Incorporating Wind and Distributed Storage into Stochastic Economic Dispatch Solutions

C. Lindsay Anderson

Cornell University

(cla28@cornell.edu)

PSERC Webinar
November 21, 2017

Acknowledgements

- Joint work with Dr. Luckny Zéphyr, Postdoctoral Associate at Cornell University
- Work supported in part by the National Science Foundation under grant ECCS-1453615, and by US Department of Energy, under Award Number DE-OE0000843*

Presentation Outline

- **Background:**
  - **Renewables and Storage**
  - **Why would we use approximate methods?**
  - **Introduction to SDDP**
- **Sample Results and Comparisons**
- **Conclusions and Future Work**

Renewable Energy Policy Globally

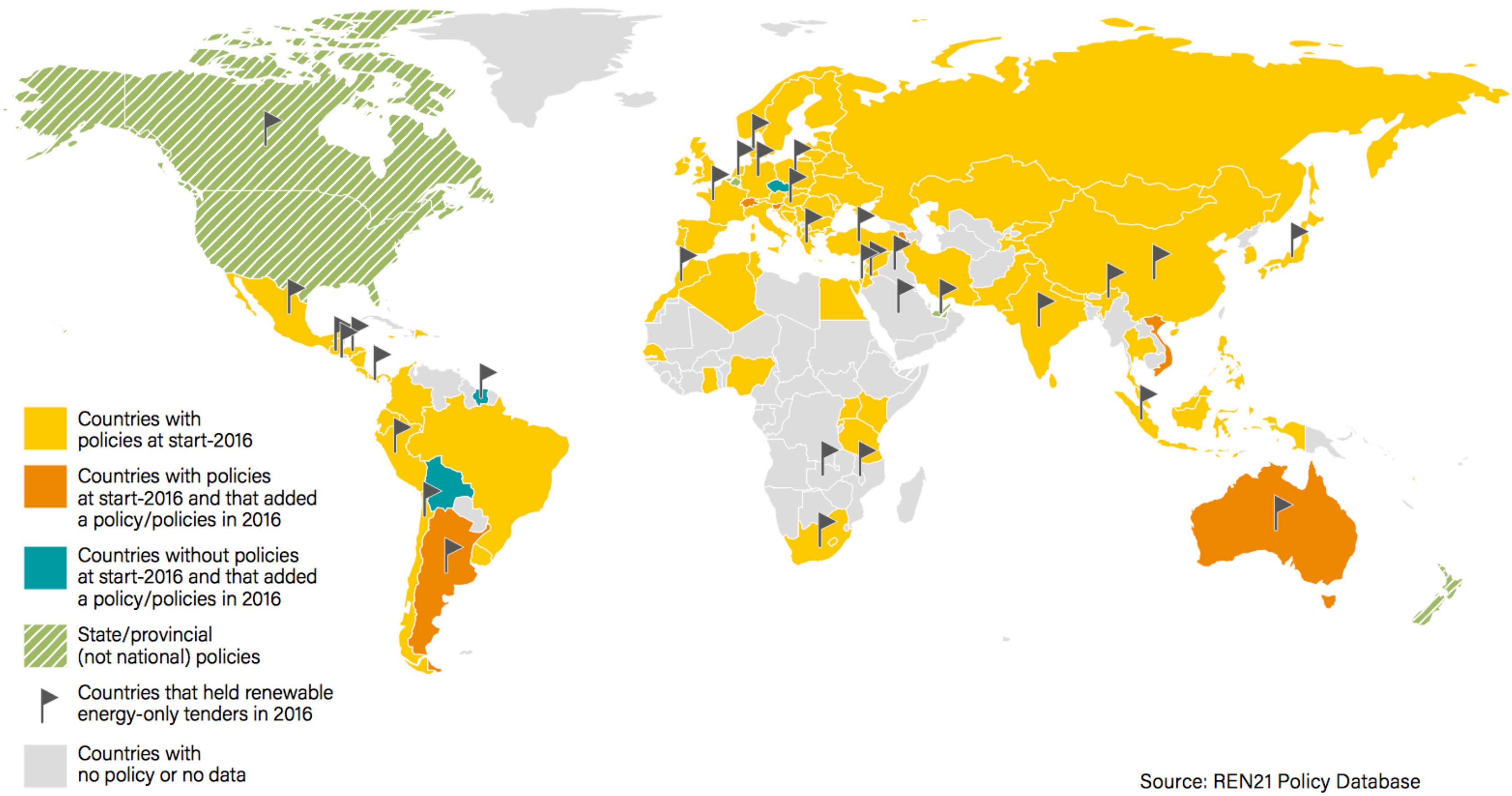
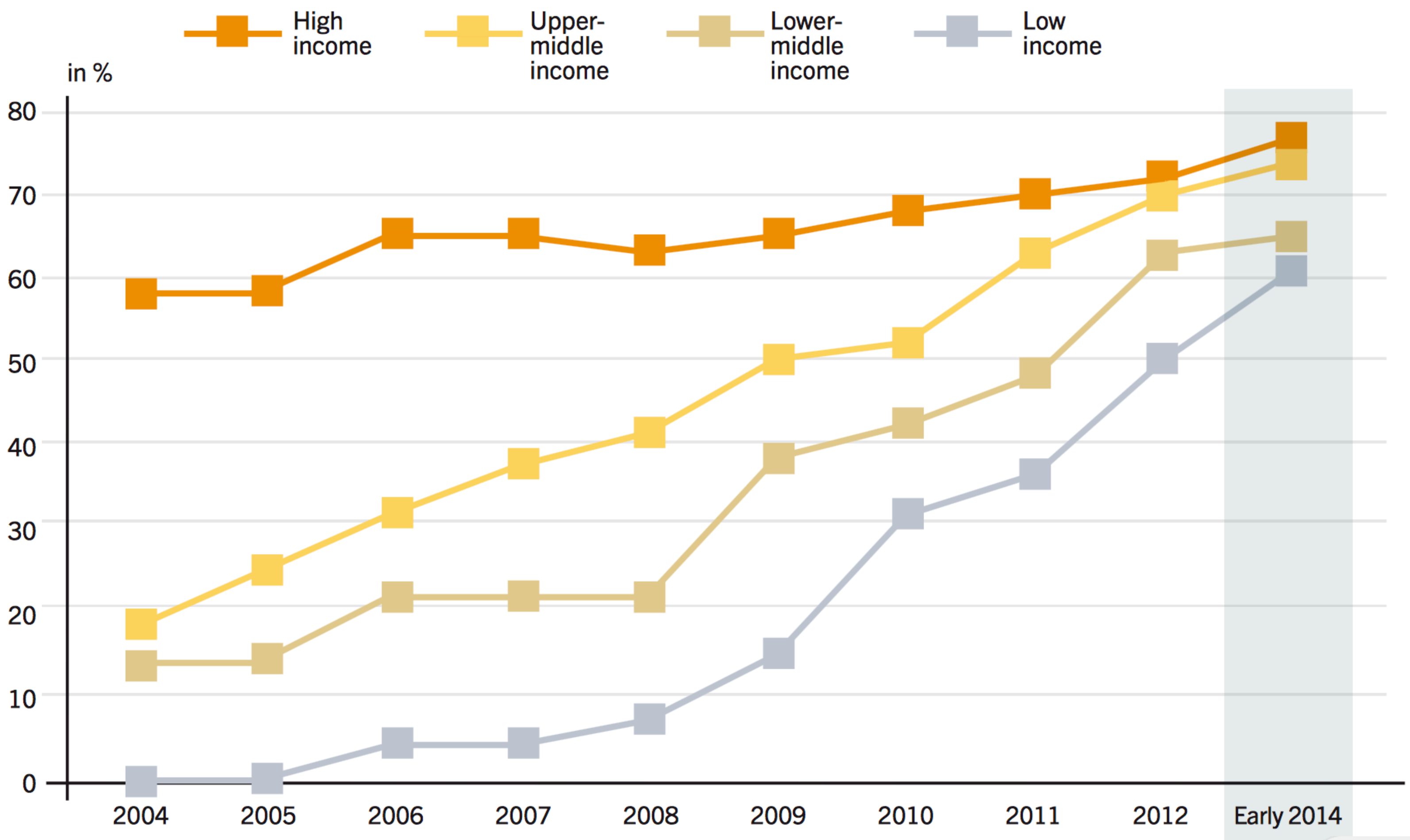


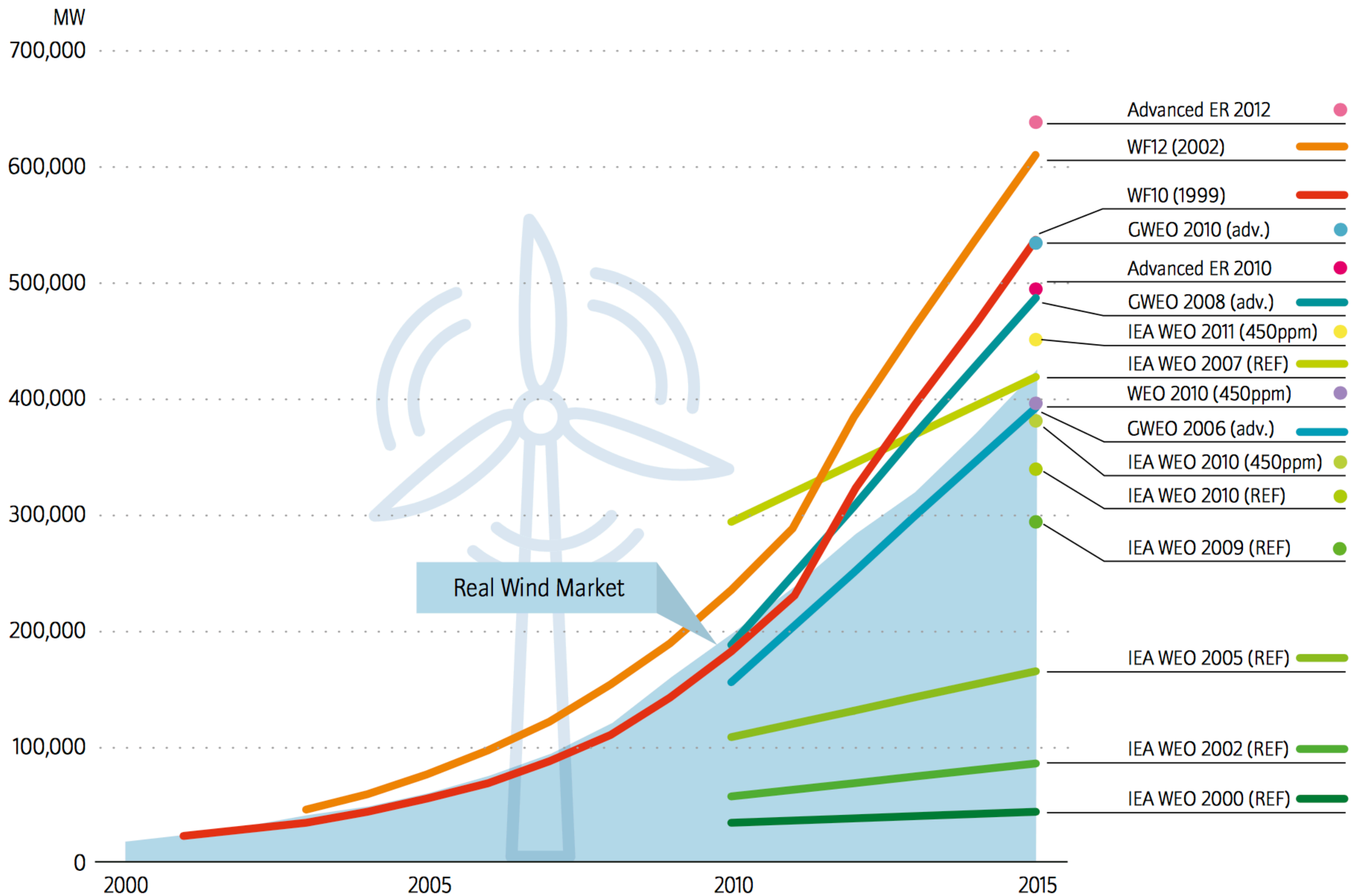
Figure: Countries with renewable energy policies by type, 2016

