

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

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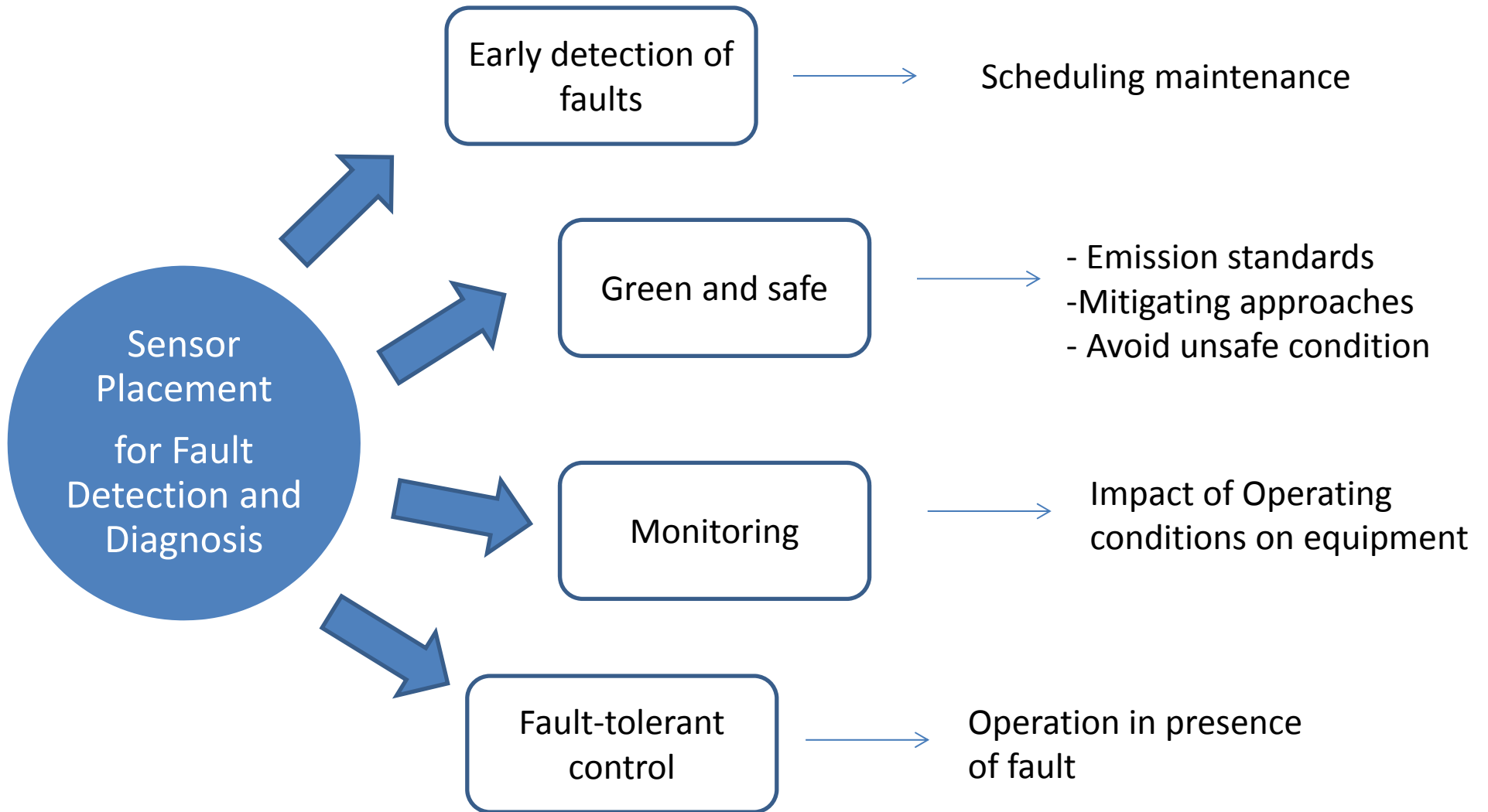
West Virginia University

Sensor Network Design Problem

- Problem
 - Which variables to measure and where (if spatial variation 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 the frequency of sampling (measurement) for different variables
 - Maintenance policies

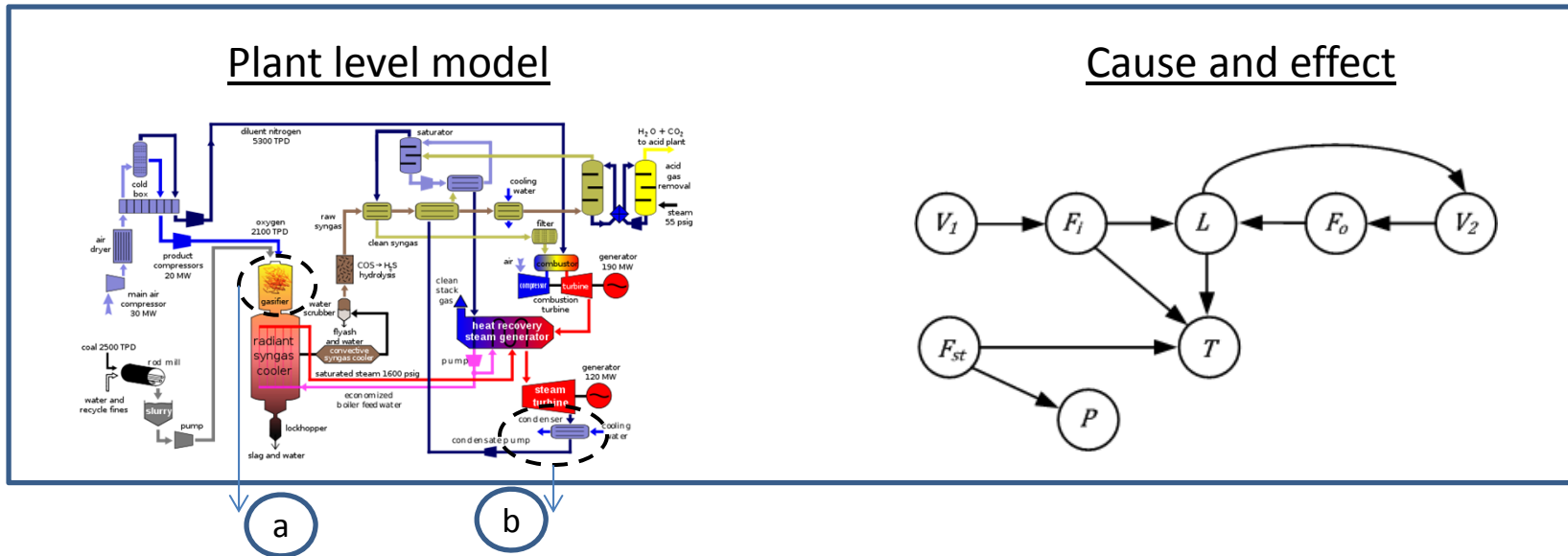
Design as well as a Retrofit problem

Motivation

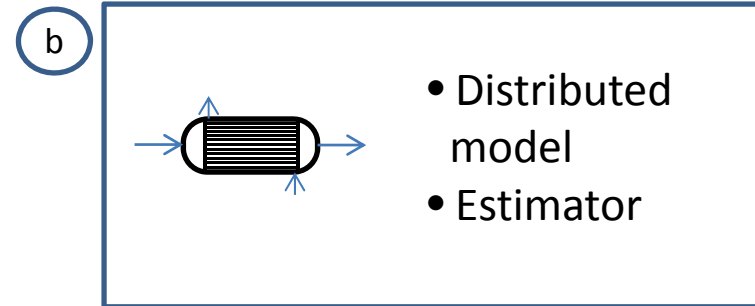
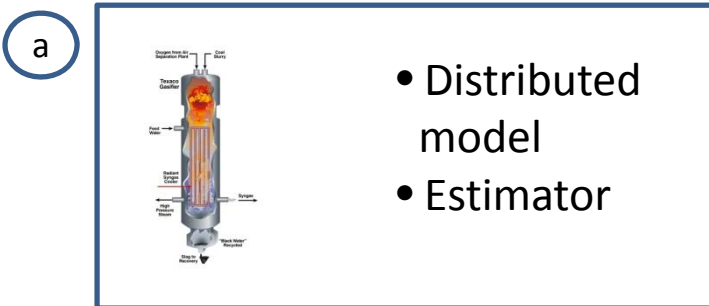


