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An Operations Model for Home Energy Management System Considering an Energy Storage System and Consumer Utility in a Smart Grid

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ABSTRACT

In this study, we propose an operations model to automate a home energy management system (HEMS) that utilizes an energy storage system (ESS) in consideration of consumer utility. Most previous studies focused on the system for the profits obtained from trading charged energy using large-scale ESS. By contrast, the present study focuses on constructing a home-level energy management system that considers consumer's utility over energy consumption. Depending on personal preference, some residential consumers may prefer consuming additional energy to earn increased profits through price arbitrage and vice versa. However, the current system could not yet reflect on this aspect. Thus, we develop an operations model for HEMS that could automatically control energy consumption while considering the level of consumer's preference and the economic benefits of using an ESS.
The results of simulations using a dataset of the Korean market show that an operations policy of charging and discharging can be changed depending on consumer's utility. The impact of this policy is not ignorable. Moreover, the technical specifications of ESS, such as self-discharge rate and round-trip efficiency, can affect the operations policy and automation of HEMS.

Keywords: Energy Management System, Energy Storage System (ESS), Consumer Utility, Smart Grid

Ⅰ. Introduction

An energy storage system (ESS) is recently highlighted because of the many benefits and applications such as provision of ancillary services, peak-time shifting, load balancing, renewable integration, stationary storage for transmission and distribution (T&D) support, and quality enhancement, because

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it can charge, store and discharge energy. Even though most applications are relevant to a utility firm or a large scale ESS, we can also think of the benefits of a small size ESS from the perspectives of residential consumers who own a battery-based ESS. Furthermore, in a smart grid which enables a residential consumer to buy or sell energy to a market over dynamically changing electricity prices, the consumer can reduce energy fee by utilizing the ESS or sometimes make profits. For example, since the energy price during the off-peak time is low in a market but the price during the peak time is high, a consumer can make money by selling the stored energy at the higher price which was purchased at the lower price. This price arbitrage could be another source of profits to residential consumers, if they have enough capacity. Thus, some literature such as Bradbury et al. (2014) and Walawalkar et al. (2007) developed price arbitrage optimization models to maximize the economic value of the ESS, but they do not focus on the small size ESS but a large scale ESS such as Flywheels and pumped hydro.

However, in this paper we would like to discuss an operations model for a small size residential ESS which has some different characteristics from a large scale ESS. In a smart grid, the residential consumer began to be able to have a power to control energy consumption depending on the using the energy control panel called In-home display (IHD) as accompanied with advanced metering infrastructure (AMI), service of the internet of things (IoT), and an energy management system (EMS). Additionally, these technologies enable a residential consumer to sell or buy energy in a smart grid, when the electricity price changes dynamically over time (Hargreaves et al., 2010). The technologies also can be interoperable with an ESS. Therefore, throughout the IHD, a residential consumer can control to charge and discharge energy and sometimes can sell the unconsumed energy in a market. However, the most operations are separately implemented and need to be done manually as monitoring the IHD as described in Krishnamurti et al. (2013), which implies that the operations policy is not optimal. However, the devices still have the potential to support personalized information to change consumer behavior and maximize the utility (Krishnamurti et al., (2013)). Also, the operations policy could be affected by the personal preference for the utility of energy consumption. Thus, it gets more important to develop a model to reflect on the consumer's utility and automatically provide optimal operations policy in the home energy management system (HEMS).

However, most operations models are derived only based on economic value, but not on the consumer's satisfaction. Of course, while firms or commercial agents may think highly of the cost-savings, residential consumers could be different. Some consumers might be interested in saving money by using the ESS, but others might want to consume more energy for their satisfaction. For instance in which electricity price changes, during summer or winter season, a consumer may want to turn on air conditioning system for a longer time by consuming the energy stored at a lower price, rather than to make profits by selling the stored energy. This person has higher preference for the utility of energy consumption than for the energy fee that the consumer has to pay. Also, this is a matter of personal preference. According to a report of Department of Energy (2017) in U.S., new patterns of consumer behavior and asset ownership such as advanced metering infrastructure (AMI) with a smart grid are creating new business model and changing information system structure, regulation and so on. Also, in order to maximize the full benefit of consumer assets, they emphasize the need for new designs for integrating information system network with the smart power grid. Moreover, electric utilities began to consider more different types of residents which are emerging with a smart grid and new devices. Kwon et al. (2010) showed that the change of consumer behavior for each different pricing scheme leads to different level of energy consumption. For example, real time pricing scheme reduces the consumption most. As an information system literature, Krishnamurti et al. (2013) studied what types of information the In-Home Display (IHD) needs to be provided in order to efficiently maximize the consumer's utility. Also, Moon (2014) showed that, when an electricity price changes over time, consumer's behavior could affect consumption pattern in a system level and make consumption increased on peak-time. Thus, in this paper we would like to discuss the personal preference in our proposed model.

Thus, this paper proposes an operations model for a home energy management system (HEMS) for a battery-based ESS considering the consumer's utility. This research differs from the existing literature in that we consider consumers' utility of consumption as well as an economic aspect. Moreover, we believe that our proposed model can help consumer automatically make a decision for ESS operations depending on their level of energy consumption utility. The proposed model is suggested in a form of a multi-objective optimization model to maximize consumer's utility and profits as utilizing an ESS. Our simulation results show that an operations policy of discharging and charging can be changed depending on consumer's utility and the impact is not ignorable. Also, it is shown that the technical specifications of an ESS such as a self-discharging rate and round-trip efficiency can affect the operations policy and automation of a HEMS is very important. These imply that a residents should consider the technical specification as purchasing the an ESS and that, since the information system service provider cannot personally support all different consumers with different level of utility on energy consumption and different specifications of the devices, it needs to develop an automated system. To gain the goal, we provide the operations models which can be embedded in the HEMS.

The structure of this paper is as follows. In Literature Review, we investigate the literature regarding ESS operations models. Then, we suggest an optimization model for ESS operations in Section III. Based on the proposed model, simulations are executed to analyze the impacts of a consumer's utility in Section IV. Also, we examine the impacts of technical specifications such as round-trip efficiency and a self-discharging rate on system performance. Then, Section V provides how our suggested model can be embedded in a decision support system and how it works. Finally, in Section VI we summarizes the major results, and provides the direction of further studies.

Ⅱ. Literature Review

In the recent SANDIA report (Akhil et al., 2013), they defined major ESS applications as follows: bulk energy services, ancillary services, transmission infrastructure services, distribution infrastructure services, and consumer energy management services. From the end-user point of view, the main objective may be to reduce the average level of primary energy consumption in order to save money. Through the data communications that are shared among other technologies or machines such as an ESS, an AMI and an IHD, the energy consumption could be controlled optimally. Also, an energy management system can help to operate, optimize and visualize energy consumption, energy load, and storage (National Institute of Standards and Technology, 2011). For the implementation, the energy management system needs a model and its algorithm to reflect the operations strategy. For example, how much energy needs to be stored at a low price during off-peak times and how much energy needs to be consumed and sold during the peak times could be a decision-making issue to a system planner, which is called arbitrage (Chen et al., 2009).

There are several studies regarding the price arbitrage using a large scale ESS. For example, what may be the most cost-effective way to improve the economic value of the ESSs for the price arbitrage has been studied (Bradbury et al., 2014). The research was conducted with the dataset of 2008 locational marginal prices (LMPs) from major nodes in seven U.S. wholesale energy markets (real-time markets). For finding cost-effective way of economics of ESSs, it compared 14 ESSs with technical functions that energy and power capacity, round-trip efficiency, and a self-discharging rate at one hour interval. In addition, it considered financial factors which lifetime of the storage devices, capital costs of the ESS, and operation costs. Similarly, a study of New York energy market arbitrage has been done. They changed energy delivery times three ways for finding optimal discharging time such 2, 4 and 10 hours (Walawalkar et al., 2007). Then they found that a charging policy can be far more important depending on the different technical specifications of an ESS than are generally recognized. Sioshansi et al. (2009) studied sensitivities of the important factors such as price arbitrage, power capacity, energy capacity, and round-trip efficiency. Also, this research showed how social welfare gains change from the perspectives of consumer and generator. At a large-scale level of ESS operations, Wade et al. (2010) evaluated the economic value for 11kV distribution network and showed that the benefits could be influenced by operating strategy. Rahimiyan et al. (2014) develop an optimization operations model for a cluster size of an ESS which can be interconnected to an EMS. Moreover, Carpinelli et al. (2014) considered a mix of cost minimization and the regret felt by the ESS sizing engineer in industrial applications. The results show that the decision maker's behavior can affect the effectiveness. Also, Sioshansi (2010) discussed consumers as well as profits made from a large scale energy storage from the social welfare perspective. The study discussed that the large utility-scale storage could affect price volatility due to an arbitrage and could make energy market price level off. The study showed the impact of a large-scale energy storage on energy market and social welfare. They mentioned that if ESSs in the energy market are introduced on a large scale, the volatility of market price would be diminishing. The ESS will discharge energy during on-peak time which will lead to decrease of price because demand will become lower than the case without the storage system and vice versa. This also implies that the price gap between off-peak and on-peak becomes smaller. Therefore, he claimed that the equilibrium can bring social welfare to all participants. In this regard, it shows the importance of pursuing social welfares and social optimum among social players; merchant storage operators, consumers, and generators and so on. Also, this research mentioned that many players have different utilities. Thus, if some players pursue their own profits not considering other player's profit, social welfare could be decreased in that they broke the equilibrium of welfare.

