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Strategic Regulatory Pathways for Decarbonizing the Power Sector via Complementarity Modeling

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NSF

Background

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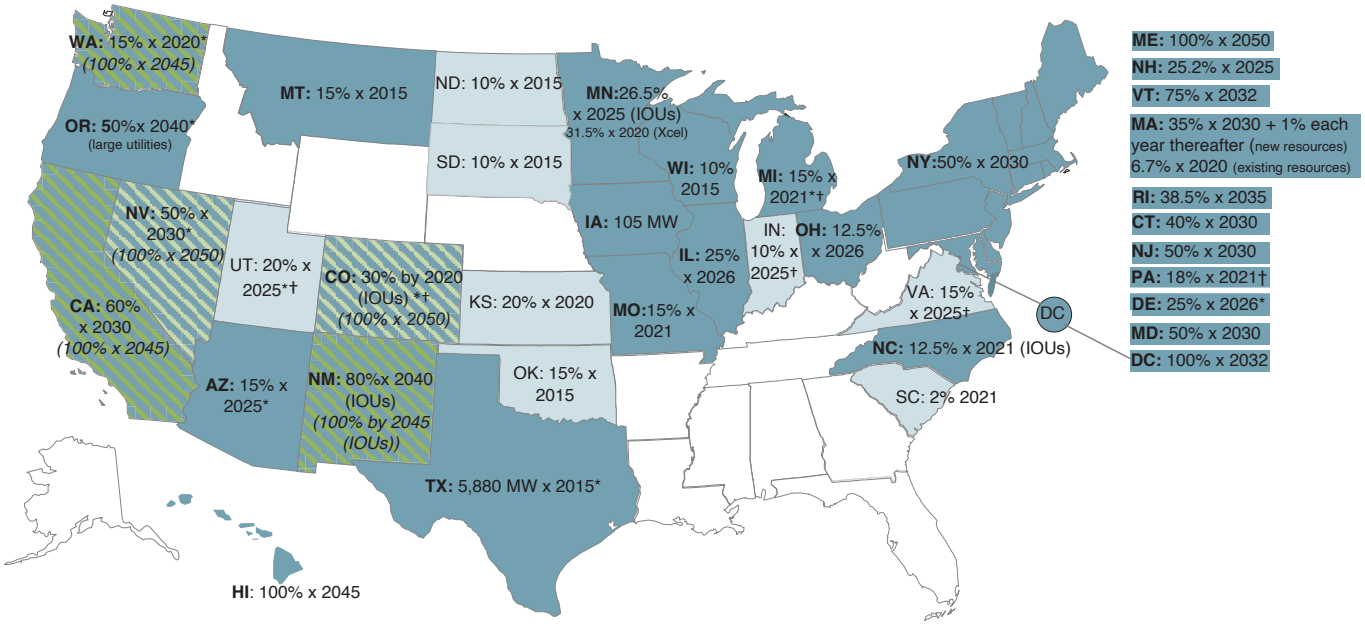
Renewable Targets in the U.S.



Renewable portfolio standard

Renewable portfolio goal

Clean energy standard

Clean energy goal

Source: DSIRE https://www.dsireusa.org/resources/detailed-summary-maps/

Current practice: Clean Energy Policymaking at a Glance

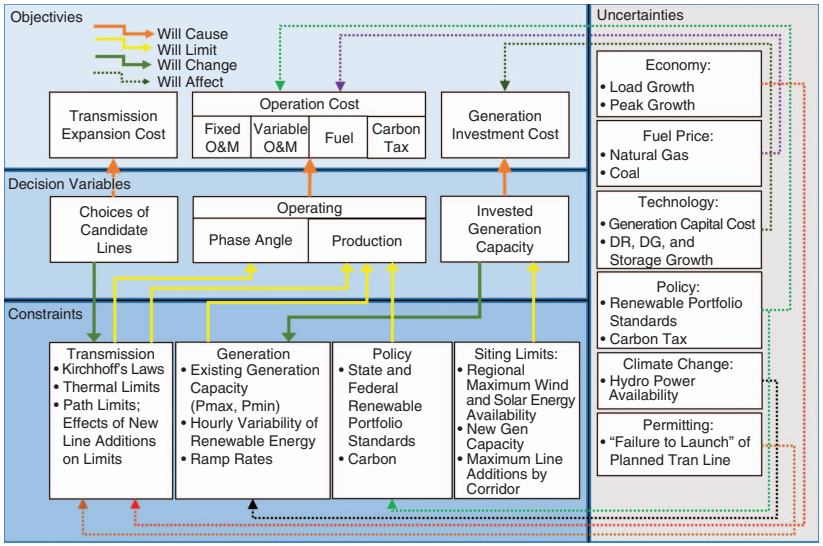


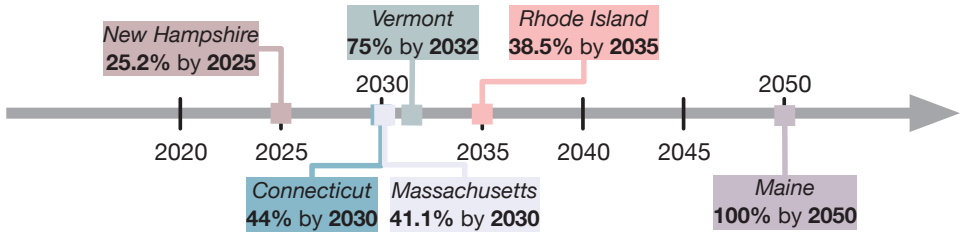
Fig. The interactions among uncertainties and optimization model components.

- Centralized planning
- "Passive" policymaking
- Limited consideration of conflicting interests and interactions among stakeholders in electricity markets
- Policy (e.g. renewable incentives or electricity tariffs) as an exogenous parameter: often parameterized, rather than optimized.
- Distribution system planning is coarse, at best

Source: Hobbs et al, "Adaptive transmission planning: implementing a new paradigm for managing economic risks in grid expansion." IEEE Power and Energy Magazine 14, no. 4 (2016): 30-40.

Background

An example:



- Renewables are driven by states
- Techno-economic coupling among states
  - Electricity markets
  - Renewable energy certificates
  - State coalitions (e.g. US Climate Alliance)

▸ *Understand strategic regulatory competition and its effect on achieving renewable goals*

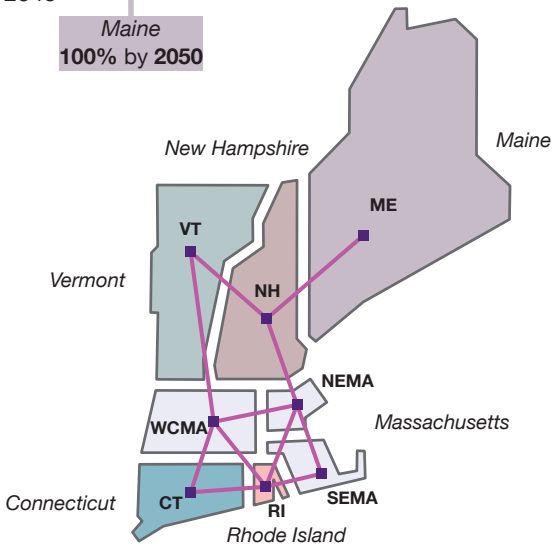
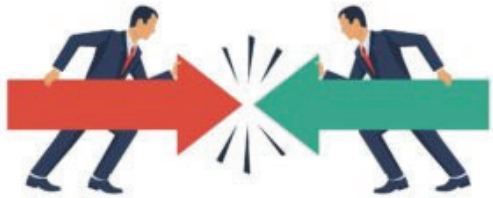


Fig. ISO New England 8-zone test system covering six states

Why competition?

- Conflicts of interests
  - Regulator: *Social welfare maximization / RPS goal*
  - Power utility/Generation companies: *Profit maximization*
  - Consumer: *Surplus maximization*



- Challenge
  - Balance the perspectives of multiple stakeholders
  - Accounts for strategic dominance among stakeholders

Background

Lack of **decision support tools** for *renewable energy policymaking*

Part I. Strategic Low-carbon Generation Expansion Planning

a.k.a. "states compete with states"

- *A Chance Constrained Equilibrium Problem with Equilibrium Constraints Model*
- *Understand strategic regulatory competition and its effect on achieving renewable goals*

Part II. Strategic Policymaking for Implementing Renewable Portfolio Standards

a.k.a. "a state refines its policy via detailed modeling"

- *A Tri-level Optimization Model*
- *Optimize policy (tariff & incentives) accounting for conflicting interests of stakeholders*

Part III. Strategic Policymaking with Information Awareness Constraints

a.k.a. "a state realizes that policymaking is more complex than modeling"

- *Impact of information awareness on decision-making*
- *T&D market environments*

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Part I. Strategic Low-carbon Generation Expansion Planning:

A Chance Constrained EPEC Approach

Overview

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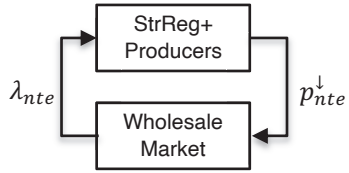
1

Bilevel programming problem
- **Upper-level:** Generation expansion problem
- **Lower-level:** Wholesale market-clearing problem



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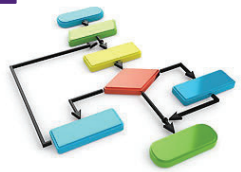
MISOCP reformulation of **CC-MPEC**

Chance constraints ▸ SOC reformulation
KKT conditions ▸ SOS-1 variables
Nonlinear term in Obj ▸ Binary expansion

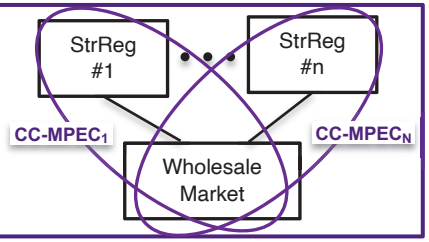
4

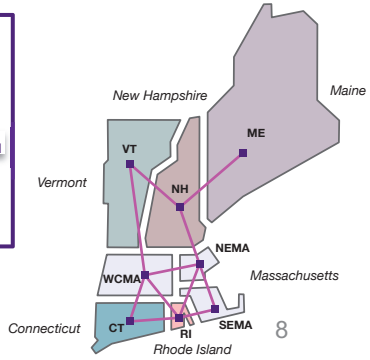


Progressive Hedging Algorithm: a scenario-based decomposition technique that is used for stochastic optimization to overcome the computational complexity

3

strategic actor ▸ scenario?



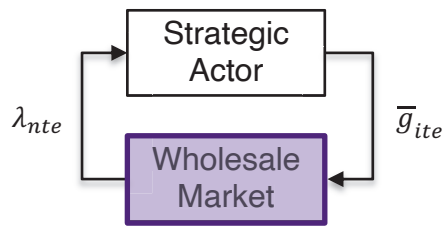


Formulation

- **Lower Level Problem (TSO): Common Follower**

$$\max\left(O^{\mathrm{WM}} := \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}\cup\hat{\mathcal{I}}} -C_i^{\mathrm{g}} g_{ite}\right)$$

- DC power flow
- Nodal power balance (dual: LMP, λ_{nte})
- Generation limit
- Line flow limit



Formulation

- **Lower Level Problem (TSO): Common Follower**

$$\max\left(O^{\mathrm{WM}} := \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}\cup\hat{\mathcal{I}}} -C_i^{\mathrm{g}} g_{ite}\right)$$

$$(\xi_{lte}):\quad f_{lte} = \frac{1}{X_l}(\theta_{o(l),t,e} - \theta_{r(l),t,e}),\ \forall l\in\mathcal{L},\ t\in\mathcal{T},$$

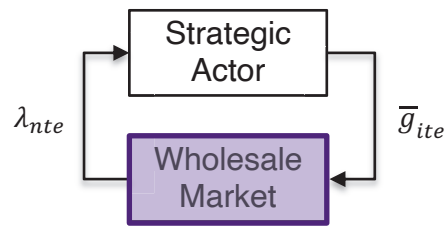
$$(\lambda_{nte}):\ \sum_{i\in\mathcal{I}_n\cup\hat{\mathcal{I}}_n} g_{ite} + \sum_{l|r(l)=n} f_{lte} - \sum_{l|o(l)=n} f_{lte} = D_{nte},$$

$$\forall n\in\mathcal{N}, t\in\mathcal{T},$$

$$(\underline{\gamma}_{ite}, \overline{\gamma}_{ite}):\quad 0 \le g_{ite} \le g^{\mathrm{o}}_{ite},\ \forall i\in\mathcal{I}\cup\hat{\mathcal{I}},\ t\in\mathcal{T},$$

$$\text{where } g^{\mathrm{o}}_{ite} = \begin{cases} \overline{g}_{ite}, & \forall i\in\mathcal{I}_s\cup\hat{\mathcal{I}}_s,\ t\in\mathcal{T}, \\ \rho_{ite}G_i^{\max} - R_{ite}, & \forall i\in\mathcal{I}_{-s}\cup\hat{\mathcal{I}}_{-s},\ t\in\mathcal{T}, \end{cases}$$

$$(\underline{\delta}_{lte}, \overline{\delta}_{lte}):\quad -F_l^{\max} \le f_{lt} \le F_l^{\max},\ \forall l\in\mathcal{L},\ t\in\mathcal{T},$$



