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Cottbus - Senftenberg

European Gas Infrastructure Expansion Planning: An Adaptive Robust Optimization Approach

in collaboration with: Matthew Schmidt, Luis Baringo, Felix Müsgens

Research seminar talk
@ BTU CS
06 July 2021

Agenda

1. Research focus
2. Methodology:
    1. Adaptive Robust Optimization (ARO)
    2. Uncertainty sets
    3. Specific tunings for our application
    4. How to approach the ARO problem?
    5. Column-and-constraint generation (or Benders-primal) algorithm
3. Results

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Uncertainty in the European Natural Gas Market

Supply Side

- Declining domestic natural gas reserves
- Redirection of gas supplies (increasing demand in Asian economies)
- Growth in worldwide LNG export capacity -> European imports from US

Demand Side

- Gas for power generation (Ambitious climate targets and policy aims, e.g., coal phase-outs)
- Long-term economic outlook subject to uncertainty
- Cold weather (production freeze-offs in US in Feb 2021)

Impact on security of supply of natural gas?

European natural gas infrastructure

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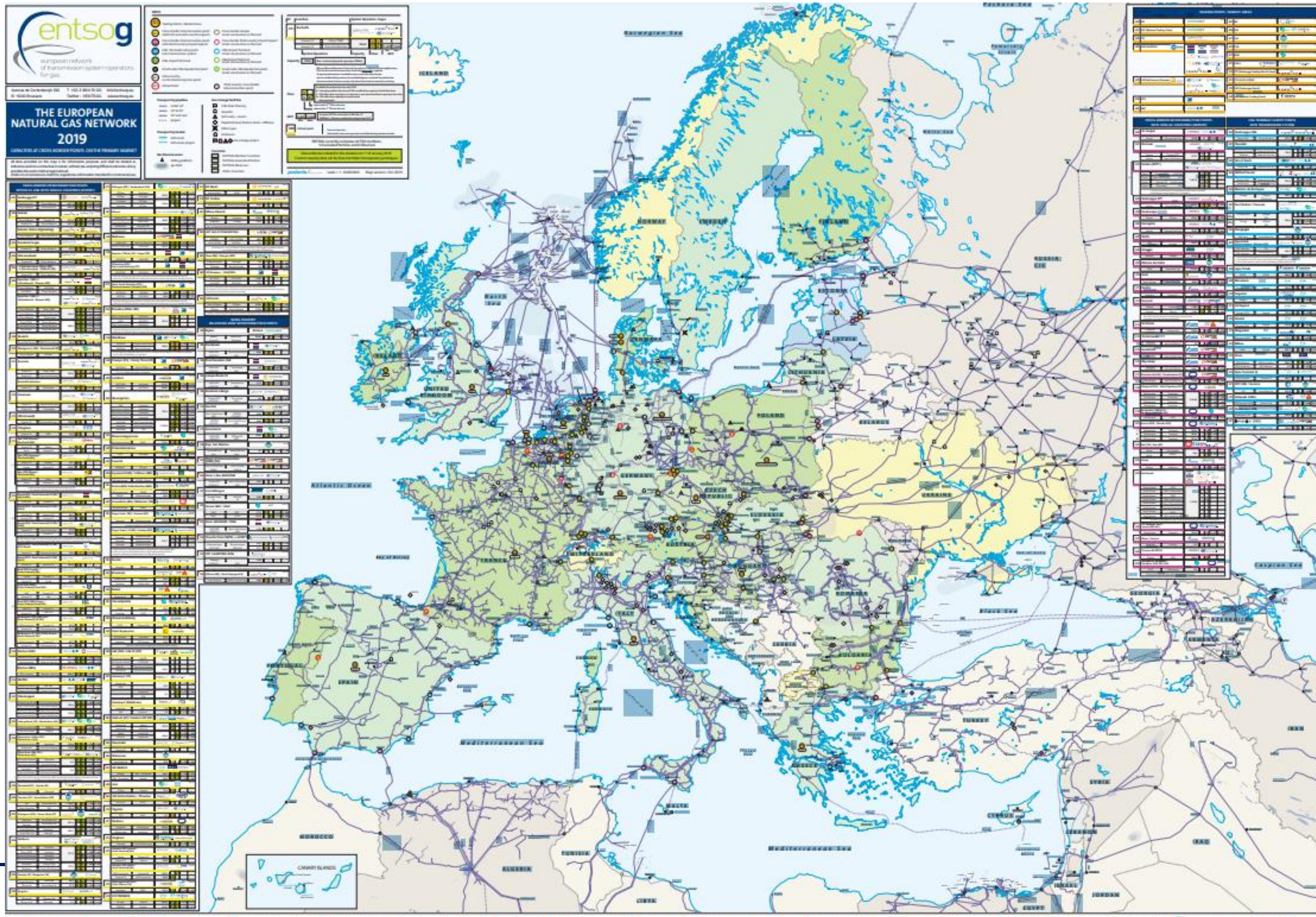

Projects of Common Interest (PCIs) included in our analysis:

