SOME METHODS FOR GENERATION & GRID OPTIMIZATION UNDER LONG-RUN UNCERTAINTIES

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Session on ""Modernizing Planning through Technology and Data: Smarter, Faster, and Leaner Planning Enabled by AI, Automation, and Computational Advances."

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Energy at Hopkins

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Overview

I. Uncertainty-aware planning: Why?

II. Stochastic Programming

III. Robust Programming

IV. Results for BPA & WECC-wide analyses

Q1: Do stochastic grid plans ***differ*?**

Q2: Are stochastic plans ***better***?

Q3: Which uncertainty ***matters*** most?

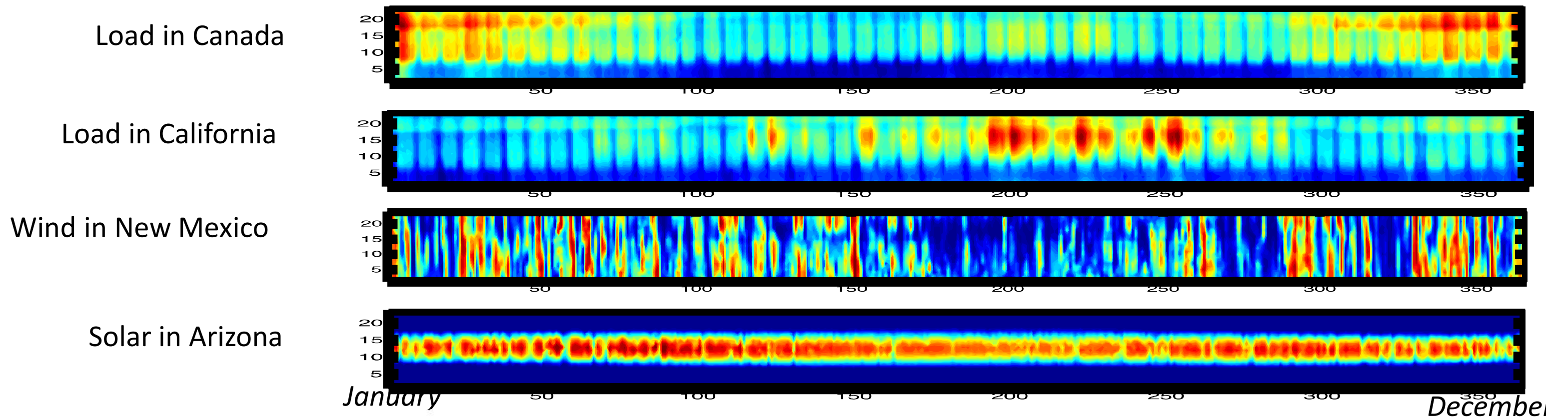
Q4: What is ***benefit of SP*** compared to other model enhancements?

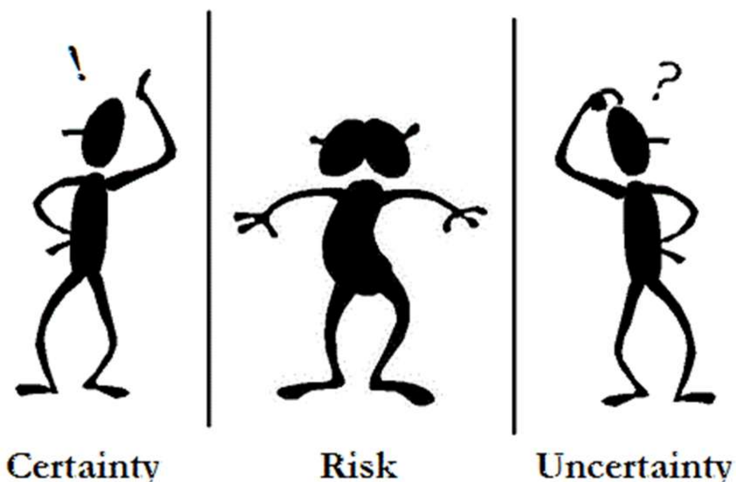
(more hours, DC load flow, unit commitment)

V. Decomposition & AI to enhance computability

I. Why Uncertainty-Aware Planning? Two challenges:

1. Operating Variability (over hours):





2. Hyper-uncertainty (over decades):

- Fuel Costs
- Demand Growth
- Technology Costs
- Carbon Policy
- DR
- PEV
- RPS
- Distributed Generation
- Coal Retirements

What Can We Learn from Uncertainty-Aware Planning?

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1. Do risks of some projects justify "wait & see"?

- Given stranded asset risks, defer until need clearer?
- "Option value" of delay should be quantified

→ ***Might build <u>less</u> under uncertainty***

2. Do some projects have a "flexibility" or "insurance" value that justifies their upfront costs?

- Does a project open up more options to deal with multiple possible futures?
- Does a project enhance exchanges between regions that hedge risks?
- Does a project provide insurance against extreme scenarios?

→ ***Might build <u>more</u> under uncertainty***

How to assess uncertainty-aware planning frameworks?

(Spyrou, Hobbs et al. 2024)

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How much $ can we save by explicitly considering risks?

	Criterion 1: Methodological capability		
Theme	How the methodological framework considers:		
Uncertainty	Space of possible states	Probabilities of states	Chronological evolution
Plans	Feasible set	Asset-temporal-spatial resolution	Future updates to plans
Consequences: Attributes	Types (e.g., reliability, cost)	Resolution	Precision
Consequences: Assessment	Different types of criteria (e.g., min-max)	Updates to criteria for assessment of plans	Process to elicit preferences

Criterion 3: Contribution to decision making and stakeholder acceptance	
Engagement goal	Number of views
For each theme in the 1st column, which goal could the framework serve: to inform, to consult, or to collaborate?	For each theme in the 1st column, can the framework consider multiple views and how?

Criterion 2: Practical applicability

- Computational resources
- Software
- Data requirements
- Human resources
- Regulatory compliance

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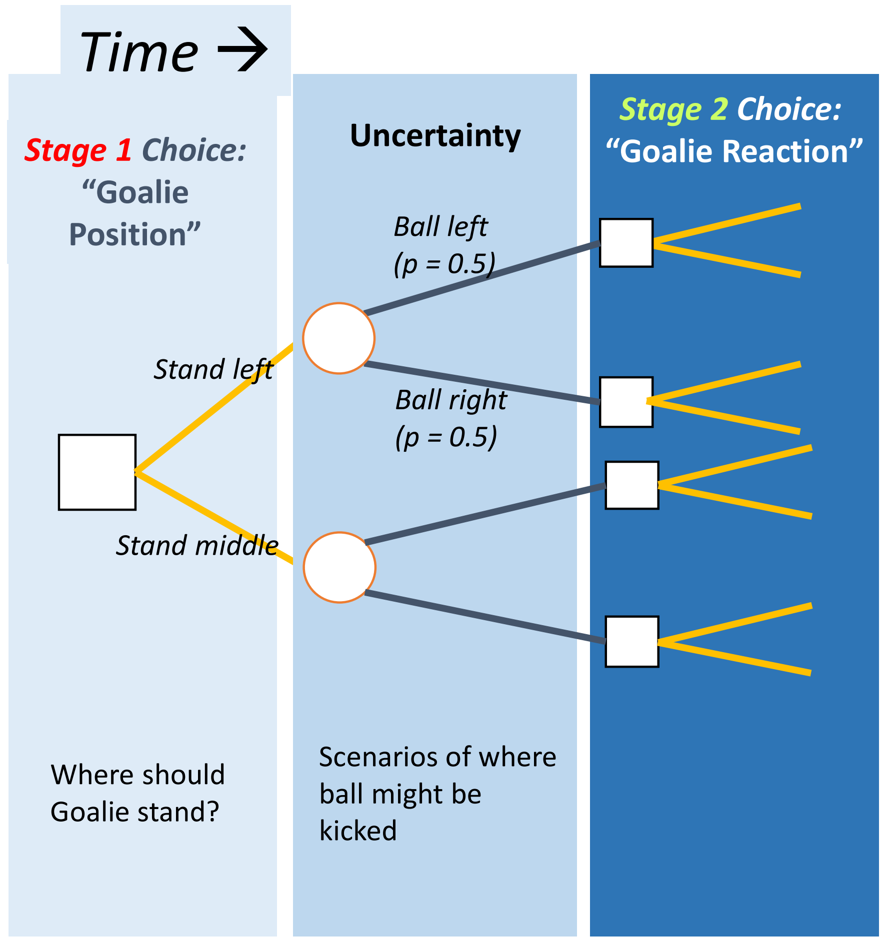
II. How does Stochastic Programming (SP) work? Uncertainty & Adaptation as a "Decision Tree"

