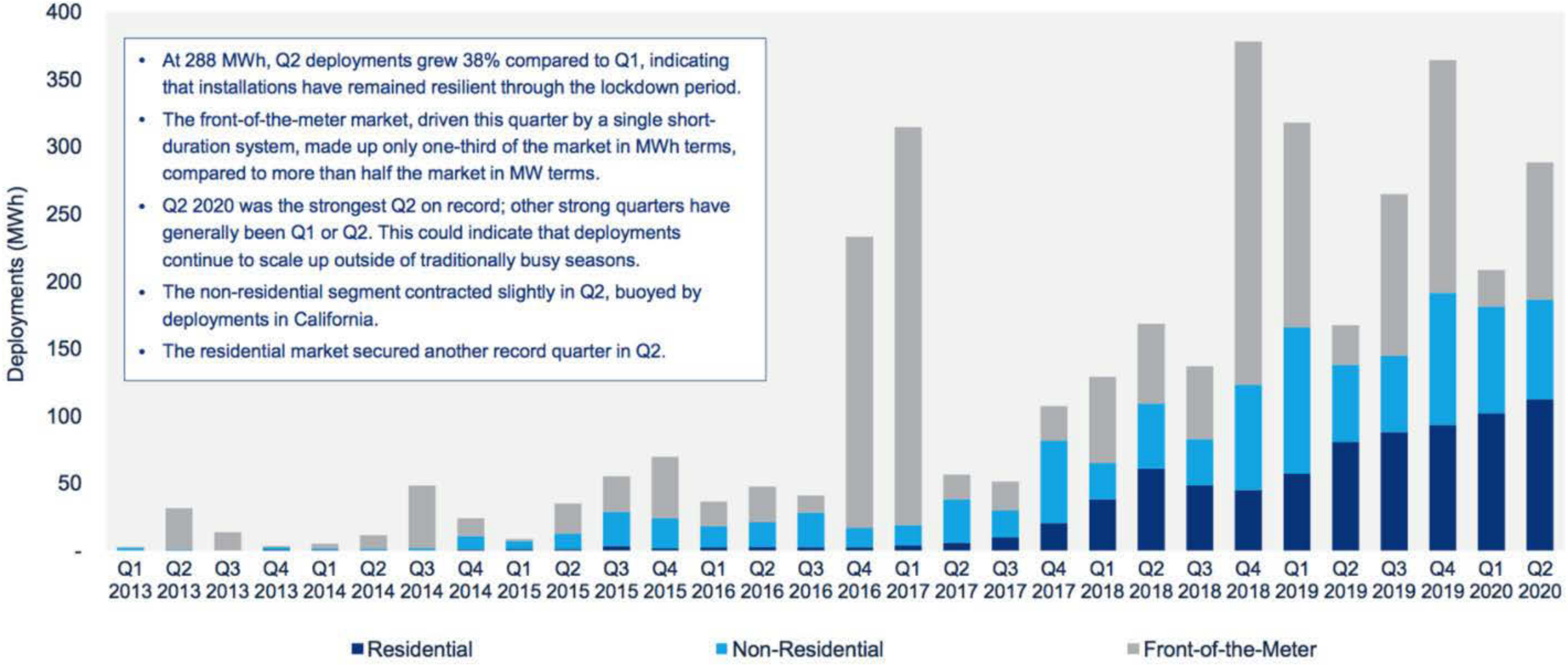
Battery Control Using Stochastic Model Predictive Control

Michael Blonsky

IEEE SmartGridComm 2020
November 11-13, 2020

U.S. market deployed 288 MWh in Q2 2020

Shorter-duration systems resulted in a MWh total that is still the fifth-highest on record

