Economic Impacts of Advanced Weather Forecasting on Energy System Operations

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Postdoc Seminar
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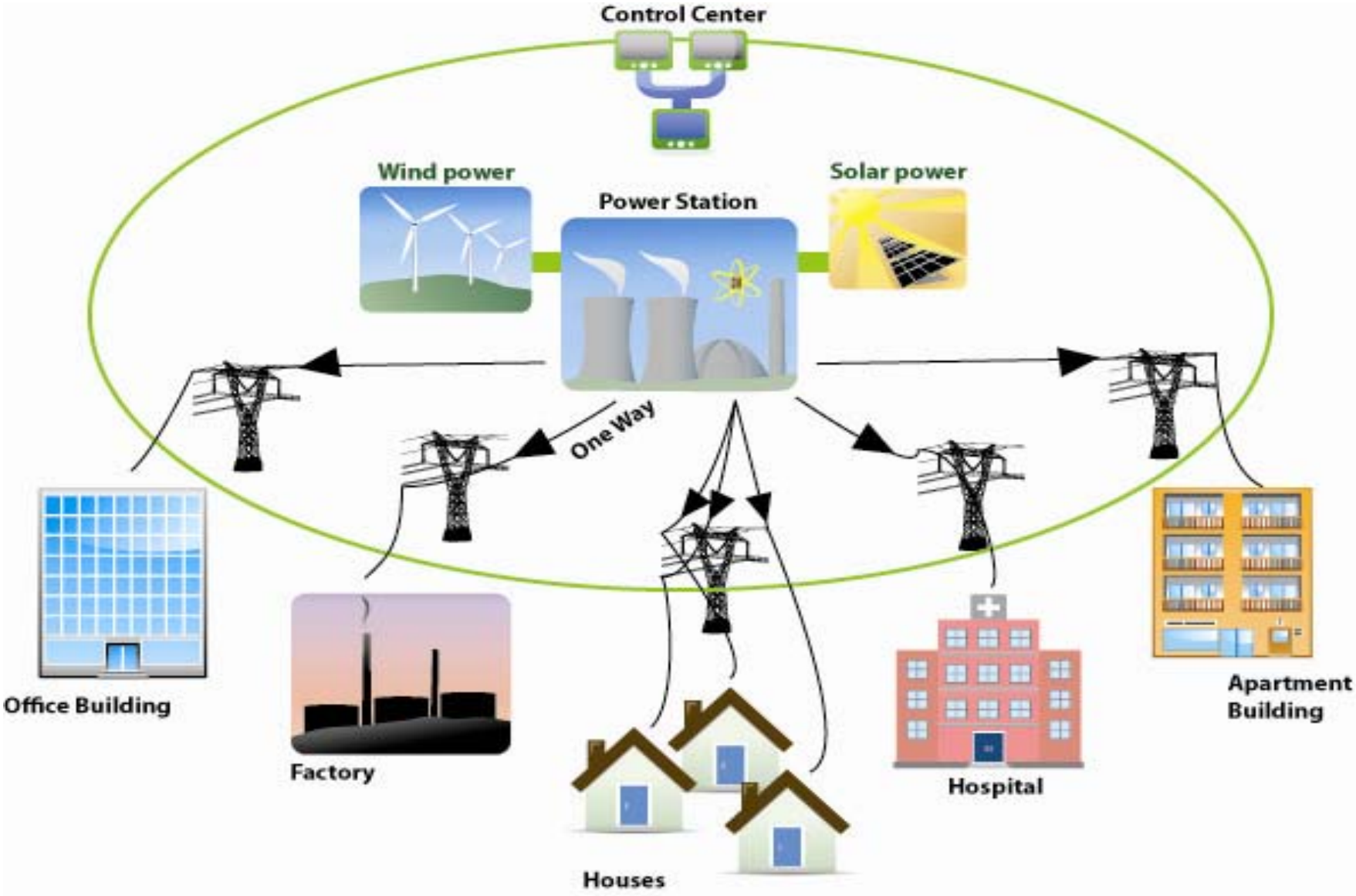
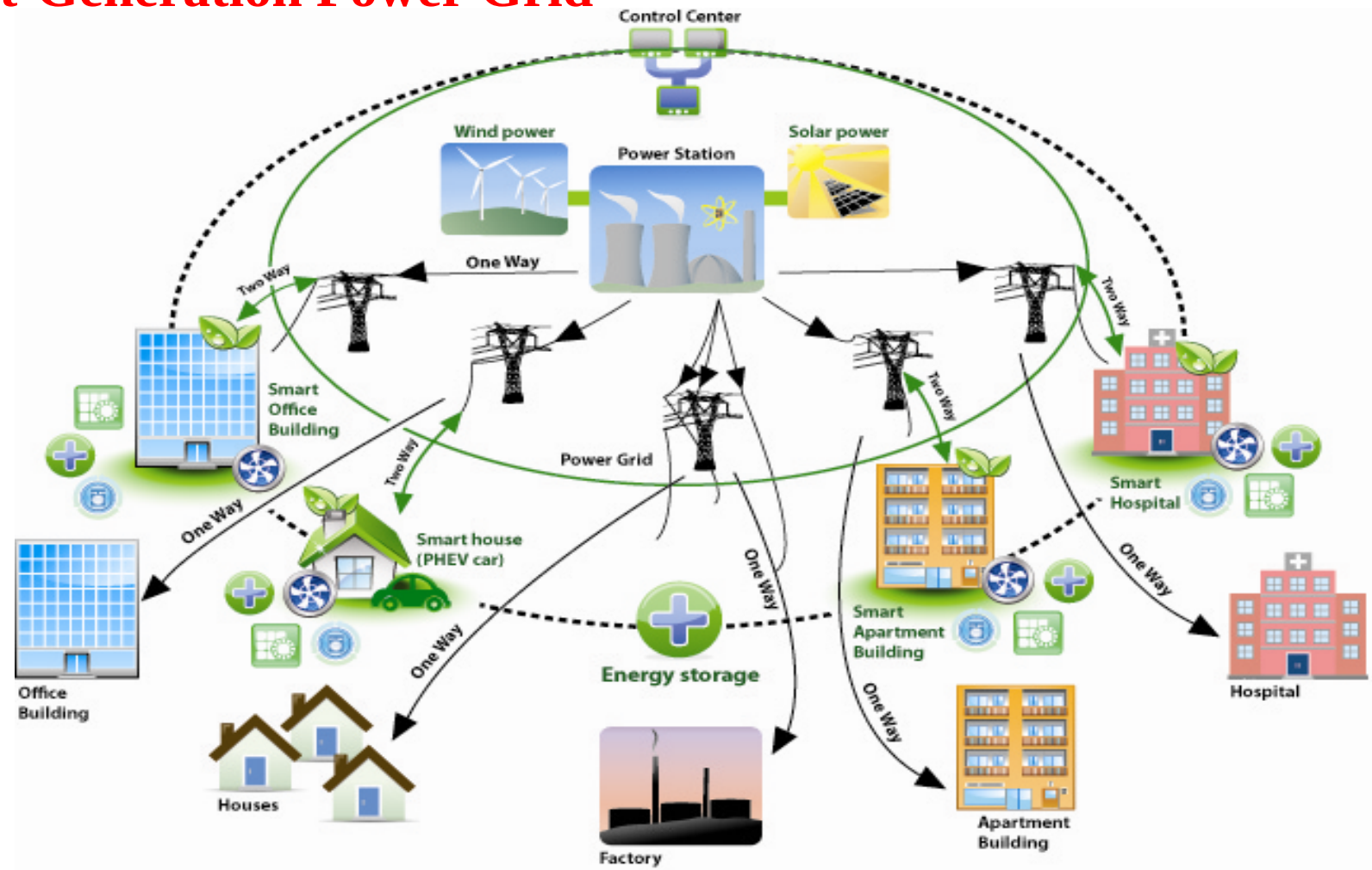
Electricity Supply - Billions $/Yr Market

Current Power Grid



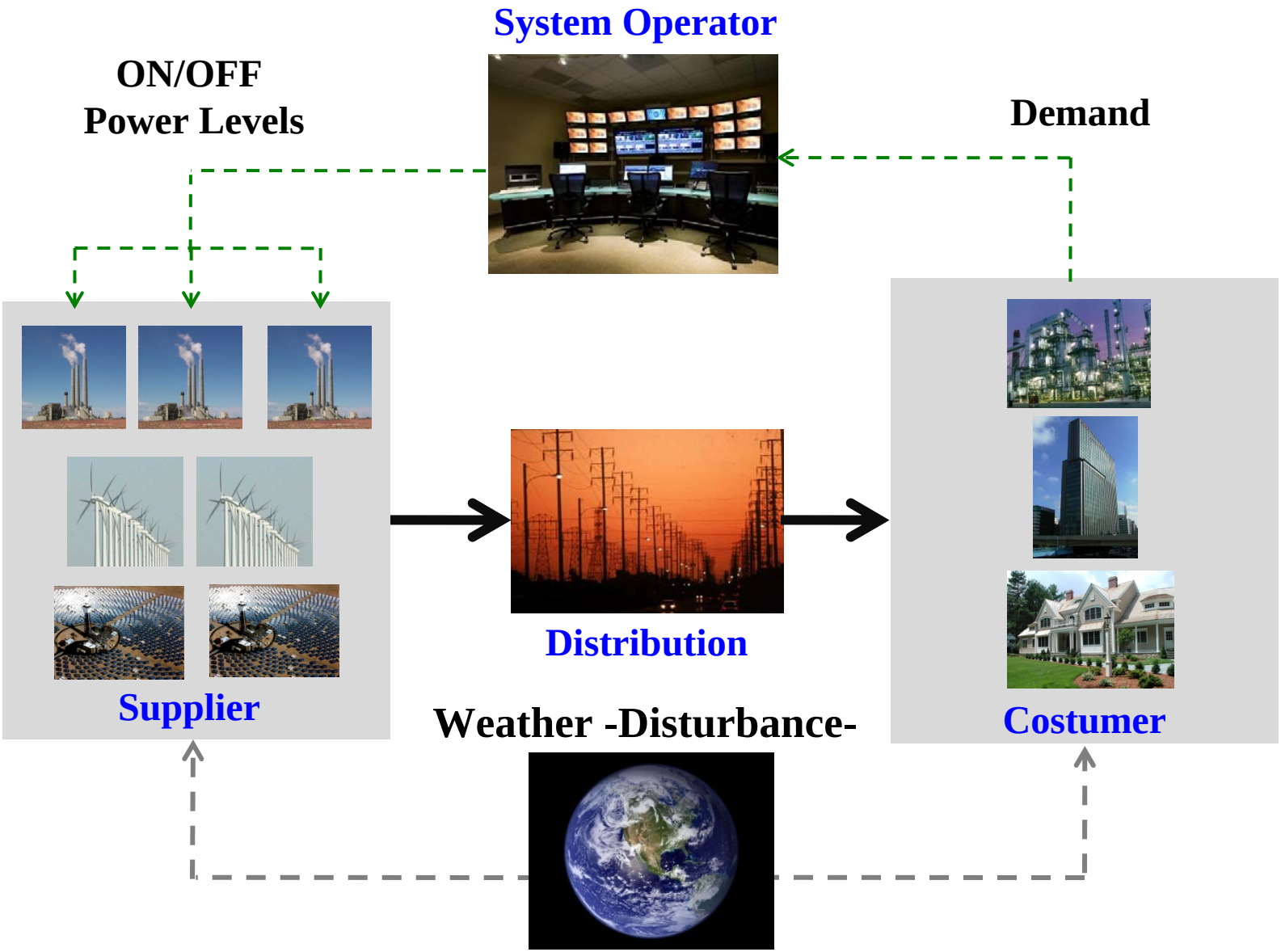
Electricity Supply - Billions $/Yr Market

