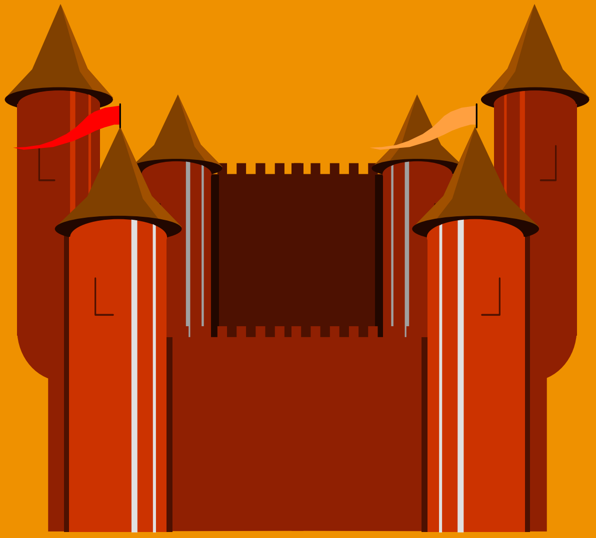
# SMART-ISO: A Stochastic, Multiscale Model of the PJM Power Grid

**FERC Technical Workshop**
**June 26, 2012**



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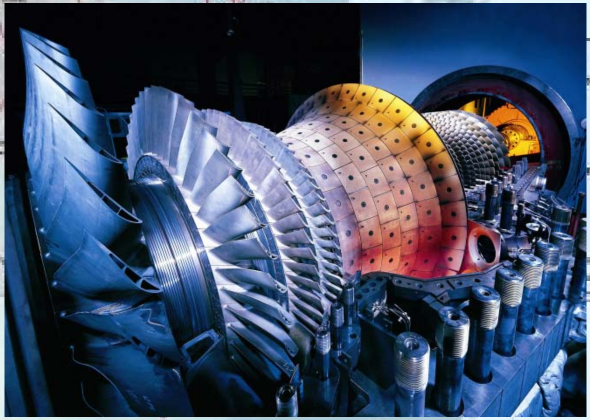
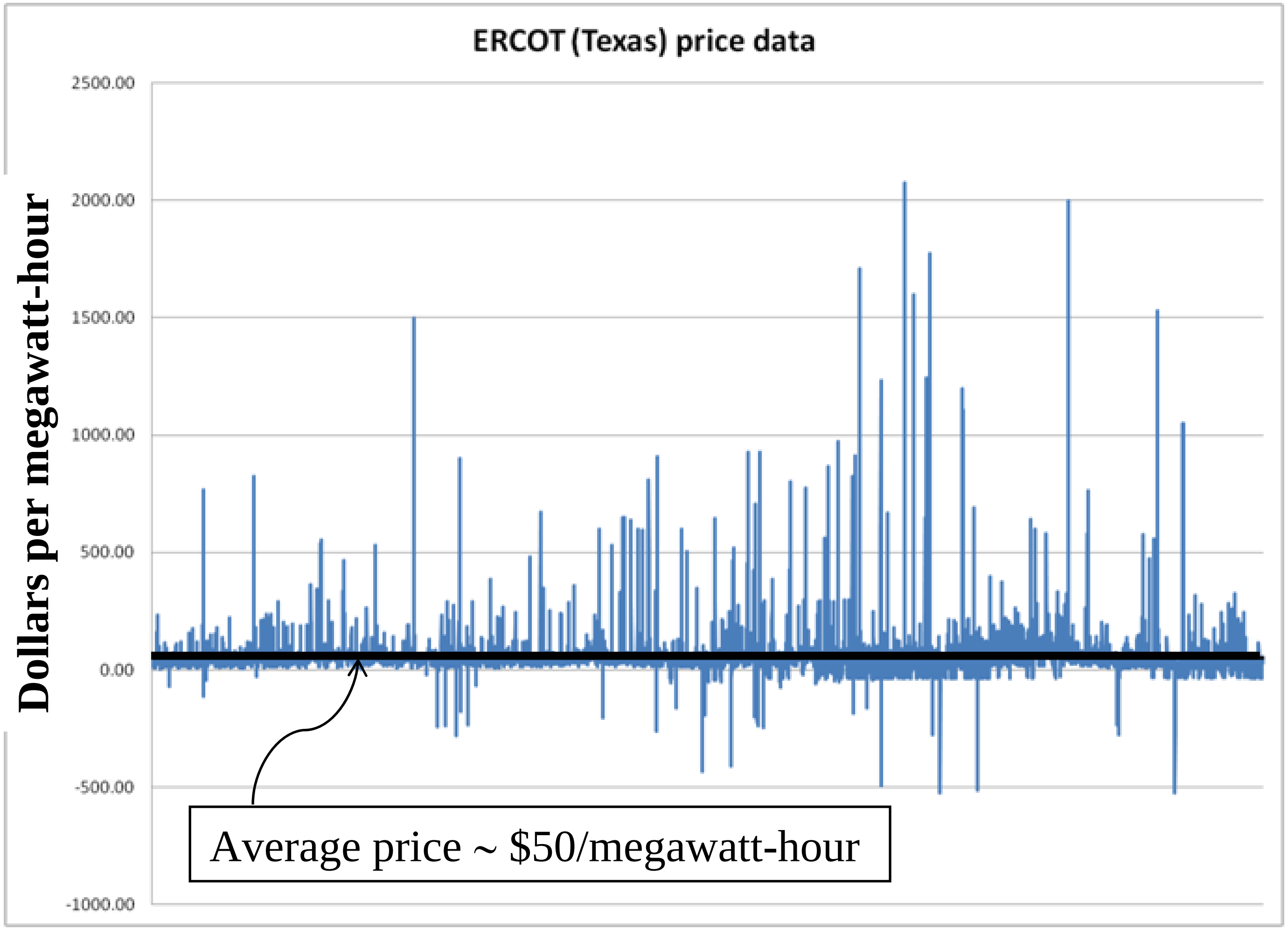
**Hugo Simao**
**PENSA Laboratory**
**Princeton University**
**http://energysystems.princeton.edu**

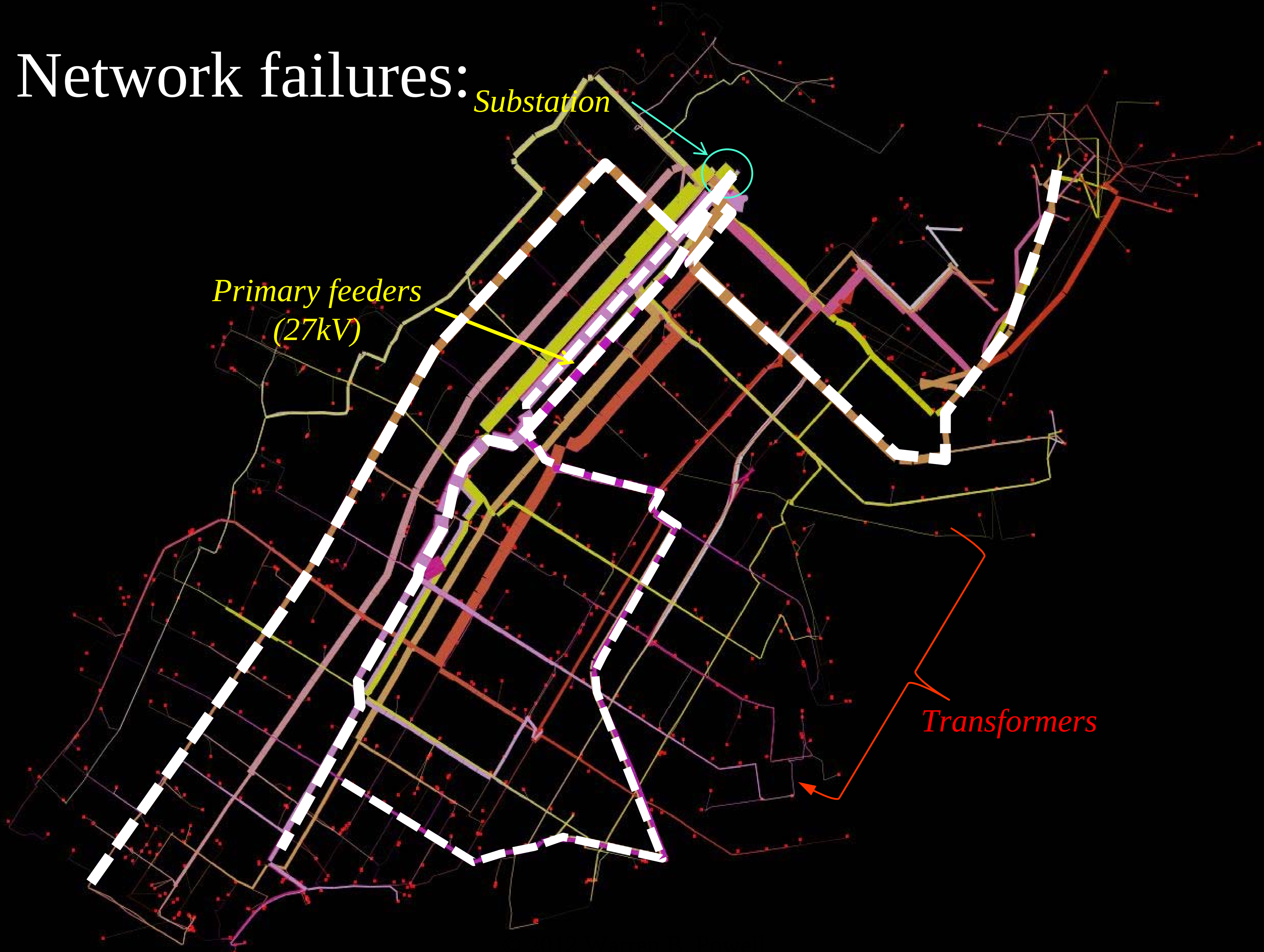
# An energy generation portfolio

# Electricity spot prices

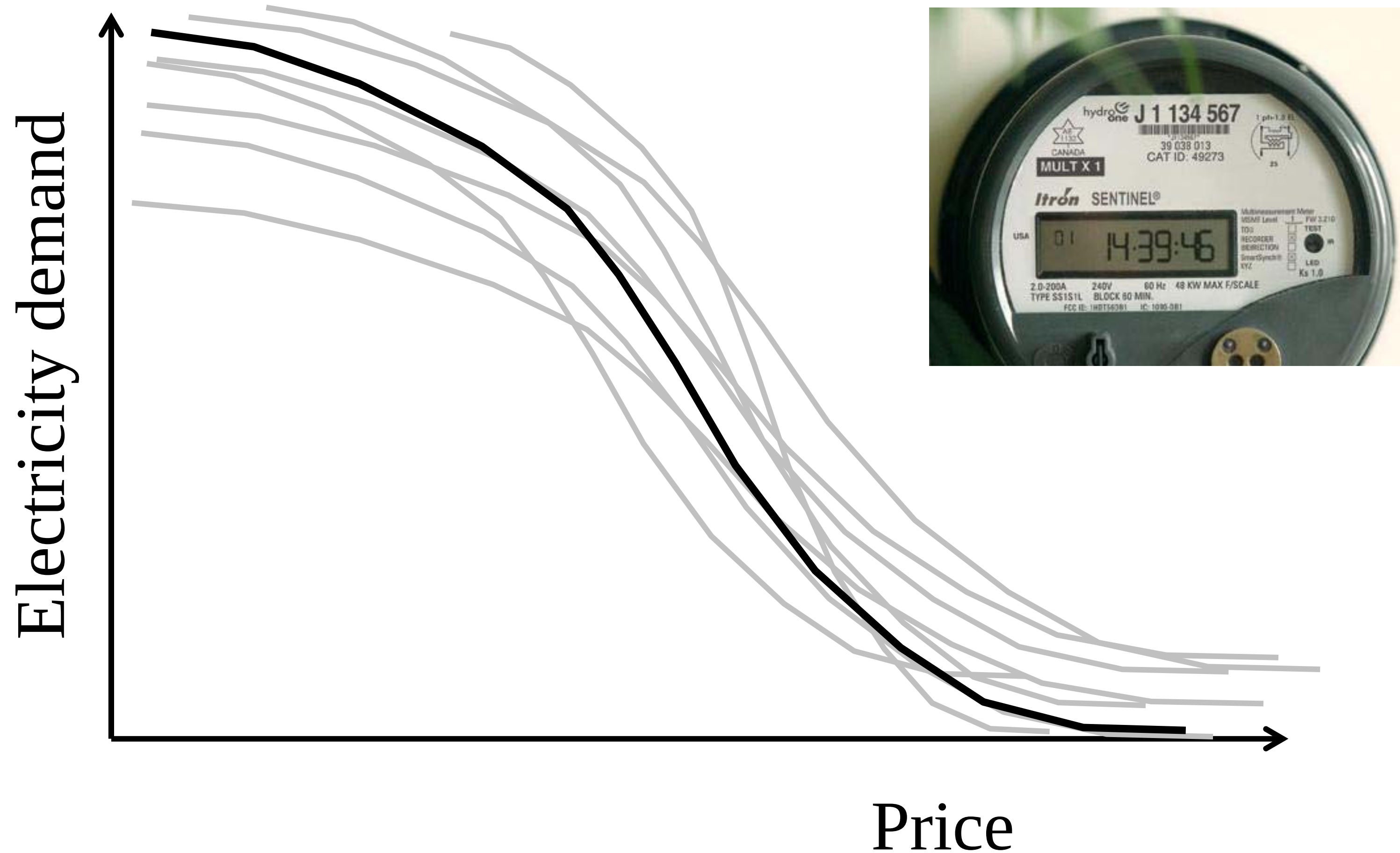


# Network failures:

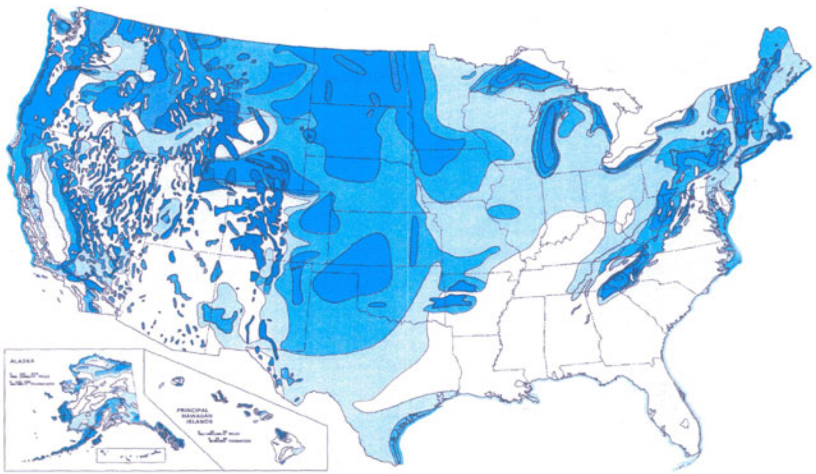


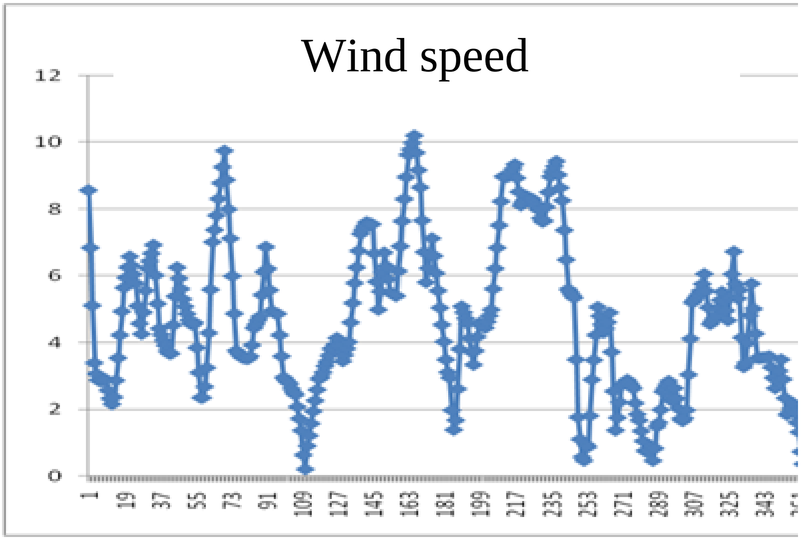
# Uncertainty in demand response

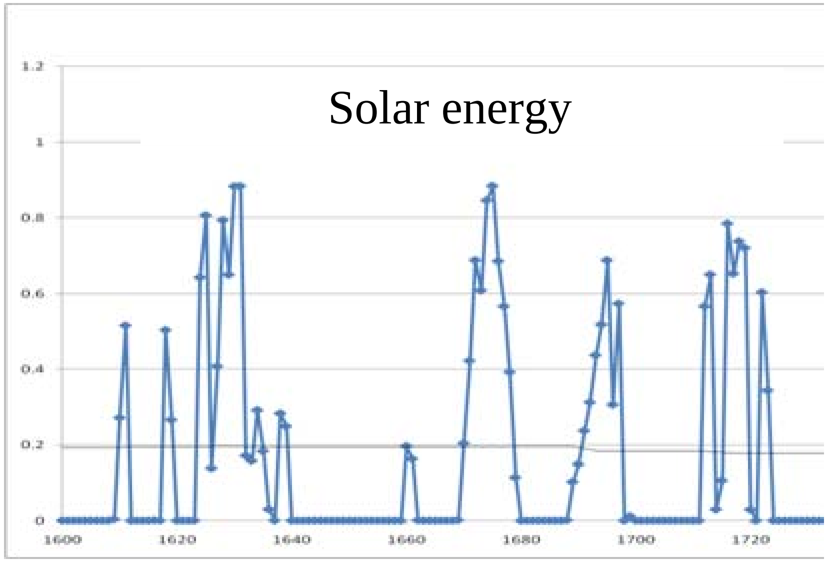
- How will the market respond to price signals?

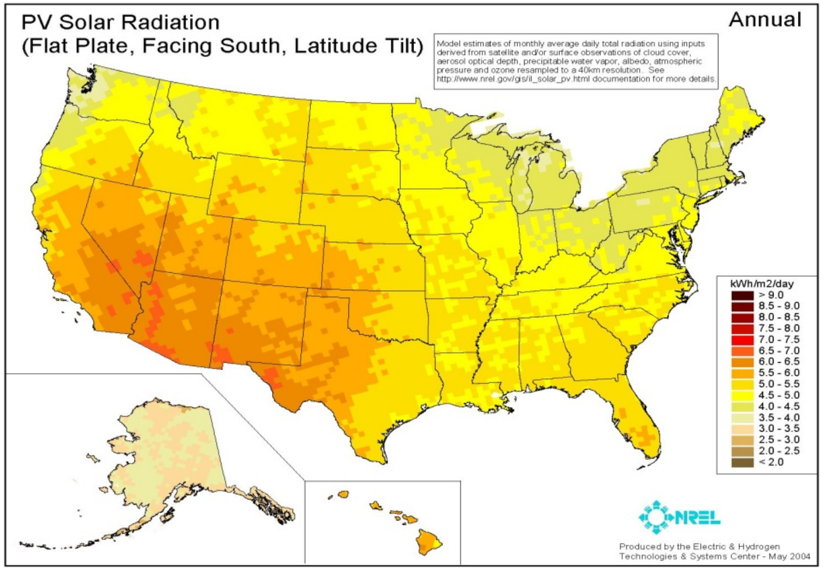


# Intermittent energy sources



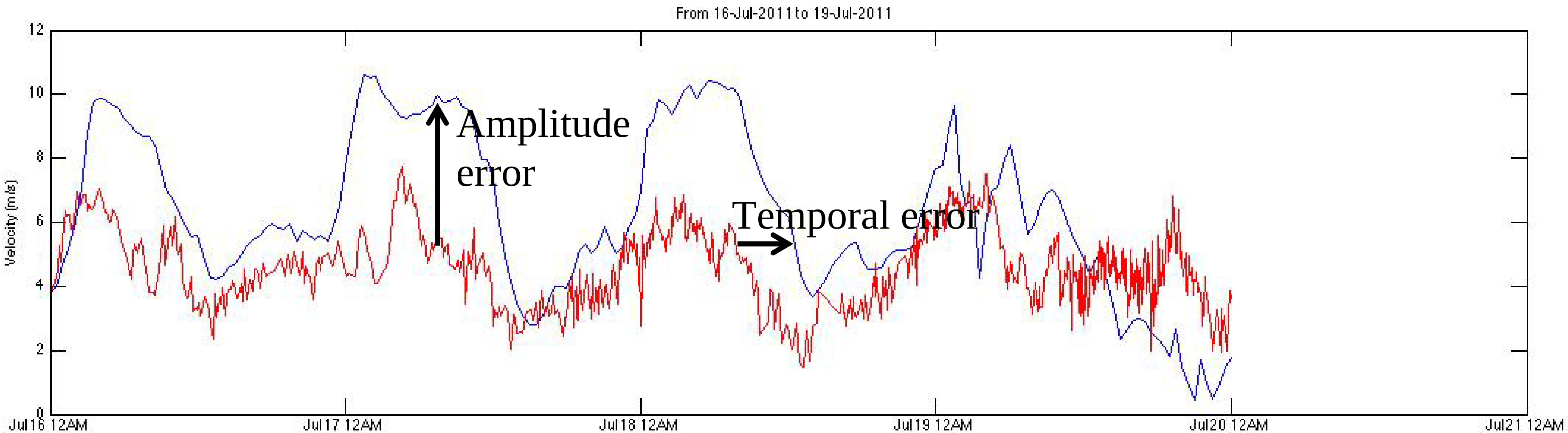


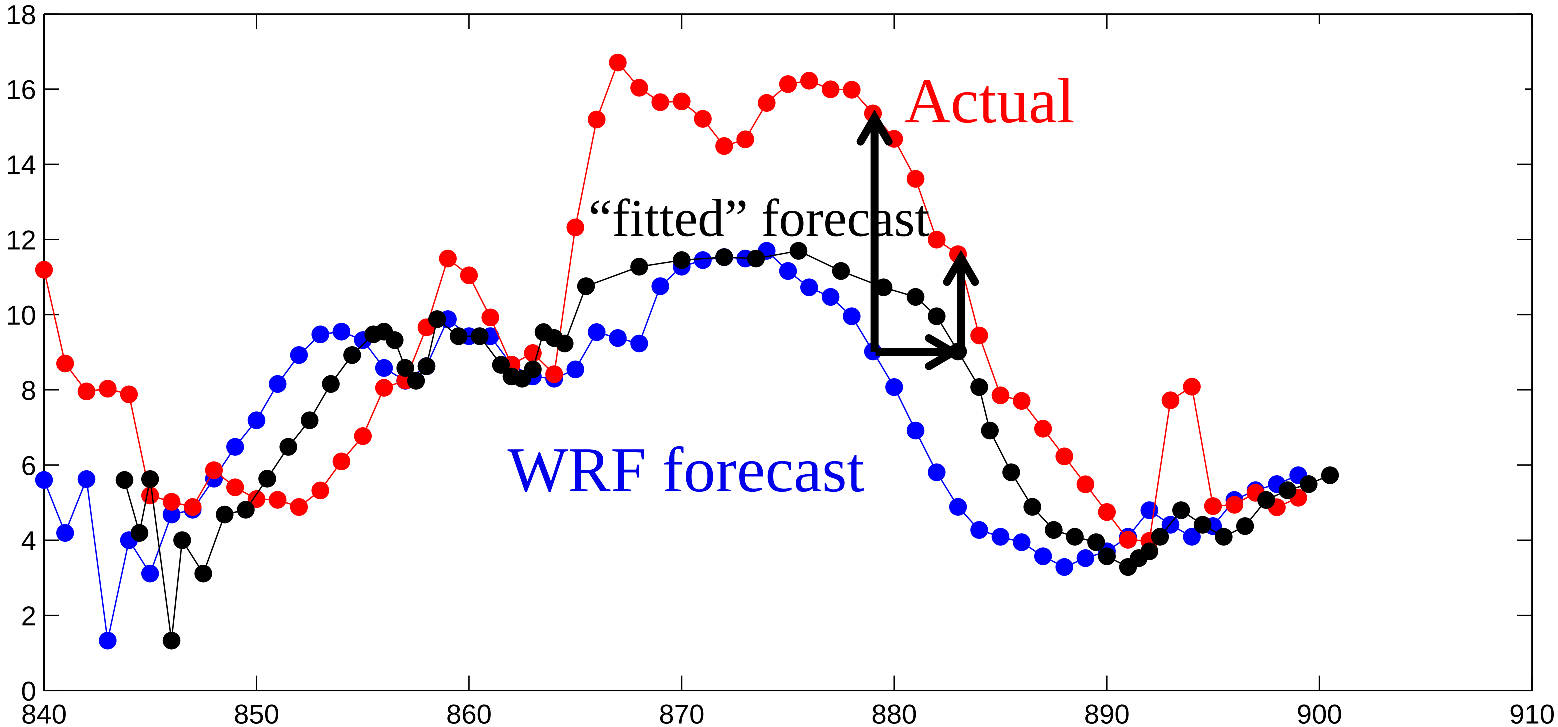
# Modeling wind forecast errors

- We need a mathematical model of the stochastic process describing errors in wind forecast
  - » We are using the “WRF” model to predict wind. WRF is a sophisticated meteorological model that can predict shifts in weather patterns.
  - » We need to separate amplitude errors (how much wind at a point in time) from temporal errors (errors in the timing of a weather shift).



