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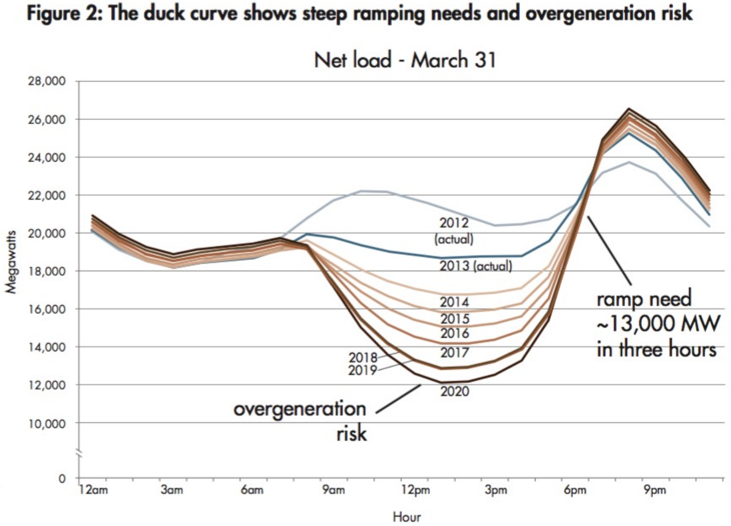
Title: Guaranteeing a physically realizable battery dispatch without charge-discharge complementarity constraints

Panel Session: Operation research for emerging resources: Hybrid power plants, Virtual power plants, Batteries and beyond

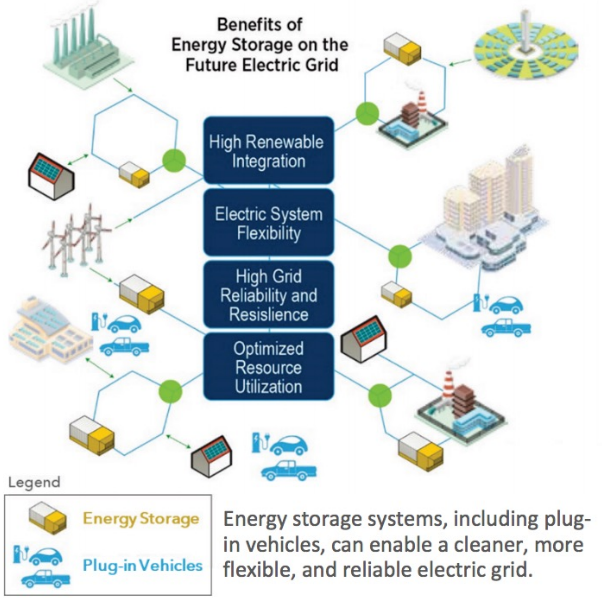
Presenters: **Nawaf Nazir (Pacific Northwest National Lab)** and Mads Almassalkhi (University of Vermont)

Increased renewable generation and battery storage

- States like California and Vermont have ambitious targets → >50% of their energy met through renewable generation



California duck curve showing a snapshot of a 24-hour period and steep ramping, source: CAISO



Energy storage provides an integrated solution to some critical energy needs, source: [1] Solving challenges in energy storage, Department of Energy report, Office of technology transitions

Challenge in battery optimization

- Batteries cannot simultaneously charge and discharge
- Results in non-convex complementarity constraints
- Can be solved as a mixed-integer program
- Not scalable, computationally expensive

$$E[k+1] = E[k] + \Delta t \eta_c P_c[k] - \frac{\Delta t}{\eta_d} P_d[k], \qquad \forall k \in \mathcal{T}$$

