

Diszkrét kétszintű optimalizálás

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Bilevel optimization

- Problem formulation

- Linear and integer bilevel programming

Complexity

- The polynomial hierarchy

- Complexity of multi-level programming

Bilevel scheduling problems

- The bilevel total weighted completion time problem

- The bilevel order acceptance problem

Bilevel lot-sizing

- Uncapacitated lot-sizing with backlogging

- The bilevel lot-sizing problem

- MIP formulations

- Computational evaluation

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Problem formulation

- ▶ Two decision makers, Leader and Follower, who make decisions sequentially, in this order
- ▶ General form: optimistic case

$$\begin{array}{ll} \min_{x,y} & f(x, y) & (1) \\ \text{subject to} & & \end{array}$$

$$L(x, y) \quad (2)$$

$$y \in \arg \min_{y'} (g(x, y') \mid F(x, y')) \quad (3)$$

- ▶ General form: pessimistic case

$$\begin{array}{ll} \min_x \max_y & f(x, y) & (4) \\ \text{subject to} & & \end{array}$$

$$L(x, y) \quad (5)$$

$$y \in \arg \min_{y'} (g(x, y') \mid F(x, y')). \quad (6)$$

Linear bilevel optimization

- ▶ 2 levels
- ▶ Variables: $x = (x^1, x^2) \in \mathbb{R}_+^{n_1+n_2}$
- ▶ Variables x^i are exclusively controlled by player i
- ▶ Formulation:

$$\begin{array}{ll} \min_x & c^{11}x^1 + c^{12}x^2 & (7) \\ \text{subject to} & \end{array}$$

$$A^{11}x^1 + A^{12}x^2 \geq b^1 \quad (8)$$

$$x^2 \in \arg \min_y (c^{22}y \mid A^{21}x^1 + A^{22}y \geq b^2). \quad (9)$$

The polynomial hierarchy

Definition (Polynomial hierarchy by Karp)

Let $L \subset S^+$ be a language over a finite alphabet. For any $k \geq 1$,

- ▶ $L \in \Sigma_k^P$ if and only if $\exists p_1, \dots, p_k$ polynomials and $L' \in \mathcal{P}$ such that for any $x \in S^+$
 $x \in L$ iff $(\exists y_1)_{p_1} (\forall y_2)_{p_2} \dots (Q y_k)_{p_k} [(x, y_1, \dots, y_k) \in L']$
- ▶ $L \in \Pi_k^P$ if and only if $\exists p_1, \dots, p_k$ polynomials and $L' \in \mathcal{P}$ such that for any $x \in S^+$:
 $x \in L$ iff $(\forall y_1)_{p_1} (\exists y_2)_{p_2} \dots (Q y_k)_{p_k} [(x, y_1, \dots, y_k) \in L']$

Definition (Polynomial hierarchy by Stockmeyer)

$\Sigma_k^P = \mathcal{NP}(\Sigma_{k-1}^P)$ with $\Sigma_0^P = \mathcal{P}$

$\Pi_k^P = \text{co-}\mathcal{NP}(\Sigma_{k-1}^P)$

Theorem (Wrathal)

The two definitions are equivalent.

Complexity of multi-level programming

Theorem (Jeroslow)

Bilevel linear programming is NP-hard.

Theorem (Jeroslow)

$(k + 1)$ -level linear programming is Σ_k^P -hard.

Theorem (Jeroslow)

k -level integer (binary) programming is Σ_k^P -hard.

Corollary

Unless the polynomial hierarchy collapses at level 1, integer (binary) k -level programs cannot be modeled by mixed integer programs of size polynomial in the size of the input, for any $k \geq 2$.

Corollary

Unless the polynomial hierarchy collapses at level 1, linear k -level programs cannot be modeled by mixed integer programs of size polynomial in the size of the input, for any $k \geq 3$.