However, a small size residential ESS has different characteristics from a large scale ESS. Information system for a large scale of an ESS to automate operations can be customized on its purpose and invested because the size of investment is sufficiently large. On the other hand, it is difficult to customize in person because different people has different preferences on the energy devices and their consumption, even though it is definitely required as mentioned in Department of Energy (2017). Advances in technology regarding the smart grid allow data communications among infrastructures like an AMI, an EMS, an IHD, and an ESS which are connected to home appliances, and so give a consumer authority to control those in a remote place as well. Thus, the consumer begins to want to control those appliances remotely and automatically, depending on their energy utility. However, in order to satisfy the consumer's needs and utility as well as to find an effective way to control the related devices, what kinds of information would be provided or how the devices would be controlled is unclear and has been studied. Fisher (2008) summarized characteristics for a not-dumb meter to be smart. For example, it has to provide multiple options for the user to choose from each elements and has to react immediately on demand. Similarly, Darby (2010) and Sæle and Grande (2011) expounded specific aspects, for example load management of appliances, which may affect and be affected by consumer behavior on the computerized IHD. Also, Krishnmurti et al. (2013) has shown that a simpler and more generalized format of information could be more effective than a personalized IHD. This implies that the personalization is necessary but the implementation needs to be simple or automated as much as possible. Likewise, previous studies for a HEMS focuses on the controllability to satisfy the need of different consumer and information feedback to different consumer's behavior, which is the difference between a large scale and a residential ESS.

However, the previous optimal price arbitrage researches fail to consider such different consumer's utility especially in a residential ESS application. Operations strategy about energy consumption and price arbitrage might be changed by consumer utility. The industrial and commercial consumers pay more attention to reducing energy costs. However, it might not apply to residential consumers as aforementioned. Some consumers may want to use more energy for their satisfaction, for example, keep air conditioner running for a longer time. In other words, depending on the consumer's utility, the pattern of energy consumption may be different. Moreover, because an ESS can store energy during off-peak time, a consumer can use the stored energy for their utility instead of selling the energy to a market during peak time in order to make profits. Also, it can bring higher utility to a consumer because the consumer can use more energy at a cheaper price. For this similar issue, there are few previous researches. For example, Conejo et al. (2010) developed an optimization model that bidirectional communication can happen in HEMS, in which they considered a utility function for a consumer as a linear function. Similarly, Ferreira et al. (2011) and Ferreira et al. (2012) applied a piecewise linear utility function to represent the pheonomenon that consumer utility increases when the energy consumption increases. However, they does not consider an ESS in an HEMS.

Given the above context, the contribution of this paper is to provide a multi-objective optimization based algorithm run by the HEMS considering a small-size residential ESS. Also, in the application of the residential ESS, the model reflects the consumer's utility which have not been paid attention to in the existing literature. From the multi-objective optimization perspective, our proposed model regards a consumer as both a profit-maximizer and a utility maximizer. Therefore, the ESS operations model from the consumers' perspectives can be embedded in home energy management system for consumer's self-automatic control.

Ⅲ. A Model for ESS Operations in Home Energy Management System

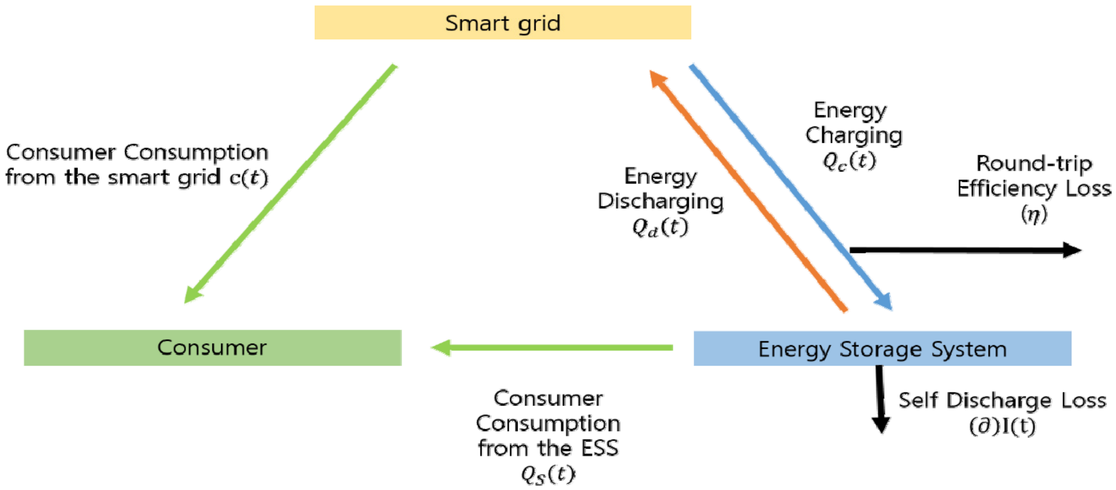
3.1. A Proposed Model for ESS

The objective of a previous price arbitrage optimization model is to maximize revenue as the ESS charges when the price is low and discharges to sell when it is high. However, the most existing models such as Walawalkar et al. (2007) fail to consider how much energy a consumer will use depending the consumer's utility. Thus, in this section, we propose a model for ESS operations including the consumer's utility in HEMS in a similar way to Conejo et al. (2010), Ferreira et al. (2012) and Rahimiyan et al. (2014). Therefore, we will develop a model based on the existing model, while incorporating the ESS aspects for a price arbitrage and utility at the same time. Before introducing our optimization model, we address assumptions as follows.

1. There are no upfront costs. For example, a purchasing cost of ESS and an installation cost could be charged to a consumer, but in this paper we regard them as a fixed cost and so do not consider. However, we consider energy fee as a variable cost that a consumer should pay for consuming and charging energy.
2. There are no transaction costs. We assume that the transactions fee to buy and sell is not charged and automatically supported by system.
3. Operations of ESS do not affect energy market prices. It is assumed that the transactions by residential consumers are too small to change volatility of electricity market prices.
4. Technically, consumers are able to buy energy from a smart grid or sell to a smart grid.

Also, we depict how ESS can be operated and how energy can be consumed in <Figure 1>. There are three core entities: smart grid, consumer, and ESS. The relationship is similar to previous researches. At a given time t, a consumer can charge the amount of energy, $Q_c(t)$, or discharge the amount $Q_d(t)$ at a market price $(\lambda(t))$. In case of necessity, the consumer can use the amount of energy $Q_s(t)$ which is stored in ESS. Also, there are energy losses during charging and storing. A consumer use energy directly from the smart grid and stored energy from the ESS.

More specifically, as shown in <Figure 1>, three different types of energy transactions occurs in the system: general transaction between a smart grid and a consumer, an internal transaction between a consumer and a storage and an external transaction between a grid and a storage. First, between a smart grid and consumer, a consumer buy the amount of energy $c(t)$ at a market price $\lambda(t)$. The second one is an internal transaction between a consumer and ESS. A consumer could use the amount of energy $Q_s(t)$ from ESS. Herein, an important thing is that a consumer can choose an energy source between a grid and ESS by comparing energy fees that the consumer has to pay. The last is an essential arbitrage transaction between a smart grid and ESS. ESS charges the amount of energy, $Q_c(t)$ at a low price and a consumer can sell the unconsumed surplus energy $Q_d(t)$ to a smart grid when the price is high. Besides, when the storage charges or discharges, there is energy loss with round-trip efficiency η. Also, there is a loss in stored energy $I(t)$ due to chemical reactions



<Figure 1> The Conceptual Model of ESS Operation with Considering Consumer' Utility

at the rate of as time passes.

A consumer wants to minimize energy fees and maximize their utility $(u(t))$ from reasonable energy consumption, which implies that objective of a consumer is required to take both into account. Therefore, the multi-objective problem can be expressed as below. At time t, a consumer can sell energy to a market by the amount of discharge, $Q_d(t)$, or should pay energy for charging $Q_c(t)$ and/or consumption $(C(t))$ at a price of $(\lambda(t))$. In other words, a consumer makes profits of $\lambda(t)Q_d(t)$ but pays $\lambda(t)Q_c(t)+\lambda(t)C(t)$. The time horizon is one year, which is 8,760 hours.

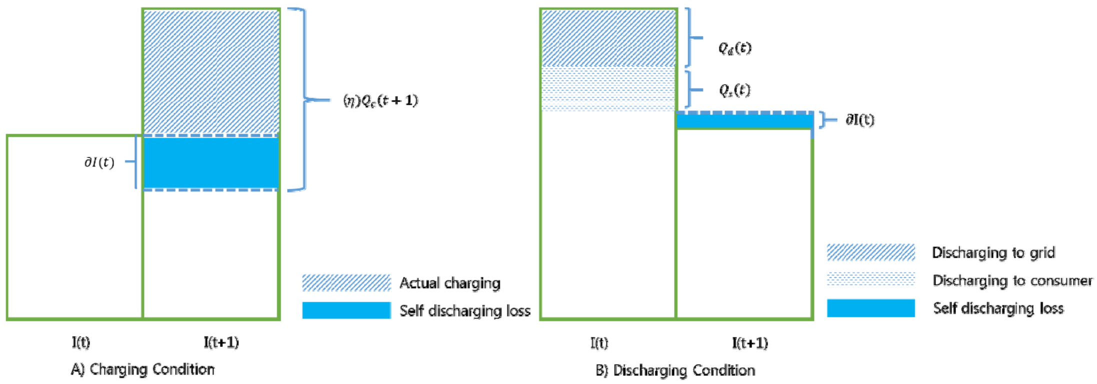
$$\max v = \sum_{t=1}^{t=8760} [u(t) - \lambda(t)(Q_c(t) + C(t) - Q_d(t))] \tag{1}$$

$$\text{where } u(t) = \alpha \log(C(t) + Q_s(t)) \tag{2}$$

Herein, $\alpha \log(C(t)+Q_s(t))$ means the consumer' utility obtained from energy consumption. Similar settings for the utility function can be found in the literature such as Conejo et al. (2010), Ferreira et al. (2012) and Rahimiyan et al. (2014). Even though the forms of a function could be different a little, the basic ideas that a utility increases when consumption increases is the same. Therefore, we use a log function as a continuous function to express that the marginal utility usually decreases as consumption increases. And the coefficient of the log function (α) is determined by consumer preference regarding consumption, which implies that a consumer who has high coefficient (α) prefers high level of consumption. Also, the source of energy consumption is both from a smart grid and from ESS and the consumer's utility arises from the both, $C(t)+Q_s(t)$.

3.2. Descriptions of Parameters and Constraints

This section describes parameters and constraints which are subject to the objective function. These constraints consist of two parts; ESS and consumers. Constraints (3) to (6) are conditions about ESS, and the constraint (7) are related to consumers' characteristics.



