Mixed Integer Quadratic Programming Based Scheduling Methods for Day-Ahead Bidding and Intra-Day Operation of Virtual Power Plant

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Received: 14 February 2019; Accepted: 9 April 2019; Published: 12 April 2019

Abstract: As distributed energy resources (DERs) proliferate power systems, power grids face new challenges stemming from the variability and uncertainty of DERs. To address these problems, virtual power plants (VPPs) are established to aggregate DERs and manage them as single dispatchable and reliable resources. VPPs can participate in the day-ahead (DA) market and therefore require a bidding method that maximizes profits. It is also important to minimize the variability of VPP output during intra-day (ID) operations. This paper presents mixed integer quadratic programming-based scheduling methods for both DA market bidding and ID operation of VPPs, thus serving as a complete scheme for bidding-operation scheduling. Hourly bids are determined based on VPP revenue in the DA market bidding step, and the schedule of DERs is revised in the ID operation to minimize the impact of forecasting errors and maximize the incentives, thus reducing the variability and uncertainty of VPP output. The simulation results verify the effectiveness of the proposed methods through a comparison of daily revenue.

Keywords: virtual power plant (VPP); energy storage system (ESS); VPP schedule; schedule revising; mixed integer programming

1. Introduction

Distributed energy sources (DERs) include renewable energy sources (RESs), energy storage systems (ESSs), and distributed generators (DGs) [1]. The use of RESs is already widespread. However, their uptake is expected to increase at an even faster rate in the near future owing to rising global concerns regarding climate change [2]. Because of the uncertainty inherent in renewable energies, increasing the renewable capacity forces the grid operator to adopt higher standards [3]. To address this issue, system operators often encourage RES owners to install ESSs. In Korea, owners who have combined ESSs to RESs can obtain additional renewable energy certificates (RECs) when power from an RES is charged to an ESS and then discharged to the grid [4]. However, most ESSs are aligned to a single renewable generator or farm, presenting a limitation from the viewpoint of the system operator.

The concept of the virtual power plant (VPP), comprising a set of DERs, has emerged to aid the efficient management of RESs. A VPP integrates the highly volatile RESs with other DERs to participate in the market as a single generator, thereby enabling efficient system operation. There are two types of VPPs: commercial and technical. A commercial VPP aggregates DERs and participates in the market as a single generator without considering the impact on the physical grid. Conversely, a technical VPP considers the real-time influence on the distribution system [5]. In this paper, VPP refers to commercial VPPs, which aggregate and manage DERs to participate in the day-ahead (DA) market and operate to fulfill the complying bid.
The ESSs are key to VPP control because they provide readily available (stored) and dispatchable energy, sufficient to cope with the fluctuations of RESs. A previous study presented linear optimization problems encountered with ESSs during load shifting or arbitrage [6]. Efforts have been made to solve an optimization problem aimed at simultaneous 15 min and 60 min auctions, and sophisticated economic analyses have been conducted in this regard for the German electricity market [7]. To ensure stable and efficient VPP operation, both bidding and operation strategies are required. Many past and ongoing studies refer to bidding issues [8–13]. VPP scheduling was categorized into short-run and long-run problems, and an optimization algorithm was presented to address the former [8]. This short-run approach is similar to an energy management system, as opposed to a VPP. A non-convex economic dispatch model was devised and solved using a distributed randomized gradient-free algorithm for a VPP consisting of DGs, RESs, and ESSs [9]. The proposed problem involved non-convex optimization programming, but the scheduling scheme was the same as that for any other VPP. An offering strategy involving a three-stage stochastic bi-level optimization model has also been proposed for a VPP [10]. It considered demand and generation uncertainties, as well as rival offers. On the other hand, the VPP structure has been viewed as a hierarchal model with a central controller rather than a single entity [11,12]. In this structure, the VPP becomes a system of systems [11] and requires an algorithm to distribute the generation among smaller VPPs and schedule each of these. To address this issue, an interactive multi-VPP dispatch model based on the demand response and game theory was proposed in [12].

However, most studies have focused on the bidding strategy stage. As mentioned earlier, VPP operators need to monitor real-time power generation and reschedule accordingly to maintain a stable output and complying bid. The authors of [13] proposed remedial strategic scheduling for a VPP that considers the intra-day (ID) market. The ID market is a newly introduced market set between the DA and real-time markets. It adjusts supply and demand according to an updated forecast [14]. Using the ID market concept, three algorithms were proposed for the DA and ID markets, and remedial scheduling was devised considering contingency factors [13]. However, because the proposed scheme does not narrow its time scale during rescheduling, it suffers from a limitation with regard to variability control of DERs. Optimization problems for sizing, bidding, and operating IPVs have been presented previously [15]. A sizing problem and a bidding problem to participate in the DM market were formulated as a linear programming problem, and model predictive control was adopted for IM participation. However, due to the differences in various market environments, the proposed method was limited to reflecting the REC revenue and stability of the IPV’s output.

