Weather Forecast-Based Optimization of Integrated Energy Systems

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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-H₂, Building Thermal Control

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

Benefits of \textbf{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

Energy Manager

Unidirectional Energy Flow

Supervisory Level (Set-Point Optimization)

Regulatory Level (Set-Point Tracking)

Bidirectional Energy Flow

Supervisory Level (Set-Point Optimization)

Regulatory Level (Set-Point Tracking)

Energy Consumer

Energy Producer

Optimization Traditionally **Reactive**, Uncertainty Handling Non-Systematic
**Benefits:** Accommodate Forecasts, Constraint Handling, Financial Objectives, Complex Models

**Deterministic**

\[
\begin{align*}
\min_{u(t)} & \quad \int_{t_\ell}^{t_\ell+N} \varphi(z(t), y(t), u(t), \mathbb{E}[\chi(t)]) dt \\
\frac{dz}{dt} &= f(z(t), y(t), u(t), \mathbb{E}[\chi(t)]) \\
0 &= g(z(t), y(t), u(t), \mathbb{E}[\chi(t)]) \\
0 &\geq h(z(t), y(t), u(t), \mathbb{E}[\chi(t)]) \\
z(0) &= x_\ell
\end{align*}
\]

**Stochastic**

\[
\begin{align*}
\min_{u(t)} & \quad \mathbb{E}_{\chi(t) \in \Omega} \left[ \int_{t_\ell}^{t_\ell+N} \varphi(z(t), y(t), u(t), \chi(t)) dt \right] \\
\frac{dz}{dt} &= f(z(t), y(t), u(t), \chi(t)) \\
0 &= g(z(t), y(t), u(t), \chi(t)) \\
0 &\geq h(z(t), y(t), u(t), \chi(t)) \\
z(0) &= x_\ell
\end{align*}
\]

**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

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

\[
\frac{dz}{dt} = f(z(t), y(t), u(t), \chi(t)) \quad \forall \chi(t) \in \Omega
\]

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

\[
\min \frac{1}{S} \sum_{k=1}^{S} \varphi(z_k, y_k, u, \chi_k)
\]

s.t. \(c(z_k, y_k, u, \chi_k) = 0\)

\(h(z_k, y_k, u, \chi_k) \leq 0\)

\(k = 1, \ldots, S\)
Basic Operational Setting

Quantifying Uncertainty Key Enabler
SAA Stochastic Programming

Approximation.

\[
\min_{\mathbf{u}} \quad \frac{1}{S} \sum_{k=1}^{S} \varphi(z_k, y_k, \mathbf{u}, \chi_k)
\]

s.t. \quad \mathbf{c}(z_k, y_k, \mathbf{u}, \chi_k) = 0

\quad \mathbf{h}(z_k, y_k, \mathbf{u}, \chi_k) \leq 0

\quad k = 1, \ldots, S

- 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)


1. Input-Output Data Sets: \[ Y_j := \chi_k \quad X_j := [\chi_{k-1}, \chi_{k-T}] \]

2. Covariance Structure: \[ V(X_j, X_i; \eta) := \eta_0 + \eta_1 \cdot \exp \left( -\frac{1}{\eta_2} \| X_j - X_i \|^2 \right) \]

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

4. Posterior Distribution: \[ Y^P = V(X^P, X, \eta^*) V^{-1}(X, X, \eta^*) Y \quad \text{Forecast Mean} \]
   \[ V^P = V(X^P, X^P, \eta^*) - V(X^P, X, \eta^*) V^{-1}(X, X, \eta^*) V(X, X^P, \eta^*) \quad \text{Covariance} \]
Uncertainty Quantification

One-Day Ahead Forecast and Samples from Posterior Distribution

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

One Hour Ahead

5 Days Ahead

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

GP (and all data-oriented approaches) Provide Accurate Interpolations 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 $k = 0, \cdots, K$

$$x_k^{ini} = M(x_{k-1}^{ini}) + W_k, \quad (1)$$

$$z_{k}^{obs} = H(x_k^{ini}) + V_k, \quad (2)$$

where

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

and

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

We want find $D(x_0^{ini}, \cdots, x_K^{ini})$’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 ...

