

Sequential penalty methods for mixed integer programs

Marianna De Santis¹ Sven de Vries²
Martin Schmidt² Lukas Winkel²

¹Department of Computer, Control, and Management Engineering,

Sapienza University of Rome, Italy



SAPIENZA
UNIVERSITÀ DI ROMA

²Department of Mathematics, Trier University, Germany



MIP 2022

Mixed-Binary Linear Complementarity Problems

The mixed-binary linear complementarity problem (MILCP) is the task to **find a vector $z \in \mathbb{R}^n$ that satisfies**

$$z \geq 0$$

$$q + Mz \geq 0$$

$$z^T(q + Mz) = 0$$

$$z_i \in \{0, 1\} \quad \text{for } i \in I \subseteq \{1, \dots, n\}$$

or to show that no such vector exists, for given

- $M \in \mathbb{R}^{n \times n}$, $M \succeq 0$
- $q \in \mathbb{R}^n$

Application context

Linear Complementarity Problems (LCPs) are an important tool for the modeling and analysis of equilibrium problems in economics, mechanics, ... [Cottle, Pang, Stone; “The Linear Complementarity Problem”; 2009]

[Gabriel, Conejo, Fuller, Hobbs; “Complementarity modeling in energy markets”; 2012]

When a subset of variables is restricted to take integer values, i.e., $z_i \in \mathbb{Z}$ for a given index set $I \subseteq \{1, \dots, n\}$ we fall in the context of MILCPs

Linear Complementarity Problems

QP reformulation

A common tool in the analysis and resolution of a Linear Complementarity Problem (LCP) is its reformulation as Quadratic Problem (QP) [Cottle et al.;2009]:

$$\begin{array}{ll} z \geq 0 & \min \quad z^\top (q + Mz) \\ q + Mz \geq 0 & \text{s.t.} \quad q + Mz \geq 0 \\ z^\top (q + Mz) = 0 & z \geq 0 \end{array}$$

Linear Complementarity Problems

QP reformulation

A common tool in the analysis and resolution of a Linear Complementarity Problem (LCP) is its reformulation as Quadratic Problem (QP) [Cottle et al.;2009]:

$$\begin{array}{ll} z \geq 0 & \\ q + Mz \geq 0 & \\ z^\top (q + Mz) = 0 & \end{array} \quad \Leftrightarrow \quad \begin{array}{ll} \min & z^\top (q + Mz) \\ \text{s.t.} & q + Mz \geq 0 \\ & z \geq 0 \end{array}$$

LCP has a solution if and only if the QP has an optimal solution with objective function value zero

MIQP reformulation of a MILCP

Equivalently we can reformulate a MILCP into a MIQP:

$$\begin{array}{ll} z \geq 0 & \min \quad z^\top (q + Mz) \\ q + Mz \geq 0 & \text{s.t.} \quad q + Mz \geq 0 \\ z^\top (q + Mz) = 0 & z \geq 0 \\ z_i \in \{0, 1\}, i \in I & z_i \in \{0, 1\}, i \in I \end{array} \quad \Leftrightarrow$$

MILCP has a solution if and only if the MIQP has an optimal solution with objective function value zero

MIQP reformulation of a MILCP

Equivalently we can reformulate a MILCP into a MIQP:

$$\begin{array}{ll} z \geq 0 & \min \quad z^\top (q + Mz) \\ q + Mz \geq 0 & \text{s.t.} \quad q + Mz \geq 0 \\ z^\top (q + Mz) = 0 & z \geq 0 \\ z_i \in \{0, 1\}, i \in I & z_i \in \{0, 1\}, i \in I \end{array} \iff$$

MILCP has a solution if and only if the MIQP has an optimal solution with objective function value zero

However, the existence of a solution of the MILCP cannot be expected in general...