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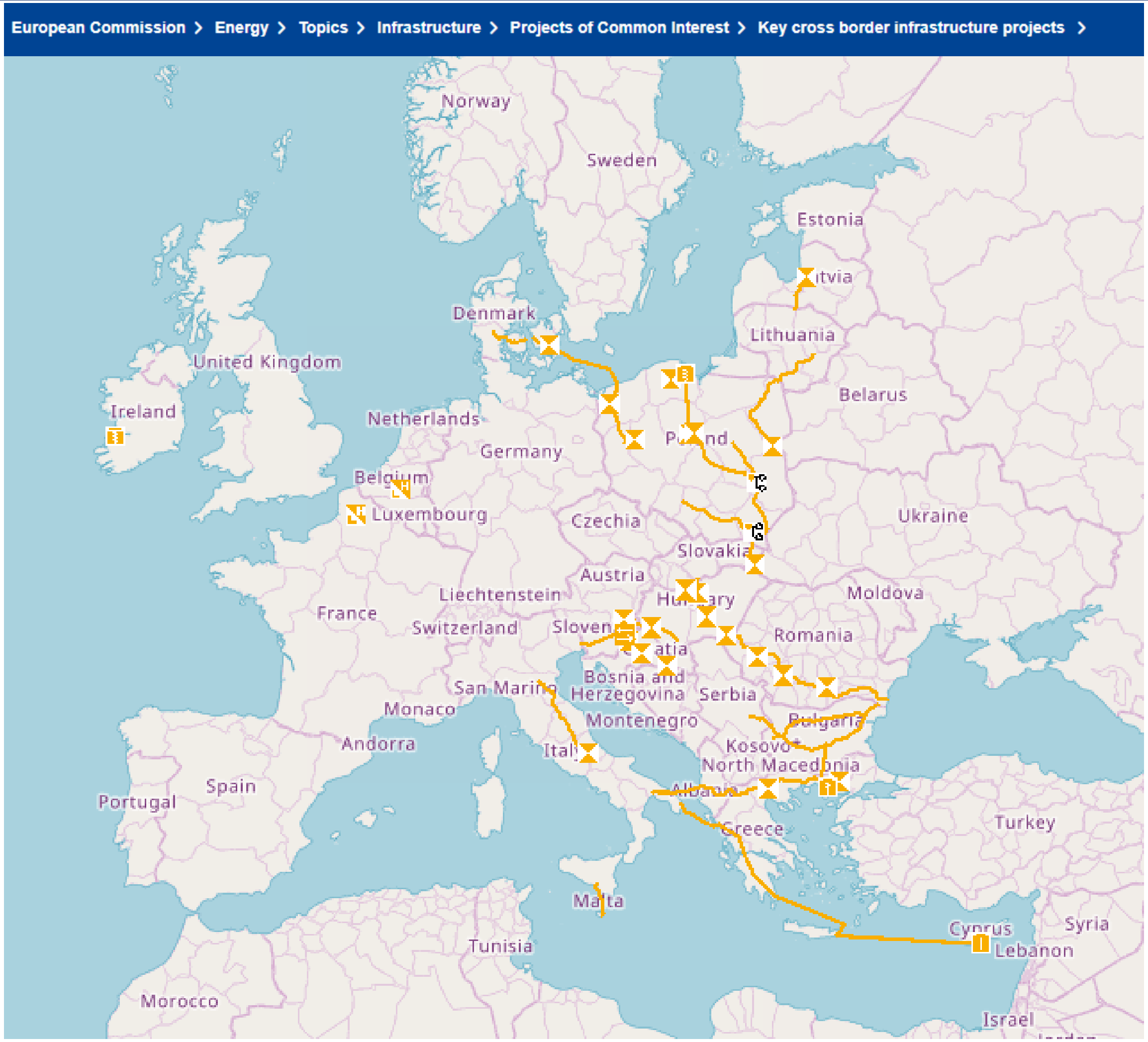
- **17 projects**
  13 interconnector pipelines
  4 LNG regasification terminals
- Combined come at a cost of **14 billion EUR**
- Add **136 bcm capacity** to the EU natural gas system



Actual contribution of PCIs to security of supply **is under debate** though...

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Artelys
OPTIMIZATION SOLUTIONS

An updated analysis on gas supply security in the EU energy transition

The report concludes that the existing EU gas infrastructure is sufficiently capable of meeting a variety of future gas demand scenarios in the EU28, even in the event of extreme supply disruption cases.

This suggests that most of the 32 gas infrastructure projects on the 4th PCI list are unnecessary from a security of supply point of view, and represent a potential overinvestment of tens of billions of EUR, supported by European public funds.

Key findings

Finding 1: Under normal market conditions, existing gas infrastructure in 2030 suffices to meet gas demand in both an "On Track" and "High Demand" scenario

Finding 3: Investments in projects included in the 4th PCI list are found to be unnecessary to safeguard security of supply in the EU28 and therefore risk to become stranded assets supported by European Union public funds. This remains true in scenarios with higher natural gas demand in 2030. Minor

Reference: Artelys, 2020. An updated analysis on gas supply security in the EU energy transition. Technical Report. Artelys OptimizationSolutions. Paris.

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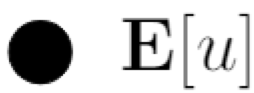
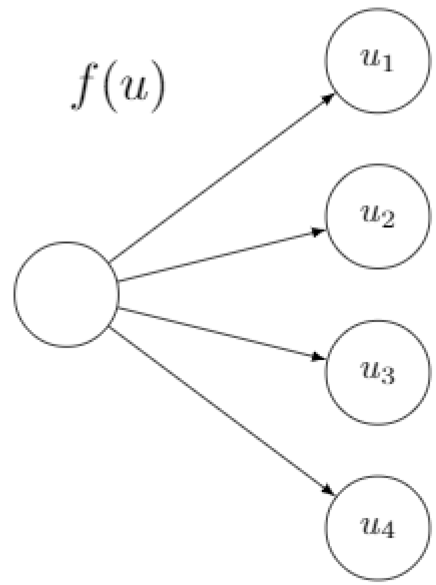
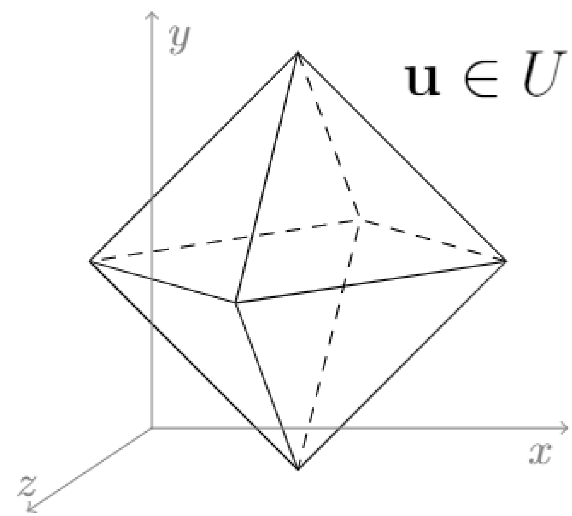
Modelling decisions under uncertainty



point estimate
(deterministic approach)



scenario tree
(stochastic approach)



uncertainty set
(robust approach)

Adaptive Robust Optimization problem

$$\min_x C_I^T x \qquad \max_u \qquad \min_y [C_O(x,u)]^T y$$

s.t. $x \in \mathbb{Z}^n$, $h(x) = 0$, $g(x) \leq 0$

s.t. $u \in U$

s.t.

$$A(x,u) \cdot y = b(x,u) : \lambda$$

$$D(x,u) \cdot y \geq e(x,u) : \mu$$

The first level (black) represents a planning strategy prior to the uncertainty realization and seeks to minimize the objective function value. Decision variables: **vector $\boldsymbol{x} \in \mathbf{X}$**

Adaptive Robust Optimization problem

$$\min_x C_I^T x \quad \text{s.t.} \quad x \in \mathbb{Z}^n, \quad h(x) = 0, \quad g(x) \leq 0$$

$$\max_u \quad \text{s.t.} \quad u \in U$$

$$\min_y [C_O(x,u)]^T y$$

s.t.

$$A(x,u) \cdot y = b(x,u) : \lambda$$

$$D(x,u) \cdot y \geq e(x,u) : \mu$$

The second level (red) represents the **uncertainty realization** in the worst possible manner within an uncertainty set (thus it seeks to max the objective function). Decision variables: **vector $\boldsymbol{u} \in \mathbf{U}$**

Adaptive Robust Optimization problem

$$\min_x C_I^T x \quad \text{s.t.} \quad x \in \mathbb{Z}^n, \quad h(x) = 0, \quad g(x) \leq 0$$

$$\max_u \quad \text{s.t.} \quad u \in U$$

$$\min_y [C_O(x,u)]^T y$$

s.t.

$$A(x,u) \cdot y = b(x,u) : \lambda$$

$$D(x,u) \cdot y \geq e(x,u) : \mu$$

The third level (blue) represents the operation actions to mitigate the effect of the uncertainty. It therefore seeks to minimize the objective function. Decision variables: vector $\boldsymbol{y} \in \boldsymbol{Y}(\boldsymbol{x}, \boldsymbol{u})$.