In this paper, mixed integer quadratic programming (MIQP)-based scheduling methods are presented for both DA market bidding and ID operation of VPPs, thus serving as a complete scheme for bidding-operation scheduling. The VPP operator is assumed to participate in the electricity market designed as part of the smart city project by the Korea Electric Power Research Institute (KEPRI), which is described later. Under the settlement rule, two different scheduling methods are presented:

1. A scheduling method for DA market bidding: The method considers the maximization of VPP revenue with a 1 h step.
2. A rescheduling method for ID operation: The method considers the minimization of the hourly generation error and 5 min generation variation with a 5 min scale.

This study makes the following contributions to the literature. (1) It proposes a rescheduling method for a VPP using a narrow timescale to cope with forecasting error and other contingencies while considering market incentives. (2) It considers the ongoing DA market and previously set (PS) schedules for DERs fed into the rescheduling method. (3) It formulates a combined ESS model to reflect the REC market. The remainder of this paper is structured as follows. Section 2 describes the market environment and scheme for bidding-operation scheduling. Section 3 introduces the scheduling methods for each problem. Section 4 presents the numerical result, and Section 5 concludes the paper.
2. Market Environment and Scheduling Scheme

2.1. Market Environment

A VPP operator is assumed to participate in the electricity market in Korea. As of yet, there are no settlement rules for VPP operators in the Korean electricity market, but plenty of studies are on-going for VPP integration. As part of the Smart City project of KEPRI, a platform and operation technology are being researched, and this study follows the settlement rule that is established for this project. Figure 1 presents VPP revenue from the market through (1) energy selling, (2) REC selling, (3) predictability incentive (PI), and (4) stability incentive (SI).

![Figure 1. VPP revenue under the electricity market of a smart city.](image)

The energy settlements are calculated by the system marginal price (SMP) and hourly generation. It is assumed that bids are accepted entirely as a result of the renewable-friendly policy, and VPP is a price taker. A REC is given per MWh of generation from the RESs and is traded in the REC market but can be considered as revenue for VPP. To inspire ESS installation, the system operator gives additional RECs if the ESS is directly combined with RESs. To obtain the weight for RECs, ESS needs to be physically connected with RES, and the generated power of the RES must pass through the ESS before being fed into the outer grid. If these conditions are met, the weight is multiplied by 5 to the discharged energy through the combined ESS. It is critical for REC revenue for the VPP, it is reflected in the methods presented in this paper. Energy selling and REC selling are relatively clear as compared to incentives.

The predictability incentive, which is represented in Equation (1), is determined by the relative difference between the hourly bid and the actual power generation of the VPP and is designed to minimize the difference.

\[
PI_n = \left(1 - \epsilon_n^P\right)P_{n}^{net}C_{n}^{AGC}
\]  

On the other hand, the stability incentive, which is presented in Equation (2), is determined by the average fluctuation rates of 5 min generation and is designed to minimize the fluctuation.

\[
SI_n = \left(1 - \epsilon_n^S\right)P_{n}^{net}C_{n}^{Cap}
\]

However, these incentives are provided only when the relative difference remains under 30%. By applying both incentives, the VPP is committed to complying with the planned generation and maintaining a constant power generation, which allows the VPP to be treated like a dispatchable generator.

2.2. Scheduling Scheme

Through the optimization problem with the forecast of RESs, a 1 h scale, a 24 h bid, and schedules for each DER are determined. After bidding in the electricity market, a VPP operator soon receives a market clearing result for the generation of the next day. In the rest of this paper, a bid will be treated as a market clearing result because the entire bid will be accepted as mentioned in Section 2.1. Because bids and schedules for each DER are set to maximize VPP revenue, a major modification from the PS...
schedule could reduce the revenue, so scheduling in the ID operation has to comply the bidding and schedules of the DA market.

To develop a scheduling method for ID operation, another RES forecasting algorithm is required. This method is for short-term forecasting with a 5 min timescale for a few hours, and it is different from the forecasting algorithm for the DA market, which forecasts with a 1 h timescale for a day or longer. This short-term forecast is updated every 5 min, and the ID operation re-scheduling method takes that and revises the schedule of the DERs every 5 min. Because recent forecasting generally has a lower error, the proposed re-scheduling scheme could cope with forecasting error. Since the incentives are calculated in an hour, so ID operation scheduling method should consider past generation history and maximize incentives. Therefore, scheduling time is narrowed over time during re-scheduling for ID operation. For example, the schedule starts at 0 AM for the first time, then start time is narrowed by 5 min for every re-scheduling. If the start time reaches 1 AM, then a new optimization problem which starts from 1 AM is constructed and re-scheduling is repeated every 5 min with narrowed time. Figure 2 summarizes the scheduling scheme.

Figure 2. Scheme for bidding-operation scheduling. During ID operation, the schedule is revised every 5 min by considering the updated forecast and PS schedule from the DA market.

