Tie-line scheduling in electric power systems under uncertainty

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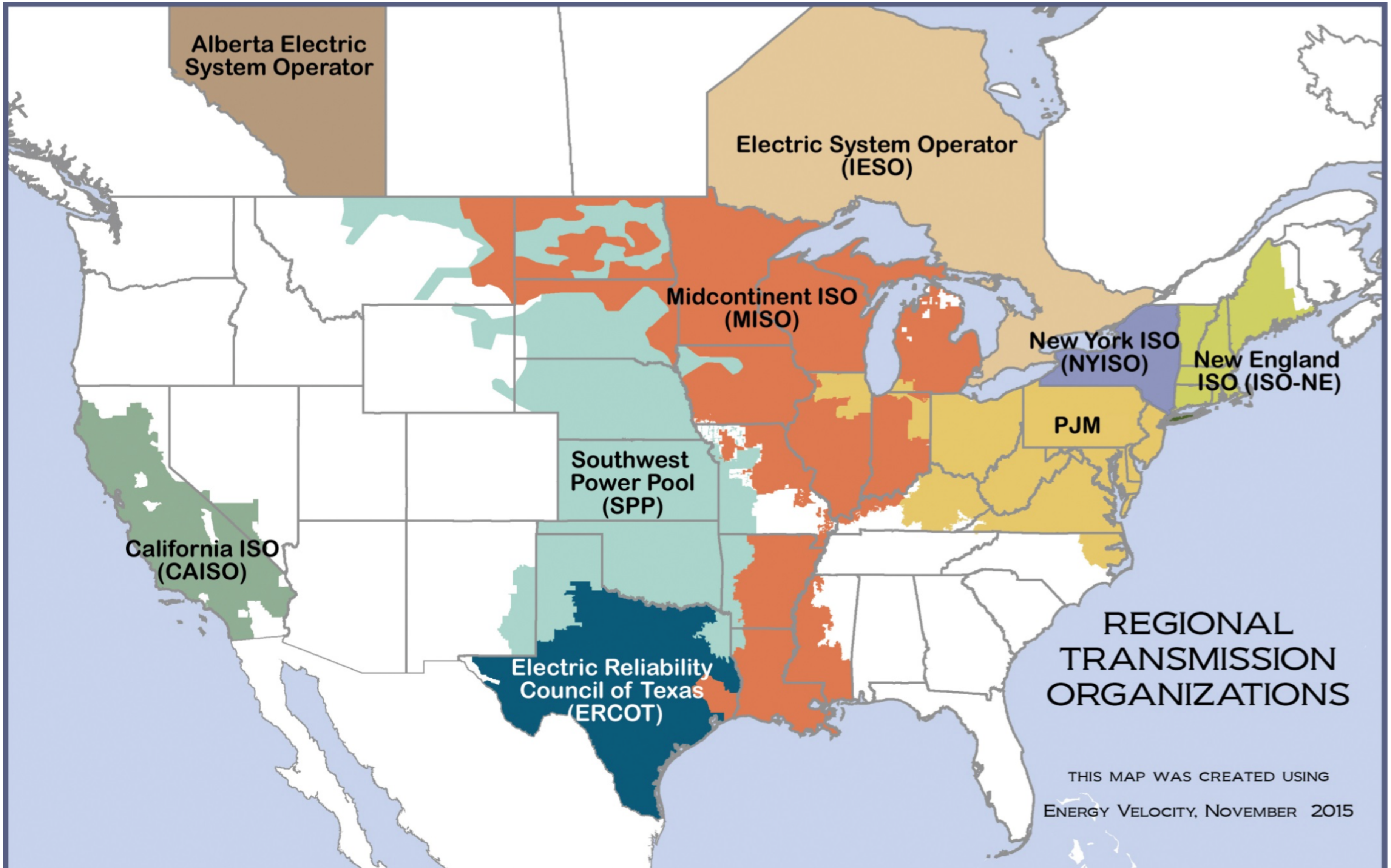
RTOs/ISOs in North America



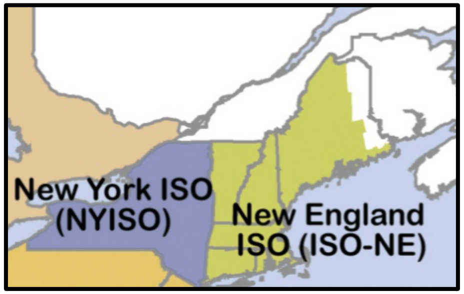
Source: http://www.ferc.gov/industries/electric/indus-act/rto.asp

What tie-lines can offer

NYISO and ISO-NE share 9 tie-lines with capacity ≈ 1800 MW. White '11

≈ 10% of NY's avg. power consumption in '09

≈ 12% of NE's avg. power consumption in '09



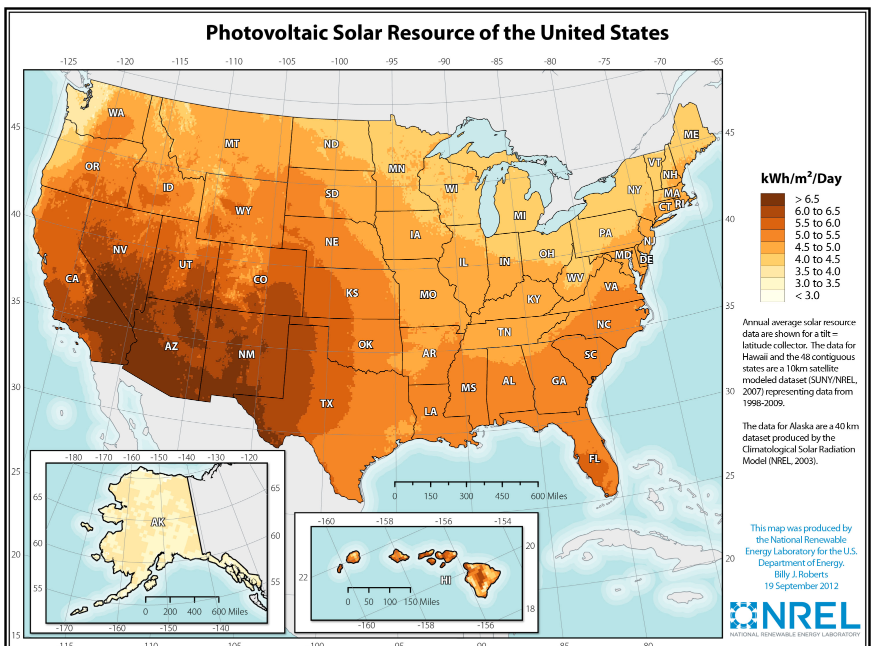
- "Each region could meet a significant portion of its power consumption with imports from the other."

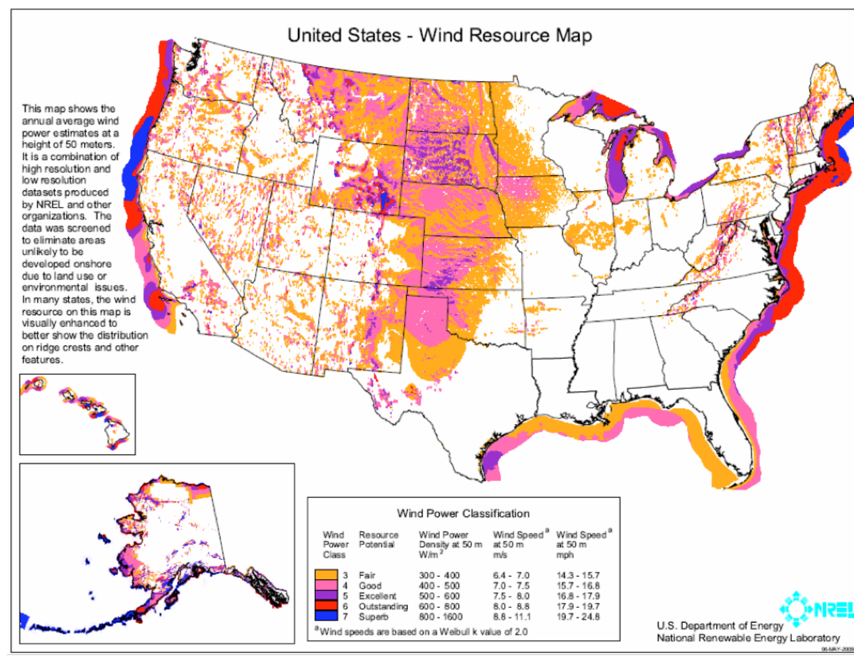
- Estimated savings in system operational costs from coordination: $784 million from '06-'10.

DOE's vision

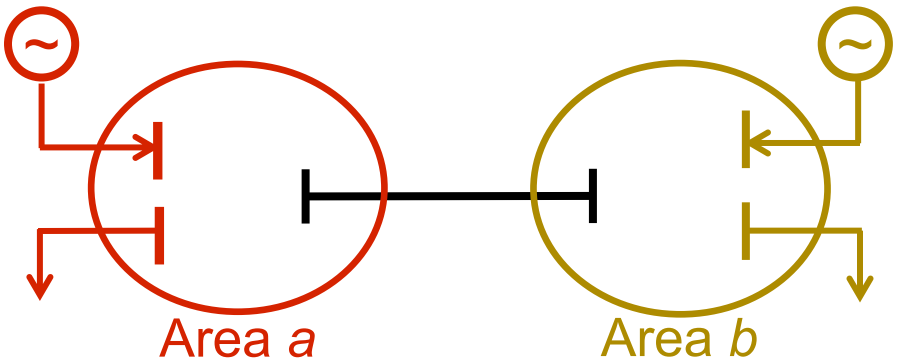
“Enable a seamless, cost-effective electricity system, from generation to end use.”

- Increases overall system efficiency
- Critical to harness geographically diverse renewable resources

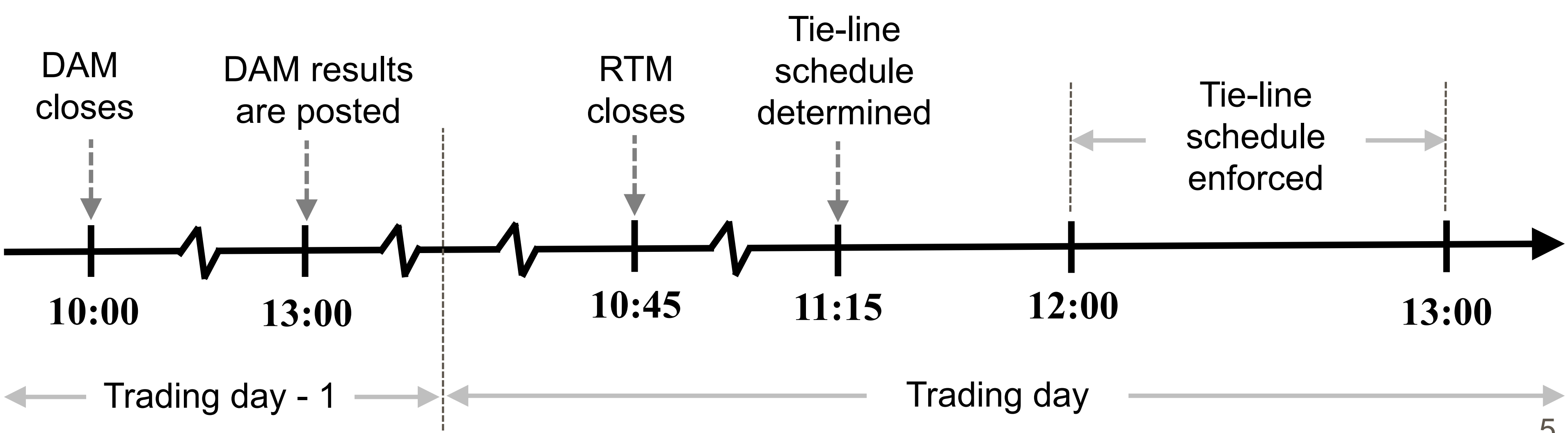




Premise of tie-line scheduling



- Scheduled prior to the time of power delivery.
- Impractical to perform joint optimization.



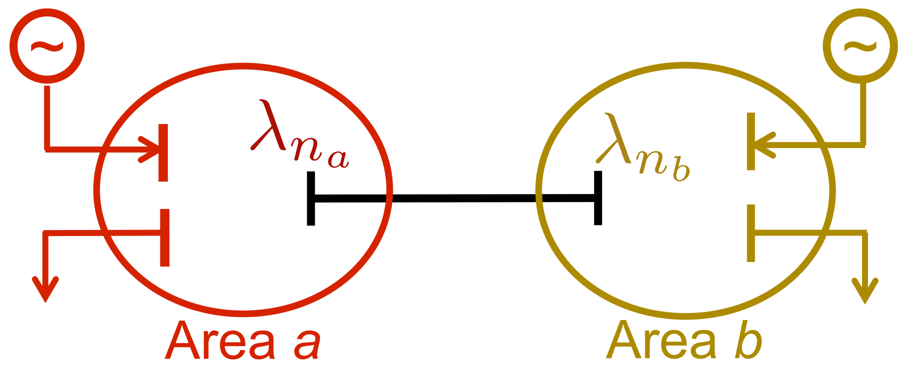
Different approaches to tie-line scheduling

- Current practice: **Coordinated Transaction Scheduling** (CTS).

