

Série dos Seminários de Acompanhamento à Pesquisa

A Solution Methodology for Wasserstein-based
Data-Driven Distributionally Robust Problems with Right-
Hand-Sided Rectangular-Supported Uncertainty

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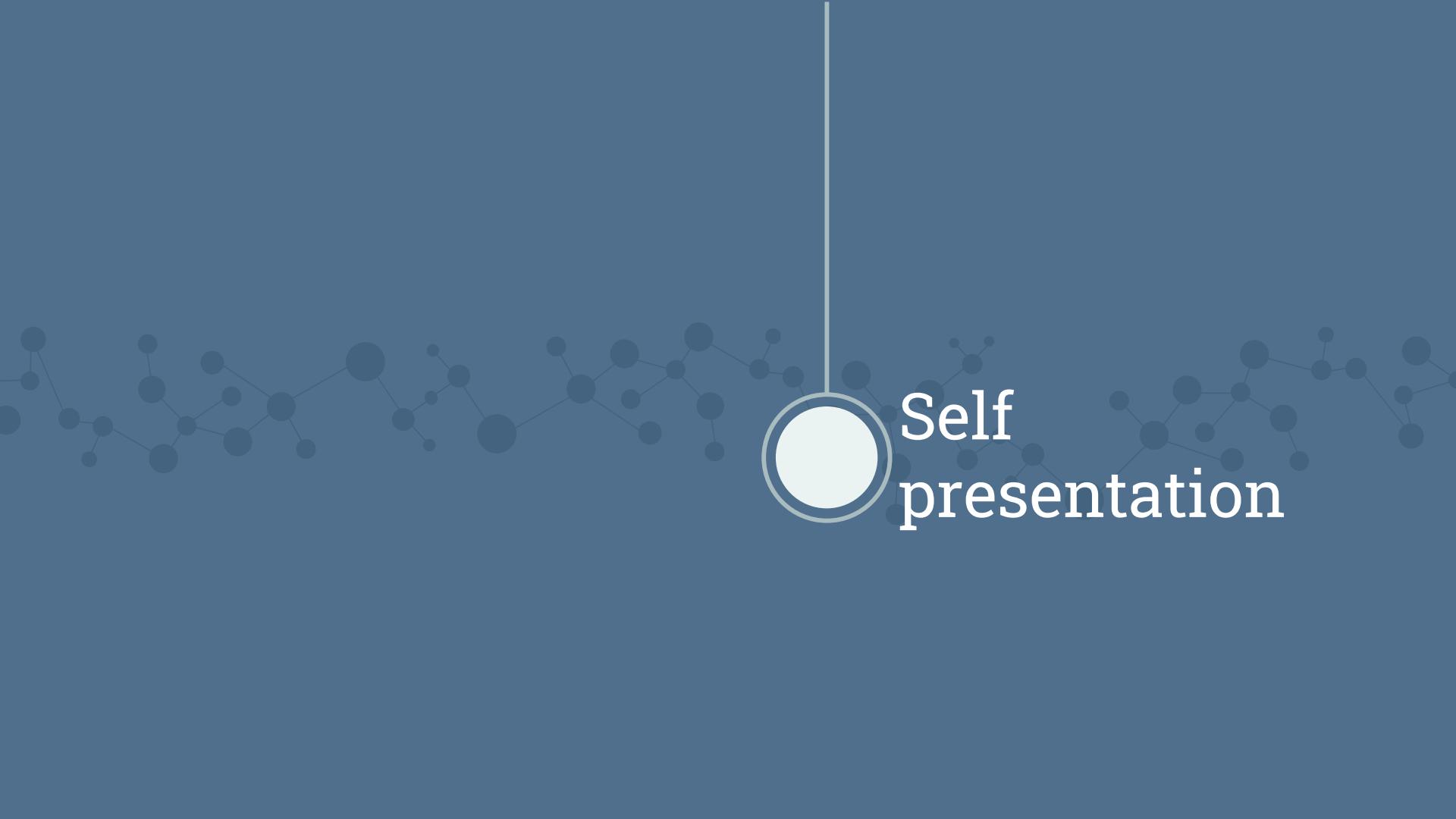
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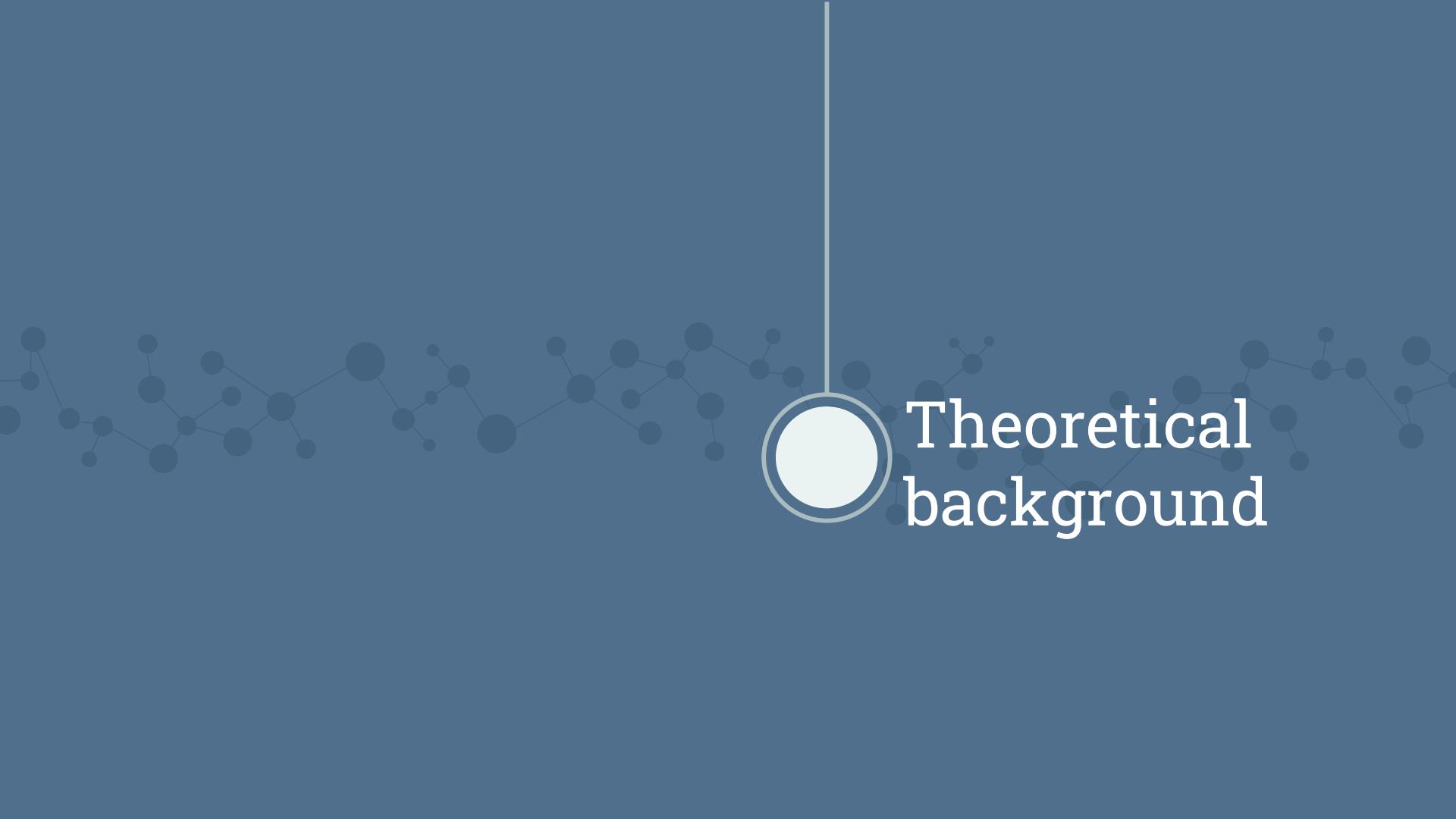
Layout da Capa: Aline Magalhães dos Santos



