Data Predictive Control for Cyber-Physical Systems

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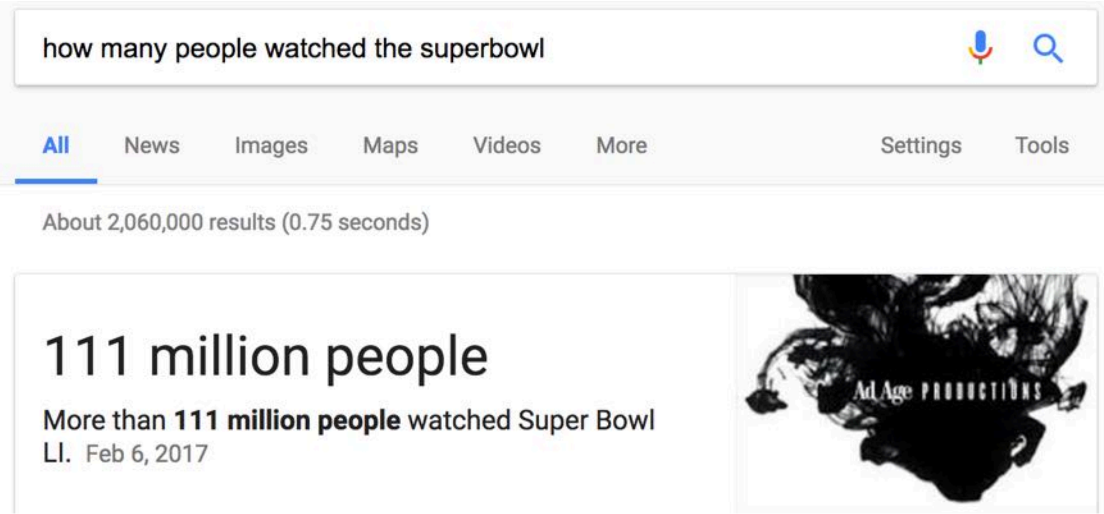
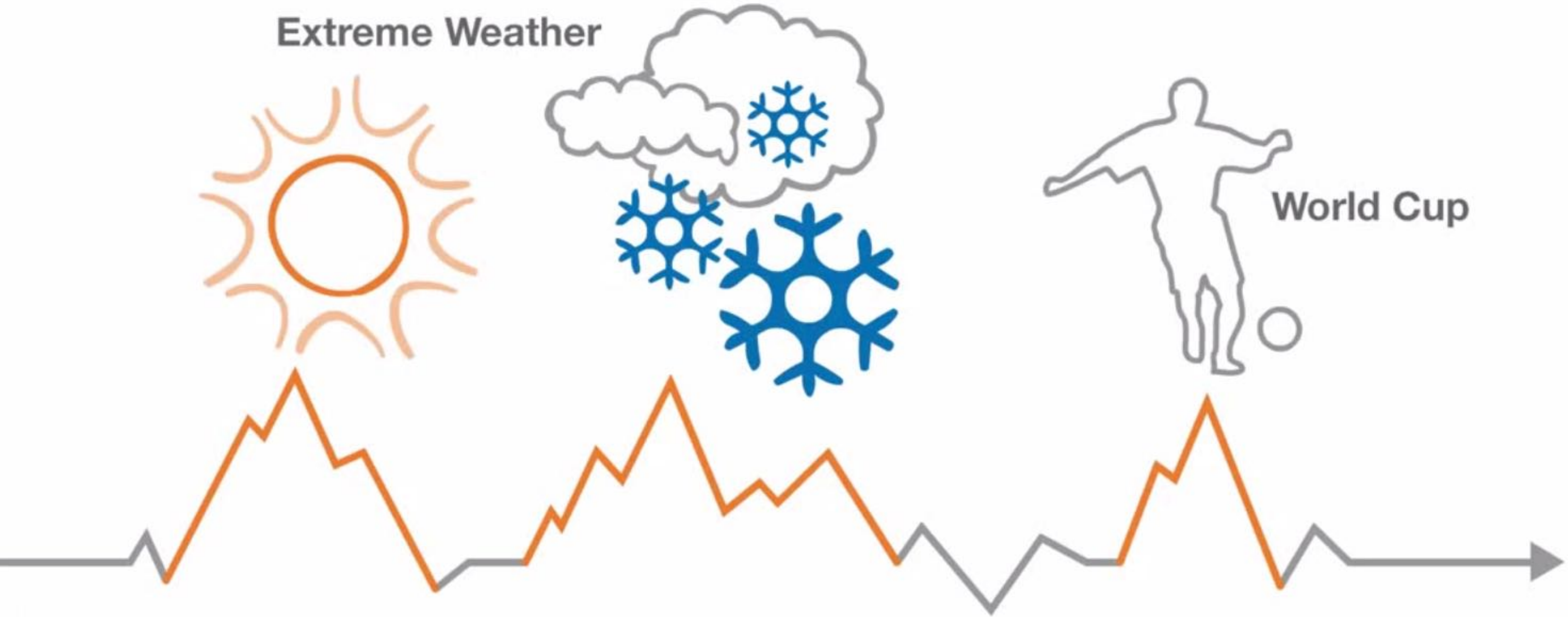
Tea Time In Britain


Peaks occur during major sporting events




Extreme Weather
World Cup

RIBE

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THE SCIENCES MIND HEALTH TECH SUSTAINABILITY EDUCATION VIDEO PODCASTS BLOGS STORE

2014 Officially Hottest Year on Record

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THE SCIENCES MIND HEALTH TECH SUSTAINABILITY EDUCATION VIDEO PODCASTS BLOGS ST

2015 Is Officially the Hottest Year on Record

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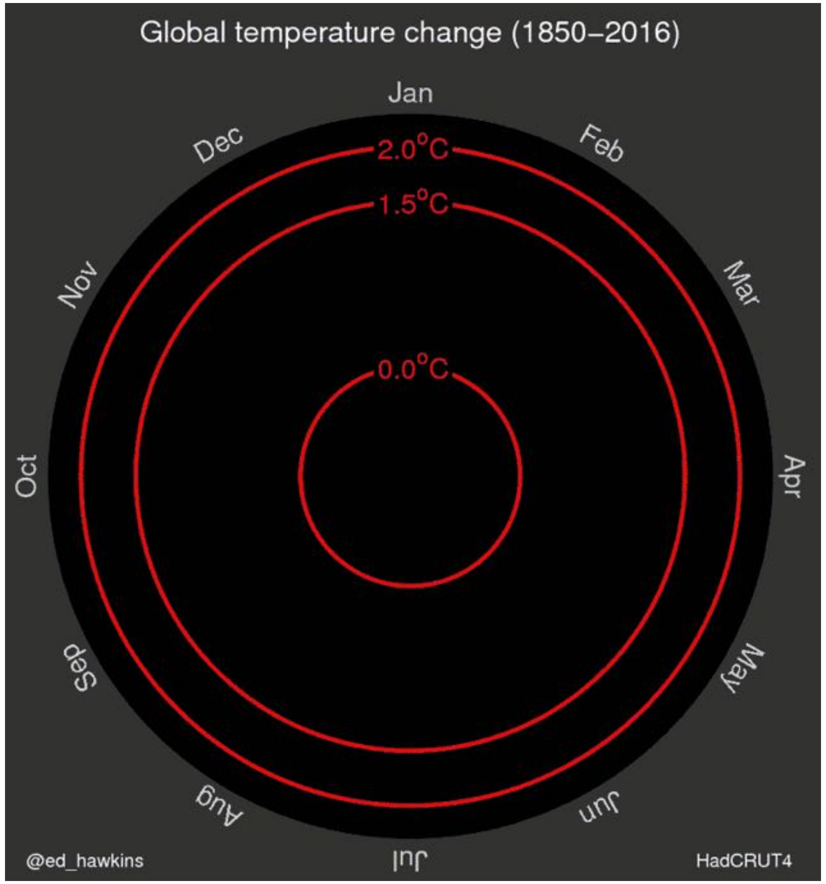
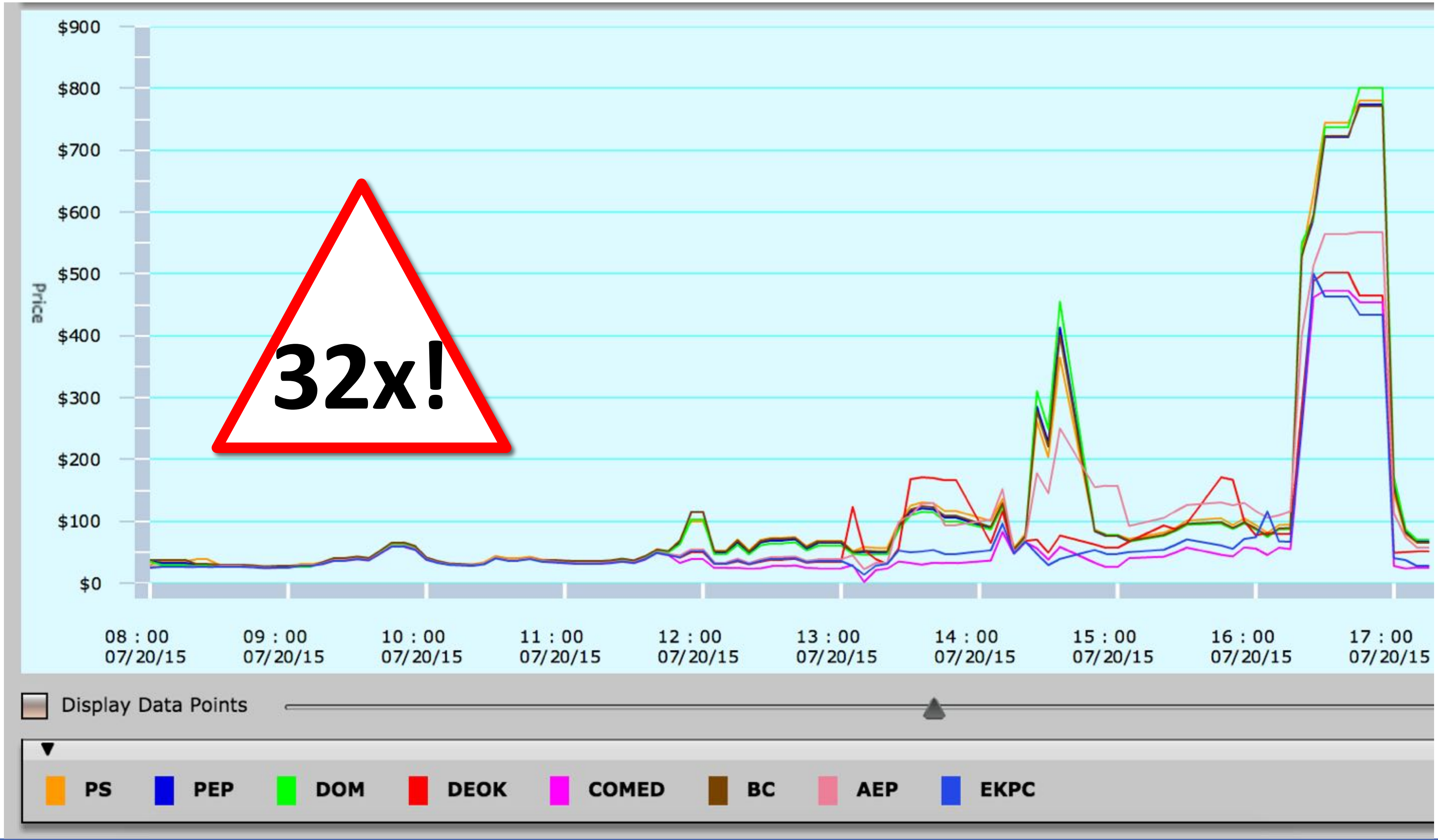
SCIENCES MIND HEALTH TECH SUSTAINABILITY EDUCATION VIDEO PODCASTS BLOGS ST

2016 Was the Hottest Year on Record



Price Volatility: Summer peak

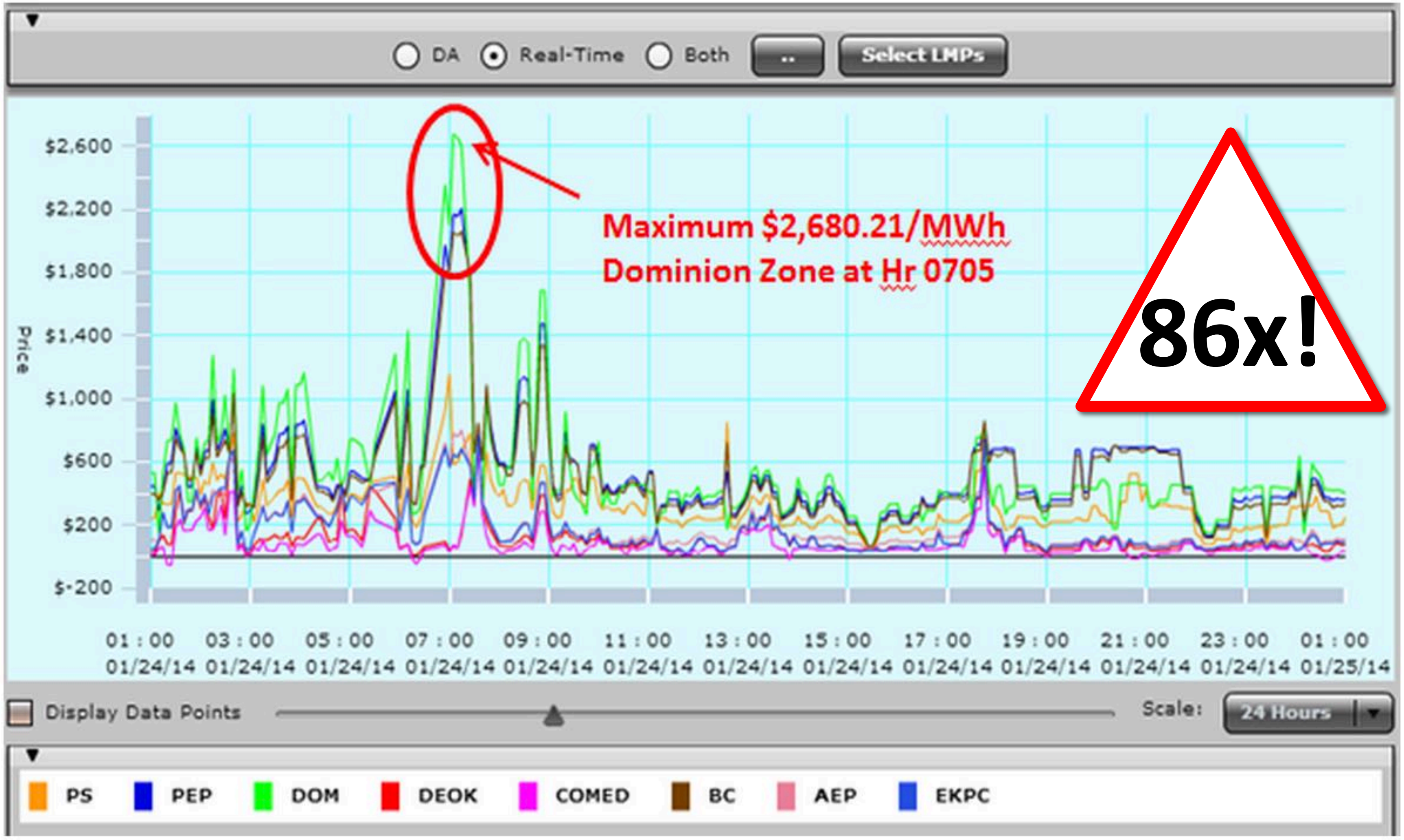
Nominal price: $25/MWh Peak Price: $800/MWh



20th, July 2015

Price Volatility: Winter peak

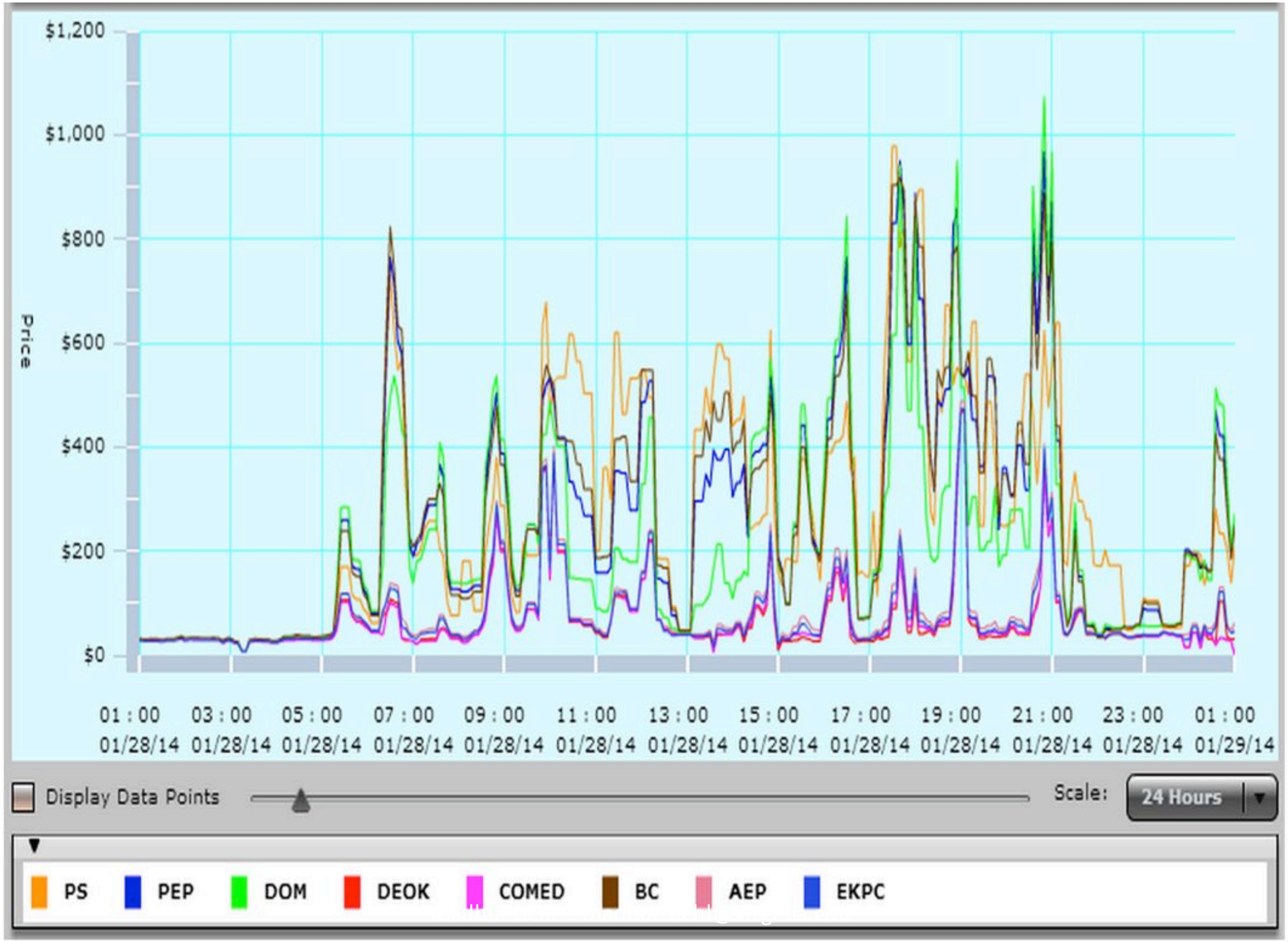
Nominal price: $31.21/MWh Peak Price: $2,680.21/MWh