...look for “approximate feasible solutions”

For practically relevant instances where non-existence occurs, one is interested in **“approximate feasible solutions”**:

points that minimize a certain infeasibility measure that **combines** both the violation of **integrality conditions** as well as of **complementarity constraints**

Penalizing the violation of complementarity and integrality

$$\begin{aligned} \min \quad & \alpha P_C(z) + (1 - \alpha) P_I(z) \\ \text{s.t.} \quad & q + Mz \geq 0 \\ & z \geq 0 \\ & z_i \leq 1, \quad i \in I \end{aligned}$$

where

- $\alpha \in [0, 1]$
- $P_C(z)$ is a function penalizing the violation of the complementarity constraints
- $P_I(z)$ is a function penalizing the violation of the integrality constraints

[Raghavachari;1969], [Giannessi, Tardella; 1998], [Zhu; 2003],
[Lucidi, Rinaldi; 2010], [De Santis, Lucidi, Rinaldi; 2013]

A nonconvex, nonsmooth reformulation of MILCP

$$\begin{aligned} \min \quad & \alpha z^\top (q + Mz) + (1 - \alpha) \sum_{i \in I} \min\{z_i, 1 - z_i\} \\ \text{s.t.} \quad & q + Mz \geq 0 \\ & z \geq 0 \\ & z_i \leq 1, \quad i \in I \end{aligned} \tag{NC}_{ref}$$

where

- $\alpha \in [0, 1]$
- $P_C(z) = z^\top (q + Mz)$
- $P_I(z) = \sum_{i \in I} \min\{z_i, 1 - z_i\}$

$P_I(z)$ is concave and piecewise linear

Features of the *penalty* branch-and-bound method

In order to globally solve problem NC_{ref} , we address a **sequence of convex quadratic smooth problems** that

Features of the *penalty* branch-and-bound method

In order to globally solve problem NC_{ref} , we address a **sequence of convex quadratic smooth problems** that

- share the same feasible set

Features of the *penalty* branch-and-bound method

In order to globally solve problem NC_{ref} , we address a **sequence of convex quadratic smooth problems** that

- share the same feasible set
- progressively increase the penalization of the integrality constraint violation

Features of the *penalty* branch-and-bound method

In order to globally solve problem NC_{ref} , we address a **sequence of convex quadratic smooth problems** that

- share the same feasible set
- progressively increase the penalization of the integrality constraint violation



the objective function slightly changes along the iterations!

Problem at the root node

At the **root node** of the branch-and-bound tree, we solve the convex smooth problem

$$\begin{aligned} \min \quad & \alpha z^\top (q + Mz) \\ \text{s.t.} \quad & q + Mz \geq 0 \\ & z \geq 0 \\ & z_i \leq 1, \quad i \in I \end{aligned}$$

obtained from Problem (NC_{ref}) by **neglecting the second term in the objective function**

Branching

Let z^* be the solution of the root node relaxation

Branching

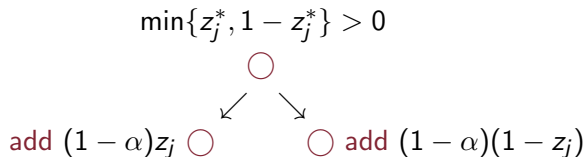
Let z^* be the solution of the root node relaxation

Choose an index $j \in I$ such that $\min\{z_j^*, 1 - z_j^*\} > 0$
and **build two children nodes:**

Branching

Let z^* be the solution of the root node relaxation

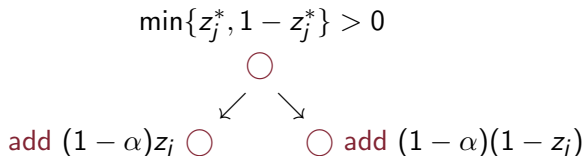
Choose an index $j \in I$ such that $\min\{z_j^*, 1 - z_j^*\} > 0$
and **build two children nodes:**



Branching

Let z^* be the solution of the root node relaxation

Choose an index $j \in I$ such that $\min\{z_j^*, 1 - z_j^*\} > 0$
and **build two children nodes:**



$$\min \quad \alpha z^\top (q + Mz) + (1 - \alpha)z_j$$

$$\text{s.t.} \quad q + Mz \geq 0$$

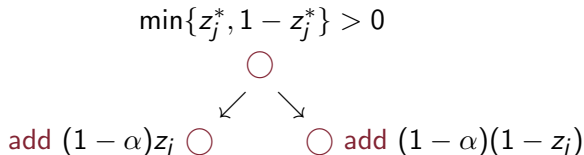
$$z \geq 0, \quad z_i \leq 1, \quad i \in I$$