Global Trend in Renewable Energy Policies



Share of Countries with Renewable Energy Policies 2004-early 2015
(Source: REN21 Global Status Report)

Wind Power Projections versus Real Market Developments



Source: Data compilation by Dr. Sven Teske, UTS/ISF

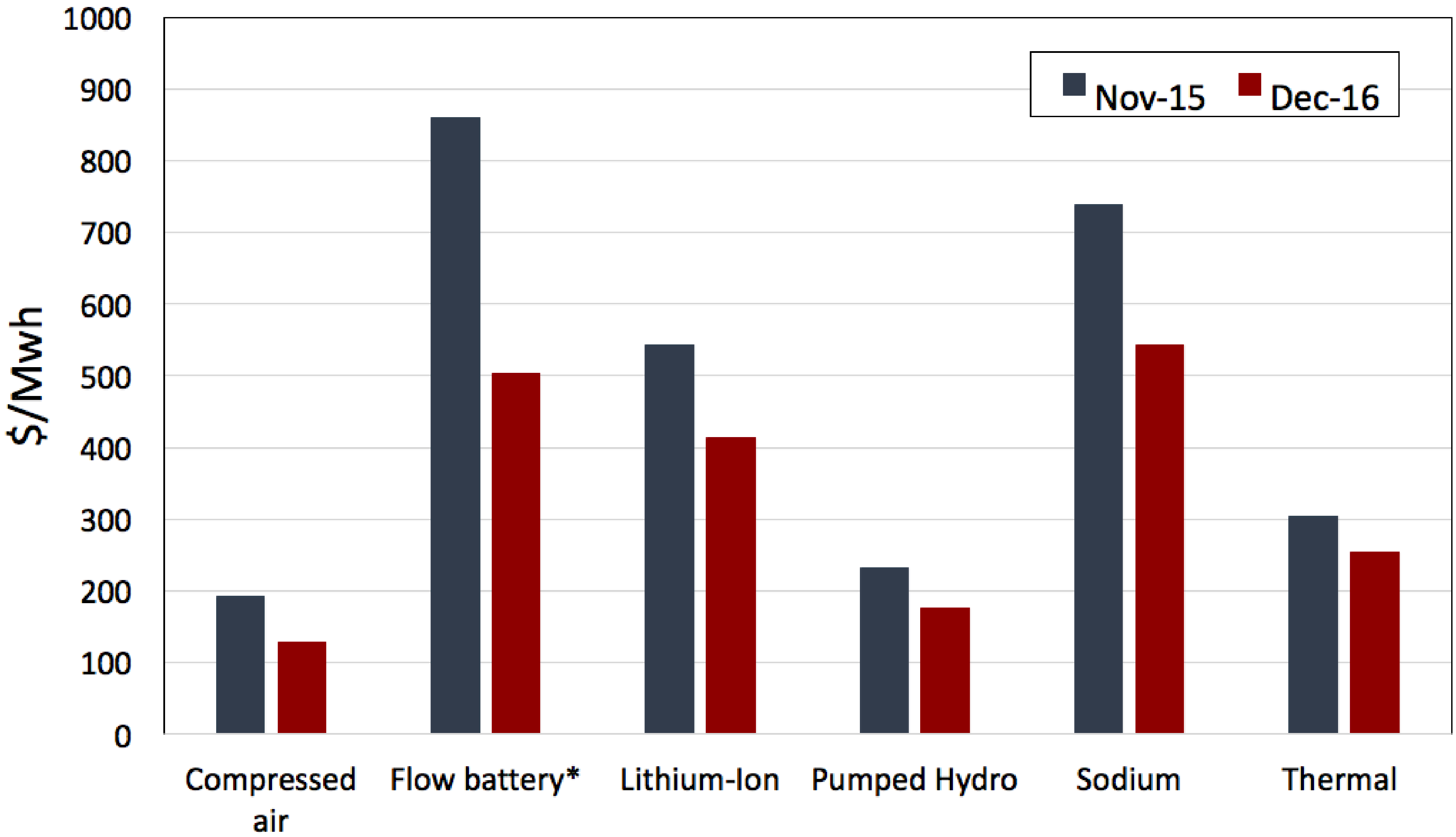
REF: Reference Scenario

Source: REN21: Global Energy Futures Report

Storage

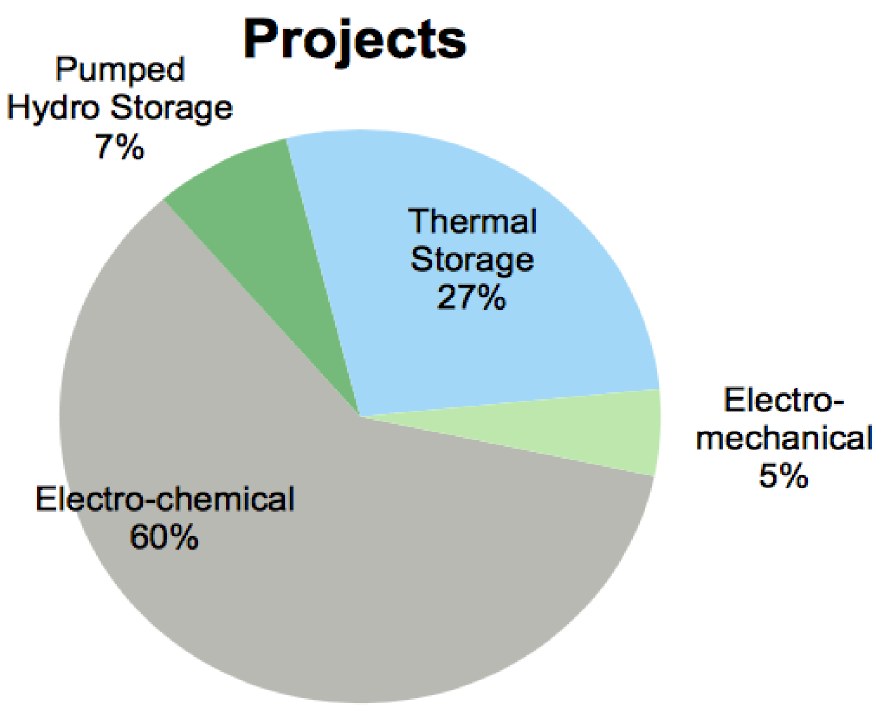
- Storage is known to be an enabling technology for high penetration of renewables
- Economics have not historically been viable, but improving!
- Significant advancements have focused on vehicle electrification
- The use of storage will support global and local efforts toward a sustainable energy system

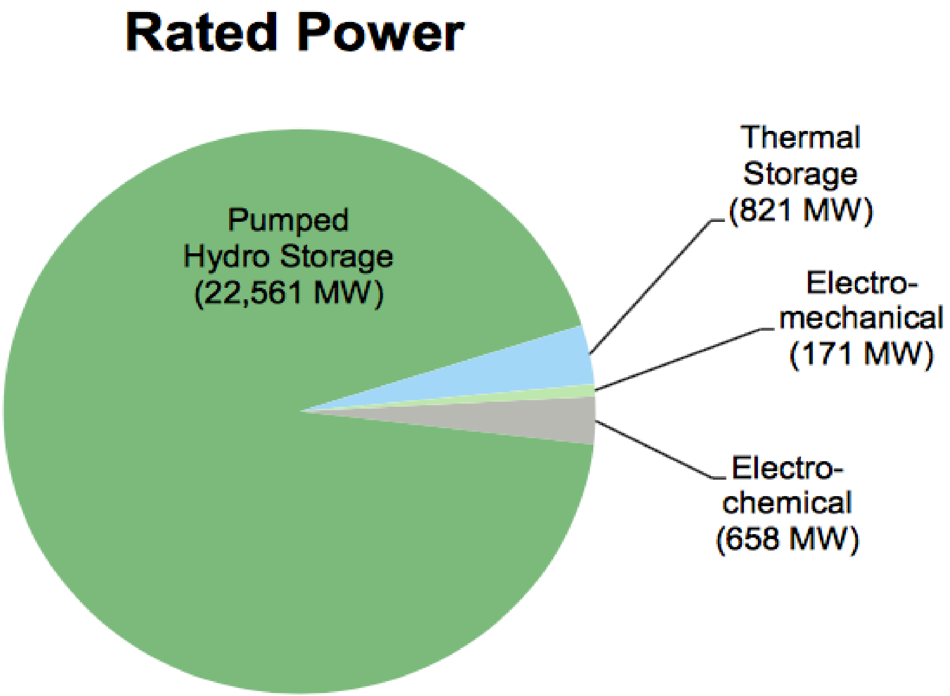
Levelized Cost of Storage (in decline)



