Multi-Objective approach to sensor placement in IGCC power plants

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MOTIVATION & BACKGROUND

Motivation

- The U.S. Energy Information Administration (EIA) predicts global demand of energy will rise by 56 % from the year 2010 to 2040.
- Renewable energy and nuclear power are fastest growing energy sources.
- Yet, 80% of the world's power is still generated from conventional sources.
- Conventional fossil fuel based power plants have low efficiency, high environmental impact.
- IGCC plants are better on both fronts.
- Hence, it makes sense to invest in research for improving performance of IGCC plants.

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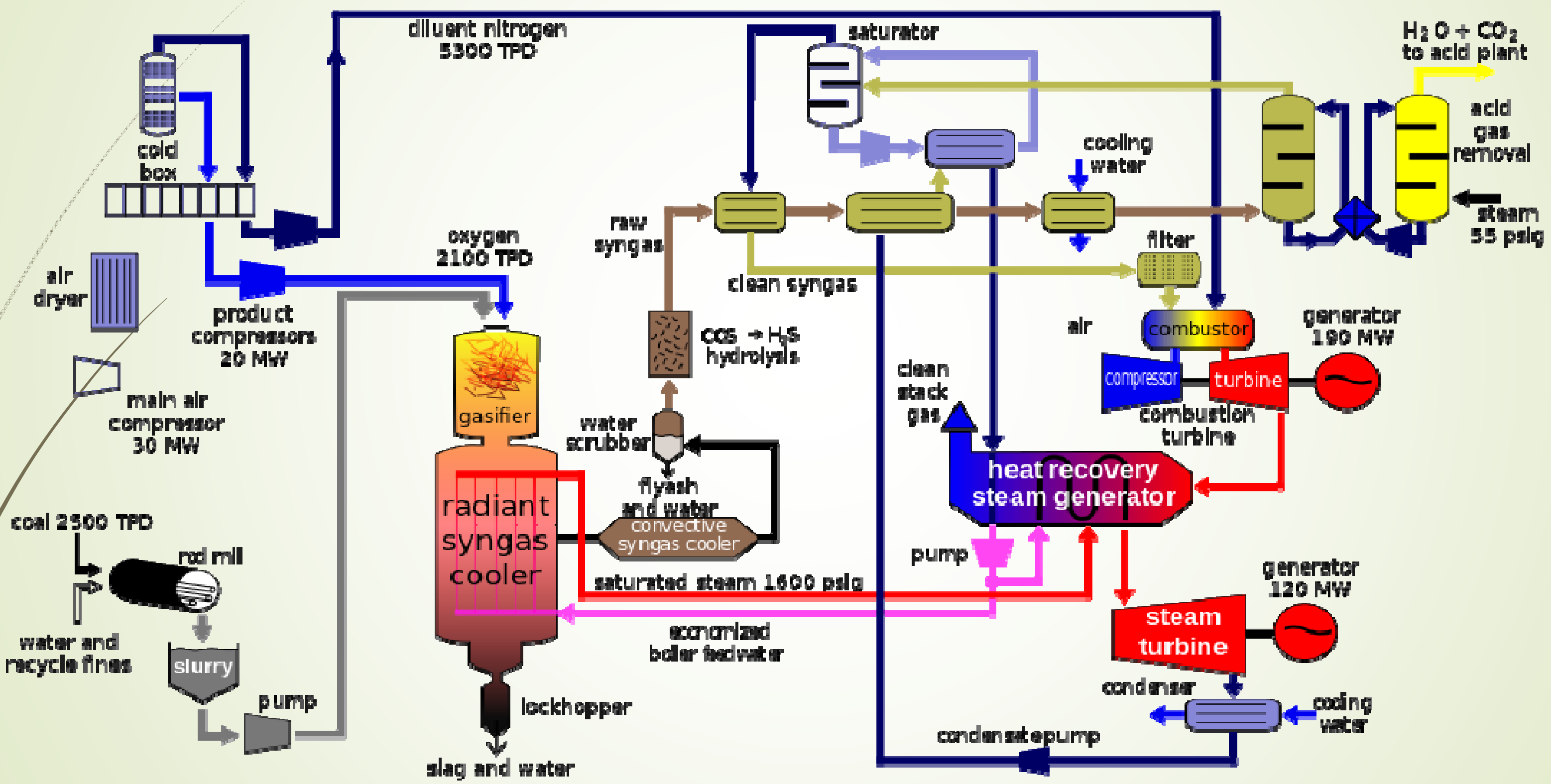
IGCC Power Plant

- *More than 80 unit operations*
- *Over 200 streams*



Picture source: Wikipedia

VIRTUAL SENSING IN IGCC PLANTS

- The process of estimating value of a variable through mathematical modeling.
  - *Eliminates need of placing direct physical means of measurement such as a sensor.*
  - *Two types – analytical and empirical*

- Advantage - Economical and less-invasive.
  - *Appropriate choice for IGCC plant due to harsh operating conditions and hundreds of process variables.*

- Disadvantage - lower measurement accuracy than actual sensing
  - *High measurement error gives rise to uncertainty in the system.*
  - *Only variables that are expensive or difficult to measure directly are measured virtually.*

SENSOR NETWORK – WHY DO WE NEED IT?

- OBSERVABILITY
  - Monitoring and controlling the process variables in real time.
  - To maintain all process variables within a safe range of operation at all times.
  - Ensures smooth, safe and reliable operation.

- EFFICIENCY
  - Certain variables that directly impact efficiency should be close to target value.
    - *Gasifier temperature*
    - *Steam to air ratio in gasifier*
    - *Air to fuel ratio in gas turbine.*
  - If these variables are above or below their optimal values, the plant will run at a sub-optimal level.

OBJECTIVES
&
PROBLEM STATEMENT

OBJECTIVES

- ***METHODOLOGY***
  - *Develop sensor deployment methodologies applicable to IGCC power plant systems.*
  - *Incorporate measurement error (uncertainty) and non-linear nature of the system in the formulation and solution of the optimal sensor deployment problem.*
- ***ALGORITHM***
  - *Develop a new algorithmic framework that can improve the computational efficiency significantly.*
- ***MULTI-OBJECTIVE APPROACH***
  - *Develop multi-objective optimal sensor deployment algorithms to provide trade-off designs between various objectives – maximizing observability & maximizing efficiency.*

PROBLEM STATEMENT

- Decision variables - ***number & location of sensors in the plant and the type of sensors.***
- Objective functions – ***maximizing observability (using FI), maximizing efficiency, minimizing cost.***
- Constraint – ***budget, mass & energy balances.***

Multi-objective
- ***Simultaneous achievement of multiple objectives***

Stochastic
- ***Uncertainty in process variables due to system and measurement noise.***

Non-linear
- ***Equations governing the physical processes in the IGCC power plant are non-linear.***

Mixed Integer
- ***Presence of integer and binary integer decision variables.***

Variables & Control

- 24 intermediate variables selected
  - They have effect on output variables and plant performance.
  - Sensors are to be installed in these locations
  - Selected based upon experience
  - Placing actual sensors reduce measurement error.
  - Place sensors strategically to gain as accurate information as possible for all these process variables.
- Without sensor – measurement error is $\pm$ 20%
- With sensor
  - Low cost sensors, error = $\pm$ 5%
  - Medium cost sensors, error = $\pm$ 2.5%
  - High cost sensors, error = $\pm$ 1%

Table 2
Intermediate and output process variables.

y_j	Description	Stream[a]	Nominal	Units
1	Gasifier syngas flow rate	RXROUT	393,475	kg/h
2	Syngas CO flow rate	RXROUT	224,637	kg/h
3	Syngas CO_2 flow rate	RXROUT	88,051	kg/h
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7	Gas turbine combustor burn temp.	POC2	1628	K
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9	Gas turbine high pressure exhaust stream temp.	GTPC3	621	K
10	Gas turbine low pressure exhaust stream temp.	GTPC9	404	K
11	Gas turbine expander output temp.	GTPOC	872	K
12	Fluegas flow rate exiting gas turbine expander	6X	5,760,623	kg/h
13	Syngas flow rate after solids removal	RAWGAS	467,200	kg/h
14	Coal slurry flow rate entering gasifier	COALD	21,170	kg/h
15	Oxygen flow rate into gasifier	O2GAS	157,452	kg/h
16	Oxygen flow rate exiting ASU	GASIFOXY	157,452	kg/h
17	Acidgas flow rate	FUEL1	344,996	kg/h
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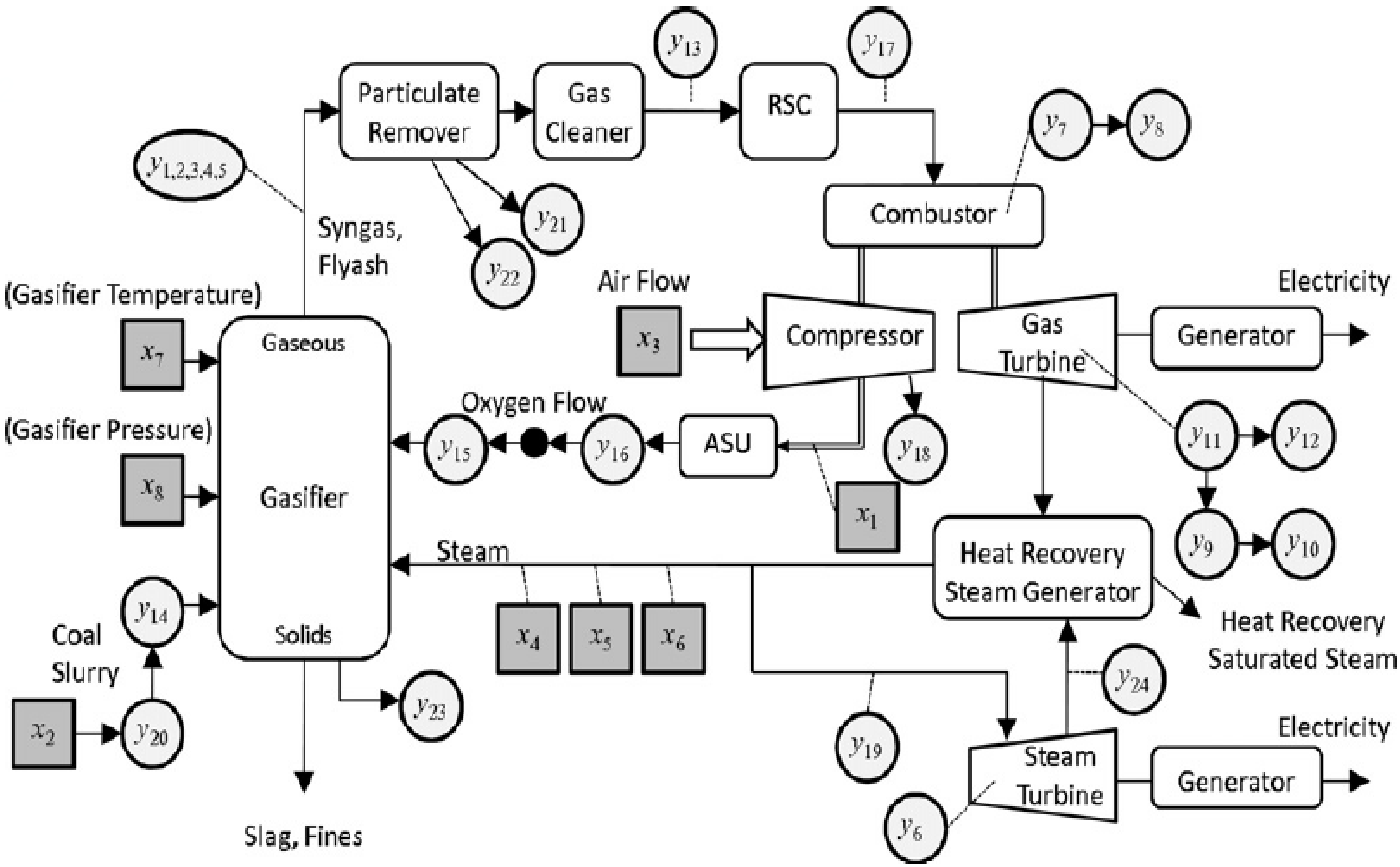
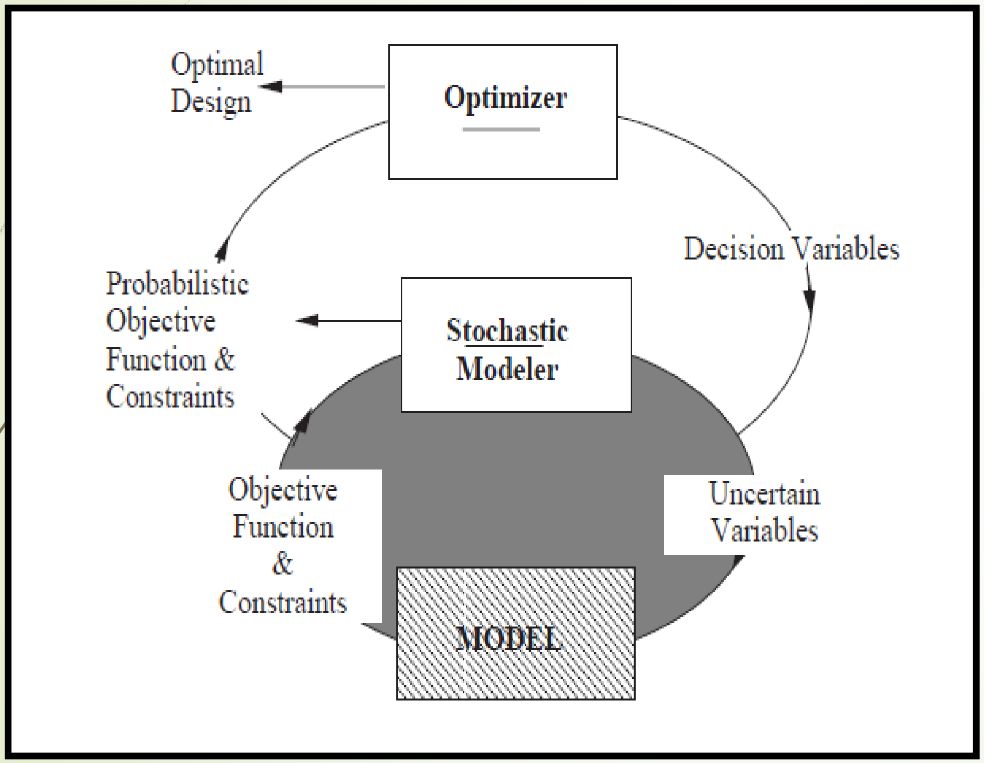
21	Slag extracted from syngas	SLAG	15,805	kg/h
22	Fines extracted from syngas	FINES	5363	kg/h
23	Gasifier heat output	QGASIF	2.47e7	Btu/h
24	Recycled HRSG steam heat output	QRDEA	3.27e8	Btu/h

