## Mixed Integer Programming Models for Non-Separable Piecewise Linear Cost Functions

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Joint work with Shabbir Ahmed and George Nemhauser.

University of Pittsburgh, 2008 – Pittsburgh, PA

## **Piecewise Linear Optimization**

 $\min f_0(x)$ s.t.  $f_i(x) \le 0 \quad \forall i \in I$  $x \in X \subset \mathbb{R}^n$ 



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∀i ∈ {0} ∪ I f<sub>i</sub>(x) : D → ℝ is a piecewise linear function (PLF) and X is any compact set.
Convex = Linear Programming. Non-Convex = NP Hard.
Specialized algorithms (Tomlin 1981, ..., de Farias et al. 2008) or Mixed Integer Programming Models (12+ papers).

## **Mixed Integer Models for PLFs**

Existing studies are for separable functions:

$$f(x) = \sum_{j=1}^{n} f_j(x_j) \text{ for } f_j(x_j) : \mathbb{R} \to \mathbb{R}$$

Contributions (Vielma et al. 2008a,b):

First models with a logarithmic # of binary variables.

 Theoretical and computational comparison: multivariate (non-separable) and lower semicontinuous functions in a unifying framework.

## Outline

 Applications of Piecewise Linear Functions. Modeling Piecewise Linear Functions. Logarithmic Formulations. Comparison of Formulations. Extension to Lower Semicontinuous Functions. Final Remarks.

## **Economies of Scale: Concave**



Single and multi-commodity network flow.
 Applications in telecommunications, transportation, and logistics.
 (Balakrishnan and Graves 1989, ..., Croxton, et al. 2007). 5/26

## **Fixed Charges and Discounts**





 Fixed Costs in Logistics.
 Discounts (e.g. Auctions: Sandholm, et al. 2006, CombineNet).
 Discounts in fixed charges (Lowe 1984).

# **Non-Linear and PDE Constraints**



p(x,t) = gas pressureq(x,t) = gas volume flow $A \frac{\partial \rho}{\partial t} + \rho_0 \frac{\partial q}{\partial x} = 0,$  $\frac{\partial p}{\partial x} = -\lambda \frac{|v|v}{2D} \rho.$ 

 Gas Network Optimization (Martin et al. 2006).

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Discretize non-linear stationary solution  $p_v = g(p_u, q_{uv})$ 

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Discretize PDE (Fügenschuh, et al. 2008)

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## **Numerically Exact Global Optimization**



 Process engineering (Bergamini et al. 2005, 2008, Computers and Chemical Eng.)

Wetland restoration (Stralberg et al. 2009).



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## **Piecewise Linear Functions: Definition**



DEFINITION 1. Piecewise Linear  $f: D \subset \mathbb{R}^n \to \mathbb{R}$ :  $f(x) := \begin{cases} m_P x + c_P & x \in P & \forall P \in \mathcal{P}. \end{cases}$ 

for finite family of polytopes  $\mathcal{P}$  such that  $D = \bigcup_{P \in \mathcal{P}} P$ 

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# **Modeling Function = Epigraph** • $epi(f) := \{(x, z) \in D \times \mathbb{R} \subset \mathbb{R}^n \times \mathbb{R} : f(x) \le z\}.$



• Example:  $f(x) \le 0 \Leftrightarrow (x, z) \in epi(f), z \le 0$ 

## **Convex Combination (CC): Univariate**



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idea: write  $(x, y) \in epi(f)$ as convex combination of (v, f(v)) for  $v \in \mathcal{V}(\mathcal{P})$ .