--> *aims to drive z_j to 0
in the respective subtree*

Branching

Let z^* be the solution of the root node relaxation

Choose an index $j \in I$ such that $\min\{z_j^*, 1 - z_j^*\} > 0$
and **build two children nodes**:



$$\begin{aligned} \min \quad & \alpha z^\top (q + Mz) + (1 - \alpha)z_j \\ \text{s.t.} \quad & q + Mz \geq 0 \\ & z \geq 0, \quad z_i \leq 1, \quad i \in I \end{aligned}$$

--> *aims to drive z_j to 0
in the respective subtree*

$$\begin{aligned} \min \quad & \alpha z^\top (q + Mz) + (1 - \alpha)(1 - z_j) \\ \text{s.t.} \quad & q + Mz \geq 0 \\ & z \geq 0, \quad z_i \leq 1, \quad i \in I \end{aligned}$$

--> *aims to drive z_j to 1
in the respective subtree*

Problem at the node $N = (l_0, l_1)$

A node $N = (l_0, l_1)$ is identified by two sets of indices:

Problem at the node $N = (I_0, I_1)$

A node $N = (I_0, I_1)$ is identified by two sets of indices:

- I_0 : set of indices $j \in I$ for which $(1 - \alpha)z_j$ is added
- I_1 : set of indices $j \in I$ for which $(1 - \alpha)(1 - z_j)$ is added

Problem at the node $N = (I_0, I_1)$

A node $N = (I_0, I_1)$ is identified by two sets of indices:

- I_0 : set of indices $j \in I$ for which $(1 - \alpha)z_j$ is added
- I_1 : set of indices $j \in I$ for which $(1 - \alpha)(1 - z_j)$ is added

The subproblem at node $N = (I_0, I_1)$ is

$$\begin{aligned} \min \quad & f_N(z) \\ \text{s.t.} \quad & q + Mz \geq 0 \\ & z \geq 0 \\ & z_i \leq 1, \quad i \in I \end{aligned}$$

with

$$f_N(z) = \alpha z^\top (q + Mz) + (1 - \alpha) \left(\sum_{j \in I_0} z_j + \sum_{j \in I_1} (1 - z_j) \right)$$

Enumerating the partitions (I_0, I_1) of $I \subseteq \{1, \dots, n\}$

The **minimum among** the optimal solutions of the problems of **all leaf nodes** of the fully enumerated branch-and-bound tree **is the optimal solution** of Problem (NC_{ref}) :

Lemma

Let z^ be an optimal solution of Problem (NC_{ref}) and z_N^* the solution at the node $N = (I_0, I_1)$. Then,*

$$f(z^*) = \min \{f_N(z_N^*) : N = (I_0, I_1) \text{ with } I_0 \cup I_1 = I \text{ and } I_0 \cap I_1 = \emptyset\}$$

Bounding and Pruning

The optimal value $f_N(z_N^*)$ of the problem defined at a node N is a local lower bound for the subtree rooted in N :

Lemma

Let $N' = (l'_0, l'_1)$ be a successor of $N = (l_0, l_1)$, i.e., $l_0 \subseteq l'_0$ and $l_1 \subseteq l'_1$. Then,

$$f_N(z_N^*) \leq f_{N'}(z_{N'}^*)$$

Bounding and Pruning

The optimal value $f_N(z_N^*)$ of the problem defined at a node N is a local lower bound for the subtree rooted in N :

Lemma

Let $N' = (l'_0, l'_1)$ be a successor of $N = (l_0, l_1)$, i.e., $l_0 \subseteq l'_0$ and $l_1 \subseteq l'_1$. Then,

$$f_N(z_N^*) \leq f_{N'}(z_{N'}^*)$$



If z_N^* is such that $f_N(z_N^*) \geq f(z_{\text{inc}}^*)$

every leaf of the subtree rooted in N cannot yield a better solution than the best known solution z_{inc}^*

Bounding and Pruning

The optimal value $f_N(z_N^*)$ of the problem defined at a node N is a local lower bound for the subtree rooted in N :