3. Scheduling Methods for DA Market Bidding and ID Operation

To determine the schedule of DERs through MIQP formulation, DERs have to be modeled mathematically. In this study, VPP consists of photovoltaic (PV) and wind turbine (WT) generators, ESSs, and DGs as DERs. As there is a slight difference in the mathematical modeling of the DER in DA market and ID operation scheduling, the DER mathematical model is described at the DA market scheduling stage. Because the presence of the combined RESs and ESSs, the set of RESs and ESS is divided into an independent set and a combined set. DERs in a set of independent RESs, ESSs, and the combined set is expressed by subscripts $i, j, k$. In addition, DERs in the DG set use the subscript $l$. These two types of RESs and ESSs are modeled differently, as described in Figure 3.
While the generation of independent RESs could only flow into the power grid, those of combined RESs could either flow into the grid or feed into an ESS. On the other hand, combined ESSs cannot be charged from the outer grid, whereas independent ESSs can. In particular, the difference between ESS models distinguishes the strategy during ID operation for combined ESSs, because their charging power is limited to combined RES generation.

3.1. Scheduling Method for DA Market Bidding

The DA market bidding scheduling method maximizes SMP and REC revenue with a 1 h step, 24 h length scheduling problem. The objective function of the scheduling problem for DA market bidding is expressed as follows:

\[
\text{Maximize } \sum_{t} \text{SMP}_{t} \cdot P_{t}^{\text{net}} + \text{REC}_{1} \cdot C_{\text{REC}} + 5 \cdot \text{REC}_{5} \cdot C_{\text{REC}} - \sum_{i} \sum_{j} f_{i}(p_{l,j}^{\text{Gen}}) - \sum_{i,sl} C_{\text{SC}}^{\text{S},s,i} - \sum_{l,k} C_{\text{SC}}^{\text{S},k,i} \quad (3)
\]

Note that REC which gains weight from the policy discussed in Section 2 is multiplied by 5.

As the net generation of VPP, \(P_{t}^{\text{net}}\) is identical with the bid of VPP at time \(t\). \(P_{t}^{\text{net}}\) is defined as follows:

\[
P_{t}^{\text{net}} = \sum_{i} p_{l,i}^{\text{RNW}} + \sum_{j} (p_{l,j}^{E2G} - p_{l,j}^{G2E}) + \sum_{k} (p_{k,j}^{E2G} + p_{k,j}^{R2G}) + \sum_{l} p_{l,j}^{\text{Gen}} \quad (4)
\]

\(\text{REC}_{5}\) is defined by market rules as follows:

\[
\text{REC}_{5} = \sum_{t \in \text{TC}} \sum_{k} (p_{k,j}^{E2G} - p_{k,j}^{R2G}) \quad (5)
\]

where \(\text{TC}\) is the set of time that is defined as “Charging Time,” which is from 10 a.m. to 4 p.m. The \(\text{REC}_{5}\) is defined as the discharged energy of combined ESS, when not in charging time minus the charged energy from the combined RES when not in charging time. Equation (5) ensures that \(\text{REC}_{5}\) is determined only by the energy charged to the ESS at the end of charging time, regardless of the discharging of the ESS in charging time.

\(\text{REC}_{1}\) is determined by the RESs generation and \(\text{REC}_{5}\) as follows:

\[
\text{REC}_{1} = \sum_{t} \left( \sum_{i} p_{l,i}^{\text{RNW}} + \sum_{k} (p_{k,j}^{R2G} + p_{k,j}^{E2G}) \right) - \text{REC}_{5} \quad (6)
\]

Some of the DERs incur a cost to generate. The most typical example is DGs that have to burn fuel to generate. The cost function of DGs is defined as the traditional generator’s quadratic function:

\[
\text{Maximize } \sum_{t} \text{SMP}_{t} \cdot P_{t}^{\text{net}} + \text{REC}_{1} \cdot C_{\text{REC}} + 5 \cdot \text{REC}_{5} \cdot C_{\text{REC}} - \sum_{i} \sum_{j} f_{i}(p_{l,j}^{\text{Gen}}) - \sum_{i,sl} C_{\text{SC}}^{\text{S},s,i} - \sum_{l,k} C_{\text{SC}}^{\text{S},k,i} \quad (3)
\]
\[
\begin{align*}
    f(P_{Gen}^{\text{Gen}}) = A_l\left(p_{Gen}^{\text{Gen}}\right)^2 + B_l\cdot p_{Gen}^{\text{Gen}} + C_l\cdot u_{Gen}^{l,t}
\end{align*}
\] (7)

As \( P_{Gen}^{\text{Gen}} \) is 0, unless \( u_{Gen}^{l,t} \) is 0 and has a certain value, if \( u_{Gen}^{l,t} \) is 1, the first two terms can be expressed without \( u_{Gen}^{l,t} \). Because ESSs cannot generate themselves, charging must precede discharging, and a charging cost is incurred if charging from the outer grid. This is reflected in the \( P^{net} \) term of the objective function by subtracting the charging power from \( P^{net} \). Moreover, as most of the ESSs consist of Li-ion batteries, the capacity of ESSs gradually decrease when repeating the state changes between charging and discharging [16]. Therefore, it is reflected in the objective function in the form of a state change penalty to prevent frequent changing of the ESS state. The large penalty for capacity degradation may decrease the economics of VPP; thus, it must be selected properly.

