Unit Commitment: Dealing with the Uncertainties

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University of California, Davis
Summer 2014 @ Technical U. Denmark

Unit commitment
Part I

Progressive Hedging:
dealing with binary variables

Transmission Network

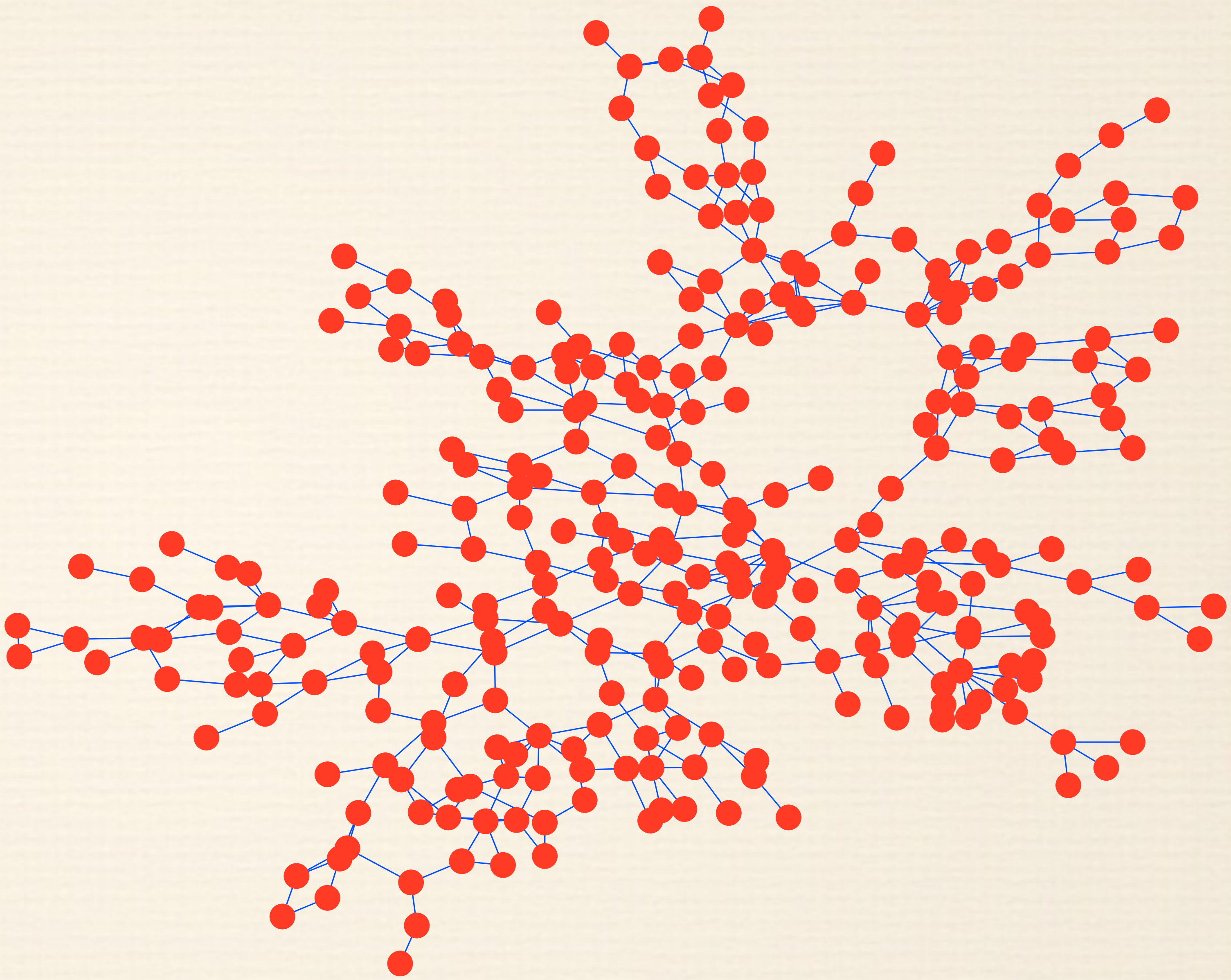
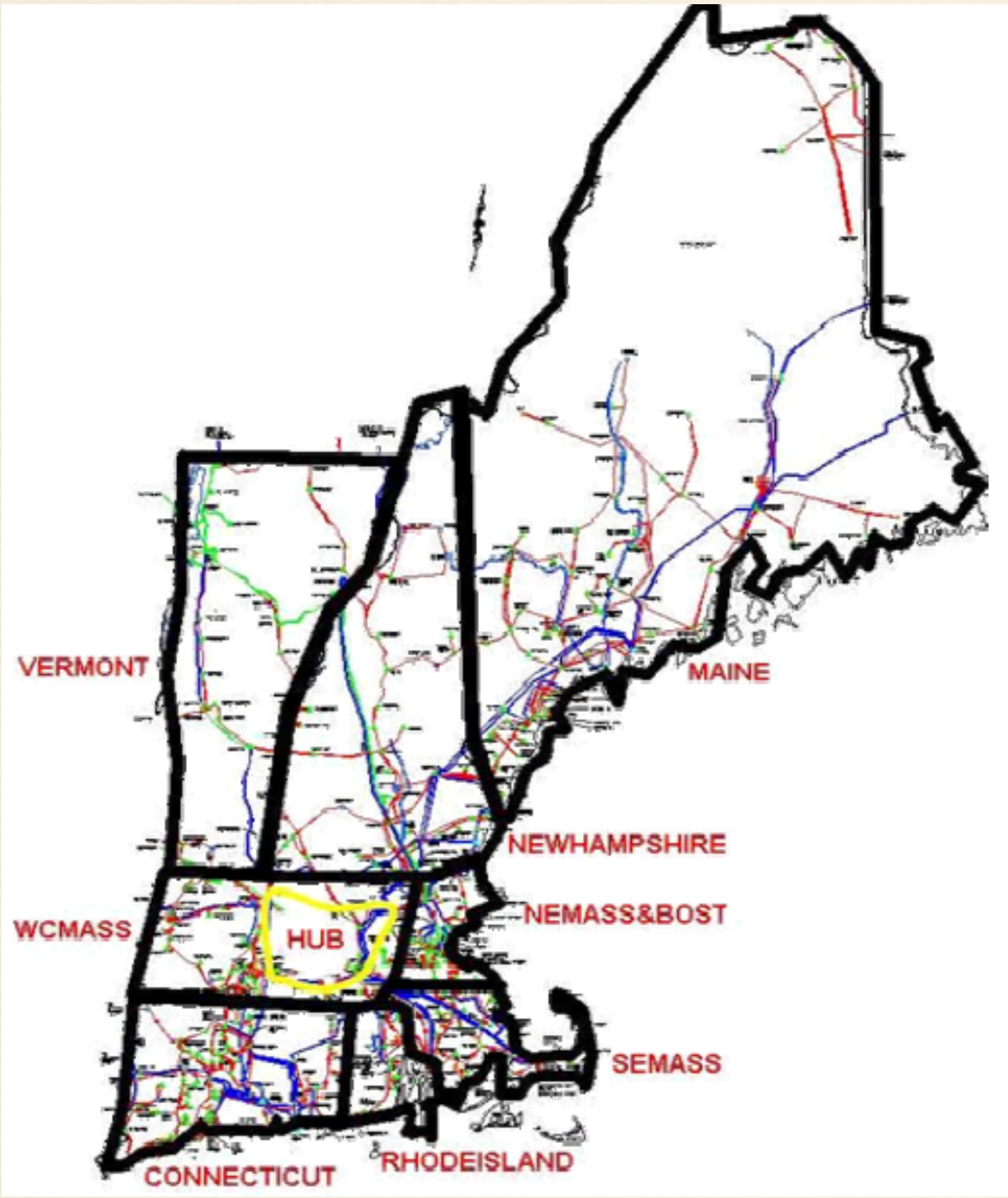


Figure 1. Topology of the IEEE 300 node system

Transmission Network



NE-ISO net ~30,000 BUS

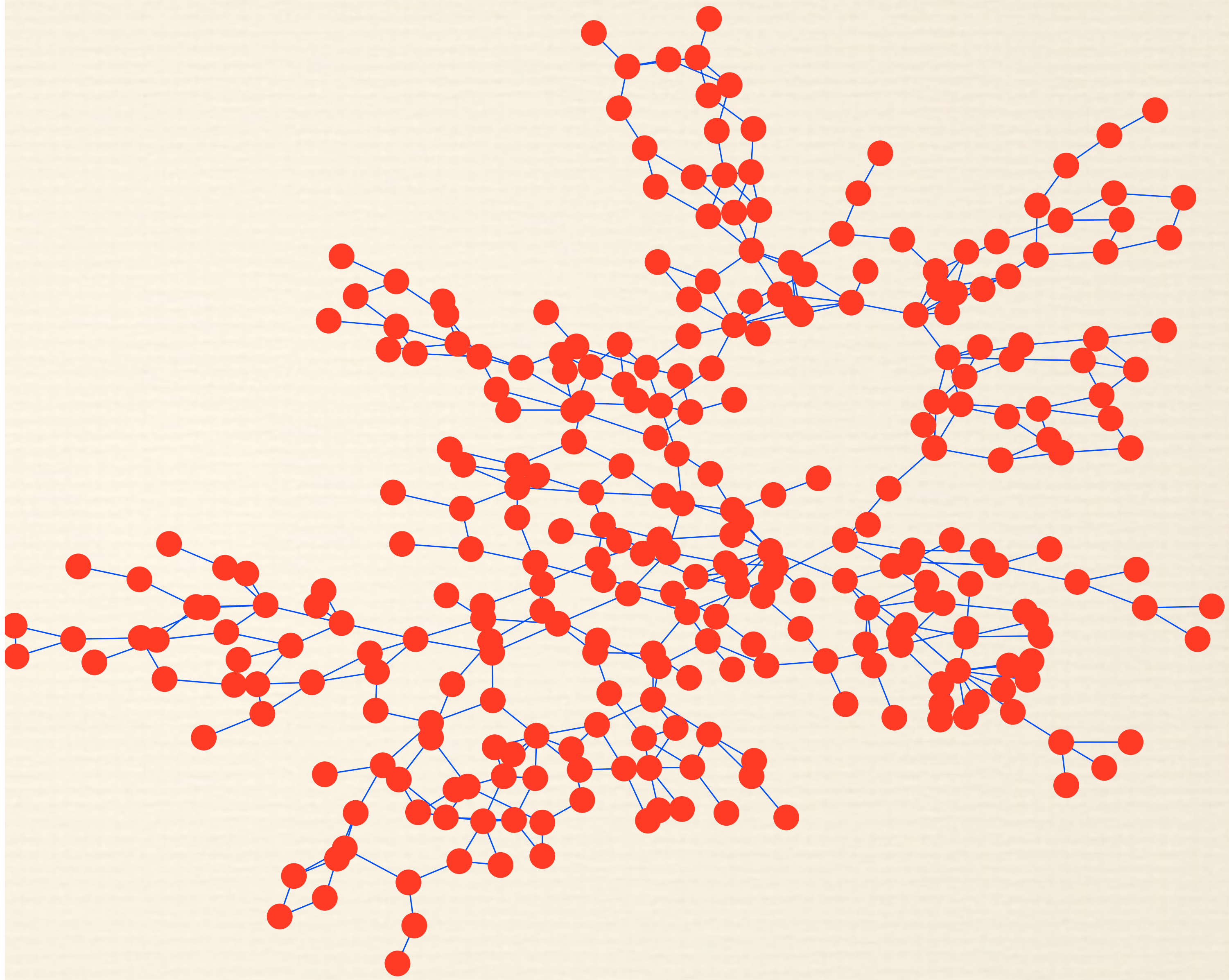


Figure 1. Topology of the IEEE 300 node system

ISO:
Independent System Operator

FERC

Federal Energy Regulatory Commission

⇩

RTO

In the US is an organization that is responsible for moving electricity over large interstate areas; coordinates, controls and monitors an electricity transmission grid that is larger with much higher voltages than the typical power company's distribution grid.

⇩

ISO

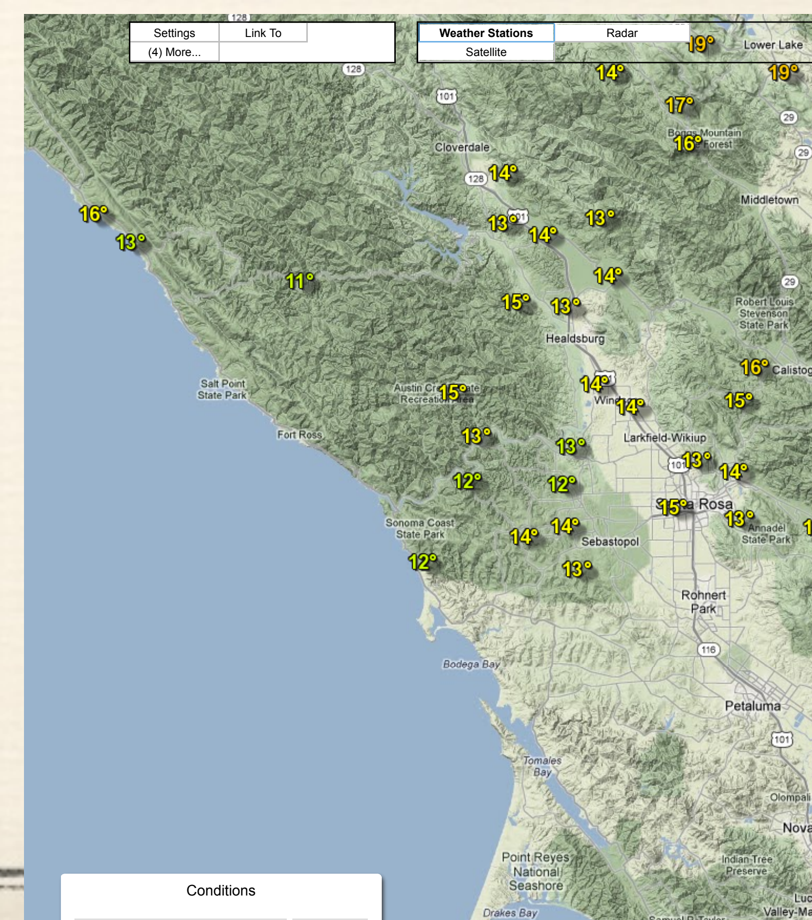
*Is an organization formed at the direction or recommendation of the **FERC,** in the areas where an ISO is established, it coordinates, controls and monitors the operation of the electrical power system, usually within a single US State, but sometimes encompassing multiple states.*

ISO New England Inc. (*ISO-NE*) *is an independent, non-profit RTO, serving Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont. Its Board of Directors and its over 400 employees* have no financial interest or ties to any company doing business in the region's wholesale electricity marketplace.

Uncertainties

- WEATHER: demand & supply (especially renewables)
- industrial-commercial environment (demand)
- seasonal, day of the week, time of the day
- contingencies: transmission lines, generators

El Cerrito, California (94530) Conditions & Forecast http://www.wunderground.com/cgi-bin/findweather/getForecast...



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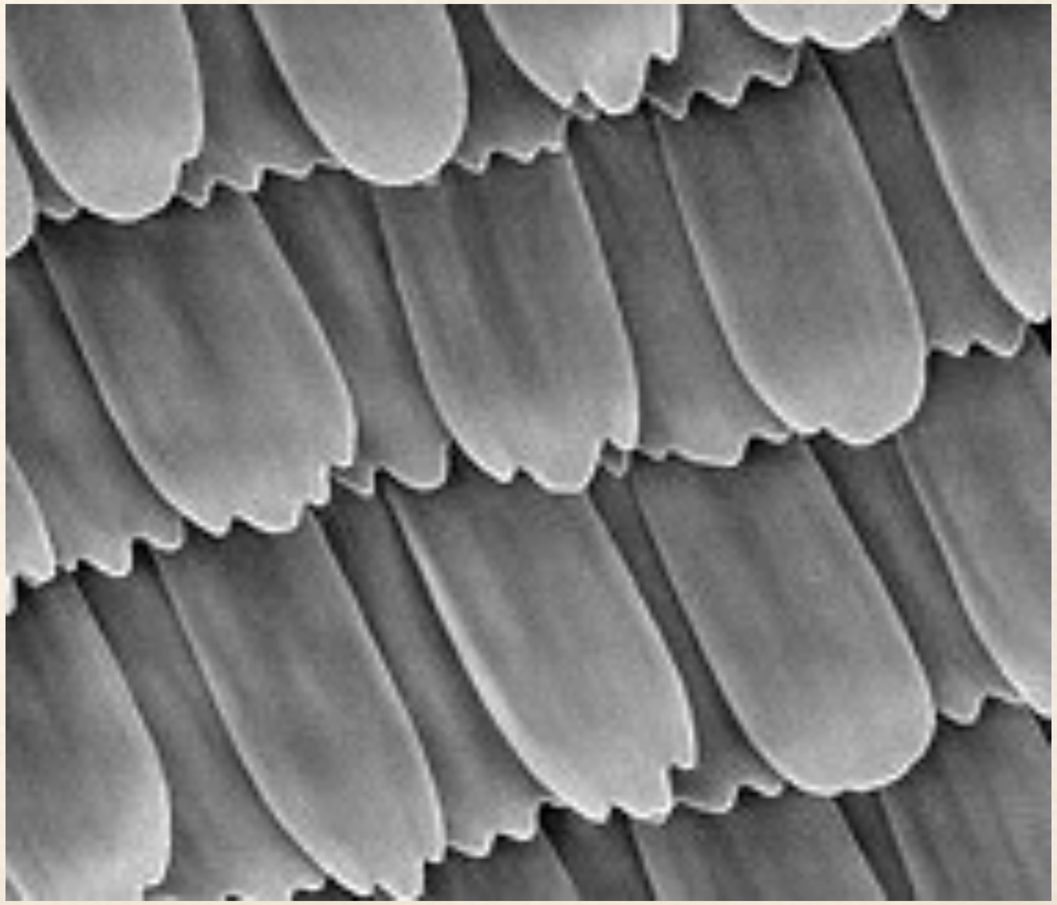

Uncertainties

- WEATHER: demand & supply (especially renewables)
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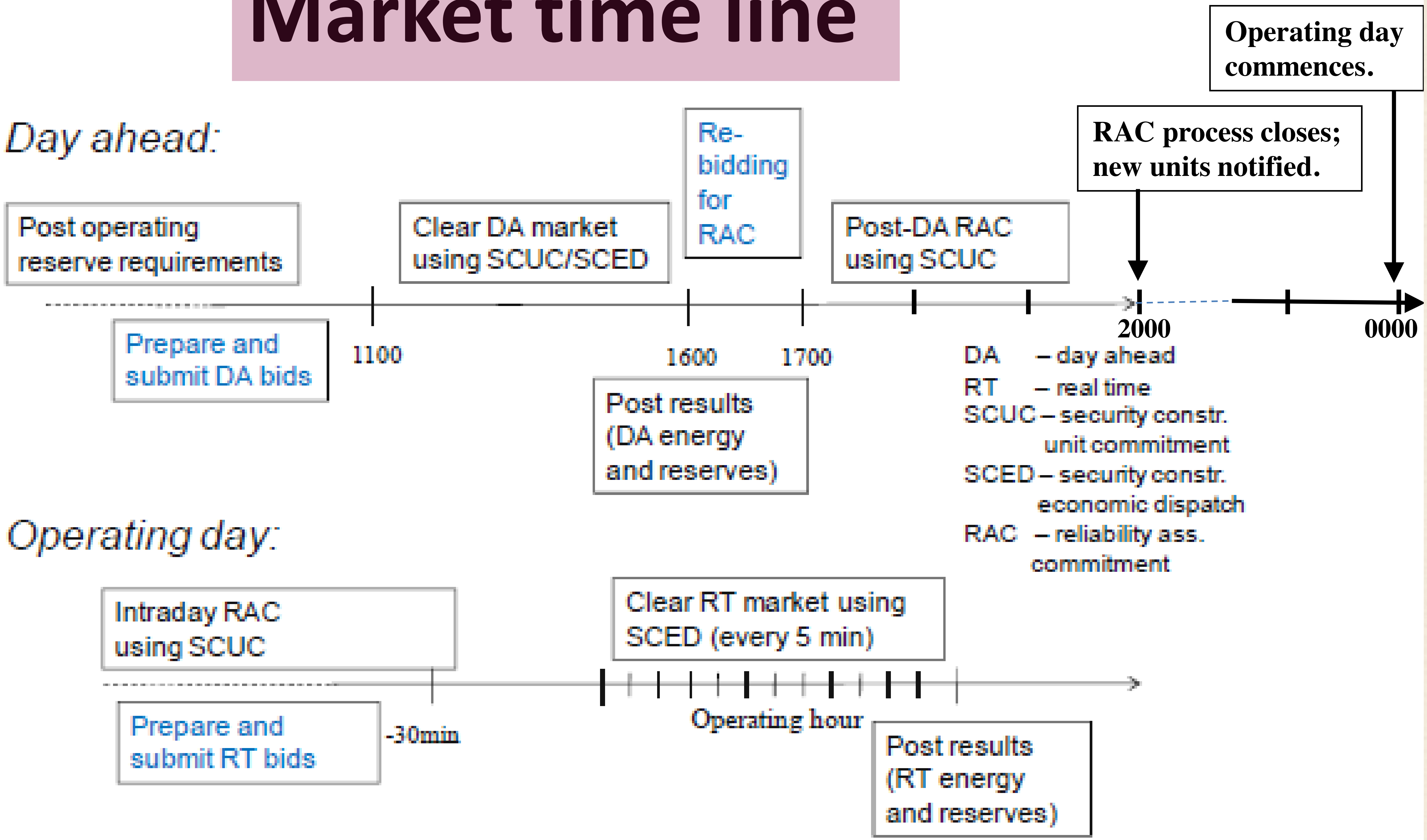
Energy Sources

