Model-Based Sensor Placement for Component Condition Monitoring and Fault Diagnosis in Fossil Energy Systems

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Sensor Network Design (SND) Problem

- Which variable to measure and where (if spatial variation is considered)
- Which physical sensors (with different properties, cost) should be used
- How many sensors (hardware redundancy) should be used for measuring a variable
- What should be a frequency of sampling for different variables
- Maintenance policies

Design as well as retrofit problem

Motivation

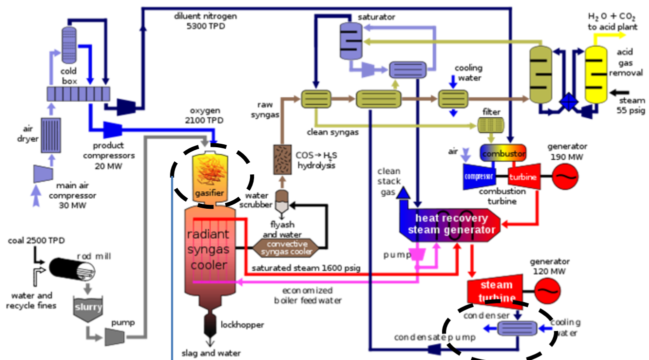
Sensor Placement

- Early detection of faults → Scheduling maintenance
- Green and safe → Emission standards, Mitigating approaches
- Efficiency → Operation in presence of fault
- Smooth control → Operation in presence of fault

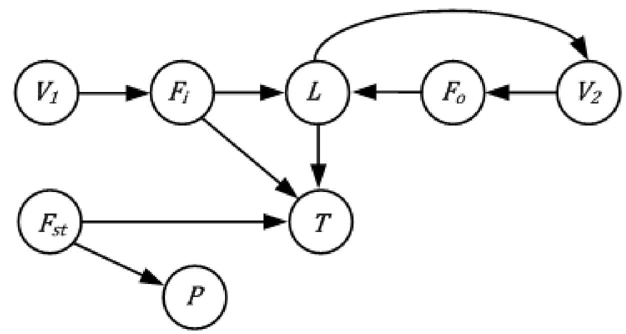
Two-Tier Approach

Tier 1 – Plant level

Plant level model



Cause and effect

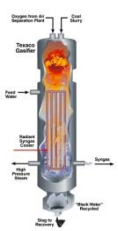


a

b

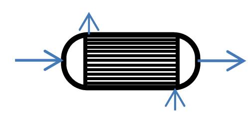
Tier 2 – Equipment Level

a



- Distributed model
- Estimator

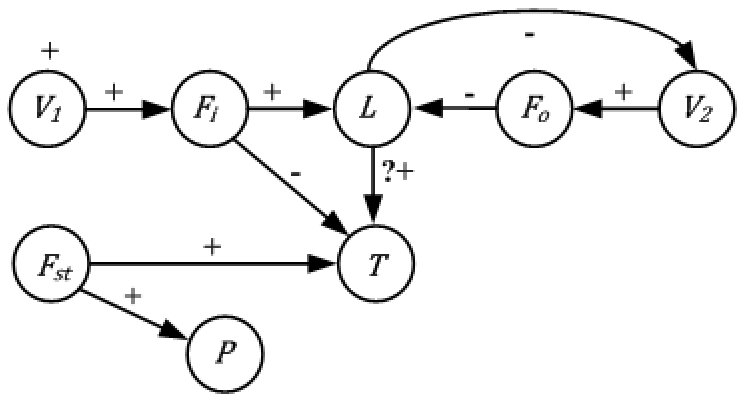
b



- Distributed model
- Estimator

Plant Level Sensor Placement: Qualitative Graph-Based Approaches

Graph-Based Approaches



DG representation:

- Only arrows
- {0,1} Matrix: Response to faults
- Numerically: Change > Threshold

SDG representation

- Arrows and signs
- {-1,0,1} Matrix: Response and direction to faults
- Numerically: Change > Threshold

<u>Result</u>

- M faults × N variable matrices for each algorithm

Integer Programming

Objective function

- minimize sensor network cost

$$\min \quad f = \sum_{j}^{N} w_j x_j$$

$$x = binary$$

Constraint

- Observability: Observe faults
- Resolution: Distinguish faults

Observable

$$[0 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0]$$

$$[0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0]$$

Observable Resolvable

$$Ax^T \geq b \qquad A = \begin{bmatrix} 1 & 0 & 0 & 1 & \cdots & 1 \\ 0 & 0 & 1 & 1 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & 1 & \cdots & 1 \end{bmatrix}_{M \times N} \quad \& \quad x_1 + x_2 + x_3 + \cdots + x_N \geq 1 \qquad b = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}_{M \times 1}$$

Decision variables

- Binary → **"1"**: Variable measured "**0**": Variable not measured
- Weight → Cost of measuring sensor

Fault Evolution Sequence Algorithm

- Enhance DG and SDG for fault resolution
- {-1,0,1} Matrix: Fault evolution sequence algorithm
- Compare sequence of responding sensors
- Pair the sensors and compare

Fault	Sequence	Pairs
F1	$S_1\ S_3\ S_2\ S_4$	$\{S_1,S_3\}\ \{S_1,S_2\}\ \{S_1,S_4\}$ $\{S_3,S_2\}\ \{S_3,S_4\}\ \{S_2,S_4\}$
F2	$S_1\ S_2\ S_3\ S_4$	$\{S_1,S_3\}\ \{S_1,S_2\}\ \{S_1,S_4\}$ $\{S_2,S_3\}\ \{S_3,S_4\}\ \{S_2,S_4\}$

Base pairs: $\{S_1,S_2\}\ \{S_1,S_3\}\ \{S_1,S_4\}\ \{S_2,S_3\}\ \{S_2,S_4\}\ \{S_3,S_4\}$

- If Pair $\subseteq$ Base pair :
  - Same sequence: "1"
  - Reverse sequence: "-1"

- If Pair $\not\subset$ Base Pair : "0"

