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The Reliability and Profitability of Virtual Power Plant with Short-Term Power Market Trading and Non-Spinning Reserve Diesel Generator

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Abstract: This study examines the profitability and reliability of a virtual power plant (VPP) with the existence of a diesel genset (DG) in the day-ahead (DA) and intra-day (ID) power markets. The study's unique contribution lies in integrating the VPP system with non-spinning reserve DG while limiting the DG operation via minimum running time and maximum number of switching times (on/off) per day. This contribution decreases the renewables' uncertainty and increases the VPP's reliability. Moreover, the study proposes an optimization model as a decision-making support tool for power market participants to choose the most profitable short-term market. The proposed model suggests choosing the DA market in 62% of time (from 579 days) based on estimated VPP power supply, and market prices. Even though there is uncertainty about VPP power supply and market prices, the division between the plan and actual profits is 1.8×10^6 Japanese yen [JPY] per day on average. The share of surplus power sold from the mentioned gap is 5.5%, which implies the opportunity cost of inaccurate weather forecasting. The results also show that the reliability of the VPP system in the presence of a DG increases from 64.9% to 66.2% for 14 h and mitigates the loss of power load by 1.3%.

Keywords: virtual power plant; mixed integer programming; short-term power market; spinning reserves

Citation: Nadimi, R.; Takahashi, M.; Tokimatsu, K.; Goto, M. The Reliability and Profitability of Virtual Power Plant with Short-Term Power Market Trading and Non-Spinning Reserve Diesel Generator. *Energies* **2024**, *17*, 2121. https://doi.org/10.3390/en17092121

Academic Editor: Jay Zarnikau

Received: 28 March 2024
Revised: 23 April 2024
Accepted: 25 April 2024
Published: 29 April 2024

1. Introduction

In recent years, the integration of distributed energy resources (DERs) into power systems has been in the spotlight of energy management systems' scholars. The virtual power plant (VPP) is a cloud-based distributor that aggregates power generation data from several DERs (wind, solar, etc.) to facilitate electricity trading and power load balancing efficiently. The feasibility of a VPP model depends on the operation strategy of DERs (technical VPP) and the electricity trading system (commercial VPP) [1]. On the one hand, the technical VPP is highly affected by weather conditions and technologies' failures, which requires a strict power planning system [2]. On the other hand, the power trading system deals with the way electricity is sold and bought between generators and suppliers to ensure the fulfilment of basic requirements (the selling/buying price, transaction volume of power, delivery time and its period, as well as block order types) of the power market [3].

Japan Electric Power Exchange (JEPX) is a trading platform for the Japan power market with forward (year/month/week), day-ahead (day), and intra-day (hour/minute) markets [4]. The JEPX was established in 2003 to facilitate financial transactions and enhance competition among market participants. Japan's retail electricity market has been fully liberalized since April 2016. A total of 738 retailers accounted for 21.3% of the total electricity volume sold in March 2022, while the share of JEPX was 30% (327.2 [TWh]) of national power trading [5]. The day-ahead (DA) and intra-day (ID) markets are among the most attractive short-term markets compared to the forward power market. According to JEPX in 2022 [6], a total of 23 contracts were signed in the forward market to supply 5.9 [MW] of power for 221.6 h with the price of 23.89 [JPY/kWh]. The minimum tradable amounts in the Japan DA and ID markets are 1 [MW] and 0.1 [MW] with a settlement period of half an hour, respectively [4].

Participants in the DA market submit their bids one day ahead, which includes power supply and price for 48 settlement periods (half an hour), before the gate closure [7]. The real electric power will be supplied the next day, while it may deviate from bid data due to uncertainty and/or contingency. As a participant in the DA and ID markets, a VPP not only needs to meet the minimum requirements of these markets but also needs to reduce its uncertainty [8] and contingency [9].

Major sources of VPP uncertainty include DERs' power generation, market price, and demand load [10,11]. Although environmental protection and maximum usage of renewables are among the initial aims of the VPP system [12], the non-spinning reserve DG decreases VPP uncertainty and increases its reliability and profitability. The main reason to integrate the DG unit with VPP is the limited usage time of a DG as a non-spinning reserve. The advantage of a non-spinning reserve DG is that it synchronizes with the VPP system for a limited time to trade off among uncertainty, market price, and fossil fuel cost. Moreover, the limited usage of a non-spinning reserve DG in the VPP system caps its carbon footprint compared to fully using it as the main VPP generator [13,14].

The purpose of this research is to investigate the effect of a non-spinning reserve DG on VPP reliability and profitability. To this end, the first step is to limit the usage time of a DG in the optimization model. This step is carried out via the minimum running time and maximum number of DG switching on/off times per day. The second step is to prioritize the usage of renewable generators. This step is figured out through a binary variable defined for the DG unit. Finally, the third step compares the fuel cost of DG power generation with grid power supply costs at dispatch time and decides about diesel operation. This step's calculations are conducted via an objective function and input power price data.

The paper structure is as follows: Section 2 reviews the relevant literature on VPP and its interaction with the short-term power markets. Section 3 introduces the VPP system and an optimization model to calculate the profitability and reliability of the VPP system. Section 4 describes the results of the proposed VPP model. Section 5 discusses the research results and implications of the proposed model in policymaking as well as future research. Section 6 provides a summary of the main results.

2. Literature Review

The VPP was conceptualized initially to use renewables effectively with combined heat and power (CHP) to deliver low-priced and reliable power to the market [12]. Depending on the VPP objectives, different optimization models have been proposed, as follows:

- Techno-economic optimization models (deterministic): The main aim of these models is to decide about VPP generation units and the economic dispatch of the selected units. These models maximize total VPP profit by minimizing capital costs and/or generation costs [15–17].
- Techno-economic optimization models (stochastic): In addition to unit commitment [18] and economic dispatch, stochastic-based optimization models uncertainties in renewable energy generation [19], generation forecasting [20], demand load forecasting [21], and market price uncertainty [22]. Chance-constraint optimization, scenario-based optimization, and stochastic robust optimization are among three well-known VPP operating optimization methods under uncertainty [23].

- Multi-objective optimization models: These models trade off the VPP objective against other contradictory objectives such as system operation cost, carbon emissions, grid stability, power loss reduction, and demand response problems [24–26].

A summary of the different mathematical models used in VPPs is given in [1], including linear programming (LP), mixed-integer LP, nonlinear programming (NLP), mixed-integer NLP, heuristic methods, and simulation models. Regardless of the stochastic models, several approaches have been proposed to reduce uncertainty in the VPP system, as follows:

Leaving the DA and ID markets: Some researchers have investigated VPP success in a low-uncertainty market. The balancing and real-time markets are popular low-uncertainty markets in which the VPP signs a contract and quickly delivers power [27,28]. In other words, shortening the time between final bid submission and power delivery is a way to reduce uncertainty.

Staying in the DA and ID markets: Some researchers have proposed staying in the DA and ID markets and working to reduce uncertainty [29]. Aggregation of several DERs [30,31], co-production of renewables [32], utilization of energy storage, and demand load management [33] are among the proposed ways to reduce uncertainty and smooth the unexpected fluctuation between demand and supply.

Other approaches: Some studies proposed information management among market participants (using information to adjust their bidding strategies, such as unplanned power outage information) to avoid unexpected bids in the ID market [34]. Coupling of DA markets [35] or ID markets [36] are among the other approaches to supply DER power between two countries with different demand load profiles. Although the integrated DA or ID markets increase transmission losses, these markets have a huge capacity to absorb surplus power with flexibility in bid price.

Position of this study: The idea of this study is to stay in the DA and ID markets, reduce the VPP uncertainty (without using stochastic models [18,19,21,22]), and measure the VPP profitability. The main differences between this study and previous research [29,30,32,33] are as follows:

- Unlike previous research, which has focused on energy storage (supply or discharge), this study utilizes energy storage along with a diesel generator (produce) to reduce uncertainty. To cap CO_2 emissions, this study proposes a non-spinning reserve DG. The proposed DG's operation is limited based on two additional constraints: (I) minimum running time and (II) maximum number of switching times per day.
- Moreover, this study suggests a mixed integer optimization model to support electric market participants in choosing the most profitable market between the DA and ID markets. The market selection is figured out in terms of power income in both markets, selling surplus power, shortage costs, and the operation costs of technologies.

Based on the two ideas mentioned, this study investigates how to reduce the VPP uncertainty and increase the profitability of the VPP system in the short-term power market. To this end, the research simulates the profitability and reliability of a centralized VPP in the Tokyo Metropolitan Area. The VPP accounted for 9.1% of the whole demand load in the Tokyo Metropolitan Area, which was 15.8 [GW] on average per 30-minute settlement period from April 2022 to October 2023 [37]. The DERs of the VPP system include solar and wind facilities, along with battery storage.