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$$f(x) := \begin{cases} x+1 & x \in [0,2] \leftarrow P_1 \\ 6-3/2x & x \in [2,4] \leftarrow P_2 \\ V(P) = \text{vertices of P.} \\ \mathcal{V}(\mathcal{P}) := V(P_1) \cup V(P_2) = \{0,2,4\}. \end{cases}$$

idea: write  $(x, y) \in epi(f)$ as convex combination of (v, f(v)) for  $v \in \mathcal{V}(\mathcal{P})$ .

$$\begin{aligned} x &= 0\lambda_0 + 2\lambda_2 + 4\lambda_4 \\ z &\ge 1\lambda_0 + 3\lambda_2 + 0\lambda_4 \\ 1 &= \lambda_0 + \lambda_2 + \lambda_4, \quad \lambda_0, \lambda_2, \lambda_4 \ge 0 \end{aligned}$$



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$$\begin{split} \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v v = x, \quad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v \left( m_P v + c_P \right) \leq z \\ \lambda_v \geq 0 \quad \forall v \in \mathcal{V}(\mathcal{P}) := \bigcup_{P \in \mathcal{P}} V(P), \quad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v = 1 \\ \lambda_v \leq \sum_{\{P \in \mathcal{P} : v \in V(P)\}} y_P \quad \forall v \in \mathcal{V}(\mathcal{P}), \quad \sum_{P \in \mathcal{P}} y_P = 1, \quad y_P \in \{0, 1\} \quad \forall P \in \mathcal{P} \end{split}$$

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## **Convex Combination (CC): Multivariate**

$$\begin{array}{l} \text{``Original Constraints''} \qquad \qquad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v v = x, \quad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v \left( m_P v + c_P \right) \leq z \\ \lambda_v \geq 0 \quad \forall v \in \mathcal{V}(\mathcal{P}) := \bigcup_{P \in \mathcal{P}} V(P), \quad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v = 1 \end{array} \\ \lambda_v \leq \sum_{\{P \in \mathcal{P} : v \in V(P)\}} y_P \quad \forall v \in \mathcal{V}(\mathcal{P}), \quad \sum_{P \in \mathcal{P}} y_P = 1, \quad y_P \in \{0, 1\} \quad \forall P \in \mathcal{P} \end{cases}$$

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$$\begin{aligned} & \text{``Extra Constraints''} \qquad & \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v v = x, \quad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v (m_P v + c_P) \leq z \\ & \lambda_v \geq 0 \quad \forall v \in \mathcal{V}(\mathcal{P}) := \bigcup_{P \in \mathcal{P}} V(P), \quad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v = 1 \\ & \lambda_v \leq \sum_{\{P \in \mathcal{P} : v \in V(P)\}} y_P \quad \forall v \in \mathcal{V}(\mathcal{P}), \quad \sum_{P \in \mathcal{P}} y_P = 1, \quad y_P \in \{0, 1\} \quad \forall P \in \mathcal{P} \end{aligned}$$

## **Convex Combination (CC): Multivariate**

Univariate (Dantzig, 1960) ... Multivariate (Lee and Wilson (2001).

# "Extra Constraints" $\sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v v = x, \quad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v (m_P v + c_P) \leq z$ $\lambda_v \geq 0 \quad \forall v \in \mathcal{V}(\mathcal{P}) := \bigcup_{P \in \mathcal{P}} V(P), \quad \sum_{v \in \mathcal{V}(\mathcal{P})} \lambda_v = 1$ **SOS2 only for univariate**

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# Existing Models are Linear on $|\mathcal{P}|$

 Other models: Multiple Choice (MC), Incremental (Inc), Disaggregated Convex Combination (DCC).

• Number of binary variables and combinatorial "extra" constraints are linear in  $|\mathcal{P}|$ .

For multivariate on a  $k \times k$  grid  $|\mathcal{P}| = O(k^2)$ .

Logarithmic sized formulations?





# SOS1, SOS2 and CC constraints.

SOS1-2 (Beale and Tomlin 1970): SOS1: At most one variable is nonzero. SOS2: Only 2 adjacent variables are nonzero.  $\checkmark$  (0,1,1/2,0,0)  $\times$  (0,1,0,1/2,0) •  $(\lambda_i)_{i \in J} \in \mathbb{R}^J_+$ , allowed sets  $(S_i)_{i \in I}$ ,  $S_i \subset J_i$ • SOS1: I = J,  $S_i = \{i\}$ . • SOS2:  $J = \{0, ..., m\}, I = J \setminus \{m\}, S_i = \{i, i+1\}.$ • CC:  $J = \mathcal{V}(\mathcal{P}), I = \mathcal{P}, S_P = V(P).$ 

