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

Award#:DE-FE0031768

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FY 22 FECM Spring R&D Project Review Meeting
Crosscutting Research (Sensors and Controls) Program
Virtual
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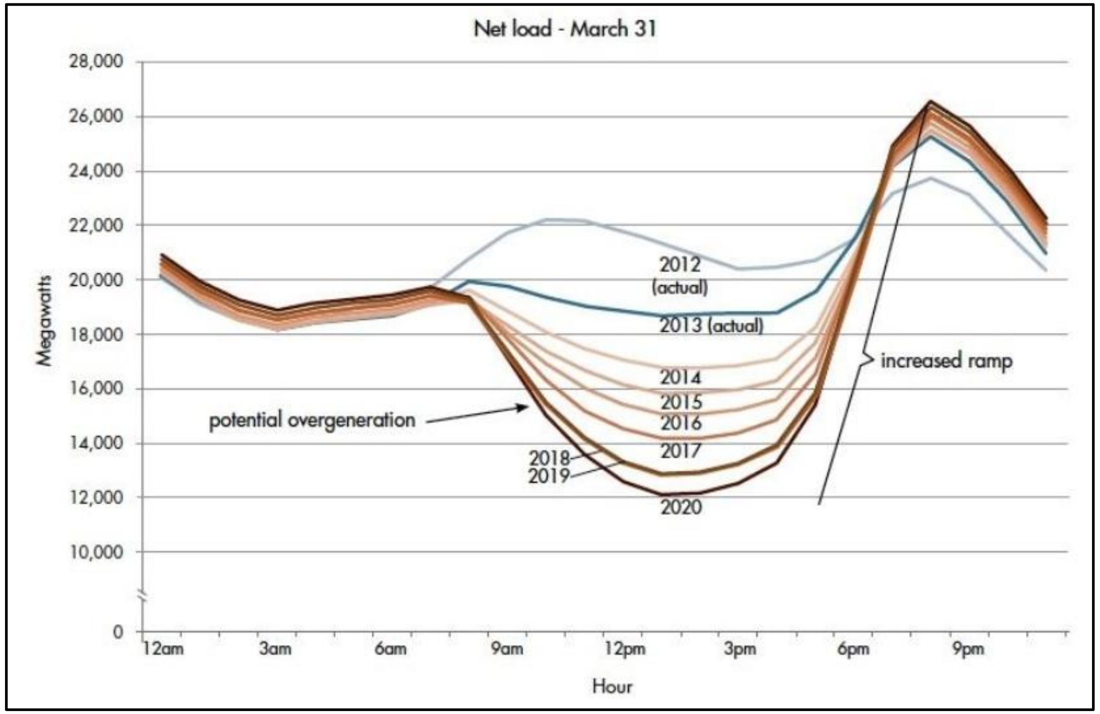
Outline

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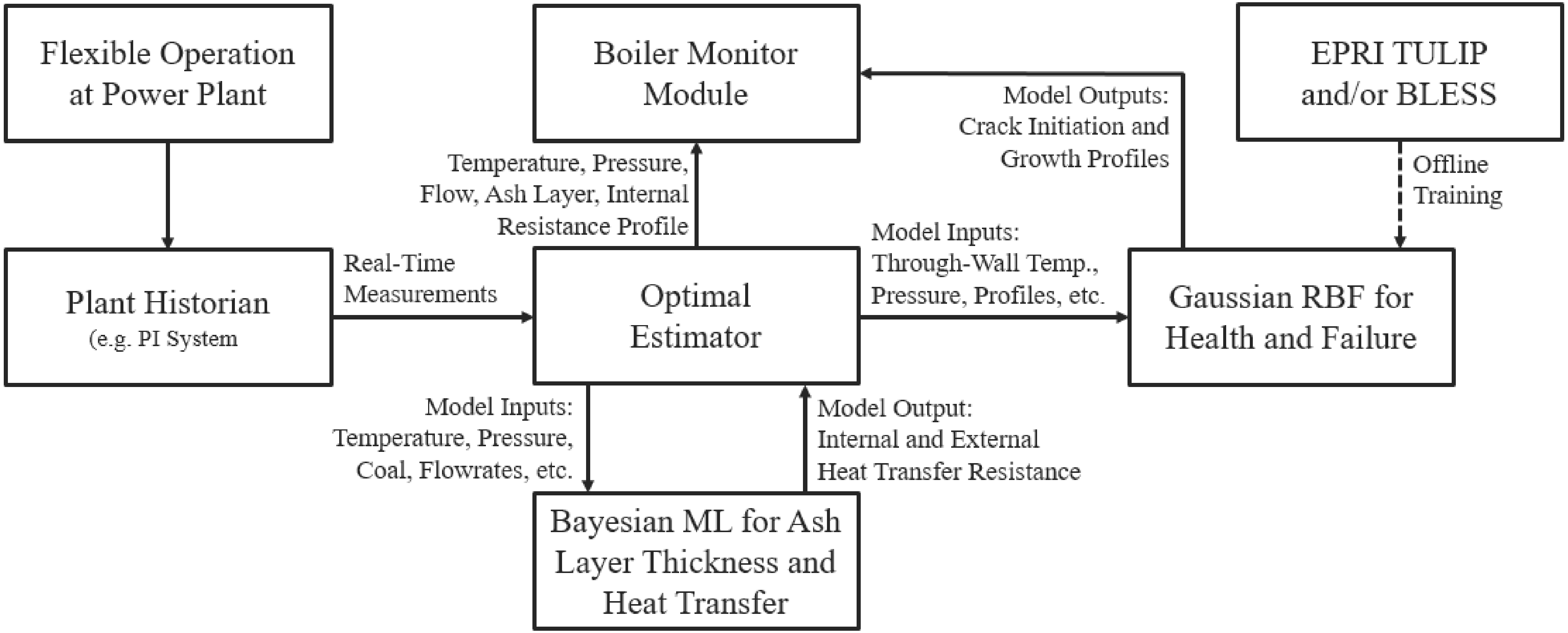
Our Approach: A Hybrid First-Principles-AI Based Approach

- **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 B
  - 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
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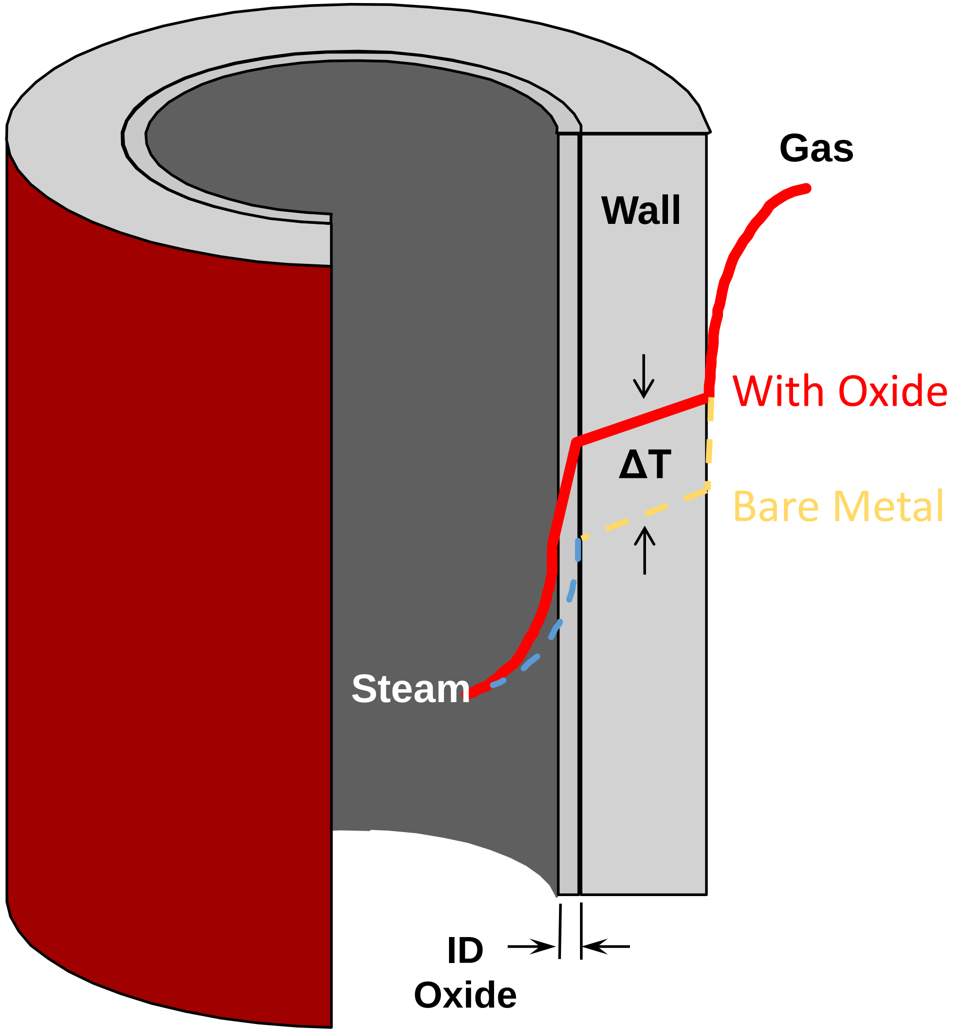
Tube Failures: Costs and Mechanisms

