
Primal-dual methods for nonconvex problems

Claudia Sagastizábal

IMECC-UNICAMP Brazil

joint with M. Cordova and W. de Oliveira

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Motivation: UC problems

Two power plants



$$y_T \in \mathcal{S}_T$$
$$\langle \mathcal{F}, x \rangle + f_T(y_T)$$
$$x \in \{0, 1\} \text{ and } y_T \leq x y^{up}$$



$$y_H \in \mathcal{S}_H$$
$$f_H(y_H)$$

$$y_T + y_H = d$$

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Two power plants (**three** in fact)



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$$y_H \in \mathcal{S}_H$$
$$f_H(y_H)$$

$$y_T + y_H = d$$

net demand, subtracting the WIND



Stylized Brazilian UC problem (2020)

$$\left\{ \begin{array}{ll} \min & \langle \mathcal{F}, x \rangle + f(y) \\ \text{s.t.} & x \in \{0, 1\}, y \geq 0 \\ & y \in \mathcal{S} \\ & By = d \\ & Cy \leq e \\ & x y_{low} \leq y \leq x y^{up} \end{array} \right. \quad \left\{ \begin{array}{l} \text{water balance} \\ \text{demand} \\ \text{flow limits} \\ \text{generation only} \\ \text{if switched on} \end{array} \right.$$

- ▶ f is convex, linear or quadratic

Real-life UC problem

Dessem com UCT: Formulação matemática



$$\min \sum_{t=1}^T \sum_{i=1}^{NUT} \alpha_i (g_i^t) + S_i^t + \alpha^T (v^T)$$

s.a.

Demanda

$$\left. \begin{aligned} \sum_{j \in A_i} g_j^t + \sum_{j \in B_i} g_h^j + \sum_{j \in C_i} (In_{j,t}^t - In_{j,t-1}^t) &= D_i^t & i = 1, \dots, NS, t = 1, \dots, T \\ In_{i,j}^t &\leq \overline{In}_{i,j} & i, j = 1, \dots, NS, t = 1, \dots, T \end{aligned} \right\} E$$

Conservação da água

FPHA

Restrições operativas

$$\left. \begin{aligned} V_i^t &= V_i^{t-1} + I_i^t - (Q_i^t + S_i^t) + \sum_{j \in M_i} (Q_j^t + S_j^t) \\ g_h^t &= FPH(V_i^t, Q_i^t, S_i^t) \\ \underline{V}_i &\leq V_i^t \leq \overline{V}_i, \quad \underline{Q}_i \leq Q_i^t \leq \overline{Q}_i, \quad \underline{g}_h^t \leq g_h^t \leq \overline{g}_h^t \end{aligned} \right\} i = 1, \dots, NH, t = 1, \dots, T \quad H$$

Restrições Térmicas:

Unit Commitment

$$\left. \begin{aligned} g_{t_i} \cdot u_i^t &\leq g_{t_i}^t \leq \overline{g}_{t_i} \cdot u_i^t & |g_{t_i}^t - g_{t_i}^{t-1}| &\leq R \\ \sum_{k=t}^{t+Ton_i-1} u_i^k &\geq Ton_i \cdot (u_i^t - u_i^{t-1}) & Cs_i (u_i^{t-1} - u_i^t) &\leq S_i^t \\ \sum_{k=t}^{t+Toff_i-1} (1 - u_i^k) &\geq Toff_i \cdot (u_i^{t-1} - u_i^t) & u_i^t &\in \{0,1\} \end{aligned} \right\} i = 1, \dots, NUT, t = 1, \dots, T \quad T$$

Real-life UC problem

	COM UCT				SEM UCT	
	VAR.	VAR. INT.	REST.	REST. INT.	VAR.	REST.
1 DIA	327649	83121	433120	163520	327649	269600
2 DIAS	349413	80979	434843	159142	349413	275701
3 DIAS	375835	92831	490513	182545	375835	307968
4 DIAS	402171	86753	481152	170721	402171	310431
5 DIAS	429323	93913	512149	184730	429323	327419
6 DIAS	453110	111214	589245	218656	453110	370589
7 DIAS	476453	109717	590785	215853	476453	374932
GERAL	400897	93586	501438	184063	400897	317375

TABELA: Quantidade média de variáveis e restrições

Real-life UC problem

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1 DIA	327649	83121	433120	163520	327649	269600
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TABELA: Quantidade média de variáveis e restrições

for the deterministic formulation...