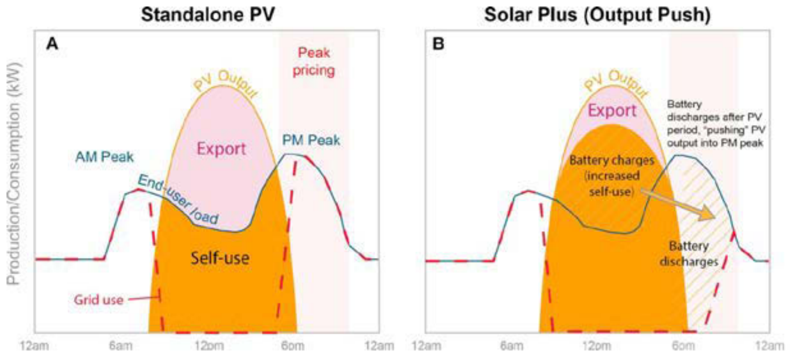


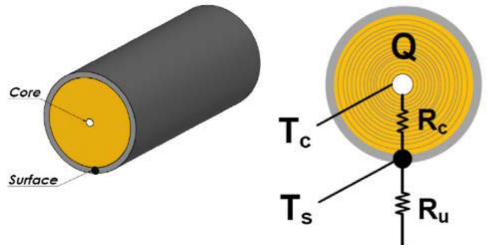
Source: WoodMac U.S. Energy Storage Monitor. https://www.woodmac.com/research/products/power-and-renewables/us-energy-storage-monitor/

Why use Behind-the-Meter Batteries?

- Control objectives:
  - Energy arbitrage
  - Demand charge reduction
  - Resilience
  - Reduced degradation

- Considerations:
  - Battery power and losses
  - Battery temperature
  - Building load



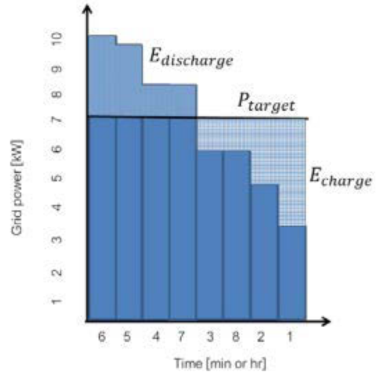


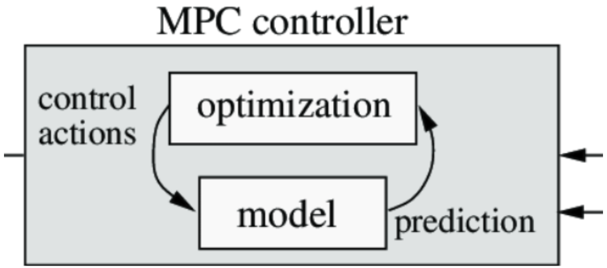
Sources:
E. O'Shaughnessy et al. https://www.sciencedirect.com/science/article/pii/S0306261918310766
X. Lin et al. http://dx.doi.org/10.1016/j.jpowsour.2014.01.097

Current Battery Controls

- Control methods:
  - Time-based schedule
  - Load following
  - Model predictive control (MPC)

- Current methods do not consider uncertainty in:
  - Building load
  - Battery temperature
  - Energy prices





Sources:
https://www.nrel.gov/docs/fy18osti/68614.pdf
https://www.researchgate.net/figure/Illustration-of-model-predictive-control_fig1_242397596

Proposed Control Framework

Proposed Model and Controller

- Stochastic Model Predictive Control (SMPC) for behind-the-meter stationary batteries
  - Gaussian distribution of inputs and states
  - Kalman Filter for state estimation

$$\frac{dSOC}{dt} = \eta_b \eta_i P_{\text{chg}} - \frac{1}{\eta_b \eta_i} P_{\text{dis}}$$

$$\frac{dT_b}{dt} = \frac{1}{C_{\text{th}}} \left((1 - \eta_b) P_{\text{chg}} + \frac{1 - \eta_b}{\eta_b} P_{\text{dis}} + \frac{T_a - T_b}{R_{\text{th}}} \right)$$

- Stochastic model includes:
  - Battery SOC
  - Battery temperature
  - Uncertainty in building load and ambient temperature
  - Measurement noise

$$\dot{x} = A_c x + B_c u + G_c z$$

$$x = \begin{bmatrix} SOC \\ T_b \end{bmatrix}, u = \begin{bmatrix} P_{\text{chg}} \\ P_{\text{dis}} \end{bmatrix}, z = \begin{bmatrix} T_a \\ P_{\text{load}} \end{bmatrix}$$

SMPC Formulation

- Objective includes:
  - Time-varying rate
  - *Demand charge
  - Degradation costs
  - Benefit of remaining SOC