Lemma

Let $N' = (l'_0, l'_1)$ be a successor of $N = (l_0, l_1)$, i.e., $l_0 \subseteq l'_0$ and $l_1 \subseteq l'_1$. Then,

$$f_N(z_N^*) \leq f_{N'}(z_{N'}^*)$$



If z_N^* is such that $f_N(z_N^*) \geq f(z_{inc}^*)$

every leaf of the subtree rooted in N cannot yield a better solution than the best known solution z_{inc}^*

and **we can prune the subtree rooted in N**

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

while $\mathcal{N} \neq \emptyset$ **do**

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

while $\mathcal{N} \neq \emptyset$ **do**

 Choose $N = (I_0, I_1) \in \mathcal{N}$

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

while $\mathcal{N} \neq \emptyset$ **do**

 Choose $N = (I_0, I_1) \in \mathcal{N}$

 Set $\mathcal{N} \leftarrow \mathcal{N} \setminus \{N\}$

 Compute $z_N^* \in \operatorname{argmin}\{f_N(z) : q + Mz \geq 0, z \in [0, 1]^n\}$

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

while $\mathcal{N} \neq \emptyset$ **do**

 Choose $N = (I_0, I_1) \in \mathcal{N}$

 Set $\mathcal{N} \leftarrow \mathcal{N} \setminus \{N\}$

 Compute $z_N^* \in \operatorname{argmin}\{f_N(z) : q + Mz \geq 0, z \in [0, 1]^n\}$

if $f(z_N^*) < f_{inc}$ **then**

 Set $z_{inc}^* \leftarrow z_N^*$, $f_{inc} \leftarrow f(z_N^*)$

end if

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

while $\mathcal{N} \neq \emptyset$ **do**

 Choose $N = (I_0, I_1) \in \mathcal{N}$

 Set $\mathcal{N} \leftarrow \mathcal{N} \setminus \{N\}$

 Compute $z_N^* \in \operatorname{argmin}\{f_N(z) : q + Mz \geq 0, z \in [0, 1]^n\}$

if $f(z_N^*) < f_{inc}$ **then**

 Set $z_{inc}^* \leftarrow z_N^*$, $f_{inc} \leftarrow f(z_N^*)$

end if

if $f_N(z_N^*) < f_{inc}$ **and** $I \setminus (I_0 \cup I_1) \neq \emptyset$ **then**

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

while $\mathcal{N} \neq \emptyset$ **do**

 Choose $N = (I_0, I_1) \in \mathcal{N}$

 Set $\mathcal{N} \leftarrow \mathcal{N} \setminus \{N\}$

 Compute $z_N^* \in \operatorname{argmin}\{f_N(z) : q + Mz \geq 0, z \in [0, 1]^n\}$

if $f(z_N^*) < f_{inc}$ **then**

 Set $z_{inc}^* \leftarrow z_N^*$, $f_{inc} \leftarrow f(z_N^*)$

end if

if $f_N(z_N^*) < f_{inc}$ **and** $I \setminus (I_0 \cup I_1) \neq \emptyset$ **then**

 Choose $j \in I \setminus (I_0 \cup I_1)$

 Set $\mathcal{N} \leftarrow \mathcal{N} \cup \{(I_0 \cup \{j\}, I_1), (I_0, I_1 \cup \{j\})\}$

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

while $\mathcal{N} \neq \emptyset$ **do**

 Choose $N = (I_0, I_1) \in \mathcal{N}$

 Set $\mathcal{N} \leftarrow \mathcal{N} \setminus \{N\}$

 Compute $z_N^* \in \operatorname{argmin}\{f_N(z) : q + Mz \geq 0, z \in [0, 1]^n\}$

if $f(z_N^*) < f_{inc}$ **then**

 Set $z_{inc}^* \leftarrow z_N^*$, $f_{inc} \leftarrow f(z_N^*)$

end if

if $f_N(z_N^*) < f_{inc}$ **and** $I \setminus (I_0 \cup I_1) \neq \emptyset$ **then**

 Choose $j \in I \setminus (I_0 \cup I_1)$

 Set $\mathcal{N} \leftarrow \mathcal{N} \cup \{(I_0 \cup \{j\}, I_1), (I_0, I_1 \cup \{j\})\}$

end if

end while

MILCP-PBB Scheme

Input: $q \in \mathbb{R}^n$, $M \in \mathbb{R}^{n \times n}$, $I \subseteq \{1, \dots, n\}$, $\alpha \in (0, 1)$