# Modeling wind forecast errors

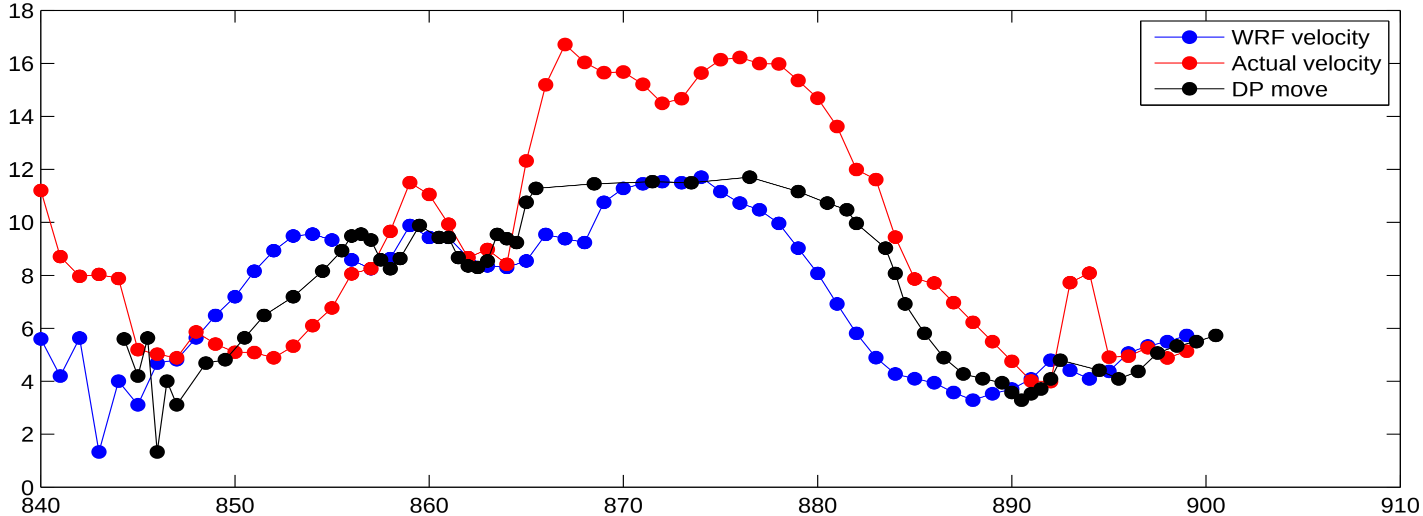
- We "fit" a forecast by optimizing temporal shifts
  - » Nonlinear cost function penalizes amplitude and penalty shifts
  - » Additional penalty for *changes* in shifts
  - » Optimized "fit" obtained by solving a dynamic program. State variable = (shift of previous point, change in two previous shifts)



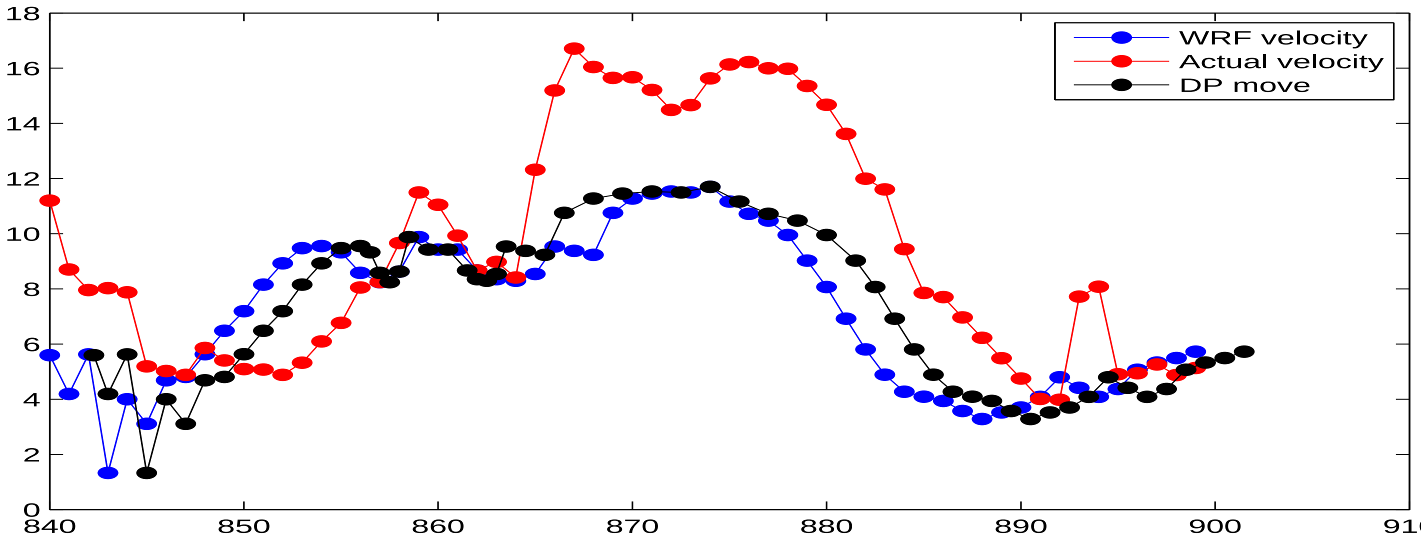
# Modeling wind forecast errors

- Results with different penalties on temporal acceleration

Low temporal acceleration penalty “overfitting”




High temporal acceleration penalty “underfitting”

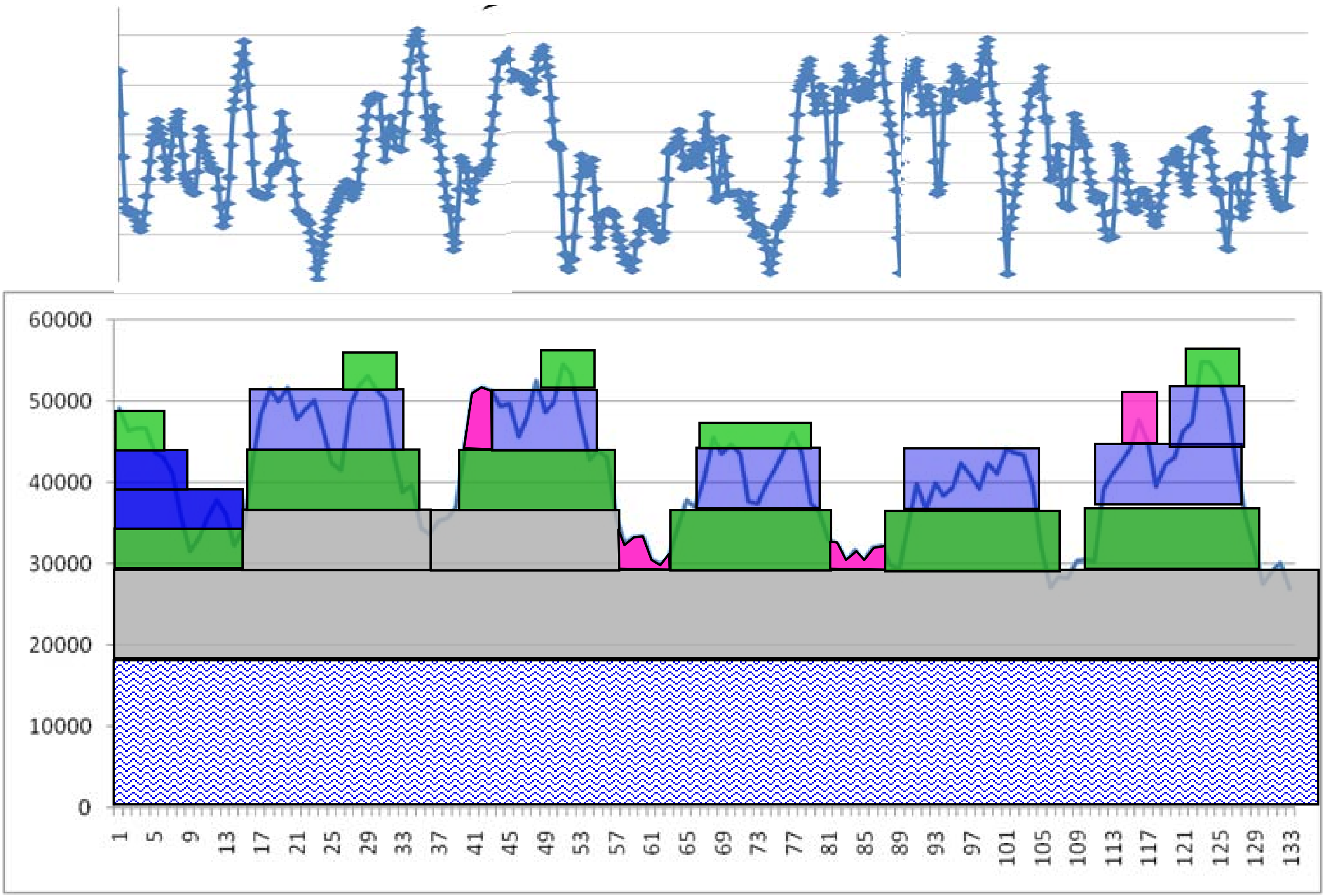


# The research goal

- The SMART family of models
  - » Stochastic, Multiscale Model for the Analysis of energy Resources, Technology and Policy
  - » SMART-ISO - A fine-grained model of the PJM power grid.

- Key features
  - » Captures different forms of uncertainty
  - » Accurate modeling of the sequencing of decisions and information, capturing day ahead, hour ahead, and real time markets, as well as a spectrum of markets in between for load curtailment and medium term energy generation (4-6 hours).
  - » Models dynamics at five-minute increments to capture generator ramp rates as well as variations in wind, solar and loads
  - » Detailed model of the power grid (~9,000 buses).

# The stochastic unit commitment problem



# Deterministic optimization models

- We can solve deterministic models using linear programming:
  - » For static problems

$$\min cx$$
$$Ax = b$$
$$x \geq 0$$

  - » For time-staged problems

$$\min \sum_{t=0}^{T} c_t x_t$$
$$A_t x_t - B_{t-1} x_{t-1} = b_t$$
$$D_t x_t \leq u_t$$
$$x_t \geq 0$$

Everyone who models deterministic optimization problems using the same notational system.

This is not at all the case when we introduce uncertainty.

# Modeling dynamic problems

- The system state:

$$S_t = \left(R_t, I_t, K_t\right) = \text{System state, where:}$$

$R_t$ = Resource state (physical state)

Energy investments, energy storage, ...

Status of generators

$I_t$ = Information state

State of the technology (costs, performance)

Climate, weather (temperature, rainfall, wind)

Market prices (oil, coal)

$K_t$ = Knowledge state ("belief state")

Belief about the effect of CO2 on the environment

Belief about the effect of fertilizer on algal blooms

*The state variable is the minimally dimensioned function of history that allows us to calculate the decision function, cost function and transition function.*

# Modeling dynamic problems

- Decisions:

$x_t$ = A decision to buy, sell, move, repair, store, price, or control

$X^\pi(S_t)$ = Decision function (or "policy"); maps states to decisions (also known as actions or controls). We generally have a family of policies/functions so we write $\pi \in \Pi$

# Modeling dynamic problems

- Exogenous information:

$$W_t = \text{New information} = \left(\hat{R}_t, \hat{D}_t, \hat{E}_t, \hat{p}_t\right)$$

$\hat{R}_t =$ Exogenous changes in capacity, reserves

New gas/oil discoveries, breakthroughs in technology

$\hat{D}_t =$ New demands for energy from each source

Demand for energy

$\hat{E}_t =$ Changes in energy from wind and solar

$\hat{p}_t =$ Changes in prices of commodities, electricity, technology

# Modeling dynamic problems

- The transition function

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

$$R_{t+1} = R_t + Ax_t + \widehat{R}_{t+1}$$ Water in the reservoir

$$p_{t+1} = p_t + \hat{p}_{t+1}$$ Spot prices

$$e_{t+1}^{Wind} = e_t^{Wind} + \hat{e}_{t+1}^{Wind}$$ Energy from wind

Also known as the:

- "System model"
- "State transition model"
- "Plant model"
- "Model"

# Stochastic optimization models

- The objective function

$$\min_{\pi} E^{\pi}\left\{\sum_{t}\gamma^{t}C\left(S_t, X^{\pi}(S_t)\right)\right\}$$

Expectation over all random outcomes

Cost function

State variable

Decision function (policy)

Finding the best policy

given the transition function:

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

» The problem is to find the best policy.


Stochastic programming
Stochastic search
Model predictive control
Optimal control
Reinforcement learning
$Q$ – learning
On-policy learning
Off-policy learning
Markov decision processes
Simulation optimization
Policy search

# Four classes of policies

## 1) Myopic policies

- » Take the action that maximizes contribution (or minimizes cost) for just the current time period:

$$X^M(S_t) = \arg\max_{x_t} C(S_t, x_t)$$

- » We can parameterize myopic policies with bonuses and penalties to encourage good long-term behavior.

- » We may use a ***myopic cost function approximation:***

$$X^M(S_t \mid \theta) = \arg\max_{x_t} \bar{C}^{\pi}(S_t, x_t \mid \theta)$$

The cost function approximation $\bar{C}^{\pi}(S_t, x_t \mid \theta)$ may be designed to produce better long-run behaviors.

# Four classes of policies

## 2) Lookahead policies

Plan over the next T periods, but implement only the action it tells you to do now:

» Deterministic forecast (most common)

$$X_t^{LA}(S_t) = \arg\max_{x_t, x_{t+1}, \ldots, x_{t+T}} C(S_t, x_t) + \sum_{t'=t+1}^{T} C(S_{t'}, x_{t'})$$

» Probabilistic lookahead

$$X_t^{LA}(S_t) = \arg\max_{x_t, x_{t+1}, \ldots, x_{t+T}} C(S_t, x_t) + \sum_{\omega \in \hat{\Omega}} p(\omega) \sum_{t'=t+1}^{T} C(S_{t'}(\omega), x_{t'}(\omega))$$

» Rolling/receding horizon procedures

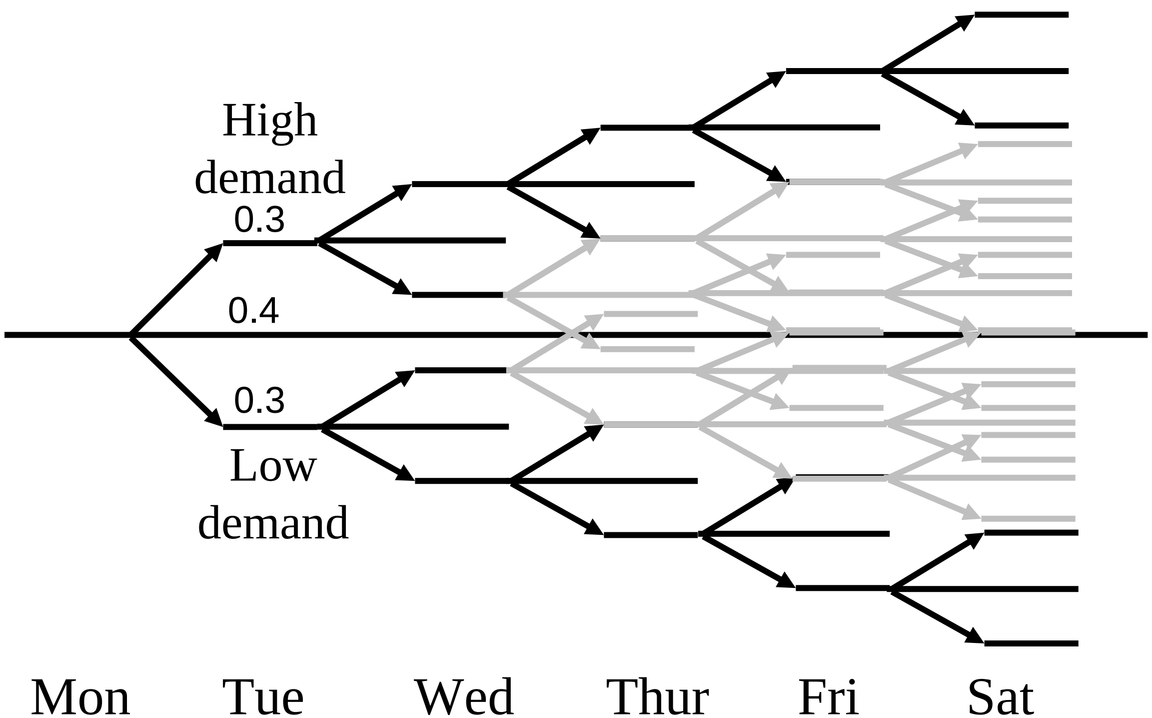
» Model predictive control

» Rollout heuristics

» Tree search (decision trees)

# Four classes of policies

- Probabilistic lookahead
  - » This formulation is popular in water resource planning



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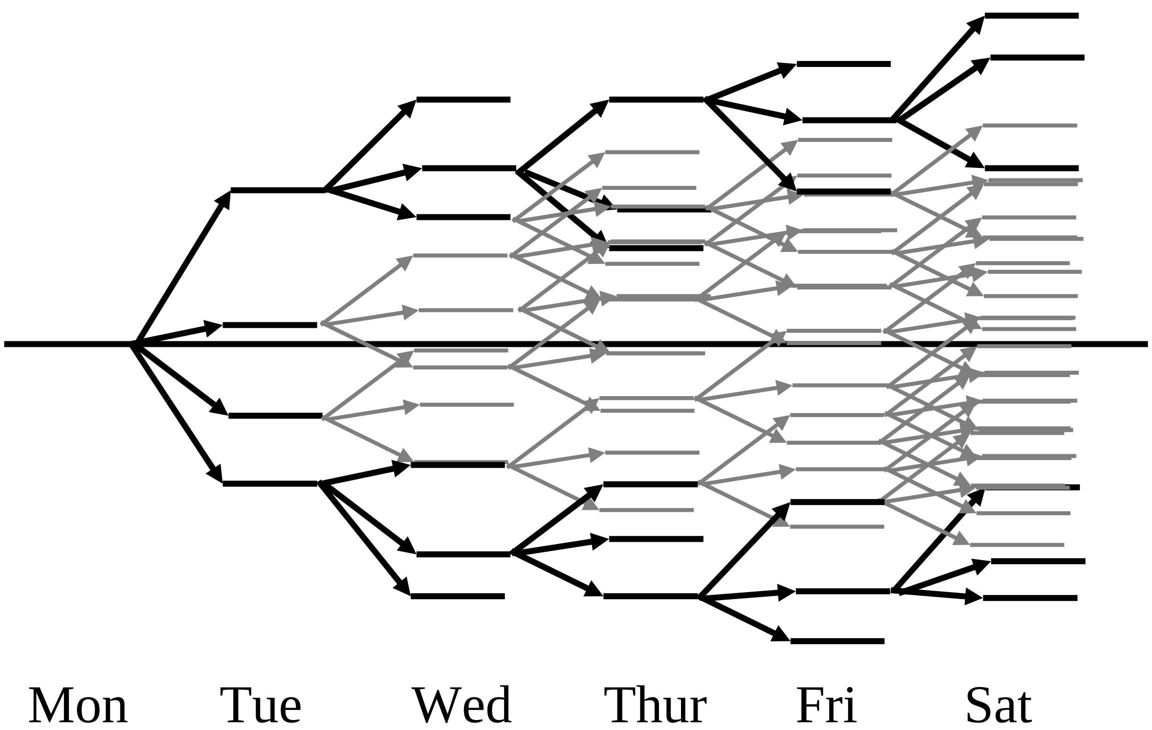
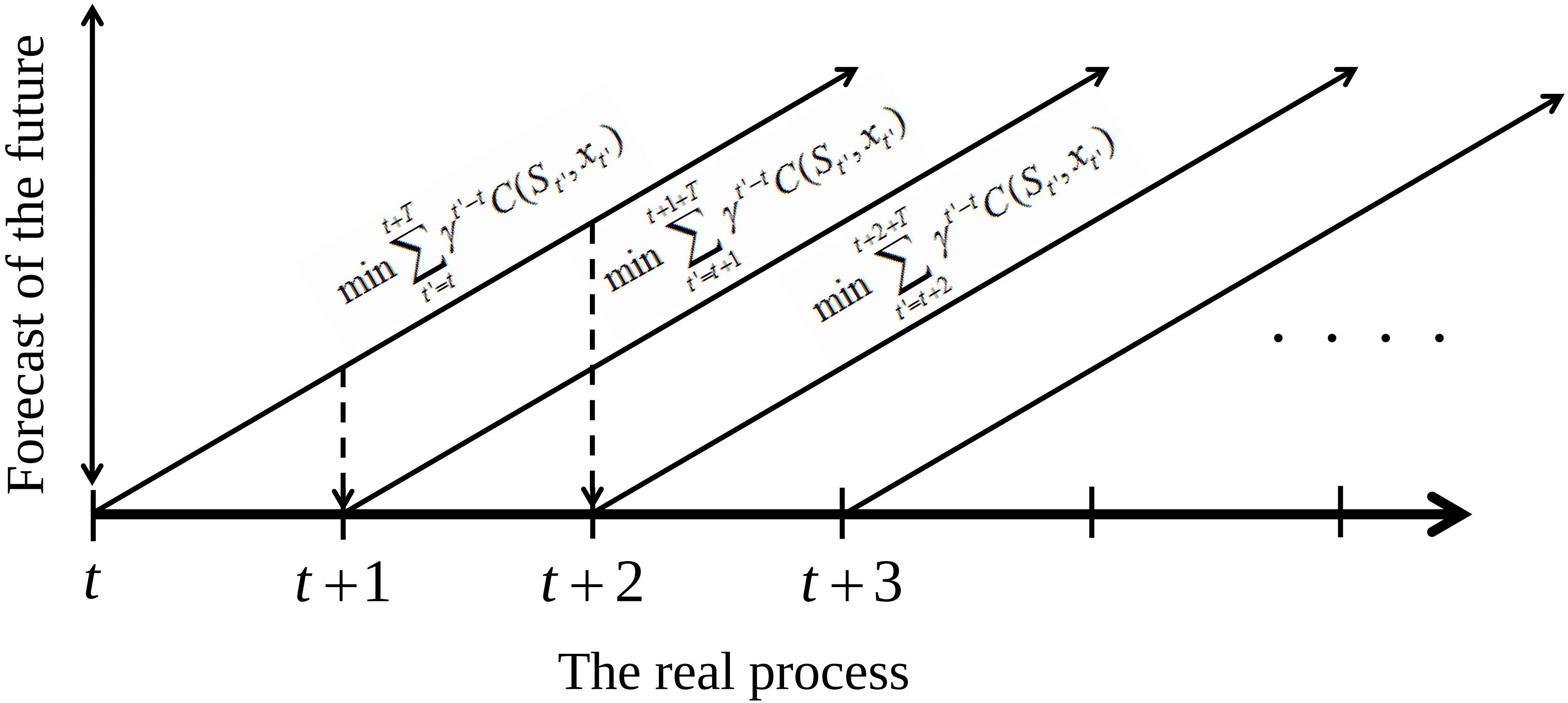


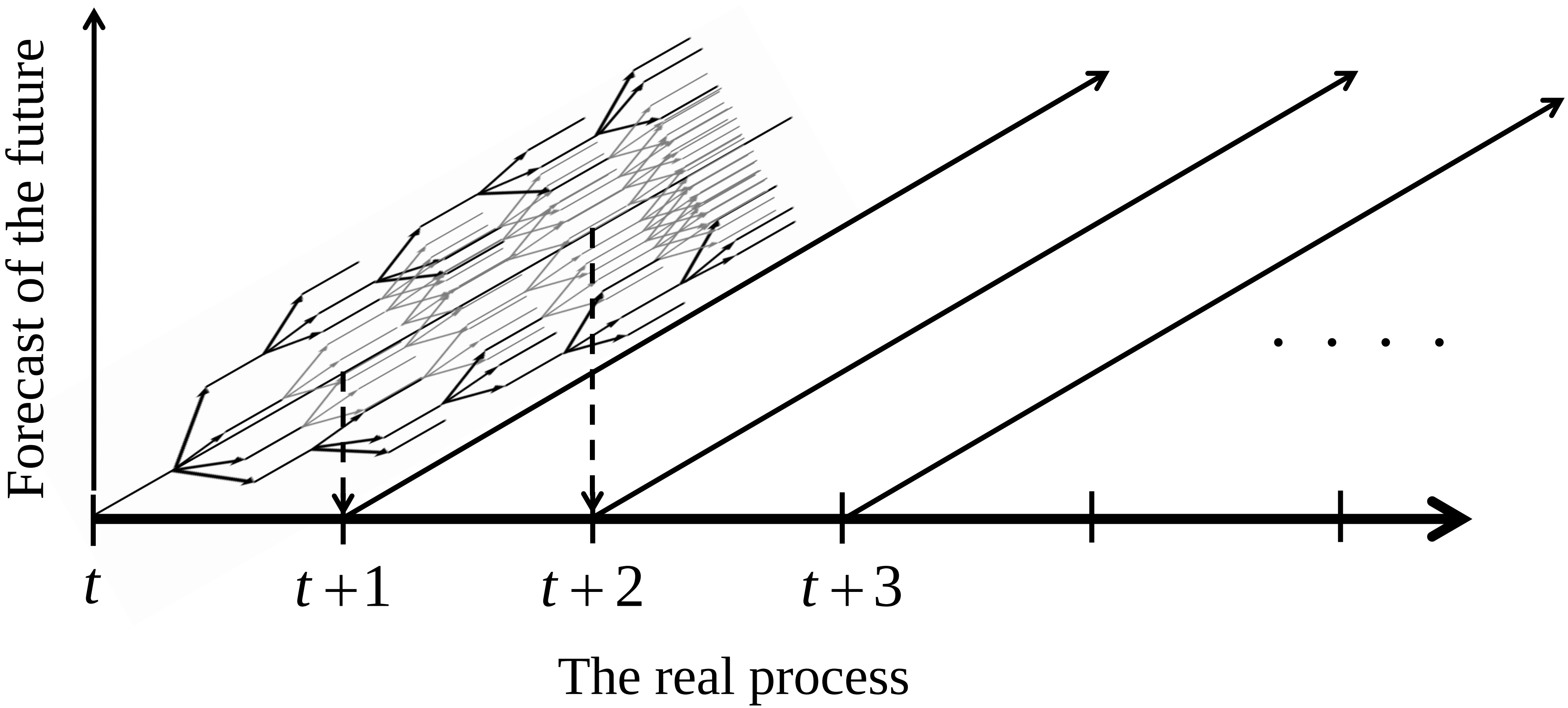
# Lookahead policies

- Lookahead policies peek into the future
  - » Optimize over point forecast of the future



# Four classes of policies

- Probabilistic lookahead
  - » Optimize over *stochastic* model of the future.