24th, January 2014

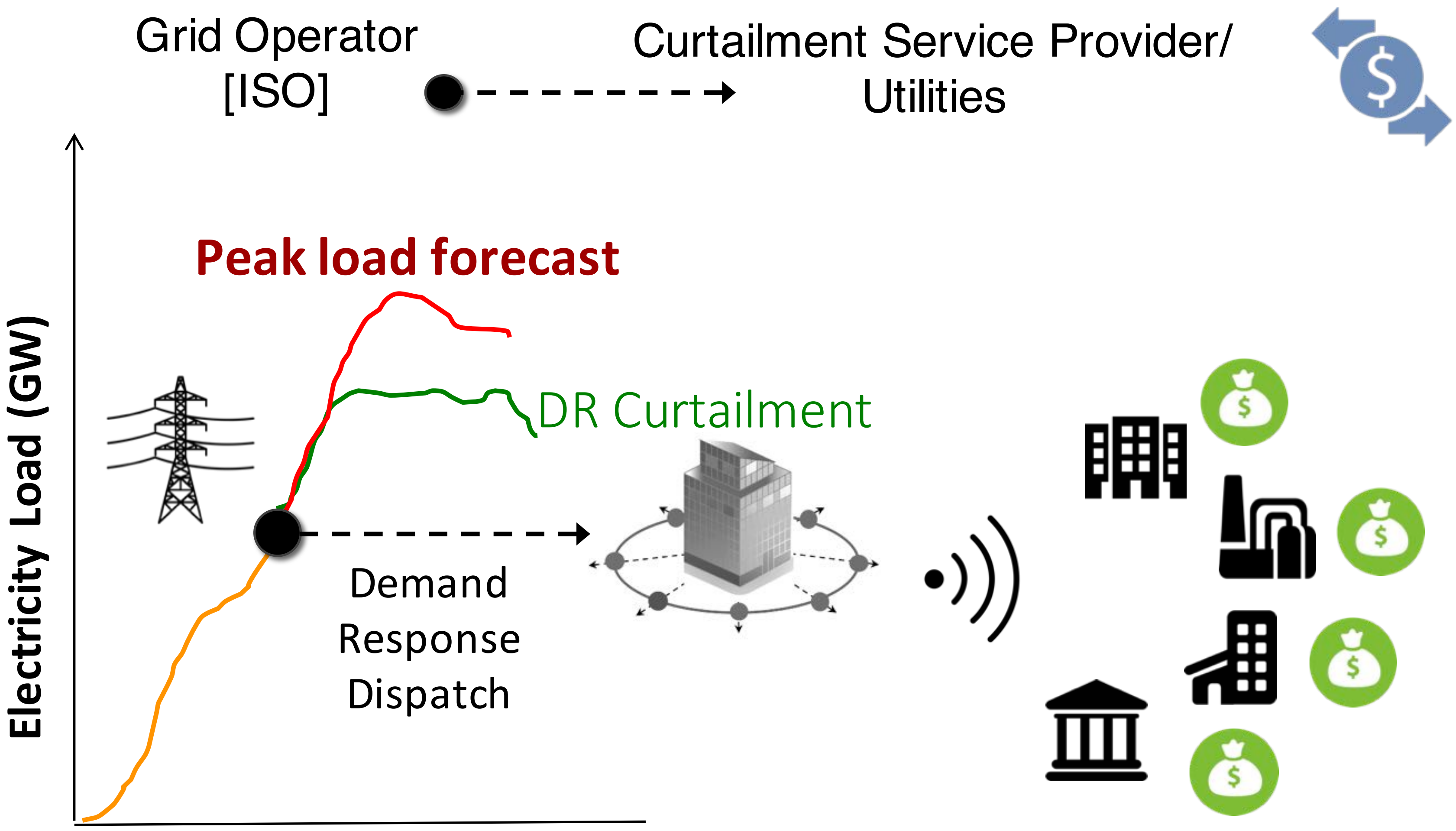
Price volatility is the new normal

PJM (ISO) Locational Marginal Prices (LMPs) example

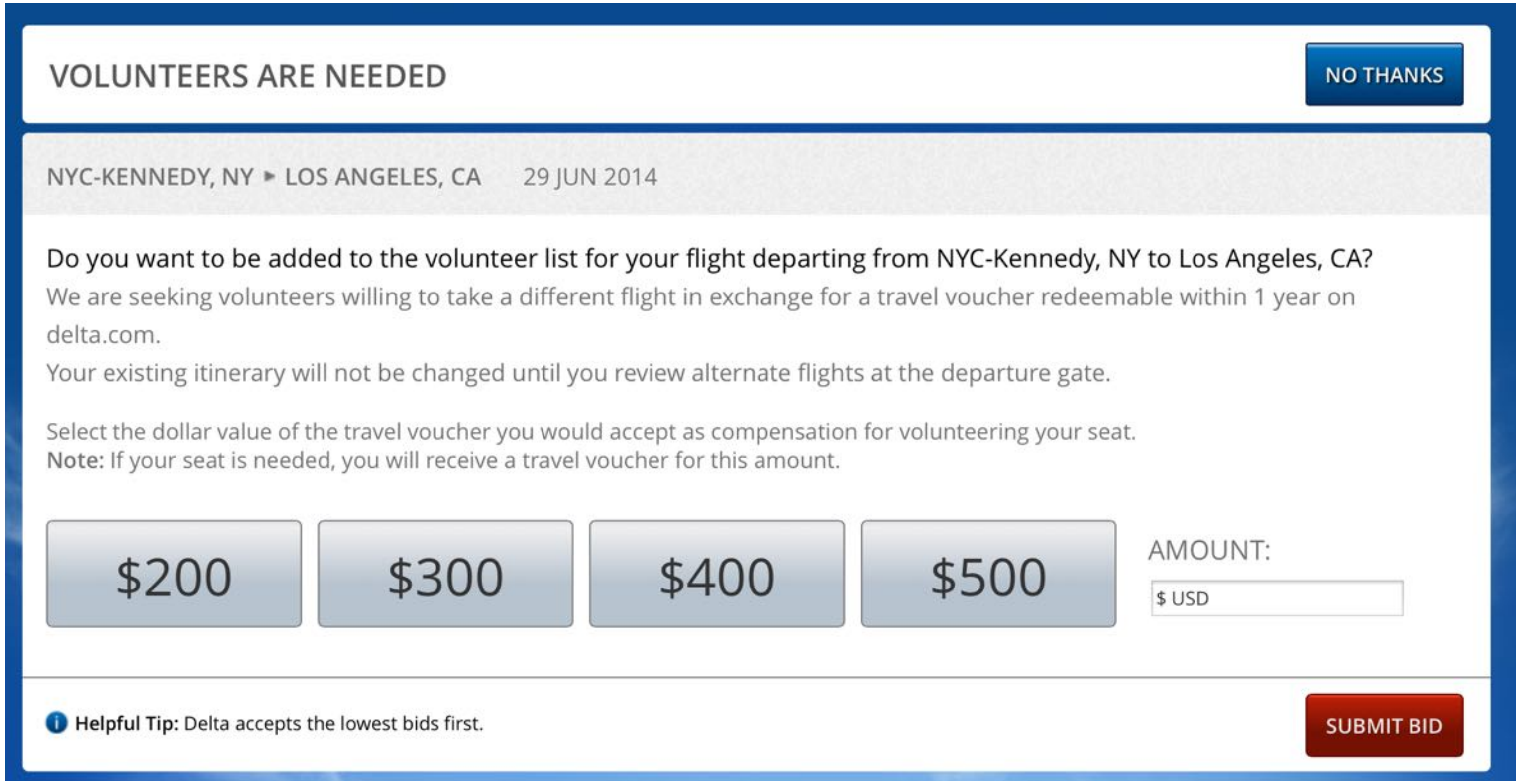


"All kilowatts are not created equally"

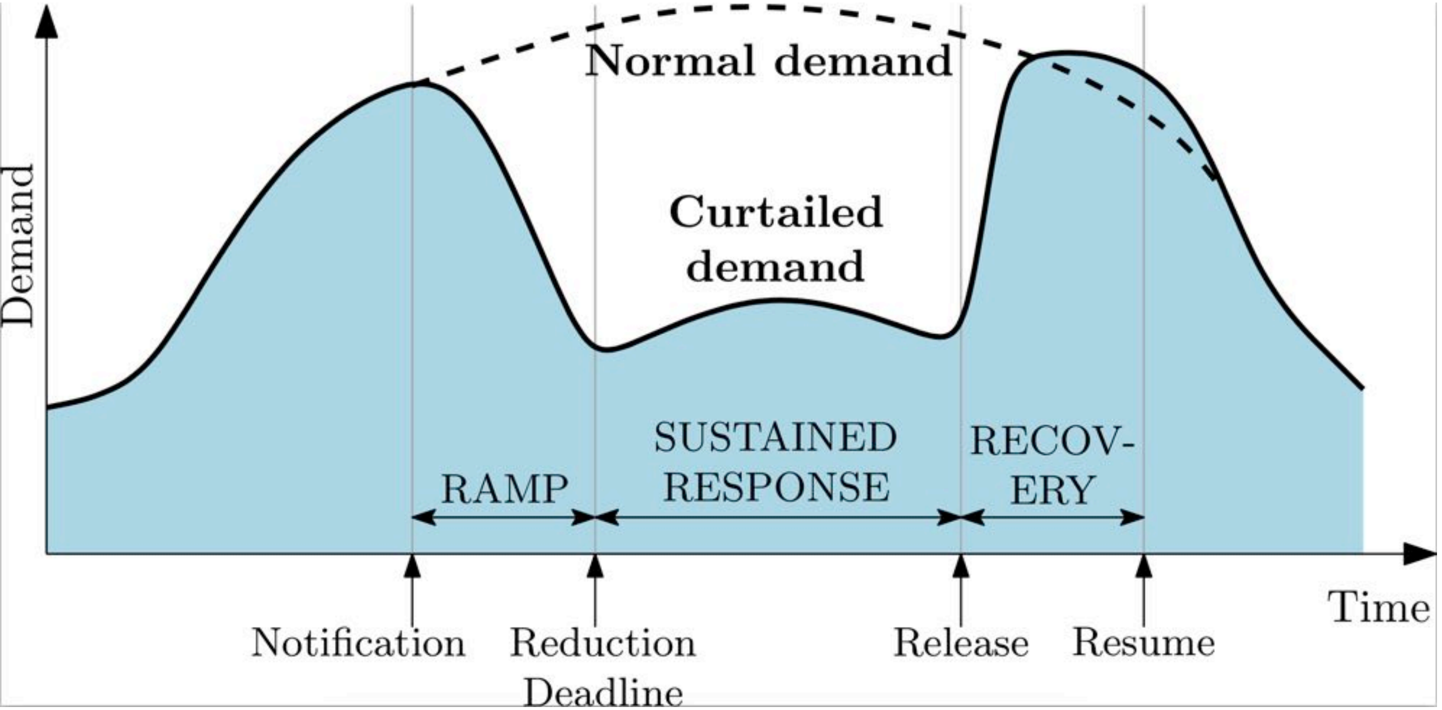
Demand Response Event

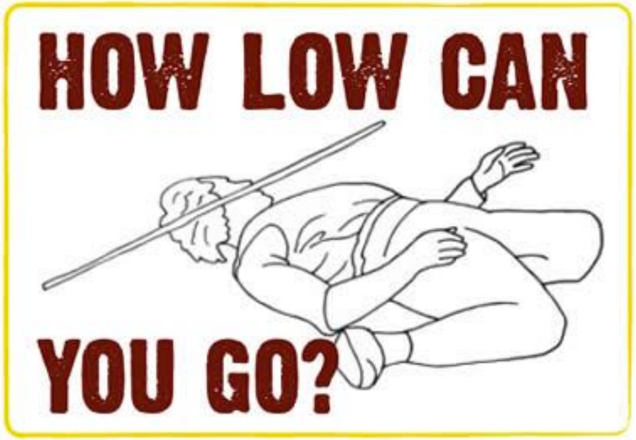


Demand Response – Looks familiar



Demand response challenges



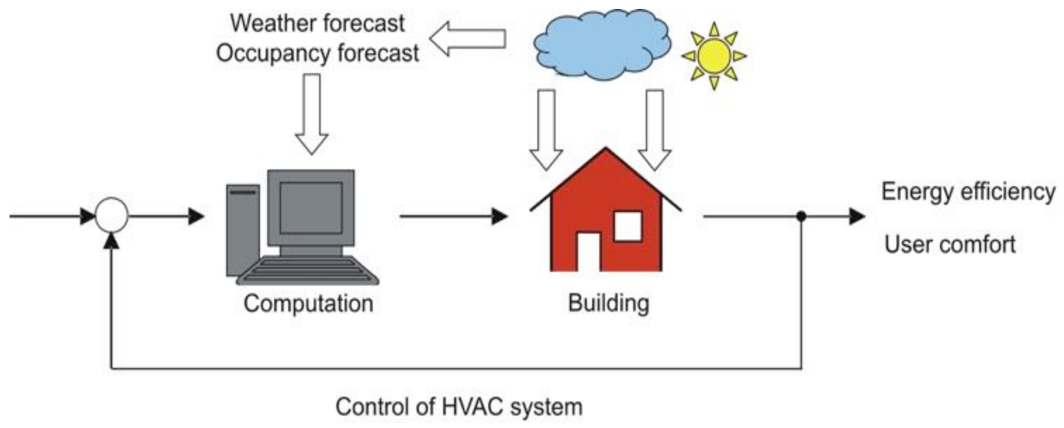



Fixed Strategy 1
Fixed Strategy 2
Fixed Strategy 3
Fixed Strategy 4
Fixed Strategy 5
$ Penalty
Baseline
Target
kW
Time
No Guarantees
Baseline
Target
kW
Time

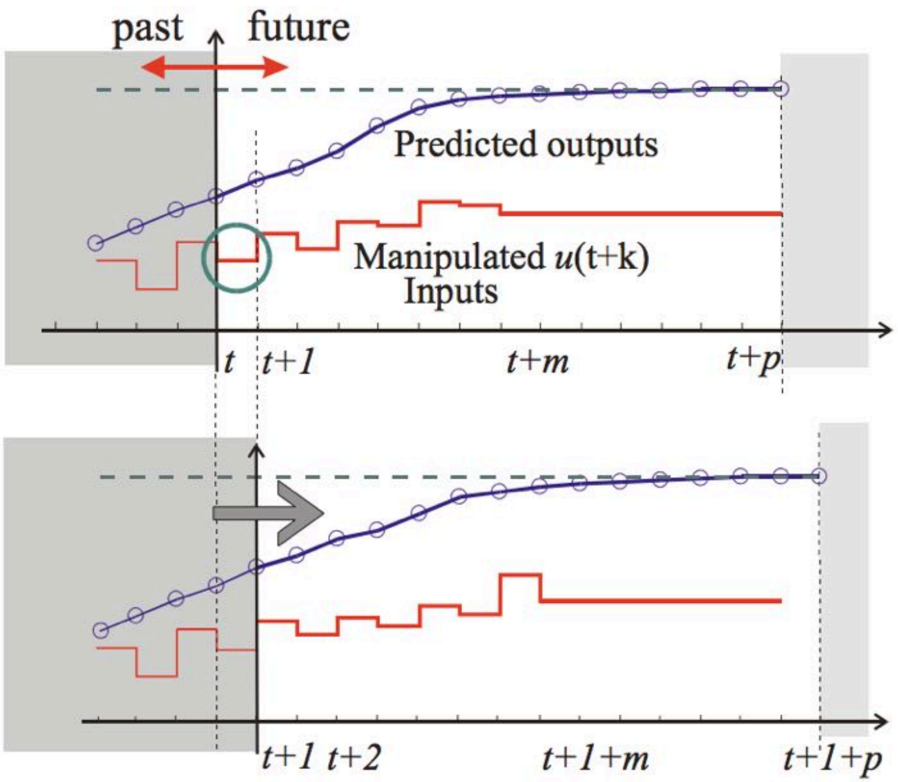
Q) What is the best change that you can make right now ?

Model-based predictive control (MPC)

Model Predictive Control (MPC)



Model Predictive Control (MPC)



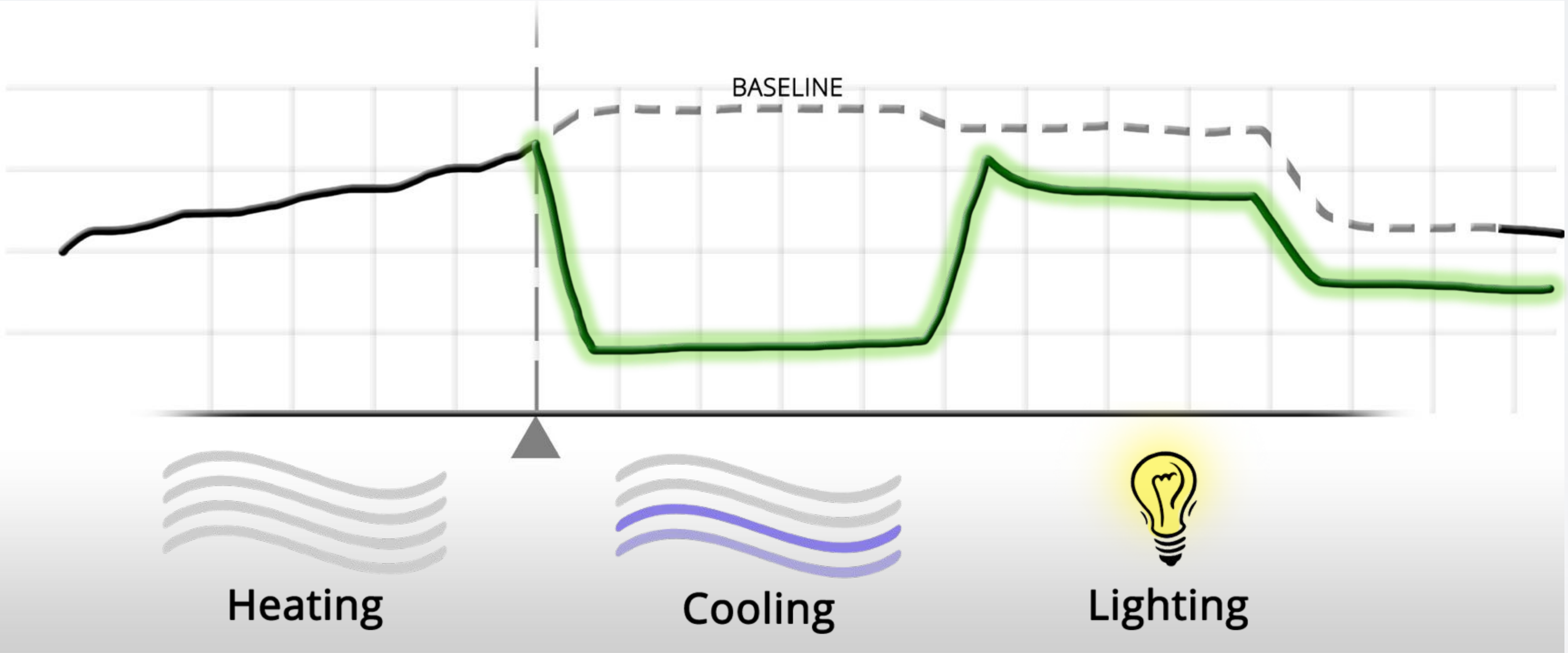
- Determine state $x(t)$
- Determine optimal sequence of inputs over horizon
- Implement first input $u(t)$
- Wait for next sampling time; $t := t + 1$

The control problem in buildings

Integrated control of:

- Heating
- Cooling
- Ventilation
- Lighting
- Blinds

Model-based predictive control for buildings



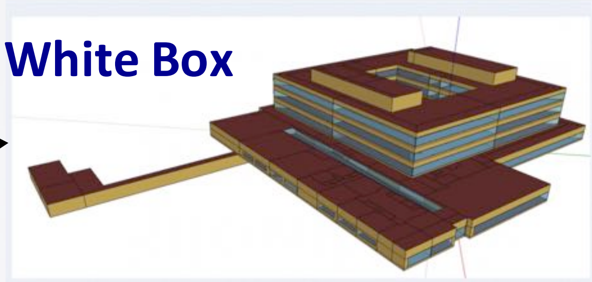
Q) What is the best change that you can make right now ?

Model-based predictive control (MPC)

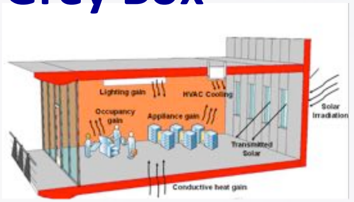
How do you build these models ?

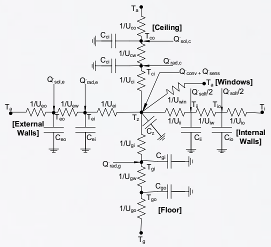
How are building models obtained today ?