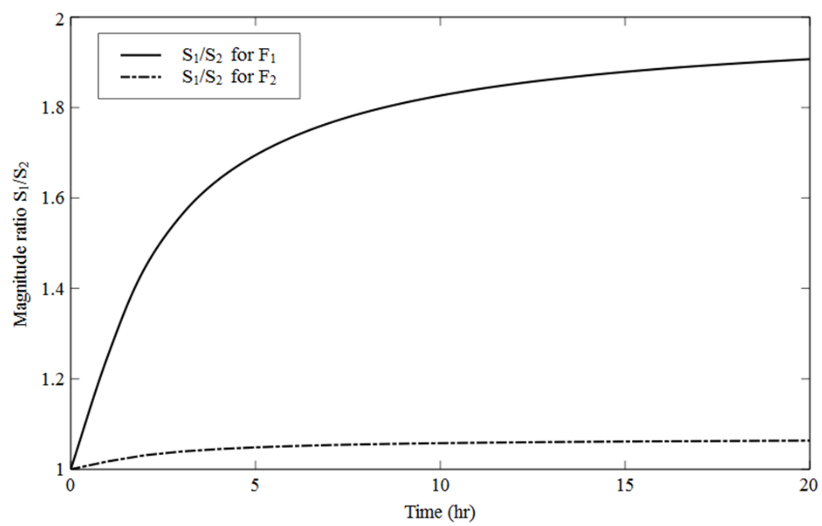
Magnitude Ratio Algorithm

- Enhance DG & SDG for fault resolution
- {-1,0,1} Matrix: Magnitude ratio

Fault	Sensor direction	
	S_1	S_2
F_1	+1	-1
F_2	+1	-1

A = Normalized measurement ratios for F1: S_1/S_2
B = Normalized measurement ratios for F2: S_1/S_2

- ➢ A >>B : "1"
- ➢ B>>A : "-1"
- ➢ A≅B≅1: "0"

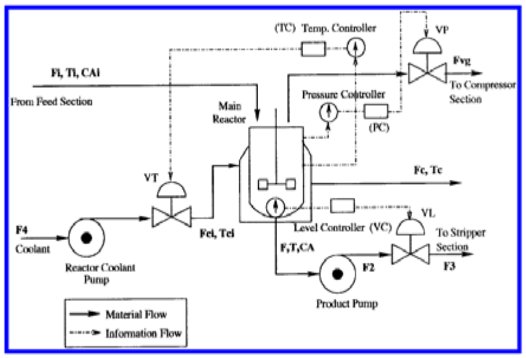


Results

Weights in optimization problem: **Cost of sensors**

Sensor type	Cost	Accuracy
Temperature	0.1	2 °F
Pressure	0.5	3% of span
Flow	1	4% of span
Level	1	1 inch
Concentration	10	0.01

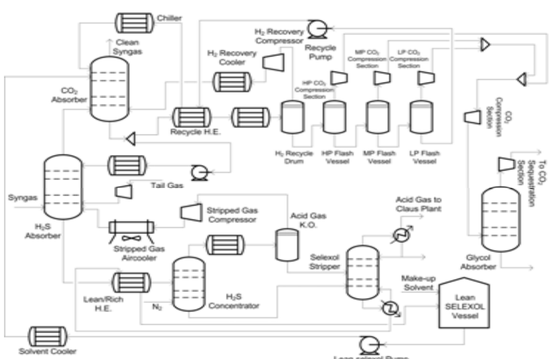
CSTR system



- 10 Faults
- 7 Sensors

Algorithms	Network cost	Irresolvable
SDG	*10.7*	1 fault
FES	***0.7***	1 fault ⊆ SDG
MR	***0.7***	**[ ]**
FES & MR	***0.7***	**[ ]**

SELEXOL process



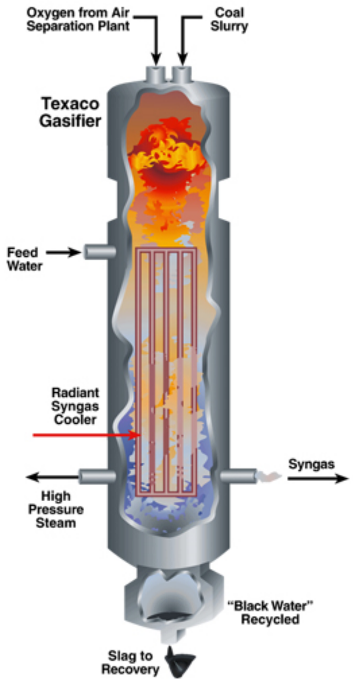
- 14 Faults
- 25 Sensors

Algorithms	Network cost	Irresolvable
SDG	*22.3*	1 fault
FES	*22.2*	**[ ]**
MR	***22.1***	**[ ]**
FES & MR	***22***	**[ ]**

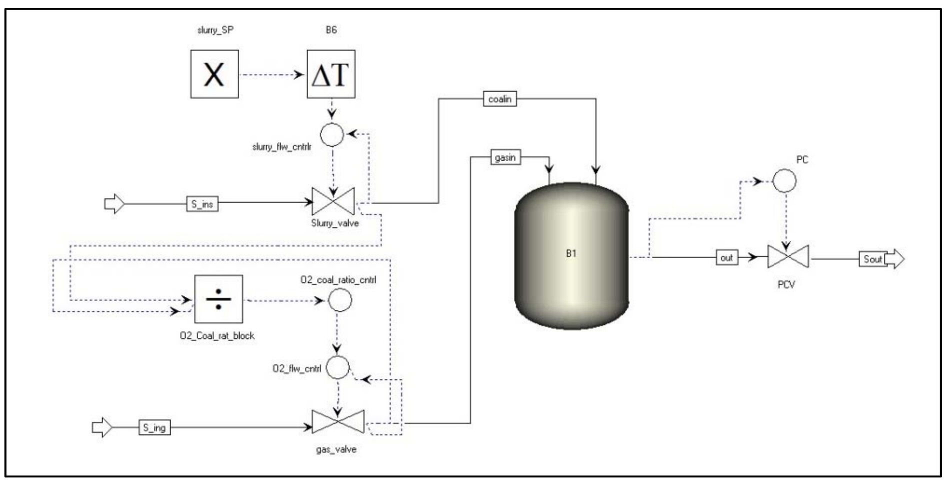
Equipment Level Sensor Placement: Model-Based Quantitative Approach

1. Gasifier
2. Water-Gas Shift Reactor

Slagging Gasifier



- Gasifier operates at temperatures of about 1200-1600°C
- Liquid slag flows on walls and is collected at bottom
- Slagging gasifier model required for fault simulation

