<u>Deterministic Global Optimization:</u> <u>Advances in Theory and Applications</u>



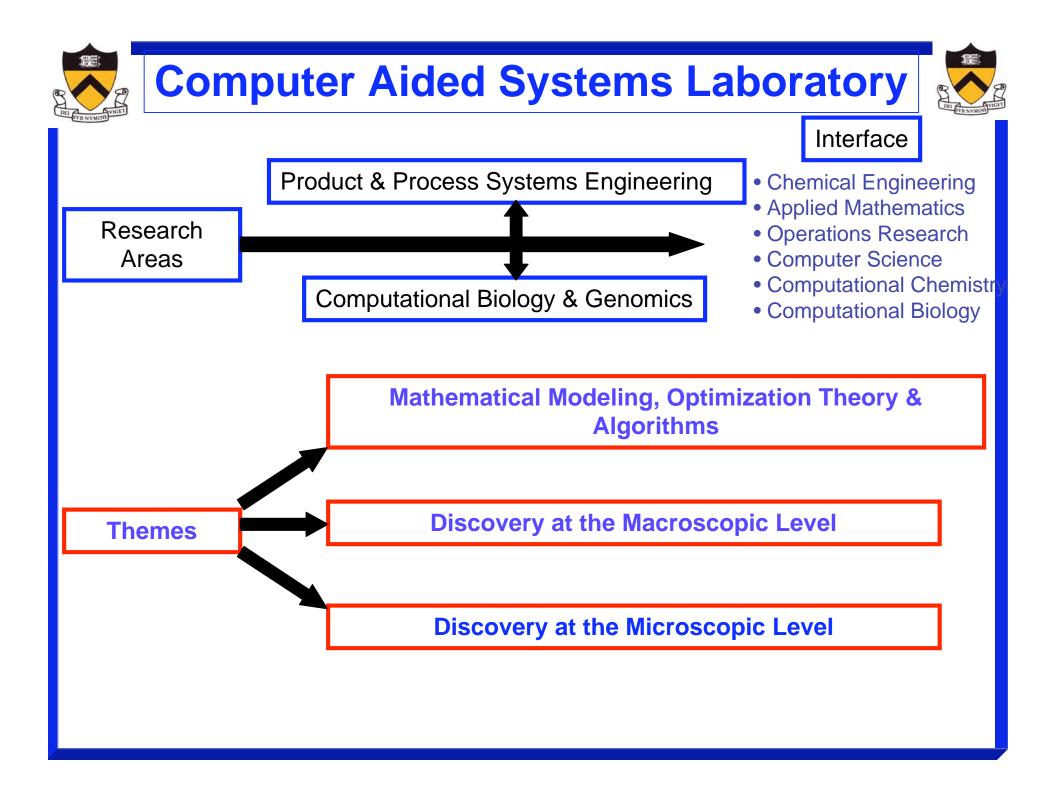
Christodoulos A. Floudas

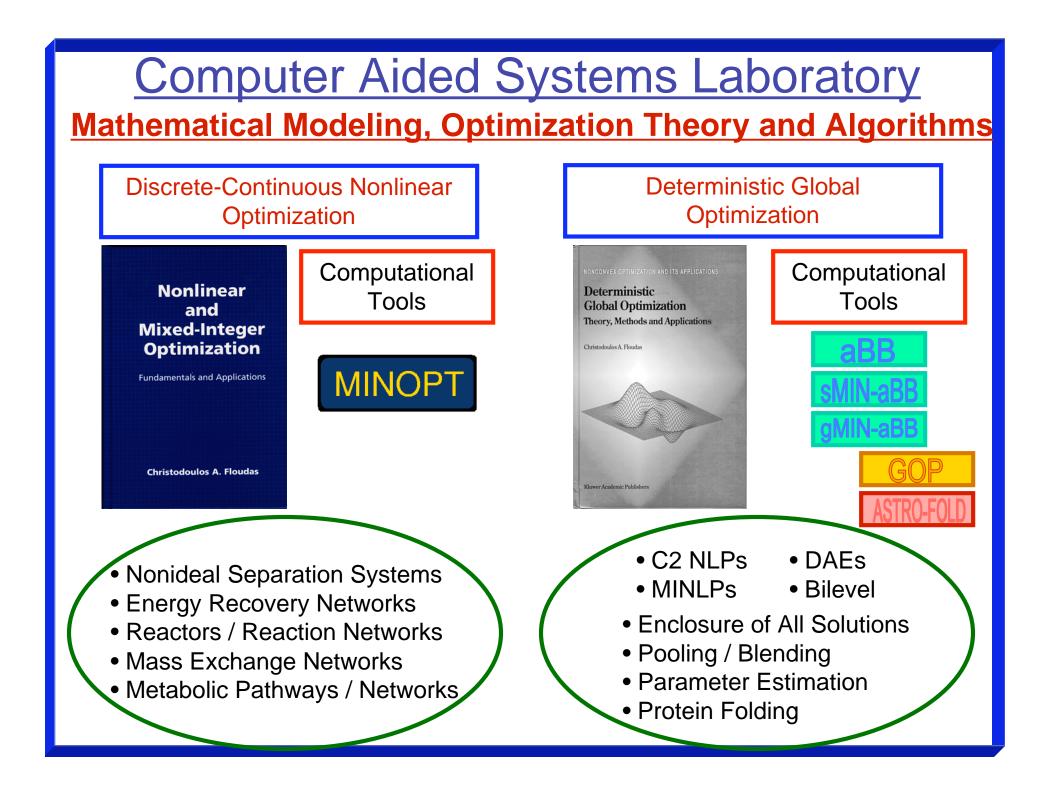
Stephen C. Macaleer `63 Professor in Engineering and Applied Science Professor of Chemical and Biological Engineering

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- Department of Chemical and Biological Engineering
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- Department of Operations Research and Financial Engineering
- Center for Quantitative Biology

(Adjiman, Androulakis, Akrotirianakis, Gounaris, Meyer, Maranas, Misener)





Computer Aided Systems Laboratory

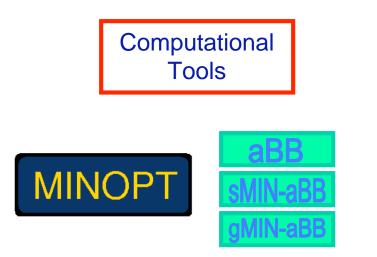
Discovery at the Macroscopic Level

Product and Process Design and Synthesis

- Methods for Design under Uncertainty
- Parameter Estimation under Uncertainty
- Topology in Metabolic Networks
- Nonideal Separations
- Phase & Chemical Reaction Equilibrium
- Parameter Estimation of Algebraic and Dynamic Models

Product and Process Operations: Scheduling, Planning & Uncertainty

- Short Term Scheduling
- Medium Range Scheduling
- Reactive Scheduling
- Scheduling under Uncertainty
- Design and Scheduling under Uncertainty
- Long term Planning





Computer Aided Systems Laboratory

Discovery at the Microscopic Level

Bioinformatics and Computational Genomics

- Structure Prediction in Protein Folding
 - Secondary Structure
 - Tertiary Structure
- Structure Refinement for NMR
- Dynamics of Protein Folding
- Protein-Protein Interactions
- De Novo Protein Design
- Topology of Signal Transduction Networks and Metabolic Pathways
- Peptide & Protein Identification via Tandem Mass Spectroscopy



Outline

- Deterministic Global Optimization: Objectives & Motivation
- Convex Envelopes:
 - Trilinear Monomials
 - Edge Concave functions
- Piecewise linearization of Bilinear terms
- Checking Convexity: Products of Univariate Functions
- PαBB: Piecewise Quadratic Perturbations
- Pooling Problems: Standard, Generalized & Extended
- Conclusions

Deterministic Global Optimization: Objectives

Objective 1

Determine a global minimum of the objective function subject to the set of constraints

Objective 2

Determine LOWER and UPPER BOUNDS on the global minimum

Objective 3

Identify good quality solutions (i.e., local minima close to the global minimum)

Objective 4

Enclose ALL SOLUTIONS of constrained systems of equations



Major Importance in Engineering Applications

Deterministic Global Optimization: <u>C² NLPs</u>

Formulation

$$\min_{\mathbf{x}} f(\mathbf{x})$$
s.t.
$$\mathbf{h}(\mathbf{x}) = \mathbf{0}$$

$$\mathbf{g}(\mathbf{x}) \leq \mathbf{0}$$

$$\mathbf{x} \in \mathbf{X} \subseteq \mathbb{R}^{n}$$

$$f, \mathbf{h}, \mathbf{g} \in C^2$$

Application Areas

- Phase Equilibrium Problems
 - Minimum Gibbs Free Energy
 - Tangent Plane Stability

•Pooling/Blending

- Parameter Estimation &
- Data Reconciliation
 - Physical Properties
- Design Under Uncertainty
- Robust Stability of Control Systems
- Structure Prediction in Clusters
- Structure Prediction in Molecules
- Protein Folding
- Peptide Docking
- NMR Structure Refinement
- Prediction of Crystal Structure

Deterministic Global Optimization: <u>MINLPs</u>

Formulation

$$\min_{\mathbf{x},\mathbf{y}} \quad f(\mathbf{x},\mathbf{y})$$

s.t.
$$\mathbf{h}(\mathbf{x},\mathbf{y}) = \mathbf{0}$$

$$\mathbf{g}(\mathbf{x},\mathbf{y}) \leq \mathbf{0}$$

$$\mathbf{x} \in \mathbf{X} \subseteq R^n$$

continuous relaxations

$$f$$
, **h**, **g** \in C^2

Application Areas

- Process Synthesis Problems
 - HENs
 - Separations/Complex Columns
 - Reactor Networks
 - Flowsheets
- Scheduling, Design, Synthesis of Batch and Continuous Processes
- Planning
- Synthesis Under Uncertainty
- Design, Synthesis of Materials
- Metabolic Pathways
- Circuit Design
- Layout Problems
- Nesting of Arbitrary Objects

<u>Deterministic Global Optimization:</u> <u>Bilevel Nonlinear Optimization, BNLPs</u>

Formulation

$$\min_{\mathbf{x},\mathbf{y}} F(\mathbf{x},\mathbf{y})$$
s.t.
$$\mathbf{H}(\mathbf{x},\mathbf{y}) = \mathbf{0}$$

$$\mathbf{G}(\mathbf{x},\mathbf{y}) \leq \mathbf{0}$$

$$\min_{\mathbf{y}} f(\mathbf{x},\mathbf{y})$$
s.t.
$$\mathbf{h}(\mathbf{x},\mathbf{y}) = \mathbf{0}$$

$$\mathbf{g}(\mathbf{x},\mathbf{y}) \leq \mathbf{0}$$

$$\mathbf{x} \in \mathbf{X} \subseteq \mathbb{R}^{n^{1}}, \mathbf{y} \in \mathbf{Y} \subseteq \mathbb{R}^{n^{2}}$$

Application Areas

- Economics
- Civil Engineering
- Aerospace
- Chemical Engineering
 - Design Under Uncertainty : Flexibility Analysis
 - Chemical Equilibrium Process Design
 - Location/Allocation in Exploration
 - Interaction of Design with Control
 - Optimal Pollution Control
 - Molecular Design
 - Pipe Network Optimization

Recent Reviews

- Floudas, Akrotirianakis, Caratzoulas, Meyer, Kallrath (2005), "Global Optimization in the 21st Century", *Computers & Chemical Engineering*, 29(6), 1185-1202.
- Floudas, and Gounaris, (2009), "A Review of Recent Advances In Global Optimization", *Journal of Global Optimization*, 45, 3-38.

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(Meyer and Floudas, JOGO, 2003)

• The convex envelope of a trilinear monomial is polyhedral over a coordinate aligned hyper-rectangular domain.

• A triangulation of the domain defines the convex envelope of the monomial.

• The correct triangulation is determined by a set of conditions related to the minimal affine dependencies of the vertices of the hyper-rectangle.

• An explicit set of formulae for the elements of the convex envelope is defined for each set of conditions.

(Meyer and Floudas, JOGO, 2003)

Positive Bounds

If $\underline{x} \ge 0$, $y \ge 0$ and $\underline{z} \ge 0$ and the auxiliary conditions apply:

 $\overline{x}y\underline{z} + \underline{x}\overline{y}\overline{z} \le \underline{x}\overline{y}\underline{z} + \overline{x}\overline{y}\overline{z} \quad \overline{x}y\underline{z} + \underline{x}\overline{y}\overline{z} \le \overline{x}\overline{y}\underline{z} + \underline{x}\overline{y}\overline{z}$

the linear equalities defining the facets of the convex envelope are:

$$w = \underbrace{yzx + xzy + xyz - 2xyz}_{W}$$

$$w = \overline{yzx + xzy + xyz - 2xyz}_{W}$$

$$w = y\overline{zx + xzy + xyz - 2xyz}_{W}$$

$$w = \overline{yzx + xzy + xyz - xyz - \overline{xyz}}_{W}$$

$$w = \frac{\theta}{\overline{x - x}} x + \overline{xzy} + \overline{xyz} + \left(-\frac{\theta x}{\overline{x - x}} - \overline{xyz} - \overline{xyz} + x\overline{yz}\right)$$

$$w = \frac{\theta}{x - \overline{x}} x + x\overline{zy} + x\overline{yz} + \left(-\frac{\theta \overline{x}}{\overline{x - x}} - \overline{xyz} - \overline{xyz} + x\overline{yz}\right)$$

$$w = \frac{\theta}{x - \overline{x}} x + x\overline{zy} + x\overline{yz} + \left(-\frac{\theta \overline{x}}{\overline{x - x}} - x\overline{yz} - \overline{xyz} + x\overline{yz}\right)$$

$$w = \frac{\theta}{x - \overline{x}} x + x\overline{zy} + x\overline{yz} + (\overline{xyz} - \overline{xyz} - x\overline{yz} + \overline{xyz})$$

(Meyer and Floudas, JOGO, 2003)

Illustration

To construct the concave envelope of $x_1x_2x_3$ for $(x_1, x_2, x_3) \in [1, 2] \times [1, 2] \times [2, 4]$. We substitute $y \leftarrow x_1, x \leftarrow x_2$, and $z \leftarrow x_3$ and check conditions:

 $\overline{x}\underline{y}\underline{z} + \underline{x}\overline{y}\overline{z} \le \underline{x}\overline{y}\underline{z} + \overline{x}\underline{y}\overline{z} \quad \overline{x}\underline{y}\underline{z} + \underline{x}\overline{y}\overline{z} \le \overline{x}\overline{y}\underline{z} + \underline{x}\overline{y}\overline{z}$

which translate into,

$\overline{x}_{2}\underline{x}_{1}\underline{x}_{3} + \underline{x}_{2}\overline{x}_{1}\overline{x}_{3} \leq \underline{x}_{2}\overline{x}_{1}\underline{x}_{3} + \overline{x}_{2}\underline{x}_{1}\overline{x}_{3}$ $(3)(1)(2) + (1)(2)(4) \leq (1)(2)(2) + (3)(1)(4)$ $14 \leq 16$

and,

 $\overline{x}_{2} \underline{x}_{1} \underline{x}_{3} + \underline{x}_{2} \overline{x}_{1} \overline{x}_{3} \leq \underline{x}_{2} \underline{x}_{1} \overline{x}_{3} + \overline{x}_{2} \overline{x}_{1} \underline{x}_{3}$ $(3)(1)(2) + (1)(2)(4) \leq (1)(1)(4) + (3)(2)(2)$ $14 \leq 16$

Both conditions hold, so we can use the substitutions in the facet defining equations.

(Meyer and Floudas, JOGO, 2003)

Facet Defining Equations

$$w = 2x_{2} + 2x_{1} + 1x_{3} - 4,$$

$$w = 8x_{2} + 12x_{1} + 6x_{3} - 48,$$

$$w = 4x_{2} + 4x_{1} + 3x_{3} - 16,$$

$$w = 4x_{2} + 6x_{1} + 2x_{3} - 16,$$

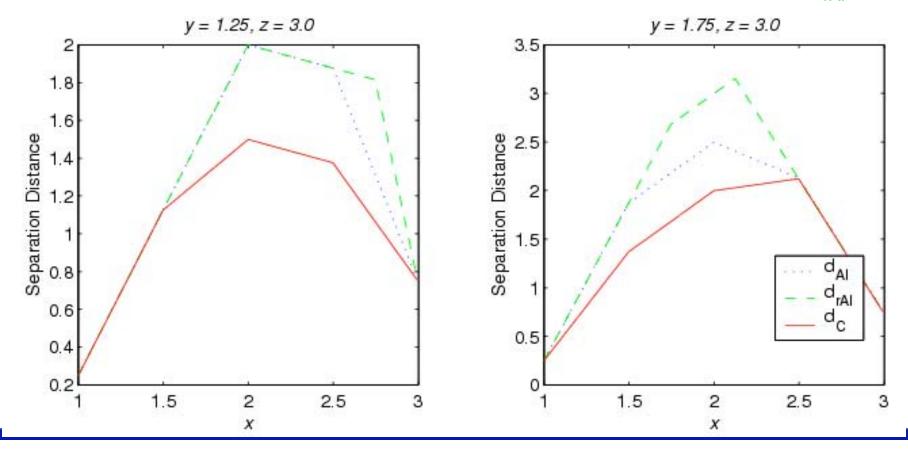
$$w = 5x_{2} + 6x_{1} + 3x_{3} - 21,$$

$$w = 3x_{2} + 4x_{1} + 2x_{3} - 11.$$

<u>Comparison with Lower Bounding</u> <u>Approximations</u>

The separation distance between the function xyz and the convex envelope (d_C) is compared with the separation distance between xyz and: • the Arithmetic Interval lower bounding approximation (d_{AI}) and,

• the Recursive Arithmetic Interval lower bounding approximation (d_{rAI}) .