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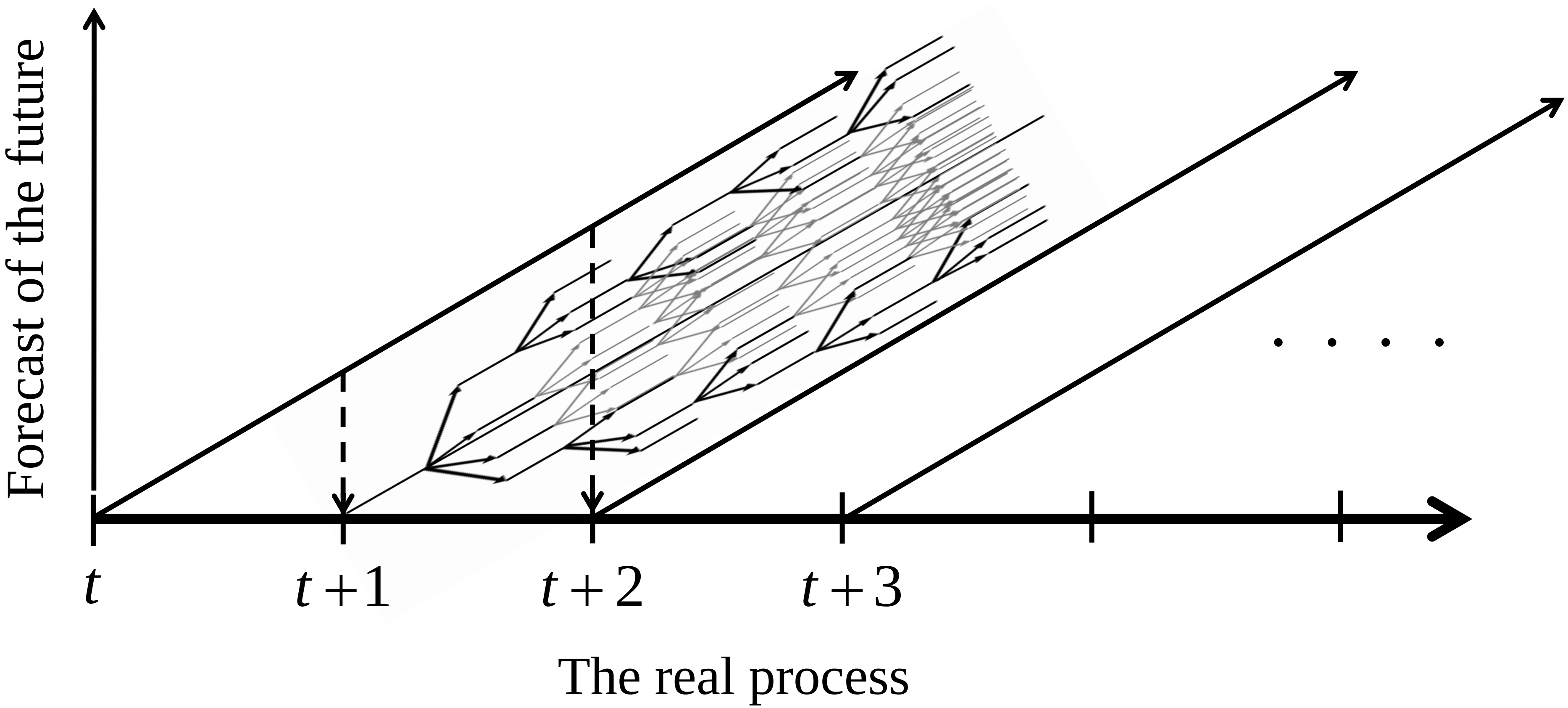

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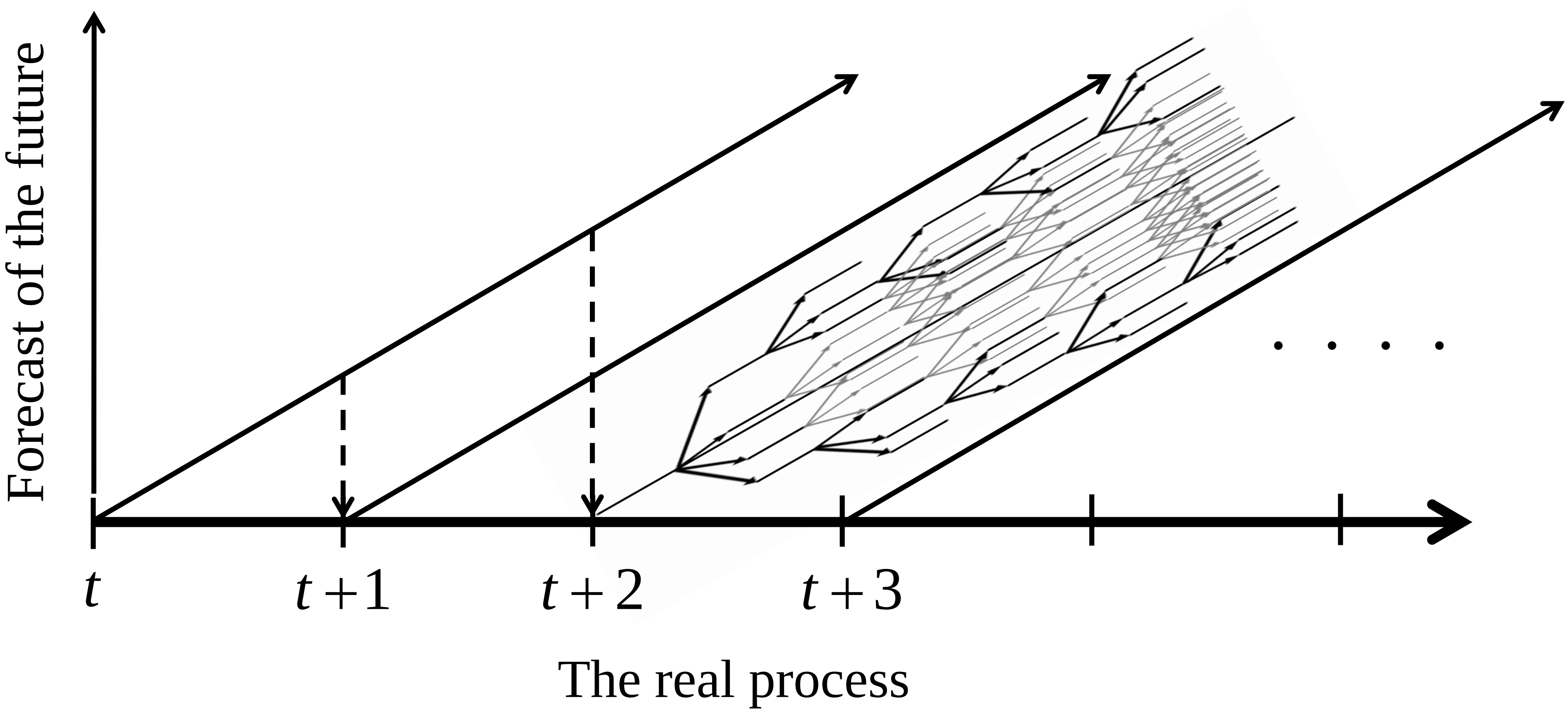


# Four classes of policies

## 3) Policy function approximations

» Lookup table

- Recharge the battery between 2am and 6am each morning, and discharge as needed.

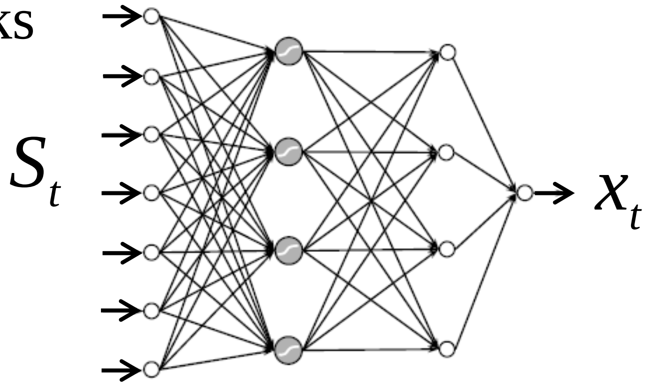
» Parameterized functions

- Recharge the battery when the price is below $\rho^{\text{charge}}$ and discharge when the price is above $\rho^{\text{discharge}}$

» Regression models

$$X^{PFA}(S_t \mid \theta) = \theta_0 + \theta_1 S_t + \theta_2 \left(S_t\right)^2$$

» Neural networks



# Four classes of policies

## 4) Policies based on value function approximations

» Using the pre-decision state

$$X^{VFA}(S_t) = \arg\max_{x_t} \left( C(S_t, x_t) + \gamma E \bar{V}_{t+1}(S_{t+1}) \right)$$

» Or the post-decision state:

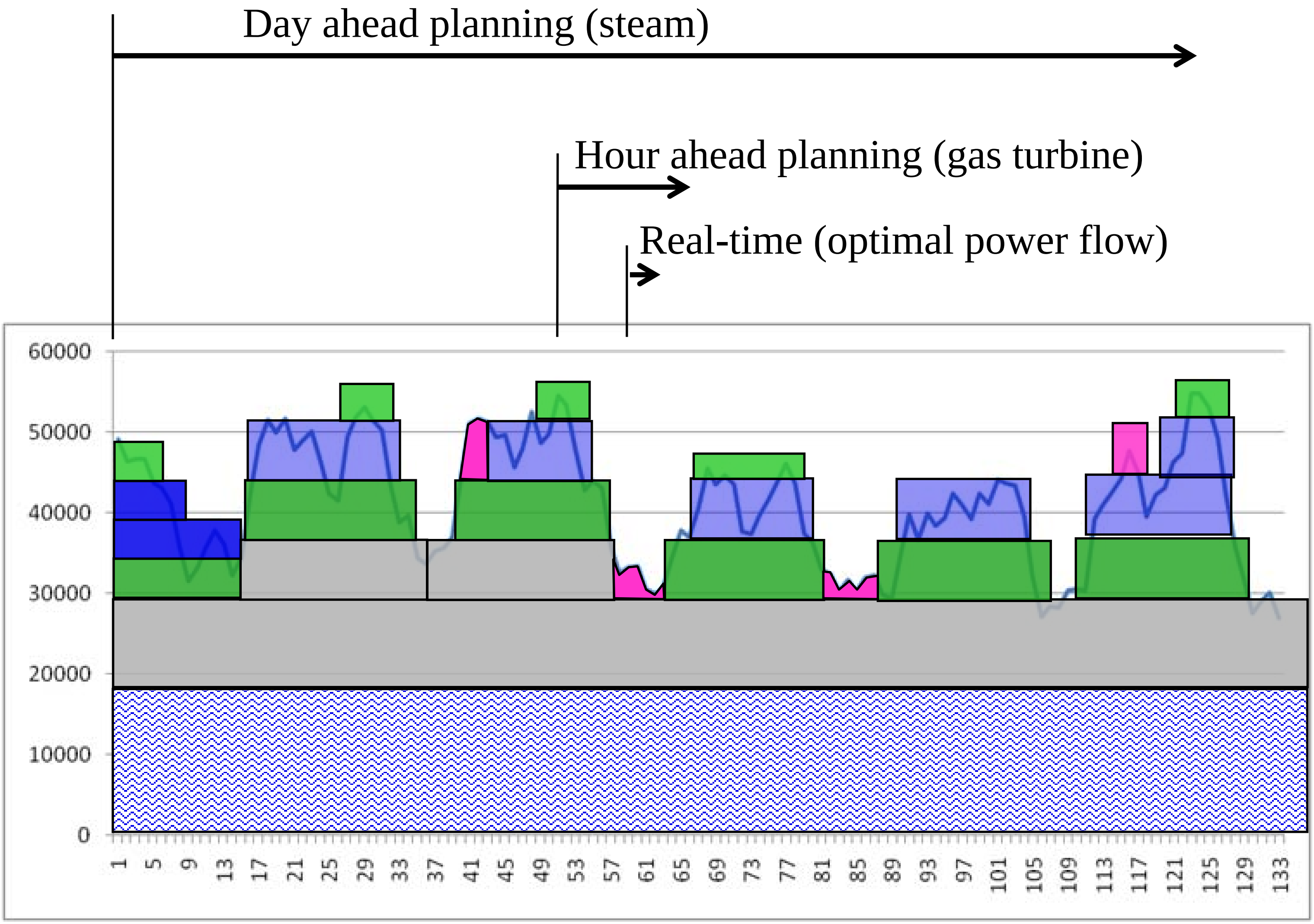
$$X^{VFA}(S_t) = \arg\max_{x_t} \left( C(S_t, x_t) + \gamma \bar{V}_{t+1}\left( S_t^x(S_t, x_t) \right) \right)$$

» This is what most people associate with “approximate dynamic programming”

# Four classes of policies

- There are three classes of approximation strategies (for costs, policies and value functions):
  - » Lookup table
    - Given a discrete state, return a discrete action or value
  - » Parametric models
    - Linear models (“basis functions”)
    - Nonlinear models
    - Neural networks
  - » Nonparametric models
    - Kernel regression
    - Dirichlet process-based models

# The time-staging of decisions



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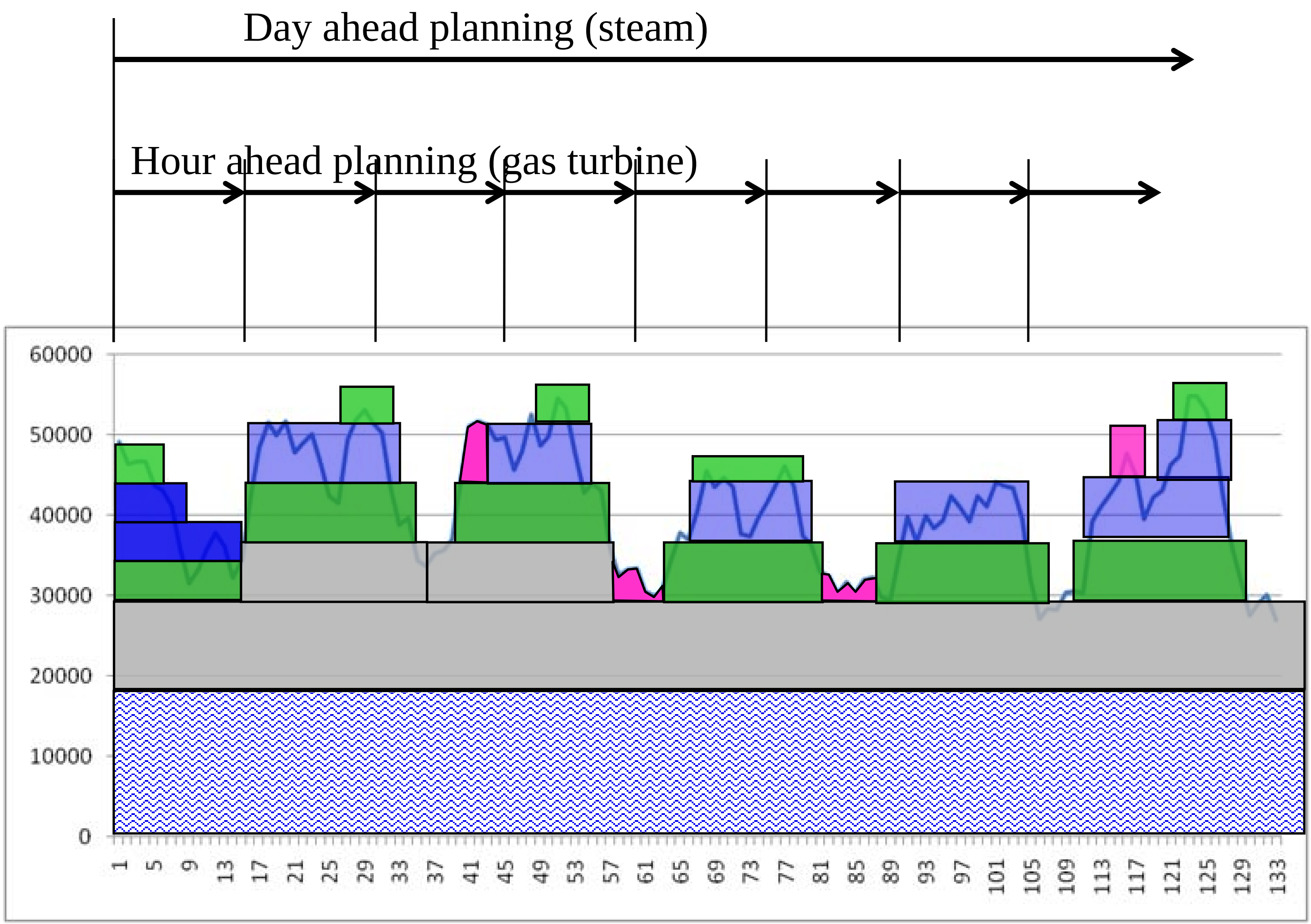

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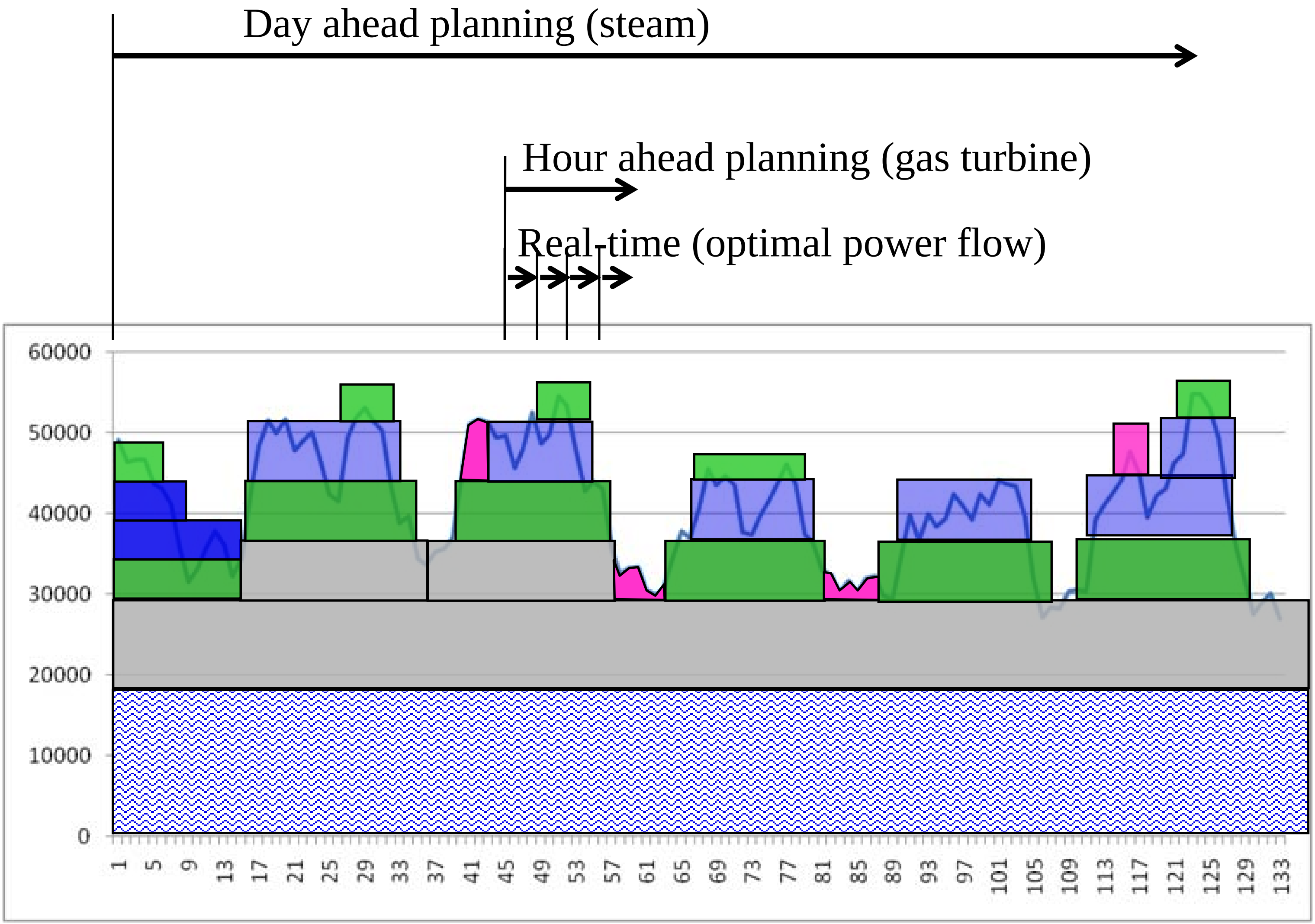

