Proactive Energy Management for Next-Generation Building Systems

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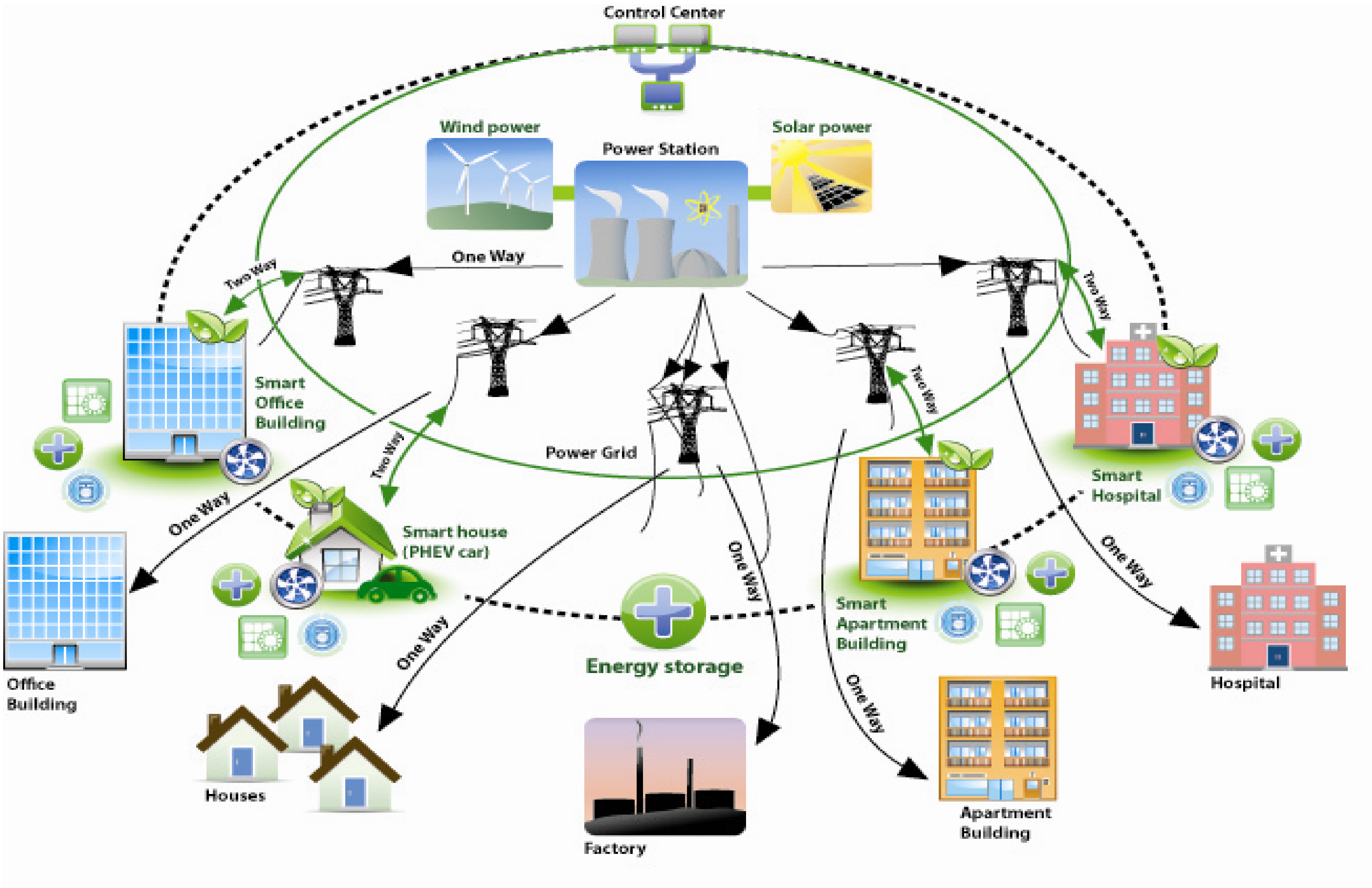
Outline

1. Next-Generation Power Grid
2. Proactive Energy Management
3. Large-Scale Optimization
4. BuildingIQ - Argonne Project
5. Conclusions and Research Challenges

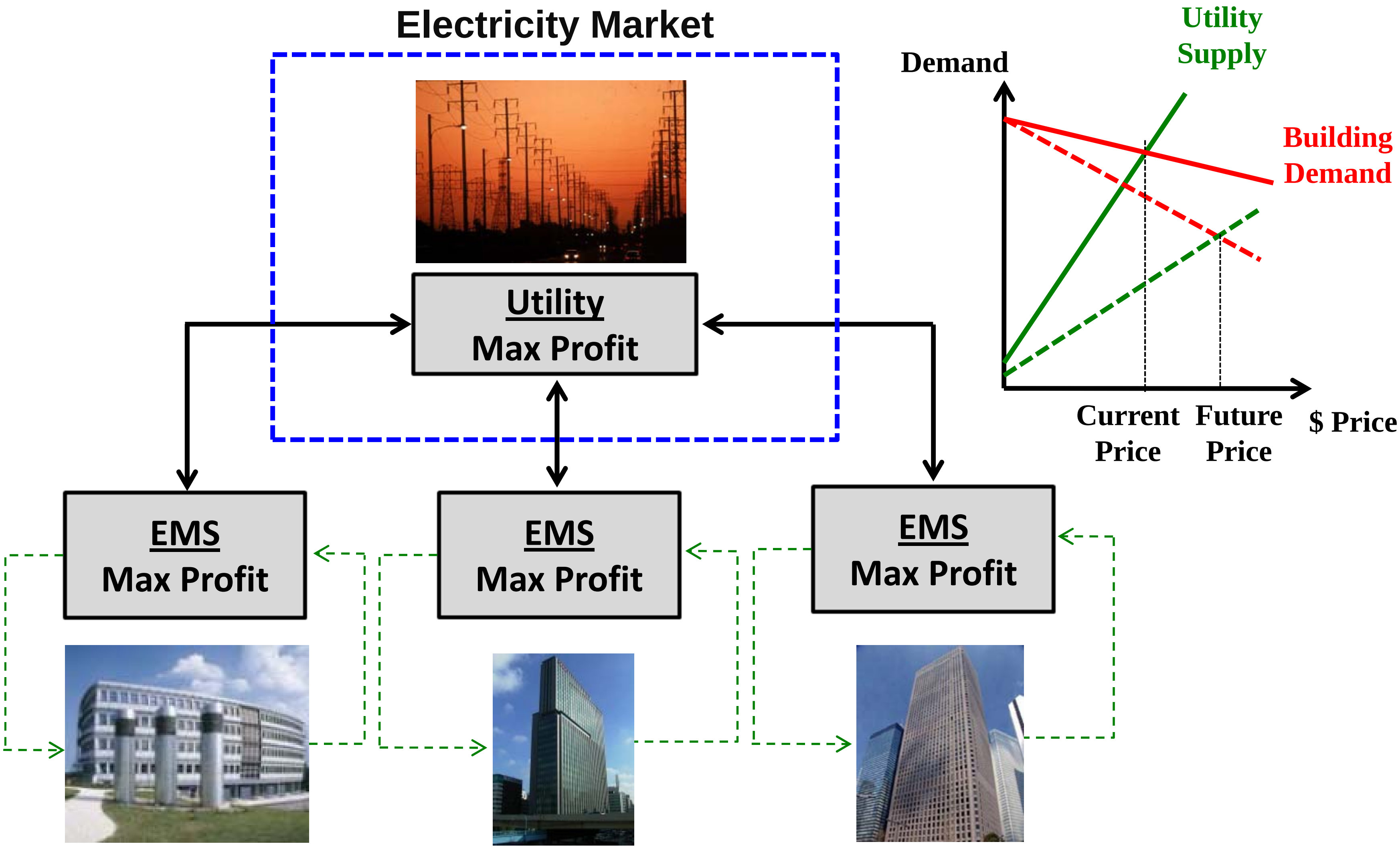
Next-Generation Grid



<u>Distributed</u> Generation and <u>Elastic</u> Demands: Real-Time Pricing, Demand-Response