Polyhedral uncertainty set example (Conejo et al. 2016):

$$P_g^{Emax} \in \left[0, \overline{P_g^{Emax}}\right] \qquad \forall g$$

$$\frac{\sum_g(\overline{P_g^{Emax}} - P_g^{Emax})}{\sum_g(\overline{P_g^{Emax}})} \leq \Gamma^G$$

$$P_d^{Dmax} \in \left[\underline{P_d^{Dmax}}, \overline{P_d^{Dmax}}\right] \quad \forall d$$

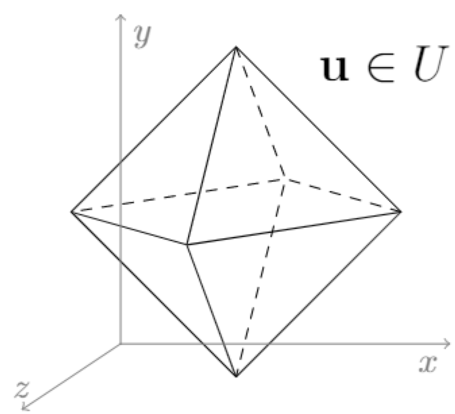
$$\frac{\sum_d(P_d^{Dmax} - \underline{P_d^{Dmin}})}{\sum_g(\overline{P_d^{Dmax}} - \underline{P_d^{Dmax}})} \leq \Gamma^D$$

$$\Gamma^G, \Gamma^D = \{0..1\}$$

$if\ \Gamma^G = 0 \rightarrow P_g^{Emax} = \overline{P_g^{Emax}}$

$if\ \Gamma^G = 1 \rightarrow P_g^{Emax} \in \left[0, \overline{P_g^{Emax}}\right]$

$if\ \Gamma^G = 0.2 \rightarrow$ up to 20% of generation capacity may be unavailable



Click to explore an example implementation of polyhedral set with a toy 6-node power network

Uncertainty set considering only vertexes of polyhedron (Baringo et al. 2020):

Uncertainty Set Formulation

$$\Omega = \{v = \tilde{v} + diag(u^+)\hat{v} - diag(u^-)\hat{v},$$
$$u^+, u^- \in \{0,1\}^m,$$
$$\sum_{k=1}^{m}(u_k^+ + u_k^-) \leq \Gamma,$$
$$u_k^+ + u_k^- \leq 1, \quad \forall k\}$$

- Polyhedral uncertainty sets employed
- Cardinality-constrained set formulation

Uncertainty Budget Constraints

- Uncertainty budgets Γ used to control robustness of the solution
- If $\Gamma = 0 \rightarrow$ all variables in vector v assume forecast values, i.e. uncertainty is absent
- If $\Gamma > 0 \rightarrow$ variables in vector v allowed to deviate from their forecast values

Uncertainty set considering only vertexes of polyhedron: gas market application

$$
\Omega = \Big\{ NG^{D^{max}}_{d,t} = \widetilde{NG}^{D}_{d,t} + z^{D}_{d}\widehat{NG}^{D}_{d,t} \quad \forall d
$$

$$
NG^{prod}_{p} = \widetilde{NG}^{P}_{p} - z^{prod}_{p}\widehat{NG}^{prod}_{p} \quad \forall p
$$

$$
z^{D}_{d} \leq \Gamma^{D}
$$

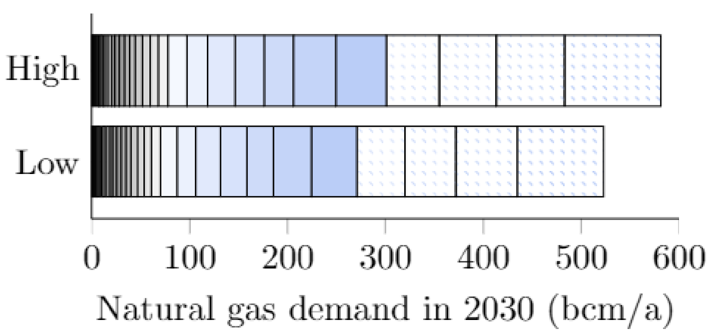
$$
z^{prod}_{p} \leq \Gamma^{P}
$$

$$
z^{D}_{d} \in \{0,1\} \quad \forall\ d
$$

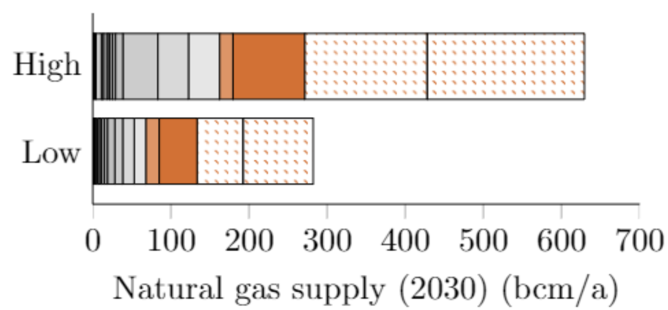
$$
z^{prod}_{p} \in \{0,1\} \quad \forall\ p \Big\}
$$

Demand deviations per unit of a budget are endogenously determined on a monthly basis -> winter demand profiles constructed to incorporate historical monthly peaks

Supply deviations per unit of a budget are endogenously determined on a yearly basis -> individual supply facilities/fields (merit-order)

