Multi-Objective Optimal Sensor Deployment Under Uncertainty for Advanced Power Systems

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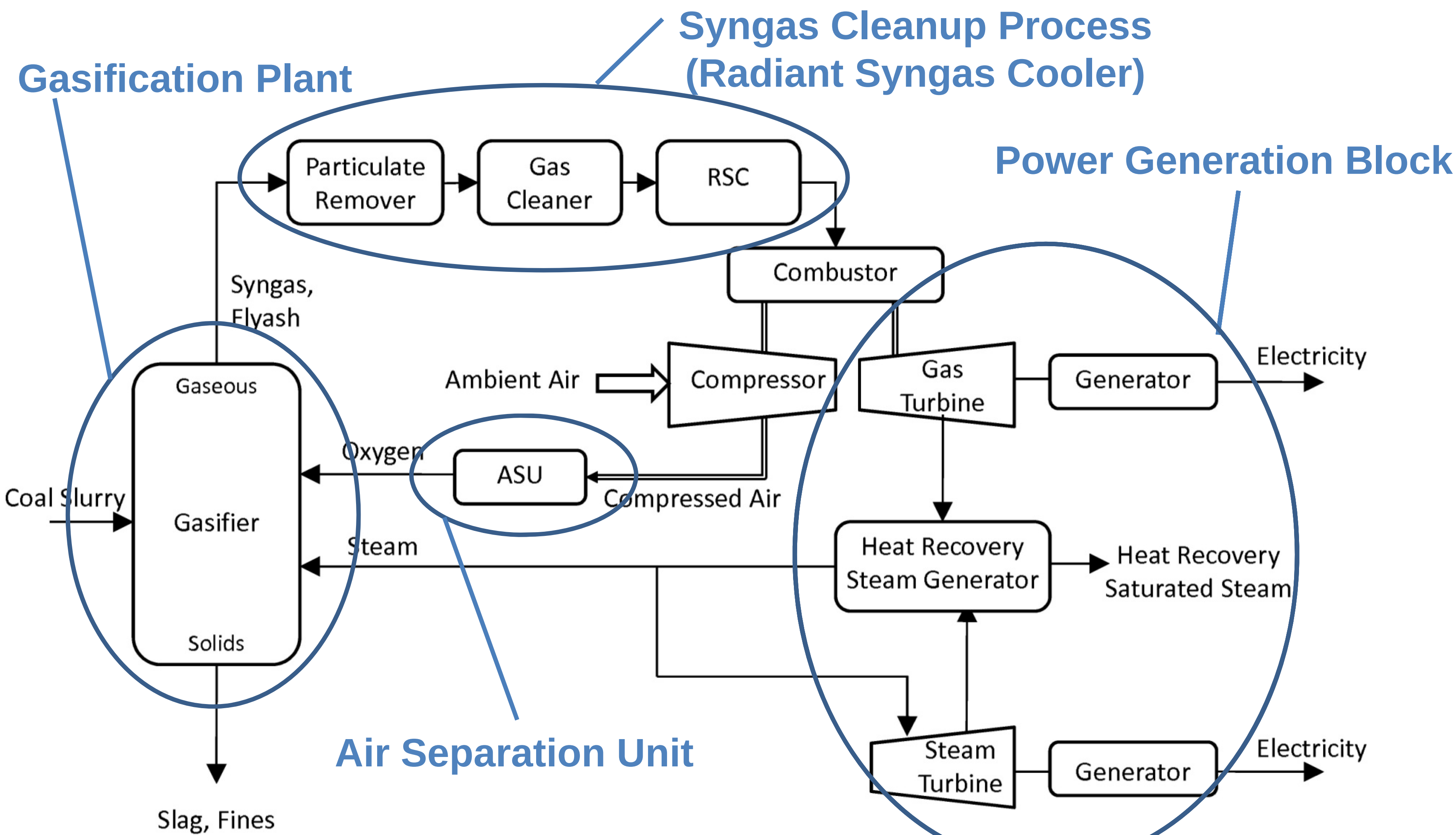
Sensor Placement Problem

- Advanced Power Systems
  - Integrated Gasification Combined Cycle (IGCC)
- Objectives
  - Determine optimal location of network of sensors
  - Minimize number of sensors in network
  - Maximize Efficiency, Maximize Observability, Minimize Cost
- Constraints
  - Mass and Energy Balances
  - Environmental factors
  - Sensor accuracy

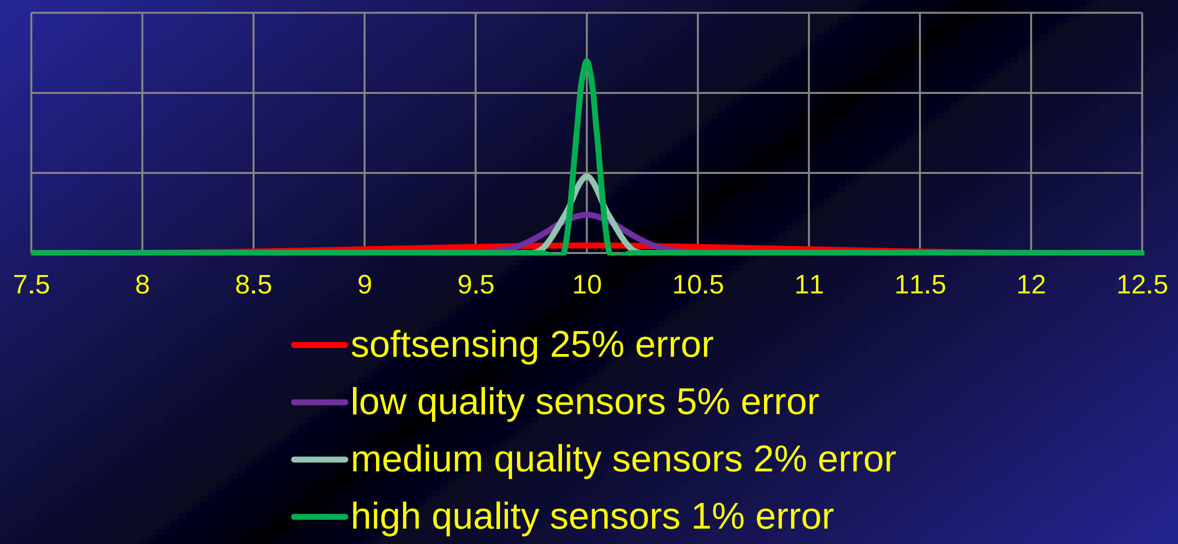
Main Elements of IGCC Plant



Model Uncertainties

- Variations to process variables lead directly to variations in the gasification performance
- Plant with no sensors use models to control variations
  - Soft sensing
  - Introduces large errors in control resulting in large variations in output variables
  - Reduced observability
- Sensors reduce errors in control
- Cost of sensors is linked to errors in sensing
  - High cost sensors, less variation
  - Low cost sensors, high variation