Buildings use <u>Optimization</u> for Energy Management: Grid-Building <u>Game</u>

Next-Generation Grid

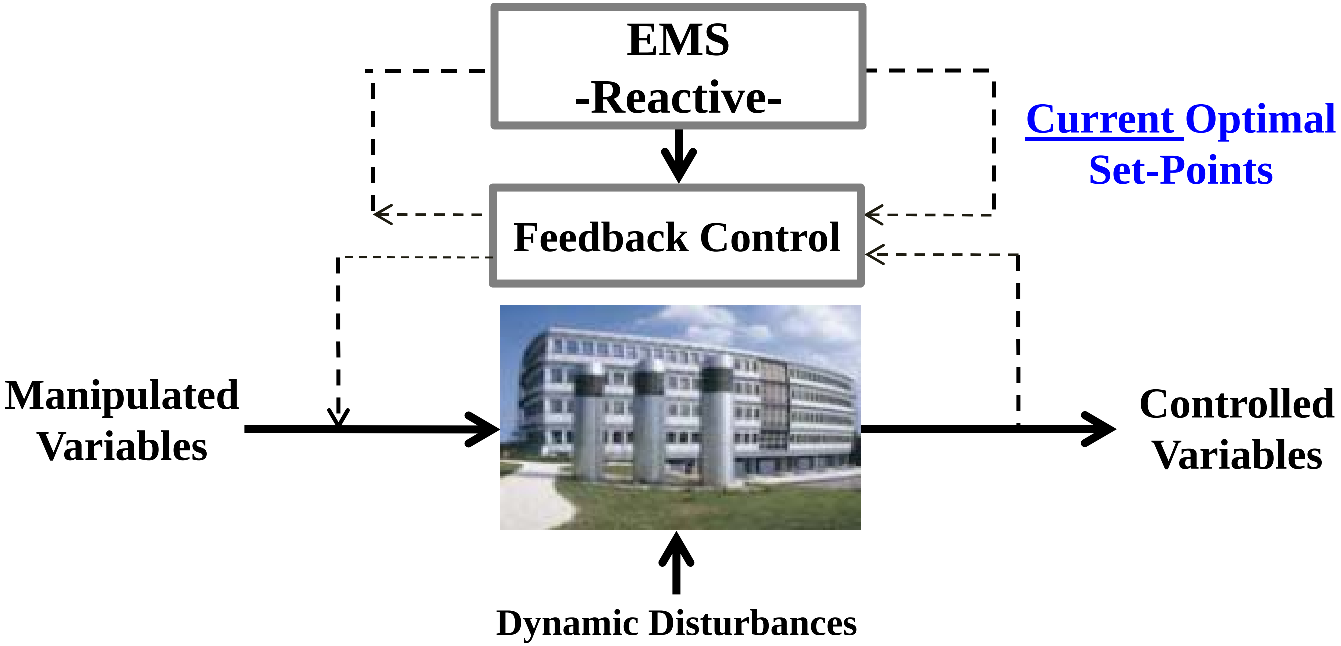


EMS Needs to Quantify Demand Accurately: Load Shedding

Price No Longer an Exogenous Disturbance: Market Learning

2. Proactive Energy Management

Feedback Control and Economics



EMS
-Reactive-

Feedback Control

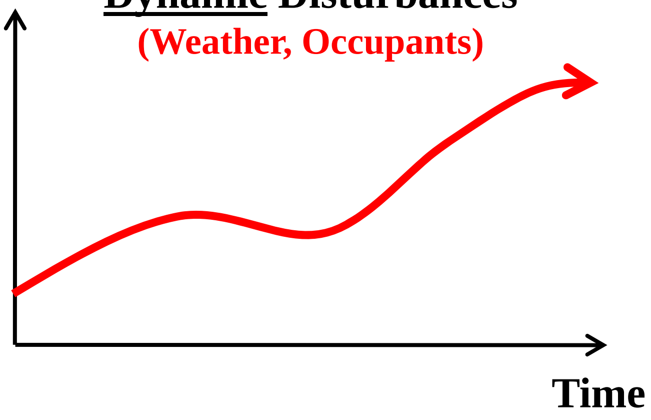
Manipulated Variables

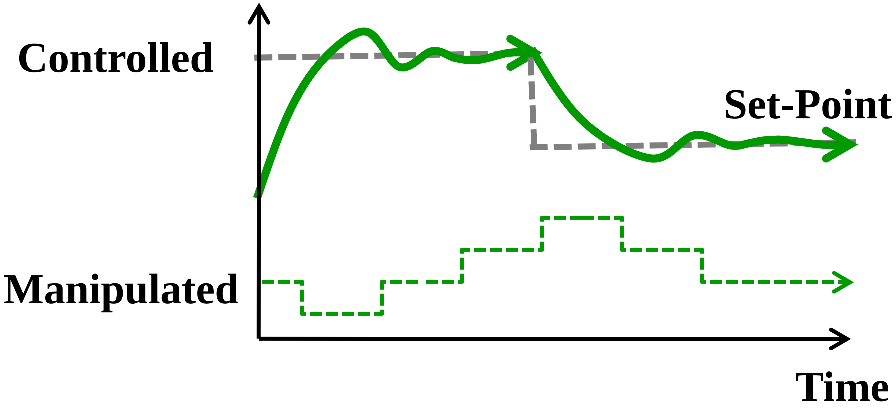
Controlled Variables

Dynamic Disturbances

<u>Current</u> Optimal Set-Points

<u>Dynamic</u> Disturbances
(Weather, Occupants)

