

# SMART-Invest: A stochastic, dynamic policy model for optimizing investment in wind, solar and storage

## **Federal Energy Regulatory Commission Workshop on Increasing Market and Planning Efficiency Through Software**

June 21-23, 2015



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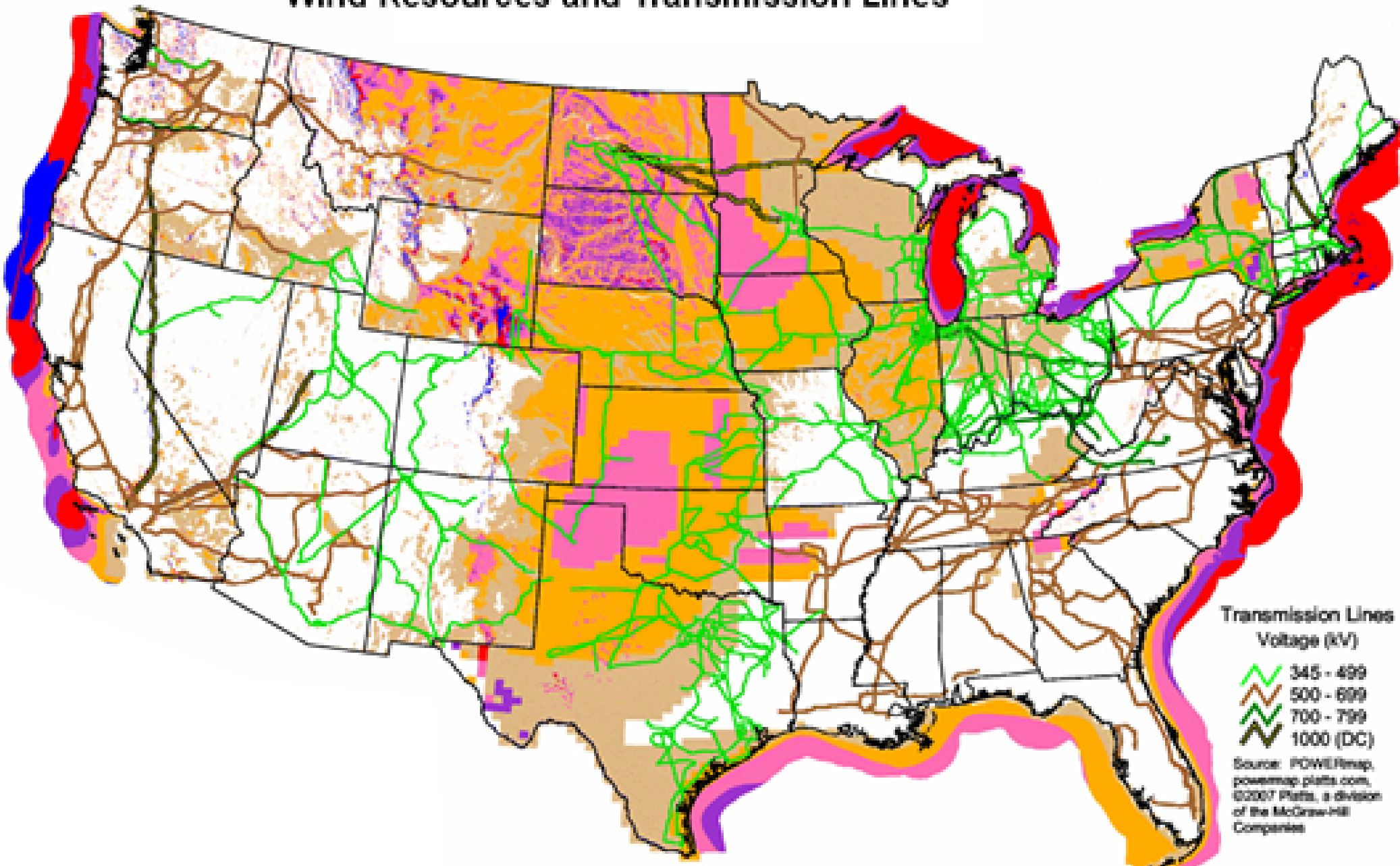
# A POLICY FRAMEWORK FOR THE 21<sup>ST</sup> CENTURY GRID: Enabling Our Secure Energy Future

JUNE 2011



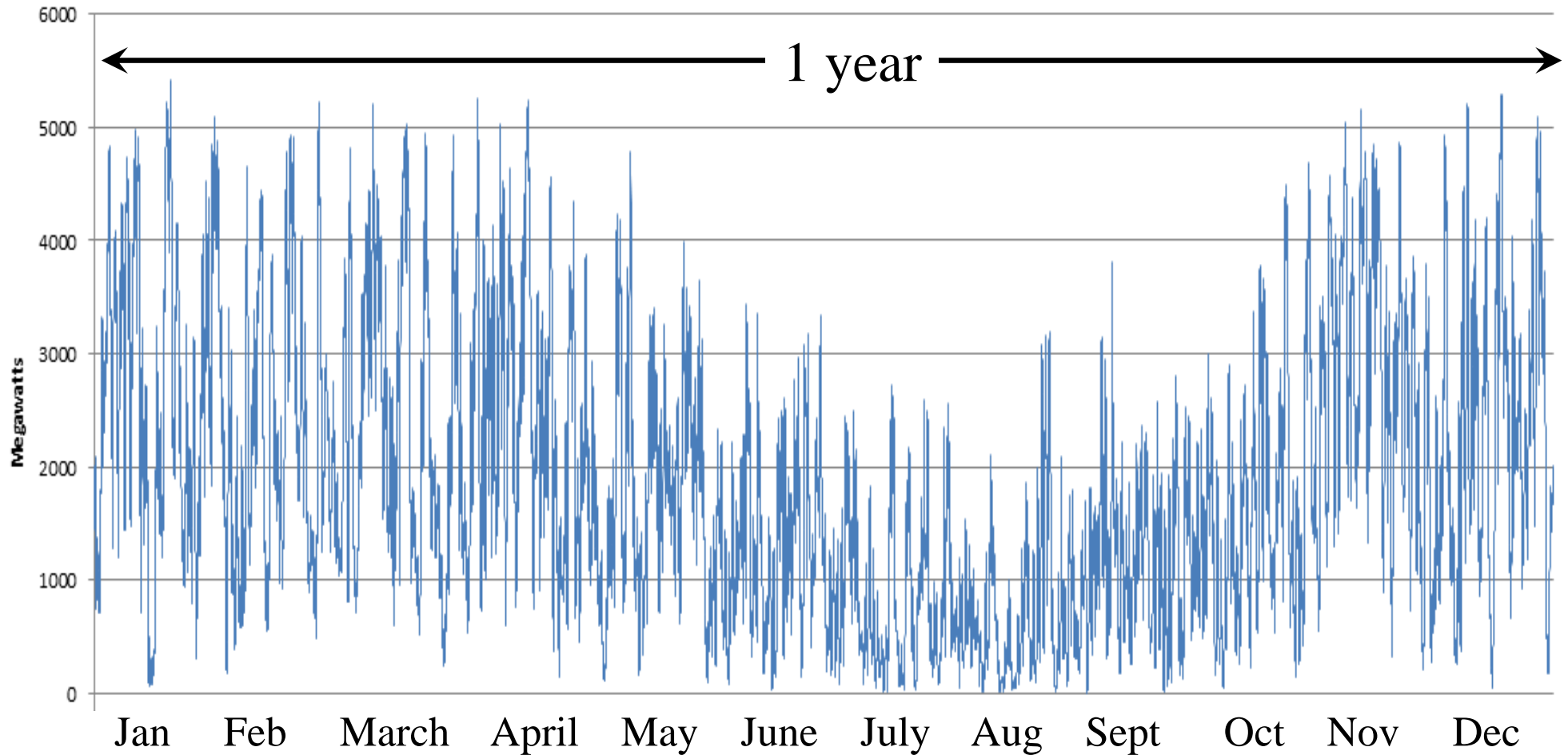
To seize the leadership position in a clean energy revolution, President Obama has set a national goal of generating 80% of our electricity from clean energy sources by 2035 and has reiterated his goal of putting one million electric vehicles on the road by 2015.

