

Working Toward...

Incorporating High Dimensional
Uncertainty and Operational **Constraints**
Into Long-Term **Generation Expansion**
Models Using **Approximate Dynamic**
Programming

Bryan Palmintier

FERC: Technical Conference on Planning Models

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Collaborators:

Mort Webster, Ignacio Perez-Arriaga

Pearl Donohoo, Nidhi Santen, Rhonda Jordan



Massachusetts Institute of Technology
Engineering Systems Division

Outline

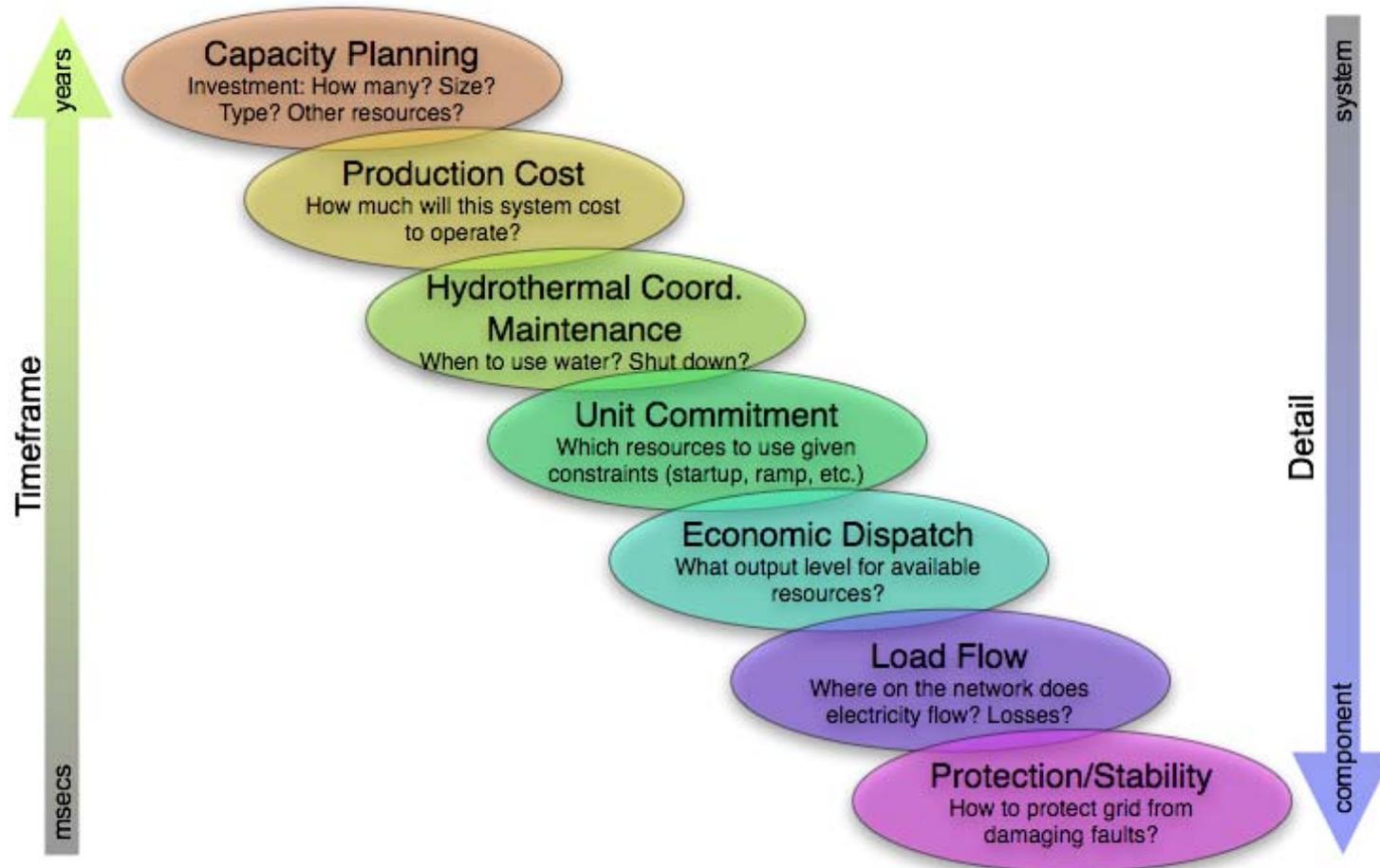
- What problem are we solving?
- Planning vs/+ Operations
- Stochastic Dynamic Problems
- (Approximate) DP
- Current Research in MIT-ESD

Caveat: More concepts than results
(stay tuned...)