- nuclear energy
- hydro-power
- thermal plants (coal, oil, shale oil, bio, rubish, . . .)
- gas turbines (natural gas, from ”cracking’)
- renewables (wind, solar, ..., ocean waves)

different characteristics

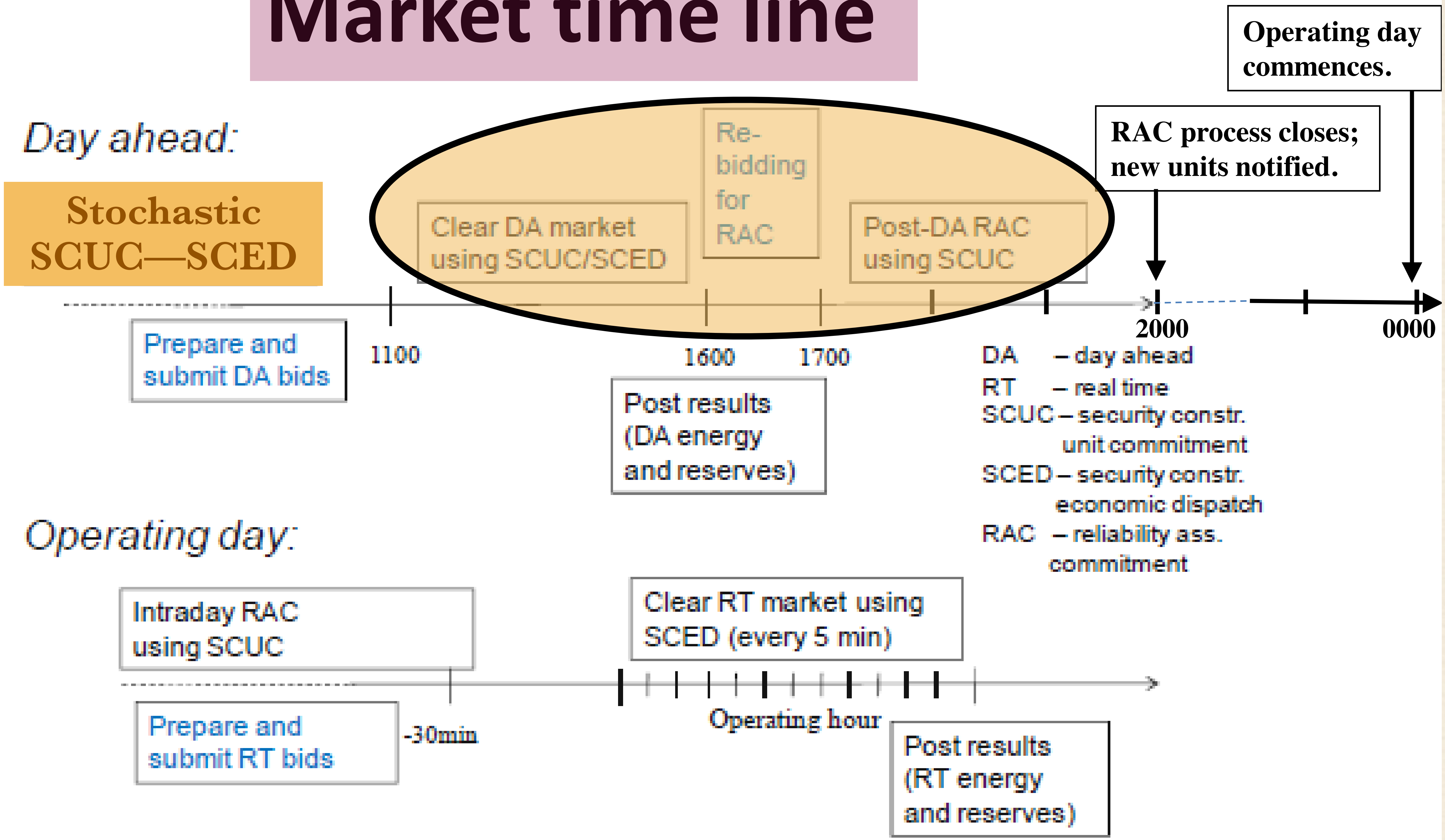
Market time line



	MISO	NYISO	PJM	ERCOT	CAISO
Market timeline	DA offers due: 11am DA results: 4pm Re-bidding due: 5pm RT offers due: OH -30 min	DA offers due: 5 am DA results: 11 am RT offers due: OH -75 min	DA offers due: noon DA results: 4pm RT offers due: 6pm DA	DA bids due (reserves): 1pm/4pm DA results (reserves): 1.30pm/6pm RT offers due: OH -60 min	DA offers: 10am DA results: 1pm RT offers: OH - 75 min

Ref: A. Botterud, J. Wang, C. Monteiro, and V. Miranda "Wind Power Forecasting and Electricity Market Operations," available at www.usaee.org/usaee2009/submissions/OnlineProceedings/Botterud_etal_paper.pdf

Market time line



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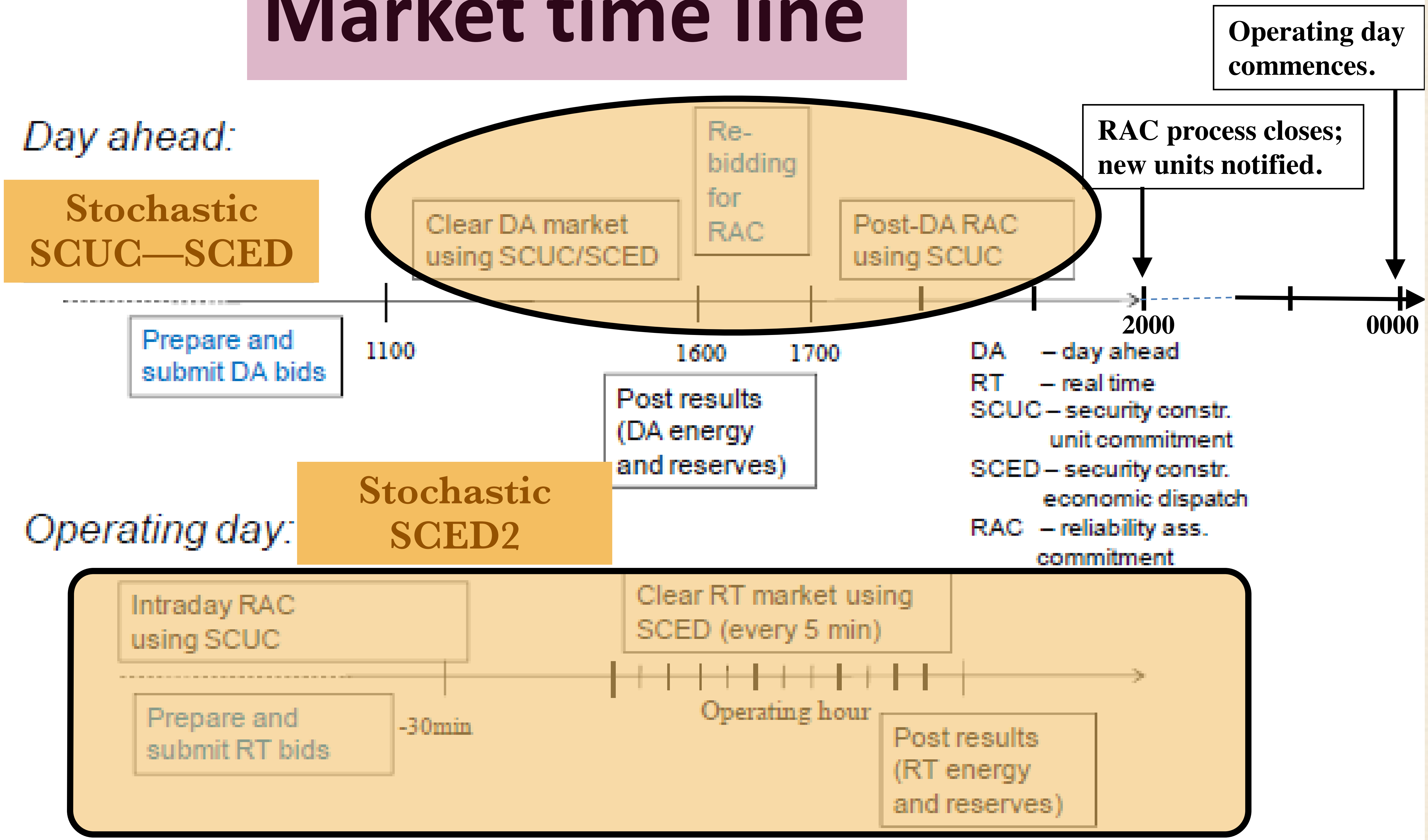

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between a rock and a hard place

MIP-CPLEX &
good ISP-codes (S. Sen & Co.)
can only handle effectively
problems of moderate size

recall "deadlines"

Our "ARPA-e Team"

- Sandia National Labs: Jean-Paul Watson, César Silva-Monroy, Ross Guttromsom (team builder), John Siirola, William Hart, …
- Iowa Sate University: Sarah Ryan, Dinakar Gade, Yonghan Feng, Youngrok Lee
- University of California, Davis: David Woodruff, Roger J-B Wets, Ignacio Rios, Kai Spürkel, Fabian Rüdel, (+ Chuangyin Dang, Julia Peyre … later this year)
- Alstom: Kwok Cheung (+ …)
- @ New-England ISO: Eugene Litvinov (& Joe Mercer, William Callan)
- Unofficial associates: Johannes Royset (NPS), Hoa Chen (UCD) - uncertainty design

Abstract Unit Commitment

$$\text{Minimize} \sum_{k\in K}\sum_{j\in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \qquad \text{with}$$

$$\sum_{j\in J} p_j(k) = D(k), \quad \forall k \in K$$

$$\sum_{j\in J} \bar{p}_j(k) \geq D(k) + R(k), \quad \forall k \in K$$

$$p_j(k), \overline{p}_j(k) \in \Pi, \quad \forall j \in J, \ \forall k \in K$$

Π region of feasible production, all generating units, all time periods. The specific nature of Π is model-dependent.

Abstract Unit Commitment

$$\text{Minimize} \sum_{k \in K} \sum_{j \in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \qquad \text{with}$$

J generating units

$$\sum_{j \in J} p_j(k) = D(k), \quad \forall k \in K$$

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Abstract Unit Commitment

$$\text{Minimize} \sum_{k \in K} \sum_{j \in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \qquad \text{with}$$

K time periods *J generating units*

$$\sum_{j \in J} p_j(k) = D(k), \quad \forall k \in K$$

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Abstract Unit Commitment

production cost

$$\text{Minimize} \sum_{k\in K} \sum_{j\in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \qquad \text{with}$$

K time periods *J generating units*

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Π region of feasible production, all generating units, all time periods. The specific nature of Π is model-dependent.

Abstract Unit Commitment

production cost *startup cost*

$$\text{Minimize} \sum_{k \in K} \sum_{j \in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \qquad \text{with}$$

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Π region of feasible production, all generating units, all time periods. The specific nature of Π is model-dependent.

Abstract Unit Commitment

production cost *startup cost* *shutdown cost*

$$\text{Minimize} \sum_{k \in K} \sum_{j \in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \quad \text{with}$$

K time periods *J generating units*

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Π region of feasible production, all generating units, all time periods. The specific nature of Π is model-dependent.

Abstract Unit Commitment

production cost — startup cost — shutdown cost

$$\text{Minimize} \sum_{k \in K} \sum_{j \in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \quad \text{with}$$

K time periods — J generating units

demand

$$\sum_{j \in J} p_j(k) = D(k), \quad \forall k \in K$$

$$\sum_{j \in J} \bar{p}_j(k) \geq D(k) + R(k), \quad \forall k \in K$$

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Π region of feasible production, all generating units, all time periods. The specific nature of Π is model-dependent.

Abstract Unit Commitment

production cost *startup cost* *shutdown cost*

$$\text{Minimize} \sum_{k \in K} \sum_{j \in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \quad \text{with}$$

K time periods *J generating units*

power output *demand*

$$\sum_{j \in J} p_j(k) = D(k), \quad \forall k \in K$$

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Abstract Unit Commitment

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production cost, startup cost, shutdown cost

K time periods, J generating units

power output, demand

$$\sum_{j \in J} p_j(k) = D(k), \quad \forall k \in K$$

max power output

$$\sum_{j \in J} \bar{p}_j(k) \geq D(k) + R(k), \quad \forall k \in K$$

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Π region of feasible production, all generating units, all time periods. The specific nature of Π is model-dependent.

Abstract Unit Commitment

production cost *startup cost* *shutdown cost*

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K time periods *J generating units*

power output *demand*

$$\sum_{j \in J} p_j(k) = D(k), \quad \forall k \in K$$

max power output *spinning reserve*

$$\sum_{j \in J} \bar{p}_j(k) \geq D(k) + R(k), \quad \forall k \in K$$

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Π region of feasible production, all generating units, all time periods.
The specific nature of Π is model-dependent.

Abstract Unit Commitment

production cost   startup cost   shutdown cost

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K time periods   J generating units

power output   demand

$$\sum_{j \in J} p_j(k) = D(k), \quad \forall k \in K$$

max power output   spinning reserve

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Π region of feasible production, all generating units, all time periods. The specific nature of Π is model-dependent.

"Stochastic Version"

Abstract Unit Commitment

min. expectation (actually: risk measure) with penalties

production cost *startup cost* *shutdown cost*

$$\text{Minimize} \sum_{k \in K} \sum_{j \in J} c_j^P(k) + c_j^u(k) + c_j^d(k) \quad \text{with}$$

K time periods *J generating units*

power output *demand*

$$\sum_{j \in J} p_j(k) = D(k), \quad \forall k \in K$$

adjust node balance eq'ns

max power output *spinning reserve*

$$\sum_{j \in J} \bar{p}_j(k) \geq D(k) + R(k), \quad \forall k \in K$$

$$p_j(k), \overline{p}_j(k) \in \Pi, \quad \forall j \in J, \ \forall k \in K$$

Π region of feasible production, all generating units, all time periods. The specific nature of Π is model-dependent.

"Stochastic Version"

Aggregation Principle in Stochastic Optimization

$\Rightarrow$ to Progressive Hedging Algorithm

Here-&-Now vs. Wait-&-See

- Basic Process: decision → observation → decision
  $x^1 \rightsquigarrow \xi \rightsquigarrow x^2_\xi$
- Here-&-Now problem! x^1
  not all contingencies can be "protected" by available instruments, i.e.
- Wait-&-See problem:
  instruments are available to cover all contingencies
  choose (x^1_ξ, x^2_ξ) after observing ξ

Stochastic Optimization: Fundamental Theorem

A here-&-now problem can be transformed in a wait-&-see problem by introducing the

appropriate `contingencies' costs (price of nonanticipativity)

Price of Nonanticipativity

$$\min \ \mathbb{E}\left\{ f_0(\boldsymbol{\xi}, x^1, x^2_{\boldsymbol{\xi}}) \right\}$$

$$x^1 \in C^1 \subset \mathbb{R}^n,$$

$$x^2_\xi \in C^2(\xi, x^1), \forall \xi.$$

Price of Nonanticipativity

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Explicit non-anticipativity

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$$\boxed{x^1_{\boldsymbol{\xi}} = \mathbb{E}\left\{ x^1_{\boldsymbol{\xi}} \right\} \quad \forall \xi}$$

Price of Nonanticipativity

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$w_\xi \perp$ subspace of constant fcns

multipliers ↗ w_ξ

$$\Rightarrow \mathbb{E}\left\{ w_\xi \right\} = 0$$

Price of Nonanticipativity

Explicit non-anticipativity

$$\min \; \mathbb{E}\left\{ f_0(\boldsymbol{\xi}, x^1, x^2_\xi) \right\}$$
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$w_\xi \perp$ subspace of constant fcns

multipliers

$$\Rightarrow \mathbb{E}\left\{ w_\xi \right\} = 0$$

$$\min \; \mathbb{E}\left\{ f_0(\boldsymbol{\xi}, x^1_\xi, x^2_\xi) + \langle w_\xi, x^1_\xi \rangle - \langle w_\xi, \mathbb{E}\{x^1_\xi\} \rangle \right\}$$

such that $x^1_\xi \in C_1, \quad x^2_\xi \in C_2(\boldsymbol{\xi}, x^1_\xi)$

Price of Nonanticipativity

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$w_\xi \perp$ subspace of constant fcns

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$$\Rightarrow \mathbb{E}\left\{ w_\xi \right\} = 0$$

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such that $x^1_\xi \in C_1, \quad x^2_\xi \in C_2(\boldsymbol{\xi}, x^1_\xi)$

Progressive Hedging Algorithm

0. w_ξ^0 such that $\mathbb{E}\{w_\xi^0\} = 0$, $\nu = 0$. Pick $\rho > 0$

1. for all ξ :

$$(x_\xi^{1,\nu}, x_\xi^{2,\nu}) \in \arg\min f_0(\xi; x^1, x^2) - \langle w_\xi^\nu, x^1 \rangle$$

$$x^1 \in C^1 \subset \mathbb{R}^{n_1},\ x^2 \in C^2(\xi, x^1) \subset \mathbb{R}^{n_2}$$

2. $\bar{x}^{1,\nu} = \mathbb{E}\{x_\xi^{1,\nu}\}$. Stop if $\left| x_\xi^{1,\nu} - \bar{x}^{1,\nu} \right| = 0$ (approx.)

otherwise $w_\xi^{\nu+1} = w_\xi^\nu + \rho\left[x_\xi^{1,\nu} - \bar{x}^{1,\nu}\right]$, return to 1. with $\nu = \nu + 1$

Progressive Hedging Algorithm

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otherwise $w_\xi^{\nu+1} = w_\xi^\nu + \rho\left[x_\xi^{1,\nu} - \bar{x}^{1,\nu}\right]$, return to 1. with $\nu = \nu + 1$

Convergence: add a proximal term

$$f_0(\xi; x^1, x^2) - \langle w_\xi^\nu, x^1 \rangle - \frac{\rho}{2}\left| x^1 - \bar{x}^{1,\nu} \right|^2$$

linear rate in $(\mathrm{x}^{1,\nu}, w^\nu)$ ... eminently parallelizable

PH: Implementation issues

implementation: choice of ρ ... scenario (×), i*th*-decision (i) dependent

(heuristic) extension to problems with integer variables

non-convexities: e.g. ground-water remediation with non-linear PDE recourse

asynchronous

partitioning (= different information feeds)

$$\min \mathbb{E}\{f(\boldsymbol{\xi},x)\} \ , \quad f(\xi,x) = f_0(x) + \iota_{C(\xi,x)}(x)$$

$S = \{\Xi_1, \Xi_2, \ldots, \Xi_K\}$ a partitioning of Ξ, $p_k = P(\Xi_k)$

$\mathbb{E}\{f(\boldsymbol{\xi},x)\} = \sum_n p_n \mathbb{E}\{f(\boldsymbol{\xi},x) \mid \Xi_n\}$ (Bundling)

defining $g(k,x) = \mathbb{E}\{f_0(\boldsymbol{\xi},x) \mid \Xi_n\}$ if $x \in C_k = \bigcap_{\xi \in \Xi_k} C_\xi$

solve the problem as: $\min \sum_{n=1}^{N} p_k g(k,x)$

Bundling

PH: binary variables

$\min\langle c, x\rangle + \sum_{\xi\in\Xi} p_\xi \langle q_\xi, y_\xi\rangle$ such that

$x \in C_1, \;\; y_\xi \in C_2(\xi, x) \;\forall\, \xi \in \Xi$

binary (integer) variables: some x's, some y_ξ's.

PH: binary variables

$\min\langle c, x\rangle + \sum_{\xi\in\Xi} p_\xi \langle q_\xi, y_\xi\rangle$ such that
$x \in C_1, \;\; y_\xi \in C_2(\xi, x) \; \forall\, \xi \in \Xi$
binary (integer) variables: some x's, some y_ξ's.

Choice of $\rho \to \rho_j$ depending on $c_j, |x_j|, \ldots$ and augmentation

Variable Fixing, in particular binaries, $x_j(s) =$ constant (k iterations)
Variable Slamming: aggressive variable fixing $x_j(s) \approx$ constant (& $c_j x_j(s)$)
"Sufficient" variable convergence $\sim$ for small values of $c_j x_j(s)$

Termination criterion: variable slamming when $x_j^\nu(\xi) - x_j^{\nu+1}(\xi)$ small

Detecting cycling behavior: (simple) hashing scheme

PH: binary variables

$\min\langle c, x\rangle + \sum_{\xi\in\Xi} p_\xi \langle q_\xi, y_\xi\rangle$ such that
$x \in C_1,\;\; y_\xi \in C_2(\xi, x)\; \forall\, \xi \in \Xi$
binary (integer) variables: some x's, some y_ξ's.

Choice of $\rho \to \rho_j$ depending on $c_j, |x_j|, \ldots$ and augmentation

Variable Fixing, in particular binaries, $x_j(s) =$ constant (k iterations)
Variable Slamming: aggressive variable fixing $x_j(s) \approx$ constant (& $c_j x_j(s)$)
"Sufficient" variable convergence $\sim$ for small values of $c_j x_j(s)$

Termination criterion: variable slamming when $x_j^\nu(\xi) - x_j^{\nu+1}(\xi)$ small

Detecting cycling behavior: (simple) hashing scheme

Enough variables fixed ⇒ clean up with CPLEX-MIP

Error Bounds

$f(\xi,x) = f_0(\xi,x^1,x^2)$ if $x^1 \in C^1, x^2 \in C^2(\xi,x^1)$; $+\infty$ else

Stochastic Program (P):

$$\min_{x\in\mathcal{M}} \mathbb{E}\left\{f(\xi,x)\right\} \text{ such that } x^1 \equiv \mathbb{E}\{x^1_\xi\}$$

Dual Program (D)

$$\max_{w\in\mathcal{M}^*} \mathbb{E}\left\{-f^*(\xi,w_\xi)\right\} \text{ such that } \mathbb{E}\{w_\xi\} = 0$$

weak duality holds: $\inf P \geq \sup \mathrm{D} \Rightarrow$ for any feasible $\hat{w}$

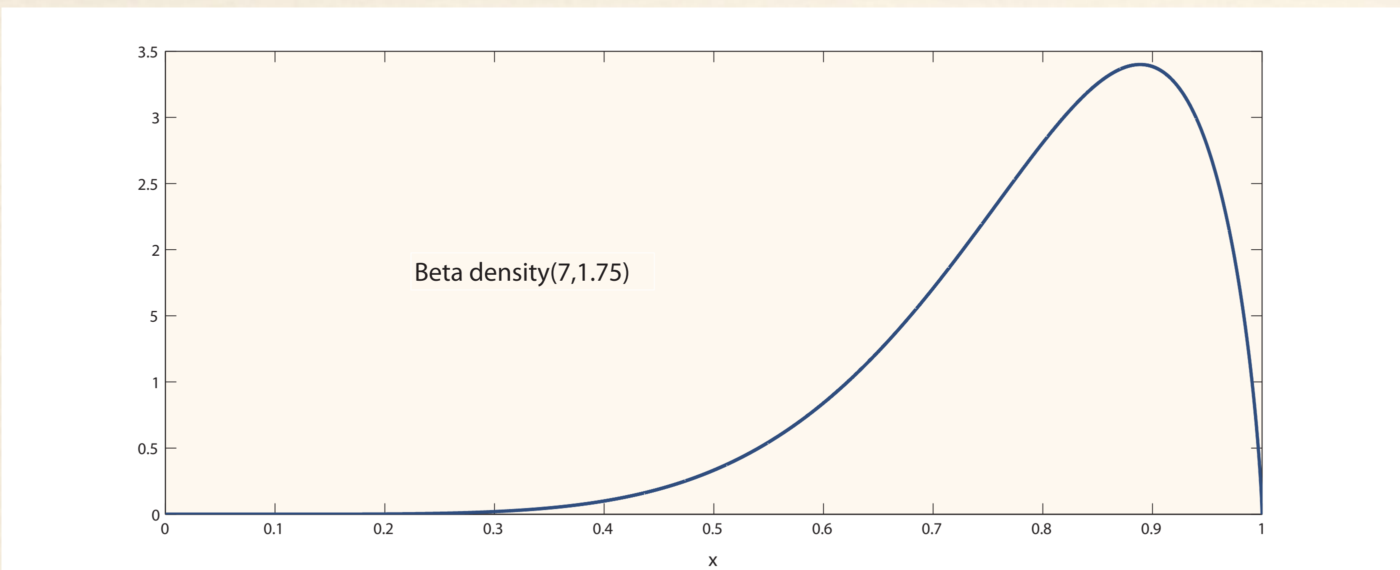
$$-f^*(\xi,\widehat{w}_\xi) = \min_x \left[f(\xi,x) + \left\langle \widehat{w}_\xi, x^1 \right\rangle, x \in \mathbb{R}^{n_1+n_2} \right]$$

yields a lower bound for (P), better if $\widehat{w}_\xi$ is near-optimal

$\Rightarrow$ rely on w^* of PH-algorithm to generate lower bound.

