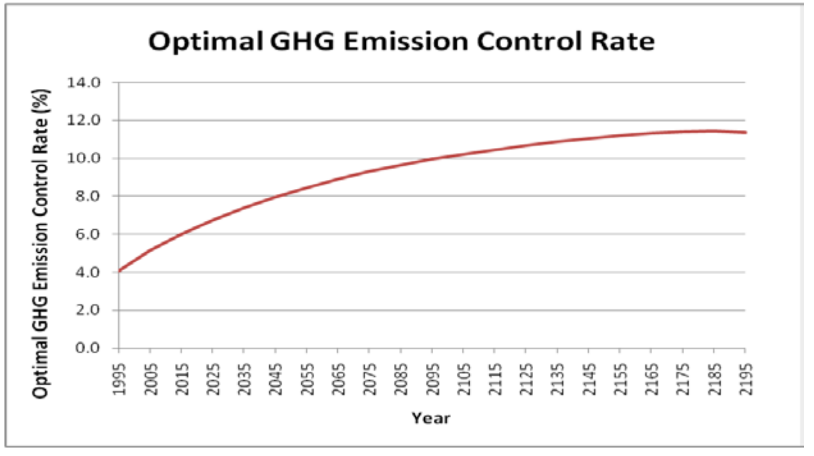
Methods for Modeling Decisions under Uncertainty for Integrated Assessment Models

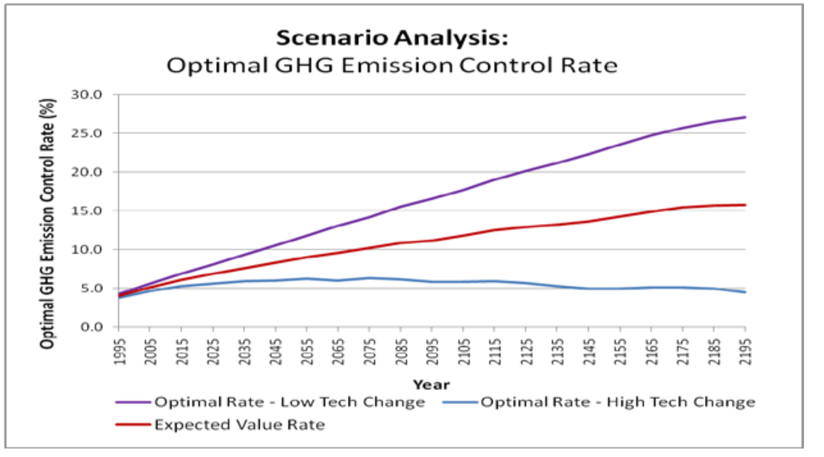
US Department of Energy Climate and Earth System Modeling PI Meeting
Uncertainty Quantification and Metrics Session
September 22, 2011 Grand Hyatt, Washington, DC

Nidhi Santen, nrsanten@mit.edu
Mort Webster, mort@mit.edu
Webster Research Group
Engineering Systems Division
Massachusetts Institute of Technology

