Risk-constrained Virtual Power Plant Operation Strategy with Demand Response Resources in Electricity Markets

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This work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea (No. 20213030160040) and by GIST Research Institute (GRI) grant funded by the GIST (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 from renewable energy products is proposed. The probabilistic distribution of photovoltaic generation was derived based on stochastic programming and used as a framework for solving the optimization problem by reflecting the uncertainty of photovoltaic generation. Moreover, a demand response modeling 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 for participating in the day-ahead electricity market. The results in a simulated Korean electricity market confirmed that the virtual power plant aggregator's profit increased when using the suggested strategy for utilizing demand response resources.

INDEX TERMS Virtual Power Plant, Demand Response, Uncertainty, Stochastic Programming, Optimization.

NOMENCLATURE

A. Parameters

| Symbol   | Description                                      |
|----------|--------------------------------------------------|
| µk,m,t   | Average power generation of PV                  |
| σk,m,t   | The standard deviation of PV                    |
| Pk,t     | Power generation of PV                          |
| Pk,red   | The predicted value of PV generation            |
| Pk,ec    | Power generation with error compensation of PV  |
| Cpv      | Rated capacity of PV                            |
| λt       | Wholesale electricity price                      |
| ferrer   | Forecasting incentive settlement price at time t|
| ηt       | Imbalance penalty                               |
| ρ        | The average successful bid rate in the day-ahead economic DR market |
| φinc,tt  | DR increment amount for error compensation      |
| φred,tt  | DR reduction amount for error compensation      |
| Lb,inc   | Upper bound for plus DR participation of load resources |

B. Variables

| Symbol   | Description                                      |
|----------|--------------------------------------------------|
| Rp,v     | Revenue of selling electrical power to market from PV generation of k generator |
| Rinc     | Revenue for participating in the PV forecasting incentive |
| Rec      | Revenue for the PV error compensation            |
| Cc       | Cost for the PV error compensation               |
| νferr    | State variable according to the prediction error rate |
| e,t      | Forecasting error rate of PV at time t           |
| eMCs     | Forecasting error of PV in MCS at time t         |
| μferr    | Forecasting error ratio of PV at time t in forecast error range ferrer |

Upper bound for minus DR participation of load resources

The constant value of forecast error ratio at forecast error ratio range ferrer

Positive infinity

Prior information generator

Threshold error
The intermittency of PV generation may cause problems in the operation of the grid and the electricity market. If the scale of PV generation is small, it has a negligible effect on the system, but 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 very useful for coping with the intermittency of renewable energy sources (RESs). Participating in the market through VPPs can support better performance than participating separately and can compensate 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 as a means to solve the intermittency of RESs, many studies consider the utilization of ESS in VPP [5-6]. In [5], the optimal operation strategy to maximize the profit of ESS with PV-centered resources under specific circumstances is proposed in Korea. Meanwhile, Lee proposes a comprehensive optimal operation 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; thus, there are clear limitations in actively utilizing ESS to support the vulnerability of RESs. Thus, there are many efforts to focus on deriving the optimal allocation of the BESSs constituting the VPP due to the low economic feasibility [7-9]. A study was conducted to estimate the optimal capacity of the ESS constituting the VPP [7], and locational allocation is also considered in [8]. Moreover, not only technical analysis but a techno-economics analysis of BESS for VPP was conducted [9].

While aggregating RESs into VPPs has considerable merit, it also has several uncertainties and drawbacks. These include uncertainty about not only renewable energy generation but demand resources, and market prices [10]. To deal with these uncertainties, most studies have adopted a stochastic programming approach [2, 11-14]. In [2], a strategy to participate in the market was suggested through the combination of conventional power generation resources and renewable energy; additionally, [11] attempted a scenario-based stochastic approach to deal with the uncertainty of VPPs composed of traditional generators and renewable energy, especially wind power. Meanwhile, [12-13] derived an optimal operation strategy through a combination of renewable energy and CHP. [12] applied a probabilistic technique to derive the optimal scheduling for power and heat demand, and [13] 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 in [14].

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 [15]. South Korea has 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 [16].

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 18.246GWh or 12.975GWh for day-ahead market participation only [17]. In Korea, approximately 4.58 GW of resources participated in the DR market for 10 months from January to October 2021, generating approximately 421.1GWh of power [18]. In PJM, most DR resources participate in load management rather than economic DR [17], 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 characteristics. Thus, we propose a method of performing error composition of PV generation through DR resources and derived an optimal operation strategy for participating in the day-ahead energy market and DR market. We focus on the following contents in this study.

1) An optimal virtual power plant operation strategy using demand response 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 multi-integer linear programming (MILP).

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

**TABLE 1. PV Forecasting Incentive implemented in Korea**

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

Meanwhile, the DR market operation results and load data is used to obtain the constraints for DR in optimization problem. DR successful bid rate is calculated by 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 which is 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 is consist of the market framework in Korea and DER modeling.

