

# Two-Period Convex Hull Closures for Big Bucket Lot-Sizing Problems

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# Outline

- 1 Introduction
  - Problem Definition
  - Brief Review
- 2 Methodology
  - Methodology
  - Using Different Norms
  - Defining Two-Period Subproblems
- 3 Computations
  - Two-Period Problems
  - Multi-Period Problems
- 4 Basic Characteristics
- 5 Conclusions

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# Lot-Sizing: What's this about?

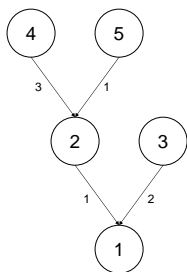
- “Items” to manufacture
- “Demands” to be satisfied
  - Forecasting (e.g., Peugeot)
  - Make-to-order (e.g., Airbus)
- “System limitations” such as capacities
- Decisions to be made each period
  - To produce or not to produce?
  - How much to produce?
  - How much to stock?
  - ...
  - **Decision factor:** Costs/revenues

# Motivation for Lot-Sizing

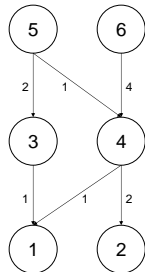
- \$\$\$!! Highly competitive markets for manufacturing companies
  - Significant area for cost improvement
  - Current automated systems even short of ensuring feasibility
- Lot-Sizing problems of realistic size/complexity too difficult for MIP solvers
  - Usually no room for expectation of optimality!
- Current polyhedral techniques usually limited to extensions of single-item techniques
  - Simply too naive to provide a thorough understanding of complicated problems
- **Question:** What can we do to obtain better lower bounds?

# Problem Description

- Multiple items and levels (BOM structure)
  - Assembly (a) or general (b) structures



(a)



(b)

- Demands
- Big-bucket capacities (items share resources)
- Extensions possible, e.g. overtime and backlogging
- Production plan minimizing total cost to be determined

# Problem Characteristics

- Decision variables (in each time period  $t$  for each item  $i$ )
  - Production setup decisions ( $y_t^i$ )
  - Production amounts ( $x_t^i$ )
  - Inventory held ( $s_t^i$ )
- Constraints
  - Flow conservation/demand satisfaction
    - Internal/external demand
  - Capacity limits (big bucket)
  - Setup-production relations

# Basic Formulation

$$\min \sum_{t=1}^{NT} \sum_{i=1}^{NI} f_t^i y_t^i + \sum_{t=1}^{NT} \sum_{i=1}^{NI} h_t^i s_t^i \quad (1)$$

$$\text{s.t. } x_t^i + s_{t-1}^i - s_t^i = d_t^i \quad t \in [1, NT], i \in \text{endp} \quad (2)$$

$$x_t^i + s_{t-1}^i - s_t^i = \sum_{j \in \delta(i)} r^{ij} x_t^j \quad t \in [1, NT], i \notin \text{endp} \quad (3)$$

$$\sum_{i=1}^{NI} (a_k^i x_t^i + ST_k^i y_t^i) \leq C_t^k \quad t \in [1, NT], k \in [1, NK] \quad (4)$$

$$x_t^i \leq M_t^i y_t^i \quad t \in [1, NT], i \in [1, NI] \quad (5)$$

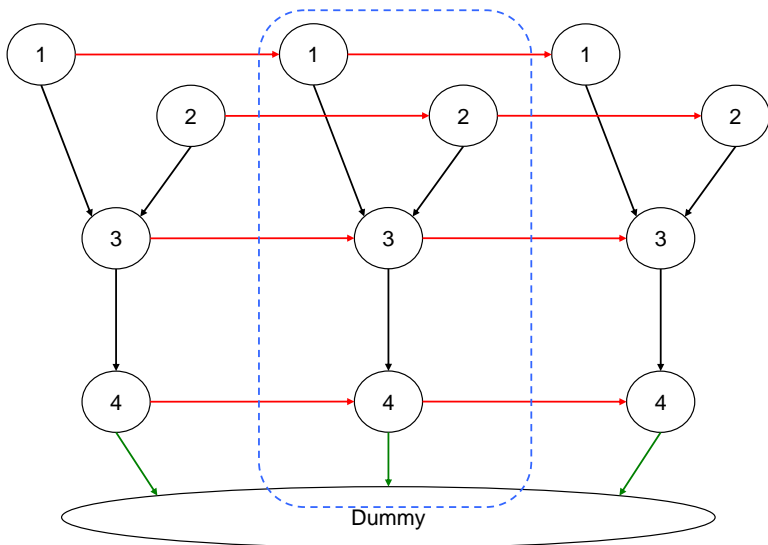
$$y \in \{0, 1\}^{NT \times NI} \quad (6)$$

