Pricing-based shared energy storage optimization for residential users with photovoltaic generation system and demand-side load management

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***Abstract*—In this paper, we investigate a problem of optimal capacities of energy storage system for the residential users and an optimal unit price energy storage system for an aggregator. We suppose that the residential users have own photovoltaic generation system and a smart meter which can schedule activation of home appliances and controls. The aggregator participates in energy market to maximize his profit by selling the storage to the residential users. Each user determines his energy consumption schedule and a required amount of storage to minimize his energy cost depending on the unit price of energy storage, price profile of electricity from the main grid and his renewable power generation capacity. We consider electricity bill from main grid and storage bill from the aggregator as users' energy cost. We formulate a problem for the aggregator to decide an optimal unit price of energy storage and a problem for each user to decide energy consumption schedule and a required amount of storage capacity. With numerical investigation, it is shown that the energy storage can reduce the energy load to main grid and shave peak power. As a result, by purchasing energy storage, users can save their energy cost by 43% in average compared to the case without energy storage.**

***Index Terms*—Energy storage system, residential photovolatic generation, home load management, aggregator, smart grids**

I. Introduction

In power markets, renewables have become the technology of choice, making up almost two-thirds of global capacity additions to 2040, thanks to falling costs and supportive government policies [1]. However, technical limitations in transmission and distribution networks, the variability of renewable power sources, people's behaviors, and energy consumption patterns have made it difficult to integrate and accommodate these sources. The integration of storage technologies has emerged as an option to expedite energy consumption from renewable sources by increasing the flexibility of the power system [2]. Energy storage can store energy when there is less demand and release the stored energy back to the system during peak periods [3].

Energy storage systems (ESSs) are especially desirable at the residential level and the adoption of the household energy storage system is expected to increase rapidly in the coming years [4]. However, considering their high acquisition, operation, and maintenance costs, isolated deployment of ESSs is not economically viable [5]. Since the idea of a shared ESS among users and network operator has been introduced in [3], the energy management problem for users with shared ESSs has been studied in the literature [3],[5]-[6].

In [7], they solved the cost minimization problem for energy consumers with demand response capability with no renewable energy integration. The self-interested users are willing to sell/buy energy to/from the shared ESS if they can achieve lower energy costs compared to the case of no energy trading while preserving their privacy in [8][9]. They proposed an iterative algorithm by which the central controller coordinates the charging/discharging values to/from the shared ESS by all users such that their individual energy costs reduce at the same time. A heuristic algorithm for optimizing the electricity cost by using the concept of load shifting and renewable power sharing among houses in the microgrid for a particular price was proposed in [6]. In [5], they have developed a stochastic analytical framework to provision a sharing-based energy storage units and shown that ESS at residential level is economically beneficial if employed in a sharing-based architecture. However, the previous works in [8]-[6] assume that the capacity of storage is assumed to be given and fixed.

ESS sizing has received some attention in the literature [5], [10]-[11]. Majority of the existing literature focus on energy storage sizing for isolated deployment of ESSs. In [5], they propose a sharing-based ESS architecture and the optimal size of ESSs is analyzed. But, the analysis in [5] do not consider renewable energy generation at each user site. In [12], we investigated an optimal capacity of shared ESS for cooperative residential users with individual photovoltaic generation system. In [13], they investigate the problem of finding optimal capacities of PV and ESS in the context of home load management in smart grids. However they assume that a user installs an individual ESS as well as PVS. In [11], they proposed a pricing-based virtual storage sharing scheme among a group of users and developed a business model that an aggregator owns and operates a central physical

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storage unit, then virtualizes the storage into separable virtual storage capacities and sells them to different users. They demonstrated that virtualization of storage will lead to more efficient use of the physical storage capacity, compared with the case where each user acquires his own physical storage. They did not take into account renewable energy sources at individual household users and assumed the original load is fixed and there is no demand response. However, users with renewable energy generation facilities will need storage and storage accompanying with demand response effects on peak shaving.

