energies

MDPI

Article

Stochastic Mixed-Integer Programming (SMIP)-Based Distributed Energy Resource Allocation Method for Virtual Power Plants

Rakkyung Ko and Sung-Kwan Joo *

The School of Electrical Engineering, Korea University, Seoul 02841, Korea; uranium92@korea.ac.kr
* Correspondence: skjoo@korea.ac.kr; Tel.: +82-2-3290-4820

Received: 28 November 2019; Accepted: 20 December 2019; Published: 21 December 2019



Abstract: Virtual power plants (VPPs) have been widely researched to handle the unpredictability and variable nature of renewable energy sources. The distributed energy resources are aggregated to form into a virtual power plant and operate as a single generator from the perspective of a system operator. Power system operators often utilize the incentives to operate virtual power plants in desired ways. To maximize the revenue of virtual power plant operators, including its incentives, an optimal portfolio needs to be identified, because each renewable energy source has a different generation pattern. This study proposes a stochastic mixed-integer programming based distributed energy resource allocation method. The proposed method attempts to maximize the revenue of VPP operators considering market incentives. Furthermore, the uncertainty in the generation pattern of renewable energy sources is considered by the stochastic approach. Numerical results show the effectiveness of the proposed method.

Keywords: virtual power plant (VPP); distributed energy resource (DER); energy storage system (ESS); VPP portfolio; DER allocation

1. Introduction

The reduction of greenhouse gases has become a critical constraint in planning the energy mix in power systems [1]. To address this issue, system operators allow the proportion of renewable energy sources (RESs), such as photovoltaic (PV) generator and wind turbine (WT), to increase in power systems. However, owing to their nature, the introduction of RESs could cause reliability issues in the power grid [2]. Their unpredictable and variable characteristics could compromise the balance of power systems. Moreover, because, in the distribution system, RES systems are usually installed in the countryside, power quality issues that include local voltage and power flow problems can occur [3].

Energy storage systems (ESSs) have attracted considerable interest as a promising technology to solve various problems with RESs. Recently, a variety of ESSs have been introduced in the power system [4]. Among the existing ESSs, lithium-ion batteries have received attention because of their high capacity, efficiency, and response speed. Li-ion batteries are often adopted to compensate for the unpredictable and variable nature of RESs [5–7]. However, it is difficult for the system operator to monitor and control individual distributed energy resources (DERs) because of the large number of RESs and locations where they are installed.

In this context, the concept of virtual power plants (VPPs) has been proposed. VPPs aggregate and control the DERs involved in the electricity market as a single generator. By doing so, the system operator can treat multiple DERs as a single generator. VPPs can be classified into two categories: Commercial and technical VPPs [8]. Commercial VPPs do not consider the physical constraints of the power grid, e.g., voltage and flow limit, whereas technical VPPs do. Nevertheless, both types of

VPPs have to participate in the electricity market, and consequently, the VPP operator has to consider revenue. Therefore, system operators usually provide market signals in the form of incentives to operate VPPs in the desired manner [9]. Pilot VPP programs are conducted in many countries [10,11]. The number of VPPs is expected to increase, owing to the increasing number of RESs. Thus, the importance of identifying an optimal DER portfolio increases. On the other hand, finding optimal resources allocation of demand response is also studied in [12–14]. Markowitz's portfolio theory is generally applied to obtain a mean-variance portfolio of demand–response resources [12]. A two-level gaming approach was made for the optimal demand response management with multiple utilities and users [13]. The reinforcement learning is applied to find optimal power company selection [14].

Many studies have been conducted to determine the optimal configuration of DERs in microgrids (MGs) [15–21]. The DER allocation problem can be formulated by a similar form of optimal sizing and placement problems because both problems involve choosing an optimal combination of DERs to maximize the revenue or minimize the expenses. The optimal placement of DERs in the MG are studied deterministically [15–17]. However, because the portfolio of a VPP cannot be changed frequently, the VPP operator needs to consider the long-term uncertainty of RESs. To this end, stochastic programming has been applied in many studies [18–21]. Furthermore, systems' constraints (e.g., voltage or flow limit) are often considered because of the sizing and placing problems usually addressed in the MG [17–20]. However, most studies consider the MG instead of VPPs; thus, there is a difference between determining the optimal investment and optimal portfolio. The MG is usually a single entity that is either connected to the power grid through a single tie line or separated from it. Therefore, the MG operator is responsible for the balance and reliability of its system. Consequently, the MG operator tends to invest in new DERs to support the MG operation. However, the VPP operator aggregates and allocates DERs that are already installed into several portfolios.