A. MARKET FRAMEWORK

1) FORECASTING RATE INCENTIVE

In the Korean electricity market, VPP operators can participate in the PV forecasting incentive system. 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, and 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%.
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:

\[
P_{k,t}^{\text{pred}} = F_k(R_k) \frac{1}{\sigma_{k,m,t} \sqrt{2\pi}} e^{- \frac{(R_k - \mu_{k,m,t})^2}{2\sigma_{k,m,t}^2}} (1)
\]

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 three categories: 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.

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.

\[
\begin{align*}
\text{Sunny} & \quad \frac{\Sigma_{t=1}^{24} P_{k,t}^{\text{CPV}}}{C_{PV}} > 5.0 [\text{p.u}] \\
\text{Rainy} & \quad \frac{\Sigma_{t=1}^{24} P_{k,t}^{\text{CPV}}}{C_{PV}} < 2.0 [\text{p.u}] \\
\text{Cloudy} & \quad \text{Otherwise}
\end{align*}
\]

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 [19]. 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:

\[
S = FS \times SC \times OS \quad (3)
\]

As our goal is DR potential calculation, how to calculate each factor is skipped here, and 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.

VPP operator submits their forecasting profile \( P_{k,t}^{\text{pred}} \) 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 which is indicated in table 1.

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

2) IMBALANCE PENALTY
In addition, KPX, a market operator, is in the process of improving the market by the introduction of an imbalance penalty system. According to their plan, the energy imbalance penalty is charged to generation companies, if their prediction error exceeds a threshold that is different for each system operator. In FERC Order 890, the penalty is suggested 10% level of energy price if the error range is in 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 as follows in table 2.
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:

\[
\max (R_{pv}^e + R_{inc} + R_{ec} - C^{ec})
\]

where \( R_{pv}^e \) is the revenue from PV generation and is calculated by the following equation:

\[
R_{pv}^e = \sum_{t} (\lambda_t \cdot P_{k,t})
\]

where \( \lambda_t \) is the wholesale price at time \( t \), \( P_{k,t} \) is the PV generation amount, and \( R_{pv}^e \) is the revenue from the PV forecasting incentive.

\[
R_{inc} = \sum_{t} (P_{k,t} \cdot \sum_{ferr} (\hat{Z}_{ferr} \cdot v_{ferr}))
\]

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

\[
R_{ec} = \sum_{t} \left( (P_{k,t}^e \cdot \sum_{ferr} (\hat{Z}_{ferr} \cdot v_{ferr})) + \eta_t \right)
\]

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

Additionally, an opportunity cost \( C^{ec} \) 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.

\[
C^{ec} = \rho \cdot \sum_{t} (\lambda_t \cdot (q^{inc}_{ferr} + q^{red}_{ferr}))
\]

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, \( q^{inc}_{ferr} \) and \( q^{red}_{ferr} \) represent the increment or reduction in DR resources activated for error compensation, respectively.

B. LINEARIZATION

\( R_{inc} \) contains a nonlinearity element and hence must be linearized to model the MILP problem. Thus, we developed a method proposed by Ko [6]. The FERR is divided into five sections in Table 1. That is if the error is bigger than 8% FERR is one, and the error belongs to 6~8% FERR is two, and so on.

\[
\mu_t^{ferr} = \epsilon_t \cdot v_t^{ferr} \quad \forall t, \forall ferr
\]

\[
\epsilon_t = \frac{p_{pred}^{k,t} - P_{k,t}}{C_{PV}} \quad \forall t
\]

\[
\sum_{ferr} v_t^{ferr} = 1, \quad ferr = 1,2,3,4,5
\]

The forecasting error \( \mu_t^{ferr} \) is multiplied by the error rate \( \epsilon_t \) and state variable \( v_t^{ferr} \).

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; \( v_t^{ferr} \) is equal to one, if the value of the error rate belongs to one of the five sections, and zero otherwise. To linearize nonlinearity, the following process was performed following the flow proposed in [6]:

\[
\begin{align*}
\epsilon_t & \geq (1 - \mu_t^{ferr}) \cdot Z + v_t^{ferr} \cdot pr^{ferr} & \quad \text{if ferr} < \text{ferr}_{max} \\
\epsilon_t & \leq (1 - \mu_t^{ferr}) \cdot Z + v_t^{ferr} \cdot pr^{ferr+1} & \quad \text{otherwise}
\end{align*}
\]

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. \( R_{inc} \) is redefined by linearization as follows:

\[
R_{inc}^e = \sum_{t} (P_{k,t} \cdot \sum_{ferr} (\hat{Z}_{ferr} \cdot v_{ferr}))
\]

\[
= \sum_{t} \sum_{ferr} (P_{k,t} \cdot \hat{Z}_{ferr} \cdot v_{ferr})
\]

\[
= \sum_{t} \sum_{ferr} (g_t^{ferr} \cdot v_{ferr})
\]

where \( g_t^{ferr} \) is the multiplication of power generation \( P_{k,t} \) and incentive price \( \hat{Z}_{ferr} \), \( h_t^{ferr} \) is calculated by multiplying the state variable \( v_{ferr} \) by \( g_t^{ferr} \).