$$E[0] = E_0$$

$$0 \leq P_c[k] \leq P_{\max}, \qquad \forall k \in \mathcal{T}$$

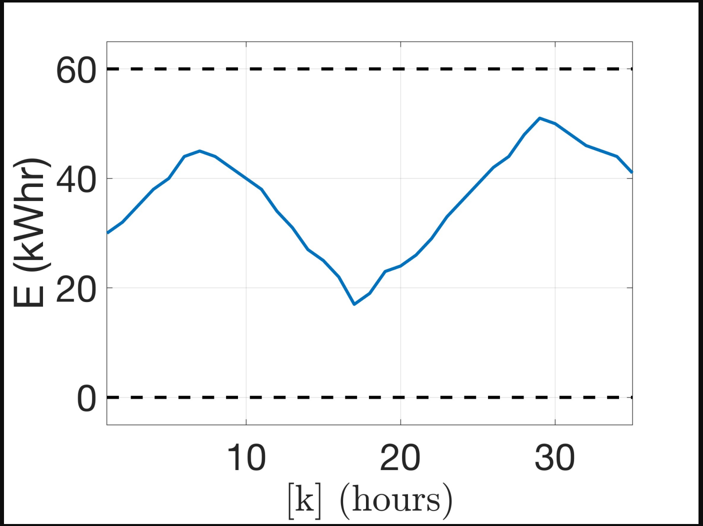
$$0 \leq P_d[k] \leq P_{\max}, \qquad \forall k \in \mathcal{T}$$

$$0 \leq E[k+1] \leq E_{\max}, \qquad \forall k \in \mathcal{T}$$

$$P_c[k] P_d[k] = 0 \qquad \forall k \in \mathcal{T}.$$

The resulting SoC trajectory can be expressed as

$$\mathbf{E}(\mathbf{P}_c, \mathbf{P}_d) = \mathbf{1}_T E_0 + \eta_c \mathbf{A}\mathbf{P}_c - \frac{1}{\eta_d} \mathbf{A}\mathbf{P}_d,$$



Traditional approaches to scalable battery optimization

Relaxed model

$$E^r[k+1]=E^r[k]+\Delta t\eta_c P_c^r[k]-\frac{\Delta t}{\eta_d}P_d^r[k],$$

$$E^r[0]=E_0$$

$$0\leq P_c^r[k]\leq P_{\max},$$

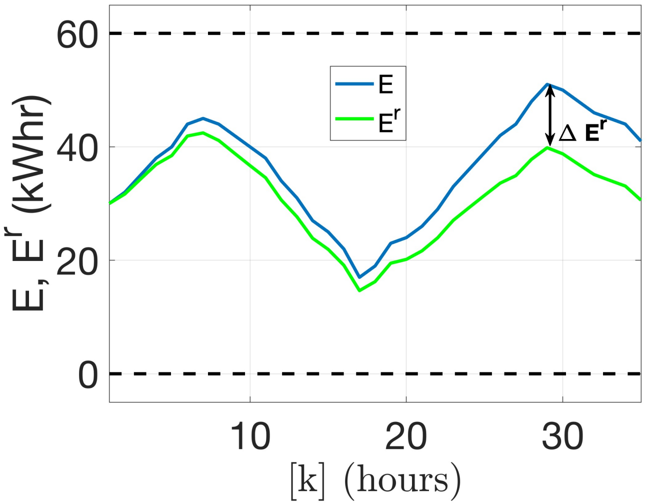
$$0\leq P_d^r[k]\leq P_{\max},$$

$$0\leq E^r[k+1]\leq E_{\max},$$

$$\mathbf{E}^r(\mathbf{P}_c^r,\mathbf{P}_d^r)=\mathbf{1}_T E_0+\eta_c\mathbf{A}\mathbf{P}_c^r-\frac{1}{\eta_d}\mathbf{A}\mathbf{P}_d^r$$

$$\mathbf{P}_c=\max\{\mathbf{0},\mathbf{P}_c^r-\mathbf{P}_d^r\},\quad \mathbf{P}_d=\max\{\mathbf{0},-(\mathbf{P}_c^r-\mathbf{P}_d^r)\},$$

$$\mathbf{P}_c-\mathbf{P}_d=\mathbf{P}_c^r-\mathbf{P}_d^r$$



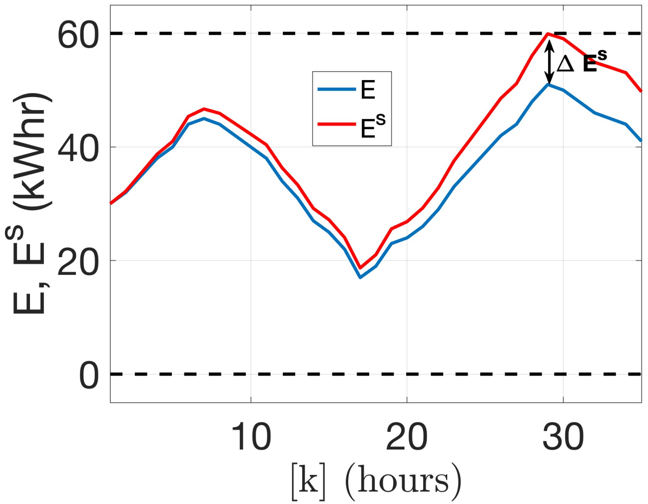
Traditional approaches to scalable battery optimization