The bilevel total weighted completion time problem

- ▶ n jobs and m parallel, identical machines, no preemption
- ▶ Leader: assigns jobs to machines ($J = J_1 \cup J_2 \cup \dots \cup J_m$)
 - ▶ Optimistic objective: $\min \sum_{j \in J} w_j^1 C_j$
 - ▶ Pessimistic objective: $\min \max \sum_{j \in J} w_j^1 C_j$
- ▶ Follower: sequences the assigned jobs on each machine

$$\min \sum_{i=1}^m \sum_{j \in J_i} w_j^2 C_j$$

- ▶ For a given machine assignment J_1, \dots, J_m , Follower solves m single machine problems $1 || \sum_j w_j^2 C_j$ by Smith's rule (WSPT order)
- ▶ Leader has to find the best assignment knowing the strategy of the Follower

Results on bilevel total weighted completion time problem

Restriction	Complexity
no restriction	decision version is NP-complete
$w^1 \equiv 1$, w^2 induces an increasing proc. time order	equivalent to $P \sum_j C_j$
$w^1 \equiv 1$, w^2 induces A decreasing proc. time order	reduces to a special MAX m -CUT problem
$w^1 \equiv 1$, w^2 arbitrary m constant	FPTAS of Sahni for $Pm \sum_j w_j C_j$ can be generalized

The structure of optimal solutions

Lemma

There is a global ordering of jobs such that in an optimal solution on each machine the job sequence respects the global order.

*In the **optimistic case** the global order is WSPT with respect to w^2 and in case of ties WSPT w.r.t. w^1 .*

*In the **pessimistic case** the global order is WSPT with respect to w^2 and in case of ties reverse WSPT w.r.t. w^1 .*

Reduction to the MAX m -CUT problem

MAX m -CUT (optimization version)

input: the number of vertices (of a complete graph) n , edge weights c_e for all the $n(n-1)/2$ edges, a number m with $m \leq n$ (all data in \mathbb{Z}_+)

output: a partitioning of the vertices into m disjoint classes

V_1, \dots, V_m such that the total weight of edges between the classes is maximized, i.e.,

$$\max_{(V_1, \dots, V_m)} \sum_{k=1}^{m-1} \sum_{\ell=k+1}^m \sum_{i \in V_k, j \in V_\ell} c_{ij}$$

where the maximum is over all m -partitions of the n nodes

Reduction: the nodes are identified with the n tasks, and

$$c_{jk} = p_j w_k^1 \quad \text{if } \frac{w_j^2}{p_j} > \frac{w_k^2}{p_k}; \text{ or } \frac{w_j^2}{p_j} = \frac{w_k^2}{p_k} \text{ and } \frac{w_j^1}{p_j} \geq \frac{w_k^1}{p_k}$$

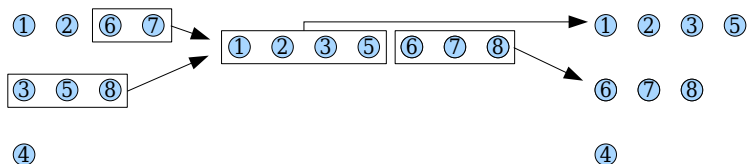
A special MAX m -CUT problem

Special weights

If $w^1 \equiv 1$ and $\frac{w_j^2}{p_j} > \frac{w_k^2}{p_k}$ iff $p_j > p_k$, then $c_{jk} = \max\{p_j, p_k\}$

Theorem

There exists an optimal solution to MAX m -CUT such that $V_1 = \{1, \dots, k_1\}$, $V_2 = \{k_1 + 1, \dots, k_2\}$, \dots , $V_m = \{k_{m-1} + 1, \dots, m\}$, where $p_j \geq p_k$ for $j < k$.



Corollary

The MAX m -CUT problem with the above weights can be solved by dynamic programming in polynomial time

The bilevel order acceptance problem

- ▶ There are n jobs with processing times p_j , due-dates d_j , and job-weights w_j^1, w_j^2 ; and a single machine
- ▶ **Leader**: selects a subset of jobs A (accepted jobs) to maximize $\sum_{j \in A} w_j^1$
- ▶ **Follower**: sequences the jobs non-preemptively to minimize $\sum_{j \in A} w_j^2 C_j$
- ▶ The solution is feasible iff the optimal solution chosen by the Follower meets the due-dates of all jobs in A
- ▶ If the Leader is **optimistic**, it selects A such that at least one optimal solution of the Follower meets all the due-dates
- ▶ If the Leader is **pessimistic**, it selects A such that all the optimal solutions of the Follower with respect to A meets all the due-dates

Results on the bilevel order acceptance problem

Restriction	Complexity
no restriction	decision version is NP-complete solvable in pseudo-poly time
$w^1 \equiv 1$	Polynomial (generalized Moore-Hodgson alg.)

