Model Based Optimal Sensor Network Design for Condition Monitoring in an IGCC Plant

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Optimal Sensor Placement for Condition Monitoring

1.2M Program for Model-Based Sensor Placement for Component Condition Monitoring

Project Team

GE Global Research
- *Modeling*
- *Estimation algorithms*
- *Optimization*

Relevant Prior Work
- *IGCC component models*
- *Model-based estimation*
- *Model-based large scale optimization*

Program Objectives: Develop and Demonstrate a model-based optimal sensor placement solution for online condition monitoring

Distributed sensor network in gasifier refractory for refractory health monitoring

Distributed sensor network in radiant syngas cooler for fouling monitoring

Technical Approach
- Gasifier and RSC model for condition monitoring
- Model-based estimation of varying refractory degradation and RSC fouling
- Model-based optimization for optimal sensor placement

Program Deliverables
- *Model-based estimation algorithm*
- *Optimization algorithm for optimal sensor placement*

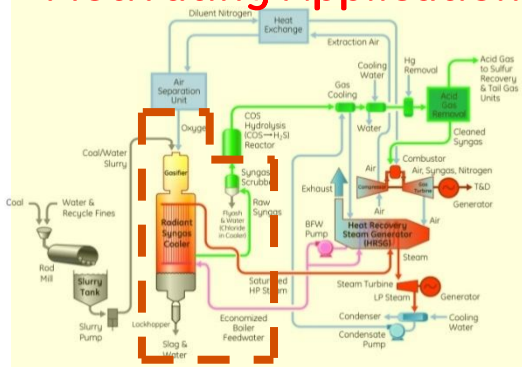
Anticipated Benefits
- *Real-time monitoring of critical component condition*
- *Increased availibility 3-5%*
- *Increased operation efficiency 1-2%*

- Develop Systematic model based computational approach for OSP
- Computer simulation demonstration on gasifier and RSC – key process units in gasification section with very harsh environment

Introduction

Combined Cycle
- Firing temperature
- Stresses

Motivating Application



IGCC
- Gasifier T
- Carbon Conv
- Refractory wear

Wind Turbine
- Stresses
- Aerodynamic Thrust

Performance, Safety requirements

Advanced controls –
- Pushing the envelope of operation and performance

Advanced sensing system –
- Online monitoring

Systematic Sensor Network Design
- Sensor type
- Number & location
- Soft sensing
- Cost
- ....

Resource, Operational constraints

"Lean" Sensor set–
- Harsh environment,
- Inadequate sensing technology
- Complexity/weight/ cost limitations

Motivation for Model-Based Sensing & Design

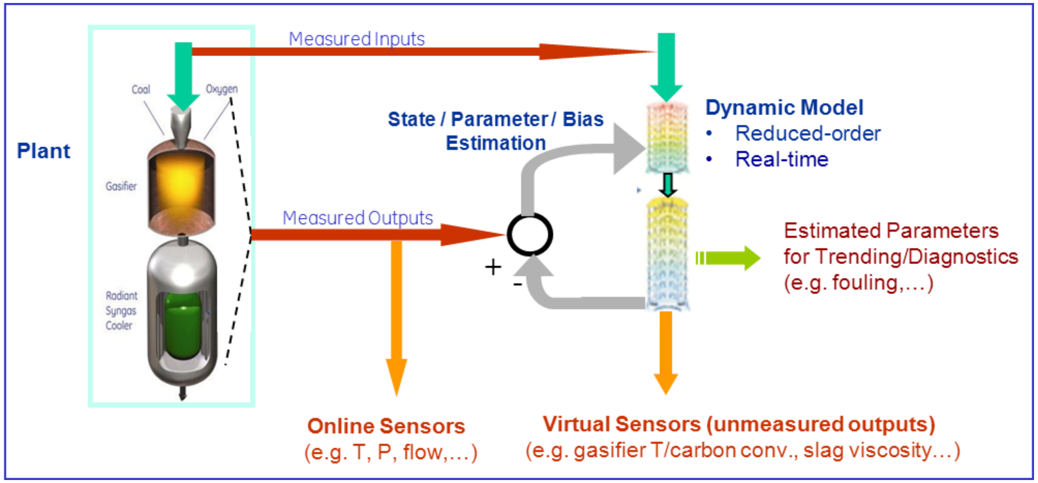
Advanced Controls
Increased sensors

Monitoring
Advanced sensor technology

Increased weight, cost, complexity.