- The optimum for **Stage 1** considers:
  - Each scenario's probability
  - How you'd adapt in **Stage 2**, given:
    - ✓ the scenario
    - ✓ options left open by Stage 1 decisions
- Stage 1's optimum might not be best for any individual scenario
  → Must evaluate flexibility provided by Stage 1 choice under all scenarios at once



"Decision Tree" Calculations: Logic of Stochastic Optimization

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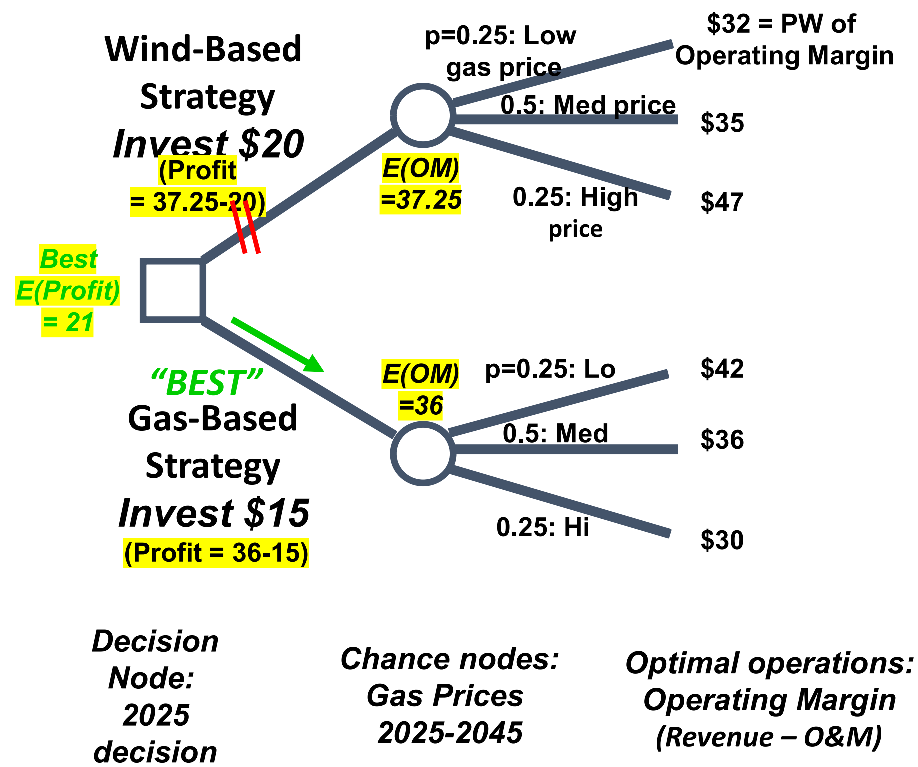
Simple example: Choose Resource

(1) Start at right end

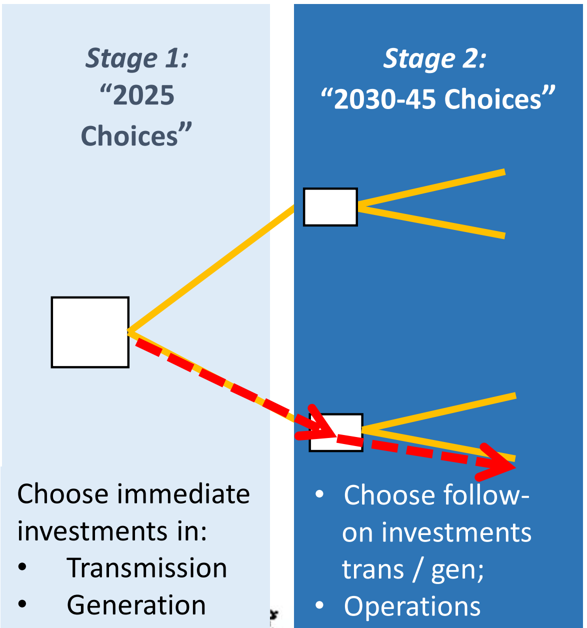
(2) Move left

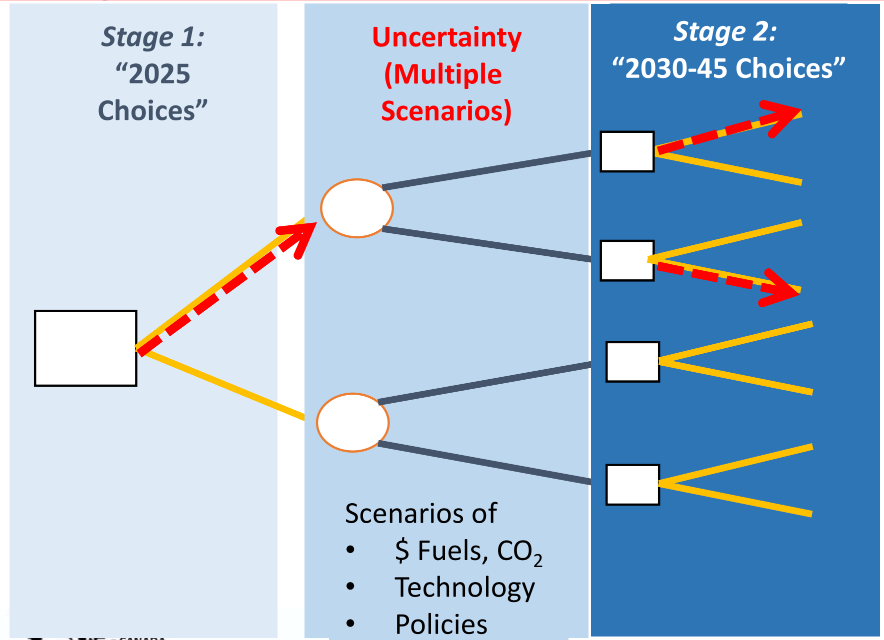
- at a chance node, calculate "expected value"
- at a decision node, choose best alternative

(3) Continue until reach left-most node

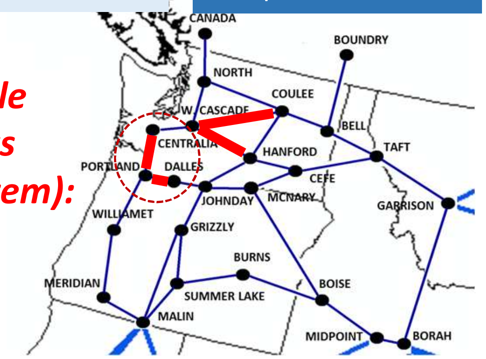


Multistage (Adaptive) Grid Planning: Single Scenario (Deterministic) *vs*. Multiscenario

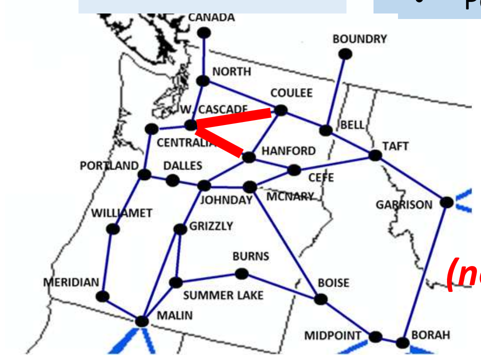




Example Results (BPA System):



1st Stage Transmission, *Deterministic*



1st Stage Transmission, *Stochastic Five Scenarios*

Stage 1 Decisions:
"PUT OFF CHOICE"
(not "INVEST MORE: INSURE & DIVERSIFY")

SP's Math Formulation: MILP

(van der Weijde, Hobbs, *Energy Economics*, 2012; Munoz, Hobbs et al., *IEEE TPWRS*; Xu, Hobbs in *Transmission Investment in Liberalized Markets*, 2020)