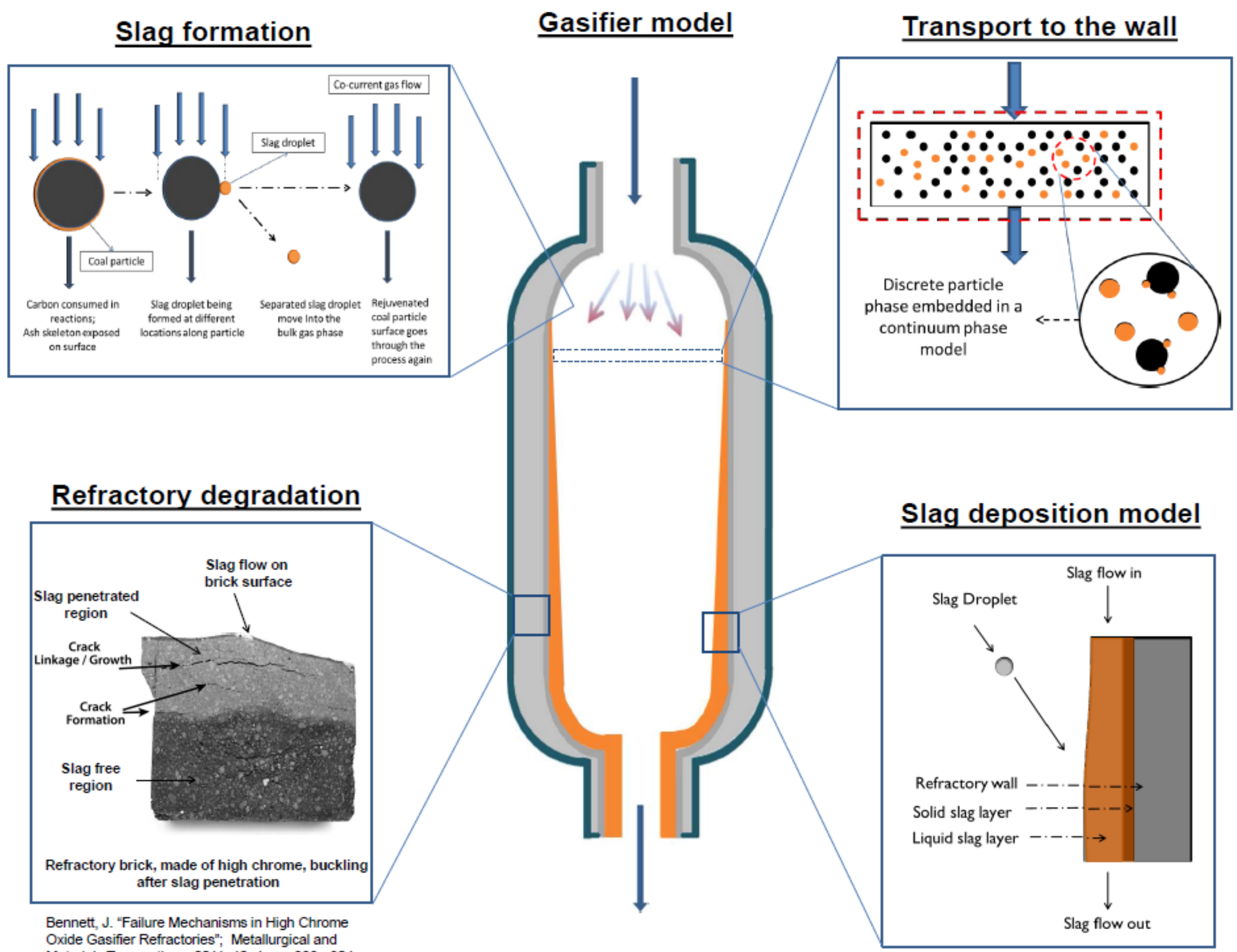


<u>Two faults of interest in the gasifier</u>

1. Slag layer thickness

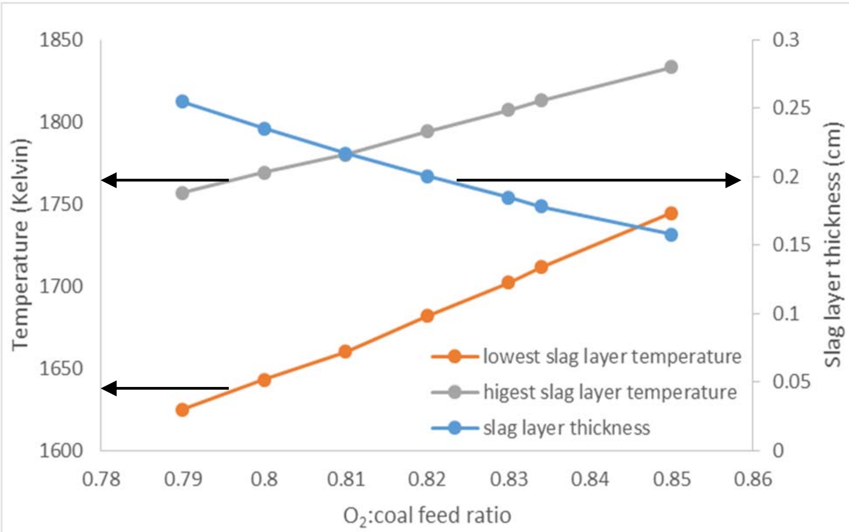
2. Refractory degradation

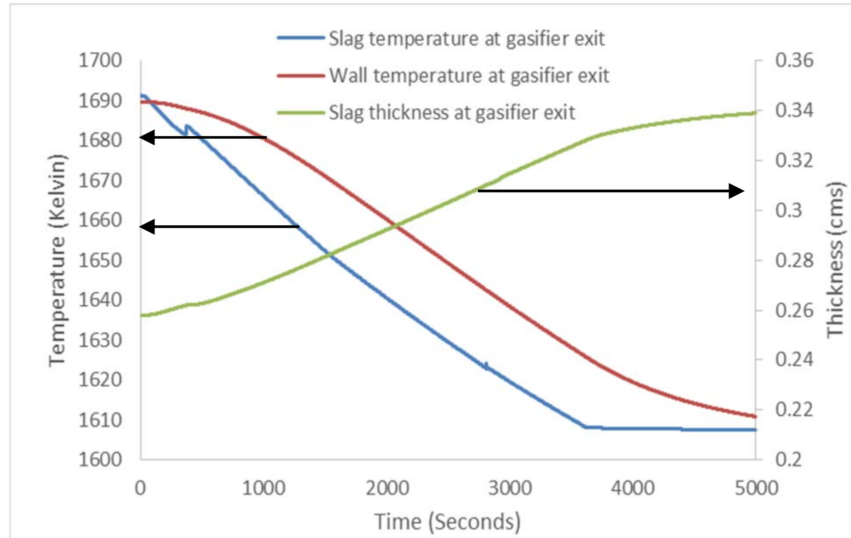
Model Development for Condition Monitoring



Bennett, J. "Failure Mechanisms in High Chrome Oxide Gasifier Refractories"; Metallurgical and Materials Transactions; 2011, 42, 4, pp. 888 - 904