Most of the constraints of the DA market bidding scheduling problem are related in the operation of ESSs. An ESS consists of a power conversion system (PCS) and battery. A battery is charged and discharged through a PCS. The PCS has a maximum discharge and charge limitation in its operation, which is expressed in the constraints (8)–(11).

\[
\begin{align*}
    \varepsilon \cdot u_{j,t} & \leq p_{\text{E}2G}^{j,t} \leq \rho_j \cdot p_{\text{max}}^{\text{dchg}, j} \cdot u_{j,t} \quad \forall j, t \quad (8) \\
    p_{\text{E}2G}^{j,t} & \leq \rho_j \cdot p_{\text{max}}^{\text{dchg}, j} \cdot (1 - u_{j,t}) \quad \forall j, t \quad (9) \\
    \varepsilon \cdot u_{k,t} & \leq p_{\text{E}2G}^{k,t} \leq \rho_k \cdot p_{\text{max}}^{\text{dchg}, k} \cdot u_{k,t} \quad \forall k, t \quad (10) \\
    p_{\text{E}2G}^{k,t} & \leq \rho_k \cdot p_{\text{max}}^{\text{dchg}, k} \cdot (1 - u_{k,t}) \quad \forall k, t \quad (11)
\end{align*}
\]

where \( \varepsilon \) is a constant that is sufficiently small to avoid affecting the scheduling. One way to achieve so is by choosing a number significantly smaller than the minimum unit covered by the system. Note that the maximum charging and discharging in the DA market bidding scheduling is limited by \( \rho_j \) and \( \rho_k \), which have values between 0 and 1, from the actual device performance. These variables are introduced to ensure that the reserve ESS capacity is prepared for unexpected changes in power generation during the ID operation stage.

The battery is also limited in the state of charge (SoC) range. The definitions of SoC are expressed as Equations (12) and (13), as the two different sets of ESSs are different charging sources. The SoC range limitation is expressed as Constraints (14) and (15).

\[
\begin{align*}
    \text{SoC}_{j,t} = \text{SoC}_{j,t-1} + \frac{p_{\text{E}2G}^{j,t} \cdot \eta_j - p_{\text{E}2C}^{j,t} / \eta_j}{\text{Cap}_j} & \quad \forall j, t \quad (12) \\
    \text{SoC}_{k,t} = \text{SoC}_{k,t-1} + \frac{p_{\text{E}2G}^{k,t} \cdot \eta_k - p_{\text{E}2C}^{k,t} / \eta_k}{\text{Cap}_k} & \quad \forall k, t \quad (13)
\end{align*}
\]

The limitations of the SoC range are expressed as constraints (14) and (15).

\[
\begin{align*}
    \text{SoC}^{\text{min}}_j \leq \text{SoC}_{j,t} \leq \text{SoC}^{\text{max}}_j & \quad \forall j, t \quad (14) \\
    \text{SoC}^{\text{min}}_k \leq \text{SoC}_{k,t} \leq \text{SoC}^{\text{max}}_k & \quad \forall k, t \quad (15)
\end{align*}
\]

Finally, the output limitation of DGs is expressed as follows:

\[
\begin{align*}
    \varepsilon \cdot u_{Gen}^{l,t} & \leq P_{Gen}^{l,t} \leq \rho_l \cdot u_{Gen}^{l,t} \quad \forall l, t \quad (16)
\end{align*}
\]

When solving the DA market bidding scheduling problems, methods are not needed to consider in case of infeasibility. The DA market bidding problem does not fail unless there is an abnormality in the input data because of a trivial solution that sets the output of all devices to zero and bids as
the sum of the forecasted RES generation. Therefore, preparing for the infeasibility of the DA market bidding scheduling problem is unnecessary. After solving the DA market bidding scheduling problem, the VPP operator offers \( P^i_t \) as a bid and saves the schedule for each ESS and DG.

### 3.2. Scheduling Method for ID Operation

In this section, the scheduling problem for ID operation is presented, and the scheduling method, which solves the scheduling problem iteratively, is discussed afterward. The ID operation scheduling method utilizes a 5 min scale, 2 h length scheduling problem. The reason for the 2 h duration is that if the schedule is followed for 1 h, the PS schedule from the DER may not be considered. Therefore, scheduling problems can be extended to more than 2 h and may be prepared for longer periods of time as the scheduling time length increases. However, longer periods require higher computational power, so there is a risk of exceeding the time limit.

The objective function of the ID operation scheduling problem is expressed:

\[
\text{Maximize } \sum_n (1 - E^P_n) p^\text{bid}_n C_{AGC}^n + \sum_n (1 - E^S_n) p^\text{bid}_n C^\text{Cap}_n - \text{Cost}
\]  

(17)

Subscript \( n \) indicates the hour in ID operation scheduling problem, whereas \( t \) indicates the 5 min interval. In Equation (17), \( n \) represents the target hour and the succeeding hour. In Equation (17), \( n \) could be target hour and next hour. Because PI and SI are not paid if \( \varepsilon^P_n \) and \( \varepsilon^S_n \), which is in Equations (1) and (2), respectively, is greater than 30%, new variables \( E^P_n, E^S_n \) are introduced as follows:

\[
E^P_n = |\varepsilon^P_n| (1 - s^P_n) + s^P_n \quad \forall n
\]

