


Article

# Risk-Based Virtual Energy Storage System Service Strategy for Prosumers

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**Abstract:** The high cost of an energy storage system (ESS) is a barrier to its use. This paper proposes a risk-based virtual ESS (V ESS) service strategy for prosumers. The basic concept of the V ESS service is to logically refer to a physical ESS by multiple users. The V ESS service can install ESS with a larger capacity compared to the case of installing ESS individually. Therefore, the V ESS reduces the cost barrier through economies of scale. Moreover, ESS is not always being utilized at its maximum in the V ESS service. Considering the risk, a V ESS can offer a greater capacity than an installed ESS capacity. In this paper, the V ESS service model suggested considers not only the economic benefit of increasing the V ESS installation capacity but also the value at risk arising from servicing a greater capacity. The V ESS service problem is formulated as a convex problem according to the V ESS installation capacity and service price by applying stochastic approximation and is optimally solved using the gradient descent method in an iterative manner. The simulation results demonstrate that, when the proposed service strategy is used, the service provider that considers the risk achieves a significantly greater economic benefit of around 30% for the 128-prosumer pair case as compared to the one that does not consider risk. The benefit of the prosumer is increased by approximately 3.5% for the 128-prosumer pair case because the mismatched quantity is reduced during the peer-to-peer energy transaction. In addition, it is discussed how the proposed V ESS service strategy achieves benefit through unit ESS cost reduction by the economics of scale and achieves increased service capacity with the multi-user diversity gain of participants.

**Keywords:** energy sharing; energy storage; energy transaction; point-to-point; renewable; sharing economy; virtual energy storage



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## 1. Introduction

Renewable energy-based power generation continues to increase in scale owing to the strengthening of regulations around greenhouse gas emissions and the decrease in the generation cost of power based on renewable energy [1]. However, the growth of renewable energy-based power generation increases operational difficulties and reduces the reliability of power systems. It is estimated that the requirement for new transmission and distribution lines worldwide to guarantee the reliability and security of power systems will be 80% greater over the next decade than that seen in the last 10 years from 2010 to 2020 [1].

Energy storage plays a vital role in ensuring the flexible operation of power systems [2]. Energy storage systems (ESSs) are used in various ways, from utility-scale applications such as black start [3,4], voltage regulation [5,6], grid fluctuation suppression [7,8], and spinning reserve [9,10], to demand-scale applications such as demand flexibility management [11,12] and energy bill reduction [13,14]. An ESS stores the surplus energy and discharges the stored energy according to operational purposes. The charge and discharge quantities determine the effectiveness of the ESS, and the ESS size determines the charge and discharge quantities. Thus, an ESS with a large size has higher effectiveness. Although the cost of ESSs continues to fall, it is still an expensive element of any power system [15], and the high cost is a barrier to the use of ESSs.

Recently, virtual ESSs (also called cloud ESSs or shared ESSs) have been introduced. The basic concept of the VESS service is to logically refer to a physical ESS [16]. The VESS service is a shared energy storage resource that provides storage services to small consumers. The basic procedure of the VESS service is composed as follows: (1) The customers participating in the service rent the ESS capacity they need. (2) The customers can decide the action of charging and discharging energy from purchased resources in the same way as they installed an individual ESS. (3) The information on the actions of each customer is sent to the VESS service provider (SP) through the communication infrastructures. (4) The VESS SP operates a centralized physical ESS to meet the needs of the aggregated actions of each customer. (5) The energy bill is settled through sub-metering between the grid operator, VESS SP, and customers. This service is similar to a cloud computing service because energy is homogeneous and able to be transmitted easily through the grid [17]. The VESS service reduces the barrier of the ESS cost due to the economies of scale. This is because the VESS service can install ESS with a larger capacity compared to the case of installing ESS individually. Increasing the installation capacity, the unit price of ESS is reduced. Moreover, customers don't always use all of their purchased resources. By modeling the underutilized condition of resources, a more effective VESS service strategy can be designed so that more ESS capacity is served than the installed ESS capacity for the operation of VESS.