A network graph is displayed against a dark blue background. A central node, represented by a white circle with a thin gray border, is connected to numerous smaller, darker gray circular nodes. These peripheral nodes are interconnected among themselves, forming a complex web of connections that radiates from the center. The overall effect is one of a social network or a complex system.

Self presentation

- Name: Carlos Andrés Gamboa Rodríguez
- PhD Student
- Period: 8
- Advisor: Davi Valladão
- Co-Advisor: Alexandre Street



Theoretical background

Stochastic optimization

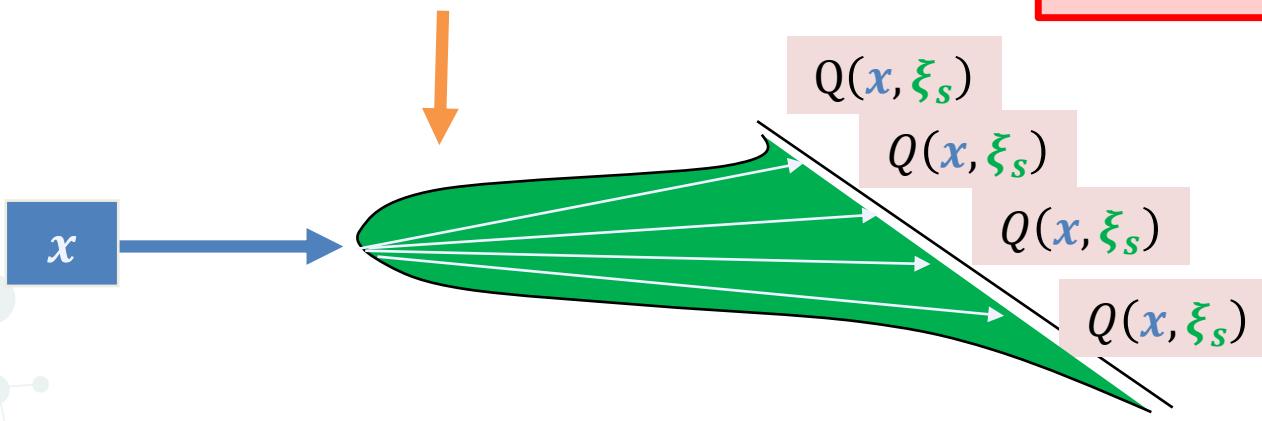


- Two-stage model

$$\min_{\boldsymbol{x} \in \mathcal{X}} \boldsymbol{c}^\top \boldsymbol{x} + \mathbb{E}[Q(\boldsymbol{x}, \xi)]$$