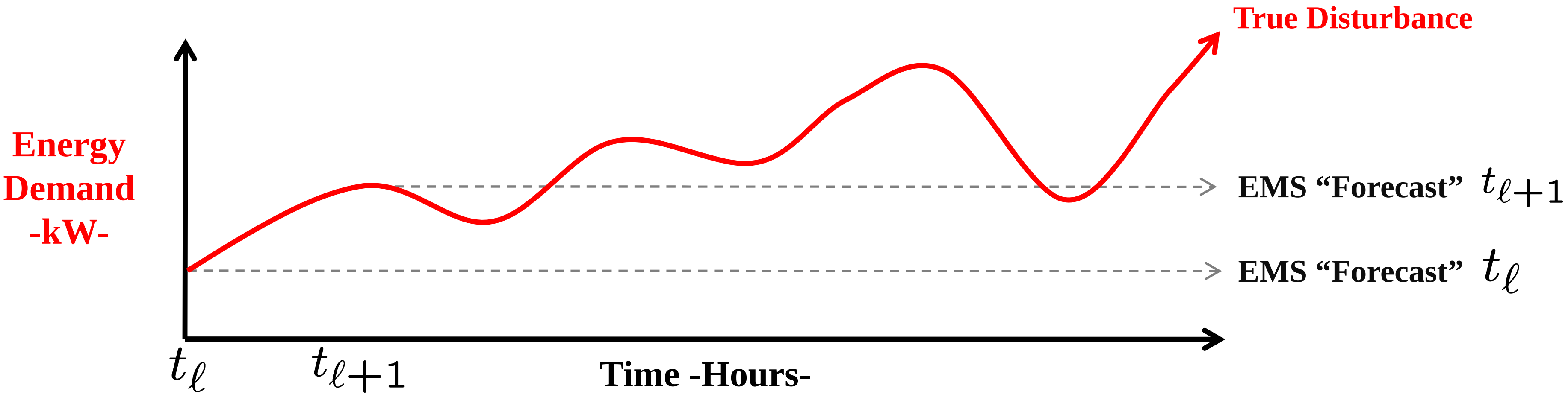


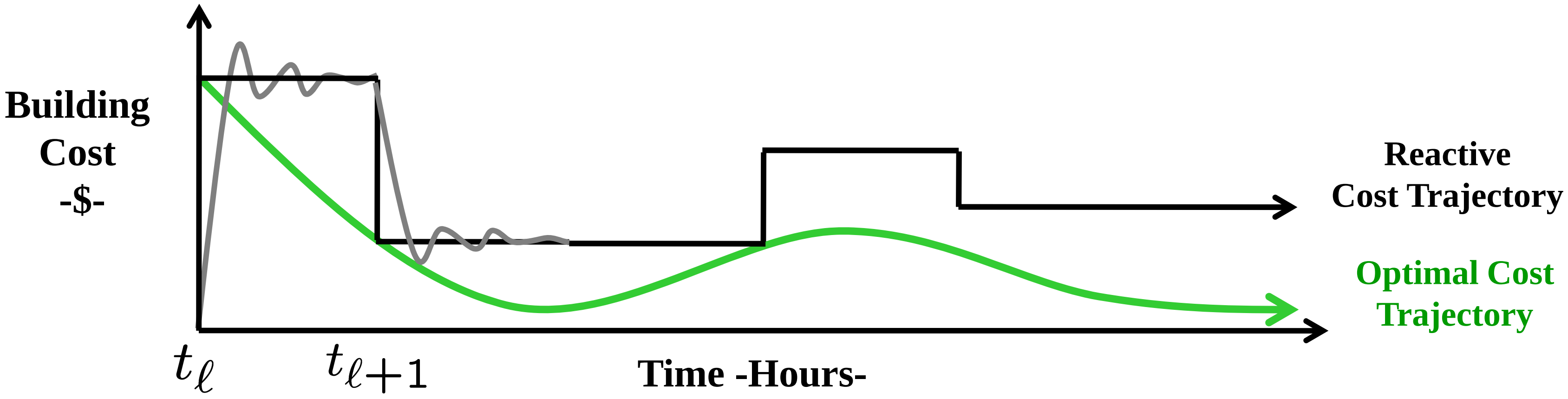


Does <u>Reactive</u> Optimization Handles <u>Dynamic</u> Effects Properly?

Feedback Control and Economics

Disturbance Handling with Reactive Optimization

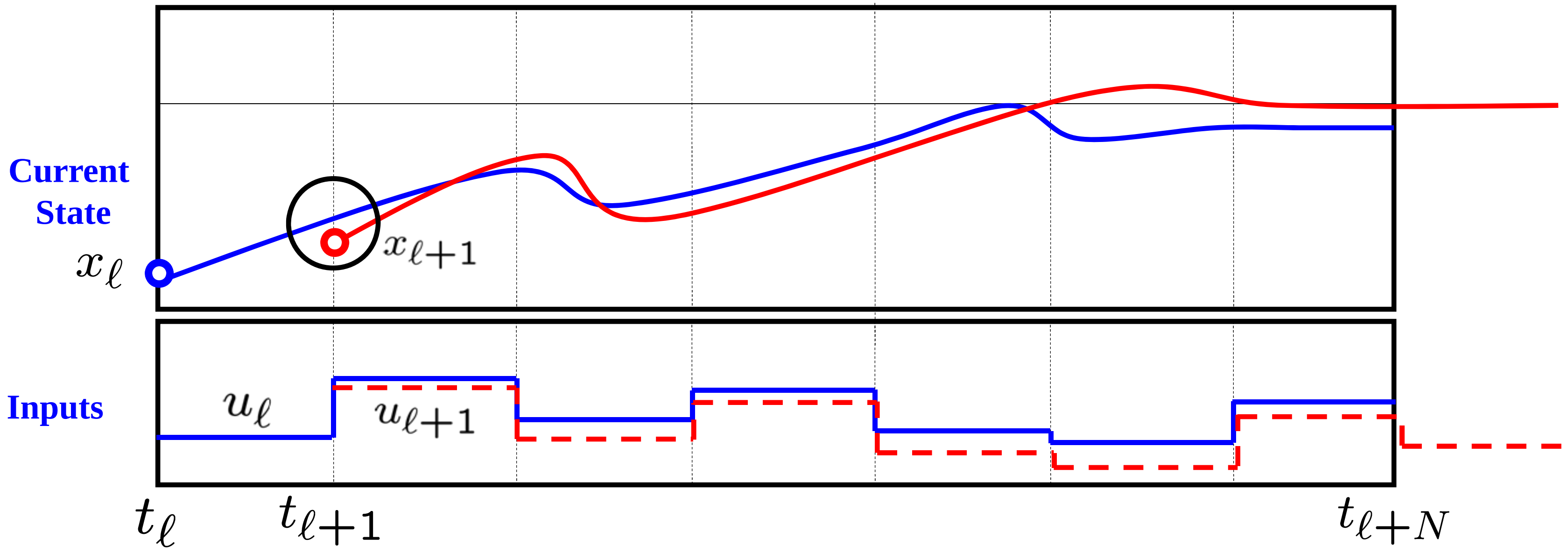




Reactive Optimization Uses Suboptimal Disturbance Info and Ignores Building Dynamics

Proactive EMS

Forecast Mismatch (Demand, Price)



