IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received April 5, 2022, accepted May 25, 2022, date of publication June 8, 2022, date of current version June 17, 2022.

*Digital Object Identifier 10.1109/ACCESS.2022.3181163*

# Virtual Power Plant Operation Strategy Under Uncertainty With Demand Response Resources in Electricity Markets

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This work was supported in part by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry and Energy (MOTIE) of the Republic of Korea under Grant 20213030160040; and in part by the GIST Research Institute (GRI), GIST, under Grant GK14660.

**ABSTRACT** The importance of resources for balancing electricity supply and demand is increasing with the decentralization of power systems; the role of demand response is being emphasized to effectively deal with the volatility of renewable energy. In this study, a model to participate in the electricity market, especially energy and demand response, utilizing demand response resources by compensating for the uncertainty of renewable energy products is proposed. The probabilistic distribution of photovoltaic generation, derived based on stochastic programming, was used as a framework for solving the optimization problem by reflecting the uncertainty of photovoltaic generation. Moreover, a demand response modelling approach to enhance flexibility was developed by estimating the maximum potential demand response capacity in an industrial load. The output of these models was used to derive an optimal operational strategy to participate in the day-ahead market. The simulated Korean electricity market results confirmed that the virtual power plant aggregator's profits increased when using the suggested strategy to utilizing demand response resources.

**INDEX TERMS** Virtual power plant, demand response, uncertainty, stochastic programming, optimization.

## NOMENCLATURE

### PARAMETERS

| | |
|---|---|
| $\mu_{k,m,t}$ | Average power generation of PV. |
| $\sigma_{k,m,t}$ | The standard deviation of PV. |
| $\mathrm{P_{k,t}}$ | Power generation of PV. |
| $\mathrm{P_{k,t}^{pred}}$ | The predicted value of PV generation. |
| $P_{k,t}^{ec}$ | Power generation with error compensation of PV. |
| $C^{PV}$ | Rated capacity of PV. |
| $\lambda_t$ | Wholesale electricity price. |
| $\zeta_t^{ferr}$ | Forecasting incentive settlement price at time $t$. |
| $\eta_t$ | Imbalance penalty. |
| $\rho$ | The average successful bid rate in the day-ahead economic DR market. |
| $\varphi_{l,t}^{inc}$ | DR increment amount for error compensation. |
| $\varphi_{l,t}^{red}$ | DR reduction amount for error compensation. |
| $L_t^{ub,inc}$ | Upper bound for plus DR participation of load resources. |
| $L_t^{ub,red}$ | Upper bound for minus DR participation of load resources. |
| $pr^{ferr}$ | Constant value of the forecast error ratio at the forecast error ratio range $ferr$. |
| Z | Positive infinity. |
| $\sigma^{prior}$ | Prior information generator. |
| $\varepsilon^{th}$ | Threshold error. |

### VARIABLES

| | |
|---|---|
| $R^{\mathrm{pv}}$ | Revenue of selling electrical power to market from PV generation of $k$ generator. |
| $R^{inc}$ | Revenue for participating in the PV forecasting incentive. |
| $R^{ec}$ | Revenue for the PV error compensation. |
| $C^{ec}$ | Cost for the PV error compensation. |
| $v_t^{ferr}$ | State variable according to the prediction error rate. |

The associate editor coordinating the review of this manuscript and approving it for publication was Madeleine Gibescu.

$\epsilon_t$ Forecasting error rate of PV at time $t$.
$\varepsilon_t^{MCS}$ Forecasting error of PV in MCS at time $t$.
$\mu_t^{ferr}$ Forecasting error of PV at time $t$ in forecast error ratio range $ferr$.
$g_t^{ferr}$ Incentive at a time in forecast error ratio range $ferr$.
$h_t^{ferr}$ Multiplication of all terms related to forecasting error interval at a time $t$ in forecast error ratio range $ferr$.
$G_t^{ferr}$ Incentive at a time in forecast error ratio range $ferr$ considering error compensation.
$H_t^{ferr}$ Multiplication of all terms related to forecasting error interval at a time $t$ in forecast error ratio range $ferr$ considering error compensation.
$L^{opt}$ Load profile scheduled from optimization.
$L^{MCS}$ Load profile scheduled from MCS.

## I. INTRODUCTION

As environmental issues emerge, efforts to pursue sustainable development are being undertaken in all industrial sectors, including the power industry. The conversion from traditional fossil-fueled power generation to eco-friendly and pollution-free technologies is already underway worldwide. Photovoltaic (PV) solar technology has shown remarkable results over the past decade, with the total capacity of solar power supplied by the end of 2019 estimated at 623.2 GW. The newly constructed solar power capacity is estimated to be 111.6 GW, approximately 18% of the total generation capacity in 2019. Of this, approximately 75.77 GW of solar power was installed in the United States, with 13.27 GW installed in 2019. Furthermore, of the total 11.23 GW solar PV capacity installed in Korea, 3.13 GW (or 27.9%) was implemented in 2019 [1].

The intermittency of PV generation may cause problems in the grid operation and the electricity market. If the scale of PV generation is modest, it has a negligible effect on the system; however, countermeasures are needed as the scale increases. The concept of a virtual power plant (VPP), which aggregate behind-the-meter (BTM) resources, including PV generation and distributed energy resources (DERs), is particularly useful for coping with the intermittency of renewable energy sources (RESs). Participating in the market through VPPs can support better performance than participating separately, compensating for the weaknesses of individual resources [2]. However, to support a large amount of RESs, a sufficient storage capacity must be provided [2]–[4].

