Battery Degradation Modeling in Hybrid Power Plants: An Island System Unit Commitment Study

Preprint

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Presented at the 2023 IEEE Power & Energy Society General Meeting (PESGM)
Orlando, Florida
July 16–20, 2023

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Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00-84791
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Suggested Citation
Huang, Jianqiao, Xin Fang, Xinyang Zhou, Jin Tan, Shuan Dong, and Andy Hoke. 2024. *Battery Degradation Modeling in Hybrid Power Plants: An Island System Unit Commitment Study: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5D00-84791. https://www.nrel.gov/docs/fy25osti/84791.pdf.

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This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office under 37772. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.

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Battery Degradation Modeling in Hybrid Power Plants: An Island System Unit Commitment Study

Jianqiao Huang, Xin Fang, Xinyang Zhou, Jin Tan, Shuan Dong, and Andy Hoke

***Abstract*—As hybrid power plants (HPPs), such as photovoltaic (PV) and battery combinations, become increasingly important in power systems with high renewable energy penetration to address PV variability and ensure grid stability. This paper focuses on the urgent need to model the coordination between PV and battery systems in HPPs while accounting for battery degradation. We present a generation scheduling model that explicitly incorporates PV-battery hybridization in the unit commitment problem. Moreover, the cost function of the HPP scheduling problem endogenously considers battery degradation with adjustable weights to strike a balance between minimizing production costs and prolonging battery life, particularly when providing energy arbitrage and ancillary services. Using a realistic island system simulation, we demonstrate that accounting for battery degradation in the scheduling problem can significantly extend battery life with only minor additional production costs.**

***Index Terms*—Hybrid power plant, PV, battery degradation, unit commitment, optimization**

NOMENCLATURE

Indices

b	Index for load buses
i	Index for generation units
p	Index for PV units
t	Index for time interval
T	Time span
l	Index for transmission lines

Constants

SU_i/SD_i	Startup/Shutdown cost of unit i
R_i^U/R_i^D	Ramp-up/Ramp-down limit for unit i
R_i^{SU}/R_i^{SD}	Ramp-up/down limit for unit i when starting up/shuntting down
$Limit_l$	Transmission limit for line l
$\hat{D}_{b,t}$	Forecast demand of load bus b at time t
$\overline{P_{p,t}}$	Forecast PV power of unit p at time t
$\overline{G}_{i,t}/\underline{G}_{i,t}$	Max/Min generation output of unit i at time t
T_i^U/T_i^D	Minimum uptime/downtime for unit i
GSF_{l-i}	Generation shift factor from bus i to line l
LP	Load-shedding penalty price
$\overline{CH}_i/\overline{DIS}_i$	Charging/discharging limit for ESS i
$\overline{SOC}_i$	Maximum state-of-charge (SOC) for ESS i
$\underline{SOC}_i$	Minimum SOC for ESS i
η_i^{min}	Charging/discharging efficiency of ESS i
RP/PFP	Regulation and PFR shortage penalty price
PFR_t^r	PFR requirement at time t
$Rg_{u,t}^r/Rg_{d,t}^r$	Regulation-up (Rg-up)/Regulation-down (Rg-dn) reserve requirement at time t

Variables

$cp_{i,t}$	Production cost for unit i at time t
$\underline{G_{i,t}}$	Generation output for unit i at time t
$\overline{G_{i,t}}$	Maximum generation for unit i at time t
$P_{p,t}$	PV power output for unit p at time t
$c_{i,t}/d_{i,t}$	Charging/discharging status of ESS i at time t
$ch_{i,t}/dis_{i,t}$	Charging/discharging power of ESS i at time t
$SOC_{i,t}$	SOC of ESS for unit i at time t
$PH_{i,t}$	HPP power output for unit i at time t
$D_{b,t}$	Scheduled demand of bus b at time t
$\Delta D_{b,t}$	Load-shedding quantity of bus b at time t
ΔPFR_t	System PFR capacity shortage at time t
ΔD_t	System load-shedding at time t
ΔRg_t^U	System Rg-up shortage at time t
ΔRg_t^d	System Rg-dn shortage at time t
$Rg_{i,t}^U/Rg_{i,t}^D$	Rg-up/Rg-dn capacity of unit i at time t
$PFR_{i,t}$	PFR capacity of unit i at time t
$v_{i,t}/u_{i,t}/w_{i,t}$	Commitment/Startup/shutdown status of unit i at time t

I. INTRODUCTION

Hybrid power plants (HPPs) usually combine a renewable energy resource with another form of generation or energy storage system (ESS) to firm electricity generation and/or other forms of power, such as heat. Compared with a single type of renewable resource, HPPs feature that (1) HPPs' power is more predictable and controllable when the mixed generation production of different resources is an anti- or inverse correlated, (2) HPPs improve the system reliability by providing grid services to alleviate the impact of forecasting errors and variability of renewable energy and loads, and (3) HPPs decrease the production cost and ensure the profitability by providing energy and other ancillary services [1].

