J Electr Eng Technol.2018; 13(1): 068-077
http://doi.org/10.5370/JEET.2018.13.1.068

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Impact of User Convenience on Appliance Scheduling of a Home Energy Management System

Je-Seok Shin*, In-Su Bae and Jin-O Kim†**

Abstract – Regarding demand response (DR) by residential users (R-users), the users try to reduce electricity costs by adjusting their power consumption in response to the time-varying price. However, their power consumption may be affected not only by the price, but also by user convenience for using appliances. This paper proposes a methodology for appliance scheduling (AS) that considers the user convenience based on historical data. The usage pattern for appliances is first modeled applying the copula function or clustering method to evaluate user convenience. As the modeling results, the comfort distribution or representative scenarios are obtained, and then used to formulate a discomfort index (DI) to assess the degree of the user convenience. An AS optimization problem is formulated in terms of cost and DI. In the case study, various AS tasks are performed depending on the weights for cost and DI. The results show that user convenience has significant impacts on AS. The proposed methodology can contribute to induce more DR participation from R-users by reflecting properly user convenience to AS problem.

Keywords: Residential demand response, Home energy management system, User Convenience, Appliance usage pattern, Appliance scheduling, Discomfort index

1. Introduction

In recent years, load management on the demand side has become more important. Load management initially focused on relatively large customers such as commercial and industrial users, because of the ease and high efficiency of their load management [1]. Smart grid technologies, which are based on the two-way exchange of electricity/ information, enable general end users to monitor and manage their power consumption. Various energy management systems (EMSs) have been developed for different load management subjects, such as factories, buildings, and homes. With the development of a variety of smart appliances and a communication and control infrastructure, residential users (R-users) are expected to significantly contribute to load management in the near future [2-4]. Thus, this study focuses on load management by residential users through home EMS (HEMS).

Various demand response (DR) programs have been developed for load management by R-users. DR programs commonly lead R-users to adjust their power consumption in response to external signals like the time-varying price, incentives, and emergency requests for load reduction [5]. Among the various DR programs, the price-based DR (P-DR) induces voluntary and non-compulsive DR participation through time-varying electricity prices [6-8]; schemes include the real-time price (RTP), critical peak price, inclining block rate, and time of use. Several studies have shown that RTP is more effective than other P-DR programs. However, it is difficult for R-users to monitor and control their power consumption in real time to RTP, and it can interfere with their DR participation [6, 9]. As one of the ways to resolve this problem, this paper considers the RTP which is announced before a day, named as day-ahead RTP (DARTP) [10-12]. Under DARTP, HEMS performs the appliance scheduling (AS) to establish a plan for using various appliances the next day. Then the HEMS notifies a result of the AS to the R-user through a communication interface. The AS result can be used as a guideline for using appliances or be reflected to the automatic control of appliances.

Several researchers have studied residential P-DR [13-17]; they mainly focused on minimizing the electricity costs by shifting the usage time or reducing the operation level of appliances within pre-specified ranges. However, the appliance usage by R-users may be influenced not only by the price, but also by other factors (i.e., the convenience for using appliances). For example, when shifting usage time of an appliance, some R-users may want to shift the usage time to more convenient times rather than times with low prices. Such R-users feel more convenience when using appliances at preferred times or operating level. Other several studies have dealt with residential P-DR considering user convenience [2,6,18-21]. However, they performed AS with certain operation ranges and preferred

† Corresponding Author: Dept. of Electrical Engineering, Hanyang University, Korea. (jokim@hanyang.ac.kr)
* Dept. of Electrical Engineering, Hanyang University, Korea. (kjboy@hanyang.ac.kr)
** Dept. of Electrical Engineering, Kangwon National University, Korea. (isbae@kangwon.ac.kr)
Received: February 22, 2017; Accepted: August 21, 2017

conditions pre-set by the user and user convenience was simply considered by the difference between the pre-set conditions and the scheduling result. Such the way may cause another inconvenience in P-DR participation through the AS because the user should sometimes adjust directly the conditions for using appliances. Furthermore, it may not be sufficient for reflecting user's preference for using appliances which can be influenced by the time-varying price or other factors.

In order to improve the above problems, this paper proposes a methodology to perform AS considering user convenience without the direct input of preferred conditions by the R-users. For this purpose, this paper first presents a methodology to model user's preferred conditions for the usage time or operating level, by applying a copula function or clustering method to the cumulative data. The comfort distribution or representative usage scenarios are obtained as the modeling results and used to formulate the degree of user convenience for major appliances as the discomfort index (DI). The AS problem is formulated in terms of cost and DI. In the case study, various AS tasks are performed to investigate the impacts of user convenience on the AS.

2. Methodology for Modeling Usage Pattern of Appliance Usage

In this paper, R-users are considered to be influenced by DARTP and other factors (e.g., outside temperature) when adjusting their appliance usage. The users would have their own usage patterns which involve their preference on the appliance usage. The closer a plan for the appliance usage is made to user's usage pattern, the more the user would feel the convenience. In this section, a methodology for modeling the usage pattern is proposed based on the copula function or clustering method. The usage pattern is modeled for appliances of the following categories [9, 16, 22]:

Deferrable appliances (DAs): appliances of which usage time is determined depending on the electricity price, within available time ranges. Typical DAs include washing machines, dishwashers, and drying machines.