- Prior to CTS:
  - Purely market based approach with virtual external bids.
  - Inefficiencies due to lack of coordination among the SOs.

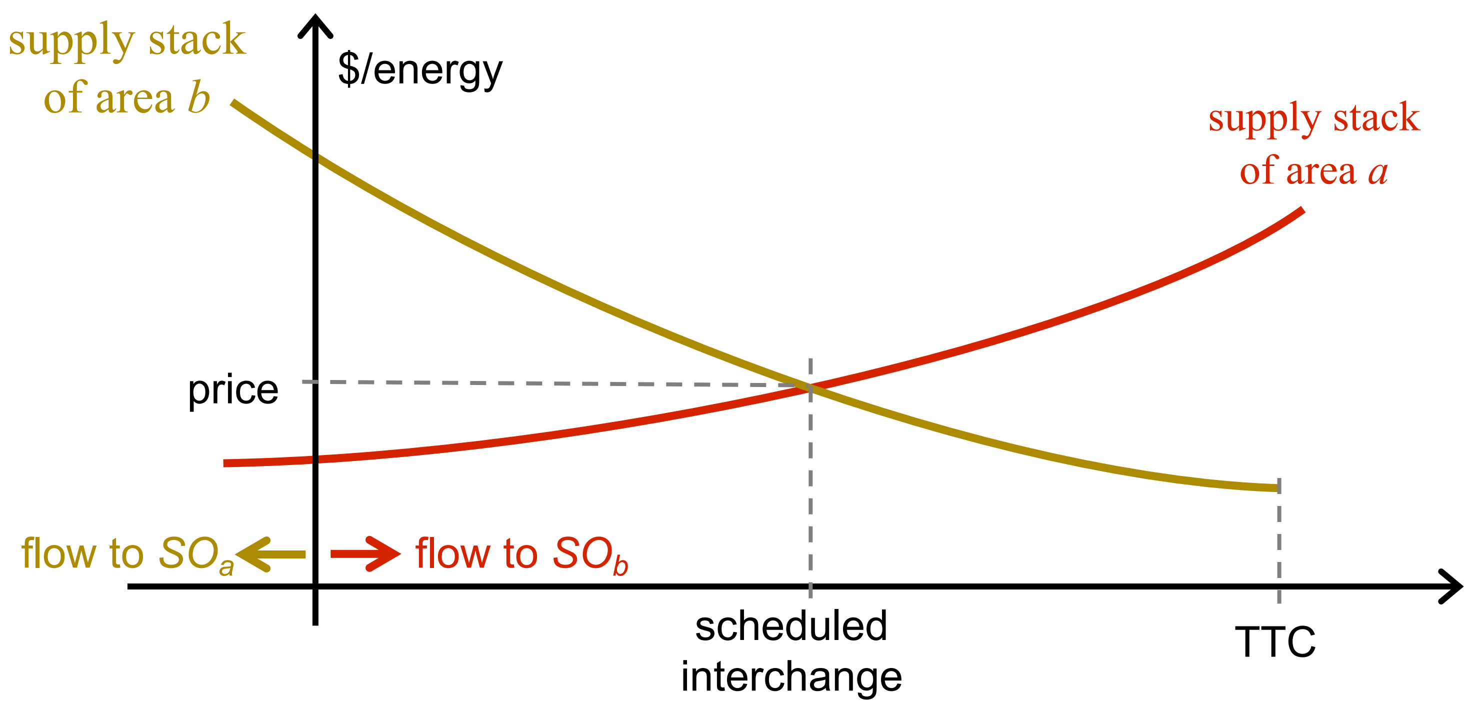
- The other extreme: **Tie optimization**
  - SOs together determine the tie-line schedule without interface bidders.
  - Can be viewed as one SO assuming a financial position in the other's market. Independent System Operators are market facilitators, and cannot assume financial positions.

The basics of tie-optimization

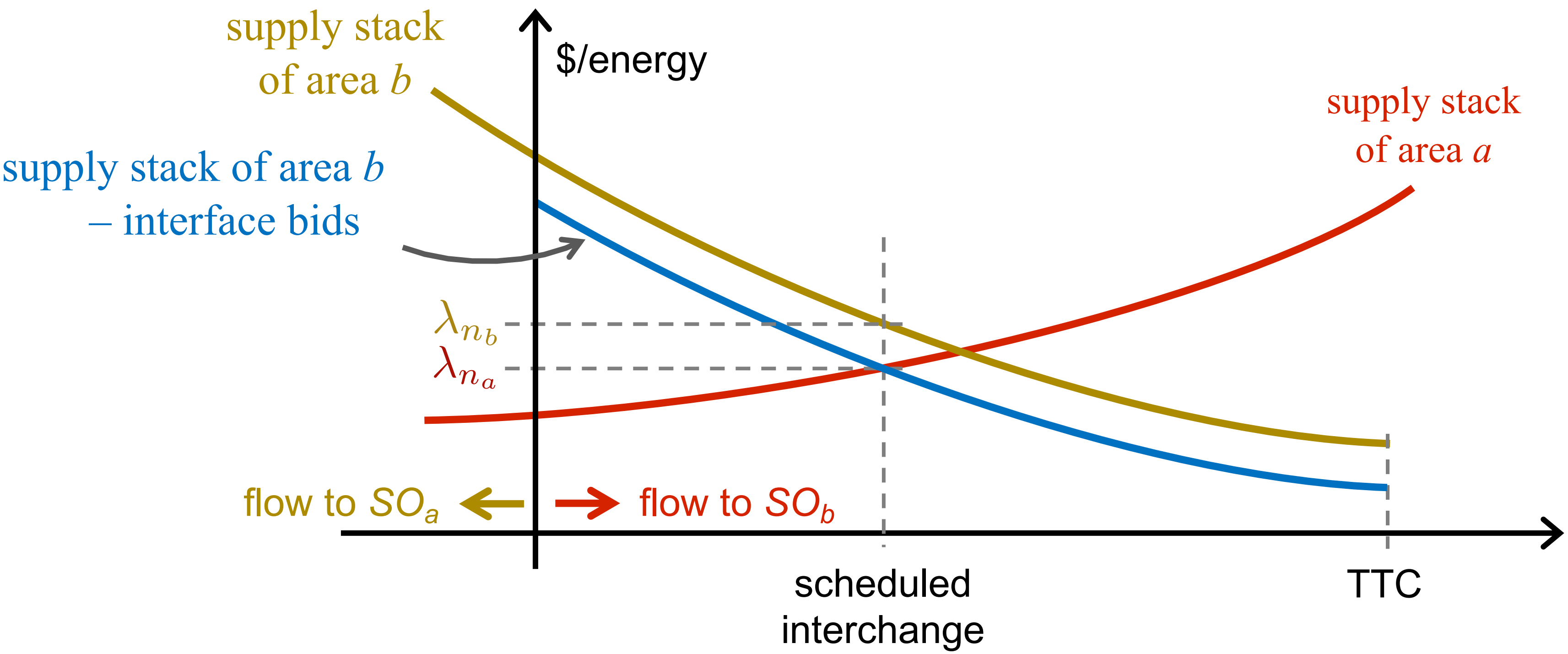


SOs compute the optimal tie-line schedule in TO.

Q1. Distributed computation of the optimal schedule.
Kim '97, Zhao '14, Ji '16.



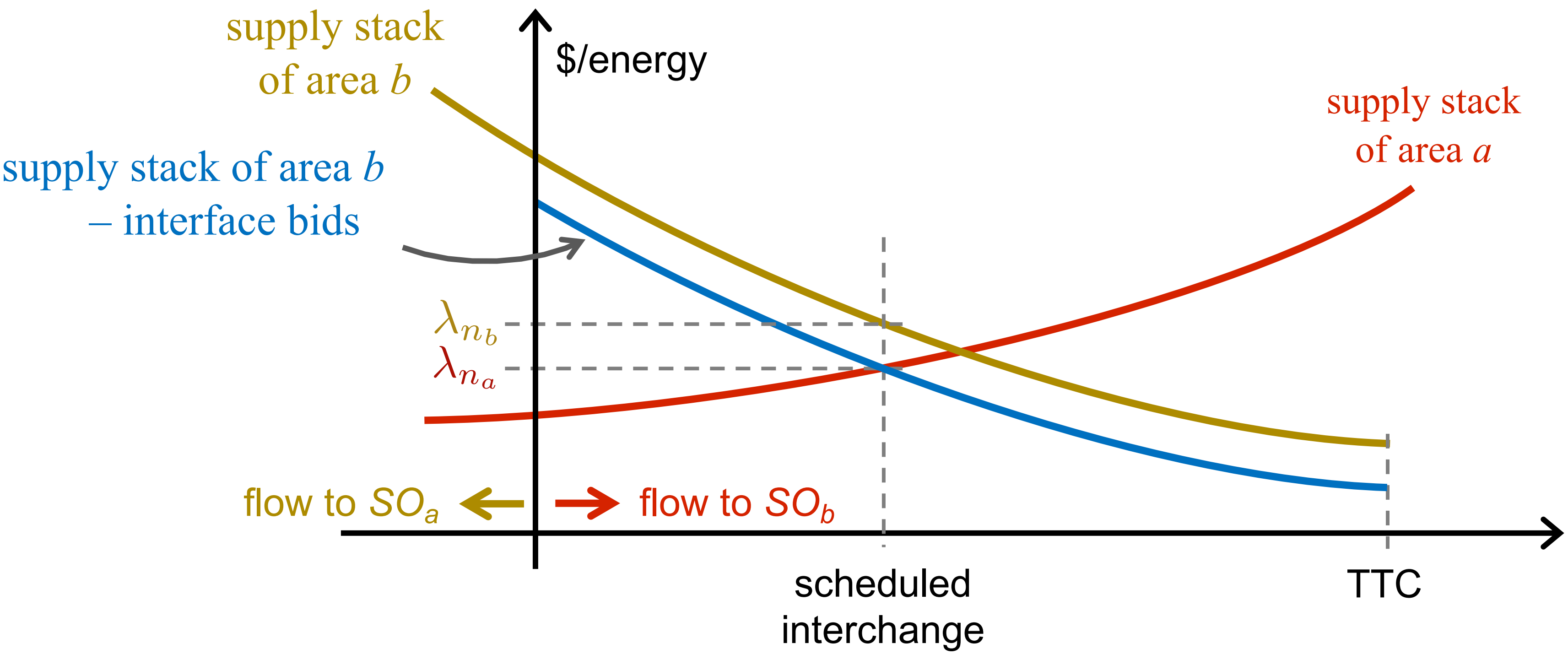
Coordinated Transaction Scheduling (CTS)



Interface bidders offer to transact energy between the areas at a price equal to the price difference between the border buses.

Shuler, Mount, Schulze, Zimmerman, and Oren '10, Baldick and Chatterjee '10.

Coordinated Transaction Scheduling (CTS)



CTS combines inter-area markets with tie-optimization.

CTS appears to distort the optimality of tie-optimization.

Q2. Is it always suboptimal?

Outline of this talk

Q1. A distributed algorithm for tie-optimization under uncertainty.

Q2. Is Coordinated Transaction Scheduling necessarily suboptimal?

Collaborators: M. Ndrio (UIUC), Y. Guo (Cornell), L. Tong (Cornell).

PSERC project M-38: Coordination Mechanisms for Seamless Operation of Interconnected Power Systems.

Industry Advisors:

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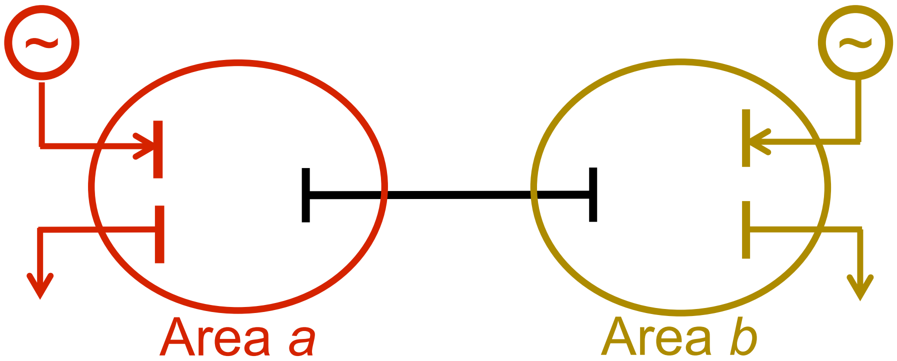
- Khosrow Moslehi *ABB*
- Feng Zhao *ISO-NE*
- Di Shi *GEIRI North America*

A distributed algorithm for tie-optimization under uncertainty



Describing area i.

n_i : number of internal buses.

$\overline{n}_i$: number of boundary buses.

