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Optimal Operation of Energy Storage Systems Considering Forecasts and Battery Degradation

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***Abstract*—Energy storage systems have the potential to deliver value in multiple ways, and these must be traded off against one another. An operational strategy that aims to maximize the returned value of such a system can often be significantly improved with the use of forecasting – of demand, generation, and pricing – but consideration of battery degradation is important too. This paper proposes a stochastic dynamic programming approach to optimally operate an energy storage system across a receding horizon. The method operates an energy storage asset to deliver maximal lifetime value, by using available forecasts and by applying a multi-factor battery degradation model that takes into account operational impacts on system degradation. Applying the method to a dataset of a residential Australian customer base demonstrates that an optimally operated system returns a lifetime value which is 160% more, on average, than that of the same system operated using a set-point-based method applied in many settings today.**

***Index Terms*—Energy storage, optimal operation, dynamic programming, forecasting, battery aging.**

I. Introduction

THE many potential benefits of energy storage systems, both for network operators and for consumers of energy, are well known, and include peak shaving, renewable energy time shifting, and price arbitrage, to name a few [1]. The costs of battery energy storage, in particular lithium-ion (Li-ion) batteries, have fallen significantly over the past decade, and are projected to fall further [2]. However, at present these systems still represent a significant investment, and in most scenarios their value can only be recovered if multiple value propositions can be exploited.

Finding the right operational strategy to maximize the returned value of an energy storage system, across multiple possible benefits, is therefore an important research problem. This strategy is often heavily dependent on forecasts of future demand, generation, and prices. In addition, battery lifetimes are dependent on their operating environment and usage patterns [3]. While some (dis)charge operations may appear to bring immediate benefits, these may be outweighed by negative impacts on battery lifetime.

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An immediate example of the benefits (and tradeoffs) of energy storage can be found in the residential sector. Premium feed-in tariffs have been introduced over the past decades in many countries to promote the uptake of residential solar photovoltaic (PV) generation. Under such tariffs, it is typically advantageous to export excess energy to the grid. However, many of these tariff arrangements are about to expire, including in Australia. The residential export tariffs taking their place value net exported energy at approximately the average wholesale price of electricity; creating a large price-differential between net imports and exports of energy. Under such a tariff structure, an energy storage system can be used to both increase "solar self-consumption" (avoiding export of energy to the grid at minimal return), while also conducting "tariff optimization" (shifting energy demand to times when the price is low).

Considering two scenarios quickly demonstrates the importance of forecasting: On a sunny day, the home owner may want their energy storage system to be empty in the morning, so that its full capacity can be used to store excess solar energy during the day. On a cloudy day, he may want the same system to be full in the morning, to have taken advantage of lower energy prices overnight. There may be multiple operational profiles that achieve the same benefit over the course of a day, but some may lead to significantly less battery degradation than others; motivating an interest in including degradation within the operational optimization.

This work addresses the shortcomings of existing approaches to energy storage operation by integrating both stochasticity and battery degradation into a single solution. The contributions of this paper are to:

(i) propose a control methodology that operates an energy storage system, given forecasts over a receding horizon, in order to deliver maximal value over the system's lifetime,
(ii) integrate a multi-factor battery degradation model into the solution to ensure operational effects on degradation are taken into account,
(iii) demonstrate the relative importance of both forecasts and degradation models, and
(iv) evaluate the performance of this methodology for a specific use case involving Australian residential consumers having roof-top PV systems, using real historical data [4] and real univariate forecasts.

II. Background

A. The Value and Adoption of Energy Storage

There are multiple benefits to using energy storage systems, and industry observers have identified and listed a large number of possible use cases [1], [5]. These use cases provide varying levels of benefits, both across different sectors (transmission, distribution, commercial/industrial, residential) and across different markets and geographies. In each case the benefit is determined by local market conditions, tariff structures, regulatory requirements, any available subsidies, as well as many other factors.

In the PJM market of the United States, for example, frequency control has been identified as perhaps the most lucrative application for energy storage systems [6], and over 160 MW of energy storage were installed in the PJM market in 2015 alone [7].

In Australia, on the other hand, behind-the-meter applications are widely expected to be among the most profitable in the near future [8], and the residential market is expected to be the biggest growth driver for the energy storage market (projected by one industry research body to grow from 1.9 megawatts in 2015 to 44 megawatts in 2016 [9]). A recent report identified the payback period for newly installed storage and solar PV systems on a flat tariff to decline from 9-12 years in 2015 to 4-6 years by 2035 [10]. With time-of-use tariffs these payback periods could fall significantly further still. As a result, many energy storage manufacturers are now introducing their products to the Australian residential market, which is demonstrating a high demand for residential storage retrofitted to existing solar PV installations, as well as the introduction of energy storage systems in new property developments [11].

Across all sectors and geographies, it is generally agreed that for the majority of applications it is essential to "value stack" – using a single energy storage system to benefit from multiple revenue streams – in order to achieve maximum profitability and return on investment. A detailed analysis considering the use of energy storage systems for a single purpose only found one use case to be profitable [12], but another study that considered value stacking found that several further applications were demonstrated to be economically attractive already today [5].

B. Optimal Operation of Energy Storage

There has been considerable work on optimal management of energy storage assets, across a number of domains. Typical applications involve the use of storage for improved operation of micro-grids [13]–[15], integration of wind generation or solar PV [16]–[22], price arbitrage [23]–[25], peak shaving [26], or for a combination of multiple benefits [27], [28].

A wide range of approaches have been proposed to optimize the operation of energy storage systems: Dynamic programming [21], [26] is flexible, but is not suited to take into account the inevitable uncertainty involved. Linear programming based approaches such as [13] are computationally efficient, but may require pre- and post-processing of input and output to take nonlinearities into account. Quadratic programming [22], and mixed integer linear (or quadratic) programming [24], [27] will find global optima but often require significant computational resources. Zhu and Hug [29] propose optimality condition decomposition to divide a large storage and generation-scheduling stochastic model predictive control problem into subproblems, enabling the use of parallel computation to speed up solutions, but solution times are still lengthy, even for the modest number of scenarios considered. Increasing attention is being given to stochastic dynamic programming (SDP)-based approaches to optimize energy storage operation. Such methods have the advantages of dynamic programming, while also being able to take into account forecast uncertainty.

