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Cloud Energy Storage System Operation with Capacity P2P Transaction

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Abstract: Research on energy storage systems (ESS) is actively aiming to mitigate against the unreliability of renewable energy sources (RES), and ESS operation and management has become one of the most important research topics. Since installing ESS for each user requires high investment cost, a study on *cloud* ESS gains attention recently. Cloud ESS refers to an ESS that is logically shared by multiple users as if they have their own ESS in their premises. In this paper, we propose a new cloud ESS sharing technique that allows capacity P2P transactions among users. Since cloud ESS is a virtual facility that is linked to an actual ESS, it is easy for users to sell the unused storage capacity to other users or to buy additional capacity from other users during operation. We also propose a system that encourages users to completely entrust the cloud ESS operator and share the extra benefit with the operator and other users. To verify the proposed method, we demonstrate the benefit of capacity P2P transaction based on real year-round data of users.

Keywords: energy storage system; cloud energy storage system; linear programming; peer-to-peer transaction; Nash bargaining; convex optimization

Citation: Sim, J.; Kim, M.; Kim, D.; Kim, H. Cloud Energy Storage System Operation with Capacity P2P Transaction. *Energies* **2021**, *14*, 339. https://doi.org/10.3390/en14020339

Received: 23 December 2020
Accepted: 7 January 2021
Published: 9 January 2021

1. Introduction

The role of energy storage system (ESS) in the future energy domain is crucial [1–3]. ESS consists of a lithium-ion battery for energy storing and a charging/discharging power electroinc device. From power generation perspective, renewable energy source (RES) is rapidly replacing conventional fossil fuel-based energy sources. Typical examples of RES are solar and wind generations, which are clean and sustainable but suffers from fluctuating generation. For example, solar power generation depends on the amount of sunlight, which varies according to time and weather conditions, and wind power generation is also highly volatile days and nights [4]. From another aspect, energy cost is the main concern of customers. Specifically, large industrial customers have huge electricity costs, so they actively seek a way to reduce electricity costs, and using ESS becomes promising by taking advantage of energy buffering [5–9]. The basic operation of ESS is to charge when the electricity price low and discharge when the electricity price is high [9]. Considering that electricity cost is highly dependent on the peak load, ESS can be also used to shave peak loads [5,8,9]. In doing this, the uncertainty of renewable generation and/or user loads should be taken into account. Specifically, to minimize the peak load under uncertainty, robust optimization has been studied [5]. Another approach is to compensate the load forecasting error by introducing a concept of marginal power using machine learning [8].

However, all of these studies assumed each customer has its own ESS in its premise, and recently, a concept of ESS sharing has been proposed. Tushar et al. proposed a system to mediate ESS transaction between residential customers and a shared facility operator [10]. Since each customer may not need to use its full storage all the time, the authors proposed

a sharing system based on Vickrey auction so that each user can sell its unused *physical* storage to a shared facility controller. The facility controller can leverage the physically distributed energy storage (DES) to manage the common facility of the residential community. Similarly, Cheng et al. proposed a *virtual* ESS that integrates small-scale DES and household refrigerators by considering thermal dynamics of refrigerators and flywheel-type ESS [11]. However, the main drawback of DES is high cost because each customer need to buy and install locally its own small scale ESS. Hence, economies of scale may not be possible.

By contrast, Liu et al. proposed a cloud energy storage system (CESS) where a central large-capacity ESS is shared by multiple customers [12,13]. The authors demonstrated the economic benefits of CESS from resource pooling, installation, maintenance and management perspectives [12]. The authors further considered the investment and operating decisions under imperfect load prediction [13]. Chen et al. proposed a model for selling CESS to customers where the price of using CESS is determined based on technical and economic data [14]; users submit their charging and discharging schedules to the operator, and the operator runs the ESS accordingly. The authors in [15] considered a business model, which allows the CESS operator interacts with customers to solve a two stage optimization problem; in the first stage the operator announces a storage rental price, and then, in the second stage, the customers submit their purchasing capacity and power scheduling. This process iterates until convergence. However, the work in [15] may not be commercially practical because rental price may change too frequently.

