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

Award#:DE-FE0031768

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Virtual
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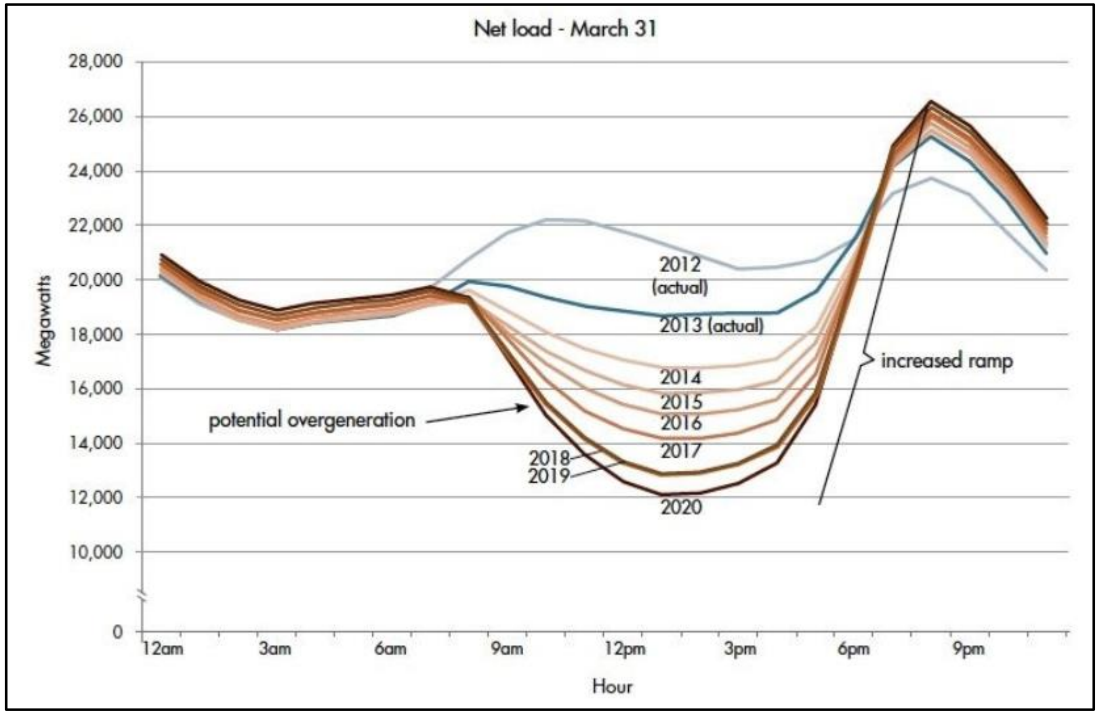
Outline

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

Motivation: Flexible Operation and Extended Life

- Renewable generation, demand response, and others require more operational flexibility from fossil energy power plants
  - 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
- Avoiding downtime more important for plant profitability than ever
  - Tube failures are traditionally the number one cause of forced outages of power generating units worldwide
  - Needs better predictive approaches

CAISO Duck Curve[1]



Net demand = Grid Demand – Renewable energy production

Source: www.caiso.com.

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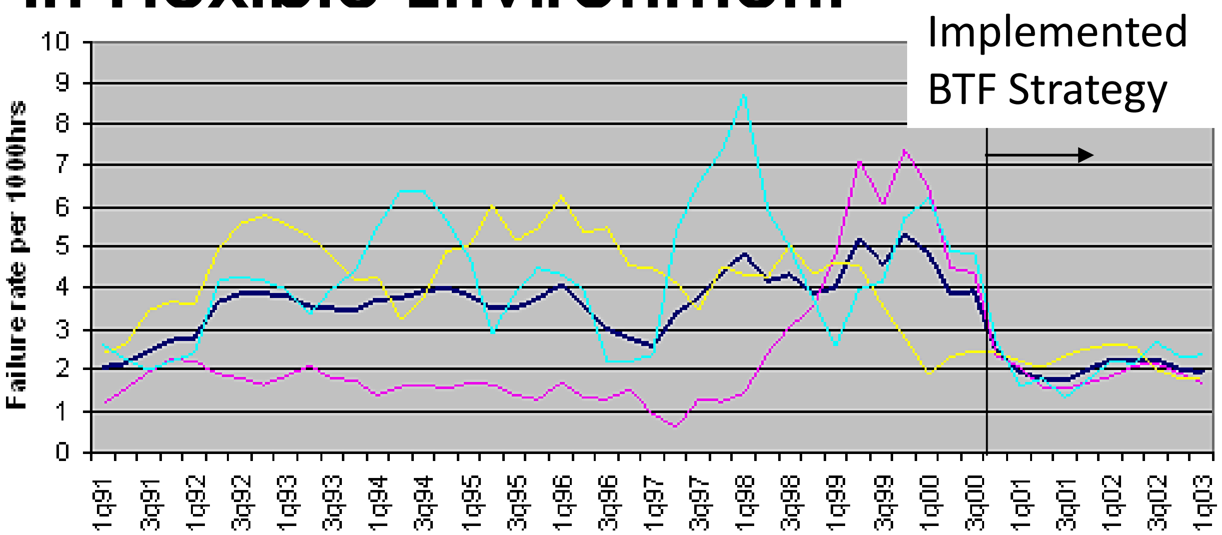
Opportunity: Predicting Damage in Flexible Environment



Actual Failure Rate Statistics from one Company Compiled data used to be available from NERC / GADS

- For predominantly base load conditions, maintenance successfully managed by statistical analysis, inspection, and RCA
  - Demand response is often beyond the original design intent of a boiler
  - Flexible operation involves complexities that require different LM approaches
  - Over-temperature operation is a key driver for failure
- An on-line health monitoring tool can be instrumental in:
  - Understanding the impacts of load and load changes on local metal temperature
    - Steamside scale growth reduces heat transfer, increases metal temperature, and self accelerates
    - Metal temperature increases accelerate creep damage: +25^{o}F (15^{o}C) will reduce life by 50%
  - Help to schedule preventative O&M more effectively and
  - Leads to control strategies for flexibility without compromising safety and reliability

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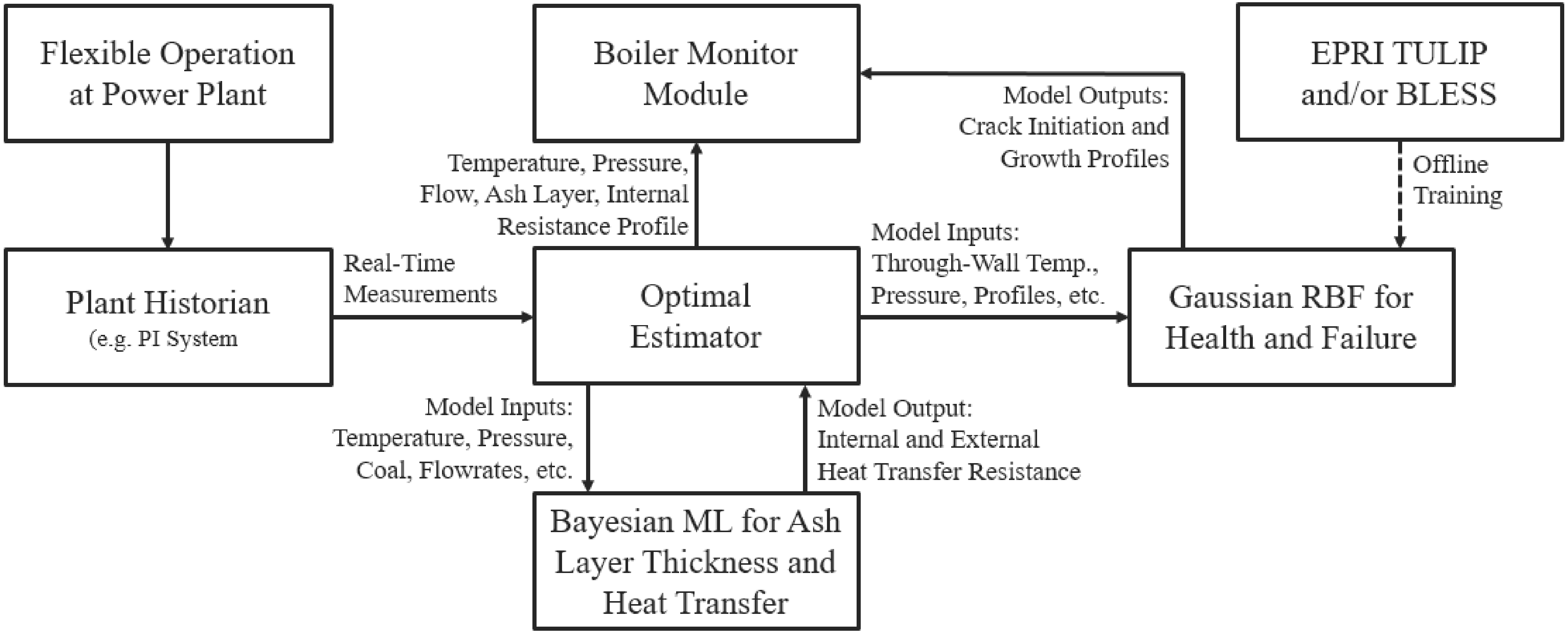
Our Approach: A Hybrid First-Principles-AI Based Approach

- **Advantages of first-principles and mechanistic models:**
  - Satisfies mass, momentum and energy balances
  - Can be predictive
  - Can provide spatial and temporal resolutions of practically all variables including those that cannot be measured (e.g., through-wall temperature of a SH tube)
- **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**
  - Mostly opposite to the first-principles models
- **This projects seeks to exploit strengths of first-principles and AI models synergistically**
  - However, the complex phenomena of interest in boilers are uncertain and time-varying
  - Must take the measurements into account
- **End goal is to develop an on-line health monitoring tool**

