Statistical Learning in Civil Infrastructure

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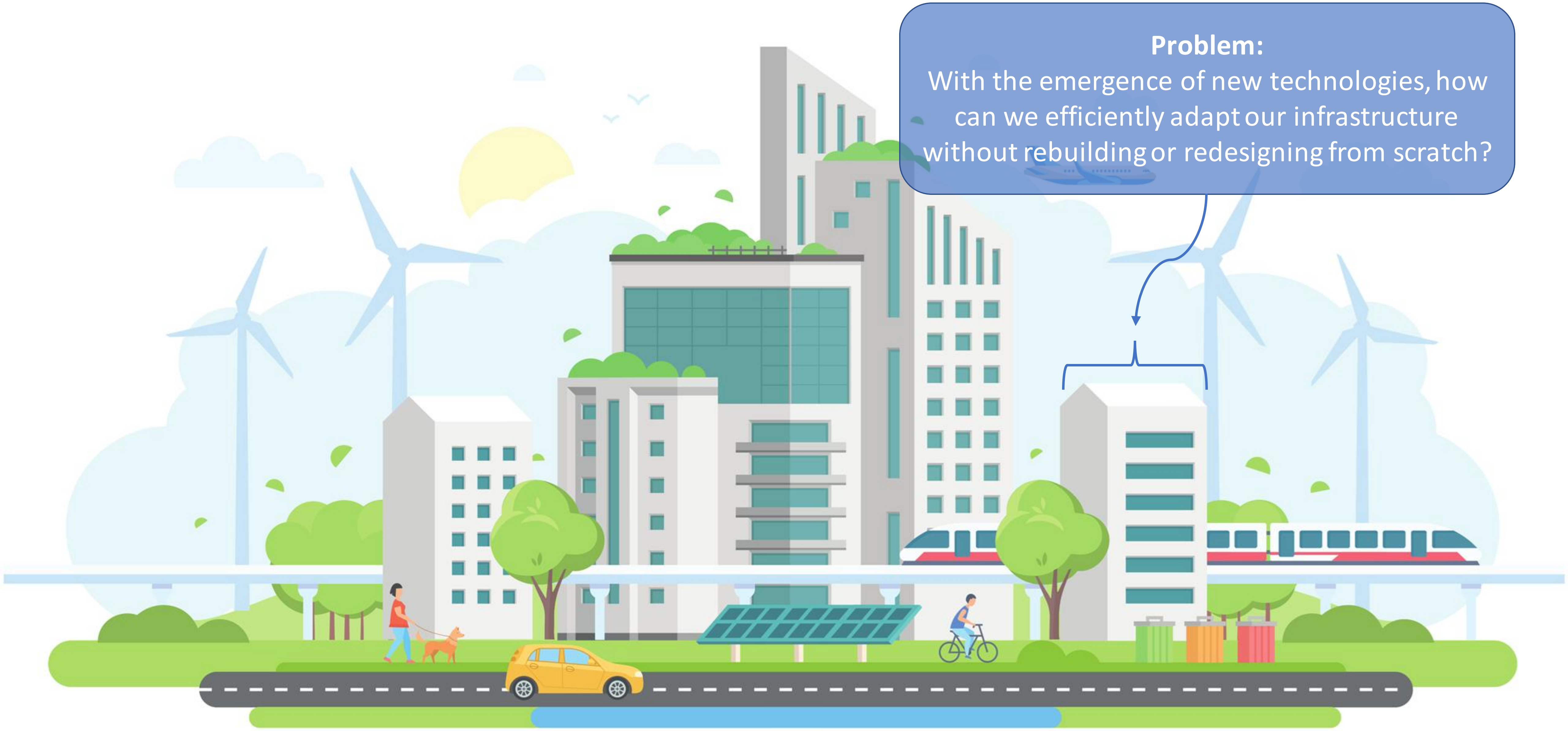
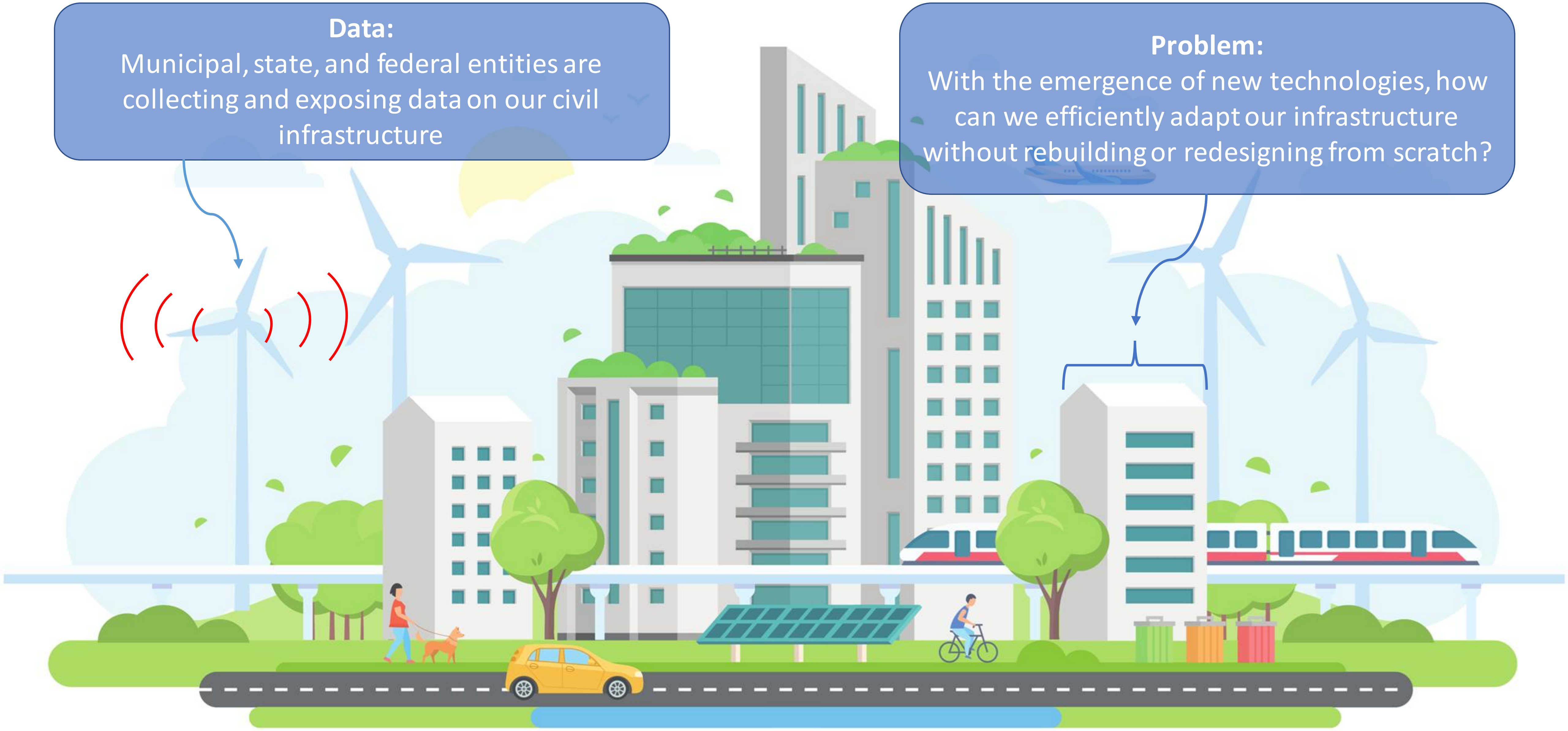

Problem:
With the emergence of new technologies, how can we efficiently adapt our infrastructure without rebuilding or redesigning from scratch?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Municipal, state, and federal entities are collecting and exposing data on our civil infrastructure
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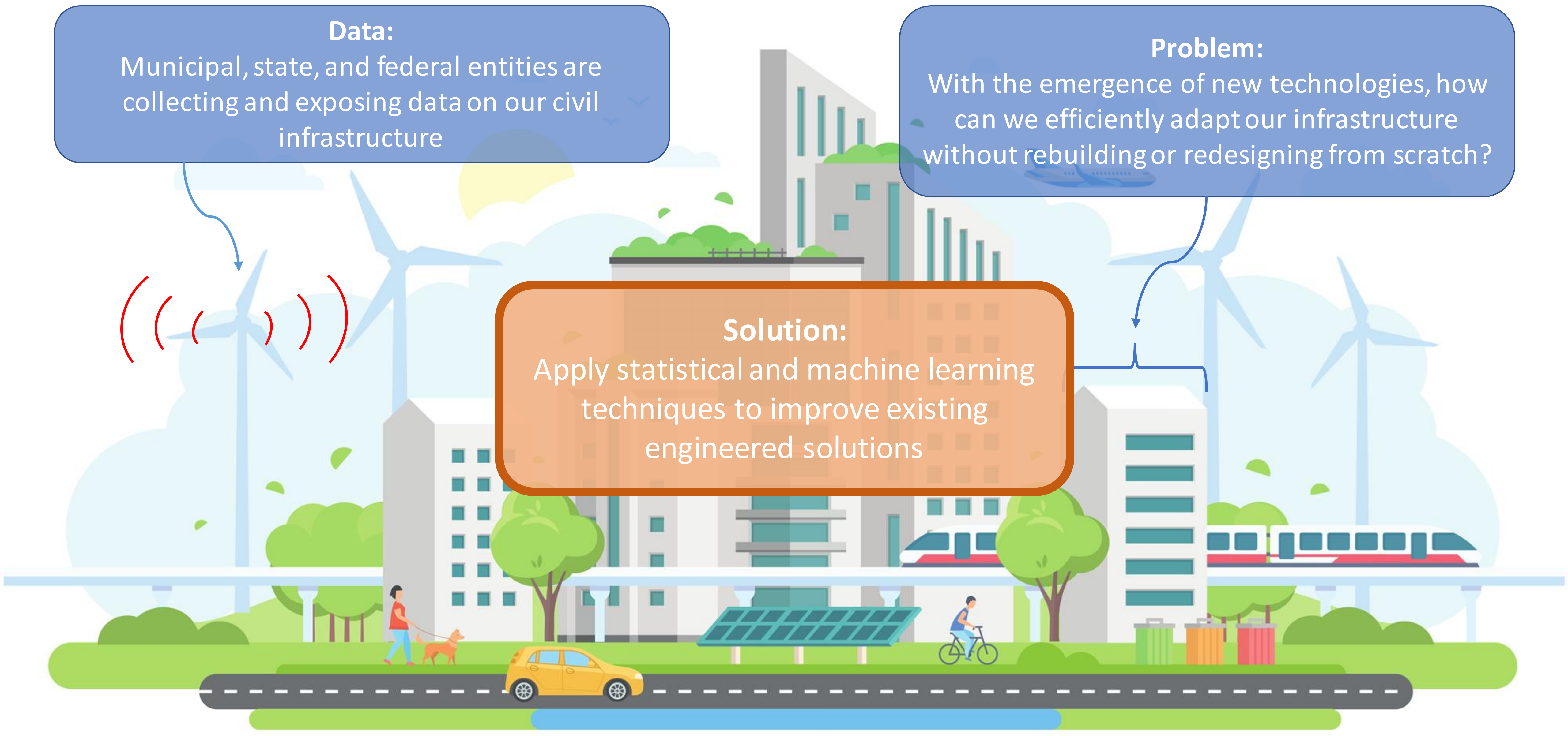
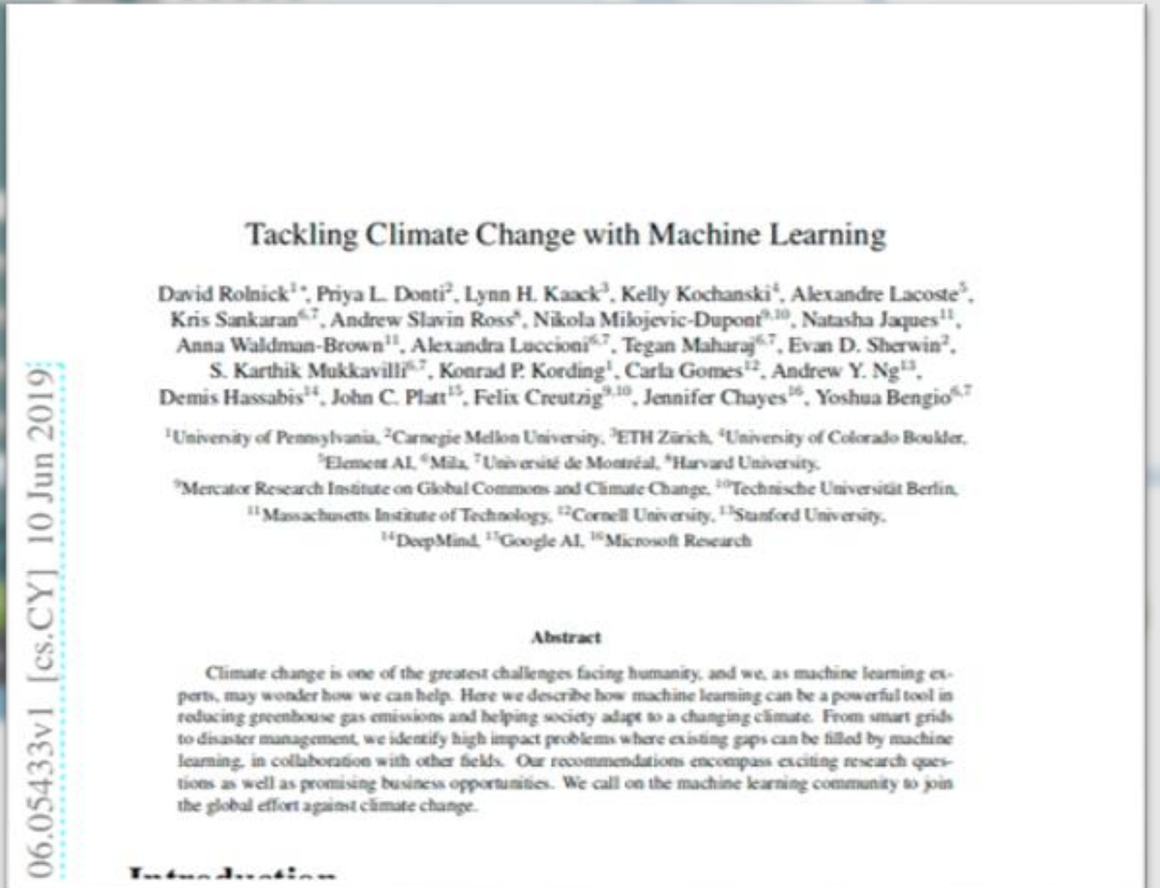

