

Comparison of discrete and continuous models for the pooling problem

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ATMOS 2011 – Saarbrücken, Germany
September 8, 2011

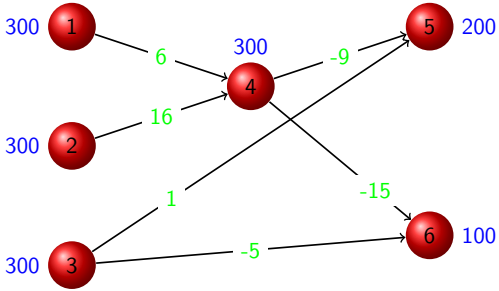


- 1 Introduction to the pooling problem
- 2 Multi-commodity flow formulation
- 3 Research motivations
- 4 Discrete model
- 5 Computational results
- 6 Summary

Introduction - traditional flow model

Parameters
Given a network with

- Arc **costs**
- Node **capacities**



Min-cost flow problem

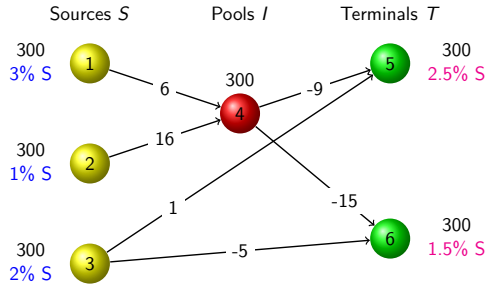
Assign flow to each arc such that the total cost is minimized

Extension of the Min-cost flow problem

Additional parameters

Relative Sulfur

- quality contents
- quality bounds



Haverly1 (Haverly, 1978)

The flow quality leaving any **pool** is defined by:
The weighted average of the quality of entering flow, where the flow values constitute the weights (linear blending)

Min-cost flow problem vs. pooling problem

Homogeneous flow (e.g. clean water)

- One flow type in the network
- Easy to solve (an LP model)

Inhomogeneous flow (e.g. Natural gas)

- More than one flow type
- Different flow qualities
 - ① Qualities are given at each source
 - ② Quality balances around each pool
 - ③ Quality restrictions at each terminal
- An NP-hard problem (Alfaki-Haugland, 2010)



- Instead of quality variables, associate a flow **commodity** with each $s \in S$
- S_i : the set of all $s \in S$ where there is a path between s and $i \in S \cup I$
- f_{ij} : the total flow along (i, j)
- y_i^s : proportion of commodity s of the flow leaving $i \in S \cup I$ ($y_i^s = 0$ if $s \notin S_i$ and $y_i^s = 1$)
- The quantity $y_i^s f_{ij}$ defines the flow of commodity s along arc (i, j)

Multi-commodity flow formulation (cont.)

- **Objective:** minimize the total cost
- In addition to the flow capacity constraints we have

$$\sum_{j \in N_i^-} y_j^s f_{ji} - \sum_{j \in N_i^+} y_i^s f_{ij} = 0, \quad s \in S_i, i \in I,$$

$$\sum_{j \in N_t^-} \left(\sum_{s \in S_j} q_s^k y_j^s - q_t^k \right) f_{jt} \leq 0, \quad t \in T, k \in K,$$

$$\sum_{s \in S_i} y_i^s = 1, \quad i \in I.$$

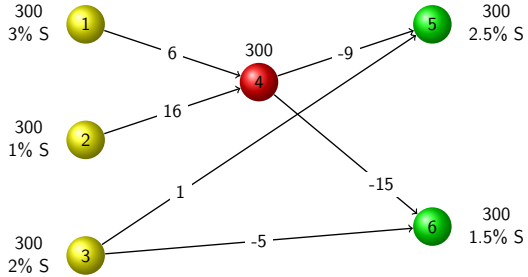
- The multi-commodity flow formulation for the pooling problem is stronger than the formulation that based on explicit quality variables (Alfaki-Haugland, 2010)



- Bilinear constraints seem inescapable in continuous models
- Traditional solution methods (e.g. Branch-and-bound) have slow convergence
- Approximate the NLP model using other well-studied models, e.g. MIP
- Strategy to find a good feasible solution in reasonable time