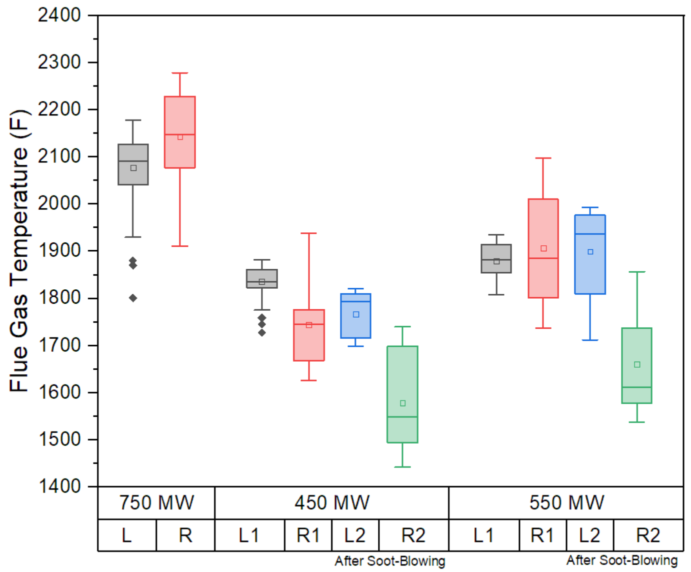
- **Boiler tube failures (BTF) are traditionally the premier cause of forced outages of coal-fired power generating units worldwide**
  - Historically, costs for BTF in the U.S. estimated to be in excess of $1B/yr in power replacement charges and maintenance costs
  - BTF typically results in a forced outage lasting three days and can cost >$3 million for replacement power
- **Over-temperature operation is a significiant cause for BTF**
  - Tube life governed by creep properties and accumulated temperature exposure
  - Uncertainty in local operating conditions is increasing as units shift away from base load
- **Steam-side oxide scale growth reduces heat transfer and increases metal temperature**
  - As metal temperature increases, rate of creep damage and oxide growth accelerates
  - +25C/45F consumes life 6x faster; the same as +33% stress

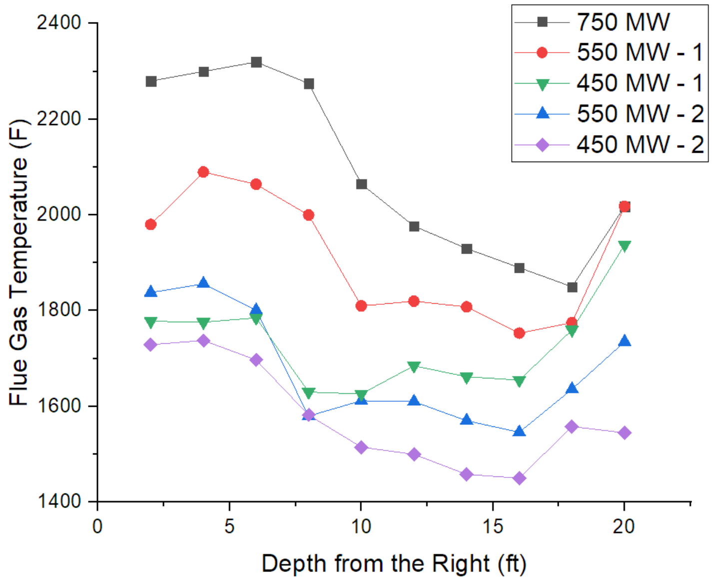


Observations from HVT Survey

(Data from host coal boiler)

- **Installed hardware at host site is providing a real-time look at local temperatures**
- **High velocity thermocouple (HVT) provides a fingerprint of flue gas temperature with unit load**
  - Up to 20' from each side of the boiler
  - Sampling at low, medium, and full load over two days
- **Flue gas temperature at this location changes with load and location**
  - Impact of soot blowing which regularly removes ash build up on tubes was a key variable to measure on-line
    - Impacted the right-side flue gas temperatures
  - Flue gas velocity (and therefore HTC) observed to change >10x location-to-location
    - This has significant impact on local tube temperature variation and implications to address in the heat transfer model





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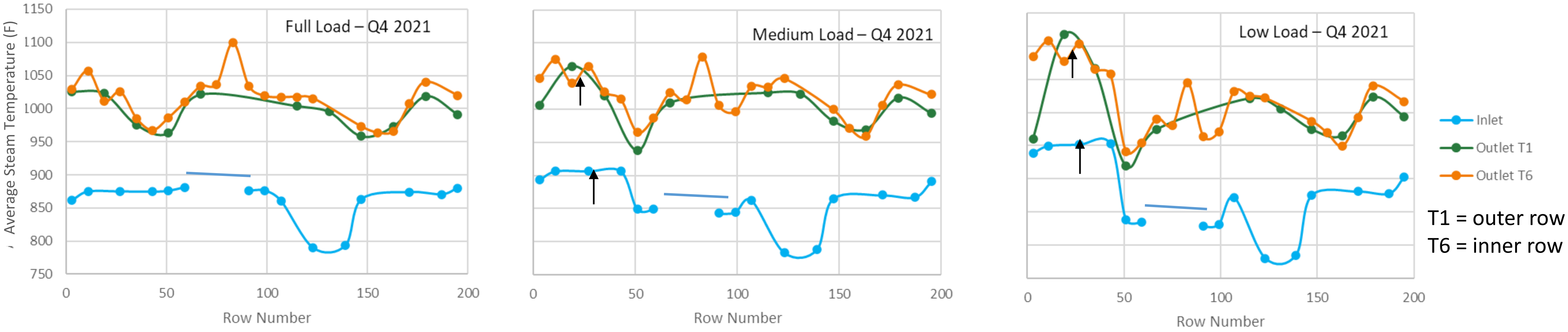
Temperature vs. Load Characteristics Across Final Superheater

(Data from host coal boiler)

- **Challenges with integrated life management and specifically prediction of tube temperature**
    - Flex ops drives transient temperature distribution along the length of the tube and width of the boiler
- **Steam temperature data shown at different load levels**
    - Observed significant local condition variation, ~30C, and influence of low load variation, ~40C
    - Higher temperature exposure during load change may be short duration, but +25C for 10 minutes could be equivalent to 1 hour of effective damage (or more)
- **Steam temperatures fluctuate across the width**
    - Low load operation produces much more temperature uncertainty across the superheater and indeed the low load operation produced the highest observed temperatures
    - Drives a need for accurate flue gas temperature measurement and explanation of these changes



Use Cases for Dynamic Lifing Tools

- **High fidelity thermal models can:**
  - Help point to the most problematic areas
  - Warn system operator of aggressive behavior
  - Justify delays to maintenance of lower temperature regions
- **Integrate real-time monitoring with damage accumulation tools**
  - Historical tool: accumulated damage over recent history for life management
  - Historical tool: identify the worst operation for creep damage
  - Predictive tool: effect of changing plant operation (e.g., more 2-shifting)
  - Predictive tool: for units close to retirement and minimizing maintenance costs
- **Tube sampling will continue to be important to benchmark damage evolution**