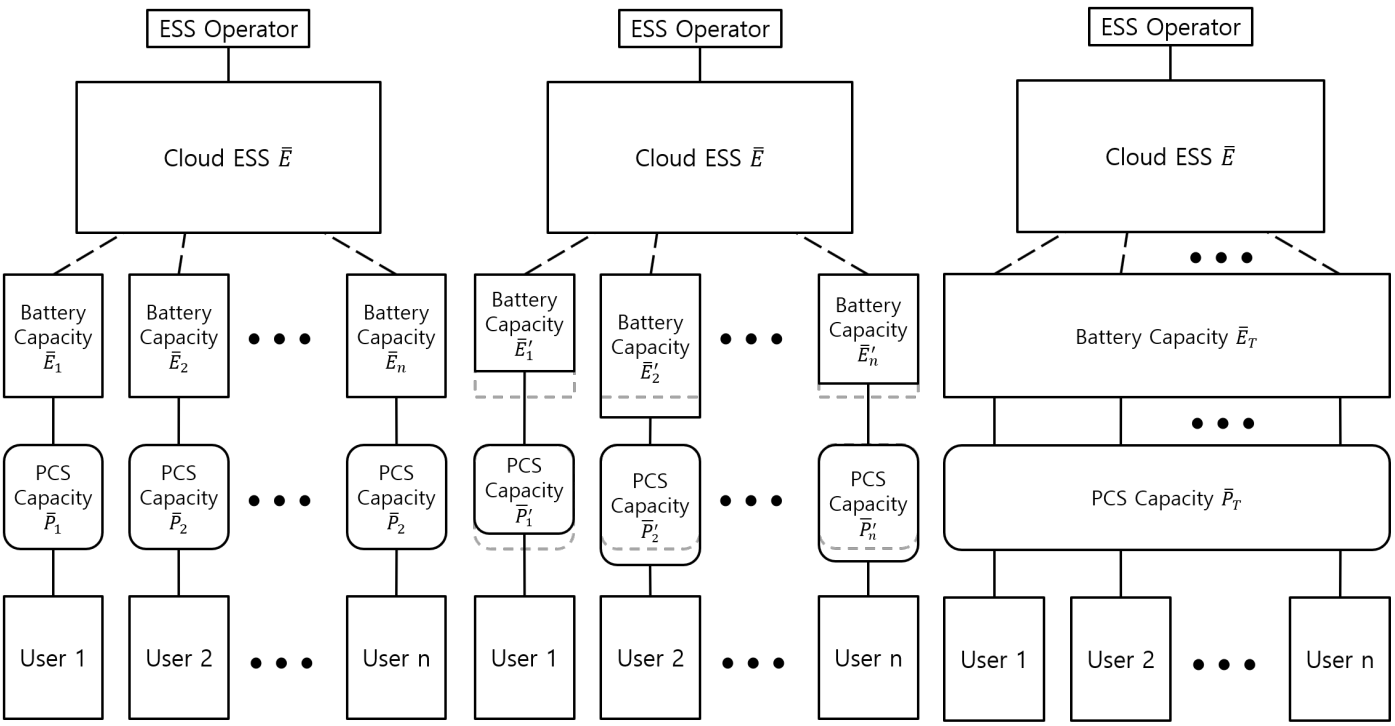
Considering that current cloud data storage services in the Internet have fixed prices with long-term contract periods, we expect the pricing of cloud energy storage would be similar from practical perspective. Hence, it is plausible that the contract period of using CESS is firmly determined by the operator such as yearly or monthly plan, and a long term contract would be cheaper but lack of flexibility than a short term contract. Hence, if there is an unexpected load change by installing new electric facilities, the customer may experience storage shortage. The opposite case, i.e., unused storage capacity may occur as well when manufacturing power consumption is reduced by the unexpected decrease of new product orders. Hence, even if a customer might think he/she rents an appropriate amount of capacity at first, it may not efficiently cope with unexpected power usage change. We mean by capacity the battery capacity (kWh) as well as power conversion system (PCS) capacity (kW). PCS is a power electronic device for charging and discharging the battery by converting power from AC to DC or from DC to AC, respectively. In this regard, we consider a novel CESS model that leverages *capacity* peer-to-peer (P2P) transaction so that customers are in the position of hedging their long-term contracts and load uncertainties. It can be also beneficial to the operator because it encourages storage purchase without concerning storage shortage or excessive buying.

The contributions of this paper is as follows. First, we propose a concept of capacity P2P transaction. Unlike the traditional P2P energy transaction, we consider the capacity P2P transaction where the unused battery capacity and PCS capacity can be exchanged among users to minimize the electricity cost. In capacity P2P transaction, the amount of capacity is determined from optimization, and the payment is determined by the generalized Nash bargaining. Second, we propose an integrated CESS operation where the operator can use the total capacity to reduce the total cost of all customers. This implies that the operator mediates the capacity P2P transaction more efficiently; customers entrust the operator and agree to pay an additional fee so that scheduling is solely determined by the operator as an auto scheduling. Finally, we provide case studies with realistic business models and pricing plans. Our experimental results show that capacity P2P transaction can be beneficial for both the operator and the customers.

2. System Model

In this section, we provide the system model. We consider three cases. Case 1 is using CESS with a fixed capacity for a certain period. In this case, each user selects and buys an appropriate price plan from the candidates proposed by the operator. This is similar

to the user's subscription of cloud data storage, e.g., Dropbox or iCloud, etc. In Case 2, capacity P2P transaction is allowed among users. In Case 3, the operator performs an integrated scheduling for charging and discharging of all users instead of distributing CESS capacity to users. Figure 1 shows the structure of CESS with n users and the operator for each case. Figure 1a shows the case when each user holds its own capacities of battery and PCS. Figure 1b shows that capacities are changed from Figure 1a due to capacity P2P transactions among users. Figure 1c shows that capacities of all users are integrated into one for resource pooling.



(**a**) Case 1 (fixed capacity) (**b**) Case 2 (capacity P2P transaction) (**c**) Case 3 (integrated scheduling)

Figure 1. CESS structures for each case.

3. Cloud Energy Storage Operations

3.1. Case 0: No ESS/CESS

Before describing Cases 1–3, we first consider the case when ESS is not present. Then, the user's electricity bill is determined by time of use (TOU) pricing and peak pricing. In the TOU pricing, the electricity price varies depending on the season and the time of day. In general, the price is cheap during low demand period and expensive during high demand period. Peak pricing is used to suppress peak load, which burdens power system facilities such as transmission lines and transformers. Peak pricing can be applied differently depending on the situations of countries. In Korea, for example, the peak pricing depends on the peak load of the month as well as the past peak loads of the previous 11 months. In this paper we consider the following formula for calculating the electricity bill using the TOU pricing and the peak pricing:

$$C_{0,i} = \left[\sum_{t \in \mathcal{M}} \mu_m(t) l_i(t) \Delta t \right] + \alpha \max \left(\max_{t \in \mathcal{M}} l_i(t), H_i \right) \tag{1}$$

where $\mathcal{M}$ is a set of time slots in month denoted by m, $\mu_m(t)$ is the TOU price for time slot t in month m, $l_i(t)$ is the load of user i for time slot t, α is the peak price coefficient, H_i is the peak load of the past 11 months prior to month m. Please note that H_i should be updated every month [5].

3.2. Case 1: Distributed CESS Operation without Capacity P2P Transaction (Baseline)

The user i determines its daily charging and discharging schedule within the purchased CESS capacity as follows.

