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... for a brighter future

Weather Forecast-Based Optimization of Integrated Energy Systems

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INFORMS San Diego, 2009

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Outline

Objective: **Integrative Study of Weather Forecast-Based Optimization**

Questions: 1: Can I do a good job in modeling weather uncertainty?

2: Is it worth it (economically)?

Research Problem

- **Interaction Weather Conditions - Operations**

On-Line Stochastic Optimization

- **Need for Consistent Uncertainty Information**

Uncertainty Quantification

- **Time-Series vs. Physics-Based Models**

Case Studies

- **Photovoltaic-H_2, Building Thermal Control**

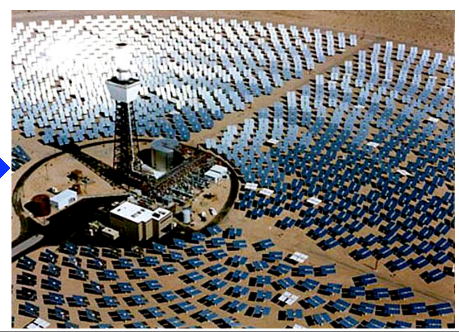
Conclusions and Future Work

Research Problem

Research Problem—Why?

- **Operation of 90% of Energy Systems is Affected by Ambient Conditions**
  - **Power Grid Management:** **Predict Demands** *(Douglas, et.al. 1999)*
  - **Power Plants:** **Production Levels** *(General Electric)*
  - **Petrochemical:** **Heating and Cooling Utilities** *(ExxonMobil)*
  - **Buildings:** **Heating and Cooling Needs** *(Braun, et.al. 2004)*
  - **Next Generation:** **Wind + Solar + Fossil** *(Beyer, et.al. 1999)*
- **Efficiency (Waste) Becoming a Major Concern: Focus on management, not only design**

Benefits of Anticipating Weather Conditions?

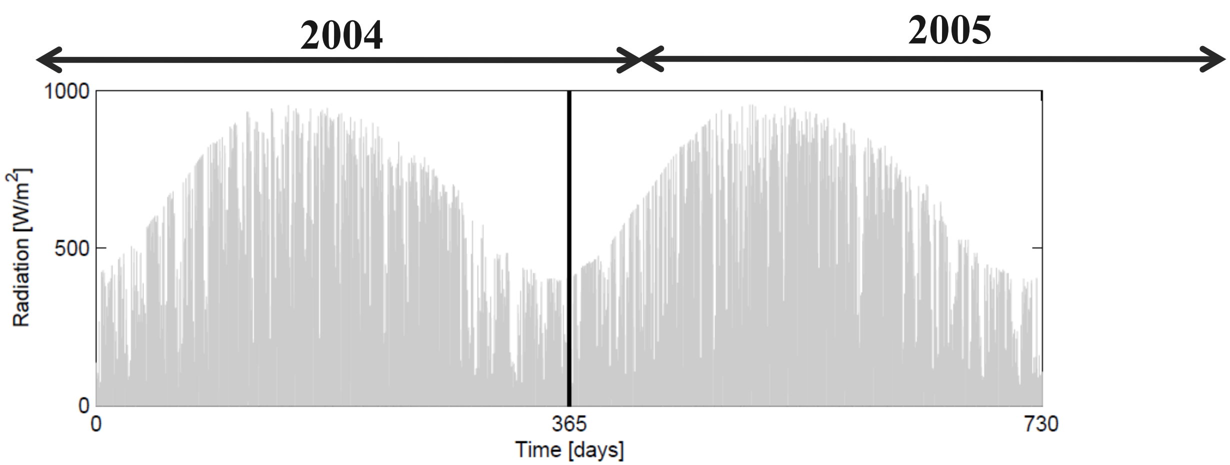


Research Problem

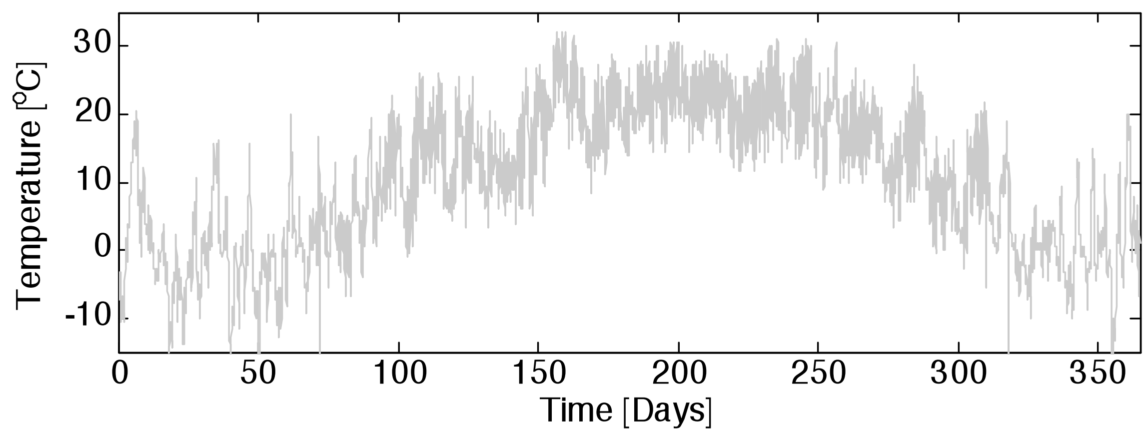
Weather Conditions (Temperature, Radiation, Wind Speed, Humidity …)

- Complex Physico-Chemical Phenomena, Spatio-Temporal Interactions
- Inherently Periodic (Day-Night, Seasonal)

Total Ground Solar Radiation
Chicago, IL



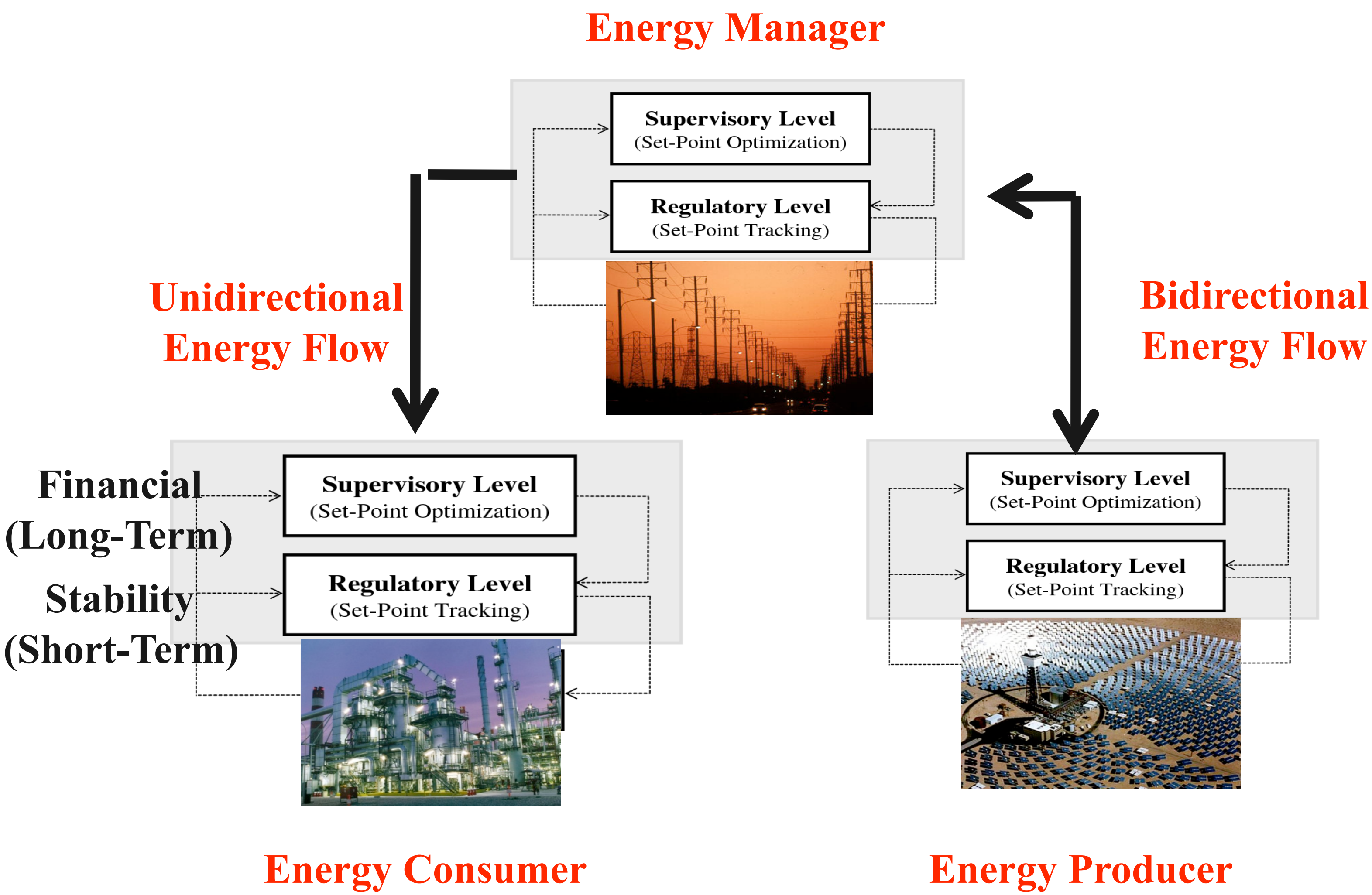
Ambient Dry-Bulb Temperature
Pittsburgh, PA



How to Handle Uncertainty?

