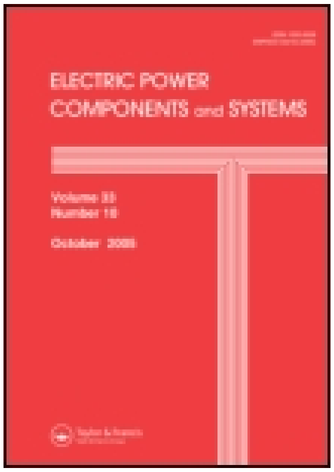

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Impact of Demand and Price Uncertainties on Customer-side Energy Storage System Operation with Peak Load Limitation

Eunsung Oh[a], Sung-Yong Son[b], Hyemi Hwang[c], Jong-Bae Park[d] & Kwang Y. Lee[e]
[a] Department of Electronics Engineering, Hanseo University, Chungcheongnam-do, Korea
[b] Department of Energy and IT, Gachon University, Gyeonggi-do, Korea
[c] Solar Energy Research Group, Korea Institute of Energy Research (KIER), Daejeon, Korea
[d] Department of Electrical Engineering, Konkuk University, Seoul, Korea
[e] Electrical and Computer Engineering Department, Baylor University, Waco, Texas, USA
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Eunsung Oh,[1] Sung-Yong Son,[2] Hyemi Hwang,[3] Jong-Bae Park,[4] and Kwang Y. Lee[5]
[1]Department of Electronics Engineering, Hanseo University, Chungcheongnam-do, Korea
[2]Department of Energy and IT, Gachon University, Gyeonggi-do, Korea
[3]Solar Energy Research Group, Korea Institute of Energy Research (KIER), Daejeon, Korea
[4]Department of Electrical Engineering, Konkuk University, Seoul, Korea
[5]Electrical and Computer Engineering Department, Baylor University, Waco, Texas, USA

CONTENTS

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Address correspondence to Jong-Bae Park, Department of Electrical Engineering, Konkuk University, 1 Hwayang-dong, Gwangin-gu, Seoul, 143-701, Korea. E-mail: jbaepark@konkuk.ac.kr

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Abstract—This article investigates customer-side energy storage system operations to minimize the electricity bill under a peak load limitation constraint and uncertain environments. Specifically, it is discussed how the demand and price uncertainties impact the system performance. It is shown that the energy storage system operation based on the Markov decision process with stochastic information has near-optimum performance, which is achieved by an iterative method with perfect information when the electricity price and demand are slightly varied. To address a problem, such as the failure of peak load reduction due to high uncertainties, two heuristic methodologies are suggested by modifying the peak load threshold and the charge/discharge reservation quantity. It is demonstrated that the proposed approach can effectively manage the uncertainties with marginal performance degradation.

1. INTRODUCTION

With the enhanced communication infrastructure and smart devices, there is growing room to develop operation and management system for improving energy efficiency and reducing cost for both power system operators and consumers [1, 2]. In particular, due to the introduction of dynamic pricing, the flexibility of customer-side operation has been increased in modern power systems [2–5].

The conventional electricity bill consists of demand and energy charges, which depend on the peak load and accumulated electricity usage, respectively. Reducing the peak load is beneficial for both power system operators and customers. The system operator can improve the system reliability as well as reduce system cost, which is tightly coupled to peak load reduction while customers can reduce their electricity usage cost [6, 7]. Actually the demand charge is designed to induce customers to try to reduce the peak load of electric utilities.

However, reducing the peak load implies a change of usual electricity usage patterns and may cause the increase of customer discomfort.

On the other hand, an energy storage system (ESS) can be a useful and prominent tool to reduce the peak load without losing customer's comfort so long as it is economical [8]. An ESS has benefits compared to the conventional shift- or reduction-based demand-side management by maintaining the same service quality since customers do not recognize whether the loads are shifted or not. However, the operation of an ESS is complex because it cannot provide electric energy more than that stored.

There are several research works on how to operate an ESS to obtain economic benefits [9, 10] and integrate the renewable energy source [11, 12]. These works, however, are mostly based on the deterministic models. In real situations, there exist uncertainties in demand and electricity price. If the demand is underestimated, then the charged electricity would be depleted earlier than for the economic operation, and it may cause failure in controlling the peak load under the desired level. It would be similar for the price when real-time dynamic pricing is applied. How to schedule charging and discharging for ESSs poses a complex problem because of its inter-temporal nature; its operation in one time step would affect its operation in other time steps that come later.

ESS operation strategies are proposed considering the uncertainties [13–18]. With the uncertainty of renewable generation, ESS operation algorithms are studied for reducing the system operational cost under isolated microgrid environments [13] and by integrating renewable generators into the electricity market [14]. Flexible optimal operation of ESSs is researched for optimal power flow problems with varying demand and price profiles [15]. Customer-side ESS operations using a simplified model introduced both unlimited and limited peak load constraints [16]. However, most of these works are based on the search method, which requires a high computational burden due to iteration processes.

Some research has been performed for stochastic ESS operations under demand or price fluctuations [17–20]. Stochastic operations based on the Markov decision process (MDP) were introduced in [17, 18]. These works deal with how to operate the ESS under uncertain environments. In [19], a stochastic optimization framework is presented for secure and efficient operation and planning of a bulk electric power system with uncertainty. A scenario-based stochastic framework is proposed to investigate the effect of uncertainty for microgrids [20]. However, much research is focused on the basic rules for ESS operations. For more reliable and practical ESS operation, it should be discussed how the uncertainties affect the ESS operation and performance.

This article focuses on dynamic ESS operation for reducing electricity bills under peak load limitation and demand and price uncertainties.

The general ESS operation problem is first formulated as a linear programming problem. To solve this problem, the problem is reformulated in the recursive form, and an optimal ESS operation is derived based on the MDP. The MDP-based algorithm (i) determines the amount of ESS charge/discharge with the current demand and price information and the stochastic properties for future values and (ii) updates the reserved ESS energy for the expected peak demand control and price change at each decision interval. This this MDP-based algorithm is then used to discuss how the demand and price uncertainties affect the electricity bill savings and the peak load shaving.

