Enabling Demand Response from Cloud Data Centers - from Sustainable IT to IT Sustainability

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Joint Capacity Planning and Operational Management for Sustainable Data Centers and Demand Response

Tan N. Le, Zhenhua Liu, Yuan Chen, Cullen Bash

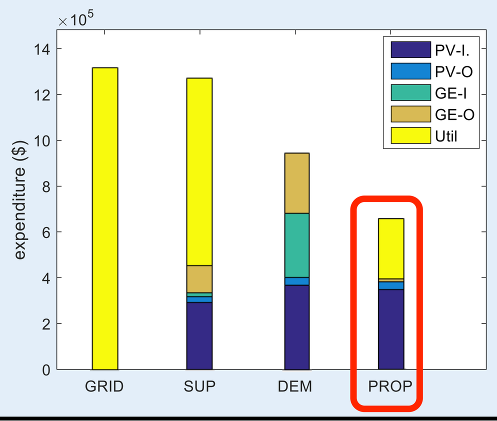
ACM e-Energy 2016

Traditionally, data center capacity planning and operational management are done separately.

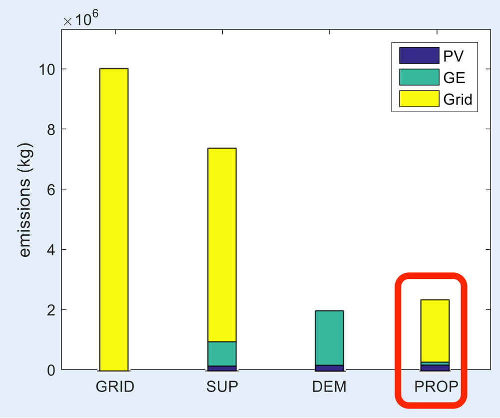
Problem: Data Centers have a large potential to participate in DR but don't.

Our Solution: Propose a framework that jointly optimizes both capacity planning and operational management for data centers participating in demand response programs.

50% cost savings:



75% emission reduction:



Optimal Energy Procurement for Geo-distributed Data Centers in Multi-timescale Electricity Markets

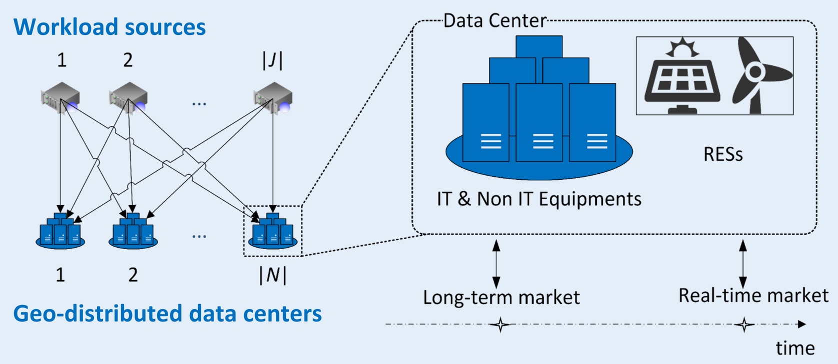
Tan N. Le, Jie Liang, Zhenhua Liu,
Ramesh K. Sitaraman, Jayakrishnan Niar, Bong J. Choi

IFIP Performance 2017

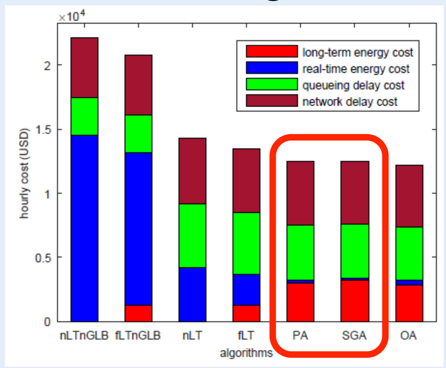
Cloud providers can significantly benefit from multi-timescale electricity markets by purchasing some of the needed electricity ahead of time at cheaper rates.

Problem: Real world dynamics make energy procurement strategy a challenge.

Our Solution: Propose two algorithms for geo-distributed data centers that utilize multi-timescale markets to minimize the electricity procurement cost.



44% cost savings:



Geographically Coordinated Frequency Control

Joshua Comden, Tan N. Le, Yue Zhao, Bong Jun Choi, Zhenhua Liu

IEEE CDC 2017

Current distributed Frequency Control laws assume that the costs between locations are *independent*.

