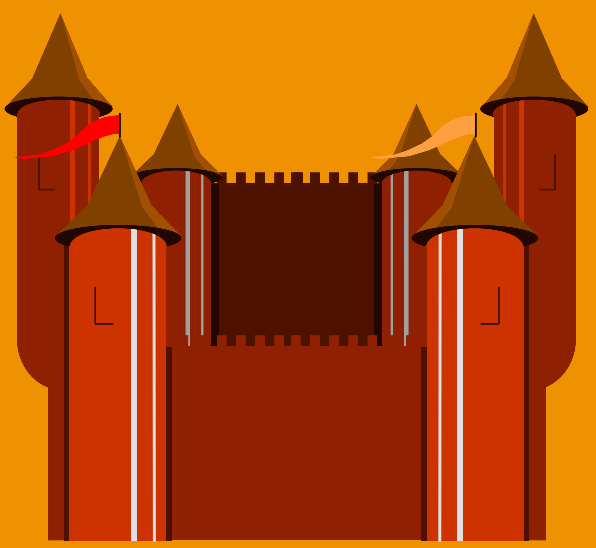
# Energy Storage and Renewables in New Jersey: Complementary Technologies for Reducing Our Carbon Footprint

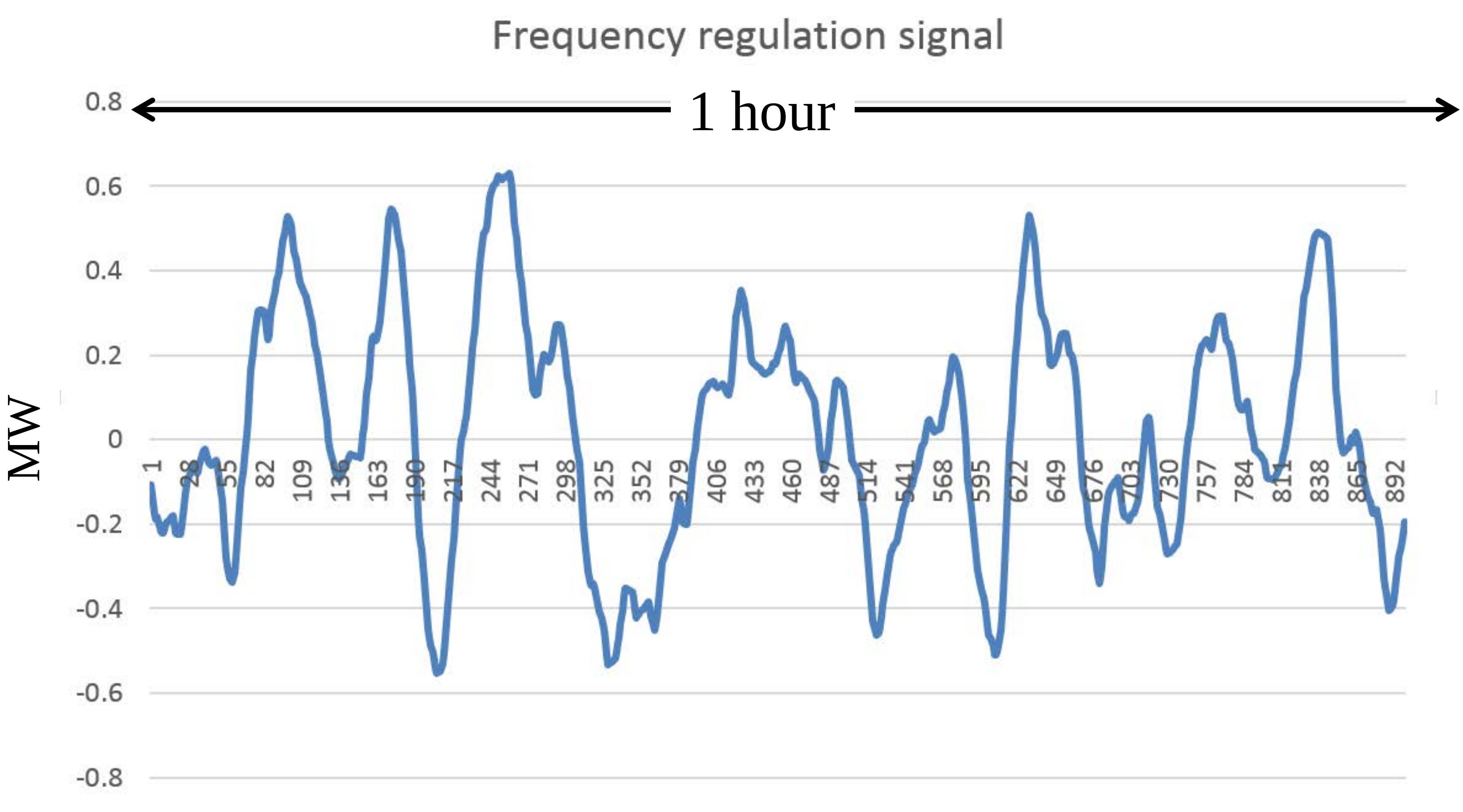
**ACEE E-filliates workshop**
**November 14, 2014**



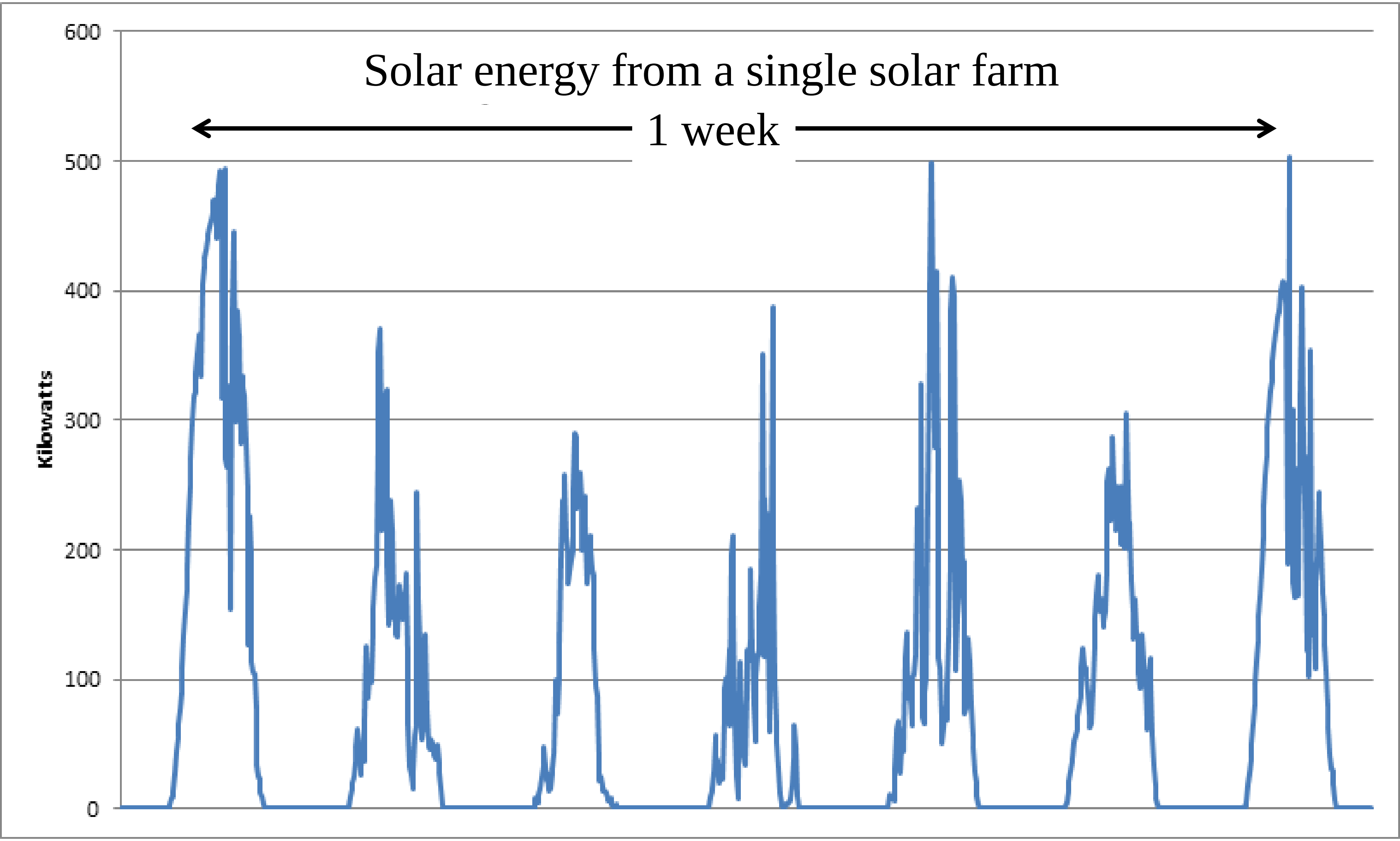

**Warren B. Powell**
**Daniel Steingart**
**Harvey Cheng**
**Greg Davies**

# Frequency regulation

- PJM sends charge/discharge signals to generators every 2 seconds to smooth out frequency/voltage variations

