IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received September 14, 2020, accepted October 7, 2020, date of publication October 14, 2020, date of current version October 26, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3031197

Optimal Energy Storage Sizing With Battery Augmentation for Renewable-Plus-Storage Power Plants

HUNYOUNG SHIN[1], (Member, IEEE), AND JIN HUR[2], (Senior Member, IEEE)
[1]Department of Electrical Engineering, Sangmyung University, Seoul 03016, South Korea
[2]Department of Climate and Energy Systems Engineering, College of Engineering, Ewha Womans University, Seoul 03760, South Korea

Corresponding author: Hunyoung Shin (hunyoung@smu.ac.kr)

This work was supported by the National Research Foundation of Korea (NRF) Grant funded by the Korean Government (MSIT) under Grant 2019R1G1A110027212.

ABSTRACT The renewable-plus-storage power plant is becoming economically viable for power producers given the maturing technology and continued cost reduction. However, as batteries and power conversion systems remain costly, the power plant profitability depends on the capacity determination of the battery energy storage system (BESS). This study explored an approach for optimal capacity determination of a BESS combined with renewable energy considering the complex degradation of lithium-ion batteries. The proposed sizing algorithm iteratively evaluates the effect of BESS operation on battery degradation and estimates the cash flows of the power plant. In addition, we studied battery augmentation that adds the storage capacity in the base system to sustain the BESS capacity throughout the project planning horizon. Using data from South Korea, we showed that both the optimal storage capacity and project profitability are higher when the BESS is combined with solar generation than when combined with wind generation. Moreover, simulation results demonstrated that the proposed battery augmentation scheme improves the project profitability by deferring the upfront cost of batteries and increasing the total revenue. The proposed approach can provide a comprehensive framework for the parties involved in a BESS project to accurately calculate the BESS sizes and maximize the project profitability.

INDEX TERMS Energy storage system, energy storage sizing, renewable energy, lithium-ion battery degradation, battery augmentation.

I. INTRODUCTION

Battery energy storage systems (BESSs) enable fast charging and discharging to effectively enhance the flexibility of power grids, especially those integrating several renewable energy sources (RESs). In practice, BESSs provide different services to power grids in many countries. For instance, in the PJM energy market, energy storage is mainly used for the provision of the frequency regulation service [1]. Likewise, the Korea Electric Power Corporation (KEPCO) installed 500 MW of energy storage systems (ESSs) for frequency regulation in South Korea. Energy storage can be used to provide power systems with solid capacity when combined with RES generation. For instance, California adopted a mandate requiring its three biggest utilities to procure 1325 MW of energy storage for consistent power supply over its power system that has high RES penetration.

As the costs of RES generation and energy storage are decreasing rapidly and the underlying technology is maturing, RES-plus-storage power plants are becoming economically viable to independent power producers and end consumers. In particular, solar-plus-storage power plants will be competitive with as much as 82% of the projected new gas peakers in the US, corresponding to 13.1 GW, within a decade [2]. In markets under government incentives for energy storage, solar-plus-storage power plants can provide a higher benefit–cost ratio than standalone solar power plants [3]. Recently, the number of RES-plus-storage projects is notably growing, with capacity penetration to interconnection queues reaching 36 GW in 2018, approximately doubling the 19 GW in 2017 [4].

The associate editor coordinating the review of this manuscript and approving it for publication was Chi-Seng Lam.

Despite the substantial decline in prices, BESSs remain costly compared to conventional power generation. Hence, the profitability of a generation project using a BESS is considerably affected by the determination of its capacity. Lithium-ion batteries are subject to capacity degradation, which is mostly determined by their components and operating conditions [5], [6]. As a BESS-based power plant project generally has a lifetime exceeding a decade, lithium-ion batteries typically undergo severe capacity fade throughout the project planning horizon. Therefore, BESS sizing neglecting battery degradation results in overestimated revenues and may severely reduce profitability. A precise BESS sizing method must consider that battery degradation is influenced by the BESS operation and specifications.

Several methods are available for BESS sizing. Oversizing is the conventional method to handle battery degradation by installing higher battery capacity than the required one to deliver the intended amount of energy at the beginning of life. Another method is battery augmentation, in which new batteries are added to the BESS over time. Battery augmentation defers initial investments and can exploit future cost reductions in batteries. In addition, it allows maintaining the battery capacity or performance at a specific level by the end of the project. Nevertheless, technical challenges should be addressed when implementing battery augmentation, such as interconnecting old and new battery racks without affecting the corresponding power electronics.

Various studies have been conducted on ESS sizing for different applications. Mercier *et al.* [7] explored the optimal sizing of a BESS for frequency regulation of an isolated power system using a dynamic simulator of load frequency control. Knap *et al.* [8] calculated the ESS capacity that provides inertial response and primary frequency reserve for achieving the target inertial response and power and frequency characteristics in a power system. Zhang *et al.* [9] considered BESS owners participating in the primary control reserve market and devised two-level profit-maximizing BESS planning. Many studies have addressed the optimal siting and sizing of BESSs for transmission networks [10], distribution networks [11], or both [12]. Co-optimizing transmission and BESS planning is achieved by a mixed-integer linear model in [13] and a stochastic multistage model in [14]. In microgrids, the ESS is an essential power asset for reliable operation and effective utilization of RESs [15]. In [16], [17], energy storage sizing for microgrids is studied considering both grid-connected and islanded modes. Various works related to BESS sizing for RES power plants consider that a BESS owner participates in the electricity markets while pursuing profit maximization [9], [18]–[23]. In this context, energy storage can be used to compensate for the difference between the predicted and actual generation, relieve the generation output variability, and arbitrage by scheduling charge and discharge profiles according to the expected electricity prices and expected RES generation. Other works have been conducted on the ESS capacity that enhances the performance of RES power plants [20], [24], [25]. In addition, the proper ESS size for stabilizing the power and frequency variance due to fluctuating RES outputs has been studied in [26], [27].

Lithium-ion battery capacity degradation has been analyzed using different methods such as chemical theory [28]–[30], experimental approach [31], and semi-experimental approach [32]–[36]. The chemical-theoretic approach allows to logically explain the causes of the degradation. However, the obtained battery degradation model often disagrees with practical battery operation. On the other hand, an experimental approach requires a large amount of data to ensure accuracy, and an empirical model for one application obtained from limited data may not be suitable for other applications. The semi-experimental approach combines both theoretical analysis with empirical observations. A mathematical model of battery capacity degradation obtained from this approach is robust for a variety of energy storage applications while agreeing with experimental data.

In the aforementioned BESS sizing studies, battery capacity degradation is disregarded or assumed to be independent of the BESS operation and size, despite being primarily determined by battery usage according to the application. Various studies [37]–[41] on battery control strategies have been conducted considering battery degradation. However, BESS sizing imposes additional challenges besides those found in the battery control problems. In fact, determining the optimal BESS size depends on the prediction of the battery degradation according to the BESS size itself. The battery degradation is affected by BESS operating conditions including depth of discharge (DoD), state of charge (SoC), and C-rate, which depend on BESS sizes. Moreover, as battery degradation is affected by various stress factors, the prediction of its trends over the BESS project planning horizon, which usually spans more than a decade, relies on numerical experiments. All these factors influencing degradation cause high nonlinearity for BESS sizing.

In addition, to the best of our knowledge, no research on a systematic scheme for battery augmentation considering BESS sizing is available. Finally, most studies on RES-plus-storage power plants consider the BESS application to energy arbitrage in wholesale electricity markets. However, RES generation is typically traded via long-term bilateral contracts, usually referred to as power purchase agreements (PPAs), rather than in wholesale electricity markets.

In this study, we aimed to address the limitations and challenges of existing BESS sizing methods. To this end, we propose an optimal BESS sizing algorithm for RES-plus-storage power plants considering the effects of BESS operation and size on battery capacity degradation. Such effects and the accurate battery degradation estimation allow to realistically determine the power plant profitability, which is directly affected by the battery capacity retention. Additionally, we integrate a battery augmentation scheme (BAS) into the proposed BESS sizing algorithm to further increase the economic benefits. The main contributions of this study can be summarized as follows:

- An optimal BESS sizing algorithm for solar-plus-storage and wind-plus-storage power plants is proposed. Unlike existing methods, the proposed algorithm can accurately calculate the battery degradation rate considering the BESS operation and size to then evaluate the cash flows of the BESS project. Therefore, BESS investors can determine the BESS capacity that maximizes profitability.
- A BAS that can be integrated into the BESS sizing algorithm is introduced. Simulation results show that battery augmentation can improve the profitability of the RES-plus-storage project. The BAS defers part of the initial battery investments, thus providing economic benefits. Furthermore, the BAS allows to achieve a more balanced cash inflow throughout the project planning horizon compared to the lack of battery augmentation.
- Regarding market conditions, a long-term contract (usually a PPA) between the project owner and off-taker is considered as a common form of renewable energy trading in many regions including the US, Europe, China, India, and South Korea. Among the various types of contracts, we adopt the time-variant energy price in South Korea as a representative example. The proposed algorithm can be tailored to other market conditions with simple modifications.

The remainder of this paper is structured as follows. Section II describes various energy compensation rules for the RES-plus-storage power plants and details the South Korean market rules. Section III presents the mathematical model of lithium-ion battery degradation based on the work by Xu *et al.* [36]. In Section IV, we propose the optimal BESS sizing algorithm and BAS for RES-plus-storage power plants. Numerical results based on real data are reported in Section V, and we finally draw conclusions in Section VI.

