Mitigation of Coincident Peak Charges via Approximate Dynamic Programming

Chase Dowling, Baosen Zhang
University of Washington
Electrical and Computer Engineering

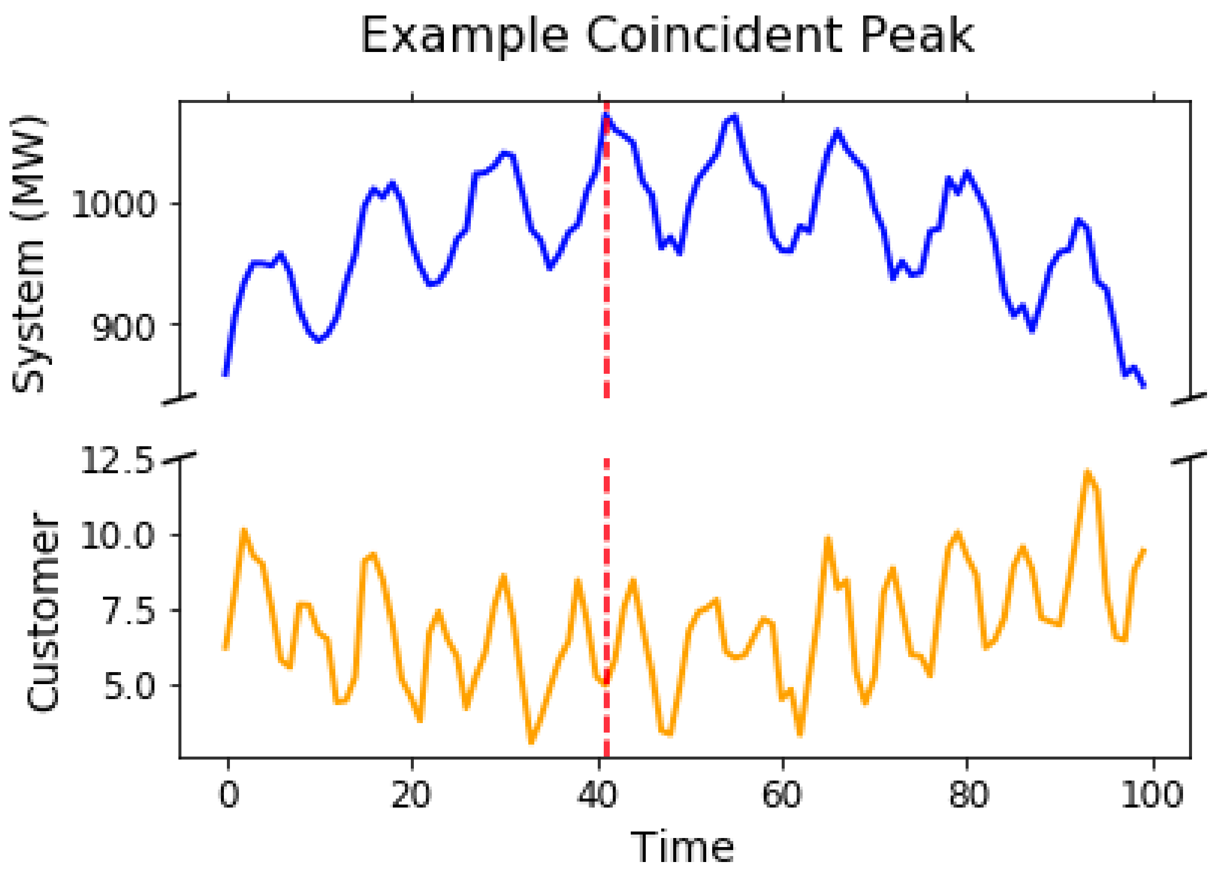
UNIVERSITY of WASHINGTON

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

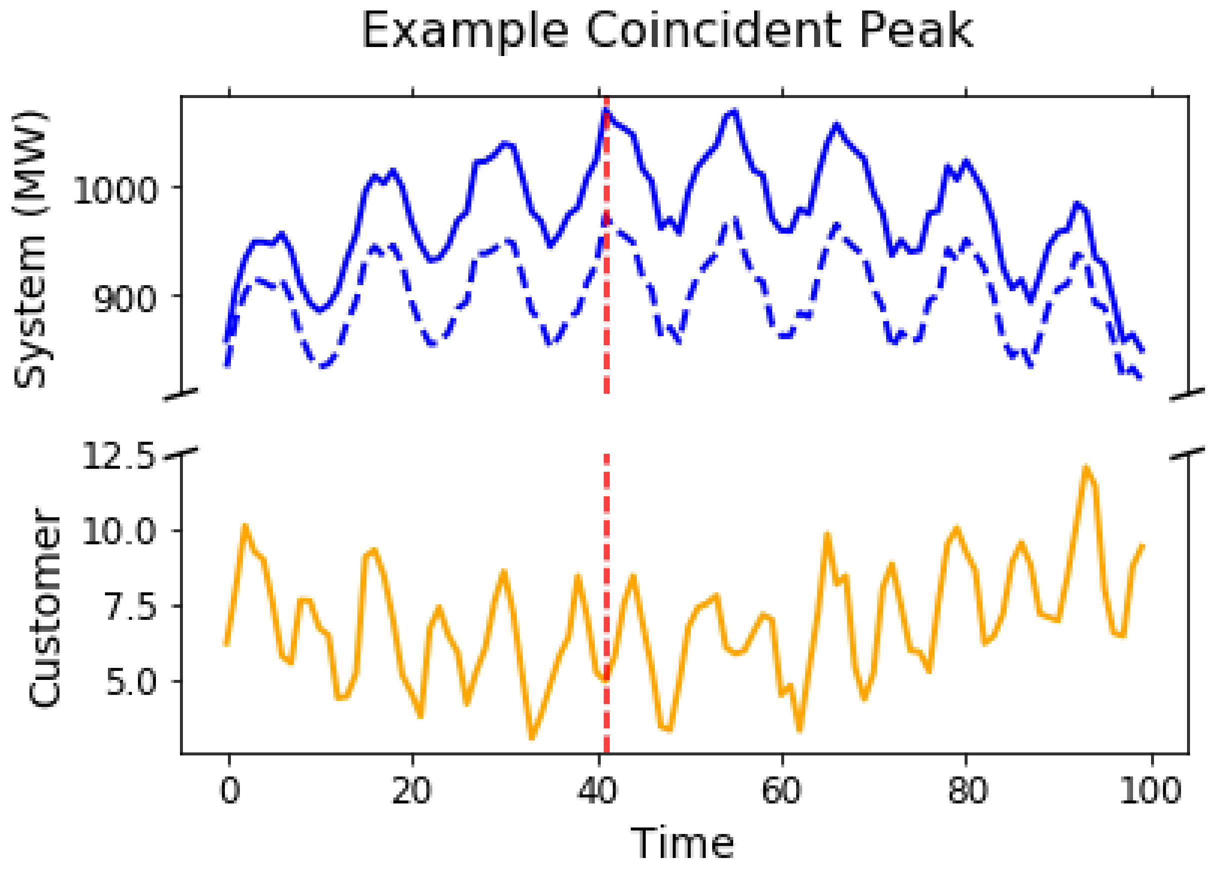


Coincident Peaks

CP rate roughly 100x more than normal time-of-use rates