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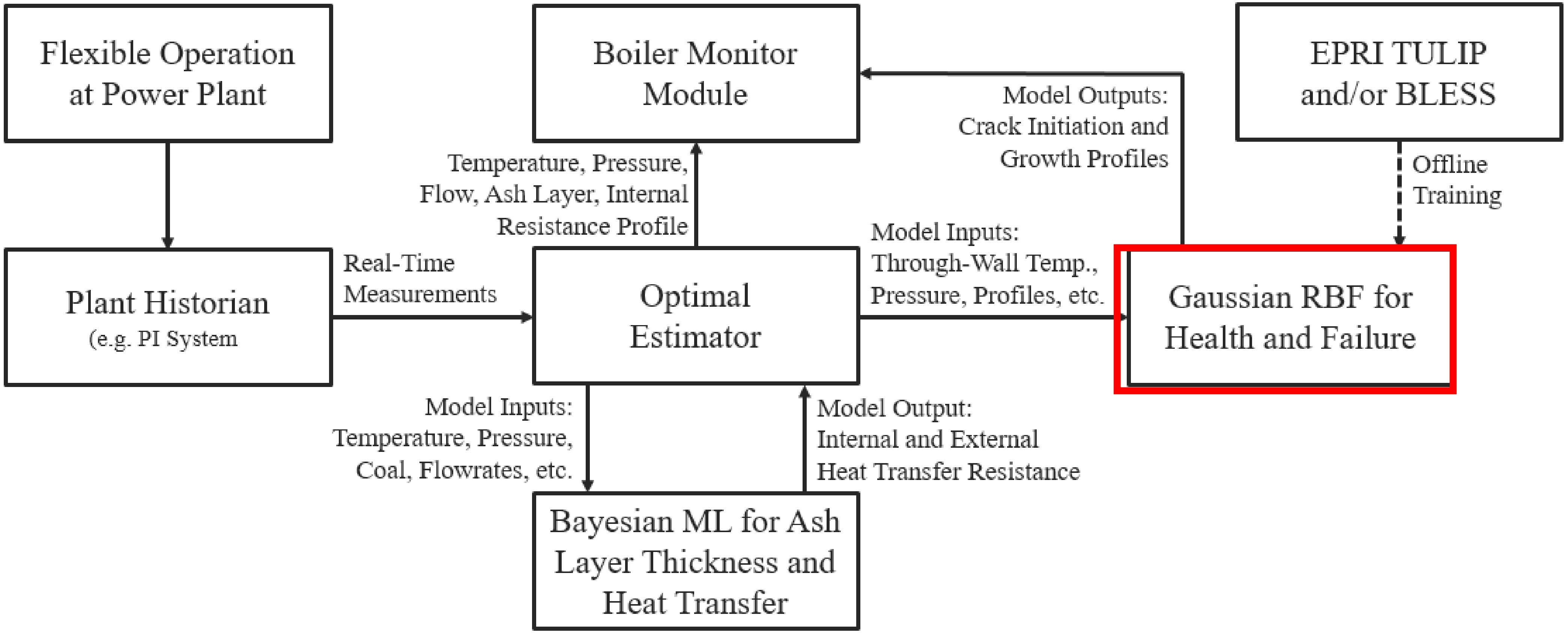
Our Approach



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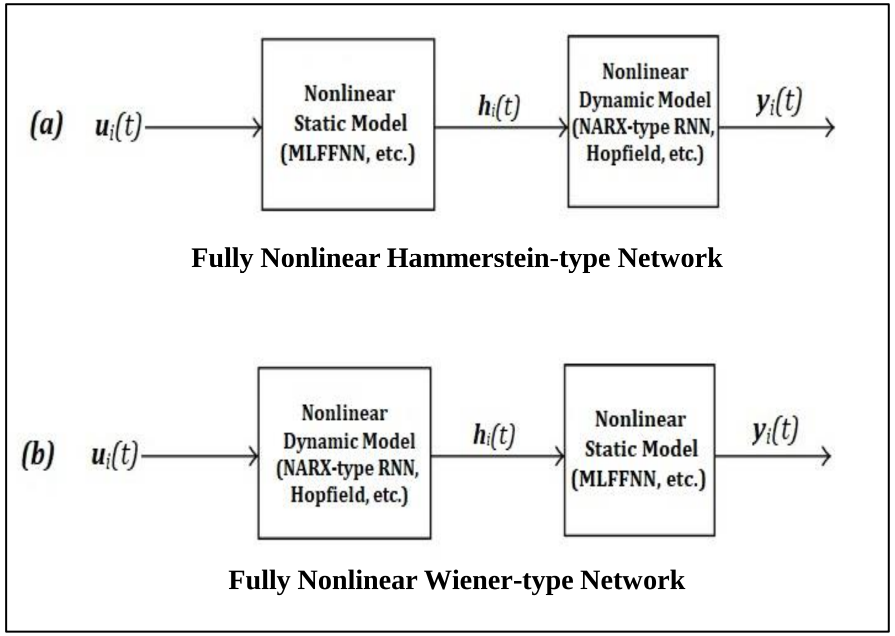
Hybrid Series and Parallel Static-Dynamic Neural Network Structure

- Conventional nonlinear static neural networks may fail to capture dynamics in complex nonlinear systems.
- Hybrid static-dynamic networks accounted for in existing literature consider a linear-time-invariant (LTI) dynamic network[1], which do not perform well for modeling highly nonlinear dynamic systems.

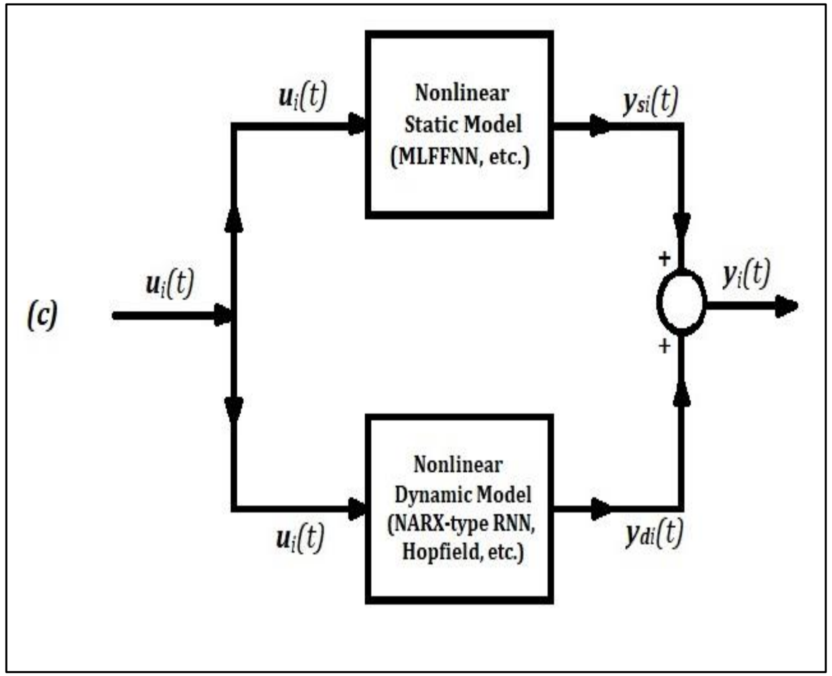
- **<u>Series Architecture</u>:**



Fully Nonlinear Hammerstein-type Network

Fully Nonlinear Wiener-type Network

- **<u>Parallel Architecture</u>:**



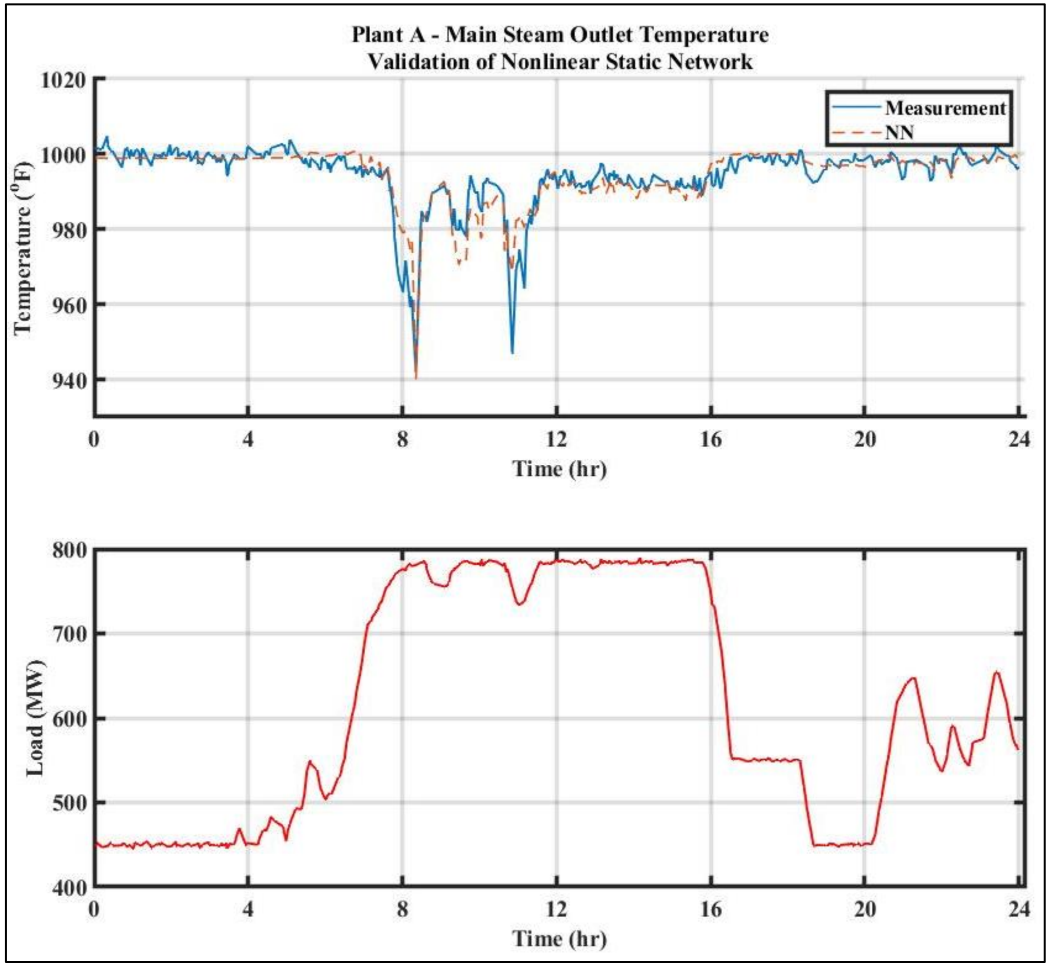
Choice for Static Model:
- Multi-layered Feedforward Neural Networks (MLFFNN)