Assumptions:

- *Each internal bus has a demand/supply asset*
- *Boundary buses have no demand/supply asset*

$g_i \in \mathbb{R}^{n_i}$: vector of dispatchable supply

$\xi_i \in \mathbb{R}^{n_i}$: vector of net demand (nominal demand – renewable supply)

$\theta_i \in \mathbb{R}^{n_i}$: vector of voltage phase angles at internal buses

$\overline{\theta}_i \in \mathbb{R}^{\overline{n}_i}$: vector of voltage phase angles at boundary buses

DC power flow equations and the transmission constraints

Notation

- $g_i \in \mathbb{R}^{n_i}$: vector of dispatchable supply
- $\xi_i \in \mathbb{R}^{n_i}$: vector of uncontrollable (net) demand
- $\theta_i \in \mathbb{R}^{n_i}$: vector of phase angles at internal buses
- $\overline{\theta}_i \in \mathbb{R}^{\overline{n}_i}$: vector of phase angles at boundary buses

$$\begin{pmatrix} B_{11} & B_{1\bar{1}} & & \\ B_{\bar{1}1} & B_{\bar{1}\bar{1}} & B_{\bar{1}\bar{2}} & \\ & B_{\bar{2}\bar{1}} & B_{\bar{2}\bar{2}} & B_{\bar{2}2} \\ & & B_{2\bar{2}} & B_{22} \end{pmatrix} \begin{pmatrix} \theta_1 \\ \overline{\theta}_1 \\ \overline{\theta}_2 \\ \theta_2 \end{pmatrix} = \begin{pmatrix} g_1 - \xi_1 \\ 0 \\ 0 \\ g_2 - \xi_2 \end{pmatrix},$$

power injection as a linear map of the phase angles

$$\left.\begin{aligned} H_1\theta_1 + \overline{H}_1\overline{\theta}_1 &\le f_1, \\ H_2\theta_1 + \overline{H}_2\overline{\theta}_2 &\le f_2, \end{aligned}\right\}$$

transmission constraints within each area

$$\overline{H}_{12}\overline{\theta}_1 + \overline{H}_{21}\overline{\theta}_2 \le f_{12}.$$

transmission constraint between the areas

A deterministic multi-area optimal power flow problem

Assumptions:

- $\xi_i, \;\; i = 1, 2$ *is known a priori.*
- *Objective is linear in generation.*

$$\text{minimize} \quad \pi_1^\top g_1 + \pi_2^\top g_2,$$

linear dispatch cost structure

$$\text{subject to}$$

$$\underline{g}_i \leq g_i \leq \overline{g}_i,$$

constraints on dispatchable supply

$$\begin{pmatrix} B_{11} & B_{1\bar{1}} & & \\ B_{\bar{1}1} & B_{\bar{1}\bar{1}} & B_{\bar{1}\bar{2}} & \\ & B_{\bar{2}\bar{1}} & B_{\bar{2}\bar{2}} & B_{\bar{2}2} \\ & & B_{2\bar{2}} & B_{22} \end{pmatrix} \begin{pmatrix} \theta_1 \\ \overline{\theta}_1 \\ \overline{\theta}_2 \\ \theta_2 \end{pmatrix} = \begin{pmatrix} g_1 - \xi_1 \\ 0 \\ 0 \\ g_2 - \xi_2 \end{pmatrix},$$

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A deterministic multi-area optimal power flow problem

Reformulate with these variables

$$\left\{ x_1 = \begin{pmatrix} g_1 \\ \theta_1 \end{pmatrix}, \quad x_2 = \begin{pmatrix} g_2 \\ \theta_2 \end{pmatrix}, \quad y = \begin{pmatrix} \overline{\theta}_1 \\ \overline{\theta}_2 \end{pmatrix}. \right.$$

$$\begin{aligned} &\text{minimize} \quad \pi_1^\top g_1 + \pi_2^\top g_2, \\ &\text{subject to} \end{aligned}$$

linear dispatch cost structure

$$\underline{g}_i \leq g_i \leq \overline{g}_i,$$

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transmission constraint between the areas

Algorithm via critical region exploration

Reformulate with these variables $\left\{ x_1 = \begin{pmatrix} g_1 \\ \theta_1 \end{pmatrix}, \quad x_2 = \begin{pmatrix} g_2 \\ \theta_2 \end{pmatrix}, \quad y = \begin{pmatrix} \overline{\theta}_1 \\ \overline{\theta}_2 \end{pmatrix}. \right.$

$$
\begin{aligned}
\text{minimize} \quad & c_1^\top x_1 + c_2^\top x_2, \\
\text{subject to} \quad & A_1^x x_1 + A_1^\xi \xi_1 + A_1^y y \leq b_1, \\
& A_2^x x_2 + A_2^\xi \xi_2 + A_2^y y \leq b_2, \\
& y \in \mathcal{Y}.
\end{aligned}
$$

a polyhedral set

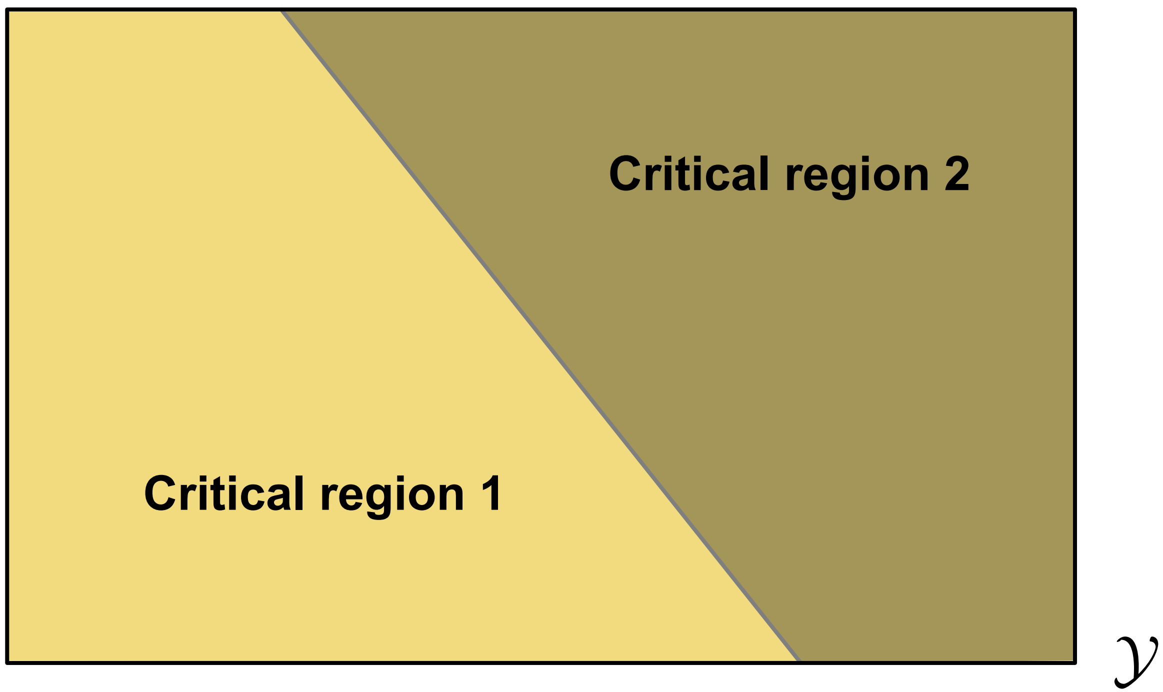
$$
\equiv \underset{y \in \mathcal{Y}}{\text{minimum}} \ [J_1^*(y, \xi_1) + J_2^*(y, \xi_2)]
$$

$$
J_1^*(y, \xi_1): \left\{
\begin{aligned}
\underset{x_1}{\text{minimize}} \quad & c_1^\top x_1, \\
\text{subject to} \quad & A_1^x x_1 + A_1^\xi \xi_1 + A_1^y y \leq b_1.
\end{aligned}
\right.
$$

A multi-parametric linear program (MPLP), linearly parameterized on the right-hand side by y. Borrelli '11.

Properties of $J_i^*(y, \xi_i)$ and the algorithm

Lemma. $J_i^*(y, \xi_i)$ is piecewise-affine and convex in y. Sets over which $J_i^*(y, \xi_i)$ is affine define a polyhedral partition of $\mathcal{Y}$.



Critical regions induced by J_1^*

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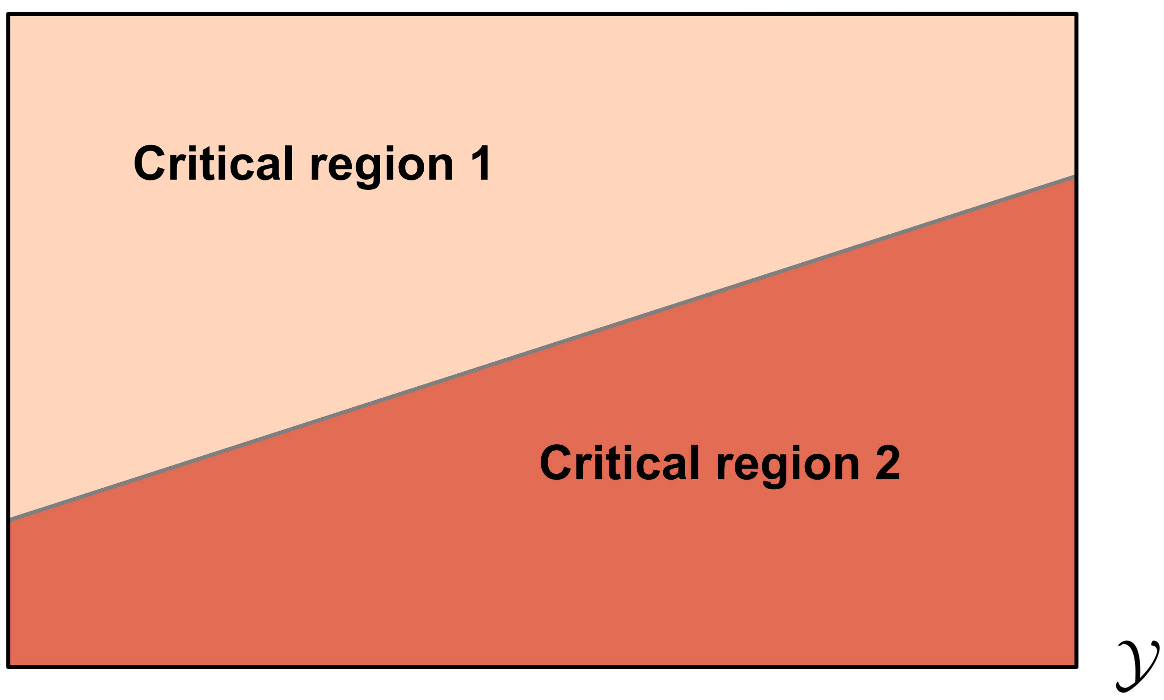

Critical regions induced by J_2^*

Properties of $J_i^*(y, \xi_i)$ and the algorithm

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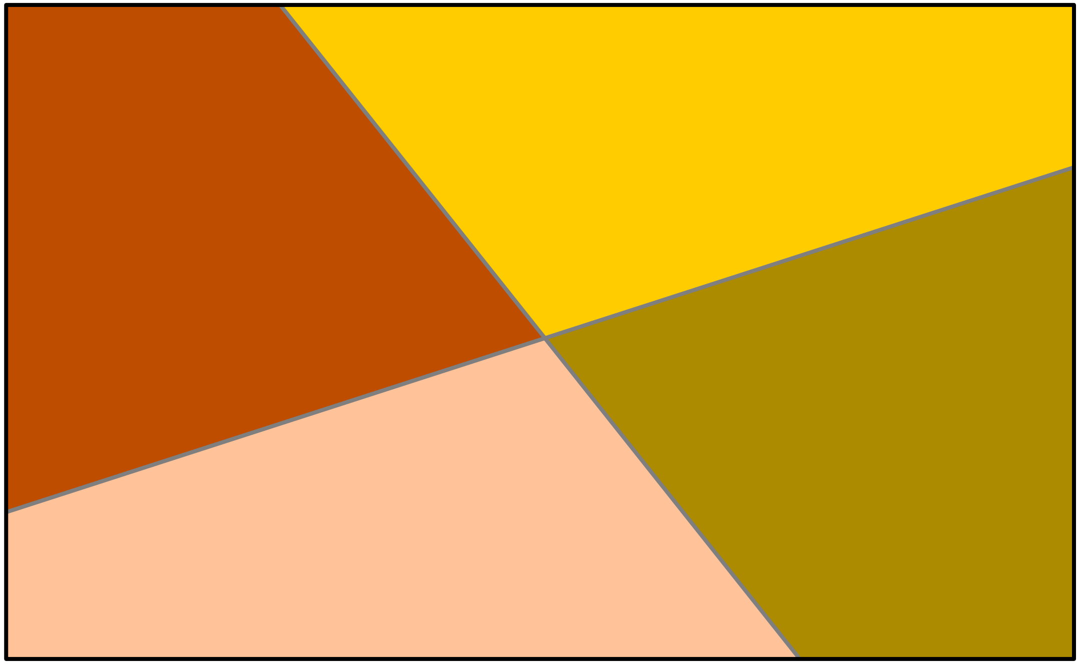