Formulation

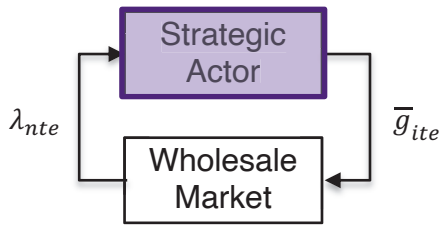
- **Upper Level Problem (Strategic actor)**

Random variable

$$\max_{\Xi^{\mathrm{SA}}} O_s^{\mathrm{SA}} := \mathbb{E}\Big[\underbrace{\sum_{e\in\mathcal{E}}\Big\{\omega_e \sum_{t\in\mathcal{T}}\Big(\sum_{n\in\mathcal{N}_s}\pi_{nt}^{\mathrm{D}} D_{nte} - \sum_{n\in\mathcal{N}_s}\lambda_{nte} p_{nte}^{\downarrow} - \overline{\tau}_s^{\mathrm{e}}\sum_{i\in\mathcal{I}_s^{\mathrm{R}}\cup\hat{\mathcal{I}}_s^{\mathrm{R}}} \boldsymbol{g}_{ite} - \sum_{i\in\mathcal{I}_s} C_i^{\mathrm{g}}\boldsymbol{g}_{ite}\Big)\Big\}}_{\textit{Expected operation profit}}\Big]$$

$$\underbrace{-\overline{\tau}_s^{\mathrm{c}}\sum_{i\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_i^{\max}}_{\textit{Capacity payment}} \underbrace{-\sum_{i\in\hat{\mathcal{I}}_s} C_i^{\mathrm{inv}} g_i^{\max}}_{\textit{Investment cost}}$$

- Renewable Portfolio Standard (RPS) requirement
- Generation output limit via *Chance Constraints*
- Ramping limits of controllable generators
- Supply demand balance
- Interface flow limit



$$\Xi^{\mathrm{SA}} = \{\overline{g}_{ite}, g_i^{\max} \geq 0;\ p_{nte}^{\downarrow}:\ \text{free}\}$$

Key **assumption**: the regulator and utility/power company act jointly and with a joint goal

Formulation

- **Upper Level Problem (Strategic actor)**

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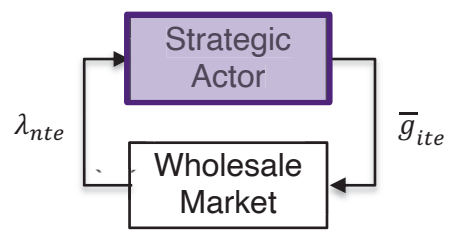
- Renewable Portfolio Standard (RPS) requirement

$$\sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}_s^{\mathrm{R}}\cup\hat{\mathcal{I}}_s^{\mathrm{R}}} \overline{g}_{ite} \geq \kappa_s \sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}_s} D_{nte},\ \forall e\in\mathcal{E},$$

$$\sum_{i\in\hat{\mathcal{I}}_s} C_i^{\mathrm{inv}} g_i^{\max} \leq B_s^{\mathrm{C}},$$

$$\sum_{t\in\mathcal{T}}\Big(P_s^{\mathrm{ET}}\sum_{i\in\mathcal{I}_s^{\mathrm{R}}\cup\hat{\mathcal{I}}_s^{\mathrm{R}}} \overline{g}_{ite}\Big) + P_s^{\mathrm{CT}}\sum_{i\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_i^{\max} \leq B_s^{\mathrm{P}},\ \forall e\in\mathcal{E}, \quad (2k)$$



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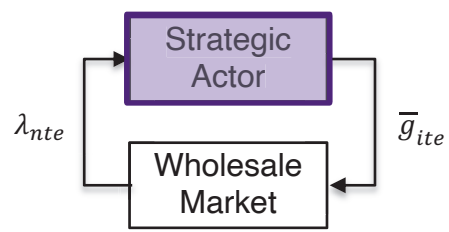
- Generation output limit via *Chance Constraints*
- Ramping limits of controllable generators



$$\mathbb{P}[\boldsymbol{g}_{ite} \le G_i^{\max}] \ge 1-\eta,\ \forall i\in\mathcal{I}_s^{\mathrm{C}}, t\in\mathcal{T}, e\in\mathcal{E},$$

$$\mathbb{P}[\boldsymbol{g}_{ite} \le g_i^{\max}] \ge 1-\eta,\ \forall i\in\hat{\mathcal{I}}_s^{\mathrm{C}}, t\in\mathcal{T}, e\in\mathcal{E},$$

$$\mathbb{P}[\boldsymbol{g}_{ite} \ge G_i^{\min}] \ge 1-\eta,\ \forall i\in\mathcal{I}_s^{\mathrm{C}}, t\in\mathcal{T}, e\in\mathcal{E},$$

$$\mathbb{P}[\boldsymbol{g}_{ite} \ge \Gamma_i g_i^{\max}] \ge 1-\eta,\ \forall i\in\hat{\mathcal{I}}_s^{\mathrm{C}}, t\in\mathcal{T}, e\in\mathcal{E},$$

$$H_i^{\min} \le \overline{g}_{ite} - \overline{g}_{i,t-1,e} \le H_i^{\max},\ \forall i\in\mathcal{I}_s^{\mathrm{C}}\cup\hat{\mathcal{I}}_s^{\mathrm{C}}, t\in\mathcal{T}, e\in\mathcal{E},$$

Formulation

- **Upper Level Problem (Strategic actor)**

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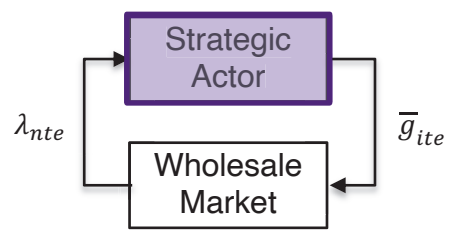

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Formulation

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- **Upper Level Problem (Strategic actor)**

Random variable

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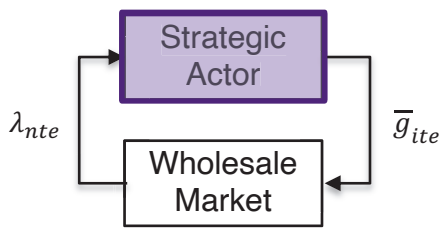
$$\underbrace{-\overline{\tau}_s^{\mathrm{c}}\sum_{i\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_i^{\max}}_{\textit{Capacity payment}} \underbrace{-\sum_{i\in\hat{\mathcal{I}}_s} C_i^{\mathrm{inv}} g_i^{\max}}_{\textit{Investment cost}}$$

- Reformulation of chance constraints

$$\overline{g}_{ite} - \alpha_{it}\Big(\sum_{j\in\mathcal{I}_s^{\mathrm{R}}} G_j^{\max}\upsilon_{jte} + \sum_{j\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_j^{\max}\upsilon_{jte}\Big) + \Phi^{-1}(1-\eta)\mathrm{Stdev}[\boldsymbol{g}_{it}] \le G_i^{\max},\ \forall i\in\mathcal{I}_s^{\mathrm{C}}, t\in\mathcal{T},$$

$$\overline{g}_{ite} - \alpha_{it}\Big(\sum_{j\in\mathcal{I}_s^{\mathrm{R}}} G_j^{\max}\upsilon_{jte} + \sum_{j\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_j^{\max}\upsilon_{jte}\Big) + \Phi^{-1}(1-\eta)\mathrm{Stdev}[\boldsymbol{g}_{it}] \le g_i^{\max},\ \forall i\in\hat{\mathcal{I}}_s^{\mathrm{C}}, t\in\mathcal{T},$$



$$\mathrm{Stdev}[\boldsymbol{g}_{it}] = \alpha_{it}\sqrt{\sum_{j\in\mathcal{I}_{s(i)}^{\mathrm{R}}}(G_j^{\max}\sigma_{jte})^2 + \sum_{j\in\hat{\mathcal{I}}_{s(i)}^{\mathrm{R}}}(g_j^{\max}\sigma_{jte})^2}$$

→ Valuable for pricing and variance control

Formulation

- **Upper Level Problem (Strategic actor)**

Random variable

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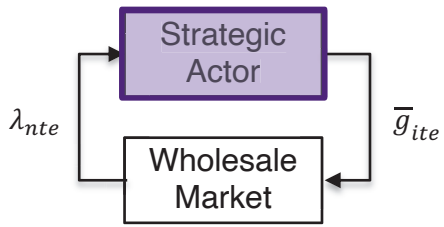
$$\underbrace{-\overline{\tau}_s^{\mathrm{c}}\sum_{i\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_i^{\max}}_{\textit{Capacity payment}} \underbrace{-\sum_{i\in\hat{\mathcal{I}}_s} C_i^{\mathrm{inv}} g_i^{\max}}_{\textit{Investment cost}}$$

- Supply demand balance
- Interface flow limit

$$\sum_{i\in\mathcal{I}_n\cup\hat{\mathcal{I}}_n} \overline{g}_{ite} + p_{nte}^{\downarrow} = D_{nte}, \quad \forall t\in\mathcal{T}, n\in\mathcal{N}_s, e\in\mathcal{E},$$

$$-P_n^{\downarrow,\max} \le p_{nte}^{\downarrow} \le P_n^{\downarrow,\max}, \ \forall t\in\mathcal{T}, n\in\mathcal{N}_s, e\in\mathcal{E},$$



CC-MPEC Formulation

- **Single-level equivalent reformulation as**
  Chance-Constrained Mathematical Problem with Equilibrium Constraints (CC-MPEC)

CC-MPEC

Generation expansion problem of the strategic actor

$$\max_{\Xi^{\mathrm{SR}}} O_s^{\mathrm{SR}} := \mathbb{E}\Big[\sum_{e\in\mathcal{E}}\Big\{\omega_e \sum_{t\in\mathcal{T}}\Big(\sum_{n\in\mathcal{N}_s}\pi_{nt}^{\mathrm{D}} D_{nte} - \sum_{n\in\mathcal{N}_s}\lambda_{nte} p_{nte}^{\perp} - P_{st}^{\mathrm{ET}}\sum_{i\in\mathcal{I}_s^{\mathrm{R}}\cup\hat{\mathcal{I}}_s^{\mathrm{R}}} \boldsymbol{g}_{ite} - \sum_{i\in\mathcal{I}_s} C_i^{\mathrm{g}} \boldsymbol{g}_{ite}\Big)\Big\}\Big] - P_s^{\mathrm{CT}}\sum_{i\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_i^{\max} - \sum_{i\in\hat{\mathcal{I}}_s} C_i^{\mathrm{inv}} g_i^{\max} \tag{2a}$$

subject to:

$$\begin{bmatrix} \underline{y}_{it} \\ x_{s(i),t,e} \end{bmatrix} \in \mathcal{K}^{u+v+1}, \quad \forall i \in \mathcal{I}_s^{\mathrm{C}} \cup \hat{\mathcal{I}}_s^{\mathrm{C}},\ t\in\mathcal{T}, \tag{5a}$$

$$\begin{bmatrix} \overline{y}_{it} \\ x_{s(i),t,e} \end{bmatrix} \in \mathcal{K}^{u+v+1}, \quad \forall i \in \mathcal{I}_s^{\mathrm{C}} \cup \hat{\mathcal{I}}_s^{\mathrm{C}},\ t\in\mathcal{T}, \tag{5b}$$

$$\sum_{i\in\mathcal{I}_s\cup\hat{\mathcal{I}}_s} \overline{g}_{ite} + p_{nte}^{\perp} = D_{nte}, \quad \forall t\in\mathcal{T}, n\in\mathcal{N}_s, e\in\mathcal{E}, \tag{2f}$$

$$-P_n^{\perp,\max} \le p_{nte}^{\perp} \le P_n^{\perp,\max}, \ \forall t\in\mathcal{T}, n\in\mathcal{N}_s, e\in\mathcal{E}, \tag{2g}$$

$$\sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}_s^{\mathrm{R}}\cup\hat{\mathcal{I}}_s^{\mathrm{R}}} \overline{g}_{ite} \ge \kappa_s \sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}_s} D_{nte}, \ \forall e\in\mathcal{E}, \tag{2h}$$

$$\sum_{i\in\hat{\mathcal{I}}_s} C_i^{\mathrm{inv}} g_i^{\max} \le B_s^{\mathrm{C}}, \tag{2i}$$

$$\sum_{t\in\mathcal{T}}\Big(P_{st}^{\mathrm{ET}}\sum_{i\in\mathcal{I}_s^{\mathrm{R}}\cup\hat{\mathcal{I}}_s^{\mathrm{R}}} \overline{g}_{ite}\Big) + P_s^{\mathrm{CT}}\sum_{i\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_i^{\max} \le B_s^{\mathrm{P}}, \ \forall e\in\mathcal{E}, \tag{2j}$$