A recent report [2] shows a substantially increased share of HPPs, i.e., 34% of all solar and 6% of wind in interconnection queues, are proposed as hybrids in the USA. One popular configuration of HPPs is solar plus storage. In [3], [4], a multi-timescale electricity market operation modeling of PV and the battery is proposed considering the temporal coupling from day-ahead to real-time market operations. The comprehensive analysis of the effects of PV and ESS on the multi-timescale

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system operation is studied. In [5], the battery and PV are independently dispatched in a microgrid. None of these works, however, has fully coordinated the dispatch of sub-components of HPP or investigated the effect of considering ESS battery degradation on the HPP dispatch results.

Battery degradation is important for modeling the battery's lifetime to reduce the overall investment cost of HPP. Therefore, how optimally coordinating HPPs of different resources while considering battery degradation is increasingly crucial in the generation scheduling problems, e.g., unit commitment (UC) and economic dispatch (ED). To fully co-control the sub-components of an HPP, we propose an operation scheme that optimally operates the HPP to provide grid services as a conventional generation unit and simultaneously extends the lifetime by reducing the battery degradation in a day ahead unit commitment (DAUC) problem consisting of twenty-four 1-hour intervals.

The main contributions of this paper are twofold: 1) we propose a mixed-integer linear programming model for HPPs providing both energy and ancillary services in the DAUC scheduling model; 2) we co-optimize the production costs of the system and the battery degradation cost of HPPs, conduct case studies to validate the efficacy of HPP modeling in a real island grid and study the effects of considering battery degradation on scheduling results.

The remaining parts of this paper are organized as follows. Section II proposes the HPP modeling respecting the battery degradation and resources hybridization. Section III embeds the HPP models into the general UC model. Section IV performs a 14-day DAUC in a real island grid to show the effectiveness of the battery degradation model in the scheduling. Section V concludes the paper.

II. Hybrid Power Plant Modeling

A. Battery Degradation Modeling

In lithium-ion batteries, which are the subject of this work, the battery capacity is reduced mainly by the depth of discharge (DOD) over time, time spent at various SOC levels, and cell temperature (Tc). In this paper, we assume that we have good thermal management, so Tc will not influence the degradation rate. We aim to reduce the degradation ascribed to the DOD by coordinating BESS and PV in each HPP. The impact of SOC will be addressed in the future.

In [6]–[8], the battery degradation can be characterized by a nonlinear function of the DOD and time t as follows:

$$S_t(t) = k_t t, \;\; S_\delta(\delta) = (k_1\delta^{k_2} + k_3)^{-1}, \tag{1a}$$
$$f_{d,i} = S_\delta(\delta) + S_t(t), \;\; L = 1 - e^{-\sum_{i=1}^{n} f_{d,i}}, \tag{1b}$$

where δ and t represent DOD and time, respectively; $S_t(t)$ and $S_\delta(\delta)$ denote the stress factors of time and DOD, respectively; $f_{d,i}$ represents the degradation at ith cycle; and L is the loss of the battery capacity. The time stress coefficient k_t and DOD stress coefficients k_1, k_2, and k_3 are given in subsection IV-C. Note that we neglect $S_t(t)$ in DAUC scheduling model but will consider $S_t(t)$ to estimate the battery degradation after solving DAUC.

The useful lifetime of the battery is the period when the loss of capacity is less than 20% of the initial capacity, i.e., $L \leq 0.2$. We then define battery degradation cost, C_L, with decision variable L as follows:

$$C_L = \frac{L}{0.2}C_0, \tag{2}$$

where C_0 denotes the battery price, $\frac{L}{0.2}$ represents the percentage of useful lifetime that was consumed. For a brand new battery, the loss of capacity, L, is 0, so its degradation cost, C_L, is 0. The battery reaches the end of life at $L = 0.2$, and the corresponding C_L equals the battery cost C_0.