A few researches have been conducted on the VESS service. Kalathil et al. introduced a VESS service that invests in electricity storage to arbitrage against time-of-use tariffs (ToUs) as an example of a sharing economy [16]. Liu et al. suggested a decision-making rule for investment in a VESS, which is a shared pool of grid-scale energy storage resources for small consumers, and demonstrated the benefit with a case study [17]. Oh and Son proposed a method to determine VESS size and service cost to minimize the electricity bill of building units in ToU [18]. Zhao et al. considered a VESS investment and pricing decision method for a group of users to minimize their electricity bill [19]. The problem in [17–19] was formulated as a two-stage optimization problem for the interaction between the SP and the participants, and was solved with an iterative search. Tushar et al. formulated an energy storage ownership sharing problem between multiple shared controllers dwelling in a residential community, and suggested an auction-based shared price solution to maximize utility [20]. Chakraborty et al. applied a coalitional game approach to determine how much capacity they could jointly acquire by minimizing the expected daily storage cost to solve an ESS sharing problem [21]. Zhong et al. proposed an online energy storage sharing operation algorithm based on the Lyapunov optimization framework with offline parameter selection to minimize the overall cost, including the electricity bill and ESS charging and discharging costs [22]. Some examples have been applied to improve system parameters such as the frequency response [23], voltage regulation [24], and uncertainty management [25]; however, in most studies, the VESS was used for electricity bill minimization. This is because the VESS is an effective way to lower the cost barrier of ESS usage. In fact, the benefits of a VESS come in two forms. For one, due to the aforementioned economies of scale, a VESS can be served at a low cost compared with an individual ESS service. The other is that the logical charging and discharging operations of several participants cancel each other out, so the actual operation is more timely. Existing studies have focused on the first benefit based on economies of scale. The second benefit was only shown experimentally in a few studies such as [18,19].

This paper proposes a VESS service strategy that not only considers the economic benefit that is presented as a unit ESS cost decrease, but also considers the multi-user benefit of increased service capacity compared with the VESS installation capacity. The work presented here builds on the author's previous work [18,25]. In [18], the VESS service architecture that consists of physically connected energy and communication infrastructures, and the logical operation of the EES virtually assigned to each participating unit are presented. Moreover, the conceptual scheme for the VESS service is presented in the architecture. However, the VESS service in [18] is operated on the risk-free condition that

the serving capacity is less than the VESS installation capacity in apartment-type factory buildings. However, this paper investigates the VESS service strategy for prosumers considering the risk that more ESS capacity is served than the installed ESS capacity for the operation of the VESS. In [25], the reinforcement-learning based VESS operation strategy is proposed to reduce wind power forecasting uncertainty. The study in [25] focuses on the VESS operation when the VESS installation capacity and service price are fixed. However, this paper proposes the VESS service strategy to determine the VESS installation capacity and service price considering the risk. Prior works such as [16–25] consider the case that the VESS provide services only within the installed capacity. The novelty of the proposed strategy is to consider the case providing more service capacity than the installed ESS capacity for the operation of the VESS. When a capacity greater than the VESS installation capacity is served, risk compensation for excess capacity occurs. This paper considers the environment in which VESS are serviced for prosumers. Prosumers are users that consume and produce energy [26]. Prosumers achieve an economic benefit by transacting energy as goods and services through peer-to-peer (P2P) energy transactions [27]. P2P energy transactions are also expected to help the grid by reducing peak demand, lowering reserve requirements, and curtailing network losses. However, prosumers have low reliability according to the stochastic nature of renewable-based sources and their dependency on human behavior. The low reliability of prosumers causes an energy mismatch in P2P energy transactions [26]. This increases the economic loss for prosumers and the operational uncertainty for utilities. To increase reliability, an ESS can be considered, but the high cost of ESS implementation acts as a barrier. A proposed VESS service reduces this barrier. For the VESS service in prosumer environments, the service benefit according to the VESS service is first modeled by considering the value at risk. By applying a stochastic approximation, the VESS service is organized into a convex problem. Two VESS service strategies are suggested, where the SP works as a profit-seeking SP to maximize its own benefit, and as a non-profit SP to maximize the benefit of participants. The experimental results show that the SP and the participants enjoy greater benefit when applying the proposed VESS service strategy considering risk than when using the strategy without considering risk. Moreover, it is discussed how the proposed VESS service strategy achieves additional benefits.

The rest of this paper is organized as follows: In Section 2, the VESS service model, including the SP, prosumer, and utility model, is described; in Section 3, the design method of the proposed VESS service strategy is discussed. In Section 4, measurement studies applied to the proposed strategy are presented, and in Section 5, the conclusions of the paper are presented.

## 2. VESS Service Model

The VESS service model for prosumers consists of three components, as shown in Figure 1: the utility grid, prosumers, and the VESS SP. The SP implements the VESS and serves the ESS based on the service price. As a participant, the prosumer purchases an allotment of the ESS that is appropriate considering the service price and their own benefit. The utility operates the grid to maintain the energy balance and charges an electricity bill for usage.