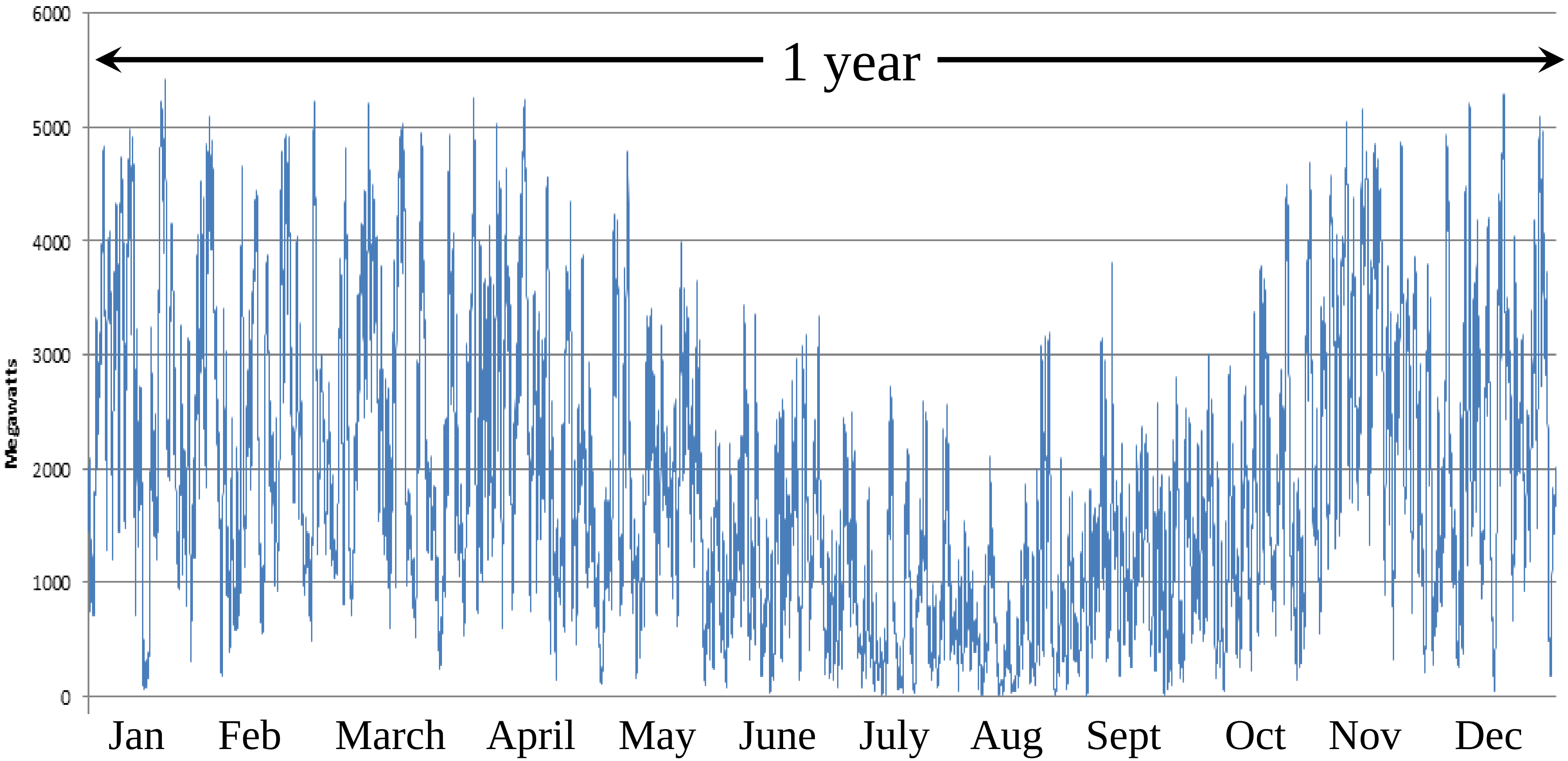


# Solar from PSE&G solar farms



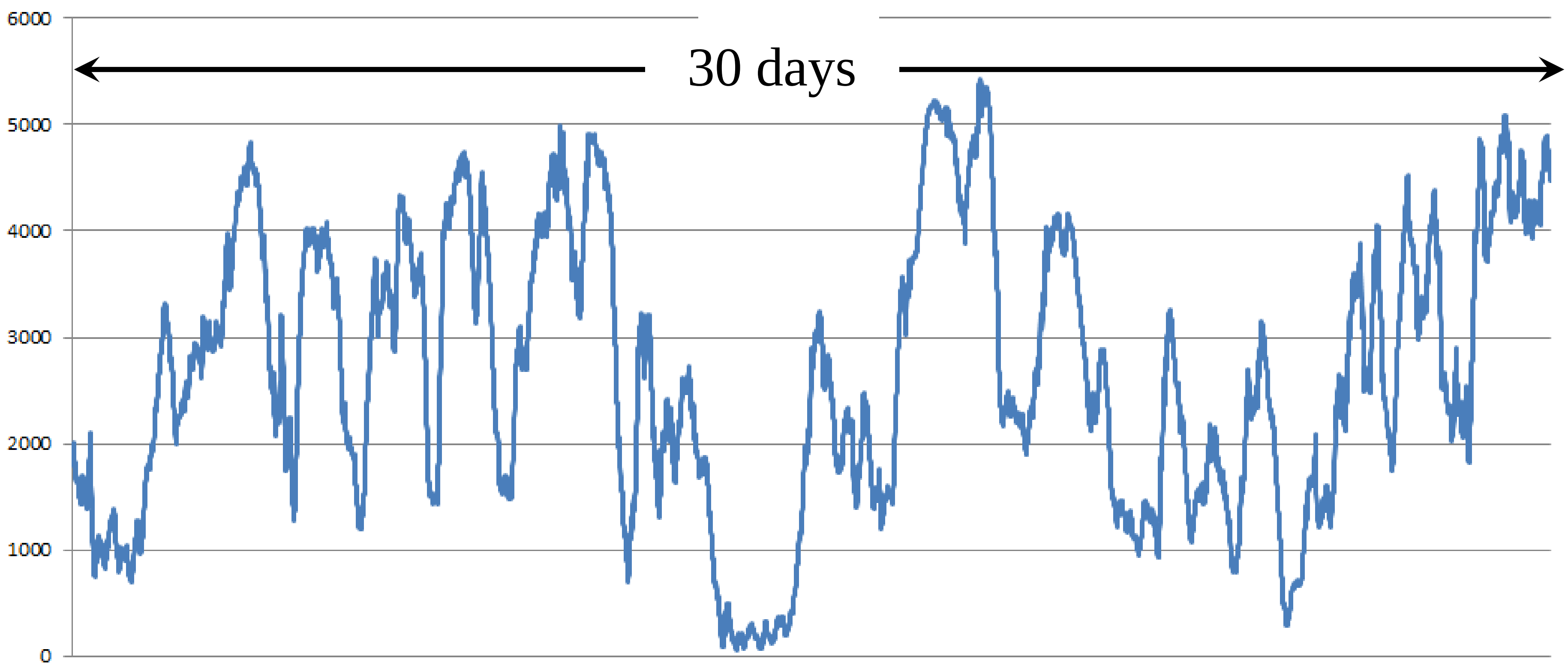
# Energy from wind

- Wind power from all PJM wind farms



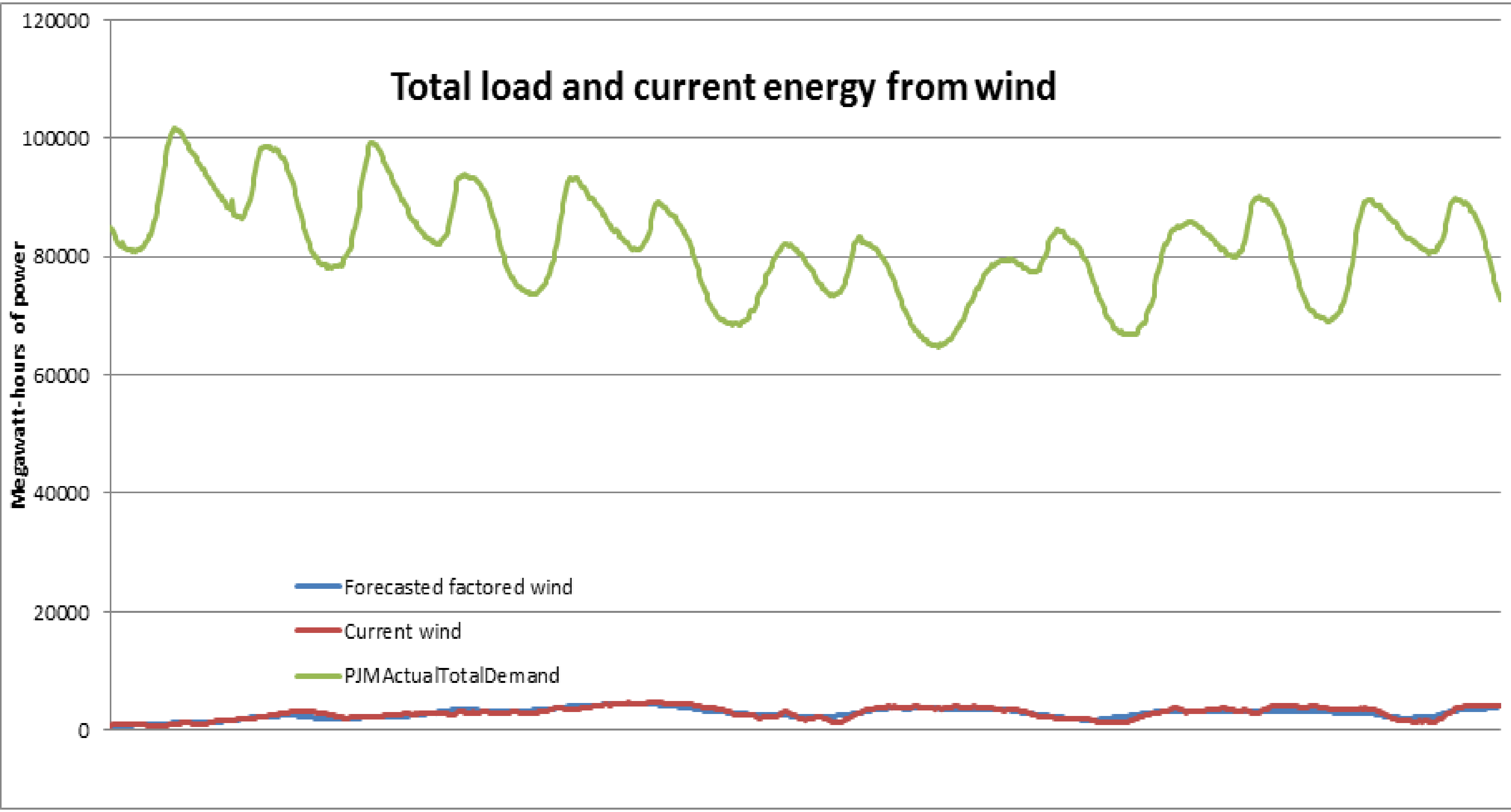
# Energy from wind

- Wind from all PJM wind farms



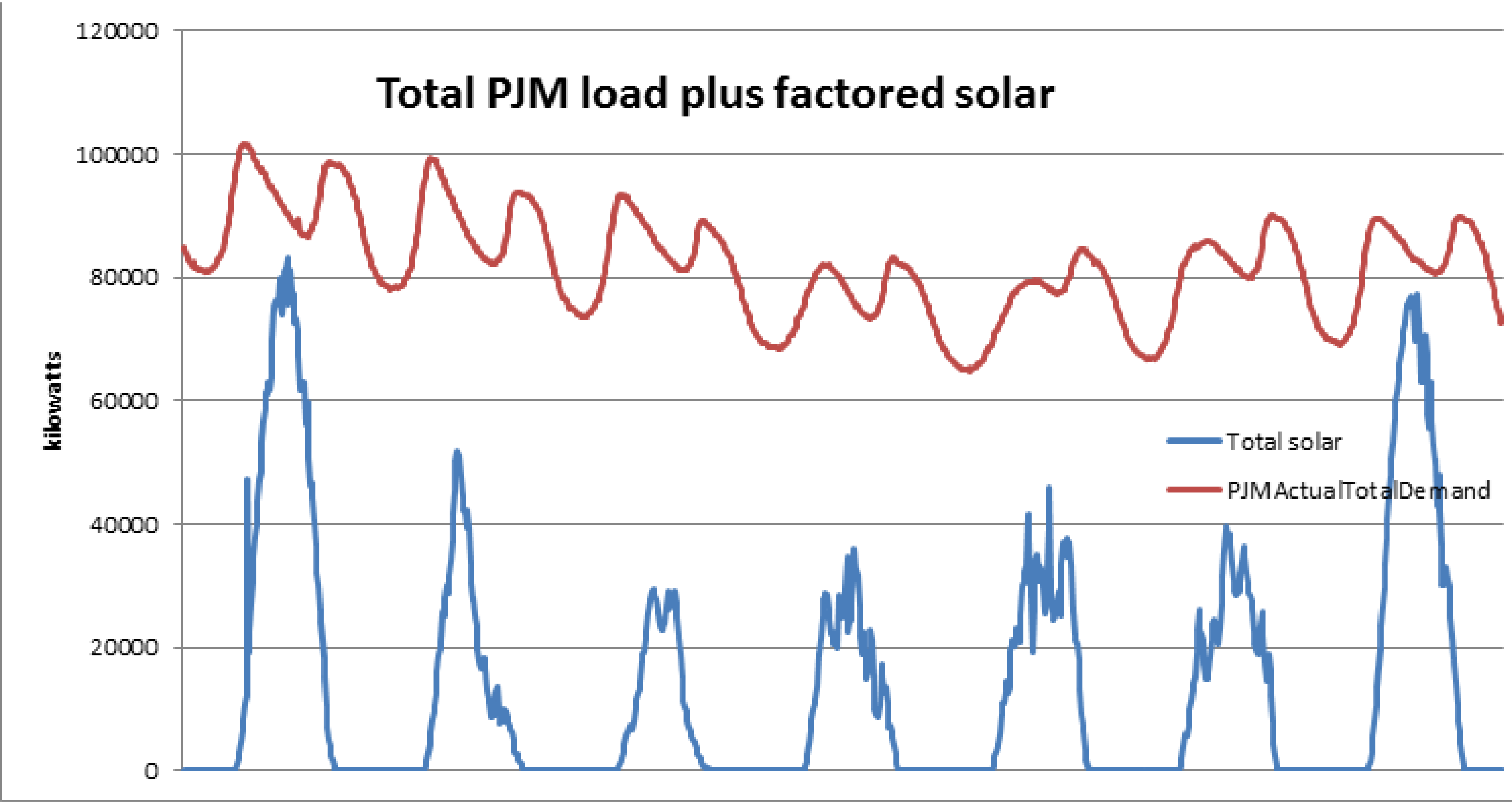
# Wind energy in PJM

- Total load vs. total current wind (January)



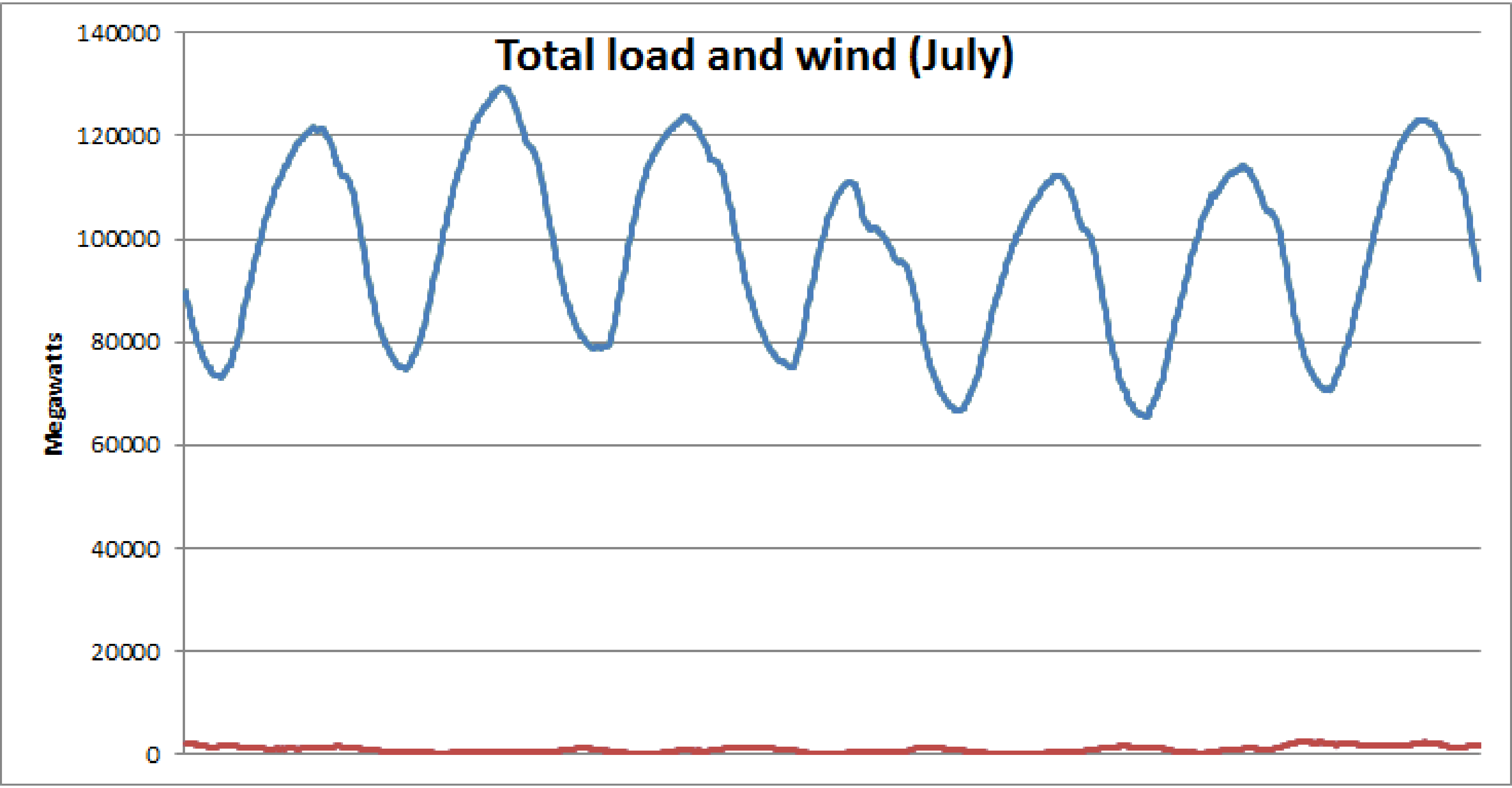
# Winter load and solar

- Total PJM load plus factored solar (January)