Augmentation function

$$m(\Delta, \lambda_{\max}; z, \lambda) = \int_0^{\Delta} \psi(z - s, \lambda, \lambda_{\max}) \varphi(\Delta; s)\, ds, \quad z \in [0, \lambda_{\max}]$$



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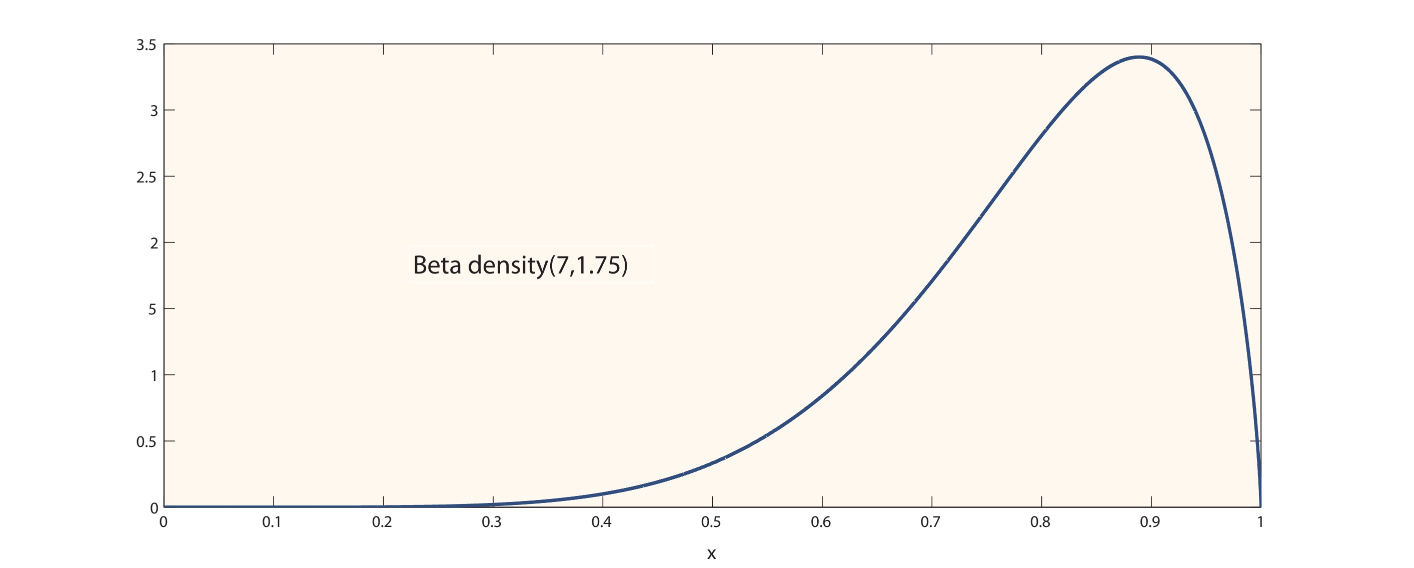
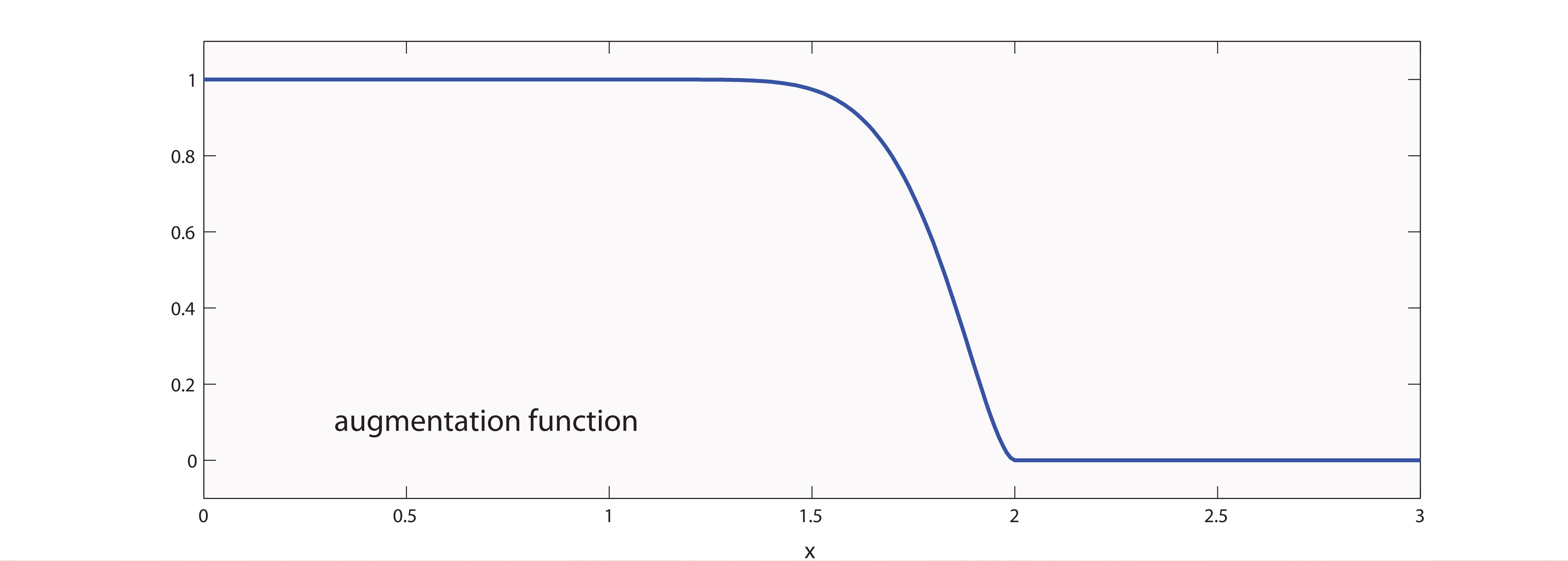
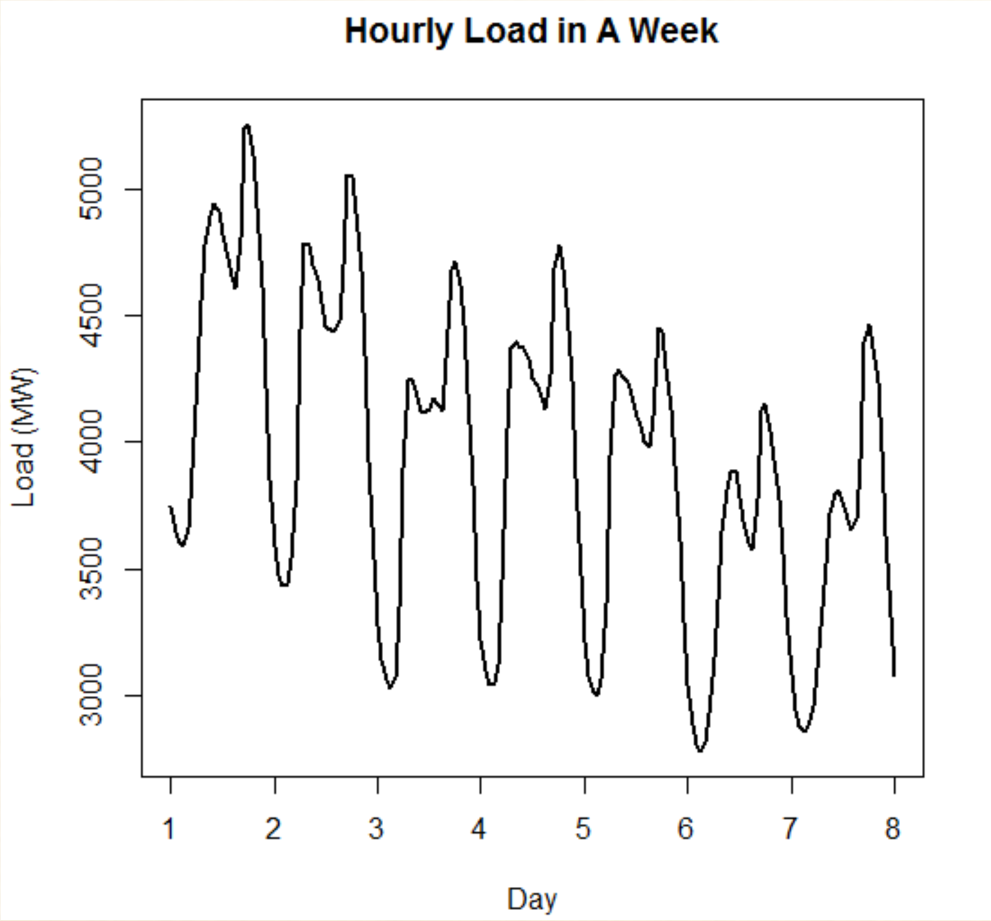


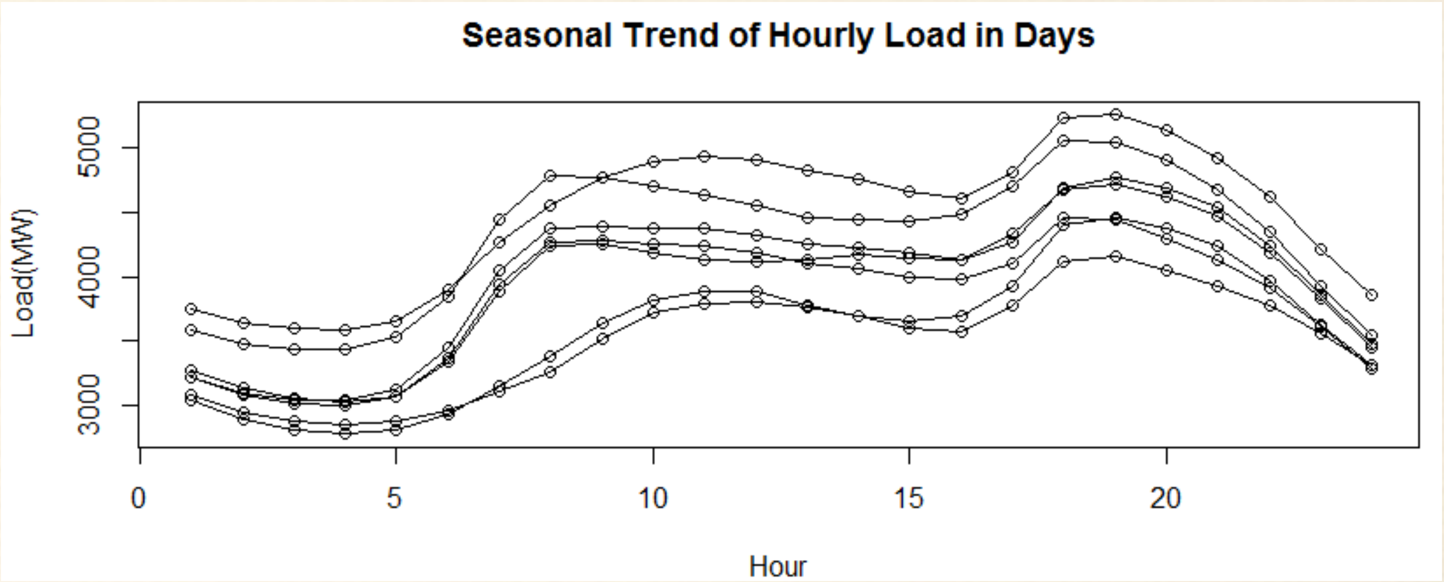


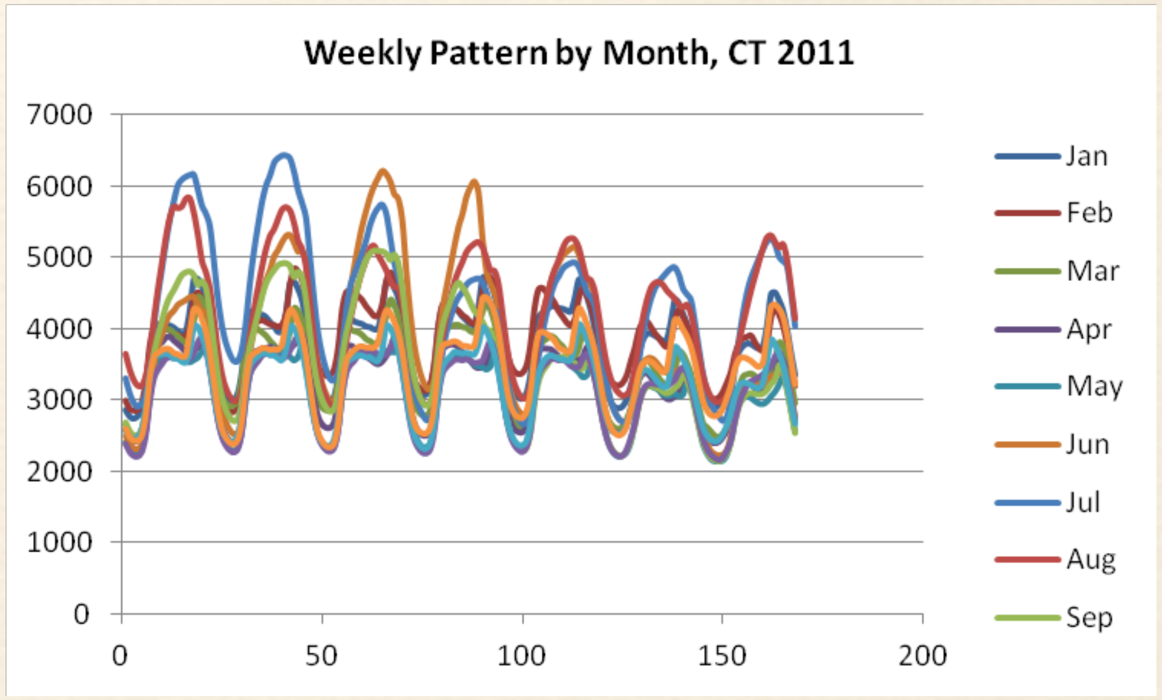
Unit commitment
Part II

Dealing with
load (demand) uncertainty

CT load exploratory process

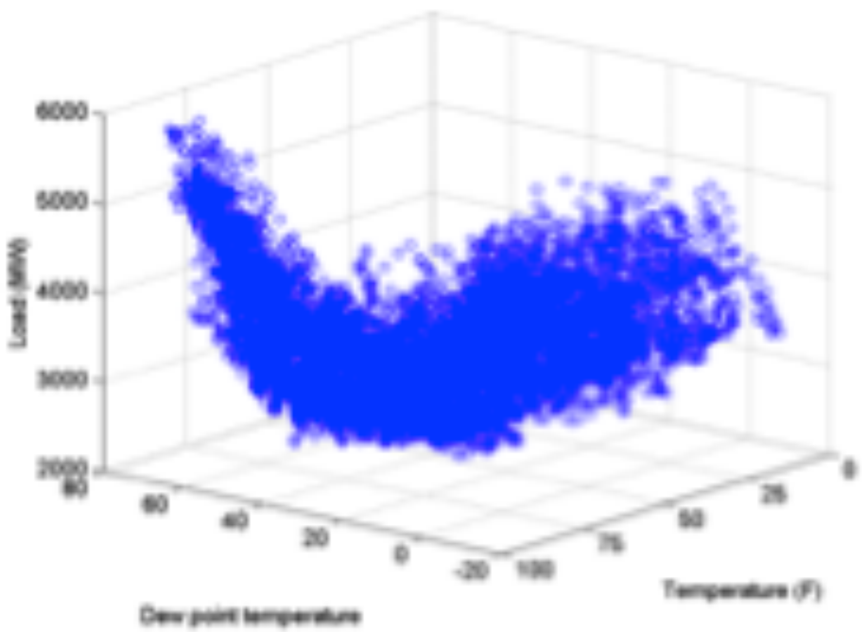




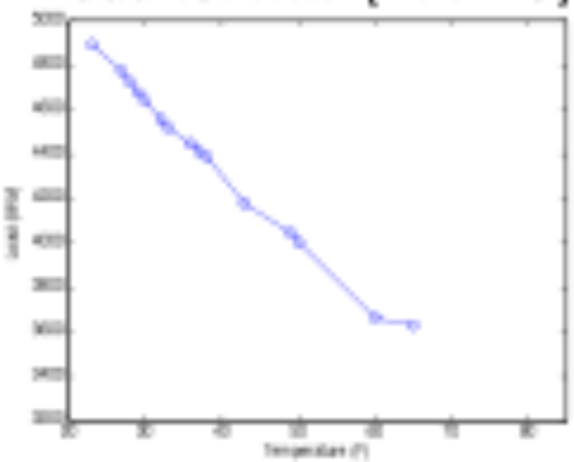


CT load vs. weather variables

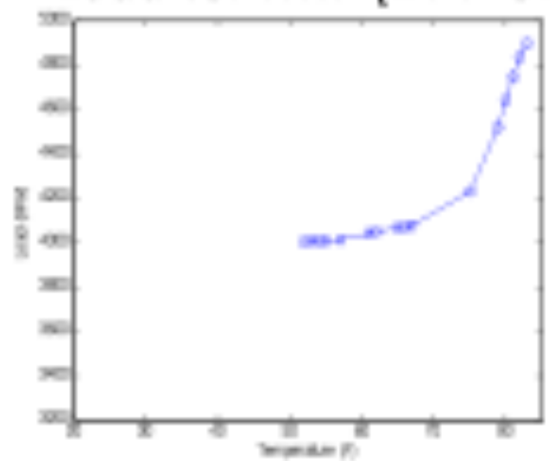
Load vs. temperature (TMP) and dew point temperature (DPT)



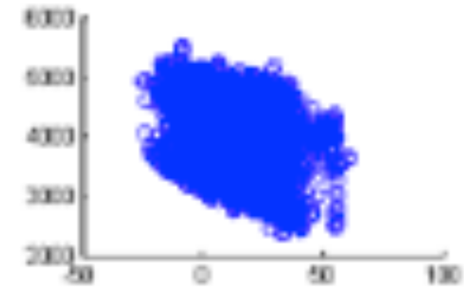
Load vs. TMP (DPT=19)



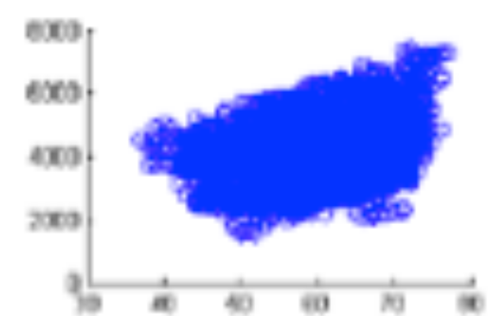
Load vs. TMP (DPT=52)



