Demand Response and Workload Management for Data Centers with Increased Renewable Penetration

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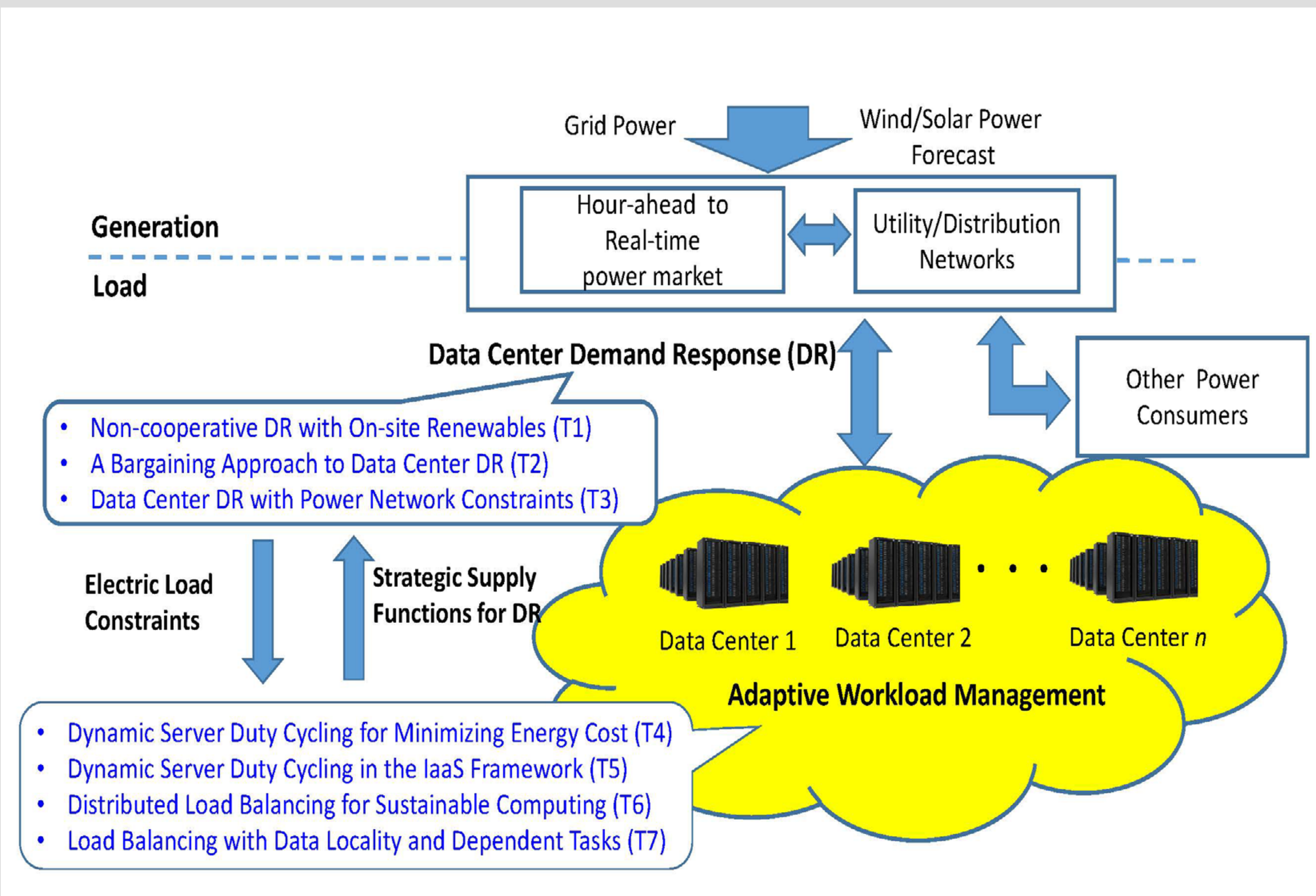
Strategic Demand Response and Workload Management towards Sustainable Data Center