Data compiled from Lazard's Levelized Cost Of Storage Analysis, Versions 1.0 and 2.0
https://www.lazard.com/media/2391/lazards-levelized-cost-of-storage-analysis-10.pdf
https://www.lazard.com/media/438042/lazard-levelized-cost-of-storage-v20.pdf

US Energy Storage Projects 2017





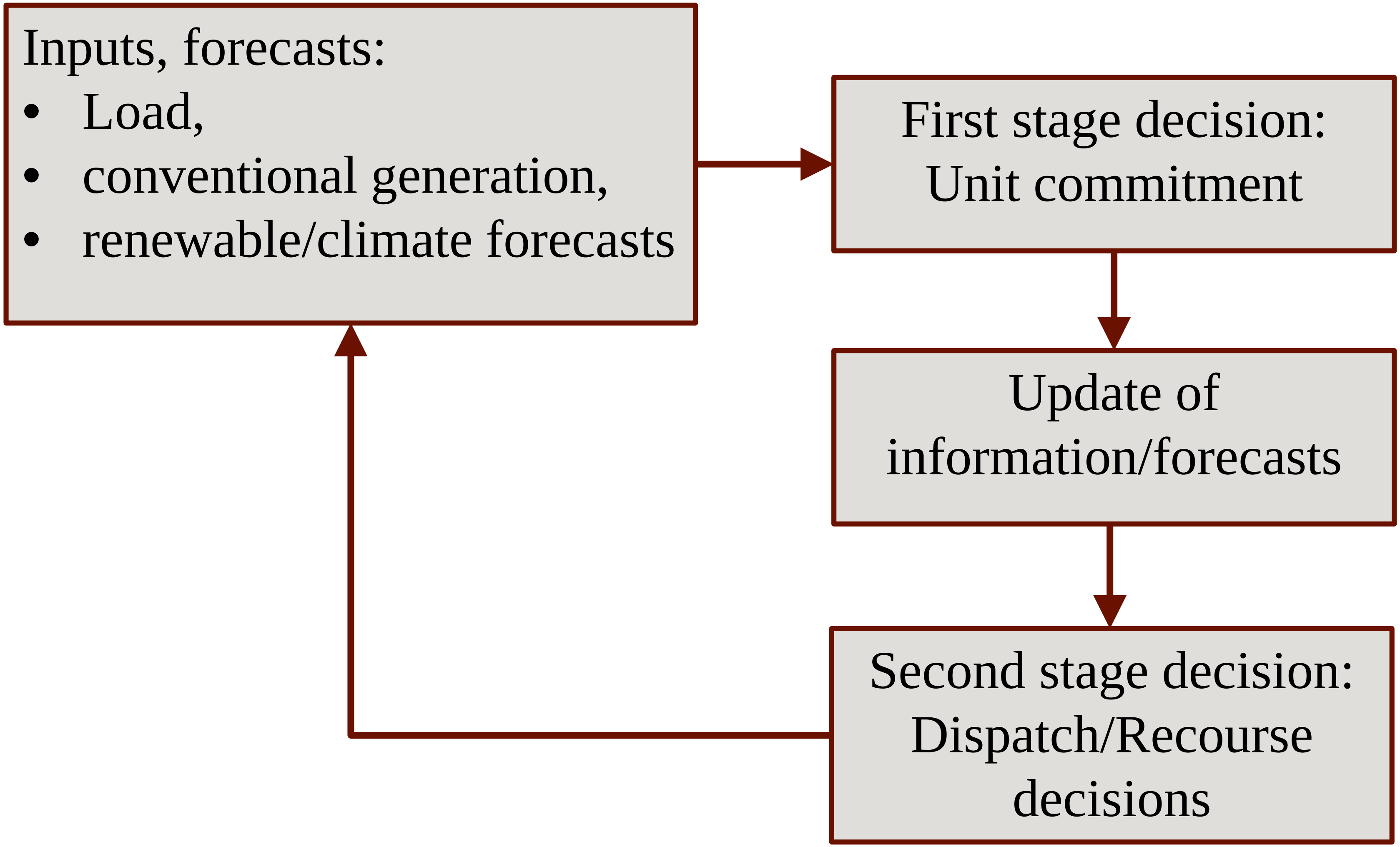
"A main challenge for energy storage is the ability to seamlessly integrate with existing systems, leading to its ubiquitous deployment."

(US DOE Grid Energy Storage Report (2013))

Incorporating Storage in Operational Decisions

The object of this project is to develop methods that incorporate storage into dispatch decisions, in an accurate, effective and scalable manner

The Power Network Decision Problem



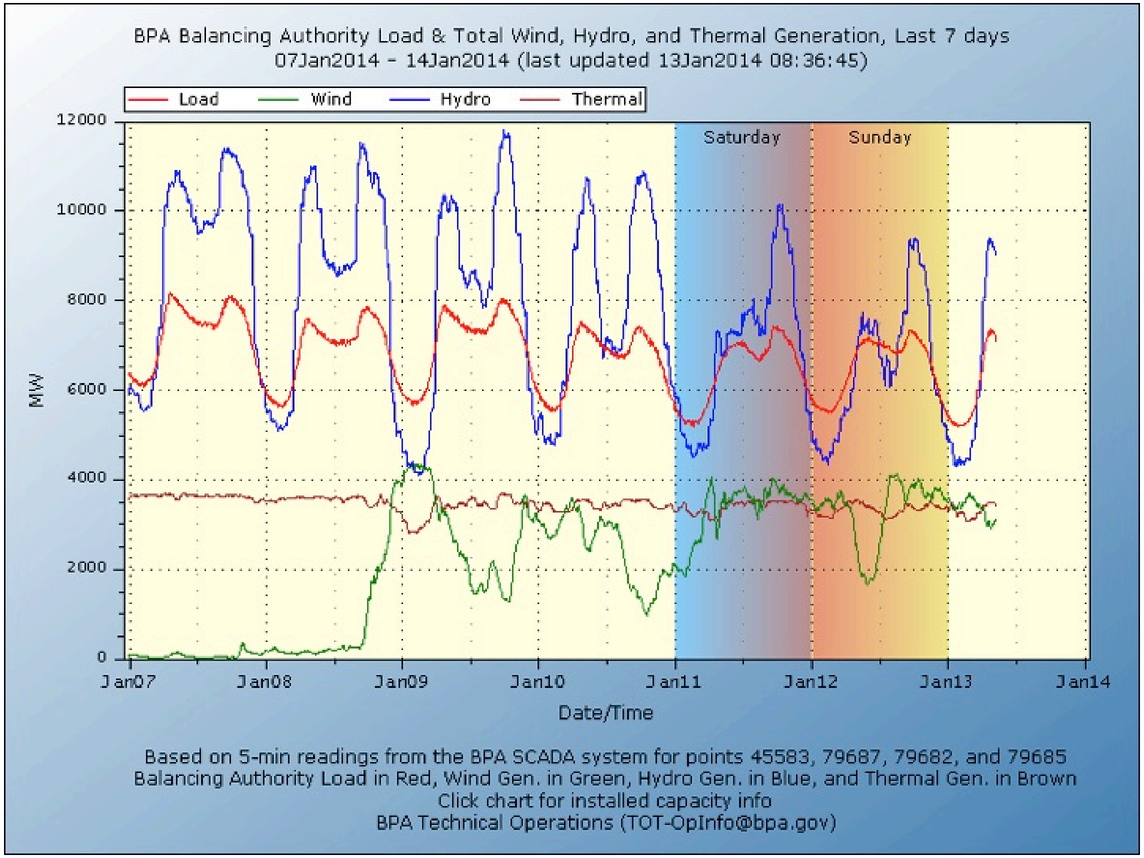
ED with Storage and Wind Integration

<u>Static constraint</u>
Power balance at all times
Transmission constraints

<u>Dynamic constraints</u>
Ramping constraints
Storage dynamics

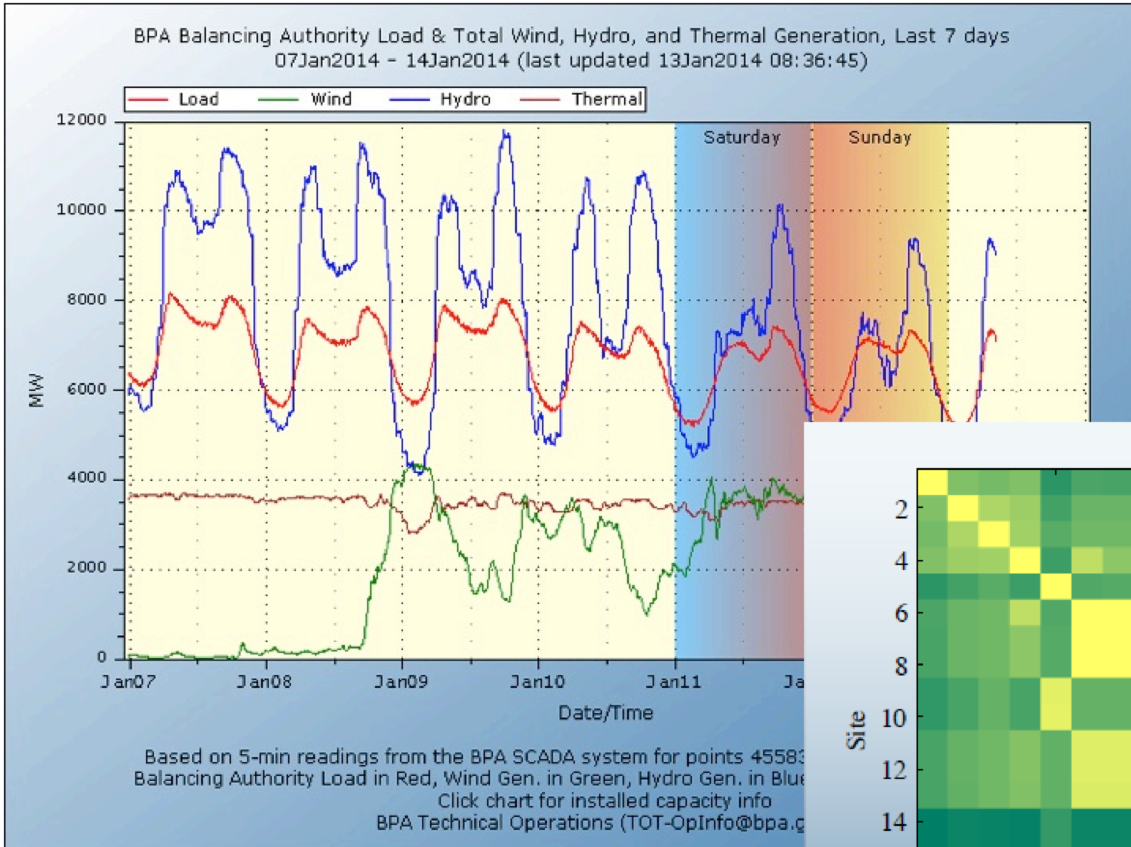
Inter-temporal dynamic decisions and constraints even more important in the presence of storage