Moreover, the failure issue that the stochastic operation cannot always satisfy the constraints caused by the uncertainties will be considered. For reducing the impacts of uncertainties, two practical strategies are suggested that change the constraint threshold of the operation problem and the amount of reserve for the future peak load reduction. The results show that the suggested approaches can effectively overcome the failure issue with very marginal performance degradation (*i.e.*, $<0.03\%$).

The remainder of this article is organized as follows: Section 2 describes the system model in terms of a customer-side power system with an ESS. In Section 3, general and recursive ESS operation problems are formulated, and the stochastic ESS operation algorithm is suggested. The impact of the demand and price uncertainties is demonstrated in Section 4. Finally, conclusions are drawn in Section 5.

2. SYSTEM MODEL

This section provides descriptions for the analytical representation of the customer-side power system model, including demand and price, and ESS. Based on these definitions, the ESS operation problem will be formulated in Section 3.

2.1. Customer-side Power System

A customer-side power system is composed of multiple devices, an ESS, and a customer-side operator, as described in Figure 1. In this work, it is assumed that an ESS is installed for one customer, but it can be extended to the case when multiple customers are served by an ESS. In this case, each customer can be considered as a device. For the ESS operation, the aggregated demand d_t (in kWh), from devices, and the price p_t (in KRW/kWh), from the electricity market, are periodically input to the operator with unit time interval ΔT (in hr). The time interval is determined considering the time period that

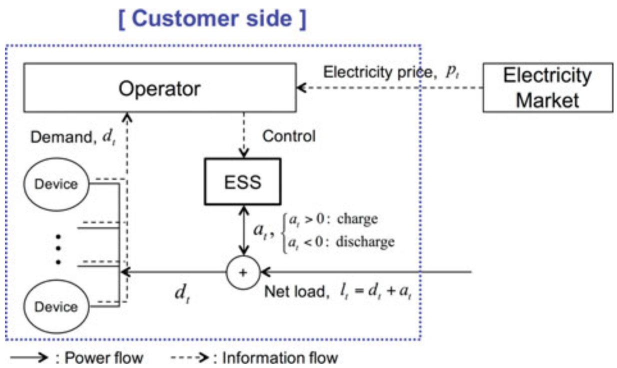


FIGURE 1. Customer-side power system model.

the demand and price are announced from devices and electricity market, respectively. After receiving the demand and price information, the operator decides how much power the ESS should charge or discharge. Consider an observation time duration T (*e.g.*, 24 hr). A set of decision epochs (time) for the operation is made $T = \{1, 2, \ldots, N\}$, where $N = T/\Delta T$, and t denotes the decision time indicator in T. Throughout the article, it is assumed that the duration of each epoch is considered as an hour, *i.e.*, $\Delta T = 1h$, which is a reasonable assumption under an hourly based pricing system.

2.2. Demand and Electricity Price

For an effective ESS operation, demand and price predictions as well as their current values are required. Many predication techniques have been suggested and developed [21, 22]. It is assumed that a prediction technique is available and provides sequences of demand forecasts $\hat{d}_t$ and price forecasts $\hat{p}_t$ and its distribution $f_d(d_t)$ and $f_p(p_t)$ for $t \in T$.

2.3. ESS

A single ESS is considered to be installed in the system, which has the capacity E (in kWh) and the energy rate per an hour (E-rate) ΔE [23]. The allowable operational action a_t of the ESS charge/discharge is equivalent to

$$-E\Delta E \le a_t \le E\Delta E. \tag{1}$$

By the operation, the state of charge (SoC) of the ESS, s_t, is changed to

$$s_t = s_{t-1} + a_{t-1}. \tag{2}$$

Likewise, the SoC is bounded in the ESS operation range as follows:

$$0 \le s_t \le E. \tag{3}$$

Let A_t be the feasible region of the ESS operation at each decision time t. It is constructed as

$$A_t = \{a_t | -E\Delta E \le a_t \le E\Delta E,\ 0 \le s_t \le E\}. \tag{4}$$

For more practical ESS modeling, additional ESS characteristic parameters, such as the charge/discharge efficiency and the depth of discharge (DoD), could be considered. But to focus on the effect of the ESS operation, the ideal ESS is considered (*e.g.*, the efficiency is 1 and DoD is 100%).

3. ESS OPERATION STRATEGY

3.2. Problem Formulation

For a power system, the ESS becomes a device to determine the amount of demand even if it could have a negative quantity, so the overall electricity bill during T is calculated when considering real-time pricing:

$$\sum_{t\in T} p_t (d_t + a_t) = \sum_{t\in T} p_t d_t + \sum_{t\in T} p_t a_t. \tag{5}$$

Because price p_t and demand d_t are the observed values, the objective function is given by

$$O(\mathbf{a}) = \sum_{t\in T} p_t a_t, \tag{6}$$

where $\boldsymbol{a}$ is the vector of the ESS operation actions during the decision epoch T.

In general, the electricity bill minimization problem considering the ESS operation can be formulated as:

$$\begin{aligned} &\min_{\mathbf{a}} \sum_{t\in T} p_t a_t \\ s.t.\quad & d_t + a_t \le l_{th}, \quad \forall t \in T, \\ & a_t \in A_t, \quad \forall t \in T, \end{aligned} \tag{7}$$

where l_{th} is the peak load threshold.

The optimization problem in Eq. (7) is a linear programming problem and can be solved with iterative algorithms using the simplex method or the interior point method [24]. However, they require perfect information on the demand and price over the whole observation period and extensive computation to solve the problem. Thus, an ESS operation strategy is proposed that could operate with imperfect demand and price information and low computational requirement.

3.2. ESS Operation Framework

The ESS operation is a sequential decision-making problem. At each decision epoch t, the operator decides the action a_t on the occupied ESS SoC s_{t-1} based on the information on demand d_t and electricity price p_t. The action choice incurs an immediate cost $p_t a_t$, and the ESS evolves to a new SoC s_t.