The mean-variance portfolio theorem proposed in [12] can be used to determine the optimal portfolio of VPPs. However, because the operation of dispatchable resources (e.g., ESS, DG) varies with RESs that are in the same VPP, the revenue of the dispatchable resources varies with the portfolio. To solve this issue, a two-stage stochastic mixed-integer programming (SMIP)-based DER allocation method is proposed in this study. The proposed method determines the optimal portfolio with aggregated resources to maximize the VPP operator's revenue considering market incentives. The uncertainty in the power generation of RESs is reflected in the proposed method by considering the yearly generation pattern. The market incentives considered in this study follow the market incentives considered in [9]. To the best of our knowledge, this paper presents the optimal DER allocation method, which considers the market incentive for the first time. The rest of this paper is structured as follows: Section 2 describes the SMIP-based DER allocation problem, Section 3 presents the numerical results of the proposed method, and Section 4 presents the conclusions.

2. Optimal Distributed Energy Resource Allocation Method for Virtual Power Plant

This section describes an optimal DER allocation method for VPPs. The proposed method determines an optimal combination of DERs in VPPs to maximize the revenue. In this study, the revenues of the energy market, renewable energy certificate (REC) market, and incentives are considered. The proposed DER allocation problem for VPPs is formulated as a two-stage optimization problem. The composition of VPPs is determined in the first stage of the problem formulation, and then, based on the solution of the first stage, the expected revenue is calculated. The second-stage problem is formulated as a day-ahead market (DAM) bidding problem modified from [9]. The allocation result needs to be represented as a binary value; the DER allocation problem needs to be formulated as an SMIP problem. The general formulation and algorithm used to solve the proposed problem are based on those proposed in [22]. Figure 1 summarizes the proposed method.

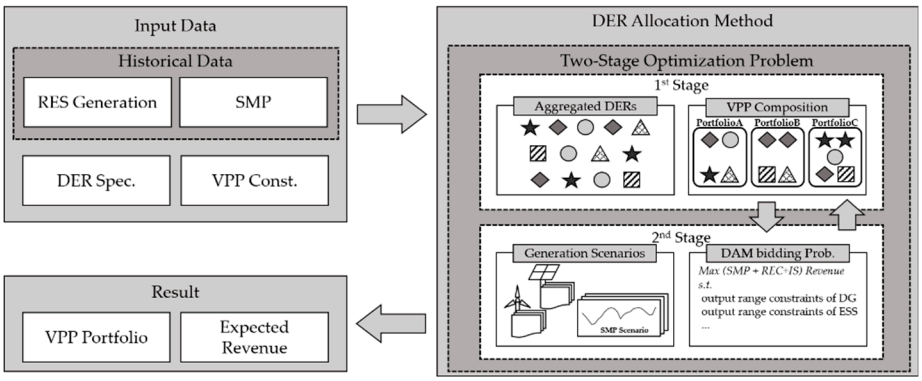


Figure 1. Block diagram of the proposed distributed energy resource (DER) allocation method for virtual power plants (VPPs).

2.1. First-Stage Problem for DER Allocation

The first-stage problem allocates DERs to compose portfolio as in Figure 1. It is assumed that the number of RESs, ESSs, and distributed generators (DGs) for the VPP operator are I, J, and L, respectively, and the VPP operator wishes to operate N VPPs.

With this assumption, the binary variables $r_{n,i}$, $e_{n,j}$, and $g_{n,i}$ are introduced. The binary variable $r_{n,i}$ is one only if RES i belongs to VPP n; this relationship holds for the other two variables. However, because the two-stage structure is applied, $r_{n,i}$, $e_{n,j}$, and $g_{n,i}$ are relaxed to continuous variables within the range 0–1 in the first-stage problem.

Because there are no expenses or revenues from allocating DERs to a VPP, the objective function of the first problem is represented as follows:

$$\min_{r,e,g,\theta} \theta \tag{1}$$

Here, θ represents the expected objective value of second-stage problems. This value is regulated by the optimal cut, which is explained later in this section.