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

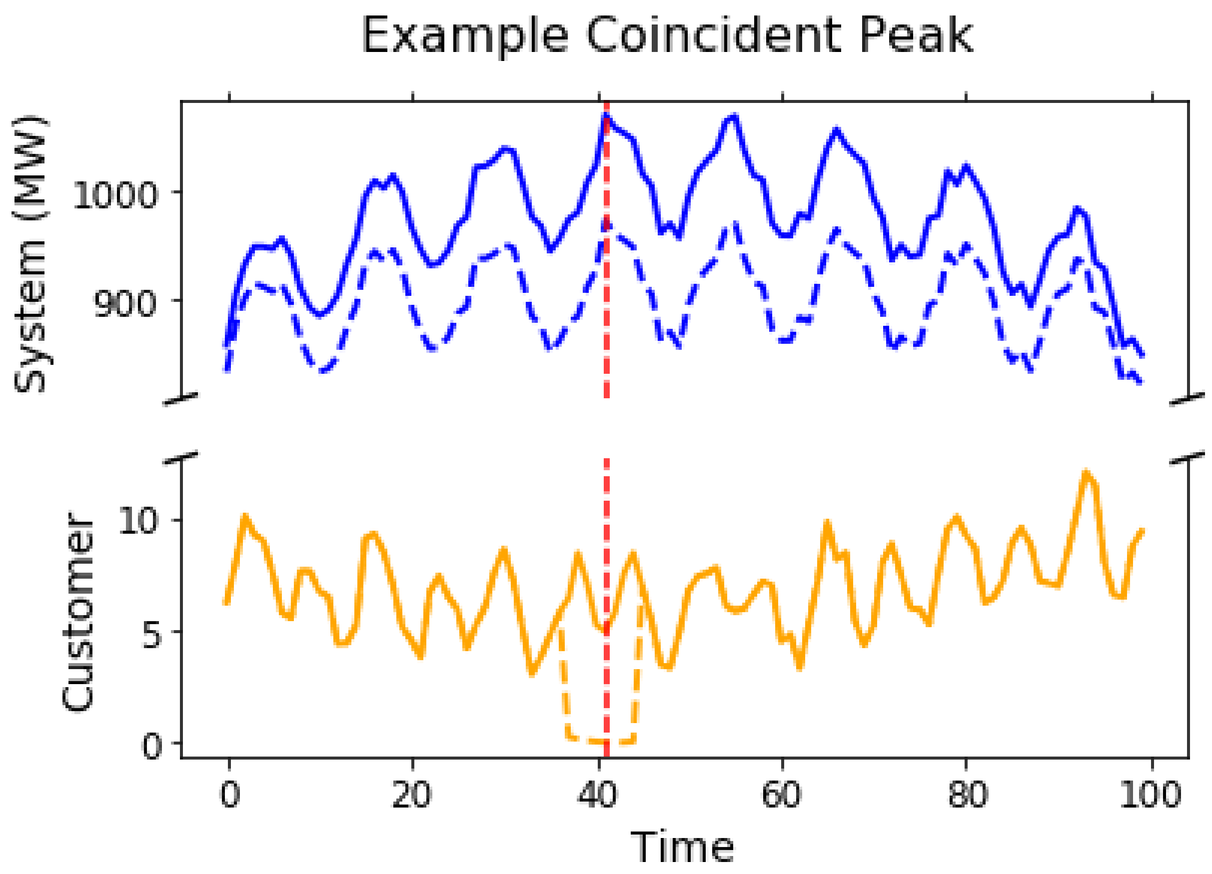
Goal is to curtail consumer demand at peaks



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

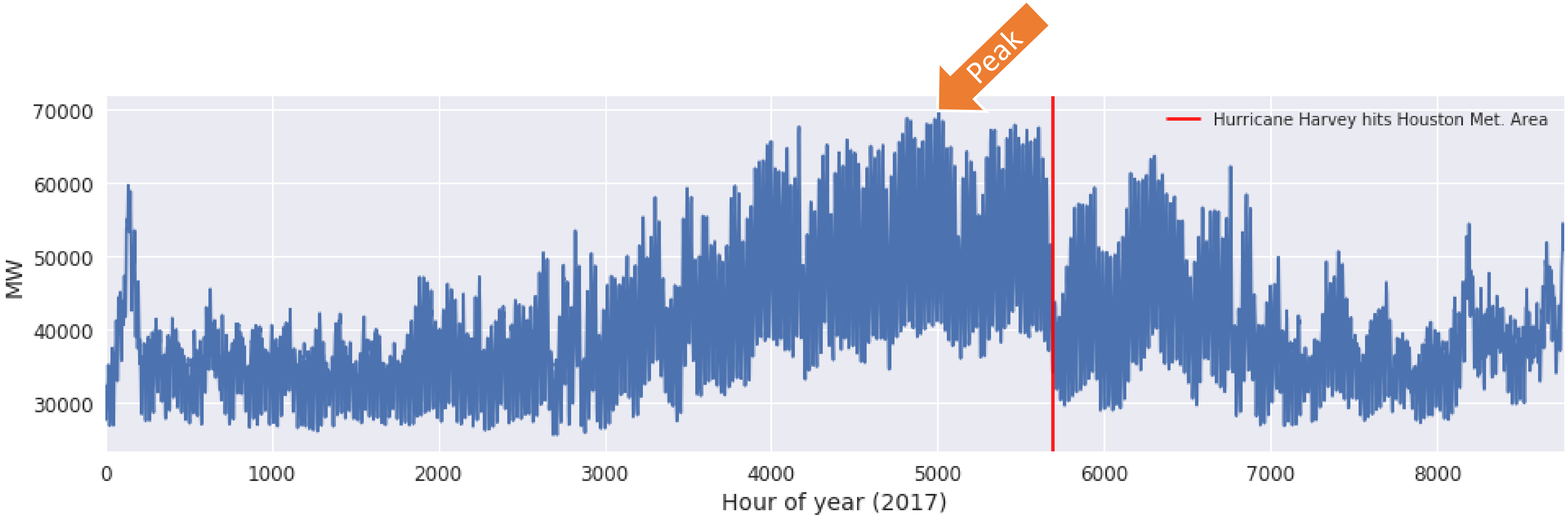
Ideally, consumers are incentivized to curtail demand during the ***moment*** of the CP --- difficult to predict