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

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

- 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.
Step 1: Moving Horizon Best State Estimation

\[
\begin{align*}
\min_{p(t), z_0} & \quad \sum (y(t_k) - y_{\ell-k+N})^T V_y^{-1} (y(t_k) - y_{\ell-k+N}) \\
\min_{p(t), z_0} & \quad \sum (y(t_k) - y_{\ell-k+N+1})^T V_y^{-1} (y(t_k) - y_{\ell-k+N+1}) \\
\frac{dz}{dt} & = \mathbf{f}(z(t), p(t), u(t)) \\
y(t) & = \mathbf{g}(z(t), p(t), u(t)) \\
z(0) & = z_0 \quad \text{Uncertain}
\end{align*}
\]

WRF Model

\[\Pi_\ell \rightarrow 0\]

Uncertainty in Current State \(x_\ell\) ?

Needed To Quantify Future Forecast
Step 2: Estimate the prior covariance matrix.

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

\[
V_{ik} \approx dd^T = \sum_j d_{ij}d_{kj}^T = \epsilon_i \cdot \epsilon_k = \begin{bmatrix}
\epsilon_0 \cdot \epsilon_0 & \epsilon_1 \cdot \epsilon_0 & \cdots & \epsilon_n \cdot \epsilon_0 \\
\epsilon_0 \cdot \epsilon_1 & \epsilon_1 \cdot \epsilon_1 & \cdots & \epsilon_n \cdot \epsilon_1 \\
\cdots & \cdots & \cdots & \cdots \\
\epsilon_0 \cdot \epsilon_n & \epsilon_1 \cdot \epsilon_n & \cdots & \epsilon_n \cdot \epsilon_n
\end{bmatrix}, \quad C_{ik} = \frac{\epsilon_i \cdot \epsilon_k}{|\epsilon_i||\epsilon_k|}.
\]

- “Guess” the diagonal of the variance matrix.
Covariance Matrix is Huge and low rank \((10^6 \times 10^6)\) But …

- Spatial Correlations Decay \textbf{Exponentially} Constantinescu, et.al., 2007
- Covariance Can be Approximated Using \textbf{Gaussian Kernels} Zavala, Constantinescu & A, 2009

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

\begin{tikzpicture}
\end{tikzpicture}
Ensemble Forecast Approach

Ensemble Forecast Approach – Use WRF as Black-Box
Sample Prior and Propagate Samples of Posterior Through Model

\[ Y_{[i,j]} := \chi_i(t_{\ell+j}) = \mathcal{M}(\mathcal{M}(\ldots \mathcal{M}(\chi_i(t_{\ell})))) \]

\[ \mathbb{E}[Y] \approx \bar{Y} := \frac{1}{NS} \sum_{i=1}^{NS} Y_{[i,:]} \]

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

Validation Results, Pittsburgh Area 2006
5 Day Forecast and +/- 3σ Intervals

Hours (August 1st-5th)
Case Studies
Hybrid Photovoltaic-H₂ System

- Operating Costs Driven by Uncertain Radiation *Ulleberg, 2004*
- Performance Deteriorated by Multiple Power Losses
**Effect of Forecast on Economics** Z., Anitescu, Krause 2009

**Hybrid Photovoltaic-H₂ System**

Chicago, IL 2004

**True Future Radiation**

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

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-H₂ 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

Short Forecasts = Aggressive Controls
Load Satisfaction Deterministic ("Optimization on Mean") vs. Stochastic

Deterministic Fails to Satisfy Load

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

Handling Stochastic Effects Particularly Critical in Grid-Independent Systems
Minimize Annual Heating and Cooling Costs

\[
\min_u \int_{t^f}^{t^f+N} [C_c(t)\varphi_c(t) + C_h(t)\varphi_h(t)] \, dt
\]

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

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

\[
\alpha'(T_I(\tau) - T_W(\tau, 0)) = -k \cdot \frac{\partial T_W}{\partial x}(\tau, 0)
\]

\[
\alpha''(T_W(\tau, L) - T_A(\tau)) = -k \cdot \frac{\partial T_W}{\partial x}(\tau, L)
\]

\[
T_I(0) = T^f_I
\]

\[
T_W(0, x) = T^f_W(x)
\]

Energy Balances

Time-Varying Electricity Prices - Peak & Off-Peak

Pittsburgh, PA 2006
Thermal Management of Building Systems

Effect of Forecast on Energy Costs

Forecast Leads to 20-80% 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
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**Future and On-Going Work**

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- Variance Reduction Control Formulations
- Integration Gaussian Process + WRF Forecasts

WRF Model Provides **Coarse** Forecasts
(Km, Hour Scales)

Gaussian Process Model to Create
**High-Fidelity** Forecasts
(Meters, Minutes)
Collaborators

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Weather Forecast-Based Optimization of Industrial Systems

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