Problem 1. *CESS charging/discharging optimization without capacity P2P transaction*

$$\text{minimize} \sum_{t \in \mathcal{D}} \mu_m(t)(l_i(t) + p_{c,i}(t) - p_{d,i}(t))\Delta t + \alpha_u \eta_i \tag{2}$$

$$\text{variables} \quad p_{c,i}(t), p_{d,i}(t), \eta_i$$

$$\text{subject to } l_i(t) + p_{c,i}(t) - p_{d,i}(t) \geq 0, \ t \in \mathcal{D}, \tag{3}$$

$$0 \leq p_{c,i}(t) \leq \bar{P}_i, \ t \in \mathcal{D}, \tag{4}$$

$$0 \leq p_{d,i}(t) \leq \bar{P}_i, \ t \in \mathcal{D}, \tag{5}$$

$$0 \leq E_i(t) \leq \bar{E}_i, \ t \in \mathcal{D}, \tag{6}$$

$$E_i(t+1) = E_i(t) + \left(u_c p_{c,i}(t) - \frac{1}{u_d} p_{d,i}(t) \right) \Delta t, \tag{7}$$

$$\sum_{t \in \mathcal{D}} \left(u_c p_{c,i} - \frac{1}{u_d} p_{d,i}(t) \right) \Delta t = 0, \tag{8}$$

$$\eta_i \geq l_i(t) + p_{c,i}(t) - p_{d,i}(t), \ t \in \mathcal{D}, \tag{9}$$

$$\eta_i \geq H_i. \tag{10}$$

As can be seen from (1), cost minimization is originally a min-max problem because of the peak load term. However, one can easily convert that into linear programming by introducing an auxiliary variable η_i [5], and thus (2)–(10) in Problem 1 is formulated as linear programming. In doing this, rather than considering monthly scheduling, we consider daily scheduling because load prediction is usually performed daily. We assume that load prediction is reasonably accurate [16,17] and beyond the scope of this paper.

The objective function in (2) is about the minimization of the electricity bill per day of the user i. Let $\mathcal{D}$ denote a set of time slots on the scheduling day. With the charging power $p_{c,i}(t)$ and the discharging power $p_{d,i}(t)$, the constraint (3) implies that power injection to the grid is not allowed, which is the current case in Korea. Charging/discharging power should satisfy the constraints of maximum purchased power $\bar{P}_i$ as in (4) and (5). The stored energy $E_i(t)$ cannot exceed the purchased CESS capacity $\bar{E}_i$ of user i as in (6), and $E_i(t+1)$ is determined from $E_i(t)$, $p_{c,i}(t)$, $p_{d,i}(t)$, the charging efficiency u_c, and the discharging efficiency u_d as in (7). Since scheduling is done daily, net energy transfer is zero during one day as in (8). The constraint (9) is used to formulate peak minimization in the form of linear programming; η_i plays a role of target peak load on the scheduling day. Please note that (10) is needed to account for the historical peak in the scheduling; only if $\eta_i \geq H_i$, we need to suppress the target peak load η_i in (1). Please note that H_i should be accordingly updated by the historical peak load up to the previous day. Finally, we use α_u instead of α to account for the daily peak cost. For example, if there are 30 days in the month of scheduling, $\alpha_u = \alpha/30$. In this way, peak load can be controlled to minimize the cost in the month [5].

Using the charging/discharging schedule and the last updated peak load obtained through the optimization process in (2), the monthly cost $C_{1,i}$ of the user i is calculated as in (11):

$$C_{1,i} = \sum_{t \in \mathcal{M}} \mu_m(t)(l_i(t) + p_{c,i}(t) - p_{d,i}(t))\Delta t + \alpha H_i + C_{R,i} \tag{11}$$

where $C_{R,i}$ is the CESS rental cost, which depends on the rental plan. Comparing (11) with (1) in Case 0, we see that charging/discharging schedules $p_{c,i}(t)$, $p_{d,i}(t)$ and ESS/CESS usage rates $C_{R,i}$ are added. As in (1), the last updated peak load H_i affects the cost calculation of the next month [5].

3.3. Case 2: Distributed CESS Operation with Capacity P2P Transaction

Users can buy additional capacity or sell the remaining capacity by leveraging capacity P2P transactions with other users if the purchased CESS capacity does not fit the expected power usage pattern. The capacity transaction among N users can be represented by the following matrix:

$$Q_E = \begin{bmatrix} q_{E,1,1} & q_{E,1,2} & \cdots & q_{E,1,N} \\ q_{E,2,1} & q_{E,2,2} & \cdots & q_{E,2,N} \\ \vdots & \vdots & \ddots & \vdots \\ q_{E,N,1} & q_{E,N,2} & \cdots & q_{E,N,N} \end{bmatrix} \tag{12}$$

where $q_{E,i,j}$ means the CESS *energy* capacity the user i buys from the user j in the unit of kWh. The amount the user i buys from the user j is equal to the amount the user j sells to the user i, so $q_{E,j,i} = -q_{E,i,j}$, and $q_{E,i,i} = 0$ because capacity transaction with oneself is of no use. Thus, $Q_E = [q_{E,i,j}]$ in (12) is a skew-symmetric matrix. Similarly, we consider $Q_P = [q_{P,i,j}]$ for the CESS *power* capacity transaction where $q_{P,i,j}$ is the PCS capacity the user i buys from the user j in the unit of kW.

Capacity P2P transaction is performed in two phases. In the first phase, the amount of capacity to be exchanged is computed as an optimization problem. In Case 1, there is no interaction among users, and optimization is performed separately per user. In Case 2, however, interactions among users are allowed through capacity P2P transaction, so the total cost minimization can be performed as follows.