Next-Generation Power Grid



- Major Adoption of Renewable -Intermittent- Resources (20-30%)
- Highly Decentralized Generation and Consumption
- Complex Market Interactions

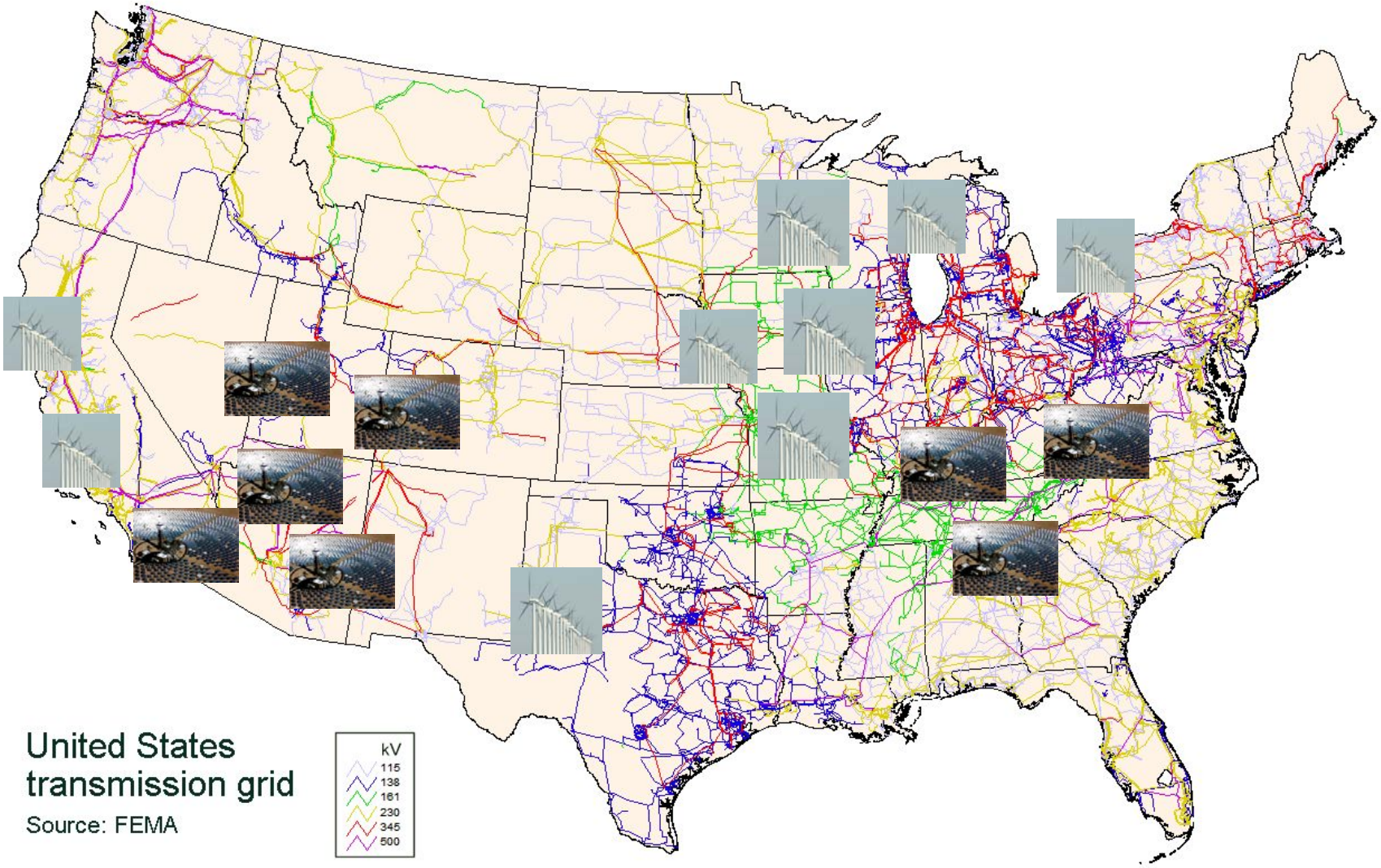
Electricity Supply - Billions $/Yr Market



Demand and Generation <u>Forecasting</u> is Critical to Minimize Reserves -Expensive-

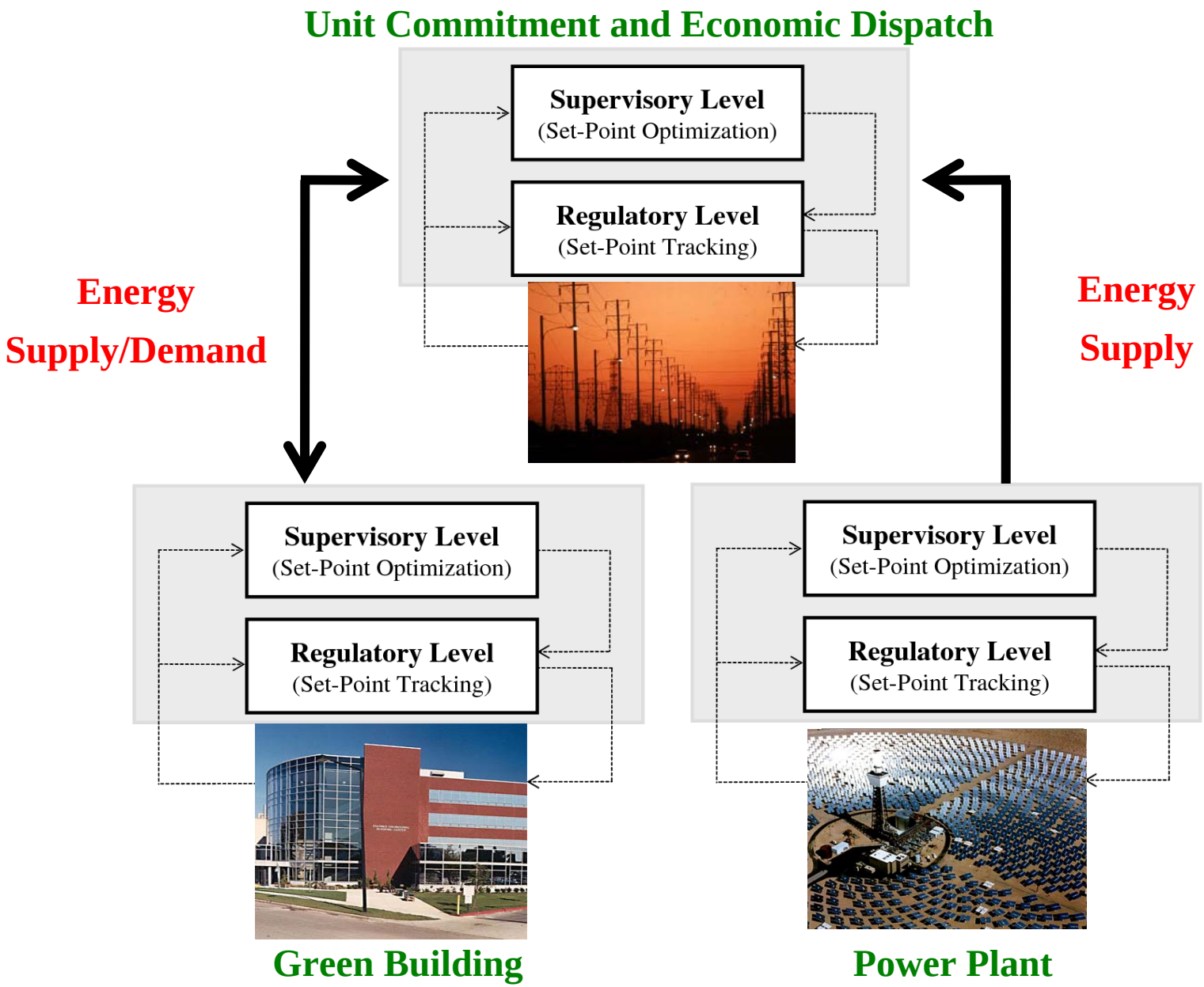
Electricity Supply - Billions $/Yr Market

Next-Generation Power Grid



Decentralized Generation Will Need <u>Decentralized Forecasts</u> - Transmission Constraints Need to Capture Spatio-Temporal Weather Correlations

Electricity Supply - Billions $/Yr Market



Outline of the Talk

1. **Weather Forecasting**

2. **Unit Commitment and Economic Dispatch**
   - **Wind Power Generation**

3. **Production Level**
   - **Photovoltaic-Hydrogen Hybrid System**

4. **Consumer Level**
   - **Building Energy Management**

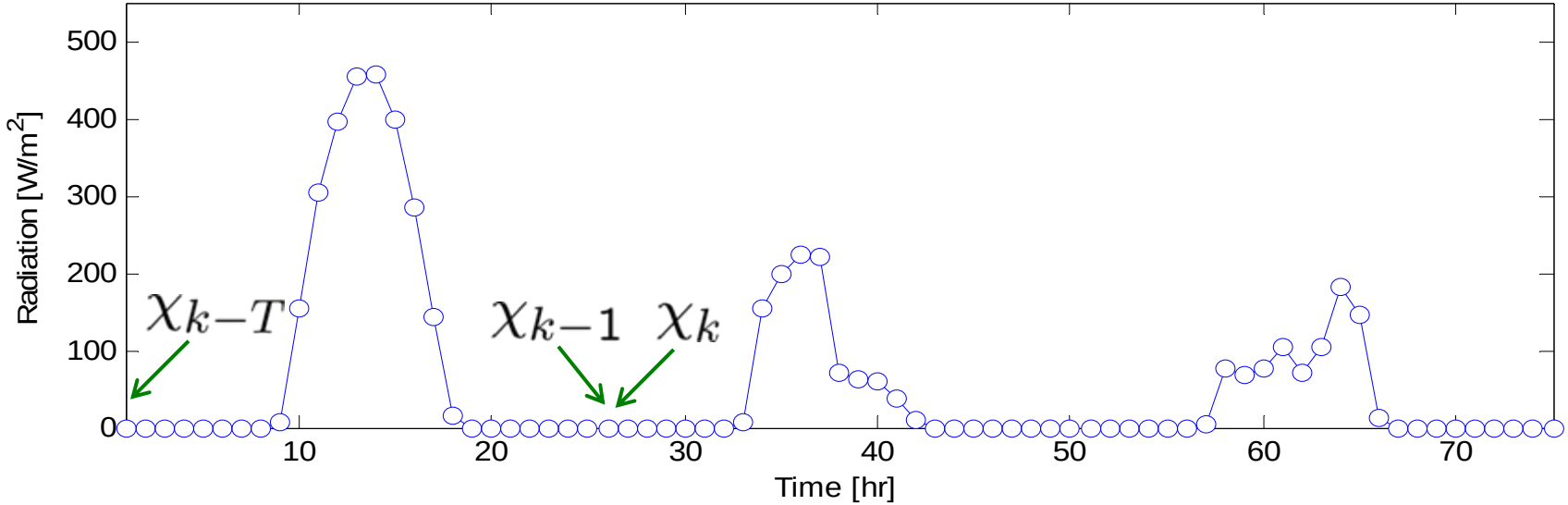
5. **Conclusions and Future Work**

1. **Weather Forecasting**

Weather Forecasting – Empirical

Quantifying Forecast Uncertainty (Time-Series vs. Physics-Based)