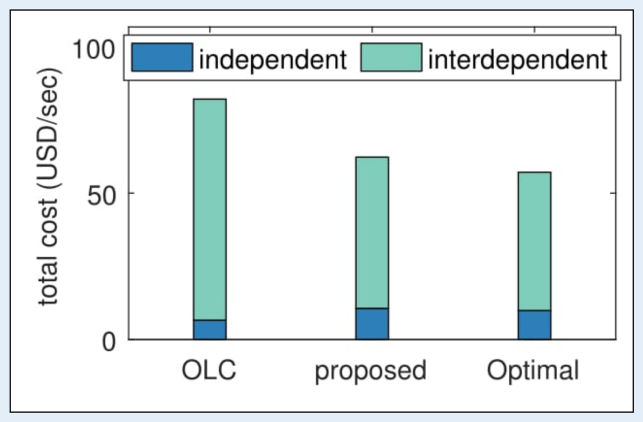
Problem: Networks of Data Centers have additional costs that are *interdependent* between locations.

Our Solution: Proposed set of distributed control laws that take into account interdependent costs.

Theorem 1: An equilibrium point of the system using the proposed control laws achieves the minimum cost.

Theorem 2: The system using the proposed control laws will asymptotically converge to an equilibrium point.

Proposed control laws lower cost closer to the optimal:



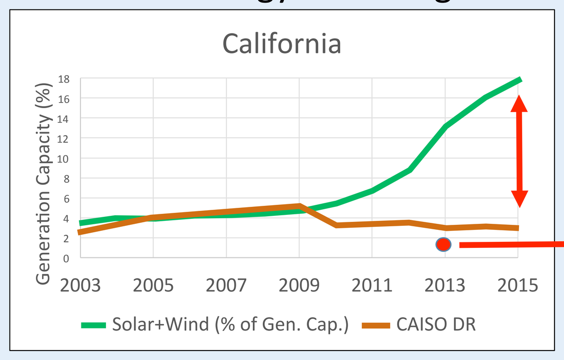
Incentivizing Reliable Demand Response with Customers' Uncertainties and Capacity Planning

Joshua Comden, Zhenhua Liu, Yue Zhao

ACM e-Energy 2017

Solar + Wind outpaces DR

Demand Response (DR) is one of the approaches considered to help integrate renewable energy into the grid.

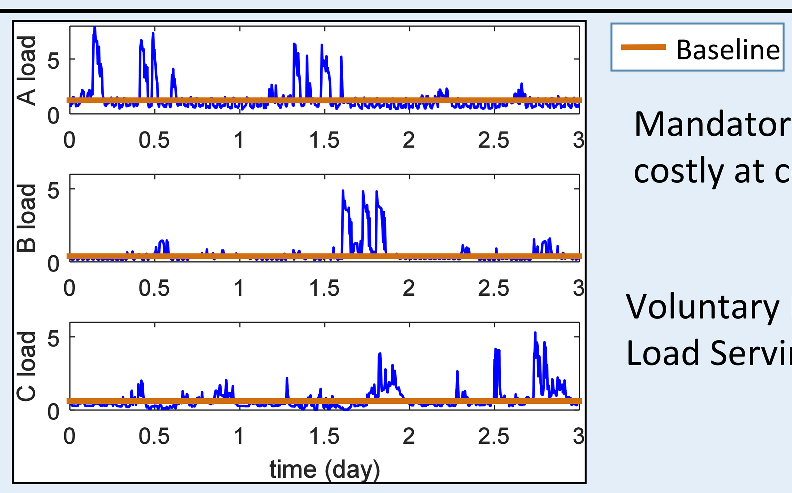


However, DR has not kept up with renewables.

California State Legislature: 1,325 MW of grid storage

http://www.energy.ca.gov/almanac/electricity_data/electric_generation_capacity.html
FERC Assessment of Demand Response and Advanced Metering Staff Reports: 2010-2016.
CAISO Demand Response Barriers Study 2009.

Customer uncertainties



UMass Trace Repository: Smart* Data Set

Mandatory DR to baseline may be costly at certain times.

vs.

Voluntary DR is not dispatchable for a Load Serving Entity (LSE).

Goal: Increase reliable DR adoption
Approach: Incorporate Customer Uncertainties
Challenges:
- LSE does not know each of the customer's uncertainties.
- Only fully mandatory DR has customers take some responsibility.