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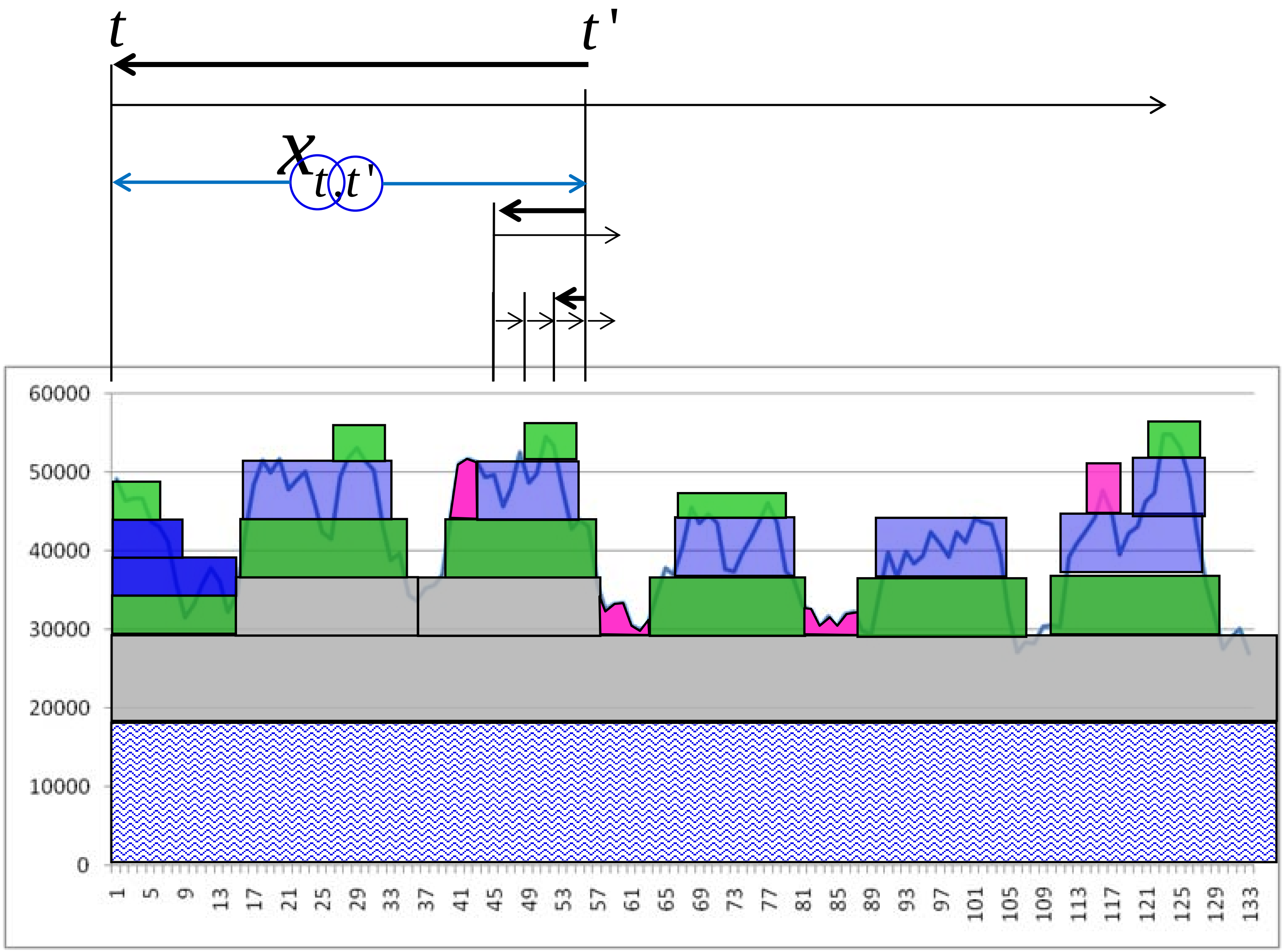

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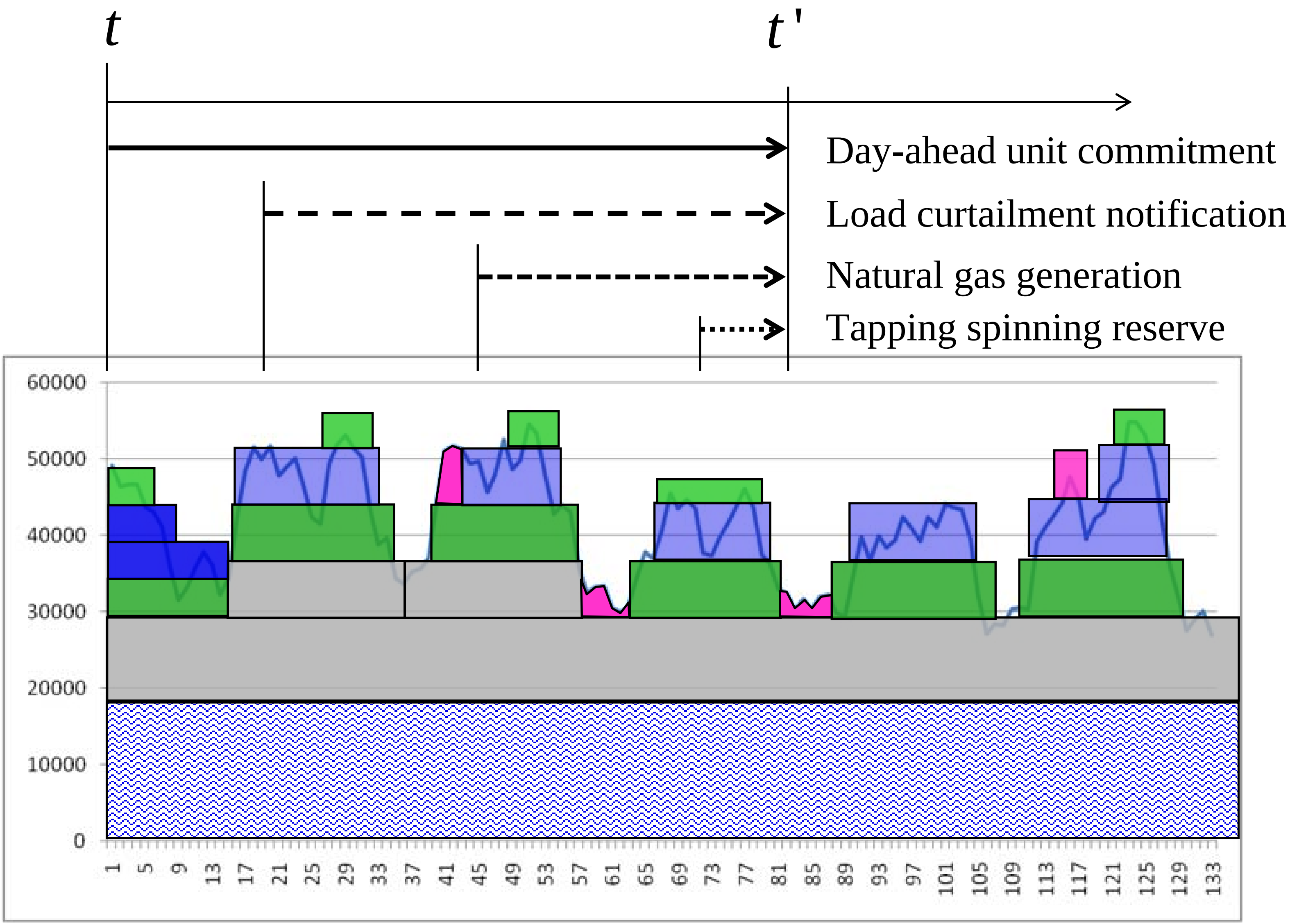

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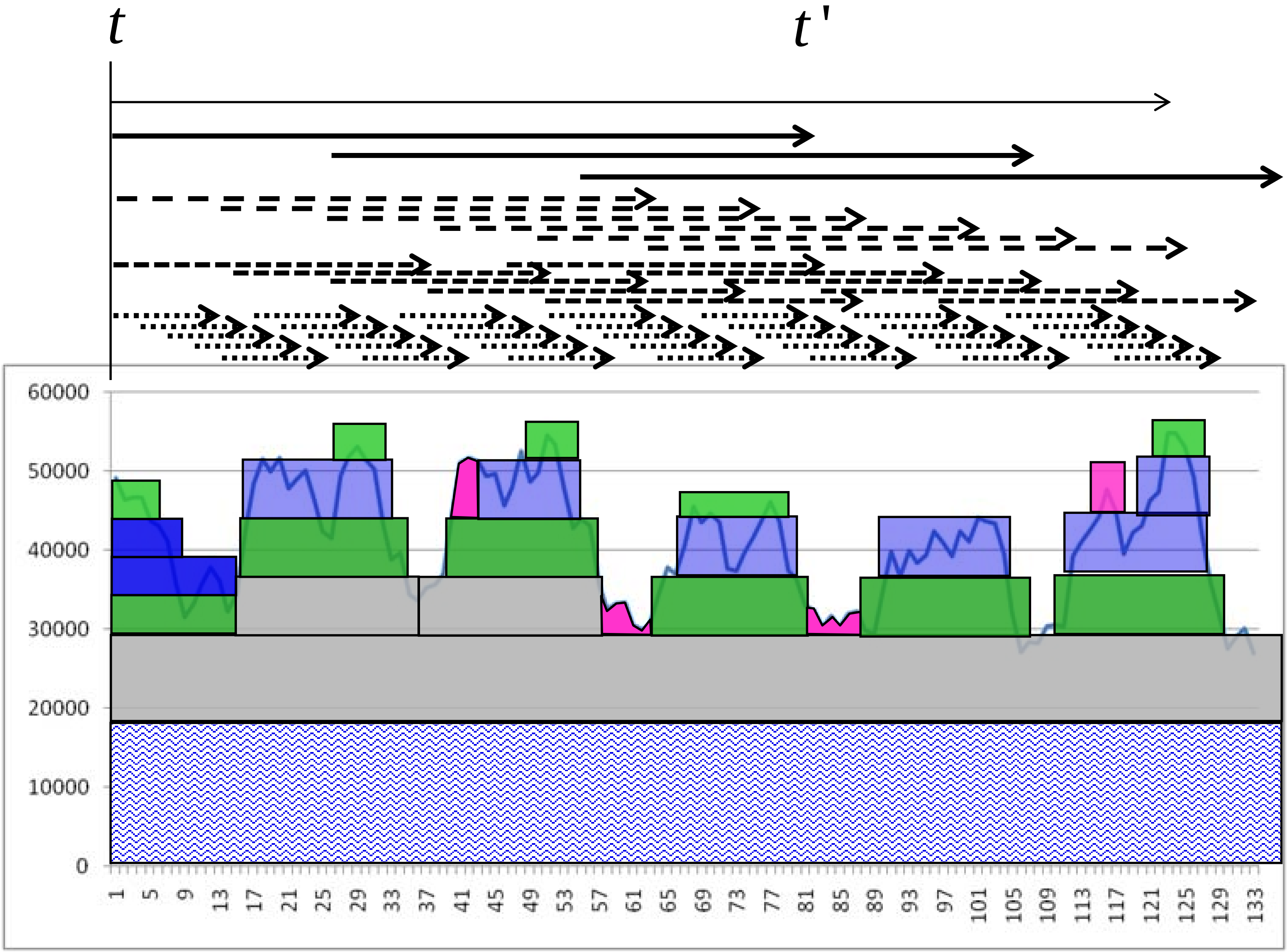

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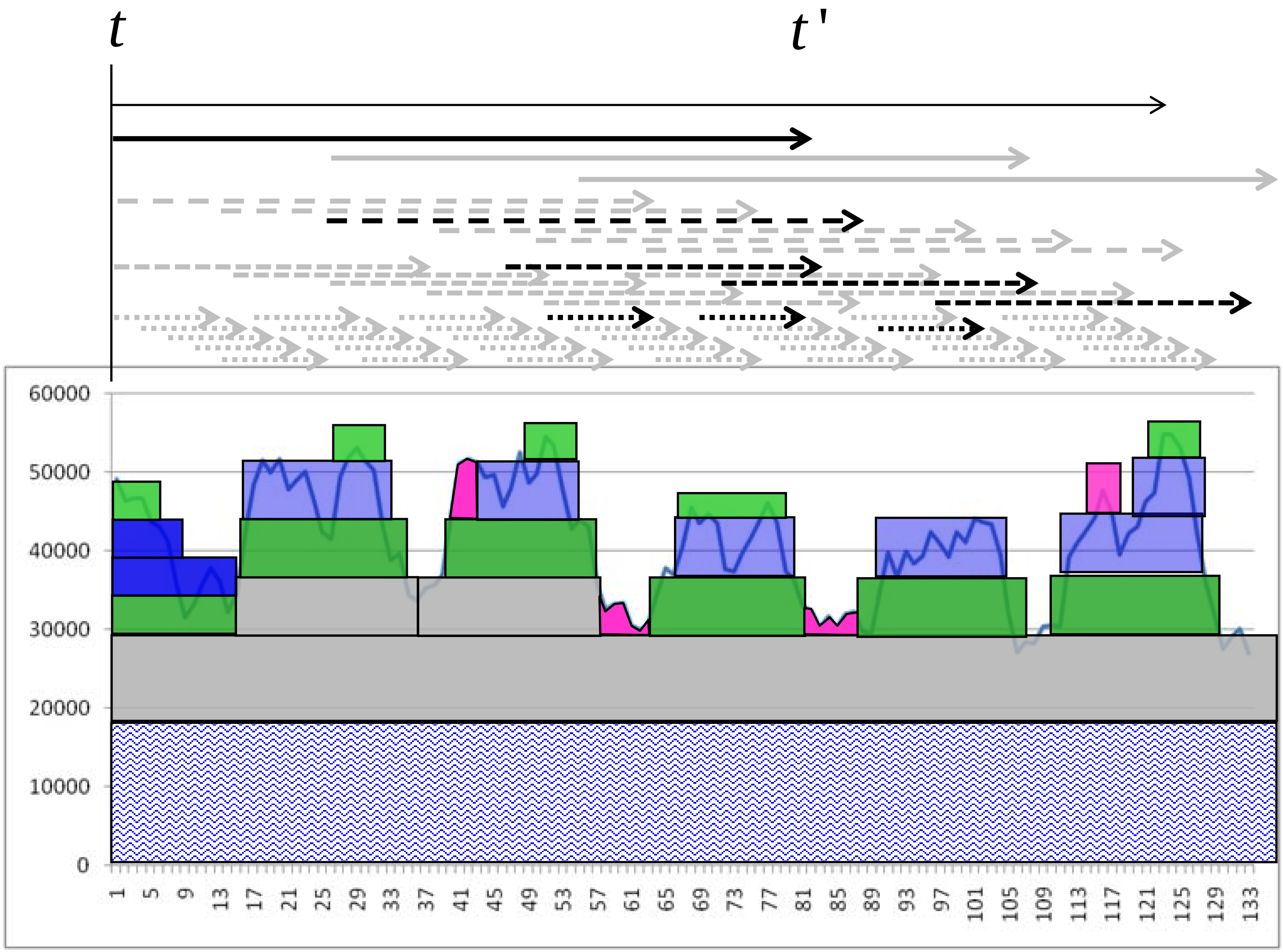


# The stochastic unit commitment problem

- A deterministic model
  - » Optimize over all decisions at the same time

$$\min_{\substack{(x_{t'})_{t'=1,\dots,24} \\ (y_{t'})_{t'=1,\dots,24}}} \sum_{t'=1}^{24} C(x_{t'}, y_{t'})$$

Steam generation

Gas turbines

  - » These decisions need to made with different horizons
    - Steam generation is made day-ahead
    - Gas turbines can be planned an hour ahead or less

# The stochastic unit commitment problem

- A stochastic model
  - » The decision problem at time *t:*

$$x_{t,t'} \qquad \min_{\substack{(x_{t,t'})_{t'=1,\ldots,24} \\ (y_{t',t'})_{t'=1,\ldots,24}}} \mathrm{E} \sum_{t'=1}^{24} C(x_{t,t'}, y_{t',t'})$$

$$y_{t',t'}$$

- $x_{t,t'}$ is determined at time *t*, to be implemented at time *t'*
- $y_{t',t'}$ is determined at time *t'*, to be implemented at time *t'*

  - » Important to recognize information content
    - At time *t*, $x_{t,t'}$ is deterministic.
    - At time *t*, $y_{t',t'}$ is stochastic.

# The stochastic unit commitment problem

- A stochastic model
  - » We capture the information content of decisions

$$\min_{\substack{(x_{t,t'})_{t'=1,\dots,24} \\ \pi}} \mathrm{E} \sum_{t'=1}^{24} C(x_{t,t'}, Y^{\pi}(S_{t'}))$$

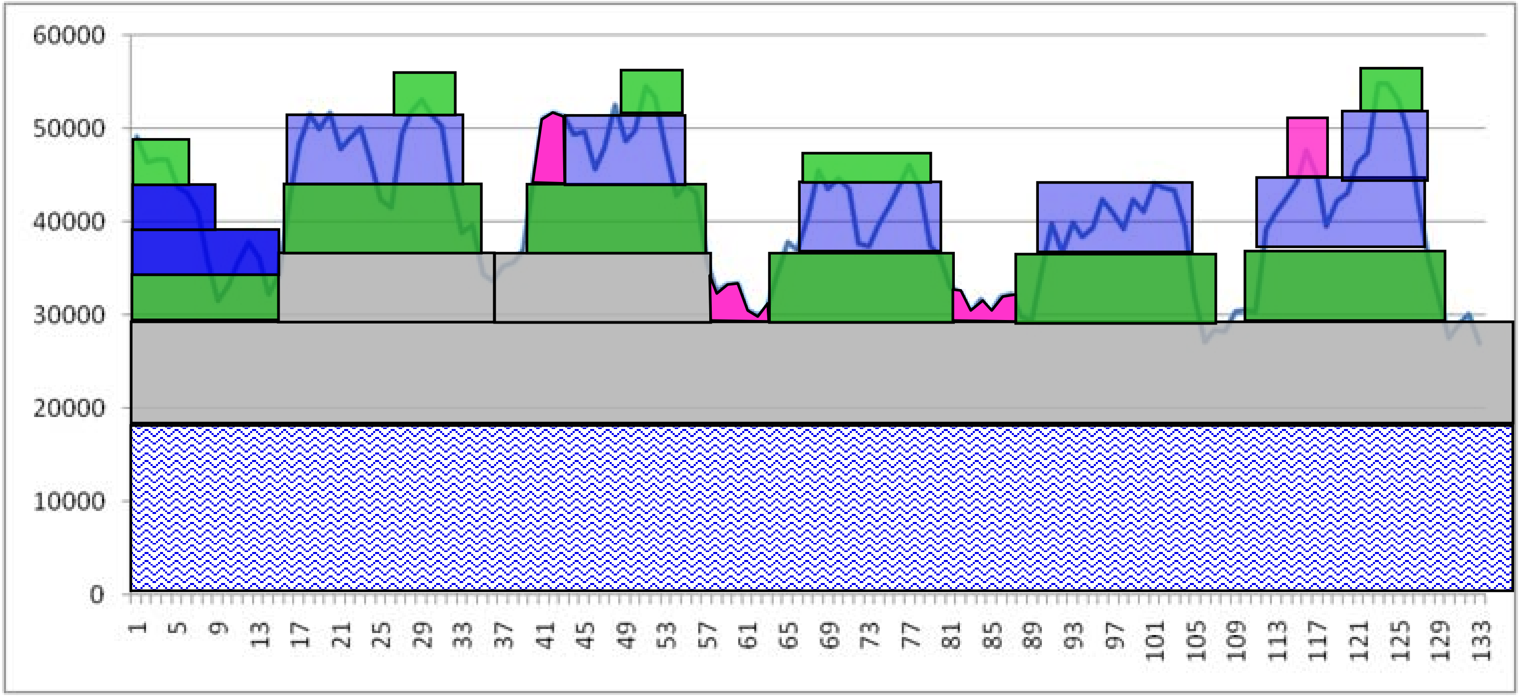
Policy

  - $x_{t,t'}$ is determined at time $t$, to be implemented at time $t'$
  - $y_{t',t'}$ is determined at time $t'$ by the policy $Y^{\pi}(S_{t'})$

  - » The policy $Y^{\pi}(S_{t'})$ is constrained by the solution $x_t$ which is influenced by two parameters:
    - $p$ is the fraction of power allocated for spinning reserve
    - $q$ is the fraction of the wind that we plan on using.

# The stochastic unit commitment problem

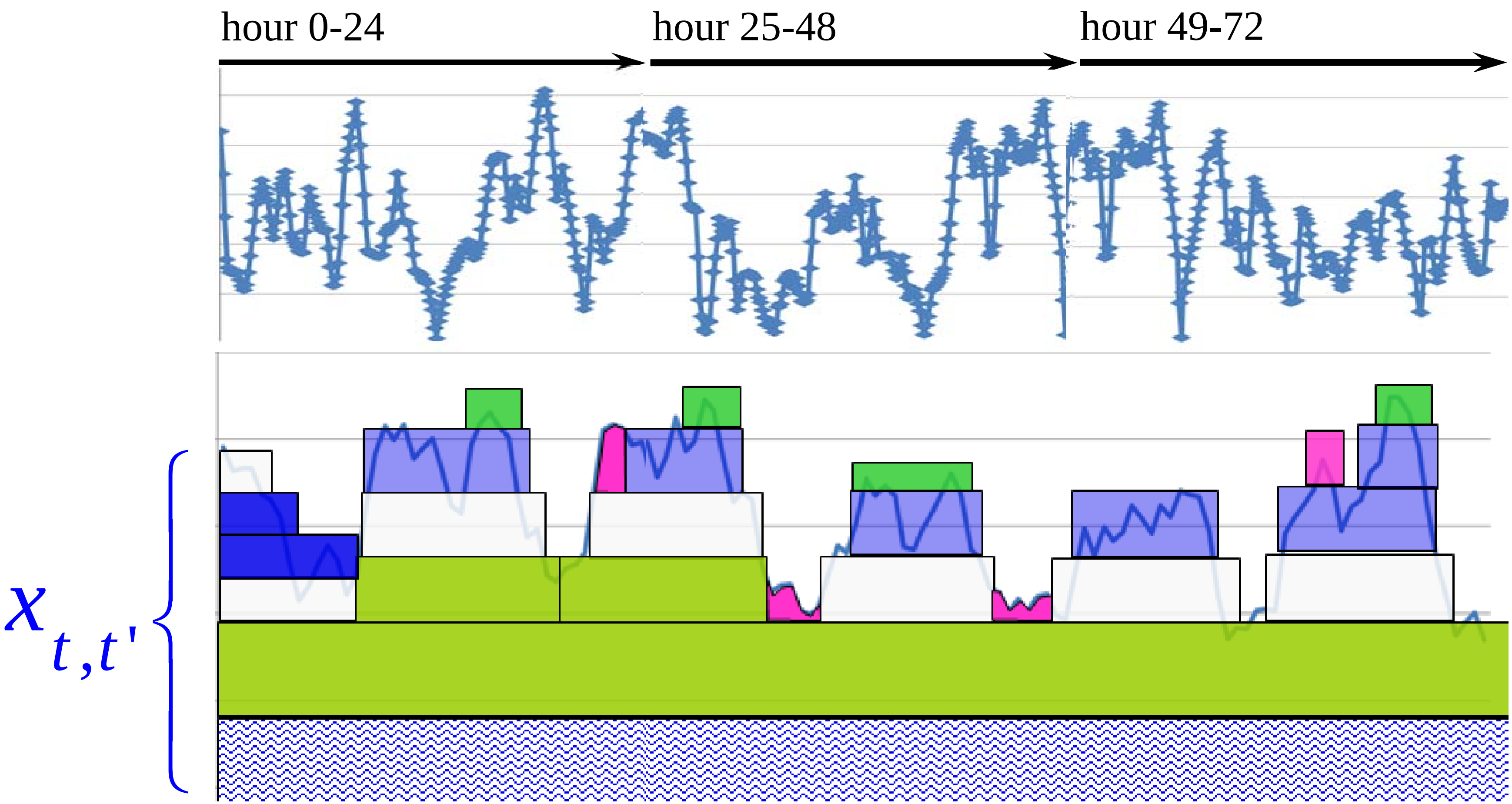
- Matching supply to demand
  - » We have to find the best way to meet demand




  - » …. Now we have to do it in the presence of significant levels of wind and solar energy.