A range of methods have been used in recent papers to explicitly consider the impact of forecast errors on the operational optimization of distributed energy resources. In [30] Tanaka *et al*. apply fuzzy logic to account for the uncertainty in PV forecasts when optimizing the operation of controllable loads. Khodaei *et al*. [31] co-optimize micro-grid planning and operation subject to uncertainty in forecasts of RES generation, load, price, and islanding events, by optimizing over uncertainty sets in the operational sub-problem (ensuring a feasible solution under a worst-case scenario). In [32] Gast *et al*. consider optimal generation and storage scheduling subject to RES forecast uncertainties, by using heuristic scheduling strategies which account for anticipated forecast errors. Many studies, [16], [18], [23], [28], [29], use stochastic approaches which explicitly model uncertain terms in the optimization as random variables with a particular probability distribution.

Qin *et al.* apply SDP to energy storage arbitrage, using forecasts for expected prices [23]. Xi *et al.* co-optimize the use of distributed energy storage for multiple benefits by applying a two stage process [28]. The first stage uses SDP to obtain an approximate solution, and the second stage applies mixed-integer programming to the outcomes to find a near-optimal policy.

Hannah *et al.* apply approximate dynamic programming to the use of energy storage in day-ahead wind commitment [16]. Related approaches, including approximate policy iteration, approximate value iteration, and direct policy search, are explored and compared in [18].

C. Battery Degradation

None of [16], [18], [23], [28] (and many similar studies) consider in detail the impact of an operational profile on battery degradation. Many evaluations of the economics of an energy storage system consider only the total throughput of energy over the system's lifetime, and assign a degradation per kWh. However, the actual impact

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on battery lifetime depends on whether this throughput occurs at extreme states of charge, as part of large cycles, or at high currents (among other factors) [3]. The use of more detailed battery degradation models is therefore required to determine an optimal operational strategy.

Modeling battery degradation is a highly non-linear, multi-parameter process. Electrochemical models capturing physical processes are the most accurate, but are difficult to tune, and due to their complexity make optimization challenging [33]. Numerical models based on empirical data are more straightforward but typically capture only a few degradation parameters.

For example, Koller *et al.* use an explicit cost function to incorporate degradation into a model predictive control based approach to energy storage operation [27]. The cost function contains quadratic terms that represent degradation due to depth of discharge, charge rate, and state of charge. Tran *et al.* use Peukert's Law to model degradation due to cycle life and depth of discharge [14].

The present authors have previously developed a framework to incorporate several numerical models into a single multi-factor battery degradation prediction tool [3]. The model captures the following factors known to accelerate degradation in Li-ion batteries: extreme temperatures; high charging and discharging rates; and cycling to high and low states of charge.

While the literature on optimal storage operation is growing, many of the existing approaches typically have one or both of the following shortcomings: they either (i) assume perfect foresight of demand and (where relevant) generation, or (ii) do not consider in detail the impacts of operational decisions on battery aging. Perfect foresight leads to unrealistically high value returns, while neglecting aging can lead to unreasonable lifetime value assessments. This work aims to integrate both stochasticity of forecasts and consideration of battery degradation into a single, unified approach to optimal battery operation.

III. Stochastic Dynamic Program (SDP)

This section introduces a SDP approach to optimally operating an energy storage system. Included in the formulation is consideration of a generation system (such as a PV system), see Fig. 1. For applications without generation, the appropriate components of the formulation can be omitted and the solution is simplified.

A. Definitions [units]

- Δt — duration of an interval [hours];
- $\mathbb{T}$ — the set of intervals in the horizon, represented by integers $\{0, 1, \ldots, T-1\}$ (there are T intervals; index T, is used to refer to the ending state of the final, $(T-1)^{\text{th}}$, interval), [];
- d_t^m — forecast demand during interval t in scenario m [kWh];
- p_t^n — forecast generation during interval t in scenario n [kWh];
- $\mathbb{P}(.)$ — marginal probability of outcome $(.)$ [];
- c_t — cost of buying grid-supplied electricity during interval t [\$[1]/kWh];
- r_t — reward for exporting electricity to the grid during interval t [\$/kWh];
- η_c, η_d — charge, discharge efficiency of the battery [];
- q_t — amount of energy in the battery at the start of interval t [kWh];
- B — total nominal battery capacity [kWh];
- $\underline{B}, \bar{B}$ — Minimum and maximum charge level allowed in battery ($q_t \in [\underline{B}, \bar{B}]$) [kWh],
- b_t — decision variable - energy to withdraw from the battery during interval t, (measured at the battery, i.e. net of losses when charging, and includes them when discharging) [kWh];
- $w(b_t)$ — cost associated with battery degradation, resulting from discharge decision b_t [\$];
- $\mathbb{D}(b_t)$ — is the fractional battery degradation resulting from discharge decision b_t, (a value of 1.0 would indicate that decision could be applied only once to a new battery, and it would then need to be replaced) [];
- $b^{\mathrm{m(ax|in)}}$ — are the maximum and minimum increase in energy of the battery over an interval ($b_t \in [b^{\min}, b^{\max}]$) [kWh];
- V, V_{init} — are an estimate for the lifetime value of the battery, and a starting estimate of this value, respectively [\$],
- N_{interv} — number of intervals simulated operation is run for [].

B. Assumptions

To simplify the presentation of the method, and to keep the solution tractable, the following assumptions are made:

- Self-discharge losses in the battery are negligible;
- Power converter losses are lumped with battery (dis)charging efficiency;
- Realized generation and demand are independent, conditional on forecasts made at $t = 0$;
- Demand and generation are stage-wise independent[2], conditional on forecasts made at $t = 0$;
- Battery (dis)charging losses are treated as fixed percentage power losses;
- The battery is maintained at its nominal operating temperature.

