Risk-Averse Model Predictive Control Design for Battery Energy Storage Systems

David Rosewater, Member, IEEE, Ross Baldick, Fellow, IEEE, and Surya Santoso, Fellow, IEEE

Abstract—When batteries supply behind-the-meter services such as arbitrage or peak load management, an optimal controller can be designed to minimize the total electric bill. The limitations of the batteries, such as on voltage or state-of-charge, are represented in the model used to forecast the system's state dynamics. Control model inaccuracy can lead to an optimistic shortfall, where the achievable schedule will be costlier than the schedule derived using the model. To improve control performance and avoid optimistic shortfall, we develop a novel methodology for high performance, risk-averse battery energy storage controller design. Our method is based on two contributions. First, the application of a more accurate, but non-convex, battery system model is enabled by calculating upper and lower bounds on the globally optimal control solution. Second, the battery model is then modified to consistently underestimate capacity by a statistically selected margin, thereby hedging its control decisions against normal variations in battery system performance. The proposed model predictive controller, developed using this methodology, performs better and is more robust than the state-of-the-art approach, achieving lower bills for energy customers and being less susceptible to optimistic shortfall.

Index Terms—Batteries, distributed energy resources, battery energy storage system (BESS), state-of-charge (SoC), energy storage, optimal control, model predictive control, load management.

NOMENCLATURE

Symbol | Decision variable description
---|---
$p$ | - ac power variable to the BESS
$P_{dc}$ | - dc power variable to the battery
$i_{bat}$ | - dc current variable to the battery
$v_{bat}$ | - battery terminal voltage
$v_s$ | - battery terminal slack voltage
$v_l$ | - dynamic battery voltage
$V_{oc}$ | - open-circuit-voltage
$s$ | - state-of-charge (“sigma”)
$\tau$ | - peak net electrical load (“tau”)

Vector, vector equation, and matrix equation notation

- If $z$ is a decision variable, $z \in \mathbb{R}^m$ is a column vector of $m$ decision variables. This is normally used to indicate decision variables at discrete times (e.g., $p$ at each time-step in a control horizon becomes $P$).
- The expression $z_{1:3}$ produces a column vector with the elements of $z$ indicated by the index(es) (in this case, the first three elements).
- The expression $z + y$ produces a column vector that is the element-wise addition of the vectors $z$ and $y$.
- For the scalar value $b$, the expression $b[1]$ denotes the multiplication of the constant $(b)$, times a vector of ones $[1]$, that produces a column vector populated with $b$.
- The vector equation $z + y = b[1]$ denotes $n$ equations, each with indexed variables (a.k.a, $z_{1}[1] + y_{1}[1] = b$, $z_{2}[2] + y_{2}[2] = b$, etc.)
- The matrix equation $A[z, y]T \leq b[1]$, where $A \in \mathbb{R}^{m \times 2}$ and $b \in \mathbb{R}^{m \times 1}$, denotes $m \times n$ equations, each with indexed variables (a.k.a, $A_{[1,1]}z_{1}[1] + A_{[1,2]}y_{1}[1] \leq b_{1}[1]$, $A_{[2,1]}z_{1}[2] + A_{[2,2]}y_{1}[2] \leq b_{1}[2]$, $A_{[1,1]}z_{2}[1] + A_{[1,2]}y_{2}[2] \leq b_{2}[1]$, etc.)

Parameters

All parameters can be found in Tables I–V.

I. INTRODUCTION

Battery Energy Storage Systems (BESS) are becoming an integral part of a resilient and efficient electrical system. Distributed energy resources (DER) such as BESS are able to support the grid through advanced control and functionality [1]. In addition to responding to local conditions of voltage and frequency, energy management systems can forecast future conditions of variables such as price and load to optimally schedule BESS operation. The time-of-use (ToU) and peak demand charge billing mechanisms are driving the adoption of BESS in commercial applications in many areas [2]. Both TOU and demand charge rate structures incentivize customers to, in aggregate, reduce system peak demand, allowing a utility to defer or avoid costly capacity upgrades [3]. A primary concern in both applications is how to make control decisions that maximize the value of the BESS to...
A common approach to controller design is called model predictive control (MPC). MPC is a real-time, state-feedback, optimal control approach that involves solving a finite-horizon online optimization problem at each time step that results in a sequence of future control actions as well as predictions of the future states [7]–[9]. In designing MPC, the choice of what model to use can be critical. The simplest BESS model assumes that changes in SoC are proportional to the energy charged or discharged from ac point of interconnection. This approach to optimal control represents the state-of-the-art and has been used for improving wind farm dispatch in Australian electricity markets [10], and achieving distribution feeder dispatchability [11]. Another common approach, based on the need for improved accuracy, is to use a BESS model that assumes that changes in SoC are proportional to the charge, in amp-hours, supplied or absorbed by the battery itself. While it has been used [12]–[14], this approach can be difficult because the feasible subspace it defines is fundamentally non-convex. Historically, the only way to apply the more accurate model to calculate optimal control schedules was to either approximate the model using pseudospectral methods [12], or to use dynamic programming [13], [14]. Further, given the precision of this type of model, the performance of optimal controllers that rely on it can be sensitive to variations in battery performance.