A polynomial algorithm for the $w^1 \equiv 1$ case

The Moore-Hodgson algorithm for $1 \parallel \sum U_j$

1. Order the jobs in EDD order: $d_1 \leq \dots \leq d_n$
2. Starting with the first job, process the jobs one-by-one. If all jobs can be completed on time, stop. Otherwise, let k_1 be the first job such that $\sum_{j=1}^{k_1} p_j > d_{k_1}$. Remove from the first k_1 jobs the one with largest p_j value, and proceed with the next job.

Modification for the bilevel order acceptance problem:

1. Order the jobs in the Follower's WSPT order: $j < k$ iff $\frac{w_j^2}{p_j} > \frac{w_k^2}{p_k}$ and in case of ties if $d_j < d_k$ ($d_j > d_k$)

Uncapacitated lot-sizing with backlogging (ULSB)

$$\min \left\{ \sum_{t=1}^n (p_t x_t + f_t y_t + h_t s_t + g_t r_t) \mid (11) - (15) \right\} \quad (10)$$

where

$$x_t + (s_{t-1} - r_{t-1}) = d_t + (s_t - r_t), \quad t = 1, \dots, n \quad (11)$$

$$x_t \leq M y_t, \quad t = 1, \dots, n \quad (12)$$

$$s_0 = s_n = r_0 = r_n = 0, \quad (13)$$

$$x_t, s_t, r_t \geq 0, \quad t = 1, \dots, n \quad (14)$$

$$y_t \in \{0, 1\}, \quad t = 1, \dots, n \quad (15)$$

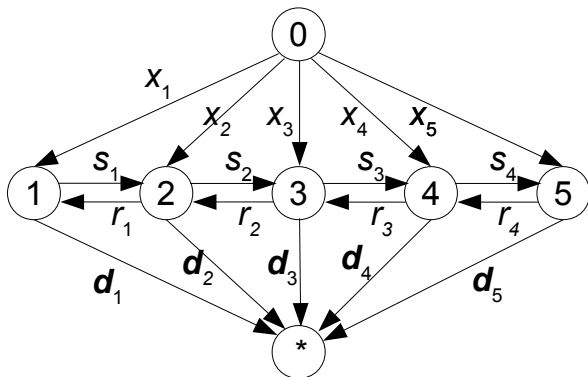
where

- ▶ The p_t, f_t, h_t, g_t are the cost parameters, the d_t are the demands
- ▶ The x_t, y_t, s_t, r_t are the variables

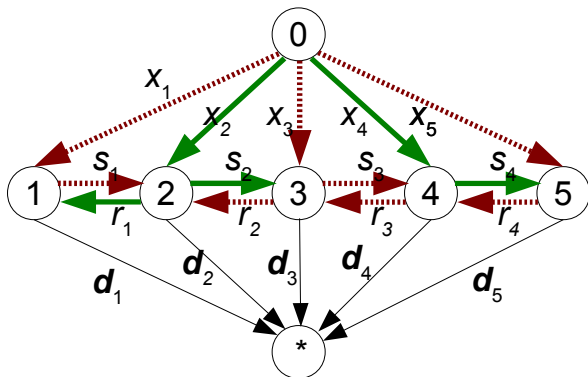
Some related work

- ▶ W. I. Zangwill, A backlogging model and a multi-echelon model of a dynamic economic lot size production system – A network approach. *Management Science*, 15(9):506–527, 1969.
- ▶ A. Federgruen, M. Tzur, The dynamic lot-sizing model with backlogging: A simple $O(n \log n)$ algorithm and minimal forecast horizon procedure. *Naval Res. Logistics* 40, 459–478, 1993.
- ▶ Y. Pochet and L. A. Wolsey. Lot-size models with backlogging: Strong reformulations and cutting planes. *Mathematical Programming*, 40:317–335, 1988.
- ▶ S. Kucukyavuz and Y. Pochet. Uncapacitated lot-sizing with backlogging: the convex hull. *Mathematical Programming, Ser. A*, 118:151–175, 2009.