Stylized UC problem: stochastic version

$$\left\{ \begin{array}{ll} \min & \langle \mathcal{F}, x \rangle + \mathbb{E}[f(y(\omega))] \\ \text{s.t.} & x \in \{0, 1\}, \quad y(\omega) \geq 0 \\ & y(\omega) \in \mathcal{S}(\omega) \\ & By(\omega) = d(\omega) \\ & Cy(\omega) \leq e(\omega) \\ & x y_{low} \leq y(\omega) \leq x y^{up} \end{array} \right. \quad \left\{ \begin{array}{l} \text{water balance} \\ \text{demand} \\ \text{flow limits} \\ \text{generation only} \\ \text{if switched on} \\ \text{ramps} \end{array} \right.$$

- ▶ f is convex, linear or quadratic
- ▶ d and e have uncertain components (wind and inflows)

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Interested in preserving separability along technologies: Lagrangian relaxation

Lagrangian relaxation 101

$$\left\{ \begin{array}{l} \min \quad f_T(x, y_T) + f_H(y_H) \\ \text{s.t.} \quad x \in \{0, 1\}, y_T \in \mathcal{S}_T \\ \quad \quad y_T \leq x y^{up} \\ \quad \quad y_H \in \mathcal{S}_H \\ \quad \quad y_T + y_H = d \quad \leftrightarrow \lambda \end{array} \right.$$

 \implies

$$L(x, y, \lambda) = f_T(x, y_T) + f_H(y_H) + \langle \lambda, d - y_T - y_H \rangle$$

Lagrangian relaxation 101

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\Updownarrow

$$\begin{aligned} L(x, y, \lambda) &= f_T(x, y_T) + f_H(y_H) \\ &\quad + \langle \lambda, d - y_T - y_H \rangle \\ &= L_T(x, y_T, \lambda) \\ &\quad + L_H(y_H, \lambda) \\ &\quad + \langle \lambda, d \rangle \end{aligned}$$

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DUAL: maxmin replaces minmax

$$\left\{ \begin{array}{l} \max_{\lambda} \min_{x, y} \quad L(x, y, \lambda) \\ \text{s.t.} \quad x \in \{0, 1\}, y_T \in \mathcal{S}_T \\ \quad \quad y_T \leq x y^{up} \\ \quad \quad y_H \in \mathcal{S}_H \end{array} \right.$$

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(duality gap)

Lagrangian relaxation - 2nd version

$$\left\{ \begin{array}{l} \min \quad f_T(x, z_T) + f_H(y_H) \\ \text{s.t.} \quad x \in \{0, 1\}, z_T \in \mathcal{S}_T \\ \quad \quad z_T \leq x y^{up} \\ \quad \quad y_H \in \mathcal{S}_H \\ \quad \quad y_T + y_H = d \\ \quad \quad y_T - z_T = 0 \quad \leftrightarrow \lambda \end{array} \right.$$

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$$\begin{aligned} L(x, y, z, \lambda) &= f_T(x, z_T) + f_H(y_H) \\ &\quad + \langle \lambda, y_T - z_T \rangle \\ &= L_T(x, z_T, \lambda) \\ &\quad + L_{HT}(y_T, y_H, \lambda) \\ &\quad + \langle \lambda, d \rangle \end{aligned}$$

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$$\implies = L_T(x, z_T, \lambda) + L_{HT}(y_T, y_H, \lambda) + \langle \lambda, d \rangle$$

DUAL: maxmin replaces minmax

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$$\text{for } \psi_T(\lambda) := \left\{ \begin{array}{l} \min \quad L_T(x, z_T, \lambda) \\ \quad \quad x \in \{0, 1\} \\ \quad \quad z_T \in \mathcal{S}_T \\ \quad \quad z_T \leq x y^{up} \end{array} \right.$$

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$$\Rightarrow L_T(x, z_T, \lambda) + L_{HT}(y_T, y_H, \lambda) + \langle \lambda, d \rangle$$

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Lagrangian relaxation - 2nd version

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(duality gap)

$$\text{for } \psi_{HT}(\lambda) := \left\{ \begin{array}{l} \min \quad L_{HT}(y_T, y_H, \lambda) \\ \quad \quad y_H \in \mathcal{S}_H \\ \quad \quad y_T + y_H = d \end{array} \right.$$