Effect of Operating Conditions

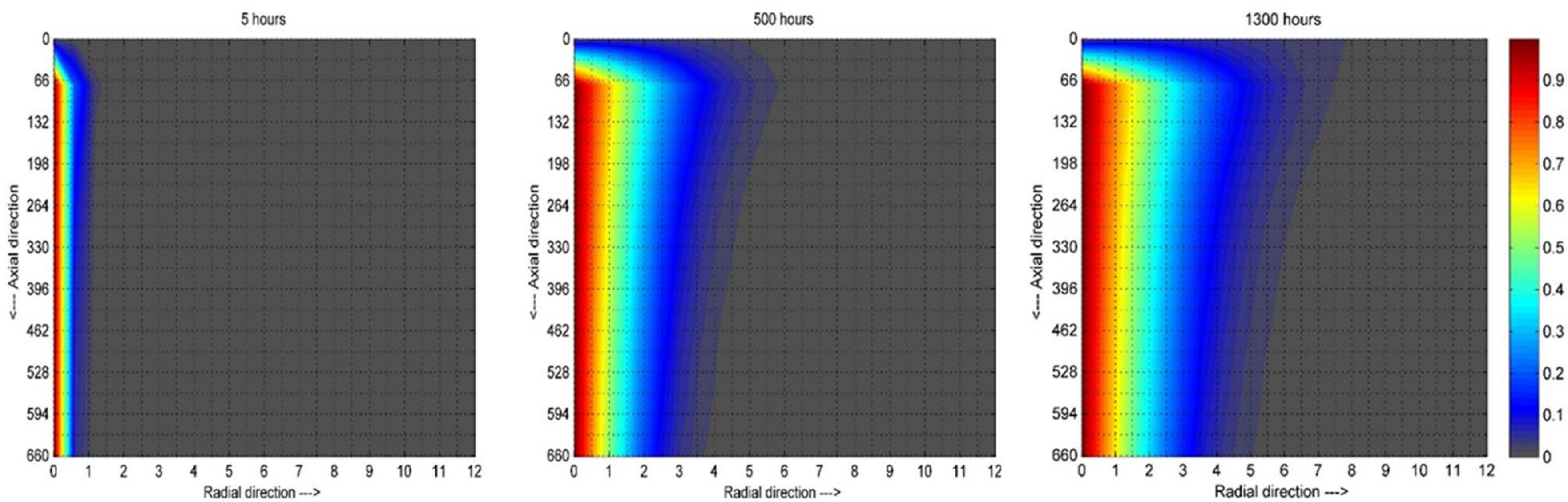




- Thickness increases by 75% for change in O_2:coal ratio from 0.79 to 0.85
- High slag temperature can accelerate the slag penetration into the refractory brick leading to faster spalling
- Low slag temperature can result in solidification of slag, leading to clogging and reduced volume for reactions

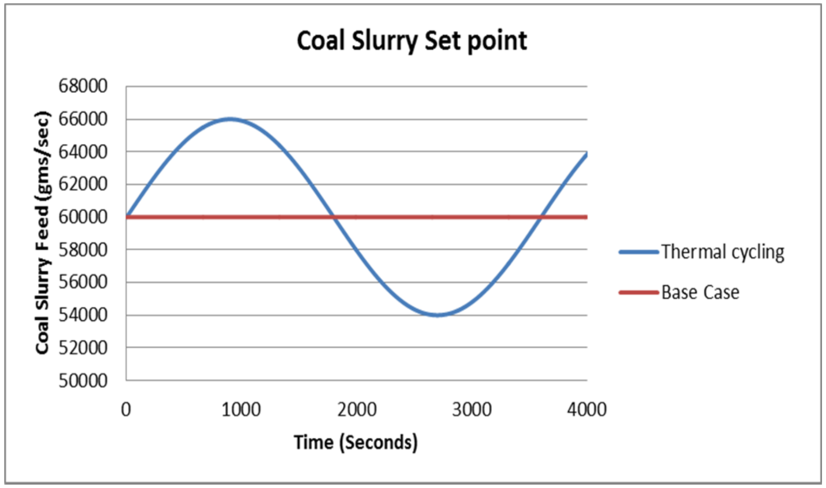
- Coal feed changed from Illinois #6 to Pittsburgh #8 coal in 1 hour
- Slag layer increases in thickness by about 30%
- Slag layer temperature approaches critical viscosity temperature if O_2/coal ratio not adjusted, could lead to solidification

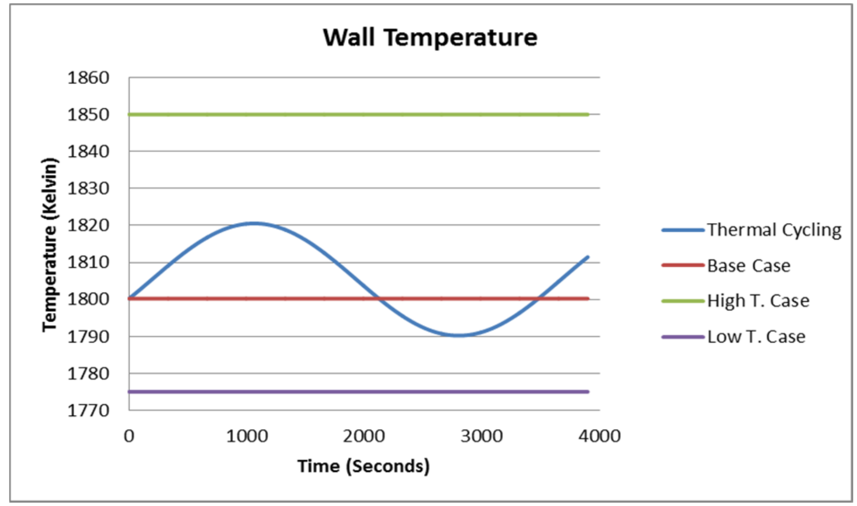
Slag Penetration

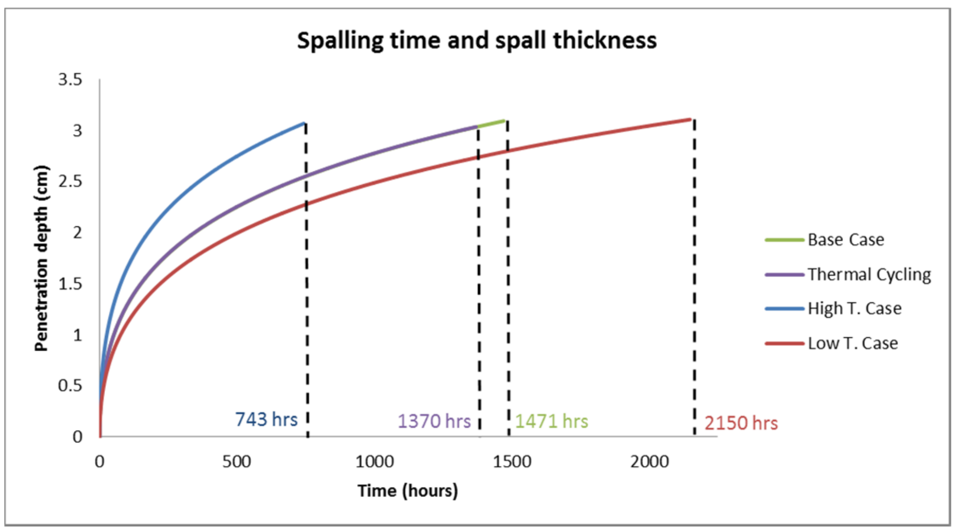


- Temperature decreases with depth
- Diffusivity is a strong function of temperature
- As slag penetrates, penetration rate slows down due to decrease in effective diffusivity and due to increasing radius

