Delivery-Risk-Aware Flexibility Scheduling and Dispatch for Aggregated Flexible Loads

Mengmeng Cai and Michael Blonsky
National Renewable Energy Laboratory
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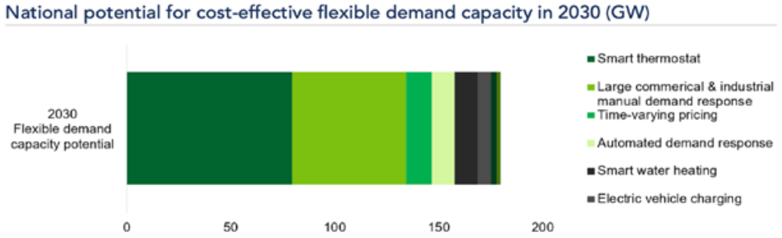
In collaboration with Elina Spyrou, Ben Hobbs, Josephine Wang, and Yudong Yin

Why Demand-Side Flexibility is Critical for Decarbonizing the Power Grid?

>> Demand-side flexibility, being a **fast-responsive, cost-effective, and zero-emissions** resource, is expected to play a key role in resource adequacy and variabilities & uncertainties management for decarbonizing the power grid.

Source: MIT news, https://news.mit.edu/2017/virtual-batteries-cheaper-cleaner-power-0324



Source: DOE, *Pathways to Commercial Liftoff: Virtual Power Plants*

>> A recent DOE report reveals ***180 GW capacity potential*** and ***13 Billions saving potential*** of demand-side flexibility in 2030.

What are the Key Challenges Faced by Aggregating Demand-Side Flexibility

There are three challenges to fully unlock the demand-side flexibility:

Lack of market incentive

Deficiency in market incentives that address the flexibility needs across all time frames: ranging from short term (e.g., operating reserve) to long term (e.g., seasonal demand flexibility).

Technical challenge

The management of a large number of small and heterogenous devices is technically complex.

Reliability issue

System operators and regulators often perceive demand-side flexibility as unreliable due to its dependency on user behaviors, which are uncertain and not entirely controllable.

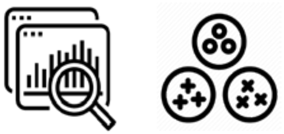
How the NREL-led ARPA-E PERFORM Project Address the Challenges?

An Integrated Paradigm For The Management Of Delivery Risk In Electricity Markets

Inform flexible loads aggregation

DER risk scores

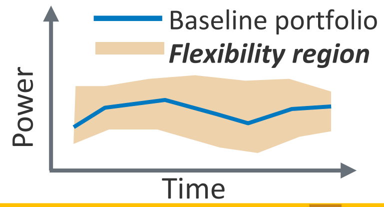
Measure the reliability of DER assets in delivering contracted flexibility



Data analytics and scoring

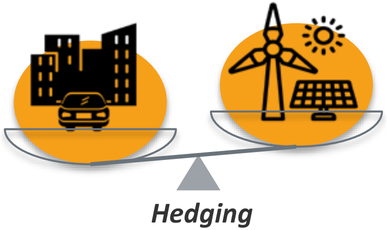
Delivery risk aware DERs participation model