Uncertainty realization

The data-generating probability distribution is known

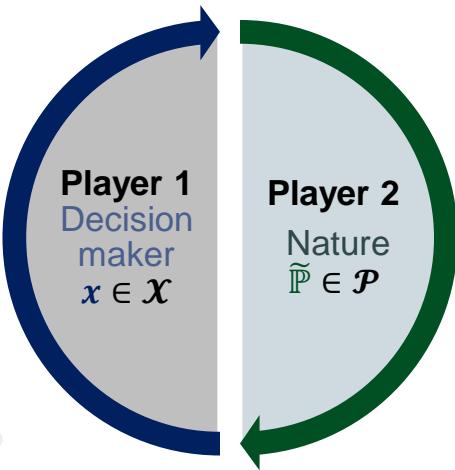


Distributionally robust optimization

- DRO two-stage model

$$\min_{\boldsymbol{x} \in \mathcal{X}} \boldsymbol{c}^T \boldsymbol{x} + \sup_{\tilde{\mathbb{P}} \in \tilde{\mathcal{P}}} \mathbb{E}^{\tilde{\mathbb{P}}} [Q(\boldsymbol{x}, \xi)]$$

Game theory interpretation



Ambiguity set:

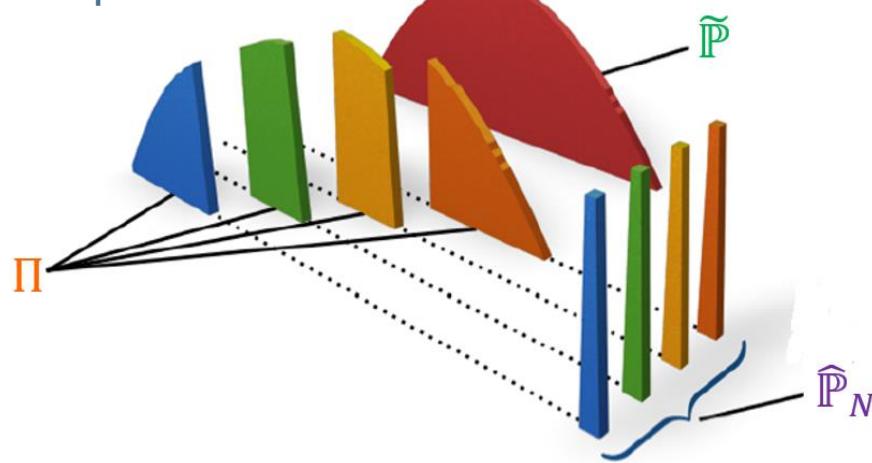
- Moment-based
- Discrepancy-based

Wasserstein ball

- Wasserstein distance

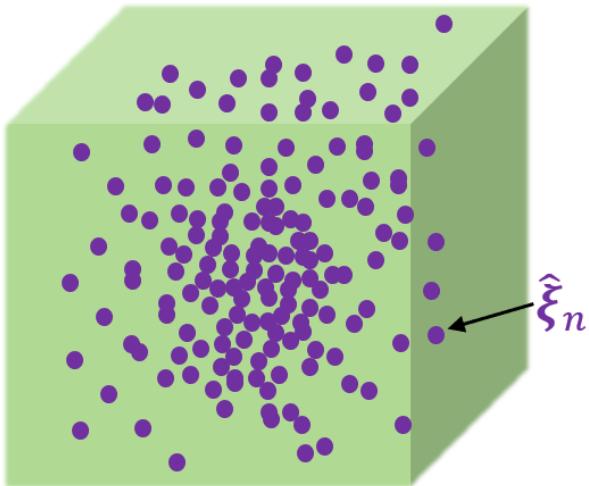
$$d_w(\tilde{\mathbb{P}}, \hat{\mathbb{P}}_N) = \inf \left\{ \int_{\Xi^2} \|\xi - \hat{\xi}_n\| d\Pi(\xi, \hat{\xi}_n) : \begin{array}{l} \Pi \text{ is a joint distribution of } \xi \text{ and } \hat{\xi}_n \\ \text{with marginals } \tilde{\mathbb{P}} \text{ and } \hat{\mathbb{P}}_N, \text{ respectively} \end{array} \right\}$$

- Transportation plan



Wasserstein ball

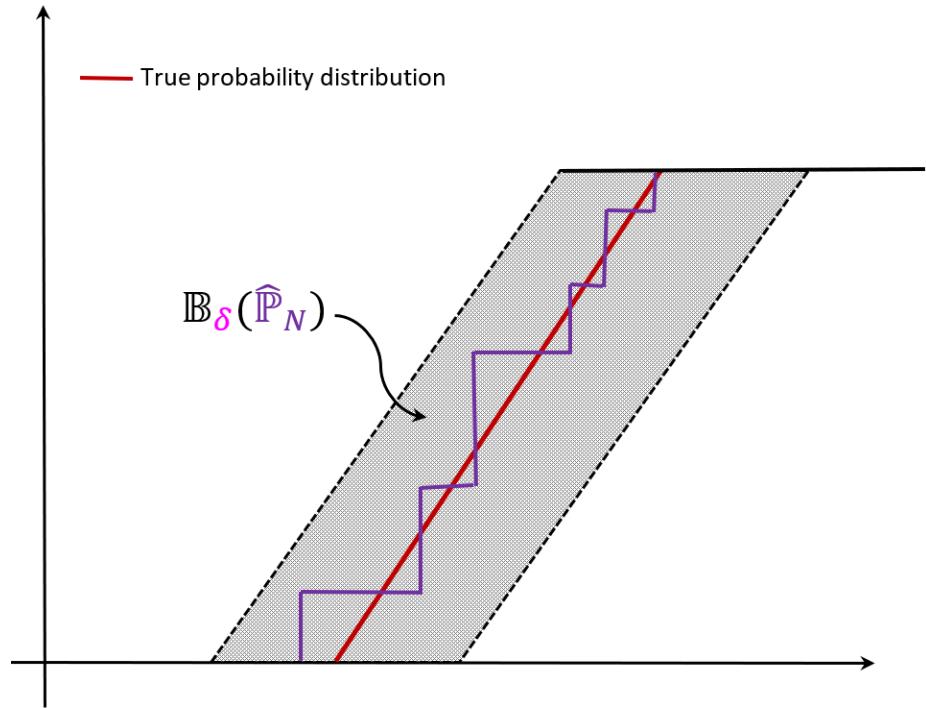
$$\Xi = \times_{i=1}^{d_\xi} [a_i, b_i]$$