Two-tier approach

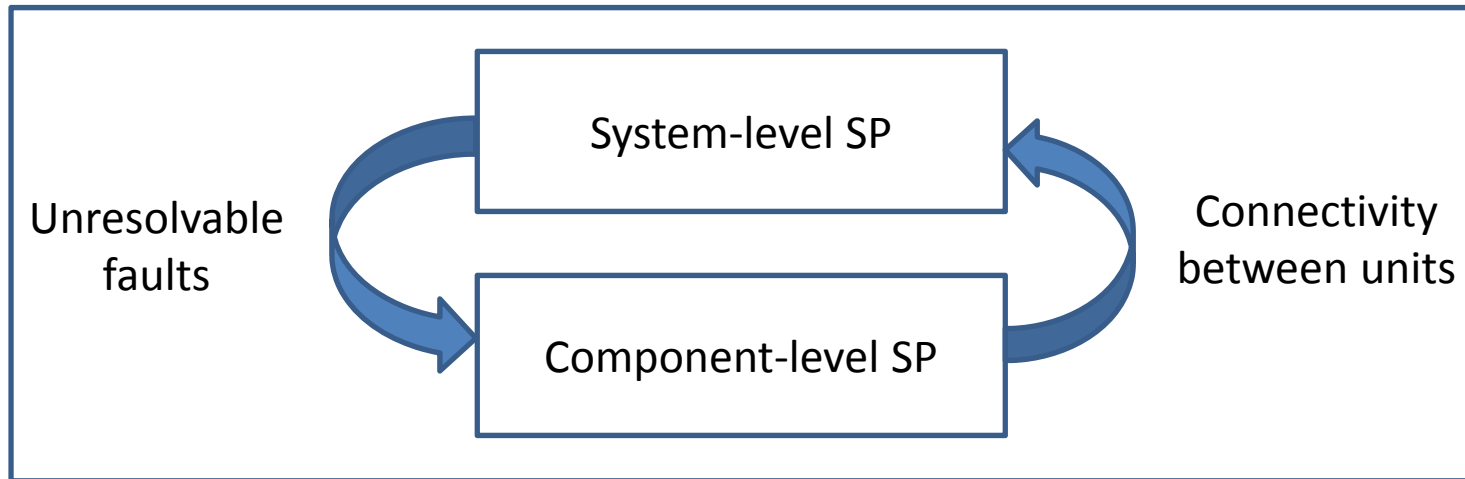
Tier 1 – Plant level



Tier 2 – Equipment Level

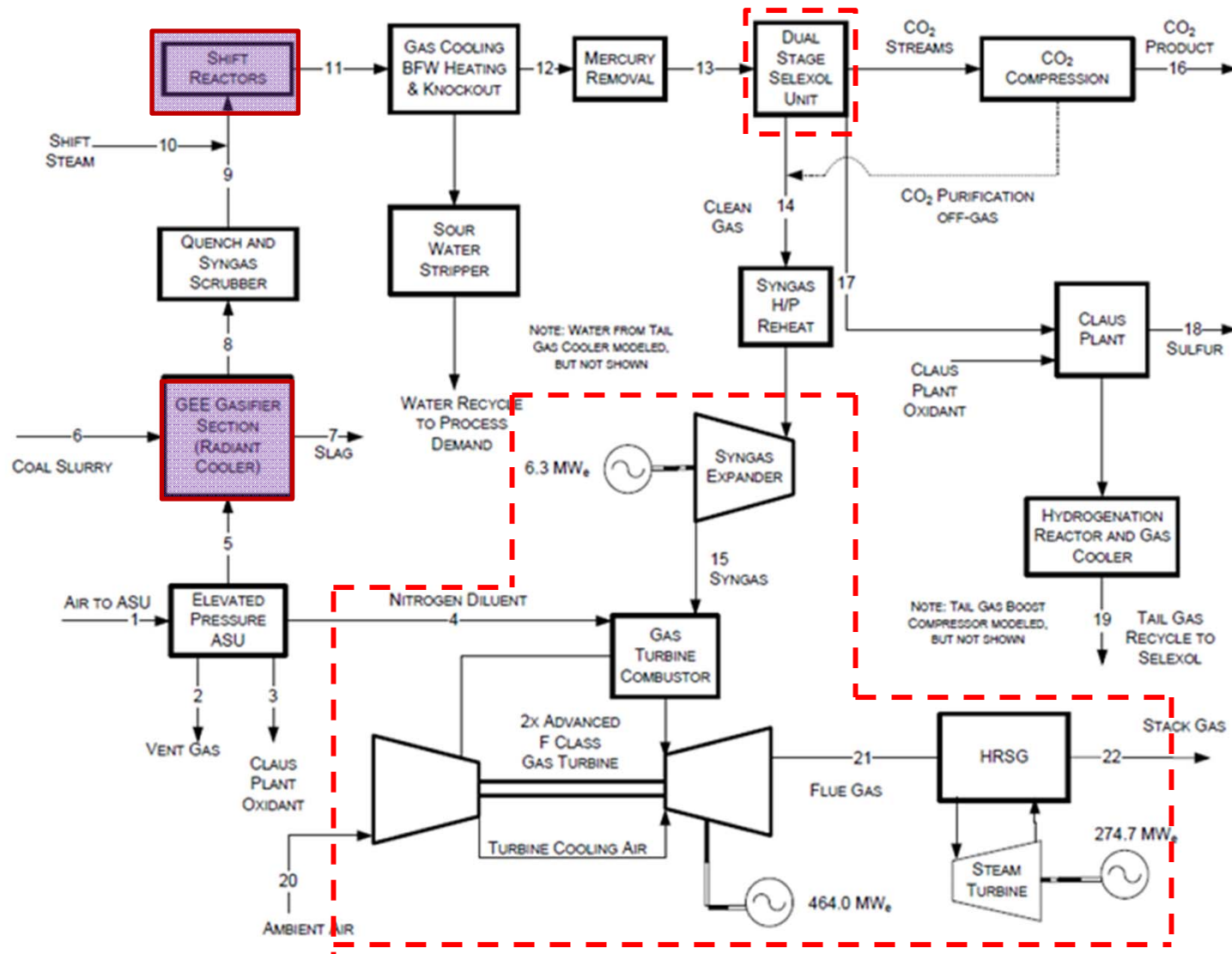


Two-tier approach

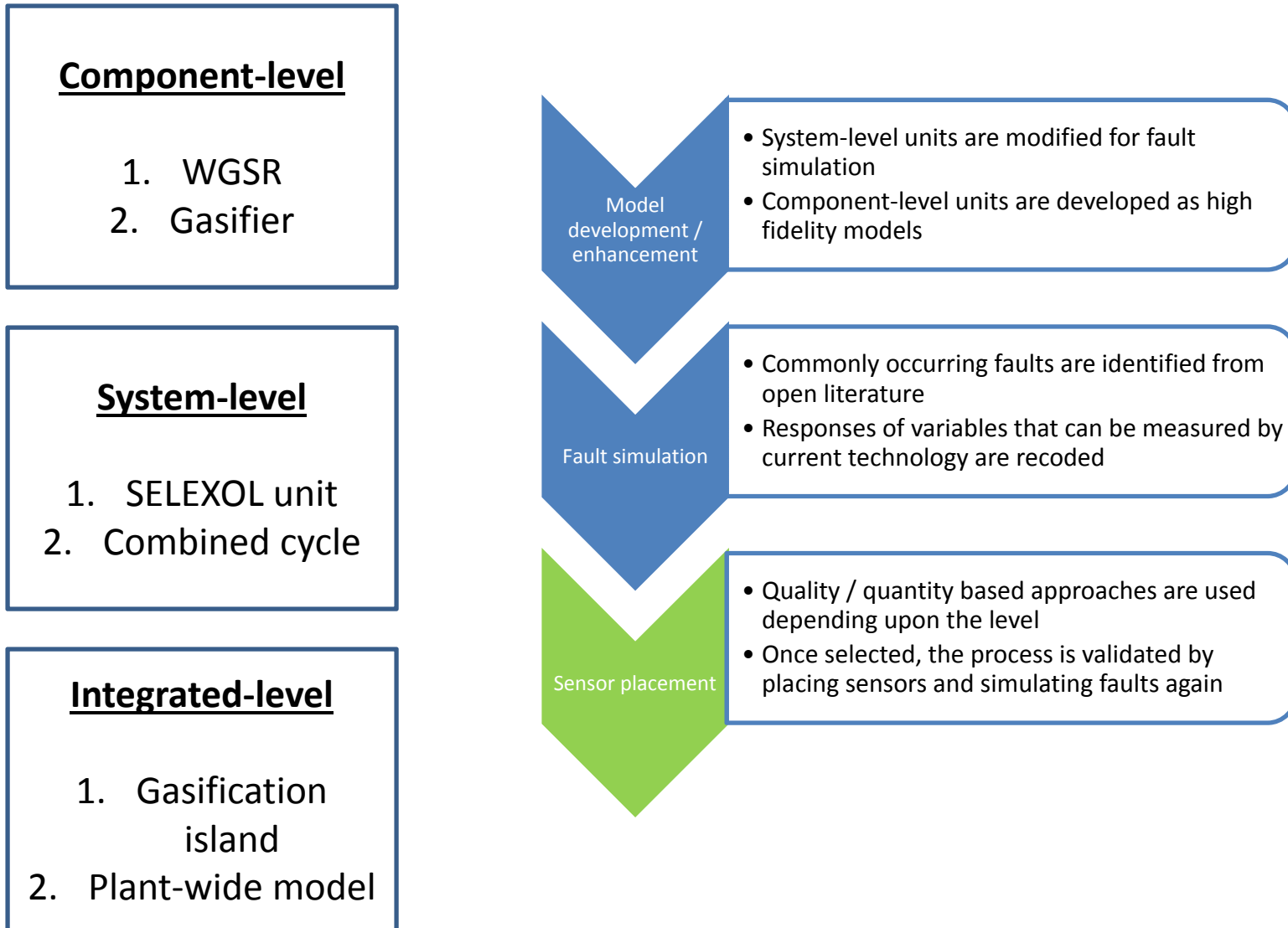


- Maximizing efficiency of sensor network
- Resolve component-level faults while taking advantage of system-level interactions
- SP problem divided into two levels, solved, and then integrated.
- Use high fidelity models for component-level fault simulation

Component level and system level for an IGCC plant with CO₂ Capture



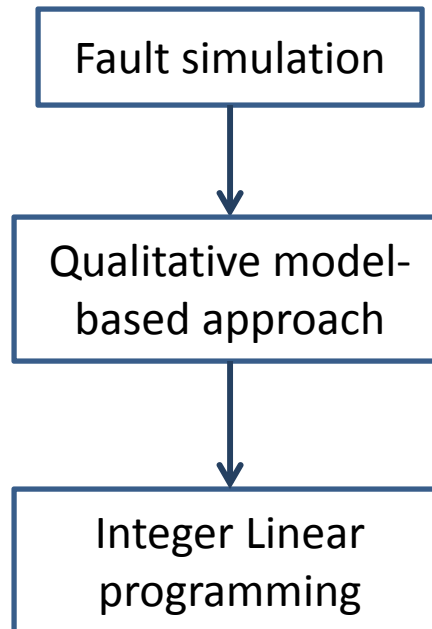
Approach



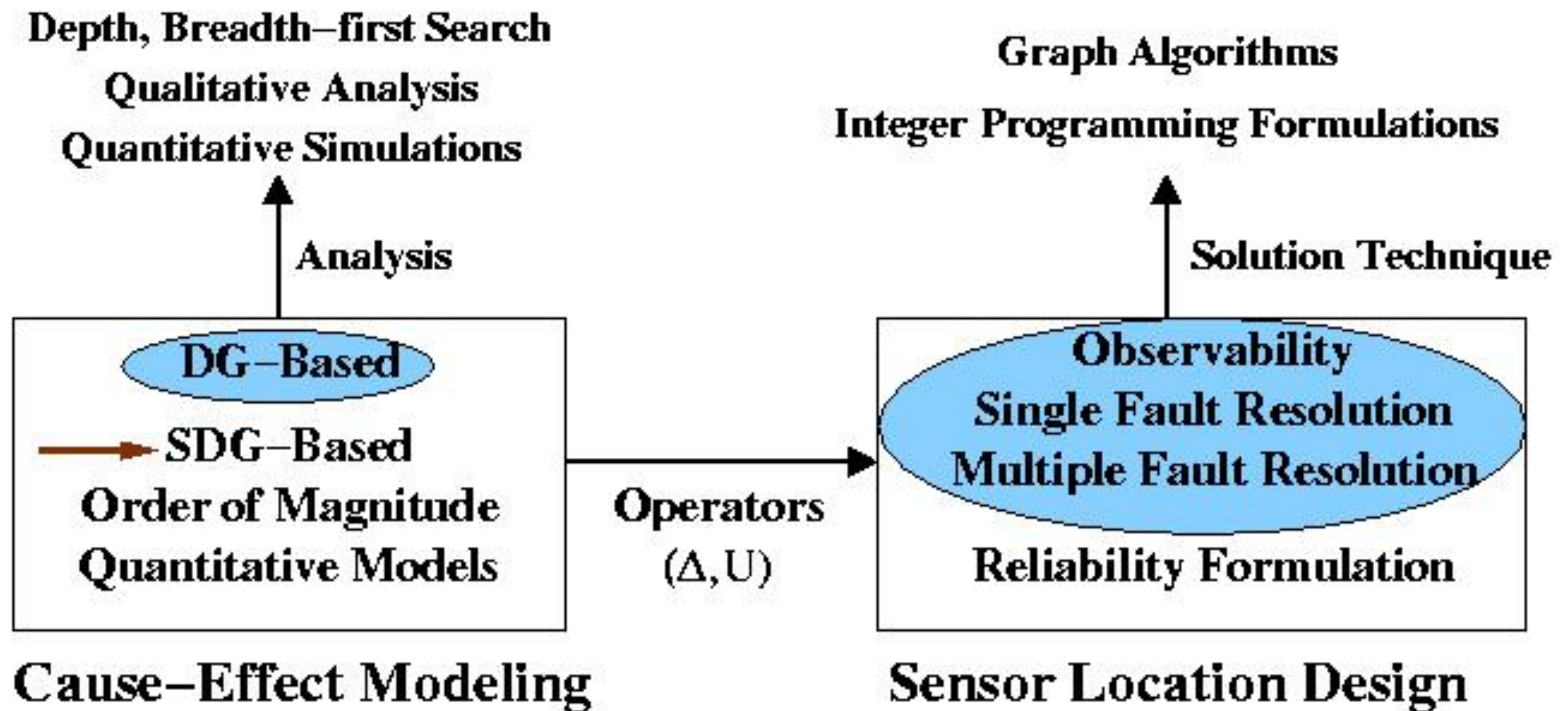
Tier 1: System Level Sensor Placement

System-level SP

- Qualitative approach: Has a fault occurred?
- Take advantage of the flowsheet connectivity
- No quantitative information of fault magnitude available

