



ExxonMobil



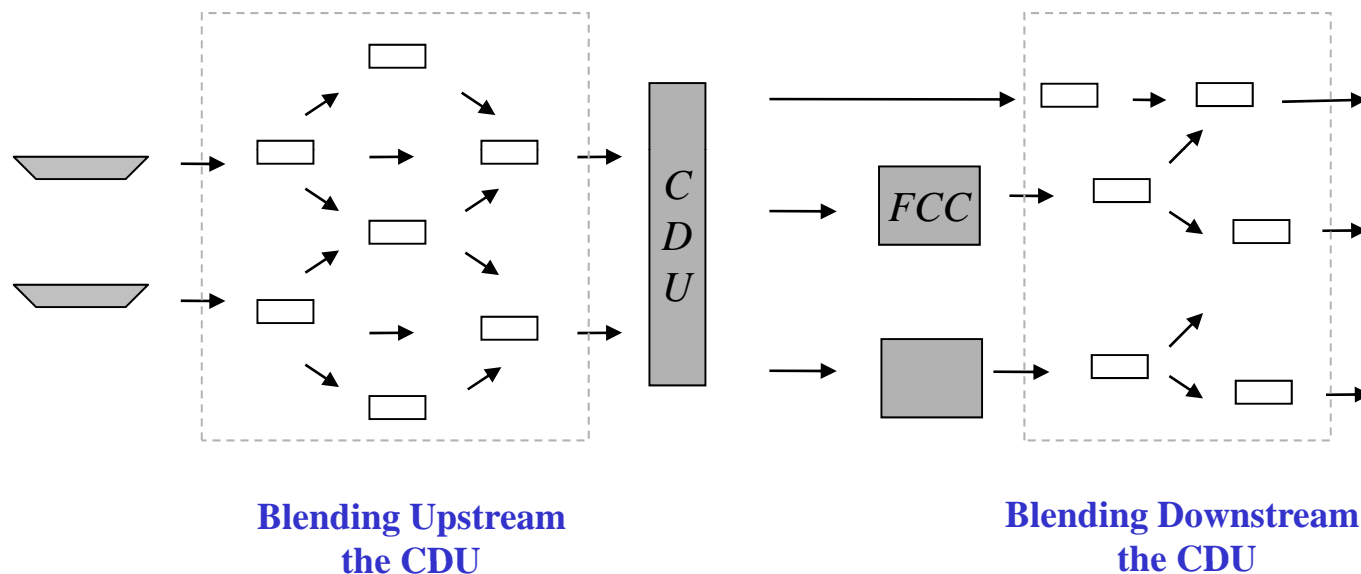
Multiperiod Blend Scheduling Problem

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Motivation

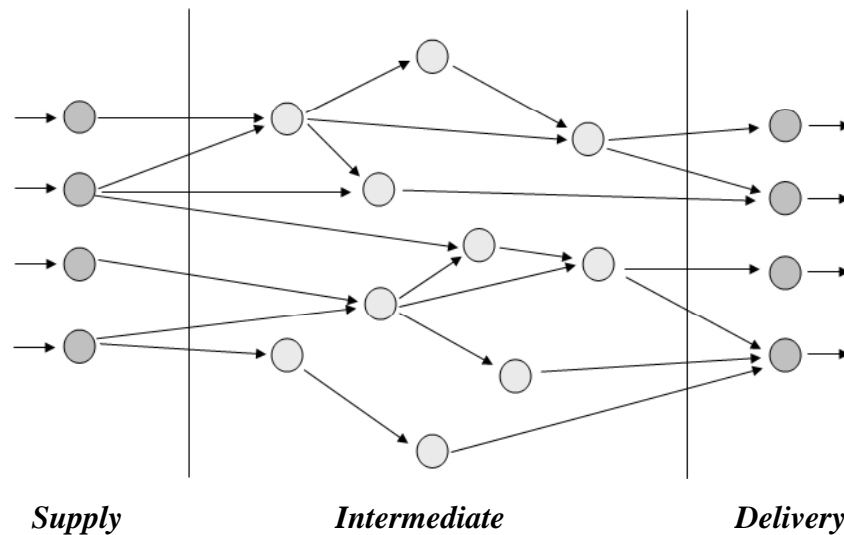
- **Large cost savings** can be achieved if the correct blending decisions are taken.
- **Models highly nonconvex** → **global optimization** techniques required.
- **Efficient solution methods** for large scale systems **remains as a challenge...**



Goal: Develop **tools and strategies** aiming at **improving the efficiency** of the solution methods for the global optimization of the **multiperiod blend scheduling problem**

General Problem Topology

The **general case** of a blending problem can be represented schematically as follows



Remarks:

Examples of **supply nodes**:

- tanks loaded by ships
- feedstocks downstream the CDU

Examples of **delivery nodes**:

- tanks feeding the CDU
- tanks delivering to final customers

Main Model Assumptions

- The **quality** of each stream/inventory is **constant** for a given **period**.
- A tank can **receive or deliver** in a given period of time but **not both**.
- **Supply** tanks keep a **constant quality**.
- **Delivery** tanks keep the **quality** within a given **range**.
- Streams **entering delivery** tanks should satisfy a **quality condition**.

Alternative Formulations

- ▶ Proposed formulations given in the **space of properties and total flows** and in the **space of individual property flows**
- ▶ Reduced the number of bilinear terms by using **GDP formulations**
- ▶ Explored the use of **redundant constraints** to improve the relaxations

Solution Methods

- ▶ Proposed a **Logic Based Outer Approximation** method to find local solutions
- ▶ Proposed a **Lagrangian Decomposition** method to find global solutions

Main Focus

Novel Relaxation Strategies

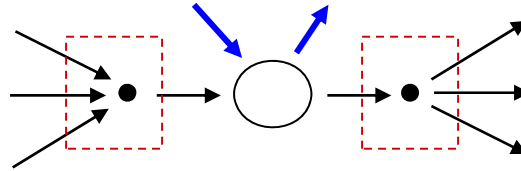
- ▶ Proposed the use of new relaxations based on **vector space properties**



Alternative Formulations

Alternative Formulations

Different space formulations



Mixer

Formulation I

Specific Property – Total Flow

$$\sum_{(j'j) \in E} F_{j'jt} S_{qj't} = Tf_{qjt}^{in}$$

Nonconvex

Formulation II

Total Property Flow

$$\sum_{(j'j) \in E} f_{qj'jt} = Tf_{qjt}^{in}$$

Splitter

Formulation I

Specific Property – Total Flow

$$\sum_{(jj') \in E} F_{jj't} = TF_{jt}^{out} S_{qj}$$

Formulation II

Total Property Flow

$$f_{qj'jt} = \xi_{jj't} Tf_{jt}^{out}$$

$$\sum_{(jj') \in E} \xi_{jj't} = 1$$

Nonconvex

Formulation I and II are **equivalent** but with **different relaxations** !