Refractory Degradation



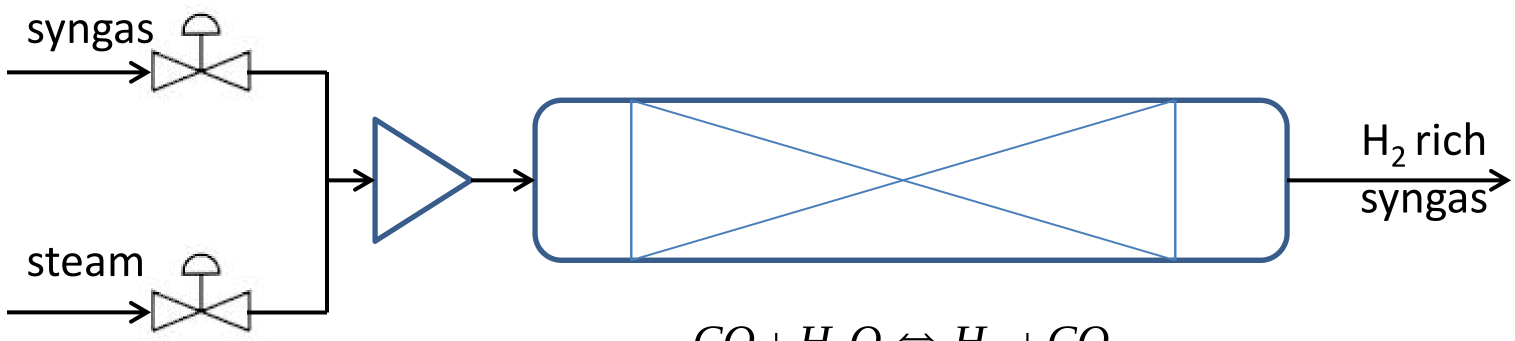




Equipment level sensor network design

2. Water gas shift reactor

Sour Water-Gas Shift Reactor (SWGSR)



$$CO + H_2O \Leftrightarrow H_2 + CO_2$$

$$COS + H_2O \Leftrightarrow H_2S + CO_2$$

Model

- 1^{st} principle, 1-D, PDAE model developed
- Reaction kinetics: data reconciliation

Application

- Simulate faults: catalyst deactivation
- Fault estimation: State estimation techniques

➢ Search space for measurement model is large **($>2^{176}$)**

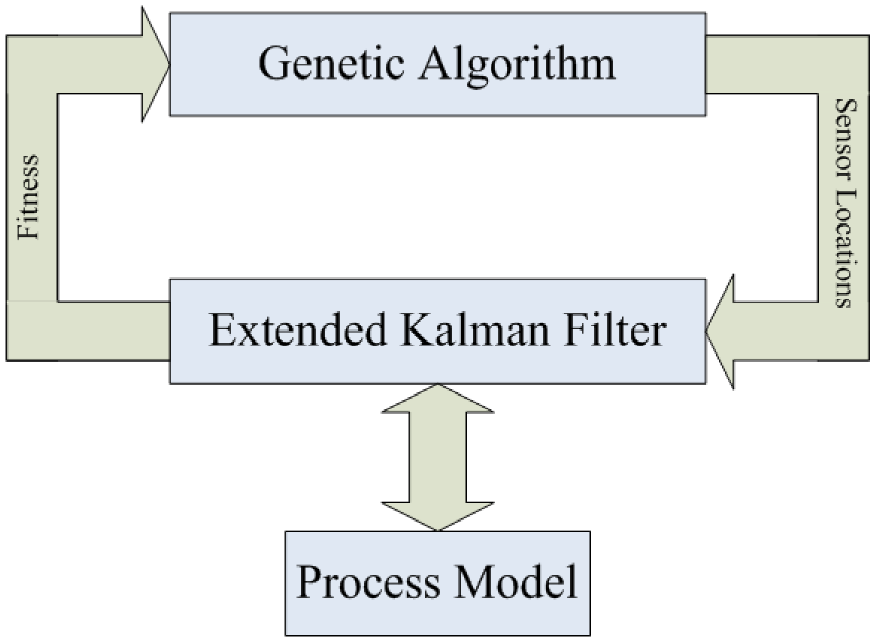
➢ Evolutionary algorithm can help us surf the space to find optimal model

Genetic Algorithm!

SND Framework for WGSR

$$e_{total} = \sum_{i=1}^{N} \left(x_{estimate,i} - x_{actual,i}\right)^2$$

$$Fitness = e^{-e_{total}}$$



$$H = \begin{bmatrix} 1 & 0 & 0 & 1 & . & . & . & 0 & 1 & 1 \end{bmatrix}$$

$$\dot{x} = f(x, z)$$

$$g(x, z) = 0$$

Estimation Technique

- **State estimation**
  - Non-linear model
  - Differential and algebraic equations (DAE)
- **Estimator must handle**
  - Non-linearity : Nonlinear model
  - DAE systems : DAE model
  - Constraints : Sum of mole/mass fractions = 1
  - Uncertainty in both differential and algebraic variables : Ergun Eq.

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

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

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

$$\omega \sim N(0,Q) \qquad \gamma \sim N(0,W) \qquad v \sim N(0,R)$$

$$subject\ to : Ex_{k+1}^{aug} = b$$

A modified EKF is proposed!

Modified EKF

- **Propagation**
  - ✓ States: Propagated by integrating nonlinear DAE solvers
  - ✓ Error covariance matrix is propagated by using linearized DAE model

$$\dot{x} = Ax + Bz \qquad Cx + Dz = 0 \quad \xrightarrow{\textit{Algebraic equations are not differentiated}} \quad \dot{x} = \left(A - BD^{-1}C\right)x \qquad z = -D^{-1}Cx \quad \longrightarrow \quad x(k+1) = \phi x \qquad z = -D^{-1}Cx$$

  - ✓ Error covariance: Error covariance matrix split between differential and algebraic states

