



ExxonMobil



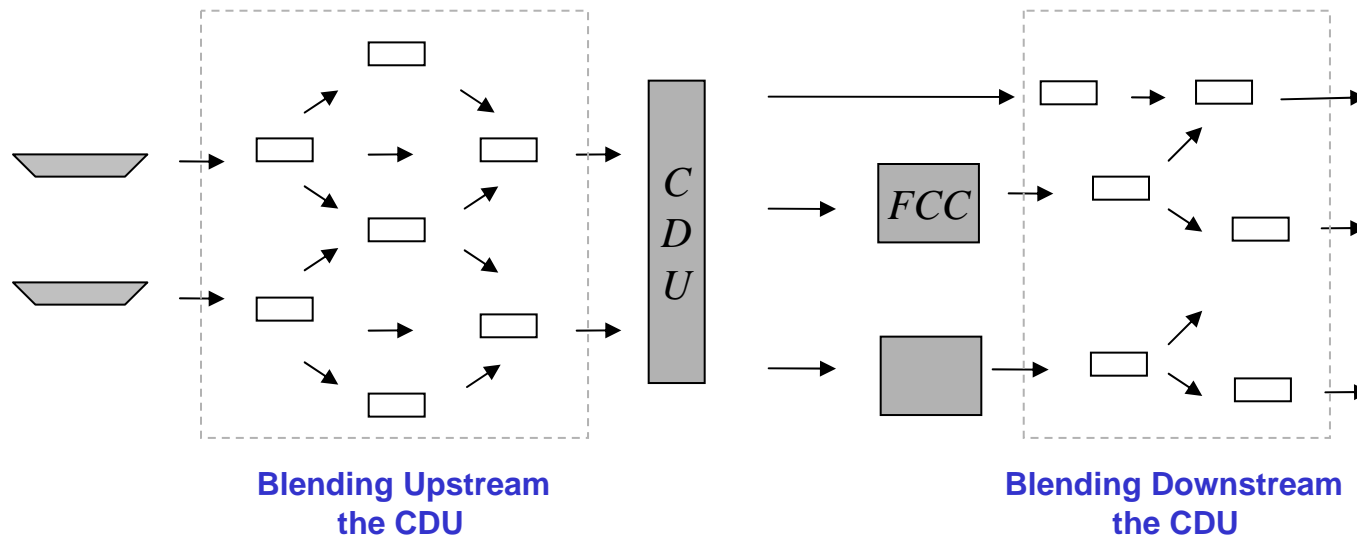
Multiperiod Blend Scheduling Problem

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Motivation

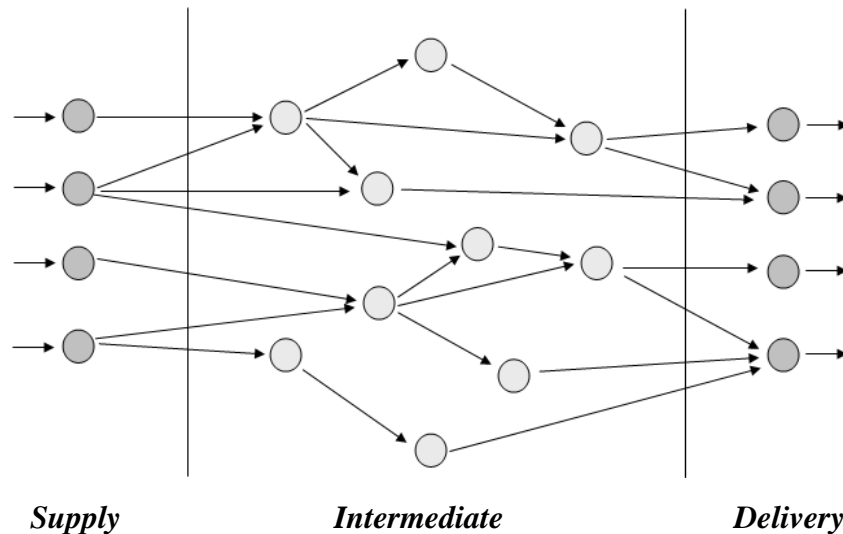
- The **scheduling problem of blending operations** arises **frequently** in the petrochemical industry.
- Although simple to represent, these **models are highly nonconvex**, leading to the need of **global optimization** techniques to find the optimal solution.
- The development of **efficient solution methods** that take care of the general case applied to 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:

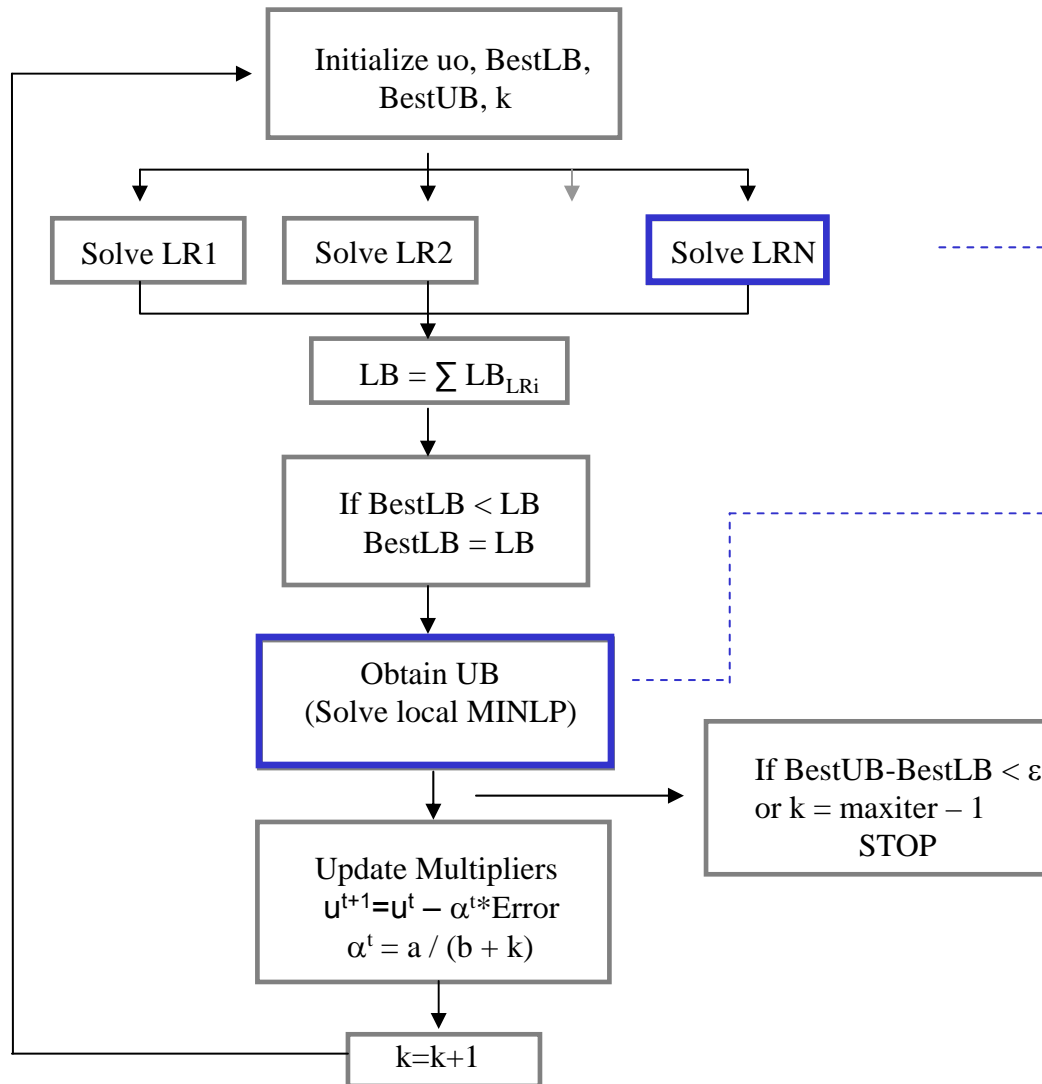
- Examples of the **supply nodes** are the tanks loaded by ships or the feedstocks downstream the CDU
- Examples of the **delivery nodes** are the tanks feeding the CDU or the tanks delivering to final customers

Important 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**.

