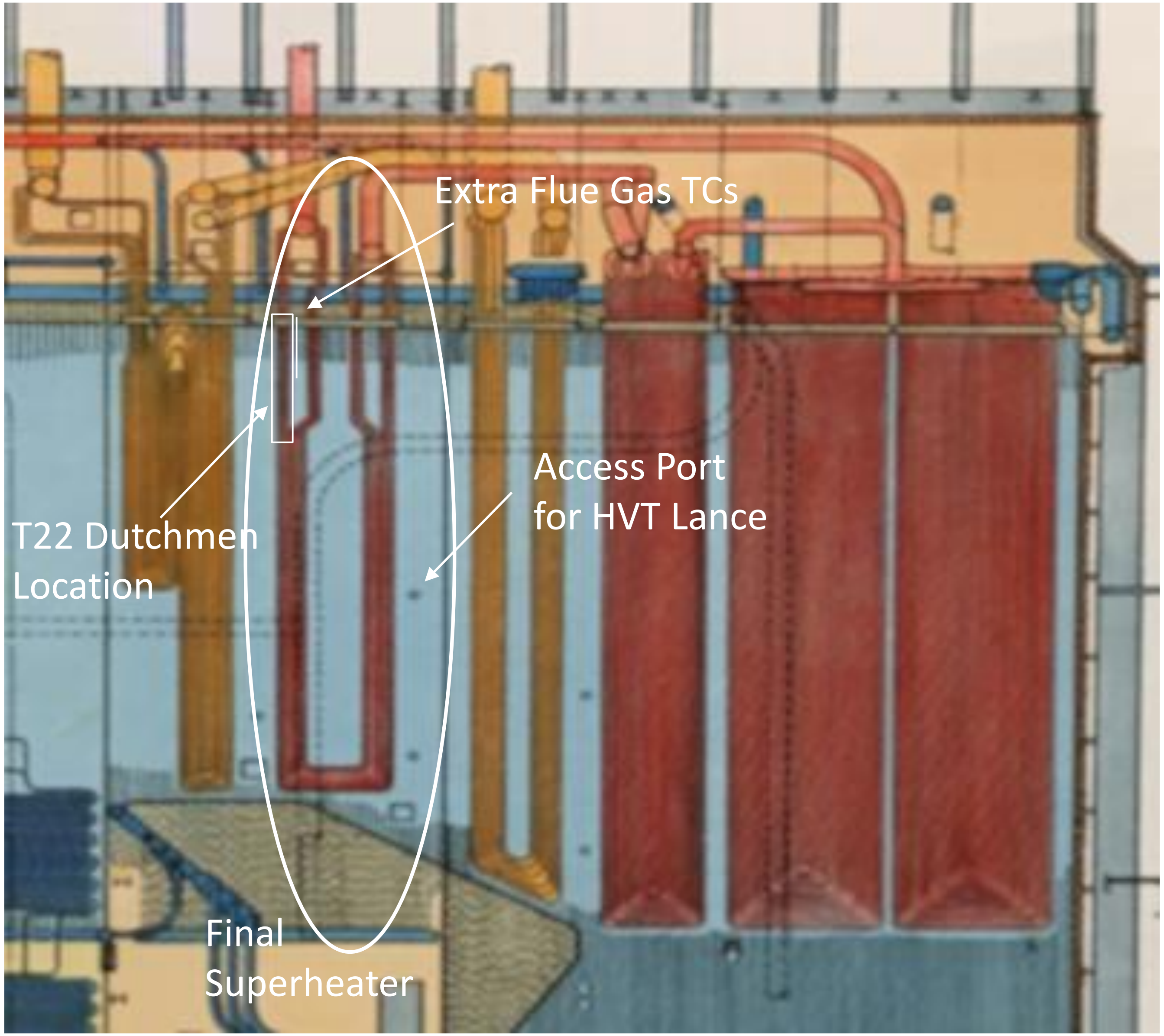


- **Database of seven ex-service materials to provide a range of real-world oxides**
  - T22, T91, T92, and 347H
  - Oxide scale thicknesses from 100 to 360 µm

Experimental Testing on Ex-Service Tubes to Reduce Uncertainty

Three Areas of Work at Plant A Unit

- **"Signature" analysis relating flue gas temperature and unit operating conditions (load) by HVT**
- **Install T22 dutchmen with TCs into Final Superheater**
  - Fabricated by commercial manufacturing to ASME B&PVC
  - Characterize damage accumulation to validate prediction
  - Installed alongside Clemson sensors
- **Extra flue gas monitoring TCs from penthouse**
- **Leveraging Southern Company supply base and standard procedures**