Solar Radiation Forecast with Gaussian Process (GP) Modeling *Z & Anitescu, 2008*



1. Input-Output Data Sets: $\mathbf{Y}_j := \chi_k \qquad \mathbf{X}_j := [\chi_{k-1},\ \chi_{k-T}]$

2. Covariance Structure : $\mathbf{V}(\mathbf{X}_j, \mathbf{X}_i, \eta) := \eta_0 + \eta_1 \cdot \exp\left(-\frac{1}{\eta_2}\|\mathbf{X}_j - \mathbf{X}_i\|^2\right)$

3. Apply Maximum Likelihood: $\log p(\mathbf{Y}|\eta) = -\frac{1}{2}\mathbf{Y}\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta)\mathbf{Y} - \frac{1}{2}\log\det(\mathbf{V}(\mathbf{X},\mathbf{X},\eta))$

4. Posterior Distribution: $\mathbf{Y}^P = \mathbf{V}(\mathbf{X}^P, \mathbf{X}, \eta^*)\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta^*)\mathbf{Y}$ **Forecast Mean**

$\mathbf{V}^P = \mathbf{V}(\mathbf{X}^P, \mathbf{X}^P, \eta^*) - \mathbf{V}(\mathbf{X}^P, \mathbf{X}, \eta^*)\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta^*)\mathbf{V}(\mathbf{X}, \mathbf{X}^P, \eta^*)$ **Covariance**

Power Industry: Empirical Models Useful Under Persistent Trends, No Spatial Correlations

Weather Forecasting with WRF

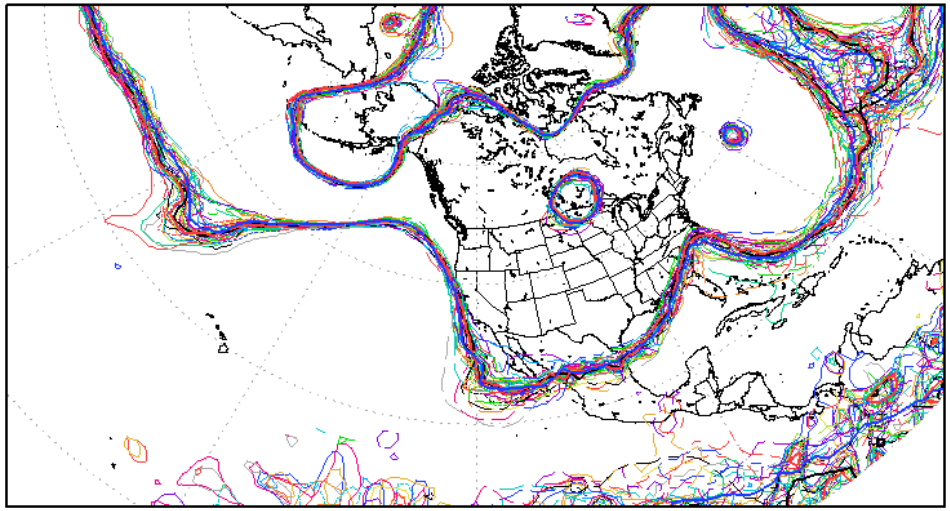
Major Advances in Meteorological Models (WRF)

- **Highly Detailed Phenomena**
- **High Complexity 4-D Fields (10^6- 10^8 State Variables)**

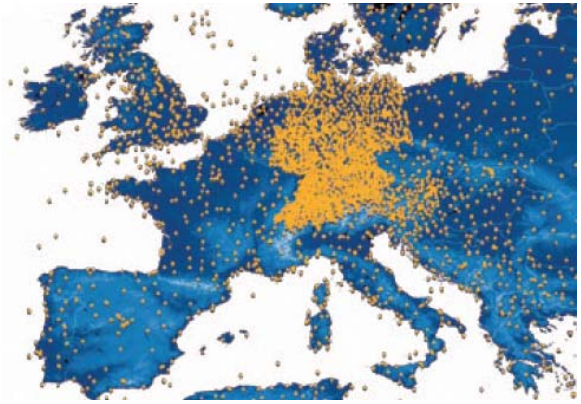
Model Reconciled to Measurements From Distributed Stations

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*



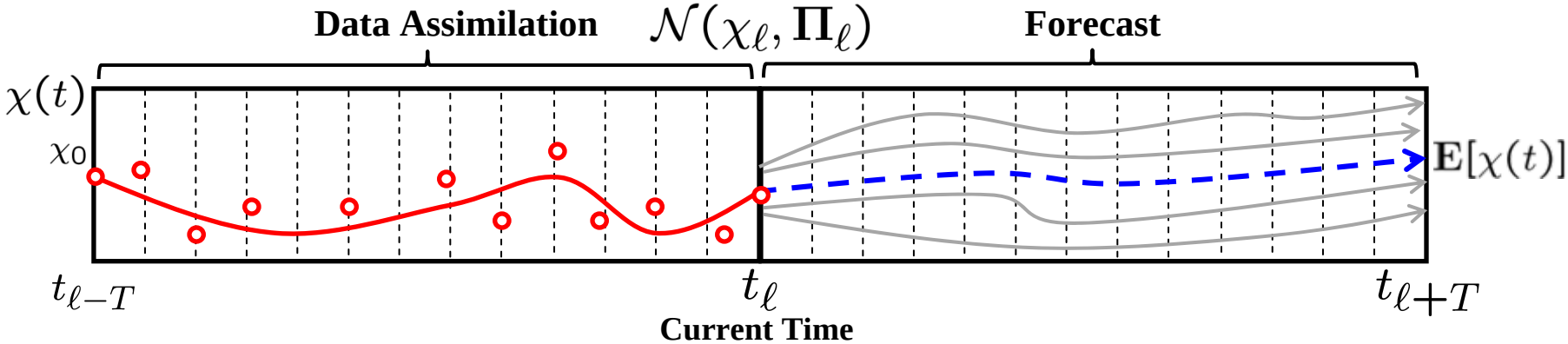
http://www.emc.ncep.noaa.gov/gmb/ens/



http://www.meteomedia.com/

Question: Is WRF Accurate and Computationally Practical Enough for Grid Operations?

Uncertainty Quantification with WRF



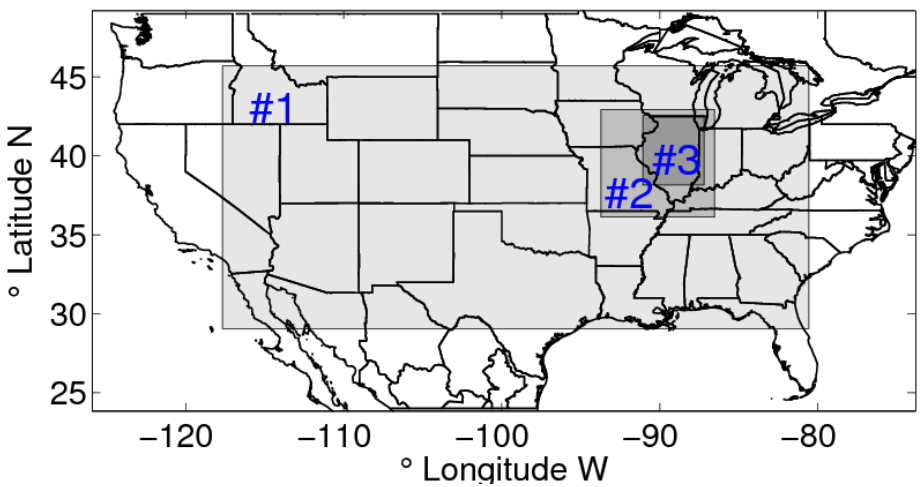
Computing Exact Covariance Matrix is Not Practical:

1) **Create Empirical Distribution of <u>Current</u> Atmospheric State** *Z, Constantinescu & Anitescu, 2009*

2) **Propagate Samples through WRF Model**

Parallelizing Closed-Loop WRF Simulations:

- **Need for Targeted Resolutions**



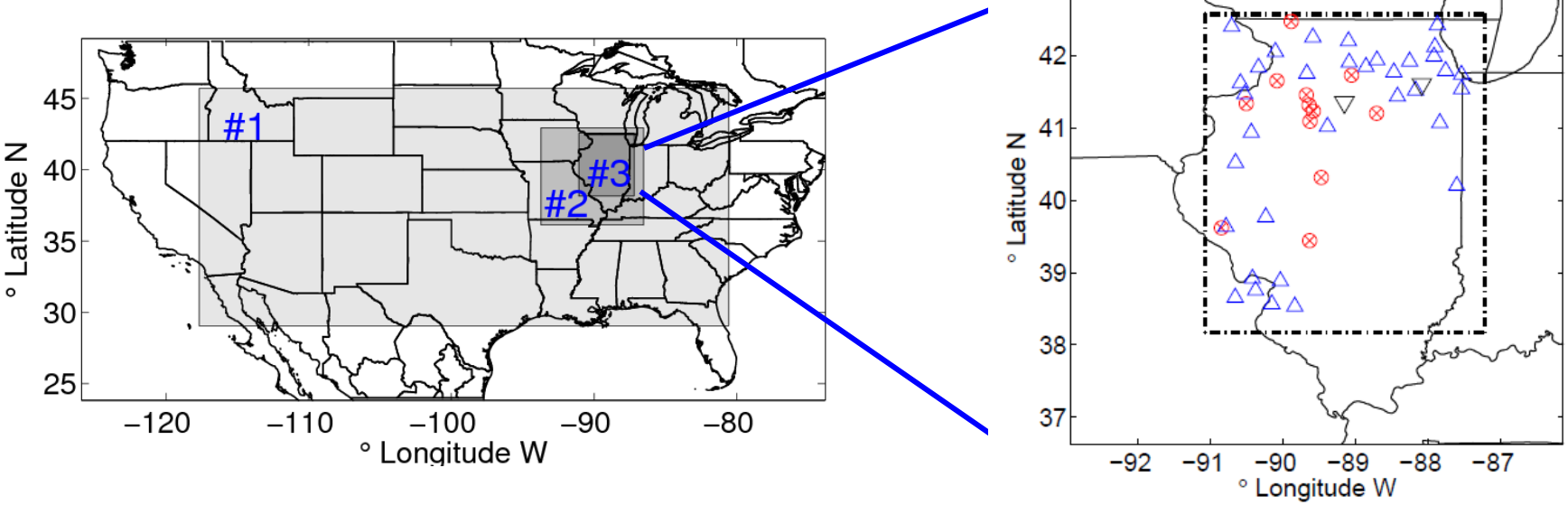
ID	Size	Grid
#1	130×60	$32\,\mathrm{km}^2$
#2	126×121	$6\,\mathrm{km}^2$
#3	202×232	$2\,\mathrm{km}^2$