Reference distribution

$$\widehat{\mathbb{P}}_N = \frac{1}{N} \sum_{n=1}^N \delta_{\widehat{\xi}_n}$$

$$\mathbb{B}_\delta d_w(\widehat{\mathbb{P}}_N) = \{\widetilde{\mathbb{P}} \in \mathcal{M}(\Xi): d_w(\widetilde{\mathbb{P}}, \widehat{\mathbb{P}}_N) \leq \delta\}$$





Reformulation of the problem

Equivalent semi-infinite optimization problem

- Parametric linear programs with RHS uncertainty

$$Q(\boldsymbol{x}, \boldsymbol{\xi}) = \min_{\boldsymbol{y} \geq 0} \boldsymbol{q}^\top \boldsymbol{y}$$

$$s.t. \quad \boldsymbol{W}\boldsymbol{y} = \boldsymbol{H}(\boldsymbol{x})\boldsymbol{\xi} + \boldsymbol{r}(\boldsymbol{x})$$

$$\min_{\boldsymbol{x} \in \mathcal{X}} \boldsymbol{c}^\top \boldsymbol{x} + \sup_{\tilde{\mathbb{P}} \in \mathcal{P}} \mathbb{E}^{\tilde{\mathbb{P}}} [Q(\boldsymbol{x}, \boldsymbol{\xi})]$$

$$\begin{aligned} & \min_{\boldsymbol{x}, \lambda, s_n} \quad \boldsymbol{c}^\top \boldsymbol{x} + \lambda \delta + \frac{1}{N} \sum_{n=1}^N s_n \\ & s.t. \quad Q(\boldsymbol{x}, \boldsymbol{\xi}) - \lambda \|\boldsymbol{\xi} - \hat{\boldsymbol{\xi}}_n\| \leq s_n, \quad \forall n \leq N, \forall \boldsymbol{\xi} \in \Xi, \\ & \quad \lambda \geq 0, \\ & \quad \boldsymbol{x} \in \mathcal{X} \end{aligned}$$



Finite extensive equivalent formulation

Semi-infinite constraint

$$Q(\mathbf{x}, \xi) - \lambda \|\xi - \hat{\xi}_n\|_1 \leq s_n, \forall n \leq N, \forall \xi \in \Xi$$



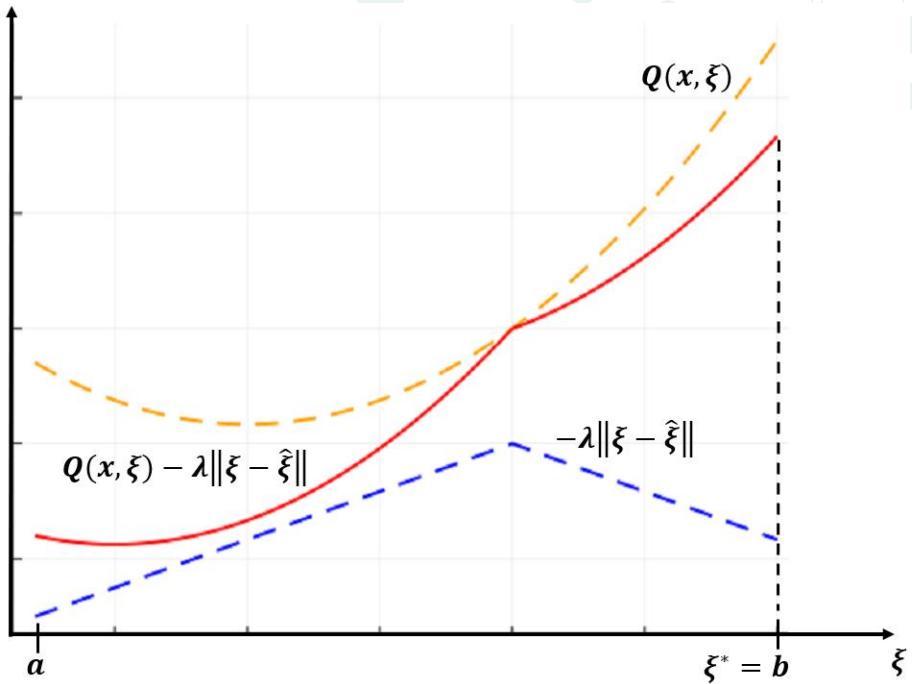
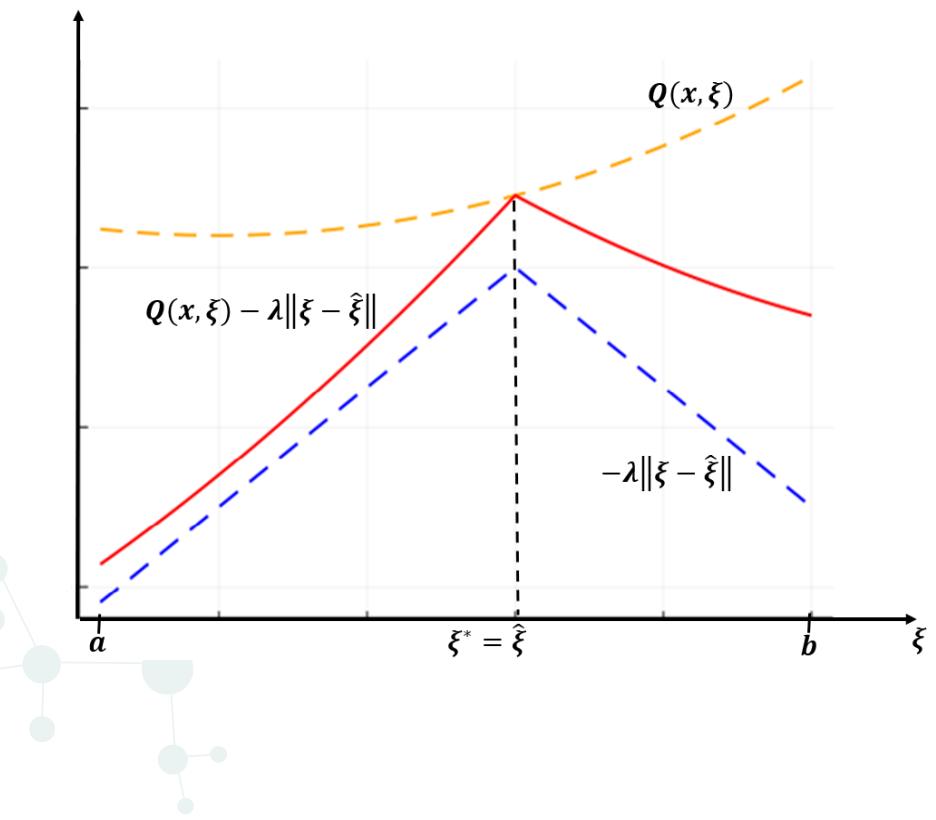
$$\sup_{\xi \in \Xi} (Q(\mathbf{x}, \xi) - \lambda \|\xi - \hat{\xi}_n\|_1) \leq s_n, \forall n \leq N$$