Increased initial cost

Model based sensing to identify cost-effective, reliable and robust solutions



Sensor Specifications
- Measurement Noise
- Accuracy (bias, drift)
- Failure rates

Sensing System Performance
- Sensitivity with respect to model/ sensor errors
- Estimation accuracy (variance)
- Robustness to failures

Kalman Filter Framework

Model Inaccuracies
- Parametric error
- Structural error

Optimal sensor placement (sensor type, number and location)

Model-Based OSP Methodology

Goals

- Develop systematic model-based computational approach for optimal sensor placement with key metrics,
- Computer simulation demonstration on gasifier and RSC
- Design methodology and tools developed for broad applications

Network requirements
- Accuracy
- Reliability
- ....

- Location constraint
- Sensor Cost

Offline Design

Optimizer
MINLP

Selected sensor set

Sensing performance (Accuracy etc.)

Estimator KF/EKF

System
(dynamic model)
- linear
- nonlinear

OSP
- Sensor type
- Number of sensors
- Sensor Location

Key design metrics
1. Solution accuracy
2. Computational efficiency

Problem Characteristics
- Mixed variable (integer/real)
- Large scale system
- Non linear constrained optimization

OSP Problem Formulation

Minimize cost: $\min_{q} c^T q$

Subject to: $C^e P_\infty(q) C^{e^T} \leq s$ (Precision constraint)

$$\sum_{\omega_k \in \Omega_q} \Pr(\omega_k)\, I(\omega_k) \geq r$$ (Reliability constraint)

$q_i = \{0,1\}, for\ \ i = 1, 2, \ldots, N$ (Location constraint)

Where, $I(\omega_k) = \begin{cases} 1, & precision\ met \\ 0, & otherwise \end{cases}$

Ω_q is the set of possible sensor failure scenarios associated with a given sensor configuration q.

Precision– Quantifies measurement accuracy using the variance of the measurement error.

Reliability – Quantifies probability that the sensor network will satisfy the precision requirement in the presence of expected individual sensor failures

$$C^e P_\infty(q) C^{e^T} \leq s$$

Steady state error covariance matrix $P_\infty \in \Re^{n \times n}$

$$\sum_{\omega_k \in \Omega_q} \boldsymbol{Pr}(\boldsymbol{\omega_k})\, \boldsymbol{I}(\boldsymbol{\omega_k}) \geq \boldsymbol{r}$$

Probability of reduced sensor set due to individual sensor failure

With the reduced sensor set, is precision met?

OSP Methodologies

Generic Formulation

$$Z^* = \min_{q,t} f(q,t)$$

$$s.t., \quad g(q,t) \le 0, q \in \{0,1\}^N$$

$$t \in \Re\hat{\ } l$$

Nonlinear constraint

Real/Integer decision space

Challenges

INLP

- Combinatorial decision space: Algorithm development for solving MINLP is an active research area as compared to integer linear programming

OSP

- Computational requirements (memory and time) of error covariance's depends on underlying system dynamics.
  - for example, 3D gasifier model has 1000's of states.
- Reliability constraint evaluation
  - Non-smooth function due to Indicator function
  - Precision evaluation and summation over combinatorial failure scenarios

Existing approaches

Seek solutions through relaxations → **Methods** Branch & Bound, Outer approximations → **Solvers** NLP (IPOPT) , SDP, LMI, Integer LP (CPLEX)

Approaches for Solving OSP (INLP) Problem

Relax (approximate feasible space) original INLP → Iterative Upper/Lower bound generation → MINLP optimal solution at convergence

Branch and Bound

- Integer constraint is relaxed
- NLPR provides lower bounds $Z^L = Z^{BB}$
- If q^{BB} $is\ integer, Z^U = Z^{BB}$, upper bound is obtained.