<Figure 2> The Inventory Status of ESS
Change of Inventory Under Charging Condition (Left)
Change of Inventory Under Discharging Condition (Right)

$$0 \leqq I(t) \leqq I_{max} \tag{3}$$

$$0 \leqq Q_d(t) + Q_s(t) \leqq Q_{max} \tag{4}$$

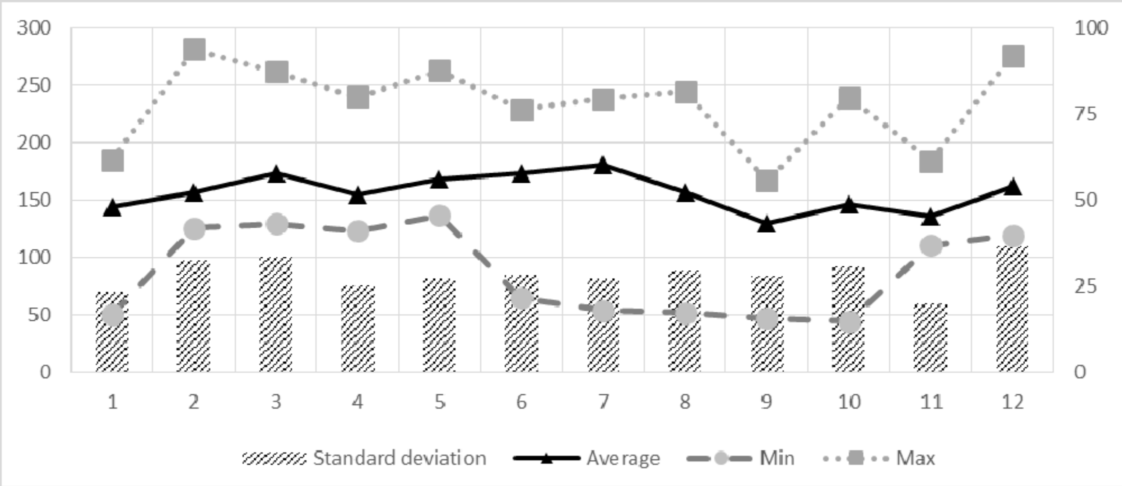
$$0 \leqq Q_c(t) \leqq Q_{max} \tag{5}$$

Let us define $I(t)$ as an inventory level of ESS at time t and I_{max} as a maximum energy storage capacity, which are described in the constraint (3). Also, from the ESS perspective, incoming energy or outgoing energy should be limited to the power capacity, Q_{max} which is the maximum capacity to charge and discharge energy in a unit time. Constraints (4) implies the limit of discharging in terms of two parts; discharging for arbitrage from a storage to grid ($Q_d(t)$) and discharging for consumer's self-consumption from the storage ($Q_s(t)$). And constraint (5) means the limit of charging from grid to storage.

$$I(t+1) = (1-\delta)I(t) + \eta Q_c(\mathrm{t}) - (Q_d(t) + Q_s(t)) \tag{6}$$

Constraint (6) depicts the ESS inventory level depending on the characteristics of mechanical specifications and operations. We need to note that the parameter δ means a self-discharging rate of ESS inventory which is related to the loss of energy due to parasitic loss in an ESS as time goes on, where these losses may be due to mechanical friction, chemical reaction, and etc.(Bradbury et al., 2014). And the parameter η means roundtrip-efficiency that is caused when we charge and discharge energy to storage. Under a perfect condition that there is no loss of ESS, the self-discharging rate is 0% and round-trip efficiency is 100%. In our operations model, these factors are exogenously given. In addition, the inventory status depending on charging or discharging condition is shown in <Figure 2>. Let us assume that ESS currently has energy inventory $I(t)$. Then, when the system charges the amount of $Q_c(t)$, the energy $\eta Q_c(\mathrm{t})$ will be stored because of round-trip efficiency. Also, under a discharging condition, the storage system discharges energy $Q_d(t) + Q_s(t)$ to a grid and a consumer. Furthermore, due to a self-discharging rate, the current inventory level will be decreased to the level of $(1-\partial)I(t)$. Accordingly, the inventory level at time t will be expressed as the constraint (6).

$$C(t)_{min} \leqq C(t) + Q_s(t) \leqq C(t)_{max} \tag{7}$$



<Figure 3> Basic Statistics of System Marginal Price (SMP) of 2012

<Table 1> Detailed Statistics of System Marginal Price (SMP) of 2012

Month	1	2	3	4	5	6	7	8	9	10	11	12
Average	144.45	157.16	174.26	155.17	168.21	174.30	181.22	157.02	130.31	146.41	136.59	161.93
Min	50.33	126.22	129.77	123.40	137.04	65.07	54.00	52.14	47.54	44.80	110.87	119.99
Max	185.35	281.76	262.23	240.15	262.98	229.42	238.61	244.75	167.07	239.54	184.28	276.42
Standard deviation	23.45	32.74	33.78	25.40	27.27	28.46	27.27	29.70	27.99	30.69	20.12	36.82
Total	Average = 157.34, Min = 44.80, Max = 281.76, STD = 32.66, *KRW											

Constraint (7) means the consumers' energy consumption. Commonly, different types of consumer have different energy consumption patterns. For considering consumer's energy utility, we represent energy consumption as $(C(t) + Q_s(t))$, which implies that the consumer can use energy from a grid and/or storage. Also, the consumption has the minimum and maximum limits, and $C(t)_{min}$ and $C(t)_{max}$.

Ⅳ. Analysis and Comparison Study

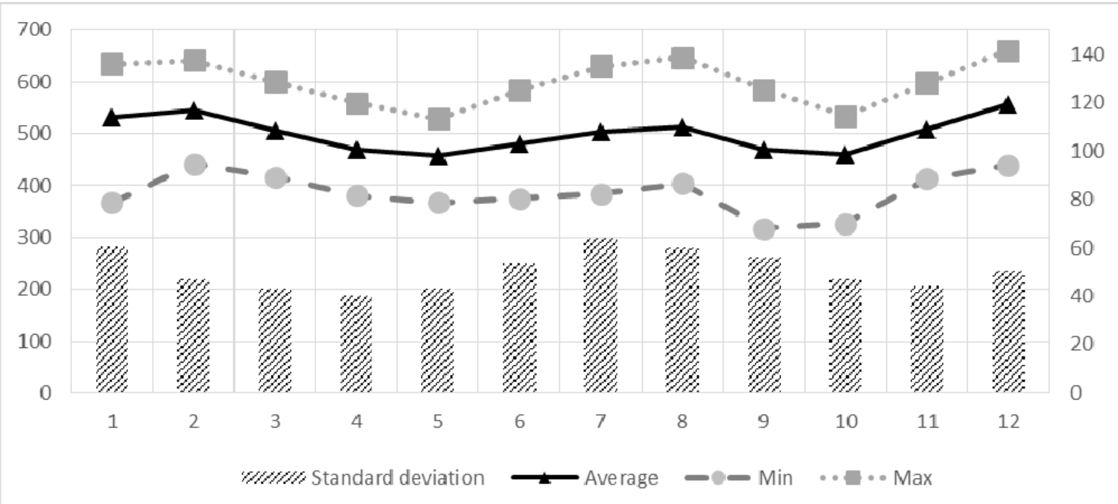
In this chapter, we analyze changes of consumers' value, as specifications of ESS and characteristics of consumer utility are changed. Then, we will investigate how consumer' utility may affect to ESS performance.

4.1. Data Description

Before experiments, we analyze the volatility of energy price. The volatility is an important factor in the aspect of price arbitrage. For the arbitrage, a consumer may want to purchase and sell energy in order to make profits from a price difference. In order to analyze, we used the data of system marginal price (SMP) to identify price volatility. We collected the data from KEPCO (Korea Electric Power Corporation) from January to December in the year of 2012. Following figure and table describe the basic statistics of the energy price. Standard deviation varies from 20.12 to 36.82 and we can see the volatility of price is quite high.

Moreover, in order to reflect the pattern of consumer demand on our experiments, we applied aggregated consumption data from KPX (Korea Power Exchange) database and standardized the dataset. Using nation-level consumption information, we standardized and derived demand information. The standardized demand was set to be 500Wh on average, because average energy consumption in Korea is approximately 500Wh per hour. We need to note that the demand pattern is similar to price pattern in that it has seasonal effects in summer and winter but it is not perfectly correlated to energy price. This is why different power generations have different variable costs and there is preventive maintenance in practice. Monthly specific data are given in the following table and figure.

The demand side information is important to determine ESS operations as charging and/or discharging. It had been pointed by other researches about demand-side management in a smart grid (Farinaccio and Zmeureanu 1999; Firth et al., 2008; Gellings and Smith 1989). These studies emphasized on different energy consumption patterns and showed importance due to technology of a smart grid in a real time pricing market. Thus, practical ESS operations need to consider both side of supply and demand and these datasets are used for our model experiments.



<Figure 4> Basic Statistics of Energy Consumption Demand

<Table 2> Detailed Statistics of Energy Consumption Demand

Month	1	2	3	4	5	6	7	8	9	10	11	12
Average	530.3	545.2	506.7	468.6	458.6	480.6	504.4	513.8	468.4	459.8	508.9	556.7
Min	366.7	442.0	416.4	380.5	367.5	374.6	384.2	404.1	317.9	326.9	412.9	440.3
Max	634.8	641.8	599.8	559.5	528.2	583.5	630.6	647.3	585.5	534.0	597.9	661.2
Standard deviation	60.6	47.0	43.1	40.3	43.0	53.5	64.0	60.1	56.0	47.0	44.1	50.4
Total	Average = 500, Min = 317.9, Max = 661.2, STD = 60.4 *W											

4.2. Effects of ESS Operations without Consumer Utility

Even if we do not consider consumer's utility function, an ESS must enable energy cost saving. Thus, we compare how much it can reduce energy cost for a reference. For our conduct experiments, we applied two scenarios and parameters of consumer utility and ESS mechanical specifications like the following table. These similar scenarios for the storage capacity which represents the storing time can be found in previous researches (Denholm and Kulcinski, 2004; Roza Jr, 1993; Sioshansi et al., 2009). Also, Lawrence Berkeley National Laboratory considered the power capacity size of a residential system mainly as 2kW to 20kW (Barbose et al. (2015) and Galen and Naïm (2016)), which might be boundaries of sizes for residential systems. Thus, to display difference depending on the size of ESS, we analyzed two scenarios: 2kW/8kWh and 20kW/80kWh.