On-Line Stochastic Optimization

Hierarchical Operations



Optimization Traditionally Reactive, Uncertainty Handling Non-Systematic

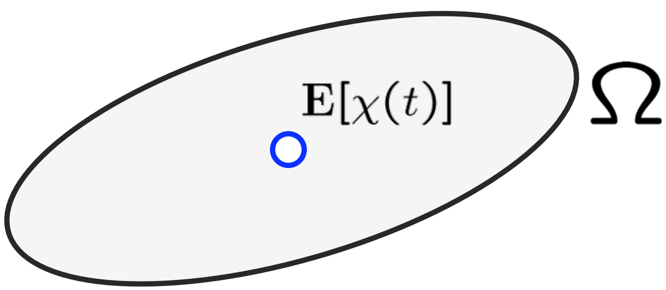
Receding Horizon Optimization

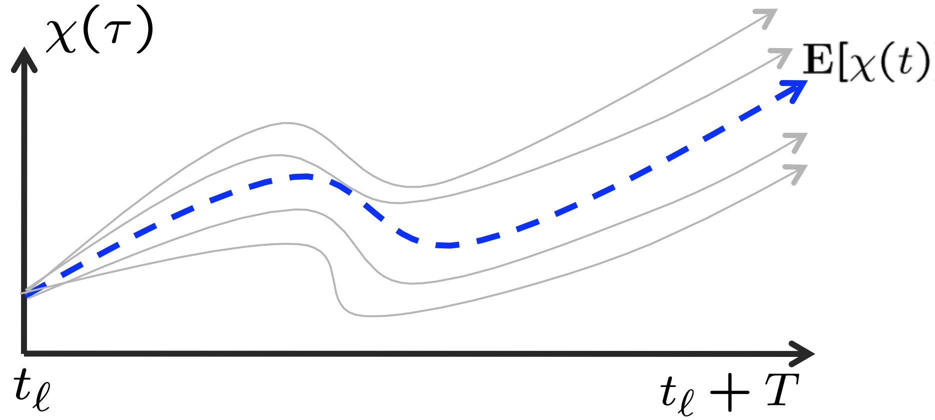
Benefits: Accommodate Forecasts, Constraint Handling, Financial Objectives, Complex Models

Deterministic

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

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





Stochastic

$$\min_{u(t)} \mathop{\mathbf{E}}_{\chi(t)\in\Omega} \left[\int_{t_\ell}^{t_{\ell+N}} \varphi(z(t), y(t), u(t), \chi(t))dt\right]$$

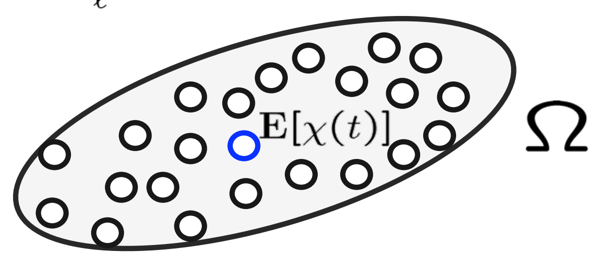
$$\left.\begin{aligned}
\frac{dz}{dt} &= \mathbf{f}(z(t), y(t), u(t), \chi(t)) \\
0 &= \mathbf{g}(z(t), y(t), u(t), \chi(t)) \\
0 &\geq \mathbf{h}(z(t), y(t), u(t), \chi(t))
\end{aligned}\right\} \quad \forall \chi(t) \in \Omega$$

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

Complexity (Solution Time)

1,000 – 10,000 Differential-Algebraic Equations

100-1000 Scenarios



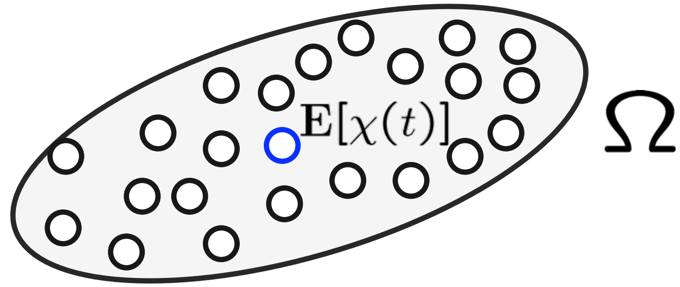
Stochastic Dynamic Optimization

Solution Strategies

- **Dynamic Programming, Taylor Series:** Handling Constraints and Nonlinearity Cumbersome
- **Polynomial Chaos:** Dense Optimization, Multivariable Quadrature
- **Sample Average Approximation (SAA):** Sparse Optimization, Constraints, General Framework

$$\min_{u(t)} \quad \mathbf{E}_{\chi(t)\in\Omega}\left[\int_{t_\ell}^{t_{\ell+N}} \varphi(z(t),y(t),u(t),\chi(t))dt\right]$$

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

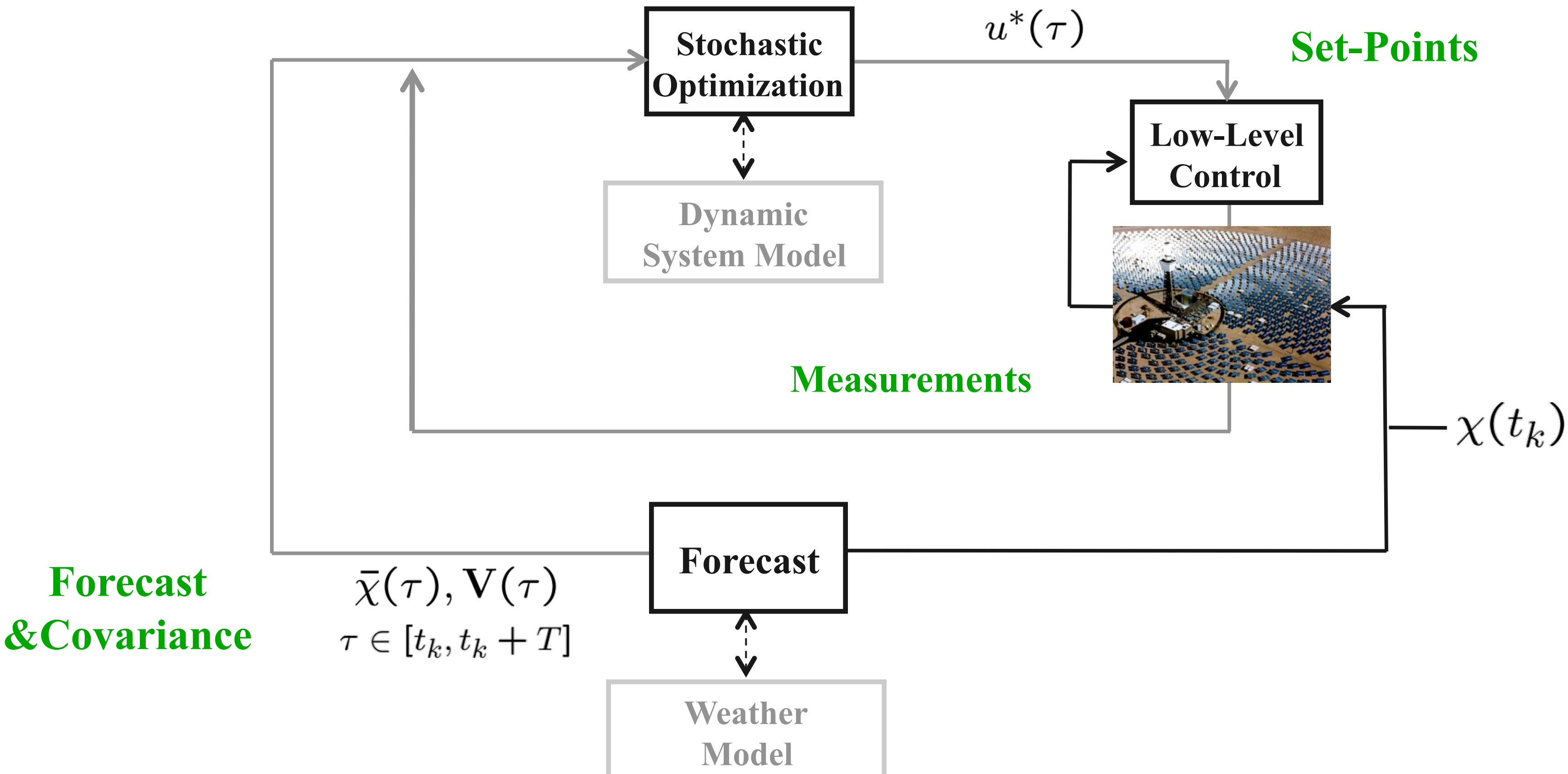


Nonlinear Programming: Exploit Fine and Coarse Structures at Linear Algebra Level

$$\begin{aligned}\min_{\mathbf{u}} \quad & \frac{1}{S}\sum_{k=1}^{S}\varphi(z_k,y_k,\mathbf{u},\chi_k)\\ \text{s.t.} \quad & \mathbf{c}(z_k,y_k,\mathbf{u},\chi_k)=0\\ & \mathbf{h}(z_k,y_k,\mathbf{u},\chi_k)\leq 0\\ & k=1,...,S\end{aligned}$$

$$\begin{bmatrix}\mathbf{K}_1 & & & & Q_1\\ & \mathbf{K}_2 & & & Q_2\\ & & \ddots & & \vdots\\ & & & \mathbf{K}_S & Q_S\\ Q_1^T & Q_2^T & \dots & Q_S^T & D_{\mathbf{u}}\end{bmatrix}\begin{bmatrix}\Delta s_1\\ \Delta s_2\\ \vdots\\ \Delta s_S\\ \Delta\mathbf{u}\end{bmatrix} = -\begin{bmatrix}r_1\\ r_2\\ \vdots\\ r_S\\ r_{\mathbf{u}}\end{bmatrix}$$