Data:
Municipal, state, and federal entities are collecting and exposing data on our civil infrastructure
Problem:
With the emergence of new technologies, how can we efficiently adapt our infrastructure without rebuilding or redesigning from scratch?
Solution:
Apply statistical and machine learning techniques to improve existing engineered solutions

Case studies in combining civil data with statistical and machine learning

-Lots of opportunity

-Growing # of examples where lack of domain knowledge leads to inactionable solutions in high reliability areas

-Immature use in control tasks



arXiv:1906.05433v1 [cs.CY] 10 Jun 2019

Tackling Climate Change with Machine Learning

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Abstract

Climate change is one of the greatest challenges facing humanity, and we, as machine learning experts, may wonder how we can help. Here we describe how machine learning can be a powerful tool in reducing greenhouse gas emissions and helping society adapt to a changing climate. From smart grids to disaster management, we identify high impact problems where existing gaps can be filled by machine learning, in collaboration with other fields. Our recommendations encompass exciting research questions as well as promising business opportunities. We call on the machine learning community to join the global effort against climate change.

Introduction

Electrical Grids: A Case Study in Coincident Peak Pricing

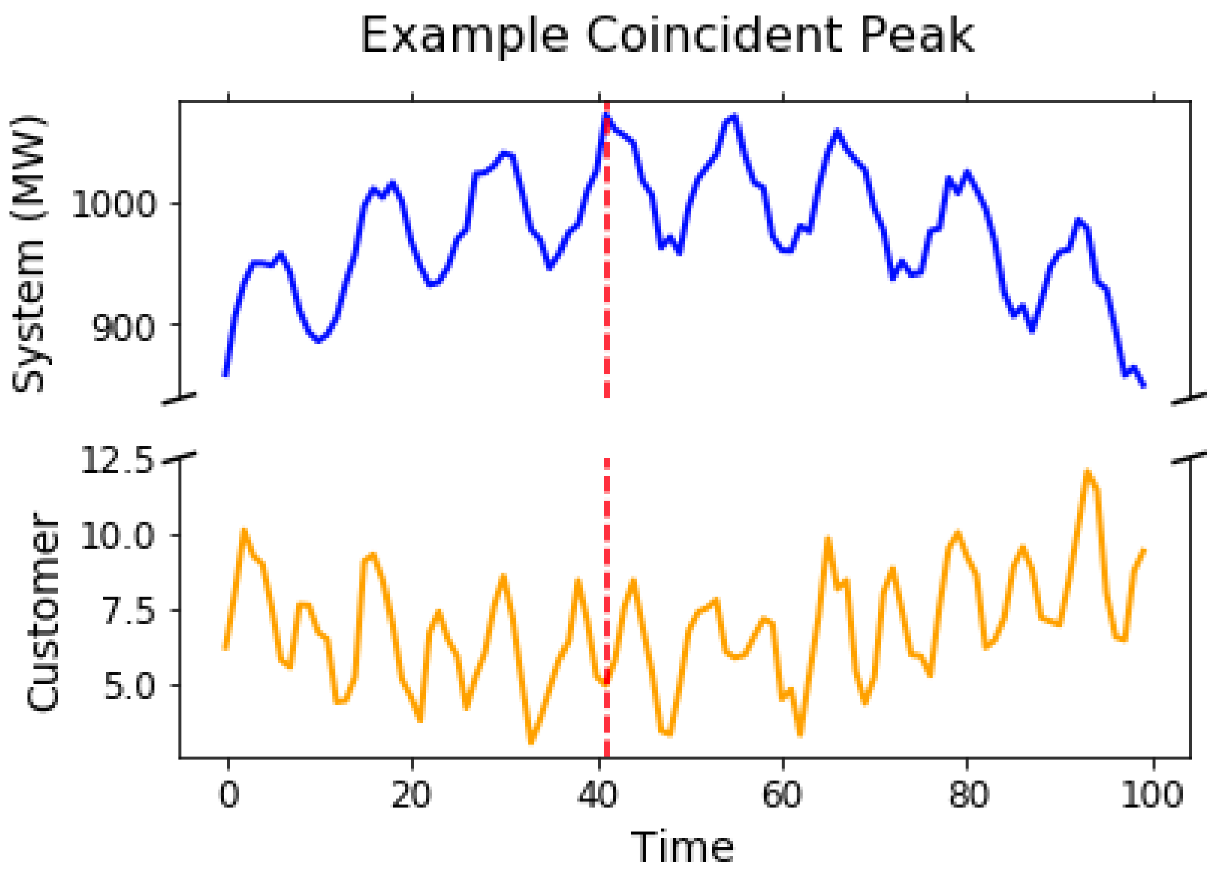
1. What is a Coincident Peak (CP) and why do we care?
2. What do system operators do with system data?
3. What can power customers do with system data?
4. Can system data tell us if CP Pricing is effective?

Coincident Peaks

An electrical customer's coincident peak (CP) is their demand at the moment of the entire system's peak.

Systems levy transmission surcharges via CP electrical rates to reduce system peaks.

Also known as Triads, Average Peak Cold Spell. Originates in French, UK power systems. Used in many US systems; being considered in CAISO

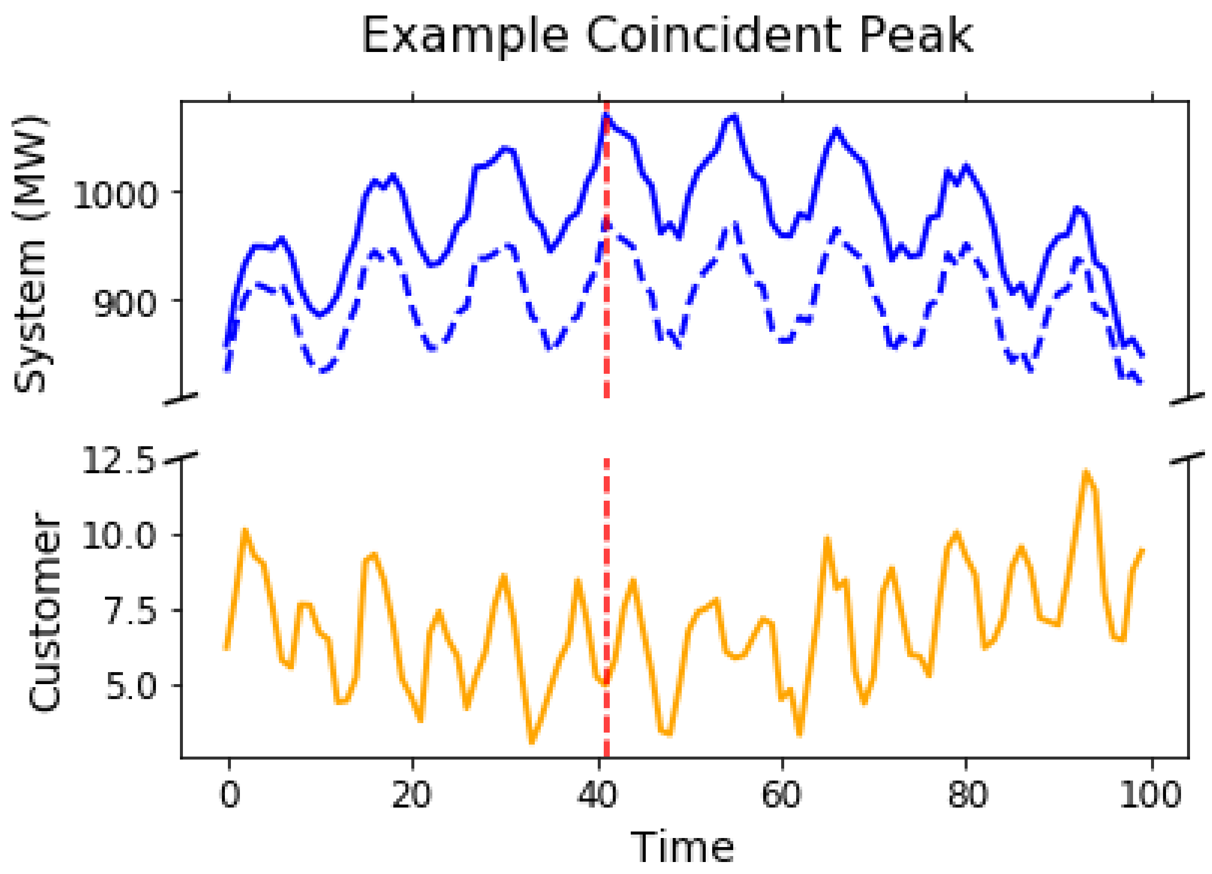


Coincident Peaks

- CP rate roughly 100x more than normal time-of-use rates
- A consumer's CP is recorded on a monthly basis
- At the end of the year, CP charges are paid

Consumers participate in exchange for discounted time-of-use rates at all other times---breaks out long term expansion costs.

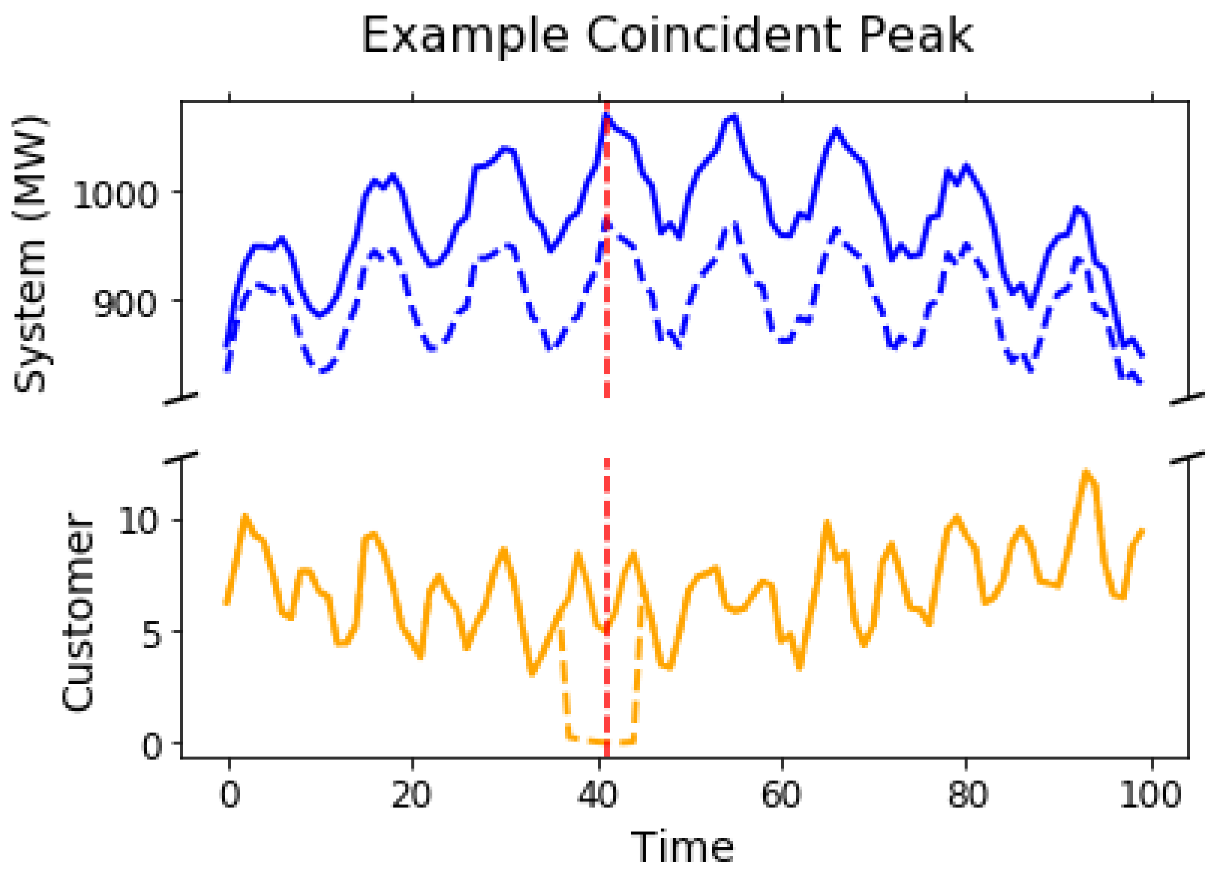
Goal is to curtail consumer demand at peaks