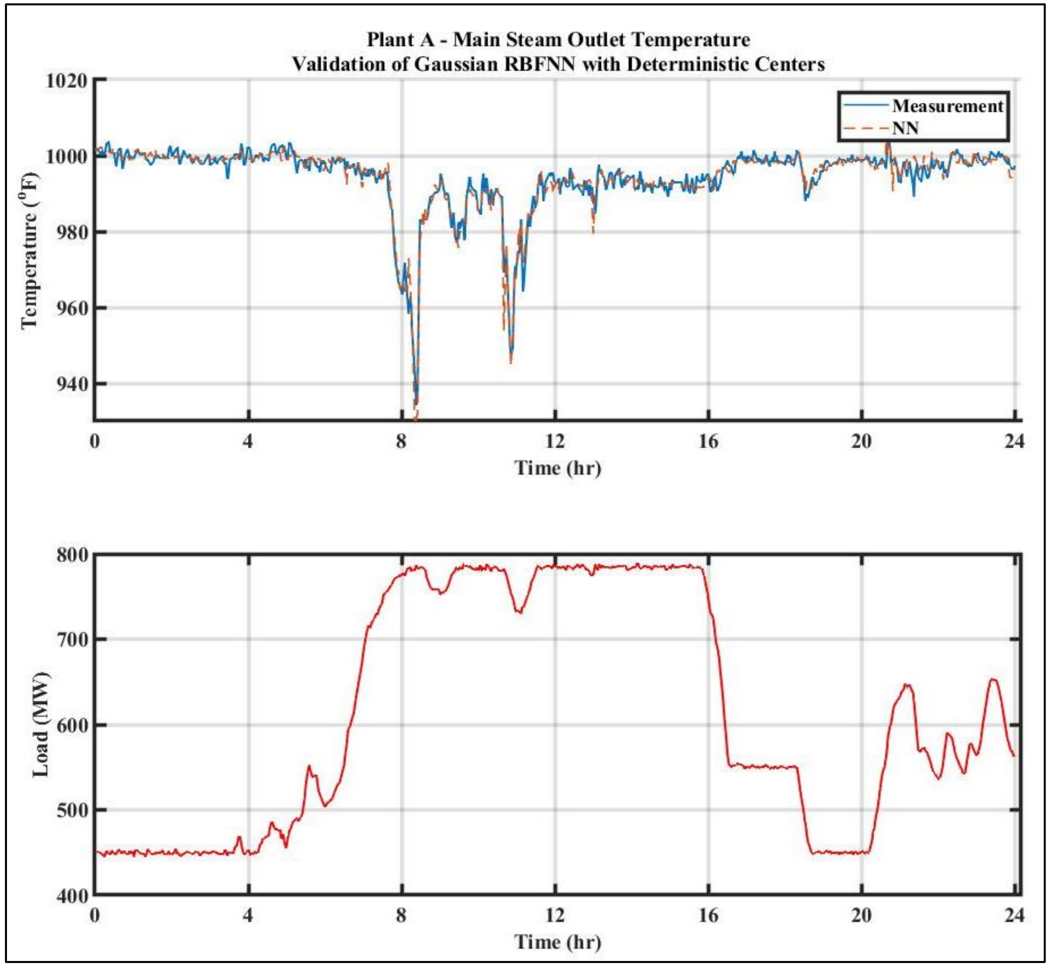
Choices for Dynamic Model:
- Nonlinear Autoregressive-type Recurrent Neural Networks with Exogenous Inputs (NARX-type RNN)
- Modified Hopfield Network with external inputs

Examples modeled by the proposed networks:
- Van de Vusse Reactor[2]
- pH Neutralization Reactor[1]
- Coal-fired Power Plant (Plant A)
- NGCC Power Plant (Plant B)
- Monoethanolamine-based post-combustion CO_2 capture pilot plant[3]

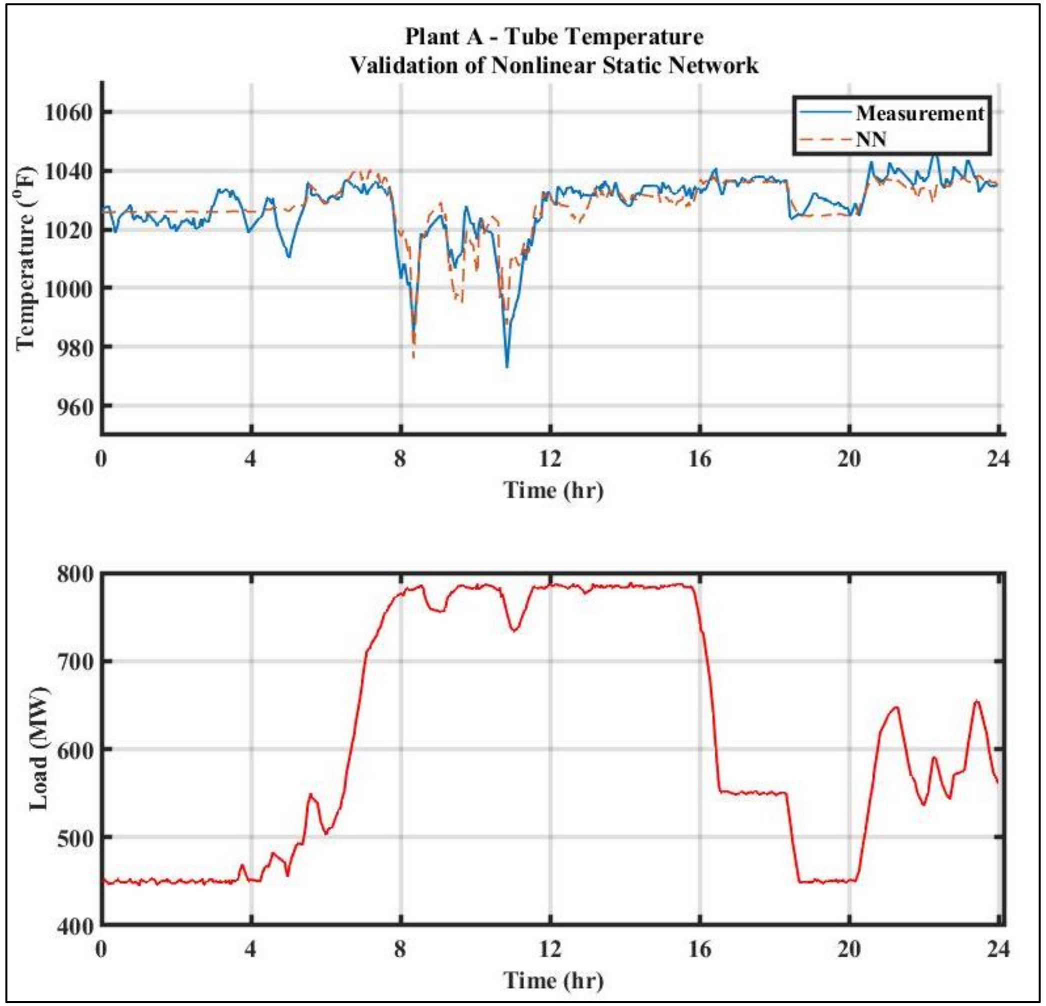
[1]. Sentoni, G. B., Biegler, L. T., Guiver, J. B. & Zhao, H. T. State-Space Nonlinear Process Modeling: Identification and Universality *AIChE J.* **44**, 2229–2239 (1998)
[2]. Ridlehoover, G. A. & Seagrave, R. C. Optimization of Van de Vusse Reaction Kinetics Using Semibatch Reactor Operation. *Ind. Eng. Chem. Fundam.* **12**, 444–447 (1973).
[3]. Chinen, A. S., Morgan, J. C., Omell, B., Bhattacharyya, D. & Miller, D. C. Dynamic Data Reconciliation and Validation of a Dynamic Model for Solvent-Based CO_2 Capture Using Pilot-Plant Data. *Ind. Eng. Chem. Res.* **58**, 1978–1993 (2019).