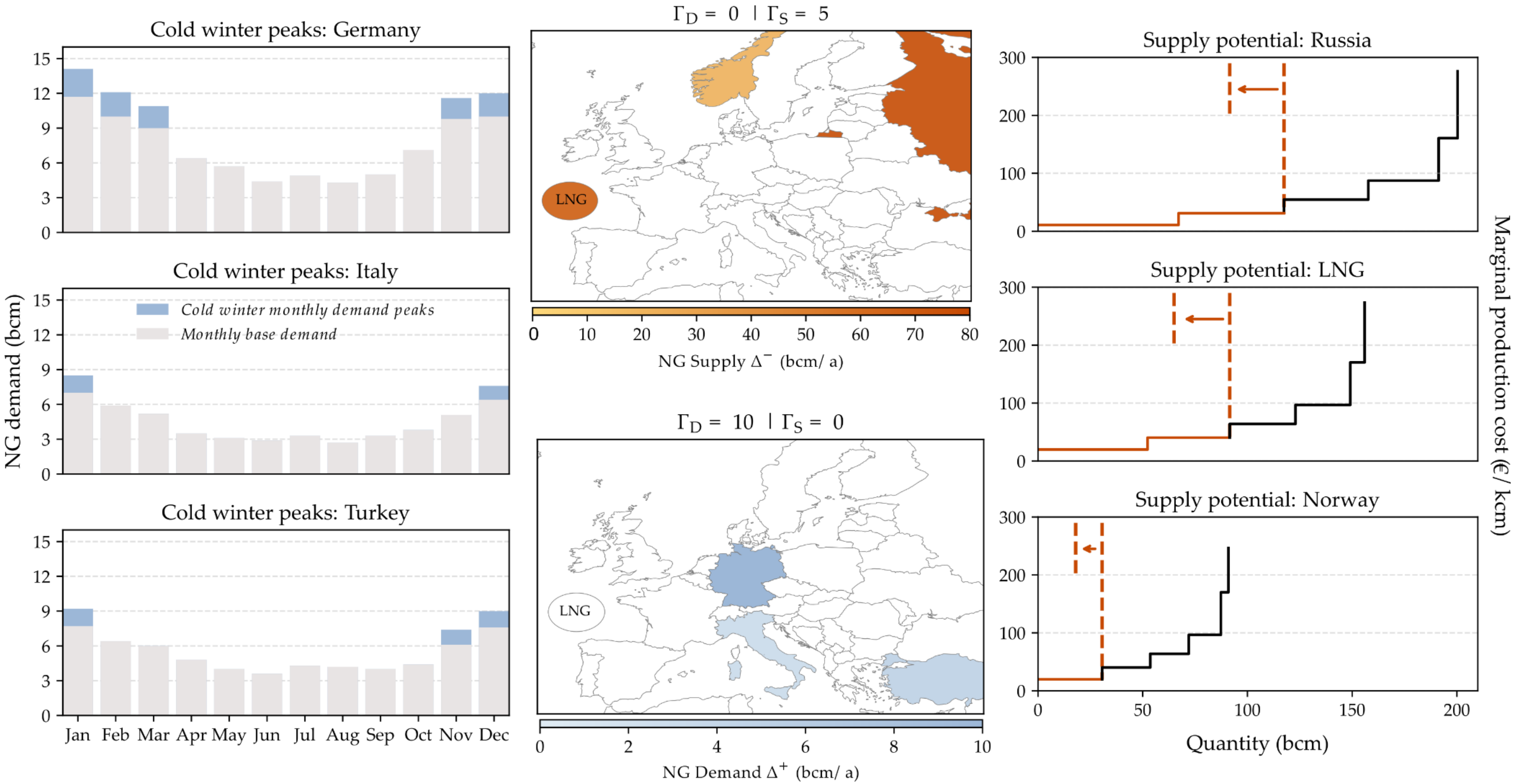


(a) Demand uncertainty set



(b) Supply uncertainty set

Uncertainty set considering only vertexes of polyhedron: *The devil is in the details*



At this point we have defined the ARO problem..

..now we find the approach to solve the monster!

Merging levels 2&3

$$\min_x C_I^T x \quad \text{s.t.} \quad x \in \mathbb{Z}^n, \quad h(x) = 0, \quad g(x) \leq 0$$

$$\max_u \quad \text{s.t.} \quad u \in U$$

$$\min_y [C_O(x,u)]^T y$$

s.t.

$$A(x,u) \cdot y = b(x,u) : \lambda$$

$$D(x,u) \cdot y \geq e(x,u) : \mu$$

Let's take the third level problem:

$$
\begin{aligned}
\min_{\boldsymbol{y}} \quad & [\boldsymbol{c}_{\mathrm{O}}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{y} \\
\text{s.t.} \quad & \boldsymbol{A}(\boldsymbol{x},\boldsymbol{u}) \cdot \boldsymbol{y} = \boldsymbol{b}(\boldsymbol{x},\boldsymbol{u}) : \quad \boldsymbol{\lambda} \\
& \boldsymbol{D}(\boldsymbol{x},\boldsymbol{u}) \cdot \boldsymbol{y} \geq \boldsymbol{e}(\boldsymbol{x},\boldsymbol{u}) : \quad \boldsymbol{\mu}
\end{aligned}
$$

Merging levels 2&3 (Conejo 2019; Mínguez et al. 2016)

And derive the dual form for this problem:

$$\begin{aligned} \min_{\boldsymbol{y}} \quad & [\boldsymbol{c}_{\mathrm{O}}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{y} \\ \text{s.t.} \quad & \boldsymbol{A}(\boldsymbol{x},\boldsymbol{u}) \cdot \boldsymbol{y} = \boldsymbol{b}(\boldsymbol{x},\boldsymbol{u}) : \quad \boldsymbol{\lambda} \\ & \boldsymbol{D}(\boldsymbol{x},\boldsymbol{u}) \cdot \boldsymbol{y} \geq \boldsymbol{e}(\boldsymbol{x},\boldsymbol{u}) : \quad \boldsymbol{\mu} \end{aligned}$$

$$\begin{aligned} \max_{\boldsymbol{\lambda},\boldsymbol{\mu}} \quad & [\boldsymbol{b}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{\lambda} + [\boldsymbol{e}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{\mu} \\ \text{s.t.} \quad & [\boldsymbol{A}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{\lambda} + [\boldsymbol{D}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{\mu} = \boldsymbol{c}_{\mathrm{O}}(\boldsymbol{x},\boldsymbol{u}) \\ & \boldsymbol{\lambda} : \quad \text{free} \\ & \boldsymbol{\mu} \geq \boldsymbol{0} \end{aligned}$$

Merging levels 2&3 (Conejo 2019; Mínguez et al. 2016)

Now we can merge the second level problem and dual of the third level

$$
\begin{aligned}
\max_{\boldsymbol{u},\boldsymbol{\lambda},\boldsymbol{\mu}} \quad & [\boldsymbol{b}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{\lambda} + [\boldsymbol{e}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{\mu} \\
\text{s.t.} \quad & \boldsymbol{u} \in \boldsymbol{\mathcal{U}} \\
& [\boldsymbol{A}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{\lambda} + [\boldsymbol{D}(\boldsymbol{x},\boldsymbol{u})]^\top \boldsymbol{\mu} = \boldsymbol{c}_{\mathrm{O}}(\boldsymbol{x},\boldsymbol{u}) \\
& \boldsymbol{\lambda} : \quad \text{free} \\
& \boldsymbol{\mu} \geq 0
\end{aligned}
$$

We still have to linearize bilinear terms that occur in dual objective.

Two in our case – one for each uncertainty budget.

Column-and-constraint generation (or Benders-primal) algorithm

Zeng, B., and Zhao, L. "Solving two-stage robust optimization problems using a column-and-constraint generation method." Operations Research Letters, 41, 5 (2013), 457-461.

Bertsimas, D., Litvinov, E., Sun, X. A., Zhao, J. and Zheng, T. "Adaptive robust optimization for the security constrained unit commitment problem." IEEE Transactions on Power Systems, 28, 1 (2013), 52-63.

