

Capacity characterization of on/off and variable flexible loads providing virtual energy storage

Prabir Barooah

With

Austin Coffman, Zhong Guo, Sean Meyn, Neil Camardella



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Acknowledgement

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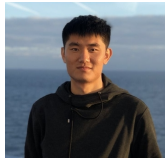
Prior work

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planning

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Zhong Guo



Neil Camardella



Sean Meyn



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Energy storage needs for a renewable-rich grid

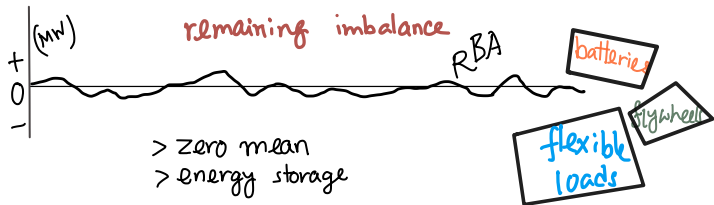
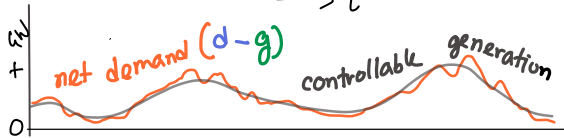
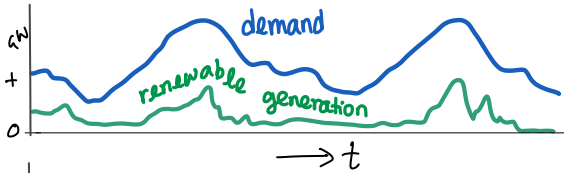
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Capacity characterization for short-term planning

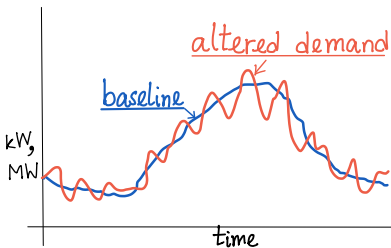
VES capacity characterization for long-term planning



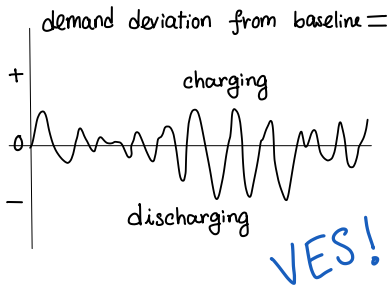
Demand flexibility can be used to provide virtual energy storage

Virtual Energy Storage: altering the power consumption of loads from the baseline demand.

Loads' perspective



Grid's perspective



Demand deviation $Y_k = \text{altered consumption } P_k - \text{baseline } P_k^b$

Loads cannot compromise their quality of service (QoS) in providing VES

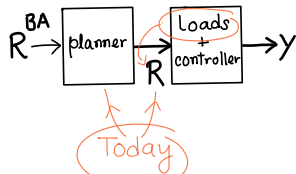
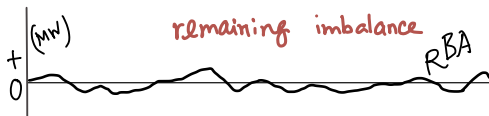
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Terminology

- ▶ R^{BA} : grid's requirement, remaining imbalance,..
- ▶ R : VES reference (for an ensemble of loads)
- ▶ feasible/within capacity: if Y can track R without violating any load's QoS, then R is within the capacity of the loads.

Two key questions

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Q1: Capacity characterization

- ▶ How to characterize VES capacity of a collection of flexible loads?
- ▶ Capacity characterization should be useful for planning

Planning horizons

1. Short term: can 10,000 water heaters deliver what is needed in the next **hour**?
2. Long term: Should the BA contract 50,000 HVAC systems or 1,000,000 for the next **year**?

Two key questions

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Q2: Robust Distributed Coordination

How to coordinate an ensemble of loads to track a VES reference signal that maybe (slightly) outside the capacity of the ensemble?