Wind Uncertainty

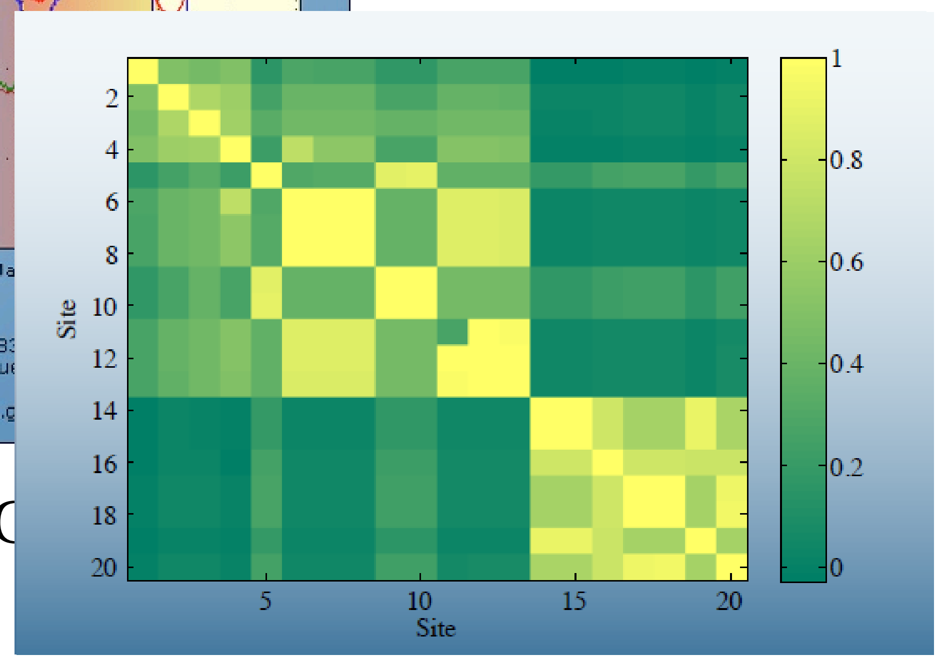


Temporal Variability of Wind Generation

Wind Uncertainty

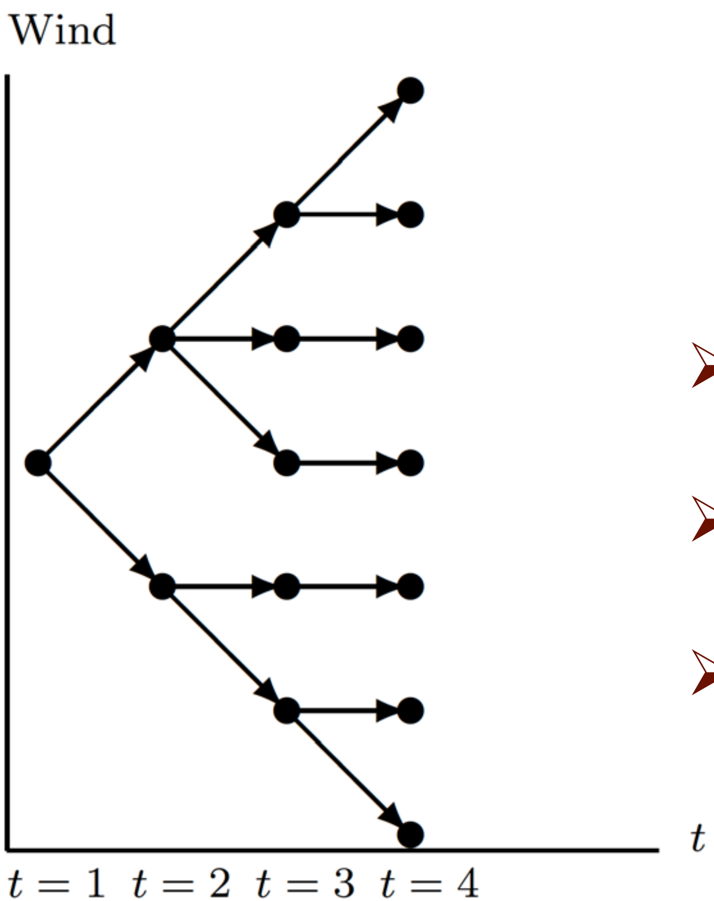


Temporal Variability of Wind



Spatial correlation between wind sites

Representing Wind Uncertainty



Example of a scenario tree

- Uncertainty increases over horizon
- Correlations are non-trivial
- Computational burden can be high

Mathematical Representation

$$\min \ \mathbb{E}\left[\sum_{t=1}^{T} c_t\left(\cdot\right)\right]$$

Subject to, for all nodes, and all time periods

$\Phi(p_t, d_t, w_t) = 0$	Power balance equations
$\Theta(\theta_t, e_t) = 0$	Power flow equations
$\Xi(s_t, \Delta_t) = 0$	Storage dynamics
$\underline{\Psi}_t \leq \Psi_t \leq \overline{\Psi}_t$	Bounds on decision variables, ramping constraints

$c_t\left(\cdot\right)$ is a cost function at period t.

Mathematical Representation

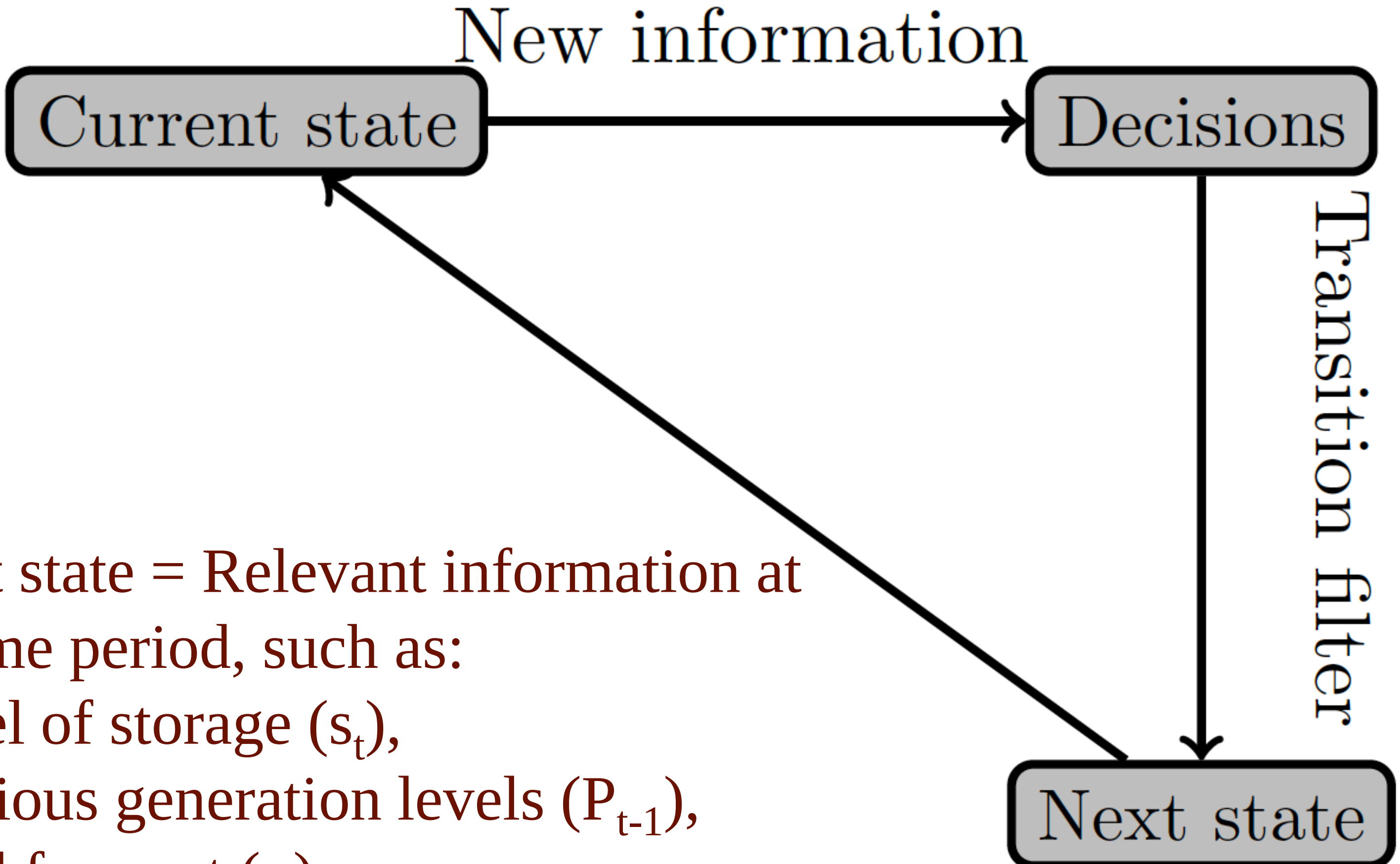
$$\min \ \mathbb{E}\left[\sum_{t=1}^{T} c_t(\cdot)\right]$$

Subject to, for all nodes, and all time periods

$\Phi(p_t, d_t, w_t) = 0$	Power balance equations
$\Theta(\theta_t, e_t) = 0$	Power flow equations
$\boxed{\Xi(s_t, \Delta_t) = 0}$	Storage dynamics
$\underline{\Psi}_t \leq \Psi_t \leq \overline{\Psi}_t$	Bounds on decision variables, ramping constraints

$c_t(\cdot)$ is a cost function at period t.

