Data Predictive Control for Volatile Energy Markets

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2015 Is Officially the Hottest Year on Record

2015 was one for the record books, says the World Meteorological Organization.

How far above or below average temperatures were in 2015
Compared with the average from 1901 to 2000

Average global surface air temperatures
Compared with the average from 1901 to 2000
Price Volatility: Summer peak

Nominal price: $25/MWh
Peak Price: $800/MWh

20th, July 2015
Price Volatility: Winter peak

Nominal price: $31.21/MWh

Peak Price: $2,680.21/MWh

24th, January 2014
Price volatility is the new normal

PJM (ISO) Locational Marginal Prices (LMPs) example
“All kilowatts are not created equally”
What about Renewables?

The duck curve shows steep ramping needs and overgeneration risk

Net load - March 31

Conventional Generation

Mega watts

12am 3am 6am 9am 12pm 3pm 6pm 9pm

ramp need
~13,000 MW
in three hours

overgeneration risk
Renewables in Germany
Price volatility in Germany’s Energy Market

Wholesale power price plummeted to **-130 euros per megawatt**

Negative wholesale prices occurred a record 25 times in 2015.

4 times more often than in 2011.

Bitte, nehmt meinen Strom! Ich zahl auch dafür! — SPIEGEL ONLINE
A Demand Response Event

- Peak anticipated due to forecast
- Electricity Load Increases
- Demand Response Dispatch
- DR Curtailment

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Intractable at large scales: Penn Campus

- 72 MW Peak (UCAP)
- 187 Buildings
- 292,000 SCADA Tags
- 4 Million Gallons of chilled water (@42F)
Economic incentives for model based control

~$28M
Annual Electricity Bill

In 2011
Peak > UCAP
30 min

$720,000
Penalty for 30 minute
End-User DR Challenges

![Diagram showing demand and time phases: Notification, RAMP, SUSTAINED RESPONSE, Recovery, Release, Resume.]

**HOW LOW CAN YOU GO?**
Demand Response Challenges

If you don't know what's going to happen when you make a change. How do you even know its worth making?

Q) Predict the building's power response when there is no DR event?

Q) Predict the power consumption profile due to a DR action?

Options

- DR Strategy A
- DR Strategy B
- DR Strategy C
- DR Strategy D

Fixed DR Strategy Example

- Increase Chilled Water Temperature Set-Point
- Increase Zone Air Temperature Set-Point
- Turn off Elevator
- Dim the Lights
Evaluate fixed DR strategies

Rule-based fixed strategies

STRATEGY 1  STRATEGY 2  STRATEGY 3

BASELINE

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Demand Response Challenges

Can we find good values for W, X, Y & Z in real-time?

Can we synthesize good DR strategies?

<table>
<thead>
<tr>
<th>DR Strategy Synthesis Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase Chilled Water Temperature Set-Point by $W^\circ C$</td>
</tr>
<tr>
<td>Increase Zone Air Temperature Set-Point by $X^\circ C$</td>
</tr>
<tr>
<td>Turn off Elevator #Y</td>
</tr>
<tr>
<td>Dim the Lights by $Z%$ unknown</td>
</tr>
</tbody>
</table>
Model Based Demand Response

- **Took 9+ months** to construct and tune EnergyPlus for the building.

- Separate models for HVAC equipment (with TRNSYS)

- **Cost and time prohibitive** to build such models
White-Box Modeling

Not always available

Model Tuning
Data
Sensor retrofits

First principles based
High fidelity
Building energy simulation

Set parameters
Floor by floor
Zone by zone
Wall by wall
Layer by layer
Equipment by equipment
Transfer geometry

Guess nominal parameter values

Hire building modeling experts

Hire building modeling experts

HVAC layout

Floor Plan

Floor Plan

TRNSYS17

EnergyPlus

First principles based
High fidelity
Building energy simulation

Guess nominal parameter values
White-Box Modeling

Cost and time prohibitive
(sensor installation, commissioning & expertise)

Not suitable for model-based control
Model complexity and uncertainty, (1000's parameters and states)
Modeling using first principles is hard!

Each building design is different. Must be uniquely modeled.

Long operational lifetimes ~50-100 years.