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

\[
\begin{align*}
 h_t^{ferr} & \geq -v_t^{ferr} \cdot Z \\
 h_t^{ferr} & \leq v_t^{ferr} \cdot Z \\
 h_t^{ferr} & \geq g_t^{ferr} - (1 - v_t^{ferr}) \cdot Z \\
 h_t^{ferr} & \leq g_t^{ferr} + (1 - v_t^{ferr}) \cdot Z
\end{align*}
\]

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

Additionally, the reorganized prediction error \( \delta_t^{ferr} \) is the product of the adjusted error rate \( \theta_t \) and the state variable.

The adjusted error rate \( \theta_t \) is calculated with the \( h_t^{ferr} \) which is the amount of electricity generated by error compensation.

\[
\delta_t^{ferr} = \theta_t \cdot v_t^{ferr} \quad \forall t, \forall ferr
\]

\[
\theta_t = \frac{\rho_{pred}^{k,t} - P_{k,t}}{\rho_{cap}} \quad \forall t
\]

\[
\begin{align*}
\theta_t & \geq (1 - \mu_t^{ferr}) \cdot Z + v_t^{ferr} \cdot pr^{ferr} & \quad \text{if ferr} < \text{ferr}_{max} \\
\theta_t & \leq (1 - \mu_t^{ferr}) \cdot Z + v_t^{ferr} \cdot pr^{ferr+1} & \quad \text{otherwise}
\end{align*}
\]

In addition, \( R_{inc}^e \) is redefined through the following linearization as follows:
The electricity generation amount $P_{ki}^{\text{ec}}$ determined by error compensation is the summation of the PV generation, DR increment amount, and DR reduction amount.

$$P_{ki}^{\text{ec}} = (P_{ki} + \varphi_{ki}^{\text{inc}} - \varphi_{ki}^{\text{red}})$$  \hspace{1cm} (19)

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

$$\begin{align*}
H_{t}^{\text{err}} & \geq -v_{t}^{\text{ferr}} \cdot Z \\
H_{t}^{\text{err}} & \leq v_{t}^{\text{ferr}} \cdot Z \\
H_{t}^{\text{err}} & \geq G_{t}^{\text{ferr}} - (1 - v_{t}^{\text{ferr}}) \cdot Z \\
H_{t}^{\text{err}} & \leq G_{t}^{\text{ferr}} + (1 - v_{t}^{\text{ferr}}) \cdot Z
\end{align*}$$  \hspace{1cm} (20)

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

$$\begin{align*}
\varphi_{t0}^{\text{inc}} & \leq L_{t}^{\text{ub,inc}} \\
\varphi_{t0}^{\text{red}} & \leq L_{t}^{\text{ub,red}}
\end{align*}$$  \hspace{1cm} (21, 22)

The constraint for the imbalance penalty is given as:

$$\eta_{t} = |P_{ki}^{\text{ec}} - P_{ki,t}| \cdot \lambda_{t} \cdot 0.1$$  \hspace{1cm} (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 the cement factory which is 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 demonstrated by Lee [19], it is difficult 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 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 $\varepsilon^{\text{MCS}}_t$ didn't exceed the threshold value $\varepsilon^{\text{th}}$ 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 $L^{\text{MCS}}$. $L^{\text{MCS}}$ assessed considering the error rate $\varepsilon^{\text{MCS}}_t$ indicates a more practical value compared to $L^{\text{opt}}$ which is a theoretical value calculated by the optimization problem. If the output of optimization model $L^{\text{opt}}$ is a feasible set, that is, $L^{\text{opt}}$ is a subset of $L^{\text{MCS}}$, VPP operators sort their load resources out for participation in the energy market and economic DR as illustrated in figure 1. In contrast, if $L^{\text{opt}}$ is unfeasible, that is, $L^{\text{MCS}}$ is not a superset of $L^{\text{opt}}$, VPP operators participate in the DR market only with their load profile.

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.

**C. RESULTS WITHOUT ERROR COMPENSATION**

The PV forecasting error was calculated when the utilization rate of the PV generation is more than 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 indicated a case in which an error occurs. The upper and lower parts of the red dotted line in figure 6 indicated 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 prediction error exceeded ±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.
The simulation results according to the optimization model are shown in figure 7. As shown in figure 7, approximately three thousand kWh was reduced due to under-generation at 8 h (50kwh per minute during 480–540 min) and five hundred kWh of DR resources were increased due to over-generation at 11 h (8kwh 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.

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.

### D. RESULTS WITH ERROR COMPENSATION

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### E. COMPARING THE 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 is increased.

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) |

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 be a disadvantage to 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.
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 and participate 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 demand response resource. At first, the PV generation profile is derived using the PV prediction model and calculates 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.

However, it is necessary to conduct a more advanced prediction model to calculate the more practical profitability of VPP operators. If the proposed model is crafted 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 be used in a way that helps not only improved profitability for VPP operators and the operational stability for the system operator.

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