(18)

\[
0.3 s^P_n \leq |\varepsilon^P_n| \quad \forall n
\]

(19)

\[
|\varepsilon^P_n| \leq 0.3 + M s^P_n \quad \forall n
\]

(20)

where \( M \) is a number that exceeds the expected maximum value of |\( \varepsilon^P_n \)|. By Equations (18)–(20), if |\( \varepsilon^P_n \)| is smaller than 0.3, \( E^P_n \) is same as |\( \varepsilon^P_n \)|, and if |\( \varepsilon^P_n \)| is larger than 0.3, \( E^P_n \) is 1. These relationships also stand for \( E^S_n \) between |\( \varepsilon^S_n \)| as follows:

\[
E^S_n = |\varepsilon^S_n| (1 - s^S_n) + s^S_n \quad \forall n
\]

(21)

\[
0.3 s^S_n \leq |\varepsilon^S_n| \quad \forall n
\]

(22)

\[
|\varepsilon^S_n| \leq 0.3 + M s^S_n \quad \forall n
\]

(23)

The \( \varepsilon^P_n \) and \( \varepsilon^S_n \) are defined as follows:

\[
\varepsilon^P_n = \left( \frac{p^\text{bid}_n - \sum_{\text{ten}} p_{\text{net}}^t}{p^\text{bid}_n} \right) \quad \forall n
\]

(24)

\[
\varepsilon^S_n = \frac{1}{11} \sum_{\text{ten}} \frac{p_{\text{net}}^{t+1} - p_{\text{net}}^1}{p^\text{bid}_n} \quad \forall n
\]

(25)

Note that the net generation in Equation (24) is divided by 12 because the time scale is 5 min. On the other hand, Equation (25) is divided by 11 because \( \varepsilon^S_n \) has an average of 11 intervals of 5 min length in an hour. Additionally, the denominators in Equations (24) and (25) are replaced by \( p^\text{bid}_n \) from \( p^\text{net}_n \) to avoid a rational function on the objective function, with the assumption that the scheduling problem forces \( p^\text{net}_n \) to be close to \( p^\text{bid}_n \) to maximize PI. With this expression, the estimated error will differ from the actual error; however, the relative difference will be minimized.

The cost term, which is the sum of Equations (26) and (27), includes the penalties for ESSs. Note that the penalty for state changes is not considered in this stage. Because discharging for
incentives will be conducted with a shallow depth of discharge, degradation in the ESS capacity is insignificant for the ID operation. What is contained in the cost terms are a penalty for loss and a penalty for operation of combined ESS.

ESS performs frequent charging to maximize incentives during operation. As mentioned in Section 3.1, the cost of charging ESSs and the revenue from discharge are determined by SMP. SMP is determined for every hour, so if the start and end SoC are the same, the same costs occur within an hour, regardless of the operation. ESSs follow SoC schedules over the time established the previous day (this is re-explained in the constraints discussion), so it can be assumed that charging costs and discharging revenues do not differ significantly. However, if frequent charging and discharging are performed, additional costs are incurred due to loss, which is described as:

$$\sum_{n} \sum_{t \in n} \sum_{j} \left( p_{j,t}^{G2E} + p_{j,t}^{G2C} \right) \left( 1 - \eta_j \right) \cdot \text{SMP}_n + \sum_{n} \sum_{t \in n} \sum_{k} p_{k,t}^{E2G} \cdot \left( 1 - \eta_k \right) \cdot \text{SMP}_n$$  \hspace{1cm} (26)

Comparing SMP and REC revenue, REC revenue is generally higher due to the price difference. Thus, in terms of revenue, combined ESSs with a 5-time weighting for REC should be committed to PS schedules rather than maximizing incentives. This is especially important during the charging time. A small penalty is given to the discharge of the combined ESS during this time, which allows the independent ESS to operate in priority over the combined ESS to avoid a decrease in REC revenue from combined ESS. This penalty is presented as Equation (27).

$$\sum_{n \in TC} \sum_{t \in n} \sum_{k} p_{j,t}^{E2G} \cdot p$$  \hspace{1cm} (27)

where $p$ is the penalty coefficient. Because there is a risk that the combined ESS will not discharge at all if the value of $p$ is too large, the $p$-value should prioritize ESS operation but be small enough to ensure that the penalty resulting from the operation of the combined ESS is not greater than the incentive increase.

The constraints in the ID operation scheduling problem are similar to the constraints in the DA market bedding scheduling problem. The constraints associated with the output of the ESSs are defined in the same form as the Constraints (8)–(11). The binary variables $u_{j,t}$, $u_{k,t}$ are used to prevent simultaneous charging and discharging, although there is no need to observe a state change. The SoC of ESS is defined as follows:

$$\text{SoC}_{j,t} = \text{SoC}_{j,t-1} + \frac{p_{j,t}^{G2E} \cdot \eta_j - p_{j,t}^{G2C} / \eta_j}{12 \cdot \text{Cap}_j} \forall j, t$$  \hspace{1cm} (28)

$$\text{SoC}_{k,t} = \text{SoC}_{k,t-1} + \frac{p_{k,t}^{R2E} \cdot \eta_k - p_{k,t}^{R2C} / \eta_k}{12 \cdot \text{Cap}_k} \forall k, t$$  \hspace{1cm} (29)

Note that, 12 is multiplied in the denominator because of the time scale.