Curtailable appliances (CAs): appliances of which on/off status and power consumption are controlled within available operational ranges. As typical CAs, there are a heating, ventilation and air conditioning (HVAC), electric water heater (EWH), and energy storage system (ESS).

2.1 Copula-based usage pattern modeling

The usage pattern of DAs can be expressed as a numerical correlation between the usage times (i.e., the start and end times) and the time-varying price. The usage pattern of HVAC can also be expressed by the inside temperature to be maintained over time, and the outside temperature. Such numerical usage patterns can be modeled by applying a copula function [23-25].

The copula function is a way to identify the dependence between two or more random variables with individual distributions and represent it as a joint probability distribution. Among various copula functions, the Gaussian copula (GC) is used in this study:

$$GC(\phi_1(x_1),...,\phi_n(x_n)) = \phi(x_1,...,x_n) \tag{1}$$

where x is a random variable that is the usage time for DAs or inside temperature for HVAC. ϕ is a standard normal distribution function.

By applying $\phi_n(x_n) = u_n$, Eq. (1) can be rewritten as

$$GC(u_1,...,u_n;Rho) = \phi_n(\phi^{-1}(u_1),...,\phi^{-1}(u_n);Rho) \tag{2}$$

where μ is the variable normalized to the uniform distribution and ϕ^{-1} is an inverse function of a standard normal distribution. Rho is the major parameter matrix for GC and can be obtained from a rank correlation coefficient such as Kendall's τ or Spearman's ρ :

$$Rho = \sin\left(\frac{\tau\pi}{2}\right) = 2\sin\left(\frac{\rho\pi}{6}\right) \tag{3}$$

Fig. 1 shows the procedure of the GC-based modeling method, which is briefly explained by using HVAC. When modeling the usage pattern of HVAC, the inside temperature (Tp_{In}) is defined as the target variable, and the outside temperature (Tp_{Out}) is defined as the reference variable. The usage pattern is modeled as the dependence between Tp_{In} and Tp_{Out}. By applying Eq. (3) to the cumulative data, the dependence between all the variables is estimated as the matrix Rho. If Tp_{In} increases as Tp_{Out} decreases, then Rho consists of negative values. Conversely, Rho has positive values. As the absolute value of Rho comes closer to 1, Tp_{In} can be regarded as influenced more significantly by Tp_{Out}.

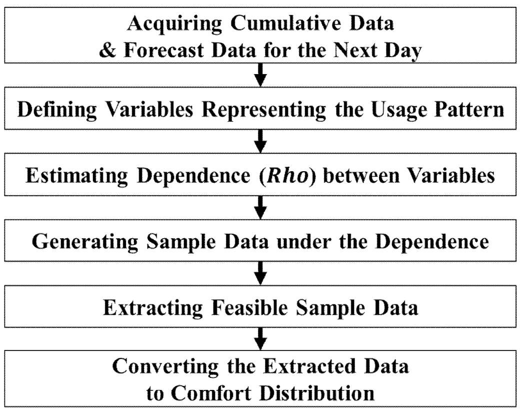


Fig. 1. Procedure of GC-based modeling

An appropriate number of sample data which have the dependence of the estimated Rho, can be generated by Eqs. (1) and (2). Fig. 2 shows the cumulative and sample data for $Tp_{Out}(72)$ and $Tp_{In}(76)$ among all variables (here, the time unit is 15 min.). Rho of them has been estimated as -0.9498.

Data corresponding to the reference variable, Tp_{Out}, among all sample data is compared with the forecasted one (Tp_{Out}^{FC}) for the next day. By Eq. (4), only the sample data which contains the data of Tp_{Out} similar to Tp_{Out}^{FC}, is extracted. Fig. 2(b) shows the extracted sample data for $Tp_{Out}^{FC}(72) = 3.2^{\circ}\mathrm{C}$.

$$ES = \left\{ SD_i \mid \sqrt{\sum_{\forall t} \left(Tp_{Out}^{SD_i} - Tp_{Out}^{FC} \right)^2 / T} \le \varepsilon_{ES} \right\} \tag{4}$$

where ES is a set of the extracted sample data, SD is sample data containing data of all variables, Tp_{Out}^{SD} is data corresponding to reference variables, T is the length of the entire time period, and ε_{ES} is the permissible error.