As a battery energy storage system (BESS) can be used to solve the intermittency of RESs, many studies consider the utilization of ESS in VPP [5], [6]. In a previous report [5], the optimal operation strategy to maximize the profit of ESS with PV-centred resources under specific circumstances is proposed in Korea. Meanwhile, Ko and Kim propose a comprehensive optimal operational strategy for VPP to participate in the Korean energy market using ESS [6]. Despite these efforts, managing supply and demand with BESS remains a challenging task because of its low profitability; Therefore, many studies on VPP focus on maximizing profits through optimal operation, and most of them use the multi-integer linear programming (MILP) technique due to its very clear advantage of the simplicity of implementation [7].

While aggregating RESs into VPPs has considerable merit, it also has several uncertainties and drawbacks. These include uncertainty about renewable energy generation, demand resources, and market prices [8], [9]. To deal with these uncertainties, most studies have adopted a stochastic programming approach [2], [10]–[13]. In an earlier study [2], a strategy to participate in the market was suggested by combining conventional power generation resources and renewable energy; additionally, Baringo and Baringo [10] attempted a scenario-based stochastic approach to deal with the uncertainty of VPPs composed of traditional generators and renewable energy, especially wind power. Meanwhile, subsequent studies [11], [12] derived an optimal operation strategy through a combination of renewable energy and CHP. Rahimi *et al.*. [11] applied a probabilistic technique to derive the optimal scheduling for power and heat demand, and Riveros *et al.*. [12] suggested a strategy to use CHP to alleviate the uncertainty of renewable energy-based VPPs. Finally, a two-step probabilistic optimal model to mitigate the uncertainty of VPPs operating solar, wind, gas turbines, ESS, and demand response (DR) was proposed [13].

In many countries, the wholesale electricity markets are being reorganized to efficiently manage the supply of RESs and DERs. In the USA (United States of America), a market system for accommodating renewable energy and DERs has already been implemented through FERC Orders 2006, 792, 719, 745, 784, 841. The most recent Order, 2222, issued in 2020, provides guidelines for the electricity market participation model through a VPP for each wholesale market operator [14]. South Korea also proposed introducing VPPs and a real-time market to respond to the volatility of renewable energy through the "9th Basic Plan for Electricity Supply and Demand" announced at the end of 2020 [15].

In contrast to ESS, many studies prove the economic efficiency of DR, and as a result, many DR markets are being activated worldwide. The DR market was introduced relatively early in the buildout of RESs in two countries: the USA and South Korea. According to a report released by Pennsylvania, New Jersey, and Maryland (PJM), which is one of the most mature DR markets in North America, the DR participation capacity was 2.1 GW as of 2021, of which annual economic DR participation was 18.246 GWh or 12.975 GWh for day-ahead market participation [16]. In Korea, approximately 4.58 GW of resources participated in the DR market for 10 months from January to October 2021, generating approximately 421.1 GWh of power [17]. In PJM, most DR resources participate in load management rather than economic DR [16], while the opposite is the case in Korea, with a considerable difference in function between the two markets.

As discussed above, to cope with the uncertainty of RESs, most of the research into VPP operation strategies focuses on alleviating fluctuations using supplementary resources. However, most researchers use backup means such as ESS or conventional generators with rapid ramping-up features. Thus, we propose a method to ascertain the error composition of PV generation through DR resources and derive an optimal operation strategy for participating in the day-ahead energy and DR markets. We focus on the following contents in this study.

1) An optimal VPP operation strategy using DR resources as auxiliary means for error compensation of PV generation.
2) Deriving an electricity market participation strategy, resulting in the profitability of the VPP operators.
3) Optimal scheduling algorithm of DR resource, developed by MILP.

The remainder of this paper is organized as follows: Chapter 2 presents the VPP model, Chapter 3 explains the optimization model for the VPP operation, and Chapter 4 discusses the simulation results based on the Korean market. Our conclusions are presented in Chapter 5.

## II. PROBLEM DESCRIPTION

Figure 1 shows the overall framework of the suggested model from the perspective of the VPP operator. The model is based on the historical data of PV, weather, market operation results, and load data. At first, the predicted PV profile is generated by combining the PV sampling model and weather forecasting. The historical data of PV generation is used to construct the PV sampling model, and the details of the model are addressed later.

Meanwhile, the DR market operation results and load data are used to obtain the constraints for DR in the optimization problem. DR successful bid rate is calculated based on the DR market data, and the load data is used to estimate the maximum available flexibility potential through DR potential model. An optimization problem is constructed with the output of the PV profile and DR constraints, and the output of the optimization model is compared with the load profile derived from the Monte Carlo Simulation (MCS). If the theoretical value, which is the output of the optimization problem, is feasible, VPP operators arrange their DR resources to participate in both markets. Otherwise, they will only participate in the DR market.

The last part of this section consists of the market framework in Korea and DER modeling.

### A. MARKET FRAMEWORK

#### 1) FORECASTING RATE INCENTIVE

VPP operators can participate in the PV forecasting incentive system in the Korean electricity market. Forecasting incentives are paid when VPP operators perform PV predictions, and the incentive standard is shown in Table 1.

If the prediction error rate exceeds 8%, the VPP operator will not receive any incentives. If the prediction error rate is between 6% and 8%, the VPP operation will receive an incentive of 3 KRW per kWh, and 4 KRW per kWh if the prediction error rate is within 6%.

VPP operator submits their forecasting profile $P^{pred}$ by 17:00 a day ahead, after that Korea Power Exchange (KPX) computes the forecasting error by comparing the submitted value and the metered value. The settlement process follows the rule indicated in Table 1.