The SoC range constraints are also identical to constraints (14) and (15). In the ID operation scheduling problem, constraints are added for SoC as follows:

$$\text{SoC}_{j,n}^{\text{min}} \leq \text{SoC}_{j,n} \leq \text{SoC}_{j,n}^{\text{max}} \forall j, n$$  \hspace{1cm} (30)

$$\text{SoC}_{k,n}^{\text{min}} \leq \text{SoC}_{k,n} \leq \text{SoC}_{k,n}^{\text{max}} \forall j, n$$  \hspace{1cm} (31)

This is to ensure that the economics of scheduling does not affect the economics of the scheduling that is determined based on SMP and REC revenue, as described earlier. Figure 4 describes the SoC change over time during ID operation. By limiting the SoC of ESSs to each hour and releasing the rest of the time, ESS operates to maximize incentives while complying a PS schedule.
As the DG’s output was determined to incremental cost to be the same as the SMP, adjustment for DG’s output can lessen the revenue of VPP, unlike ESS. Thus, the output of the DG is constrained to the same extent as PS schedule. Constraints for DG output is expressed as follows:

\[ p_{\text{Gen}}^n(l, t) = p_{\text{Gen,PS}}^n(l, t) \quad \forall l, n, t \in n \]  

(32)

As shown in Figure 2, the schedule for ID operation is re-scheduled every five minutes, while the time length is narrowed. Assuming that the \( n \)-th hour and \((n+1)\)-th hour are scheduled, the generation history of DERs for past time and the short-term forecast of RESs for future time are needed to minimize the \( \varepsilon_n^p, \varepsilon_n^s \). The constraint for past time is described as follows:

\[ p_{\text{net}}^t = p_{\text{net, his}}^t \quad \forall t < t^{\text{str}} \]  

(33)

The constraints that force the other DER schedules, which are before \( t^{\text{str}} \), have to be created.

4. Numerical Result

In this section, a numerical result of proposed methods is presented. First, input data of each DERs are presented, then market data and result of DA market bidding and ID operation will be described through two subsections. The VPP for simulation consists of 1 WT, 1 independent ESS, 1 combined PV and ESS, and 1 DG. The simulation is conducted in an Intel Core i5-4690 with 8GB of RAM using the CPLEX solver.

The prediction and generation of each RES are presented in Figure 5. Compared to the 1 h prediction, the 5 min prediction has lower differences.

**Figure 4.** Change in SoC during ID operation and the PS schedule for each hour. The SMP and REC revenue are maximized by following the PS schedule hourly SoC, while incentives are maximized through free intra-hour charging.

**Figure 5.** 1 h prediction for DA market bidding, 5 min prediction, and 5 min generation history for ID operation of (a) combined PV (b) WT.
Parameters of ESSs are presented in Table 1. ESS efficiency is set to 96% round-trip efficiency. Finally, the coefficients of the cost function and the output range of DG is presented in Table 2. Coefficients of DG’s cost function are from [17].

Table 1. Parameters of combined and independent ESSs.

| Name                | \( P_{\text{max, chrg}} \) (kW) | \( P_{\text{max, dchg}} \) (kW) | Cap (kWh) | SoC_{\text{min}} (%) | SoC_{\text{max}} (%) | \( \eta \) (%) | \( C^\text{SC} \) (W) |
|---------------------|----------------------------------|----------------------------------|------------|-----------------------|-----------------------|----------------|---------------------|
| ESS1 (Combined)     | 150                              | 150                              | 300 kWh    | 10                    | 90                    | 98             | 1000                |
| ESS2 (Independent)  | 200                              | 200                              | 450 kWh    | 10                    | 90                    | 98             | 1000                |

Table 2. Coefficients of the cost function and output range of DG.

| Name | \( A \) (W/kWh^2) | \( B \) (W/kWh) | \( C \) (W) | \( P_{\text{max}} \) (kW) |
|------|-------------------|----------------|------------|--------------------------|
| DG1  | 0.341             | 3.267          | 330        | 140                      |

4.1. Numerical Result for DA Market Bidding

SMP data for simulation is presented in Figure 6. REC price is set to be 100,000 W/MWh.

![SMP data for simulation](image)

Figure 6. SMP data for simulation.

Based on the presented parameters, scheduling for DA market bidding is performed. Figure 7a represents the \( P_{\text{bid}} \) and the sum of the power generation of RESs. Compared to the sum of the RESs power generation, \( P_{\text{bid}} \) has a higher value by the generation of DG as shown in Figure 7b. It can be observed that incremental costs of DG are the same as the SMP of each time. The value of \( \rho_j \) and \( \rho_k \) are set as 50%.

![Figure 7](image)

Figure 7. (a) \( P_{\text{bid}} \) and (b) the sum of generation of RESs.