Alternative Formulations

Redundant Constraints*

The **total property flow** to the delivery site is constrained by an upper and lower bound. This information is lost when $CF_{qj't-1}^B = C_{qj't-1}^B F_{qj't-1}^B$ is relaxed.

$$C_{qj't}^L F_{jj't} - M(1 - x_{jj't}) \leq CF_{qj't-1}^B \quad \forall q \in Q, j \in J^B, j' \in J^D, (jj') \in E, t \in T$$

$$CF_{qj't-1}^B \leq C_{qj't}^U F_{jj't} + M(1 - x_{jj't}) \quad \forall q \in Q, j \in J^B, j' \in J^D, (jj') \in E, t \in T$$

For any two properties q and q' (in any stream or inventory) the ratio between the **total property flow** of q to q' is the same as the ratio between **specific property value**. This is lost when the problem is relaxed.

$$CF_{qj't-1}^B C_{q'jt-1}^B = CF_{q'jt-1}^B C_{qj't-1}^B \quad \forall q, q' \in Q, j \in J^B, j' \in (J^D \cup J^B), (jj') \in E, t \in T$$

$$CI_{qj't-1}^B C_{q'jt-1}^B = CI_{q'jt-1}^B C_{qj't-1}^B \quad \forall q, q' \in Q, j \in J^B, t \in T$$

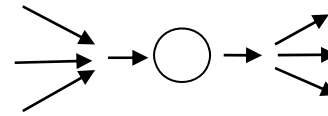
The **property balance** around each “splitter” should be held. This is lost when the bilinear terms are relaxed.

$$\sum_{(j'j) \in E} f_{qj'jt} = Tf_{qjt}^{out} \quad \forall q \in Q, j \in J^B, t \in T$$

* Ruiz and Grossmann, 2010 “Using redundancy to strengthen the relaxation of nonconvex MINLPs”
To appear in Computers and Chemical Engineering Journal

Generalized Disjunctive Programming

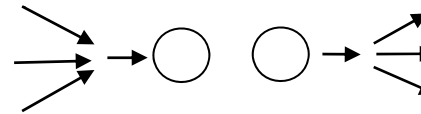
Traditional MINLP Formulation



One general state

$$C_{qjt}^B I_{jt} = C_{qjt-1}^B I_{jt-1} + \sum_{\substack{j' \in J^P \\ (j'j) \in E}} C_{qj'}^P F_{j'jt} + \sum_{\substack{j' \in J^B \\ (j'j) \in E}} C_{qjt-1}^B F_{j'jt} - \sum_{\substack{j' \\ (j'j) \in E}} C_{qjt-1}^B F_{j'jt} \quad \forall q \in Q, j \in J^B, t \in T$$

Proposed GDP Formulation



Two states

$$\left[\begin{array}{c} Y_{jt} \\ C_{qjt}^B I_{jt} = C_{qjt-1}^B I_{jt-1} + \sum_{\substack{j' \in J^P \\ (j'j) \in E}} C_{qj'}^P F_{j'jt} + \\ \sum_{\substack{j' \in J^B \\ (j'j) \in E}} C_{qjt-1}^B F_{j'jt} \quad \forall q \in Q, j \in J^B, t \in T \end{array} \right] \vee \left[\begin{array}{c} \neg Y_{jt} \\ C_{qjt}^B = C_{qjt-1}^B \quad \forall q \in Q, j \in J^B, t \in T \end{array} \right]$$

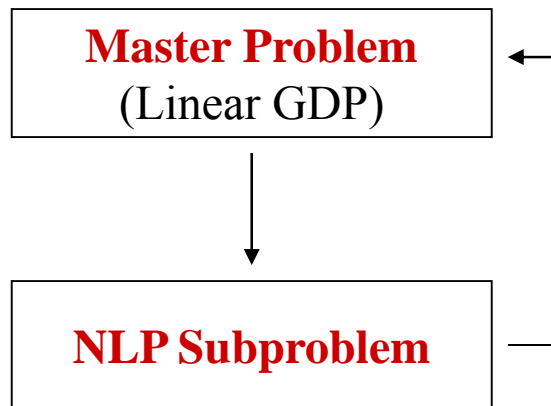
By exploiting the underlying logic structure of the problem, a reduction of the number of bilinear terms can be achieved



Solution Methods

Logic Based Outer-Approximation

Outline of the Logic Based OA



*No guaranty a
global solution!*

LGDP Master:

- Relax bilinear terms using McCormick envelopes.
- Solve MIP using the Hull Reformulation.

NLP Subproblem:

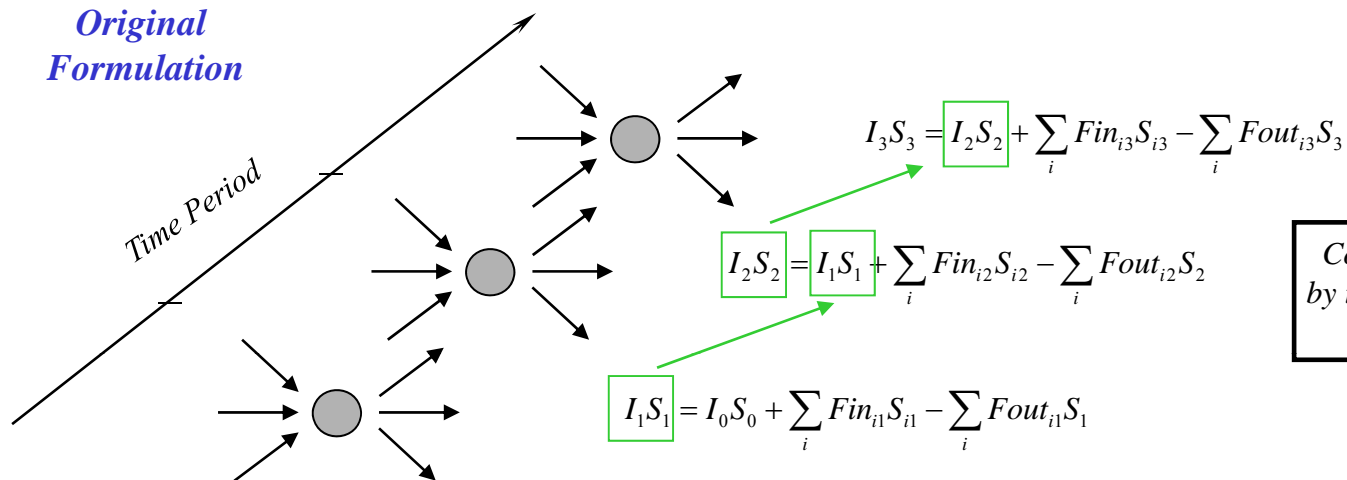
- Fix boolean variables from master problem.
- Eliminate not active disjuncts
- Solve small NLP formulation

Iteration Step:

- Generate linear cuts on solution point of NLP subproblem.

