
Optimization and Uncertainty Quantification for Next-Generation Power Markets and Operations

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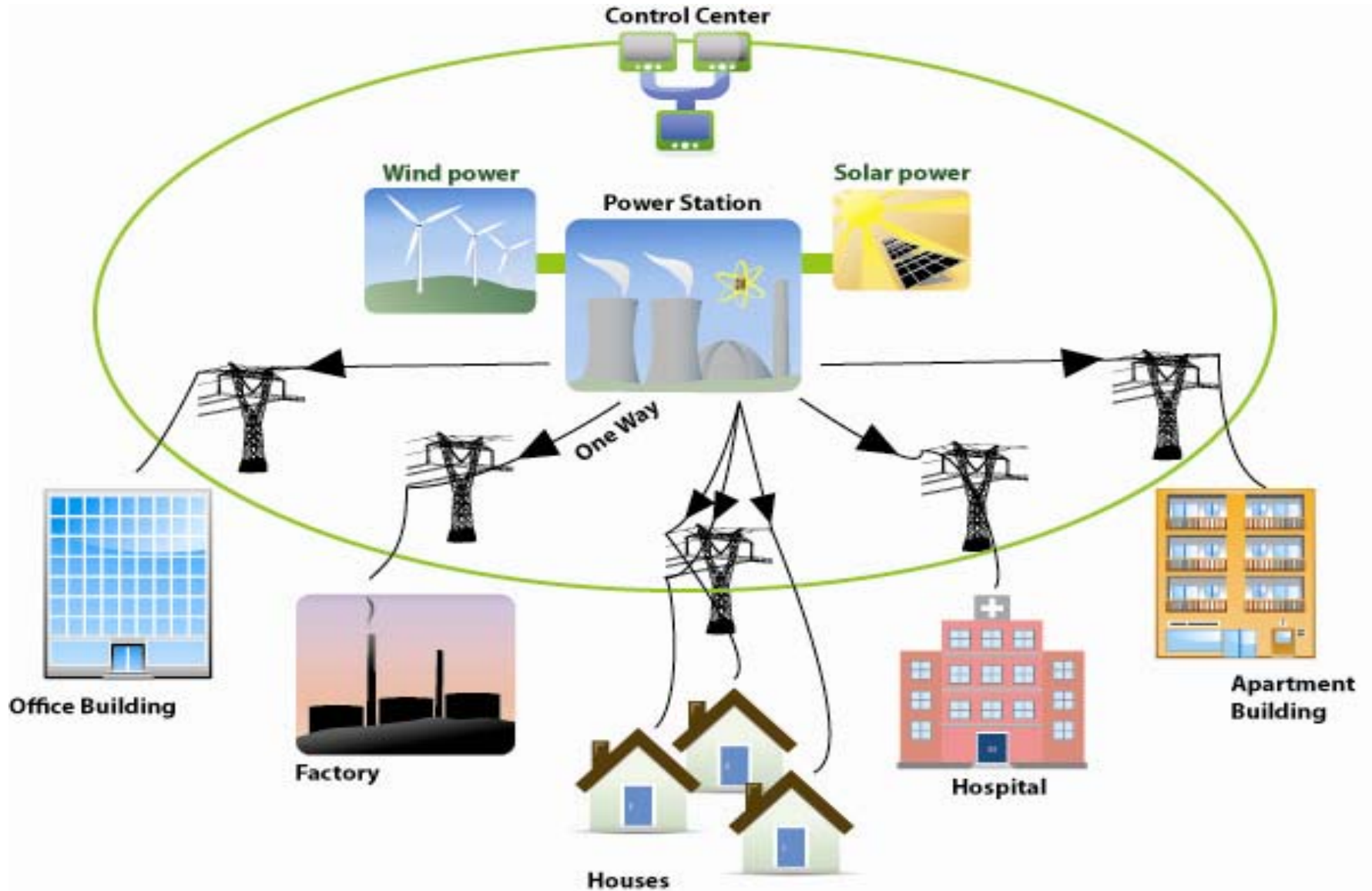
Mihai Anitescu, Emil Constantinescu, Sven Leyffer, Todd Munson

IBM T. J. Watson Center

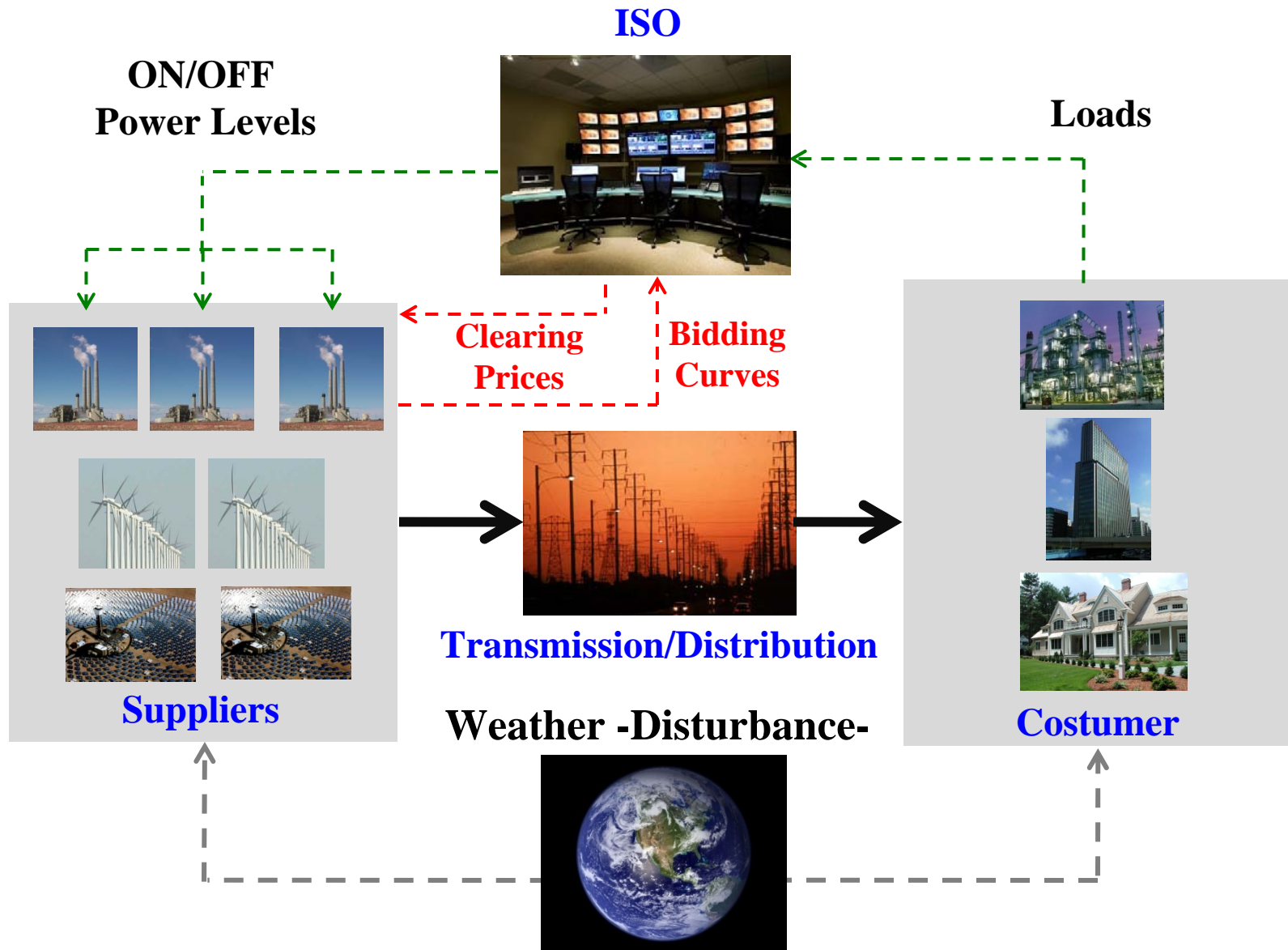
April 13th, 2010

Motivation

Current Grid



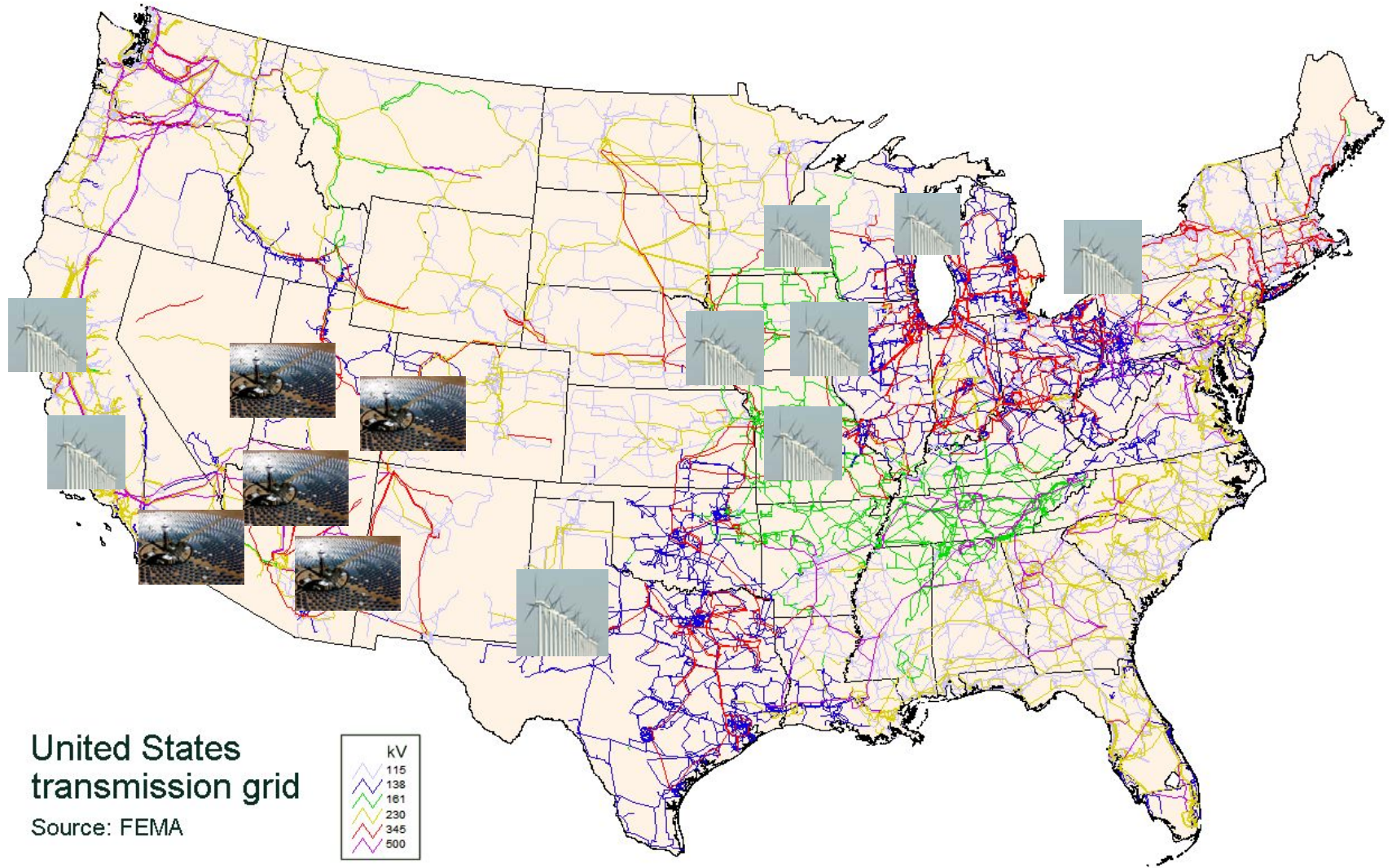
Power Grid as a Feedback System



Weather Drives Markets and Operations – Forecasting is Critical

Motivation

Smart Grid



Loads and Generation Exhibit **Complex Spatio-Temporal** Correlations at Multiple Scales

Some Research Questions

- **Demand is function of Weather (Physical) and Human Behaviors (Non-Physical)**
 - How to target weather forecasts to ISO, GENCOs, and TRNSCOs needs?
 - How to quantify and deal with uncertainty?
 - *Stochastic Programming vs. Reserves*
- **Price is function of feedback interactions between GENCOs, TRANSCO and ISO**
 - How to forecast prices?
 - *Game-Theoretical vs. Agents vs. Statistical Models*
 - How to develop effective bidding strategies?
- **In Smart Grid, costumers will become active market participants (demands also result from market feedbacks)**
 - How to model “smart” costumers?