Introduction

- Most current IAMs are structured for deterministic analyses





Source: DICE-99 Model

But…

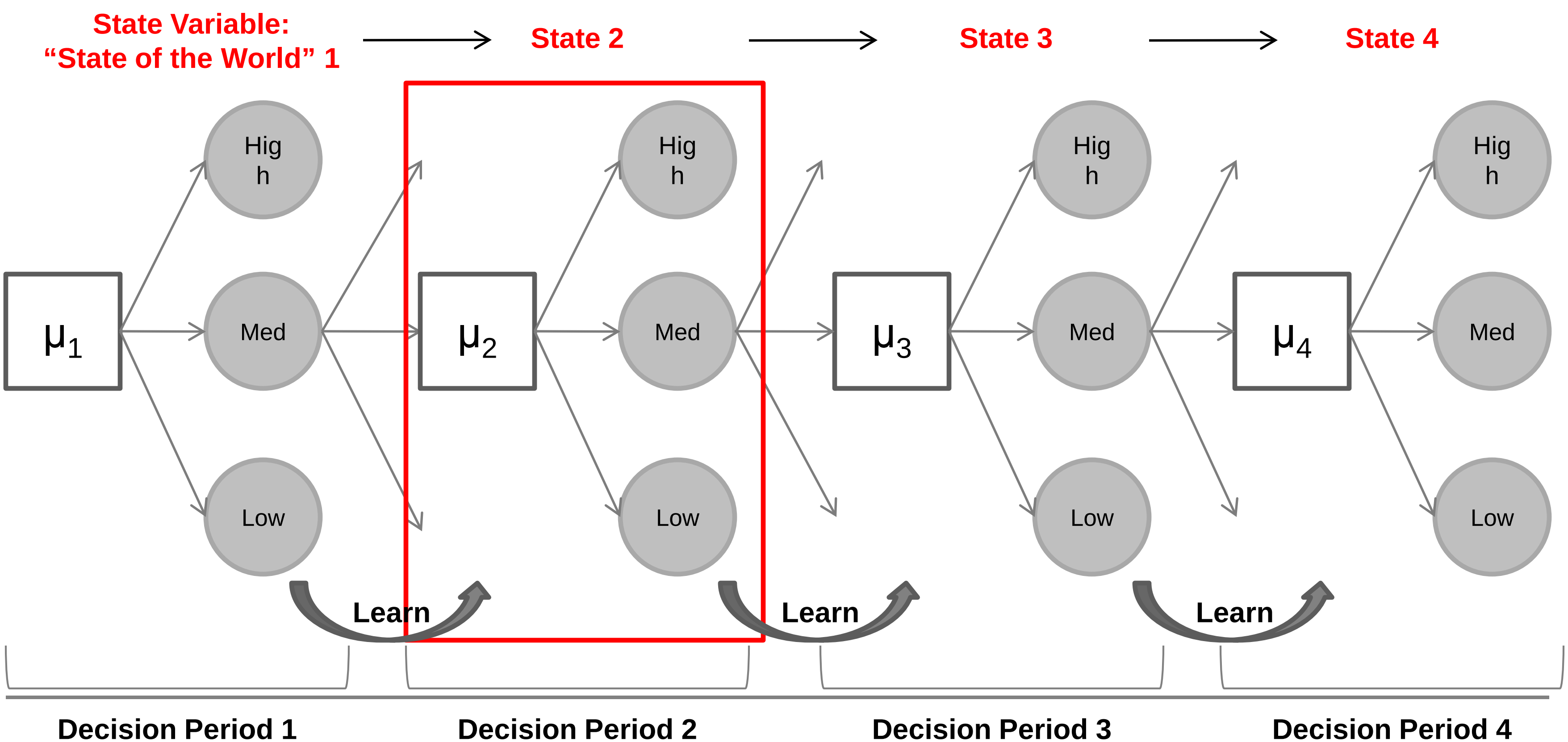
- The climate change policy problem is *inherently* stochastic. For example:
  - uncertainty in rate of clean capital technological improvement
  - uncertainty in climate system response to temperature change
- We can learn about these uncertainties over time and revise decisions
- We lack good *stochastic* climate policy (IAM) models due to computational limitations

Overview: Sequential decision making under uncertainty (1 of 2)

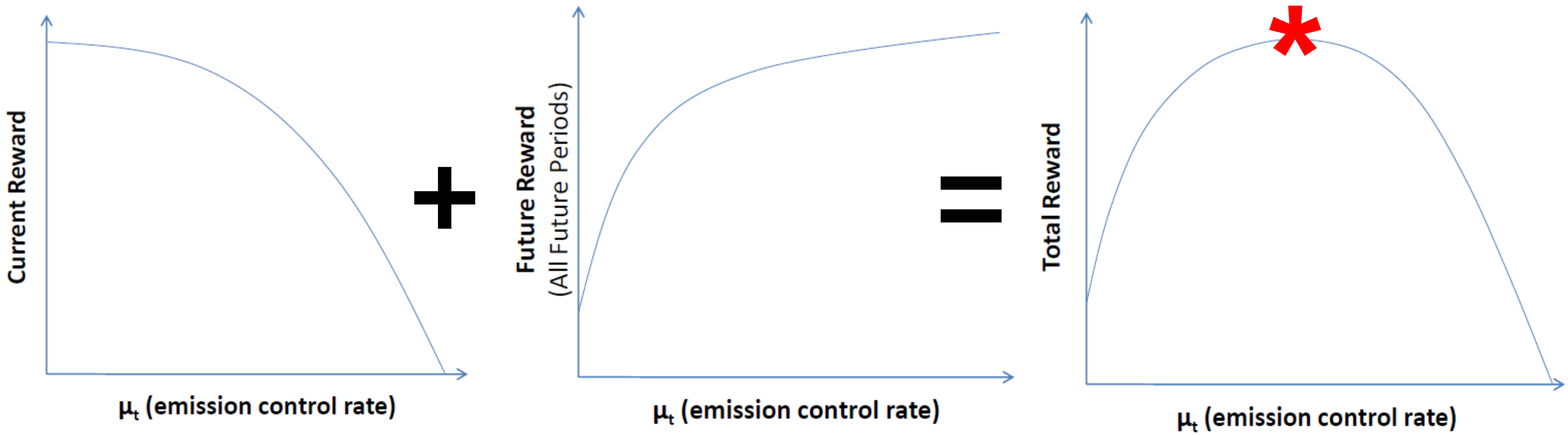
Decision: μ = GHG (or carbon) emission control rate