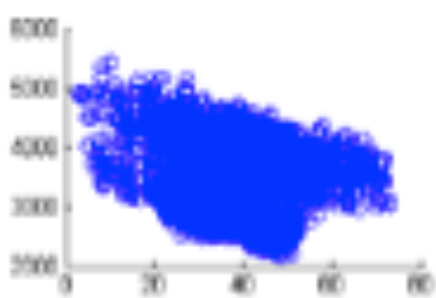
Load vs. DPT in Jan



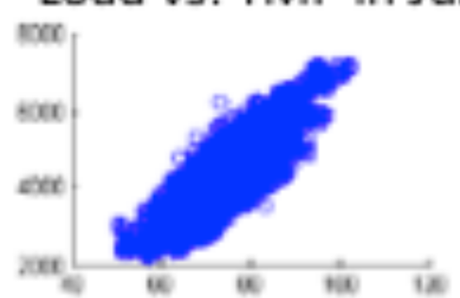
Load vs. DPT in Aug

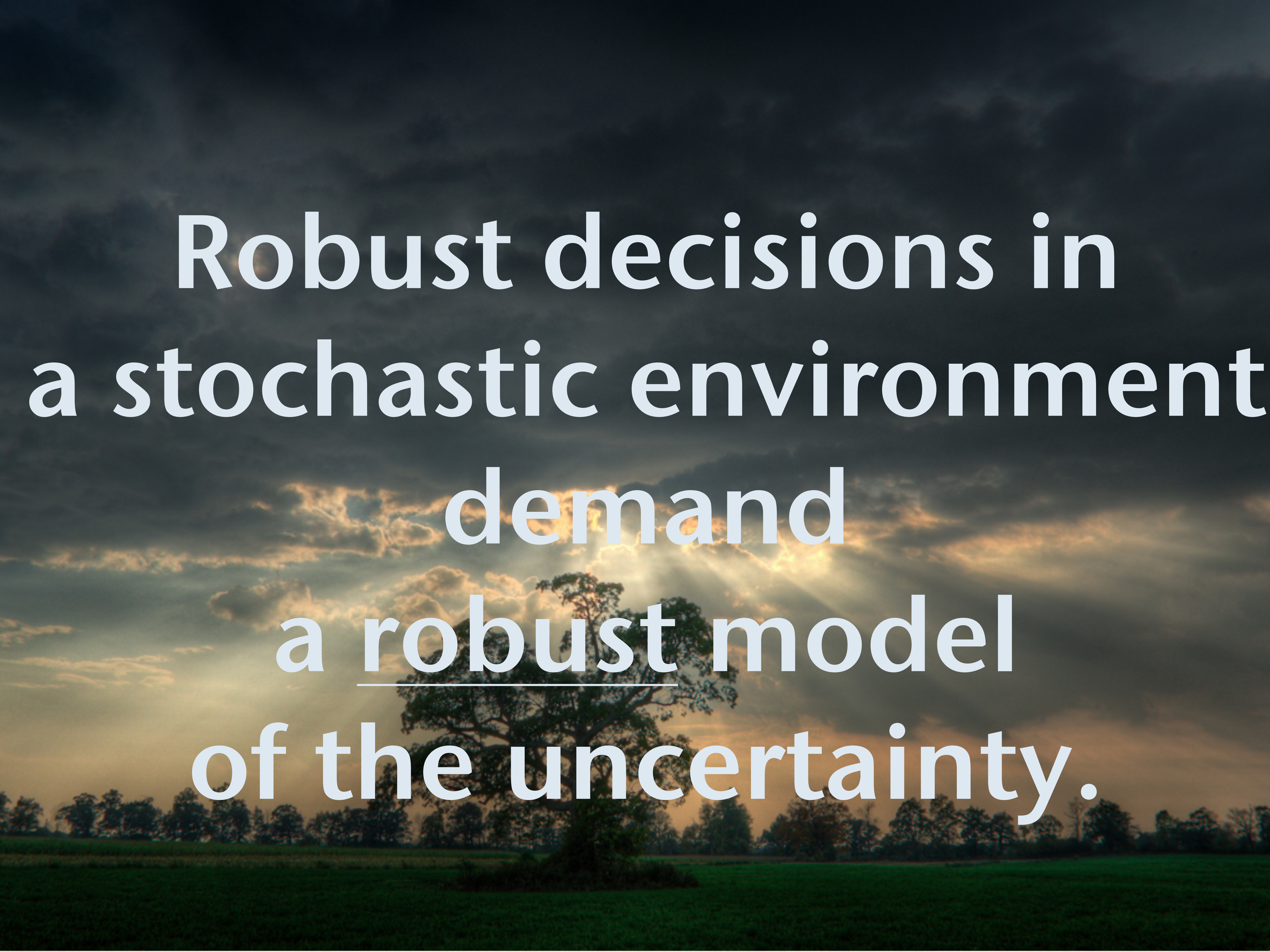


Load vs. TMP in Mar

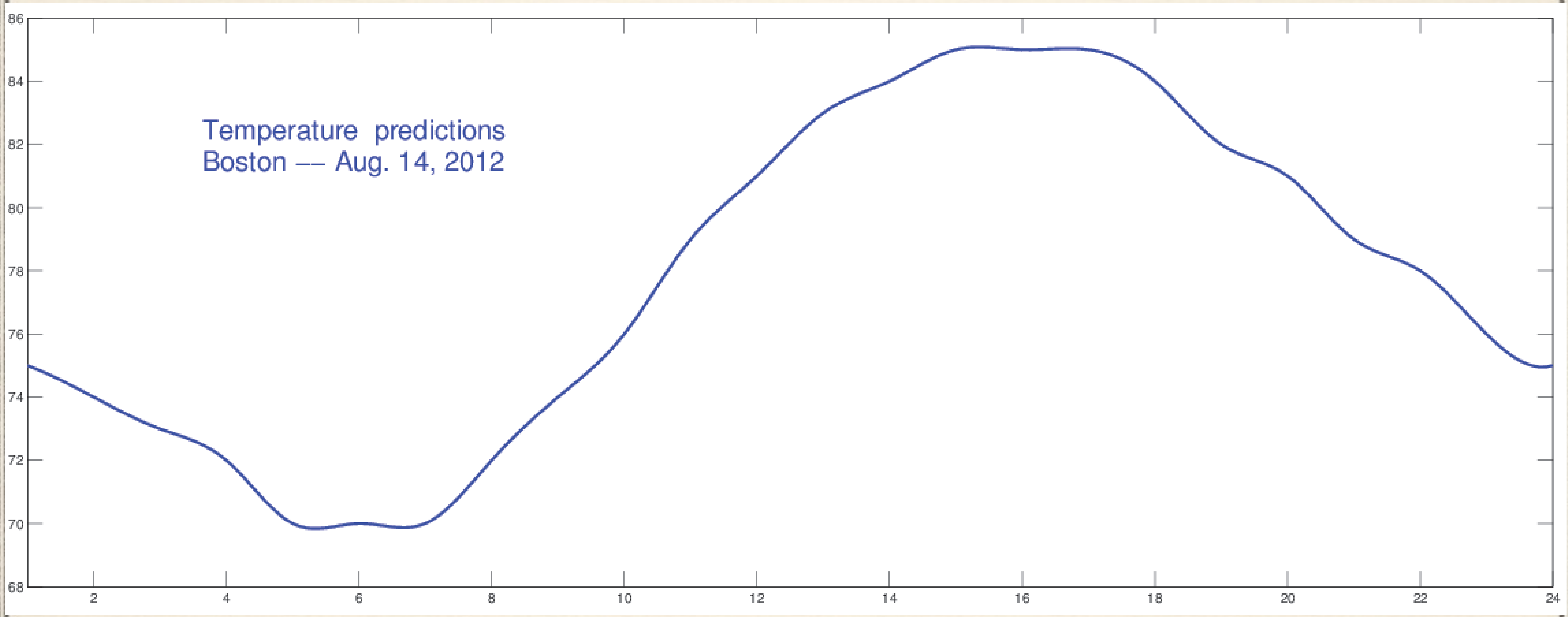


Load vs. TMP in Jul




Robust decisions in
a stochastic environment
demand
a robust model
of the uncertainty.

from predictions on day D-1 to load forecasts on day D



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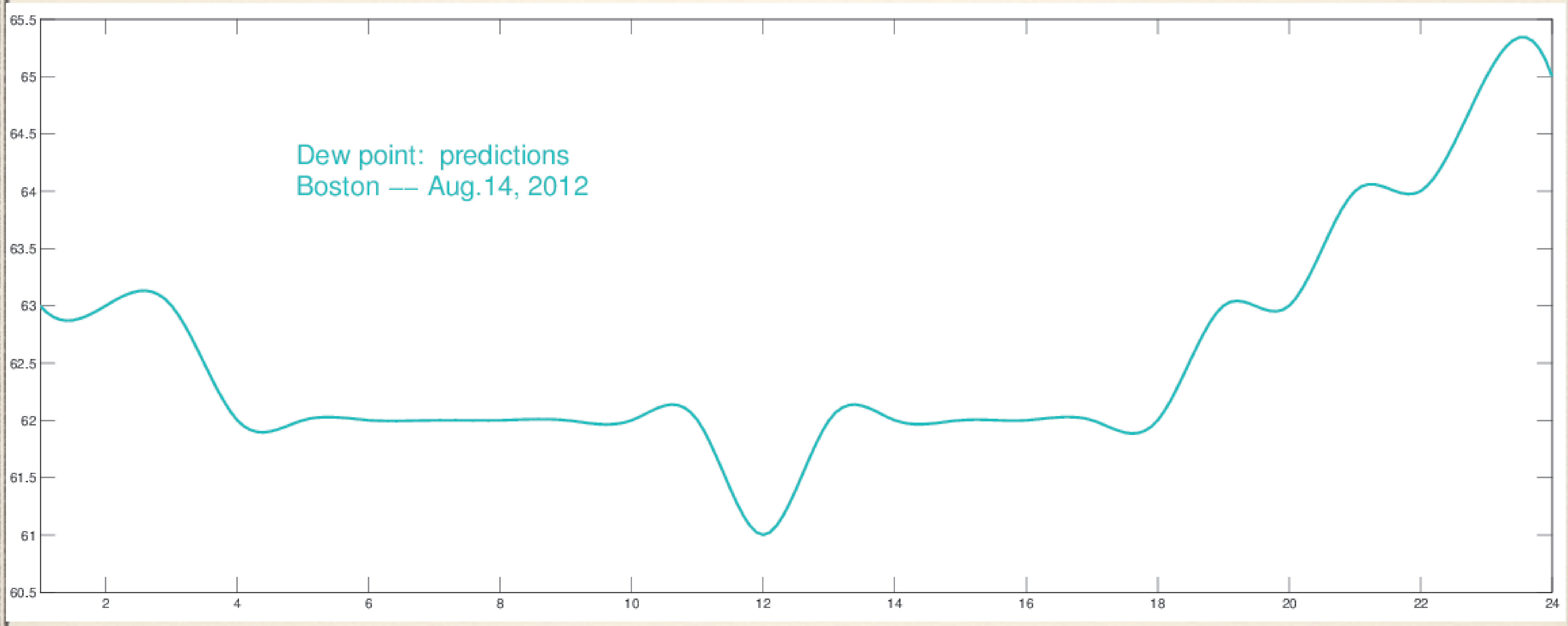

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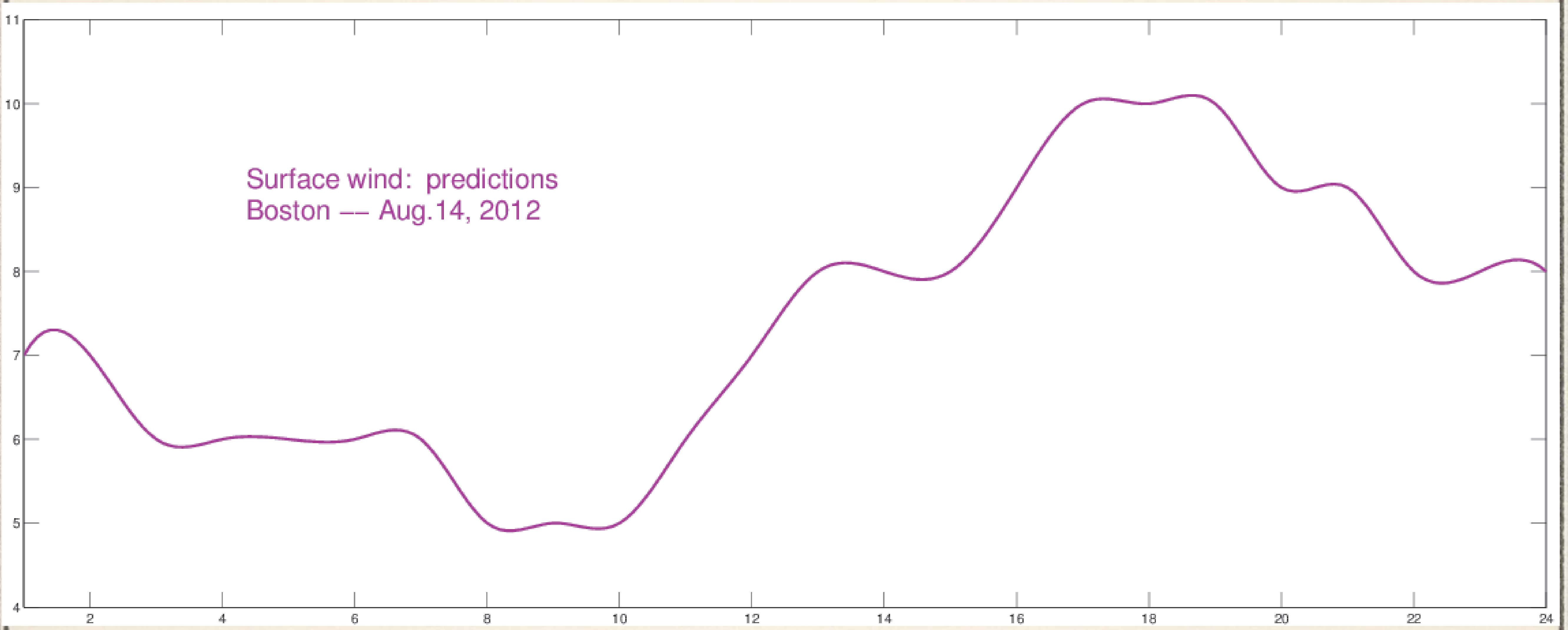
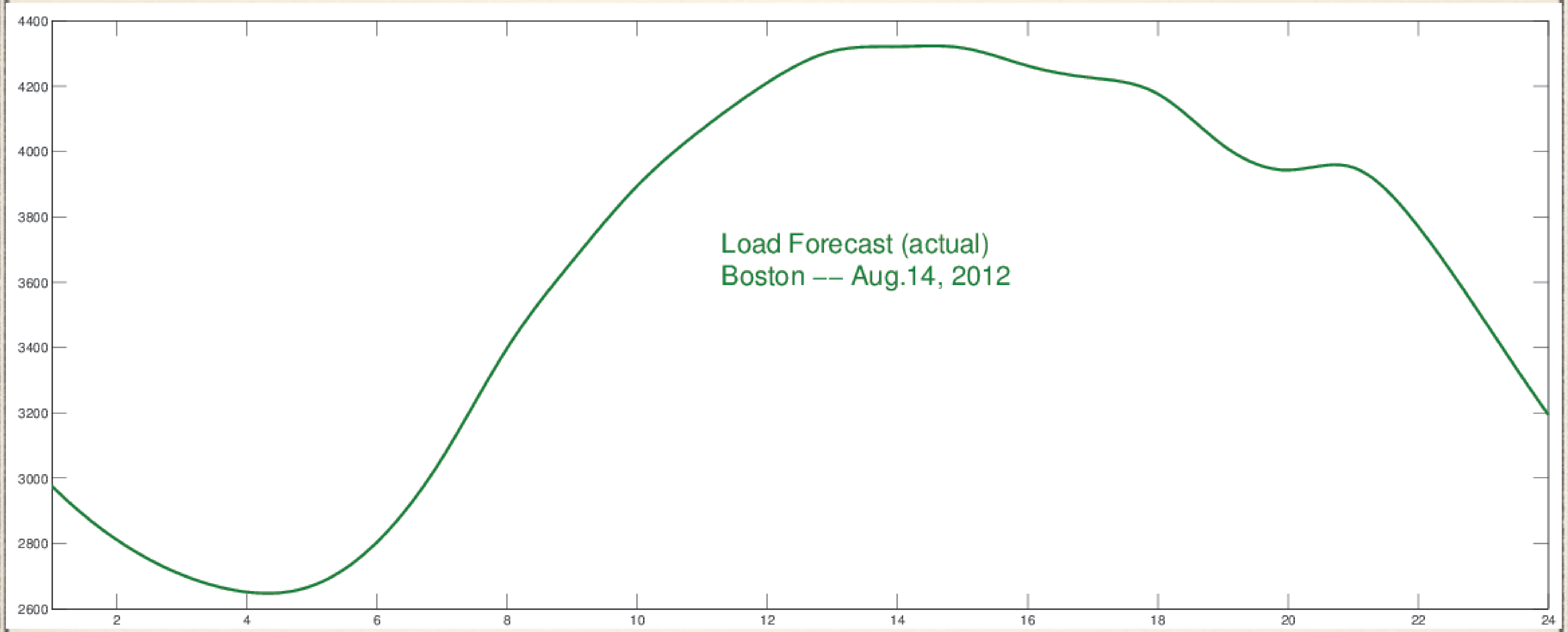


… to load on day D

to be delivered-load: $l(t)$

$$= \text{fcn}\big(\text{temp}(\tau \le \text{t}), \text{dewpt}(\tau \le \text{t}), \text{clcover}(\tau \le \text{t}), \text{wind}(\tau \le \text{t})\big),\ \ t \le 24$$



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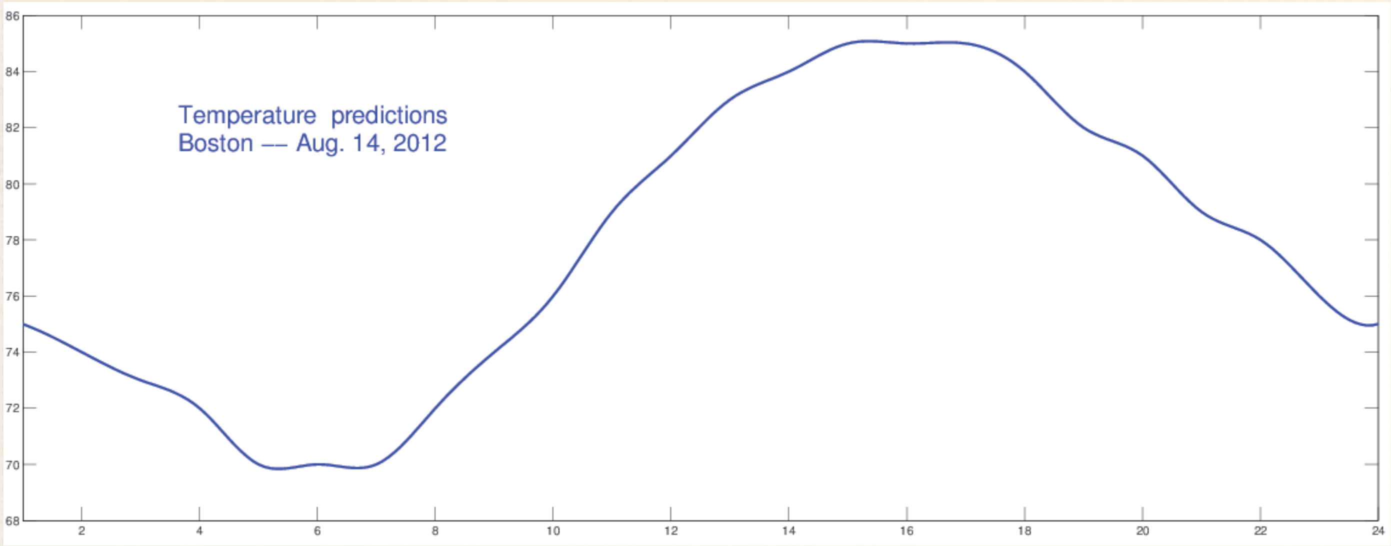
But that wouldn't capture the uncertainty!
one would expect:

from predictions on day D-1 to load forecasts on day D



THE DATA

from predictions on day D-1 to load forecasts on day D

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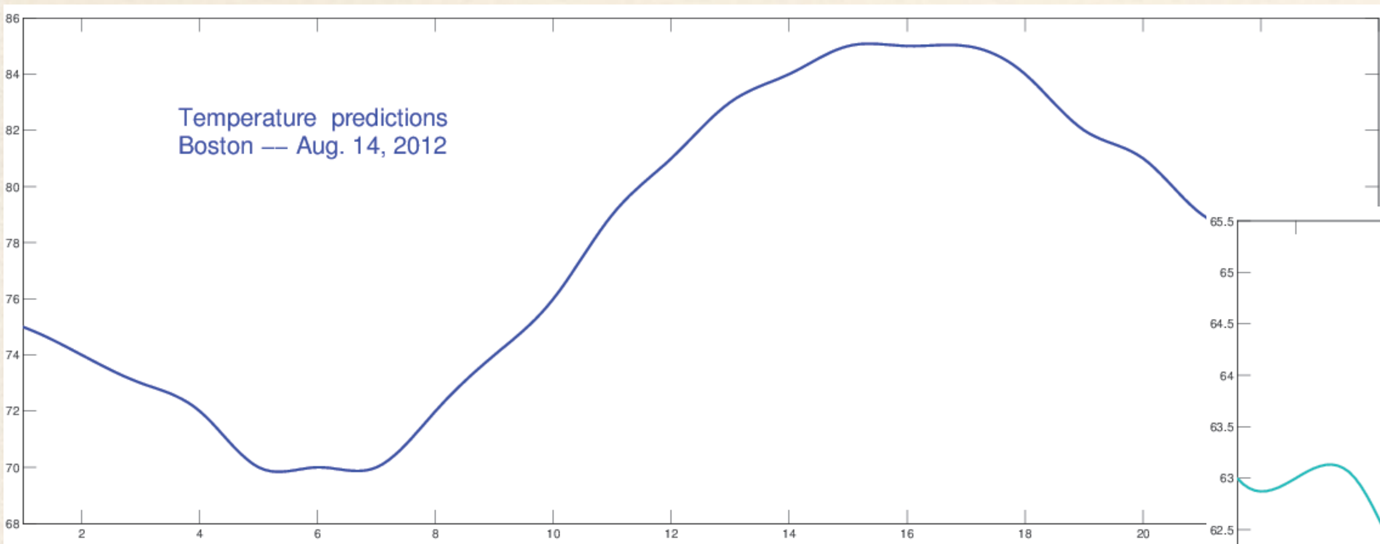

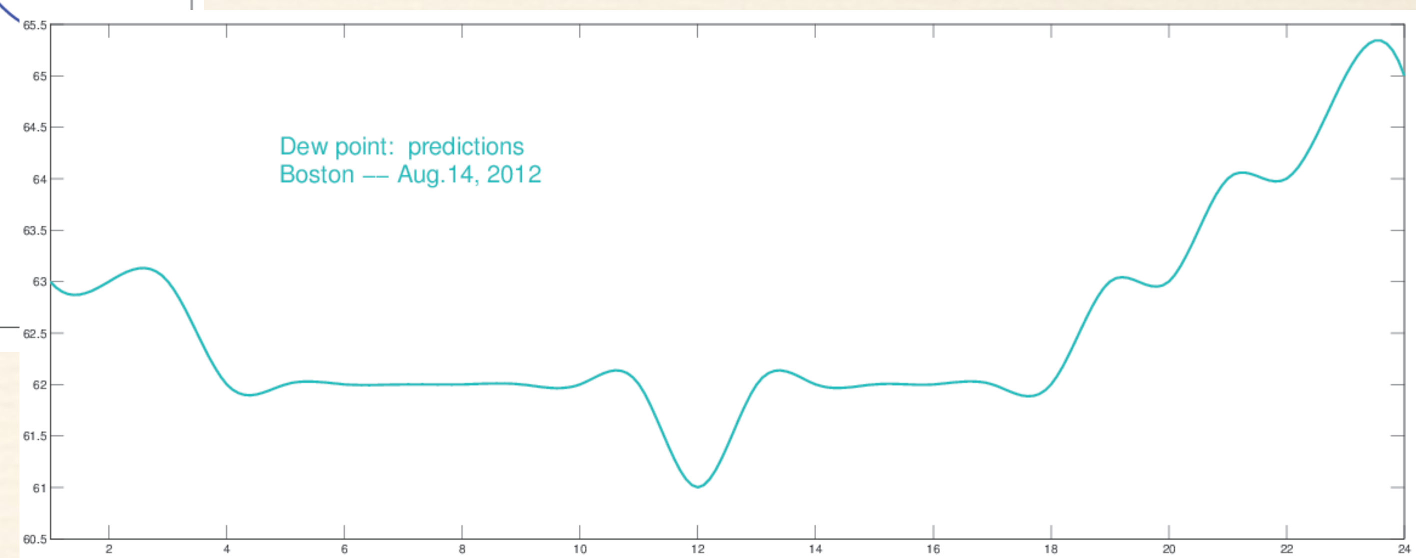

from predictions on day D-1
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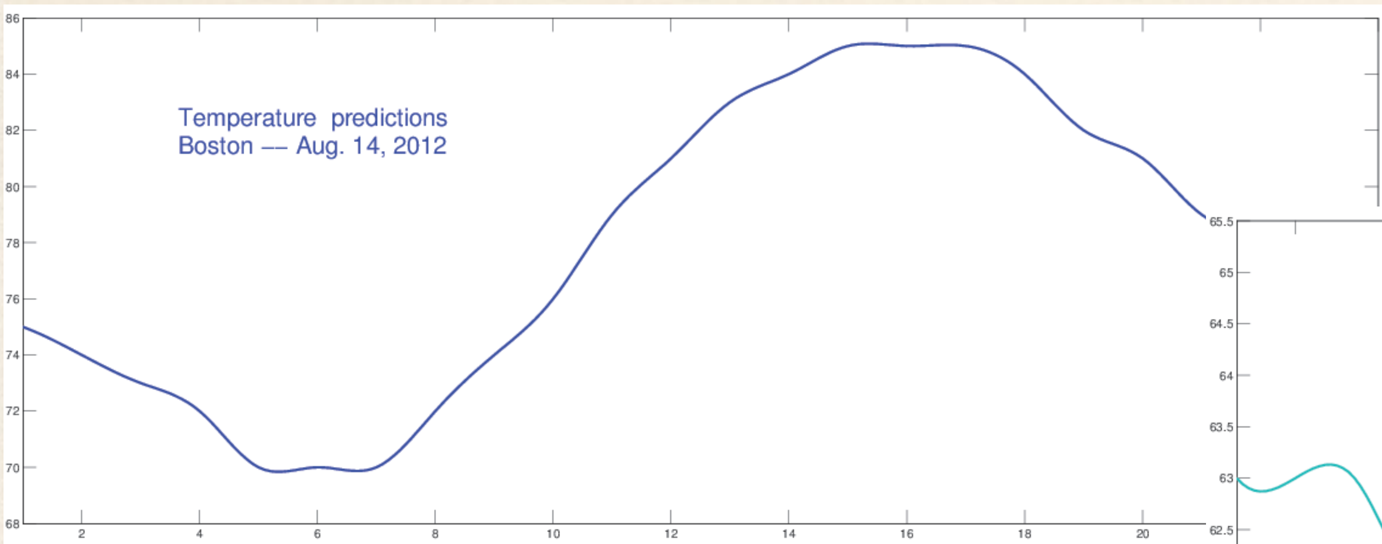