Figure 8 represents the change in the charging, discharging and SoC of each ESS. The independent ESS charges at 2 to 4 AM when the SMPs are lowest, and discharges in the high-SMP period to
maximize SMP revenue. Combined ESS starts charging in the charging time and discharges at high SMP times during the discharging time to maximize REC and SMP revenues.

![Figure 8](image-url) Change in the charging, discharging, and SoC of (a) independent ESS and (b) combined ESS.

Among the scheduling results bid, SoC of each ESS and generation of DG is handed over to the ID operation scheduling problem.

### 4.2. Numerical Result for ID Operation

In this subsection, an ID operation scheduling method is applied with 5 min prediction and generation data which represented in Figure 5. The AGC and capacity price are set as 0.9 $/kW$ and 7.05 $/kWh$ each for the ID operation scheduling method. In the rest of this subsection, the method is presented and the analysis performed, such as incentive changes by iteration, SoC following of ESS, revenue change from DA market schedule and more.

First, the effectiveness of the iteration is verified. Figure 9 presents the values of $\varepsilon_n^F$ and $\varepsilon_n^P$ assuming that DERs complies a schedule determined by each iteration. It is clear that $\varepsilon_n^S$ has a tendency to decrease as each iteration is repeated. $\varepsilon_n^P$, on the other hand, is increasing, because the AGC price is small compared to the capacity price, so as to maximize SI at the expense of PI. Basically, the iteration of re-scheduling leads relative differences ($\varepsilon_n^P$, $\varepsilon_n^S$) to be decreased, however, this purpose can be failed if an error of the prediction method is significantly large.

![Figure 9](image-url) The $\varepsilon_n^F$ and $\varepsilon_n^P$ assuming that DERs complies a schedule determined by each iteration.

Figure 10 shows the PS SoC schedule of each ESS and result of ID operation scheduling method. Note that SoC values at each time means SoC at the end of that time. For example, 30% SoC at 3 a.m. means SoC should be 30% at just before 4 a.m. Therefore, the SoC value at ID operation stage appears to lag behind schedule. By comparing PS SoC schedule and the result of the method, it can be observed
that the result follows well the PS SoC schedule with allowed range. This result keeps SMP and REC revenue of ID operation scheduling intact while DERs operate to maximize incentive revenue.

![Figure 10](image1.jpg)

**Figure 10.** PS schedule and result of ID operation scheduling method of (a) an independent ESS and (b) a combined ESS.

Figure 11 shows the result of the ID operation scheduling method (\(P_{\text{net}}\)) and generation with PS schedule (\(P_{\text{net,PS}}\)) and compares with bid. The generation with PS schedule is the generation when the DERs complies schedule set the previous day which maintains the same output for one hour. Comparing the result of the method and generation with PS schedule, it can be found that the result of the proposed method complies bid well, and the fluctuation of \(P_{\text{net}}\) is smaller than its of \(P_{\text{net,PS}}\). This feature is analyzed in Figure 12.

![Figure 11](image2.jpg)

**Figure 11.** Bid (\(P_{\text{bid}}\)), result of ID operation scheduling method (\(P_{\text{net}}\)) and generation with PS schedule (\(P_{\text{net,PS}}\)).

![Figure 12](image3.jpg)

**Figure 12.** (a) \(\epsilon^P_n\) (b) \(\epsilon^S_n\) comparing between generation with PS schedule and result of ID operation method.
Note that values over 40% are cut off from the graph since incentives are not given if values are over 30%. Comparing $\varepsilon^S_n$ and $\varepsilon^P_n$, an average $\varepsilon^S_n$ of ID result is larger than the value with the PS schedule, whereas an average $\varepsilon^S_n$ with ID result is significantly smaller than the value with the PS schedule. This is due to the difference between the AGC price and the capacity price, because the latter has a much higher value. As a result, the ID operation scheduling method gives VPP priority to SI over PI.

The change in revenue is presented in Table 3. The REC revenue is intact while the SMP revenue slightly decreases. Comparing incentive revenues, the PI slightly decreases whereas the SI increases. As a result, the two scheduling methods presented were successful in determining the bid and in maintaining SMP and REC revenues against forecast errors during the intra-day operation while increasing incentive revenues.

### Table 3. Revenue of PS schedule and ID operation.

|             | SMP (₩) | REC (₩) | PI (₩) | SI (₩) | Revenue (₩) |
|-------------|---------|---------|--------|--------|-------------|
| PS Schedule | 225,828 | 281,684 | 3833   | 24,555 | 535,900     |
| ID operation| 226,113 | 277,904 | 3683   | 31,526 | 539,227     |

Finally, the effect of chaining of the $\rho_j$ and $\rho_k$ is analysis. Figure 13 show the change of revenues subject to change of $\rho_j$ and $\rho_k$. Those two values are equal to each step, changes from 0 to 100% by 10% step.

![Figure 13. Change in (a) SMP and REC, and (b) PI and SI subject to the value of $\rho_j$ and $\rho_k$.](image)

With low values of $\rho_j$ and $\rho_k$, the REC revenue is significantly low because the combined ESS cannot be fully charged due to limitation. On the other hand, SI is lowers as $\rho_j$ and $\rho_k$ rises, since the narrow headroom for unexpected generation change of RESs. Since these tendencies are observed at extreme values, the value of $\rho_j$ and $\rho_k$ has to be chosen in a moderate range considering the variability of VPP.

