Minimization of cumulative aging in batteries: a grid-based approach

Yu-Hsin (Bryant) Huang, Yaser Marafee, Raja Selvakumar

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Abstract

In this study we uniquely focus on the translation of portable size battery kinetic information to grid level analysis for a time-variant system. We characterize the effective charging policies based on fluctuating demand and grid supply. We have constructed a dynamic programming framework to understand the effects of drawing power from the grid when compared against the cumulative aging of the battery. We present a formulation that includes two time-variant states and one control variable. We observe that with increasing the tuning parameter α, we delay the charging/discharging of batteries and therefore observe the impact of cycle life on the battery. A capacity fade of less than 1% is observed over a 24h time period, and fade of 7% is observed over a full week. Future work would be keyed on simplifying some of the coupled and nonlinear constraints to additionally include temperature dynamics and multiple battery nodes.

Introduction

Motivation and Background

Electrification of renewable energy integration and automobile transportation is essential towards the reduction of greenhouse gas emission and therefore the impact of global warming [1] The importance of energy storage devices can be seen in consumer electronics, electric vehicles, and grid storage. With increasing diversification in renewable and intermittent power supplies, larger integration of energy storage systems is imminent.

The main issue with batteries is aging during their lifetime due to the decrease in capacity, which leads to voltage decay and loss of power. There are numerous electrochemical mechanisms to describe aging [2, 3, 4]. However, characterization is challenging due to diverse time scales and complex nonlinearities in these models. Dynamic parameter estimation and battery state-of-charge (SOC) analysis remain complex topics.

As Figure 1 demonstrates, some of the studied impacts on battery aging is the cycle time, depth-of-discharge (DOD), and storage life. It is observed that amongst these parameters, it is the cycle lifetime that affects the lithium evolution the strongest. A more involved

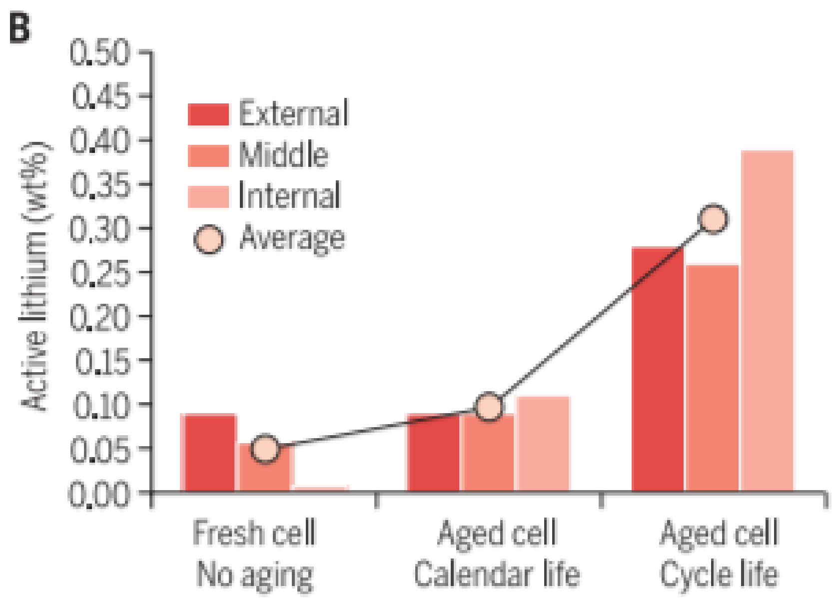

Figure 1. *Evolution of active lithium upon aging of a Li-ion cell. Note that lithium evolution at the anode increases more prominently with battery cycling.* [1].

discussion is presented in the Relevant Literature section; the purpose of this early statement is to illustrate the direction of our research interests.

To that end, this project focuses on development of an optimization model which combines the two challenging aspects of battery modelling: the grid storage and cell aging mechanisms. With regards to the grid storage framework, we remodel the conventional grid network as a source-sink problem. The input $G(k)$ is defined as the grid power generated at time k, which represents the variable power derived from combining nonrenewable and renewable energy sources. Subsequently $d(k)$ represents the time-variant demand response that depends on the change in hourly demand from residential, commercial, and industrial buildings. This transformation is shown in Figure 2. Note that this formulation is robust for multiple batteries, although computational time scales exponentially with the addition of each state. This progression is shown in the Appendix.