KKT conditions of the wholesale electricity market-clearing problem

$$(\xi_{lte}):\ f_{lte} = \frac{1}{X_l}\big(\theta_{s(l),t,e} - \theta_{r(l),t,e}\big), \ \forall l\in\mathcal{L},\ t\in\mathcal{T}, \tag{2l}$$

$$(\lambda_{nte}):\ \sum_{i\in\mathcal{I}_n\cup\hat{\mathcal{I}}_n} g_{ite} + \sum_{l|r(l)=n} f_{lte} - \sum_{l|s(l)=n} f_{lte} = D_{nte}, \quad \forall n\in\mathcal{N}, t\in\mathcal{T}, \tag{2m}$$

$$-C_i^{\mathrm{g}} + \lambda_{n(i),t,e} + \underline{\gamma}_{ite} - \overline{\gamma}_{ite} = 0, \quad \forall i\in\mathcal{I}\cup\hat{\mathcal{I}}, t\in\mathcal{T}, e\in\mathcal{E}, \tag{6d}$$

$$\xi_{lte} + \lambda_{r(l),t,e} - \lambda_{s(l),t,e} + \underline{\delta}_{lte} - \overline{\delta}_{lte} = 0, \quad \forall l\in\mathcal{L},\ t\in\mathcal{T},\ e\in\mathcal{E}, \tag{6e}$$

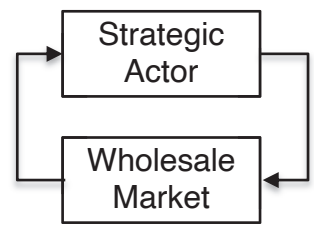
$$-\sum_{l|s(l)=n}\frac{\xi_{lte}}{X_l} + \sum_{l|r(l)=n}\frac{\xi_{lte}}{X_l} = 0, \quad \forall n\in\mathcal{N},\ t\in\mathcal{T},\ e\in\mathcal{E}, \tag{6f}$$

$$0 \le g_{ite} \perp \underline{\gamma}_{ite} \ge 0, \quad \forall i\in\mathcal{I}\cup\hat{\mathcal{I}},\ t\in\mathcal{T},\ e\in\mathcal{E}, \tag{6g}$$

$$0 \le g_{ite}^{\mathrm{o}} - g_{ite} \perp \overline{\gamma}_{ite} \ge 0, \quad \forall i\in\mathcal{I}\cup\hat{\mathcal{I}},\ t\in\mathcal{T},\ e\in\mathcal{E}, \tag{6h}$$

$$0 \le f_{lte} - F_l^{\min} \perp \underline{\delta}_{lte} \ge 0, \quad \forall l\in\mathcal{L},\ t\in\mathcal{T},\ e\in\mathcal{E}, \tag{6i}$$

$$0 \le F_l^{\max} - f_{lte} \perp \overline{\delta}_{lte} \ge 0, \quad \forall l\in\mathcal{L},\ t\in\mathcal{T},\ e\in\mathcal{E}, \tag{6j}$$



Multi-leader-common-follower (MLCF) problem

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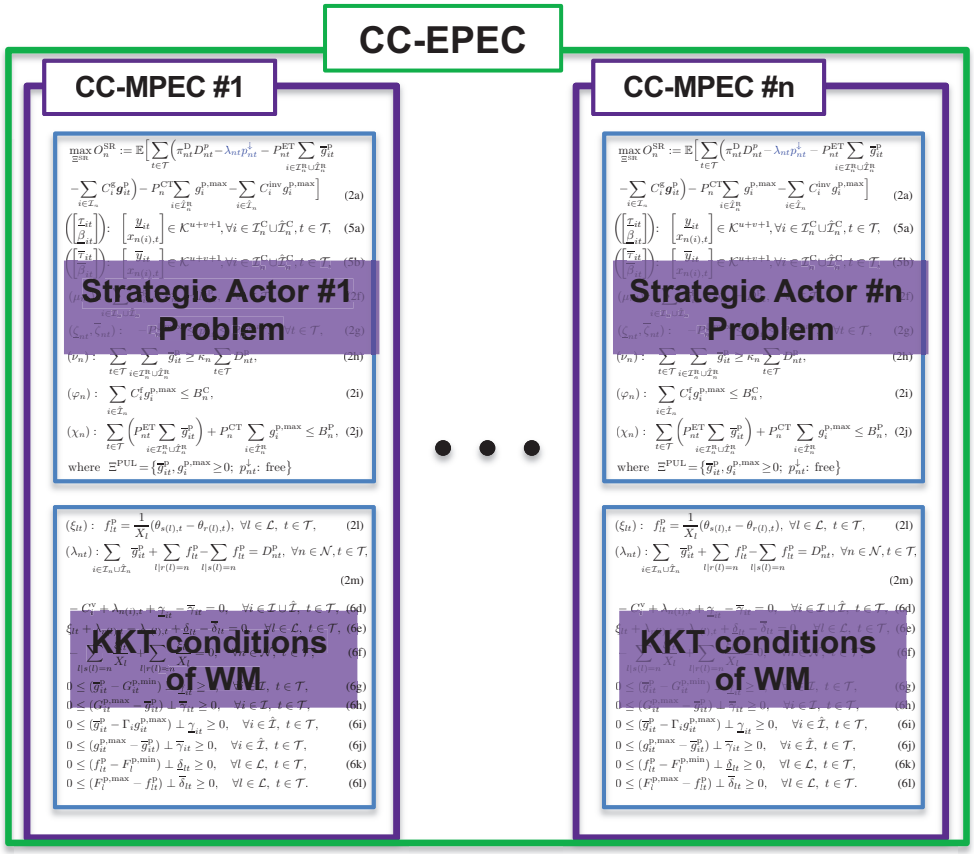
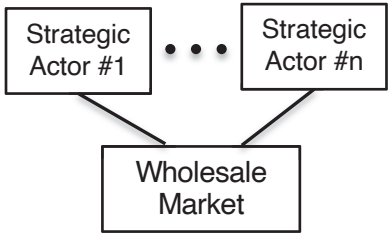
- **Multiple MPECs with a common lower-level problem**

CC-EPEC (Equilibrium Problem with Equilibrium Constraints)





Linearization

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1) Complementarity constraints:

$$0 \leq \lambda \perp x \geq 0$$ Can be recast as $$\lambda, x \in \mathrm{SOS1}$$

SOS1 variables are available supported by MIP solvers (Gurobi, CPLEX, etc.)

- Special Ordered Set of type 1 (SOS1) – at most one variable in set may be non-zero
- Commercial solvers try to reformulate SOS constraints into a big-M representation during presolve

2) Nonlinear term in the objective function:

$$\max_{\Xi^{\mathrm{SA}}} O_s^{\mathrm{SA}} := \mathbb{E}\Big[\sum_{e\in\mathcal{E}}\Big\{\omega_e \sum_{t\in\mathcal{T}}\Big(\sum_{n\in\mathcal{N}_s}\pi_{nt}^{\mathrm{D}} D_{nte} - \sum_{n\in\mathcal{N}_s}\lambda_{nte} p_{nte}^{\downarrow} - \overline{\tau}_s^{\mathrm{e}}\sum_{i\in\mathcal{I}_s^{\mathrm{R}}\cup\hat{\mathcal{I}}_s^{\mathrm{R}}} \boldsymbol{g}_{ite} - \sum_{i\in\mathcal{I}_s} C_i^{\mathrm{g}} \boldsymbol{g}_{ite}\Big)\Big\}\Big] - \overline{\tau}_s^{\mathrm{c}}\sum_{i\in\hat{\mathcal{I}}_s^{\mathrm{R}}} g_i^{\max} - \sum_{i\in\hat{\mathcal{I}}_s} C_i^{\mathrm{inv}} g_i^{\max} \tag{4.2a}$$

Binary Expansion Approach [Pereira et al, 2005]

- Linearization of continuous times continuous variables as Mixed-integer linear constraints

$$\lambda_{nte} = \underline{\lambda}_n + \Delta\lambda \sum_{k=1}^{K} 2^{k-1} z_{ntke}, \quad z_{ntke} \in \{0,1\}, \tag{9a}$$

$$\lambda_{n(i),t,e} g_{ite} = \underline{\lambda}_{n(i)} g_{ite} + \Delta\lambda \sum_{k=1}^{K} 2^{k-1} s_{itke}, \tag{9b}$$

where:

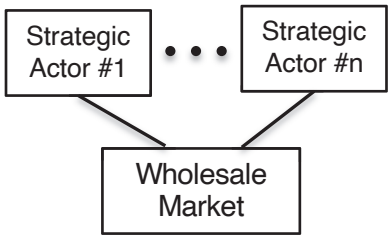
$$0 \leq s_{itke} \leq g_i^{\max} z_{n(i),tke},$$

$$g_{ite} - g_i^{\max}(1 - z_{n(i),t,k,e}) \leq s_{n(i),t,k,e} \leq g_{ite}.$$

How to Solve a Stochastic EPEC?

- **Analytical solution**
  - Exist for trivial cases, always with a limit on the number of strategic actors (typically, two or three)
- **NCP reformulation**
  - Can't be solved within 72 hours
- **"Diagonalization" (after linearization)**
  - Computationally prohibitive, even with two players
  - No solution quality guarantee

Algorithm	Metric	1 scenario	10 scenarios
Diagonalization	# of iterations	11	18
	Total time, s	6,711	14,007



- More scenarios → more time
- On the other hand, very few iterations (used later)

An Alternative Solution Technique: Progressive Hedging

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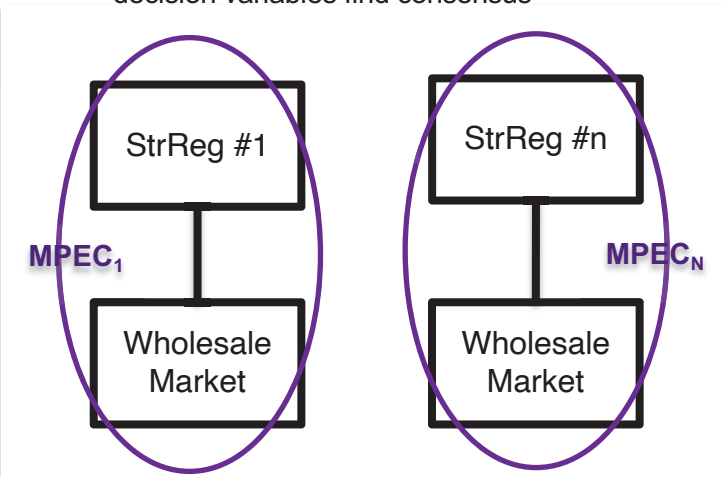
- **Decomposition Technique – Progressive Hedging**
  1) Hedge the common decision variables as individual variables of each problem
  2) Iteratively solve each problem with the penalty added objective function until the common decision variables find consensus



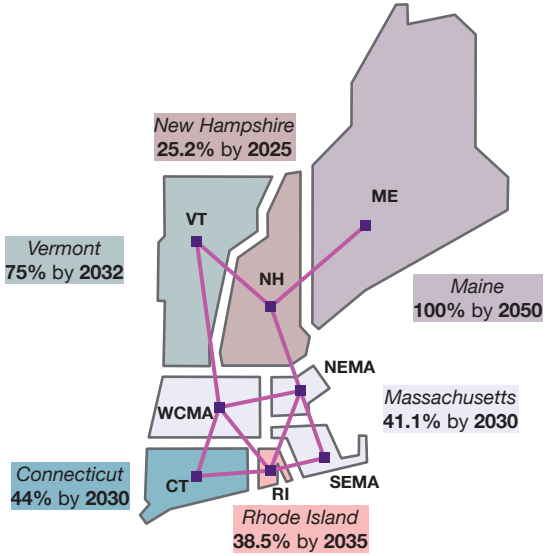
Hedge Lower Level Decisions▶
***N** independent CC-MPECs*

For **s** in **States**
  Solve **MPEC$_s$[x] := min O$_s$ [x]**
Obtain **E[x$^{(0)}$]**
While **Stdev[x$^{(i)}$] > ϵ**
  For **s** in **States**
    Penalize **(x$^{(i)}$-E[x$^{(i-1)}$])** in **O$_s$ [x]**
    Solve **MPEC$_s$ [x$^{(i)}$]**
  Obtain **E[x$^{(i)}$]**

$$\min\{O_{\mathrm{P}}^{(i,k)} + \overbrace{\frac{\rho}{2}||\mathbf{p}^{(i,k)} - \mathbf{p}^{(i,k-1)}||^2}^{\text{Policy equilibrium}} + \overbrace{\frac{\rho}{2}||\boldsymbol{\lambda}^{(i,s,k)} - \boldsymbol{\lambda}^{(i,s,k-1)}||^2 + \sum_{s\in\mathcal{S}} \boldsymbol{\lambda}^{(i,s,k)}\mathbf{m}_{\mathrm{PH}}^{(i,s,k-1)}}^{\text{Price equilibrium via consensus}}\},$$

ISO New England 8-zone Test System

76 controllable generators, 16 renewable generators



Julia v1.2 / JuMP v0.20 / Gurobi v8.1

Line	From Zone	To Zone	Distance (miles)	Resistance (ohms)	Reactance (ohms)	Reactance (per unit)
1	ME	NH	115.00	19.09	54.05	0.05
2	VT	NH	100.00	16.60	47.00	0.04
3	VT	WCMA	150.00	24.90	70.50	0.06
4	WCMA	NH	86.00	14.28	40.42	0.03
5	NEMA/BOST	WCMA	80.00	13.28	37.60	0.03
6	NEMA/BOST	NH	63.00	10.46	29.61	0.02
7	NEMA/BOST	SEMA	30.00	4.98	14.10	0.01
8	WCMA	CT	30.00	4.98	14.10	0.01
9	WCMA	RI	65.00	10.79	30.55	0.03
10	NEMA/BOST	RI	40.00	6.64	18.80	0.02
11	CT	RI	64.00	10.62	30.08	0.03
12	SEMA	RI	20.00	3.32	9.40	0.01

Case A: One strategic actor
Case B: Multiple strategic actors

Retirement scenarios:
Base / Coal ret. / Coal & Nuclear ret.