Our Approach



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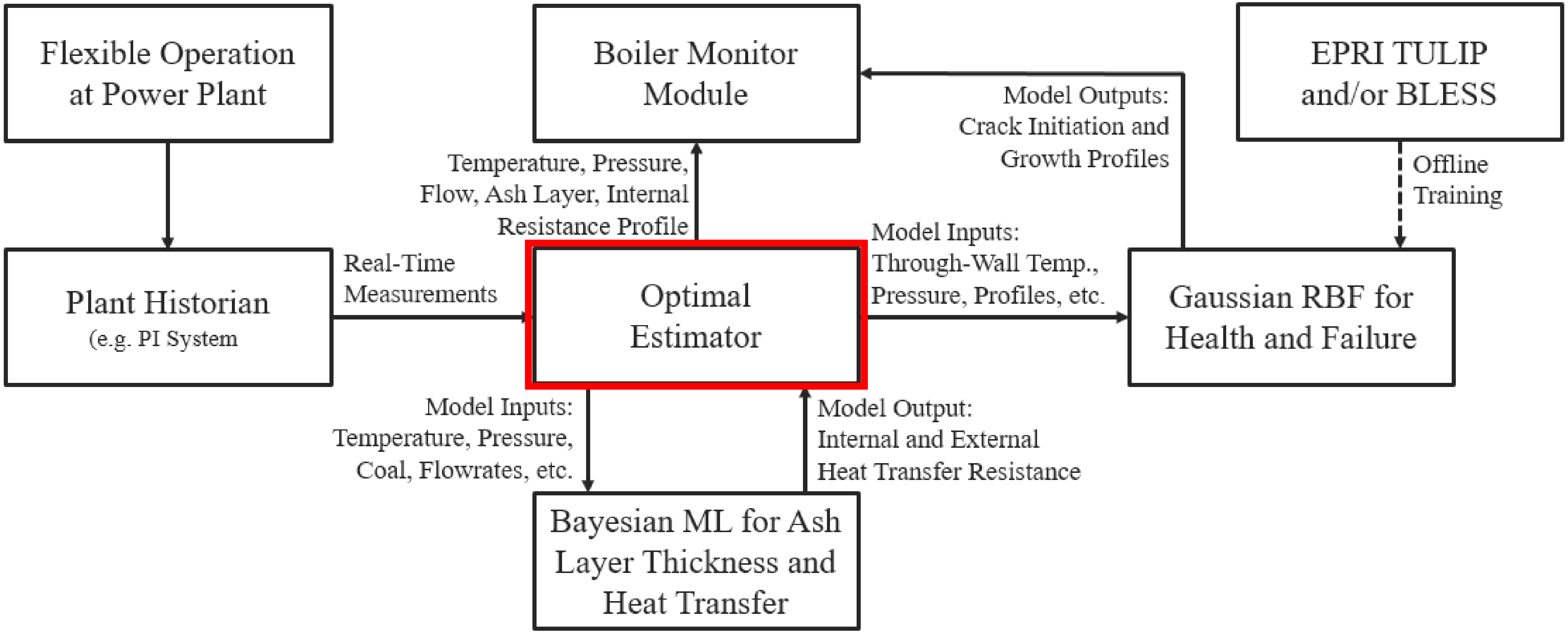
Project Objectives (Tasks)

- Task 1.0 Project Management and Planning

- Task 2 – Hybrid Model Development, Validation, and Implementation at Plant Barry (mainly WVU)
  - Subtask 2.1 – Plant Data Evaluation
  - Subtask 2.2 – Adapting the First-Principles Model to Plant Barry
  - 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 Barry

- Task 3 – Validation and Integration of Hybrid Model at Plant Barry (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

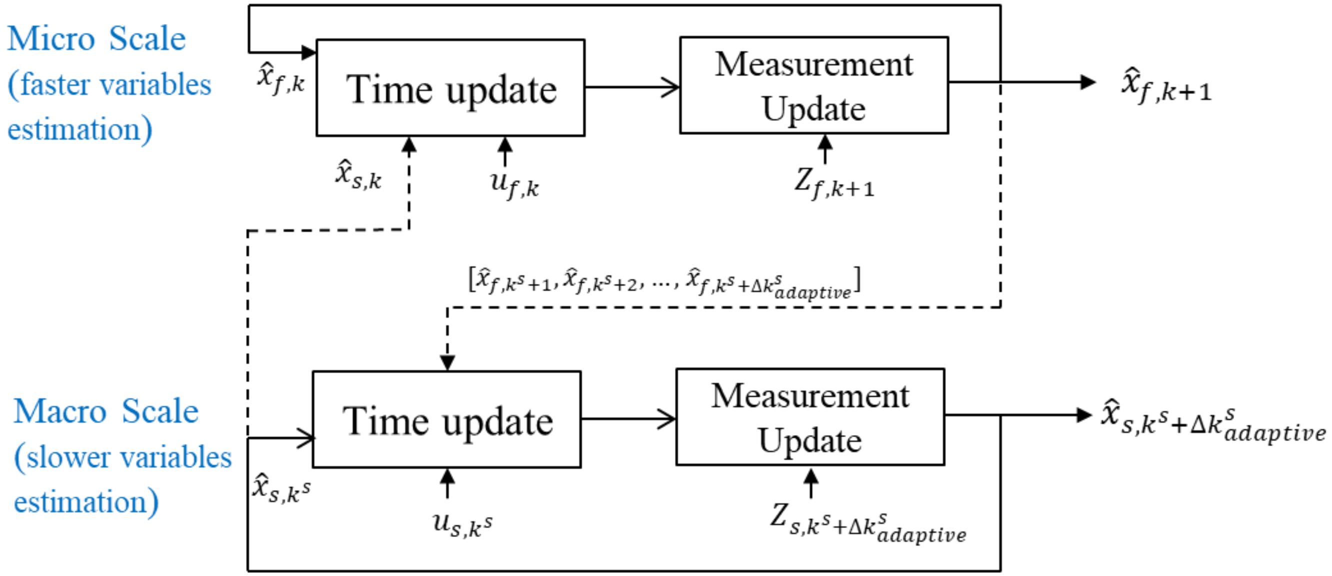


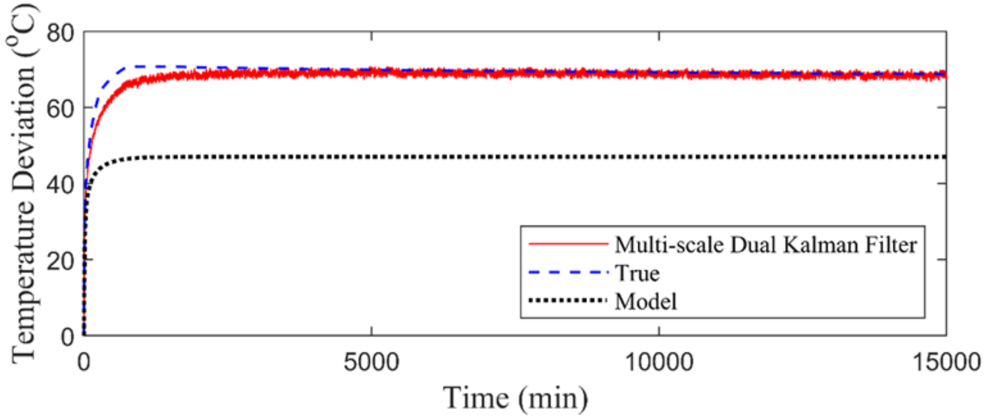
Optimal Estimator

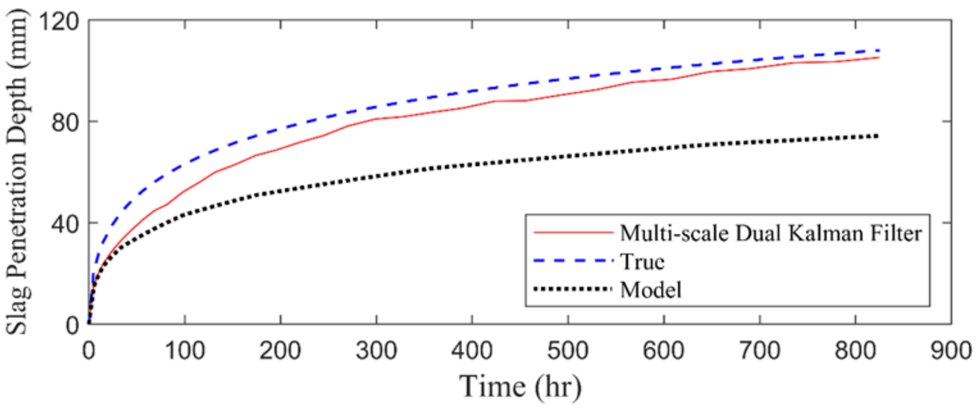
- **Multi-Rate Dual Filtering Approach for Nonlinear Differential Algebraic Equation Systems[1,2]**
  - **Key enabling approach for health monitoring**
  - **Incorporates adaptive sampling rate for slow variables**