[a] Stream notation refers to DOE/NETL model [11].



Particulate Remover
Gas Cleaner
RSC
Combustor
y_{13}
y_{17}
y_7
y_8
$y_{1,2,3,4,5}$
y_{21}
y_{22}
Syngas, Flyash
(Gasifier Temperature)
x_7
Gaseous
Gasifier
Solids
(Gasifier Pressure)
x_8
Coal Slurry
y_{14}
x_2
y_{20}
y_{23}
Slag, Fines
Air Flow
x_3
Compressor
Gas Turbine
Generator
Electricity
Oxygen Flow
y_{15}
y_{16}
ASU
y_{18}
x_1
y_{11}
y_{12}
y_9
y_{10}
Steam
x_4
x_5
x_6
Heat Recovery Steam Generator
Heat Recovery Saturated Steam
y_{24}
y_{19}
Steam Turbine
Generator
Electricity
y_6

GENERALIZED STOCHASTIC PROGRAMMING FRAMEWORK



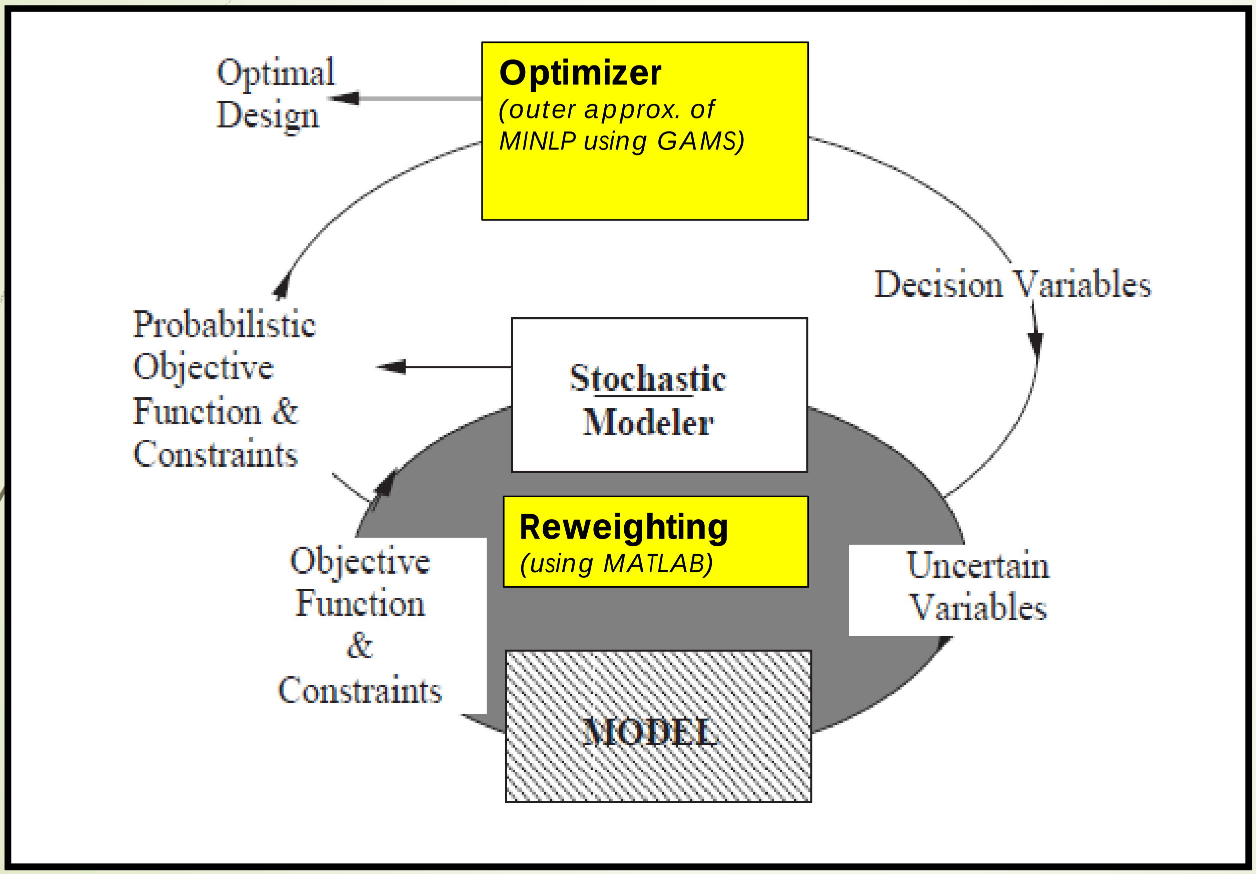
- Specify uncertainties in key input parameters in terms of probability distributions.
- Sample the distribution of the specified parameter in an iterative fashion.
- The model is evaluated for each of these sample points to determine the probabilistic value of objective function& constraints.
- Derivative estimation through perturbation analysis

Ref: BONUS Algorithm for Large Scale Stochastic Non-linear Stochastic Algorithm Problems, U. Diwekar, A., David, Springer 2013

ALGORITHMIC FRAMEWORK BASED ON BONUS

B- Better
O- Optimization for
N- Non-Linear
U- Uncertain
S- Systems

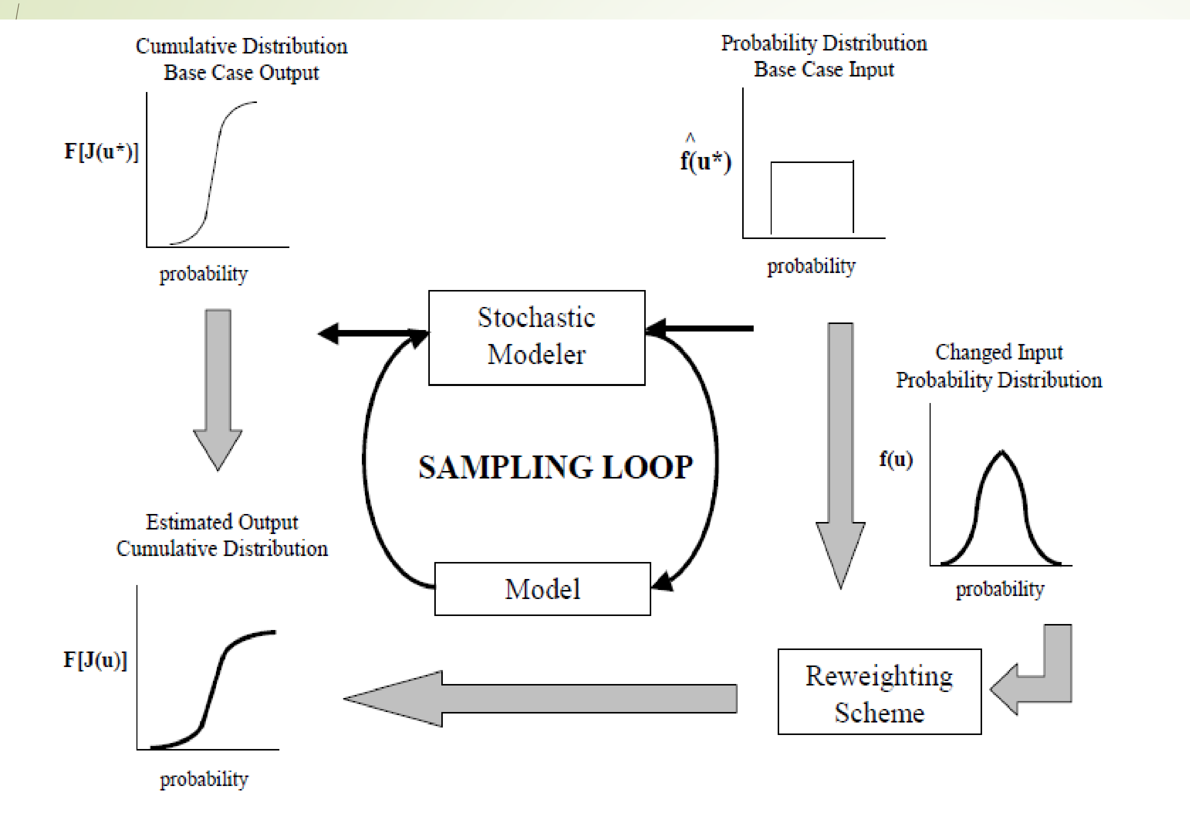
STOCHASTIC PROGRAMMING FRAMEWORK



Computational time for 800 samples reduced from 18 hours (ASPEN) to less than a minute (BONUS).