Minimize Future Future Cost

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

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

Building Dynamic Model

Operational Constraints

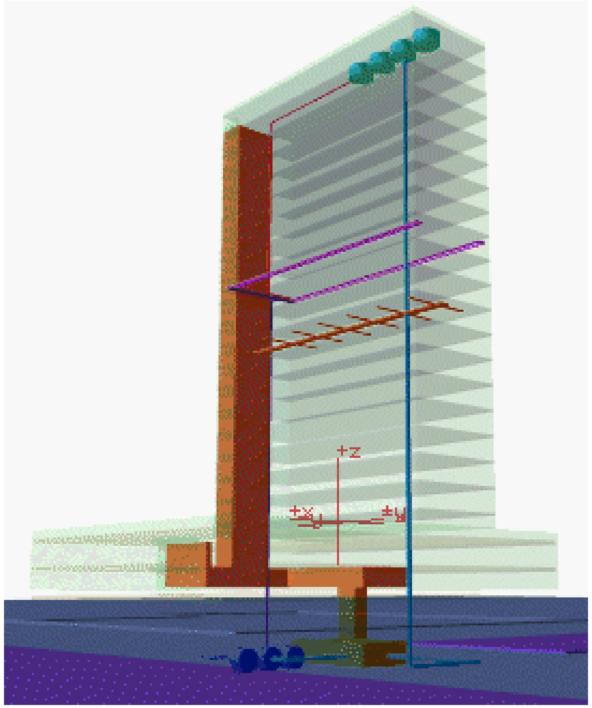
$$\min_{u(t)} \int_{t_{\ell+1}}^{t_{\ell+N+1}} \varphi(z(t), y(t), p(t), u(t))dt$$

$$\begin{aligned} \frac{dz}{dt} &= \mathbf{f}(z(t), p(t), u(t)) \\ 0 &= \mathbf{g}(z(t), p(t), u(t)) \\ 0 &\geq \mathbf{h}(z(t), p(t), u(t)) \\ \boxed{z(0) = x_{\ell+1}} \end{aligned}$$

Proactive EMS Allows to Anticipate Weather, Room Schedules, Occupant Behavior, …

Adopted in Chemical, Power, and Aerospace Industry *Honeywell, ABB, Boeing, Praxair, Shell, ExxonMobil*

Building Energy Management



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

Minimize Future Cooling and Heating Costs

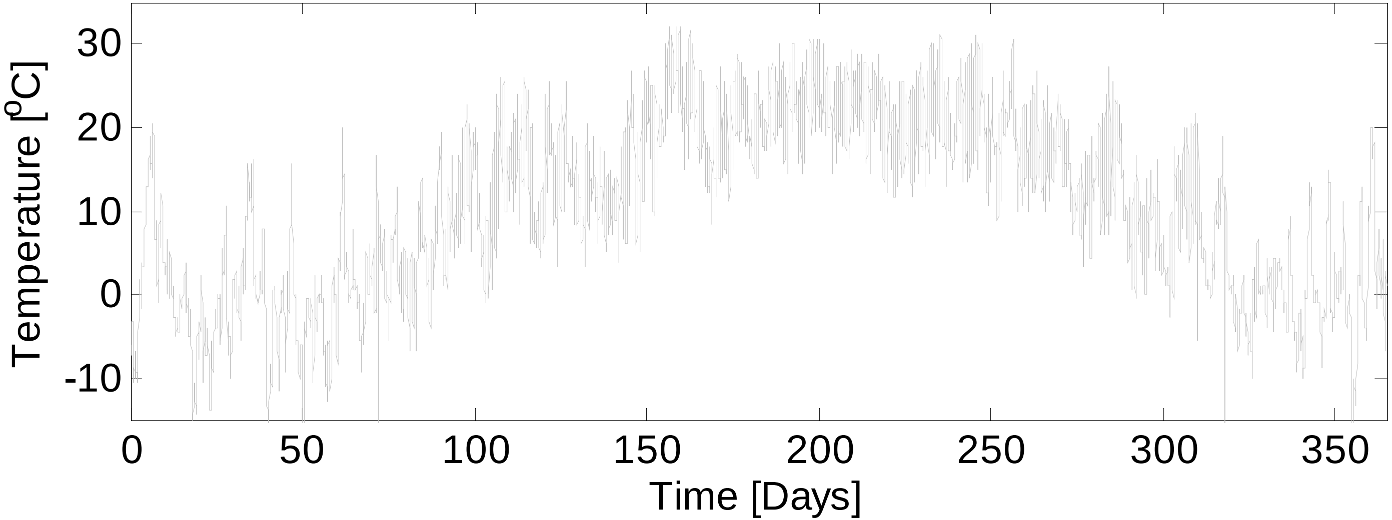
$$\min_{u(t)} \int_{t_\ell}^{t_{\ell+N}} [C_c(t)\varphi_c(t) + C_h(t)\varphi_h(t)]\,dt$$