Column-and-constraint generation (or Benders-primal) algorithm (Conejo 2019)

Master problem: $\boldsymbol{u} = \boldsymbol{u}^{(k)}, \boldsymbol{k} = 1, \ldots, \boldsymbol{\nu},$ fixed

$$\begin{aligned}
\min_{\boldsymbol{x},\boldsymbol{\eta},\boldsymbol{y}^{(k)},\boldsymbol{k}=1,\ldots,\boldsymbol{\nu}} \quad & \boldsymbol{c}_{\mathrm{I}}^{\top}\boldsymbol{x} + \boldsymbol{\eta} \\
\text{s.t.} \quad & \boldsymbol{h}(\boldsymbol{x}) = 0 \\
& \boldsymbol{g}(\boldsymbol{x}) \leq 0 \\
& \boldsymbol{\eta} \geq [\boldsymbol{c}_{\mathrm{O}}(\boldsymbol{x}, \boldsymbol{u}^{(k)})]^{\top}\boldsymbol{y}^{(k)} & \boldsymbol{k} = 1, \ldots, \boldsymbol{\nu} \\
& \boldsymbol{A}(\boldsymbol{x}, \boldsymbol{u}^{(k)}) \cdot \boldsymbol{y}^{(k)} = \boldsymbol{b}(\boldsymbol{x}, \boldsymbol{u}^{(k)}) & \boldsymbol{k} = 1, \ldots, \boldsymbol{\nu} \\
& \boldsymbol{D}(\boldsymbol{x}, \boldsymbol{u}^{(k)}) \cdot \boldsymbol{y}^{(k)} \geq \boldsymbol{e}(\boldsymbol{x}, \boldsymbol{u}^{(k)}) & \boldsymbol{k} = 1, \ldots, \boldsymbol{\nu}
\end{aligned}$$

$$\Downarrow$$

$$\boldsymbol{x}^{(\nu)}, \boldsymbol{\eta}^{(\nu)}$$

$$(\& \quad \boldsymbol{y}^{(k)}, \boldsymbol{k} = 1, \ldots, \boldsymbol{\nu})$$

Column-and-constraint generation (or Benders-primal) algorithm (Conejo 2019)

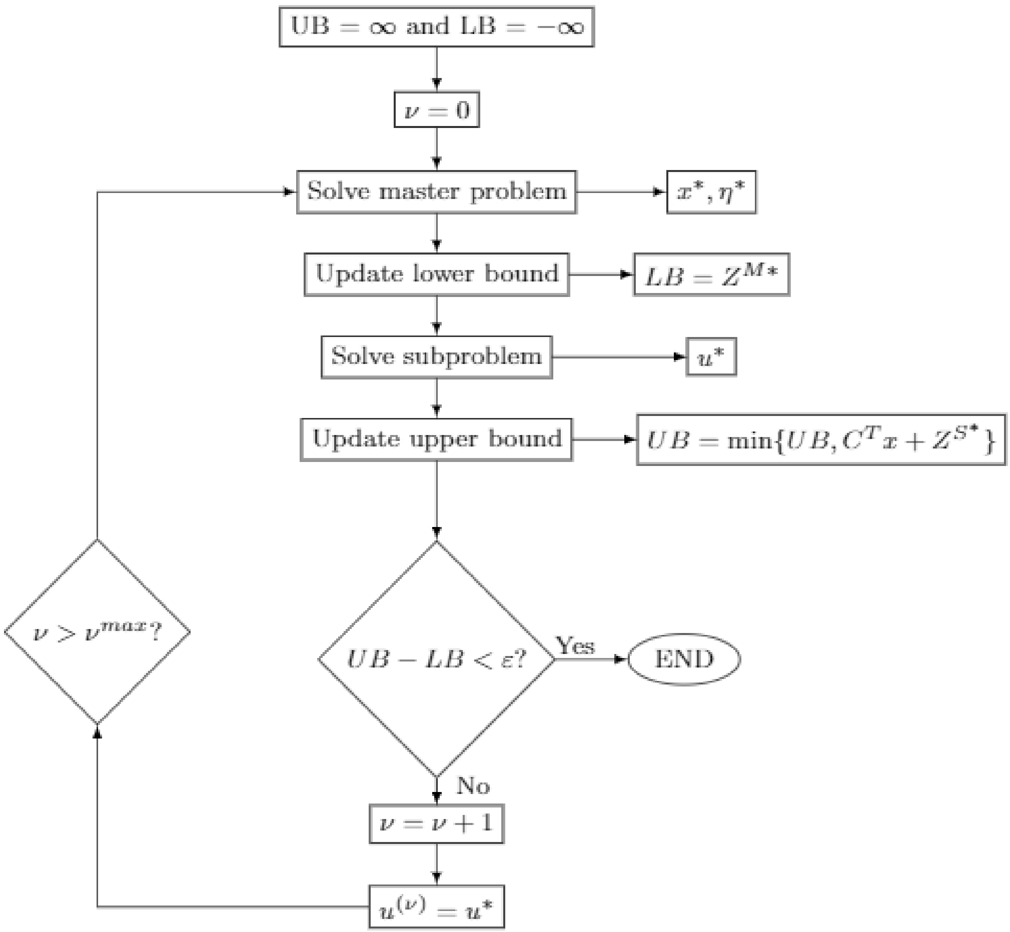
Subproblem: $\boldsymbol{x} = \boldsymbol{x}^{(\nu-1)}$ fixed

$$
\begin{aligned}
\max_{\boldsymbol{u},\boldsymbol{\lambda},\boldsymbol{\mu}} \quad & [\boldsymbol{b}(\boldsymbol{x}^{(\nu-1)},\boldsymbol{u})]^\top \boldsymbol{\lambda} + [\boldsymbol{e}(\boldsymbol{x}^{(\nu-1)},\boldsymbol{u})]^\top \boldsymbol{\mu} \\
\text{s.t.} \quad & \boldsymbol{u} \in \boldsymbol{\mathcal{U}} \\
& [\boldsymbol{A}(\boldsymbol{x}^{(\nu-1)},\boldsymbol{u})]^\top \boldsymbol{\lambda} + [\boldsymbol{D}(\boldsymbol{x}^{(\nu-1)},\boldsymbol{u})]^\top \boldsymbol{\mu} = \boldsymbol{c}_{\mathrm{O}}(\boldsymbol{x}^{(\nu-1)},\boldsymbol{u}) \\
& \boldsymbol{\lambda} : \quad \text{free} \\
& \boldsymbol{\mu} \geq \boldsymbol{0}
\end{aligned}
$$

$$\Downarrow$$

$$\boldsymbol{u}^{(\nu)}, \boldsymbol{\lambda}^{(\nu)}, \boldsymbol{\mu}^{(\nu)}$$