Variations

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

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



Total hourly electrical demand in Texas, 2017

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

Utilities/distributors

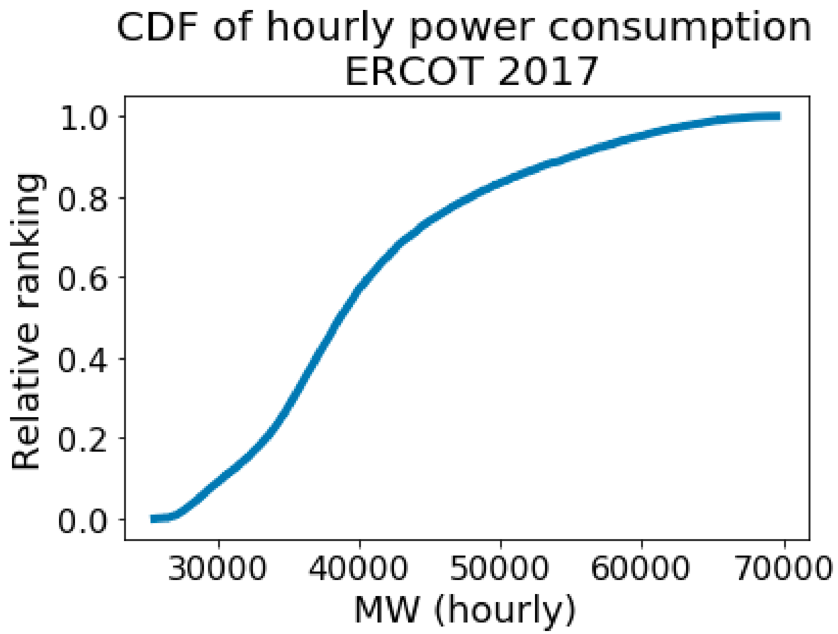
Large consumers

Predicting Coincident Peaks

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

Predicting a rare binary events hard, a consumer can instead hedge their bets

Replace strict max operator with cumulative distribution function



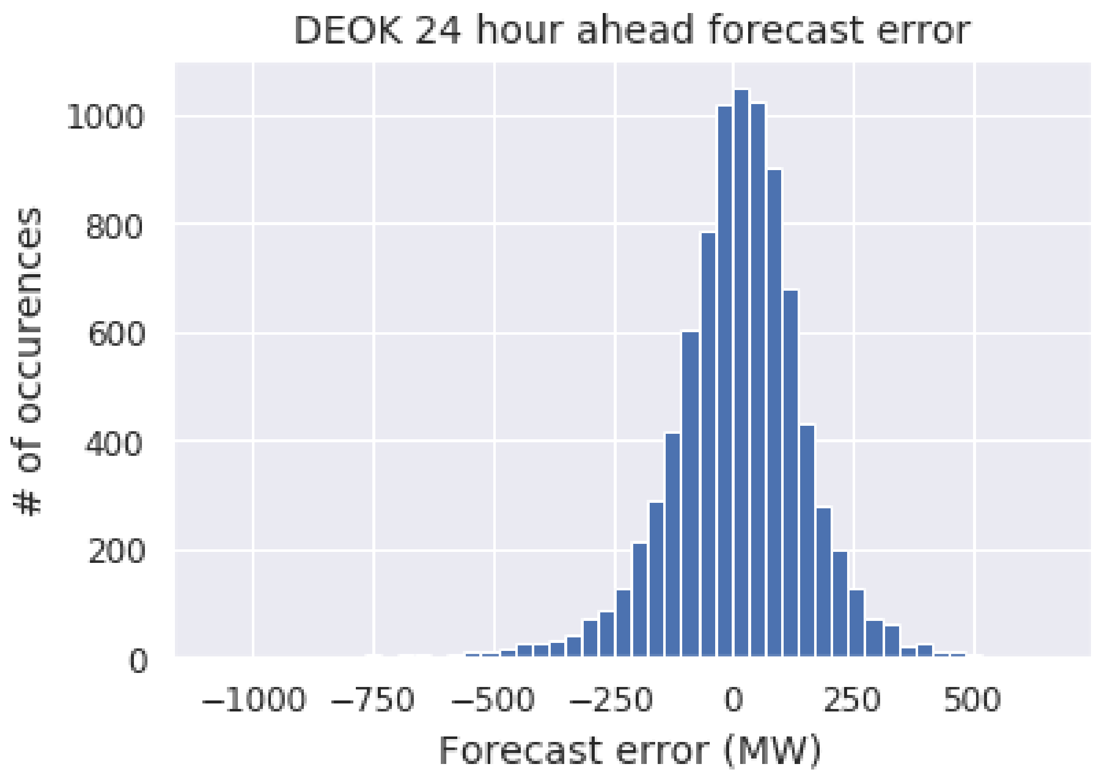
$$\left\{ x_{c^*} \,|\, c^* = \operatorname*{argmax}_{c \in T} s_c \right\} \Rightarrow \mathrm{CDF}(x_t) = P(X \leq x_t)$$

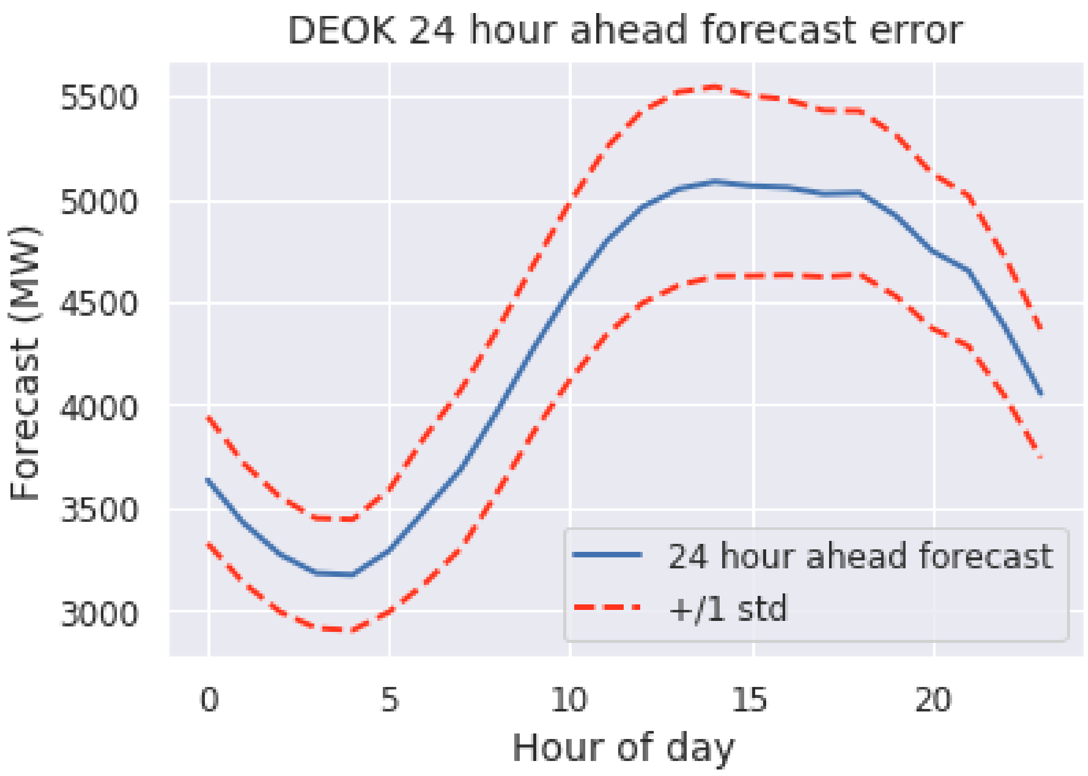
"Coincident Peak Prediction Using a Feed-Forward Neural Network" CP Dowling, D Kirschen, B Zhang - 2018 IEEE Global Conference on Signal and Information Processing, 2018

Coincident Peak Timing

If consumers can predict CP timing
strategic behavior emerges

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





July 8, 2018

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

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

Consumer Goal: Maximize expected reward

Current Solution: Small Consumer Perspective

Responding to operator signals

40% CP consumers in ERCOT <10 MW (1 STD of forecast error between 200-500 MW)

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

Small Consumer Perpsective

System Noise

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

Consumer Reward

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

Baseline: Naive Strategy

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

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

Proposed Solution: Small Consumer Perspective

- No ramping constraints
- Dynamic Programming
  - Optimal strategy

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

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

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

Probability of a Coincident Peak

Can we do better than trying to forecast CDF and arbitrarily hedging? Alternatives to optimizing over Monte Carlo (stochastic optimization)?