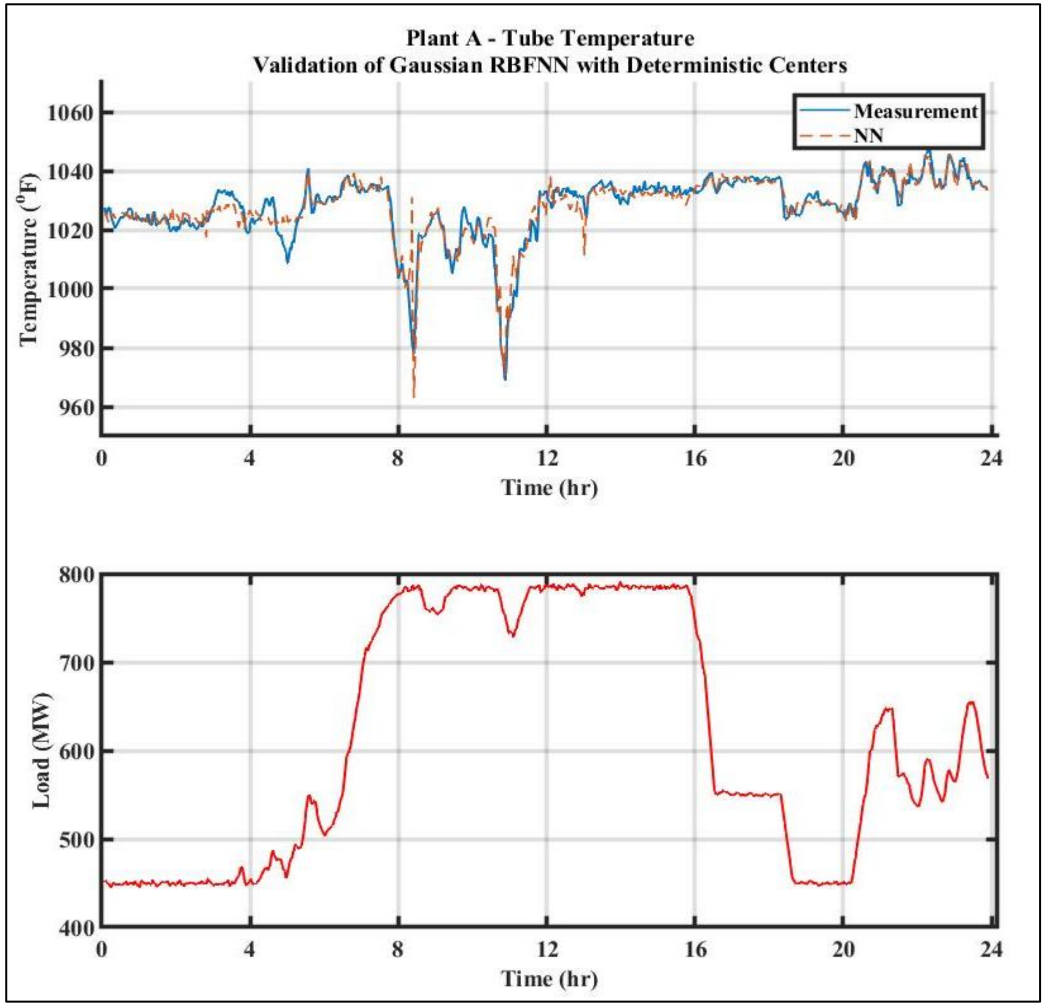
Model Validation for Main Steam Outlet Temperature (Plant A)





Model Validation for Tube Temperature (Plant A)





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Comparison in Validation Performance

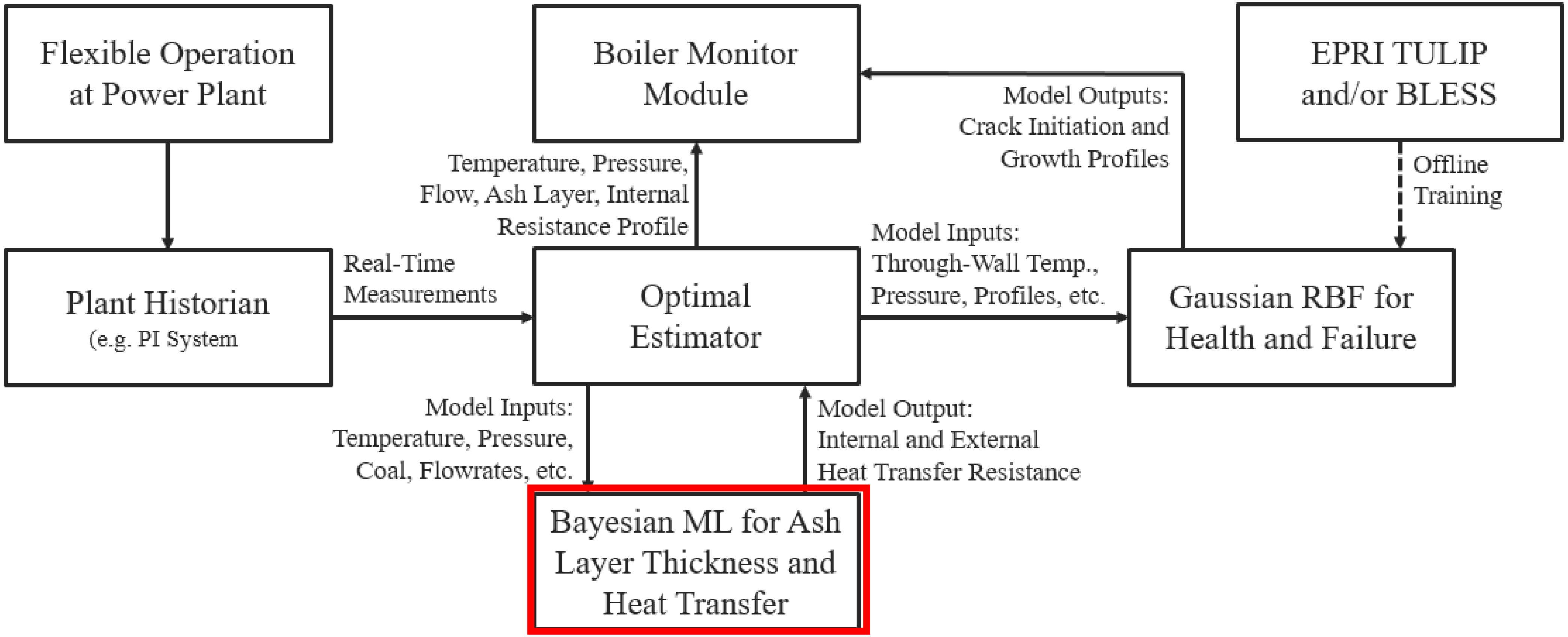
The following tables show the comparison among the different models in predicting the main steam outlet temperature and tube temperature, in terms of the normalized RMSE and overall computational time required during model development.

$$RMSE_i = \left[\frac{1}{t_n} * \sum_{t=1}^{t_n}\left(\frac{y_{i,tar}(t) - y_{i,NN}(t)}{y_{i,tar}(t)}\right)^2\right]^{\frac{1}{2}}$$

Types of Network	Normalized Root Mean Square Error, RMSE		Overall Computational Time (for 24 hr data)
	Main Steam Outlet Temperature	Tube Temperature	
Nonlinear Static MLFFNN	3.3×10^{-3}	4.2×10^{-3}	5.2 sec
Gaussian RBFNN	2.3×10^{-3}	3.3×10^{-3}	0.24 sec
Hammerstein-type Series Network	0.7×10^{-3}	0.8×10^{-3}	22.8 sec
Parallel Static-Dynamic Network	1.1×10^{-3}	1.5×10^{-3}	37.1 sec

- The Hammerstein-type of fully nonlinear series static-dynamic network shows the minimum error (~0.07%) while predicting both the outlet main steam temperature and tube temperature profiles.
- The Gaussian RBFNN accounts for the least computational time (0.24 sec) during model development, although it shows a slightly inferior prediction error (~0.3 %).

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

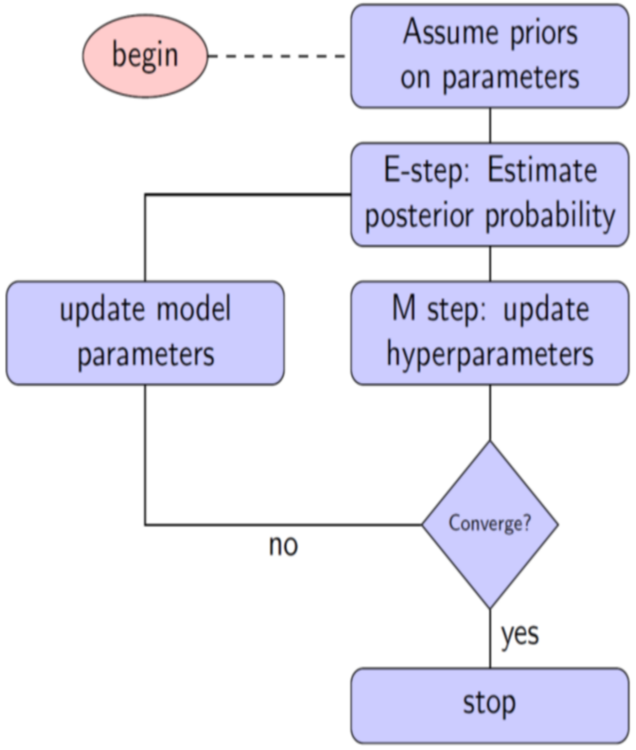
$$\pi(\theta|y) = \frac{l(y|\theta)p(\theta)}{m(y)}$$