Facilitate DERs flexibility scheduling and dispatch



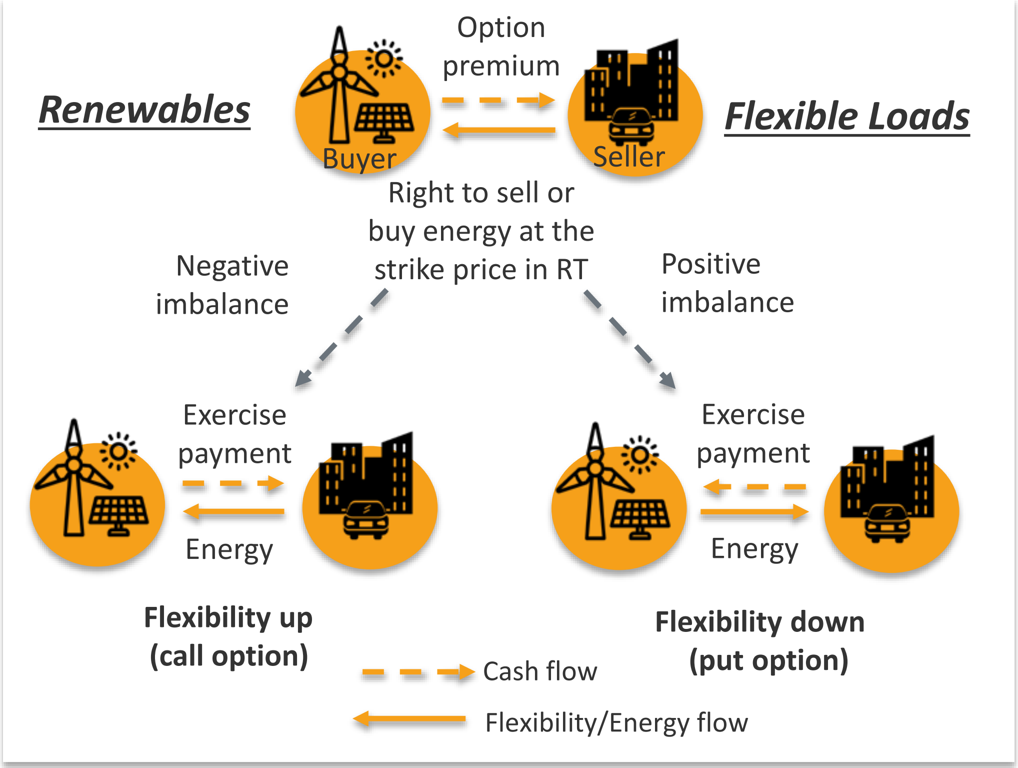
Wholesale flexibility option

Enable system-wide flexibility trading at transparent prices to mitigate DA-RT netload imbalance



Inform flexible loads flexibility offering and dispatch

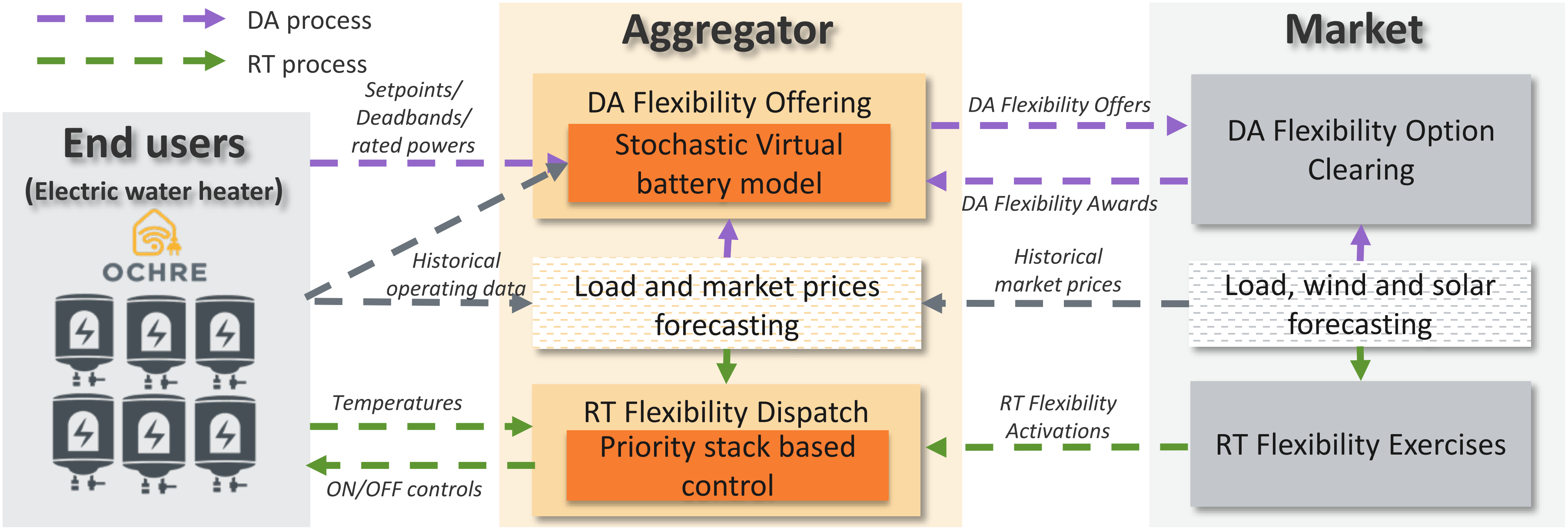
Framework of the Flexibility Option



>> Renewables (buyer) purchase ***flexibility up/down*** in day-ahead (DA) from flexible loads (seller) in exchange of the ***right*** to ***buy/sell*** extra energy in real-time (RT) at strike prices, resembling ***call and put options*** in the finance market.

Renewables overestimated	Renewables underestimated
↓	↓
Exercise ***Flexibility up***	Exercise ***Flexibility down***
↓	↓
Reduce consumption (charging)	Increase consumption (discharging)

Framework of the **Delivery-Risk-Aware** DERs Participation Model

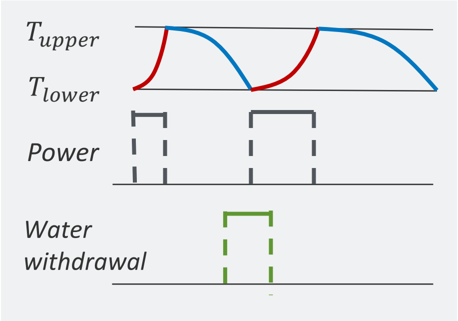


>> To ensure the successful participation of flexible loads in the flexibility option market, it requires:

1. A DA flexibility offering capability to accurately quantify the **aggregated feasible operating region** of flexible loads and make strategic offers.
2. A RT flexibility dispatch capability to efficiently **disaggregate the unit-level control commands** in response to the flexibility activation.