3. Materials and Methods

Figure 1 illustrates the flows of data and power in the proposed centralized virtual power plant. The VPP itself is not the owner of the DERs, but it manages their power production and sells it in the JEPX short-term markets. The VPP in Figure 1 includes commercial and technical VPPs. The technical VPP monitors the actual operation of the DERs, their operation costs, and their utilization. In contrast, the commercial VPP interacts with the power market via the estimation of bid data that are extracted from DERs planning capacity, demand load estimation, and weather forecasting [2]. The commercial VPP enters the short-term power markets (DA and ID markets) through a single daily power generation profile. The single daily power generation profile is created by aggregating all profiles received from the technical VPP. The proposed VPP optimizes its profit via prior and posterior information and switching between day-ahead and intra-day markets.

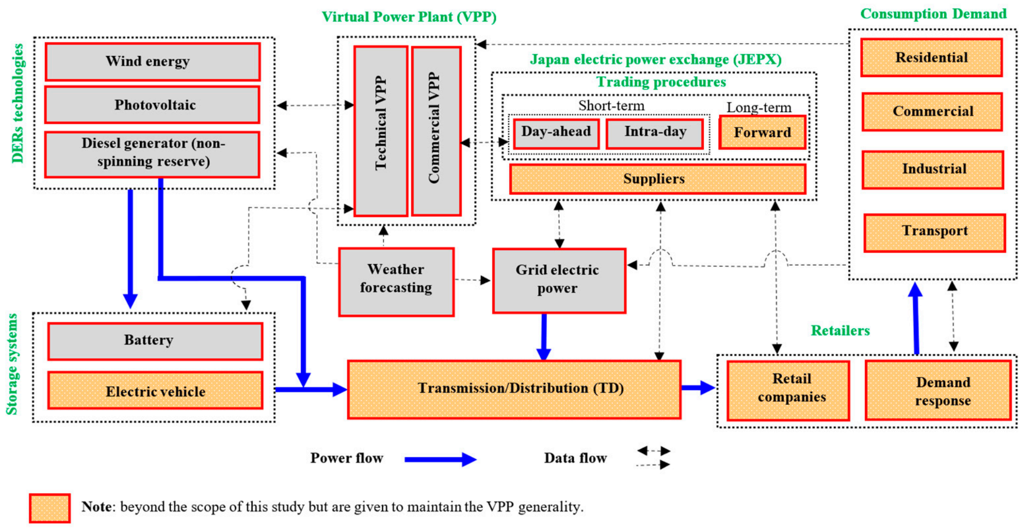

Figure 1. Virtual power plant framework and its interaction with the power market and network.

Short-term market with prior information: The commercial VPP will participate in the DA market if the estimated single-day power generation profile and discharge energy from the battery meet the minimum power requirements of the DA market. The mixed integer optimization model is used in this phase to maximize the estimated VPP profit by selecting either the DA or ID market.

Short-term market with posterior information: The commercial VPP will participate in the ID market if either of the following conditions is met:

- The estimated VPP power supply does not meet the minimum tradable amount of the DA market, or
- The optimization model suggests the ID market.

The actual VPP profit is calculated based on posterior information at the end of the next day. The gap between this phase and the estimated phase is widened by poor weather forecasting data, which increases the VPP cost.

3.1. Descriptions of VPP Models

The VPP model maximizes its profit (total income—total cost) at the end of the "Actual phase" as shown in Figure 2. If the VPP meets the DA market requirements, then part of or whole of the estimated demand, $D_t^{Total,E}$, will be fulfilled by the VPP supply. In other words, if the VPP size is large enough to satisfy the estimated demand, then the entire demand will be considered a VPP demand. Otherwise, a portion of the estimated demand will be assumed to be a VPP demand. The portion of the estimated demand, which is called the bidding data, $S_t^{VPP,Bid}$, is clarified after conducting auctions in the power market. The bidding data includes paired data as ($S_t^{VPP,Bid}$, P_t^*) by which the total expected VPP profit is calculated for the "Planning phase". The term P_t^* indicates the market power price which the * sign implies either the 'DA' or 'ID' terms.

This paper uses Equation (1) to calculate the VPP demand load data (because the scope of the current research is not to propose the best bidding strategy):

$$\begin{cases} D_t^{DA} = S_t^{VPP,Bid} \ \ where \ \ S_t^{VPP,Bid} = \max(\Phi\_DA, S_t^{VPP,E}) \\ D_t^{ID} = S_t^{VPP,Bid} \ \ where \ \ S_t^{VPP,Bid} = \max(\Phi\_ID, S_t^{VPP,E}) \end{cases} \quad (1)$$

It is worth noting that if $S_t^{VPP,E} = 0$, then $S_t^{VPP,Bid}$ will be equal to zero. The actual profit is calculated at the end of the "Actual phase" based on the following cases:

- The actual power supply by the VPP ($S_t^{VPP,A}$) is equal to $S_t^{VPP,Bid}$: In this case, the actual profit is the same as the expected profit,
- $S_t^{VPP,A} > S_t^{VPP,Bid}$: In this case, the actual profit will be greater than the expected profit due to selling the surplus power. The generation cost of surplus power should be deducted from the selling price,
- $S_t^{VPP,A} < S_t^{VPP,Bid}$: In this case, the unmet demand should be supplied by energy storage and either a non-spinning reserve DG or grid power. The actual profit decreases in terms of power purchases from the grid, diesel operation costs, and a drop in the selling price compared to the planning price (P_t^*).

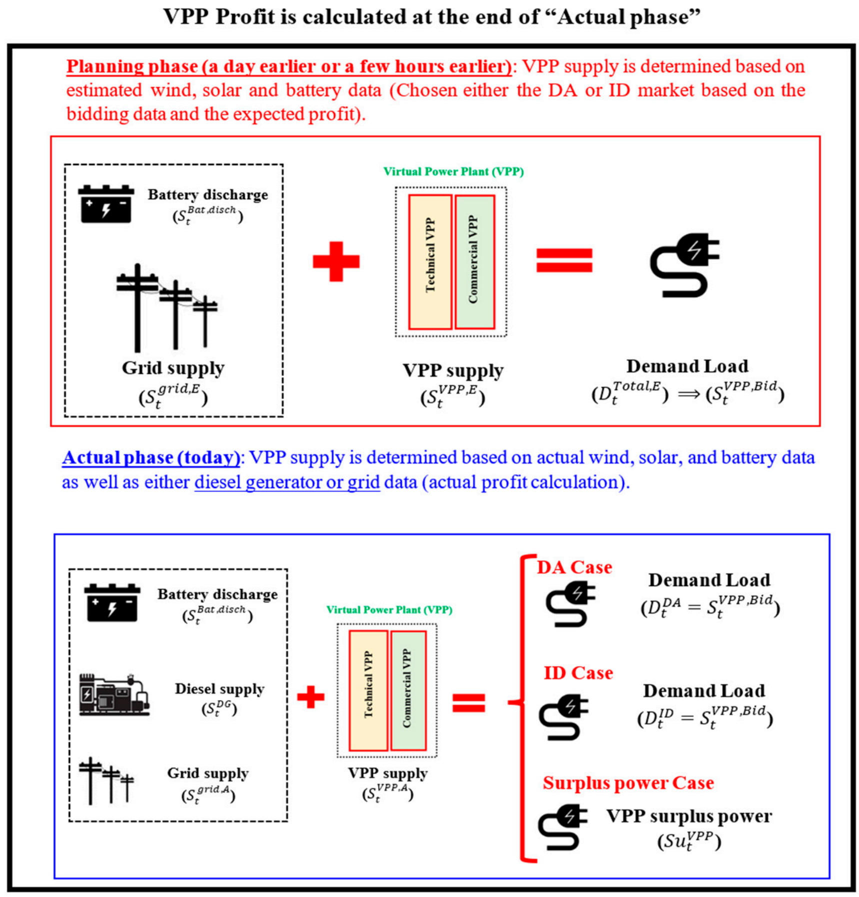

Figure 2. Planning and actual phases of the VPP model.

3.2. VPP Mathematical Model

This section represents the mathematical equations of the proposed model, which include two objective functions and constraints such as power balance, the VPP's resource generation, energy storage, and DG constraints.