In essence, this problem is solved by an MDP [25], presented next.

In the beginning of the decision epoch t, the operator receives the current demand and electricity price, (*i.e.*, d_t and p_t), the forecasted demand and electricity price (*i.e.*, $\hat{d}_n$ and $\hat{p}_n$, where $n \in \{t+1, \cdots, N\}$), and the stochastic characteristics. Therefore, the action is made to minimize the expected electricity bill at decision epoch t. Under this constraint, the problem in Eq. (7) can be reformulated in the recursive form

$$\begin{aligned} u_t(p_t) &= \min_{a_t \in A_t} \{p_t a_t + \mathrm{E}[u_{t+1}(p_{t+1})|a_t]\}, \\ &\text{s.t.} \quad d_t + a_t \le l_{th}, \end{aligned} \tag{8}$$

where $\mathrm{E}[\cdot]$ is the expectation operation.

The Markov decision problem expressed in Eq. (8) can be solved optimally by backward induction [25]. At decision epoch N, there is only one valid action to minimize the electricity bill. At $t = N-1$, the operator can choose the action with the expected action at $t = N$. Recursively, the operator decides the current action with the expected actions in advance. It means that at each decision time, the operator determines the ESS operation by analyzing an inductively defined single-state problem with the current information and its stochastic property.

3.3. MDP-based Optimal ESS Operation

The performance of the Markov decision maker depends on the possible action set. In the problem at hand, the feasible region of the ESS operation occurs as the action set at each decision epoch. Using Eq. (2), the feasible region of the ESS operation in Eq. (4) is expressed as

$$A_t = \{a_t | a_t^{\min} \le a_t \le a_t^{\max}\}, \tag{9}$$

where $a_t^{\min} = \max\{-E\Delta E, -s_t\}$ and $a_t^{\max} = \min\{E\Delta E, E - s_t\}$.Assuming $\Delta E \ge 1$ (this assumption is reasonable in the sense that ESSs, which have small capacity and high E-rate, such as lithium ion batteries, are considered at the customer side [26–28]), the action set is addressed as

$$-s_t \le a_t \le E - s_t, \quad \forall t \notin T. \tag{10}$$

Applying the backward induction method, the reward at decision epoch N becomes

$$u_N(p_N) = \min_{a_N} p_N a_N, \tag{11}$$

and the optimal action to minimize the electricity bill is determined as

$$a_N^* = a_N^{\min} = -s_N. \tag{12}$$

The action should satisfy the peak load limitation constraint as well as the electricity bill minimization. Under the optimal action, the peak load limitation constraint is reconstructed as

$$a_N^* + d_N \le l_{th} \rightarrow a_{N-1} \ge -s_{N-1} + d_N - l_{th}. \tag{13}$$

This condition bounds the action set at decision epoch $N-1$,

$$-s_{N-1} + [d_N - l_{th}]^+ \le a_{N-1} \le E - s_{N-1}, \tag{14}$$

where $[x]^+ = \max\{0, x\}$. This means that the peak load limitation constraint at decision epoch N affects the action at decision epoch $N-1$, not that at the decision epoch N.

When $t = N-1$, the reward is calculated as

$$\begin{aligned} u_{N-1}(p_{N-1}) &= \min_{a_{N-1}}\{p_{N-1}a_{N-1} + p_N a_N^*\} \\ &= \min_{a_{N-1}}\{(p_{N-1} - P_N)a_{N-1} - p_N s_{N-1}\}. \end{aligned} \tag{15}$$

The reward in Eq. (15) is a linear function, so it is minimized when the action is chosen either $-s_{N-1} + [d_N - l_{th}]^+$ if $p_{N-1} - p_N > 0$ or $E - s_{N-1}$ if $p_{N-1} - p_N \le 0$. Under this constraint, the optimal action is decided as

$$a_{N-1}^* = -s_{N-1} + R_{N-1}(d_N, p_N), \tag{16}$$

where

$$\begin{aligned} R_{N-1}(d_N, p_N) &= E \cdot \Pr(p_{N-1} \le p_N) \\ &+ E_{d_N}[d_N - l_{th}]^+ \cdot \Pr(p_{N-1} > p_N). \end{aligned} \tag{17}$$

Comparing with the optimal action at the decision epoch N, a_{N-1}^* has an additional term $R_{N-1}(d_N, p_N)$. The term is reserved for the expected price saving ($p_{N-1} - p_N \le 0$) and the expected peak load reduction ($[d_N - l_{th}]^+$) on $N-1$ onward operations.

The peak load limitation constraint at decision epoch $N-1$ also limits the action set at decision epoch $N-2$,

$$\begin{aligned} a_{N-1}^* + d_{N-1} \le l_{th} &\rightarrow a_{N-2} \ge -s_{N-2} \\ &+ d_{N-1} - l_{th} + R_{N-1}(d_N, p_N). \end{aligned} \tag{18}$$

Likewise, for $t < N$, the optimal action is expressed as

$$a_t^* = -s_t + R_t(\vec{d}_{t+1}^N, \vec{p}_{t+N}^N), \tag{19}$$

where $\vec{d}_{t+1}^N = \{d_{t+1}, d_{t+2}, \ldots, d_N\}$, $\vec{p}_{t+1}^N = \{p_{t+1}, p_{t+2}, \ldots, p_N\}$, and

$$\begin{aligned} R_t\left(\vec{d}_{t+1}^N, \vec{p}_{t+1}^N\right) &= E \cdot \Pr(p_t \le p_{t+1}) + E_{\vec{d}_{t+1}^N}\Big[d_{t+1} - l_{th} \\ &+ R_{t+1}(\vec{d}_{t+2}^N, \vec{p}_{t+2}^N)\Big]^+ \cdot \Pr(p_t > p_{t+1}). \end{aligned} \tag{20}$$

Consequently, the MDP-based optimal ESS operation is summarized as

$$a_t^* = \begin{cases} -s_t + R_t\left(\vec{d}_{t+1}^N, \vec{p}_{t+1}^N\right), & \text{when } t \in [1, N), \\ -s_N, & \text{when } t = N. \end{cases} \tag{21}$$

Because $R_t(\vec{d}_{t+1}^N, \vec{p}_{t+1}^N)$ can be predetermined, the operator just updates it with the present price information and decides the ESS operation at each decision epoch. Therefore, it has low computational intensity compared with the algorithm based on the iterative method to solve the optimization problem in Eq. (7).