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

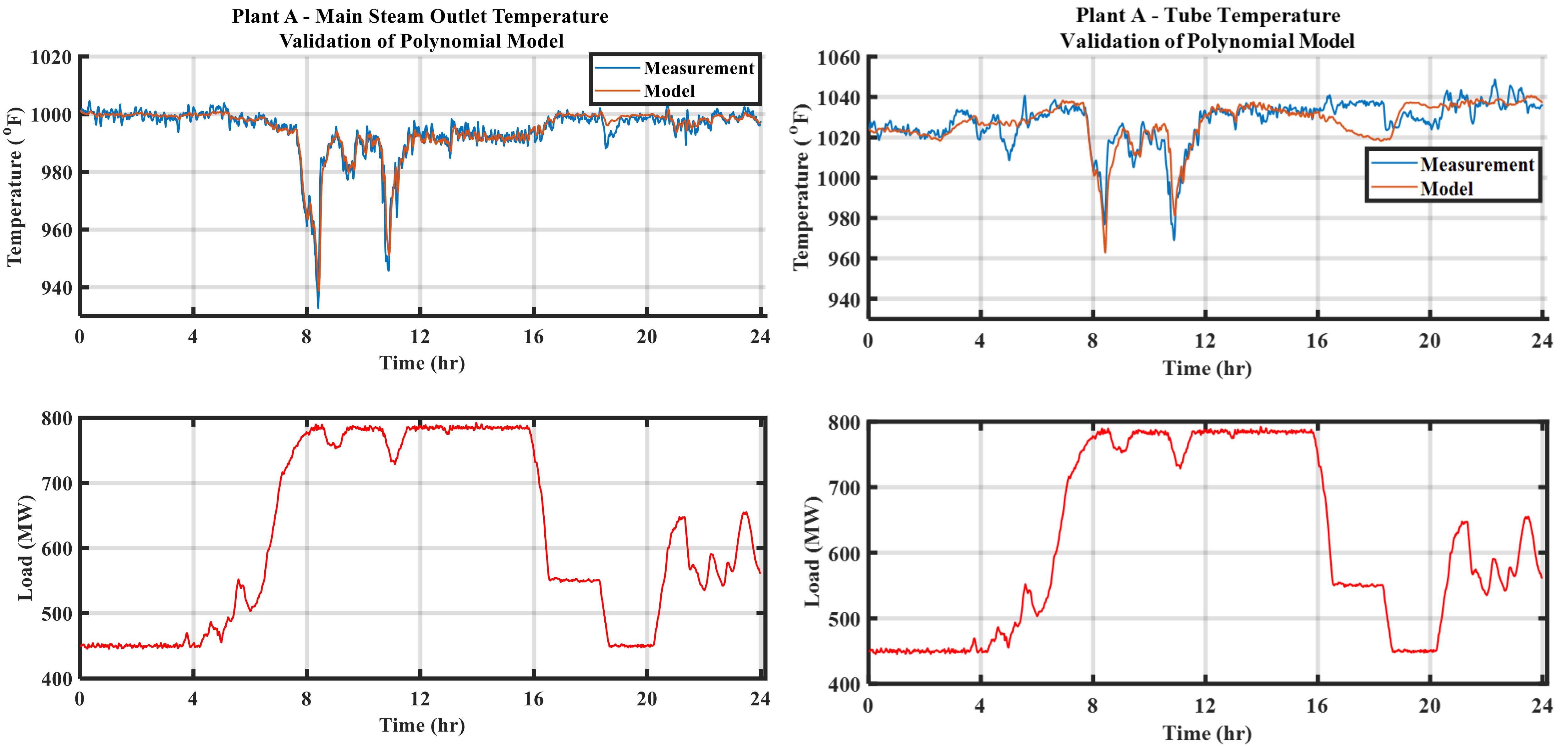
- Objective

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

EM Algorithm



Model Validation for Outlet Steam and Tube Temperature (Plant A)



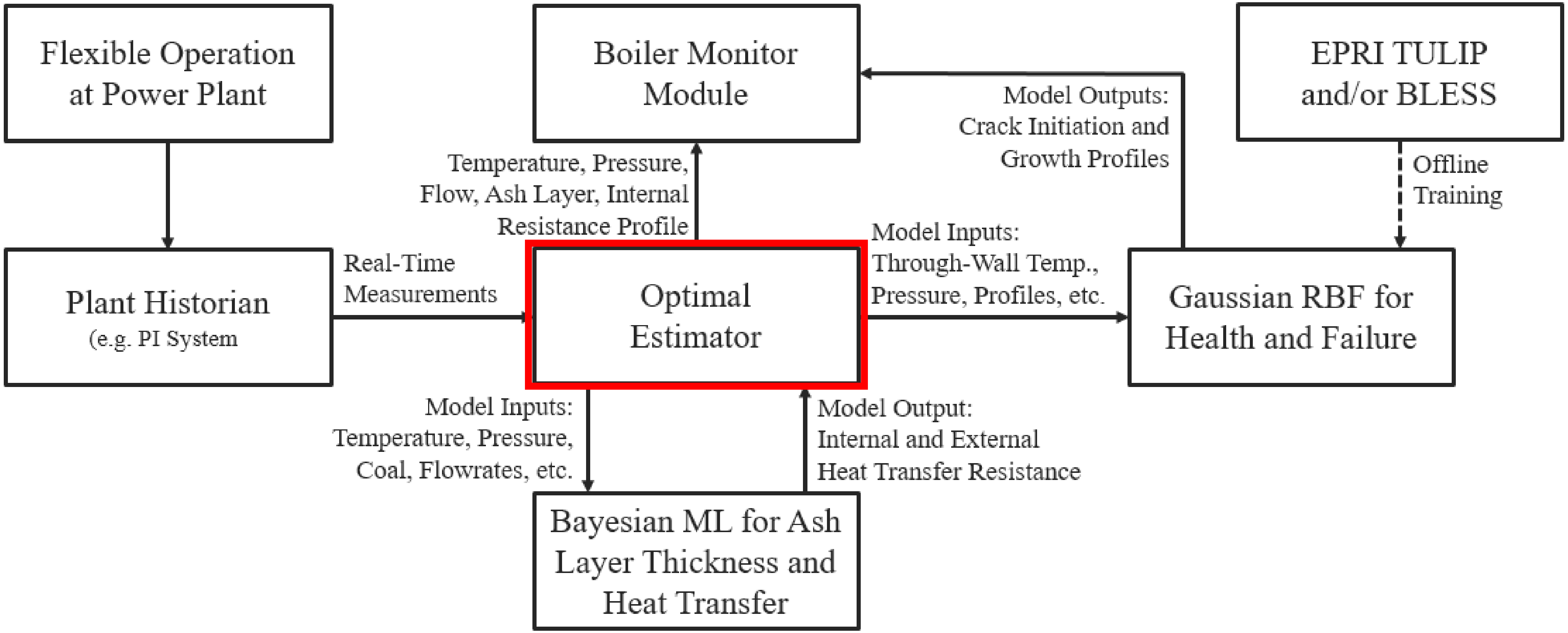
Plant B

Model	No. of Parameters	Root Mean Square Error, RMSE (°F)		
		Steam Outlet Temp.	Flue Gas Temp.	Tube Temp.
Bilinear Model (Previously)	57	1.21	0.98	1.64
Polynomial model from best subset selection	33	1.06	1.00	1.47

Plant A

Model	No. of Parameters	Root Mean Square Error, RMSE (°F)		$AICc + 2C_{ev}(\Sigma)$
		Steam Outlet Temp.	Flue Gas Temp.	
Bilinear Model (Previously)				
Polynomial model from best subset selection	18	2.68	6.79	

Our Approach



Model and Estimation Approach

- **Dynamic, cross-flow, 3-D model of the superheater/reheater based on equations for the conservation of mass and energy**
- **1D mass and energy balances in the directions of water and flue gas flows**
- **Rigorous properties model and heat transfer calculations at each control volume**
- **Metal tubes considered thick-walled considering conduction across them**
- **Non-Linear DAE system[2]**

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

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

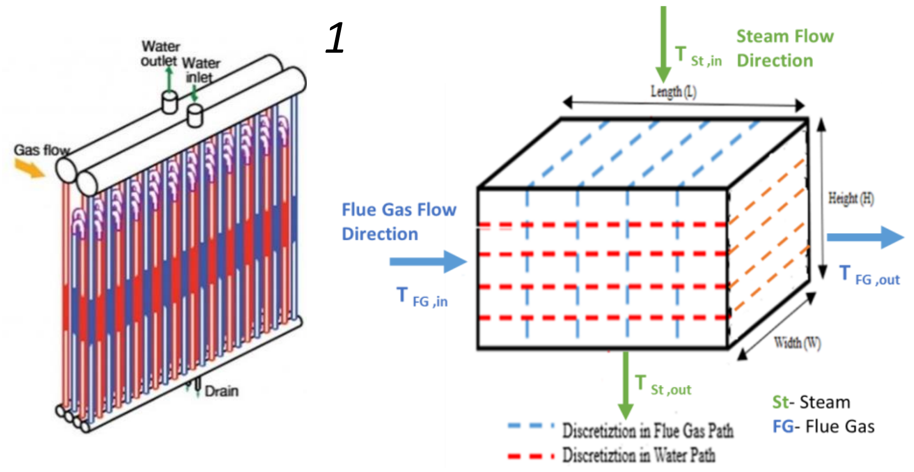
$$y_{k+1} = h(x_{k+1}, z_{k+1}) + v_{k+1}$$