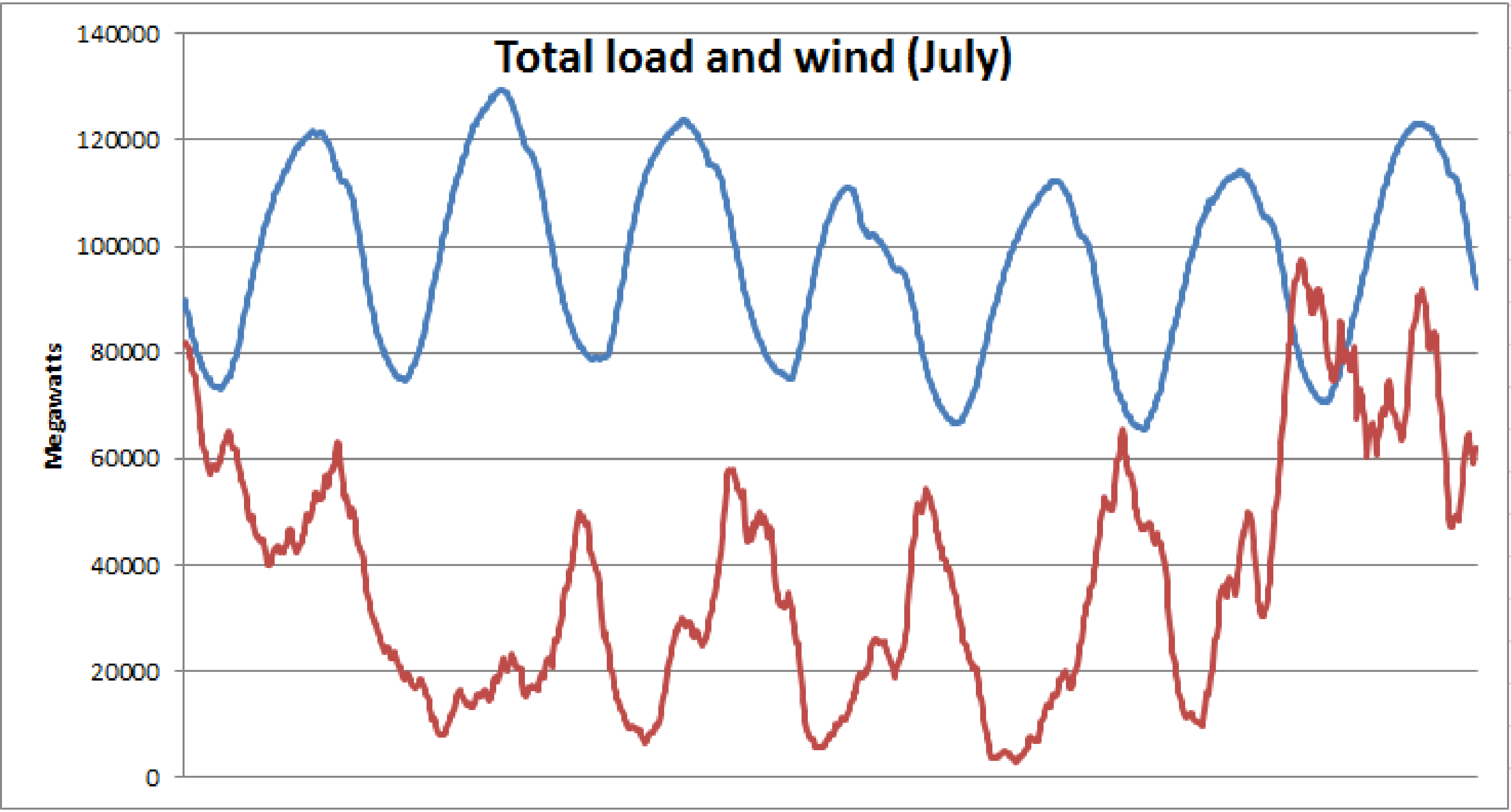
# Wind energy in PJM

- Total PJM load plus actual wind (July)



# Summer load and wind

- Total PJM load plus actual wind (July)



# 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

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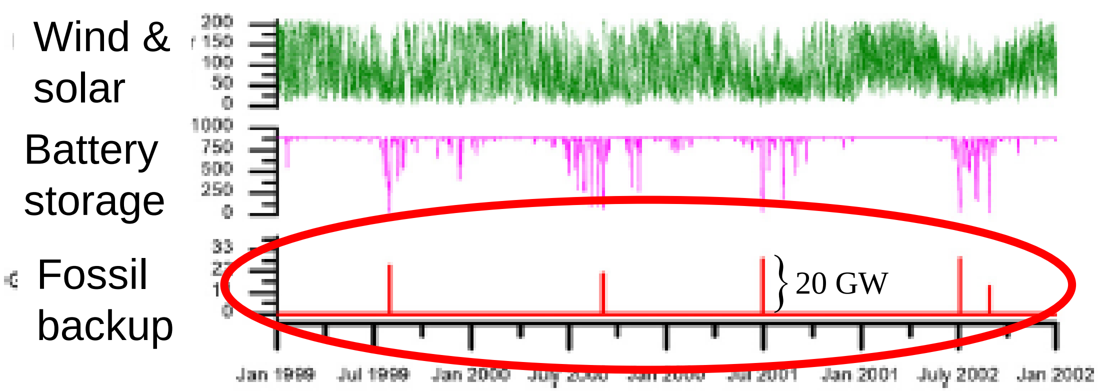
[b] *Department of Energy Management, Delaware Technical Community College, Newark, DE 19713, USA*
[c] *Center for Carbon-Free Power Integration, School of Marine Science and Policy, College of Earth Ocean and Environment, University of Delaware, Newark, DE 19716, USA*
[d] *Energy and Environmental Policy Program, College of Engineering, University of Delaware, Newark, DE 19716, USA*
[e] *Center for Electric Technology, DTU Elektro, Danmarks Tekniske Universitet, Kgs. Lungby, Denmark*

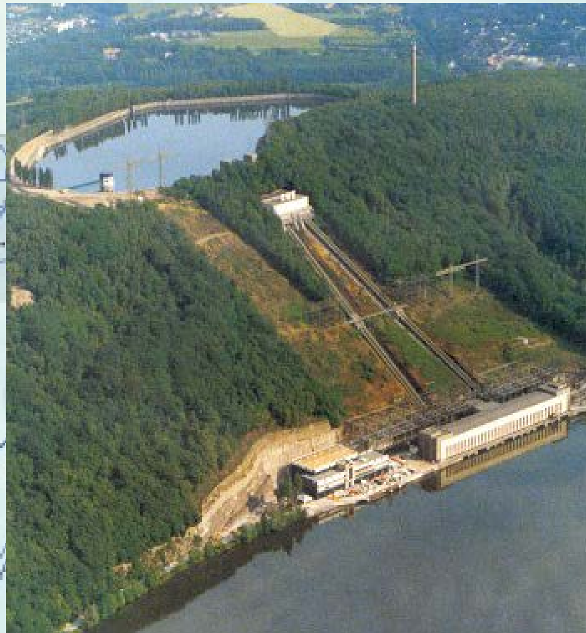
HIGHLIGHTS

- 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.

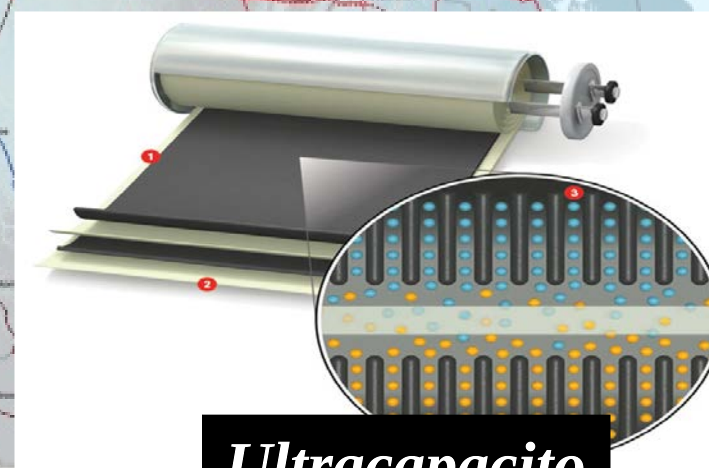
GRAPHICAL ABSTRACT




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



Lead-acid or lithium-ion



Ultracapacito
rs

# Research challenges

- How do we control a battery storage system? Challenges include:
  » Managing a single storage device to handle multiple revenue streams, over multiple time scales
  » Controlling a storage system in the presence of a multidimensional "state of the world"
  » Controlling dozens to hundreds of storage devices spread around the grid.
- How do we design storage systems?
  » What type of storage device(s)?
  » How many are needed?
  » How should they be distributed across the grid?
- How does storage change the economics of renewables?

# Revenue streams

- Frequency regulation
- Power quality management
- Battery arbitrage
- Energy shifting
- Demand peak management - Many utilities impose charges based on peak usage over a month, quarter or even a year.
- Peak management for avoiding capacity expansion
- Backup power for outages

seconds

minutes

hours

days-weeks

weeks-months

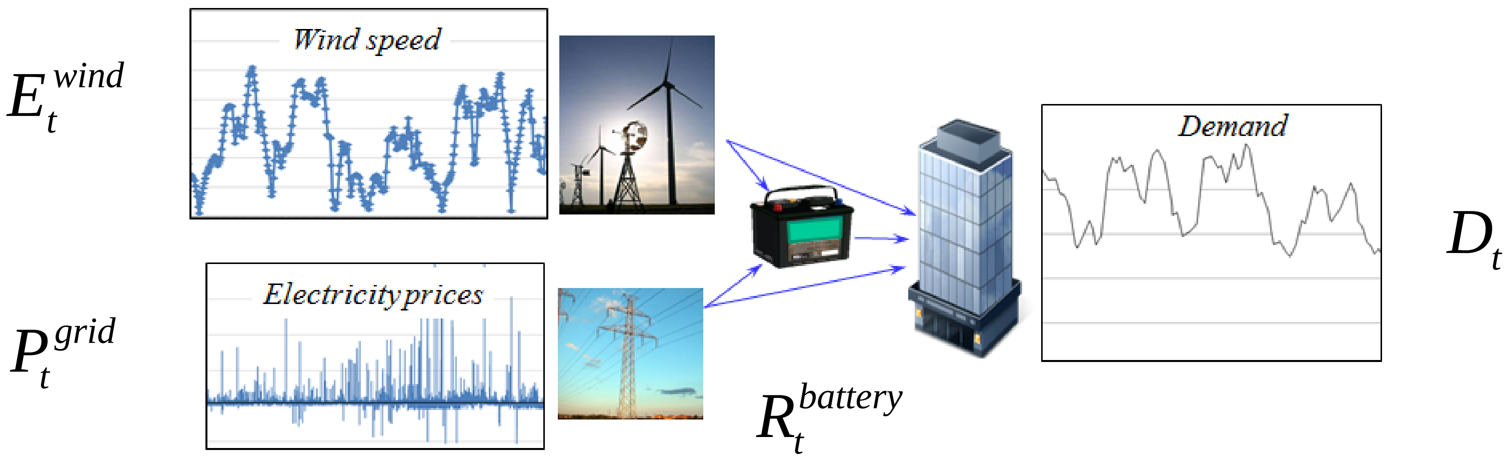
months-years

# Research goals

- To design an algorithm that produces near-optimal policies that handle the following problem characteristics:
  - » Responds to predictable time-dependent structural patterns over hourly, daily and weekly cycles in generation and loads.
  - » Able to simultaneously optimize over multiple revenue streams, balanced against maximizing the lifetime of the battery.
  - » Able to handle time scales ranging from seconds to minutes, hours and days.
  - » Handles uncertainty in energy generation, prices and loads.
  - » Handles "state of the world" variables such as weather conditions, network conditions and prices.
  - » For some applications, we need to scale to large numbers (tens to hundreds, but perhaps thousands) of grid-level storage devices.
  - » Ability to incorporate forecasts of wind or solar energy, loads, and weather.
  - » Needs to be computationally very fast.

# A storage problem

- Energy storage with stochastic prices, supplies and demands.




$$E_{t+1}^{wind} = E_t^{wind} + \hat{E}_{t+1}^{wind}$$

$$P_{t+1}^{grid} = P_t^{grid} + \hat{P}_{t+1}^{grid}$$

$$D_{t+1}^{load} = D_t^{load} + \hat{D}_{t+1}^{load}$$

$$R_{t+1}^{battery} = R_t^{battery} + x_t$$

$W_{t+1}$ = Exogenous inputs

$S_t$ = State variable

$x_t$ = Controllable inputs

# A storage problem

- Bellman's optimality equation

$$V(S_t) = \min_{x_t \in \mathcal{X}} \left( C(S_t, x_t) + \gamma \mathbb{E} V(S_{t+1}(S_t, x_t, W_{t+1})) \right)$$

$$\begin{bmatrix} E_t^{wind} \\ P_t^{grid} \\ D_t^{load} \\ R_t^{battery} \end{bmatrix} \qquad \begin{bmatrix} x_t^{wind-battery} \\ x_t^{wind-load} \\ x_t^{grid-battery} \\ x_t^{grid-load} \\ x_t^{battery-load} \end{bmatrix} \qquad \begin{bmatrix} \hat{E}_{t+1}^{wind} \\ \hat{P}_{t+1}^{grid} \\ \hat{D}_{t+1}^{load} \end{bmatrix}$$

# Managing a water reservoir

- Backward dynamic programming in one dimension

Step 0: Initialize $V_{T+1}(R_{T+1}) = 0$ for $R_{T+1} = 0,1,\ldots,100$

Step 1: Step backward $t = T, T-1, T-2, \ldots$

Step 2: Loop over $R_t = 0,1,\ldots,100$

Step 3: Loop over all decisions $0 \le x_t \le R_t$

Step 4: Take the expectation over all rainfall levels (also discretized):

Compute $Q(R_t, x_t) = C(R_t, x_t) + \sum_{w=0}^{100} V_{t+1}(\min\left\{R^{\max}, R_t - x + w\right\}) P^W(w)$

End step 4;

End Step 3;

Find $V_t^*(R_t) = \max_{x_t} Q(R_t, x_t)$

Store $X_t^{\pi^*}(R_t) = \arg\max_{x_t} Q(R_t, x_t)$. (This is our policy)

End Step 2;

End Step 1;

# Managing cash in a mutual fund

- Dynamic programming in multiple dimensions

Step 0: Initialize $V_{T+1}(S_{T+1}) = 0$ for all states.