$$\dot{x}(t) = f(x, y, u, w, t); \qquad g(x, y, t) = 0$$

$$z = h(x, y, v, t); \qquad \text{with } w\sim(0, Q)\ ,\ \ v\sim(0, R)$$



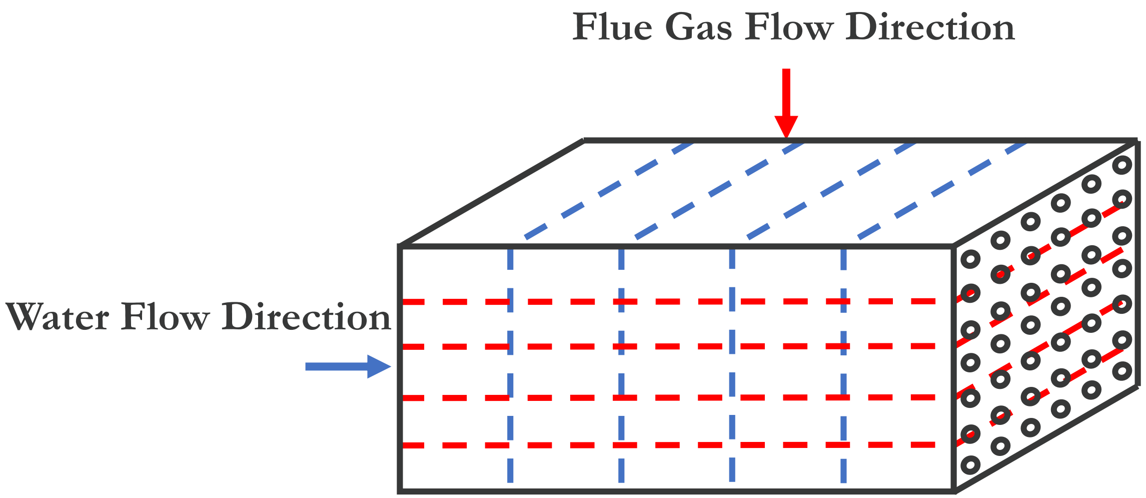


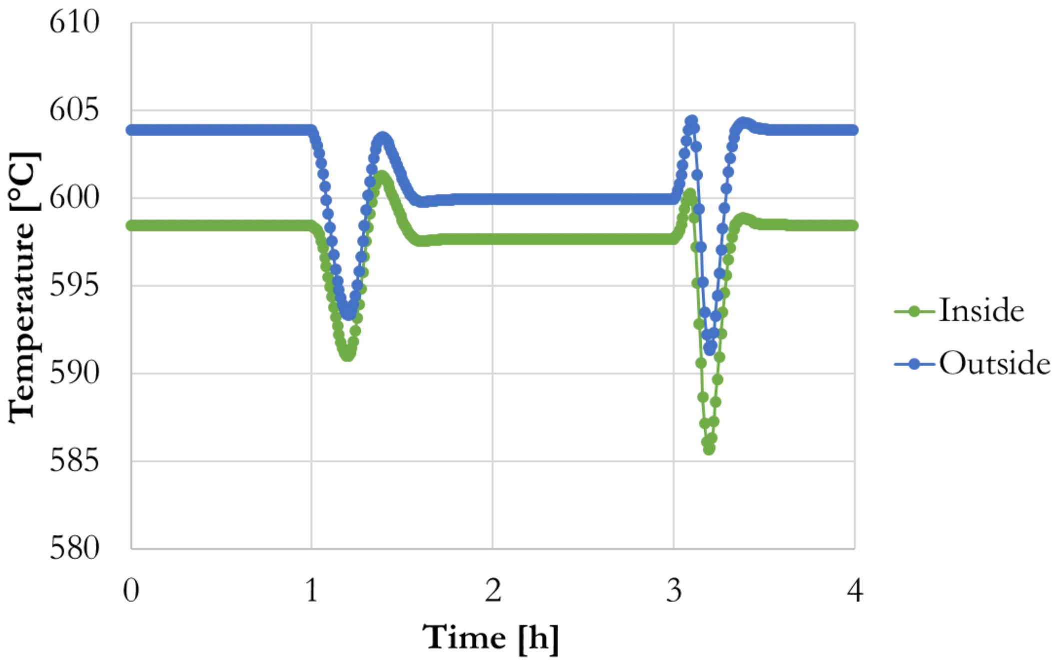


[1]**Huang Q, Bhattacharyya D, Computers & Chemical Engineering, 141, 106985, 2020**
[2]**Huang Q, Bhattacharyya D, Industrial and Engineering Chemistry Research, 56, 9858-9867, 2017**

First-Principles Model

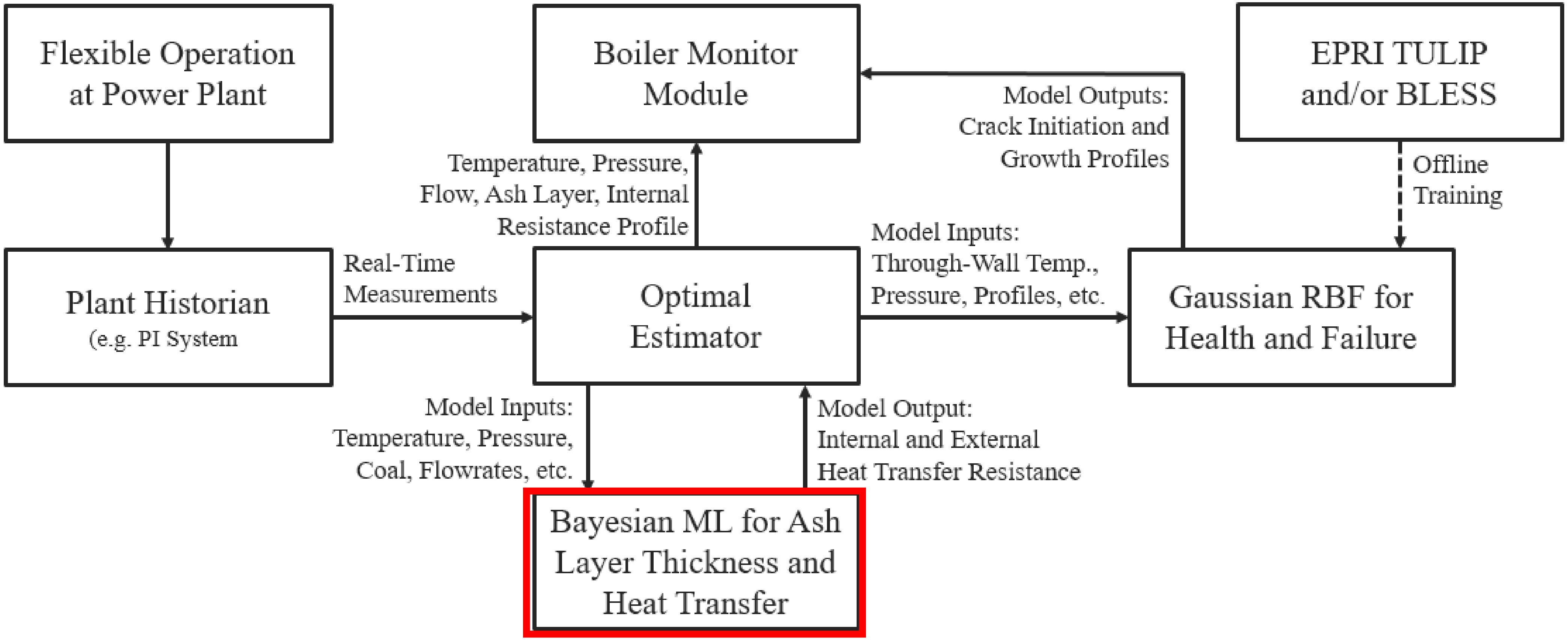
- **Development of first-principles models**
  - **Focus on reheater/superheater**
  - **Developing spatially distributed, dynamic, partial differential algebraic models**
  - **Based on mass, momentum, and energy balances**
  - **Thermal hold up in tubes and tube through-wall temperature dynamics are modeled**
  - **Validation with the plant data**





Finishing SH of a SCPC plant ramped from 100% to 60% at 1 h (5%/min) then back to 100% at 3 h (5%/min)

Our Approach



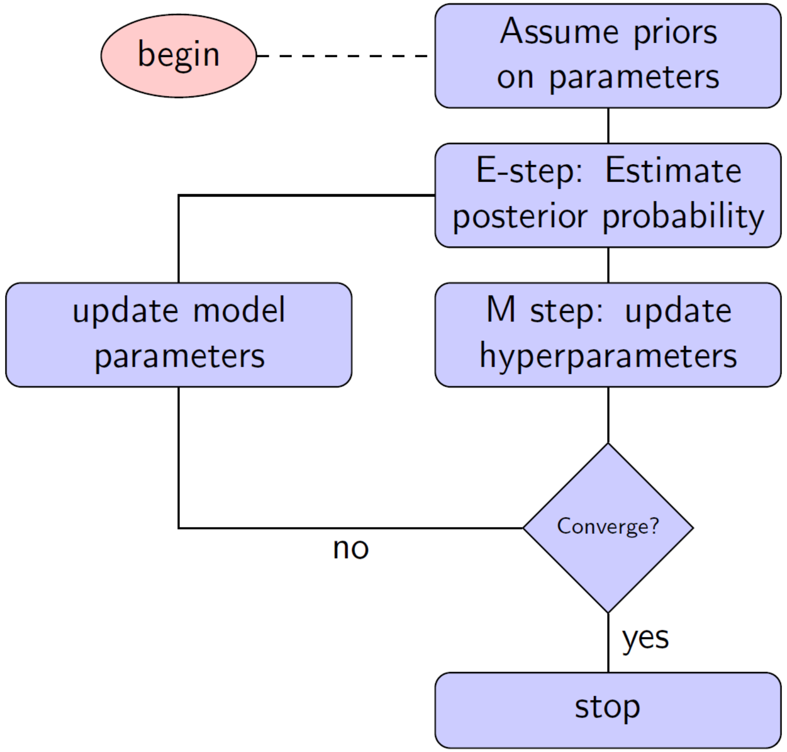
Bayesian Machine Learning

- **Bayesian Machine Learning (ML)**
  - **Ash deposit and internal scaling are time-varying and stochastic.**
  - **A Bayesian ML framework has been developed for learning time-varying stochastic systems[1,2] (funded by DE-FE0012451)**