White Box

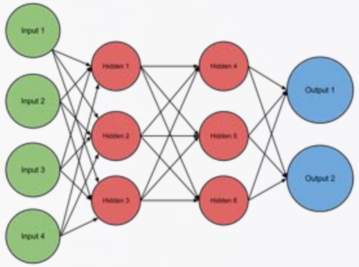


Grey Box



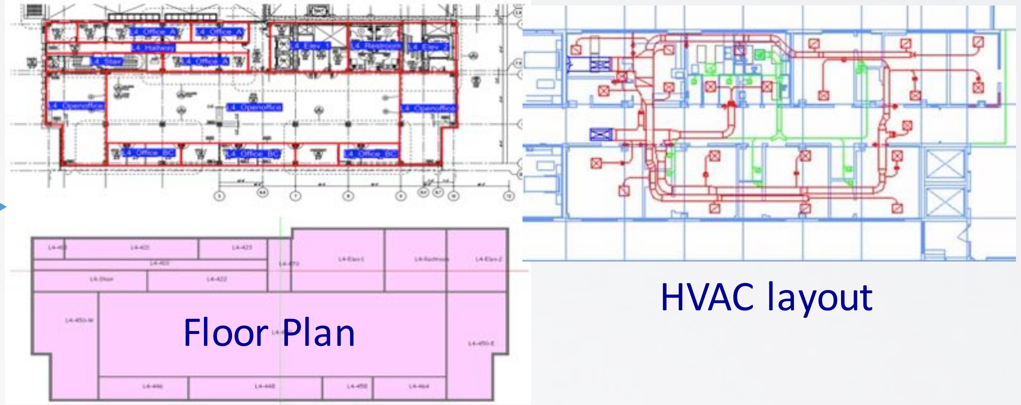


Black Box



Building energy modeling using first-principles

Not always available



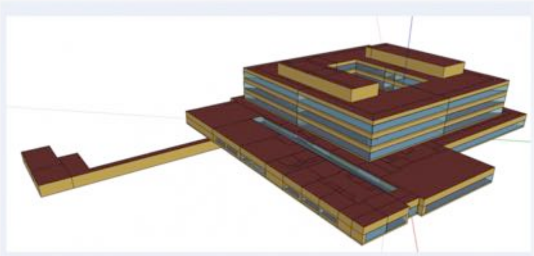
HVAC layout

Model Tuning
Data
Sensor retrofits

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

Guess nominal parameter values

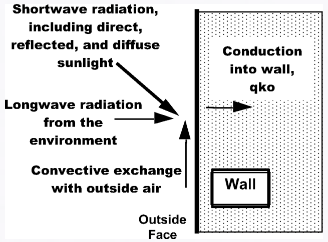
Hire building modeling experts



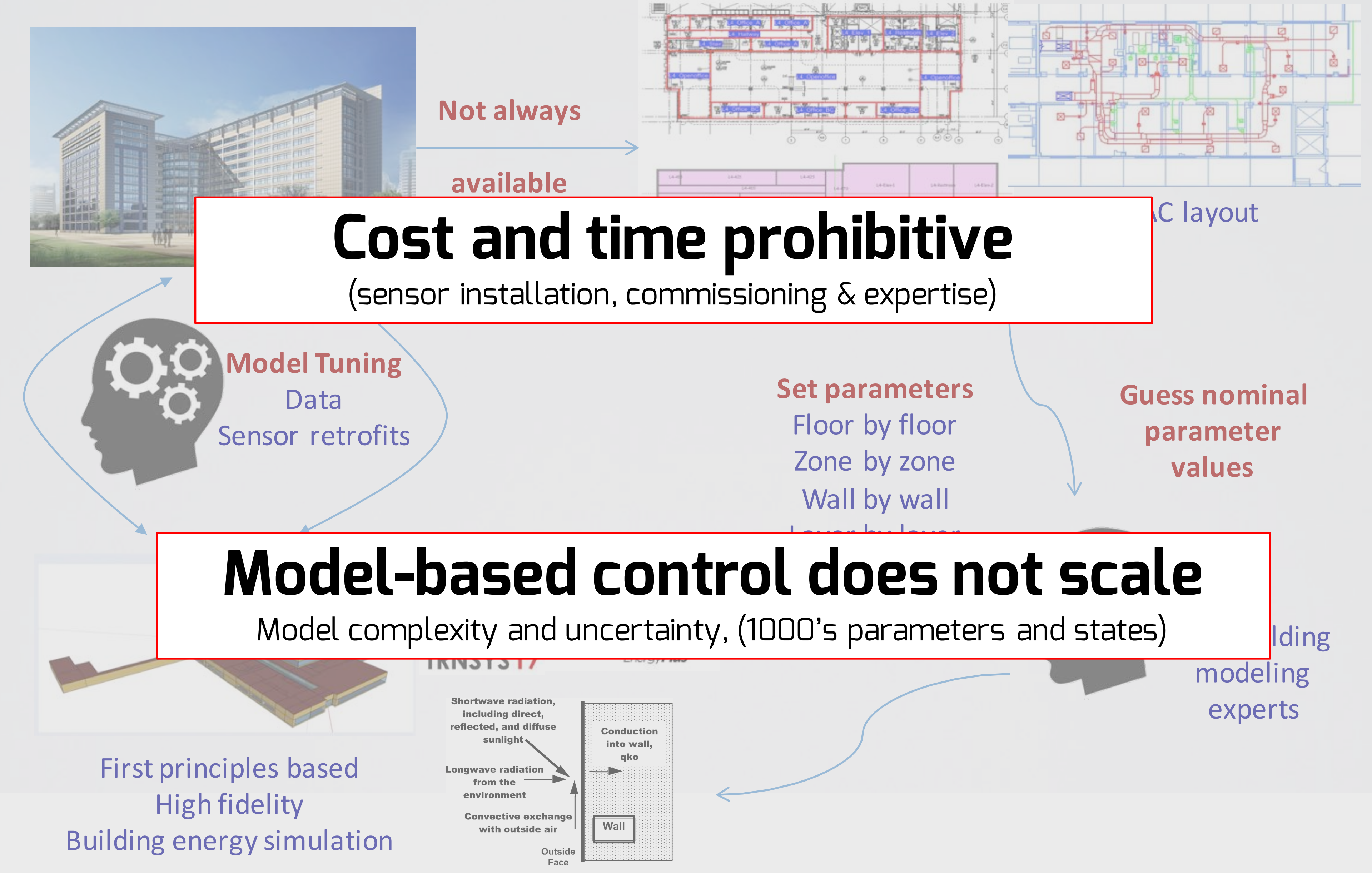
TRNSYS 17

EnergyPlus

First principles based building energy simulation



Building energy modeling using first-principles



Cost and time prohibitive

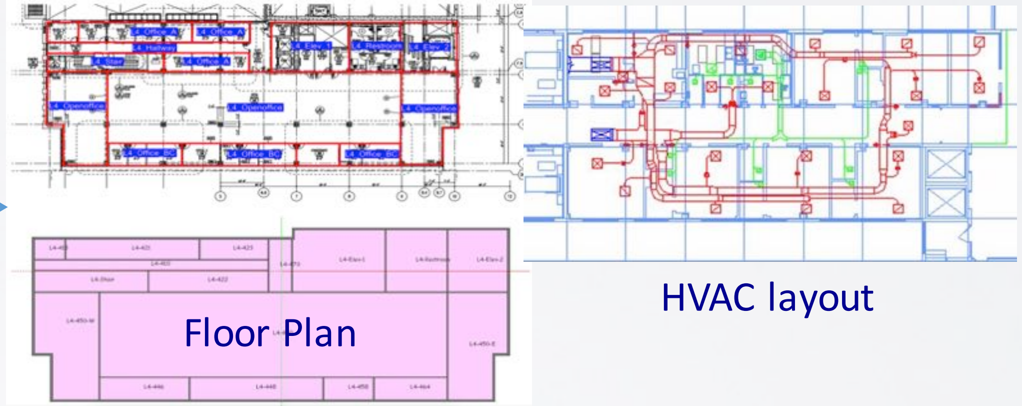
(sensor installation, commissioning & expertise)

Model-based control does not scale

Model complexity and uncertainty, (1000’s parameters and states)

Grey-Box (Inverse) Modeling

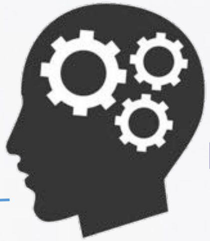
Not always available



Parameter Estimation
Data
Sensor retrofits

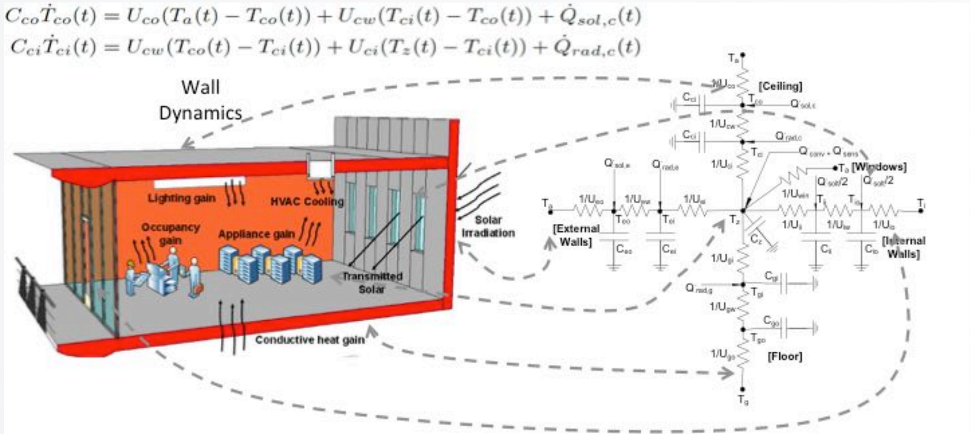
Set parameters
Floor by floor
Zone by zone
~~Wall by wall~~
~~Layer by layer~~
Equipment by equipment
Transfer geometry

Guess nominal parameter values



Hire building modeling experts

Lumped Parameter 'RC' model

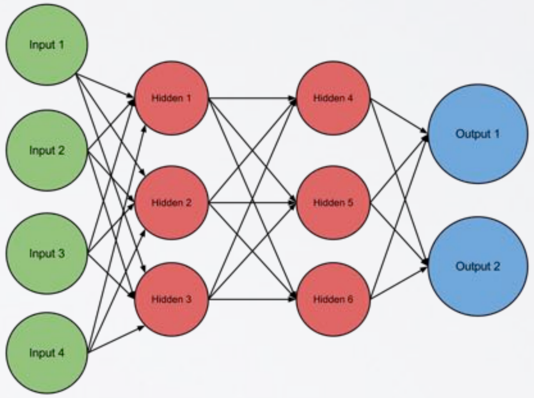


Black-Box Modeling

Data

Feature engineering

Could be automated



Not well aligned with control synthesis

Coarse grained predictions

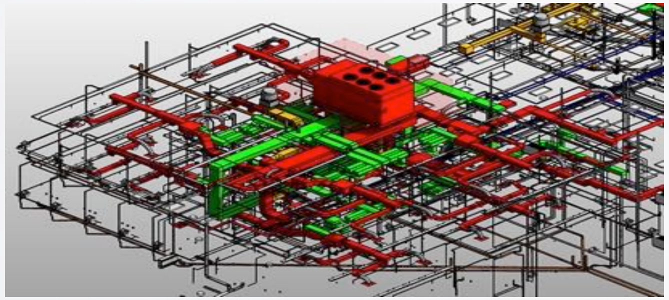
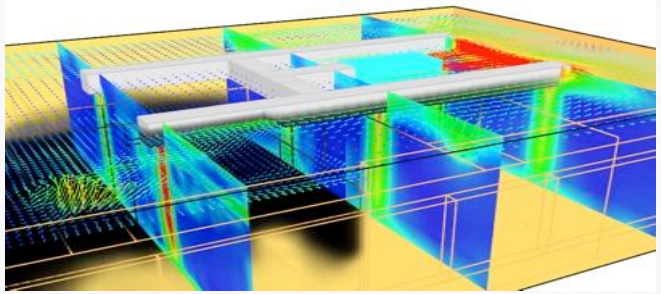
Non-physical parameters

Modeling using first principles is hard !



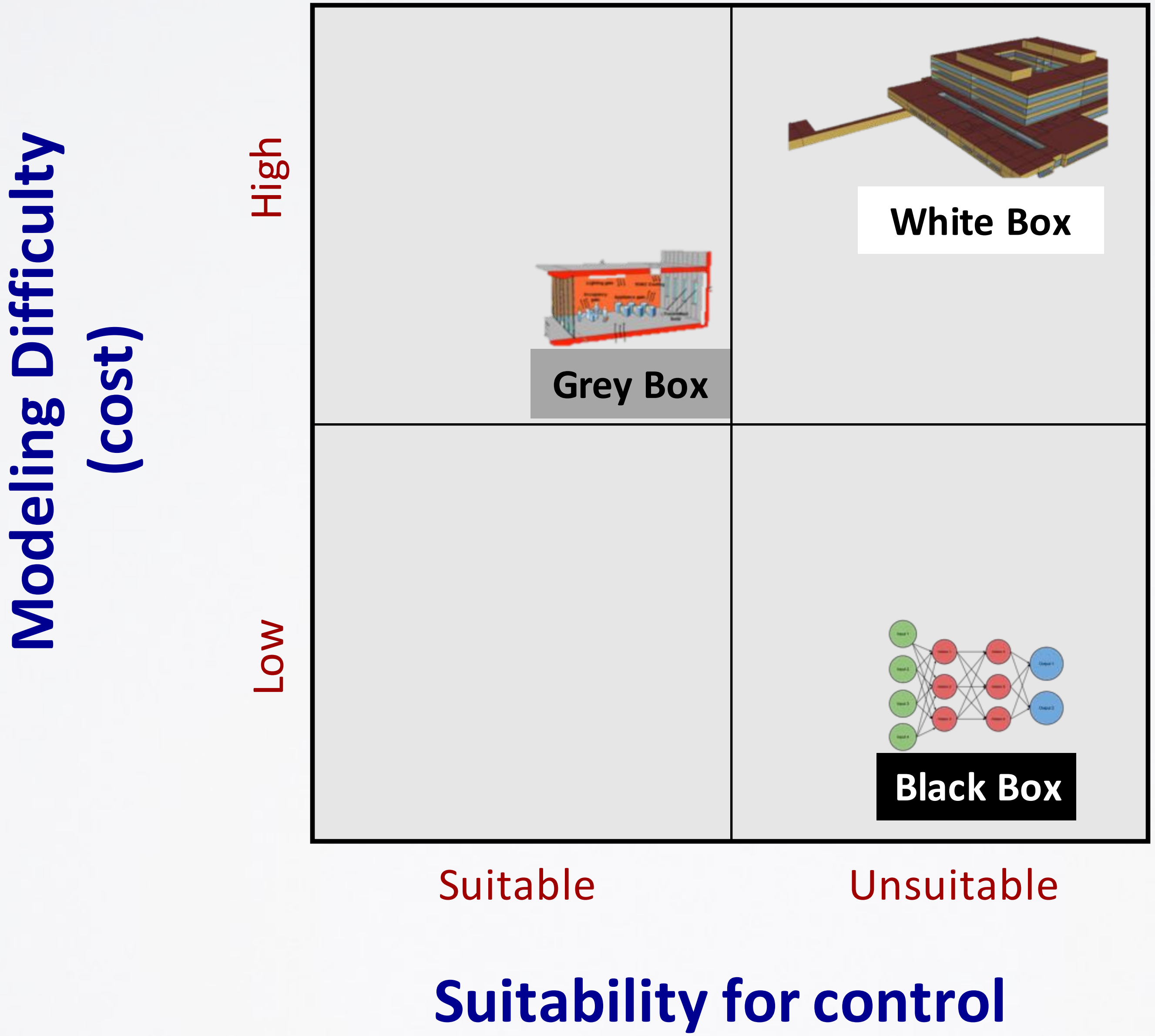
Each building design is different.
Must be uniquely modeled


Long operational lifetimes
~50-100 years

Too many sub-systems
Non-linear interactions

Energy Systems Modeling

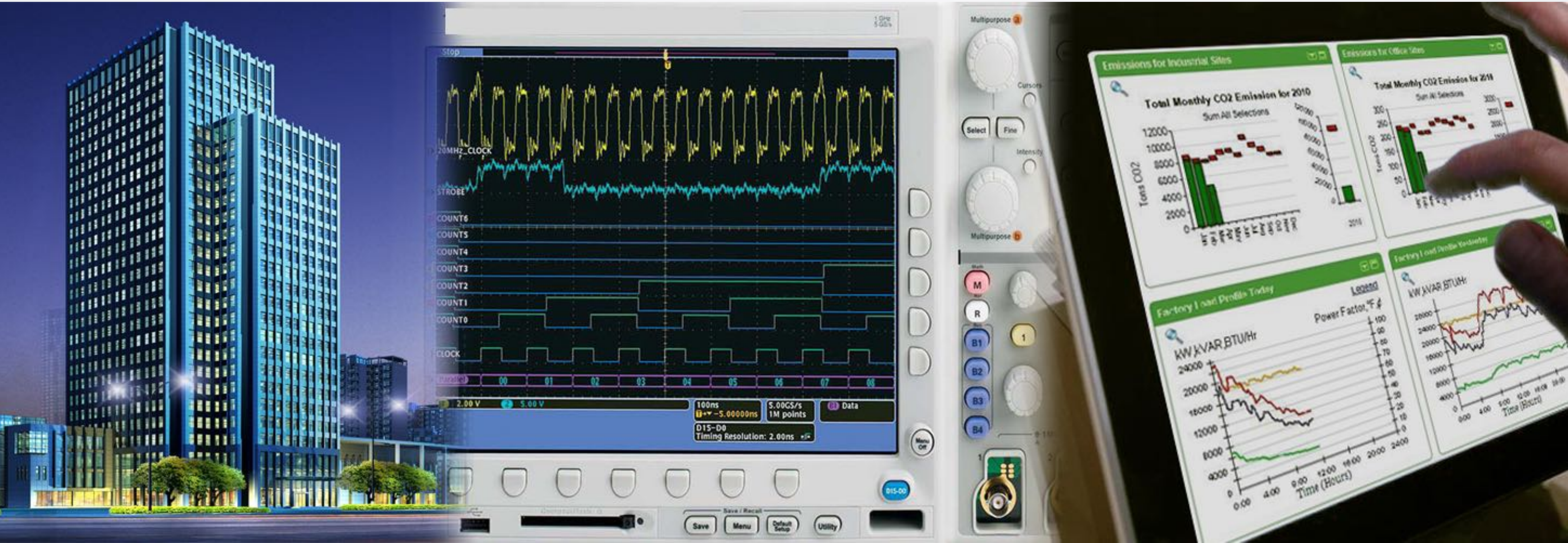


Data-Driven Demand Response

DR-Advisor

Can we get the best of both worlds ?

- Simplicity of rule-based DR
- Predictive capability of model-based DR

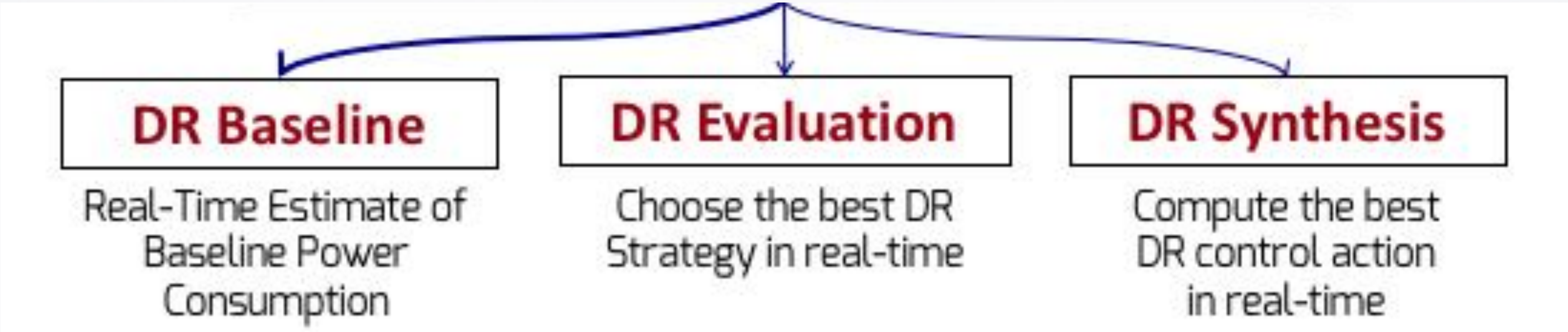


Data-Driven predictive control

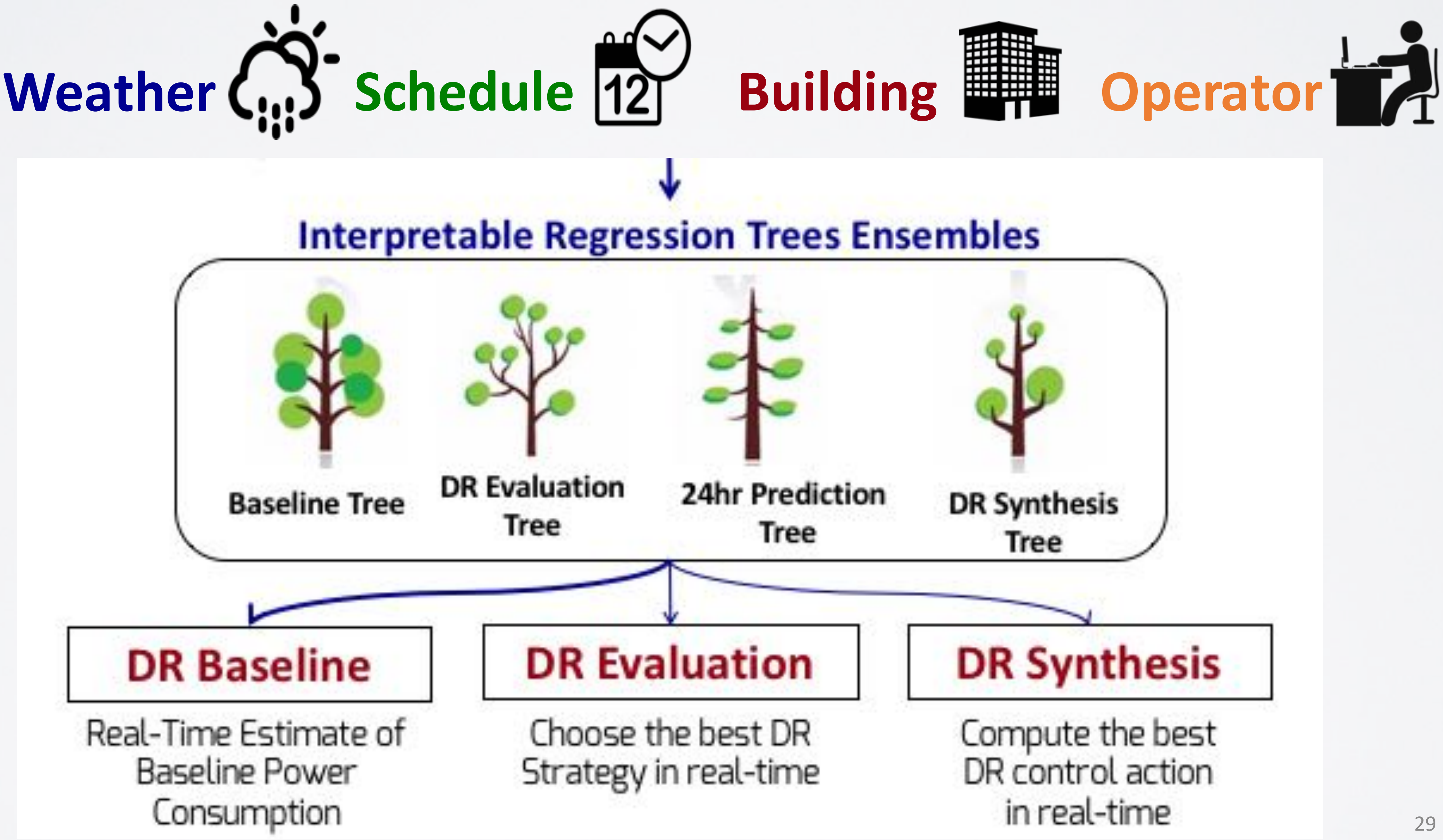
Weather  **Schedule** **Building**  **Operator** 