Coincident Peaks

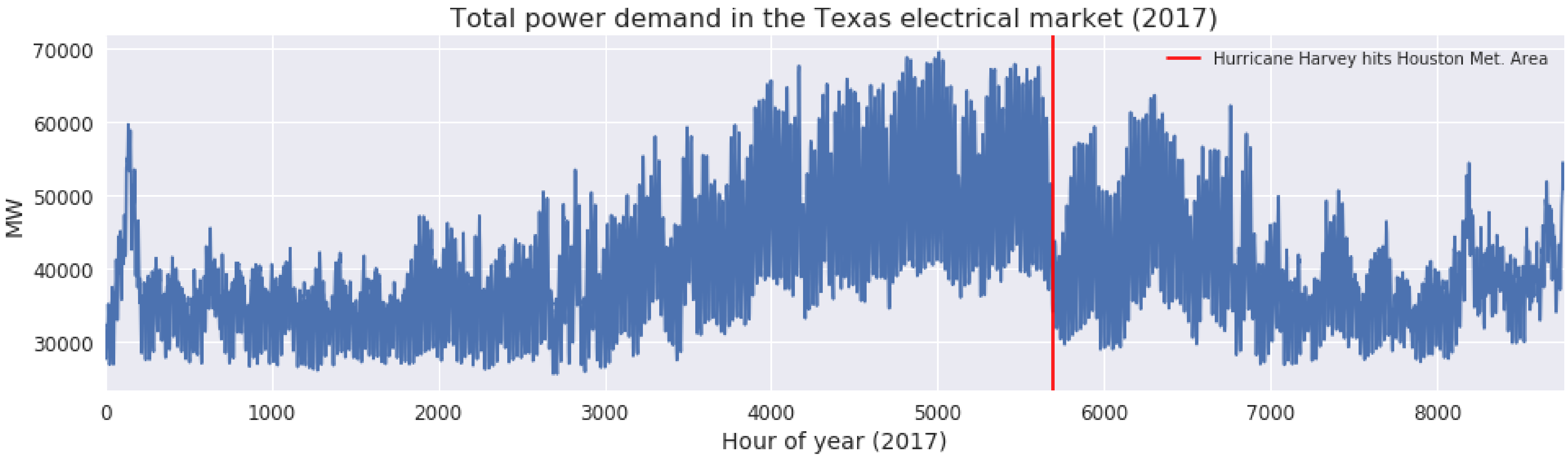
4 MW consumer paying average ERCOT wholesale prices ($40/MWh), roughly $1.4 million in electricity costs per working year,$300k of which per year to consume electricity at CP hour

Consumers are incentivized to curtail demand during the moment of the CP



Current Solutions: Variations

- Seasonal: UK, PJM, DEOK, winter ACS
- Monthly: ERCOT 4-CP, CAISO 12-CP
- Annually: "Peak Load Pricing" (Boiteux, 1949)



Current Solutions: Variations

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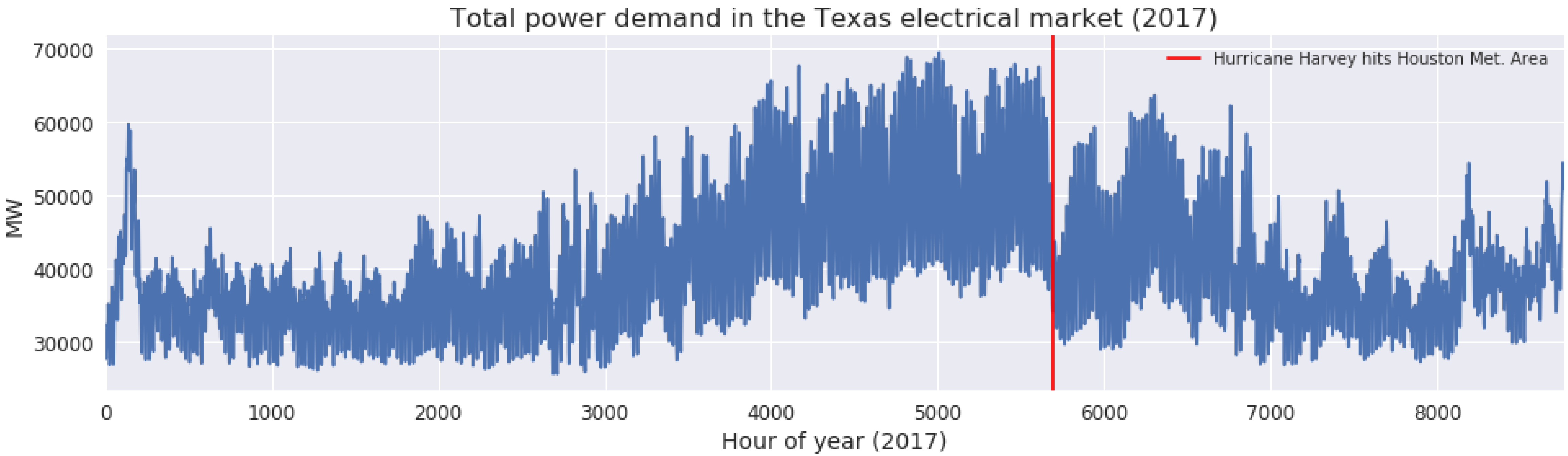
Assumption #1:
1-CP pricing hour over a known, finite time horizon

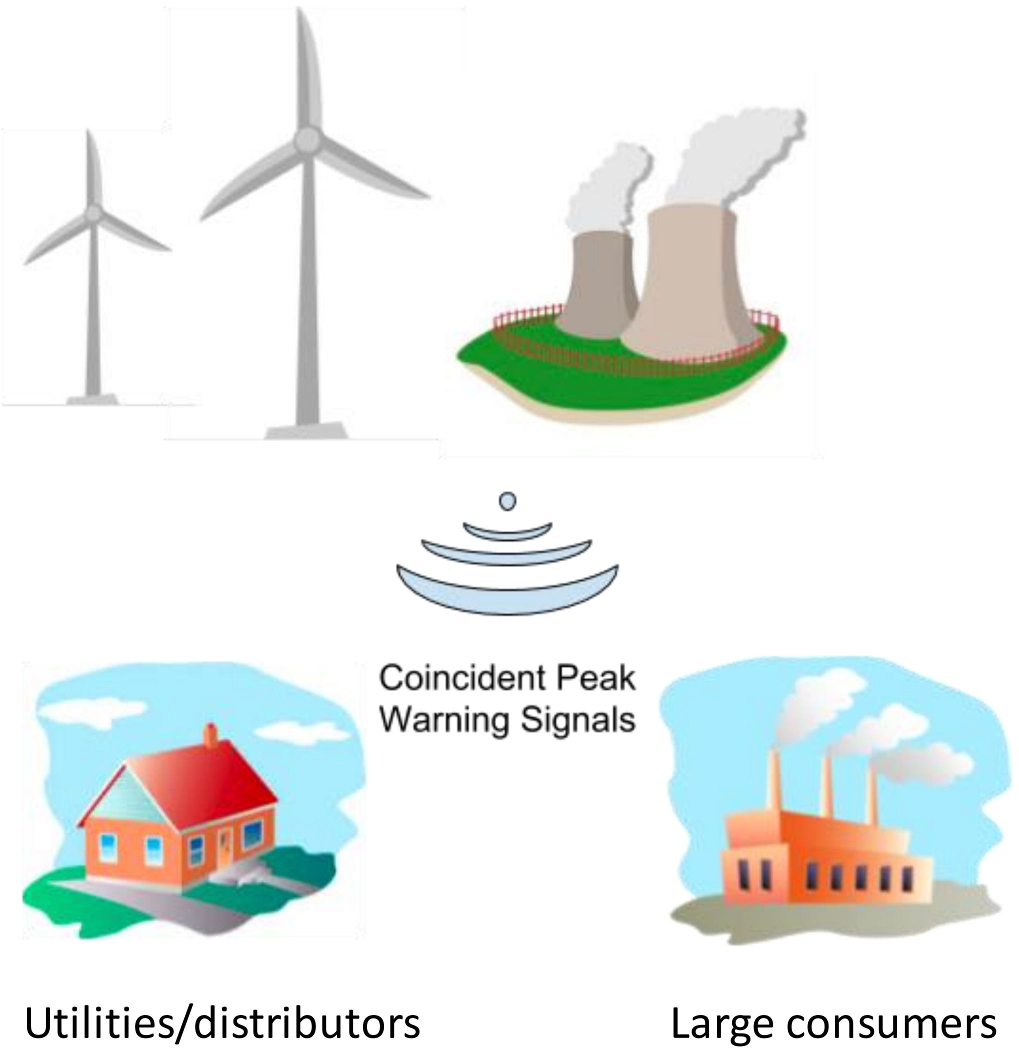


Current Solutions

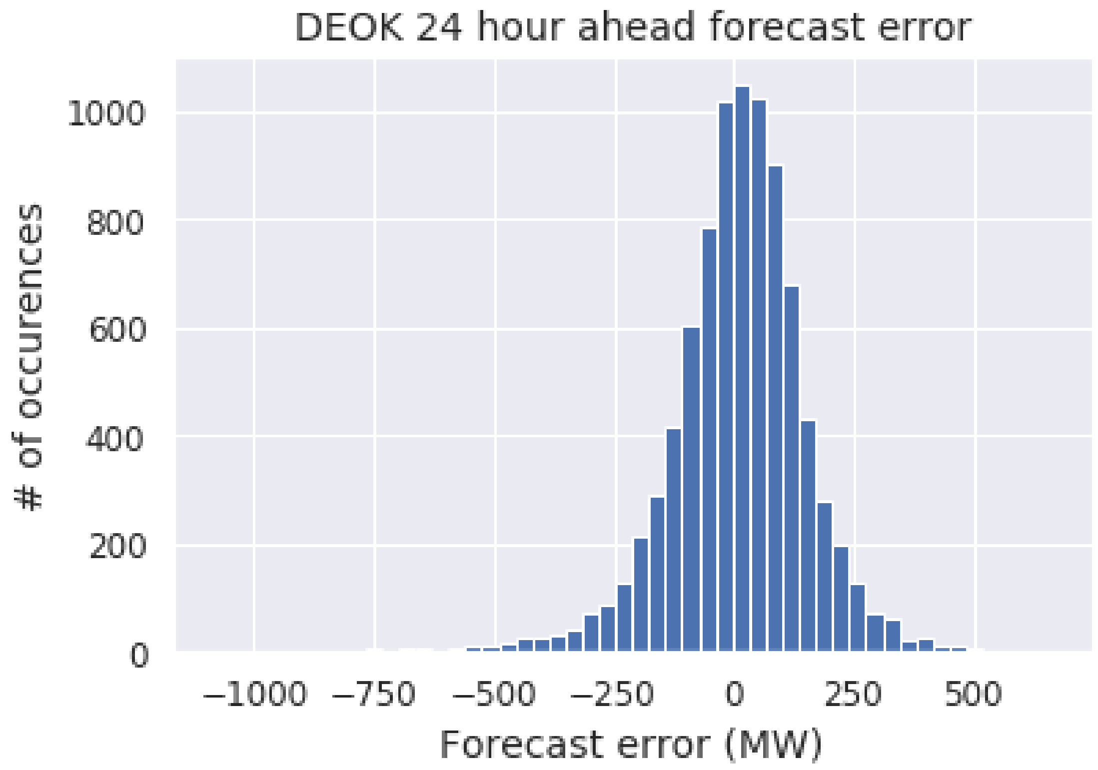
Operators broadcast signals, e.g. Fort Collins PUD:

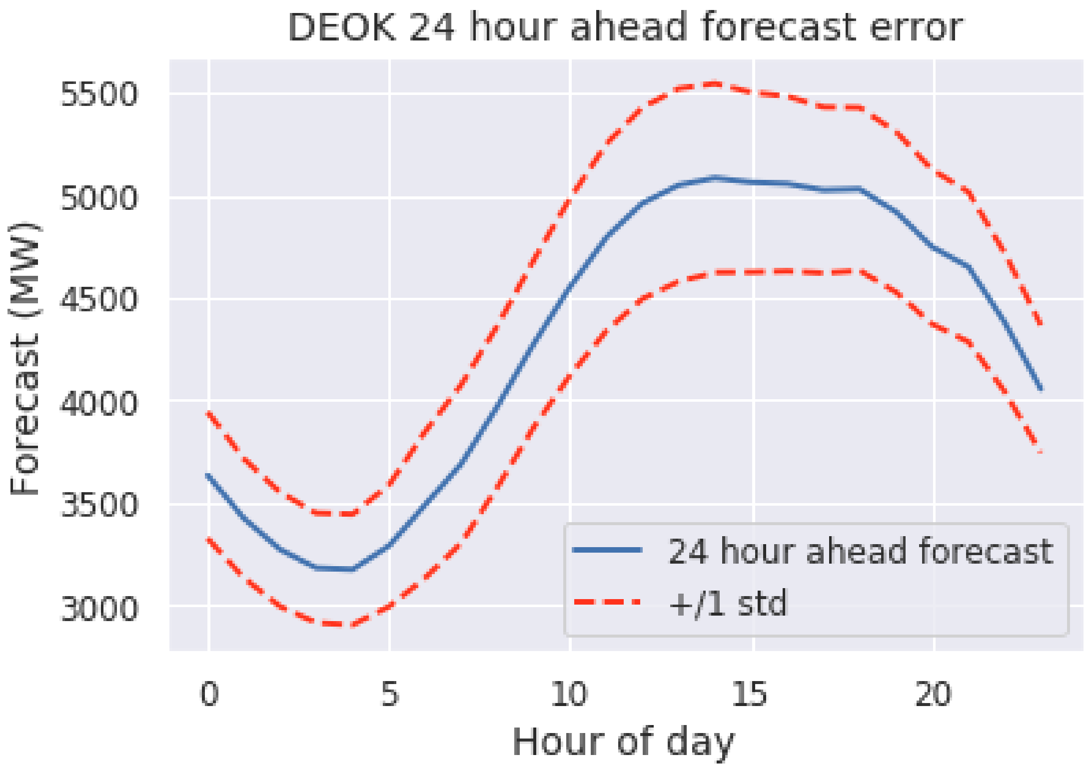
- Sends out signals about 10 days out of month
- Signals can come with less than one hour lead time, can last multiple hours
- Customers know when CP's should occur, e.g. hot day, afternoon

Too many signals, still hard to predict rare events



Coincident Peak Timing

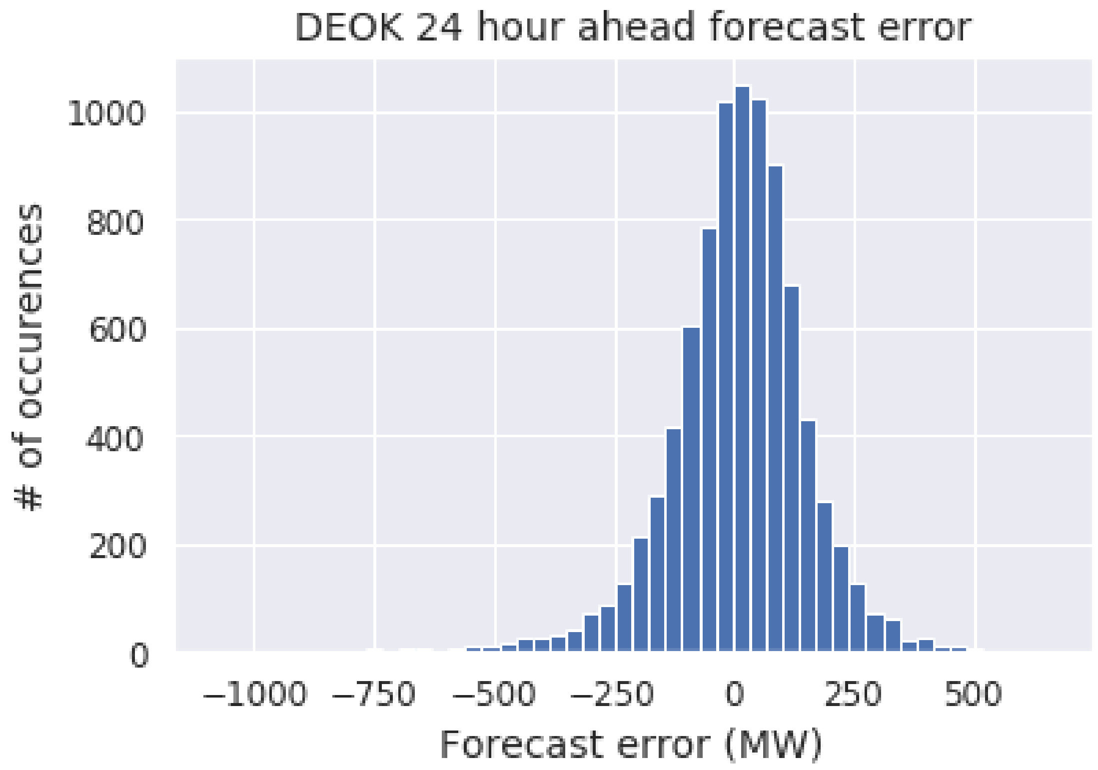


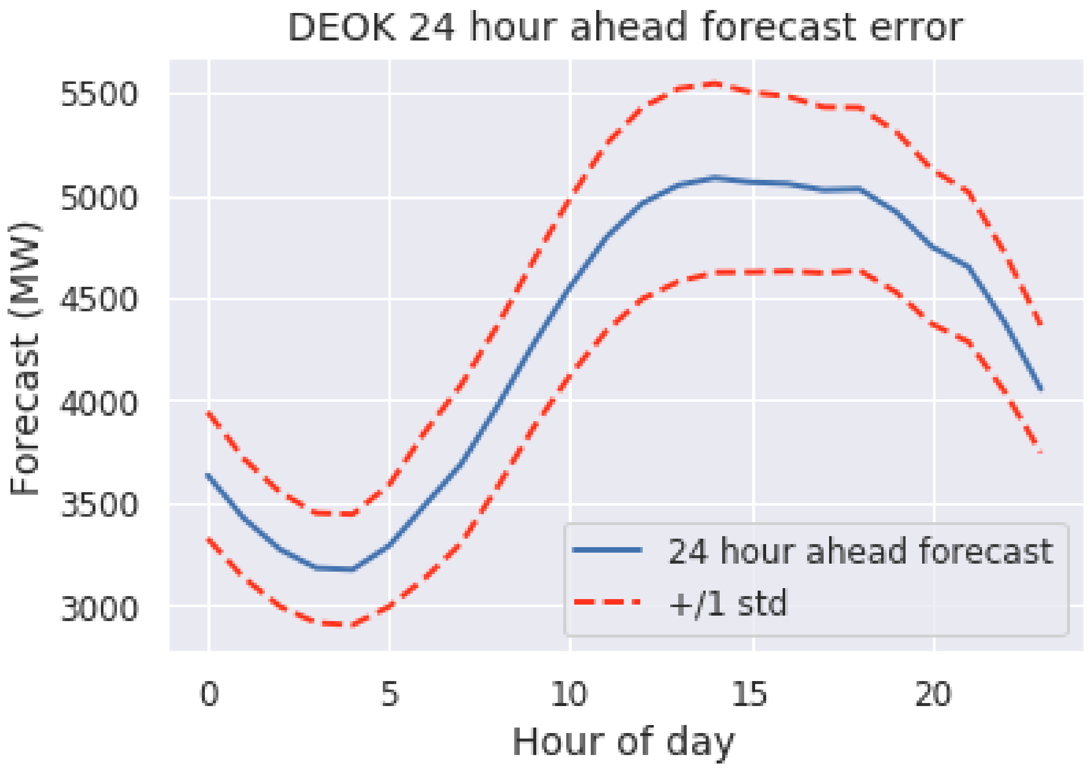


July 8, 2018

Coincident Peak Timing

Assumption #2:
Noise in the system is Gaussian, 0 mean





July 8, 2018

Current Solution: Operator Perspective

Forecast error is stationary, variance is not, even across matching times

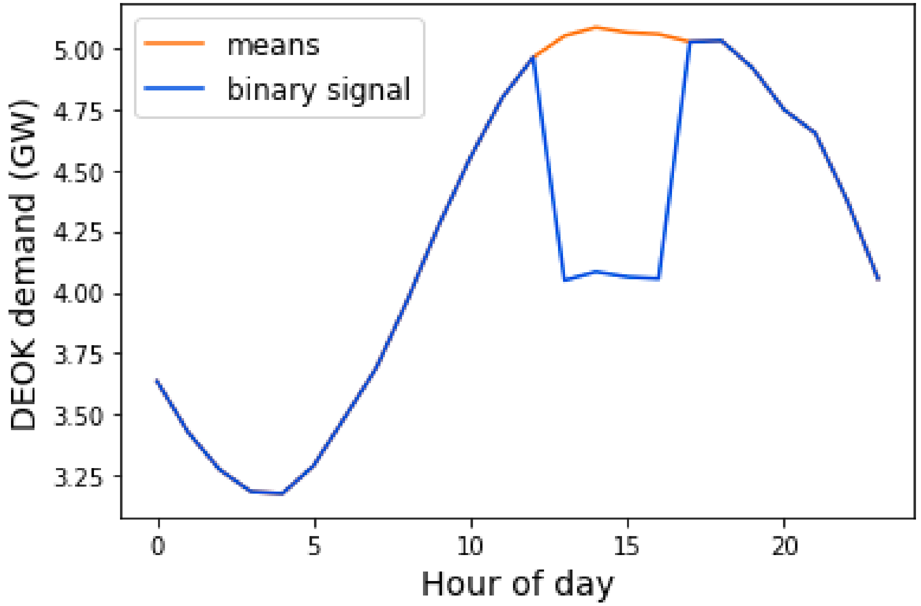
Optimize binary peak/no-peak signal timing against forecast + scenario generation

Scenarios

Binary signal

$$\underset{t \in T}{\text{minimize}} \left[\frac{1}{N} \sum_{i=1}^{N} \max_{t} \left\{ X_t^{(i)} - \mathbf{1}[t] \cdot m \right\} \right]$$

$$\text{subject to} \quad \sum_{t} \mathbf{1}[t] \leq S$$



1 GW of DR services for 4 hours

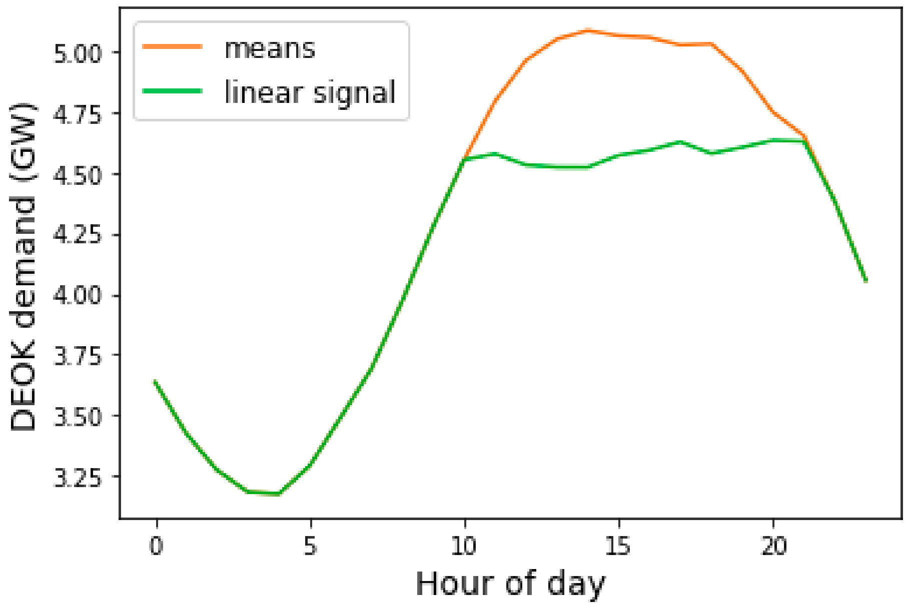
Flexible Demand Response

Continuous signals based on estimated curtailment budget

$$\underset{\mathbf{m}}{\text{minimize}} \left[\frac{1}{N} \sum_{i=1}^{N} \max_{t} \left\{ X_t^{(i)} - m_t \right\} \right]$$