By assumption, 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

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

Dynamic Programming

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

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

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

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

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

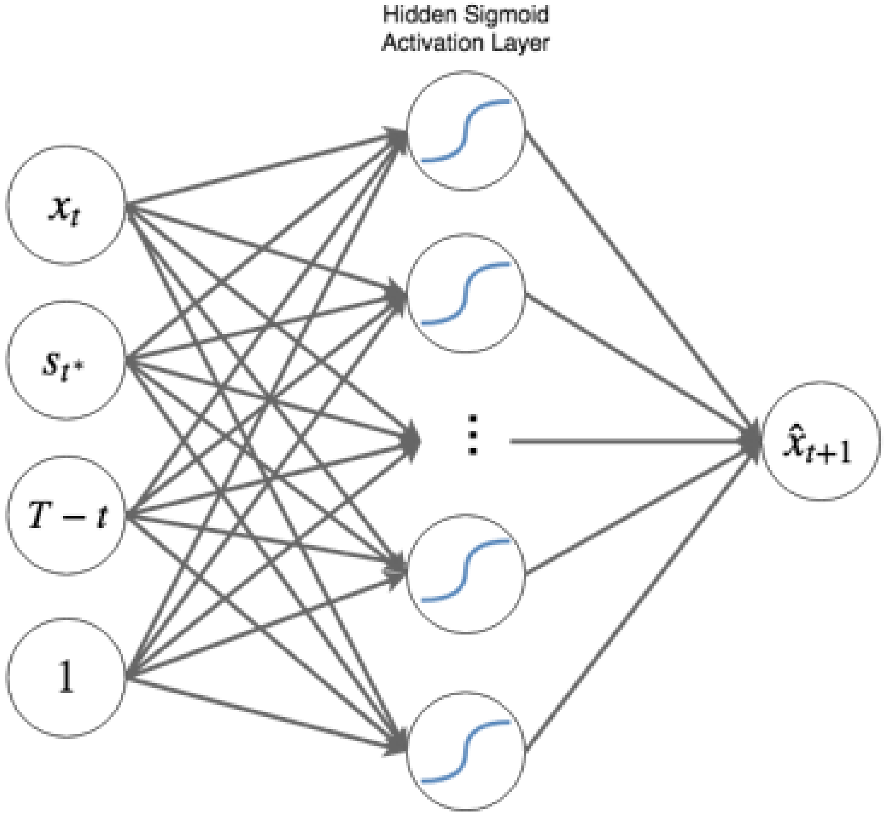
Approximate Dynamic Programming

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

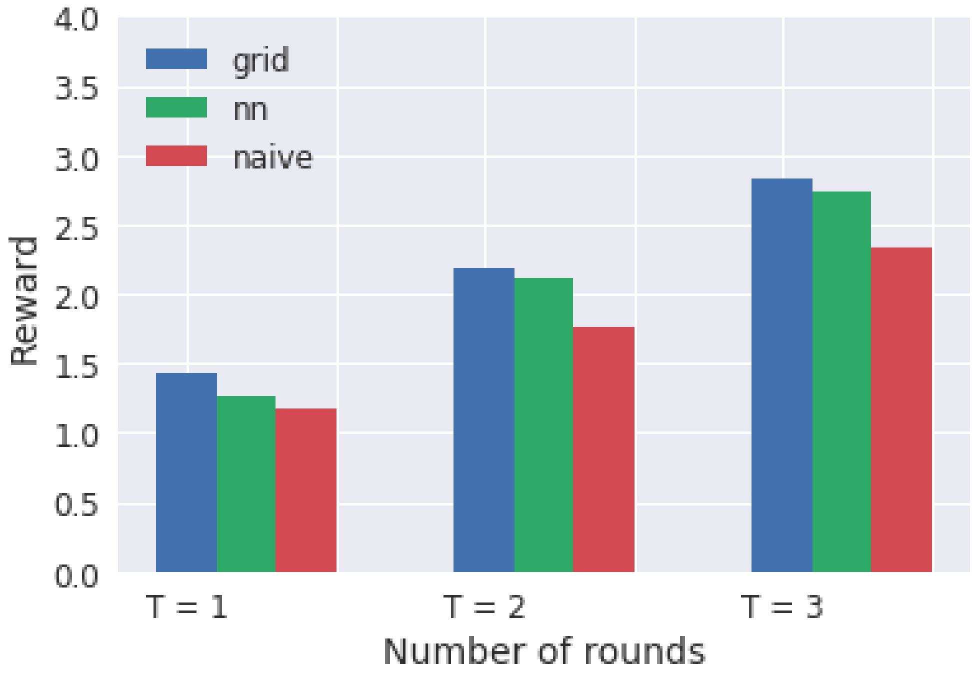
We use realizations to train a deterministic policy to choose optimal plays