Structure of the EDP Decision Process



Current state = Relevant information at each time period, such as:

- ✓ Level of storage (s_t),
- ✓ previous generation levels (P_{t-1}),
- ✓ wind forecast (r_t)
- ✓ past wind output (w_{t-1})…

Mathematical Formulation with Decision Process

For $t = T, T-1, \cdots, 1$:

$$F_t(s_t, p_{t-1}, w_{t-1}) = \min\left\{c_t(\cdot) + \mathbb{E}\left[F_{t+1}(s_{t+1}, p_t, \tilde{W}_t)\right]\right\}$$

$$\text{S.t.} \quad \Phi(p_t, d_t, w_t) = 0$$

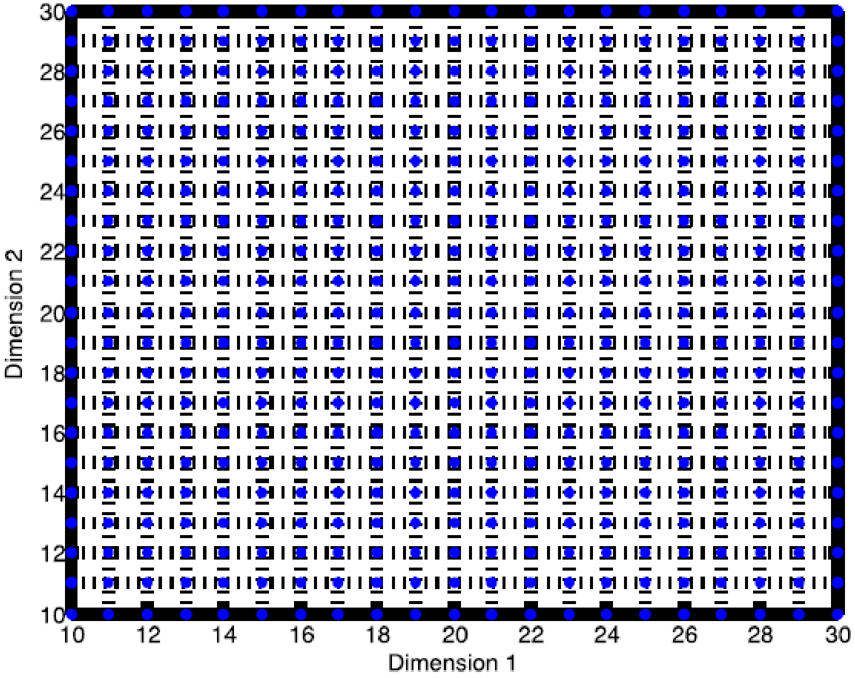
$$\Theta(\theta_t, e_t) = 0$$

$$\Xi(s_t, \Delta_t) = 0$$

$$\underline{\Psi}_t \leq \Psi_t \leq \overline{\Psi}_t$$

- $F_{t+1}(s_{t+1}, p_t, w_t)$, called *cost-to-go* is the cost from period $t+1$ through the end of the horizon.
- Two sources of complexity:
  - Computation of an expectation
  - Optimization step for **each** *state value* (s_t, p_{t-1}, w_{t-1})

Example of Discretization



Consider a 2-dimensional state space

Or consider:
5 wind turbines, 5 storage devices and 5 generators; Each dimension discretized into 10 levels (in each time period);

In total
10^5 x 10^5 x 10^5 $=10^{15}$ grid points.

The problem cannot be solved for all discrete state values (s_t, p_{t-1}, w_{t-1}).

Curse of Dimensionality

- For instance, excluding the ramping constraints, and the wind farms
- Let n be the number of storage units, and
- assume each storage level is discretized into k values each

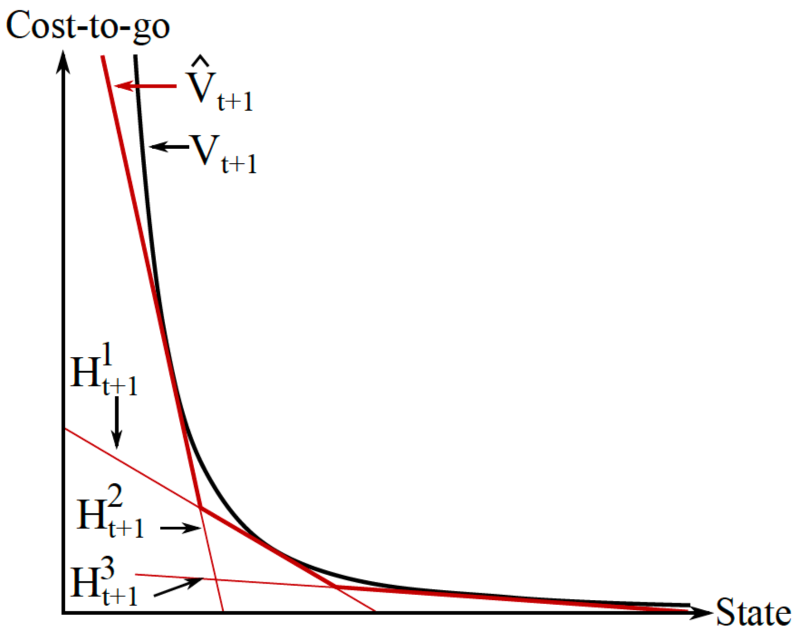
n	k	Size of the grid
2	7	49
5	7	16 807
7	7	823 543
10	7	282 475 249
13	7	96 889 010 407
15	7	4 747 561 509 943

Approximation via Stochastic Dual Dynamic Programming (SDDP)

- Developed by Pereira and Pinto (1985, 1991), borrowing ideas from Bender's decomposition
- Main idea : No discretization of the space, but sampling
- Success stories in hydrothermal system management problems
- Alternates between
  - forward (to sample the state space), and
  - backward loop (to refine the approximation)

SDDP Approximation

- Replace $\mathbb{E}\left[F_{t+1}(s_{t+1}, p_t, \tilde{W}_t)\right]$ (assumed to be convex) with some **lower bound** $\hat{V}_{t+1}(s_{t+1}, p_t, w_t)$.



- $\hat{V}_{t+1}(s_{t+1}, p_t, w_t) := \max_i \{H^i_{t+1}(s_{t+1}, p_t, w_t) | i \in I\}$

SDDP Formulation

For $t = T, T-1, \cdots, 1$

$$\hat{F}_t(s_t, p_{t-1}, w_{t-1}) = \min \left\{ \sum_{t=1}^{T} c_t\left(\cdot\right) + \rho_{t+1} \right\} \tag{1}$$

$$\text{S.t.} \quad \Phi(p_t, d_t, w_t) = 0 \tag{2}$$

$$\Theta(\theta_t, e_t) = 0 \tag{3}$$

$$\Xi(s_t, \Delta_t) = 0 \tag{4}$$

$$\underline{\Psi}_t \leq \Psi_t \leq \overline{\Psi}_t \tag{5}$$

$$\rho_{t+1} \geq \tilde{c}^i_{t+1} + \tilde{g}_{s^i_{t+1}} s_{t+1} + \tilde{g}_{p^i_t} p_t + \tilde{g}_{w^i_t} w_t, \ \ 1 \leq i \leq I \tag{6}$$

$[\tilde{c}^i_{t+1}, \tilde{g}_{p^i_t}, \tilde{g}_{w^i_t}]$ are computed at period $t+1$.

SDDP Formulation

For $t = T, T-1, \cdots, 1$

$$\hat{F}_t(s_t, p_{t-1}, w_{t-1}) = \min \left\{ \sum_{t=1}^{T} c_t(\cdot) + \rho_{t+1} \right\} \quad (1)$$

$$\text{S.t.} \quad \Phi(p_t, d_t, w_t) = 0 \quad (2)$$

$$\Theta(\theta_t, e_t) = 0 \quad (3)$$

$$\Xi(s_t, \Delta_t) = 0 \quad (4)$$

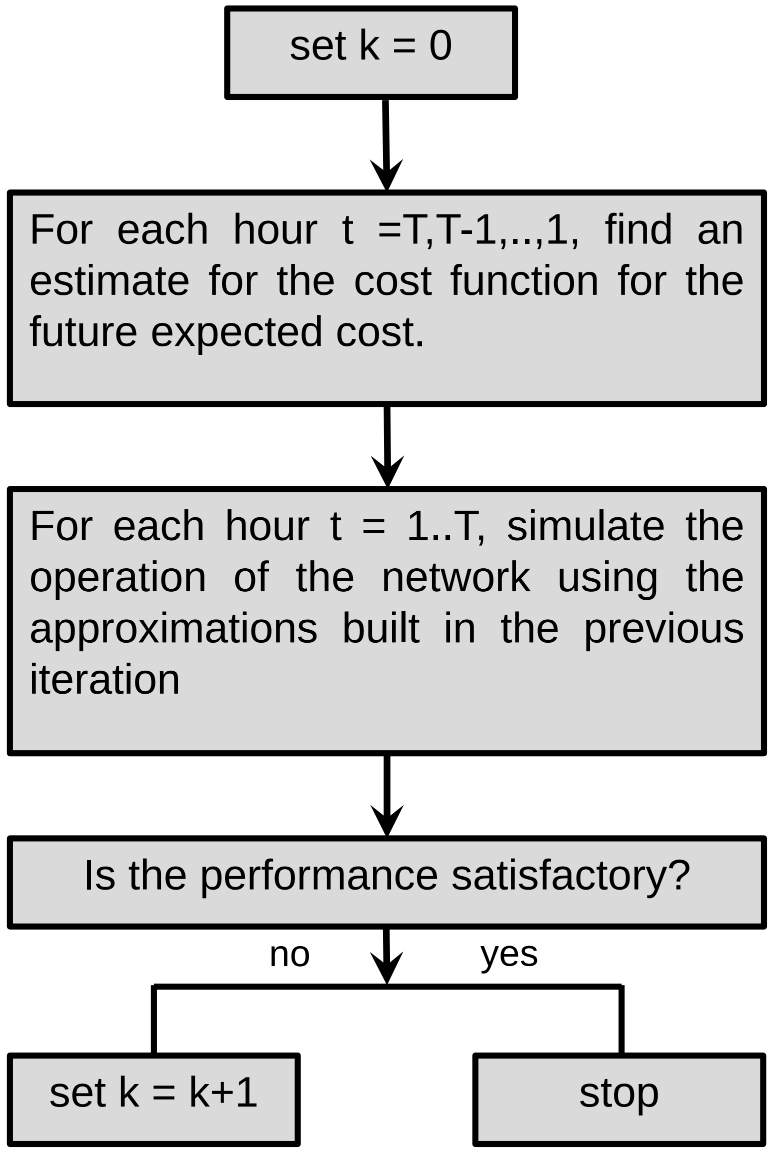
$$\underline{\Psi}_t \leq \Psi_t \leq \overline{\Psi}_t \quad (5)$$

$$\rho_{t+1} \geq \tilde{c}^i_{t+1} + \tilde{g}_{s^i_{t+1}} s_{t+1} + \tilde{g}_{p^i_t} p_t + \tilde{g}_{w^i_t} w_t, \quad 1 \leq i \leq I \quad (6)$$

Faster computation of the (approximate) value function

$[\tilde{c}^i_{t+1}, \tilde{g}_{p^i_t}, \tilde{g}_{w^i_t}]$ are computed at period $t+1$.