Note that the proposed stochastic algorithm can return infeasible solutions in two cases. (1) At initial decision epoch $t = 1$, the ESS should be discharged. The ESS SoC is empty at initial decision epoch because the operator discharges all ESS energy to minimize the electricity bill at the final decision epoch in Eq. (12). (2) The ESS capacity is not enough to satisfy the peak load limitation constraint, such as $d_t > l_{th} - E$. In this article, these cases will be ignored. Actually, to prevent the first case of the infeasible solution, it could be assumed that the operation is started when the demand is very low (*e.g.*, 2:00 AM). And the second problem is not an operation issue but a system design issue.

4. ESS OPERATIONAL IMPACT OF UNCERTAINTIES

Under uncertain environments, the MDP-based ESS operation as shown in Eq. (21) is worked with a stochastic information. For operational reliability, the operator can reserve the amount of ESS for future decision. The reserved amount affects the system performance that is expressed as the objective function. And a problem can occur even if the operator reserves the amount of ESS for satisfying constraints when the uncertainty becomes high (*e.g.*, increasing the forecast error). This section empirically discusses the impact of uncertainties that affect the ESS objective and constraint.

A customer-side power system with a 1-kWh ESS is considered to demonstrate the performance of the ESS operation during one day. The set of decision epochs is constructed as $T = \{1, 2, \cdots, N = 24\}$. The demand and price are randomly generated to check the impact of uncertainties, and the data set is applied, which is gathered from a typical building in Korea.

4.1. Impact on Electricity Bill Savings

Electricity bill saving, which is the objective in this work, through ESS operation is observed under varying the constraints as well as the demand and price, which are modeled as Gaussian distributed random variables [19, 21] with the mean

$$\begin{aligned} \hat{d}_t &= 0.5 \times \{2 - \sin(2\pi(t+4)/N)\}\,(\text{kWh}), \\ \hat{p}_t &= 60 \times \{2 - \sin(2\pi(t+4)/N)\}\,(\text{KRW/kWh}), \end{aligned} \tag{22}$$

and the variance. The values in Eq. (22) illustrate the typical customer-side model of Korea that the average demand during one day is 12 kW and the average price per kWh is 120 KRW [29]. The variance is changed according to the

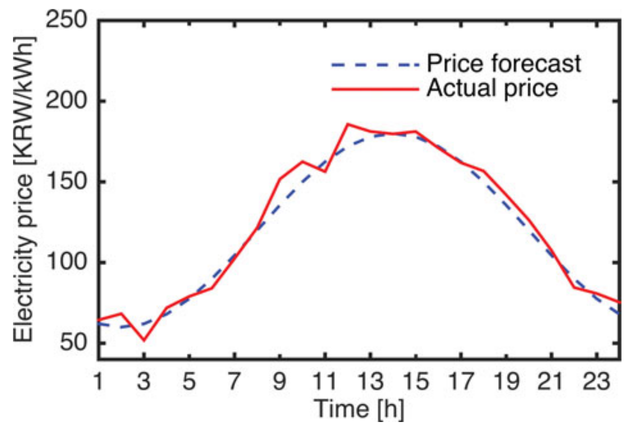


FIGURE 2. An example of actual price and price forecast when the forecast error is 3%.

average forecast error $\mathrm{E}[|\hat{d}_t - d_t|/d_t]$ or $\mathrm{E}[|\hat{p}_t - p_t|/p_t]$ in the results. In Figure 2, an example of actual price and price forecast is shown when the forecast error is considered as 3%.

In Figure 3(a), electricity bill saving is illustrated when only demand forecast error is considered. The electricity bill saving is slightly decreased when the demand forecast error is increasing but is very marginal, *e.g.*, 0.02% with 10% peak load reduction requirement and 3% demand forecast error. However, when the peak reduction requirement becomes strong, from 2% to 10%, the amount of electricity bill saving is greatly reduced. The ESS operator reserves some amount of energy for future demand control. When the forecast error and peak reduction requirement are increased, the reserved amount should be raised. When the required reserve amount is increased, the probability of electricity bill savings is reduced. This is because the flexibility for operation is restricted by the reserve constraint. The electricity bill saving is marginally decreased by the demand forecast error, but it is linearly reduced when increasing the peak reduction requirement. This means that the peak reduction requirement has more influence than the forecast error when demand forecast error is considered.

The relation between electricity bill savings and price forecast errors is provided in Figure 3(b). The electricity bill saving by the ESS operation is reduced when the price forecast error is increased. Similar to the effect of demand uncertainty, the ESS operator reserves some amount on ESS charge/discharge for providing against the price uncertainty. The reservation term limits the operational degree of freedom. The MDP-based ESS operation contains the reservation term, expressed as $R_t(\vec{d}_{t+1}^N, \vec{p}_{t+1}^N)$ for preparing uncertainties for future decision. When calculating the term, the demand uncertainty is neglected in some cases (e.g., when the ESS is