Critical regions induced by the aggregate cost

Properties of $J_i^*(y, \xi_i)$ and the algorithm

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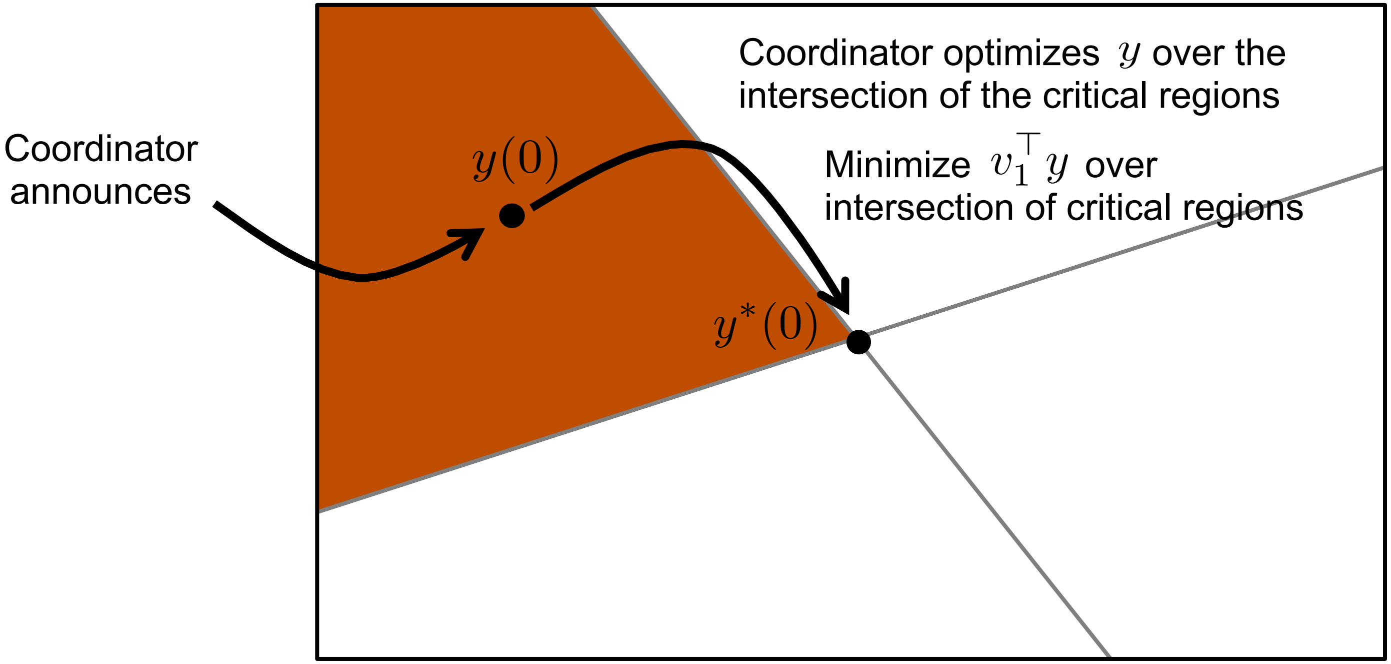

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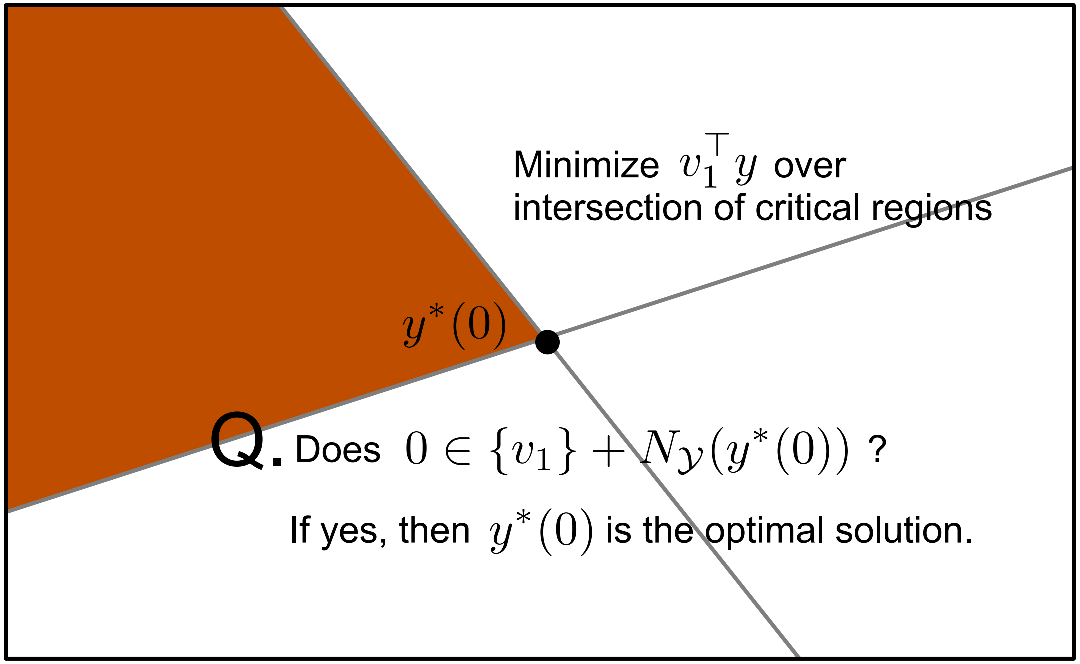

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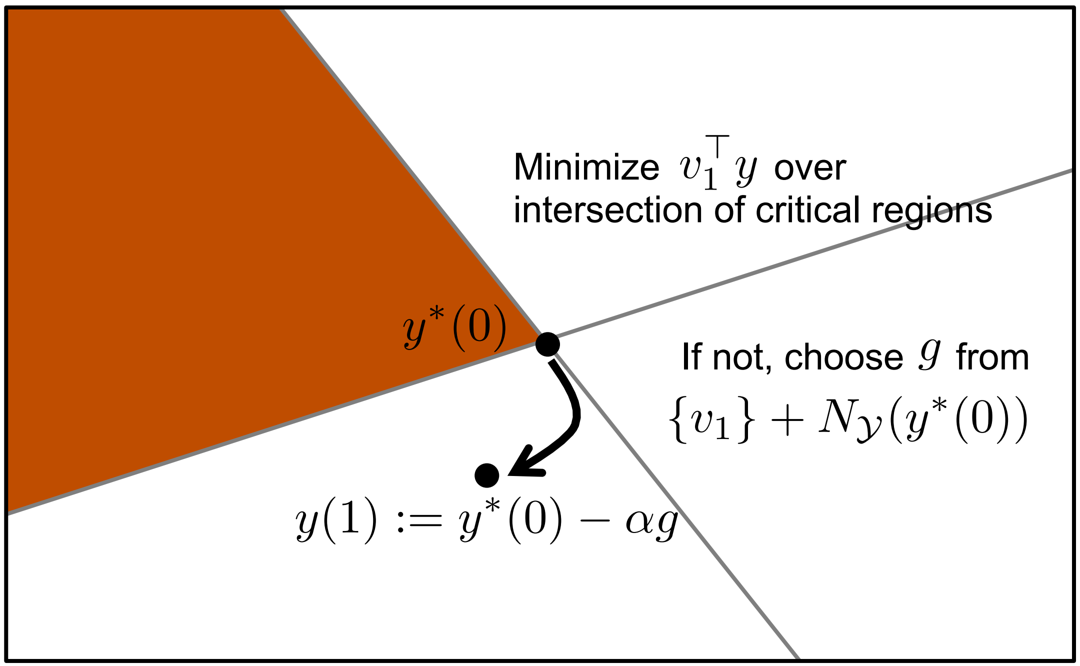

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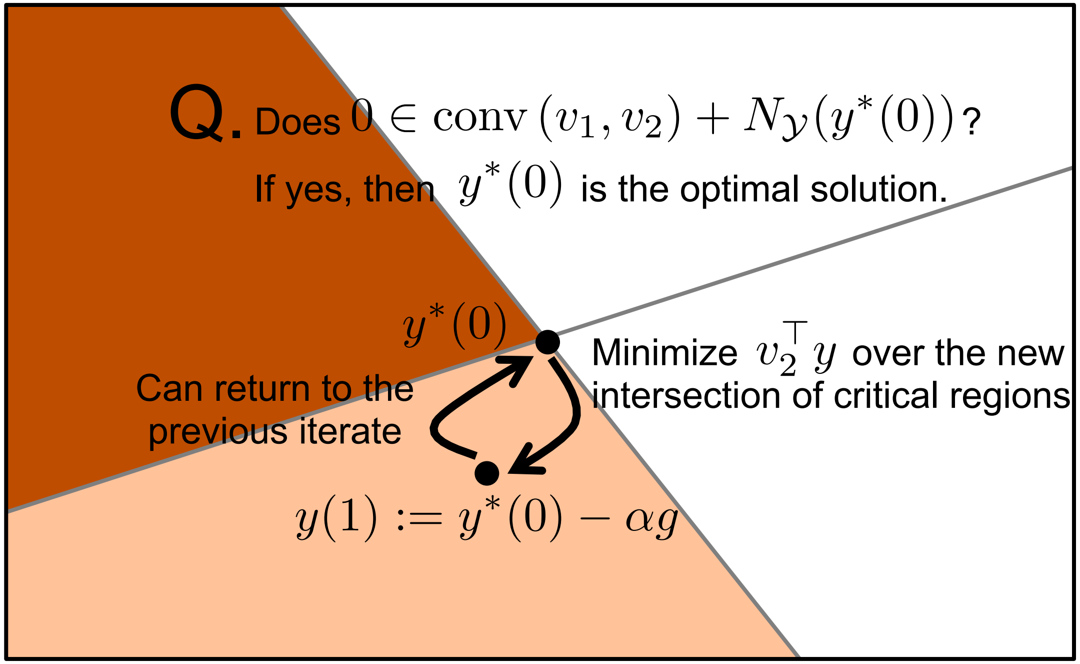

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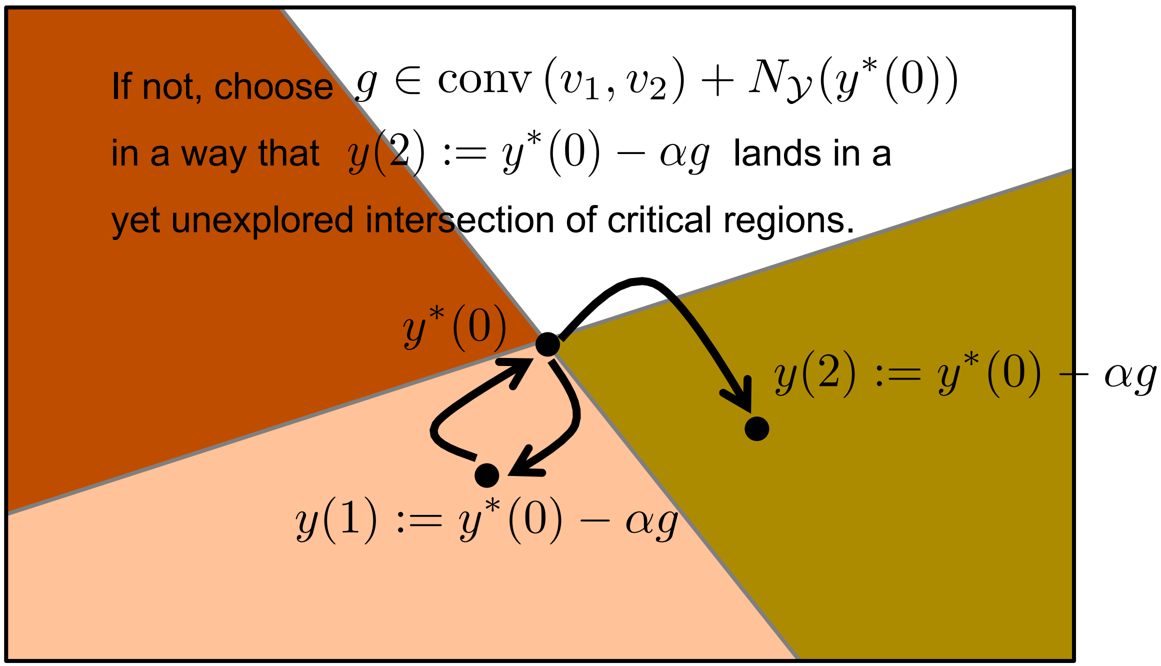

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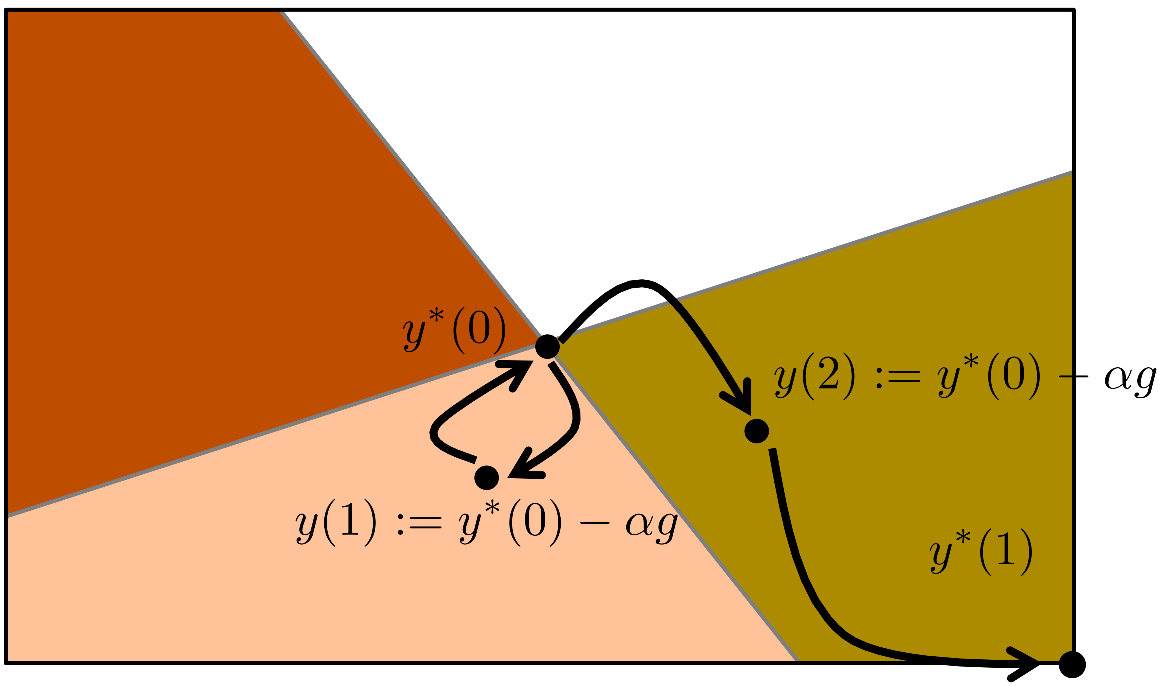


Iterate till optimality is reached

Features of critical region exploration

Theorem. Critical region exploration converges in finitely many iterations to the optimal tie-line schedule.