Time-varying OPF

Example application: volt/var control

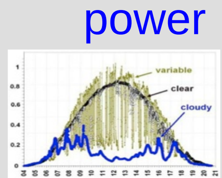
- Control reactive outputs of smart inverters to stabilize voltages
- Can be formulated as OPF
- … but background loads, real solar power fluctuate continuously

static OPF

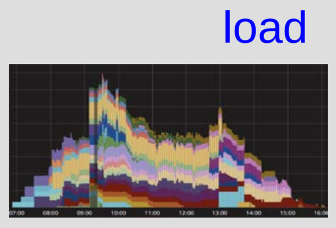
$$p_i(t) - p_i^{\mathrm{L}}(t) + \mathrm{j}\big(q_i(t) - \mathrm{j}q_i^{\mathrm{L}}(t)\big) = \sum_{k \in \mathcal{N}^+} V_i(t)V_k^*(t)Y_{ik}^*$$

$$\begin{array}{ll} \text{min} & \operatorname{tr}\left(CVV^H\right) \\ \text{over} & (V,s,l) \\ \text{subject to} & s_j = \operatorname{tr}\left(Y_j^H VV^H\right) \\ & l_{jk} = \operatorname{tr}\left(B_{jk}^H VV^H\right) \\ & \underline{s}_j \le s_j \le \overline{s}_j \\ & \underline{l}_{jk} \le l_{jk} \le \overline{l}_{jk} \\ & \underline{V}_j \le |V_j| \le \overline{V}_j \end{array}$$

solar power



background load



measurements available in real-time

Track optimal solution of time-varying OPF

Uncertainty will continue to increase
Real-time measurements increasingly become available on seconds timescale
Must, and can, close the loop in the future

Need theory for time-varying optimization

$$\min_{x \in \mathbb{R}^n} \; c(x,t) + h(x,t)$$
$$\text{s. t.} \quad f^{in}(x,t) \le 0$$
$$f^{eq}(x,t) = 0$$