Data-Driven predictive control

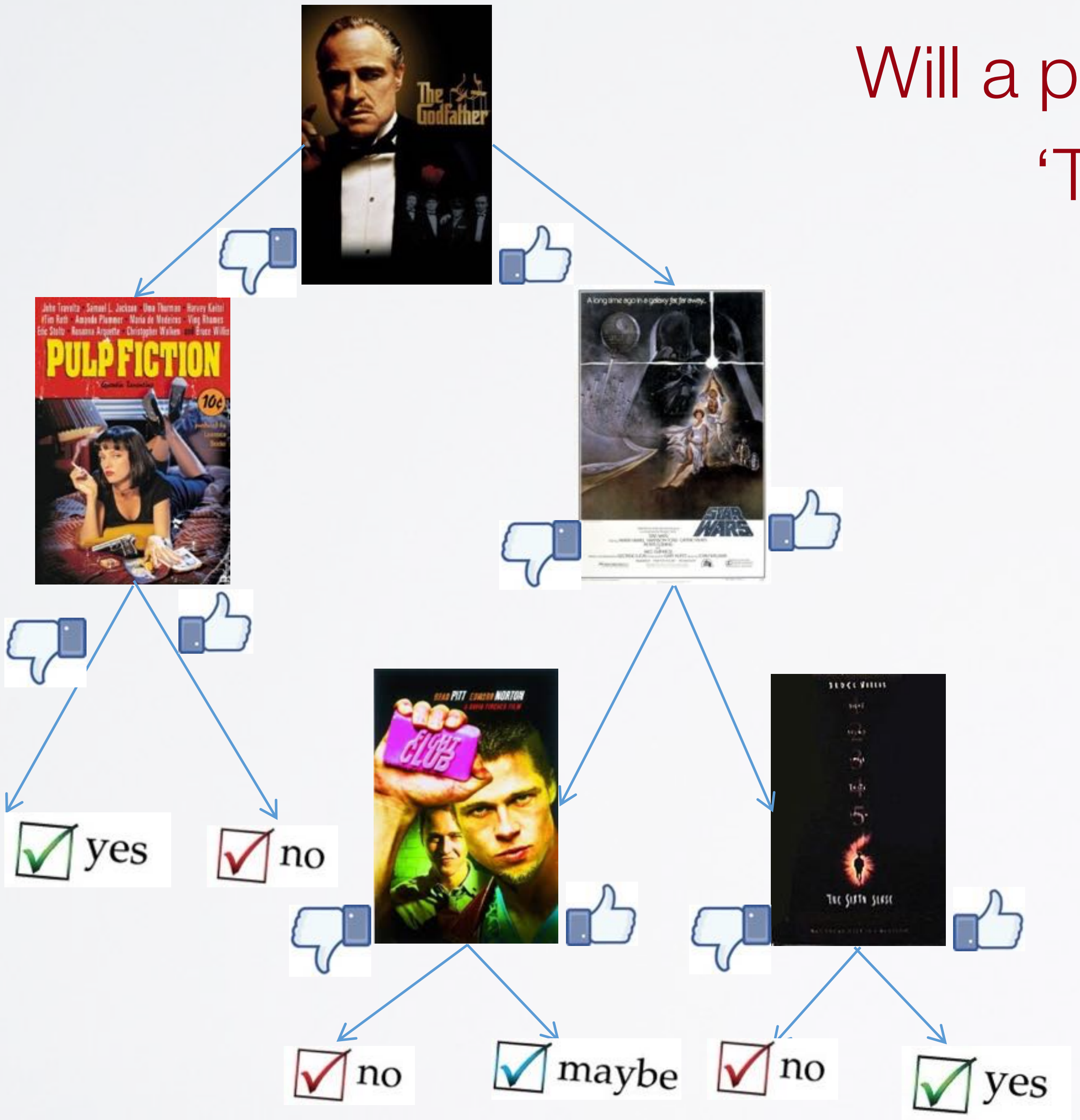
Weather **Schedule** **Building** **Operator**



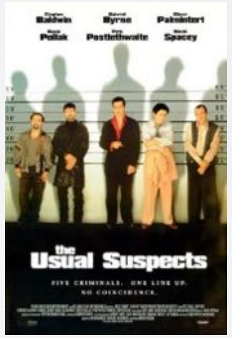
Data-Driven predictive control



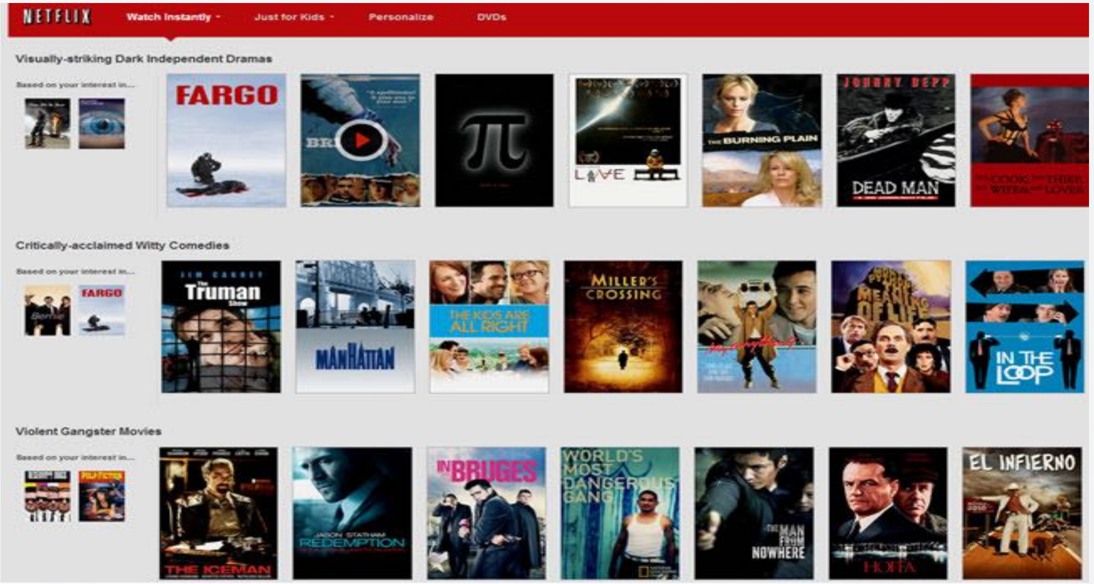
The Netflix of Energy Management Systems



Will a person like the movie
'The Usual Suspects' ?



Make Recommendations

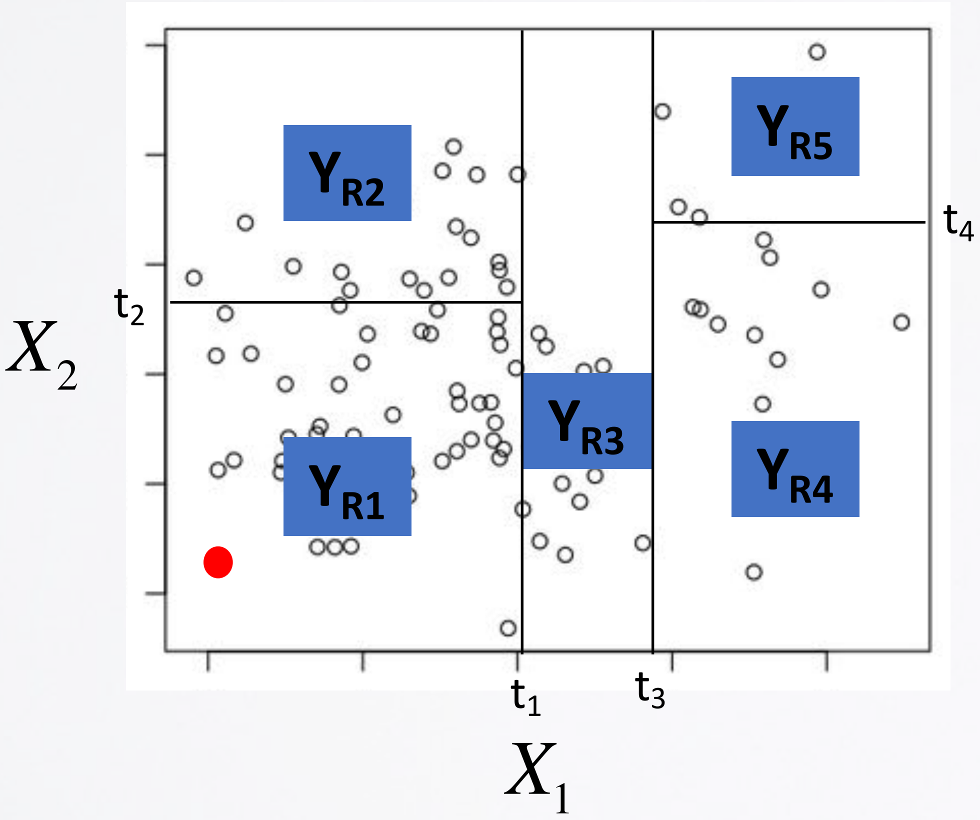


Tree construction algorithm: CART

$$Y = f(X_1, X_2, \ldots, X_m)$$

Response
(Power Consumption)

Predictors
(Temperature, TimeOfDay, …)



- Split at $X_1 = t_1$
- For $X_1 < t_1$ split at $X_2 = t_2$
- For $X_1 > t_1$ split at $X_1 = t_3$
- For $X_1 > t_3$ split at $X_2 = t_4$

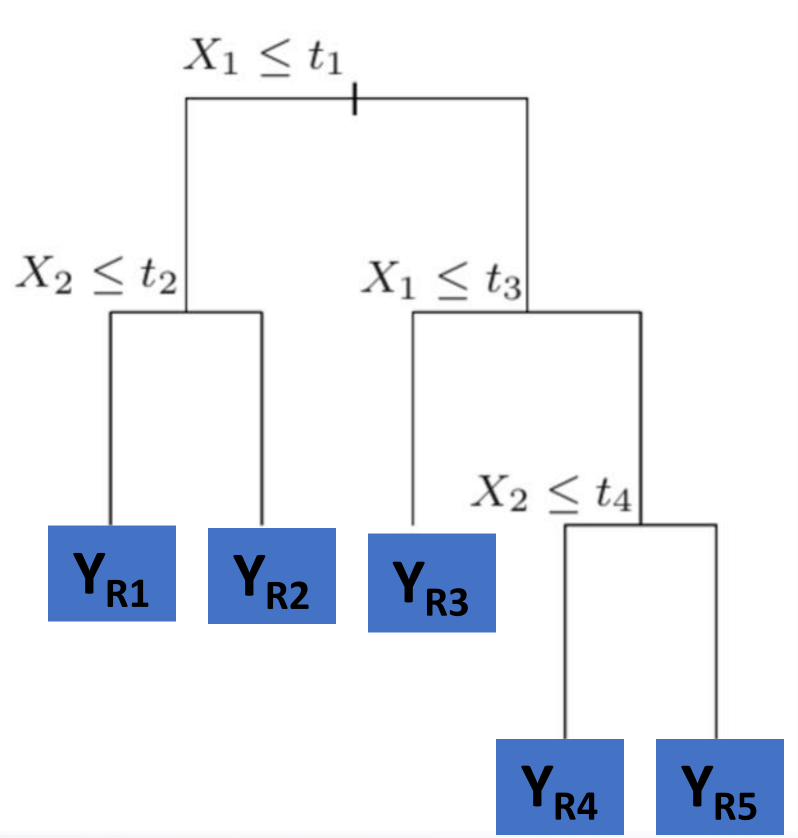
Cell Model: **Average**

Tree construction algorithm: CART

$$\underbrace{Y}_{\text{Response}} = f\underbrace{(X_1, X_2, \ldots, X_m)}_{\text{Predictors}}$$

Response
(Power Consumption)

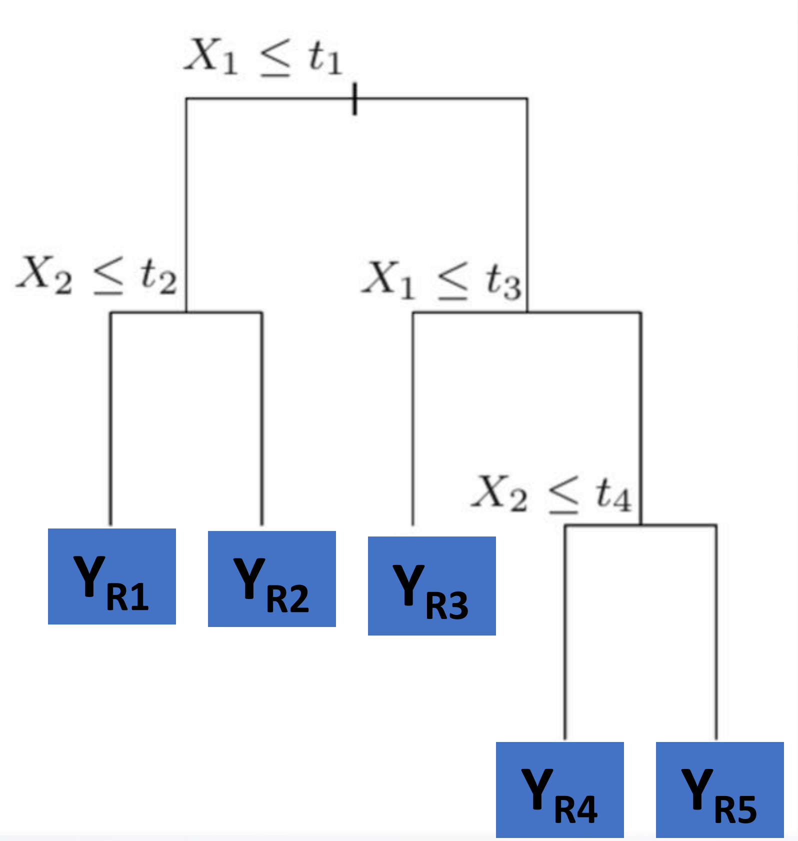
Predictors
(Temperature, TimeOfDay, …)



- Split at $X_1 = t_1$
- For $X_1 < t_1$ split at $X_2 = t_2$
- For $X_1 > t_1$ split at $X_1 = t_3$
- For $X_1 > t_3$ split at $X_2 = t_4$

Cell Model: **Average**

Tree construction algorithm: CART



1. Stopping criteria.
   i. MinLeaf
2. Splitting criteria.
3. Variable selection.
4. Pruning.

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

Data Description

Weather

	A	B	C
1	Time Of Day	Boiler 1 Outlet SetPoint	Perimeter Bottom 3 ZAT
2	Day of Week	Chiller 1 Outlet SetPoint	Perimeter Bottom 4 ZAT
3	Day of Month	Chiller 2 Outlet SetPoint	Perimeter Mid 1 ZAT
4	Basement Zone Air Temperature	Zone Cooling Set Point	Perimeter Mid 2 ZAT
5	Ground Floor Plenum Temperature	Chilled Water Set Point	Perimeter Mid 3 ZAT
6	Core Bottom Zone Air Temperature	Building Lighting Set Point	Perimeter Mid 4 ZAT
7	Core Mid Zone Air Temperature	Zone Heating Set Point	Perimeter Top 1 ZAT
8	Core Top Zone Air Temperature	Hot Water Set Point	Perimeter Top 2 ZAT
9	Mid Floor Plenum Temperature	Perimeter Bottom 1 ZAT	Perimeter Top 3 ZAT
10	Top Floor Plenum Temperature	Perimeter Bottom 2 ZAT	Perimeter Top 4 ZAT
11	**Outdoor Dry Bulb Temperature**	**Outdoor Humidity**	**Wind Speed**
12	**Wind Direction**	**Incident Solar Irradiation**	Building Power Consumption

Data Description

Proxy Variables

	A	B	C
1	Time Of Day	Boiler 1 Outlet SetPoint	Perimeter Bottom 3 ZAT
2	Day of Week	Chiller 1 Outlet SetPoint	Perimeter Bottom 4 ZAT
3	Day of Month	Chiller 2 Outlet SetPoint	Perimeter Mid 1 ZAT
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10	Top Floor Plenum Temperature	Perimeter Bottom 2 ZAT	Perimeter Top 4 ZAT
11	Outdoor Dry Bulb Temperature	Outdoor Humidity	Wind Speed
12	Wind Direction	Incident Solar Irradiation	Building Power Consumption

Data Description

Schedule/Set-Point

	A	B	C
1	Time Of Day	Boiler 1 Outlet SetPoint	Perimeter Bottom 3 ZAT
2	Day of Week	Chiller 1 Outlet SetPoint	Perimeter Bottom 4 ZAT
3	Day of Month	Chiller 2 Outlet SetPoint	Perimeter Mid 1 ZAT
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11	Outdoor Dry Bulb Temperature	Outdoor Humidity	Wind Speed
12	Wind Direction	Incident Solar Irradiation	Building Power Consumption

Data Description

Building's State

	A	B	C
1	Time Of Day	Boiler 1 Outlet SetPoint	Perimeter Bottom 3 ZAT
2	Day of Week	Chiller 1 Outlet SetPoint	Perimeter Bottom 4 ZAT
3	Day of Month	Chiller 2 Outlet SetPoint	Perimeter Mid 1 ZAT
4	Basement Zone Air Temperature	Zone Cooling Set Point	Perimeter Mid 2 ZAT
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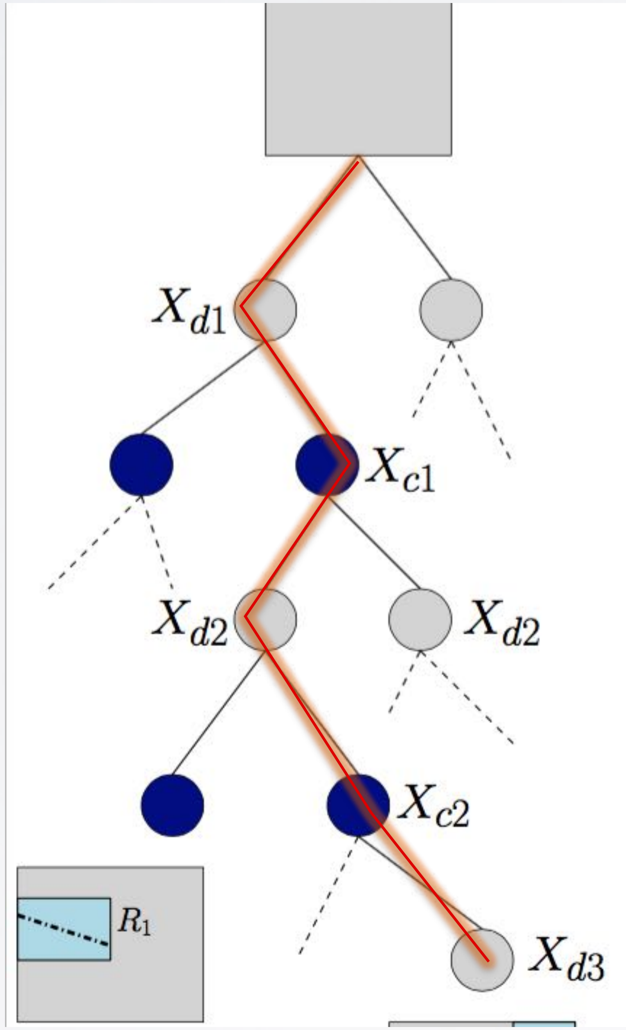
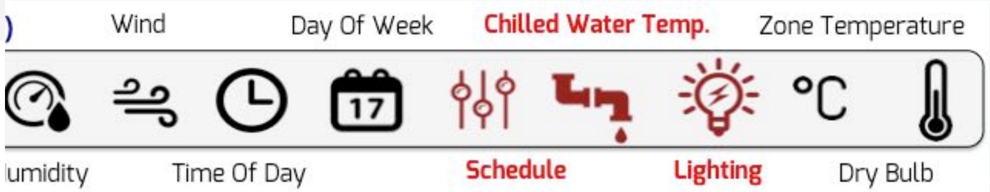
8	Core Top Zone Air Temperature	Hot Water Set Point	Perimeter Top 2 ZAT
9	Mid Floor Plenum Temperature	Perimeter Bottom 1 ZAT	Perimeter Top 3 ZAT
10	Top Floor Plenum Temperature	Perimeter Bottom 2 ZAT	Perimeter Top 4 ZAT
11	Outdoor Dry Bulb Temperature	Outdoor Humidity	Wind Speed
12	Wind Direction	Incident Solar Irradiation	Building Power Consumption