This paper makes two fundamental contributions to the state-of-the-art: 1) formulation of an optimal controller for a residential lithium-ion battery system, based on the more accurate charge reservoir model (Section III) with upper and lower bounds to check the viability of solutions found through gradient based methods (Section V), and 2) a method to modify the controller to be risk-averse to variations in battery performance (Section VI). In Section VII we demonstrate the improved controller performance, due to using the more accurate model, and demonstrate how the risk-averse modification makes it more robust to model uncertainty. Together, these contributions make up an advanced methodology for designing BESS controllers that perform better and are more robust than those designed through traditional methods. Section VIII concludes with a summary of the assumptions that we use for our case study and a discussion of the results obtained.
the paper with a summary of the results and a discussion of the broad applicability of the proposed control design approach.

II. ENERGY RESERVOIR MODEL

Energy Reservoir Model (ERM) refers to a class of models that calculates SoC as a function of energy into and out of the BESS. The ERM is widely used in battery energy storage control problems [10], [11], [15]–[17] and has the advantage of being linear in charge and discharge power. This allows for convex, and therefore computationally efficient, formulations of the optimal control problem. The ERM formulation used here is shown in (3). Definitions for parameters are given in Table II.

\[
\min_{x \in \mathbb{R}^{n+2}} \Delta t c^T (l + \mathbf{p}^+ + \mathbf{p}^-) + \tau d + \Pi_1 \| \mathbf{p}^+ + \mathbf{p}^- \|^2_2 
\]

subject to:

\[Q_{\text{cap}} \mathbf{D} \mathbf{z} = \eta_e \mathbf{p}^+ + \mathbf{p}^-\]  
\[s_{[1]} = s_0\]  
\[s_{[1]} = s_{[n]}\]  
\[0 \leq \mathbf{p}^+ \leq p_{\text{max}}[1]\]  
\[p_{\text{min}}[1] \leq \mathbf{p}^- \leq 0\]  
\[s_{\text{min}}[1] \leq \mathbf{s} \leq s_{\text{max}}[1]\]  
\[1 + \mathbf{p}^+ + \mathbf{p}^- \leq \tau[1]\]

where \(x = \{ \mathbf{p}^+, \mathbf{p}^-, \mathbf{s}, \tau \} \in \mathbb{R}^{n+2}, \mathbf{p}^+ \in \mathbb{R}_+^n\) is the ac electrical power discharged from the battery system, \(\mathbf{s} \in \mathbb{R}^{n+1}\) is the SoC, \(\tau \in \mathbb{R}\) is the peak demand power and the differential matrix \(D\) is shown in (4).

\[
D = \frac{1}{\Delta t} \begin{bmatrix}
-1 & 1 & 0 & \cdots & 0 \\
0 & -1 & 1 & 0 & \cdots \\
\vdots & \ddots & \ddots & \ddots & \ddots \\
0 & 0 & -1 & 1 & \cdots \\
\end{bmatrix}_{n \times (n+1)}
\]

An \(\ell_2\) norm regularization is applied in (3a) and scaled by the constant \(\Pi_1\) to even out peak battery power when it is not needed. The constraint (3b) ensures that control decisions are made based on the current estimated SoC (\(s_0\)). The constraint (3c) represents the intuitive assumption that the BESS will continue to operate after the end of the current control horizon and that the next period will be similar to this one. While not necessary in closed-loop implementation, (3c) makes simulation results easier to interpret and compare.