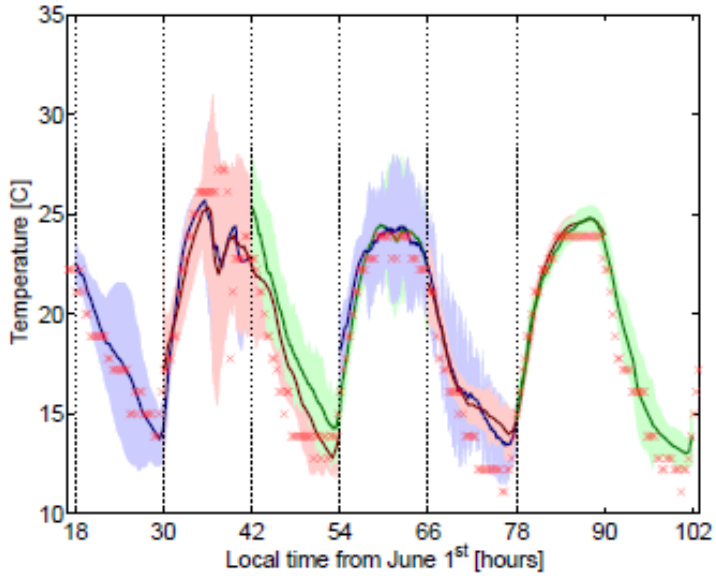
CPUs	Wall-time [hr]
4	50
8	28
16	17
32	10

Jazz Cluster @ MCS

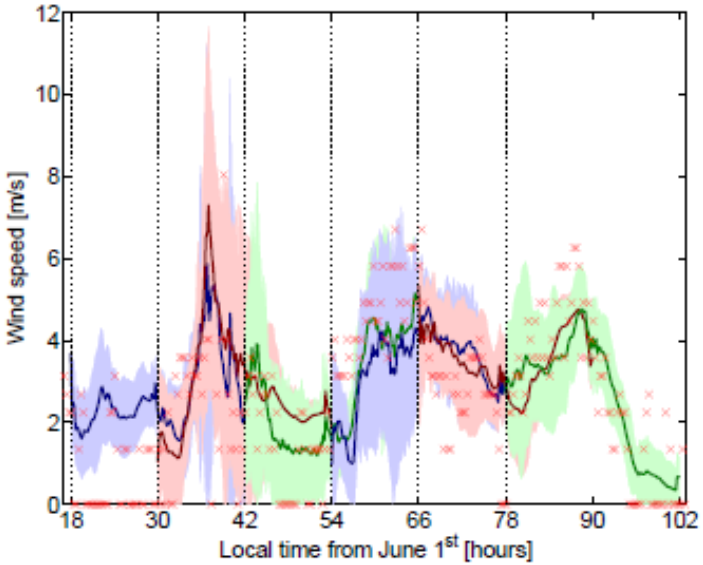
Uncertainty Quantification with WRF

Validation Results (Illinois, 2006) with NOAA Data





Temperature [°C]

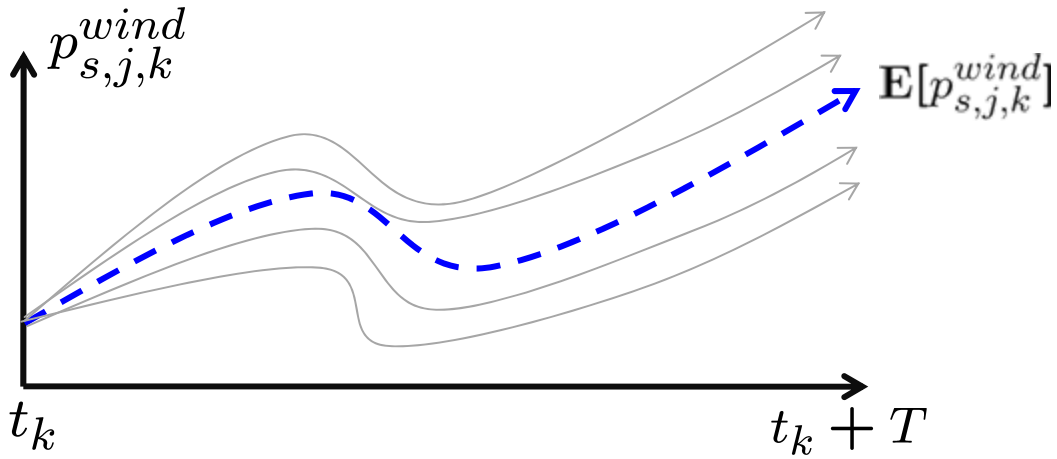


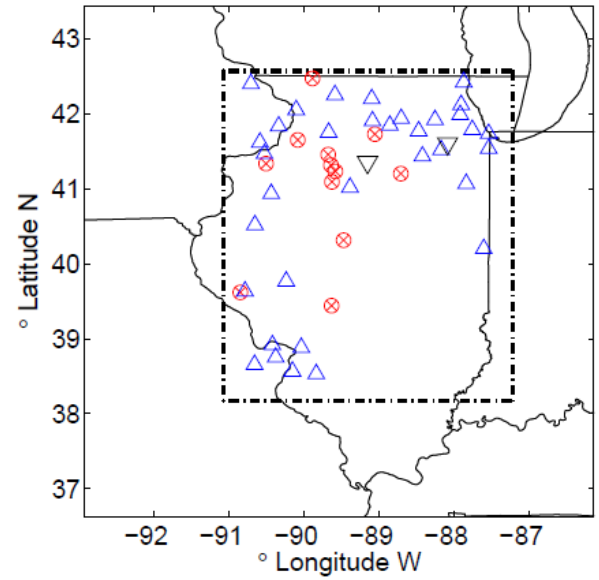
Wind Speed [m/s]

2. Unit Commitment and Energy Dispatch

Unit Commitment-Energy Dispatch

Unit Commitment & Energy Dispatch with Uncertain Wind Power Generation





$$\min_{p_{s,j,k},\overline{p}_{s,j,k},\nu_{j,k}} \varphi(p^{wind}_{s,j,k}) := \frac{1}{N_S}\sum_{s\in\mathcal{S}}\left(\sum_{j\in\mathcal{N}}\sum_{k\in\mathcal{T}} c^p_{s,j,k} + c^u_{j,k} + c^d_{j,k}\right)$$

$$\text{s.t.} \sum_{j\in\mathcal{N}} p_{s,j,k} + \sum_{j\in\mathcal{N}_{wind}} p^{wind}_{s,j,k} = D_k,\ s\in\mathcal{S}, k\in\mathcal{T}$$

$$\sum_{j\in\mathcal{N}} \overline{p}_{s,j,k} + \sum_{j\in\mathcal{N}_{wind}} p^{wind}_{s,j,k} \geq D_k + R_k,\ s\in\mathcal{S}, k\in\mathcal{T}$$

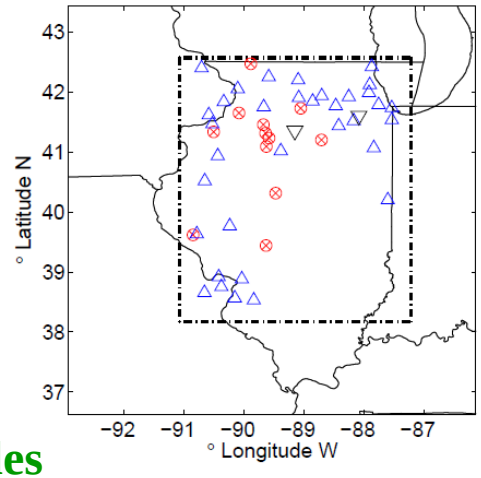
Determine Cost-Optimal On/Off and Power Profiles for Set of Generators

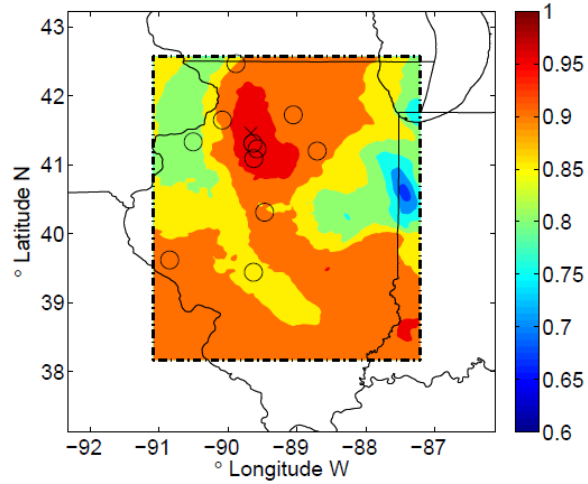
- **Consider Dynamics of Start-Up, Shutdown, and Set-Point Changes**
- **Computationally Intensive Optimization Problem**

Integrative Closed-Loop Study

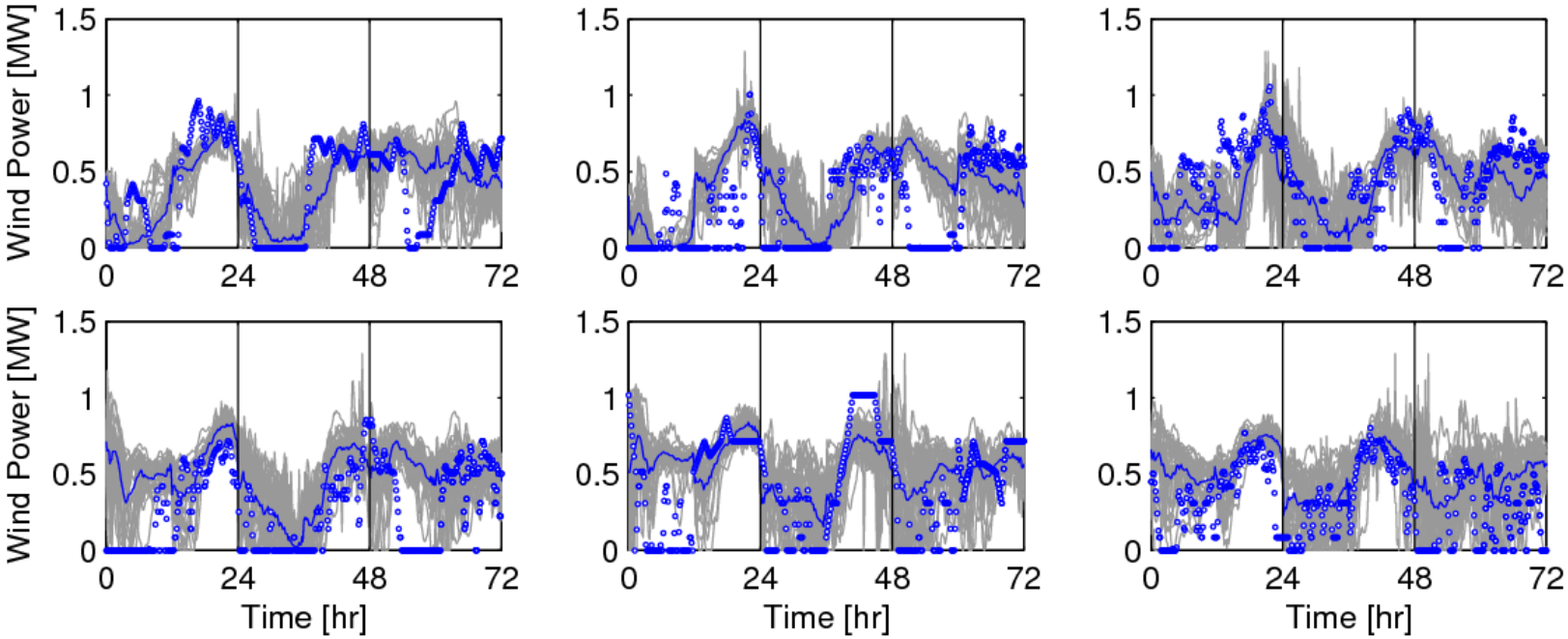
Analyze Effects of Large Adoption Levels of Wind Power