DR Strategy Evaluation





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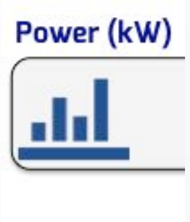
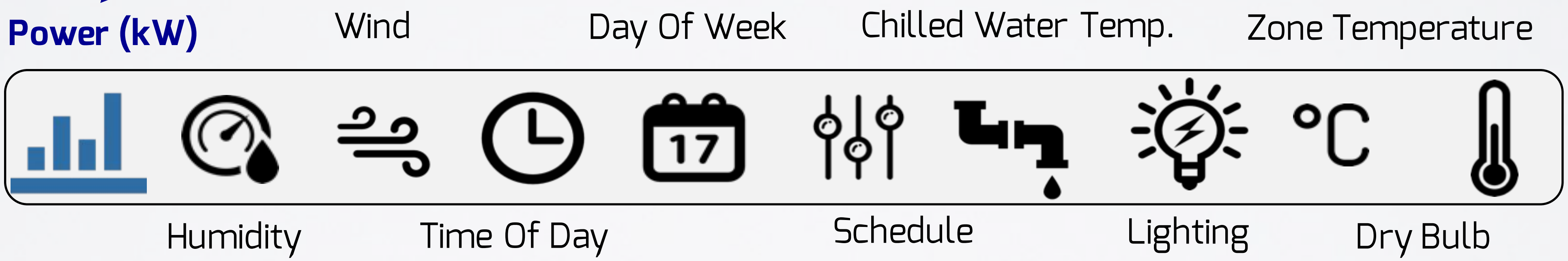


Auto regressive trees: For Finite horizon prediction

DR-Advisor

$$Y = f(\underbrace{X_1, X_2, \ldots, X_m}_{})$$

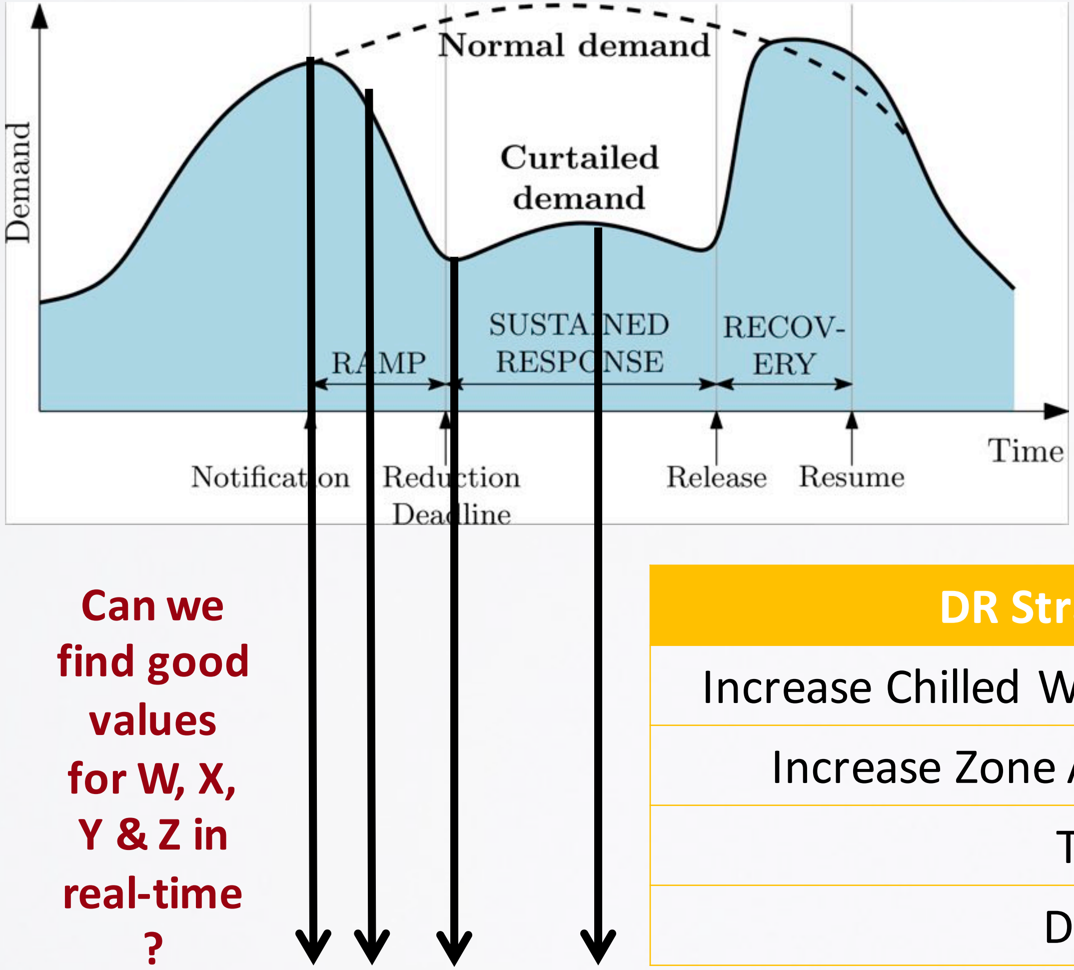


ART(δ)

$$\hat{Y}(t+1) = f([X_1(t), X_2(t), \ldots, X_m(t), Y(t-1), Y(t-2), \ldots., Y(t-\delta)])$$

Demand Response Challenges

What is the best change that you can make right now ?



Can we **synthesize** good DR strategies ?

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

DR Strategy Synthesis Example
Increase Chilled Water Temperature Set-Point by **W °C**
Increase Zone Air Temperature Set-Point by **X°C**
Turn off Elevator **#Y**
Dim the Lights by **Z%**

unknown

Regression trees for **control synthesis**

$$Y = f(X_1, X_2, \ldots, X_m)$$

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

Humidity Time Of Day **Schedule** **Lighting** Dry Bulb

Response
(Power Consumption)

Non-Manipulated Variables
[Disturbances]

Manipulated Variables
[control]

Regression trees for control synthesis

Time Of Day	Boiler 1 Outlet SetPoint	Perimeter Bottom 3 ZAT
Day of Week	Chiller 1 Outlet SetPoint	Perimeter Bottom 4 ZAT
Day of Month	Chiller 2 Outlet SetPoint	Perimeter Mid 1 ZAT
Basement Zone Air Temperature	**Zone Cooling Set Point ?**	Perimeter Mid 2 ZAT
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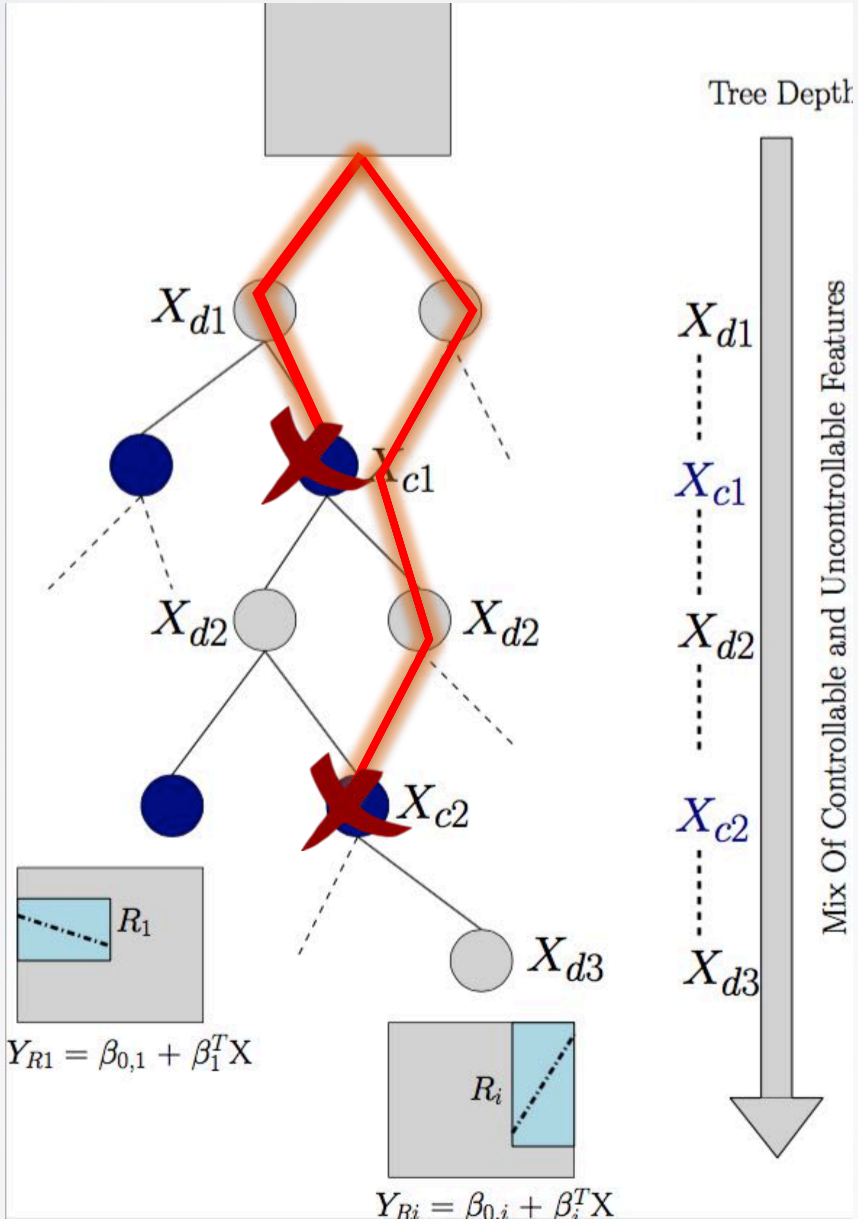
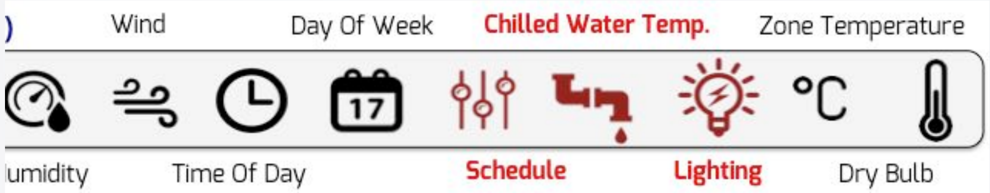
Wind Direction	Incident Solar Irradiation	Building Power Consumption

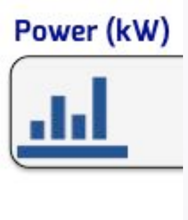
Regression trees for control synthesis





Cannot specify order of appearance of variables in tree depth

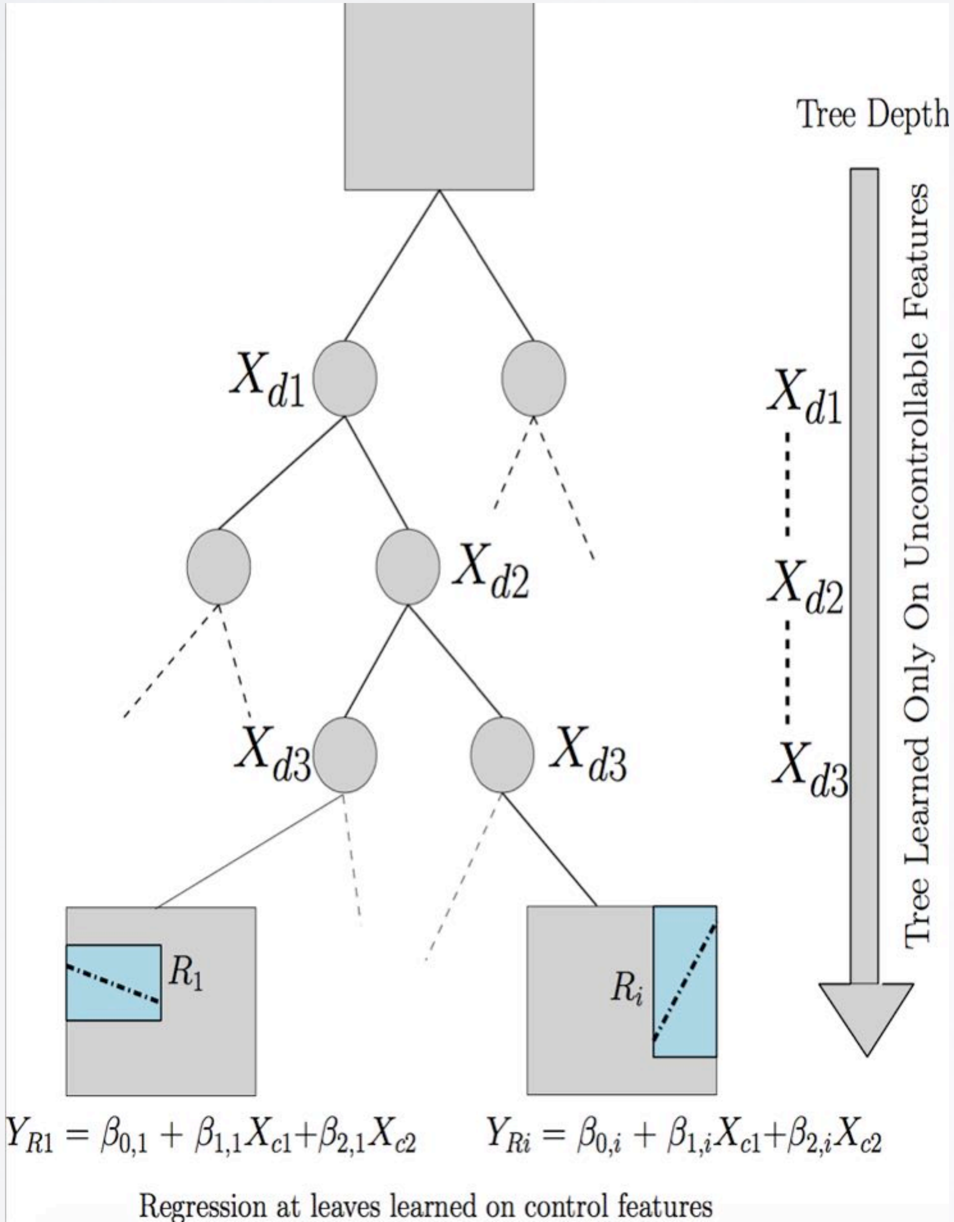
$$\min_{j,s}\left[\min_{c_L}\sum_{x_i\in R_L(j,s)}(y_i-c_L)^2+\min_{c_R}\sum_{x_i\in R_R(j,s)}(y_i-c_R)^2\right]$$



No forecast for manipulated variables

(we want to compute values for these)

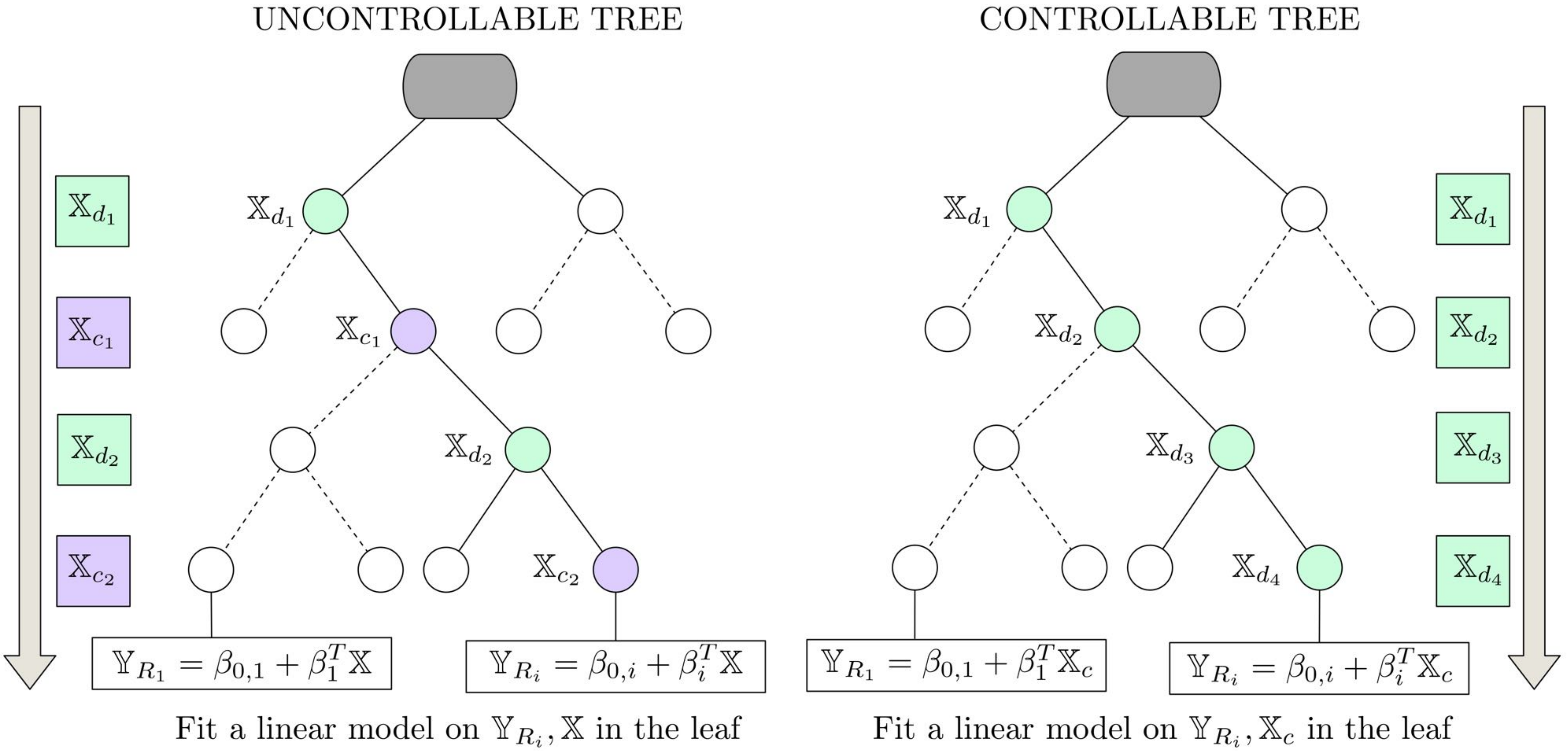
Separation of variables



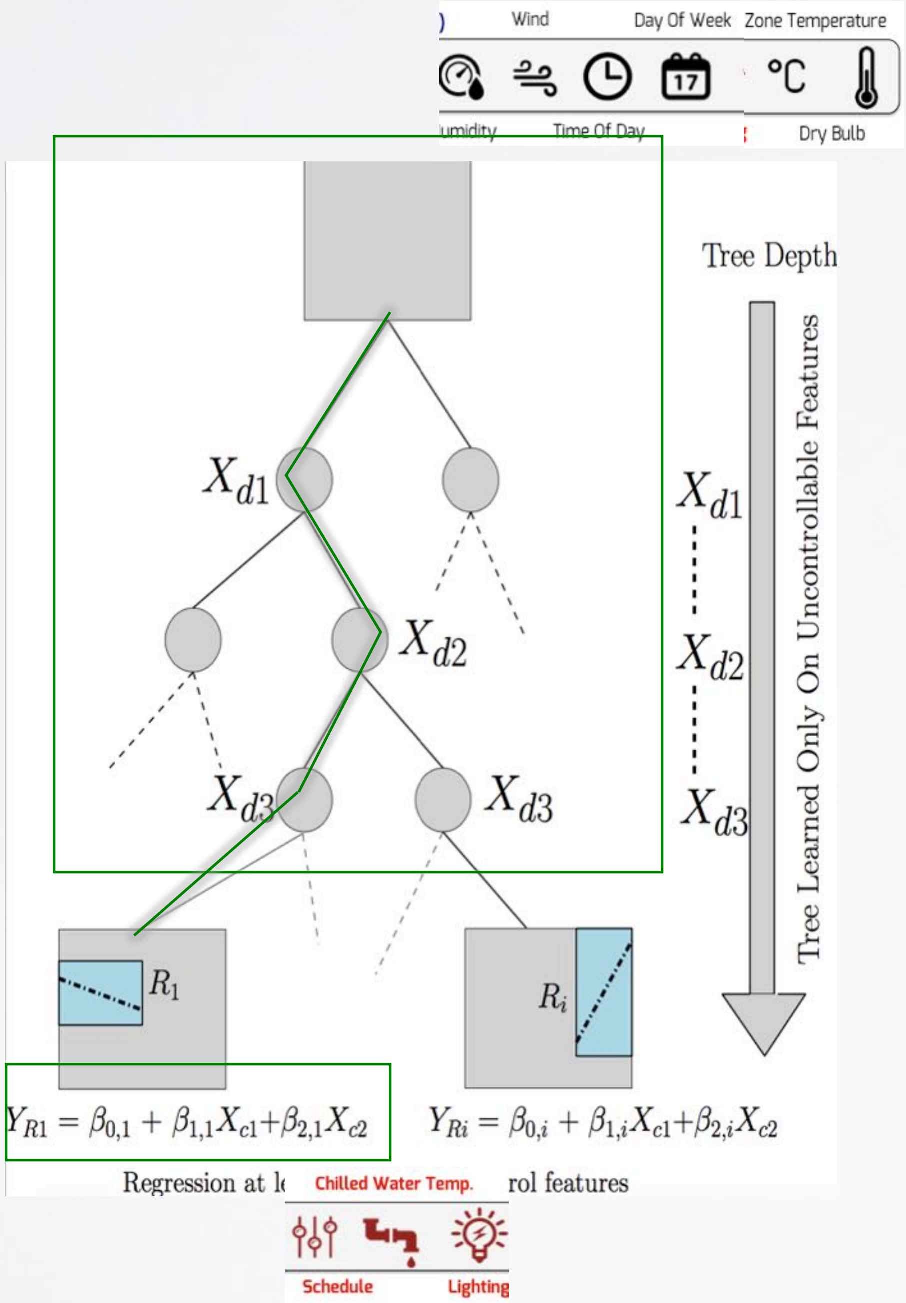
Tree learned only on non-manipulated (disturbances) variables/features