Problem 2. *Total cost minimization by capacity P2P transaction*

$$\textit{minimize} \sum_{i \in \mathcal{N}} \left(\sum_{t \in \mathcal{D}} \mu_m(t)(l_i(t) + p_{c,i}(t) - p_{d,i}(t))\Delta t + \alpha_u \eta_i \right) \tag{13}$$

$$\textit{variables} \;\; p_{c,i}(t), p_{d,i}(t), \eta_i, q_{E,i,j}, q_{P,i,j}, \; i \in \mathcal{N}$$

$$\textit{subject to} \; q_{E,i} = \sum_{j \neq i} q_{E,i,j}, \; q_{P,i} = \sum_{j \neq i} q_{P,i,j} \tag{14}$$

$$\sum_{i \in \mathcal{N}} q_{E,i} = 0, \sum_{i \in \mathcal{N}} q_{P,i} = 0 \tag{15}$$

$$l_i(t) + p_{c,i}(t) - p_{d,i}(t) \geq 0, \; t \in \mathcal{D}, \; i \in \mathcal{N}, \tag{16}$$

$$0 \leq p_{c,i}(t) \leq \bar{P}_i + q_{P,i}, \; t \in \mathcal{D}, \; i \in \mathcal{N}, \tag{17}$$

$$0 \leq p_{d,i}(t) \leq \bar{P}_i + q_{P,i}, \; t \in \mathcal{D}, \; i \in \mathcal{N}, \tag{18}$$

$$0 \leq E_i(t) \leq \bar{E}_i + q_{E,i}, \; t \in \mathcal{D}, \; i \in \mathcal{N}, \tag{19}$$

$$E_i(t+1) = E_i(t) + \left(u_c p_{c,i}(t) - \frac{1}{u_d} p_{d,i}(t) \right) \Delta t, \; t \in \mathcal{D}, \; i \in \mathcal{N}, \tag{20}$$

$$\sum_{t \in \mathcal{D}} \left(u_c p_{c,i} - \frac{1}{u_d} p_{d,i}(t) \right) \Delta t = 0, \; i \in \mathcal{N}, \tag{21}$$

$$\eta_i \geq l_i(t) + p_{c,i}(t) - p_{d,i}(t), \; t \in \mathcal{D}, \; i \in \mathcal{N}, \tag{22}$$

$$\eta_i \geq H_i, \; i \in \mathcal{N} \tag{23}$$

Please note that Problem 2 differs from Problem 1 in that it employs capacity P2P transaction variables such as $q_{E,i,j}$ and $q_{P,i,j}$, with which the total cost minimization is performed first. In doing this $q_{E,i}$ and $q_{P,i}$ in (14) are related with the other constraints; since it is P2P transaction, the net exchanged amount should be zero as in (15). The purchased capacities affect the PCS capacity in (17), (18) and the battery capacity in (19).

In the second phase, P2P payment is determined by the generalized Nash bargaining considering the benefit of each user by participating in the capacity P2P transaction [18]. The generalized Nash bargaining is a cooperative game theory and provides a fair Pareto optimal solution that satisfies the four axioms: individual rationality, Pareto optimality,

independence of irrelevant alternatives, and independence of linear transformations [18]. The generalized Nash bargaining differs from the Nash bargaining by removing the axiom of symmetry, and thus can capture the scenario where players have different market powers. Problem 2 only minimizes the total cost of users but does not tell how to distribute the increased profit to users. Therefore, we need to solve the generalized Nash bargaining problem, which is a process to distribute profit to market participants in proportional to transaction volume of each user [18].

When the monthly fee $C^o_{2,i}$ of the user i is determined using the solution of Problem 2 as in (24):

$$C^o_{2,i} = \sum_{t \in \mathcal{M}} \mu_m(t)(l_i(t) + p_{c,i}(t) - p_{d,i}(t))\Delta t + \alpha H_i + C_{R,i} \tag{24}$$

the P2P payment is computed using the generalized Nash bargaining as follows.

Problem 3. *P2P payment by the generalized Nash bargaining*

$$\textit{maximize} \prod_{i \in \mathcal{N}} \left(C_{1,i} - \left(C^o_{2,i} + \pi_i\right)\right)^{a_i} \tag{25}$$

$$\textit{subject to} \;\; \pi_i = \sum_{j \neq i} \pi_{i,j}, \; i \in \mathcal{N}, \tag{26}$$

$$\sum_{i \in \mathcal{N}} \pi_i = 0 \tag{27}$$

In (25), $\pi_{i,j}$ is the payment from the user i to the user j, and π_i is the net payment of user i. The objective function in (25) is called Nash product, which is the product of profits of all users by participating in capacity P2P transaction. In this payment process, we include the market power denoted by a_i to capture the contribution of each user for capacity P2P transaction [18]. Problem 3 can be easily turned into a convex optimization problem by taking log of (25) as follows.

$$\text{maximize} \sum_{i \in \mathcal{N}} \log \left(C_{1,i} - (C^o_{2,i} + \pi_i)\right)^{a_i} \tag{28}$$

$$\text{subject to} \;\; \pi_i = \sum_{j \neq i} \pi_{i,j}, \; i \in \mathcal{N}, \tag{29}$$

$$\sum_{i \in \mathcal{N}} \pi_i = 0 \tag{30}$$

Please note that we focus on π_i, i.e., the net payment of user i instead of every P2P payment $\pi_{i,j}$ because it suffices from net payment perspective [18].