Basic Operational Setting



Quantifying Uncertainty Key Enabler

Digression about the Suitability of Stochastic Programming for Energy Systems w Renewables

SAA Stochastic Programming Approximation.

$$
\begin{aligned}
\min_{\mathbf{u}} \quad & \frac{1}{S}\sum_{k=1}^{S} \varphi(z_k, y_k, \mathbf{u}, \chi_k) \\
\text{s.t.} \quad & \mathbf{c}(z_k, y_k, \mathbf{u}, \chi_k) = 0 \\
& \mathbf{h}(z_k, y_k, \mathbf{u}, \chi_k) \leq 0 \\
& k = 1, \ldots, S
\end{aligned}
$$

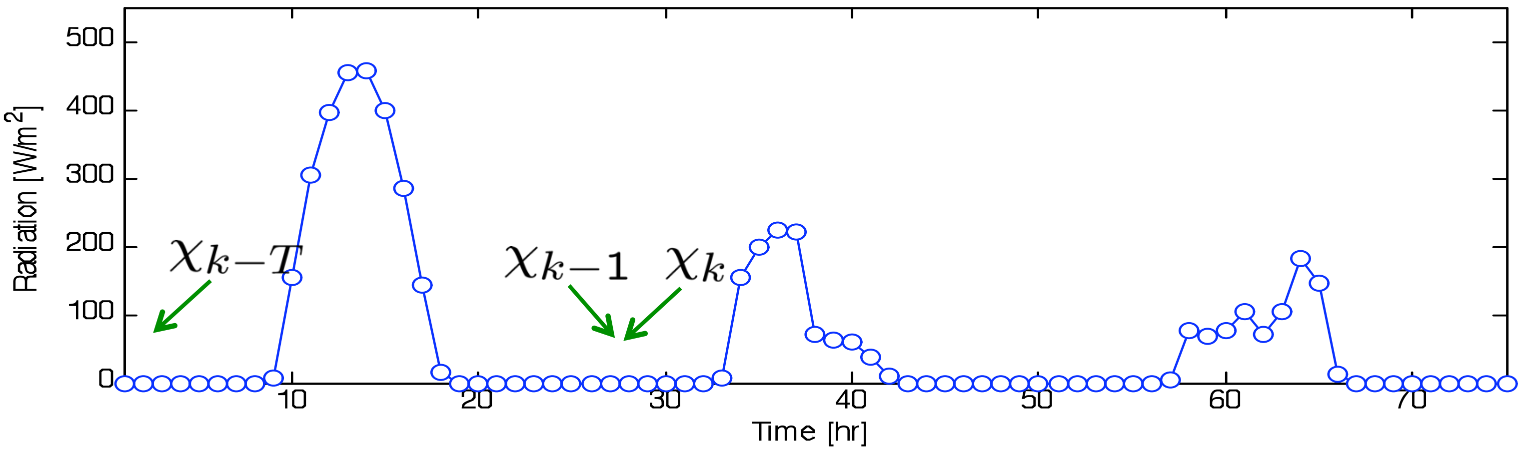
- Stochastic programming is a well-studied paradigm of operations research.
- Nevertheless, one weakness is that it assumes a distribution is given.
- In most applications of interest, the distribution is not given. It has to be modeled from data using some knowledge of the application.
- If the uncertainty originates in weather forecast, there is a strong empirical and theoretical basis to create the distribution, or, at least to sample from it.
- To our knowledge this is the first time even a moderately complex energy system was managed using stochastic programming with real and operational weather uncertainty.

Uncertainty Quantification

Uncertainty Quantification

Quantifying Model Uncertainty (Data-Based (Time-Series) vs. Physics-Based)

Solar Radiation Forecast with Gaussian Process (GP) Modeling *Zavala & A, 2008*



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

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

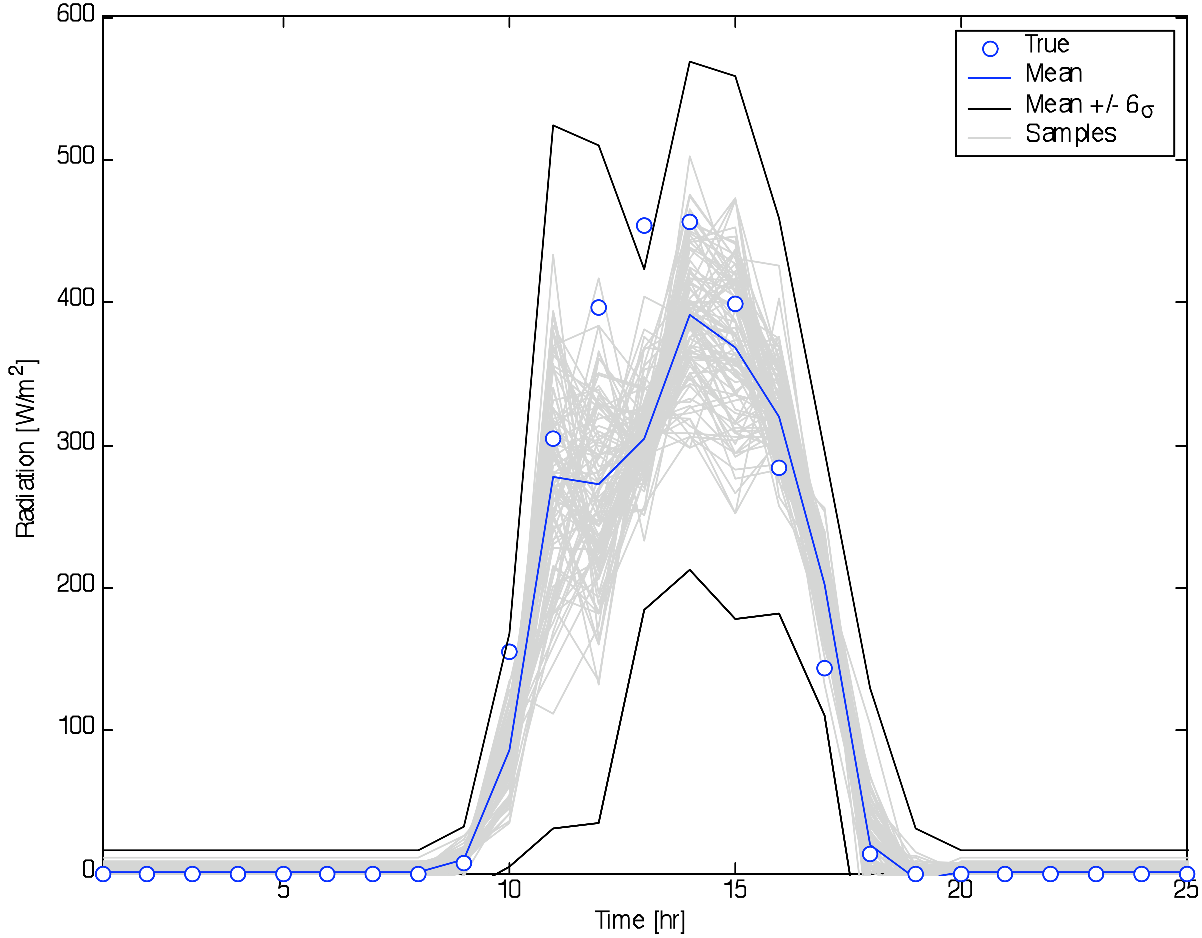
3. Apply Maximum Likelihood: $\log p(\mathbf{Y}|\eta) = -\frac{1}{2}\mathbf{Y}\mathbf{V}^{-1}(\mathbf{X},\mathbf{X},\eta)\mathbf{Y} - \frac{1}{2}\log\det(\mathbf{V}(\mathbf{X},\mathbf{X},\eta))$

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**

Uncertainty Quantification

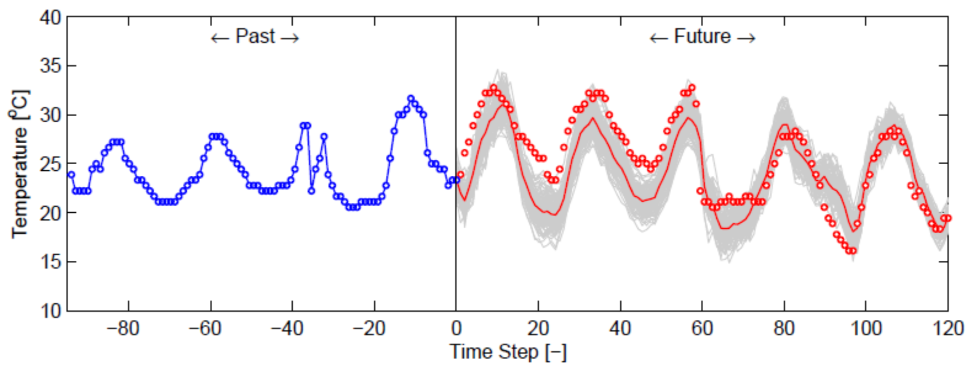
One-Day Ahead Forecast and Samples from Posterior Distribution