Network representation of ULSB



Extreme point solutions for ULSB



Bilevel lot-sizing

Rules of the game

- ▶ Both decision makers solve an uncapacitated lot-sizing problem with backloging
- ▶ The Leader has external demand (d_t^1)
- ▶ The Leader's production (x_t^1) equals the supply received from the Follower
- ▶ The Follower's demand (δ_t) is set by the Leader
- ▶ Both the Leader and the Follower may backlog some of its demand
- ▶ The Follower pays the backloging cost to the Leader as penalty for late delivery
- ▶ In those periods when the Follower backlogs, there is no delivery to the Leader ($r_t^2 x_t^1 = 0$)
- ▶ If the Follower does not backlog in some period t , then it supplies all the demands from the last supply point, i.e., $\sum_{u=t'+1}^t \delta_u$, where t' is the last supply point ($x_{t'}^1 > 0$) or $t' = 0$

Formulation

$$\text{Minimize } \sum_{t=1}^n (p_t^1 x_t^1 + f_t^1 y_t^1 + h_t^1 s_t^1 + g_t^1 r_t^1 - g_t^2 r_t^2) \quad (16)$$

subject to

$$x_t^1 + s_{t-1}^1 - r_{t-1}^1 = d_t^1 + s_t^1 - r_t^1, \quad t = 1, \dots, n \quad (17)$$

$$\boxed{r_t^2 = \sum_{\tau=1}^t (\delta_\tau - x_\tau^1)}, \quad t = 1, \dots, n \quad (18)$$

$$x_t^1 \leq M y_t^1, \quad t = 1, \dots, n \quad (19)$$

$$\boxed{x_t^1 \leq M(1 - \beta_t^2)}, \quad t = 1, \dots, n-1 \quad (20)$$

$$s_0^1 = s_n^1 = r_0^1 = r_n^1 = 0, \quad (21)$$

$$x_t^1, r_t^1, s_t^1, \delta_t \geq 0, \quad t = 1, \dots, n \quad (22)$$

$$y_t^1 \in \{0, 1\}, \quad t = 1, \dots, n \quad (23)$$

Formulation (cont.d)

$$\begin{pmatrix} y^2 \\ x^2 \\ s^2 \\ r^2 \\ \beta^2 \end{pmatrix} \in \arg \min \left\{ \sum_{t=1}^n (p_t^2 x_t^2 + f_t^2 y_t^2 + h_t^2 s_t^2 + g_t^2 r_t^2) \mid (25) - (31) \right\}$$

where $x_t^2 + (s_{t-1}^2 - r_{t-1}^2) = \delta_t + (s_t^2 - r_t^2), \quad t = 1, \dots, n$ (24)

$$x_t^2 \leq M y_t^2, \quad t = 1, \dots, n$$
 (25)

$$s_0^2 = s_n^2 = r_0^2 = r_n^2 = 0,$$
 (26)

$$x_t^2, s_t^2, r_t^2 \geq 0, \quad t = 1, \dots, n$$
 (27)

$$y_t^2 \in \{0, 1\}, \quad t = 1, \dots, n$$
 (28)

$$\boxed{r_t^2 \leq M \beta_t^2}, \quad t = 1, \dots, n-1$$
 (29)

$$\boxed{\beta_t^2 \in \{0, 1\}}, \quad t = 1, \dots, n-1.$$
 (30)