Fig. 3 shows the extracted sample data for Tp_{In} and

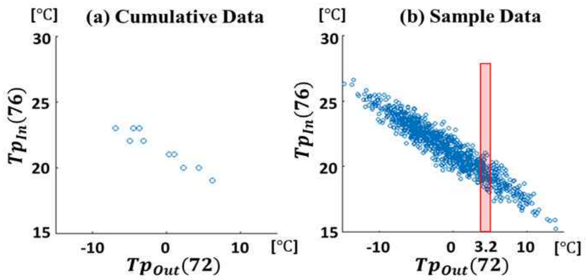


Fig. 2. Cumulative and sampling data generated by GC

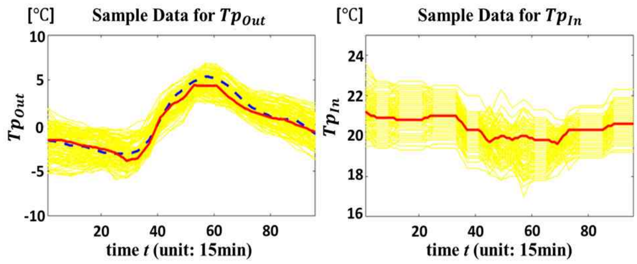


Fig. 3. Extracted sample data for Tp_{In} and Tp_{Out}

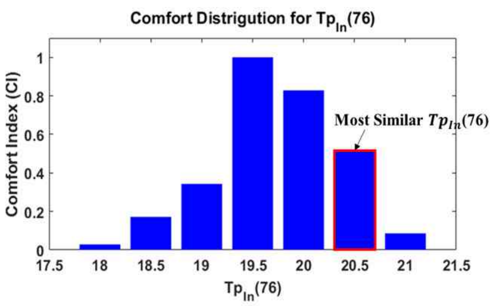


Fig. 4. Comfort distribution for $Tp_{In}(76)$

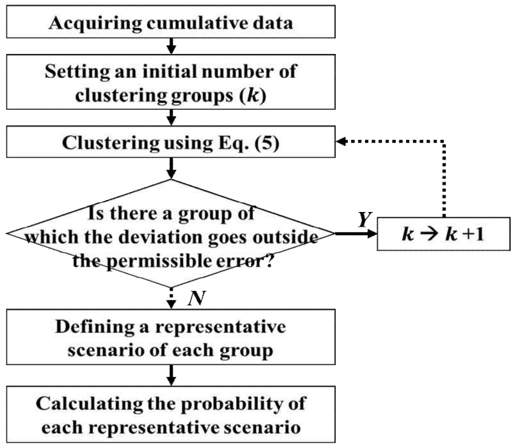


Fig. 5. Procedure for clustering-based modeling

Tp_{Out} during the entire time period, where lines represent the extracted sample data. The thick and dotted line is Tp_{Out}^{FC}, while the thicker lines represent Tp_{Out} and Tp_{In} of the most similar sample data to Tp_{Out}^{FC}.

By counting the number of data of the extracted Tp_{In} for each time, the frequency distribution for each time is obtained. This is then converted to the comfort distribution through the normalization process. Fig. 4 shows the comfort distribution for $Tp_{In}(76)$, which indicates that the R-user has different preferences depending on Tp_{In}.

2.2 Clustering-based usage pattern modeling

The usage pattern of EWH is related to the hot water usage. Expressing when and how much hot water is used through any comfort distribution is difficult. Appliances, such as EWH can be modeled by a scenario-based approach applying a clustering method. Fig. 5 shows the procedure of K-clustering-based method for modeling the usage pattern.

Among the cumulative data for the hot water usage, the similar data is grouped together by using Eq. (5) [26].

$$\arg\min_{k,S} \left\{ \sum_{i=1}^{k} \sum_{j \in S_i} \sum_{\forall t} \sqrt{\left| \theta_j(t) - \overline{\theta_i(t)} \right|^2} \le \varepsilon_{KC} \right\} \tag{5}$$

where S is the set of representative scenarios, k is the number of groups, $\theta_j(t)$ is the data at time t (for an EWH, this is the quantity of heat for the used hot water), $\overline{\theta_i}(t)$ is data corresponding to the centroid of the i-th group, and ε_{KC} is the permissible error. The centroid of each group is defined as the representative scenario, and its probability is calculated as the ratio of the number of data in the group to the total cumulative data.

3. Appliance Scheduling Formulation

The AS problem can be expressed by an objective function which is formulated with two terms: the electricity cost, EC and discomfort index, DI.

$$\min F = \omega_{EC} \times \frac{EC - EC^{Min}}{EC^{Max} - EC^{Min}} + \omega_{DI} \times \frac{DI - DI^{Min}}{DI^{Max} - DI^{Min}} \quad (6)$$

where ω_{EC} and ω_{DI} are weighting factors. Depending on the weighting factors, diverse plans for using appliances can be established. EC and DI are normalized by their min/maximum values, respectively. Under conditions of $\omega_{EC} = 1$ and $\omega_{DI} = 0$, $EC^{\min}$ and $DI^{\max}$ can be calculated, and $EC^{\max}$ and $DI^{\min}$ can be obtained under conditions of $\omega_{EC} = 0$ and $\omega_{DI} = 1$.

3.1 AS Problem for DAs

The electricity cost of DA, EC_{DA} is expressed by

$$EC_{DA} = \sum_{\forall t} \pi(t) \cdot P_{DA}^{R} \cdot \mu_{DA}(t) \quad (7)$$

where π is DARTP, P_{DA}^{R} is the rated power of DA, and μ_{DA} is a status variable and is 0 or 1 depending on whether the DA is stopped or operating, respectively.

By the copula-based method, the comfort distribution for DAs is obtained as in Fig. 6, where CI is the comfort index normalized to have 1 as a maximum value. DI is calculated by $1-CI$. t_{DA}^{α} and t_{DA}^{β} indicate the available time range for using DA beyond the threshold. $t_{DA}^{\alpha,BF}$ and $t_{DA}^{\beta,BF}$ represent the best fitted start and end times.