Model Uncertainties



Mixed Integer Nonlinear, Stochastic Optimization Problem

- Determine location of on-line sensors to maximize observability of system, maximize efficiency subject to budget constraint

$$\max_{y_{j,\tau} \in Y} \quad \sum_{\tau=1}^{T} \sum_{j=1}^{S^{out}} f_{j,\tau}(\psi) y_{j,\tau}, \sum_{\tau=1}^{T} \sum_{j=1}^{S^{out}} E_{j,\tau}(\psi, y_{j,\tau})$$

$$\text{s.t.} \quad \sum_{\tau=1}^{T} \sum_{j=1}^{S^{out}} C_{j,\tau}\, y_{j,\tau} \le B$$

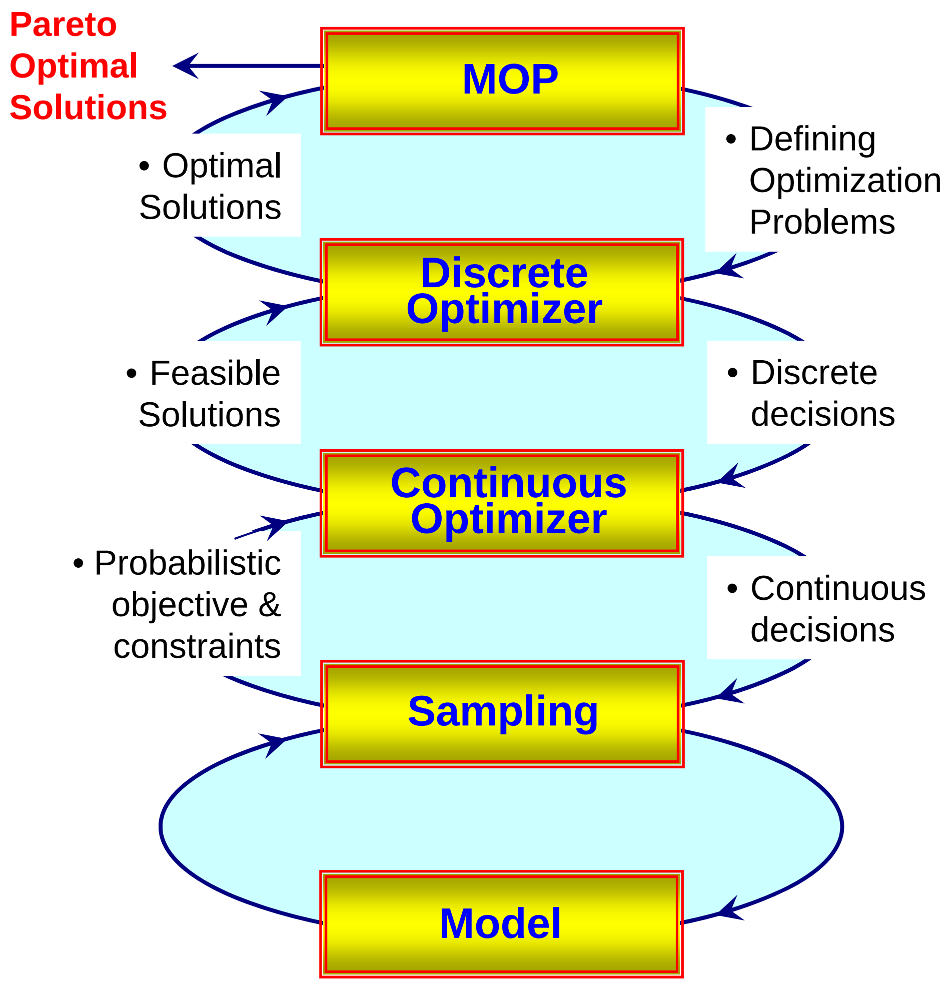
$$\sum_{\tau=1}^{T} y_{j,\tau} \le 1, \qquad j = 1,2,\ldots,S^{out}$$

$$y_{j,\tau} \in \{0,1\}, \qquad j = 1,2,\ldots,S^{out}, \tau = 1,2,\ldots,T$$

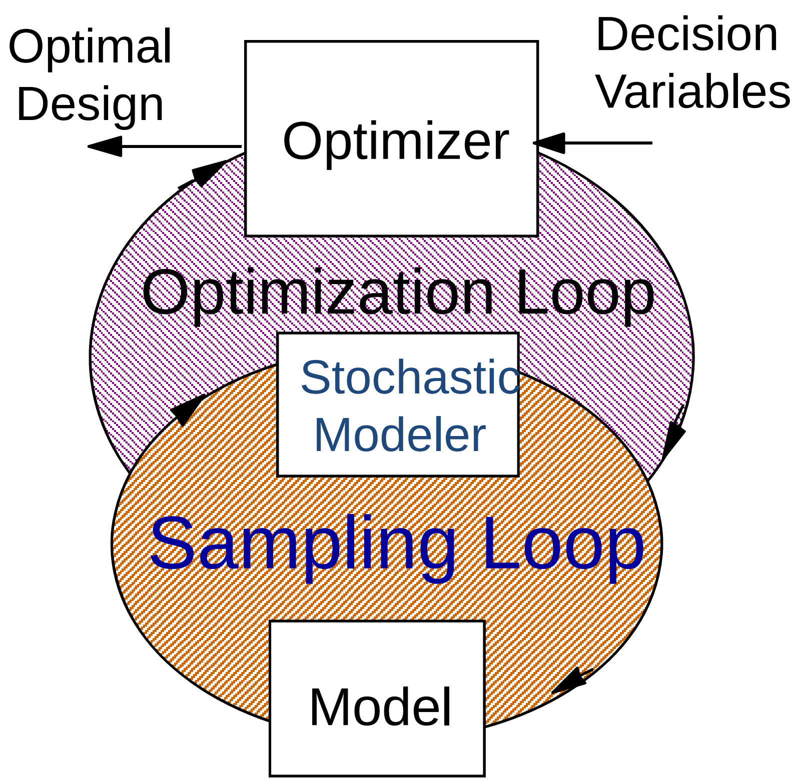
Mass and Energy Balances around the Plant

- ψ = network of on-line sensors;
- $f_{j,\tau}(\psi)$ = level of observability resulting from the placement of sensor type τ at location *j;*
- $E_{,\tau}(\psi, yj)$ = efficiency as a nonlinear function of placement of sensor type τ at location *j*

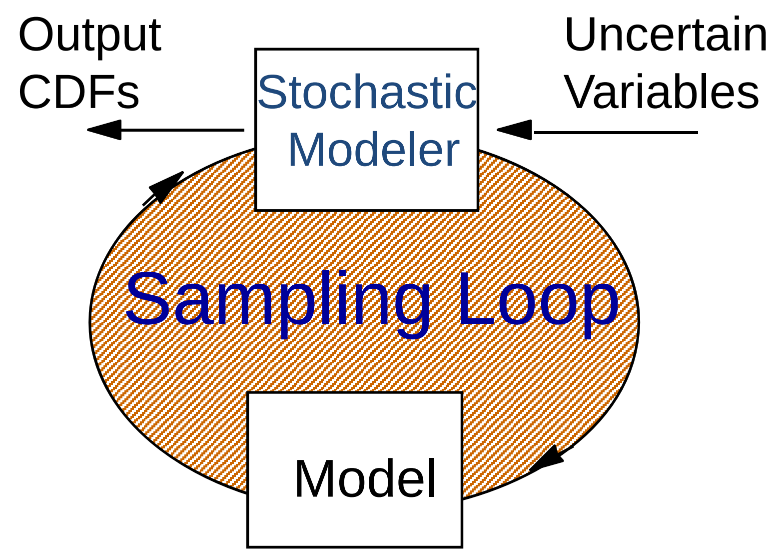
Multi-objective Optimization under Uncertainty