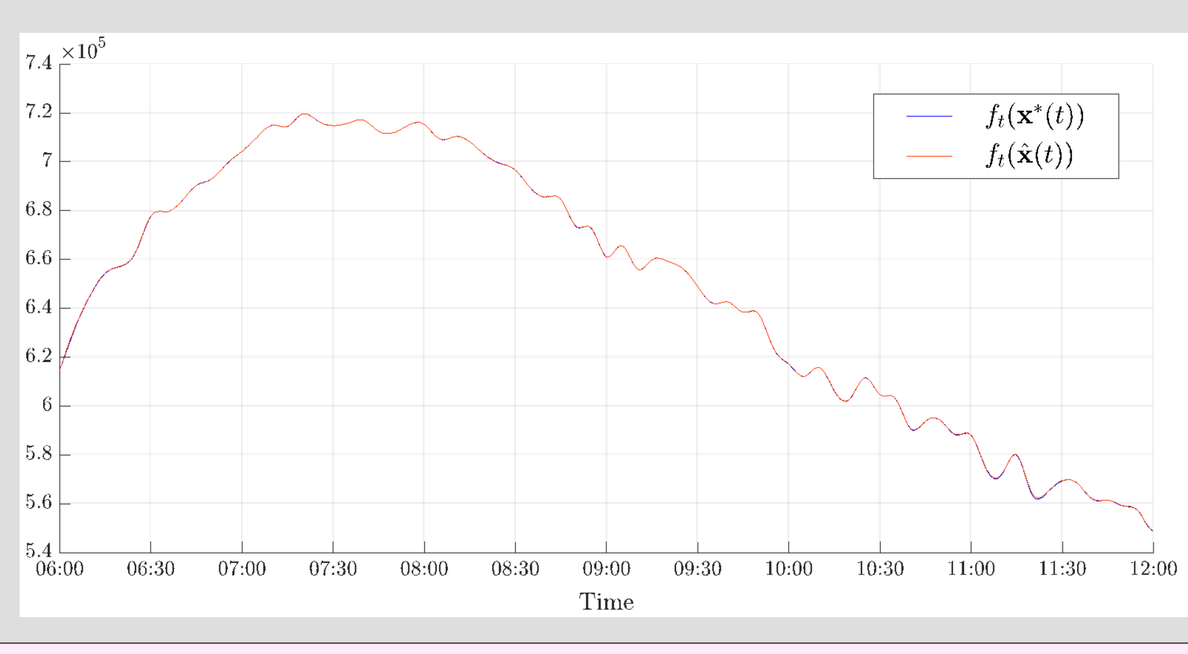
Assumptions

- $c(x,t), f^{in}(x,t), f^{eq}(x,t)$: twice cont. differentiable
- $h(x,t)$: closed proper convex

Time-varying Optimization KKT condition:

$$-\nabla_x c(x^*(t),t) - \begin{bmatrix} J_{f^{in},x}(x^*(t),t) \\ J_{f^{eq},x}(x^*(t),t) \end{bmatrix}^T \begin{bmatrix} \lambda^*(t) \\ \mu^*(t) \end{bmatrix} \in \partial_x h(x^*(t),t),$$
$$f^{in}(x^*(t),t) \in N_{\mathbb{R}^m_+}(\lambda^*(t)),$$
$$f^{eq}(x^*(t),t) = 0.$$

Tracking performance



Strategic Participation of Data Centers

1) Non-cooperative Data Center Demand Response (DR); a Stackelberg game approach

data center n strategy: $\max_{d_n \ge 0} p d_n - C_n(d_n - R_n, W_n, p)$

utility n strategy: $\min_{p \ge 0} \mathbb{E}_{\{W_n, R_n\}} \{h\left(D - \sum_n d_n^*(W_n,p)\right) + p \sum_n d_n^*(W_n,p)\}$