One can determine the market power of user i by the amount of energy capacity transaction as shown in (31).

$$a_i = \frac{\sum_{j \neq i} Q_{E,i,j}}{\sum_{i \in \mathcal{N}} \sum_{j \neq i} Q_{E,i,j}} \tag{31}$$

This makes sense because PCS capacity is usually proportional to the battery capacity in practice. In (31), $Q_{E,i,j}$ is the sum of absolute daily P2P transaction $|q_{E,i,j}|$ for 1 month, so a_i is the ratio of the total capacity transaction of user i over the total capacity transaction of all users. The reason for using market power is to balance the influence and rewards of participants in the market [18]. The payment is done using skew-symmetric matrix such as the capacity transaction, and the cost can be obtained by optimization in (28). Let $\pi_{2,i}$ denote the solution of (28). The monthly cost $C_{2,i}$ of the user i is finally calculated through the above process as follows. Then, after P2P payment, the cost of user i is

$$C_{2,i} = C^o_{2,i} + \pi_{2,i}. \tag{32}$$

3.4. Case 3: Integrated CESS Operation

In Cases 1 and 2, charging/discharging schedule proceeds within the CESS capacity each user buys, so cost reduction is limited within the capacity each user owns. On the other hand, in Case 3, users entrust the operator's scheduling. The operator who takes over CESS operation can use ESS by integrating CESS of all users to minimize the total electricity bill from resource pooling perspective. Hereby, the operator can use the CESS facility with maximum efficiency, and users can use capacities of CESS more flexibly. The optimization for scheduling charging and discharging and the payment are determined in two steps as follows.

Problem 4. *Entrusted CESS operation*

$$\begin{aligned}
&\textit{minimize} \sum_{i\in\mathcal{N}}\left(\sum_{t\in\mathcal{D}}\mu_m(t)(l_i(t)+p_{c,i}(t)-p_{d,i}(t))\Delta t+\alpha_u\eta_i\right) && (33)\\
&\textit{variables}\ \ p_{c,i}(t), p_{d,i}(t), \eta_i,\ i\in\mathcal{N}\\
&\textit{subject to}\ l_i(t)+p_{c,i}(t)-p_{d,i}(t)\geq 0,\ t\in\mathcal{D},\ i\in\mathcal{N}, && (34)\\
&\qquad 0\leq\sum_{i\in\mathcal{N}}p_{c,i}(t)\leq\bar{P}_T,\ t\in\mathcal{D},\ i\in\mathcal{N}, && (35)\\
&\qquad 0\leq\sum_{i\in\mathcal{N}}p_{d,i}(t)\leq\bar{P}_T,\ t\in\mathcal{D},\ i\in\mathcal{N}, && (36)\\
&\qquad 0\leq E(t)\leq\bar{E}_T,\ t\in\mathcal{D},\ i\in\mathcal{N}, && (37)\\
&\qquad E(t+1)=E(t)+\sum_{i\in\mathcal{N}}\left(u_c p_{c,i}(t)-\frac{1}{u_d}p_{d,i}(t)\right)\Delta t,\ t\in\mathcal{D}, && (38)\\
&\qquad \sum_{t\in\mathcal{D}}\left(u_c p_{c,i}-\frac{1}{u_d}p_{d,i}(t)\right)\Delta t=0,\ i\in\mathcal{N}, && (39)\\
&\qquad \eta_i\geq l_i(t)+p_{c,i}(t)-p_{d,i}(t),\ t\in\mathcal{D},\ i\in\mathcal{N}, && (40)\\
&\qquad \eta_i\geq H_i,\ i\in\mathcal{N} && (41)
\end{aligned}$$

The optimization in (33) differs from (2) and (13) by integrating charging/discharging schedule. This process also proceeds on a daily basis.

Then, the payment is determined after the calculation of the monthly fee as shown in (42).

$$C^o_{3,i}=\sum_{t\in\mathcal{M}}\mu_m(t)(l_i(t)+p_{c,i}(t)-p_{d,i}(t))\Delta t+\alpha H_i+C_{R,i} \tag{42}$$

In Cases 1 and 2, the users schedule charging/discharging themselves. In Case 3, however, the operator schedules charging/discharging of all users, and thus the operator claims an additional profit by reducing the social cost. The payment including the additional profit of the operator can be obtained by Nash bargaining as follows.

Problem 5. *Payment optimization for integrated CESS*

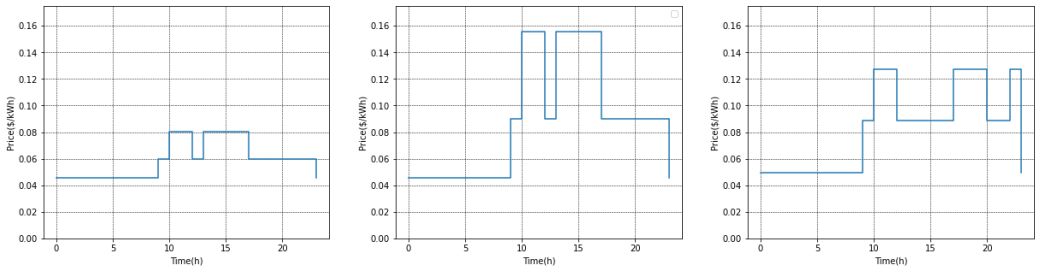
$$\begin{aligned}
&\textit{maximize} \prod_{i\in\mathcal{N}}\left(C_{2,i}-(C^o_{3,i}+\pi_i)\right)\times\sum_{i\in\mathcal{N}}\pi_i && (43)\\
&\textit{subject to}\ \sum_{i\in\mathcal{N}}\pi_i\geq 0 && (44)
\end{aligned}$$

Please note that the operator is included in the payment in the form of $\sum_{i\in\mathcal{N}}\pi_i$, which corresponds to the additional profit of the operator. Unlike (28) in Problem 3, $\sum_{i\in\mathcal{N}}\pi_i$ is not zero. Thus, it is not a simple capacity P2P transaction, and we use Nash bargaining. Problem 5 can be convexified by taking log of (43) Let the solution of (43) be $\pi_{3,i}$. Then, the final monthly cost is as follows.

$$C_{3,i} = C^{o}_{3,i} + \pi_{3,i} \tag{45}$$

4. Case Study

In this section, we show the results of the proposed models. The data used in the case study is the load profile of industrial users provided by Korea Electronic Power Corporation (KEPCO). The power unit is kW, and the time unit is 1 h. The TOU price is as shown in Figure 2, and the peak price is 8.32 $/kW per month. The charging/discharging efficiency of CESS is 90%.