## Wind Resources and Transmission Lines



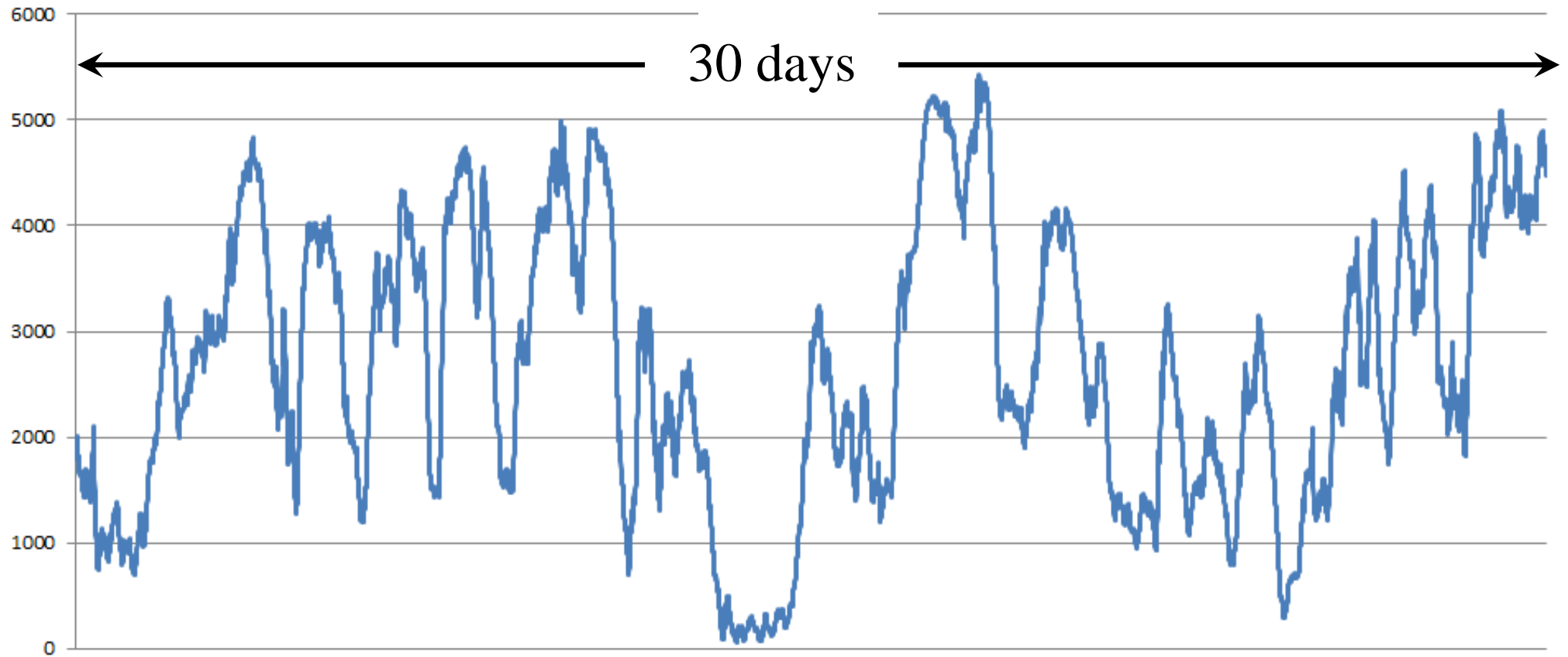
# Energy from wind

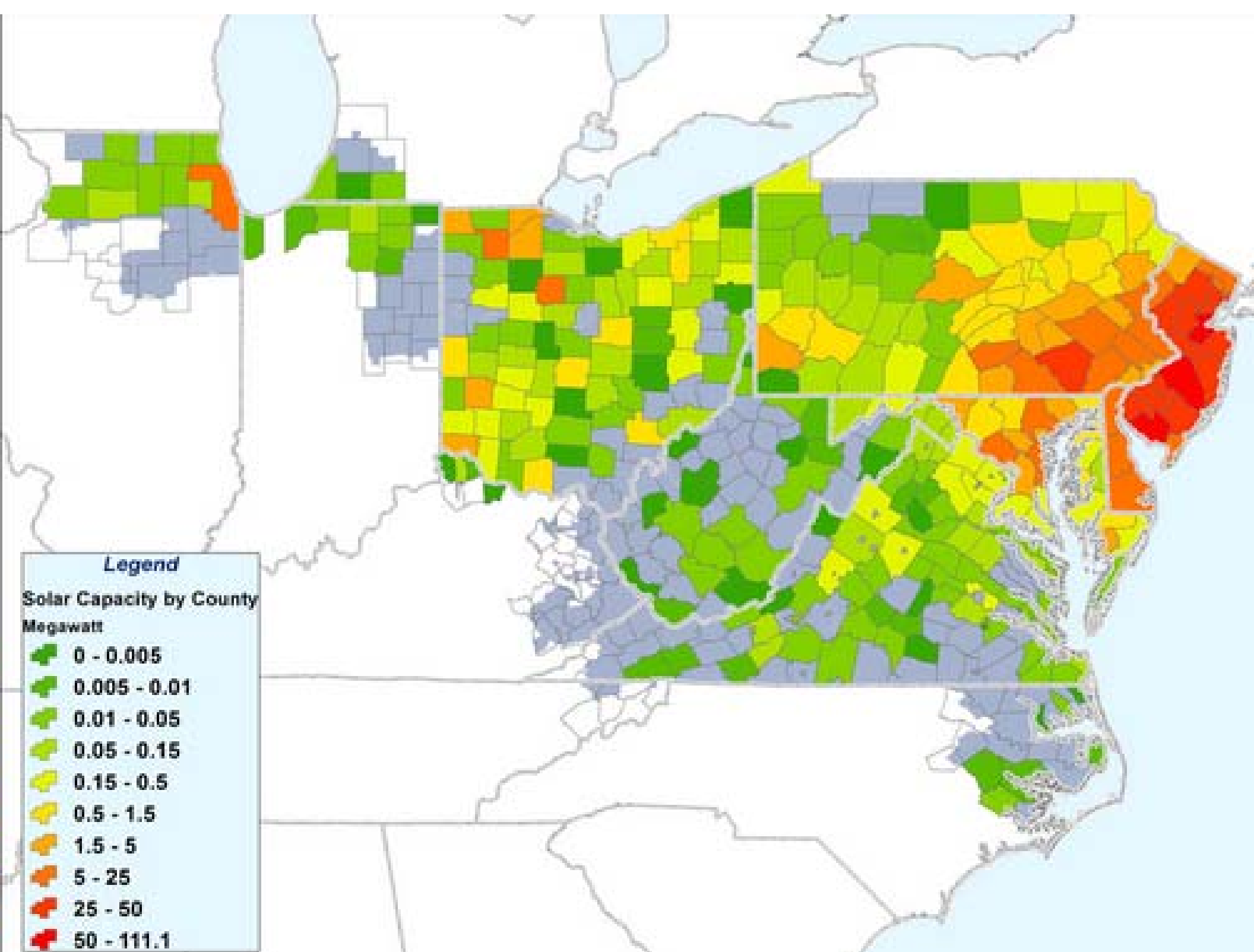
□ Wind power from all PJM wind farms



# Energy from wind

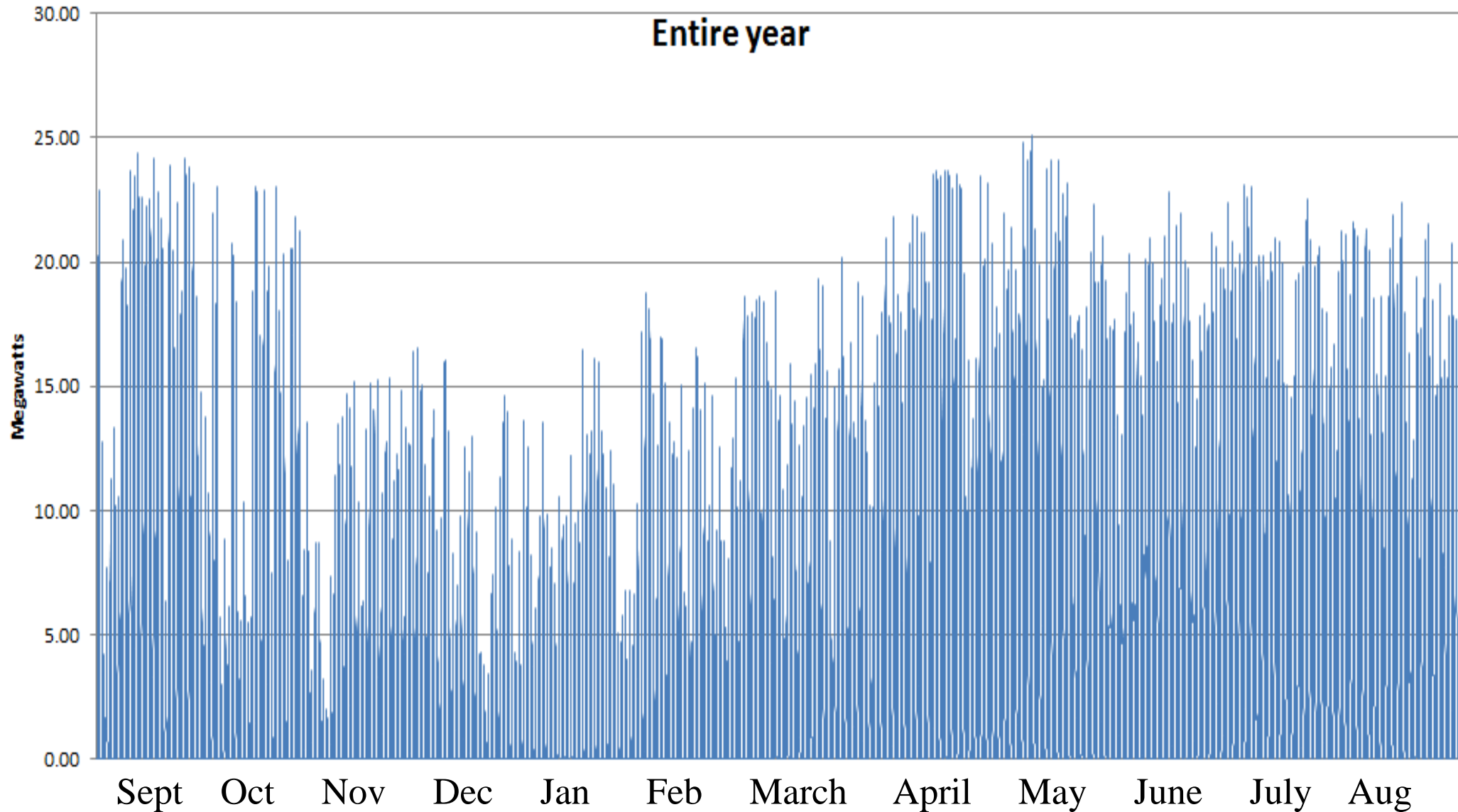
□ Wind from all PJM wind farms





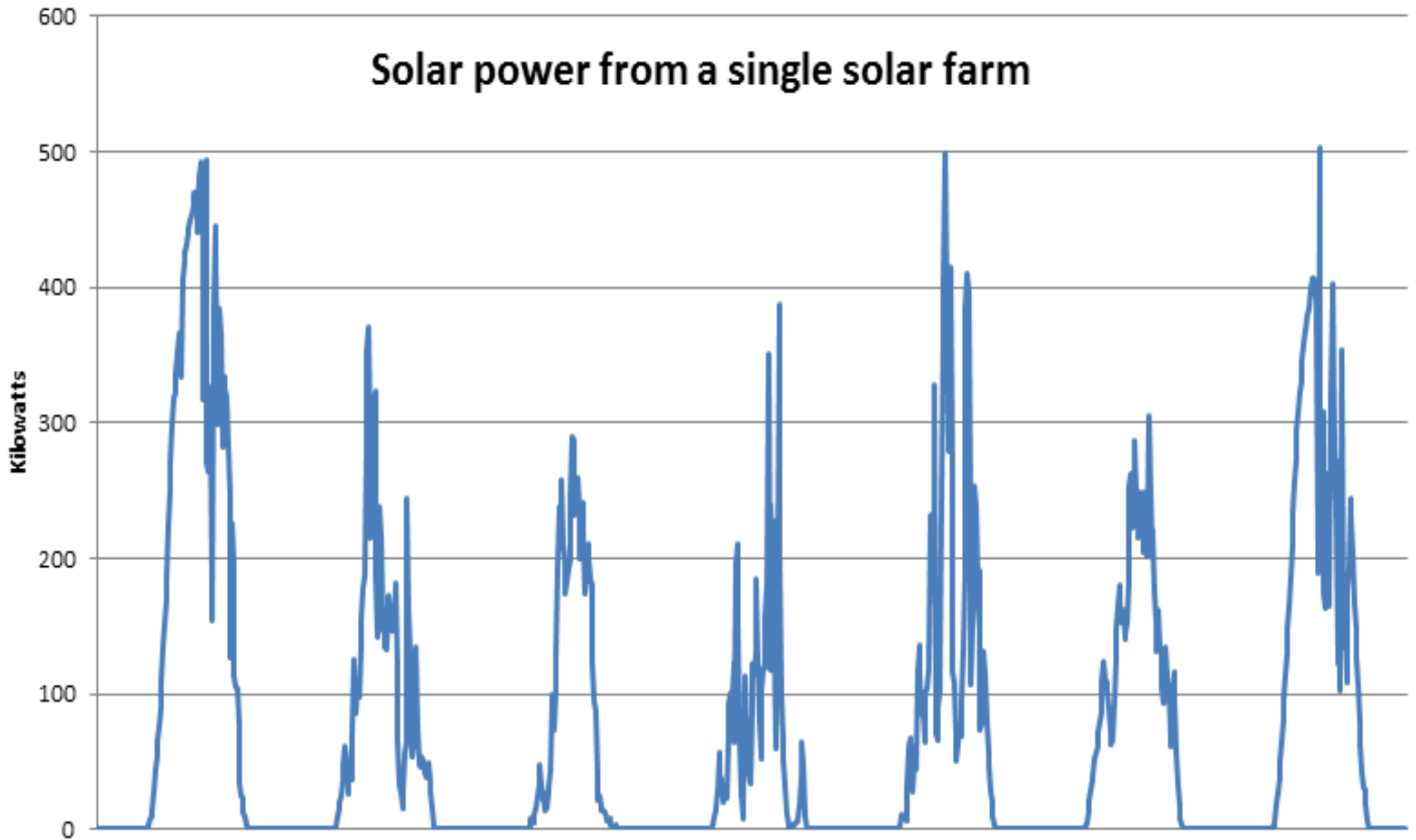