Case study

- **Computational Performance**
  - ✓ The CC-MPEC takes up to 7 hours to be solved for each cases, and the results are used as initial solutions of iteration 0 in the PH algorithm
  - ✓ The PH algorithm for the CC-EPEC takes 61, 29, 19 iterations to converge in each retirement scenario with 3% convergence tolerance
  - ✓ Each subproblem takes from 1 minute to 2.64 hours to solve and the entire iterations to converge have been completed in 32 hours on average. The number of iteration and relative convergence are shown in Fig. 4.

TABLE I. COMPUTING TIMES [S]

Cases	Average time per iter	Max time per iter	Total time	Iterations required
Basecase	2,976	9,516	181,581	61
Coal ret.	2,476	7,365	71,802	29
Coal & Nuclear ret.	5,786	2,706	92,577	19

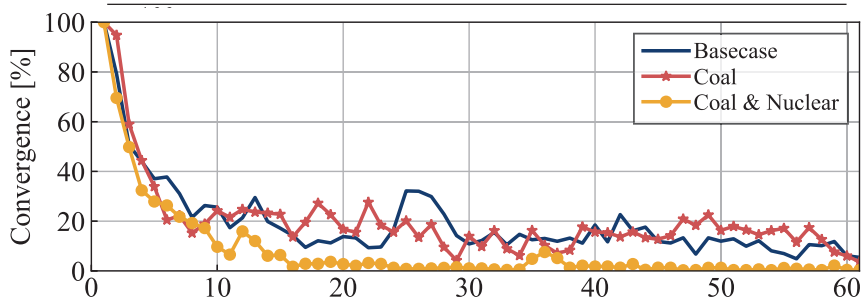


Fig 4. Relative convergence of the proposed PH algorithm

Case study

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A. One strategic regulator case (CC-MPEC)

- ✓ In all three scenarios, the capacity of **renewable** installations are identical as they must meet the same individual RPS requirements in each region
- ✓ Further installations of **renewables** are prevented by relatively high capital costs and low capacity factors

- ✓ Installations of **controllable** generation resources are not needed in ME and NH since they have a sufficient amount of existing capacity to provide reserve in all the retirement scenarios
- ✓ In cases of the state of VT, CT and RI, the investments in **controllable** resources are made in retirement scenarios to 1) replenish retiring resources 2) export surplus generation to neighb-oring states

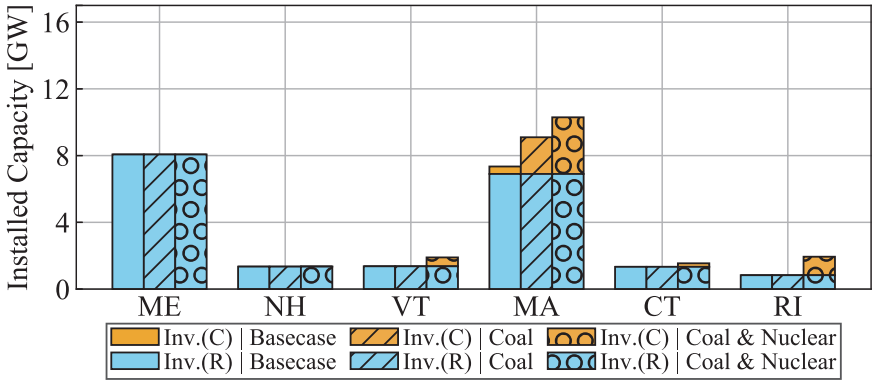

Fig 1. Generation expansion decisions of one strategic regulator case (CC-MPEC)

Centralized planning model

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- **Benchmark case: Centralized planning model [Munoz *et. al.*]**
  1) Centralized grid expansion planning model
  2) A single entity makes investment decisions throughout the entire system

$$\max O^{\mathrm{B}} := \sum_{e\in\mathcal{E}} \left[\omega_e \sum_{t\in\mathcal{T}} \left(\sum_{n\in\mathcal{N}} \pi^{\mathrm{D}}_{nt} D_{nte} - \sum_{i\in\mathcal{I}\cup\hat{\mathcal{I}}} C^{\mathrm{g}}_i g_{ite} - \sum_{i\in\mathcal{I}^{\mathrm{R}}\cup\hat{\mathcal{I}}^{\mathrm{R}}} \overline{\tau}^{\mathrm{e}}_{s(i)} g_{ite} \right)\right] - \sum_{i\in\hat{\mathcal{I}}^{\mathrm{R}}} \overline{\tau}^{\mathrm{c}}_{s(i)} g^{\max}_i - \sum_{i\in\hat{\mathcal{I}}} C^{\mathrm{inv}}_i g^{\max}_i \tag{13a}$$

subject to:

$$G^{\min}_i \le g_{ite} \le G^{\max}_i - r_{ite},\ \forall i \in \mathcal{I}^{\mathrm{C}}, t\in\mathcal{T}, e\in\mathcal{E}, \tag{13b}$$

$$\Gamma_i g^{\max}_i \le g_{ite} \le g^{\max}_i - r_{ite},\ \forall i \in \hat{\mathcal{I}}^{\mathrm{C}}, t\in\mathcal{T}, e\in\mathcal{E}, \tag{13c}$$

$$\sum_{i\in\mathcal{I}_n\cup\hat{\mathcal{I}}_n} g_{ite} + \sum_{l|r(l)=n} f_{lte} - \sum_{l|o(l)=n} f_{lte} = D_{nte}, \quad \forall n\in\mathcal{N}, t\in\mathcal{T}, e\in\mathcal{E}, \tag{13d}$$

$$\sum_{i\in\mathcal{I}^{\mathrm{C}}\cup\hat{\mathcal{I}}^{\mathrm{C}}} r_{ite} \ge R_{te}, \quad \forall t\in\mathcal{T}, e\in\mathcal{E}, \tag{13e}$$

$$f_{lte} = \frac{1}{X_l}(\theta_{o(l),t,e} - \theta_{r(l),t,e}),\ \forall l\in\mathcal{L},\ t\in\mathcal{T}, e\in\mathcal{E}, \tag{13f}$$

$$-F^{\max}_l \le f_{lte} \le F^{\max}_l,\ \forall l\in\mathcal{L},\ t\in\mathcal{T}, e\in\mathcal{E}, \tag{13g}$$

$$\sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}^{\mathrm{R}}_s\cup\hat{\mathcal{I}}^{\mathrm{R}}_s} \overline{g}_{ite} \ge \kappa_s \sum_{t\in\mathcal{T}} \sum_{n\in\mathcal{N}_s} D_{nte},\ \forall e\in\mathcal{E}, \tag{13h}$$

$$\sum_{i\in\hat{\mathcal{I}}_s} C^{\mathrm{inv}}_i g^{\max}_i \le B^{\mathrm{C}}_s, \tag{13i}$$

$$\sum_{t\in\mathcal{T}} \left(\overline{\tau}^{\mathrm{e}}_s \sum_{i\in\mathcal{I}^{\mathrm{R}}_s\cup\hat{\mathcal{I}}^{\mathrm{R}}_s} g_{ite} \right) + \overline{\tau}^{\mathrm{c}}_s \sum_{i\in\hat{\mathcal{I}}^{\mathrm{R}}_s} g^{\max}_i \le B^{\mathrm{P}}_s,\ \forall e\in\mathcal{E}. \tag{13j}$$

F. Munoz et al., "An engineering-economic approach to transmission planning under market and regulatory uncertainties: Wecc case study," *IEEE Transactions on Power System*, vol. 29, no. 1, pp. 307–317, 2014.

Case study

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A. One strategic regulator case (CC-MPEC)

- ✓ Unlike the centralized planning model that maximizes a global social-welfare, CC-MPEC maximizes its own social-welfare and therefore it yields different **controllable** generation expansions by a strategic regulator
- ✓ Strategic acting ME and NH shows no difference from the benchmark.
- ✓ In the cases of VT or MA being strategic, their strategic behavior lead to less **controllable** generation installed
- ✓ On the other hand, CT and RI decide to install more **controllable** capacity than the benchmark under the Coal & Nuclear retirement scenario since the combined capital and operation cost is smaller than the cost of importing electricity from other regions

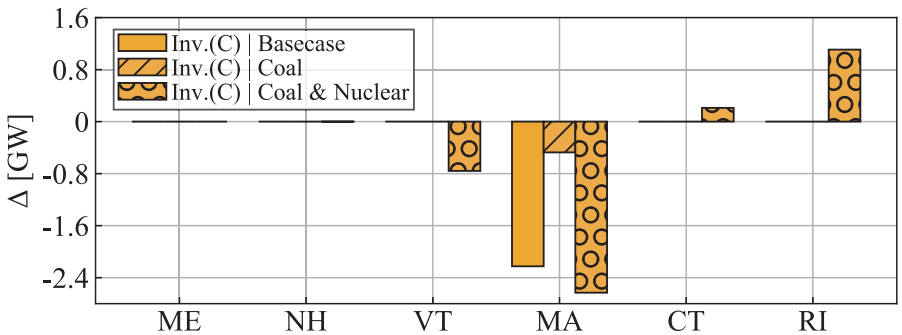

Fig 2. The difference of investments in controllable resources (Δ, [GW]) between the CC-MPEC and the centralized planning benchmark case

Case study

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B. Multiple strategic regulators case (CC-EPEC)

- ✓ In all three scenarios, the capacity of **renewable** installations are identical as they must meet the same individual RPS requirements in each region
- ✓ In contrast to the CC-MPEC, nearly all regulators adjust their strategies in response to competitors' actions, and hence, a greater amount of **controllable** generation resources is installed.

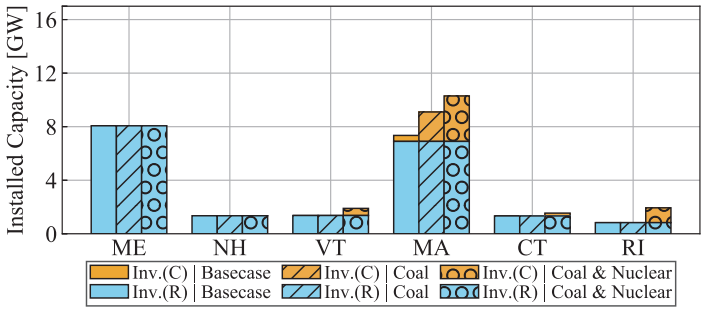

Fig 1. Generation expansion decisions of one strategic regulator case (CC-MPEC)

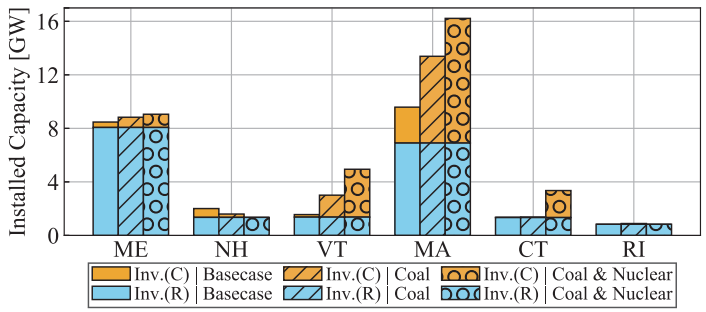

Fig 3. Generation expansion decisions of multiple strategic regulators case (CC-EPEC)

Case study

- **Investment & operating costs**
  - ✓ All costs show the same trend in one strategic regulator case and multiple strategic regulators case but generally increased in multiple regulators case due to the competition

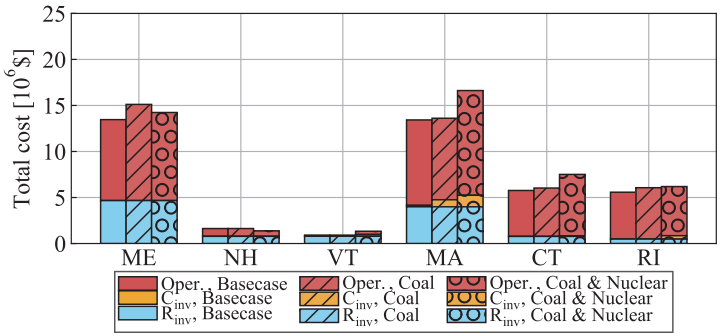

Fig 5. Investment and operating costs under different retirement scenarios (CC-MPEC)

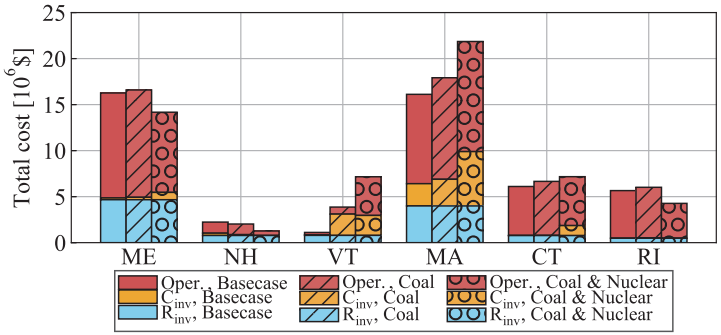

Fig 6. Investment and operating costs under different retirement scenarios (CC-EPEC)

Conclusion

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- We devised a CC-EPEC model to investigate the **effects of regulatory competition on achieving RPS goals**.