Leaf Model Regression with manipulated variables

Separation of variables



mbCRT: Model Based Control with Regression Trees



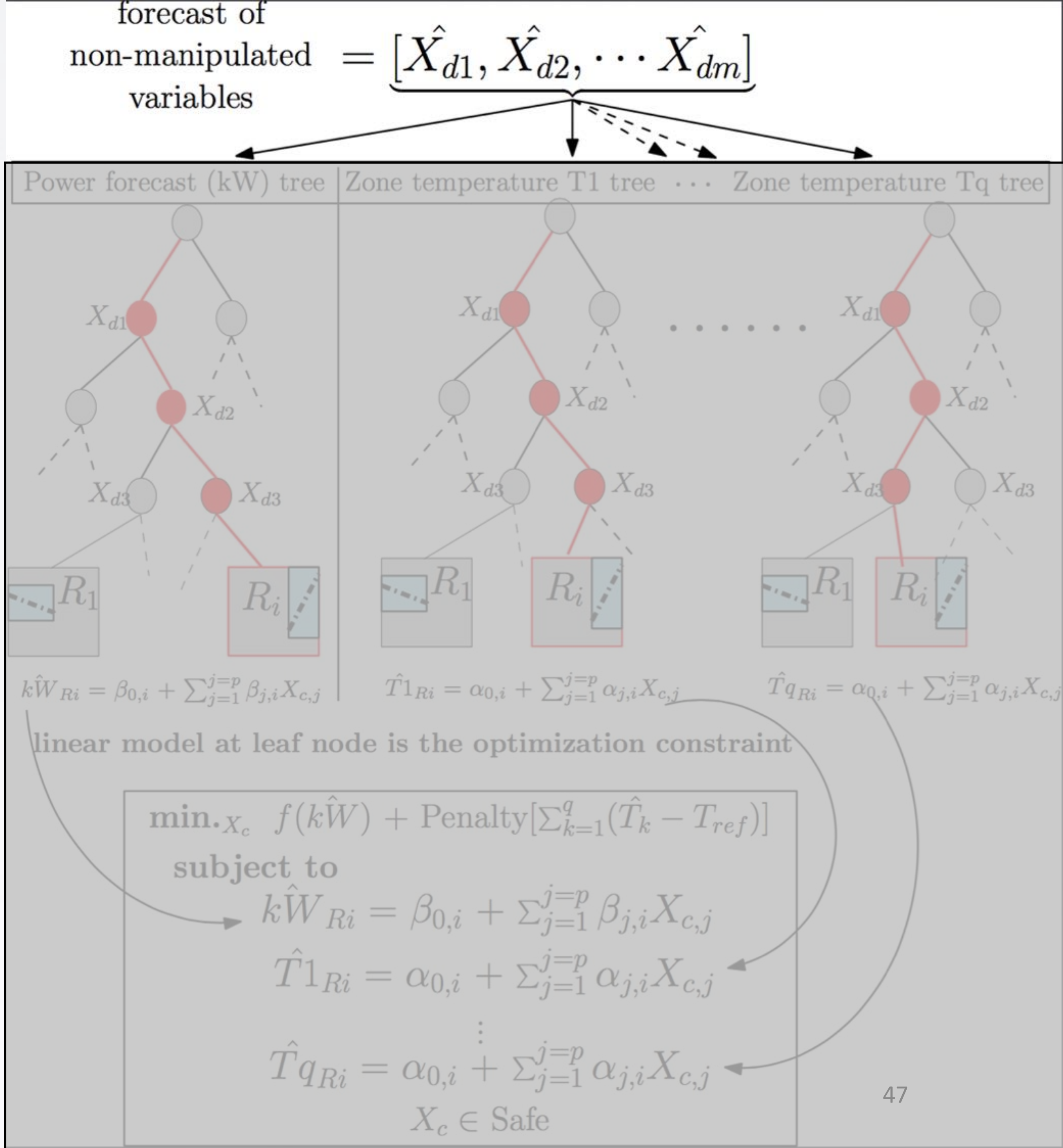
Algorithm 1 mbCRT: Model Based Control With Regression Trees

DESIGN TIME
procedure MODEL TRAINING
  Separation of Variables
  Set $\mathbb{X}_c \leftarrow$ Controllable Features
  Set $\mathbb{X}_d \leftarrow$ Uncontrollable Features
  Build the *uncontrollable* tree T_{mrt} with $\mathbb{X}_d$
  for all Regions R_i at the leaves of T_{mrt} **do**
    Fit linear model $Y_{Ri} = \beta_{0,i} + \beta_i^T \mathbb{X}_c$
  end for
end procedure
RUN TIME
procedure CONTROL SYNTHESIS
  At time t obtain forecast $\hat{\mathbb{X}}_d(t+1)$ of disturbances $\hat{X_{d1}}(t+1), \hat{X_{d2}}(t+1), \cdots$
  Using $\hat{\mathbb{X}}_d(t+1)$ determine the leaf and region R_{rt}
  for Region R_{rt} **do**
    Solve optimization in Eq11 for optimal control action $\mathbb{X}_c^*(t)$
  end for
end procedure

$$\begin{aligned} \underset{\mathbb{X}_c}{\text{minimize}} \quad & f(Y_{Ri}) \\ \text{subject to} \quad & Y_{Ri} = \beta_{0,i} + \beta_i^T \mathbb{X}_c \\ & \mathbb{X}_c \in \mathbb{X}_{safe} \end{aligned}$$

[During a Demand Response Event]

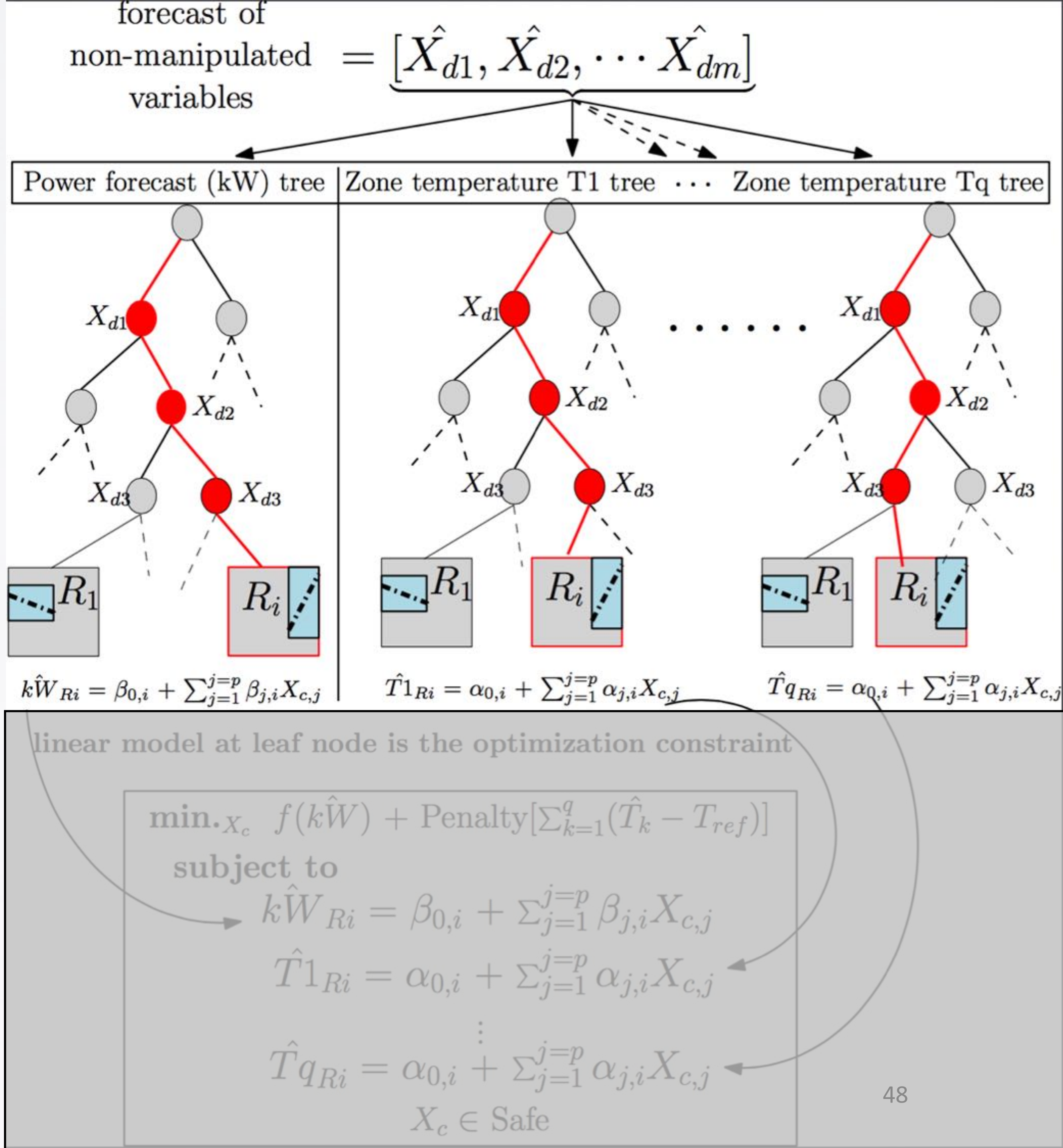
1 Disturbance (weather) forecast



[During a Demand Response Event]

1 Disturbance (weather) forecast

2 Online control-model selection
[using mode-based regression trees]

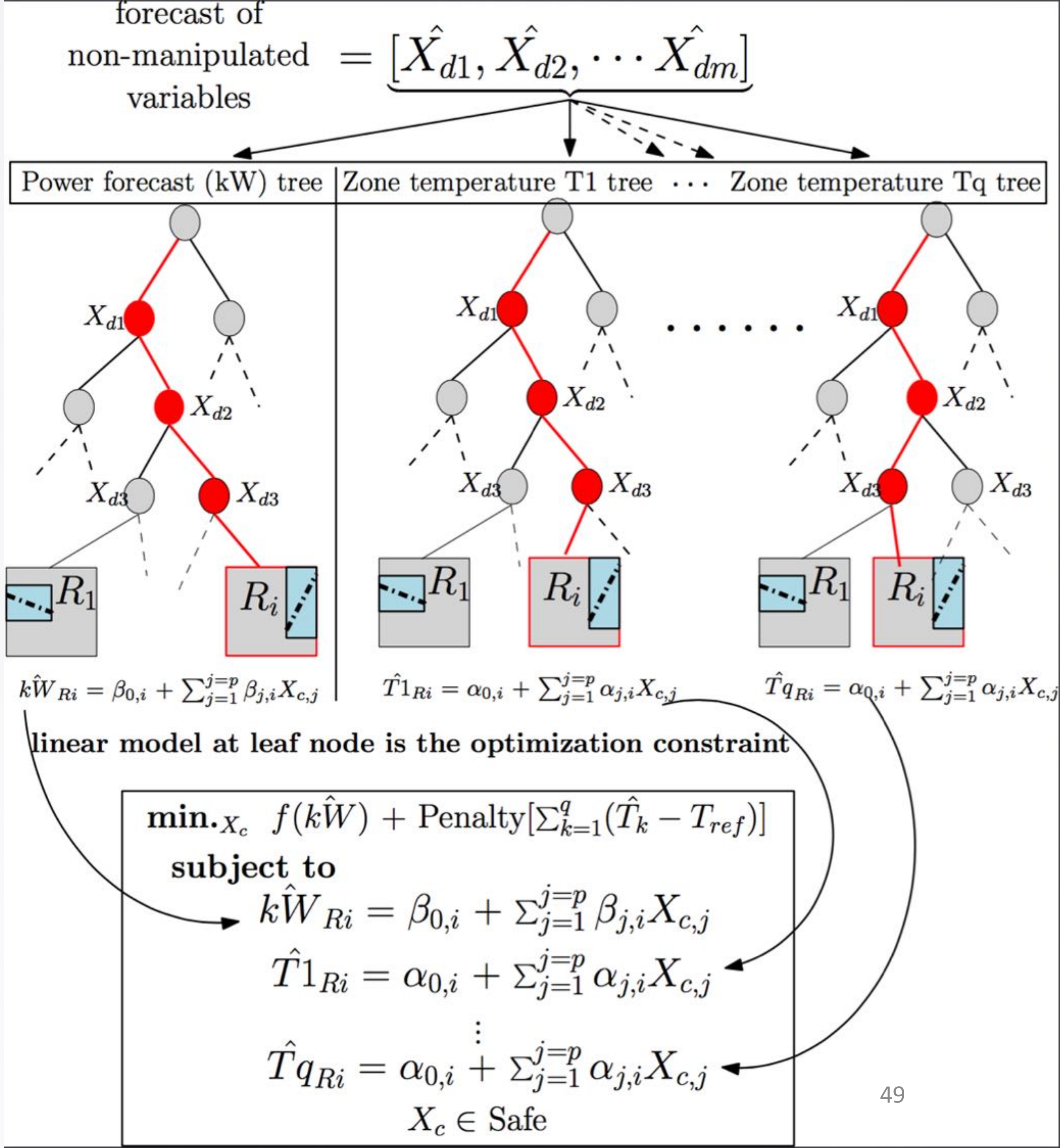


[During a Demand Response Event]

1 Disturbance forecast

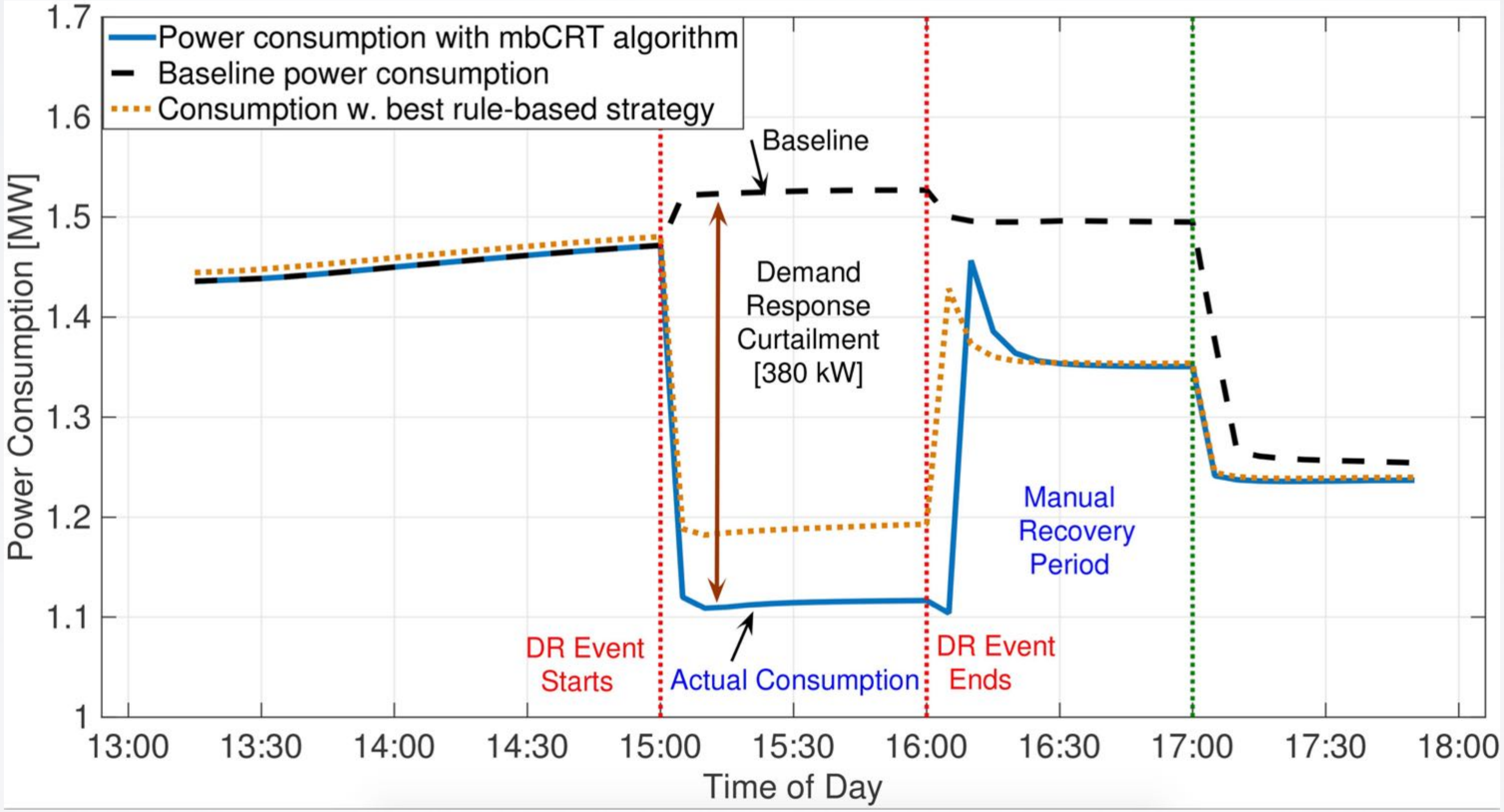
2 Online control-model selection
[using mode-based regression trees]