Single input model

$$E^s[k+1] := E^s[k] + \eta \Delta t P_b[k], \qquad \forall k \in \mathcal{T}$$
$$E^s[0] = E_0$$
$$-P_{\max} \le P_b[k] \le P_{\max} \qquad \forall k \in \mathcal{T}$$
$$0 \le E^s[k+1] \le E_{\max}. \qquad \forall k \in \mathcal{T}$$

The simplified model's SoC trajectory is then

$$\mathbf{E}^s(\mathbf{P}_b) = \mathbf{1}_T E_0 + \eta \mathbf{A} \mathbf{P}_b.$$



Linear robust battery dispatch (RBD)

$$\min_{\mathbf{P}_c - \mathbf{P}_d} \quad f(\mathbf{P}_c - \mathbf{P}_d)$$

$$\text{s.t} \quad \mathbf{0} \leq \mathbf{1}_T E_0 + \eta_c \mathbf{A}\mathbf{P}_c - \frac{1}{\eta_d}\mathbf{A}\mathbf{P}_d$$

$$\mathbf{E}_{\max} \geq \mathbf{1}_T E_0 + \eta \mathbf{A}(\mathbf{P}_c - \mathbf{P}_d)$$

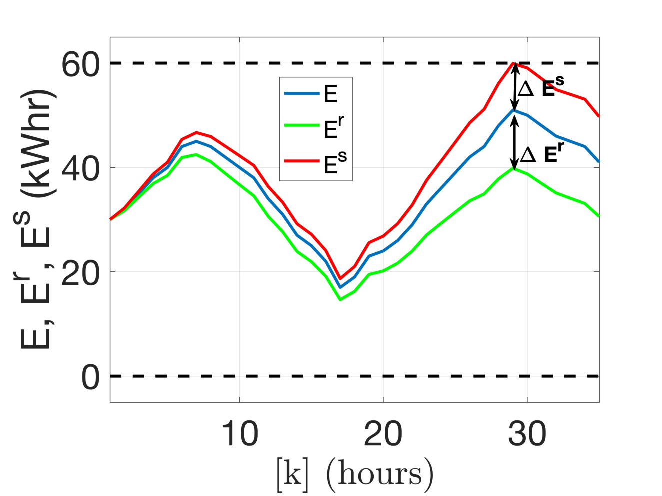
$$0 \leq \mathbf{P}_c \leq \mathbf{1}_T P_{\max}$$

$$0 \leq \mathbf{P}_d \leq \mathbf{1}_T P_{\max}$$

$$\mathbf{P}_c + \mathbf{P}_d \leq \mathbf{1}_T P_{\max}$$

Lemma III.1. *If inputs* $\mathbf{P}_b = \mathbf{P}_c - \mathbf{P}_d = \mathbf{P}_c^r - \mathbf{P}_d^r$ *satisfy* $\mathbf{P}_c \cdot \mathbf{P}_d = \mathbf{0}$ *and* $\mathbf{P}_c^r \cdot \mathbf{P}_d^r \geq \mathbf{0}$, *then* $\mathbf{E}^r(\mathbf{P}_c^r, \mathbf{P}_d^r) \leq \mathbf{E}(\mathbf{P}_c, \mathbf{P}_d) \leq \mathbf{E}^s(\mathbf{P}_b)$.

$$\Delta \mathbf{E}^r \leq \left(\frac{1}{\eta_d} - \eta_c\right)\mathbf{A}\mathbf{1}_T \frac{P_{\max}}{2}.$$

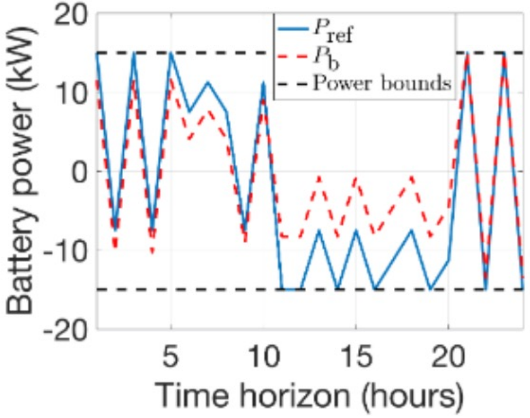


- [2] Nawaf Nazir, Mads Almassalkhi, “Guaranteeing a physically realizable battery dispatch without charge-discharge complementarity constraints,” IEEE PES Letters