Algorithm Procedure



Algorithm Procedure

```
Inputs : Initial state
Initialize stopping criterion
while stopping criterion not met do
    Simulate M trajectories of wind output
    Forward Loop
    for For each wind value do
        for For each time period (from the first to the last) do
            Solve the current approximate problem
            Store the optimal decisions
        end for
    end for
    Backward Loop
    for each time period, starting at the last one do
        for each optimal decision from the previous forward loop do
            sample K wind values for the current period
            for each sampled wind value do
                solve the approximate problem using the trial decisions from the previous forward pass
                calculate $[\tilde{c}^i_{t+1}, \tilde{g}_{p^i_t}, \tilde{g}_{w^i_t}]$
            end for
        end for
    end for
    update the convergence criterion
end while
```

Sample Results

1. ‘Validation’ results with IEEE 9-bus test system
    - Comparison with SDP as a ”true” solution

2. Testing with IEEE 57- and 118-bus systems
    - four correlated wind farms
    - 30% capacity factor
    - 20% wind penetration
    - four storage units at highest load buses

A good approximate algorithm should prescribe when to charge, and discharge the batteries, based upon the load profile and battery characteristics.

Preliminary Results: IEEE 9-bus system

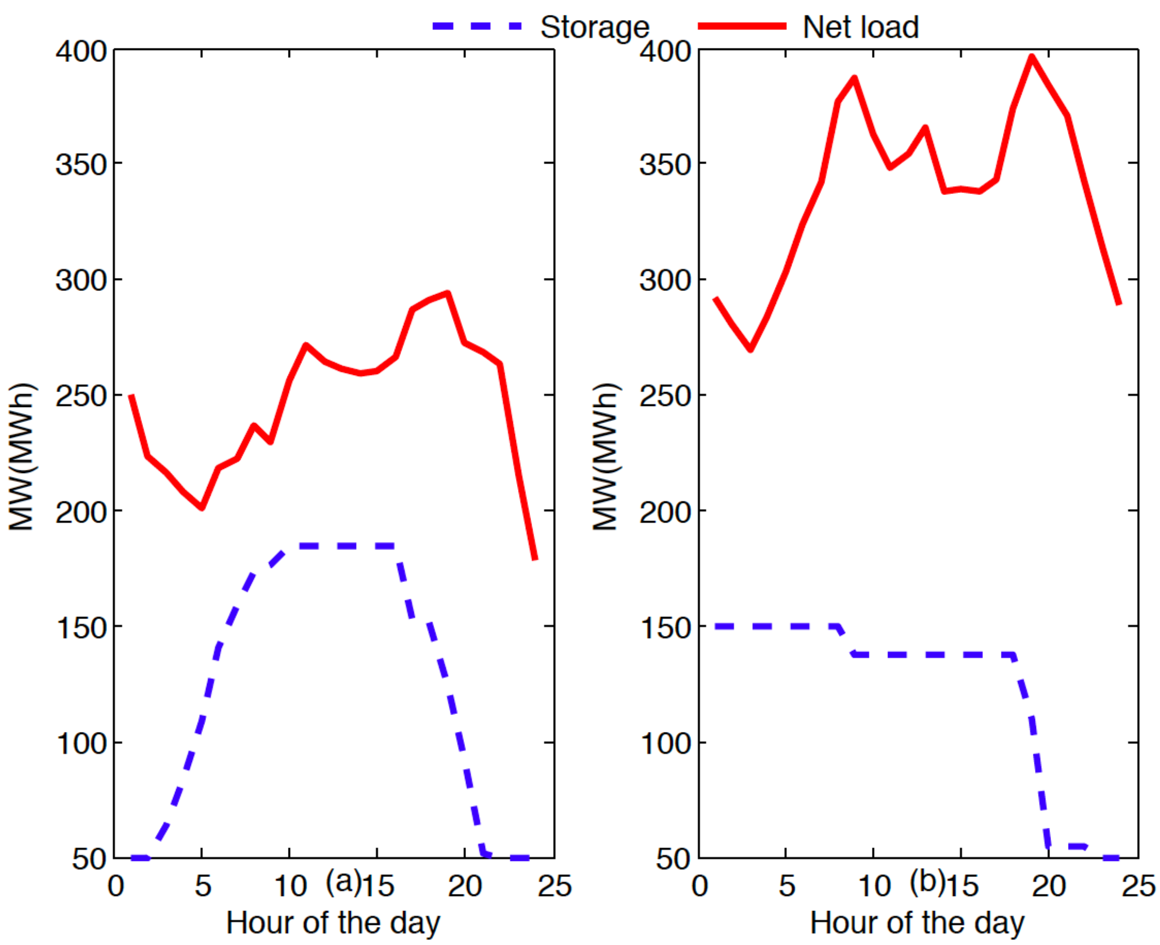


Figure: Example of storage trajectory when charging (discharging) cost is low

Preliminary Results: IEEE 9-bus system

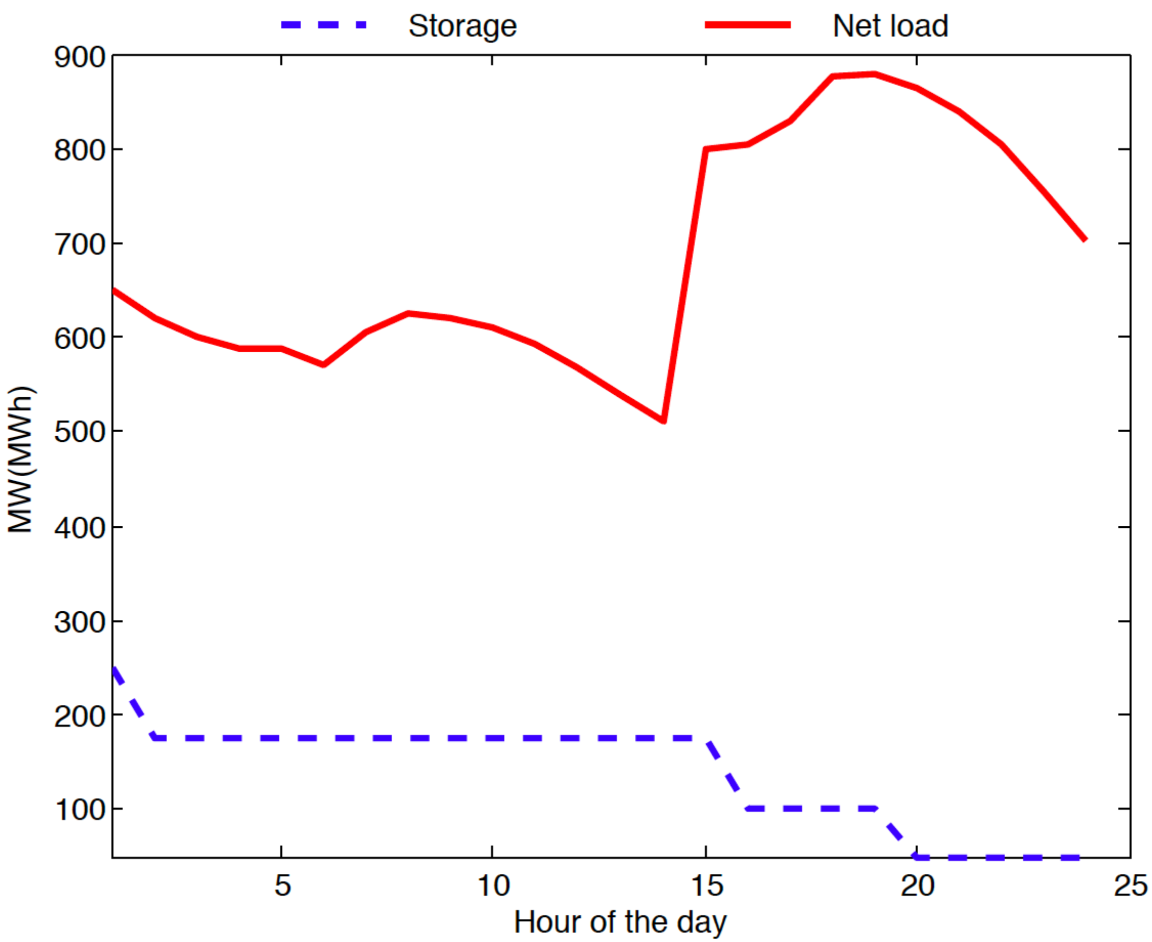


Figure: Example of storage trajectory when charging (discharging) cost is high

Benchmarking to SDP

Table: CPU time in seconds: SDDP and SDP

Method	Run 1	Run 2
SDDP	499.35	1 876.22
SDP	13 038.16	12 726.88

10-30 mins versus 3.5 hours

Table: Solution cost: SDDP and SDP

Method	Run 1			
	Min	Max	Mean	Stand. deviation
SDDP	78 622.29	162 215.38	126 872.83	21 812.53
SDP	75 392.76	161 872.07	125 968.26	22 922.10
Method	Run 2			
	Min	Max	Mean	Stand. deviation
SDDP	88 691.21	164 333.09	134 267.42	19 210.77
SDP	85 882.05	164 333.09	133 981.13	19 657.52

Benchmarking to SDP

Validation experiments conducted on the IEEE 9-bus test system

- differential allocation of storage resources,
- responsive to individual storage parameters
- accurate relative to SDP solution, but
- significantly less computational burden