Ref: BONUS Algorithm for Large Scale Stochastic Non-linear Stochastic Algorithm Problems, U. Diwekar, A., David, Springer 2013

BONUS & Reweighting



Ref: BONUS Algorithm for Large Scale Stochastic Non-linear Stochastic Algorithm Problems, U. Diwekar, A., David, Springer 2013

- Initial uniform distributions (lower & upper bound) assumed for decision variables.
- PDFs of Decision & uncertain variables form base distributions.
- BONUS samples solution space of objective function using base distributions.
- As decision variables change, the distributions for the objective function &constraints also change.
- BONUS algorithm estimates objective function & constraints based on ratios of the probabilities for the current and the base distributions.
- Thus, BONUS avoids sample model runs in subsequent iterations.

MULTI-OBJECTIVE OPTIMIZATION

Multi-objective approach

- Objectives: maximize fisher information, efficiency, minimize cost

- Constraint method, a posterior method for generating pareto set where
  - *The multi-objective problem is transformed into a series of single objective problems.*
  - *Any single objective is optimized while the rest are converted into constraints with lower & upper bounds.*

- Lower bound to cost corresponds to using no sensors, i.e., zero (0).
- Upper bound to cost corresponds to using high accuracy sensors for all 24 locations.

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STEPS IN OUR SOLUTION

- 2-tier constraint method
- To derive only feasible solutions, Divide cost values into 10 bins between upper and lower bound.
- For each cost, solve single optimization problem to maximize efficiency and calculate the corresponding FI.
- Similarly, for each cost, solve single optimization problem to maximize FI and calculate the corresponding efficiency.

STEPS (contd..)

- Derive upper & lower bounds of efficiency & FI & generate pay-off tables for each cost,
- For each pay-off table, select feasible values of efficiency in small increments and solve single optimization problems to find maximum FI for each of these values.
- Generate the complete pareto surface (trade-offs) by solving multiple single objective problems.
- Plot the complete pareto surface and analyze.

MAXIMIZING FISHER INFORMATION

$$\max_{w_{j,\tau} \in W} \sum_{\tau=1}^{3} \sum_{j=1}^{Sout} f_{j,\tau}(w, Y)\, w_{j,\tau}$$

Subject to

$$\sum_{\tau=1}^{3} \sum_{j=1}^{Sout} C_{j,\tau}\, w_{j,\tau} \leq B \quad j = 1, 2, \ldots S_{out}$$

$$\sum_{\tau=1}^{3} w_{j,\tau} \leq 1,$$

Mass & Energy Balances

$$f_j^A(\mathbf{w}, \mathbf{Y}) = 1 - I_{Y_j}^{ns}(\theta_{y_j}) / I_{Y_j}^{s}(\theta_{y_j} | w_j = 1),$$

- Fisher information: a probabilistic nonlinear function
- Constraint on cost
- Stochastic Mixed integer nonlinear programming problem

MAXIMIZING EFFICIENCY

$$\max_{W_{j,\tau} \in W} \sum_{\tau=1}^{3} \sum_{j=1}^{Sout} E_{j,\tau}(w, Y)\, w_{j,\tau}$$

$$\sum_{\tau=1}^{3} \sum_{j=1}^{Sout} C_{j,\tau}\, w_{j,\tau} \leq B$$

$$\sum_{\tau=1}^{3} w_{j,\tau} \leq 1, \quad j = 1, 2, \ldots, S_{out}$$

Mass & Energy Balances

- Second Objective – maximize expected value of plant thermal Efficiency
- Constraint – budget
- Efficiency depends upon only certain variables – coal feed rate, gas turbine electric power, steam turbine electric power etc.
- $E = \frac{Pwrnet}{Fcoalc * Fmf * HOC}$

Mass & Energy balance equations:

The mass balance equation is given by:

$$\frac{\mathrm{d}M_i}{\mathrm{d}t} = \sum Y_{i,\mathrm{in}}\dot{M}_{\mathrm{in}} - \sum Y_{i,\mathrm{out}}\dot{M}_{\mathrm{out}} + \sum R_i$$

Where

$Y_{i,in}$ = mass concentration of content *I* in inlet flow
M_{in} = inlet mass flow rate
$Y_{i,out}$ = mass concentration of content *i* in outlet flow
M_{out} = outlet mass flow rate
R_i = net production rate of *i* by chemical reactions.

The energy balance equation is given by:

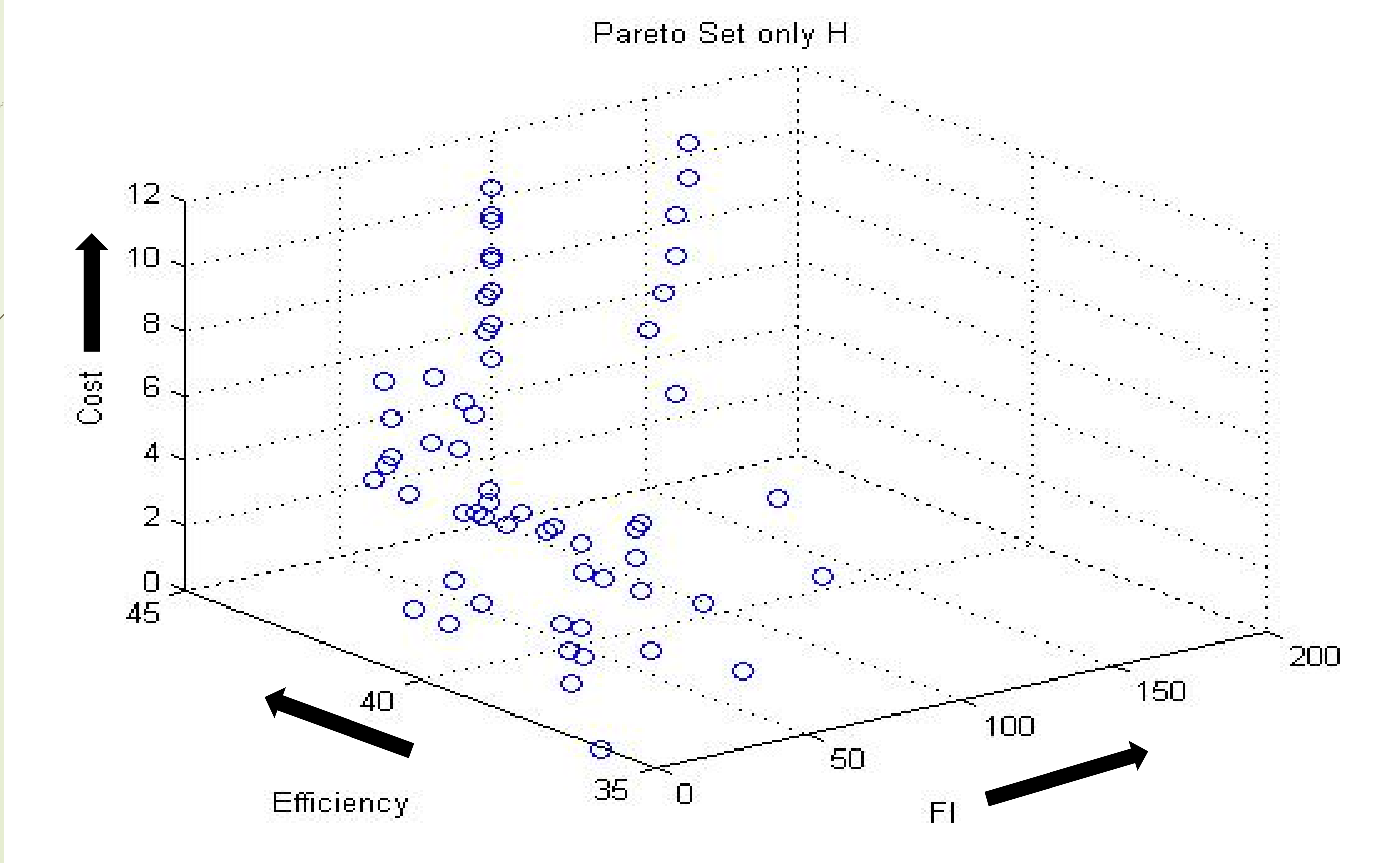
$$\frac{\mathrm{d}U}{\mathrm{d}t} = \sum \dot{H}_{i,\mathrm{in}} - \sum \dot{H}_{j,\mathrm{out}} + \sum \dot{Q}_k + \sum P_m$$