The case study presented in Section III considers a battery which is owned by, and operated in the interests

[1]Throughout this paper \$ refers to Australian Dollars

[2]This assumption dramatically simplifies the formulation. Stage-wise independence (conditional on the forecasts made at the start of the horizon), is reasonable for earlier intervals of a horizon, as no information is ignored. Further into the horizon, this approximation is less justified (because if it were possible to re-forecast for later intervals, given the realized values of earlier intervals, the forecasts would likely change). The impact of this increasing approximation error is somewhat offset by using this SDP formulation within a model-predictive-controller framework; any decision made t intervals into the horizon will have $t-1$ opportunities for recourse before it is implemented.

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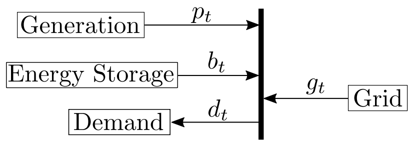

Fig. 1: Block diagram showing positive convention for energy flows. b_t is controlled. b_t and g_t take negative values when energy is transmitted to the battery or grid.

of, a residential customer, and further assumes that the grid can provide power as and when required. However, such an assumption can not be made in all cases and in other applications the objective of the optimization might seek to reduce undesirable impacts on the grid.

C. SDP Formulation

The optimization is formulated as a SDP, with the battery state-of-charge, q_t, providing a complete description of the system *state*, and the interval within the control horizon, t, representing the *stage*. It is necessary to discretize q_t, and consequently the amount of energy transferred in or out of the battery during an interval, b_t, must be chosen from a finite set of values.

Let $CTG_t(q_t)$, be the minimum expected cost-to-go from stage t given that there are q_t kWh in the battery at the start of interval t. Also let $STC_t(b_t)$ be the state-transition-cost for stage t, if control action b_t has been chosen (STC is also a function of the realized values of generation and demand, but these are omitted for brevity). The recursive relationship for the minimum cost-to-go is then:

$$CTG_t(q_t) = \min_{b_t}\{\mathbb{E}[STC_t(b_t)] + CTG_{t+1}(q_t - b_t)\} \quad (1)$$

where $\mathbb{E}[.]$ is the expected value (over all possible realizations of p_t and d_t). Included in (1) is the state update rule; if one chooses to discharge b_t kWh from a battery containing q_t kWh, it will result in a battery containing $(q_t - b_t)$ kWh, one interval later.

Let $\hat{b}_t$ be the amount of energy provided to the grid when b_t kWh of energy are withdrawn from the battery. This is defined as follows:

$$\hat{b}_t = \begin{cases} b_t/\eta_c & b_t < 0 \\ b_t\eta_d & b_t \geq 0 \end{cases} \quad (2)$$

where η_c and η_d are the charging and discharging efficiencies of the battery which lie in the range $(0, 1]$.

The expected value of the state transition cost is then:

$$\mathbb{E}[STC_t(b_t)] = \sum_{m=1}^{M}\sum_{n=1}^{N}(\mathbb{P}(d_t^m)\mathbb{P}(p_t^n)$$
$$(c_t[d_t^m - p_t^n - \hat{b}_t]^+ - r_t[d_t^m - p_t^n - \hat{b}_t]^- + w(b_t))) \quad (3)$$

where $[.]^+$ represents taking the positive component, *i.e.* $[x]^+ = \max(0, x)$, similarly $[x]^- = \max(0, -x)$. In (3) a summation is taken over realizations of the stochastic variables, *i.e.* summing over all MN possible realizations of demand and generation in interval t; with each weighted by its probability of occurrence. The three terms within the sum are, in order, the cost of energy imports, the reward received for energy exports (only one of the first two terms can have a non-zero value), and a cost associated with using up some of the available life of the battery. The battery degradation cost is determined as follows:

$$w(b_t) = \mathbb{D}(b_t) \cdot V \quad (4)$$

where $\mathbb{D}(b_t)$ is a degradation function which returns the fractional life utilization of a battery (dis)charging decision, b_t, and V represents battery value (in terms of the cost-savings it can offer to the user through its operation). By appropriately choosing V this formulation approximately maximizes the lifetime value of the battery, and allows the use of any battery degradation model which can return a fractional life utilization based on b_t and q_t.

The procedure for setting the battery value, V, is described in Algorithm 1. Apart from an initialization period (the first τ_{init} intervals) during which the battery value takes its replacement cost (to avoid large oscillations between highly cautious and reckless use of the battery early in its operation) a battery's value is determined entirely based on the ratio of its cumulative value, $\mathcal{V}$, and damage, $\mathcal{D}$, so far in its operation. Cumulative value is defined as the total cost-saving, compared to operation if no battery were available, so represents the opportunity cost of using up some of the available life of the battery.

Algorithm 1 Setting a Battery Value, V

```
V ← V_init
b ← {}                                  ▷ Sequence of discharge decisions so far
for τ = 1 ... N_interv do
    b_0^* ← SDP solution for horizon [τ, τ + T − 1]
    b̄_0 ← min([p_0 − d_0]^+, b_0^*)          ▷ See Section V-B
    b ← {b, b̄_0}
    Apply b̄_0 to battery
    D ← 𝔻(b)                             ▷ Cumulative degradation
    V ← Cumulative battery value
    if τ > τ_init then
        V ← V/D
battery lifetime value ← V
```

Provided the future value of the battery (in terms of the cost-savings it can deliver to the user) reflect those in its operation to date, this feedback allows a convenient means of maximizing the lifetime value of a battery. Empirical results indicate that V will converge after a few weeks of operation, but V will update in response to changing conditions, for example in the household's demand profile.