$$\dot{x} = F(x, u, \theta) + v;\; y = g(x) + \omega$$

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

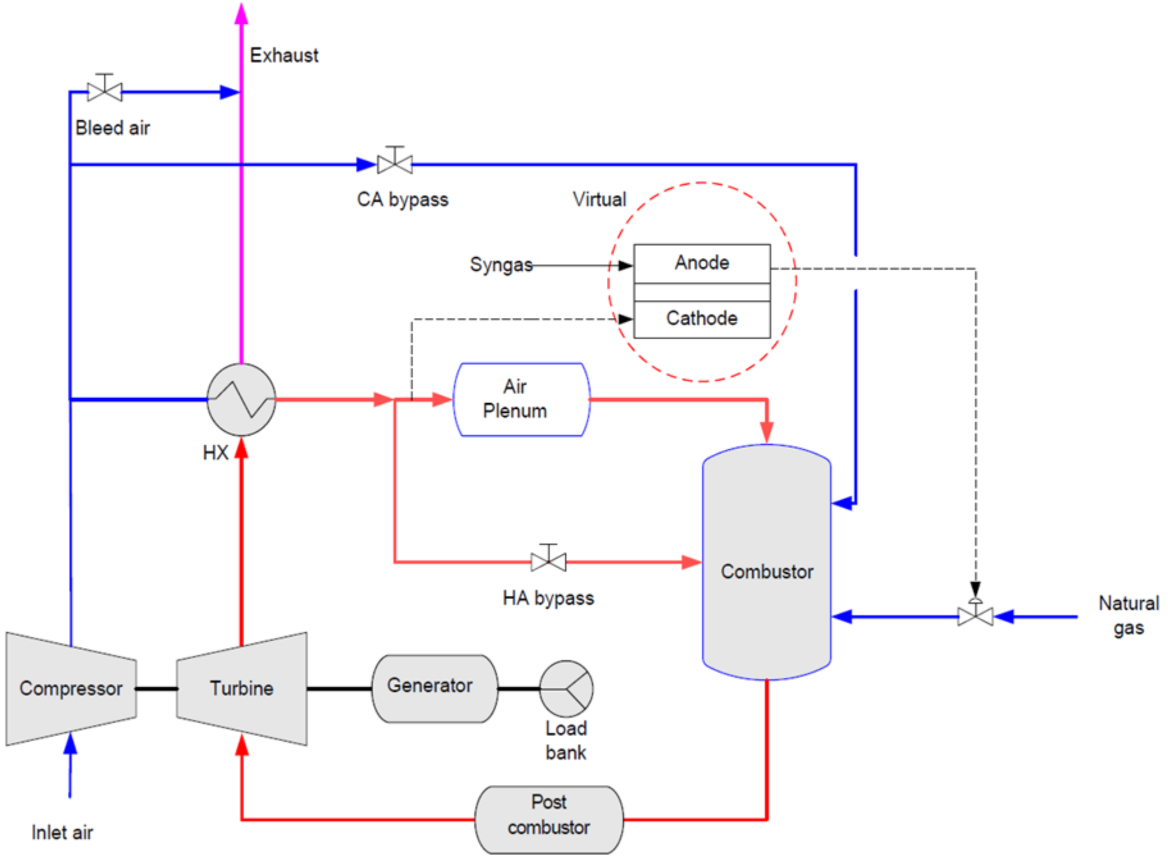
$$\hat{y}^*, \theta^* = \max_{\hat{y},\theta} p(\hat{y}, \theta|y)$$

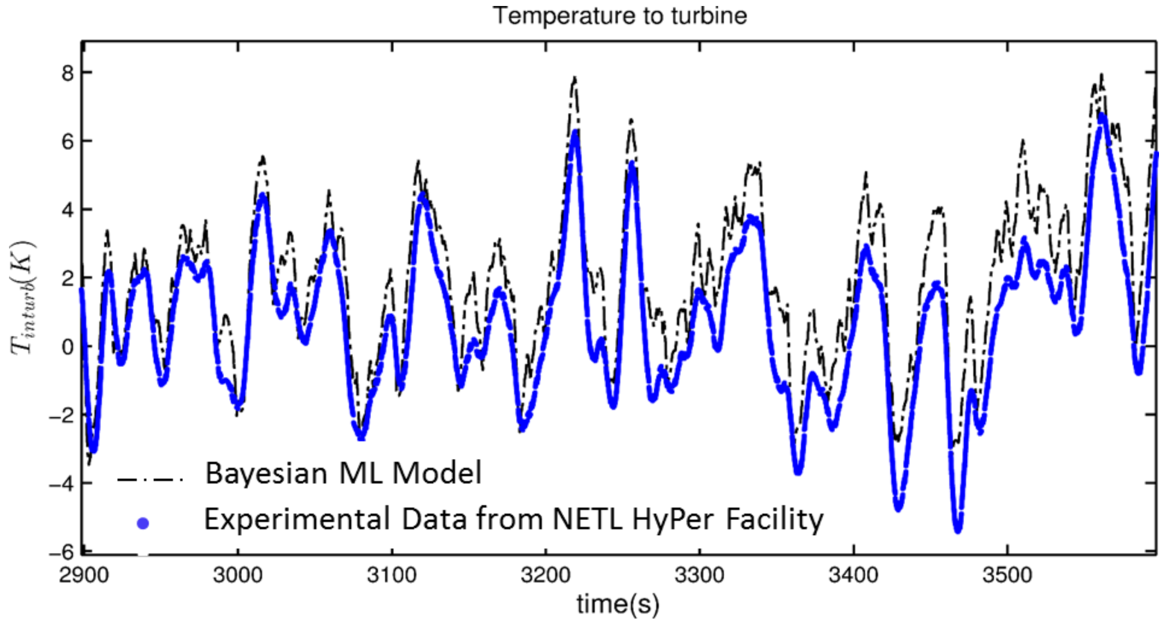


[1]Bankole S, Bhattacharyya D, Journal of Process Control, 71, 116-129, 2018
[2]Bankole S, Bhattacharyya D, Chemical Engineering Science, 203, 475-488, 2019

Prior Works at WVU

- **Bayesian Machine Learning (ML) Approach Validation[1,2]**
  - **Performance for the NETL HyPer facility**





[1]Bankole S, Bhattacharyya D, Journal of Process Control, 71, 116-129, 2018
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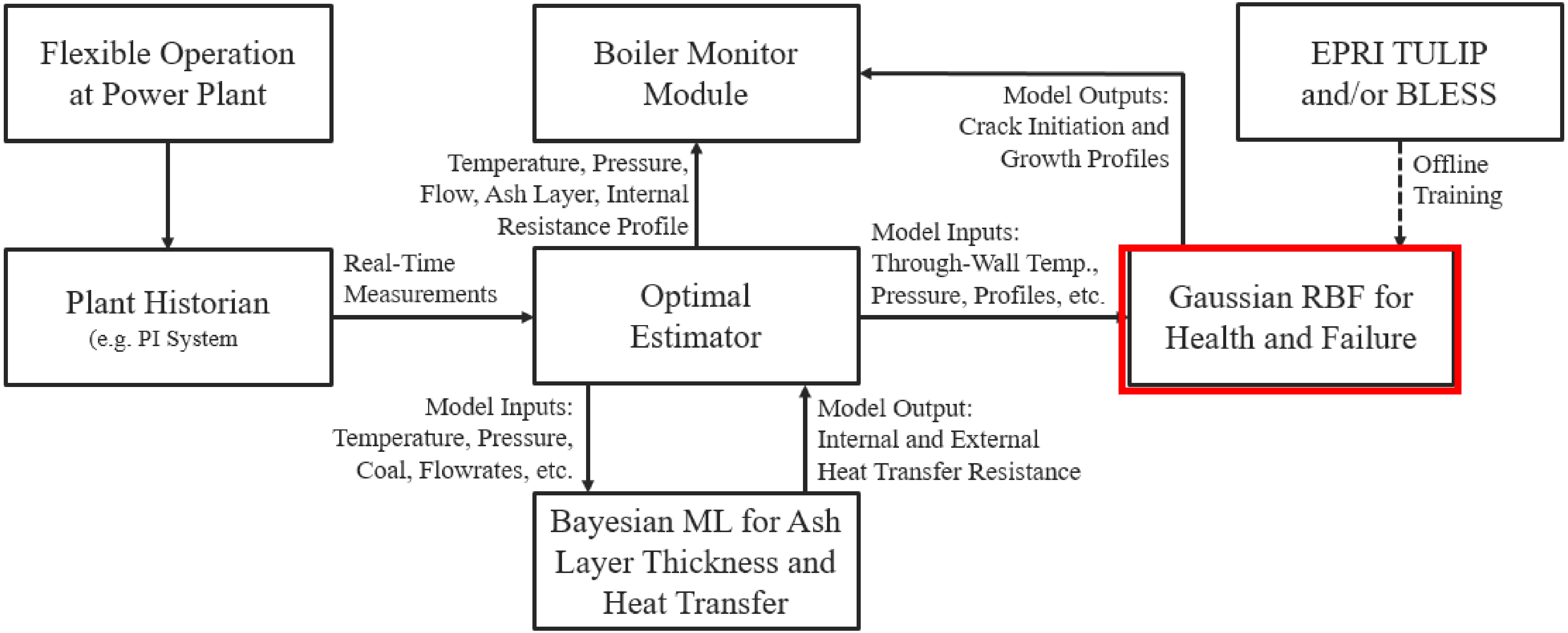
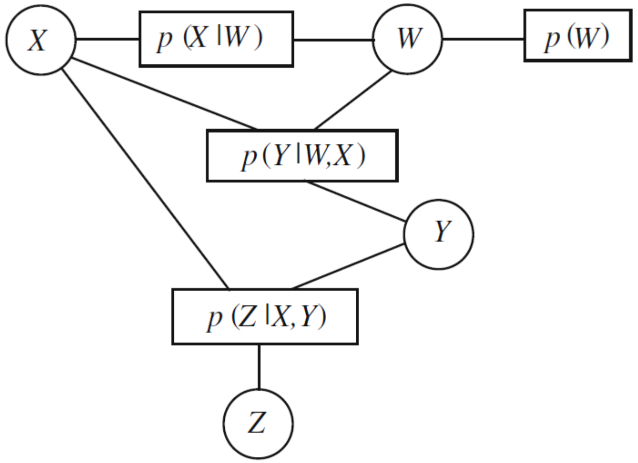
Our Approach