Oracle problem

$$\begin{aligned} & \min_{\theta, \alpha, \xi} && \theta^\top r(\mathbf{x}) + [H^\top(\mathbf{x})\theta]^\top \xi - \lambda \mathbf{1}^\top \alpha \\ & \text{s.t.} && \alpha \geq \xi - \hat{\xi}_n, \\ & && \alpha \geq \hat{\xi}_n - \xi, \\ & && W^\top \theta \leq q, \\ & && \xi \in \Xi \end{aligned}$$

Solution of the oracle problem



Finite extensive equivalent formulation

Proposition

There exists an optimal solution ξ^* for the oracle problem such that $\xi_i^* \in \{(\hat{\xi}_n)_i, a_i, b_i\}$ for all $i = 1, \dots, d_\xi$

- Optimal solution of the oracle problem

$$\hat{\Xi}_n = \times_{i=1}^{d_\xi} \{a_i, (\hat{\xi}_n)_i, b_i\} = \{\xi_\ell^*\}_{\ell \in \mathcal{L}_n}, \text{ onde } \mathcal{L}_n = \{1, \dots, |\hat{\Xi}_n|\}$$

Finite extensive equivalent formulation

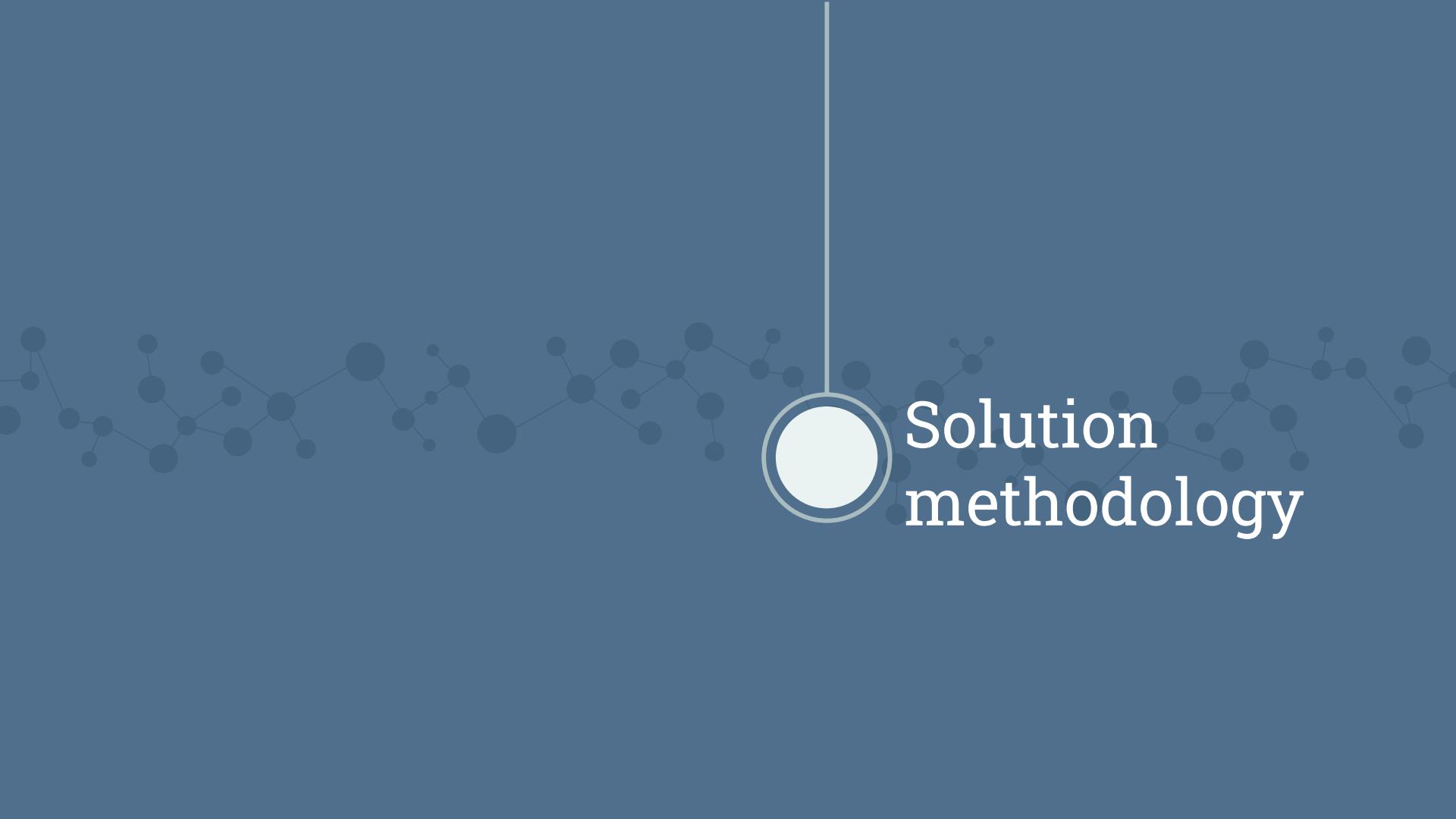
Proposed reformulation

$$\begin{aligned} \min_{\boldsymbol{x}, \lambda, s_n} \quad & \boldsymbol{c}^\top \boldsymbol{x} + \lambda \delta + \frac{1}{N} \sum_{n=1}^N s_n \\ \text{s. t.} \quad & Q(\boldsymbol{x}, \boldsymbol{\xi}_\ell^*) - \lambda \|\boldsymbol{\xi}_\ell^* - \hat{\boldsymbol{\xi}}_n\|_1 \leq s_n, \quad \forall \ell \in \mathcal{L}_n, \forall n \leq N \\ & \lambda \geq 0, \\ & \boldsymbol{x} \in \mathcal{X} \end{aligned}$$

Existing reformulations

Mehrotra:
Computational
intractable ($N \cdot 3^{d_\xi}$)

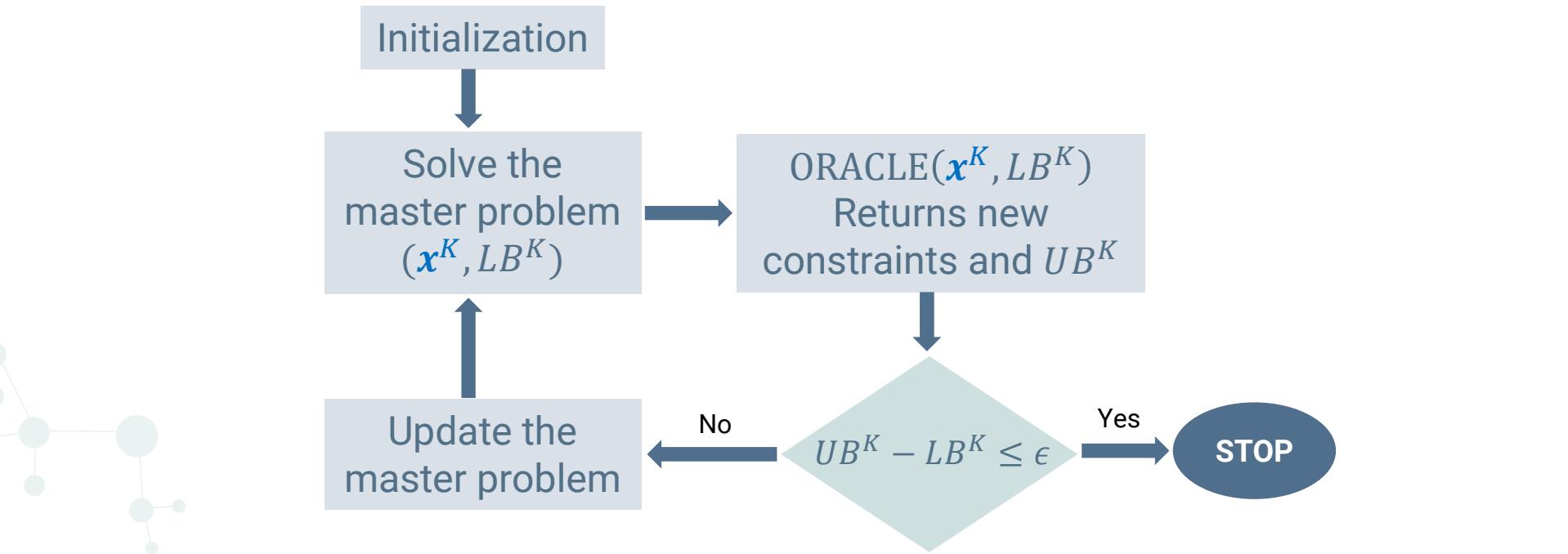
Kuhn:
The resulting PL has
generically
exponential size