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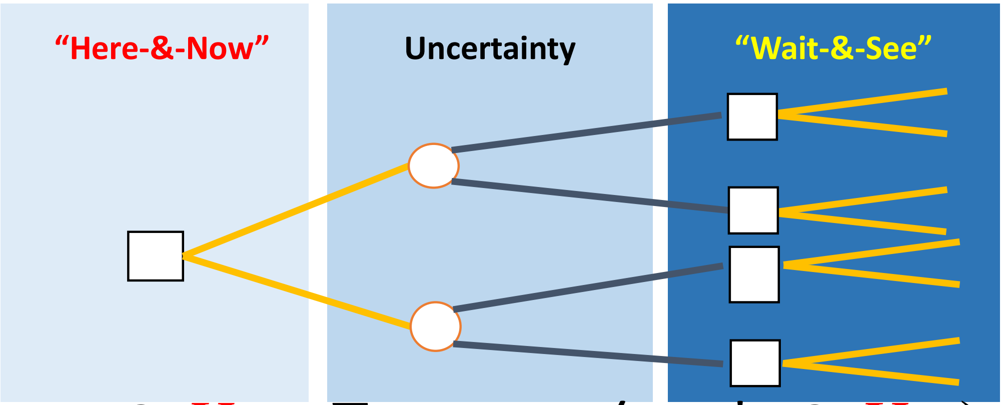

$$\text{MIN NPV Cost} = C_1 X_1 + \Sigma_{\text{scenarios } S} (P_S \ast C_2 X_{2,S})$$

$$\text{Subject to:} \quad A_{1,1} X_1 \leq B_1$$

$$\{A_{2,1,S} X_1 + A_{2,2,S} X_{2,S} \leq B_{2,S}\}, \quad \forall S$$

- **Decision variables X's include:**
  - ***Investments***: transmission (and if "cooptimize": gen, DSM, storage ….)
  - ***Operations***: generator, storage, DR dispatch, phase shifter settings… (*production costing or short-run market simulation)*
- **Constraints include:**
  - Kirchhoff's Laws
  - Generator and transmission capacity / operating restrictions
  - Siting restrictions
  - Emissions caps, renewable portfolio standards

Our Hypothetical BPA Implementation of JHSMINE
(Johns Hopkins Stochastic Multistage Integrated Network Evaluation)

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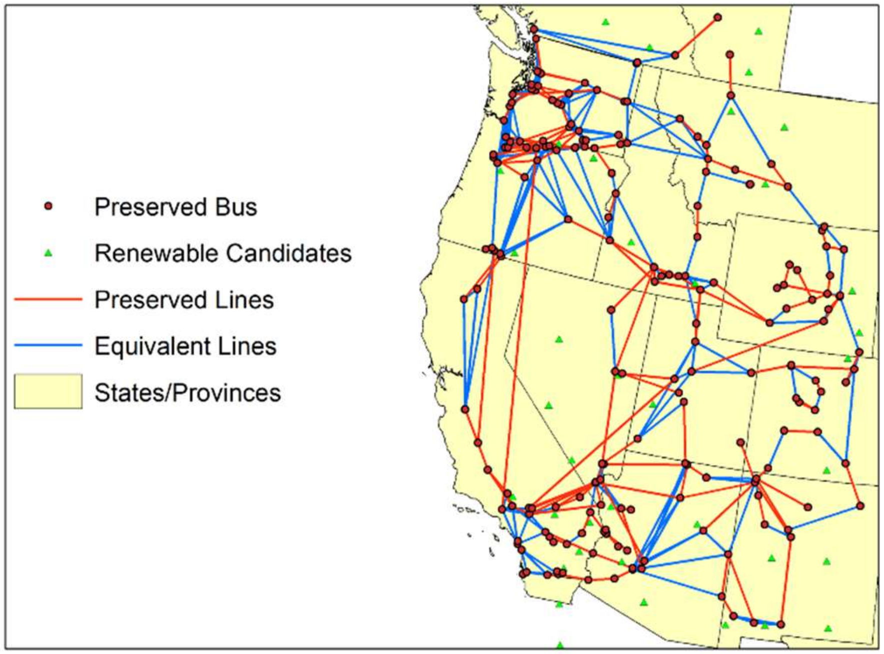
- BPA/WECC Stochastic Programming model (JHU):
  - Here-&-now: Decide 2018, online 2024
  - Wait-&-see: Decide 2024, online 2030
  - 8 Scenarios, 11 Uncertain variables
- ~10^1 load blocks per year (so could solve many times)
- Investment variables:
  - All WECC lines
  - New unannounced siting projections: assume competitive generators respond to LMPs



Example 300-bus network
(developed by JHU for WECC analyses, with help of ASU)
Pipes & Bubbles or Linearized DC OPF (KCL/KVL)

Uncertainties considered in hypothetical BPA/WECC study

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	Uncertainty	Hi (3)	Lo (1)	Medium
1	Carbon Cost Years Implement	2020	Never	2026
2	Wind Build cost decay rate	6 times base case decay rate	0.75 times base case decay rate	Defined by NREL ATB Rate varies by Year
3	Solar Build cost decay rate	2 times base case decay rate	0.75 times base case decay rate	Defined by NREL ATB Rate varies by Year
4	Fuel Price	2% APR	0.25% APR	1.125% (average of 2% and 0.25%)
5	Base Demand Growth (Each area demand growth determined by base + Area specific demand growth)	1.92% (1.5 times base value)	0.565% (Half base value)	1.13%
6	Base Peak Demand (Each area peak growth determined by base + Area specific demand growth)	1.7% APR (1.5 times base value)	0.64% APR (Half base value)	1.28% APR
7	Hydro CF	1.35 x base values	0.65 x base values	1 x base values
8	Initial Line Multiplier	1.25 x base costs	1.25 x base costs	1.25 x base costs
	Late Line Multiplier	1.5 x base costs	1 x base costs	1.25 x base costs
9	Total Solar subgrid Init Penetration	0.10%	0.10%	0.10%
	Total Solar subgrid linear AGR	0.60%	0.20%	0.4% (average of 0.6% and 0.2%)
10	DER Solar subgrid Init Penetration	0.10%	0.10%	0.10%
	DER Solar subgrid linear AGR	0.22%	0.05%	0.0135% (average of 0.22% amd 0.05%)
11	Solar SW Init Penetration	2.00%	2.00%	2.00%
	Solar SW linear AGR	0.80%	0.50%	0.65% (average of 0.8% and 0.5%)

Scenario #	Probability	Scenario String
1	0.125	33331113333
2	0.125	33131113111
3	0.125	31313333333
4	0.125	31111131111
5	0.125	13333313333
6	0.125	13133313111
7	0.125	11311131333
8	0.125	11113333111

Summary: Introduction to SP

- SP asks: what choices *now* minimize prob-weighted cost, considering:
  - Impacts over all scenarios
  - *Immediate* “here-&-now” decisions:
    - Made ***without*** knowing which scenario will occur
    - Hem in or open up later options
  - *Later* “wait-&-see”/recourse decisions:
    - Adaptation made *after* knowing which scenario will occur
- SP widely used in power systems (see references) and other fields
  - 100M variables or more handled in gen-trans planning problems using decomposition methods (Munoz, Watson, Hobbs, 2016)
- Elaborate versions can consider $\geq$ 2 decision stages
- But: *Curse* of dimensionality: # variables go up exponentially

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III. Another Approach: Robustness-Based Methods

- ~~**Scenarios + Probabilities**~~ → **Uncertainty Set**
  - ✓ Either a Set of Scenarios or Continuous Range of Possible Futures
  - ✓ Maximize Robustness: Minimize {worst outcome among all scenarios/possible outcomes}
  - ✓ **Three well-known "Robustness" methods:**

(1) "Robust Optimization": Choose plan to MIN worst outcome over infinite set of possible futures (Malcolm, Zenios 1994)

- ✓ Highly challenging for large problems, especially if later "adaptation" (wait-and-see recourse)

(2) "Robust Decision Making": (a) Define set of candidate plans,

(b) evaluate each under each scenario,

(c) choose plan to MIN worst outcome over scenarios (Cervigni et al. 2015)