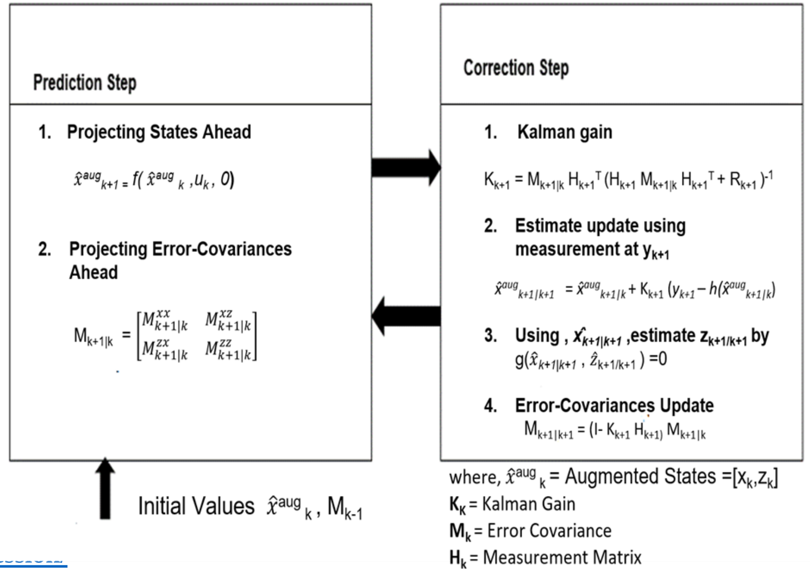
S.T. : $Ex^{aug}_{k+1} = b$

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

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

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

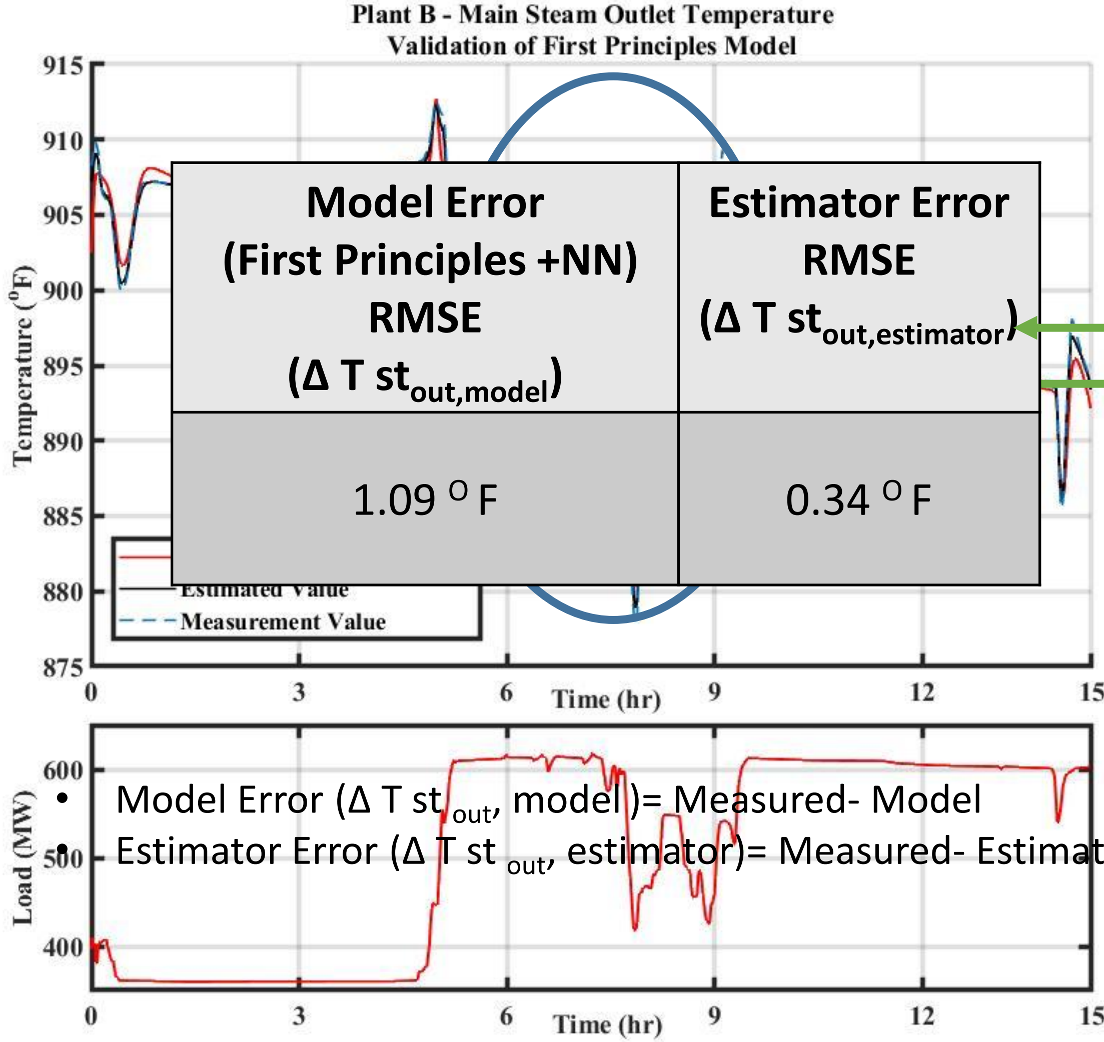




[1]Combined Cycle Journal Retrieved from https://www.ccj-online.com/2q_2012-outage-handbook/7f-users-group/7f-users-group-hrsg-spotlight

[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.

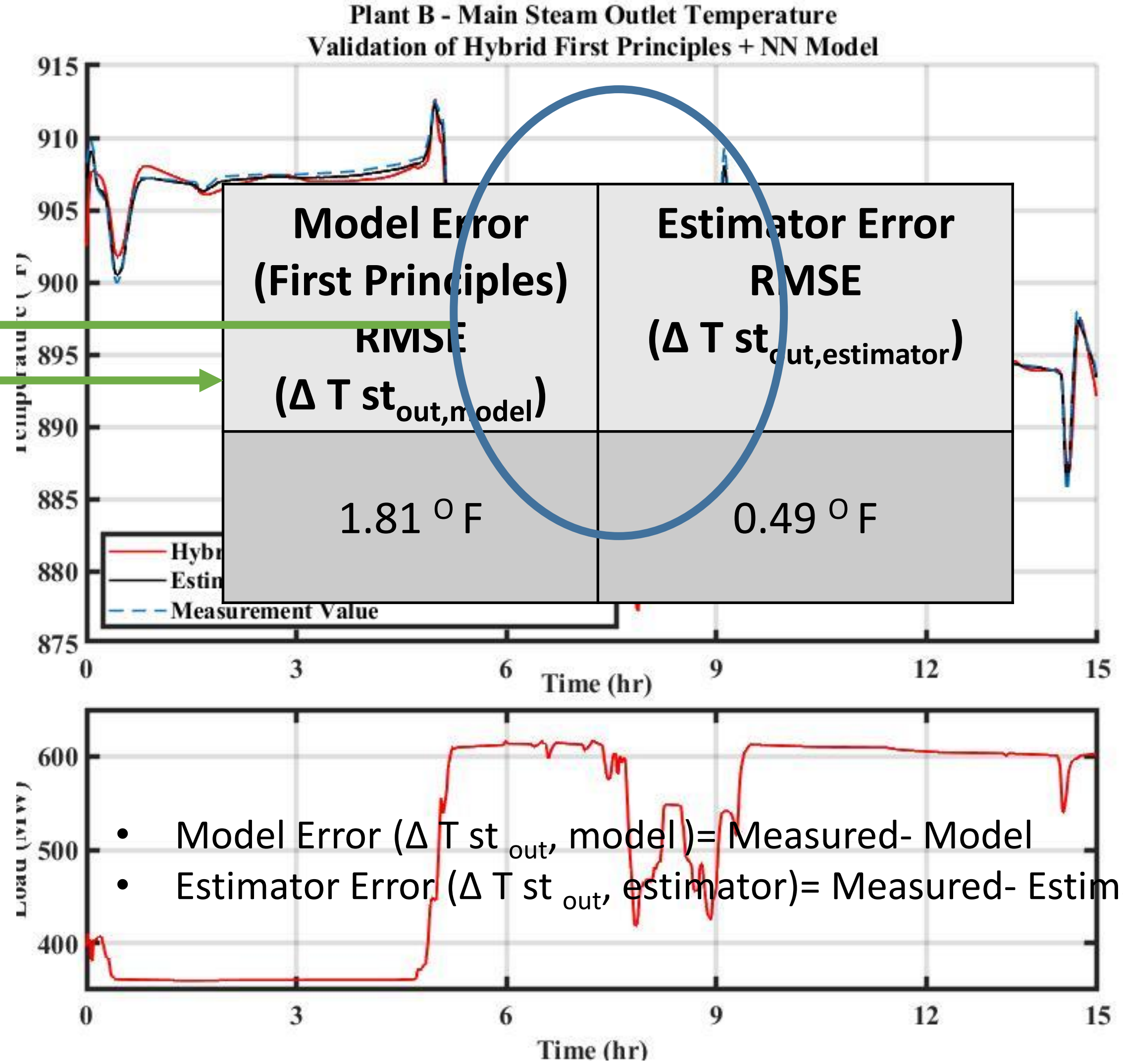
Model Validation for Outlet Steam Temperature (Plant B)