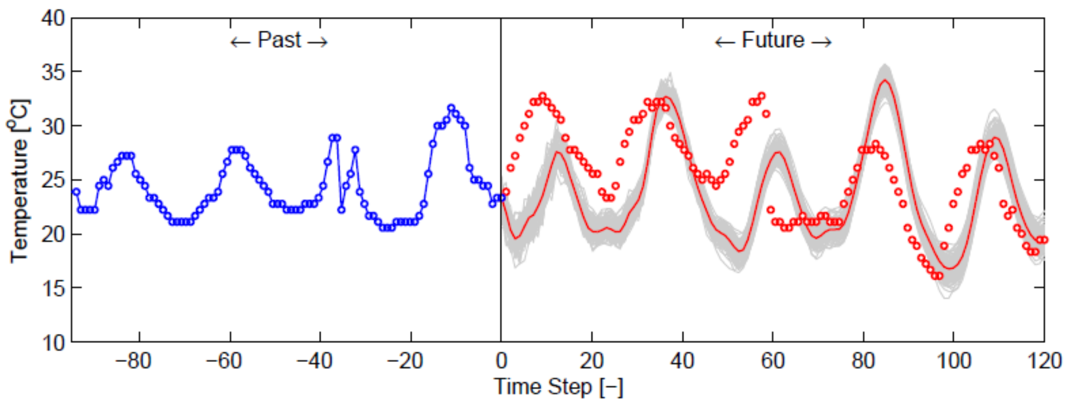
Covariance Structure *Sort of* Makes Physical Sense, Wide Uncertainty Bounds

Uncertainty Quantification

Ambient Temperature Forecast with GP Modeling *Zavala, A, et.al. 2009*



One Hour Ahead



5 Days Ahead

Time-Series Cannot Capture Physical Effects (Spatial), Inconsistent Uncertainty Bounds

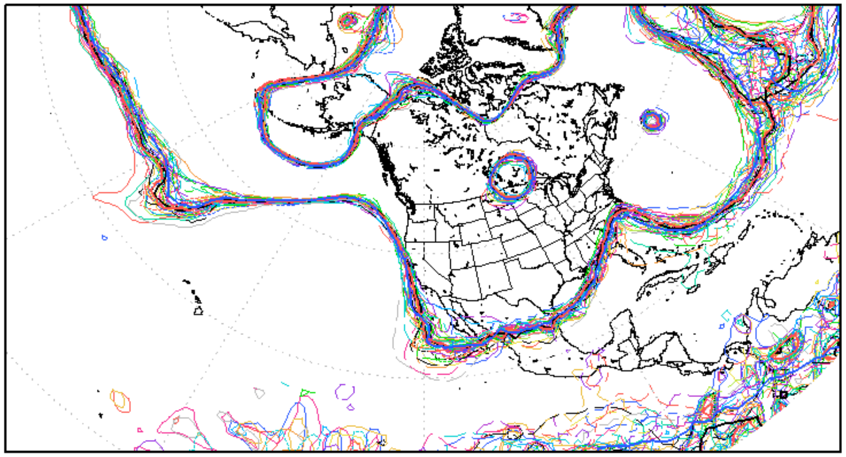
GP (and all data-oriented approaches) Provide Accurate <u>Interpolations</u> but Poor Extrapolations (e.g. Geostatistics)

Uncertainty Quantification

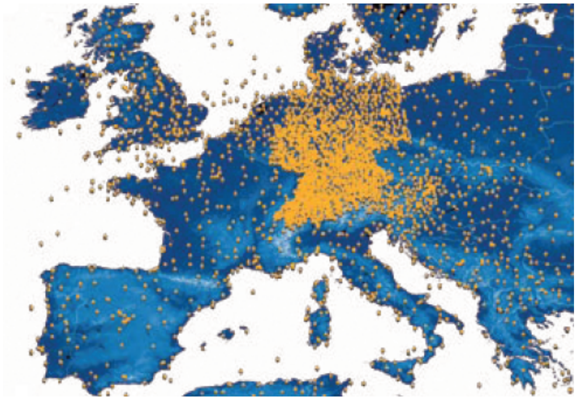
- **Advanced Meteorological Models (WRF)**
    - **Detailed Physico-Chemical Phenomena**
    - **High Complexity 4-D Fields (10^6 States)**

- **Model Reconciled to Measurements From Multiple Stations**

- **Reconciliation Techniques:**
    - **3-D Var** *Courtier, et.al. 1998*
    - **4-D Var (Moving Horizon Estimation)** *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/

Uncertainty in dynamical systems: 1. Data

- Assume a time-discretized process with imperfect initial state and forcing information and noisy measurements.

The dynamic model is depicted as for $k = 0, \cdots, K$

$$\mathbf{x}_k^{in} = M(\mathbf{x}_{k-1}^{in}) + W_k, \quad (1)$$

$$z_k^{obs} = H(\mathbf{x}_k^{in}) + V_k, \quad (2)$$

where

$$W_k \approx N(\bar{\mathbf{x}}_k, Q_k^{-1})$$

and

$$V_k \approx N(\mathbf{0}, R_k^{-1}).$$

We want find $D(\mathbf{x}_0^{in}, \cdots, \mathbf{x}_K^{in})$'s mean and variance.

Uncertainty in dynamical systems: 2. the posterior.

- Under the typical 4D Var assumptions (normality of noise and input) we can write down the posterior …

$$P(x_k^{in}, x_{k-1}^{in}, \cdots, x_0^{in} | z_0^{obs}, z_1^{obs}, z_2^{obs}, \cdots, z_k^{obs}) = C_k \tilde{C}_k \frac{\exp\left(-\frac{1}{2} f(X^{in}, Z^{obs})\right)}{P(Z^{obs})}.$$

$$f(X^{in}, Z^{obs}) = \sum_{i=0}^{k} (x_i^{in} - \bar{x}_i - \tilde{y}(t_{i-1}, x_{i-1}^{in}))^T Q_i^{-1} (x_i^{in} - \bar{x}_i - \tilde{y}(t_{i-1}, x_{i-1}^{in}))$$
$$+ \sum_{i=0}^{k} (z_i^{obs} - h_i(\tilde{y}^{\perp}(t_i, x_i^{in})))^T R_i^{-1} (z_i^{obs} - h_i(\tilde{y}^{\perp}(t_i, x_i^{in})))$$

- A very difficult distribution to sample from.
- Solution: first, find the best estimate of the state.
- Then, approximate the prior covariance by an ergodic/Gaussian Process method.

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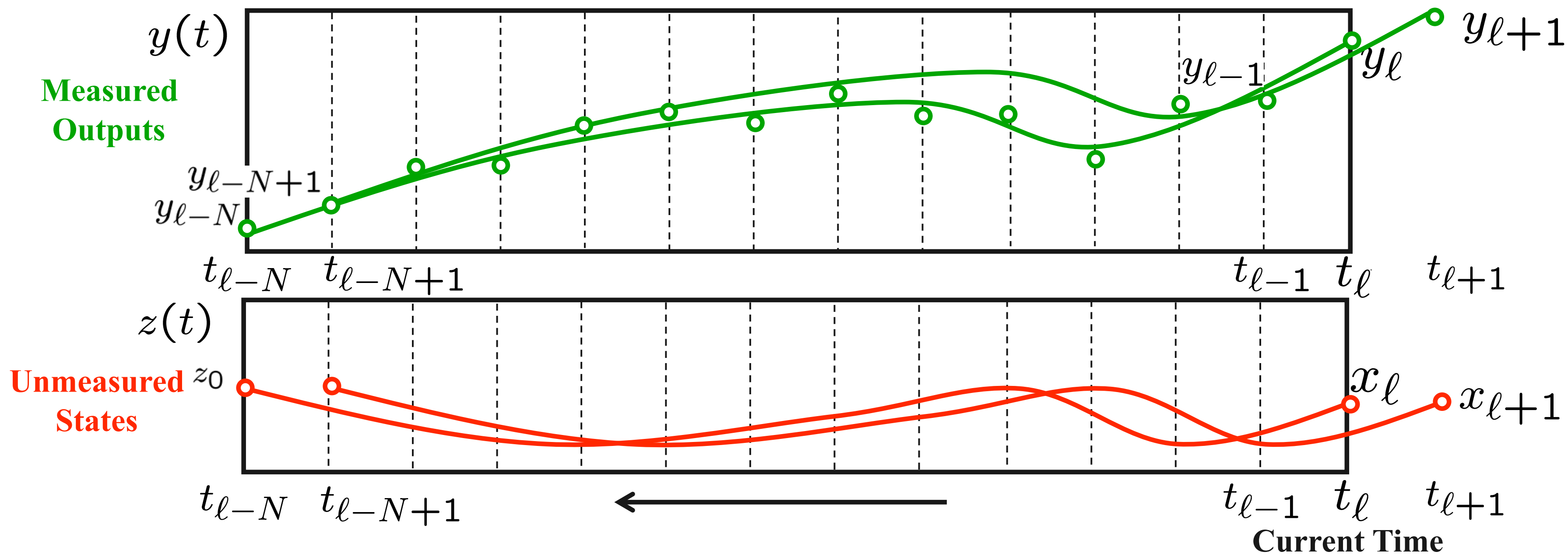
Step 1: Moving Horizon Best State Estimation

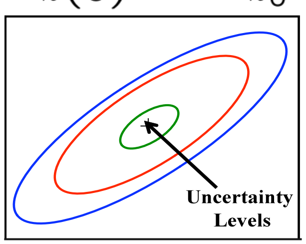


$$\min_{p(t),\,z_0} \sum (y(t_k) - \underline{y_{\ell-k+N}})^T \mathbf{V}_y^{-1} (y(t_k) - y_{\ell-k+N})$$

WRF Model

$$\begin{aligned} \frac{dz}{dt} &= \mathbf{f}\left(z(t), p(t), u(t)\right) \\ y(t) &= \mathbf{g}(z(t), p(t), u(t)) \\ z(0) &= z_0 \end{aligned}$$

Uncertain



$\Pi_\ell \rightarrow 0$

$$\min_{p(t),\,z_0} \sum (y(t_k) - y_{\ell-k+N+1})^T \mathbf{V}_y^{-1} (y(t_k) - y_{\ell-k+N+1})$$

$$\begin{aligned} \frac{dz}{dt} &= \mathbf{f}\left(z(t), p(t), u(t)\right) \\ y(t) &= \mathbf{g}(z(t), p(t), u(t)) \\ z(0) &= z_0 \end{aligned}$$

Uncertainty in Current State x_ℓ ?