- ✓ Computationally practical, but no recourse/adaptation

(3) "Adaptive Robust DM": (a) Define set of candidate *base* plans,

(b) under each scenario, *"adapt"* plan under scenarios where it does badly,

(c) choose plan to MIN worst *"adapted"* outcome over scenarios (Moreira et al. 2016)

- ✓ There are many methods to identify plan/scenario combinations that need adaptation (Step (b)); then use heuristics or optimization for Step (c)

Adaptive RDM for Bangladesh Power Sector (World Bank)

(Jiang, Vogt-Schilb, Spyrou, Hobbs, 2025)

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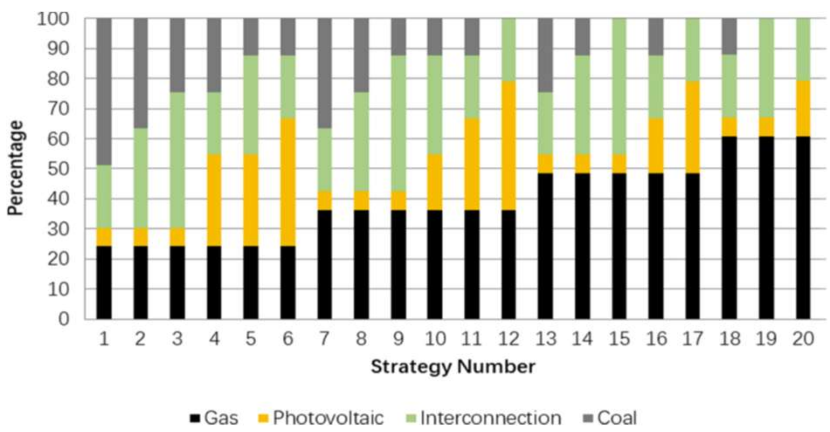
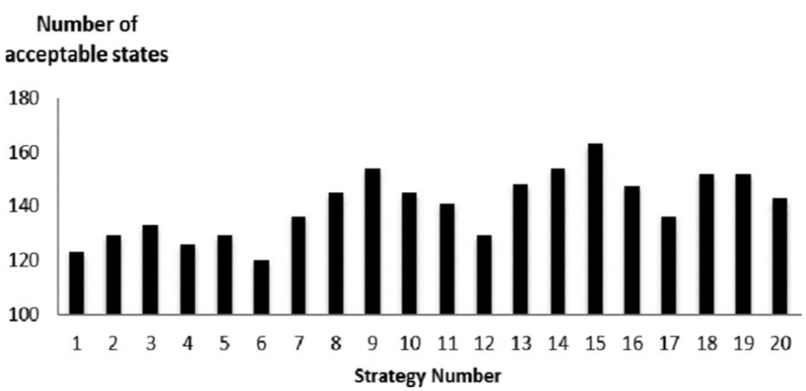
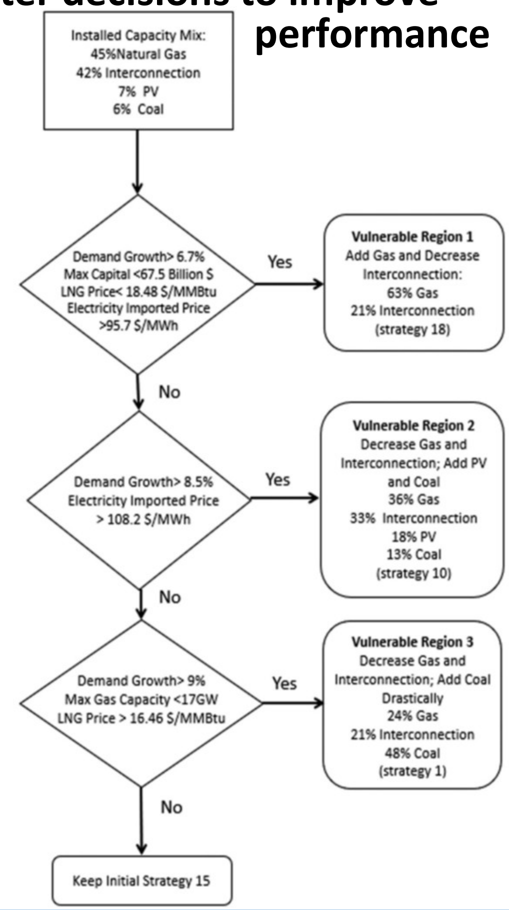
Step (a) Define set of plans to evaluate



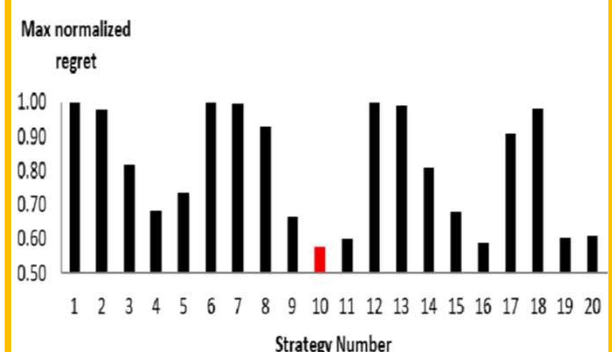
Step (b) ID unacceptable plan-scenario combos



Step (b) (Cont'd) … & then adapt later decisions to improve performance



Step (c) Choose plan that MIN worst performance



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IV. SP *vs*. Single-Scenario ("Deterministic") Model

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- Deterministic provides best plan for 1 scenario
  - gives insight into other scenarios only through laborious sensitivity analysis
- SP balances first cost *vs.* robustness to various scenarios
- The "cost" to use SP is:
  - Time/effort to characterize uncertainties

    ➔Need to automate this process
  - Computational intensity

    ➔Deploy decomposition with HPC

What Difference Does SP Make Relative to Single Scenario Optimization?

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- Impact: *If you consider all scenarios at once, what happens to:*
  1. "Here-&-now" grid investments?
  2. Probability-weighted cost? (saved $ from optimizing 1st stage investment?)
     - Effective risk-hedges
     - Avoid stranded assets

- How to quantify the benefit of including uncertainty?

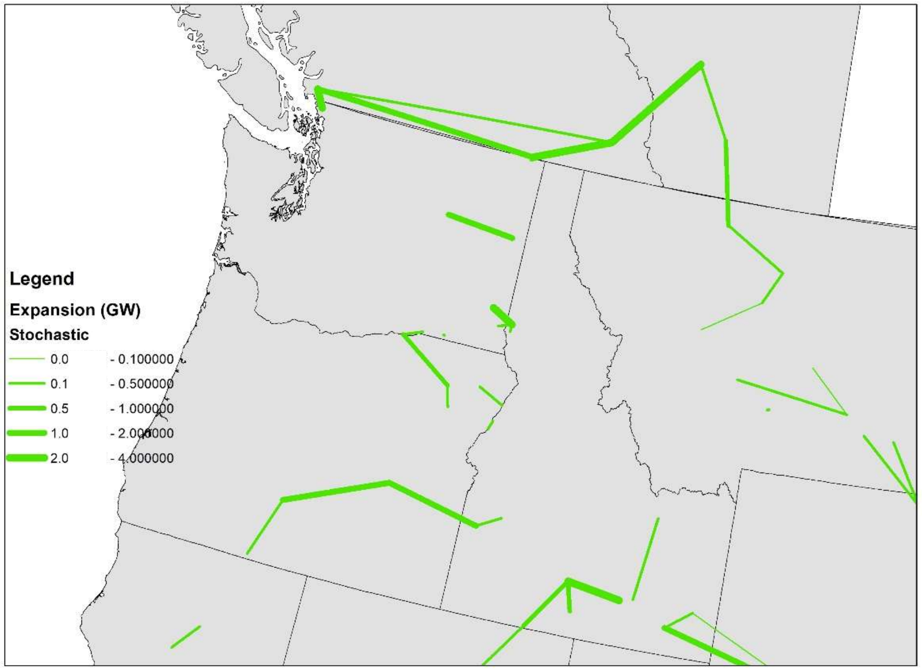
  Step 1, Consider all 8 scenarios:
  - Full SP → *build **X** in first stage (2018), expected cost = $670B*