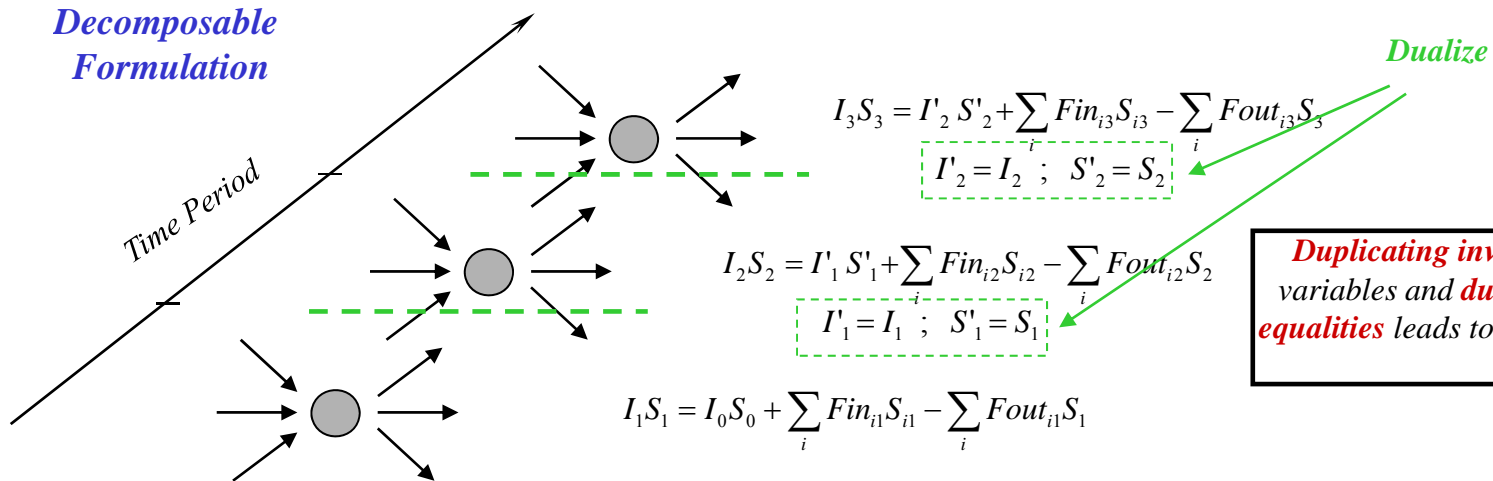
Lagrangian decomposition

Original Formulation



Constraints are **linked** together by the **inventory** and **composition** variables

Decomposable Formulation

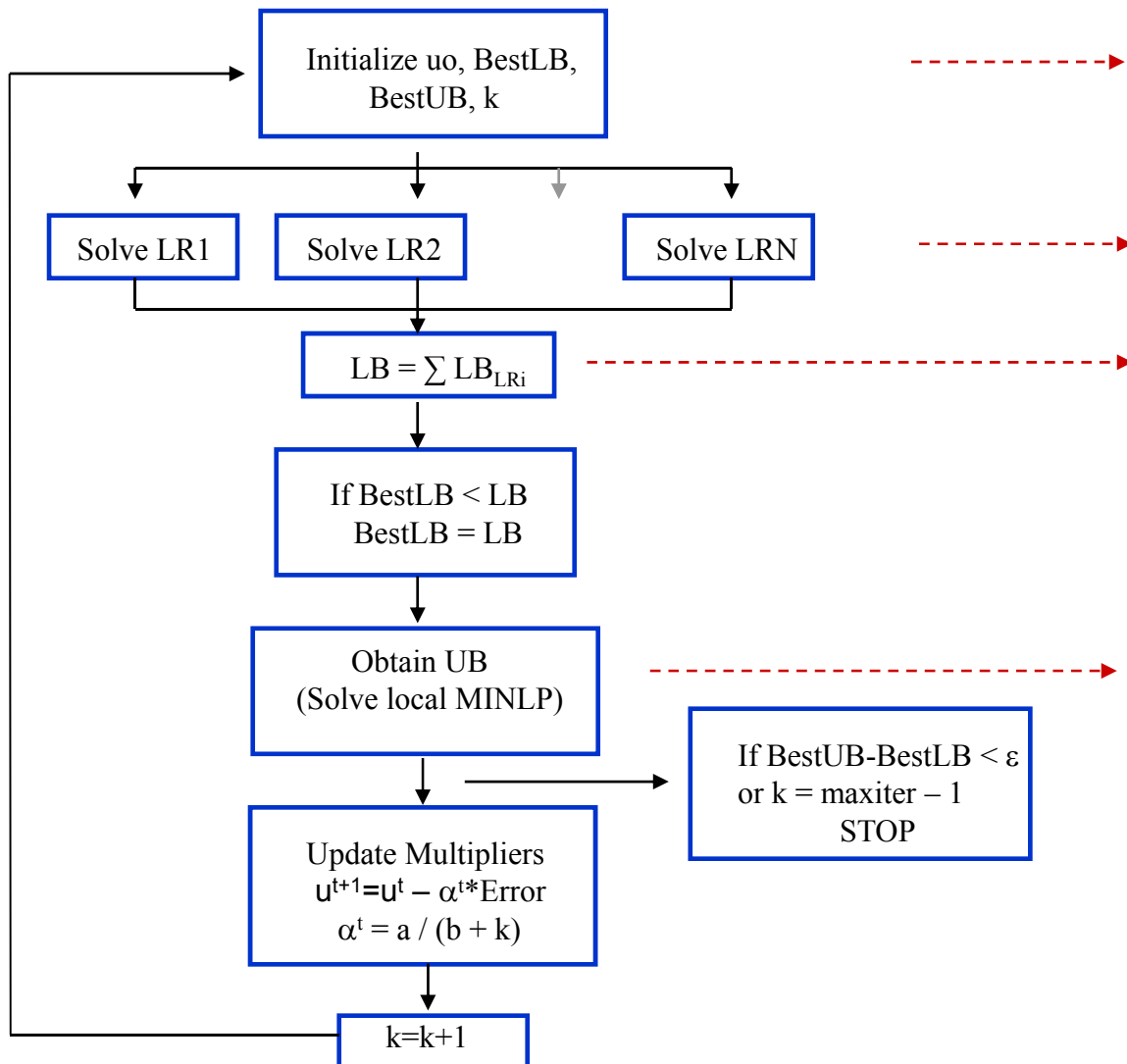


Duplicating inventory and composition variables and **dualizing** the correspondent equalities leads to a temporal **decomposable** structure

Solution Methods

Lagrangian decomposition (Algorithm)

Outline of the Lagrangian decomposition method



uo represents the dual multipliers;
BestLB, the best lower bound;
BestUB, the best upper bound and **k**,
 the iter counter