- Commitment /Dispatch with WRF for 3 Days of Operation (Adoption Level 20%)





Wind Power Profiles

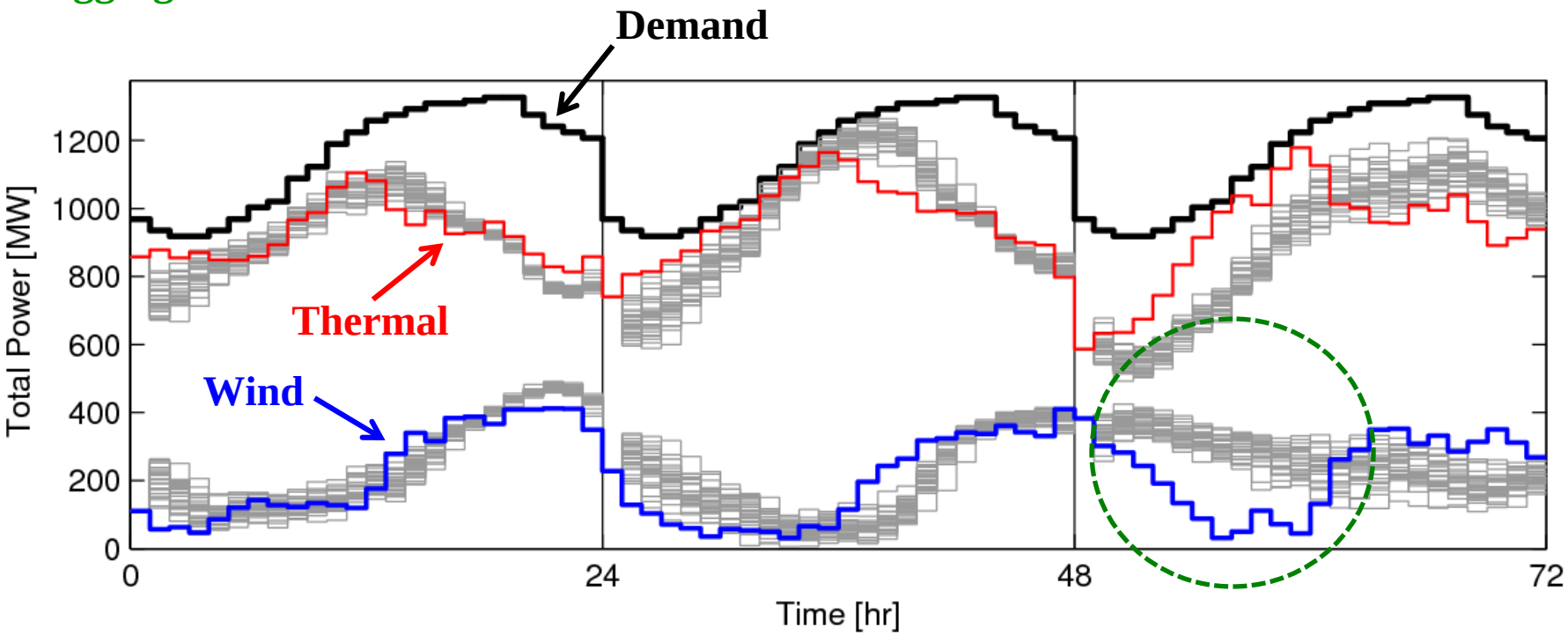


Integrative Closed-Loop Study

Analyze Effects of Large Adoption Levels of Wind Power

- Commitment /Dispatch with WRF for 3 Days of Operation (Adoption Level 20%)

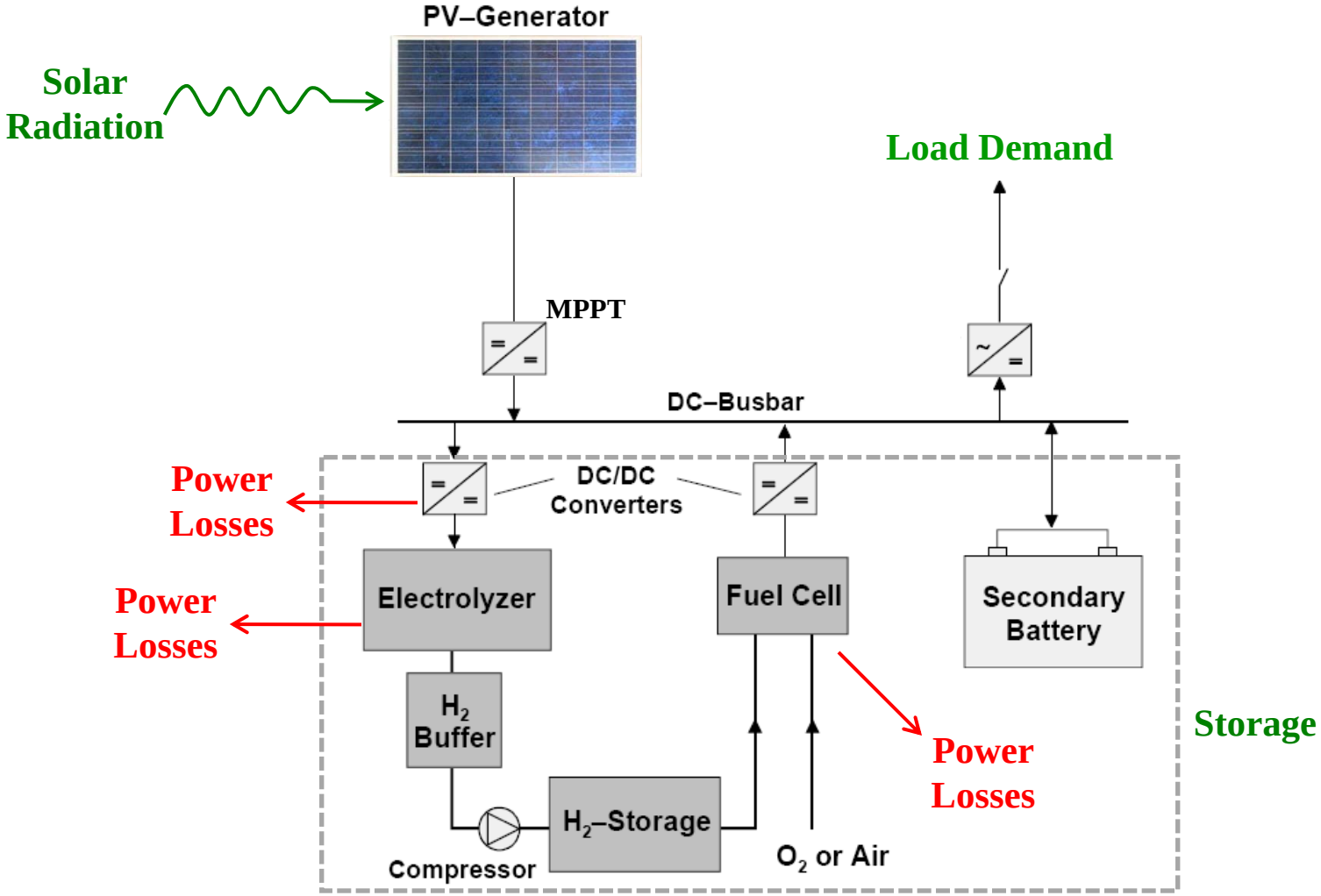
Aggregated Power Profiles



- WRF In General Accurate, Tight Uncertainty Bounds, But Excursions Do Occur
- Hypothesis: Need to Tailor Data Assimilation Step

2. Production Level

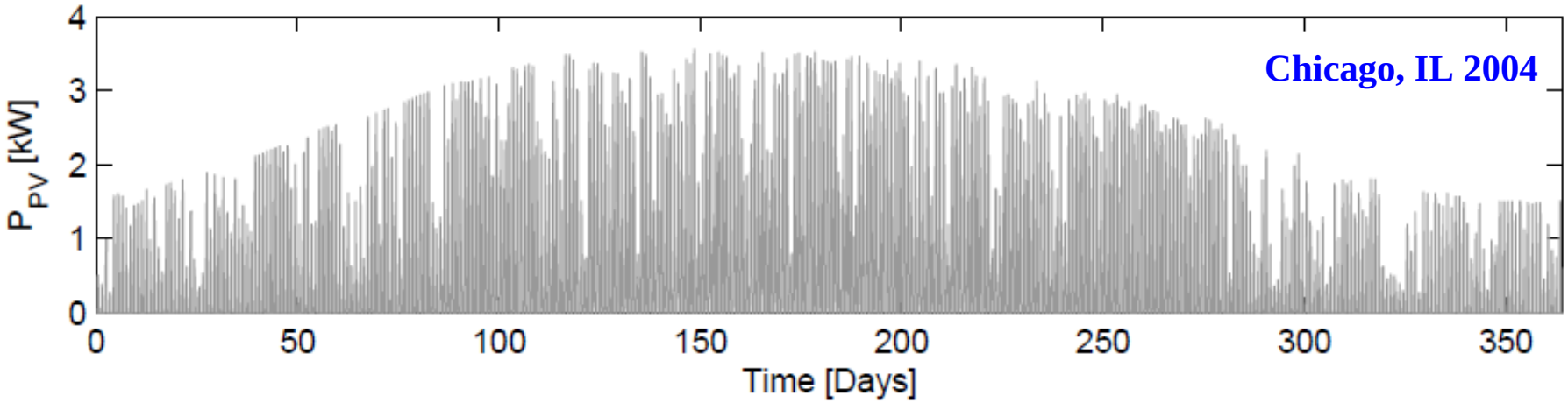
Hybrid Photovoltaic-H_2 System



- **Candidate for Decentralized Power Generation (Buildings, Home)**
- **Operating Costs Driven by <u>Uncertain</u> Radiation** *Ulleberg, 2004*
- **Performance Deteriorated by Multiple <u>Power Losses</u>**