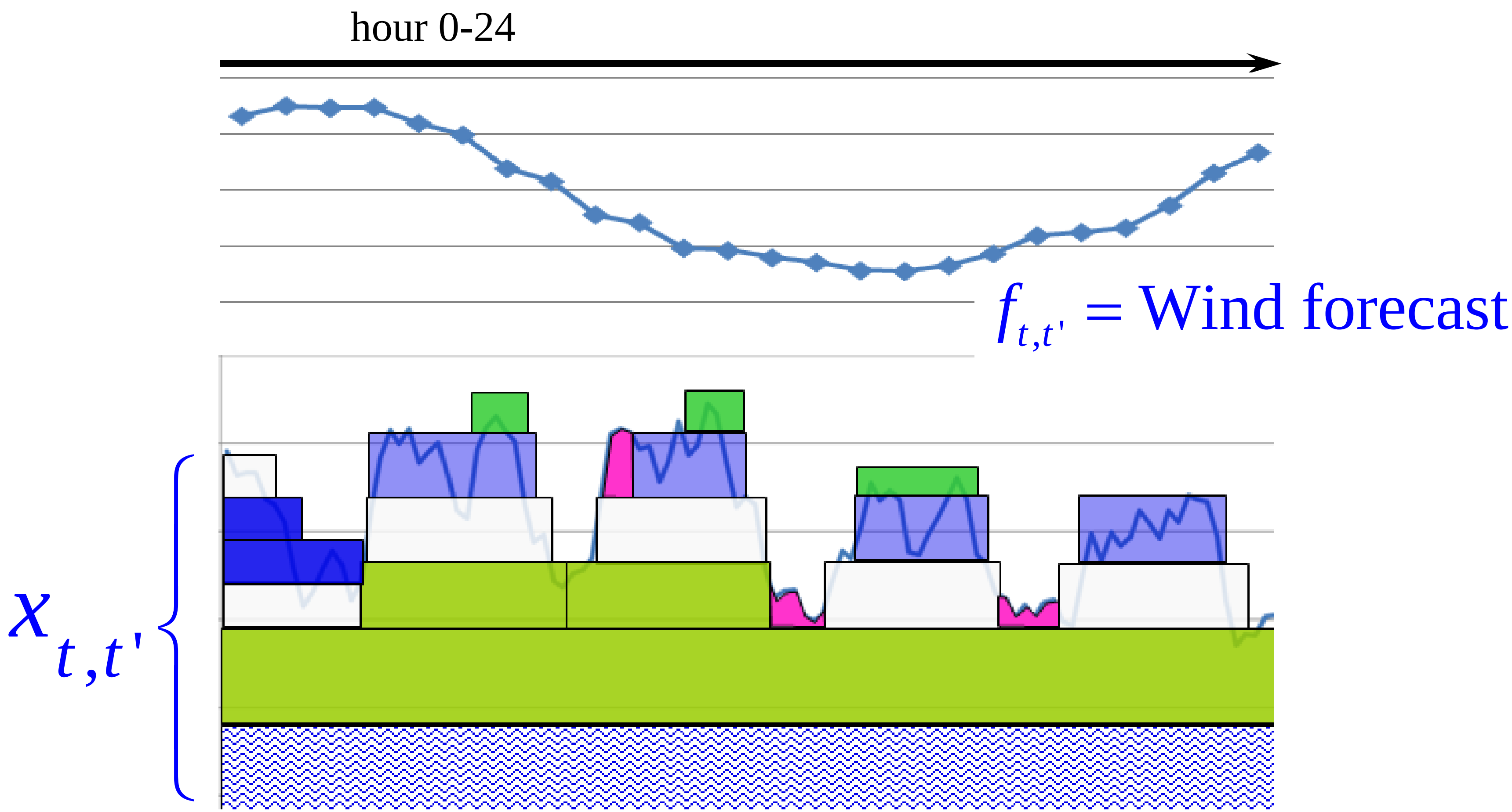
# The stochastic unit commitment problem

- The unit commitment problem
  - » Rolling forward with perfect forecast of actual wind, demand, …



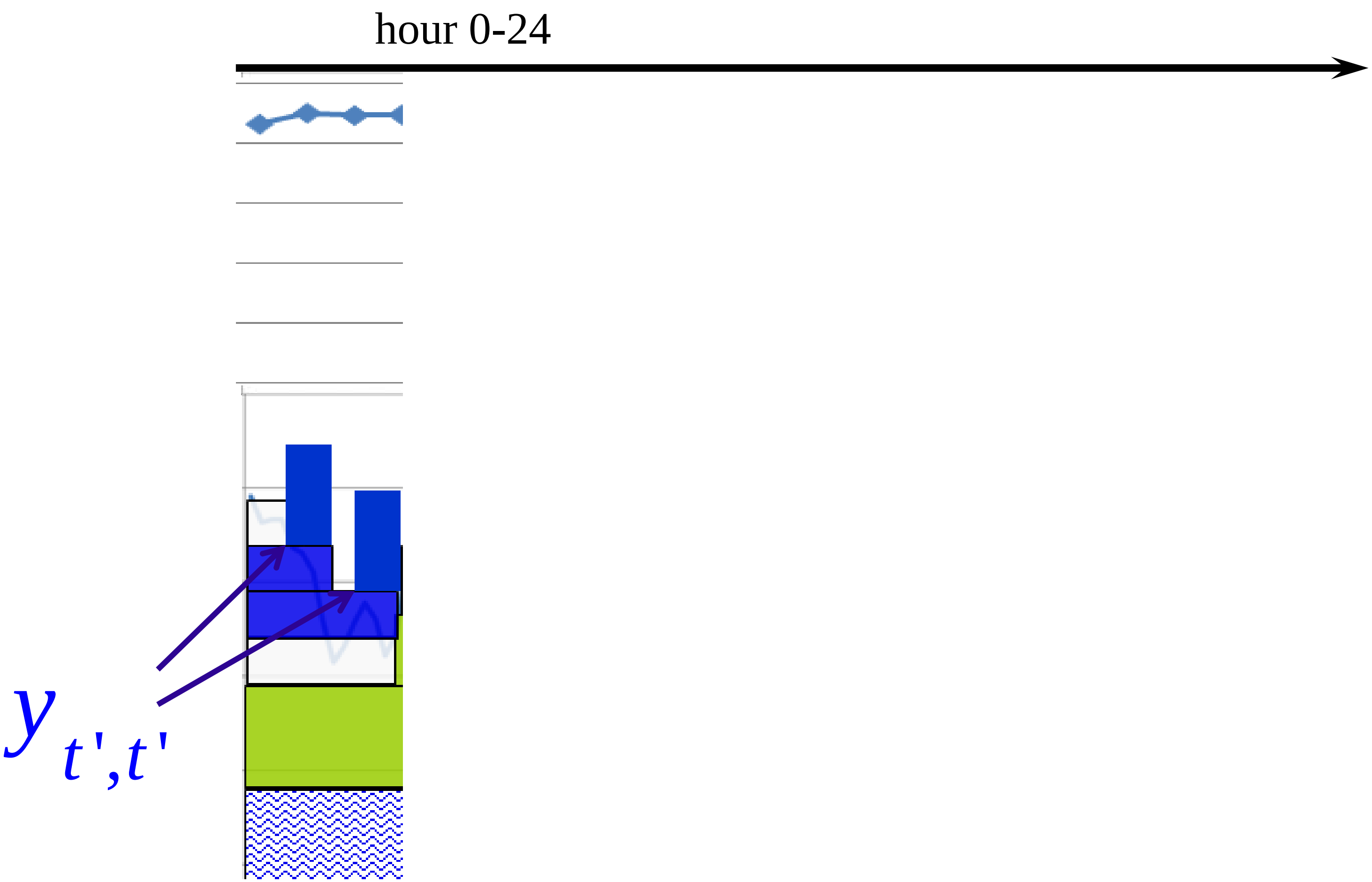
# The stochastic unit commitment problem

- When planning, we have to use a *forecast* of energy from wind, then live with what *actually* happens.



# The stochastic unit commitment problem

- The unit commitment problem
  - » Stepping forward observing actual wind, making small adjustments



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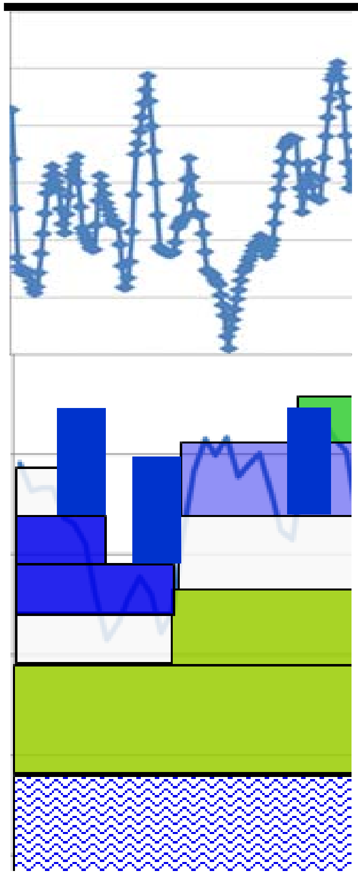
hour 0-24



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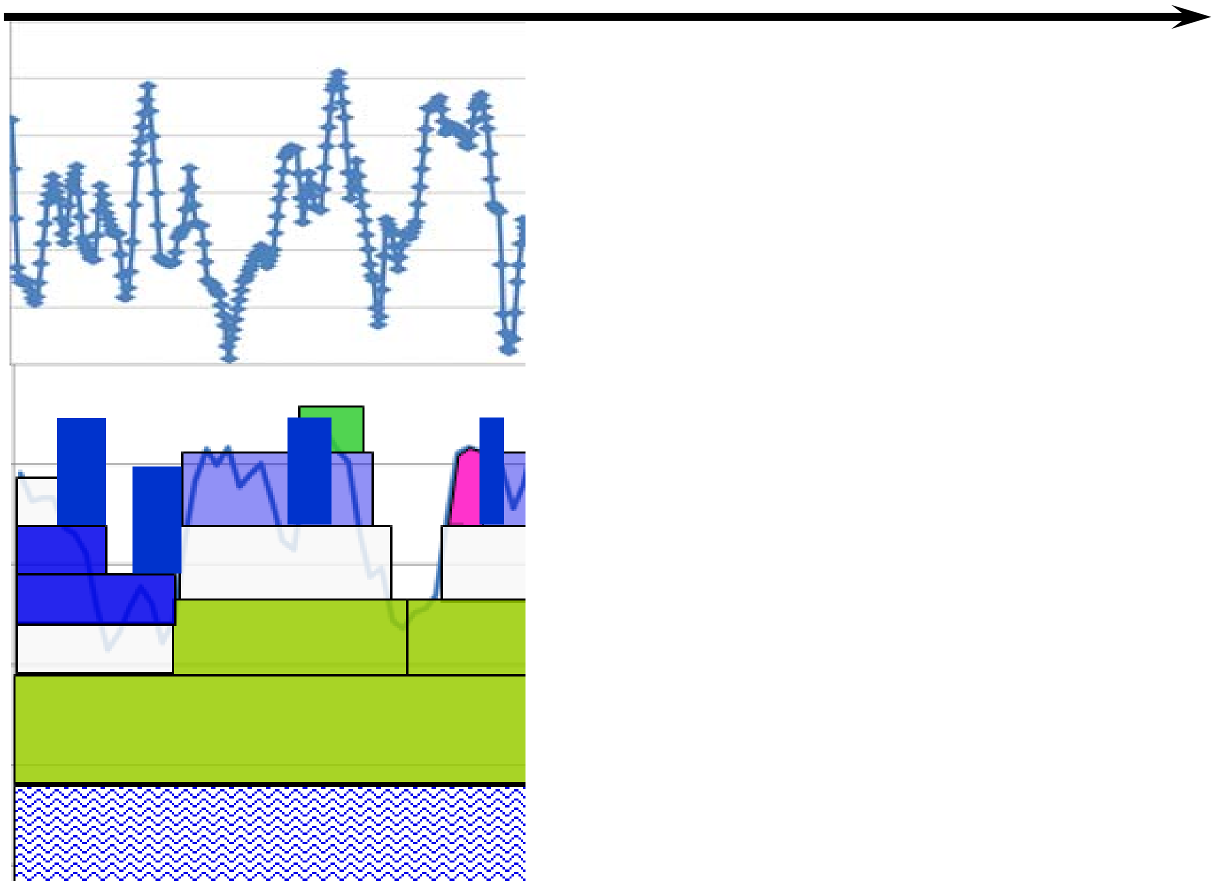

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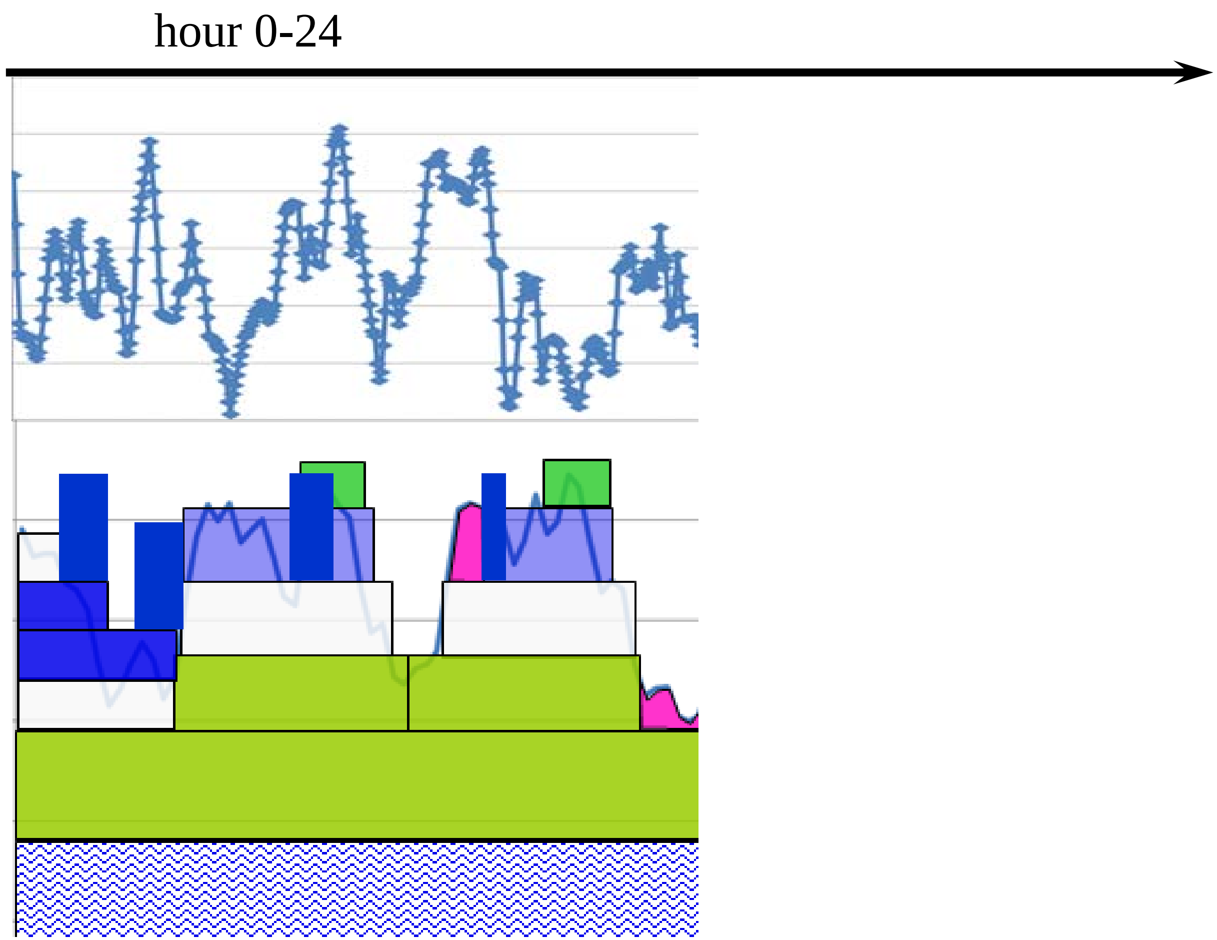

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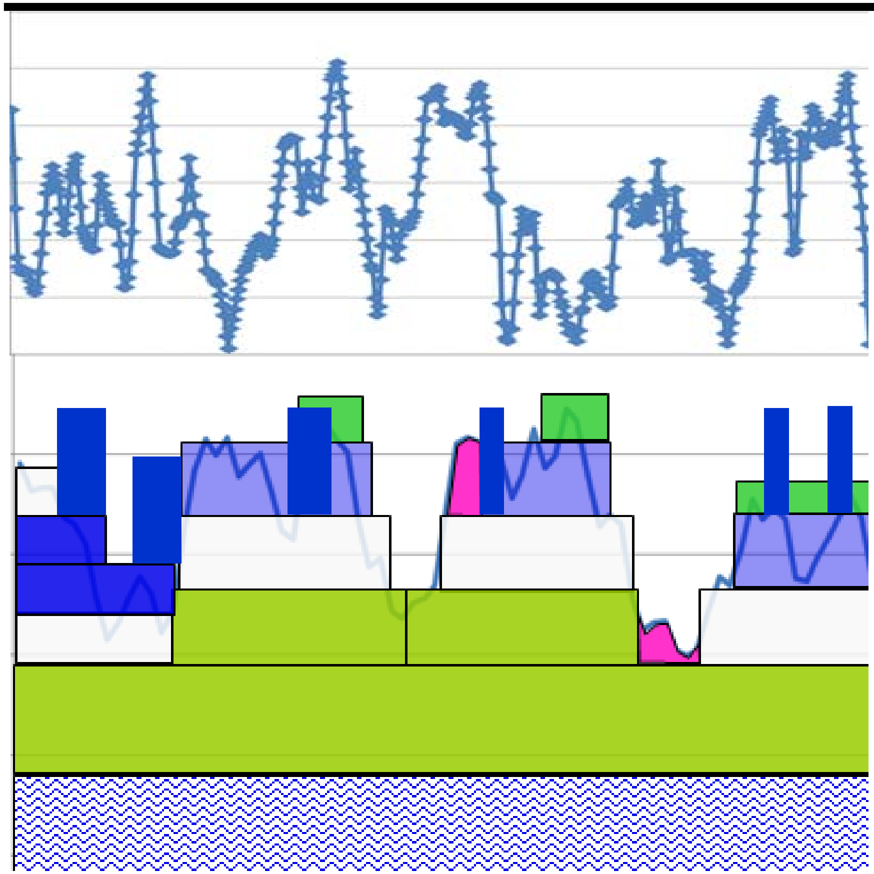

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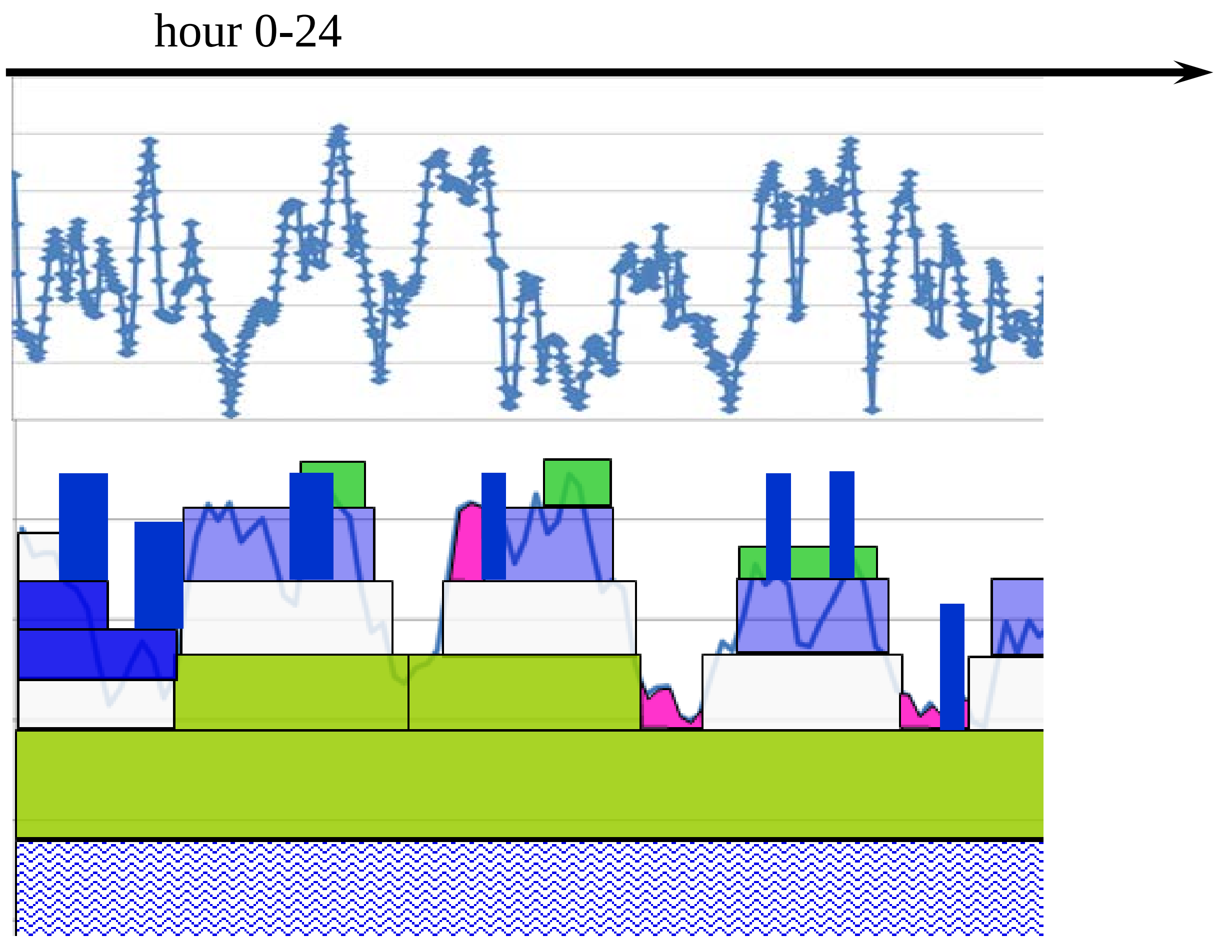

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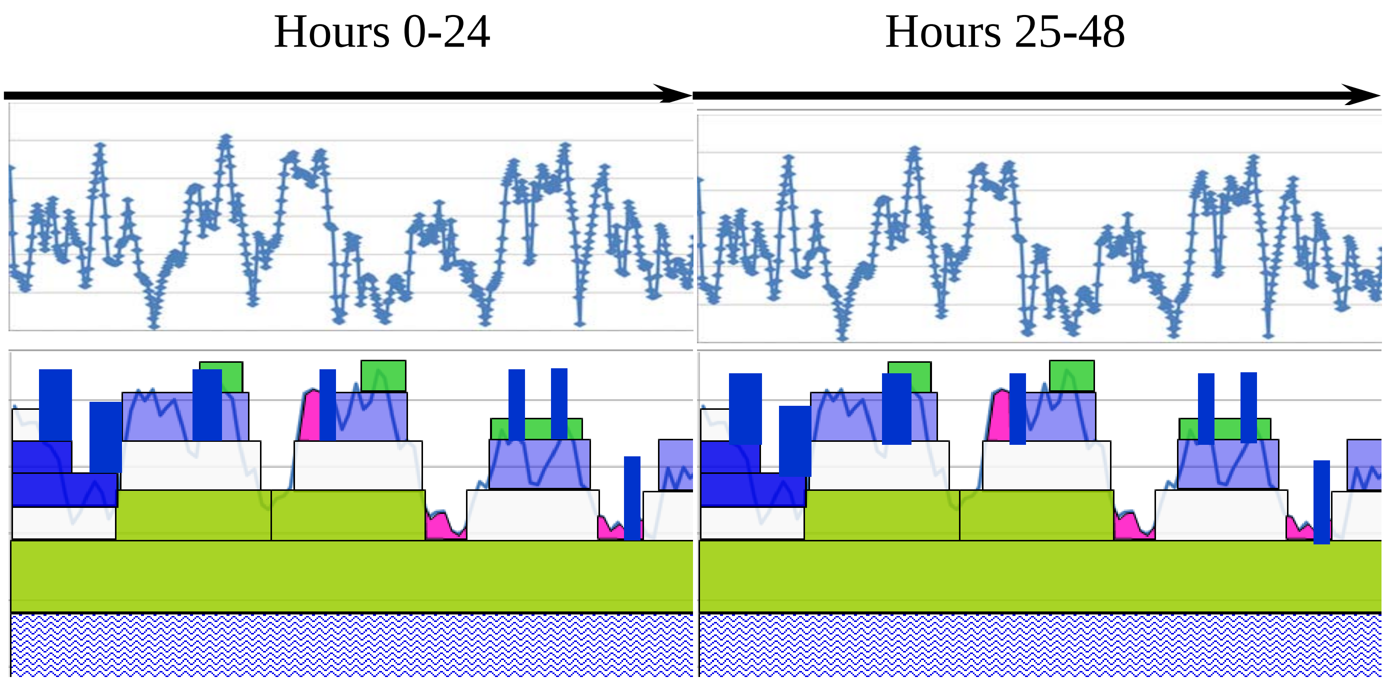
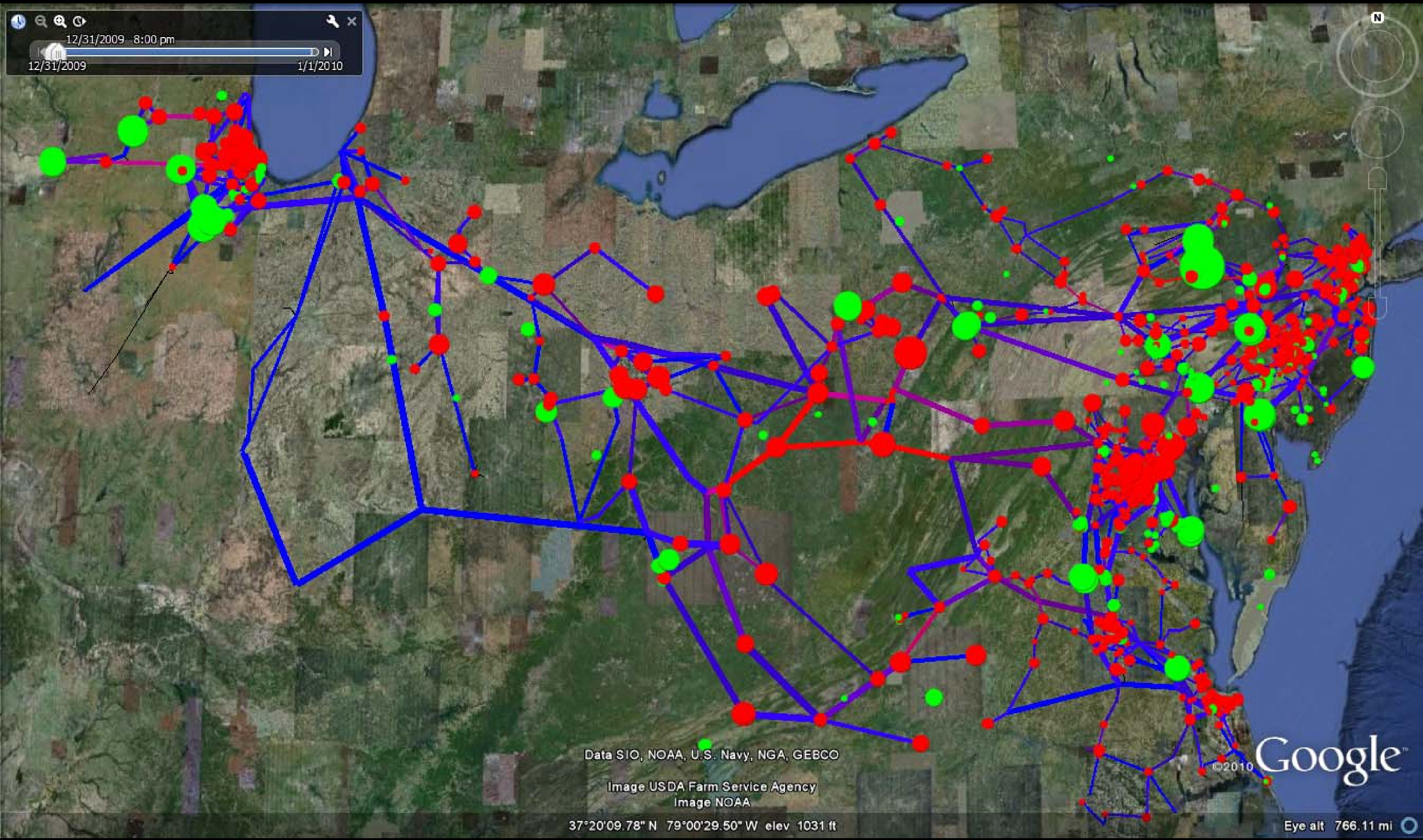