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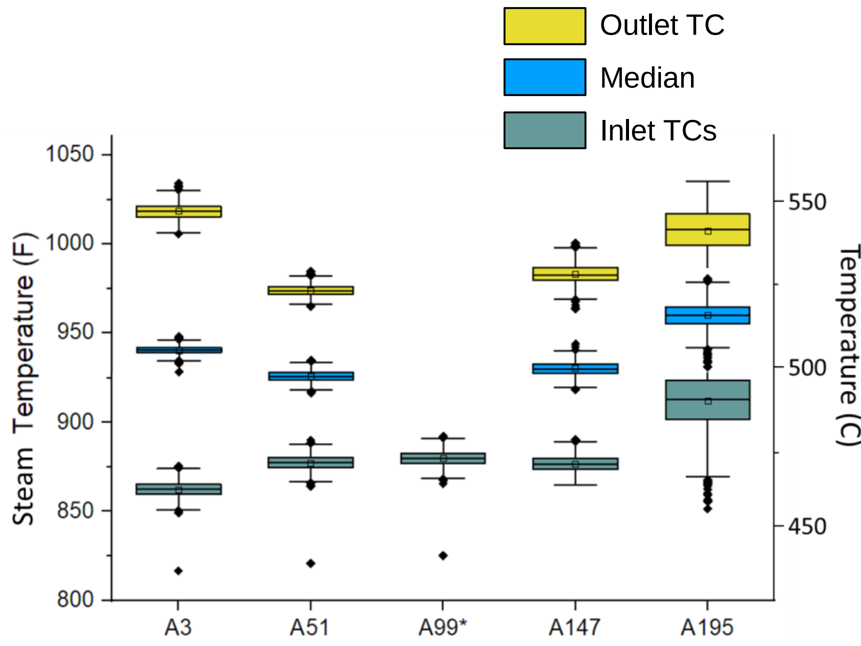
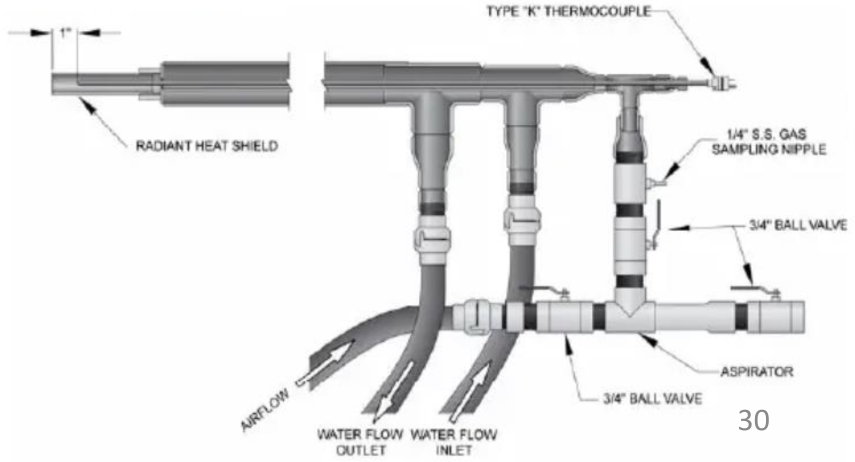
Temperature Distribution in Plant A Unit Final Superheater

- **Flue gas temperature measurement is a critical input to the model**
  - Known to vary across width with a preference for dutchmen on the edges
- **HVT to provide a fingerprint of flue gas measurements**
  - Sampling performed at low, medium, and full load
    - One snapshot in time (a day) and only 20’ from either side
    - Anticipate to run for one day in Spring and again after dutchmen are installed
  - Flue gas measurements then correlated to heat pickup in steam by inlet-outlet TCs
  - Access port is just ahead of the final superheater at mid-elevation
- **Combine this inspection with hanging TC wires from the roof of the boiler (beneath penthouse)**





Plant-Specific Data to Validate Model Parameters

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Conclusions

- **Collaboration between research and industry providing significant benefit to this project's applicability to actual plants**
  - Model development is integrated with in-plant demonstration
  - Ex-service material characterization narrows uncertainty in materials
- **Boiler tube life management is an expensive industry issue**
  - Damage to components is becoming less predictable with flexible operation
- **Preliminary validation using operational data**
  - Estimator-based approach and AI models including show good feasibility
- **Future work will focus on:**
  - Extending the fidelity of first-principles model, DAE estimator, and probabilistic NN model
  - Handling noise for the Bayesian ML approach
  - Validation of the hybrid approach using additional plant data under wider set of conditions
- **On-track with respect to timeline, milestones, and budget leading into a Fall plant installation effort**

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Thank you for your attention

Questions?

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Boiler Tube Life Management:

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