Output: A global optimum z^* of Problem (NC_{ref})

Set $\mathcal{N} \leftarrow \{(\emptyset, \emptyset)\}$, $f_{inc} \leftarrow \infty$, $z_{inc}^* \leftarrow \text{none}$

while $\mathcal{N} \neq \emptyset$ **do**

 Choose $N = (I_0, I_1) \in \mathcal{N}$

 Set $\mathcal{N} \leftarrow \mathcal{N} \setminus \{N\}$

 Compute $z_N^* \in \operatorname{argmin}\{f_N(z) : q + Mz \geq 0, z \in [0, 1]^n\}$

if $f(z_N^*) < f_{inc}$ **then**

 Set $z_{inc}^* \leftarrow z_N^*$, $f_{inc} \leftarrow f(z_N^*)$

end if

if $f_N(z_N^*) < f_{inc}$ **and** $I \setminus (I_0 \cup I_1) \neq \emptyset$ **then**

 Choose $j \in I \setminus (I_0 \cup I_1)$

 Set $\mathcal{N} \leftarrow \mathcal{N} \cup \{(I_0 \cup \{j\}, I_1), (I_0, I_1 \cup \{j\})\}$

end if

end while

return z_{inc}^*

Finite termination

Theorem

Algorithm MILCP-PBB terminates after finitely many steps with a global optimal solution of Problem (NC_{ref}) .

Finite termination

Theorem

Algorithm MILCP-PBB terminates after finitely many steps with a global optimal solution of Problem (NC_{ref}) .

Remark

Note that in our branch-and-bound method, there is no direct analogy to pruning due to infeasibility.

In case at a node we find a feasible solution for the MILCP we stop the algorithm

Adding simple cuts

Within the node subproblem we include simple bound constraints:

$$\begin{aligned} \min \quad & f_N(z) \\ \text{s.t.} \quad & q + Mz \geq 0 \\ & z \in [0, 1]^n \\ & z_j \leq 0.5 \text{ if } j \in I_0 \\ & z_j \geq 0.5 \text{ if } j \in I_1 \end{aligned}$$

Adding simple cuts

Within the node subproblem we include simple bound constraints:

$$\begin{aligned} \min \quad & f_N(z) \\ \text{s.t.} \quad & q + Mz \geq 0 \\ & z \in [0, 1]^n \\ & z_j \leq 0.5 \text{ if } j \in I_0 \\ & z_j \geq 0.5 \text{ if } j \in I_1 \end{aligned}$$

Lemma

Let z_N^* be an optimal solution at node N when simple cuts are included. Then,

$$f(z^*) = \min \{f_N(z_N^*) : N = (I_0, I_1) \text{ with } I_0 \cup I_1 = I\}$$

Adding simple cuts

finite termination

Lemma

Let $N' = (I'_0, I'_1)$ be a successor of some node $N = (I_0, I_1)$ in the branching tree, i.e., $I_0 \subseteq I'_0$ and $I_1 \subseteq I'_1$ holds. Further, let $z_N^*, z_{N'}^*$ be optimal solutions of nodes N and N' , respectively, when simple cuts are used. Then,

$$f_N(z_N^*) \leq f_{N'}(z_{N'}^*)$$

holds.

Theorem

Algorithm MILCP-PBB remains correct when simple cuts

$$z_j \leq 0.5 \text{ for all } j \in I_0, \quad z_j \geq 0.5 \text{ for all } j \in I_1$$

are added at any node $N = (I_0, I_1)$.

Numerical results

Randomly generated instances

We built matrices $M \in \mathbb{R}^{n \times n}$ with
 $n \in \{50, 100, 150, 200, 250, 300, 350, 400, 450, 500\}$.

Numerical results

Randomly generated instances

We built matrices $M \in \mathbb{R}^{n \times n}$ with
 $n \in \{50, 100, 150, 200, 250, 300, 350, 400, 450, 500\}$.

We then built vectors $q \in \mathbb{R}^n$ in four different ways, each reflecting a certain “degree of feasibility” in the resulting instance.

Numerical results

Randomly generated instances

We built matrices $M \in \mathbb{R}^{n \times n}$ with
 $n \in \{50, 100, 150, 200, 250, 300, 350, 400, 450, 500\}$.