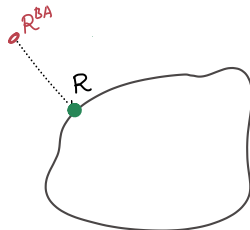
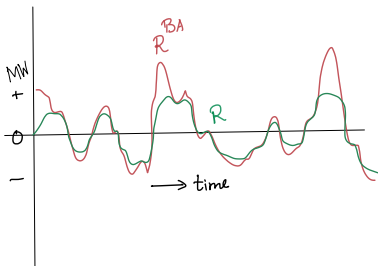
Answers in today's talk

(TCL: thermostatically controlled load)

Ans to Q1.1: Capacity characterization of on/off loads for short-term planning (hour)

Given a prediction of the BA's requirement $\{R_k^{BA}\}_{k=1}^H$, determine the best reference $\{R_k\}_{k=1}^H$ for a collection of TCLs that is within their capacity:

- ▶ *Within capacity*: no single TCL need to violate its local quality of service.
- ▶ *Best reference*: R is closest to R^{BA} within some set Ω .



Answers in today's talk (briefly)

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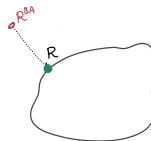
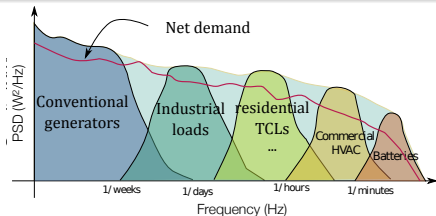
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Ans to Q1.2: Capacity characterization for long-term planning (year)

Given a statistical characterization of BA's requirement, determine how many loads are needed to meet the BA's requirement.



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Ans to Q2: How to design coordination algorithms that are robust to inaccurate capacity estimates?

- ▶ Coordination algorithm should fail gradually if R_k is beyond capacity.
- ▶ Not true for most prior works, esp. those using dual ascent.

NOT in today's talk (advertisement)

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Ans to Q2: How to design coordination algorithms that are robust to inaccurate capacity estimates?

- ▶ Coordination algorithm should fail gradually if R_k is beyond capacity.
- ▶ Not true for most prior works, esp. those using dual ascent.

A proposed solution

- ▶ Coffman, Hale and Barooah, "Resource allocation with local QoS: Flexible loads in the power grid", CCTA, August 2020.
- ▶ **Next week!** Wed, August 26, 16:40-17:00, Paper WeC3.3.

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Q1.1: Capacity characterization of on/off TCLs, for short term planning

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“Aggregate Flexibility of Thermostatically Controlled Loads”, Hao, Sanandaji, Poola, Vincent, *IEEE Trans. on Power Systems*, 2015.

- ▶ The only QoS considered is the indoor temperature deviation (air conditioner):

$$\tilde{\theta}_k \triangleq \theta_k - \theta_{\text{set}}, \text{ constraint: } |\tilde{\theta}_k| \leq \Delta.$$

- ▶ Ignore on/off nature; assume power is continuously variable: $Y_k^j = P_k - P_k^{\text{baseline}}$.

- ▶ Model of indoor temperature deviation $\tilde{\theta}_k^j$ of the j -th TCL:

$$\tilde{\theta}_{k+1}^j = a^j \tilde{\theta}_k^j + b^j Y_k^j.$$

- ▶ Define “total” quantities over N TCLs:

$$Y_k = \sum_{j=1}^N Y_k^j \quad (\text{power deviation}) \quad Z_k := \sum_{j=1}^N \tilde{\theta}_k^j \quad (\text{temperature deviation})$$

- ▶ Ensemble model: $Z_{k+1} = aZ_k + bY_k$.

Capacity as a constraint on power deviation Y_k

A total power deviation signal Y_k is within capacity if

1. $0 \leq (Y_k + P_k^b) \leq \text{total rated power.}$
2. $Z_0 = 0, Z_{k+1} = aZ_k + bY_k, |Z_k| \leq N\Delta.$

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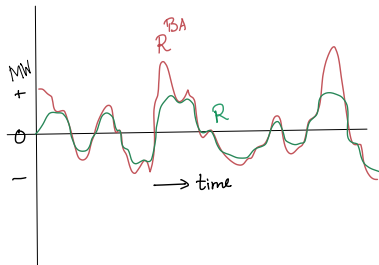
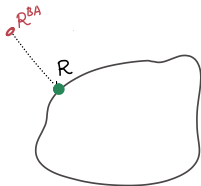
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Can be used for short term reference planning:



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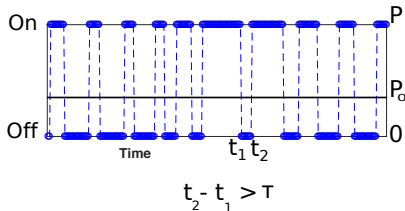
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Individual load's quality of service (QoS)

1. Temperature
2. Cycling/lock-out
3. Total energy use over a billing period

Cycling constraint of a load

A load can flip on/off only once in any time interval of length τ :



Related literature

1. Sanandaji, Vincent, Poolla, "Ramping rate flexibility of residential hvac loads", IEEE TSE'16.
2. Zhao, Zhang, Hao, Kalsi, "A geometric approach to aggregate flexibility modeling of thermostatically controlled loads". IEEE TPS'17.
3. Ziras, You, Bindner, Vrettos, "A new method for handling lockout constraints on controlled TCL aggregations", PSCC'18.