However, because L is nonlinear as expressed in (1b), it is computationally heavy to solve DAUC considering the battery degradation cost, C_L. To this end, we approximate the nonlinear degradation cost with respect to DOD, δ, by the following linear function:

$$L = a\delta + b, \tag{3}$$

where a and b are coefficients and constants of the linear regression. Their value can be calculated by the least square method. Substitute (3) into (2) to get the linearized degradation cost $\bar{C}_L$ in terms of δ as:

$$\bar{C}_L = \frac{a\delta + b}{0.2}C_0. \tag{4}$$

The linear degradation cost can be further expressed by the battery discharging and charging power $dis_{i,t}$ and $ch_{i,t}$ as:

$$\bar{C}_L = \frac{aC_0(dis_{i,t} + ch_{i,t})}{0.4E} + \frac{C_0 b}{0.2}. \tag{5}$$

where E denotes the initial capacity of the battery. Now we have a linear cost function $\bar{C}_L$ with respect to decision variables $dis_{i,t}$ and $ch_{i,t}$, which will later be integrated into DAUC with adjustable weight k for improved battery lifespan in Section III-A.

B. Constraints for the Hybridization

We schedule each HPP as a generator while satisfying the operational constraints of sub-component PV and battery:

$$P_{p,t} + dis_{i,t} - ch_{i,t} \geq 0, \tag{6a}$$
$$c_{i,t} + d_{i,t} \leq 1, \tag{6b}$$
$$ch_{i,t} \leq c_{i,t}\overline{CH}_i, \quad dis_{i,t} \leq d_{i,t}\overline{DIS}_i, \tag{6c}$$
$$SOC_{i,t} - SOC_{i,(t-1)} = ch_{i,t}\eta_i - dis_{i,t}/\eta_i, \tag{6d}$$
$$\underline{SOC}_i \leq SOC_{i,t} \leq \overline{SOC}_i, \tag{6e}$$
$$0 \leq P_{p,t} \leq \overline{\boldsymbol{p}_{p,t}}, \tag{6f}$$

where constraint (6a) ensures that the battery can only charge from local PV. The constraints of battery include charging/discharging status (6b), the maximum charging/discharging power limit (6c), and the SOC limit (6d)-

(6e). The PV has power limit (6f). Moreover, we consider the battery round-trip efficiency, η_i. Binary variables are $c_{i,t}$, $d_{i,t}$ in (6b), and continuous variables are $dis_{i,t}$, $ch_{i,t}$, $SOC_{i,t}$, and $P_{p,t}$.

III. Unit Commitment model

A. Objective Function

The objective function of the UC problem usually includes the operational cost of traditional units—represented by their generation costs associated with their startup and shutdown costs—as well as the shortage penalties for the energy, regulation, and PFR services. To prolong the lifetime of batteries while minimizing the operational cost, the objective function is updated with a weighted sum of the operational cost and the linear battery degradation (5) as follows:

$$\sum_{t\in T}\sum_{i\in g}\big(SU_i u_{i,t} + SD_i w_{i,t} + cp_{i,t}\big) + LP\cdot\Delta D_t + PFP\cdot\Delta PFR_t + RP\cdot(\Delta Rg_t^U + \Delta Rg_t^d) + k\cdot\bar{C}_L, \quad (7)$$

where the parameter k functions as the trade-off between the cost of production and battery life to be determined. Note that the production cost, $cp_{i,t}$, of the traditional thermal unit in (7) can be approximated by a piece-wise linear function from its quadratic production cost curve. In this model, we assume that the operational energy price of PV is 0. For ancillary services, the bidding prices are zero.

B. Constraints for the Single Unit

The constraints for traditional thermal units are similar to those in [9] and are presented as follows for completeness,