Example

Optimal solution of a sample problem

t	1	2	3	4	5	6	7	8	9	10
d_t^1	71	84	43	21	4	81	59	44	32	46
x_t^1	82	73	68			82.49	57.51	55.46	21.93	44.61
s_t^1	11		25	4		1.49		11.46	1.39	
r_t^1										
δ_t	82	73	68		42.72	39.77	57.51	55.46	21.93	44.61
x_t^2	82	141				140.00		122.00		
s_t^2		68				57.51		66.54	44.61	
r_t^2					42.72					

$$\begin{aligned}
 f^1 &= 100 & p^1 &= 1 & h^1 &= 6 & g^1 &= 18 \\
 f^2 &= 492 & p^2 &= 1 & h^2 &= 2 & g^2 &= 6
 \end{aligned}$$

Example

Optimal solution of a sample problem

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$$\begin{aligned} f^1 &= 100 & p^1 &= 1 & h^1 &= 6 & g^1 &= 18 \\ f^2 &= 492 & p^2 &= 1 & h^2 &= 2 & g^2 &= 6 \end{aligned}$$

Definition

Let OP^2 be the set of those $(\bar{x}^2, \bar{y}^2, \bar{s}^2, \bar{r}^2, \bar{\delta})$ vectors such that $\sum_{t=1}^n \bar{\delta}_t = \sum_{t=1}^n d_t^1$, and $(\bar{x}^2, \bar{y}^2, \bar{s}^2, \bar{r}^2)$ is an optimal solution for the ULSB of the Follower w.r.t. demand $\bar{\delta}$.

Let $Z^{ULSB}(\delta)$ denote the optimum value of ULSB for fixed $\delta > 0$

Question

Does OP^2 admit a compact (extended) mixed integer formulation?

Answer

YES! Idea: use an extended formulation for ULSB with δ in the objective function only.

Formulation MIP-1 (cont.d)

Lemma

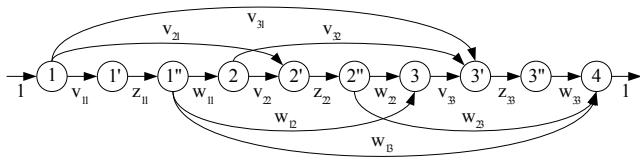
(Pochet and Wolsey (1988)) The optimum value of ULSB equals the optimum value of the following mathematical program

$$L^{SP}(\delta) = \min \sum_{k=1}^n \left(\sum_{\ell=1}^{k-1} a_{k\ell} v_{k\ell} + p_k \delta_k z_{kk} + \sum_{\ell=k+1}^n b_{k\ell} w_{k\ell} \right) + \sum_{t=1}^n f_t z_{tt}$$

subject to a shortest path formulation in the network below, where

$a_{k\ell} = p_k \delta_{\ell, k-1} + \sum_{t=\ell}^{k-1} g_t \delta_{\ell, t}$ for $1 \leq \ell < k \leq n$, and

$b_{k\ell} = p_k \delta_{k+1, \ell} + \sum_{t=k}^{\ell-1} h_t \delta_{t+1, \ell}$ for $1 \leq k < \ell \leq n$, and $\delta_{k, \ell} = \sum_{t=k}^{\ell} \delta_t$ for $1 \leq k \leq \ell \leq n$.



Formulation MIP-1 (cont.d)

The dual of the shortest path formulation is

$$D^{SP}(\delta) = \max \phi_1^2 \quad (32)$$

subject to

$$\left. \begin{aligned} \phi_t^2 - \phi_{k'}^2 &\leq a_{k,t}, & k = t, \dots, n \\ \phi_{t'}^2 - \phi_{t''}^2 &\leq p_t^2 \delta_t + f_t^2, \\ \phi_{t''}^2 - \phi_{k+1}^2 &\leq b_{t,k}, & k = t, \dots, n \end{aligned} \right\} \text{ for all } t = 1, \dots, n. \quad (33)$$

By the strong duality of linear programming $Z^{ULSB}(\delta) = D^{SP}(\delta)$ for any fixed $\delta \geq 0$.