We suppose that coefficient of consumer utility (a) is zero in order to see the performance difference between scenarios with and without ESS. Note that, when the consumer utility is zero, consumption does occurs not from the storage system but from the grid. Evaluation of the performance given is <Table 4>. The result shows that ESS could be effective on cost savings. When power and energy storage capacity is higher, the amount of cost savings also increases. Comparing scenario 4.2-A and 4.2-B, performance of Scenario 4.2-B is 10 times higher than that of Scenario 4.2-A.

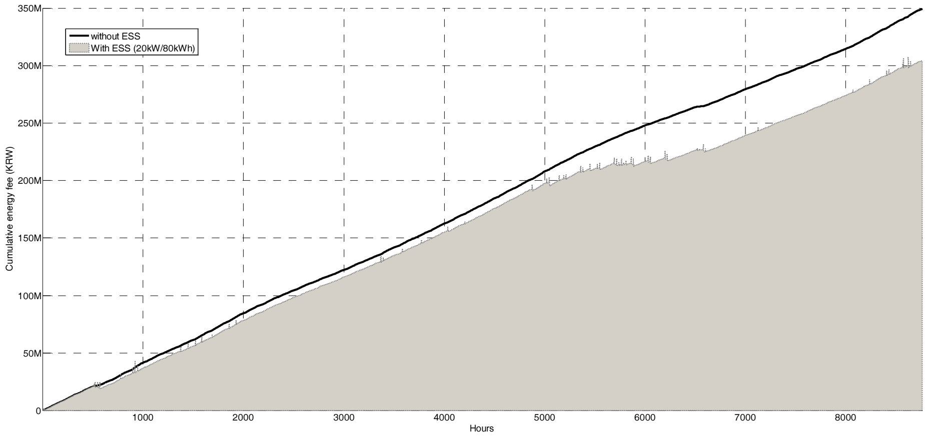
Then, we analyze cumulative energy cost savings between with and without ESS. <Figure 5> shows how much a consumer needs to cumulatively pay for two cases throughout 8760 hours from January to December. The solid line shows cumulative energy fee that a consumer should pay without operating ESS and the dotted line above a shaded region represents a cumulative energy fee as ESS is operated. In early hours, there is slight difference between two lines, but the difference becomes clearer after 5000 hours, which implies that ESS is more beneficial to a consumer. The reason is that since the period is a summer season, energy prices become higher and more volatile and so profits from price arbitrage

<Table 3> The Basic Status for Analyzing Effects of ESS Operation

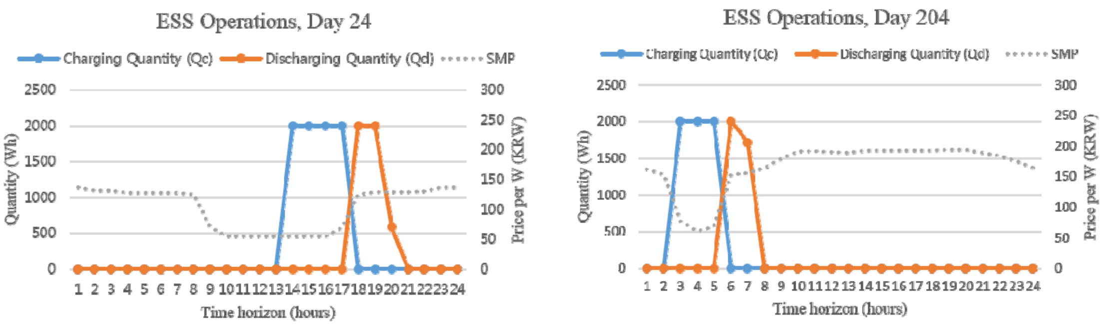
Parameters	Scenario 4.2-A	Scenario 4.2-B
Round-trip efficiency (η)	80%	80%
Self-discharging rate (δ)	10%	10%
Power capacity (Q_{max})	2kW	20kW
Storage capacity (I_{max})	8kWh (4 hour)	80kWh (4 hour)
Consumer utility (a)	0	0

<Table 4> The Analysis Result of ESS Operational Effectiveness

Energy fee (KRW)	Scenario 4.2-A (2kW/8kWh)	Scenario 4.2-B (20kW/80kWh)
Operation with ESS	345,095,610	304,632,714
Operation without ESS	349,591,487	349,591,487
Cost savings	(-4,495,877)	(-44,958,773)
Saving cost Percentage	-1.286%	-12.86%



<Figure 5> Cumulative Hourly Energy Cost Savings for Non-ESS and ESS Operations



(a) ESS Operations, Day 24(t:553~576) **(b) ESS Operations, Day 204(t:4873~4896)**

<Figure 6> Operations Schedule for ESS
Charging Schedule, Discharging Schedule and Energy Price for 24 hours on 24th day (Left)
Charging Schedule, Discharging Schedule and Energy Price for 24 hours on 204th day (Right)

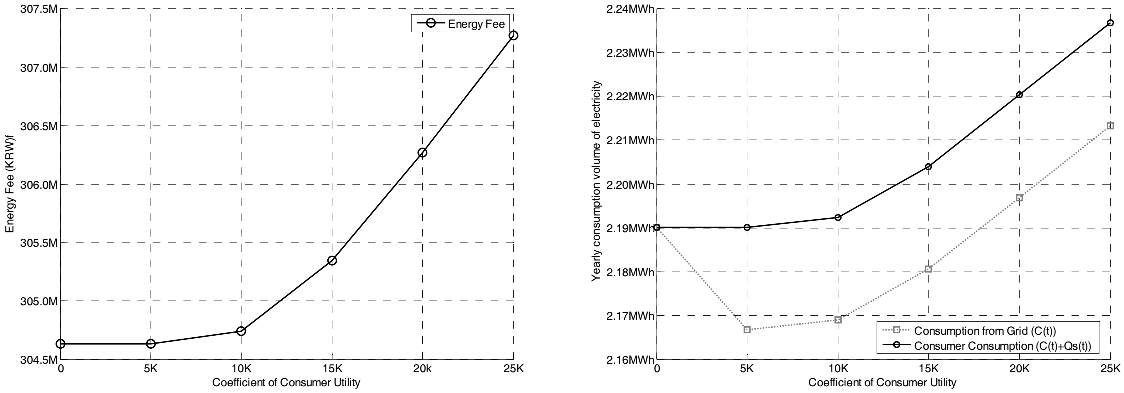
increases. As shown in <Figure 6>, ESS charges when energy prices are low and discharges when prices are high. However, energy prices, SMPs on 24^{th} day (from 553 to 576 hour) in the left graph are relatively lower and less volatile than energy prices on 204^{th} day (from 4873 to 4896 hour) in the right graph. Likewise, during the summer, a consumer can make more profits than the other seasons. Therefore, cumulative profits from the storage system after 5000 hours become larger and so difference between non-ESS operations and ESS operations becomes clearer as in <Figure 5>.

4.3. Effects of ESS Operations with Consumer Utility

In this section, we consider consumer utility to ESS operations. For the case without considering consumer utility, energy storage system discharges only to a grid. However, in consideration of consumer utility, the utility affects storage discharging policies in two ways of external discharge and internal discharge. External discharge is an arbitrage transaction between grid and ESS, which is similar to the arbitrage in the existing models. However, in-

<Table 5> The Scenarios for Analyzing Effects of Consumer's Utility

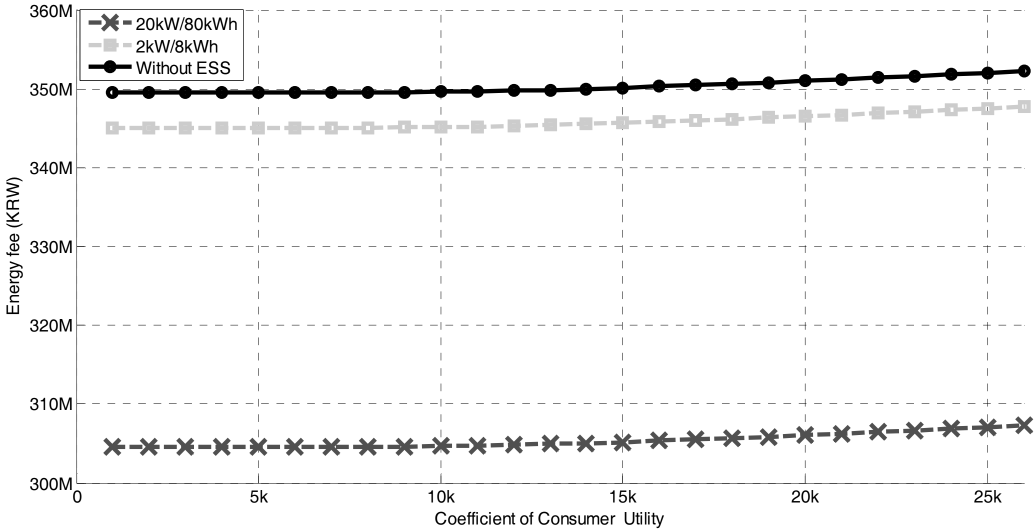
Fixed Parameter	Scenario 4.3-A	Scenario 4.3-B
Round-trip efficiency (η)	80%	80%
Self-discharging rate (δ)	10%	10%
Power capacity (Q_{max})	2kW	20kW
Storage capacity (I_{max})	8kWh (4 hour)	80kWh (4 hour)
Range of coefficient (a)	0 to 25000	



<Figure 7> Change of Energy Fees and Consumption According to Coefficient of Consumer utility
Energy fees for different levels of consumer utility (Left)
Consumption volume of energy for different levels of consumer utility (Right)

ternal discharging policy is determined by energy flow between ESS and consumer. Suppose a consumer who has high utility on energy consumption. The consumer may feel more satisfaction from increased consumption of energy. Also, the consumer can retrieve necessary energy from a grid and/or storage and sometimes charge remaining energy to make profits by price arbitrage. However, a consumer who has lower utility on consumption compared to cost saving would prefer selling energy to a market. Therefore, preference for the consumption will affect ESS operations policies, more specifically charging and discharging rules. To identify this utility effect, we change the coefficient of consumer's utility function (a). The scenarios of these analyses are given in <Table 5>, where Scenario 4.3-A and Scenario 4.3-B means by the cases of a small size storage and a large size storage respectively. Also, we repeated this experiment for two scenarios.