- The CC-EPEC is computationally demanding and, therefore, the PH algorithm was customized to solve the CC-EPEC efficiently.

- The case study reveals:
  1) Compared to the benchmark, strategic behavior tends to **reduce the controllable generation capacity needed to support RPS goals** for a single strategic actor in all but aggressive retirement scenarios.
  2) The case with multiple strategic actors leads to **an increased expansion of controllable generators, regardless of the retirement scenario.**
  3) Aggressive retirement scenarios strongly **influence the controllable generation capacity needed to achieve RPS goals**, regardless of the number of strategic actors.

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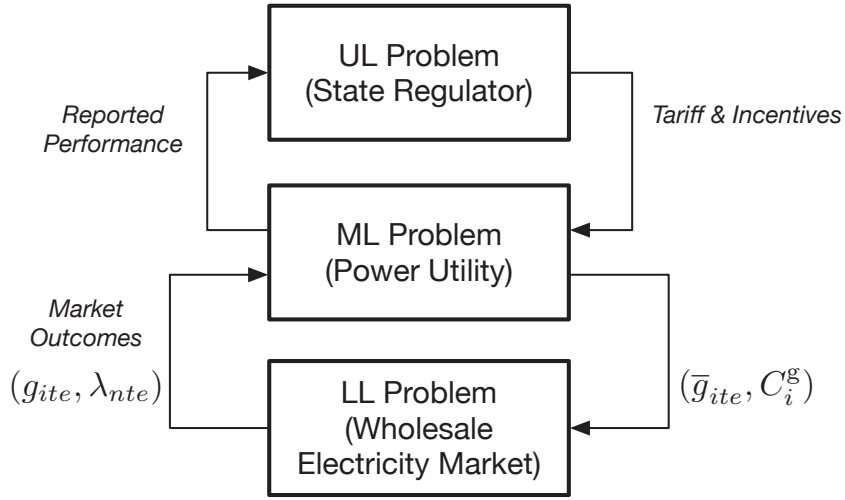
Part II. Strategic Policymaking for Implementing Renewable Portfolio Standards:

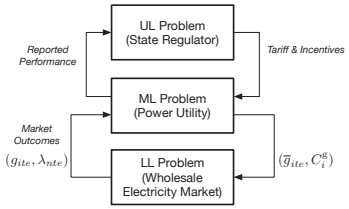
A Tri-level Optimization Approach

Model Framework

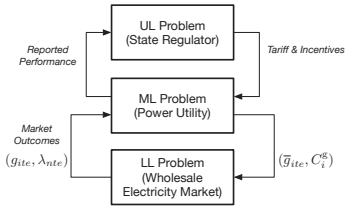


Model Description – UL

A. Upper-Level Problem



Model Description - ML



Model Description - ML

- Assume linear marginal benefit function: $\mathrm{MU} = M - Nd$
- Utility function:

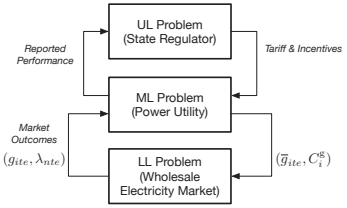
$$U(d_{nte}) = \begin{cases} Md_{nte} - \frac{N}{2}d_{nte}^2 & \text{if} \quad 0 \leq d_{nte} \leq \frac{M}{N}, \\ \frac{M}{N} & \text{if} \quad d_{nte} \geq \frac{M}{N}, \end{cases} \tag{3a}$$

- Consumer surplus maximization:

$$\max \ \mathrm{CS}_{nte} := (Md_{nte} - \frac{1}{2}Nd_{nte}^2) - \pi_{nt}d_{nte} \tag{4a}$$

Optimality condition:

Model Description - LL



Solution methods

- **Reformulation as a bilevel problem** by applying Strong Duality to the LL
- **Implement Column-and-Cut Generation (C&CG) algorithm** to solve the bilevel problem iteratively

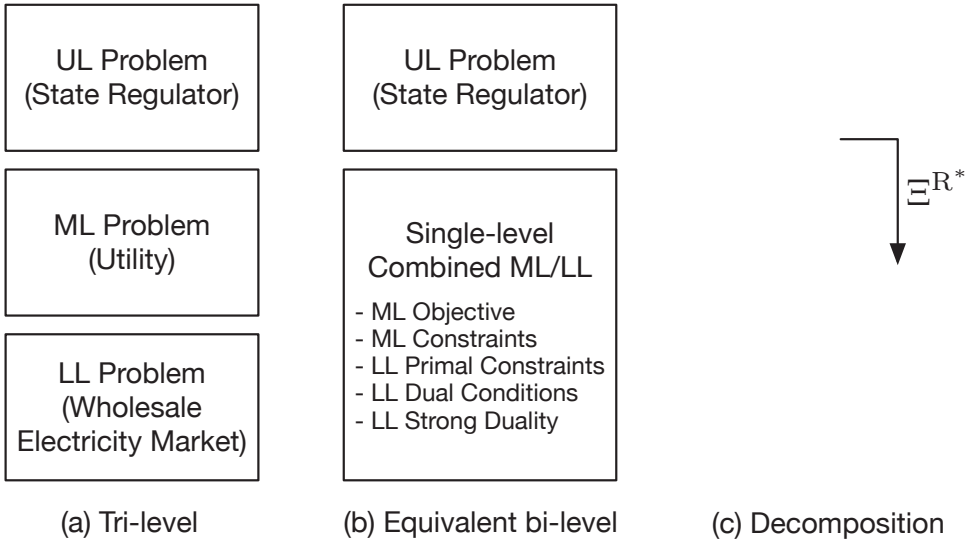


Fig. Solution Methods

Equivalent bi-level problem

$$
\begin{aligned}
&\text{Eq. (2)} && : \text{UL problem} && (10a)\\
&\Xi_e^{\mathrm{U}} \cup \Xi_e^{\mathrm{W}} \in \arg\Big[&& && \\
&\quad \text{Eqs. (6a), (6g), (6h), (8)} && : \text{ML problem} && \\
&\quad \text{Eqs. (7b)–(7e)} && : \text{LL primal constraints} && (10b)\\
&\quad \text{Eqs. (9b)–(9d)} && : \text{LL dual constraints} && \\
&\quad O_e^{\mathrm{W}} = O_e^{\mathrm{DW}} && : \text{LL strong duality} \ \Big] &&
\end{aligned}
$$

Bilinear QP

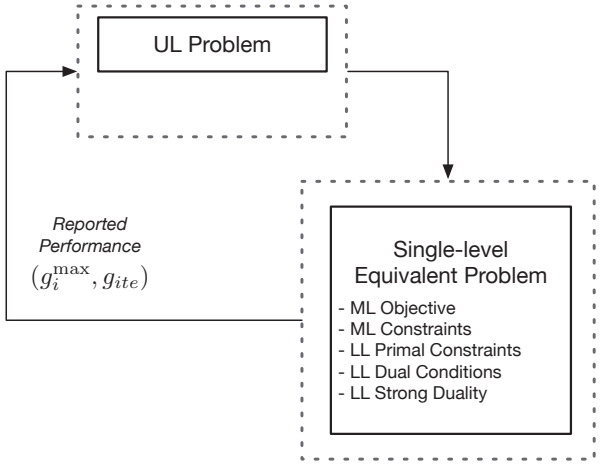
- Note duality approach is not applicable to (10b) due to bilinear terms:

$$\tau^{\mathrm{e}} g_{ite}, \tau^{\mathrm{c}} g_i^{\max}, \lambda_{n(i),t,e} g_{ite}$$

$$
\begin{aligned}
\max_{\Xi_e^{\mathrm{U}}} O_e^{\mathrm{U}} := \sum_{e\in\mathcal{E}} \omega_e \Big[& \sum_{t\in\mathcal{T}} \sum_{n\in\mathcal{N}_s} \pi_{nt} d_{nte} + \sum_{t\in\mathcal{T}} \sum_{i\in\hat{\mathcal{I}}^{\mathrm{R}}\cup\mathcal{I}^{\mathrm{R}}} \tau^{\mathrm{e}} g_{ite} \\
& + \sum_{i\in\hat{\mathcal{I}}^{\mathrm{R}}} \tau^{\mathrm{c}} g_i^{\max} - \sum_{t\in\mathcal{T}} \Big(\sum_{n\in\mathcal{N}_s} \lambda_{nte} d_{nte} - \sum_{i\in\mathcal{I}\cup\hat{\mathcal{I}}} \lambda_{n(i),t,e} g_{ite} \Big) \qquad (6a) \\
& - \sum_{i\in\hat{\mathcal{I}}} C_i^{\mathrm{inv}} g_i^{\max} - \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}} C_i^{\mathrm{g}} g_{ite} \Big]
\end{aligned}
$$

Cutting Plane Algorithm

- **Column-and-Cut Generation (C&CG) method**
  - ✓ A cutting-plane approach to primal variables (c.f. Benders' decomposition exploits dual information)
  - ✓ Solve the problem iteratively using a master-slave structure



Cutting Plane Algorithm

- **Tri-level problem (compact form)**

$$
\begin{aligned}
\min_{x,y}\ & x^\top A y + a^\top x && \text{(13a)} \\
\text{s.t.}\quad & x^\top B y + b^\top y \le c, && \text{(13b)} \\
& y \in \arg\max_{y}\ x^\top A y + y^\top C y + a^\top x + d^\top y, && \text{(13c)} \\
& \qquad \text{s.t.}\quad x^\top D y + y^\top E y + e^\top y \le f && \text{(13d)}
\end{aligned}
$$

UL optimization problem

Single-level equivalent problem (ML & LL combined)

where $x = \Xi^{\mathrm{UL}},\ y = \Xi^{\mathrm{ML}} \cup \Xi^{\mathrm{LL}}$.