Lemma

$(\hat{x}^2, \hat{y}^2, \hat{s}^2, \hat{r}^2, \hat{\delta}) \in OP^2$ if and only if $\sum_{t=1}^n \delta_t = \sum_{t=1}^n d_t^1$, and there exists $\hat{\phi}^2$ such that $(\hat{x}^2, \hat{y}^2, \hat{s}^2, \hat{r}^2, \hat{\beta}, \hat{\delta}, \hat{\phi}^2)$ satisfies the constraints (25)-(31), (33), and the equation

$$\sum_{t=1}^n (p_t^2 x_t^2 + f_t^2 y_t^2 + h_t^2 s_t^2 + g_t^2 r_t^2) = \phi_1^2. \quad (34)$$

Formulation MIP-1 (cont.d)

The complete formulation:

$$\text{MIP-1 : } \min \left\{ \sum_{t=1}^n (p_t^1 x_t^1 + f_t^1 y_t^1 + h_t^1 s_t^1 + g_t^1 r_t^1 - g_t^2 r_t^2) \left| \begin{array}{l} (17)-(19), \\ (21)-(23), \\ (25)-(31), \\ (33),(34) \end{array} \right. \right\}.$$

Lemma

We have the following correspondence between the feasible solutions of the bilevel lot-sizing problem and that of MIP-1:

- (i) Any feasible solution of MIP-1 can be projected onto a feasible solution of the bilevel lot-sizing problem of the same value.*
- (ii) Conversely, any feasible solution of the bilevel lot-sizing problem can be extended to a feasible solution of MIP-1 of the same value.*

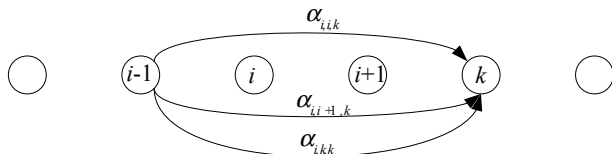
Formulation MIP-2

- ▶ Again, based on a shortest path formulation

$$\alpha_{ijk} = \begin{cases} 1 & \text{the requests } \delta_i, \dots, \delta_k \text{ are produced in } j \in \{i, \dots, k\} \\ 0 & \text{otherwise} \end{cases}$$

- ▶ If $\alpha_{ijk} = 1$, then $s_{i-1}^2 = s_k^2 = 0$, and $r_{i-1}^2 = r_k^2 = 0$.
- ▶ Cost associated with α_{ijk} :

$$c_{ijk} = a_{j,i} + f_j + p_j \delta_j + b_{j,k}$$



Formulation MIP-2 (cont.d)

$$\text{MIP-2 : } \min \sum_{t=1}^n (p_t^1 x_t^1 + f_t^1 y_t^1 + h_t^1 s_t^1 + g_t^1 r_t^1 - g_t^2 r_t^2)$$

subject to the constraints of the Leader, and

$$r_t^2 \leq M(1 - \beta_t^2), \quad t = 1, \dots, n-1$$

$$\beta_t^2 = \sum_{i \leq t < j \leq k} \alpha_{i,j,k}, \quad t = 1, \dots, n-1$$

$$\sum_{i \leq t \leq k} \sum_{i \leq j \leq k} \alpha_{i,j,k} = 1, \quad t = 1, \dots, n$$

$$a_{j,i} + f_j + p_j \delta_j + b_{j,k} + \phi_{i-1} \geq \phi_k, \quad 1 \leq i \leq j \leq k \leq n$$

$$a_{j,i} + f_j + p_j \delta_j + b_{j,k} + \phi_{i-1} \leq \phi_k - M'(1 - \alpha_{i,j,k}), \quad 1 \leq i \leq j \leq k \leq n$$

$$\phi_0 = 0,$$

$$\alpha_{i,j,k} \in \{0, 1\}, \quad 1 \leq i \leq j \leq k \leq n.$$

Definition

A solution to the bilevel lot-sizing problem is an extreme point solution if the Follower's part is an extreme point solution of ULSB with demands δ_t .

Assumption $g_t^2 + h_t^2 > 0$ for all $t = 1, \dots, n - 1$.

This assumption excludes that a solution with $r_t^2 s_t^2 > 0$ is optimal for the Follower.

Lemma

Under the assumption, if the bilevel optimization problem admits an optimal solution, then it admits an extreme point optimal solution.