II. ENERGY COMPENSATION RULES FOR RES-PLUS-STORAGE POWER PLANTS

A. POWER PURCHASE AGREEMENTS

A PPA is a long-term contract that governs the sale and purchase of electrical energy between a power producer and a utility off-taker, often for a fixed price. PPAs are widespread in energy markets and particularly important in renewable energy sectors. In practice, renewable energy is commonly sold through PPAs for various reasons, such as the ease of project financing and hedging given the risk of fluctuating energy prices and varying RES generation. Combining energy storage to RES is a viable option to mitigate such a risk encountered when participating in the wholesale electricity markets. However, the regulatory and market design in many countries are not yet adequate for incorporating energy storage as market participating generators. Therefore, a RES-plus-storage power plant is usually compensated by PPAs rather than the wholesale markets.

The PPAs for RES-plus-storage projects should be established differently from those for projects without energy storage given the unique characteristics of BESSs. According to an analysis of 38 RES-plus-storage PPAs in the US [3], the various methods to compensate storage within the PPAs can be categorized into three options: time-invariant energy prices, time-variant energy prices, and capacity payment.

1) **Time-invariant energy prices:** This compensation method simply bundles the storage cost into the overall energy price. The ESS operation is specified in the PPA.
2) **Time-variant energy prices:** In this method, energy prices during peak generation periods are assumed to soar up to multiple times their normal level. For example, several PPAs in Nevada, such as that in Arrow Canyon, allow peak energy pricing from 16:00 to 21:00 each day throughout June–August. In South Korea, the energy discharged from the ESS during peak generation periods on each day is eligible for additional REC (renewable energy certificate) multipliers.
3) **Capacity payment:** Some projects have capacity and energy PPAs for the energy storage to be compensated through a fixed capacity payment. A new contract option in eight recent projects in Hawaii allows treating RES-plus-storage as "renewable dispatchable generation." For compensation, the utility makes a fixed payment per month for the "dispatchable capacity" and a variable payment to cover operation and maintenance costs.

We focus on the second option as case study for optimal BESS sizing. In particular, we consider the time-variant energy pricing rules for RES-plus-storage power plants in South Korea and derive the corresponding BESS operation algorithm for accurate sizing. Nevertheless, the proposed sizing algorithm can integrate other compensation options without major changes, as further detailed in Section IV-C.

B. ENERGY COMPENSATION RULES IN SOUTH KOREA

A renewable portfolio standard is mandatory for power generation companies to supply a proportion of the total power generation from RESs. A REC is a tradable commodity that proves the RES energy generated by the power producer. One REC is endowed per megawatt hour of generation. Although both the generated energy and RECs can be sold in the corresponding spot markets, the price volatility is a serious risk to investors, especially the small ones. To address their concerns, the South Korean government implemented "fixed-price contracts" in 2017 to allow power producers to jointly trade the generated energy and RECs as one product with KEPCO, which is the only electricity utility in South Korea, at a fixed price over a long term.

As RES power plants have different economical values depending on their type and capacity, different REC multipliers are imposed per REC to both promote the balanced development of various RESs and foster the competitivity between different RESs [42]. Table 1 lists various REC multipliers for solar and wind power plants according to the type of facility. Although the government endows high REC multipliers to RES-plus-storage power plants, not all the energy discharged

TABLE 1. REC multipliers for RES power plants based on the types of RES and facility.

RES	Facility	REC multiplier
Solar	On-land	0.7–1.2
	On-building	1.0–1.5
	With ESS	4.0
Wind	Onshore	1.0
	Offshore	2.0–3.5
	With ESS	4.0

TABLE 2. Non-peak generation periods for RES-plus-storage power plants.

RES	Period of year	Non-peak gen. period
Solar	All	0:00–10:00 16:00–24:00
Wind	March 17–June 06	09:00–12:00
	June 17–September 20	13:00–17:00
	September 21–November 14	18:00–21:00
	November 15–March 16	09:00–12:00

from an ESS is eligible for the increased multipliers. For instance, energy produced by a RES during peak generation and discharged from the ESS during the non-peak generation periods, as listed in Table 2, is subject to the REC multiplier of 4.0.

III. LITHIUM-ION BATTERY DEGRADATION

Lithium-ion batteries are subject to capacity degradation as they are used. Therefore, it is necessary to consider battery degradation in BESS sizing. The capacity degradation rate depends on many factors. Thus, it is difficult to obtain an accurate degradation model. In this paper, we employ the battery capacity degradation model proposed by Xu *et al.* [36], who used chemical theory to model the battery capacity retention with respect to multiple stress factors and determined the model parameters according to experimental data. In addition, they calculated the total aging of lithium-ion batteries as the sum of cycling aging and calendar aging. The stress factors determining the capacity retention are the levels of DoD and SoC, C-rate, cycle count, temperature, and total operation time.

The aging models for the stress factors are defined as follows [36]:

$$\text{DoD}: \ f_{DoD}(DoD) = (k_{DoD_1} DoD^{k_{DoD_2}} + k_{DoD_3})^{-1}, \tag{1a}$$

$$\text{SoC}: \ f_{SoC}(SoC) = e^{k_{SoC}(SoC - SoC_{ref})}, \tag{1b}$$

$$\text{C-rate}: \ f_C(C) = e^{k_C(C - C_{ref})}, \tag{1c}$$

$$\text{Temp.}: \ f_T(T) = e^{k_T(T - T_{ref}) \cdot \frac{T_{ref}}{T}}, \tag{1d}$$

where k_{DoD_1}, k_{DoD_2}, and k_{DoD_3} are the DoD aging model coefficients, and k_{SoC}, k_C, and k_T are the SoC, C-rate, and temperature aging model coefficients, respectively. The reference values per stress factor are $SoC_{ref} = 50\%$, $C_{ref} = 1C$, and $T_{ref} = 25°\text{C}$. As a result, the model of battery capacity degradation combines cycling aging and calendar aging as follows [36]:

$$f_d = \sum_{i=1}^{N} f_{DoD}(DoD_i) f_{SoC}(SoC_i) f_C(C_i) f_T(T_i) n_i + k_t H f_{SoC}(SoC_{avg}) f_T(T_{avg}), \tag{2}$$

where i is the cycle index and N is the number of cycles. The cycle count is obtained by using the rainflow-counting algorithm [43], in which H is the total operation time in seconds, and SoC_{avg} and T_{avg} are the average SoC level $(\sum_{i=1}^{N} SoC_i/N)$ and temperature $(\sum_{i=1}^{N} T_i/N)$ across all cycles, respectively.

Considering the battery residual capacity and solid electrolyte interphase [44] for capacity degradation, the final model for the battery state of health (SoH[1]) is given by [36]

$$SoH = p_{SEI} \cdot e^{-r_{SEI} f_d} + (1 - p_{SEI}) \cdot e^{-f_d}. \tag{3}$$

The model parameters for the aging and SoH models are calculated using experimental data from lithium-ion manganese-oxide batteries [36]. Although we adopt eq. (3) to model battery degradation, alternative definitions include the model by Stroe *et al.* [32] based on experimental data from lithium iron phosphate batteries.

IV. PROPOSED BESS SIZING ALGORITHM AND BAS

We propose an optimal BESS sizing strategy that maximizes the economic value of BESS installation into an existing RES power plant. Subsequently, we introduce a complementary BAS for further increasing the profitability. We begin by analyzing the BESS charging and discharging schedules aiming to maximize revenue.

A. BESS OPERATION

As we consider the South Korean time-variant energy price, a comparison of the prices in different periods is essential to develop the BESS sizing algorithm. From Table 1, the electricity discharged during non-peak generation periods is compensated with SMP + 4.0 · REC per megawatt hour, where SMP represents the system marginal prices.[2] As the market value per REC is comparable to the SMP in South Korea, it is economically optimal to store RES generation during peak-generation periods until reaching the full BESS capacity to then discharge the energy during non-peak generation periods. Algorithm 1 details this optimal BESS operation.

Given the BESS energy capacity or equivalently battery capacity (E_{BAT}), the algorithm first checks whether time t is within a non-peak generation period. If not, the BESS charges energy ($E_{\mathrm{Ch}}(t)$) until reaching its maximum energy level ($E_{\mathrm{BAT,max}}$), which is obtained as $R \cdot E_{\mathrm{BAT}}$, where R is the maximum DoD range (e.g., 90%). $E_{\mathrm{Ch}}(t)$ is determined by the

[1] SoH defines the condition of a battery as the remaining capacity divided by the nominal capacity.

[2] In South Korea, the SMP is used as the wholesale market price calculated without considering transmission constraints.