Uncertainty: High/Med/Low = "clean" energy technology improvement rate

State Variable: "holds" information about the past needed to make a new decision



Overview: Sequential decision making under uncertainty (2 of 2)



<u>Objective of the Stochastic Problem</u>

choose μ(t) to maximize **Bellman Value** (Total Reward) in each time period:

$$V_t^*(S_t) = \max_{\mu(t)}(\underbrace{C_t(S_t, \mu_t)}_{\text{Current Reward}} + \underbrace{E[V_{t+1}(S_{t+1})|S_t, \mu_t]}_{\text{Expected Future Reward}})$$

Motivation: DICE stochastic dynamic program results and "curse of dimensionality"

The "curse of dimensionality"

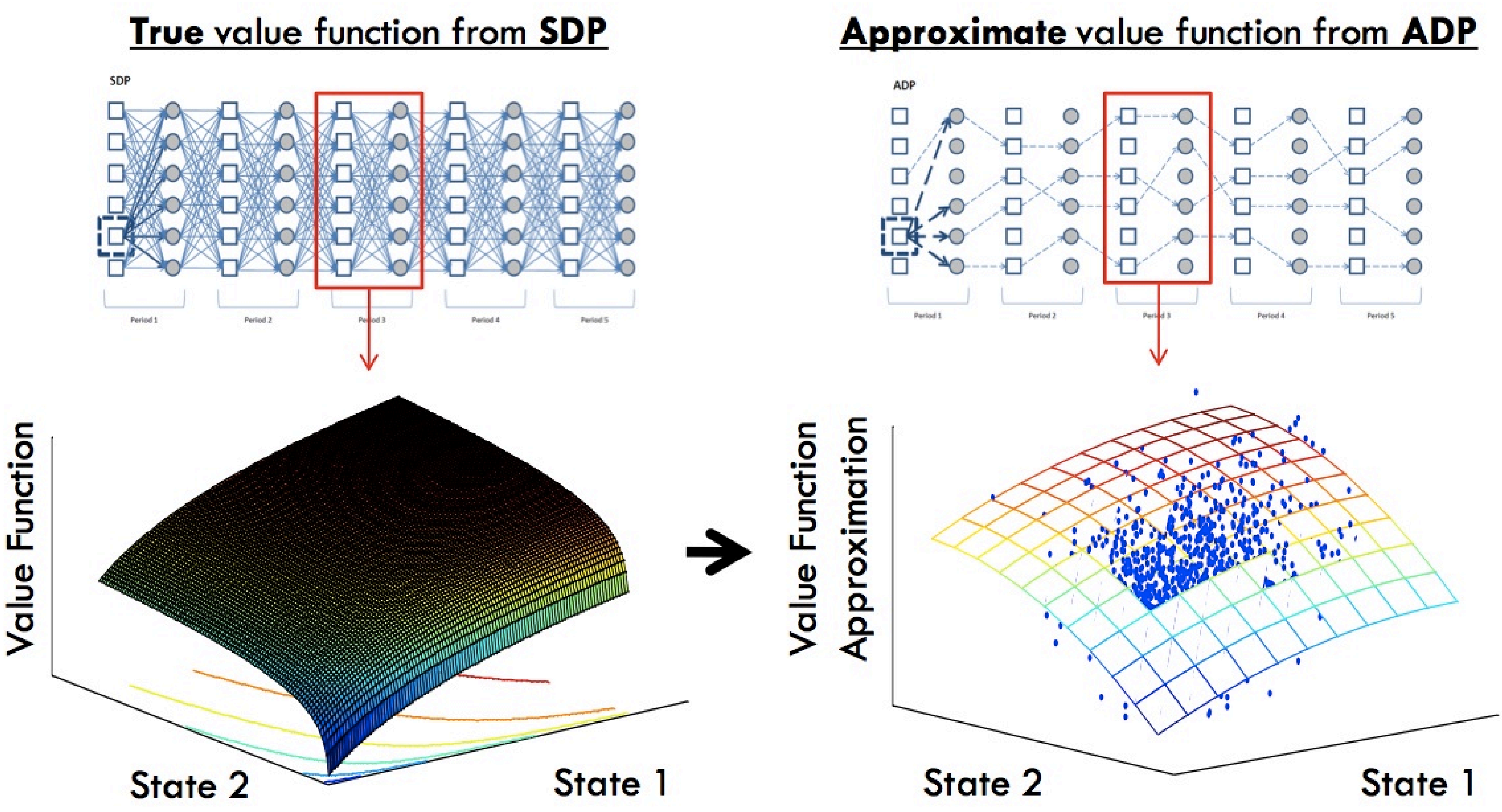
- limited decisions and stages (1 decision made at 100/100/150 years)
- coarse state and action resolutions
- long run times
  - 3-stage DICE SDP took ~12 days to solve on a new 64-bit desktop PC (2010)