- Constraints include:
  - Non-negativity constraints
  - SOC bounds
  - *Max temperature bound
  - State equation

* includes back-off magnitude

$$
\begin{aligned}
J = &\sum_{k=1}^{n_k} c_{\text{tou},k} T_s \overline{P}_{\text{tot},k} \\
&+ c_{\text{peak}} \max_{k\in[1,n_k]} \left(\overline{P}_{\text{tot},k} - P_{\text{peak},0} + \zeta_P \sigma_{P_{\text{load},k}}, 0\right) \\
&+ \beta_P \sum_{k=1}^{n_k} \left(P_{\text{chg},k}^2 + P_{\text{dis},k}^2\right) \\
&+ \beta_T \sum_{k=1}^{n_k} \max\left(\overline{T}_{b,k} - T_{\text{high}}, 0\right)^2 \\
&+ c_{\text{tou},n_k} \eta_b \eta_i \overline{SOC}_{n_k}
\end{aligned}
$$

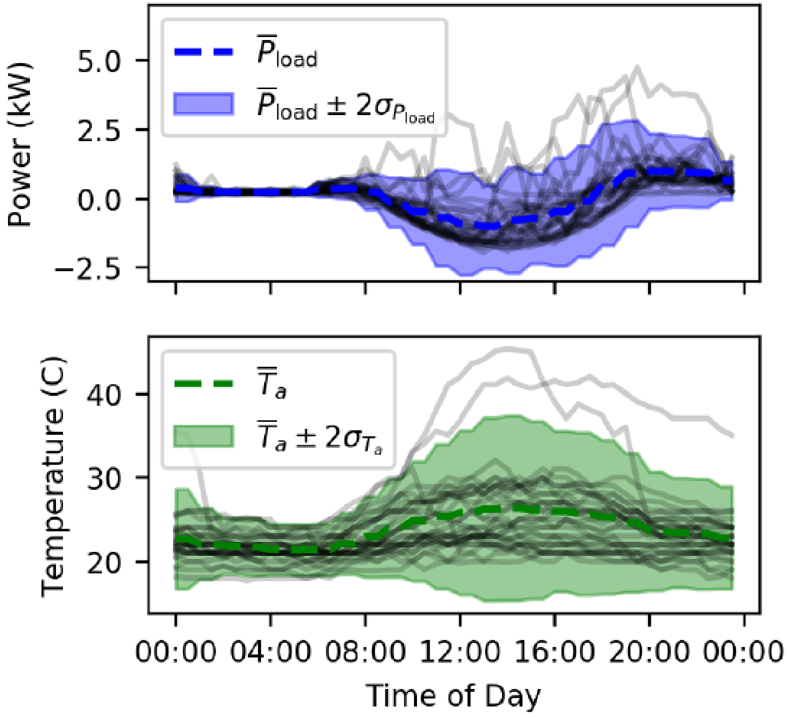
$$
\begin{aligned}
&u_k \geq 0 \\
&SOC_{\min} \leq \overline{SOC}_k \leq SOC_{\max} \\
&\overline{T}_{b,k} \leq T_{\max} - \zeta_T \sigma_{T_{b,k}} \\
&\overline{x}_k = A\overline{x}_{k-1} + Bu_{k-1} + G\overline{z}_{k-1} \\
&\forall k \in [1, n_k]
\end{aligned}
$$

Results

Results

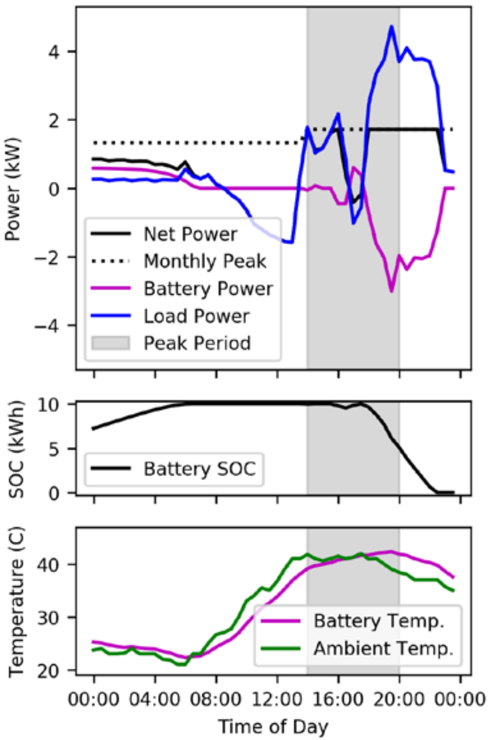
- Tested control algorithms:
  - MPC, perfect forecast
  - MPC, baseline forecast
  - SMPC, baseline forecast
  - SMPC, with high risk
  - SMPC, with AR Model
  - SMPC, with high risk + AR Model