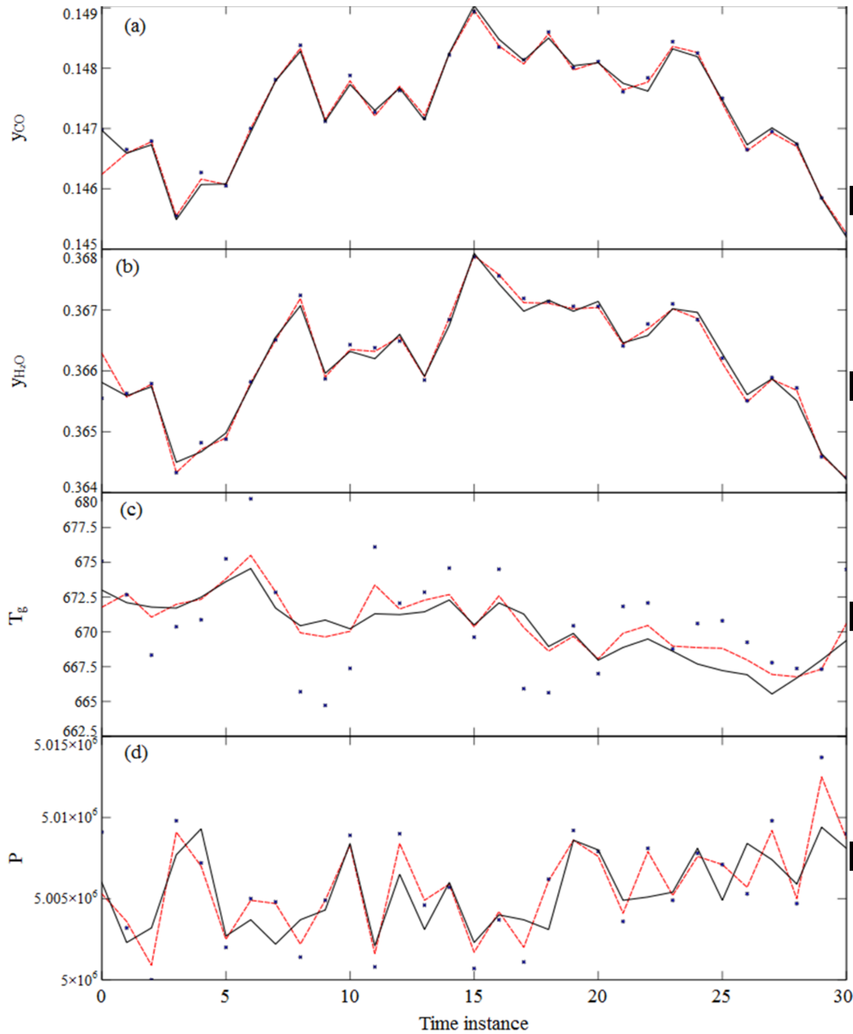
$$P_{k+1|k} = \begin{bmatrix} P_{k+1|k}^{xx} & P_{k+1|k}^{xz} \\ P_{k+1|k}^{zx} & P_{k+1|k}^{zz} \end{bmatrix} = \begin{bmatrix} \phi P_{k|k}^{xx}\phi^T + GQG^T & P_{k+1|k}^{xx}\left(D^{-1}C\right)^T \\ \left(D^{-1}C\right)P_{k+1|k}^{xx} & \left(D^{-1}C\right)P_{k+1|k}^{xx}\left(D^{-1}C\right)^T + W \end{bmatrix}$$

- **Correction**
  - ✓ Solve optimization problem

$$\min_{\hat{x}_{k+1|k+1}^{aug,c}} = \left(\hat{x}_{k+1|k+1}^{aug,c} - \hat{x}_{k+1|k}^{aug}\right)^T P_{k+1|k}^{-1}\left(\hat{x}_{k+1|k+1}^{aug,c} - \hat{x}_{k+1|k}^{aug}\right) + \left(y_{k+1} - C\hat{x}_{k+1|k+1}^{aug,c}\right)^T R^{-1}\left(y_{k+1} - C\hat{x}_{k+1|k+1}^{aug,c}\right)$$

$$\textit{subject to}: E\hat{x}_{k+1|k+1}^{aug,c} = b$$

Modified EKF - Estimation



RMSE	
Measured data	Estimate
1.029×10^{-4}	0.891×10^{-4}
1.031×10^{-4}	0.874×10^{-4}
4.9×10^{-3}	1.7×10^{-3}
4.847×10^{-4}	3.994×10^{-4}

Actual (-), measured (*) and estimated (--) at middle of the reactor

Computational Complexity

- Each generation of GA
  - Population : 16 Individual
  - Each individual (Measurement model) : EKF estimation
  - EKF is simulated for 20 sample instant ; 20 times nonlinear process model is numerically integrated
  - 320 times nonlinear process model is numerically integrated
- Each generation takes ≈ 40 seconds in parallel in HPCC
  - 10K generation ≈ 5 days
- How to reduce the computation time?
  - Optimize the code ✓
  - Run in parallel ✓
  - Use of simplified model

Simplification of WGSR model

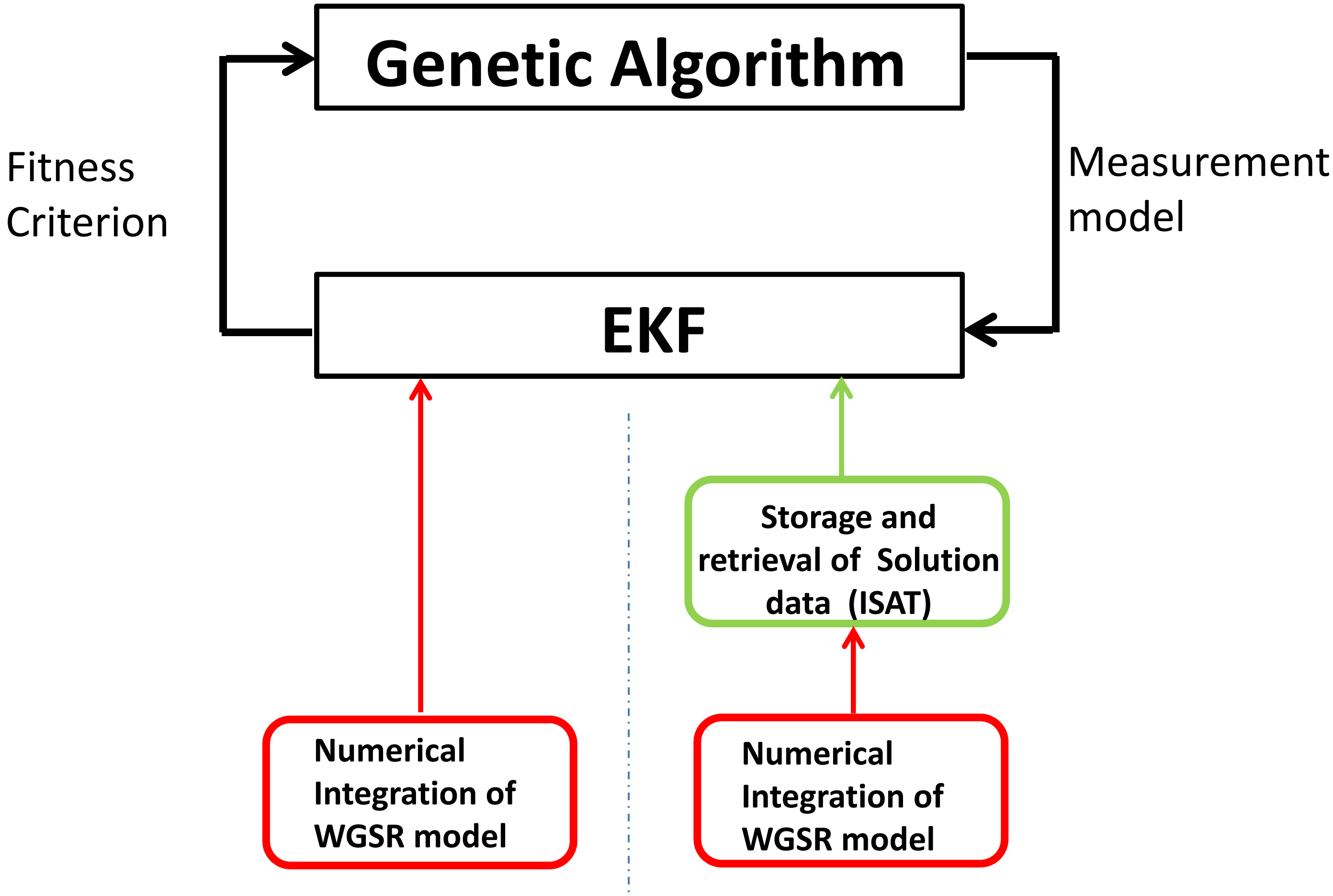
- **Scaling analysis** of current WGSR model identifies following
  - ✓Conduction phenomenon can be negligible
  - ✓Species balance equations can be quasi steady
  - ✓Catalyst and gas phase temperatures can be made equal
- Number of species balance equations can be reduced using stoichiometric relations