Algorithm 1 BESS Operation

Input: BESS energy capacity, E_{BAT}
Data: RES generation, $E_{\text{RES}}(t)$, $\forall t$
Initialization ($t = 1$, $SoC(1) = SoC_{\text{int}}$);
while $t < T + 1$ **do**
  if $t \notin$ *non-peak period* **then**
    if $E_{BAT,rem}(t) = E_{BAT,max} - E_{BAT}(t) > 0$ **then**
      $E_{\text{Ch}}(t) = \rho_{\text{RES-BAT}} \cdot \min\{E_{\text{RES}}(t),\ P_{\text{PCS}},\ E_{\text{BAT,rem}}(t)\}$;
    else
      $E_{\text{Ch}}(t) = 0$;
    end
    $E_{\text{BAT}}(t+1) = E_{\text{BAT}}(t) + E_{\text{Ch}}(t)$;
  else if $t \in$ *non-peak period* **then**
    if $t \in$ *beginning of non-peak period* **then**
      $t^* = t$;
      $E^*_{\text{Dch}} = \frac{E_{\text{BAT}}(t^*) - E_{\text{BAT,min}}}{\text{REC duration}}$;
    end
    $E_{\text{Dch}}(t) = \min\{E^*_{\text{Dch}}, P_{\text{PCS}}\}$;
    $E_{\text{BAT}}(t+1) = E_{\text{BAT}}(t) - E_{\text{Dch}}(t)$;
  $t := t + 1$;
end

RES generation ($E_{\text{RES}}(t)$) but limited by the nominal capacity of the power conversion system (PCS) (P_{PCS})[3] and remaining energy capacity in the BESS ($E_{\text{BAT,rem}}(t)$), which is calculated as $E_{\text{BAT,max}} - E_{\text{BAT}}(t)$ where $E_{\text{BAT}}(t)$ is the energy stored in the battery at time t. If time t is within a non-peak generation period, the BESS discharges energy ($E_{\text{Dch}}(t)$) until the minimum energy level ($E_{\text{BAT,min}}$), with the discharging rate being determined as follows. First, E^*_{Dch}, a candidate discharge rate, is determined as the available energy in the BESS at the beginning of the non-peak generation period, (t^*), divided by the duration of the non-peak generation periods: $E^*_{\text{Dch}} = (E_{\text{BAT}}(t^*) - E_{\text{BAT,min}})/(\text{REC duration})$. If E^*_{Dch} is greater than P_{PCS}, the discharging energy for time t, $E_{\text{Dch}}(t)$, is P_{PCS}. Otherwise, $E_{\text{Dch}}(t)$ is E^*_{Dch}.

Algorithm 1 is designed to optimally work for the South Korean PPA. Due to the energy compensation rule, the stochasticity of renewable generation can be omitted in the algorithm. However, under other compensation rules, the stochasticity of renewable generation may play an important role to obtain optimal BESS operation and sizing algorithms [17]–[19], [45], [46].

B. CALCULATION OF NET PRESENT VALUE

The net present value (NPV) represents the current cash flows generated by a project over a specific period and is widely used to estimate whether a project will result in a net profit or loss. BESS sizing aims to find the optimal combination of power capacity (in kilowatts) and energy capacity (in kilowatts hour) that maximizes the NPV over the project planning horizon. The power and energy capacities of the BESS are determined by the size of the PCS and batteries, respectively. The NPV of the BESS installation in the RES system over Y years of the project with PCS capacity (P_{PCS}) and battery capacity (E_{BAT}) is calculated as

$$\text{NPV}_Y(P_{\text{PCS}}, E_{\text{BAT}}) = \sum_{y=1}^{Y} \frac{\text{CF}_y(P_{\text{PCS}}, E_{\text{BAT},y})}{(1+r)^y} - C_{\text{int}}(P_{\text{PCS}}, E_{\text{BAT}}), \quad (4)$$

where $\text{CF}_y(P_{\text{PCS}}, E_{\text{BAT},y})$ is the net cash flow during year y, r is the discount rate, and $C_{\text{int}}(P_{\text{PCS}}, E_{\text{BAT}})$ is the initial investment of the BESS comprising the PCS and battery costs:

$$C_{\text{int}}(P_{\text{PCS}}, E_{\text{BAT}}) = C_{\text{PCS}} \cdot P_{\text{PCS}} + C_{\text{BAT}} \cdot E_{\text{BAT}}, \quad (5)$$

with C_{PCS} and C_{BAT} being the unit prices for the PCS and battery, respectively. The usable battery capacity in year y ($E_{\text{BAT},y}$) is determined by the battery degradation over previous years and battery augmentation, if applicable. The net cash flow, $\text{CF}_y(P_{\text{PCS}}, E_{\text{BAT},y})$, is the difference between the cash in or revenue, $\text{Rev}_y(P_{\text{PCS}}, E_{\text{BAT},y})$, and the cash out or cost, $C_y(P_{\text{PCS}}, E_{\text{BAT},y})$, during year y:

$$\text{CF}_y(P_{\text{PCS}}, E_{\text{BAT},y}) = \text{Rev}_y(P_{\text{PCS}}, E_{\text{BAT},y}) - C_y(P_{\text{PCS}}, E_{\text{BAT},y}).$$

The revenue during year y comprises the income from both discharging power from the BESS and supplying RES generation directly to the grid:

$$\text{Rev}_y(P_{\text{PCS}}, E_{\text{BAT},y}) = \sum_{t=1}^{T} \Big[\lambda_{\text{BESS}} \cdot \rho_{\text{BAT-AC}} \cdot E_{\text{Dch},y}(t) + \lambda_{\text{RES}} \cdot \rho_{\text{RES-AC}} \Big(E_{\text{RES},y}(t) - \frac{E_{\text{Ch},y}(t)}{\rho_{\text{RES-BAT}}} \Big) \Big], \quad (6)$$

where t indicates the hour in a year, and thus $T = 8760$ h, λ_{BESS} and λ_{RES} are the prices for electricity from the BESS and RES, respectively, and $\rho_{\text{BAT-AC}}$ and $\rho_{\text{RES-BAT}}$ are the efficiency factors from the BESS to the grid and from the RES power plant to the BESS, respectively. Using the electricity pricing rule in Section II-B and the BESS operation algorithm in Section IV-A, the energy discharged from the BESS is compensated at $\lambda_{\text{BESS}} = \text{SMP} + 4.0 \times (\text{REC Price})$ per kilowatt hour. In addition, the remaining RES power after charging the BESS is priced at $\lambda_{\text{RES}} = \text{SMP} + \text{REC Price}$ per kilowatt hour.

The costs in year y include the annual operations and maintenance cost of the BESS and the income tax from selling the electricity. In addition, the opportunity cost, which is the potential gain from the standalone RES power plant, must be included in the costs, because we analyze the NPV of the BESS installation project. Therefore, we obtain

$$C_y(P_{\text{PCS}}, E_{\text{BAT},y}) = C_{\text{O\&M},y}(P_{\text{PCS}}, E_{\text{BAT}}) + C_{\text{tax},y}(P_{\text{PCS}}, E_{\text{BAT},y}) + C_{\text{Opp},y}. \quad (7)$$

[3] We consider hourly generation, the PCS capacity in kilowatts can be directly used as the limit for charging and discharging energy over time t.

We assume the annual operations and maintenance cost to be 1% of the investment cost of BESS and the income tax to be 10%: $C_{\mathrm{O\&M},y}(P_{\mathrm{PCS}}, E_{\mathrm{BAT}}) = 0.01 \times C_{\mathrm{int}}(P_{\mathrm{PCS}}, E_{\mathrm{BAT}})$ and $C_{\mathrm{tax},y}(P_{\mathrm{PCS}}, E_{\mathrm{BAT},y}) = 0.1 \times \mathrm{Rev}_y(P_{\mathrm{PCS}}, E_{\mathrm{BAT},y})$, respectively. The opportunity cost is calculated as

$$C_{\mathrm{Opp},y} = \lambda_{\mathrm{RES}} \cdot \rho_{\mathrm{RES\text{-}AC}} \sum_{t=1}^{T} E_{\mathrm{RES},y}(t).$$

The variables associated with the BESS, $E_{\mathrm{Ch},y}(t)$ and $E_{\mathrm{Dch},y}(t)$, and RES generation, $E_{\mathrm{RES},y}(t)$, are affected by the performance of the BESS and the RES power plant, whose performance degrades over the project operation time. Thus, these variables differ according to year y even under the same BESS operation.

C. BESS SIZING

The overall process for optimal BESS sizing is described in Figure 1. First, the PCS and battery capacities are determined, with the maximum and minimum values being based on the type of RES and its generation capacity. The algorithm is composed of three loops. The first two loops search the optimal BESS power and energy capacities, and the third loop calculates the battery SoH and annual revenue and cost. The PCS size, which represents power capacity of the BESS, establishes the outer (first) loop. The battery capacity in the second loop is determined considering the PCS capacity and the energy-to-power (E/P) ratio in hours[4] as PCS capacity × E/P ratio. The algorithm uses the E/P ratio instead of kilowatt hours to examine the capacity because 1) a pair of power capacity and E/P ratio is frequently used to describe the BESS size and 2) it allows searching the energy capacity in more detail regarding the capacity from the first loop. Given the PCS and battery capacities, the battery SoH, revenues, and costs are evaluated annually in the third loop. The BESS operation algorithm allows to determine the stress factors for battery degradation, such as SoC, C-rate, time, and cycle count, and the SoH in year y (SoH_y) can be obtained using eq. (3). The BESS operation also allows to evaluate of the revenue and cost in year y from the charging and discharging schedules and using eq. (6) and (7), respectively. After each iteration of the annual loop, the capacities of the RES-plus-storage power plant are updated based on the calculated SoH and the degradation rate of the RES systems. This process is repeated until the last year of the project planning horizon. To include battery augmentation, the BAS in Section IV-D is applied after calculating the annual SoH.

After the annual loop, the algorithm evaluates the NPV for the PCS and battery capacities by combining the revenue and cost from eq. (4). When all the iterations are completed, the algorithm selects the PCS and battery capacities providing the highest NPV as the optimal BESS capacity.

To consider other markets, two processes in the sizing algorithm should be modified while maintaining the overall algorithm flow. First, the BESS operation algorithm in the annual loop must be adjusted to the conditions of the market under consideration. Second, the revenue in eq. (6) should be redefined using the energy prices for that market.