Hybrid Photovoltaic-H_2 System

Effect of Forecast on Economics *Z. Krause & Anitescu, 2009*



Radiation Forecast

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

Minimize Power Losses

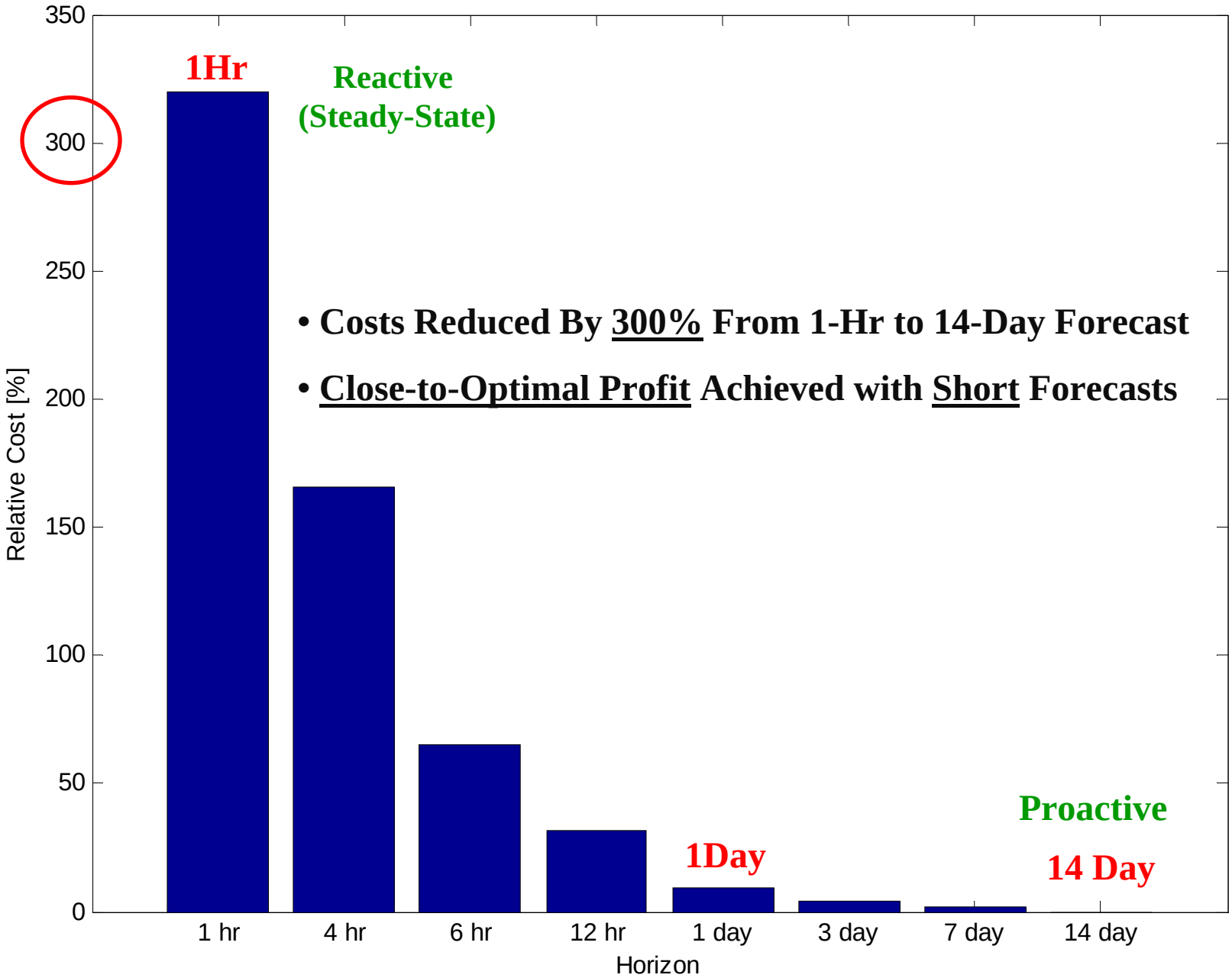
$$\begin{aligned} \frac{dz}{dt} &= \mathbf{f}(z(t), y(t), u(t), \chi(t)) \\ 0 &= \mathbf{g}(z(t), y(t), u(t), \chi(t)) \\ 0 &\geq \mathbf{h}(z(t), y(t), u(t), \chi(t)) \\ z(0) &= x_\ell \end{aligned}$$

Power Balances

State-of-Charge, Fuel Cell and Electrolyzer Limits

- **Forecast Horizon of <u>One Year</u> – Minimum Cost**
- **Receding-Horizon with <u>1hr, 1 Day, …,14 Days</u> Forecast - 8,700 Problems per Year**

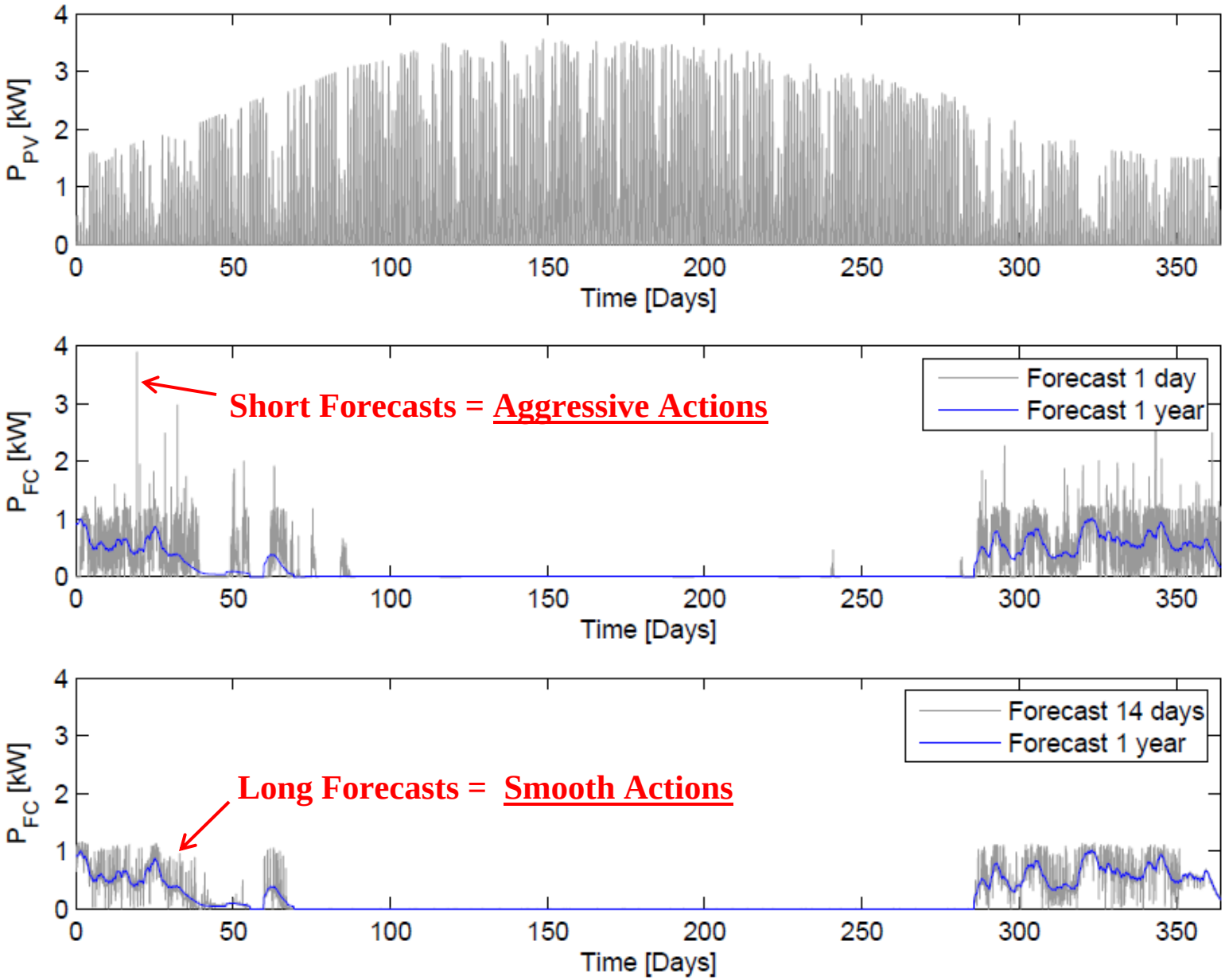
Hybrid Photovoltaic-H_2 System



- Costs Reduced By 300% From 1-Hr to 14-Day Forecast
- Close-to-Optimal Profit Achieved with Short Forecasts

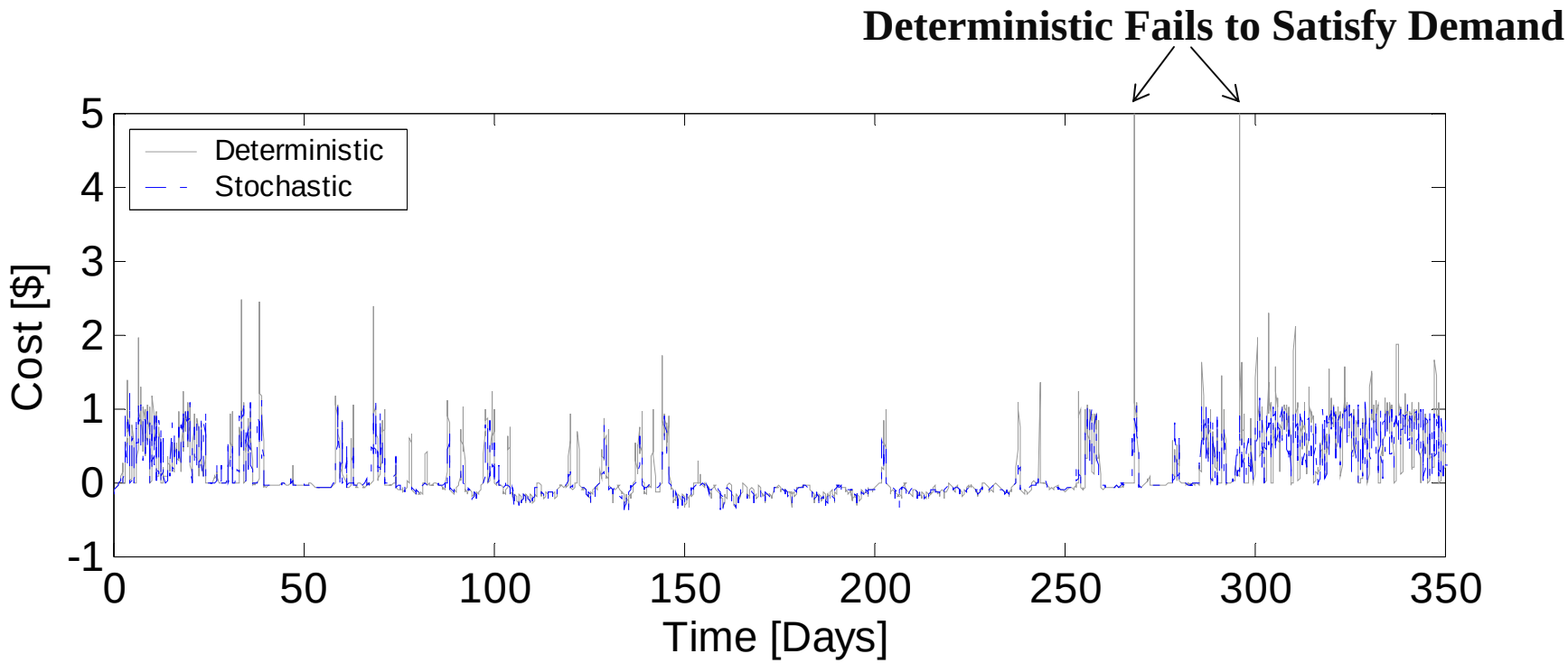
Hybrid Photovoltaic-H_2 System

Profiles of Fuel Cell Power



Hybrid Photovoltaic-H_2 System

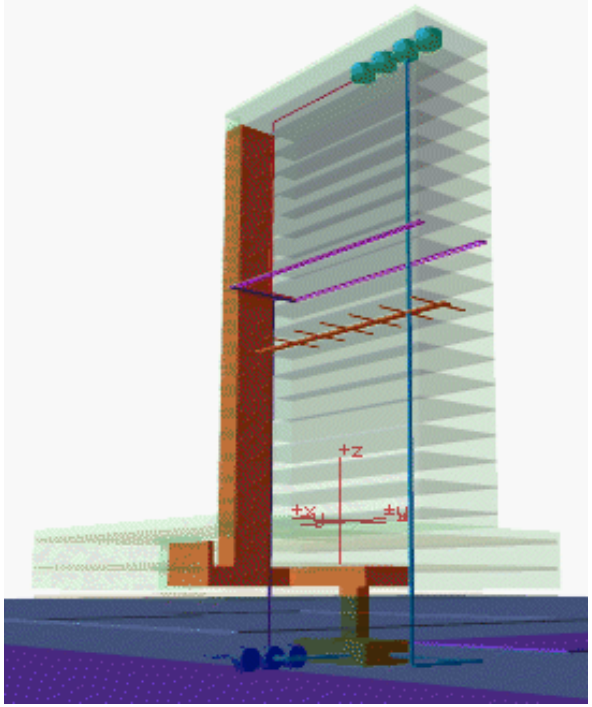
Load Satisfaction Deterministic vs. Stochastic