Needed To Quantify Future Forecast

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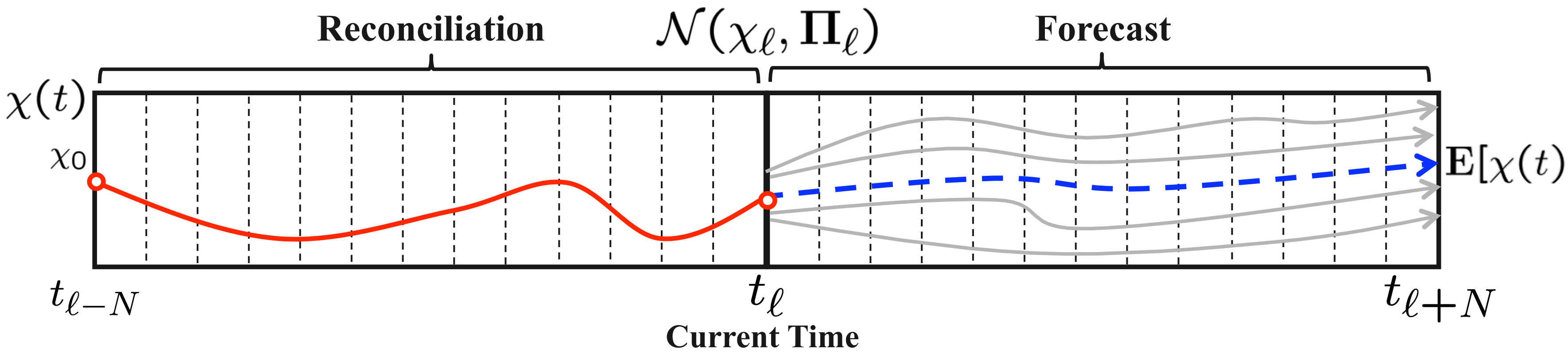
Step 2: Estimate the prior covariance matrix.



•Use some form of an ergodic hyptohesis. Take $d_{ij} \in \mathbb{R}^{N\times(2\times 30\text{days})}$,

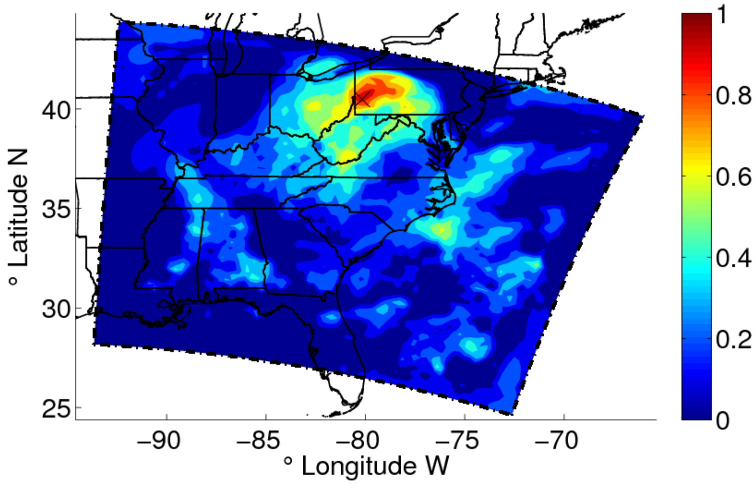
$$\mathbf{V}_{ik} \approx \mathbf{d}\mathbf{d}^{\mathbf{T}} = \sum_j d_{ij} d_{kj}^T = \epsilon_i \cdot \epsilon_k = \left[\begin{array}{c|c|c|c} \epsilon_0 \cdot \epsilon_0 & \epsilon_1 \cdot \epsilon_0 & \cdots & \epsilon_n \cdot \epsilon_0 \\ \epsilon_0 \cdot \epsilon_1 & \epsilon_1 \cdot \epsilon_1 & \cdots & \epsilon_n \cdot \epsilon_1 \\ \cdots & \cdots & \cdots & \cdots \\ \epsilon_0 \cdot \epsilon_n & \epsilon_1 \cdot \epsilon_n & \cdots & \epsilon_n \cdot \epsilon_n \end{array}\right], \quad \mathbf{C}_{ik} = \frac{\epsilon_i \cdot \epsilon_k}{|\epsilon_i||\epsilon_k|}.$$

•"Guess" the diagonal of the variance matrix

Step 2 b: Fit to a Gaussian Process.

Covariance Matrix is Huge and low rank (10^6 x 10^6) But …

- **Spatial Correlations Decay <u>Exponentially</u>** *Constantinescu, et.al., 2007*
- **Covariance Can be Approximated Using Gaussian Kernels** *Zavala, Constantinescu & A, 2009*



$$\Pi_{:,i,j} = \exp\left(-\frac{(x_j - x_i)^2 + (y_j - y_i)^2}{L_H^2} - \frac{(z_j - z_i)^2}{L_V^2}\right)$$

Ensemble Forecast Approach

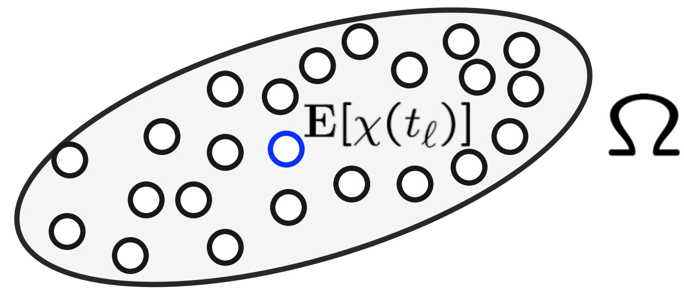
Ensemble Forecast Approach – Use WRF as <u>Black-Box</u>

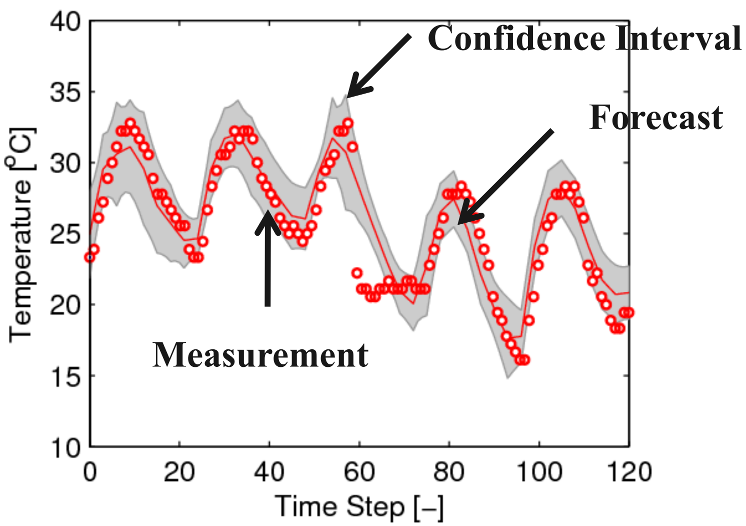
Sample Prior and Propagate Samples of Posterior Through Model

$$\mathbf{Y}_{[i,j]} := \chi_i(t_{\ell+j}) = \underbrace{\mathcal{M}(\mathcal{M}(\ldots\mathcal{M}}_{j \text{ times}}(\chi_i(t_\ell))))$$

$$\mathbf{E}[\mathbf{Y}] \approx \bar{\mathbf{Y}} := \frac{1}{NS}\sum_{i=1}^{NS}\mathbf{Y}_{[i,:]}$$

$$\mathbf{V} \approx \frac{1}{NS-1}\sum_{i=1}^{NS}(\mathbf{Y}_{[i,:]}-\bar{\mathbf{Y}})(\mathbf{Y}_{[i,:]}-\bar{\mathbf{Y}})^T$$