# Solar energy

## ● PSE&G solar farms



# Solar energy

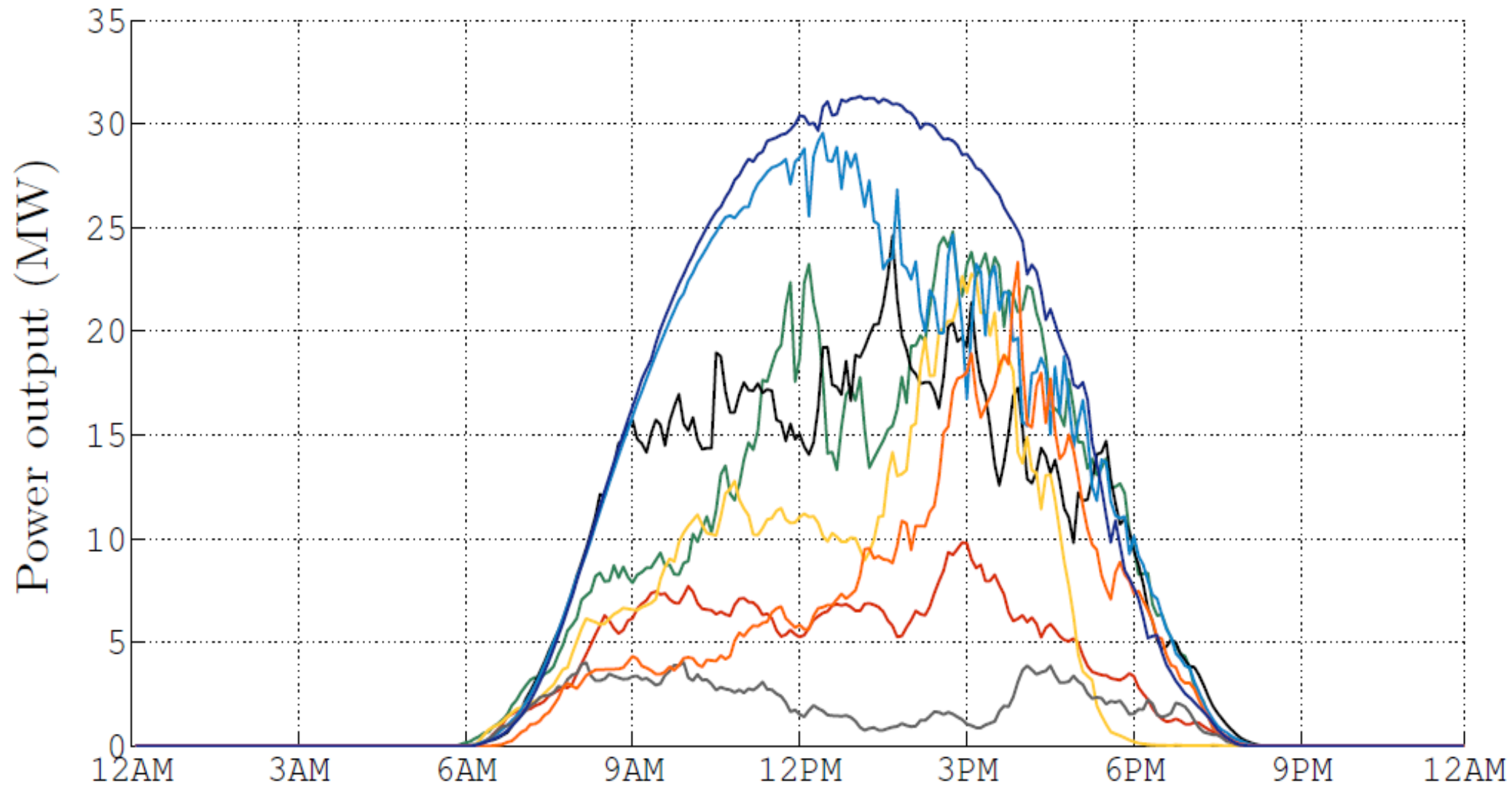
Solar power from a single solar farm





# Solar energy

## ● Within-day sample trajectories



# 99.9 percent from renewables!

Cost-minimized combinations of wind power, solar power and electrochemical storage, powering the grid up to 99.9% of the time

