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Operation Strategy for Maximizing Revenue of an Energy Storage System With a Photovoltaic Power Plant Considering the Incentive for Forecast Accuracy in South Korea

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ABSTRACT Adequate policies or incentives are needed to support investment in renewable energy industries. However, renewable power plant operators in South Korea may face the risk of finding it difficult to recoup their capital cost in the absence of a peak-biased incentive for the power plant with energy storage systems (ESS). Incentives for the forecast accuracy of the power plant will be adopted after the abolition of the incentive. This study explores the impact of incentives on power plant operations. In this study, we propose an ESS optimization model combined with a photovoltaic power plant. We design a coordinated model of the power plant to model the structures of revenues and costs based on actual power generation and a forecast error ratio. Optimization problems from the model are formulated as mixed integer linear programming to maximize revenue with the incentive for forecast accuracy. The revenue of the incentive is designed to reflect the unit price of the incentive, varying with the forecast error ratio. The effects of incentive adoption are evaluated in comparison with the absence of incentives.

INDEX TERMS Energy storage system, forecast accuracy, incentive, photovoltaic power plant, renewable energy certificate.

NOMENCLATURE

A. INDICES

- t 1-hour time step in $[1 : t^{\max}]$.
 s Scenario in $[1 : s^{\max}]$.
 rf Forecast error interval in $[1 : rf^{\max}]$.

B. PARAMETERS

- smp_t System marginal price at time t , (won/kWh).
 REC_t Price of renewable energy certificate at time t , (won/kWh).
 C^{PV} Rated capacity of photovoltaic panels, (kW).
 C^{ESS} Rated capacity of energy storage system, (kW).

- $\omega^{VO\&M}$ Variable O&M cost of energy storage system, (won/kWh).
 $\eta^{ESS,eff}$ Turnaround efficiency of energy storage system (%).
 $SOC^{\min}/SOC^{\max}$ Minimum/maximum state of charge of energy storage system, (kWh).
 η^{ch}/η^{dch} Charging/discharging efficiency of energy storage system, (%).
 σ_s Probability of scenario s .
 inc_{rf} Unit price of incentive for forecast accuracy at forecast error region rf , (won/kWh).
 pr_{rf} Constant value of forecast error ratio at forecast error region rf .
 $P_t^{PV,f}$ Forecasted electrical power of photovoltaic panels at time t , (kWh).
 Z Positive infinity.

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C. VARIABLES

R_t^{sell}	Revenue of selling electrical power to electricity market at time t , (won).
$R_t^{forecast}$	Revenue of the incentive for forecast accuracy at time t , (won).
C_t^{ESS}	Operation cost of energy storage systems at time t , (won).
$P_{t,s}^{PCC,a}$	Actual electrical power at the point of common coupling at time t in scenario s , (kWh).
$P_t^{PCC,f}$	Forecasted electrical power at the point of common coupling at time t , (kWh).
$P_{t,s}^{PV,a}$	Actual electrical power of photovoltaic panels at time t in scenario s , (kWh).
$P_{t,s}^{ch,a} / P_{t,s}^{dch,a}$	Actual charge/discharge power of energy storage systems at time t in scenario s , (kWh).
$P_t^{ch,f} / P_t^{dch,f}$	Forecasted charge/discharge power of energy storage systems at time t , (kWh).
$\varepsilon_{t,s}$	Forecast error ratio at time t in scenario s .
$\mu_{t,s,rf}$	Forecast error ratio at time t in scenario s in forecast error region rf .
$g_{t,s,rf}$	Product of actual power and unit price of incentive at time t in scenario s in forecast error region rf .
$h_{t,s,rf}$	Multiplication of all terms related to forecast error interval at time t in scenario s in forecast error region rf .

D. BINARY VARIABLES

$v_{t,s,rf}$	Status of a forecast error region rf .
$\delta_{t,s}^{ch,a} / \delta_{t,s}^{dch,a}$	Status of actual charging/discharging operation of energy storage system at time t in scenario s .
$\delta_t^{ch,f} / \delta_t^{dch,f}$	Status of forecasted charging/discharging operation of energy storage system at time t .

I. INTRODUCTION

With the development of sustainable power systems, utilizing renewable energy sources (RES), including wind and solar energy, is indispensable for supplying pollution-free energy [1]. Many countries have adopted renewable energy policies to promote innovation in sustainable development [2]. Along with global trends, in South Korea, the increase in electricity from renewable energy sources (RES-E) is realized by policy instruments, including renewable portfolio standards (RPS) [3]. The RPS obligates major electric power suppliers to procure a certain percentage of RES-E in their electricity generation mix. This obligation can be fulfilled in two ways: 1) suppliers generate RES-E themselves; and 2) suppliers purchase a renewable energy certificate (REC) issued for all RES-E. RECs can be bought and sold on the REC market. The trading volume has increased as the number of issued RECs increased from 4.1 million

RECs in 2012 to 35.0 million RECs in 2019 [4]. The volume continued to increase with the growth of RES-E.

From the perspective of RES suppliers, RECs are needed to recover their investment costs. The suppliers can earn the RECs by multiplying the amount of RES-E generated by the REC weight [3]. The REC weight varies with the type of RES. A photovoltaic (PV) power plant can have various weights, ranging from 0.7 to 1.2. For example, if the amount of power generated from the PV plant is 1 MWh, the REC with a range of 0.7–1.2 is issued. In addition, an energy storage system (ESS) combined with a PV power plant can earn four times the REC for the discharging power [5]. The RES supplier with the ESS could earn additional profits with a large REC weight. With this large one, the supplier could consider the combination of the ESS with its plant. They could also determine the operation and planning strategy of the ESS to maximize economic profit [6]. However, the large REC weight of the ESS will vanish by the end of 2020. Alternative measures would be needed to recover RES suppliers' investment costs and pursue additional profits instead of earning the vanished REC weight.

The ESS can provide various services, such as complementary energy, arbitrage, reserves, and black start, to support the operation of power systems and the RES [7]. Among these services, RES suppliers might be interested in complementary energy and arbitrage rather than reserves, black start, etc., because they want to make additional profits or minimize the difference between the forecasted and actual generation [8]. When charged with excess RES-E, the ESS can receive low-cost energy to reduce charging costs and curtailed energy [9]. Otherwise, the ESS can discharge electricity to earn profits and supply less electricity. RES suppliers can control electricity production and estimate operation costs by charging/discharging the ESS.