Climate policy decisions need to be made at shorter intervals and at finer resolutions.

A much simpler model than the one we need already takes far too long to run!

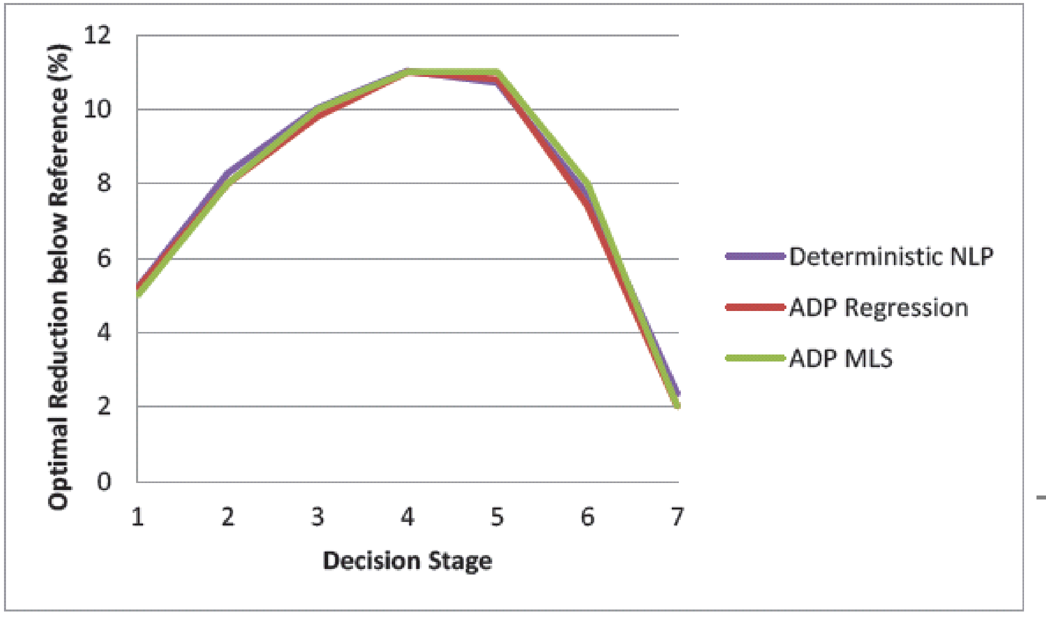
Stochastic Dynamic Programming (SDP) v. Approximate Dynamic Programming (ADP)

Two Components to ADP: Sampling and Value Function Approximation



New DICE ADP Model (1 of 2)