Cory Budischak<sup>a,b,\*</sup>, DeAnna Sewell<sup>c</sup>, Heather Thomson<sup>c</sup>, Leon Mach<sup>d</sup>, Dana E. Veron<sup>c</sup>, Willett Kempton<sup>a,c,e</sup>

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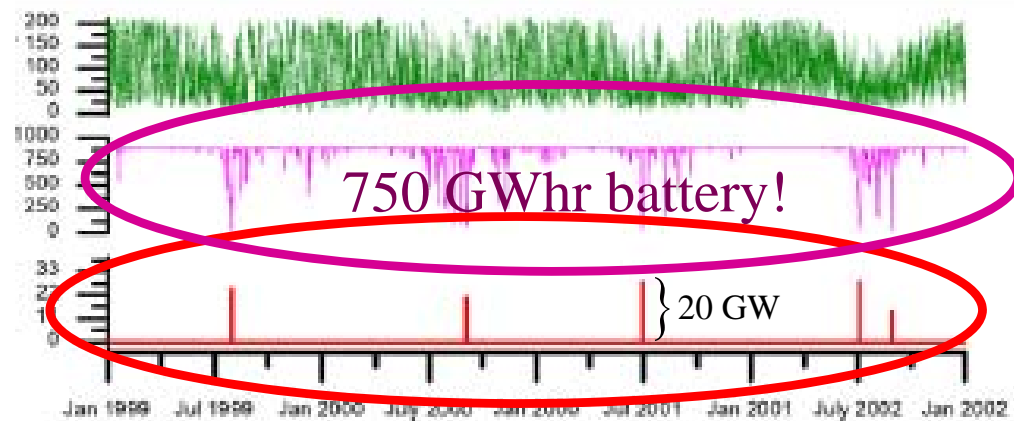
<sup>e</sup> Center for Electric Technology, DTU Elektro, Danmarks Tekniske Universitet, Kgs. Lyngby, Denmark

## HIGHLIGHTS

- ▶ We modeled wind, solar, and storage to meet demand for 1/5 of the USA electric grid.
- ▶ 28 billion combinations of wind, solar and storage were run, seeking least-cost.
- ▶ Least-cost combinations have excess generation (3× load), thus require less storage.
- ▶ 99.9% of hours of load can be met by renewables with only 9–72 h of storage.
- ▶ At 2030 technology costs, 90% of load hours are met at electric costs below today's.

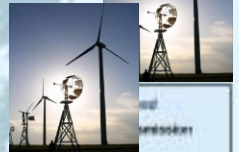
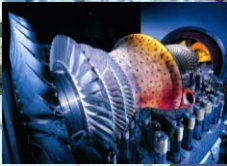
## GRAPHICAL ABSTRACT

Wind &  
Solar  
Battery  
Storage  
Fossil  
Backup



Load was met with renewable generation and storage 99.9% of hours over 4 years; fossil backup needed on few occasions

# SMART-ISO





# A spectrum of models

## ● Budischak et al

- » Model is 6 lines of code:
- » Store energy if  $\text{wind} + \text{solar} > \text{load}$
- » Withdraw if  $\text{wind} + \text{solar} < \text{load}$
- » Optimize (total enumeration) investment in wind, solar and storage.
- » Assume grid is available at all times for instantaneous backup.
- » Enumerates “28 billion configurations”

## ● SMART-Invest

- » Aggregate model of PJM energy markets and planning process.
- » Models entire year in hourly increments.
- » No grid model.
- » But does explicitly plan day-ahead steam generation, and hour-ahead gas turbines.
- » Optimized robust policies using reserve optimization.
- » Requires that all loads be covered by wind, solar, storage and fossil.

## ● SMART-ISO

- » Detailed model of unit commitment, grid constraints, planning process
- » Robust policy using optimized reserves.
- » Performs week-long simulations in 5-minute increments.
- » 2-3 hours for a single week-long simulation.

# SMART-Invest

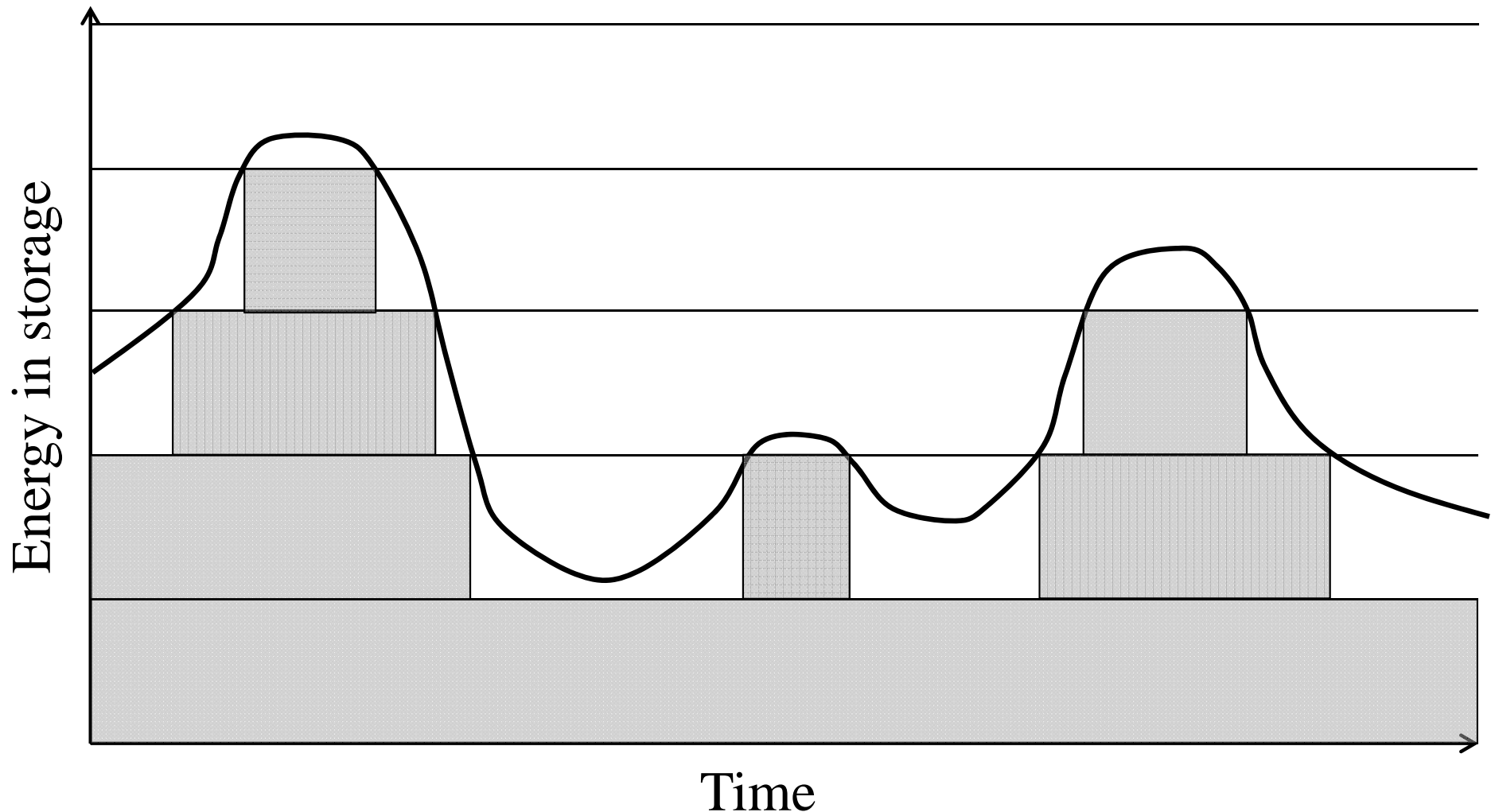
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## ● Features:

- » Find the optimal mix of wind, solar and storage, in the presence of two types of fossil generation:
  - Slow (steam) generation, which is planned 24 hours in advance
  - Fast (turbine) generation, which is planned 1 hour in advance
  - Real-time ramping of all fossils within ramping limits
- » Simulates entire year in hourly increments, to capture all forms of variability (except subhourly)
- » Minimizes investment and operating costs, possibly including SRECs and carbon tax.
- » Able to directly specify the cost of fossil generation (anticipating dramatic reduction in fossils).
- » Properly accounts for the marginal cost of each unit of investment.