Step 1: Step backward $t = T, T-1, T-2, \ldots$

Step 2: Loop over $S_t = \left(R_t, D_t, p_t, E_t\right)$ (four loops)

Step 3: Loop over all decisions $x_t$ (a problem if $x_t$ is a vector)

Step 4: Take the expectation over each random dimension $\left(\hat{D}_t, \hat{p}_t, \hat{E}_t\right)$

Compute $Q(S_t, x_t) = C(S_t, x_t) +$

$$\sum_{w_1=0}^{100} \sum_{w_2=0}^{100} \sum_{w_3=0}^{100} V_{t+1}\left(S^M\left(S_t, x_t, W_{t+1} = (w_1, w_2, w_3)\right)\right) P^W(w_1, w_2, w_3)$$

End step 4;

End Step 3;

Find $V_t^*(S_t) = \max_{x_t} Q(S_t, x_t)$

Store $X_t^{\pi^*}(S_t) = \arg\max_{x_t} Q(S_t, x_t)$. (This is our policy)

End Step 2;

End Step 1;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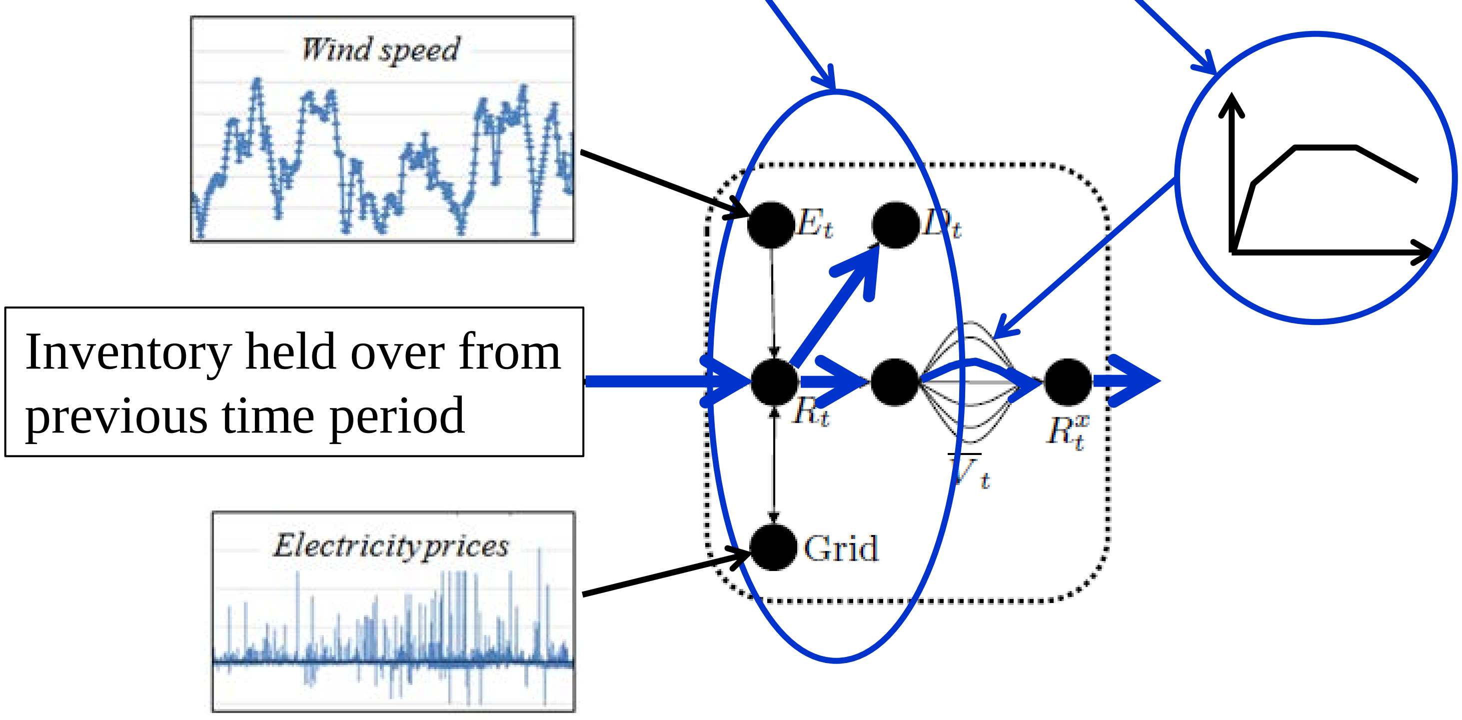
# Approximate dynamic programming

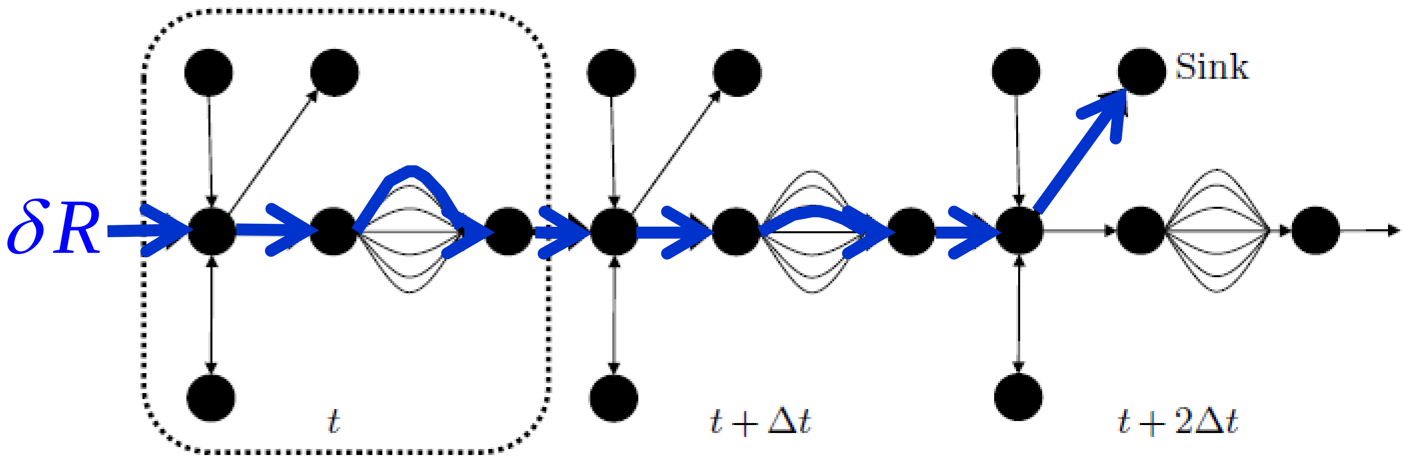
- Bellman's optimality equation
  - » We approximate the value of energy in storage:

$$V_t(S_t) = \min_{x_t \in \mathcal{X}} \left( C(S_t, x_t) + \gamma \bar{V}_t^x \left( S_t^x (S_t, x_t) \right) \right)$$



# Approximate dynamic programming

- We update the piecewise linear value functions by computing estimates of slopes using a backward pass:

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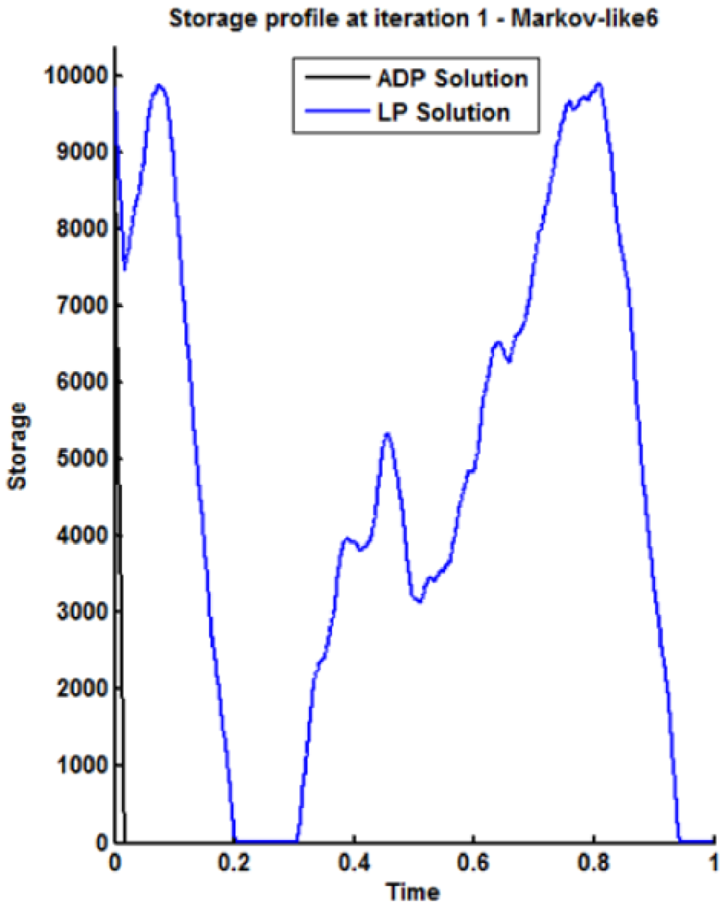
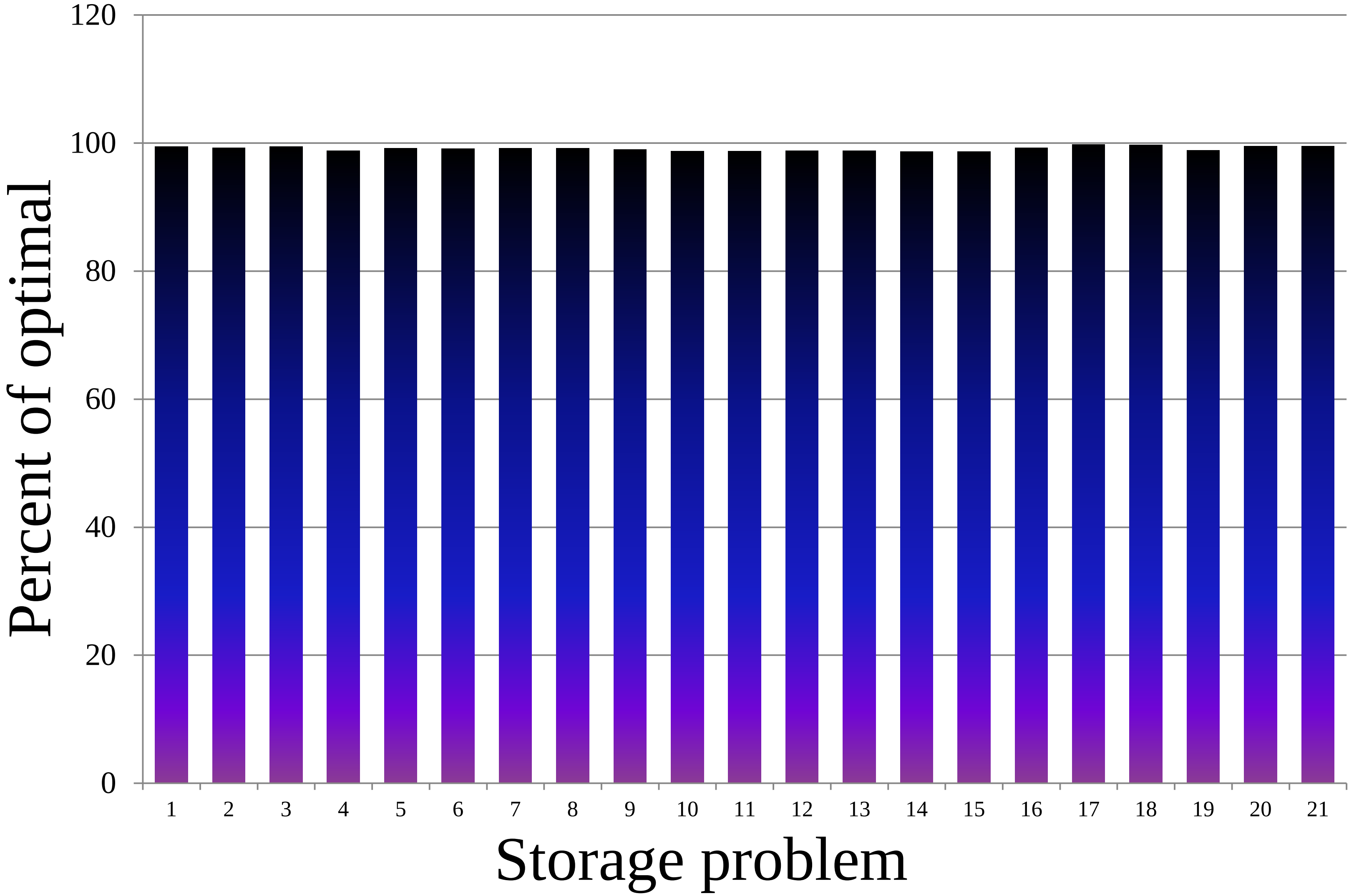
# Approximate dynamic programming

- Testing on a deterministic problem demonstrates that we can precisely capture optimal time-dependent behavior:



# Approximate dynamic programming

- Benchmarking against optimality on a stochastic model



# Approximate dynamic programming

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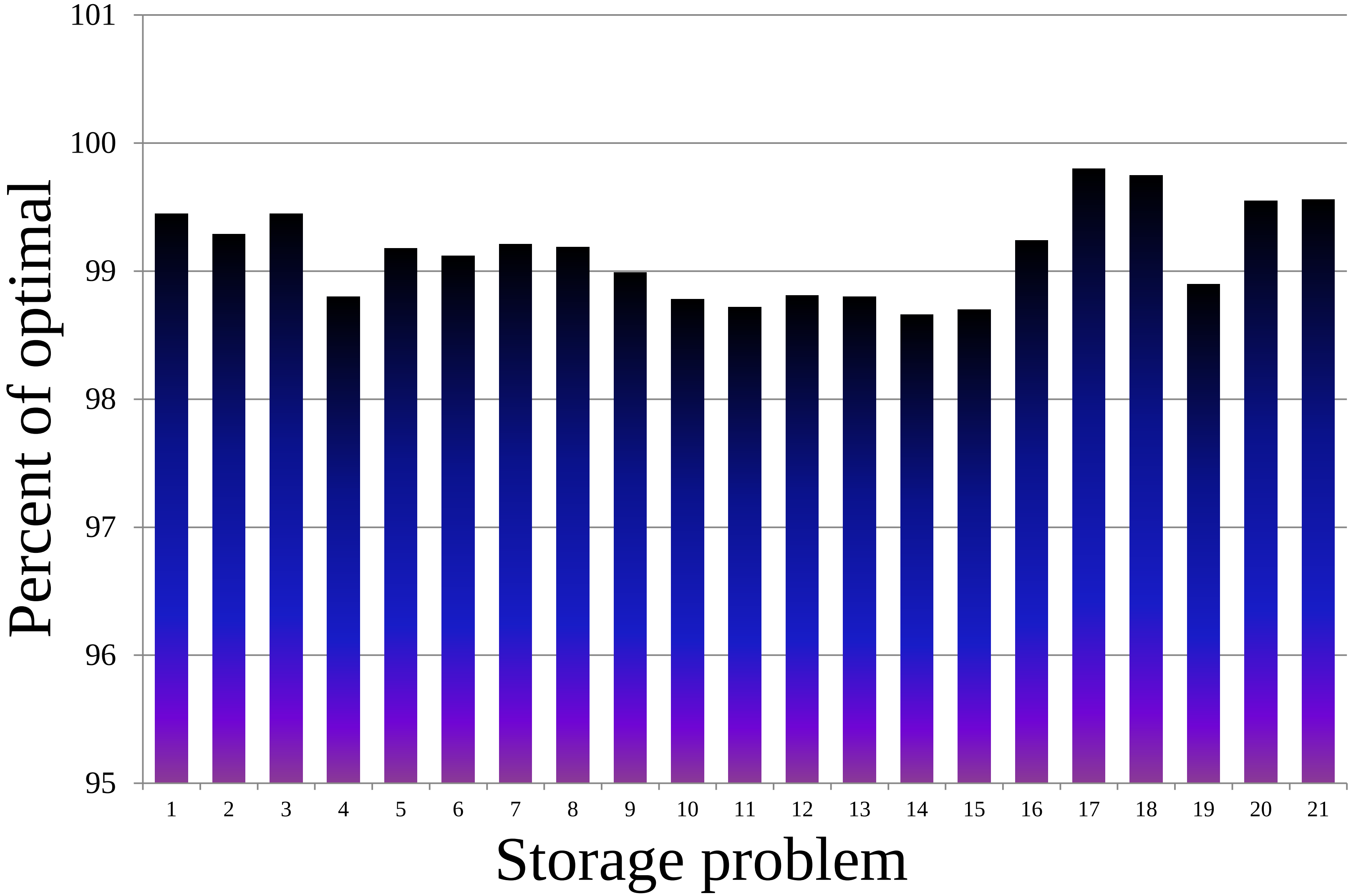
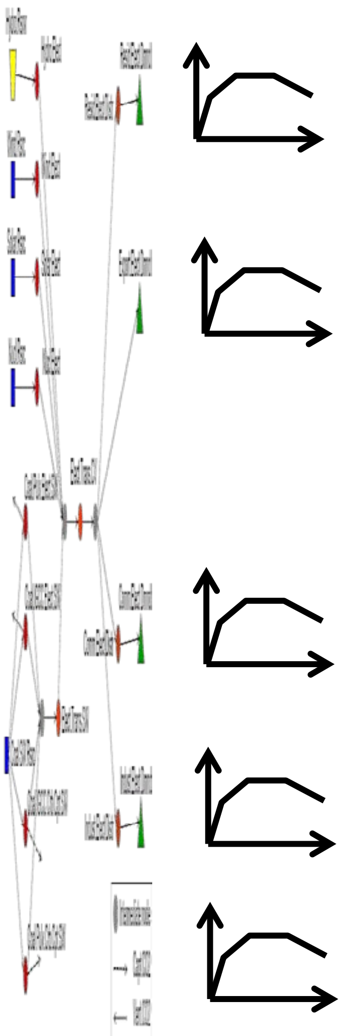


Legend
Backbone Transmission
Voltage (kV)
Backbone Substations
Voltage (kV)

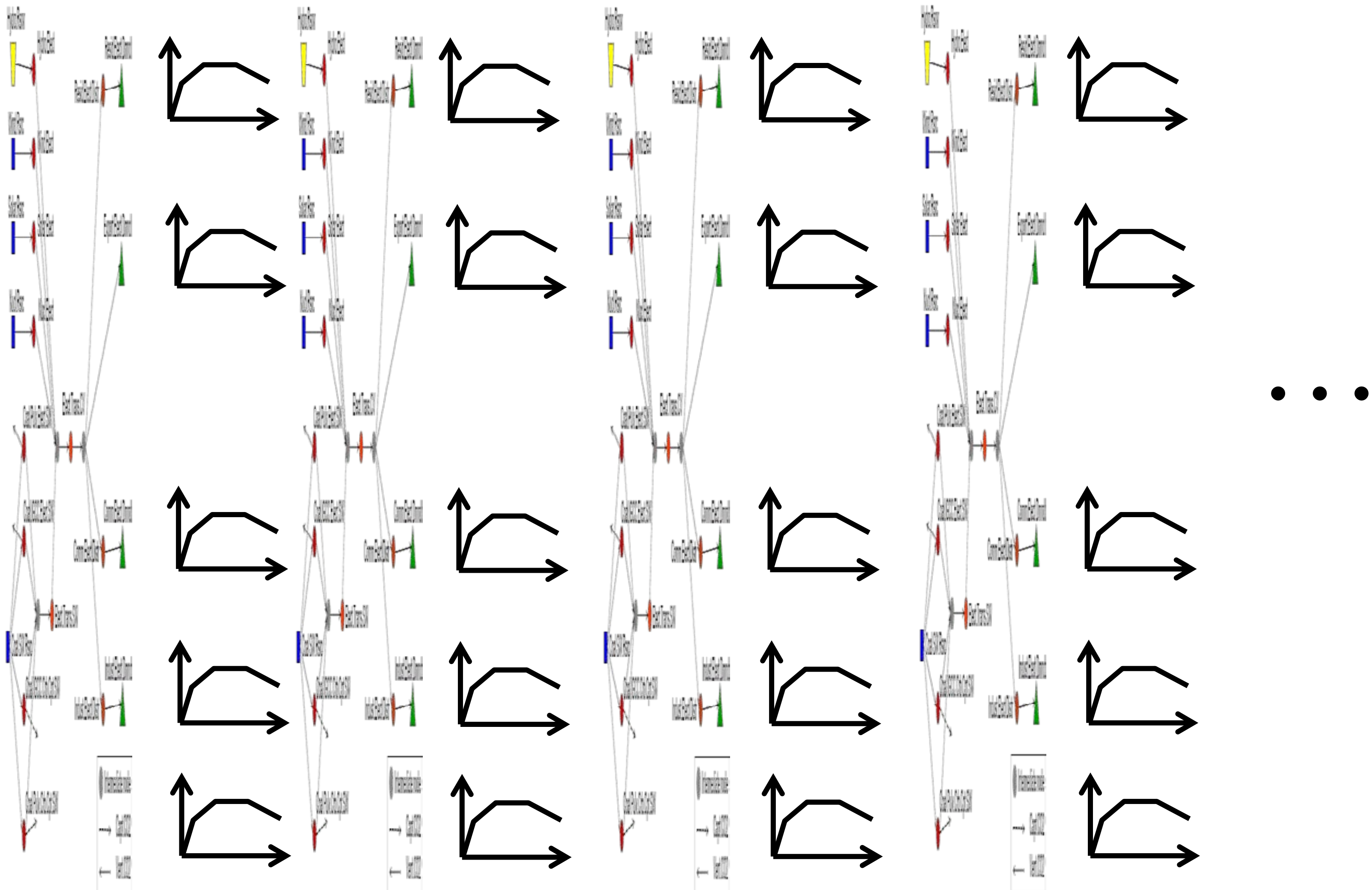
# Grid level storage control



# Grid level storage control

Monday

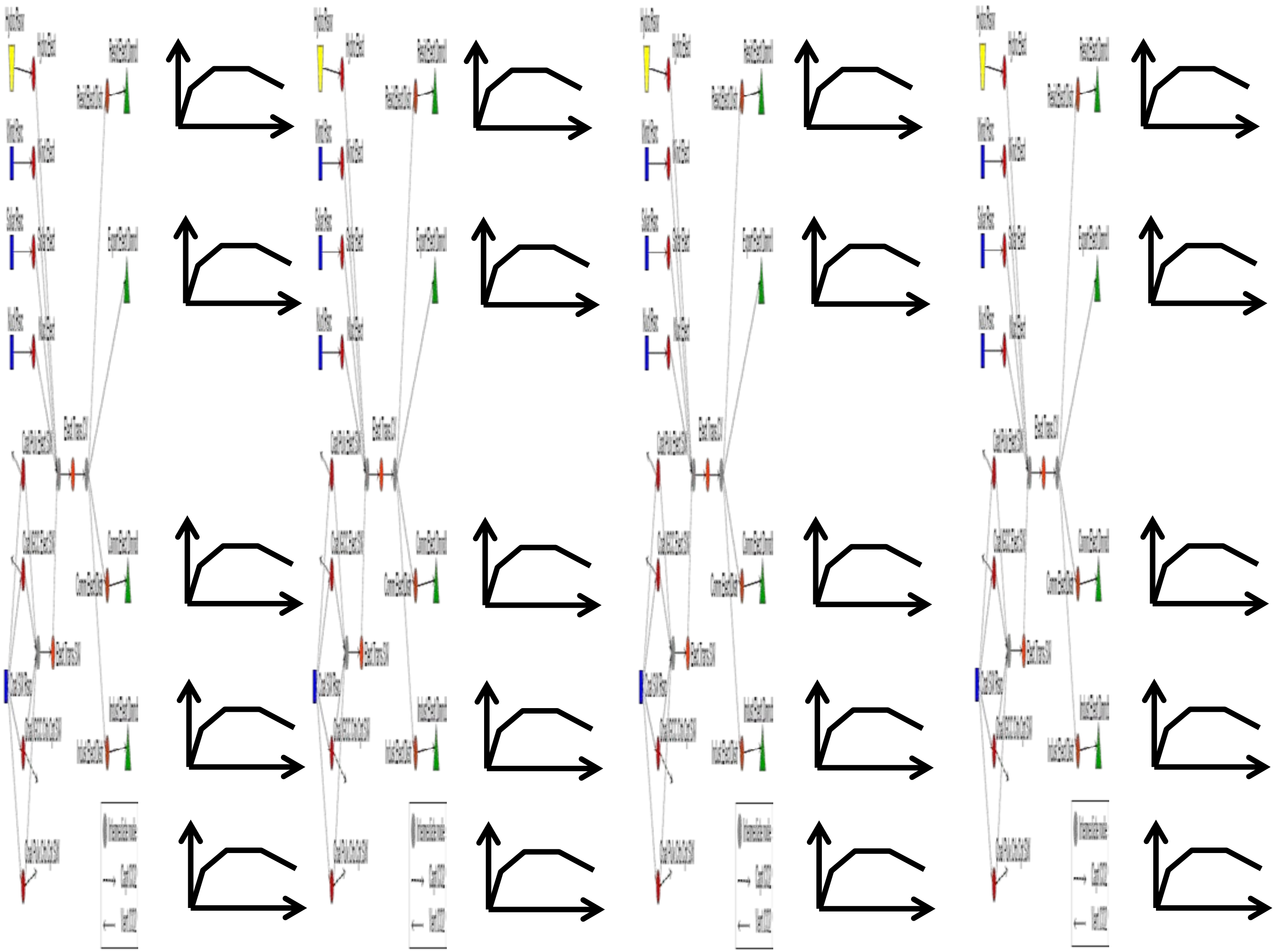
**Time** **:05** **:10** **:15** **:20**



# Grid level storage control

Monday

**Time** **:05** **:10** **:15** **:20**



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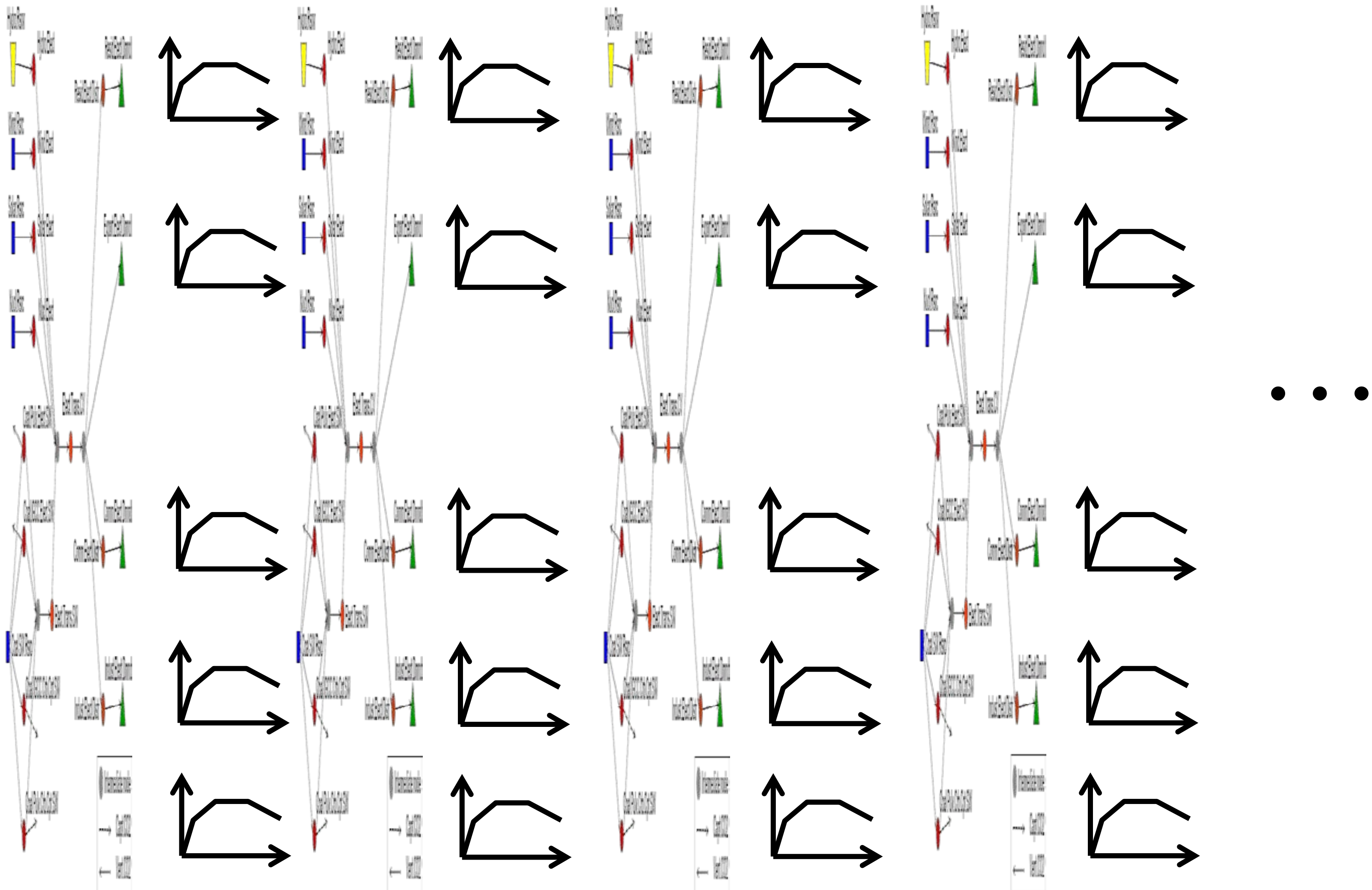
# Grid level storage control