3.2.1. VPP Objective Function

The following formula is used to calculate the expected profit in the planning phase:

$$Max \sum_{t=1}^{48} \Big[B^{DA}\big(D_t^{DA}P_t^{DA} - max(\Phi_{ID}, D_t^{DA} - S_t^{VPP,E})P_t^{ID}\big) + (1 - B^{DA})\big(D_t^{ID}P_t^{ID} - max\,(\Phi_{ID}, D_t^{ID} - S_t^{VPP,E})P_t^{ID}\big) - (G_t^{Wind,E} + G_t^{Solar,E})C^{VPP}\Big] \quad (2)$$

where $(D_t^* - S_t^{VPP,E})$ is the estimated grid power supply or $S_t^{grid,E}$. Moreover, the term $max(\Phi_{ID}, D_t^* - S_t^{VPP,E})$ is considered in the objective function if $S_t^{grid,E} > 0$, otherwise, it will be equal to zero. It is worth mentioning that the value of the second *max* function in Equation (2) is specified before running the initial *max* function. The gap between P_t^{DA} and P_t^{ID} implies the magnitude of the opportunity cost ("The loss of other alternatives when one alternative is chosen", Oxford dictionary). The opportunity cost can occur here via switching from the best market to another due to limited information about weather data (uncertainty in DER power generation).

The expected profit function is implemented in the presence of VPP constraints, except for Equations (8) and (25)–(44). Furthermore, power supply by the DG (S_t^{DG}) is excluded from Equation (7), and the variable $S_t^{grid,p}$ is replaced with $S_t^{grid,A}$. The DA market will be selected if the unknown binary variable, B^{DA}, is equal to one; otherwise, the ID market will be chosen. At the end of the next day, the actual profit is calculated as follows:

$$Max \sum_{t=1}^{48} [B^{DA} D_t^{DA} P_t^{DA} + (1 - B^{DA}) D_t^{ID} P_t^{ID} + Su_t^{VPP,max} P_t^{ID} Su^{share} - S_t^{grid,A,max} P_t^{ID} \\ -(G_t^{Wind,A} + G_t^{Solar,A}) C^{VPP} - S_t^{DG,A} C^{DG}] \quad (3)$$

where $S_t^{grid,A}$ is equal to $(D_t^* - S_t^{VPP,A})$, and $S_t^{grid,A,max}$ is equal to max ($S_t^{grid,A}$, Φ_{ID}). It is worth mentioning that in Equation (3), the binary variable, B^{DA}, is known and replaced by the expected profit calculation. The model's constraints will determine if the unmet demand is fulfilled by DG power or grid power. Once the VPP relies on grid power to fulfill its shortage of electricity, it is charged the imbalance cost by the system operator. This study uses the average seasonal ID price (P_t^{ID}) as a proxy for the imbalance cost. Furthermore, the model assumes any shortage or surplus power is settled in the ID market before gate closure (not the real-time market).

3.2.2. VPP Constraints

The "+" sign in Equations (4)–(9) is replaced with "A" or "E" for the actual and estimated profit objective functions, respectively. The solution of the VPP model must satisfy several constraints, as follows:

A. Supply–demand balancing constraint:

$$S_t^{VPP,+} - Sl_t^{Negative} + Sl_t^{Positive} = B^{DA} D_t^{DA} + (1 - B^{DA}) D_t^{ID} \quad (4)$$

$$Sl_t^{Negative} \times Sl_t^{Positive} \leq 0 \quad (5)$$

$$S_t^{Bat,ch} + Su_t^{VPP} \leq Sl_t^{Negative} \quad (6)$$

$$S_t^{Bat,disch} + S_t^{grid,p} + S_t^{DG,p} \leq Sl_t^{Positive} \quad (7)$$

$$S_t^{grid,p} \times S_t^{DG,p} \leq 0 \quad (8)$$

$$S_t^{VPP,+} = G_t^{Wind,+} + G_t^{PV,+} + S_t^{Bat,disch} - S_t^{Bat,ch} \quad (9)$$

The balance between demand and supply is guaranteed via Equations (4)–(9). Equation (4) specifies that the total power supply from the VPP technologies, grid, DG (transmission and distribution losses can be added here), and battery charge/discharge must be equal to the total demand in each period, t. In the planning phase, the right-hand side of Equations (4) is D_t^{DA}, while in the actual phase the amount of B^{DA} will be known and either of D_t^{DA} or D_t^{ID} will be selected. Equations (5)–(8) assure either of the following cases:

- Charging power into the battery and surplus power, or
- Discharging power from the battery and either the grid or DG power supply.

Equation (9) represents that VPP power supply consists of power generation by DERs, and battery discharging minus battery charging power.

B. Technological constraints of DERs:

The "+" sign in Equations (10) and (11) is replaced with "A" or "E" for the actual and estimated profit objective functions, respectively.

$$0 \leq G_t^{Wind,+} \leq G_{max}^{Wind} \tag{10}$$

$$0 \leq G_t^{Solar,+} \leq G_{max}^{Solar} \tag{11}$$

Equations (10) and (11) imply that the output power of solar panels and wind turbines must be less than the value of their nominal capacity. This study uses $S_t^{VPP,A}$ data directly (without access to DER generation separately), but to keep the generality of the model, Equations (9)–(11) are given here.

C. Energy storage constraints:

$$S_t^{Bat,ch} \leq Battery\ capacity \tag{12}$$

$$S_t^{Bat,disch} \leq S_{max}^{Bat,disch} \tag{13}$$

$$S_t^{Bat,disch} \leq SOC_{t-1}^{Bat} \tag{14}$$

$$S_t^{Bat,disch} \leq Sl_t^{Positive} \tag{15}$$

$$S_t^{Bat,disch} \geq SOC_{t-1}^{Bat} - M_1 \times (1 - B_t^{Bat,disch}) \tag{16}$$

$$S_t^{Bat,disch} \geq Sl_t^{Positive} - M_1 \times B_t^{Bat,disch} \tag{17}$$

$$S_t^{Bat,ch} \leq Battery\ capacity - SOC_{t-1}^{Bat} \tag{18}$$

$$S_t^{Bat,ch} \leq Sl_t^{Negative} \tag{19}$$

$$S_t^{Bat,ch} \geq (Battery\ capacity - SOC_{t-1}^{Bat}) - M_1 \times (1 - B_t^{Bat,ch}) \tag{20}$$

$$S_t^{Bat,ch} \geq Sl_t^{Negative} - M_1 \times B_t^{Bat,ch} \tag{21}$$

$$SOC_t^{Bat} = SOC_{t-1}^{Bat} - S_t^{Bat,disch} + S_t^{Bat,ch} \tag{22}$$

$$SOC^{min} \leq SOC_t^{Bat} \leq SOC^{max} \tag{23}$$

$$SOC_{t=0}^{Bat} = Initial\ SOC \tag{24}$$

Equations (12) and (13) set the upper bounds for charging and discharging battery power in each period. The amount of $S_{max}^{Bat,disch}$ is calculated from battery capacity and three autonomy hours. Equations (14) and (21) confine the amount of discharging and charging power from/into the battery while considering the SOC of the battery. For example, Equations (14) and (17) are equal to $S_t^{Bat,disch} = \min(SOC_{t-1}^{Bat}, Sl_t^{Positive})$. The term M_1 specifies an arbitrary large value greater than the maximum value of charging and discharging. For confidence, the value of M_1 is set to be the battery capacity 589,200. Equations (22) and (23) represent the energy balance of the battery and its boundaries. Equation (24) finally assigns an initial value to the SOC of the battery.

D. Non-spinning reserve diesel generator constraint:

$$G_{min}^{DG} \leq G_t^{DG} \leq G_{max}^{DG} \tag{25}$$

$$G_t^{DG} \geq S_t^{DG,p} \tag{26}$$

$$B_t^{DG,i} \leq \left(1 + S_t^{DG,p} - \varepsilon\right) \tag{27}$$

$$S_t^{DG,p} \leq M_2 \times B_t^{DG,i} \tag{28}$$

$$In_t^{DG,cmrt} = B_t^{DG,i} \times \left(In_{t-1}^{DG,cmrt} + 1\right),\ \ In_{t=0}^{DG,cmrt} = 0,\ In_t^{DG,cmrt} \in \{0, 1, \ldots, 48\} \tag{29}$$

$$In_{t-1}^{DG,csmrt} = In_{t-1}^{DG,cmrt} \times \left(1 - B_t^{DG,i}\right) \times B_{t-1}^{DG,i},\ In_{t=0}^{DG,csmrt} = 0, B_{t=0}^{DG,i} = 0, In_t^{DG,csmrt} \in \{0, 1, \ldots, 48\} \tag{30}$$

$$B_{t-1}^{DG,m} \times M_2 \geq \left(In_{t-1}^{DG,csmrt} - L\right) + \varepsilon, \quad B_{t=0}^{DG,m} = 0 \tag{31}$$

$$\left(1 - B_{t-1}^{DG,m}\right) \times M_2 \geq \left(L - In_{t-1}^{DG,csmrt}\right) - \varepsilon \tag{32}$$

$$In_t^{DG,csmso} = In_{t-1}^{DG,csmso} + B_{t-1}^{DG,m}, \quad In_{t=0}^{DG,csmso} = 0 \tag{33}$$

$$B_{t-1}^{DG,f} \times M_2 \geq \left(In_{max}^{DG,soo} - In_{t-1}^{DG,csmso}\right),\ B_{t=0}^{DG,f} = 0 \tag{34}$$

$$B_{t-1}^{DG,f} \times M_2 \geq \left(\varepsilon - In_{t-1}^{DG,csmso}\right) \tag{35}$$

$$\sum_{i=t-k+1}^{t} B_t^{DG} = k \quad \forall\, t \in [1, .., 48]\ where\ \{B_t^{DG,i} \times B_t^{DG,m} \times B_t^{DG,f} = 1\} \tag{36}$$

$$S_t^{DG,A} = S_t^{DG,p} \times B_t^{DG} \tag{37}$$

$$S_t^{grid,A} = \left(S_t^{Bat,disch} + S_t^{grid,p} + S_t^{DG,p}\right) - S_t^{DG,A} \tag{38}$$