# Logarithmic Formulation for SOS1

$$\sum_{j=0}^{3} \lambda_{j} = 1, \quad \lambda_{0}, \lambda_{1}, \lambda_{2}, \lambda_{3} \ge 0, \text{ at most } 1 \ \lambda_{j} \text{ is nonzero.}$$
  
Allowed sets:  $S_{0} = \{0\}, S_{1} = \{1\}, S_{2} = \{2\}, S_{3} = \{3\}.$ 

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• Injective function:  $B: \{0, \dots, m-1\} \rightarrow \{0, 1\}^{\lceil \log_2 m \rceil}$ • Variables:  $w \in \{0, 1\}^{\lceil \log_2 m \rceil}$ • Idea:  $\lambda_j > 0 \Leftrightarrow w = B(j)$ 

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$$i \quad S_i \quad B(i)$$

$$0 \quad \{0\} \longrightarrow 0 \quad 0 \quad \lambda_1 + \lambda_3 \le w_1$$

$$B: \{0, \dots, 1\} \longrightarrow \{0, 1\} | \log m$$

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# **Logarithmic Formulation for SOS2**

 $\sum_{j=0}^{4} \lambda_j = 1, \quad \lambda_0, \dots, \lambda_4 \ge 0, \text{ only 2 adjacent } \lambda_j \text{'s ar nonzero.}$ Allowed sets:  $S_i = \{i, i+1\} \text{ for } i \in \{0, \dots, 3\}.$ 

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# Logarithmic Formulation for SOS2

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# Logarithmic Formulation for SOS2

2 
$$(\{2,3\}) \longrightarrow 0$$
 1  $\lambda_0 + \lambda_1 \le (1 - w_2)$ 

$$3 \quad \underbrace{\{3,4\}} \longleftrightarrow \begin{array}{c} \mathbf{1} \quad \mathbf{1} \\ w_1 \quad w_2 \in \{0,1\} \end{array} \qquad \lambda_3 + \lambda_4 \leq w_2$$

## **Logarithmic Formulation for SOS2**

 $\sum_{j=0}^{4} \lambda_j = 1, \quad \lambda_0, \dots, \, \lambda_4 \ge 0, \text{ only } 2 \text{ adjacent } \lambda_j \text{'s ar nonzero.}$ Allowed sets:  $S_i = \{i, i+1\}$  for  $i \in \{0, ..., 3\}$ . i  $S_i$ B(i)• Where is  $\lambda_2$  ?!  $(\{0,1\}) \longleftrightarrow 0 0$ 0  $\lambda_0 \leq w_1$ 1  $(\{1,2\})$  $\lambda_4 \le (1 - w_1)$ 

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 $(\{2,3\}) \longleftrightarrow 0 \mid 1 \quad \forall \lambda_0 + \lambda_1 \le (1 - w_2)$ 2 $3 \quad \boxed{\{3,4\}} \longrightarrow \boxed{1} \quad \boxed{1} \quad \lambda_3 + \lambda_4 \leq w_2$  $w_1 \ w_2 \in \{0, 1\}$ 

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## Logarithmic Formulation for SOS2

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# **Logarithmic Formulation for SOS2**

 $\sum_{j=0}^{4} \lambda_j = 1, \quad \lambda_0, \dots, \, \lambda_4 \ge 0, \text{ only } 2 \text{ adjacent } \lambda_j \text{'s ar nonzero.}$ Allowed sets:  $S_i = \{i, i+1\}$  for  $i \in \{0, ..., 3\}$ . i  $S_i$ B(i)• Where is  $\lambda_2$  ?!  $\{0,1\}$   $\longleftrightarrow$  0 0 0  $\lambda_2 \leq w_1$ In general:  $\lambda_0 + \lambda_4 \le (1 - w_1)$  $(\{1,2\})$ 1 1 0 B(i) and B(i+1) $\lambda_0 + \lambda_1 \le (1 - w_2)$ (2,3)21 differ in one component  $({3,4})$  $\lambda_3 + \lambda_4 \le w_2$ 3 Gray Code.  $w_1 \ w_2 \in \{0, 1\}$ 

### **Independent Branching: Dichotomies**



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### Independent Branching for 2 var CC

- Select Triangle by forbidding vertices.
- 2 stages:
  - Select Square by SOS2 on each variable.
    Select 1 triangle from each square.