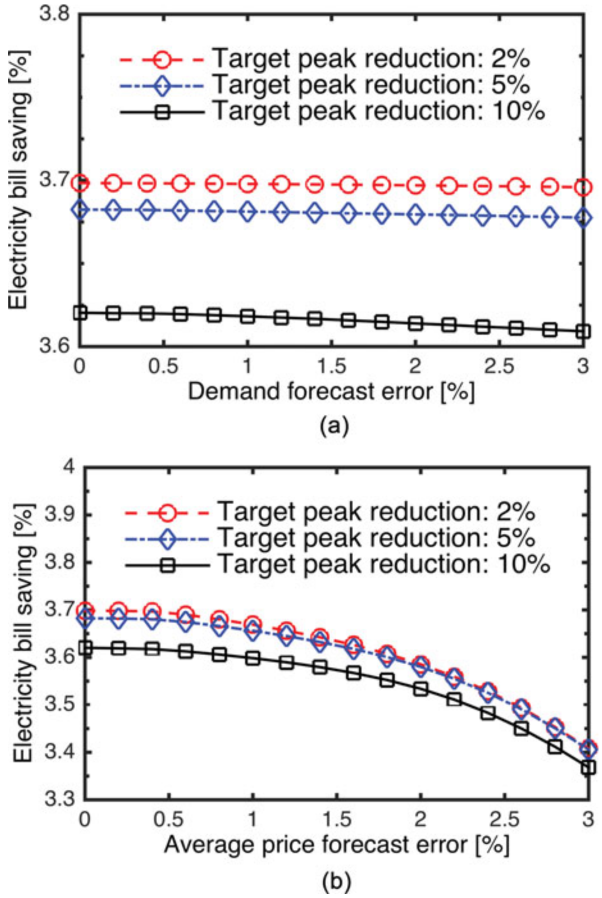


FIGURE 3. Comparison of electricity bill savings at 2, 5, and 10% peak load reduction constraints: (a) electricity bill savings versus demand forecast error and (b) electricity bill savings versus price forecast error.

fully charged), but the price uncertainty affects every decision time and is accumulated. Therefore, the electricity bill saving is exponentially decreasing with increasing price forecast error.

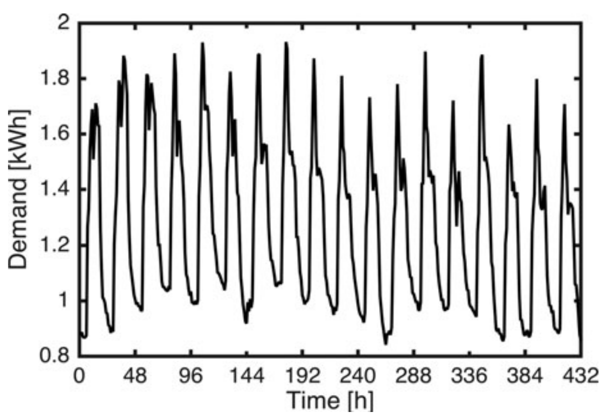


FIGURE 4. Modified demand data recorded from the typical building of Korea in March 2013.

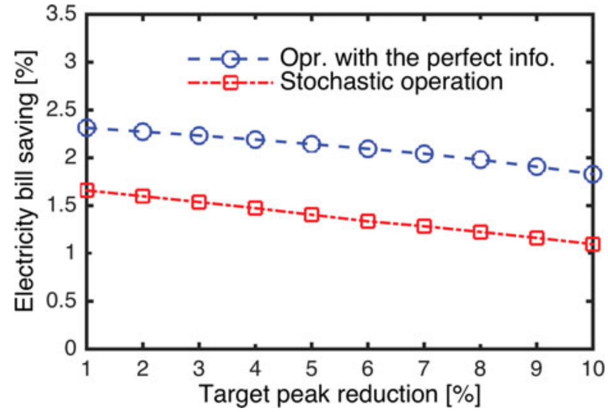


FIGURE 5. Electricity bill saving with varying target peak reduction using Korea demand set.

To obtain more realistic observations, the demand set recorded from a typical building in Korea on March 2013 was acquired. The daily demand of collected data sets is 300 kW on average. Due to the assumption of a 1-kWh ESS, it is scaled

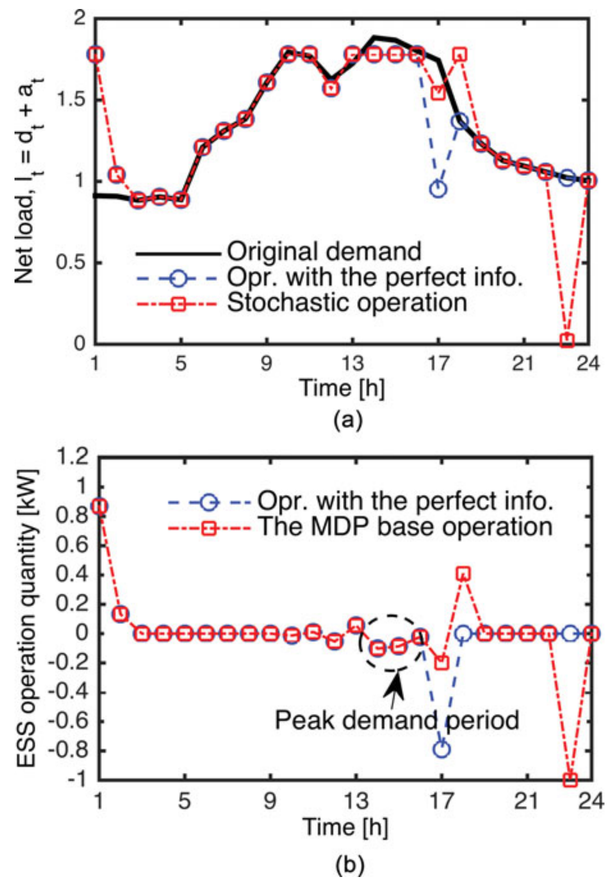


FIGURE 6. Example of net load and ESS operation quantity with 5% peak reduction target: (a) net load and (b) ESS operation quantity.

down to 30 kW per day, as shown in Figure 4. The MDP-based ESS operator has information of the forecast demand and assumes that the demand forecast error is 2% [30] and has the perfect information of the price because the building uses a predetermined time-of-use tariff of KEPCO's Industrial (B)–A-I [29].