The results for the scenario 4.3-A are shown in <Figure 7>. For different levels of consumption utility (a), we identify the impacts on the change of energy fee that a consumer has to pay and the change of consumption, where the energy fee is calculated by the equation, $\sum_{t=1}^{8760} \lambda(t)(C(t)+Q_c(t)-Q_d(t))$. The increase of coefficient of consumer utility leads to increasing consumption of energy. But, marginal increments of energy fee and consumption are significantly increasing as utility coefficient increases for a certain interval. For example, as the coefficient is larger than 10,000, fees and consumption increase drastically. The increment of Y-value, when X-value changes



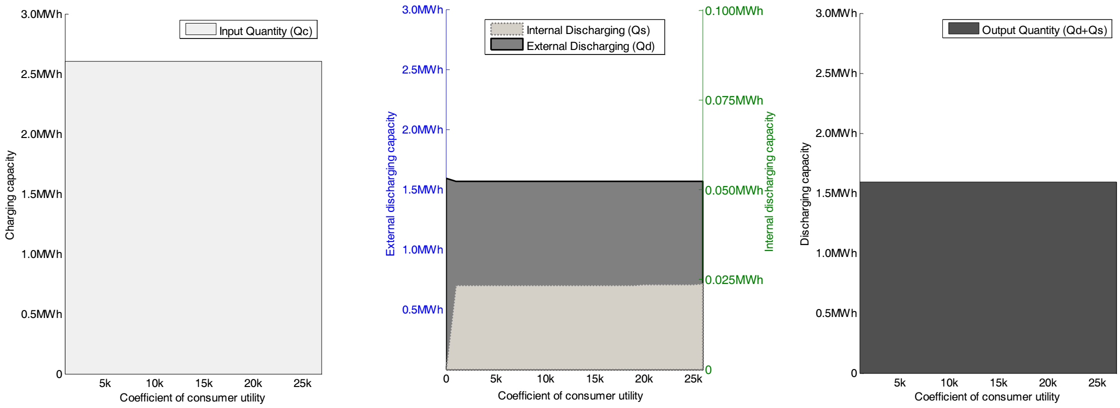
<Figure 8> The Difference of Energy Fees for Different ESS Capacities

from 10,000 to 20,000, is much larger than the increment as X-value changes from 0 to 10,000. This implies that a consumer who originally has lower preference to consumption can gain much higher utility by paying a little bit more. Moreover, the right graph in <Figure 7> shows the change of consumption, where a dotted line means the amount of energy retrieved directly from a grid and a solid line means the total consumption that is a sum of consumptions from a grid and a storage. The total energy consumption, a solid line, increases as utility for consumption increases. However, the dotted line decreases for an interval between 0 and 5000 on the X-axis and then increases. In other words, the consumption of energy from a storage increases for this interval. This result shows that a consumer uses stored energy which was bought at a cheaper price in advance, rather than more expensive energy directly retrieved from a smart grid. Furthermore, this implies that a consumer having lower preference to energy consumption can utilize the ESS more efficiently.

Moreover, <Figrue 8> shows the impacts of power capacity on performance. The top, middle and bottom lines represents the energy fees without considering an ESS, with adopting small size storage (Scenario 4.3-A), and with adopting a large size storage (Scenario 4.3-B), respectively. Similar to the previous analysis, <Figrue 8> shows that more power capacity leads to lower energy fee. However, we need to note that it is quite difficult to conclude that a consumer has to adopt power capacity as large as possible to reduce energy fee, because we did not consider an ESS installation cost in our model.

4.4. Impact of Efficiencies on the Performance

In this section, we discuss the impact of efficiencies on the performance. We investigate how a self-discharging rate and round-trip efficiency affect the total operational efficiency of an ESS. The operational efficiency needs to be calculated considering losses that occur not only when an ESS charges and dis-



<Figure 9> Charge Volume at Every Coefficient of Consumers' Utility (Left)
Internal and External Discharge Volume at Every Coefficient of Consumers' Utility (Middle)
Sum of Discharge Volume at Every Coefficient of Consumers' Utility (Right)

charges but also as time passes. Therefore, let us define the operational efficiency by comparing total discharging volume to total charging volume as follows:

$$\text{Operational efficiency} = \frac{\text{External Discharging Volume} + \text{Internal Discharging Volume}}{\text{Charging Volume}} = \frac{\Sigma(Q_d(t) + Q_s(t))}{\Sigma Q_c(t)} \quad (7)$$

<Figure 9> shows the example of operational efficiency calculated for the scenario 4.3-B. The left figure shows the amount of charged energy. And then the storage will discharge internally to a consumer or externally to a grid, as shown in the middle of the figure. The right figure shows the total volume discharged from the storage. When a self-discharging rate is 10% and round-trip efficiency is 80%, the operational efficiency becomes 60.94%. Similarly, we investigate the change of the operational efficiencies for different self-discharging rates, round-trip efficiencies and interactions of both in the following subsections.

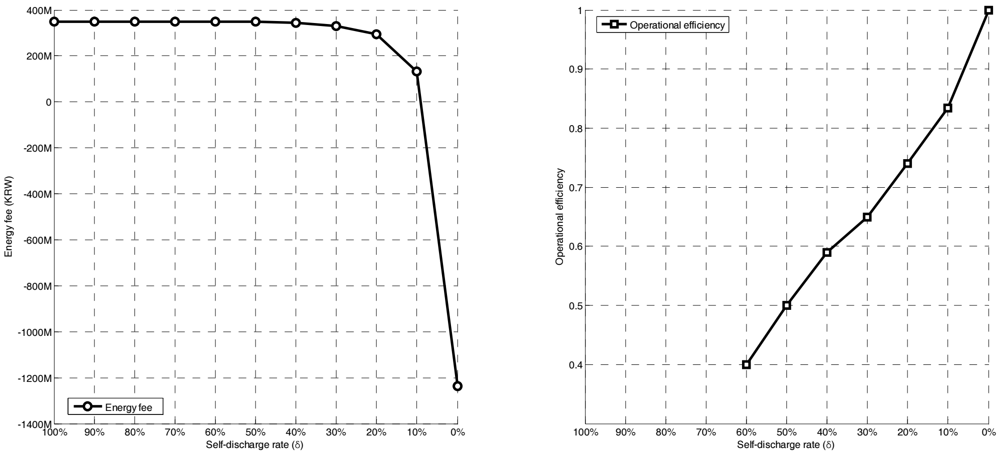
4.4.1. Impact of Efficiencies on the Performance - Self-discharging Rate

Self-discharge is the loss of energy due to parasitic loss in an ESS, where these losses may be due to mechanical friction, chemical reactions, and etc., depending on the technology (Bradbury et al., 2014). The self-discharging rate is a measure of how quickly a cell will lose its energy due to unwanted chemical actions within the cell. The rate depends on the cell chemistry and the temperature. Typical self-discharging rates for common batteries are as follows: Lead Acid varies from 4% to 6% per month, Nickel Cadmium are from 15% to 20% per month, Nickel Metal Hydride is around 30% per month, and Lithium is from 2% to 3% per month (Electropaedia, 2014). Because of this property, we need to consider and do analysis to identify sensitivity of a self-discharging rate. In this analysis, we examine the performance of a self-discharging rate in an interval of 10%. Other variables are controlled as given in the following table.

For this analysis, the results are shown in

<Table 6> The Parameters for Analyzing Effects of a Self-discharging Rate

Fixed Parameter	Basic Status
Round-trip efficiency (η)	100% (no loss)
Self-discharging rate (δ)	0% ~ 100%
Power capacity (Q_{max})	20kW
Storage capacity (I_{max})	80kWh (4 hour)
Consumer utility function (a)	0



<Figure 10> Energy Fee and Operational Efficiency Under a Self-discharging Rate
Change of Energy Fee by a Self-discharging Rate (δ) (Left)
Change of Operational Efficiency by a Self-discharging Rate (δ) (Right)

<Table 7> The Impact of a Self-discharging Rate on Operational Efficiency
*A Shaded Part Means an Inflection Point of Operational Efficiency

Self-discharging rate (δ)	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%	0%
Operational efficiency	-	-	-	-	40.00%	50.00%	58.96%	65.00%	74.00%	83.43%	100%
Improvement of efficiency	-	-	-	-	-	10.00%	8.96%	6.04%	9.00%	9.43%	16.57%

<Figure 10>. When the self-discharging rate is low implying small loss of energy, we can see the energy fee goes negative, which means that an ESS makes profits to a consumer by selling energy to a market and a consumer does not need to pay. Also, corresponding operational efficiency becomes 1 as shown in a right graph. Also, we can see that energy fee starts dropping very drastically when the self-discharging rate is between 0% and 30%.

Also, from the right hand side of <Figure 10> and <Table 7>, we can see that there is an inflection point of operational efficiency. The slope of operational efficiency, improvement of efficiency, increases by 10%, 8.96%, 6.04%, 9%, 9.43%, and 16.57%. For the self-discharging rates higher than 30%, improvement of efficiency decreases from 10% to 6.04%. But, for the rates under 30%, the marginal operational efficiency increases from 6.04% to 16.57%. This implies that a self-discharging rate could be very critical on the total ESS operational efficiency beyond a certain threshold.