With useful services provided by the ESS, the ESS can also supplement operation and planning of the RES plant generating intermittent power. The operation strategy for a community-based storage system was proposed to reduce the loss at the PV coupling points and maximize the profit for the community [10]. The control strategy of an energy system coordinated with a supercapacitor was presented to smooth the power fluctuations of the PV and to maintain the state of charge (SOC) from approaching its lower limits [11]. The coordinated planning framework for the RES and ESS was proposed to recover the investment costs in the centralized electricity market by varying the investment tax credit [12]. In addition, the on-site ESS with wind farms was used to handle wind imbalances and to provide ancillary services by optimizing the bidding of energy and reserves [13]. In short, the proper utilization of the ESS can help operators and planners maximize their profits under intermittent RES-E.

The above applications of the ESS are sufficient to make operators and planners of the RES profitable, but operation and planning of the ESS in Korea are merely simple strategies that charge from the grid during off-peak hours and discharge the energy during peak hours [6], [9], [14]. With the high REC

weight during peak hours, the optimal sizing methodology of the ESS with the RES was proposed to maximize the economic profit for the RES [6]. The peak-biased discharging operation of the ESS could make it difficult to mitigate the variability of the RES because the ESS would not discharge the energy during off-peak hours. The effects of imposing incentives were evaluated to promote the discharging of energy during off-peak hours to solve this problem [14]. In addition, the operation strategy for the ESS was presented to reduce the amount of curtailment of the RES and to ensure system reliability without considering the economic profit [9]. With the abovementioned strategies, the economic profit from the REC weight might be an important part of ESS operations in Korea.

While operations and planners of the ESS with RES require a chance to earn economic profit alternatives to the REC weight in Korea, no existing study has focused on ESS operation strategies without REC incentives. To address this gap, we evaluated the optimal operation strategy of the ESS with the RES by considering incentives for the forecast accuracy of the RES. This study addresses the following aspects.

- 1) The optimal operation strategy of the ESS combined with a PV power plant is proposed.
- 2) The incentive for forecast accuracy of the RES under the circumstances where the subsidy from the RPS policy is reduced is considered.
- 3) The ESS scheduling algorithm, formulated using mixed integer linear programming (MILP), is developed.

The rest of this paper is organized as follows: Section II presents the optimization model that maximizes the revenues of the PV power plant with a coordinated model. Section III analyzes the results by adopting the incentive for the forecast accuracy through numerical results. Section IV discusses the results and future work. Section V outlines the study's conclusions.

II. PROBLEM STRUCTURE

A. COORDINATED MODEL OF A PV POWER PLANT WITH AN ESS

This study considers a coordinated model of a PV power plant with an ESS, as shown in Fig. 1. The PV power plant is connected to an electricity grid via a point of common coupling (PCC). The electrical power from the PV panels and ESSs can be transmitted to the electricity grid via the PCC. In this study, the ESS charging power comes only from the PV panels.

The PV power plant operator can sell the electricity transmitted via the PCC to the electricity grid or electricity market. Unlike the peak-biased revenue earned only during the peak time, the revenue after vanishing the REC weight for the ESS comprises the sold electrical power at the PCC without consideration of peak/off-peak hours [3], [5], [6], [10], [14]. Under absence or reduction of conventional incentives for the power plant operation, the operators would be willing to seek other incentives to recoup their costs. Hence, an incentive for the forecast accuracy of the RES in the new policy is

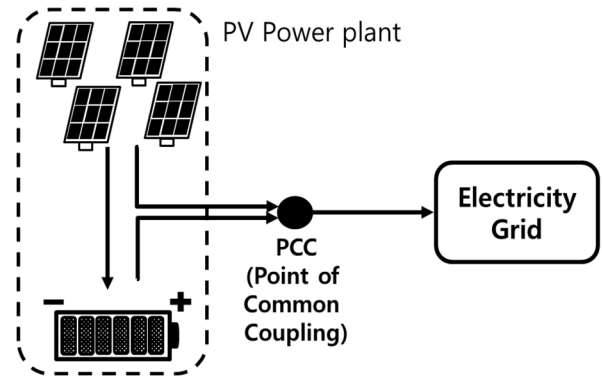


FIGURE 1. Coordinated model of a PV power plant with an ESS.

TABLE 1. Unit price of incentive for forecast accuracy [15].

Unit price of incentive (won/kWh)	Range of forecast error ratio
3	6 – 8%
4	≤ 6%

a solution to obtaining other incentives. The new incentive is assessed using the forecast error ratio at the PCC [15]. According to the ratio, the unit price of the incentive is set, as presented in Table 1.

In this table, a lower ratio of forecast error results in a higher unit price. The revenue of the PV power plant would be maximized when a large amount of electrical power at the PCC is sold and when a ratio of forecast error is under 6%. Therefore, PV power plant operators can maximize their revenue by controlling an amount of electrical power at the PCC and the ratio of forecast error with the PV power generation and the charging/discharging power of the ESS.

In short, the operator as shown in Fig. 1 could have two operation strategies: 1) earning the revenues from selling the power to the grid, 2) earning the revenues from incentive for forecast accuracy.

B. OBJECTIVE FUNCTION

We define a revenue and expense model for a PV power plant. The revenue model is composed of revenue from selling electrical power to the electricity market, R_t^{sell} , and revenue from the incentive for the forecast accuracy, $R_t^{forecast}$. The expense model of operation of the ESS, C_t^{ESS} , can vary with the total amount of charging and discharging power. The revenue model and the expense model are described as follows:

$$\text{Maximize } \sum_{\forall t} (R_t^{sell} + R_t^{forecast} - C_t^{ESS}). \quad (1)$$

The revenue and expense are modeled based on the expectation value of the actual electrical power at the PCC. The expectation value could be determined by multiplying the probability and the actual power of each scenario. Out of the revenue model, the selling price is settled by the expectation value and a combination of the system marginal price (SMP)

and the REC price. The SMP represents the wholesale price at which suppliers purchase electricity in Korean electricity market. The REC price represents the additional source of revenue for their generated power. With the SMP and the REC, the operators can earn the revenue at the wholesale market, expressed as

$$R_t^{sell} = \left[\sum_{\forall s} (\sigma_s \cdot P_{t,s}^{PCC,a}) \right] \times (smp_t + REC_t) \forall t. \quad (2)$$