Column-and-constraint generation (or Benders-primal) algorithm



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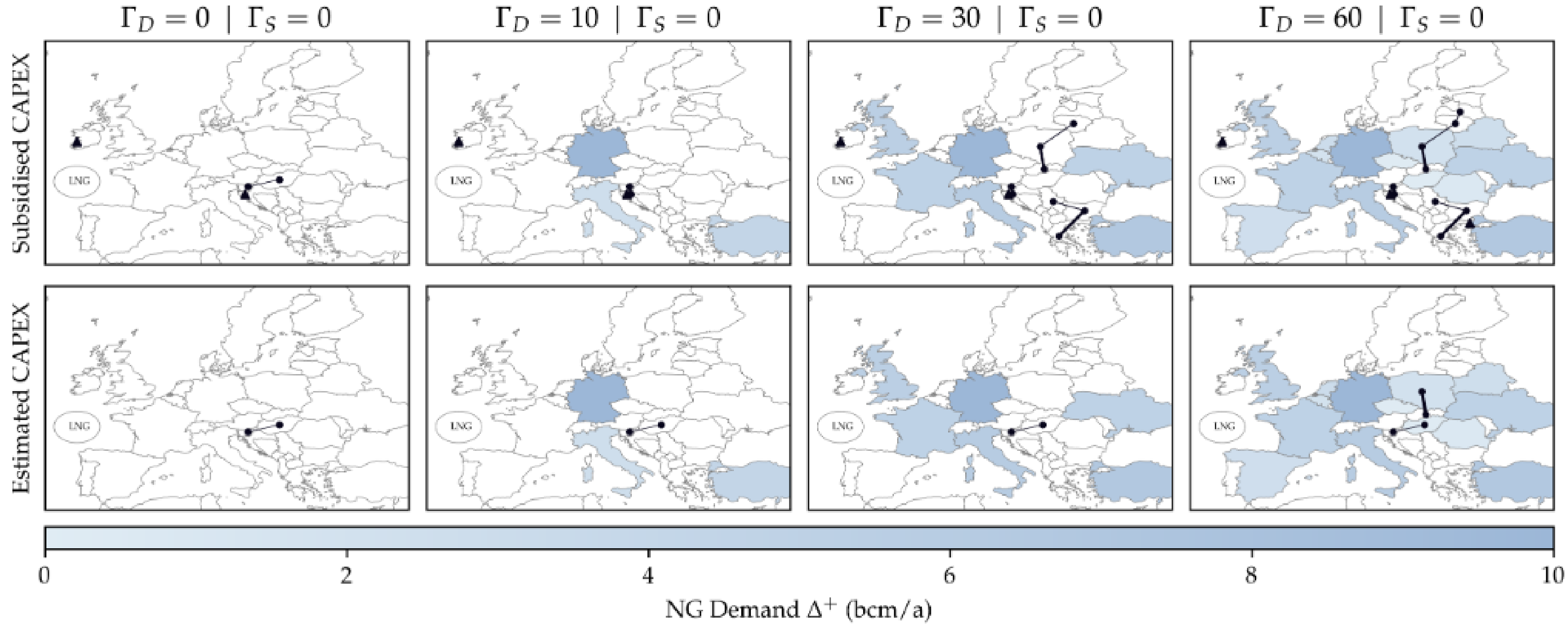
3. **Results**

Res. 1: Robust expansion considering cold-winter gas demand spikes

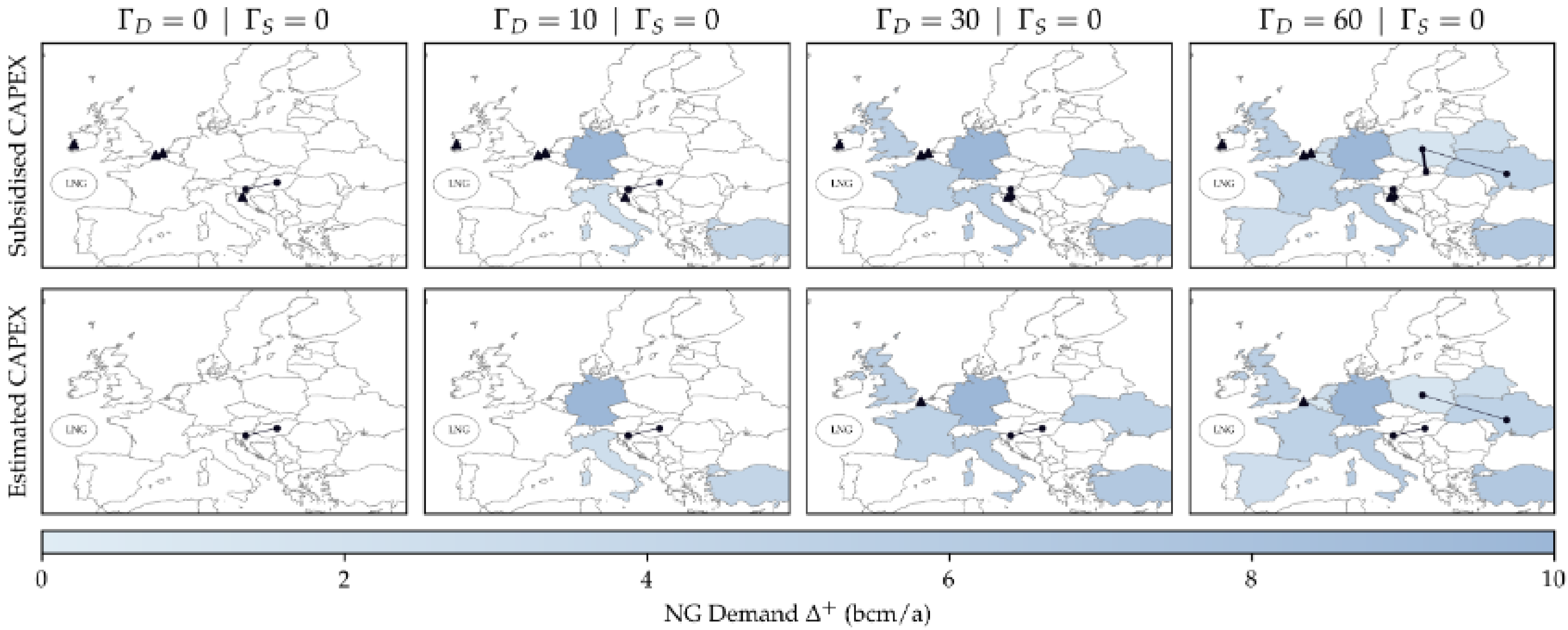
Scenario Settings			PCIs in Robust Expansion Plan																	ARO output (bcm)		
CAPEX	Γ_D	Γ_S	LT-PL	DK-PL	LV-LT	BG-SB	HU-RO	HU-SI	SI-AT	SK-HU	PL-SK	HR-SI	GR-BG	GR-IT	TR-BG	IE-LNG	HR-LNG	PL-LNG	GR-LNG	Γ_D^*	$\sum$ Cap	LS
Subsidy	0	0						■								■	■			0	1.4	0
Subsidy	10	0										■				■	■			17	10.4	0
Subsidy	30	0									■	■				■	■			38	15.1	1.3
Subsidy	60	0	■		■	■					■	■	■			■	■		■	52	31.9	2.5
Estimate	0	0						■												0	1.4	0
Estimate	10	0						■												17	1.4	0
Estimate	30	0						■												38	1.4	1.3
Estimate	60	0						■			■									52	7.1	2.5