Key idea of the proof:
There are finitely many critical regions to explore!

Advantages of this algorithm:
- Converges in finitely many iterations. It typically requires less iterations than different Lagrangian relaxation based methods.
- Does not require the SOs to reveal their dispatch cost structure and/or network information within each area.

Possible disadvantage:
- Difficult to provide guarantees on convergence rate (as of yet).

A deterministic multi-area optimal power flow problem ...recap

$$\begin{aligned}\text{minimize} \quad & c_1^\top x_1 + c_2^\top x_2, \\ \text{subject to} \quad & A_1^x x_1 + A_1^\xi \xi_1 + A_1^y y \le b_1, \\ & A_2^x x_2 + A_2^\xi \xi_2 + A_2^y y \le b_2, \\ & y \in \mathcal{Y}.\end{aligned} \equiv \underset{y \in \mathcal{Y}}{\text{minimum}} \; [J_1^*(y, \xi_1) + J_2^*(y, \xi_2)]$$

The robust counterpart

$$\underset{y \in \mathcal{Y}}{\text{minimum}} \left[\left(\underset{\xi_1 \in \Xi_1}{\text{maximum}} \; J_1^*(y, \xi_1) \right) + \left(\underset{\xi_2 \in \Xi_2}{\text{maximum}} \; J_2^*(y, \xi_2) \right) \right]$$

Uncertainty sets are polytopes with small number of vertices

Solving the robust counterpart

Key idea: Sequentially update (ξ_1, ξ_2) and y.

Fix (ξ_1^k, ξ_2^k). Find y^k by solving the following via critical region exploration.

$$\underset{y \in \mathcal{Y}}{\text{minimize}} \quad \left\{ \left(\max_{p=1,\ldots,k} J_1^*(y, \xi_1^p) \right) + \left(\max_{p=1,\ldots,k} J_2^*(y, \xi_2^p) \right) \right\}.$$

Fix y^k. Update $(\xi_1^{k+1}, \xi_2^{k+1})$ via a mixed-integer linear program.

$$\underset{\xi_i}{\text{maximize}} \quad J_i^*(y^k, \xi_i), \quad \text{subject to} \quad \xi_i \in \text{vertex set of } \Xi_i.$$

Iterate till y^k satisfies:

$$J_1^*(y^k, \xi_1^{k+1}) + J_2^*(y^k, \xi_2^{k+1}) = \max_{p=1,\ldots,k} J_1^*(y^k, \xi_1^p) + \max_{p=1,\ldots,k} J_2^*(y^k, \xi_2^p).$$

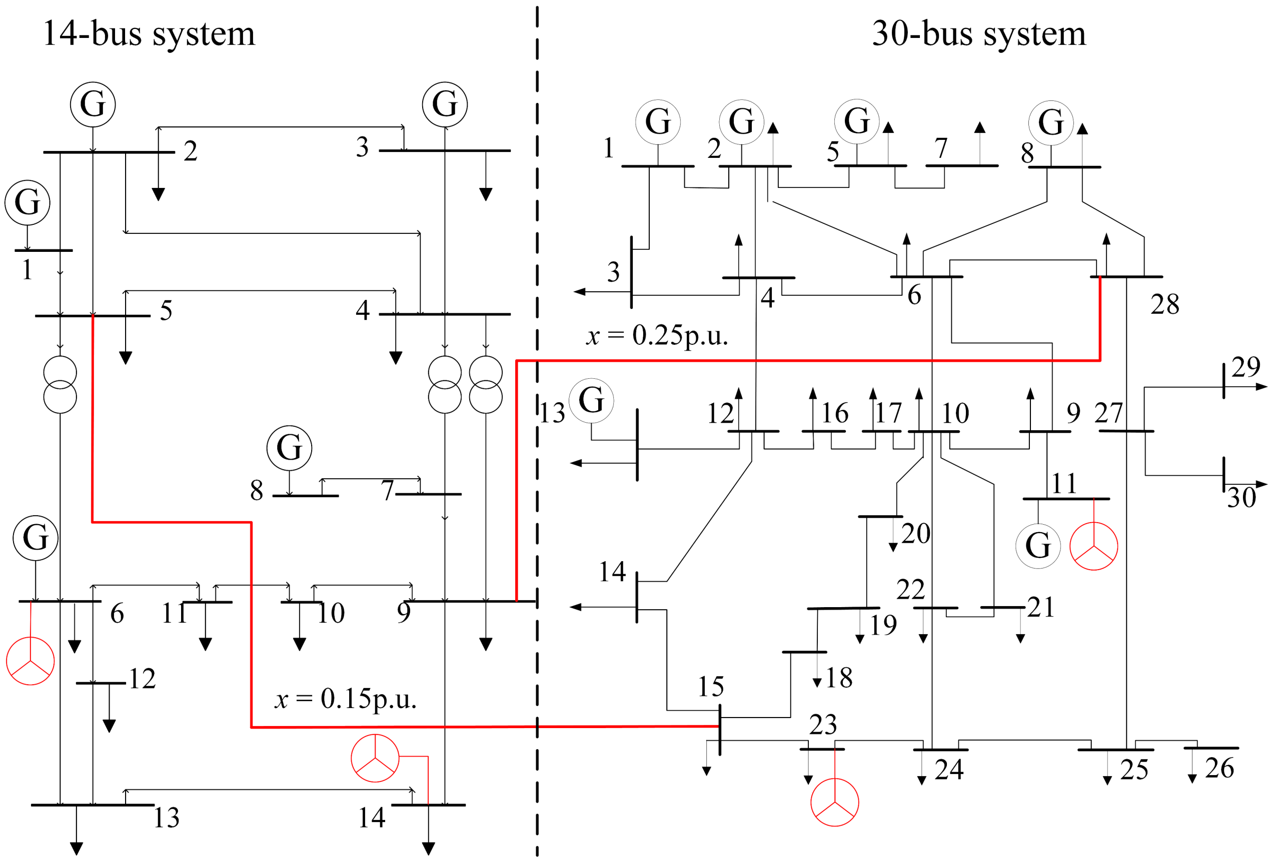
Features of the algorithm for the robust counterpart

Theorem. The sequential update via critical region exploration and the MILP converges in finitely many iterations to the optimal robust tie-line schedule.

Key idea of the proof:
There are finitely many vertices of the uncertainty polytope.

Advantages of this algorithm:
- Finite step convergence. It typically converges in very few iterations.
- Does not require disclosure of dispatch cost structure, network information, uncertainty set within each area.

Possible disadvantage:
- Difficult to provide guarantees on convergence rate, and MILP makes it unlikely to find one.



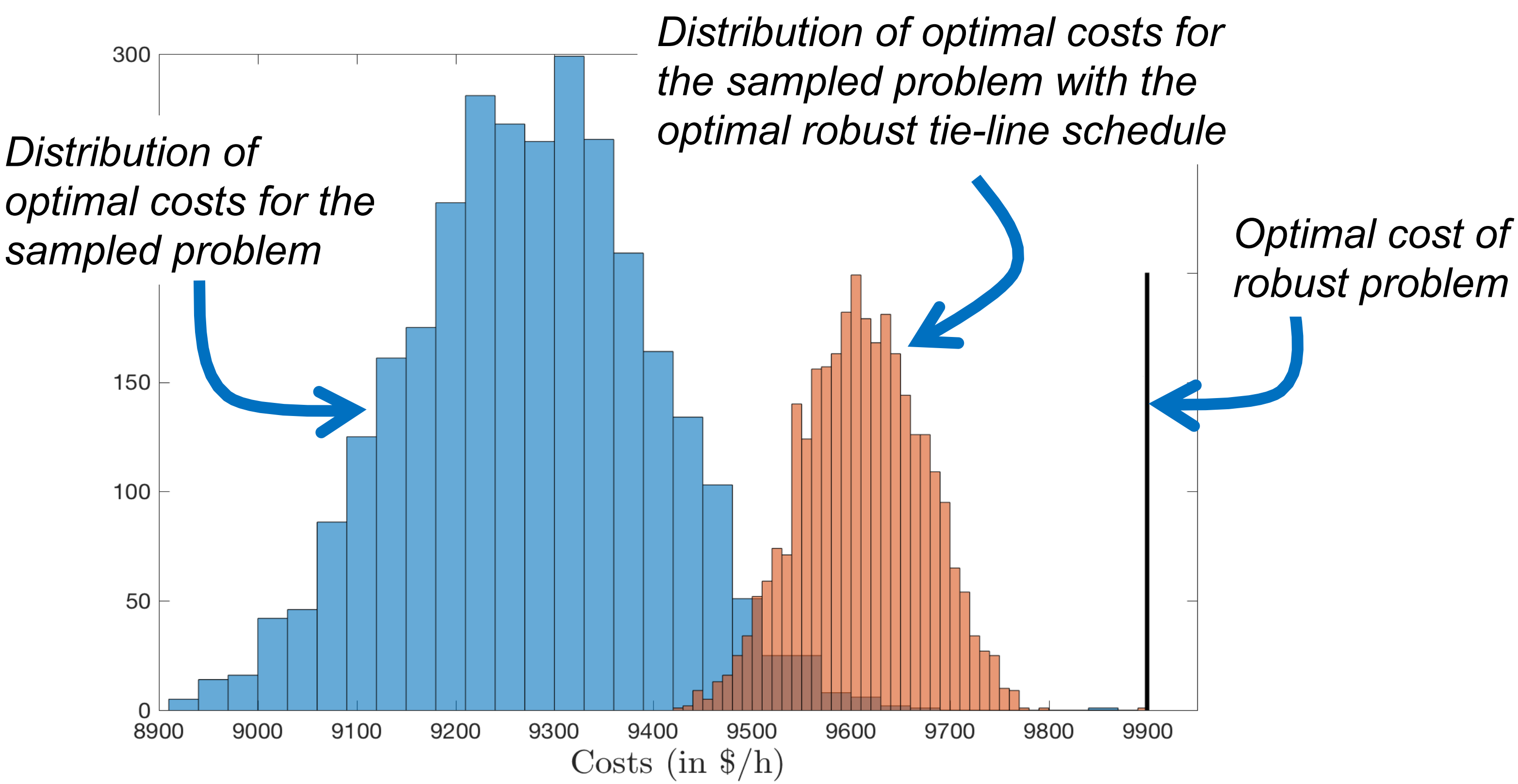
IEEE 14-bus + IEEE 30-bus

- 4 wind generators. Available capacity varies between 15MW and 25MW.
- Load at each bus varies between 98% and 102% of nominal value.
- 100MW capacity imposed on all lines

Summary of results on the IEEE 14+30 bus test systems

Sample (ξ_1, ξ_2) uniformly at random. Solve a deterministic problem with that sample. Compare the optimal cost and run-time.

Run-time (robust) ≈ 10 . Run-time (deterministic)



More empirical results

# areas	# buses	# uncertain variables	# iterations in rob. alg.	Run-time of rob. alg. (in ms)	Run-time of joint problem (in ms)
2	87	91	1	719.6	310.0
2	175	179	1	871.1	340.5
2	236	240	1	1732.6	391.5
2	418	42	1	1020.7	455.7
2	418	422	4	6124.5	461.4
3	354	360	3	4127.4	655.8
3	536	54	1	2557.6	699.7
3	536	546	3	18359.8	701.2

Observation: Runtime of algorithm for the robust counterpart depends strongly on the number of uncertain parameters.

Outline of this talk

Q1. A distributed algorithm for tie-optimization under uncertainty.