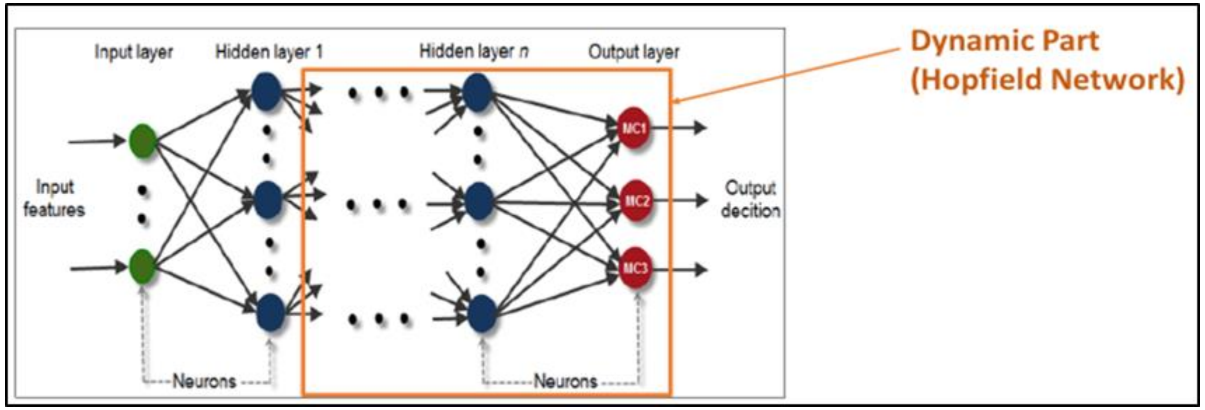
Dynamic and Probabilistic NN

- **Gaussian Radial Basis Function (RBF) Network**

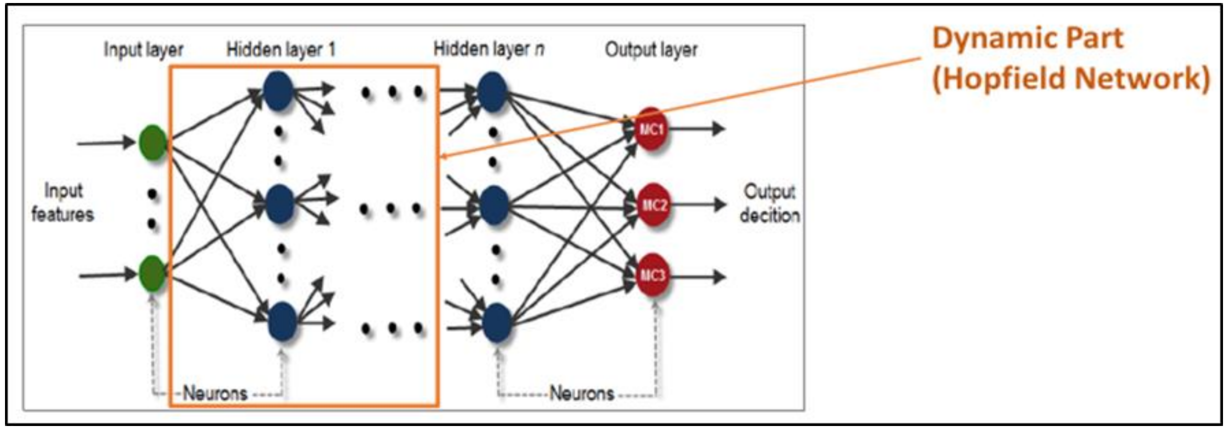
  - **A Gaussian adaptive RBF will be developed**
  - **Currently deterministic hybrid static-dynamic networks have been developed**
  - **Efficient solution algorithms for these hybrid structures are being developed**