1. In the Estimated CAPEX scenario **two projects** are built: HU-Sl & Pl-SK
2. Three ($\Gamma_D = 0$) to nine ($\Gamma_D = 60$) projects are built in the Subsidized CAPEX scenario
3. The optimal expansion plan remarkably **captures the PCI projects that are in the final realisation stage** (KrK terminal in Croatia, as well as LT-PL, BG-SB, PL-SK, GR-BG)
4. After all, up to **8 projects** (from 17) are never realized

Res. 2: … considering cold-winter gas demand spikes and investment options beyond PCI list

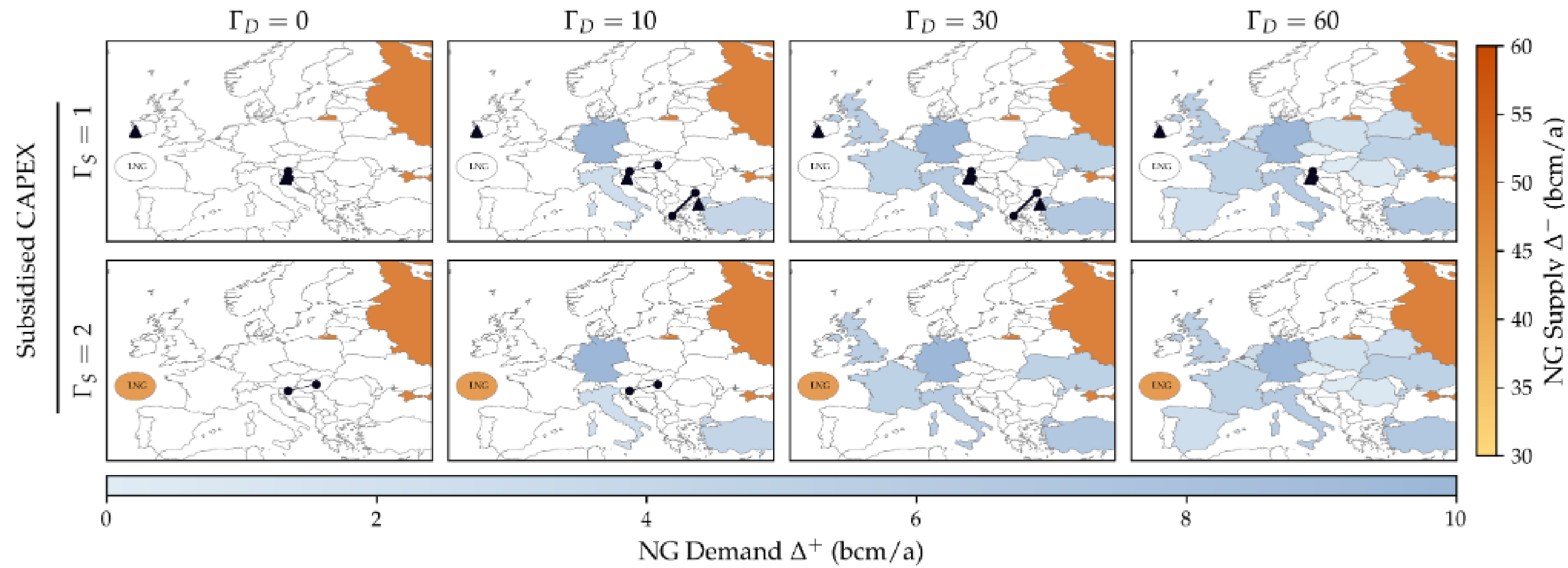
Scenario/UB			PCIs in Robust Expansion Plan																	non-PCI			ARO Output		
CAPEX	Γ_D	Γ_S	LT-PL	DK-PL	LV-LT	BG-SB	HU-RO	HU-SI	SI-AT	SK-HU	PL-SK	HR-SI	GR-BG	GR-IT	TR-BG	IE-LNG	HR-LNG	PL-LNG	GR-LNG	UA-PL	BE-LNG	FR-LNG	Γ_D^*	$\sum$ Cap	LS
Subsidy	0	0																					0	17.7	0
	10	0																					17	17.7	0
	30	0																					38	21.3	1.3
	60	0																					52	29.2	2.5
Estimate	0	0																					0	1.4	0
	10	0																					17	1.4	0
	30	0																					38	10.0	1.3
	60	0																					52	11.2	2.5



1. (Subsidised CAPEX): despite investment options include more than **100 projects** (17 PCI and 92 non-PCI), the solution entails **9 projects** with the **majority of these being PCI projects.**
2. The non-PCI investments include **one pipeline (UA-PL)** and **two regasification terminals** in Belgium and France – both are interesting from the system perspective.
3. **Partial substitution** of PCIs by non-PCI projects (GR-LNG, GR-BG and BG-SB).
4. (Estimated CAPEX): highlights the value of HU-Sl and UA-PL (is expected)

Res. 3: … considering cold-winter gas demand spikes and supply shortages

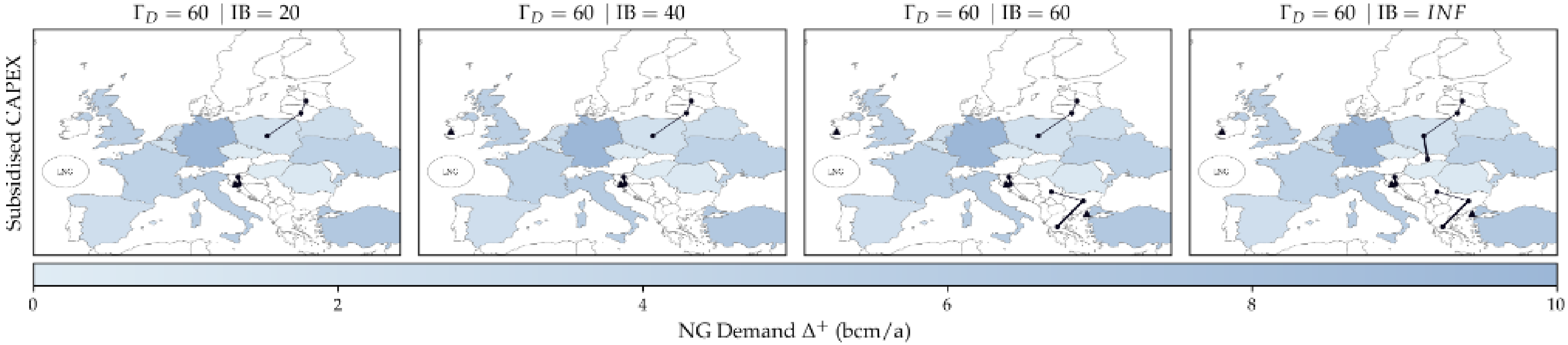
Scenario Settings			PCIs in Robust Expansion Plan																	ARO Output (bcm)			
CAPEX	Γ_D	Γ_S	LT-PL	DK-PL	LV-LT	BG-SB	HU-RO	HU-SI	SI-AT	SK-HU	PL-SK	HR-SI	GR-BG	GR-IT	TR-BG	IE-LNG	HR-LNG	PL-LNG	GR-LNG	Γ_D*	Γ_S*	$\sum$ Cap	LS
Subsidy	0	1										■				■	■			0	45	10.4	0
	10	1				■		■					■			■	■		■	17	45	19.7	2.5
	30	1				■						■	■			■	■		■	38	45	23.3	12.1
	60	1										■				■	■			52	45	10.4	25.4
Subsidy	0	2						■												0	96	1.4	13.6
	10	2						■												17	96	1.4	30.8
	30	2																		38	96	0	51.8
	60	2																		52	96	0	65.1