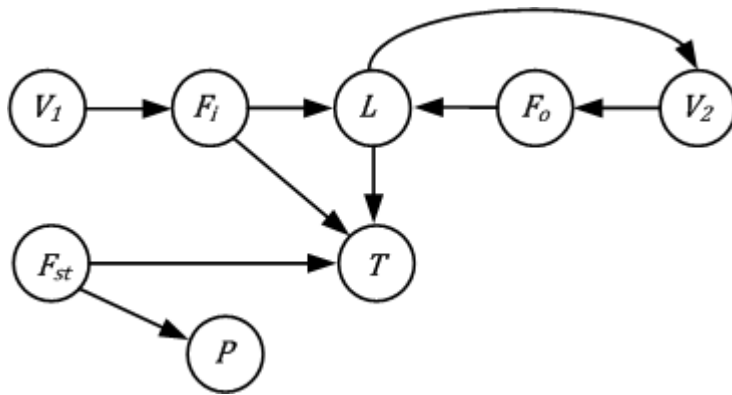


System-Level SP: General Strategy



Graph Based Approaches

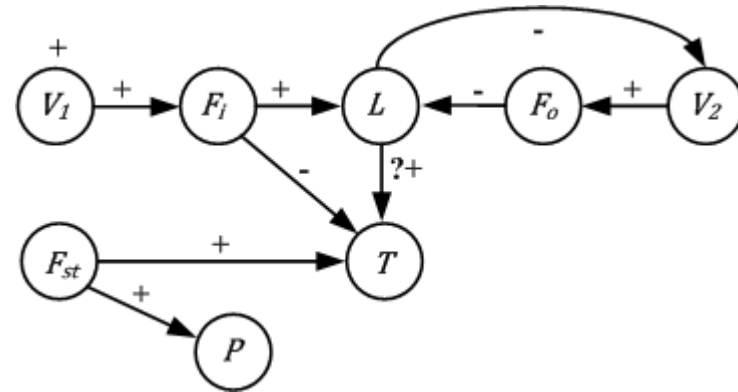
DG Representation



DG

- Change in variable $>$ Threshold \rightarrow Assign "1"
- Otherwise \rightarrow Assign "0"

SDG Representation



SDG

- Variable goes over threshold \rightarrow Assign "1"
- Variable goes below threshold \rightarrow Assign "-1"
- Otherwise \rightarrow Assign "0"

Fault observability

- Observability → Only response, not the direction → Matrix from DG
- SDG carries same information

$$A = \begin{bmatrix} 1 & 0 & 0 & 1 & \cdots & 1 \\ 0 & 0 & 1 & 1 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & 1 & \cdots & 1 \end{bmatrix}_{M \times N}$$

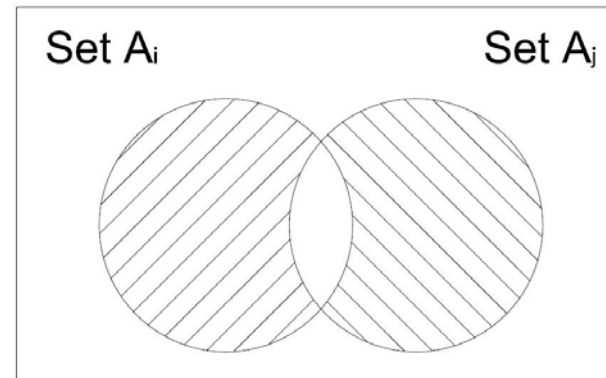
- Faults must be observed by at least one sensor

$$x_1 + x_2 + x_3 + \cdots + x_N \geq 1 \quad \rightarrow \quad b = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}_{M \times 1}$$

Fault resolution

- Add $\binom{M}{2}$ pseudo faults
- Pseudo-fault: Symmetric difference of a pair of faults
- Symmetric difference:
 - From Venn diagram
 - Matrix from SDG

$$B_{ij} = A_i \cup A_j - A_i \cap A_j$$



- Constraint matrix
 - $A \rightarrow$ Augment observability and resolution
 - $b \rightarrow$ vector of ones

Integer Programming

Objective function

- Minimize sensor network cost $\min f = \sum_j^N w_j x_j$

Constraint

- Observability and resolution $Ax^T \geq b$

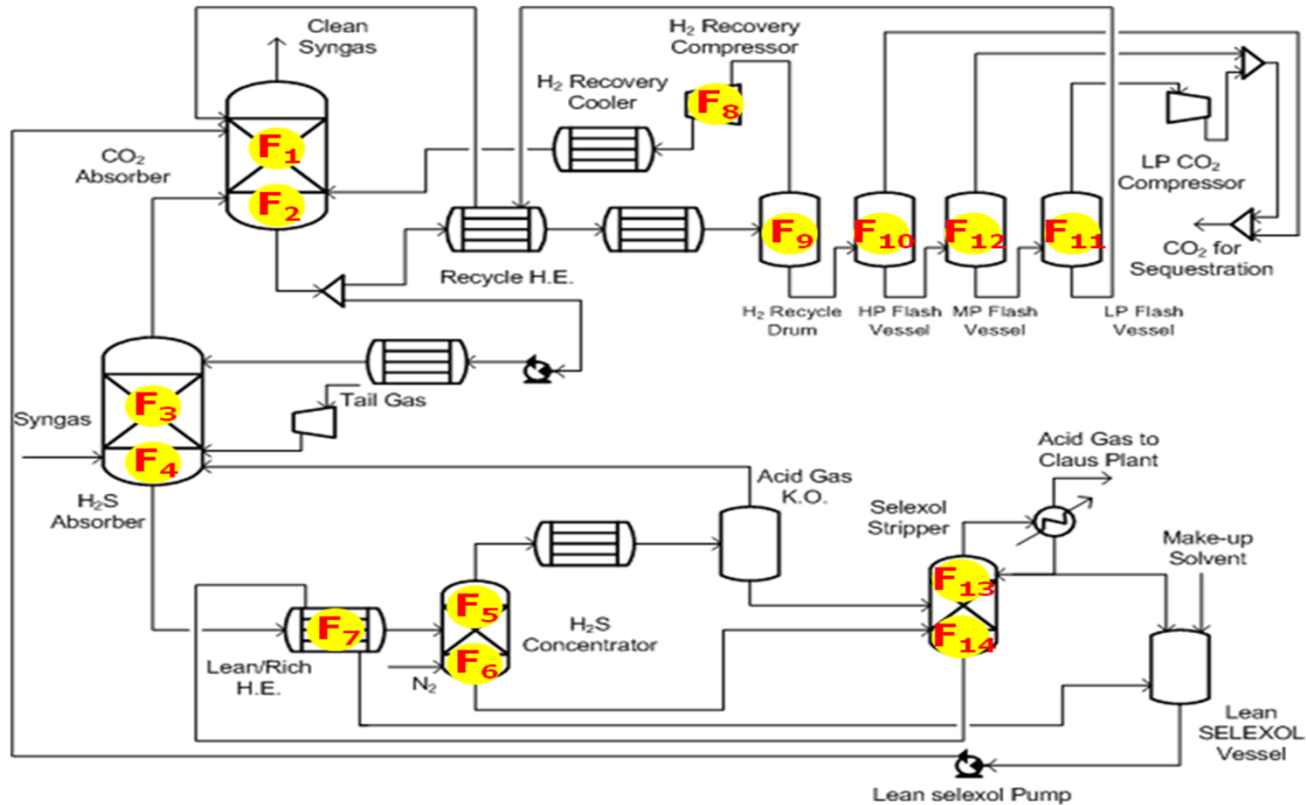
Decision variables

- Binary \rightarrow “**1**”: Variable measured “**0**”: Variable not measured
- Weight \rightarrow Cost of measuring sensor

Fault Simulation

Faults

- Type: Process knowledge/experience/open literature
- Magnitude: Designed/desired and tolerance



Results for plant wide sensor placement

Observability:

Sensor: Make-up solvent flow

Resolution:

DG: 4 Temperature sensors + 2 Flow sensors

Irresolvable faults: 15 faults

SDG: 2 Temperature sensors + 2 Flow sensors

Irresolvable faults: 15 faults , same as DG

- Number of sensors reduced in SDG
- All faults are not resolvable by DG/SDG

Enhancement to these algorithms helps in resolving more faults

Magnitude Ratio Algorithm

Motivation

$A = S_1/S_2$ for F_1

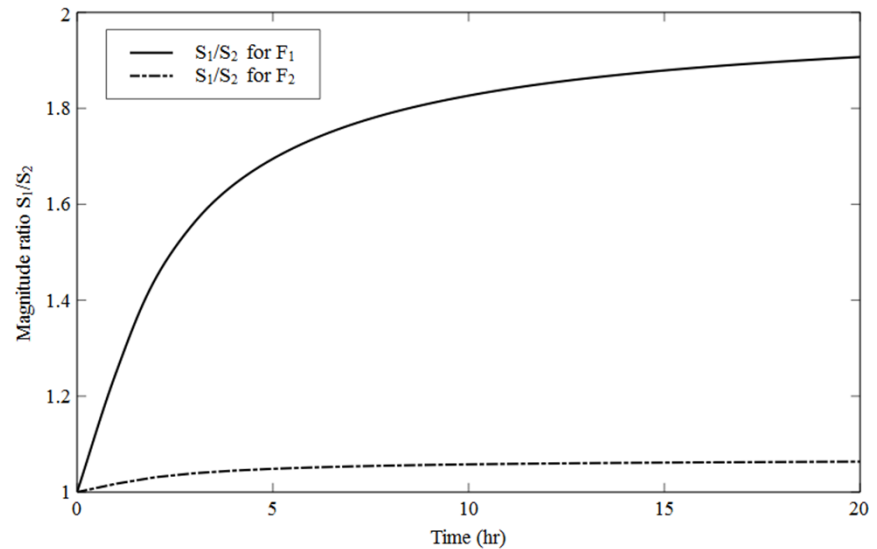
$B = S_1/S_2$ for F_2

➤ $A \gg B$

➤ $B \gg A$

➤ $A \cong B \cong 1$

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



Magnitude Ratio Algorithm

Magnitude ratio is defined as:

$$\mathbf{R}_{ij} = \frac{\mathbf{S}_i / \mathbf{S}_{i,SS}}{\mathbf{S}_j / \mathbf{S}_{j,SS}}$$

- \mathbf{R}_{ij} is pair of all variables and treated as a pseudo-sensors

Magnitude ratio algorithm:

- Define: Threshold (λ)
- If $\mathbf{R}_{ij} > \lambda$, assign "1"
- If $\mathbf{R}_{ij} < 1/\lambda$, assign "-1"
- Otherwise, assign "0"

Magnitude Ratio Algorithm

- $\binom{N}{2}$ pseudo sensors added to the decision variables
- Cost of the pseudo-sensors is set to zero
- Constraints:

$$(1 - x_i) + (1 - x_j) + x_{ij} \geq 1$$

$$(1 - x_{ij}) + x_i \geq 1$$

$$(1 - x_{ij}) + x_j \geq 1$$

Further Enhancement to SDG Algorithm

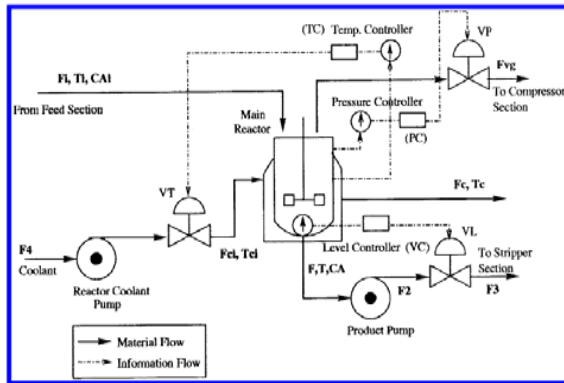
Fault evolution sequence algorithm

- Fault response sequence
- Comparing sequence of pairs can help in resolving faults

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	$S_1 S_2 S_3 S_4$	$\{S_1, S_2\}$ $\{S_1, S_3\}$ $\{S_1, S_4\}$ $\{S_2, S_3\}$ $\{S_2, S_4\}$ $\{S_3, S_4\}$

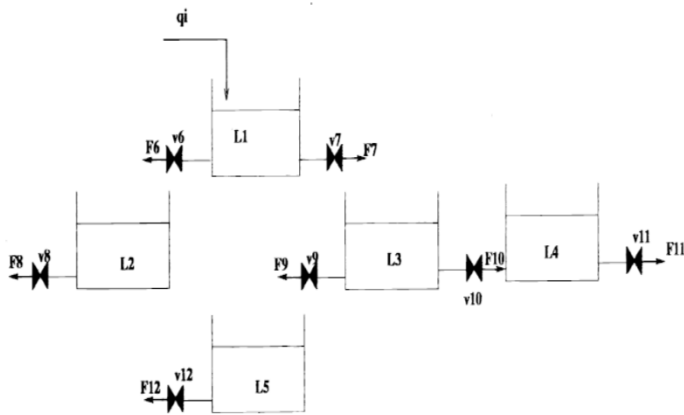
Magnitude Ratio Results

CSTR system



Algorithms	Sensors	Irresolvable
SDG	$[T_c, VT, VP], C_A$	1 fault
FES	$[T_c, VT, VP]$	1 fault \subseteq SDG
MR	$[T_c, VT, VP]$	[]
FES & MR	$[T_c, VT, VP]$	[]