So far, no tractable method to relate cycling constraints to power deviation

$$m_k^j = \begin{cases} 1 & \text{TCL } j \text{ is on at } k \\ 0 & \text{TCL } j \text{ is off at } k \end{cases}$$

Challenge: nonlinear integer constraint at the individual:

- ▶ Minimum lock-out time for j -th TCL is τ^j :

$$\sum_{\ell=1}^{\tau^j} |m_{k-\ell}^j - m_{k-\ell-1}^j| \leq 1, \quad \forall k.$$

Main idea

Translate constraints to “fraction of loads that are” (no integers!)

$n_k^{\text{on}} \triangleq$ fraction of loads that are on at k

$f_k^{\text{on}} \triangleq$ fraction of loads that flipped on (from off to on) at k

$s_k^{\text{on}} \triangleq$ fraction of loads that are stuck on at k

And, similarly, $f_k^{\text{off}} := \dots\dots, s_k^{\text{off}} := \dots\dots$

(i) Quasi-homogeneous assumption:

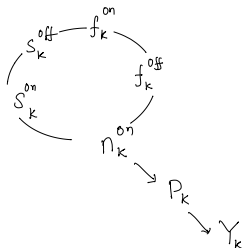
Power consumption of the ensemble is equivalent to n_k^{on} :

$$n_k^{\text{on}} = \frac{1}{\sum_j P_j^{\text{rated}}} (Y_k + P_k^b)$$

(ii) Evolution of various fractions

Example:

$$s_k^{\text{on}} = s_{k-1}^{\text{on}} + f_k^{\text{on}} - f_{k-\tau}^{\text{on}}$$



Capacity characterization: a set of constraints on...

$$\psi_k := [Y_k, Z_k, n_k^{\text{on}}, s_k^{\text{on}}, s_k^{\text{off}}, f_k^{\text{on}}, f_k^{\text{off}}]$$

$$Z_k = aZ_{k-1} + bY_{k-1}, -C \leq Z_k \leq C,$$

$$n_k^{\text{on}} = \frac{1}{\sum_j P_j^{\text{rated}}} (Y_k + P_k^b),$$

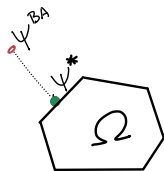
$$n_k^{\text{on}} = n_{k-1}^{\text{on}} + f_{k-1}^{\text{on}} - f_{k-1}^{\text{off}}$$

$$s_{k-1}^{\text{on}} \leq n_k^{\text{on}} \leq 1 - s_{k-1}^{\text{off}},$$

$$s_k^{\text{on}} = s_{k-1}^{\text{on}} + f_{k-1}^{\text{on}} - f_{k-\tau-1}^{\text{off}}$$

$$s_k^{\text{off}} = s_{k-1}^{\text{off}} + f_{k-1}^{\text{off}} - f_{k-\tau-1}^{\text{on}}$$

$$s_k^{\text{on}}, s_k^{\text{off}}, f_k^{\text{on}}, f_k^{\text{off}}, n_k^{\text{on}} \in [0, 1]$$



Reference computation as convex optimization

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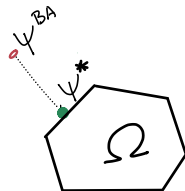
$$\psi \triangleq [Y_k, Z_k, n_k^{\text{on}}, s_k^{\text{on}}, s_k^{\text{off}}, f_k^{\text{on}}, f_k^{\text{off}}], k = 1, \dots, H$$

$$\psi^{\text{BA}} \triangleq [R_k^{\text{BA}}, 0, 0, 0, 0, 0], k = 1, \dots, H,$$

$$\min_{\psi} J(\psi) = (\psi^{\text{BA}} - \psi)^T M (\psi^{\text{BA}} - \psi)$$

$$\text{s.t. } \psi \in \Omega,$$

$$\sum_{k=1}^H Y_k = 0, \quad (\text{energy cons. same as baseline})$$



Optimal VES reference R is the first component, Y^* of ψ^*

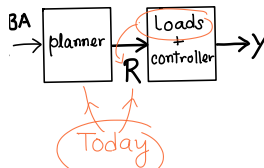
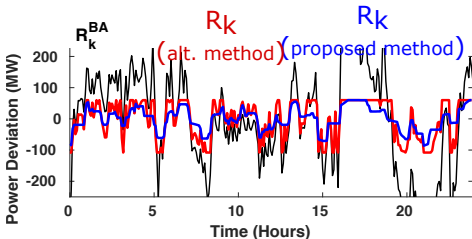
Unique VES reference for the ensemble, R , for a given remaining imbalance $\{R_k^{\text{BA}}\}$.