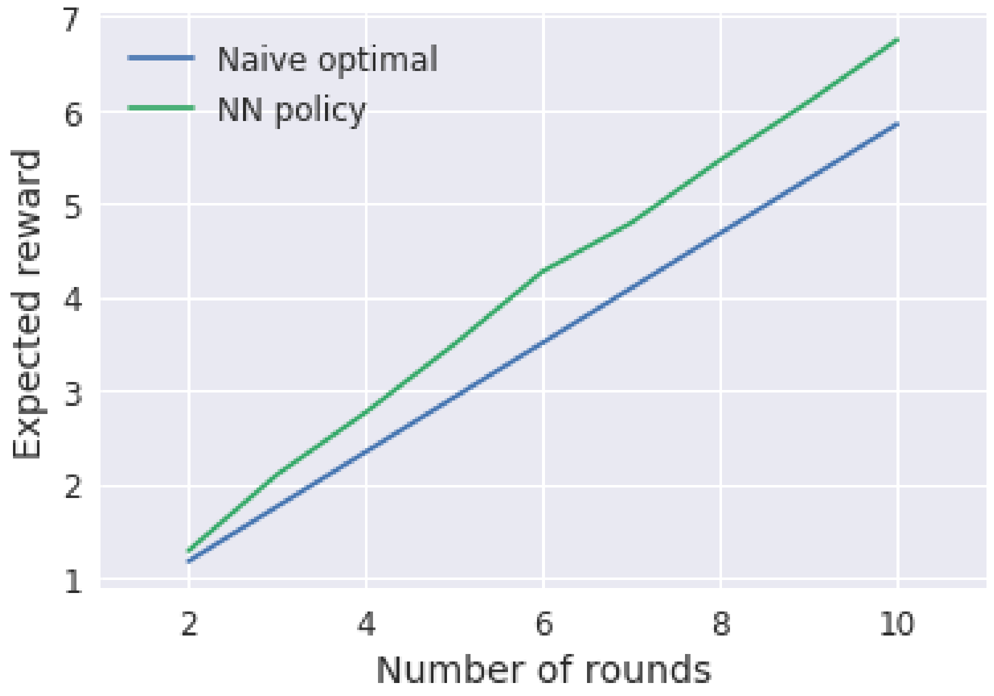
Approximate Dynamic Programming

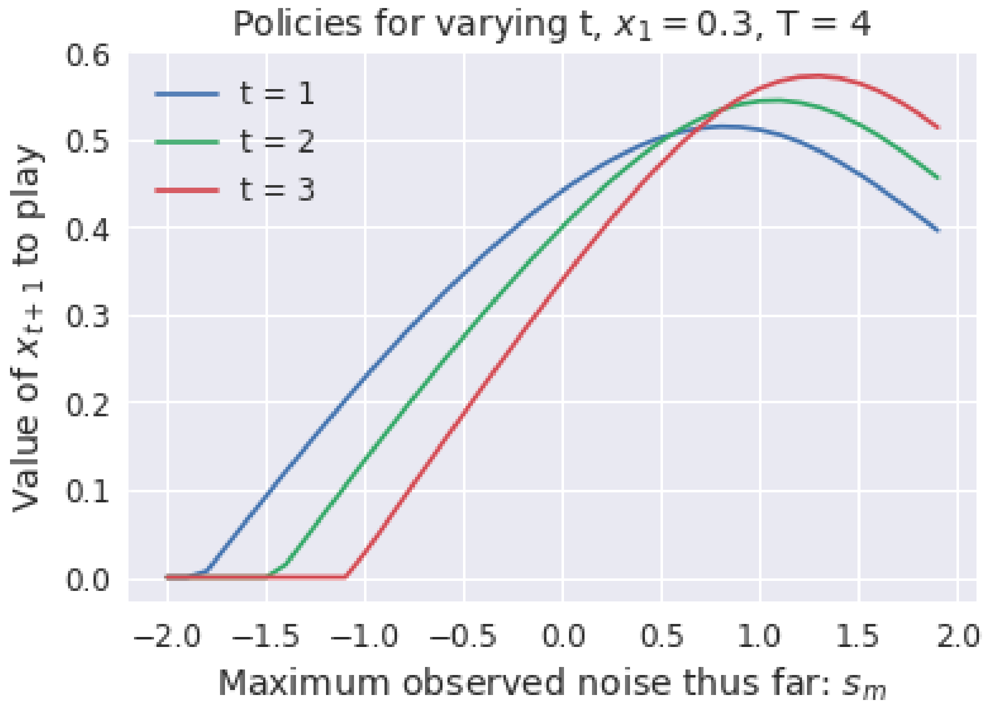
Utility function: $g(x_t) = 2\log(1 + x_t^2)$

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

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

Current Solution: Large Consumer Perspective

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

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?

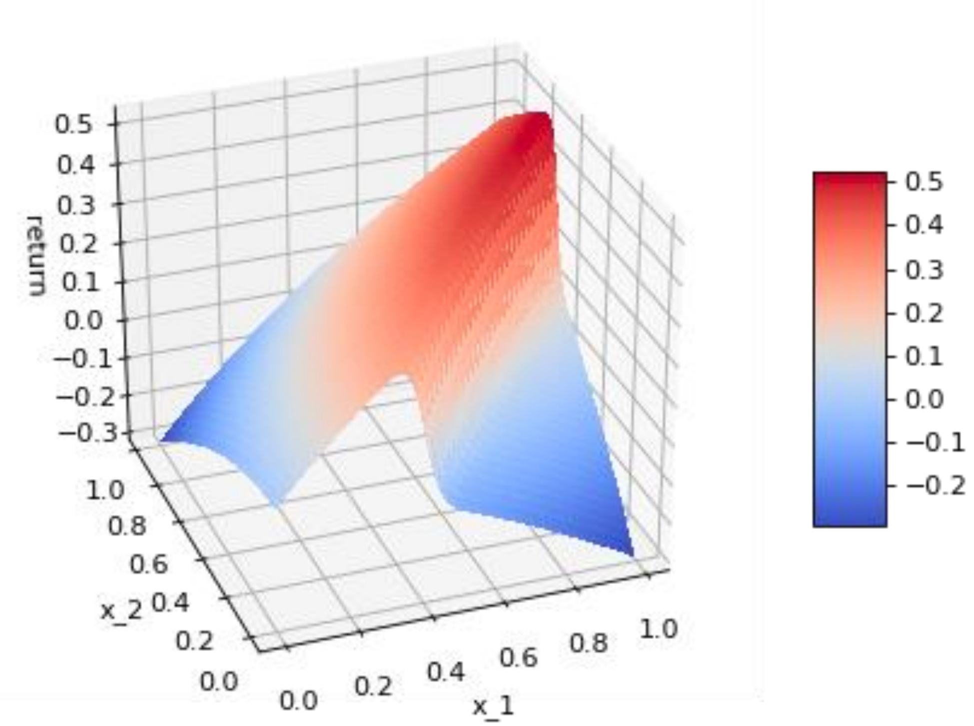
Jay Zarnikau and Dan Thal, “The response of large industrial energy consumers to four coincident peak (4cp) transmission charges in the Texas (ERCOT) market,” Utilities Policy, 2013

Large Consumer Perspective

Challenging Outlook

- 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)

No guarantees, try learning anyway!



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

Large Consumer: Policy Gradient

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

Policy Gradient Procedure:

For epochs:

-Realize game sequence over T

Ignoring non-concavity

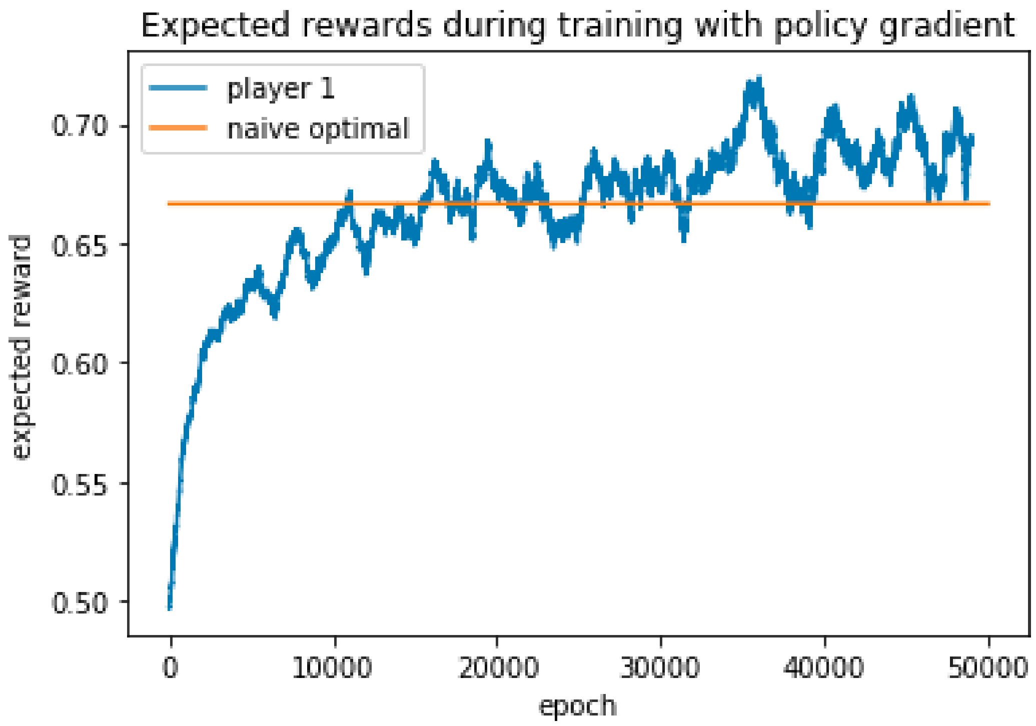
-For each player compute: $\hat{x}_t^{(i)} = x_t^{(i)} + \eta \left(\frac{\partial R}{\partial x_t^{(i)}} \right)$