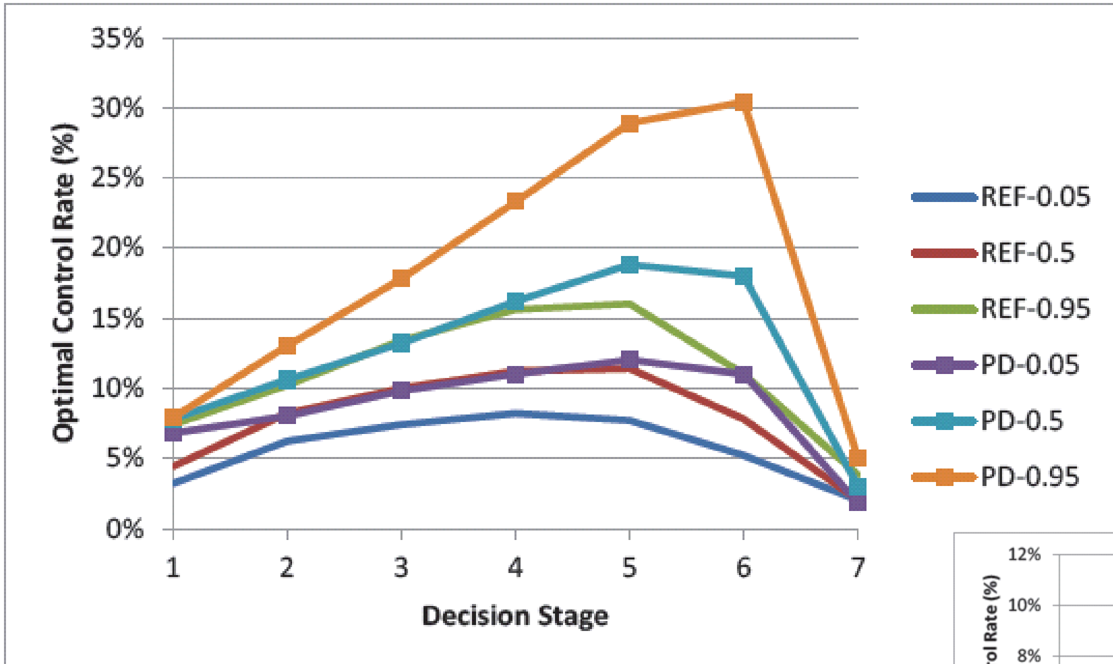
- Working Paper here: http://esd.mit.edu/WPS/2011/esd-wp-2011-12.pdf
- Implementation: ADP for 7-period stochastic DICE (50-year steps)
  - objective: maximize $(C_t(S_t, \mu_t) + E[V_{t+1}(S_{t+1})|S_t, \mu_t])$ ← "Bellman Value"
    - Current Utility: $C_t(S_t, \mu_t)$
    - Expected Future Utility: $E[V_{t+1}(S_{t+1})|S_t, \mu_t]$
  - single decision: μ(t)
  - single uncertainty (with and without path-dependency): abatement cost
  - state variable: K(t)—capital stock level, TE(t)—current temperature
- Solves in ~1-3 mins!
- New Model Validation