III. CHARGE RESERVOIR MODEL

Charge Reservoir Model (CRM) refers to a class of models that calculates SoC as a function of charge (current integrated over time) into and out of the battery itself. The CRM is also used in battery energy storage control problems and has the advantage of being more accurate over a longer time horizon or over larger range of SoC [12]. The disadvantage of the CRM is that the subspace of feasible solutions is fundamentally non-convex. Therefore, it is more computationally complex and difficult integrate into an on-board controller [13]. The CRM formulation used here is shown in (5). The parameters for this model are listed in Table III.

\[
\min_{\mathbf{x}_c \in \mathbb{R}^{8n+3}} \Delta t c^T (l + \mathbf{p}) + \tau d + \Pi_1 \| \mathbf{p} \|^2_2 + \Pi_2 \| \mathbf{v}_s \|_1 
\]

subject to:

\[\phi_0 \mathbf{p}^2 + \phi_1 \mathbf{p} + \phi_2 \geq \mathbf{p}_{\text{dc}}\]  
\[\mathbf{p}_{\text{dc}} = (i_{\text{bat}}^+ + i_{\text{bat}}^-) v_{\text{bat}}\]  
\[v_{\text{bat}} = v_{oc}[1] + R_0(i_{\text{bat}}^+ + i_{\text{bat}}^-) + \mathbf{v}_s\]  
\[v_{oc} = \alpha \mathbf{s}^2 + \beta \mathbf{s} + \gamma \mathbf{s} + \delta\]  
\[C_{\text{cap}} \mathbf{D} \mathbf{z} = \eta_e i_{\text{bat}}^+ + i_{\text{bat}}^-\]  
\[s_1 = s_0\]  
\[s_1 = s_{n+1}\]  
\[p_{\text{min}}[1] \leq \mathbf{p} \leq p_{\text{max}}[1]\]  
\[s_{\text{min}}[1] \leq \mathbf{s} \leq s_{\text{max}}[1]\]  
\[v_{\text{min}}[1] \leq v_{\text{bat}} \leq v_{\text{max}}[1]\]  
\[\mathbf{0} \leq i_{\text{bat}}^+ \leq i_{\text{max}}[1]\]  
\[i_{\text{min}}[1] \leq i_{\text{bat}}^+ \leq 0\]  
\[1 + \mathbf{p} \leq \tau[1]\]

where \(\mathbf{x}_c = \{ \mathbf{p}, \mathbf{p}_{\text{dc}}, i_{\text{bat}}^+, i_{\text{bat}}^-, \mathbf{v}_{\text{bat}}, \mathbf{v}_s, v_{oc}, \mathbf{z}, \tau \} \in \mathbb{R}^{8n+3}, \mathbf{p}_{\text{dc}} \in \mathbb{R}^n\) is the dc electrical power provided to battery, \(v_{\text{bat}} \in \mathbb{R}^n\) is the battery terminal voltage, \(\mathbf{v}_s \in \mathbb{R}_+^n\) is the slack voltage used in calculation of an upper bound, \(v_{oc} \in \mathbb{R}^{n+1}\) is the battery open-circuit voltage, and \(\tau \in \mathbb{R}\) is the peak power demand. The CRM objective includes a \(\ell_2\) norm power regularization and an \(\ell_1\) norm slack voltage cost, weighted by the constant \(\Pi_2\). The weight \(\Pi_2\) is chosen, using a simple trial and error sweep, to be the smallest value that is still large enough to drive the slack voltage to zero under normal operation. The CRM includes constraints on inverter conversion efficiency (5b), Ohm’s law relating dc power, voltage and current (5c), the battery equivalent circuit model (5d), and the open-circuit voltage curve (5e). Note that the inverter conversion efficiency (5b) is a convex inequality that collapses to an equality as long as energy prices in the objective are positive. This model uses the big cell method discussed in [18]. These additional parameters and constrains allow the CRM to more accurately represent the physical dynamics of battery systems.

IV. EXTENDED CRM FOR SIMULATION

To perform a pseudo-empirical analysis of the optimal schedules calculated from each model we simulate how the battery system would respond to each control signal using an extended CRM that incorporates additional constraints and parameters to improve its accuracy. The simulation model uses

| Name                          | Symbol | Value         |
|-------------------------------|--------|---------------|
| Energy Capacity*              | \(Q_{\text{cap}}\) | 5.944 kWh    |
| Energy Efficiency*            | \(\eta_e\) | 61.7%        |
| Maximum Power Discharge       | \(p_{\text{max}}\) | 7 kW         |
| Maximum Power Charge          | \(p_{\text{min}}\) | 7 kW         |
| Maximum SoC                   | \(s_{\text{max}}\) | 95%          |
| Minimum SoC                   | \(s_{\text{min}}\) | 20%          |
| Regularization Weight         | \(\Pi_1\) | 0.001 $/kW^2$ |

* derived from experimental analysis on a residential lithium-ion battery system
Fig. 2. Open-circuit voltage constraint satisfying (5e).