Original vs. Simplified Model

Properties	Original model	Simplified model
No. of PDEs	8	1
No. of ODEs	1	3
No. of algebraic equations	0	4
Types of PDE solved	Parabolic	First order hyperbolic
Steady state simulation time, sec	75	1
Dynamic simulation time, sec	110	40

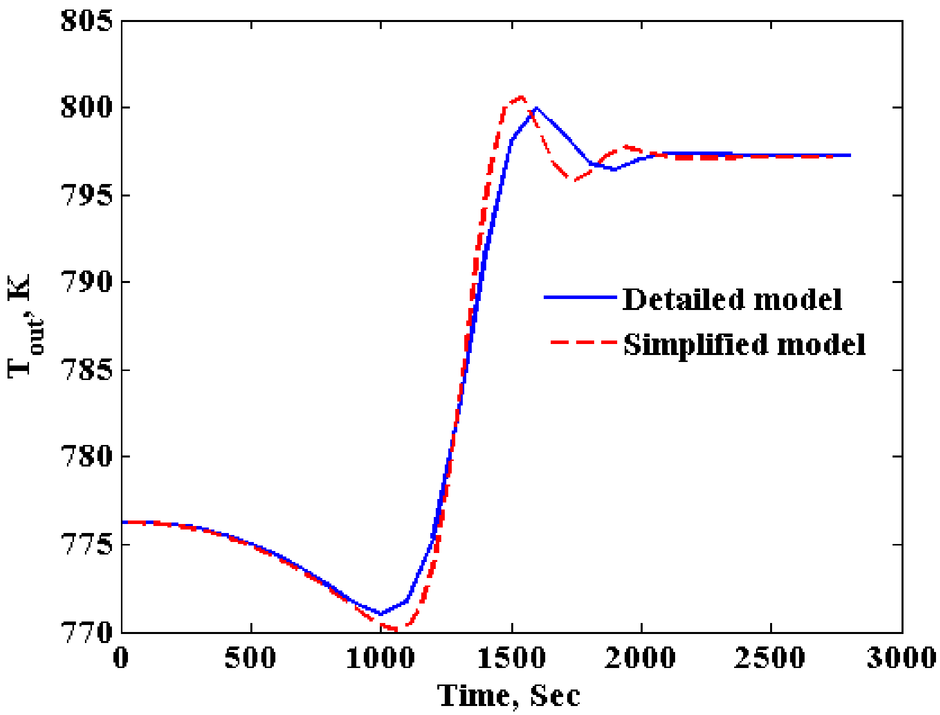
In-Situ Adaptive Tabulation (ISAT)

Use of storage and retrieval approach such as ISAT is investigated for computational efficiency



Simulation Results

Dynamic response for step up in inlet temperature



Computational efficiency per sample time

- Numerical simulation: **0.7 sec** (Detailed model)
- Numerical simulation: **0.12 sec** (Simplified model)
- ISAT (Retrieval): **0.0027 sec**