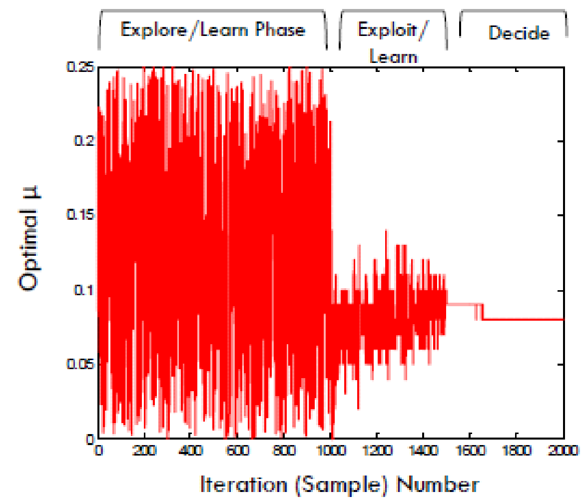


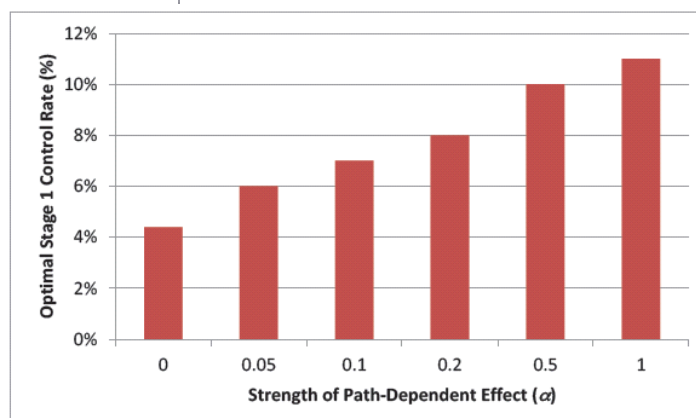
New DICE ADP Model (2 of 2)

Results of Numerical Experiments with DICE ADP Model

- Uncertainty (REF) v. path-dependent uncertainty (PD) in abatement costs







Conclusions: ADP Advantages and Challenges

Main Advantages

- Overcomes the "curse of dimensionality" (ability to model several decisions, types and numbers of uncertainties, and time-periods in a fraction of time for a comparable SDP)
- Explicitly represents uncertainty with learning/adaptation
- Method of forward sampling (through uncertainties and decisions) lends to more easily representing sequential path-dependent decisions over other comparable approaches.

Main Challenges

- Falls under the general class of heuristic methods for global optimization
- Value function approximation methods are sensitive to complexity and type of decision problem
- Final solution can be sensitive to initial value function approximation. More research needs to be done studying the tradeoff between "explore v. exploit" methods.

Upcoming Related Work

- **ADP formulation of DICE extensions**
  (Webster & Santen-MIT, Popp-Syracuse/NBER, and Fisher-Vanden-PSU)
  - ENTICE/ENTICE-BR[4,5] modifies DICE to include endogenous technological change and investments in clean energy R&D
  - We will be modeling these additional R&D investment decisions, and
  - including uncertainties about breakthrough technological change activity & climate sensitivity

- **MIT Integrated Global System Modeling Framework (MIT IGSM) ADP**
  (Jennifer Morris, MIT ESD PhD Candidate, Dissertation Topic)

[4] Popp, D. (2004). "ENTICE: Endogenous Technological Change in the DICE Model of Global Warming." *Journal of Environmental Economics and Management 48(1): 742-768.*

[5] Popp, D. (2006). "ENTICE-BR: Backstop Technology in the ENTICE Model of Climate Change." *Energy Economics 28 (2): 188-222.*