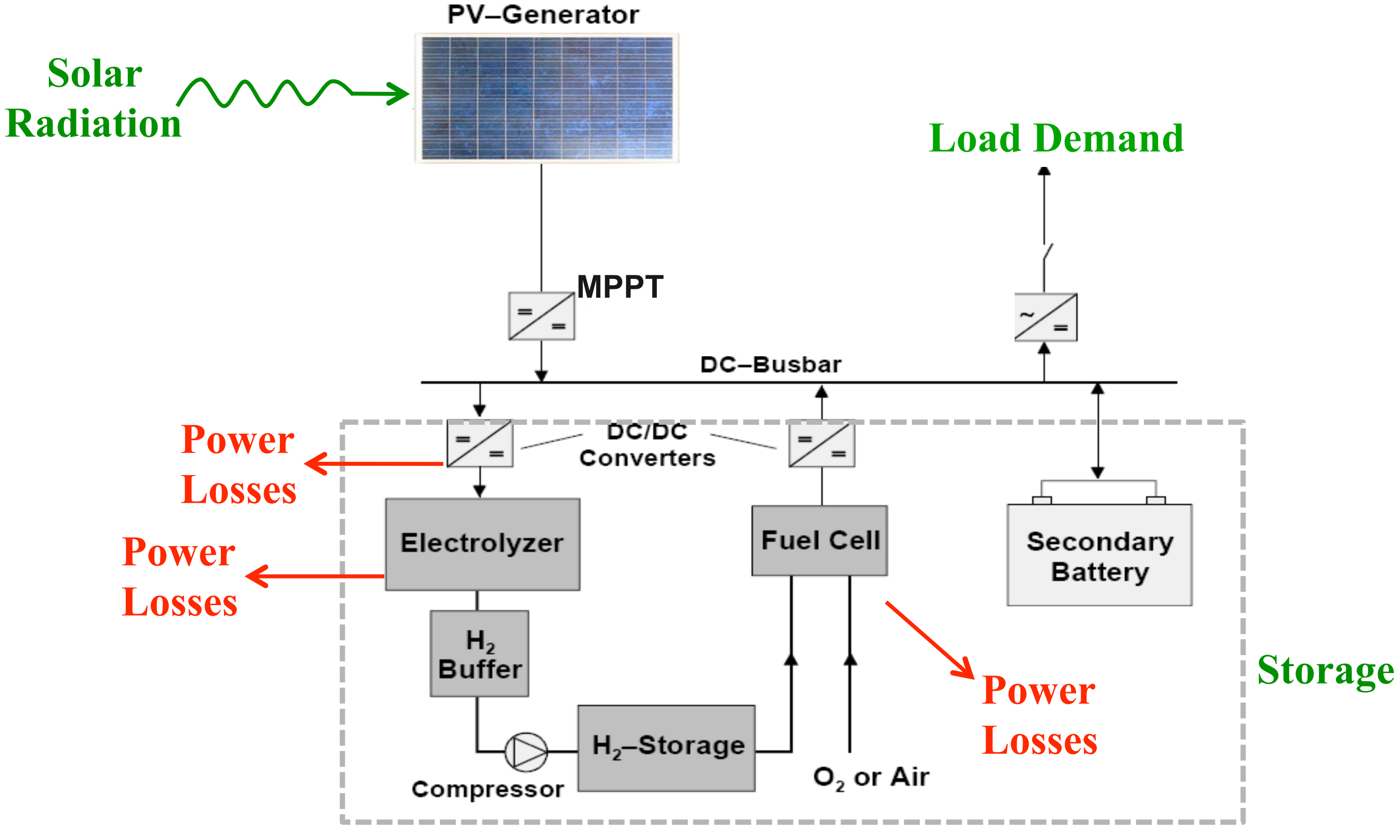
Hours (August 1st-5th)

Validation Results, Pittsburgh Area 2006

5 Day Forecast and +/- 3s Intervals

Case Studies

Hybrid Photovoltaic-H_2 System

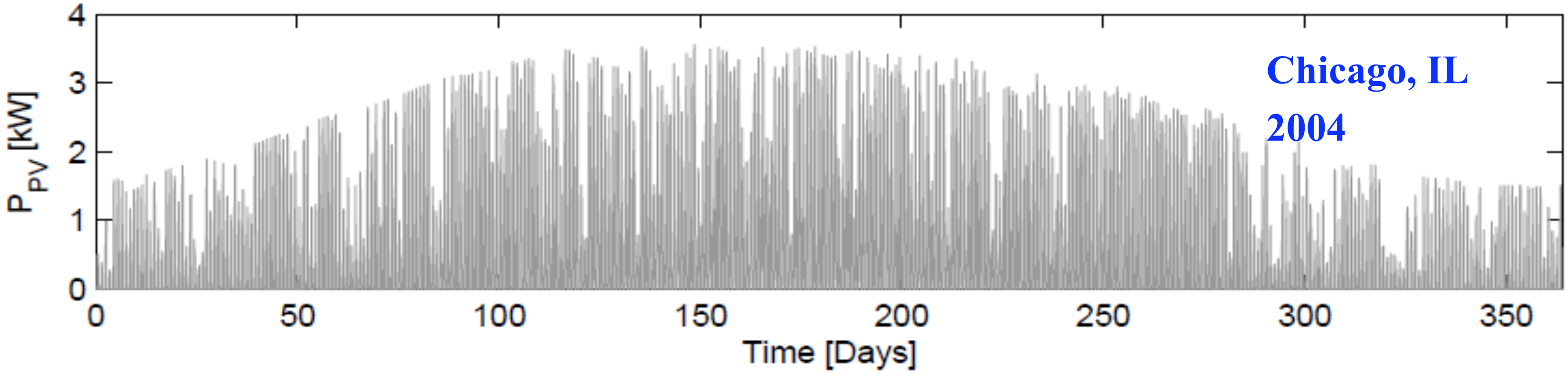


• **Operating Costs Driven by <u>Uncertain</u> Radiation** *Ulleberg, 2004*

• **Performance Deteriorated by Multiple <u>Power Losses</u>**

Hybrid Photovoltaic-H_2 System

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



True Future Radiation

$$\begin{aligned}
\min_{u(t)} \quad & \int_{t_\ell}^{t_{\ell+N}} \varphi(z(t), y(t), u(t), \chi(t))\,dt \\
\frac{dz}{dt} &= \mathbf{f}(z(t), y(t), u(t), \chi(t)) \\
0 &= \mathbf{g}(z(t), y(t), u(t), \chi(t)) \\
0 &\geq \mathbf{h}(z(t), y(t), u(t), \chi(t)) \\
z(0) &= x_\ell
\end{aligned}$$

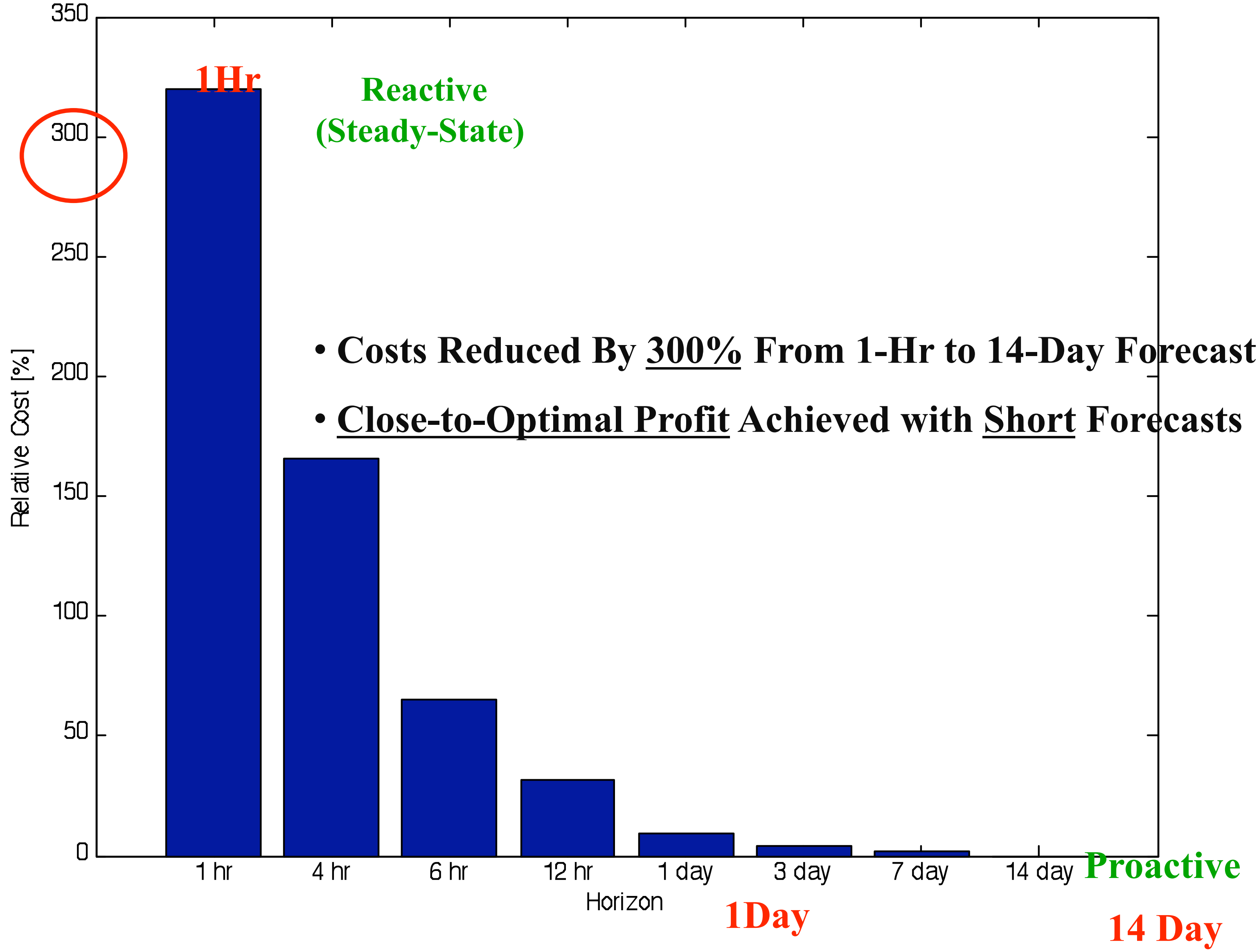
Minimize Operating Costs + Maximize H_2 Production

Energy Balances

State-of-Charge, Fuel Cell and Electrolyzer Limits

- **Forecast Horizon of One Year** – **Highest Achievable Profit**
- **Receding-Horizon with 1hr, 1 Day, …,14 Days Forecast** - **8,700 Problems in Each Scenario**