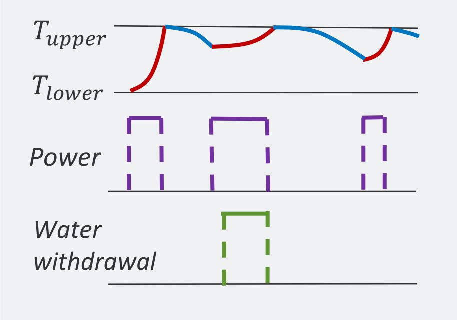
Definition of the Delivery Risk

Baseline control (Following the deadband control)



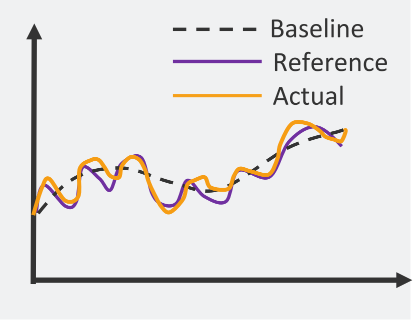
Reshaping power consumption

Modified control (Overwriting the deadband control)



Aggregating the reshaped power consumption

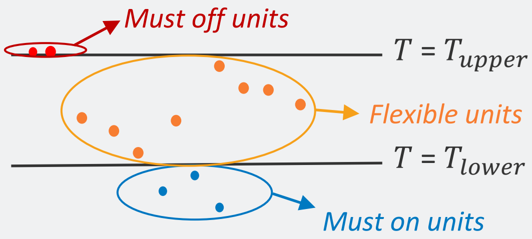
Flexibility offered at the fleet-level



Disaggregating the control commands

>> Priority stack based control (fleet-level): prioritize flexible loads with lowest state of the charge, $SoC = \frac{T - T_{lower}}{T_{upper} - T_{lower}}$, to be turned on until the aggregated power consumption is closest to the reference power consumption.

>> Delivery risk: occurs when there aren't enough flexible units available. (Driven by stochastic user behaviors and long-duration flexibility activations)



Stochastic Virtual Battery Model: How the Demand-Side Flexibility is Quantified?

<u>Energy State Transition:</u> $$E_{t+1} = E_t + \eta(P_t - \widetilde{P}_t^{baseline})$$

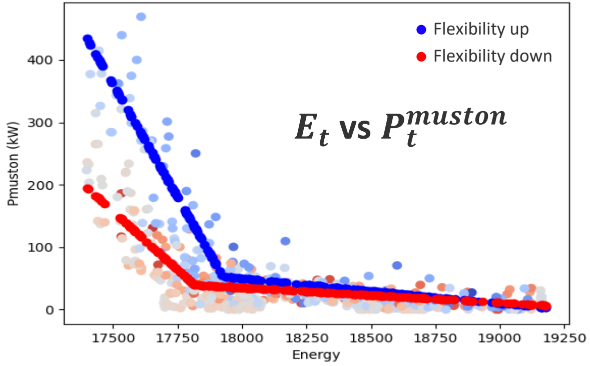
<u>Energy constraints:</u> $$E_t^{lower} \le E_t \le E_t^{upper}$$

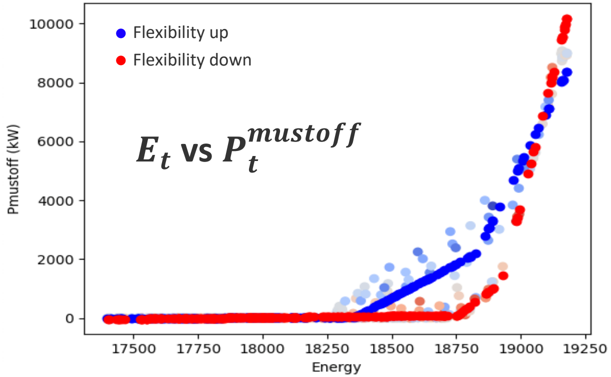
<u>Power constraints:</u> $$P_t^{muston}(E_t) \le P_t \le P^{rated} - P_t^{mustoff}(E_t)$$

E_t: energy state; P_t: power consumption; $\widetilde{P}_t^{baseline}$: estimated baseline power consumption;
E_t^{lower} and E_t^{upper}: lower and upper bounds of the energy states;
P^{rated}: sum of rated power for all units;
P_t^{muston} and $P_t^{mustoff}$: sum of rated powers for all muston and mustoff units