Too many sub-systems
Non-linear interactions
Closely coupled operation
Time varying disturbances
How are building models obtained today?
Black-Box Modeling

Data

Feature engineering

Could be automated

Not well aligned with control synthesis

Coarse grained predictions

Non-physical parameters
Modeling for Cyber-Physical Energy Systems

Suitability for control

Modeling Difficulty (cost)

High

Low

Suitable

Unsuitable

White Box

Grey Box

This talk

Black Box
Bridging **Machine Learning** and **Control Systems**

Data-driven Energy Scheduling & Control
How can buildings respond to massive swings in energy prices?
Data-Driven Demand Response

Can we get the best of both worlds?

- Simplicity of rule-based DR
- Predictive capability of model-based DR
Data-Driven Demand Response Recommender System
Existing solutions are reactive

DR-Advisor does prediction & control
The Netflix of Energy Management Systems

Will a person like the movie ‘The Usual Suspects’?

Make Recommendations
Data Description

**Weather**
- Temperature
- Humidity
- Wind Speed
- Wind Direction

**Schedule**
- Time Of Day
- Day of Week
- Set Points

**Building**
- Chilled Water Temp
- Lighting Power
- Zone Temperature
- Power Consumption
Build a Family of Regression Trees

**Historical Data**

- Temperature
- Wind
- Day Of Week
- Chilled Water Temp.
- Zone Temperature
- Humidity
- Time Of Day
- Schedule
- Lighting
- Power (kW)

**DR Baseline**
- Real-Time Estimate of Baseline Power Consumption

**DR Evaluation**
- Choose the best DR Strategy in real-time

**DR Synthesis**
- Compute the best DR control action in real-time
Very easily interpretable

- Building operators are used to operating a system with fixed logic and rules.

- Complex models go through a long calculation routine and involve too many factors.
  - Not easy for a human engineer to judge if the operation/decision is correct or not
Interpretable Regression Tree Models

Is Outside dry bulb temperature > 77°F?
- Yes
- No
  - Is it a Tuesday?
    - Yes
    - No
      - Is the SAT > 58°F?
        - Yes
        - No
          - Is Time of Day in 1300-1400 hrs?
            - ... ...
              - Yes

Predicted Power: 163 kW
95% confidence [159.5, 165.7]

There is traceability around how the recommendation was arrived at so that operators can understand it and recalibrate if necessary.
Baseline Prediction: Building 101

Located at The Navy Yard, Philadelphia

Headquarters of the DoE’s Consortium for Building Energy Innovation

Training Data: 2014
Testing Data: Feb 2015

Prediction Accuracy: 96.84%
Can we synthesize good DR strategies?

Can we find good values for W, X, Y & Z in real-time?

**DR Strategy Synthesis Example**

<table>
<thead>
<tr>
<th>Action</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase Chilled Water Temperature Set-Point</td>
<td>W °C</td>
</tr>
<tr>
<td>Increase Zone Air Temperature Set-Point</td>
<td>X °C</td>
</tr>
<tr>
<td>Turn off Elevator</td>
<td>#Y</td>
</tr>
<tr>
<td>Dim the Lights</td>
<td>Z%</td>
</tr>
</tbody>
</table>

unknown
Synthesize new DR strategies

DR-Advisor is data-driven and operates in real-time

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Heating  Cooling  Lighting
Regression trees for control

\[ Y = f(X_1, X_2, \ldots, X_m) \]

Response (Power Consumption)

Non-Manipulated Variables [Disturbances]

Manipulated Variables [control]