The constraints of the first-stage problems are related to the number of DERs and the capacity of the VPP. DERs are allowed to participate in only one VPP. These constraints are represented as follows:

$$\sum\nolimits_{n\in N} r_{n,i} = 1 \quad \forall i \tag{2}$$

$$\sum\nolimits_{n\in N} e_{n,j} = 1 \quad \forall j \tag{3}$$

$$\sum\nolimits_{n\in N} g_{n,l} = 1 \quad \forall l \tag{4}$$

The minimum and maximum numbers of DER constraints are expressed as follows:

$$N^{min} \le \sum\nolimits_{i\in I} r_{n,i} + \sum\nolimits_{j\in J} e_{n,j} + \sum\nolimits_{l\in L} g_{n,l} \le N^{max} \quad \forall n \tag{5}$$

where N^{min} and N^{max} are the minimum and maximum numbers of DERs in a VPP.

The minimum and maximum capacity of VPP constraints are described as follows:

$$Cap^{min} \le \sum\nolimits_{i\in I} Cap_i \cdot r_{n,j} + \sum\nolimits_{j\in J} P^{max}_{dchg,j} \cdot e_{n,j} + \sum\nolimits_{l\in L} P^{max}_{l} \cdot g_{n,l} \le Cap^{max} \quad \forall n \tag{6}$$

where Cap^{min} and Cap^{max} are the minimum and maximum capacities of the VPP, $P^{max}_{dchg,j}$ is the maximum discharging power of ESS j, and P^{max}_{l} is the maximum generated power of DG l. In RESs, ESSs, and

DGs, the rated capacity, maximum discharging power, and maximum output power are directly used as the capacity of the resource.

The combined PV and ESS scheme proposed in [9] is adopted in this study. Combined resources need to be in the same VPP to earn additional RECs. These constraints are described as follows:

$$r_{n,i} = e_{n,j} \quad \forall n,\ (i,j) \in K \tag{7}$$

The set K consists of combined PV generators and ESSs. The last constraints are the optimality cuts. Generally, optimal cuts are represented as follows:

$$E_s x + \theta \geq e_s \tag{8}$$

In this study, the algorithm used to solve the SMIP problem is taken from [22], and the optimality cut is generated as follows:

$$\theta \geq (qs^s - L)\left(\sum_{i \in S^s} x_i - \sum_{i \notin S^s} x_i\right) - (qs^s - L)\left(\left|S^s\right| - 1\right) + L \quad \forall s \tag{9}$$

where qs^s is the expected objective value of the second stage, L is the lower bound of qs^s, and S^s is the set of variables with a value of one. In Equation (9), s stands for the order of optimal cuts. Generally, feasibility cuts are introduced when the second stage is infeasible. However, feasibility cuts are unnecessary in the proposed method because the second-stage problem is always feasible.

2.2. Second-Stage Problem for DAM Bidding

The second-stage problem is formulated following the scheduling method for DAM bidding proposed in [9] with some modifications. Each second-stage problem maximizes the revenue for each day. After solving 365 problems, the average revenue is returned. The objective function of the second-stage problem is described as follows:

$$Maximize \sum_{n \in N}\left\{\sum_{t \in T} SMP_t \cdot P^{net}_{n,\,t} + C_{REC} \cdot \left(REC^1_n + 5 \cdot REC^5_n\right) - \sum_{t \in T}\sum_{l \in L} f^R_l\left(P^{DG}_{n,l,t}\right) + \sum_{t \in T}\left(1 - \varepsilon^s_{n,t}\right) \cdot Cap^{VPP}_n \cdot C^{SI}_t\right\} \tag{10}$$

where SMP_t is the system marginal price (SMP) at time t, $P^{net}_{n,\,t}$ is the net generation of VPP n at time t, C_{REC} is the REC price, REC^1_n and REC^5_n are the received REC of VPP n with weights 1 and 5, respectively, f^R_l is the relaxed cost function of DG l, $P^{DG}_{n,l,t}$ is the generation of DG l in VPP n at time t, $\varepsilon^s_{n,t}$ is the ramp rate of VPP n at time t, Cap^{VPP}_n is the capacity of VPP n, and C^{SI}_t is the stability incentive price at time t.