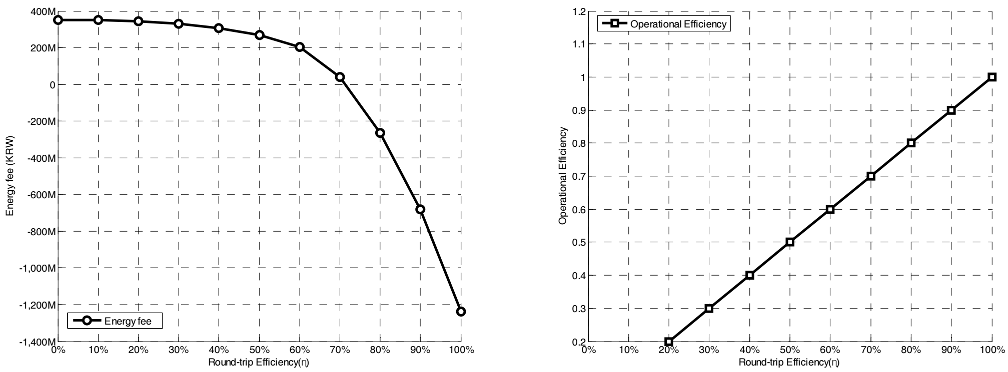
4.4.2. Impact of Efficiencies on the Performance – Round-trip Efficiency

Round-trip efficiency is the ratio of output-to-input energy for a storage device. In general, storage system use direct current whereas grid system uses alternating current. Thus, it needs a converter, so called power conversion system (PCS). Transformation process occurs loss of energy. It is called round-trip efficiency, and it occurs due to the limitation of mechanical technology. Thus, we conduct experiments regarding round-trip efficiency and operational efficiency. Other parameters are given in <Table 8>.

Results about round-trip efficiency are shown in <Figure 11> and <Table 9>. The trends of changes of energy fee and operational efficiency are similar to those of a self-charging rate. However, one different characteristic of round-trip efficiency is a constant slope of operational efficiency. Round-trip efficiency is directly connected to the operational efficiency. For example, if round trip efficiency increases by 10%, operational efficiency increases by 10%.

<Table 8> The Parameters for Analyzing Effects of Round-trip Efficiency

Fixed Parameter	Basic Status
Round-trip efficiency (η)	0% ~ 100%
Self-discharging rate (δ)	0% (no loss)
Power capacity (Q_{max})	20kW
Storage capacity (I_{max})	80kWh (4 hour)
Consumer utility function (a)	0



<Figure 11> Energy Fee and Operational Efficiency Under Round-trip Efficiency (η)
Change of Energy Fee by Round-trip Efficiency (η) (Left)
Change of Operational Efficiency by Round-trip Efficiency (η) (Right)

<Table 9> The Impact of Round-trip Efficiency on Operational Efficiency

Round-trip Efficiency(η)	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Operational Efficiency	-	-	20%	30%	40%	50%	60%	70%	80%	90%	100%

4.3.3. Interaction between a Self-discharging Rate and Round-trip Efficiency

The total operational efficiency is determined by both efficiencies; a self-discharging rate and round-trip efficiency. Therefore, we need to consider those efficiencies simultaneously. <Table 10> shows the variations by interaction between a self-discharging rate and round-trip efficiency.

This table can give a managerial implication for predicting operational efficiency and also can give a guideline to establish management plan. For example, suppose that a self-discharging rate is 10% and round-trip efficiency is 80%. In this case, operational efficiency is 60.94%. Under this condition, if a service provider would like to improve efficiency of an ESS or to construct a new ESS, he or she might improve a self-discharging rate rather than round-trip efficiency or it might be better policy to purchase ESS with a lower self-discharging rate. The reason is that the increment of a self-discharging rate by 10% improves operational efficiency by 19.06% (=80.00-60.94), while the increment of round-trip efficiency by 10% improves operational efficiency by 10.96% (=71.90-60.94).

Also, we need to note that the total operational efficiency cannot be calculated by a simple multiplication. For example, the operational efficiency is 80% as round-trip rate is 0.8 with a self-discharging rate of 1, but the operational efficiency is 83.43% as a self-discharging rate is 0.1 with round-trip efficiency of 0. We can see that the latter cannot be calculated by the multiplication of 0.9 (=1-0.1) and 1. Furthermore, when we consider combination of two scenarios, the multiplication value is 0.6674 (= but it is not equal to the operational efficiency 60.94% given in the table). This result is caused because self-discharging occurs continuously over time and so the losses can be different depending on the operations schedule. For example, discharging at time *t* and at time *t+1* will be different because the operations of discharging at time *t+1* result in more loss during the one hour, and so the amount of loss will be different even for the same ESS.

4.5. The Impact of Energy Storage Capacity

In this section, we consider the impact of energy storage capacity on operational efficiency. In a prior study (Akhil et al., 2013), the ESS for arbitrage is

<Table 10> The Interaction between a Self-discharging Rate and Round-trip Efficiency to Operational Efficiency

Interaction to operational efficiency		Self-discharging rate (lower value is better)						
		0.6	0.5	0.4	0.3	0.2	0.1	0
Round-trip efficiency (high value is better)	0.2	-	-	-	-	-	-	20.00%
	0.3	-	-	-	-	-	-	30.00%
	0.4	-	-	-	-	-	-	40.00%
	0.5	-	-	-	-	40.00%	40.94%	50.00%
	0.6	-	-	-	42.00%	43.73%	47.53%	60.00%
	0.7	-	-	42.00%	47.95%	51.14%	53.51%	70.00%
	0.8	-	40.00%	48.00%	50.62%	57.73%	60.94%	80.00%
	0.9	-	45.00%	54.00%	57.56%	63.40%	71.90%	90.00%
	1.0	40.00%	50.00%	58.96%	65.00%	74.00%	83.43%	100.00%

discussed for the 1-1000kW size of power capacity and for 2-6 hour discharging time of energy storage capacity. Similarly, we conduct simulations for identifying relationship between operational efficiency and energy storage capacities of 2-8 hours for a given power capacity 20kW. Scenarios and parameters for the analysis are given in <Table 11>. Scenario 4.5-A is the base scenario to check the impact of storage capacity for a fixed round-trip efficiency and self-discharging rate. Also, Scenario 4.5-B and Scenario 4.5-C are the cases in which a self-discharge rate and round-trip efficiency varies.

4.5.1. The Impact of Storage Capacity - (Scenario 4.5-A)

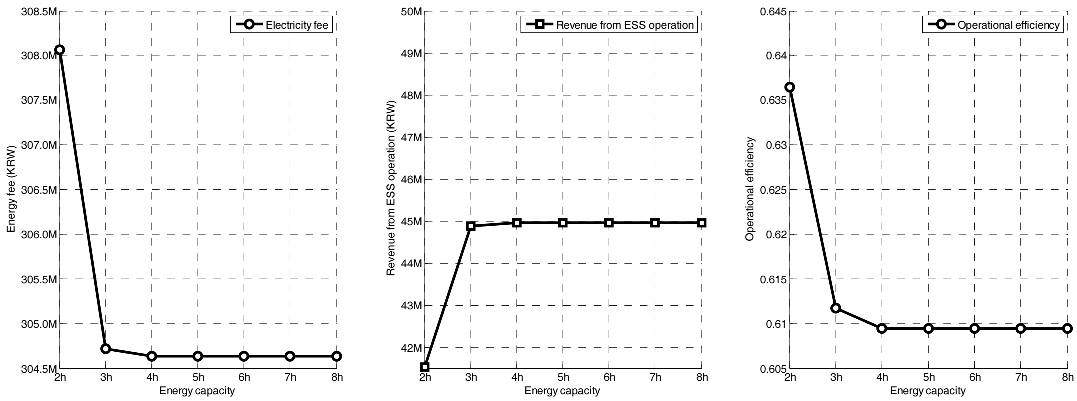
In this section, we examine the impacts of storage capacity when round-trip efficiency and a self-discharging rate are fixed and storage capacity varies from 40kWh to160 kWh. For the different storage capacities, we derived results about energy fee, operating revenue, and operational efficiency. Like our intuition, energy fee that a consumer should pay is decreasing and operating revenue that a consumer can make by sales of energy are increasing when storage capacity increases. However, interestingly, the operational efficiency of an ESS is decreasing as the capacity increases. This result happens because as charging duration becomes longer the amount of loss becomes larger. Also, for these all graphs, we could see that there exist thresholds which energy fee, revenue, and operational efficiency are not improved beyond. As shown in <Figure 12> and <Table 12>, the threshold is 4-hour storage capacity. This implies that 4-hour energy capacity is an optimal point to maximize profit and efficiency on the given situation. Also, we could see that the changes of energy fee, revenue, and efficiency are very sensitive to the storage capacity smaller than 4-hour.

4.5.2. The Impact of Storage Capacity with Various Self-discharging Rates (Scenario 4.5-B)

In this section, we study sensitivities of energy storage capacity and a self-discharging rate while setting perfect round-trip efficiency condition. As in <Figrue 14>, the storage capacity in X-axis changes from 2 hours to 8 hours, and revenues that a consumer can make and operational efficiencies are plotted along the Y-axis. Also, the analyses are repeated for different self-discharging rates from 0 to 0.6 labeled as SDR. As shown in <Figure 13>, when the self-discharging rate (SDR) become lower, the revenue significantly increases. Also, the difference between a lower self-discharging rate and a higher rate becomes larger, when energy capacity increases. Moreover, we can see that operational efficiency decreases as the self-discharging rate becomes higher. Also, from <Table 13>, we can also find the thresholds max-

<Table 11> The Scenarios for Analyzing Impacts of Energy Capacity on Operational Efficiency

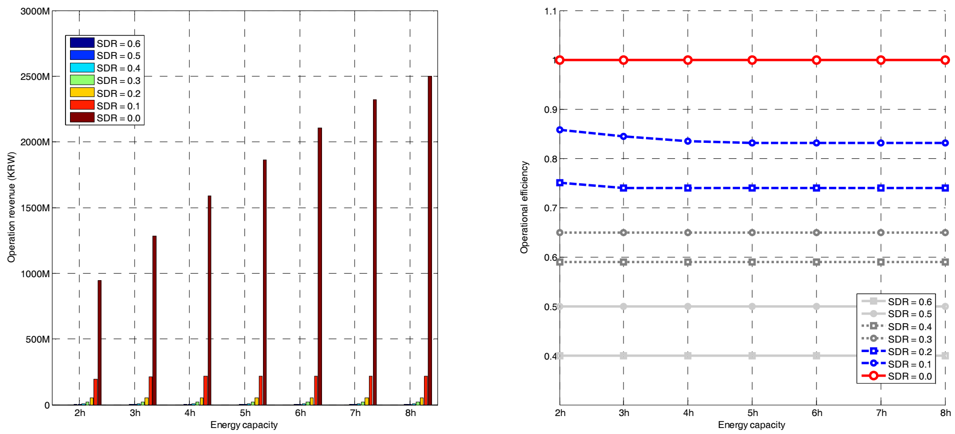
Fixed Parameter	Scenario 4.5-A	Scenario 4.5-B	Scenario 4.5-C
Round-trip efficiency (η)	80%	100% (No loss)	0% ~ 100%,
Self-discharging rate (δ)	10%	0% ~ 100%,	0% (No loss)
Power capacity (Q_{max})	20kW	20kW	20kW
Storage capacity (I_{max})	40kWh~160kWh (2h~8h)	40kWh~160kWh (2h~8h)	40kWh~160kWh (2h~8h)
Consumer utility function (a)	0	0	0