Future is On the Integration - Real-Time Grid Simulation

Massive Numerical Problems - Where and How to Solve them?

Outline of the Talk

1. Argonne's Research on Optimization

2. Recent Work

- **Market Equilibrium Models**
- **Uncertainty Quantification and Weather Forecasting**
- **Stochastic Unit Commitment**
- **Real-Time Energy Management of Co-Generation and Building Systems**

3. Conclusions and On-Going Projects

1. Argonne's Research on Optimization

Argonne's Research on Optimization

Nonlinear Programming and Complementarity

- **Sven Leyffer, Todd Munson and Mihai Animescu**

Mixed-Integer Nonlinear Programming (MINLP)

- **Sven Leyffer**

Stochastic Programming and Uncertainty

- **Mihai Animescu, Emil Constantinescu, VZ**

Automatic Differentiation and Graph Partitioning

- **Paul Hovland, Jean Utke, and Ilya Safro**

Markets and Grid Modeling

- **Todd Munson and VZ**

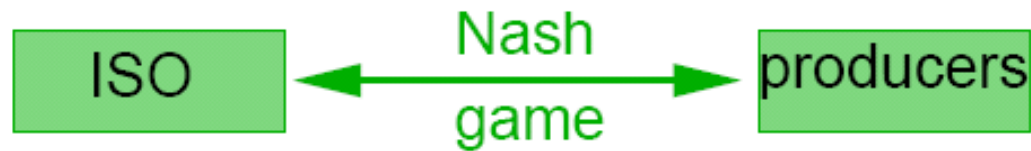
Real-Time Optimization and Automatic Control

- **VZ**

2. Recent Work

Market Equilibrium Models

Market Equilibrium Models (Leyffer and Munson)



Nash Game: non-cooperative equilibrium of several producers

$$z_i^* \in \begin{cases} \operatorname{argmin}_{z_i} & b_i(\hat{z}) \\ \text{subject to} & c_i(z_i) \geq 0 \end{cases} \quad \text{producer } i$$

- $\hat{z} = (z_1^*, \dots, z_{i-1}^*, z_i, z_{i+1}^*, \dots, z_l^*)$
- All producers/players are equal

- Find equilibrium by simultaneously solving KKT conditions of all players

Nonlinear Complementarity Problem – PATH Solver *Ferris & Munson*

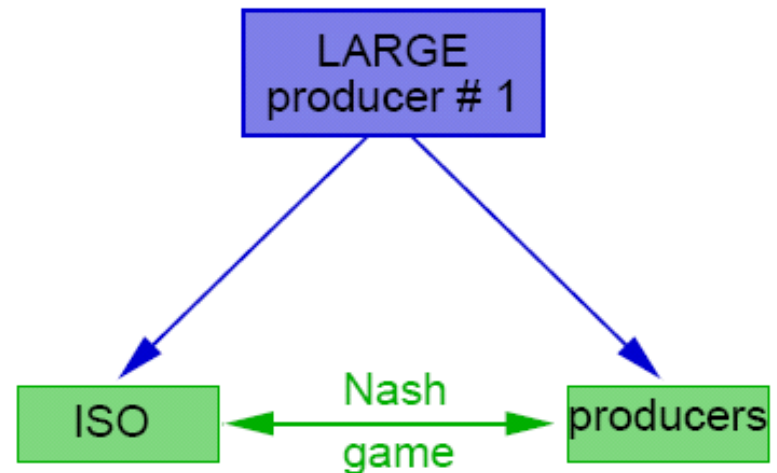
$$\begin{aligned} \nabla b(z) - \nabla c(z)\lambda &= 0 \\ s - c(z) &= 0 \\ 0 \leq \lambda \perp s &\geq 0 \end{aligned}$$

Market Equilibrium Models

Stackelberg Games

Single dominant producer & Nash followers

$$\left\{ \begin{array}{l} \text{minimize}_{x \geq 0, y} f(x, y) \\ \text{subject to } h(x, y) = 0 \\ 0 \leq y_1 \perp y_2 \geq 0 \end{array} \right.$$



Nash game ($h(x, y) = 0$) parameterized in leader's variables x
Mathematical Program with Equilibrium Constraints (MPEC)

Market Equilibrium Models

Approaches:

1. Apply nonlinear solver directly ... relax complementarity
2. Penalize equilibrium minimize $f(x) + \pi x_1^T x_2$
 - Well behaved smooth problem: constraints satisfy MFCQ
 - Anitescu: $\pi^* < \infty$ and $X_1 x_2 \leq 0 \Rightarrow$ strongly-stationary
 - How to adjust π ? ... L., Lopez-Calva & Nocedal
3. Relax equilibrium $X_1 x_2 \leq \tau e$ & $x_1, x_2 \geq -\delta e$
 - Well behaved smooth problem
 - Adjust $\tau \searrow 0$ or $\delta \searrow 0$... not both

Aim: NLP solver with small modification that works for MPECs

Key Observations after Numerical Testing *Leyffer*

- NLP Solvers (IPOPT, Knitro, FilterSQP) Faster than Specialized MPEC Solvers
- Fast Local Convergence ~ Newton's Method, Linear Algebra

2. Recent Work

Uncertainty Quantification and Weather Forecasting

Uncertainty Quantification (Constantinescu, Zavala and Anitescu)

Major Advances in Meteorological Models (WRF)

Highly Detailed Phenomena

High Complexity 4-D Fields (10^6 - 10^8 State Variables)



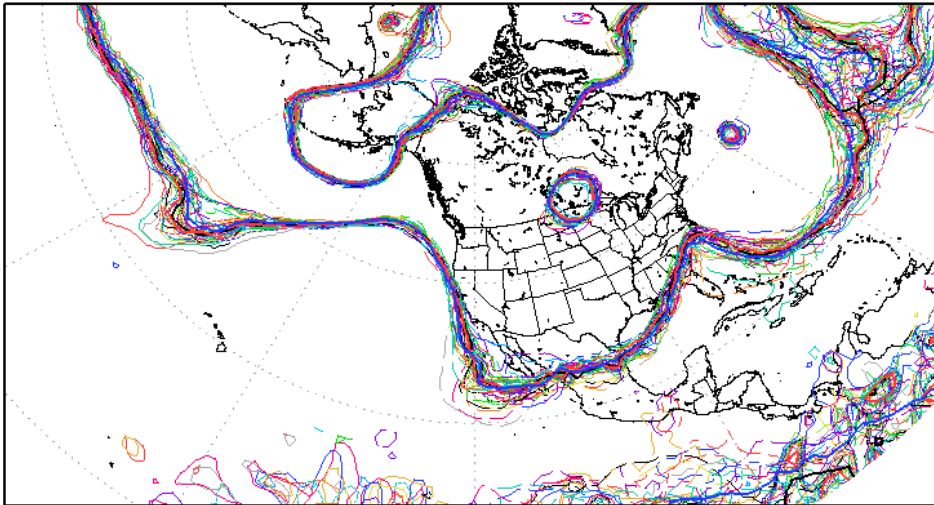
Model Reconciled to Measurements From Meteo Stations

Data Assimilation Techniques:

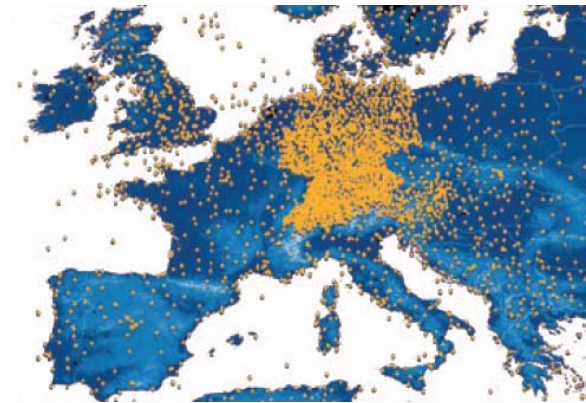
3-D Var *Courtier, et.al. 1998*

4-D Var *Navon et.al., 2007*

Extended and Ensemble Kalman Filter *Eversen, et.al. 1998*



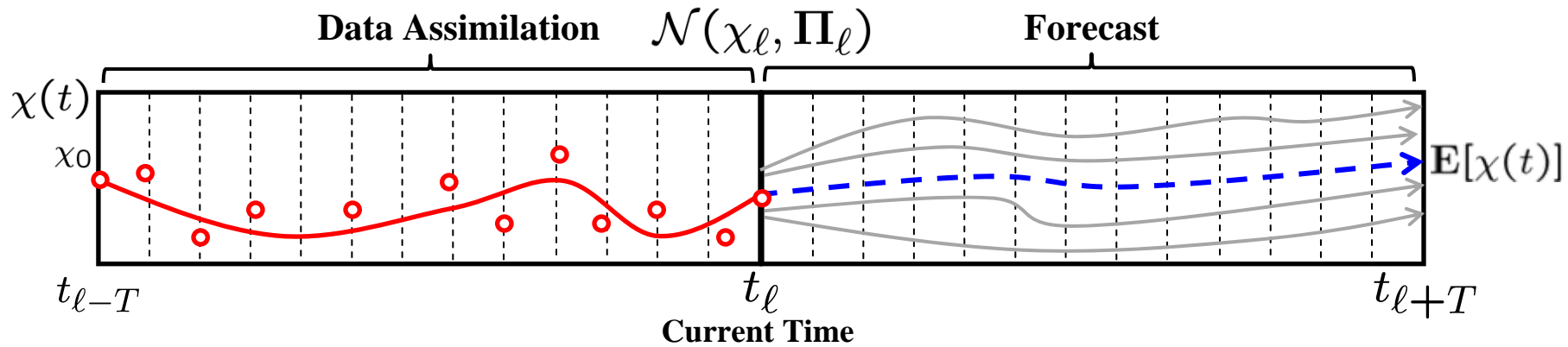
<http://www.emc.ncep.noaa.gov/gmb/ens/>



<http://www.meteoedia.com/>

Is WRF Computationally Practical Enough for Real-Time Operations?