Q2. Is Coordinated Transaction Scheduling necessarily suboptimal?

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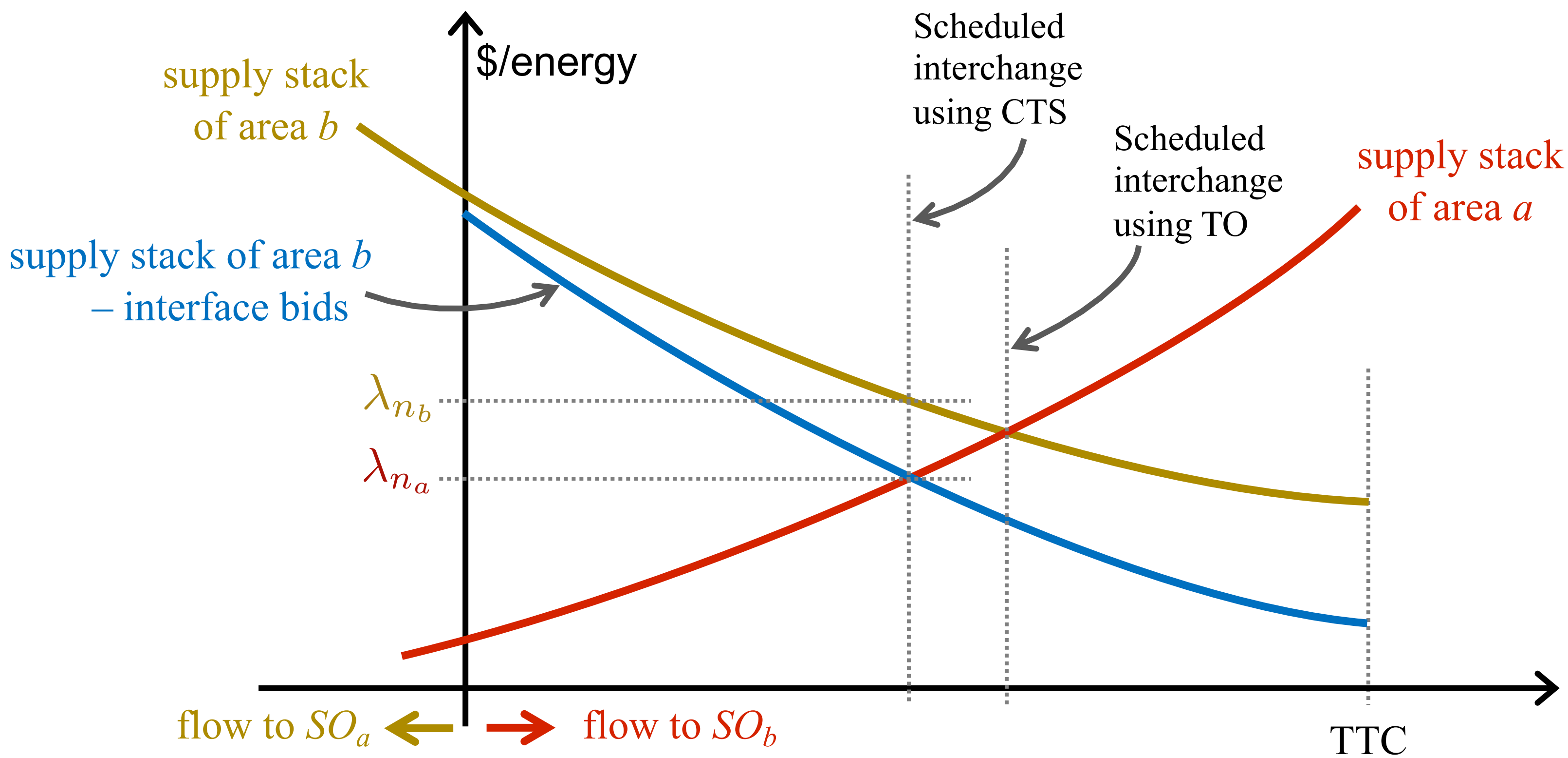
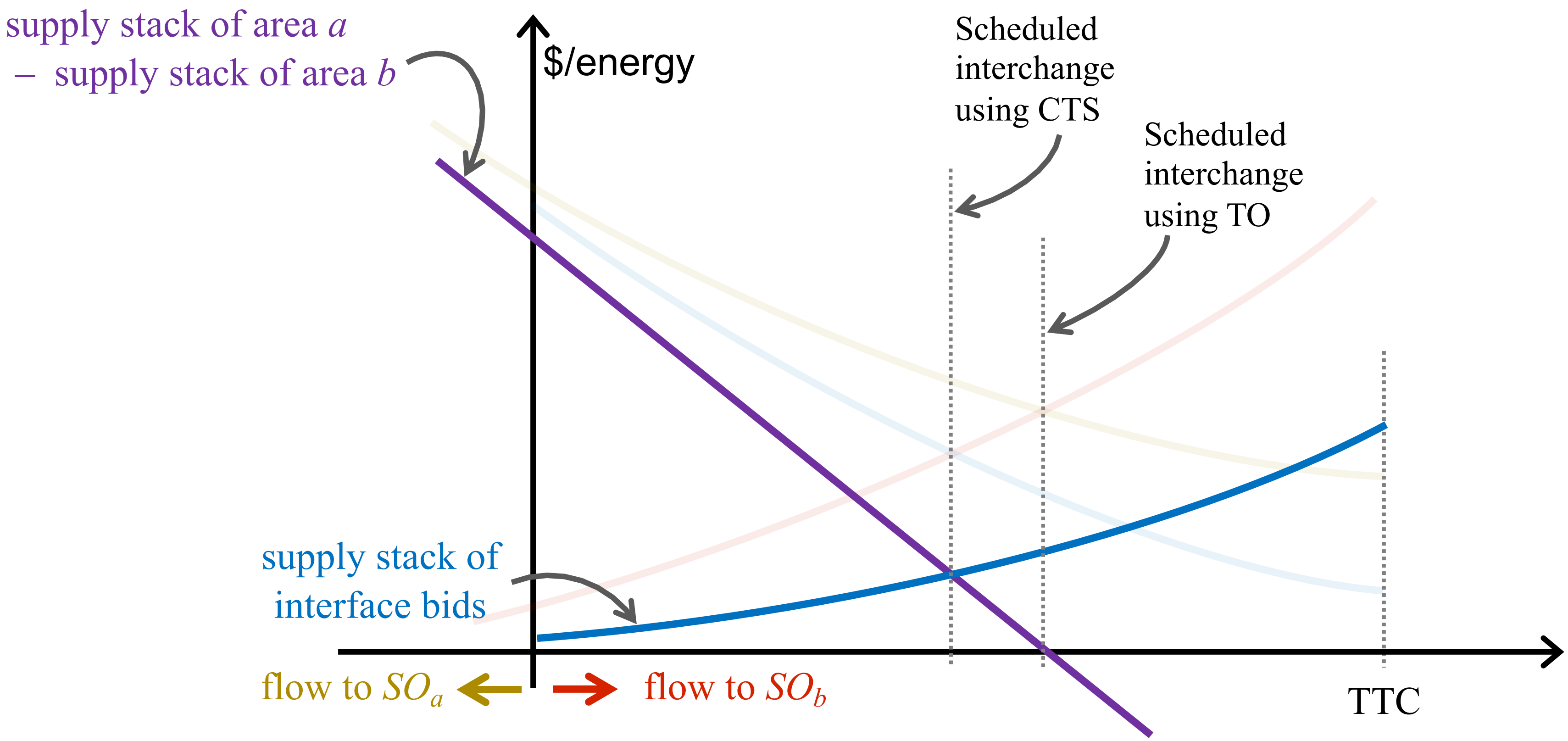
Is Coordinated Transaction Scheduling always suboptimal?

Explaining Coordinated Transaction Scheduling



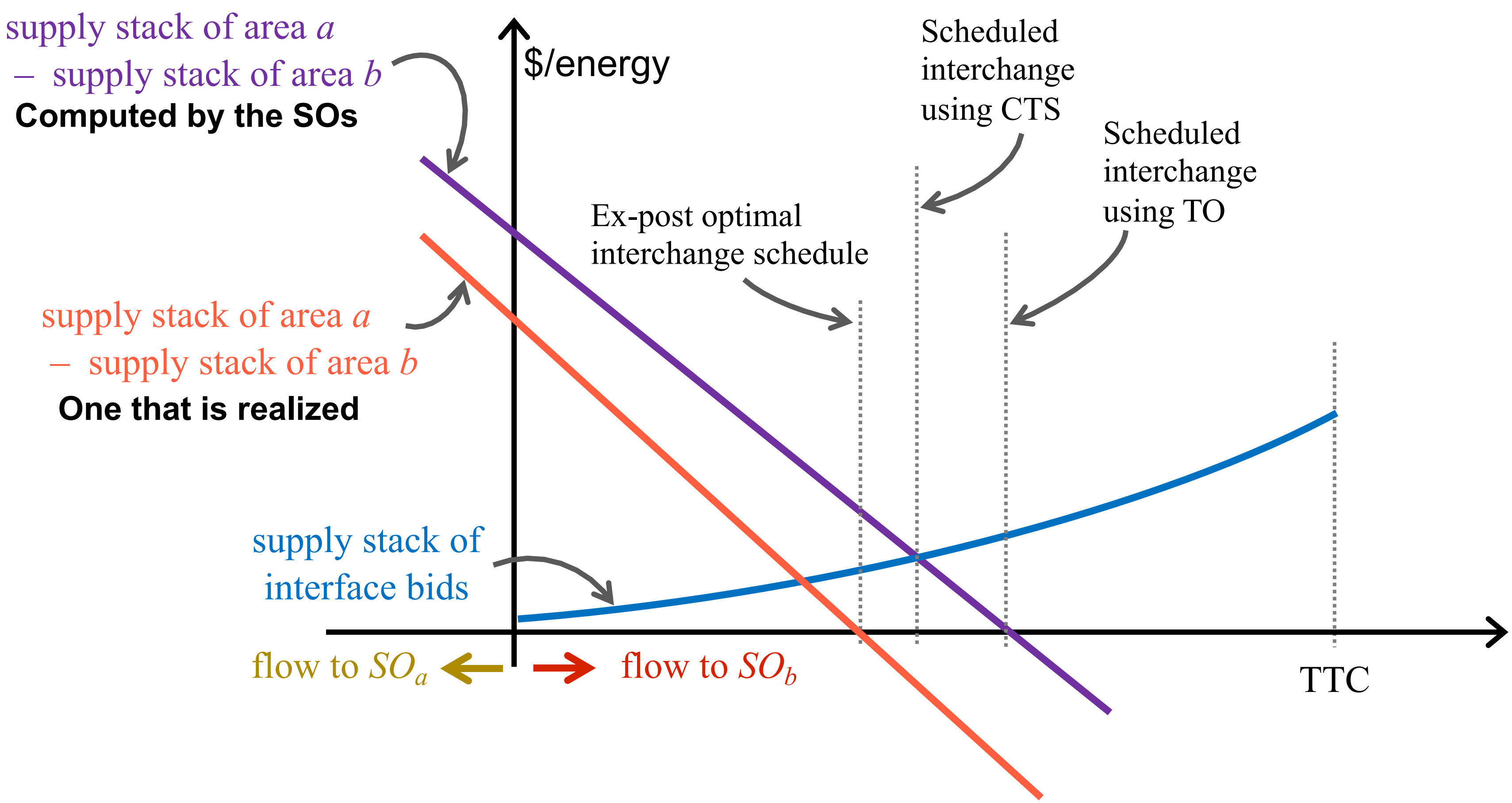
CTS market participants offer to transact energy between the areas at a price equal to the price difference between the boundary buses in the two areas.