Optimization under Uncertainty



Stochastic Optimization



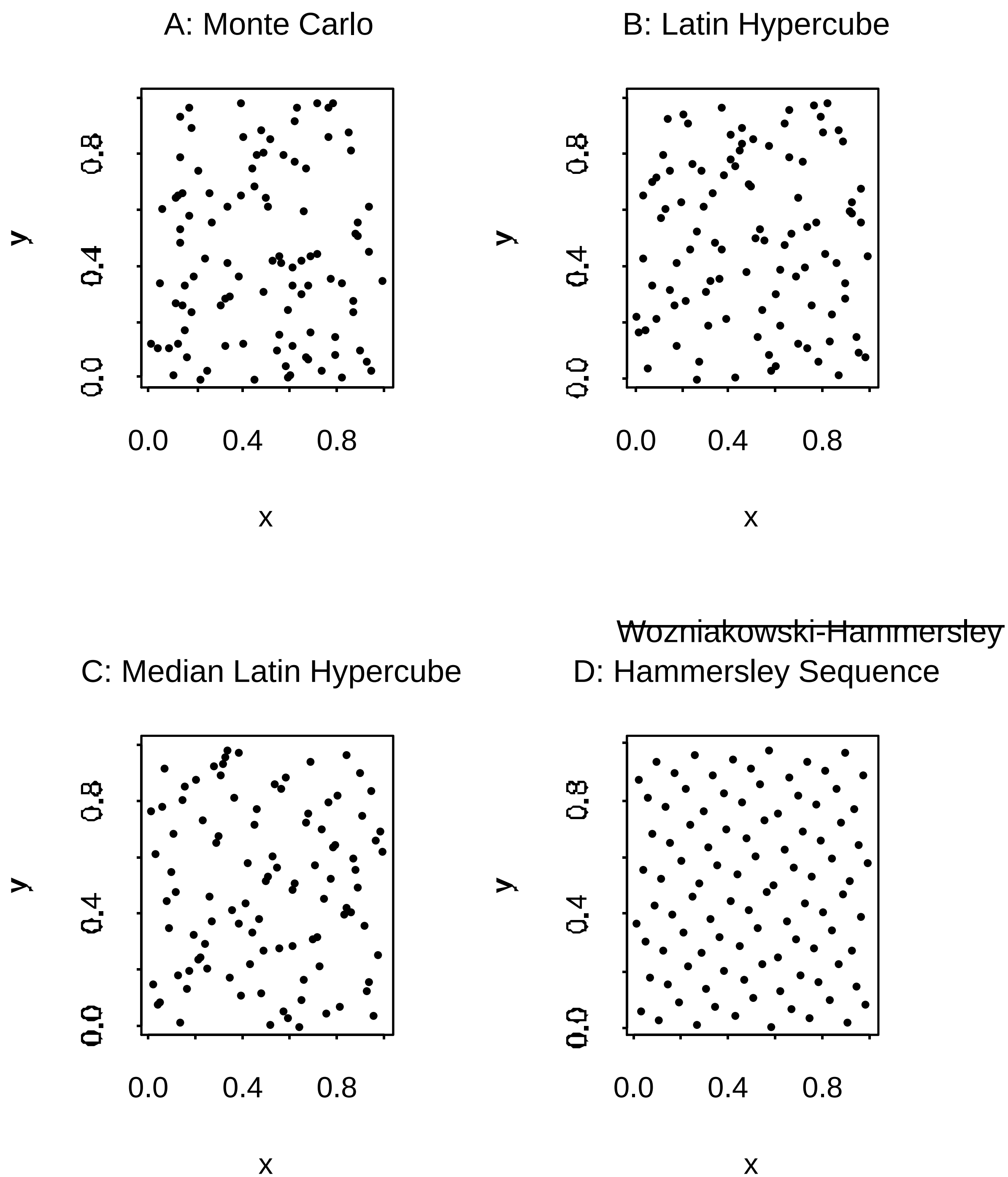
Stochastic Modeling

Important Properties of Sampling Techniques

- Independence / Randomness
- Uniformity

In most applications, the actual relationship between successive points in a sample has no physical significance, hence, randomness of the sample for approximating a uniform distribution is not critical (Knuth, 1973).

Once it is apparent that the uniformity properties are critical to the design of sampling techniques, constrained or stratified sampling becomes appealing (Morgan and Henrion, 1990).

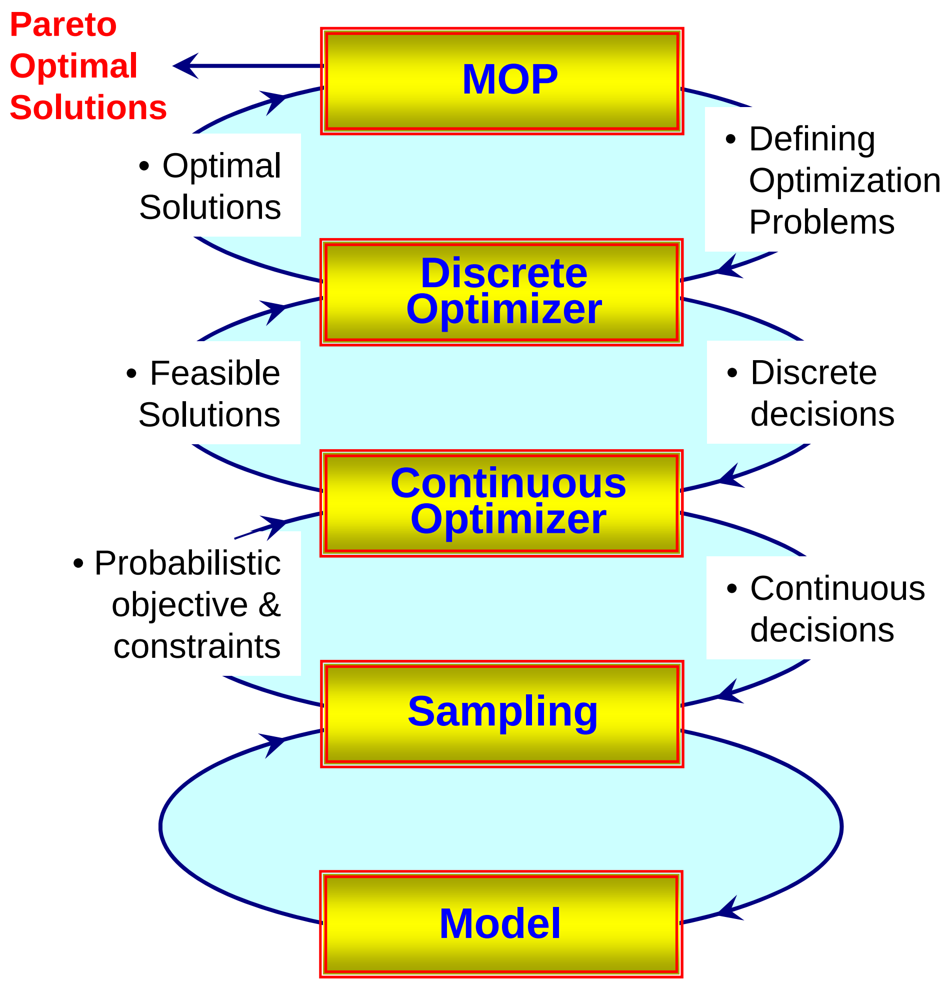

A: Monte Carlo
B: Latin Hypercube
~~Wozniakowski-Hammersley~~
C: Median Latin Hypercube
D: Hammersley Sequence
0.0
0.4
0.8
x
y

Novel Sampling Technique

- Hammersley Sequence Sampling (HSS) based on a Quasi-random number generator
- HSS sampling is at least 3 to 100 times faster than LHS or MCS.
- HSS is preferred sampling for stochastic modeling and/or stochastic optimization.