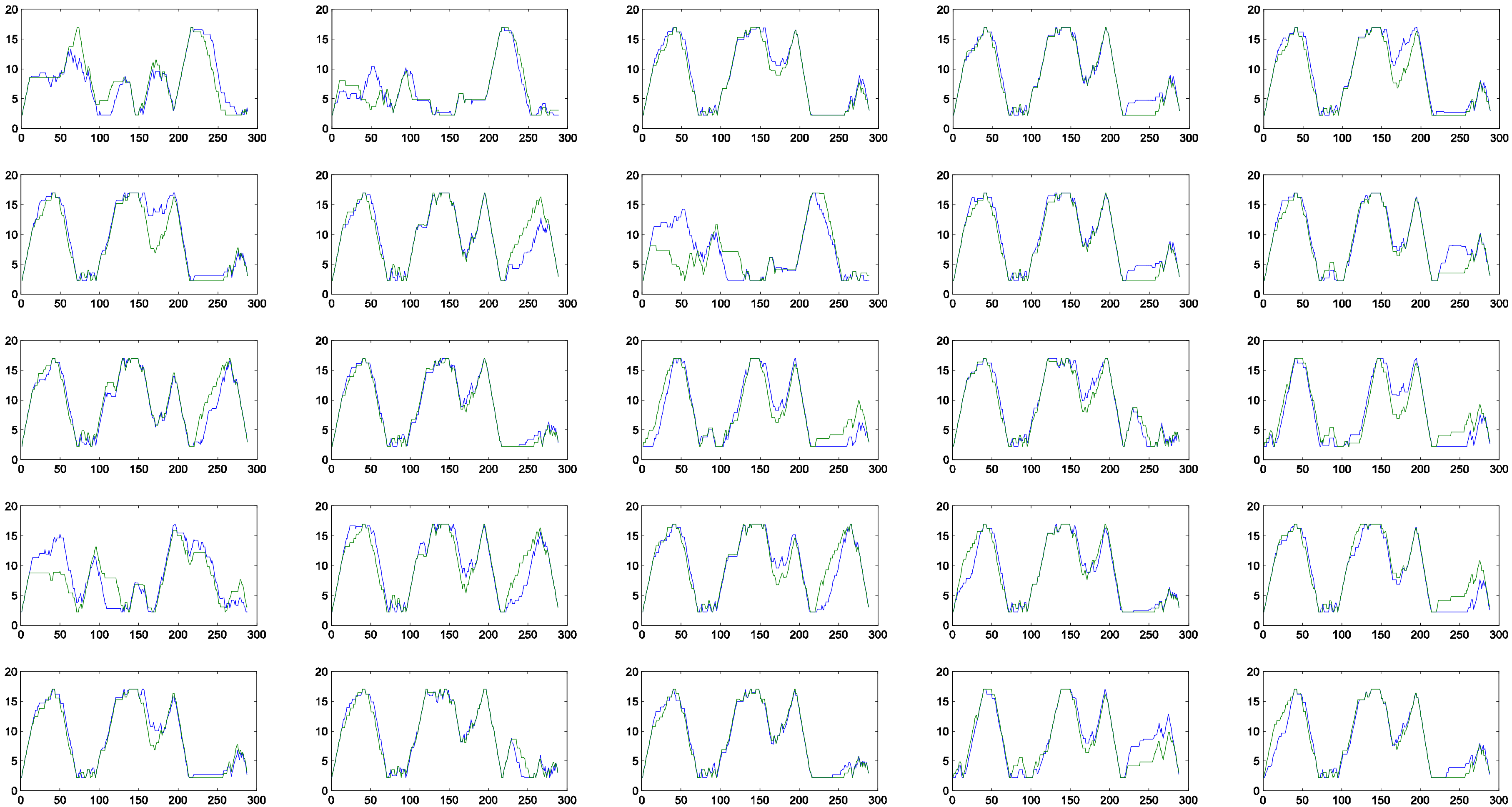
Monday

**Time** **:05** **:10** **:15** **:20**

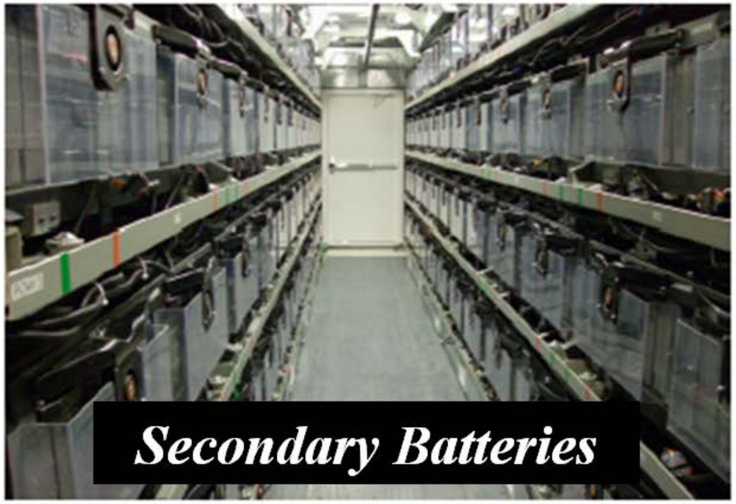


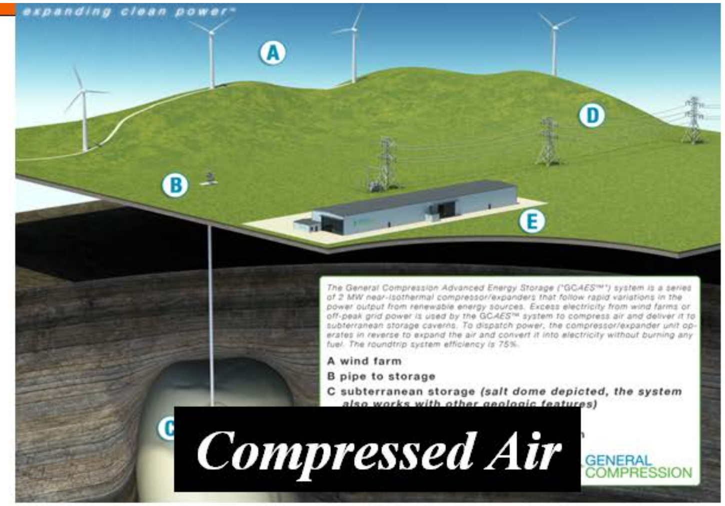
# Grid level storage control

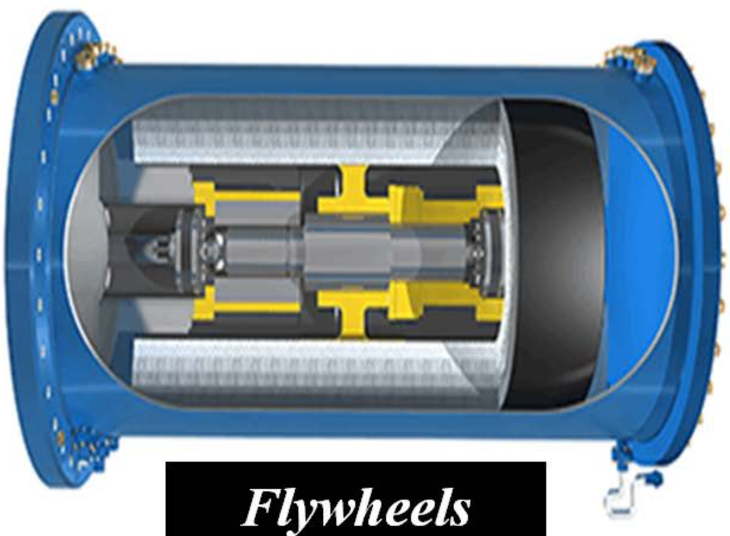
- Approximate dynamic programming (blue) vs. optimal using linear programming (green)

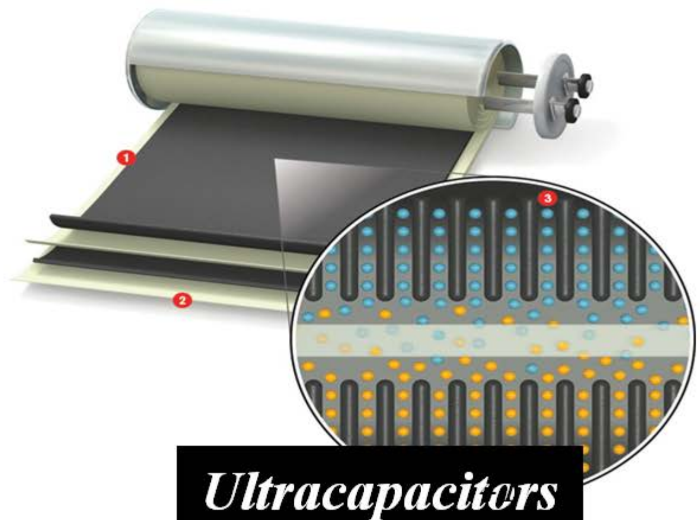


# Heterogeneous fleets of batteries



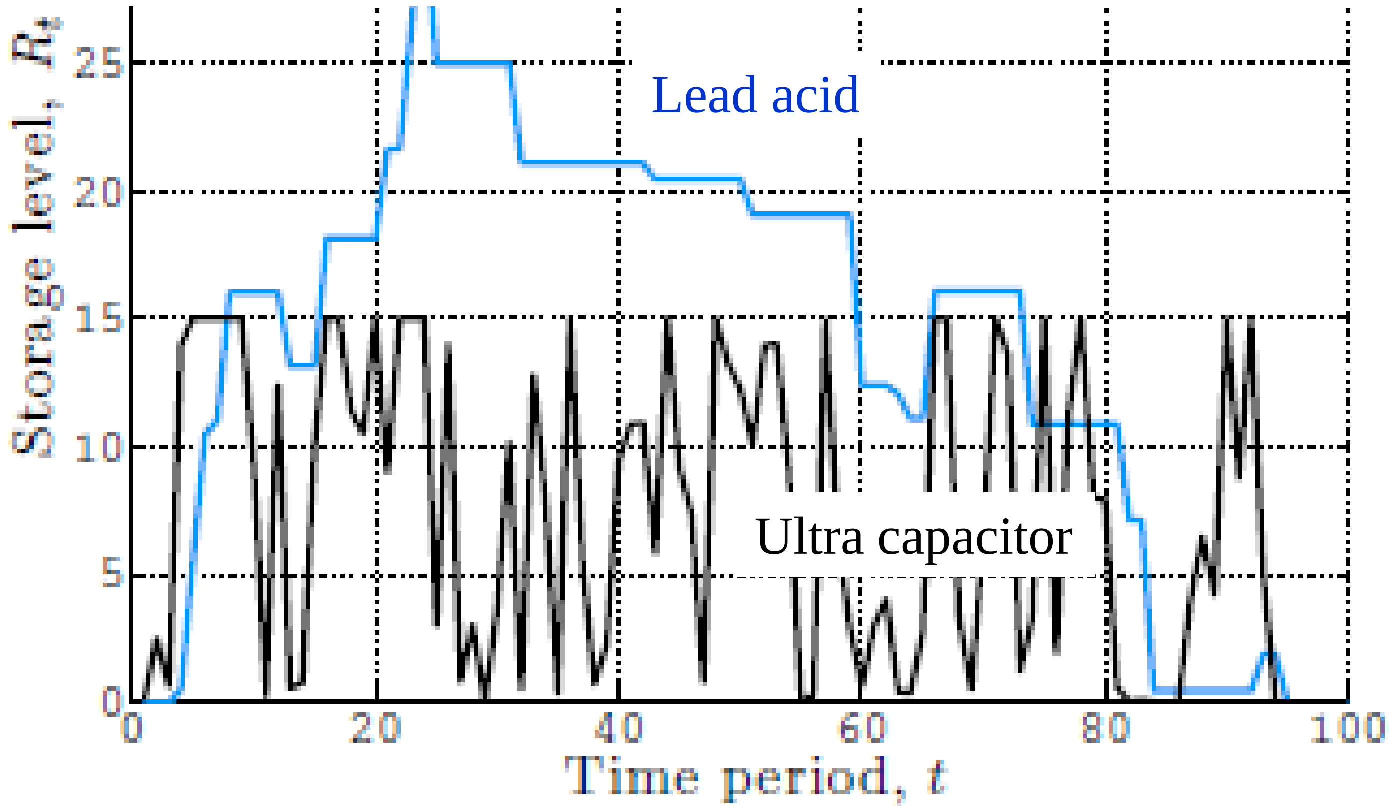



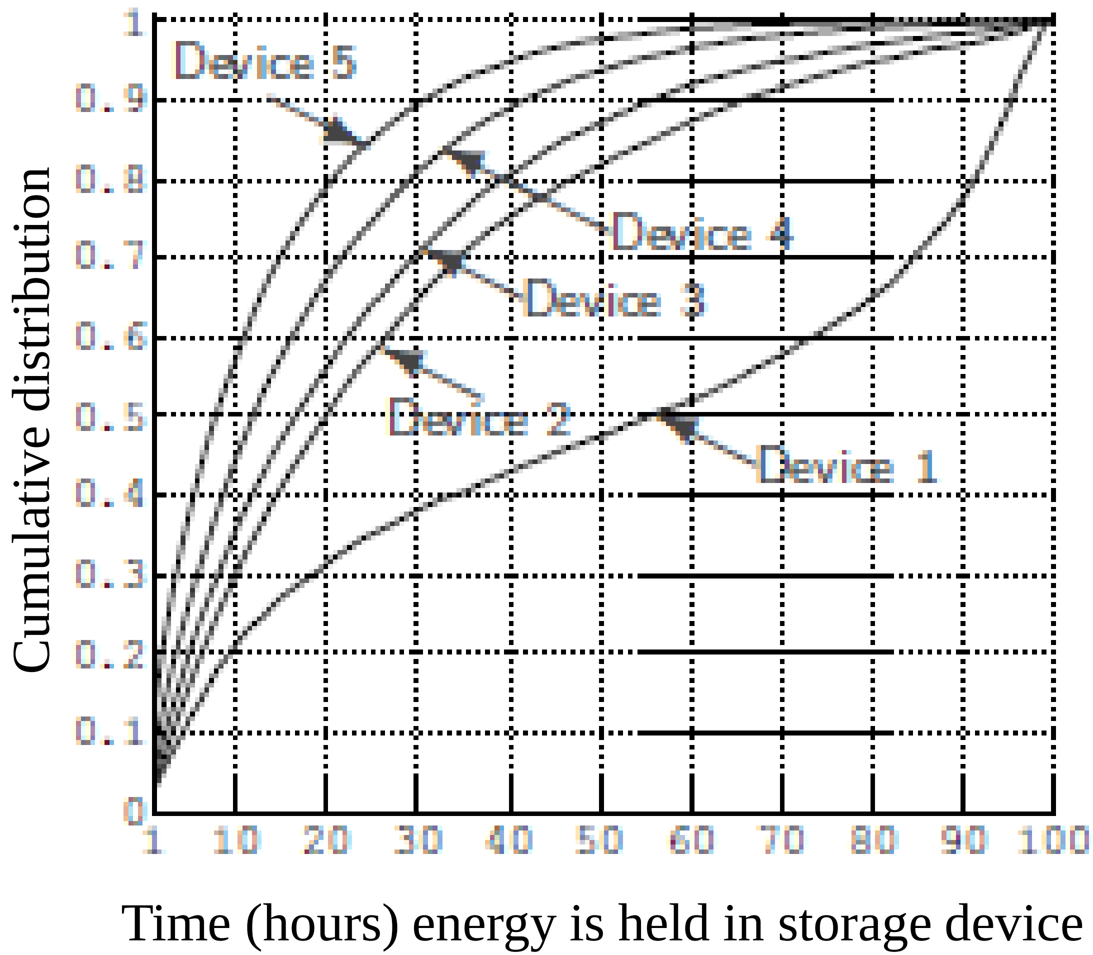
# Heterogeneous fleets of batteries

- A tale of two batteries
  - » Ultracapacitor – High power, high efficiency, low capacity
  - » Lead acid – Lower power, lower efficiency, high capacity