**TABLE 1.** PV forecasting incentive implemented in korea.

| Forecasting error ration range | Incentive settlement (KRW/kWh) |
|---|---|
| $\geq 8\%$ or $\leq -8\%$ | 0 |
| $6-8\%$ | 3 |
| $\leq 6\%$ or $\geq -6\%$ | 4 |

**TABLE 2.** Imbalance penalty parameters.

| Forecasting error ration range | Imbalance Penalty (KRW/kWh) |
|---|---|
| $\geq 8\%$<br>$\geq -8\%$ | 10% of real-time price $\lambda_t$ |

#### 2) IMBALANCE PENALTY

In addition, KPX, a market operator, is in the process of improving the market by introducing an imbalance penalty system. According to the plan, the energy imbalance penalty is charged to generation companies if their prediction error exceeds a different threshold for each system operator. In FERC Order 890, the penalty is suggested at 10% of the energy price level if the error range is 1.5–7.5%, and a 25% penalty if the error range exceeds 7.5%. Following this recommendation, each system operator charges for the over-generation or under-generation according to the prediction error. As there is currently no standard in Korea, we consider the imbalance penalty referring to the FERC Order 890 and current Korean market rules. The imbalance penalty is shown in Table 2.

### B. DER MODELLING

PV sampling model and the DR potential model (Figure 1) are addressed here.

#### 1) PV SAMPLING MODEL

A sampling model was created by modeling the normal distribution of each solar resource $k$ at time $t$. The model is represented by the following equation:

$$P_{k,t}^{pred} = F_k\left(R_k\right) \frac{1}{\sigma_{k,m,t}\sqrt{2\pi}} e^{-\left(\frac{R_k-\mu_{k,m,t}}{\sqrt{2}\sigma_{k,m,t}}\right)^2} \tag{1}$$

where $\mu_{k,m,t}$ denotes the average power generation of the PV, and $\sigma_{k,m,t}$ is the standard deviation of the PV generation.

Furthermore, to reflect the prediction error of solar power generation caused by weather conditions, the days were classified into sunny, cloudy, and rainy days. Because solar power generation is affected by illumination and solar radiation, solar power generation is highest on sunny days, lower on cloudy days, and lowest on rainy days.

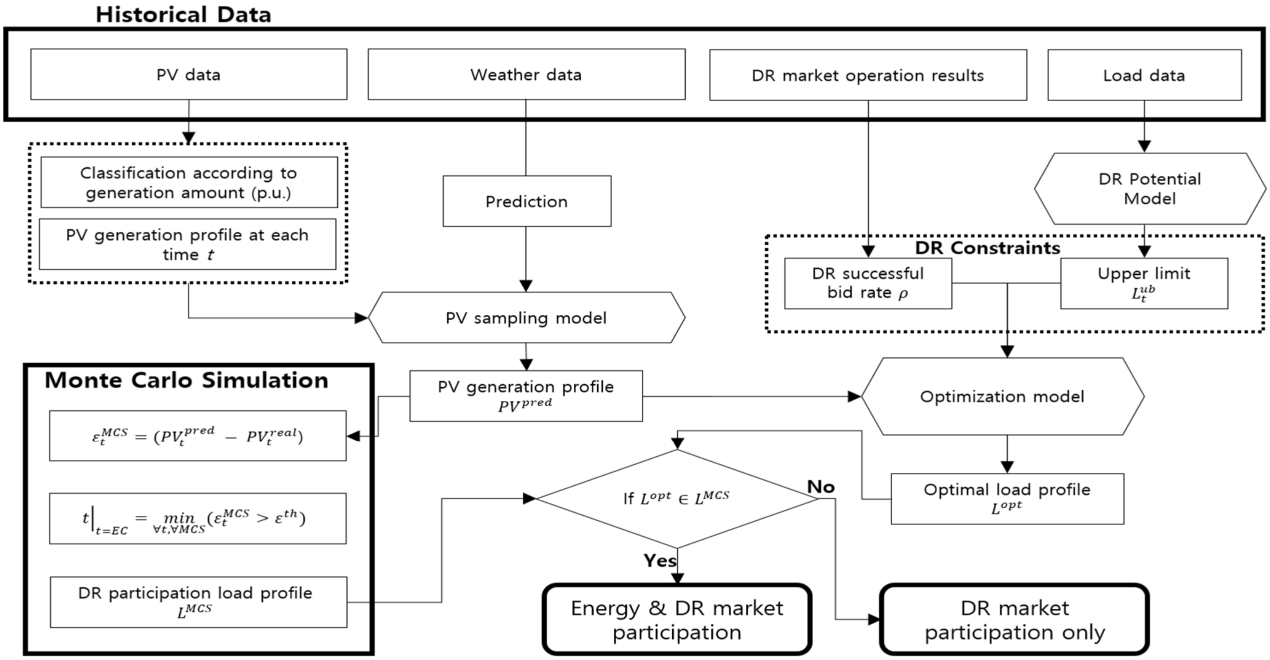


**FIGURE 1.** Architecture of the proposed model.

Accordingly, the weather was classified according to the per-unit value of the solar power generation data by dividing the daily utilization rate of the solar power generator by the rated capacity of the PV generator.

The classification is as follows: if the per-unit value of the daily power generation data is bigger than 5, it is a sunny day, and a rainy day if it is less than 2; otherwise, it is a cloudy day.

$$\begin{cases} Sunny\ If\ \frac{\sum_{t\in 24} \mathrm{P_{k,t}}}{C^{PV}} > 5.0\,[p.u] \\ Rainny\ If\ \frac{\sum_{t\in 24} \mathrm{P_{k,t}}}{C^{PV}} < 2.0\,[p.u] \\ Cloudy\ Otherwise \end{cases} \tag{2}$$

The data distribution according to the weather of the VPP aggregate resource is shown in Figure 2.

### 2) DR POTENTIAL MODEL

It is possible to establish a strategy for VPP operators only when they can estimate available DR capacity. Thus, we describe DR potential-score-estimation model following Lee's suggestion [18]. A summarization of the mechanism is as follows: calculate the frequency score of power consumption (FS), the consistency score of power consumption (CS), and the operation score (OS) from the historical data. Then, the potential score S is defined by the multiplication of the aforementioned factors as follows:

$$S = FS \times SC \times OS \tag{3}$$

As our goal is to calculate the DR potential, detailed calculations for each factor are not mentioned here. Briefly, we scored the DR flexibility scale based on data analysis of the load pattern and compared the actual DR reduction performance of cement factories during DR events.