(Meyer and Floudas, Math. Programming, 2005)

Definition:

Edge-concave functions are a class of functions that admit a vertex polyhedral convex envelope (Tardella, 2008)

Several classes of functions are edge-concave on certain domains:

- Concave functions over polytopes
- Multilinear functions over hypercubes (Rikun, 1997)

Theorem (Tardella, 2003): Function f(x) defined on a box is edge-concave iff it is componentwise concave. When f(x) is also twice continuously differentiable, edge-concavity is equivalent to:

$$f_{x_i,x_i}(\mathbf{x}) \le 0 \quad \forall i=1,\cdots,n$$

(Meyer and Floudas, *Math. Programming*, 2005) Edge-concave function $f: conv(V) \rightarrow R$

Set of vertices of hyperrectangle $V = \{x^1, x^2, ..., x^{2^n}\} \in \mathbb{R}^n$

ALGORITHM

Step1: Dominance Relations

Evaluate function at each vertex point x^i and determine the dominant subsets $X = \{x^i : i \in P(\lambda)\} \subseteq V$

(Meyer and Floudas, Math. Programming, 2005)

Edge-concave function $f : conv(V) \rightarrow R$

Set of vertices of hyperrectangle $V = \{x^1, x^2, ..., x^{2^n}\} \in \mathbb{R}^n$

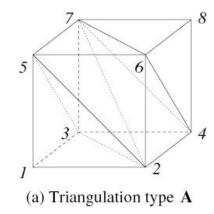
ALGORITHM

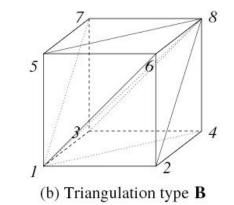
Step1: Dominance Relations

Evaluate function at each vertex point x^i and determine the dominant subsets $X = \{x^i : i \in P(\lambda)\} \subseteq V$

Step2: Triangulation Class

Determine the triangulation type (6 triangulation types for 3D cube)





(Meyer and Floudas, Math. Programming, 2005)

Edge-concave function $f : conv(V) \rightarrow R$

Set of vertices of hyperrectangle $V = \{x^1, x^2, ..., x^{2^n}\} \in \mathbb{R}^n$

ALGORITHM

Step1: Dominance Relations

Evaluate function at each vertex point x^i and determine the dominant subsets $X = \{x^i : i \in P(\lambda)\} \subseteq V$

Step2: Triangulation Class

Step3: Reorientation

Determine the triangulation type (6 triangulation types for 3D cube)

Apply Transformation: Representative triangulation \rightarrow Current triangulation

(Meyer and Floudas, Math. Programming, 2005)

Edge-concave function $f : conv(V) \to R$ Set of vertices of hyperrectangle $V = \{x^1, x^2, ..., x^{2^n}\} \models R^n$

ALGORITHM

Step1: Dominance Relations

Evaluate function at each vertex point x^i and determine the dominant subsets $X = \{x^i : i \in P(\lambda)\} \subseteq V$

Step2: Triangulation Class

Determine the triangulation type (6 triangulation types for 3D cube)

Step3: Reorientation

Apply Transformation: Representative triangulation \rightarrow Current triangulation

Step4: Compute Facets

Solve linear system of equations:

Calculate FDH from the cells of the current triangulation

$$\begin{bmatrix} 1 & x_1^{i_1} & x_2^{i_1} & x_3^{i_1} \\ 1 & x_1^{i_2} & x_2^{i_2} & x_3^{i_3} \\ 1 & x_1^{i_3} & x_2^{i_3} & x_3^{i_3} \\ 1 & x_1^{i_4} & x_2^{i_4} & x_3^{i_4} \end{bmatrix} \begin{bmatrix} \pi_0 \\ \pi_1 \\ \pi_2 \\ \pi_3 \end{bmatrix} = \begin{bmatrix} f(x^{i_1}) \\ f(x^{i_2}) \\ f(x^{i_3}) \\ f(x^{i_3}) \\ f(x^{i_4}) \end{bmatrix}$$

FDH is:
$$w = \langle \pi, x \rangle + \pi_0$$

(Meyer and Floudas, *Math. Programming*, 2005)

Consider function f(**x**):

$$egin{array}{rll} f(x_1,\,x_2,\,x_3) &=& 2\cdot x_1\cdot x_2+2\cdot x_1\cdot x_3+2\cdot x_2\cdot x_3-0.2\cdot x_1\cdot x_2\cdot x_3\ &x_i &\in& \left[-10,\,10
ight],\ i=1,2,3 \end{array}$$

The function must be **edge-concave** because:

$$\frac{\partial^2 f}{\partial x_1^2} = \frac{\partial^2 f}{\partial x_2^2} = \frac{\partial^2 f}{\partial x_3^2} = 0$$

(Meyer and Floudas, Math. Programming, 2005)

 $egin{array}{rll} f(x_1,\,x_2,\,x_3) &=& 2\cdot x_1\cdot x_2+2\cdot x_1\cdot x_3+2\cdot x_2\cdot x_3-0.2\cdot x_1\cdot x_2\cdot x_3\ &x_i &\in& \left[-10,\,10
ight],\ i=1,2,3 \end{array}$

ALGORITHM

Step1: Dominance Relations

Function is perturbed so that non-dominated and dominated subsets coincide

Step2: Triangulation Class

Dominance relations match vertex pattern of triangulation type A

Step3: Reorientation

Step4: Compute Facets

FDH is calculated using cells of triangulation A:

 $f(\mathbf{x}) \geq -16 + 8 \cdot x_1 + 10.4 \cdot x_2 + 4 \cdot x_3$

Standard vertex orientation [1 2 3 4 5 6 7 8] becomes

problem-specific orientation [1 3 2 4 5 7 6 8]

- $f(\mathbf{x}) \geq -80 + 16 \cdot x_1 + 12.8 \cdot x_2 + 10 \cdot x_3$
- $f(\mathbf{x}) \geq -180 + 20 \cdot x_1 + 18 \cdot x_2 + 20 \cdot x_3$
- $f(\mathbf{x}) \geq -160 + 16 \cdot x_1 + 16.8 \cdot x_2 + 20 \cdot x_3$
- $f(\mathbf{x}) \geq -100 + 20 \cdot x_1 + 14 \cdot x_2 + 10 \cdot x_3$

(Meyer and Floudas, Math. Programming, 2005)

 $\begin{array}{rcl} f(x_1,\,x_2,\,x_3) &=& 2 \cdot x_1 \cdot x_2 + 2 \cdot x_1 \cdot x_3 + 2 \cdot x_2 \cdot x_3 - 0.2 \cdot x_1 \cdot x_2 \cdot x_3 \\ & x_i &\in& [-10,\,10]\,,\ i=1,2,3 \end{array}$

 $\min f(x_1, x_2, x_3) = f(-10, 10, -10) = f(-10, -10, 10) = f(10, -10, -10) = -400$

Comparison of underestimation techniques:	Lower Bnd	CPU
Edge-concave technique (Meyer and Floudas, 2005):	- 400	<mark>0.01 s</mark> (GAMS)
Recursive arithmetic intervals (Maranas and Floudas, 1995):	-600	0.01 s (GAMS)
Second-order semidefinite relaxation (Henrion et al., 2007):	-405.72	0.22 s (Matlab)
Third-order semidefinite relaxation (Henrion et al., 2007):	-400	0.40 s (Matlab)

(Meyer and Floudas, Math. Programming, 2005)

Now consider function g(**x**):

 $g(x_1, x_2, x_3) = 1.7502 \cdot x_1 - 0.6031 \cdot x_1 \cdot x_2 - 0.0403 \cdot x_1 \cdot x_3 + 0.0738 \cdot x_1 \cdot x_2^2 + 0.0116 \cdot x_1 \cdot x_2 \cdot x_3 - 0.0026 \cdot x_1 \cdot x_2^3 - 0.0010 \cdot x_1 \cdot x_2^2 \cdot x_3$

 $x_1 \in [0, 2], x_2 \in [6.4, 10], x_3 \in [0, 5]$

g(x) is not edge-concave because one of the partials is sometimes greater than 0:

$$\frac{\partial^2 g}{\partial x_2^2} = 2 \cdot 0.0738 \cdot x_1 + 6 \cdot (-0.0026) \cdot x_1 \cdot x_2 + 2 \cdot (-0.0010) \cdot x_1 \cdot x_3 \neq 0$$

But $g(\mathbf{x})$ can be written as the sum of an **edge-concave** function and an extra term:

$$\begin{array}{lll} g(x_1,\,x_2,\,x_3) &=& (1.7502\cdot x_1 - 0.6031\cdot x_1\cdot x_2 - 0.0403\cdot x_1\cdot x_3 + 0.0490\cdot x_1\cdot x_2^2 + \\ && 0.0116\cdot x_1\cdot x_2\cdot x_3 - 0.0026\cdot x_1\cdot x_2^3 - 0.0010\cdot x_1\cdot x_2^2\cdot x_3) + 0.0248\cdot x_1\cdot x_2^2 \end{array}$$

(Meyer and Floudas, Math. Programming, 2005)

 $g(x_1, x_2, x_3) = (1.7502 \cdot x_1 - 0.6031 \cdot x_1 \cdot x_2 - 0.0403 \cdot x_1 \cdot x_3 + 0.0490 \cdot x_1 \cdot x_2^2 + 0.0116 \cdot x_1 \cdot x_2 \cdot x_3 - 0.0026 \cdot x_1 \cdot x_2^3 - 0.0010 \cdot x_1 \cdot x_2^2 \cdot x_3) + 0.0248 \cdot x_1 \cdot x_2^2$

 $x_1 \in [0, 2], x_2 \in [6.4, 10], x_3 \in [0, 5]$

Comparison of underestimation techniques:	ower Bnd	CPU
Global solution	0	
Edge-concave algorithm with an extra term underestimated using recursive arithmetic (Meyer and Floudas, 2005) : Recursive arithmetic intervals only (Maranas and Floudas, 1995) :	-10.61 -13.56	<mark>0.01 s</mark> (GAMS) 0.01 s (GAMS)
Second-order semidefinite relaxation (Henrion et al., 2007) : Third-order semidefinite relaxation (Henrion et al., 2007) :	-infinity 0	0.56 s (Matlab) 0.44 s (Matlab)

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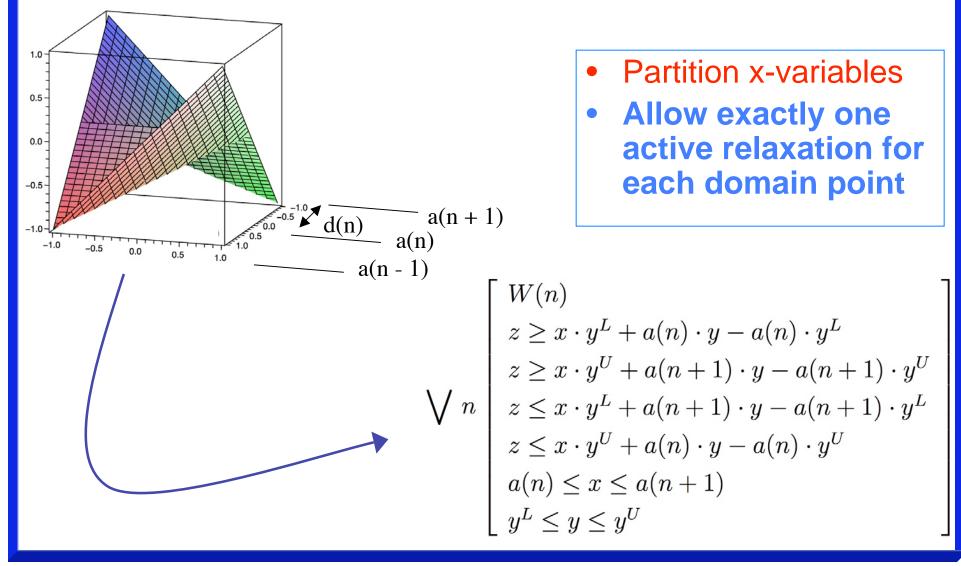
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Relaxation Development: Disjunctive Formulation

Balas [1979]; Floudas [1995]; Wicaksono & Karimi, AIChE J. [2008]



Piecewise Relaxation of Bilinear Programs

- 10 relaxation schemes from Wicaksono & Karimi, AIChE J. [2008] & 5 additional schemes from Gounaris, Misener, Floudas, Ind. Eng. Chem. Res. [2009] using ab initio domain partitioning
- 3 formulation classes:
 - big-M
 - convex hull
 - incremental cost
- Multiple design choices:
 - choice of which variable to partition
 - number of partition segments
 - uniform grid or not

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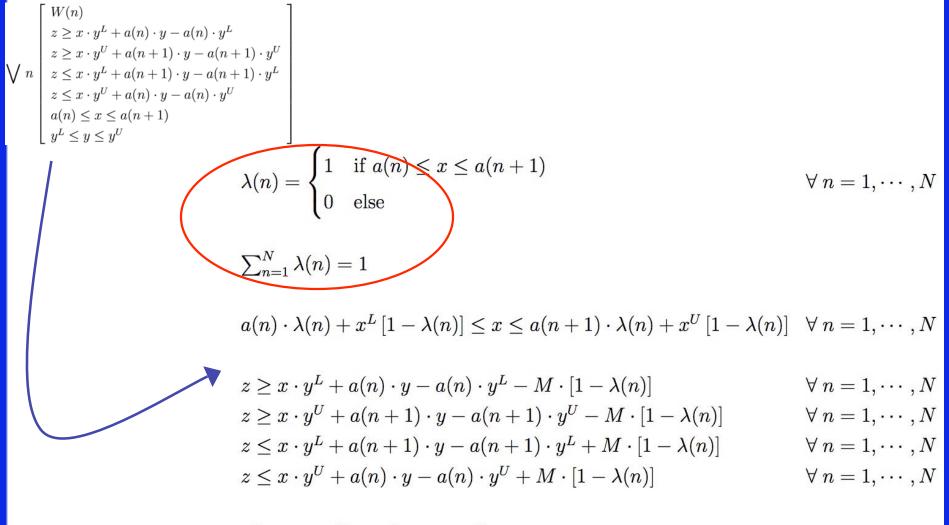
Relaxation Development: Big-M Reformulation

Meyer & Floudas, AIChE J. [2006]; Wicaksono & Karimi, AIChE J. [2008]

 $x^L \le x \le x^U; \quad y^L \le y \le y^U$

Relaxation Development: Big-M Reformulation

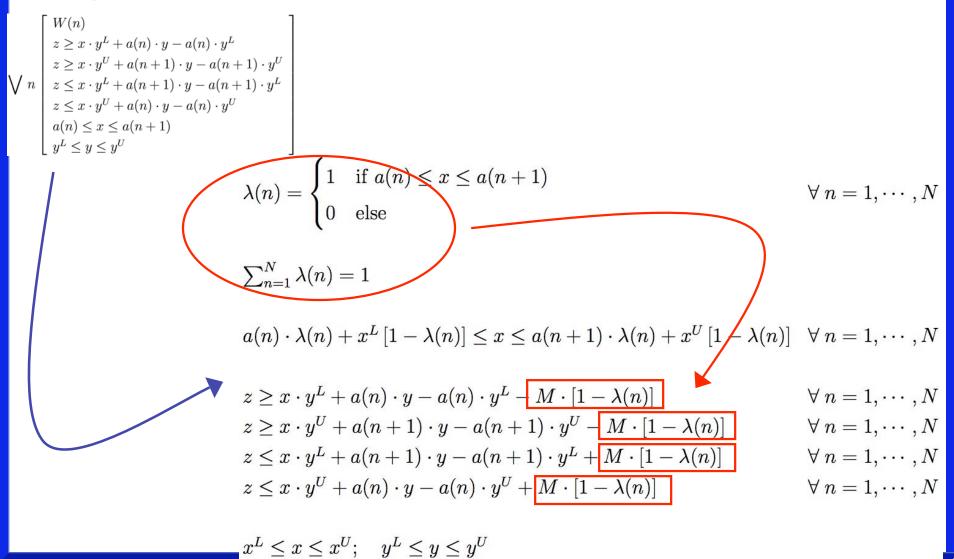
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Relaxation Development: Big-M Reformulation

Meyer & Floudas, AIChE J. [2006]; Wicaksono & Karimi, AIChE J. [2008]



Relaxation Development: Convex Hull Reformulation

Karuppiah & Grossmann, Comput. Chem. Eng. [2006]; Wicaksono & Karimi, AIChE J. [2008]

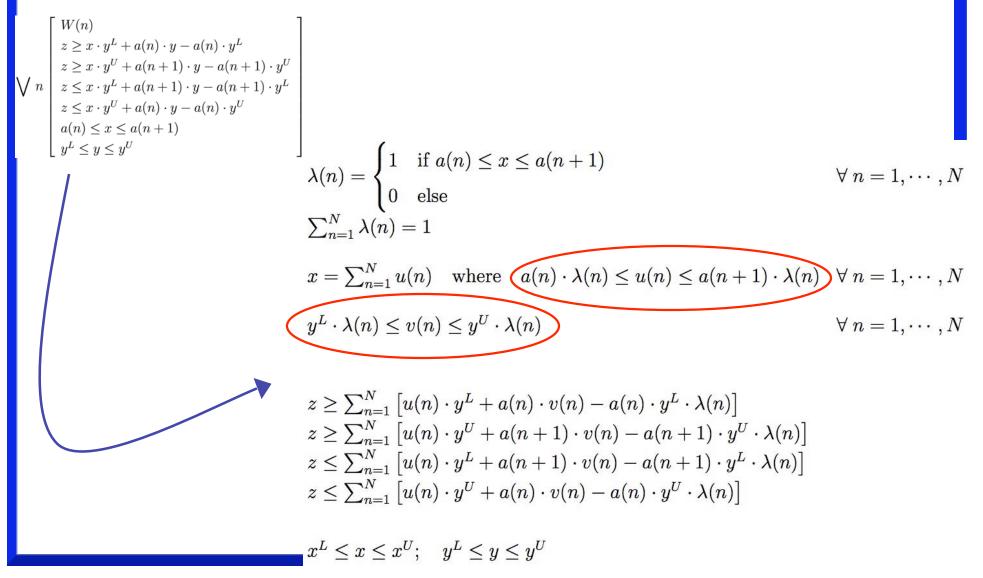
$$\bigvee n \begin{bmatrix} W(n) \\ z \ge x \cdot y^{U} + a(n+1) \cdot y - a(n+1) \cdot y^{U} \\ z \le x \cdot y^{U} + a(n+1) \cdot y - a(n+1) \cdot y^{U} \\ z \le x \cdot y^{U} + a(n+1) \cdot y - a(n+1) \cdot y^{U} \\ z \le x \cdot y^{U} + a(n) \cdot y - a(n) \cdot y^{U} \\ a(n) \le x \le a(n+1) \\ y^{U} \le y \le y^{U} \end{bmatrix}$$

$$\lambda(n) = \begin{cases} 1 & \text{if } a(n) \le x \le a(n+1) \\ 0 & \text{else} \\ \sum_{n=1}^{N} \lambda(n) = 1 \\ x = \sum_{n=1}^{N} u(n) \text{ where } a(n) \cdot \lambda(n) \le u(n) \le a(n+1) \cdot \lambda(n) \quad \forall n = 1, \cdots, N \\ y^{L} \cdot \lambda(n) \le v(n) \le y^{U} \cdot \lambda(n) \\ \forall n = 1, \cdots, N \end{cases}$$

$$z \ge \sum_{n=1}^{N} [u(n) \cdot y^{L} + a(n) \cdot v(n) - a(n) \cdot y^{L} \cdot \lambda(n)] \\ z \ge \sum_{n=1}^{N} [u(n) \cdot y^{U} + a(n+1) \cdot v(n) - a(n+1) \cdot y^{U} \cdot \lambda(n)] \\ z \le \sum_{n=1}^{N} [u(n) \cdot y^{U} + a(n+1) \cdot v(n) - a(n+1) \cdot y^{U} \cdot \lambda(n)] \\ z \le \sum_{n=1}^{N} [u(n) \cdot y^{U} + a(n+1) \cdot v(n) - a(n+1) \cdot y^{U} \cdot \lambda(n)] \\ z \le \sum_{n=1}^{N} [u(n) \cdot y^{U} + a(n+1) \cdot v(n) - a(n+1) \cdot y^{U} \cdot \lambda(n)] \\ x \le \sum_{n=1}^{N} [u(n) \cdot y^{U} + a(n) \cdot v(n) - a(n) \cdot y^{U} \cdot \lambda(n)] \\ x^{L} \le x \le x^{U}; \quad y^{L} \le y \le y^{U} \end{cases}$$