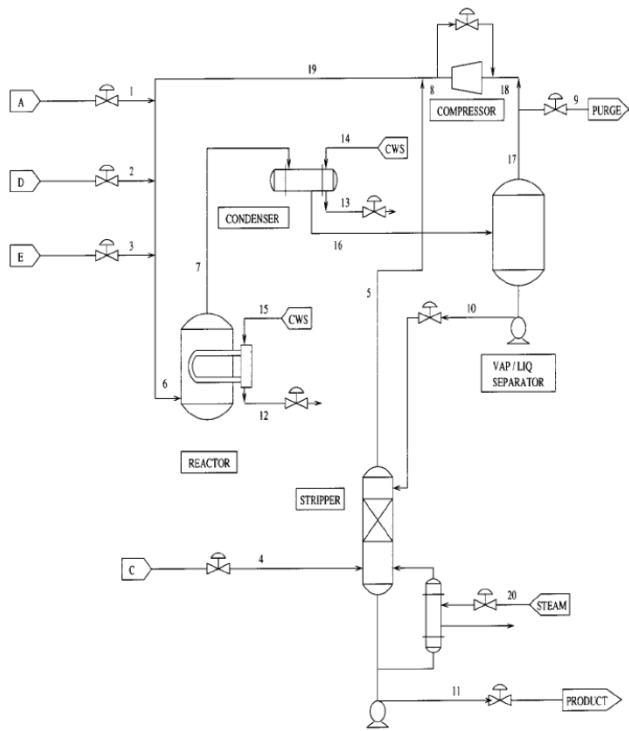
Five-tank



Algorithms	Sensors	Irresolvable
SDG	$[L2, F10], L5, L4$	1 fault
FES	$[L2, F10], F12$	[]
MR	$[L2, F10], L5$	[]
FES & MR	$[L2, F10], L5$	[]

Magnitude Ratio Results

TE process

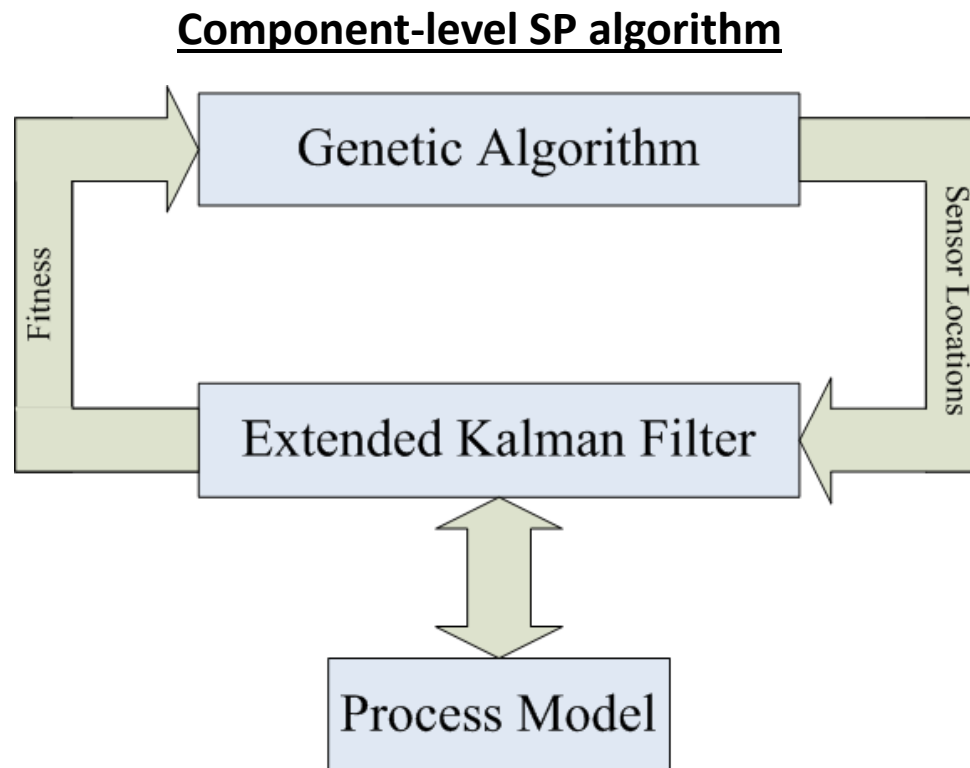


Alg.	Sensors	Irresolvable
SDG	$[F1, F9, F11, Tcs, VLs, VLp], F10, F2, Tcr$ <u>5 Flow, 2 Temp. and 2 Level Sensors</u>	10 fault sets
FES	$[F1, F9, F11, Tcs, VLs, VLp], F10, Pr$ <u>4 Flow, 1 Temp., 2 Level and 1 Pressure Sensors</u>	6 fault sets \subseteq SDG
MR	$[F1, F9, F11, Tcs, VLs, VLp], Pr$ <u>3 Flow, 1 Temp., 2 Level and 1 Pressure Sensors</u>	Same as FES
FES&MR	$[F1, F9, F11, Tcs, VLs, VLp], Pr$ <u>3 Flow, 1 Temp., 2 Level and 1 Pressure Sensors</u>	Same as FES

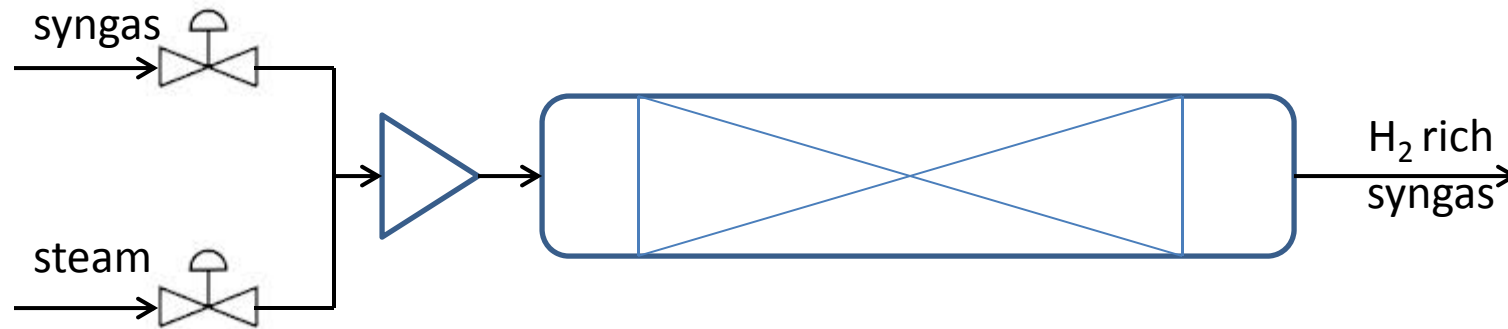
Tier II: Distributed Sensor Placement

Component-level SP

- Interested in condition monitoring
- Faults cannot be resolved from a system-level scope
- Estimation of unmeasurable states



Water gas shift reactor (WGSR)



- 1st principle, 1-D, PDAE model developed using conservation equations in MATLAB
- Reaction kinetics obtained by data reconciliation from erroneous / noisy data from literature
- Simulate faults such as catalyst deactivation over time

Model Summary

- Total equations : 76
 - 53, differential
 - 23, algebraic
- Hence the system becomes a DAE system
- Total states are 76
- The equations are solved in MATLAB with ODE15S

Estimator

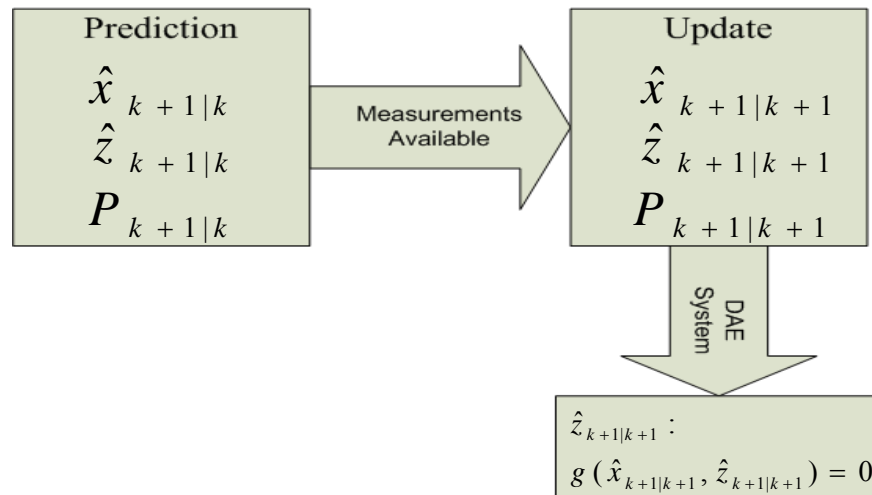
- State Estimation
 - Process models is nonlinear with a system of differential and algebraic equations (DAE)
- Nonlinear estimator that can handle DAE systems is required
 - Extended Kalman filter for DAE systems

Summary of State Estimation

- DAE system is linearized at each time step as:

$$\begin{cases} \dot{x} = Ax + Bz \\ 0 = Cx + Dz \end{cases} \rightarrow \begin{bmatrix} \dot{x} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} A & B \\ -D^{-1}CA & -D^{-1}CB \end{bmatrix} \begin{bmatrix} x \\ z \end{bmatrix}$$

- Prediction and update steps of EKF for DAE systems:

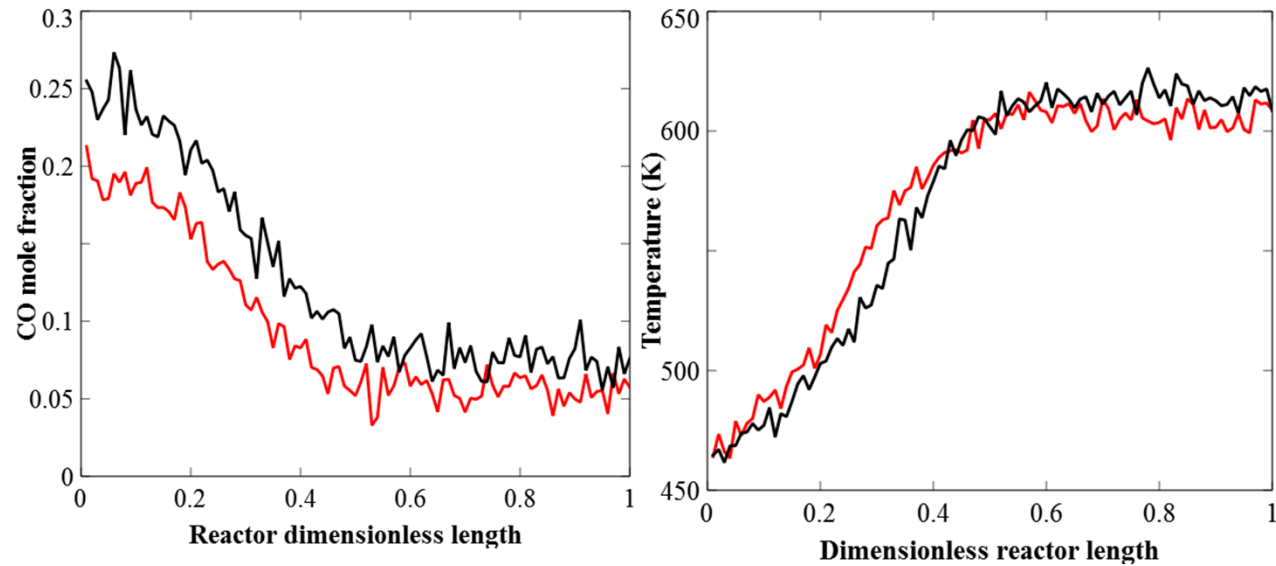


Fault Simulations

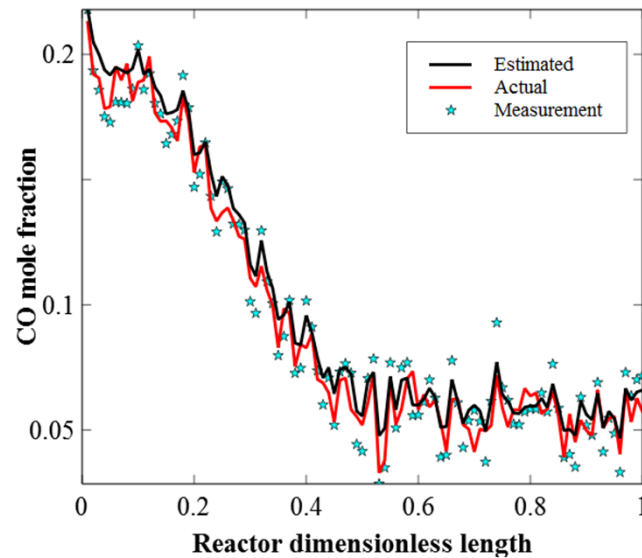
- Porosity of the catalyst bed → modify ε
- Catalyst deactivation → change the pre-exponential factor at specific location of the reactor
- Change in surface area of the catalyst leading to changes in the effectiveness factor