Example

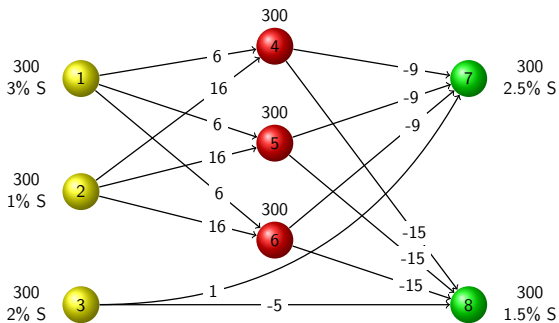
$y_4^1, y_4^2 \in [0, 1] \leftarrow y_4^1, y_4^2 \in \{0, \frac{1}{2}, 1\}$. Since $y_4^1 + y_4^2 = 1$



$$\text{discretized proportions} = \begin{pmatrix} 0 & 1 \\ \frac{1}{2} & \frac{1}{2} \\ 1 & 0 \end{pmatrix}$$

Example

Then the discretized version of Haverly1 is shown below:



$$\text{discretized proportions} = \begin{pmatrix} 0 & 1 \\ \frac{1}{2} & \frac{1}{2} \\ 1 & 0 \end{pmatrix}$$

The discrete model

- Extend the network to include the additional pools
- Each pool j corresponds to a unique combinations set the discretized proportions
- Define:

$$p_j = \begin{cases} 1, & \text{if pool } j \text{ is chosen,} \\ 0, & \text{otherwise,} \end{cases}$$

and impose the constraint $\sum_j p_j = 1$

- Now the pooling problem is approximated by an MIP model with objective function value $z(n)$ that converges to the true global optimum as $n \rightarrow \infty$

n is # discretized points

Instance characteristics

- 35 large-scale instances
- BARON to solve the continuous model
- CPLEX to solve the discrete model
- With one hour of CPU time

Group	#instances	Size of node and quality sets				#arcs range
		$ S $	$ I $	$ T $	$ K $	
arbC	5	8	6	6	4	57 – 82
arbD	5	12	10	8	5	114 – 166
arbE	5	10	10	15	12	181 – 248
stdA	10	20	10	15	24	171 – 407
stdB	6	35	17	21	34	384 – 1044
stdC	4	60	15	50	40	811 – 1451

Instance	Continuous model		Discrete model		
	LB	UB	$z(n = 2)$	$z(n = 3)$	$z(n = 5)$
arbC0	-1352.72	-1352.72	-1262.38	-1348.83	-1350.30
arbC1	-673.86	-673.86	-508.00	-615.50	-655.62
arbC2	-1716.62	-1716.62	-1688.69	-1705.81	(-1710.76)
arbC3	-1512.10	-1512.10	-1489.70	-1505.43	(-1508.92)
arbD0	-1994.00	-1571.11	-1833.33	-1911.35	—
arbD2	-2071.00	-2065.85	-2069.06	-2070.16	—
stdA0	-37402.74	-5383.70	-31990.52	-34175.71	(-34853.43)
stdA1	-30362.74	-29276.56	-24590.16	-25179.84	(-28389.31)
stdA2	-23044.16	-23044.16	-19846.94	-20666.60	(-21795.71)
stdA3	-41113.10	-31258.05	-36233.75	-37116.64	(-38624.98)
stdA4	-42999.89	-8770.94	-38126.91	(-39331.58)	(-39345.90)
stdA5	-28257.75	-6369.59	-26447.07	(-27008.30)	(-26729.51)
stdA6	-42463.05	-9555.82	-41777.00	(-42022.93)	(-41829.91)
stdA7	-44682.25	-5762.08	-42582.29	(-43309.48)	(-42227.89)
stdA8	-30666.87	-6576.76	-30341.61	(-30435.00)	(-30265.99)
stdA9	-21933.99	-14059.98	-21887.77	(-21891.96)	(-21527.08)
stdB0	-45441.79	-9075.24	-40171.43	(-41036.54)	(-40600.32)
stdB1	-65468.81	-34069.43	-60720.54	(-62445.97)	(-61858.06)
stdC0	-98792.76	-2400.00	(-77517.74)	(-79384.25)	—
stdC1	-119006.17	-12114.75	(-97290.27)	(-91215.32)	—
stdC2	-135916.19	-6342.08	(-117024.36)	(-115594.77)	—



- 1 Discretized the pooling problem by MIP model
- 2 The discrete model gives a good feasible solution even with coarse discretizations.
- 3 Computational experiments indicate that the discretized model is superior to the continuous approach in most of the cases
- 4 The discrete model inherits error in the original model



Thanks for your attention!