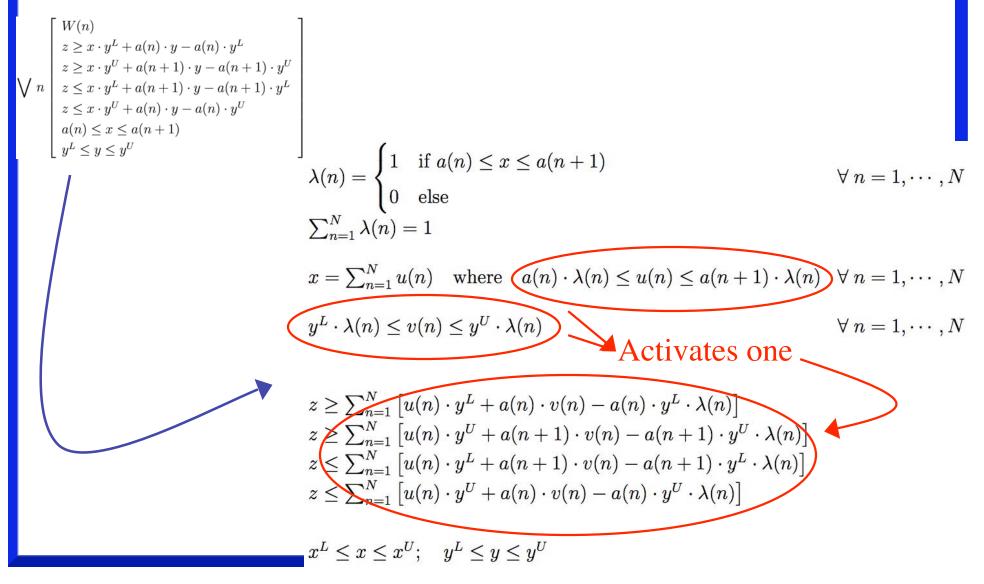
Relaxation Development: Convex Hull Reformulation

Karuppiah & Grossmann, Comput. Chem. Eng. [2006]; Wicaksono & Karimi, AIChE J. [2008]



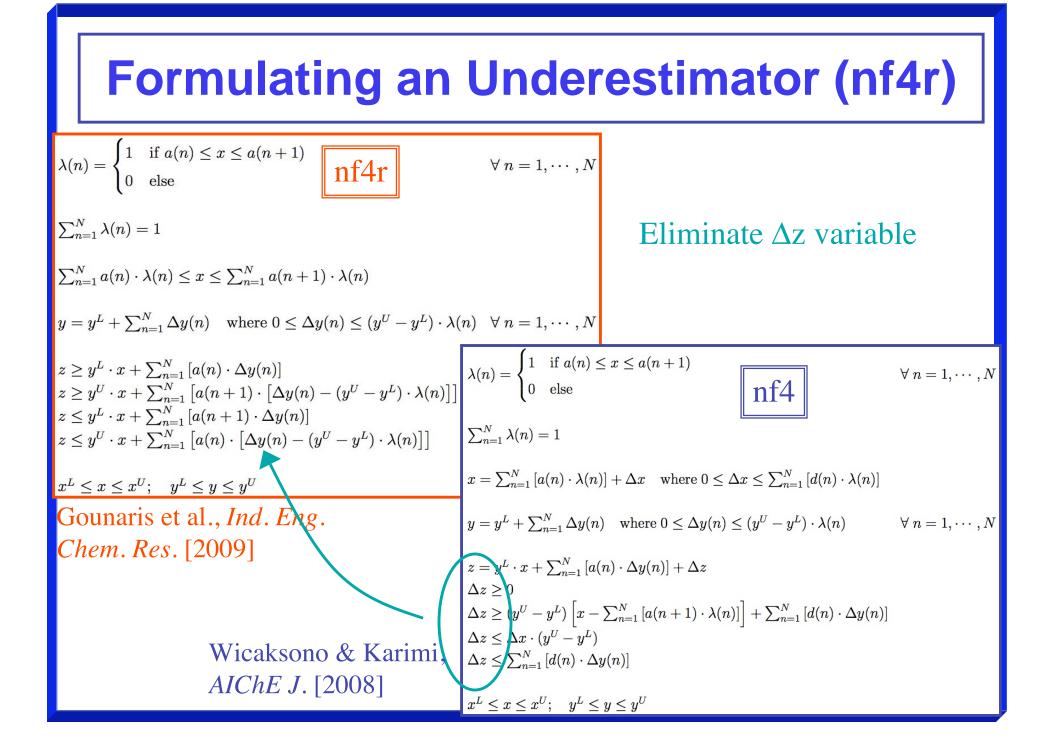
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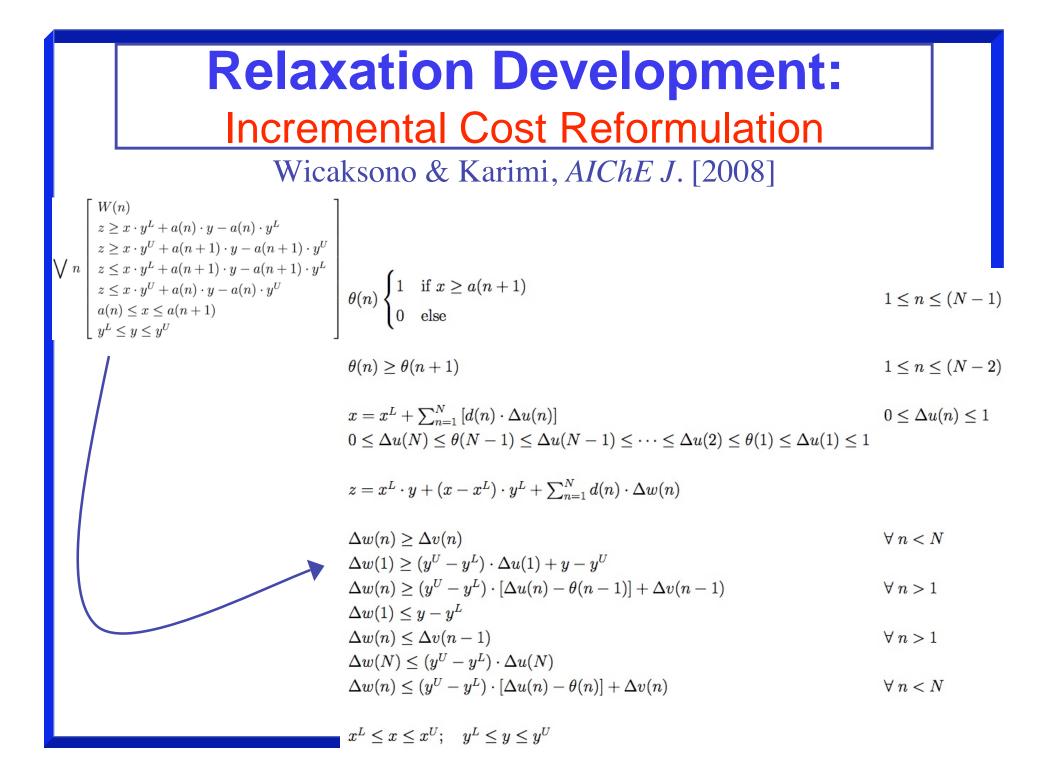
Karuppiah & Grossmann, Comput. Chem. Eng. [2006]; Wicaksono & Karimi, AIChE J. [2008]

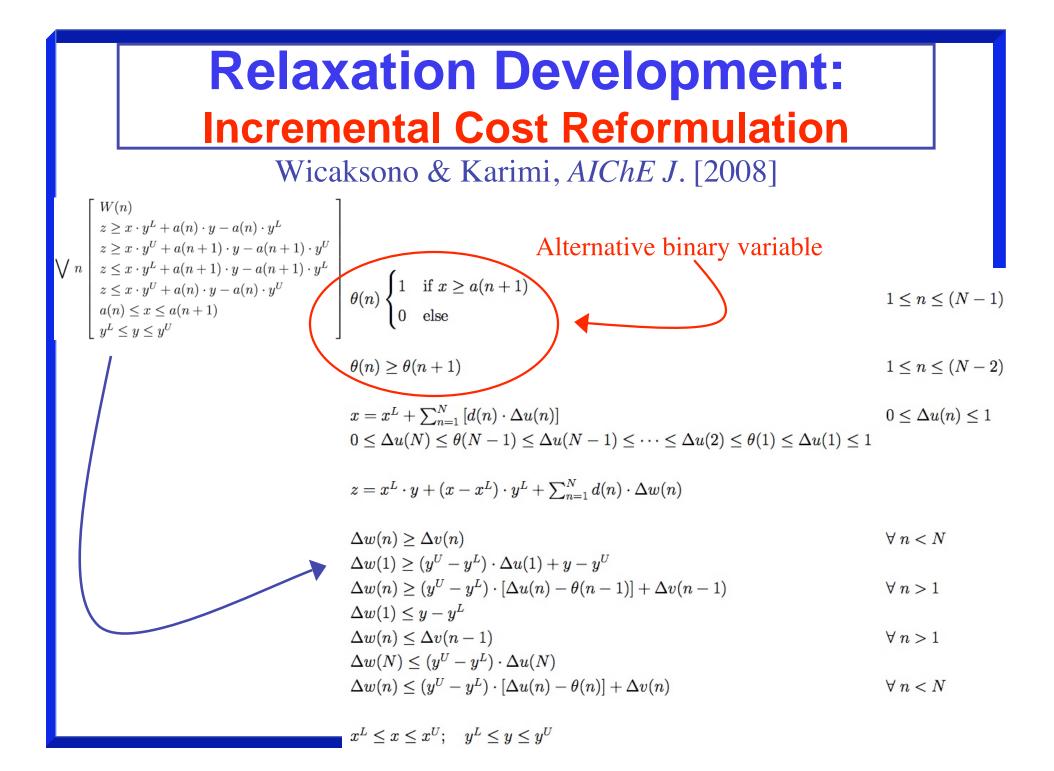


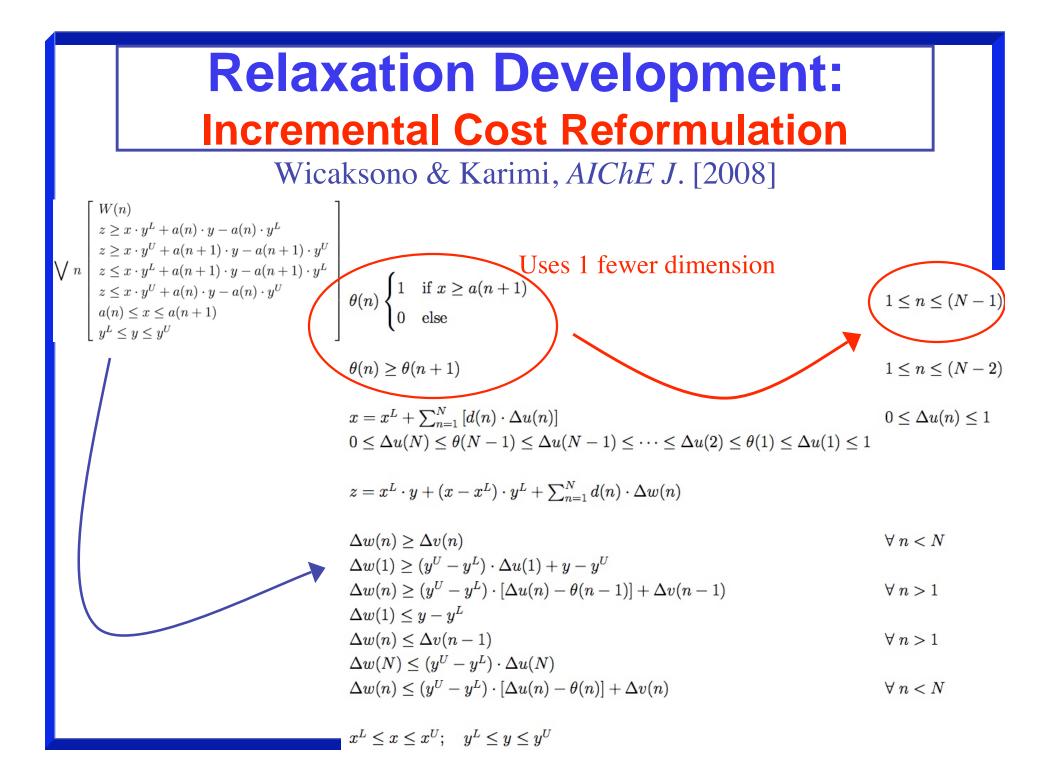


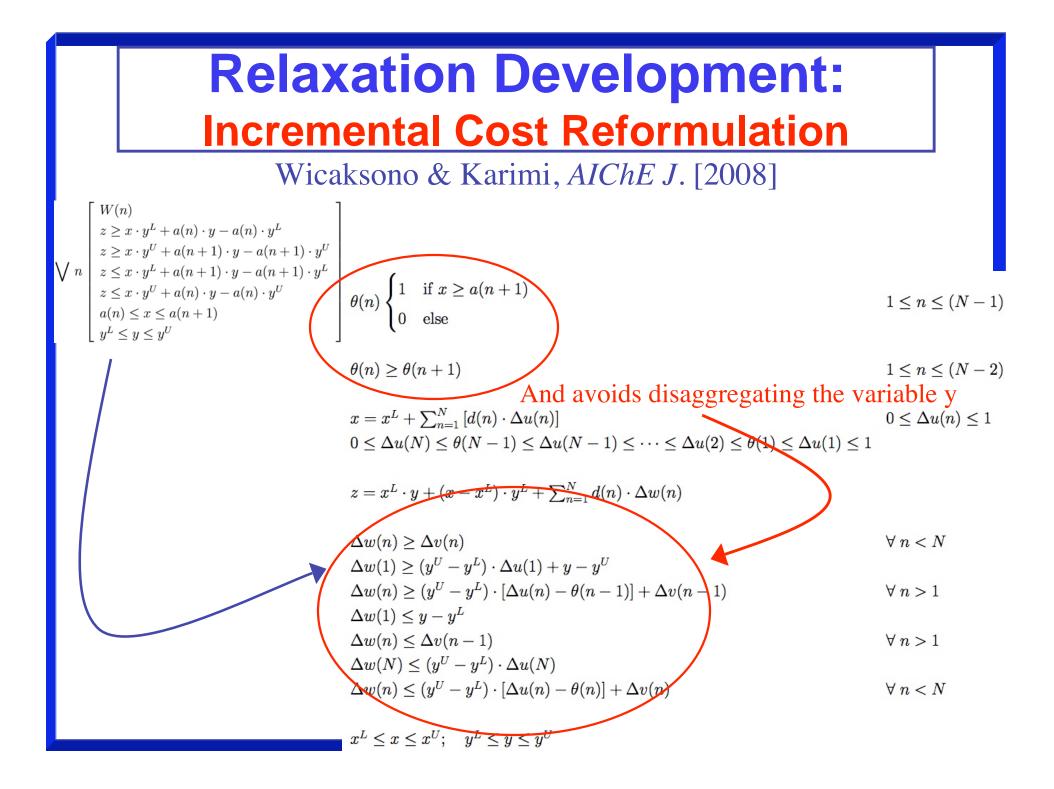
$$\begin{split} \lambda(n) &= \begin{cases} 1 & \text{if } a(n) \leq x \leq a(n+1) \\ 0 & \text{else} \end{cases} \quad \forall n = 1, \cdots, N \\ \sum_{n=1}^{N} \lambda(n) &= 1 \\ \sum_{n=1}^{N} a(n) \cdot \lambda(n) \leq x \leq \sum_{n=1}^{N} a(n+1) \cdot \lambda(n) \\ y &= y^{L} + \sum_{n=1}^{N} \Delta y(n) \quad \text{where } 0 \leq \Delta y(n) \leq (y^{U} - y^{L}) \cdot \lambda(n) \quad \forall n = 1, \cdots, N \\ z \geq y^{L} \cdot x + \sum_{n=1}^{N} [a(n) \cdot \Delta y(n)] \\ z \geq y^{U} \cdot x + \sum_{n=1}^{N} [a(n+1) \cdot [\Delta y(n) - (y^{U} - y^{L}) \cdot \lambda(n)]] \\ z \leq y^{U} \cdot x + \sum_{n=1}^{N} [a(n+1) \cdot \Delta y(n)] \\ z \leq y^{U} \cdot x + \sum_{n=1}^{N} [a(n) \cdot (\Delta y(n) - (y^{U} - y^{L}) \cdot \lambda(n)]] \\ z \leq y^{U} \cdot x + \sum_{n=1}^{N} [a(n) \cdot ([\Delta y(n) - (y^{U} - y^{L}) \cdot \lambda(n)]]] \\ x^{L} \leq x \leq x^{U}; \quad y^{L} \leq y \leq y^{U} \\ \text{Gounaris et al., Ind. Eng.} \\ Chem. Res. [2009] \\ \text{Wicaksono \& Karimi, \\ AIChE J. [2008] \end{cases} \quad \forall n = 1, \cdots, N \\ x = x \leq x^{U}; \quad y^{L} \leq y \leq y^{U} \\ x = \sum_{n=1}^{N} [a(n) \cdot \Delta y(n)] + \Delta x \quad \text{where } 0 \leq \Delta x \leq \sum_{n=1}^{N} [a(n) \cdot \Delta y(n)] \\ z \leq y^{U} - y^{L} + \sum_{n=1}^{N} [a(n) \cdot \Delta y(n)] + \Delta x \quad \text{where } 0 \leq \Delta x \leq \sum_{n=1}^{N} [a(n) \cdot \lambda(n)] \\ y = y^{L} + \sum_{n=1}^{N} [a(n) \cdot \Delta y(n)] + \Delta x \quad \text{where } 0 \leq \Delta x \leq \sum_{n=1}^{N} [a(n) \cdot \Delta y(n)] \\ x \leq x \leq x^{U}; \quad y^{L} \leq y \leq y^{U} \\ x = x^{L} \cdot x + \sum_{n=1}^{N} [a(n) \cdot \Delta y(n)] + \Delta x \quad \text{where } 0 \leq \Delta x \leq \sum_{n=1}^{N} [a(n) \cdot \Delta y(n)] \\ x \leq x \leq x^{U}; \quad y^{L} \leq y \leq y^{U} \end{aligned}$$