HSS $\longrightarrow$ LHHS $\longrightarrow$ HSS2

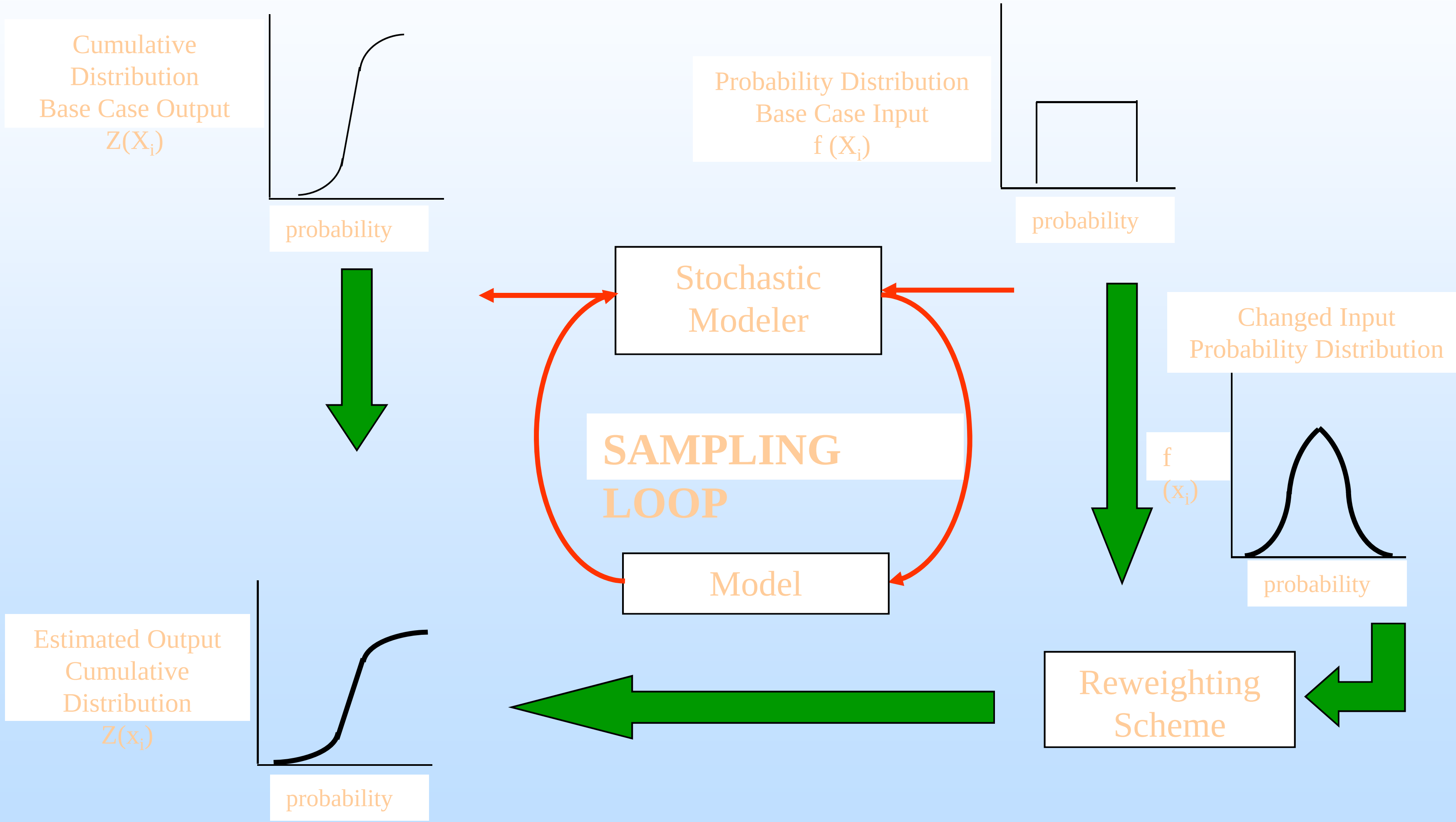
Multi-objective Optimization under Uncertainty



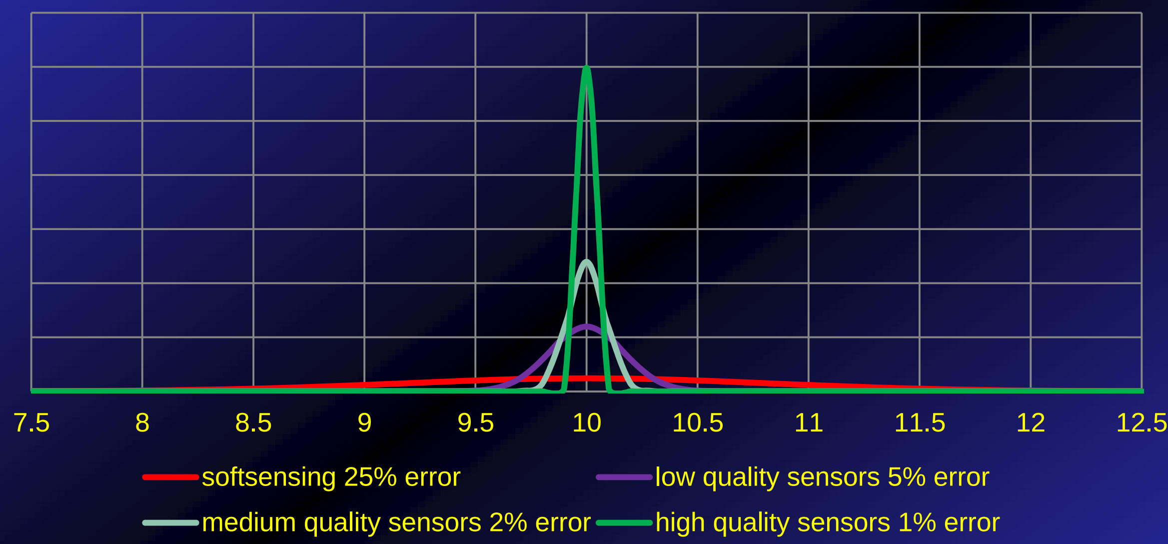
Simulation Technique

- Simulate IGCC process N_s times
  - Comprehensive plant model in ASPEN Plus environment
  - Hammersley sequence sampling used to generate uniform spaced samples across *d*-dimensional sample space
- Better Optimization for Nonlinear Uncertain Systems (BONUS) (Sahin and Diwekar, 2004)