In this paper, we investigate a problem of optimal capacities of energy storage system and its optimal price for residential users who have own photovoltaic generation system and a smart meter which can schedule activation of home appliances and controls. We consider an important player, so called *aggregater*, who owns and operates an energy storage system. The aggregator virtualizes the storage into separable virtual storage capacities and sells them to different users. The aggregator decides an unit price of storage to maximize her profit. Depending on the unit price of energy storage, price profile of electricity from the main grid and his renewable power generation capacity, each user determines his energy consumption schedule and a required amount of storage capacity to minimize his energy cost (including electricity bill from main grid and storage bill from the aggregator), and purchase the amount of storage capacity from the aggregator. A user charges the remaining energy of the electric energy generated in its photovoltaic system and discharges his storage to satisfy demand. Also we consider that users have a smart meter which can schedule activation of home appliances and controls, residential energy generation and storage system. We formulate a problem for the aggregator to decide an optimal unit price of energy storage and a problem for each user to decide energy consumption schedule and a required amount of storage. With numerical investigation, it is shown that the energy storage can reduce the energy load to main grid and shave peak power and thus users' energy cost.

The rest of this paper is organized as follows. Section II introduces our system model including PV generation, energy storage system and residential load control model. In Section III, the problems are formulated for users and for the aggregator. Section IV provides some numerical results, which include optimal unit price of storage, users' load profile, peak load, and finally energy cost with compared with the case of which ESS is not installed. Section V concludes this paper.

II. System model

We consider a set of $N > 1$ users. Users are all connected to the main grid, which consists of conventional fossil fuel based energy generation units. We assume that each user has its own solar photovoltaic generators supplying a part or all of their loads over time. We consider that an aggregator owns and operates the central storage. The aggregator sells a storage to users. Users purchase the capacity to store energy when there is less demand and release the stored energy back to the system during their peak load. By purchasing the storage system from the aggregator, a user can charge the remaining quantity of the electric energy generated in its photovoltaic system and discharge his storage to satisfy his demand and thus reduce his peak as well as total consumption of the electricity bill.

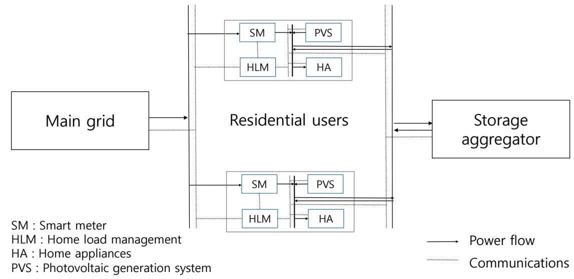

Fig. 1. System structure.

We assume an operation horizon by $\mathcal{H} \triangleq \{1, 2, \ldots, H\}$. At the beginning of each operation horizon, the aggregator determines the unit price q^{es} of storage capacity for this horizon and announces it to users. Each user $n \in \mathcal{N}$ decides the storage capacity for the next operation horizon and storage schedule for each time slot h, reports them to the aggregator [11]. And we assume that each user is equipped with a smart meter that has a home load management capability for scheduling the household energy consumption as well as photovolatic generation system (PVS) and energy storage system (ESS). The energy generated in PVS (located at user n's home) at hour h can be immediately used for the user at that time or be stored in the storage (purchased from the aggregator).

A. Photovoltaic generation model

We assume that the amount of electricity a solar panel produces is upper-bounded by the area of solar panels. Photovoltaic energy generation profiled, denoted by $g_n[h]$ is

$$g_n[h] \leq \kappa_n[h]\bar{c}_n^{pv}, \tag{1}$$

where $\bar{c}_n^{pv}$ is solar panels' power capacity of user n and $\kappa_n[h](> 0)$ is an hourly power production efficiency of PVS. $\kappa_n[h]$ is forecasted and given to the system, which mainly depends on the availability of the solar radiation that is a function of sky clearness index.