Observations

Numerical tests using Lagrangian Relaxation with temporal decomposition

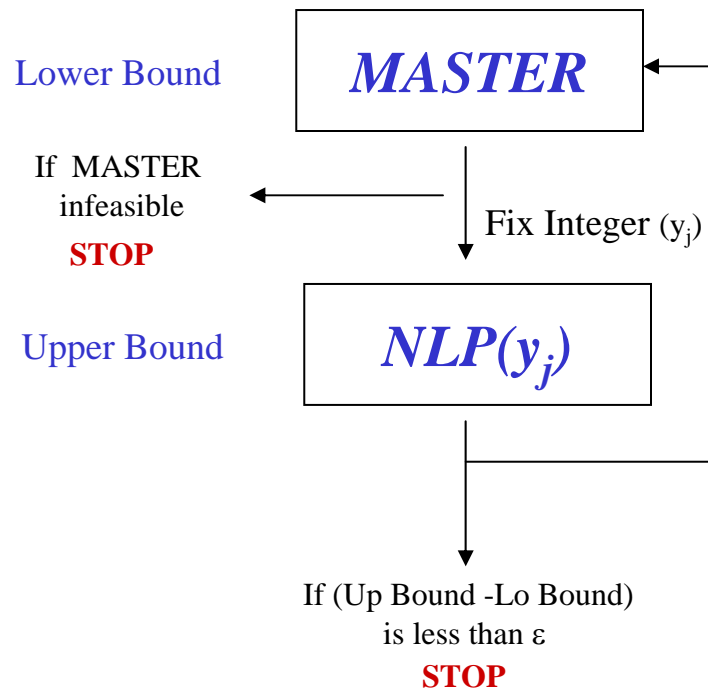


1- High computational time required in sub-problems (> 5min)

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

$$f_{qjt} \leq F_{yt} C_{qit-1}^{UP} + C_{qit-1} F_{yt}^{LO} - C_{qit-1}^{UP} F_{yt}^{LO}$$

$$f_{qjt} \leq F_{yt} C_{qit-1}^{LO} + C_{qit-1} F_{yt}^{UP} - C_{qit-1}^{LO} F_{yt}^{UP}$$

$$f_{qjt} \geq F_{yt} C_{qit-1}^{UP} + C_{qit-1} F_{yt}^{UP} - C_{qit-1}^{UP} F_{yt}^{UP}$$

$$f_{qjt} \geq F_{yt} C_{qit-1}^{LO} + C_{qit-1} F_{yt}^{LO} - C_{qit-1}^{LO} F_{yt}^{LO}$$

Bounds of variables

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

Remarks

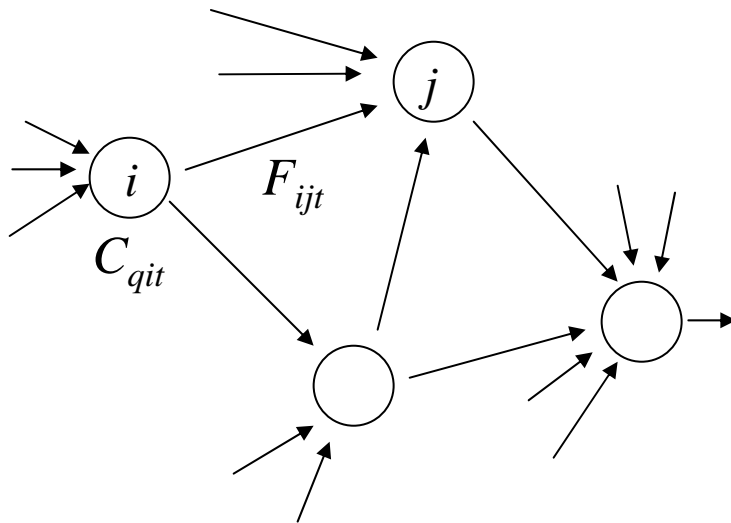
- **Reducing the number of bilinear** terms in NLP(y_j) leads to a more **robust formulation**
- Having **good bounds** for the variables is of main importance to find **tight relaxations**