The RESs receive RECs for their power generation. One REC is given for 1 MWh generation; however, additional RECs could be given if the RES is combined with an ESS. The additional RECs are calculated as follows:

$$REC_{n,5} = \sum_{t \notin TC}\sum_{(i,j) \in K}\left(P^{E2G}_{n,j,t} - P^{R2E}_{n,i,t}\right) \tag{11}$$

where TC is the charging time, and $P^{E2G}_{n,j,t}$ is the discharge amount of ESS j in VPP n at time t; $P^{R2E}_{n,\,i,t}$ is the charge amount of the ESS from the combined PV generator i in VPP n at time t. The number of RECs with weight one are calculated as follows:

$$REC^1_n = \sum_{t \in T}\left(\sum_{i \in I} P^{RNW}_{i,t} r_{n,i} + \sum_{(i,j) \in K}\left(P^{R2G}_{n,i,t} + P^{E2G}_{n,j,t}\right)\right) - REC^5_n \tag{12}$$

where $P^{RNW}_{i,t}$ is the generation of RES i at time t, $P^{R2G}_{n,i,t}$ is the amount of power from PV generator i in VPP n, which directly flows to the grid without being charged to the ESS at time t.

The cost function of DG is linearized because the quadratic term cannot be used for the integer L-shape method [22]. The linearized cost function of DG is expressed as follows:

$$f_l^R\left(P_{n,l,t}^{DG}\right) = \left(A_l P_l^{max} + B_l\right)P_{n,l,t}^{DG} + C_l u_{n,l,t} \tag{13}$$

where A_l, B_l, and C_l are the coefficients of the original cost function of DG, P_l^{max} is the maximum generation of DG l, and $u_{n,l,t}$ is the binary variable, which is one only if DG l in VPP n is generating power at time t.

The net generation of each VPP is calculated as follows:

$$P_{n,t}^{net} = \sum_{i\in I} P_{i,t}^{RNW}\cdot r_{n,i} + \sum_{j\in J}\left(P_{n,j,t}^{E2G} - P_{n,j,t}^{G2E}\right) + \sum_{(i,j)\in K}\left(P_{n,i,t}^{R2G} + P_{n,j,t}^{E2G}\right) + \sum_{l\in L} P_{n,l,t}^{DG} \quad \forall n,t \tag{14}$$

where $P_{n,j,t}^{G2E}$ is the charging amount of ESS j in VPP n at time t.

The ramp rate of each VPP is needed to calculate incentives; $\varepsilon_{n,t}^{s}$ in constraint (10) represents the ramp rate of the VPP. Additionally, the ramp rate needs to be represented by its absolute value; thus, $\varepsilon_{n,t}^{s}$ is related to $P_{n,t}^{net}$ as follows:

$$\varepsilon_{n,t}^{s} = \left|\frac{P_{n,t}^{net} - P_{n,t-1}^{net}}{Cap_n^{VPP}}\right| \quad \forall n,t \tag{15}$$

Note that the denominator is replaced by the capacity of the VPP instead of $P_{n,t}^{net}$ to avoid the rational form of the objective function.

The constraints for the operation of ESSs are expressed as follows:

$$0 \le P_{n,j,t}^{E2G} \le P_{dchg,j}^{max}\cdot e_{n,j} \quad \forall n,j,t \tag{16}$$

$$0 \le P_{n,j,t}^{E2G} \le P_{chrg,j}^{max}\cdot e_{n,j} \quad \forall n,j,t \tag{17}$$

$$0 \le P_{n,j,t}^{G2E} \le P_{i,t}^{RNW}\cdot e_{n,j} \quad \forall n,\ (i,j)\in K,t \tag{18}$$

where $P_{chrg,\,j}^{max}$ is the maximum charging power of ESS j.

The state of charge (SoC) is the indicator of the energy remaining in the ESS, and is calculated as follows:

$$SoC_{j,t} = SoC_{j,t-1} + \frac{\eta_j \sum_{n\in N} P_{n,j,t}^{G2E} - \frac{\sum_{n\in N} P_{n,j,t}^{E2G}}{\eta_j}}{EC_j} \quad \forall j,t \tag{19}$$

where $SoC_{j,t}$ is the SoC of ESS j at time t, EC_j is the maximum stored energy of ESS j, and η_j is the efficiency of ESS j. Generally, the SoC of ESSs is limited to a certain range. The SoC range constraint is represented as follows:

$$SoC_j^{min} \le SoC_{j,t} \le SoC_j^{max} \quad \forall j,t \tag{20}$$

Finally, the constraint for the generation of DG is expressed as follows:

$$\varepsilon\cdot u_{n,l,t}^{DG}\cdot g_{n,l} \le P_{n,l,t}^{DG} \le P_l^{max}\cdot u_{n,l,t}^{DG}\cdot g_{n,l} \quad \forall n,l,t \tag{21}$$

where ε is a constant introduced to indicate the operation state of the DG, which needs to be set to a value sufficiently small so as to not affect the DAM bidding problem.