Outer Approximation

- Nonlinear constraint is relaxed
- M-OA provides lower bounds $Z^L = Z^{OA}$
- Primal provides upper bounds $0, Z^U = Z^{OA}$, upper bound is obtained.

$$NLPR: \quad \min_{q,t}\ f(q,t)$$
$$g(q,t) \le 0, q \in [0,1]^{\bar{N}}, t \in \Re^l,\ \bar{N} \le N$$

$$Primal: \quad min_t f(q^{OA}, t)$$
$$g(q^{OA}, t) \le 0, t \in \Re^l.$$

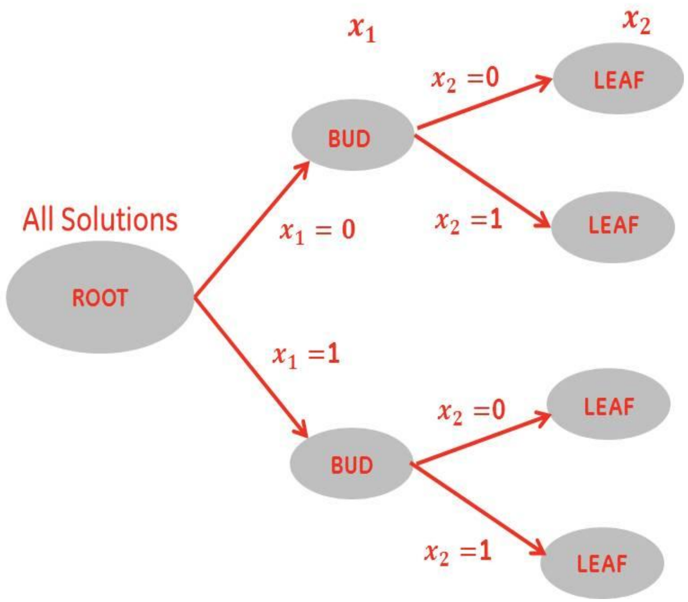
$$MOA: \quad min_{\alpha,q,t}\ \alpha$$
$$f(q^k, t^k) + \nabla f_{|(q^k,t^k)} \begin{pmatrix} q - q^k \\ t - t^k \end{pmatrix} \le \alpha$$
$$g(q^k, t^k) + \nabla g_{|(q^k,t^k)} \begin{pmatrix} q - q^k \\ t - t^k \end{pmatrix} \le 0$$
$$\sum_{i \in B^j} q_i^j - \sum_{i \in NB^j} q_i^j \le |B^j| - 1, j \le k$$
$$q \in \{0,1\}^N, t \in \Re^l, \alpha \in \Re, q^k \in \mathbf{\Pi}$$