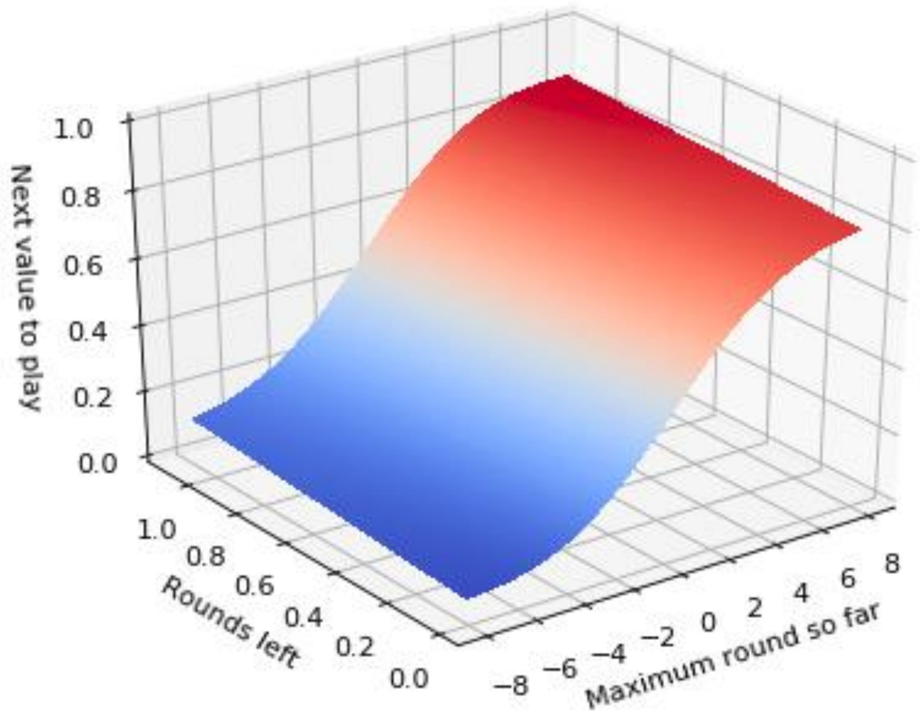
-Gradient decsent on new plays: $\mathcal{L}\left(\phi_i(x_t^{(i)}), \phi_i(\hat{x}_t^{(i)})\right)$

Single Player Policy Gradient

No access to prediction of next round

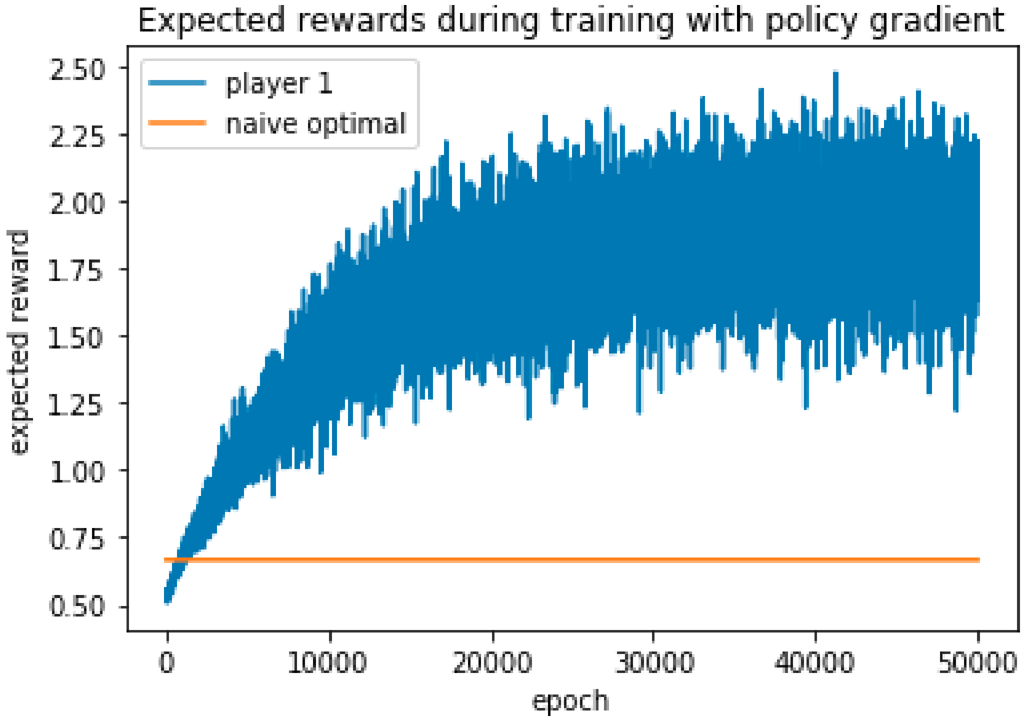
All utility functions: $g_t = \log(1 + x_t)$