We then built vectors $q \in \mathbb{R}^n$ in four different ways, each reflecting a certain “degree of feasibility” in the resulting instance.

More precisely, we built instances for which $z \in \mathbb{R}^n$ exists so that

(a) only $q + Mz \geq 0$, $z \geq 0$ are guaranteed to be satisfied,

Numerical results

Randomly generated instances

We built matrices $M \in \mathbb{R}^{n \times n}$ with
 $n \in \{50, 100, 150, 200, 250, 300, 350, 400, 450, 500\}$.

We then built vectors $q \in \mathbb{R}^n$ in four different ways, each reflecting a certain “degree of feasibility” in the resulting instance.

More precisely, we built instances for which $z \in \mathbb{R}^n$ exists so that

- (a) only $q + Mz \geq 0$, $z \geq 0$ are guaranteed to be satisfied,
- (b) only $q + Mz \geq 0$, $z \geq 0$ and $z_i \in \{0, 1\}$, $i \in I$ are guaranteed to be satisfied,

Numerical results

Randomly generated instances

We built matrices $M \in \mathbb{R}^{n \times n}$ with
 $n \in \{50, 100, 150, 200, 250, 300, 350, 400, 450, 500\}$.

We then built vectors $q \in \mathbb{R}^n$ in four different ways, each reflecting a certain “degree of feasibility” in the resulting instance.

More precisely, we built instances for which $z \in \mathbb{R}^n$ exists so that

- (a) only $q + Mz \geq 0, z \geq 0$ are guaranteed to be satisfied,
- (b) only $q + Mz \geq 0, z \geq 0$ and $z_i \in \{0, 1\}, i \in I$ are guaranteed to be satisfied,
- (c) only $q + Mz \geq 0, z \geq 0$ and complementarity ($z^{*\top}(q + Mz^*) = 0$) are guaranteed to be satisfied,

Numerical results

Randomly generated instances

We built matrices $M \in \mathbb{R}^{n \times n}$ with $n \in \{50, 100, 150, 200, 250, 300, 350, 400, 450, 500\}$.

We then built vectors $q \in \mathbb{R}^n$ in four different ways, each reflecting a certain “degree of feasibility” in the resulting instance.

More precisely, we built instances for which $z \in \mathbb{R}^n$ exists so that

- (a) only $q + Mz \geq 0, z \geq 0$ are guaranteed to be satisfied,
- (b) only $q + Mz \geq 0, z \geq 0$ and $z_i \in \{0, 1\}, i \in I$ are guaranteed to be satisfied,
- (c) only $q + Mz \geq 0, z \geq 0$ and complementarity ($z^{*\top}(q + Mz^*) = 0$) are guaranteed to be satisfied,

We created 10 instances for every size n and the types (a)–(c), yielding 300 different instances in total.

Numerical results on the use of simple cuts

Performance Profiles

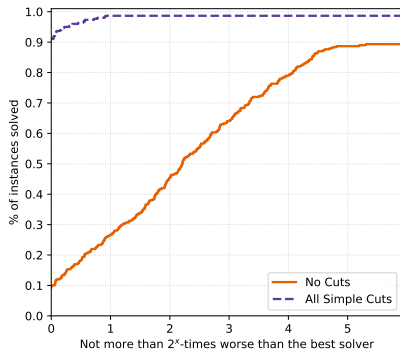
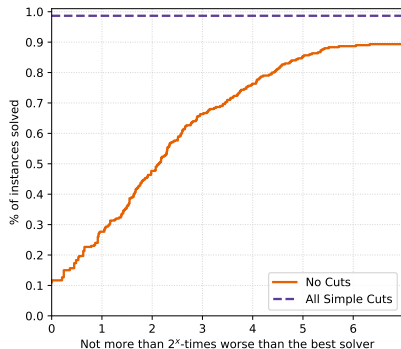


Figure: Performance profiles: number of nodes (left), running time (right)