The sizing algorithm applies brute-force search to explore the solutions from all the possible ranges of battery and PCS capacities. Although this type of search is computationally inefficient, the computation time can be substantially shortened by setting the search ranges appropriately. Furthermore, as our goal is to obtain the optimal BESS planning over a long period, it is more important to guarantee the solution accuracy than to improve the computational efficiency to obtain the solution.

[4]The E/P ratio describes the ratio of the energy capacity to the power capacity of the BESS [47], [48].

D. BESS SIZING WITH BAS

Some BESS projects should sustain a minimum energy capacity over the planning horizon. As an energy project typically operates for more than a decade, batteries experience severe capacity degradation, and ensuring capacity retention to the minimum requirement throughout the project planning horizon is difficult. Although oversizing can be a feasible solution, to ensure sufficient energy capacity over such long periods may require installing excessive battery capacity upfront. In this case, the project profitability can substantially decrease.

Alternatively, battery augmentation allows to sustain the total energy capacity of a BESS throughout its lifetime by adding battery capacity to the base system, rotating batteries in the system, or both. Given its economic benefit, battery augmentation is being increasingly adopted by BESS installers and project developers. Nevertheless, obtaining the optimal BAS is difficult due to the complex factors that must be considered. For instance, the effect of additional batteries on the performance of the whole BESS may be difficult to determine. In addition, battery cost prediction is also required for optimal battery augmentation.

We aim to propose a BAS to be easily combined with the BESS sizing algorithm proposed in Section IV-C rather than obtain an optimal BAS.

Algorithm 2 Battery Augmentation Algorithm

Input: $E_{\mathrm{BAT},y}$
Compute SoH_{y+1} to predict $E_{\mathrm{BAT},y+1} = E_{\mathrm{BAT}} \cdot SoH_{y+1}$;
if $E_{BAT,y+1} < E_{BAT}^{Req}$ **then**
  $\hat{r}_{\mathrm{deg}} = \frac{SoH_{y_{\mathrm{LastAug}}} - SoH_{y+1}}{y+1-y_{\mathrm{LastAug}}}$;
  $E_{\mathrm{BAT},y}^{\mathrm{Aug}} = \min\{E_{\mathrm{BAT}}\hat{r}_{\mathrm{deg}}(Y-y) - E_{\mathrm{BAT},y} + E_{\mathrm{BAT}}^{\mathrm{Req}}, E_{\mathrm{BAT}} - E_{\mathrm{BAT},y}\}$;
  $E_{\mathrm{BAT},y} := E_{\mathrm{BAT},y} + E_{\mathrm{BAT},y}^{\mathrm{Aug}}$;
end

Algorithm 2 describes the proposed BAS that can be integrated into the annual loop of the BESS sizing algorithm shown in Figure 1. The timing and capacity of battery additions are determined as follows:

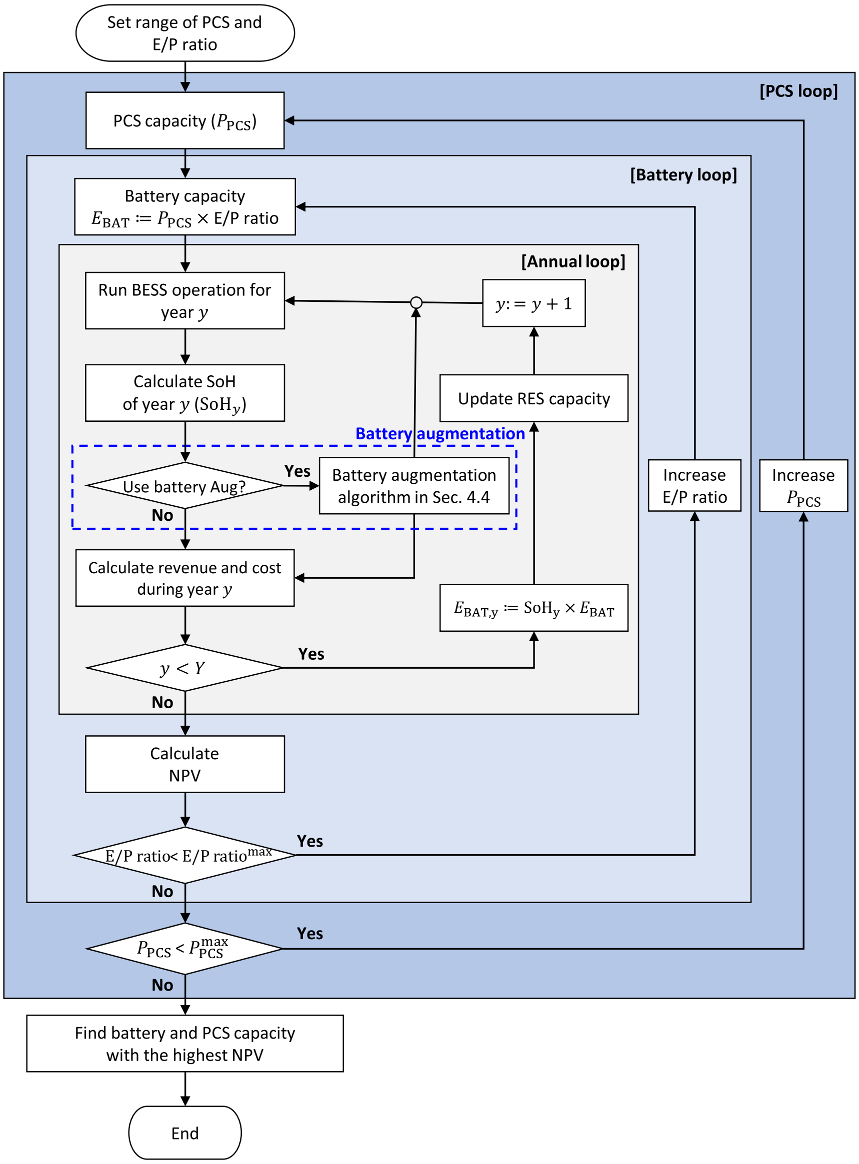


FIGURE 1. Proposed BESS sizing algorithm. Battery augmentation (dashed box) is optional.

1) For year y, calculate SoH_{y+1} using eq. (3) to predict the battery capacity retention at the end of that year, $E_{BAT,y+1}$. Check whether $E_{BAT,y+1}$ satisfies the minimum energy requirement, as illustrated in curve (1) in Figure 2.
2) If $E_{BAT,y+1} < E_{BAT}^{Req}$, where E_{BAT}^{Req} is the minimum energy capacity that must be guaranteed during the project planning horizon, apply battery augmentation. Estimate the battery degradation rate ($\hat{r}_{deg}$) as the rate of SoH variation between the year of the last battery augmentation and the current year, as illustrated in curve (2) in Figure 2.
3) Calculate the augmented capacity ($E_{BAT,y}^{Aug}$) as the minimum between $E_{BAT}\hat{r}_{deg} \cdot (Y - y) - E_{BAT,y} + E_{BAT}^{Req}$ and $E_{BAT} - E_{BAT,y}$. The former expression indicates energy capacity to be added to satisfy the minimum capacity required for the remaining project time based on the estimated degradation rate, $\hat{r}_{deg}$. This is illustrated in curves (3) and (4) in Figure 2. The latter expression implies that the capacity of battery additions is restricted by the initial BESS capacity. Without this constraint, the augmentation algorithm may require installing large additional batteries. This would require additional balance of the system and storage containers to accommodate the batteries, consequently incurring high costs.

The rate of battery capacity degradation declines over time as the BESS operates for a fixed maximum DoD, which can be estimated from eq. (3) (see, for example, Figure 5). Thus, $\hat{r}_{deg}$ may overestimate the battery degradation during

TABLE 3. Parameter values used for simulations.

Parameter	Description	Value
λ_{RES}	PPA price for RES generation	167.68 USD/MWh
λ_{BESS}	PPA price for BESS generation	375.42 USD/MWh
$\rho_{\text{RES-AC}}$	Efficiency RES system–grid	96.03%
$\rho_{\text{BAT-AC}}$	Efficiency battery–grid	93.60%
$\rho_{\text{RES-BAT}}$	Efficiency RES system–battery	88.08%
C_{BAT}	BESS price without PCS	Trend in Figure 3
C_{PCS}	PCS price	70 USD/kW
r	Discount rate for NPV	3.0% per year
k	RES system degradation	1.0% per year (solar) 1.5% per year (wind)

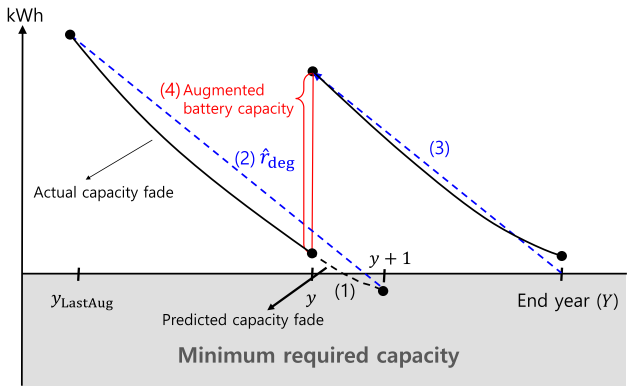


FIGURE 2. Illustration of parameters in proposed BAS.

the remaining project time. Consequently, $E^{\text{Aug}}_{\text{BAT},y}$ may also be greater than the required battery capacity for augmentation. Hence, the BAS convergence is guaranteed.