B. Energy storage model

Let a stock variable $s_n[h]$ be per-slot energy storage profile measured at the end of time slot h. Two flow variables $s_n^c[h]$ and $s_n^d[h]$ denote per-slot energy charging and discharging profile of user n at hour h, respectively. Then

$$s_n[h] = \beta s_n[h-1] + s_n^c[h] - s_n^d[h], \quad \text{for } h > 1, \tag{2}$$

where $0 \leq \beta \leq 1$ is a leakage rate that represents the decrease in the energy level with the passage of time. We assume that

$$s_n^c[h] \leq \delta_c \left(g_n[h] - g_n^u[h]\right), \tag{3}$$
$$s_n^d[h] \leq s_n[h-1], \quad \text{for } h > 1, \tag{4}$$

where $g_n^u[h]$ denotes energy generated by PV at hour h and immediately used at that time slot in user n. To complete the equation in (2), we define an auxiliary variable $s[0]$ to represent an initial state of energy storage. We assume that $s[0] = s[H]$, which is, to ensure that the storage keeps a desired level of charge at the end of time horizon of analysis and to prevent any type of free leakage from or free influx into energy storage. Furthermore, the storage capacity purchased by user n, denoted by c_n^{es} is depending on user n's charge and discharge decision and the energy level. c_n^{es} can be determined by the following constraint.

$$s_n[h] \leq c_n^{es}. \tag{5}$$

There are some energy losses during the charging and discharging processes of the energy storage in practice, which are specified by charging and discharging efficiency parameters, denoted by $0 < \delta_c < 1$ and $0 < \delta_d < 1$, respectively.

C. Residential load control

We assume that the energy consumption by home appliances $a \in \mathcal{A}_n$ per time unit for user n is controlled by home load management (HLM), denoted by $\{x_n^a[h]\}$. For each user n, let $\mathcal{A}_n$ denote a set of household appliances. $x_n^a[h]$ can be determined depending on the appliance's energy consumption pattern. We consider three types of the appliances according to energy consumption pattern: non-shiftable, power-shiftable and time-shiftable [13]. Non-shiftable appliances such as heaters consume a fixed amount of energy ζ_n^a during a fixed operation period. The consumption requirement by non-shiftable appliances can be written as

$$x_n^a[h] = \begin{cases} \zeta_n^a, & \text{if } h \in \{h_n^{as}, \cdots, h_n^{af}\}. \\ 0, & \text{elsewhere.} \end{cases} \tag{6}$$

For power-shiftable appliances such as electric vehicles, the smart meter will schedule flexible power. They have a standby (lower) power(η^{al}) and a maximum working power (η^{am}). Thus, the the scheduling is constrained by

$$\eta^{al} \leq x_n^a[h] \leq \eta^{am}. \tag{7}$$

For a time-shiftable case, the smart meter is able to control the switch of electricity supply corresponding to the energy consumption pattern during the scheduled period. Suppose that appliance $a \in A_n$ has a fixed energy consumption $[p_n^a[1], \cdots, p_n^a[H]]$. The schedule result $\left[x_n^a[1], \cdots, x_n^a[H]\right] \triangleq \mathbf{x}_n^a$ has to be exactly the same as one of the cyclic shifts. We define a matrix form $\mathbf{P}_n^a$ as

$$\mathbf{P}_n^a = \begin{bmatrix} p_n^{a,1} & p_n^{a,2} & \cdots & p_n^{a,23} & p_n^{a,24} \\ p_n^{a,24} & p_n^{a,1} & \cdots & p_n^{a,22} & p_n^{a,23} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_n^{a,2} & p_n^{a,3} & \cdots & p_n^{a,24} & p_n^{a,1} \end{bmatrix}, \tag{8}$$

where superscript h in an element $p_n^{a,h}$ denotes the starting time of shift. The switch control for the time-shiftable appliance can be represented by a binary integer vector $\mathbf{u}_n^a = [u_n^a[1], \cdots, u_n^a[H]]$. Time-shiftable appliances are assumed not to be allowed to stop once they start and the constraint can be written as

$$\sum_{h \in \mathcal{H}} u_n^{a,h} = 1. \tag{9}$$

We can write the schedule plan for time-shiftable appliances as

$$\mathbf{x}_n^a = \mathbf{P}_n^a \mathbf{u}_n^a. \tag{10}$$

Notice that (11) is applicable for time-shitable but non-power shitable scheduling. For a time-shitable and power-shiftable (e.g. electric vehicles), (11) can be modified to describe flexible energy consumption as follow:

$$\mathbf{P}_n^{al} \mathbf{u}_n^a \leq \mathbf{x}_n^a \leq \mathbf{P}_n^{am} \mathbf{u}_n^a, \tag{11}$$

where $boldP_n^{al}$ and $\mathbf{P}_n^{am}$ denotes the lower and the upper bound matrix of energy consumption, respectively. Each element of $\mathbf{P}_n^{al}$ and $\mathbf{P}_n^{am}$ is filled with η^{al} and η^{am}.