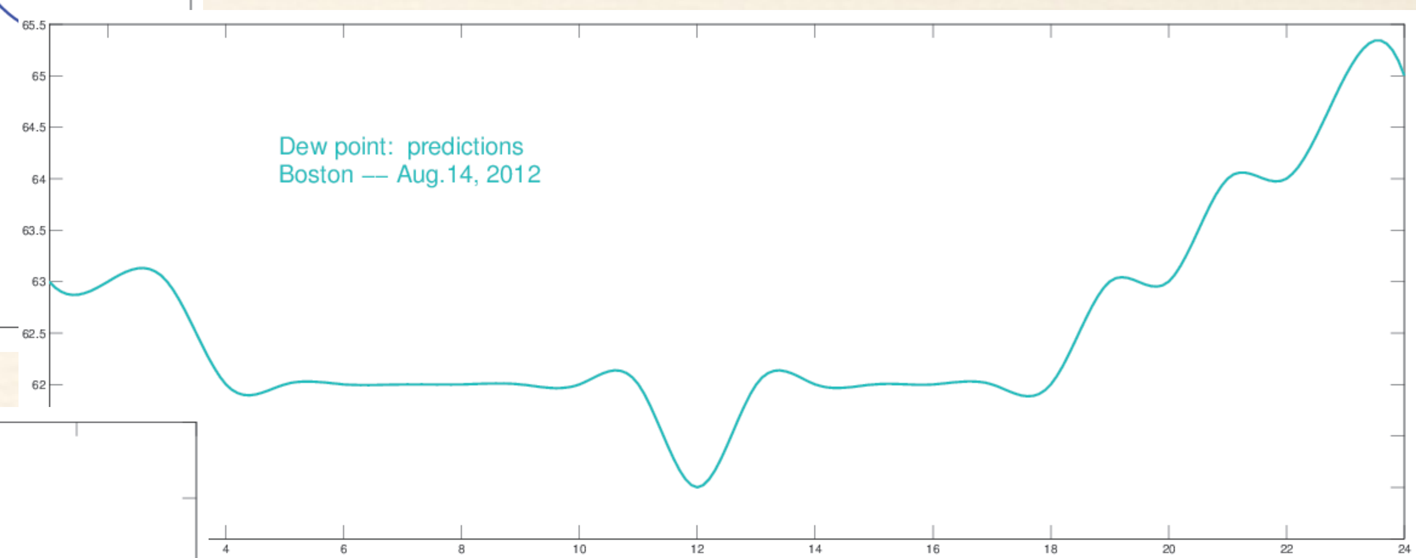

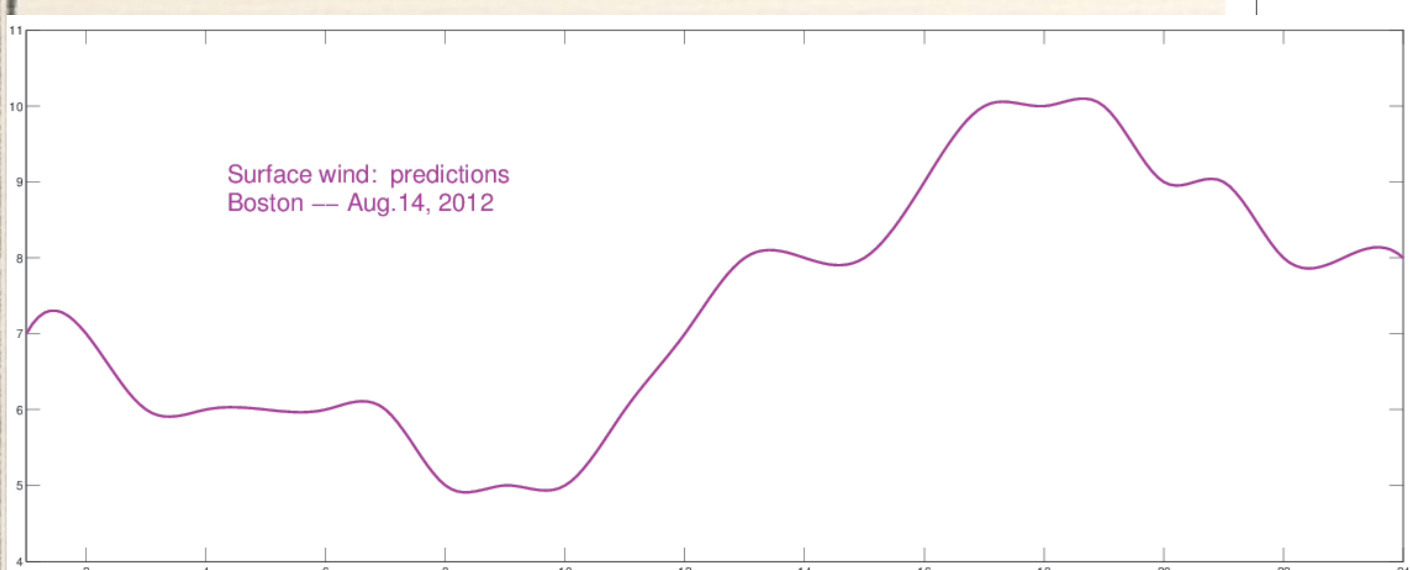

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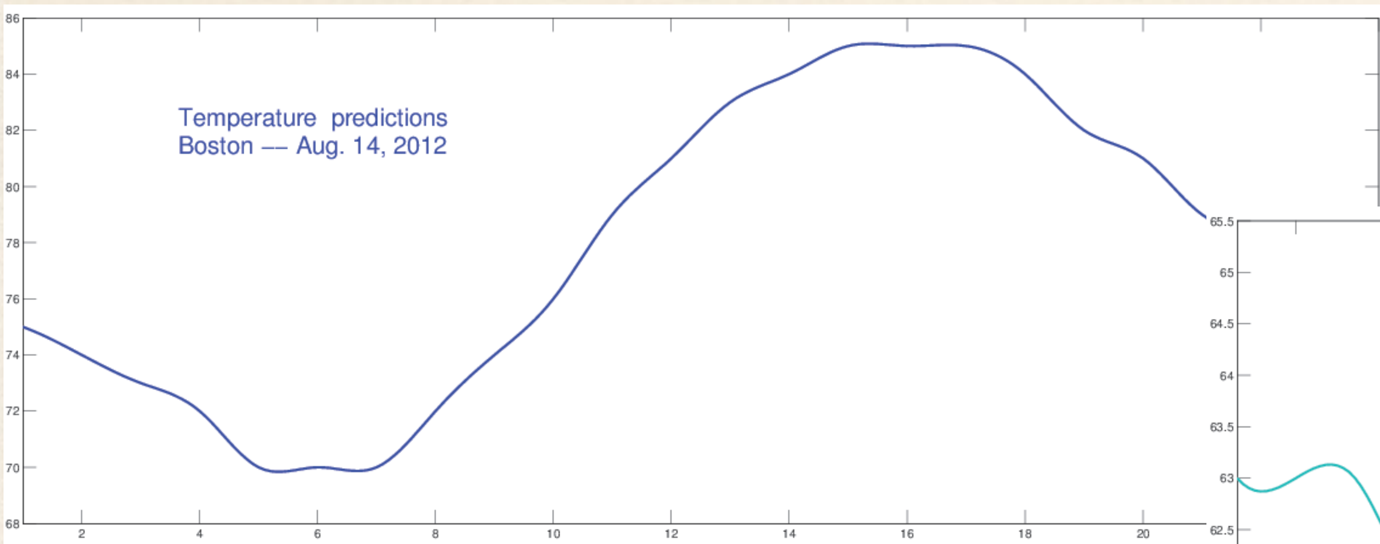
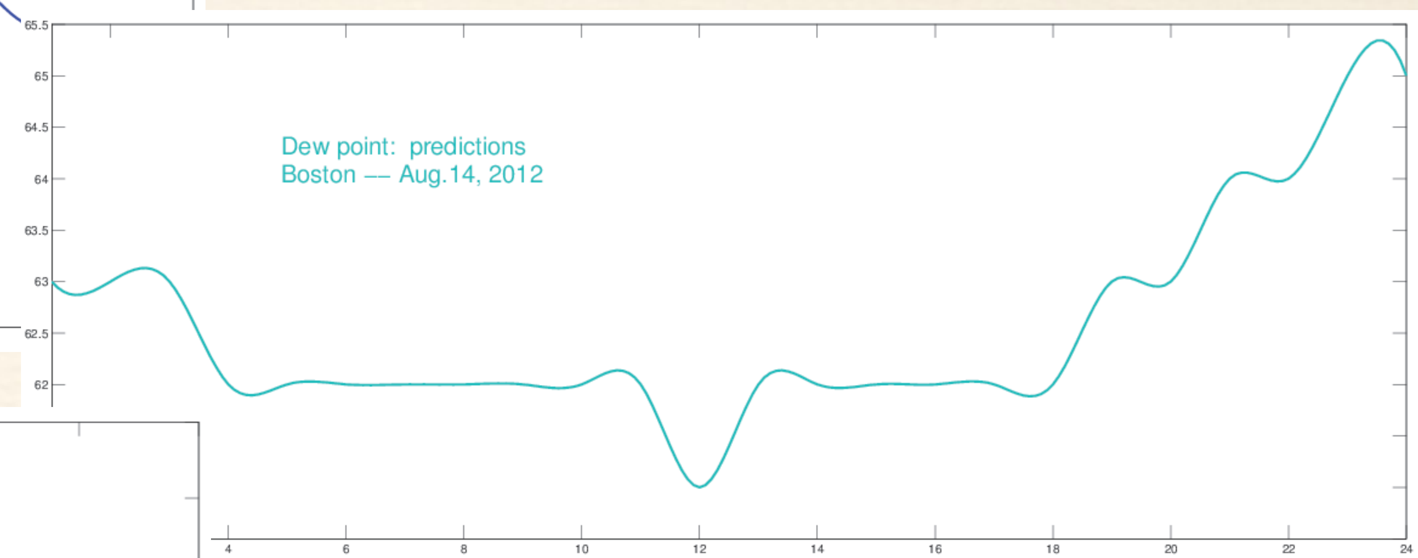
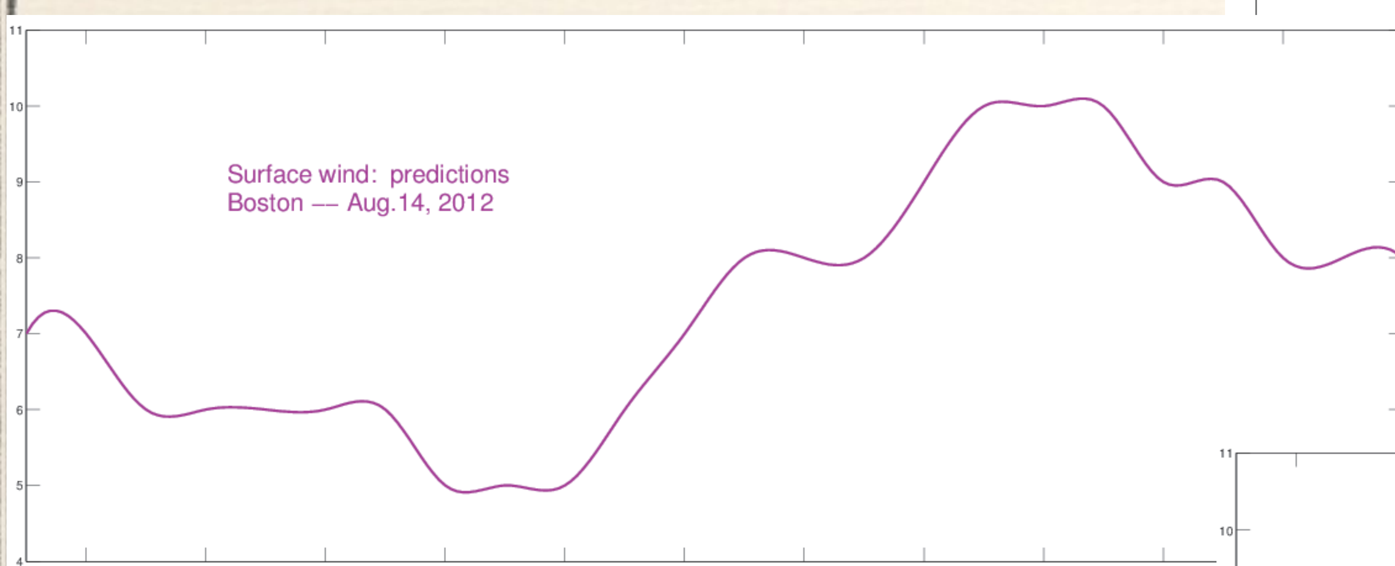
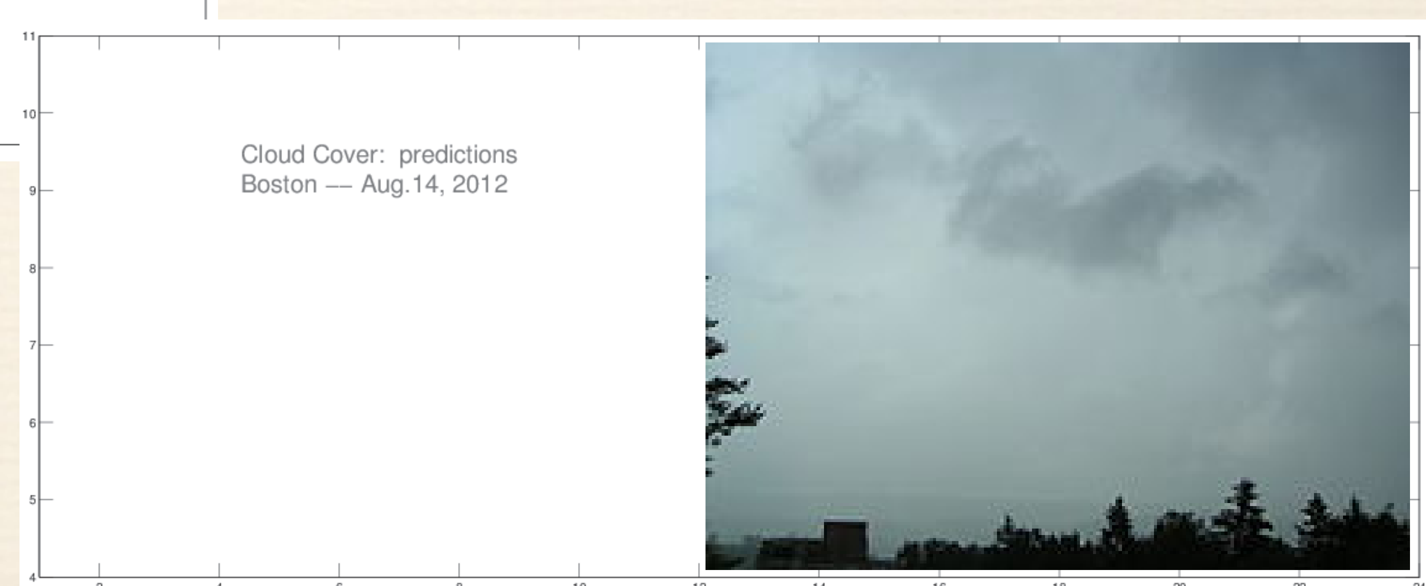


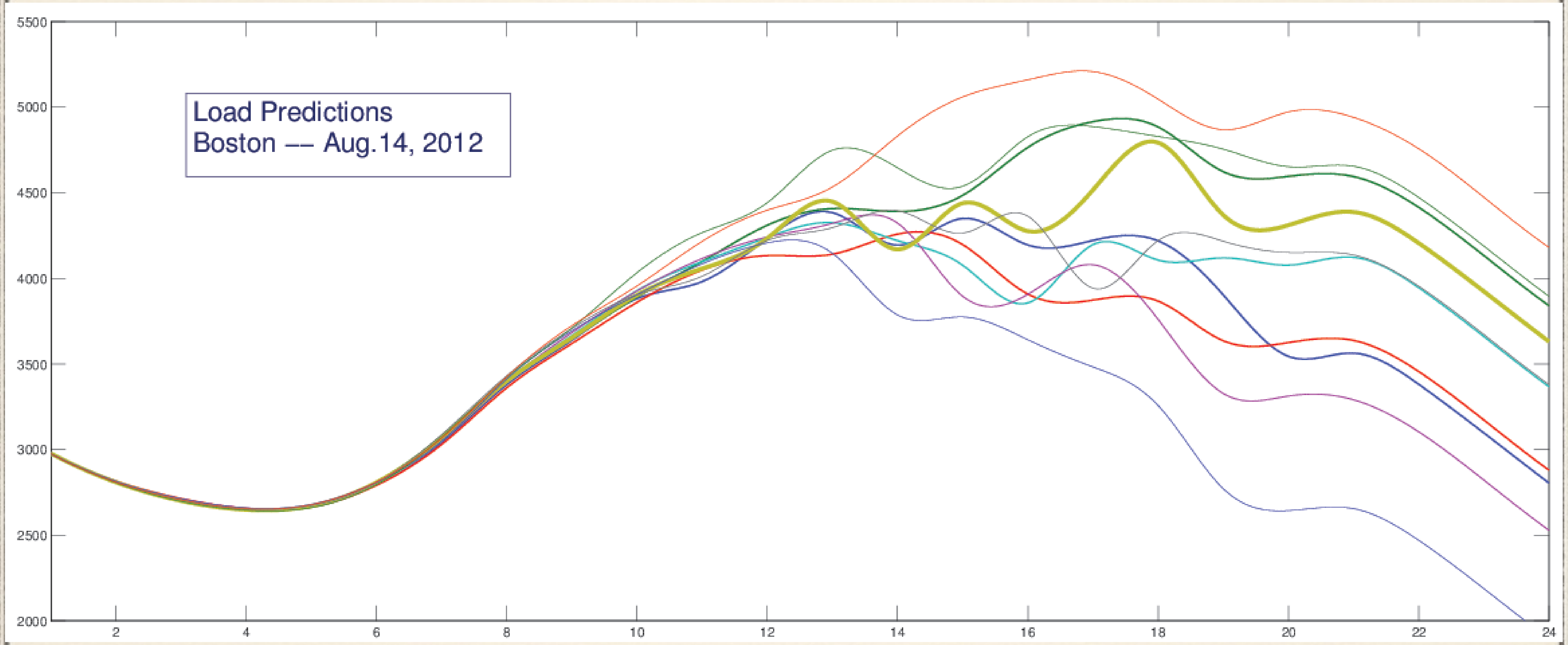






NOAA: ACTUALS

“Realistic” Forecasts



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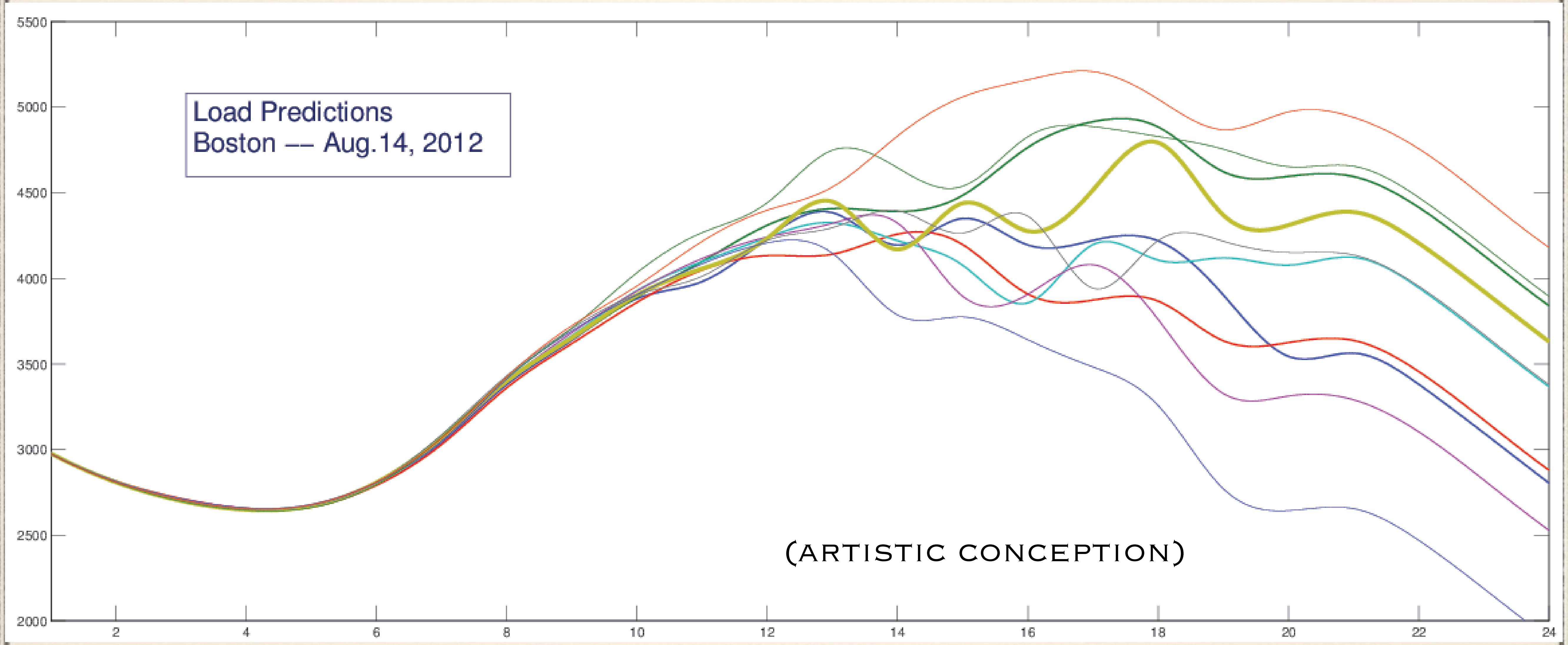

Troubling Issues

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- weather prediction @ 11 a.m. better @ 11 p.m.

  … but too late!