The costs of battery augmentation include the battery cost and related operations and maintenance cost. Additional costs such as those from labor are also included and assumed to be 10% of the battery cost. These costs should be reflected in the annual cost in eq. (7) when applying the BAS.

V. SIMULATION RESULTS

A. SIMULATION DATA

We evaluate the proposed algorithms using field data obtained from hourly measurements in solar and wind power plants of South Korea during 2017, whose capacities are 1 and 33 MW, respectively. For a fair comparison of the revenues, we normalize the capacities to 10 MW. The energy price for the RES-plus-storage power plant corresponds to the average SMP and RES prices in 2019, which are 89.49 and 62.95 KRW/kWh, respectively. Hence, the PPA price for RES generation is $\lambda_{RES} = 152.44$ KRW/kWh, and that for BESS discharging during RES generation is $\lambda_{ESS} = (89.49 + \text{multiplier} \cdot 62.95)$ KRW/kWh. When the REC multiplier is 4.0, λ_{ESS} becomes 341.29 KRW/kWh, which is approximately 2.4 times λ_{RES}. The PPA period for the RES-plus-storage power plants is set to 15 years. Hereinafter,

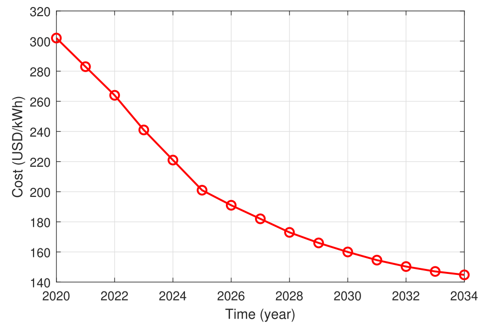


FIGURE 3. Costs for BESS excluding PCS from 2020 to 2034.

the Korean won (KRW) is converted into US dollars (USD) at an exchange rate of 1100 KRW/USD. For the BESS costs, the historical costs and projections in [49] are employed as reference. Figure 3 shows the cost projections for a BESS excluding the PCS from 2020 to 2034. Only the cost projection before 2031 is available in [49]. Thus, we use curve fitting to predict the costs after that year.

Table 3 lists the parameter values used for the simulations. The variations of battery temperature are neglected because they are complex to evaluate in numerical experiments. Instead, we assume a constant temperature of 25°C obtained from air-conditioning [32], [36].

The simulations were conducted using MATLAB 2019b on a computer with the Intel Core i7-4790 CPU and 16 GB RAM.

B. ESS OPERATION AND BATTERY DEGRADATION

Figure 4 shows the four 24-hour profiles of solar and wind generation and the battery SoC levels when applying the BESS operation algorithm. The power and energy capacities of the BESS are set to 6 MW and 27 MWh, respectively, and the maximum DoD range is set to 0.9. The combination of solar power patterns in the diurnal cycle and uniform non-peak solar generation periods leads to similar daily SoC patterns with large changes. In contrast, the wind power outputs are more irregular, but their daily variation is smaller than the solar power outputs. In addition, non-peak wind generation

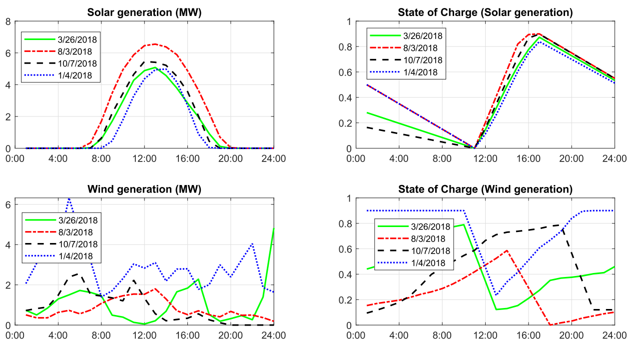


FIGURE 4. RES generation and SoC profiles by applying BESS operation algorithm. Each curve corresponds to a season .

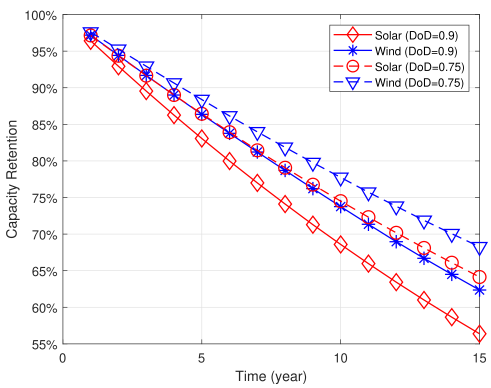


FIGURE 5. Battery capacity retention of RES-plus-storage power plant at different maximum DoD ranges.

periods vary according to the season. Therefore, the daily SoC profile for wind generation exhibits a variety of patterns with relatively smaller SoC changes than solar generation.

Figure 5 shows the battery capacity retention curves for the RES-plus-storage power plants obtained by applying the BESS operation algorithm for power and energy capacities of 6 MW and 27 MWh, respectively. For both RESs, a higher maximum DoD range causes more severe battery capacity degradation. When comparing solar and wind generation, the BESS combined with solar generation shows higher degradation than that combined with wind generation, because the daily SoC variation is usually larger for solar generation, as shown in Figure 4. The final capacity retention in Figure 5 may be very small compared to that of multiple studies.[5] To guarantee suitable capacity retention, the BESS owner may add battery racks to the base system.

C. CASE STUDIES

1) BESS SIZING AND ECONOMIC ANALYSIS FOR SOLAR GENERATION

Figure 6 shows the NPVs, final SoHs, total revenues, and total costs of various PCS capacities and E/P ratios for solar generation without the BAS. The total revenue is the sum of discounted cash inflows at the rate listed in Table 3. The total cost includes the annual cost in eq. (7) and the initial facility investment cost in eq. (5), and it is discounted by the discount rate. In Figures 6(c) and (d), larger PCS and higher E/P ratio result in higher revenues and costs. In Figure 6(b), the final SoH level is generally low, being below 63%, over the entire search space. Especially when the PCS capacity is low and the E/P ratio is low, the usable battery capacity in the final year can be less than 55% of the nominal value. It remains unclear whether the final SoH increases with the PCS capacity at a fixed E/P ratio. Using a larger PCS allows the BESS to operate at higher C-rate, and larger SoC variations occur within a cycle, accelerating the battery capacity degradation. On the other hand, at fixed E/P ratio, a larger PCS results in larger battery capacity, mitigating the battery capacity degradation, as shown in Figure 6(b).

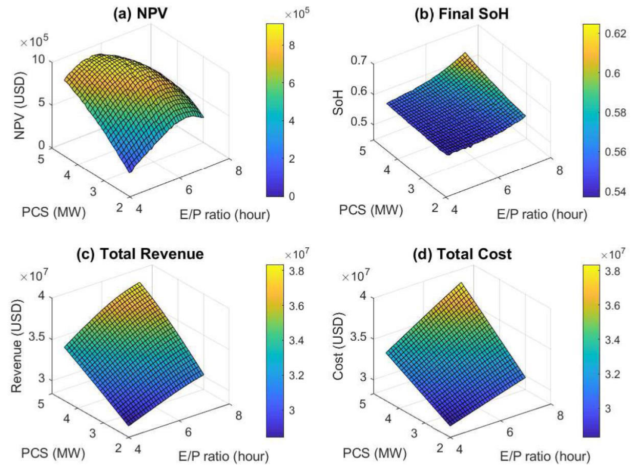


FIGURE 6. NPV, final SoH, total revenue, and total cost per combination of PCS capacity and E/P ratio for 10 MW of solar generation.

Figure 6(a) shows the simulation results for the NPV under various PCS capacities and E/P ratios. The optimal BESS capacity is that corresponding to the PCS size and E/P ratio providing the highest NPV.

Table 4 lists the optimal BESS capacities and corresponding NPVs and final SoHs for a BESS installed in a RES power plant with and without the BAS. The proposed BESS sizing algorithm retrieves a 4600 kW PCS and 5.9-hour battery storage, totaling 27,140 kWh. For solar generation, energy storage with long duration is preferable because the BESS added to the solar power plant experiences harsh battery degradation from the large SoC variations shown in Figure 4. The estimated NPV is 910, 500 USD, indicating that the BESS installation in the solar system is profitable considering the South Korean market. However, the final SoH is low, being only 56.7%, after BESS operation for 15 years. To maintain the SoH at a moderate level, for instance 80%, throughout the project operation, battery augmentation should be adopted.

We also compare the BESS sizing method with two benchmarks to verify its effectiveness. The first benchmark performs BESS sizing using the proposed algorithm but

[5] In many studies, the end of life for lithium-ion batteries are set to 80% of their nominal capacity, although smaller levels are sometimes adopted, such as 60 and 70%, practically.

TABLE 4. BESS capacity providing the highest NPV and its final SoH for four types of installations.