(**a**) TOU for spring and fall (**b**) TOU for the summer (**c**) TOU for the winter

Figure 2. TOU pricing system for each season.

4.1. CESS Business Model

A proper business model is needed to benefit both users and the operator. A business model with various products can give users a wide range of choices and profit the operator by attracting more users. CESS is to profit users by reducing electricity bill, so it is important to induce users to buy large capacity for a long period. In general, the larger the sales volume or the longer the contract period is, the cheaper the unit cost is. This is also the case of cloud data storage. In the case of capacity P2P transaction, users can have additional profits by signing a long-term contract and trading the unused capacity through capacity P2P transactions.

An example of CESS business model is shown in Table 1. The considered CESS usage standard fee is $1.25/kWh per month, which is calculated based on the cost $150/kWh of ESS with 10 year lifetime; the ESS cost is based on the market analysis where the battery cost has decreased from $1160/kWh to $176/kWh [19].

Table 1. An example of CESS price plans.

Contract	50 kWh	100 kWh	500 kWh	1 MWh
1 year	(1) $2250	(2) $3900	(3) $16,500	(4) $30,000
3 months	(5) $675	(6) $1170	(7) $4950	(8) $9000
Integration	(9) base+extra (distribution payment)			

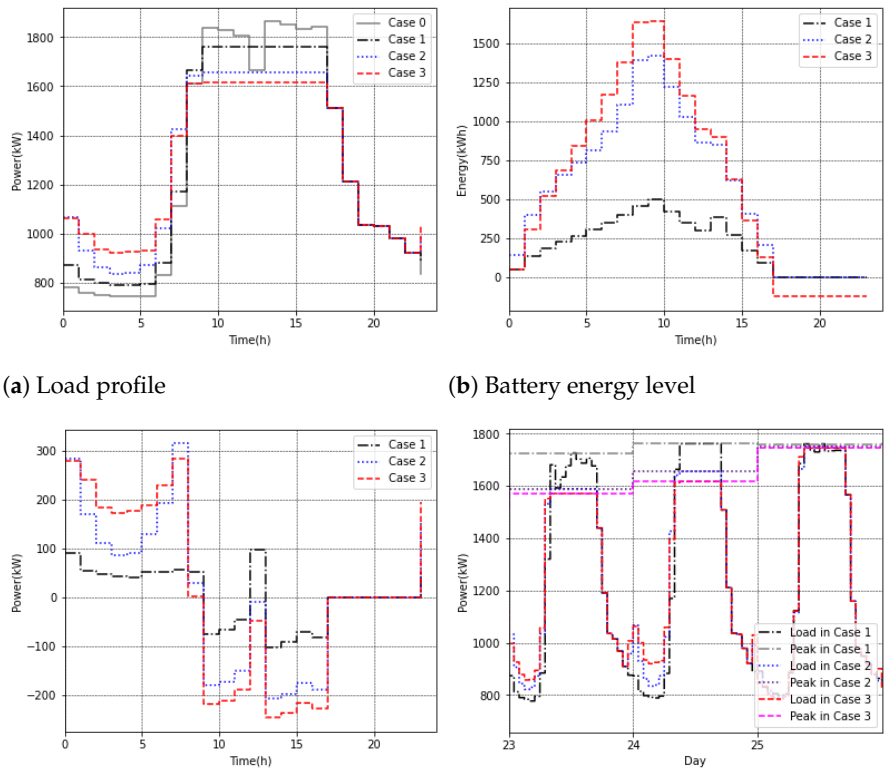
In this model, one-year contract with 1 MWh has the unit cost as twice as the CESS usage standard fee under the assumption that the half of the ESS capacity is sold, and considered it as the base cost of the business model. For the capacity of 500 kWh, 100 kWh, and 50 kWh, 10%, 30%, and 50% of the base cost are additionally charged, respectively. For the contract period of 3 months, 20% of the base cost is additionally charged. Please note that Table 1 is an example, and the commercial business plan may be determined differently. In Case 1, users can select one plan from the above models. In Case 2, one can make capacity P2P transaction with other users when the purchased capacity is excess or in short for some period. In Case 3, since the operator integrates ESS capacity, an operational fee is charged. The simulation setup in terms of average power per year, power usage variation and the selected plan for each user is summarized in Table 2.

Table 2. Average and standard deviation power per year and the selected plan of each user.

User Data	User 1	User 2	User 3	User 4
Average power per year (kW)	954	2882	1230	1193
Standard deviation of power per year (kW)	303	1547	399	386
Selected plan	(3)	(4)	(3)	(3)

4.2. CESS Operation Results

Figures 3–6 show load profiles, battery energy levels, charging/discharging scheduling, and peak load updates of each user on 24 July as an example.