Each **subproblem (LR_i)** from the
 decomposition is solved

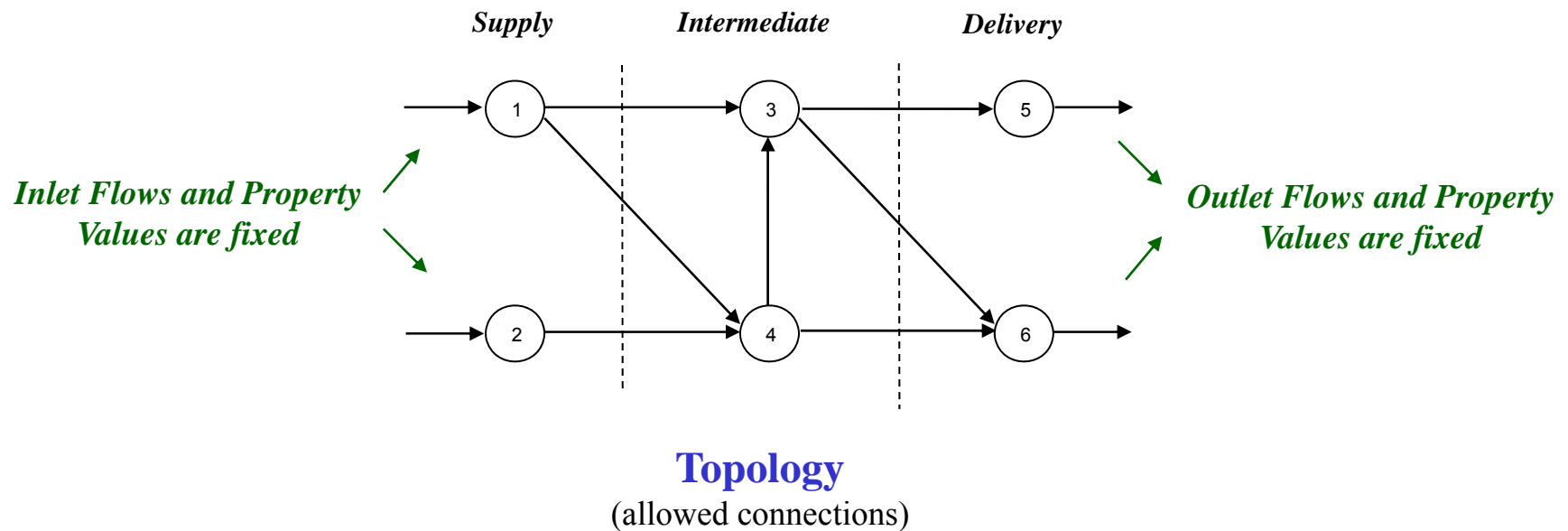
A **lower bound for the original
 nonconvex** problem can be obtained
 by adding up the solution of each
 (LR_i) (i.e. LB_{LR_i})

Any local optimization algorithm can
 be used to find an UB. (e.g. **The logic
 based outer-approximation** applied
 on the GDP formulation)

Solution Methods

Illustrative Example

The **implementation** of the **Lagrangian Decomposition** method has been tested in the following simple case

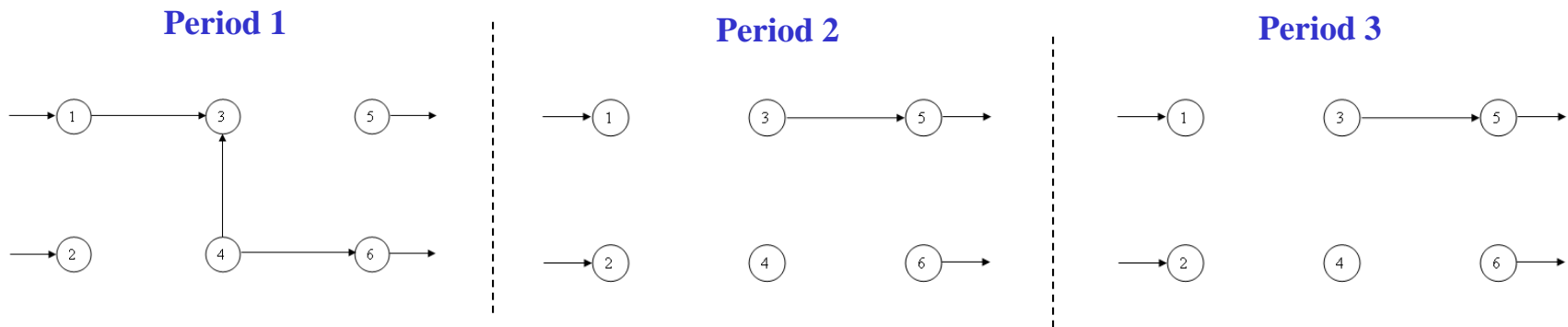


Network Description:

- Two Supply, Intermediate and Delivery nodes
- Two properties transported
- Three time periods

Lagrangian Decomposition

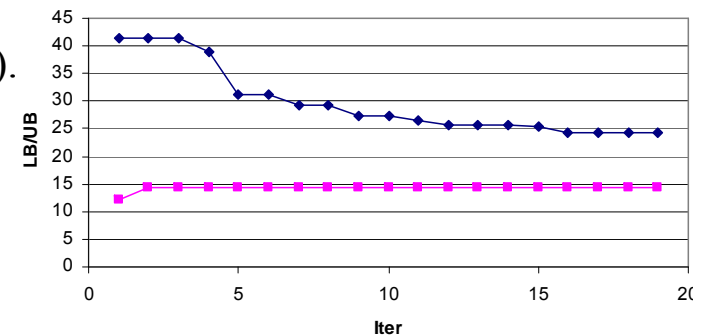
Representation of the nonzero flow streams in the different periods for the global optimal solution



Global Solution ($Z = 14.22$) (verified with BARON)

Remarks

- Forced to stop after **20 iterations** (no improvement observed).
- **Finds the global solution ($Z = 14.22$)**
- The existence of the **duality gap** is due to the **nonconvex** nature of the problem