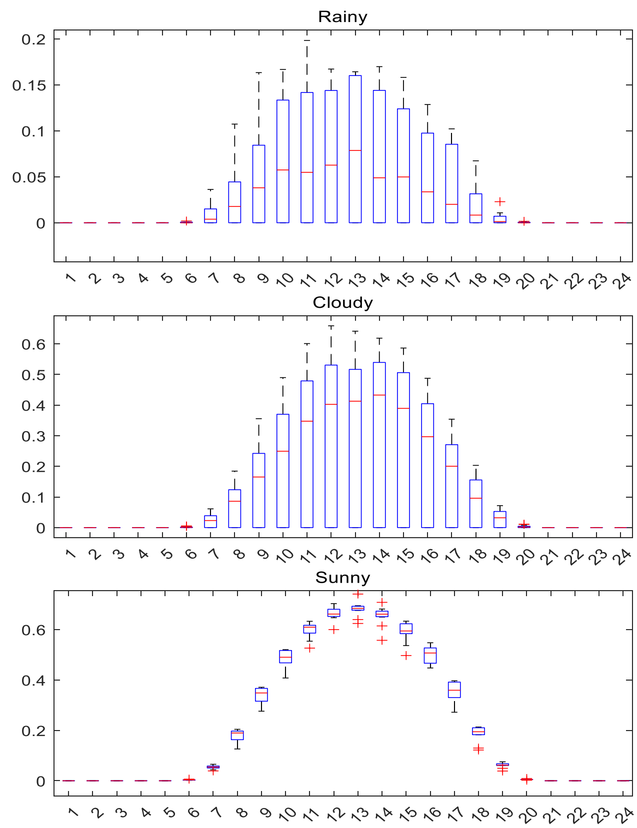


**FIGURE 2.** PV generation distribution for each classification.

## III. MATHEMATICAL MODEL

In Chapter 3, an optimization model is presented to derive an optimal operation strategy for participation in the electricity market from the perspective of VPP operators.

### A. OBJECTIVE FUNCTION

The objective function for optimal operation of the VPP is as follows:

$$max(R^{pv} + R^{inc} + R^{ec} - C^{ec}) \tag{4}$$

where $R_k^{pv}$ is the revenue from PV generation, calculated by the following equation:

$$R^{pv} = \sum_{\forall T} (\lambda_t \cdot P_{k,t}) \tag{5}$$

where $\lambda_t$ is the wholesale price at the time $t$, $P_{k,t}$ is the PV generation amount, and $R_k^{inc}$ is the revenue from the PV forecasting incentive.

$$R^{inc} = \sum_{\forall T} \left(P_{k,t} \cdot \sum_{\forall ferr} \left(\zeta_t^{ferr} \cdot \nu_t^{ferr}\right)\right) \tag{6}$$

where $\zeta_t^{ferr}$ is the forecasting incentive settlement price at time $t$ with the forecasting error rate range (FERR), and $\nu_t^{ferr}$ is a state variable according to the prediction error rate.

$R_k^{ec}$ shows the revenue from the error compensation.

$$R^{ec} = \sum_{\forall T} \left(\left(P_{k,t}^{ec} \cdot \sum_{\forall ferr} \left(\left(\zeta_t^{ferr}\right) \cdot \nu_t^{ferr}\right)\right) + \eta_t\right) \tag{7}$$

where $\eta_t$ represents the profit from error compensation by not paying an imbalance penalty.

Additionally, an opportunity cost $C_k^{ec}$ is incurred owing to error compensation. In other words, when the flexible load resource is used as a DR resource rather than as a means of covering the PV uncertainty, they earn DR settlement profits, which are converted into opportunity costs.

$$C^{ec} = \rho \cdot \sum_{\forall T} \left(\lambda_t \cdot \left(\varphi_{l,t}^{inc} + \varphi_{l,t}^{red}\right)\right) \tag{8}$$

where $\rho$ is the average winning rate in the day-ahead economic DR market. Even if the load resource is utilized as an economic DR resource, there is no guarantee that it will participate in the 100% DR market; hence, the market performance is calculated and reflected. Moreover, $\varphi_{l,t}^{inc}$, and $\varphi_{l,t}^{red}$ represent the increment or reduction in DR resources activated for error compensation, respectively.

### B. LINEARIZATION

$R_k^{inc}$ contains a nonlinearity element and hence must be linearized to model the MILP problem. Thus, we developed a method proposed by Ko and Kim [6]. The FERR is divided into five sections in Table 1. That is, if the error exceeds 8%, FERR is one; if the error is within 6–8%, FERR is two, etc.

$$\mu_t^{ferr} = \epsilon_t \cdot \nu_t^{ferr} \forall t, \forall ferr \tag{9}$$

$$\epsilon_t = \frac{P_{k,t}^{pred} - P_{k,t}}{C^{PV}} \forall t \tag{10}$$

$$\sum_{\forall ferr} \nu_t^{ferr} = 1, ferr = 1, 2, 3, 4, 5 \tag{11}$$

The forecasting error $\mu_t^{ferr}$ is multiplied by the error rate $\epsilon_t$ and state variable $\nu_t^{ferr}$.