Type	PCS (kW)	E/P ratio (h)	Battery cap. (kWh)	NPV (USD)	Final SoH
Solar	4600	5.9	27,140	910,500	56.7%
Solar (BAS)	4400	7.20 (=5.50+0.94+0.76)	31, 680 (=24,200+4136+3344)	985,649	80.3%
Wind	2400	3.4	8160	−862, 341	56.7%
Wind (BAS)	2400	4.46 (=3.4+0.59+0.47)	10, 704 (=8160+1418+1126)	−827, 723	80.4%

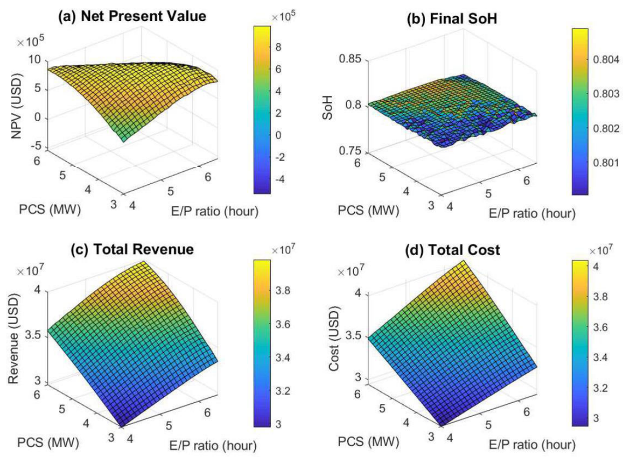


FIGURE 7. NPV, final SoH, total revenue, and total cost per combination of PCS capacity and E/P ratio for 10 MW of solar generation when using BAS.

neglecting battery degradation, as in [42]. In this case, the calculated BESS size is 4900 kW PCS and 5.2-hour battery storage, yielding an estimated NPV of 854,633 USD, which is 6.2% lower than that (910,500 USD) obtained when considering battery degradation. Thus, we can conclude that considering battery degradation in sizing produces a higher economic value in the BESS project. The second benchmark uses the same BESS sizing algorithm but considers the battery degradation trend estimated from a different application, the primary frequency control adopted in the German market [50]. In this benchmark, the calculated BESS size is 4600 kW PCS and 6.7-hour battery storage. The estimated NPV is 784,559 USD, being 13.8% lower than that obtained considering the battery degradation estimated from BESS operation established in the South Korean PPA. Therefore, the optimal BESS sizing depends on accurate estimation of the battery degradation considering the BESS operation.

Figure 7 shows the simulation results when integrating the proposed BAS into BESS sizing. Although the NPVs, final SoHs, total revenues, and total costs are calculated considering the BAS, the E/P ratio only represents the initial condition. Figure 7(b) shows that the final SoHs are higher than the predefined minimum requirement of 80% regardless of the BESS capacity when applying the BAS. The PCS capacity and E/P ratio that provide the highest NPV are 4.4 MW and 5.5 h, respectively.

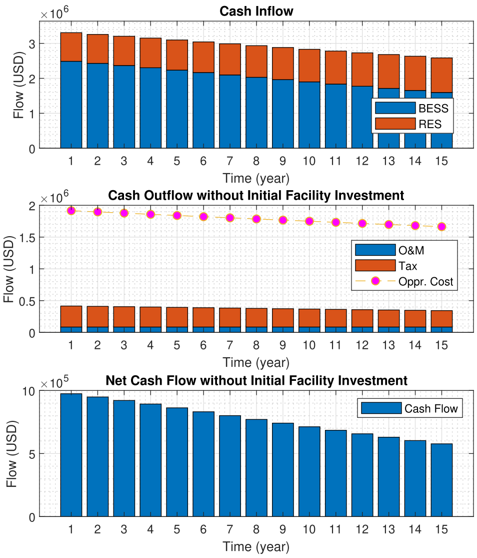
The third row of Table 4 presents the simulation results for the optimal BESS capacity when using the proposed BAS. The algorithm retrieves two augmentations, with batteries of 4136 and 3344 kWh being added in years 6 and 11, respectively. Thus, the total installed battery capacity is the sum of the initial capacity (24,200 kWh) and the added capacities (4136 kWh + 3344 kWh), totaling 31,680 kWh. The battery augmentations increase the NPV from 910, 500 to 985, 649 USD, representing an improvement of 8.5%. This financial gain is mainly due to the initial cost reductions in lithium-ion batteries and the time value of money. In fact, the BAS defers part of the initial investment, and the battery costs are expected to decrease in the future.

Figure 8 shows the annual cash flows from operating the solar-plus-storage power plant. In the top graph of Figure 8(a), the annual cash inflows decrease over time by the power plant degradation. The revenue obtained from BESS discharging constitutes approximately 69% of the total, despite the BESS accounting for only 42% of the generation. This high revenue is due to the high REC multiplier applied to the BESS. As the opportunity cost represents the revenue obtained from a standalone solar power plant, it decreases over time due to the solar panel degradation. In Figure 8(b), installing the augmented batteries charge additional 922, 783 and 593, 894 USD to the cash flows in years 6 and 11, respectively. The initial BESS installation costs are 7, 616, 400 and 8, 518, 280 USD with and without the BAS, respectively. By applying the BAS, the BESS owner can achieve more consistent cash inflows throughout the project operation, obtaining an increase in total revenue from 44, 096, 358 to 44, 782, 068 USD.

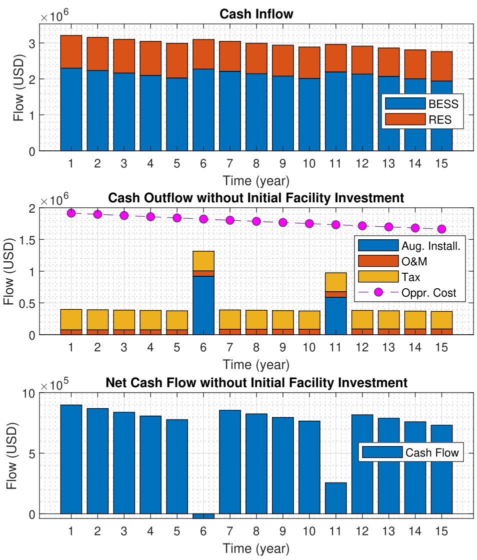
The simulation time to produce the solution was 1072 seconds when BAS was not considered. With the BAS, the simulation time increased to 1280 seconds.

2) BESS SIZING AND ECONOMIC ANALYSIS FOR WIND GENERATION

Figures 9 and 10 show the NPVs, final SoHs, total revenues, and total costs of various PCS capacities and E/P ratios for wind generation without and with the BAS, respectively. Unlike solar generation, the NPVs are negative for any BESS capacity when using wind generation. Although the BAS can improve the NPV from -862,341 to -827,723 USD, it remains negative. Figure 10(b) shows that the BAS allows achieving



(a) Without BAS



(b) With BAS

FIGURE 8. **Annual cash flows from solar-plus-storage power plant.**

the final SoHs higher than 80% for every combination of PCS capacities and E/P ratios. Table 4 shows that the optimal BESS capacity for wind generation is notably smaller than that for solar generation. When the BAS is not considered, the algorithm retrieves a 2400 kW PCS and 3.4-hour battery storage, totaling 8160 kWh. If the BAS is included, the algorithm retrieves two battery augmentations where batteries of 1418 and 1126 kWh are added in years 6 and 11, respectively. The total installed battery capacity is 10,704 kWh (8160 kWh + 1418 kWh + 1126 kWh).

This low economic feasibility is attributed to two factors: 1) the probabilistic characteristics of wind generation during the peak generation period and 2) the high variability in the duration of the peak and non-peak wind generation periods. Figure 11 shows the histograms of solar and wind power outputs during the corresponding peak generation periods.

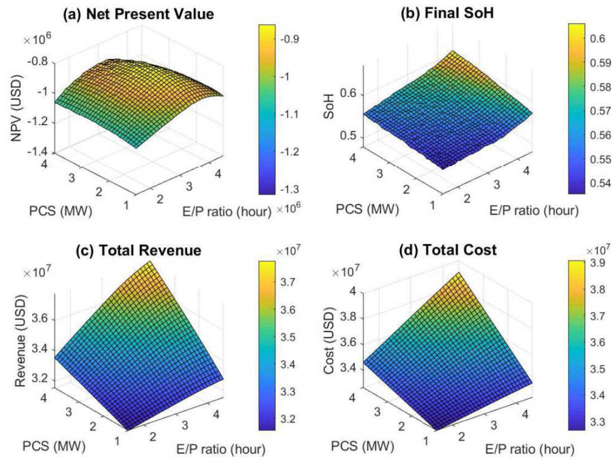


FIGURE 9. **NPV, final SoH, total revenue, and total cost per combination of PCS capacity and E/P ratio for 10 MW of wind generation.**

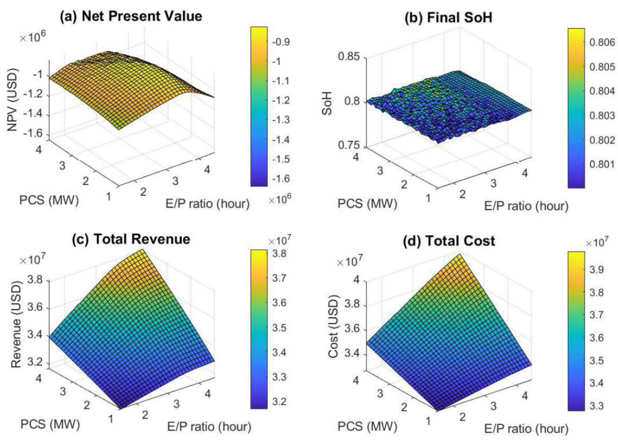
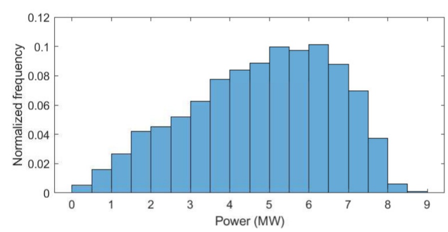
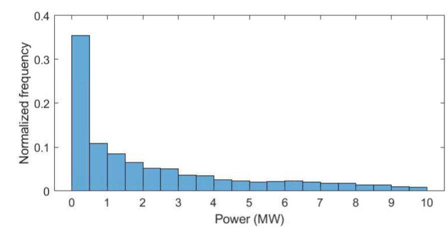