# The value of storage

- The marginal value of storage
  - » On the margin, value of storage can be expensive!



# SMART-Invest

## ● The investment problem:

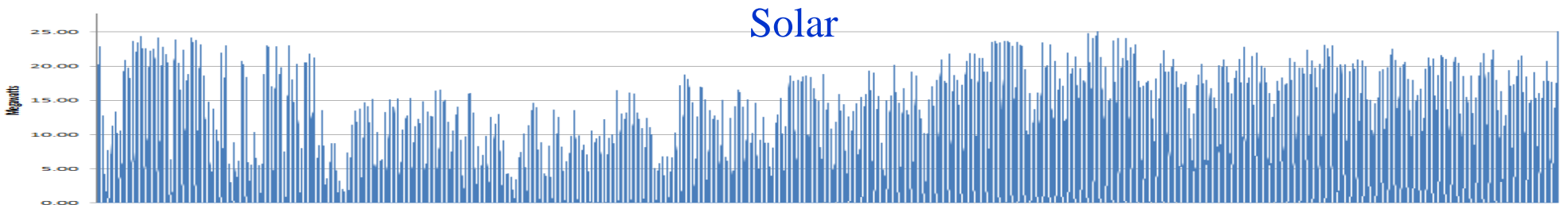
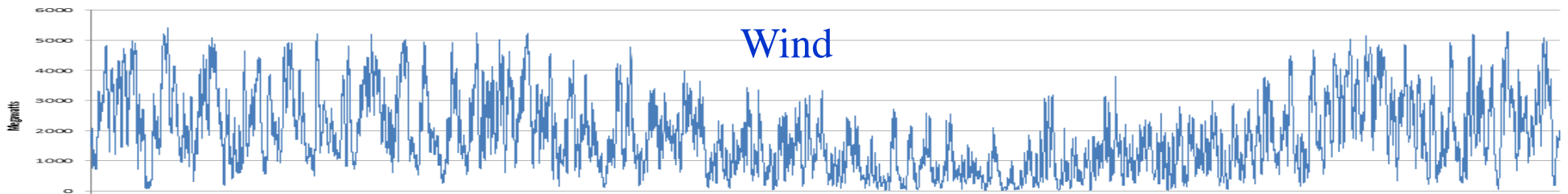
$$\min_{x_i^{Inv}, i \in I} \left( C^{inv}(x^{inv}) + \sum_{t=1}^{8760} C_t^{opr}(S_t, X_t^{opr}(S_t | x^{inv})) \right)$$

Capital investment cost in wind, solar and storage

Investment cost in wind, solar and storage.

Operating costs of fossil generators, energy losses from storage, misc. operating costs of renewables.

$X^{opr}(S_t)$  is the operating policy.



# SMART-Invest

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## ● Operational planning

36 hour planning horizon using forecasts of wind and solar

24 hour notification of steam

1 hour notification of gas

Real-time storage and ramping decisions (in hourly increments)

- » Meet demand while minimizing operating costs
- » Observe day-ahead notification requirements for generators
- » Includes reserve constraints to manage uncertainty
- » Meet aggregate ramping constraints (but does not schedule individual generators)



# Designing robust operating policies

## 1) Policy function approximations (PFAs)

» Lookup tables, rules, parametric functions

## 2) Cost function approximation (CFAs)

$$\gg X^{CFA}(S_t | \theta) = \arg \min_{x_t \in X_t^\pi(\theta)} \bar{C}^\pi(S_t, x_t | \theta)$$

## 3) Policies based on value function approximations (VFAs)

$$\gg X^{VFA}(S_t) = \arg \min_{x_t} \left( C(S_t, x_t) + \gamma \bar{V}_t^x \left( S_t^x(S_t, x_t) \right) \right)$$

## 4) Lookahead policies

» *Deterministic lookahead/rolling horizon proc./model predictive control*

$$X_t^{LA-D}(S_t) = \arg \min_{\tilde{x}_t, \dots, \tilde{x}_{t+H}} C(\tilde{S}_t, \tilde{x}_t) + \sum_{t'=t+1}^T C(\tilde{S}_{t'}, \tilde{x}_{t'})$$

» *Stochastic lookahead /stochastic program/Monte Carlo tree search*

$$X_t^{LA-S}(S_t) = \arg \min_{\tilde{x}_t, \tilde{x}_{t+1}, \dots, \tilde{x}_{t+T}} C(\tilde{S}_t, \tilde{x}_t) + \sum_{\tilde{\omega} \in \tilde{\Omega}_t} p(\tilde{\omega}) \sum_{t'=t+1}^T \gamma^{t'-t} C(\tilde{S}_{t'}(\tilde{\omega}), \tilde{x}_{t'}(\tilde{\omega}))$$

» *“Robust optimization”*

$$X_t^{LA-RO}(S_t) = \arg \min_{\tilde{x}_t, \dots, \tilde{x}_{t+H}} \max_{w \in W_t(\theta)} C(\tilde{S}_t, \tilde{x}_t) + \sum_{t'=t+1}^T C(\tilde{S}_{t'}(w), \tilde{x}_{t'}(w))$$

# Stochastic optimization models

- The objective function

$$\min_{\pi} E^{\pi} \left\{ \sum_{t=0}^T \gamma^t C(S_t, X_t^{\pi}(S_t)) \right\}$$

Expectation over all  
random outcomes

Cost function

State variable

Decision function (policy)

Finding the best policy

Given a *system model* (transition function)

$$S_{t+1} = S^M(S_t, x_t, W_{t+1}(\omega))$$

We call this the *base model*.

# Robust policies

## ● Lookahead model:

» Objective function

$$X_t^\pi(S_t | \theta, (x_g^{inv})_{g \in \mathcal{G}}) = \arg \min_{(\tilde{x}_{t,t'})_{t'}} \sum_{t'=t}^{t+n^T} \sum_{g \in \mathcal{G}} \left( c_g^{opr} \tilde{x}_{t,t',g}^{gen} + c^{cb} \tilde{x}_{t,t'}^{bc} + \frac{c^{db}}{e^d} \tilde{x}_{t,t'}^{bd} \right)$$

» Reserve constraint:

$$\sum_{g \in \mathcal{G}} \tilde{x}_{t,t',g}^{gen} = \theta f_{t,t'}^d \rightarrow \text{Tunable policy parameter}$$

» Other constraints:

- Ramping
- Capacity constraints
- Conservation of flow in storage
- ....

# Robust policies

## ● Policy search – Optimizing reserve parameter

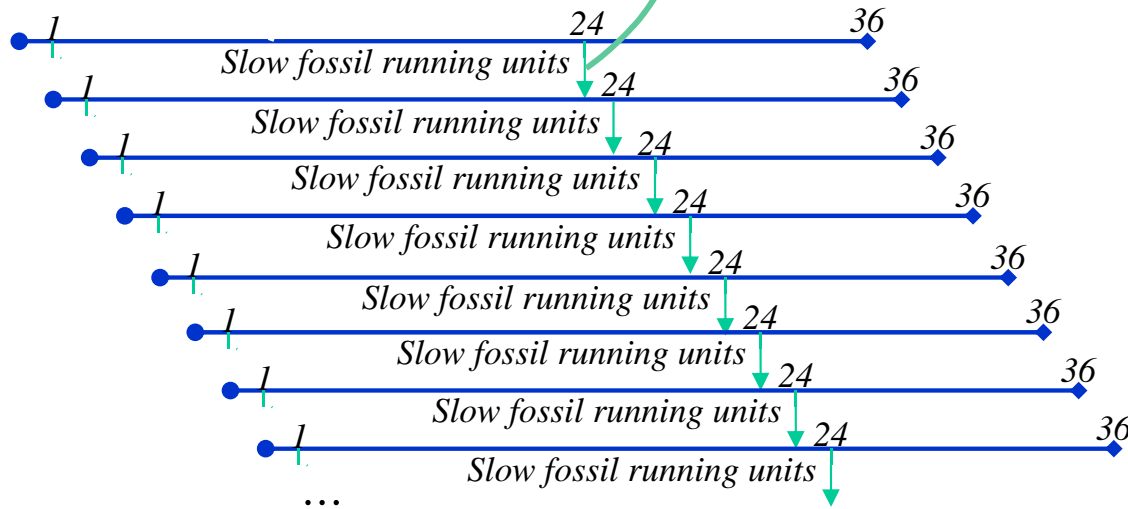
CO <sub>2</sub> tax \$/tonne	Wind MW	Solar MW	Batt. MWh	Wind Gen. (%)	Opt. $\theta$
0	0	0	0	0.0	1.000
50	51284	170	19738	19.0	0.985
80	82066	3741	4556	29.8	0.998
100	80250	6584	6005	29.2	1.001
150	120251	33372	30939	42.0	1.020
0	0	0	0	0.0	1.000
0	51284	170	19738	18.8	1.191
0	80250	6584	6005	29.2	1.041
0	120251	33372	30939	40.7	1.197
0	120251	33372	30939	40.7	1.197
50	120251	33372	30939	41.0	1.134
80	120251	33372	30939	42.2	1.011
100	120251	33372	30939	42.1	1.011