UL decisions

ML&LL decisions

Cutting Plane Algorithm

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- **Master problem (compact form)**

$$
\begin{aligned}
\min_{x,y} \quad & x^\top A y + a^\top x && \text{(14a)} \\
\text{s.t.} \quad & x^\top B y + b^\top y \le c, && \text{(14b)} \\
& x^\top D y + y^\top E y + e^\top y \le f, && \text{(14c)} \\
& \Big[\, x^\top A y + y^\top C y + a^\top x + d^\top y \ge \\
& \quad x^\top A y^{(j-1)*} + {y^{(j)}}^\top C y^{(j)} + a^\top x + d^\top y^{(j-1)*}, && \text{(14d)} \\
& \quad x^\top D y^{(j)} + {y^{(j)}}^\top E y^{(j)} + e^\top y^{(j-1)*} \le f, && \text{(14e)} \\
& \Big], \quad \forall j \le k.
\end{aligned}
$$

UL objective & constraints

ML&LL constraints

Primal-cut w.r.t ***ML objective***
(Column & cut generation)

Primal-cut w.r.t
ML & LL constraints
(Column & cut generation)

w/ oracular knowledge $\boldsymbol{y^{(j-1)*}}$ (given from previous subproblems)

- **Sub-problem (compact form)**

$$
\begin{aligned}
y^{(j)} \in \arg\max_{y} \quad & {x^{(j-1)*}}^\top A y + y^\top C y + a^\top x^{(j-1)*} + d^\top y && \text{(15a)} \\
\text{s.t.} \quad & {x^{(j-1)*}}^\top D y + y^\top E y + e^\top y \le f && \text{(15b)}
\end{aligned}
$$

Equivalent bilevel objective

Equivalent bilevel constraints

w/ policy $\boldsymbol{x^{(j-1)*}}$ (given from master problem of current iteration)

Case Study

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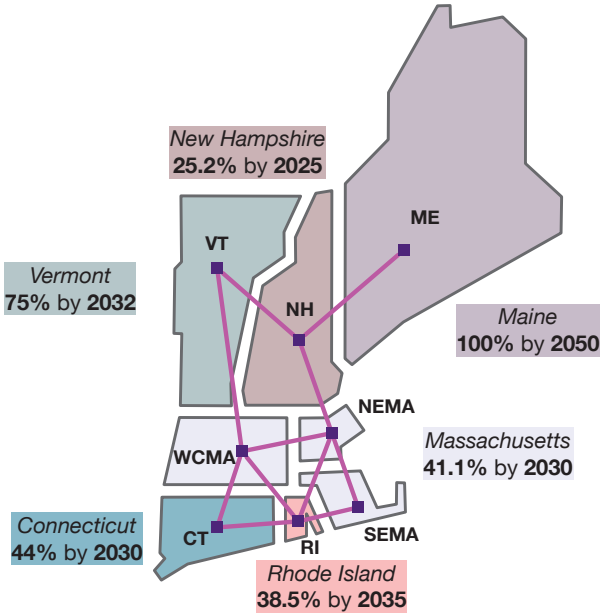
ISO New England 8-zone Test System

76 controllable generators, 16 renewable generators



julia JuliaOpt KNITRO High Performance Computing New York University

Julia v1.3 / JuMP v0.21 / KNITRO v12.1 on NYU HPC

KNITRO solver setting

par_blasnumthreads 10
ms_enable 1
ms_maxsolves 300
ms_terminate 0
maxit 100,000

Case study - NH

- **Policy, payments**
  - ✓ As the state regulator supervises the payment that the power utility receives, it sets **a lower electricity tariff when a higher incentive** is implemented.
  - ✓ $20/MWh of energy-based incentive brings a similar amount of decrease in the electricity tariff when $600/kW of capacity- based incentive is set, while achieving the same RPS goal.

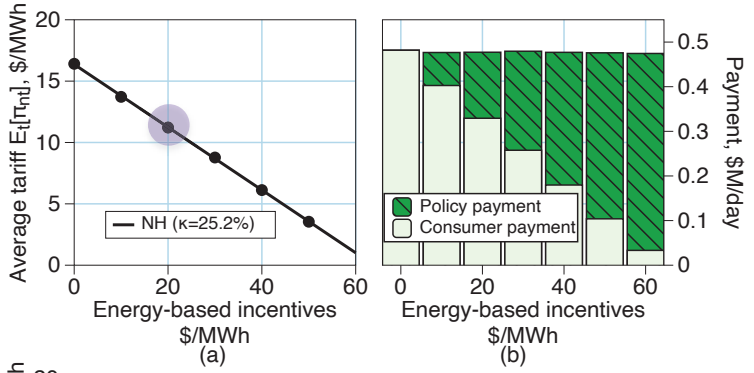


Fig 1. (a) (a) Relationship between the optimal **energy-based incentives** and electricity tariff and (b) comparison between the consumer payment and the cost of **energy-based incentives**.

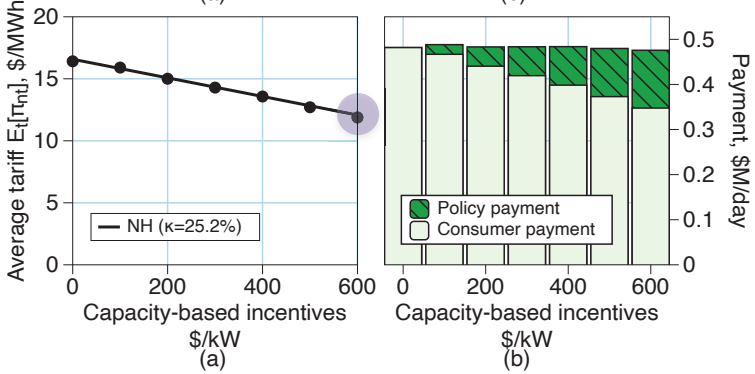


Fig 2. (a) Relationship between the optimal **capacity-based incentives** and electricity tariff and (b) comparison between the consumer payment and the cost of **capacity-based incentives**.

Case study - NH

- **Policy, payments**
  - ✓ As the state regulator supervises the payment that the power utility receives, it sets **a lower electricity tariff when a higher incentive** is implemented.
  - ✓ $20/MWh of energy-based incentive brings a similar amount of decrease in the electricity tariff when $600/kW of capacity- based incentive is set, while achieving the same RPS goal.

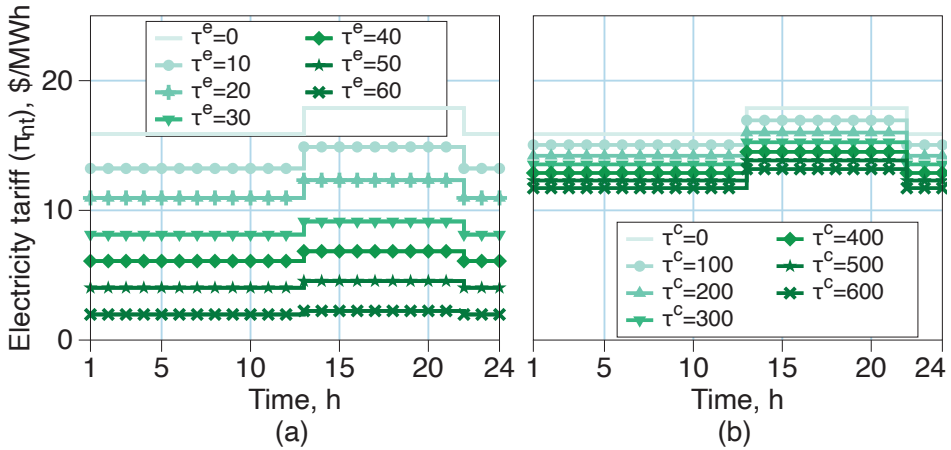
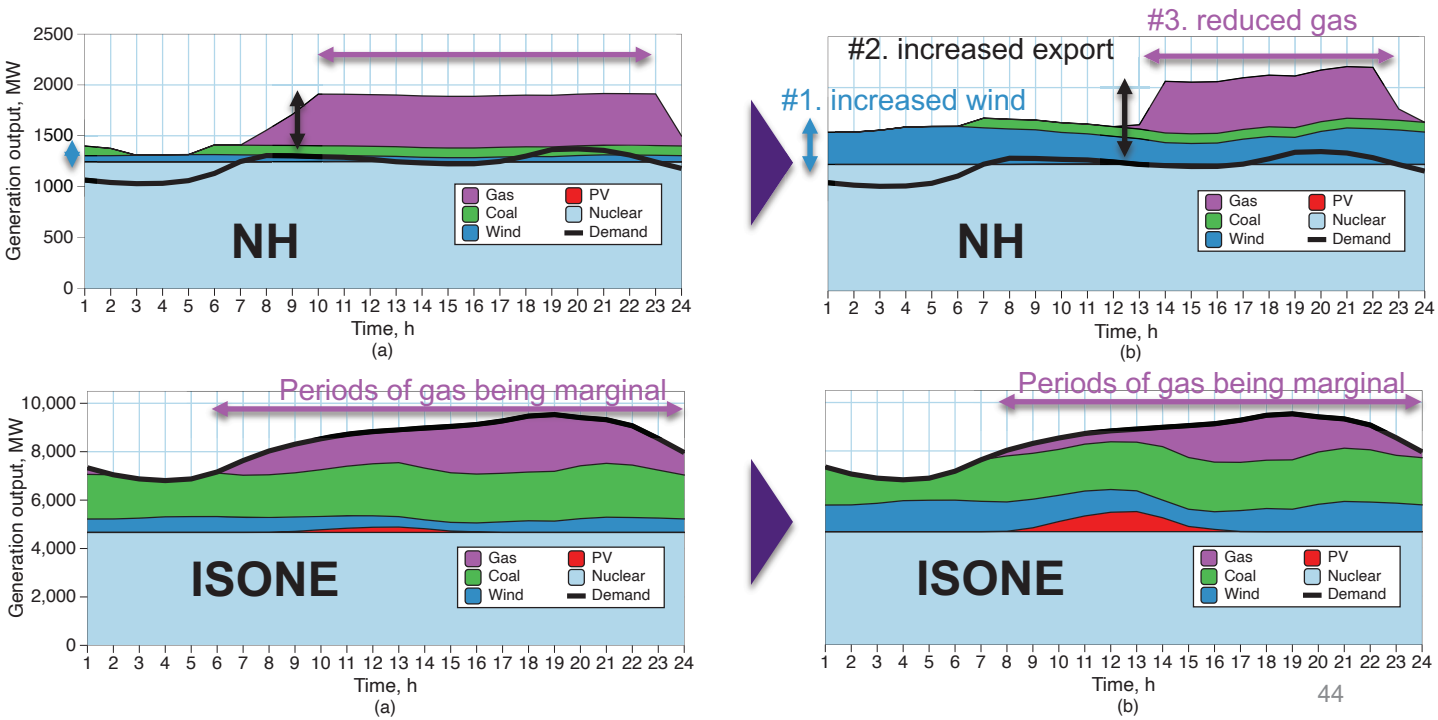


Fig 3. Optimal time-of-use (TOU) electricity tariffs for (a) energy-based and (b) capacity-based incentives. The darker the color, the higher the value of incentives.

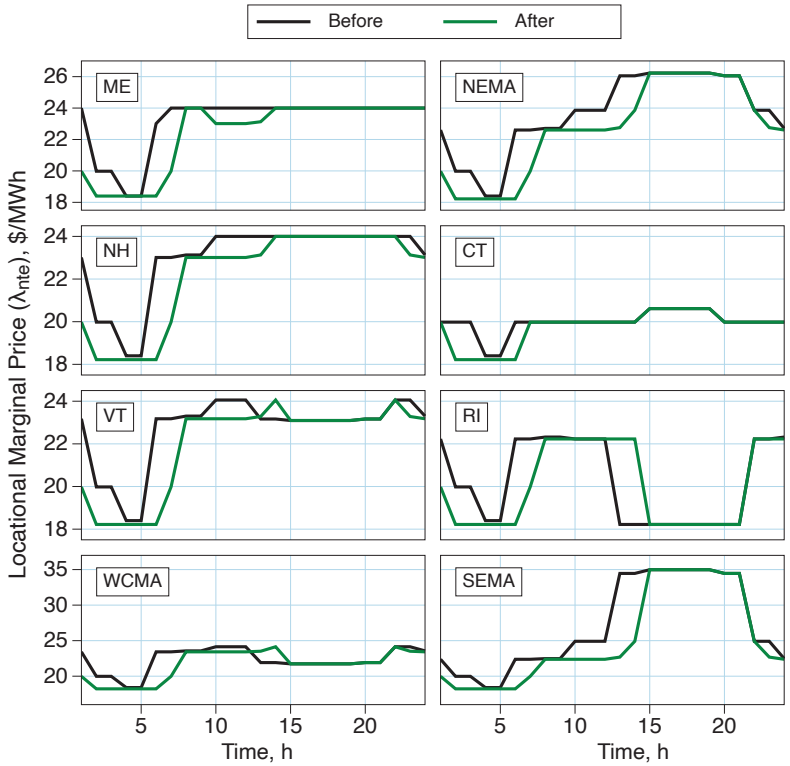
Case study - NH

- **Generation dispatch**
  - ✓ After installing 602MW of wind generator,
    1) Increase in wind dispatch
    2) Increase in net export
    3) Reduced gas dispatch



Case study - NH

- **Locational Marginal Price**
  - ✓ As a result of this change in dispatch, location marginal prices (LMPs) of the system is also decreased by ≈2.5% overall



Case study

- **Policy, payments**
  - ✓ A **higher RPS** goal requires **a higher value of the incentive** to maintain the same electricity tariff, in turn yielding a greater policy payment to the power utility

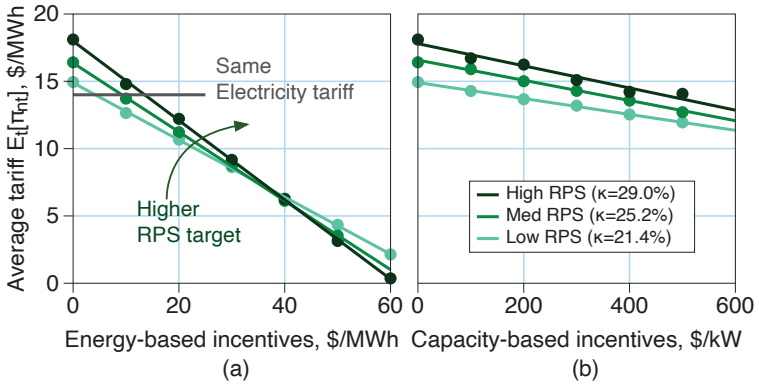


Fig 5. Sensitivity of the relationship between the optimal incentives and electricity tariff to an RPS goal.