3 Real time optimization
[with dynamical constraints]



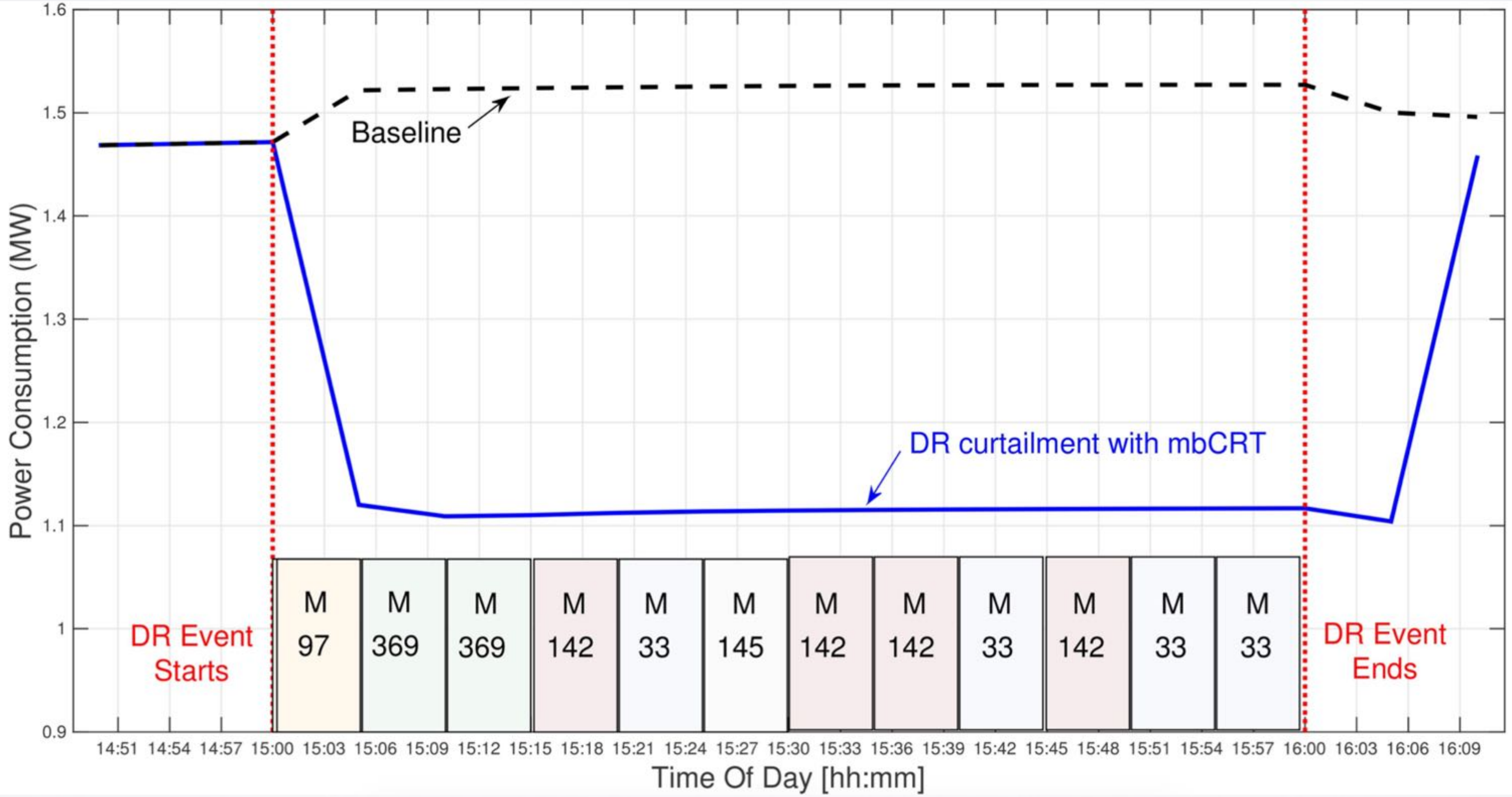
DR Strategy Synthesis

Sustained response of 380 kW



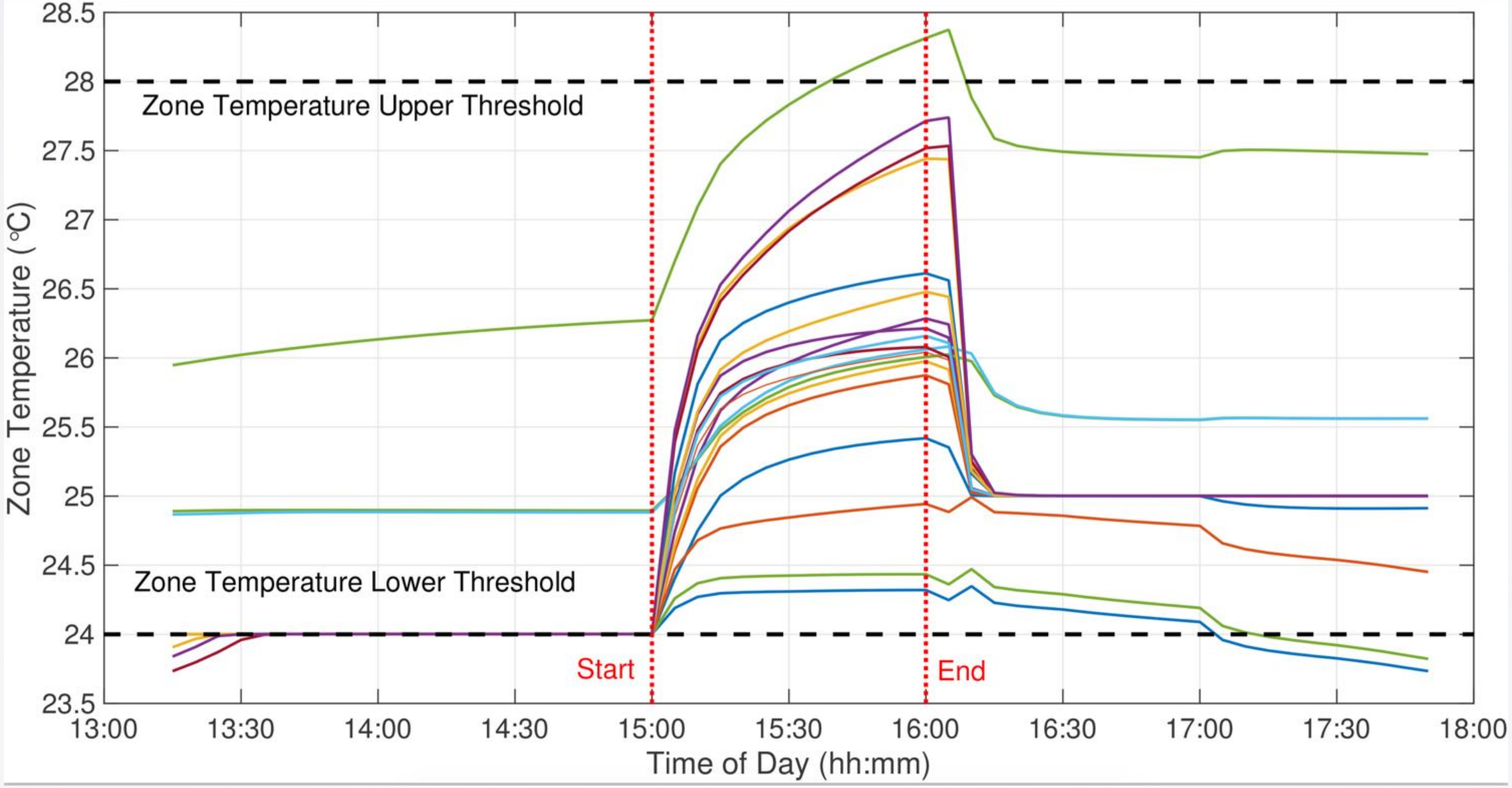
DR Strategy Synthesis

Correct linear model at the leaf is chosen at each time-step for the

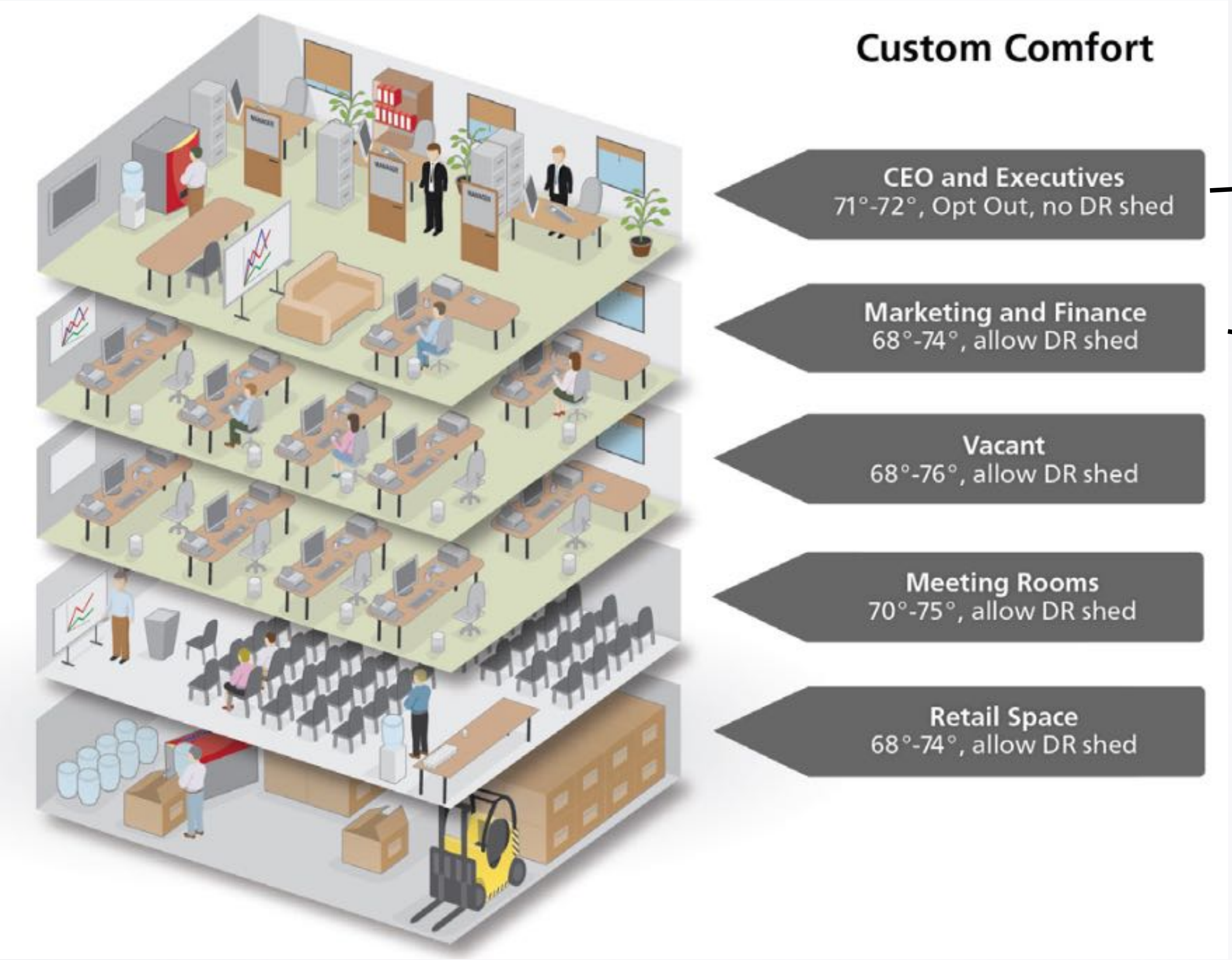


DR Strategy Synthesis

Thermal Comfort Maintained



Different zone priorities



$$\mathbf{min.}_{X_c} \quad f(k\hat{W}) + \text{Penalty}[\Sigma_{k=1}^{q}(\hat{T}_k - T_{ref})]$$

subject to

$$k\hat{W}_{Ri} = \beta_{0,i} + \Sigma_{j=1}^{j=p} \beta_{j,i} X_{c,j}$$

$$\hat{T}1_{Ri} = \alpha_{0,i} + \Sigma_{j=1}^{j=p} \alpha_{j,i} X_{c,j}$$

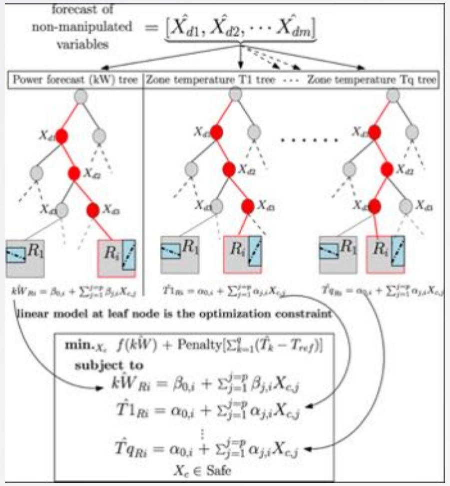
$$\vdots$$

$$\hat{T}q_{Ri} = \alpha_{0,i} + \Sigma_{j=1}^{j=p} \alpha_{j,i} X_{c,j}$$

$$X_c \in \text{Safe}$$

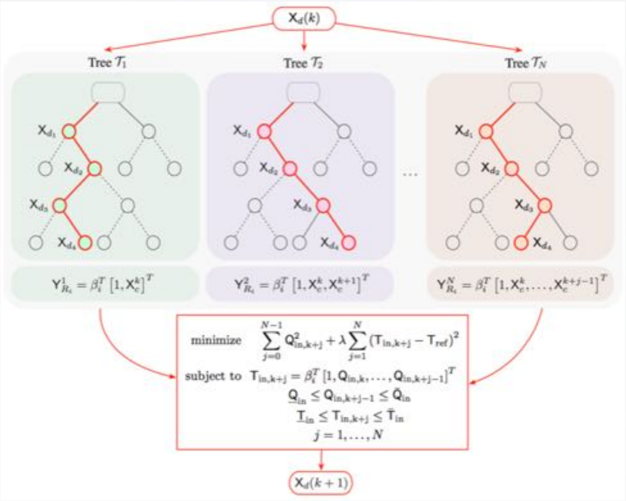
Foundations of Data Predictive Control for CPS

Single-step look ahead
[with single reg. trees]



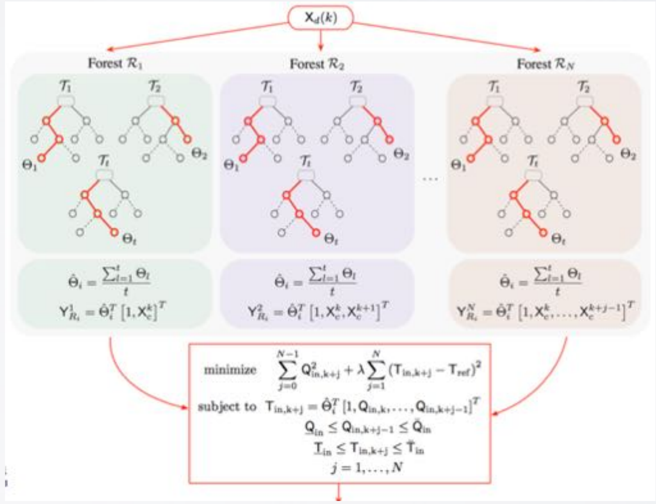
mbCRT

Finite receding horizon
[with single reg. trees]



DPC-RT

Finite receding horizon
[with ensemble models]



Ensemble-DPC

DPC

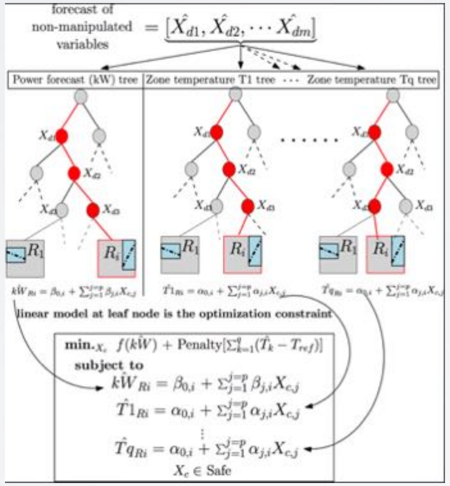
$$
\begin{aligned}
\text{minimize} \quad & \sum_{j=0}^{N-1} \mathsf{Q}_{\mathsf{in,k+j}}^2 + \lambda \sum_{j=1}^{N} (\mathsf{T}_{\mathsf{in,k+j}} - \mathsf{T}_{\mathsf{ref}})^2 \\
\text{subject to} \quad & \mathsf{T}_{\mathsf{in,k+j}} = \beta_i^T \left[1, \mathsf{Q}_{\mathsf{in,k}}, \ldots, \mathsf{Q}_{\mathsf{in,k+j-1}}\right]^T \\
& \underline{\mathsf{Q}}_{\mathsf{in}} \leq \mathsf{Q}_{\mathsf{in,k+j-1}} \leq \bar{\mathsf{Q}}_{\mathsf{in}} \\
& \underline{\mathsf{T}}_{\mathsf{in}} \leq \mathsf{T}_{\mathsf{in,k+j}} \leq \bar{\mathsf{T}}_{\mathsf{in}} \\
& j = 1, \ldots, N.
\end{aligned}
$$

MPC

$$
\begin{aligned}
\text{minimize} \quad & \sum_{j=0}^{N-1} \mathsf{Q}_{\mathsf{in,k+j}}^2 + \lambda \sum_{j=1}^{N} (\mathsf{T}_{\mathsf{in,k+j}} - \mathsf{T}_{\mathsf{ref}})^2 \\
\text{subject to} \quad & x_{k+j} = Ax_{k+j-1} + Bu_{k+j-1} + B_d d_{k+j-1} \\
& \underline{\mathsf{Q}}_{\mathsf{in}} \leq \mathsf{Q}_{\mathsf{in,k+j-1}} \leq \bar{\mathsf{Q}}_{\mathsf{in}} \\
& \underline{\mathsf{T}}_{\mathsf{in}} \leq \mathsf{T}_{\mathsf{in,k+j}} \leq \bar{\mathsf{T}}_{\mathsf{in}} \\
& j = 1, \ldots, N
\end{aligned}
$$

Foundations of Data Predictive Control for CPS

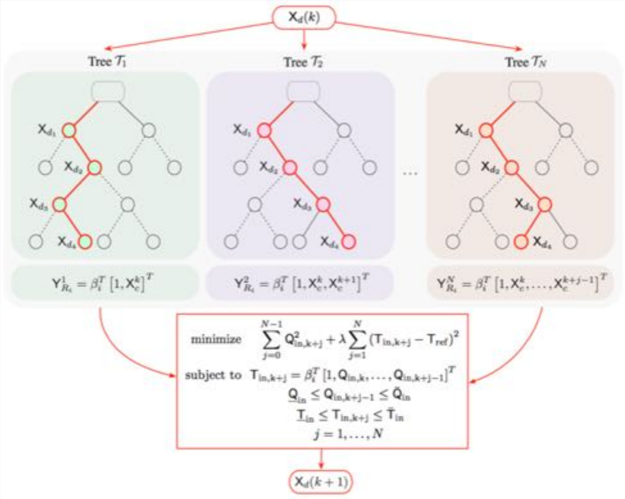
Single-step look ahead [with single reg. trees]



mbCRT

- ICCPS '16, BuildSys 15, CISBAT 15, Journal of Applied Energy
- Best Paper Award (SRC TECHCON-IoT): 'Sometimes, Money Does Grow on Trees'
-Ph.D. Dissertation: Madhur Behl, UPenn (2016)

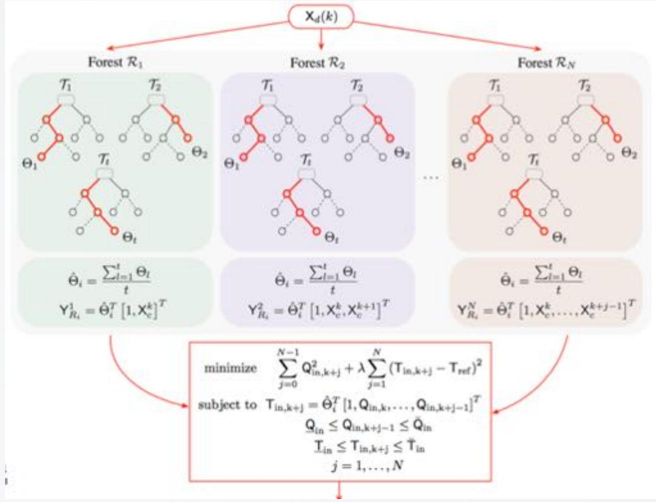
Finite receding horizon [with single reg. trees]



DPC-RT

- ACM BuildSys 16 (Best Presentation Award)
- ACM Transactions of Cyber Physical Systems.

Finite receding horizon [with ensemble models]

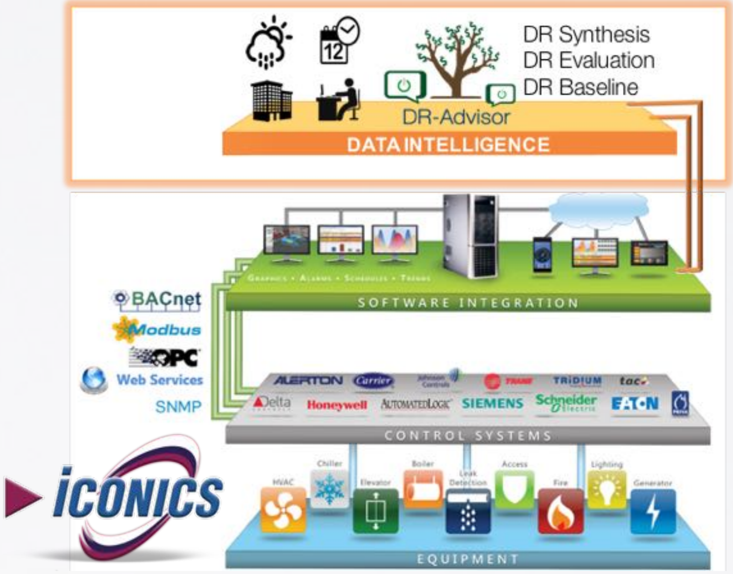


Ensemble-DPC

- American Control Conference 17 *(Best Energy Systems Paper Award)*

Demand Response Recommendation System

DR-Advisor



98.9%
Prediction Accuracy

↓25%
Less energy consumption

↑37%
More DR revenue

Sometimes, Money Does Grow On Trees.