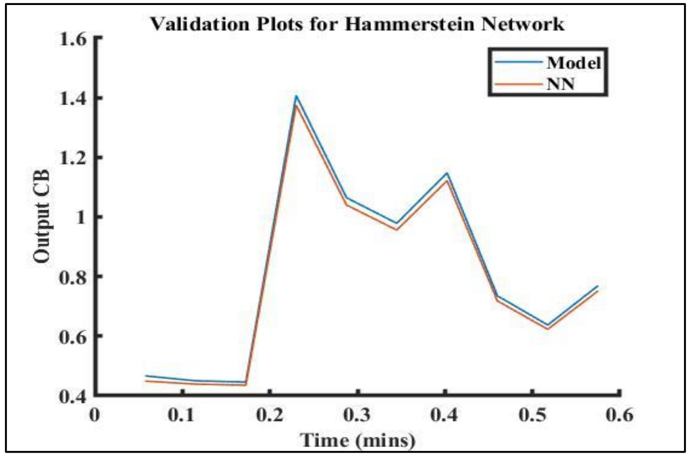
Hammerstein-Type Network

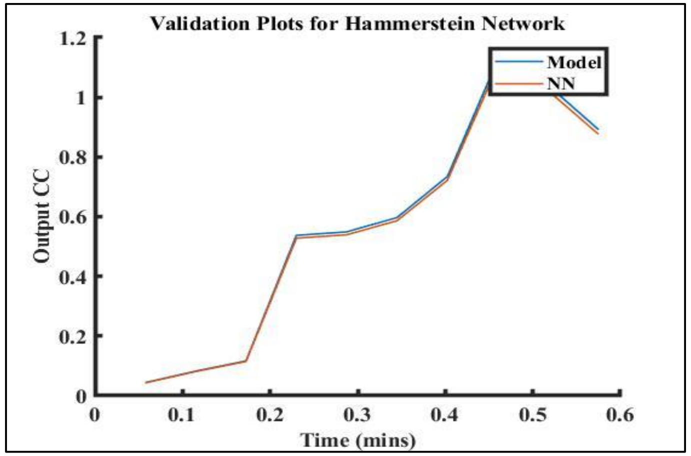


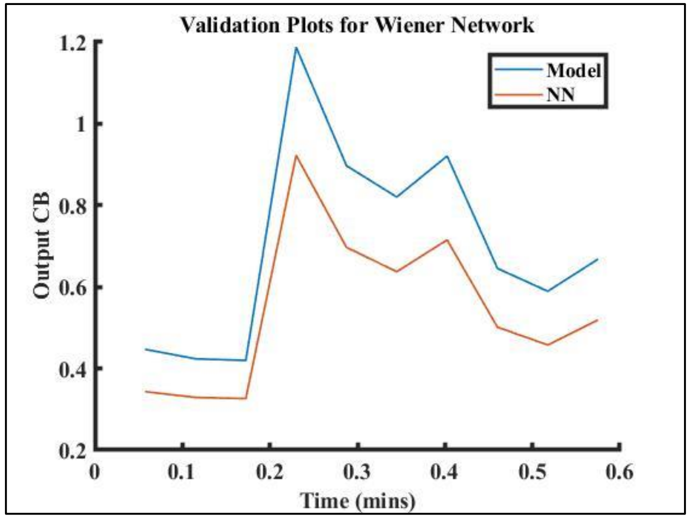
Wiener-Type Network

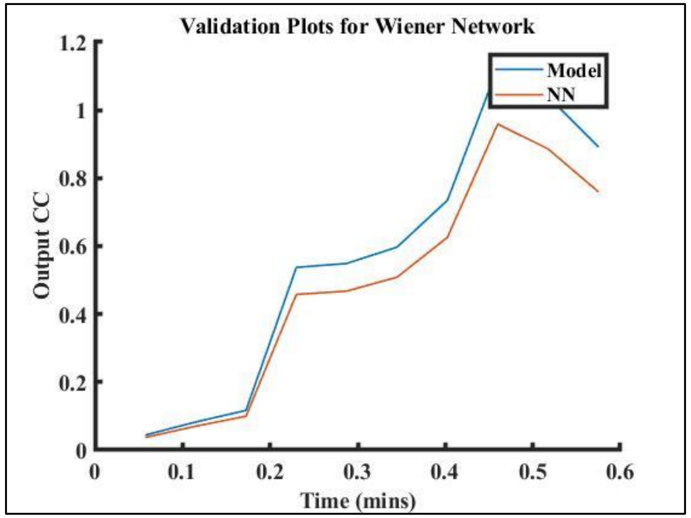


Hybrid Static-Dynamic NN



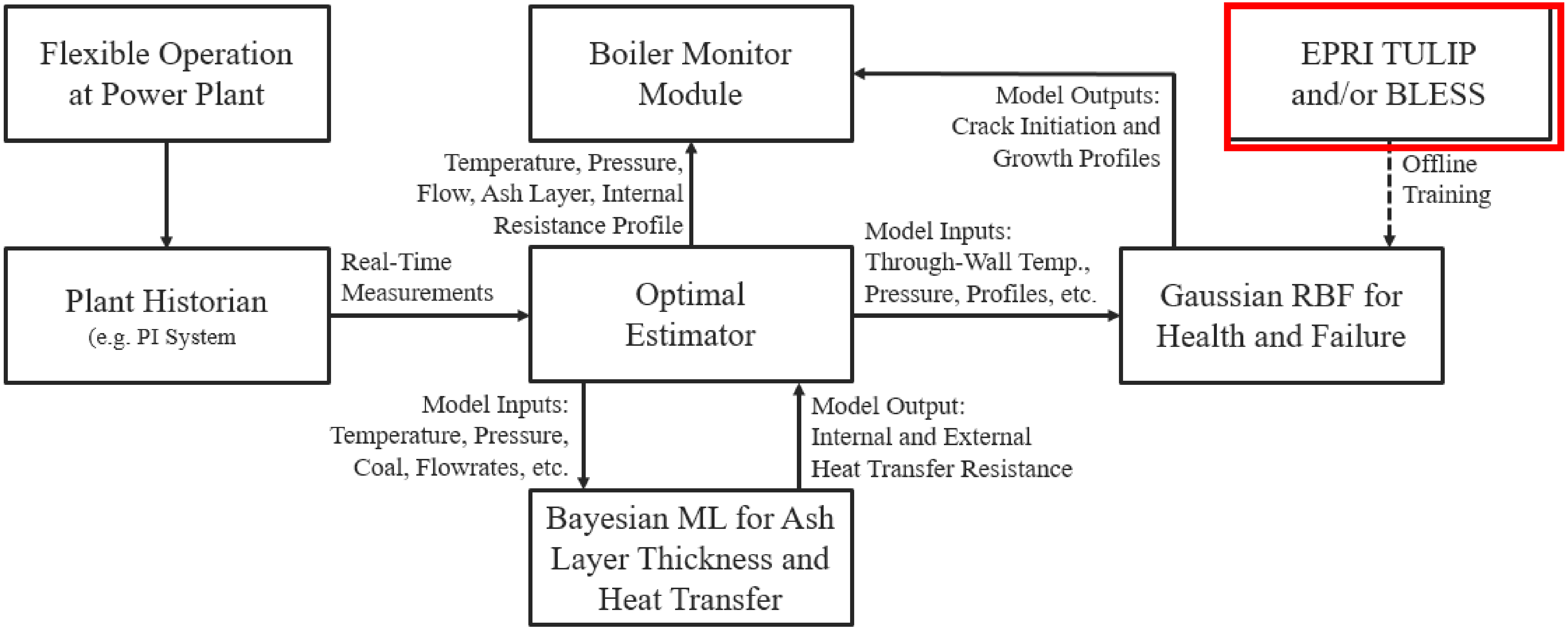






- **A fully Newtonian approach is developed for solving the NN**
- **For a reactive system, the Hammerstein-type network takes about half the number of iterations and yields mean squared error that is about two order of magnitude superior compared to the Wiener-type network**

Our Approach



Task A: Building on a Simple Demonstration

- Starting with the AUSC Steam Loop
  - Demonstration loop in AUSC Boiler DOE project
  - Single loop, known inlet and outlet just to this loop
  - Ni-based materials and stainless steels minimize the impact of oxide growth over the duration
  - Uniform heat transfer (single plane in the boiler)
  - Stainless steel rings provide a way to benchmark local temperature in ~five place
- Key Objectives:
  - 1D prediction of mean wall temperature distribution along the length
- What do we know:
  - Geometry (length, bends, wall thicknesses)
  - Materials along length and physical properties
  - Operational data from 2012 – 2014
    - Steam inlet and outlet temperature with time
    - Steam pressure and flow through the loop
    - Gas temperature outside the loop (!)
- What do we not know:
  - Temperature along the length (to be predicted)
    - Can estimate based on the oxides and metallurgy in Super 304H samples
  - Heat flux can be estimated via this model prediction

Plant Barry AUSC Steam Loop

- Plant Barry operated a high temperature (>700C) steam loop for 2.5 years
- This work becomes baseline for physics-based model
  - Well documented operational history from Barry plant historian
  - Uniform external gas temperature along the length (measured!)
  - Stainless steel used in the loop can be a benchmark for temperature
- Metallurgical characteristics estimate effective temperature
  - Time dependent features describe the actual time-varying operational temperature
  - Includes: oxide scale thickness, extent of creep damage, sigma phase formation, etc.

Outlet Temperatures

>1000F (538C) ~17,000 hrs
>1100F (593C) ~16,930 hrs
>1200F (649C) ~15,080 hrs
>1300F (704C) ~7,970 hrs
>1400F (760C) ~5,310 hrs

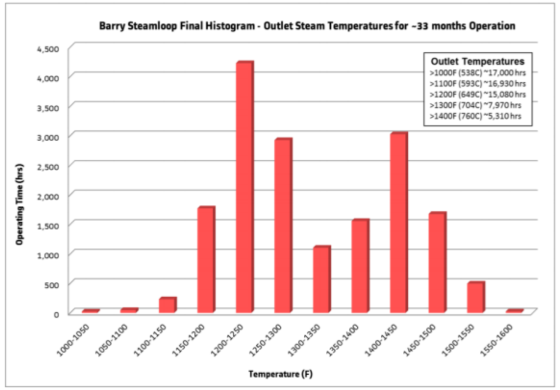
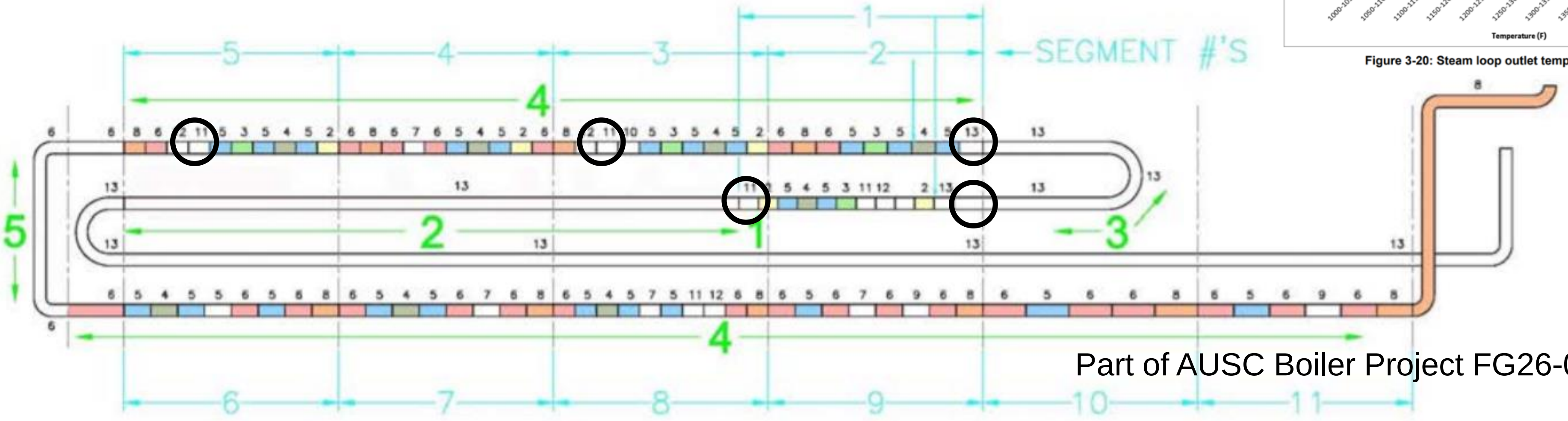


Figure 3-20: Steam loop outlet temperature histogram

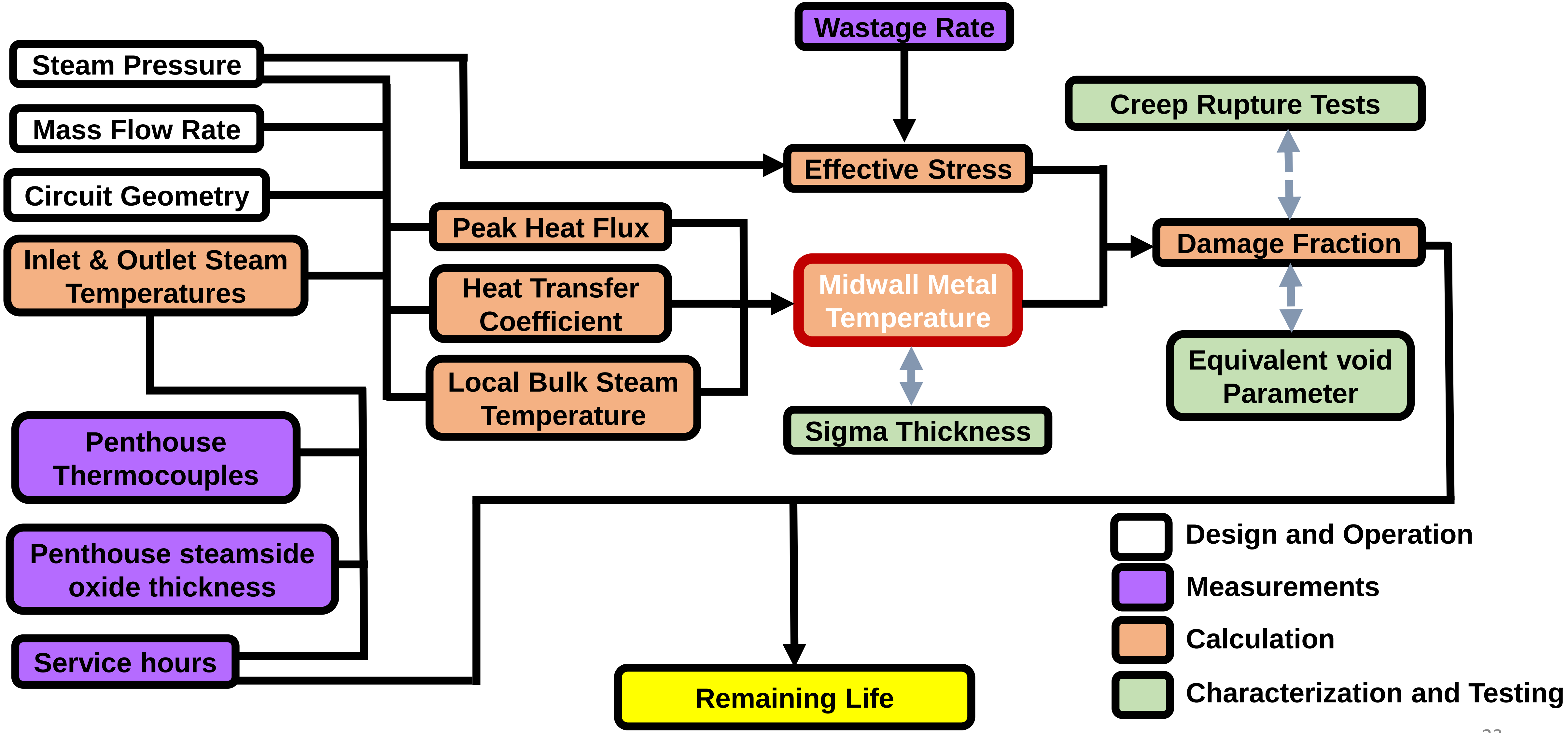
MATERIAL LIST

2	SUPER304H	8	IN 740
3	HR3C	9	HAYNES 282
4	HR6W	10	AMSTAR TS
5	HAYNES230	11	EN33 LASER
6	CCA 617	12	EN622 LASER
7	ALLOY617B	13	TP304H