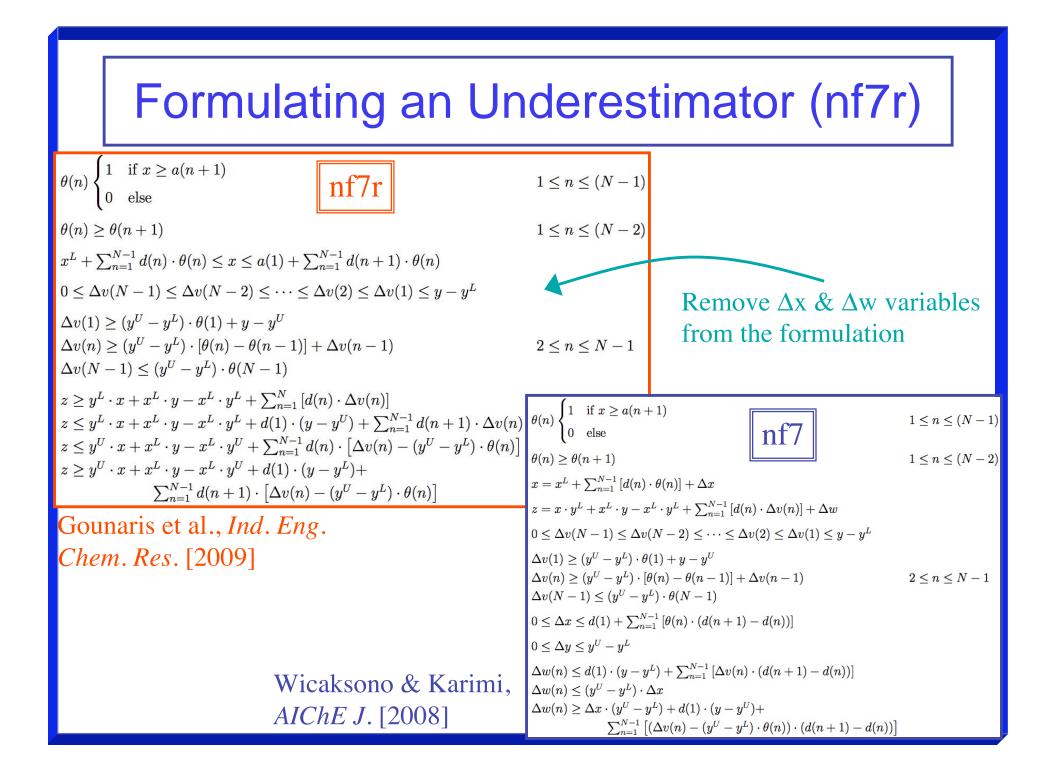








Formulating an Un	derestimator (nf7r)
$\theta(n) \begin{cases} 1 & \text{if } x \ge a(n+1) \\ 0 & \text{else} \end{cases} \qquad $	$1 \le n \le (N-1)$
$\theta(n) \ge \theta(n+1)$	$1 \le n \le (N-2)$
$\begin{aligned} x^L + \sum_{n=1}^{N-1} d(n) \cdot \theta(n) &\leq x \leq a(1) + \sum_{n=1}^{N-1} d(n+1) \cdot \theta(n) \\ 0 &\leq \Delta v(N-1) \leq \Delta v(N-2) \leq \dots \leq \Delta v(2) \leq \Delta v(1) \leq y - y^L \end{aligned}$	
$\begin{aligned} \Delta v(1) &\geq (y^U - y^L) \cdot \theta(1) + y - y^U \\ \Delta v(n) &\geq (y^U - y^L) \cdot [\theta(n) - \theta(n-1)] + \Delta v(n-1) \\ \Delta v(N-1) &\leq (y^U - y^L) \cdot \theta(N-1) \end{aligned}$	$2 \le n \le N-1$
$\begin{split} z &\geq y^L \cdot x + x^L \cdot y - x^L \cdot y^L + \sum_{n=1}^N \left[d(n) \cdot \Delta v(n) \right] \\ z &\leq y^L \cdot x + x^L \cdot y - x^L \cdot y^L + d(1) \cdot (y - y^U) + \sum_{n=1}^{N-1} d(n+1) \cdot \Delta v(n) \\ z &\leq y^U \cdot x + x^L \cdot y - x^L \cdot y^U + \sum_{n=1}^{N-1} d(n) \cdot \left[\Delta v(n) - (y^U - y^L) \cdot \theta(n) \right] \\ z &\geq y^U \cdot x + x^L \cdot y - x^L \cdot y^U + d(1) \cdot (y - y^L) + \\ \sum_{n=1}^{N-1} d(n+1) \cdot \left[\Delta v(n) - (y^U - y^L) \cdot \theta(n) \right] \end{split}$	$ \theta(n) \begin{cases} 1 & \text{if } x \ge a(n+1) \\ 0 & \text{else} \end{cases} & 1 \le n \le (N-1) \\ \theta(n) \ge \theta(n+1) & 1 \le n \le (N-2) \\ x = x^L + \sum_{n=1}^{N-1} [d(n) \cdot \theta(n)] + \Delta x \end{cases} $
Gounaris et al., <i>Ind. Eng.</i> <i>Chem. Res.</i> [2009]	$z = x \cdot y^{L} + x^{L} \cdot y - x^{L} \cdot y^{L} + \sum_{n=1}^{N-1} [d(n) \cdot \Delta v(n)] + \Delta w$ $0 \le \Delta v(N-1) \le \Delta v(N-2) \le \dots \le \Delta v(2) \le \Delta v(1) \le y - y^{L}$ $\Delta v(1) \ge (y^{U} - y^{L}) \cdot \theta(1) + y - y^{U}$ $\Delta v(n) \ge (y^{U} - y^{L}) \cdot \theta(1) + y - y^{U}$ $\Delta v(n) \ge (y^{U} - y^{L}) \cdot \theta(1) + y - y^{U}$
	$\begin{split} \Delta v(n) &\geq (y^U - y^L) \cdot [\theta(n) - \theta(n-1)] + \Delta v(n-1) \\ \Delta v(N-1) &\leq (y^U - y^L) \cdot \theta(N-1) \\ 0 &\leq \Delta x \leq d(1) + \sum_{n=1}^{N-1} [\theta(n) \cdot (d(n+1) - d(n))] \\ 0 &\leq \Delta y \leq y^U - y^L \end{split}$
Wicaksono & Karimi, AIChE J. [2008]	$\begin{split} \delta &= \Delta y = g g \\ \Delta w(n) &\leq d(1) \cdot (y - y^L) + \sum_{n=1}^{N-1} \left[\Delta v(n) \cdot (d(n+1) - d(n)) \right] \\ \Delta w(n) &\leq (y^U - y^L) \cdot \Delta x \\ \Delta w(n) &\geq \Delta x \cdot (y^U - y^L) + d(1) \cdot (y - y^U) + \\ &\sum_{n=1}^{N-1} \left[(\Delta v(n) - (y^U - y^L) \cdot \theta(n)) \cdot (d(n+1) - d(n)) \right] \end{split}$



Piecewise Relaxation of Bilinear Programs

 10 relaxation schemes from Wicaksono & Karimi, AIChE J.
 [2008] & 5 additional schemes from Gounaris et al., Ind. Eng. Chem. Res. [2009] using ab initio domain partitioning

• 3 formulation classes:

- big-M
- convex hull
- incremental cost
- Multiple design choices:
 - choice of which variable to partition
 - number of partition segments
 - uniform grid or not

Applying Relaxation to a Representative Benchmark Problem [Audet et al., Manag. Sci. 2004] 'y'- variant 'p'- variant -4500 -4500 2.00-5000 -5000 Lower Bound Bound 1.50 -5500 -5500 -ower 0.25 0.25 -6000 -6000 -6500 -6500 2 1 3 9 10 11 12 13 14 15 2 3 10 11 12 13 14 15 4 Number of Partitions Number of Partitions Global minimum Underestimate using uniform partitioning Variable length partitioning controlled by parameter γ

[Wicaksono & Karimi, AIChE J., 2008]: $r = r^{L} + \left(\frac{n}{2}\right)^{\gamma} (r^{U} - r^{U})^{\gamma}$

 $x_n = x^L + \left(\frac{n}{N}\right)^{\gamma} (x^U - x^L) , \ 0 \le n \le N$

Comparison of the Relaxation Formulations

Number of runs* that failed to reach optimality within total CPU time limit of 1 h

Class	Formulation	Partitioning level N						
C1855		2	3	4	5	7	10	15
	bm	_	_	11	20	33	66	140
Die M	nf1	-	_	11	22	31	63	124
Big–M	nf2g	-	—	11	21	33	59	114
	nf2	-	-	10	21	31	62	118
	ch	_	_	1	5	8	18	43
	tch	_	_	1	5	12	27	71
Convex	nf3	_	_	_	4	7	15	53
Combination	nf4l	_	_	1	5	7	11	28
	nf4	_	-	_	4	7	10	25
	nf4r	-	-	1	5	7	8	23
	nf5		_	_	4	6	9	32
Incrementel	nf6	_	_	_	3	6	8	20
Incremental Cost	nf6t	_	_	_	3	6	9	20
COST	nf7	_	_	_	_	5	8	19
	nf7r	_	_	_	1	6	8	16

To compare the formulations, finely partition the bilinear terms in the test case pooling problems and stress test the relaxation formulations to see which ones most often solve within a time limit.

*Out of a total of 480 runs for each entry.

Gounaris et al., Ind. Eng. Chem. Res. [2009]

Comparison of the Relaxation Formulations

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Use the mos	Use the most reliable formulations for						62	118
large-scale 1	nooling pro	hle	m۹	S			18	43
large seale	large-scale pooling problems						27	71
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		nf2g	_	_	11	21	33	59	114
	Use the mos	t reliable f	orr	nu	lati	ons	for	62	118
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l	laige seale p				-			27	71
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1		nf4	_	_	_	4	7	10	25
	_	nf4r	—	-	1	5	7	8	23
		nf5		_	_	4	6	9	32
	Incremental	nf6	_	_	_	3	6	8	20
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Outline

- Deterministic Global Optimization: Objectives & Motivation
- Convex Envelopes:
 - Trilinear Monomials
 - Edge Concave functions
- Piecewise linearization of Bilinear terms
- Checking Convexity: Products of
 Univariate Functions
- PαBB: Piecewise Quadratic Perturbations
- Pooling Problems: Standard, Generalized & Extended
- Conclusions

Products of Univariate Functions

(Gounaris and Floudas, JOTA, 2008)

$$f(\underline{x}) = \prod_{i=1}^{N} f_i(x_i) = f_1(x_1) f_2(x_2) \dots f_n(x_n)$$

When is f(x) convex?

Products of Univariate Functions

(Gounaris and Floudas, JOTA, 2008)

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 When is f(x) convex?

Sufficient Conditions

- Every factor should be strictly positive An even number of factors are allowed to instead be strictly negative and strictly concave
- Every factor should be strictly convex
- For every factor: $f_i(x_i)f_i''(x_i) (f_i'(x_i))^2 \ge 0$

Products of Univariate Functions

(Gounaris and Floudas, JOTA, 2008)

$$f(\underline{x}) = \prod_{i=1}^{N} f_i(x_i) = f_1(x_1) f_2(x_2) \dots f_n(x_n) \qquad \text{When is } f(\underline{x}) \text{ convex}$$

Sufficient Conditions

• Every factor should be strictly positive An even number of factors are allowed to instead be strictly negative and strictly concave

?

- Every factor should be strictly convex
- For every factor: $f_i(x_i) f_i''(x_i) (f_i'(x_i)) \ge 0$

These conditions are in fact necessary if all factors share the same functional form

Products of Univariate Functions

(Gounaris and Floudas, JOTA, 2008)

$$f(\underline{x}) = \left\{\frac{1.8}{x_2} + 1.2x_2 - \frac{3\log(1 - x_1)}{x_2} - 2x_2\log(1 - x_1)\right\} \frac{e^{x_3 - x_4}}{x_4^{1.2}} \qquad \text{Is f(x) convex in } \left[\frac{1}{3}, \frac{2}{3}\right]^4 ?$$

Products of Univariate Functions

(Gounaris and Floudas, JOTA, 2008)

$$f(\underline{x}) = \left\{ \frac{1.8}{x_2} + 1.2x_2 - \frac{3\log(1 - x_1)}{x_2} - 2x_2\log(1 - x_1) \right\} \frac{e^{x_3 - x_4}}{x_4^{1.2}} \qquad \text{Is f(x) convex in } \left[\frac{1}{3}, \frac{2}{3} \right]^4 ?$$
$$= f_1(x_1) f_2(x_2) f_3(x_3) f_4(x_4)$$

$$f_1(x_1) = 0.6 - \log(1 - x_1)$$
$$f_2(x_2) = \frac{2x_2^2 + 3}{x_2}$$

$$f_3(x_3) = e^{x_3}$$

$$f_4(x_4) = \frac{e^{-x_4}}{x_4^{1.2}}$$

Yes!because all four functions satisfy the sufficient conditions in [1/3,2/3]

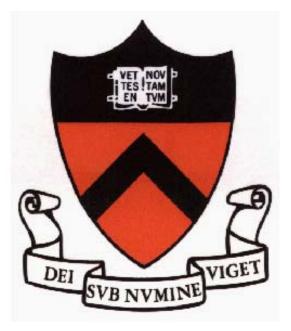
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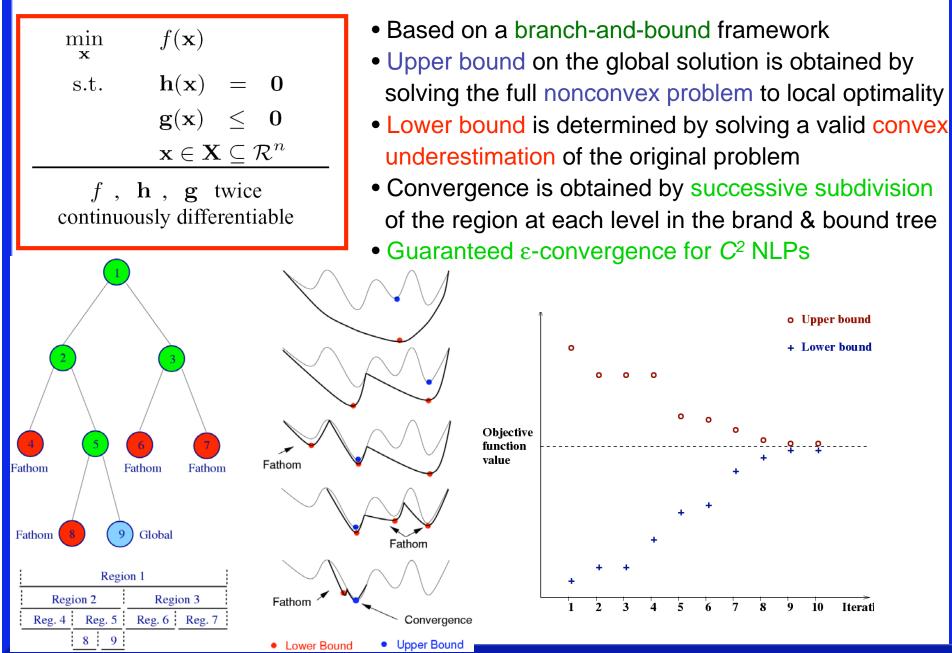
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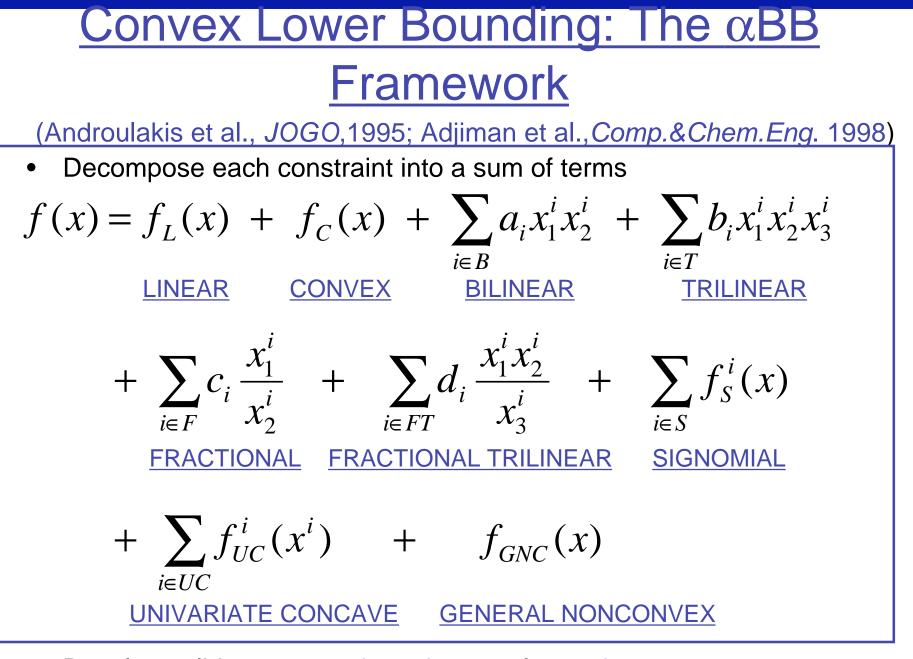


Christodoulos A. Floudas

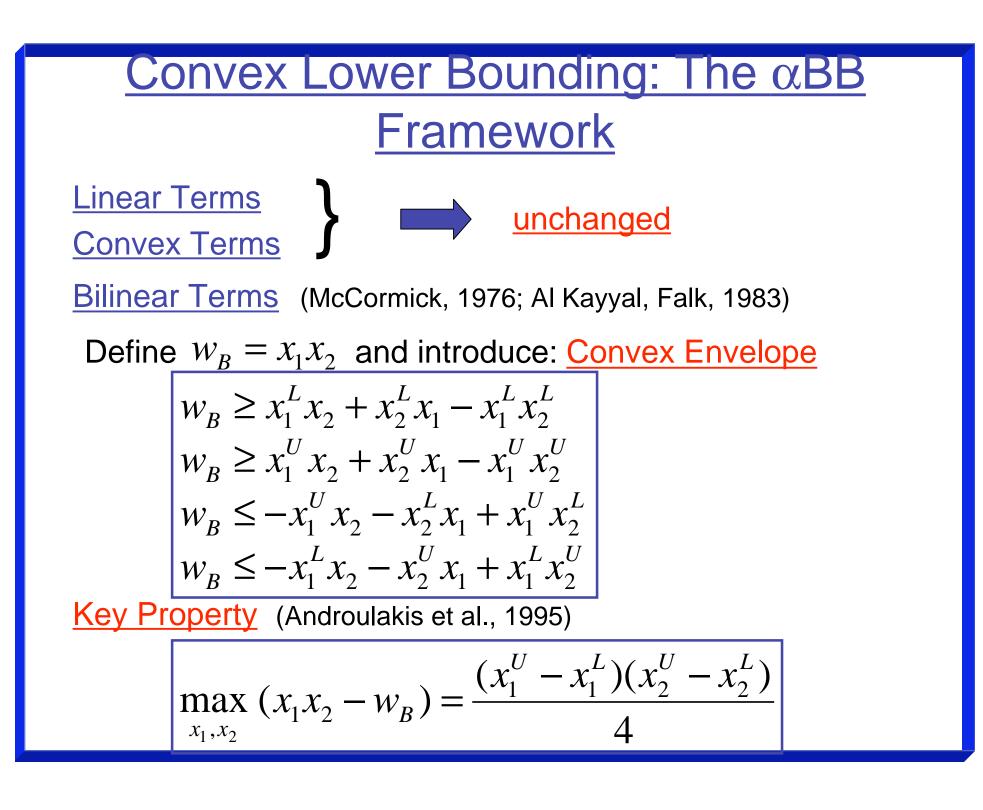
Princeton University

<u>C² NLPs - The αBB Framework</u>





Develop valid <u>convex underestimators</u> for <u>each term</u>



<u>Convex Lower Bounding: The αBB</u>

Framework

General C² Nonconvex Terms (Maranas, Floudas, 1994; Androulakis et. al, 1995) $L(x) = f_{GNC}(x) - \sum_{i=1}^{n} \alpha_i (x_i^U - x_i) (x_i - x_i^L)$ $\alpha \ge \max \left\{ 0, -\frac{1}{2} \min_{i, x^L \le x \le x^U} \lambda_{i, H}(x) \right\}$ **P1:** $f_{GNC}(x) \ge L(x)$ **P2:** $f_{GNC}(x) = L(x)$ at corner points **P3**: L(x) is convex in $\begin{bmatrix} x^L, x^U \end{bmatrix}$ **P4**: $L^{D_1}(x) \ge L^{D_2}(x)$ where $D_1 \subseteq D_2$ P5: Maximum Separation Distance $\max(f_{GNC}(x) - L(x)) = \frac{1}{4} \sum_{i=1}^{n} \alpha_i (x_i^U - x_i^L)^2$ P6: Convexity of L(x)