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

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

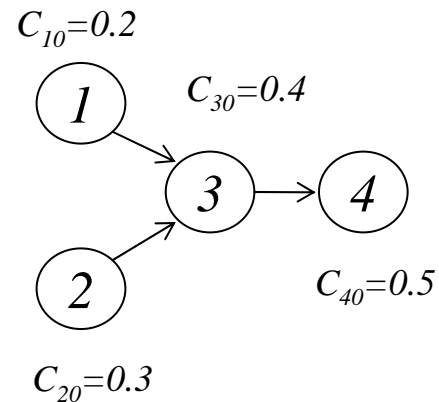
$$C_{qit}^{LO} \geq \min_{(i,j) \in E} (C_{qjt-1}^{LO}) \quad \forall q, i, t > 1$$

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



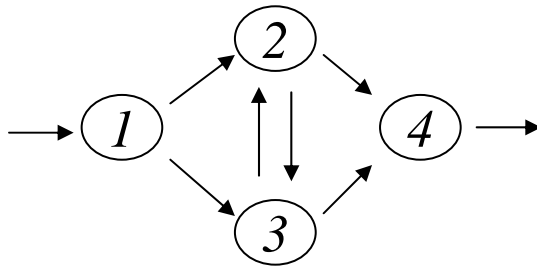
	t=0		t=1		t=2	
	LO	UP	LO	UP	LO	UP
Node 1	0.2	0.2	0.2	0.2	0.2	0.2
Node 2	0.3	0.3	0.3	0.3	0.3	0.3
Node 3	0.4	0.4	0.2	0.4	0.2	0.4
Node 4	0.5	0.5	0.4	0.5	0.2	0.5

**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**

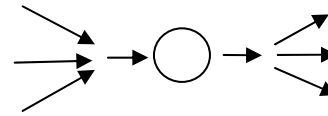
$$C_{qit} \geq \min \left(\frac{I_{qit-1} C_{qit-1} + \sum_{(i,j) \in E} F_{jit} C_{qjt-1}}{I_{qit}} \right) \geq \frac{I_{qit-1}^{LO} C_{qit-1}^{LO} + \sum_{(i,j) \in E} F_{jit}^{LO} C_{qjt-1}^{LO}}{I_{qit}^{UP}} \quad \forall q, i, t$$