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- cloud cover (no historical prediction data) -- only actuals are available
- model to be used for the stochastic load predictions model: SDE, time series, ??? all inappropriate

Stochastic Load Process ⇛ Scenarios

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a) segmentation: season + day characteristics

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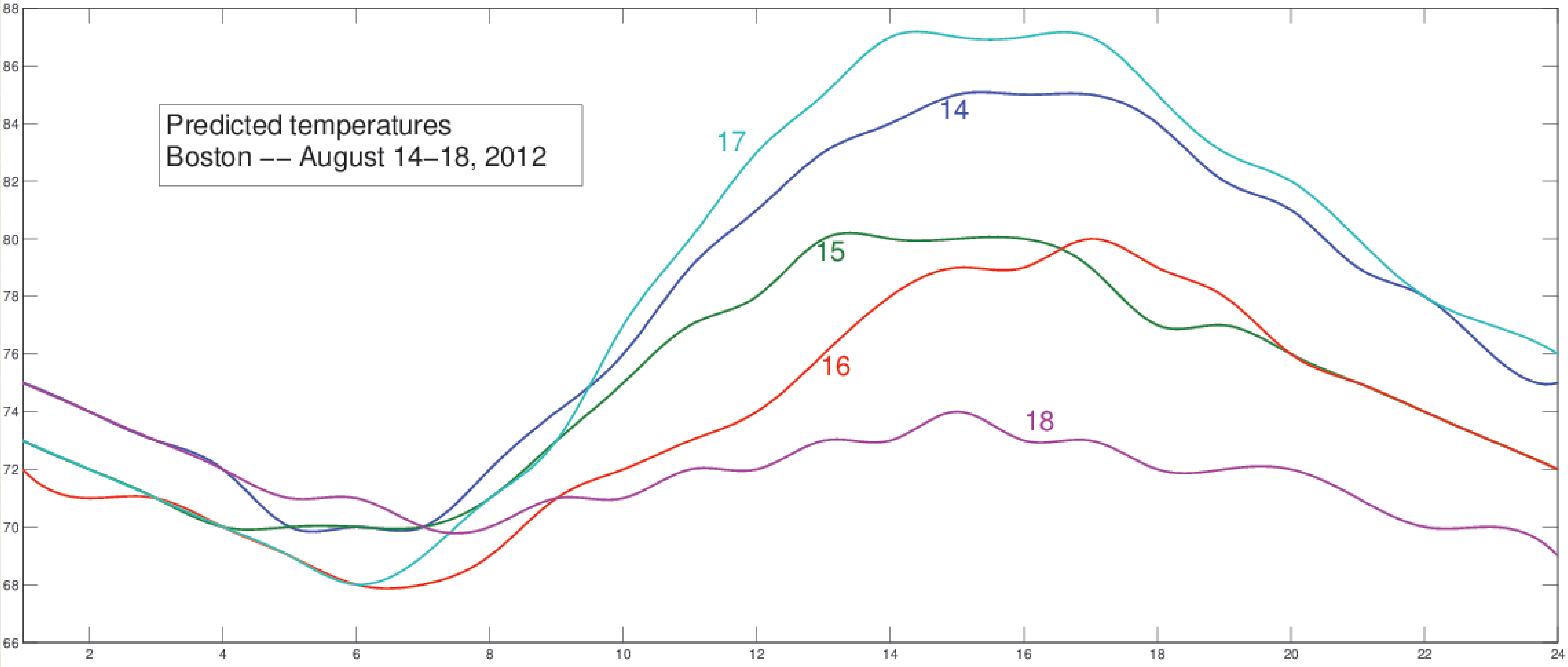
HOW THIS IS CARRIED OUT ?
d) conditional distribution of errors => process
e) discretization of the process => scenarios

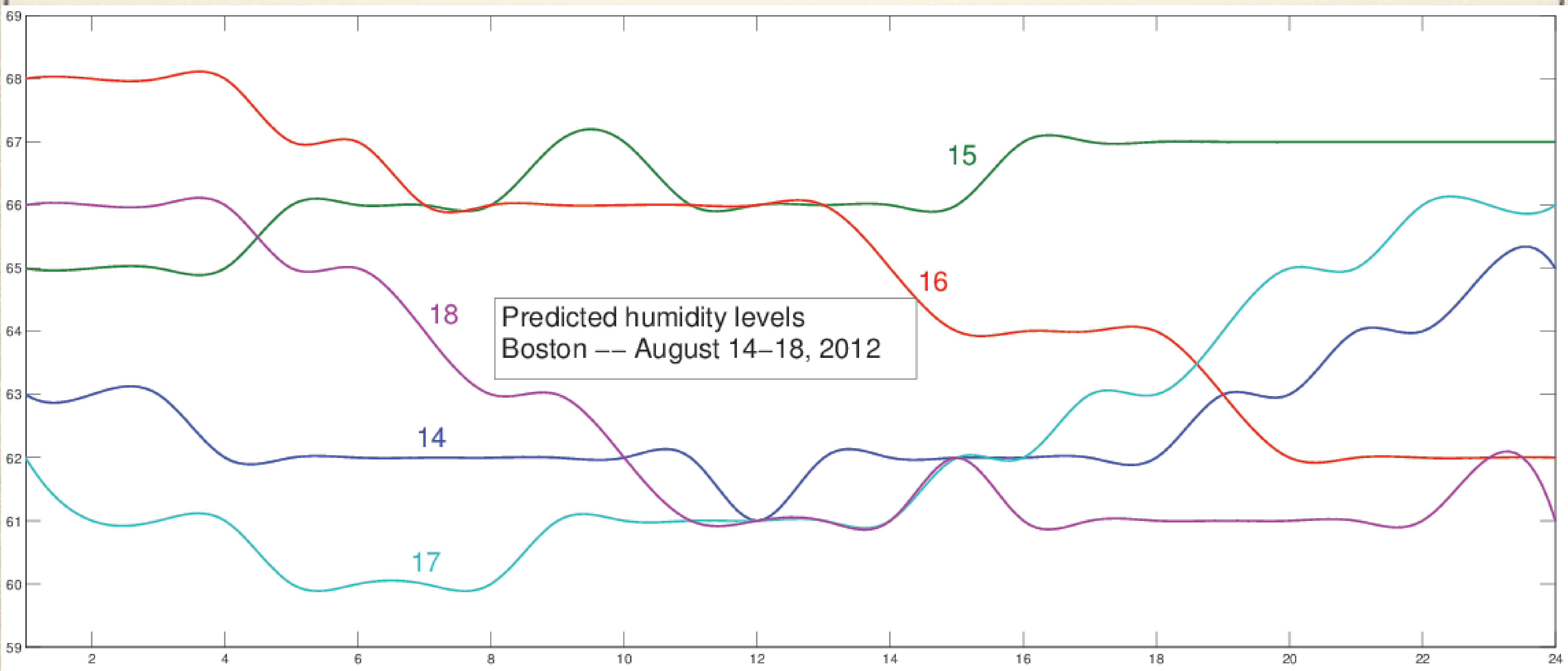
Segmentation

- ~ similars, analogs (± standard) to enrich data: Wednesday rule, zone rule?
- seasons: (factor analysis, 'heuristics')
  - ± spring & fall : temperature
  - winter: temperature & cloud cover
  - summer: temperature & dew point
- wind power (at present): handled independently based on 3TIER analogs total load ≈ load scenario - wind power scenario

Summer segment “#1”



Summer segment “#1”



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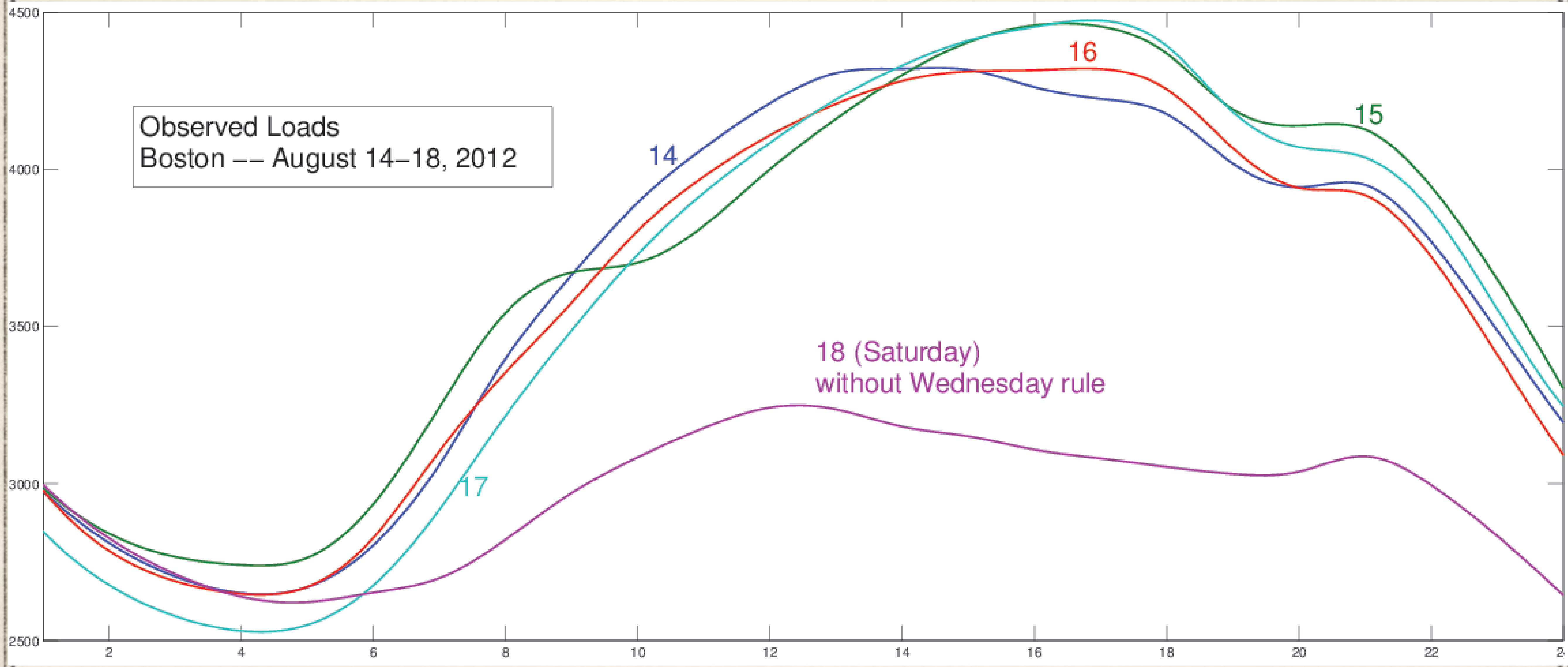
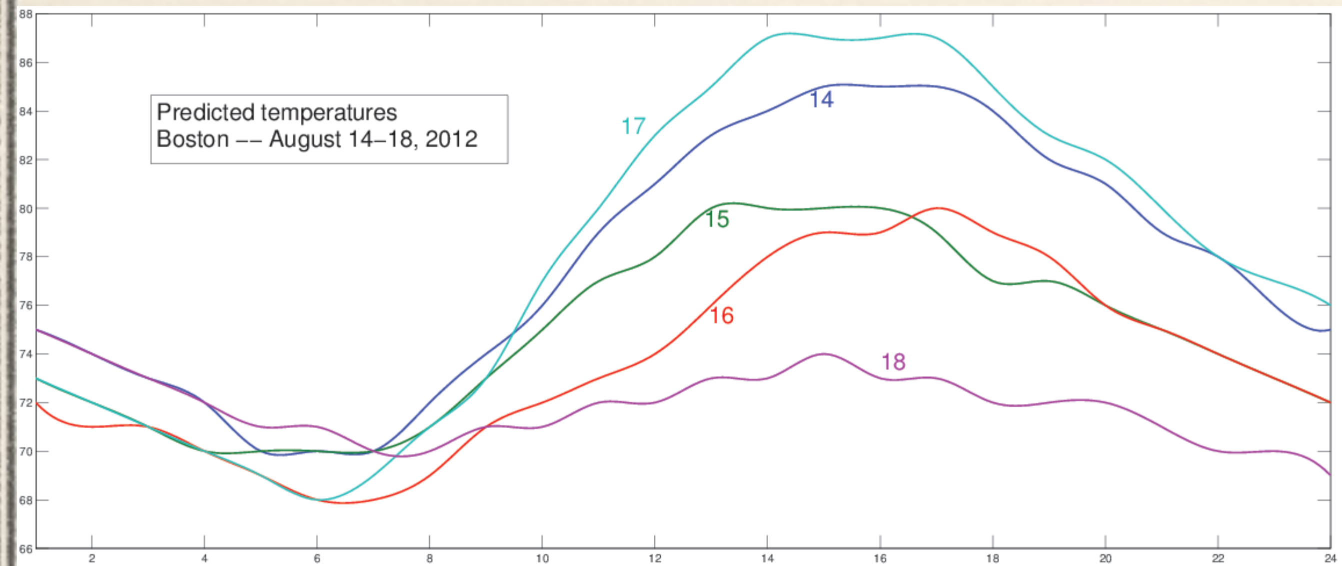
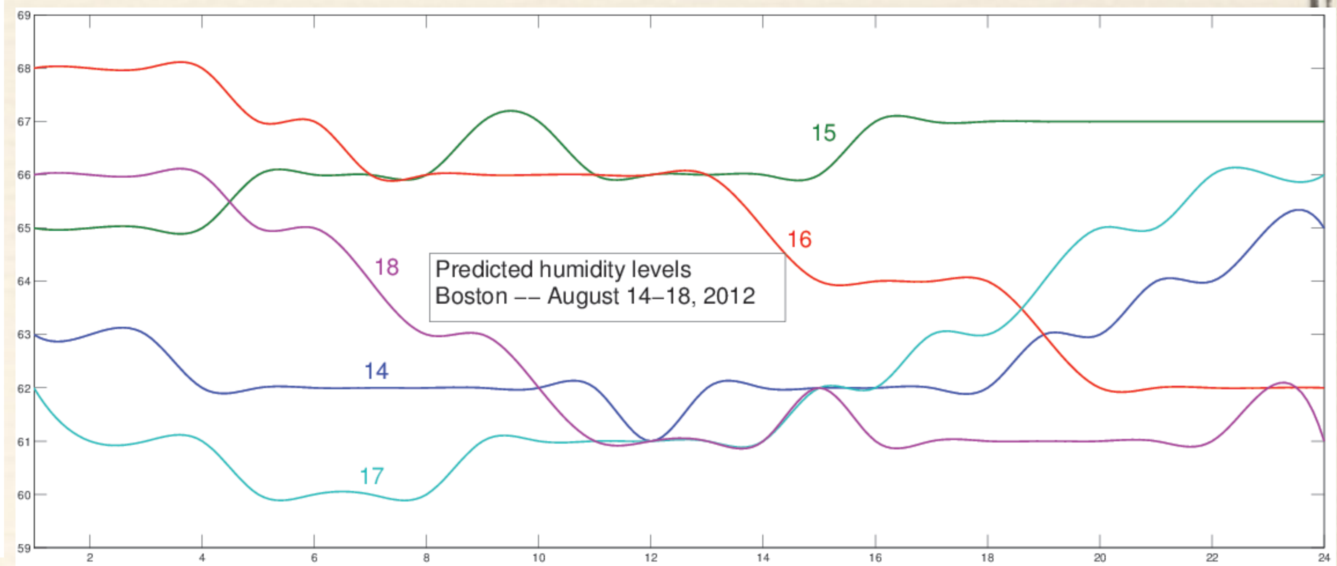
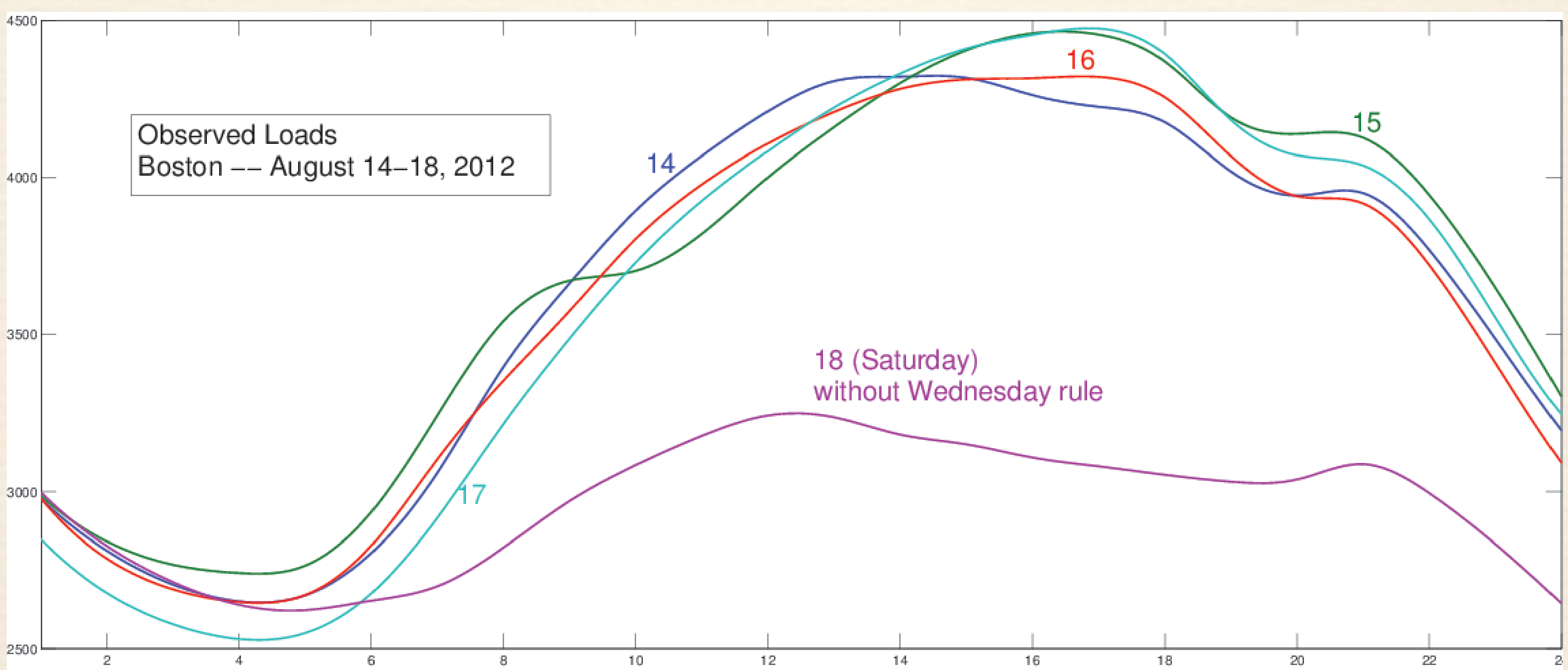


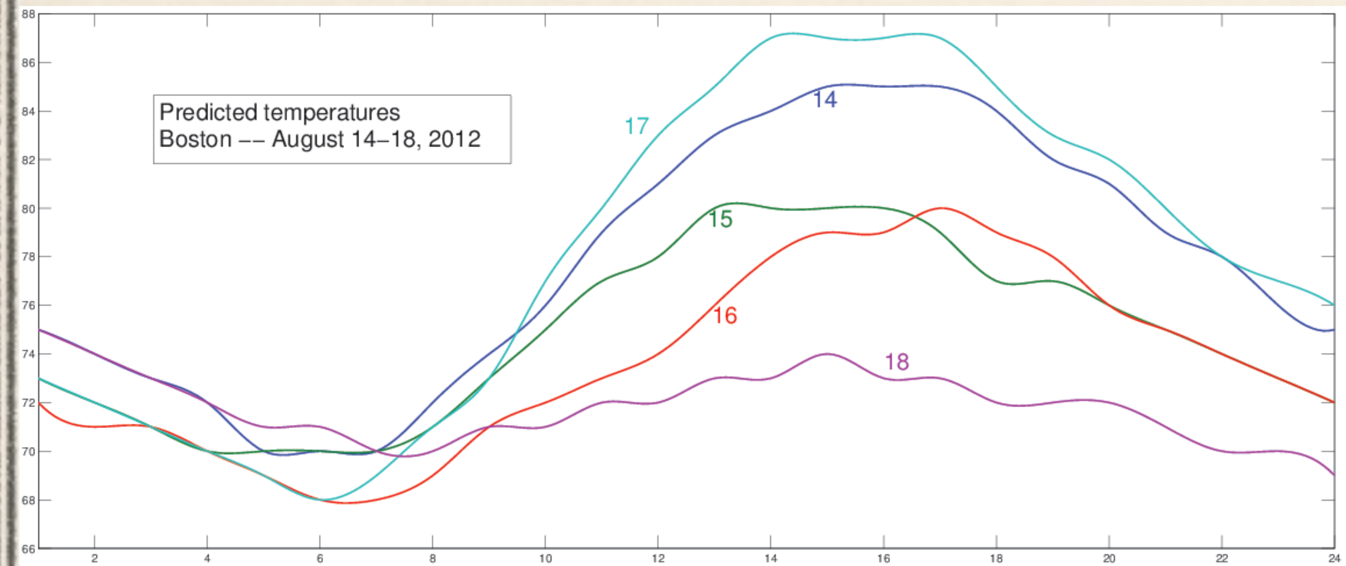


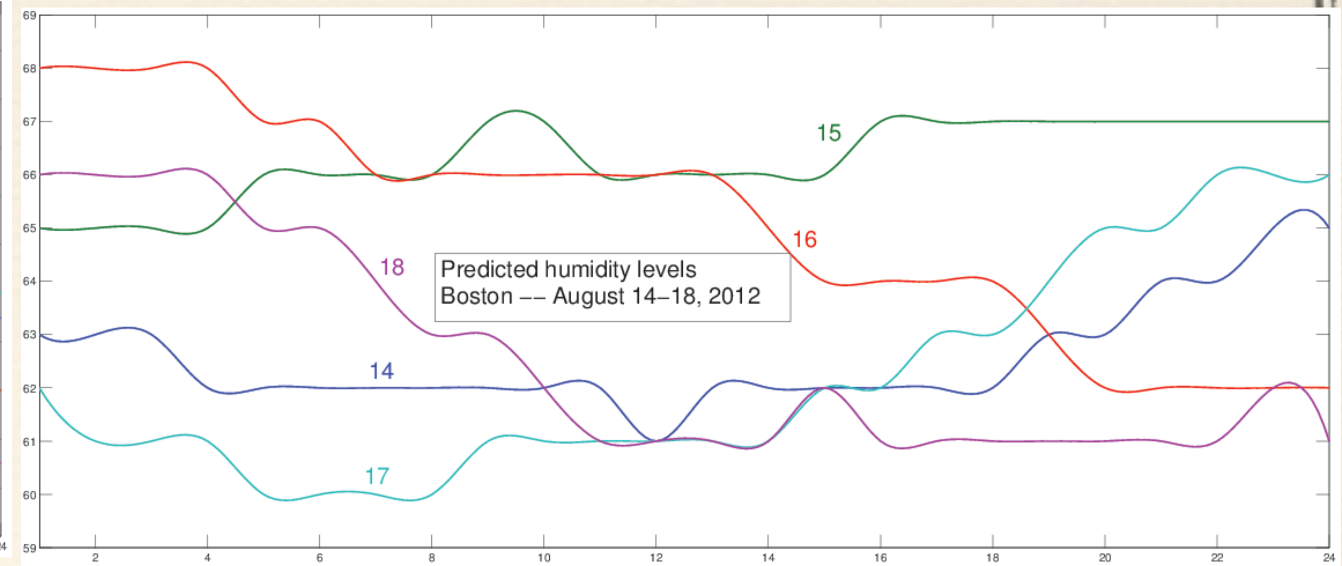


from day d-1 $\Rightarrow$ possible load on day d $\quad d = 14, \ldots, 18$

1. regression(temp. curve, humid. curve) $\Rightarrow$ 'expected' load curve
2. get distribution of the errors (hourly, ... at any time)