Figure 5 shows the amount of electricity bill saving with varying target peak reduction requirements using the demand data set of Korea. The dashed–dotted red line with squares expresses the electricity bill saving from the MDP-based operator, and the results, which are operated with the perfect information as deterministic values, are illustrated as the dashed blue line with circles. Similar to the result of ideal cases in Figure 3(a), the electricity bill saving is almost linearly decreased with more strong peak reduction requirements. Tight peak reduction requirement limits the room for operation for electricity bill saving. However, the degradation of electricity bill saving of the MDP-based operation is less than 1% compared to the results with the perfect information.

An example of the demand profiles reflecting ESS operation and ESS operation quantity are presented with a 5% peak reduction target in Figure 6. In Figure 6(a), the original demand illustrated as the black line is changed to the squared red dashed–dotted line by the MDP-based ESS operation and the circled blue dashed line by the operation with the perfect information. The operator with the perfect information fully discharges the quantity of ESS because the operator knows that there is no required demand exceeding the peak reduction requirement after 17 hr. The MDP-based operator also discharges some quantity of ESS, but some quantity of ESS should remain to provide the possible peak reduction after 17 hr. This is because the MDP-based operator just has the stochastic information of the demand. However, there is little difference between the operations, which is why the electricity bill saving has a similar value in Figure 5.

To clarify the operation, the ESS operation quantities are presented in Figure 6(b). The positive value means that the ESS is charged from the grid and vice versa. It is presented that the ESS is simply charged at nighttime (*i.e.*, 1–2 hr) and discharged at the peak demand duration (*i.e.*, 12, 14, and 15 hr) when the operator knows the perfect information, as shown by the circled blue dashed line. The MDP-based operator of the squared red dashed–dotted line is similarly worked, but the additional charging and discharging operations occur to prepare the future peak cutting after the peak demand duration.

4.2. Impact on Peak Load Cut

The uncertainty first restricts the electricity bill saving, as described in the previous results. Particularly, the price uncertainty has a significant impact to the electricity bill saving.

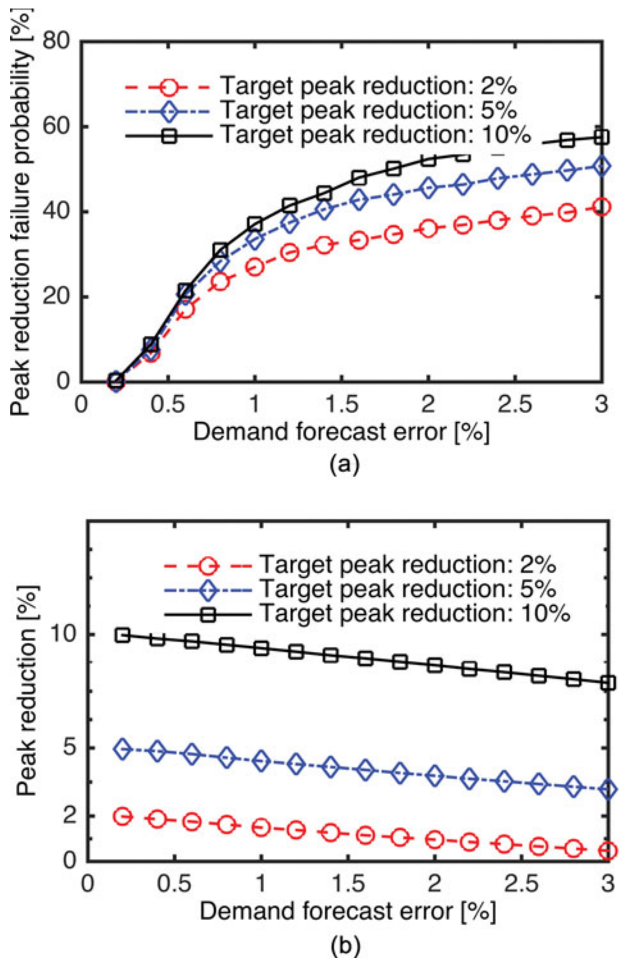
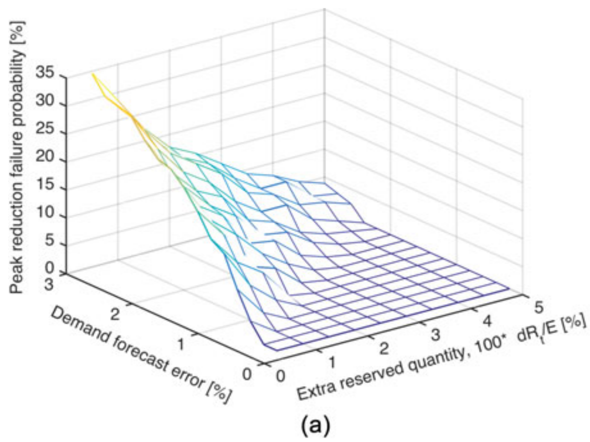


FIGURE 7. Effect of demand forecast error at 2, 5, and 10% peak load reduction requirements: (a) peak reduction failure probability and (b) peak reduction when failure occurs.

The demand uncertainty has less impact on the electricity bill saving but makes it difficult to reflect the peak load limitation. For reducing the required demand, the ESS is discharged, and the amount of discharge is decided based on the SoC, which is reserved at the previous decision for onward demand reduction. When the demand uncertainty becomes high, difficulty grows in determining the reserve for future peak demand control, and the operation result does not satisfy the peak load limitation constraint.

The probability of peak reduction failure is shown with various demand forecast error and peak reduction requirements in Figure 7(a). For increasing demand forecast error, the peak reduction failure probability is also increased. This is because demand forecasting is the basis of how much quantity should be reserved for future peak demand. Increasing target peak reduction also makes the peak reduction failure probability high since the tight peak reduction requirement reduces the room for operation.