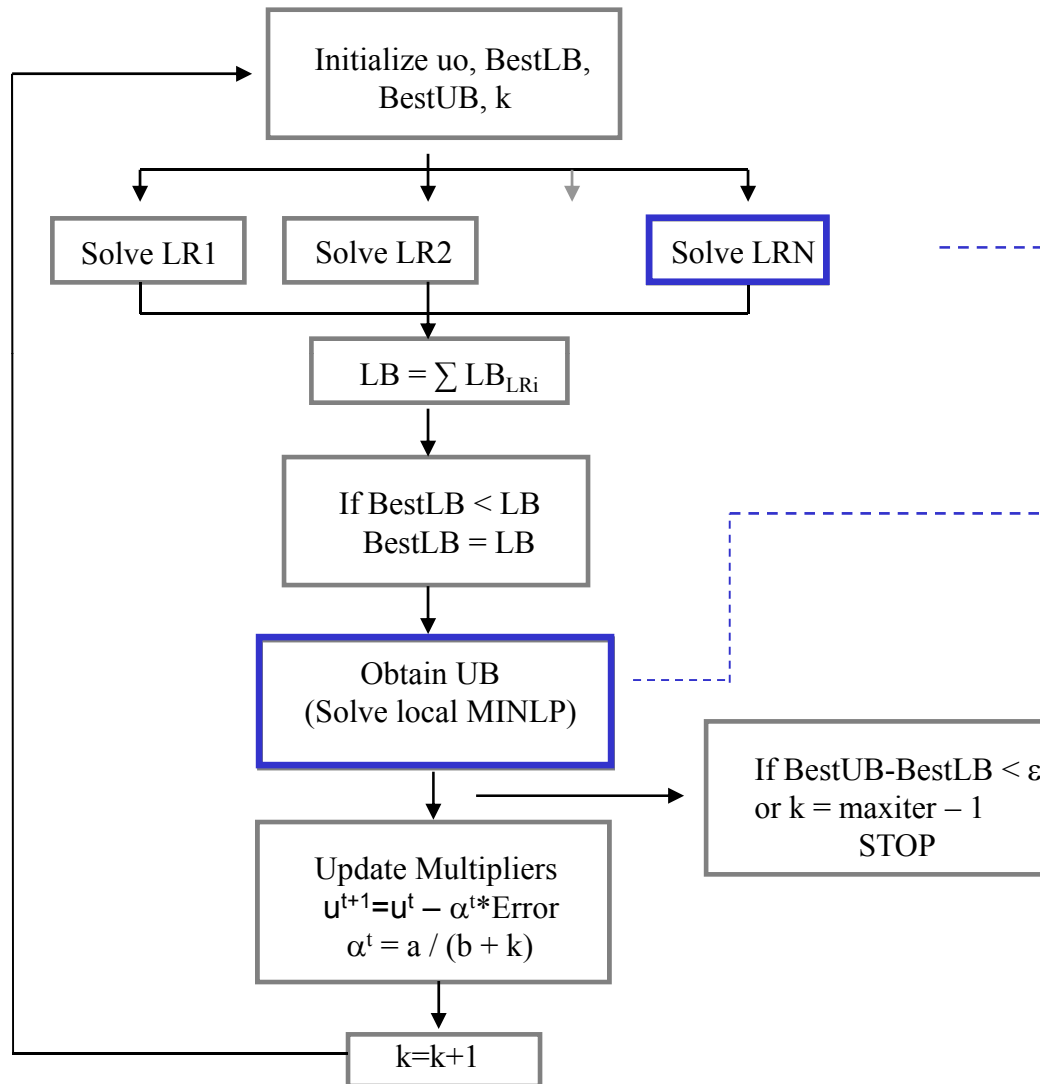


Generation of Real-world Instances

		Lower Bound	Upper Bound	
Structure	Nodes	J^P, J^B, J^D	4	10
	Properties	Q	4	10
	Periods	T	40	100
	Edges	E	40% of all possible edges	100% of all possible edges
	P_{jt}	0	100	Bounds on Variables
	D_{jt}	0	100	
	S_{qj}^P	0	1	
	S_{qj}^{B0}	0	1	
	S_{qj}^L, S_{qj}^U	0	1	
	I_j^L, I_j^U, I_j^0	0	100	
	F_{jj}^L, F_{jj}^U	0	100	

This table was used to generate random instances

Numerical tests using Lagrangian Relaxation with temporal decomposition

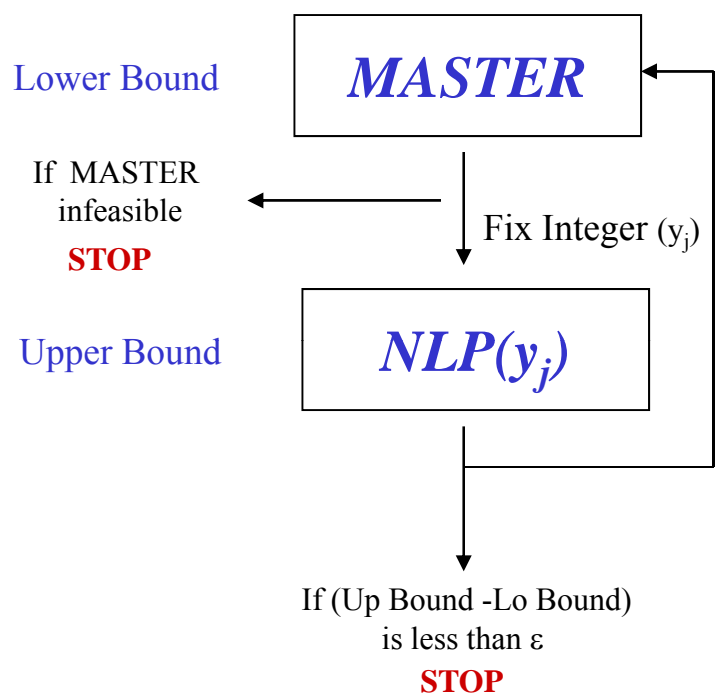


1- High computational time required in sub-problems (> 5min)

2- Difficulties to find local solutions

How do we tackle these issues?

Finding Local Solutions Outer Approximation Method



The MASTER problem can be tightened by adding McCormick Convex envelopes for the bilinear terms

$$f_{qijt} \leq F_{ijt} C_{qit-1}^{UP} + C_{qit-1} F_{ijt}^{LO} - C_{qit-1}^{UP} F_{ijt}^{LO}$$

$$f_{qijt} \leq F_{ijt} C_{qit-1}^{LO} + C_{qit-1} F_{ijt}^{UP} - C_{qit-1}^{LO} F_{ijt}^{UP}$$

$$f_{qijt} \geq F_{ijt} C_{qit-1}^{UP} + C_{qit-1} F_{ijt}^{UP} - C_{qit-1}^{UP} F_{ijt}^{UP}$$

$$f_{qijt} \geq F_{ijt} C_{qit-1}^{LO} + C_{qit-1} F_{ijt}^{LO} - C_{qit-1}^{LO} F_{ijt}^{LO}$$