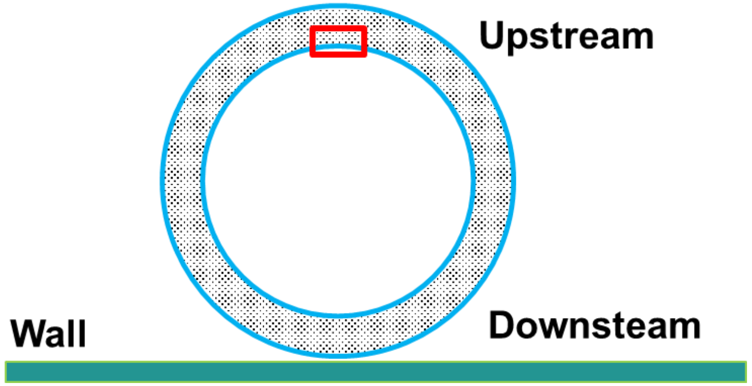
Part of AUSC Boiler Project FG26-01NT41175

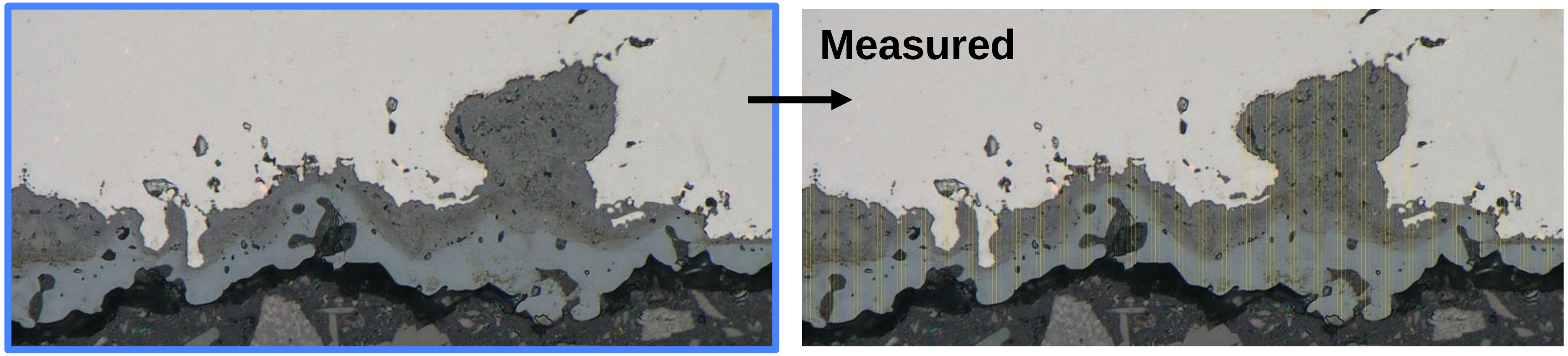
Roadmap of Factors for Estimating Temperature

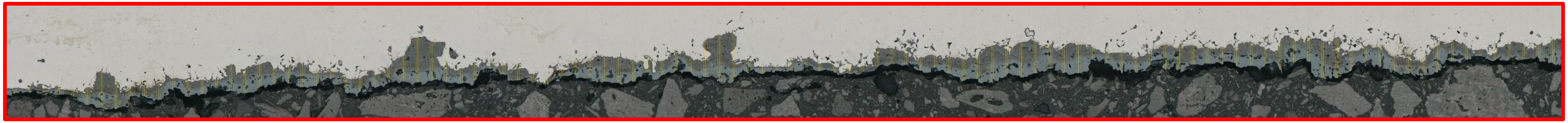


Super 304H Tube Section 1A – Hot Side

- Unlike oxide scale from a ferritic material, the steam oxide in an austenitic steel is complex
  - non-uniform scale with oxide nodules







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Task B: Applying the Simple Model to Relevant Tubes

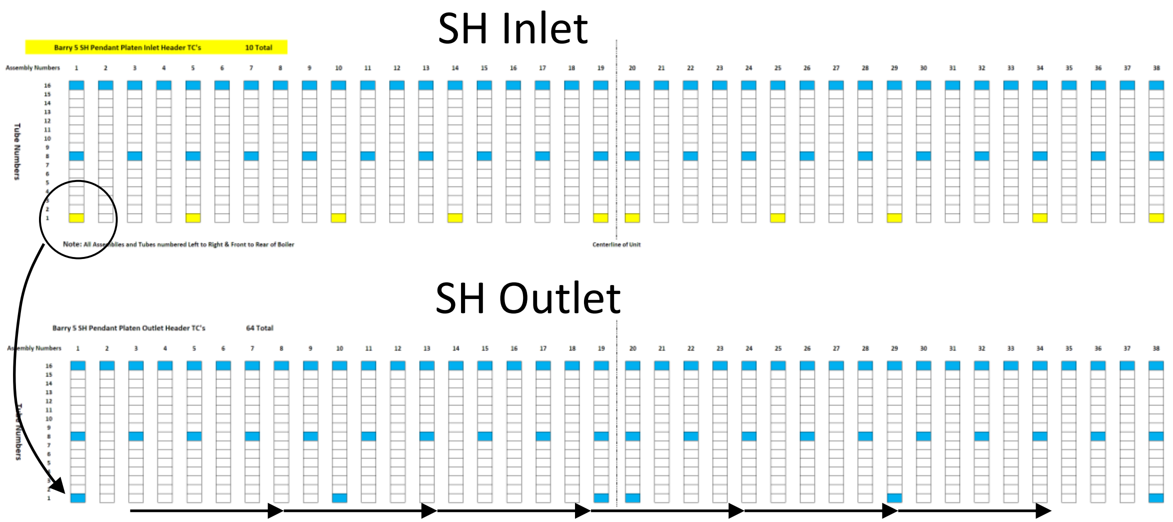
- Take thermal model from AUSC Steam Loop, apply it to a row of superheater tubes to predict mean metal temperature

- B1: Start with a window of steady-state operation
  - Real boiler configuration with temperature distributions along the width of the boiler
  - Steady-state conditions expected to be more uniform

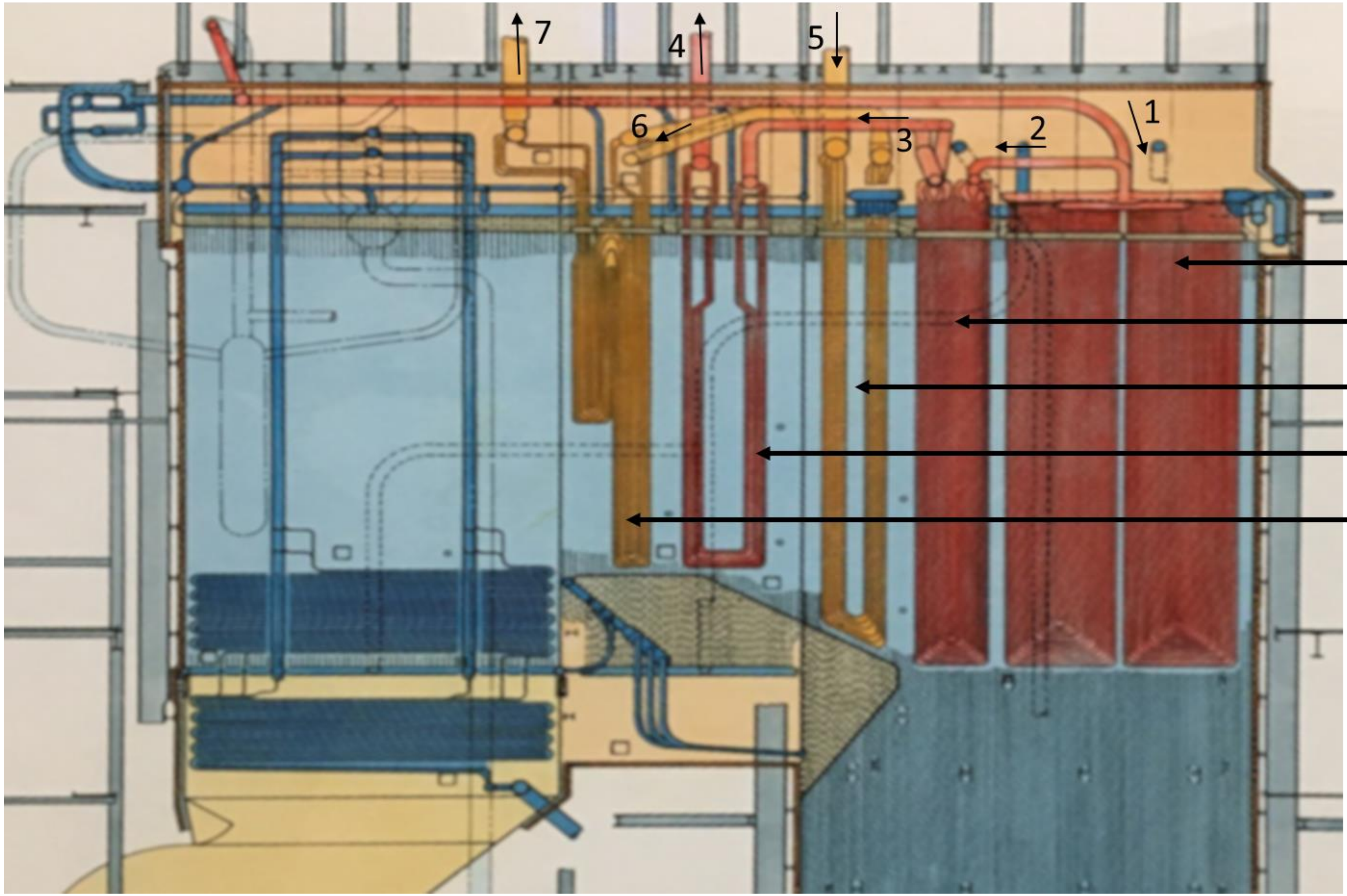
- B2: Real operational data over transients, low load
  - This is where steam flow and flue gas flow may diverge across the width of the boiler
  - Anticipated to produce temperature peaks and excursions in different tubes