  Step 2, Consider only 1 scenario ("medium" values for 11 uncertain variables)
  - Single scenario model → *build **Y** in 1st stage.* ***Do immediate investments change?***
  - Then re-run full SP, but constrain 2018 decisions = ***Y***
    - But all other decisions unconstrained (post-2018 lines, generator investment)
    - Cost increases (adding constraints increases cost) to say $672*B*
    - "**Benefit of including uncertainty**" = increase in cost ($2B). ***Does the change matter?***

Q1: How do SP *vs*. deterministic grid plans differ: 1st Stage Grid Investments

1st Stage Solution (decide in 2018, online in 2024 in all scenarios)

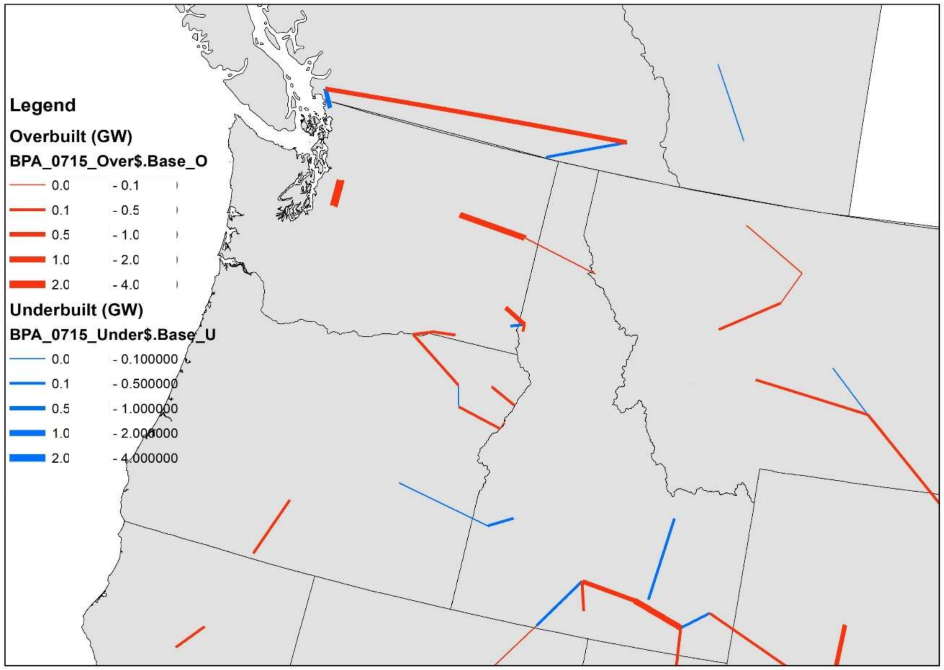
→ *Uncertainty-aware optimization delays some investments ("wait for information"); but expands others (as "insurance")*



Stochastic Programming

1st stage transmission expansion Cost:

WECC-wide: $5240M; BPA: $706M



***Single Scenario Solution (All "Medium")**: <u>Changes</u> relative to SP*

(Blue is underbuilt; Red is overbuilt compared to SP solution)

1st stage transmission investment:

WECC-wide: $5310M, BPA $934M

Q2: Benefit of Including Multiple Long Run Scenarios

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- Benefit of including uncertainty for planning 1st stage **BPA** internal & intertie lines: $320M (Expected present worth EPW)

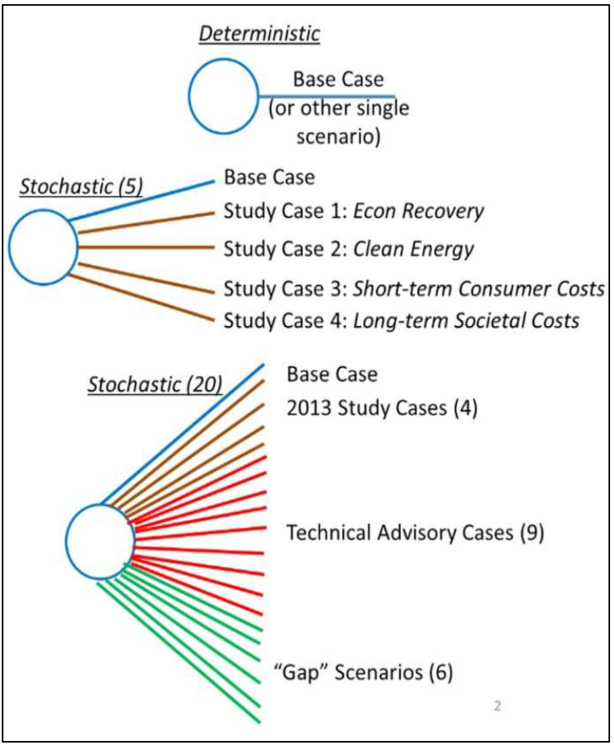
- … And for planning 1st stage **WECC** internal & intertie lines : $1675M (EPW)

Q2: Are stochastic solutions better for <u>un</u>considered scenarios?

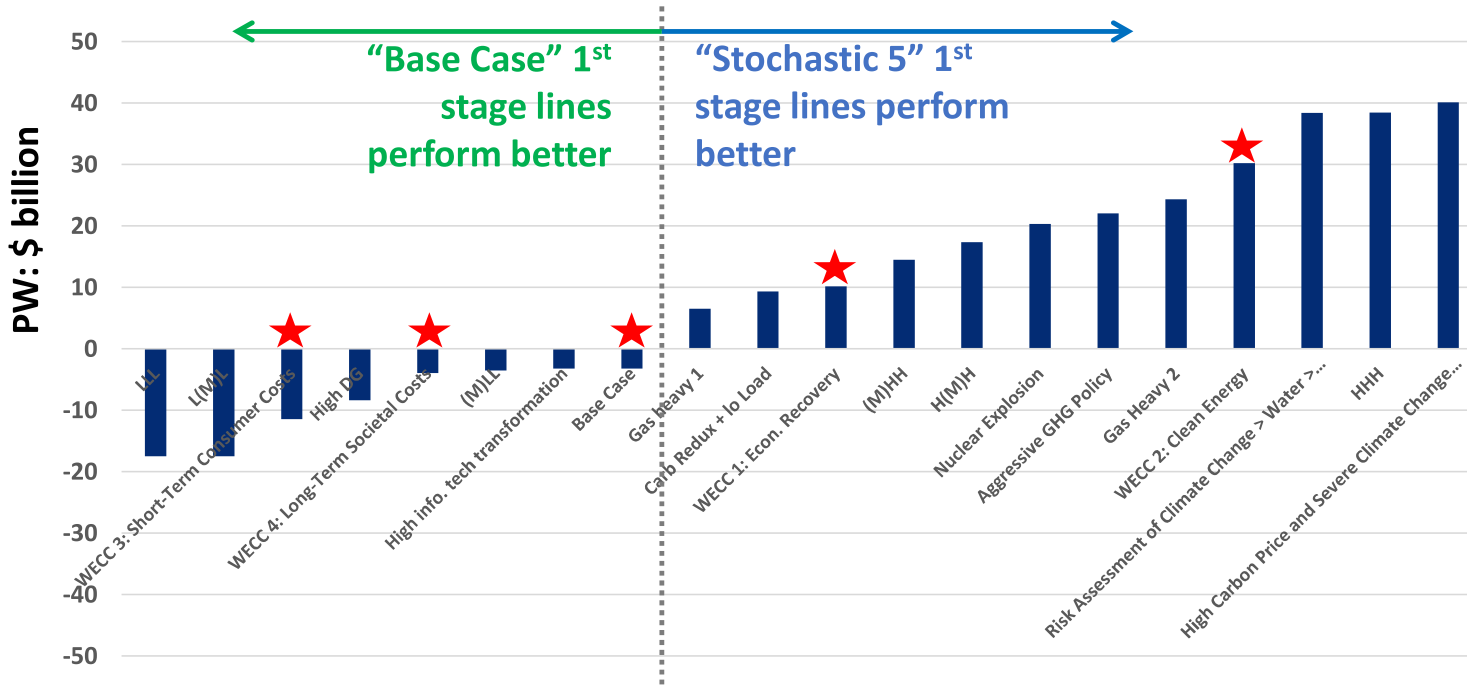
(Xu, Hobbs et al., *Power & Energy Magazine, 14(4), 2016*)

Are they more robust against scenarios not considered?