Lagrangian relaxation - 3rd version

$$\left\{ \begin{array}{l} \min \quad f_T(x, z_T) + f_H(y_H) \\ \text{s.t.} \quad x \in \{0, 1\}, z_T \in \mathcal{S}_T \\ \quad \quad z_T \leq x y^{up} \\ \quad \quad y_H \in \mathcal{S}_H \\ \quad \quad y_T + y_H = d \\ \quad \quad y_T - z_T = 0 \end{array} \right. \quad \leftrightarrow \lambda$$

$$\text{either } \left\{ \begin{array}{l} \min \quad f(p) \\ \text{s.t.} \quad p \in \mathcal{S} \\ \quad \quad F(p) = 0 \end{array} \right. \quad \leftrightarrow \lambda$$

$p=(x,y,z)$

Lagrangian relaxation - 3rd version

$$\text{either } \begin{cases} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \end{cases} \quad \begin{array}{l} p=(x,y,z) \\ \leftrightarrow \lambda \end{array}$$

Lagrangian relaxation - 3rd version

$$\text{either } \begin{cases} \min_{p=(x,y,z)} & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \leftrightarrow \lambda \end{cases}$$

$$\text{or } \begin{cases} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \leftrightarrow \lambda \\ & \sigma(F(p)) \leq 0 \leftrightarrow \rho \in \mathbb{R} \end{cases}$$

$$\begin{aligned} \sigma(t) &= \|t\| \text{ or } \frac{1}{2}\|t\|^2 \\ \sigma(0) &= 0 \end{aligned}$$

Lagrangian relaxation - 3rd version

relation?

$$\text{either } \begin{cases} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \end{cases} \begin{array}{l} p=(x,y,z) \\ \\ \leftrightarrow \lambda \end{array}$$

$$\text{or } \begin{cases} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \\ & \sigma(F(p)) \leq 0 \end{cases} \begin{array}{l} \\ \\ \leftrightarrow \lambda \\ \leftrightarrow \rho \end{array}$$

$$\sigma(t) = \|t\| \text{ or } \frac{1}{2}\|t\|^2 \\ \sigma(0) = 0$$

Lagrangian relaxation - 3rd version

OC1: $\exists(\bar{p}, \bar{\lambda}) \in \mathcal{S} \times \mathbb{R}^m :$
 $F(\bar{p}) = 0$

and

$$0 \in f'(\bar{p}) + N_P(\bar{p}) + F'(\bar{p})\bar{\lambda}$$

either $\left\{ \begin{array}{l} \min_{p=(x,y,z)} f(p) \\ \text{s.t. } p \in \mathcal{S} \\ F(p) = 0 \end{array} \right. \leftrightarrow \lambda$

Lagrangian relaxation - 3rd version

OC1: $\exists(\bar{p}, \bar{\lambda}) \in \mathcal{S} \times \mathbb{R}^m :$
 $F(\bar{p}) = 0$

and

$$0 \in f'(\bar{p}) + N_{\mathcal{P}}(\bar{p}) + F'(\bar{p})\bar{\lambda}$$

$$\text{either } \begin{cases} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \end{cases} \begin{array}{l} p=(x,y,z) \\ \leftrightarrow \lambda \end{array}$$

$$\text{or } \begin{cases} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \\ & \sigma(F(p)) \leq 0 \end{cases} \begin{array}{l} \leftrightarrow \lambda \\ \leftrightarrow \rho \end{array}$$

$$\sigma(t) = \|t\| \text{ or } \frac{1}{2}\|t\|^2$$
$$\sigma(0) = 0$$

Lagrangian relaxation - 3rd version

OC1: $\exists(\bar{p}, \bar{\lambda}) \in \mathcal{S} \times \mathbb{R}^m :$
 $F(\bar{p}) = 0$

and

$$0 \in f'(\bar{p}) + N_P(\bar{p}) + F'(\bar{p})\bar{\lambda}$$

OC2: $\exists(\bar{p}, \bar{\lambda}, \bar{\rho}) \in \mathcal{S} \times \mathbb{R}^m \times \mathbb{R}_+ :$
 $F(\bar{p}) = 0, \quad \sigma(F(\bar{p})) \leq 0$

and

$$0 \in f'(\bar{p}) + N_P(\bar{p}) + F'(\bar{p})\bar{\lambda} \\ + \bar{\rho} F'(\bar{p})\sigma(F(\bar{p}))$$