# SMART-ISO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Data SIO, NOAA, U.S. Navy, NGA, GEBCO
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37°20'09.78" N 79°00'29.50" W elev 1031 ft
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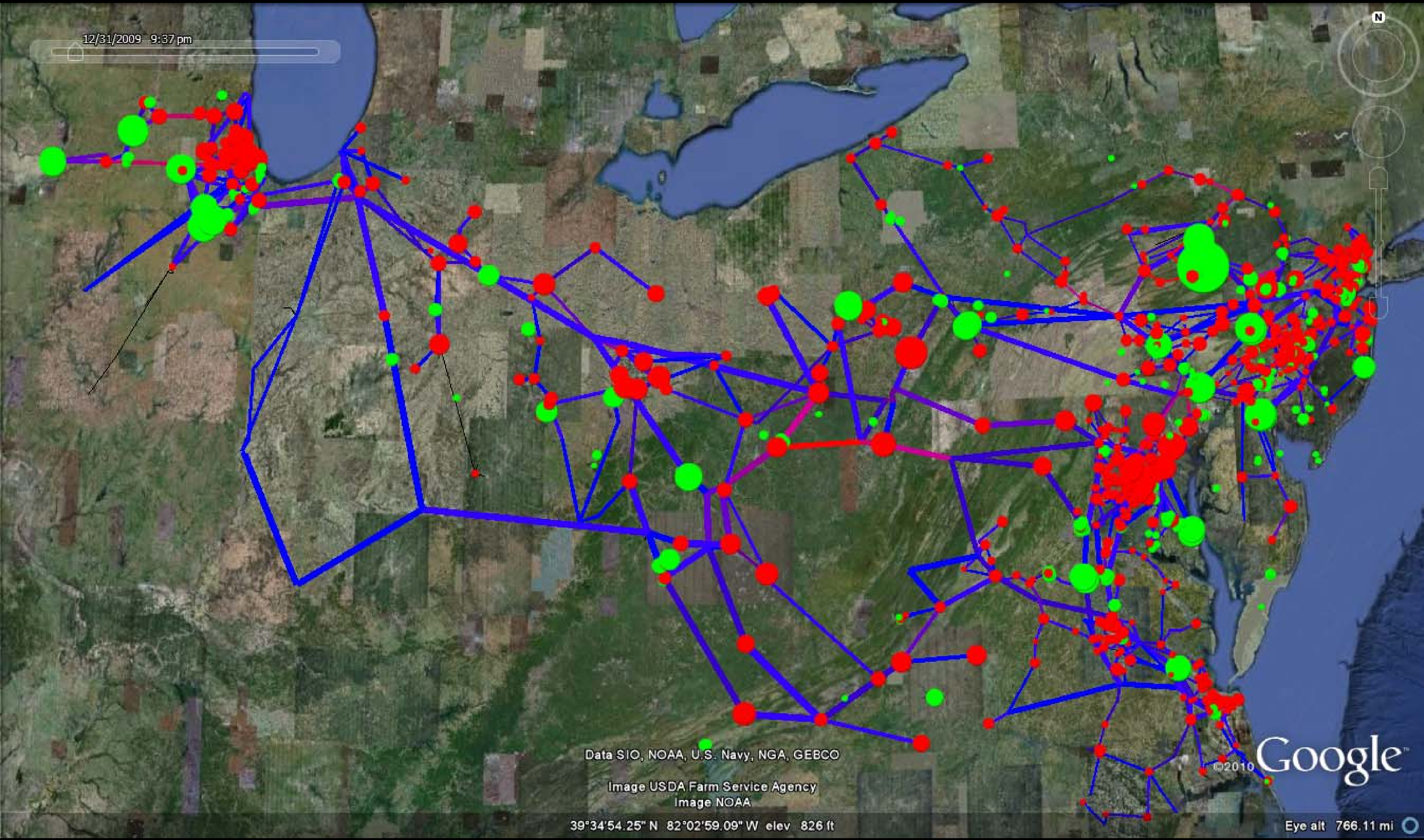
# SMART-ISO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39°34'54.25" N 82°02'59.09" W elev 826 ft
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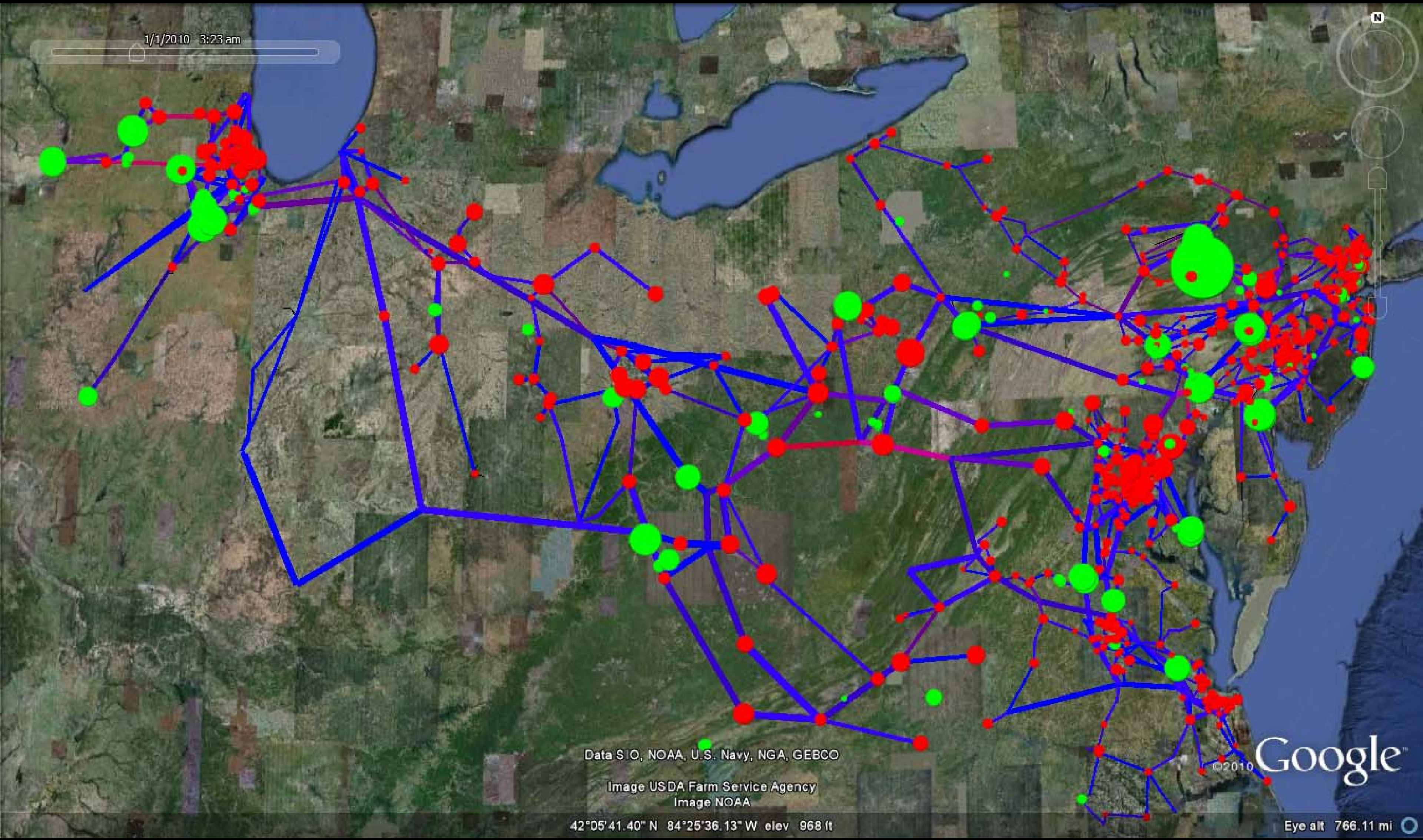

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Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image USDA Farm Service Agency
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Eye alt 766.11 mi

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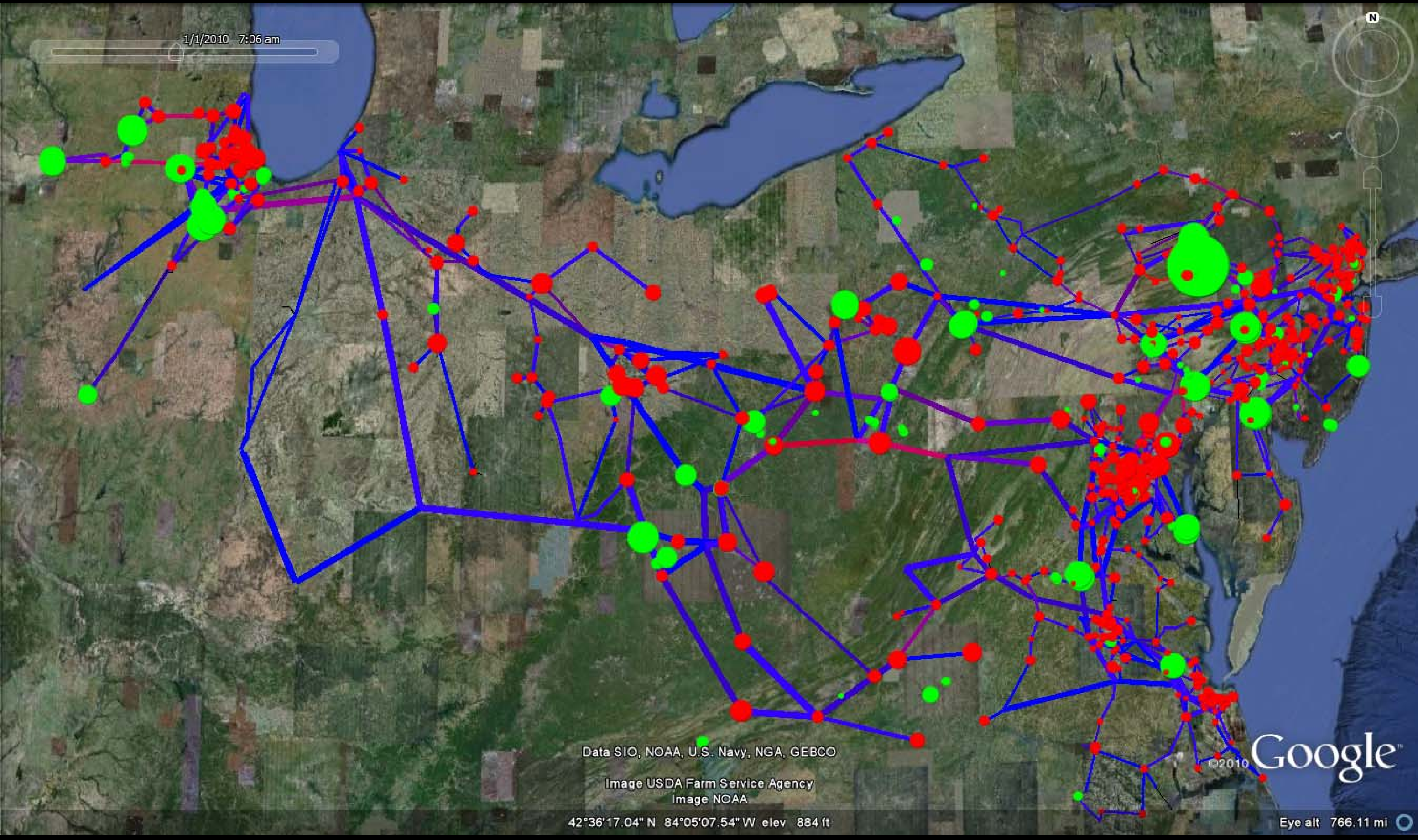

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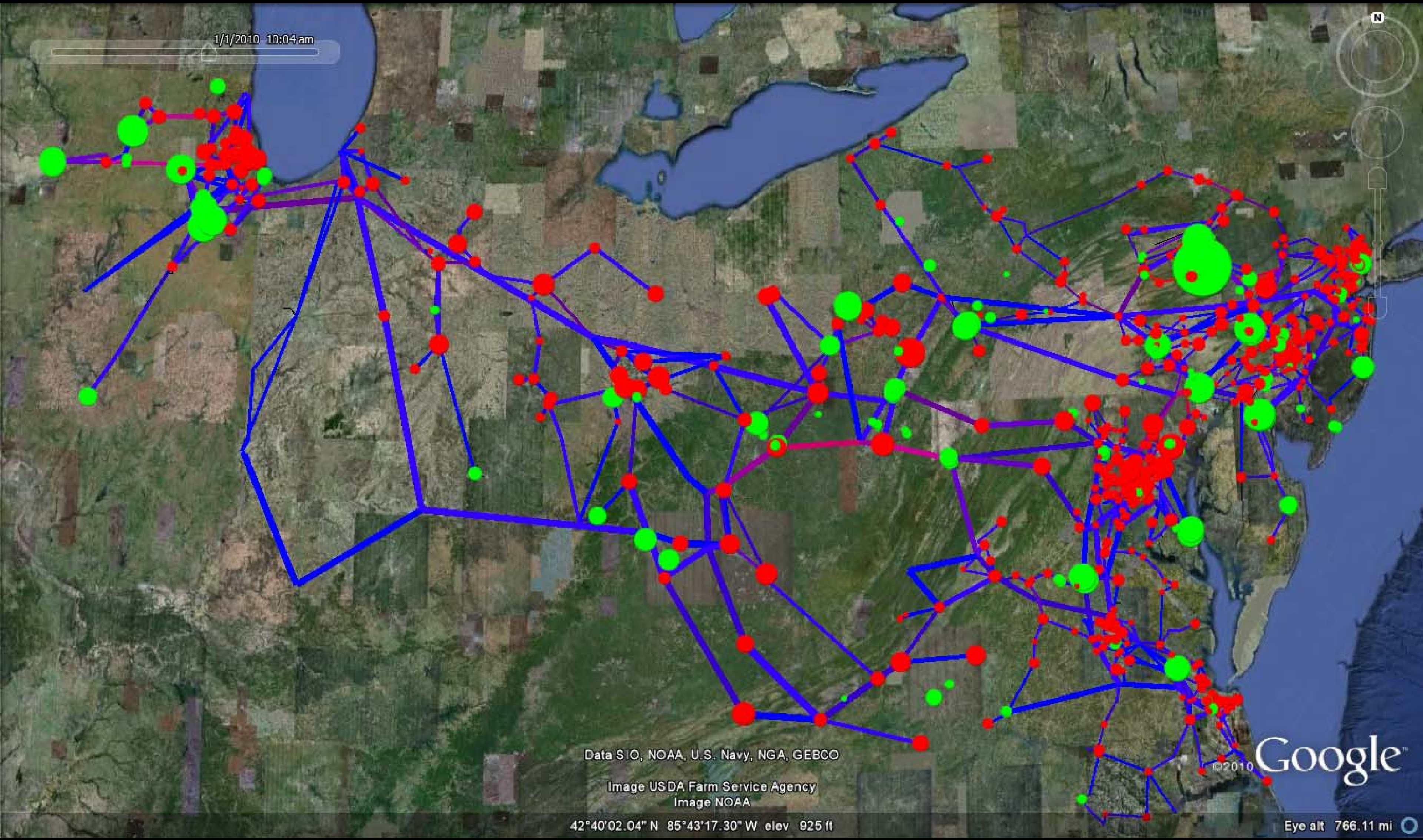
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image USDA Farm Service Agency
Image NOAA
©2010 Google
42°36'17.04" N 84°05'07.54" W elev 884 ft
Eye alt 766.11 mi

# SMART-ISO



1/1/2010 10:04 am
N
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image USDA Farm Service Agency
Image NOAA
©2010 Google
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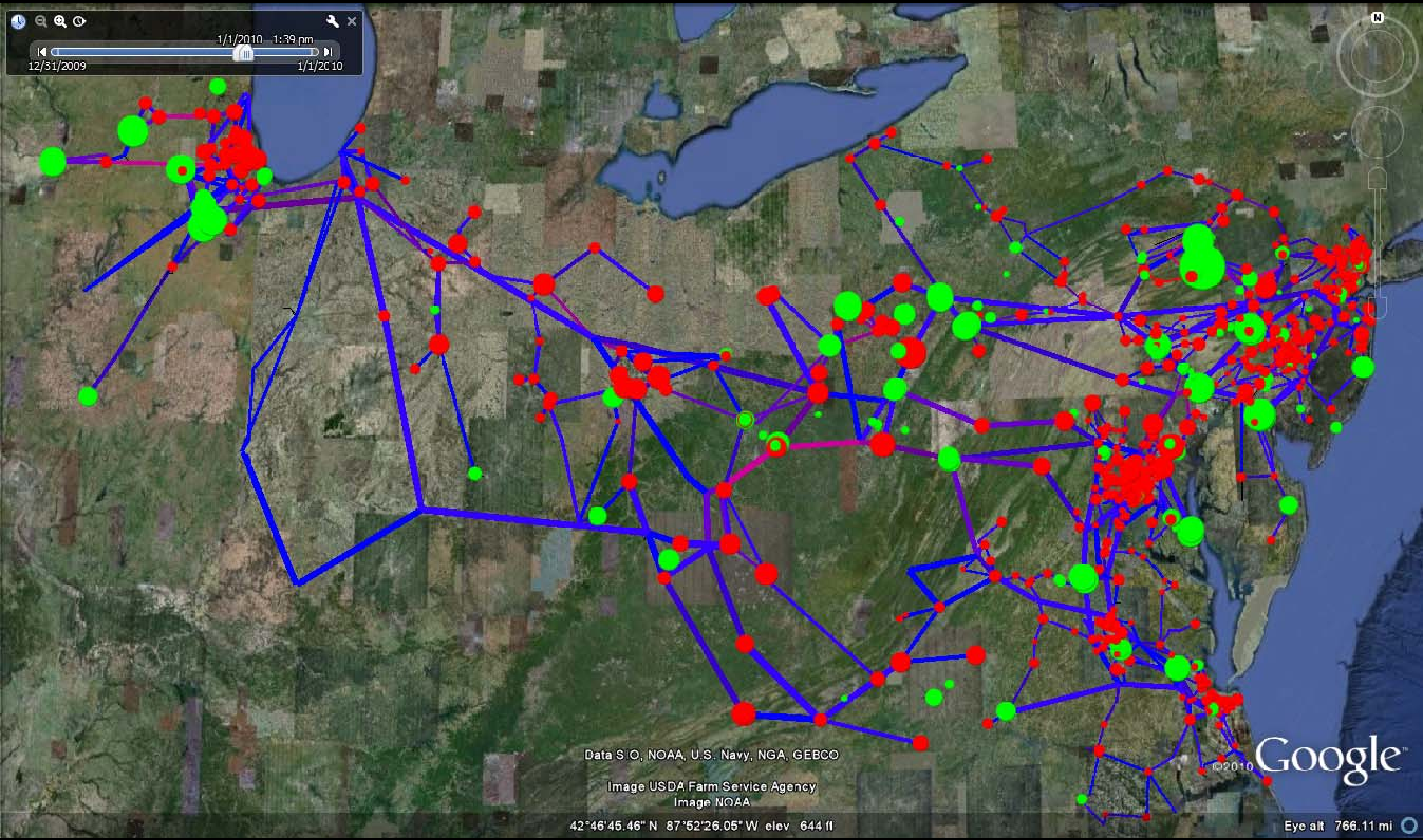
Eye alt 766.11 mi

# SMART-ISO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12/31/2009
1/1/2010
Data SIO, NOAA, U.S. Navy, NGA, GEBCO
Image USDA Farm Service Agency
Image NOAA
©2010
Google
42°46'45.46" N 87°52'26.05" W elev 644 ft
Eye alt 766.11 mi
N

# The value of wind

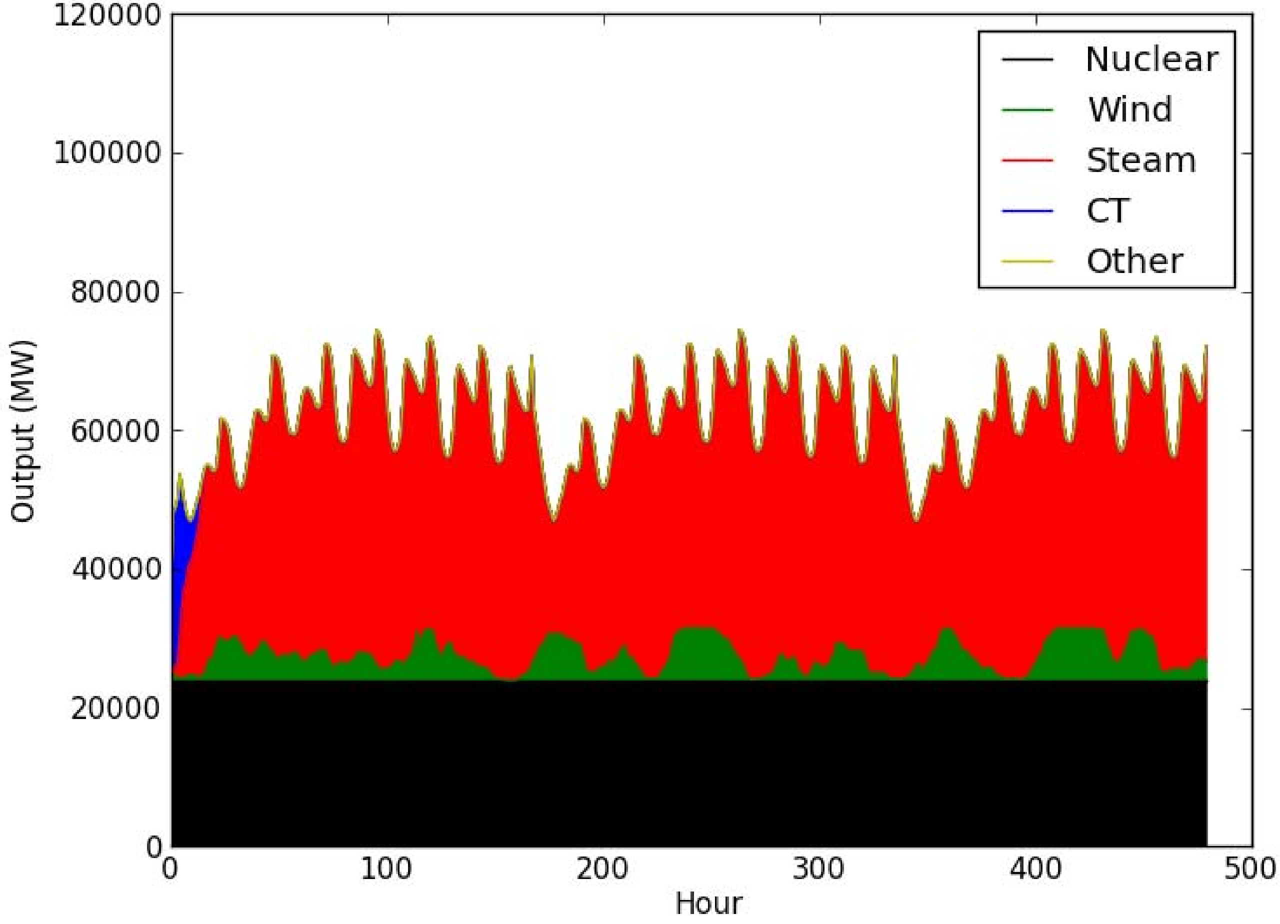
- Prototypical research question: What is the relative cost of uncertainty vs variability?