DR and Capacity Planning

Planning Decision — Capacity: κ — $t=0$

Real-time Realization — $t>0$

DR policy: $\boldsymbol{x}(D,\boldsymbol{\delta},\boldsymbol{C}(\cdot))$

Aggregate mismatch: D
Individual mismatches: $\boldsymbol{\delta}$
Customer Costs: $\boldsymbol{C}(\cdot)$

time

Long-term Social Cost Problem

Minimize expected social cost with capacity constraints:

$$\min_{\kappa,\boldsymbol{x}} C_{cap}(\kappa)+\mathbb{E}_{D,\boldsymbol{\delta},\boldsymbol{C}}\left[\dots\right]$$

s.t.

$$\max_{D,\boldsymbol{\delta}} \dots \left(D-\sum_i \dots\right)\dots$$

where $C_{cap}(\cdot)$ and $C_g(\cdot)$ are the costs to the LSE for purchasing and utilizing reserve capacity, respectively.

Optimal Solution

Real-time Optimal: allow $\boldsymbol{x}$ to be different for any $D,\boldsymbol{\delta},\boldsymbol{C}(\cdot)$:

$$-\kappa< D-\sum_i \dots \qquad C'_i(x^*_i)=\dots$$

(non-binding capacity constraint) (equal marginal costs)

Optimal capacity:

$$C_{cap}'(\kappa^*)=\mathbb{E}_{D,\dots}$$

where $\theta(\kappa)$ is the sum of the real-time dual variables for the capacity constraints.

DR Contract Design

Linear contract: $x_i(D,\delta_i)=\alpha_i D+\beta_i\dots$

✓ Simple and easy to implement
✓ Real-time Optimal form for quadratic cost functions

Theorem 1: The Long-term Social Cost Problem with the Linear Contract is a convex optimization problem.

Incentive payment to Customer i: $\pi_i\alpha_i+\lambda_i\beta_i+\mu\dots$

Prices (π_i,λ_i,μ_i) separate the social cost problem:

Customer

$$\min_{\alpha_i,\beta_i,\gamma_i}\mathbb{E}_{D,\delta_i}[C_i(\alpha_i D+\beta\dots$$

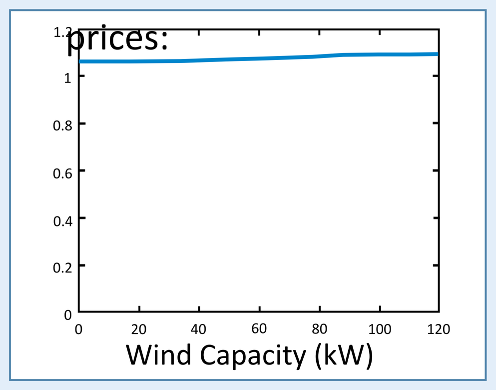
LSE

$$\min_{\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma},\kappa} C_{cap}(\kappa)+\mathbb{E}_{D,\boldsymbol{\delta}}\left[\sum_i \dots\left(D-\sum_i(\alpha_i D+\beta_i\delta_i+\gamma_i)\right)\right]$$

Distributed Algorithm

0. Initialize: LSE sets $(\boldsymbol{\pi},\boldsymbol{\lambda},\boldsymbol{\mu}):=0$ and iteration $k=0$.
1. Each customer solves its separated problem for $(\alpha_i,\beta_i,\gamma_i)$ and sends to LSE.
2. LSE solves its separated problem for $(\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma})$, updates prices: (π_i,λ_i,μ_i) and sends to customers. $k:=k+1$
3. Repeat Steps 1-2.

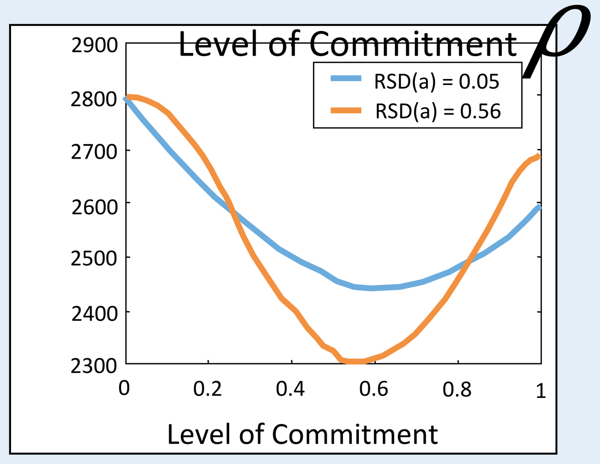
Theorem 2: The trajectory of prices converges to the optimal Linear Contract prices for Long-term Social Cost.



Linear Contract Social Cost is within 10% of Optimal Social Cost.

Adding Flexible Commitment

To avoid high customer cost periods:



Customer commits to ρ fraction of timeslots to follow the Linear Contract based on realized β_i.

$(1-\rho)$ of highest $C_i(\cdot)$ timeslots can be avoided.

Lowering the Level of Commitment from $\rho=1$ reduces Social Cost.