either $\left\{ \begin{array}{l} \min_{p=(x,y,z)} f(p) \\ \text{s.t. } p \in \mathcal{S} \\ F(p) = 0 \end{array} \right\} \leftrightarrow \lambda$

or $\left\{ \begin{array}{l} \min f(p) \\ \text{s.t. } p \in \mathcal{S} \\ F(p) = 0 \leftrightarrow \lambda \\ \sigma(F(p)) \leq 0 \leftrightarrow \rho \end{array} \right.$

$$\sigma(t) = \|t\| \text{ or } \frac{1}{2}\|t\|^2 \\ \sigma(0) = 0$$

Lagrangian relaxation - 3rd version

OC1: $\exists(\bar{p}, \bar{\lambda}) \in \mathcal{S} \times \mathbb{R}^m :$
 $F(\bar{p}) = 0$

and

$$0 \in f'(\bar{p}) + N_P(\bar{p}) + F'(\bar{p})\bar{\lambda}$$

OC2: $\exists(\bar{p}, \bar{\lambda}, \bar{\rho}) \in \mathcal{S} \times \mathbb{R}^m \times \mathbb{R}_+ :$
 $F(\bar{p}) = 0, \quad \sigma(F(\bar{p})) \leq 0$

and

$$0 \in f'(\bar{p}) + N_P(\bar{p}) + F'(\bar{p})\bar{\lambda} \\ + \bar{\rho} F'(\bar{p})\sigma(F(\bar{p}))$$

either $\begin{cases} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \end{cases} \leftrightarrow \lambda$

$p=(x,y,z)$

or $\begin{cases} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \\ & \sigma(F(p)) \leq 0 \end{cases} \leftrightarrow \lambda, \rho$

$$\sigma(t) = \|t\| \text{ or } \frac{1}{2}\|t\|^2 \\ \sigma(0) = 0$$

Lagrangian relaxation - 3rd version

$$\left\{ \begin{array}{ll} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \quad \leftrightarrow \lambda \\ & \sigma(F(p)) \leq 0 \quad \leftrightarrow \rho \end{array} \right.$$

Lagrangian relaxation - 3rd version

$$\left\{ \begin{array}{ll} \min & f(p) \\ \text{s.t.} & p \in \mathcal{S} \\ & F(p) = 0 \quad \leftrightarrow \lambda \\ & \sigma(F(p)) \leq 0 \quad \leftrightarrow \rho \end{array} \right. \implies L(p, \lambda, \rho) = f(p) + \langle \lambda, F(p) \rangle + \rho \sigma(F(p))$$

Lagrangian relaxation - 3rd version

$$\left\{ \begin{array}{l} \min f(p) \\ \text{s.t. } p \in \mathcal{S} \\ F(p) = 0 \quad \leftrightarrow \lambda \\ \sigma(F(p)) \leq 0 \quad \leftrightarrow \rho \end{array} \right. \Rightarrow L(p, \lambda, \rho) = f(p) + \langle \lambda, F(p) \rangle + \rho \sigma(F(p))$$

DUAL: maxmin replaces minmax

$$\left\{ \begin{array}{l} \max_{\lambda, \rho} \min_p L(p, \lambda, \rho) \\ \text{s.t. } p \in \mathcal{S} \end{array} \right.$$

Lagrangian relaxation - 3rd version

$$\left\{ \begin{array}{l} \min f(p) \\ \text{s.t. } p \in \mathcal{S} \\ F(p) = 0 \\ \sigma(F(p)) \leq 0 \end{array} \right. \begin{array}{l} \Leftrightarrow \lambda \\ \Leftrightarrow \rho \end{array} \Rightarrow L(p, \lambda, \rho) = f(p) + \langle \lambda, F(p) \rangle + \rho \sigma(F(p))$$

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$$\left\{ \begin{array}{l} \max_{\lambda, \rho} \min_p L(p, \lambda, \rho) \\ \text{s.t. } p \in \mathcal{S} \end{array} \right. \Rightarrow \max_{\lambda} \psi(\lambda, \rho) \quad \text{for } \psi(\lambda, \rho) := \min_{p \in \mathcal{S}} L(p, \lambda, \rho)$$