$$\text{subject to} \quad \sum_{t=1}^{T} m_t \leq M$$

$$m_t \geq 0$$



4 GWh total of DR services

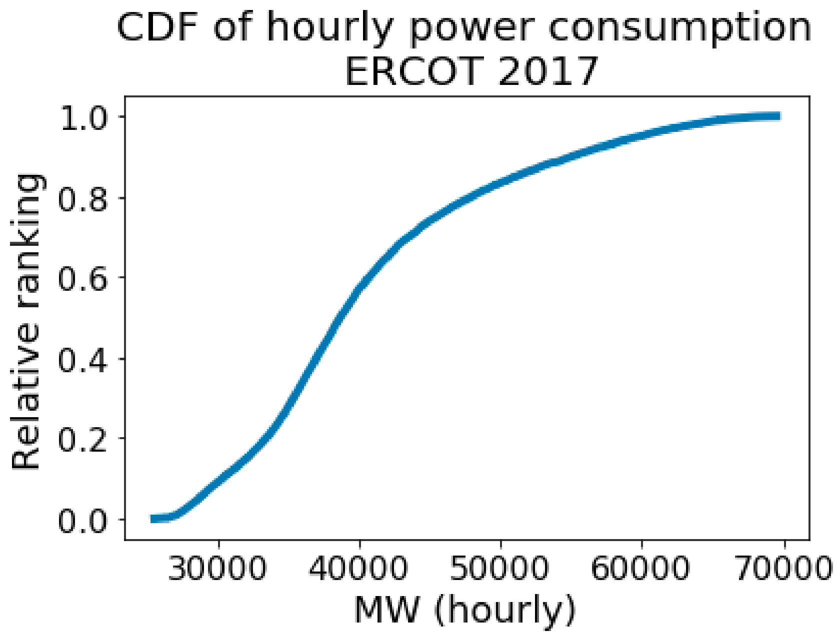
Predicting Coincident Peaks

Can we do better than optimizing over Monte Carlo? (i.e. is more data going to help us?)

System operators are constrained to sending out early signals (> 24 hours)

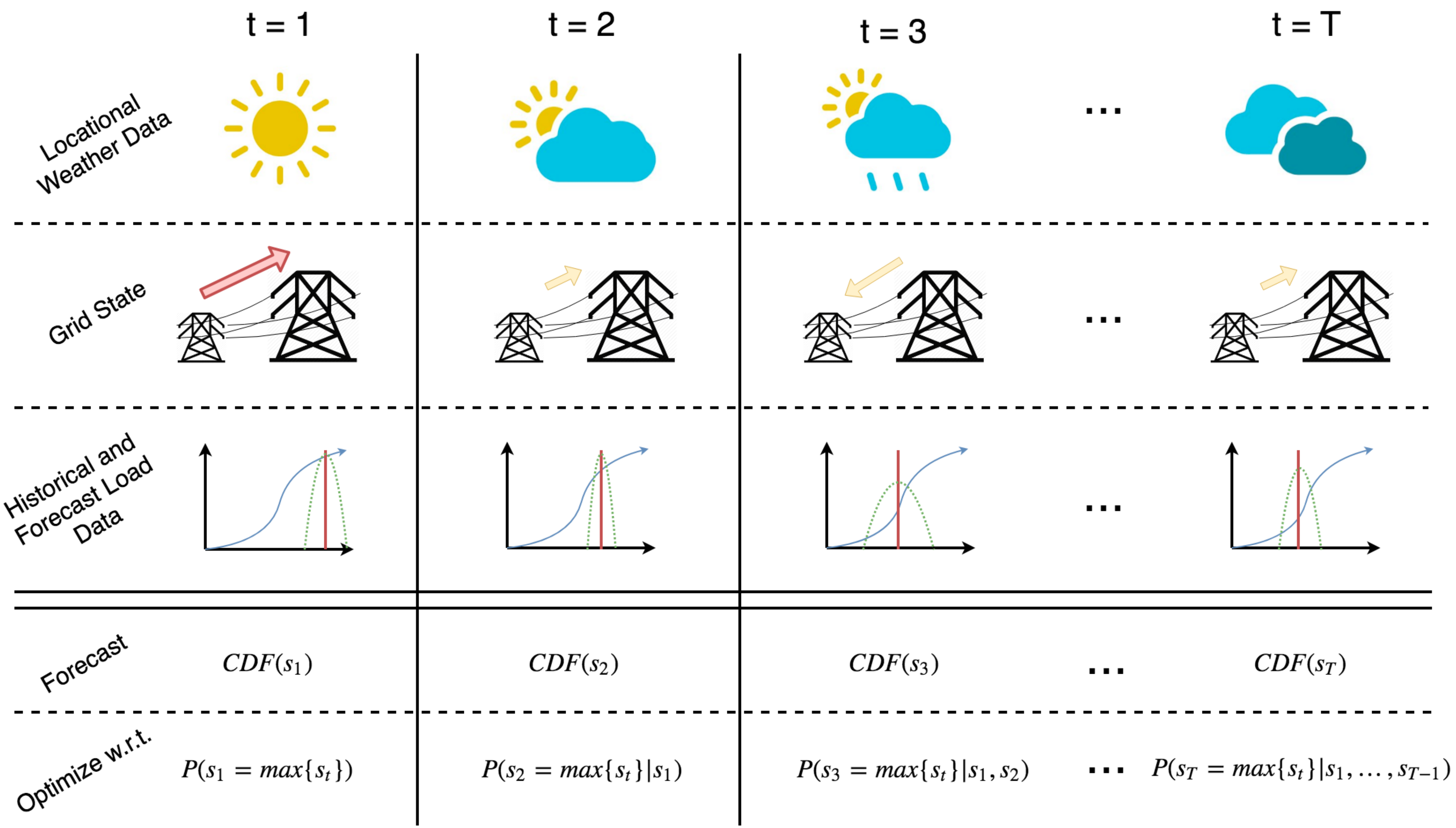
Predicting a rare binary events hard, hedge our bets?

Replace strict max operator with cumulative distribution function



$$\left\{ x_{c^*} \,|\, c^* = \operatorname*{argmax}_{c \in T} s_c \right\} \Rightarrow \mathrm{CDF}(x_t) = P(X \leq x_t)$$

1: "Coincident Peak Prediction Using a Feed-Forward Neural Network" CP Dowling, D Kirschen, B Zhang - 2018 IEEE Global Conference on Signal and Information Processing, 2018


t = 1
t = 2
t = 3
t = T
Locational Weather Data
Grid State
Historical and Forecast Load Data
Forecast
$CDF(s_1)$
$CDF(s_2)$
$CDF(s_3)$
$CDF(s_T)$
Optimize w.r.t.
$P(s_1 = max\{s_t\})$
$P(s_2 = max\{s_t\}|s_1)$
$P(s_3 = max\{s_t\}|s_1, s_2)$
$P(s_T = max\{s_t\}|s_1, \ldots, s_{T-1})$

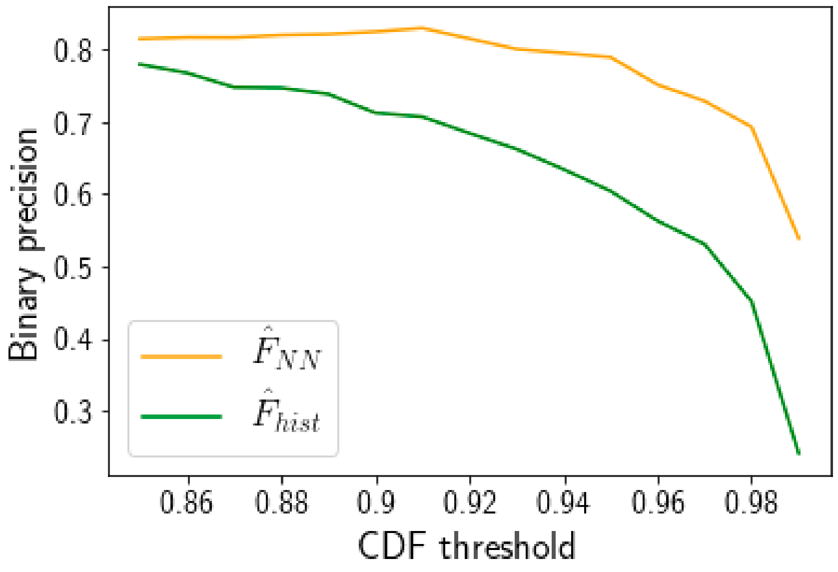
Predicting Coincident Peaks

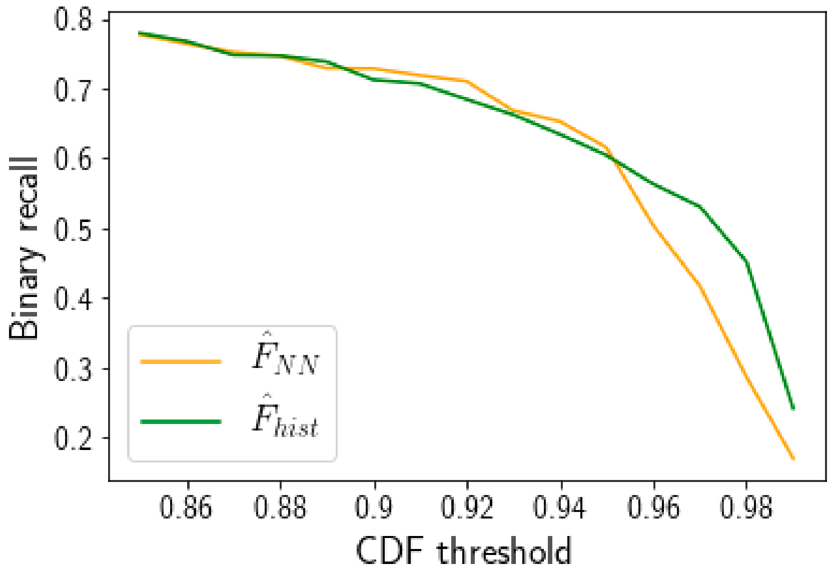
- Train a simple, feedforward NN to predict CDF output of next 24 hours system demands
  - Exponentially weighted L1 loss

$$F(s_{t+1}) = \begin{cases} 1 & CDF(s_{t+1}) > \alpha \\ 0 & \text{otherwise} \end{cases}$$

- Training data: weather, transmission, hourly demand ERCOT 2010-2016

- Test data: ERCOT 2017



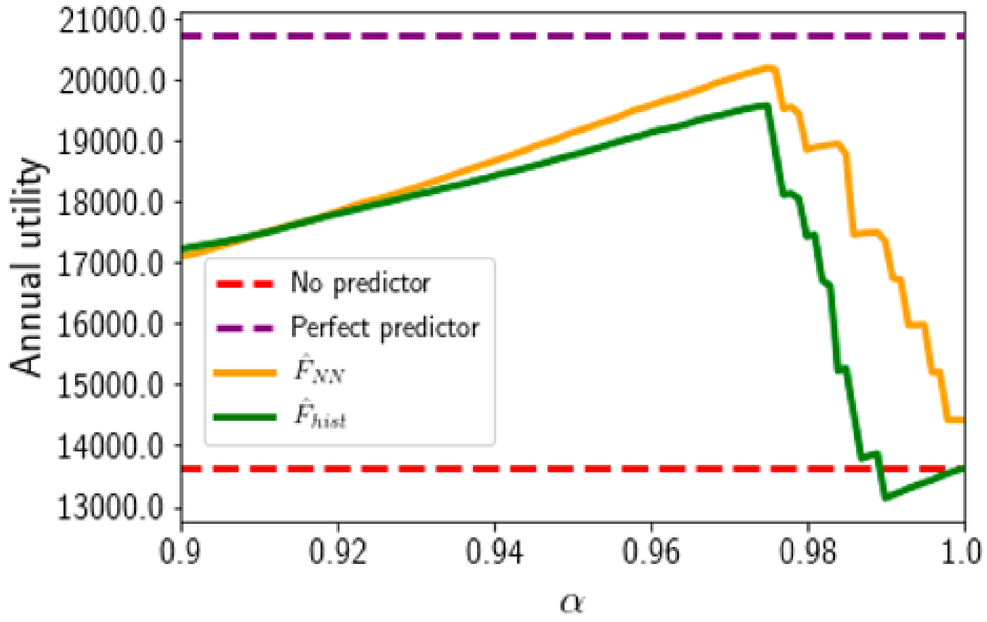


Predicting Coincident Peaks

Hypothetical business

Curtail demand linearly up to some budget

Some traction to be gained predicting system peaks --- let's take a more principled approach



CDF Curtailment Threshold

Small Consumer Perpsective

System Noise

$$s_t \sim \mathcal{N}(0, \sigma^2)$$

Consumer Reward

$$R = \sum_{t=1}^{T} g(x_t) - \pi_{cp} \left\{ x_{c^*} \middle| c^* = \operatorname*{argmax}_{c \in T} s_c \right\}$$

Naive Solution

Ignore system noise; amortize coincident peak costs across all time periods

$$0 = T \cdot g'(x) - \pi_{cp} x$$

Current Solution: Small Consumer Perspective

Responding to operator signals

40% CP consumers in ERCOT <10 MW (1 STD of forecast error in 100's of MW)

Consumer's CP timing determined by system noise (forecast is known) independent of their power demand at any time

Core Assumptions

1. Single peak over known finite time period

   (No averaging of multiple peaks/time periods)

2. System noise is Gaussian, corresponding to forecast error

$$R = \sum_{t=1}^{T} g(x_t) - \pi_{cp} \left\{ x_{c^*} \,|\, c^* = \operatorname*{argmax}_{c \in T} s_c \right\}$$

Probability of a Coincident Peak

Can do better than optimizing over Monte Carlo. Can we do better than trying to forecast CDF and arbitrarily hedging?