> $L(x) \text{ is convex if } H_{GNC}(x) + 2Diag(\alpha_i)$ is positive semidefinite $\forall \alpha \in [x^L, x^U]$

<u>Rigorous Calculations of α : The α BB</u>

Framework

(Adjiman, Floudas, 1996; Adjiman et al., 1998a,b)

- Derive Hessian matrix, H(x), of $f_{GNC}(x)$
 - Compute INTERVAL Hessian in $\begin{bmatrix} x^L, x^U \end{bmatrix}$ $\begin{bmatrix} H(x) \end{bmatrix}_j = \begin{bmatrix} h_{ij}^L(x), h_{ij}^U(x) \end{bmatrix}$

$$-H \subseteq [H]$$

- Compute α : $[H] + 2Diag(\alpha)$ is P.S.D

Uniform Diagonal Shift Matrix

<u>O(n²) Methods</u>

Key Ideas

<u>O(n³) Methods</u>

- Gerschgorin Theorem
- Hertz
 - Lower Bounding Hessian
 - Mori-Kokane
 - E-Matrix Approach

Non-Uniform Diagonal Shift Matrix

- Scaled Gerschgorin Theorem
- H-Matrix
- Semi-definite Programming

Scaled Gerschgorin Theorem: The αBB

Framework

Gerschgorin Theorem for real matrices:

$$\lambda_{\min} \geq \min_{i} \left(h_{ii} - \sum_{j \neq i} |h_{ii}| \right)$$

Theorem for Interval Matrices (Adjiman et al., 1998a,b)

$$\alpha_{i} = \max\left[0, -\frac{1}{2}\left[h_{ii}^{L} - \sum_{j \neq i} \max\left(h_{ii}^{L}\right|, \left|h_{ii}^{U}\right|\right) \frac{d_{j}}{d_{i}}\right]\right]$$

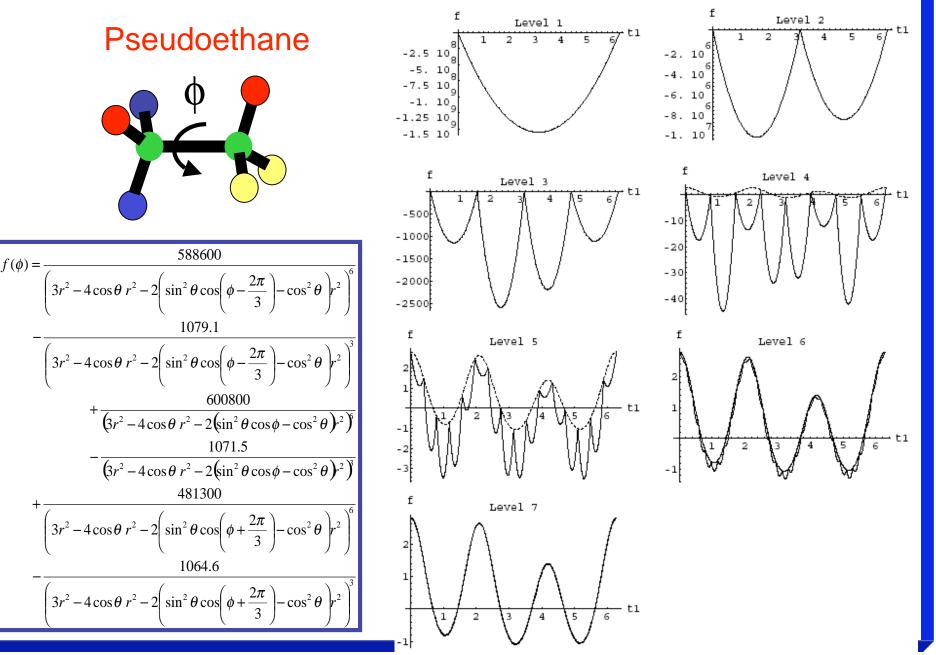
$$\left[H_{NT}\right] + 2Diag\left(\alpha_{i}\right) \text{ is positive semidefinite}$$

- *d* is a positive vector

Use
$$d_i = 1$$
 or $d_i = x_i^U - x_i^L$

Inexpensive and simple technique

<u>C² NLPs - Illustrative Example</u>



<u>αBB Underestimator:</u> <u>Room for Improvement?</u>

$$q(x) = \sum_{i=1}^{n} \alpha_i \left(x_i - \underline{x}_i \right) \cdot \left(\overline{x}_i - x_i \right)$$

- Curvature of the perturbation function is constant.
- The eigenvectors of the Hessian matrix of the perturbation function are aligned with the coordinate axes.

<u>A Refinement of the α BB Underestimator</u>

Meyer, Floudas, JOGO, (2005)

Central Idea

- Partition the domain into subregions.
- Calculate the α parameters in each subregion.
- Construct an underestimator for the whole domain using these α 's.

Properties of the Underestimator Function

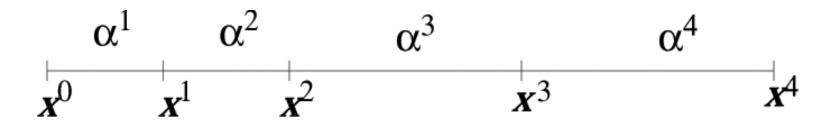
- smoothness
- convexity
- underestimation

Structure of the Underestimator Function

- sum of piecewise quadratic univariate functions
- underestimator matches function at vertices

Piecewise C²-Continuous Underestimator

- Partition interval $[\underline{x}_i, \overline{x}_i]$ into N_i subintervals.
- Endpoints of the subintervals: $x_i^0, x_i^1, \dots, x_i^{N_i}$.



A smooth convex underestimator f(x) in an interval $x \in [\underline{x}, \overline{x}]$:

$$\phi(x) \coloneqq f(x) - q(x)$$

$$q(x) \coloneqq \sum_{i=1}^{n} q_i^k(x_i) \quad \text{for } x_i \in \left[x_i^{k-1}, x_i^k\right]$$

$$q_i^k(x_i) \coloneqq \alpha_i^k\left(x_i - x_i^{k-1}\right) \cdot \left(x_i^k - x_i\right) + \beta_i^k x_i + \gamma_i^k$$

Joining the Pieces

• Smoothness: function q_i^k and their gradients must match at the internal endpoints x_i^k .

• Tight at extrema: $q_i(x) = 0$ at $\{\underline{x}_i, \overline{x}_i\}$.

 $q_{i}^{k}(x_{i}^{k}) = q_{i}^{k+1}(x_{i}^{k}) \text{ for all } k = 1, \dots, N_{i} - 1$ $\frac{dq_{i}^{k}(x_{i}^{k})}{dx_{i}} = \frac{dq_{i}^{k+1}(x_{i}^{k})}{dx_{i}} \text{ for all } k = 1, \dots, N_{i} - 1$ $q_{i}^{1}(x_{i}^{0}) = 0$ $q_{i}^{N_{i}}(x_{i}^{N_{i}}) = 0$

Expands to a linear system in β and γ .

Formulae for β and γ

Linear System

$$\beta_{i}^{k} x_{i}^{k} + \gamma_{i}^{k} = \beta_{i}^{k+1} x_{i}^{k+1} + \gamma_{i}^{k+1} \qquad \text{for all } k = 1, ..., N_{i}$$

$$-\alpha_{i}^{k} \left(x_{i}^{k} - x_{i}^{k-1}\right) + \beta_{i}^{k} = \alpha_{i}^{k+1} \left(x_{i}^{k+1} - x_{i}^{k}\right) + \beta_{i}^{k+1} \qquad \text{for all } k = 1, ..., N_{i}$$

$$\beta_{i}^{1} x_{i}^{0} + \gamma_{i}^{0} = 0$$

$$\beta_{i}^{N_{i}} x_{i}^{N_{i}} + \gamma_{i}^{N_{i}} = 0$$

$$\frac{\text{Solution}}{\beta_{i}^{1} = \left(\sum_{k=1}^{N_{i}-1} s_{i}^{k} \left(x_{i}^{k} - x_{i}^{N_{i}}\right)\right) / \left(x_{i}^{N_{i}} - x_{i}^{0}\right)}$$

$$\beta_{i}^{k} = \beta_{i}^{1} + \sum_{j=1}^{k-1} s_{j}^{j} \qquad \text{for all } k = 2, ..., N_{i}$$

$$\gamma_{i}^{k} = -\gamma_{i}^{1} x_{i}^{0} - \sum_{j=1}^{k-1} s_{j}^{j} \qquad \text{for all } k = 1, ..., N_{i}$$
where $s_{i}^{k} = -\alpha_{i}^{k} \left(x_{i}^{k} - x_{i}^{k-1}\right) - \alpha_{i}^{k+1} \left(x_{i}^{k+1} - x_{i}^{k}\right).$

Illustration: Lennard-Jones Potential Energy Function

 $f(x) = \frac{1}{x^{12}} - \frac{2}{x^6}$ in the interval $[\underline{x}, \overline{x}] = [0.85, 2.00].$

First term: convex, dominates when x is small

 Second term: concave, dominates when x is large Minimum eigenvalues:

$$\min f'' = \begin{cases} \frac{156}{\overline{x}^{14}} - \frac{84}{\overline{x}^8} & \text{if } \overline{x} \le 1.21707 \\ -7.47810 & \text{if } [\underline{x}, \overline{x}] \ge 1.21707 \\ \frac{156}{\underline{x}^{14}} - \frac{84}{\underline{x}^8} & \text{if } \underline{x} \ge 1.21707 \end{cases}$$

Illustration: Lennard-Jones

Standard α BB underestimator:

$$f(x) - \frac{7.47810}{2} \left(\overline{x} - x\right) \cdot \left(x - \underline{x}\right)$$

2 subinterval underestimator:

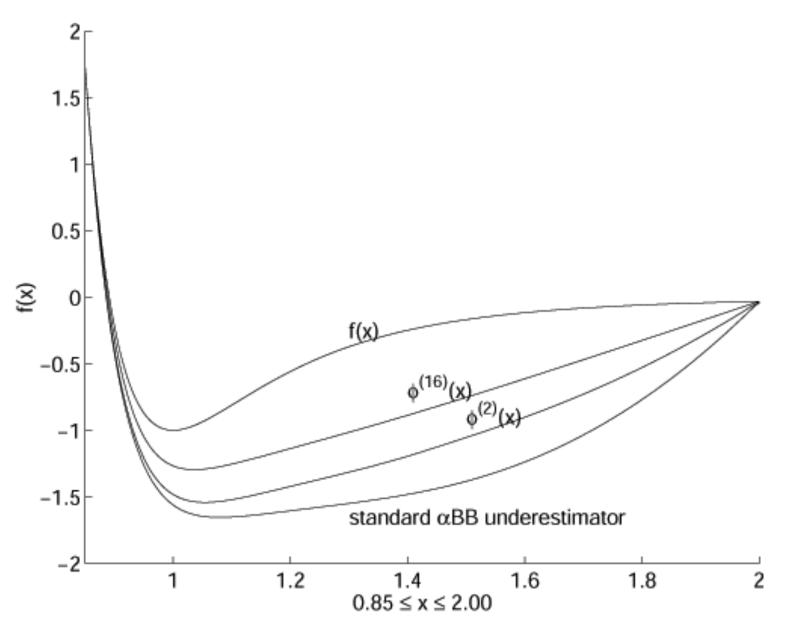
k	X ^k	min <i>f"</i>	α^k	β^k	γ^k
0	0.850				
1	1.425	-7.47810	3.73905	1.62764	-1.38349
2	2.000	-3.84462	1.92231	-1.62764	3.25528

Underestimator when $0.850 \le x \le 1.425$:

 $f(x) - (3.73905(1.425 - x) \cdot (x - 0.850) + 1.62764x - 1.38349)$ Underestimator when $1.425 \le x \le 2.00$:

 $f(x) - (1.92231(2.000 - x) \cdot (x - 1.425) - 1.62764x + 3.25528)$

Illustration: Lennard-Jones



<u>Outline</u>

- Deterministic Global Optimization: Objectives & Motivation
- Convex Envelopes:
 - Trilinear Monomials
 - Edge Concave functions
- Piecewise linearization of Bilinear terms
- Checking Convexity: Products of Univariate Functions
- PαBB: Piecewise Quadratic Perturbations
- Pooling Problems: Standard, Generalized
 & Extended Towards addressing Large Scale Global Optimization Problems
- Conclusions

Motivation:

Globally Optimizing Standard, Generalized, and Extended Pooling Problems

- **Applications** of pooling problems include:
 - Refining & Petrochemical
 - Crude Oil Scheduling
 - Combining Process Streams into Products
 - Wastewater Treatment
 - Removing heavy metals, organic matter, etc. from process streams
 - Supply Chain Operations
 - Communications
- Pooling is necessitated by limited storage conditions requiring blending multiple streams into intermediate nodes or pools

Relevant Publications

- Misener & Floudas. Global Optimization of Large-Scale Generalized Pooling Problems: Quadratically Constrained MINLP Models. *Ind. Eng. Chem. Res.* 49:5424-5438, 2010.
- Misener, Gounaris & Floudas. Mathematical Modeling and Global Optimization of Large-Scale Extended Pooling Problems with the (EPA) Complex Emissions Constraints. *Comp. Chem. Eng.*, 34, 1432-1456, 2010.
- Misener & Floudas. Advances for the Pooling Problem: Modeling, Global Optimization, and Computational Studies. *Appl. Comput. Math.*, 8:3-22, 2009.
- Gounaris, Misener & Floudas. Computational Comparison of Piecewise-Linear Relaxations for Pooling Problems. *Ind. Eng. Chem. Res.*, 48:5742-5766, 2009.



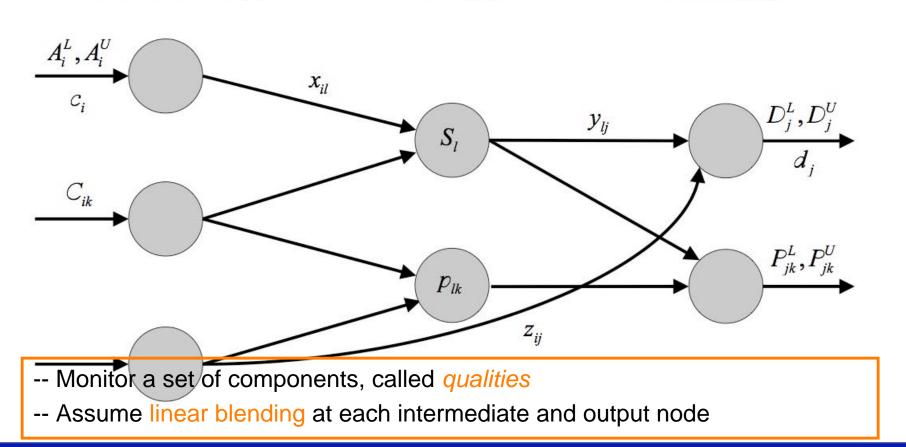
Standard Pooling Problem: NLP with Quadratic Nonconvex Terms

Haverly, ACM SIGMAP Bulletin [1978]; Floudas & Aggarwal, Comput. Chem. Eng. [1990]; Floudas & Visweswaran, Comput. Chem. Eng. [1990]; Lodwick, ORSA J. Comput. [1992]; Ben-Tal et al., Math. Prog. [1994]; Adhya et al., Ind. Eng. Chem. Res. [1999]; Foulds et al., Optimization [1992]; Quesada & Grossmann, Comput. Chem. Eng. [1995]; Tawarmalani & Sahinidis [2002]; Meyer & Floudas, AIChE J. [2006]; Pham et al., Ind. Eng. Chem. Res. [2009]

Pools (L)

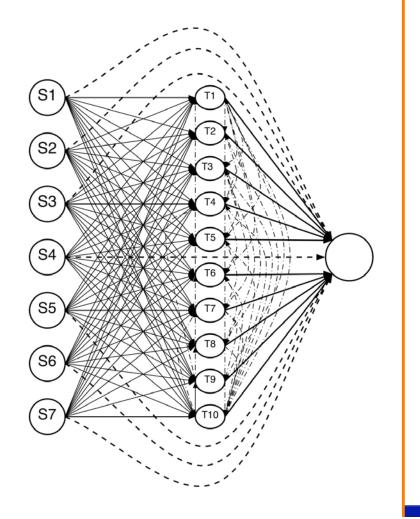
Products (J)

Raw Materials (I)



Generalized Pooling Problems: MINLP with Quadratic Nonconvex Terms

Galan & Grossmann, Ind. Eng. Chem. Res. [1998]; Bagajewicz, Comp. Chem. Eng. [2000]; Lee & Grossmann, Comp. Chem. Eng. [2003]; Audet et al., Manag. Sci. [2004]; Meyer & Floudas, AIChE J. [2006]; Karuppiah & Grossmann, Comp. Chem. Eng. [2006]