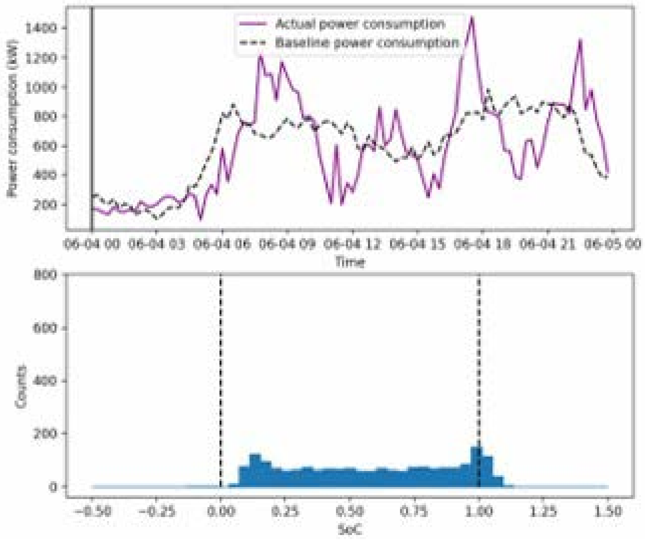
» $\widetilde{P}_t^{baseline}$ provides an interface for modeling the uncertainty in user behaviors (e.g., hot water withdraw for EWH) / weather condition (e.g., ambient temperature for HVAC)

» P_t^{muston} and $P_t^{mustoff}$ are modelled as piecewise linear functions of E_t.





Intuition Behind the Unbalanced Power Constraints



Distribution of SoCs across units varies over time when the fleet is alternatively providing ***flexibility up*** *and* ***flexibility down****.*

	Charging (Flexibility down)	Discharging (Flexibility up)
Distribution of SoC	Becomes narrower	Becomes wider
Moving direction	Towards the 1.0 upper bound	Towards the 0.0 lower bound
Driver of the SoCs variation at the unit level	Greater driven by the ***priority-stack control***, which is more certain	Greater driven by the ***hot water withdrawal***, which is more uncertain

The ***wider*** *the spread of the SoC distribution the* ***tighter*** *the power constraints*

SOTA Virtual Battery Model Based on Control Theory

$$\frac{dL(t)}{dt} = \eta U(t) - \alpha U(t)$$
$$\underline{L}(t) \le L(t) \le \overline{L}(t)$$
$$\underline{U}(t) \le U(t) \le \overline{U}(t)$$

Inner approximation:

$$\overline{L}(t) = -\underline{L}(t) = \frac{\alpha_k}{\alpha_k + |\alpha - \alpha_k|} \cdot \frac{\eta}{\eta_k} \cdot \min\left(\frac{c_k|\overline{T_k} - \widetilde{T_k}|}{\beta_k}, \frac{c_k|\underline{T_k} - \widetilde{T_k}|}{\beta_k}\right)$$
$$\underline{U} = \max_k\left(-\frac{\widetilde{\boldsymbol{P}_k}(\boldsymbol{t})}{\beta_k}\right)$$
$$\overline{U} = \min_k\left(\frac{P_k^{rated} - \widetilde{\boldsymbol{P}_k}(\boldsymbol{t})}{\beta_k}\right)$$

Compared with the state-of-the-art VBM:

1. Rely on baseline consumption forecasts at the aggregate-level, which are more predictable.
2. Able to control the conservative level of the model.
3. Can capture how the controls from the previous time steps affect the power constraints at the current time step.

[1] Hale, Elaine, Matt Leach, Brady Cowiestoll, Yashen Lin, and Daniel Levie. *Methods for Computing Physically Realistic Estimates of Electric Water Heater Demand Response Resource Suitable for Bulk Power System Planning Models*. No. NREL/TP-6A40-82315. National Renewable Energy Lab.(NREL), Golden, CO (United States), 2022.
[2] Hao, He, Borhan M. Sanandaji, Kameshwar Poolla, and Tyrone L. Vincent. "Aggregate flexibility of thermostatically controlled loads." *IEEE Transactions on Power Systems* 30, no. 1 (2014): 189-198.

Delivery Risk Aware DA Flexibility Offering

Expected Revenue

$$\max_{P_t^{flex,\uparrow}, P_t^{flex,\downarrow}} DA_{premium} + RT_{exercise} - RT_{penalty}$$

$$DA_{premium} = \sum_{S_M} \pi_{S_M} \sum_{T_{hour}} \left[\left(\tilde{\alpha}_{t,s_M}^{\uparrow} - \theta_t^{\uparrow} \cdot \beta_t^{\uparrow}\right) \cdot P_t^{flex,\uparrow} + \left(\theta_t^{\downarrow} \cdot \beta_t^{\downarrow} + \tilde{\alpha}_{t,s_M}^{\downarrow}\right) \cdot P_t^{flex,\downarrow} \right]$$