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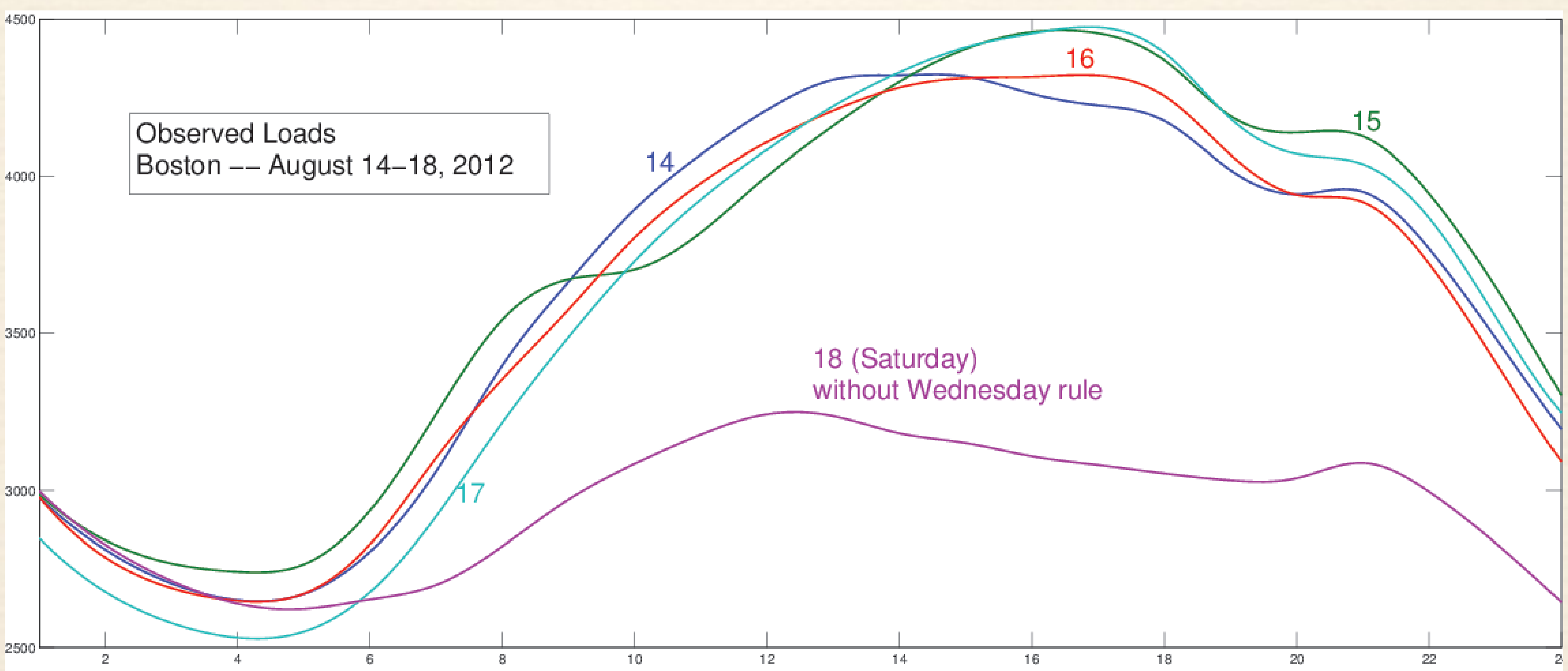


The Regression Problem

find a function r that minimizes errors (with respect to $\|\square\|$)

$$\sum_{\text{days d in segment}} \sum_{\text{hours h in day}} \left\| r\left((tmp_{d,h}, hum_{d,h})\right) - \text{load}_{d,h} \right\|$$

an infinite dimensional problem!

Our approach: rely on 2-dimensional epi-splines ("innovation")

- epi-splines approximate with arbitrary accuracy 'any' function
- epi-splines are completely determined by a finite # of parameters
- allows (via constraints) to include 'soft' (non-data) information

The Errors Distributions

Given segment # and associated r, for fixed hour h

$$e_{d,h} = \text{load}_{d,h} - r\big((tmp_{d,h}, hum_{d,h})\big),\ d \in \text{segment \#}$$

$\Rightarrow$ estimate the density f_h of the errors (at h in segment #)

yields an overall estimate of the 'volatility' (in fact, more)

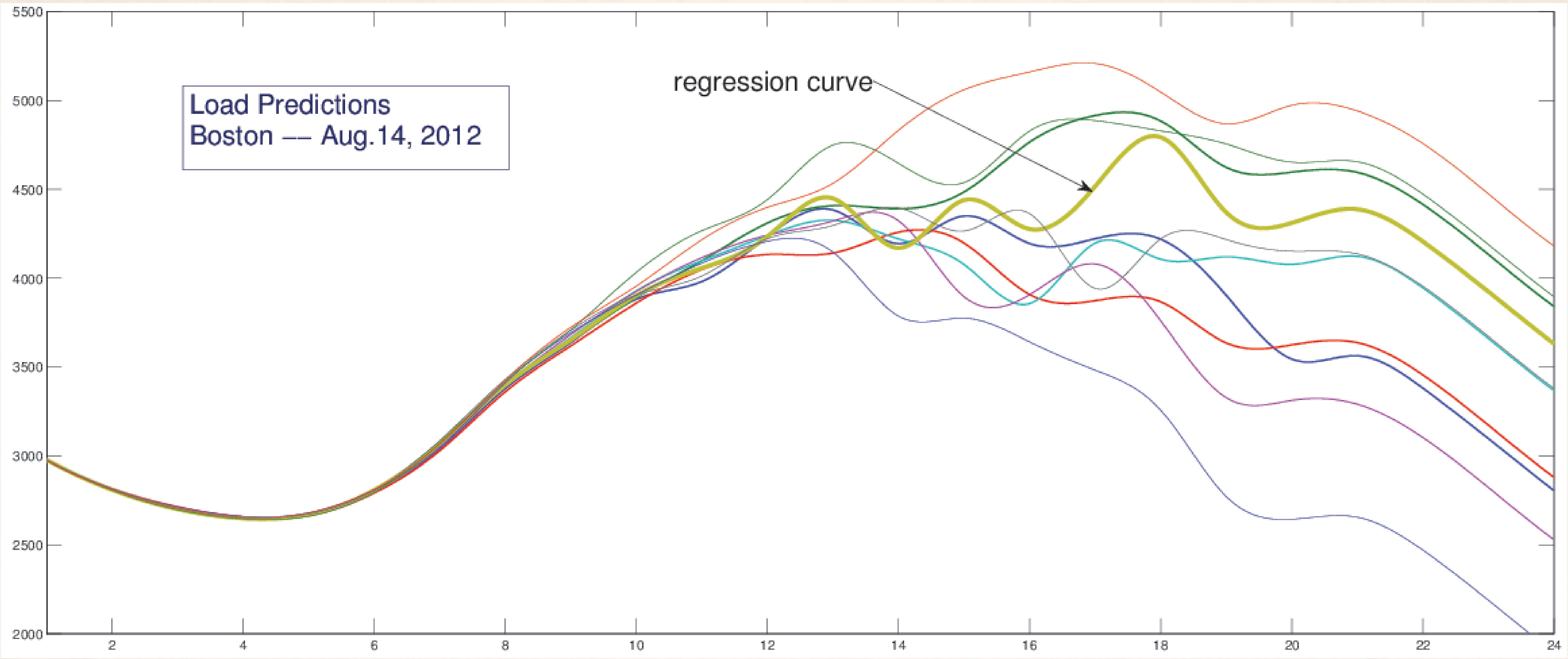
another infinite dimensional problem & data might be scarce

Our approach: estimation via exponential epi-spline (novel):

- $f_h = \exp(-s_h)$, s_h an epi-spline $\quad (\Rightarrow f_h \geq 0)$
- same properties as epi-spline, could include unimodality restriction

… et voilà!

regression curve & sampling from errors distribution



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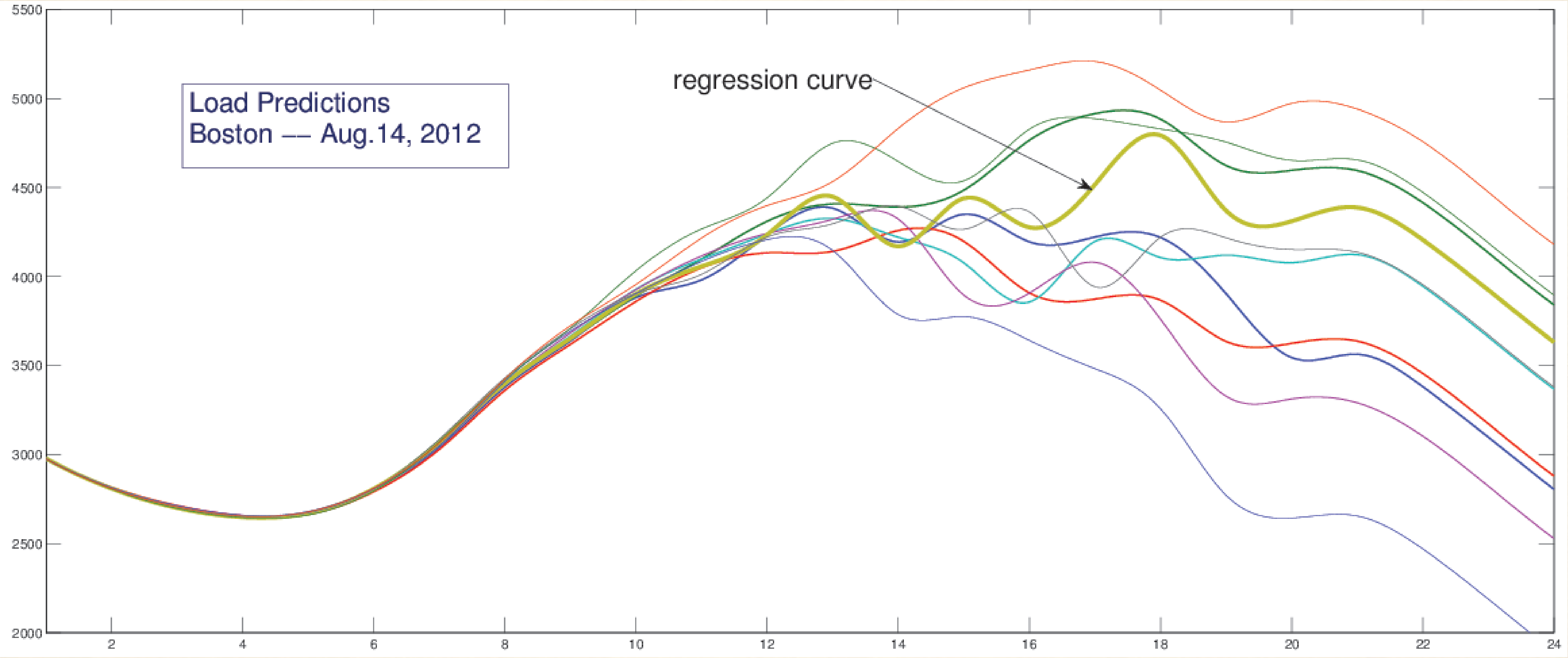

$a.$ how many samples? $10^3, 10^5, ...?$

$b.$ conditioning: @10 o'clock above or below the regression curve

Approximation foundation

Function Identification Problem: optim., diff. eqtns, processes, ...

(FIP) find $f \in \arg\min \left\{ \psi(f) \middle| f \in F \subset \mathcal{F} \right\}$

here $\mathcal{F} =$ lsc-fcns$(\mathbb{R}^n)$ more generally a Polish space

$\mathcal{F}$-approximation: aw-topology ~ $dl(f, g)$ epi-distance

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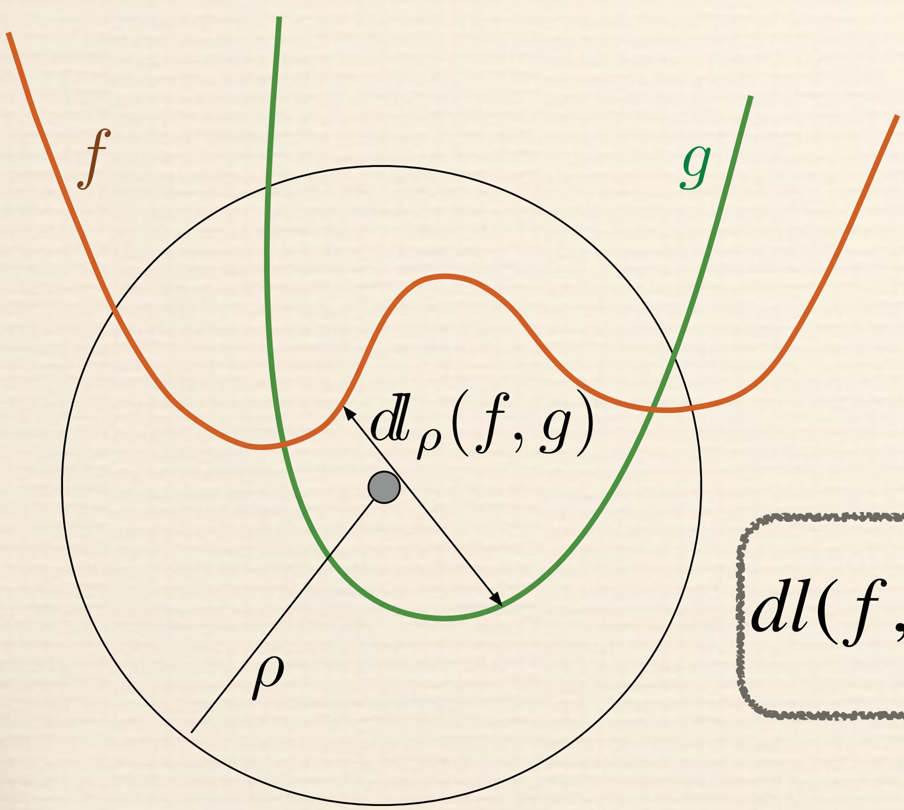
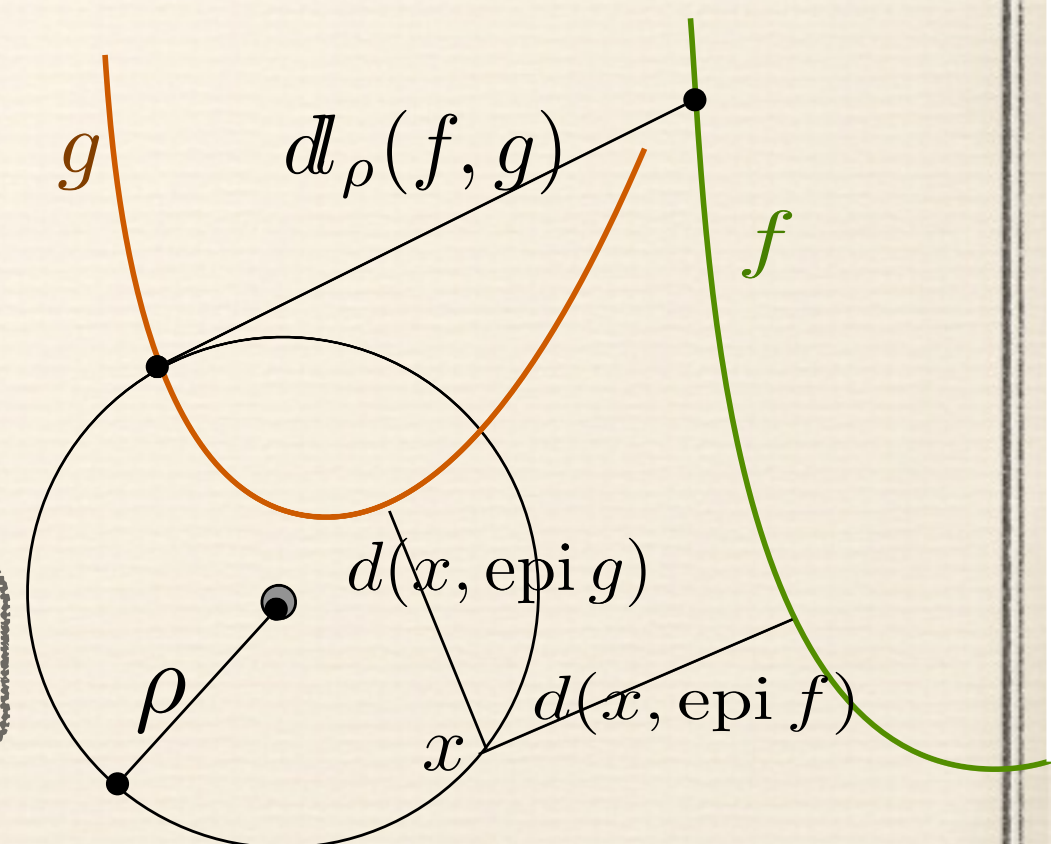


$$dl(f,g) = \int_0^\infty dl_\rho(f,g)e^{-\rho}\,d\rho$$



Epi-splines

$\mathcal{R} = \{R_1, \ldots R_N \text{ open}\}$ partitions (no overlap) $B = \bigcup_{k=1}^{N} \operatorname{cl} R_k$ (closed)

$\text{poly}^p(\mathbb{R}^n)$ defined by $n_p \leq (n+p)!/(n!p!)$ real parameters

lsc epi-spline $s : \mathbb{R}^n \to \overline{\mathbb{R}}$ with partition $\mathcal{R}$ of order $p \in \mathbb{N}_0$ if

on each R_k $s \in \text{poly}^p(\mathbb{R}^n)$, $s \equiv \infty$ on $\mathbb{R}^n \setminus B$, s is lsc on $\mathbb{R}^n$

then $s \in \text{e-spl}_n^p(\mathcal{R}) \ldots\ldots \subset$ lsc-fcns(B) $\subset$ lsc-fcns($\mathbb{R}^n$)

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- 1. $\forall p \in \mathbb{N}_0$, infnite refinement $\{\mathcal{R}^\nu\}_{\nu=1}^{\infty}$ of closed $B \subset \mathbb{R}^n$

  $\bigcup_{\nu=1}^{\infty} \text{e-spl}_n^p(\mathcal{R}^\nu)$ is dense in lsc-fcns(B)

  refinements: boxes, simplexes, ...

- 2. When $(FIP^\nu) \to_{\text{epi}} (FIP)$, $s^k \in \arg\min(FIP^{\nu_k})$, $dl(s^k, f) \to 0$

  then $f \in \arg\min(FIP)$.

a few applications

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- curve fitting: F known properties of the curve

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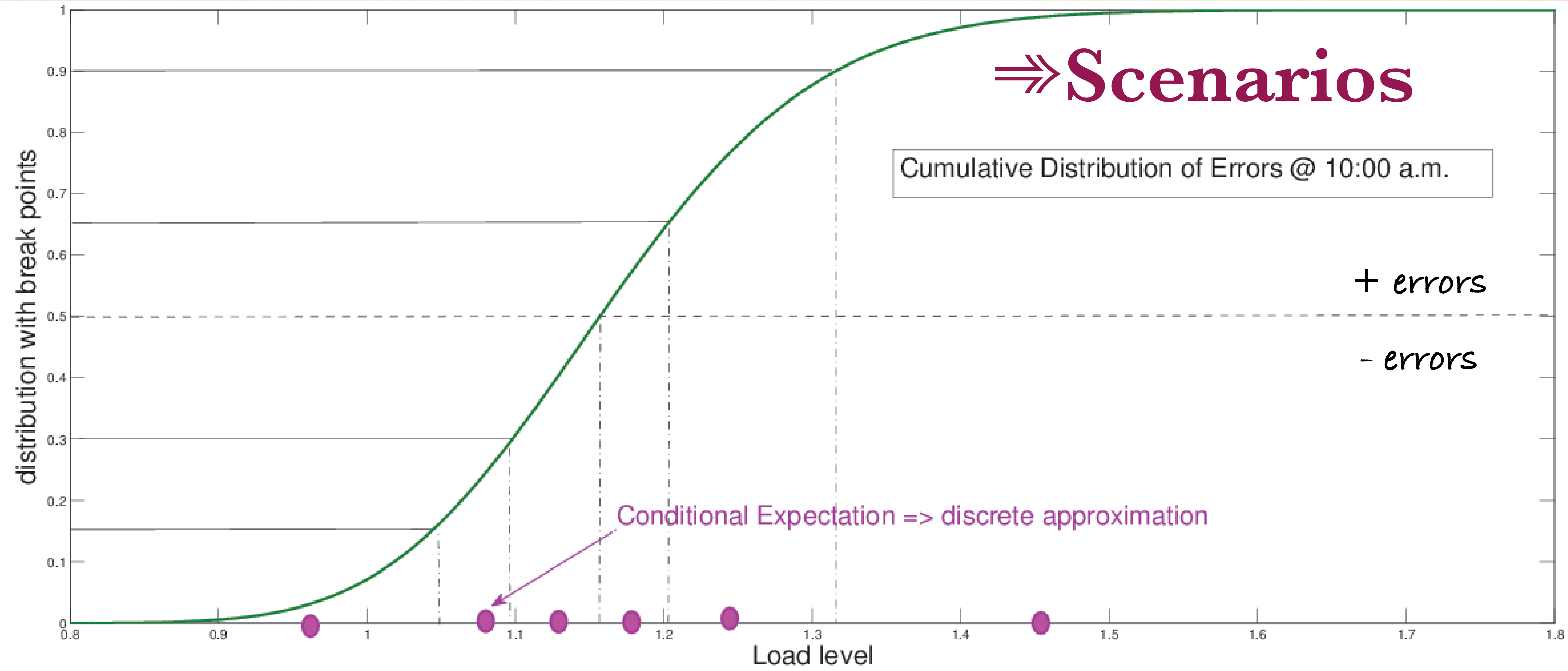
- uncertainty quantification in a harmonic excitation
- building stochastic processes: commodities prices, e-loads, …
- density estimation: ψ max. likelihood (captures observations), F soft information: support, shape, bounded moments, Bayesian, ..