3. Numerical Results

In this section, the numerical results of the proposed method are presented. The input data of the DERs are presented first; then, a case study employing the proposed method is conducted in two different scenarios: (1) Low incentive, and (2) high incentive. A total of 12 DERs and 6 RESs

are considered in the case study. The capacity of the RESs is presented in Table 1. Table 2 lists the properties of the ESSs utilized for the case study. ESS1 and ESS2 are combined with PV1 and PV2, respectively, to earn additional RECs, and ESS3 and ESS4 are independent, which are usually used for arbitrage and fluctuation minimization. In the rest of this section, the maximum charge is treated as the identical value of maximum discharge. The allowed SoC range of all ESS is set to be 10–90%.

Table 1. Capacity of renewable energy sources (RESs) considered for the case study.

Name	PV1	PV2	PV3	PV4	WT1	WT2
Capacity (kW)	97.5	99	248	292.5	510	600

Table 2. Properties of energy storage systems (ESSs) used for the case study.

Name	P^{max}_{chrg} (kW)	EC (kWh)	Connected PV
ESS1	99	300	PV1
ESS2	99	300	PV2
ESS3	100	250	-
ESS4	100	250	-

Table 3 lists the properties of the DG. Two similar DGs are utilized for the case study. Table 4 lists the input parameters of the VPPs. Two VPPs with 5–10 DERs and 500 kW to 20 MW capacity are considered. The stability incentive price is set differently in each case. The first case is a low incentive case, where the stability incentive price is set to be 0.9 won/kW, following the AGC price in [9]. The second case assumes a future scenario, which shows the importance of the ramping capability of the system due to the increasing penetration of RESs. The simulation is conducted in an Intel Core i5 with 8 GB of RAM using the CPLEX solver. The computation time of the proposed method is dependent on the number of DERs and scenarios for second stage. Among the two factors, the number of DERs is the dominant factor because of the combination of VPP will increase exponentially for the number of DERs. In this study, 365 days are considered, and the optimization process takes between an hour or two. However, because the registration of VPP resources into the VPP market is not frequently needed but only a few times in a year, the proposed method is believed to be applicable.

Table 3. Properties of distributed generators (DGs) used for the case study.

Name	P^{max} (kW)	A (won/kWh)	B (won/kWh)	C (won/kWh)
DG1	50	0.341	32.67	330
DG2	50	0.341	32.67	330

Table 4. Parameters related to the VPP.

$nVPP$	C^{min} (kW)	C^{max} (kW)	N^{min}	N^{max}	C^{SI} (won/kWh)	C^{REC} (won/kWh)
2	500	20,000	5	10	0.9	70

3.1. Low Incentive Case

Table 5 presents the result of the proposed method in the low incentive scenario.

Table 5. DER allocation results in the low incentive scenario.

VPP	Included DERs
VPP1	PV1, PV4, WT2, ESS1, ESS3, DG1
VPP2	PV2, PV3, WT1, ESS2, ESS4, DG2

VPP1 and VPP2 have capacities of 1239 and 1106 kW, respectively. The objective function, which represents the expected value of the total revenue from both VPPs, has a value of 1,674,027 won. As presented in Table 4, the combined PV generator and ESS are allocated in the same VPP. Figure 2 depicts the DAM bidding results in the second stage.