Solution methodology

Decomposition method

- Iterative procedure that converges to the optimal solution of the problem



Column and constraint generation

- Master problem is a linear programming relaxation of the original problem

$$\mathcal{L}_n^K \subseteq \mathcal{L}_n$$

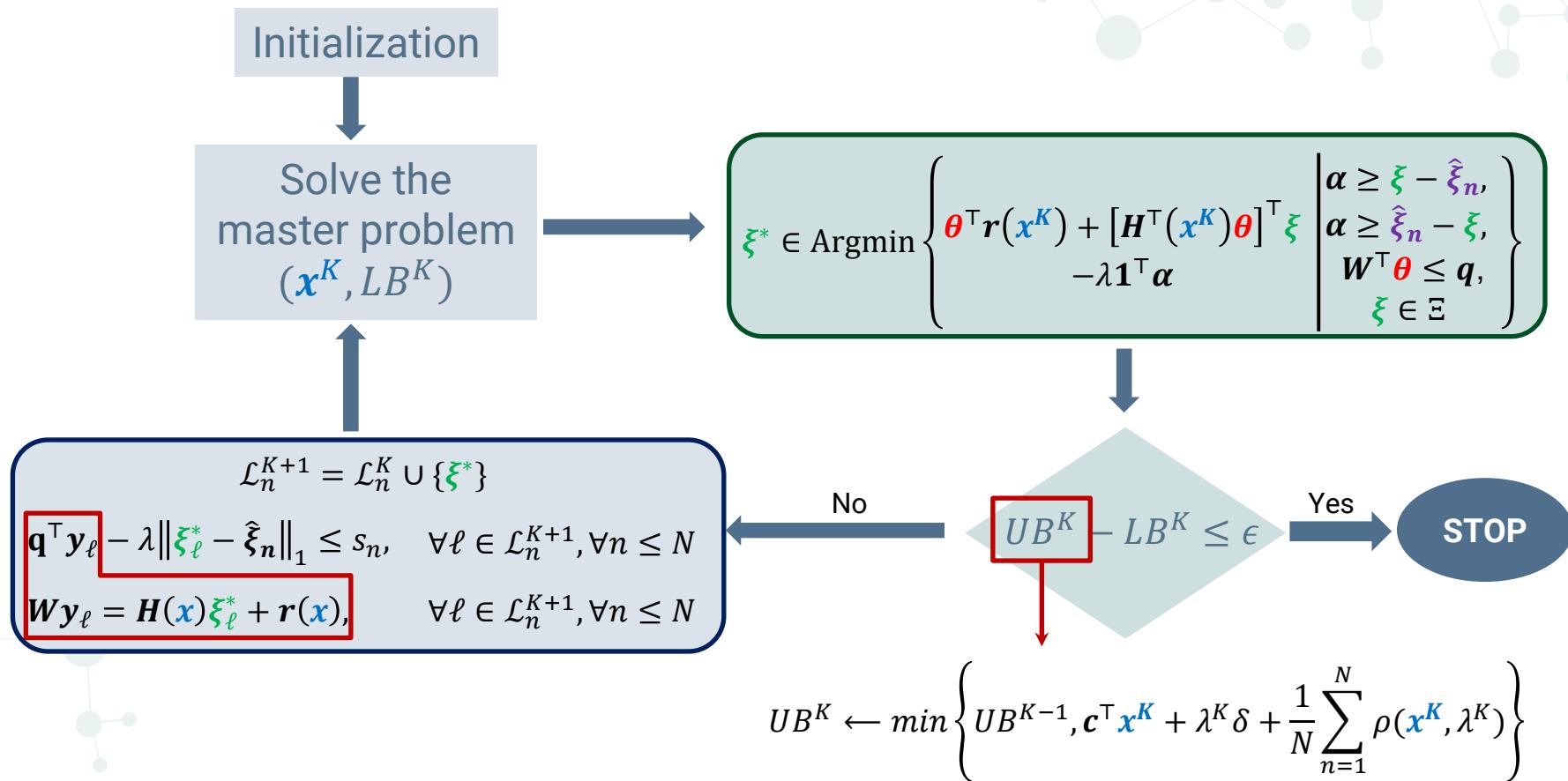
Original problem

$$\begin{aligned} \min_{\mathbf{x}, \lambda, s_n} \quad & \mathbf{c}^\top \mathbf{x} + \lambda \delta + \frac{1}{N} \sum_{n=1}^N s_n \\ \text{s. t.} \quad & Q(\mathbf{x}, \xi_\ell^*) - \lambda \|\xi_\ell^* - \hat{\xi}_n\|_1 \leq s_n, \quad \forall \ell \in \mathcal{L}_n, \forall n \leq N \\ & \lambda \geq 0, \\ & \mathbf{x} \in \mathcal{X} \end{aligned}$$

Relaxed problem

$$\begin{aligned} \min_{\mathbf{x}, \lambda, s_n} \quad & \mathbf{c}^\top \mathbf{x} + \lambda \delta + \frac{1}{N} \sum_{n=1}^N s_n \\ \text{s. t.} \quad & q^\top \mathbf{y}_\ell - \lambda \|\xi_\ell^* - \hat{\xi}_n\|_1 \leq s_n, \quad \forall \ell \in \mathcal{L}_n^K, \forall n \leq N \\ & \mathbf{W} \mathbf{y}_\ell = \mathbf{H}(\mathbf{x}) \xi_\ell^* + \mathbf{r}(\mathbf{x}), \quad \forall \ell \in \mathcal{L}_n^K, \forall n \leq N \\ & \lambda \geq 0, \\ & \mathbf{x} \in \mathcal{X} \end{aligned}$$