Power (kW) Wind Day Of Week Chilled Water Temp. Zone Temperature

Humidity Time Of Day Schedule Lighting Dry Bulb
Regression trees for control

<table>
<thead>
<tr>
<th>Time Of Day</th>
<th>Boiler 1 Outlet SetPoint</th>
<th>Perimeter Bottom 3 ZAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day Of Week</td>
<td>Chiller 1 Outlet SetPoint</td>
<td>Perimeter Bottom 4 ZAT</td>
</tr>
<tr>
<td>Day Of Month</td>
<td>Chiller 2 Outlet SetPoint</td>
<td>Perimeter Mid 1 ZAT</td>
</tr>
<tr>
<td>Basement Zone Air Temperature</td>
<td>Zone Cooling Set Point</td>
<td>Perimeter Mid 2 ZAT</td>
</tr>
<tr>
<td>Ground Floor Plenum Temperature</td>
<td>Chilled Water Set Point</td>
<td>Perimeter Mid 3 ZAT</td>
</tr>
<tr>
<td>Core Bottom Zone Air Temperature</td>
<td>Building Lighting Set Point</td>
<td>Perimeter Mid 4 ZAT</td>
</tr>
<tr>
<td>Core Mid Zone Air Temperature</td>
<td>Zone Heating Set Point</td>
<td>Perimeter Top 1 ZAT</td>
</tr>
<tr>
<td>Core Top Zone Air Temperature</td>
<td>Hot Water Set Point</td>
<td>Perimeter Top 2 ZAT</td>
</tr>
<tr>
<td>Mid Floor Plenum Temperature</td>
<td>Perimeter Bottom 1 ZAT</td>
<td>Perimeter Top 3 ZAT</td>
</tr>
<tr>
<td>Top Floor Plenum Temperature</td>
<td>Perimeter Bottom 2 ZAT</td>
<td>Perimeter Top 4 ZAT</td>
</tr>
<tr>
<td>Outdoor Dry Bulb Temperature</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind Direction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoor Humidity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incident Solar Irradiation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wind Speed</td>
<td></td>
<td>Building Power Consumption</td>
</tr>
</tbody>
</table>
Regression trees for control

Cannot specify order of appearance of variables in tree depth

\[
\begin{align*}
\min_{j,s} \left[ \min_{c_L} \sum_{x_i \in R_L(j,s)} (y_i - c_L)^2 + \min_{c_R} \sum_{x_i \in R_R(j,s)} (y_i - c_R)^2 \right]
\end{align*}
\]

No forecast for manipulated variables
(we want to compute values for these)
Separation of variables

Tree learned only on non-manipulated (disturbances) variables/features

Leaf Model Regression with manipulated variables

Regression at leaves learned on control features
mbCRT: Model Based Control with Regression Trees

Algorithm 1 mbCRT: Model Based Control With Regression Trees

1: **DESIGN TIME**
2: **procedure** MODEL TRAINING
3:  \textit{Separation of Variables}
4:  Set $X_c \leftarrow$ Controllable Features
5:  Set $X_u \leftarrow$ Uncontrollable Features
6:  Build the uncontrollable tree $T_{u_{tree}}$ with $X_u$
7:  \textbf{for} all Regions $R_i$ at the leaves of $T_{u_{tree}}$ \textbf{do}
8:     Fit linear model $Y_{c,t} = \beta_{0,i} + \beta_{i}^T X_c$
9:  \textbf{end for}
10: **end procedure**
11: **RUN TIME**
12: **procedure** CONTROL SYNTHESIS
13:  At time $t$ obtain forecast $\hat{X}_u(t+1)$ of disturbances
14:  $X_{d1}(t+1), X_{d2}(t+1), \cdots$
15:  Using $\hat{X}_u(t+1)$ determine the leaf and region $R_{ct}$
16:  \textbf{for} Region $R_{ct}$ \textbf{do}
17:     Solve optimization in Eq11 for optimal control action $X_c(t)$
18:  \textbf{end for}
19: **end procedure**

minimize $f(Y_{c,t})$

subject to $Y_{c,t} = \beta_{0,i} + \beta_{i}^T X_c$

$X_c \in X_{safe}$
Disturbance forecast
[At run-time]

1. Disturbance forecast

2. Online control-model selection

\[
\text{forecast of non-manipulated variables} = [\hat{X}_{d1}, \hat{X}_{d2}, \ldots, \hat{X}_{dm}]
\]

Power forecast (kW) tree | Zone temperature T1 tree | Zone temperature Tq tree

\[
kW_{Ri} = \beta_{0,i} + \sum_{j=1}^{p} \beta_{j,i} X_{c,j}
\]

\[
T_{1Ri} = \alpha_{0,i} + \sum_{j=1}^{p} \alpha_{j,i} X_{c,j}
\]

\[
T_{qRi} = \alpha_{0,i} + \sum_{j=1}^{p} \alpha_{j,i} X_{c,j}
\]