  » Scenario 1: Stochastic wind – We forecast wind, but the actual does not match the forecast

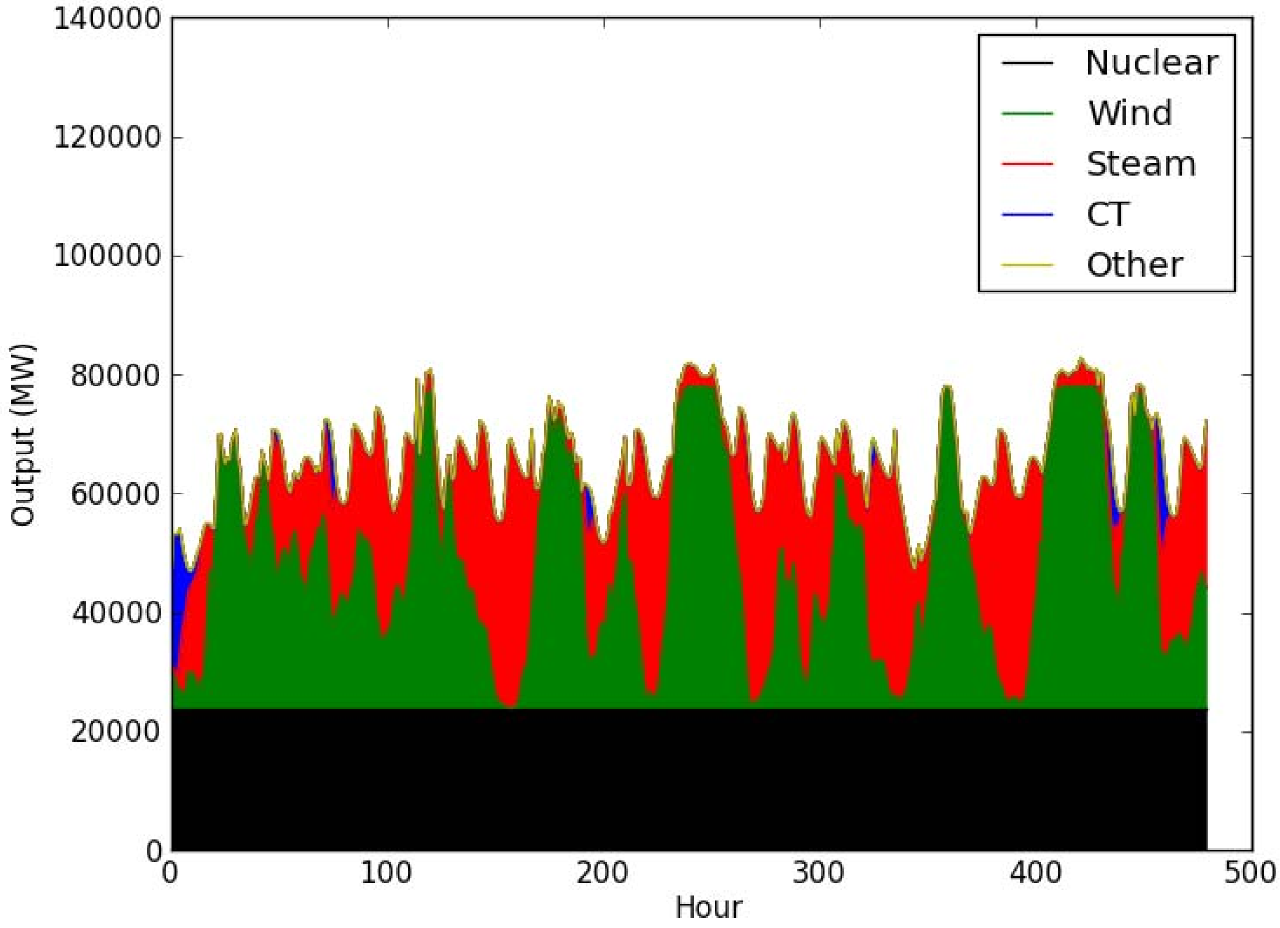
  » Scenario 2: Deterministic wind – Wind is variable, but we can forecast it perfectly

  » Scenario 3: Constant wind – Wind generates energy at a constant (and perfectly known) value

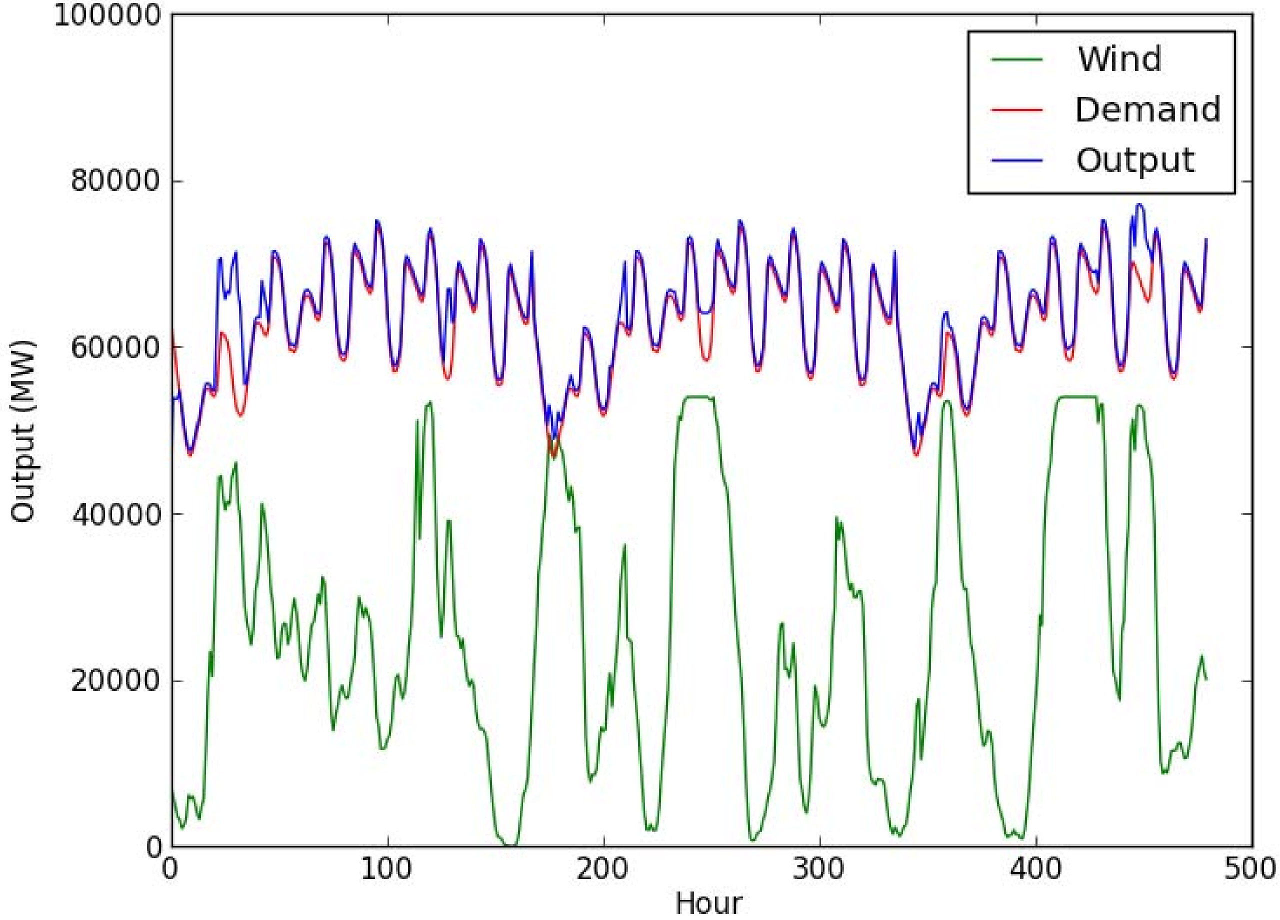
# Perfect forecast – 5 percent wind



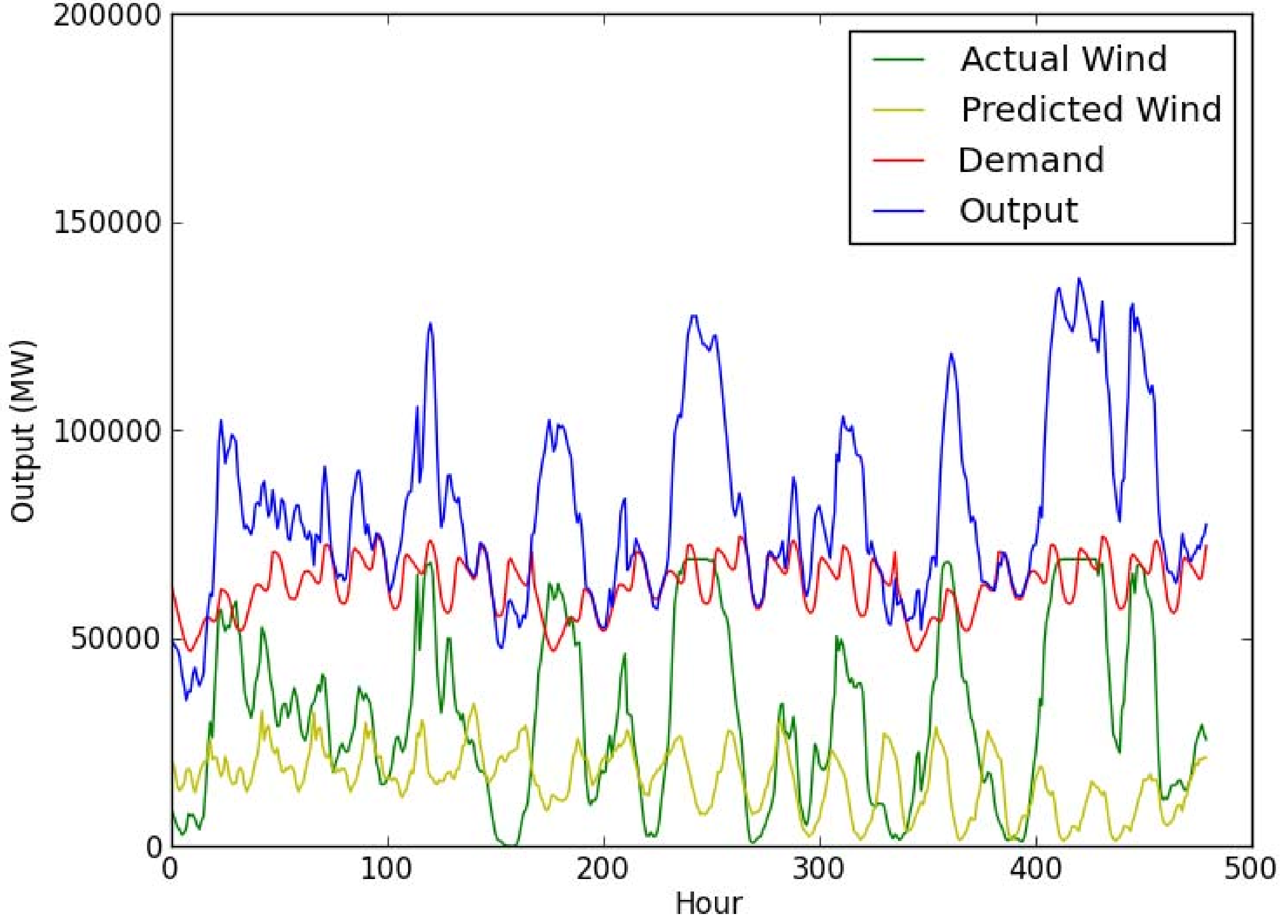
# Perfect forecast – 40 percent wind



# Perfect forecast – 40 percent wind

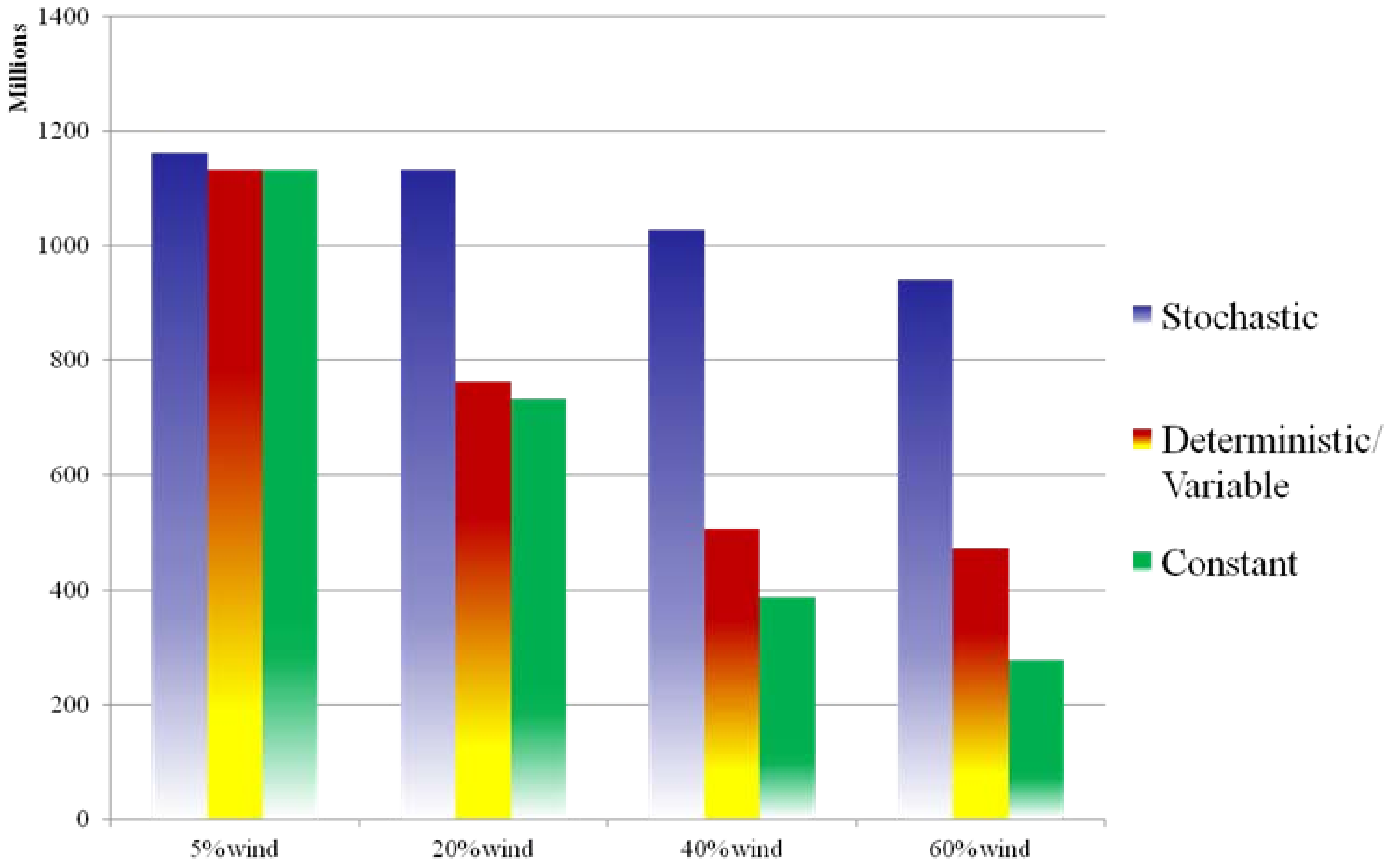


# Imperfect forecast – 40 percent wind



# The stochastic unit commitment problem

- ❑ The effect of modeling uncertainty in wind



# Features

- Running (but still being calibrated)
  - » Day-ahead, DC-constrained robust unit commitment model running on 9,000 bus PJM grid.
  - » Hour-ahead NG generator commitment model (unconstrained)
  - » Five-minute increment simulator modeling wind speeds and generator ramp rates using January, 2010 PJM data.
- Anticipated for fall, 2012
  - » Completing conversion from PJM generator data to Ventyx generator data
  - » DC grid constraints for hour-ahead model
  - » ACOPF for simulator (five minute increments)
  - » Extend to entire 2010 dataset (we finally cracked the code to model PJM load nodes to PSSE bus nodes).
  - » Expansion to entire eastern interconnect (all generators, but just high voltage transmission lines outside of PJM footprint).

# Features

- Anticipated for 2013
  - » Validation, validation, validation
  - » Improved approximations of AC power flow in lookahead models
  - » Integrating medium term (4-12 hours) generation commitments
  - » Demand response strategies
    - Active load curtailment
    - Dynamic pricing
  - » Full modeling of the eastern interconnect
  - » Web interface to allow others to run the model and perform studies
  - » Parallel implementation to accelerate processing time

# Features

- Ongoing
  - » Validation against different performance metrics to improve confidence in the model.
    - Calibration against day-ahead and real-time LMPs
    - Comparisons with actual loads
  - » A major research effort will be the continual enhancement of policies for making decisions to improve cost and robustness
    - Hybrid deterministic lookahead policy with correction terms
    - Policy function approximations for time-dependent problems
    - Stochastic programming with scenario trees?
  - » Development of SMART-ISO as a test bed for algorithms and policies developed by other research groups.

# SMART-ISO website

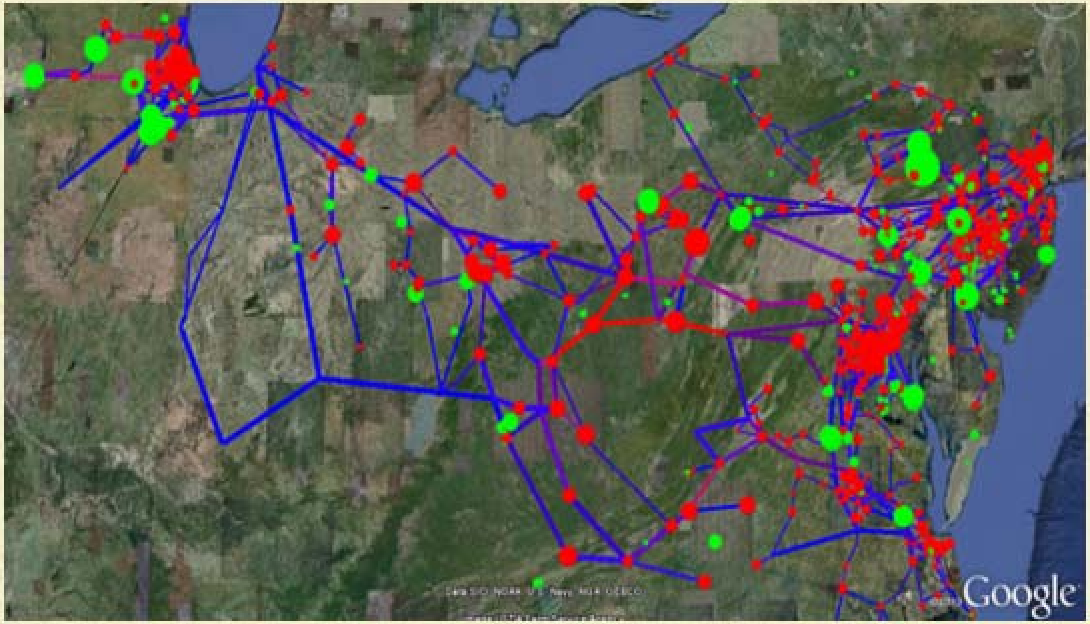
http://energysystems.princeton.edu/smartiso.htm

## SMART-ISO

SMART-ISO is a stochastic, multiscale model of grid operations under development at PENSA, which is currently being built around the full PJM grid. The purpose of this website is to provide ongoing documentation of what we have accomplished, what we are working on and features that we hope to develop in the near future. (If you have been to this website before, be sure to hit your refresh button to ensure you have the latest version.)

When the model settles down, we will begin providing indications of "what is new." For now (summer, 2012) the model is going through rapid evolution and we ask for everyone's patience.

- Overview of SMART-ISO
- Studies (ongoing and anticipated)
- Features (current and planned)
- Supporting data
- System components
- Handling uncertainty
- Documentation
- The SMART-ISO development team




**Overview of SMART-ISO**

# The PENSA team

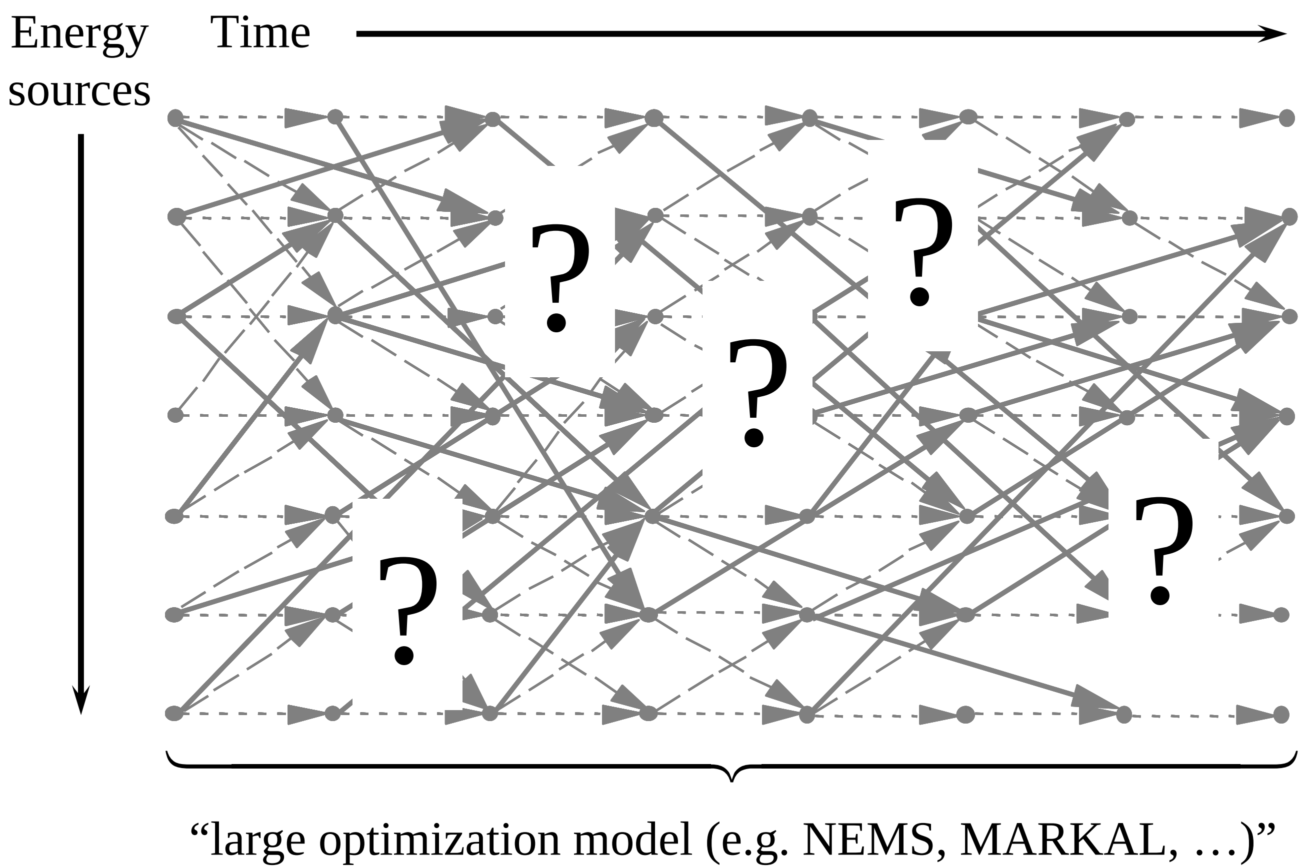
- Faculty
  - » Warren Powell (Director)
  - » Ronnie Sircar (ORFE)
  - » Craig Arnold (MAE)
  - » Rob Socolow (MAE)
  - » Elie Bou-Zeid (Civil)
- Graduate students
  - » Warren Scott (ORFE)
  - » Ethan Fang (ORFE)
  - » DH Lee (COS)
  - » Daniel Salas (CBE)
  - » Yinzhen Jin (CEE)
  - » Dan Jiang (ORFE)
  - » Harvey Cheng (EE)
  - » Andre Jonasson (ORFE)
- Staff/post-docs
  - » Hugo Simao (deputy director)
  - » Boris Defourny
  - » Arta Jamshidi
  - » Ricardo Collado
  - » Somayeh Moazeni
  - » Javad Khazaei
- Undergraduate interns (2012)
  - » Tarun Sinha (MAE)
  - » Stephen Wang (ORFE)
  - » Henry Chai (ORFE)
  - » Ryan Peng (ORFE)
  - » Christine Feng (ORFE)
  - » Joe Yan (ORFE)
  - » Austin Wang (ORFE)