Estimation of states in presence of noise

- Catalyst deactivation



- State estimation



Problem formulation for optimization

- At each time step, a noisy measurement of the states are made:

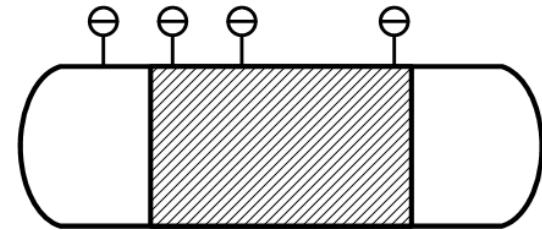
$$y_k = Hx_k + v_k$$

- where, H matrix is constructed from a binary vector

$$[1 \ 0 \ 0 \ 1 \ . \ . \ . \ 0 \ 1 \ 1]$$

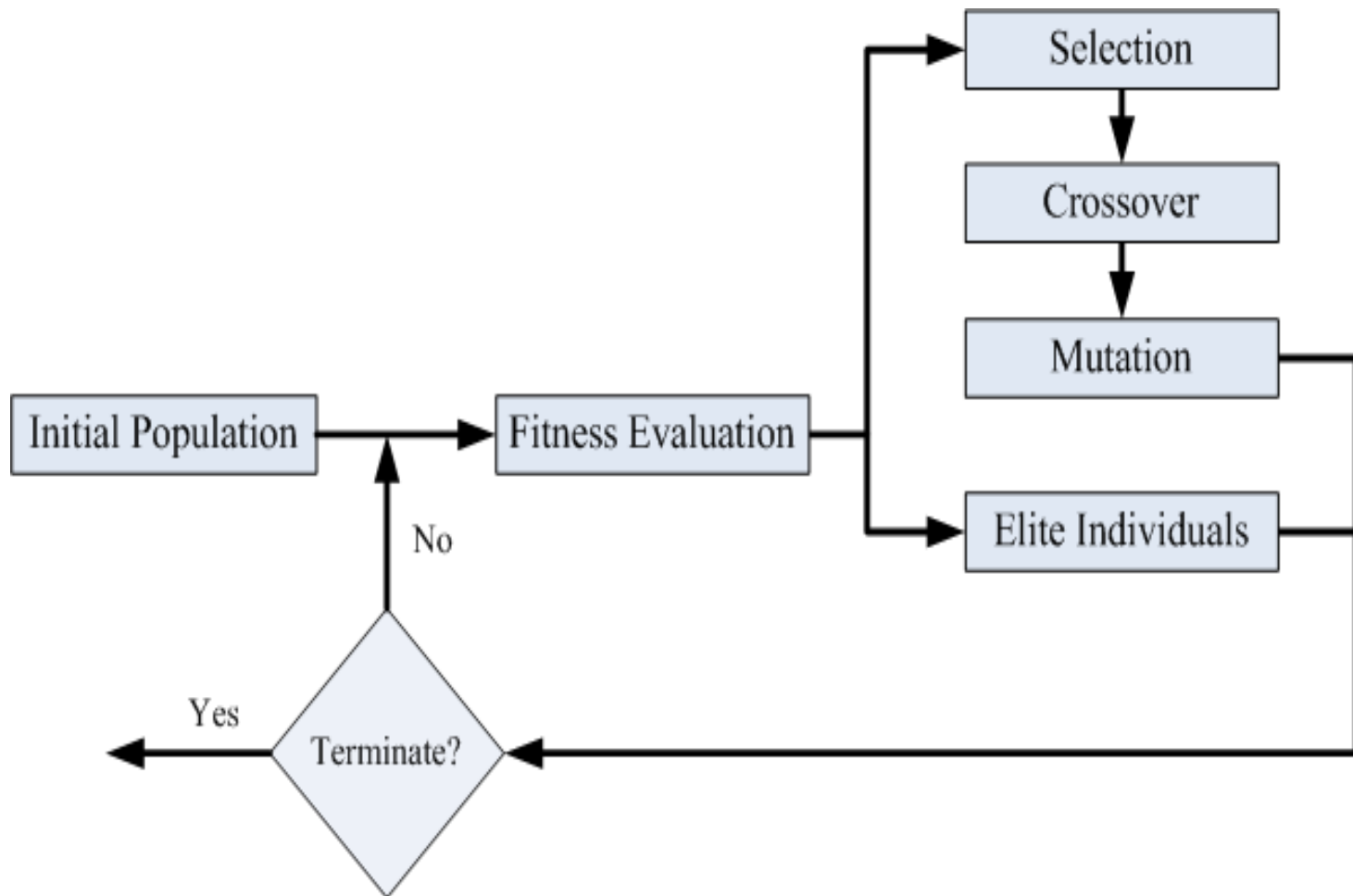
- The binary vector contains the sensors information:

- Location
- Number
- Type



- Search space for measurement model is huge (2^{400})
- Evolutionary algorithm can help us surf the space to find optimal model
- **Genetic Algorithm!**

Genetic Algorithm



Simulation

- The nonlinear system is simulated with ramp disturbances which includes:
 - 5% increase in inlet temperature (from 550 to 575.5 K)
 - 20% increase in syngas CO mole fraction (from 0.31 to 0.372)
- The system is simulated with the following specifications:
 - Process noise: 10^{-2}
 - Concentration, pressure and temperature measurement noise: 10^{-2}
 - Error covariance: 10^{-4}

Genetic Algorithm

- The fitness function, as reported previously, is calculated as:

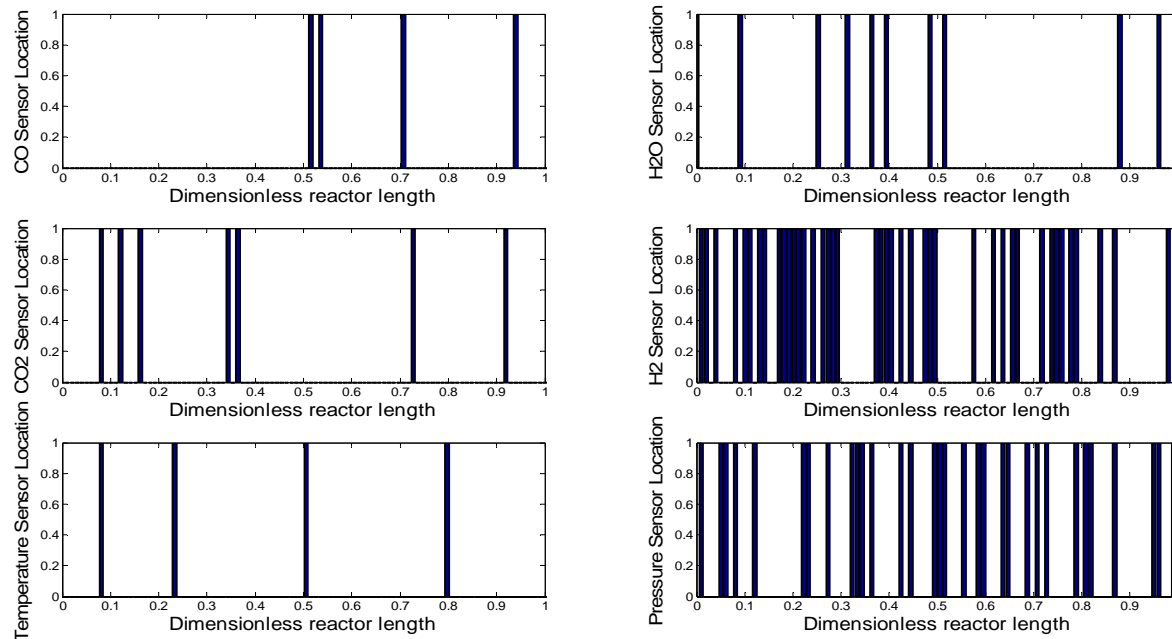
$$e_{total} = \sum_1^{707} (x_{estimated} - x_{actual})^2$$
$$Fitness = \exp(-e_{total})$$

- Fitness function is normalized by the fitness of the individual where all states are measured.

$$Normalized\ Fitness = \frac{\exp(-e_{total,100\ sensors})}{\exp(-e_{total,607\ sensors})}$$

GA Results

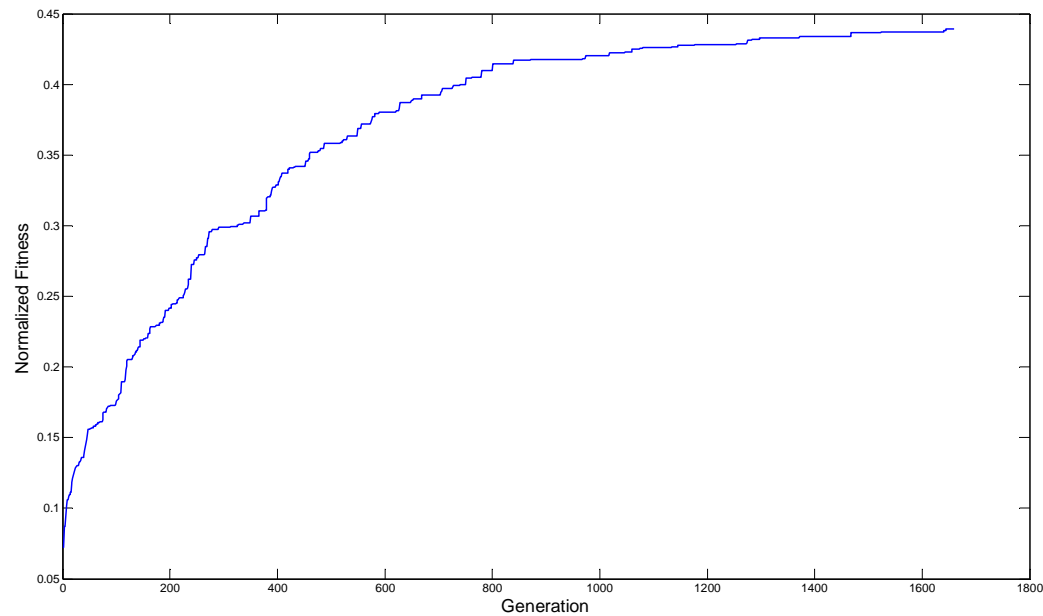
- Value 1, shown as a bar, indicates that a sensor has to be placed at the specified location of the reactor
- The figure is prepared with information from current generation of the GA algorithm.