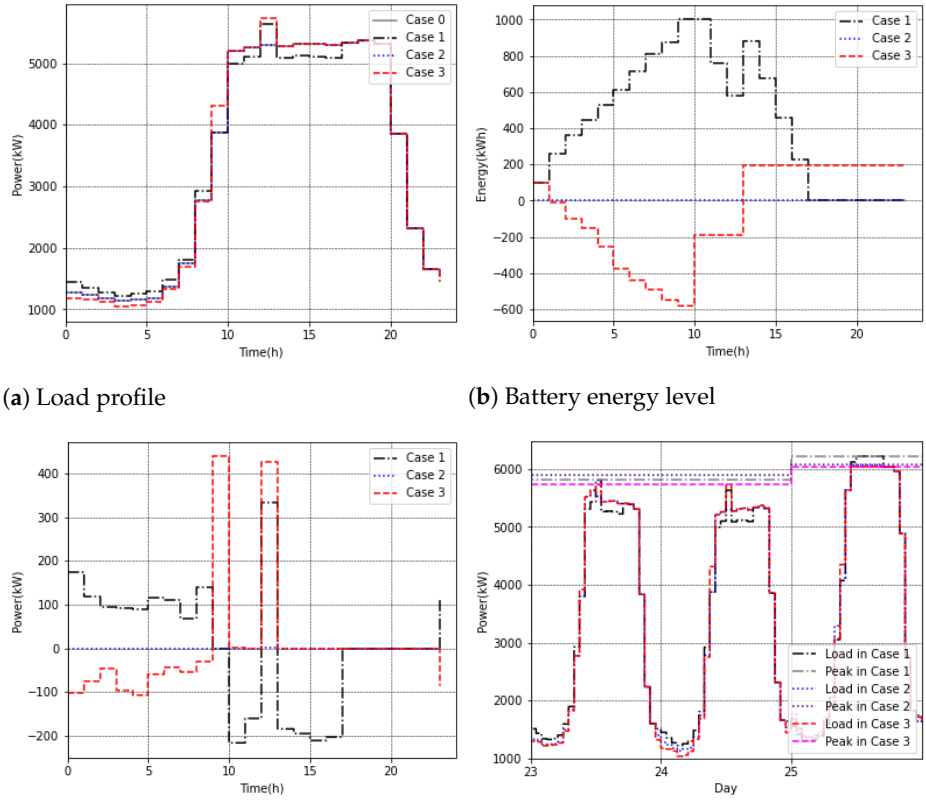


(**a**) Load profile (**b**) Battery energy level

(**c**) Charging schedule (**d**) Peak update

Figure 3. Results of user 1 in each case.

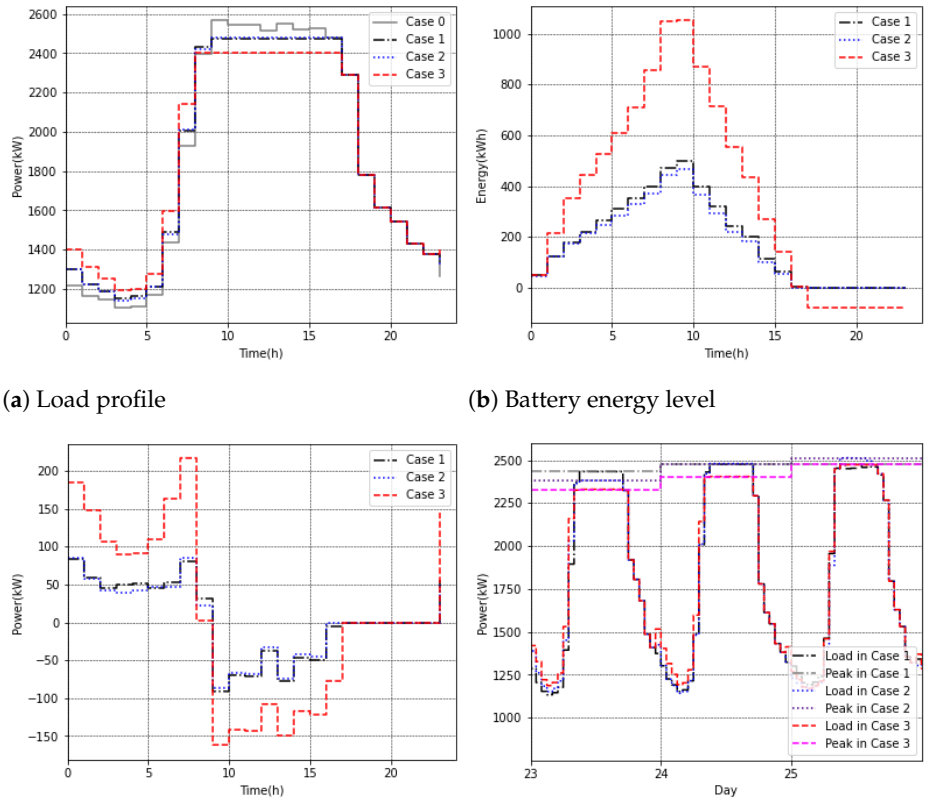
Figure 3 shows the results of user 1 for each case. The load profile of Case 1 is clearly distinct from that of Case 0; it has a pattern rising a little by charging after midnight, keeping a constant load from 9 AM to 5 PM. The change of load profiles comes from the TOU price fluctuation. In Case 1, user 1 discharges power from 9 AM to 12 PM when TOU is high, charges when TOU is temporarily low around noon, and discharges again until 5 PM. Battery energy level and charging/discharging scheduling of Case 1 also vary in accordance with the TOU price. Interestingly, Figure 3b implies that user 1 buys additional capacity from others to reduce the peak load; we see that the energy level of Case 2 and Case 3 are increased. Figure 3d explains why this happens. It shows the load profiles before and after the day of interest, i.e., 24 July; since the peak load of the 24th is higher than that of the 23rd, user 1 need to have more battery capacity to suppress the peak load.