The error rate $\epsilon_t$ is determined by dividing the difference between the predicted value and the actual measured value by the PV generator's nameplate capacity; $\nu_t^{ferr}$ is equal to one if the error rate value belongs to one of the five sections, and zero otherwise. To linearize nonlinearity, the following process was performed following the flow proposed by Ko and Kim [6]:

$$\begin{cases} \begin{cases} \epsilon_t \geq -\left(1 - \nu_t^{ferr}\right) \cdot Z + \nu_t^{ferr} \cdot pr^{ferr} \\ \epsilon_t \leq \left(1 - \nu_t^{ferr}\right) \cdot Z + \nu_t^{ferr} \cdot pr^{ferr+1} \end{cases} & if\ ferr < ferr^{max} \\ \begin{cases} \epsilon_t \geq -\left(1 - \nu_t^{ferr}\right) \cdot Z + \nu_t^{ferr} \cdot pr^{ferr} \\ \epsilon_t \leq \left(1 - \nu_t^{ferr}\right) \cdot Z + \nu_t^{ferr} \end{cases} & otherwise \end{cases} \tag{12}$$

where $pr^{ferr}$ is the parameter used to distinguish five sections, the values of $pr^1, pr^2, pr^3, pr^4$, and$pr^5$ are $-1, -0.08, -0.06, 0.06$, and$0.08$, respectively, and Z represents the positive infinity. $R_k^{inc}$ is redefined by linearization as follows:

$$\begin{aligned} R_k^{inc} &= \sum_{\forall T} (P_{k,t} \cdot \sum_{\forall ferr} \left(\zeta_t^{ferr} \cdot \nu_t^{ferr}\right)) \\ &= \sum_{\forall T} \sum_{\forall ferr} \left(P_{k,t} \cdot \zeta_t^{ferr} \cdot \nu_t^{ferr}\right) \\ &= \sum_{\forall T} \sum_{\forall ferr} \left(g_t^{ferr} \cdot \nu_t^{ferr}\right) \\ &= \sum_{\forall T} \sum_{\forall ferr} \left(h_t^{ferr}\right) \end{aligned} \tag{13}$$

where $g_t^{ferr}$ is the multiplication of power generation $P_{k,t}$ and incentive price $\zeta_t^{ferr}$, $h_t^{ferr}$ is calculated by multiplying the state variable $\nu_t^{ferr}$ by $g_t^{ferr}$.

As a result, non-linear constraint (12) is converted to linear inequality constraint as follows:

$$\begin{cases} \begin{cases} h_t^{ferr} \geq -\nu_t^{ferr} \cdot Z \\ h_t^{ferr} \leq \nu_t^{ferr} \cdot Z \end{cases} \\ \begin{cases} h_t^{ferr} \geq g_t^{ferr} - \left(1 - \nu_t^{ferr}\right) \cdot Z \\ h_t^{ferr} \leq g_t^{ferr} + \left(1 - \nu_t^{ferr}\right) \cdot Z \end{cases} & \forall t, \forall ferr \end{cases} \tag{14}$$

The result of $h_t^{ferr}$ depends on the state variable in (12).

Additionally, the reorganized prediction error rate $\delta_t^{ferr}$ is the product of the adjusted error rate $\theta_t$ and the state variable. The adjusted error rate $\theta_t$ is calculated with the $P_{k,t}^{ec}$, which is the amount of electricity generated by error compensation (15)–(17), as shown at the bottom of the next page.

In addition, $R_k^{ec}$ is redefined through the following linearization as follows:

$$\begin{aligned} R_k^{ec} &= \sum_{\forall T} (\left(P_{k,t}^{ec} \cdot \sum_{\forall ferr} \left(\zeta_t^{ferr} \cdot \nu_t^{ferr}\right)\right) + \eta_t) \\ &= \sum_{\forall T} (\sum_{\forall ferr} \left(P_{k,t}^{ec} \cdot \zeta_t^{ferr} \cdot \nu_t^{ferr}\right) + \eta_t) \\ &= \sum_{\forall T} (\sum_{\forall ferr} \left(G^{ferr} \cdot \nu_t^{ferr}\right) + \eta_t) \\ &= \sum_{\forall T} (\sum_{\forall ferr} \left(H_t^{ferr}\right) + \eta_t) \end{aligned} \tag{18}$$

The electricity generation amount $P_{k,t}^{ec}$ determined by error compensation is the summation of the PV generation, DR increment amount, and DR reduction amount.

$$P_{k,t}^{ec} = \left(P_{k,t} + \varphi_{l,t}^{inc} - \varphi_{l,t}^{red}\right) \tag{19}$$

Similar to the above linearization process constraints, the constraints formed through error compensation are as follows:

$$\left\{\begin{array}{l}\left\{\begin{array}{l}H_t^{ferr} \geq -v_t^{ferr} \cdot Z \\ H_t^{ferr} \leq v_t^{ferr} \cdot Z\end{array}\right. \\ \left\{\begin{array}{l}H_t^{ferr} \geq G_t^{ferr} - (1 - v_t^{ferr}) \cdot Z \\ H_t^{ferr} \leq G_t^{ferr} + (1 - v_t^{ferr}) \cdot Z\end{array}\right. \quad \forall t, \forall ferr\end{array}\right. \tag{20}$$

For the upper bound for DR participation of load resources, each value derived from the DR potential model was applied as follows:

$$\varphi_{l,t}^{inc} \leq L_t^{ub,inc} \tag{21}$$

$$\varphi_{l,t}^{red} \leq L_t^{ub,red} \tag{22}$$

The constraint for the imbalance penalty is given as:

$$\eta_t = \left|P_{k,t}^{ec} - P_{k,t}\right| * \lambda_t * 0.1 \tag{23}$$

## IV. SIMULATION AND DISCUSSION

### A. COMPOSITION OF VIRTUAL POWER PLANT

VPP resources were aggregated by combining eight PV generators participating in the Korean electricity market. The generation capacity of the VPP exceeded 10 MW. Load resources used as auxiliary power sources, through industrial buildings that mostly participate in the DR market, should be classified as CVPPs. Information on the aggregated VPP resource is presented in Table 3.

Figure 3 presents the results of our analysis of the historical data of the PVs. Based on this, a sampling model was created by modeling the normal distribution of each solar resource $k$ at time $t$.

Meanwhile, Figure 4 shows the load data of a cement factory, which are used in this case study, and the customer baseline load (CBL) on the day when the actual reliability DR event was issued (13 June 2019).