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

Dynamic Model

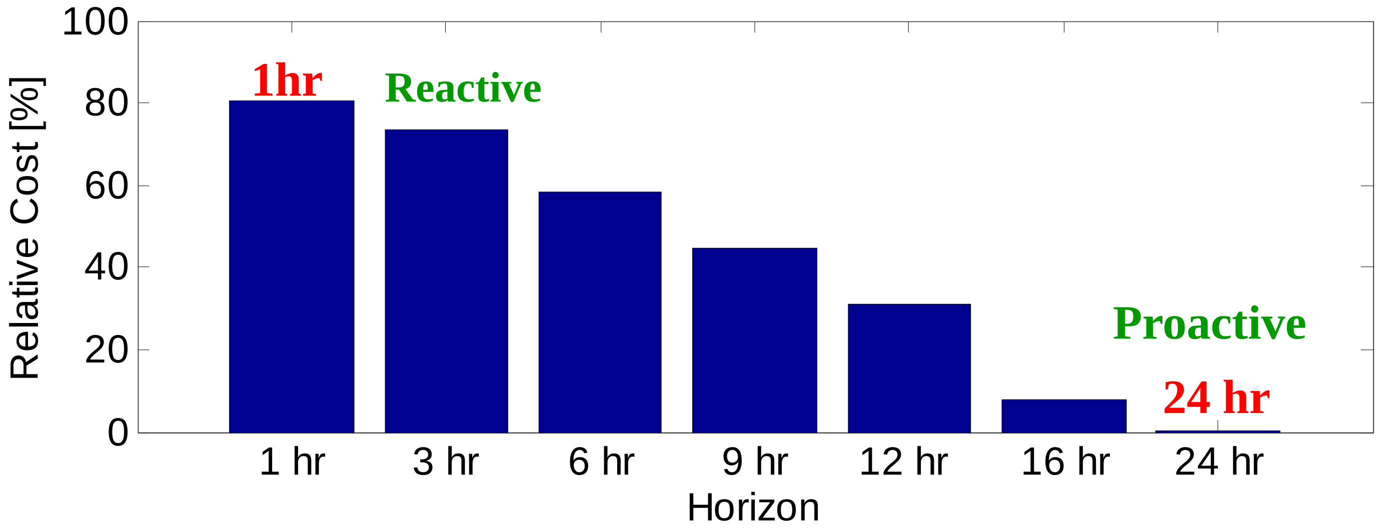
-Heat Transfer-

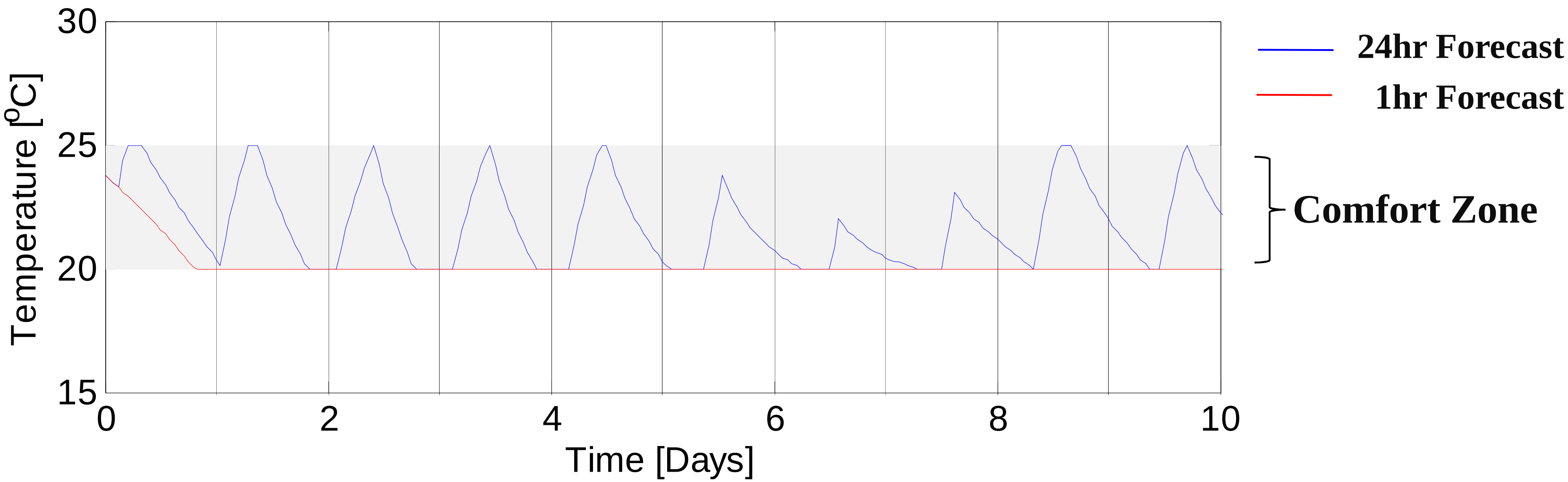
Ambient Temperature, Pittsburgh, PA 2006



Building Energy Management

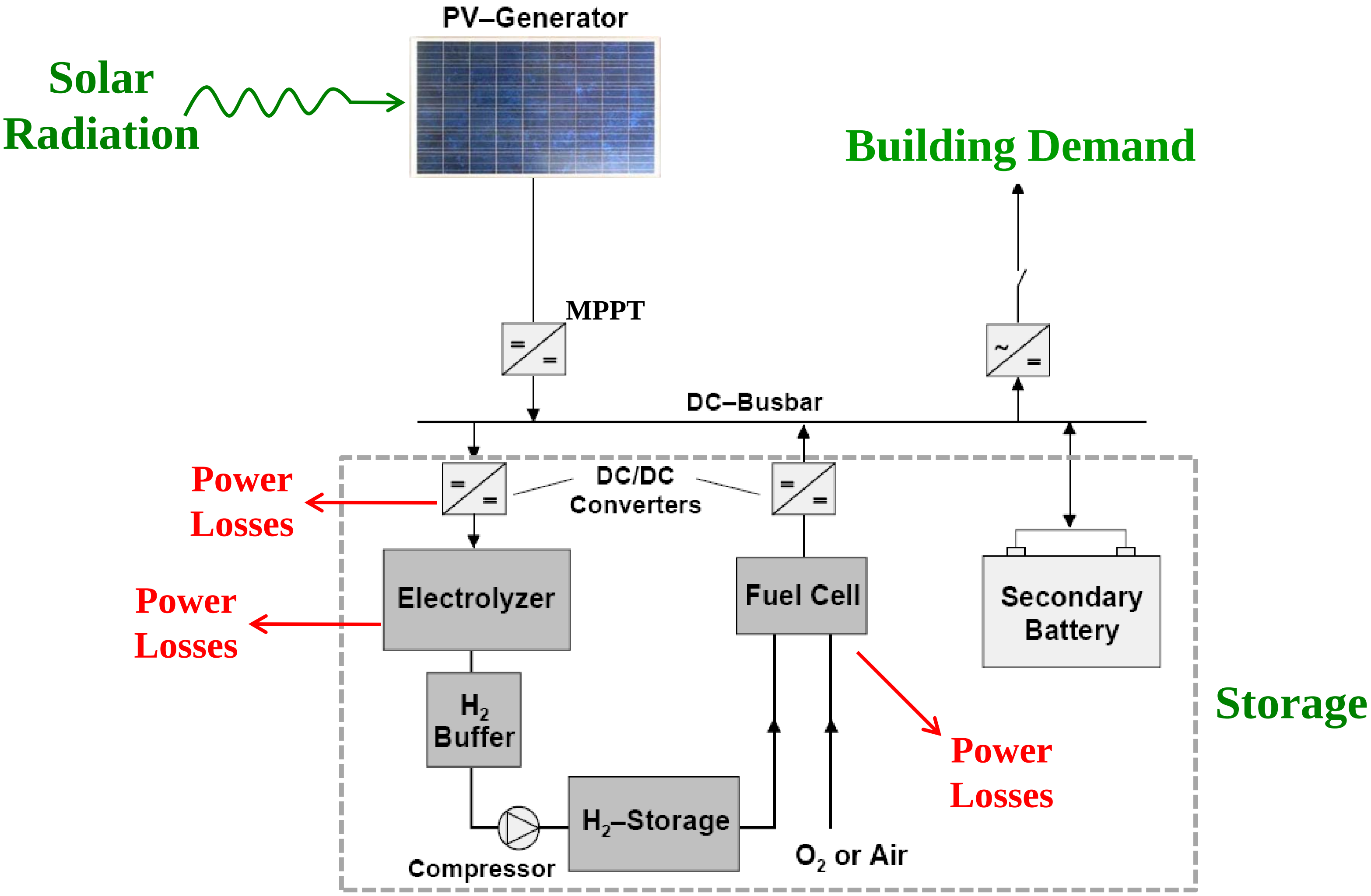
Effect of Foresight on Energy Costs





Proactive EMS Implicitly Forecasts Demand and Exploits Comfort Zone: Load Shedding