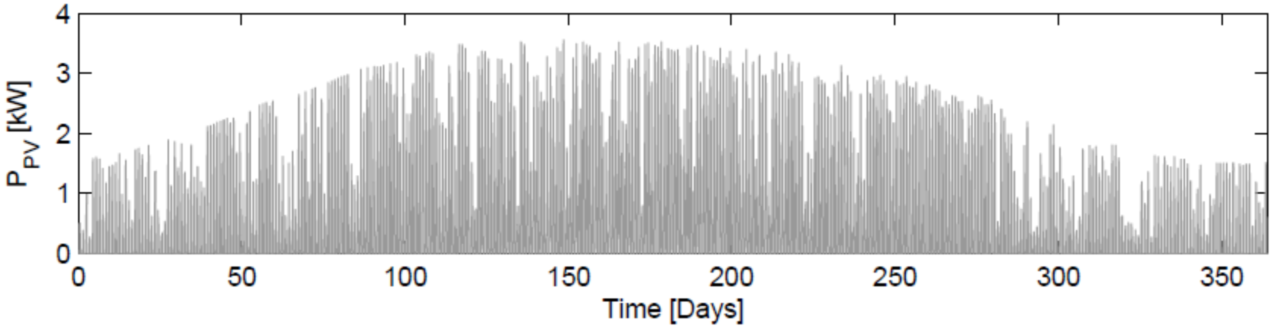
Hybrid Photovoltaic-H_2 System

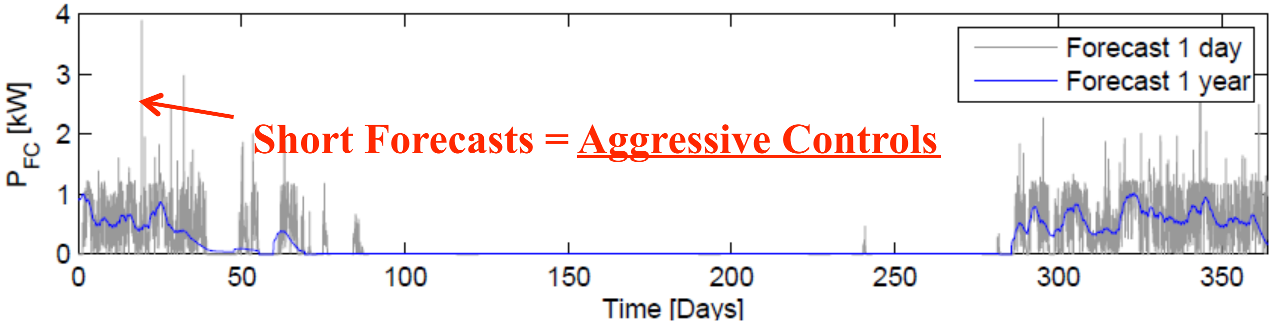


- **Costs Reduced By <u>300%</u> From 1-Hr to 14-Day Forecast**
- **<u>Close-to-Optimal Profit</u> Achieved with <u>Short</u> Forecasts**

Hybrid Photovoltaic-H_2 System

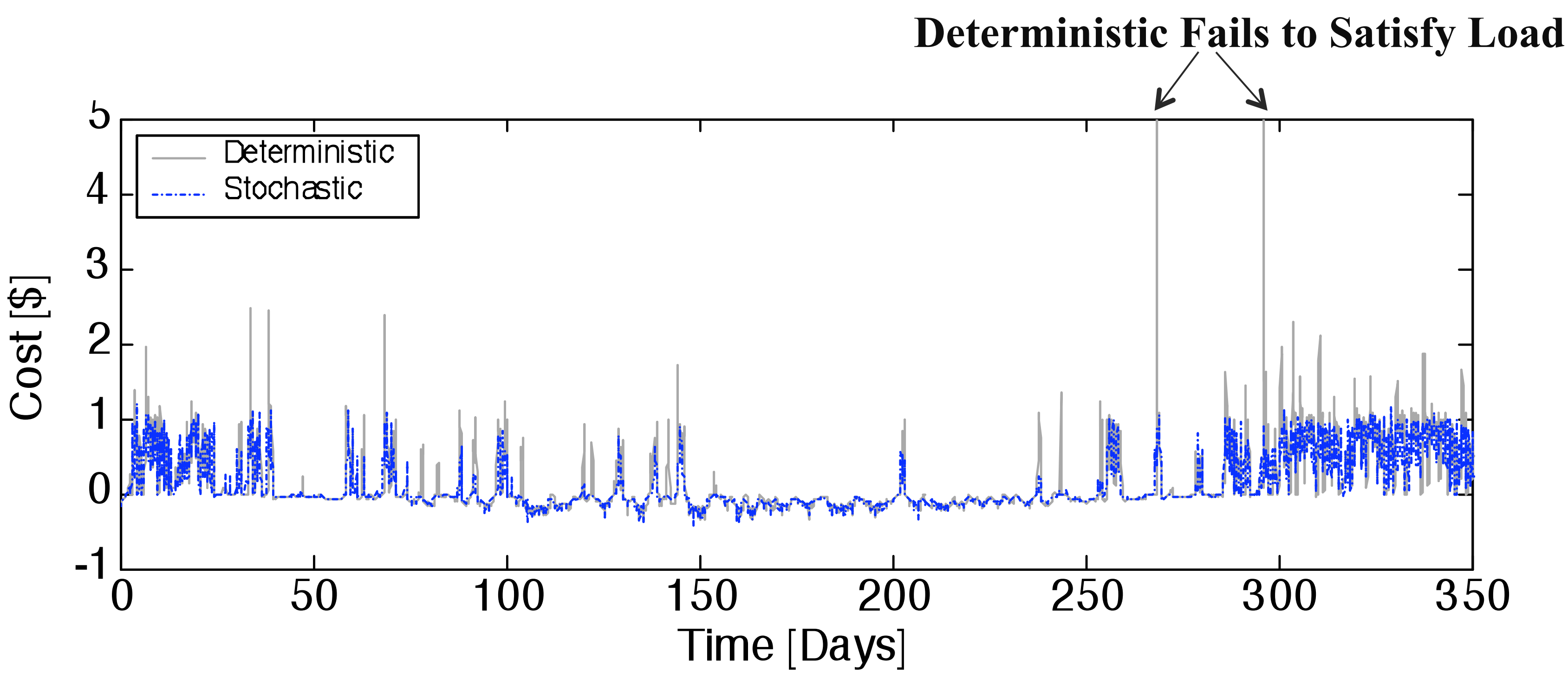
Profiles of Fuel Cell Power





Hybrid Photovoltaic-H_2 System

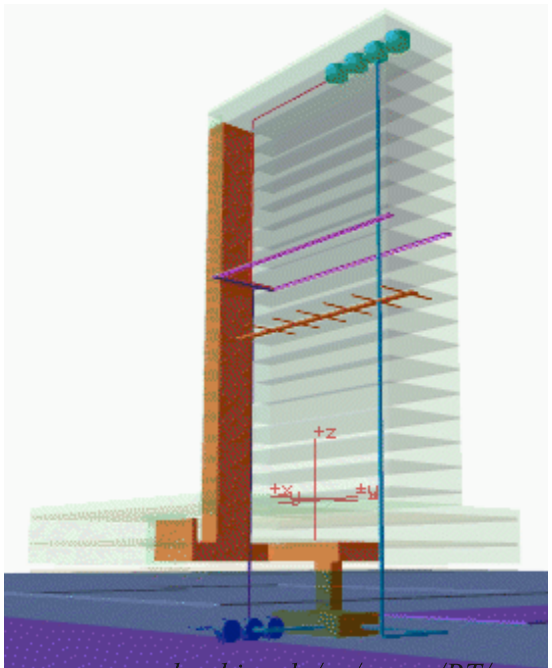
Load Satisfaction Deterministic ("Optimization on Mean") vs. Stochastic



Therefore, the alternative to stochastic programming can turn out infeasible !!

Handling Stochastic Effects Particularly Critical in Grid-Independent Systems

Thermal Management of Building Systems



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

Minimize Annual Heating and Cooling Costs

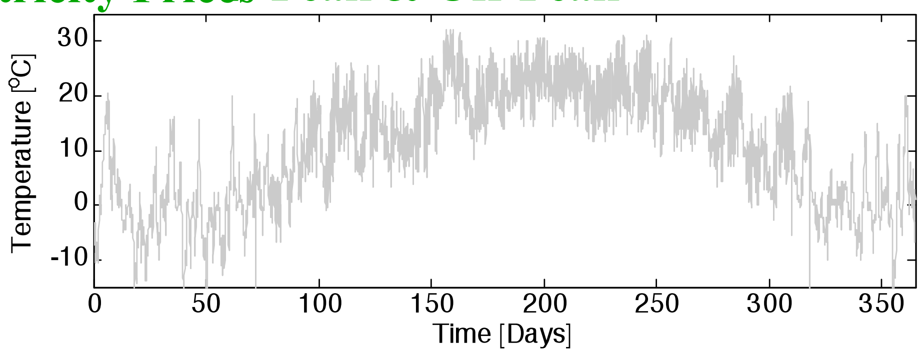
$$\min_{u(t)} \int_{t_\ell}^{t_{\ell+N}} \left[C_c(t)\varphi_c(t) + C_h(t)\varphi_h(t)\right] dt$$

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

Energy Balances

NLP with 100,000 Constraints & 20,000 Degrees of Freedom

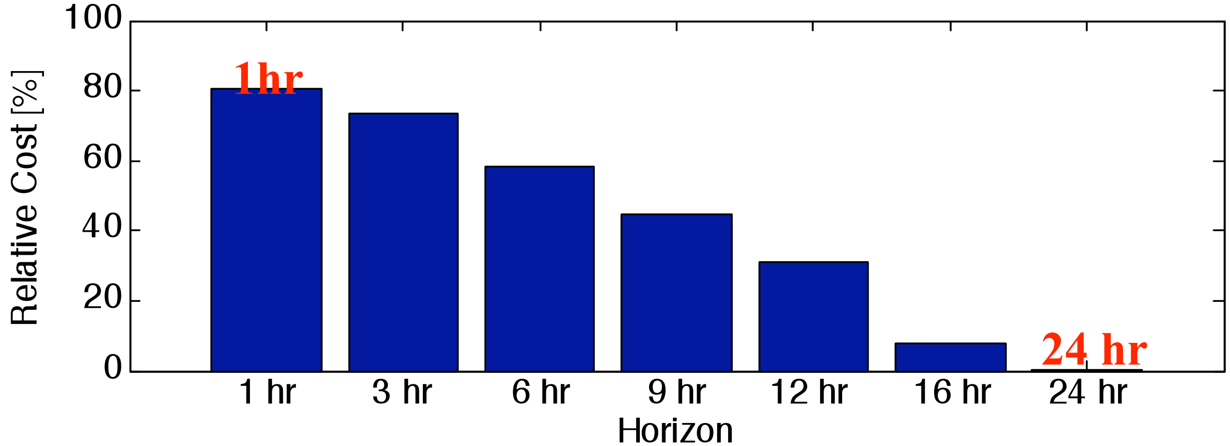
Time-Varying Electricity Prices → Peak & Off-Peak