# Relationships outside of Princeton

- Lawrence Livermore National Laboratory
  - » High performance computing for energy
- Cornell University
  - » AFOSR-funded project on optimal learning in materials, joint with Peter Frazier in ORIE
  - » Computational sustainability, joint with Carla Gomes in CS
- Columbia University – CCLS
  - » Finishing: load curtailment of buildings
  - » Starting next year: optimal control of HVAC systems
- University of Delaware
  - » Effect of energy from off-shore wind

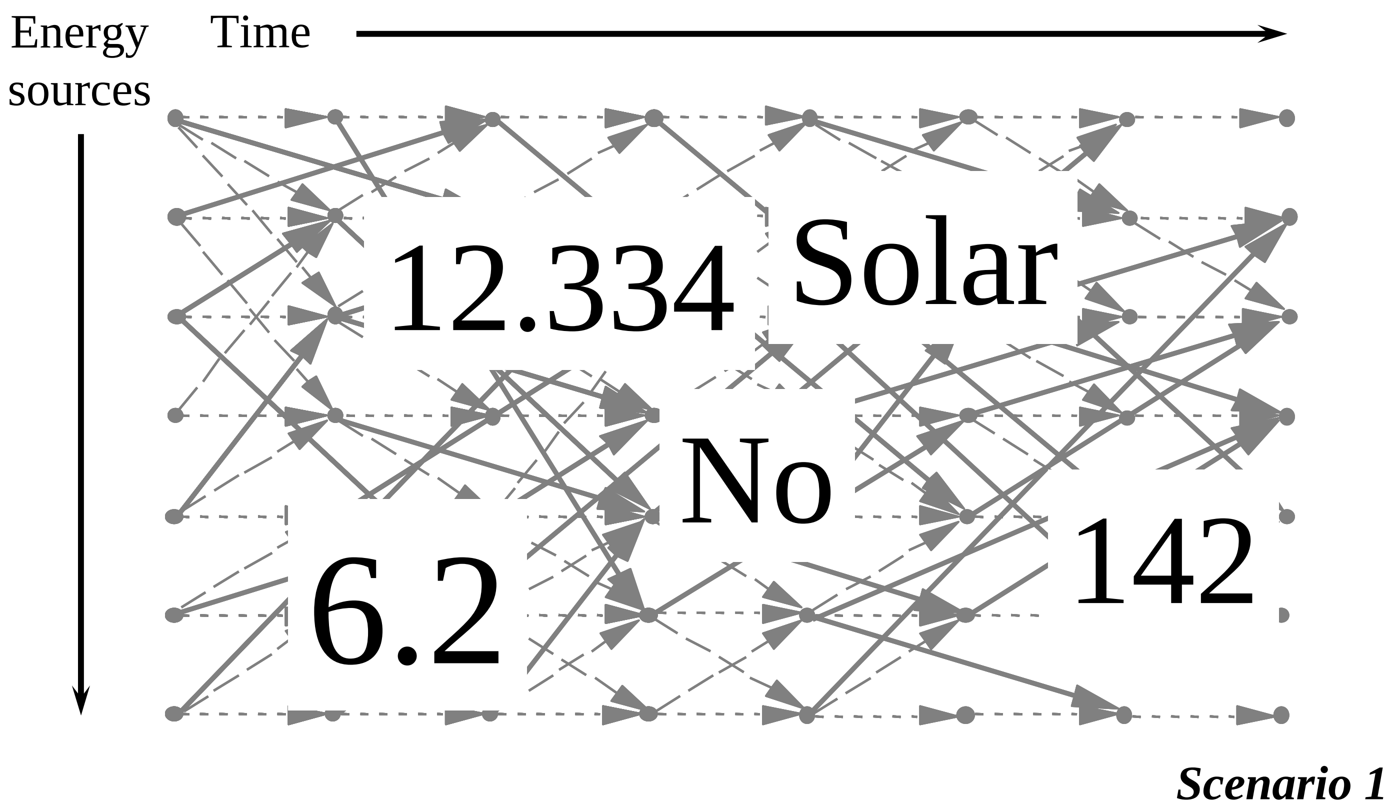
# Linear programming with uncertainty

- Mixing optimization and uncertainty



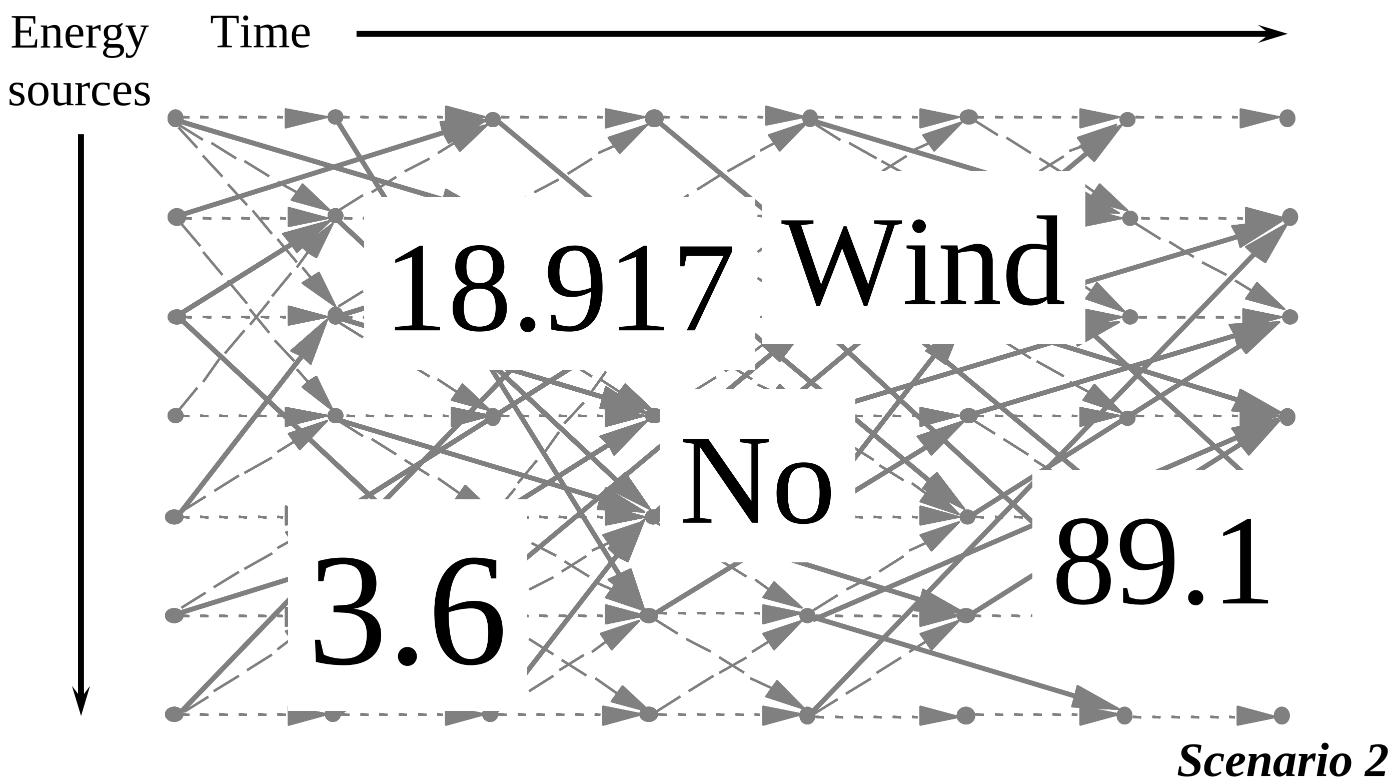
# Linear programming with uncertainty

- Mixing optimization and uncertainty



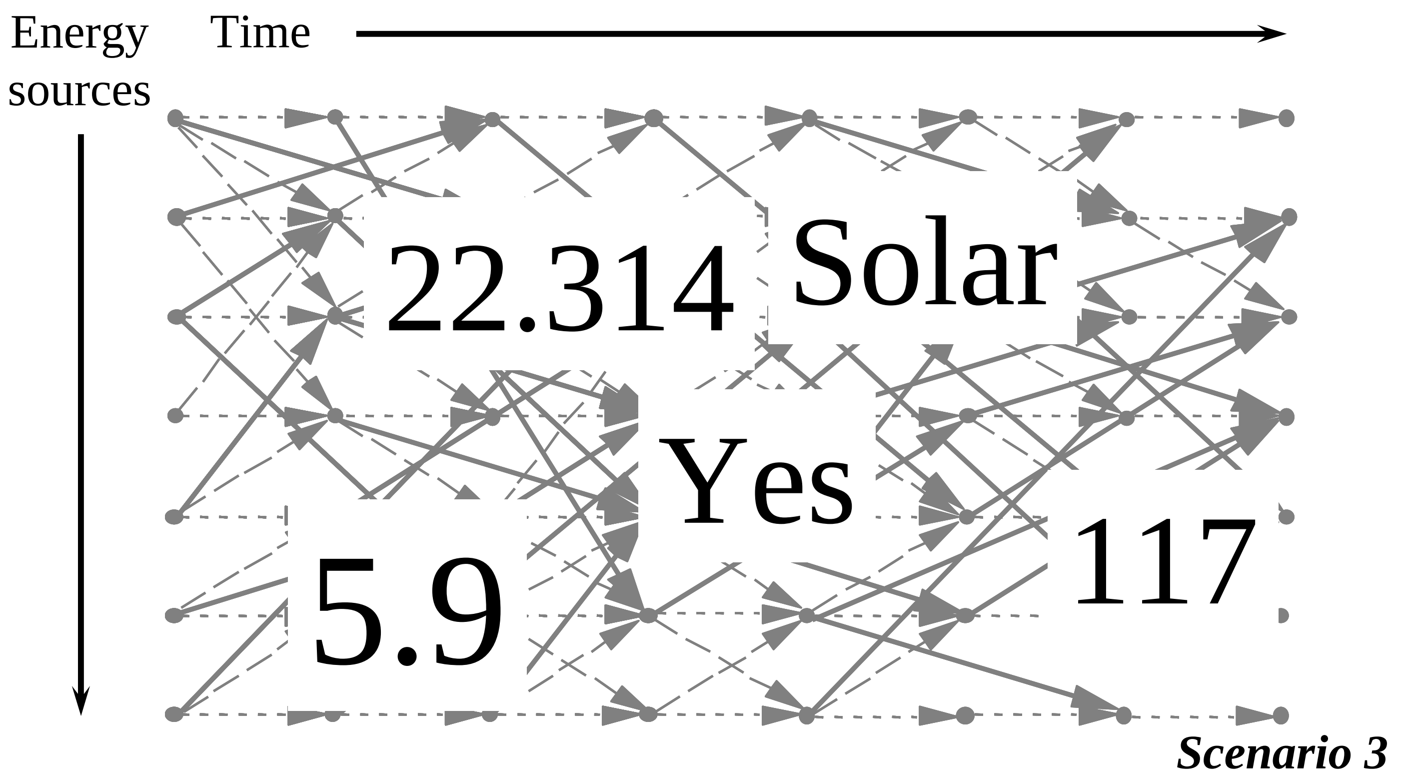
# Linear programming with uncertainty

- Mixing optimization and uncertainty

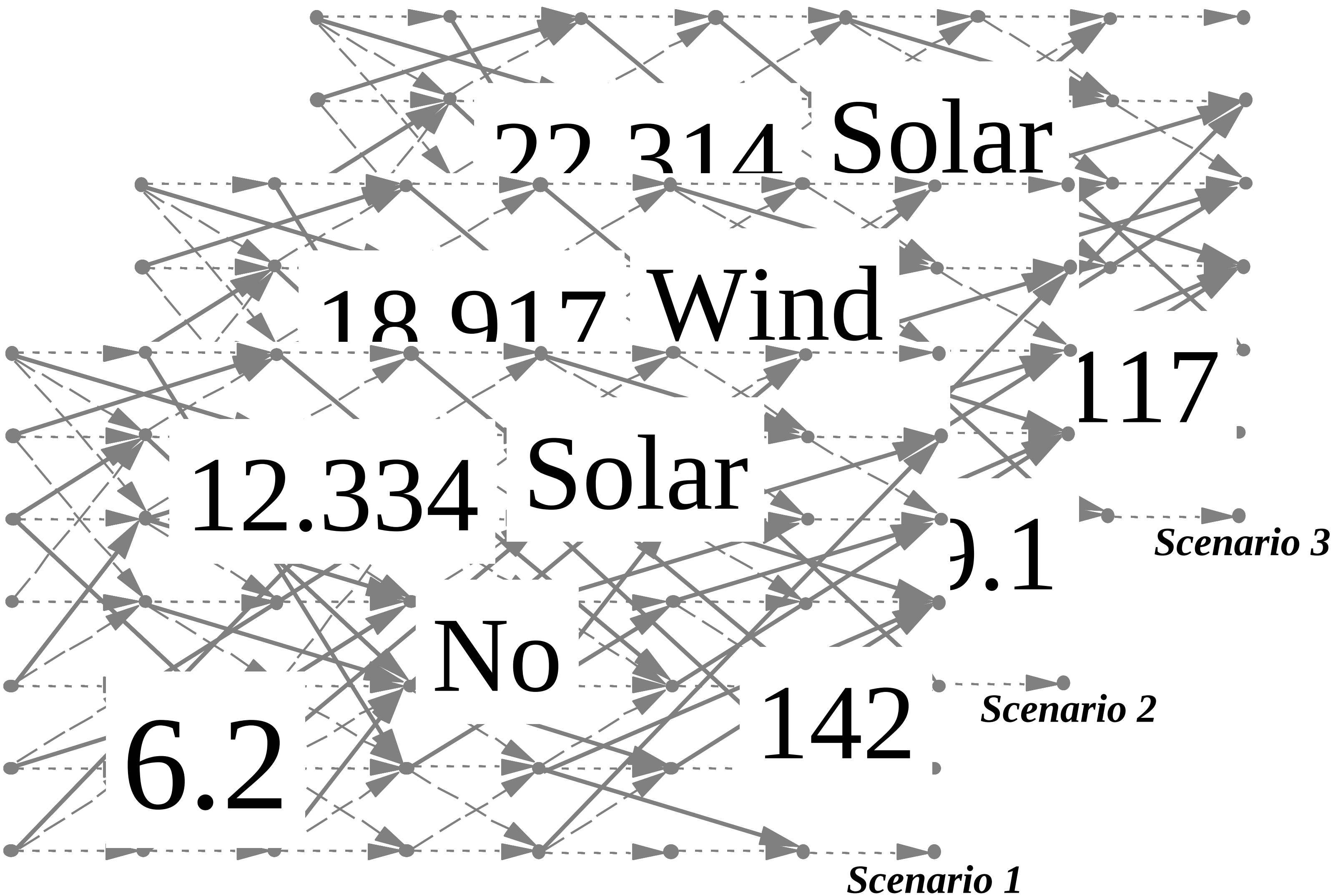


# Linear programming with uncertainty

- Mixing optimization and uncertainty



# Linear programming with uncertainty

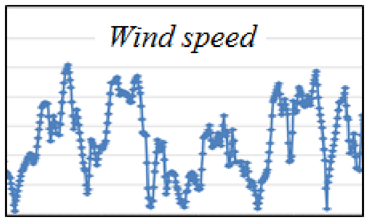



***Now we have to combine the results of these three optimizations to make decisions.***

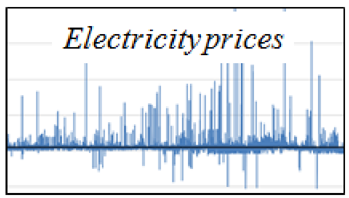
# Optimizing battery storage

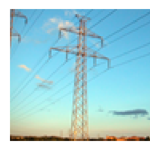
- Energy storage with stochastic prices, supplies and demands.

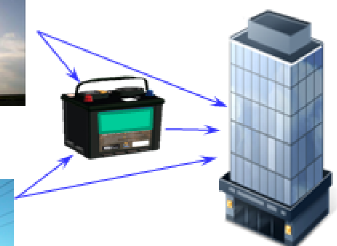
$E_t^{wind}$



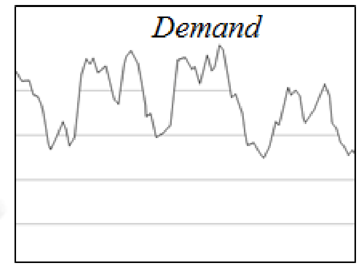

$P_t^{grid}$





$R_t^{battery}$




$D_t$

$$
\begin{aligned}
E_{t+1}^{wind} &= E_t^{wind} + \hat{E}_{t+1}^{wind} \\
P_{t+1}^{grid} &= P_t^{grid} + \hat{P}_{t+1}^{grid} \\
D_{t+1}^{load} &= D_t^{load} + \hat{D}_{t+1}^{load} \\
R_{t+1}^{battery} &= R_t^{battery} + Ax_t
\end{aligned}
$$

$W_{t+1}$ = Exogenous inputs

$S_t$ = State variable

$x_t$ = Controllable inputs

# Optimizing battery storage

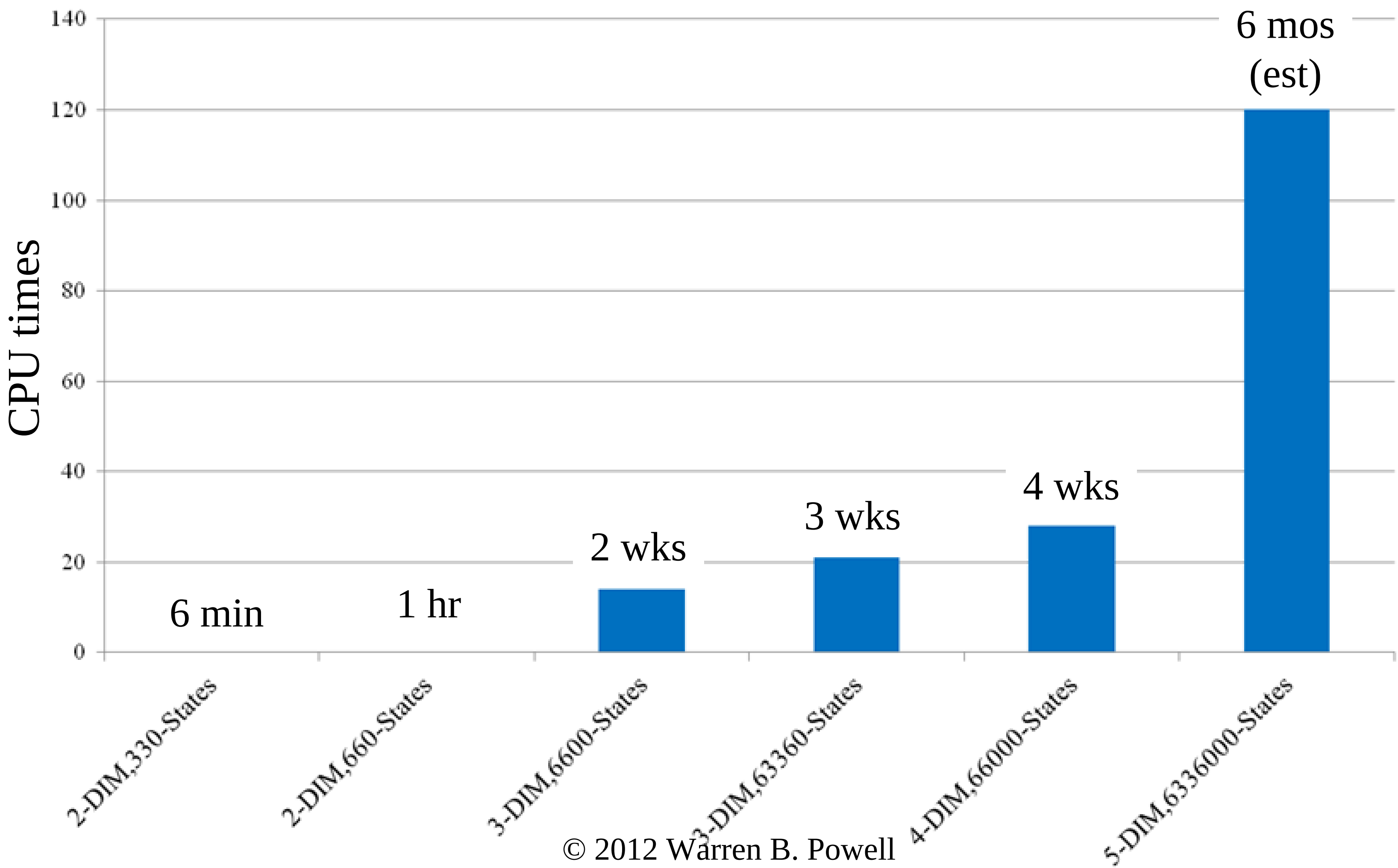
- Bellman's optimality equation

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

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

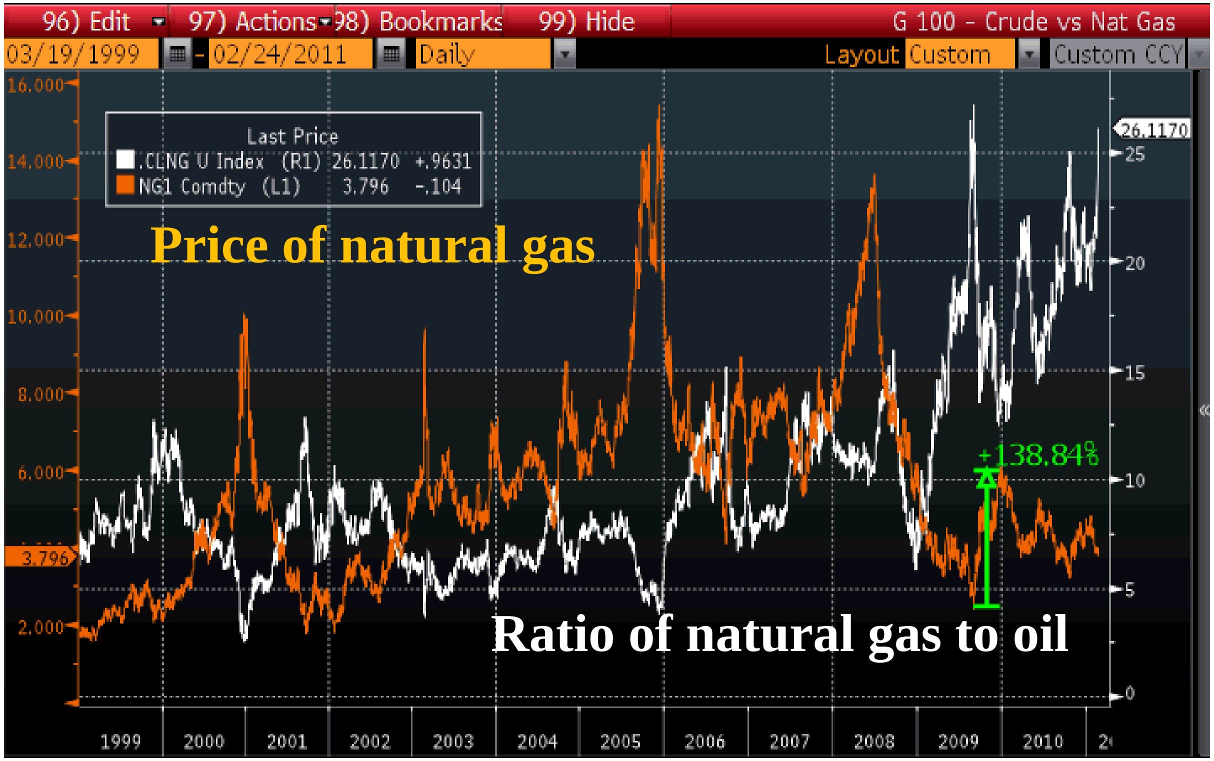
# Optimizing battery storage

- Finding an optimal solution using exact methods:



# Commodity prices

- The price of natural gas
  - » Reflects global and local economies, competing global commodities (primarily oil), policies (e.g. toward $CO_2$), and technology (e.g. fracking).



# Anticipated studies

- Analysis of off-shore wind
  - Ongoing study with University of Delaware
  - Model the effect of high levels of wind penetration on the power grid, with accurate modeling of generation and power flows
- Energy storage
  - How to optimize energy storage devices over the grid?
  - How to optimally bid storage capacity in the day-ahead and hour-ahead markets?
- Demand side management
  - How to manage households and industry to balance loads, especially in the presence of renewables?

# SMART-ISO

- The progress report
  - » We have the full PJM network from FERC
  - » 5-minute loads from PJM
  - » Generator data from Ventyx
  - » Day-ahead unit commitment using DC power flow model
  - » Accurate hour-ahead model of gas generators
  - » Simulates in 5-minute increments
  - » … are we there yet?