E. Additional constraints to adjust the actual profit objective function:

$$S_t^{grid,A,max} \geq S_t^{grid,A} \tag{39}$$

$$S_t^{grid,A,max} \geq \Phi_{ID} \tag{40}$$

$$S_t^{grid,A,max} \leq S_t^{grid,A} + M_1 B_t^{grid} \tag{41}$$

$$S_t^{grid,A,max} \leq S_t^{grid,A} + M_1\left(1 - B_t^{grid}\right) \tag{42}$$

$$Su_t^{VPP,max} = B_t^{Su} Su_t^{VPP,A} \tag{43}$$

$$Su_t^{VPP,A} - \left(\Phi_{ID} - \varepsilon\right) \leq M_1 B_t^{Su} \tag{44}$$

Equation (25) sets the minimum and maximum loading limits for the DG to avoid overconsumption of DG fuel. Equation (26) guarantees that the power supply by the DG is less than or equal to its generation. The diesel genset is turned on if the following conditions are met:

1. The initial binary variable of the DG becomes one, or $B_t^{DG,i} = 1$: Equations (27) and (28) assign a binary value for the initial DG indicator by which the DG's operation is tracked.
2. Minimum running time of the DG, or $In_{min}^{DG,mrt} = L \times \Delta t$: The minimum running time is used to avoid starting the DG on and off frequently because of inefficient fuel burning in the startup, warmup, unload, and cool-down phases. The minimum running time depends on several factors, such as fuel price, diesel capacity, the control unit of the VPP, and so on (at least 30 min is required because the startup and warmup phases take at least 4 minutes, and the shutdown and cool-down phases take more than or equal to 6 min) [38,39], but 30 min is the lowest value. Equation (33) finds the startup time for the DG via the $In_{min}^{DG,mrt}$ variable if the DG is called on. Equations (29)–(32) count the number of consecutive settlement periods to ensure that their cumulative values are greater than or equal to L. The terms $In_t^{DG,cmrt}$ and $In_{t-1}^{DG,csmrt}$ calculate the count and cumulative sum of the consecutive settlement periods. The middle binary variable of the DG, $B_t^{DG,m}$, represents if the DG meets the minimum running time constraint. The ε and M_2 indicate the epsilon (small value) and a big value (upper bound), respectively. This study sets 0.0005 and 48 for ε and M_2, respectively.
3. Maximum switching on/off times per day, or $In_{max}^{DG,soo}$: Equations (33)–(36) figure out if the number of GD switching times is less or equal to its threshold. The variable $In_t^{DG,csmso}$ adds up the cumulative sum until its value is less than the $In_{max}^{DG,soo}$ value using the middle binary variable of the DG. The final binary variable of the DG, $B_t^{DG,f}$, specifies the settlement periods in which the DG is allowed to operate based on the maximum switching times' condition. Equation (36) finally calculates the DG indicator, which represents which settlement period is turned on.

Equations (37) and (38) update the power supply by the DG and grid network. Equations (39)–(44) guarantee that the selling/buying power requirement to/from the ID market is met. According to Equations (43) and (44), if $Su_t^{VPP,A}$ is greater than or equal to Φ_{ID}, then the amount of selling surplus will be equal to $Su_t^{VPP,A}$, otherwise, it will be zero.

3.3. Reliability and Profitability of the VPP System

Reliability: The VPP system is 100% reliable if it supplies power based on its commitment (bidding data) without relying on grid data. Thus, the failure rate of the VPP system, λ, is defined as the percentage of grid power incorporation needed to fulfill the bidding data as follows:

$$\lambda_t^{VPP} = \frac{S_t^{grid,A}}{D_t^*} \implies \lambda = \frac{\sum_{t=1}^{T} \lambda_t^{VPP}}{T} \tag{45}$$

Equation (45) considers the time and the amount of power purchased from the grid in the reliability calculation. Based on Equation (45), any power purchase from the grid network is considered a downtime [40] of the VPP system. Therefore, the following equation is used to calculate the reliability of the VPP system:

$$R_h = e^{-\lambda \times h} \times 100, \quad 0 \le h \le 24\ \mathrm{h} \tag{46}$$

The term R_h indicates the reliability of the VPP system or the probability of the VPP system supplying continuous power for a specific hour without relying on grid power.

Profitability: The VPP will earn all its profit if it generates all declared bidding data without relying on grid power; otherwise, its profit will decline. The VPP will keep its profit and fulfill its bidding if the DG generates power at a cheaper cost than the ID market price. Thus, the DG profit protection is calculated as follows:

$$Profit\ Protection = S_t^{DG,A} \left| P_t^{DA} - P_t^{ID} \right| \tag{47}$$

3.4. Model Data

As shown in Table 1, the scope of data in this research is limited to market and power generation data. The former data was obtained from the JEPX website. The latter data was downloaded from the Tokyo Electric Power Company's website (TEPCO). Power generation data consisted of actual and estimated data, which indirectly considered the weather impact on DERs power generation and demand load variations.

Table 1. Data types and their sources.

Data	Type of Data	Data Collected Period	Data Resolution	Reference
Demand load	Estimated Actual	1 April 2022–31 October 2023	30-min	[37]
Renewable power generation	Estimated Actual			
Non-renewable power generation	Estimated Actual			
Electric power prices	Day-ahead Intra-day	1 April 2022–31 October 2023	30-min	[6]
Electric power volume	Day-ahead Intra-day			

4. Results

The proposed model maximizes the daily profit calculated from selling electric power in both the DA and ID markets, operation and maintenance costs of technologies, and power purchased from the grid. Table 2 represents operation costs and the initial values of the model's parameters, as well as additional data about VPP unit supply cost and capacity calculation for the DG and battery.

Table 2. Initial values of the optimization model's parameters.

Unit	Parameters	Initial Value	Reference
Battery	Initial SOC [kWh]	117,840	Assumed
	Max discharge * [kWh]	196,400	Assumed
	Capacity * [kWh]	589,200	Estimated
Diesel	Maximum capacity [kW]	84,400	Estimated
	Min power generation [kW]	$0.3 \times 84{,}400$	[41]
	Natural gas fuel cost [JPY/kWh]	9.75587 **	[42]
	Min diesel running time [min]	$L \times \Delta t = 30$	[38]
	Warmup and cool-down time [min]	10	
	Max switching on/off per day	2	Assumed
VPP	Supply cost [JPY/kWh]	2.6208	Estimated
Market	Minimum DA requirement [kW]	1000	[4]
Surplus power	Selling surplus power in ID market [%]	100	Assumed

* Three hours of autonomy ** = 0.067×145.61 (as of 13 December 2023, the exchange rate is 1 USD = 145.61 JPY).

VPP supply cost: According to [43], the operation and maintenance costs of wind turbines account for 20–25 percent of the total levelized cost per kWh produced over their lifespan. In 2022, the levelized cost of wind energy was 20 [JPY/kWh] [44]. Therefore, the estimated operation and maintenance cost of wind energy will be equal to 4.5 [JPY/kWh].

According to [45], Japan installed 8767 [MW] solar power capacity by 2020, and its annual generation was 89,279.55 [GWh] [46]. The operation and maintenance costs of utility-scale solar power are around 4200 [JPY/kW] [47]. Therefore, the estimated operation and maintenance cost of solar power is 2.45 [JPY/kWh].