Operational constraints are implemented as follows:

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- Energy flow balance is ensured by defining energy from the grid, during interval t, as $g_t = d_t^m - p_t^n - \hat{b}_t$, in (3), and asserting that the grid will supply/accept energy over an interval as required.
- Rates of charging and discharging are kept feasible by limiting the minimum (most negative) and maximum values of b_t, i.e. $b_t \in [b^{\min}, b^{\max}]$
- Battery capacity constraints are respected by further limiting the minimum and maximum values of b_t for particular states, i.e.:

$$\begin{aligned} b_t &\leq \min(q_t - \underline{B},\, b^{\max}) \\ b_t &\geq \max(q_t - \bar{B},\, b^{\min}) \end{aligned} \tag{5}$$

The minimization given in (1) is performed using backwards induction. The optimal cost-to-go from the end of the final interval, $CTG_T(q_T)$, is zero for all possible ending states, q_T (the horizon is complete so there is no further cost). For each preceding stage, $t = \{T-1, \ldots, 0\}$, and each possible state to be in at the start of that stage, q_t, the feasible charge decision which minimizes (1) is found by exhaustive search of the finite set of possible values. This process is repeated, moving back through the horizon, till the minimum cost-to-go from the start of the first stage $CTG_0(q_0)$, is found (q_0, the starting state-of-charge for a particular horizon, is known).

This SDP is solved for a receding horizon as a model predictive controller; once solved, the first decision, b_0, is implemented and a new solution is computed one interval later. Solving the SDP iteratively in this way allows updated forecasts and changing conditions to be taken into account. The SDP approach proposed in this paper is straightforward to implement; all simulated operation and optimization demonstrated in this paper was written in a standalone JAVA program.

IV. Case Study

The SDP approach outlined in Section III-C was applied to a case study involving residential customers having existing solar PV generation systems. The forecast and control horizon was chosen as 24-hours, *i.e.* 48-intervals long with the 0.5-hour interval data available for the case study.

A. Data

1) Demand and generation: The demand and generation dataset for this study is derived from the publicly available Ausgrid 'Solar Home Electricity Data' [4]. It contains three years of half-hourly meter readings (kWh over the half-hour interval) for 300 households in the state of New South Wales, Australia, all of whom have a solar PV system. Each customer's total demand and solar generation are separately metered. Of the 300 customers, only the 93 which had no missing data for all of 2011-2013 were considered. Of these customers, those with annual demand in the range [4000-8000]kWh, and an average daily PV kWh/kWp yield of more than 3.0, were selected; these values were fairly typical and this selection avoided customers whose PV system only came on-line part-way through the period. Finally, those customers with a ratio of annual PV output to demand in the range [0.3, 0.6] were considered; these values were chosen to find customers who are likely to be good candidates for energy storage (and so for whom the question of how to optimally operate energy storage is of most interest). This subset included 16 customers.

2) Battery: Li-ion batteries are emerging as the technology of choice for residential applications. A survey of existing Li-ion battery products was undertaken (see *e.g.* [34]), and a set of typical parameters for commercially available offerings was chosen, as presented in Table I.

3) Electricity Tariffs: Electricity import and export tariffs reflect those commonly available in New South Wales. Import is charged as a two-part time-of-use tariff, with electricity costing \$0.40/kWh from 7:00AM – 10:00PM and \$0.20/kWh at other times. Export is fixed at \$0.05/kWh.

B. Benchmarks: set-point control

The standard approach for many energy storage products today is to apply set points, [35], [36]. These vary between products, but typically allow the installer or energy customer to choose the timing and rate of battery (dis)charge in advance, according to a strategy most relevant to the circumstances. As a result, set point control is considered a realistic and useful benchmark against which to compare other methods. Two versions of set point control are implemented:

1) Basic set point control (BSP): Most set point controllers are capable of maximizing solar self-consumption at all times. The BSP controller selects a battery discharge of $b_t = d_t - p_t$ at all times, subject to state-of-charge and rate-of-charge constraints.

2) Advanced set point control (ASP): A more advanced set point controller was also used for benchmarking purposes, to emulate more advanced systems that trade-off solar self-consumption and tariff optimization, by using the strategy depicted in Fig. 2. Any excess PV generation is used to charge the battery. In addition the ASP controller has a degree of tariff optimization: the battery charges when prices are low (up to SoC_{target}) and discharges when prices are high, and there is excess local demand to be met. The target charge level, SoC_{target}, is set to 50%[3], which allows for a useful trade-off between solar self-consumption and tariff optimization, and tends to keep the battery at an intermediate SoC which should reduce degradation.

C. Forecasting Demand and Generation

Recent studies, for example [37], have shown that state-of-the-art univariate forecasting methods suffer rel-

[3]A brief sensitivity study showed that ASP out-performed BSP over a wide range of SoC_{target} values, and that a value of 50% provided the most improvement for most customers

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TABLE I: Baseline battery parameters

Parameter	Symbol	Value	Units
Capacity	B	5	kWh
Usable Charge Range	$[\underline{B}, \bar{B}]$	[0, 4.75]	kWh
(Dis)Charging efficiency	η_c, η_d	0.94	[]
Maximum charge current	$I_{ch,\max} = -b^{\min}/(B\Delta t)$	0.5	C
Maximum discharge current	$I_{d,\max} = b^{\max}/(B\Delta t)$	1.0	C
Nominal charge current	$I_{ch,\text{nom}}$	0.125	C
Nominal discharge current	$I_{d,\text{nom}}$	0.25	C
Nominal Cycle Life	CL_{nom}	3650	No.
Nominal State of Charge	$SoC_{av,\text{nom}}$	50	%
Nominal Depth of Discharge	DoD_{nom}	100	%
Maximum battery life		25	years
Initial Battery Value	V_{init}	1500	$/kWh

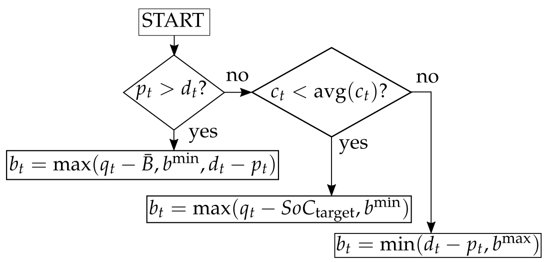

Fig. 2: Advanced set point (ASP) control algorithm

atively high errors when used to forecast the consumption of individual households. Similarly, forecasting the output of individual solar roof-top PV systems can be subject to significant error, due to unpredictable shading and soiling effects [35], [38].

The purpose of this work is not to propose novel forecasting methods, but rather to apply existing techniques within a novel approach to battery operation. Therefore two standard and well-known univariate methods are applied to forecasting demand and generation:

1) Naive Periodic (NP): Sets the forecast for each interval to the realized value from 24-hours ago.