Low carbon tax,  
increased usage  
of slow fossil,  
requires higher  
reserve margin  
~19 percent

High carbon  
tax, shift from  
slow to fast  
fossil, requires  
minimal reserve  
margin ~1 pct



*The tentative plan is discarded*



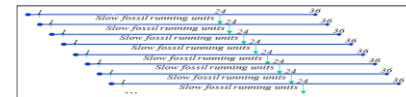
- » Model plans using rolling 36 hour horizon
- » Steam plants are locked in 24 hours in advance
- » Gas turbines are decided 1 hour in advance

# Parallelization

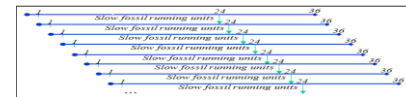
## ● The simulation

- » It was very important to model the entire year so that we capture all forms of variability, including seasonal.
- » This means solving 8,760 linear programs to compute a single simulation.
- » Solution: We divided the problem into 52 weeks, where we would simulate 8 days, using a 1-day warmup:

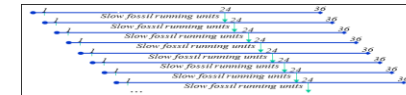
# Week 1



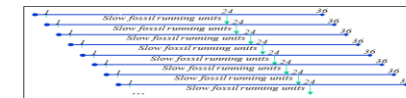
## Week 2



## Week 3

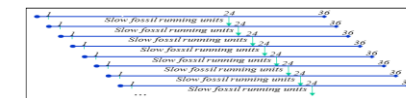


## Week 4



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## Week 52



# Parallelization

## ● CPU times with and without parallelization

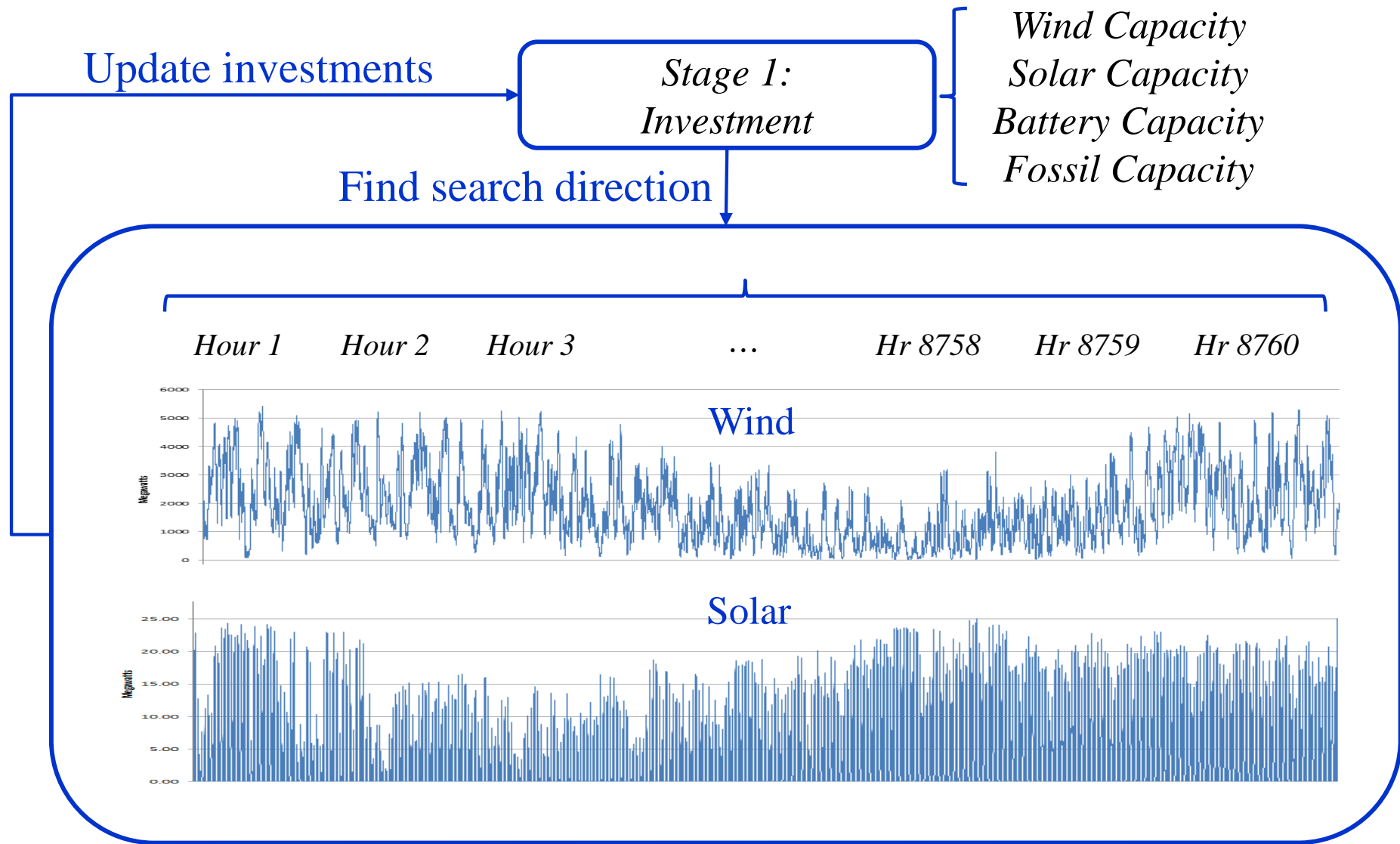
	without parallelization	with parallelization
Complete offer stack	8738 s	1786 s
Aggregated offer stack	135 s	30 s

## ● Objective functions with and without parallelization

	without parallelization	with parallelization
Wind (MW)	93718.15	93699.62
Solar (MW)	8619.51	8610.29
Battery (MWh)	6365.69	6442.68

» Errors in optimal solution introduced by parallelization were .02, .10 and 1.2 percent, respectively.

# SMART-Invest





# The search algorithm

## ● Gradient-based search

» Let

$$F(x^{inv}) = C^{inv}(x^{inv}) + \sum_{t=1}^{8760} C_t^{opr}(S_t, X_t^{opr}(S_t | x^{inv}))$$

» Compute numerical derivatives:

$$\frac{\partial F(x^{inv})}{\partial x_i^{inv}} = \frac{F(x_i^{inv} + \delta_i) - F(x_i^{inv})}{\delta_i}$$

$$\nabla_x F(x^{inv}) = \begin{pmatrix} \frac{\partial F(x^{inv})}{x_{wind}^{inv}} \\ \vdots \\ \frac{\partial F(x^{inv})}{x_{solar}^{inv}} \end{pmatrix}$$