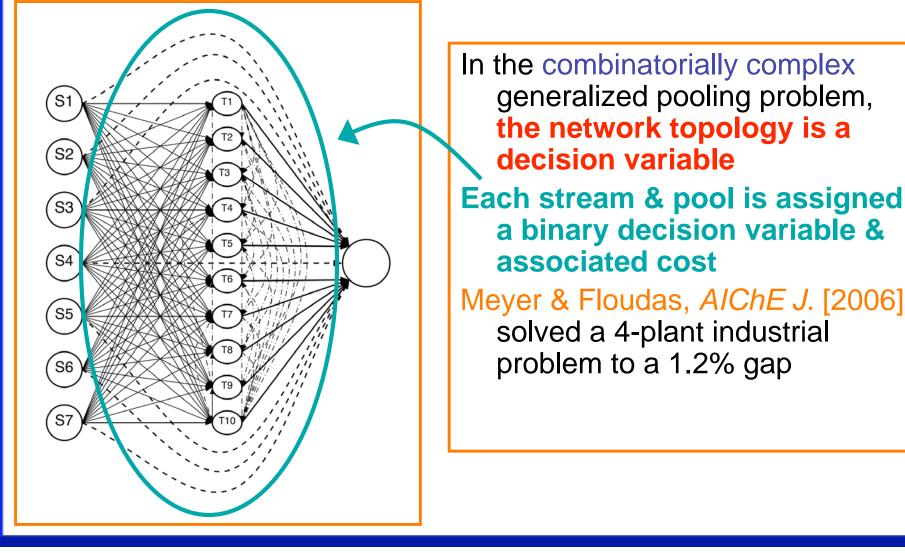
In the combinatorially complex generalized pooling problem, the network topology is a decision variable

Each stream & pool is assigned a binary decision variable & associated cost

Meyer & Floudas, AIChE J. [2006] solved a 4-plant industrial problem to a 1.2% gap

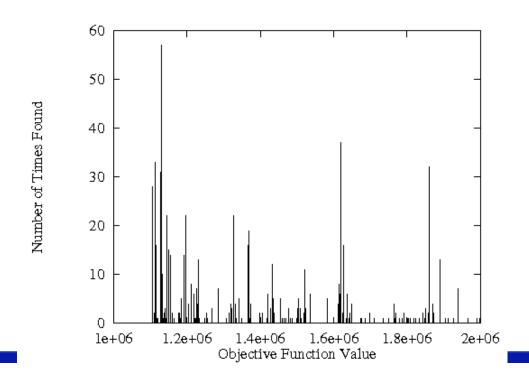
Generalized Pooling Problems

Galan & Grossmann, Ind. Eng. Chem. Res. [1998]; Bagajewicz, Comp. Chem. Eng. [2000]; Lee & Grossmann, Comp. Chem. Eng. [2003]; Audet et al., Manag. Sci. [2004]; Meyer & Floudas, AIChE J. [2006]; Karuppiah & Grossmann, Comp. Chem. Eng. [2006]

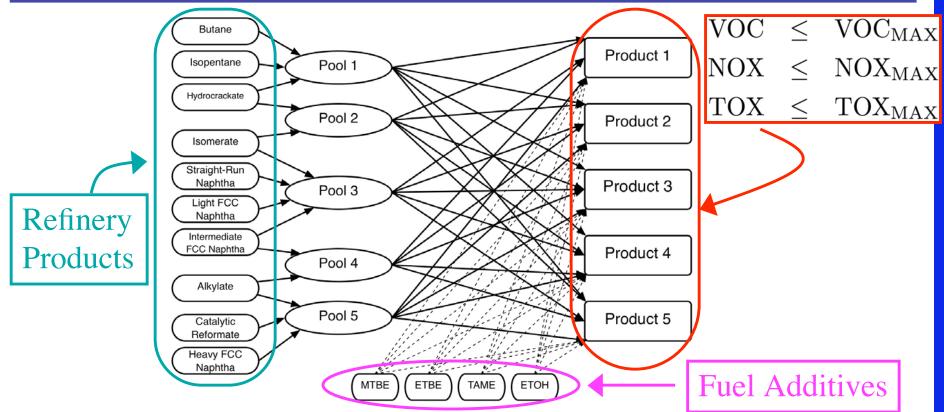


Solutions Using GAMS/DICOPT and Random Starting Points

- Continuous variables initialized with uniformly distributed random numbers
- Binary variables initialized by rounding the uniformly distributed numbers in [0,1] to the nearest integer
- DICOPT used to solve problem from 1000 starting points.
- Number of times best known solution was found: 0.

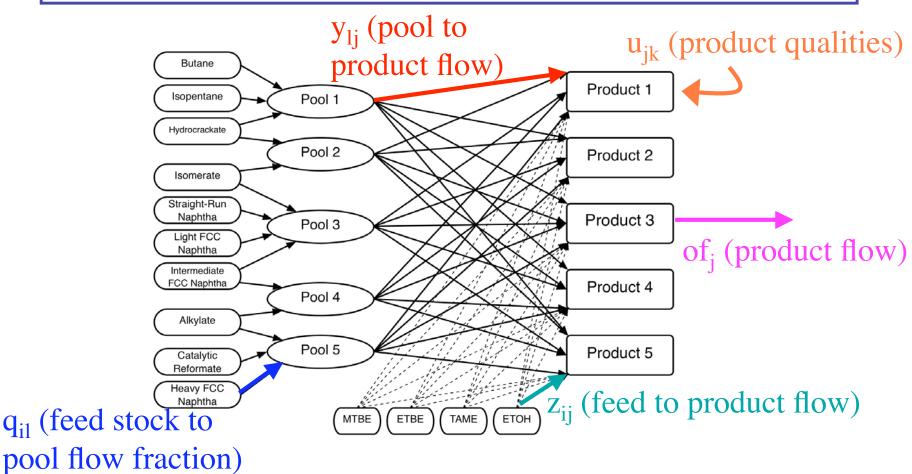


The Extended Pooling Problem: MINLP with General Nonconvex Constraints



 Given refinery exit streams, meet volatile organics, NO_x, & toxic emissions standards for each gasoline blend according to the EPA Complex Emissions Model & legislative bounds

Extended Pooling Problem: Standard Backbone



- Monitor the set of 11 components in the EPA Complex Emissions Model
- Assume linear blending at each intermediate & output node for all components except Reid Vapor Pressure (RVP), which blends nonlinearly

The Extended Pooling Problem

 The extended pooling problem incorporates the EPA Complex Emissions Model Constraints and associated legislative bounds on volatile organics (VOC), NO_X, and toxic (TOX) emissions into the constraint set:



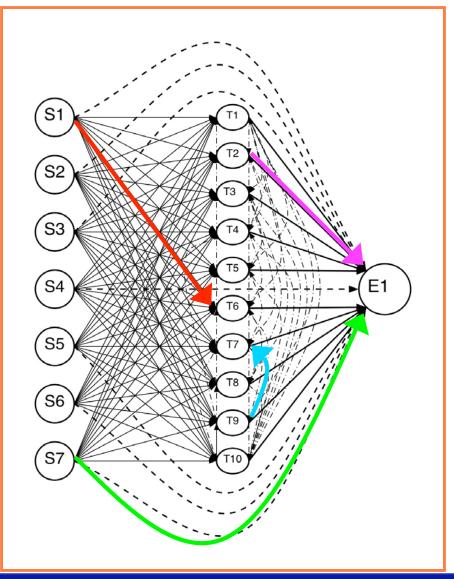
<u>Outline</u>

- Deterministic Global Optimization: Objectives & Motivation
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Generalized Pooling Problem

Meyer & Floudas, AIChE J. [2006]; Misener & Floudas, Ind. Eng. Chem. Res. [2010]

- Topology: 7 sources; 1 or 2 sinks; multiple possible treatment plants
- Possible connections: source to plant; source to sink; plant to plant; plant to sink



$$\begin{array}{c} \begin{array}{c} \underset{a,b,c,d,q,y^{a},y^{b},y^{c},y^{d},y^{e}}{\text{min}} z^{P} = \sum\limits_{s \in S} \sum\limits_{e \in E} c_{se}^{a}a_{se} + \sum\limits_{i \in T} \sum\limits_{e \in E} c_{ib}^{b}b_{ie} \\ + \sum\limits_{s \in S} \sum\limits_{e \in E} c_{se}^{a}a_{se} + \sum\limits_{i \in T} \sum\limits_{e \in E} c_{ib}^{b}b_{ie} \\ + \sum\limits_{i \in T} \sum\limits_{i' \in T \setminus \{i\}} (c_{i'}^{c} + c_{i'}^{e})c_{ii'} + \sum\limits_{s \in S} \sum\limits_{i \in T} (c_{st}^{d} + c_{i}^{e})d_{st} \\ + \sum\limits_{i \in T} \sum\limits_{i' \in T \setminus \{i\}} (c_{i'}^{c} + c_{i'}^{e})c_{ii'} + \sum\limits_{s \in S} \sum\limits_{i \in T} (c_{st}^{d} + c_{i}^{e})d_{st} \\ + \sum\limits_{i \in T} \sum\limits_{i' \in T \setminus \{i\}} c_{i'}^{wy}y_{i'}^{c} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{i'}^{wy}y_{i}^{d} \\ + \sum\limits_{i \in T} \sum\limits_{i' \in T \setminus \{i\}} c_{i'}^{wy}y_{i}^{e'} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{i'}^{wy}y_{i}^{d} \\ + \sum\limits_{i \in T} \sum\limits_{i' \in T \setminus \{i\}} c_{i'}^{wy}y_{i}^{e'} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{i'}^{wy}y_{i}^{d} \\ + \sum\limits_{i \in T} c_{i'}^{e'}y_{i}^{e'} \\ d_{st} - y_{si}^{d}\overline{d}_{st} \leq 0 \\ c_{i'}y_{i}^{d}\overline{d}_{st} \leq 0 \\ c_{i'}y_{i}^{d}\overline{d}_{st} \leq 0 \\ c_{i'}y_{i}^{d'} - c_{i'} \leq 0 \\ c_{i'}y_{i}^{d'}\overline{d}_{st} \leq 0 \\ \sum\limits_{s \in S} a_{se}q_{cs}^{\text{vource}} + \sum\limits_{t \in T} b_{te}q_{ct} \leq q_{c}^{\max} \\ \sum\limits_{i \in T} c_{i'}^{\max}y_{i}^{e'} \\ d_{st} - y_{i}^{d}\overline{d}_{st} \leq 0 \\ \\ \times \left(\sum\limits_{s \in S} a_{s}\right) \\ The objective, which represents water treatment \\ cost, reflects both the variable costs of flow rates & the fixed costs of activating each plant or connection \\ = (1 - r_{ct}) \\ \sum\limits_{i' \in T \setminus \{i\}} c_{i'} - \sum\limits_{i' \in T \setminus \{i\}} c_{i'} + \sum\limits_{s \in S} d_{s'} = \sum\limits_{e \in E} b_{ie} \\ \times \left(\sum\limits_{i' \in T \setminus \{i\}} c_{i'}q_{i'} + \sum\limits_{s \in S} d_{s'}q_{s'}^{mource}\right) \\ y_{ti'}^{C} + y_{t't}^{C} \leq 1 \end{array}$$

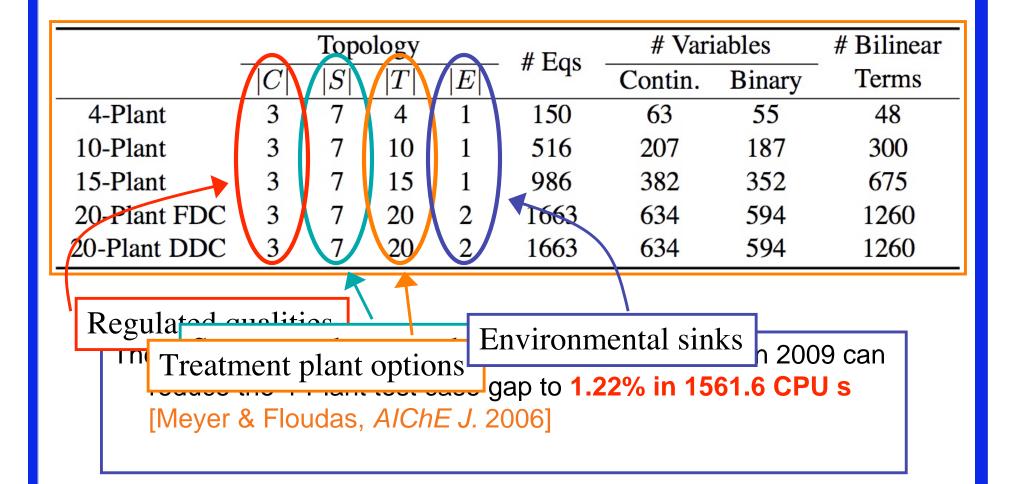
$$\begin{array}{c} \begin{array}{c} \underset{a,b,c,d,q,y^{a},y^{b},y^{c},y^{d},y^{e}}{\text{min}} z^{P} = \sum\limits_{s \in S} \sum\limits_{e \in E} c_{se}^{a} e_{se} + \sum\limits_{t \in T} \sum\limits_{e \in E} c_{b}^{b} e_{b} e_{te} \\ = \sum\limits_{t \in T} \sum\limits_{i \in T} c_{se}^{a} e_{se} + \sum\limits_{t \in T} \sum\limits_{e \in E} c_{b}^{b} e_{b} e_{te} \\ + \sum\limits_{t \in T} \sum\limits_{i \in T} (c_{tt}^{c} + c_{t}^{e})c_{tt} + \sum\limits_{s \in S} \sum\limits_{i \in T} (c_{st}^{d} + c_{t}^{e})d_{st} \\ + \sum\limits_{i \in T} \sum\limits_{i \in T} c_{ij}^{v} y_{ie}^{a} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{ij}^{v} y_{ie}^{d} \\ + \sum\limits_{x \in S} \sum\limits_{e \in E} c_{x}^{v} y_{xe}^{a} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{ij}^{v} y_{je}^{d} \\ + \sum\limits_{x \in S} \sum\limits_{i \in T} c_{ij}^{v} y_{ii}^{c} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{ij}^{v} y_{jd}^{d} \\ + \sum\limits_{x \in S} \sum\limits_{e \in E} c_{x}^{v} y_{xe}^{v} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{ij}^{v} y_{jd}^{d} \\ + \sum\limits_{x \in S} \sum\limits_{e \in E} c_{x}^{v} y_{xi}^{v} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{xj}^{v} y_{jd}^{d} \\ + \sum\limits_{x \in S} \sum\limits_{i \in T} c_{xi}^{v} y_{xi}^{v} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{xi}^{v} y_{sd}^{d} \\ + \sum\limits_{i \in T} \sum\limits_{i \in T} c_{ij}^{v} y_{it}^{v} + \sum\limits_{s \in S} \sum\limits_{i \in T} c_{xi}^{v} y_{sd}^{d} \\ + \sum\limits_{x \in S} c_{xi}^{v} y_{xi}^{e} \\ + \sum\limits_{i \in T} \sum\limits_{i \in T} c_{xi}^{v} y_{xi}^{v} \\ + \sum\limits_{x \in S} c_{xi}^{v} y_{xi}^{v} \\ + \sum\limits_{i \in T} c_{xi}^{v} y_{xi}^{v} y_{xi}^{v} \\ + \sum\limits_{i \in T} c_{xi}^{v} y_{xi}^{v} \\ + \sum\limits_{i$$

Problem Definition [Misener & Floudas, Ind. Eng. Chem. Res. 2010] $y_{s,e}^{u} \cdot \underline{a}_{s,e} \leq a_{s,e} \leq y_{s,e}^{u} \cdot \overline{a}_{s,e}$ $\min z_p = \sum_{\substack{s \in S \\ e \in E}} \left(c^a_{s,e} \cdot a_{s,e} + c^{ya}_{s,e} \cdot y^a_{s,e} \right) + \sum_{\substack{t \in T \\ e \in E}} \left(c^b_{t,e} \cdot b_{t,e} + c^{yb}_{t,e} \cdot y^b_{t,e} \right) +$ $y_{t,e}^b \cdot \underline{b}_{t,e} \leq b_{t,e} \leq y_{t,e}^b \cdot \overline{b}_{t,e}$ $\sum_{t \in T} \left(c^{c}_{t,t'} \cdot c_{t,t'} + c^{yc}_{t,t'} \cdot y^{c}_{t,t'} \right) + \sum_{t \in T} \left(c^{d}_{s,t} \cdot d_{s,t} + c^{yd}_{s,t} \cdot y^{d}_{s,t} \right) +$ $y_{t,t'}^c \cdot \underline{c}_{t,t'} \leq c_{t,t'} \leq y_{t,t'}^c \cdot \overline{c}_{t,t'}$ $t' \in T \setminus \{t\}$ $y_{s,t}^d \cdot \underline{d}_{s,t} \leq d_{s,t} \leq y_{s,t}^d \cdot \overline{d}_{s,t}$ The material balances are equivalent to $y_t^e \cdot \underline{e}_t \leq \sum c_{t,t'} + \sum b_{t,e} \leq y_t^e \cdot \overline{e}_t$ the Meyer & Floudas, AIChE J. [2006] formulation except that they now permit $t' \in T \setminus \{t\}$ multiple sinks (output nodes) $f_s^{\text{source}} = \sum a_{s,e} + \sum d_{s,t}$ $t' \in T \setminus \{t\}$ $s \in S$ $q_{c,t} \cdot \left[\sum_{t' \in T \setminus \{t\}} c_{t,t'} + \sum_{e \in E} b_{t,e} \right] \quad \forall c \in C; t \in T \quad \left[\sum_{s \in S} d_{s,t} + \sum_{t' \in T \setminus \{t\}} c_{t',t} = \sum_{t' \in T \setminus \{t\}} c_{t,t'} + \sum_{e \in E} b_{t,e'} \right]$ $\sum f_s^{\text{source}} = \sum a_{s,e} + \sum b_{t,e}$ $q_{c,e}^{\max} \cdot \left(\sum_{\alpha} a_{s,e} + \sum_{t \in T} b_{t,e} \right)$ $s \in S$ $\substack{s \in S \\ e \in E}$ $\substack{t \in T \\ e \in E}$ $f_e^{\text{sink,max}} \ge \sum_{s \in S} a_{s,e} + \sum_{t \in T} b_{t,e}$ $\sum q_{c,s}^{\text{source}} \cdot a_{s,e} + \sum q_{c,t} \cdot b_{t,e}$ $s \in S$ $y_{t,t'}^c + y_{t',t}^c \le 1$