The shares of solar and wind power in Japan's total electricity generation were 9.9% and 0.9%, respectively, in 2022 [48]. Therefore, the estimated VPP operation and maintenance cost in this study is 2.6208 [JPY/kWh].

It is worth mentioning that the storage operation and maintenance costs were insignificant compared to the wind and solar costs. The estimated variable operation and maintenance cost of a battery is 0.3 [cents/kWh/year], while its fixed value ranges between \$6–20/kW/year [49]. To this end, this research skipped considering it in the calculations.

Diesel and battery capacity: To calculate the DG and battery capacity, first the average actual and estimated power generation for each settlement were calculated (Figure 3) from April 2022 to October 2023. If the actual renewable power in a specific settlement was greater than the estimated power, then their difference was assumed to charge into the battery. If the actual renewable power in a specific settlement was less than the estimated power, then their difference was considered discharging power. After that, the following calculations were used to extract the battery capacity:

$$Battery\ capacity = autonomy\ hours \times min\ (charging\ power,\ discharging\ power)$$

$$charging\ power = max\ (charging\ power_1, \ldots, charging\ power_{48})$$

$$discharging\ power = max\ (discharging\ power_1, \ldots, discharging\ power_{48})$$

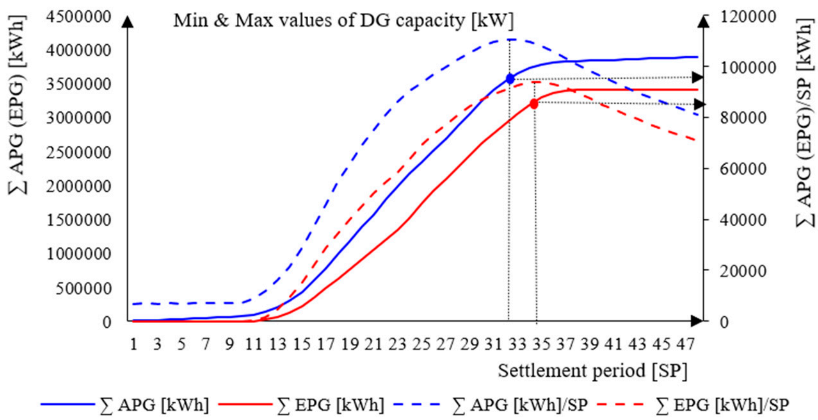

Figure 3. Average actual (estimated) power generation (APG vs. EPG) of renewables.

This study assumed three hours of autonomy for battery discharge. If the discharge value was greater than the SOC value, then their difference was assumed to be fulfilled via a diesel generator. The maximum amount of these difference values was considered the diesel capacity (84,400 [kW]). The rational designing method proposed in [50,51] was applied to avoid DG oversizing. According to Figure 3, the DG capacities based on estimated and actual power generation are 85,126 [kW] and 98,286 [kW], which imply that the selected DG size is acceptable.

4.1. VPP Optimization Model's Results

The proposed optimization model was implemented in GEKKO [52] for 579 days (Table 1). According to the expected optimization model (Equations (2) and its constraints), the VPP is recommended to participate in the ID market for 217 days. The importance of the expected optimization model in market selection arises from the closeness of the VPP power generation and minimum power requirement of the market, as well as the DA and ID price variations.

A time series of the actual power generation of the DERs and demand load data for four days are shown in Figure 4 (upper half). It is worth noting that the DERs' estimation power is assumed to be the demand load in this study by considering the lower bounds for the DA and ID markets given in Equation (1). This is an important issue because the daily and annual profits depend on demand load (or the DERs' estimation power in this study). The actual power generation in the early hours of four days is slightly greater than the bidding data, while there is a large gap between them in the afternoons and evenings. The lower half in Figure 4 displays the share of energy storage, the DG, and grid power in balancing the demand load. As shown in the lower half of Figure 4, significant power was purchased from the grid network in the afternoon and evening of the last two days. The DG generated power for two consecutive hours on 11 August and for four hours on 12 and 14 August, while the power shortage on 10 August was supplied by the battery and grid power. DG production depends on the shortage of electricity, the SOC of the battery, the DG capacity, and the DG constraints (minimum running time and maximum switching on/off times per day).

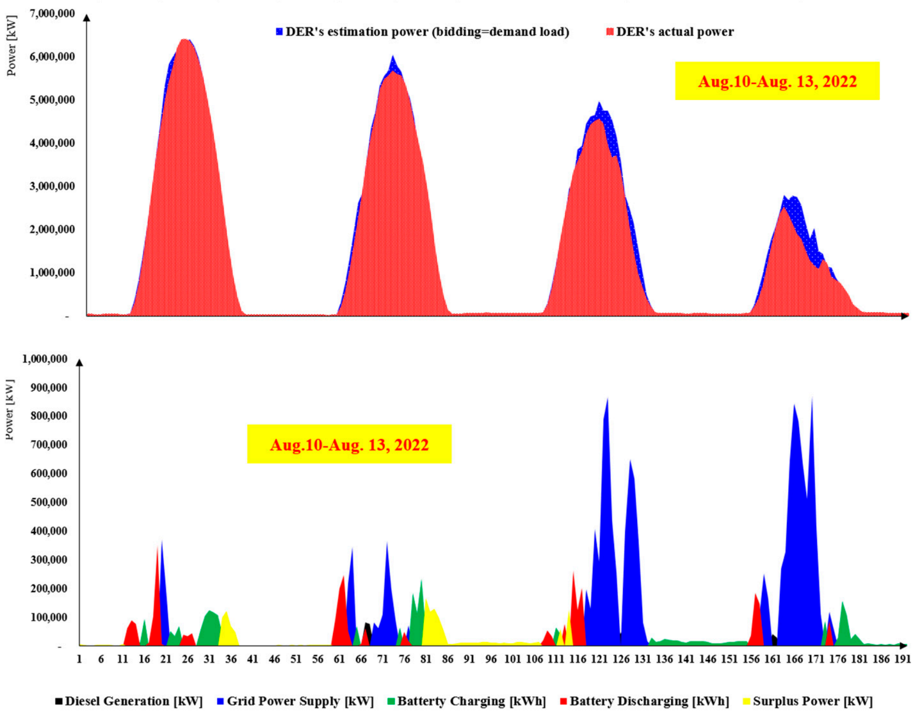

Figure 4. The upper half of the graph represents the demand load and actual renewable energy generation data. The lower half of the graph indicates power supply by the DG, grid, and surplus power, as well as battery charge and discharge.

Figure 5 demonstrates the expected and actual profit of the VPP system based on the proposed optimization model, which switches between the DA and ID markets. The expected value indicates the amount of profit based on either the DA or ID data in the planning phase one day ahead. The actual value also represents the total profit calculated at the end of the day. The gap between the monthly data for these two metrics implies the estimation or uncertainty of DER generation. The total expected and actual profits over 19 months were 561,979 and 560,918 million JPY, respectively. The share of selling surplus power accounted for 5.5% of the expected profit, which implies an underestimation of DER generation. If the VPP submitted the best bid, it would increase the actual profit to 30,937 $\times$ 10^6 JPY. In other words, the opportunity cost of inaccurate weather forecasting was 5.5%, or 5.3 $\times$ 10^6 JPY per day.

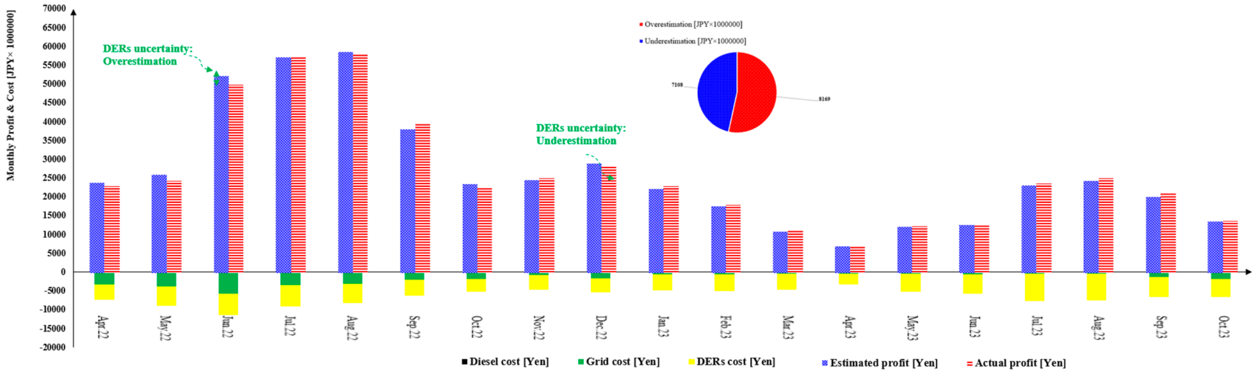

Figure 5. Monthly power generation costs plus expected and actual profit of the VPP system.