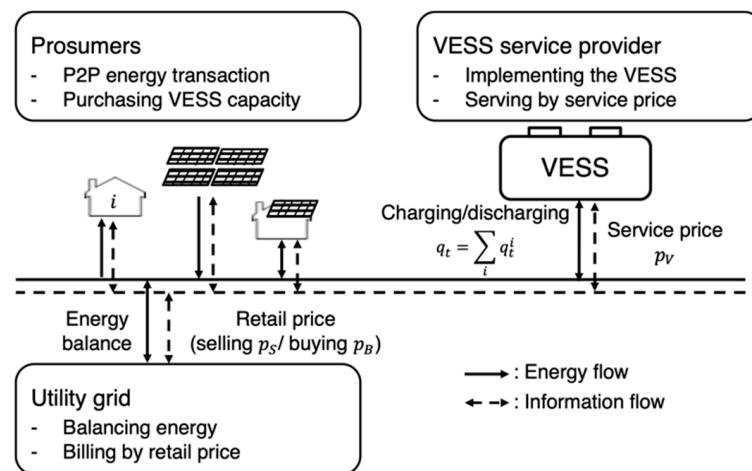


Figure 1. Virtual energy storage system service model for prosumers.

### 2.1. VESS SP Model

As the SP installs and operates the VESS, it incurs cost and receives compensation for this cost through a service charge. The SP may be an independent SP for VESS services, or a utility may operate as a non-profit to increase the stability of the distributed grid operation.

The main cost of the VESS service is in installing a VESS. Let  $c_0$  be the VESS capacity for charging and discharging the energy service. The VESS cost related to the capacity is modeled as [18]

$$p_C(c_0) = \alpha_1 \exp(-\alpha_2 c_0) + \alpha_3 [\$/\text{kWh}], \tag{1}$$

where  $c_0$  [kWh] is the energy capacity of the VESS. The power capacity of the VESS is determined as  $c_0/2$  h [kW], assuming a maximum service time of 2 h.  $\alpha_1$ ,  $\alpha_2$ , and  $\alpha_3$  are the ESS cost parameters according to the ESS characteristics. Here,  $\alpha_1$  and  $\alpha_2$  indicate the variable costs according to ESS size, such as the manufacturing cost, and  $\alpha_3$  indicate fixed cost parameters such as the operation and management cost. In (1), the unit VESS cost is exponentially reduced by increasing the VESS capacity. This is because by increasing VESS capacity, the VESS equipment and maintenance costs are reduced [28]. This is a basic advantage of economies of scale.

Assuming the unit service price of the VESS is  $p_V$  [\$/kWh], the benefit to the SP is measured as

$$B_0(c_0, p_V) = p_V \sum_{i \in \mathcal{I}} c_i - p_C(c_0) c_0, \tag{2}$$

where  $i$  is the unit index for participating in the VESS service, and  $\mathcal{I} = \{1, \dots, i, \dots, I\}$  is the set of participants.  $c_i$  is the ESS service capacity purchased by unit  $i$ .

The prior research for VESS reviewed in the Introduction section shows that the SP achieves benefit due to the price difference between  $p_V$  and  $p_C$ . Moreover, in the service problem formulation, there is the constraint that the serving capacity,  $\sum_{i \in \mathcal{I}} c_i$ , must be less than or equal to the VESS capacity,  $c_0$ . This is a measure of service stability. However, the proposed SP model considers installing a smaller VESS capacity than the serving capacity. This model expects higher benefits, but there are service risks. Therefore, in the proposed VESS service model, the benefit of the SP, including risks, can be rewritten as

$$B_0^V(c_0, p_V) = p_V \sum_{i \in \mathcal{I}} c_i - p_C(c_0) c_0 - R(c_0, c_i), \tag{3}$$

where  $R(c_0, c_i)$  is the value at risk (VaR) according to the VESS capacity and serving capacity as described in Section 3.2. To measure the VaR, the VESS capacity and serving capacity should be expected. The VESS capacity is installed by the SP. The serving capacity depends on the service price and the stochastic characteristics of the participant. The service price is

determined by the SP and the stochastic characteristics can be obtained through the historic data of the participant. A more detailed description is expressed in Section 3.2.

### 2.2. Prosumer Model

When unit  $i$  conducts energy trading as a prosumer in the P2P energy transaction mechanism according to the guaranteed minimum trading rule, the benefit of unit  $i$  is measured as [26]

$$B_i = p_T e_i - p_B \epsilon_i^- + p_S \epsilon_i^+, \quad (4)$$

where  $p_T$ ,  $p_B$ , and  $p_S$  are the P2P energy transaction price, buying price from the grid, and selling price to the grid;  $e_i$  is the P2P energy transaction quantity of unit  $i$ , and  $\epsilon_i^-$  and  $\epsilon_i^+$  are the mismatched quantities of unit  $i$  that remain or fall short of the P2P transaction quantity, respectively.