Over 1.2 million sq ft modeled at the University of Pennsylvania

6 floor building U. L'Aquila, Italy

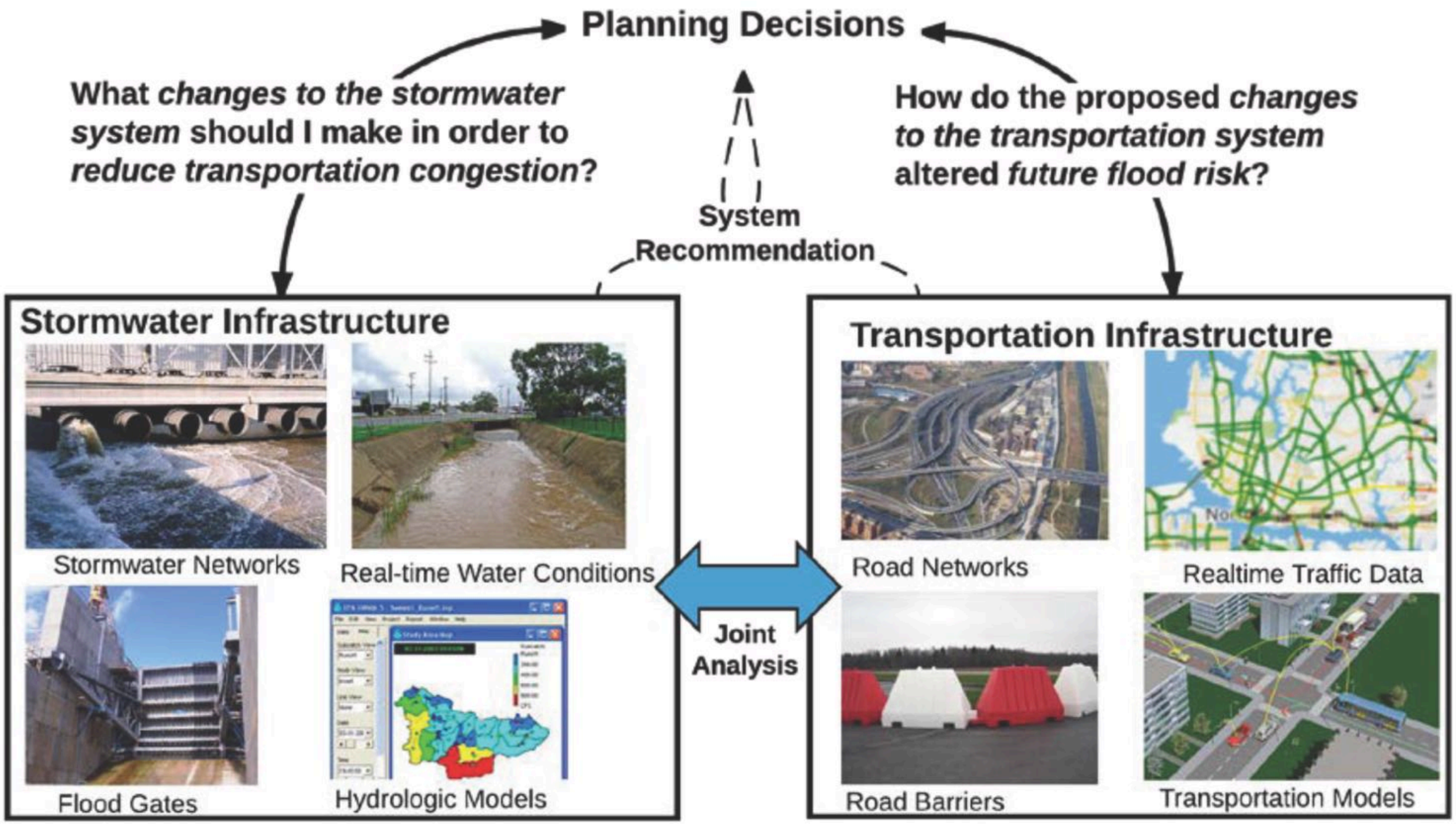
2016 DoE CLEANTECH Prize
NSF SBIR small business.

EXPRESSO LOGIC
machine learning for control engineering

conEdison

$ 45,600 in 4 months

Storm water Flooding – Transportation Modeling



Data Predictive Control for Cyber-Physical Systems

Energy Systems

Industrial Systems

Modeling for predictive control is cost and time prohibitive!

Stormwater-Transportation Systems

Data Predictive Control (DPC)
(bridges the gap)

Machine Learning
model output

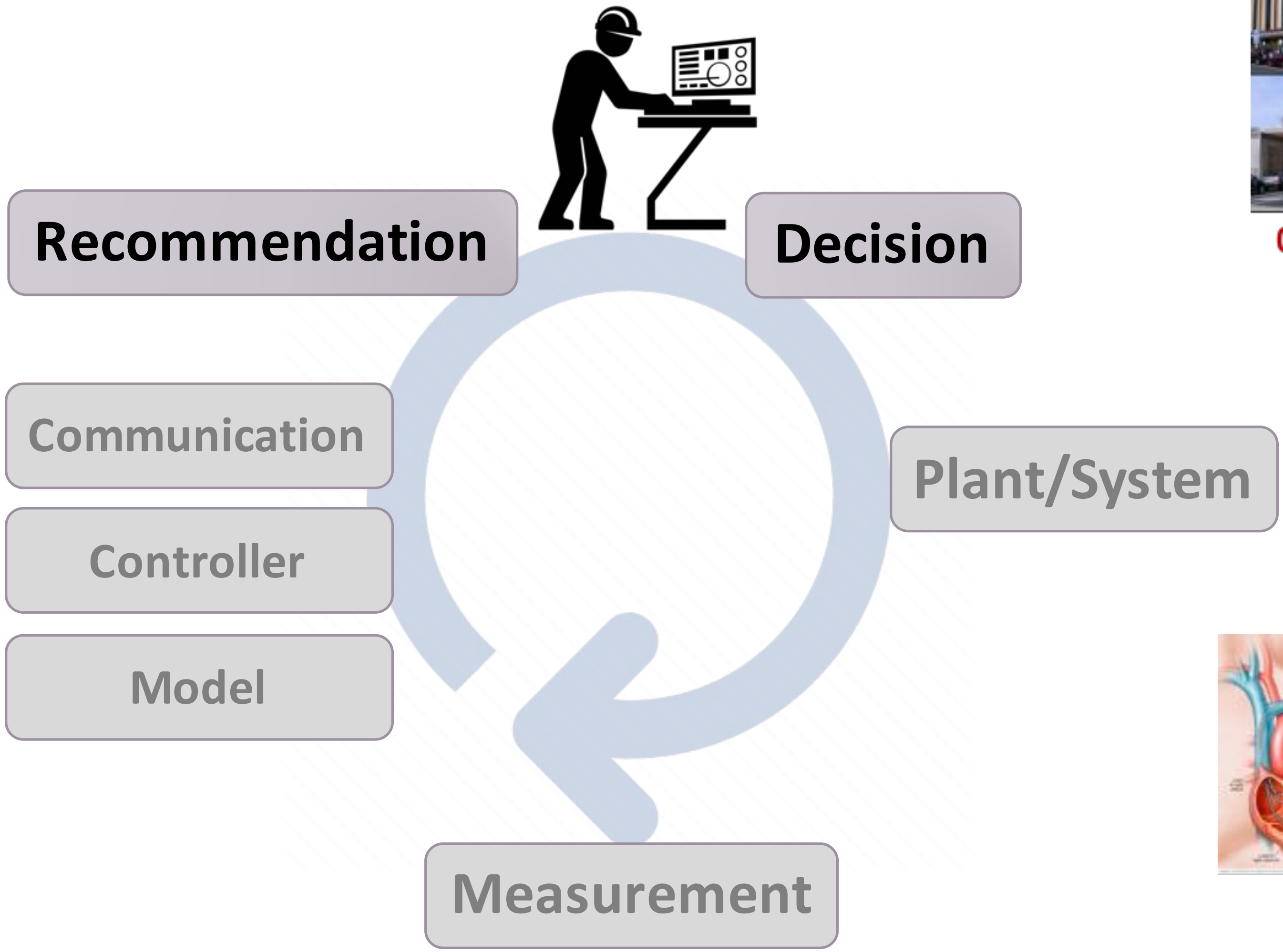
(suitable for prediction)

- Lack of well defined gradients
- Limitations of non-linear models
- Lack of interpretability
- Lack of stability/performance guarantees

Control Synthesis
model input

(requires structural properties)

Operator in the loop



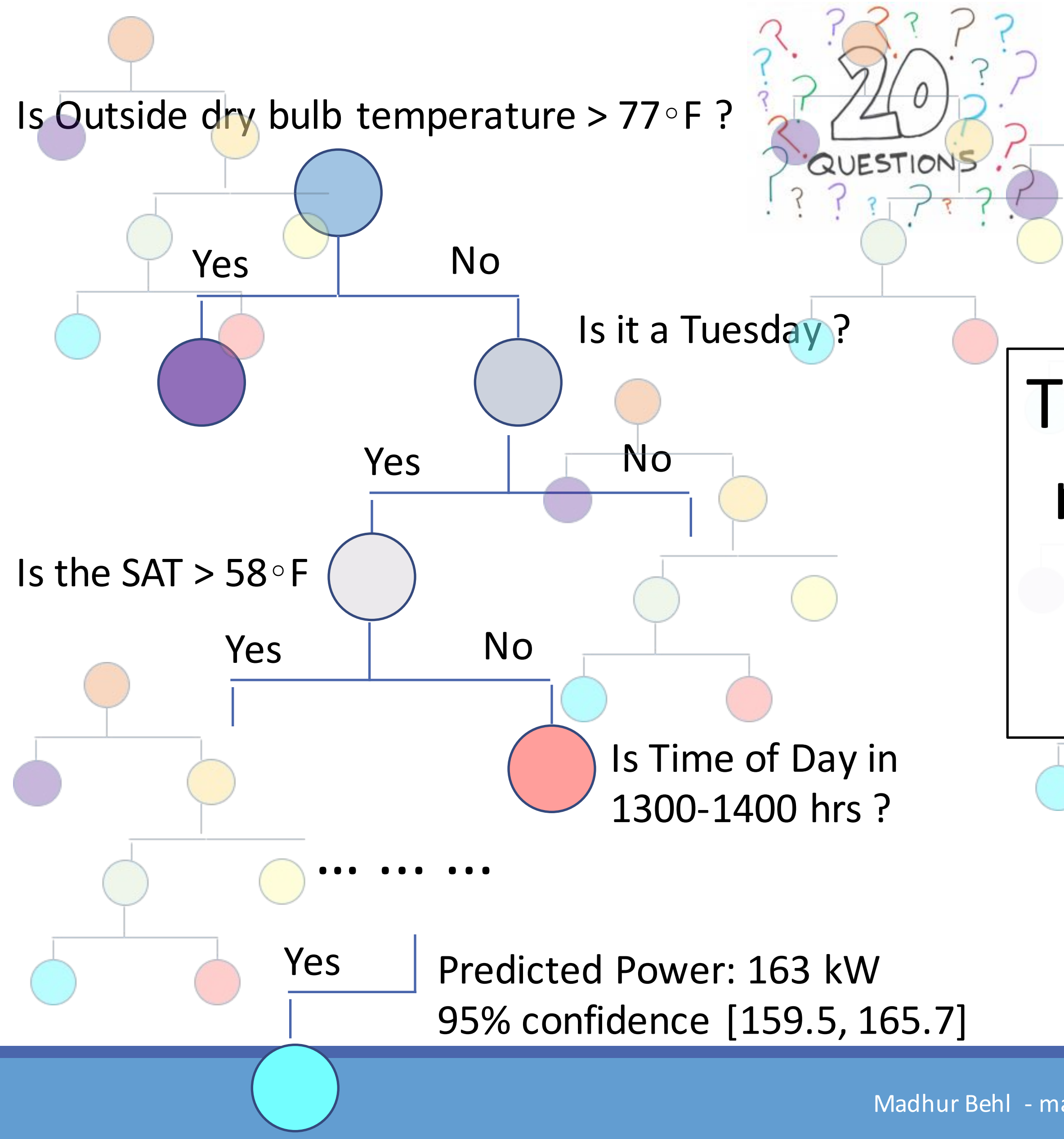
Cyber-Physical Energy Systems

Critical Infrastructures & Smart Cities

Automotive Cyber-Physical Systems

Medical Cyber-Physical Systems

Interpretable Regression Tree models



There is **traceability** around how the recommendation was arrived at so that **operators can understand it and recalibrate** if necessary.

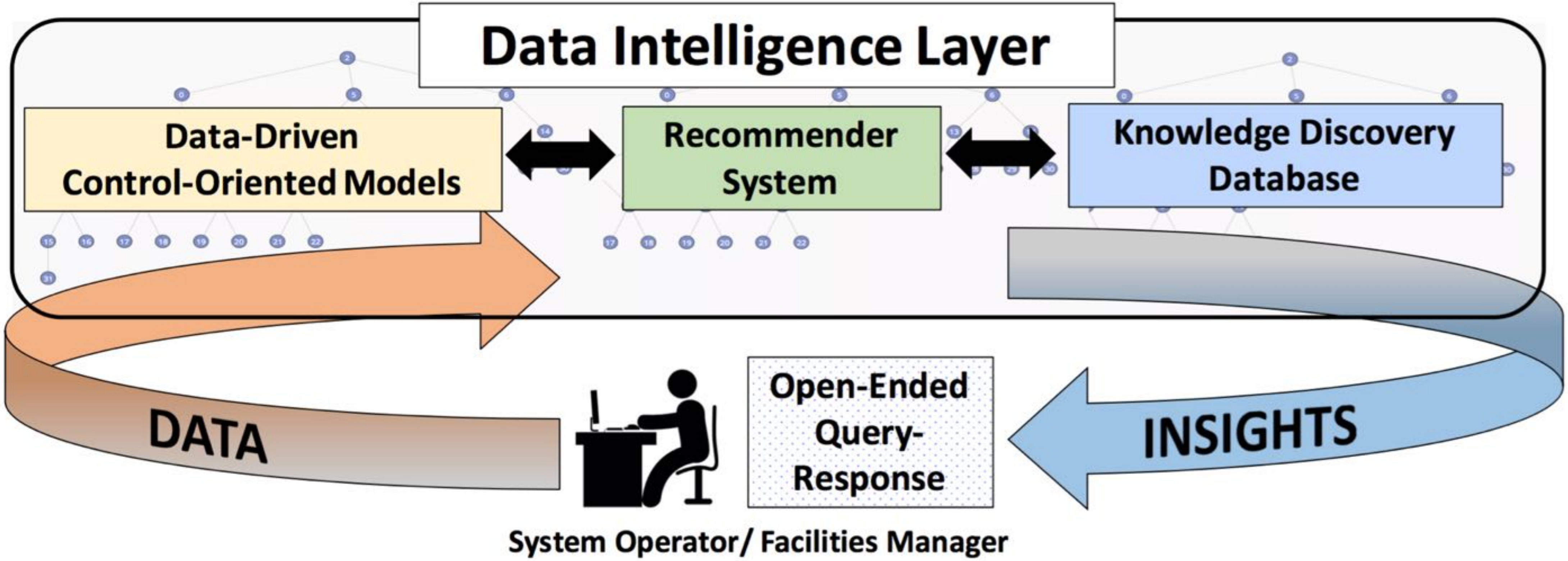
Interactive Analytics

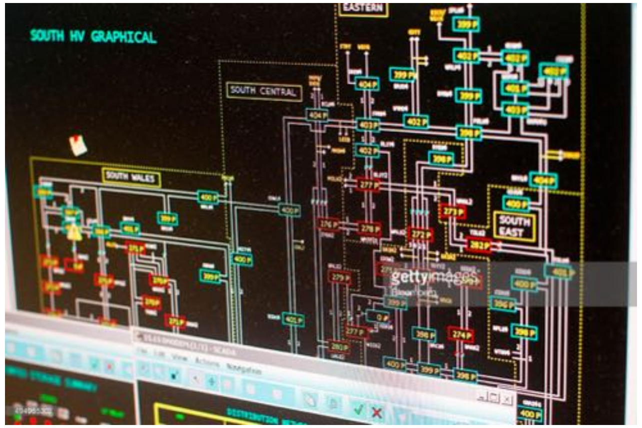
What is happening ?	Data discovery and exploration
Why did it happen ?	Reporting and analysis
What could happen ?	Predictive analytics and modeling
What action to take ?	Decisions and recommendations

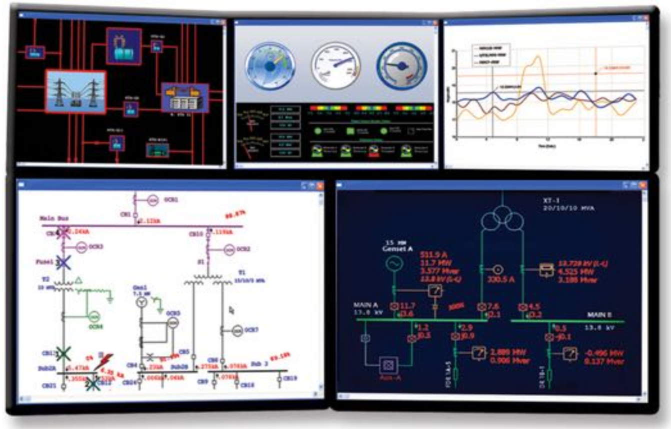
(Q) Under what conditions does Rice Hall consume > 75 kW ?

(A) Rice Hall consumes > 75 kw when:

Dry Bulb Temp: 22.6 °C	**Wet Bulb Temp: 6.4 °C**	**Humidity: 50.2 %**
Wind Speed: 0.85 m/s	**Wind Gusts: 4.72 m/s**	**Solar Irr: 552.5 W/m^2**
HDD: 1.8	**Wind Dir: 36°E**	**CDD: 0.6**
It is either a Tuesday or Thursday	**Time is between 1300-1600 hrs**	**July**


Data Intelligence Layer
Data-Driven Control-Oriented Models
Recommender System
Knowledge Discovery Database
DATA
INSIGHTS
Open-Ended Query-Response
System Operator/ Facilities Manager


SOUTH HV GRAPHICAL



What I do..

- Modeling
- Control
- Optimization
- Implementation
- Safety

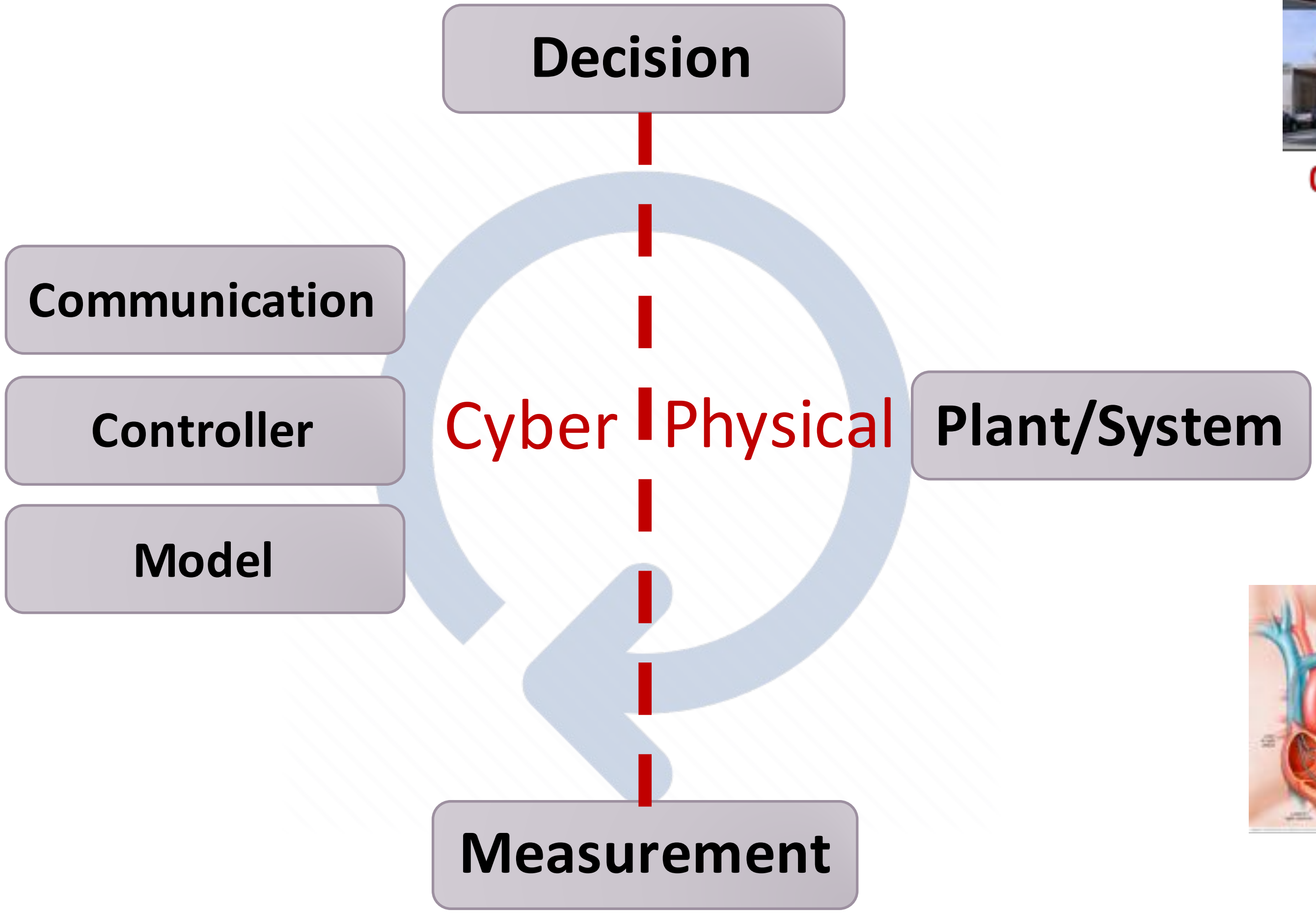
Cyber-Physical Energy Systems

Critical Infrastructures & Smart Cities

Medical Cyber-Physical Systems

Automotive Cyber-Physical Systems

Closing the CPS loop with data



Cyber-Physical Energy Systems

Critical Infrastructures & Smart Cities

Automotive Cyber-Physical Systems

Medical Cyber-Physical Systems

'All models are wrong, but some are useful.'

\- George E.P. Box

madhur.behl@virginia.edu