Day-ahead flexibility up and down prices

$$RT_{exercise} = \frac{1}{4} \sum_{S_M} \pi_{S_M} \sum_{t' \in T15m} \left[\tilde{I}_{t',s_M}^{\uparrow} \cdot \beta_{t'}^{\uparrow} \cdot P_{t'}^{flex,\uparrow} + \tilde{I}_{t',s_M}^{\downarrow} \cdot \beta_{t'}^{\downarrow} \cdot P_{t'}^{flex,\downarrow} \right]$$

Real-time flexibility activation indicators

$$RT_{penalty} = \frac{1}{4} \sum_{S_P} \pi_{S_P} \sum_{S_M} \pi_{S_M} \sum_{t' \in T15m} \tilde{\gamma}_{t',s_M} \cdot \left| \delta_{t',s_M,s_P} \right|$$

Real-time energy price

Subject to:

Virtual Battery Model

$$E_{t''+1,s_M,s_P} = E_{t'',s_M,s_P} + \eta\left(P_{t'',s_M,s_P}^{estimation} - \tilde{P}_{t'',s_P}^{baseline}\right)$$

$$P_{t''}^{min} \le P_{t'',s_M,s_P}^{estimation} \le P_{t''}^{max}$$

$$E_{t'',s_M,s_P}^{min} \le E_{t'',s_M,s_P} \le E_{t'',s_M,s_P}^{max}$$

Reference Consumption

$$P_{t',s_M}^{reference} = P_{t'}^{energy} - \tilde{I}_{t',s_M}^{\uparrow} \cdot P_{t'}^{flex,\uparrow} + \tilde{I}_{t',s_M}^{\downarrow} \cdot P_{t'}^{flex,\downarrow}$$

Delivery Risk Quantification

$$\delta_{t',s_M,s_P} = P_{t',s_M,s_P}^{estimation} - P_{t',s_M}^{reference}$$

- $P_{t'}^{flex,\uparrow}, P_{t'}^{flex,\downarrow}$: *flexibility up and down quantity offers.*
- $\beta_t^{\uparrow}$ *and* $\beta_t^{\downarrow}$: *flexibility up and down strike price offers*
- δ_{t',s_M,s_P}: *Delivery risk.*
- $P_{t'}^{energy}$: *DA energy bids, mean of* $\tilde{P}_{t''}^{baseline}$
- $\tilde{P}_{t'',s_P}^{baseline}$: *Baseline consumption forecast under scenario* s_P
- π_{s_P} *and* π_{s_M}: *probabilities of the baseline consumption and market scenarios.*
- $\theta_t^{\uparrow}$ *and* $\theta_t^{\downarrow}$: *probabilities when flexibility up and down are activated.*
- $P_{t',s_M}^{reference}$: *reference consumption*
- $P_{t'',s_M,s_P}^{estimation}$: *estimated actual consumption*

>> $P_{t',s_M,s_P}^{estimation,*}$ *will intentionally deviate from* $P_{t',s_M}^{system\_ref,*}$, *causing **expected** delivery risk, which is different from **unexpected** delivery risk.*

t, t', t'' indicate the time indexes at hourly, 15-min and 5-min resolutions, s_P and s_M indicate the baseline consumption scenario and market scenario, respectively.

Delivery Risk Aware RT Flexibility Dispatch

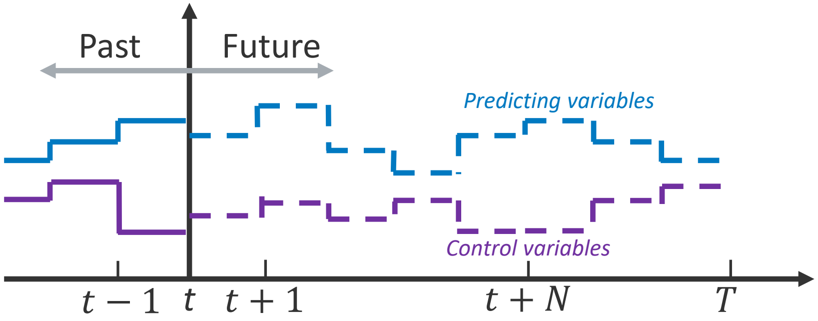
$$\min_{P_{t''}^{estimation}} RT_{penalty}$$

Subject to:

$$E_{t''+1,s_M,s_P} = E_{t'',s_M,s_P} + \eta(P_{t''}^{estimation} - \tilde{P}_{t''}^{baseline})$$
$$P_{t''}^{min} \le P_{t''}^{estimation} \le P_{t''}^{max}$$
$$E_{t'',s_M,s_P}^{min} \le E_{t'',s_M,s_P} \le E_{t'',s_M,s_P}^{max}$$
$$P_{t',s_M}^{reference} = P_{t'}^{energy} - \tilde{I}_{t',s_M}^{\uparrow} \cdot P_{t'}^{flex,\uparrow} + \tilde{I}_{t',s_M}^{\downarrow} \cdot P_{t'}^{flex,\downarrow}$$
$$\delta_{t',s_M,s_P} = P_{t'}^{estimation} - P_{t',s_M}^{reference}$$