FIGURE 10. **NPV, final SoH, total revenue, and total cost per combination of PCS capacity and E/P ratio for 10 MW of wind generation when using BAS.**



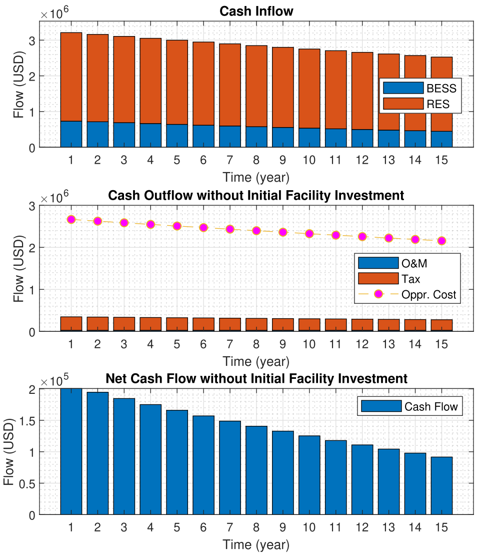
(a) Solar generation



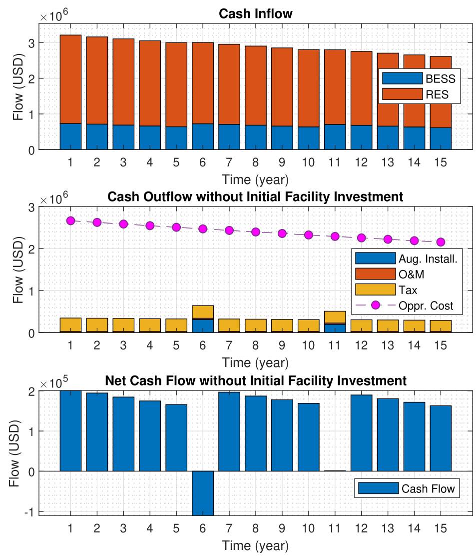
(b) Wind generation

FIGURE 11. **Empirical probability density functions for solar and wind output during peak generation periods.**

Using a small PCS and a large battery may be economically beneficial for wind generation because the wind power



(a) Without BAS



(b) With BAS

FIGURE 12. Annual cash flows from wind-plus-storage power plant.

distribution is heavily skewed toward low outputs. However, the BESS must discharge power during non-peak generation periods to benefit from a high REC multiplier. As the duration of the non-peak generation period for wind generation is substantially shorter than that of the peak generation period, the BESS power cannot be fully discharged during the former. To prevent this problem, a larger PCS may be installed, but it may not provide an economic benefit given the skewness of the wind power distribution. Therefore, both the PCS and battery should have low capacity for wind-plus-storage power plants.

Regarding solar generation, the durations of the peak and non-peak generation periods are more balanced. In fact, the ratio between these durations is approximately 1:3, unlike that between the corresponding durations of wind generation, which is approximately 6.3:1. Moreover, the distribution of solar generation is less skewed than that of wind generation, as shown in Figure 11. Therefore, installing a medium-sized PCS is economically advantageous under solar generation. Regarding the battery size, a long-duration BESS is required to efficiently collect the solar generation, mostly during the peak-generation periods.

Overall, the balanced durations of peak and non-peak generation periods and the balanced solar power distribution enable BESS efficiency and profitability. In addition, we consider that under the time-variant energy pricing, it is economically beneficial for the BESS operator to stipulate balanced durations of the peak and non-peak generation periods in the PPA.

Figure 12 shows the cash flows for the wind-plus-storage power plant with the PCS and battery capacities listed in Table 4. The revenues from BESS discharging are considerably smaller than those from directly supplying wind power to the grid due to the low BESS capacity. Nevertheless, the economic benefits of the BAS for solar generation, including the reduced initial costs, expected future reduction of battery costs, and increased revenue, remain valid for wind generation.

VI. CONCLUSION

We propose an approach to calculate the optimal capacity of a BESS combined with solar and wind generation considering the influence of lithium-ion battery degradation on the project cash flows. For a given BESS capacity, the proposed method first evaluates the SoH by applying the BESS operation algorithm to then update the battery capacity retention, and finally evaluate the annual cash flow. This process is repeated annually in the BESS sizing algorithm. In addition, we propose a BAS to defer investments and leverage the expected reduction of battery costs over time. The proposed BAS determines the timing and capacity of batteries to be added based on the predicted battery degradation rates.

We simulate the proposed algorithms considering South Korean market rules and data. Integrating a BESS with solar generation is profitable, whereas the NPV of integrating a BESS with wind generation is expected to be negative. For a RES system of a given size, the optimal PCS and battery capacities are considerably larger for solar generation than for wind generation. These differences in project profitability and optimal sizes are attributed to the probabilistic characteristics of RES power outputs and the different durations of the peak and non-peak generation periods. The simulations demonstrate that the proposed BAS can considerably improve the NPV for both solar and wind generation. Nevertheless, the NPV remains negative for wind-plus-storage power plants.

The proposed approach can provide a comprehensive framework for the parties involved in a BESS project, including project developers, engineering, procurement and construction providers, and independent power producers, to accurately determine the BESS sizes instead of simply considering battery degradation regardless of the BESS operation and capacity. In addition, we introduce a systematic BAS that can be easily integrated into the BESS sizing algorithm. The simulation results show that an efficient BESS depends on balanced peak and non-peak generation periods for the pricing rules of the PPA, leading to improved NPVs. The proposed sizing approach can be adapted to other applications by, for example, modifying the BESS operation algorithm and calculation of revenues and costs.

The proposed BAS is a suboptimal method. To achieve optimality, we should consider complex multistage optimization incorporating the effect of augmented batteries on the performance of the whole BESS. In future work, we will develop an advanced BAS to find approximate solutions to the optimization problem while maintaining moderate complexity. Additionally, the optimal sizing of BESS for the provision of multiple services is another interesting topic. For this purpose, it may be necessary to adopt decision making under uncertainty such as stochastic optimization and Markov decision processes.

REFERENCES

[1] N. Günter and A. Marinopoulos, "Energy storage for grid services and applications: Classification, market review, metrics, and methodology for evaluation of deployment cases," *J. Energy Storage*, vol. 8, pp. 226–234, Nov. 2016.

[2] Greentech Media. *Just How Much Business Can Batteries Take From Gas Peakers?*. Accessed: Apr. 23, 2020. [Online]. Available: https://www.greentechmedia.com/articles/read/just-how-much-business-can-batteries-take-from-gas-peakers

[3] P. L. Denholm, R. M. Margolis, and J. D. Eichman, "Evaluating the technical and economic performance of PV plus storage power plants," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-6A20-68737, 2017.

[4] M. Bolinger, J. Seel, and D. Robson, "Utility-scale solar: Empirical trends in project technology, cost, performance, and PPA pricing in the United States–2019 edition," Lawrence Berkeley Nat. Lab., Berkeley, CA, USA, Tech. Rep., Dec. 2019.

[5] M. R. Palacín, "Understanding ageing in li-ion batteries: A chemical issue," *Chem. Soc. Rev.*, vol. 47, no. 13, pp. 4924–4933, 2018, doi: 10.1039/C7CS00889A.

[6] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A review on lithium-ion battery ageing mechanisms and estimations for automotive applications," *J. Power Sources*, vol. 241, pp. 680–689, Nov. 2013.

[7] P. Mercier, R. Cherkaoui, and A. Oudalov, "Optimizing a battery energy storage system for frequency control application in an isolated power system," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1469–1477, Aug. 2009.

[8] V. Knap, S. K. Chaudhary, D.-I. Stroe, M. Swierczynski, B.-I. Craciun, and R. Teodorescu, "Sizing of an energy storage system for grid inertial response and primary frequency reserve," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 3447–3456, Sep. 2016.

[9] Y. J. Zhang, C. Zhao, W. Tang, and S. H. Low, "Profit-maximizing planning and control of battery energy storage systems for primary frequency control," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 712–723, Mar. 2018.

[10] J. Xiao, L. Bai, Z. Zhang, and H. Liang, "Determination of the optimal installation site and capacity of battery energy storage system in distribution network integrated with distributed generation," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 3, pp. 601–607, Feb. 2016.

[11] X. Wang, M. Yue, E. Muljadi, and W. Gao, "Probabilistic approach for power capacity specification of wind energy storage systems," *IEEE Trans. Ind. Appl.*, vol. 50, no. 2, pp. 1215–1224, Mar. 2014.

[12] M. Motalleb, E. Reihani, and R. Ghorbani, "Optimal placement and sizing of the storage supporting transmission and distribution networks," *Renew. Energy*, vol. 94, pp. 651–659, Aug. 2016.

[13] F. Zhang, Y. Song, and Z. Hu, "Mixed-integer linear model for transmission expansion planning with line losses and energy storage systems," *IET Gener., Transmiss. Distrib.*, vol. 7, no. 8, pp. 919–928, Aug. 2013.

[14] T. Qiu, B. Xu, Y. Wang, Y. Dvorkin, and D. S. Kirschen, "Stochastic multistage coplanning of transmission expansion and energy storage," *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 643–651, Jan. 2017.