The unit benefit is enhanced by reducing the mismatched quantity by utilizing the VESS service. By applying a higher VESS capacity, the unit can manage a greater mismatched quantity. However, the unit pays a service fee for using the VESS service. Therefore, the benefit to unit  $i$  when using VESS service capacity  $c_i$  is calculated as

$$B_i^V(c_i) = (p_B - p_T)\Delta\epsilon_i^-(c_i) - (p_T - p_S)\Delta\epsilon_i^+(c_i) - p_V c_i, \quad (5)$$

where  $\Delta\epsilon_i^-(c_i)$  and  $\Delta\epsilon_i^+(c_i)$  are reduced mismatched quantities when using the VESS service capacity,  $c_i$ , respectively.

### 2.3. Utility Model

As a grid operator, the utility transmits the energy for the energy balance of the mismatched energy during the P2P energy transaction and the charging/discharging energy of the VESS. It announces the retail electricity price, that is, selling to grid  $p_S$  and buying from grid  $p_B$ . The retail price can control access by prosumers and the VESS to the grid. However, this paper focuses on the VESS service problem for prosumers. Therefore, it is assumed that the grid is securely operated by the utility, and that the retail price is fixed.

## 3. VESS Service Strategy

For the VESS service, the SP should decide the VESS installation capacity and service price considering the VaR. The service price can be adjusted according to the unit's participation situation, but it is difficult to change the VESS capacity after implementation [29,30]. Moreover, the VESS capacity has a significant influence on the service price and VaR. In this section, the proposed VESS service strategy is described to determine the VESS installation capacity and service price considering the effect of risk.

### 3.1. Service Fee

The VESS service fee is the first term of the benefit due to the SP in (3). It is determined according to the service price,  $p_V$ , and the serving capacity purchased by participating units,  $\sum_{i \in \mathcal{I}} c_i$ . The serving capacity is also determined by the service fee paid by the unit and the benefit of mismatch management by the VESS service, as shown in (5). Increasing the serving capacity increases the mismatch management benefit to the unit, but the increment of the benefit is reduced [30]. The service fee is paid linearly to the unit according to the service capacity. Therefore, the benefit to the unit becomes a concave function, and the unit can select the purchased serving capacity.

It is assumed that the mismatched quantity of unit  $i$ ,  $\epsilon_i$ , in (5) has stochastic properties as described by the probability density function,  $f_{\epsilon_i}(x)$ , and cumulative distribution function,  $F_{\epsilon_i}(x)$ . In [30], the absolute mismatched quantity with service capacity  $c_i$  can be calculated as:

$$\mathbb{E}\{|\epsilon_i(c_i)|\} = |\mu_i| + 2 \left[ \sigma_i^2 f_{\epsilon_i}(c_i) - c_i \{1 - F_{\epsilon_i}(c_i)\} \right], \quad (6)$$

where  $\mathbb{E}\{\cdot\}$  is the expected operation, and  $\mu_i$  and  $\sigma_i$  are the mean and standard deviation of the mismatched quantity,  $\epsilon_i$ , respectively.

Substituting (6) into (5), the expected benefit of unit  $i$  is calculated according to the symmetric property of the mismatched quantity as follows:

$$\mathbb{E}\{B_i^V(c_i)\} = \frac{(p_B - p_S)}{2} \mathbb{E}\{|\Delta\epsilon_i(c_i)|\} - p_V c_i, \tag{7}$$

and the serving capacity to maximize the expected benefit of the unit is obtained to solve the condition

$$\frac{\partial \mathbb{E}\{B_i^V(c_i)\}}{\partial c_i} = 0. \tag{8}$$

As mentioned above, because the benefit of the unit is a concave function, a unique serving capacity is achieved according to the service price.

The stochastic properties of the mismatched quantity are modeled as random values in a set of distributions in the exponential family, such as normal and exponential distributions [26,30]. This means that the mismatched quantity is expressed according to the first and second characteristics, that is,  $\mu_i$  and  $\sigma_i$ . This information was measured using historical data. To implement the VESS, the SP predicts the serving capacity of each unit before the VESS service. The SP can expect the serving capacity purchased by the units to solve (8).

### 3.2. Value at Risk

The VaR is the cost of the risk that occurs when the VESS capacity is less than the sum of the serving capacity purchased by the units.