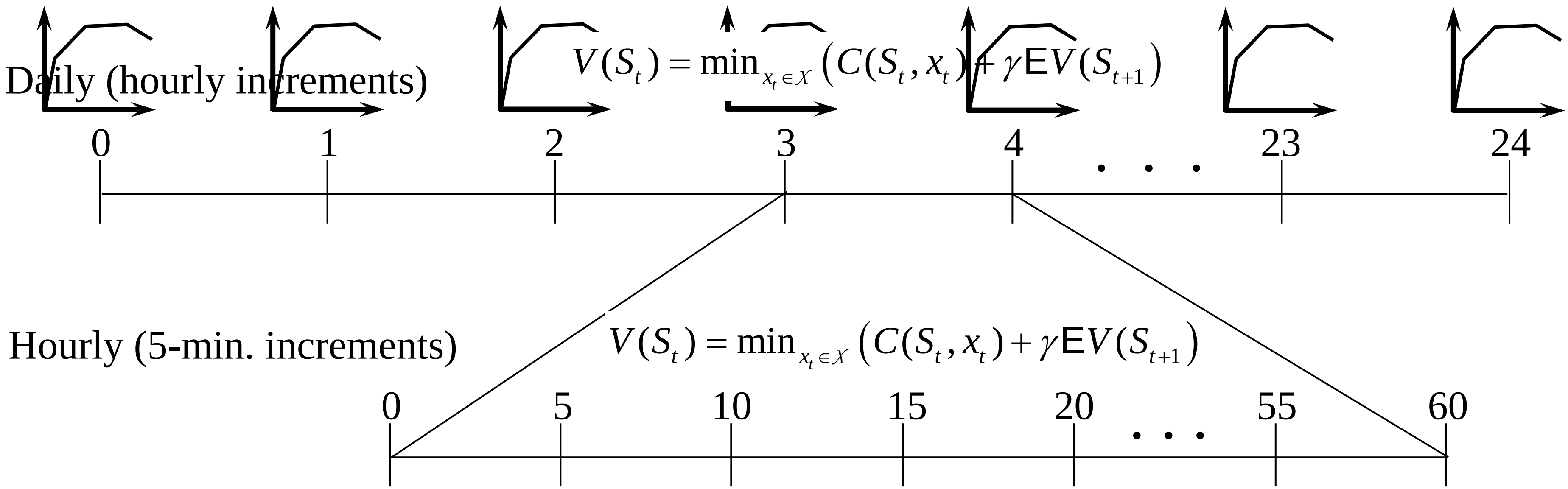


# Heterogeneous fleets of batteries

- Control algorithm adapts to characteristics of each storage device



# Handling multiple time scales



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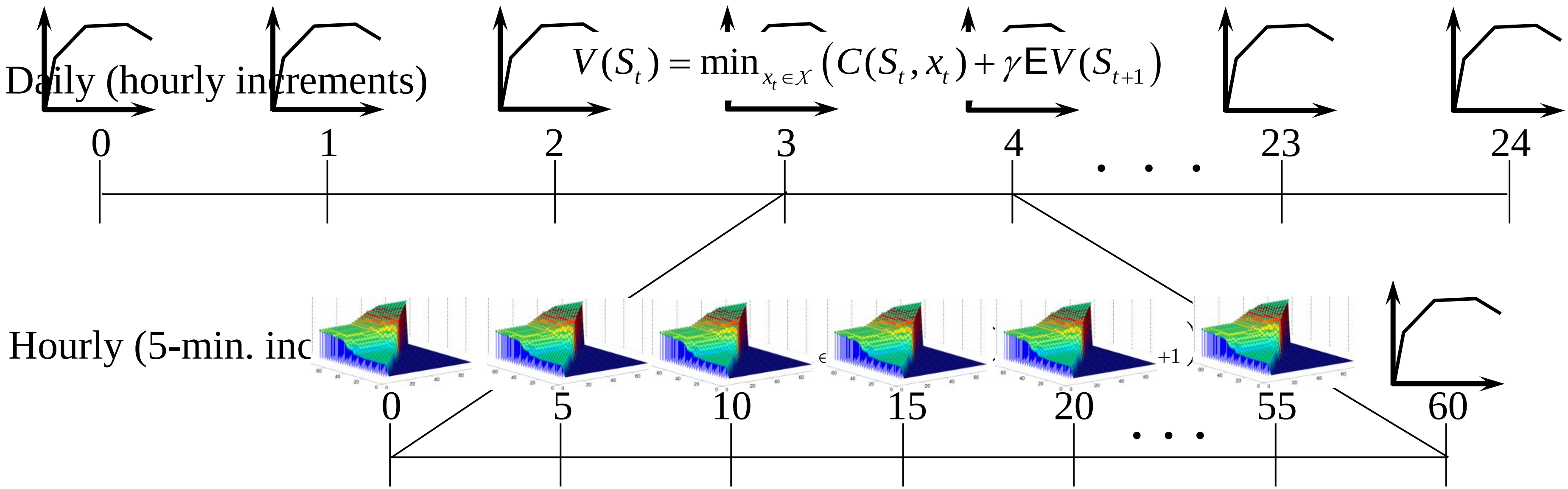
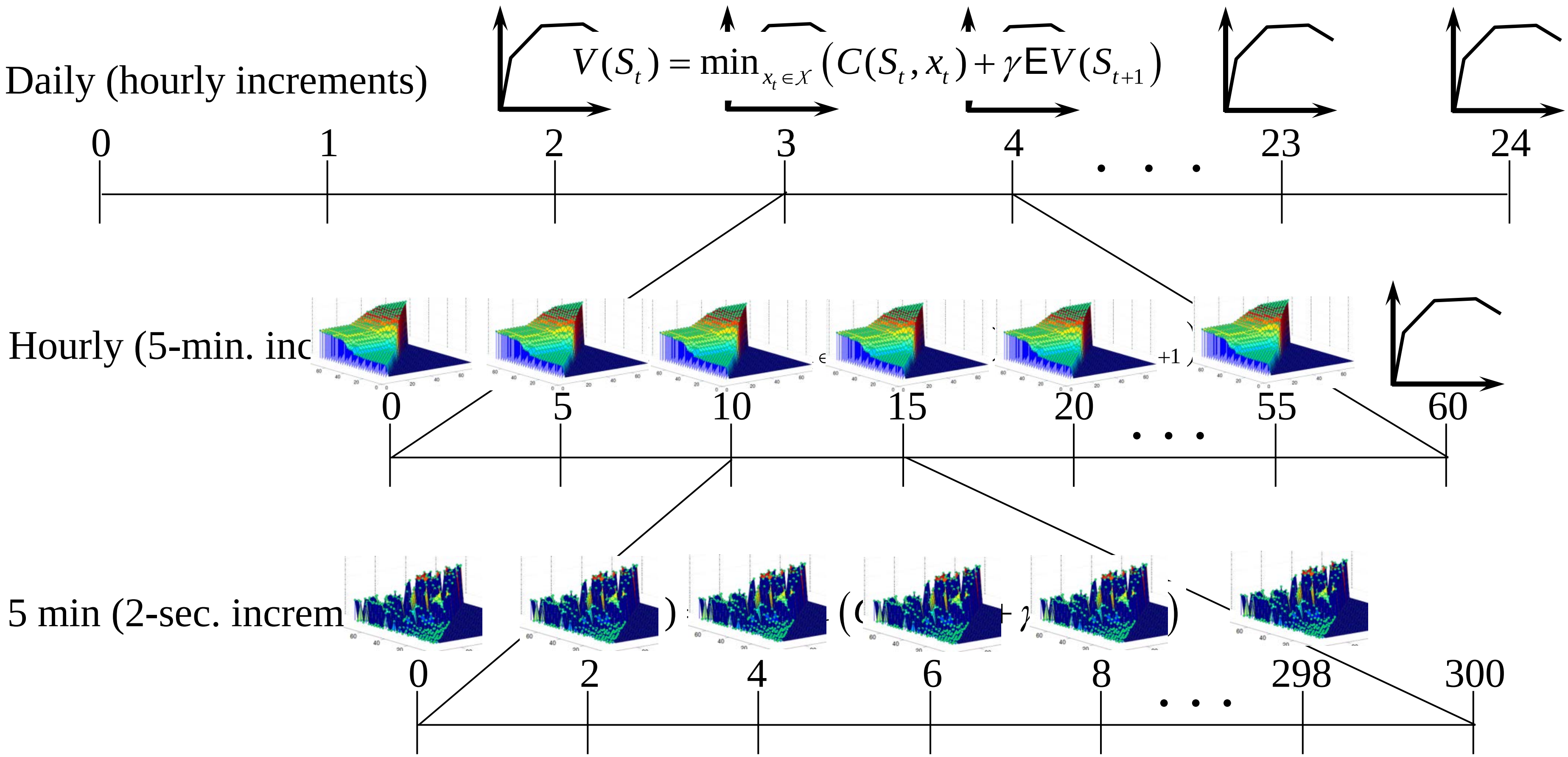
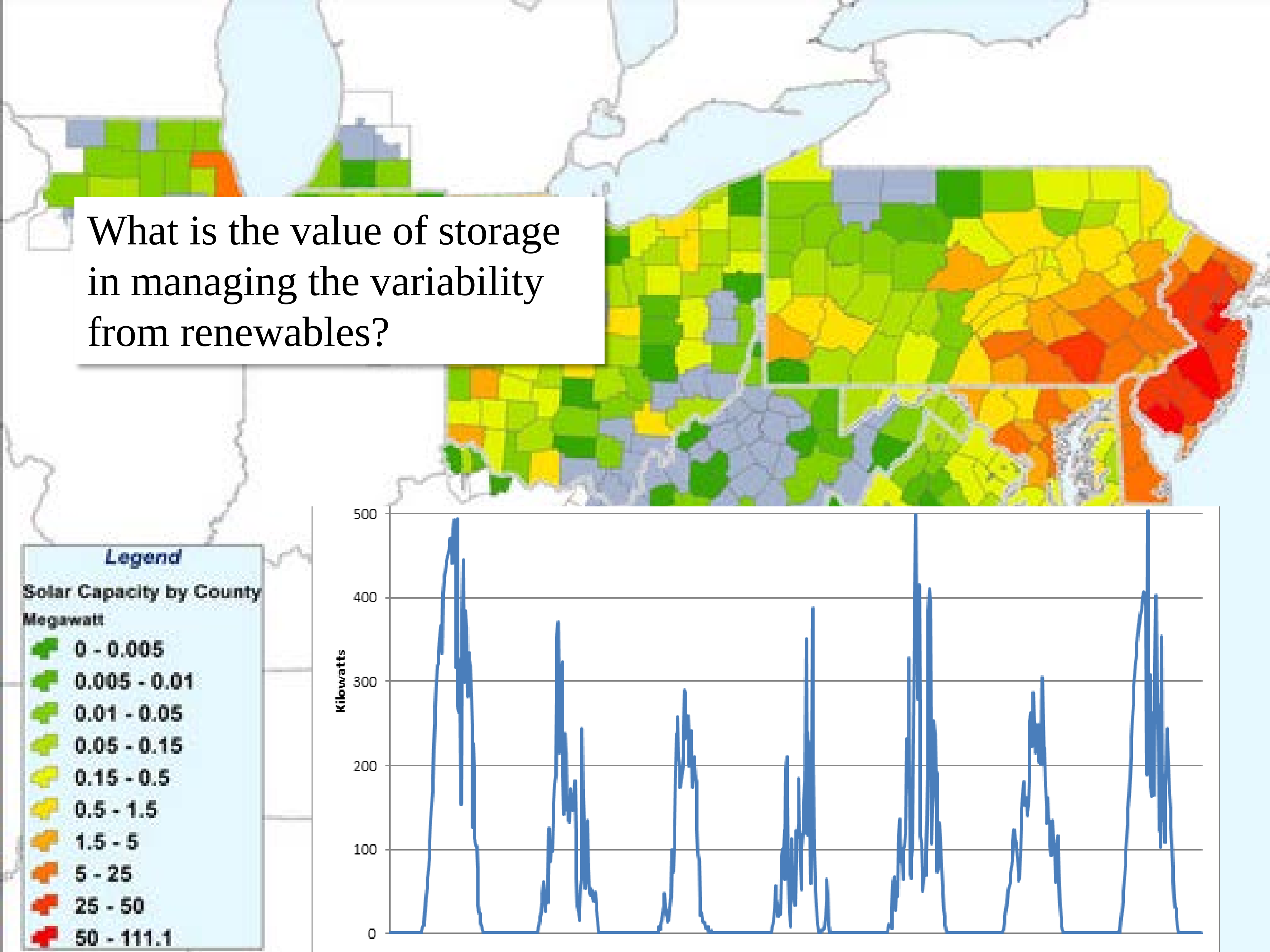