$$x \geq 0 \quad (7)$$

$$s \geq 0 \quad (8)$$

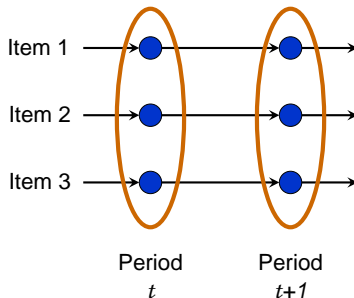


# As a Fixed Charge Network



# What do we know?

- Many of the test problems are challenging
- We do not have an adequate approximation of the convex hull of the **multi-item, single-machine, single-level capacitated problems!** (Akartunalı and Miller [2007])



- Generalizing the “bottleneck flow” model of Atamtürk and Muñoz [2004]

# The Model to Study

$$x_{t'}^i \leq \tilde{M}_{t'}^i y_{t'}^i \quad i = [1, \dots, NI], t' = 1, 2 \quad (9)$$

$$x_{t'}^i \leq \tilde{d}_{t'}^i y_{t'}^i + s^i \quad i = [1, \dots, NI], t' = 1, 2 \quad (10)$$

$$x_1^i + x_2^i \leq \tilde{d}_1^i y_1^i + \tilde{d}_2^i y_2^i + s^i \quad i = [1, \dots, NI] \quad (11)$$

$$x_1^i + x_2^i \leq \tilde{d}_1^i + s^i \quad i = [1, \dots, NI] \quad (12)$$

$$\sum_{i=1}^{NI} (a^i x_{t'}^i + ST^i y_{t'}^i) \leq \tilde{C}_{t'} \quad t' = 1, 2 \quad (13)$$

$$x, s \geq 0, y \in \{0, 1\}^{2 \times NI} \quad (14)$$

- Let  $X^{2PL} = \{(x, y, s) | (9) - (14)\}$

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# Two-Period Relaxation: Basics

- *Motivation 1:* Two-period problems are computationally easy to solve
  - Our experience from heuristic frameworks
- *Motivation 2:* There are recent promising results on closures
  - E.g. on MIR and Split Closures (Andersen, Cornuejols, Dash, Günlük, Lodi, ...)
- *Motivation 3:* 1-period problems are not strong enough
  - Miller, Nemhauser and Savelsbergh [2000], [2003]; Jans and Degraeve [2004]
- **Basic idea:** Generating cuts to separate an LPR solution over the convex hull of the two-period problems
  - *Advantage:* No need for information about the structure of two-period problems
  - *Caution:* But we want to understand the structure of two-period problems

# Separation Over the Two-Period Convex Hull

LPR of the original problem  $\Rightarrow$  A solution  $(\tilde{x}, \tilde{y}, \tilde{s})$

$L^1$  (Manhattan distance) problem:

$$z^1 = \min_{\Delta, \lambda} \sum_i [(\Delta_s^-)^i + \sum_{t'=1}^2 (\Delta_x^+)^i_{t'} + (\Delta_x^-)^i_{t'} + (\Delta_y^+)^i_{t'} + (\Delta_y^-)^i_{t'}]$$

$$\text{s.t. } \tilde{x}_{t'}^i = \sum_k \lambda_k (x_k)^i_{t'} + (\Delta_x^+)^i_{t'} - (\Delta_x^-)^i_{t'} \quad \forall i, t' = 1, 2 \quad (\alpha_{t'}^i)$$

$$\tilde{y}_{t'}^i = \sum_k \lambda_k (y_k)^i_{t'} + (\Delta_y^+)^i_{t'} - (\Delta_y^-)^i_{t'} \quad \forall i, t' = 1, 2 \quad (\beta_{t'}^i)$$

$$\tilde{s}^i \geq \sum_k \lambda_k (s_k)^i - (\Delta_s^-)^i \quad \forall i \quad (\gamma^i)$$

$$\sum_k \lambda_k \leq 1 \quad (\eta)$$

$$\lambda_k \geq 0, \Delta \geq 0$$

# Separation Over the Two-Period Convex Hull (cont'd)

The dual of the  $L^1$  problem:

$$\max_{\alpha, \beta, \gamma, \eta} \sum_{i=1}^{NI} \sum_{t'=1}^2 (\tilde{x}_{t'}^i \alpha_{t'}^i + \tilde{y}_{t'}^i \beta_{t'}^i) + \sum_{i=1}^{NI} \tilde{s}_k^i \gamma^i + \eta \quad (15)$$

$$\text{s.t.} \quad \sum_{i=1}^{NI} \sum_{t'=1}^2 ((x_k)_{t'}^i \alpha_{t'}^i + (y_k)_{t'}^i \beta_{t'}^i) + \sum_{i=1}^{NI} (s_k)^i \gamma^i + \eta \leq 0 \quad \forall k \quad (16)$$

$$-1 \leq \alpha_{t'}^i \leq 1 \quad \forall i, t' \quad (17)$$

$$-1 \leq \beta_{t'}^i \leq 1 \quad \forall i, t' \quad (18)$$

$$-1 \leq \gamma^i \leq 0 \quad \forall i \quad (19)$$

$$\eta \leq 0 \quad (20)$$

# Separation Over the Two-Period Convex Hull (cont'd)

## Theorem

Let  $z^1 > 0$  for  $(\tilde{x}, \tilde{y}, \tilde{s})$ , and  $(\bar{\alpha}, \bar{\beta}, \bar{\gamma}, \bar{\eta})$  be optimal dual values. Then,

$$\sum_{i=1}^{NI} \sum_{t'=1}^2 (\bar{\alpha}_{t'}^i x_{t'}^i + \bar{\beta}_{t'}^i y_{t'}^i) + \sum_i \bar{\gamma}^i s^i + \bar{\eta} \leq 0 \quad (21)$$

is a valid inequality for  $\text{conv}(X^{2PL})$  that cuts off  $(\tilde{x}, \tilde{y}, \tilde{s})$ .

## Proof.

Validity: Using (16),  $\bar{\gamma} \leq 0$  and  $\lambda \geq 0$ .

Violation for  $(\tilde{x}, \tilde{y}, \tilde{s})$ : Using (15) □



# Generating Extreme Points for Separation

- How to generate  $(x_k, y_k, s_k)$ ?
  - Using column generation
  - Solve the pricing problem using the optimal  $(\bar{\alpha}, \bar{\beta}, \bar{\gamma}, \bar{\eta})$ :

$$\begin{aligned} \max_{x, y, s} z_P &= \sum_i \sum_{t'=1}^2 (\bar{\alpha}_{t'}^i x_{t'}^i + \bar{\beta}_{t'}^i y_{t'}^i) + \sum_i \bar{\gamma}^i s^i + \bar{\eta} \\ \text{s.t. } (x, y, s) &\in X^{2PL} \end{aligned}$$

- If  $z_P > 0$ , then the solution is an extreme point of  $X^{2PL}$ ;  
otherwise, generating extreme points is done

# Separation Algorithm

**repeat**

Solve the distance problem for  $\text{conv}(X^{2PL})$

**if**  $z^1 = 0$  **then** break

**else** Solve column generation problem

**if**  $z_P \leq 0$  **then** break

**else** Add new extreme point

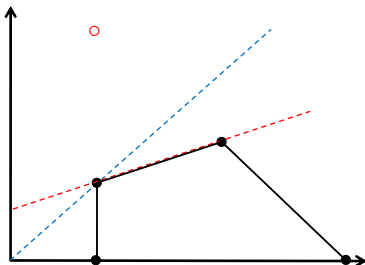
**until**  $z^1 = 0$  **or**  $z_P \leq 0$

**if**  $z^1 = 0$  **then**  $(\tilde{x}, \tilde{y}, \tilde{s}) \in \text{conv}(X^{2PL})$

**else** Add the violated cut (21)

# Separation Over Two-Period Convex Hull: Other Norms

- Different norms
  - $\Rightarrow$  Different convergence
  - $\Rightarrow$  Different cuts
- Example:  $K = \{(1, 0), (1, 1), (2.5, 1.5), (4, 0)\}$ ,  $\tilde{x} = (1, 3)$ .
  - $L^1$ : Distance  $z_1 = 2$ ; cut  $-x_1 + x_2 \leq 0$ .
  - $L^\infty$ : Distance  $z_\infty = 1.5$ ; cut  $-0.25x_1 + 0.75x_2 - 0.5 \leq 0$ .
  - $L^2$ : Distance  $z_2 = \sqrt{3.6}$ ; cut  $1.2x_1 - 3.6x_2 + 2.4 \geq 0$ .