The ramping down score of Cement Factory 2 was 0.2783 using the suggested methodology, with a calculated ramping-up score of 0.2290. Because Cement Factory 2 caused a > 13,000 kWh reduction with a ramping down score of 0.2783, the minimum ramping-up capacity should be 10,500 kWh from the ramping-up score of 0.2290 by simple linearity. However, as Lee [18] demonstrated, it is difficult

**TABLE 3. Composition of virtual power plant.**

| Resources | Location | Capacity or Average Power | Period |
|---|---|---|---|
| PV1 | Ye-Cheon | 2.0 MW | June. 2017–2019 |
| PV2 | Gu-Mi | 0.992 MW | |
| PV3 | Jin-Ju | 0.905 MW | |
| PV4 | Sam-Cheon-Po | 1.35 MW | |
| PV5 | Gwang-Yang | 3.097 MW | |
| PV6 | Yeong-Am | 1.33 MW | |
| PV7 | Se-Jong | 1.63 MW | |
| PV8 | An-San | 1.49 MW | |
| Load1 | Un-confirmed | 69.78 MWh | |
| Load2 | | 33.45 MWh | |
| VPP | CVPP | 12.794MW<br>103.2MWh | |

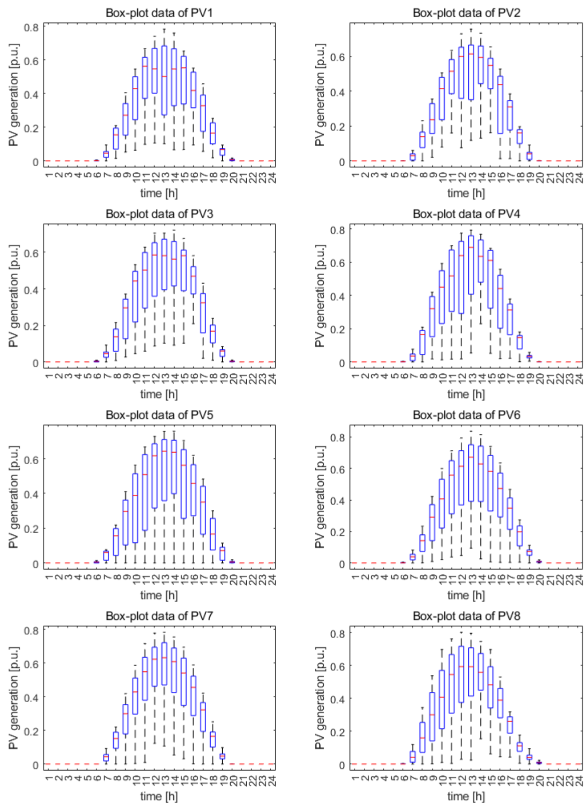


**FIGURE 3. Historical data of PV generation.**

$$\delta_t^{ferr} = \theta_t \cdot v_t^{ferr} \forall t, \forall ferr \tag{15}$$

$$\theta_t = \frac{P_{k,t}^{pred} - P_{k,t}^{ec}}{P^{cap}} \forall t \tag{16}$$

$$\left\{\begin{array}{ll}\left\{\begin{array}{l}\theta_t \geq -\left(1 - v_t^{ferr}\right) \cdot Z + v_t^{ferr} \cdot pr^{ferr} \\ \theta_t \leq \left(1 - v_t^{ferr}\right) \cdot Z + v_t^{ferr} \cdot pr^{ferr+1}\end{array}\right. & if\ ferr < ferr^{max} \\ \left\{\begin{array}{l}\theta_t \geq -\left(1 - v_t^{ferr}\right) \cdot Z + v_t^{ferr} \cdot pr^{ferr} \\ \theta_t \leq \left(1 - v_t^{ferr}\right) \cdot Z + v_t^{ferr}\end{array}\right. & otherwise\end{array}\right. \tag{17}$$

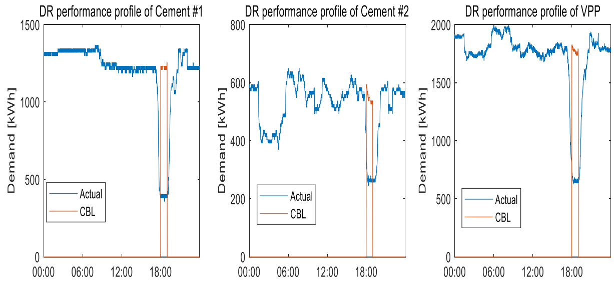


**FIGURE 4.** DR performance results with CBL during DR event.

**TABLE 4.** Results of DR flexibility potential.

| Load Data | Cement #1 | Cement #2 | VPP |
|---|---|---|---|
| CBL (kWh) | 74,404 | 34,802 | 109,206 |
| Metered data (kWh) | 23,206 | 16,262 | 39,486 |
| DR reduction (kWh) | 51,198 | 18,540 | 69,738 |
| S (ramp down) | 0.3563 | 0.2783 | 0.3249 |
| S (ramp up) | 0.2011 | 0.2290 | 0.2197 |
| DR capacity (down) -real performance | 45,000 | 13,000 | 58,000 |
| DR capacity (up) -assumed amount | 3,000 | 3,500 | 6,500 |

to accumulate ramping-up resources compared to ramping down; hence, we assumed that the minimum ramping-up capability was 3,500 kWh. Contrarily, as Factory 1 recorded a ramping-up score of 0.2011, which is approximately 90% of that of Factory 2, it was assumed that the ramping-up capability was approximately 3,000 kWh. Therefore, it was assumed that there was a potential of 58,000 kWh in the case of ramping down based on actual DR performance and a potential of approximately 6,500 kWh in the case of ramping-up for the VPP resources, as shown in Table 4.