Sensor locations on the dimensionless reactor length after 470 generations

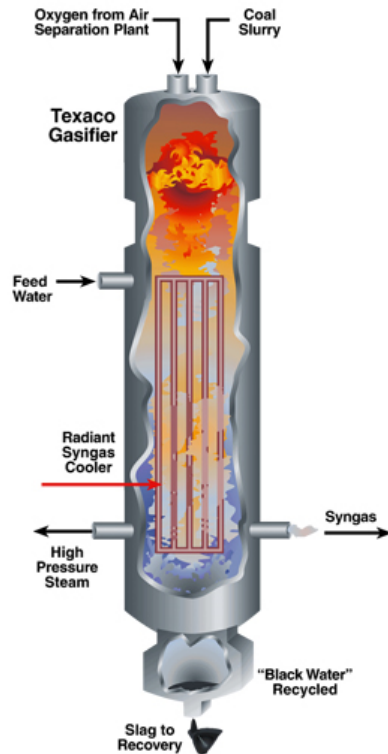
GA results

- A fixed number of sensors (=100) is assumed and the genetic algorithm is run to find best combination of the sensors.
- The fitness is normalized with the case that all measurable states are measured.



Distributed Sensor Placement In Gasifier

Gasifier-Model



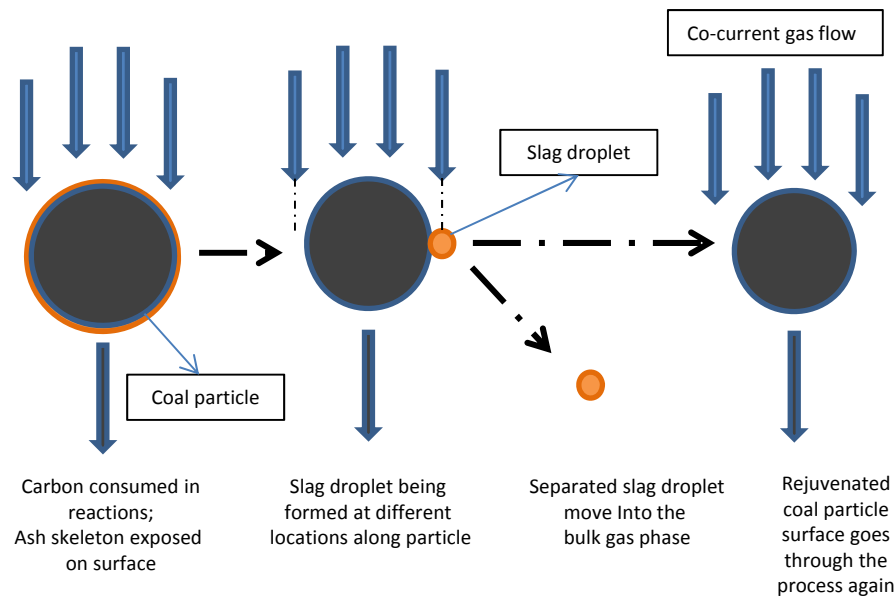
- Gasifier operates at temperatures of about 1200-1600°C
- Liquid slag flows on walls and is collected at bottom
- Gasifier model developed at WVU does not consider slagging phenomenon
- Slag penetration mainly responsible for refractory degradation