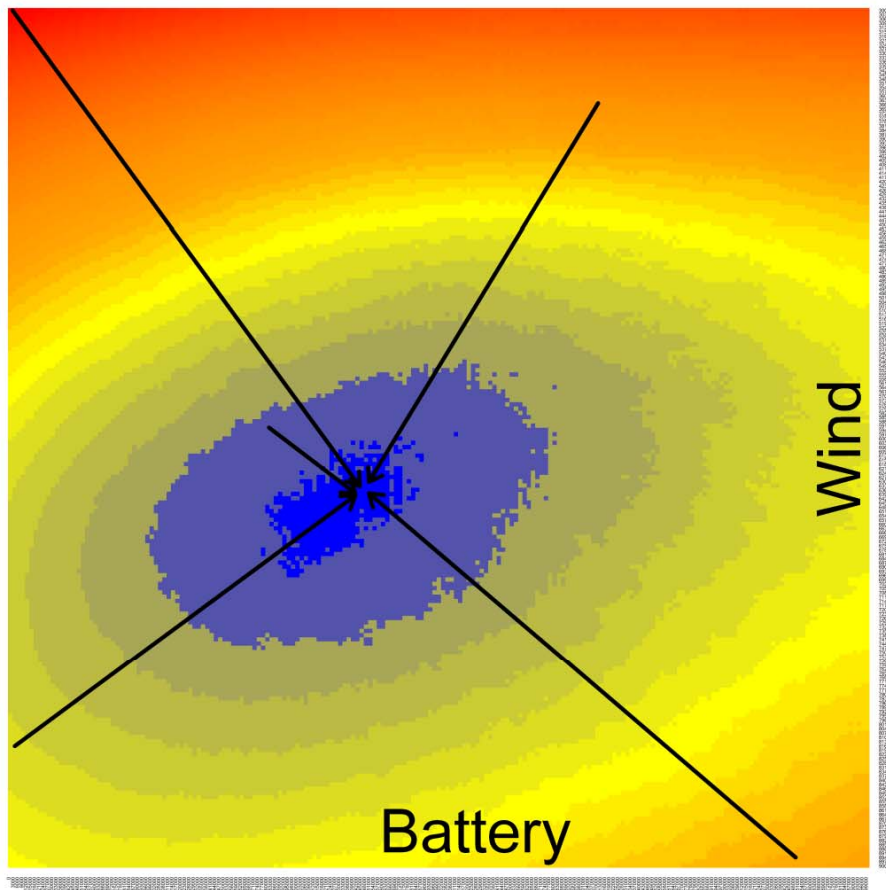
» Update investment solution

$$x^{n+1} = x^n - \alpha_n \nabla_x F(x^n, W^{n+1})$$

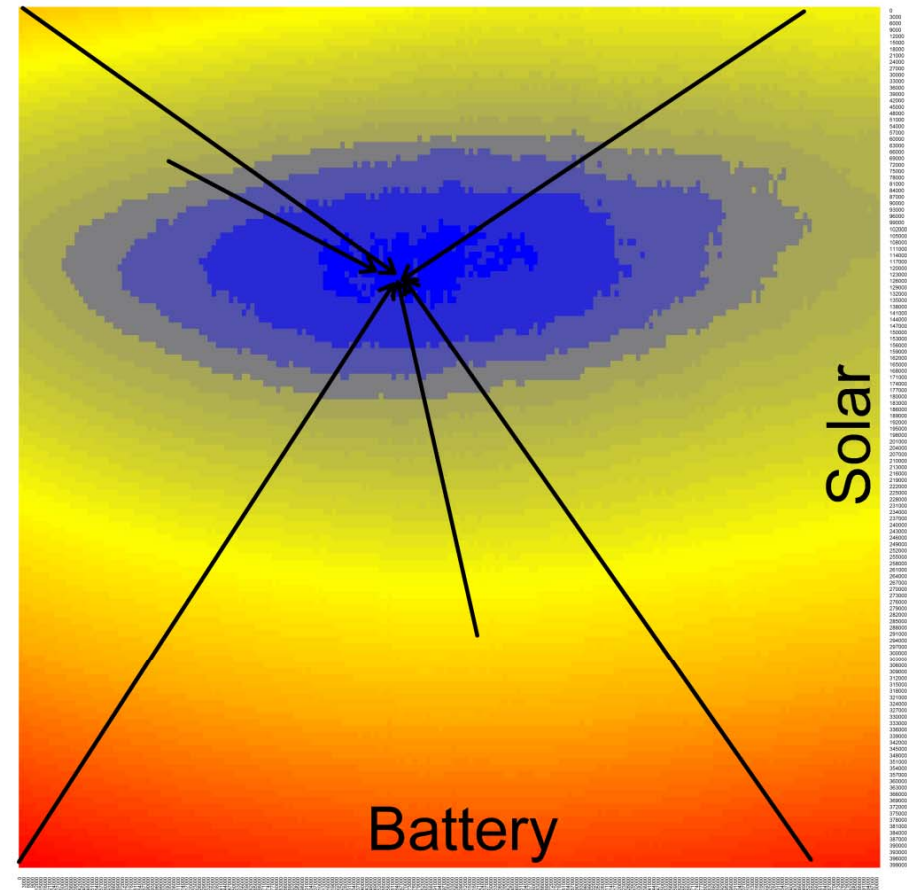
» We then use an adaptive stepsize rule that finds the largest stepsize that produces an improvement (but we limit how small it may be).

# The search algorithm

- Robustness of stochastic search algorithm



(a) Solar capacity is fixed.



(b) Wind capacity is fixed.

*Different Starting Points*

# The search algorithm

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- Empirical performance of algorithm
  - » Starting the algorithm from different starting points appears to reliably find the optimal (determined using a full grid search).
  - » Algorithm tended to require  $< 15$  iterations:
    - Each iteration required 4-5 simulations to compute the complete gradient
    - Required 1-8 evaluations to find the best stepsize
    - Worst case number of function evaluations is  $15 \times (8+5) = 195$ .
    - Budischak paper required “28 billion” for full enumeration (used super computer)
  - » Run times
    - Aggregated supply stack: ~100 minutes
    - Full supply stack: ~100 hours

# Policy studies

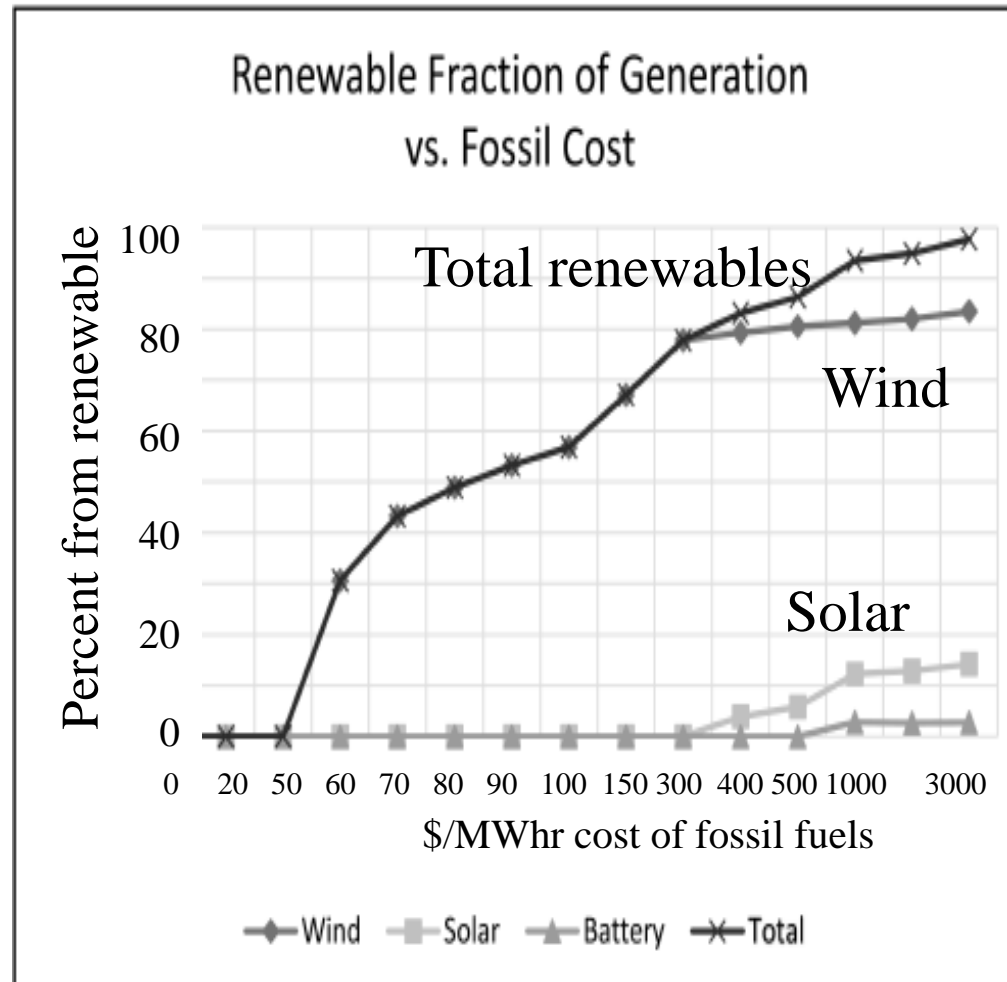
## ● Base cost parameters

» Data taken from eia.gov

	Wind	Solar	Battery	Slow Fossil	Fast Fossil
Capital cost (\$/MW)	2,213,000	3,873,000	500,000	1,023,000	676,000
Yearly oper. cost (\$/MW/yr)	39,550	24,690	0	15,370	7,040
Life time (year)	30	30	15	30	30
Ramp up rate (frac. of cap.)	1	1	1	0.038	1
Ramp down rate (frac. of cap.)	1	1	1	0.037	1