Capacity Planning is a Hard Stochastic Dynamic Problem

- Stochastic
 - Growth, Prices, Outages, Hydro
 - Renewables, Demand Response, Policy, Technology
- Dynamic
 - New information over time
 - Sequential decision making (recourse)
- Hard...

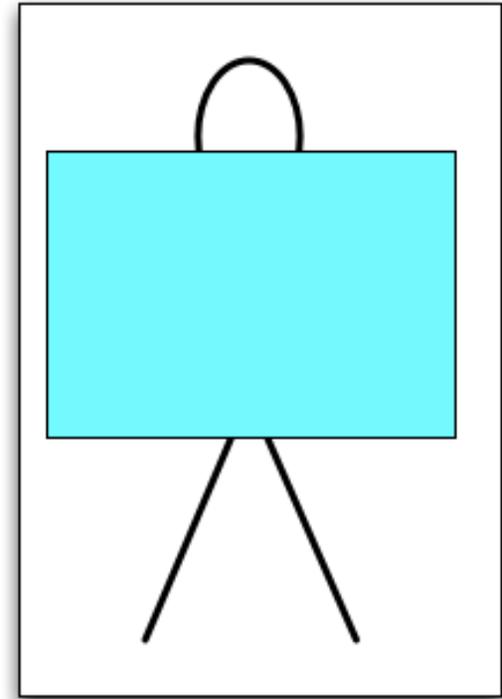
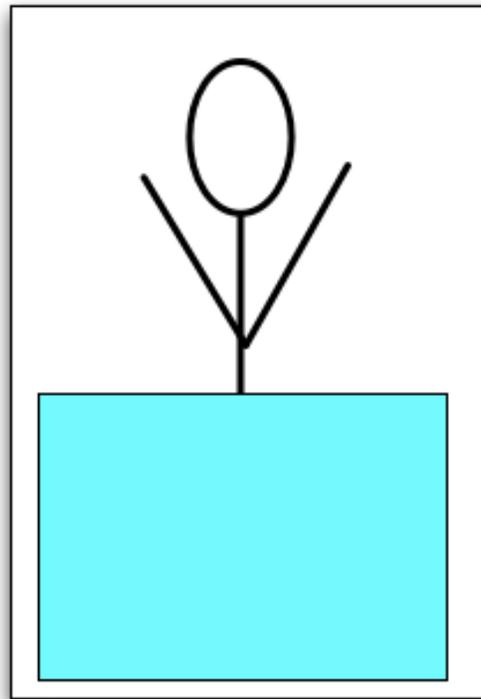
Electric Power Model Types