Answer for WECC-wide analysis: Yes, the "Stochastic 5" 1st stage lines perform better against the withheld 15 scenarios than the "Base Case" (1 scenario) 1st stage lines



Cost increase by scenario for "Base Case" *vs.* "Stochastic 5" plan (equal probabilities, 300 bus model, "wait-&-see" decisions optimized by scenario)



★ *Included in "Stochastic 5" Model; other 15 scenarios not in model*

Q3: Which Uncertainties Matter Most?

- There are many uncertain variables: *which* might affect your plan?
  - ✓ Literature: a few scenarios yield most of the benefit of SP
  - ✓ Computationally efficient to focus on them

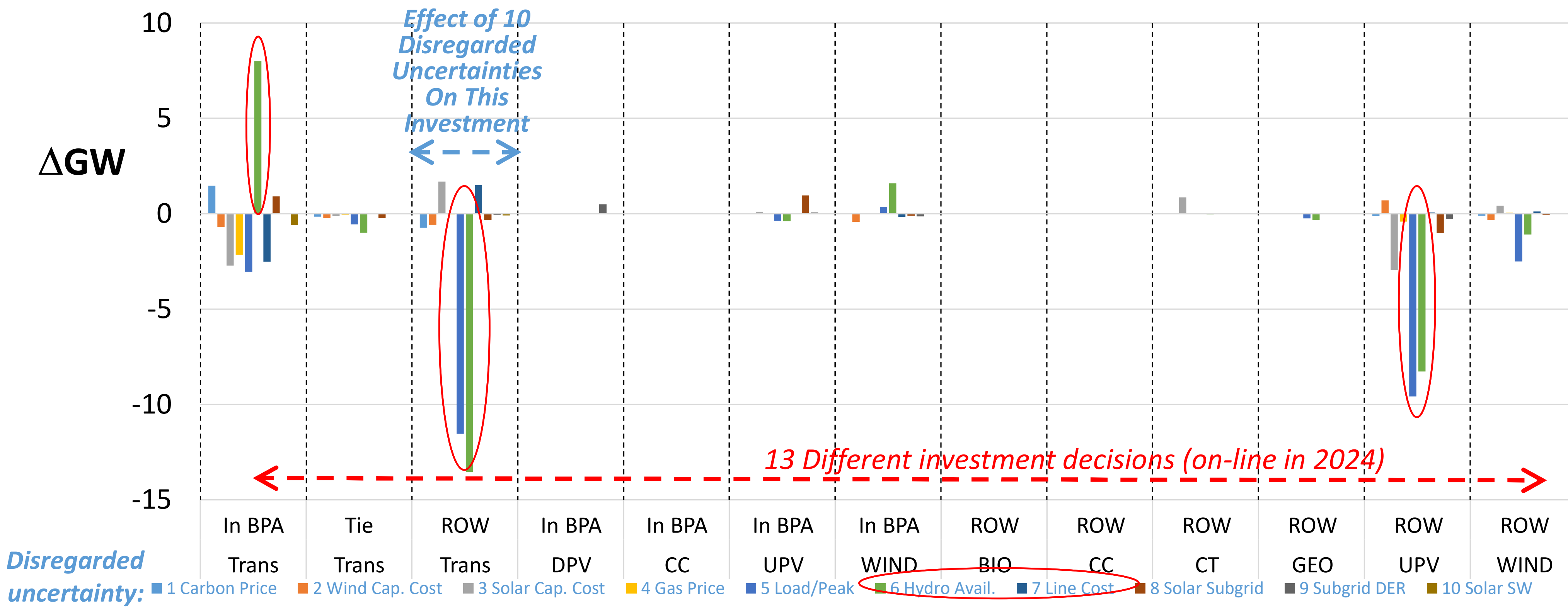
- Measuring effect: *If you consider uncertainty "A", what happens to:*
  1. Near-term transmission investments? (build what and where?)
  2. Cost? (how much decrease because of more robust performance later?)

Q3: Change in 2018 Investments

- For each of 10 uncertainties: drop 1 at a time (use its "medium" value in all scenarios) and re-run SP
- Changes" in 1st stage investment compared to "all uncertainty" SP

  "+" → dropping uncertainty *increases* investment

  "-" → *decreased* investment



Q4: Benefits of SP *vs*. Other Model Enhancements

(Xu, Hobbs, *IET Generation, Transmission & Distribution*, 13(13), 2019)

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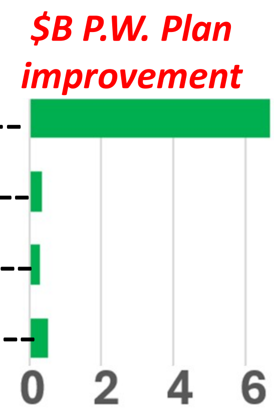
What is the economic value of improving realism of transmission planning models?

Compare for WECC:

- Multiple scenarios (stochastic programming)---------
- Enhance Network model (KCL v. KCL/KVL v. hybrid)--
- More hours (wind, solar, load variability)--------------
- Including unit commitment constraints & costs-------



(Compared to $26B net benefit for base plan)

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V. AI Can Already Help with Operations & Planning

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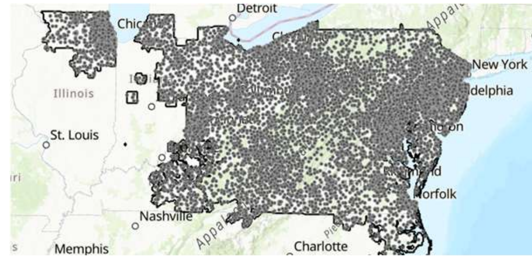
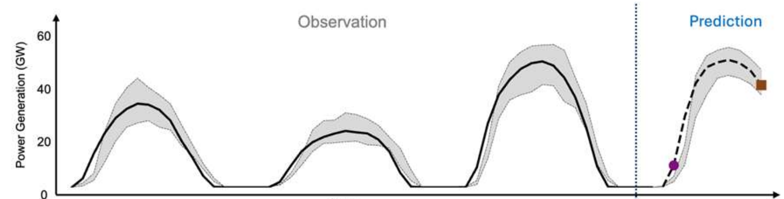
- **AI copes with rapidly increasing dimensionality**
  - More nodes (TSO-DSO integration) & time periods
  - More physical accuracy (inverter-based resources; AC instead of pipes & bubbles)



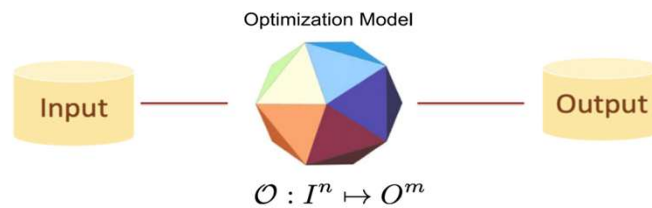
PJM: 16997 nodes

- **AI can create better uncertainty sets**
  - "Polynomial Chaos Expansion" captures multiple uncertainty sources and accounts for correlations



Moradi et al. 2025

- **AI enables tractable sensitivity analysis**
  - Solve problem many times quickly over different inputs