The second element of our project involves using a dynamic programming (DP) framework to minimize cumulative aging of the batter(ies) presented in the system. We try to investigate the capacity fade from parameters such as time, temperature, depth of discharge (DOD), and discharge rate as presented in Equation 1:

$$Q_{loss} = B \exp(\frac{-E_a}{RT})(A_h)^z \tag{1}$$

where Q_{loss} is the percentage of capacity loss, B is the pre-exponential factor, E_a is the activation energy, R is the gas constant, T is the absolute temperature, and A_h is the amp-hour throughput, which is expressed as A_h = (cycle number) $\cdot$ (DOD) $\cdot$ (full cell capacity), and z is the power law factor. The work done by Wang et. al [5] presents a relationship for the capacity fade from temperature and C-rate effects. The estimated values for a LiFePO4 battery are provided in the Technical Description section.

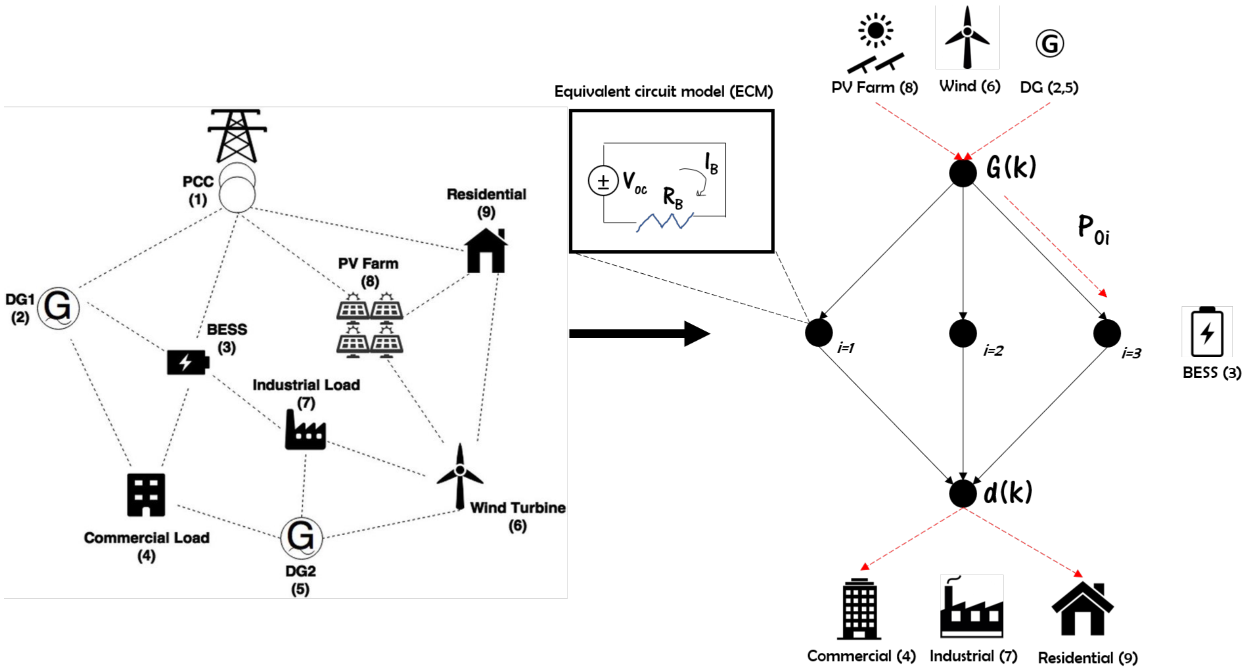

Figure 2. *Grid transformation of a typical microgrid network into a max flow problem. The inherent assumption is that we use prior knowledge on the evolution of $G(k)$ and $d(k)$ as supply and demand. The remaining surplus or shortage will be taken from the batteries at each node i. Figure adapted from* [8].