### B. DAY-AHEAD MARKET PARTICIPATION

VPP operators conduct MCS to establish a day-ahead market participation strategy. At this time, scenarios for the PV prediction profile are generated, and an error rate is derived for each scenario by comparing it with the real generation amount. The error rates for each period derived by the following mechanism are calculated in advance, and the error rate distribution is shown in Figure 5.

As Figure 5 demonstrates, before 8 a.m. and after 7 p.m., the maximum value of each error rate $\varepsilon_t^{MCS}$ did not exceed the threshold value $\varepsilon^{th}$ which is 8% in the Korean electricity market. That is, VPP operators organize their load resources to participate in the energy market by compensating for a PV error between 8 a.m. and 7 p.m. when PV production is active.

Therefore, VPP operators reflect the determined prior error rate to prepare their load profile $L^{MCS}$.

$L^{MCS}$ assessed considering the error rate $\varepsilon_t^{MCS}$ indicates a more practical value compared to $L^{opt}$, which is a theoretical value calculated by the optimization problem. If the output of the optimization model $L^{opt}$ is a feasible set, that is, $L^{opt}$ is a subset of $L^{MCS}$; A condition for satisfying error compensation is satisfied. That is, VPP operators sort their load resources out for participation in the energy market by

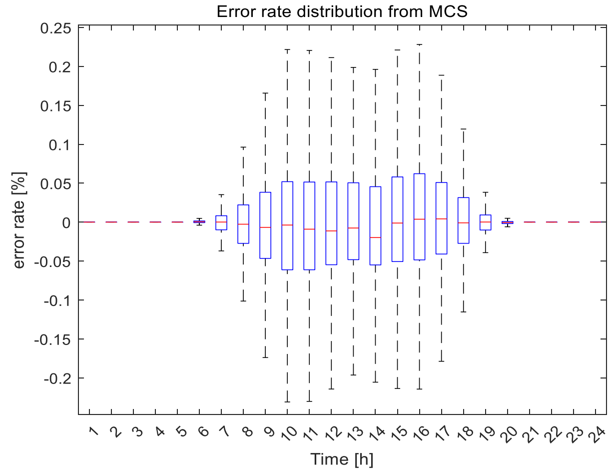


**FIGURE 5.** Prior error rate distribution.

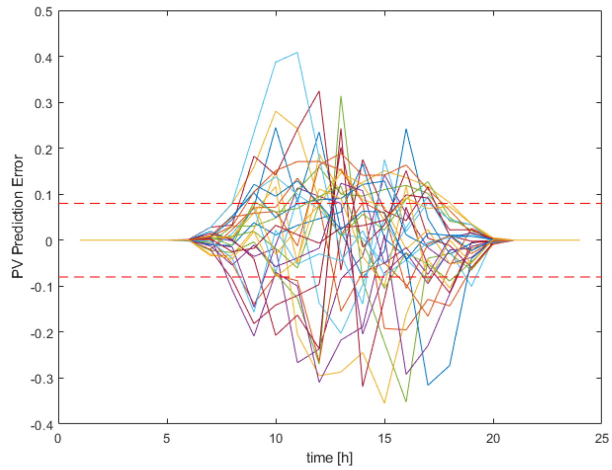


**FIGURE 6.** PV forecasting error rate during a month.

compensating their PV error and economic DR. In contrast, if $L^{opt}$ is unfeasible; $L^{MCS}$ is not a superset of $L^{opt}$; VPP operators participate in the DR market only, as illustrated in Figure 1.

Consequently, VPP operators make their decision to participate in the day-ahead market with the above strategy. If the prediction is successful, the VPP operator will earn more profits by participating in the energy and DR market with the error compensation of PV generation by activating their DR resources.

### C. RESULTS WITHOUT ERROR COMPENSATION

The PV forecasting error was calculated when the utilization rate of the PV generation exceeded 10% at each time. If the prediction error was within 8%, it was considered that no error had occurred in the PV forecasting incentive settlement. The upper and lower parts of the red dotted line in Figure 6 indicate a case in which an error occurs. The upper and lower parts of the red dotted line in Figure 6 indicate a case in which an error occurs.

The average error rate for each generator per month was calculated through the number of times (a) when the

**TABLE 5. PV error rates without error compensation.**

| | PV1 | PV2 | PV3 | PV4 | PV5 | PV6 | PV7 | PV8 | VPP |
|---|---|---|---|---|---|---|---|---|---|
| (a) | 126 | 51 | 110 | 114 | 132 | 74 | 186 | 178 | 112 |
| (b) | 250 | 232 | 238 | 221 | 239 | 294 | 261 | 241 | 287 |
| Prob. (%) | 50.5 | 22.1 | 46.1 | 51.6 | 55.2 | 25.1 | 71.3 | 73.8 | 38.9 |