With operational data we can perform this analysis, but it will require in-service validation

- What we know:
  - Geometry, materials, and TC locations
  - One-to-one correlation between inlet and outlet TCs
  - Oxide thermal conductivity (do we need more accuracy?)
  - Oxide growth rates
- What we do not know:
  - Actual wall thickness of these tubes
  - Interpolating on the tubes where we don't have TCs
  - External, local gas temperature



Validation: Barry Unit 5 Boiler Layout



Pendant Division Superheater

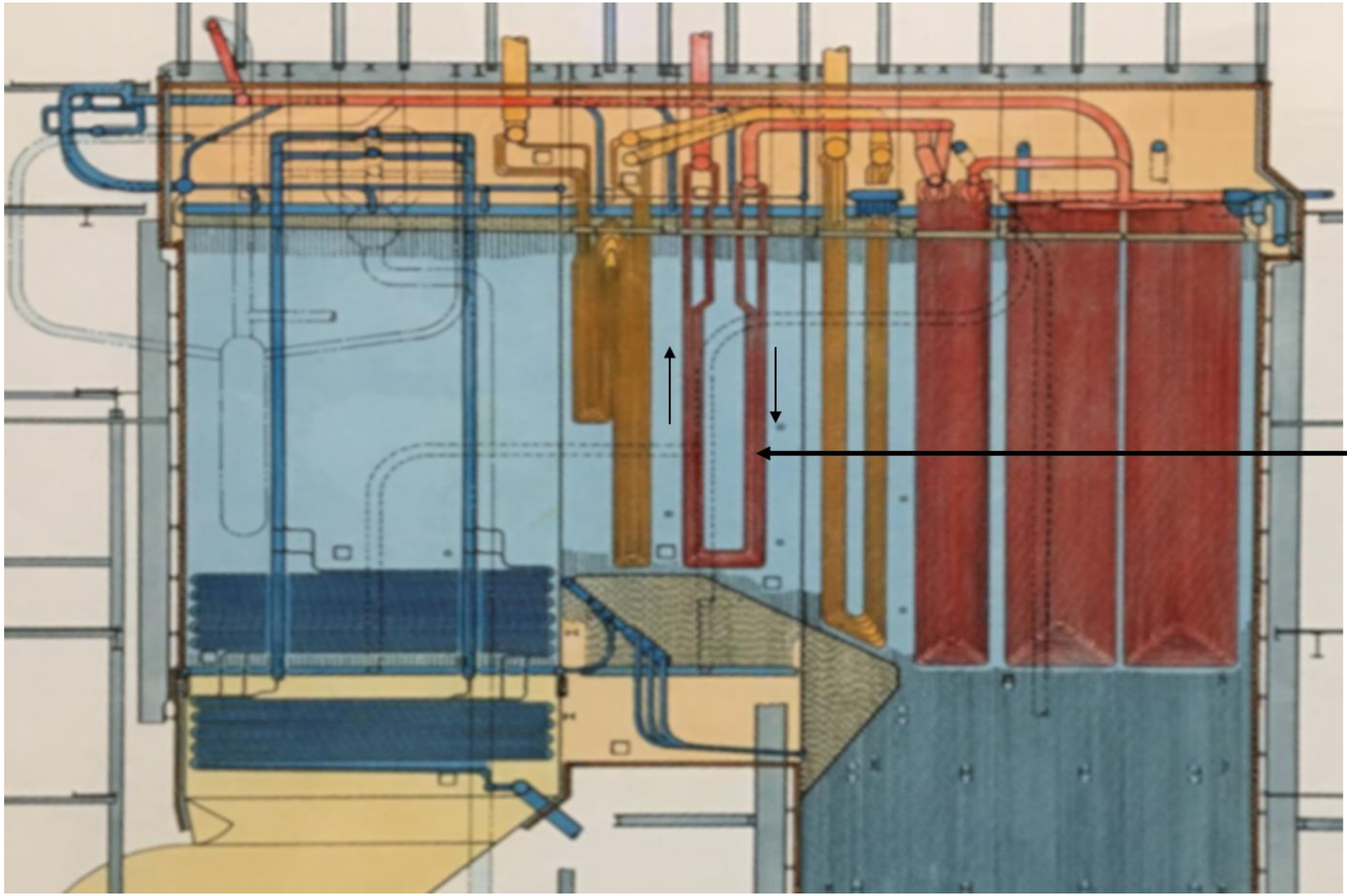
Pendant Platen Superheater

Pendant Spaced Front Reheater

Pendant Spaced Superheater

Pendant Spaced Rear Reheater

Validation: Barry Unit 5 Boiler Layout



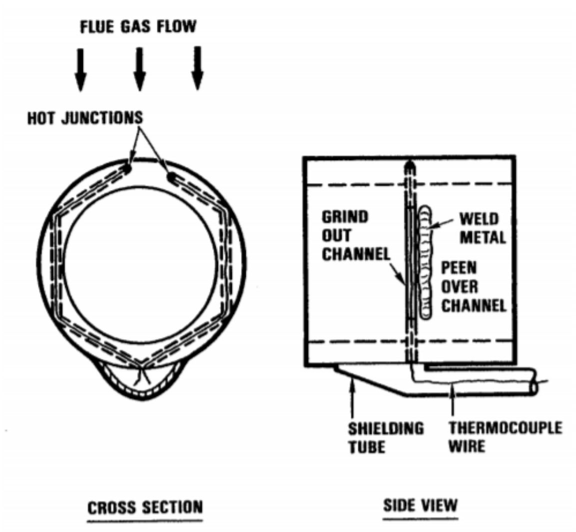
Pendant Spaced Superheater

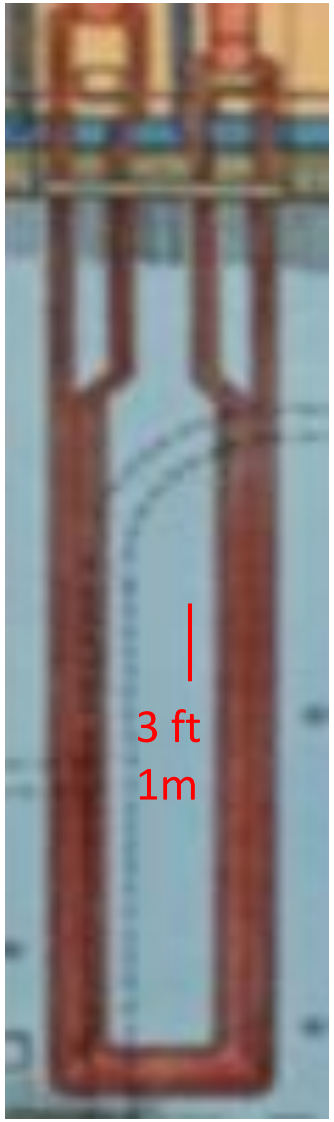
Material: entirely 347H
Tubes: 197 rows x 6 per row
TCs: 17 on inlet, 58 on outlet

Inlet T: ~900F
Outlet T: ~1000F

Final Superheater "Pendant Spaced Superheater"

- Current configuration is all 347H and not ideal for project
  - Project aims to capture the influence of oxide growth on temperature
  - 347H not expected to show significant oxide growth between outages (~2 years)
- The project will use this opportunity to install hardware and produce a controlled experiment
  - Propose replacing lengths of tubes with T22 with installed TCs
  - Considering options for optimal placement of installed hardware
    - Is strictly the hottest length of most interest, and most economical
    - And which tube(s) along the width of the boiler: edge vs. center
- Considering options for temperature sensors
  - Traditional TC wires on the surface or mid-wall
  - Commercial TC heat flux sensors
  - Coaxial cable sensors with Clemson's DOE project
  - Biggest challenge is the need to protect wire leads
- Project planning for a Fall 2021 outage





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Conclusions

- Boiler tube life management is an expensive industry issue
  - Scheduling maintenance becoming less predictable with flexible operation
- Temperature fluctuations across rows of tubes a large unknown
  - Metal temperature drives damage accumulation
- The hybrid first principles-AI approach provides take advantages of synergies between physics-based and data-driven modeling
- Validation of Model Predictions:
  - Pursuing several approaches through monitoring, independent modeling, and characterization
  - Plant Barry partnership a great opportunity

Acknowledgement

- Gratefully acknowledge funding from DOE-NETL through Grant#DE-FE0031768 for this project
- Support from NETL project manager Maria Reidpath

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Thank you for your attention

Questions?