1. ΓS= [1] results in adjustment of the solution space: LT-PL, LV-LT, PL-SK are eliminated | GR-LNG, GR-BG are substitutes.
2. ΓS= [2] hits LNG supply, which has a reverberating effect on the projects aimed at bringing gas north from the Adriatic region (GR-BG, HR-Sl, BG-SB).
3. The ARO solution generally entails fewer investments with decreasing supply.

Res. 4: ... considering cold-winter gas demand spikes and investment budget

Scenario/UB				PCIs in Robust Expansion Plan																	Solution Info (MEUR/bcm)			
CAPEX	Γ_D	Γ_S	IB	LT-PL	DK-PL	LV-LT	BG-SB	HU-RO	HU-SI	SI-AT	SK-HU	PL-SK	HR-SI	GR-BG	GR-IT	TR-BG	IE-LNG	HR-LNG	PL-LNG	GR-LNG	IB*	Δ IC	Δ TC	∑ Cap
Subsidy	60	0	20	■		■							■					■			19.6	43.2	55	11.5
	60	0	40	■		■							■				■	■			37.9	24.9	27	14.3
	60	0	60	■		■	■						■	■			■	■		■	58.7	4.1	4.3	27.2
	60	0	inf	■		■	■					■	■	■			■	■		■	62.8	0	0	31.9



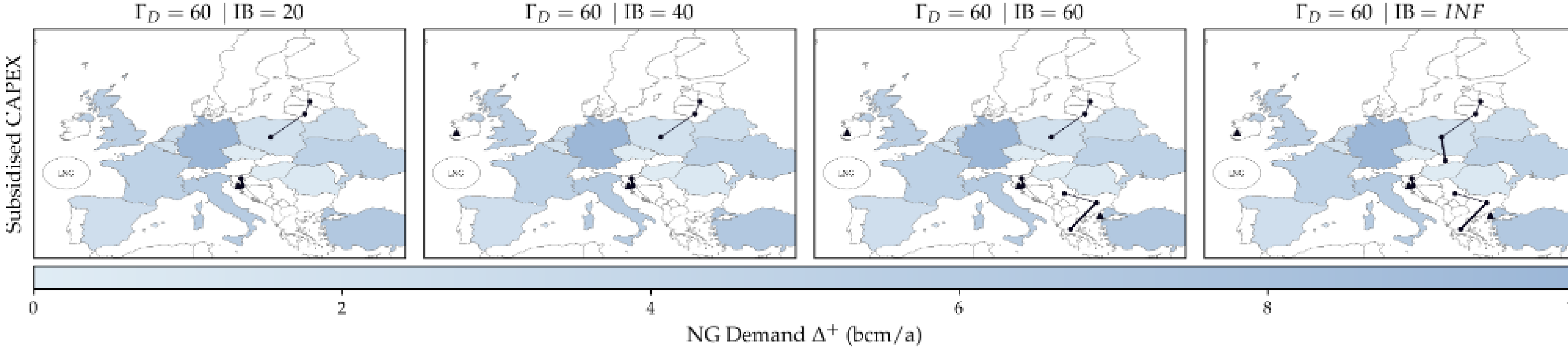
- ΔIC - the difference between the most expensive investment mix (when no constraint on IB is imposed) and the optimal solution in each scenario.
- ΔTC - the difference between the total costs (objective value of the subproblem) of each scenario and the total costs of the solution absent the investment budget.

Thus:

- (a) $\Delta TC \geq \Delta IC$, i.e., investment decisions must have a positive (or zero) impact on the objective value
- (b) the model setup void of an investment budget yields by definition the lowest objective value.

Res. 4: … considering cold-winter gas demand spikes and investment budget

Scenario/UB				PCIs in Robust Expansion Plan																	Solution Info (MEUR/bcm)			
CAPEX	Γ_D	Γ_S	IB	LT-PL	DK-PL	LV-LT	BG-SB	HU-RO	HU-SI	SI-AT	SK-HU	PL-SK	HR-SI	GR-BG	GR-IT	TR-BG	IE-LNG	HR-LNG	PL-LNG	GR-LNG	IB*	Δ IC	Δ TC	∑ Cap
Subsidy	60	0	20	■		■							■					■			19.6	43.2	55	11.5
Subsidy	60	0	40	■		■							■				■	■			37.9	24.9	27	14.3
Subsidy	60	0	60	■		■	■						■	■			■	■		■	58.7	4.1	4.3	27.2
Subsidy	60	0	inf	■		■	■					■	■	■			■	■		■	62.8	0	0	31.9



1. If IB = inf, the solution includes **9 PCI projects**, among them **3 regasification terminals** and **six pipeline interconnectors**.
2. If IB = 20 MEUR, the ARO model prefers **4 projects** *(these are under construction!)*:
    1. LT-PL to establish a physical interconnection between the Baltic States and Poland;
    2. LV-LT to strengthen interconnection between Baltic States;
    3. HR-LNG and HR-Sl to provide access to LNG supplies for the Balkan region.
3. If IB = 40 MEUR, IE-LNG is added to the investment mix.
4. If IB = 60 MEUR, HR-LNG and the chain of relevant pipeline projects (GR-BG and BG-SB) is added.

Summary (1): methodology

1. ARO allows for dropping assumptions that a finite number of uncertainty realizations exist with respective (known) probabilities.
2. ARO is particularly suitable when decisions are costly and protection against the worst-case scenario is a must.
3. ARO allows for robustness control.
4. Accuracy of ARO models generally does not depend on the accuracy of the uncertainty description.

Summary (2): application

1. Uncertainty in the European natural gas market is increasing → economic rationale and necessity of PCIs to ensure security of supply are subject of debate.

2. Proposed **ARO model is particularly suitable to capture long-term uncertainty** in European gas market.

3. The robust solutions, which endogenously identify the stresses in the system, indicate **a consistent preference for specific projects**, many of which are currently **in the final stage of development**.

4. Results follow a general consensus that **economic feasibility of PCIs under non-subsidized conditions is limited**.

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