Cogeneration Systems



Solar Radiation

Building Demand

Power Losses

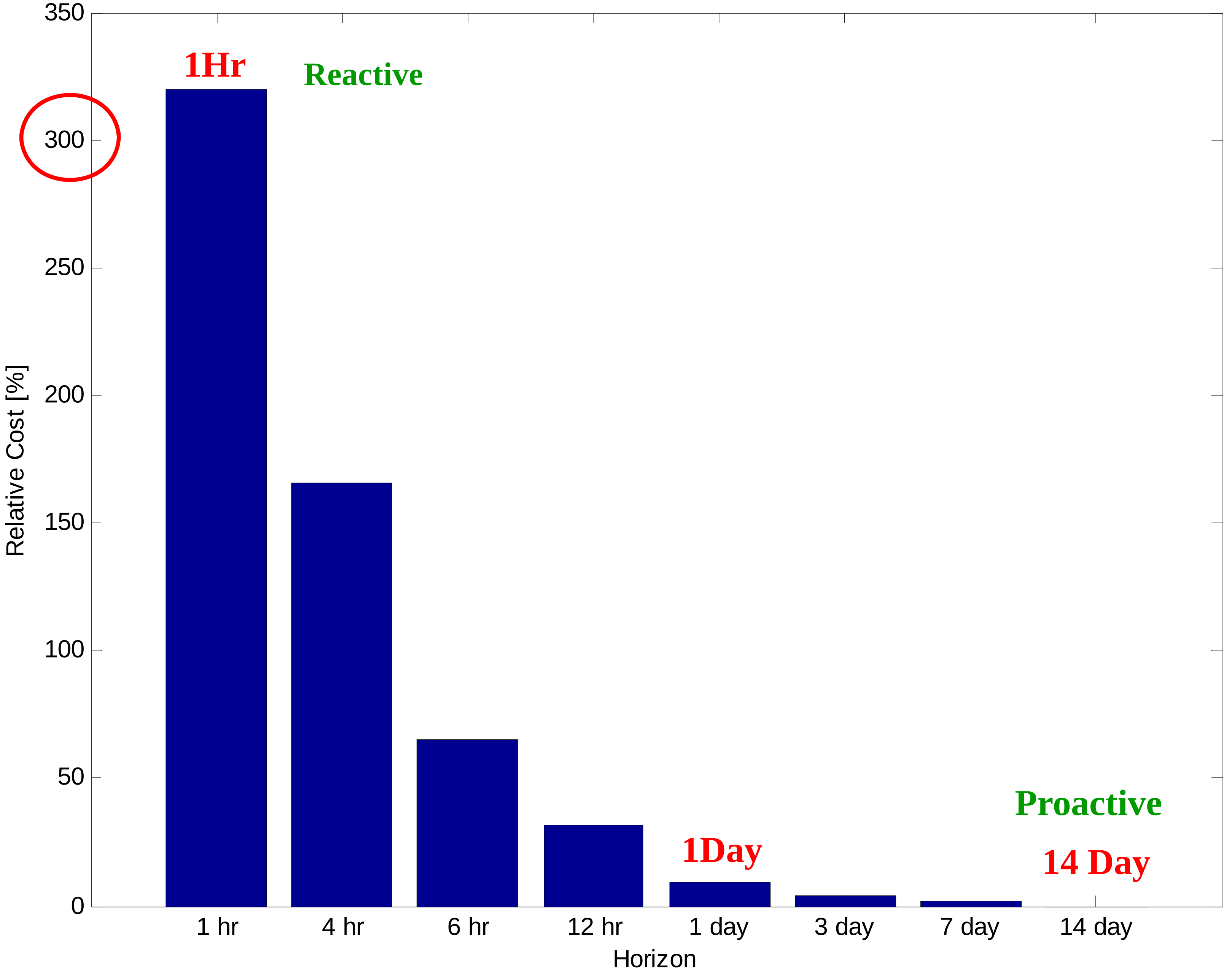
Power Losses

Power Losses

Storage

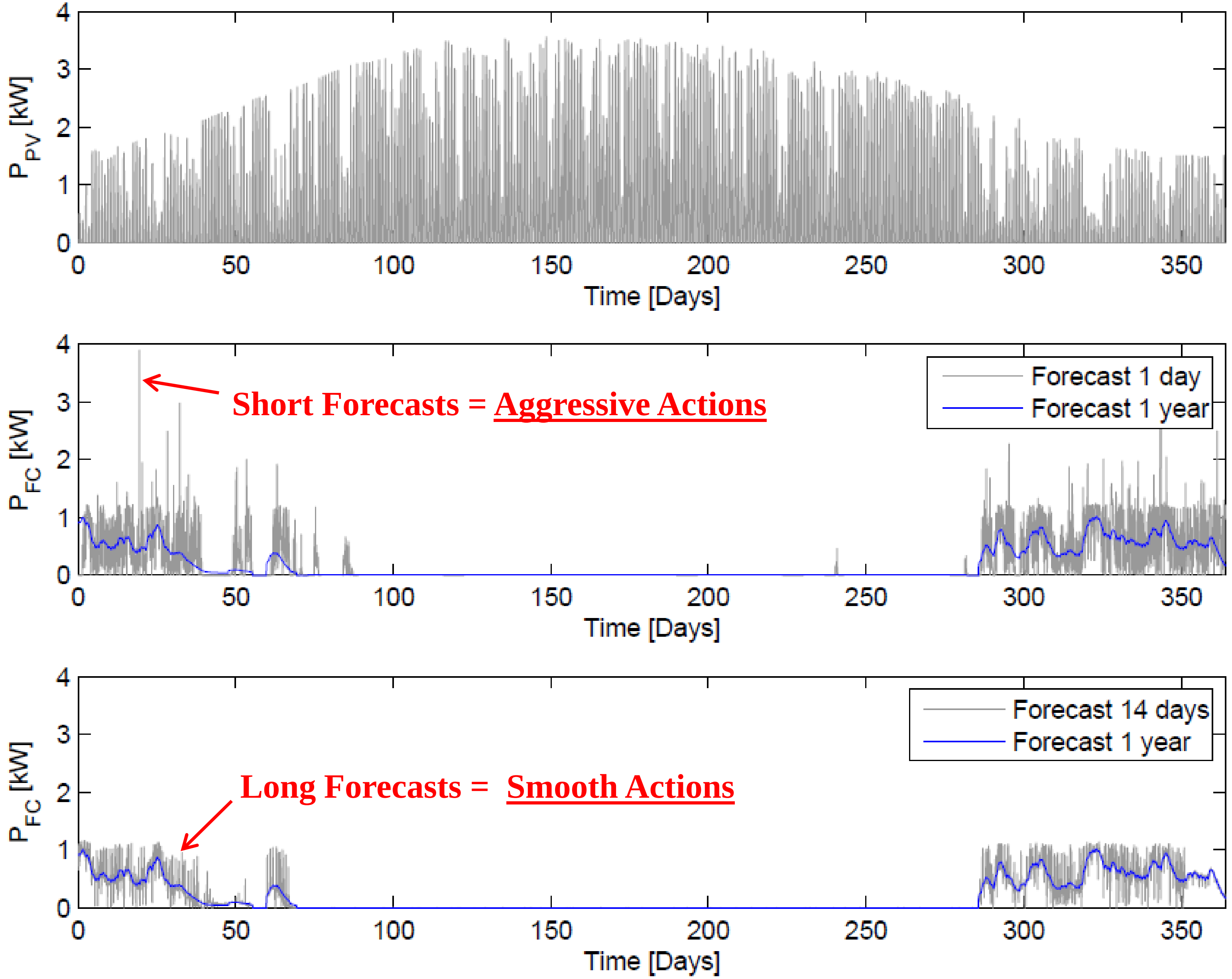
- **Fuel Cell Hybrids Candidates for On-Site Generation**
- **Performance Deteriorated by Storage and Conversion Losses**

Cogeneration Systems



Cogeneration Systems

Profiles of Fuel Cell Power



Short Forecasts = Aggressive Actions

Long Forecasts = Smooth Actions

3. Large-Scale Optimization

Large-Scale Optimization

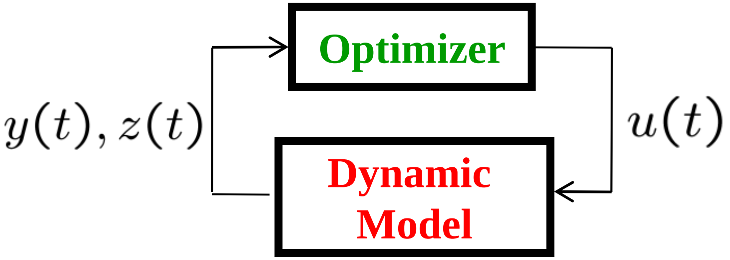
Optimization of Differential-Algebraic Systems (DAEs)