Problem Definition [Misener & Floudas, Ind. Eng. Chem. Res. 2010]

$$\begin{split} \min z_{p} &= \sum_{\substack{s \in S \\ e \in E}} \left(c_{s,e}^{a} \cdot a_{s,e} + c_{s,e}^{ya} \cdot y_{s,e}^{a} \right) + \sum_{\substack{t \in T \\ e \in E}} \left(c_{t,e}^{b} \cdot b_{t,e} + c_{t,e}^{yb} \cdot y_{t,e}^{b} \right) + \left| y_{s,e}^{a} \cdot e \cdot \underline{a}_{s,e} \leq a_{s,e} \leq y_{s,e}^{a} \cdot \overline{a}_{s,e} \right| \\ \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} \left(c_{t,t'}^{c} \cdot c_{t,t'} + c_{t,t'}^{yc} \cdot y_{t,t'}^{c} \right) + \sum_{\substack{t \in T \\ s \in S}} \left(c_{s,t}^{d} \cdot d_{s,t} + c_{t,t'}^{yc} \cdot y_{t,t'}^{c} \right) + \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} \left(c_{t,t'}^{d} \cdot c_{t,t'} + c_{t,t'}^{yc} \cdot y_{t,t'}^{c} \right) + \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} \left(c_{t,t'}^{d} \cdot c_{t,t'} + c_{t,t'}^{yc} \cdot y_{t,t'}^{c} \right) + \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} \left(c_{t,t'}^{d} \cdot c_{t,t'} + c_{t,t'}^{yc} \cdot y_{t,t'}^{c} \right) + \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} \left(c_{t,t'}^{d} \cdot c_{t,t'} + c_{t,t'}^{yc} \cdot y_{t,t'}^{c} \right) + \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} \left(c_{t,t'}^{d} \cdot c_{t,t'} + c_{t,t'}^{yc} \cdot c_{t',t'}^{d} \right) \\ \left(1 - r_{c,t} \right) \cdot \left[\sum_{\substack{s \in S \\ s \in S}} q_{c,s'}^{source} \cdot d_{s,t} + \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} q_{c,t'} \cdot c_{t',t'}^{yc} + \sum_{\substack{s \in S \\ t' \in T \setminus \{t\}}} q_{c,t'} \cdot c_{t,t'}^{yc} + \sum_{\substack{s \in S \\ t \in T}} d_{s,t} + \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} q_{c,t'} \cdot c_{t,t'}^{yc} + \sum_{\substack{s \in S \\ t \in T}} d_{s,t} + \sum_{\substack{t \in T \\ t' \in T \setminus \{t\}}} q_{c,s'} \cdot c_{t,t'}^{yc} + \sum_{\substack{t \in T \\ t \in T}} b_{t,e} \right) \\ \\ \sum_{s \in S} q_{s,cs}^{source} \cdot a_{s,e} + \sum_{\substack{t \in T \\ t \in T}} q_{c,t'} \cdot b_{t,e} \\ \sum_{s \in S} q_{s,cs}^{source} \cdot a_{s,e} + \sum_{\substack{t \in T \\ t \in T}} d_{t,t'}^{yc} + y_{t'}^{yc} + y_{t'}^{yc} \\ (t,t') + y_{t',t'}^{yc} \leq 1 \\ \end{array} \right)$$

Sizes of the Case Studies



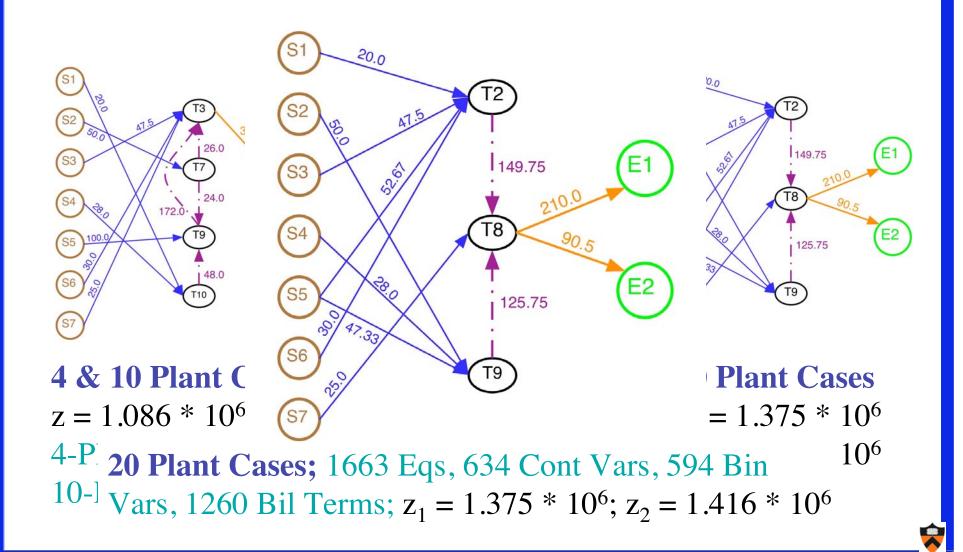
Sizes of the Case Studies

		Торо	ology		# Eqs	# Vari	ables	# Bilinear
	C	S	T	E	# Eqs	Contin.	Binary	Terms
4-Plant	3	7	4	1	150	63	55	48
10-Plant	3	7	10	1	516	207	187	300
15-Plant	3	7	15	1	986	382	352	675
20 Plant FDC	3	7	20	2	1663	634	594	1260
20-Plant DDC	3	7	20	2	1663	634	594	1260
		(
The best-k	nown	algor	ithm	But th	ne probl	ems we a	ctually	an
reduce t	he 4-	Plant	test	want	to addre	ess are m		er
[Meyer a	& Flou	udas,	AICh	EJ.Z	000]			-

Optimal Case Study Topologies SI 300.5 26.0 26.0 24.0 172.0. 24.0 172.0. 100.0 **S**5 30.0 48.0 S6 4 & 10 Plant (T10 $z = 1.086 * 10^{6}$ (S7 4-Plant: 20 2 C 4 Plant Case; $z = 1.086 * 10^6$; 150 Eqs, 63 Con 10-Pla Vars, 55 Bin Vars, 48 Bilin Terms, **38.2 CPU s**

Optimal Case Study Topologies 300.5 26.0 155.2 24.0 172.0. 28.0 100. 42.8 **S**5 30.0 27.2 S6 4 & 10 Plant ($z = 1.086 * 10^{6}$ **S**7 4-Plant 15 Plant Case; $z = 9.437 * 10^6$; 986 Eqs., 382 Cont 10-Pla Vars, 352 Bin Vars, 675 Bil Terms, 2490 CPU s

Optimal Case Study Topologies



Optimizing the 4-Plant Test Case

	Table 4: Bro	anch & Boi	und Result	ts for the 4 Pla	ent Test Case (Serial Op	timization)	
N	Root N	lode	#	Г	ermination		CPU Ti	me (s)
IN	Relaxation	CPU (s)	Nodes	Lower Bnd	Upper Bnd	% Gap	Solving	Total
McC	$7.219\cdot 10^5$	0.1	5000*	$1.082\cdot 10^6$	$1.106\cdot 10^6$	2.2	773.9	7112.5
RLT	$7.223 \cdot 10^{5}$	0.5	1712	1 025 106	1 086 106	0.1	7826	² 720.0
3	$9.607 \cdot 10^{5}$	29	95	Trade-off:	Rlxns with	many p	partitions	190.1
5	$9.896 \cdot 10^{5}$	59	7	tend to be t	ighter but r	lxns wit	th few	38.2
7	$1.00 \frac{5}{5} \cdot 10^6$	56	_	partitions to	•			39.1
10	$1.041 \cdot 10^{6}$	16 <mark>.</mark> 6	3			- quicki	y 	54.1
15	$1.086 \cdot 10^{6}$	109.3	1	$1.086 \cdot 10^{6}$	$1.086\cdot 10^6$	< 0.1	109.31	111.6
*Branc	h-and-bound tr	ee limited to	5000 node	es				

 The best known algorithms in 2003 run on a machine in 2009 can reduce the 4-Plant test case gap to 1.22% in 1561.6 CPU s [Meyer & Floudas, AIChE J. 2006]



Optimizing the 4-Plant Test Case

	_	Tahle 4 · Bran	ch & Round	Result	s for the 4 Pla	nt Test Case (Se	erial Op	timization)	
N	T	he new algo	orithms v	ve ha	ve explore	ed can addı	ess	CPU Ti	me (s)
1	t h	he new algo ne same prob	olem to a	a 0 1 4	76 gan in	38 CPU s (ัล โ	Solving	Total
111							^a [773.9	7112.5
R	te	en-fold impr	ovemen	t in oi	ne-Iortieth	n the time)		7 <mark>83.6</mark>	2720.0
3		$9.607 \cdot 10^{\circ}$	2.9	95	$1.085\cdot10^{\circ}$	$1.086 \cdot 10^{\circ}$	0.1	80.36	190.1
5		$9.896\cdot 10^5$	5.9	7	$1.085\cdot 10^6$	$1.086\cdot 10^6$	0.1	25.07	38.2
7		$1.005 \cdot 10^{6}$	5.6	5	$1.085 \cdot 10^{6}$	$1.086 \cdot 10^{6}$	0.1	33.25	39.1
10	0	Balancing	this trad	e-off	with inter	mediate		50.37	54.1
15	5						• . •	109.31	111.6
*I	Bran	partitioning	g genera	tes th	e smalles	t total CPU	time		

 The best known algorithms in 2003 run on a machine in 2009 can reduce the 4-Plant test case gap to 1.22% in 1561.6 CPU s [Meyer & Floudas, AIChE J. 2006]

Optimizing the 15-Plant Test Case

Using our experience with the 4- & 10-Plant test cases, solve the 15-Plant test case with N = 5 on the same Linux workstation & converge to 0.1% in 2489.76 s. Moving the same problem to parallel CPLEX on a Beowulf cluster confirms that N = 5 is still appropriate.

Table 6. Branch & Bound Results for the 15 Plant Test Case (8 Threaded Parallel Optimization)

<i>Tuble</i> 0	. Drunci	n & Bouna Kes	suits jor il	ne 15 Fiuni Ie	si Cuse (0-11	reaueu I a	ruitei Ophie	iizaii0n)
	N	Root Node	#	Т	ermination		Total	
	11	Relaxation	Nodes	Lower Bnd	Upper Bnd	% Gap	CPU s	
	McC	$7.129\cdot 10^5$	891	$9.424 \cdot 10^{5}$	$9.437 \cdot 10^5$	0.1	15940.90	
	RLT	$7.132\cdot 10^5$	967	$9.343\cdot 10^5$	$9.437\cdot 10^5$	0.1	66592.25	
	3	$9.002\cdot 10^5$	7	$9.343\cdot 10^5$	$9.437\cdot 10^5$	0.1	1141.98	
	5	$9.345\cdot 10^5$	1	$9.345\cdot 10^5$	$9.437 \cdot 10^{5}$	< 0.1	784.81	
	7	$9.408\cdot 10^5$	9	$9.343\cdot 10^5$	$9.437 \cdot 10^{5}$	0.1	1874.73	
	10	$9.345\cdot 10^5$	1	$9.345\cdot 10^5$	$9.437 \cdot 10^{5}$	< 0.1	912.03	
	15	$9.345\cdot 10^5$	1	$9.345 \cdot 10^5$	$9.437 \cdot 10^5$	< 0.1	2397.24	_

Optimizing the 20-Plant Test Cases: Fixed Disposal Costs

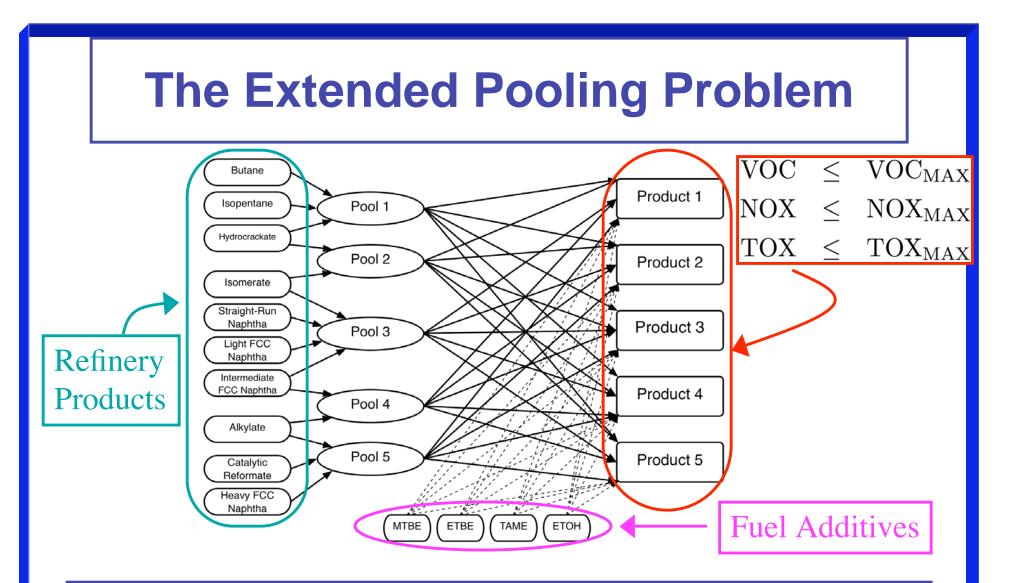
The test cases with 1260 bilinear terms are challenging, so employ additional strategies:

(1) Limit partitioned terms to those related to commonly-used plants(2) Solve MILP relaxation to a tight gap only in later nodes of the BB tree

N	г	#			Sumination	<i>(</i>)		L.,
1		Nodes	Lo		ning on a <mark>sel</mark>	-		e
Μ	ſcC	2462	~ '		terms help	s the con	ivergence	
	LT	8166		$268 \cdot 10^{6}$	For a topol			
Pa	artitior	ning on al	120	Treatmer	longer solv	es in a re	asonable ti	me
N	I = 3	49	1.:	$338 \cdot 10^{6}$	1.010.10	2.1	50000	
L	imited	Partition	ing	-)
Ν	I = 3	331	1.3	$362 \cdot 10^{6}$	$1.375 \cdot 10^{6}$	0.9	360000*	
Ν	I = 5	17	1.2	$210 \cdot 10^{6}$	$1.555 \cdot 10^{6}$	22.2	360000*	
*I	Branch	-and-boun	d tre	e limited to	$3.6 imes 10^5$ CPI	U s (100 hc	ours)	

<u>Outline</u>

- Deterministic Global Optimization: Objectives & Motivation
- Convex Envelopes:
 - Trilinear Monomials
 - Edge Concave functions
- Piecewise linearization of Bilinear terms
- Checking Convexity: Products of Univariate Functions
- PαBB: Piecewise Quadratic Perturbations
- Pooling Problems: Standard, Generalized
 & Extended Towards addressing Large Scale Global Optimization Problems
- Conclusions



 Given refinery exit streams, meet volatile organics, NO_X, & toxic emissions standards for each gasoline blend according to the EPA Complex Emissions Model & legislative bounds

MINLP Model of the Extended Pooling Problem

 To integrate the EPA Complex Emissions Model into problem framework, introduce outflow variable (of_j) from each product:

$$of_j = \sum_{l:(l,j)\in T_Y} y_{l,j} + \sum_{i:(i,j)\in T_Z} z_{i,j} \quad \forall j$$

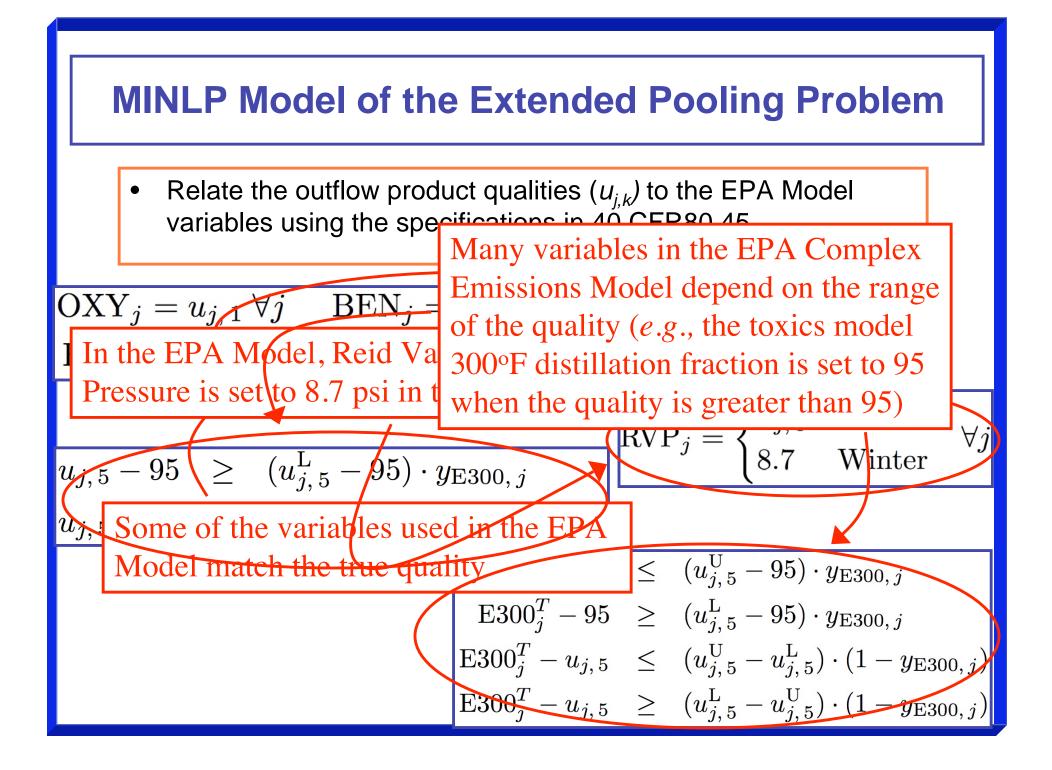
and define the product qualities $(u_{i,k})$ that blend linearly:

$$(u_{j,k}) \cdot (of_j) = \sum_{\substack{l:(l,j) \in T_Y\\i:(i,l) \in T_X}} C_{i,k} \cdot q_{i,l} \cdot y_{l,j} + \sum_{\substack{i:(i,j) \in T_Z}} C_{i,k} \cdot z_{i,j} \quad \forall j, \forall k$$

and Reid Vapor Pressure, which blends by a power law:

$$\widehat{u_{j,3}} \cdot (of_j) = \sum_{i:(i,l)\in T_X} \sum_{l:(l,j)\in T_Y} C_{i,3}^{1.25} \cdot q_{i,l} \cdot y_{l,j} + \sum_{i:(i,j)\in T_Z} C_{i,3}^{1.25} \cdot z_{i,j} \quad \forall j$$

$$\widehat{u_{j,3}} = u_{j,3}^{1.25}$$



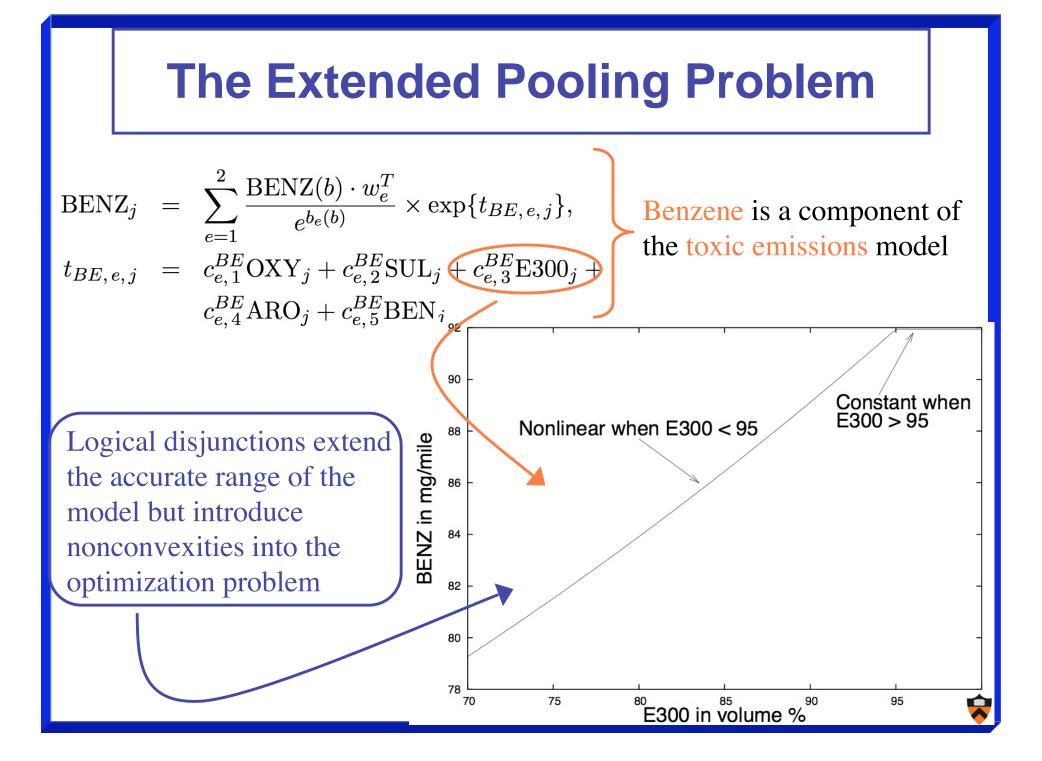
The Extended Pooling Problem

$\begin{aligned} \text{TOX}_{j} = & \text{BENZ}_{j} + \text{FORM}_{j} + \text{ACET}_{j} + \text{BUTA}_{j} + \\ & 10 \cdot \text{NEBENZ}_{j} + \text{POM}_{j} \quad \forall j \end{aligned}$