Numerical comparison on branching rules

Performance Profiles

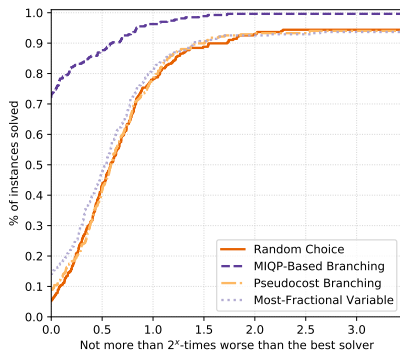
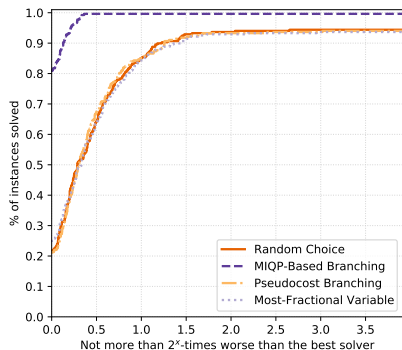


Figure: Performance profiles: number of nodes (left), running time (right)

MIQP-based branching rule

We presolve single-binary-variable MIQPs, one for each $z_j, j \in I$:

$$\min_{z \in \mathbb{R}^n} z^\top (q + Mz) \quad (1a)$$

$$\text{s.t. } q + Mz \geq 0, z \geq 0, \quad (1b)$$

$$z_j \in \{0, 1\}. \quad (1c)$$

measuring the impact of the j -th variable on the infeasibility of the problem

MIQP-based branching rule

We presolve single-binary-variable MIQPs, one for each $z_j, j \in I$:

$$\min_{z \in \mathbb{R}^n} z^\top (q + Mz) \quad (1a)$$

$$\text{s.t. } q + Mz \geq 0, z \geq 0, \quad (1b)$$

$$z_j \in \{0, 1\}. \quad (1c)$$

measuring the impact of the j -th variable on the infeasibility of the problem

We sort the indices $j \in I$ in decreasing order with respect to the optimal objective function values

Comparison with other approaches

An MILP reformulation, with additional binary variables and big-M constraints

[Gabriel, Conejo, Ruiz, Siddiqui; 2013]

$$\min_{z, z', z'', \rho, \sigma} \quad \alpha \sum_{i=1}^n \rho_i + (1 - \alpha) \sum_{i \in I} \sigma_i \quad (2a)$$

$$\text{s.t.} \quad z \geq 0, \quad q + Mz \geq 0, \quad (2b)$$

$$z \leq Bz' + \rho, \quad (2c)$$

$$q + Mz \leq B(1 - z') + \rho, \quad (2d)$$

$$0 \leq z_I \leq z'' + \sigma, \quad (2e)$$

$$z'' - \sigma \leq z_I \leq 1, \quad (2f)$$

$$z \in \mathbb{R}^n, \quad z' \in \{0, 1\}^n, \quad z'' \in \{0, 1\}^I, \quad (2g)$$

$$\sigma \in \mathbb{R}_{\geq 0}^I, \quad \rho \in \mathbb{R}_{\geq 0}^n. \quad (2h)$$

variables: $3n + 2|I|$, ($n + |I|$ constrained to be binary)

Comparison with other approaches

An MIQP reformulation, no big-M constraints

$$\min_{z, z', \sigma} \quad \alpha z^\top (q + Mz) + (1 - \alpha) \sum_{i \in I} \sigma_i \quad (3a)$$

$$\text{s.t.} \quad z \geq 0, \quad q + Mz \geq 0, \quad (3b)$$

$$0 \leq z_I \leq z' + \sigma, \quad (3c)$$

$$z' - \sigma \leq z_I \leq 1, \quad (3d)$$

$$z \in \mathbb{R}^n, \quad z' \in \{0, 1\}^I, \quad (3e)$$

$$\sigma \in \mathbb{R}_{\geq 0}^I. \quad (3f)$$

variables: $n + 2|I|$, ($|I|$ constrained to be binary)

Comparison with GUROBI addressing the MILP and the MIQP reformulations

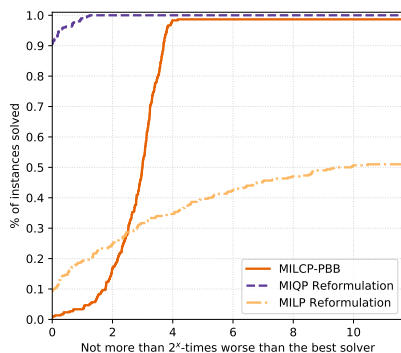
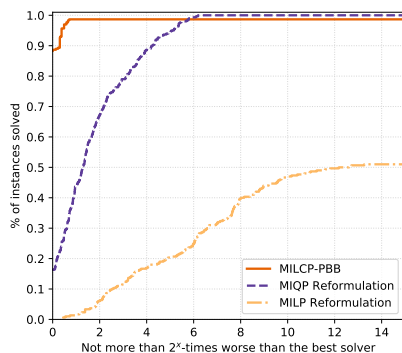