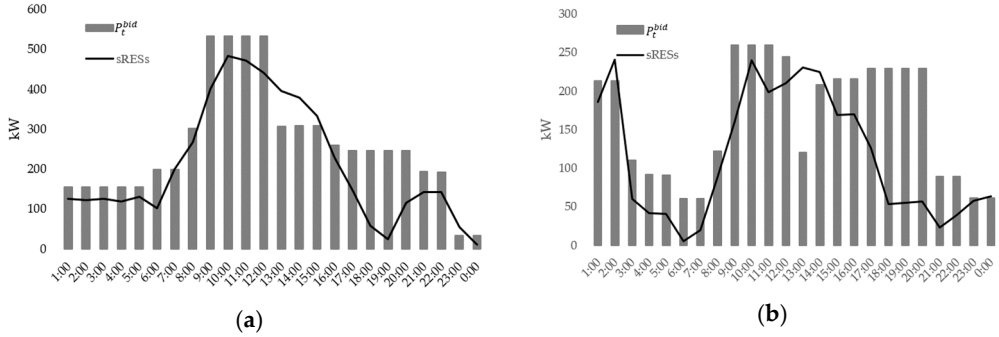


Figure 2. Optimal day-ahead market (DAM) bidding result of (**a**) VPP1 and (**b**) VPP2 in the second stage; sRESs represents the sum of the RESs generation in the low incentive scenario.

As depicted in Figure 2, the bid of the VPPs is determined based on the sum of the generation of the RESs. The bid is generally higher than the sRESs, owing to the generation of the DG. The ESSs discharge when the SMP is high to maximize the SMP revenue.

To show the effectiveness of the proposed method, the bidding results of VPPs with different compositions are compared. Because the VPP can earn the SMP, REC, and incentive revenue without the operation of the ESS, this basic revenue needs to be removed during the comparison. To do so, the basic revenue is calculated by removing the ESS. Table 6 depicts the expected daily revenue of each VPP in comparison with the basic revenue in the low incentive scenario.

Table 6. Revenue changes with respect to the basic revenue in the low incentive scenario (unit: Korean Won).

Case	Combined Revenue	SMP Revenue	REC Revenue	Incentive Revenue
Case 0	113,663	6525	107,183	−96
Case 1	113,565	6542	107,183	−180
Case 2	113,106	6173	107,183	−286
Case 3	113,059	5825	107,183	31
Case 4	113,058	5823	107,183	32

In Table 6, case 0 represents the results of the proposed method, and the other cases represent the results with VPPs with different compositions. The overall revenue change is increased by 113,663 won, which corresponds to 7.3% of the basic revenue. The SMP and incentive revenue change vary with the composition of the VPP, whereas the REC revenue change remains constant. This is because the additional RECs were maximized in all cases, and the sum of the generation of RESs remains the same regardless of the composition of the VPP. A trade-off between the SMP and incentive revenue was observed. Comparing case 0 with cases 4 and 3, the SMP revenue of case 0 is higher than those in the other cases; in contrast, the increase in the incentive revenue in case 0 is lower than those in the other cases. Because the incentive price is low, the ESSs are operated to maximizing the SMP revenue despite an increase in the variability. As a result, SMP result change in Table 6 is positive, whereas incentive result change is negative.

3.2. High Incentive Case

For the high incentive case, the incentive price is set to 22 won/kWh, which is the average regulation capability clearing price of PJM. Table 7 presents the DER allocation result in the high incentive case.

Table 7. DER allocation results in the high incentive scenario.

VPP	Included DERs
VPP1	PV1, PV3, ESS1, DG1, DG2
VPP2	PV2, PV3, PV4, WT1, WT2, ESS2, ESS3, ESS4

As the incentive price changes, the composition of the VPP also changes. The capacity of the two VPPs is 544.5 and 1800.5 kW. Most of the ESSs are allocated to VPP2 for suppressing the fluctuation of the WTs. DGs are allocated to VPP1, which includes only PV generators to increase the net generation of the VPP when one PV generator cannot operate. The bidding results on the same day in each case are depicted in Figure 3. Comparing Figure 3a,b, it can be observed that the fluctuation of both VPPs is significantly decreased in the high incentive scenario.