Linear model at leaf node is the optimization constraint

\[
\min_{X_c} f(kW) + \text{Penalty}[\sum_{k=1}^{n} (\hat{T}_k - T_{ref})]
\]

subject to

\[
kW_{Ri} = \beta_{0,i} + \sum_{j=1}^{p} \beta_{j,i} X_{c,j}
\]

\[
T_{1Ri} = \alpha_{0,i} + \sum_{j=1}^{p} \alpha_{j,i} X_{c,j}
\]

\[
\vdots
\]

\[
T_{qRi} = \alpha_{0,i} + \sum_{j=1}^{p} \alpha_{j,i} X_{c,j}
\]

\[X_c \in \text{Safe}\]
[At run-time]

1. Disturbance forecast
2. Online control-model selection [using regression trees]
3. Real time optimization [with dynamical constraints]
Different zone priorities

Custom Comfort

CEO and Executives
71°-72°, Opt Out, no DR shed

Marketing and Finance
68°-74°, allow DR shed

Vacant
68°-76°, allow DR shed

Meeting Rooms
70°-75°, allow DR shed

Retail Space
68°-74°, allow DR shed

\[
\begin{align*}
\text{min}_{X_c} & \quad f(k\hat{W}) + \text{Penalty} \left( \sum_{k=1}^{p} (\hat{T}_k - T_{ref}) \right) \\
\text{subject to} & \quad k\hat{W}_{Ri} = \beta_{0,i} + \sum_{j=1}^{p} \beta_{j,i} X_{c,j} \\
& \quad \hat{T}_1 = \alpha_{0,i} + \sum_{j=1}^{p} \alpha_{j,i} X_{c,j} \\
& \quad \vdots \\
& \quad \hat{T}_q = \alpha_{0,i} + \sum_{j=1}^{p} \alpha_{j,i} X_{c,j} \\
& \quad X_c \in \text{Safe}
\end{align*}
\]
DR Strategy Synthesis

Sustained response of 380 kW
Correct linear model at the leaf is chosen at each time-step for the
DR Strategy Synthesis

Thermal Comfort Maintained

Zone Temperature Upper Threshold

Zone Temperature Lower Threshold

Start

End

Time of Day (hh:mm)
DR Revenue

Reservation Incentive: $25/kW/month

Curtailment revenue: $1/kWh

Peak curtailment: 331 kW

Energy reduction: 327.4 kWh

~5 events/month for 4 months (summer)

$ 45,600/$120,317

37.9% Savings for the Summer Season
Advantages

98.9% Prediction Accuracy
Less consumption than a fixed strategy
More DR revenue

NO EXPENSIVE AUDITS
DR RECOMMENDATIONS
NO ADDITIONAL SENSORS
SUSTAINED LOAD CURTAILMENT
THERMAL COMFORT GUARANTEES
OUTPERFORMS FIXED DR STRATEGIES

We’ve built novel algorithms that bridge the gap between machine learning and control synthesis.
Who is it for?

Global DR market worth $24.71 billion by 2022

North America smart demand response market by application, (USD Million)
C/I/I Customers  Pilot Deployments

Over 1.2 million sq ft modeled at the University of Pennsylvania

6 floor building
75 kW PV
U. L'Aquila, Italy

The Philadelphia Navy Yard
• Unregulated electrical micro-grid
• Commercial and industrial buildings
• Network Operations Center access

U. L'Aquila, Italy
Upload Training and Testing data

Upload by category
Data Predictive Control (DPC)

Physical System
(large scale, “messy” dynamics, domain experts)

Control Synthesis
(assumes model is available)

Learning
(predictive modeling from data)
48 Months for model capture
4 Months for control implementation
Data Predictive Control

Physical Systems

Data-Driven Control-Oriented Modeling and Control Synthesis

Control Design

Receding horizon control

Stability/Performance bounds

Avoid Modeling Costs

Interpretable Solutions [Operator in the loop]
Foundations of Data Predictive Control

**mbCRT (2014)**

Single-step look ahead
[with single regression trees]

**DPC-RT (2015)**

Finite receding horizon
[with single regression trees]

**Ensemble-DPC (2016)**

Finite receding horizon
[with ensemble models]
“Essentially all models are wrong, but some are useful”

- George E.P. Box

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