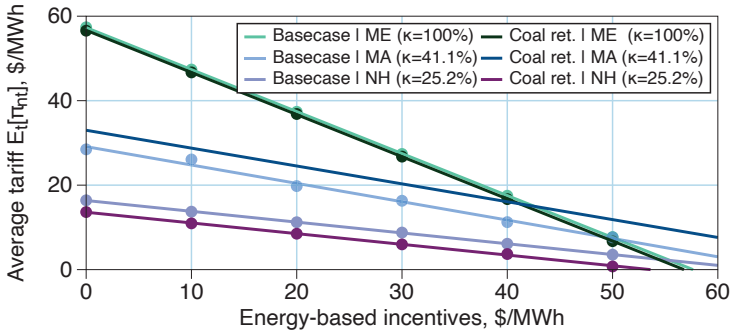


Fig 6. Sensitivity of the relationship between the optimal incentives and electricity tariff in ME, MA and NH to coal retirements.

Conclusion

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- **Effects of regulatory competition**
  - Compared to the uniform-policy benchmark, strategic behavior tends to **reduce the controllable generation capacity needed to support RPS goals** for a single strategic actor.
  - Multiple strategic actors leads to **an increased expansion of controllable generators, regardless of the retirement scenario.**
  - Aggressive retirement scenarios strongly **influence the controllable generation capacity needed to achieve RPS goals**, regardless of the number of strategic actors.

- **Effects of strategic policymaking**
  - Both the energy- and capacity-based **incentives linearly depend on** the average tariff. As the average tariff reduces, which in turn leads to a lower consumer payment, greater energy and capacity-based incentives are needed to achieve the same RPS goal.
  - A more **ambitious RPS target** requires either an increased electricity tariff (consumer payment) or higher RES incentives (policy support)

- **Computational performance**
  - Complexity of **uncertain renewable resources** were addressed by chance-constraints.
  - Both **Bi-level and Tri-level** structured problems were successfully solved by resorting to exact reformulations and algorithmic enhancements via PH and CCG algorithms.

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Part III. Strategic Policymaking with Information Awareness Constraints

Information Asymmetry

- **Examples of information asymmetry in electricity markets**
  - Regulator ↔ Power Utility: *Future Policy*
  - Power Utility ↔ DER Aggregator: *T&D Network profile*
  - Consumer ↔ Power Utility: *Consumer preference, Demand profile*

Background: Information Asymmetry

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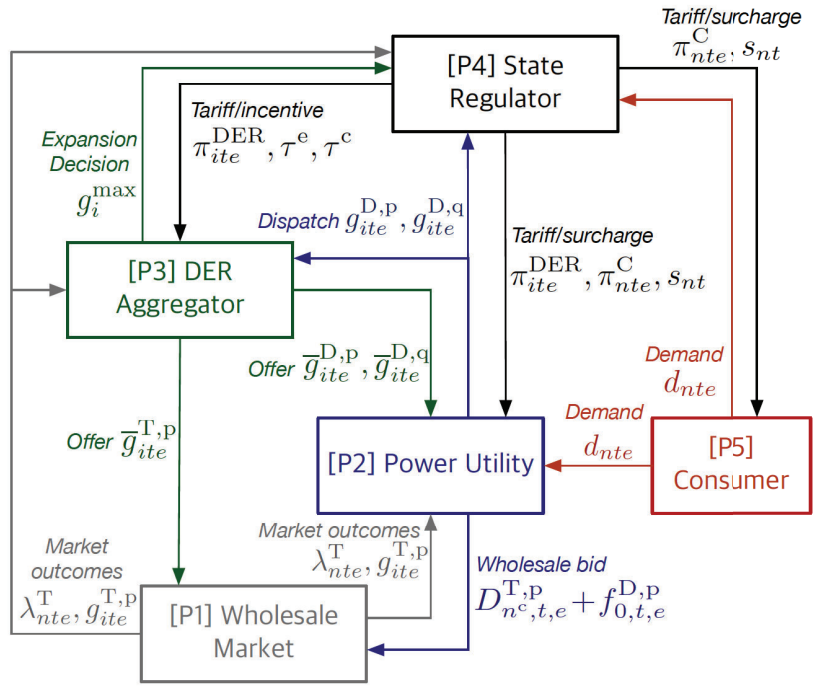
Table 1. A summary of the types of information that each actor has and needs.

Needs \ Knows	Consumers	Third-party Developers and Aggregators	Utilities	Regulator
Consumers		Revenue opportunities	Future rates, resource costs	Future regulatory policy
Third-party Developers and Aggregators	Ability and willingness to participate		Network characteristics, power flow, load profiles	Future regulatory policy
Utilities	Consumption and DER investment preferences	Operation preferences		Future regulatory policy
Regulator	Consumption and DER investment preferences	Operation preferences, investment costs	Costs, network characteristics, power flow, load profiles	

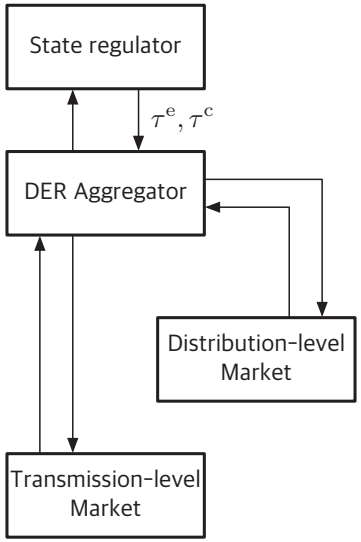
Model Framework

- **Information-aware/unaware model** for the state regulator



Model Framework

- **Information-aware/unaware model** for state regulator



- **State regulator:** Incentive design
- **DER Aggregator:** generation expansion planning
- **T&D market:** generation dispatch

Model Framework

State Regulator	Objective	• Maximize social-welfare (in-state)
	Decisions	• Renewable energy support incentives
	Constraints	• Renewable support budget
		• RPS requirement
		• DER Aggregator revenue adequacy
DER Aggregator	Objective	• Maximize profit
	Decisions	• Generation expansion plans
		• Generation offers in the transmission/distribution-level market
	Constraints	• Generation output limits
		• Regional supply demand balance
Transmission/Distribution-level electricity market (respectively)	Objective	• Minimize total generation cost
	Decisions	• Generation dispatch signals
		• LMP/DLMP (byproduct)
	Constraints	• Generation output limits
		• Transmission/Distribution line flow limits
		• Power flow constraints (DC/LinDist)
		• Nodal supply demand balance

- *DER Aggregator – Information-aware model*

$$\max_{\Xi^{\mathrm{A}}} \sum_{t\in\mathcal{T}} \sum_{e\in\mathcal{E}} \omega_e \Big[\sum_{i\in\mathcal{I}\cup\hat{\mathcal{I}}} \Big((\lambda^{\mathrm{T}}_{n(i),t,e} - C^{\mathrm{o}}_i) g^{\mathrm{T,p}}_{ite} + (\lambda^{\mathrm{D}}_{n(i),t,e} - C^{\mathrm{o}}_i) g^{\mathrm{D,p}}_{ite} \Big) + \sum_{i\in\hat{\mathcal{I}}^{\mathrm{R}}\cup\mathcal{I}^{\mathrm{R}}} g_{ite}\tau^{\mathrm{e}} \Big] + \sum_{i\in\hat{\mathcal{I}}^{\mathrm{R}}} \tau^{\mathrm{c}} g^{\max}_i - \sum_{i\in\hat{\mathcal{I}}} C^{\mathrm{inv}}_i g^{\max}_i \tag{1a}$$

Maximize profit

$$0 \le \overline{g}^{\mathrm{T,p}}_{ite} + \overline{g}^{\mathrm{D,p}}_{ite} \le G^{\mathrm{p,max}}_i, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}, e \in \mathcal{E}, \tag{1b}$$

$$0 \le \overline{g}^{\mathrm{T,p}}_{ite} + \overline{g}^{\mathrm{D,p}}_{ite} \le g^{\max}_i, \quad \forall i \in \hat{\mathcal{I}}, t \in \mathcal{T}, e \in \mathcal{E}, \tag{1c}$$

Generation output limits

subject to:

$$\Xi^{\mathrm{D}} \cup \Xi^{\mathrm{T}} \in \arg\Big[\text{Eq. (2)}: \quad \text{D-Market problem} \tag{1d}$$

$$\Xi^{\mathrm{T}} \in \arg\{\text{Eq. (3)}: \ \text{T-Market problem}\}\Big] \tag{1e}$$

T&D market awareness

Model Framework

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- *DER Aggregator – Information-unaware model*

$$\mathrm{O}^{\mathrm{DER}} := \sum_{t\in\mathcal{T}}\sum_{e\in\mathcal{E}}\omega_e\Big[\sum_{i\in\mathcal{I}\cup\hat{\mathcal{I}}}\Big((\lambda^{\mathrm{T}}_{n(i),t,e}-C^{\mathrm{o}}_i)g^{\mathrm{T,p}}_{ite}+(\boldsymbol{\lambda}^{\mathrm{D}}_{n(i),t,e}-C^{\mathrm{o}}_i)g^{\mathrm{D,p}}_{ite}\Big) + \sum_{i\in\hat{\mathcal{I}}^{\mathrm{R}}\cup\mathcal{I}^{\mathrm{R}}} g_{ite}\tau^{\mathrm{e}}\Big] + \sum_{i\in\hat{\mathcal{I}}^{\mathrm{R}}}\tau^{\mathrm{c}}g^{\max}_i - \sum_{i\in\hat{\mathcal{I}}}C^{\mathrm{inv}}_i g^{\max}_i$$

Forecast random variable

$$\max_{\Xi^{\mathrm{DER}}} \ \mathrm{CVaR}[\mathrm{O}^{\mathrm{DER}}] \qquad (6a)$$

Risk-based profit maximization

$$\underline{G}_i \le \overline{g}^{\mathrm{T}}_i + \overline{g}^{\mathrm{D}}_i \le \overline{g}_i, \quad \forall i\in\mathcal{I}, \qquad (6b)$$

$$0 \le \overline{g}^{\mathrm{T}}_i + \overline{g}^{\mathrm{D}}_i \le g^{\max}_i, \quad \forall i\in\hat{\mathcal{I}}, \qquad (6c)$$

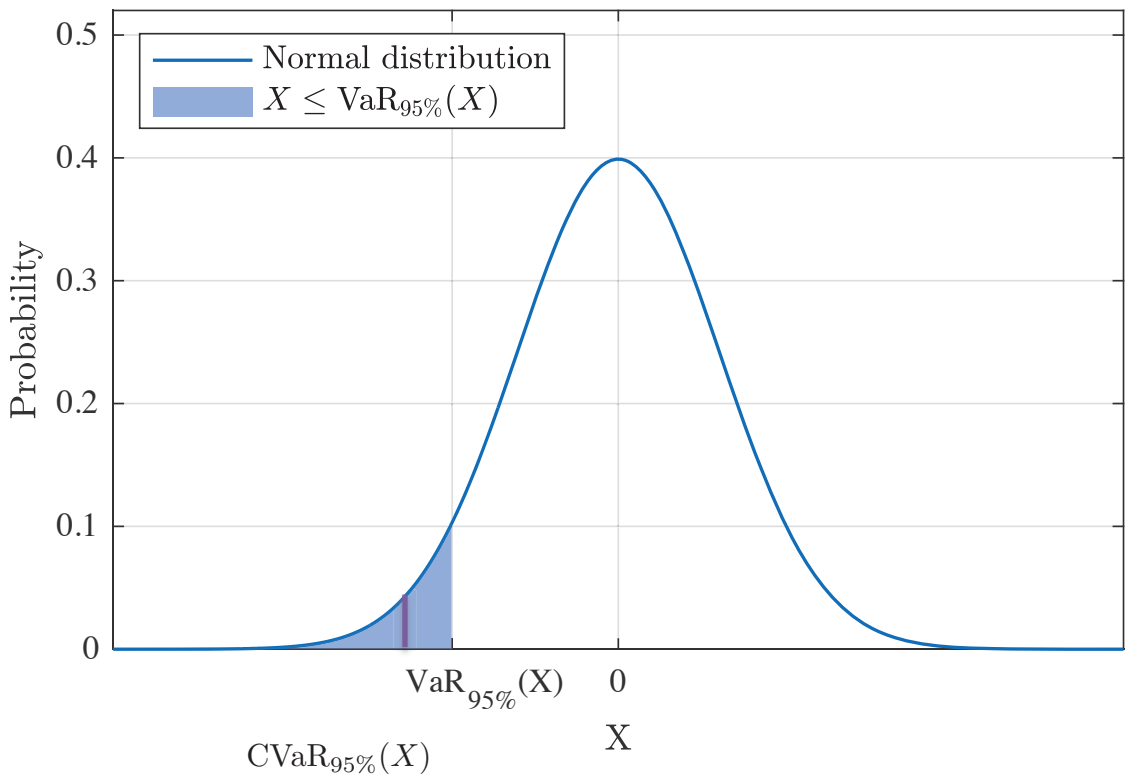
Generation output limits

subject to:

$$\lambda^{\mathrm{T}}_{n^{\mathrm{T}}(i)} \in \arg\{\text{Eq. (3)}\}: \qquad \text{T-Market problem} \qquad (6d)$$