2) Data Center Demand Response (DR); A Bargaining Approach

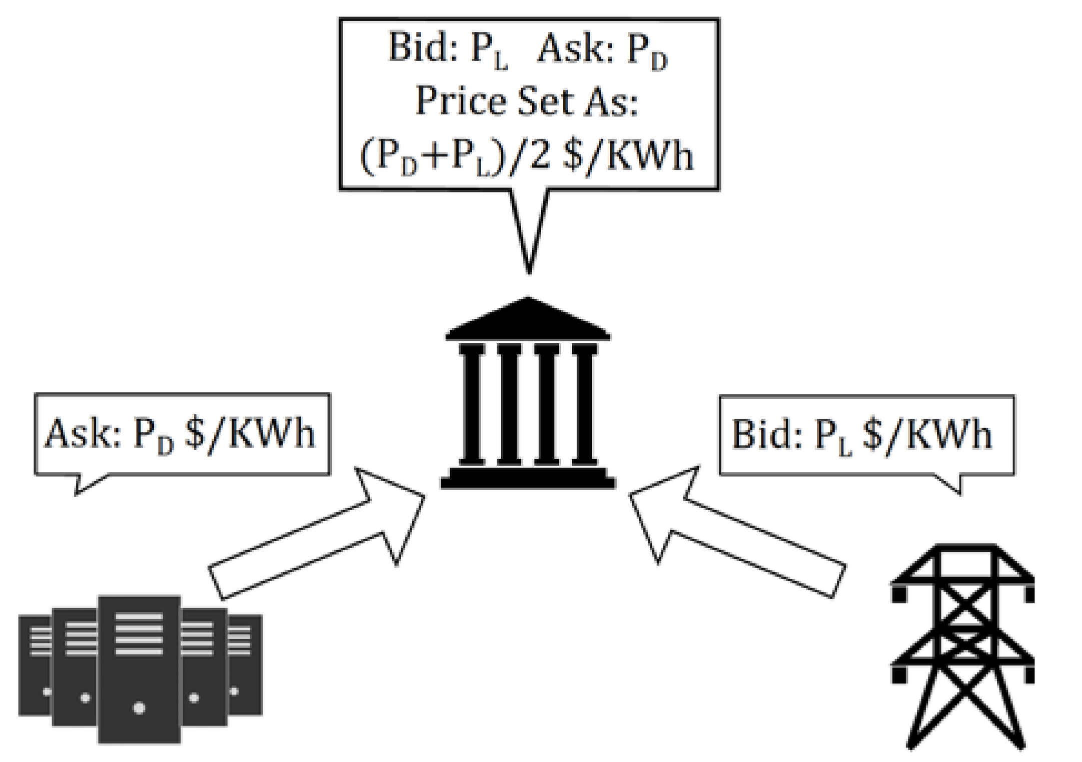


Figure: An illustration of the bargaining process

demand: $d(p) = \arg\max_q h(D) - h(D-q) - pq$

supply: $s(p) = \arg\max_q pq - C(q)$

The bargaining process

Algorithm 1 The bargaining process

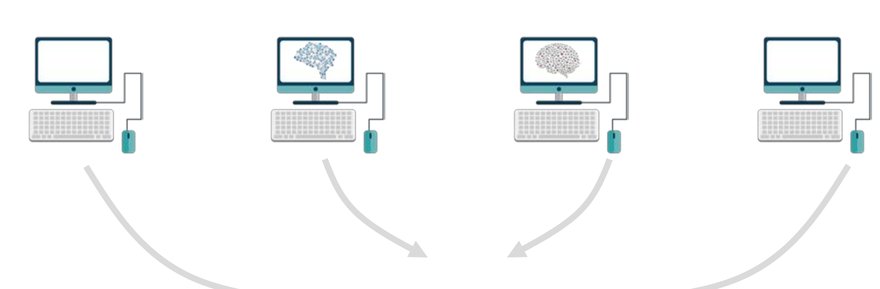
Input: arbitrator gives an initial value $\epsilon \sim exp(\mu)$
Output: decide: bargaining succeed/fail
iteration: $k = 0$
while not stable **do**
  if k=odd **then**
    utilities change bids p_L, in response to data-centers' asks
  else if k=even **then**
    data-centers change asks p_D, in response to utilities' bids
  $k++$;
final spread: $\Delta p = p_L - p_D$
if $\Delta p \ge \epsilon$ **then**
  return bargaining succeed
else if $\Delta p < \epsilon$ **then**
  return bargaining fail

Resource Allocation in Data Centers

- Efficient resource allocation in data centers can reduce energy usage, thus reducing the load on the power grid
- We consider the problem of assigning arriving tasks to a server
- Each task has a reward associated with it: Goal: Maximize reward in a given time
- Key Challenge: When a task takes too long to complete, should we interrupt it and lose its reward or should we continue to process it to completion?

Bandit Problem:

- K job types: Type-k task takes a random **completion time** $X_n^{(k)}$.
- A random **reward** $R_n^{(k)}$ is obtained once the task is completed.
- For a **time budget** t, maximize total reward in [0, t]
- Completion time and reward might be **heavy-tailed**.
- Existing **MAB** models do not apply



Algorithm and Performance Analysis

Proposed Algorithm: UCB-BwI

- Estimate reward-rate, i.e., reward per unit time of each task from empirical observations
- Add an upper confidence bound to the above estimate
- Typically upper confidence bound is based on an exponential concentration inequality. Key Idea: since the distributions can be heavy-tailed, use the median-of-means estimator to obtain a concentration inequality

Theorem 1. (Regret Upper Bound for UCB-BwI)

$$\boldsymbol{Regret(\tau) \le O(K)\, log(T) + O(K)}$$

- Cayci, Eryilmaz and Srikant (ACM SIGMETRICS 2018)