The short blanket problem

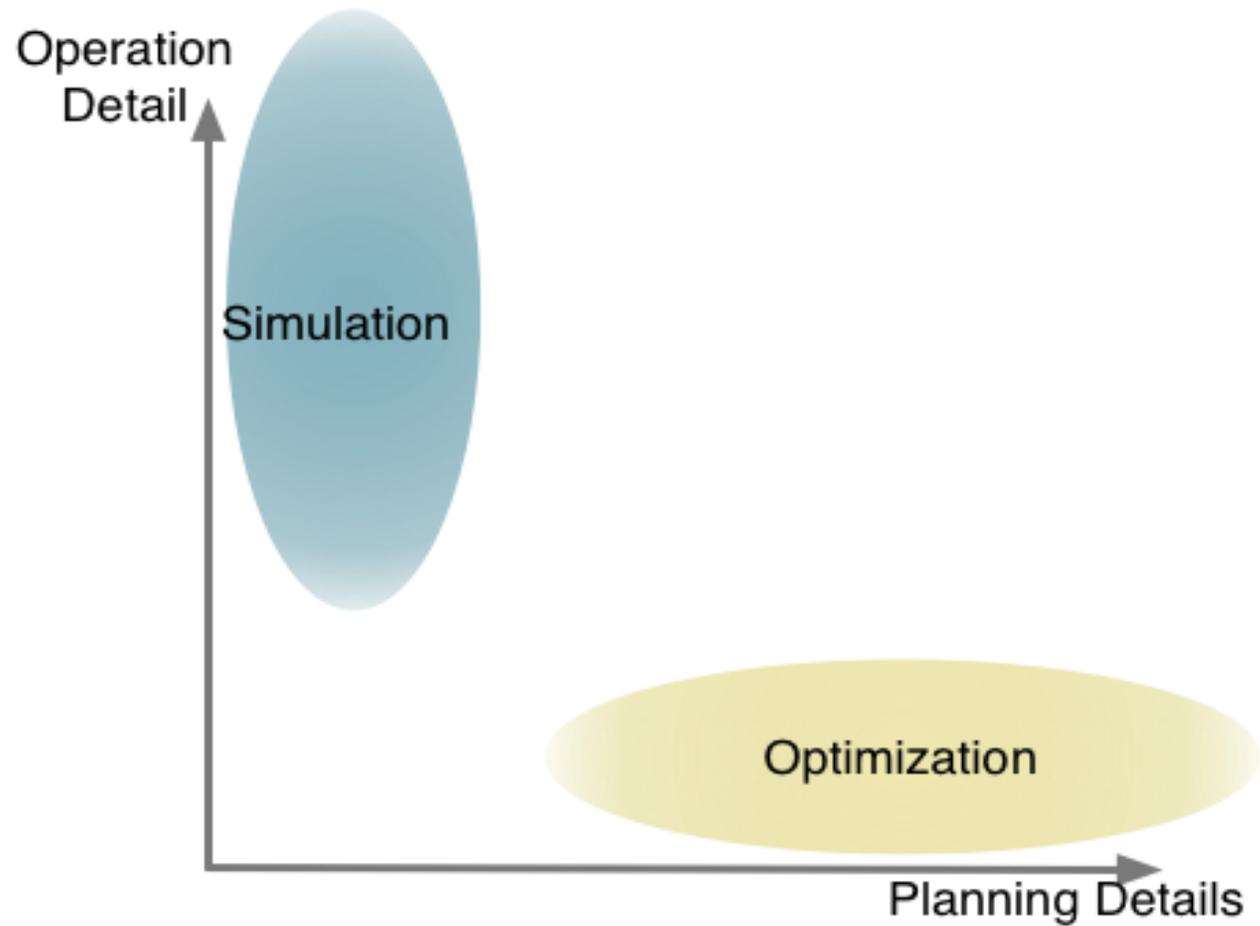
Investment
Decisions

Operational
Details

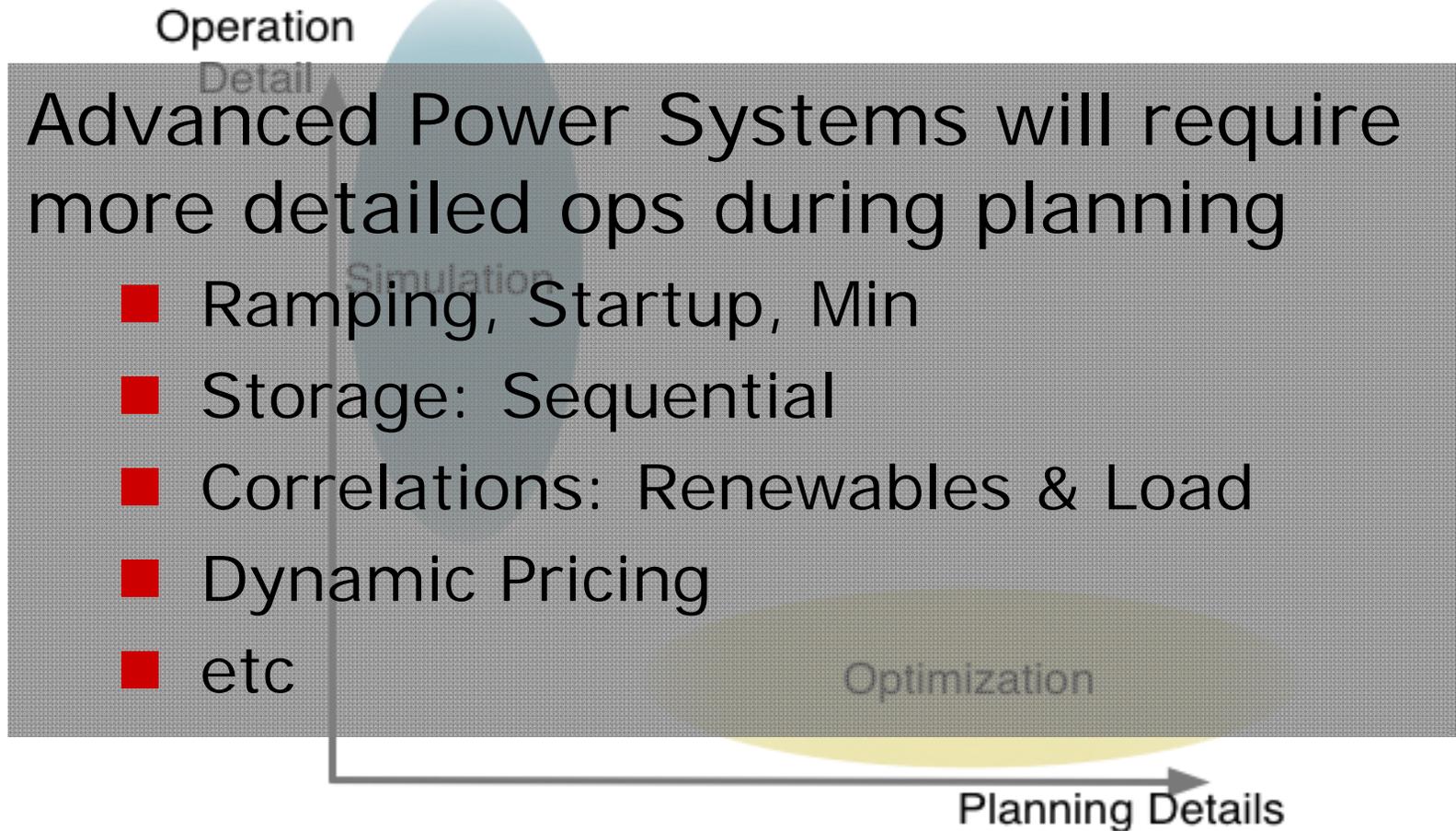


Need to approximate

Operations vs Planning



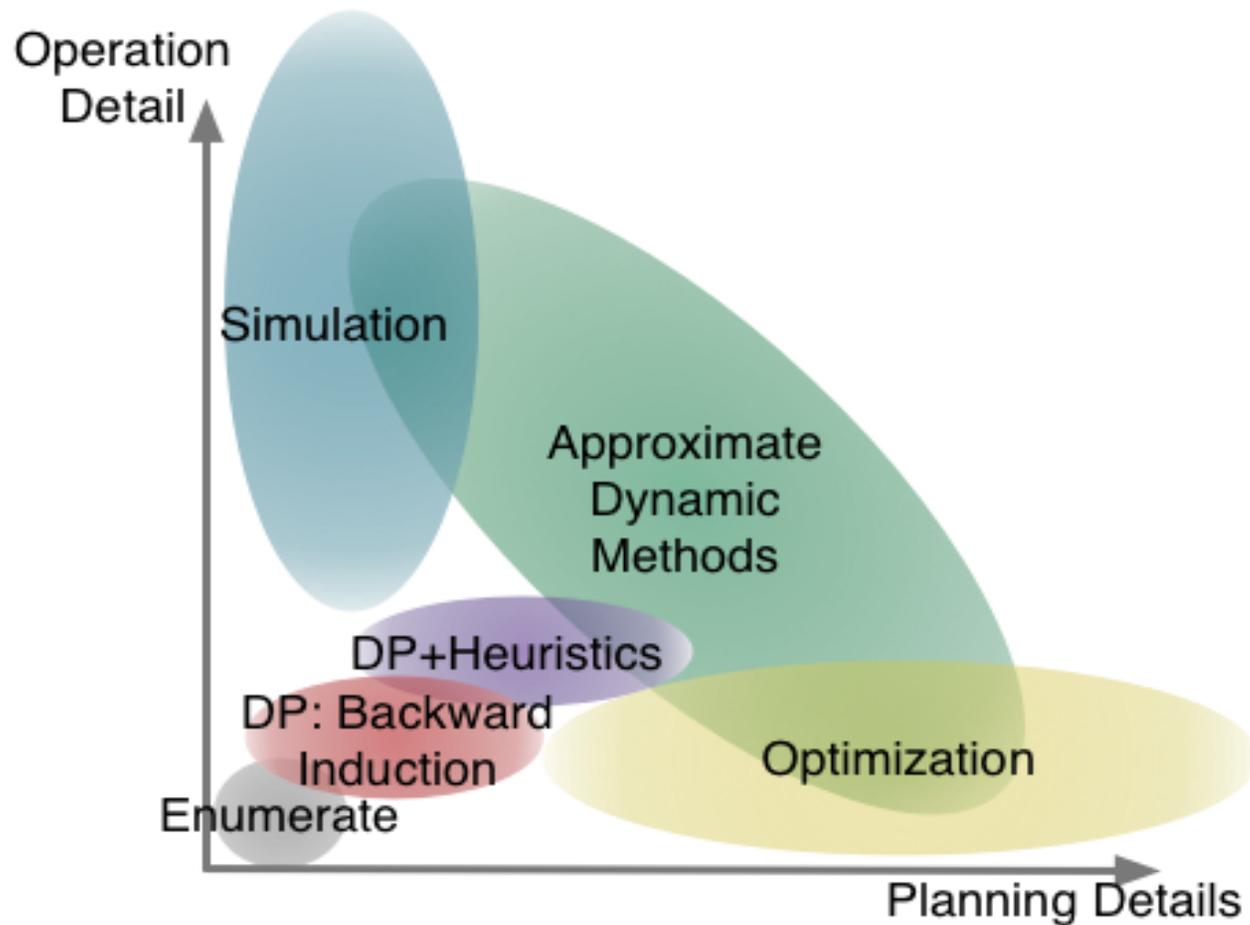
Operations vs Planning



Stochastic Dynamic Modeling

- Scenario Analysis (SA)
 - Exogenous uncertainty
- Stochastic Programming (SP)
 - Fixed Scenario trees
- (Stochastic) Dynamic Program. (DP)
 - Backward Induction via Bellman's
- Approximate DP (ADP)
 - Machine learning