Let  $r(c_0, c_i)$  define the risk as the quantity that must be served to units beyond the capacity of the VESS. To balance the risk, the SP purchases or sells energy on the grid. Therefore, the VaR can be expressed as

$$R(c_0, c_i) = \frac{(p_B + p_S)}{2} r(c_0, c_i). \tag{9}$$

The serving capacity is the total ESS action of the units to reduce the mismatched quantity. Let  $x = -\sum_{i \in \mathcal{I}} \epsilon_i$  be the total serving capacity. The expected risk was measured as follows:

$$\mathbb{E}\{r(c_0, c_i)\} = \mathbb{E}\left\{x \mid c_0 < x \leq \sum_{i \in \mathcal{I}} c_i\right\}. \tag{10}$$

Assuming that the serving capacity is a normally distributed random variable with mean  $\mu = \sum_{i \in \mathcal{I}} \mu_i$  and standard deviation  $\sigma = \sqrt{\sum_{i \in \mathcal{I}} \sigma_i^2}$ , the expected risk is approximated using the inverse Mills ratio [31] as

$$\mathbb{E}\{r(c_0, c_i)\} \approx \mu - \sigma \frac{\phi\left(\frac{\sum_{i \in \mathcal{I}} c_i - \mu}{\sigma}\right) - \phi\left(\frac{c_0 - \mu}{\sigma}\right)}{\Phi\left(\frac{\sum_{i \in \mathcal{I}} c_i - \mu}{\sigma}\right) - \Phi\left(\frac{c_0 - \mu}{\sigma}\right)}, \tag{11}$$

where  $\phi(z)$  and  $\Phi(z)$  are the probability density function (PDF) and cumulative distribution function (CDF) of a standard normal distribution, respectively.

Substituting (11) into (9), the expected VaR is calculated as

$$\mathbb{E}\{R(c_0, c_i)\} = \frac{(p_B + p_S)}{2} \mathbb{E}\{r(c_0, c_i)\}. \tag{12}$$

The expected VaR is directly related to the expected risk. The expected risk quantity has a monotonically increasing property according to the gap between the VESS capacity and the total serving capacity. Therefore, when the serving capacity is decided according to the service fee, the SP can expect a VaR according to the VESS installation capacity.



### 3.3. VESS Installation Capacity

The unit cost of the VESS is modeled as an exponentially decreasing function with the ESS cost parameters  $\alpha_1, \alpha_2$ , and  $\alpha_3$ , as shown in (1). By applying the Li-ion battery as a VESS, the ESS cost parameters can be determined by using the value of previous research [18] or by fitting the value of references [28], as shown in Figure 2. The value in [28] is a newer value than that in [18]. The value in [18] refers to the data of “Lazard’s leveled cost of storage analysis-version 3.0” published in 2017, and [28] “Lazard’s leveled cost of storage analysis-version 6.0” published in 2020. The figure shows that by technical enhancement, the hard costs of implementing an ESS, such as material and energy density, is reduced, and this is expressed as the starting point; however, the soft costs, such as operations and management, are similar, and are expressed as the values presented as the slopes.

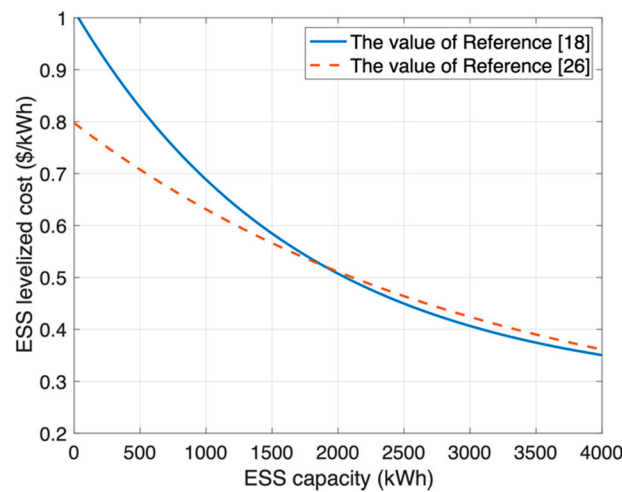


Figure 2. ESS leveled cost varying ESS capacity.

The VESS capacity cost is determined by the product of the unit ESS cost,  $p_C(c_0)$ , and the VESS capacity,  $c_0$ , that is,  $p_C(c_0) \times c_0$ . The gradient of the unit ESS cost is less than 1; hence, the VESS capacity cost becomes a non-decreasing concave function of VESS capacity. Therefore, from an economic point of view, the VESS is installed with the smallest capacity. However, as the VESS capacity decreases, the VaR in (12) increases. Moreover, the unit ESS cost determines the marginal value of the service price  $p_V$  in (7). A high service price lowers the unit’s service participation, and the serving capacity purchased units can be reduced to lower than the VESS installation capacity.

### 3.4. VESS Service Strategy

The VESS service is operated according to various operational purposes. The SP can serve to maximize its own benefit or to operate non-profitably.

When the SP works as a profit-seeking SP, the service price and VESS capacity are set to maximize Equation (3). The service fee, VaR, and VESS capacity cost in (3) satisfy the convex property according to the service price and VESS capacity. Therefore, the service price and VESS capacity are determined through methods such as the gradient descent method and the Newton–Raphson method in an iterative manner [32]:

$$\begin{aligned} p_V^{k+1} &= p_V^k + \Delta_k \frac{\partial B_0^V(c_0, p_V)}{\partial p_V}, \\ c_0^{k+1} &= c_0^k + \Delta_k \frac{\partial B_0^V(c_0, p_V)}{\partial c_0}, \end{aligned} \tag{13}$$

where  $\Delta_k$  is the step size at iteration  $k$ .