Where

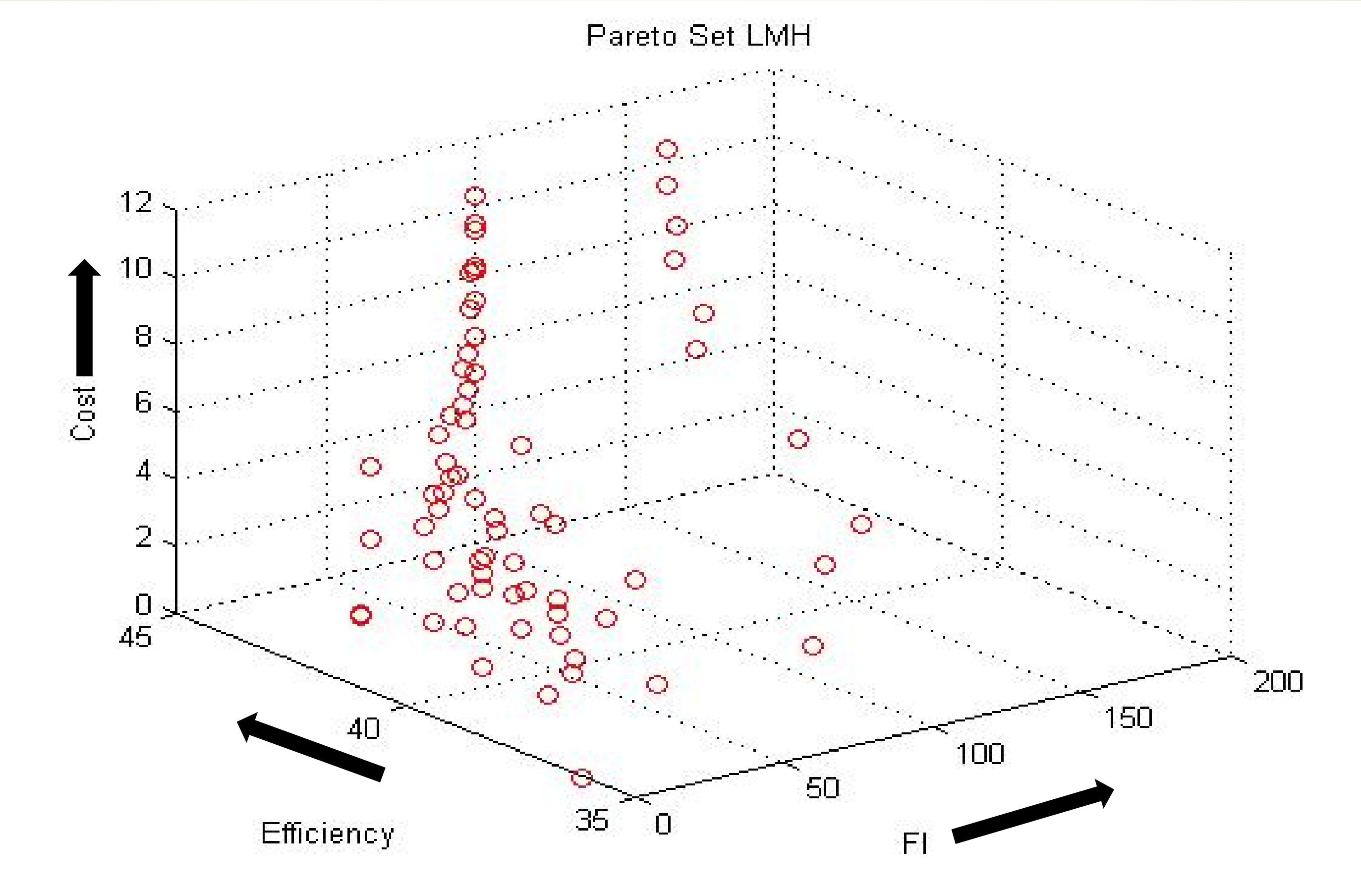
U = internal energy in block
$H_{i,in}$ = enthalpy flow rate of content *i* in the inlet flow
$H_{j,out}$ = enthalpy flow rate of content *j* in the outlet flow
Q_k = heat flow
P_m = mechanical power.

RESULTS & DISCUSSIONS

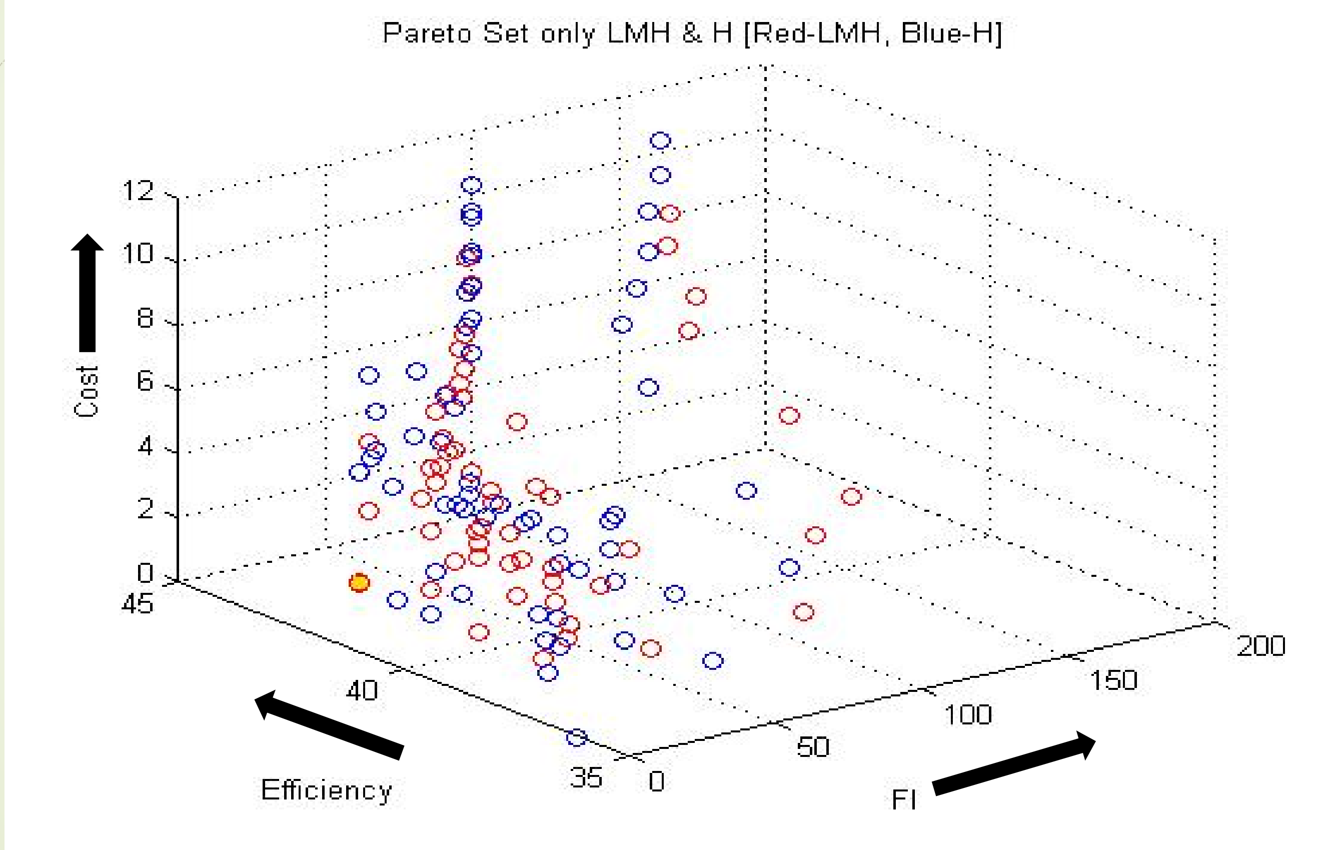
Pareto set using only High Accuracy Sensors



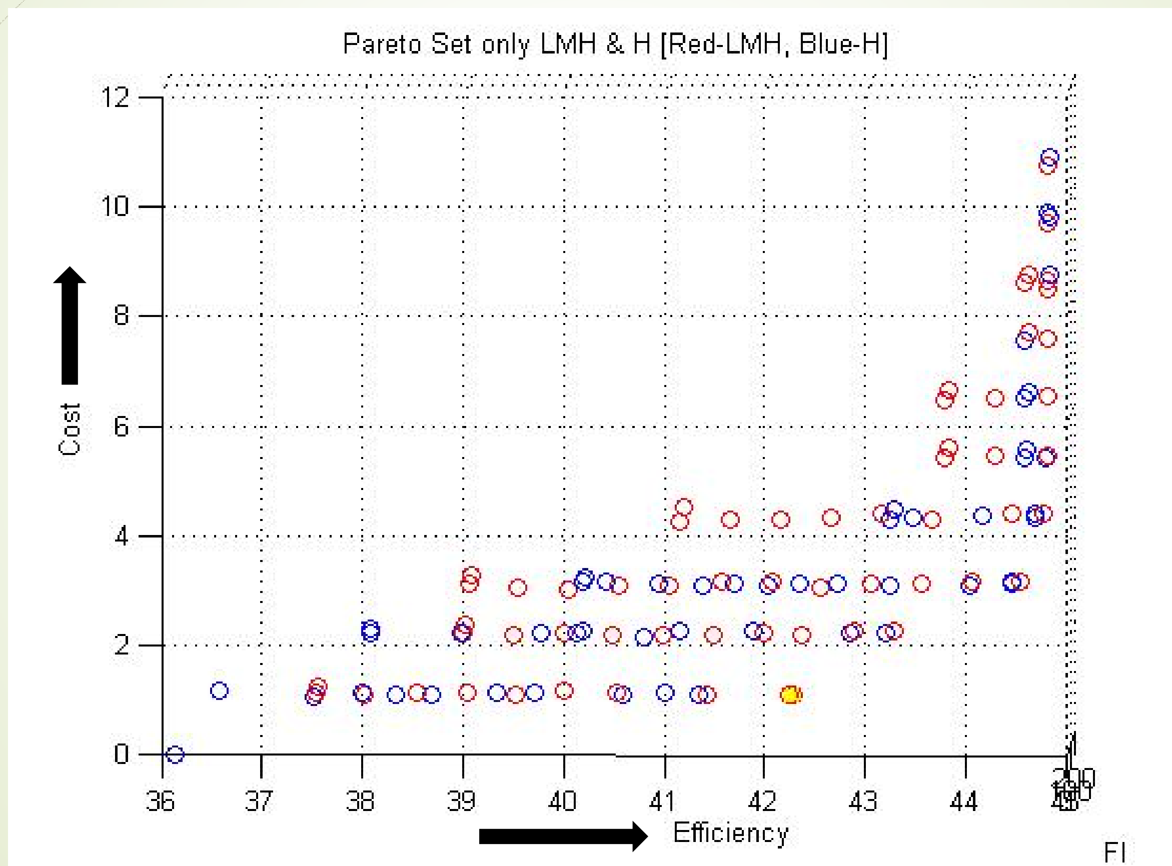
Pareto set using Low, Medium & High Accuracy Sensors