TABLE III
CHARGE RESERVOIR MODEL PARAMETERS

| Name                           | Symbol | Mean | σ     |
|--------------------------------|--------|------|-------|
| Charge Capacity*              | C_{cap} | 135.2 Ah | 2.6 Ah |
| Coulombic Efficiency*         | η_{c}  | 94.6% | 0.74% |
| Inverter Efficiency Coefficient* | φ_{I} | -4.7865e-07 |
| Inverter Efficiency Coefficient* | φ_{P} | 0.99107 |
| Battery Internal Resistance*  | R_{0}  | 15.35 mΩ | 0.34 mΩ |
| Maximum Power Discharge       | P_{max} | 7 kW |
| Maximum Power Charge          | P_{min} | 7 kW |
| Maximum SoC                   | v_{max} | 95% |
| Minimum SoC                   | v_{min} | 20% |
| Maximum Battery Voltage       | v_{max} | 58.8 V |
| Minimum Battery Voltage       | v_{min} | 46.2 V |
| Maximum Current Discharge     | i_{max} | 150 A |
| Maximum Current Charge        | i_{min} | 150 A |
| Regularization Weight         | Π_{1}  | 0.001 $/kW^2$ |
| Slack Voltage Weight          | Π_{2}  | 0.035 $/V^2$ |

TABLE IV
ADDITIONAL EXTENDED CRM PARAMETERS

| Cubic Spline Fit*             | Symbol | Value |
|-------------------------------|--------|-------|
| Dynamic Resistance*           | R_{1}  | 0.491 Ω |
| Dynamic Capacitance*          | C_{1}  | 1.019 F |
| 0.19 ≤ ζ ≤ 0.263             | α      | -59.303 |
| 0.263 ≤ ζ ≤ 0.340             | β      | 5.4337 |
| 0.340 ≤ ζ ≤ 0.416             | γ      | 6.6949 |
| 0.416 ≤ ζ ≤ 0.492             | δ      | 49.7 |
| 0.492 ≤ ζ ≤ 0.568             | -      | 5.306 |
| 0.568 ≤ ζ ≤ 0.643             | -      | 51.171 |
| 0.643 ≤ ζ ≤ 0.720             | -      | 51.553 |
| 0.720 ≤ ζ ≤ 0.795             | -      | 52.14 |
| 0.795 ≤ ζ ≤ 0.869             | -      | 53.215 |
| 0.869 ≤ ζ ≤ 0.95              | -      | 54.192 |

slightly different functions and parameters, enabling an analysis of the effects of model and parameter uncertainty on controller performance. The modified constraints are shown in (6). The parameters for these modified constraints are shown in Table IV.

\begin{align}
\text{v}_{\text{bat}} &= v_{\text{oc}} + R_{0}(i_{\text{bat}}^+ + i_{\text{bat}}^-) \\
\text{Dv}_{1} &= \frac{1}{R_{1}C_{1}}v_{1} + \frac{1}{C_{1}}(i_{\text{bat}}^+ + i_{\text{bat}}^-) \\
\text{v}_{\text{oc}} &= α(ζ)(ζ - ζ(ζ))^3 - β(ζ)(ζ - ζ(ζ))^2 \\
&\quad -γ(ζ)(ζ - ζ(ζ)) - δ(ζ)
\end{align}

where $v_{1} \in \mathbb{R}^n$ is the dynamic voltage component of the battery’s terminal voltage, $ζ: [0, 1] \mapsto [0, 1]$ is a piecewise constant function whose value is equal to the start of each SoC range when passed values within the range. For example, $ζ(0.22) = 0.19$, and $ζ(0.32) = 0.263$. This is a common approach to implementing cubic-splines that keeps coefficient magnitudes relatively low. The extended CRM uses (5b), (5c), and (5f) through (5n) from base model. Constraint (5d) is modified to (6a) and the additional constraint (6b) is added to represent the dynamic response of battery voltage to changes in current. Note that the slack voltage is not needed this model as it is only used for simulation. Constraint (5e) is then modified to (6c) to more closely approximate the relationship between SoC and open-circuit voltage with a piecewise cubic-spline fit, as has been shown to be highly accurate [19].