Our group consists of three chemical engineering masters students in the Product Development Program. We have all taken classes in electrochemical systems, ranging from mathematical fundamentals to first steps of solid-electrolyte interphase (SEI) modelling. These experiences provide us an advantage to test the differences between black-box and white-box modelling approaches. As a team, our goal is to learn advanced control and parameter estimation techniques, so we hope to demonstrate this in our project results.

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Relevant Literature

Battery aging can be classified into two main categories: calendar aging and cycle aging [6]. The former is associated with the phenomena and the consequences of battery storage and cycle aging corresponds to the influence of battery utilization time. Calendar aging is the irreversible process of lost capacity during storage. The battery is degraded due to self storage. Temperature effects greatly contribute to calendar aging as side reactions are facilitated and cause capacity fade, as shown in Figure 3. The other principal variable under investigation in calendar aging is the State of Charge (SOC). The state of charge is equivalent to the ratio of the current battery energy to the maximum capacity. While operating at an increased SOC may result in greater energy throughput, this also results in larger capacity fade as indicated earlier in Equation 1. These mechanisms are described by electrochemical models, performance based models, and equivalent circuit based (ECM) models.

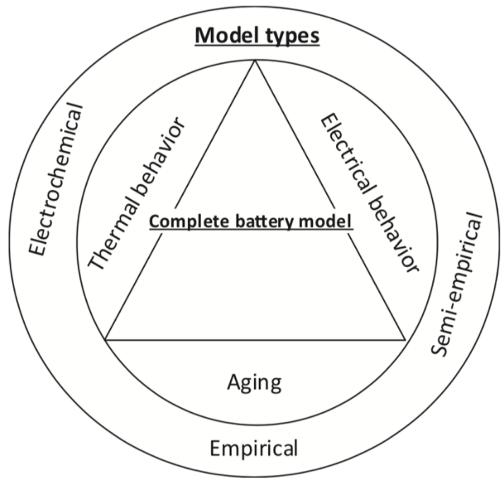

Figure 3. *Different battery modelling schemes.* [7]

Focus of this Study

For the purposes of this study, we aim to consider the effects of temperature and cycle aging on the battery SOC. As existing grid optimization models operate on the premise of minimizing cost of electricity usage [10] or fuel usage [11] or some affine combination of the two. We present here the first consideration of evaluating costs for a aging of larger scale grid storage battery systems by using microkinetic analysis of effects of cycle time and temperature on cumulative aging.

Key contributions

In this study we uniquely focus on the translation of portable size battery kinetic information to grid level analysis for a time-variant system. We characterize the effective charging policies based on fluctuating demand and grid supply.

Technical description

Assumptions

We first itemize the assumptions we have made for this model:

- Power can be drawn from the main power source, and we assume it has a maximum capacity G_{max} over all time N
- Power flow from the source is unidirectional (i.e. we only consider charging)
- The node represents a power distribution center, where the balance from power demanded and power transmitted is the power storage
- Battery temperature is constant with ambient conditions

- Power throughput is controlled at a constant C-rate[1]
- Grid batteries used are Li-ion
- Final state of charge is 0.3 (at the end of the simulation time step)
- Only one battery node is considered for the scope of the results of this project, while the formulation is written for many nodes.

Formulation

We now define our grid and the appropriate parameters. Our operating framework was first presented in Figure 2. Table 1 includes all the definitions for the variables and parameters used in this formulation.

The objective function is to minimize the cumulative aging across all nodes $i \in [1, I]$, as shown in Equation 2. Note that I represents the total nodes in the grid space. As aforementioned, however, implementing a model for multiple nodes grows rapidly in complexity without use of techniques like Approximate Dynamic Programming (ADP) and decoupling the coupled affine constraint as given by Equation 7.