Uncertainty Quantification



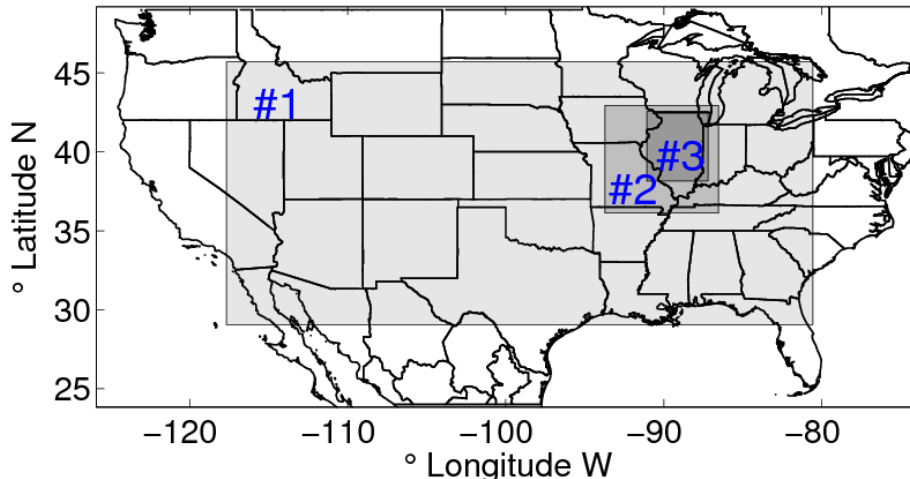
Computing and Storing Exact Covariance Matrix is Impractical:

- 1) Create Empirical Distribution of Current Atmospheric State
- 2) Propagate Samples through WRF Model

Making WRF Feasible:

Grid-Targeted Resolutions and Computational Resources

ID	Size	Grid
#1	130 × 60	32 km ²
#2	126 × 121	6 km ²
#3	202 × 232	2 km ²



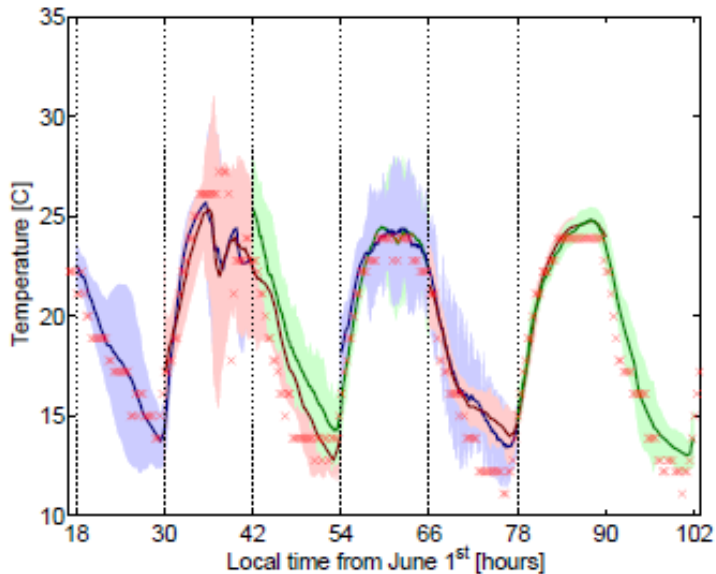
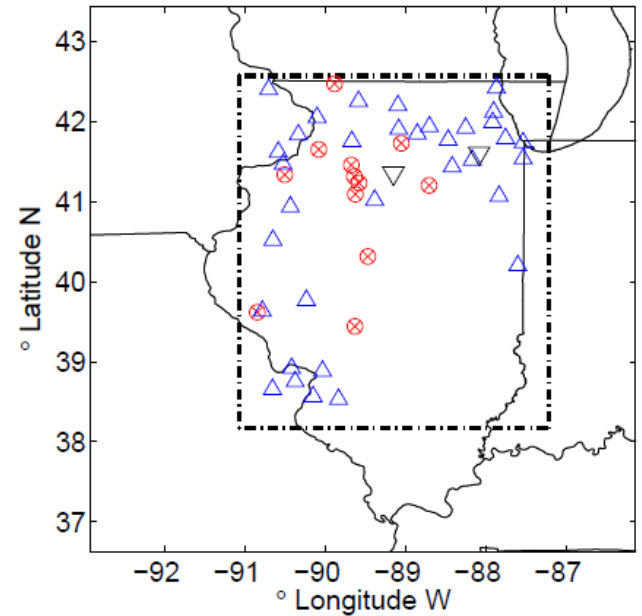
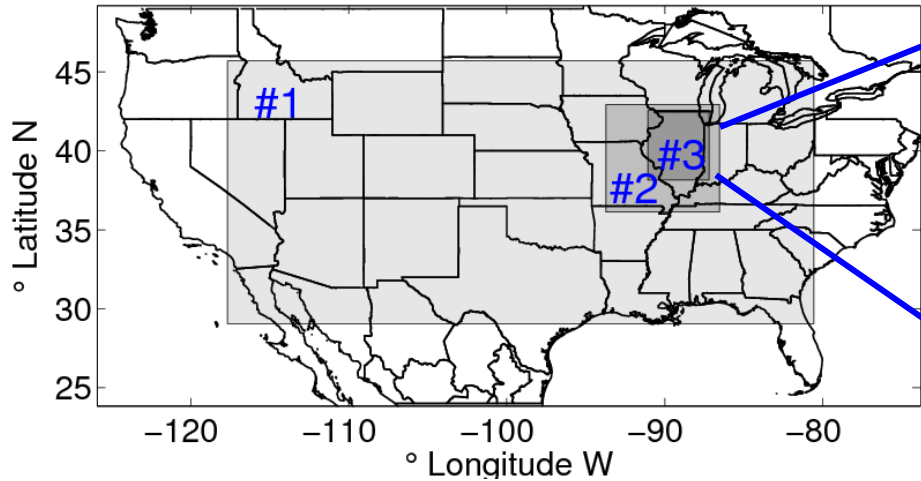
CPU's	Wall-time [hr]
4	50
8	28
16	17
32	10

Jazz Cluster at Argonne National Lab

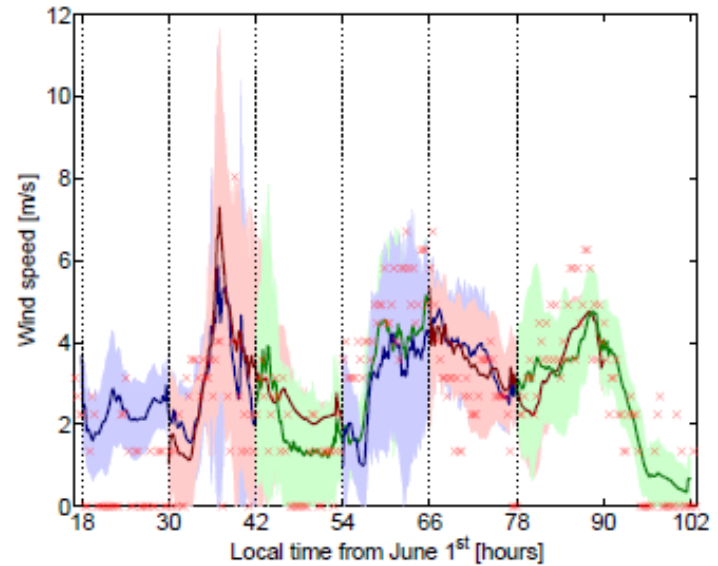
- ✓ Illinois [2km]: 500 processors
- □ US [2 km]: ~50,000 processors
- □ US [1 km]: ~400,000 processors

Uncertainty Quantification

Validation Results (Illinois, 2006) with NOAA Data



Temperature [°C]

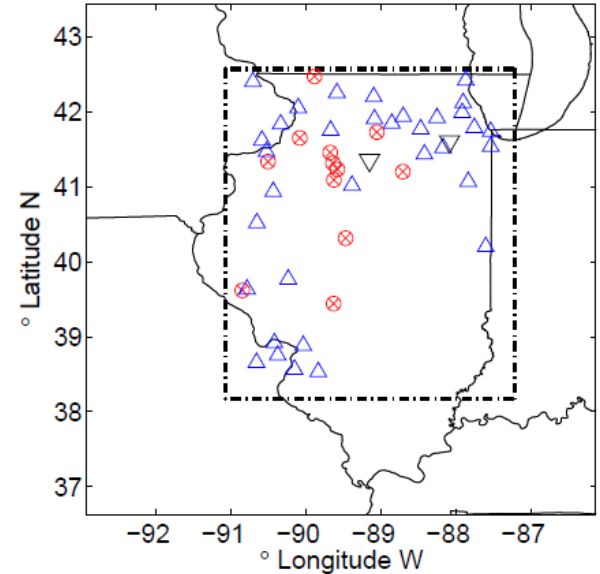
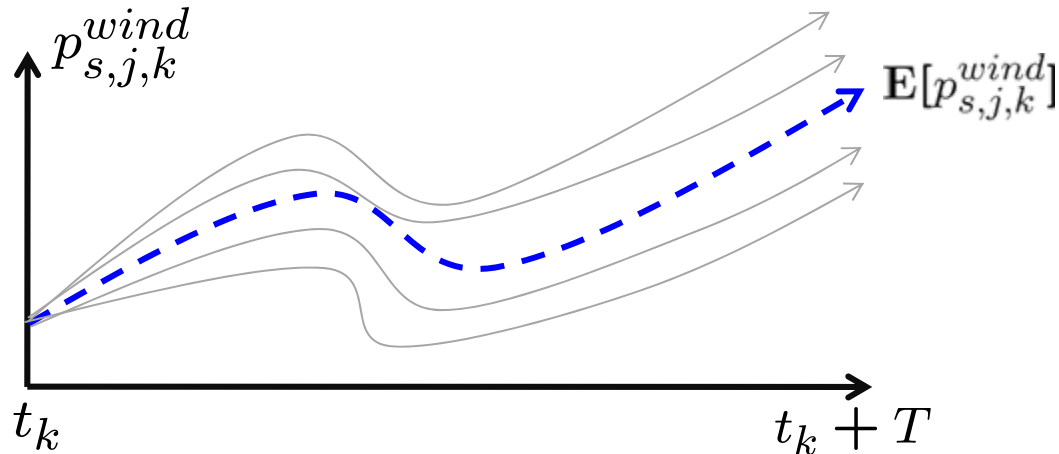


Wind Speed [m/s]

2. Recent Work

Stochastic Unit Commitment

Stochastic Unit Commitment (Zavala, Constantinescu and Anitescu)



$$\begin{aligned} \min_{p_{s,j,k}, \bar{p}_{s,j,k}, \nu_{j,k}} \quad & \varphi(p_{s,j,k}^{wind}) := \frac{1}{N_S} \sum_{s \in \mathcal{S}} \left(\sum_{j \in \mathcal{N}} \sum_{k \in \mathcal{T}} c_{s,j,k}^p + c_{j,k}^u + c_{j,k}^d \right) \\ \text{s.t.} \quad & \sum_{j \in \mathcal{N}} p_{s,j,k} + \sum_{j \in \mathcal{N}_{wind}} p_{s,j,k}^{wind} = D_k, \quad s \in \mathcal{S}, k \in \mathcal{T} \\ & \sum_{j \in \mathcal{N}} \bar{p}_{s,j,k} + \sum_{j \in \mathcal{N}_{wind}} p_{s,j,k}^{wind} \geq D_k + R_k, \quad s \in \mathcal{S}, k \in \mathcal{T} \end{aligned}$$