<Figure 12> The Impact of Energy Storage Capacity
Change of Energy Fee by Energy Storage Capacity (Left)
Change of Revenue from ESS Operation by Energy Storage Capacity (Middle)
Change of Operational Efficiency by Energy Storage Capacity (Right)

<Table 12> The Results of Energy Capacity on Operational Efficiency
* A Shaded Part Represents a Threshold

Energy Capacity	2h	3h	4h	5h	6h	7h	8h
Operational Efficiency	63.65%	61.17%	60.94%	60.94%	60.94%	60.94%	60.94%
Operation Revenue (million KRW)	41.53	44.87	44.96	44.96	44.96	44.96	44.96

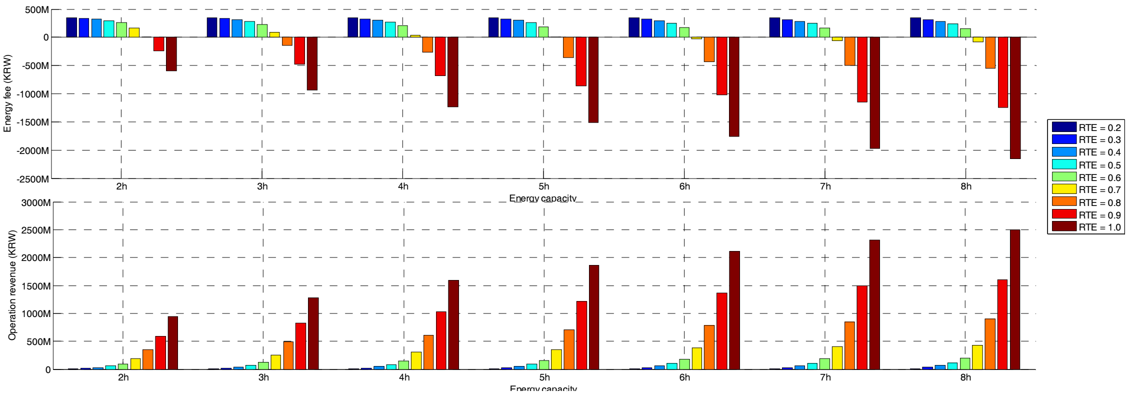


<Figrue 13> The Impact of Energy Capacity with Various Self-discharge Rates
Revenue for Different Self-discharging Rates and Energy Capacities (Left)
Operational Efficiency for Different Self-discharging Rates and Energy Eapacities (Right)

imizing revenue. For a self-discharging rate of 0.2 and 0.1, the corresponding threshold is 3-hour and 5-hour capacity, respectively. And we can see that for the higher self-discharging rate, 2-hour storage

<Table 13> Operational Efficiency for Different Self-discharging Rates and Energy Capacities
* A Shaded Part Represents Thresholds

Interaction to operational efficiency		Self-discharging rate (the lower is the better) (**δ**)						
		0.6	0.5	0.4	0.3	0.2	0.1	0
Energy Storage Capacity	2h	40.00%	50.00%	58.96%	65.00%	75.12%	85.78%	100.00%
	3h	40.00%	50.00%	58.96%	65.00%	74.00%	84.42%	100.00%
	4h	40.00%	50.00%	58.96%	65.00%	74.00%	83.43%	100.00%
	5h	40.00%	50.00%	58.96%	65.00%	74.00%	83.09%	100.00%
	6h	40.00%	50.00%	58.96%	65.00%	74.00%	83.09%	100.00%
	7h	40.00%	50.00%	58.96%	65.00%	74.00%	83.09%	100.00%
	8h	40.00%	50.00%	58.96%	65.00%	74.00%	83.09%	100.00%



<Figure 14> The Impact of Energy Capacity with Various Round-trip Efficiencies

capacity of an ESS is enough to perform optimally.

4.5.3. The Impact of Storage Capacity with Various Round-trip Efficiencies (Scenario 4.5-C)

Scenario 4.5-C investigates the impact of storage capacity when round-trip efficiency varies and a self-discharging rate is fixed. Since round-trip efficiency is directly connected to operational efficiency, we can see that the energy fee decreases and revenue steadily increases as round-trip efficiency (RTE) increases as shown in <Figure 14>. This result suggests that larger energy storage capacity make their operation revenue increase. However, we need to note that larger size of ESS costs more.

In summary, the above results from subsections 4.5.1 to 4.5.3 show that, even though an ESS has the same energy capacity, the energy fee and operation revenue can be different depending on round-trip efficiency and a self-discharging rate. More importantly, how much energy is charged and discharged or how large a size of an ESS is required also needs to be changed depending on the efficiency and the rate.

Findings from the above simulation results and their implications can be summarized as follows.

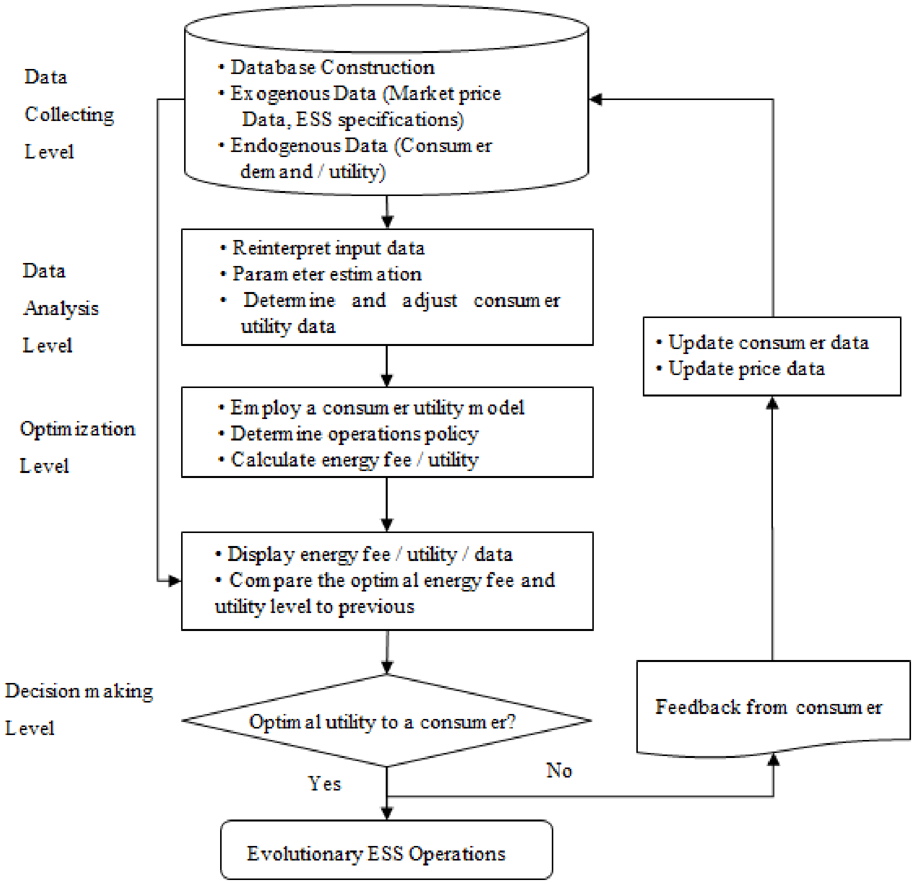
1) An ESS is more effective to a consumer who is more interested in maximizing profits from the perspectives of energy fee and consumption than a consumer who seeks a higher utility from energy consumption.
2) A self-discharging rate may be very critical on the total ESS operational efficiency beyond a certain threshold. In other words, an ESS with lower self-discharging rate than the threshold can be much more efficiently operated.
3) The operational efficiency considering both a self-discharging and round-trip efficiency cannot be easily estimated by simple calculation such as multiplication, so our result can provide a guidance to determine ESS specifications.
4) For the different level of self-charging rate, the optimal energy storage capacity can be different and the operations policy can be changed.

Ⅴ. Description of Decision Support System

In this research, we proposed an ESS operations model with consumers' utility which can be applied to automation of an ESS. Unlike previous model which considered only price arbitrage of an ESS, our model focuses on the automation of ESS operation reflecting on the consumer's utility on energy consumption. Because most consumers do not care about an ESS but are interested in profits and their own utilities, energy management system is required to satisfy the consumers' needs. Also, the system has to be able to suggest different operations policies depending on different levels of utility. Besides, as mentioned in Krishnamurti et al. (2013), what types of information the In-Home Display (IHD) needs to be provided, what types of dataset is required and how the information is communicated is very important. In this research, we showed that, for the device to be much smarter and automatically react to a consumer, more data and information would be required in addition to generic characteristics as shown in Krishnamurti et al. (2013) and Abrahamse et al. (2005). Thus, in this section we describe how the proposed model and algorithm can be embedded in the decision support system.

At the data collecting level as in <Figure 15>, our model requires database to collect exogenous data and endogenous data. Since profits come from price arbitrage, the database needs market price data of energy. Also, technical specifications of an ESS such as round-trip efficiency and a self-discharging rate should be included in the database because performance of an ESS is closely related as shown in our results. Moreover, on the consumer side, data of historical consumption and preference to the consumption are required. Then, at the data analysis level, we need to reinterpret the data and transform into structured data which is appropriate for our operations model. In other words, since many different types of datum are imported from the ESS, other machines and a consumer but data required for our operations model is limitative, the data needs to be reorganized and sorted so as to be used efficiently.