(**a**) Load profile (**b**) Battery energy level

(**c**) Charging schedule (**d**) Peak update

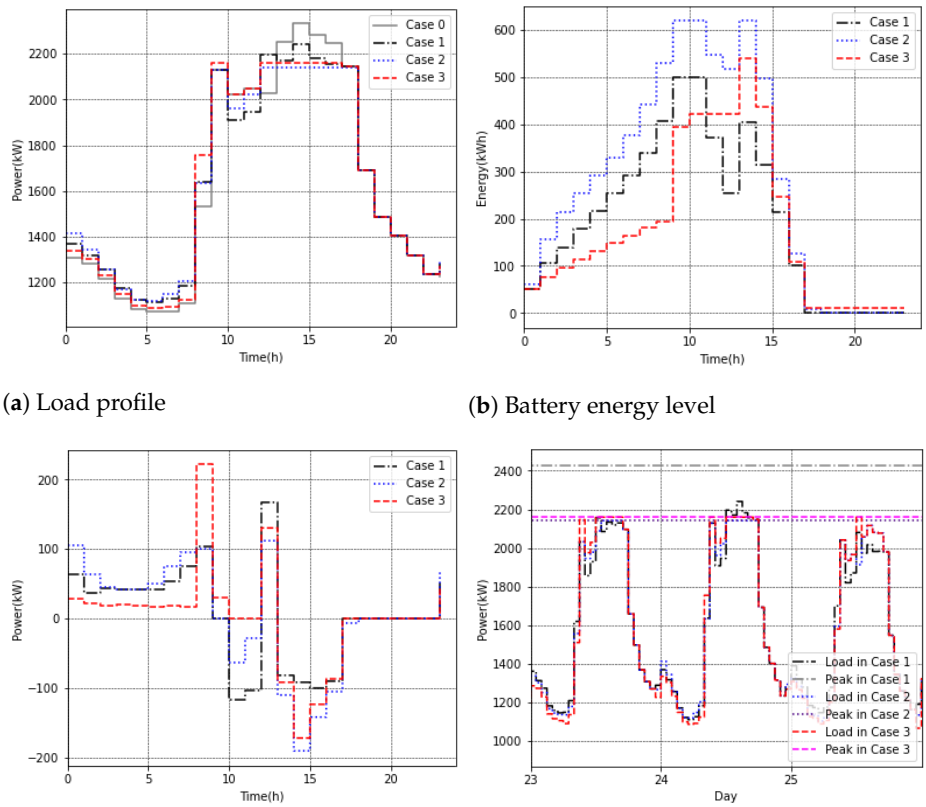
Figure 4. Results of user 2 in each case.



(**a**) Load profile (**b**) Battery energy level

(**c**) Charging schedule (**d**) Peak update

Figure 5. Results of user 3 in each case.



(**a**) Load profile (**b**) Battery energy level

(**c**) Charging schedule (**d**) Peak update

Figure 6. Results of user 4 in each case.

Figure 4 shows the results of user 2 for each case. We observe two interesting things here. As can be seen in Figure 4b, user 2 sells all of its battery capacity in Case 2. This is mainly because the peak load of the previous day is already high, so user 2 does not need to reduce the peak load on the 24th. Instead, user 2 decides to sell its battery capacity to others. Furthermore, in Case 3, the energy level of user 2 becomes temporarily negative. This can happen because each user does not have battery capacity constraint, but only the collective usage of all users need to satisfy the total battery constraint.

Figure 5 shows the results of user 3 for each case. As can be seen, the battery energy level of Case 3 is quite different from those of Case 1 and Case 2, which shows the importance of integrated scheduling. As can be seen in Figure 5d, the peak load on the 24th is increased from that of the 23rd. Hence, user 3 need to suppress it as much as possible by leveraging capacity P2P transaction. In addition, capacity transaction of Cases 2 and 3 is opposite, which can happen because of relaxing the individual capacity constraints. Finally, Figure 6 shows the results of user 4 for each case. In overall, using CESS are all beneficial, and Cases 1, 2 and 3 exhibit similar results.

Finally, Table 3 shows the yearly costs of all users, operator profit, social cost and social benefit. It can be seen that all cases with CESS operation reduce costs compared to Case 0. Furthermore, the costs are reduced from Case 1 to Case 3 for each user. The operator also has profit by selling the CESS and/or collecting fee for integrated operation. Social cost is the sum of all users' cost minus the operator's profit. Please note that the operator's profit in Case 3 is increased from Case 1 or Case 2 because it collects the additional fee $\sum_{i \in \mathcal{N}} \pi_i$. Social benefit is the amount of reduced cost from Case 0.

Table 3. Yearly costs of users, profit of the operator, social costs and social benefits for each case.

Unit: $	User 1	User 2	User 3	User 4	Operator Profit	Social Cost	Social Benefit
Case 0	828,908	2,676,769	1,065,879	1,059,694	-	5,631,249	-
Case 1	820,223	2,662,954	1,061,921	1,049,258	42,000	5,552,358	78,891
Case 2	812,529	2,648,494	1,053,724	1,040,944	42,000	5,513,691	117,558
Case 3	809,625	2,645,590	1,050,850	1,038,045	44,900	5,499,210	132,039

5. Conclusions

In this paper, we proposed a new concept of capacity P2P transaction in CESS to minimize the electricity cost; unlike the conventional P2P transaction where energy is traded, we considered the P2P transaction of cloud energy storage *capacity*. Hence, if a user needs more cloud energy storage capacity, it can buy from others who are willing to sell it (Case 2). We also proposed a more flexible operation of CESS by entrusting the operator and paying an additional fee for collective operation (Case 3). The proposed methods consist of two steps: cost minimization by convex optimization and payment settlement by Nash bargaining. Based on the year-round real data of commercial and industrial customers, we verified that two proposed methods reduce the electricity cost compared to the baseline (Case 1) where capacity P2P transaction is not allowed. Hence, allowing capacity P2P transaction is beneficial both to the customers and the CESS operator by reducing the total cost and increasing the social benefit.

Author Contributions: J.S. designed the algorithm, performed the simulations, and prepared the manuscript as the first author. M.K. validated the algorithm. D.K. provided data for the simulation and validated the algorithm. H.K. led the entire project and research. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Smart City R&D project of the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport under Grant 19NSPS-B152996-02.

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

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