The revenue from the incentive is described from the novel revenue model of PV power plant operators willing to receive incentives for forecast accuracy. The additional revenue could be determined by the actual power at the PCC and the unit price that varies with the ratio of forecast error. From the unit price and the range of forecast error ratio, the forecast error ratio region is separated by several intervals. Although this revenue is reward for the forecast accuracy, it is settled by the actual power instead of the forecast error ratio according to the Korean market rules [15]. The interval-varying unit price in Table 1 is utilized with the actual power for a settlement of a somewhat indirect reward. Therefore, the revenue of the forecast accuracy is determined by the interval-varying unit price of incentive and the actual power. This revenue is described as

$$R_t^{forecast} = \sum_{\forall s} \left(\sigma_s \cdot P_{t,s}^{PCC,a} \cdot \left[\sum_{rf} (v_{t,s,rf} \cdot inc_{rf}) \right] \right) \forall t, \quad (3)$$

where $v_{t,s,rf}$ is the status of a forecast error interval rf at time t in each scenario s . inc_{rf} is the unit price of the incentive for the forecast error according to the interval rf . The assessment of incentives for forecast errors is described in the following section. Meanwhile, the actual power at the PCC in a scenario is described as

$$P_{t,s}^{PCC,a} = P_{t,s}^{PV,a} + P_{t,s}^{dch,a} - P_{t,s}^{ch,a} \quad \forall t, \forall s. \quad (4)$$

The above power comprises the actual power of the PV panels, $P_{t,s}^{PV,a}$, the discharge power, $P_{t,s}^{dch,a}$, and the charge power, $P_{t,s}^{ch,a}$. The cost of the ESS is also modeled based on the expectation value of the actual charge/discharge power and the variable operation and maintenance (O&M) cost of the ESS. The ESS cost is given by

$$C_t^{ESS} = \left[\sum_{\forall s} (\sigma_s \cdot (P_{t,s}^{ch,a} + P_{t,s}^{dch,a})) \right] \times \omega^{VO\&M} \forall t. \quad (5)$$

In this optimization problem, the PV power plant operator can maximize the revenue by adjusting the amount of actual power at the PCC with the charge/discharge power.

C. ASSESSMENT OF INCENTIVES FOR FORECAST ERROR

The forecast error at the PCC depends on the difference between the actual and forecasted values of the electrical power. The ratio of the forecast error is then calculated

by dividing the difference by the total capacity behind the PCC [15]. This ratio is described as follows:

$$\varepsilon_{t,s} = \frac{P_t^{PCC,f} - P_{t,s}^{PCC,a}}{C^{PV} + C^{ESS}} \quad \forall t, \forall s, \quad (6)$$

where $\varepsilon_{t,s}$ is the ratio of forecast error at the PCC at time t in each scenario s . The capacity of the total PV panels and the ESS are represented by C^{PV} and C^{ESS} , respectively. In addition, $P_t^{PCC,f}$ is the forecasted electrical power at the PCC, expressed as

$$P_t^{PCC,f} = P_t^{PV,f} + P_t^{dch,f} - P_t^{ch,f} \quad \forall t, \quad (7)$$

where $P_t^{PV,f}$ is the forecasted power of PV panels. $P_t^{ch,f}$ and $P_t^{dch,f}$ are the forecasted charge and discharge powers, respectively. Similar to (4), the forecasted power comprises the forecasted power of the PV panels, the forecasted discharge power and the forecasted charge power.

Under the new policy, the incentive in (3) depends on the forecast error interval determined by the forecast error ratio in (6). According to Table 1, the unit price of the incentive is limited to the range of forecast error ratio, 6-8%. If the forecast error is lower than 6%, the actual power at the PCC is settled at the highest of unit price of incentive, 4 won/kWh. In addition, if the forecast error is greater than 6% and lower than 8%, the actual power is settled at 3 won/kWh. Otherwise, if the forecast error is greater than 8%, the actual power is not settled with incentive. Hence, the forecast error ratio is limited between -0.08 (represented as 8% with under-estimated prediction) to 0.08 (represented as 8% with over-estimated prediction). An overview of the decision process is shown in Fig. 2.

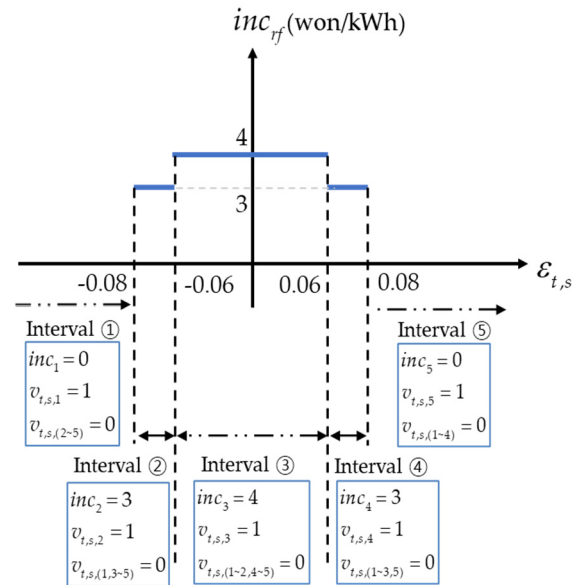


FIGURE 2. Overview of decision process of forecast error interval.

As shown in Fig. 2, the unit price of the incentives varies with the ratio of the forecast error listed in Table 1. The forecast error ratio in Fig. 2 is arranged from a negative to

positive ratio. The underestimated power at the PCC could lead to a negative ratio; otherwise, the overestimated power could lead to a positive ratio. The unit price and forecast error can be divided into five intervals according to the range of the ratios in Table 1. First, interval ① indicates that the underestimated forecast error ratio is greater than 8%. The unit price of the incentive in this interval is zero, and the value of the status of the forecast error interval is 1, while the values of other intervals are all zero. Second, interval ② indicates that the underestimated forecast error ratio is between 6% and 8%. The unit price in this interval is 3 won/kWh, as shown in Table 1, and the value of the status of the forecast error interval is 1. Third, interval ③ indicates that the forecast error ratio is less than 6%. The unit price of incentive is the highest among intervals, and the value of the status of only this interval is 1. Finally, the decision process of the values of intervals ④ and ⑤ is similar to that of intervals ① and ②. With these procedures, the ratio of the forecast error is described with the status of the forecast error interval as

$$\mu_{t,s,rf} = \varepsilon_{t,s} \cdot v_{t,s,rf} \quad \forall t, \forall s, \forall rf, \quad (8)$$

where $\mu_{t,s,rf}$ is the forecast error ratio in the forecast error interval rf . Multiplication of the ratio and status yields the forecast error ratio in each forecast error interval. If the forecast error ratio is 3%, the status value related to interval ③ takes 1, while the other values are zero. Then, the ratio in each forecast error interval varies with the value of the status in each interval. The condition of the status is required because it can only be selected once for a single interval, as follows:

$$\sum_{rf} v_{t,s,rf} = 1 \quad \forall t, \forall s. \quad (9)$$

With this condition, the status of the forecasted interval described in (3) can be determined according to the forecast error ratio.