Operations + Planning



Why Dynamic Programming

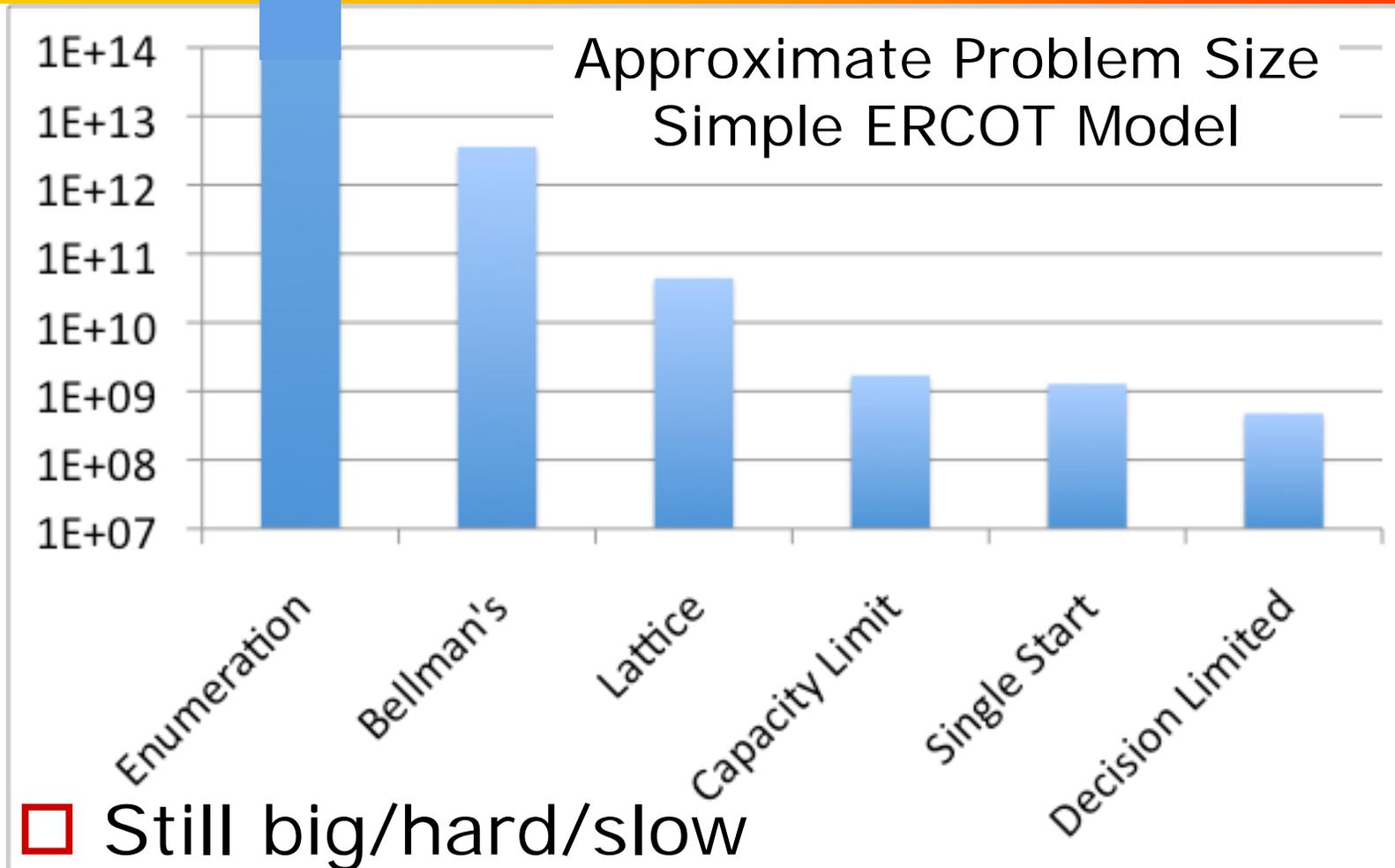
- Endogenous Uncertainty (vs SA)
 - Get rid of crystal ball
 - Actionable decision(s)
 - Value for flexibility
- Decision dependant uncertainty (vs SP)
 - Generation depends on Transmission
 - Efficiency investment
 - Fuel costs (Economic equilibrium)
 - Learning by doing
 - Climate Change