2) Multiple Linear Regression (MLR): The forecast over the horizon is considered to be some linear combination of the previous D days of realized values[4]. The forecast is:

$$\boldsymbol{F} = \boldsymbol{X}\boldsymbol{\beta} \tag{6}$$

Where $\boldsymbol{F} \in \mathbb{R}^{1\times T}$ is a row vector of forecast values for the next T intervals, $\boldsymbol{X} \in \mathbb{R}^{1\times TD}$ is a row vector of realized values for the previous TD intervals, and $\boldsymbol{\beta} \in \mathbb{R}^{TD\times T}$ is a matrix of parameters selected for a particular customer using linear regression on a training dataset. For the data considered in this paper $D = 5$ days worth of data provided reasonable performance for both PV and demand forecasting (on an unseen validation dataset). For best performance any forecast model should not be trained on a static historical dataset, since load patterns can change over time (for example, with the purchase of an electric vehicle); however, in the present case study we consider forecasts trained on 1-year of data, and use those forecasts on data from the following year.

These simple univariate methods only make use of data which is available locally; advanced forecasting methods making use of, for example, meteorological inputs would likely offer improved performance. Even with univariate methods, some improvement can probably be made using more advanced models; Taylor *et al.* , [39], demonstrate several univariate methods which outperform a naive (weekly) periodic forecast for short-term forecasting of national demand. However, as the results in Section V show, even simple forecasting methods offer significant improvements in the value returned over a battery's lifetime. Our case study considers point forecasting methods (in the SDP formulation presented above there is a single scenario for each interval in the horizon (M=N=1) with an associated probability of occurrence of 1.0).

3) Perfect Foresight (PF): For comparison an artificial perfect foresight (zero error) forecast is also considered. Since perfect forecasts cannot be achieved this is not a realistic case, but is useful to consider as it provides a strict upper (non-tight) bound on how much additional value better forecasts could provide.

D. Battery Degradation

Three different approaches are used for the degradation model $\mathbb{D}(b_t)$ of Equation (4). They are presented here, in order, from least accurate to most accurate.

1) Fixed per kWh: The fixed per kWh degradation model assumes that the number of kWh which can be put into, and withdrawn from, a battery is fixed (*i.e.* no other factors affect degradation):

$$\mathbb{D}_{\text{fixed}}(b_t) = \frac{|b_t|}{CL_{\text{nom}} \cdot (DoD_{\text{nom}}/100\%) \cdot 2 \cdot B} \tag{7}$$

CL_{nom} and DoD_{nom} [%] are the cycle life and depth-of-discharge of the battery under nominal conditions. Hence, the denominator in (7) gives the number of charging and discharging kWh the battery can tolerate over its serviceable life.

2) Static multi-factor model: The second model is the 'static' multi-factor battery degradation model described in [3], which was developed separately, and is not a contribution made in this paper:

$$\mathbb{D}_{\text{static}}(b_t, q_t) = \frac{0.5/CL_{\text{nom}}}{nCL\Big(I_d(b_t), I_{ch}(b_t), SoC_{av}(b_t, q_t), DoD(b_t)\Big)} \tag{8}$$

where I_{ch} and I_d are the charging and discharging currents [C = hr^{-1}] associated with decision b_t, and SoC_{av} and DoD are the average state-of-charge and depth-of-discharge [%] caused by decision b_t (given

[4]In general Multiple Linear Regression would include additional regressors such as forecast temperature, dummy variables to encode the day of the week etc. For simplicity the univariate case is considered.

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there are q_t kWh in the battery at the start of interval t). nCL is a function which computes the normalized cycle life of the battery under particular operational conditions, the details of which are given in the Appendix. Under the nominal conditions given in Table I ($I_{d,\text{nom}}, I_{ch,\text{nom}}, SoC_{av,\text{nom}}, DoD_{\text{nom}}$), nCL evaluates to 1.0, and the degradation evaluates to $0.5/CL_{\text{nom}}$; therefore CL_{nom} full cycles can be tolerated under nominal conditions (an individual discharge, b_t, represents only a half-cycle). The normalized cycle life function compensates for variations of the operational conditions ($I_d, I_{ch}, SoC_{av}, DoD$), from nominal conditions.

The static degradation model, as formulated in [3], is suitable for computing the number of cycles to failure for a given set of operational parameters ($I_d, I_{ch}, SoC_{av}, DoD$), however to make use of this model within the SDP, a means of computing the degradation of an individual (dis)charging decision is required. To achieve this, each decision is treated as if it were a half-cycle. For example if b_t is positive it is treated as a discharging half-cycle, and assigned a degradation based on I_d ($I_d(b_t) = b_t/B\Delta t$), it is assumed that I_{ch} takes its nominal value, and SoC_{av} and DoD are found as ($SoC_{av}(q_t, b_t) = 100(q_t - 0.5b_t)/B$) and ($DoD(b_t) = 100b_t/B$). This simplification allows the application of the degradation model within the dynamic program, but potentially introduces additional errors into the degradation model; because a series of (dis)charge decisions which form part of a larger amplitude state-of-charge cycle will be treated as individual smaller half-cycles.

3) Dynamic multi-factor model: The third degradation model uses the dynamic (rain-flow cycle) based method detailed in [3], which takes a time-history of (dis)charge decisions, identifies individual cycles using rain-flow counting, and then determines the total degradation of all cycles.