We know forecast error is a unimodal distribution, then probability of a peak directly:

$$p_t := P(s_{t+1} \text{is peak for all T} | s_1, s_2, \ldots, s_t)$$

If IID

$$p_t = P(t + 1 \text{is max of any} T - t) \cdot P(\text{any next} T - t > s_m) = \frac{1}{T - t}(1 - P(s \leq s_m)^{(T-t)})$$

Proposed Solution: Small Consumer Perspective

- No ramping constraints
- Dynamic Programming
  - Optimal strategy

$$\underset{x_1, x_2, \ldots, x_T}{\text{maximize}} \quad \mathbb{E}[R_T]$$
$$\text{subject to} \quad x_t \in [0, \bar{x}]$$

- Ramping constraints
- Approximate dynamic programming
  - Near-optimal strategy

$$\underset{x_1, x_2, \ldots, x_T}{\text{maximize}} \quad \mathbb{E}[R_T]$$
$$\text{subject to} \quad x_t \in [0, \bar{x}]$$
$$x_t \in [x_{t-1} - \delta, x_{t-1} + \delta]$$

2: "Mitigation of Coincident Peak Charges via Approximate Dynamic Programming" CP Dowling, B Zhang - IEEE Conference on Decision and Control, 2019 (to appear)

Dynamic Programming

Optimize going backwards in time, let t = T-1

$$\mathbb{E}_{s_T}[R] = \mathbb{E}_{s_T}\left[\sum_{t=1,\ldots T-1} g(x_t) + g(x_T) - \pi_{cp}\{x_{c^*} | c^* = \underset{c \in T}{\operatorname{argmax}}[s_c]\}\right] \qquad (1)$$

$$= \sum_{t=1,\ldots T-1} g(x_t) + g(x_T) - \pi_{cp}[(1 - p_T)x_{c^*} + p_T x_T] \qquad (2)$$

And we optimize w.r.t to x_T . Continuing backwards, we have that the optimal play for any t is x_t such that

$$0 = g'(x_t) - \pi_{cp} p_t$$

Adding Ramping Constraints

If we add a ramping constraint $x_t \in [x_{t-1} - \delta, x_{t-1} + \delta]$ then we have that,

x'_t solves $0 = g'(x_t) - \pi_{cp} p_t$

The optimal $x^*_t \in [x_{t-1} - \delta, x_{t-1} + \delta]$

and minimizes $|x'_T - x^*_T|$

$$\mathbb{E}[R_T] = \mathbb{E}_{s_1}\left[g(x_1) - \pi_{cp} p_1 x_1 + \mathbb{E}_{s_2}\left[g(x_2) - \pi_{cp} p_2 x_2 \ldots \; + \mathbb{E}_{s_T}\left[g(x_T) - \pi_{cp} p_T x_T\right]\right]\right]$$

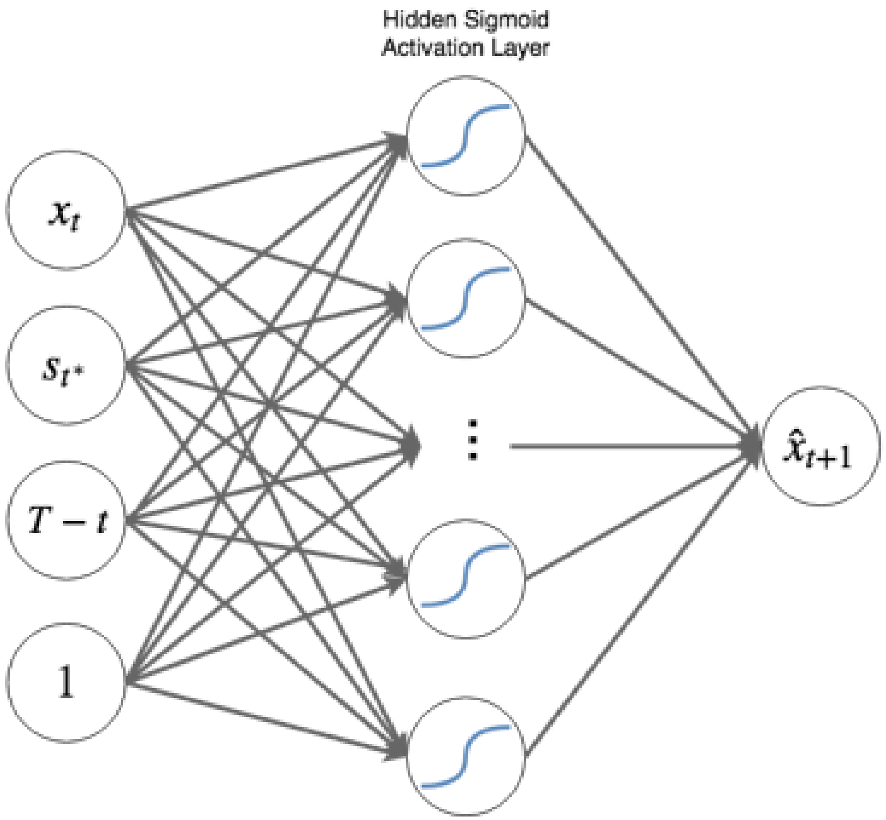
Approximate Dynamic Programming

Only way to find true optimal is grid search

At each time t, sample paths amongst ramp-constrained options using known forecast error distribution

Typically this Monte Carlo path sampling procedure chooses the best path

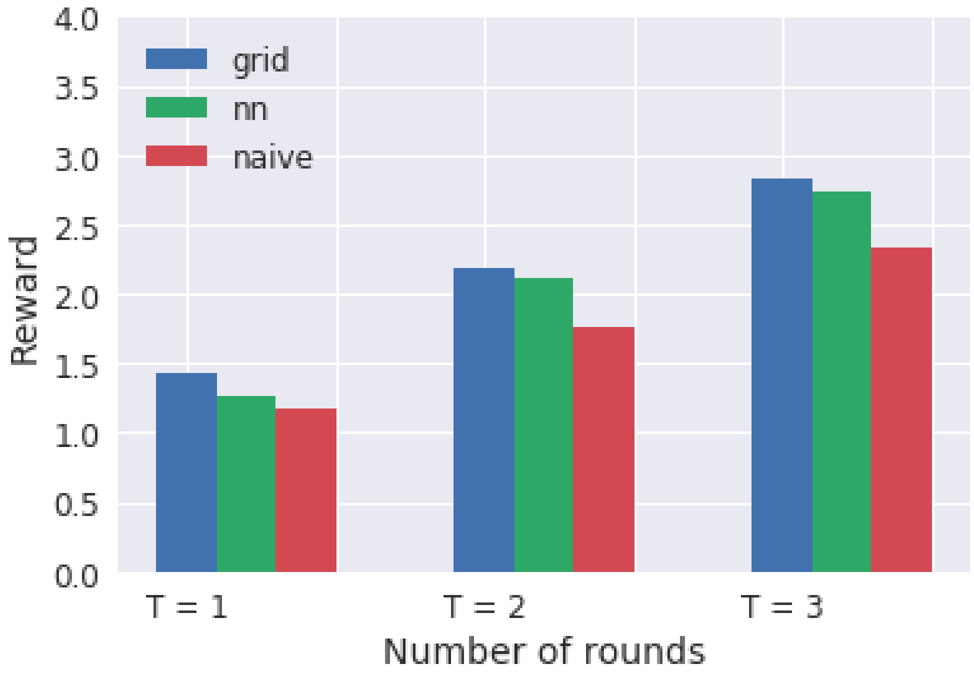
We use realizations to train deterministic policy to choose otpimal plays



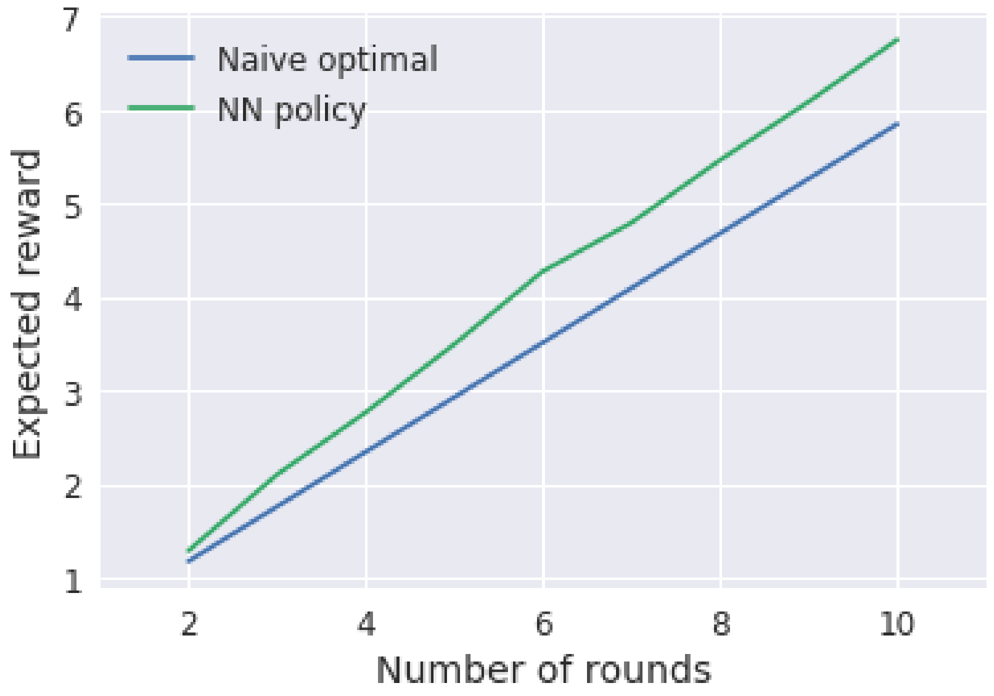
Approximate Dynamic Programming

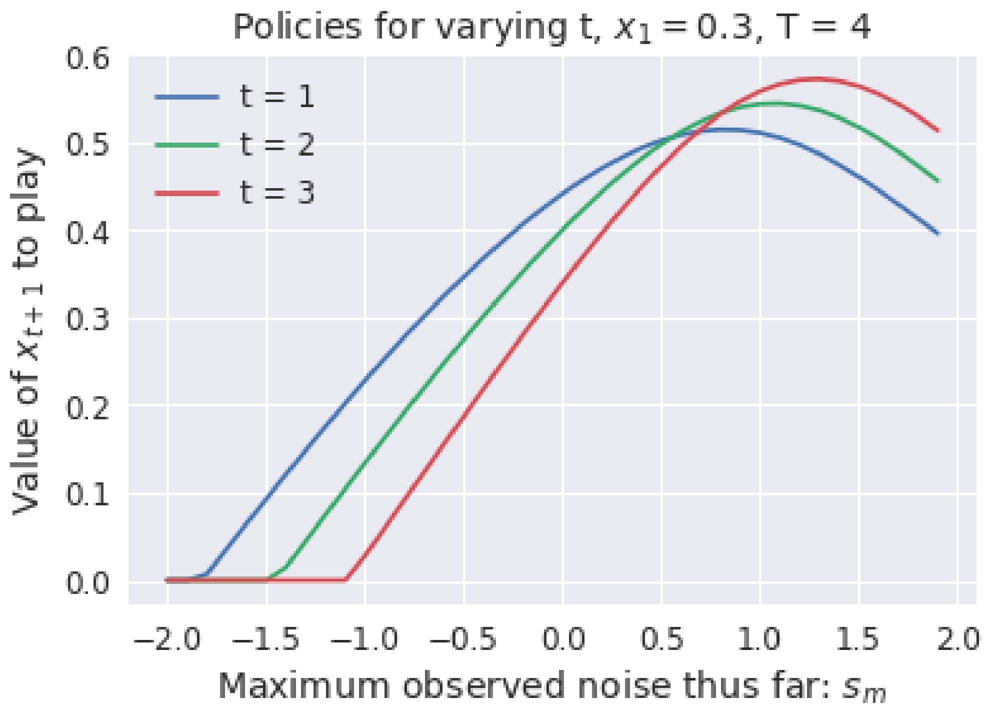
Utility function: $g(x_t) = 2\log(1 + x_t^2)$