Model Error (First Principles +NN) RMSE (Δ T $st_{out,model}$)	Estimator Error RMSE (Δ T $st_{out,estimator}$)
1.09 ^{O} F	0.34 ^{O} F

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

Initial T_o = 910^o F (near inlet steam value)

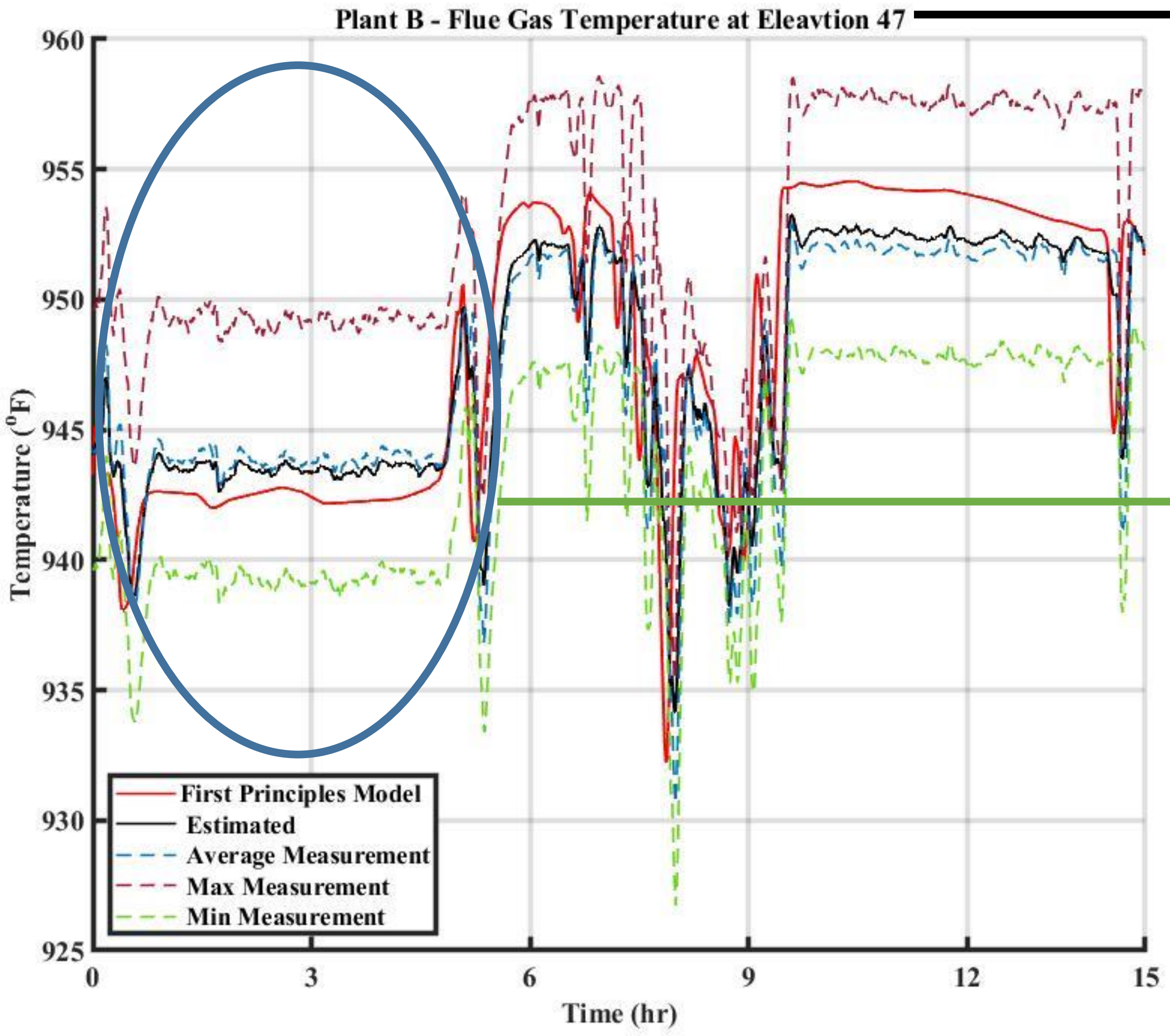


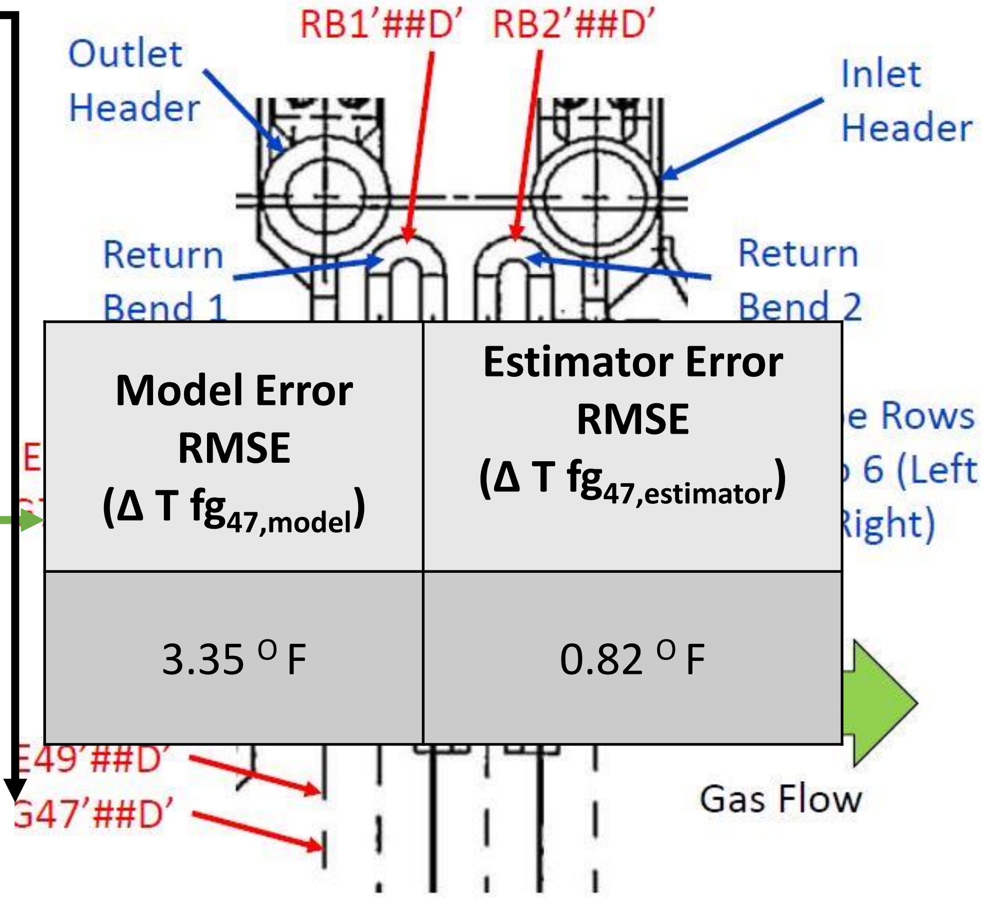
Model Error (First Principles) RMSE (Δ T $st_{out,model}$)	Estimator Error RMSE (Δ T $st_{out,estimator}$)
1.81 ^{O} F	0.49 ^{O} F

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

Initial T_o = 910^o F (near inlet steam value)

Model Validation for Flue Gas Temperature (Plant B)





Model Error RMSE ($\Delta T\ fg_{47,model}$)	Estimator Error RMSE ($\Delta T\ fg_{47,estimator}$)
3.35 ^{O}F	0.82 ^{O}F

HPSH1 Coil Profile View - Top

- Model Error ($\Delta T\ fg_{47,model}$)= Measured- Model
- Estimator Error ($\Delta T\ fg_{47,estimator}$)= Measured- Estimator

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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 and extending capabilities further
  - 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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Disclaimer:

Thank you for your attention

Questions?