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$$\bar{L} = \{(r, s) \in J :$$

$$r \text{ even and } s \text{ odd} \}$$

$$= \{\text{square vertices} \}$$

$$\bar{R} = \{(r, s) \in J :$$

$$r \text{ odd and } s \text{ even} \}$$

$$= \{\text{diamond vertices} \}$$

# **Strength of LP Relaxations**

### Sharp Models: LP = lower convex envelope.



(a)  $\operatorname{epi}(f)$ .

(b)  $\operatorname{conv}(\operatorname{epi}(f))$ .

All popular models are sharp.
Locally Ideal: LP = Integral (All but CC, even Log).
Locally ideal implies Sharp.

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Locally ideal implies Sharp.

# **Computational Results**

#### Instances

- Transportation problems (10x10 & 5x2).
- Univariate: Concave Separable Objective.
- Multivariate: 2-commodity.
- Functions: affine in k segments or k x k grid triangulation (100 instances per k).
- Solver: CPLEX 11 on 2.4Ghz machine.
- Logarithmic versions of CC = Log, DCC=DLog.



 $(x, y) \rightarrow g(||(x, y)||)$ Concave PLF  $g(\cdot)$ 

# Univariate Case (Separable)



# Univariate Case (Separable)



# Univariate Case (Separable)



# Univariate Case (Separable)



### Multivariate Case (Non-Separable)









$$f(x,y) := \begin{cases} 3 & (x,y) \in (0,1]^2 \\ 2 & (x,y) \in \{(x,y) \in \mathbb{R}^2 : x = 0, y > 0\} \\ 2 & (x,y) \in \{(x,y) \in \mathbb{R}^2 : y = 0, x > 0\} \\ 0 & (x,y) \in \{(0,0)\}. \end{cases}$$

$$f(x) := \begin{cases} m_P x + c_P \quad x \in P \quad \forall P \in \mathcal{P} \\ 0 & (x,y) \in \{(0,0)\}. \end{cases}$$
Finite family of copolytopes
$$P = \{x \in \mathbb{R}^n : a_i x \le b_i \,\forall i \in \{1, \dots, p\}, \\ a_i x < b_i \,\forall i \in \{p, \dots, m\}\} \end{cases}$$

### Lower Semicontinuous PLFs



 $P = \{ x \in \mathbb{R}^n : a_i x \le b_i \,\forall i \in \{1, \dots, p\}, \\ a_i x < b_i \,\forall i \in \{p, \dots, m\} \}$ 

$$f(x,y) := \begin{cases} 3 & (x,y) \in (0,1]^2 \\ 2 & (x,y) \in \{(x,y) \in \mathbb{R}^2 : x = 0, y > 0\} \\ 2 & (x,y) \in \{(x,y) \in \mathbb{R}^2 : y = 0, x > 0\} \\ 0 & (x,y) \in \{(0,0)\}. \end{cases}$$

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copolytopes
#### Lower Semicontinuous Functions

### **Lower Semicontinuous Models**

- Direct from Disjunctive Programming (Jeroslow and Lowe)
  - "Extreme point" = DCC.
  - Traditional = Multiple Choice (MC).



- MC, DCC, DLog are locally ideal and sharp.
- Computations: 2-commodity FC discount function.

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# **Multivariate Lower Semicontinuous**



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# **Multivariate Lower Semicontinuous**



### **Multivariate Lower Semicontinuous**



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# **Final Remarks**

- Unifying theoretical framework: allows for multivariate non-separable and lower semicontinuous functions.
- First logarithmic formulations: Theoretically strong and provides significant computational advantage for large  $|\mathcal{P}|$ .
- Revive forgotten formulations and functions: MC and fixed charge discount function.