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

Finding Local Solutions

Reduced number of bilinear terms

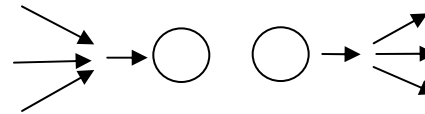
Traditional MINLP Formulation



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



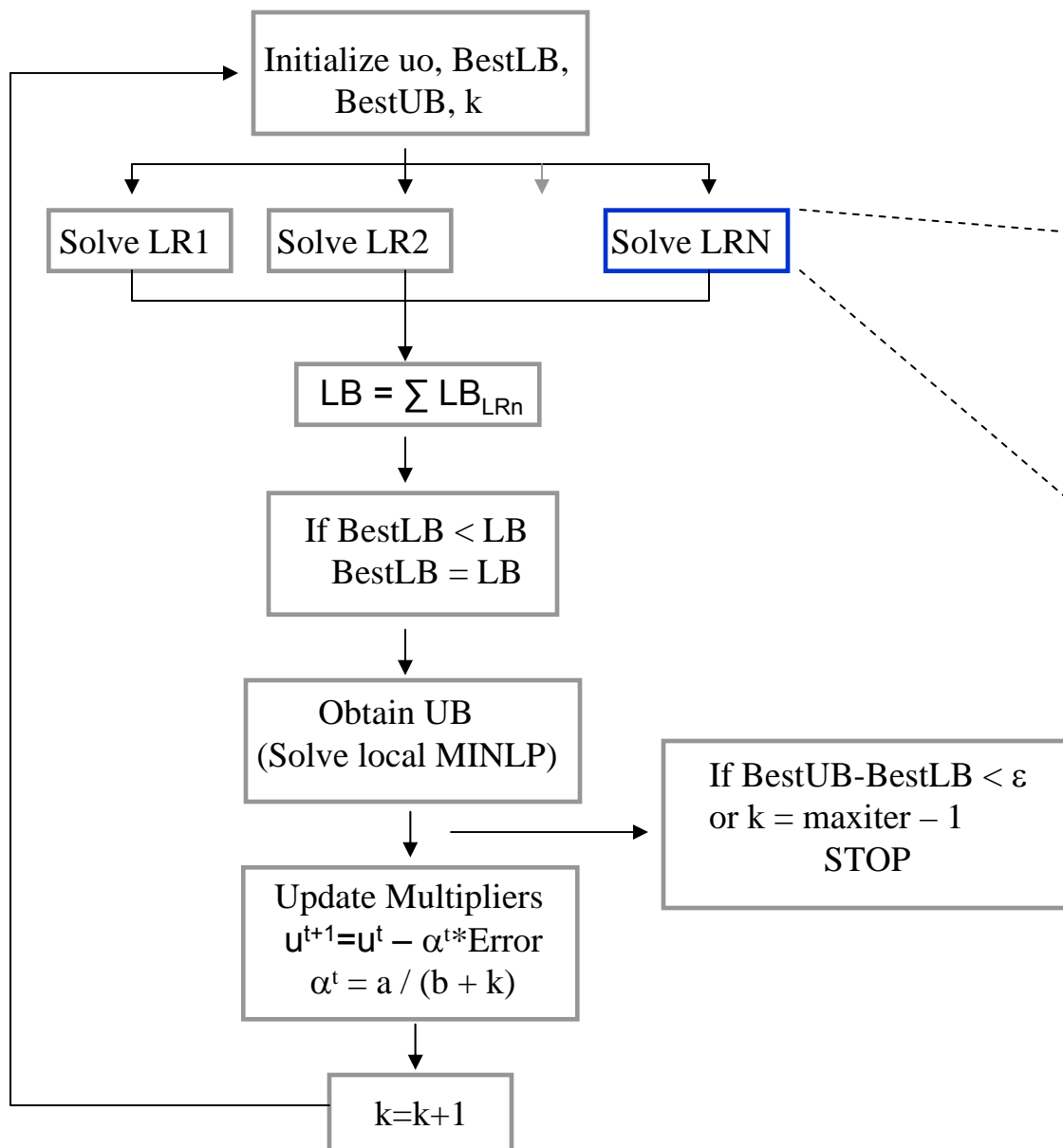
Performance Analysis

- 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**

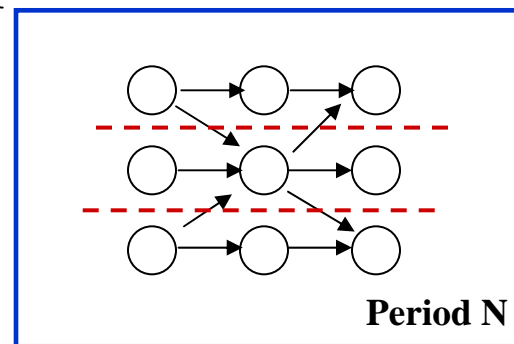
Remarks

- 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 L_{Ri} 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