The simulation timestep is 1 second, meaning that it is executed 900 times between controller time steps (with $Δt = 15$ minutes). The extended CRM is implemented in simulation using the Battery-Inverter fleet model discussed in [20]. The resulting schedules are distinguished by the tags ‘calculated’, which stands for the optimal schedules calculated using the ERM or CRM, and ‘achieved’, which stands for the results of simulating the calculated schedule using the extended CRM. The discrepancy between ‘calculated’ and ‘achieved’ schedules is a result of inaccurate parameters and unrepresented battery system characteristics in the ERM and CRM models.

V. Bounding the Global Minimum

The nonlinear CRM optimization problem shown in (5) is non-convex. Further, it can be shown that the Lagrangian of this problem is not pseudoconvex as defined in [21]. If it had either of these properties then we would know that any minimum found would be in the set of global minima but as it is, we cannot make this guarantee. Because of this some argue that gradient based methods such as Newton-Raphson are not viable for CRM optimization due to local minima in the solution space [14]; however, we find this not to be the case. Our contribution to the state-of-the-art is to bound the global minimum of this problem such that if we find a local minimum inside this range, we can be confident that it is, or is close to, the globally optimal solution. An upper bound to a minimization problem can be found by restricting the feasible set (adding additional constraints) while a lower bound can be calculated by expanding the feasible set (relaxing or removing constraints) [22].

To calculate a convex lower bound we relax the non-convex constraints to their convex hulls. First, the constraint (5b) is modified to the include positive and negative dc power (7a). We then relax the ohm’s power law constraint (5c) to a convex space bounded by eight affine surfaces as shown in Fig. 3 and represented in (7b) and (7c). To do this while maintaining feasibility we split the dc power into separate positive and negative decision variables. Finally, we relax the open-circuit-voltage constraint (5e) to the convex hull shown in Fig. 2.
and represented in (7d). The resulting convex problem in (7) provides a lower bound on the global minimum of (5).

\[
\min_{x_c} \Delta T e^T (l + p) + \tau d + \Pi_1 ||p||_2^2 + \Pi_2 ||v_s||_1
\]
\[
x_c \in \mathbb{R}^{n+3}
\]
\[
p_{dc}^+ \in \mathbb{R}^n
\]
\[
p_{dc}^- \in \mathbb{R}^n
\]

subject to: (5d) and (5f) through (5n) unchanged

restricting (5c) \( p_{dc} = (i_{bat}^+ + i_{bat}^-)v_{ocmin} \) (8a)

restricting (5d) \( v_{ocmin} = v_{oc[1:n]} + \rho_0 (i_{bat}^+ + i_{bat}^-) + v_s \) (8b)

approx. (5e) \( v_{oc} = v_{ocmin}[1] + v_1 + v_2 + v_3 + v_4 + v_5 \) (8c)

\[
\varsigma = \varsigma_{min}[1] + \varsigma_1 + \varsigma_2 + \varsigma_3 + \varsigma_4 + \varsigma_5
\]

\[
[v_1, v_2, v_3, v_4, v_5]^T = A_1[\varsigma_1, \varsigma_2, \varsigma_3, \varsigma_4, \varsigma_5]^T
\]

\[
5_{seg} w_1 \leq \varsigma_1 \leq 5_{seg}
\]

\[
5_{seg} w_2 \leq \varsigma_2 \leq 5_{seg} w_1
\]

\[
5_{seg} w_3 \leq \varsigma_3 \leq 5_{seg} w_2
\]

\[
0 \leq \varsigma_4 \leq 5_{seg} w_3
\]

\[
0 \leq \varsigma_5 \leq 5_{seg} w_4
\]

where \( v_1, v_2, v_3, v_4, v_5 \in \mathbb{R}^n \) are the linear segment voltages, \( \varsigma_1, \varsigma_2, \varsigma_3, \varsigma_4, \varsigma_5 \in \mathbb{R}^n \) are the linear segment states-of-charge, \( w_1, w_2, w_3, w_4 \in [0, 1]^n \) are Boolean variables that ensure that the segments maintain correct ordering.

With these bounds and properties established, we can use an off-the-shelf primal-dual, interior-point method to solve the optimal control problem using the CRM. The freely downloadable modeling language Pyomo [23], [24] and nonlinear solver Ipopt [25] are used to implement this algorithm efficiently and the code and data we used are available as supplemental material attached to the digital version this article. The nonlinear solver Gurobi is used for calculation of the upper bound as it is able to efficiently work with integer variables [26].

VI. REDUCING CONTROL SENSITIVITY TO UNCERTAINTY

Parameters such as capacity are functions of many physical mechanisms we do not consider in the model. To consider

![Fig. 3. Convex Relaxation of Ohms Power Law (5c), split between positive and negative current.](image-url)
Fig. 4. Notional examples of risk-neutral and risk-averse control bill savings probability density functions.