D. LINEARIZATION OF REVENUE AND FORECAST ERROR

Although the forecast error ratio can be determined by multiplying the ratio and the value of the status, the multiplication forms in (3) and (8) must be linearized to model the MILP optimization problem.

The linearization of (8) proceeds as follows:

$$\begin{cases} \begin{cases} \varepsilon_{t,s} \geq -(1-v_{t,s,rf}) \cdot Z + v_{t,s,rf} \cdot pr_{rf} \\ \varepsilon_{t,s} \leq (1-v_{t,s,rf}) \cdot Z + v_{t,s,rf} \cdot pr_{rf+1}, \end{cases} & \text{if } rf < rf^{\max} \\ \begin{cases} \varepsilon_{t,s} \geq -(1-v_{t,s,rf}) \cdot Z + v_{t,s,rf} \cdot pr_{rf} \\ \varepsilon_{t,s} \leq (1-v_{t,s,rf}) \cdot Z + v_{t,s,rf}, \end{cases} & \text{otherwise} \end{cases} \quad \forall t, \forall s, \quad (10)$$

where pr_{rf} is the constant value of the forecast error ratio in the interval rf . Z represents positive infinity. If $\varepsilon_{t,s}$ is -0.07 (when the forecast error ratio is 7%), the value of the status in interval ② (or $v_{t,s,2}$) takes on 1 when pr_2 and pr_3 are -0.08 and -0.06 , respectively. The ratio in other intervals is larger than negative infinity and smaller than positive infinity

because the other values of the status are zero. In short, this process can change the nonlinear equation in (8) to the linear form in (10) for modelling the MILP optimization problem.

Equation (3) should also be linearized because the revenue is a nonlinear form comprising a multiplication of the variable representing the actual power and the variable describing the status of the forecast error interval. Equation (3) can be linearized for the MILP optimization problem as follows:

$$\begin{aligned} R_t^{\text{forecast}} &= \sum_{\forall s} \left(\sigma_s \cdot P_{t,s}^{\text{PCC},a} \cdot \left[\sum_{\forall rf} (v_{t,s,rf} \cdot inc_{rf}) \right] \right) \\ &= \sum_{\forall s} \left(\sigma_s \cdot \left[\sum_{\forall rf} (P_{t,s}^{\text{PCC},a} \cdot inc_{rf} \cdot v_{t,s,rf}) \right] \right) \\ &= \sum_{\forall s} \left(\sigma_s \cdot \left[\sum_{\forall rf} (g_{t,s,rf} \cdot v_{t,s,rf}) \right] \right) \\ &= \sum_{\forall s} \left(\sigma_s \cdot \left[\sum_{\forall rf} h_{t,s,rf} \right] \right), \quad \forall t \end{aligned} \quad (11)$$

where $g_{t,s,rf}$ is the product of the actual power and the unit price of incentive in the forecast error interval. $h_{t,s,rf}$ is the multiplication of all terms related to the forecast error interval. With the sums of variables shown in the last term of (11), the revenue of the forecast can be linearized. In addition, the linear inequality constraints of $g_{t,s,rf}$ and $h_{t,s,rf}$ are as follows:

$$\begin{cases} h_{t,s,rf} \geq -v_{t,s,rf} \times Z \\ h_{t,s,rf} \leq v_{t,s,rf} \times Z \\ \begin{cases} h_{t,s,rf} \geq g_{t,s,rf} - (1-v_{t,s,rf}) \times Z \\ h_{t,s,rf} \leq g_{t,s,rf} + (1-v_{t,s,rf}) \times Z \end{cases} \end{cases} \quad \forall t, \forall s, \forall rf. \quad (12)$$

The result of $h_{t,s,rf}$ depends on the status value in (10). If the forecast error ratio is in interval ①, only $h_{t,s,rf}$ of interval ① can take on $g_{t,s,rf}$ of interval ①, representing the product of the unit price of the incentive and the actual power, regardless of the value of the actual power.

E. OPERATION CONSTRAINTS OF ESS

The charge and discharge power constraints of the ESS are influenced by the SOC limit. The SOC is limited within a range from the minimum SOC level to the maximum SOC level.

$$\begin{cases} SOC^{\min} \leq SOC_t^f \leq SOC^{\max} \\ SOC^{\min} \leq SOC_{t,s}^a \leq SOC^{\max} \end{cases} \quad \forall t, \forall s. \quad (13)$$

In addition, the SOC is determined by the charging–discharging operations, and the SOC is assumed to be

initialized to half of the ESS capacity:

$$SOC_t^f = \begin{cases} Cap^{ESS}/2 + P_t^{ch,f} \times \eta^{ESS,eff} \\ -P_t^{dch,f} / \eta^{ESS,eff}, & \text{if } t = 1 \\ SOC_{t-1}^f + P_t^{ch,f} \times \eta^{ESS,eff} \\ -P_t^{dch,f} / \eta^{ESS,eff}, & \text{otherwise} \end{cases} \quad \forall t, \quad (14)$$

$$SOC_{t,s}^a = \begin{cases} Cap^{ESS}/2 + P_{t,s}^{ch,a} \times \eta^{ESS,eff} \\ -P_{t,s}^{dch,a} / \eta^{ESS,eff}, & \text{if } t = 1 \\ SOC_{t-1,s}^a + P_{t,s}^{ch,a} \times \eta^{ESS,eff} \\ -P_{t,s}^{dch,a} / \eta^{ESS,eff}, & \text{otherwise} \end{cases} \quad \forall t, \quad \forall s. \quad (15)$$

The amount of charge or discharge power is limited by the multiplication of the capacity and the ESS charging–discharging efficiency in single time steps. In addition, the ESS can only operate in charge or discharge modes at a single time step. These characteristics are given by

$$\begin{cases} 0 \leq P_t^{ch,f} \leq \eta^{ch} \times \delta_t^{ch,f} \times Cap^{ESS} \\ 0 \leq P_t^{dch,f} \leq \eta^{dch} \times \delta_t^{dch,f} \times Cap^{ESS} \end{cases} \quad \forall t, \quad (16)$$

$$\begin{cases} 0 \leq P_{t,s}^{ch,a} \leq \eta^{ch} \times \delta_{t,s}^{ch,a} \times Cap^{ESS} \\ 0 \leq P_{t,s}^{dch,a} \leq \eta^{dch} \times \delta_{t,s}^{dch,a} \times Cap^{ESS} \end{cases} \quad \forall t, \quad \forall s, \quad (17)$$

$$\delta_t^{ch,f} + \delta_t^{dch,f} \leq 1 \quad \forall t, \quad (18)$$

$$\delta_{t,s}^{ch,a} + \delta_{t,s}^{dch,a} \leq 1 \quad \forall t, \quad \forall s. \quad (19)$$

Although the charging or discharging speed of the ESS is fast enough to be fully charged or discharged in several minutes, the ESS in this study is assumed to be continuously charged or discharged for 1 h at a 1 C rate [16].