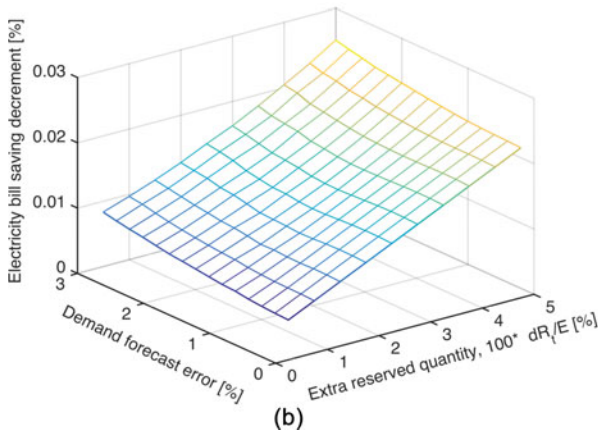


FIGURE 8. Effect of the forced extra reserve for future peak reduction at 5% peak load reduction requirement: (a) peak reduction failure probability and (b) electricity bill saving decrement.

Figure 7(b) presents how much demand is reduced when the required peak reduction requirements fail. It is shown that the amount of peak reduction is linearly decreasing for the increasing demand forecast error in all peak reduction targets. Based on these observations, a simple approach is first suggested for avoiding the failure that the peak load threshold could be more flexibly established (*e.g.*, αl_{th}, where $\alpha < 1$) considering peak reduction target and recorded demand forecast error.

Another way to reduce the failure is to force an extra reserve for future peak reduction when calculating the reserved term, *e.g.*, $R_t(\vec{d}_{t+1}^N, \vec{p}_{t+1}^N) + dR_t$. The failure probability is illustrated in Figure 8(a) when the forced extra reservation is applied for the 5% peak load reduction target. It is shown that the failure is dramatically decreased (*i.e.*, less than 10% failure probability when an additional 3.5% of the ESS capacity is reserved for future peak load reduction). The reservation increment limits the electricity bill saving; however, the decrease is relatively small compared to that without the extra reservation, *e.g.*, $<$0.03% when the 5% extra reservation of the ESS capacity is considered, as shown in Figure 8(b).

5. CONCLUSIONS

This article solves the ESS operation problem for electricity bill minimization under a peak load limitation constraint in customer-side power systems. An environment is considered that the operator has imperfect information about the demand and price. Taking into account the uncertainty, a stochastic ESS operation algorithm is suggested based on the MDP, and how demand and price uncertainties affect to the system performance is discussed. Additionally, two heuristic approaches for reducing the effect of uncertainties are suggested by modifying the peak load threshold and the reserve term.

Future works will include an investigation on scalability issues in the optimization problem, design and comparison of more effective operational algorithms, and extensions to consider more realistic models, such as ESS characteristics and demand types.

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REFERENCES

[1] Farhangi, H., "A road map to integration: Perspectives on smart grid development," *IEEE Power Energy Mag.*, Vol.. 12, No. 3, pp. 52–66, May 2014.

[2] Varaiya, P. P., Wu, F. F., and Bialek, J. W., "Smart operation of smart grid: Risk-limiting dispatch," *Proc. IEEE*, Vol. 99, No. 1, pp. 40–57, January 2011.

[3] Pedrasa, M. A. A., Spooner, T. D., and MacGill, I. F., "Scheduling of demand side resources using binary particle swarm optimization," *IEEE Trans. Power Syst.*, Vol. 24, No. 3, pp. 1173–1181, August 2009.

[4] Li, N., Chen, L., and Low, S. H., "Optimal demand response based on utility maximization in power networks," *Proceedings of the 2011 IEEE/PES General Meeting*, Detroit, MI, 24–28 July 2011.

[5] Kinhekara, N., Padhya, N. P., and Guptab, H. O., "Multi-objective demand side management solutions for utilities with peak demand deficit," *Int. J. Electr. Power Energy Syst.*, Vol. 55, pp. 612–619, February 2014.

[6] Borenstein, S., "The long-run efficiency of real-time electricity pricing," *Energy J.*, Vol. 26, No. 3, pp. 93–116, February 2005.

[7] Mohsenian-Rad, A. H., and Leon-Garcia, A., "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Trans. Smart Grid*, Vol. 1, No. 2, pp. 120–133, September 2010.

[8] Gyuk, I., Kulkarni, P., Sayer, J., Boyes, J., Corey, G., and Peek, G., "The united states of storage [electric energy storage]," *IEEE Power Energy Mag.*, Vol.. 3, No. 2, pp. 31–39, March 2005.

[9] Xu, Y., and Singh, C., "Adequacy and economy analysis of distribution systems integrated with electric energy storage and renewable energy resources," *IEEE Trans. Power Syst.*, Vol. 27, No. 4, pp. 2332–2341, November 2012.

[10] Sugihara, H., Yokoyama, K., Saeki, O., Tsuji, K., and Funaki, T., "Economic and efficient voltage management using customer-owned energy storage systems in a distribution network with high penetration of photovoltaic systems," *IEEE Trans. Power Syst.*, Vol. 28, No. 1, pp. 102–111, February 2013.

[11] Tewari, S., and Mohan, N., "Value of NAS energy storage toward integrating wind: Results from the wind to battery project," *IEEE Trans. Power Syst.*, Vol. 28, No. 1, pp. 532–541, February 2013.

[12] Chandra, S., Gayme, D. F., and Chakrabortty, A., "Coordinating wind farms and battery management systems for inter-area oscillation damping: A frequency-domain approach," *IEEE Trans. Power Syst.*, Vol. 29, No. 3, pp. 1454–1462, May 2014.

[13] Ross, M., Hidalgo, R., Abbey, C., and Joos, G., "Energy storage system scheduling for an isolated microgrid," *IET Renew. Power Gener.*, Vol. 5, No. 2, pp. 117–123, March 2011.

[14] Jain, N., Singh, S. N., and Srivastava, S. C., "Meta-heuristic approach for distributed generation planning in electricity market paradigm," *Proceedings of the 2012 IEEE/PES General Meeting*, San Diego, CA, 22–26 July 2012.

[15] Gabash, A., and Li, P., "Flexible optimal operation of battery storage systems for energy supply networks," *IEEE Trans. Power Syst.*, Vol. 28, No. 3, pp. 2788–2797, August 2013.