Bounds of variables

Similarly for terms $I_{qit} C_{qit}$

Remarks

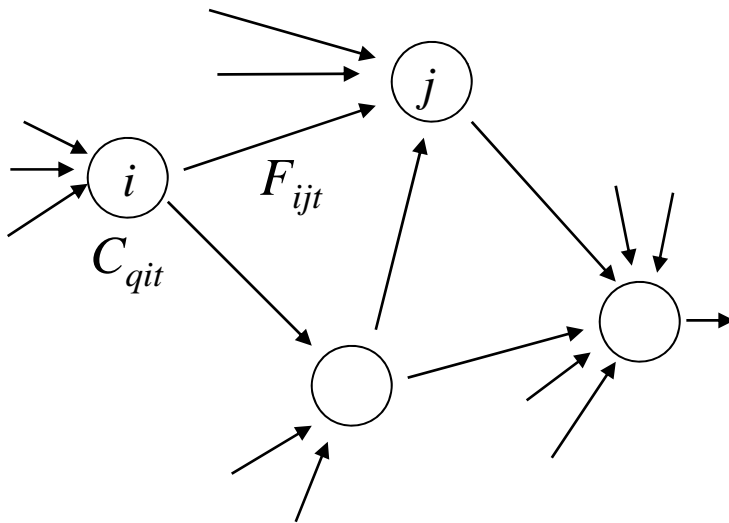
- **Reducing the number of bilinear** terms in NLP(y_j) leads to a more **robust formulation**
- Having **good bounds** for the variables is of main importance to find **tight relaxations**

Finding Local Solutions

Tighter bounds for variables (I)

Observation

If **two streams** are **mixed** together, the **concentration** of any given component in the mixture is always **higher/lower** than the **minimum/maximum** concentration in the streams



Mathematical Representation

$$C_{qit} \geq \min_{(i,j) \in E} (C_{qjt-1}) \quad \forall q, i, t$$

$$C_{qit} \leq \max_{(i,j) \in E} (C_{qjt-1}) \quad \forall q, i, t$$

How can we use it to infer bounds for the compositions?

Finding Local Solutions

Tighter bounds for variables (II)

Lower Bounds

$$C_{qit}^{LO} = C_{qi0} \quad \forall q, i, t = 1$$

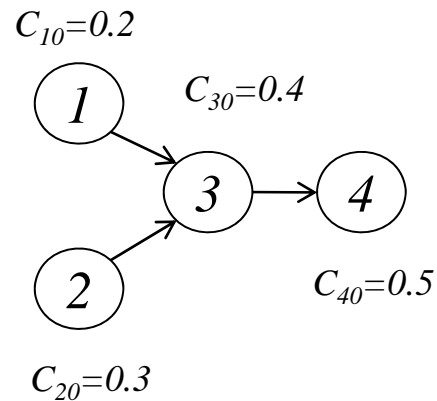
$$C_{qit}^{LO} \geq \min_{(i,j) \in E} (C_{qjt-1}^{LO}) \quad \forall q, i, t > 1$$

Upper Bounds

$$C_{qit}^{UP} = C_{qi0} \quad \forall q, i, t = 1$$

$$C_{qit}^{UP} \leq \max_{(i,j) \in E} (C_{qjt-1}^{UP}) \quad \forall q, i, t > 1$$

Illustrative Example



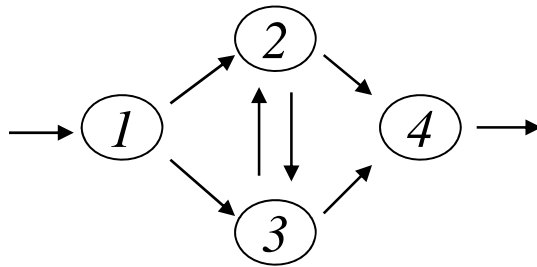
	t=0		t=1		t=2	
	LO	UP	LO	UP	LO	UP
Node 1	0.2	0.2	0.2	0.2	0.2	0.2
Node 2	0.3	0.3	0.3	0.3	0.3	0.3
Node 3	0.4	0.4	0.2	0.4	0.2	0.4
Node 4	0.5	0.5	0.4	0.5	0.2	0.5

**Lower and upper bound tightening can be achieved
in the preprocessing step**

Finding Local Solutions

Tighter bounds for variables (III)

Performance Analysis



Predicted lower bounds at first **MASTER** problem

	Global Optimum	Using original bounds	Using inferred bounds
Instance 1	-2900	-4958	-4083
Instance 2	-10900	-20958	-14650

Remark

Improvements in the bounds prediction can be obtained if lower/upper bounds of **flows and inventory** levels are **considered**

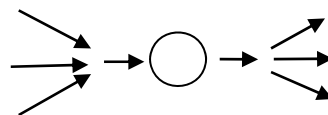
$$C_{qit} \geq \min \left(\frac{I_{qit-1} C_{qit-1} + \sum_{(i,j) \in E} F_{jit} C_{qjt-1}}{I_{qit}} \right) \geq \frac{I_{qit-1}^{LO} C_{qit-1}^{LO} + \sum_{(i,j) \in E} F_{jit}^{LO} C_{qjt-1}^{LO}}{I_{qit}^{UP}} \quad \forall q, i, t$$

$$C_{qit} \leq \max \left(\frac{I_{qit-1} C_{qit-1} + \sum_{(i,j) \in E} F_{jit} C_{qjt-1}}{I_{qit}} \right) \leq \frac{I_{qit-1}^{UP} C_{qit-1}^{UP} + \sum_{(i,j) \in E} F_{jit}^{UP} C_{qjt-1}^{UP}}{I_{qit}^{LO}} \quad \forall q, i, t$$

Finding Local Solutions

Reduced number of bilinear terms

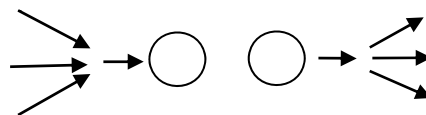
Traditional MINLP Formulation



One general state

$$C_{qjt}^B I_{jt} = C_{qjt-1}^B I_{jt-1} + \sum_{\substack{j' \in J^P \\ (j',j) \in E}} C_{qj'}^P F_{j'jt} + \sum_{\substack{j' \in J^B \\ (j',j) \in E}} C_{qjt-1}^B F_{j'jt} - \sum_{\substack{j' \\ (j',j) \in E}} C_{qjt-1}^B F_{j'jt} \quad \forall q \in Q, j \in J^B, t \in T$$

Proposed GDP Formulation



Two states

$$\left[\begin{array}{c} Y_{jt} \\ C_{qjt}^B I_{jt} = C_{qjt-1}^B I_{jt-1} + \sum_{\substack{j' \in J^P \\ (j',j) \in E}} C_{qj'}^P F_{j'jt} + \\ \sum_{\substack{j' \in J^B \\ (j',j) \in E}} C_{qjt-1}^B F_{j'jt} \quad \forall q \in Q, j \in J^B, t \in T \end{array} \right] \vee \left[\begin{array}{c} \neg Y_{jt} \\ C_{qjt}^B = C_{qjt-1}^B \quad \forall q \in Q, j \in J^B, t \in T \end{array} \right]$$

By exploiting the underlying logic structure of the problem, a reduction of the number of bilinear terms can be achieved