$$\begin{aligned}
&u_{i,t} + w_{i,t} \le 1, && (8a)\\
&v_{i,t} - v_{i,t-1} \le u_{i,t} - w_{i,t}, && (8b)\\
&\textstyle\sum_{\tau=t-T_i^U+1}^{t} u_{i,t} \le v_{i,t}, && (8c)\\
&\textstyle\sum_{\tau-t-T_i^D+1}^{t} w_{i,t} \le 1 - v_{i,t}, && (8d)\\
&\overline{G_{i,t}} - G_{i,t-1} \le R_i^U v_{i,t-1} + R_i^{SU} u_{i,t}, && (8e)\\
&G_{i,t-1} - G_{i,t} \le R_i^D v_{i,t} + R_i^{SD} w_{i,t}, && (8f)\\
&\overline{G_{i,t}} \le \overline{G}_{i,t} v_{i,t}, && (8g)\\
&G_{i,t} + Rg_{i,t}^U \le \overline{G_{i,t+1}}, && (8h)\\
&G_{i,t} + PFR_{i,t} \le \overline{G_{i,t+1}}, && (8i)\\
&G_{i,t} - Rg_{i,t}^D \ge G_{i,t+1}^{min} v_{i,t+1}, && (8j)\\
&Rg_{i,t}^D - R_i^D \le G_{i,t} - G_{i,t-1}, && (8k)\\
&G_{i,t} - G_{i,t-1} \le R_i^U - Rg_{i,t}^U, && (8l)\\
&v_{i,t}, u_{i,t}, w_{i,t} \in \{0,1\}. && (8m)
\end{aligned}$$

We consider the start-up and shut-down trajectories of conventional generators in (8c) and (8d). In addition, (8e) – (8g) show the ramping rate constraints for units; (8h) – (8l) impose the limitation for the ancillary services.

C. System-Wide Constraints

The system constraints include the power balance constraint for every time interval, system regulation reserve, PFR, and thermal constraints of transmission lines as follows:

$$\begin{aligned}
&\textstyle\sum_{i\in g}(G_{i,t} + P_{p,t}) - \sum_{b\in B}(\hat{D}_{b,t} - \Delta D_{b,t}) = 0, && (9a)\\
&\textstyle\sum_{i\in g} PFR_{i,t} + \Delta PFR_t \ge PFR_t^r, && (9b)\\
&\textstyle\sum_{i\in g} Rg_{i,t}^U + \Delta Rg_t^U \ge Reg_{u,t}^r, && (9c)\\
&\textstyle\sum_{i\in g} Rg_{i,t}^D + \Delta Rg_t^d \ge Reg_{d,t}^r, && (9d)\\
&-Limit_l \le \textstyle\sum_{i\in Lg} GSF_{l-i}\,(G_{i,t} + P_{p,t}), && (9e)\\
&-\textstyle\sum_{b\in Lb} GSF_{l-b}(\hat{D}_{b,t} - \Delta D_{b,t}) \le Limit_l. && (9f)
\end{aligned}$$

D. DAUC Considering HPP

We present the DAUC problem formulation scheduling the dispatch of thermal units, HPP, and other renewable energy resources used in the case study as follows:

$$\begin{aligned}
&\min\ (7), && (10)\\
&\text{s.t. } (5), (6), (8), (9).
\end{aligned}$$

IV. Case Study

A. Simulation Setup

In this section, we will study the impact of the hybridization on the production cost and demonstrate the effectiveness of the linear degradation cost on extending the battery lifespan in a 2-week DAUC of an island system. We have four batteries, including one standalone battery and three sub-component batteries in three HPPs. They occupy 14.6% of generation capacity. We refer to the details of the system to [10].

The 2-week DAUC has 14 sequential DAUC problems. Each DAUC contains twenty-four 1-hour intervals. We use Pyomo to formulate the optimization problem and centrally solve the problem using the FICO-XPRESS solver.

B. Impact of PV and Battery Hybridization

The following two cases are simulated to study the effect of the HPP modeling on HPP dispatch and production cost.

- Case 1: Dispatch PV and BESS independently.
- Case 2: Dispatch each HPP as a generator.

1) Dispatch of HPP: The optimal dispatch of HPPs is plotted in Fig. 1. Compared to Case 1, the HPP behaves like a generator in Case 2.

2) Production Cost: The daily production costs under the two cases are presented in TABLE I. Compared with Case 1, Case 2 increases the production cost by 0.18%, attributed to the operation constraint that the battery can only be charged from collocated PV. While in Case 1, the battery can charge from the grid, which leads to a slightly lower operational cost. In real-world hybrid power plants (HPP), the same organization usually owns the collocated PV and batteries. It is a common constraint that BESS cannot be charged from the grid for HPP owners related to eligibility of the BESS for the