- Dealing with Large Number of Scenarios and Units
- Impact of WRF Accuracy and Uncertainty on Reliability
- Capturing More Detailed Physics (Ramps, Power Flow)

Parallel Stochastic Programming (Petra and Anitescu)

Structure of Optimization Problem Permeates Down to Linear Algebra

- Preserve Convergence of Simplex and Interior-Point Solvers (Avoid Lagrangean Relaxation)
- Dynamic Load Balancing, MPI, C++ Implementation

$$\text{Min}_{x, y_1, y_2, \dots, y_N} f(x) + \frac{1}{N} \sum_{i=1}^N g_i(y_i)$$

$$A_0 x = b_0$$

$$A_1 x + B_1 y_1 = b_1$$

$$A_2 x + B_2 y_2 = b_2$$

$$\vdots \quad \quad \quad \ddots \quad \quad \quad \vdots$$

$$A_N x + B_N y_n = b_n$$

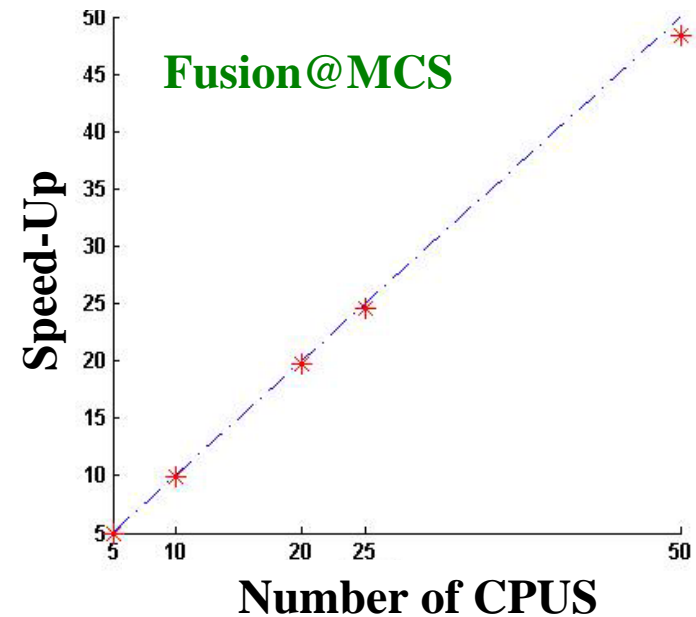
$$x \geq 0, \quad y_1 \geq 0, \quad y_2 \geq 0, \quad \dots \quad y_N \geq 0$$



-Nearly perfect scalability with scenarios
(building and unit commitment)

-Up to 10⁶-10⁷ variables and constraints feasible

-Bottlenecks due to coupling can be avoided with
Matrix-Free Schur strategy



Stochastic Unit Commitment

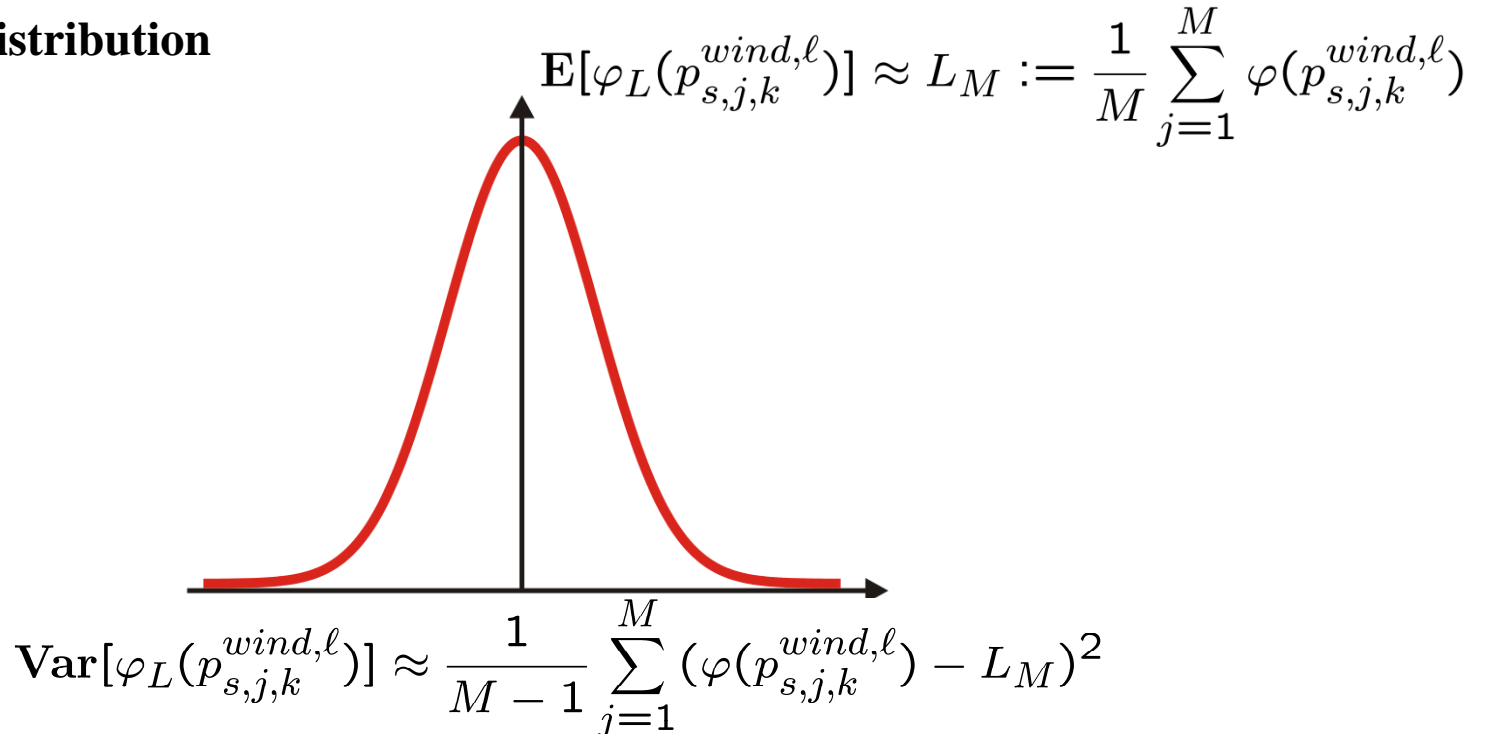
Issue: Integration Uncertainty Quantification & Stochastic Programming

- Forecast Probability Distribution is NOT Explicitly Available
- Few Weather Realizations (~ 50) → Optimal Cost Never Known Exactly!

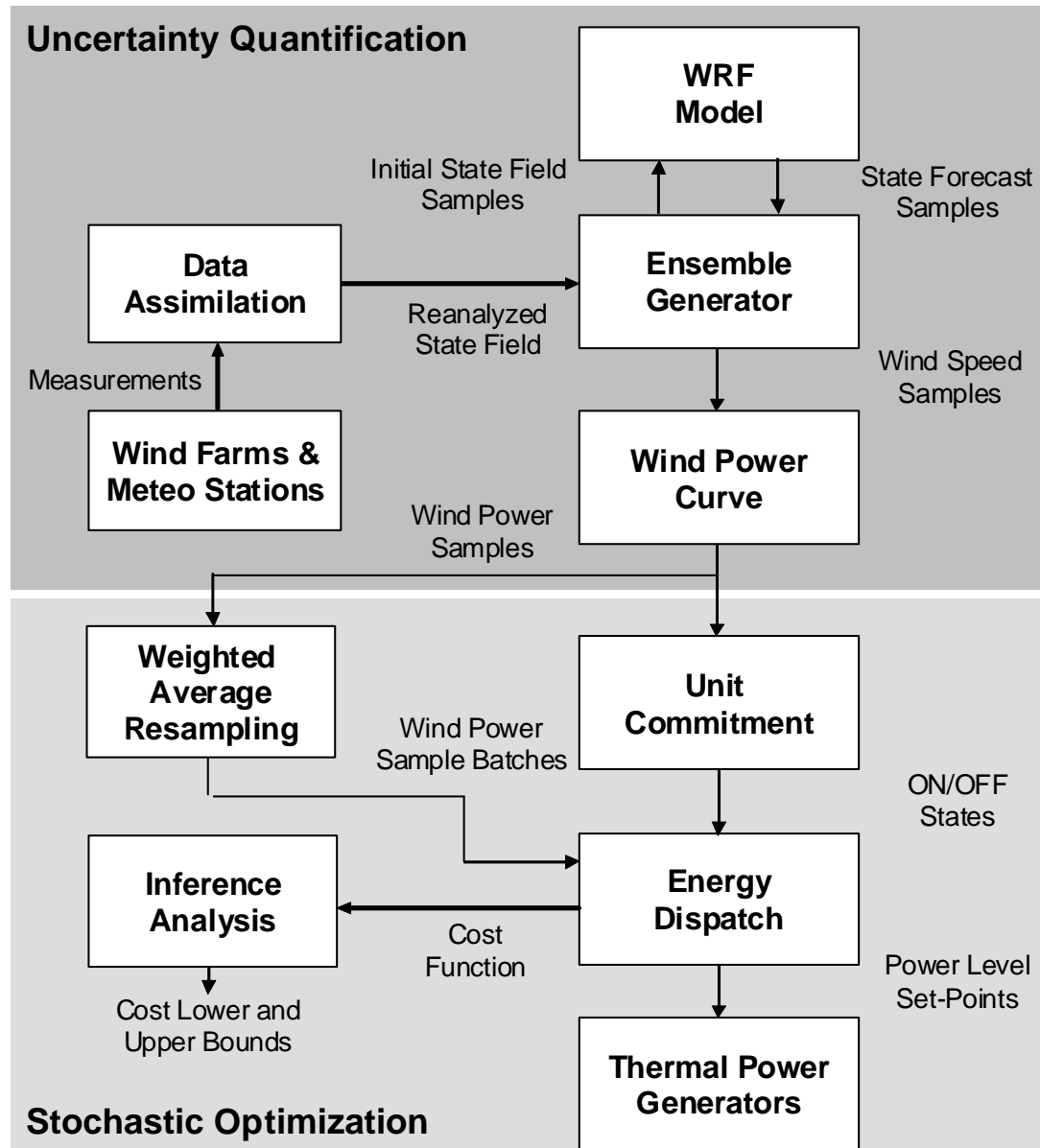
Generating More Realizations? Inference Analysis with Resampling

- 1) Sample Weights on Hyperplane $\sum_{s \in \mathcal{S}} w_{s,\ell} = 1$ and Compute $p_{s,j,k}^{wind,\ell} = \sum_{s \in \mathcal{S}} w_{s,\ell} \cdot p_{s,j,k}^{wind}$
- 2) Solve Stochastic Problem with M Batches of Realizations