# Separation Over Two-Period Convex Hull: Other Norms

- $L^\infty$  almost identical
  - Still a linear model
    - Similar to  $L^1$  problem
    - Fewer variables
  - Methodology and theory remains almost identical
- $L^2$  (Euclidean distance) trickier
  - PSD matrix  $\Rightarrow$  use of QP strong duality
  - Details to follow ...
  - *Remark:* Current QP solvers are almost as fast as LP solvers
- Combinations of different norms?
  - More on this in computational results ...

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- Combinations of different norms?
  - More on this in computational results ...

# Using Euclidean Distance ( $L^2$ )

$$z^2 = \min_{\Delta, \lambda} \sum_i \left[ [(\Delta_s)^i]^2 + \sum_{t'=1}^2 ([(\Delta_x)_{t'}^i]^2 + [(\Delta_y)_{t'}^i]^2) \right]$$

$$\text{s.t. } \tilde{x}_{t'}^i = \sum_k \lambda_k (x_k)_{t'}^i + (\Delta_x)_{t'}^i \quad \forall i, t' = 1, 2 \quad (\alpha_{t'}^i)$$

$$\tilde{y}_{t'}^i = \sum_k \lambda_k (y_k)_{t'}^i + (\Delta_y)_{t'}^i \quad \forall i, t' = 1, 2 \quad (\beta_{t'}^i)$$

$$\tilde{s}^i \geq \sum_k \lambda_k (s_k)^i - (\Delta_s)^i \quad \forall i \quad (\gamma^i)$$

$$\sum_k \lambda_k \leq 1 \quad (\eta)$$

$$\lambda_k \geq 0, \Delta_s \geq 0, \Delta_x, \Delta_y \text{ free}$$

# Using Euclidean Distance: Dual

$$z_D = \max_{\Delta, \alpha, \beta, \gamma} - \sum_i \left[ [(\Delta_s)^i]^2 + \sum_{t'=1}^2 [(\Delta_x)_{t'}^i]^2 + [(\Delta_y)_{t'}^i]^2 \right]$$

$$- \left( \sum_{i=1}^{NI} \sum_{t'=1}^2 (\tilde{x}_{t'}^i \alpha_{t'}^i + \tilde{y}_{t'}^i \beta_{t'}^i) + \sum_{i=1}^{NI} \tilde{s}^i \gamma^i + \eta \right)$$

$$\text{s.t.} \quad \sum_{i=1}^{NI} \sum_{t'=1}^2 ((x_k)_{t'}^i \alpha_{t'}^i + (y_k)_{t'}^i \beta_{t'}^i) + \sum_{i=1}^{NI} (s_k)^i \gamma^i + \eta \geq 0 \quad \forall k$$

$$\alpha_{t'}^i = -2(\Delta_x)_{t'}^i \quad \forall i, t'$$

$$\beta_{t'}^i = -2(\Delta_y)_{t'}^i \quad \forall i, t'$$

$$-\gamma^i \geq -2(\Delta_s)^i \quad \forall i$$

$$\gamma \geq 0, \eta \geq 0, \Delta_s \geq 0, \alpha, \beta, \Delta_x, \Delta_y \text{ free}$$



# Using Euclidean Distance: Theory

## Theorem

Let  $z^2 > 0$  for  $(\tilde{x}, \tilde{y}, \tilde{s})$ , with optimal primal values  $(\bar{\Delta}_x, \bar{\Delta}_y, \bar{\Delta}_s, \bar{\lambda})$ , and  $(\bar{\alpha}, \bar{\beta}, \bar{\gamma}, \bar{\eta})$  be the associated optimal dual values. Then,

$$\sum_i \sum_{t'=1}^2 (\bar{\alpha}_{t'}^i x_{t'}^i + \bar{\beta}_{t'}^i y_{t'}^i) + \sum_i \bar{\gamma}^i s^i + \bar{\eta} \geq 0 \quad (22)$$

is a valid inequality for  $\text{conv}(X^{2PL})$  that cuts off  $(\tilde{x}, \tilde{y}, \tilde{s})$ .