DP Challenges

- Curse(s) of Dimensionality

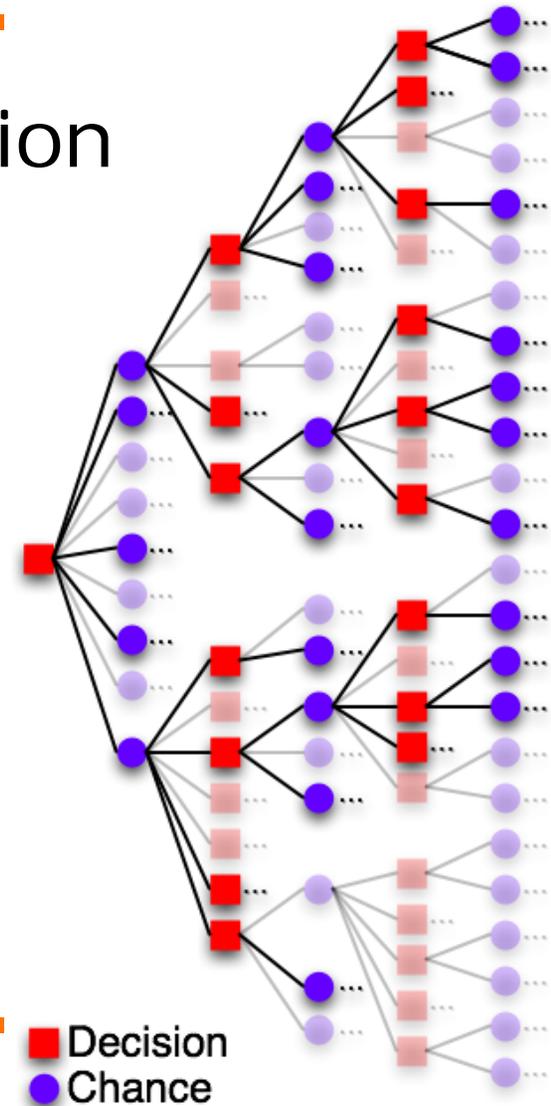
- Backward Induction assumes Markov
- Expensive sub-problem (Operations)