Lower Bound Distribution



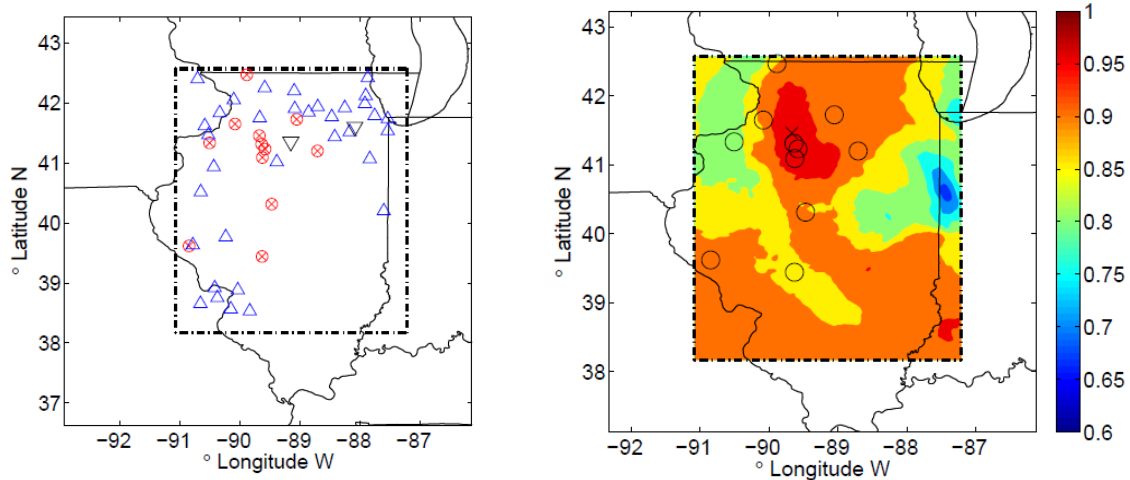
Stochastic Unit Commitment



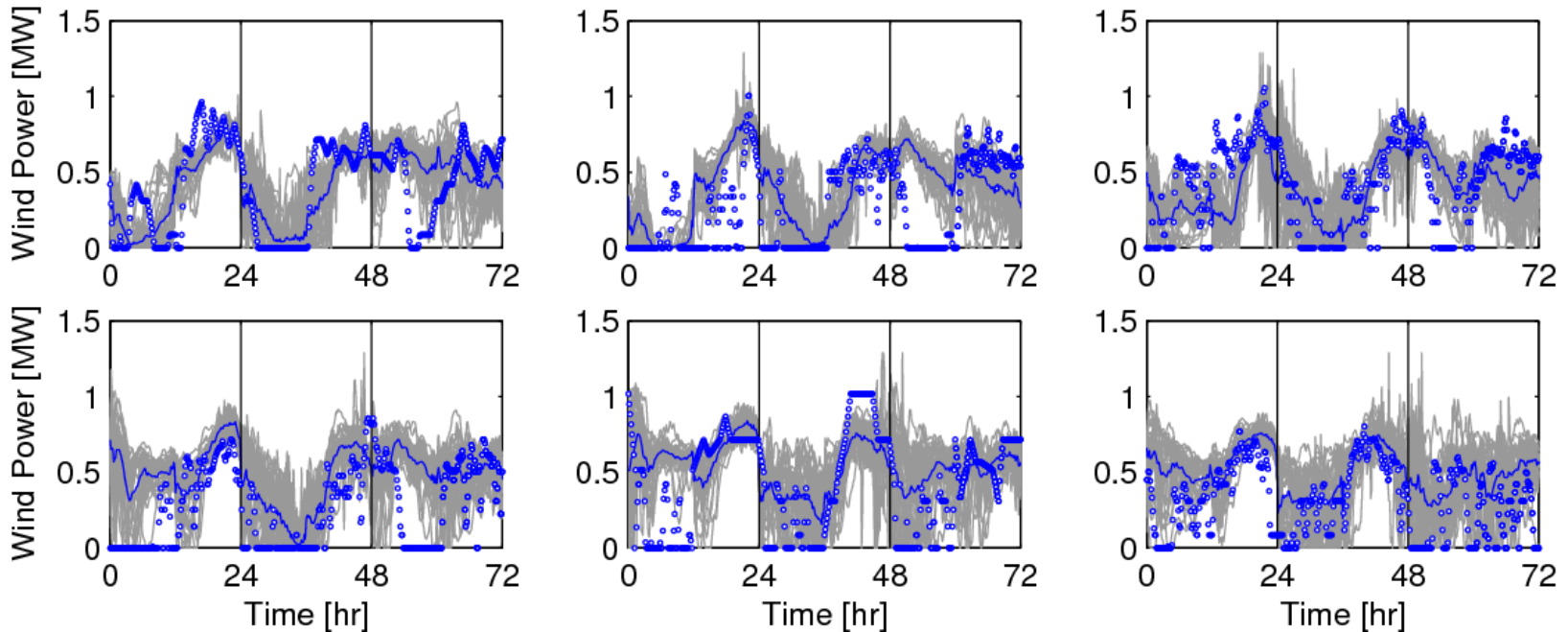
WRF Resolution and Realizations Must be Adapted in Real-Time (Transients)

Stochastic Unit Commitment

3 Days of Operation (Wind Adoption Level 20%)

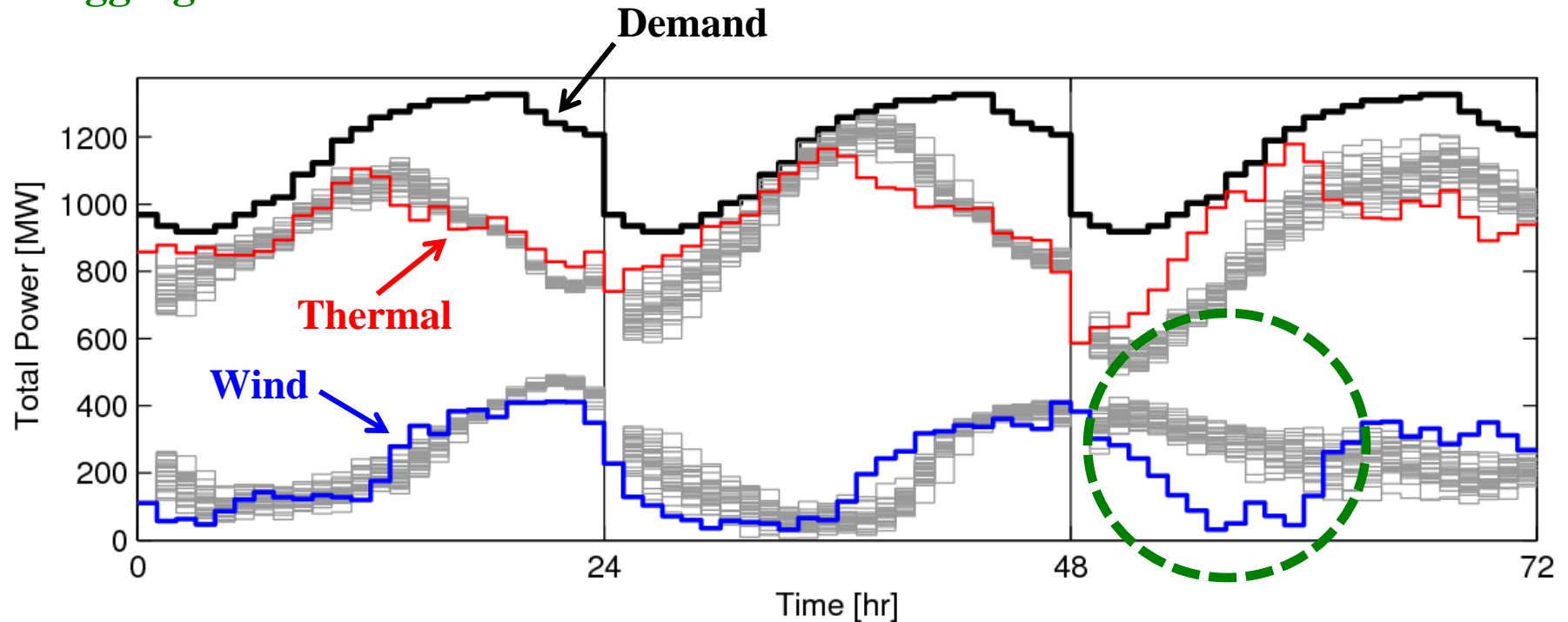


Wind Power Profiles



Stochastic Unit Commitment

Aggregated Power Profiles

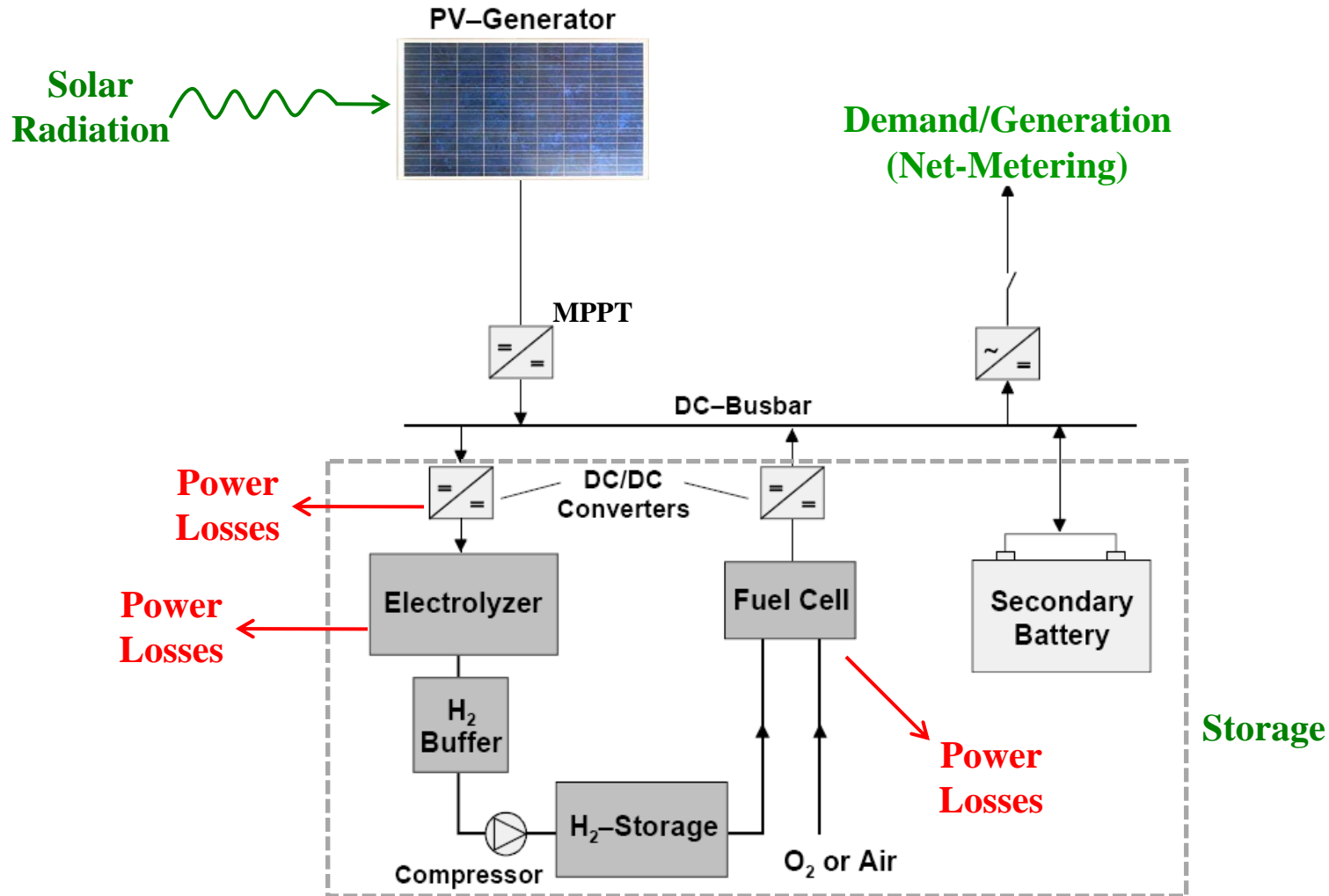


- **WRF is -In General- Accurate with Tight Uncertainty Bounds**
- **Inference Analysis Reveals that 30 WRF Samples are Sufficient to Estimate Cost!**
Cost ~ \$474,000, Upper Bound σ^2 (1,082 \$²), Lower Bound σ^2 (1,656 \$²)
- **However, Excursions Do Occur: Probability Distribution of 3rd Day is Inaccurate!**
Need to Tailor Resolution of Data Assimilation Step, Missing Physics?