$$\min \sum_{k \in N} \sum_{i \in I} \big(\alpha \ln Q_i(k) + c(k) P_{0i}(k) \big) \tag{2}$$

$$\ln Q_i(k) = \ln(B) - \frac{E_A}{RT_i(k)} + z \ln \frac{W_{h,i}(k)}{V_i(k)} \quad \forall k \in 1..N, i \in 1..I \tag{3}$$

$$W_{h,i}(k+1) = W_{h,i}(k) + |p_{b,i}(k)| \Delta t \quad \forall k \in 1..N, i \in 1..I \tag{4}$$

$$E_i(k+1) = E_i(k) - p_{b,i}(k) \Delta t \quad \forall k \in 1..N, \forall i \in 1..I \tag{5}$$

$$P_{0i}(k) = d(k) - p_{b,i}(k) \quad \forall k \in 1..N, \forall i \in 1..I \tag{6}$$

$$\sum_{i \in I} P_{0i}(k) \leq G(k) \quad \forall k \in 1..N, \forall i \in 1..I \tag{7}$$

$$E_{\min} \leq E_i(k) \leq E_{\max} \quad \forall k \in 1..N, i \in 1..I \tag{8}$$

$$0 \leq W_{h,i}(k) \leq W_{h,\max} \quad \forall k \in 1..N, i \in 1..I \tag{9}$$

$$-P_{\text{batt, max}} \leq p_{b,i}(k) \leq P_{\text{batt, max}} \quad \forall k \in 1..N, i \in 1..I \tag{10}$$

Equation 2 represents the cost minimization equation. α here is the key tuning parameter that has thus far not been determined in literature surveys. In particular, if one tunes the $\frac{\alpha}{c(k)}$ ratio, this will present a minimization frontier that exists for a range of time evolving values. While a Pareto Frontier wasn't calculated for this project, this is an additional step that we recommend.

[1] This is based on the relationship between power and energy as: $\frac{P}{E}$ = C-rate. Based on the work by Wang et. al, we follow a C-rate of C/2

Equation 3 is the linearized logarithmic expression for the percent capacity loss. Note mainly here that we have transformed the current throughput $A_{h,i}$ to the power throughput $W_{h,i}$. This is primarily done to describe the battery charging dynamics that are presented in Equation **??**. We describe the evolution of the battery dynamics in Equations 4-6. In order to maintain some understanding of the energy state E_i, this transforms into a state variable. Equation 7 now poses the main challenge for our model as with increasing numbers of batteries, the optimization function will represent coupled dynamics. For future work, the authors recommend starting with simple test cases (i.e. 2 nodes) with smaller grid sizes to account for two-state dynamics repeated across two nodes. Equations 8-10 are simply the state constraints on the variables.

$$\rho C V_B \dot{T}_i(k) = h A_s \left(T_i(k) - T_\infty\right) + R_B \left(\frac{p_{b,i}(k)}{V_i(k)}\right)^2 \quad \forall k \in 1..N, i \in 1..I \tag{11}$$

$$T_i(k) + \dot{T}_i(k)\Delta t = T_i(k+1) \quad \forall k \in 1..N, i \in 1..I \tag{12}$$

$$T_{\min} \leq T_i(k) \leq T_{\max} \quad \forall k \in 1..N, i \in 1..I \tag{13}$$

$$V_i(k) = V_{oc,i}(k) - I_i(k) R_B \quad \forall k \in 1..N, i \in 1..I \tag{14}$$

$$Q_{\text{cap, i}}(k) = Q_{\max}\left(1 - Q_i(k)\right) \quad \forall k \in 1..N, i \in 1..I \tag{15}$$

$$0 \leq I_i(k) \leq I_{\max} \quad \forall k \in 1..N, i \in 1..I \tag{16}$$

The above equations represent the temmperature dynamics of the system, which is where the major complications arise in the battery state dynamics. We present the formulation but recognize that due to computational limitations, we are unable to pursue the effects of temperature evolution on battery aging. A further study could linearize and otherwise relax some of the provided constraints.

We now discuss the dynamic programming (DP) framework for this project. Let $V(k)$ represent the cumulative capacity fade and power generation from time step k to total time N. We define control variables $p_{b,i}(k)$ as u_k $\forall i$ and state variables $W_{h,i}(k), E_i(k)$ as x_k $\forall i$:

$$V_k(x_k) = \min_{u_k, x_k} \left\{ \sum_{i \in I} \left(\alpha \cdot Q_i(k) + c(k) \cdot \left(d_i(k) - u_i(k)\right)\right) + V(k+1) \right\} \quad \forall k \in 1..N \tag{17}$$

We finally establish the boundary condition:

$$V(N+1) = 0$$

Table 1 presents a cumulative list of all the parameters and values used in the formulation.