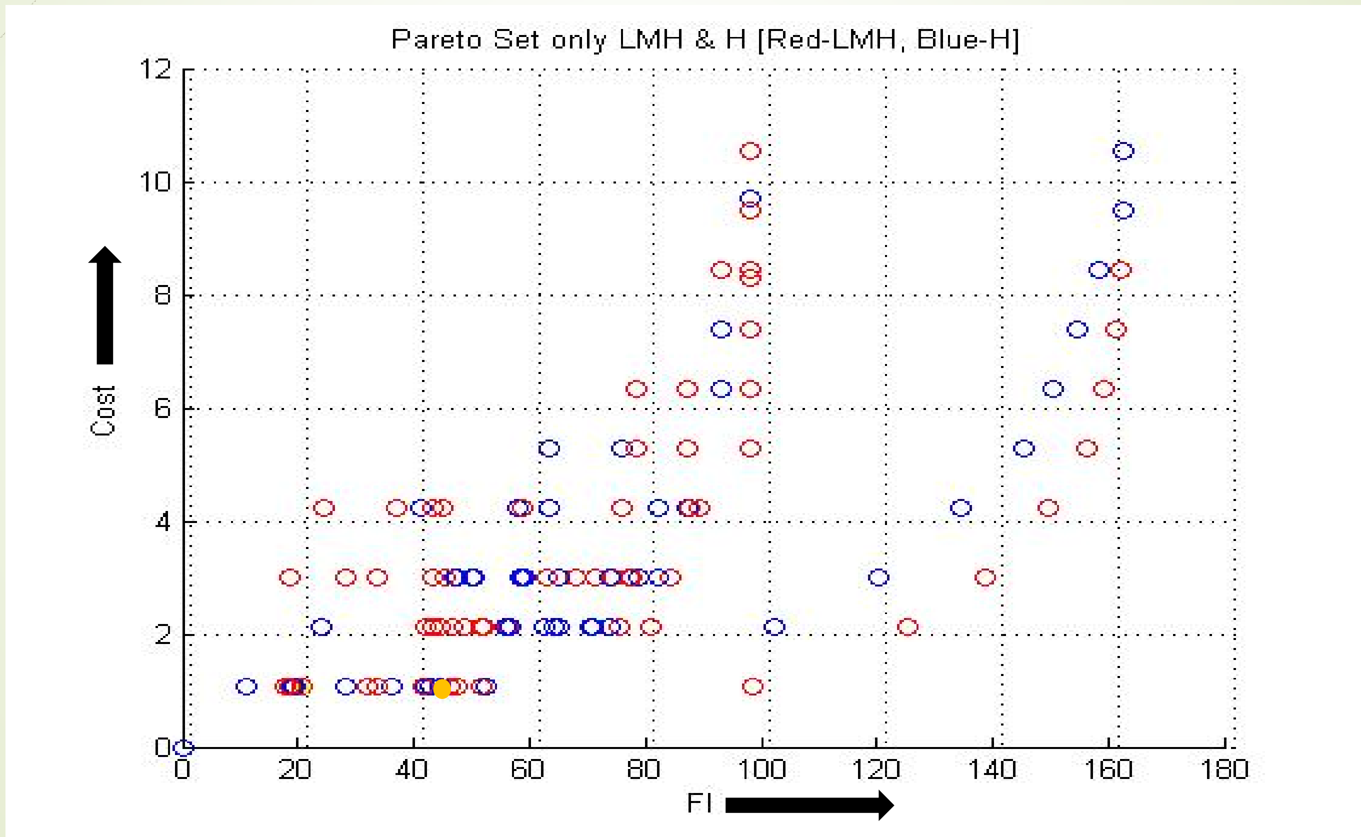
Low Cost – High efficiency



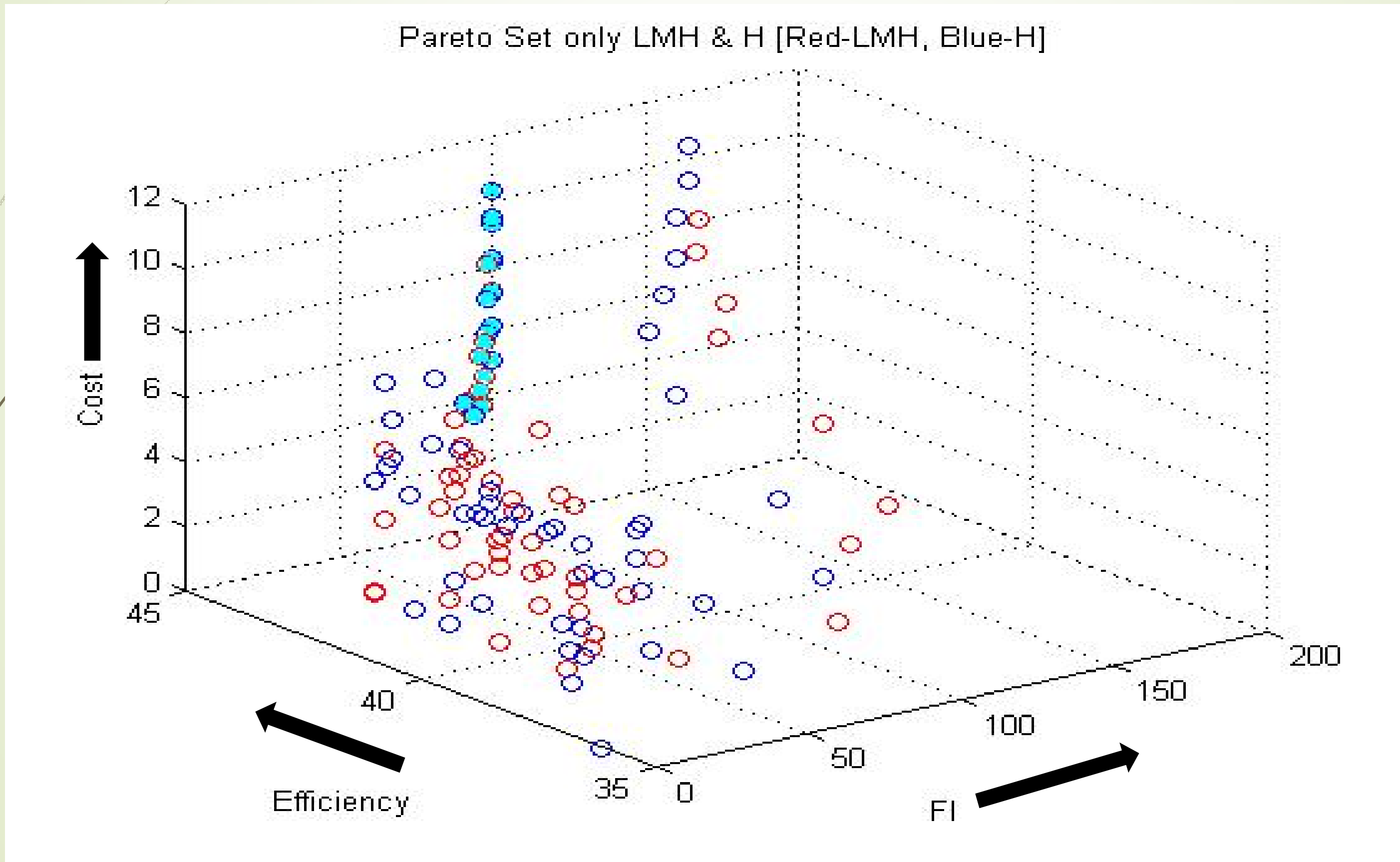
Low Cost – High efficiency



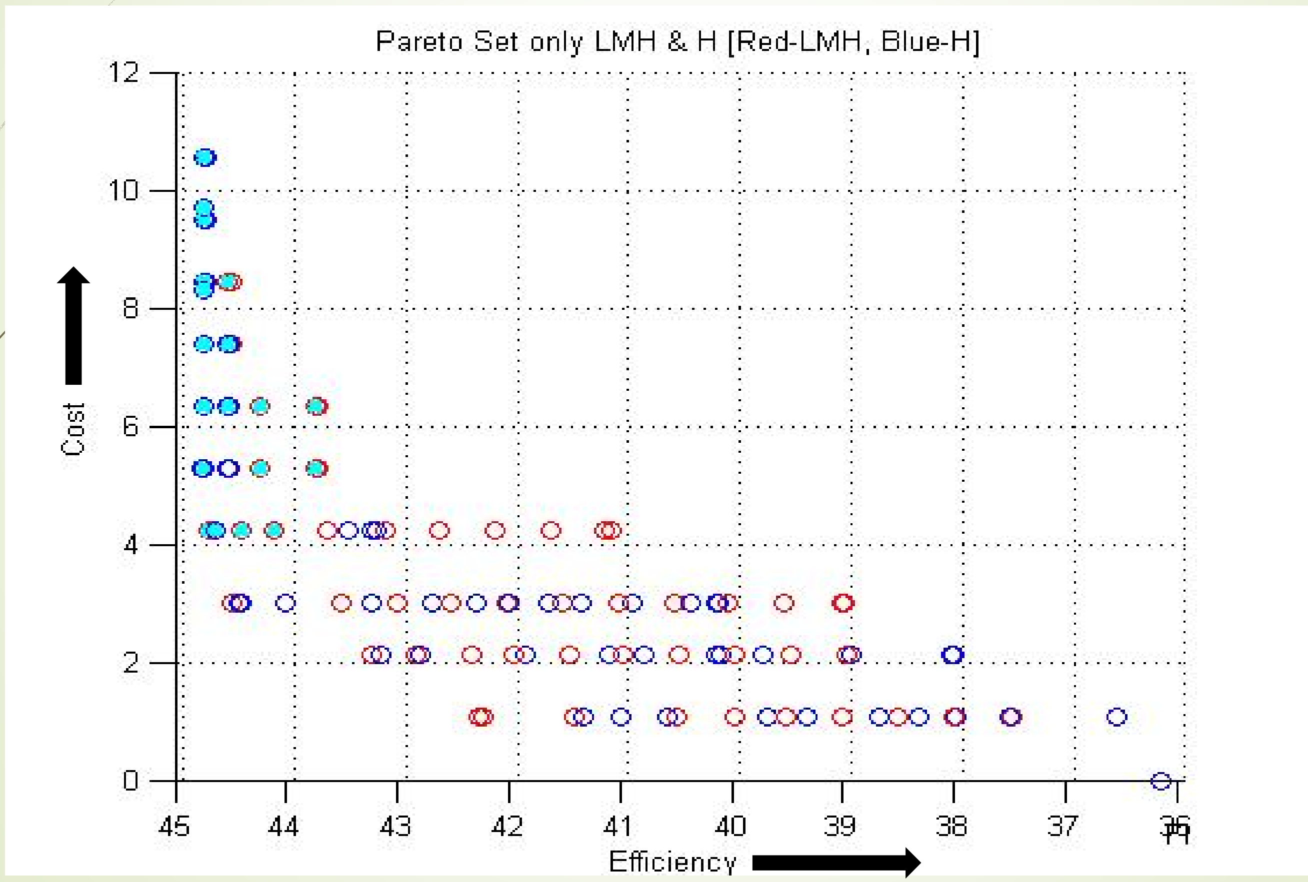
Low Cost – Low FI – High Efficiency



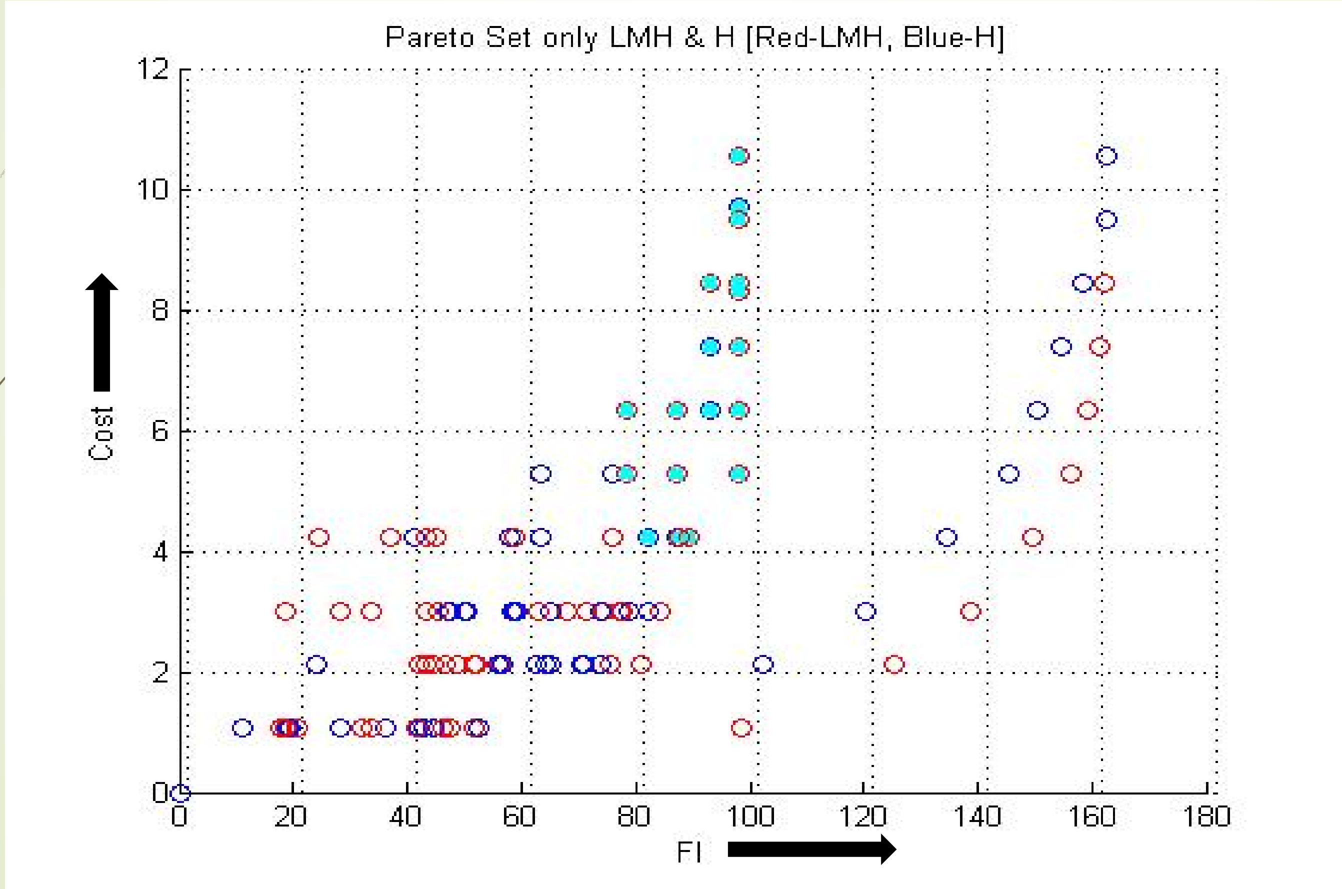