Figure 5 shows that the highest cost of the system belongs to DER technologies, followed by grid cost (power purchased from the grid). The monthly cost of the DG is not remarkable compared to the DERs and grid costs because of the DG's constraints. In other words, the defined DG's constraints do not allow the DG to generate power anytime.

4.2. VPP Reliability and Profitability Results

Figure 6 depicts the failure rates and reliability curves with and without a diesel generator in the VPP system. The curve implies the probability of supplying continuous power (without relying on grid power) for 24 h. As shown in Figure 6, the minimum daily reliability of the current VPP system is 48%, which indicates the stability of the proposed VPP system to fulfill the whole bidding data in a day. For any period, shorter than 24 h, the reliability of the VPP power supply increases. For example, the VPP system is reliable enough to supply continuous power for 14 h with a probability of 64.9% without the DG. In contrast, the probability of generating less power than the demand load (bidding data) in 14 h is 36% (the loss of load). Adding the DG with an 84,400 [kW] capacity increases the reliability of the VPP system by 66.2% and mitigates the loss of power load by 1.3%. In other words, the DG with an 84,400 [kW] capacity compensates 1.3% of the DER uncertainty. The reliability of the VPP system will reach 68% if the diesel generator capacity increases to 253,200 [kW]. The VPP system will be more stable if its failure rate decreases (reducing its dependency on grid power). Generally, the VPP system's reliability increases if the gap between bidding and estimated renewable power generation data narrows.

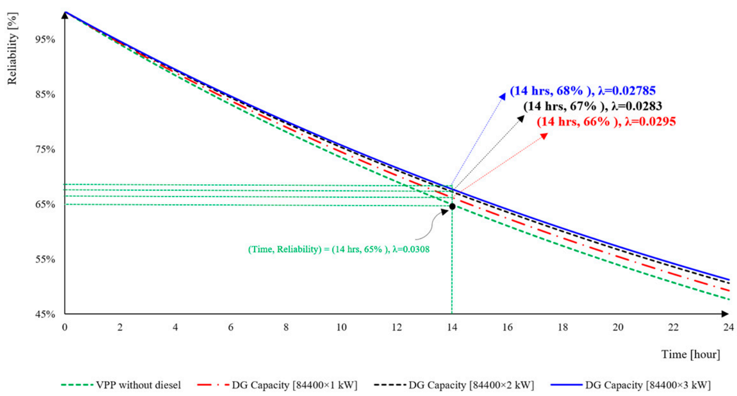

Figure 6. Reliability curves for the VPP system under three different DG capacities.

As shown in Figure 7, the annual profit protection of the DG in the VPP system is 223×10^6 [JPY] with an 84,400 [kW] DG capacity. The annual profit protection increases by more than the proportional change in the DG capacity. The results of the annual DG profit protection imply that variable returns scale with an increase in the capacity of the DG. Furthermore, the findings of reliability and profitability infer that the VPP system can increase its profit by adding the DG to the system. Selection of the correct DG capacity is very important in the uncertainty reduction of the VPP system, which depends on the DG constraints set on the optimization model, bidding data, and accurate estimation of DER power generation.

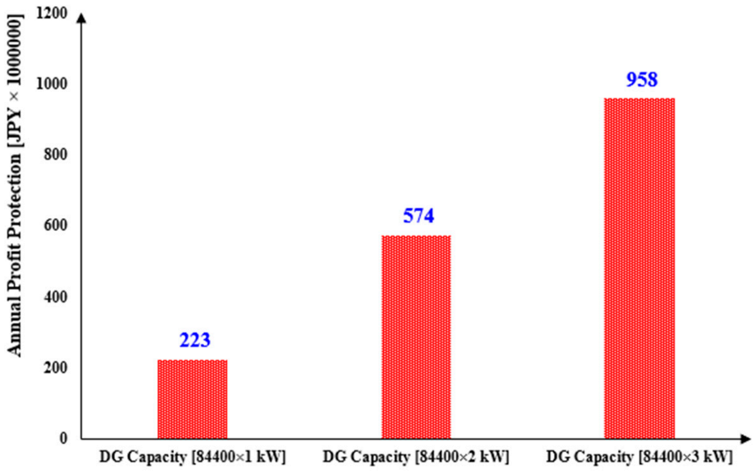

Figure 7. Profitability of the VPP system under three different DG capacities.

5. Discussion

The technical and commercial VPP should work closely together to reduce the VPP's uncertainty. The former one indicates the VPP's operation strategy of DERs, and the latter one focuses on the electric power trading market. A successful VPP system attempts to decrease the uncertainty of the VPP system and increase profitability and reliability.

VPP profit after switching between the DA and ID markets: According to the proposed model, a VPP system will be able to stay in the short-term market if it combines various DER technologies to meet the minimum power requirement of the market. A successful policy implementation involves establishing a large VPP generation capacity or reducing the minimum power requirement of the market. These two factors provide a competitive power market with further VPP systems that are trying to increase their profitability and reduce their uncertainty. This study proposed a VPP system with 1.5 GW average generation capacity to meet the DA power market. The model selected either the DA or ID markets by calculating and comparing their daily profits. The model selected 217 days out of 579 days to take part in the ID market, while for the remaining days, the DA market was beneficial to the VPP.

VPP profit with the existence of a non-spinning DG: Although the optimization model chose the market with extra profit, uncertainty in weather forecasting (DER generation capacity) changed the final profit notably. The final VPP profit was more than the expected profit because of a slight bias toward underestimating the DER generation capacity. The proposed non-spinning reserve DG was able to compensate for a part of the forecasting error (1.3%). The non-spinning reserve DG protected some profit that could have been lost (annual profit protection was 223×10^6 JPY). Thus, it is proposed to use a diesel generator in the VPP system to make up for a part of the forecasting error and increase the reliability of the VPP system.

Future work will investigate small-scale VPP constraints under the current JEPX system, particularly the long consecutive bid interval and minimum power requirement.

6. Conclusions

This research investigated the profitability and reliability of a VPP model with a 1.5 GW generation capacity in Tokyo Metropolitan Area, Japan. To calculate the profitability of the VPP system, a two-step optimization model was proposed. In the first step, a profitable daily market between the day-ahead (DA) and intra-day (ID) markets was selected based on estimated generation and declared bidding data one day ahead (expected profit). In the second step, the actual generation data was used to calculate the actual profit at the end of the day. Then, the reliability of the VPP system in the selected market was calculated. Although the reliability of the VPP system was highly influenced by its capacity, the non-spinning reserve diesel generator (DG) was used for compensating a part of the weather forecasting division (renewable power generation). Two constraints of minimum running time and maximum switching on/off times per day were applied to limit the DG power generation to profitable hours as well as to cap the carbon footprint of the DG.

The proposed optimization model suggested the ID market for 217 days out of 579 days (38%). Participating in the DA market generated a greater profit for the VPP in the remaining days. The total expected and actual profit were 561,979 and 560,918 million JPY for 19 months, respectively (in this study 1 USD = 145.61 JPY). The share of surplus power selling was 30,937 $\times$ 10^6, which implied the opportunity cost of inaccurate weather forecasting. Inaccurate weather forecasting (DER power generation) caused the VPP to submit bid data that was different from the best bid.

The reliability analysis data showed that the proposed VPP was able to fulfill the bidding data continuously for 24 h with a probability of 48%. The reliability of the VPP system varied exponentially for a period of less than 24 hours. The daily reliability of the VPP system to supply continuous power for 14 h was 64.9%. In contrast, the probability of generating less power than the demand load in 14 h was ~36% (the loss of load). Adding a DG with an 84,400 [kW] capacity increased the reliability of the VPP system by 66.2% and mitigated the loss of power load by 1.3%. The annual profit protection of the DG with the stated DG capacity was 223 $\times$ 10^6 JPY. An increase in the DG capacity increased the annual profit protection by more than a proportional change, which implied increasing returns to scale profit protection.

Author Contributions: Conceptualization, R.N., and M.G.; methodology, R.N., M.T., K.T. and M.G.; software, R.N.; validation, R.N. and M.G.; formal analysis, R.N.; investigation, R.N. and M.G.; resources, M.G.; data curation, R.N. and M.G.; writing—original draft preparation, R.N.; writing—review and editing, R.N., M.T., K.T. and M.G.; visualization, R.N.; supervision, M.G.; project administration, M.G.; funding acquisition, M.G. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Council for Science, Technology, and Innovation (CSTI). Cross-ministerial Strategic Innovation Promotion Program (SIP), the third period of SIP "Smart energy management system", Grant Number JPJ012207 (Funding agency: JST).