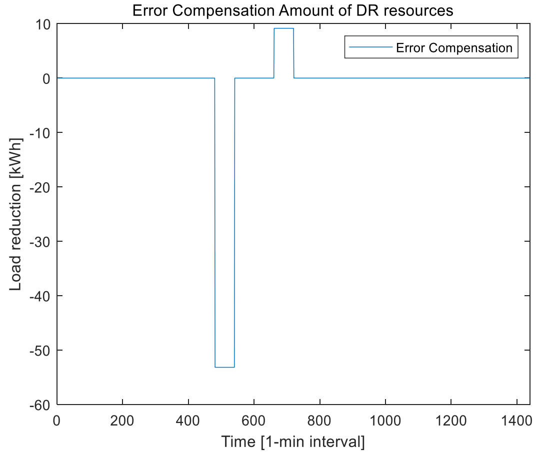


**FIGURE 7. DR resources utilized for error compensation.**

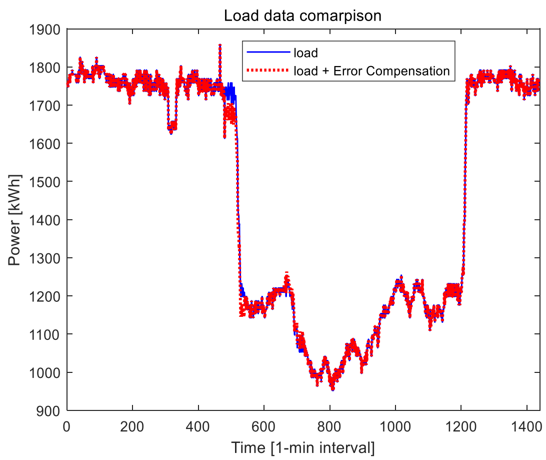


**FIGURE 8. Load pattern with error compensation.**

prediction error exceeded $\pm$ 8% compared to the number of days (b) that satisfied the generator utilization rate of 10% or more (Table 5). In the case where error compensation using DR resources was not performed, that is, when participation in the market occurred only through solar resources, the error rates of each generator and VPP solar sets were as listed in Table 5.

## *D. RESULTS WITH ERROR COMPENSATION*

The simulation results according to the optimization model are shown in Figure 7. As shown in Figure 7, approximately 3,000 kWh were reduced due to under-generation at 8 h (50 kWh per minute during 480–540 min), and 500 kWh of DR resources were increased due to over-generation at 11 h (8 kWh per minute during 660–720 min). The load pattern changes according to DR participation due to load reduction or increment are shown in Figure 8.

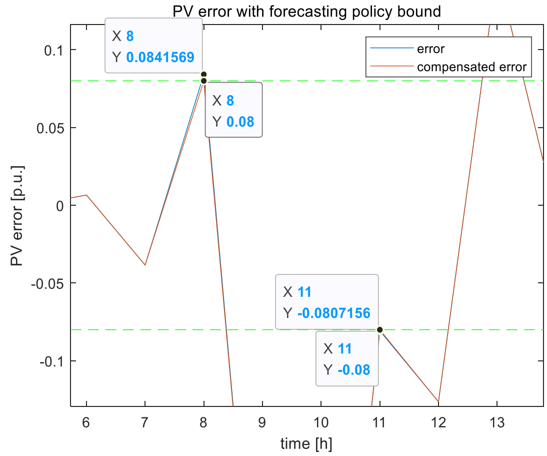


**FIGURE 9. PV error rate of VPP through error compensation.**

Before error compensation of the DR resource, the errors recorded were 8.42% at 8 h and 8.07% at 11 h, both exceeding the 8% mark (Figure 9).

The reduced and increased DR resources were 5.5% and 8.45% of the upper boundary that can be used as DR resources, 58,000 and 6,500 kWh, respectively; thus, there was room for more DR resources to be utilized for error compensation with 94.5% and 91.55%, respectively.

However, if the VPP operator increased its DR resource to compensate for the PV forecasting error, the opportunity cost of not participating in DR was greater than the profit obtained through incentives. Thus, DR resources were limited to 8%, which is the boundary for forecasting incentives.

Thus, VPP operators will make efforts to reduce solar prediction errors by only up to 8% of the boundary, which can disadvantage the system operator. The system operator aims to reduce uncertainties caused by PV generation as much as possible, but for VPP operators, the more they try to reduce prediction errors to less than 8% using their DR resources, the less profitable they are. That is, VPP operators aim to maximize their profit, and the system operator aims to mitigate the PV uncertainties. Therefore, it is necessary to improve the market system to resolve this mismatch.

## *E. COMPARING RESULTS*

VPP operators can participate in the energy market with PV resources and the DR market with load resources when they fail to predict PV error. On the other hand, if load resources are exercised in error compensation, the VPP operators participate in the energy market not only with PV resources but load resources, and their expected payoff increases.

An additional profit of 489,219 KRW was generated by participating in the day-ahead energy market with error compensation. However, an opportunity cost of participating in an economic DR of 62,110 KRW is incurred, resulting in a net profit of 427,109 KRW. In addition, 28,530 KRW is incurred from the opportunity benefit for imbalances, resulting in a total profit of KRW 455,639.

**TABLE 6. PV error comparison.**

| | VPP – without EC | VPP – with EC |
|---|---|---|
| (a) | 112 | 102 |
| (b) | 287 | 287 |
| Prob. (%) | 38.9 | 35.5% |
| Profitability | DR market only | Energy + DR market (+54,257,496 KRW/yr) |

As indicated in Table 6, VPP operators reduce the error probability from 38.9% to 35.5%; consequently, the average additional income is 4,521,485 KRW per month.

In conclusion, through the error composition technique using DR resources proposed in this study, if VPP aggregators collect PV and load resources, participating in the power market as presented in this study, they are expected to earn approximately 54,257,496 KRW annually.

## V. CONCLUSION

An optimal VPP operation strategy is proposed to mitigate the uncertainty of PV generation with a DR resource. At first, the PV generation profile is derived using the PV prediction model and used to calculate the available DR resource timely. DR market operation data and load data are used to calculate DR constraints. MILP optimization problem is solved with the output of the PV sampling model and the DR potential model. Finally, the optimization results provide a market participation strategy for the VPP operator. The case study results produced based on the Korean power market are expected to increase the profitability of VPP operators based on the error compensation technique. However, institutional improvements should be required to resolve the mismatch between the profitability of VPP operators and system operators.

Nevertheless, it is necessary to establish a more advanced prediction model to calculate the more practical profitability of VPP operators. If the proposed model is trained using data analysis-based classification or prediction, the results will be very practical from the point of view of VPP operators. Moreover, in this study, we considered only the strategy of participating in the day-ahead market. Thus, a further study that considers real-time market participation is expected to help improve profitability for VPP operators and enhance the operational stability of the system operator.

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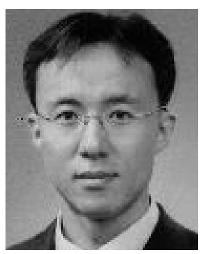

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