An extension is applied to each model which allows consideration of calendar degradation (due to the passage of time). This is modeled as a minimum per interval degradation, providing a lower bound to the value which other methods can return:

$$\mathbb{D}(.) = \max\left(\mathbb{D}_{\text{model}}(.), \frac{\text{interval duration [yrs]}}{\text{max. battery life [yrs]}}\right) \quad (9)$$

V. Results and Discussion

A. State-Space Discretization

The SDP formulation presented requires assuming that only a finite number of discrete states-of-charge are possible. This is an approximation as a battery could be charged by an arbitrarily small fraction of a kWh. To determine a sufficiently large number of states for our numerical experiments, a sensitivity study was carried out, the results of which are presented in Fig. 3. The expected value delivered by the baseline battery for 4 customers based on a 1-year simulated operation, using a SDP with a PF forecast are shown. The values are normalized to the value of the same battery operated

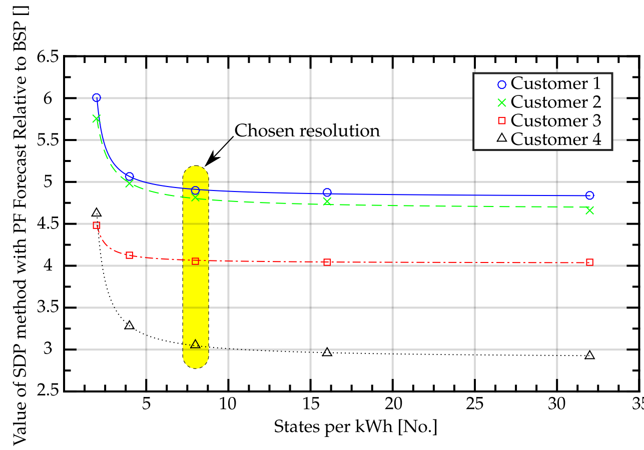

Fig. 3: Selecting the state-space discretization: Expected lifetime value of battery operated with SDP control with PF forecast, relative to value achieved with BSP control, with increasing state-of-charge resolution. Markers show the data, and lines show a rational polynomial fit.

using BSP control. A rational polynomial with linear numerator and denominator was fitted to the results for each customer. Using this fit an estimate of the value ratio at an infinite state-of-charge resolution was obtained, and the number of states required to get within 3% of this value was found[5]. The average number of states required across the 4 customers was 7.4, so based on this, all subsequent results are solved with 8 states per kWh.

B. Handling Discrete Time Intervals

The data available for this study are cumulative energy consumption (in kWh) over 30-minute intervals [4], and a fair estimate of the performance of the various control methods in an on-line setting needs to be made. The set-point controller is able to make real-time decisions based on instantaneous power measurements. To represent the net-effect of this behavior, the same comparisons are carried out, using aggregate energy values for the time period for which the charging decision is being made.

The SDP controller, on the other hand, requires forecasts of PV and demand values into the future, and is a discrete interval controller. It takes a non-negligible amount of time to run the optimization (∼30 seconds on a single core of a desktop computer[6]), therefore needs to make decisions based on forecasts available at the start of this computation. Without data at a finer time-resolution it is not possible to exactly represent the performance of the SDP-based controller. As a compromise the optimal charging behavior for the horizon starting during interval t, is solved using only information which is available at the start of that interval (realized values for

[5] 3% was selected as an appropriate value given the significant uncertainties associated with degradation modeling

[6] Intel® Core™ i7-4770 CPU @ 3.40GHz

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demand and PV up to and including interval $t-1$, but forecasts for intervals $\{t,\ldots,t+47\}$). This approach can heavily penalize the SDP method if there are significant forecast errors, because it suggests the controller would make a (dis)charge decision at the start of interval t, and continue to apply it even as that interval unfolds and forecasts are shown to be poor. Instead set-point recourse of the SDP discharge decision is considered: if b_0^* is the optimal first interval discharge decision from the SDP, this is modified so that discharging the battery does not increase exports, i.e. the implemented discharge is: $\bar{b_0} = \min([p_0 - d_0]^+, b_0^*)$.

C. Operational Impact of Considering Battery Degradation

Fig. 4 shows an example customer's battery operation for a typical 24-hour period, when degradation is either considered or neglected in the optimization. Power imported from the grid (bottom panel) is similar between the two cases, notably there is minimal exporting of energy over the horizon. However, the SoC profiles (second-bottom panel) are quite different; the profile optimized with consideration of battery degradation avoids extreme states-of-charge, and charges more slowly.

D. Improvement to Battery Lifetime Value & Annual Returns

Fig. 5 shows the lifetime value estimated for the baseline battery, based on a 1-year simulated operation for the 16 selected customers, when operating the battery using different control methods. The lifetime value is the reduction in cost of meeting local demand achieved by having a battery available (i.e. compared to an uncontrolled PV system where any excess supply (demand) is met immediately by grid exports (imports)), divided by the fractional battery degradation over the year. Similar plots were produced for 2.5kWh and 10kWh batteries, and similar relative results were found, although larger batteries had higher absolute lifetime values.

Fig. 5 demonstrates that the method used to operate a battery significantly affects the value delivered over its life. The four SDP-based results demonstrate the importance of considering battery degradation in the optimization. Batteries operated using SDP control, a NP forecast, but not considering battery degradation offer reduced lifetime value compared to one operated with consideration of battery degradation; the controller neglecting degradation focuses solely on short-term value resulting in a short lifetime. The three controllers which consider degradation offer significantly improved lifetime value compared to the BSP method, averaging 130%, 160% and 260% more for the controllers provided with the NP, MLR, and PF forecasts respectively. Using advanced point or probabilistic forecasts would likely close some of the gap between controllers provided with real forecasts, and that given a perfect foresight (PF) forecast.

Fig. 6 shows the net annual return from a 5kWh battery. Here, instead of maximizing lifetime value, we