Two-stage model for slag deposition

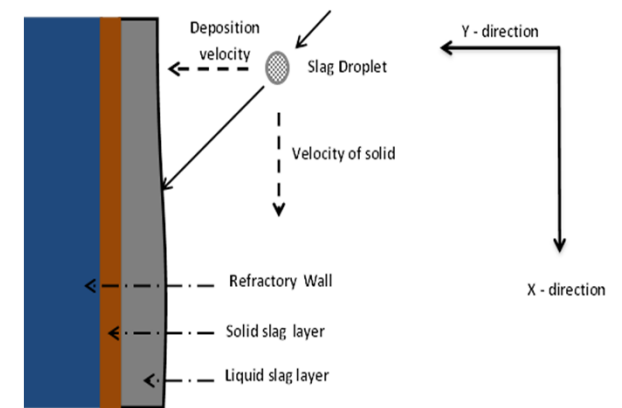
1. Slag formation and detachment

2. Slag deposition and flow

Model Development

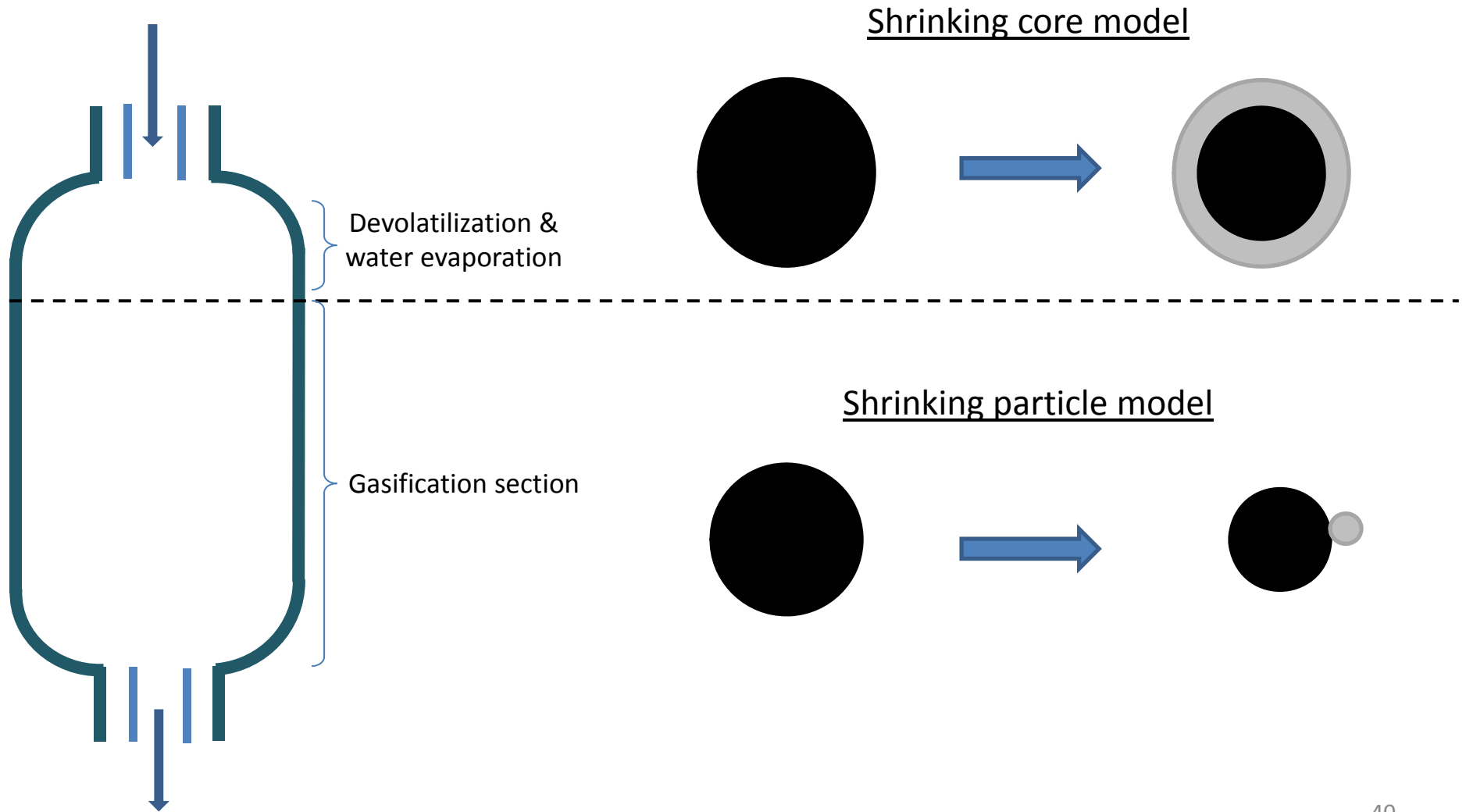


Slag formation on char particle

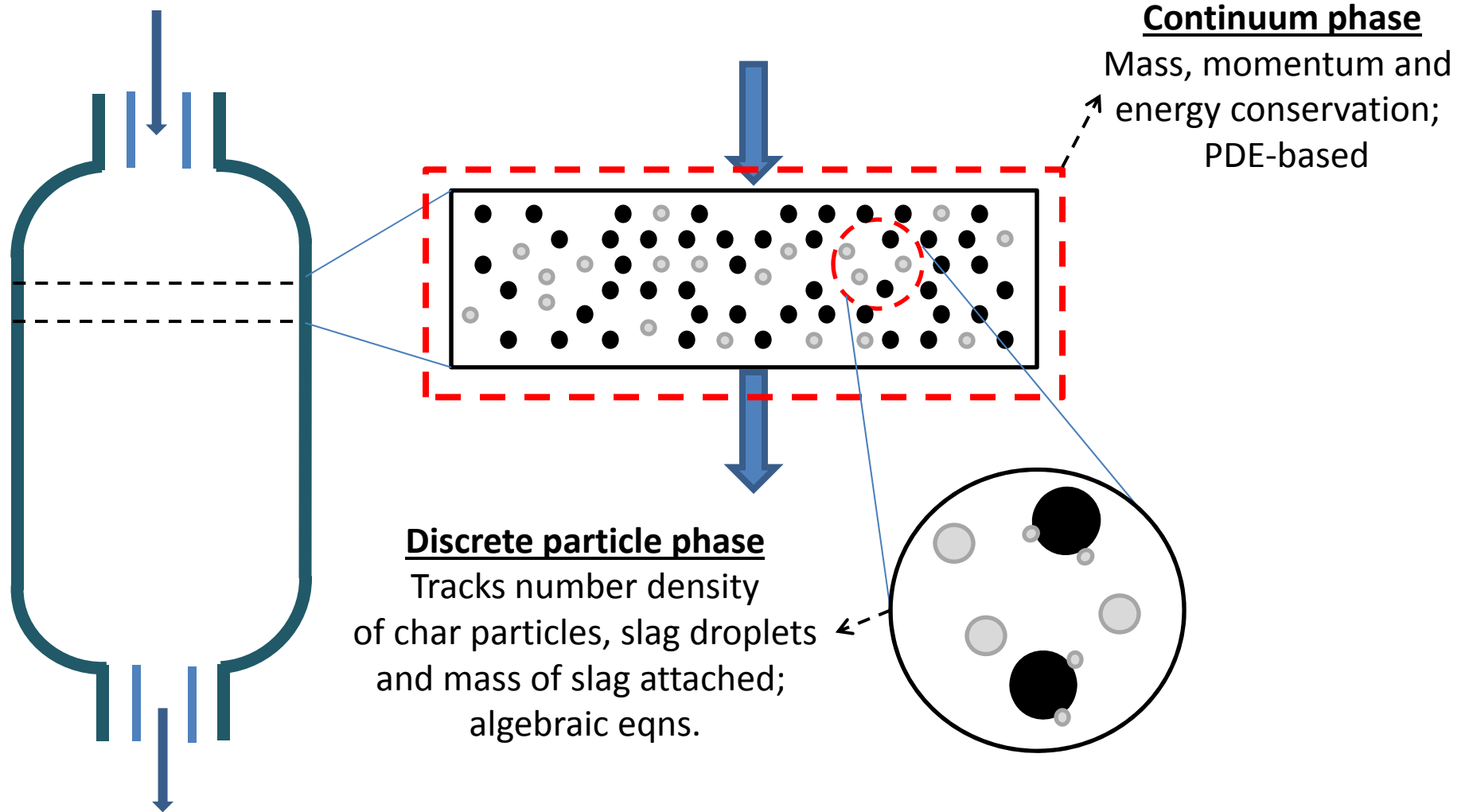


Slag deposition

Reaction Models Used in Non-Slagging and Slagging Gasifier Section

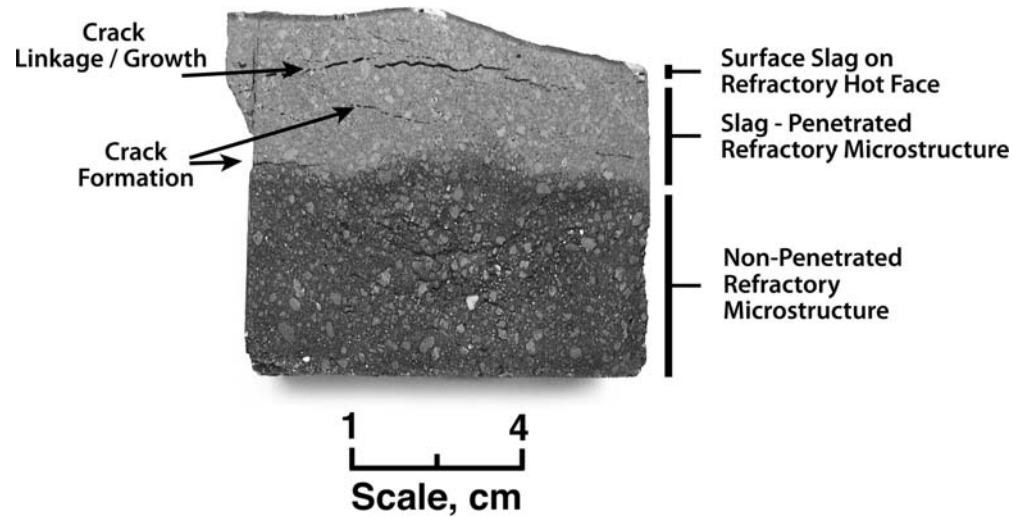


Integration of Continuum and Discrete Particle Phase



Gasifier Fault - Refractory Degradation

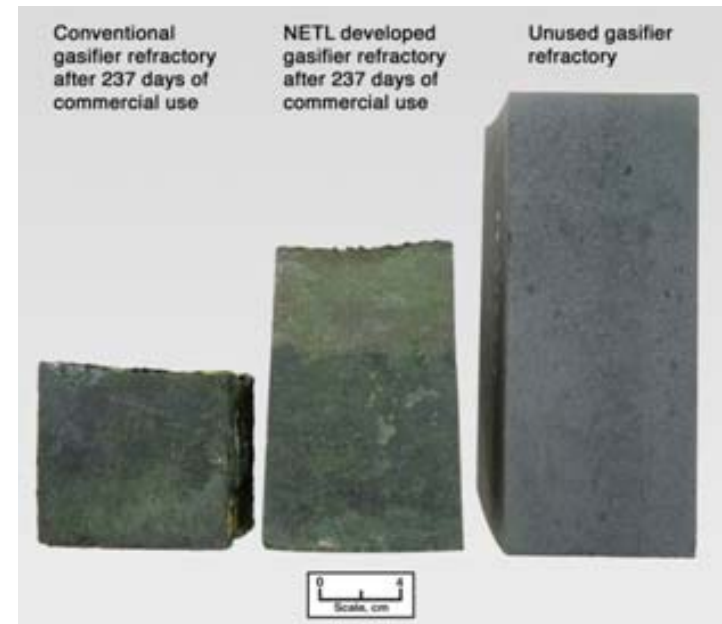
☐ Slag penetration



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

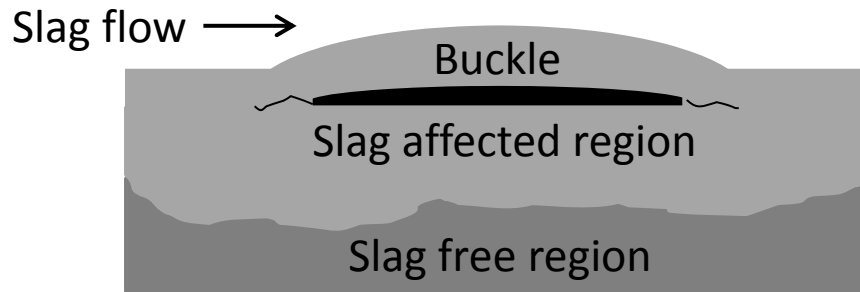
☐ Spalling

- ☐ Tensile Spalling
- ☐ Compressive Spalling



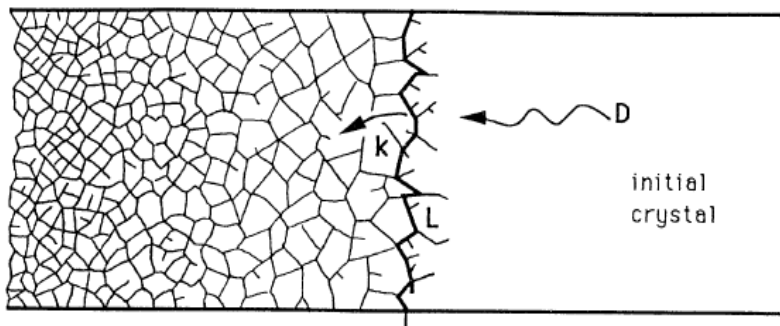
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Compressive Spalling



- $\text{Fe}^{3+}/\text{Cr}^{3+}$ substitution
- Results in Buckling

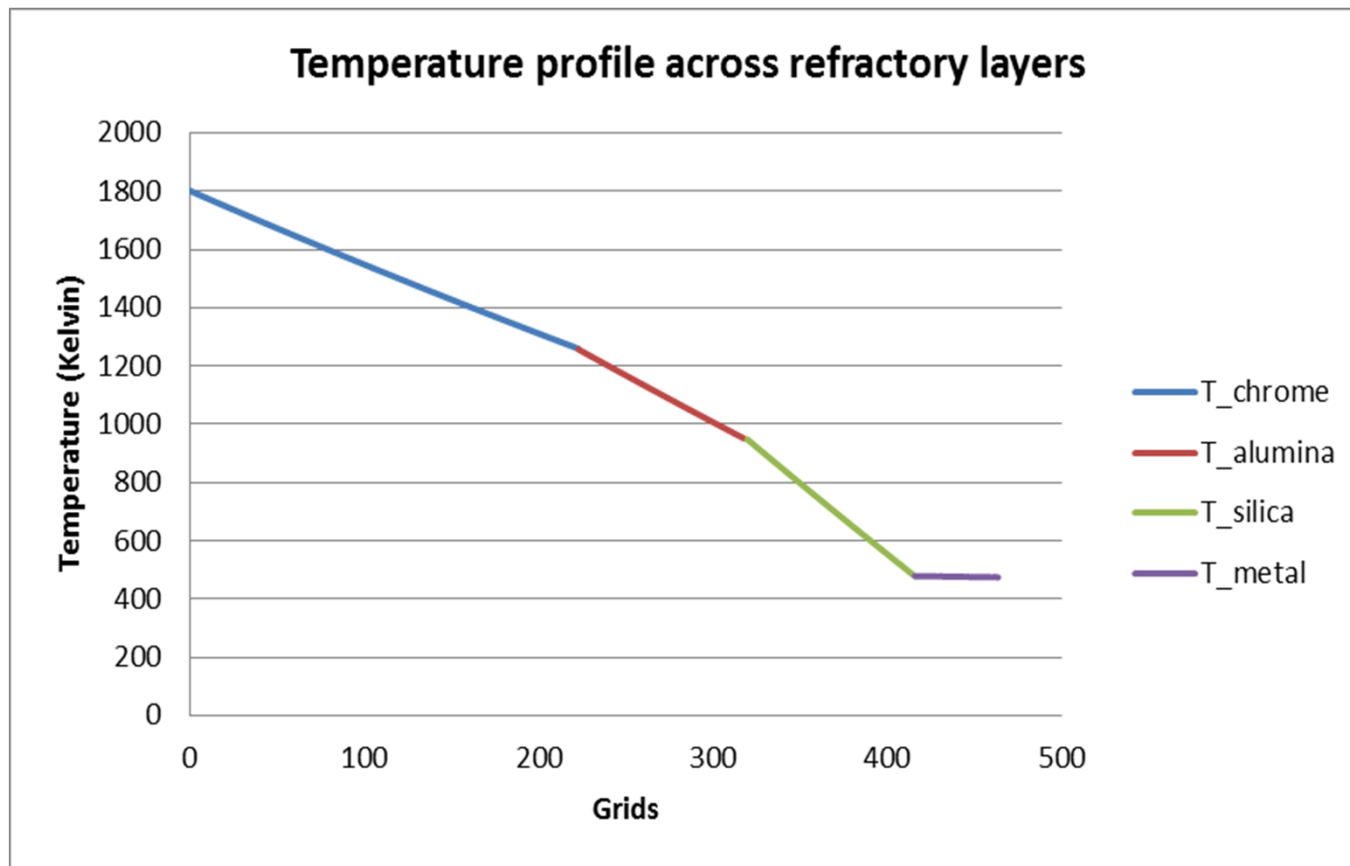
Tensile Spalling



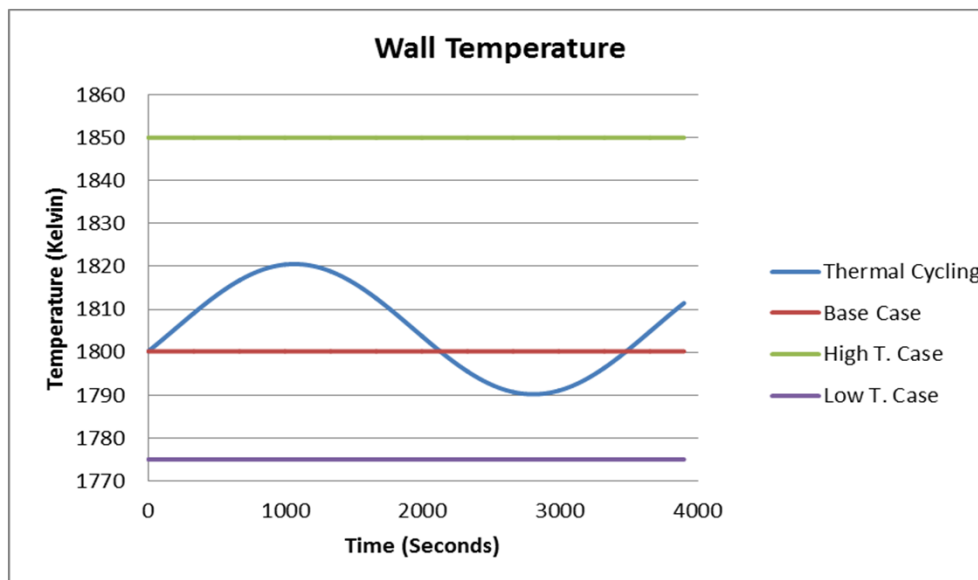
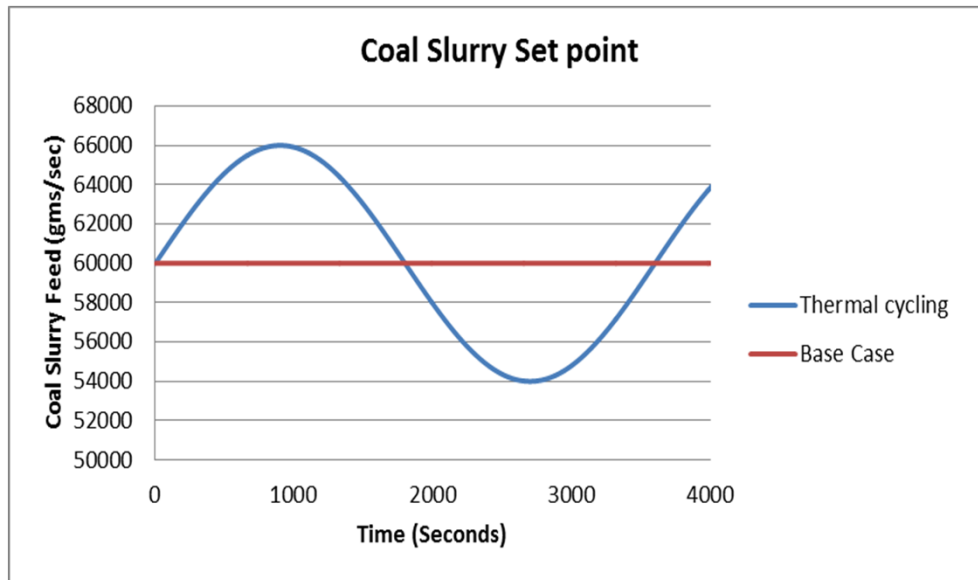
- Cr^{3+} migration
- Cracked structure