For each appliance, daily requirement E_n^a should be met by its total daily energy consumption

$$\sum_{h \in \mathcal{H}} x_n^a[h] \geq E_n^a. \tag{12}$$

Finally, the energy requirement can be met by supplying from main grid, PV generation and the storage. Let $l_n[h]$ denote energy load profile by user n at hour h. Then the total load needed by user n is constrained by

$$l_n[h] + g_n^u[h] + \delta_d s_n^d[h] \geq x_n^a[h] + l_n^c[h]. \tag{13}$$

where $g_n^u[h]$ is energy generated by PV at hour h and immediately used at that time slot by user n and $s_n^d[h]$ is energy discharged from the energy storage for user n at hour h. δ_d represents discharging efficiency ($0 \leq \delta_d \leq 1$). Notice that $l_n[h]$ is energy purchased from the main grid with a priori known prices.

III. Problem Formulation

A. User n's optimization problem

Given the storage unit price q^{es} determined by the aggregator, each user n decides the optimal storage schedule $s_n^c[h]$ and $s_n^d[h]$ in time slot h and the optimal capacity c_n^{es} to minimize his cost. User n's cost consists of two parts, one is the storage payment $q^{es} c_n^{es}$ to aggregator and the other is the electricity bill to the grid operator. If user n's electricity consumption from the main grid is $l_n[h]$ in time slot $h \in \mathcal{H}$, user n's electricity bill in $\mathcal{H}$ is :

$$\sum_{h \in \mathcal{H}} \rho[h] l_n[h] + \rho^{peak} \max_{h \in \mathcal{H}} \{l_n[h]\}, \tag{14}$$

where $\rho[h]$ is the unit price for energy consumption in time slot h, and ρ^{peak} is the unit price for the peak power consumption per slot in a billing cycle. To reduce the system peak, the utility company usually sets ρ^{peak} much higher than $\rho[h]$ [11]. Based on the demand charge tariff, there is a clear incentive for a user to shave the peak load.

User n's optimization problem P-U$_n$:

$$\min \quad q^{es}c_n^{es} + \sum_{h\in\mathcal{H}} \rho(h)l_n[h] + \rho^{peak} \max_{h\in\mathcal{H}} \{l_n[h]\} \quad (15)$$

$$\text{subject to} \quad (1)-(7) \text{ and } (9)-(13), \quad (16)$$

$$\text{all variables are nonnegative}, \quad (17)$$

$$u_n^a[h] = 0 \text{ or } 1. \quad (18)$$

In problem P-U$_n$, the unit price q^{es} is assumed to be fixed in the stage of solving this problem. We denote the optimal solutions to problem P-U$_n$ as $l_n{}^*[h]$, $s_n^c[h]^*(q)$, $s_n^d[h]^*(q)$ and $c_n^{es*}(q)$.

The aggregator determines the storage unit price q^{es} to maximize her profit. The aggregator is paid the total amount of $q^{es} \sum_{n\in\mathcal{N}} c_n^{es*}(q)$. We consider the degradation cost of storage. Repeated charging and discharging cause degradation of the energy storage devices [14]. We adopt the linear operation cost model in the literature [11]-[15].

$$\text{COST}(q^{es}) = q^{op} \sum_{n\in\mathcal{N}} \sum_{h\in\mathcal{H}} \left(s_n^c[h]^*(q^{es}) + s_n^d[h]^*(q^{es}) \right), \quad (19)$$

where q^{op} is the unit cost of charge and discharge amount and $s_n^c[h]^*(q)$ and $s_n^d[h]^*(q)$ are optimal decisions of user n by solving problem P-U$_n$. We formulates aggregator's optimization problem as follows :