NO duality gap

Lagrangian relaxation - 3rd version

$$\left\{ \begin{array}{l} \min f(p) \\ \text{s.t. } p \in \mathcal{S} \\ F(p) = 0 \\ \sigma(F(p)) \leq 0 \end{array} \right. \begin{array}{l} \Leftrightarrow \lambda \\ \Leftrightarrow \rho \end{array} \Rightarrow L(p, \lambda, \rho) = f(p) + \langle \lambda, F(p) \rangle + \rho \sigma(F(p))$$

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NO duality gap

Sharp/Proximal Lagrangian

$$\sigma(t) = \|t\| \text{ or } \frac{1}{2} \|t\|^2$$

Lagrangian relaxation - 3rd version

$$\left\{ \begin{array}{l} \min f(p) \\ \text{s.t. } p \in \mathcal{S} \\ F(p) = 0 \\ \sigma(F(p)) \leq 0 \end{array} \right. \begin{array}{l} \Leftrightarrow \lambda \\ \Leftrightarrow \rho \end{array} \Rightarrow L(p, \lambda, \rho) = f(p) + \langle \lambda, F(p) \rangle + \rho \sigma(F(p))$$

DUAL: maxmin replaces minmax

$$\left\{ \begin{array}{l} \max_{\lambda, \rho} \min_p L(p, \lambda, \rho) \\ \text{s.t. } p \in \mathcal{S} \end{array} \right. \Rightarrow \max_{\lambda} \psi(\lambda, \rho) \quad \text{for } \psi(\lambda, \rho) := \min_{p \in \mathcal{S}} L(p, \lambda, \rho)$$

NO duality gap

Sharp/Proximal Lagrangian

NOTE: ρ is a dual variable

$$\sigma(t) = \|t\| \text{ or } \frac{1}{2} \|t\|^2$$

GAL: Generalized Augmented Lagrangians

Chapter 11K [RW99], on Nonconvex Duality

$\mathcal{D}(p, v, w) := f(p) : F(p) = v, \sigma(F(p)) \leq w$ is level-bounded in $p \in \mathcal{S}$
locally uniformly in (v, w)

Theorem 11.59 (duality without convexity)

- ▶ Optimal solutions to the primal and dual problems, resp. \bar{p} and $(\bar{\lambda}, \bar{\rho})$, are saddle points of the Lagrangian

$$\left. \begin{array}{l} \bar{p} \text{ minimizes the primal} \\ (\bar{\lambda}, \bar{\rho}) \text{ maximizes the dual} \end{array} \right\} \iff \inf_{\rho} L(p, \bar{\lambda}, \bar{\rho}) = L(\bar{p}, \bar{\lambda}, \bar{\rho}) = \sup_{\lambda, \rho} L(\bar{p}, \lambda, \rho)$$

- ▶ Exact penalty $\iff \exists (\bar{\lambda}, \bar{\rho}) \in \arg \max \psi(\lambda, \rho)$

\implies no need to drive $\rho \rightarrow \infty$, as in the augmented Lagrangian

GAL: algorithmic scheme

$$\left. \begin{array}{l} \bar{p} \quad \text{minimizes the primal} \\ (\bar{\lambda}, \bar{p}) \quad \text{maximizes the dual} \end{array} \right\} \iff \inf_{\rho} L(\rho, \bar{\lambda}, \bar{p}) = L(\bar{p}, \bar{\lambda}, \bar{p}) = \sup_{\lambda, \rho} L(\bar{p}, \lambda, \rho)$$

- ▶ **Primal Step:** Given (λ^k, ρ^k) current multipliers,
 p^k solves $\min_{\rho} L(\rho, \lambda^k, \rho^k)$ ($\implies \psi(\lambda^k, \rho^k) = L(\rho^k, \lambda^k, \rho^k)$)

- ▶ **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ one iteration to solve $\max_{\lambda, \rho} \psi(\lambda, \rho)$

GAL: algorithmic scheme

$$\left. \begin{array}{l} \bar{p} \quad \text{minimizes the primal} \\ (\bar{\lambda}, \bar{p}) \quad \text{maximizes the dual} \end{array} \right\} \iff \inf_{\rho} L(\rho, \bar{\lambda}, \bar{p}) = L(\bar{p}, \bar{\lambda}, \bar{p}) = \sup_{\lambda, \rho} L(\bar{p}, \lambda, \rho)$$