Conditioning & Discretization



a. identify all observed load curves in each sub-segment

b. for each sub-segment: re-calculate regression and errors distribution

c. repeat for each sub-segment @ (say, 1 p.m.) $\Rightarrow$ sub-sub-segment

Unit commitment
Part II

Dealing with
renewables-supply uncertainty

Wind & Solar

- wind and solar: complementary balance ±
- wind scenarios: 3TIER analogues (ARPA-e 😃)
- scenario building (state-of-the-art)
- stochastic process building with soft information coming from the dynamics (started)

Building Wind Scenarios

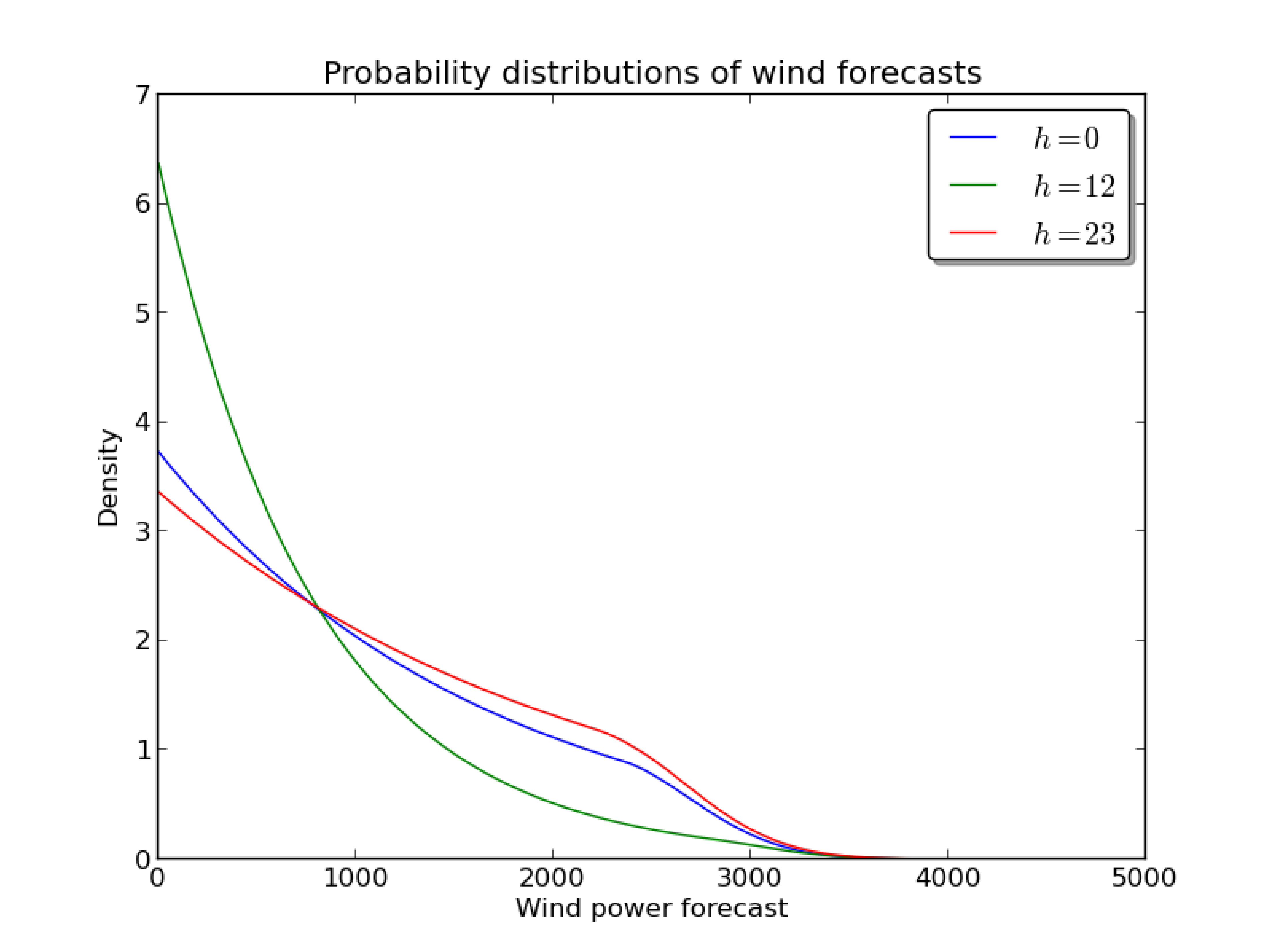
errors: $e_t^d = a_t^d - f_t^d$ (Bonneville Power Administration)

1. distribution of the forecast for hours of interest
2. segment errors (per day) according to forecast wind power
3. compute conditional error distribution

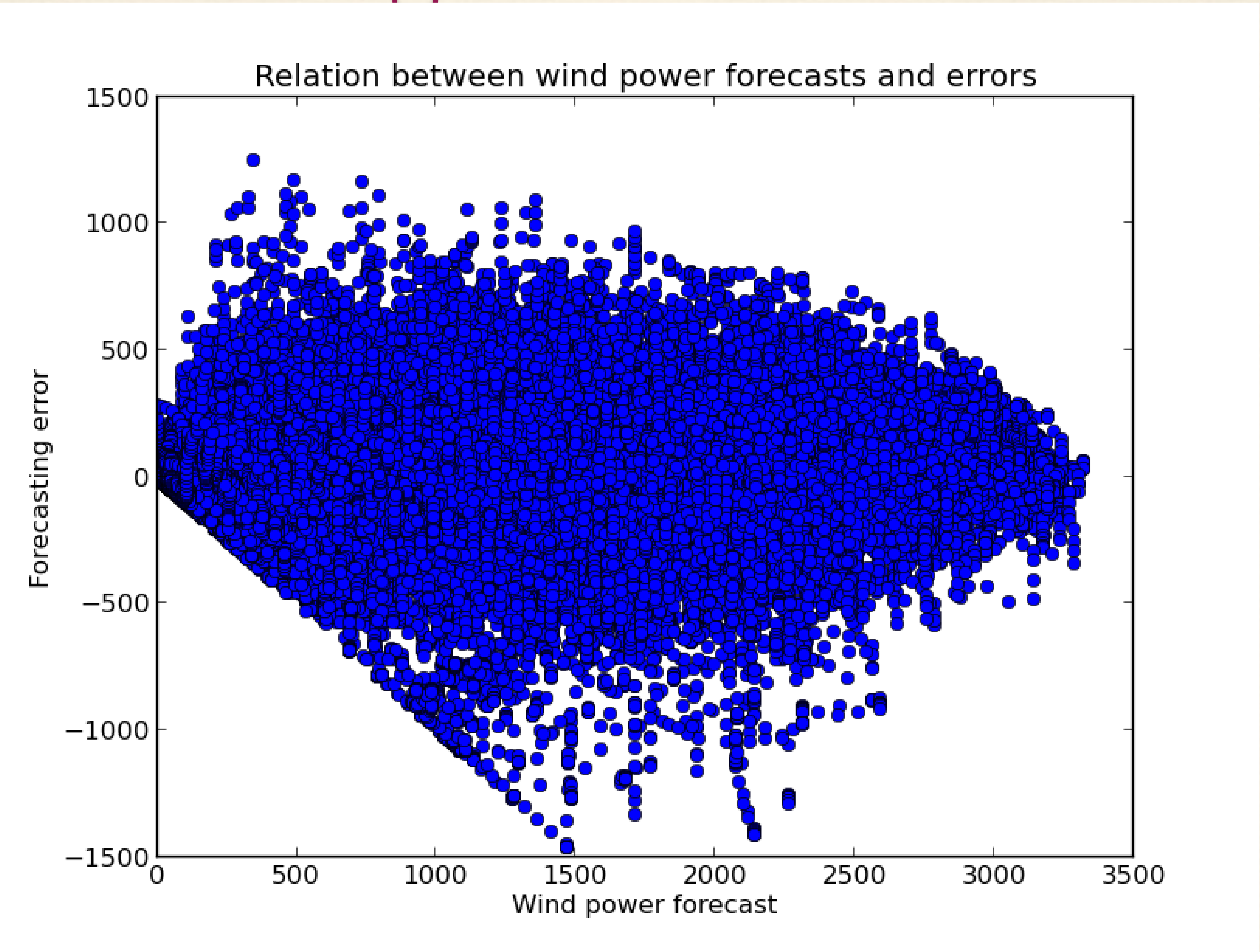
Scenarios: - generate scenario for the errors

- generate scenario paths (discrete process)

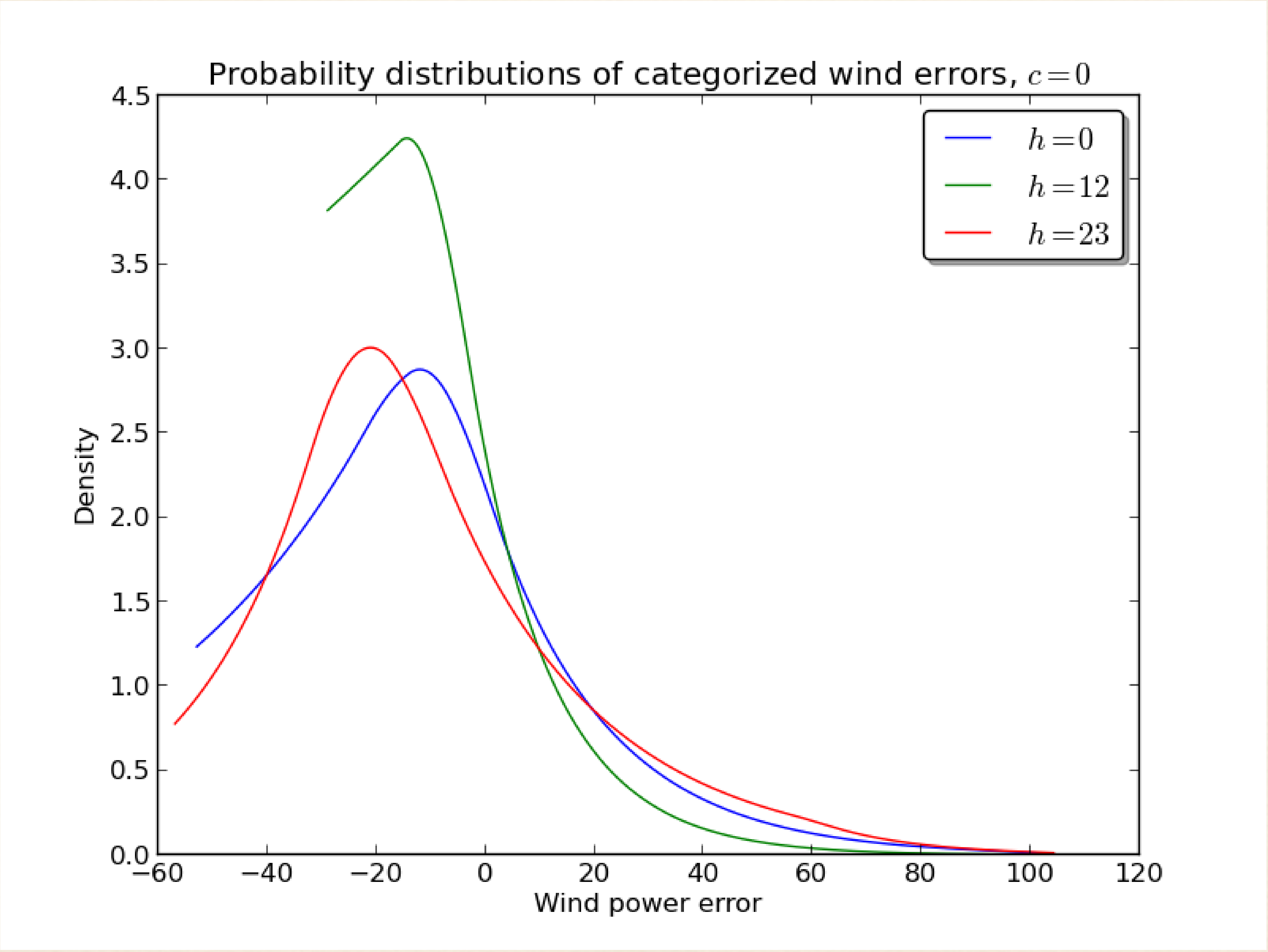
Building Wind Scenarios



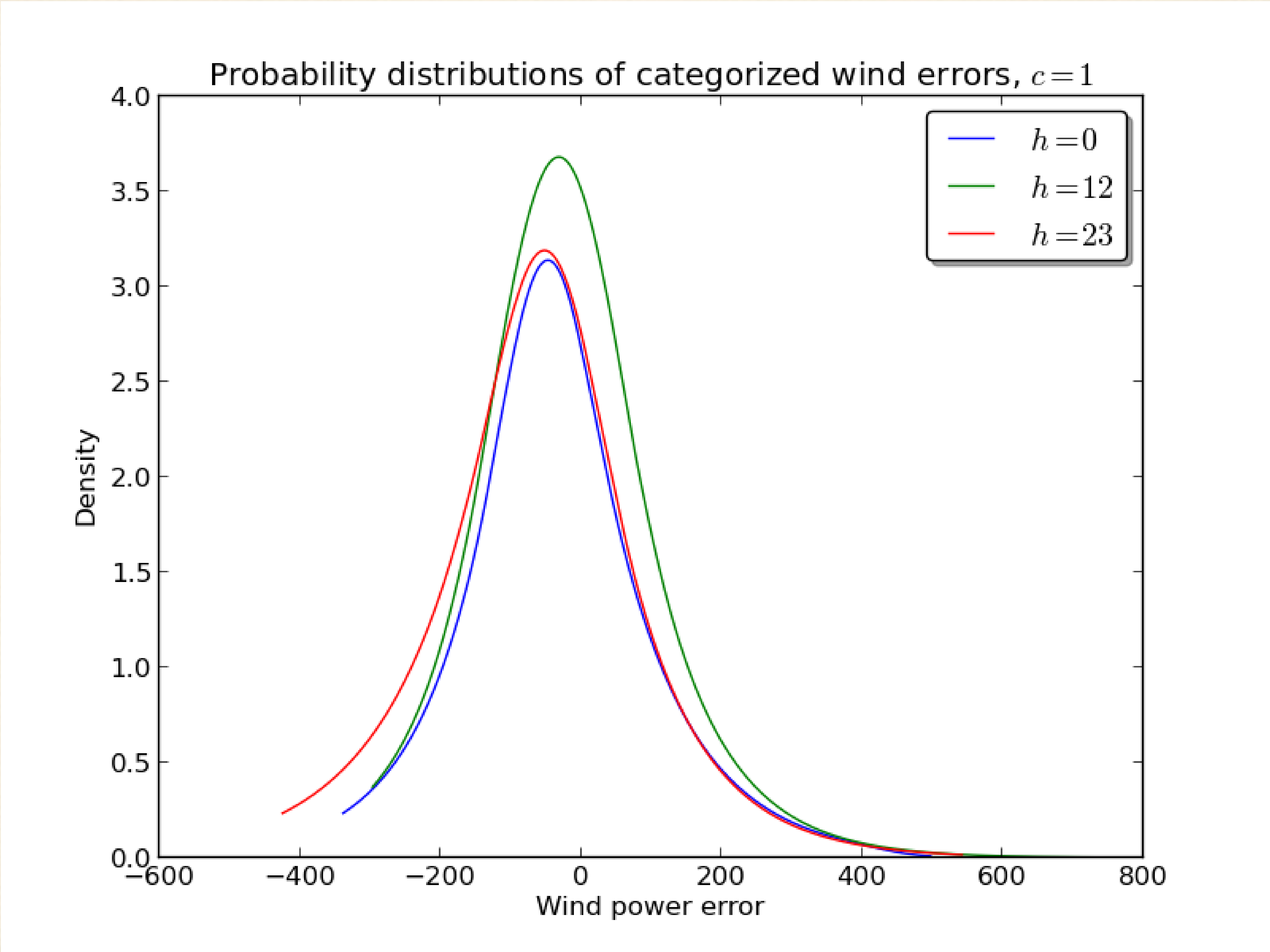
Building Wind Scenarios



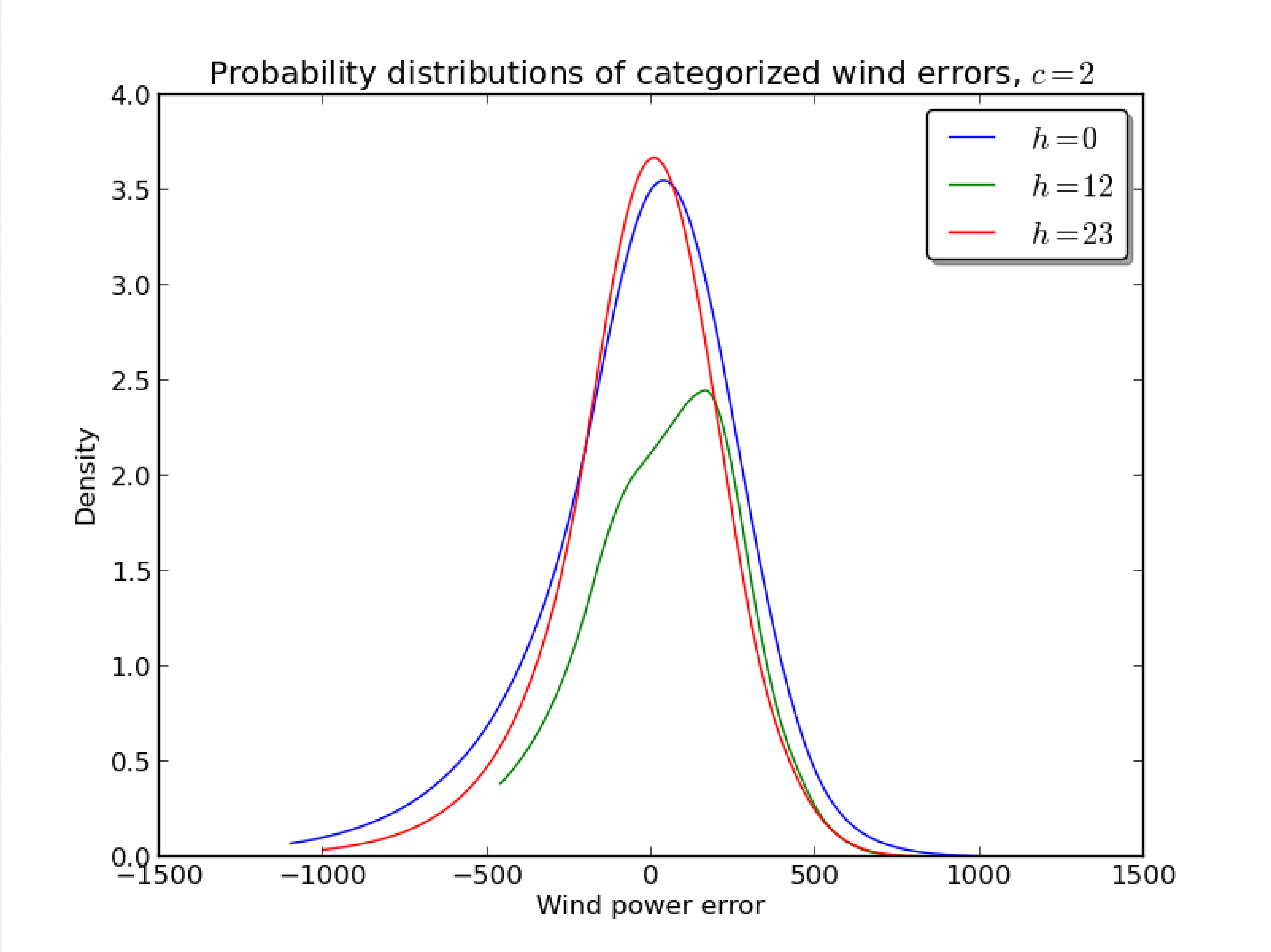
Building Wind Scenarios



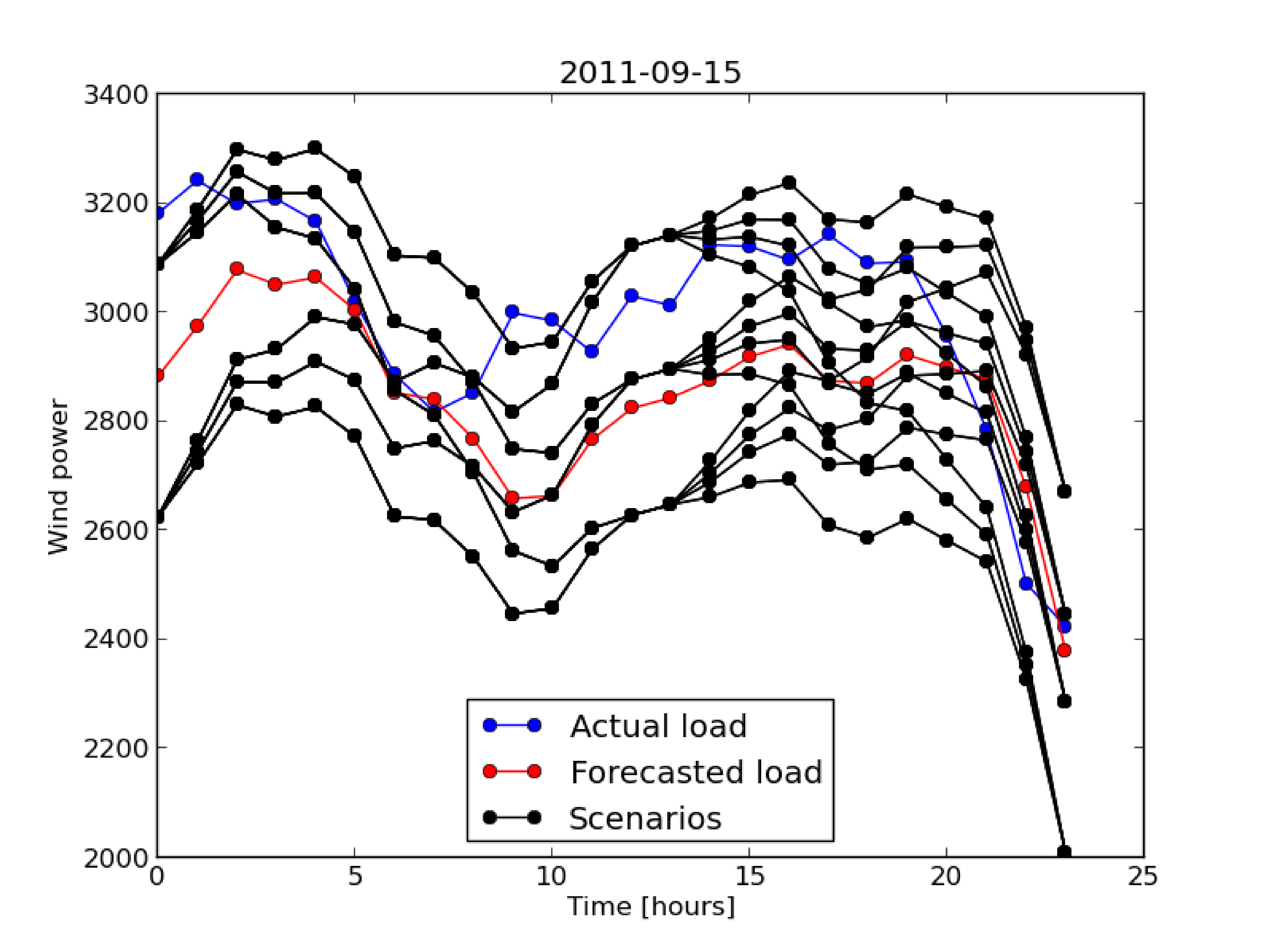
Building Wind Scenarios



Building Wind Scenarios



Building Wind Scenarios



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Blackout