Numerical example of VES reference planning

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R^{BA} : from Bonneville Power Administration.

Loads: 60,000 air conditioners, $P_{rated}^j \sim U[5.6, 7]$ kW.



Proposed method: BA Accounts for loads' cycling constraints

Alternate method: BA **does not** account for loads' cycling constraints

Proof by closed loop simulation: Goldilocks and the three BAs

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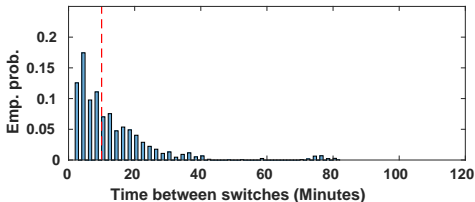
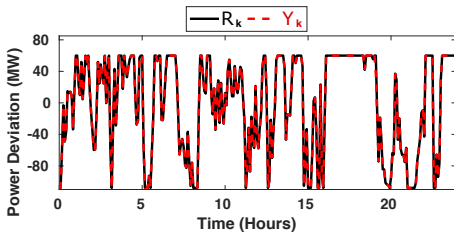
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1. BA plans reference ignoring loads' cycling constraints, and it forces ACs to disregard cycling constraints. (**dictatorial BA**)
2. BA plans reference ignoring loads' cycling constraints, but loads enforce cycling constraints. (**oblivious BA**)
3. Both the BA and the loads account for load's cycling constraints. (**considerate BA**)

Tracking in scenario 1: Dictatorial BA

Reference tracking by ensemble and individuals' QoS:



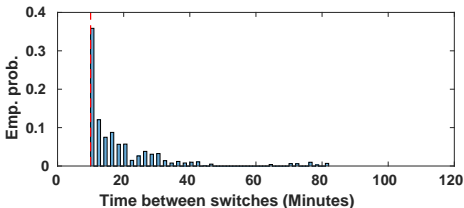
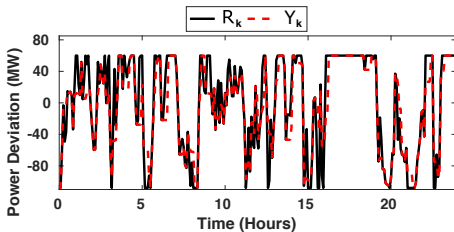
What we expect:

1. The ACs to cycle frequently.
2. **Good** reference tracking.

The dictatorial BA destroyed everyone's AC's in obtaining VES!

Tracking in scenario 2: Oblivious BA

Reference tracking by ensemble and individuals' QoS:



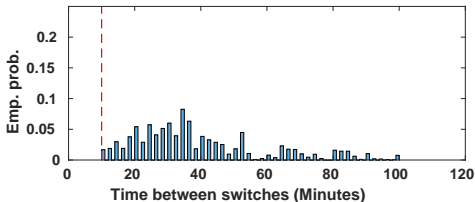
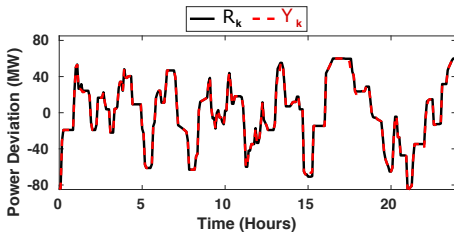
What we expect:

1. The ACs to satisfy their cycling constraints.
2. **Poor** reference tracking.

The oblivious BA paid the price in reference tracking error!

Tracking in scenario 3: Considerate BA (Proposed Method)

Reference tracking by ensemble and individuals' QoS:



What we expect:

1. The ACs to satisfy cycling QoS.
2. **Good** reference tracking.

The considerate BA asked for just the right amount, so both parties were happy!