[15] X. Tang, W. Deng, and Z. Qi, "Investigation of the dynamic stability of microgrid," *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 698–706, Mar. 2014.

[16] S. X. Chen, H. B. Gooi, and M. Q. Wang, "Sizing of energy storage for microgrids," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 142–151, Mar. 2012.

[17] H. Khorramdel, J. Aghaei, B. Khorramdel, and P. Siano, "Optimal battery sizing in microgrids using probabilistic unit commitment," *IEEE Trans. Ind. Informat.*, vol. 12, no. 2, pp. 834–843, Apr. 2016.

[18] E. Nasrolahpour, S. J. Kazempour, H. Zareipour, and W. D. Rosehart, "Strategic sizing of energy storage facilities in electricity markets," *IEEE Trans. Sustain. Energy*, vol. 7, no. 4, pp. 1462–1472, Oct. 2016.

[19] P. Harsha and M. Dahleh, "Optimal management and sizing of energy storage under dynamic pricing for the efficient integration of renewable energy," *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1164–1181, May 2015.

[20] R. Arghandeh, J. Woyak, A. Onen, J. Jung, and R. P. Broadwater, "Economic optimal operation of community energy storage systems in competitive energy markets," *Appl. Energy*, vol. 135, pp. 71–80, Dec. 2014.

[21] K. Bradbury, L. Pratson, and D. Patiño-Echeverri, "Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets," *Appl. Energy*, vol. 114, pp. 512–519, Feb. 2014.

[22] H. Thu Le and T. Quang Nguyen, "Sizing energy storage systems for wind power firming: An analytical approach and a cost-benefit analysis," in *Proc. IEEE Power Energy Soc. Gen. Meeting-Convers. Del. Electr. Energy 21st Century*, Jul. 2008, pp. 1–8.

[23] M. Dicorato, G. Forte, M. Pisani, and M. Trovato, "Planning and operating combined wind-storage system in electricity market," *IEEE Trans. Sustain. Energy*, vol. 3, no. 2, pp. 209–217, Apr. 2012.

[24] J. Galtieri and P. T. Krein, "Solar variability reduction using off-maximum power point tracking and battery storage," in *Proc. IEEE 44th Photovoltaic Specialist Conf. (PVSC)*, Jun. 2017, pp. 3214–3219.

[25] N. Müller, S. Kouro, P. Zanchetta, P. Wheeler, G. Bittner, and F. Girardi, "Energy storage sizing strategy for grid-tied PV plants under power clipping limitations," *Energies*, vol. 12, no. 9, p. 1812, May 2019.

[26] M. Yue and X. Wang, "Grid inertial response-based probabilistic determination of energy storage system capacity under high solar penetration," *IEEE Trans. Sustain. Energy*, vol. 6, no. 3, pp. 1039–1049, Jul. 2015.

[27] P. Li, R. Dargaville, F. Liu, J. Xia, and Y.-D. Song, "Data-based statistical property analyzing and storage sizing for hybrid renewable energy systems," *IEEE Trans. Ind. Electron.*, vol. 62, no. 11, pp. 6996–7008, Nov. 2015.

[28] G. Ning and B. N. Popov, "Cycle life modeling of lithium-ion batteries," *J. Electrochem. Soc.*, vol. 151, no. 10, p. A1584, 2004.

[29] R. Spotnitz, "Simulation of capacity fade in lithium-ion batteries," *J. Power Sources*, vol. 113, no. 1, pp. 72–80, Jan. 2003.

[30] J. Vetter, P. Novák, M. R. Wagner, C. Veit, K. C. Möller, J. O. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, and A. Hammouche, "Ageing mechanisms in lithium-ion batteries," *J. Power Sources*, vol. 147, nos. 1–2, pp. 269–281, 2005.

[31] O. Erdinc, B. Vural, and M. Uzunoglu, "A dynamic lithium-ion battery model considering the effects of temperature and capacity fading," in *Proc. Int. Conf. Clean Electr. Power*, Jun. 2009, pp. 383–386.

[32] D.-I. Stroe, M. Swierczynski, A.-I. Stroe, R. Laerke, P. C. Kjaer, and R. Teodorescu, "Degradation behavior of lithium-ion batteries based on lifetime models and field measured frequency regulation mission profile," *IEEE Trans. Ind. Appl.*, vol. 52, no. 6, pp. 5009–5018, Nov. 2016.

[33] D.-I. Stroe, V. Knap, M. Swierczynski, A.-I. Stroe, and R. Teodorescu, "Operation of a grid-connected lithium-ion battery energy storage system for primary frequency regulation: A battery lifetime perspective," *IEEE Trans. Ind. Appl.*, vol. 53, no. 1, pp. 430–438, Jan. 2017.

[34] X. Hu, H. Yuan, C. Zou, Z. Li, and L. Zhang, "Co-estimation of state of charge and state of health for lithium-ion batteries based on fractional-order calculus," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 10319–10329, Nov. 2018.

[35] X. Hu, F. Feng, K. Liu, L. Zhang, J. Xie, and B. Liu, "State estimation for advanced battery management: Key challenges and future trends," *Renew. Sustain. Energy Rev.*, vol. 114, Oct. 2019, Art. no. 109334.

[36] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. S. Kirschen, "Modeling of lithium-ion battery degradation for cell life assessment," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1131–1140, Mar. 2018.
[37] Z. Zhang, C. Guan, and Z. Liu, "Real-time optimization energy management strategy for fuel cell hybrid ships considering power sources degradation," *IEEE Access*, vol. 8, pp. 87046–87059, 2020.
[38] A. Maheshwari, N. G. Paterakis, M. Santarelli, and M. Gibescu, "Optimizing the operation of energy storage using a non-linear lithium-ion battery degradation model," *Appl. Energy*, vol. 261, Mar. 2020, Art. no. 114360. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261919320471
[39] M. Lee, J. Park, S.-I. Na, H. S. Choi, B.-S. Bu, and J. Kim, "An analysis of battery degradation in the integrated energy storage system with solar photovoltaic generation," *Electronics*, vol. 9, no. 4, p. 701, Apr. 2020. [Online]. Available: https://www.mdpi.com/2079-9292/9/4/701
[40] Y. Zhou, H. Obeid, S. Laghrouche, M. Hilairet, and A. Djerdir, "A disturbance rejection control strategy of a single converter hybrid electrical system integrating battery degradation," *Energies*, vol. 13, no. 11, p. 2781, Jun. 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/11/2781
[41] C. Zhang, D. Wang, B. Wang, and F. Tong, "Battery degradation minimization-oriented hybrid energy storage system for electric vehicles," *Energies*, vol. 13, no. 1, p. 246, Jan. 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/1/246
[42] J. Kong, S. T. Kim, B. O. Kang, and J. Jung, "Determining the size of energy storage system to maximize the economic profit for photovoltaic and wind turbine generators in South Korea," *Renew. Sustain. Energy Rev.*, vol. 116, Dec. 2019, Art. no. 109467.
[43] S. Downing and D. Socie, "Simple rainflow counting algorithms," *Int. J. Fatigue*, vol. 4, no. 1, pp. 31–40, Jan. 1982.
[44] E. Peled, "The electrochemical behavior of alkali and alkaline earth metals in nonaqueous battery systems—The solid electrolyte interphase model," *J. Electrochem. Soc.*, vol. 126, no. 12, pp. 2047–2051, 1979.
[45] P. Pinson, G. Papaefthymiou, B. Klockl, and J. Verboomen, "Dynamic sizing of energy storage for hedging wind power forecast uncertainty," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2009, pp. 1–8.
[46] K. Baker, G. Hug, and X. Li, "Energy storage sizing taking into account forecast uncertainties and receding horizon operation," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 331–340, Jan. 2017.
[47] K. Mongird, V. Viswanathan, P. Balducci, J. Alam, V. Fotedar, V. Koritarov, and B. Hadjerioua, "Energy storage technology and cost characterization report," Pacific Northwest Nat. Lab., (PNNL), Richland, WA, USA, Tech. Rep. PNNL-28866, 2019.
[48] J. Leadbetter and L. G. Swan, "Selection of battery technology to support grid-integrated renewable electricity," *J. Power Sources*, vol. 216, pp. 376–386, Oct. 2012.
[49] "Energy storage system costs survey 2018," Bloomberg New Energy Finance, New York, NY, USA, Tech. Rep., 2018.
[50] B. Xu, "Degradation-limiting optimization of battery energy storage systems operation," M.S. thesis, Dept. Inf. Technol. Elect. Eng., ETH Zurich, Zürich, Switzerland, 2013.

HUNYOUNG SHIN (Member, IEEE) received the B.S. degree in radio and communication engineering and the M.S. degree in electrical engineering from Korea University, Seoul, South Korea, and the Ph.D. degree from the Department of Electrical and Computer Engineering, The University of Texas at Austin, Austin, TX, USA, in December 2017. In 2018, he joined LG CNS as a Managing Consultant and participated in energy storage system planning projects. He is currently an Assistant Professor with Sangmyung University, Seoul. His research interests include optimization of power systems, risk-hedging strategies, and pricing rule in electricity markets.

JIN HUR (Senior Member, IEEE) received the B.S. and M.S. degrees in electrical engineering from Korea University, Seoul, South Korea, in 1997 and 1999, respectively, and the Ph.D. degree in electrical and computer engineering from The University of Texas at Austin, in 2012. He is currently an Associate Professor with the Department of Climate and Energy Systems Engineering, Ewha Womans University. His research interest includes integrate high level of variable generating resources into electric power systems.