Discussion

We now present the main conclusions from this project. Figure 4 represents the battery state evolution over a full day with only considering fluctuation in grid energy price, and not considering the battery aging cost. This policy minimizes the use of the battery in general

Table 1. List of parameters and variables used in formulation

Symbol	Description	Units	Value
α	Fixed cost of capacity loss	[$]	50
$c(k)$	Grid energy cost at time k	[$/kW]	0.02[a]
$Q_i(k)$	% capacity loss of node i at k	[-]	
B	Pre-exponential factor	[-]	30,330
E_A	Activation energy	[J/mol]	-31,500
R	Gas law constant	[J/mol*K]	8.314
T_∞	Ambient temperature	[K]	298
z	Power law factor	[-]	0.552
$V_i(k)$	Voltage at node i at time k	[J]	
$W_{h,i}(k)$	Power throughput	[J]	
$E_i(k)$	Energy state	[J]	
$p_{b,i}(k)$	Power surplus/shortage	[W]	
$P_{0i}(k)$	Power delivered from grid to i	[W]	
$G(k)$	Grid variable power supply	[W]	50E3[b]
$d(k)$	Variable demand	[W]	25E3
Δt	Simulation time step	[h]	1
N	Total simulation time	[h]	24
E_{min},E_{max}	Min and max energy limits[c]	[W-h]	792, 79200[d]
$W_{h,min}$,$W_{h,max}$	Min and max power throughput limits	[W-h]	0, 24·E_{max}
$P_{batt,max}$	Maximum battery charge/discharge limit	[W]	0.9·E_{max}/dt

[a]Time variant cost calculated from hourly electricity given in CE295 HW3, Spring 2018
[b]Value estimated based on existing grid capacities, this is the max value
[c]This is derived from the C-rate.
[d]Determined using the A-h throughput from Wang et. al [5].

and just meets the demand as required. This is different from the results shown in Figure 5, where as α increases, there is a noticable delay in charging/discharging from the battery. This indicates that the DP recognizes the aging equation accounts for the time evolution of the battery state and tries to draw more power from the grid (as long as its within the the operating limits of the battery). This is a remarkable finding that shows the power of the minimization function. Finally, Figure 6 proves this hypothesis by showing for a week-long optimization, in the first day the demand does not draw power from the battery at all! So cumulative aging is decreased because overall usage of the battery decreases itself. We'd also like to note here that the calculated values of 7% capacity fade over a week long period matches what we expect from literature values [5].

We would now like to enumerate the key takeaways from this project and further discussion items:

- The equation for capacity loss is based on a 2.2Ah battery which lead to an unreasonable capacity loss when the battery that is being minimized has a much larger capacity.

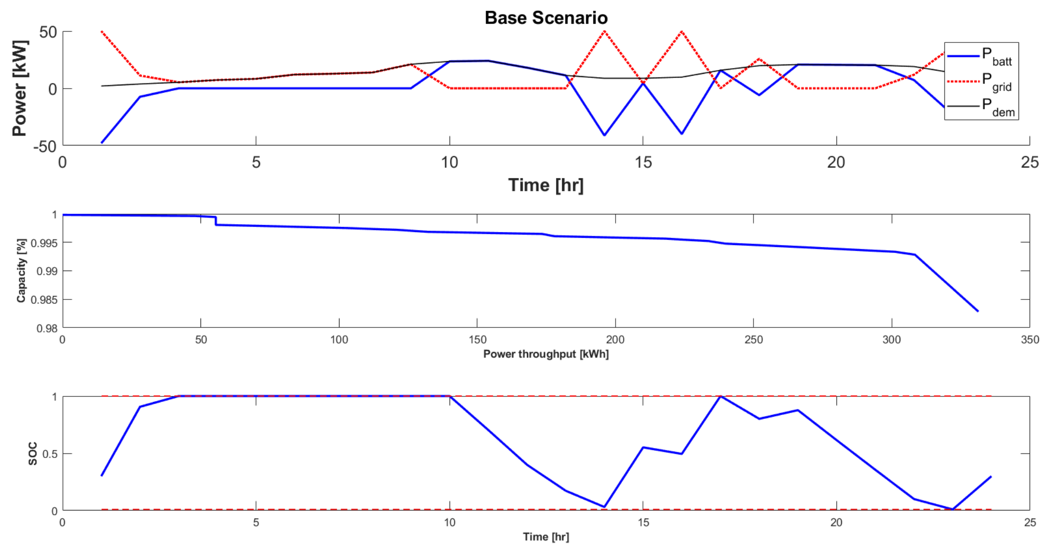

Figure 4. *Grid based optimization using* $\alpha = 0$

Thus, we had to tune the equation to give reasonable capacity losses that would yield similar quantitative results to the plots provided in literature.