Aggregator's optimization problem P-A:

$$\max_{q^{es}>0} \quad \pi = q^{es} \sum_{n\in\mathcal{N}} c_n^{es*}(q) - \text{COST}(q^{es})). \quad (20)$$

IV. Numerical Results

In the simulation, we consider one day as the operation horizon, which is equally divided into $H = 24$ time slots. We consider a system with nine users. We have designated that the amount of electricity requirement and owned PV capacity are different according to the users. Specifically, the first three users (user1$\sim$user3) are modelled as consumers with large power consumption, the next three users (user4$\sim$user6) as with medium power consumption, and the last three users (user7$\sim$user9) as with the smallest consumption. We use appliances and power consumption patterns from [13] (Table 4 therein). We assume that the installed capacity of PV of each user is 5 kW for large power consumption users (user1$\sim$user3), and 3 kW for the others (user4$\sim$user9), respectively. We use hourly production efficiency $\kappa_n[h]$ in PVS in [12] and [13]. Profile of solar energy for each user is shown in Fig. 2. The electricity prices over the period of planning are shown in Table I. The peak demand charge per month is $\rho^{peak} = 1\$/kW$. We set the operation cost $q^{op} = 1$ cents/kWh [11]. We assume that $\beta = 1$, $\delta_c = \delta_d = 0.95$ for ESS parameters. For performance benchmark, we consider the case where users do not purchase ESS from aggregator (labeled as 'w/o ESS' in the figures). The simulation has been carried out using CPLEX 12.6.3.0 in GAMS 24.7.4.

TABLE I
THE PRICE OF ELECTRICITY (CENTS/KWH).

hour (h)	1$\sim$4	5	6$\sim$7	8$\sim$20	21	22$\sim$24
price ($\rho[h]$)	7.5	8.6	9.8	10.6	10.8	9.8

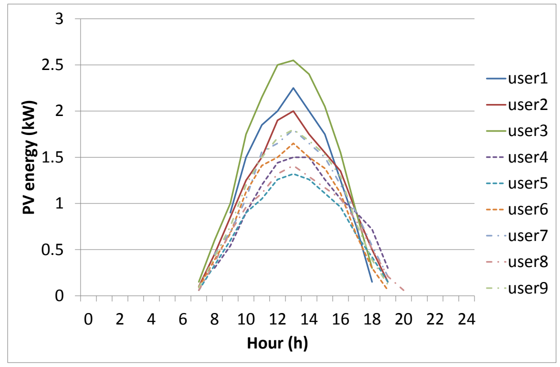

Fig. 2. Hourly capacity factor of PV generation.

Fig. 3 shows the aggregator's profit with respect to storage unit price q^{es}. It is observed that the aggregator's profit is not monotone in storage price. In our numerical example, the aggregator's profit is maximum when the price is about 14 cents/kWh.

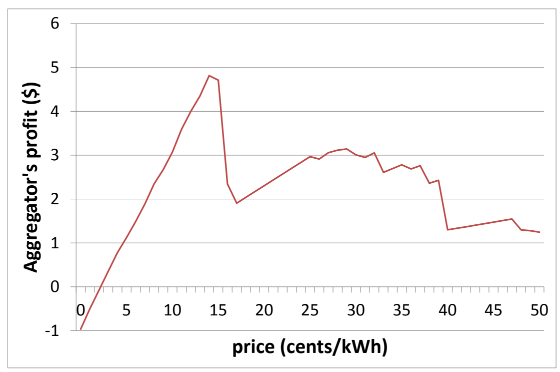

Fig. 3. Aggregator's profit.