Finally, the ESS can be charged only from the electrical power generated by the PV panels according to the following conditions:

$$P_t^{ch,f} \leq P_t^{PV,f} \quad \forall t, \quad (20)$$

$$P_{t,s}^{ch,a} \leq P_{t,s}^{PV,a} \quad \forall t, \quad \forall s. \quad (21)$$

III. NUMERICAL RESULTS

Computational studies were performed using R software and GAMS to validate the proposed model. The scenario generation and reduction of PV power generation were conducted using R software. The proposed MILP optimization problems were implemented in GAMS with the Cplex solver.

A. ASSUMPTIONS

The proposed optimization model was examined with a 1491.6 kW PV power plant in Yeongam, South Korea [17]. In addition, the capacity of the ESS in the plant was assumed to be 1000 kWh for the utility scale [16]. The key parameters for the optimization model with the plant and ESS are listed in Table 2.

In the table, the operation conditions for the ESS regarding the minimum/maximum SOC level, turnaround, and charging

TABLE 2. Key parameters for optimization model.

Parameter	Value
$SOC^{\min} / SOC^{\max}$	20%/95%
Turnaround efficiency	90%
Discharging/charging efficiency	90%/90%
Variable O&M cost of ESS	11.42 won/kWh
REC unit price	46.25 won/kWh

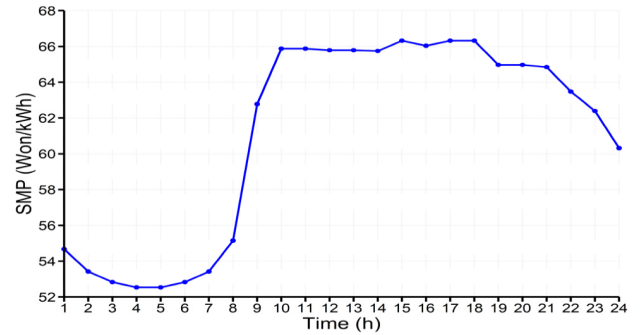


FIGURE 3. Actual SMP profile in summer 2020.

and discharging efficiencies are presented. The turnaround efficiency represents the power loss ratio incurred by inner operations as shown in Equation (14) and Equation (15). The charging and discharging efficiency describe the power loss ratio occurring in charging and discharging operation as shown in Equation (16) and Equation (17). In addition, the variable O&M cost of the ESS is adjusted to an hourly price by dividing 1% of the investment cost by the number of hours per year [18]. The REC unit price is assumed to be the actual REC unit price in summer 2020 [19]. With these parameters, the SMP profile is assumed to be the actual SMP profile in summer 2020, as shown in Fig. 3 [20].

The SMP during between 1 and 8 AM. is low when the total consumption of electricity seems to be low. In contrast, the SMP during between 9 AM and 12 AM is relatively high since the peak load occurs. With these characteristics, the operator would be expected to sell the electricity during between 9 AM and 12 AM.

B. SCENARIO GENERATION AND REDUCTION OF PV POWER GENERATION

The actual power of the PV panels in this study can be determined by scenarios generated from the forecasted power and its error distribution. The forecasted power was estimated by the generation profile of the PV power plant in the summer of 2020 [21]. A Gaussian distribution was considered to model the error. The mean value and standard deviation of the distribution are assumed to be 108% of the forecasted power and 25% of its power at each time, respectively. In short, the random variable of the actual power is represented around the value of forecasted power. With this distribution, a Monte

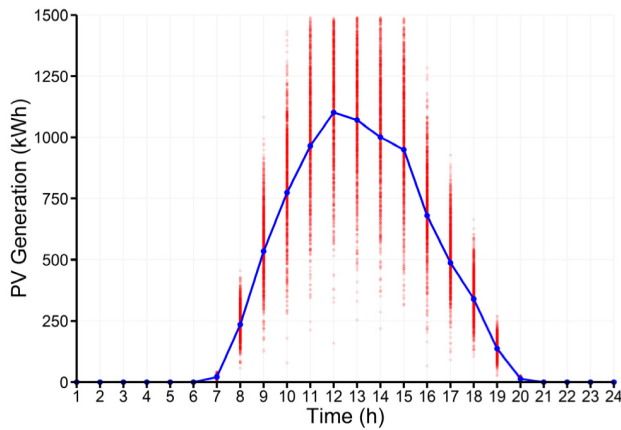


FIGURE 4. Forecasted power and scenarios of actual power of photovoltaic power plant.

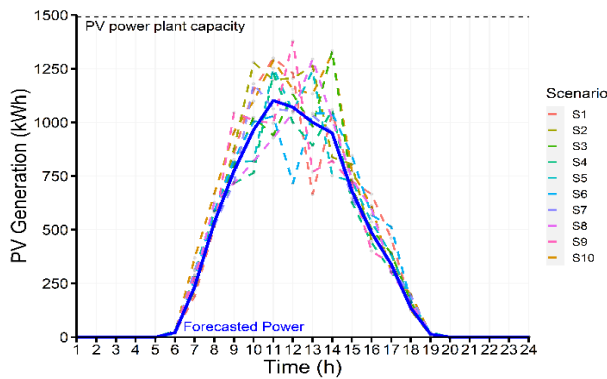


FIGURE 5. Reduced scenarios of actual power.

Carlo simulation was used to generate 1000 scenarios for each forecasted power, as shown in Fig. 4. In this figure, the forecasted power is represented by a solid line, and the scenarios are depicted by dot plots.

Although all points of the actual power scattered around the forecasted power could be useful for considering all operation scenarios, a scenario reduction technique is required to decrease the computational burden. A scenario reduction technique using *k*-medoids clustering was applied to reduce and sort out the scenarios [22]. With this technique, we reduced the number of scenarios to 10, as shown in Fig. 5. The probability of each scenario of PV power generation is shown in Fig. 6.

C. OPTIMIZATION CASE CATEGORIZATION

We compared the results of the proposed optimization model with those of the optimization model that did not consider the incentive for forecast accuracy. With this comparison, we intended to evaluate the effectiveness of considering the incentive in the ESS operation in the absence of the REC incentive. The results were categorized as Case A and Case B to simplify the expression of the results. Case A corresponds to a base case in which the PV power plant operator does not consider the incentive for the forecast accuracy.