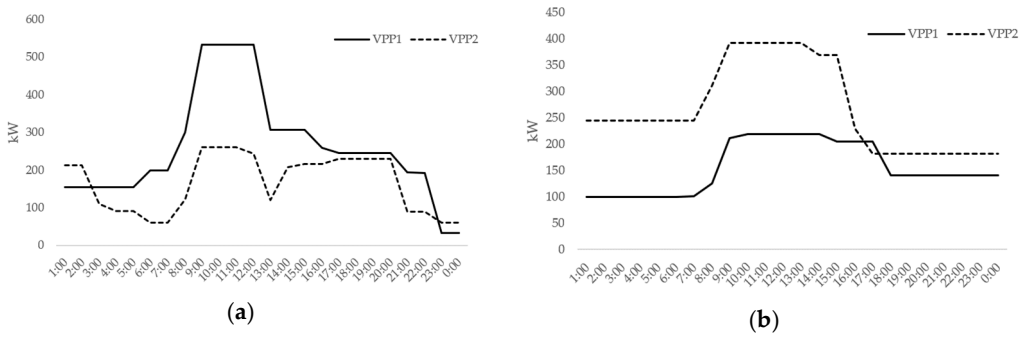


Figure 3. Bidding results of VPPs on the same day in the (**a**) low and (**b**) high incentive scenarios.

Table 8 depicts the expected daily revenue of each VPP in comparison with the basic revenue in the high incentive scenario. In the Table 8, the SMP revenue change of the optimal portfolio is relatively lower than other cases in the high incentive scenario. This indicates that the ESSs are operated for the incentive revenue that is worth more than SMP revenue. The change in the REC revenues are the same in all cases; additionally, they are the same as the REC revenues in the low incentive scenario. Because RECs are calculated based on the amount of generation of the RESs, the revenue will not change if the same generation pattern is used. The most significant difference between the low incentive cases is in the incentive revenue. Unlike in the low incentive case, the optimal portfolio (case 0) has the highest incentive revenue change. As the incentive price increases, the difference in the overall revenue between portfolios increases. Consequently, the DER allocation problem becomes more important as RES penetration increases.

Table 8. Revenue changes with respect to the basic revenue in the high incentive scenario (unit: Korean Won).

Case	Combined Revenue	SMP Revenue	REC Revenue	Incentive Revenue
Case 0	132,699	9676	107,183	20,895
Case 1	131,408	9466	107,183	19,505
Case 2	127,787	9077	107,183	16,190
Case 3	124,595	10,604	107,183	12,233
Case 4	120,548	10,208	107,183	8666

4. Conclusions

In this paper, an SMIP-based DER allocation method incorporating the market incentive was proposed. The proposed method is a first attempt to allocate DERs to VPPs in order to maximize the average SMP, REC, and incentive revenue. The yearly generation patterns and SMP data are applied to reflect the uncertainty of RESs and the market price. A case study was conducted to show the effectiveness of the proposed method. The result of the proposed method was compared to the other portfolios with different compositions. It is shown in the numerical results that the proposed method enables a VPP aggregator to find the optimal portfolio in terms of expected revenue. Also, by comparing scenarios of low and high incentives, the potential uses of the proposed method for the future scenarios are demonstrated. For the future work, the financial risk has to be considered during DER allocation. The proposed method is expected to contribute to the efficient resource allocation and operation of an VPP when the VPP is settled in a practical market.