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

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

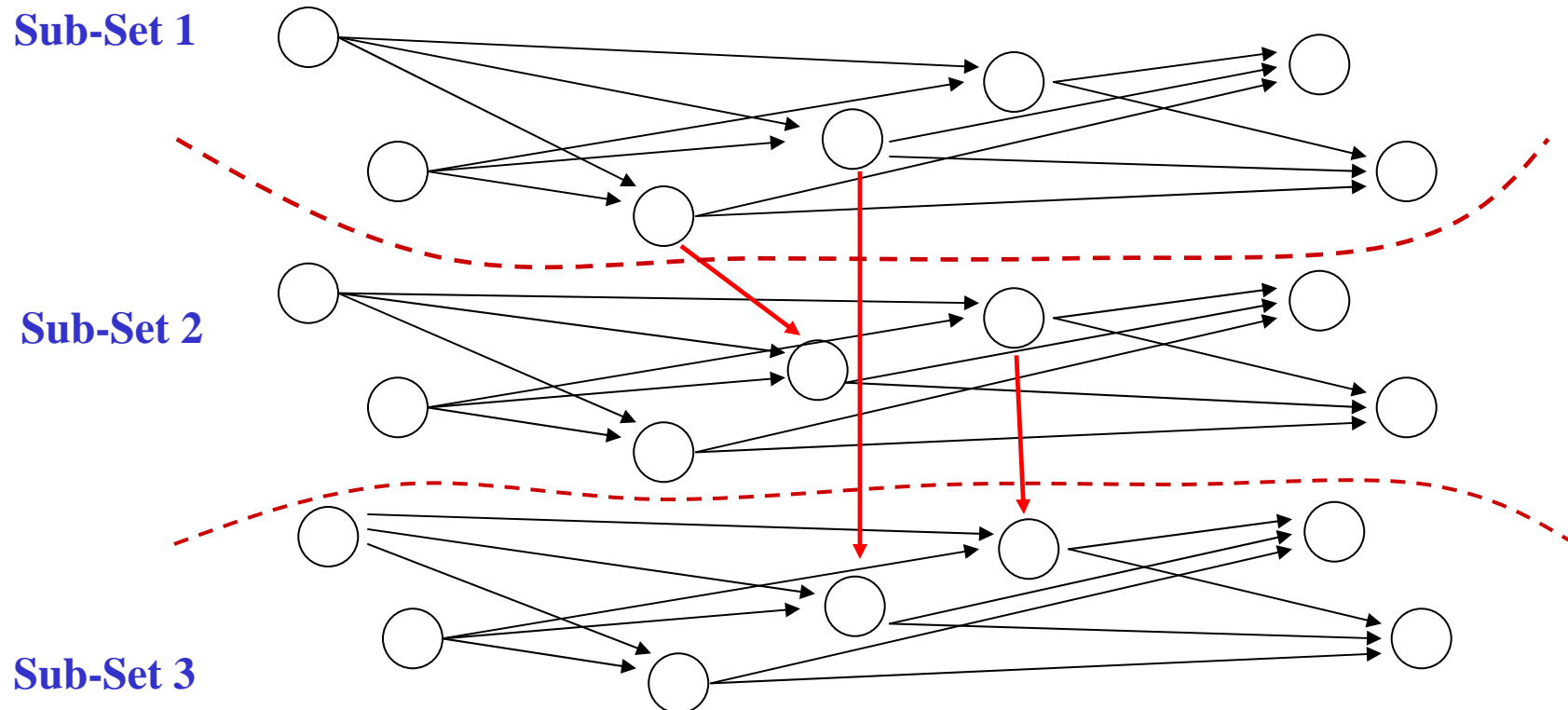
$$y_{jk} \geq z_{ijk} \quad \forall ijk$$

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

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

Solution of *LRi* sub-problems

Minimal cut-edge with fixed nodes example



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



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**

Remarks

- Proposed a **new formulation and bounding procedure** to find **local solutions** more easily.
- Explored the **spatial decomposition** of each LR sub-problem to speed up convergence. A **systematic decomposition** approach was proposed.

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 ?)