DI_{DA} is evaluated considering both the comfort distribution and best fitted operating times. In Eq. (8), the first term means the average of inconvenience level during using DA and second term means the ratio of a difference between the scheduled and best fitted times for start and end times, to each possible time range, respectively [6]:

$$\begin{aligned} DI_{DA} = {} & \gamma_{DA} \times \left(1 - \frac{1}{Task_{DA}} \times \sum_{t=t_{DA}^{\alpha}}^{t_{DA}^{\beta}} CI_{DA}(t) \cdot \mu_{DA}(t) \right) + (1-\gamma_{DA}) \\ & \times \frac{1}{2} \left(\frac{\sqrt{(ST_{DA} - t_{DA}^{\alpha,BF})^2}}{(t_{DA}^{\beta} - Task_{DA}) - t_{DA}^{\alpha,BF}} + \frac{\sqrt{(ET_{DA} - t_{DA}^{\beta,BF})^2}}{t_{DA}^{\beta,BF} - (t_{DA}^{\alpha} + Task_{DA})} \right) \end{aligned} \quad (8)$$

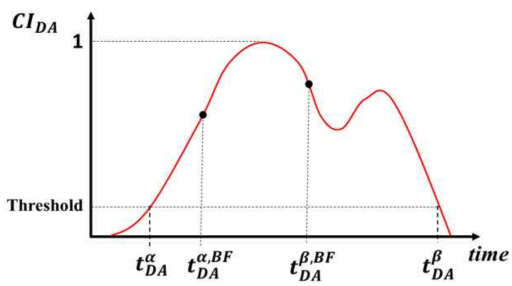


Fig. 6. Comfort distribution of DA

where γ_{DA} is a weights between the two terms. $Task_{DA}$ is the required operating time of DA and represented by Eq. (9). ST_{DA} and ET_{DA} are the scheduled start and end times and expressed by Eq. (10).

$$\sum_{\forall t} \mu_{DA}(t) = Task_{DA}, \qquad t_{DA}^{\alpha} \le t \le t_{DA}^{\beta} \quad (9)$$

$$\begin{aligned} ST_{DA} &= \min_{t} \left\{ t \mid \mu_{DA}(t) = 1, \quad t_{DA}^{\alpha} \le t \le t_{DA}^{\beta} \right\} \\ ET_{DA} &= \max_{t} \left\{ t \mid \mu_{DA}(t) = 1, \quad t_{DA}^{\alpha} \le t \le t_{DA}^{\beta} \right\} \end{aligned} \quad (10)$$

DAs are divided into types depending on the continuity of operation: non-interruptible (NDA) and interruptible (IDA). Once NDS start, they operate continuously until $Task_{DA}$ is satisfied. IDAs can be stopped and restarted sometimes until $Task_{DA}$ is satisfied. These constraints are represented by

$$\begin{aligned} & \sum_{t=t_{DA}^{\alpha}}^{t_{DA}^{\beta}} \left(\mu_{DA}(t-1) - \mu_{DA}(t) \right)^2 = 2 && \text{if) DA is NDA} \\ & \sum_{t=t_{DA}^{\alpha}}^{t_{DA}^{\beta}} \left(\mu_{DA}(t-1) - \mu_{DA}(t) \right)^2 = 2 \times NI_{DA} && \text{if) DA is IDA} \end{aligned} \quad (11)$$

where $\mu_{DA}(t_{DA}^{\alpha} - 1) = 0$, NI_{DA} and dlt_{DA} are the number of times and the delay duration an IDA can be stopped during operation, respectively, and $ET_{DA} - ST_{DA} + 1 \le dlt_{DA}$.

3.2 AS Problem for HVAC

The electricity cost of HVAC, EC_{HVAC} is

$$EC_{HVAC} = \sum_{\forall t} \pi(t) \cdot P_{HVAC}^{R} \cdot \mu_{HVAC}(t) \quad (12)$$

where P_{HVAC}^{R} is the rated power of HVAC and μ_{HVAC} is a status variable and can have one of discrete values equally split within 0 and 1 to consider diverse operational states rather than a simple on/off operation.

Fig. 7 shows the comfort distribution for Tp_{In} at a certain time, where Tp_{In}^{a} and Tp_{In}^{β} indicate the allowable range of Tp_{In} at that time, and Tp_{In}^{BF} is the best fitted one.

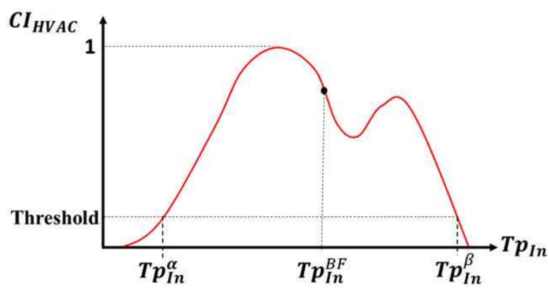


Fig. 7. Comfort distribution for Tp_{In} at a certain time t

DI_{HVAC} of HVAC can be calculated by Eq. (13), where the first term means total inconvenience level during using HVAC. The second term means the ratio of the difference between the scheduled and best fitted Tp_{In} to its possible range.