Heuristics within traditional DP



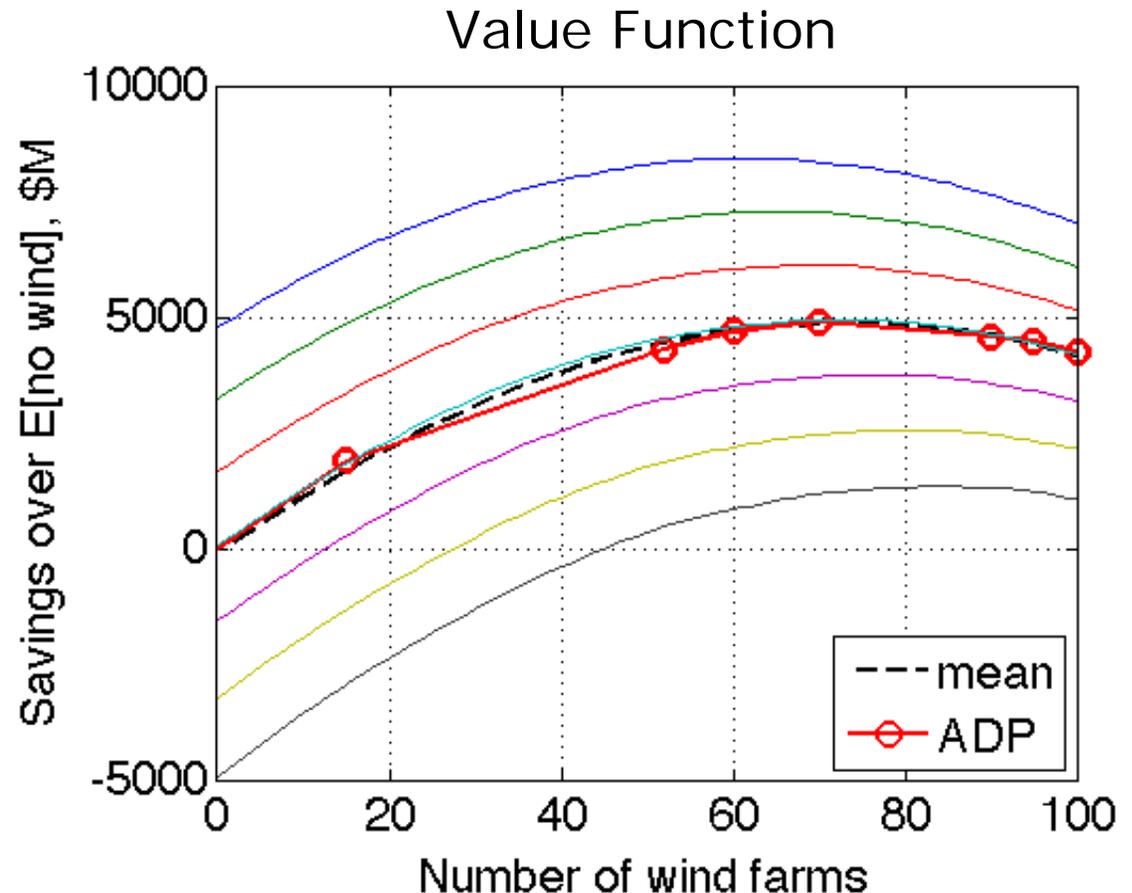
Introducing ADP

- Simulation+AI+Optimization
 - Forward Sampling
 - Learning
 - Ignore Dead Ends



ADP: Approximating Values

- Recursive Regression
- Update nearby
- Scenarios collapse to single value
- Size: 700 -> 11



Advantages of ADP

- Complex, n-Dimensional Uncertainty
 - Monte Carlo: fast (initial) convergence
 - Path Dependency (vs DP)
 - Multi-objective for free
 - Find environmental, political near-best from the value space
 - Performance
 - vs Dynamic Programming!
 - vs Stochastic Programming??
-

ADP challenges

- ❑ Always an Approximation
- ❑ Heuristics require tuning
- ❑ Transparency?

The operations sub-problem

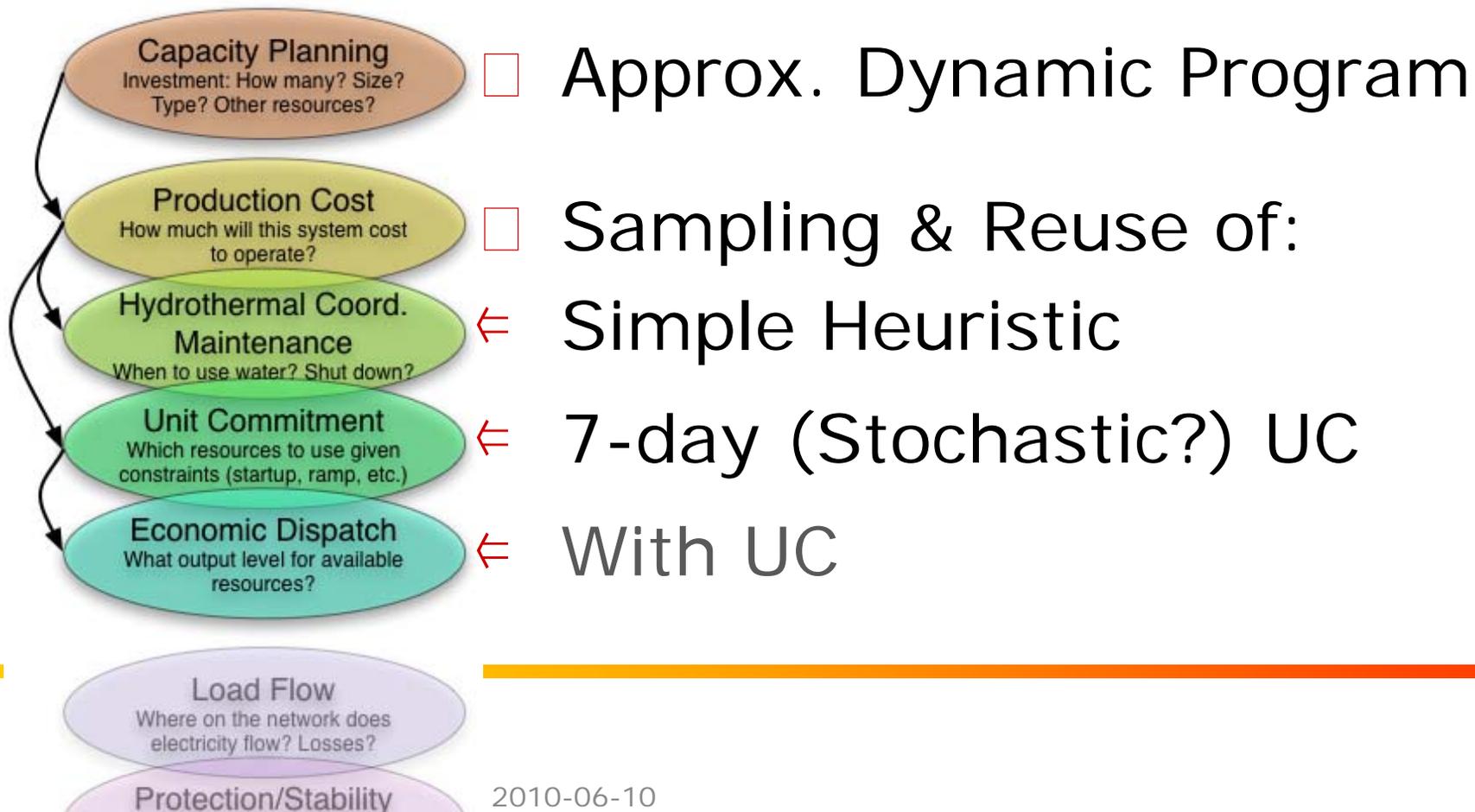
- Do we need to run...
 - All 8760? (x10?)
 - Every scenario?
- Sample of relevant periods
 - Typical weeks?
 - Joint Distribution of load & uncertainty
- Iterative refinement (ADP learning)
 - Start with improved LDC estimate
 - Refine with sampled week of production cost
 - Increase detail (SCUC) on later passes