- In order to incorporate more batteries in the system, we would need to account for charge/discharge power for each battery in the constraints. We faced a great challenge in trying to implement this in dynamic programming. Perhaps using a ADP framework and relaxing some constraints could lead to convex optimization.

- We were able to corporate temperature as a third state, however, due to high computational requirements, the grid size had to be reduced which resulted in inaccurate interpolations because the grid size is small. Since the grid size ranges of the energy state, power throughput, and temperature are all different, this yields different grid sizes and therefore parameter sensitivity would be quite high.

- One would consider the practical values used in the simulation. Of course we have estimated parameter values based on previous homeworks and some literature survey, but this system should be robust to handle more realistic parameters. If not, the authors advise exploring a modified capacity loss equation that may include some post-exponential "correction factor" that accounts for this.

Executive Summary

In this study we uniquely focus on the translation of portable size battery kinetic information to grid level analysis for a time-variant system. We characterize the effective charging policies based on fluctuating demand and grid supply. We have constructed a dynamic programming framework to understand the effects of drawing power from the grid

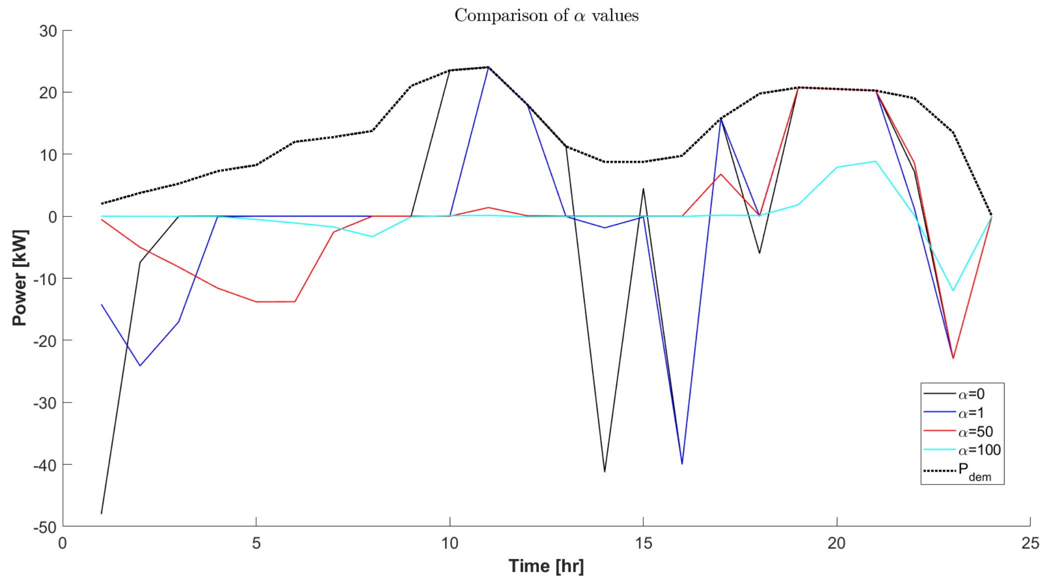

Figure 5. *Grid based optimization using different values of* α

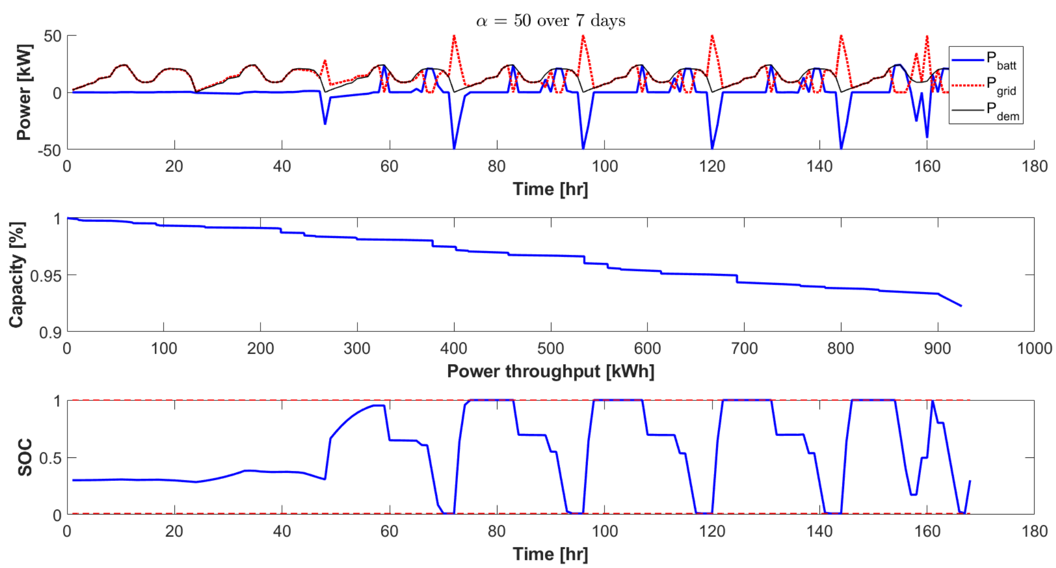

Figure 6. *Week long optimization based on* $\alpha = 50$