Incorporating Uncertainty Information is Critical for Robust Demand Satisfaction

3. Consumer Level

Thermal Management of Building Systems



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

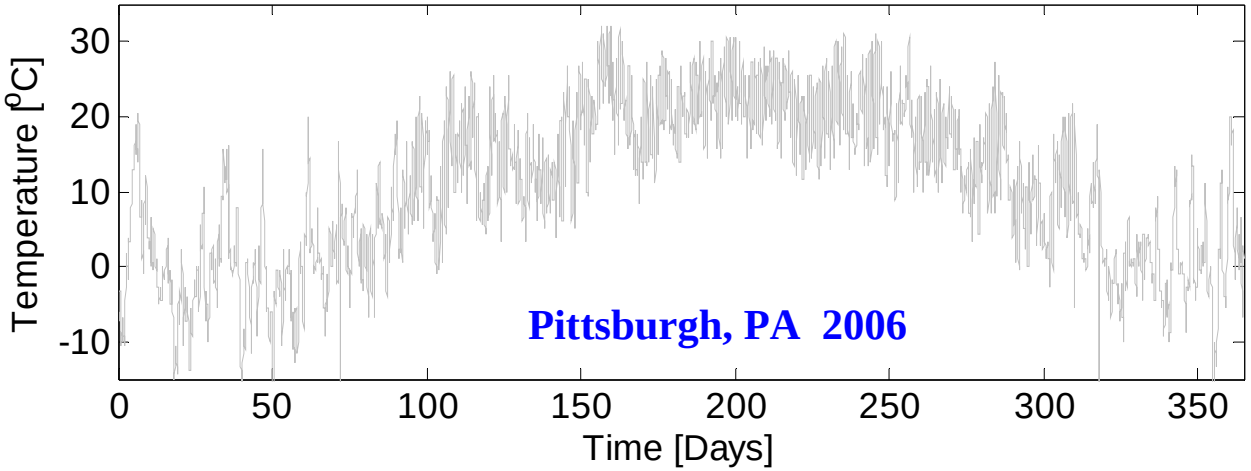
Minimize Annual Heating and Cooling Costs

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

$$\begin{aligned}
C_I \cdot \frac{\partial T_I}{\partial \tau} &= \varphi_h(\tau) - \varphi_c(\tau) - S \cdot \alpha' \cdot (T_I(\tau) - T_W(\tau, 0)) \\
\frac{\partial T_W}{\partial \tau} &= \beta \cdot \frac{\partial^2 T_W}{\partial x^2} \\
\alpha' \left(T_I(\tau) - T_W(\tau, 0)\right) &= -\mathbf{k} \cdot \left.\frac{\partial T_W}{\partial x}\right|_{(\tau,0)} \\
\alpha'' \left(T_W(\tau, L) - T_A(\tau)\right) &= -\mathbf{k} \cdot \left.\frac{\partial T_W}{\partial x}\right|_{(\tau,L)} \\
T_I(0) &= T_I^\ell \\
T_W(0, x) &= T_W^\ell(x)
\end{aligned}$$

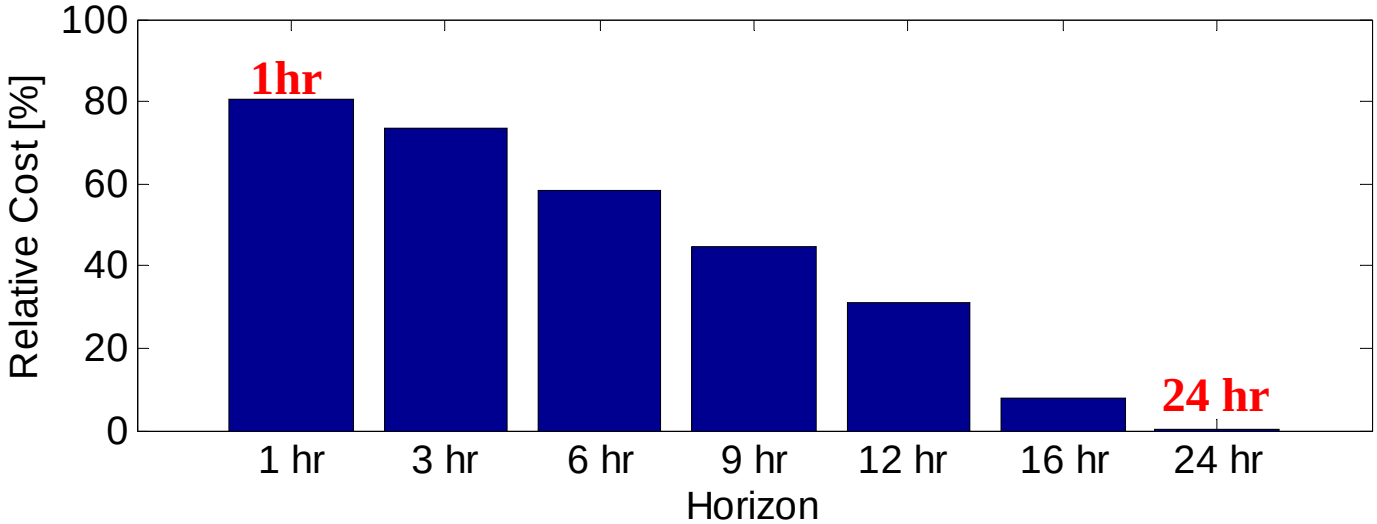
Building Energy Balances

Time-Varying Electricity Prices → Peak & Off-Peak

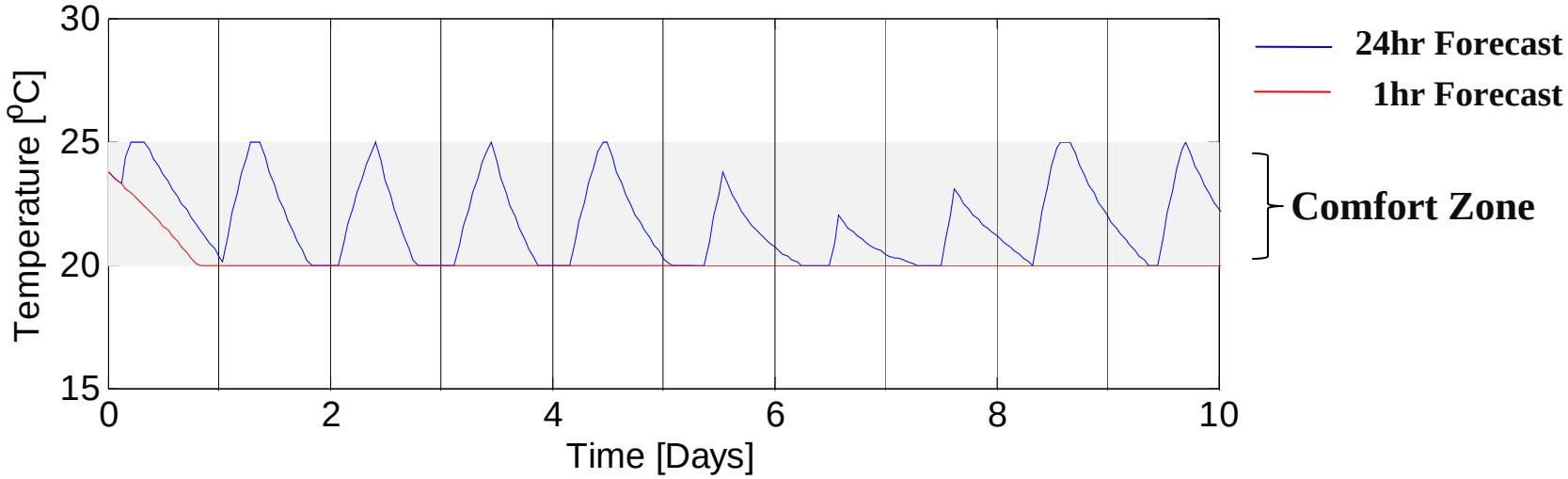


Thermal Management of Building Systems

Effect of Forecast on Energy Costs



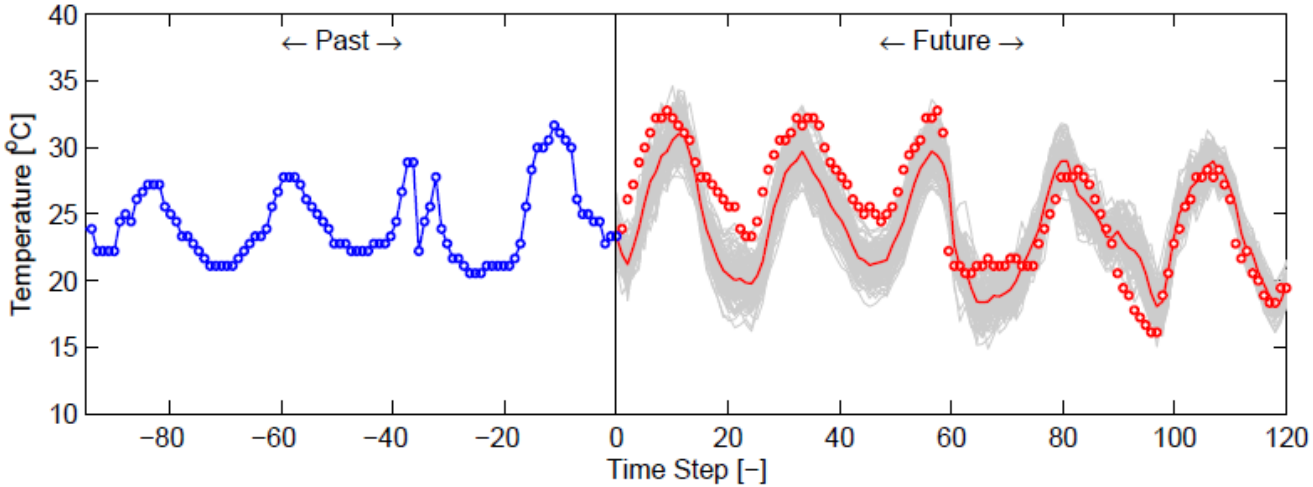
Forecast Leads to 10-40% Cost Reduction (Depends on Insulation Quality)