$$DI_{HVAC} = \frac{1}{T}\sum_{\forall t}\left\{\begin{array}{l}\gamma_{HVAC} \times \left(1 - CI_{HVAC}(Tp_{In}(t))\right) + (1-\gamma_{HVAC}) \times \\ \left(\left(\dfrac{\sqrt{(Tp_{In}(t) - Tp_{In}^{BF}(t))^2}}{\max\{Tp_{In}^{BF}(t) - Tp_{In}^{\alpha}(t), Tp_{In}^{\beta}(t) - Tp_{In}^{BF}(t)\}}\right)\right)\end{array}\right\} \tag{13}$$

The dynamic equation for Tp_{In} according to HVAC operation over time can be represented by [16, 27]

$$\begin{aligned} Tp_{In}(t+1) &= \varepsilon_{HVAC} \cdot Tp_{In}(t) \\ &\quad + (1-\varepsilon_{HVAC})\left\{Tp_{Out}(t) \pm \frac{CoP_{HVAC} \cdot P_{HVAC}^{R} \cdot \mu_{HVAC}(t)}{A_{In}}\right\} \end{aligned} \tag{14}$$

where $Tp_{In}^{\alpha}(t) \le Tp_{In}(t) \le Tp_{In}^{\beta}(t)$, ε_{HVAC} is a heat emission constant, CoP_{HVAC} is the coefficient of HVAC performance, and A_{In} is the thermal mass inside the room.

3.3 AS Problem for EWH

In the case of EWH, the hot water usage pattern is modeled as several representative scenarios. Therefore, the electricity cost of EWH, EC_{EWH} can be expressed as the expected cost for all scenarios:

$$EC_{EWH} = \sum_{\forall S}\left\{\sum_{\forall t}\pi(t) \cdot P_{EWH}^{S} \cdot \mu_{EWH}^{S}(t)\right\} \cdot Pb^{S} \tag{15}$$

where P_{EWH}^{R} is the rated power of an EWH, μ_{EWH}^{S} is a status variable under a scenario S and can have one of several discrete values between 0 and 1. Pb^{S} is the probability of the scenario S.

Fig. 8 depicts the representative scenarios for the hot water usage expressed in terms of the quantity of heat.

At first, AS for EWH is performed considering a scenario S. Then, the scheduling result is checked as regards whether the hot water demand of other scenarios ($\hat{S}$) is met or not. If the hot water demand is not met, R-user would feel inconvenience depending on the unmet demand. Under scenario S, the expected amount of the hot water demand unmet for other scenarios, DI_{EWH}^{S} can be expressed by (16) and (17):

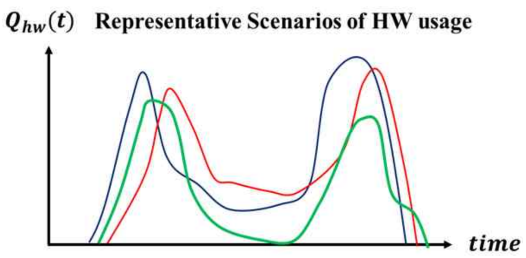


Fig. 8. Representative scenarios for hot water usage

$$DI_{EWH}^{S} = \sum_{\forall \hat{S}}\sum_{\forall t} nd^{\hat{S},S}(t) \cdot Pb^{\hat{S}} \tag{16}$$

$$nd^{\hat{S},S}(t) = \begin{cases} 0 & if)\ Q_{Tk}^{\hat{S},S}(t) \ge Q_{HW}^{\hat{S}}(t) \\ Q_{HW}^{\hat{S}}(t) - Q_{Tk}^{\hat{S},S}(t) & otherwise \end{cases} \tag{17}$$

where $Q_{HW}^{\hat{S}}$ is the heat quantity of hot water used according to scenario $\hat{S}$, and $Q_{Tk}^{\hat{S},S}$ is the heat quantity of water within a water tank, under the situation that R-user uses hot water in accordance with $\hat{S}$ but EWH operates according to S. $nd^{\hat{S},S}$ is the heat quantity of a shortfall in hot water within the tank under such the situation.

The expected DI_{EWH} for all of the scenarios is

$$DI_{EWH} = \sum_{\forall S} DI_{EWH}^{S} \cdot Pb^{S} \tag{18}$$

The dynamic equation and constraint for $Q_{Tk}^{\hat{S},S}$ can be expressed by [27]

$$\begin{aligned} Q_{Tk}^{\hat{S},S}(t+1) &= Q_{Tk}^{\hat{S},S}(t) - Q_{HW}^{\hat{S}}(t) + CoP_{EWH} \cdot P_{EWH}^{R} \cdot \mu_{EWH}^{S}(t) \\ &\quad - \frac{A_{Tk} \cdot (Q_{Tk}^{\hat{S},S}(t) - Q_{Out})}{V_{Tk} \cdot R_{Tk}} \end{aligned} \tag{19}$$

where $Q_{Tk}^{Min} \le Q_{Tk}^{\hat{S},S}(t) \le Q_{Tk}^{Max}$, CoP_{EWH} is the coefficient of the EWH performance and A_{Tk}, V_{Tk}, and R_{Tk} are the cross-section area, volume, and thermal coefficient of resistivity, respectively, of the water tank. Q_{Tk}^{Min} and Q_{Tk}^{Max} are the min/maximum limits for the heat quantity of hot water in the tank, respectively.