Strengthening the formulations

- ▶ Bounds on variables

$Z_t = \min_{u \geq t+1} (p_u + \sum_{v=t}^{u-1} g_v)$ is the minimum cost incurred by backlogging a unit of production from period t to a later period.

$S_t = \min_{1 \leq u < t} (p_u + \sum_{v=u}^{t-1} h_v)$ is the minimum cost of stocking a unit production from an earlier period to t .

Lemma

The backlogged quantities r_t and the stock levels s_t in any extreme point optimal solution of ULSB satisfy

$$(Z_t - p_t)r_t \leq f_t, \text{ for } t = 1, \dots, n-1 \quad (\text{B})$$

$$(S_t - p_t)s_{t-1} \leq f_t, \text{ for } t = 1, \dots, n-1 \quad (\text{B})$$

- ▶ Cuts

Lemma

Extreme point solutions satisfy

$$s_{t-1}^2 \leq M(1 - y_t^2 - \beta_t^2), \quad t = 2, \dots, n \quad (\text{C})$$

Computational experiments

- ▶ For each $n \in \{10, 15, 20, 25, 30, 40, 50\}$, 100 random instances with parameters

$$\begin{aligned} f_t^1 &\leftarrow U[100, 200] & p_t^1 &\leftarrow U[1, 5] & h_t^1 &\leftarrow U[2, 20] & g_t^1 &\leftarrow U[4, 40] \\ f_t^2 &\leftarrow U[250, 1000] & p_t^2 &\leftarrow U[2, 10] & h_t^2 &\leftarrow U[1, 10] & g_t^2 &\leftarrow U[2, 20] \\ d_t^1 &\leftarrow U[0, 100] \end{aligned}$$

- ▶ Implementation in FICO XPRESS Mosel environment
- ▶ Tests performed on a workstation with Intel Xeon CPU (2.5 GHz), Linux operating system

Results

		opt	LB gap (%)		UB gap (%)		time (sec)	
			max	avg	max	avg	max	avg
MIP-1	$n = 10$	100	0.00	0.00	0.00	0.00	0.49	0.16
	$n = 20$	100	0.00	0.00	0.00	0.00	9.91	1.14
	$n = 30$	100	0.00	0.00	0.00	0.00	188.00	16.75
	$n = 40$	88	17.36	0.89	16.99	0.47	1200.44	329.86
	$n = 50$	53	15.09	2.91	12.38	1.88	1200.90	749.97
MIP-1B	$n = 10$	100	0.00	0.00	0.00	0.00	0.53	0.16
	$n = 20$	100	0.00	0.00	0.00	0.00	13.83	1.19
	$n = 30$	100	0.00	0.00	0.00	0.00	357.02	22.00
	$n = 40$	90	19.68	0.79	16.99	0.46	1200.30	322.78
	$n = 50$	59	14.41	2.51	11.85	1.94	1200.58	714.31
MIP-1C	$n = 10$	100	0.00	0.00	0.00	0.00	0.61	0.18
	$n = 20$	100	0.00	0.00	0.00	0.00	8.41	1.20
	$n = 30$	100	0.00	0.00	0.00	0.00	248.62	16.07
	$n = 40$	92	16.99	0.60	17.82	0.46	1200.30	248.81
	$n = 50$	51	15.19	2.77	11.81	1.88	1200.65	730.48
MIP-1CB	$n = 10$	100	0.00	0.00	0.00	0.00	0.76	0.27
	$n = 20$	100	0.00	0.00	0.00	0.00	8.82	1.54
	$n = 30$	100	0.00	0.00	0.00	0.00	158.35	14.74
	$n = 40$	96	17.02	0.46	16.99	0.44	1200.26	227.71
	$n = 50$	65	12.11	1.97	11.51	1.83	1200.55	645.94
MIP-2	$n = 10$	100	0.00	0.00	0.00	0.00	35.65	17.93
	$n = 20$	0	70.73	43.06	2974.59	1515.28	1200.00	1200.00
MIP-2B	$n = 10$	100	0.00	0.00	0.00	0.00	46.83	10.57
	$n = 20$	0	59.32	17.79	192.80	108.28	1200.00	1200.00