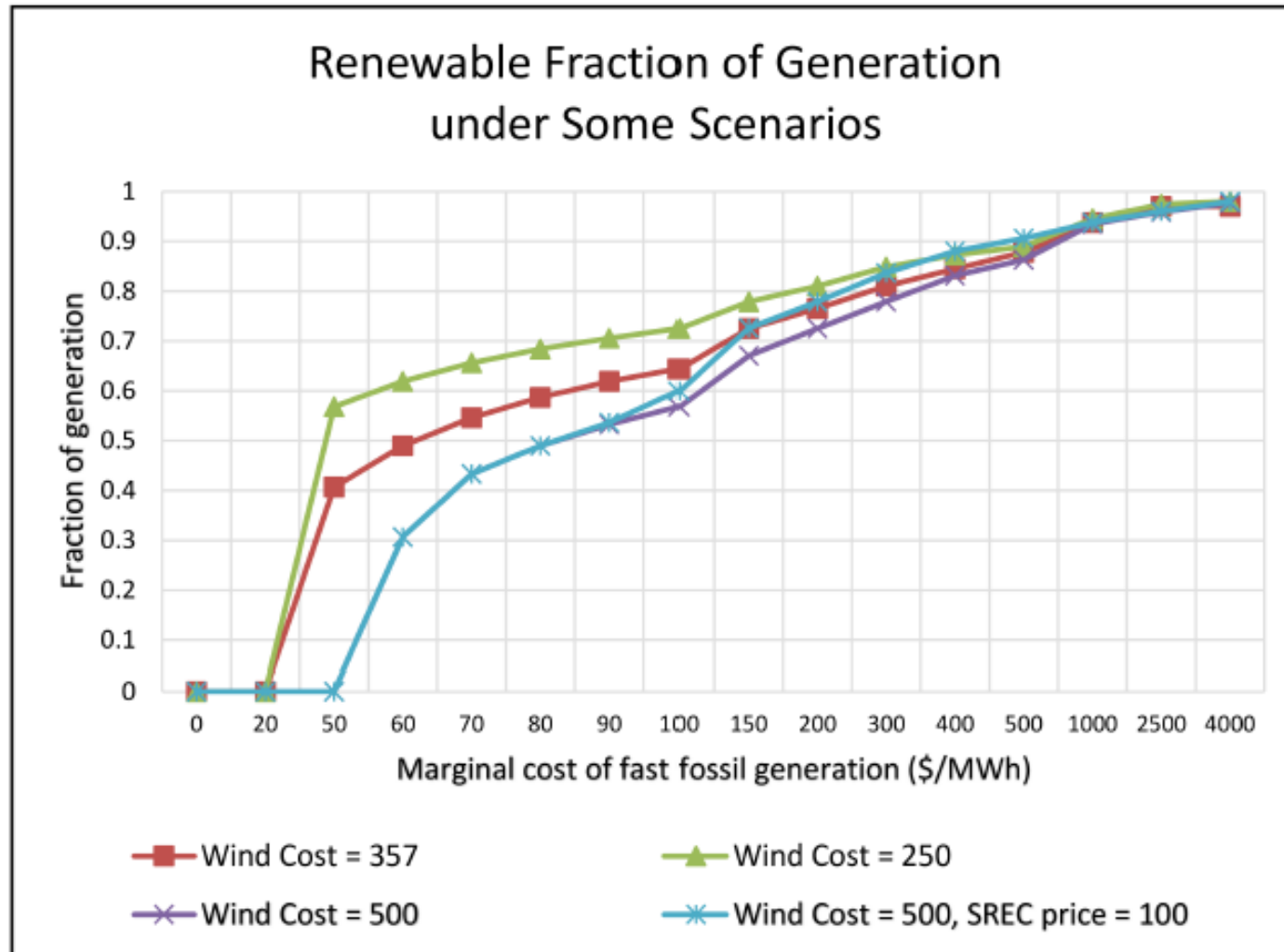
# Policy studies

## Renewables as a function of cost of fossil fuels



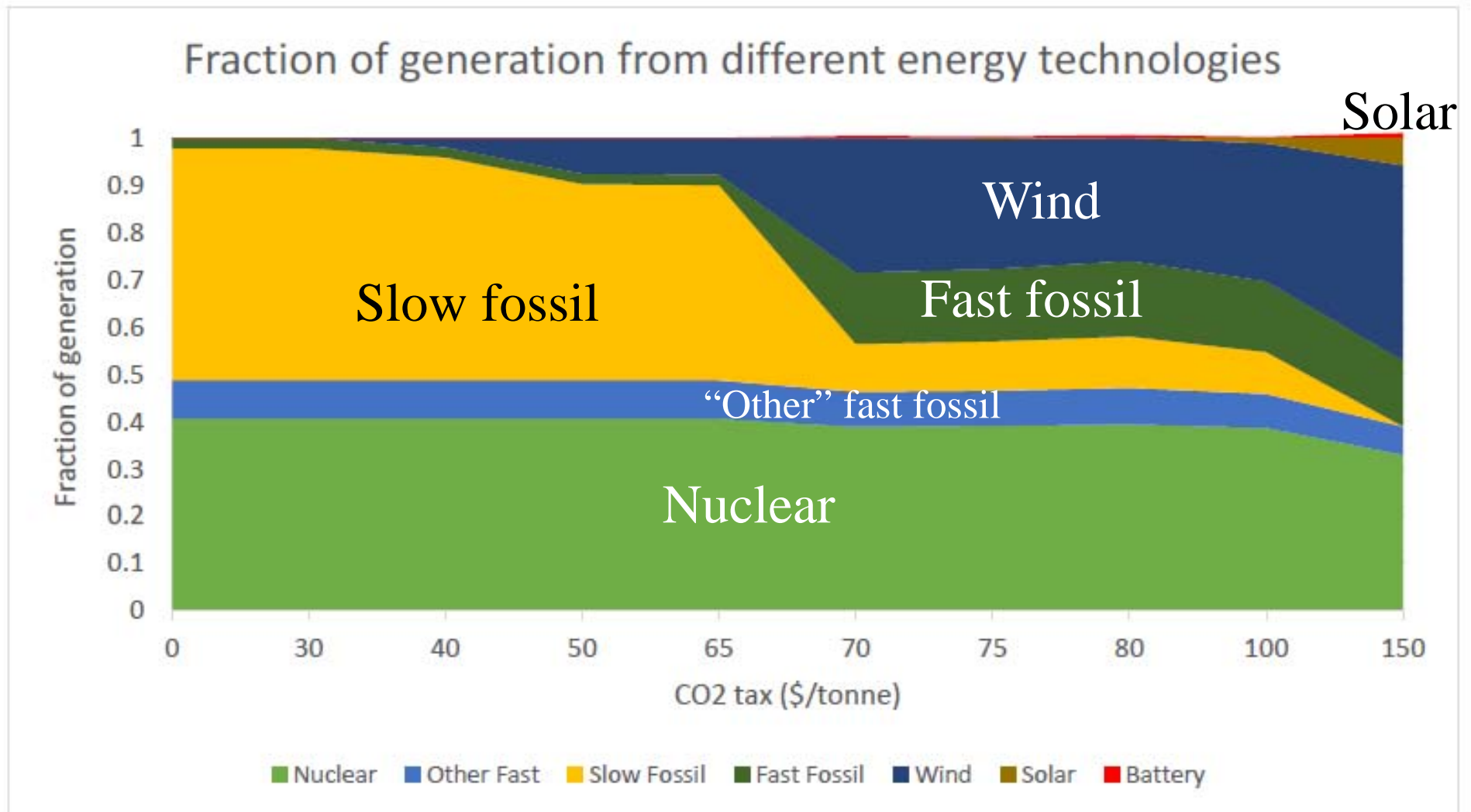
# Policy studies

## ● Sensitivity to wind costs



# Policy studies

## ● Sensitivity to CO2 tax.





# SMART-Invest

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## SMART-Invest

SMART-Invest is designed as a streamlined version of SMART-ISO to allow it to find optimal mixes of wind, solar and storage. It models the entire year (in hourly increments), capturing wind, solar storage, as well as fast and slow fossil generation.

Slow and fast fossil generation is planned (at an aggregate level) using a rolling 36-hour horizon (optimized every hour). Slow generation is fixed 24 hours in advance; fast fossil generation is fixed 1 hour in advance. Slow and fast generation may be tuned (within ramp rates) in real time, responding to actual wind and solar. Storage is used as needed.

The model optimizes across the mix of investments using a descent vector computed using numerical derivatives. Each evaluation of the objective function involves optimizing over all 8,760 hours (52 weeks are run in parallel to improve speed).

Major features of the model include:

- o Careful modeling of the variability and uncertainty of renewables over the entire year, at the one-hour level.
- o We assume that fast and slow fossil generation will be part of any energy portfolio involving wind, solar and storage, which means that we have to handle the need to make advance commitments (we commit to slow fossil 24 hours in advance, while fast fossil is committed 1 hour in advance).
- o Modeling of the full energy stack, but not the grid, and not individual generators.