3.4 AS Problem for ESS

ESS is considered as an option to further reduce the electricity cost. The objective function for the ESS can be expressed by

$$\begin{aligned} \min F_{ESS} &= \sum_{\forall t}\pi(t) \times \left(P_{Other}(t) + P_{ESS}^{R} \cdot \mu_{ESS}(t)\right) \\ P_{Other}(t) &= P_{BA}(t) + \sum_{\forall DA} P_{DA}(t) + P_{HVAC}(t) + P_{EWH}(t) \end{aligned} \tag{20}$$

Where P_{BA} is a total power consumption of basic appliances which are not the subject of AS, P_{ESS}^{R} is the rated power of ESS when charging or discharging power. μ_{ESS} is a status variable with a discrete value between -1 and 1; the positive values indicate a charging operation, whereas the negative values represent discharging.

The ESS operation is limited by the allowable range of the state of charge (SOC). This can be represented by

$$SOC_{ESS}(t) = SOC_{ESS}(t-1) + \frac{P_{ESS}^{R} \cdot \mu_{ESS}(t)}{E_{ESS}^{R} \cdot \eta_{ESS}^{\mu_{ESS}(t)}} \quad (21)$$

$$\text{where } SOC_{ESS}^{Min} \le SOC_{ESS}(t) \le SOC_{ESS}^{Max}$$

where E_{ESS}^{R} is the rated energy capacity of the ESS, η_{ESS} is the charging/discharging efficiency, and SOC_{ESS}^{Min} and SOC_{ESS}^{Max} are the min/maximum limits, respectively.

4. Numerical Case Study

Various AS tasks are performed according to ω_{EC} and ω_{DI} to investigate the impacts of user convenience on AS.

Table 1. Detailed Information on Appliances

Appliances		P_{DA}^{R} [kw]	$Task_{DA}$	dlt_{DA}	NI_{DA}
			(the time unit : 15 min.)		
DA_1	IDA	[0.55, 0.55, 0.75, 0.75]	4	4	2
DA_2	IDA	[0.55, 0.55, 0.75, 0.75]	4	4	2
DA_3	IDA	[0.75, 0.75]	2	6	2
DA_4	NDA	[1.2, 1.2]	2	0	1
DA_5	NDA	[0.6, 0.6, 0.6, 0.75, 0.75]	5	0	1
DA_6	IDA	[1.0, 1.0, 0.75, 0.75]	4	2	2
HVAC	$P_{HVAC}^{R}=3.0\text{kW},\ \varepsilon_{HVAC}=0.95,\ CoP_{HVAC}=25,\ A_{In}=1.2$				
EWH	$P_{EWH}^{R}=2.0\text{kW},\ CoP_{EWH}=300,\ A_{Tk}=8, V_{Tk}=125,$ $R_{Tk}=12,\ Q_{out}=300,\ Q_{Tk}^{Min}=2{,}500,\ Q_{Tk}^{Max}=10{,}000$				
ESS	$P_{ESS}^{R}=1.2\text{kW},\ E_{ESS}^{R}=3.6\text{kWh},\ \eta_{ESS}=1.0,$ $E_{ESS}^{Init}=1.8\text{kWh},\ SOC_{ESS}^{Max}=1.0,\ SOC_{ESS}^{Min}=0.3$				

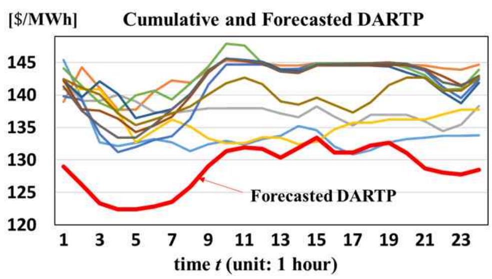


Fig. 9. Cumulative and forecasted DARTP

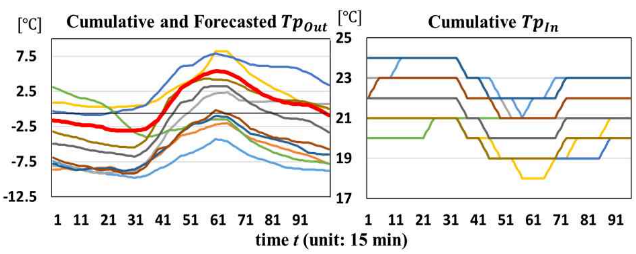
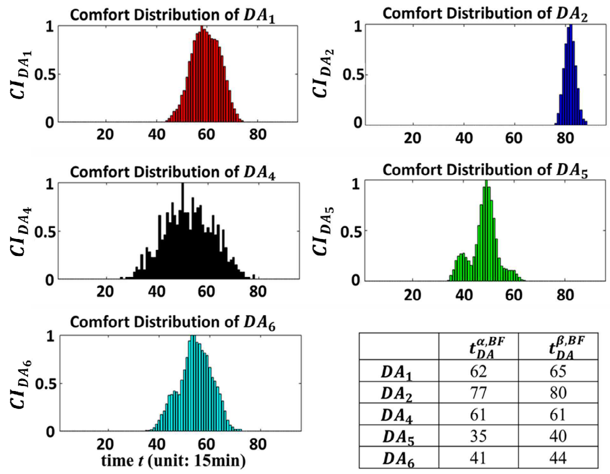