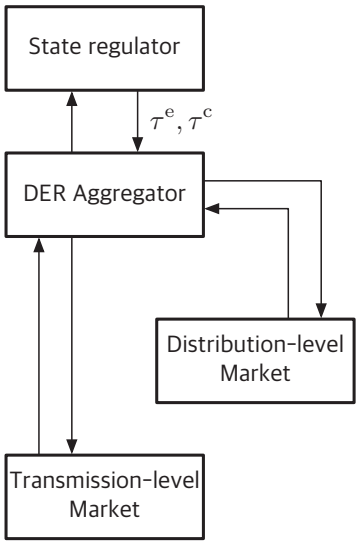
T- market awareness

Conditional Value-at-Risk (CVaR)



Solution Technique

- Optimality Conditions + Decomposition Algorithm



Solution Technique

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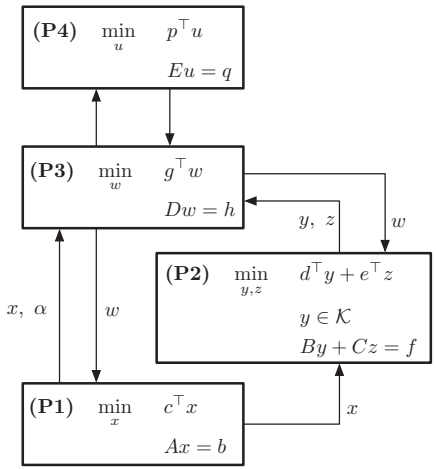
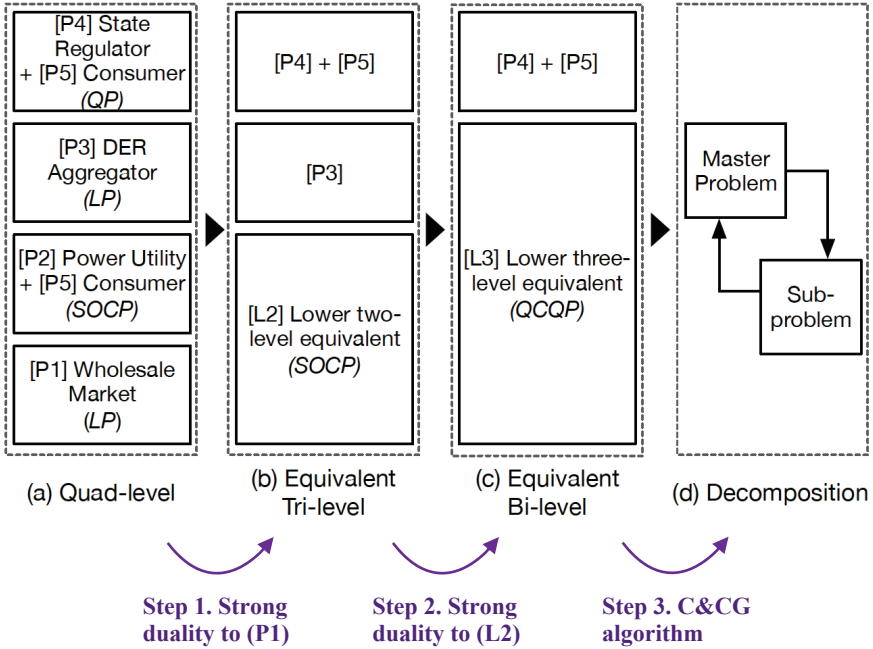


Fig. Simplified quad-level problem



Preliminary results

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- **Test systems**
  - ✓ NYISO 11-bus system (Wholesale-level marketplace)
  - ✓ Manhattan 7-bus system (Distribution-level marketplace)
  - ✓ RPS goal 50% by 2030

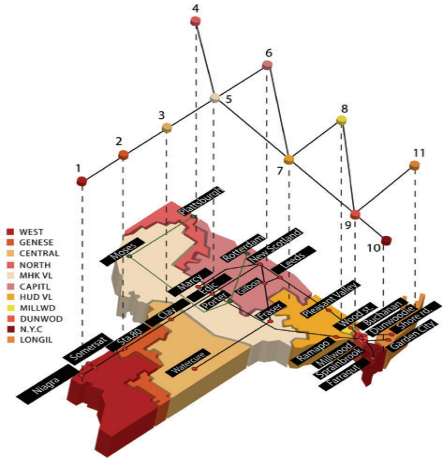

Fig. NYISO 11-bus system

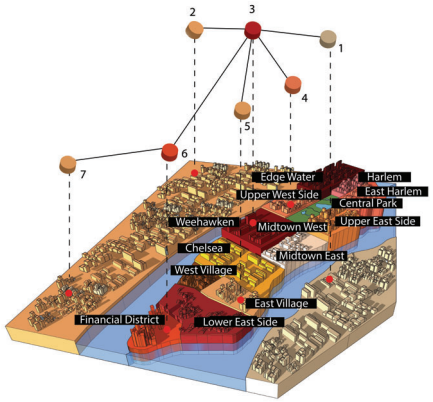

Fig. Manhattan 7-bus system

- **Computational environment**
  - ✓ Julia v1.5.3 / JuMP Package
  - ✓ KNITRO Solver v12.2.2
  - ✓ NYU High Performance Computing

julia KNITRO®

High Performance Computing
New York University

Preliminary results

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- **Generation Expansion Decisions**
  - ✓ **Investment decisions are the same** for both information-aware/unaware cases
  - ✓ Renewable installation is driven by RES incentives
  - ✓ Investment in conventional generators has not been made

*Unit: MW

Generators	As-Is	To-Be
Natural Gas	8,087	8,087
Oil	1,472	1,472
Wind	**0**	**9,698**
Total Capacity	9,559	19,257
Peak Demand	9,397	9,397

Table. Investment in NYISO Zone J

*Unit: MW

Generators	As-Is	To-Be
Natural Gas	716	716
Oil	0	0
PV	**0**	**5,458**
Total Capacity	716	6,174
Peak Demand	2,100	2,100

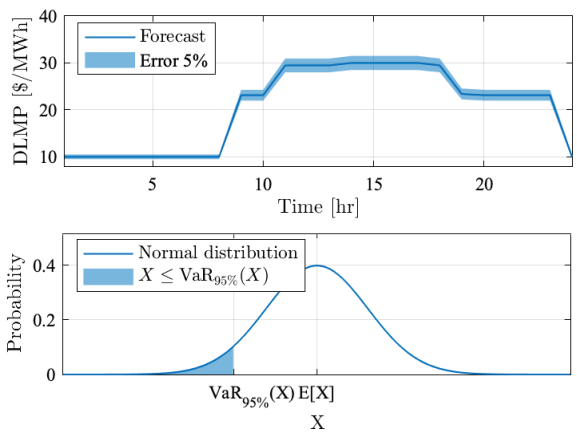
Table. Investment in Manhattan

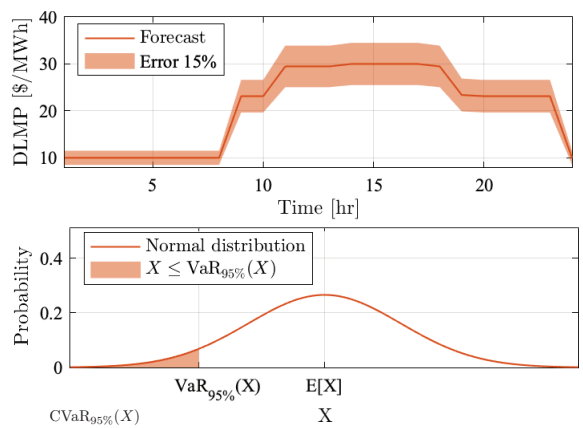
Preliminary results

- **Impact of DLMP Forecast Error**
  - ✓ Information-aware model shows the smallest RES incentive τ^e to achieve the same RPS goal (and thus, the smallest total cost O^{Reg})
  - ✓ Total cost O^{Reg} increases under higher DLMP forecast errors

	Information Unaware			Information Aware
DLMP forecast error	**5%**	**10%**	**15%**	**-**
$O^{\text{Reg}}, M\$$	19.619	19.630	19.641	19.194
$\tau^e, \$/MWh$	82.305	82.350	82.395	80.522

Table. Regulatory decision comparison between information aware/unaware models





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1. J. Kim, R. Mieth, and Y. Dvorkin, "Computing a Strategic Decarbonization Pathway: A Chance-Constrained Equilibrium Problem," *IEEE Transactions on Power Systems, early access,* 2021.

2. B. Unel, S. Bialek, J. Kim, and Y. Dvorkin, "Energy Transition, Distributed Energy Resources, and the Need for Information," *International Association for Energy Economics Energy*, 2020

3. J. Kim, S. Bialek, B. Unel and Y. Dvorkin, "Strategic Policymaking for Implementing Renewable Portfolio Standards: A Tri-level Optimization Approach," under review in IEEE Transactions on Power Systems. Available at: https://arxiv.org/abs/2009.01336

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Thank you for your attention!

Appendix. SOCP Power Flow Equation

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❑ Branch Flow Model [M. Farivar & S.H. Low, 2013]

- Extension of DistFlow model [Baran & Wu, 1989]
- Exactness of relaxation of (16) for radial distribution networks is proven by [S.H. Low, 2012]

$$V_i - V_j = z_{ij} I_{ij}, \quad \forall (i,j) \in E \tag{1}$$

$$S_{ij} = V_i I_{ij}^*, \quad \forall (i,j) \in E \tag{2}$$

$$\sum_{k:j\to k} S_{jk} - \sum_{i:i\to j} (S_{ij} - z_{ij}|I_{ij}|^2) + y_j^* |V_j|^2 = s_j. \tag{3}$$

$$p_j = \sum_{k:j\to k} P_{jk} - \sum_{i:i\to j} (P_{ij} - r_{ij}\ell_{ij}) + g_j v_j, \quad \forall j \tag{13}$$

$$q_j = \sum_{k:j\to k} Q_{jk} - \sum_{i:i\to j} (Q_{ij} - x_{ij}\ell_{ij}) + b_j v_j, \quad \forall j \tag{14}$$

$$v_j = v_i - 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) + (r_{ij}^2 + x_{ij}^2)\ell_{ij} \quad \forall (i,j) \in E \tag{15}$$

$$\ell_{ij} = \frac{P_{ij}^2 + Q_{ij}^2}{v_i}, \quad \forall (i,j) \in E. \tag{16}$$

Squared magnitude

Put I_{ij} into (1)

Squared magnitude

Appendix. Second Order Conic Program (SOCP)

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❑ Second Order Conic Program

- A SOCP is a convex optimization problem of the form below
- SOCPs can be solved with great efficiency by interior point methods through commercial solvers (e.g. Gurobi, CPLEX, Xpress)

$$\min_x f^T x \tag{1}$$

$$||A_i x + b_i||_2 \leq c_i^T x + d_i, \;\; i = 1, \ldots, m, \tag{2}$$

$$where \; A_i \in \mathbb{R}^{k_i \times n}, \; b_i \in \mathbb{R}^{k_i}, \; c_i \in \mathbb{R}^n \; and \; d_i \in \mathbb{R}. \tag{3}$$

Appendix. Linearization of multiplication of a continuous and a binary variable

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❑ Big-M method

- The expression z=x·δ where x is a **continuous** variable and δ is a **binary** variable can also be linearized fairly easily. The exact form depends on the bounds of x. Assume x has lower bound x^{lo} and upper bound x^{up}, then we can form the inequalities:

$$\boxed{\begin{gathered}\min\{0, x^{lo}\} \leq z \leq \max\{0, x^{up}\} \\ x^{lo} \cdot \delta \leq z \leq x^{up} \cdot \delta \\ x - x^{up} \cdot (1-\delta) \leq z \leq x - x^{lo} \cdot (1-\delta)\end{gathered}}$$

- The last restriction is essentially a big-M constraint:

$$\boxed{x - M_1 \cdot (1-\delta) \leq z \leq x + M_2 \cdot (1-\delta)}$$

- where M1, M2 are chosen as tightly as possible while not excluding z=0 when δ=0.
  For the special case xlo=0 this reduces to:

$$\boxed{\begin{aligned}&z \in [0, x^{up}] \\ &z \leq x^{up} \cdot \delta \\ &z \leq x \\ &z \geq x - x^{up} \cdot (1-\delta)\end{aligned}}$$

- The construct z=x·δ can be used to model an OR condition: "z=0 OR z=x".