Real-time Penalty

Same constraints from the DA flexibility offering problem



Model predictive control

Initial energy state (E_0)

Solve the ***RT flexibility dispatch optimization*** problem at time t'' to determine the $P_{t''}^{estimation,RT,*}$

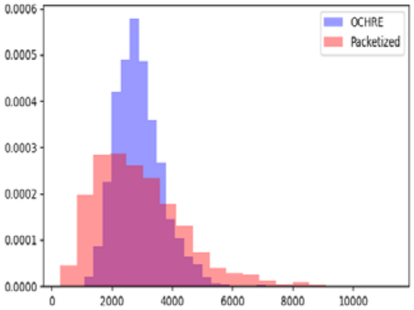
Run the ***priority stack-based control*** to decide the unit-level controls

Run OCHRE to get the actual power consumption ($P_{t''}^{actual}$) and updated energy state ($E_{t''}$)

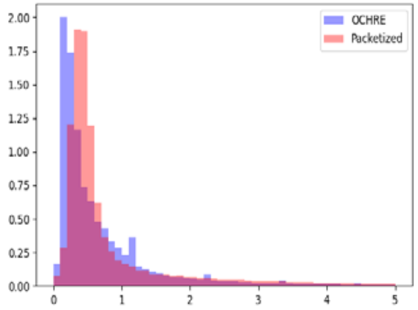
$E_{t''}$

Performance of the VBM

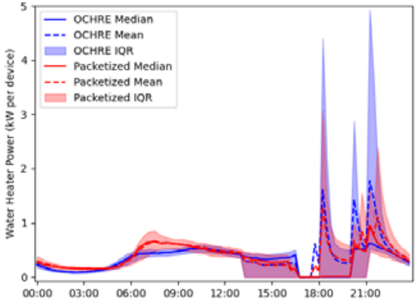
- A highly heterogeneous and uncertain water heaters fleet with 2000 units has been simulated using ***OCHRE.***
- With inputs from ***ResStock*** considering realistic assumptions on ***device heterogeneity*** and ***user behavior uncertainties*** in the New England area.
- Distributions of the simulated consumption data has been validated against ***field data*** collected by Packetized Energy.



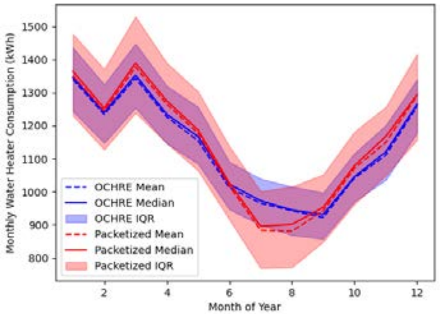
Annual energy consumption (kWh)



Event energy consumption (kWh)



Daily power consumption profiles (kW)

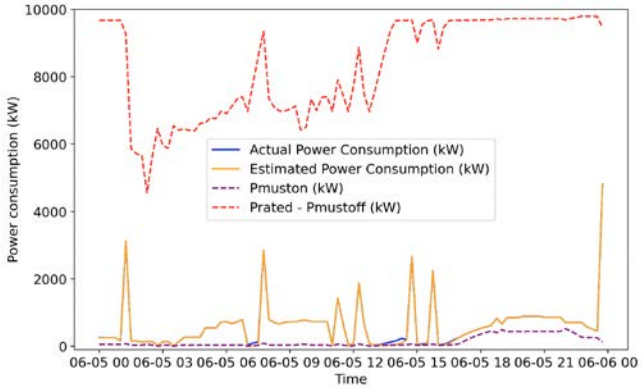


Monthly energy consumption profiles (kWh)

Performance of the VBM

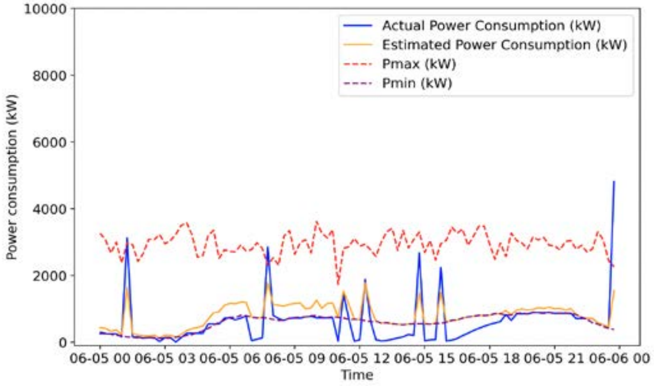
*Over a one-day period with **14,122.7 kWh** baseline energy consumption*