When the SP is a non-profit SP, the service price and VESS capacity are set to satisfy the following conditions:

$$p_V \sum_{i \in \mathcal{I}} c_i = p_C(c_0) c_0 + R(c_0, c_i). \quad (14)$$

This condition is solved according to the relationship between the service price and VESS capacity. This means that the solution is expressed as a bound solution.

Note that the ESS utilization is affected by the ESS operation strategy and constraints such as voltage magnitude limits, branch thermal limits, and ESS charge or discharge limits. Moreover, the ESS operation is decided by the participating unit. This paper is focused on the VESS installation capacity and service price for the VESS service. Therefore, it is assumed that the ESS is operated to minimize the mismatching quantity of each participated unit considering the capacity constraint such as ESS charge or discharge limits. The serving capacity purchased by the participated unit reflects the ESS operation to determine the VESS service strategy.

#### 4. Results and Discussion

In this section, to verify the effectiveness of the proposed VESS service strategy, the benefits to the SP and units are measured, and the effects of the characteristics of the system parameters are discussed. To perform simulations, the ESS cost parameters were set as  $\alpha_1 = 0.6$ ,  $\alpha_2 = 0.000032$ , and  $\alpha_3 = 0.19$ , fitting the value in [28]. The experimental environment presented in [26] was used as the P2P energy transaction for prosumers. The prosumers traded energy using the central P2P energy transaction mechanism in [26]. The daily energy transaction was the prosumer-traded energy within the same pair for a day. The transaction was measured every half hour. The prices for buying from and selling to the grid were assumed to be  $p_B = 0.15$  \$/kWh and  $p_S = 0.10$  \$/kWh, which are the average electricity prices in the U.S. [33]. The P2P energy transaction price was set to  $p_T = 0.125$  \$/kWh. The average daily demand and uncertainty of the prosumers were uniformly distributed in the range of (20, 30) kWh and (0, 30)%, which is the reference case in [26].

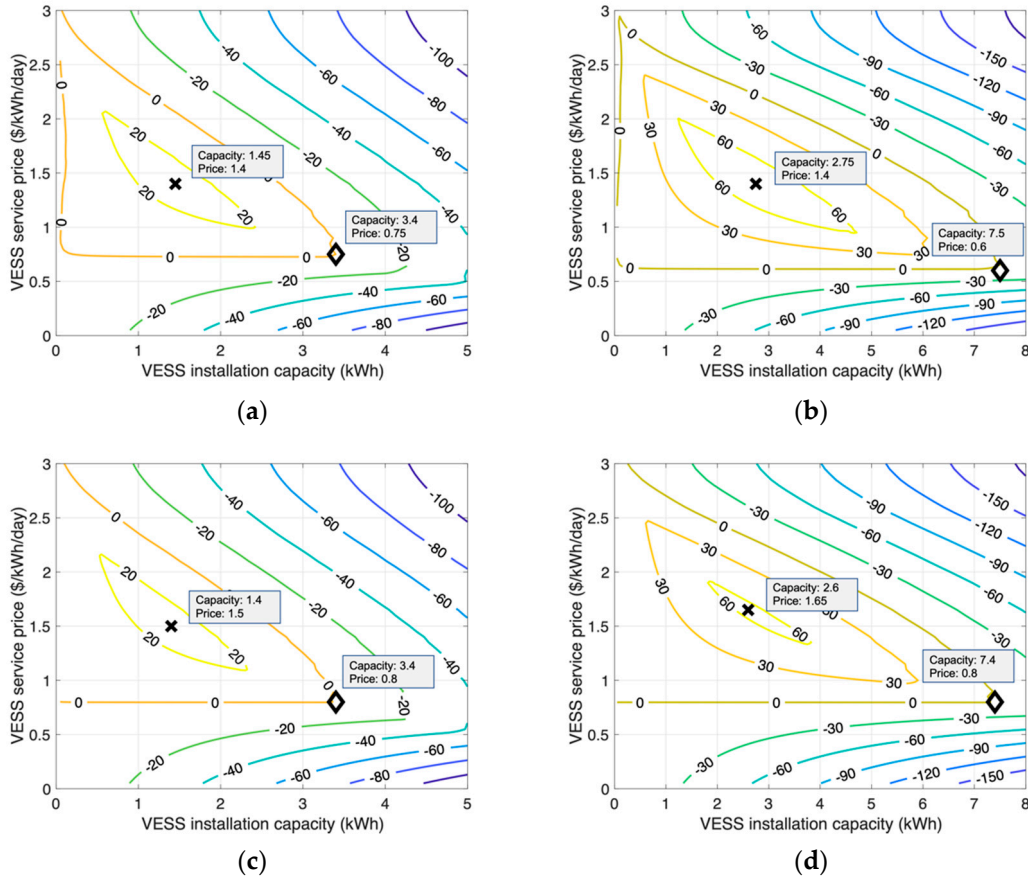
Figure 3 shows the monthly benefit of SP according to the VESS installation capacity and service price, with eight prosumer pairs in Figure 3a, and 16 pairs in Figure 3b, by applying the proposed VESS service strategy. To evaluate the effectiveness of the proposed VESS service strategy, the results using the VESS service strategy without considering VaR are compared in Figure 3c,d with eight pairs and 16 pairs, respectively. In the figures, the points marked as X are the optimal points for maximizing the benefit to the SP when the SP is profit-seeking. As mentioned above, the operational point of the non-profit SP is expressed as the line where the benefit to the SP is 0, as shown in the figures. The points marked as diamonds are the optimal points for maximizing the benefit of units in a non-profitable service operation.