$$B = \{i | q_i = 1\}, NB = \{i | q_i = 0\}$$

$$\forall k\ (iteration), Z^{L,k} \le Z^* \le Z^{U,k}$$

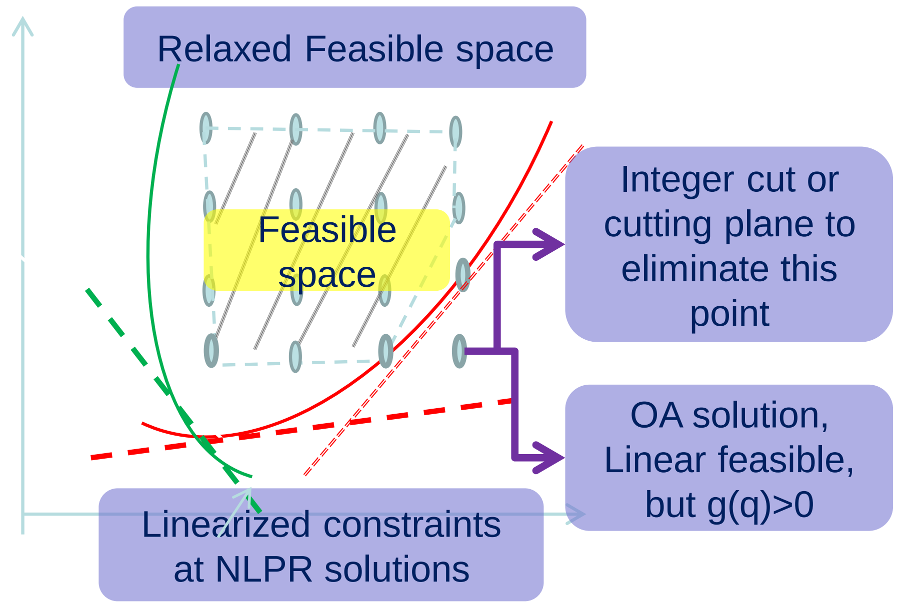
Existing Methods

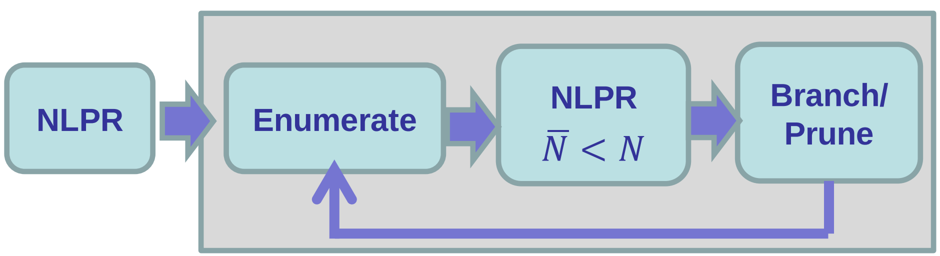
Branch & Bound



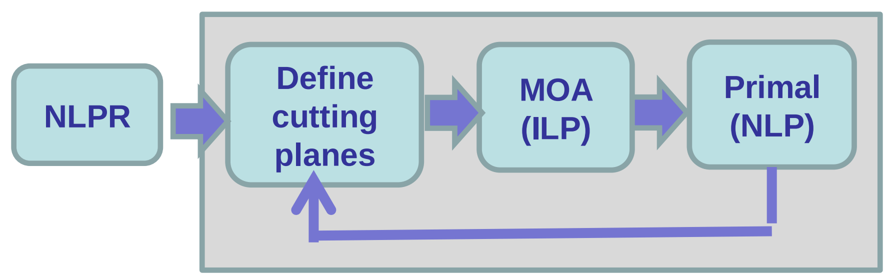
A full enumeration tree in BB algorithm with two integer variables (Chinneck 2010)

Outer Approximation





BB Algorithm Schematic



OA Algorithm Schematic

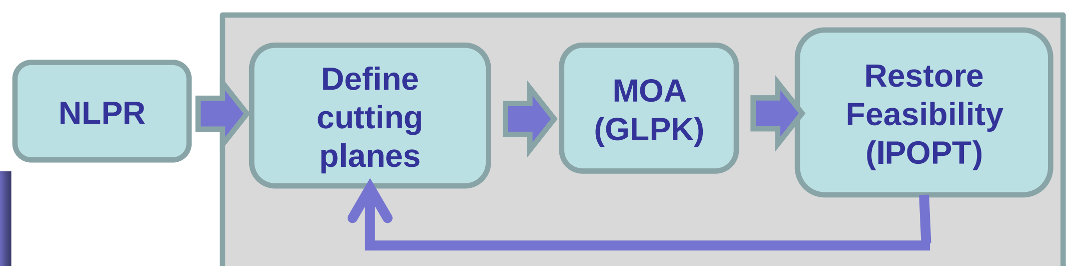
Proposed Methodology for Solving INLP

Applicability of existing methods for solving OSP for condition monitoring

Method	Pros	Potential issues
Branch and Bound	• Directly applicable to OSP • Can deal with pure integer space	1.Enumeration 2.Faster covariance computation 3.Gradient computations
Outer Approximation	• Primal problem is over real variables • Cannot be directly applied to OSP	1.Faster covariance computation 2.Gradient computations

Proposed INLP Framework

- Pure integer space
- Faster Lyapunov based Error covariance matrix
- Analytical Gradients
- State of the art NLP solvers for computation efficiency.



OSP for Refractory wear monitoring for Gasifier

Optimization Results for 1D model

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Model Enhancement

Gasifier

- Model based estimation of unknown gasifier wear through temperature measurements.