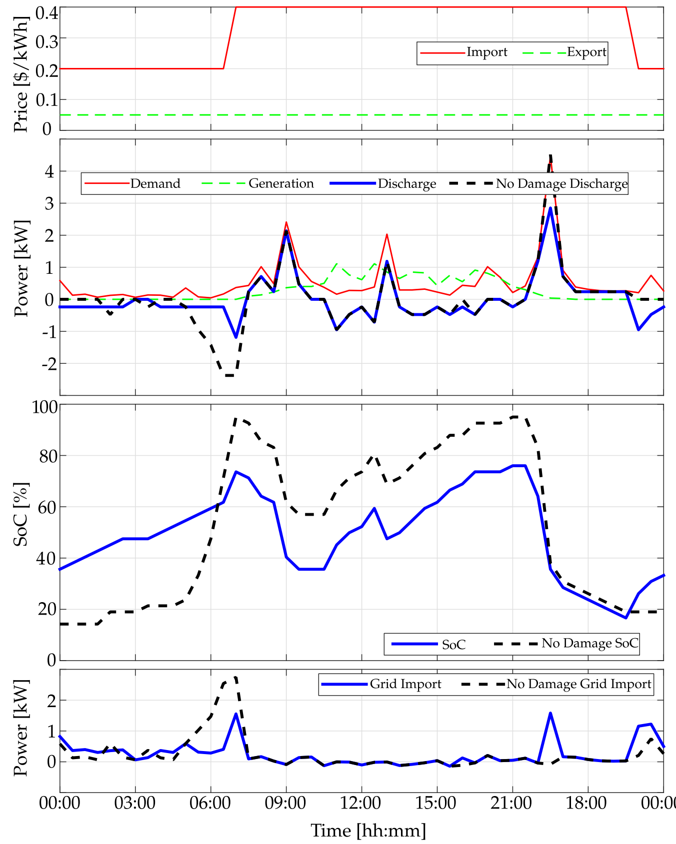

Fig. 4: A demonstration of the impact of considering battery degradation: Charging profile for an example customer's battery over a 24-hour period, solved using SDP with a zero-error forecast. Top to bottom the panels show (i) Import/Export prices, (ii) Demand, generation and battery discharge power, (iii) Battery SoC, (iv) Grid import power. Solid blue and dashed black lines show performance of a controller which either considers or ignores battery degradation, respectively.

assume a fixed battery replacement cost (fixed V in (4)), and look at the annual return on the capital investment in the battery, where the annual net income is the cost reduction in the electricity bill, less the depreciation of the battery asset (due to degradation). Fig. 6 illustrates the importance of factoring battery degradation into the optimization; at a battery replacement cost of 500 $/kWh (which is expected to be commercially available before 2020 in Australia, [10]) a controller provided with a NP forecast achieves a net return of $+2.3\%$ when battery degradation is considered, but a loss when degradation is ignored within the optimization (with a return of -3.1%) .

E. Sensitivity to Degradation Model Considered

In the results presented in Figs. 5 and 6 the static multi-factor degradation model has been used for both the optimization and simulated operation. This represents the ideal case where the optimization method has available perfect knowledge of how its (dis)charging

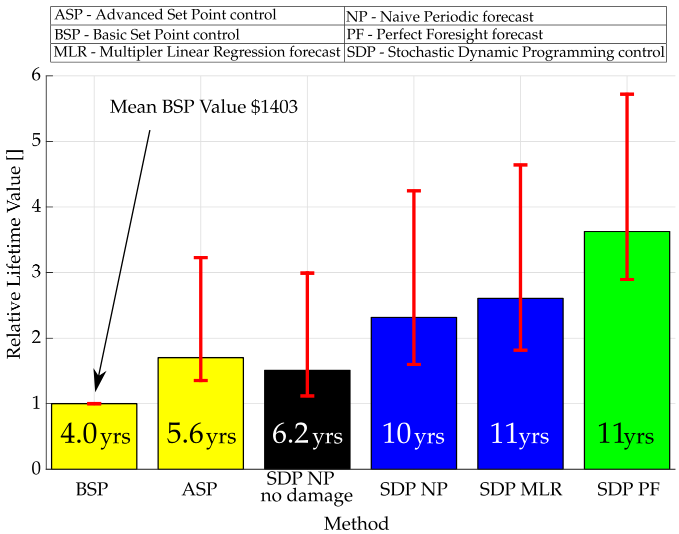

Fig. 5: Lifetime value of 5kWh battery operated using different methods. For each customer the value is relative to that of the same battery operated using BSP. Bars show the mean and whiskers show the range of ratios for the set of 16 customers. Numbers within bars indicate the mean predicted battery life, *i.e.* $1/\mathcal{D}$ where $\mathcal{D}$ is the cumulative degradation from 1-year of simulated operation.

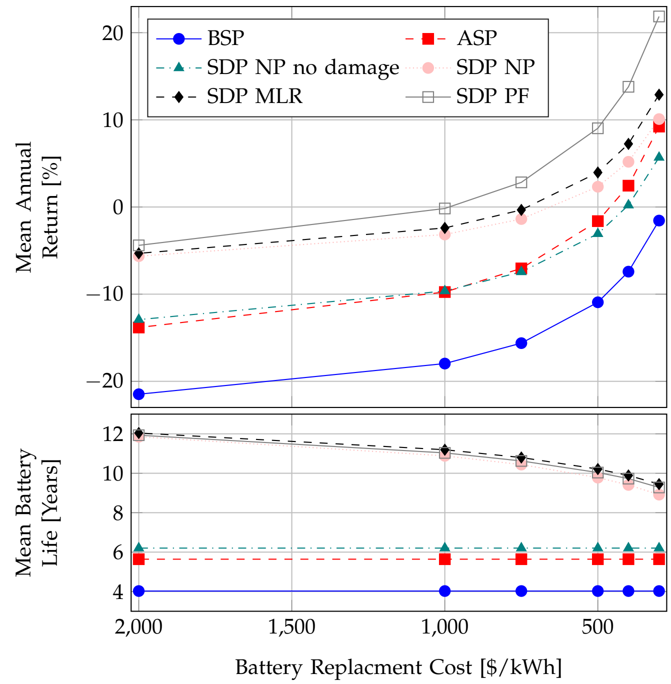

Fig. 6: Annual Return on Investment of 5kWh battery operated using different methods, net of depreciation due to battery degradation. The top panel shows the mean return based on 1-year's operation, and the bottom panel the mean expected battery life.

decisions will degrade the battery. In practice, significant uncertainty exists when modeling (and even measuring) battery degradation. Fig. 7 shows the performance of the SDP controller provided with a PF forecast compared to the set-point methods, when the simulated operation uses the dynamic multi-factor battery degradation model, but the optimization uses a fixed per kWh and static multi-factor degradation model. The performance improvement is reduced compared to that presented in Fig. 5, but is still significant when the static multi-factor degradation model is used.