High Cost – High Efficiency – low FI



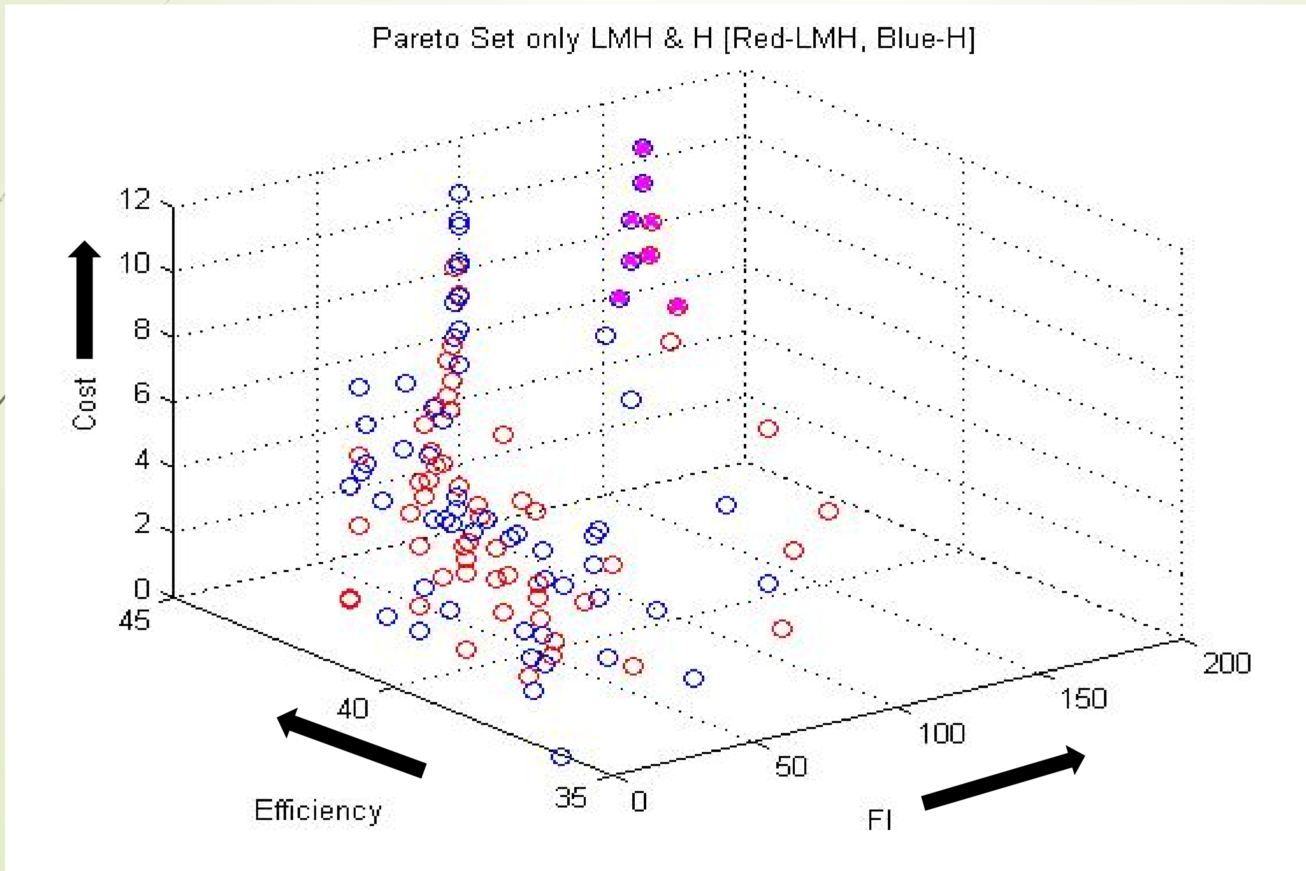
High Cost – High Efficiency – low FI



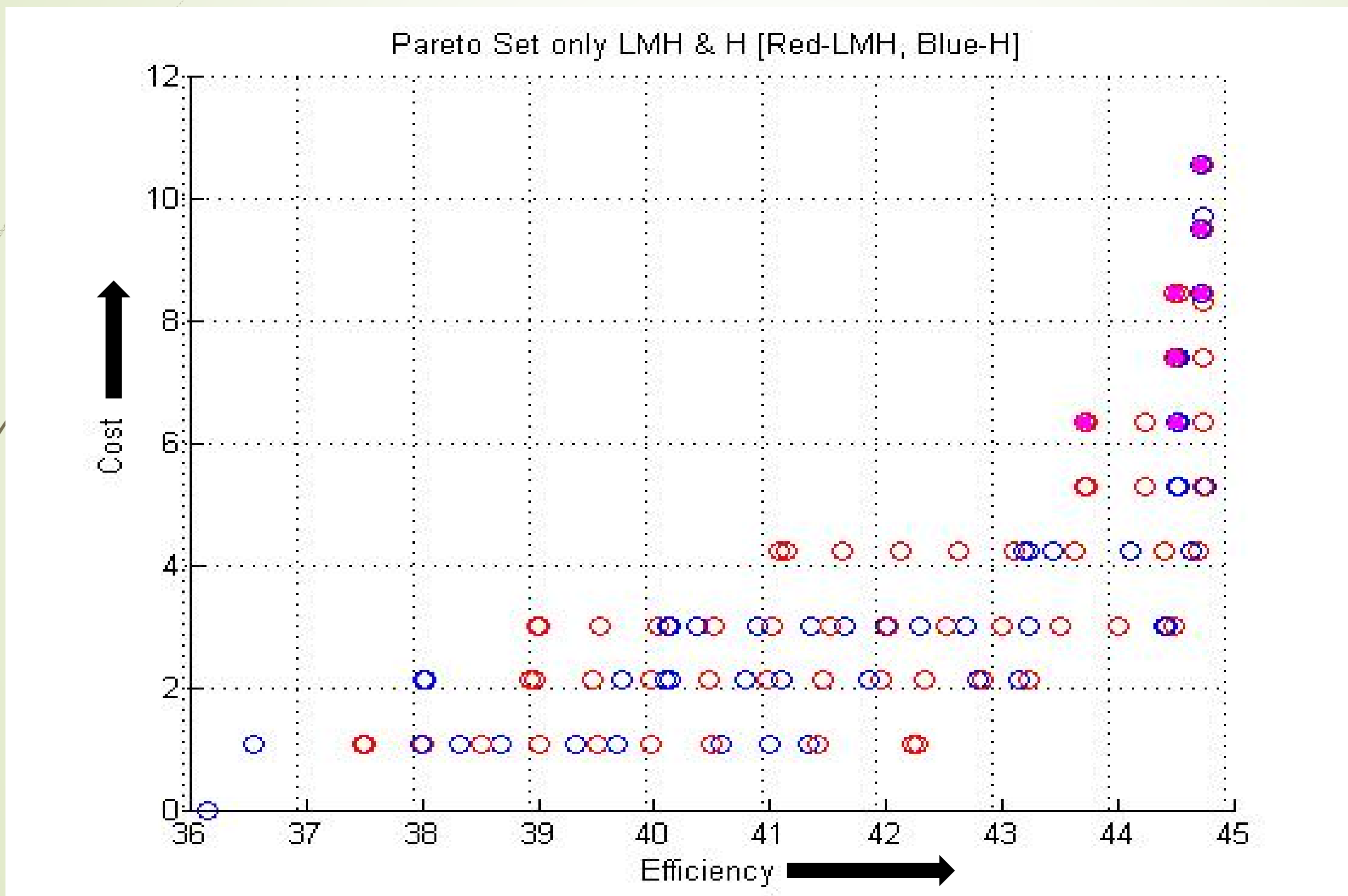
High Cost – High efficiency – low FI



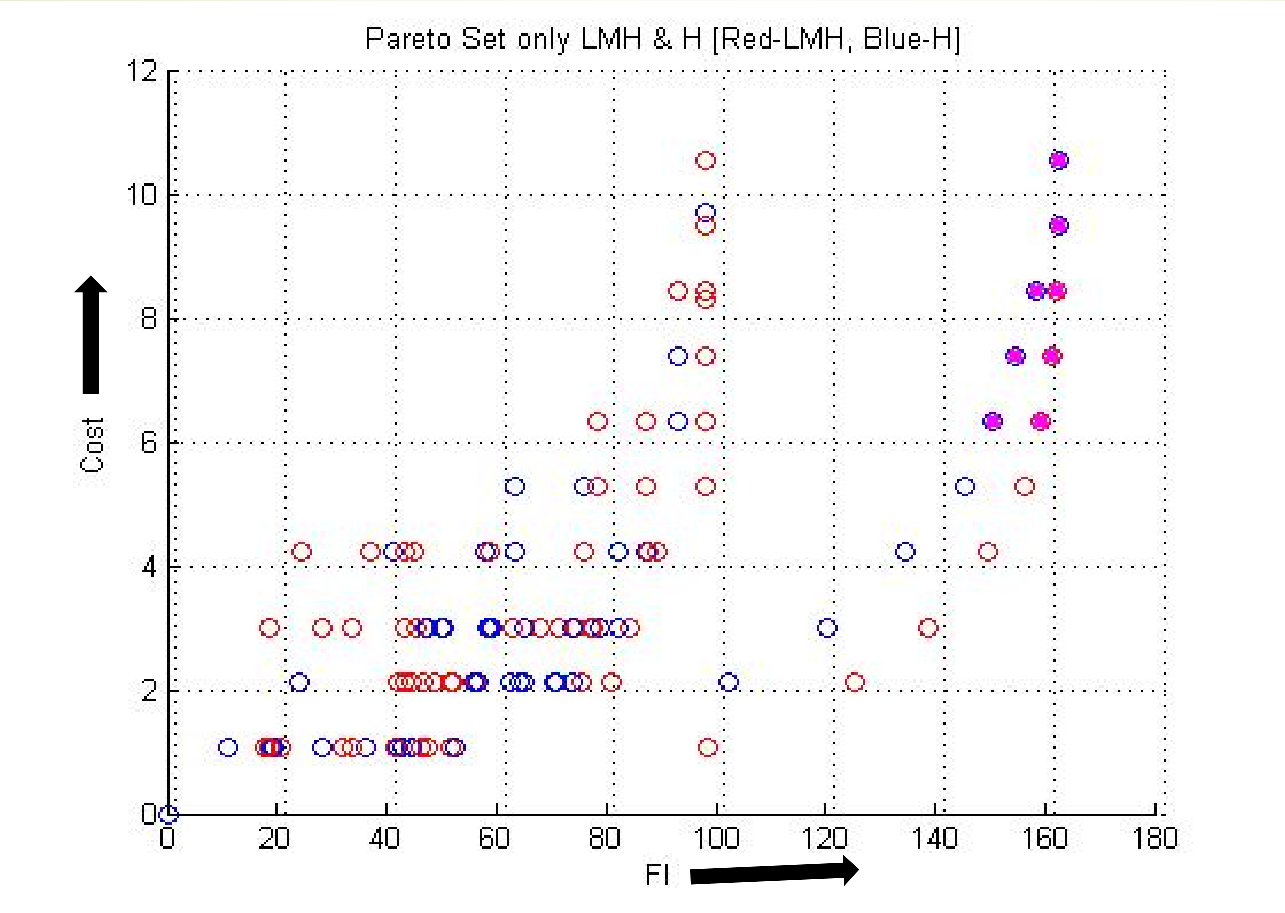
High Cost – High efficiency – High FI