- ▶ **Primal Step:** Given (λ^k, ρ^k) current multipliers,
 p^k solves $\min_{\rho} L(\rho, \lambda^k, \rho^k)$ ($\implies \psi(\lambda^k, \rho^k) = L(\rho^k, \lambda^k, \rho^k)$)
 $p^k := \mathcal{A}^{\text{ex}}(\lambda^k, \rho^k)$

- ▶ **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ one iteration to solve $\max_{\lambda, \rho} \psi(\lambda, \rho)$

GAL: algorithmic scheme

$$\left. \begin{array}{l} \bar{p} \quad \text{minimizes the primal} \\ (\bar{\lambda}, \bar{p}) \quad \text{maximizes the dual} \end{array} \right\} \iff \inf_{\rho} L(\rho, \bar{\lambda}, \bar{p}) = L(\bar{p}, \bar{\lambda}, \bar{p}) = \sup_{\lambda, \rho} L(\bar{p}, \lambda, \rho)$$

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 $p^k := \mathcal{A}^{\text{ex}}(\lambda^k, \rho^k)$

- ▶ **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ one iteration to solve $\max_{\lambda, \rho} \psi(\lambda, \rho)$

How easy is to find p^k ?

GAL: algorithmic scheme

$$\left. \begin{array}{l} \bar{p} \quad \text{minimizes the primal} \\ (\bar{\lambda}, \bar{p}) \quad \text{maximizes the dual} \end{array} \right\} \iff \inf_{\rho} L(\rho, \bar{\lambda}, \bar{p}) = L(\bar{p}, \bar{\lambda}, \bar{p}) = \sup_{\lambda, \rho} L(\bar{p}, \lambda, \rho)$$

- **Primal Step:** Given (λ^k, ρ^k) current multipliers,
 p^k solves $\min_{\rho} L(\rho, \lambda^k, \rho^k)$ ($\implies \psi(\lambda^k, \rho^k) = L(\rho^k, \lambda^k, \rho^k)$)
 $p^k := \mathcal{A}^{\text{ex}}(\lambda^k, \rho^k)$

- **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ one iteration to solve $\max_{\lambda, \rho} \psi(\lambda, \rho)$

How easy is to find p^k ?

$$L(\rho, \lambda, \rho) = L_T(x, z_T, \lambda) + L_{HT}(y_T, y_H, \lambda) + \langle \lambda, d \rangle + \rho \|y_T - z_T\|$$

GAL: algorithmic scheme

$$\left. \begin{array}{l} \bar{p} \quad \text{minimizes the primal} \\ (\bar{\lambda}, \bar{p}) \quad \text{maximizes the dual} \end{array} \right\} \iff \inf_p L(p, \bar{\lambda}, \bar{p}) = L(\bar{p}, \bar{\lambda}, \bar{p}) = \sup_{\lambda, \rho} L(\bar{p}, \lambda, \rho)$$

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How easy is to find p^k ?

$$L(p, \lambda, \rho) = L_T(x, z_T, \lambda) + L_{HT}(y_T, y_H, \lambda) + \langle \lambda, d \rangle + \rho \|y_T - z_T\|$$

Separability is lost!

GALs: difficulties

- ▶ **Primal Step:** Given (λ^k, ρ^k) current multipliers,

Instead of p^k solves $\min_p L(p, \lambda^k, \rho^k)$

$$(\implies \psi(\lambda^k, \rho^k) = L(p^k, \lambda^k, \rho^k))$$

$$p^k := \mathcal{A}^{\text{ex}}(\lambda^k, \rho^k)$$

GALs: difficulties

- ▶ **Primal Step:** Given (λ^k, ρ^k) current multipliers,
Instead of p^k solves $\min_p L(p, \lambda^k, \rho^k)$ $(\implies \psi(\lambda^k, \rho^k) = L(p^k, \lambda^k, \rho^k))$
 $p^k := \mathcal{A}^{\text{ex}}(\lambda^k, \rho^k)$
 $p^k := \mathcal{A}^{\text{inex}}(\lambda^k, \rho^k) \approx \min_p L(p, \lambda^k, \rho^k)$
with an error $E^k := L(p^k, \lambda^k, \rho^k) - \psi(\lambda^k, \rho^k) \in [0, \eta]$
Error is unknown, η bounds approximation inaccuracy