Results : Gasifier

Steady state temperature profile

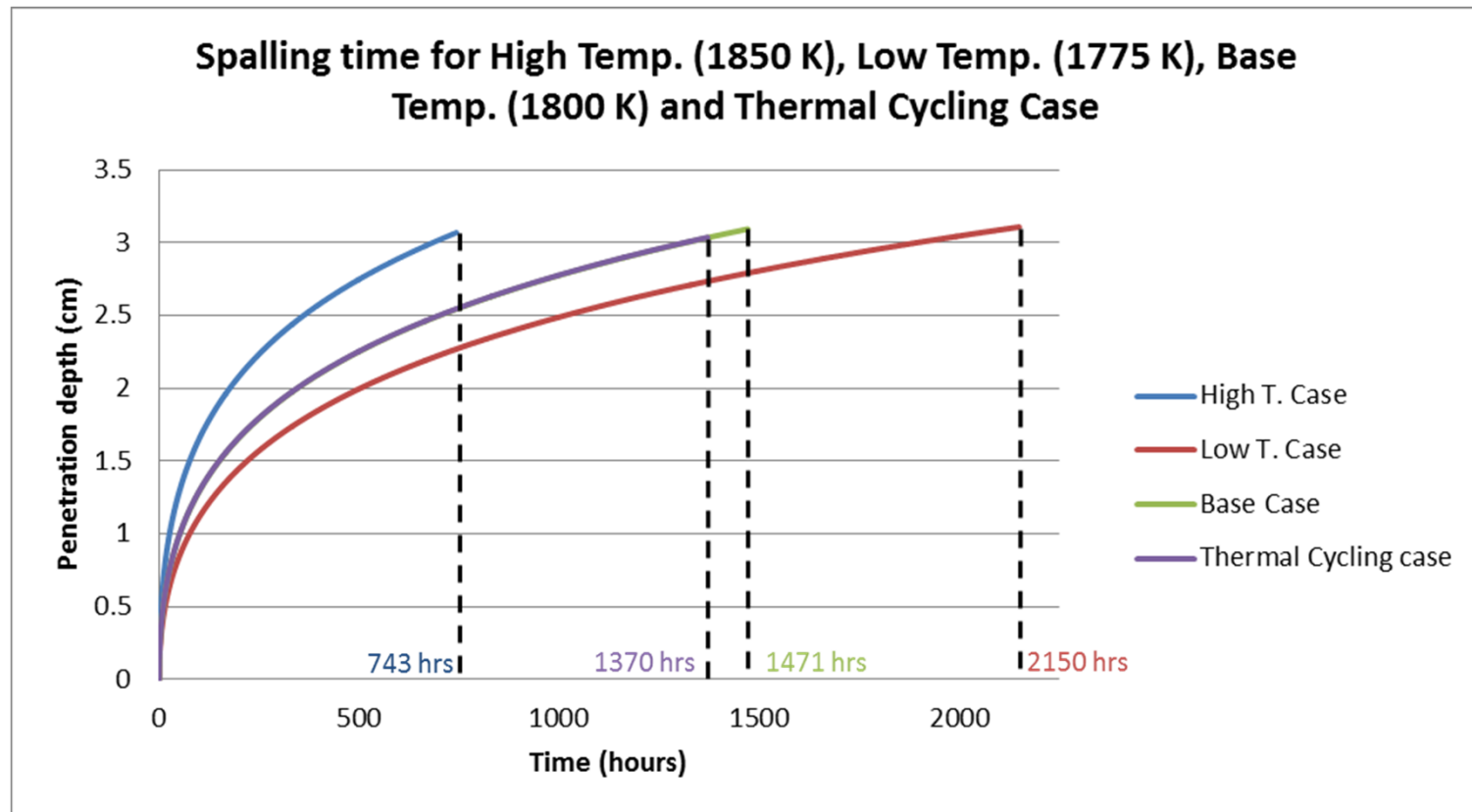


Testing: Base, Thermal Cycling, High and Low Case



- Coal slurry SP was oscillated using sinusoidal function with period of 1 hour
- Slag model wall temperature was found for this input and fit
- Wall temperature was used as boundary condition for Refractory Degradation model
- Gasifier model and Degradation model operate at different time scales

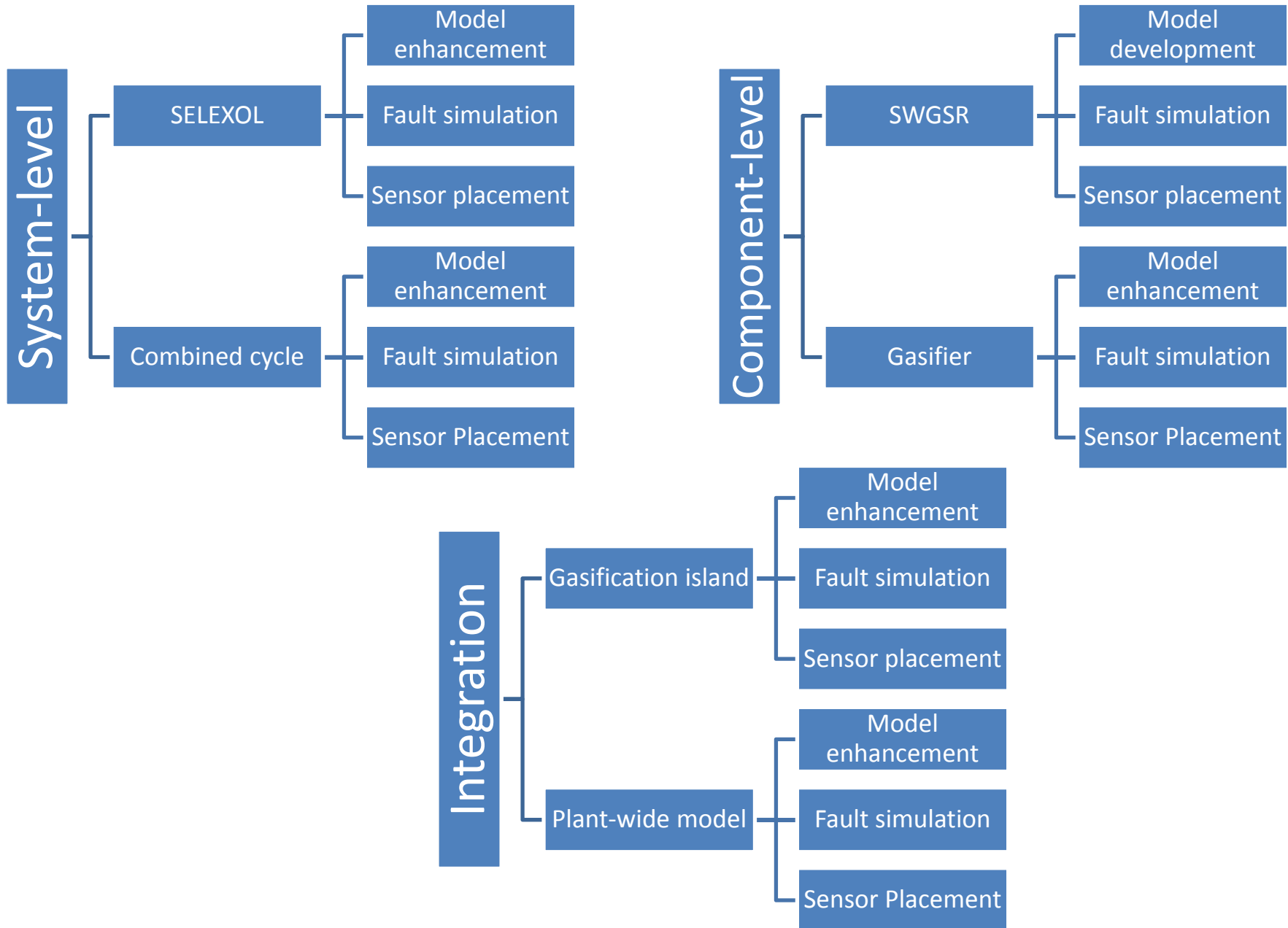
Results : Refractory Spalling time



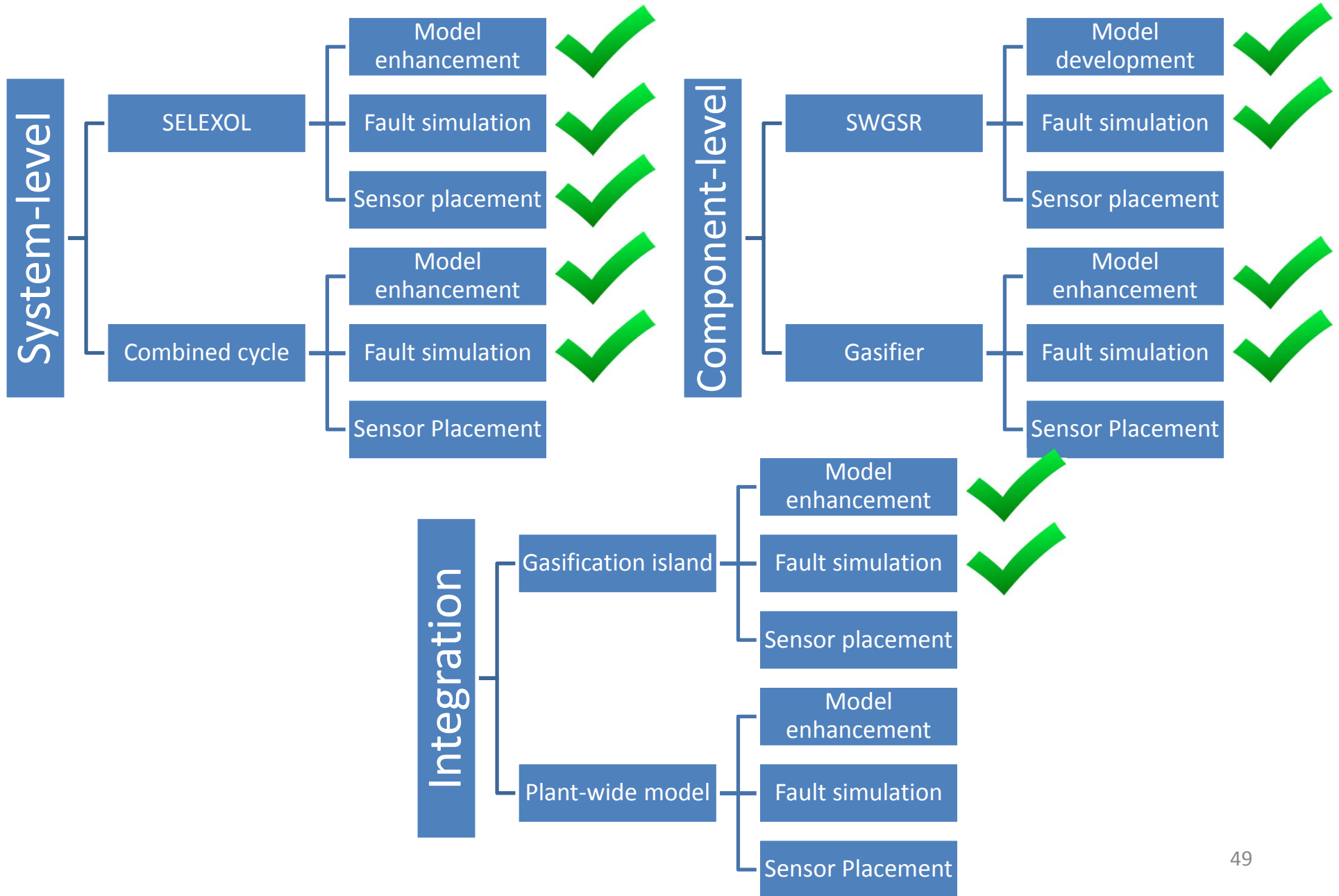
Future work

- Develop a reduced order gasifier model for estimation
- Implement distributed sensor placement algorithms on the gasifier
- Integrating the gasifier model into the gasification Island
- Perform two tier sensor placement algorithm

Current status



Current status



Acknowledgment

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