when compared against the cumulative aging of the battery. We present a formulation that includes two time-variant states and one control variable. Our results indicate control policies that fluctuate with the tuning parameter α, which represents the cost of losing power to capacity fade. We observe that with increasing this tuning parameter, we delay the charging/discharging of batteries and therefore observe the impact of cycle life on the battery. Future work would be keyed on simplifying some of the coupled and nonlinear constraints to additionally include temperature dynamics and multiple battery nodes.

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Appendix

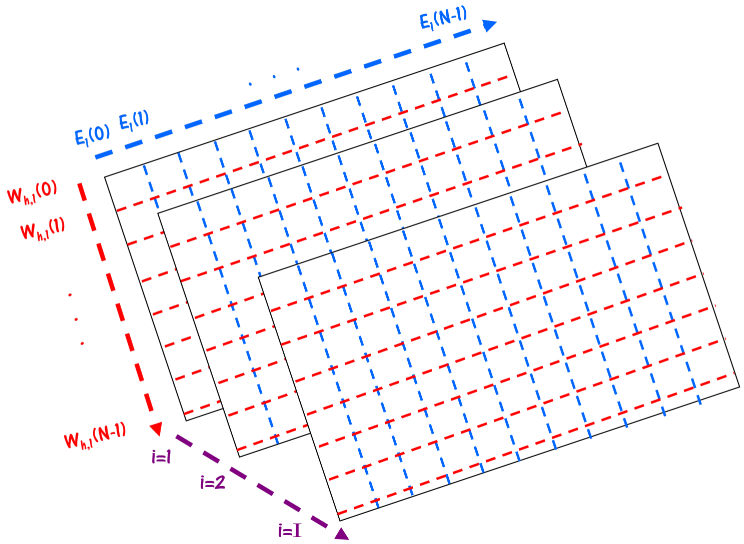

Figure A 1. *Computational scaling of increasing number of states and number of nodes processed. Increasing the number of states increases the complexity exponentially.*

Acknowledgments

We'd like to thank Professor Scott Moura for his extensive feedback and help in developing the formulation for this project. Most helpful was breaking the problem down into solvable portions and determining what is feasible and what is practical in emulating battery state dynamics.

We'd also like to acknowledge Bertrand Travecca for providing astute observations on simplifying some constraint of the problem and how to further develop the project analysis.

About the authors

Yu-Hsin (Bryant) Huang is an Asian kid who fools around and gets a Masters of Science in Chemical Engineering in his spare time.

Yaser Marafee is a rich Arab kid who just wants to make money.

Raja Selvakumar apologizes for the lowbrow humor above and misses his mom's home-cooked meals.