## Proof.

Using a similar approach to the previous proof and also using the strong duality theorem for QP. □

# Defining Two-Period Subproblems

- **Question 1:** On which two periods to run the separation?
  - We can look at all the two-period problems ( $NT - 1$  of them)
- **Question 2:** Which period's stock is represented by  $s^i$ ?
  - Let  $\phi(i) \in [t + 1, \dots, NT]$  be the horizon parameter for each  $i$
  - Obvious choice:  $t + 1$ , i.e.,  $s^i = s_{t+1}^i$
  - Then, parameters are defined as follows ( $\forall i, t' = 1, 2$ ):
    - $\tilde{M}_{t'}^i = M_{t+t'-1}^i, \tilde{C}_{t'}^i = C_{t+t'-1}^i$
    - $\tilde{d}_{t'}^i = d_{t+t'-1, t+1}^i$ , i.e.,  $\tilde{d}_1^i = d_{12}^i$  and  $\tilde{d}_2^i = d_2^i$ .
- **Observation 1:** If a number of periods following  $t + 1$  have no setups, their demands should be incorporated
- **Observation 2:** If a setup occurs after  $t + 1$ ,  $(\ell, S)$  inequalities will be weakened if that period's demand is in

# Two-Period Convex Hull Closure Framework

- Following Miller, Nemhauser, Savelsbergh (2000)

$$\phi(i) = \max\{t' \mid t' \geq t + 1, \sum_{t''=t+1}^{t'} y_{t''}^i \leq y_{t+1}^i + \Theta\}$$

where  $\Theta \in (0, 1]$  is a random number

- Let  $X_t^{2PL}$  be  $X_t^{2PL}(\phi(1), \phi(2), \dots, \phi(NI))$

Solve LPR of the original problem

→  $(\tilde{x}, \tilde{y}, \tilde{s})$

**for**  $t=1$  **to**  $NT-1$

Define  $X_t^{2PL}$

Apply two-period convex hull separation algorithm

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# Computational Results: Two-Period Problems

- *2PCLS* instances: 20 problems with two periods only and with two to six items
  - **cdd** might provide the full description of the convex hull
    - Generate all the extreme points and rays of the LPR
    - Eliminate all the fractional extreme points
    - Using these integral extreme points, generate all the facets of the integral polyhedron
  - The more items share a resource, the more the structure tends to resemble that of an uncapacitated problem
- The separation algorithm implemented in Mosel (Mosel version 2.4.0, Xpress 2008A package)
- XLP based on a strong formulation using all violated  $(\ell, S)$  inequalities (Barany et al. [1984])

## Computational Results: Two-Period Problems (cont'd)

Instance	NI	XLP	IP	# cuts ( $L^1$ )	# cuts ( $L^\infty$ )	# cuts ( $L^2$ )
2pcls01	3	17.033	25	11	8	17
2pcls02	3	12.6253	19	13	7	7
2pcls03	3	76.5345	104	5	3	1
2pcls04	2	14.7674	19	4	2	1
2pcls05	3	38.39	52	8	6	4
2pcls06	3	117.375	173	5	6	5
2pcls07	2	36.5	43	2	1	1
2pcls08	2	21.45	26	7	2	2
2pcls09	2	129	153	2	3	3
2pcls10	3	17.6539	24	1	3	1

## Computational Results: Two-Period Problems (cont'd)

Instance	NI	XLP	IP	# cuts ( $L^1$ )	# cuts ( $L^\infty$ )	# cuts ( $L^2$ )
2pcls11	3	71.7209	102	4	1	1
2pcls12	3	46.68	69	4	1	2
2pcls13	4	85.6256	113	7	7	9
2pcls14	4	70.2961	81	6	8	5
2pcls15	4	54.1848	74	6	3	1
2pcls16	4	34.0844	39	6	7	4
2pcls17	5	164.858	211	39	19	14
2pcls18	5	57.0825	97	34	10	6
2pcls19	6	115.131	150	11	6	1
2pcls20	6	59.2412	89	34	11	5

## Computational Results: Two-Period Problems (cont'd)

Instance	$L^\infty$		$L^2$	
	# cuts	# cols/ite	# cuts	# cols/ite
2pcls01	8	41.44	17	27.06
2pcls02	7	43.88	7	24.38
2pcls03	3	26.25	1	14
2pcls04	2	10	1	25
2pcls05	6	43.14	4	20.8
2pcls06	6	43.71	5	20.17
2pcls07	1	15	1	7
2pcls08	2	17.67	2	8.67
2pcls09	3	19.5	3	8.75
2pcls10	3	27.5	1	14
2pcls13	7	72.75	9	35.27
2pcls17	19	135.35	14	63.73
2pcls20	11	137.83	5	64.5