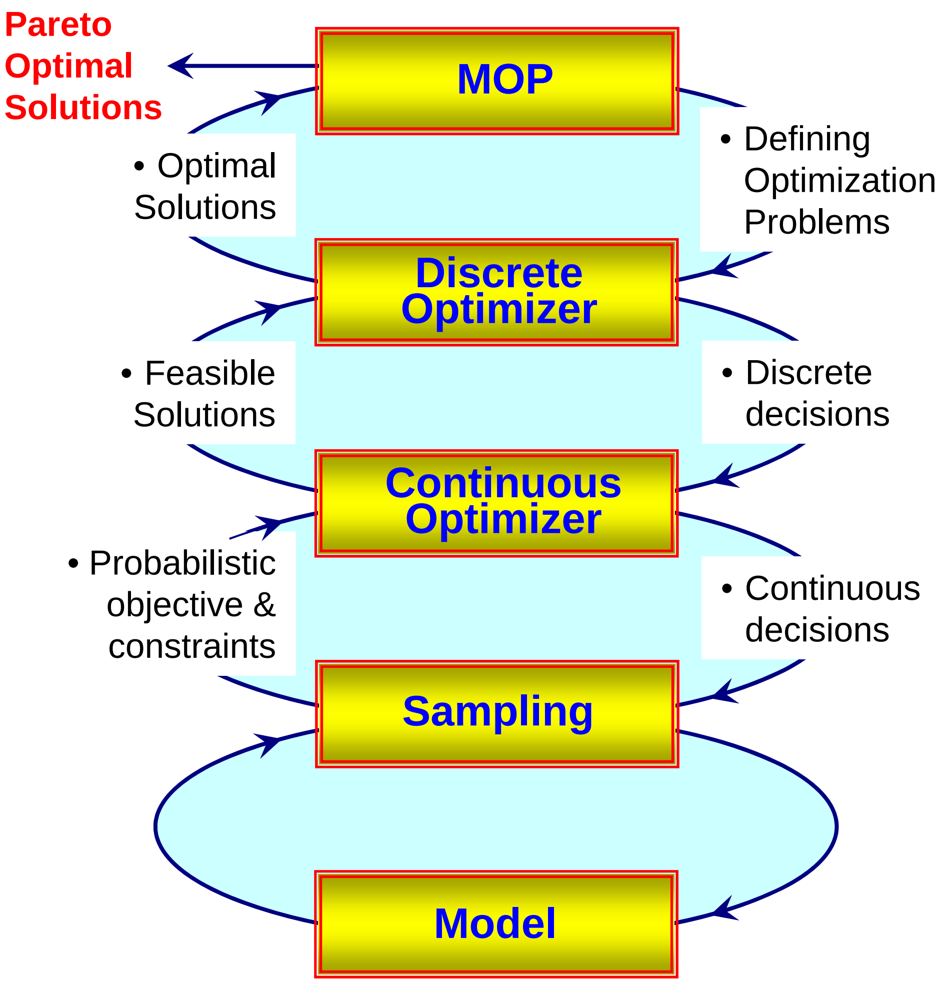
Better Optimization of Nonlinear Uncertain Systems (BONUS)



Model Uncertainties



Multi-objective Optimization under Uncertainty



A Simple Multi-objective Linear Example

Max $Z1 = 6x1 + x2$

$Z2 = - x1 + 3x2$

subject to:

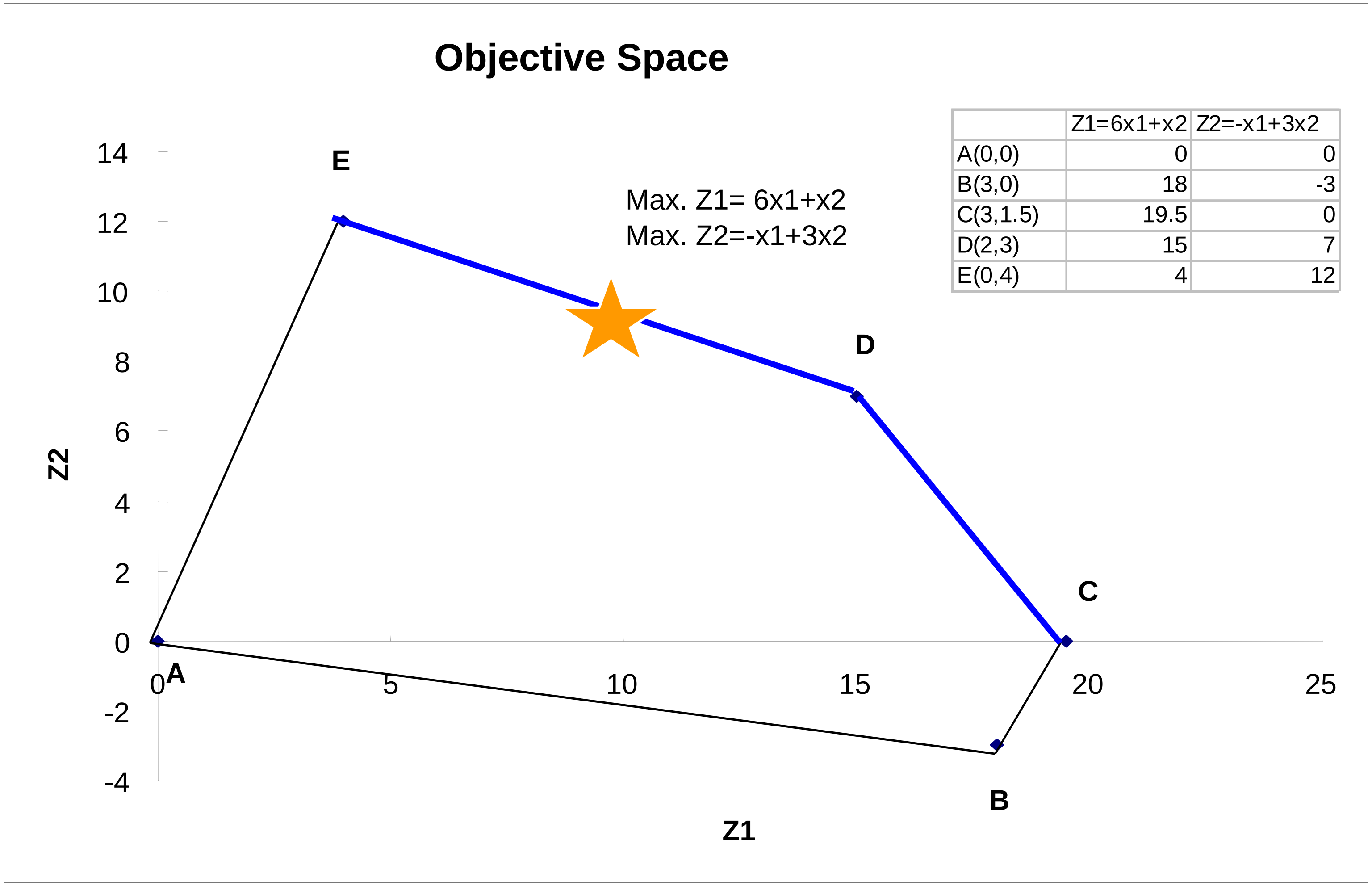
$3x1 + 2x2 \leq 12$

$3x1 + 6x2 \leq 24$

$x1 \leq 3$

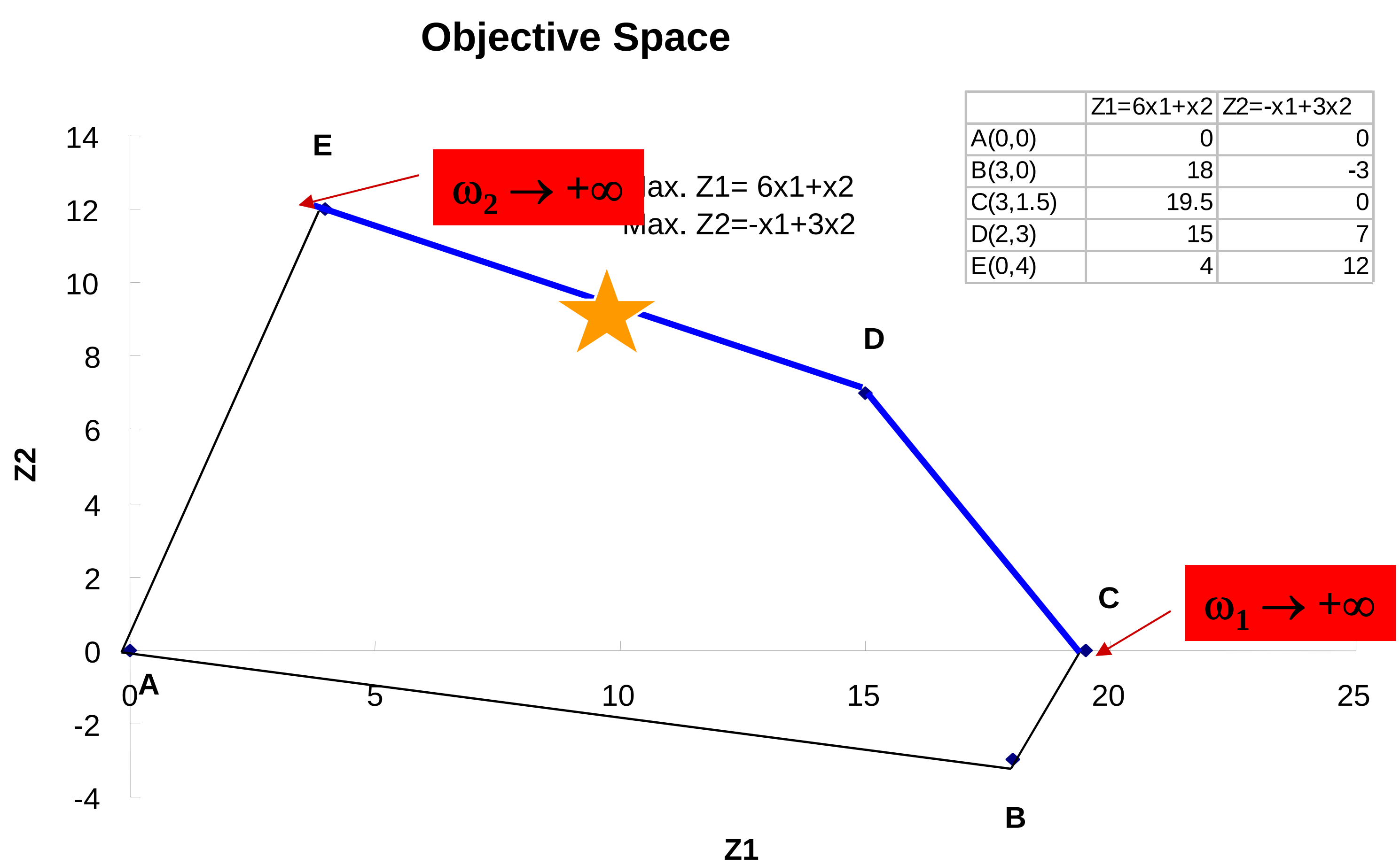
$x1, x2 \geq 0$

Weighting Method: Max.$Y=\omega_1 * Z_1 + \omega_2 * Z_2$



	Z1=6x1+x2	Z2=-x1+3x2
A(0,0)	0	0
B(3,0)	18	-3
C(3,1.5)	19.5	0
D(2,3)	15	7
E(0,4)	4	12