Explaining Coordinated Transaction Scheduling



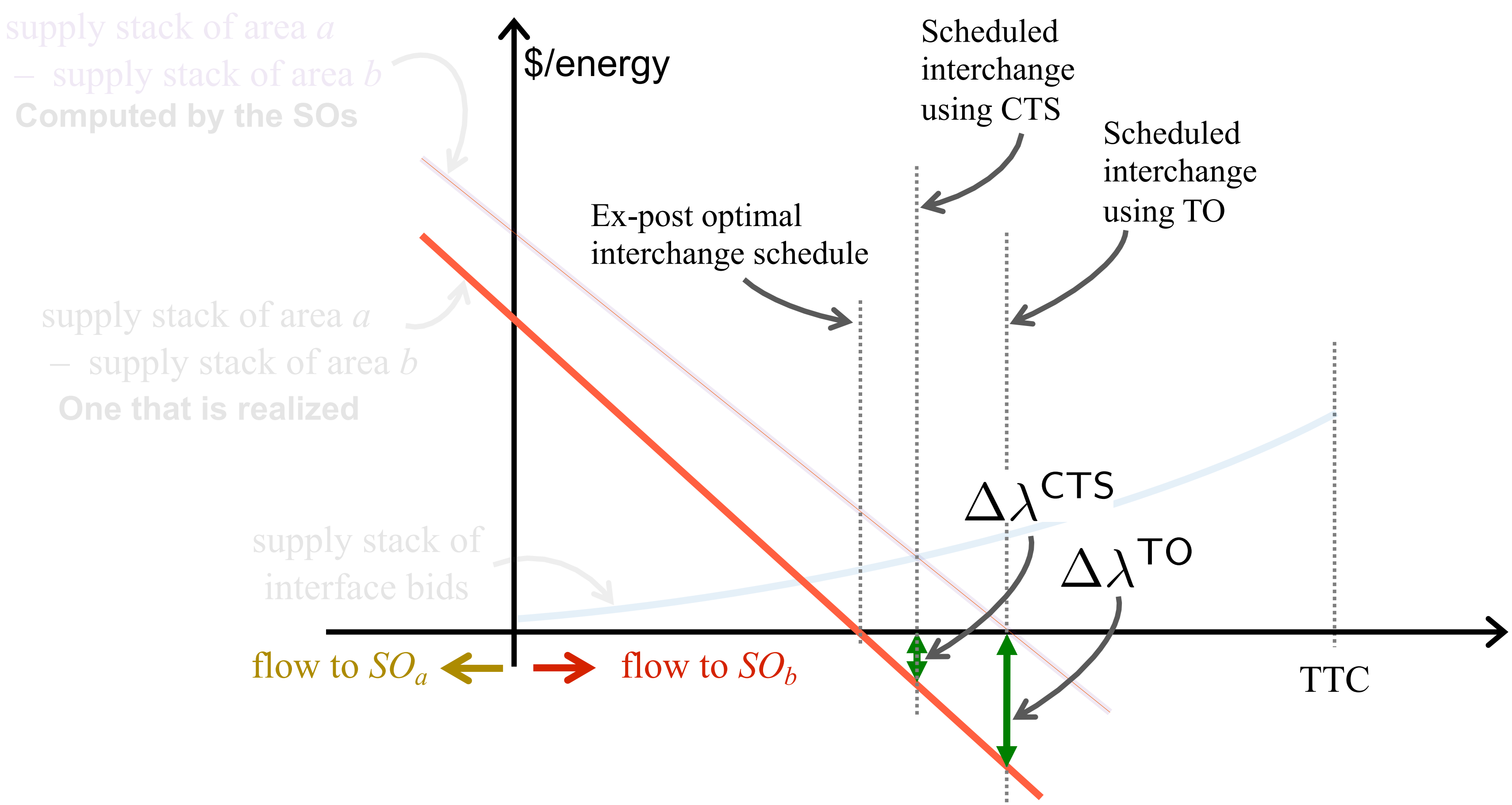
CTS market participants are like suppliers offering against an inverse demand function defined by the difference of the supply stacks of the two areas.

Interchange schedule of CTS v/s TO



Supply stack of area a – supply stack of area b is computed based on forecasts.

Interchange schedule of CTS v/s TO



Realized price spread of CTS can be less than that of TO.
Will that happen, given the strategic incentives of the bidders?

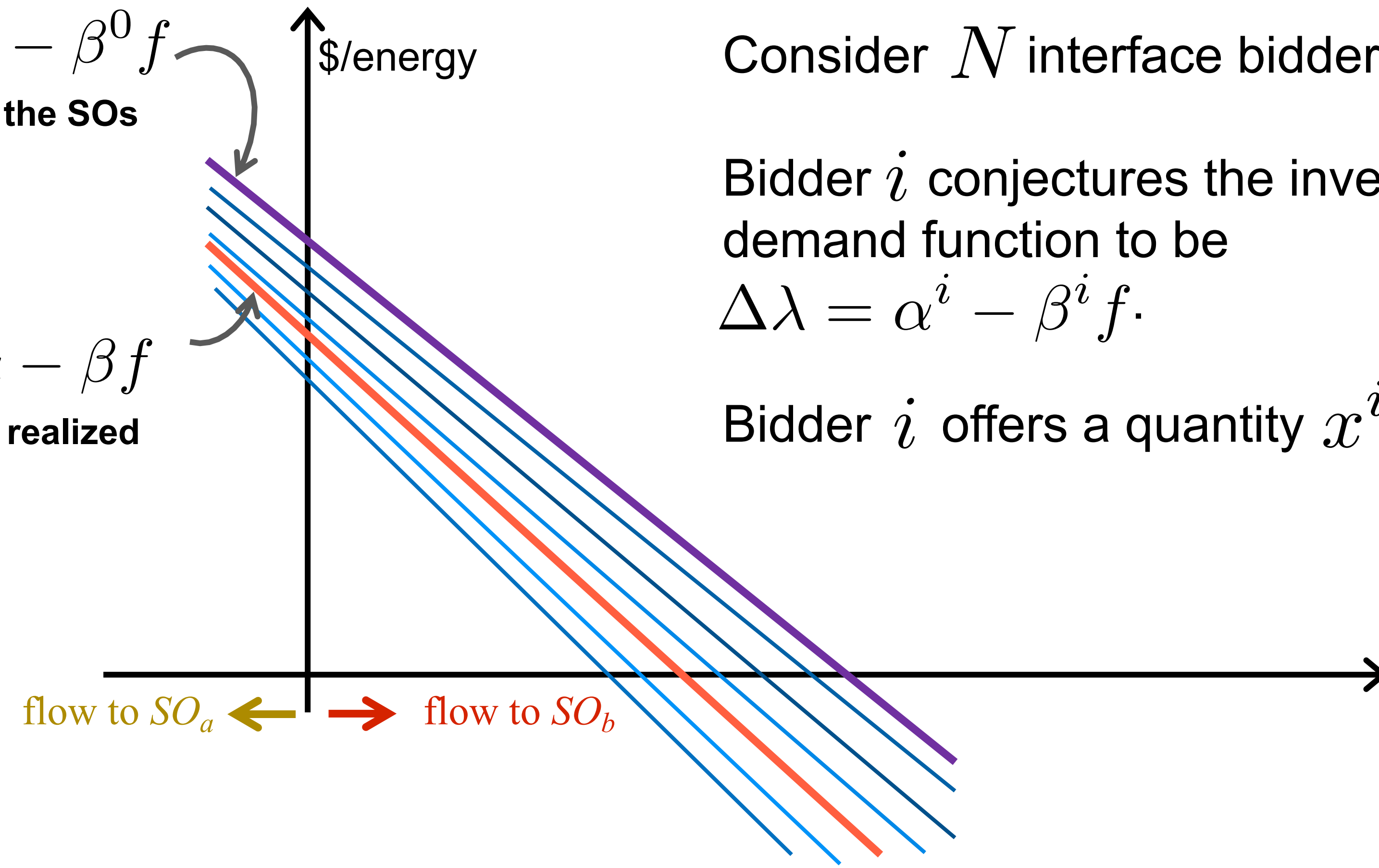
Market based interchange scheduling (not CTS) as a Cournot competition

$$\Delta\lambda = \alpha^0 - \beta^0 f$$

Computed by the SOs

$$\Delta\lambda = \alpha - \beta f$$

One that is realized



Consider N interface bidders.

Bidder i conjectures the inverse demand function to be $\Delta\lambda = \alpha^i - \beta^i f$.

Bidder i offers a quantity x^i.

Conjectured revenue of bidder i : $\pi^i(x^i, x^{-i}) := \left(\alpha^i - \beta^i \sum_{i=1}^{N} x^i\right) x^i$.

The market outcome as a Nash equilibrium

Theorem. The unique Nash equilibrium $(x_*^1, \dots, x_*^N)$ of the Cournot game among the interface bidders is given by

$$x_*^i = \gamma^i - \frac{N}{N+1}\overline{\gamma},$$

where $\gamma^i = \alpha^i / \beta^i$, and $\overline{\gamma} = \frac{1}{N}\sum_{i=1}^N \gamma^i$.

$$f^{\mathsf{IB}} = \sum_{i=1}^{N} x_*^i = \frac{N}{N+1}\overline{\gamma}; \quad \Delta\lambda^{\mathsf{IB}} = \alpha - \frac{N}{N+1}\beta\overline{\gamma}$$

$$f^{\mathsf{TO}} = \frac{\alpha^0}{\beta^0} := \gamma^0; \quad \Delta\lambda^{\mathsf{TO}} = \alpha - \beta\gamma^0$$

Conclusions from the Cournot formulation

Observation 1. If interface bidders have better average conjectures than the SOs, then the resulting price spread can be lower than that in TO.

$$\left|\frac{N}{N+1}\overline{\gamma} - \frac{\alpha}{\beta}\right| \approx \left|\overline{\gamma} - \frac{\alpha}{\beta}\right| < \left|\gamma^0 - \frac{\alpha}{\beta}\right| \implies \left|\Delta\lambda^{\mathsf{IB}}\right| < \left|\Delta\lambda^{\mathsf{TO}}\right|.$$

Observation 2. When the average conjecture of the interface bidders is the same as that of the SOs, then the outcome of interface bidding will approach that in TO, as the number of bidders grows.

$$\overline{\gamma} = \gamma^0 \implies \lim_{N\to\infty} \frac{N}{N+1}\overline{\gamma} = \gamma^0.$$

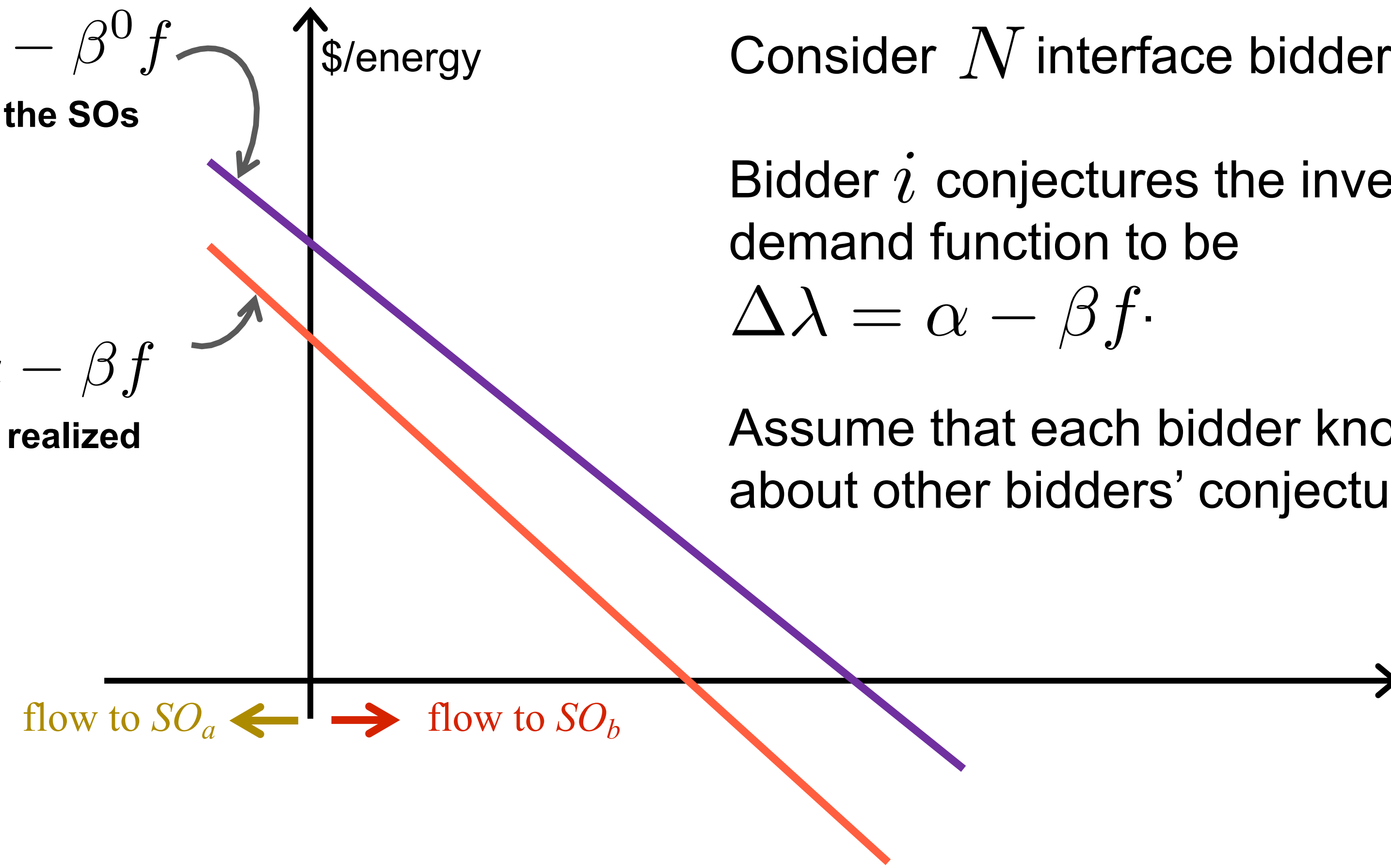
CTS with interface bidders that have perfect foresight

$$\Delta\lambda = \alpha^0 - \beta^0 f$$

Computed by the SOs

$$\Delta\lambda = \alpha - \beta f$$

One that is realized



Consider N interface bidders.

Bidder i conjectures the inverse demand function to be $\Delta\lambda = \alpha - \beta f$.

Assume that each bidder knows about other bidders' conjectures.

Each market participant bids $(\Delta\lambda_i, x_i, \text{flow direction}_i)$.