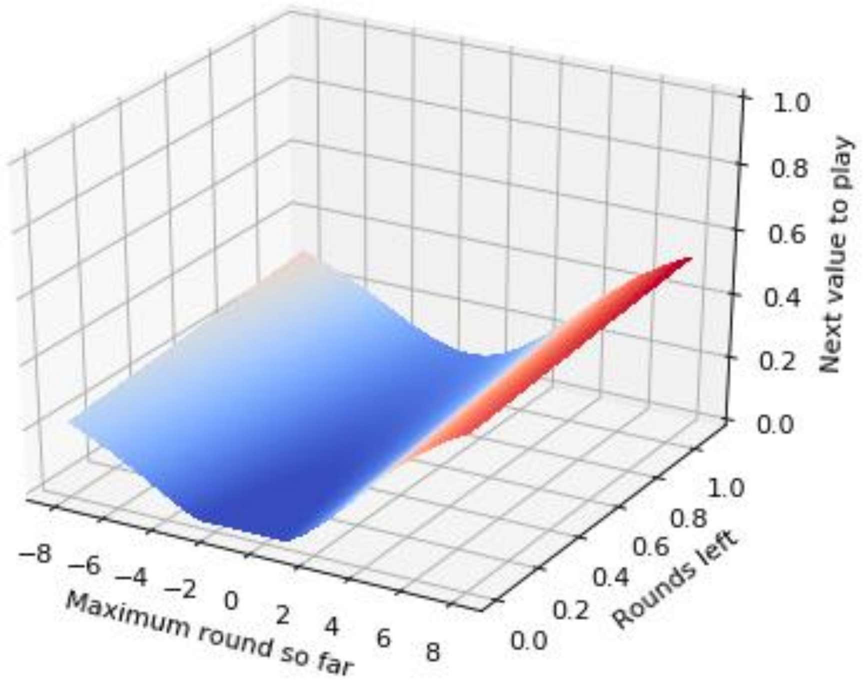


Single Player Policy Gradient

Noisy access to prediction of next round

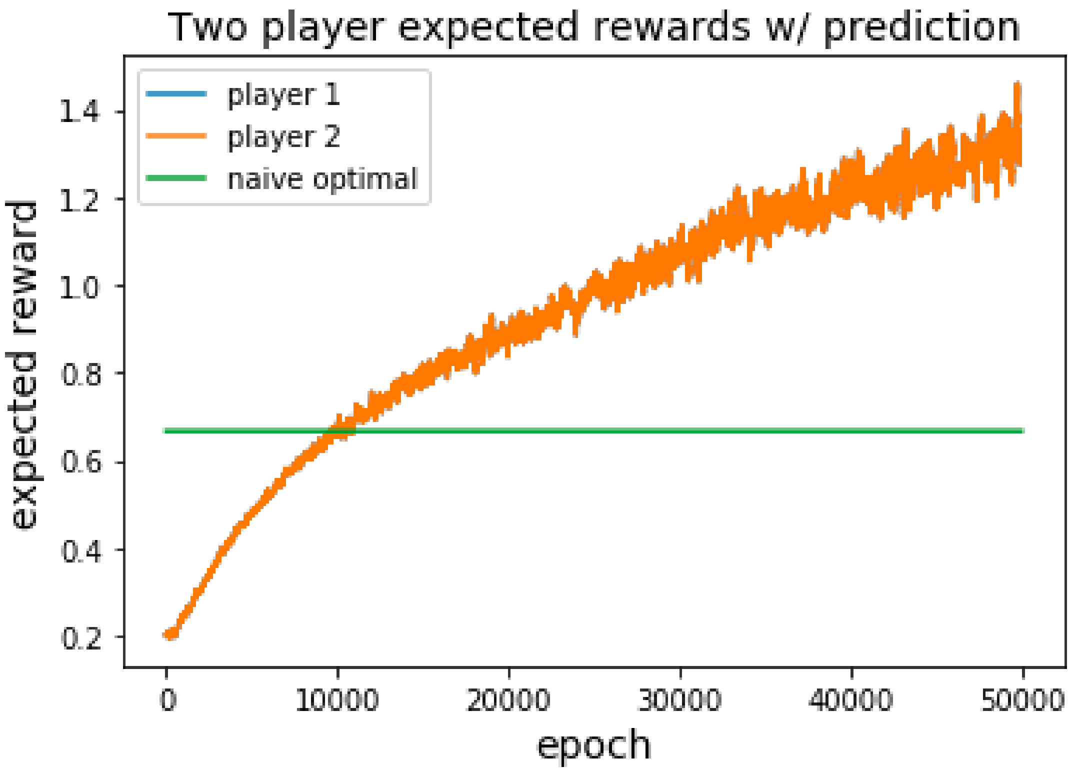


Fixed prediction



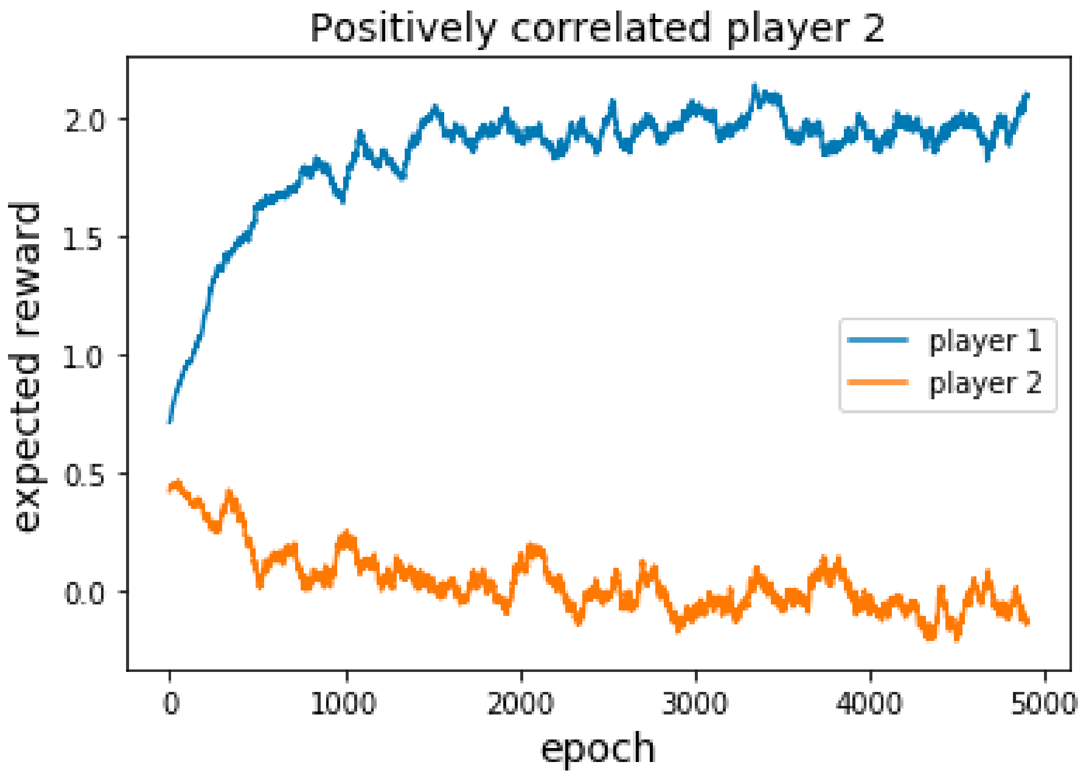
Multi Player Policy Gradient

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



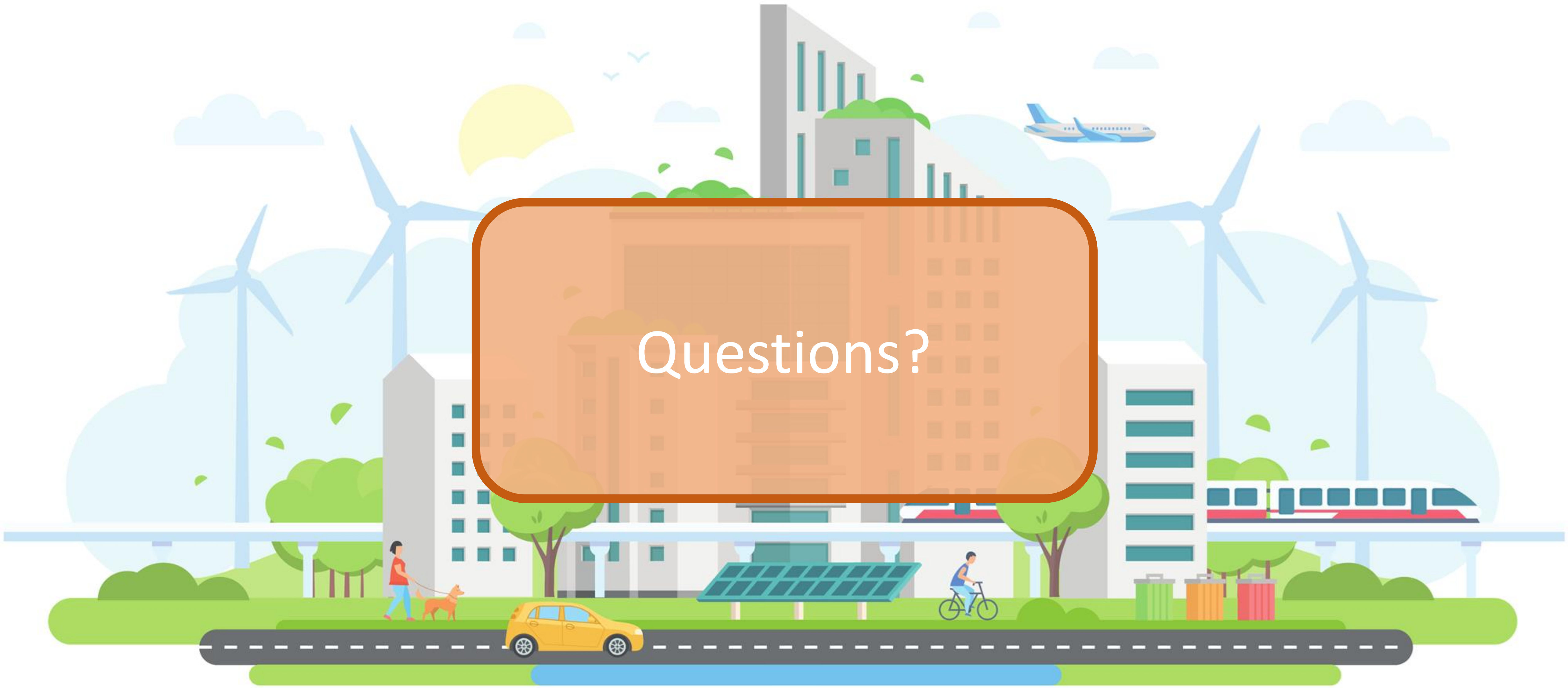
Summary

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?