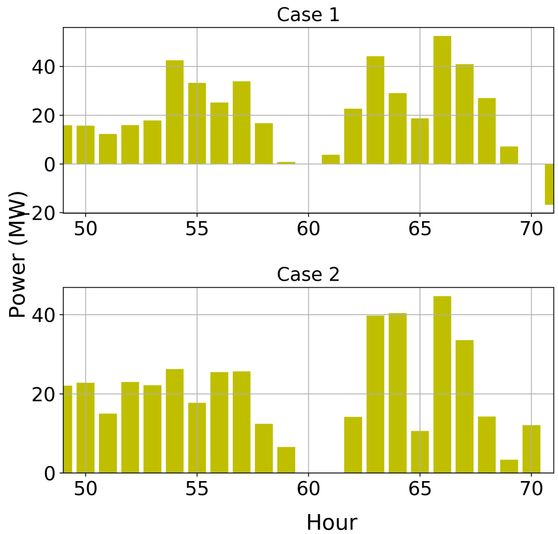

Fig. 1: Comparison of HPP dispatch under different HPP modelings.

U.S. Federal investment tax credit for renewable energy plants. Case 2 is designed to model HPPs based on this condition.

If the batteries and PV are owned by different owners, the system operators might not have this local charging requirement. Or, if the HPP owners have different interconnection requirements that allow charging from the grid, Case 1 will be the better operation model for HPPs.

TABLE I: Production cost ($1 M)

Case	Min	Max	Mean	Std	Sum
Case 1	0.2902	0.5647	0.4365	0.0811	6.1116
Case 2	0.2912	0.5650	0.4373	0.0812	6.1224

TABLE II: Battery lifespan

	Battery Lifespan (yr.)			
k	**XP**	**M014**	**M0041**	**M0042**
0	4.86	5.71	5.76	5.52
0.02	4.92	5.78	5.65	5.71
0.2	5.52	5.86	6.98	5.95
0.8	7.07	7.22	8.06	7.24
1	7.30	7.40	7.91	7.38
1.3	6.72	7.37	7.63	7.77
2	7.11	7.46	8.13	7.56
8	12.71	13.26	12.24	12.44
13	12.71	13.58	12.37	12.22
20	13.38	13.73	12.52	12.22
25	13.31	14.10	12.17	12.44

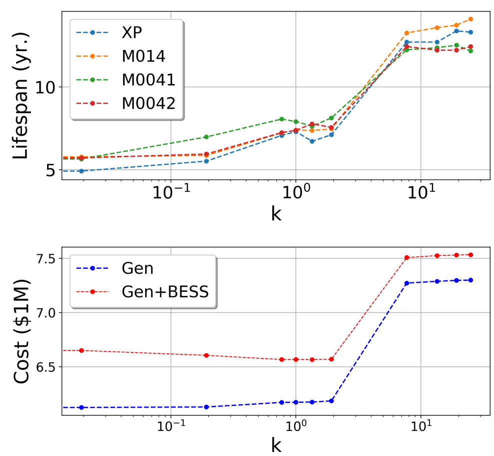

Fig. 2: The battery lifetime (up); the generation cost, Gen, together with the total cost, Gen+BESS, (down) using different k values.

C. Impact of Battery Degradation

We run a 14-day DAUC with different k values to study the effect of the weighted linear degradation cost $k \cdot \bar{C}_L$ on the battery lifetime, total production cost, dispatch, and SOC. Recall that k serves as the weighting factor of $\bar{C}_L$ in our objective function (7). The coefficients in (1) are set to 1.4×10^5, -5.01×10^{-1}, -1.23×10^5, and 4.14×10^{-10} for k_1, k_2, k_3, and k_t, respectively. We use the nonlinear model to calculate the battery degradation. The battery price, C_0, is estimated by multiplying the initial capacity by the unit price $\$250/\mathrm{kWh}$ [11].

1) Battery Lifetime: The four batteries are indexed by XP, M014, M0041, and M0042. We estimate their lifespan based on the 2-week battery degradation rate in TABLE II. The maximum lifespan is 15.31 years when we only consider the time stress factor. As shown in TABLE II, with the increasing value of k, the lifespan of batteries becomes larger. Particularly, the lifespan is larger than 12 years with $k = 25$.

2) Total Cost: The total cost is the sum of the generation cost and the battery degradation cost. We plot the lifespan of the battery, generation cost, and total cost in Fig. 2. As shown in the figure, with the increasing value of k, both the generation cost and the lifespan become larger. The minimum overall cost is $\$6.498 \times 10^6$ when $k = 1.3$.