Example of Optimal Storage Strategy

118-bus system

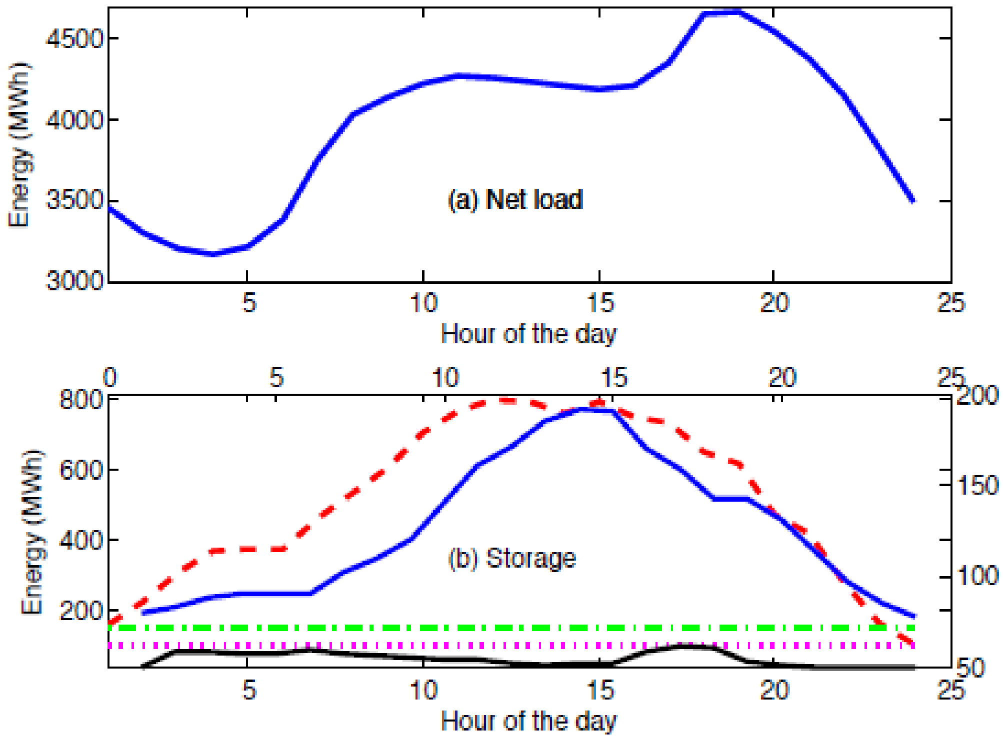
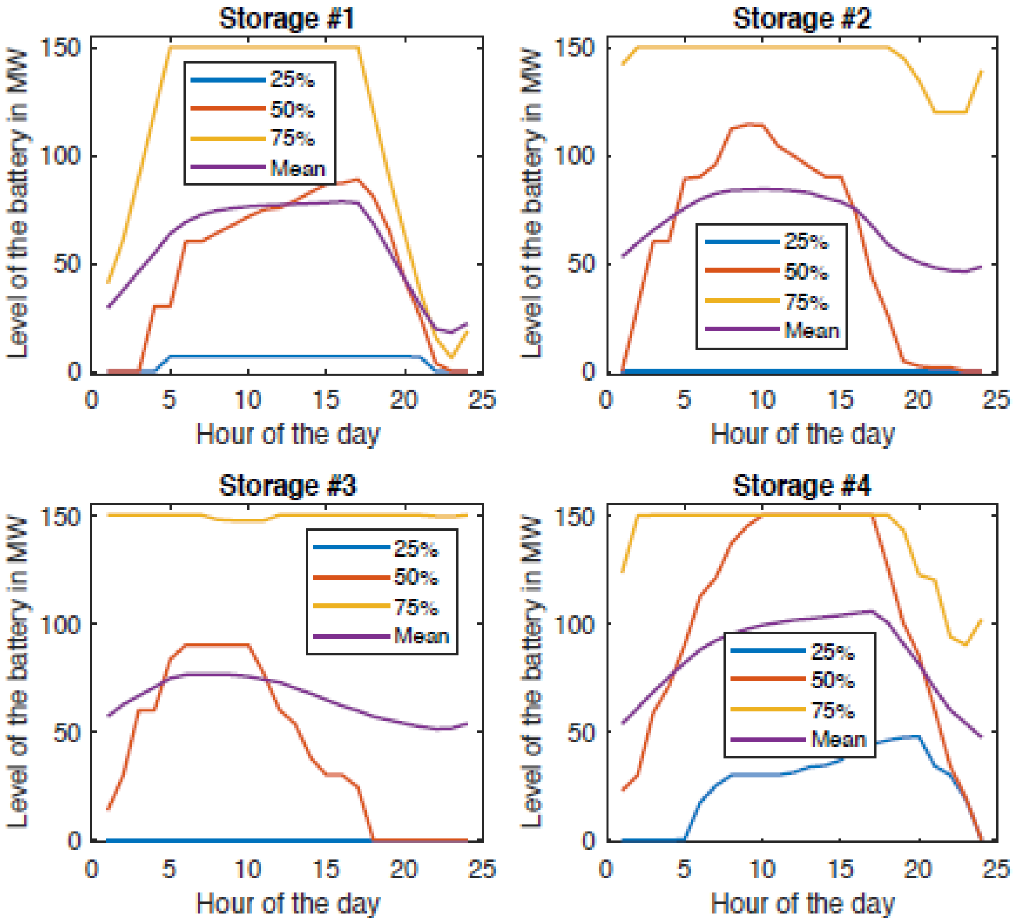


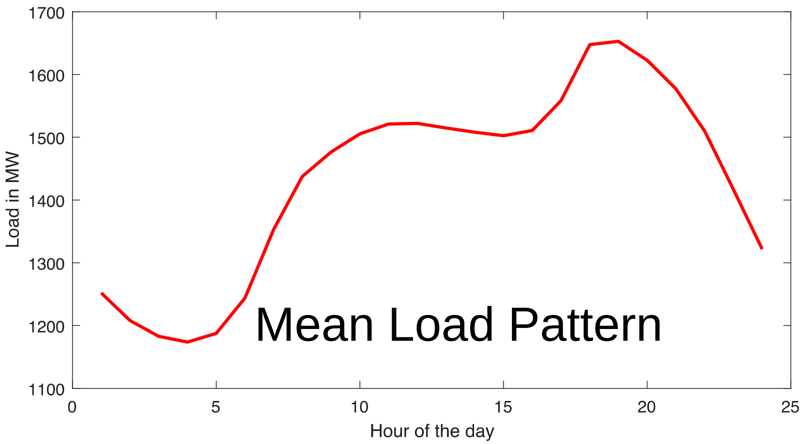
Figure: Mean storage trajectory (over 100 simulations) : five storage units and one wind farm