Proposed VBM



***191.27 kWh (1.4%)** delivery risk*

Baseline VBM



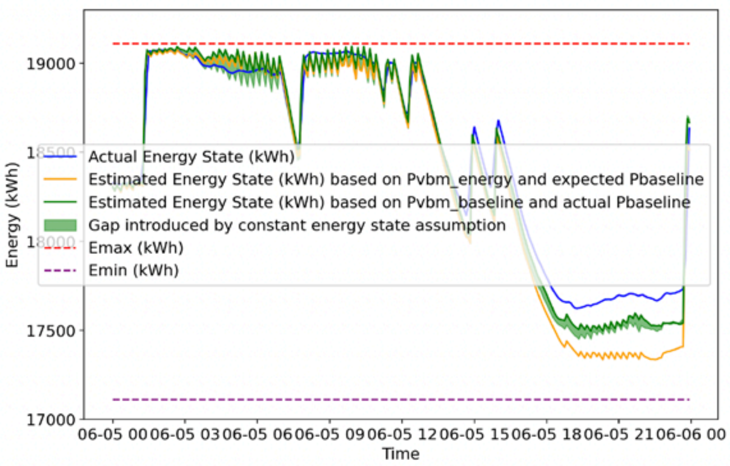
***8466.45 kWh (60.0%)** delivery risk*

Expected power consumption trajectories and power constraints obtained from two VBMs

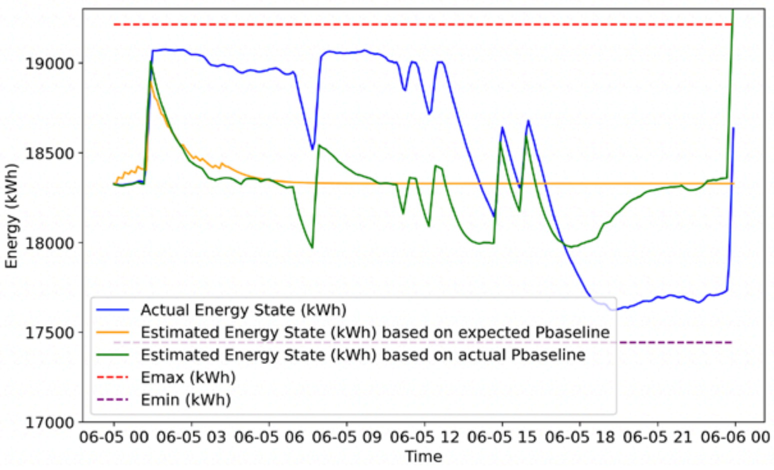
Performance of the VBM

*Over a one-day period with **14,122.7 kWh** baseline energy consumption*

Proposed VBM

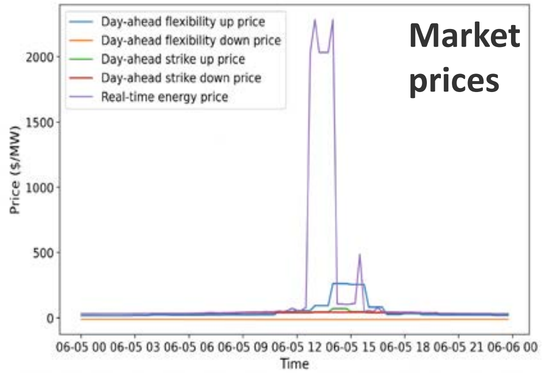


Baseline VBM

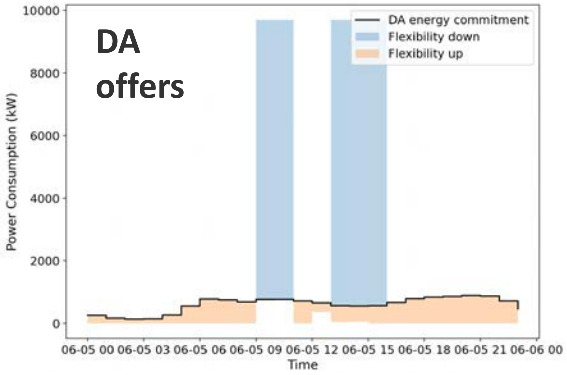


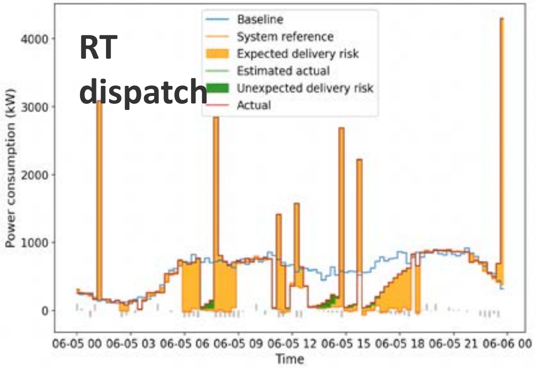
Expected energy state trajectories and energy constraints obtained from two VBMs