Weighting Method: Max.Y=ω_1*Z_1+ω_2*Z_2



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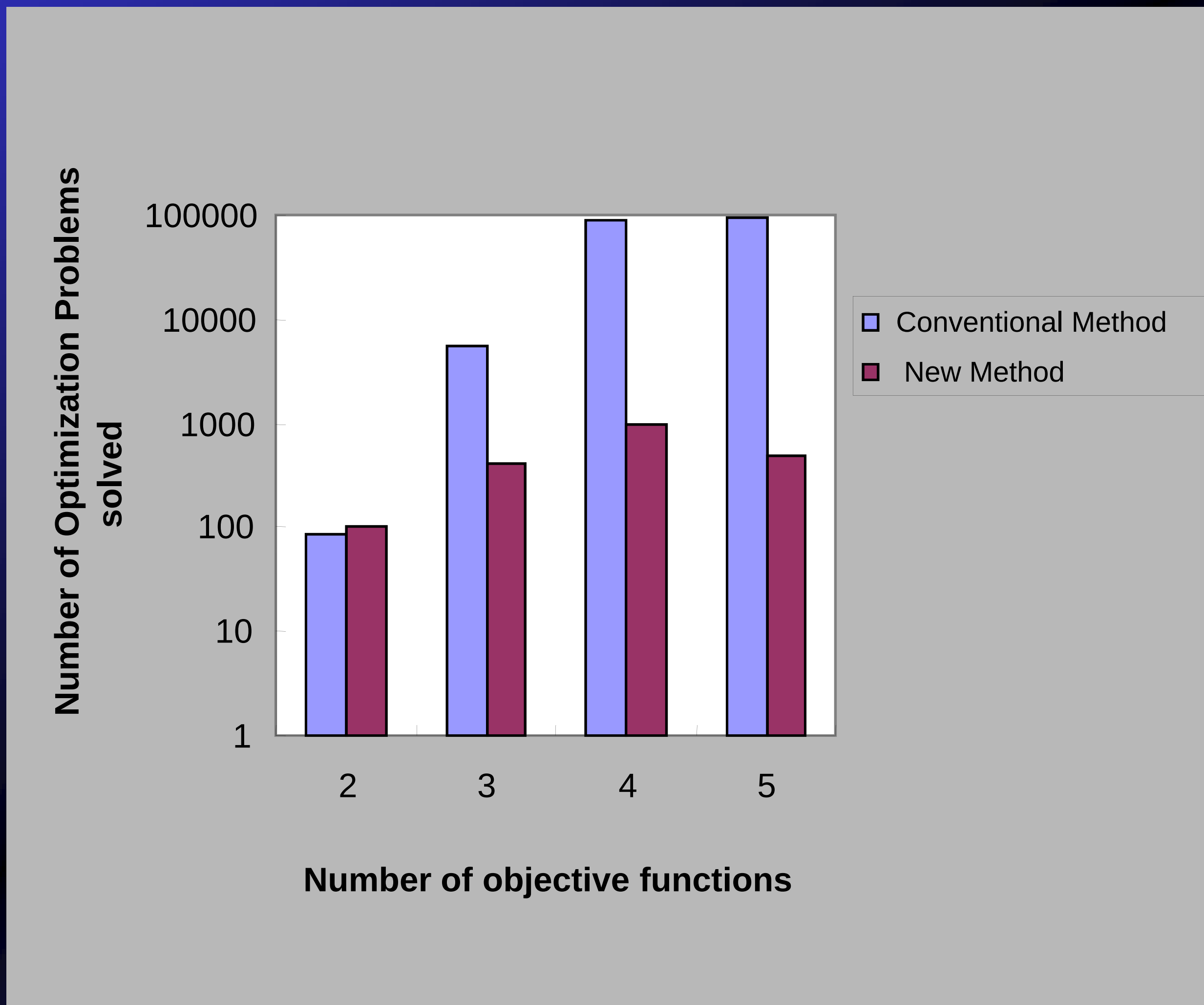
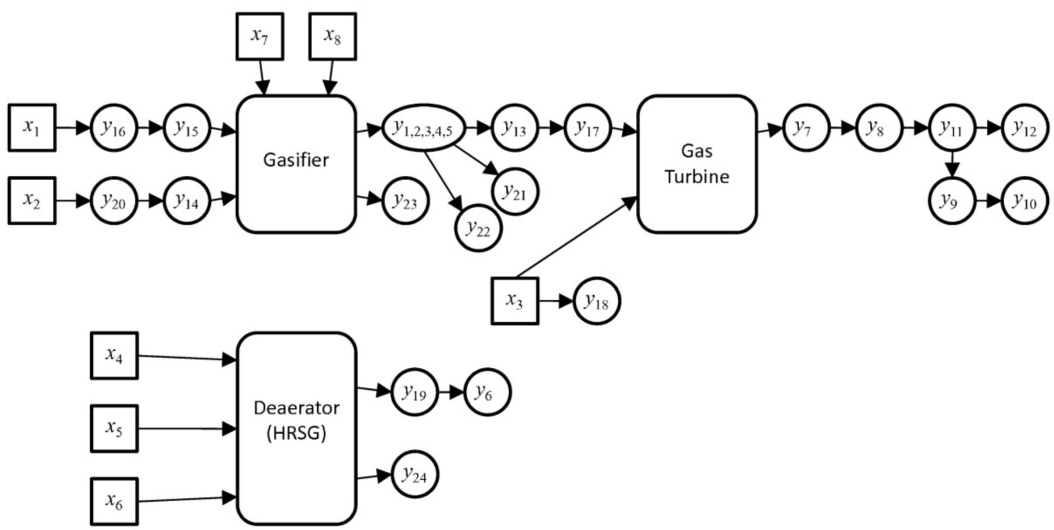
Comparison of the New MINSOOP Algorithm with the Conventional Method



IGCC Process Flowchart & Sensor Placement

- Generate flowchart to determine downstream variables
- Define $\gamma_{i,j}$ = 1 (0) if variable *j* is downstream of variable *i*
- Distribution

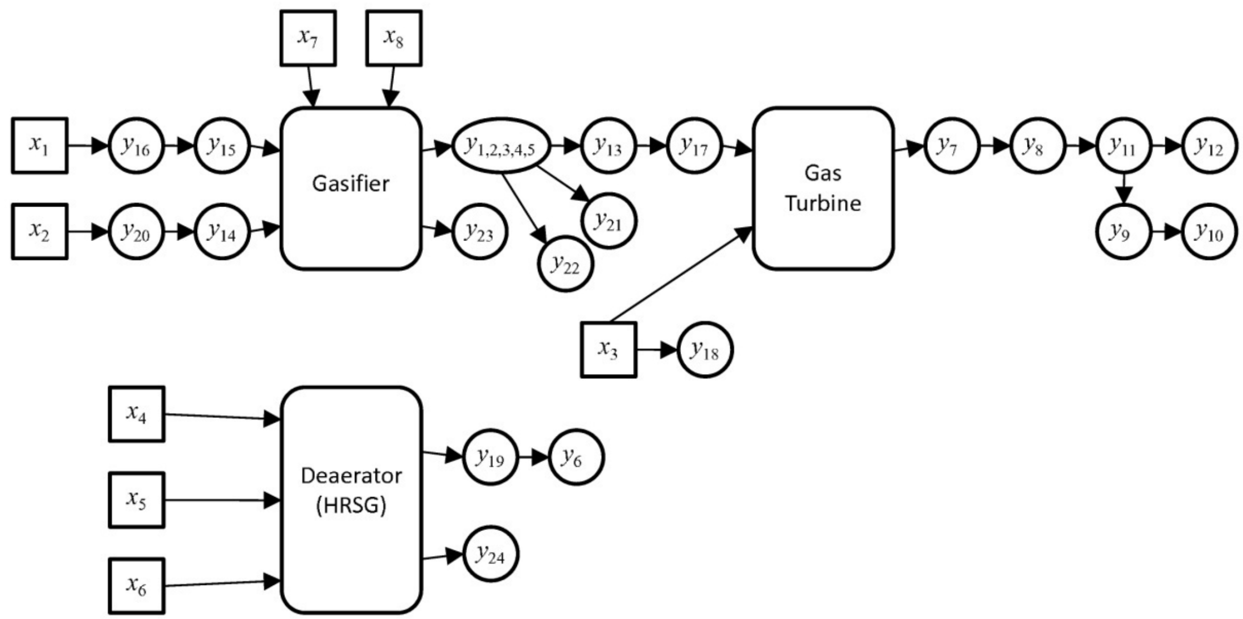
$$f_t(y_j) = f_0(y_j) \prod_{i=1}^{S^{in}} \left(1 + \gamma_{i,j} \left(\frac{f_t(x_i)}{f_0(x_i)} - 1 \right) \right)$$



Important Input, Intermediate and Output Variables

- Input process variables
  - 8 variables, including
    - Oxygen, coal slurry, air flow rates
    - Recycled HRSG steam temperature & pressure
    - Gasifier temperature & pressure
- Intermediate and output process variables
  - 24 variables, including
    - Syngas flow rate, temperature, pressure
    - CO, CO_2 flow rates
    - Gas turbine combustor, high & low pressure exhaust temperature
    - Oxygen, coal, air flow rates into gasifier
    - Slag & fines flow rates

Position\ Accuracy ->
1 Gasificer syngas flowrate
2 Syngas CO flowrate
3 Syngas CO2 flowrate
4 Syngas temp.
5 Syngas pressure
6 LP steam turbine temp.
7 Gas turbine burn temp.
8 Gas turbine exit temp.
9 Gas turbine HP stream temp.
10 Gas turbine LP stream temp.
11 Gas turbine expand. out temp.
12 Oxygen flowrate exit expan.
13 Syngas flow solids removal
14 Coal slurry flowrate gasifier
15 Oxygen flowrate gasifier
16 Oxygen flowrate exit ASU
17 Acid gas flowrate FUEL1
18 Gas turbine compre. flowrate
19 HP steam turbine flowrate
20 Coal feed flow rate
21 Slag from syngas
22 Fines from syngas
23 Gasifier heat output
24 HRSG steam heat output