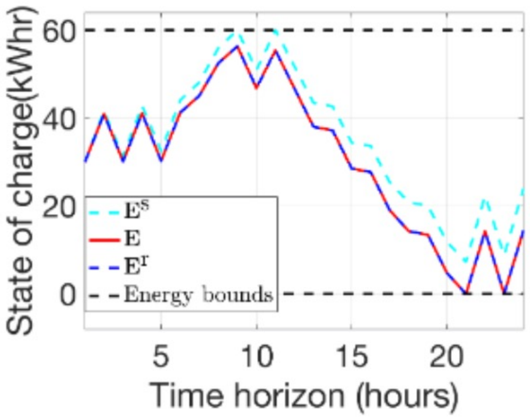
Simulations results and comparisons

TABLE I
SOLVE TIME (SEC) AND POWER TRACKING RMSE (KW) COMPARISON WITH INCREASING BATTERIES FOR RBD VS MIP VS NLP

	RBD		MIP		NLP	
Batteries	Time	RMSE	Time	RMSE	Time	RMSE
10	1.7	47.8	16.3	43.7	5.1	54
100	3.1	478.7	271.8	437.8	50.5	478.7
200	6.3	957.4	1114	866	133.2	1190.2
500	11.5	2327.4	–	–	351.6	2415.2
1000	22.6	4787.1	–	–	1115	4787.1



Tracking a battery reference power signal P_{ref} with the net battery output $P_b \in [-P_{max}, P_{max}]$.



Comparison between predicted SoC (E^S, E^r) and actual SoC E resulting from optimized dispatch with the energy limits [0, 60].

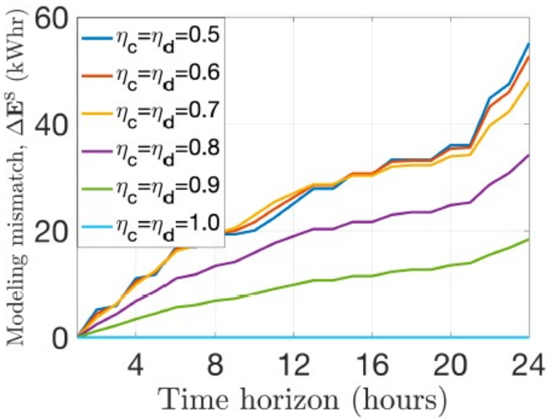
Simulations results and conclusions

Conclusions

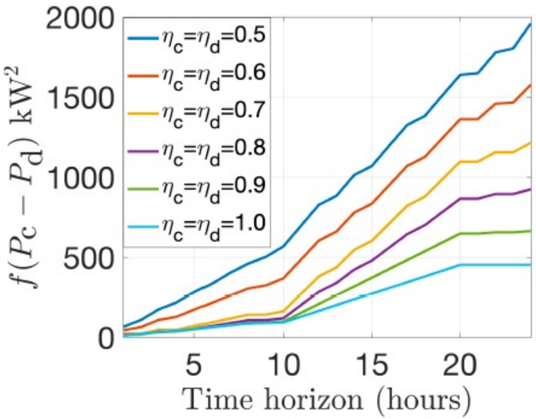
- A new linear formulation to optimally dispatch batteries
- Guaranteeing satisfaction of SoC constraints
- Avoiding non-convex/MIP formulations

Future work:

- Incorporate battery constraints into optimal power flow and MPC formulations
- Study impact of conservativeness on practical case-studies



Modeling mismatch obtained for different $\eta_c = \eta_d$ efficiencies.



Corresponding cumulative objective function values $\left(\left(P_{ref}[k] - P_b[k]\right)^2\right)$ showing reduced tracking performance with increased modeling mismatch (i.e., lower efficiencies).

Thank you! Questions/comments?

This work was supported by the U.S. Department of Energy's Advanced Research Projects Agency—Energy (ARPA-E) under Award DE-AR0000694. The work of Mads Almassalkhi was supported in part by the National Science Foundation (NSF) under Award ECCS-2047306.

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