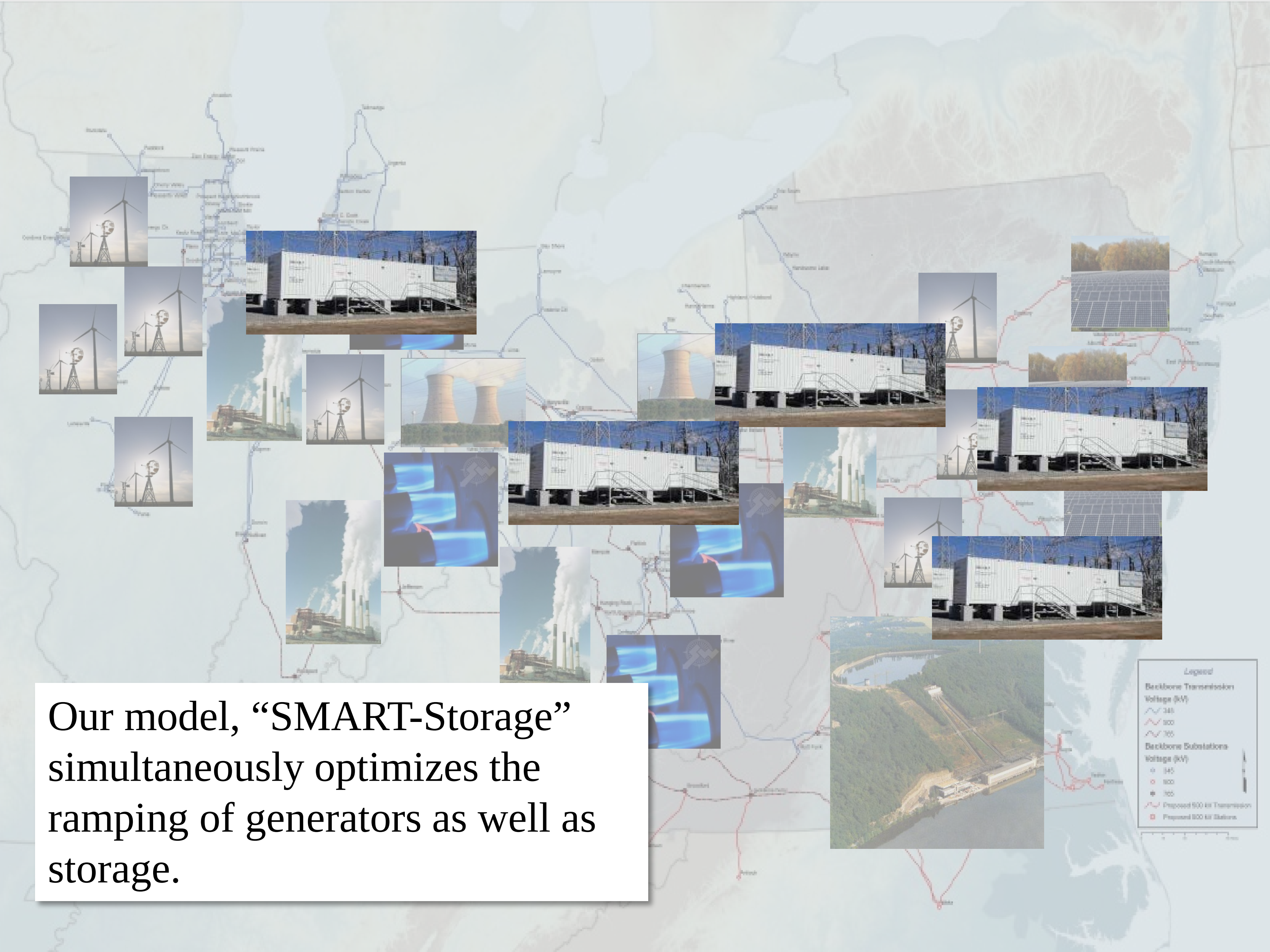
# Handling multiple time scales




*There are 43,200 2-second increments in a day, over 300,000 in a week.*

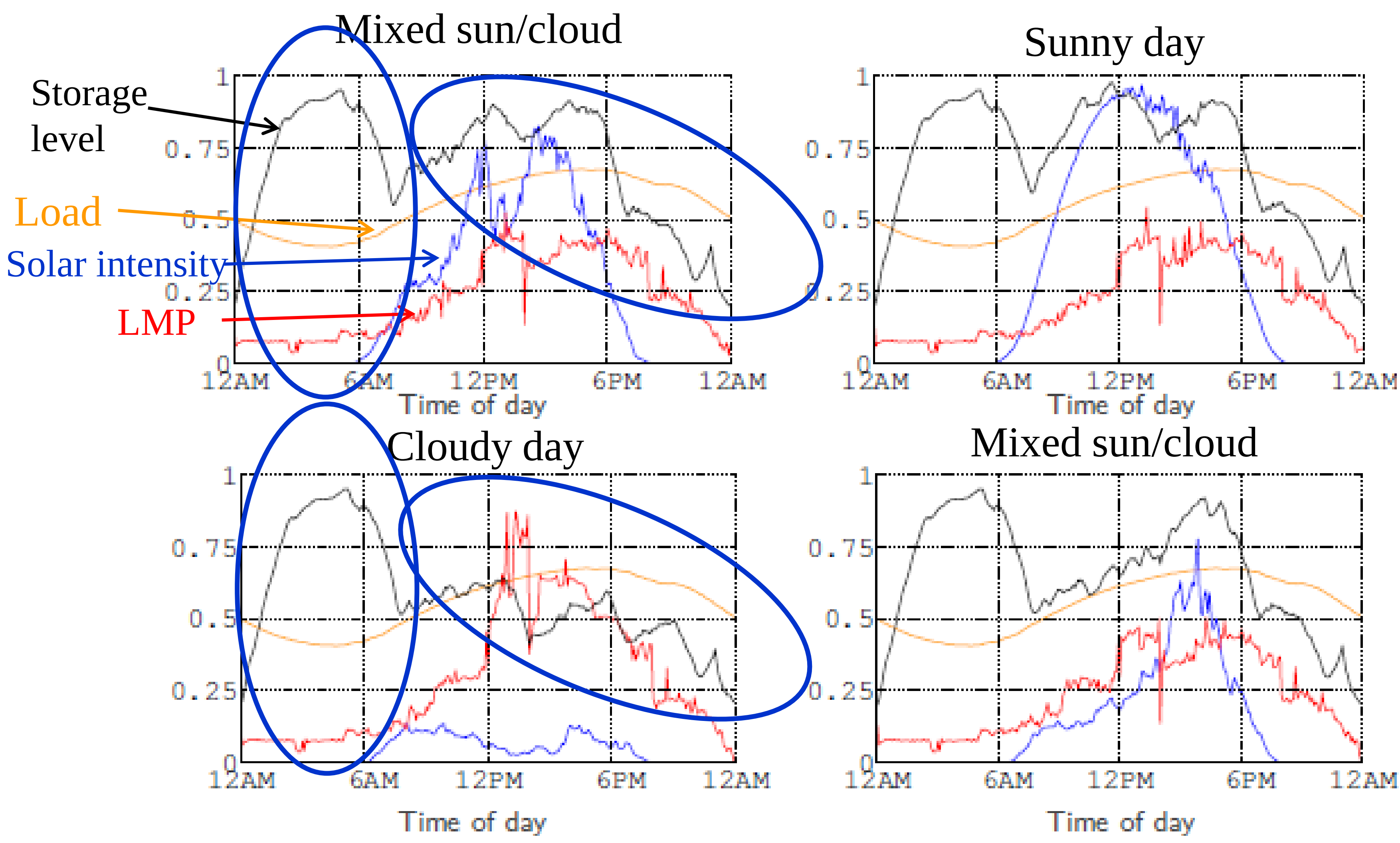
What is the value of storage in managing the variability from renewables?





Our model, “SMART-Storage” simultaneously optimizes the ramping of generators as well as storage.

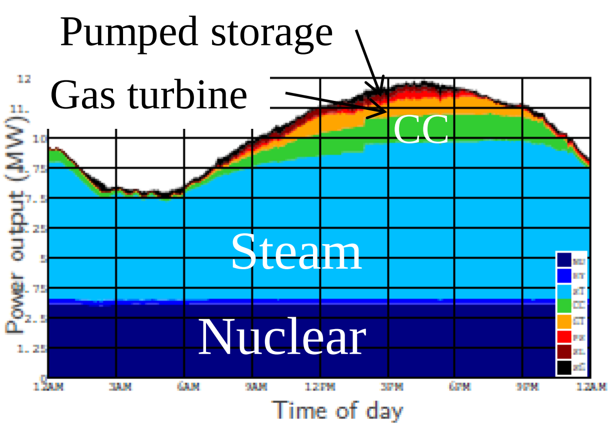
# Solar-storage experiments

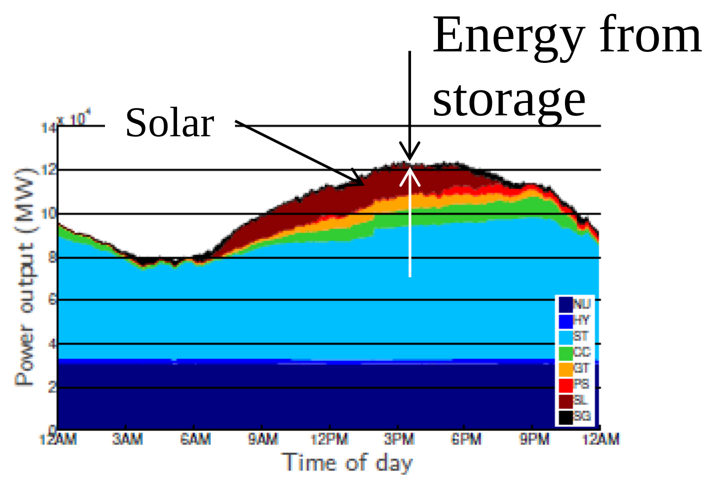


Solar = 2.3GW
Storage = 12Gwh/600MW

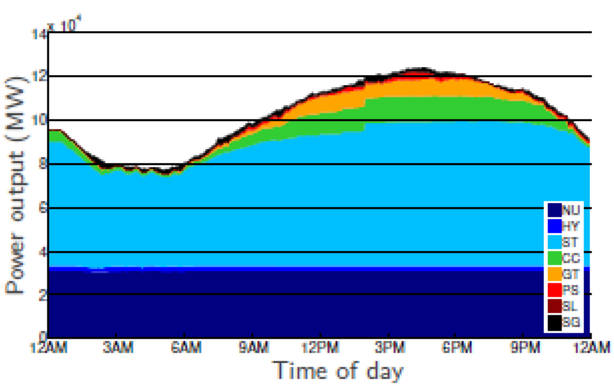
Solar = 23GW
Storage = 12Gwh/600-MW

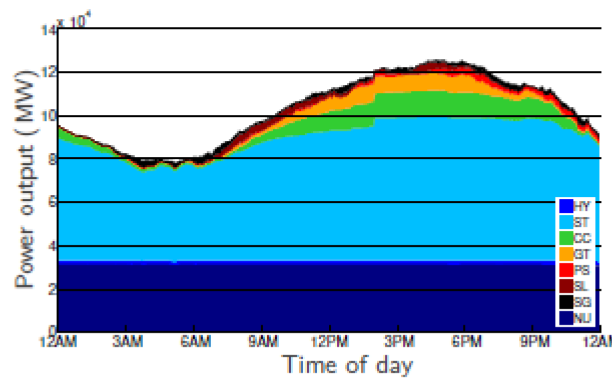
Sunny day




Cloudy day



# Solar-storage experiments

**Load covered by solar %**

| Storage Capacity | Solar capacity 23MW | 230MW | 2.3GW | 11.5GW | 23GW |
|---|---|---|---|---|---|
| 0MWh | 0.007 | 0.07 | 0.74 | 2.45 | 4.82 |
| 12MWh | 0.007 | 0.07 | 0.74 | 2.56 | 4.94 |
| 120MWh | 0.007 | 0.07 | 0.74 | 2.54 | 4.91 |
| 1.2GWh | 0.007 | 0.07 | 0.74 | 2.51 | 4.89 |
| 6GWh | 0.007 | 0.07 | 0.74 | 2.49 | 4.87 |
| 12GWh | 0.007 | 0.07 | 0.74 | 2.47 | 4.84 |

Ta

**% of solar used**

| Storage Capacity | Solar capacity 23MW | 230MW | 2.3GW | 11.5GW | 23GW |
|---|---|---|---|---|---|
| 0MWh | 99.33 | 98.63 | 95.29 | 82.31 | 63.50 |
| 12MWh | 99.40 | 98.64 | 96.70 | 83.53 | 64.66 |
| 120MWh | 99.44 | 98.66 | 95.75 | 83.39 | 64.30 |
| 1.2GWh | 99.99 | 98.70 | 95.66 | 82.97 | 64.24 |
| 6GWh | 99.99 | 98.66 | 95.68 | 82.85 | 64.12 |
| 12GWh | 99.99 | 98.64 | 95.64 | 82.54 | 64.03 |

# Solar-storage experiments

- Some conclusions:

  » The model will ***only*** put energy in storage when storage is the ***only*** way to meet fast variations in generation and loads.

  » The reason is the losses that are incurred when converting energy is stored.  It is ***always*** better to ramp down a generator during periods of high energy generation from wind or solar, than to store the energy and use it better.

  » ***The idea that the conversion losses do not matter when the energy is free is a myth****….* It only applies when the total generation from renewables ***exceeds*** the total load (which was never the case in our experiments).

# Research goals

- To design an algorithm that produces near-optimal policies that handle the following problem characteristics:
  - » Responds to predictable time-dependent structural patterns over hourly, daily and weekly cycles in generation and loads.
  - » Able to simultaneously optimize over multiple revenue streams, balanced against maximizing the lifetime of the battery.
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  - » Ability to incorporate forecasts of wind or solar energy, loads, and weather.
  - » Needs to be computationally very fast.

*Thank you!*

*For more information see:*

*http://energysystems.princeton.edu*