Thank You

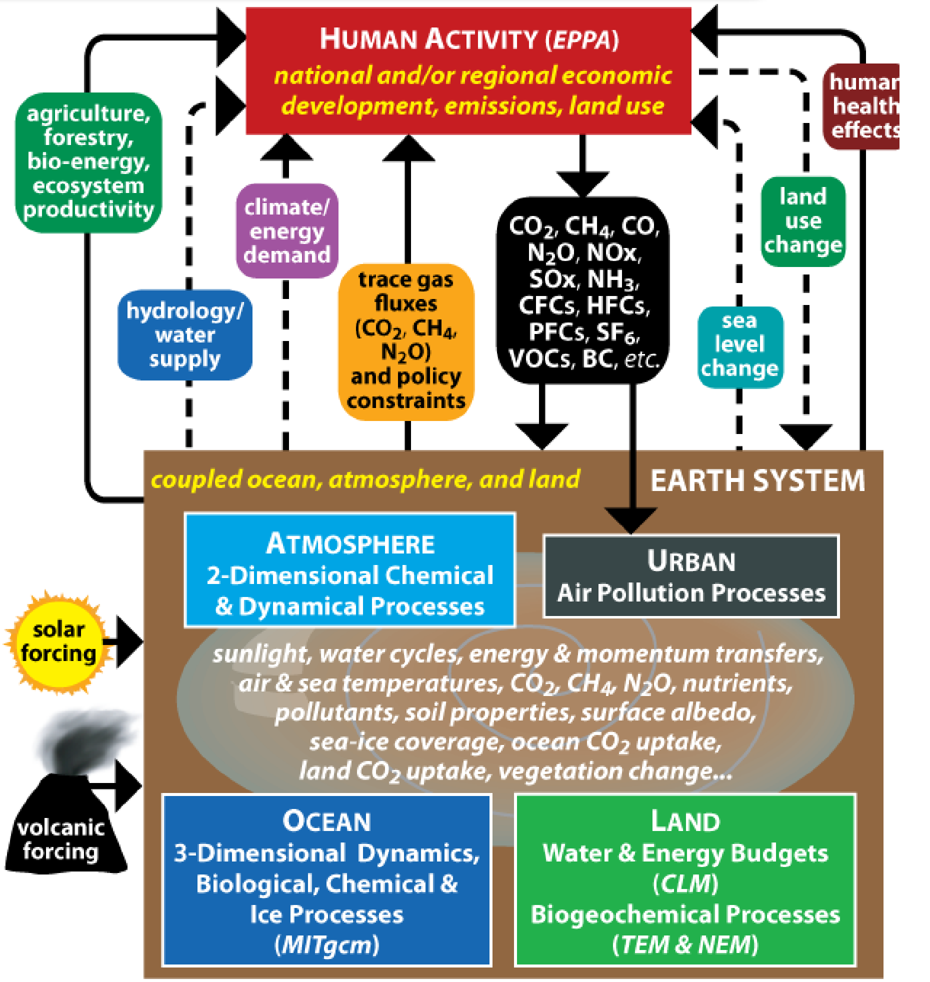
Acknowledgements
U.S. Department of Energy Grant No. DE-SC0003906
U.S. National Science Foundation Grant No. 0825915
Karen Fisher-Vanden – Penn State University
David Popp – Syracuse University/NBER

Webster Research Group

Sample Doctoral Students' Research Projects

Research Question: *Under a long-term climate stabilization target, how do uncertain technology costs, and the ability to learn and adapt decisions over time, affect near-term emission mitigation decisions? - Jennifer Morris, MIT ESD*

- **Integrated Assessment Models (IAMs)** couple human and climate systems and are valuable decision support tools
- However, most IAM analyses are **deterministic**
- How can we capture technological **uncertainty** and ability to **revise decisions** over time in an IAM?
- **Curse of Dimensionality** limits application of Dynamic Programming
- **Approximate Dynamic Programming** to the rescue!!!
- ADP IAM can provide important insight into **near-term mitigation strategies and climate policy design**



MIT Integrated Global System Modeling Framework (IGSM)

Environmental and R&D policy portfolio optimization under technology change uncertainty: the case of the U.S. electricity sector

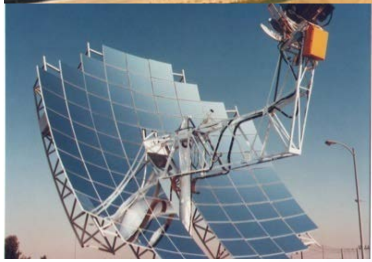
Nidhi R. Santen, ESD Ph.D. Candidate

Research Question:

"What is the optimal balance between near-term regulatory policy and clean electricity technology R&D expenditures, given the uncertainty in returns to R&D?"

Objectives:

- Develop an integrated policy and long-range generation capacity planning modeling framework to evaluate the impact of uncertain electricity technology improvements on optimal policy planning.
- Evaluate the trade-offs between "development-focused" and "adoption-focused" climate and technology policies, considering uncertainty (& breakthroughs) in R&D returns.



Approach:

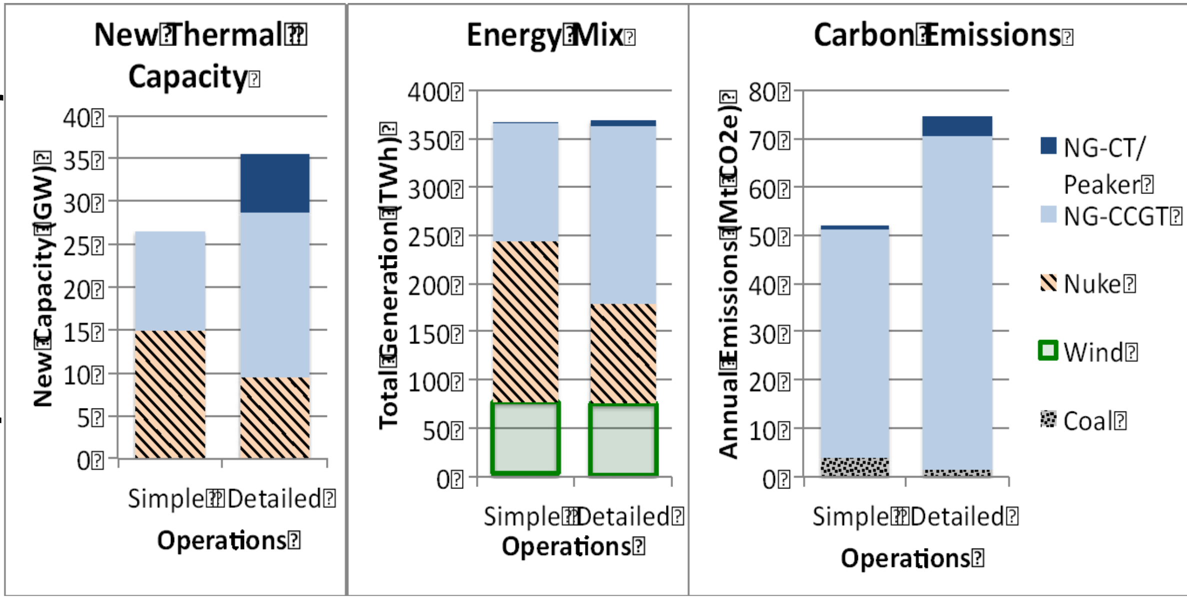
- Couple a policy-induced technology change model with a national-level electricity generation capacity planning model. Use patent citation data to empirically calibrate relationships between R&D and generation technology costs.
- Use stochastic optimization techniques to model a range of sequential environmental and R&D policy decisions under uncertain (endogenous) R&D returns, and study optimal near-term policies. Study associated electricity generation capacity and carbon-dioxide emission evolutions.
  - Use approximate dynamic programming (ADP) to capture the large number of decisions and uncertainties at each stage, and the long time-horizon of the policy and generation capacity planning processes (while keeping the problem tractable).

Photo Credits (from top): (1) http://www.usmc.mil (2) http://www.pelamiswave.com (3) www.scientificamerican.com (4) Sandia National Labs (4) http://www.metaefficient.com (5) http://img.dailymail.co.uk (6) https://inlportal.inl.gov

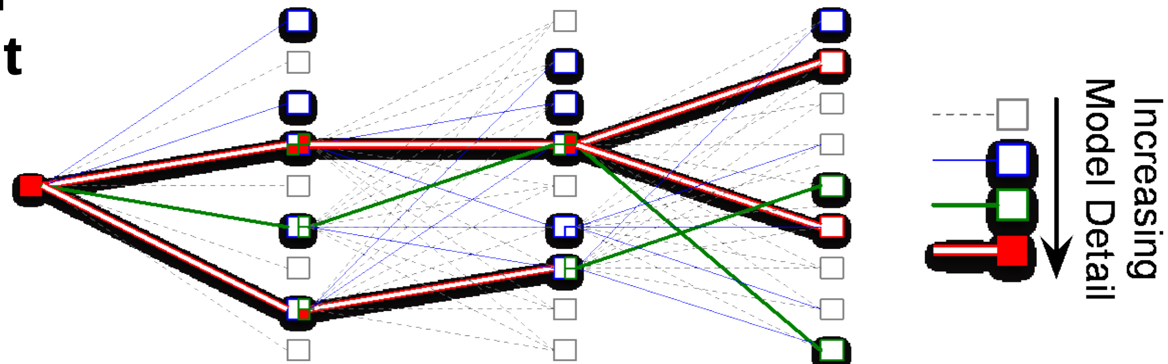
Operating Constraints in Stochastic Electricity Planning

By Bryan Palmintier

- Operational **Flexibility** Key for **Renewables** and **Emissions** Assessment



- **New methods** for ops + planning:
  - Efficient Long-term **Unit Commitment**
  - **Multi-Fidelity Approximate Dynamic Programming**



b_p@mit.edu

MIT ESD
Massachusetts Institute of Technology
Engineering Systems Division