C&CG algorithm



Bender's multi-cut

- Master problem for the Bender's multi-cut algorithm

$$(\boldsymbol{\theta}_n^k, \boldsymbol{\xi}_n^k) \in \text{Argmin}\{\text{ORACLE}(\boldsymbol{x}^k, \lambda^k)\}$$

Original problem

$$\begin{aligned} \min_{\boldsymbol{x}, \lambda, s_n} \quad & \boldsymbol{c}^\top \boldsymbol{x} + \lambda \delta + \frac{1}{N} \sum_{n=1}^N s_n \\ \text{s.t.} \quad & \boldsymbol{\theta}_d^\top \boldsymbol{r}(\boldsymbol{x}) + [\boldsymbol{H}^\top(\boldsymbol{x}) \boldsymbol{\theta}_d]^\top \boldsymbol{\xi}_\ell^* \quad \forall (d, \ell) \\ & - \lambda \|\boldsymbol{\xi}_\ell^* - \hat{\boldsymbol{\xi}}_n\|_1 \leq s_n, \quad \in \mathcal{D} \times \mathcal{L}_n, \forall n \leq N \\ & \lambda \geq 0, \\ & \boldsymbol{x} \in \mathcal{X} \end{aligned}$$

Relaxed problem

$$\begin{aligned} \min_{\boldsymbol{x}, \lambda, s_n} \quad & \boldsymbol{c}^\top \boldsymbol{x} + \lambda \delta + \frac{1}{N} \sum_{n=1}^N s_n \\ \text{s.t.} \quad & [\boldsymbol{\theta}_n^k]^\top \boldsymbol{r}(\boldsymbol{x}) + [\boldsymbol{H}^\top(\boldsymbol{x}) \boldsymbol{\theta}_n^k]^\top \boldsymbol{\xi}_n^k \quad \forall k \leq K, \forall n \leq N \\ & - \lambda \|\boldsymbol{\xi}_n^k - \hat{\boldsymbol{\xi}}_n\|_1 \leq s_n, \\ & \lambda \geq 0, \\ & \boldsymbol{x} \in \mathcal{X} \end{aligned}$$



Bender's single-cut

- Master problem for the Bender's single-cut algorithm

$$\mathcal{L} = \bigcup_{n=1}^N \mathcal{L}_n$$

Original problem

$$\begin{aligned} \min_{\boldsymbol{x}, \lambda, s_n} \quad & \boldsymbol{c}^\top \boldsymbol{x} + \lambda \delta + \beta \\ \text{s.t.} \quad & \frac{1}{N} \sum_{n=1}^N \left(\boldsymbol{\theta}_d^\top \boldsymbol{r}(\boldsymbol{x}) + [\boldsymbol{H}^\top(\boldsymbol{x}) \boldsymbol{\theta}_d]^\top \boldsymbol{\xi}_\ell^* \right) \forall (d, \ell) \in \mathcal{D} \times \mathcal{L}, \\ & \lambda \geq 0, \\ & \boldsymbol{x} \in \mathcal{X} \end{aligned}$$



Relaxed problem

$$\begin{aligned} \min_{\boldsymbol{x}, \lambda, s_n} \quad & \boldsymbol{c}^\top \boldsymbol{x} + \lambda \delta + \beta \\ \text{s.t.} \quad & \frac{1}{N} \sum_{n=1}^N \left([\boldsymbol{\theta}_n^k]^\top \boldsymbol{r}(\boldsymbol{x}) + [\boldsymbol{H}^\top(\boldsymbol{x}) \boldsymbol{\theta}_n^k]^\top \boldsymbol{\xi}_n^k \right) \forall k \leq K, \\ & \lambda \geq 0, \\ & \boldsymbol{x} \in \mathcal{X} \end{aligned}$$



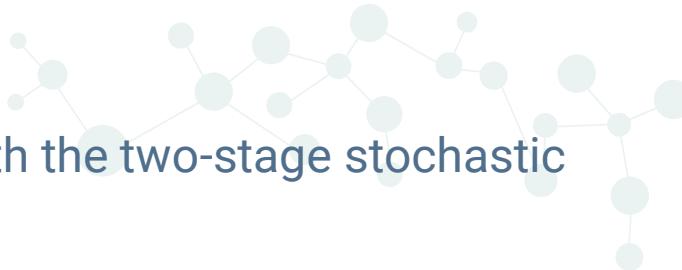
Results

Numerical experiment

- We test our proposed solution methodology with the two-stage stochastic (single-bus) unit commitment problem
 - First-stage decision:
 - Commit decisions
 - Second-stage decisions:
 - Economic dispatch
 - Uncertainty:
 - Uncertain net electricity load
 - Load – Uncertain renewable generation



Thermal generators



Load – Uncertain renewable generation

Results

- Illustrative example of a system with 5 thermal generators

Iteration <i>K</i>	C&CG	Benders multi-cut	Benders single-cut
	<i>UB - LB</i>	<i>UB - LB</i>	<i>UB - LB</i>
1	1273245	1404389	1404388
2	0	147243	282048
3		135559	135559
4		8471	48166
5		8064	19806
6		10656	19806
7		1670	19490
8		1274	16295
9		5548	16295
10		756	16295
11		1278	16295
12		2946	16295
13		760	15564
14		799	15564
15		863	15041
16		799	14310
17		0	13777
40			9142
80			3857
160			2218
165			0
Time (CPUs)	3394	26622	148127

- System with 14 and 54 thermal generators

Method	Syst-14	Syst-54
	Time (CPUs)	Time (CPUs)
C&CG	15365	24225
Bender's multi-cut	27833	-
Bender's single-cut	38379	-



References

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