For small number of rounds we can brute force grid search to ensure a deterministic policy learned from Monte Carlo sampled paths approaches the true optimal solution



Approximate Dynamic Programming





Small Consumer Perspective

System Noise

$$s_t \sim \mathcal{N}(0, \sigma^2)$$

Consumer Reward

$$R = \sum_{t=1}^{T} g(x_t) - \pi_{cp} \left\{ x_{c^*} \,|\, c^* = \operatorname*{argmax}_{c \in T} s_c \right\}$$

Large Consumer Perspective

System Noise

$$s_t = \sum_{j=1}^{N} x_t^{(j)} + \epsilon_t$$

Consumer Reward

$$R_{(i)} = \sum_{t=1}^{T} g_{(i)}(x_t^{(i)}) - \pi_{cp} \left\{ x_{c^*} \,|\, c^* = \operatorname{argmax}_{c \in T} s_c \right\}$$

Current Solution: Large Consumer Perspective

Studies have suggested 4% peak reduction efficacy --- no counterfactual data[3]

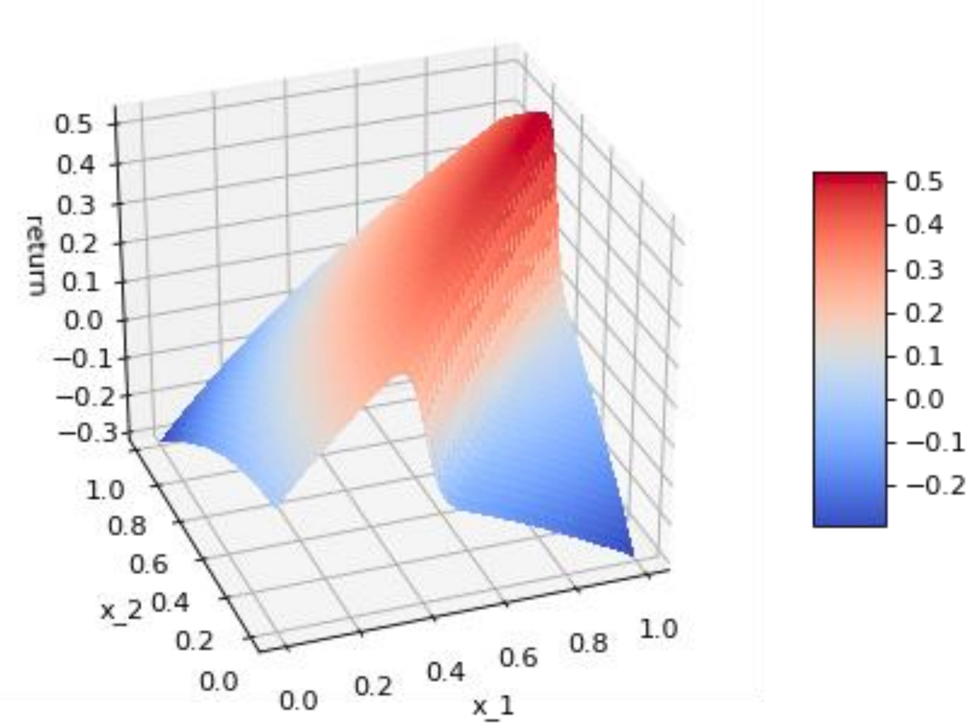
Many large consumers (distribution utilities) lack flexibility, are highly correlated

- Increasingly diverse energy products in deregulated markets
- Increasingly flexible grid; what happens when large consumers try to learn an optimal policy for curtailment during system peak?

3. Jay Zarnikau and Dan Thal, "The response of large industrial energy consumers to four coincident peak (4cp) transmission charges in the Texas (ERCOT) market," Utilities Policy, 2013

Large Consumer Perspective

- Now a game theory setting (Cournot competition); consumer choices impact all other consumers' rewards
- Not concave game
- No potential function
- Need to iteratively play game & learn from results (a multi-agent RL problem)



Two player, two round game, fixed choice of plays for opposing player

Large Consumer: Policy Gradient

Initialize player policies: $\phi_{(i)}(x_t^{(i)}, \max\{s_1, \dots s_t\}, \bar{s}_{t+1}, T - t, 1) = x_{t+1}^{(i)}$

Policy Gradient Procedure:

For epochs:

-Realize game sequence over T

Ignoring non-concavity

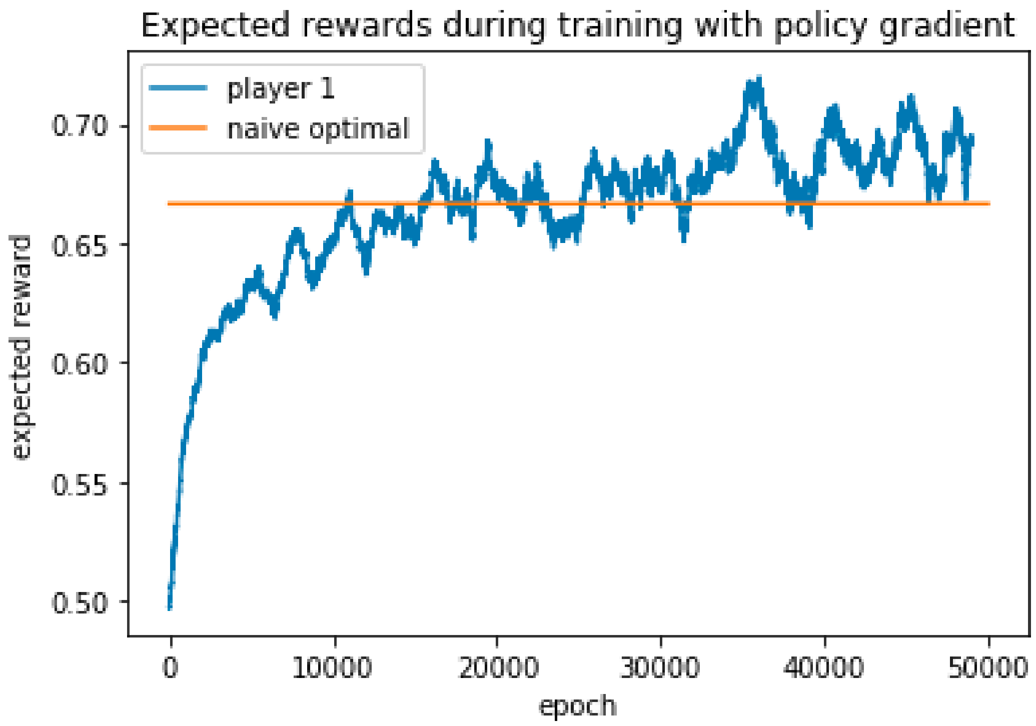
-For each player compute: $\hat{x}_t^{(i)} = x_t^{(i)} + \eta \left(\frac{\partial R}{\partial x_t^{(i)}} \right)$

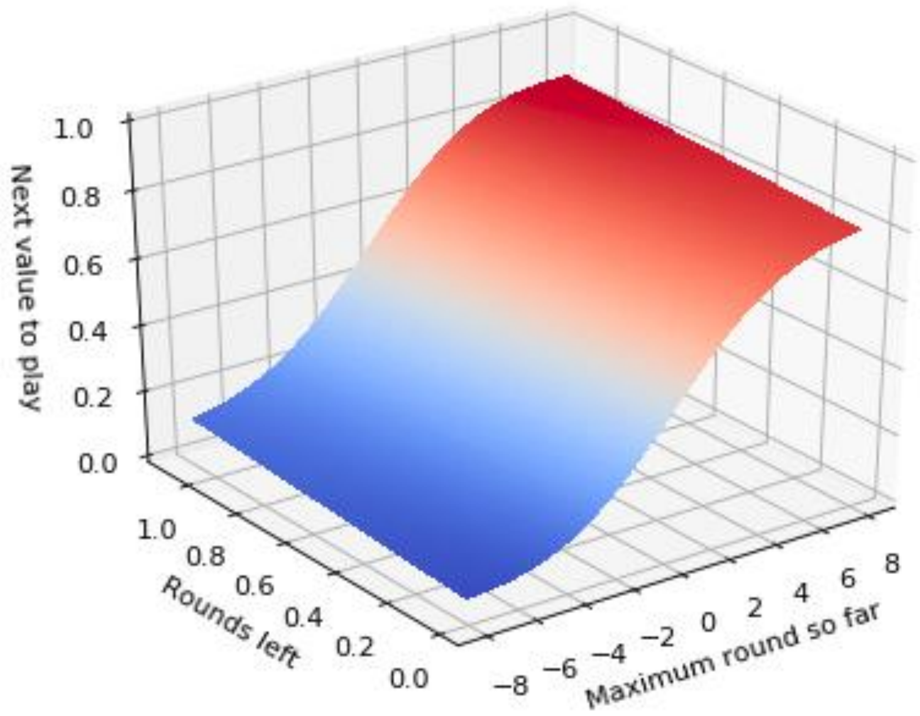
-Gradient decsent on new plays: $\mathcal{L}\left(\phi_i(x_t^{(i)}), \phi_i(\hat{x}_t^{(i)}) \right)$

Single Player Policy Gradient

No access to prediction of next round

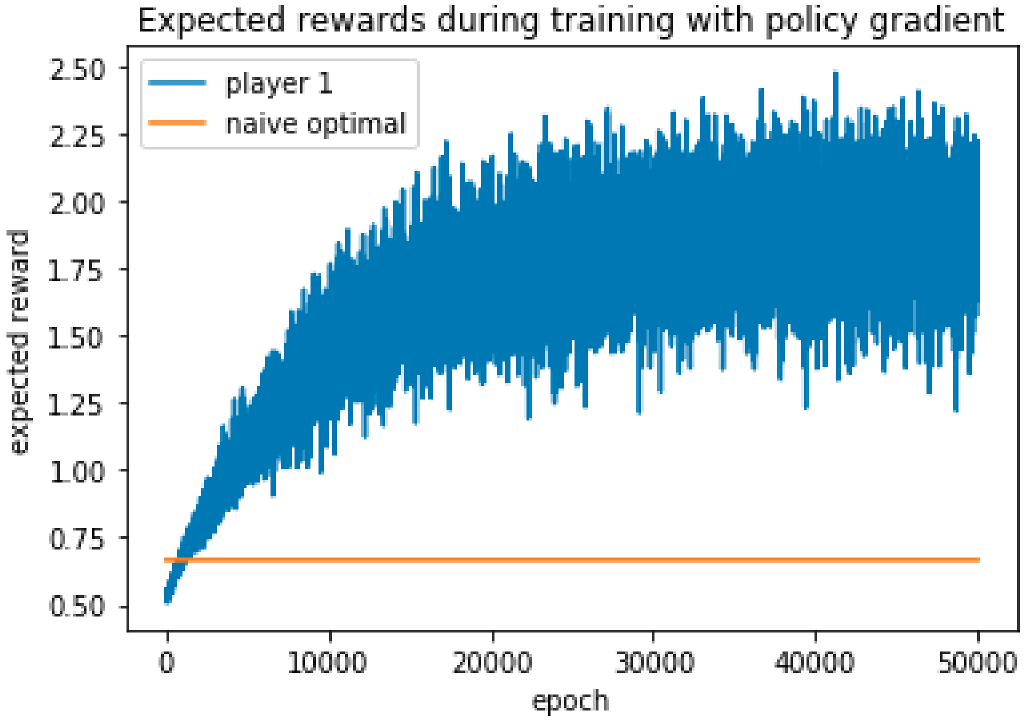
All utility functions: $g_t = \log(1 + x_t)$