All of the damage models presented are subject to modeling errors. Battery degradation is a highly non-linear process and stochastic (*i.e.* even under identical conditions, nominally identical batteries can have different operational lives). The results presented in Fig. 7 suggest that there is a level of robustness to model errors when choosing the degradation model, and that even fairly basic consideration of battery degradation can significantly increase battery lifetime value. The following observations can be made regarding the conditions under which each of the models should be relatively accurate:

- The fixed per kWh damage model should be accurate when all charge-discharge cycles occur at the nominal conditions listed in Table 1.
- The static multi-factor degradation model should be accurate when charge-discharge cycles occur near to nominal conditions (*i.e.* we are at or close to nominal conditions except for a single factor, for example charging current), and battery charge/discharge half-cycles occur in a single interval.
- The dynamic multi-factor degradation model should be accurate when charge-discharge cycles occur near to nominal conditions.

The dynamic multi-factor degradation model has the fewest qualifications, and is considered the most accurate of the three models used. This is why it is used as the simulated operation degradation model when producing the results for Fig. 7.

VI. Conclusion & Further Work

A method for operating an energy storage asset that trades off multiple value propositions in an optimal way has been presented. The method uses stochastic dynamic programming in a model predictive control framework to repeatedly choose the best charge or discharge decision to maximize the returned value of the energy storage asset over its lifetime. Forecasts of generation and demand are applied as part of the solution and are shown to improve the returned value. Likewise an understanding of the operational impacts on battery degradation is integrated into the solution and is shown to lead to decisions that significantly extend asset lifetime.

The performance of this method has been assessed in a case study focusing on residential customers having solar PV generation and a home energy storage system, using a dataset of real historical demand and PV generation data for several Australian residential

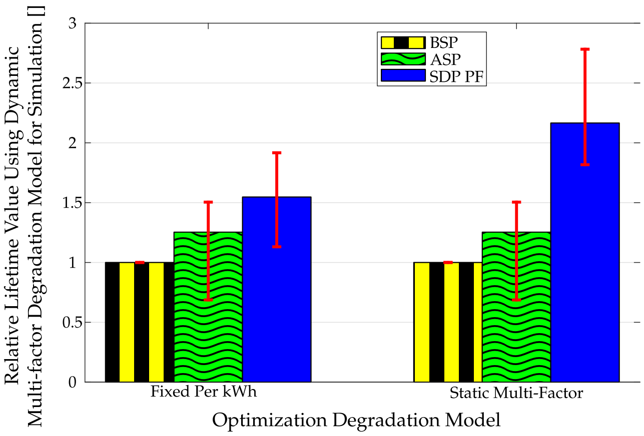

Fig. 7: Relative lifetime value of 5kWh battery, simulated to degrade according to the dynamic multi-factor degradation model, operated using BSP, ASP, and SDP with zero-error forecast. The SDP optimization uses the battery degradation model indicated on the x-axis

customers. Using the method proposed in this paper, in conjunction with relatively simple multiple linear regression forecasts, was shown to improve lifetime value by an average of 160% relative to basic set-point control representative of many systems in operation today. Such significant changes in the value which a battery delivers over its life are likely to make residential batteries economical to own and operate sooner, and for a larger number of residential users.

In future work we are interested in integrating time-value-of-money effects, choosing long-term operational optimization that also considers repeated battery replacements, understanding and mitigating any negative operational impacts on the grid, and evaluating how much additional value probabilistic forecasts provide.

Appendix
Details of Multi-Factor Degradation Model

The multi-factor degradation model used in this study is taken from [3], here we reproduce details of the normalized cycle life function which appears in Equation (8) for convenience. The factors affecting degradation are assumed to be approximately independent. This allows the cycle life of a battery under any particular set of conditions ($I_d, I_{ch}, SoC_{av}, DoD$), to be computed as the nominal cycle life, CL_{nom}, adjusted by a series of factors, each of which accounts for a different parameter being altered from its nominal value. In this study, we have removed temperature from the factors affecting battery degradation, assuming that the batteries will be maintained at their nominal temperatures, T_{nom}, throughout their operational life.

The normalized cycle life is then:

$$nCL(I_d, I_{ch}, SoC_{av}, DoD) = nCL_1(I_d) \cdot nCL_2(I_{ch}) \cdot nCL_3(SoC_{av}, DoD) \quad (10)$$

TABLE II: Multi-factor Degradation Model Parameters from [3]

Parameter	e	f	g	h	
Value	4464	-0.1382	-1519	-0.4305	
Parameter	m	n	o	p	
Value	5963	-0.6531	321.4	0.03168	
Parameter	q	s	t	u	v
Value	1471	214.3	0.6111	0.3369	-2.295

The individual normalized cycle lives which account for each parameter being at non-nominal values are then given as:

$$nCL_1(I_d) = \frac{e \cdot \exp(fI_d) + g \cdot \exp(hI_d)}{e \cdot exp(fI_{d,\text{nom}}) + g \cdot \exp(hI_{d,\text{nom}})} \quad (11)$$

$$nCL_2(I_{ch}) = \frac{m \cdot \exp(nI_{ch}) + o \cdot \exp(pI_{ch})}{m \cdot exp(nI_{ch,\text{nom}}) + o \cdot \exp(pI_{ch,\text{nom}})} \quad (12)$$

$$nCL_3(SoC_{av}, DoD) = \frac{CL_4(DoD, SoC_{av})}{CL_4(DoD_{\text{nom}}, SoC_{av,\text{nom}})} \quad (13)$$

Where CL_4 is an equation giving the expected cycle life under varying (SoC_{av}, DoD) conditions:

$$CL_4(DoD, SoC_{av}) = q + (\frac{u}{2v}(s + 100u) - 200t)DoD + s \cdot SoC_{av} + t \cdot DoD^2 + u \cdot DoD \cdot SoC_{av} + v \cdot SoC_{av}^2 \quad (14)$$

And where the parameters (Table II) have been fitted to data-sets to capture how cycle life varies with discharge current (e, f, g, h), charging current (m, n, o, p), and jointly with the average state-of-charge and depth-of-discharge (q, s, t, u, v). [3] provides details on how the parameters were fitted to experimental results.

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