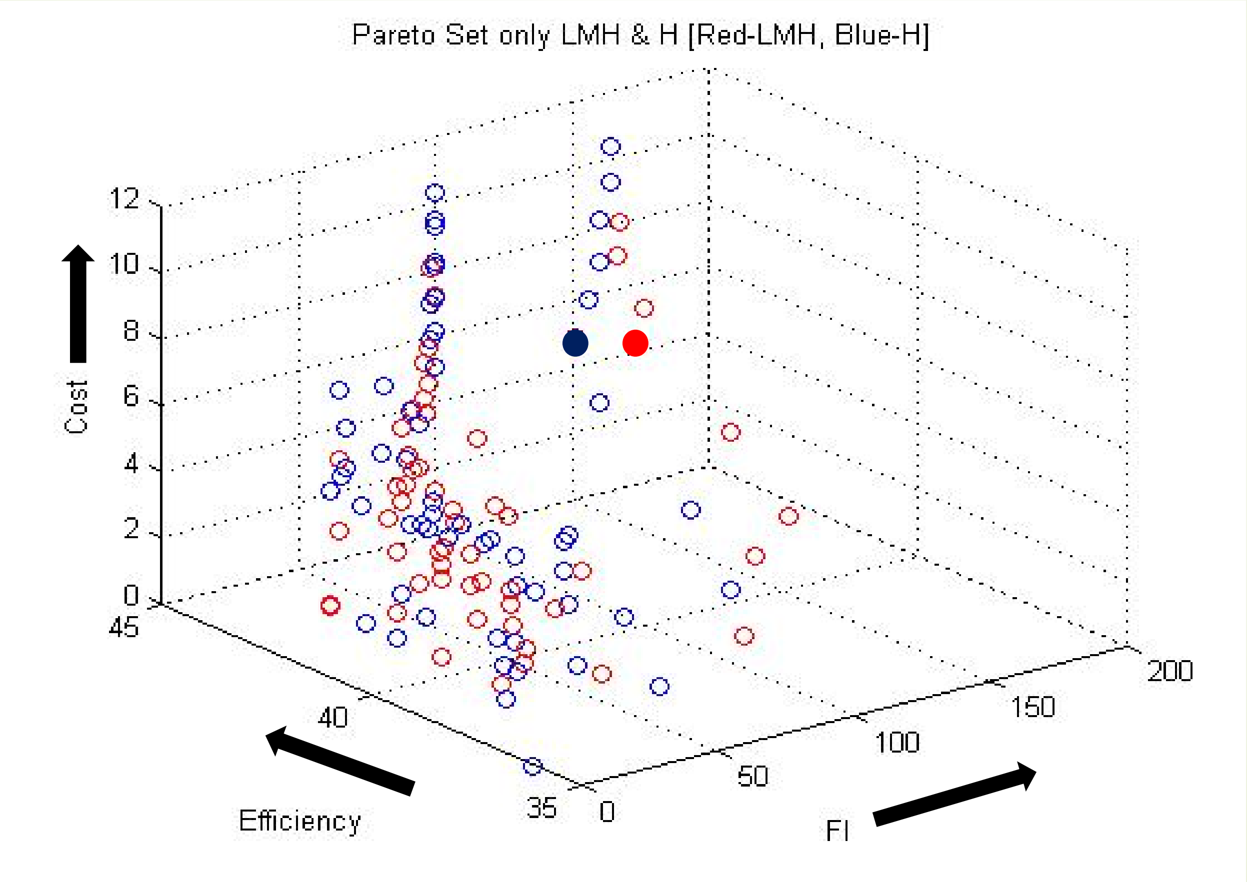
High Cost – High efficiency – High FI



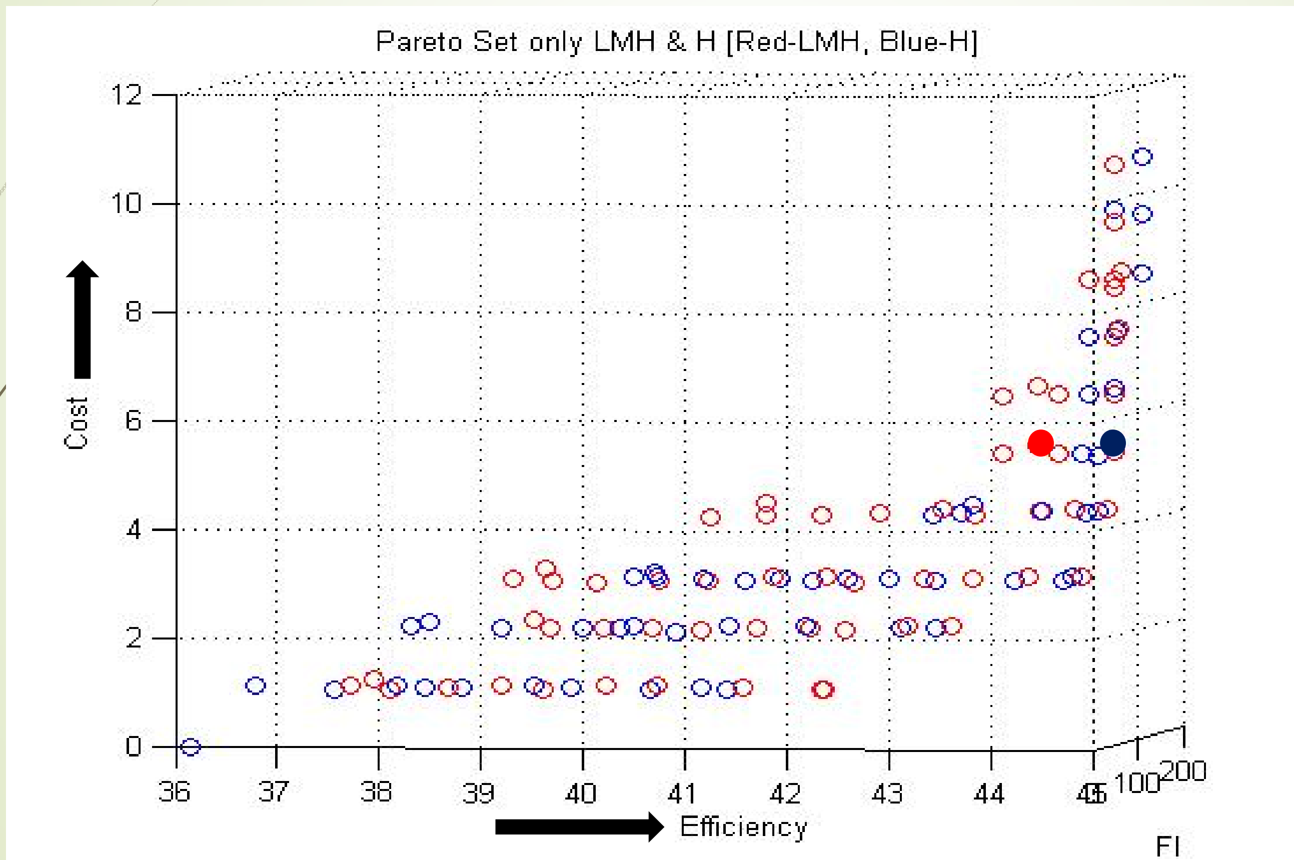
High Cost – High efficiency – High FI



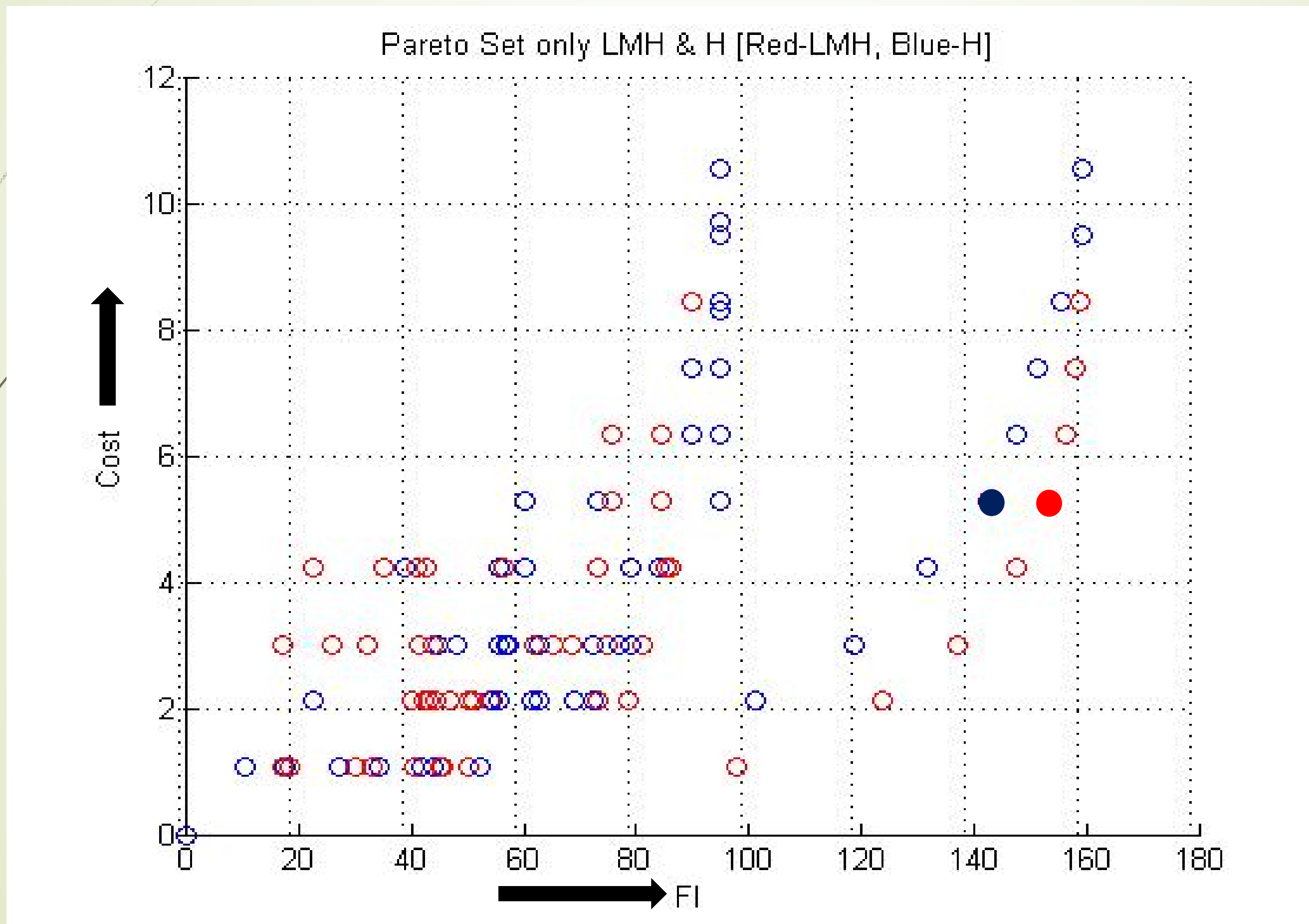
Moderate Cost – High efficiency – High FI