Data Availability Statement: The original data presented in the study are openly available in 1-TEPCO Power Grid, https://www.tepco.co.jp/en/forecast/html/download-e.html, 2-Japan Electric Power Exchange, https://www.jepx.jp/electricpower/market-data/spot/.

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

Nomenclature

Nomenclature
Majority of variables' format: $A_C^{B,D}$ **A** refers to Demand, Generation, Supply, Price, Surplus, State of charge (SOC), Cost, Integer/Binary/Slack variables, **B** specifies source of power supply (technology), demand sources, market types, share of selling power, negative/positive slack variable **C** indicates settlement period, minimum or maximum capacity for a technology, and **D** represents additional information such as estimated or actual power supply, For example, $S_t^{grid,E}$: represent estimated grid supply power at settlement period t.

Input Variables	Description	Unit
$D_t^{Total,E}$	Total estimated demand load at period t	kW
D_t^{DA}	VPP day-ahead (DA) demand load at period t	kW
D_t^{ID}	VPP intra-day (ID) demand load at period t	kW
$G_t^{Wind,A}$	Actual power generation by wind turbine at period t	kW
$G_t^{Wind,E}$	Estimated power generation by wind turbine at period t	kW
$G_t^{Solar,A}$	Actual power generation by solar panel at period t	kW
$G_t^{Solar,E}$	Estimated power generation by solar panel at period t	kW
G_t^{DG}	Power generation by tDG at period t	kW
P_t^{DA}	Day-ahead power price at period t	\$/kW
P_t^{ID}	Intra-day power price at period t	\$/kW
$S_t^{VPP,E}$	Estimated VPP power supply at period t	kW
$S_t^{VPP,Bid}$	VPP power supply based on bid data at period t	kW
$S_t^{VPP,A}$	Actual VPP power supply at period t	kW
Intermediate Variables	**Description**	**Unit**
SOC_t^{Bat}	Battery state of charge at period t	kW
Decision variable	**Description**	**Unit**
	Continuous	
$S_t^{Bat,disch}$	Discharging power from battery at period t	kW
$S_t^{Bat,ch}$	Charging power into battery at period t	kW
$S_t^{grid,E}$	Estimated supply power by grid at period t	kW
$S_t^{grid,p}$	Possible supply power by grid at period t	kW
$S_t^{grid,A}$	Actual supply power by grid at period t	kW
$S_t^{grid,A,max}$	Maximum between $S_t^{grid,A}$ and Φ_{ID} at period t	kW
$S_t^{DG,p}$	Possible supply power by DG at period t	kW
$S_t^{DG,A}$	Actual supply power by DG at period t	kW
Su_t^{VPP}	VPP surplus power at period t	kW
$Su_t^{VPP,max}$	Maximum between Su_t^{VPP} and Φ_{ID} at period t	kW
	Binary	
B^{DA}	Binary variable for day-ahead market	
B_t^{grid}	Binary variable for grid power selling at period t	
B_t^{Su}	Binary variable for surplus power selling at period t	
B_t^{DG}	Binary variable for DG at period t	
$B_t^{DG,i}$	Initial binary variable for operation of DG at period t	
$B_t^{DG,m}$	Middle binary variable for operation of DG at period t	
$B_t^{DG,f}$	Final binary variable for operation of DG at period t	
$B_t^{Bat,ch}$	Binary variable for battery charging at period t	
$B_t^{Bat,disch}$	Binary variable for battery discharging at period t	

Integer		
$In_t^{DG,cmrt}$	Counting number of running times for each possible operation period at period t	
$In_t^{DG,csmrt}$	Cumulative sum of running times for a day until period t	
$In_t^{DG,csmso}$	Cumulative sum of maximum switching on/off times until period t per day	
$In_{min}^{DG,mrt}$	Minimum running time of DG operation (minute)	
$In_{max}^{DG,soo}$	Maximum number of DG switching on/off times per day	
Slack variable	**Description**	**Unit**
$Sl_t^{Negative}$	Negative slack variable at period t	kW
$Sl_t^{Positive}$	Positive slack variable at period t	kW
Model Parameters	**Description**	**Unit**
$S_{max}^{Bat,disch}$	Maximum discharging power from battery at period t	kW
SOC^{max}	Maximum SOC of battery (80% of battery capacity)	kWh
SOC^{min}	Minimum SOC of battery (20% of battery capacity)	kWh
C^{DG}	Operation cost of DG	\$/kWΔt
C^{VPP}	Operation cost of VPP	\$/kWΔt
G_{max}^{DG}	Maximum power generation capacity of DG	kW
G_{max}^{Wind}	Max power generation capacity of wind turbine	kW
G_{max}^{Solar}	Max power generation capacity of solar panel	kW
G_{min}^{DG}	Minimum power generation of DG	kW
Su^{share}	Share of selling surplus power in ID market	%
Other symbols	**Description**	
R_h	VPP system reliability at hour h	%
λ_t^{VPP}	VPP system failure rate at period t	%
λ	Failure rate of the VPP system	%
Δt	Settlement period (here 30 min)	minute
ε	Epsilon or small value (here $\varepsilon = 0.0005$)	
M_1	Big number or Big-M (here M_1 = 589,200)	
M_2	Big number or Big-M (here M_2 = 48)	
T	Time horizon of optimization (Number of days $\times$ settlement periods)	
Φ_{DA}	Minimum tradable amount in DA market	kW
Φ_{ID}	Minimum tradable amount in ID market	kW

References

1. Naval, N.; Yusta, J.M. Virtual power plant models and electricity markets—A review. *Renew. Sustain. Energy Rev.* **2021**, *149*, 111393. [CrossRef]
2. Hobbs, B.F. Optimization methods for electric utility resource planning. *Eur. J. Oper. Res.* **1995**, *83*, 1–20. [CrossRef]