GALs: difficulties

- ▶ **Primal Step:** Given (λ^k, ρ^k) current multipliers,
Instead of p^k solves $\min_p L(p, \lambda^k, \rho^k)$ $(\implies \psi(\lambda^k, \rho^k) = L(p^k, \lambda^k, \rho^k))$

$$p^k := \mathcal{A}^{\text{ex}}(\lambda^k, \rho^k)$$
$$p^k := \mathcal{A}^{\text{inex}}(\lambda^k, \rho^k) \approx \min_p L(p, \lambda^k, \rho^k)$$

with an error $E^k := L(p^k, \lambda^k, \rho^k) - \psi(\lambda^k, \rho^k) \in [0, \eta]$

Error is unknown, η bounds approximation inaccuracy

- ▶ **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ one iteration to solve $\max_{\lambda, \rho} \psi(\lambda, \rho)$
Subgradient (Uzawa), Cutting-planes (DW), **Bundle**

GALs: difficulties

- ▶ **Primal Step:** Given (λ^k, ρ^k) current multipliers,
Instead of p^k solves $\min_p L(p, \lambda^k, \rho^k)$ $(\implies \psi(\lambda^k, \rho^k) = L(p^k, \lambda^k, \rho^k))$

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Subgradient (Uzawa), Cutting-planes (DW), **Bundle**

When is $\mathcal{A}^{\text{inex}}$ sufficiently good?

GALs: difficulties

- ▶ **Primal Step:** Given (λ^k, ρ^k) current multipliers,
Instead of p^k solves $\min_{\rho} L(\rho, \lambda^k, \rho^k)$ ($\implies \psi(\lambda^k, \rho^k) = L(\rho^k, \lambda^k, \rho^k)$)

$$p^k := \mathcal{A}^{ex}(\lambda^k, \rho^k)$$
$$p^k := \mathcal{A}^{inex}(\lambda^k, \rho^k) \approx \min_{\rho} L(\rho, \lambda^k, \rho^k)$$

with an error $E^k := L(p^k, \lambda^k, \rho^k) - \psi(\lambda^k, \rho^k) \in [0, \eta]$
Error is unknown, η bounds approximation inaccuracy

- ▶ **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ one iteration to solve $\max_{\lambda, \rho} \psi(\lambda, \rho)$
Subgradient (Uzawa), Cutting-planes (DW), **Bundle**

When is \mathcal{A}^{inex} sufficiently good?

Primal points may not be sufficiently good

GALs: difficulties

- ▶ **Primal Step:** Given (λ^k, ρ^k) current multipliers,
Instead of p^k solves $\min_{\rho} L(\rho, \lambda^k, \rho^k)$ $(\implies \psi(\lambda^k, \rho^k) = L(\rho^k, \lambda^k, \rho^k))$
 $p^k := \mathcal{A}^{ex}(\lambda^k, \rho^k)$
 $p^k := \mathcal{A}^{inex}(\lambda^k, \rho^k) \approx \min_{\rho} L(\rho, \lambda^k, \rho^k)$
with an error $E^k := L(p^k, \lambda^k, \rho^k) - \psi(\lambda^k, \rho^k) \in [0, \eta]$
Error is unknown, η bounds approximation inaccuracy
- ▶ **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ one iteration to solve $\max_{\lambda, \rho} \psi(\lambda, \rho)$
Subgradient (Uzawa), Cutting-planes (DW), **Bundle**

When is \mathcal{A}^{inex} sufficiently good?

Primal points may not be sufficiently good

When to stop?

GALs: primal-dual bundle scheme

- ▶ **Primal Step:** Given $(\hat{\lambda}^k, \hat{\rho}^k)$ current good multipliers,
 $p^k := \mathcal{A}^{inex}(\hat{\lambda}^k, \hat{\rho}^k) \approx \min_p L(p, \hat{\lambda}^k, \hat{\rho}^k) = \psi(\hat{\lambda}^k, \hat{\rho}^k)$
- ▶ **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ one iteration to solve $\max_{\lambda, \rho} \psi(\lambda, \rho)$

Bundle of p^i 's: defines a simple QP, with

- ▶ a matrix Γ^F with $|B_k|$ columns $F(p^i) \in \mathbb{R}^m$
- ▶ Γ^σ with $|B_k|$ columns $\sigma(F(p^i)) \in \mathbb{R}$

$$\min \left\{ \frac{1}{2t_k^F} \langle \Gamma^F \alpha, \Gamma^F \alpha \rangle + \frac{1}{2t_k^\sigma} \langle \Gamma^\sigma \alpha, \Gamma^\sigma \alpha \rangle + \langle q, \alpha \rangle : \alpha \in \Delta \right\}$$

gives $\lambda^{k+1} = \hat{\lambda}^k + t_k^F \Gamma^F \alpha^k$ and $\rho^{k+1} = \hat{\rho}^k + t_k^\sigma \Gamma^\sigma \alpha^k$