  $\Rightarrow$ Transient 3-D thermal model of the refractory lining to relate the effects of hot surface wear on potential thermal sensors placed in the refractory lining

  $\Rightarrow$ Initial OSP algorithm development and testing with 1-D model

RSC

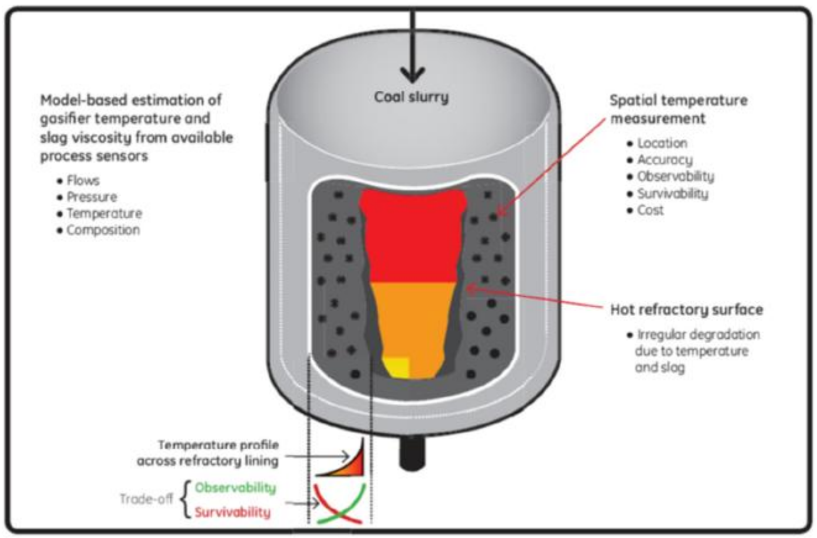
- Model based estimation of unknown fouling through heat flux, temperature and strain in addition to existing sensors

  $\Rightarrow$ Transient RSC model capturing the effect of non-uniform axial fouling profile in RSC tube on heat flux, temperature and strain.

1-D Gasifier Model

Heat Balance

- Full problem: non-uniform wear → 3D
- Reduced problem: uniform wear → 1D



1D Heat Balance

$$\left(\frac{\rho C_p}{\kappa}\right)\frac{\partial T}{\partial t} = \frac{\partial^2 T}{\partial r^2} + H,$$

20 Temperature states
15 measurements
(possible sensor locations)

13 uncertain Parameters

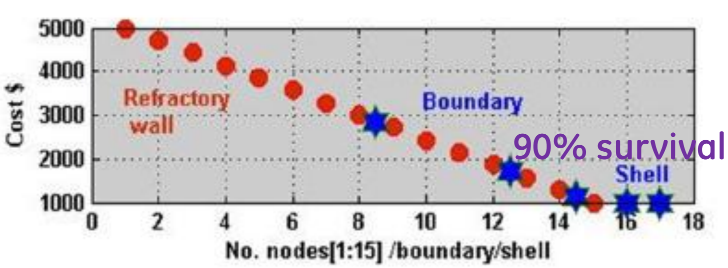
↓

Kalman Filter
Linearized models, Noise statistics

↓

Refractory Wear Estimate

Sensor Metrics*



Performance Metrics

$$C^e P_\infty(q) C^{e^T} \leq \sim 5\%\ t_{Brick}$$

$$\sum_{\omega_k \in \Omega_q} \Pr(\omega_k)\, I(\omega_k) \geq 0.9$$

* The cost is scaled and not representative of the actual sensor cost

OSP for 1D Model: Only Precision Constraint

Parameters are accurate

Hot | 6 | 7 | 8 | Interface 16 | 9 | 10 | 11 | 12 | Interface 17 | 13 | 14 | Interface 18 | Shell 19 | 15 | Shell 20 | Cold

Three possible optimal locations
Sensor at 6,15 OR
Sensor at 6,19 OR
Sensor at 6, 20

Parameters are uncertain (Markov model)

Hot | 6 | 7 | 8 | Interface 16 | 9 | 10 | 11 | 12 | Interface 17 | 13 | 14 | Interface 18 | Shell 19 | 15 | Shell 20 | Cold

Only one possible optimal Location

Model	Optimal Cost ($)	Optimization Time (s)
No parametric error	4571.4*	400
WITH parametric errors	6428.6*	2015

- Model errors impacts estimation
- Total optimization times increase

Extension to include "reliability".