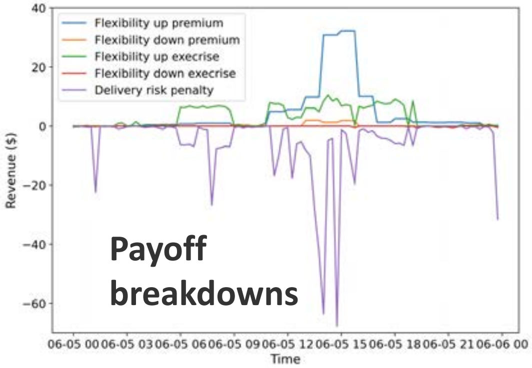
Performance of the DA Offering and RT Dispatch Results



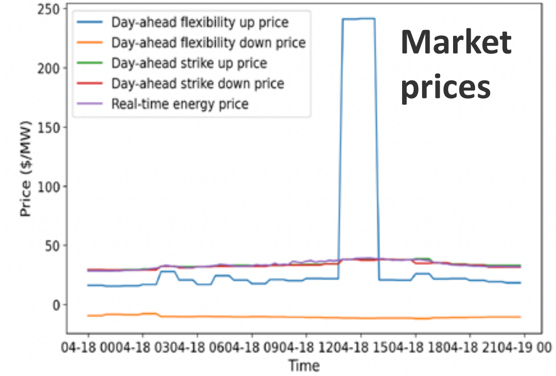
	With FO participation		No FO participation
	Expectation	Actual	
Option premium (DA)	$ 446.3		$0
Exercise payment (RT)	$292.7	$ 292.7	$0
Penalty (RT)	$ -345.5	$ -524.7	$0
Unexpected delivery risk (kWh)	0	191.27 kWh	0
Total payoff	$ 487.7	$308.4	$0



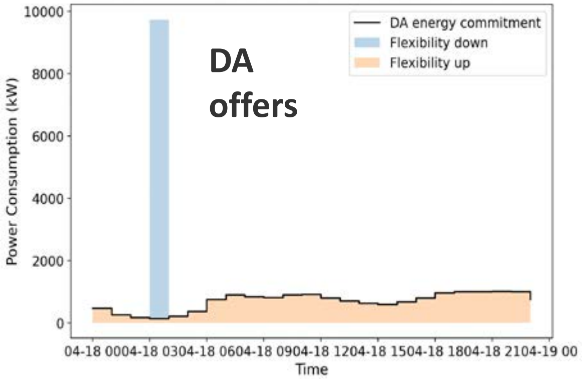


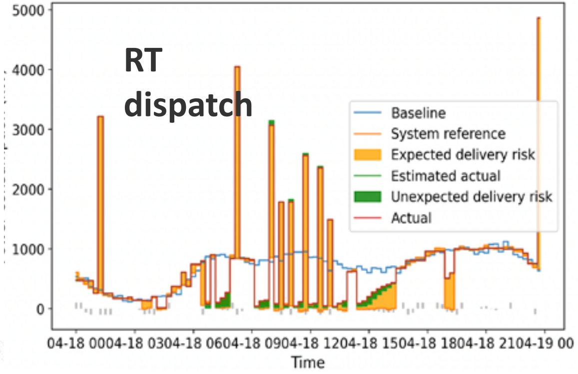


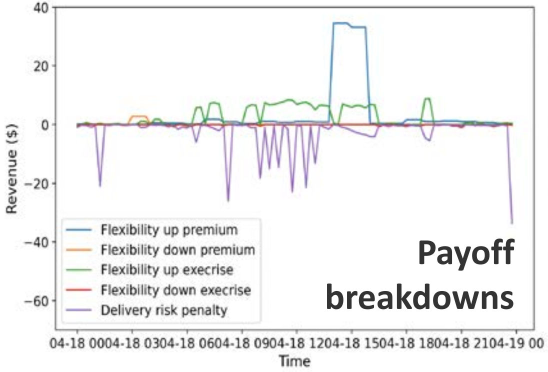
Performance of the DA Offering and RT Dispatch Results



	With FO participation		No FO participation
	Expectation	Actual	
Option premium (DA)	$ 339.5		$0
Exercise payment (RT)	$227.0	$ 227.0	$0
Penalty (RT)	$ -226.7	$ -260.4	$0
Unexpected delivery risk (kWh)	0	496.4 kWh	0
Total payoff	$339.8	$306.2	$0







Conclusion and Future Works

Conclusion

- An easily deployable ***virtual battery model*** has been proposed.
- An integrated ***delivery-risk-aware demand-side flexibility participation model*** has been derived.
- Performance of the proposed solution has been ***validated against a high-fidelity end use modeling tool*** taking highly heterogenous demand-side resource and realistic user behavior models into account.

Future work

- Integrating with price forecasting.
- Implementing DER scores-informed aggregations and analyzing how the DER scores can help improve the total payoff.
- Conduct annual simulation.
- Further improve performance of the delivery-risk-aware demand-side flexibility participation model through learning-based optimization.

Thank you

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Mengmeng.Cai@nrel.gov

Michael.Blonsky@nrel.gov

https://www.nrel.gov/grid/flare.html

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