Fig. 5. Relative benefits of risk-averse control based on model accuracy/precision, given an asymmetric risk application.
**TABLE VI**

**SUMMARY OF RESULTS FROM SIMULATED CONTROL SCENARIOS**

| Controller Scenario | Sim-Model* | Total Bill | % Savings | Optimistic Shortfall** |
|---------------------|------------|------------|-----------|------------------------|
| Baseline            | –          | $310.88    | –         | –                      |
| ERM OL Cal          | –          | $274.91    | 11.6%     | –                      |
| ERM OL Ach mean     | –          | $273.93    | 11.9%     | –0.98                  |
| ERM CL Ach mean     | –          | $273.56    | 12.0%     | –1.35                  |
| ERM CL Ach extreme  | –          | $273.69    | 12.0%     | –1.32                  |

**upper bound**

| CRM OL Cal          | –          | $269.55    | 13.3%     | –                      |
| CRM OL Ach mean     | –          | $274.98    | 11.5%     | $5.43                  |
| CRM CL Ach mean     | –          | $269.55    | 13.3%     | $0.00                  |
| CRM CL Ach extreme  | –          | $292.53    | 5.9%      | $22.98                 |

**lower bound**

| RA CRM OL Cal       | –          | $271.22    | 12.8%     | –                      |
| RA CRM OL Ach mean  | –          | $271.17    | 12.8%     | –0.05                  |
| RA CRM CL Ach mean  | –          | $271.08    | 12.8%     | –0.14                  |
| RA CRM CL Ach extreme | –         | $271.21    | 12.8%     | –0.01                  |

✓ denotes that the solution to the non-convex problem satisfies the bound

* The extended CRM is used to simulate the BESS being controlled. It’s parameters are selected to represent average behavior ‘mean’, or ‘extreme case’ lower than normal available energy as described in Section VI

** Optimistic Shortfall compares the bill achieved by applying control action to the simulated BESS to the open-loop calculated bill from each controller

Cal - calculated, Ach - achieved, OL - open-loop, CL - closed-loop, RA - risk-averse

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A. Open-Loop Control

The optimal ‘calculated’ schedules, along with the ‘achieved’ schedules, for the customer using the ERM and CRM in open-loop are shown in Fig. 6. The resulting net load curves for their control schedules are shown in Fig. 7 and 8. While the ERM is clearly more computationally efficient than the CRM, optimal schedules can be calculated using either model in just a few seconds on a mid-range laptop (hardware used for this study: i7-7600U CPU at 2.8 GHz) meaning either approach could be used for on-board control.

For the customer introduced in Section I, the baseline cost of electrical service is $311 ($61 energy, $250 peak demand). The schedule calculated using the ERM reduces this by 11.6% to $275. The schedule calculated using the CRM reduces the cost of electrical service by 13.3% to $270. These bill reductions come primarily from the BESS reducing the peak electrical load by 14.38% (ERM) and 16.0% (CRM) respectively. As this bill falls between the calculated upper and lower bounds on the global minimum, we are confident that the minimum calculated is, or is close to, the global. While a $5 improvement in savings over the ERM does not sound significant in absolute terms, it is important to remember the scale of power systems. With approximately 5 million commercial customers in the U.S. currently eligible for tariffs with a demand charge rate of at least $15/kW [6], a 14.7% improvement in cost savings, over the ERM, from a simple change in software would have a significant impact. Note that a IEEE 1547-2018 compliant inverter would be able support local grid voltage with volt-var [1] while applying this control schedule.

While the CRM more accurately forecasts SoC, in this case, improved accuracy makes the CRM more susceptible than the ERM to overestimating future SoC and hence not being able to supply sufficient energy during the critical peak. This phenomena is illustrated in Fig. 8 where the achieved net load, derived by simulating the extended CRM using the calculated power schedule, has a peak significantly higher than the calculated net load. The gap between calculated and achieved net load schedules comes from the BESS being unable to supply sufficient energy to shave the complete peak, needing to curtail its discharge prematurely. This gap creates a large optimistic shortfall, where the achieved bill is $5.43 higher than the calculated bill. We demonstrate in the next section that this optimistic shortfall can be mostly eliminated with closed loop control.