Finding Local Solutions

Numerical Results

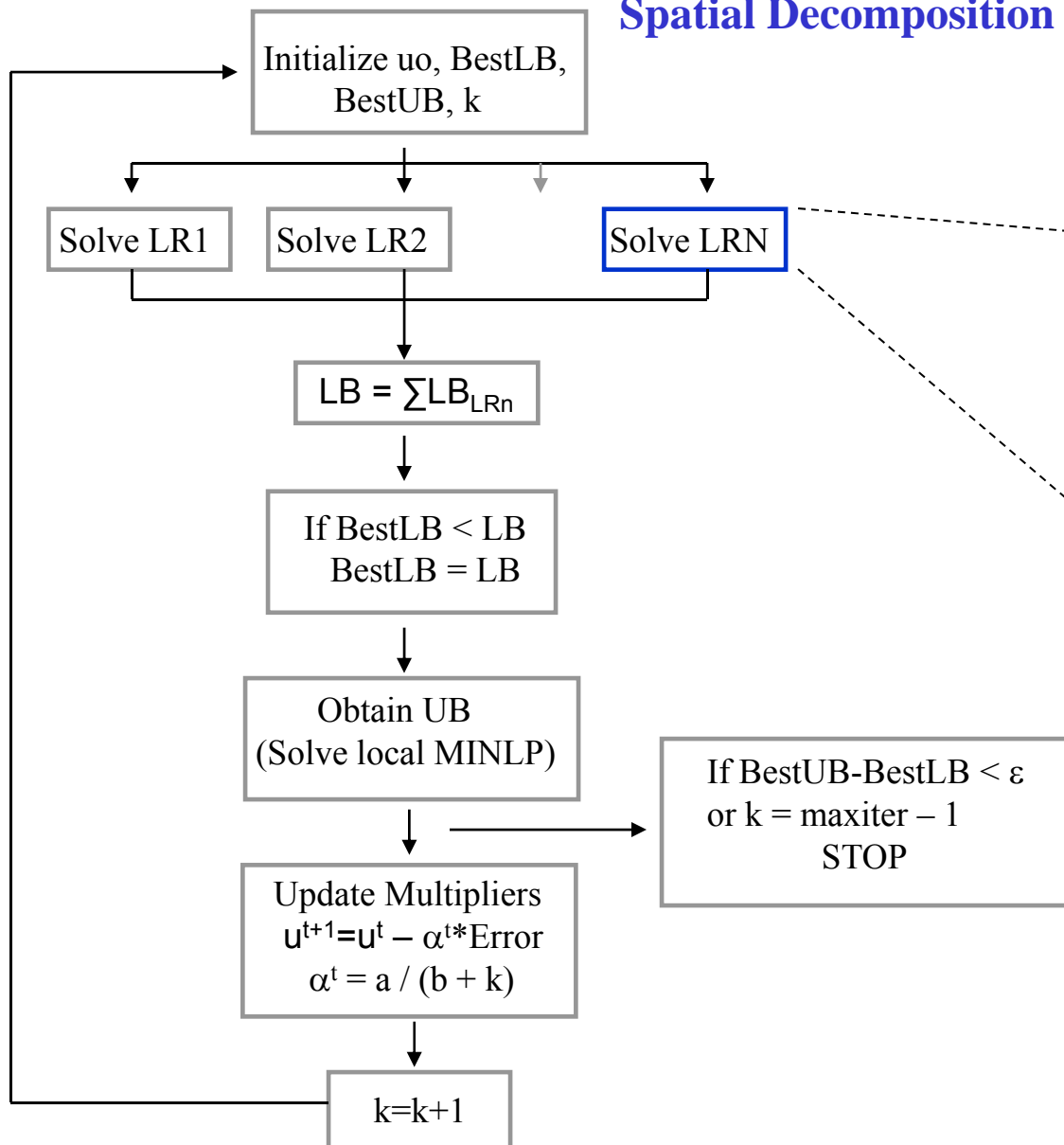
Performance Analysis

- 11 **random instances**
- Outer approximation solver **DICOPT(GAMS)**
- Three different formulations (all using McCormick envelopes):
 - 1- Original MINLP
 - 2- Formulation with reduced number of bilinear terms
 - 3- Formulation with reduced number of bilinear terms plus bound tightening
- Forced to **stop after 10 iterations or 30 minutes**

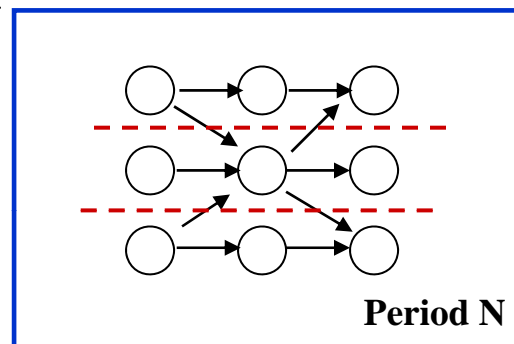
Remarks

- Formulation (2) and (3) found **feasible solutions** in more than **70%** of instances
- Formulation (3) **outperformed** Formulation (2) in **20%** of the instances
- Formulation (1) led to a large number of **“false” infeasible** problems

Solution of LR_i sub-problems Spatial Decomposition



Spatial Decomposition



How do we decompose it spatially?