Author Contributions: Conceptualization, S.-K.J.; methodology, R.K.; supervision, S.-K.J.; writing—original draft, R.K.; writing—review and editing, R.K. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (No. NRF-2017R1A2B2004259). 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. 20181210301430).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Cheng, Y.; Zhang, N.; Lu, Z.; Kang, C. Planning multiple energy systems toward low-carbon society: A decentralized approach. *IEEE Trans. Smart Grid.* **2019**, *10*, 4859–4869. [CrossRef]
2. Skea, J.; Anderson, D.; Green, T.; Gross, R.; Heptonstall, P.; Leach, M. Intermittent renewable generation and maintaining power system reliability. *IET Gener. Transm. Distrib.* **2008**, *2*, 82–89. [CrossRef]
3. Ceaki, O.; Vatu, R.; Mancasi, M.; Porumb, R.; Seritan, G. Analysis of electromagnetic disturbances for grid-connected PV plants. In Proceedings of the 2015 Modern Electric Power Systems (MEPS), Wroclaw, Poland, 6–9 July 2015.
4. Faisal, M.; Hannan, M.A.; Ker, P.J.; Hussain, A.; Mansor, M.B.; Blaabjerg, F. Review of energy storage system technologies in microgrid applications: Issues and challenges. *IEEE Access* **2018**, *6*, 35143–35164. [CrossRef]
5. Foiadelli, F.; Roscia, M.; Zaninelli, D. Optimization of storage devices for regenerative braking energy in subway systems. In Proceedings of the 2006 IEEE Power and Energy Society General Meeting (PESGM), Montreal, QC, Canada, 18–22 June 2006.
6. Gong, Y.; Jiang, Q.; Baldick, R. Ramp event forecast based wind power ramp control with energy storage system. *IEEE Trans. Power Syst.* **2016**, *31*, 1831–1844. [CrossRef]
7. Lee, H.; Shin, B.Y.; Han, S.; Jung, S.; Park, B.; Jang, G. Compensation for the power fluctuation of the large scale wind farm using hybrid energy storage applications. *IEEE Trans. Appl. Supercond.* **2012**, *22*. [CrossRef]
8. Pudjianto, D.; Ramsay, C.; Strbac, G. Virtual power plant and system integration of distributed energy resources. *IET Renew. Power Gener.* **2007**, *1*, 10–16. [CrossRef]
9. Ko, R.; Kang, D.; Joo, S.K. Mixed integer quadratic programming based scheduling methods for day-ahead bidding and intra-day operation of virtual power plant. *Energies* **2019**, *12*, 1410. [CrossRef]
10. Lv, M.; Lou, S.; Liu, B.; Fan, Z.; Wu, Z. Review on power generation and bidding optimization of virtual power plant. In Proceedings of the International Conference on Electrical Engineering and Informatics (ICELTICs 2017), Banda Aceh, Indonesia, 18–20 October 2017.
11. Hatziargyriou, N.D.; Tsikalakis, A.G.; Karfopoulos, E.; Tomtsi, T.K.; Karagiorgis, G.; Christodoulou, C.; Poullikkas, A. Evaluation of virtual power plant (VPP) operation based on actual measurements. In Proceedings of the 7th Mediterranean Conference and Exhibition on Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2010), Agia Napa, Cyprus, 7–10 November 2010.
12. Chae, J.; Joo, S.K. Demand response resource allocation method using mean-variance portfolio theory for load aggregators in the Korean demand response market. *Energies* **2017**, *10*, 879. [CrossRef]

13. Chai, B.; Chen, J.; Yang, Z.; Zhang, Y. Demand response management with multiple utility companies: A two-level game approach. *IEEE Trans. Smart Grid* **2014**, *5*, 722–731. [CrossRef]
14. Apostolopoulos, P.A.; Tsiropoulou, E.E.; Papavassiliou, S. Demand response management in smart grid networks: A two-stage game-theoretic learning-based approach. *Mob. Netw. Appl.* **2018**, 1–14. [CrossRef]
15. Lu, S.; Li, Y.; Xia, H. Study on the configuration and operation optimization of CCHP coupling multiple energy system. *Energy Conv. Manag.* **2018**, *177*, 773–791. [CrossRef]
16. Mashayekh, S.; Stadler, M.; Cardoso, G.; Heleno, M. A mixed integer linear programming approach for optimal DER portfolio, sizing, and placement in multi-energy microgrids. *Appl. Energy* **2017**, *187*, 154–168. [CrossRef]
17. Armendáriz, M.; Heleno, M.; Cardoso, G.; Mashayekh, S.; Stadler, M.; Nordström, L. Coordinated microgrid investment and planning process considering the system operator. *Appl. Energy* **2017**, *200*, 132–140. [CrossRef]
18. Wang, Z.; Chen, B.; Wang, J.; Kim, J.; Begovic, M.M. Robust optimization based optimal DG placement in microgrids. *IEEE Trans. Smart Grid* **2014**, *5*, 2173–2182. [CrossRef]
19. HassanzadehFarda, H.; Jaliliana, A. Optimal sizing and location of renewable energy based DG units in distribution systems considering load growth. *Int. J. Elect. Power Energy Syst.* **2018**, *101*, 356–370. [CrossRef]
20. Ehsan, A.; Yang, Q. Scenario-based investment planning of isolated multi-energy microgrids considering electricity, heating and cooling demand. *Appl. Energy* **2019**, *235*, 1277–1288. [CrossRef]
21. Mavromatidis, G.; Orehounig, K.; Carmeliet, J. Design of distributed energy systems under uncertainty: A two-stage stochastic programming approach. *Appl. Energy* **2018**, *222*, 932–950. [CrossRef]
22. Laporte, G.; Louveaux, F.V. The integer L-shaped method for stochastic integer programs with complete recourse. *Oper. Res. Lett.* **1993**, *13*, 133–142. [CrossRef]



© 2019 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).