B. Closed-Loop Control

Closed-loop control recalculates the optimal schedule at each time step. The net loads achieved by both closed-loop ERM and CRM based controllers are shown in Fig. 9. When implemented on the ERM, closed-loop control generates a small negative optimistic shortfall (optimistic surplus). This is because, as it starts to shave the peak load at a level based
on its underestimation of capacity, the SoC is updated and the controller has more energy to work with than expected. It then applies this excess energy to a discharge during the window of peak ToU price that is coincident with peak load. The CRM based model predictive controller reduces the optimistic shortfall from $\$5.43$ (open-loop, see Fig. 8) to $\$0.00$ (closed-loop). This is a result of the open-loop controller not supplying sufficient charge to reach $\varsigma_{\text{max}}$ before the beginning of the peak. The closed-loop controller is able to adjust for the insufficient charge and have enough energy to shave the peak completely.

C. Risk-Averse Closed-Loop Control

The physical parameters of a BESS vary under normal operation and these variations can have a large impact on the optimistic shortfall of a controller. Fig. 10 shows the sensitivity of the total bill achieved by the CRM and RA CRM due to variations in capacity. When the battery’s capacity is at its mean value and above ($\mu$, $+1\sigma$, $+2\sigma$, and $+3\sigma$), the risk-neutral CRM has a slight performance advantage. However, when the battery’s capacity is below expectations ($-1\sigma$, $-2\sigma$, and $-3\sigma$), the risk-neutral CRM’s performance drops off, producing an optimistic shortfall up to $\$22.98$ in the ‘extreme case’ at $\varsigma_{\text{cap}} = -3\sigma$, while the performance of the risk-averse controller does not decline. In terms of peak net load reduction, the risk-neutral controller is only 50% confident it will reduce the peak by 16.0%, but it has a roughly one in six chance it will reduce the peak less than 14%. In contrast, the risk-averse controller is 99.87% confident that it can reduce the peak by 15.4%. This achieves the goal of making the controller more robust to battery model uncertainty.

VIII. Conclusion

In this paper we develop and demonstrate an advanced methodology for designing BESS controllers under ToU price arbitrage and peak demand charge management applications. A state-of-the-art ERM is used as the baseline for control performance comparison. The proposed CRM based model predictive controller outperforms the ERM based controller by achieving a lower total electric bill when pseudo-empirically applied in an example scenario. Because peak load management has asymmetric risk for overestimating available energy, we then shape the uncertainty of the CRM to consistently underestimate capacity. This risk-averse CRM yields better controller performance than the ERM and is more robust to variations in BESS performance than the CRM. This methodology for designing BESS controllers can be applied in a broad range of energy storage applications, wherever the risk profile of a scheduled service is asymmetric. Incremental improvements in controller performance can reduce the cost of deploying storage to make the grid more efficient and resilient.

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REFERENCES

[1] IEEE Standard for Interconnection and Interoperability of Distributed Energy Resources With Associated Electric Power Systems Interfaces, IEEE Standard 1547-2018, pp. 1–138, Apr. 2018.
[2] A. A. Aklil et al., “DOE/EPRI 2013 electricity storage handbook in collaboration with NRECA,” Sandia Nat. Lab., Albuquerque, NM, USA, Rep. SAND2013–5131, 2013. [Online]. Available: http://www.sandia.gov/ess/publications/SAND2013–5131.pdf
[3] F. Stern and J. Spencer, “Chapter 10: Peak demand and time-differentiated energy savings cross-cutting protocol,” NREL, Golden, CO, USA, Rep. NREL/TS-7A40–68566, 2017.
[4] T. A. Nguyen and R. H. Byrne, “Maximizing the cost-savings for time-of-use and net-metering customers using behind-the-meter energy storage systems,” in Proc. North Amer. Power Symp. (NAPS), Sep. 2017, pp. 1–6.
[5] EPRI OpenDSS Test Circuits. CKT5 Loadshape, Revision 22.6, Accessed Jun. 2019. [Online]. Available: http://smartgrid.epri.com/SimulationTool.aspx
[6] J. McLaren and S. Mullendore, “Identifying potential markets for behind-the-meter battery energy storage: A survey of U.S. demand charges,” Nat. Renew. Energy Lab., Golden, CO, USA, Rep. NREL/BR-6A20–68963, 2017.
[7] E. F. Camacho and C. B. Alba, Model Predictive Control. London, U.K.: Springer, 2013.
[8] D. A. Copp and J. P. Hespahna, “Simultaneous nonlinear model predictive control and state estimation,” Automatica, vol. 77, pp. 143–154, Mar. 2017.
[9] B. Heidzak, V. G. Agelidis, and M. Jang, “A model predictive control system for a hybrid battery-ultracapacitor power source,” IEEE Trans. Power Electron., vol. 29, no. 3, pp. 1469–1479, Mar. 2014.
[10] A. Khataianfar, M. Khalid, A. V. Savkin, and V. G. Agelidis, “Improving wind farm dispatch in the Australian electricity market with battery energy storage using model predictive control,” IEEE Trans. Sustain. Energy, vol. 4, no. 3, pp. 745–755, Jul. 2013.
[11] F. Sossan, E. Namor, R. Cherkaoui, and M. Paolone, “Achieving the dispatchability of distribution feeders through prosumers data driven forecasting and model predictive control of electrochemical storage,” IEEE Trans. Sustain. Energy, vol. 7, no. 4, pp. 1762–1777, Oct. 2016.
[12] S. Teleke, M. E. Baran, S. Bhattacharya, and A. Q. Huang, “Optimal control of battery energy storage for wind farm dispatching,” IEEE Trans. Energy Convers., vol. 25, no. 3, pp. 787–794, Sep. 2010.