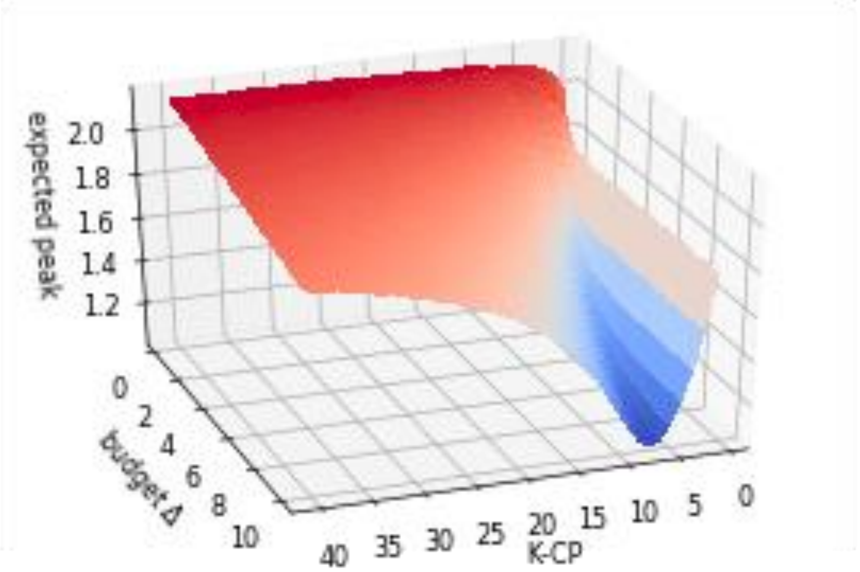


Coincident Peak: Order Statistics

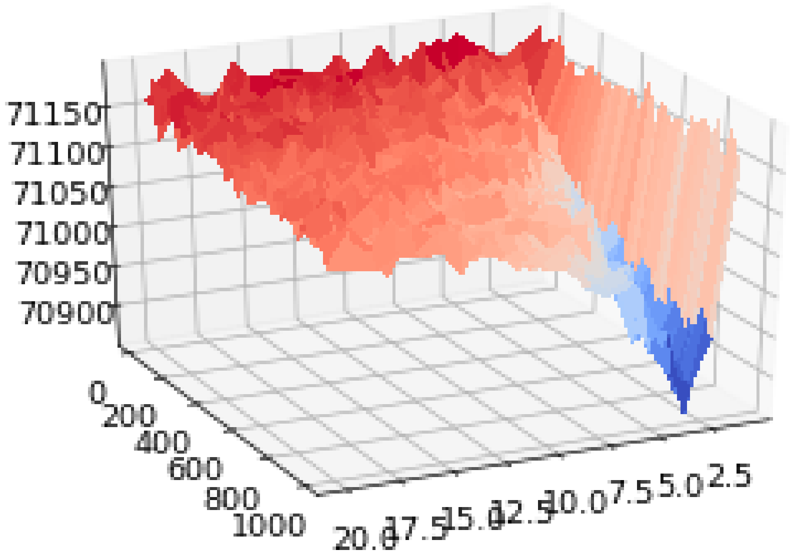
A limited number of CP billing periods yeilds the best peak reduction regardless of budget

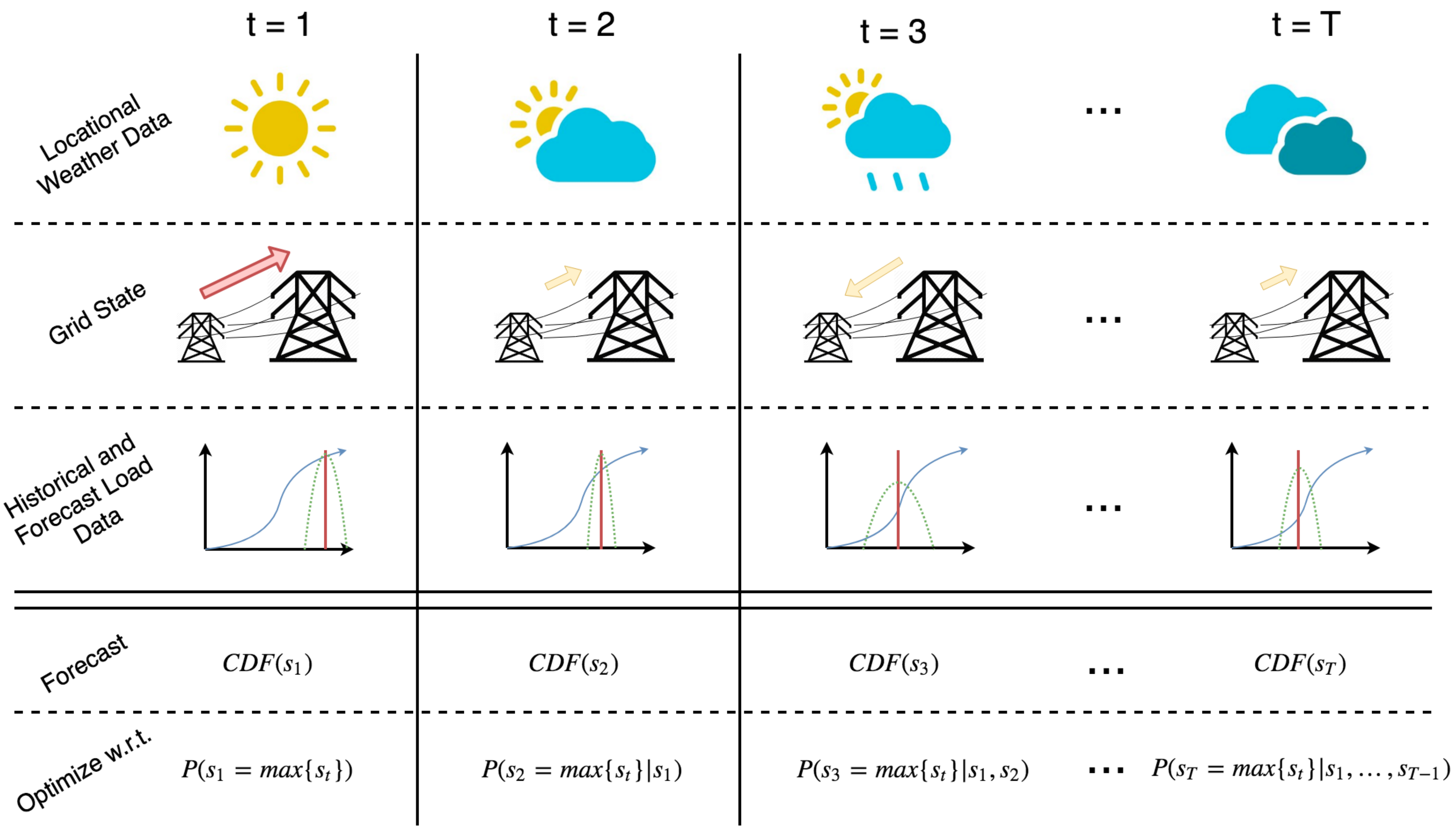
For a total budget M, reduce top K CP by K/M

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



ERCOT August 2018 Peak Days , T = 40




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.
$P(s_1 = max\{s_t\})$
$P(s_2 = max\{s_t\}|s_1)$
$P(s_3 = max\{s_t\}|s_1, s_2)$
$P(s_T = max\{s_t\}|s_1, \ldots, s_{T-1})$