TABLE II
OPTIMAL STORAGE CAPACITIES. (KWH)

user1	user2	user3	user4	user5	user6	user7	user8	user9
8.89	4.00	6.49	5.78	1.60	4.86	6.38	1.73	0.97

Fig. 4-6 and Table II show the users' results of the storage price of 14 cents/kWh. Table II shows the optimal capacities of storage for each user. Fig. 4 represents the sum of the electricity drawn from the main grid for all users. For the case of 'w/o ESS', it demands a lot of energy during the night time (when photovoltaic systems cannot generate the electricity) compared to the daytime. It is observed that the energy demand of the case of 'ESS purchase' is almost smoothed over the day. This is because the surplus energy made in the photovoltaic system can be charged in storage and utilized it later. The peak power for the case of 'ESS purchase' is 0.68 kW while the peak power for the case of 'w/o ESS' is 6.68 kW. In Fig. 5,

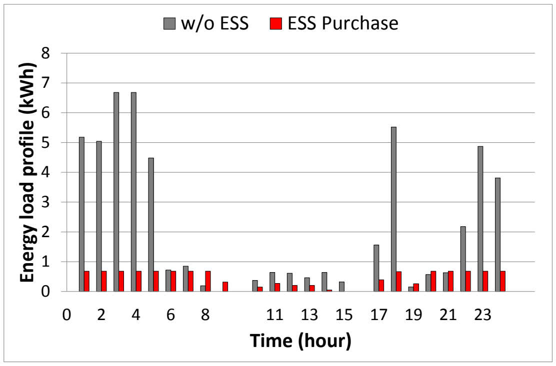

Fig. 4. Users' energy load profile.

we can see that the peak power of each user can be shaved dramatically by utilizing the energy storage system. It is noted that user3, and user6∼user9 satisfy all their energy demands with their own power generation and they are not in demand for electricity from the main grid. Fig. 6 shows the energy

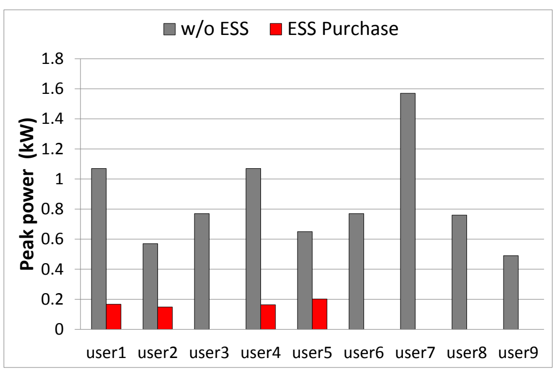

Fig. 5. Peak Power.

cost of users. All users can reduce their cost by storing the remaining PV energy during the day and by using at night. In Fig. 6, the energy cost of users reduce to $17 \sim 78\%$ (43% in average) by purchasing the storage.

V. Conclusions

In this paper, we studied a problem of optimal capacities of energy storage system and its optimal price for residential users who have own photovoltaic generation system and a smart meter which can schedule activation of home appliances

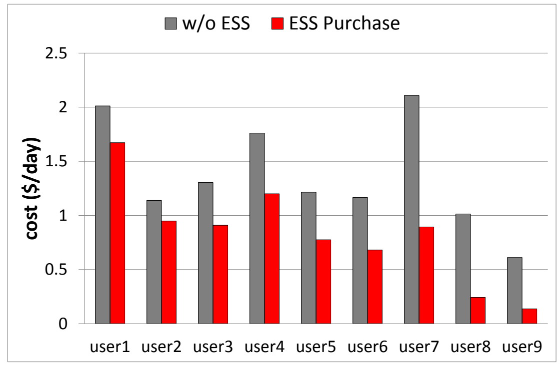

Fig. 6. Users' cost.

and controls. We considered an important player, so called *aggregater*, who owns and operates an energy storage system. The aggregator virtualizes the storage into separable virtual storage capacities and sells them to different users. The aggregator decides an unit price of storage to maximize his profit. Depending on the unit price of energy storage, price profile of electricity from the main grid and his renewable power generation capacity, each user determines his energy consumption schedule and a required amount of storage capacity to minimize his energy cost (including electricity bill from main grid and storage bill from the aggregator), and purchase the amount of storage from the aggregator. We formulated a problem for the aggregator to decide an optimal unit price of energy storage and a problem for each user to decide energy consumption schedule and a required amount of storage. With numerical investigation, it is shown that the energy storage can reduce the energy load to main grid and shave peak power. As a result, purchasing energy storage reduces the users' energy cost by 43% in average compared to the case without energy storage.

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