[13] Y. Riffonneau, S. Bacha, F. Barnuel, and S. Ploix, “Optimal power flow management for grid connected PV systems with batteries,” IEEE Trans. Sustain. Energy, vol. 2, no. 3, pp. 309–320, Jul. 2011.

[14] Y. Levron, J. M. Guerrero, and Y. Beck, “Optimal power flow in microgrids with energy storage,” IEEE Trans. Power Syst., vol. 28, no. 3, pp. 3226–3234, Aug. 2013.

[15] T. Wang, H. Kamath, and S. Willard, “Control and optimization of grid-tied photovoltaic storage systems using model predictive control,” IEEE Trans. Smart Grid, vol. 5, no. 2, pp. 1010–1017, Mar. 2014.

[16] D. Rosewater, S. Ferreira, D. Schoenwald, J. Hawkins, and S. Santoso, “Battery energy storage state-of-charge forecasting: Models, optimization, and accuracy,” IEEE Trans. Smart Grid, vol. 10, no. 3, pp. 2453–2462, May 2019.

[17] S.-K. Kim, J.-Y. Kim, K.-H. Cho, and G. Byeon, “Optimal operation control for multiple BESSs of a large-scale customer under time-based pricing,” IEEE Trans. Power Syst., vol. 33, no. 1, pp. 803–816, Jan. 2018.

[18] R. Xiong, J. Cao, Q. Yu, H. He, and F. Sun, “Critical review on the battery state of charge estimation methods for electric vehicles,” IEEE Access, vol. 6, pp. 1832–1843, 2018.

[19] M. Chen and G. A. Rincon-Mora, “Accurate electrical battery model capable of predicting runtime and I-V performance,” IEEE Trans. Energy Convers., vol. 21, no. 2, pp. 504–511, Jun. 2006.

[20] D. Rosewater and S. Gonzalez, “Implementation of a grid connected battery-inverter fleet model,” Sandia Nat. Lab., Albuquerque, NM, USA, Rep. SAND18–11692, 2018.

[21] H. D. Sherali and C. M. Shetty, Nonlinear Programming Theory and Algorithms, 3rd ed. M. S. Bazaraa, Ed. Hoboken, NJ, USA: Wiley, 2006.

[22] S. Burer and A. N. Letchford, “Non-convex mixed-integer nonlinear programming: A survey,” Surveys Oper. Res. Manag. Sci., vol. 17, no. 2, pp. 97–106, 2012. [Online]. Available: http://www.optimization-online.org/DB_FILE/2012/02/3378.pdf

[23] W. E. Hart et al., Pyomo—Optimization Modeling in Python, vol. 67, 2nd ed. New York, NY, USA: Springer, 2017.

[24] W. E. Hart, J.-P. Watson, and D. L. Woodruff, “Pyomo: Modeling and solving mathematical programs in python,” Math. Program. Comput., vol. 3, no. 3, pp. 219–260, 2011.

[25] A. Wächter and L. T. Biegler, “On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming,” Math. Program., vol. 106, no. 1, pp. 25–57, Mat. 2006. [Online]. Available: https://doi.org/10.1007/s10107-004-0559-y

[26] Gurobi Optimization, LLC. (2018). Gurobi Optimizer Reference Manual. [Online]. Available: http://www.gurobi.com

[27] J. L. Devore and N. R. Farnum, Applied Statistics for Engineers and Scientists, 2nd ed., C. Crockett, Ed. Belmont, CA, USA: Thomson Brooks, 2005.