* The cost is scaled and not representative of the actual sensor cost

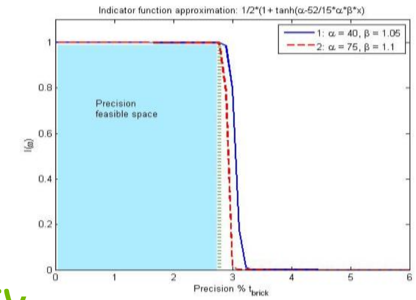
Computing Reliability

- Set of all possible failures (Ω_q) is a power set $(2^{|B|})$
- Indicator function is non-smooth and approximation is required.

$$\sum_{\omega_k \in \Omega_q} \Pr(\omega_k)\, I(\omega_k) \geq 0.9$$

$$\sum_{\omega_k \in \Omega_q} \Pr(\omega_k)\, I_{smooth}(\omega_k) \geq 0.9$$

Ensure convexity



- **Approach 1:** Solve the full Reliability problem (NLP)
  - Computing the failure scenarios for only those sensors that affect the estimation precision the most (reduces the size of Ω_q)
  - Indicator function approximation

- **Approach 2:** Design the minimal cost sensor network that achieves desired precision and then add redundancies to meet reliability
  - Addition of multiple sensors till reliability is met (OR)
  - Addition of sensors with highest precision sensitivity

Approach 1
Computation effort

⟺

Approach 2
Suboptimal cost

OSP for 1D Model: With Reliability

Approach 1

$$\min_{q} c^T q$$

$$C^e P_\infty(q) C^{e^T} \leq \sim 5\%\ t_{Brick}$$

$$\sum_{\omega_k \in \Omega_q} \Pr(\omega_k)\, I_{smooth}(\omega_k) \geq 0.9,$$

$$q_i = [0,1], \qquad for\ \ i = 1, 2, \ldots, 15$$

Approach 2

$$\min_{q} c^T q$$

$$C^e P_\infty(q) C^{e^T} \leq \sim 5\%\ \ t_{Brick}$$

$$q_i = [0,1],^{\bar{N}}\ \bar{N} \leq 15$$

Get the precision optimal solution with the BB framework, if this meets reliability then stop, else

Branch with respect to the highest sensor sensitivity index for the bud node selection

Solve the precision NLP problem till convergence

Hot

Optimal Sensor Placement

Cold

6	7	8	Interface 16	9	10	11	12	Interface 17	13	14	Interface 18	Shell 19	15	Shell 20

Optimal Cost: $ 7857*

Method 1	Optimal Cost ($)	No Iterations	Time (s)/iter
Approach 1 (BB + NLP-Full)	7857*	~110	~165s
Approach 2 (BB + NLP-Precision)	7857*	~1200	~1s

- Need approximations for the reliability constraint

OR

- Need effective mechanisms to shrink feasible space

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* The cost is scaled and not representative of the actual sensor cost

Progress Summary

- ✓ Model: Developed the 1D and 3D models for Gasifier and detailed model for RSC fouling.
- ✓ Algorithms: Developed INLP framework (OA-INLP and BB) applicable for OSP
  - ✓ Focused on computational efficiency improvement.
  - ✓ Analytical and faster ways of gradient computations.
  - ✓ Leverage state of the art NLP as well as ILP solvers.
- ✓ Case study: Implemented the algorithms on a 1D model of a gasifier to design the sensor network for monitoring refractory wear:
  - ✓ Considered measurement and modeling errors for robust monitoring
  - ✓ Implemented the reliability constraint using original formulation as well as approximation.
  - ✓ Identified the implementation challenges in designing reliable sensor networks
    - ✓ Tradeoff's between solution accuracy and optimization time

Continuing Work (2012)

Algorithm

- Computationally efficient approximations for reliability constraint.
- Relaxation of precision constraint (soft constraint) for design trade-off.

Modeling

- Identify sub problem in 3-D gasifier exploiting problem structure for covariance estimation: Trade-off between estimation accuracy and in problem size (memory requirement)

Applications

- Integration of OSP algorithm with 3-D gasifier model and RSC model
- Define the test cases to assess OSP algorithm performance
- Demonstrate the performance of the OSP algorithm