2. Recent Work

Real-Time Energy Management of Co-Generation and Building Systems

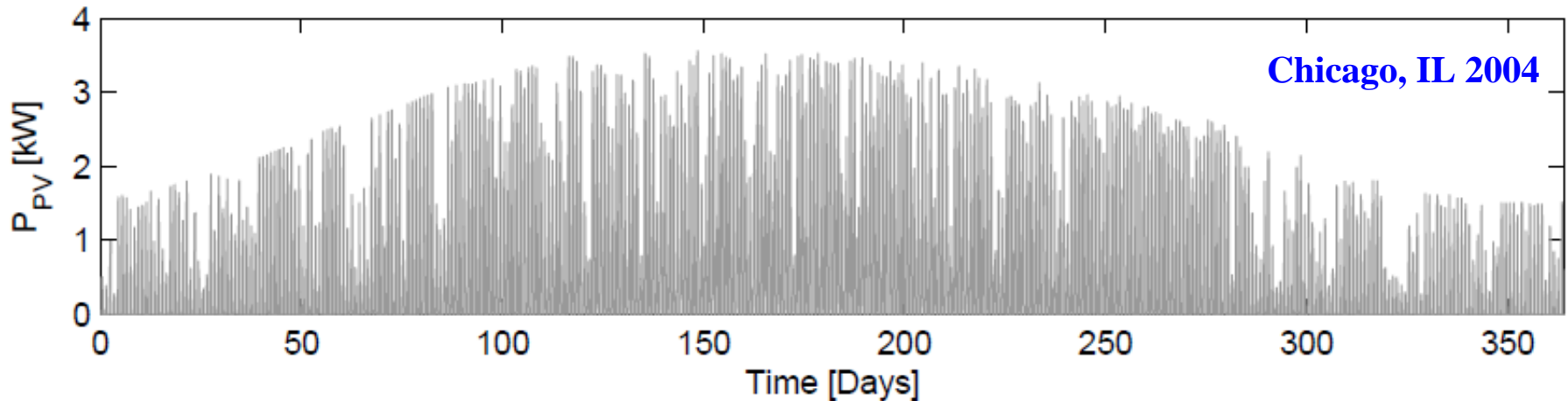
Energy Management (Zavala and Anitescu)



- Fuel Cells for Distributed Generation -Building is Market Participant-
- Operation Driven by Dynamic Patterns of Solar Radiation *Ulleberg, 2004*

Energy Management

Proactive Energy Management



Radiation Forecast



$$\min_{u(t)} \int_{t_\ell}^{t_\ell+N} \varphi(z(t), y(t), u(t), \chi(t)) dt$$

Minimize Power Losses

$$\frac{dz}{dt} = f(z(t), y(t), u(t), \chi(t))$$

Dynamic Model of Hybrid System (DAE)

$$0 = g(z(t), y(t), u(t), \chi(t))$$

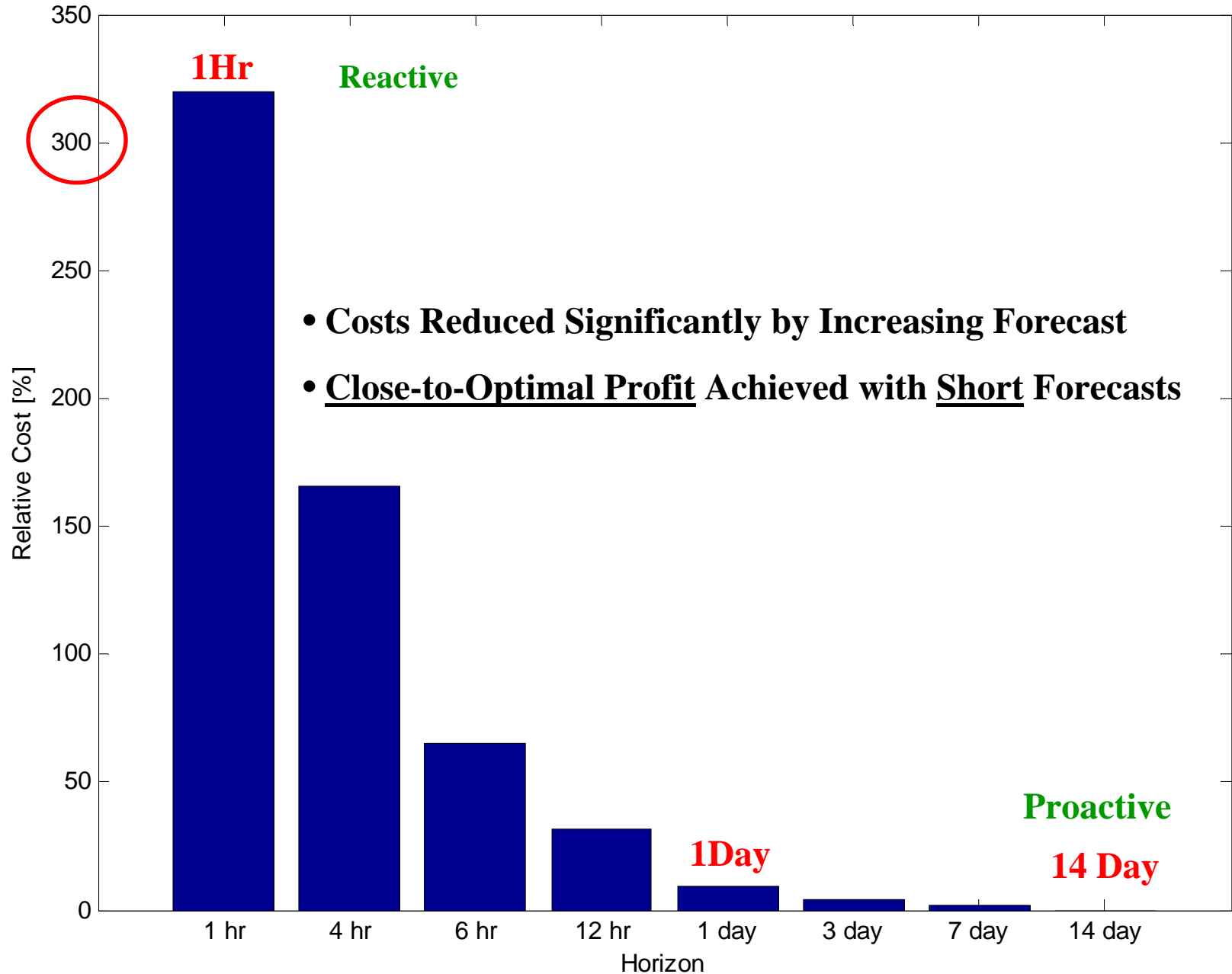
$$0 \geq h(z(t), y(t), u(t), \chi(t))$$

State-of-Charge, Fuel Cell and Electrolyzer Limits

$$z(0) = x_\ell$$

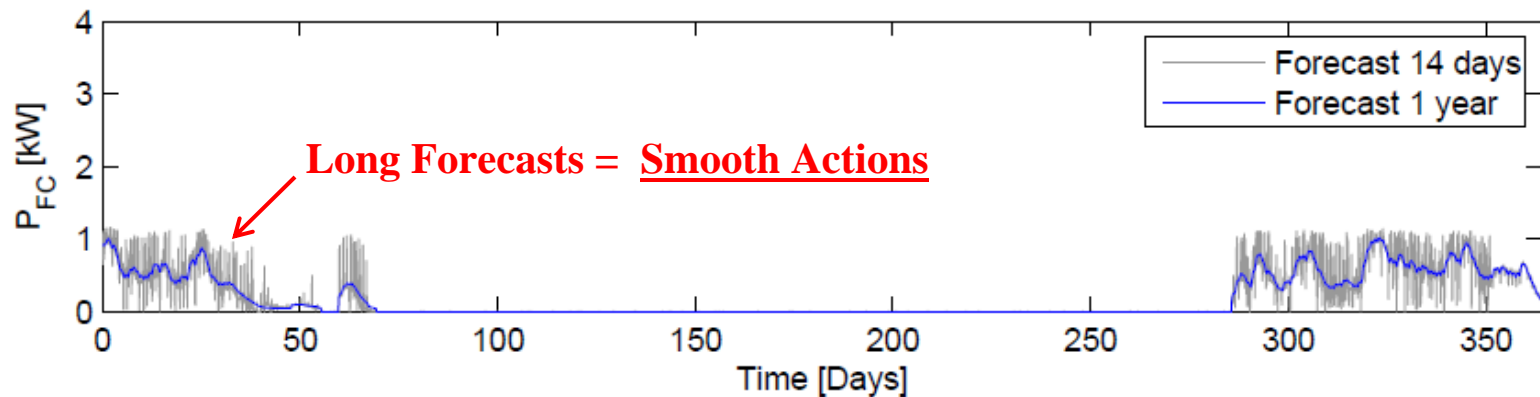
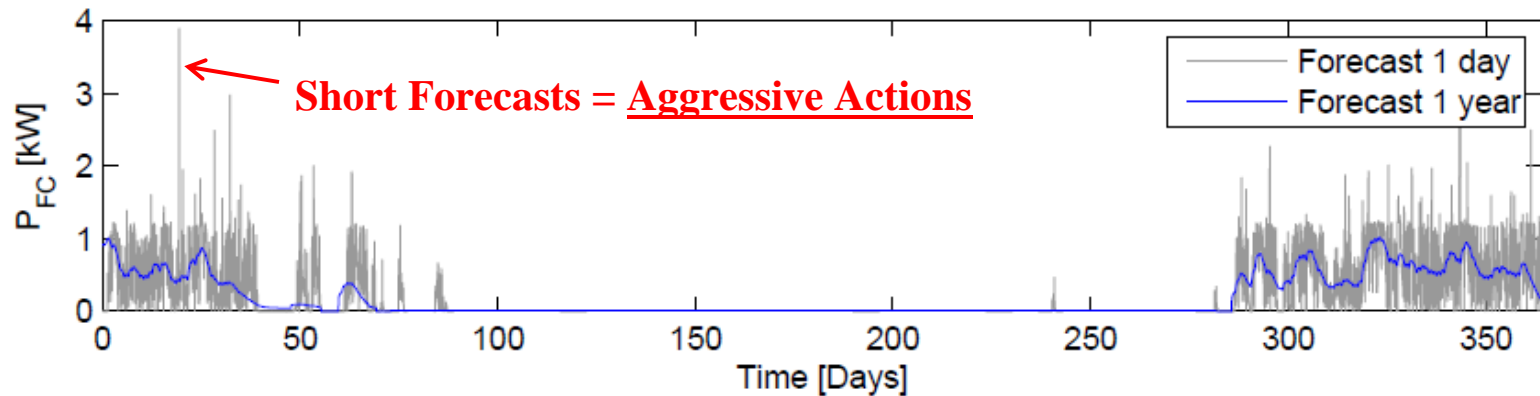
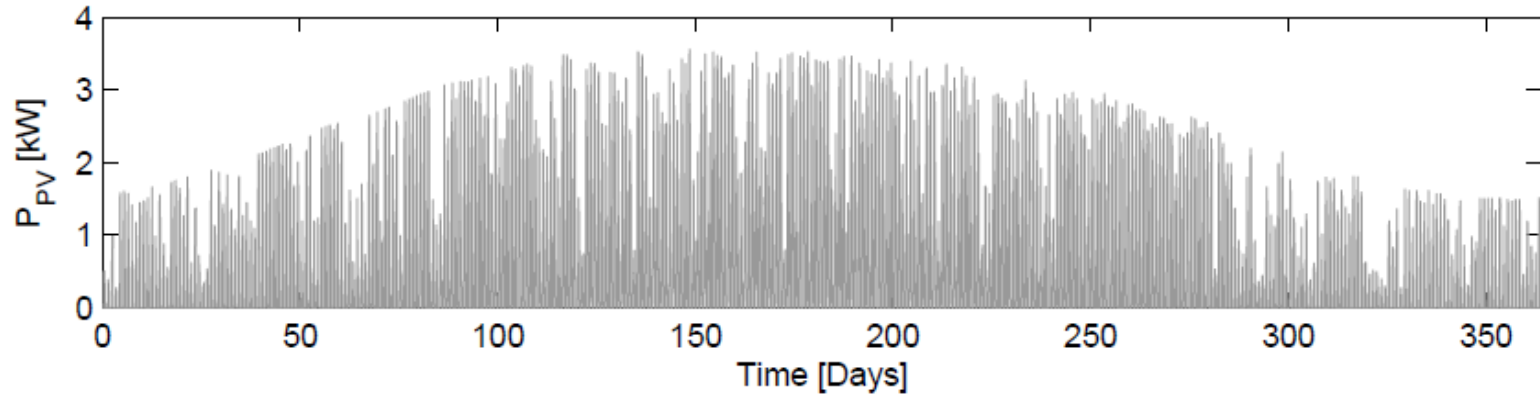
- Real-Time Energy Management Technology is Reactive (Johnson Controls, Siemens)
- Proactive Management with Forecast Horizon of 1hr, 1 Day, ..., 14 Days
- Large-Scale Optimal Control - IPOPT + Sparse Linear Algebra (Nested Dissection)