3. Bukar, A.L.; Hamza, M.F.; Ayub, S.; Abobaker, A.K.; Modu, B.; Mohseni, S.; Brent, A.C.; Ogbonnaya, C.; Mustapha, K.; Idakwo, H.O. Peer-to-peer electricity trading: A systematic review on current developments and perspectives. *Renew. Energy Focus* **2023**, *44*, 317–333. [CrossRef]
4. JEPX. *Japan Wholesale Electric Power Exchange Trading Guide*; JEPX: Tokyo, Japan, 2019.
5. The Electric Power Industry in Japan 2023. Japan Electric Power Information Center (JEPIC). Available online: https://www.jepic.or.jp/en/data/epijpdf.html (accessed on 5 December 2023).
6. JEPX Trading Market Data. Japan Electric Power Exchange, 28 November 2003. Available online: https://www.jepx.jp/electricpower/market-data/spot/ (accessed on 10 November 2023).
7. Mashhour, E.; Masoud, M.-T.S. Bidding Strategy of Virtual Power Plant for Participating in Energy and Spinning Reserve Markets—Part I: Problem Formulation. *IEEE Trans. Power Syst.* **2011**, *26*, 949–956. [CrossRef]
8. Rouzbahani, H.M.; Karimipour, H.; Lei, L. A review on virtual power plant for energy management. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101370. [CrossRef]
9. Zhu, J.; Ihara, S. The market for spinning reserve and its impacts on energy prices. In Proceedings of the IEEE Power Engineering Society Winter Meeting, Singapore, 23–27 January 2000.
10. Yu, S.; Fang, F.; Liu, Y.; Liu, J. Uncertainties of virtual power plant: Problems and countermeasures. *Appl. Energy* **2019**, *239*, 454–470. [CrossRef]
11. 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]
12. Dielmann, K.-P.; Velden, A.V.D. Virtual power plants (VPP)—A new perspective for energy generation? In Proceedings of the 9th International Scientific and Practical Conference of Students, Post-Graduates Modern Techniques and Technologies, Tomsk, Russia, 7–11 April 2003.
13. Hasankhani, A.; Vahidi, B.; Riahy, G.H. Replacing Diesel Generator with Wind Turbine & LI-ION Battery in Virtual Power Plant. *Sci. Int.* **2014**, *26*, 583–587.
14. Elwan, A.A.; Habibuddin, M.H.; Arief, Y.Z.; Sharan, S.N.A.M.; Mokhtar, A.S.B.; Idris, R.B.M. Optimization of Distributed Generators in a Virtual Power Plan Using Mixed Integer Linear Programming Method. In *Renewable Power for Sustainable Growth*; Springer: Singapore, 2024.
15. Abiodun, K.; Hood, K.; Cox, J.L.; Newman, A.M.; Zolan, A.J. The value of concentrating solar power in ancillary services markets. *Appl. Energy* **2023**, *334*, 120518. [CrossRef]
16. Wang, Q.; Zhang, C.; Ding, Y.; Xydis, G.; Wang, J.; Østergaard, J. Review of real-time electricity markets for integrating distributed energy resources and demand response. *Appl. Energy* **2015**, *138*, 695–706. [CrossRef]
17. Haugen, M.; Farahmand, H.; Jaehnert, S.; Fleten, S. Representation of uncertainty in market models models for operational planning and forecasting in renewable power systems: A review. *Energy Syst.* **2023**. [CrossRef]
18. Wozabal, D.; Rameseder, G. Optimal bidding of a virtual power plant on the Spanish day-ahead and intraday market for electricity. *Eur. J. Oper. Res.* **2020**, *280*, 639–655. [CrossRef]
19. Nadimi, R.; Tokimatsu, K. Applying consumption time analysis to measure fundamental energy needs: A method to quantify households' energy services. *MRS Energy Sustain.* **2022**, *9*, 501–517. [CrossRef]
20. Gomes, I.; Pousinho, H.; Melício, R.; Mendes, V. Stochastic coordination of joint wind and photovoltaic systems with energy storage in day-ahead market. *Energy* **2017**, *124*, 310–320. [CrossRef]
21. Zamani, A.G.; Zakariazadeh, A.; Jadid, S. Day-ahead resource scheduling of a renewable energy based virtual power plant. *Appl. Energy* **2016**, *169*, 324–340. [CrossRef]
22. Valitov, N.; Maier, A. Asymmetric information in the German intraday electricity market. *Energy Econ.* **2020**, *89*, 104785. [CrossRef]
23. Epexspot. European Market Coupling. Available online: https://www.epexspot.com/en/marketcoupling#single-day-ahead-coupling-sdac (accessed on 12 December 2023).
24. Le, H.L.; Ilea, V.; Bovo, C. Integrated European intra-day electricity market: Rules, modeling and analysis. *Appl. Energy* **2019**, *238*, 258–273. [CrossRef]
25. TEPCO Power Grid. TEPCO. Available online: https://www.tepco.co.jp/en/forecast/html/download-e.html (accessed on 1 November 2023).
26. Wang, H.; Riaz, S.; Mancarella, P. Integrated techno-economic modeling, flexibility analysis, and business case assessment of an urban virtual power plant with multi-market co-optimization. *Appl. Energy* **2019**, *259*, 114142. [CrossRef]
27. Cavazzini, G.; Benato, A.; Pavesi, G.; Ardizzon, G. Techno-economic benefits deriving from optimal scheduling of a Virtual Power Plant: Pumped hydro combined with wind farms. *J. Energy Storage* **2021**, *37*, 102461. [CrossRef]
28. Abdullah, W.S.W.; Osman, M.; Kadir, M.Z.A.A.; Verayiah, R.; Aziz, N.F.A.; Rasheed, M.A. Techno-economics analysis of battery energy storage system (BESS) design for virtual power plant (VPP)—A case study in Malaysia. *J. Energy Storage* **2021**, *83*, 102568. [CrossRef]
29. Zheng, X.; Chen, H.; Xu, Y.; Li, Z.; Lin, Z.; Liang, Z. A mixed-integer SDP solution to distributionally robust unit commitment with second order moment constraints. *CSEE J. Power Energy Syst.* **2020**, *6*, 374–383.
30. Ahmadian, A.; Ponnambalam, K.; Almansoori, A.; Elkamel, A. Optimal Management of a Virtual Power Plant Consisting of Renewable Energy Resources and Electric Vehicles Using Mixed Integer Linear Programming and Deep Learning. *Energies* **2023**, *16*, 1000. [CrossRef]

31. Sharadga, H.; Hajimirza, S.; Balog, R.S. Time series forecasting of solar power generation for large-scale photovoltaic plants. *Renew. Energy* **2020**, *150*, 797–807. [CrossRef]
32. Dong, Z.; Zhang, Z.; Huang, M.; Yang, S.; Zhu, J.; Zhang, M.; Chen, D. Research on day-ahead optimal dispatching of virtual power plants considering the coordinated operation of diverse flexible loads and new energy. *Energy* **2024**, *297*, 131235. [CrossRef]
33. Baringo, A.; Baringo, L. A Stochastic Adaptive Robust Optimization Approach for the Offering Strategy of a Virtual Power Plant. *IEEE Trans. Power Syst.* **2017**, *32*, 3492–3504. [CrossRef]
34. Naughton, J.C. A Modelling Framework for Virtual Power Plants under Uncertainty. Ph.D. Thesis, University of Birmingham, Birmingham, UK, 2022.
35. Liu, X.; Ni, Y.; Sun, Y.; Wang, J.; Wang, R.; Sun, Q. Multi-VPPs power-carbon joint trading optimization considering low-carbon operation mode. *J. Energy Storage* **2024**, *83*, 110786. [CrossRef]
36. Yan, X.; Gao, C.; Jiang, H.; Francois, B. Multi-objective optimization and profit allocation of virtual power plant considering the security operation of distribution networks. *J. Energy Storage* **2024**, *89*, 111607. [CrossRef]
37. Song, H.; Gu, M.; Liu, C.; Amani, A.M.; Jalili, M.; Meegahapola, L.; Yu, X.; Dickeson, G. Multi-objective battery energy storage optimization for virtual power plant applications. *Appl. Energy* **2023**, *352*, 121860. [CrossRef]
38. Lambert, M.; Hassani, R. Diesel genset optimization in remote microgrids. *Appl. Energy* **2023**, *340*, 121036. [CrossRef]
39. Nadimi, R.; Goto, M.; Tokimatsu, K. The impact of diesel operation time constraint on total cost of diesel-based hybrid renewable power system simulation model. *Renew. Energy Focus* **2023**, *44*, 40–55. [CrossRef]
40. Kwag, H.-G.; Kim, J.-O. Reliability modeling of demand response considering uncertainty of customer behavior. *Appl. Energy* **2014**, *122*, 24–33. [CrossRef]
41. Goudarzi, A.; Li, Y.; Xiang, J. Efficient energy management of renewable resources in microgrids. In *Renewable Energy Microgeneration Systems*; Academic Press: Cambridge, MA, USA, 2021; pp. 285–321.
42. GlobalPetrolPrices.com. Available online: https://www.globalpetrolprices.com/natural_gas_prices/ (accessed on 13 December 2023).
43. About Wind Energy—The Facts. Available online: https://www.wind-energy-the-facts.org/operation-and-maintenance-costs-of-wind-generated-power.html (accessed on 12 December 2023).
44. Kikuchi, Y.; Ishihara, T. Assessment of capital expenditure for fixed-bottom offshore wind farms using probabilistic engineering cost model. *Appl. Energy* **2023**, *341*, 120912. [CrossRef]
45. Yamazaki, M.; NEDO; Ikki, O.; RTS Corporation. *National Survey Report of PV Power Applications in Japan*; NEDO: Kawasaki, Japan, 2020.
46. International Renewable Energy Agency. Energy Profile Japan. 2020. Available online: https://www.irena.org/-/media/Files/IRENA/Agency/Statistics/Statistical_Profiles/Asia/Japan_Asia_RE_SP.pdf (accessed on 25 March 2024).
47. Kimura, K. *Solar Power Generation Costs in Japan Current Status and Future Outlook*; Renewable Energy Institute: Tokyo, Japan, 2019.
48. ISEP. Share of Electricity from Renewable Energy Sources in Japan (Preliminary). Institute for Sustainable Energy Policies. 2022. Available online: https://www.isep.or.jp/en (accessed on 12 December 2023).
49. Jackson, N.D.; Gunda, T.; Gayoso, N.; Desai, J.; Walker, A. *Operations, Maintenance, and Costconsiderations for PV+Storage in the United States*; Sandia National Laboratories: Albuquerque, NM, USA, 2022.
50. Yang, Z.; Radchenko, M.; Andrii, R.; Mikielewicz, D.; Radchenko, R. Gas Turbine Intake Air Hybrid Cooling Systems and a New Approach to Their Rational Designing. *Energies* **2022**, *15*, 1474. [CrossRef]
51. Radchenko, M.; Radchenko, A.; Radchenko, R.; Kantor, S.; Konovalov, D.; Kornienko, V. Rational loads of turbine inlet air absorption-ejector cooling systems. *J. Power Energy* **2022**, *236*, 450–462. [CrossRef]
52. Beal, L.D.R.; Hill, D.C.; Martin, R.A.; Hedengren, J.D. GEKKO Optimization Suite. *Processes* **2018**, *6*, 106. [CrossRef]