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

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

Simulation-Based Approach

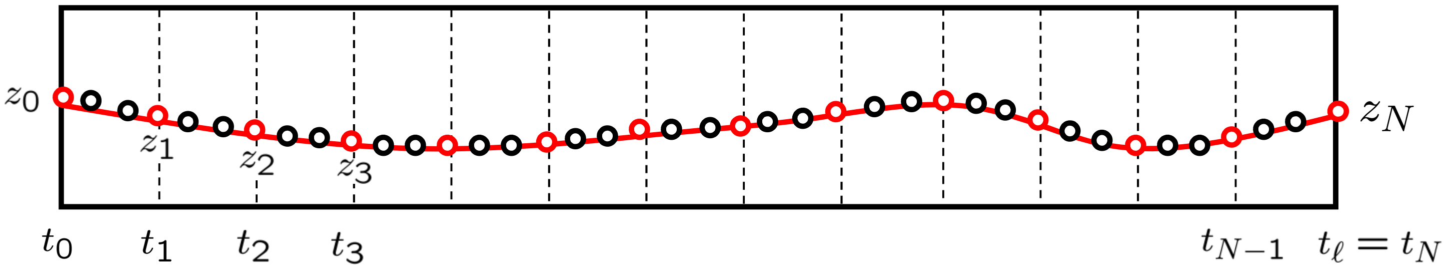
e.g., EnergyPlus : Highly <u>Inefficient</u>



Optimizer

Dynamic Model

Full-Discretization (Finite-Elements, Collocation)



Optimizer

Discretized Dynamic Model

$$\begin{aligned} \min \quad & f(w) \\ \text{s.t.} \quad & c(w) = 0 \\ & w \geq 0 \end{aligned}$$

<u>Sparse</u> Nonlinear Optimization

- **Model Solved <u>Only Once</u>, At Optimal Point** *Betts, Biegler, Renfro & Morshedi, Ghattas*
- **Exact Function <u>Derivatives</u> : Key for <u>Fast</u> Convergence**

Large-Scale Optimization

Full-Space Sparse Solvers – Knitro, IPOPT, LOQO *Byrd & Nocedal 2001, Wachter & Biegler, 2006*

Sparse Nonlinear Optimization

$$\begin{aligned} \min \quad & f(w) \\ \text{s.t.} \quad & c(w) = 0 \\ & w \geq 0 \end{aligned}$$

Optimality Conditions –KKT-

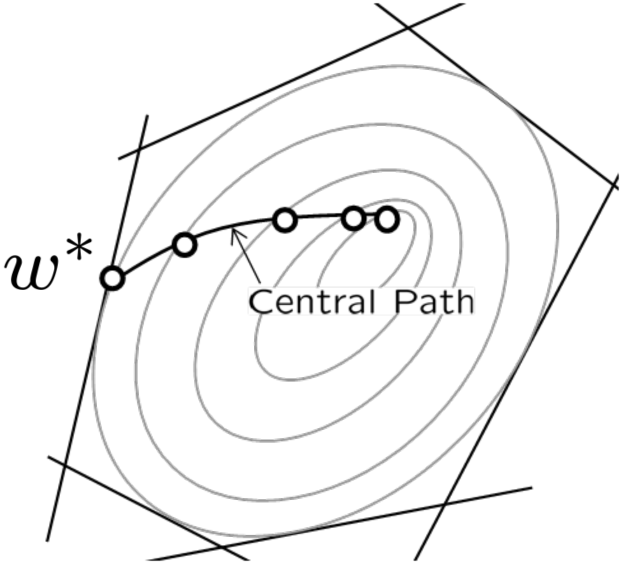
$$\begin{aligned} \nabla_w f(w) + \nabla_w c(w)\,\lambda - \nu &= 0 \\ c(w) &= 0 \\ W \cdot V &= \mu e \end{aligned}$$

Newton's Method, Solve Linearized System:

KKT Matrix

$$\begin{bmatrix} H_j & A_j \\ A_j^T & \end{bmatrix} \begin{bmatrix} \Delta w \\ \Delta \lambda \end{bmatrix} = - \begin{bmatrix} \nabla_w \mathcal{L}(w_j, \lambda_j) \\ c(w_j) \end{bmatrix}$$

Search Step **Optimality Conditions**

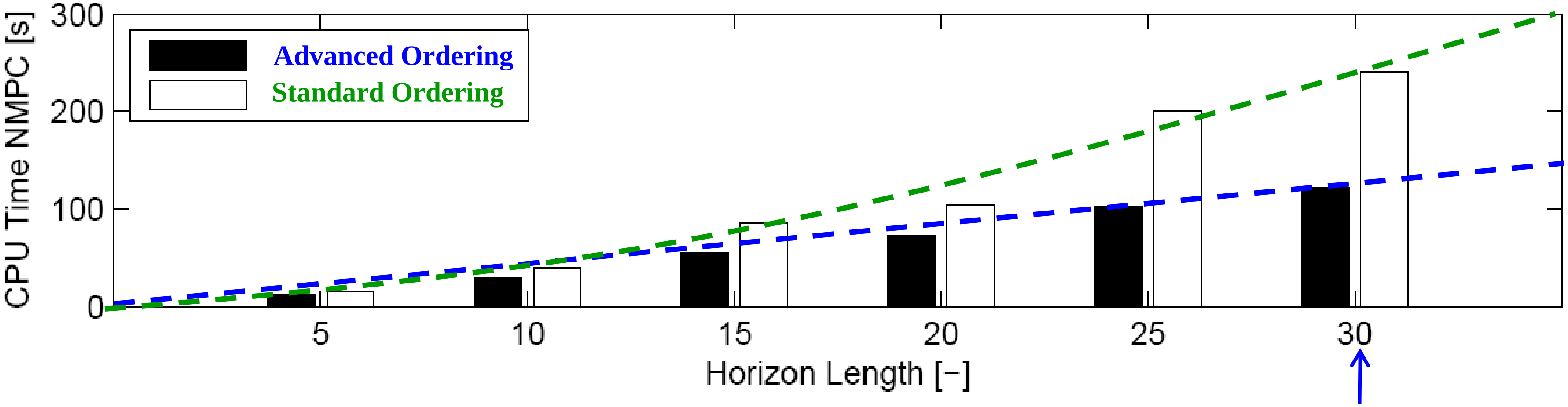


Factorization of KKT Matrix is Critical Computational Step- *Z, Laird &Biegler, 2006*

Problem Sparsity Exploited with Specialized Linear Algebra Solvers

Computational Results

Scalability of DAE Optimization *Z & Biegler, 2008*



350,000 Constraints & 1,000 Controls

Scalability in Industrial Chemical Processes – Standard Personal Computer *Z, & Biegler, 2008*

Problem	DAEs	Constraints	Controls	Solution Time
Polyethylene	**1,000**	71,000	60	≈ 5 min
Air Separation	**1,600**	110,000	200	≈ 2 min
Polyethylene (PDE)	**10,000**	350,000	1,000	≈ 2 min