Fig. 10. Cumulative data of Tp_{Out} and Tp_{In}



	$t_{DA}^{\alpha,BF}$	$t_{DA}^{\beta,BF}$
DA_1	62	65
DA_2	77	80
DA_4	61	61
DA_5	35	40
DA_6	41	44

Fig. 11. Comfort distributions of DAs

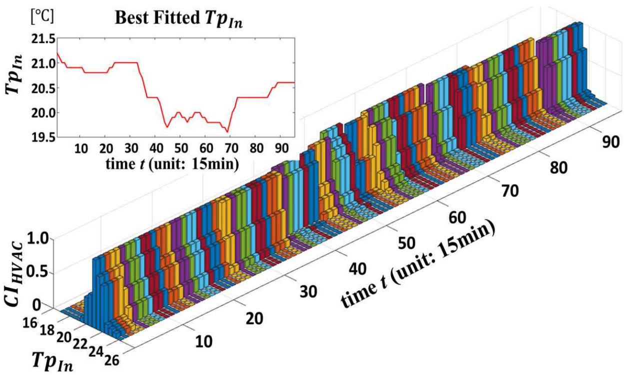


Fig. 12. Comfort distributions for Tp_{In}

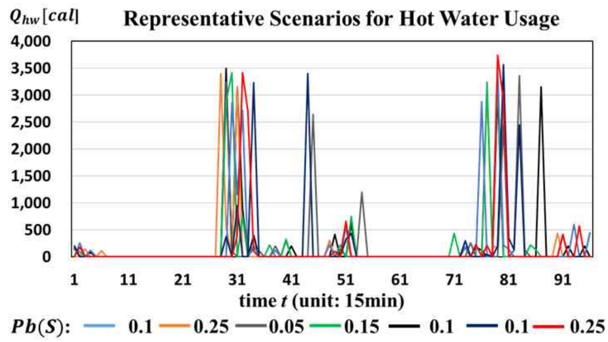


Fig. 13. Representative scenarios for hot water usage

The subject of AS consists of six DAs and HVAC, EWH, and ESS. Table 1 presents detailed information for the appliances, where DA_1, DA_2 and DA_3 mean the 1st, 2nd, and 3rd usage of a dishwasher during the day, respectively. DA_4, DA_5, and DA_6 are a vacuum cleaner, a washing machine, and an electric laundry dryer.

Fig. 9 shows the cumulative and forecasted DARTP with the unit of 1hour. Fig. 10 represents the cumulative and forecasted Tp_{Out} and Tp_{In} with the unit of 15 min.

Because DA_3 is mainly used at late night, it is assumed to react only to DARTP. Therefore, its usage pattern is not modeled. Fig. 11 shows the modeling results for other five DAs together with their best fitted times.

Fig. 12 shows the comfort distribution for Tp_{In} over time together with the best fitted Tp_{In}.

Fig. 13 shows the representative scenarios for the hot water usage obtained by the clustering-based method.

In order to compare diverse results of AS depending on the weighting factors ω_{EC} and ω_{DI}, several cases are defined:

– Base Case: Focusing fully on economic efficiency (i.e., $\omega_{EC} = 1.0, \omega_{DI} = 0$).
– Case I: Focusing fully on user convenience (i.e., $\omega_{EC} = 0, \ \omega_{DI} = 1.0$).
– Case II: AS under condition of $\omega_{EC} = 0.75, \ \ \omega_{DI} = 0.25$.
– Case III: AS under condition of $\omega_{EC} = 0.5, \ \omega_{DI} = 0.5$.
– Case IV: AS under condition of $\omega_{EC} = 0.25, \omega_{DI} = 0.75$.

Each appliance may operate with more states than the two states (i.e., 'on and off'). The AS problem is to determine the status variables, μ of each appliance over the entire time period and is solved based on the branch and bound method (B&B) [28], in this paper.

Table 2 presents the AS results for all DAs. In Base Case, individual DAs operate during times with low electricity prices within the respective allowable time ranges. As increases, the operating time moves to more convenient times (i.e., times closer to the modeled usage pattern).

Figs. 14 and 15 show the AS results for HVAC in the Base Case and Case I. In the Base Case, HVAC operates less frequently but with a higher power when operating to satisfy Tp_{In} of the minimum level and to minimize the cost. Thus, EC_{HVAC} is \$2.525, while DI_{HVAC} is 0.9461. Meanwhile, in Case I, the HVAC operates more frequently with a lower power to maximize the level of convenience of the R-user. As a result, EC_{HVAC} increases to \$2.945, while DI_{HVAC} decreases to 0.0979.