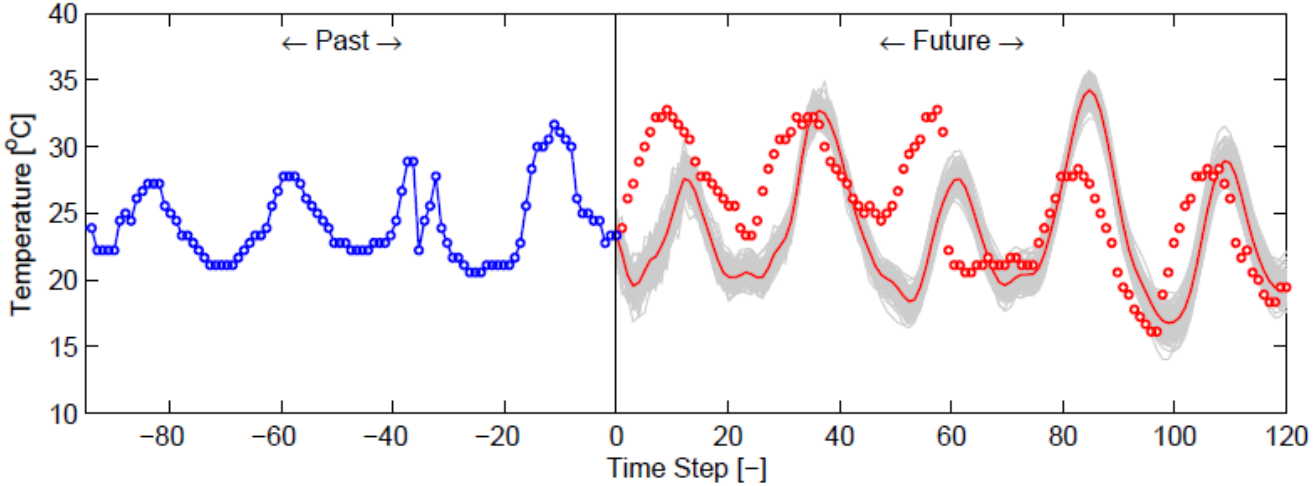
Exploit Comfort Zone and Weather Info to Shift Electricity Demand *Braun, 1990*

Weather Forecasting - Empirical

Empirical Model Validation Results, Pittsburgh Area 2006 *Z, Anitescu, et.al. 2009*



One Hour Ahead

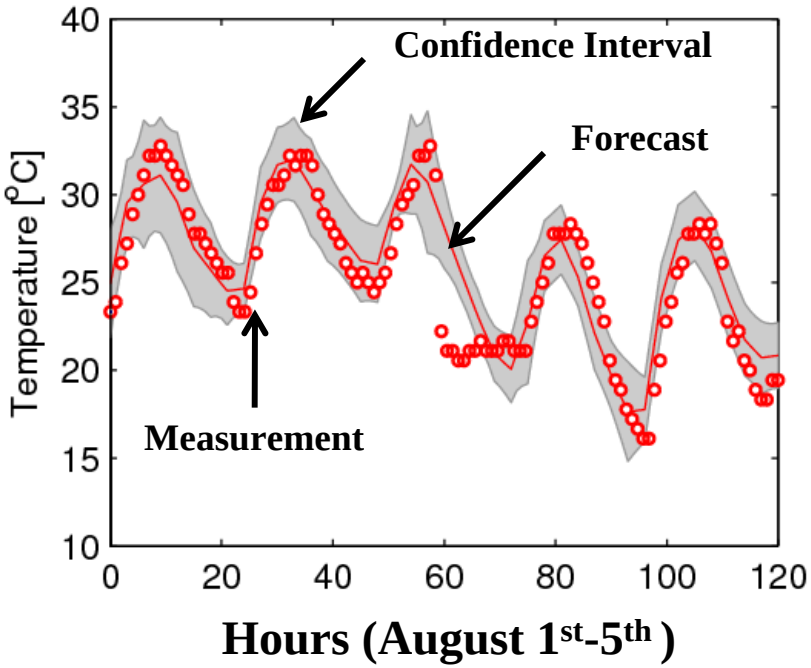


5 Days Ahead

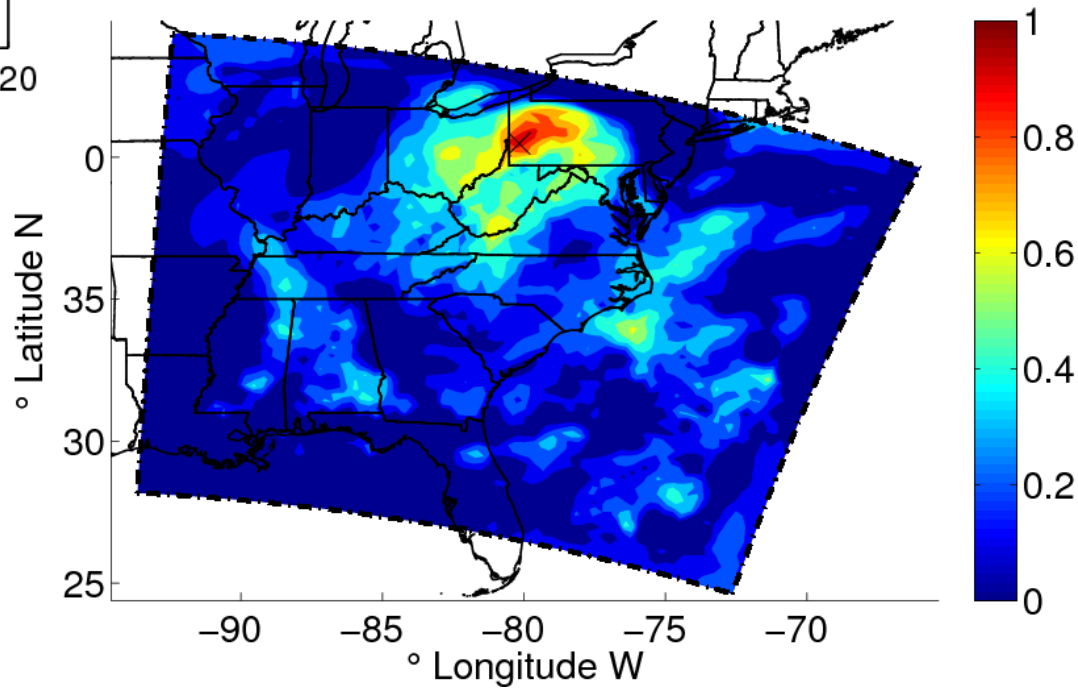
Empirical Model Cannot Capture Weak Periods, Inconsistent Uncertainty Bounds

Weather Forecasting - WRF

WRF Validation Results, Pittsburgh Area 2006 **5 Days Ahead Forecast** *Z, Anitescu, et.al. 2009*

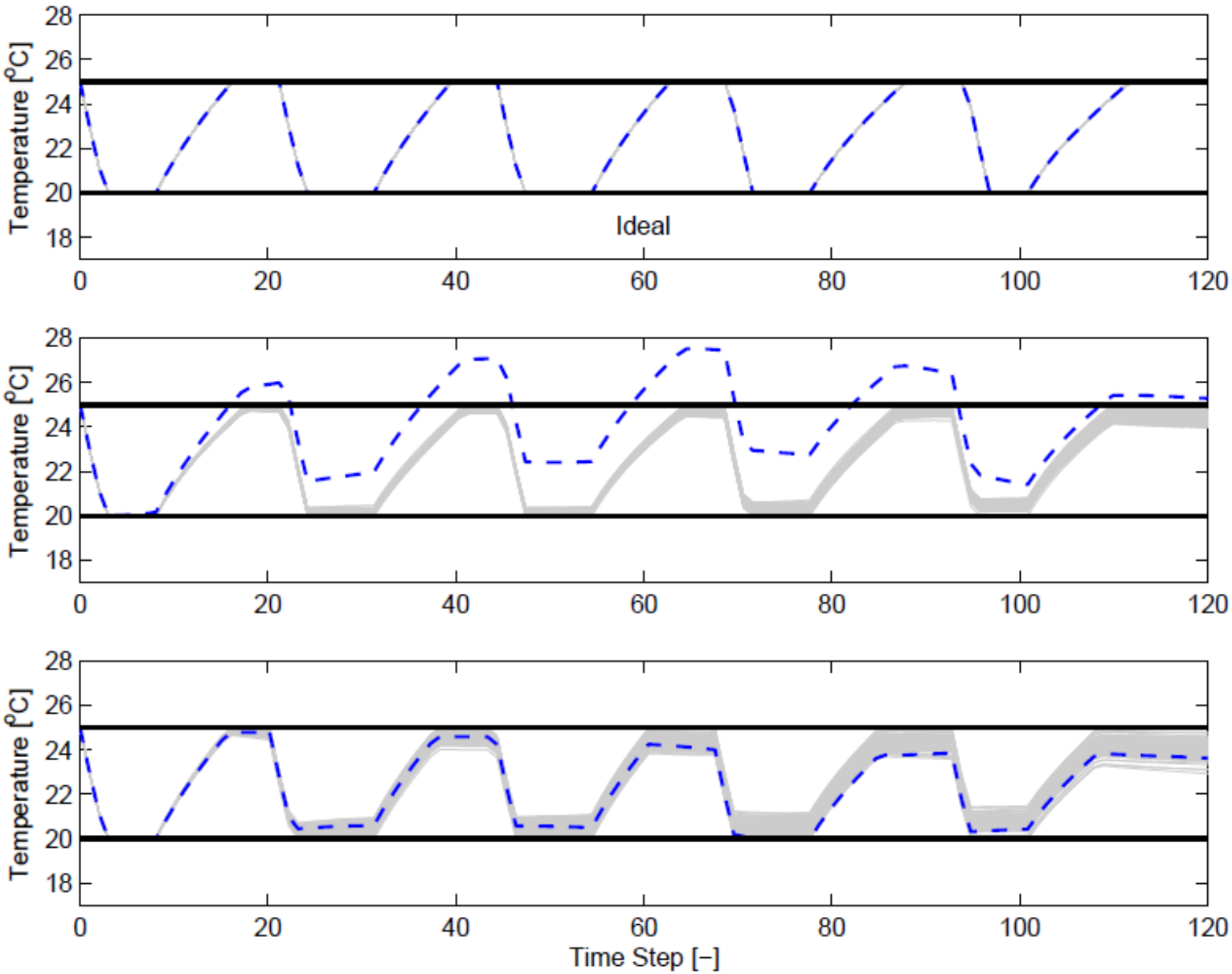


Temperature Correlation Mapping



Thermal Management of Building Systems

Energy Manager Performance with Different Forecast Models



Perfect Forecast

Empirical Model

WRF

4. Conclusions and Future Work

Conclusions and Open Issues

Next-Generation Power Grid

- Highly Accurate and Distributed Weather Forecasts

Framework for Integration of Weather Forecasting in Power Grid Operations

- Tighter and Consistent Uncertainty Bounds for Lower Costs and Robustness

Exploit Advances in Weather Prediction Models

- Predictive Capabilities Astonishing - Temperature, Wind Speed, Radiation

Open Issues

- Integration of Hierarchical Levels in Power Grid (Market Interactions)
- Mapping WRF Forecasts to High Resolutions
- Forecast of Distributed Demands and Transmission Effects

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