Example of Optimal Storage Strategy

57-bus system



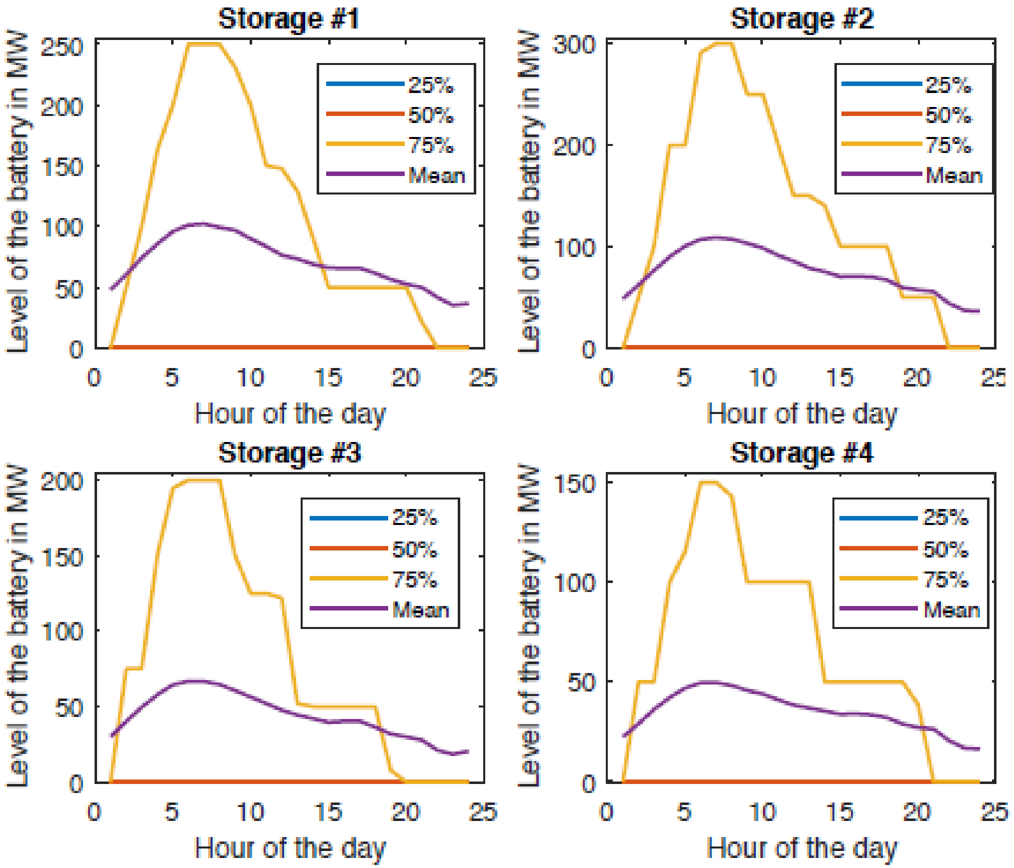
Storage Use Patterns



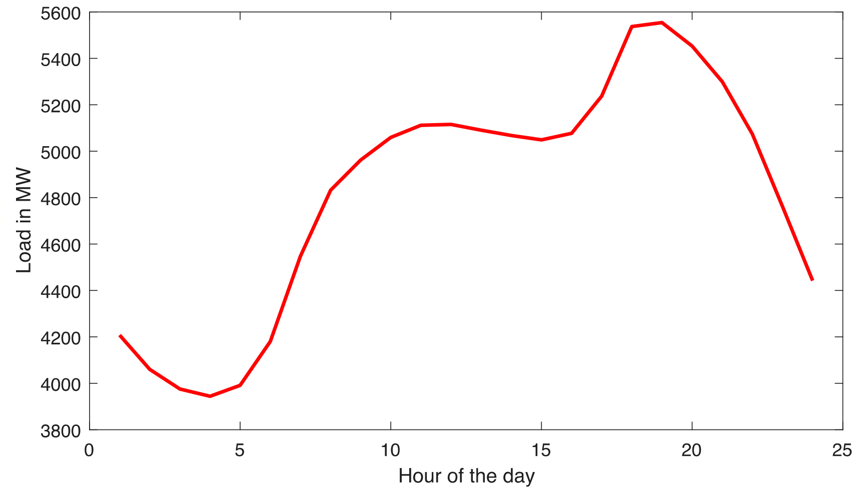
Mean Load Pattern

Example of Optimal Storage Strategy

118-bus system



Storage Use Patterns

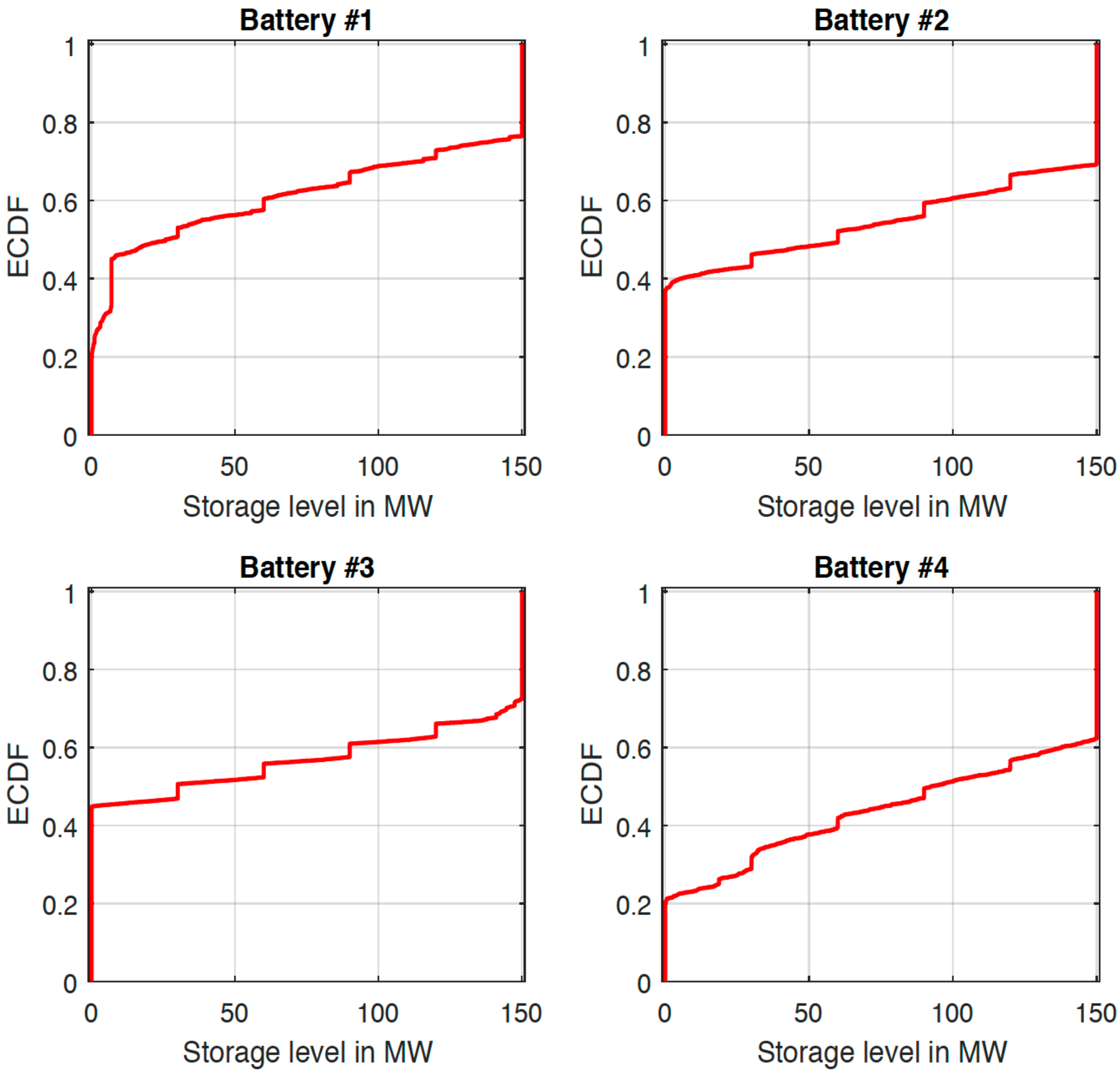


Patterns of storage use

- mean storage trajectory follows the load pattern of the system, and
- cheaper storage is used more frequently.

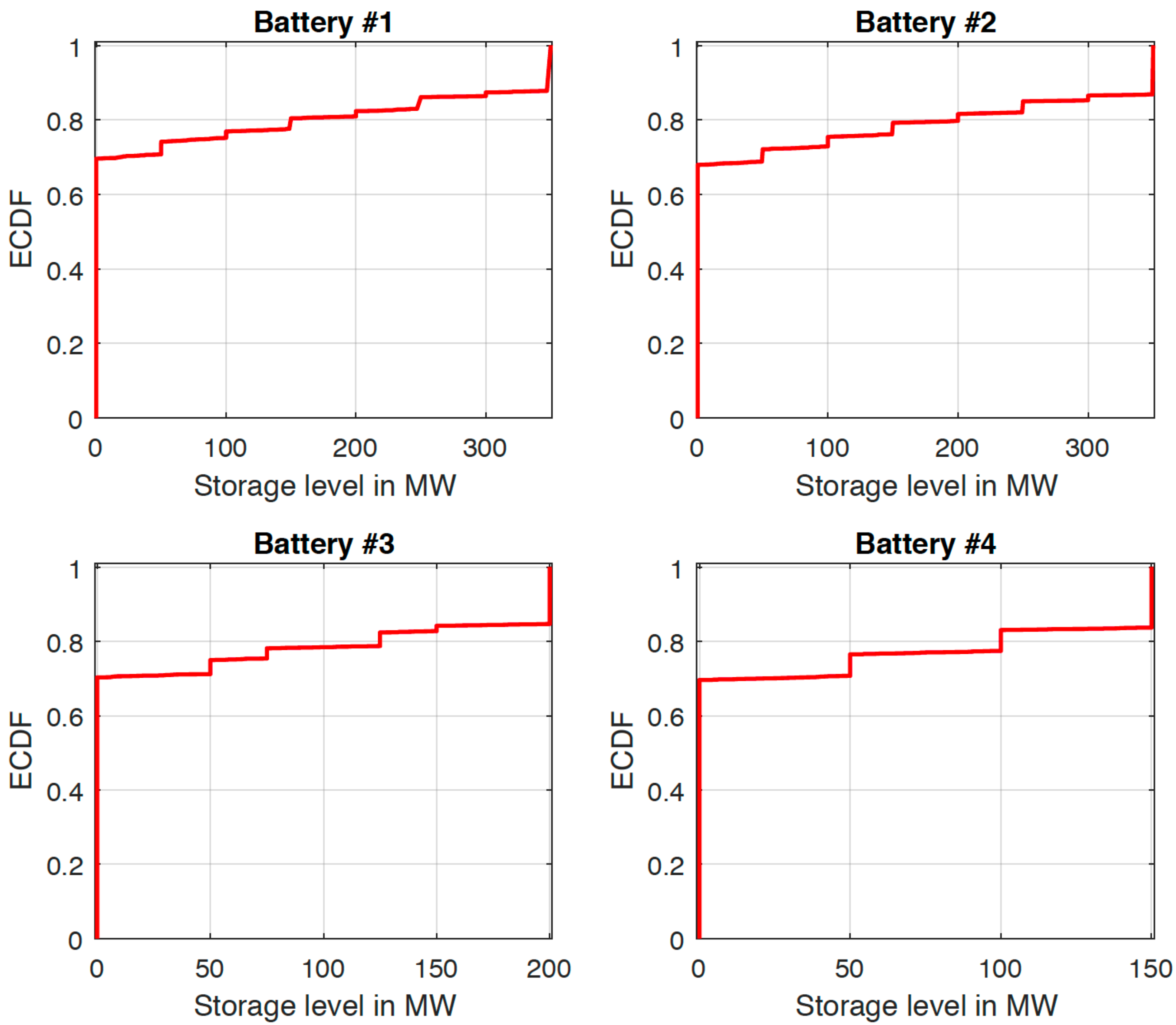
Optimal Utilization of Batteries

IEEE 57-bus system



Optimal Utilization of Batteries

IEEE 118-bus system



Comparing Solution Times

Table: Computation time in seconds for different number of buses, storage facilities and wind farms

# buses	$\|S\|$	$\|M\|$	Time	# buses	$\|S\|$	$\|M\|$	Time
30	1	1	1 229.80	118	1	1	2 399.35
30	5	1	1 582.67	118	5	1	2 444.99
30	5	5	1 323.88	118	5	5	2 453.89
57	1	1	1 388.09	118	10	5	2 179.62
57	5	1	1 454.47	118	20	10	2 248.39
57	5	5	1 396.26	300	1	1	4 159.16
57	10	5	1 597.71	300	5	1	4 234.72
89	1	1	1 570.67	300	5	5	4 570.01
89	5	1	1 709.68	300	10	5	4 617.65
89	5	5	1 575.09	300	20	10	5 036.37
89	10	5	1 737.32				

The solution time seems to remain reasonable as the size of the network and the dimension of the state space increase.

SDDP Summary

- like SDP, allows optimization of the trade-off between here-and-now reward against the value of future flexibility
- exhibits appropriate use of storage units
- approximation manages the dimensionality problem for computational tractability,
- relatively easy to implement,

SDDP allows the effective dynamic optimization with computation time and solution accuracy

Conclusions

- The challenge of distributed storage can be handled with accurate approximate methods
- Individual storage facilities can be modeled individually and operated in a jointly optimal way
- Related work considers the importance of accounting for correlation among wind sites

Next Steps

- testing on larger systems, with high penetration, more distributed units
- operational parameters for existing facilities and will be useful in future

Questions?

Lindsay Anderson

(cla28@cornell.edu)