- Scenario parameters:
  - 1 residential customer with PV
  - TOU rate
  - 1-month period for demand charge
  - 30-min time resolution
  - 24-hour horizon

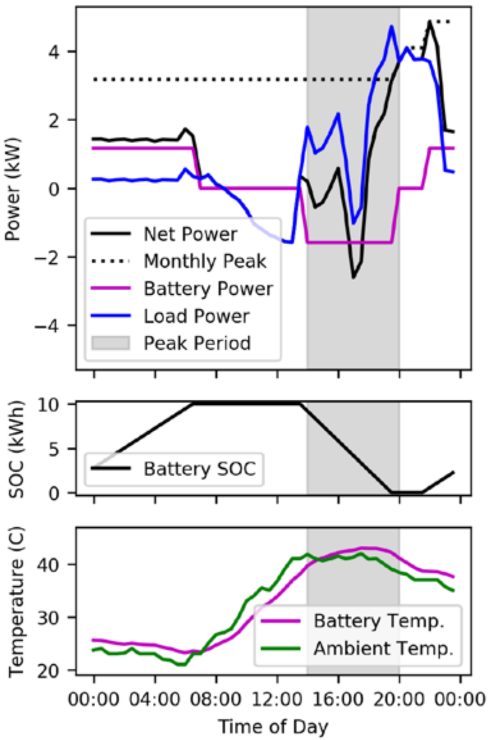


Results: MPC vs. SMPC

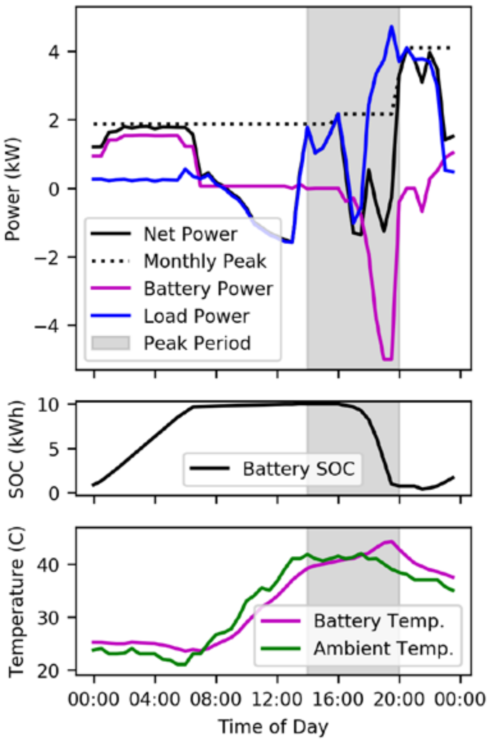
MPC – Perfect



MPC – Baseline

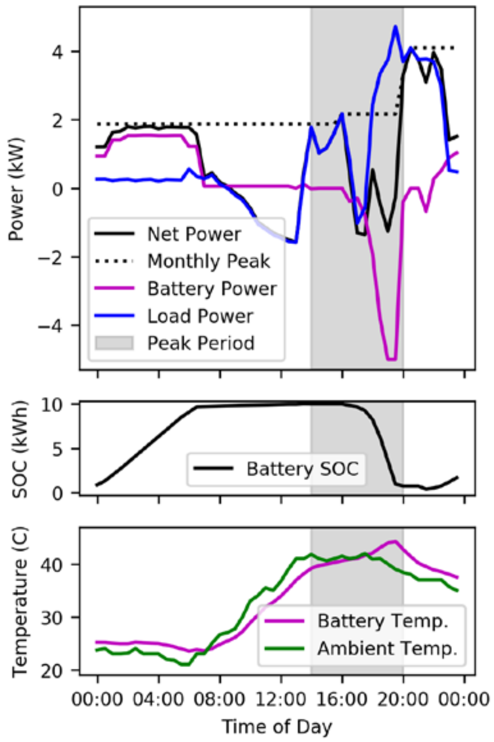


SMPC – Baseline

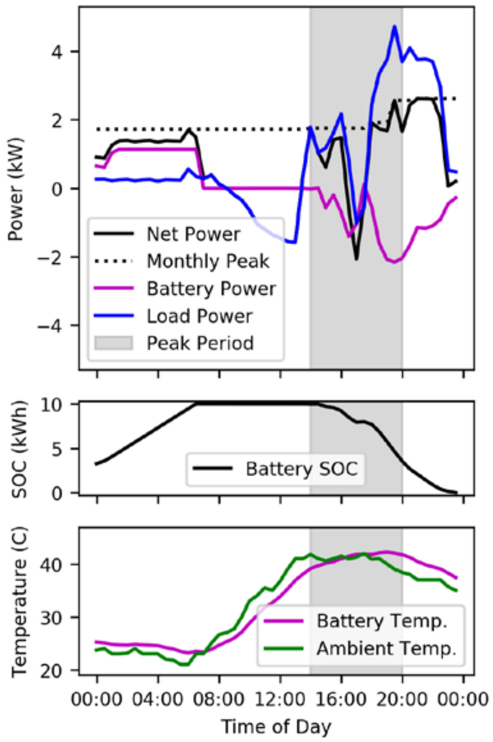


Results: Forecast Accuracy and Risk Tolerance

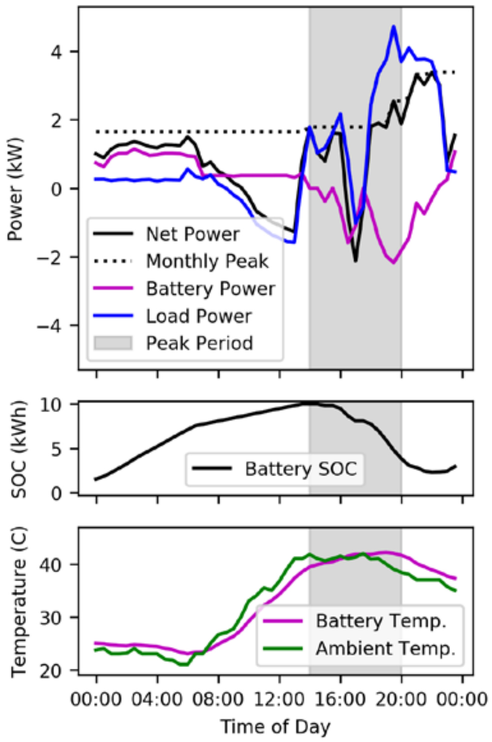
SMPC – Baseline



SMPC – AR Model



SMPC – AR + High Risk



Results: Cost Comparison

Scenario	TOU Cost	Demand Cost	Other Costs	Total Cost
No Battery	$-2.01	$40.47	$0	$38.47
Perfect Forecast	$-26.62	$14.74	$10.81	$-1.07
MPC Baseline	$-33.20	$41.64	$11.50	$19.94
SMPC Baseline	$-31.17	$35.07	$11.10	$15.01
SMPC, High Risk	$-32.89	$35.07	$11.23	$13.41
SMPC, AR Model	$-23.62	$25.96	$10.49	$12.83
AR + High Risk	$-30.65	$29.52	$10.69	$9.56

Conclusions

- Proposed method includes:
  - Thermo-electric battery model
  - Stochastic MPC battery control with TOU and demand charge costs
- Findings:
  - SMPC performs better than MPC with uncertainty in the forecast
  - Reducing forecast uncertainty improves SMPC performance
  - SMPC enables risk tolerance to vary the performance of relative costs

Thank You

www.nrel.gov

Michael Blonsky

Research Engineer | Power Systems Engineering Center

Michael.Blonsky@nrel.gov

NREL/PR-5D00-79754

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

NREL

Transforming ENERGY