In the case of a profit-seeking SP, when comparing the benefits to the SP considering VaR and without considering VaR, the values are \$28.8 and \$30.2 monthly for the eight pairs and \$66.5 and \$81.0 for the 16 pairs, respectively. The results show that the SP can achieve more benefit using the proposed VESS service strategy considering VaR compared with not considering VaR. The absolute benefit to the SP is low. This is because the ESS cost is still high, even if a VESS is applied. However, the benefit to the SP applying the proposed VESS service strategy considering VaR compared with that without considering VaR increases with the number of prosumer pairs, as shown in Figure 4.

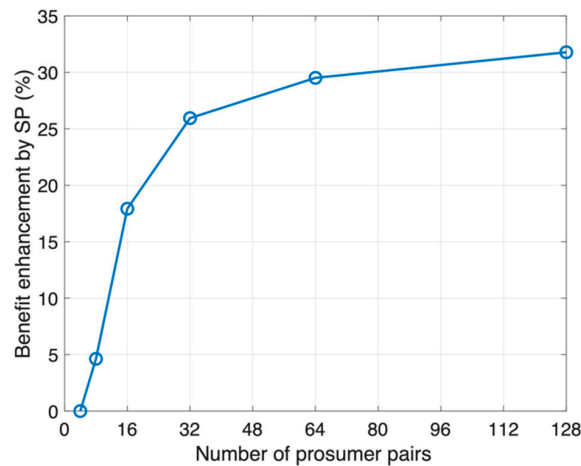
Figure 4 presents the benefit enhancement of the SP applying the proposed VESS service strategy compared with not considering VaR. It is shown that increasing the number of prosumer pairs, the benefit enhancement by the proposed VESS service strategy is increased. This is because by increasing the number of prosumer pairs, the unit ESS cost can be reduced with increasing serving capacity compared with the results in Figure 3a,b. Moreover, owing to multi-user diversity, the cost reduction according to the consideration of VaR is increased. The benefit enhancement ratio is saturated when the number of



prosumer pairs is larger than 32. This means that the VESS service strategies considering VaR and without considering VaR have the similar benefit enhancement ratio. However, even in this case, using the proposed VESS service strategy, the SP achieves more than 30% additional benefit.



**Figure 3.** Monthly benefits of SP as a function of VESS installation capacity and service price when varying prosumer pairs and VaR consideration; (a) Results for eight pairs considering VaR. (b) Results for 16 pairs considering VaR. (c) Results for 8 pairs without considering VaR. (d) Results for 16 pairs without considering VaR.



**Figure 4.** Benefit enhancement of the SP after applying the proposed VESS service strategy considering VaR compared with not considering VaR.

To check the effect of VaR, Figure 5 shows the VESS installation capacity and serving capacity purchased by units when the proposed VESS service strategy is used. In fact,

the VESS installation capacity and service price in Figure 3 show similar values for the results considering VaR and those not considering VaR, that is, the results in Figure 3a,c and in Figure 3b,d. In the case without considering VaR, the VESS serves within the VESS installation capacity range. However, in the proposed VESS service strategy, the VESS can serve more than the VESS installation capacity when the VaR is considered. As shown in Figure 4, when the VESS service strategy is applied, approximately 10% and 30% greater capacity than the VESS installation capacity is served for eight pairs and 16 pairs, respectively. When the number of prosumer pairs is increased, more capacity than the VESS installation capacity can be served. This means that by increasing the number of prosumer pairs, the SP using the proposed VESS service strategy achieves more benefit by considering the VaR.