Existing Optimization Technology Suitable for Large-Scale Energy Management

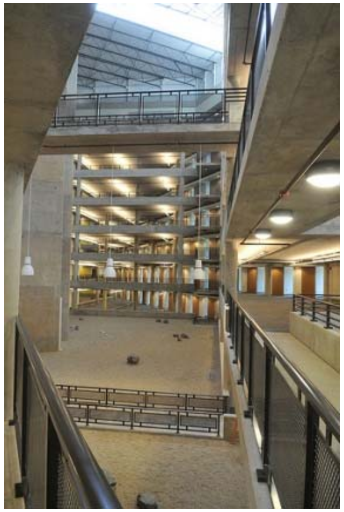
4. BuildingIQ – Argonne Project

Building Energy Management

Collaborative Project: Argonne-Building IQ

“Proactive Energy Management for Building Systems”

Mike Zimmerman, Tom Celinski, Peter Dickinson (BIQ), Dane Skow and Victor Zavala (ANL)

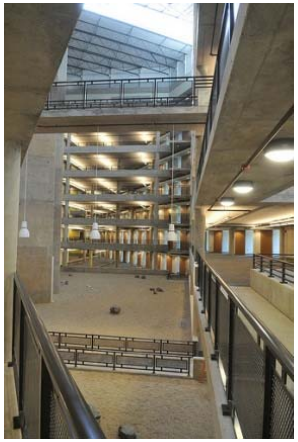


Building Energy Management

Inputs

- Weather forecast
- Zone temp settings & <u>occupant feedback</u>
- Heat Gains
- Energy costs

Machine Learning Dynamic Model



Outputs

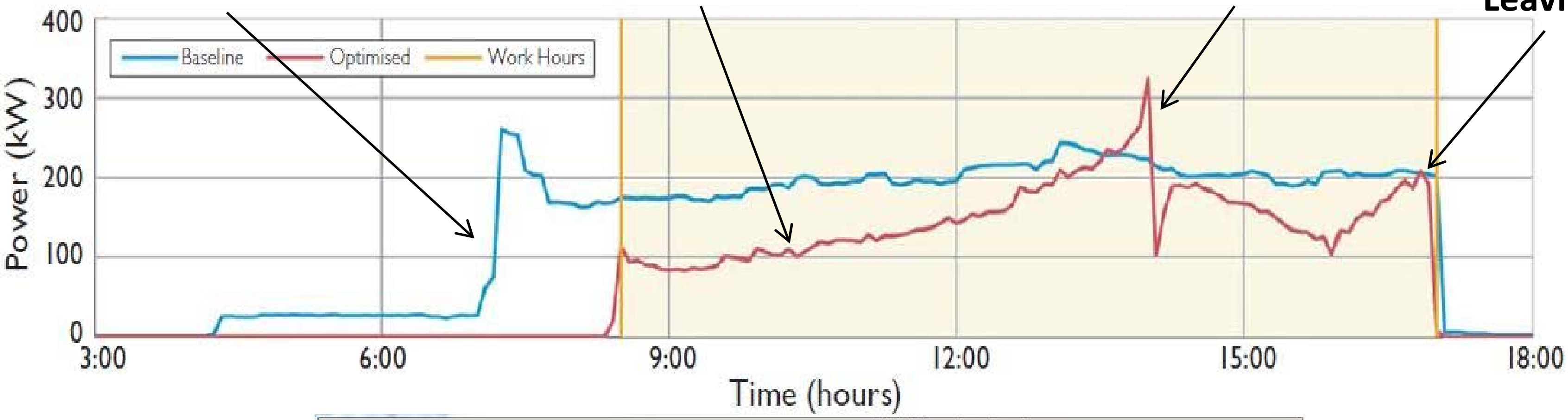
- Humidity
- Cooling Schedule
- Zone Temperature
- Etc ...

- **Solves <u>DAE Optimization Problem</u> with Machine Learning Model**
  Solved Every 10 Minutes, Forecast of 1-2 Hours
  Building Model Re-Trained Daily
  Machine Learning Alternative for Low-Cost <u>Deployment</u>

- **Key Trade-Off:** Human Comfort vs. Energy Cost vs. CO_2 emissions

- **Challenges:** Increase <u>Spatio-Temporal</u> Resolution
  Large-Scale Machine Learning
  Physical Models for HVAC System

Building Energy Management

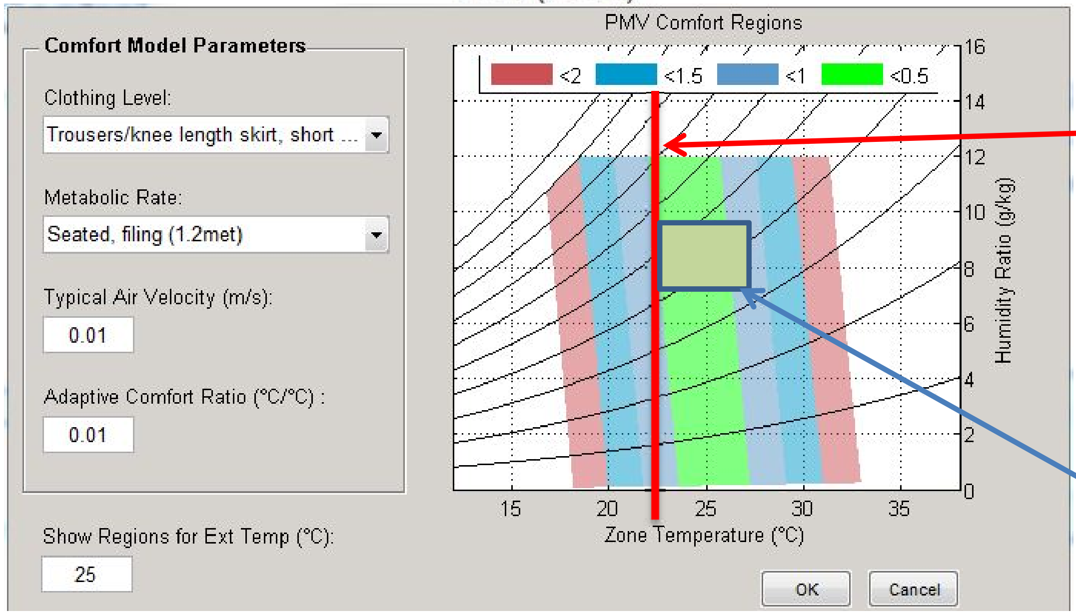


Original profile

Optimised profile

Pre-cooling

Occupants Leaving



Comfort Model Parameters

Clothing Level: Trousers/knee length skirt, short ...

Metabolic Rate: Seated, filing (1.2met)

Typical Air Velocity (m/s): 0.01

Adaptive Comfort Ratio (°C/°C) : 0.01

Show Regions for Ext Temp (°C): 25

Fixed set-point

Comfort Zone Exploitation

Currently Being Implemented at Argonne's TCS Building – Deployment 12/2010

Expected Yearly Savings of ~10% – $O(10^5)/yr$

5. Conclusions and Research Challenges

Conclusions and Research Challenges

Need Proactiveness in Formulation to Capture Disturbance Trends
- Weather, Storage, Demand, Price, …

Mature Optimization Technology for Proactive Energy Management
- State Estimation, Optimal Control, and Real-Time Optimization

Machine Learning+Physics Models Critical for Low-Cost Deployment
- Minimize Development Time

Challenges
- Dealing with Discrete Decisions (ON/OFF)
- Energy-Oriented Room and Computing Scheduling
- Occupant Sensor Placement and Observability

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