3) Dispatch of Units: We plot the dispatch of inverter-based renewable energy resources, traditional generators, and batteries on a typical day, the third day, under three cases:

- Case 1: Overlook the battery degradation with $k = 0$,
- Case 2: Upweight the battery degradation with $k = 2$,
- Case 3: Upweight the battery degradation with $k = 25$.

As shown in Fig. 3, among the three cases with different k values, $k = 2$ and $k = 0$ have very similar dispatch profiles that BESS charges at high renewable electricity generation (HREG) level and otherwise discharges. However, when $k = 25$, BESS is idle most of the time. It results in large amounts of renewable energy curtailment at the HREG level and an increase in the dispatch of traditional generators at other times.

4) SOC of BESS: The SOC on the same typical day is depicted in Fig. 4. Note that the SOC is consistent with the charging and discharging pattern of batteries in the lower figure of Fig. 3. Specifically, SOC increases at HREG level, and decreases at other times with $k = 0$ and $k = 2$, whereas

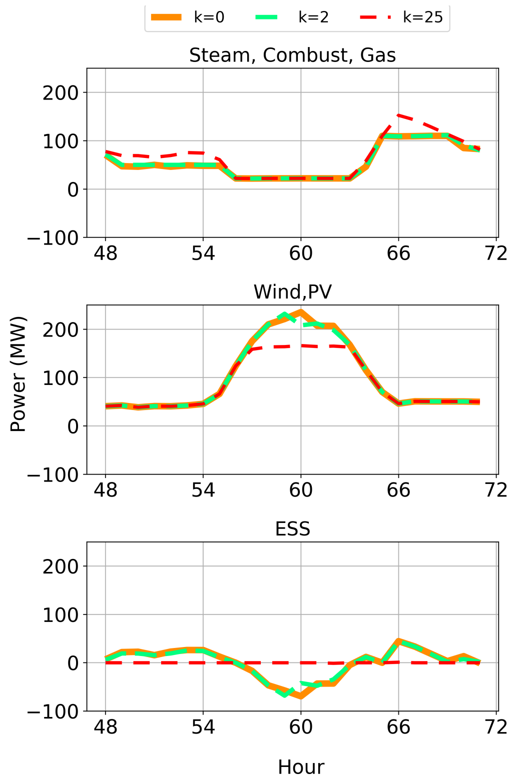

Fig. 3: The dispatch of traditional unit (up), renewable energy resource (middle), and the BESS (down) using different k values.

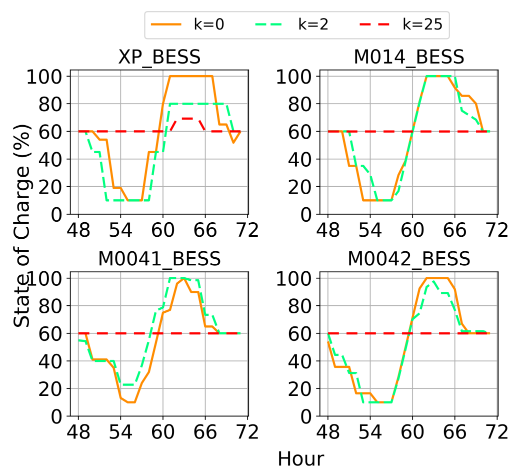

Fig. 4: SOC of BESS using different k values.

SOC remains 60% with $k = 25$.

V. CONCLUSION

In this paper, we embedded the proposed HPP model respecting the battery degradation into the UC problem of an island system. The 2-week simulation results show that compared with independently dispatching PV and battery, the coordinated control of PV and battery in HPP produces a minor increase in the production cost. Moreover, the proposed formulation can extend the battery lifespan by explicitly modeling the degradation cost in the objective function. The sensitivity study finds out the desired value of the degradation penalty factor to achieve the minimum overall cost, the sum of the generation cost and the cost for the battery degradation. This demonstrates the efficacy of the proposed scheduling model with battery degradation cost.

In the future, we will extend the research in three directions. First, we will formulate more operational constraints, e.g., the inverter constraints for AC-coupled and DC-coupled HPP. Second, we will derive a more accurate penalty for the cycle aging and consider partial calendar aging due to the SOC to further reduce the overall costs. Third, we will study the effect of real-time AGC signals on the lifespan of the battery.

VI. ACKNOWLEDGEMENT

The authors would like to thank Hawaii Electric for providing the model of the island grid. This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE). Funding is provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office under 37772. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains, and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work or allow others to do so for U.S. Government purposes.

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