There are three regulated components in the EPA Model: volatile organics, NO_X , & toxic emissions Toxics emissions (TOX_j) is the sum of six components: exhaust benzene $(BENZ_j)$, formaldehyde (FORM_j), acetaldehyde (ACET_j), 1,3-butadiene (BUTA_j), nonexhaust benzene (NEBENZ_j), & polycyclic organic matter (POM_j) Emissions standards must be met for each product *j*

The Extended Pooling Problem Each of the three regulated emissions is modeled with a nonlinear expression. The toxics model is the only convex one of the three. $\text{TOX}_i \in \text{BENZ}_i + \text{FORM}_i + \text{ACET}_i + \text{BUTA}_i +$ $10 \cdot \text{NEBENZ}_i + \text{POM}_i \quad \forall j$ $\operatorname{BENZ}_{j} = \sum_{e^{b_e(b)}}^{2} \frac{\operatorname{BENZ}(b) \cdot w_e^T}{e^{b_e(b)}} \times \exp\{t_{BE,e,j}\},$ e=1 $t_{BE,e,j} = c_{e,1}^{BE} \text{OXY}_j + c_{e,2}^{BE} \text{SUL}_j + c_{e,3}^{BE} \text{E300}_j +$ $c_{e,4}^{BE} ARO_j + c_{e,5}^{BE} BEN_j$

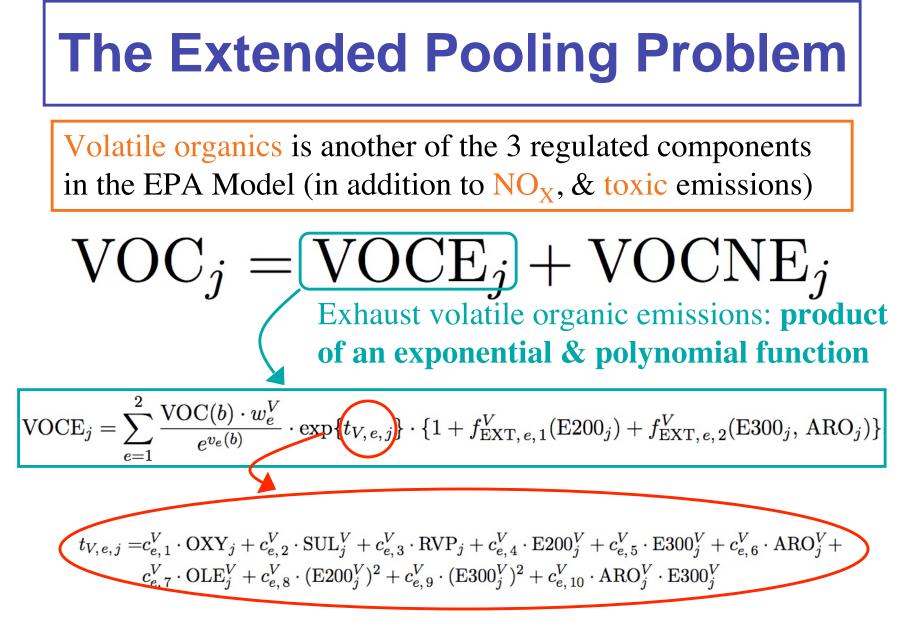
nonlinear (albeit convex) equation



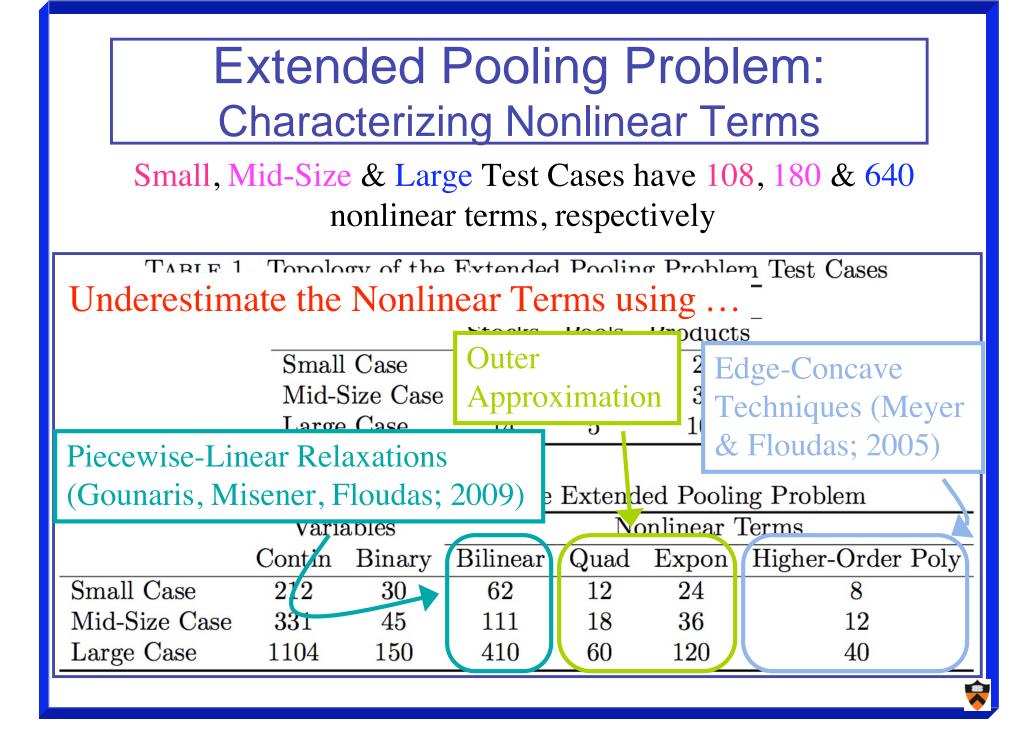
The Extended Pooling Problem

Volatile organics is another of the 3 regulated components in the EPA Model (in addition to NO_X , & toxic emissions)

$$VOC_{j} = VOCE_{j} + VOCNE_{j}$$
In the summer, the non-exhaust volatile organic emissions are a **non-convex quadratic function** of Reid Vapor Pressure
$$VOCNE_{j} = \begin{cases} 0.0 & \text{Winter} \\ \alpha_{1}^{V} + \alpha_{2}^{V} \cdot \text{RVP}_{j} + \alpha_{3}^{V} \cdot \text{RVP}_{j}^{2} & \text{Summer} \end{cases} \forall j$$



The function in the exponential is itself nonconvex



Extended Pooling Problem: Relaxation of EPA Model for NEBENZ

- The paradigm of edge-concavity efficiently generates a tight lower bound on the EPA Model of nonexhaust benzene (a toxic emissions component)
- The EPA nonexhaust benzene model would be edge-concave iff:

Generate a tight relaxation by subtracting a term from NEBENZ_j to
satisfy the 2nd derivative property. Derive convex hull of the edge-
concave portion using the method of Meyer & Floudas, *Math. Prog.*
[2005] & relax the remaining portion with recursive arithmetic
[2005] & relax the remaining portion with recursive arithmetic
[2005] & sahinidis, *J. Global Optim.*, 2001]
$$\partial BEN_j^2$$

The st equation is not valid, so NEBENZ is not edge concave. But:
NEBENZ_j - $\alpha'_4 \cdot RVP_j^2 \cdot BEN_j$
is edge-concave when:
 $\alpha'_4 = \alpha_4^{NB} + 3 \cdot \alpha_6^{NB} \cdot RVP_j^L + \alpha_7^{NB} \cdot MTB_j^L$

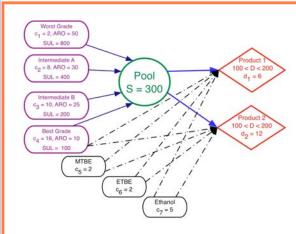
Extended Pooling Problem: Relaxation of EPA Model for NEBENZ

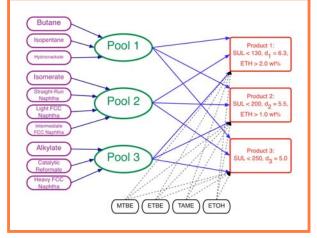
Tardella, *Discret. Appl. Math.* [1988]; Tardella [2003, 2008]; Maranas & Floudas, *J. Global Optim.* [1995]; Ryoo & Sahinidis, *J. Global Optim.* [2001]; Meyer & Floudas, *Math. Prog.* [2005]

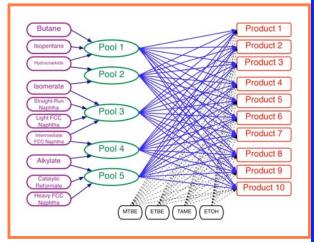
 Generating the convex hull of the edge-concave portion with the Meyer & Floudas, Math. Prog. [2005] method produces 22% improvement in the relaxation lower bound without requiring extra time:

	Recursive Arith RIx	Edge-Concave Based Relax.
LB of NEBENZ in Reg1 (mg/mile)	-13.56	10.61
CPU (s)	0.01	0.01
LB of NEBENZ in Reg2 (mg/mile)	-11.49	9.01
CPS (s)	< 0.01	< 0.01

Extended Pooling Problem: Characterizing the Case Studies







• Small

- -214 Contin Vars
- -30 Binary Vars
- –108 Nonlin Terms

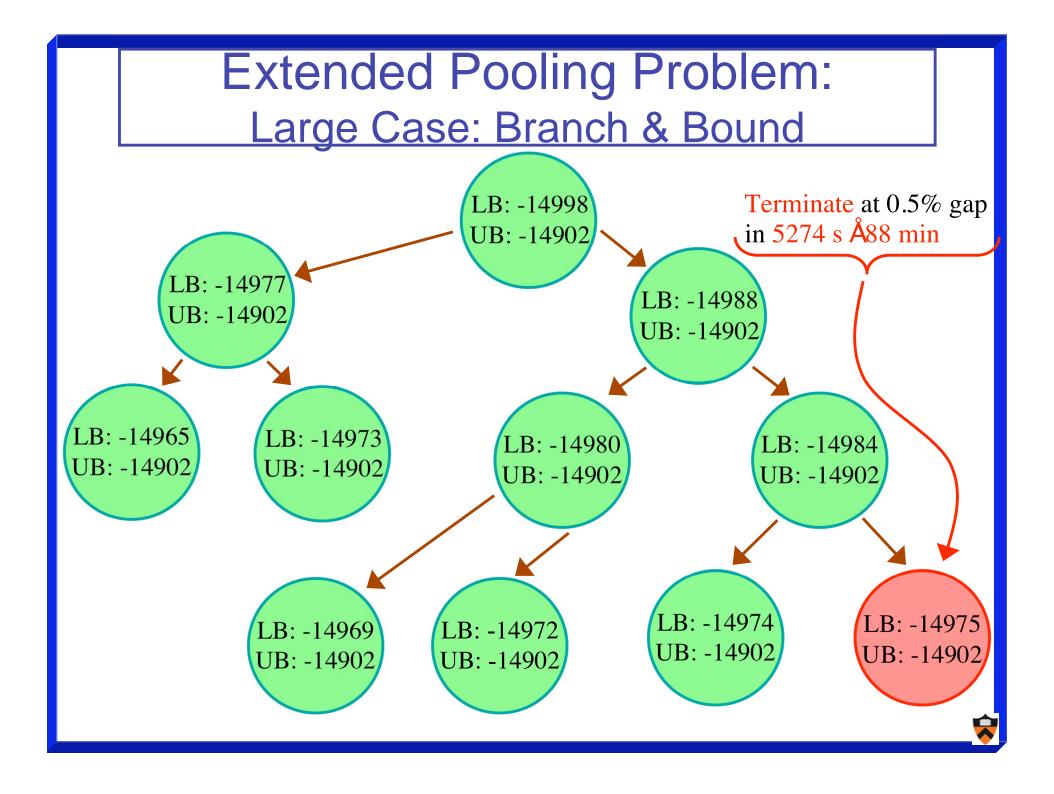
• Mid-Size

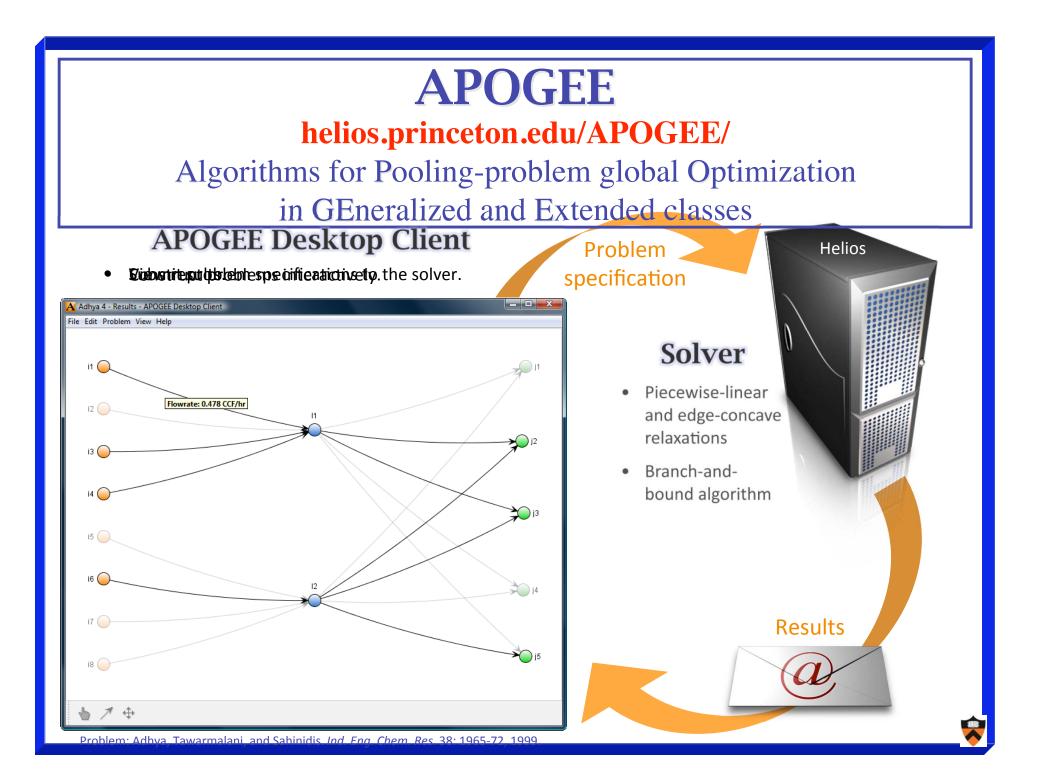
- -331 Contin Vars
- -45 Binary Vars
- –180 Nonlin Terms

• Large

- –1104 Contin Vars
- -150 Binary Vars
- –640 Nonlin Terms







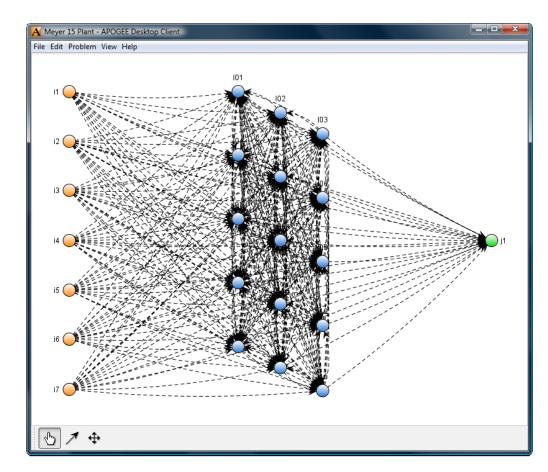
Globally Optimize Pooling Problems in Three Classes

	A Large EPA - APOGEE Desktop Client
A Edit Node Properties	W Help
Inputs Pools Outputs	
Output ID: j01 Change ID	
Description: Product 1	
Product demand:	j02
✓ Lower bound: 100 ft³/sec	
Upper bound: 700 ft³/sec	j03
Revenue: \$ 8 / ft ³	
Stream Qualities EPA Definitions	
Production Specs	j05
Season: Summer 👻	
Region: Region 1	j06
Emissions	107
VOC limit: 1,600 mg/mile	
NOX limit: 1,300 mg/mile	111 JUL 108
TOX limit: 95 mg/mile	
	i13 (1) (1) (1) (1) (1) (1) (1) (1) (1) (1)
	i14 j10
	OK Cancel
Problem	

Problem Complexity

- Monitor complexity as problem is constructed.
- Globally optimize large-scale instances.

Problem Complexity ('P'-formulation)		
Continuous Variables		
Flowrates		
Input-pool:		105
Input-put:		105
Pool-output:		15
Pool-pool:	+	210
Total:		337
Pool Quality Levels		
Number of pools:		15
Number of qualities:	×	3
Total:		45
Binary Variables		
Optional connections:		337
Bilinear Terms		
Pool-output connections:		15
Pool-Pool connections:		+ 210
		225
Number of qualities	:	× 3
Total:		675



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Conclusions

Motivational Areas & Review of contributions
Convex Envelopes: Trilinear Monomials; Edge Concave Functions
Piecewise Relaxation of Bilinear Terms
Checking Convexity:Products of Univariate Functions
PαBB: Piecewise Quadratic Perturbation Based αBB
Generalized & Extended Pooling Problems: Large
Scale Global Optimization Successes

Exciting theoretical and algorithmic advances with potential impact on several application areas

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Imperial College SAS **Rutgers University** University of Delaware Praxair **Princeton University Cornell Medical School Process Combinatorics Rutgers University** BASF D.F. Shaw Harvard Medical School Penn State University Dana Farber Cancer Institute **Princeton University** University of Vienna **Cornell University CCSF Pavilion Technologies** AspenTech, BASF