Energy Management



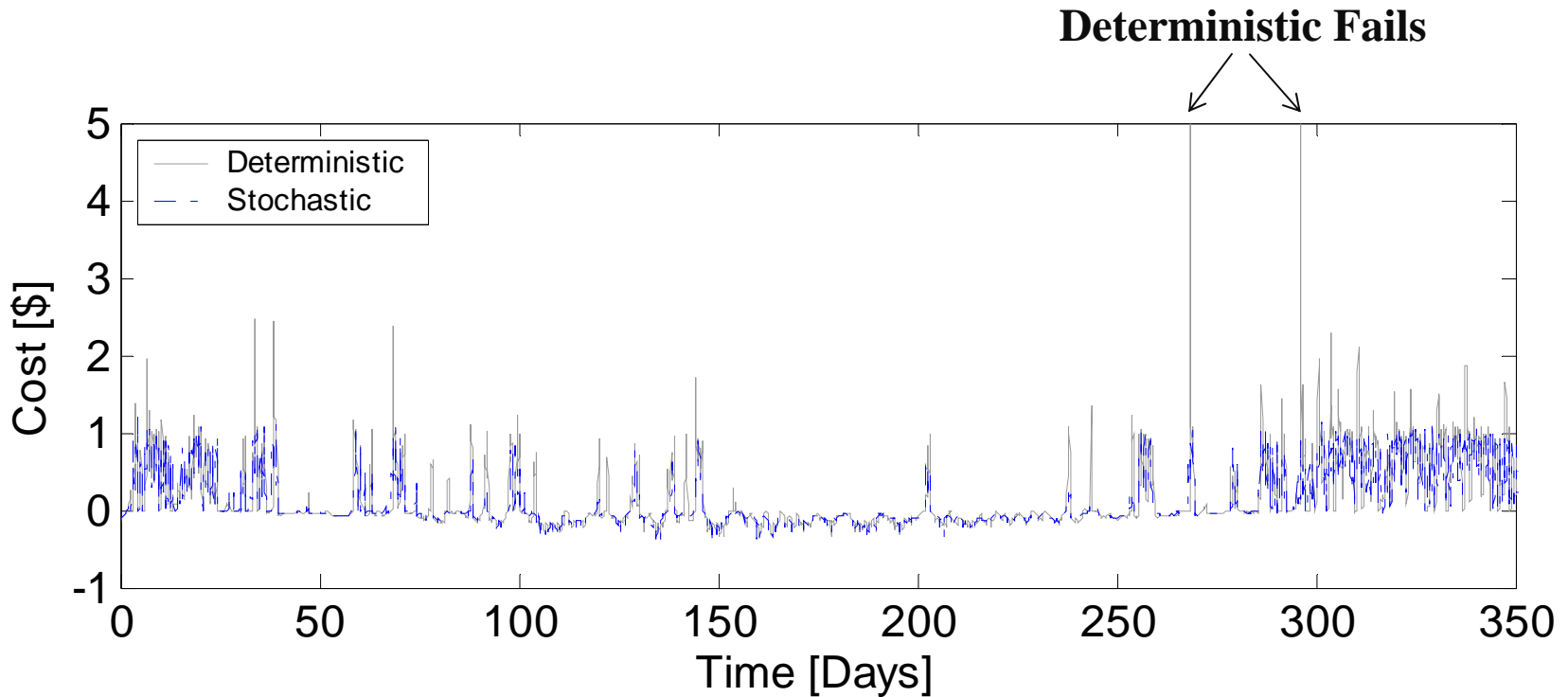
Energy Management

Profiles of Fuel Cell Power



Energy Management

Reliability Deterministic vs. Stochastic



Proactive Manager Implicitly Forecasts Electricity Demand Profile

- Ability to Capture Market Interactions

Energy Management

Minimize Daily Energy Costs

$$\min_{u(t)} \int_{t_\ell}^{t_\ell+N} [C_c(t)\varphi_c(t) + C_h(t)\varphi_h(t)] dt$$

$$C_I \cdot \frac{\partial T_I}{\partial \tau} = \varphi_h(\tau) - \varphi_c(\tau) - S \cdot \alpha' \cdot (T_I(\tau) - T_W(\tau, 0))$$

$$\frac{\partial T_W}{\partial \tau} = \beta \cdot \frac{\partial^2 T_W}{\partial x^2}$$

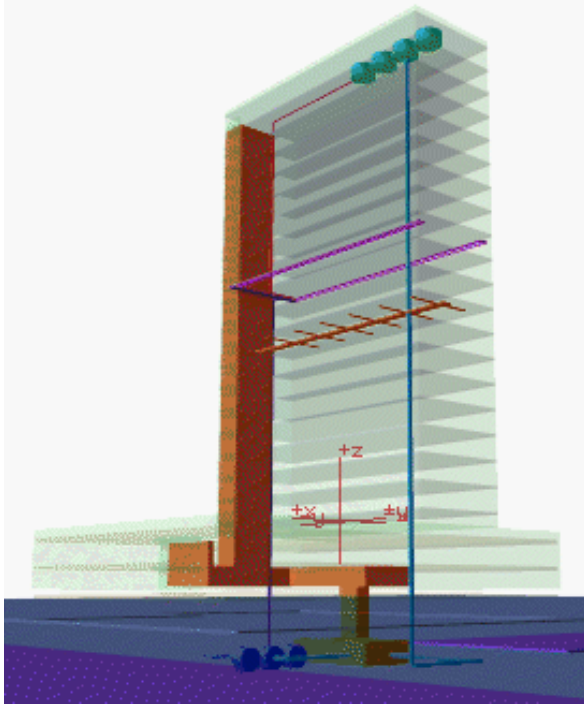
$$\alpha' (T_I(\tau) - T_W(\tau, 0)) = -\mathbf{k} \cdot \frac{\partial T_W}{\partial x} \Big|_{(\tau, 0)}$$

$$\alpha'' (T_W(\tau, L) - T_A(\tau)) = -\mathbf{k} \cdot \frac{\partial T_W}{\partial x} \Big|_{(\tau, L)}$$

$$T_I(0) = T_I^\ell$$

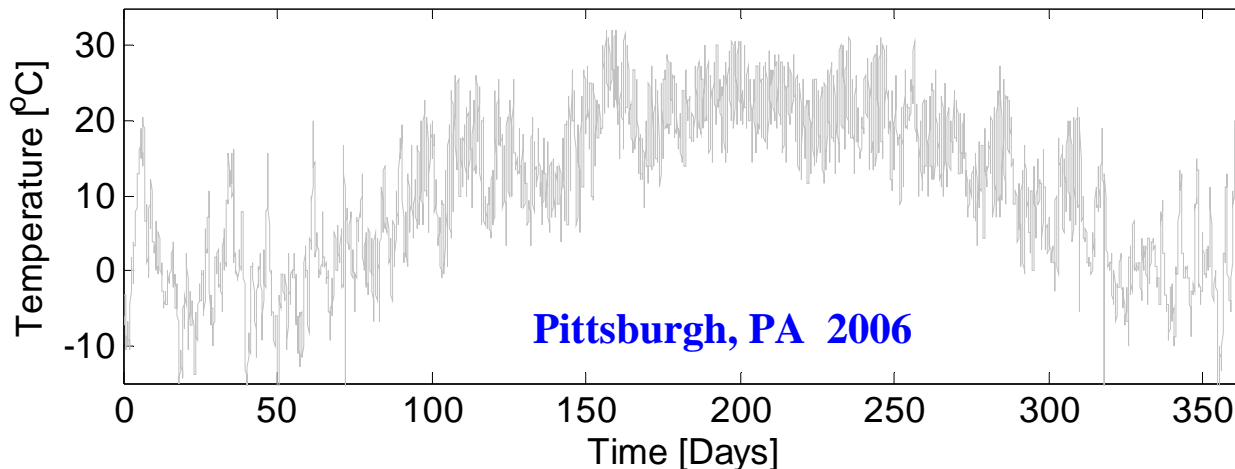
$$T_W(0, x) = T_W^\ell(x)$$

Dynamic Building Model (PDE)