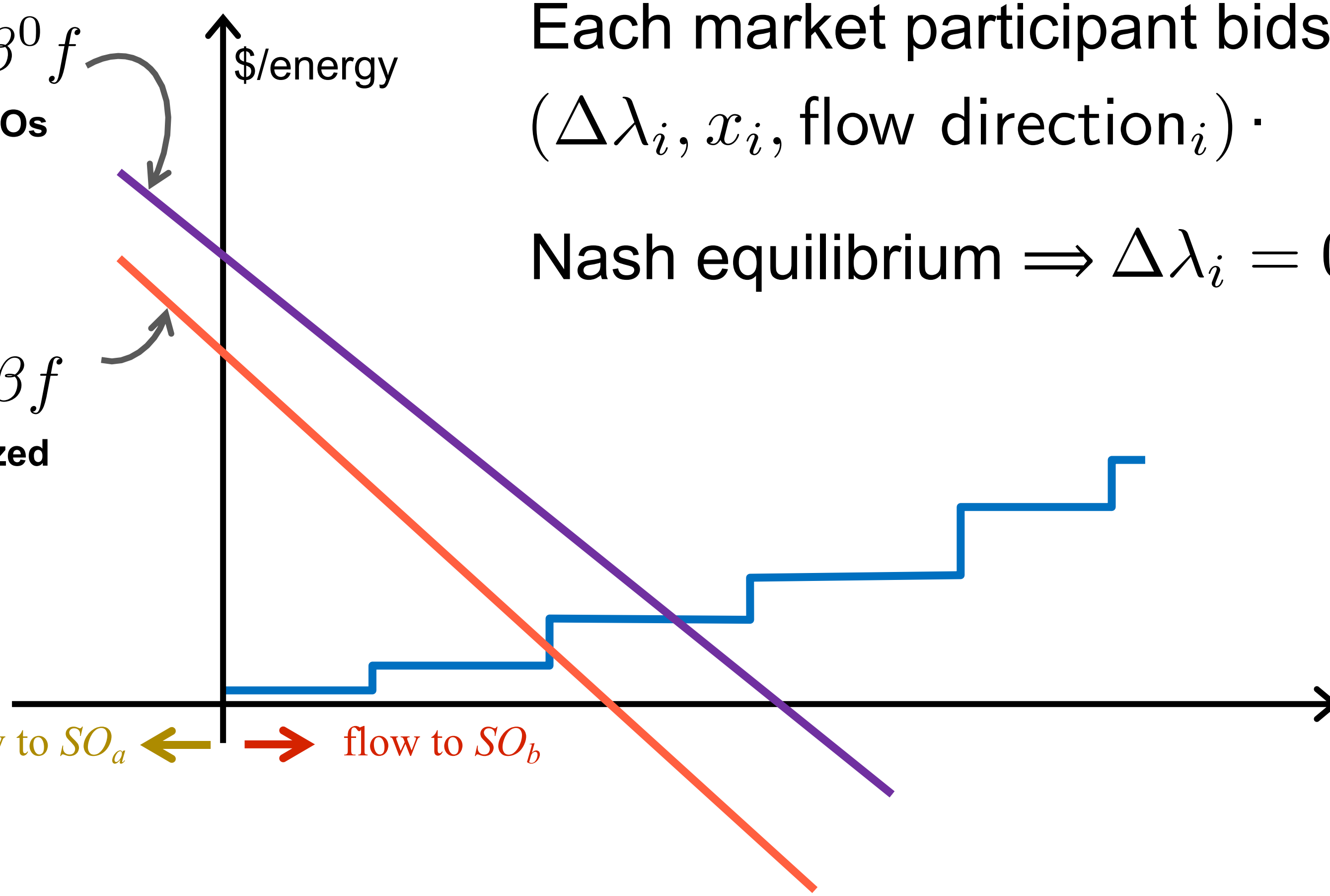
Any Nash equilibrium has zero price offers.

$$\Delta\lambda = \alpha^0 - \beta^0 f$$

Computed by the SOs

$$\Delta\lambda = \alpha - \beta f$$

One that is realized



Each market participant bids $(\Delta\lambda_i, x_i, \text{flow direction}_i)$.

Nash equilibrium $\Longrightarrow \Delta\lambda_i = 0$.

Non-zero equal prices can be sustained in a *repeated* game.

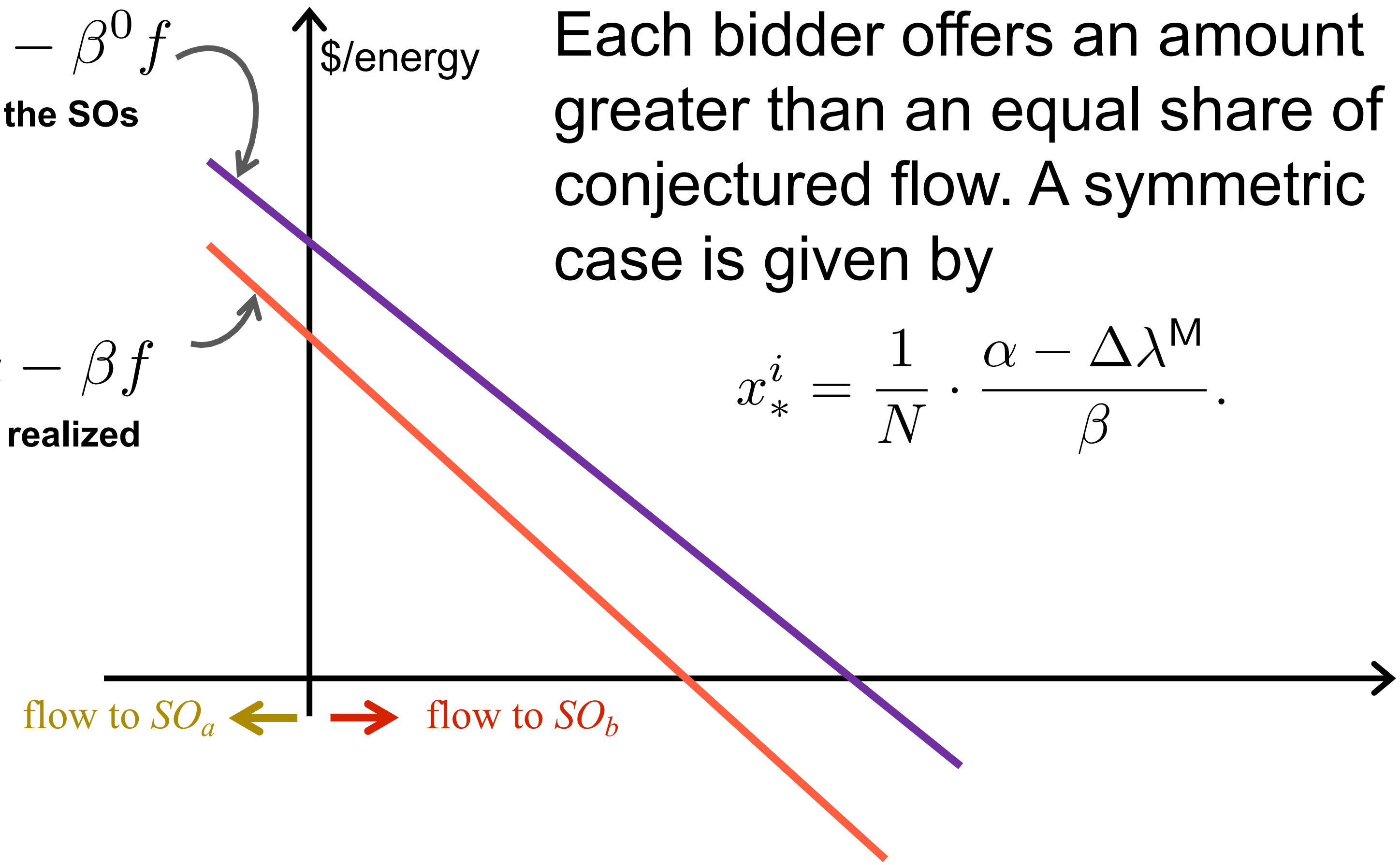
The case with possibly non-zero but equal price bids $\Delta\lambda^{\mathsf{M}}$

$$\Delta\lambda = \alpha^0 - \beta^0 f$$

Computed by the SOs

$$\Delta\lambda = \alpha - \beta f$$

One that is realized



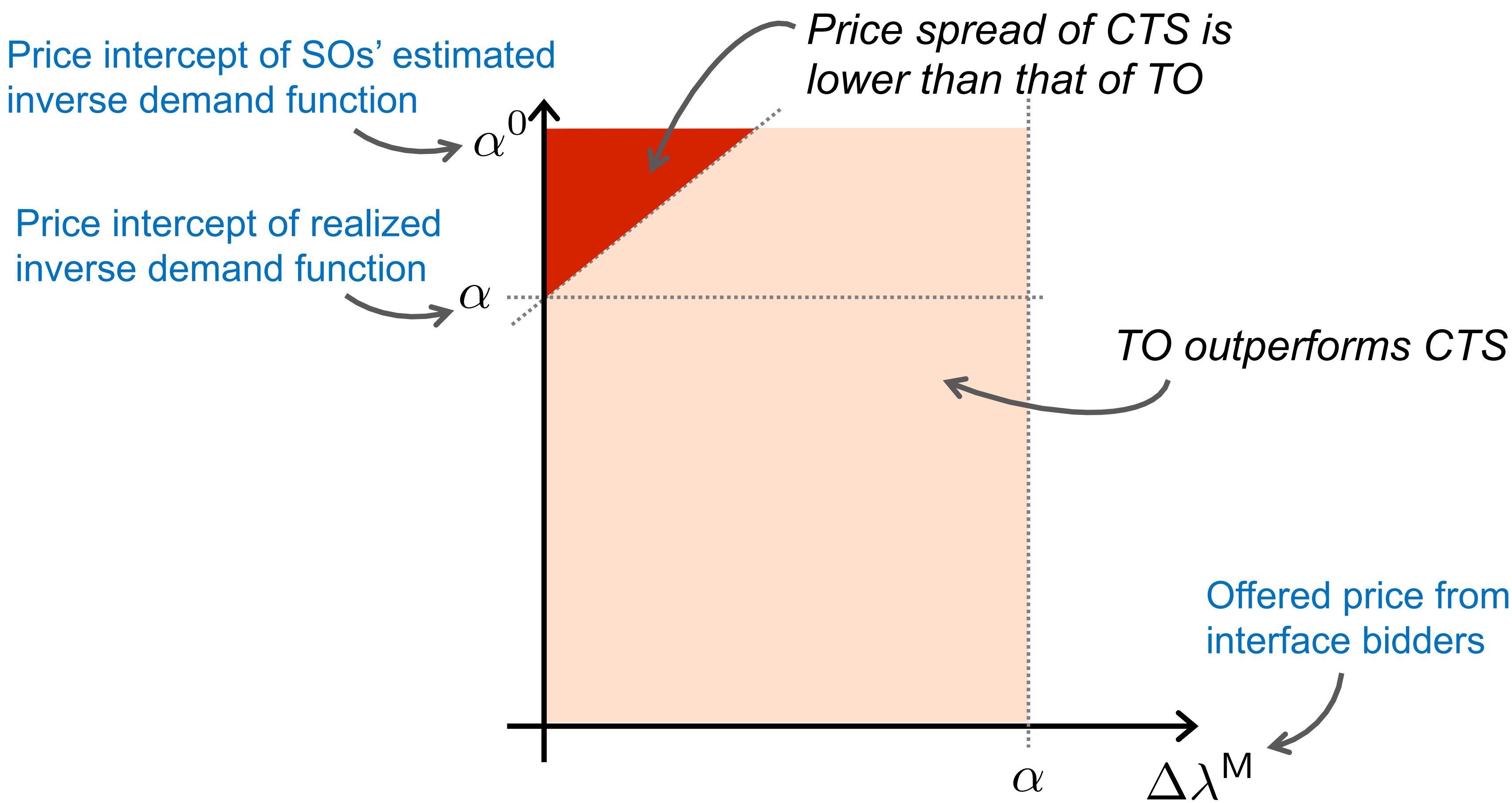
Each bidder offers an amount greater than an equal share of the conjectured flow. A symmetric case is given by

$$x_*^i = \frac{1}{N} \cdot \frac{\alpha - \Delta\lambda^{\mathsf{M}}}{\beta}.$$

The SOs clear the market against their forecasted demand function: $f^{\mathsf{CTS}} = \left[\frac{\alpha^0 - \Delta\lambda^{\mathsf{M}}}{\beta^0}\right]_0^{\frac{\alpha - \Delta\lambda^{\mathsf{M}}}{\beta}}$.

CTS versus TO with interface bidders that have perfect foresight

Visualizing the case with $\beta = \beta^0$.



CTS versus TO

- Roughly, if interface bidders have better conjectures on the inverse demand functions than the SOs, then the price spread in CTS can be lower than that in TO.

- Is it realistic that interface bidders have better information than the SOs?

Summary

Q1. A distributed algorithm for tie-optimization under uncertainty.

Q2. Is Coordinated Transaction Scheduling necessarily suboptimal?

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Questions?

Thank you!

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