# Computational Results: Multi-Period Problems

*tr6-15 detailed results (30 iterations):*

	$L^1$		$L^2$		
	lim=100	lim=150	lim=100	lim=150	lim=150
	$\phi(i)$	$\phi(i)$	$t + 1$	$t + 1$	$\phi(i)$
2PL	37,234.6	37,298.8	37,306.7	37,306.8	37,331.2

*Trigeiro instances results:*

	tr6-15	tr6-30	tr12-15	tr12-30
XLP	37,201	60,946	73,848	130,177
2PL	37,364	61,096	73,962	130,350
OPT	37,721	61,746	74,634	130,596
Gap closed	31.35%	18.75%	14.50%	41.29%

# Computational Results: Multi-Period Problems (cont'd)

TDS instances *preliminary* results with  $L^\infty$  approach:

	BK511131	BK511141	BK521131	BK521142
XLP	92,602	125,307	92,350	124,988
2PL	117,540	148,936	115,071	139,118
Best Sol.	120,303	162,629	118,217	153,805
Gap was	29.91%	29.78%	28.01%	23.06%
Gap now	2.35%	9.19%	2.73%	10.56%
	BK512131	BK512132	BK521132	BK522142
XLP	90,733	90,814	94,257	119,559
2PL	110,125	110,546	114,676	133,461
Best Sol.	113,536	112,809	117,423	148,471
Gap was	25.13%	24.22%	24.58%	24.18%
Gap now	3.10%	2.05%	2.40%	11.25%



# Two-Period Model: Assumptions

- This section is far from complete!
- **Assumptions:**
  - $0 < \tilde{M}_t^i, \forall t \in \{1, \dots, NT\}, \forall i \in \{1, \dots, NI\}$ 
    - Otherwise  $x_t^i = 0$
  - $ST^i < \tilde{C}_t, \forall t \in \{1, \dots, NT\}, \forall i \in \{1, \dots, NI\}$ 
    - Otherwise  $y_t^i = 0, x_t^i = 0$

## Proposition

$\text{conv}(X^{2PL})$  is full-dimensional.

# Two-Period Model: Trivial Facets

## Proposition

The following inequalities are facet-defining for  $\text{conv}(X^{2PL})$ :

- 1  $x_t^i \geq 0, t \in \{1, 2\}, i \in \{1, \dots, NI\}$
- 2  $y_t^i \leq 1, t \in \{1, 2\}, i \in \{1, \dots, NI\}$  if  $ST^{i'} < \tilde{C}_t - ST^i$   
 $\forall i' \in \{1, \dots, NI\} \setminus \{i\}$
- 3  $x_t^i \leq \tilde{d}_t^i y_t^i + s^i, t \in \{1, 2\}, i \in \{1, \dots, NI\}$  if  $a^i \tilde{d}_t^i + ST^i \leq \tilde{C}_t$

# Two-Period Model: Less-Trivial Facets

- More to discover - still in progress
  - Usual suspects: Inequalities based on covers (Padberg et al. (1984), Goemans (1989), Miller et al. (2002), Atamtürk and Muñoz (2004), ...)

## Proposition

$$x_1^i + x_2^i \leq \tilde{d}_1^i y_1^i + \tilde{d}_2^i + s^i, \forall i \in \{1, \dots, NI\}$$

is facet-defining if  $a^i \tilde{d}_t^i + ST^i < \tilde{C}_t \forall t \in \{1, 2\}$ .

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# Conclusions

- Study of a stronger relaxation
  - A new framework independent from defining families of valid inequalities or reformulations a priori, although expected output is to define new valid inequalities using the results from the framework
  - To our knowledge, this is an original approach in lot-sizing literature
- Different norms useful to generate cuts and improve lower bounds significantly
  - Euclidean and  $L^\infty$  approaches computationally much more efficient than Manhattan approach
    - Observed both on the efficiency of cuts and on the number of extreme points generated in column generation before termination



# Ongoing Work

- Completing computational results on realistic size problems
  - Resolve computational issues
- Polyhedral analysis of the two-period relaxation
  - Careful analysis of the inequalities generated by the framework and the facets from **cdd**
  - Significant potential to identify new families of valid inequalities