Contribution

1. A computation friendly characterization of capacity of TCL ensembles to provide VES.
2. A balancing authority can use this method to compute the “largest feasible” reference signal for a load ensemble under its jurisdiction (convex optimization).
3. The method accounts for all three QoS metrics for the consumer: (i) indoor temperature, (ii) **cycling**, and (ii) **energy use**.

References

- (i) Coffman, Camardella, Meyn, and Barooah, “Flexibility capacity of TCLs with cycling constraints”, *Amer. Control Conf.*, July 2020, ArXiv:1909.11497, 2019.
- (ii) Coffman, Bušić, and Barooah, “Aggregate Capacity for TCLs providing Virtual Energy Storage with cycling constraints”, *IEEE Conf. on Decision and Control, Dec. 2019*.

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Q 1.2: Capacity characterization of continuously variable loads, for long term planning

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Capacity characterization based on statistics of grid's needs

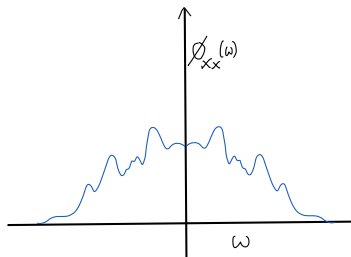
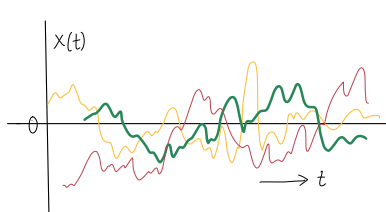
- ▶ Problem: instead of the signal $\{R_k^{\text{BA}}\}$, only statistics of the stochastic process \mathbf{R}_k^{BA} is given. How do you determine if N loads are enough to deliver?
- ▶ Approach: use spectral density.

Reference

- (i) Coffman, Guo, and Barooah, "A spectral characterization of aggregate capacity of flexible loads for grid support", *Amer. Control Conference*, July 2020.

Spectral density

The spectral density $\Phi_{XX}(\omega)$ of a zero-mean W.S.S. stochastic process $X(t)$ is the Fourier transform of its autocorrelation function.



For simplicity, consider one HVAC load

QoS Constraints

1. Actuator constraint: $\max_t |Y(t)| < C_1$
2. Actuator (rate) constraint: $\max_t |Y(t + \delta) - Y(t)| < C_2$ (fixed δ)
3. Temperature constraint: $\max_t |\tilde{\theta}(t)| < C_3$
4. Energy or utility bill constraint: $\max_t |\tilde{E}(t)| < C_4$

Recall, for a load, $\tilde{E}(t) = \int_0^t Y(\eta) d\eta$.

1. Replace by probabilistic constraints

1. Actuator constraint: $Prob(|Y(t)| < C_1) > 1 - \epsilon_1$
2. ...

2. Obtain sufficient condition from Chebycheff inequality

If X is zero mean and $var(X) < a$ then $P(|X| < C) > 1 - \frac{a}{C^2}$.

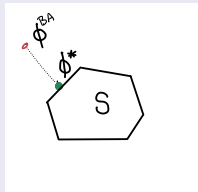
3. Convert to constraints on the PSD of Y

Variance of $X(t)$ is related to integral of $\Phi_{XX}(\omega)$.

4. Planning through projection onto a constraint set

$$\Phi^* = \arg \min_{\Phi} \int_0^{\infty} (\Phi(\omega) - \Phi^{(BA)}(\omega))^2 d\omega$$

s.t. $\Phi \in S$.



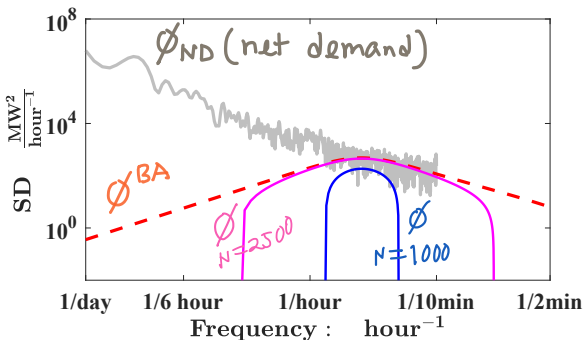
Numerical example

BA: Bonneville Power Administration.

BA's requirement: the part of net demand limited to [2, 8] hours time scale.

Loads: HVAC systems in large commercial buildings. For each building, $|Y| \leq 40$ kW,
 $\leq \pm 2^\circ$ F,...

Result:



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**Distributed Control of
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Financial support from NSF and BTO(DOE) gratefully acknowledged