After that, the manipulated data is launched on the optimization engine. The optimization engine estimates profits that a consumer will earn and provides charging and discharging policies. These results can be shown in in-home display (IHD) or advanced metering infrastructure (AMI) which can be controlled by a consumer. In addition, the ESS decision support system developer can customize an ESS operations model and the consumer can decide the level of utility, for example low-utility, medium-utility and high-utility. From the information such as profits,



<Figure 15> Decision Support System of ESS Operations (i.e., HEMS)

efficiency and utility shown in IHD, a consumer makes a decision regarding satisfaction. The feedback is reflected on the next time horizon of optimization. Based on the updated feedback, the system updates exogenous and endogenous data. Throughout this process and algorithm, a system can adjust consumer utility and bring different management policies and performance.

Ⅵ. Conclusions and Further Studies

We proposed an ESS operations model for home energy management system considering consumer's utility in which we maximize profits obtained by price arbitrage. While most researches focus only on large-scale ESS energy management system and are interested in how much a consumer can make profits throughout the arbitrage, we notice that some segments of consumers at home are more likely to enjoy energy consumptions. Thus, we suggest an operations model for a residential consumer who has multi-objectives to lower energy fee by price arbitrage and increase utility as controlling trade-off between two. From the model, our paper discusses the impacts of consumer's utility on the performance and operations policies for HEMS. Also, we investigated the impacts of technical specification of ESS on operational efficiency of the whole system and revenue.

In this paper, we compared scenarios in which consumer utility is considered or not. The result shows that there are difference on operations policies, especially to a consumer with lower utility. Specifically, a consumer who originally has lower preference to consumption can gain much higher utility only by paying a little bit more. This result shows that a consumer having lower preference to energy consumption can utilize the ESS more efficiently to gain more utility, because the consumer can use cheaper stored energy rather than more expensive energy directly retrieved from a smart grid.

Moreover, a self-discharging rate or round-trip efficiency is likely to be regarded simply as a factor of benefit reduction. However, we found that the operational efficiency of the whole system cannot be calculated by a simple multiplication of two parameters, and a self-discharging rate and round-trip efficiency can affect operations policies and the optimal size of energy storage capacity. Our results show that there exists a threshold that operational efficiency does not change even though energy storage capacity increases. Since energy fee is not reduced beyond the threshold, a consumer does not need to have larger storage capacity than the threshold. Besides, we found that how much energy is charged and discharged or how large size of an ESS is required could be very sensitive to round-trip efficiency and a self-discharging rate. Especially, it is shown that when the rate is lower and the efficiency is higher, revenues that a consumer makes increase significantly. This implies that a self-discharging rate and round-trip efficiency can be very crucial factor that should be considered when a consumer purchases an ESS. Furthermore, our analyses show that a self-discharging rate and round-trip efficiency leads to the change of operations policy and the technological specifications are very important factors to be considered, not to mention reduction of benefits. In a smart grid that an electricity price changes over time and also consumer's utility needs to be satisfied as described in Fisher (2008), Darby (2010), and Department of Energy (2017), the system becomes more complex, which emphasizes the necessity of an automated control model in the energy management system.

However, in this paper, we do not consider uncertainty which could be very important factor as in Carpinelli et al. (2014) and Moon (2014). Since market price uncertainty and consumer demand uncertainty as mentioned in Carpinelli et al. (2014) and Moon (2014) can change profits and operations policy, taking uncertainty into account might be extension of this research. Also, our proposed model does not consider upfront costs such as a purchasing cost and an installation cost of an ESS with HEMS. For example, if the upfront costs do not increase linearly with respect to the size or they are very dependent on technologies, the operations policy could be changed. Also, the consideration of those costs would be more practical for our model to be applicable to industry. Moreover, updating rule can be included in our model as another extension. In our model, a consumer needs to update utility information and energy management system re-optimizes periodically. But, embedding machine learning in the system can produce results more conveniently. Such an evolutionary algorithm can help a consumer not necessarily give any feedback to the system in the long term.

Acknowledgments

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<References>

[1] Akhil, A. A., Huff, G., Currier, A. B., Kaun, B. C., Rastler, D. M., Chen, S. B., et al. (2013). DOE/EPRI 2013 electricity storage handbook in collaboration with NRECA. *Report SAND2013-5131*, Sandia National Laboratories.

[2] Abrahamse, W., Steg, L., Vlek, C., Rothengatter, T., (2005). A review of intervention studies aimed at household energy conservation. *Journal of environmental psychology, 25*, 273-291.

[3] Barbose, G. L., N. R. Darghouth, D. Millstein, M. Spears, R. H. Wiser, M. Buckley, R. Widiss and N. Grue. (2015). Tracking the Sun VIII: The Installed Price of Residential and Non-Residential Photovoltaic Systems in the United States, *Lawrence Berkeley National Laboratory (LBNL)*, Berkeley, CA (United States).

[4] Bradbury, K., Pratson, L., & Patiño-Echeverri, D. (2014). Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets. *Applied Energy, 114*(0), 512-519.

[5] Carpinelli, G., di Fazio, A. R., Khormali, S., & Mottola, F. (2014). Optimal sizing of battery storage systems for industrial applications when uncertainties exist. *Energies, 7*(1), 130-149.

[6] Chen, H., Cong, T. N., Yang, W., Tan, C., Li, Y., & Ding, Y. (2009). Progress in electrical energy storage system: A critical review. *Progress in Natural Science, 19*(3), 291-312.

[7] Conejo, A.J., Morales, J.M., Baringo, L., (2010). Real-time demand response model. *Smart Grid, IEEE Transactions on, 1*, 236-242.

[8] Darby, S., (2010). Smart metering: what potential for householder engagement? *Building Research & Information, 38*, 442-457.

[9] Denholm, P., and Kulcinski, G. L. (2004). Life cycle energy requirements and greenhouse gas emissions from large scale energy storage systems. *Energy Conversion and Management, 45*(13), 2153-2172.

[10] Department of Energy. (2017). Transforming the Nation's Electricity System: The Second Installent of the QER.

[11] Electropaedia (2014). Battery Performance Characteristics.

[12] Farinaccio, L., and Zmeureanu, R. (1999). Using a pattern recognition approach to disaggregate the total electricity consumption in a house into the major end-uses. *Energy and Buildings, 30*(3), 245-259.

[13] Ferreira, R., Barroso, L.-A., Carvalho, M., Kelman, R., Lino, P., and Valenzuela, P. (2011) The role of correlated prices in demand response: A robust optimization approach. In *Innovative Smart Grid Technologies (ISGT Latin America), 2011 IEEE PES Conference on*, (pp. 1-7): IEEE

[14] Ferreira, R. S., Barroso, L. A., and Carvalho, M. M. (2012). Demand response models with correlated price data: A robust optimization approach. *Applied Energy, 96*(0), 133-149.

[15] Firth, S., Lomas, K., Wright, A., and Wall, R. (2008). Identifying trends in the use of domestic appliances from household electricity consumption measurements. *Energy and Buildings, 40*(5), 926-936.

[16] Fischer, C., (2008). Feedback on household electricity consumption: a tool for saving energy? *Energy efficiency 1*, 79-104

[17] Galen, L. B. and R. D. Naïm. (2016). *Tracking the Sun IX: The Installed Price of Residential and Non-Residential Photovoltaic Systems in the United States*, avaiable at https://emp.lbl.gov/sites/all/files/tracking_the_sun_ix_report.pdf

[18] Gellings, C. W., and Smith, W. M. (1989). Integrating

demand-side management into utility planning. *Proceedings of the IEEE, 77*(6), 908-918.

[19] Hargreaves, T., Nye, M., and Burgess, J. (2010). Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors. *Energy Policy, 38*(10), 6111-6119.

[20] Krishnamurti, T., Davis, A.L., Wong-Parodi, G., Wang, J., Canfield, C., (2013). Creating an in-home display: Experimental evidence and guidelines for design. *Applied Energy, 108*, 448-458.

[21] Kwon, J.-H., S.-M. Han, S.-w. Park, D.-C. Choi and K. Balho. (2010). Analysis of The Impact of Demand Response by Dynamic Pricing for Residential Customers. *The Korean Institute of Electrical Engineer*s, pp. 548-549.

[22] Moon, Y. (2014). Demand Response Real Time Pricing Model for Smart Grid Considering Consumer Behavior and Price Elasticity. *Journal of the Korean Operations Research and Management Science Society, 39*(1), 49-67.

[23] Moon, Y. (2014). Optimal Time to Invest Energy Storage System under Uncertainty Conditions. *Energies, 7*(4), 2701-2719.

[24] National Institute of Standards and Technology (2011). *NIST Framework and Roadmap for Smart Grid Interoperability Standards*. avaiable at https://www.nist.gov/document-2643

[25] Rahimiyan, M., Baringo, L., Conejo, A.J., (2014) Energy management of a cluster of interconnected price-responsive demands. *IEEE Transactions on Power System,s 29*, 645-655.

[26] Roza Jr, R. R. (1993). *Compendium of Pumped Storage Plants in the United States*. In: ASCE

[27] Sæle, H., and Grande, O. S. (2011). Demand response from household customers: experiences from a pilot study in Norway. *Smart Grid, IEEE Transactions on, 2*(1), 102-109.

[28] Sioshansi, R. (2010). Welfare impacts of electricity storage and the implications of ownership structure. *Energy Journal, 31*(2), 173.

[29] Sioshansi, R., Denholm, P., Jenkin, T., and Weiss, J. (2009). Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects. *Energy economics, 31*(2), 269-277.

[30] Wade, N. S., Taylor, P., Lang, P., and Jones, P. (2010). Evaluating the benefits of an electrical energy storage system in a future smart grid. *Energy Policy, 38*(11), 7180-7188.

[31] Walawalkar, R., Apt, J., and Mancini, R. (2007). Economics of electric energy storage for energy arbitrage and regulation in New York. *Energy Policy, 35*(4), 2558-2568.

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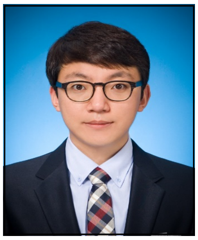

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