CURRENT RESEARCH

Mort Webster's Lab
MIT's Engineering Systems Division

(My) Current Research: Unit Commitment in Planning

Designing Advanced Power Systems: Renewables, Active Demand, Storage



Current Research: Technology Change

Integrating Policy-Induced Technology Change Dynamics into U.S. Electricity Generation Capacity Planning

Nidhi R. Santen

Main Objectives:

1. Develop an integrated modeling approach for evaluating the effect of uncertain R&D-induced electricity technology improvements on optimal policy planning.
2. Evaluate the trade-offs between “development-focused” and “adoption-focused” climate and technology policies, considering uncertainty in R&D returns.

Approach:

1. Empirically characterize uncertainty in R&D returns for several supply- and demand-side electricity technologies using patent citation data.
2. Couple an induced technology change model with a national-scale capacity planning model using patent citations to calibrate novel relationships between R&D returns and generation technology costs, technology availability years, and demand growth.
3. Use ADP to model sequential policy decisions under uncertain R&D returns, and study optimal near-term policies and associated electricity generation capacity evolutions.



Current Research: Transmission Planning

Heuristics for Dynamic, Long-term Transmission Planning

Pearl Donohoo

- State of the art planning is static or dynamic optimization of simplified systems without foresight and limited treatment of uncertainty beyond reliability analysis
- Dimensionality precludes
- Transmission infrastructure is long lived, requiring robustness to variety of future generation and market configurations
- Relationship between transmission development and generation development is persevered, despite restructuring which decouples the investment

Current Research: Electrification in Africa

Incorporating Demand Dynamics into Long-term Electrification Planning: the Case of Tanzania

Rhonda Jordan

□ National Goals in Tanzania:

- Meet Existing & Future Electricity Demand
- Increase Access
- Improve/Maintain Quality of Service

□ Extreme poverty

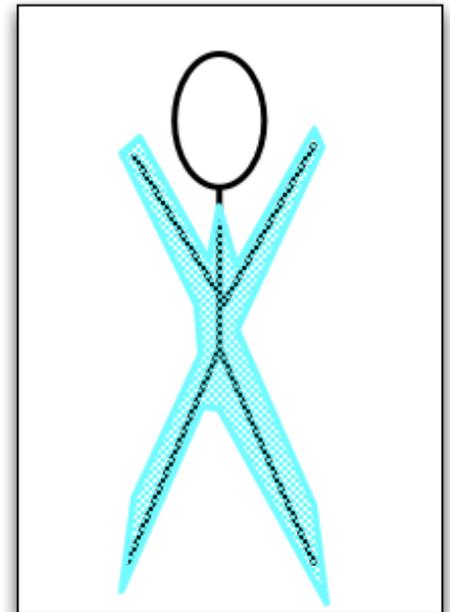
- High sensitivity to price & service quality
- Demand MUST be endogenous

□ How should the Ministry meet targets?

- What production? New capacity? New grid & off-grid connections? What subsidy should be offered?

Conclusions

- ❑ Approximation inherent in all methods
- ❑ Trade some ops detail for improved stochastic planning models
- ❑ ADP shows promise
 - Capture rich problem detail
 - AI + Simulation + Optimization
 - A custom trimmed loosely woven blanket?
- ❑ Looking for “real-world” partners



Questions?

Contact...
Bryan Palmintier
b_p@mit.edu

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