- ▶ **Goodness:** New primal point $p^{k+1} := \mathcal{A}^{inex}(\lambda^{k+1}, \rho^{k+1})$ is good if it gives a larger Lagrangian value than $p^k = \mathcal{A}^{inex}(\hat{\lambda}^k, \hat{\rho}^k)$
- ▶ **Stopping test:** checks, up to η ,
 - ▶ primal feasibility
 - ▶ optimality gap

GALs: primal-dual bundle scheme

Convergence within the error η of \mathcal{A}^{inex}

Theorem (Primal-dual convergence)

For the subsequence $\{p^k, \hat{\lambda}^k, \hat{\rho}^k\}$

- ▶ all cluster points (if any) of $\{\hat{\lambda}^k, \hat{\rho}^k\}$ are dual η -solutions
- ▶ all cluster points of p^k are primal η -solutions
- ▶ the optimality gap eventually vanishes

GALs: primal-dual bundle scheme

Convergence within the error η of \mathcal{A}^{inex}

Theorem (Primal-dual convergence)

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- ▶ all cluster points (if any) of $\{\hat{\lambda}^k, \hat{\rho}^k\}$ are dual η -solutions
- ▶ all cluster points of p^k are primal η -solutions
- ▶ the optimality gap eventually vanishes

Versatile

- ▶ DC programming
- ▶ Sparse optimization
- ▶ UC

DC programming: \mathcal{A}^{ex}

Global solution to

$$\begin{cases} \min & \frac{1}{2} \langle p, Mp \rangle + \langle q, p \rangle - \max_{1 \leq i \leq N} \{ \langle \alpha_i, p \rangle + \beta_i \} \\ \text{s.t.} & Ap = b \end{cases}$$

found by solving N QP's

$$\begin{cases} \min & \frac{1}{2} \langle p, Mp \rangle + \langle q, p \rangle - \langle \alpha_i, p \rangle - \beta_i \\ \text{s.t.} & Ap = b, \end{cases}$$

Alternative: Proximal Lagrangian with $\sigma(F(p)) = \frac{1}{2} \|Ap - b\|^2$, with

$$\psi(\lambda, \rho) = \min_{1 \leq i \leq N} \left(\min \frac{1}{2} \langle p, Mp \rangle + \langle q - \alpha_i, p \rangle - \beta_i + \langle \lambda, Ap - b \rangle + \frac{\rho}{2} \|Ap - b\|^2 \right)$$

► **Primal Step:** $p^k := \mathcal{A}^{ex}(\hat{\lambda}^k, \hat{\rho}^k) = \min_p L(p, \hat{\lambda}^k, \hat{\rho}^k)$

Solve N LP's: $0 = Mp + q - \alpha_i + A^\top \lambda + \rho A^\top (Ap - b)$ for $1 \leq i \leq N$

► **Dual Step:** Solve 1 QP to find $(\lambda^{k+1}, \rho^{k+1})$

Unit Commitment: \mathcal{A}^{inex}

Sharp Lagrangian

$$L(\rho, \lambda, \rho) = L_T(x, z_T, \lambda) + L_{HT}(y_T, y_H, \lambda) + \langle \lambda, d \rangle + \rho \|y_T - z_T\|$$

- ▶ **Primal Step:** ADMM-like inexact minimization

$$\mathcal{A}^{inex}(\hat{\lambda}^k, \hat{\rho}^k) \left\{ \begin{array}{l} \min_{x, z_T} L_T(x, z_T, \hat{\lambda}^k) + \frac{\hat{\rho}^k}{2} \|y_T^{k-1} - z_T\| \\ \min_{y_T, y_H} L_{HT}(y_T, y_H, \hat{\lambda}^k) + \frac{\hat{\rho}^k}{2} \|y_T - z_T^{k-1}\| \\ + \langle \hat{\lambda}^k, d \rangle \end{array} \right.$$

- ▶ **Dual Step:** $(\lambda^{k+1}, \rho^{k+1})$ defined using QP solution α_k

Numerical Assessment

- ▶ UniToy OK!
- ▶ On progress for real-life instances