Plant-Wide Sensor Placement

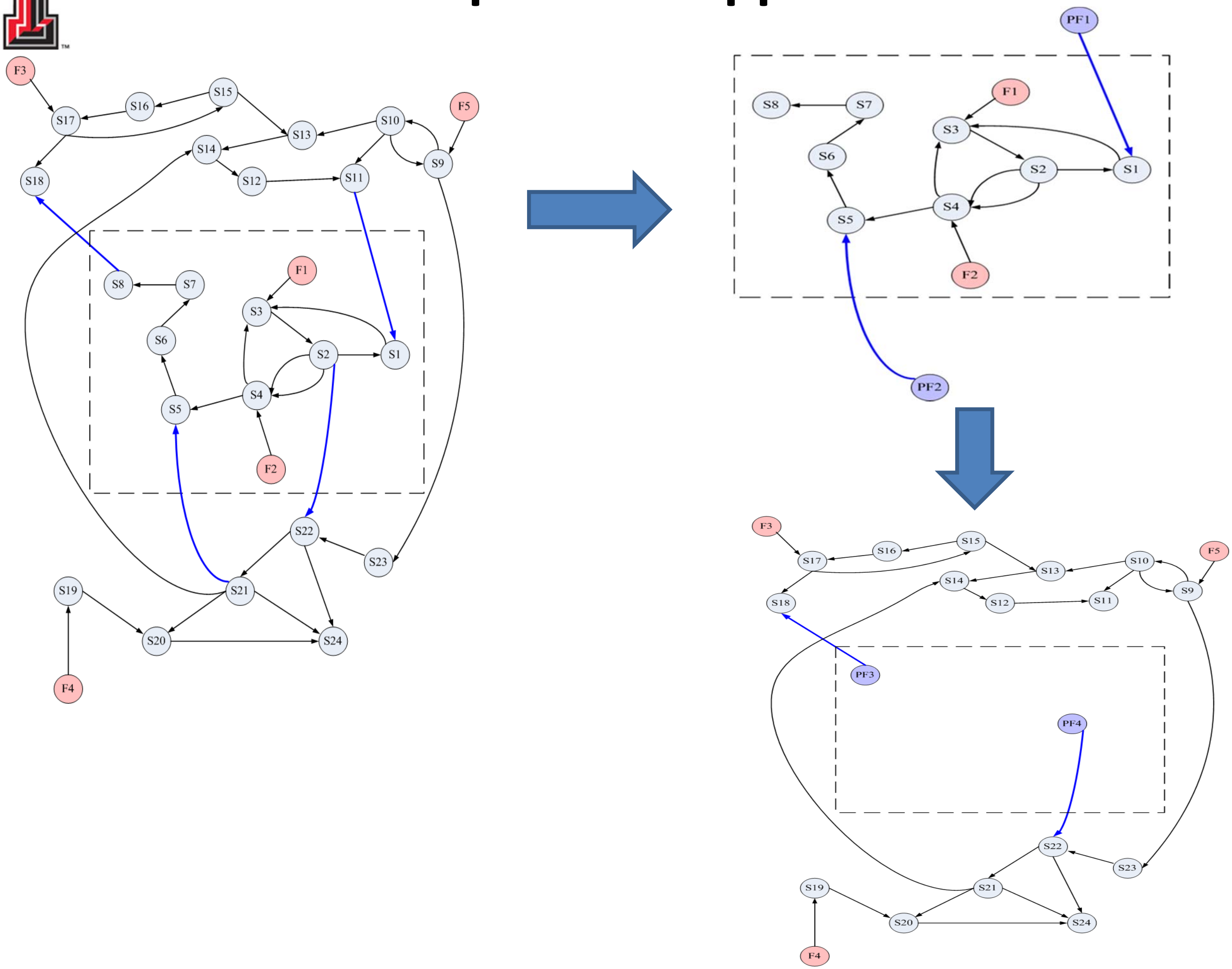
SND for Large Networks

- Large networks
  - Many state and fault nodes
- Sensor placement for fault diagnosis
  - Might become computationally complex
    - Resolution problems because of the nested symmetric difference operations in graph-based approaches
  - Difficult to nest models of different level of granularity such as graph models, and PDE models

Decomposition Strategy

- Decomposition of the large network to sub-networks
- Definition of pseudo-faults to avoid solution iteration between sub-networks

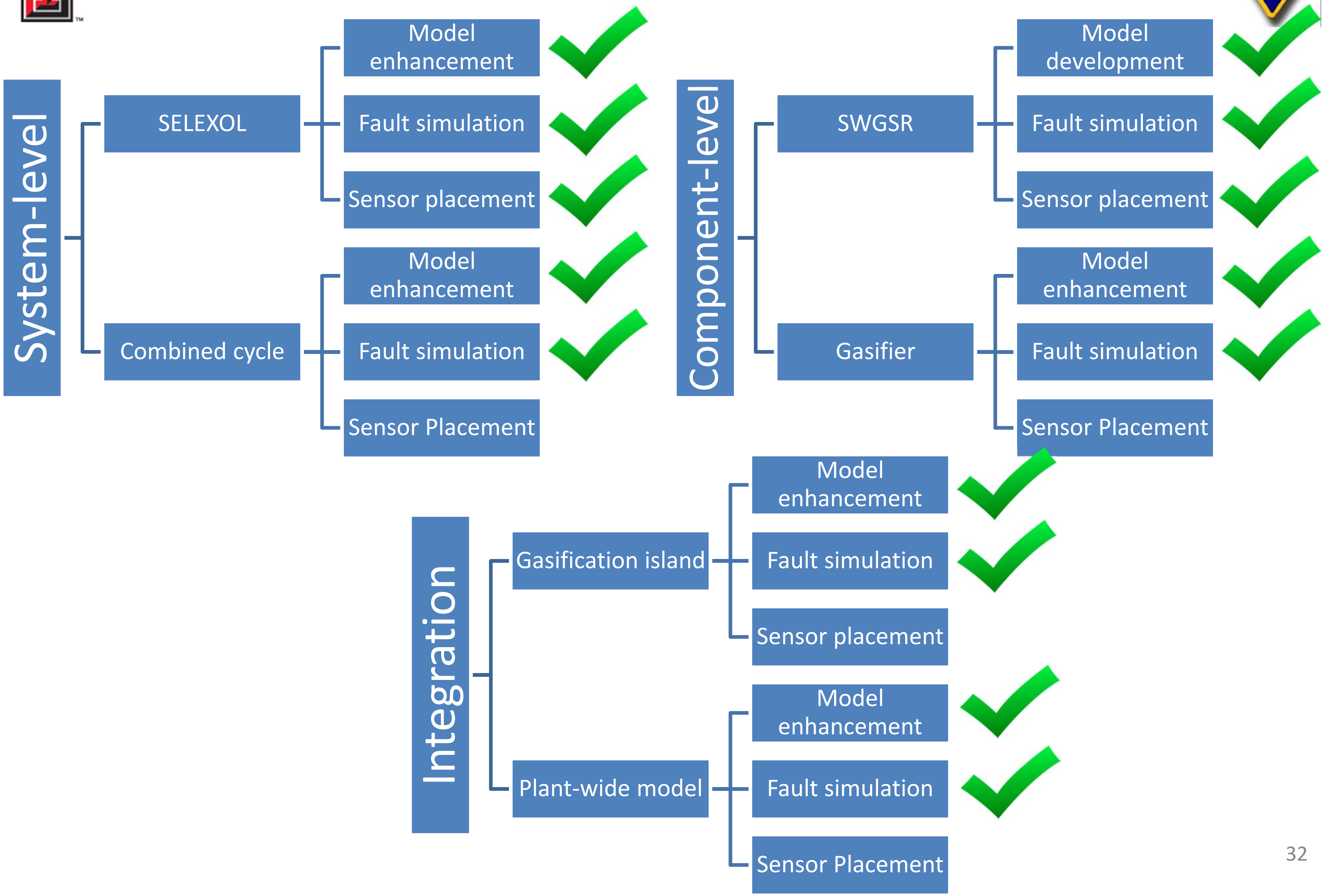
Decomposition Approach



Solution Characteristics - Decomposition

- Expected high computational enhancements for largely naturally partitionable systems
- Forced partitioning can result in large number of pseudo-faults
- Sub-networks can use models of different levels of granularity
  - Graph, Algebraic, ODE, PDE
- Optimal sub-network partitions
  - Specialize k-way partitioning, sub-modular function approaches for the sensor placement problem

Current status



Future work

- Complete SND for the combined cycle unit
- Synthesize sensor network for the gasifier using a reduced order model
- Use the simplified model and ISAT approach for the sensor network design of SWGSR
- Perform two tier sensor placement using the proposed decomposition approach

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Thank You