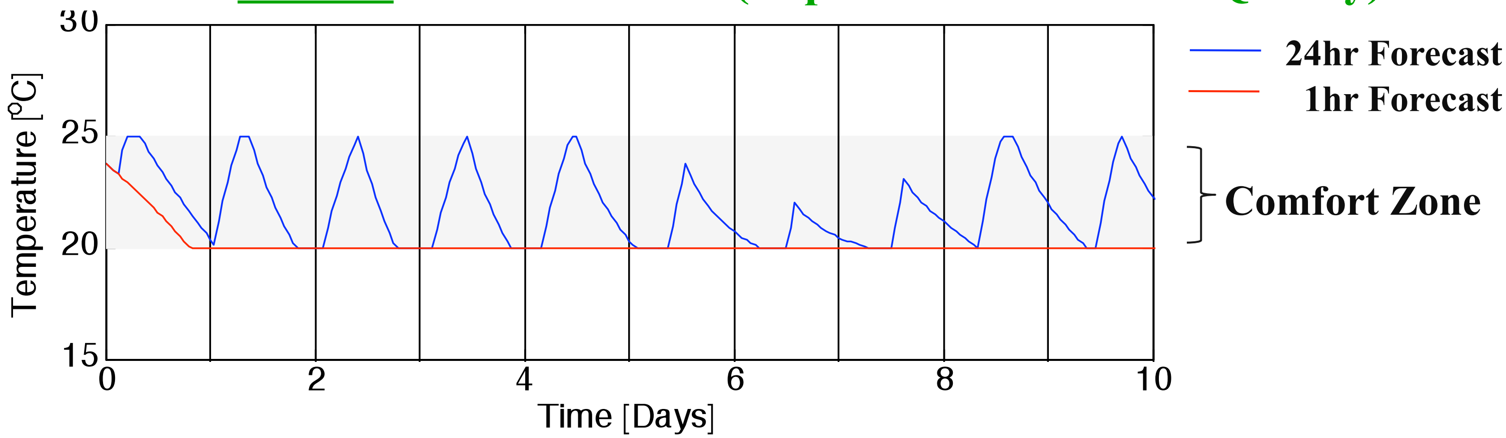
Pittsburgh, PA 2006

Thermal Management of Building Systems

Effect of Forecast on Energy Costs



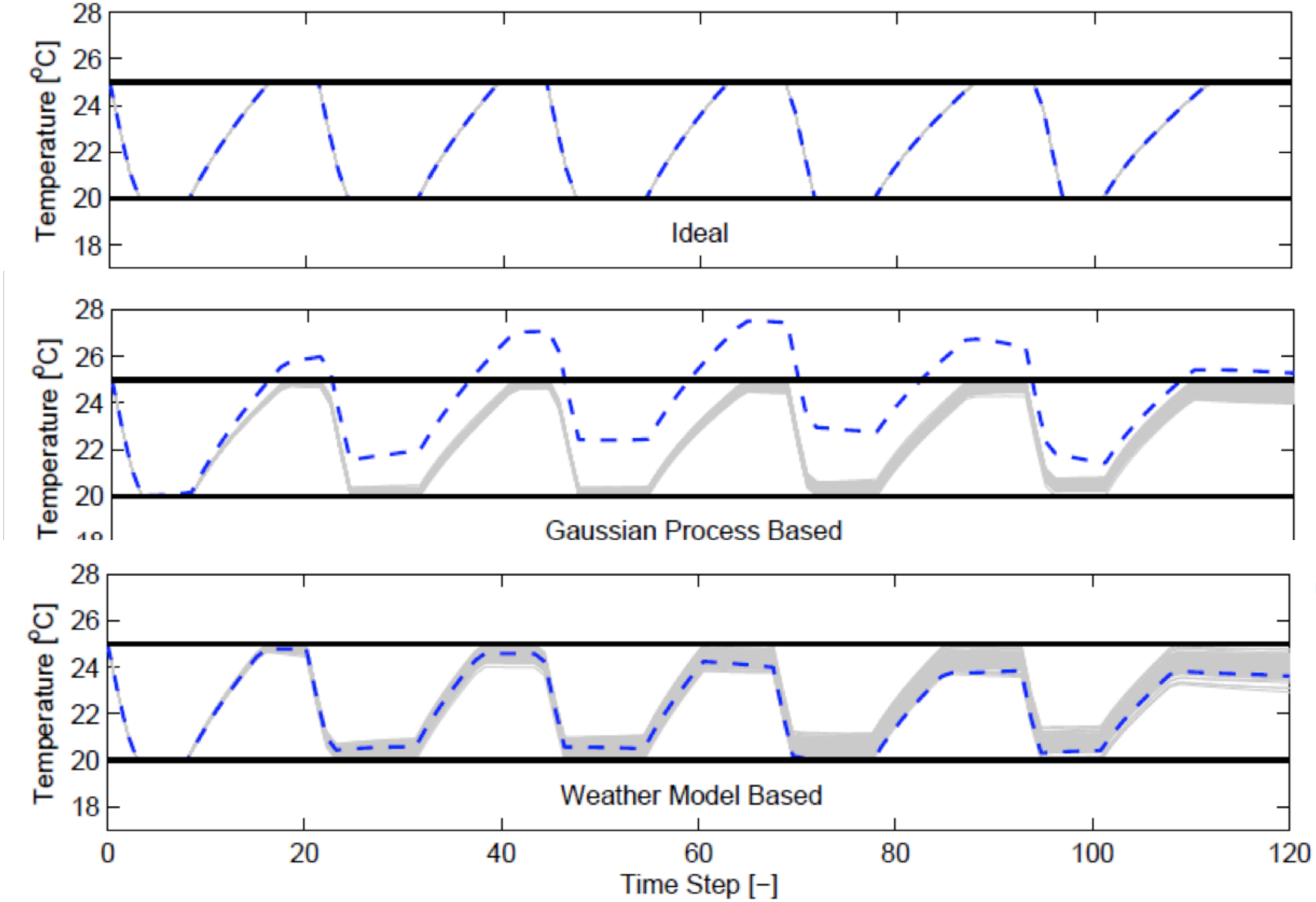
Forecast Leads to <u>20-80%</u> Cost Reduction (Depends on Insulation Quality)



Exploit Comfort Zone and Weather Info to Heat/Cool when Cheaper *Braun, 1990*

Thermal Management of Building Systems

Performance Optimizer using WRF and GP Model Forecasts



Perfect Forecast

Gaussian Process Model

WRF Model

Conclusions and Future Work

Conclusions and Future Work

Integrative Study of Weather Forecast-Based Optimization

WRF Model + Ensemble Approach + Stochastic Receding-Horizon

Important Economic Benefits, Niche Market is Huge

New Algorithms and Formulations Needed

- We showed that stochastic formulation matters (deterministic results in big losses).
- We showed that weather forecast inclusions results in 20-80% cost reduction
- Weather uncertainty is a hard, important, problem that data-only methods (such as GP) are unlikely to crack

Future and On-Going Work

Convergence of SAA Approximations for Stochastic Receding-Horizon

Variance Reduction Control Formulations

Integration Gaussian Process + WRF Forecasts

Including Uncertainty from Energy Markets in the Formulation

Conclusions and Future Work

Integrative Study of Weather Forecast-Based Optimization

- WRF Model + Ensemble Approach + Stochastic Receding-Horizon
- Important Economic Benefits, Niche Market is Huge
- New Algorithms and Formulations Needed

Future and On-Going Work

- Convergence of SAA Approximations for Stochastic Receding-Horizon
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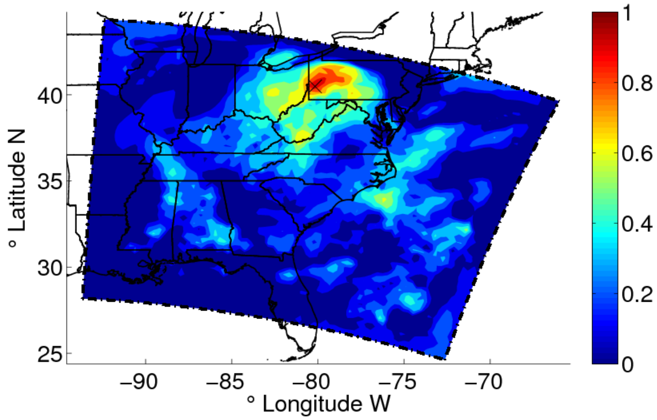

WRF Model Provides <u>Coarse</u> Forecasts
(Km, Hour Scales)
Gaussian Process Model to Create
<u>High-Fidelity</u> Forecasts
(Meters, Minutes)

Collaborators

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Weather Forecast-Based Optimization of Industrial Systems

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March 30th, 2009

Weather Forecast-Based Optimization of Integrated Energy Systems

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