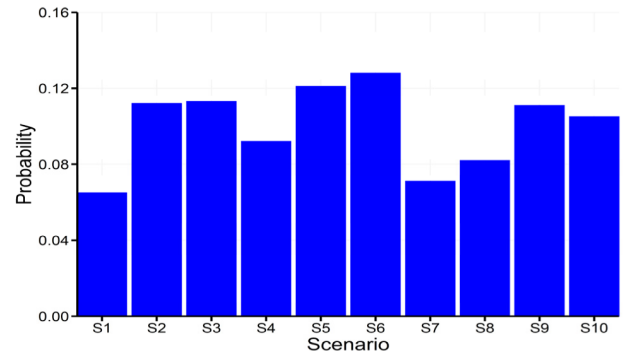


FIGURE 6. Probability of each scenario.

TABLE 3. Summary of optimization case configuration.

Case	Incentive for forecast accuracy	Description
A	X	Base case
B	O	Proposed optimization

TABLE 4. Optimal revenue results of PV power plant operation in a day.

Result [1,000 won]	Case A	Case B
Average revenue for selling electricity	974.88	974.41
Average revenue for forecast accuracy	0	31.79
Average ESS operation cost	0	0.5
Average total revenue	974.88	1005.69

The ESS would be controlled along with the SMP because the operator in Case A could care less about the forecast error. Case B assumed that the operator would consider the forecasted power and the actual power at the PCC owing to the incentive for forecast accuracy. The ESS would be controlled by strategies such that the operator in Case B could minimize the forecast error of the combination of PV power generation and the charge/discharge power of the ESS. These cases are summarized in Table 3.

D. OPTIMIZATION CASE RESULTS

The optimal revenue results for the PV power plant operation are listed in Table 4.

The average revenue and cost are represented in Table 4 because scenarios of the actual power of the PV panels were considered.

The average revenue for selling electricity in both cases was almost the same, as this revenue would be assessed by the actual power at the PCC. In other words, the forecast error might not influence the revenue for selling electricity.

The average revenue for forecast accuracy is only represented in Case B. This revenue accounted for almost 3% of the average total revenue. Although the revenue for selling electricity was the same in both cases, the consideration of incentives for forecast accuracy would result in significant revenue.

The average ESS operation cost was also only represented in Case B. Although the ESS operation is expected to contribute to an increase in the revenue, as shown in the results of conventional research [6], [10], [14], the ESS operation cost was not represented in Case A or was as low as in Case B. These results imply that the actual charge/discharge power of the ESS is low.

Although the actual operation of the ESS was anticipated to be low, the total revenue in Case B was greater than that in Case A owing to the revenue for forecast accuracy. To analyze the details of revenues and costs, the forecasted and actual power at the PCC were depicted, and profiles of forecast error ratio according to scenario were represented. The results of the power and forecast error ratio for Case A are depicted in Fig. 7. Fig. 7(a) shows the forecasted and actual power of each scenario at the PCC. Fig. 7(b) shows the average forecast error ratio and forecast error ratio for each scenario. Fig. 7(c) shows the forecast and average of the actual charge/discharge power of the ESS with the profiles of each scenario. Similarly, the results for Case B are shown in Fig. 8.

The difference between the forecasted power and the actual power at the PCC, as shown in Figs. 7(a) and 8(a), could imply an estimated forecast error. The difference range is from -382 to 355 kWh in Case A, and from -422 to 427 kWh in Case B. The average of the actual power at the PCC in Case A tended to be greater than the forecasted power, owing to the overestimated power generation scenarios shown in Fig. 5. By contrast, the average actual power at the PCC in Case B was sometimes less than the forecasted power at 13:00 and 19:00.

The forecast ratios in Figs. 7(b) and 8(b) reveal similar aspects of the difference range in Figs. 7(a) and 8(a). In addition, the average forecast error ratio in Case A tended to be smaller than that in Case B. These results seem to show that the optimized model without considering the incentive for forecast accuracy could minimize the forecast error. Even if the forecast ratio in Case B could be greater than the ratio in Case A, the PV power plant could earn an incentive when the forecast ratio is in that range.

The forecast accuracy trend could be adjusted by the forecasted and actual charge/discharge power of the ESS, as shown in Figs. 7(c) and 8(c). The ESS, as shown in Fig. 7(c), was not utilized in all times and scenarios. There was no need to control the ESS in Case A in the absence of an incentive. However, the operation strategies of the ESS, as shown in Fig. 8(c), are used to adjust the forecasted and actual charge/discharge power. The increase in the forecasted charge power could result in a decrease in the forecasted power at the PCC. This increase could also provide the PV power plant operator with a chance to discharge power during the high SMP region between 09:00 and 19:00. The ESS was sometimes forecast to be charged during that time range when the discharge power was short.

With the forecasted charge/discharge power of the ESS, the actual charge/discharge power adjusted the forecast ratio, as shown in Fig. 8(b). When the forecasted charge power was

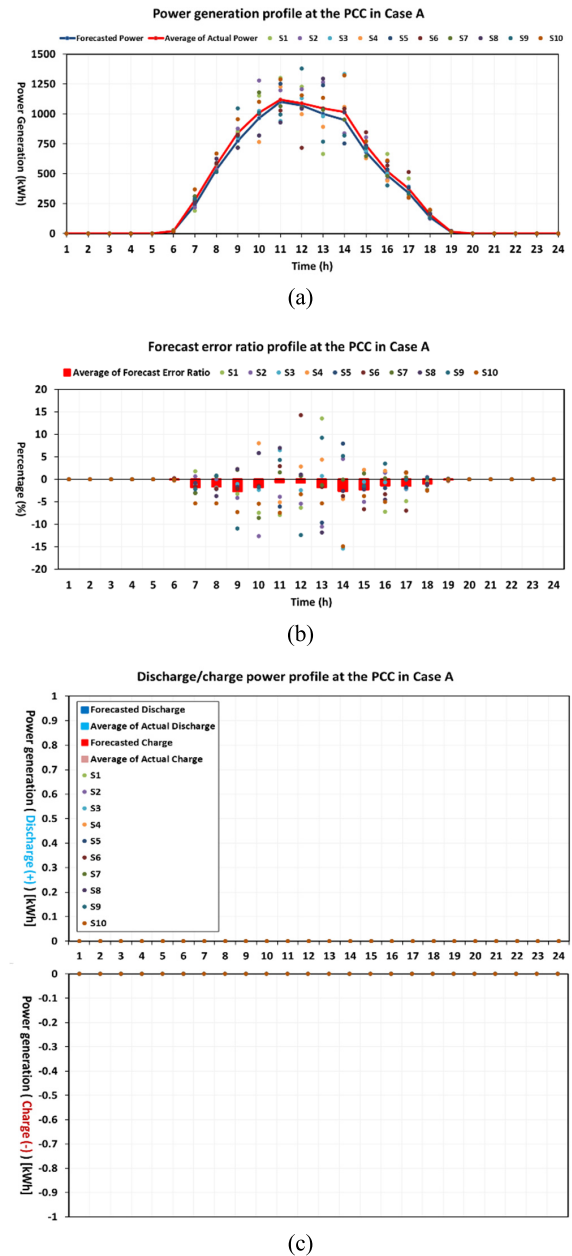


FIGURE 7. Profiles of results in Case A.

high between 06:00 and 09:00, the actual charge power was low at that time. This strategy results in a negative forecast ratio. At the same time, the forecasted discharge power was higher than the actual discharge power. This strategy results in a positive forecast ratio. By using these strategies, the forecasted ratio between 06:00 and 08:00 changed from positive in Fig. 7(b) to negative in Fig. 8(b). At 09:00, the trend changed from negative to positive.