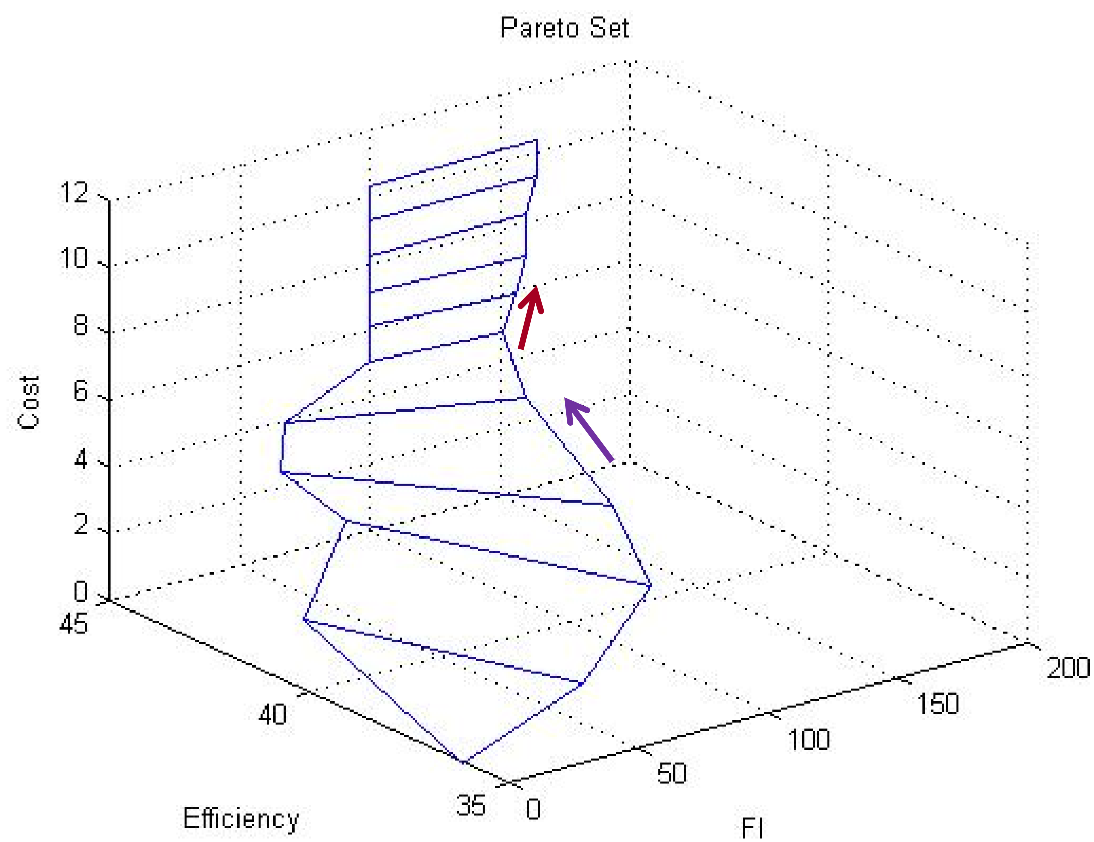
Sample Space

- N_s = 800, uniformly distributed using Hammersley sequence sampling method
- Sensors placed on input variables with six-sigma variation spanning +/-20% of the nominal value
- Resulting Fisher information about the downstream variables obtained when no sensors are placed in the network, $I_{\underline{Yj}}^{ns}(\theta_{yj})$ and reweighting
- Resulting efficiency is obtained by reweighting

Solutions

Cost	Maximize Observability: Sensor Locations																							Efficiency	FI
Cost	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Efficiency	FI
0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.3614	0
1055000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	H	H	-	-	-	H	-	-	-	-	0.3656	52.41
2110000	H	H	H	-	-	-	-	-	-	-	-	-	-	H	H	H	-	-	-	H	-	-	-	-	0.3805	101.78
3000000	H	H	H	-	H	-	-	-	-	-	-	-	-	H	H	H	H	-	-	H	-	-	-	-	0.4017	119.51
4220000	H	H	H	-	H	-	-	-	H	H	H	-	H	H	H	H	H	-	-	H	-	-	-	-	0.4324	133.18
5275000	H	H	H	H	H	-	-	-	H	H	H	-	H	H	H	H	H	-	-	H	-	-	-	-	0.4456	144.04
6330000	H	H	H	H	H	-	H	-	H	-	H	-	H	H	H	H	H	-	-	H	-	-	-	-	0.4456	148.99
7385000	H	H	H	H	H	-	H	-	H	H	H	-	H	H	H	H	H	-	-	H	H	-	-	-	0.4456	152.97
8300000	H	H	H	H	H	H	H	H	H	H	H	-	H	H	H	H	H	-	-	H	-	-	H	-	0.4478	156.91
9700000	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	-	H	H	H	H	-	0.4478	160.84
10550000	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	-	H	H	H	H	-	0.4478	160.84

Cost	Maximize Efficiency : Sensor Locations																							Efficiency	Eff_FI
Cost	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Efficiency	Eff_FI
0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.3614	0
1055000	-	-	-	-	H	-	-	-	-	-	-	-	H	-	-	-	-	-	-	-	-	-	-	-	0.4133	18.55
2110000	H	-	-	-	H	-	-	-	-	-	-	-	H	H	H	-	-	-	-	-	-	-	-	-	0.4318	62.77
3000000	H	-	-	H	H	-	-	-	-	-	-	-	H	H	-	-	-	-	-	-	-	-	-	-	0.4444	56.82
4220000	H	-	-	H	H	-	-	H	-	-	-	-	H	H	-	-	-	-	-	-	-	-	-	-	0.4466	61.77
5275000	H	-	-	H	H	-	-	H	-	-	-	-	H	H	H	H	-	-	-	-	-	-	-	-	0.4478	96.39
6330000	H	-	-	H	H	-	-	H	-	-	-	-	H	H	H	H	-	-	-	-	-	-	-	-	0.4478	96.39
7385000	H	-	-	H	H	-	-	H	-	-	-	-	H	H	H	H	-	-	-	-	-	-	-	-	0.4478	96.39
8300000	H	-	-	H	H	-	-	H	-	-	-	-	H	H	H	H	-	-	-	-	-	-	-	-	0.4478	96.39
9700000	H	-	-	H	H	-	-	H	-	-	-	-	H	H	H	H	-	-	-	-	-	-	-	-	0.4478	96.39
10550000	H	-	-	H	H	-	-	H	-	-	-	-	H	H	H	H	-	-	-	-	-	-	-	-	0.4478	96.39


Pareto Set
Cost
12
10
8
6
4
2
0
45
40
35
Efficiency
0
50
100
150
200
FI

Conclusions

- Sensor placement in power plant is a stochastic mixed integer nonlinear programming problem
- Novel sampling approach and BONUS algorithm can solve this large scale stochastic programming problem
- Maximize efficiency, maximize observability and minimize cost for good performance coverts the problem into multi-objective stochastic programming problem
- Novel algorithmic framework can provide solution to this real world problem.