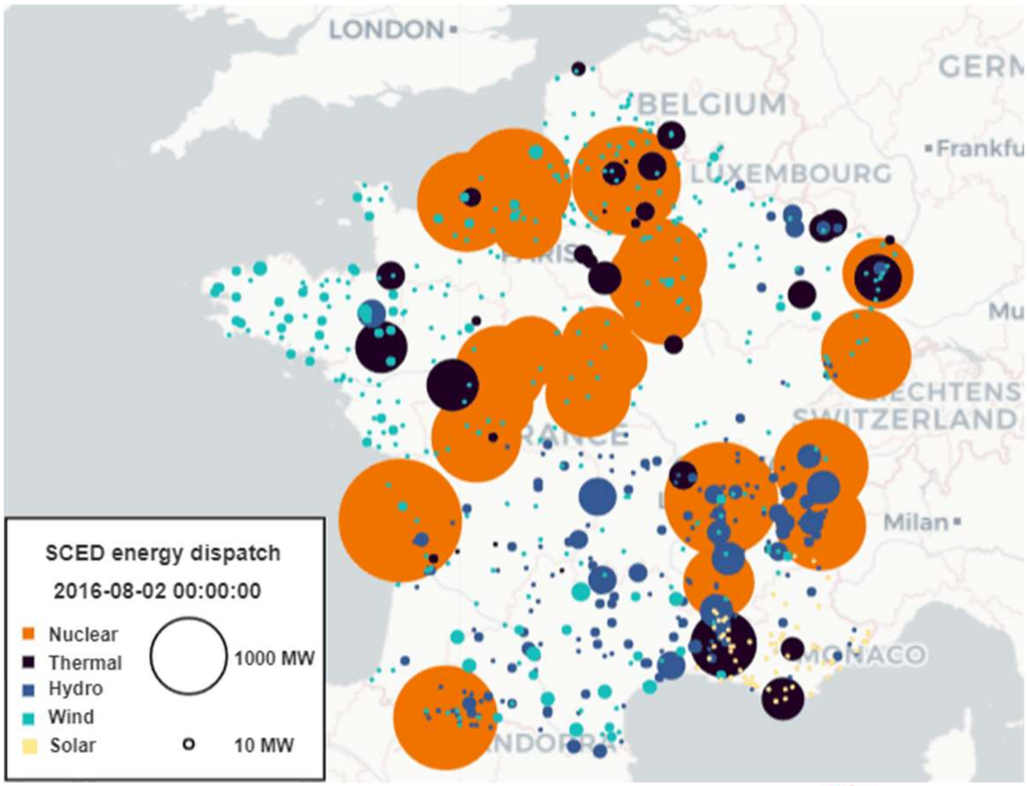


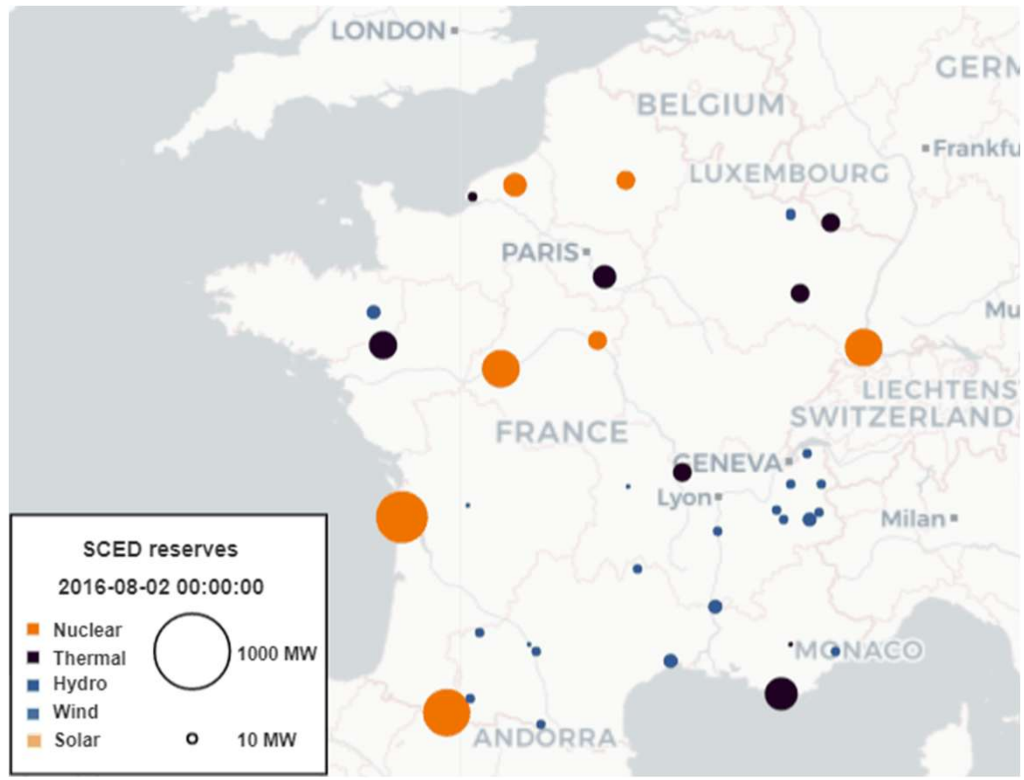
AI4OPT & van Hentenryck

- **AI enables mapping of the input uncertainty into output uncertainty:**
  - Discrete distributions for binary decisions (e.g., build line)
  - Continuous distributions for capacity decisions (e.g., build X of generation capacity of type Y)

Liang et al. 2023.

Example: Security-Constrained Economic Dispatch
(courtesy of Pascal van Hentenryck)



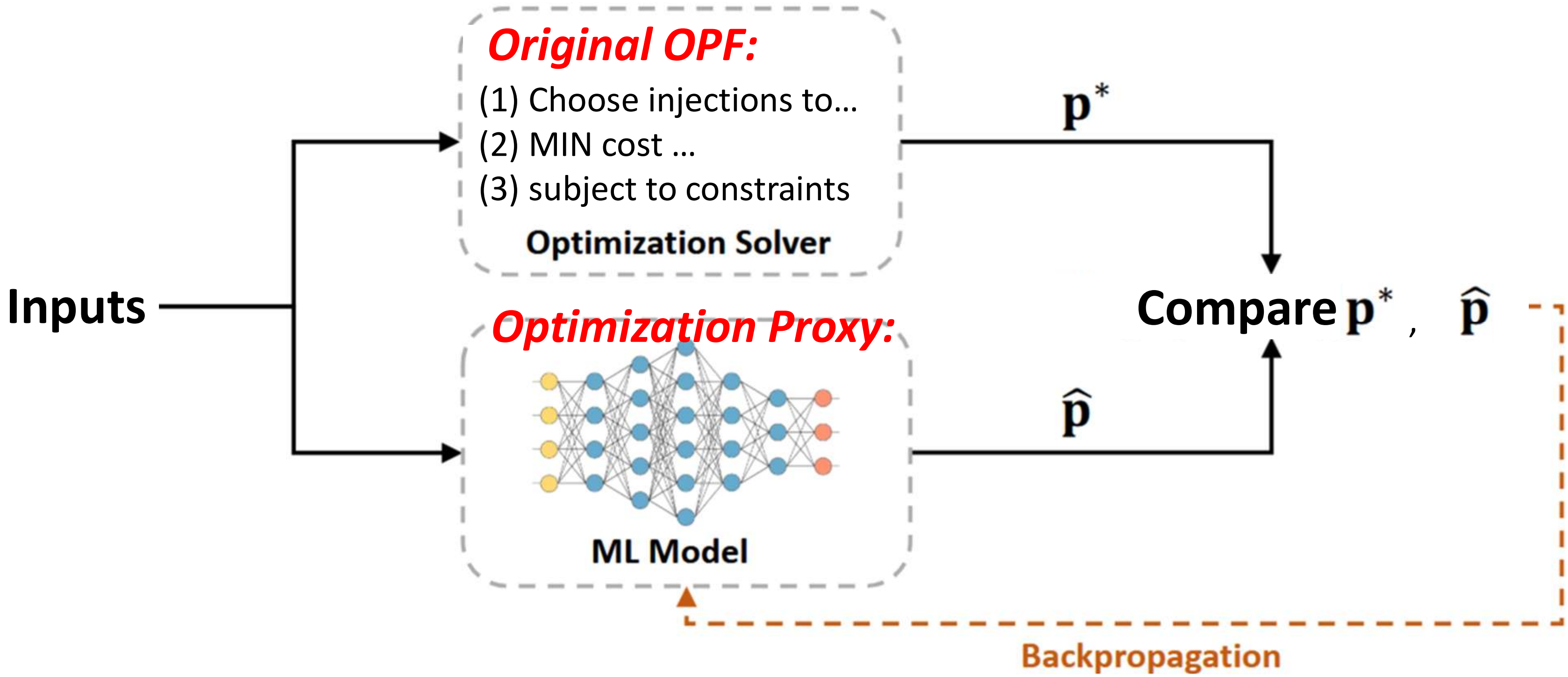


AI Institute for Advances in Optimization

AI (Neural Net) AC-OPF Solution (Chen, Tanneau, Van Hentenryck 2023)

➢ Example (case 30000_goc):

- ✓ 30,000 busses, 3526 generators, 10,648 lines
- ✓ End-to-End Learning and Repair (E2ELR): Input sampling time 63 hr; Training time 20 min (below)
- ✓ E2ELR AI solution: 11.1 ms (Cf. Gurobi: 4746 ms)