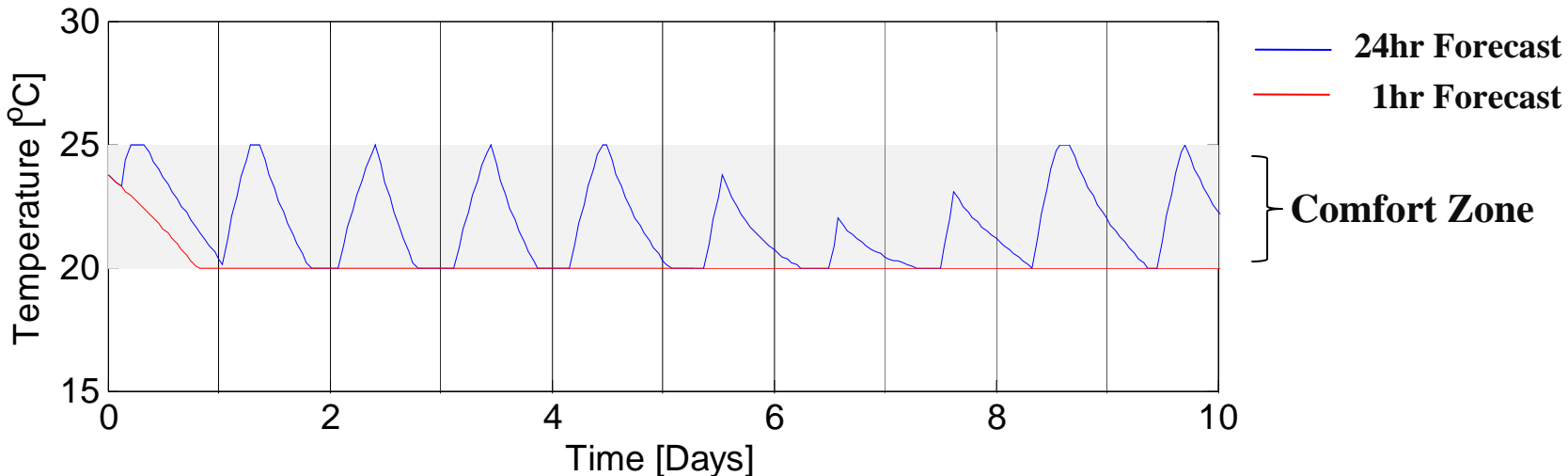
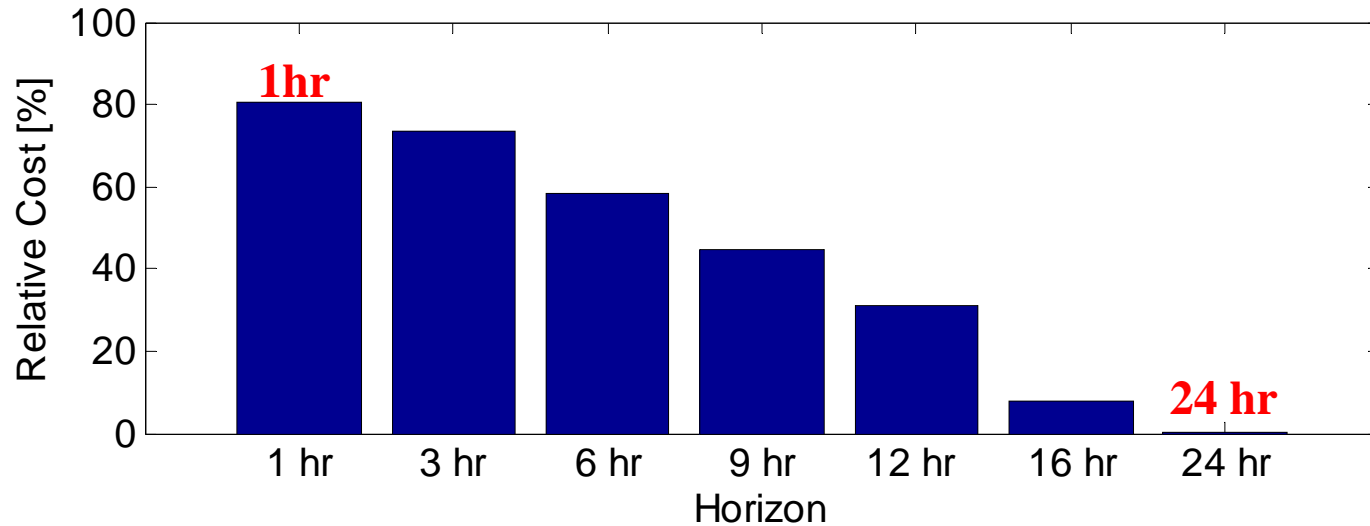
www.columbia.edu/cu/gsap/BT/LEVER/

Time-Varying Electricity Prices (Peak & Off-Peak)



Energy Management

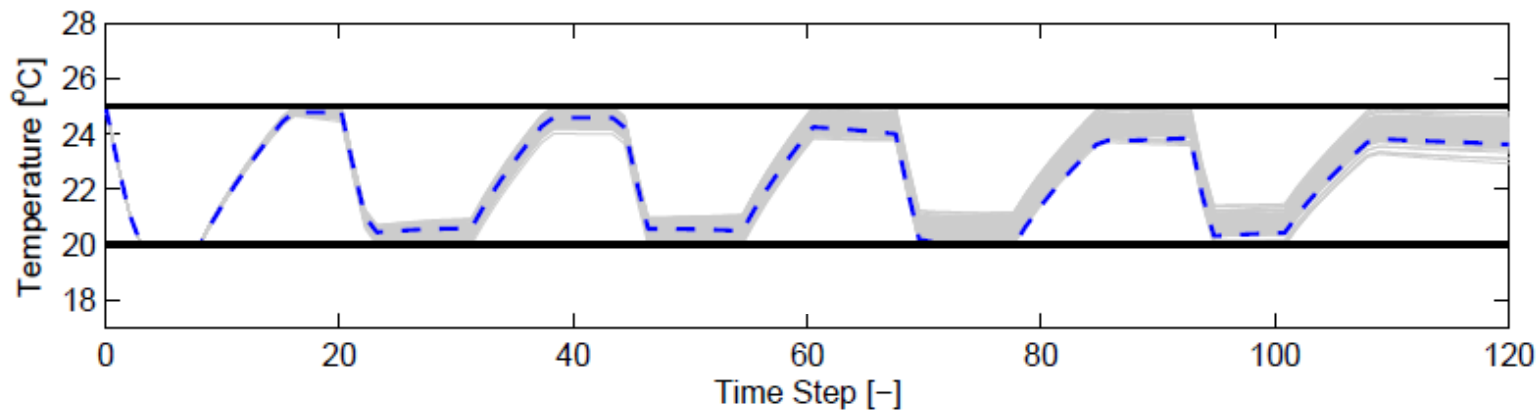
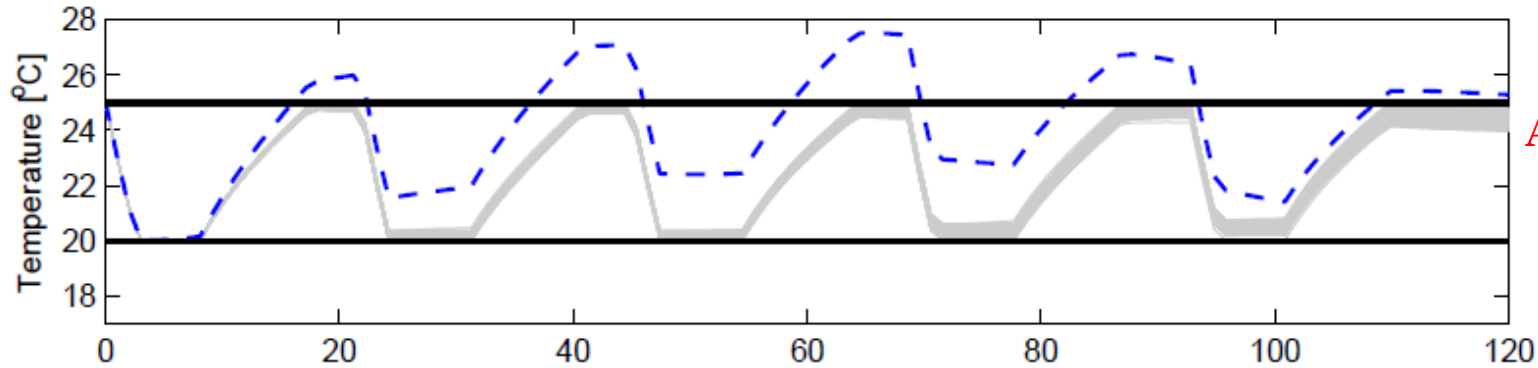
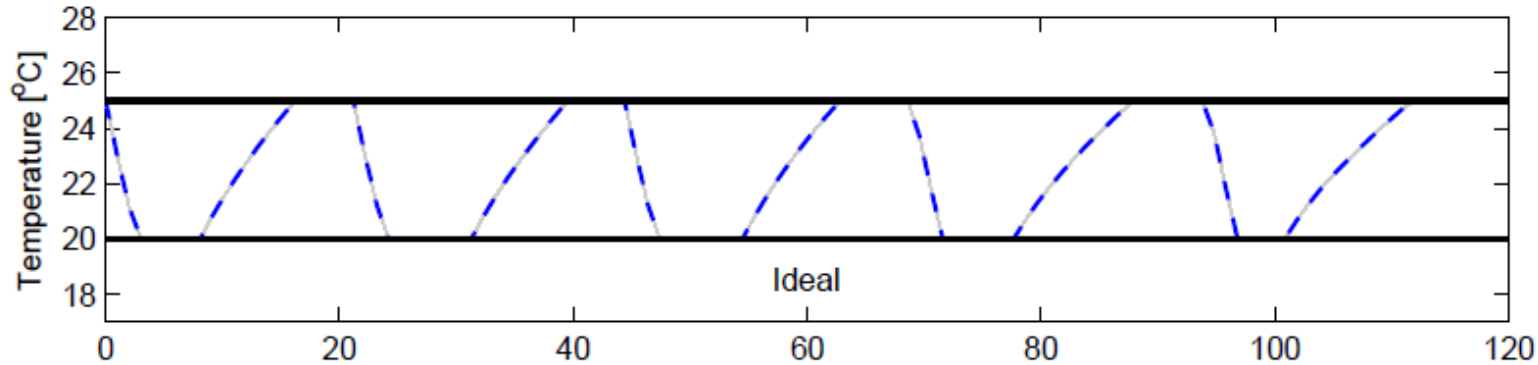
Effect of Forecast on Costs



Proactive Manager Implicitly Forecasts Demand Profile

Energy Management

Proactive Manager with Different Weather Forecast Models



5. Conclusions and On-Going Projects

Conclusions and On-Going Projects

Smart Grid

- Market and Demand Forecasts with Detailed Uncertainty Information
- Deregulation Forcing Game-Oriented Formulations and Algorithms

Many Advances in Optimization Algorithms BUT LACK OF INTEGRATION

- Economic Potential of Optimization Has Not Been Fully Exploited

Vision

- Grid Simulator to Assess Effects of Forecasting in Market and Operations

Market Models Used for Real-Time Price Forecasting

Unit Commitment with Transmission (MINLP)

New Modeling Paradigms (Continuous-Time)

Real-Time Optimization (Synchronization, Warm-Starts, Exploit Periodicity)

- How to Generate Low Cost Forecasts for ISOs, GENCOs, TRNSCOs?

Grid-Oriented Resolution Constrained by Computational Resources

- Integrative Studies to Assess and Motivate New Optimization Technology

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