Solution of LRi sub-problems

Minimal cut-edge with fixed nodes

Objective: Minimize the edges that cross the boundaries of each subset

Incidence Matrix

$$\min \sum_{ijk} A_{ij} (y_{ik} - z_{ijk})$$

$$s.t. \sum_k y_{ik} = 1 \quad \forall i$$

$$\sum_i y_{ik} = \alpha_k \quad \forall k$$

Number of nodes in disjoint subsets

If $y_{ik} = 1$ then the node i belongs to the subset k

$$1 - y_{ik} - y_{jk} + z_{ijk} \geq 0 \quad \forall ijk$$

$$y_{ik} \geq z_{ijk} \quad \forall ijk$$

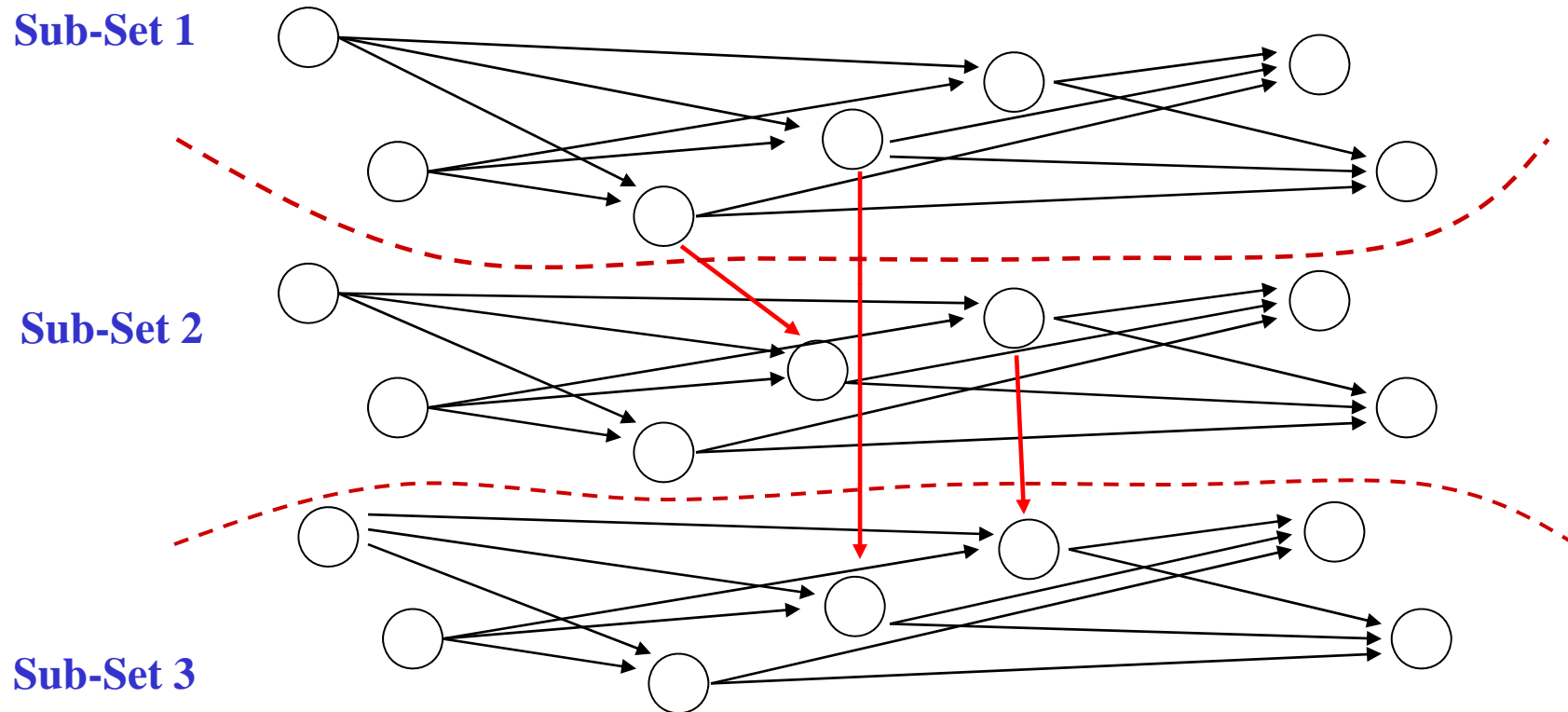
$$y_{jk} \geq z_{ijk} \quad \forall ijk$$

$$\longrightarrow z_{ijk} = y_{ik} y_{jk}$$

$$\sum_{ij} z_{ijk} = \alpha_k^2 \quad \forall k \longrightarrow \text{cut!}$$

Solution of L_{Ri} sub-problems

Minimal cut-edge with fixed nodes example



Dualized constraints necessary: **$3(n+1)$**
(n: number of properties considered)



Solution Methods

Solution of LR_i sub-problems

Numerical Results



-Baron takes 347 seconds (**~6min**) to solve the problem with a solution of **20954.8**

-The spatial decomposition solves the problem in **1 iteration**:

MIP separation problem:		5 seconds
Sub-problem 1:	(sol: 6096.0)	1.6 seconds
Sub-problem 2:	(sol: 11451.8)	1.4 seconds
Sub-problem 3:	(sol: 3407.0)	1.5 seconds
TOTAL:	<u>(sol: 20954.8)</u>	<u>9.5 seconds</u>

Remarks:

- Even though it is not expected for general problems to converge in one iteration, **even with 15 iterations, the time necessary would be ~1 min**



Novel Relaxations

Vector space properties to strengthen the relaxation



Algebraic Representation

$$\sum_{i \in I_n} (F_{in} P_{in}^j) - F_{on} P_{in}^j = 0$$

$$\sum_{i \in I_n} F_{in} - F_{on} = 0$$

Vectorial Representation

$$\begin{matrix} v_{F_n} \perp v_E \\ v_{P_n^j} \perp v_{F_n} \end{matrix} \rightarrow \text{Vector Space Interaction Exposed}$$

$$v_{F_n} = (F_1, F_2, \dots, F_{|I_n|}, F_o)$$

$$v_E = (1, 1, \dots, 1, -1)$$

$$v_{P_n^j} = (P_1^j, P_2^j, \dots, P_{|I_n|}^j, -P_o^j)$$

Exploit interaction to develop cuts (3-D Case)

$$\begin{matrix} v_{F_n} \perp v_E \\ v_{P_n^j} \perp v_{F_n} \end{matrix} \Rightarrow v_F \times v_P = \alpha v_F$$

$$\alpha = \frac{\|v_P\| \sqrt{3} \sin \theta}{\|v_F\|}, 0 \leq \theta \leq 2\pi$$

Cuts
(for a given j and n)

$$\begin{matrix} \beta_i \leq \alpha F_i^{up} + \alpha^{io} F_i - \alpha^{io} F_i^{up} & \beta_1 = P_o - P_2 \\ \beta_i \leq \alpha F_i^{io} + \alpha^{up} F_i - \alpha^{up} F_i^{io} & \beta_2 = P_1 - P_o \\ \beta_i \geq \alpha F_i^{up} + \alpha^{up} F_i - \alpha^{up} F_i^{up} & \beta_o = P_1 - P_2 \\ \beta_i \geq \alpha F_i^{io} + \alpha^{io} F_i - \alpha^{io} F_i^{io} & \end{matrix}$$

Table – Comparison of the performance of proposed approach with traditional relaxations

Instance	GO	Traditional Approach			Proposed Approach		
		LB	Nodes	Time(s)	LB	Nodes	Time(s)
1	82.78	78.25	11	20	81.6	4	9
2	151.96	142.10	35	30	144.30	17	17
3	5.19	4.86	87	109	5.05	6	22
4	9.79	8.22	650	542	8.78	365	325
5	12.60	12.48	5	19	12.60	1	17
6	-264.01	-574.5	877	596	-530.0	460	321
7	-1308.0	-1985.3	97	77	-1930.0	63	56



All problems were solved using a Pentium(R) CPU 3.4 GHz and 1GB RAM

Pooling problems!

*Ruiz J.P. and Grossmann I.E. 2010, “Exploiting Vector Space Properties for the Global Optimization of Process Networks” , Optimization Letters

Remarks

- ▶ Proposed formulations given in the **space of properties and total flows** and in the **space of individual property flows**
- ▶ Reduced the number of bilinear terms by using **GDP formulations**
- ▶ Explored the use of **redundant constraints** to improve the relaxations
- ▶ Proposed a **Logic Based Outer Approximation** method to find local solutions
- ▶ Proposed a **Lagrangian Decomposition** method to find global solutions
- ▶ Proposed the use of new relaxations based on **vector space properties**

Future Work

- Implement **spatial decomposition** of the sub-problems within the **global optimization framework**.
- Add **cuts to strengthen relaxation for LR** (from Vector Space Analysis?)