The forecasted discharge power tended to be more frequent than the forecasted charge power between 09:00 and 19:00 in Fig. 8(c). The actual power from the PV panels tended to be higher than the forecasted power because the forecast ratio was negative, as shown in Fig. 7(b). The PV power plant operator increases the forecasted discharge power to change

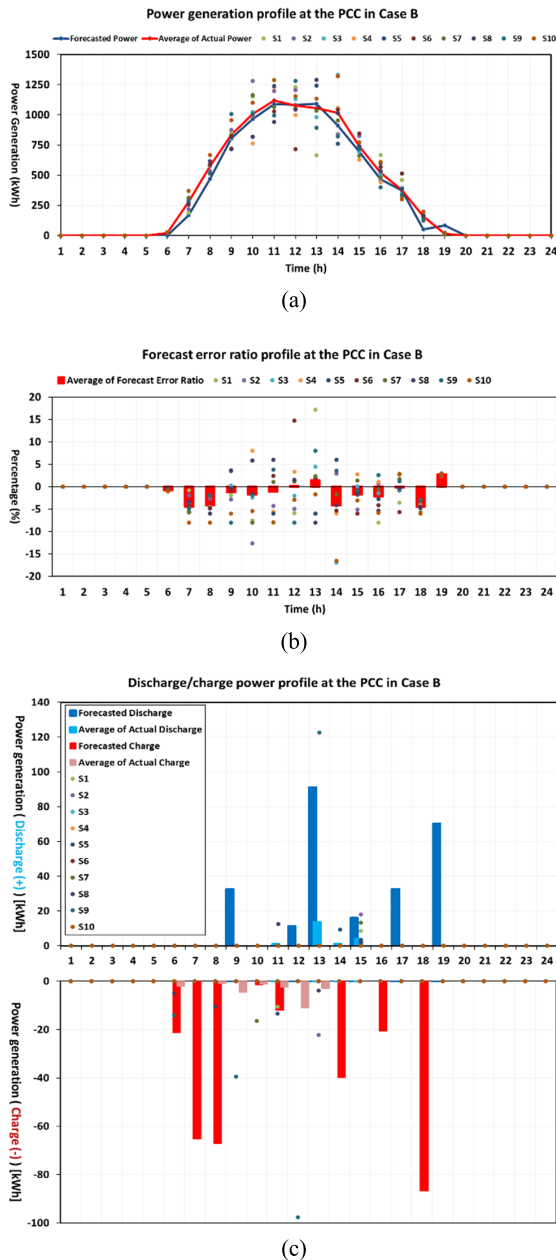


FIGURE 8. Profiles of results in Case B.

this trend to the opposite trend. If the actual power from the PV panels is estimated to be greater than the forecasted power, the operator can increase the forecasted discharge power to reduce the forecast error. Otherwise, the operator decreases the power at the PCC by reducing the forecasted discharge power or increasing the forecasted charge power. Although all the power would not be adjusted for all times, the charge/discharge power could be controlled to be the desired forecast ratio.

The ESS operation strategies in Case A were worthless because the ESS was not utilized in all scenarios, as shown in Fig. 7(c). In short, the PV power plant operator in Case A only sold the actual PV power generation in Fig. 7(a) along with the SMP in Fig. 3. In contrast to the results in Case A,

the operation strategies in Case B pursued additional revenue by adjusting the forecasted power and the actual power at the PCC with the charge/discharge power.

IV. DISCUSSION

The results in Case A show that the operation strategies of the operator depend only on the SMP profile and scenarios of the actual power. The PV power plant operator would not utilize the ESS in the absence of the REC incentive and the incentive for forecast accuracy. In contrast, in order to earn an incentive for forecast accuracy, the operator in Case B adjusted the forecast and actual power at the PCC by controlling the charge/discharge power of the ESS. Operation strategies in Case B would be required to recoup the capital costs of PV power plants in the absence of an REC incentive.

However, this study has several limitations. Although the PV power plant operator could earn the incentive by adjusting the forecast accuracy, the actual operation of the ESS was considerably low from the operation results of the actual charge/discharge power in Case B. The reason for low utilization of the ESS may be the low unit price of incentive. Theoretically, the charge/discharge power of the ESS can influence the forecast error ratio by controlling the forecasted and actual power. If the actual power at the PCC will be anticipated to be much lower than the forecasted power, the forecasted charge power can contribute to reduce the forecast error ratio. In addition, the actual discharge power can also contribute to increase the actual power settled at the SMP and the REC price. With these operation strategies, operators would plan the share of the revenues from the incentive and selling the electricity. However, this planning strategies would be effective when the unit price of the incentive is appropriately similar to the SMP and the REC price. According to Table 1, Table 2 and Fig. 3, the unit price of incentive for the forecast accuracy is much smaller than the SMP and the REC price. Under this unit price of the incentive, operators focus on the revenues from selling the electricity rather than the revenues from the incentive. They would earn the revenues from the incentive with the minimum amount of charge/discharge operation since the unit price of the incentive is much smaller than the SMP, the REC price and the variable O&M cost of the ESS. Therefore, in actual cases, adjusting the forecast error ratio would have a small influence on the revenues for operators under the low unit price of the incentive. In addition, the low utilization of the ESS in an actual operation seemed to result from the criteria of the incentive for forecast accuracy. Even if the ESS is not actually utilized, the operator can earn an incentive when the forecast accuracy is within the criteria of the incentive. This characteristic mainly influences the adjustment of the forecast value of the charge/discharge power. The desired forecast ratio can be achieved by adjusting the forecast value, but the low utilization of the ESS in actual operation may affect real-time operations. With incentives for forecast accuracy, penalties for imbalances and incentives for real-time operations are required to manage real-time imbalances by utilizing the ESS.