Figure 6 shows the benefit enhancement of each unit obtained by participating in the VESS service. When the SP works as a profit-seeking SP, the benefit of the unit is neglected. This is because the VESS installation capacity and service price are determined at the point where the benefit of the unit is non-negative and the benefit of the SP is maximized. The result in Figure 6 is measured in the non-profit SP case, such as the point marked by a diamond in Figure 3. This point is where the benefit of the unit is maximized, and the benefit of the SP is non-negative. Similar to the increase in benefit to the SP, the increase in benefit to the unit increases with the number of prosumer pairs. This is because the units also receive a benefit from the VESS by reducing the unit ESS cost and increasing the serving capacity compared with the VESS installation capacity, similar to the benefit to the SP.

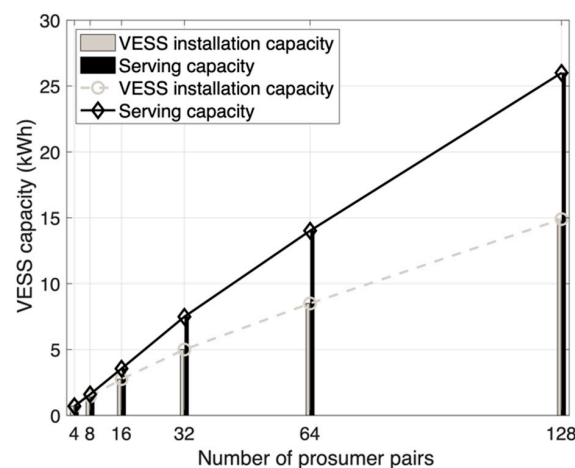


Figure 5. Comparison of VESS installation capacity and serving capacity purchased by units.

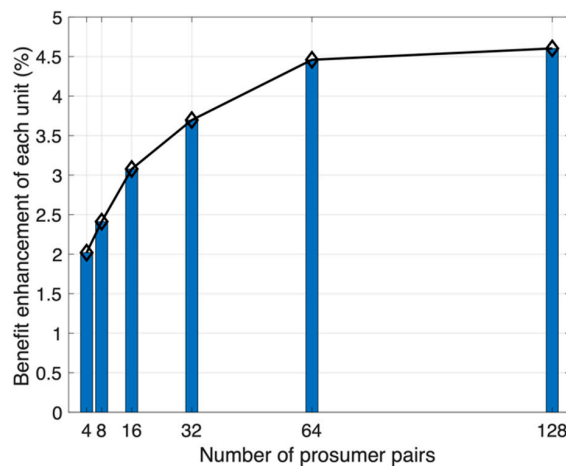


Figure 6. Benefit enhancement of each unit when using the VESS service.

## 5. Conclusions

This paper proposed a VESS service strategy that considered risk. The proposed VESS strategy determines the VESS service parameters of the VESS installation capacity and service price according to the operation purposes of the SP, that is, whether it is a profit-seeking SP or a non-profit SP. The VESS service model was first described by considering the unit ESS cost reduction by increasing the VESS installation capacity, and also by considering the effect of VaR according to the gap between the VESS installation capacity and the serving capacity. Assuming the stochastic property of units, the VESS service strategy is formulated as a convex problem and is solved by applying the gradient descent method in an iterative manner. The simulation results demonstrate that, in the case of a profit-seeking SP, the proposed VESS service strategy improves the benefit to the SP by approximately 30% compared with not considering the risk when the number of prosumer pairs is 128. The simulation also shows the same trend for the benefit to the prosumer when the SP works as a non-profit SP. In addition, the performance achieved by the VESS service strategy was evaluated in terms of multi-user diversity and the effect of VaR according to the number of prosumer pairs. The VESS service is achieved through the unit ESS cost reduction according to the economics of scale. However, if multi-user diversity is considered, similar to the proposed VESS service strategy, numerous other benefits can be obtained. As the participants that are accessing the VESS service do not perform the same operation, it is possible to service a higher capacity of participants in the VESS installation capacity, by considering the VaR as in the proposed VESS service strategy. Therefore, the benefit of the proposed VESS service strategy is characterized by an increase in the number of prosumer pairs.

Research on VESS services is at an early stage. This paper shows that a VESS service that considers risk can outperform one that does not consider risk. However, the absolute benefit of the VESS service is small because of the high cost of ESSs. Therefore, the problem of the SP and the method for obtaining additional benefits using a VESS could be the subject of further research. Moreover, this paper considered only a simple system model such as a simple assumption of the ESS operation. The VESS service strategy could be extended to not only consider the service strategy in the SP aspect but to also include system constraints such as the ESS operation in participants. In addition, by including the power system requirements, the system model could be extended for a more realistic world.

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