## 5. Conclusions

In this paper, MIQP-based scheduling methods for both DA market bidding and ID operation of VPP is presented. DA market bidding scheduling method determines 1 h long bid for market participation, and ID operation scheduling method determines 5 min step DERs operation iteratively for coping with forecast error. Each method maximizes SMP, REC revenue and incentive revenue. A numerical simulation is conducted for the proposed methods to verify the effectiveness of them. As a result, it can be observed that each scheduling methods achieved its purpose. Especially, the ID operation scheduling method succeeds in increasing the incentive without harming REC and SMP revenue significantly.
Author Contributions: R.K. performed the research and wrote the paper. D.K. helped with the simulation. S.-K.J. provided guidance for the research and revised the paper.

Acknowledgments: This research was supported by a research grant from KEPCO (No. CX72166553). This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (No. NRF-2017R1A2B2004259).

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

Acronyms

VPP Virtual Power Plant
MIQP Mixed Integer Quadratic Programming
DA Day-Ahead
ID Intra-Day
SMP System Marginal Price
REC Renewable Energy Certification
AGC Automatic Generation Control
DER Distributed Energy Resource
PI Predictability Incentive
SI Stability Incentive
RES Renewable Energy Source
PV Photovoltaic
WT Wind Turbine
ESS Energy Storage System
DG Distributed Generators
PS Previously Set
PCS Power Conversion System

Nomenclature

\( P_{\text{I}} \) Predictable incentive in \( n \)-th hour (₩)
\( S_{\text{I}} \) Stability incentive in \( n \)-th hour (₩)
\( \varepsilon_n \) Relative difference between bid and actual generation at the \( n \)-th hour (%)
\( \varepsilon_n^p \) Average relative difference between the generation at two adjacent times at the \( n \)-th hour (%)
\( s_n \) Binary variable equal to 1 if only \(|\varepsilon_n^p|\) is larger than 0.3 (30%) at the \( n \)-th hour
\( s_n^p \) Binary variable equal to 1 if only \(|\varepsilon_n^p|\) is larger than 0.3 (30%) at the \( n \)-th hour
\( C_{\text{AGC}} \) AGC price for traditional generators at the \( n \)-th hour (₩/kW)
\( C_{\text{Cap}} \) Capacity price for traditional generators at the \( n \)-th hour (₩/kW)
\( P_{\text{net}} \) Net generation of VPP at the \( n \)-th hour (kW)
\( \text{SMP}_t \) SMP at time \( t \) (₩/kWh)
\( \text{REC}_1 \) Given REC with 1 weight in a day
\( \text{REC}_5 \) Given REC with 5 weight in a day
\( C_{\text{REC}} \) REC price (₩)
\( P_{\text{net}}^t \) Net generation of VPP at the time \( t \) (kW)
\( P_{\text{net}}^t \) is the history of \( P_{\text{net}}^t \) (kW)
\( \text{Bid}_n \) Bid at the \( n \)-th hour (kW)
\( \text{RNW}_{ij} \) Generation of RES \( i \) at time \( t \) (kW)
\( \text{E}_{ij} \) Discharged power (ESS to Grid) of ESS \( j \) at time \( t \) (kW)
\( \text{E}_{ij} \) Charged power (Grid to ESS) of ESS \( j \) at time \( t \) (kW)
\( \text{E}_{ij} \) Charged power (Renewable to ESS) of ESS \( j \) at time \( t \) (kW)
\( P_{\text{max}} \) Maximum discharging powers of ESS \( j \) and \( k \) (kW)
\( P_{\text{max}} \) Maximum charging powers of ESS \( j \) and \( k \) (kW)
Binary variable, which equals 1 if there is a state change of ESS $j$, $k$ at time $t$

Binary variables, which are equal to 1 only if ESS $j$ or $k$ is discharging at time $t$

Limit coefficient of charging and discharging of ESS $j$, $k$

Efficiency of PCS in ESS $j$, $k$ (%)

SoC of ESS $j$, $k$ at time $t$ (%)

Lower bound of SoC of the ESS $j$, $k$ (%)

Upper bound of SoC of the ESS $j$, $k$ (%)

Capacity of ESS $j$, $k$ (kWh)

SoC lower bound of ESS $j$, $k$ at the $n$-th hour (%)

Upper bound of ESS $j$, $k$ at the $n$-th hour (%)

Penalty for the state change of ESS $j$, $k$ (W)

Generation of DG $l$ at time $t$ (kW)

Maximum generation of DG $l$ (kW)

Binary variable equal to 1 only if DG $l$ is generating at time $t$

Cost function of DG $l$ (W)

Coefficient of cost function of DG $l$ (W/kW)$^2$

Coefficient of cost function of DG $l$ (W/kW)$^2$

Coefficient of cost function of DG $l$ (W)

Pre-Scheduled generation of DG $l$, at the $n$-th hour (kW)

Very first time, which is considered re-scheduling

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