Hence, future studies can consider an optimization problem with incentives or penalties for real-time operations.

V. CONCLUSION

We evaluated the incentive for forecast accuracy in a PV power plant in South Korea. A coordinated model of a plant with an ESS was designed. In this model, a PV power plant operator can provide an incentive for forecast accuracy according to the forecast error ratio. An optimization problem from this model was developed to maximize the revenue of the operator. The objective function comprised revenues for selling electricity and incentives for forecast accuracy, except for the costs of the ESS. With an SMP and an REC price, the revenues reflected the estimated power for scenarios of actual PV generation. The incentives were estimated by the forecast error ratio described by the difference between the forecasted value and the actual power at the PCC. A linearization process was applied to the constraints of incentives varying with the ratio to be modeled as an MILP problem. Other constraints were also included to reflect ESS operation. Numerical results were obtained with the operation characteristics of the ESS and the profiles of the SMP and REC. In addition, the scenario reduction technique using k -medoids clustering was applied to the proposed model to reduce the computational burden. The results show that the operator can earn additional revenue from incentives for forecast accuracy. To pursue incentives, the forecasted and actual charge/discharge power of the ESS were adjusted to manage the forecast accuracy. The incentive for forecast accuracy could be expected to recoup the capital costs of the PV power plant in the absence of incentives for the ESS operation.

REFERENCES

- [1] S. M. Vaziri, B. Rezaee, and M. A. Monirian, "Utilizing renewable energy sources efficiently in hospitals using demand dispatch," *Renew. Energy*, vol. 151, pp. 551–562, May 2020.
- [2] Y. Lu, Z. A. Khan, M. S. Alvarez-Alvarado, Y. Zhang, Z. Huang, and M. Imran, "A critical review of sustainable energy policies for the promotion of renewable energy sources," *Sustainability*, vol. 12, no. 12, pp. 5078–5107, Jun. 2020.
- [3] T.-H. Kwon, "Policy mix of renewable portfolio standards, feed-in tariffs, and auctions in South Korea: Are three better than one?" *Utilities Policy*, vol. 64, pp. 101056–101061, Jun. 2020.
- [4] Korea Energy Agency. (2020). *Information of REC Market*. [Online]. Available: <https://onerec.kmos.kr/portal/index.do>
- [5] Korea Energy Agency. (2020). *Renewable Portfolio Standard Guide*. [Online]. Available: https://www.knrec.or.kr/business/rps_guide.aspx
- [6] 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, pp. 109467–109479, Dec. 2019.
- [7] A. M. Elshurafa, "The value of storage in electricity generation: A qualitative and quantitative review," *J. Energy Storage*, vol. 32, Dec. 2020, Art. no. 101872.
- [8] C. Kath, W. Nitka, T. Serafin, T. Weron, P. Zaleski, and R. Weron, "Balancing generation from renewable energy sources: Profitability of an energy trader," *Energies*, vol. 13, no. 1, pp. 205–219, Jan. 2020.
- [9] C. Lee, S. Im, J. Jung, and B. Lee, "BESS deployment strategy in Jeju carbon-free islands for reducing renewable energy curtailment," *Energies*, vol. 13, no. 22, pp. 6082–6094, Nov. 2020.
- [10] D. Kim, H. Kim, and D. Won, "Operation strategy of shared ESS based on power sensitivity analysis to minimize PV curtailment and maximize profit," *IEEE Access*, vol. 8, pp. 197097–197110, Oct. 2020.
- [11] W. Ma, W. Wang, X. Wu, R. Hu, F. Tang, and W. Zhang, "Control strategy of a hybrid energy storage system to smooth photovoltaic power fluctuations considering photovoltaic output power curtailment," *Sustainability*, vol. 11, no. 5, pp. 1324–1345, Mar. 2019.
- [12] K. Tian, W. Sun, W. Liu, and H. Song, "Coordinated RES and ESS planning framework considering financial incentives under centralized electricity market," *CSEE J. Power Energy Syst.*, early access, Oct. 6, 2020, doi: 10.17775/CSEEJPES.2020.02400.
- [13] T. Rodrigues, P. J. Ramírez, and G. Strbac, "Risk-averse bidding of energy and spinning reserve by wind farms with on-site energy storage," *IET Renew. Power Gener.*, vol. 12, no. 2, pp. 165–173, Nov. 2017.
- [14] W. Ko, J. Lee, and J. Kim, "The effect of a renewable energy certificate incentive on mitigating wind power fluctuations: A case study of Jeju Island," *Appl. Sci.*, vol. 9, no. 8, pp. 1647–1661, Apr. 2019.
- [15] Korea Power Exchange. (2021). *Rules for Korean Electricity Market*. [Online]. Available: <https://www.kpx.or.kr/www/selectBbsNttView.do?key=29&bbsNo=114&nttNo=21790&searchCtgr=&searchCnd=all&searchKwd=&pageIndex=1&integrDeptCode=>
- [16] Samsung SDI. (2018). *ESS Batteries by Samsung SDI*. [Online]. Available: http://www.samsungsdi.co.kr/upload/ess_brochure/201803_SamsungSDI%20ESS_EN.pdf
- [17] Korea Electrical Engineering & Science Research Center. (2020). *Information of PV Power Plant in Korea*. [Online]. Available: http://www.powernms.kr/power/plant/view.do?bd_gb=&bd_cd=&bd_item=¤tPage=8&plantId=734
- [18] Y. Joo, J. Shin, D. Seo, and S. Park, "Economic evaluation of ESS and natural gas generator for expansion of new and renewable generation," *Trans. Korean Hydrogen New Energy Soc.*, vol. 29, no. 4, pp. 363–369, Aug. 2018.
- [19] KEPCO. (2021). *REC Trading Report*. [Online]. Available: https://onerec.kmos.kr/portal/rec/selectRecReport_tradePerformanceList.do?key=1971
- [20] Korea Power Exchange. (2020). *SMP Report*. [Online]. Available: https://www.kpx.or.kr/www/contents.do?key=225&status=land&issueDate=20210205&_encrypted=bWMSYnoNUQZWNIxN4c3D93ovZYSTGXWpNeR1G3EL4XFmBSGDp6jXqXv0fCOicQIn%2Byg9Ic9UOnemx54yY3Z0Cjbp89g%2Bm9hCPivlPQuc%3D
- [21] Korean Rural Community Corporation. (2021). *Photovoltaic Power Plant Generation Report*. [Online]. Available: <https://www.data.go.kr/data/15005796/fileData.do>
- [22] A. K. Jain and R. C. Dubes, *Algorithms for Clustering Data*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1988.



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