[16] Oh, E., Son, S.-Y., and Park, J.-B., "Customer-side energy storage system operation strategies under uncertain environments," *Proceedings of the 2013 the International Conference on Electrical Engineering*, pp. 383–388, Xiamen, China, 14–17 July 2013.

[17] Koutsopoulos, I., Hatzi, V., and Tassiulas, L., "Optimal energy storage control policies for the smart power grid," *Proceedings of the IEEE International Conference on Smart Grid Communications,* Brussels, Belgium, 17–20 October, October 2011.

[18] Kim, J. H., and Powell, W. B., "Optimal energy commitments with storage and intermittent supply," *Operat. Res.*, Vol. 59, No. 6, pp. 1347–1360, November 2011.

[19] Murillo-Sanchez, C. E., Zimmerman, R. D., Anderson, C. L., and Thomas, R. J., "Secure planning and operations of systems with stochastic sources, energy storage, and active demand," *IEEE Trans. Smart Grid*, Vol. 4, No. 4, pp. 2220–2229, December 2013.

[20] Mohammadia, S., Soleymanib, S., and Mozafarib, B., "Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices," *Int. J. Electr. Power Energy Syst.*, Vol. 54, pp. 525–535, January 2014.

[21] Gross, G., and Galiana, F. D., "Short-term load forecasting," *Proc. IEEE*, Vol. 75, No. 12, pp. 1558–1573, December 1987.

[22] Doulai, P., and Cahill, W., "Short-term price forecasting in electric energy market," *Proceedings of the International Power Engineering Conference*, pp. 749–754, Singapore, 17–19 May 2001.

[23] Massachusetts Institute of Technology, "A guide to understanding battery specifications," Technical Report, December 2008.

[24] Boyd, S., and Vandenberghe, L., "Linear programming," in *Convex Optimization*. Cambridge, UK: Cambridge University Press, Chap. 1.2.2, 2004.

[25] Puterman, M. L., "Finite-horizon Markov decision processes," in *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. Hoboken, NJ: John Wiley & Sons, Inc., Chap. 4, 1994.

[26] Divya, K. C., and Østergaard, J., "Battery energy storage technology for power systems—an overview," *Electr. Power Syst. Res.*, Vol. 79, No. 4, pp. 511–520, April 2009.

[27] Kintner-Meyer, M., Balducci, P., Jin, C., Nguyen, T., Elizondo, M., Viswanathan, V., Guo, X., and Tuffner, F., "Energy storage for power systems applications: A regional assessment for the northwest power pool," Pacific Northwest National Lab. Technical Report PNNL-19300, April 2010.

[28] Byrne, R. H., and Silva-Monroy, C. A., "Estimating the maximum potential revenue for grid connected electricity storage: Arbitrage and regulation," Sandia National Lab. Technical Report SAND2012-3863, December 2012.

[29] Korea Electric Power Corp., "Statistics of electric power in Korea," White Paper, May 2013.

[30] Wi, Y.-M., Kim, J.-H., Joo, S.-K., Park, J.-B., and Oh, J.-C., "Customer baseline load (CBL) calculation using exponential smoothing model with weather adjustment," *Proceedings of the IEEE PES Transmission & Distribution Conference & Exposition: Asia and Pacific*, pp. 1–4, Seoul, Korea, 26–30 October 2009.

BIOGRAPHIES

Eunsung Oh received his B.S., M.S., and Ph.D. in electrical engineering at Yonsei University, Seoul, Korea, in 2003, 2006, and 2009, respectively. From 2009 to 2011, he was a postdoctoral researcher in the Department of Electrical Engineering at the University of Southern California's Viterbi School of Engineering. From 2011 to 2012, he was a senior researcher at Korea Institute of Energy Technology Evaluation and Planning, Korea. From 2012 to 2013, he was a research professor in the Department of Electrical Engineering at Konkuk University, Korea. He is currently an assistant professor in the Department of Electrical and Computer Engineering at Hanseo University, Korea. His main research interests include the design and analysis of algorithms for green communication networks and smart grids.

Sung-Yong Son received his B.S. and M.S. from Korea Advanced Institute of Science and Technology (KAIST), Korea, in 1999 and 1992, respectively, and his Ph.D. in mechanical engineering from University of Michigan, Ann Arbor, in 2000. From 2000 to 2005, he worked at 4DHomeNet and Icross-technology, respectively. He is an associate professor in the Department of Electrical Engineering, Gachon University, Korea. His main research interests include smart grids and smart homes.

Hyemi Hwang received her B.S. and M.S. in electrical engineering at Kangwon National University, Korea, in 2002 and 2004, respectively. She has been a senior researcher at KIER since 2005. She is currently pursuing a doctorate in electrical engineering at Konkuk University. Her main research interests include photovoltaic power generation systems, dispersed generation systems, and new and renewable energy economics and policy.

Jong-Bae Park received his B.S., M.S., and Ph.D. in electrical engineering at Seoul National University Seoul, Korea, in 1987, 1989, and 1998, respectively. He is currently a professor in the Department of Electrical Engineering at Konkuk University, Korea. He was a researcher at Korea Electric Power Corp. (KEPCO) during 1989–1998 and a resident researcher of Electric Power Research Institute (EPRI) during 2006–2008. His main research interests include power system economics, computational intelligence, operations, and planning.

Kwang Y. Lee received his B.S. in electrical engineering in 1964 from Seoul National University, his M.S. in electrical engineering in 1968 from North Dakota State University, and his Ph.D. in systems science in 1971 from Michigan State University. He was elected as a fellow of IEEE in January 2001 for his contributions to the development and implementation of intelligent system techniques for power plants and power systems control and is a life fellow of IEEE since January 2008. He has been working in the area of power plants and power systems control for over 30 years at Michigan State, Oregon State, University of Houston, Pennsylvania State University, and Baylor University, where he is the professor and chairman of the Department of Electrical and Computer Engineering. His research interests include control, operation, and planning of power and energy systems; computational intelligence and intelligent control and their applications to power and energy systems, and modeling, simulation, and control of microgrids with renewable and distributed energy sources.