Moderate Cost – High efficiency – High FI



Moderate Cost – High efficiency – High FI



Sensor Locations – L, M, H sensors

Sensor Locations

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
H	M	L	M	H	M	L	L	L	L	L	-	H	H	H	H	H	L	-	H	L	L	L	-

Cost - $5275000, FI - 154.81, Efficiency - 0.4377

L- 10, M-3, H-8, Nil - 3

Sensor Locations – only H sensors

Sensor Locations

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
H	H	H	H	H	-	-	-	H	H	H	-	H	H	H	H	H	-	-	H	-	-	-	-

Cost - $5275000, FI – 144.04, Efficiency – 0.4456

H-13, Nil - 11

Table 2
Intermediate and output process variables.

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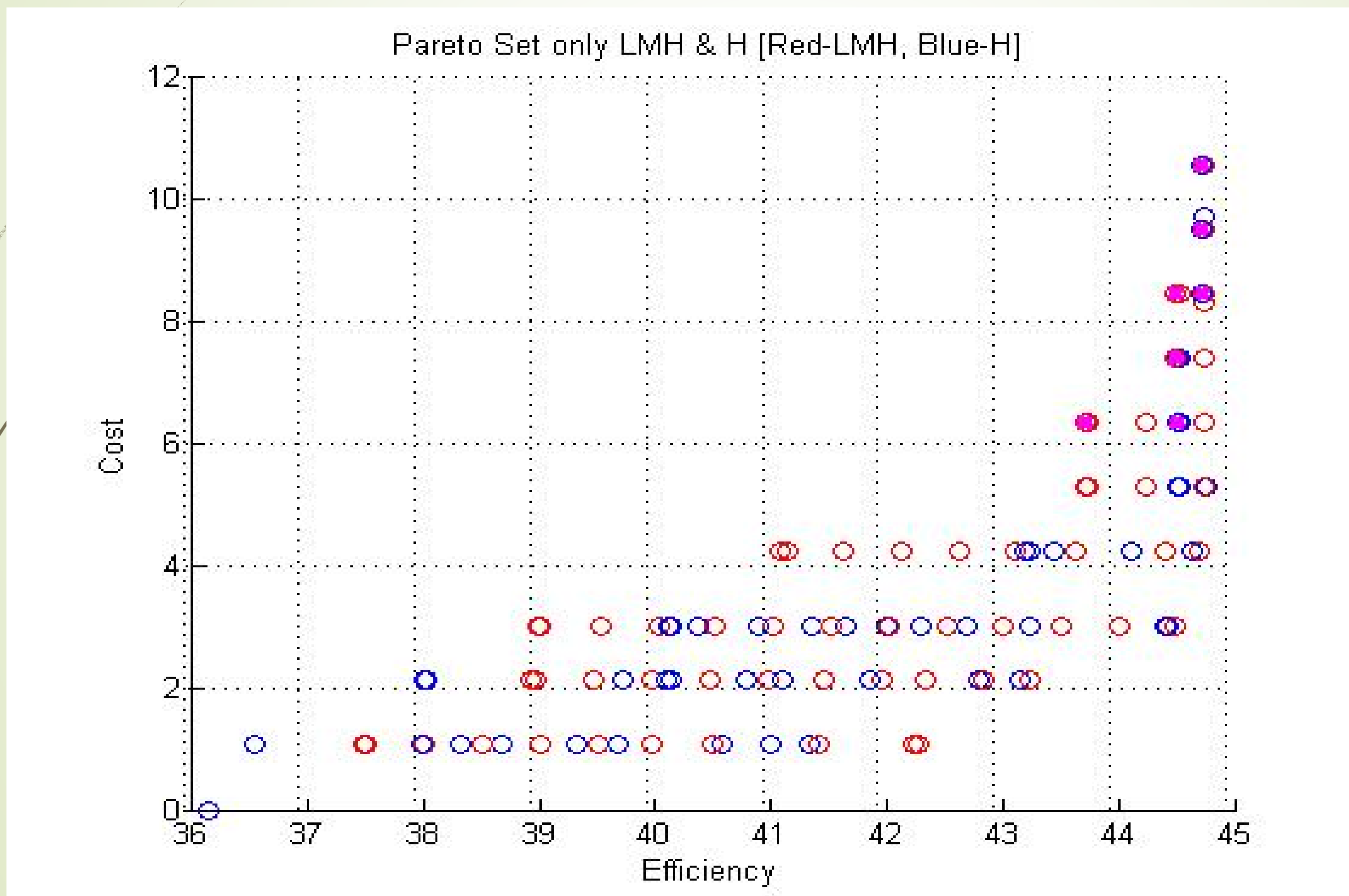
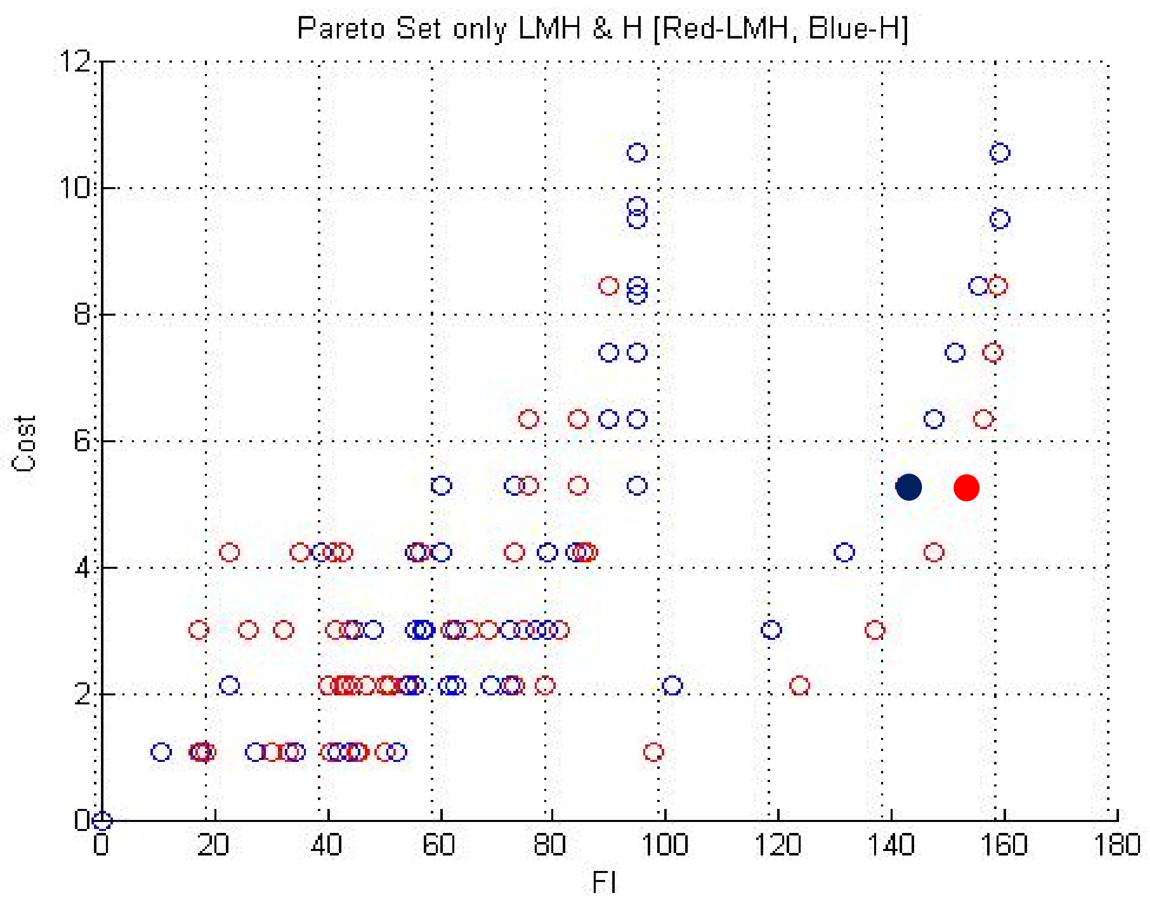
High Cost – High efficiency – High FI



Moderate Cost – High efficiency – High FI



INFERENCES

- Maximizing efficiency is cheaper than maximizing FI.
- Even if we are trying to maximize efficiency, a budget of $5.27 million is sufficient.
- Even if we are trying to maximize both, a budget of $ 7.38 million is sufficient.

SUMMARY

- Initial sample generated from ASPEN
- Off-line APSEN simulations for the fixed number of samples
- Algorithmic framework based on BONUS for single objective optimization
- Feasible solutions by fixing cost bins apriori
- 2-tier constraint method for solving multi-objective optimization.
- Pareto surface generation for decision makers
- Analysis of pareto surface can help determine the solution for desired trade-off.

KEY CONTRIBUTIONS

Objectives satisfied

- Developed sensor deployment methodology which incorporates non-linearity and uncertainty - a framework for virtual sensing and hybrid hardware and virtual sensing in power plants.
- Developed computationally efficient algorithm -significant reduction in the number of model runs to be solved for optimization and the number of samples for the uncertainty analysis
- Obtained tradeoffs between multiple objectives.

FUTURE WORK

- Comparison of stochastic approach to SND with dynamic simulation approach to determine which is more computationally efficient.
- Include other objective functions, e.g., CO2 capture efficiency.
- Application of this methodology to dynamic sensor problems.
- Extension of this methodology to other systems which have a black box model.

Thank You