Opportunity for AI: Fast Operating Subproblem Solutions for Decomposition-based Multi-Stage Transmission and Generation Planning

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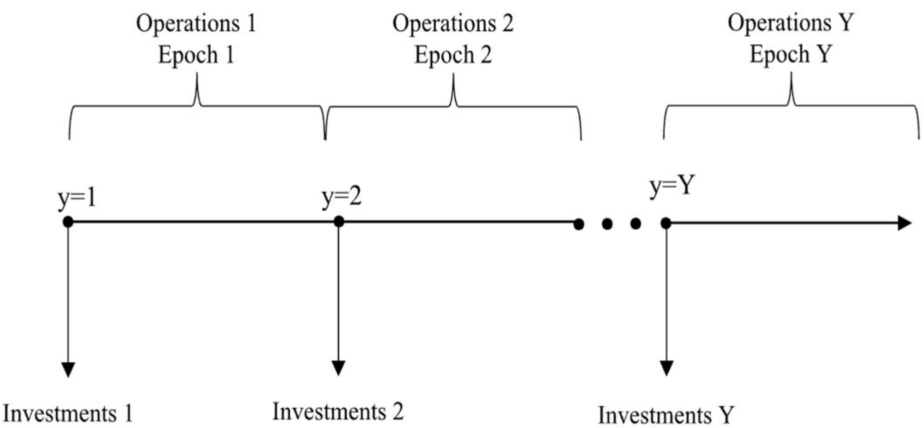
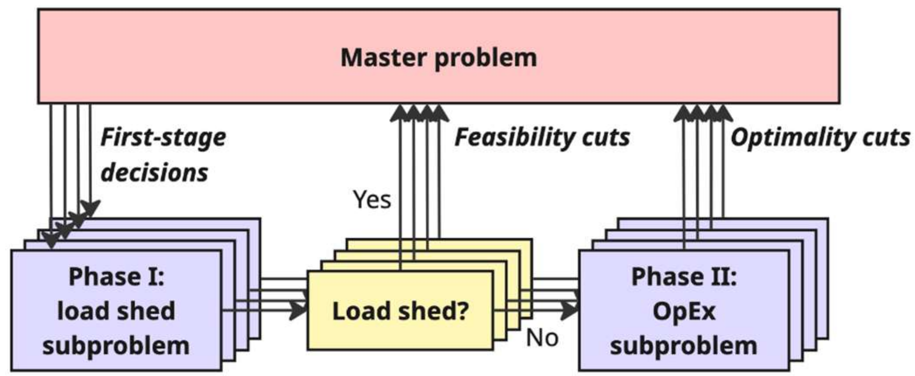
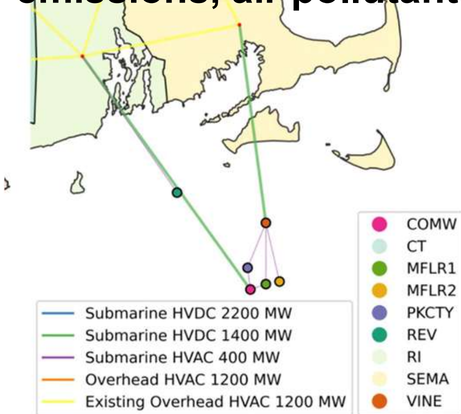


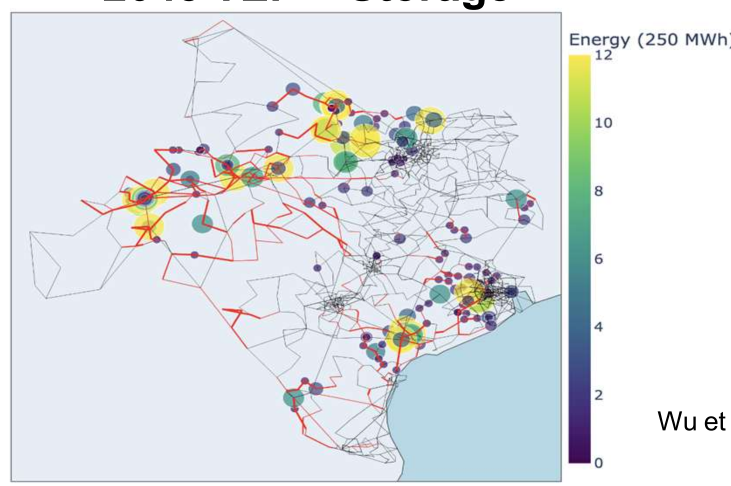


Multi-objective optimization (cost + emissions, air pollutants + resiliency



Khanal, 2024

2045 TEP + Storage



Wu et al, 2025

For additional decomposition example, see EPRI Sponsored Report by Qingyu Xu and BF Hobbs, JHSMINE Version 2.1

Conclusion

JOHNS HOPKINS
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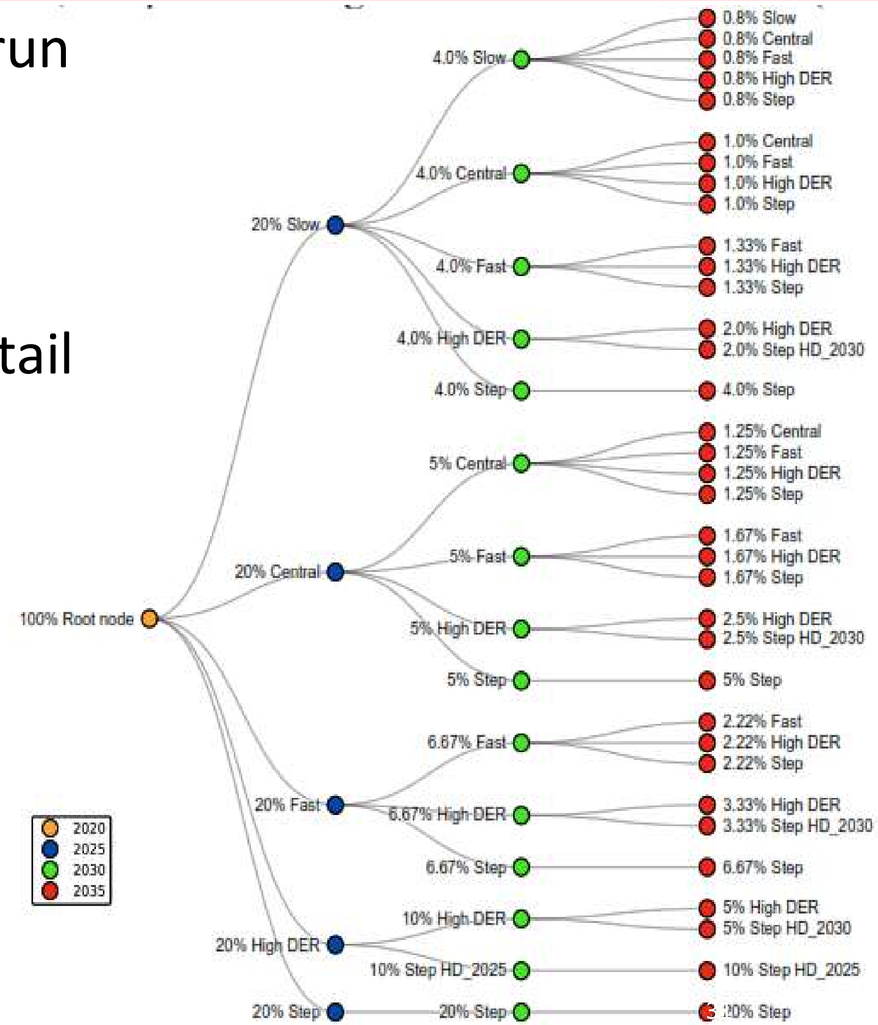
- Uncertainty-aware planning with many long-run scenarios is *practical* using SP or RDM
  - E.g., AEMO Integrated System plan
    (Figure source: Pierluigi Mancarella, UMelbourne, personal communication)

- Decomposition & AI will allow much more detail

- Considering uncertainty makes *by far* the most difference in first-stage transmission decisions and economic benefits
  - All forecasts wrong, so consider a wide range of scenarios
  - And how our system would adapt to them



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