Figure: Performance profiles: number of nodes (left), running time (right)

Comparison with GUROBI addressing the MIQP

Harder test set (300 instances with $n = 100, \dots, 600$)

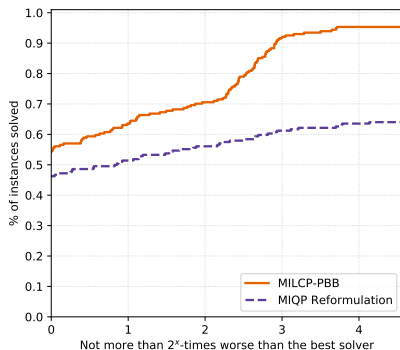
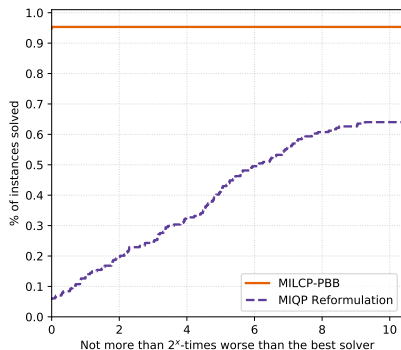


Figure: Performance profiles: number of nodes (left), running time (right)

Conclusions

We presented a **penalty branch-and-bound method** for MILCPs

- the method is able to compute a solution **if one exists or it computes an approximate solution** that minimizes an infeasibility measure based on the violation of the integrality and complementarity conditions of the problem
- the objective function slightly changes along the nodes so that **the penalization of the integrality constraint violation is progressively increased**

Future work

...useful for MILPs?

Under specific assumption on $P = \{x \in \mathbb{R}^n : Ax \leq b\}$ we can prove that $\epsilon > 0$ exists such that

$$\begin{array}{ll} \min & c^\top x \\ \text{s.t.} & Ax \leq b \\ & x_i \in \{0, 1\}, \quad i \in I \end{array} \quad \Leftrightarrow \quad \begin{array}{ll} \min & c^\top x + \frac{1}{\epsilon} \sum_{i \in I} \min\{x_i, 1 - x_i\} \\ \text{s.t.} & Ax \leq b \\ & x \in [0, 1]^n \end{array}$$

Future work

...useful for MILPs?

Under specific assumption on $P = \{x \in \mathbb{R}^n : Ax \leq b\}$ we can prove that $\epsilon > 0$ exists such that

$$\begin{array}{ll} \min & c^\top x \\ \text{s.t.} & Ax \leq b \\ & x_i \in \{0, 1\}, \quad i \in I \end{array} \quad \Leftrightarrow \quad \begin{array}{ll} \min & c^\top x + \frac{1}{\epsilon} \sum_{i \in I} \min\{x_i, 1 - x_i\} \\ \text{s.t.} & Ax \leq b \\ & x \in [0, 1]^n \end{array}$$



we can use our branch-and-bound framework to solve the nonconvex nonsmooth reformulation of MILPs!

Future work

...useful for MILPs?

Under specific assumption on $P = \{x \in \mathbb{R}^n : Ax \leq b\}$ we can prove that $\epsilon > 0$ exists such that

$$\begin{array}{ll} \min & c^\top x \\ \text{s.t.} & Ax \leq b \\ & x_i \in \{0, 1\}, \quad i \in I \end{array} \quad \Leftrightarrow \quad \begin{array}{ll} \min & c^\top x + \frac{1}{\epsilon} \sum_{i \in I} \min\{x_i, 1 - x_i\} \\ \text{s.t.} & Ax \leq b \\ & x \in [0, 1]^n \end{array}$$



we can use our branch-and-bound framework to solve the nonconvex nonsmooth reformulation of MILPs!

Thanks for your attention!