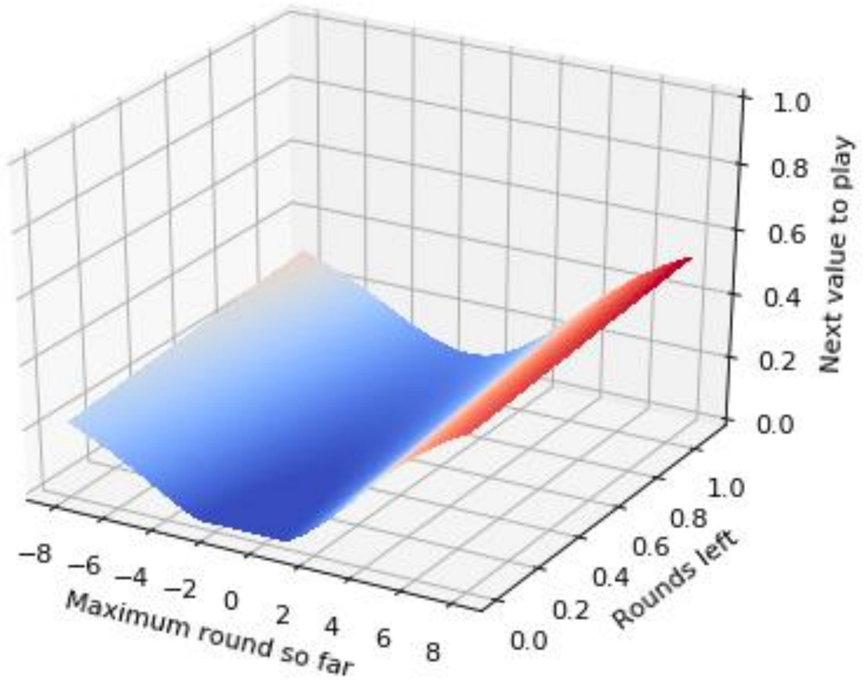


Single Player Policy Gradient

Noisy access to prediction of next round

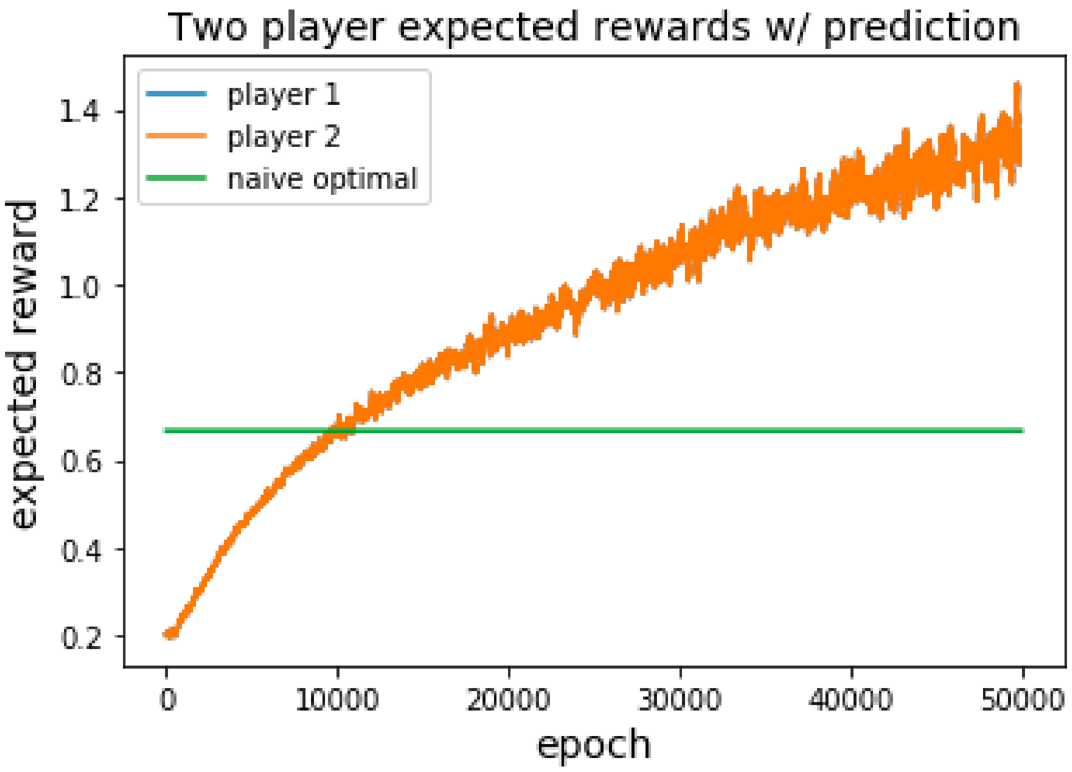


Fixed prediction



Multi Player Policy Gradient

Identical utility functions



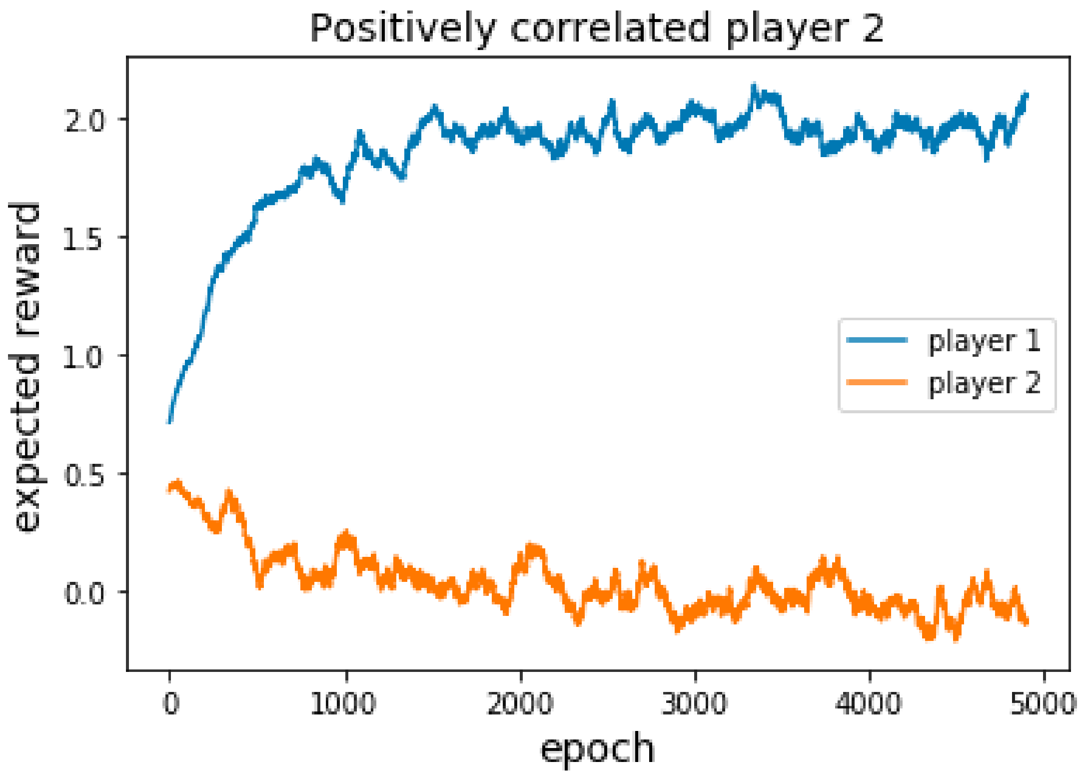
Multiple Correlated Players

- Player 1 independent, player 2 positively correlated (i.e. stochastic function of) player 1

$$x_t^{(2)} = x_t^{(2)} + \alpha \cdot \mathrm{Unif}(0,1) \cdot x_t^{(1)}$$

- Both players have access to noisy predictions

- Large consumers are strongly correlated in markets that currently use CP pricing



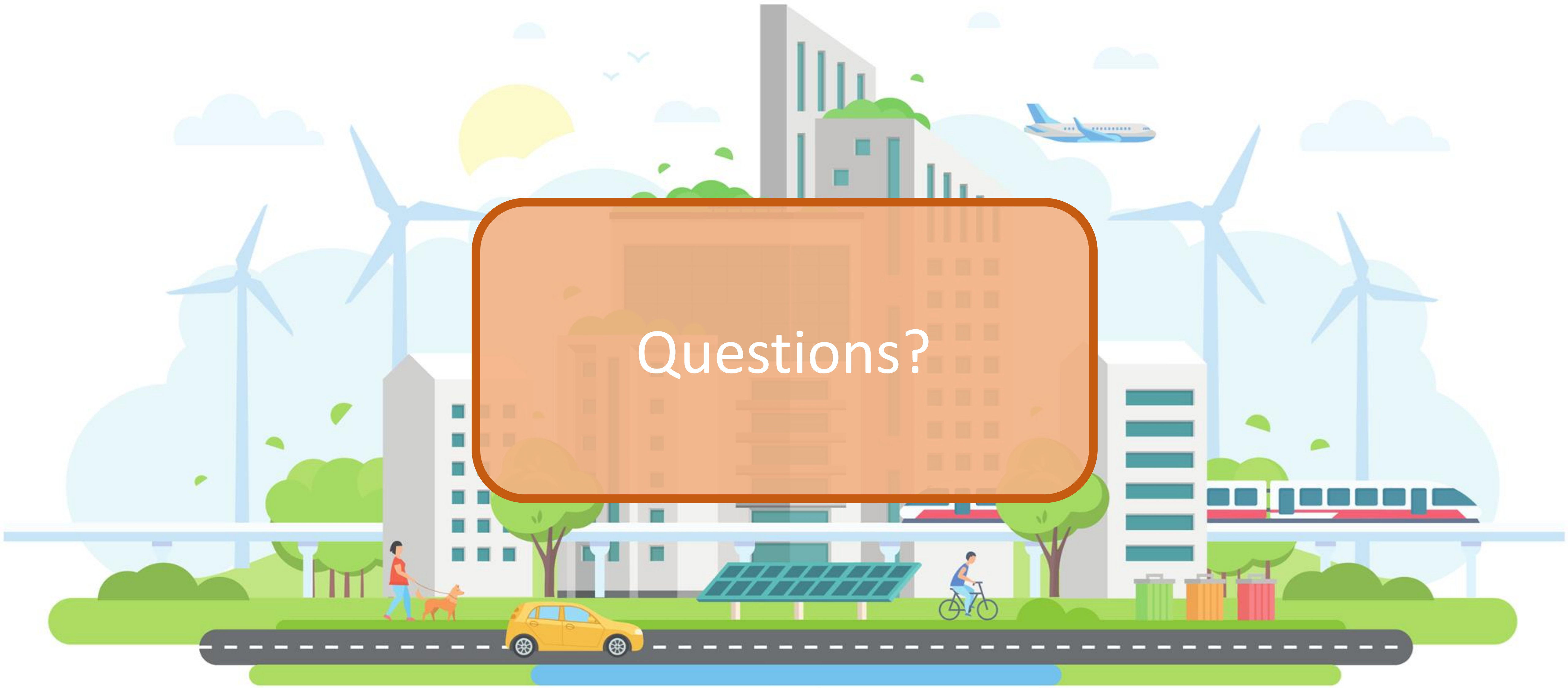
Summary

1. Taking into account weather, grid transmission state, and demand data improves coincident peak timing prediction.

2. Small players can use dynamic or approximate dynamic program to optimally curtail using publically available data without peak warning signals.

3. Large players can learn effective CP cost mitigation strategies --- current work on determining existence of correlated equilibrium. Without noise, naïve solution is Nash equilibrium

Questions?

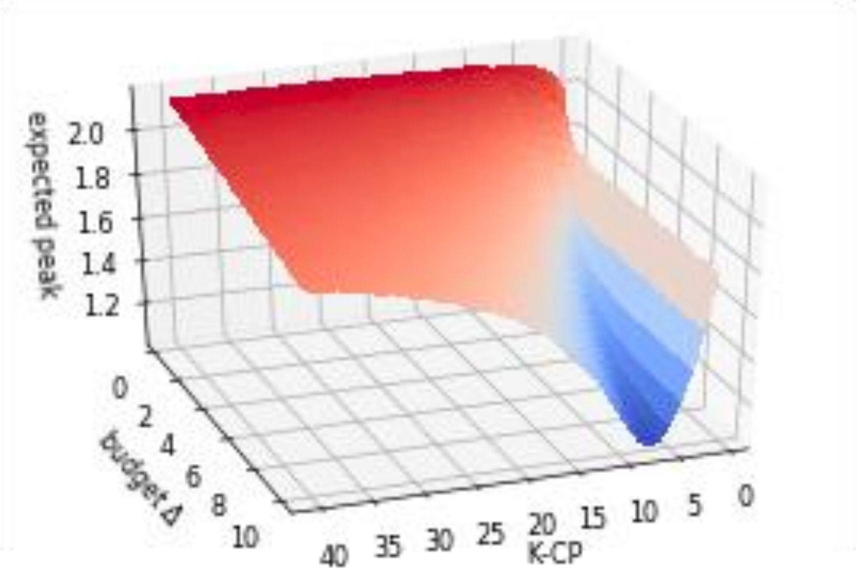


Coincident Peak: Order Statistics

A limited number of CP billing periods yeilds the best peak reduction regardless of budget

For a total budget M, reduce top K CP by K/M

X ~ N(0,1) , T = 40



ERCOT August 2018 Peak Days , T = 40