Table 2. AS Results for DAs

No. Case	No. DA	$\mu_{DA}(t) = 1$	EC_{DA}	DI_{DA}	No. DA	$\mu_{DA}(t) = 1$	EC_{DA}	DI_{DA}
Base	1	49-52	84.7	0.684	2	86-89	83.2	0.941
I		61-64	85.2	0.126		81,82 85,86	83.4	0.397
II		61-64	85.2	0.126		81-83, 85	83.5	0.238
III		61-64	85.2	0.126		81-84	83.6	0.183
IV		57-60	86.7	0.064		80-83	84	0.122
Base	3	17, 20	45.9	-	4	26, 27	74.1	0.988
I		17,20	45.9	-		27, 28	74.1	0.986
II		17, 20	45.9	-		27, 28	74.1	0.986
III		17,20	45.9	-		49, 50	78.2	0.16
IV		17, 20	45.9	-		49, 50	78.2	0.16
Base	5	33-37	106.9	0.839	6	35, 36, 39, 40	113.8	0.866
I		33-37	106.9	0.839		49-52	114.1	0.278
II		48-52	107.8	0.178		49-52	114.1	0.278
III		48-52	107.8	0.178		50-53	114.4	0.177
IV		47-51	108	0.15		52-55	115	0.066

Table 3 presents the numerical AS results of HVAC for all cases, where EC_{HVAC} increases as the user convenience for HVAC is more weighted.

Fig. 16 shows the AS results for the EWH in the Base Case and Case I, where thick lines represent the power consumption of EWH over time and the dotted lines denote the quantities of heat for hot water in the tank.

Compared with the Base Case, EWH operates more frequently in Case I to keep water in the tank at a higher Q_{Tk} for preparing for various scenarios of the hot water

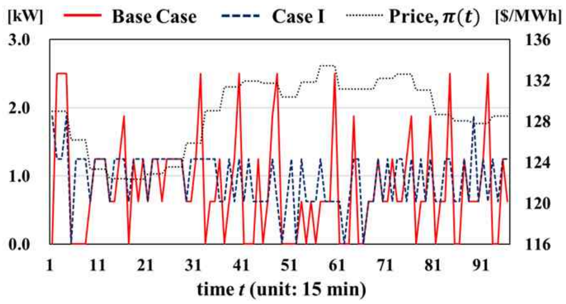


Fig. 14. Results of AS for HVAC in Base Case and Case I

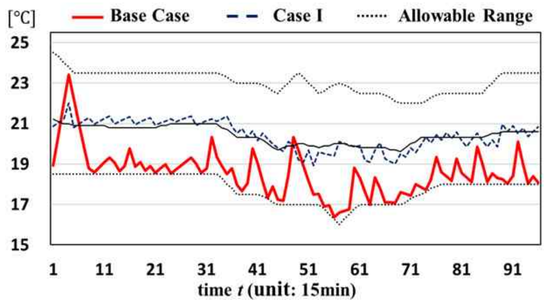


Fig. 15. Results of Tp_{In} in Base Case and Case I

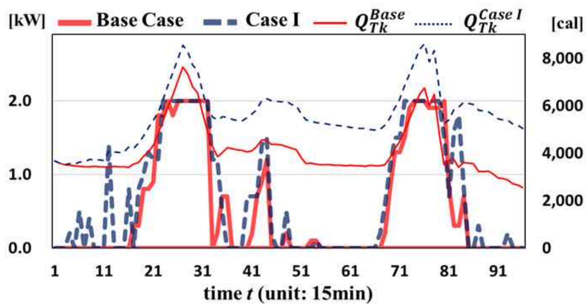


Fig. 16. Results of AS for EWH

Table 3. Numerical Results for HVAC and EWH

Cases	ω_{EC}	EC_{HVAC}	DI_{HVAC}	EC_{EWH}	DI_{EWH}
Base	1	2.525	0.946	1.674	3284.896
I	0.75	2.762	0.146	1.778	1051.624
II	0.5	2.863	0.109	1.843	730.122
III	0.25	2.924	0.099	1.980	201.201
IV	0	2.944	0.098	2.090	45.105

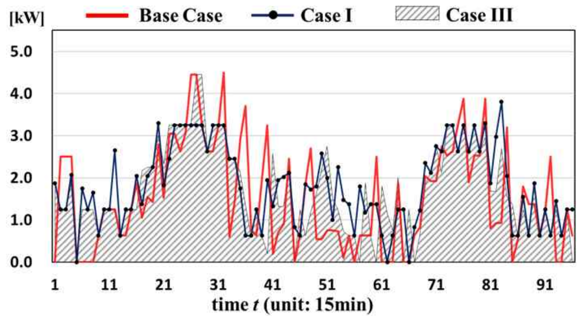


Fig. 17. AS results for all appliances

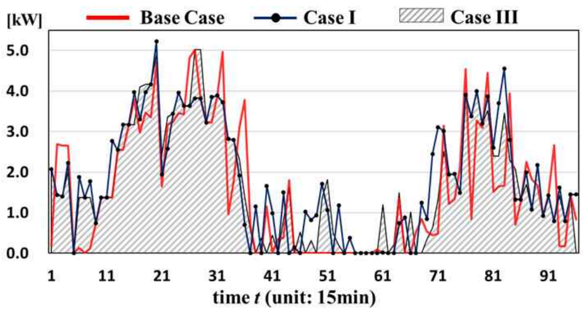


Fig. 18. AS results for all appliances with ESS

usage. Table 3 also presents the numerical results of EWH in detail, where the tradeoff between EC_{EWH} and DI_{EWH} can be observed.

Fig. 17 shows the final results of AS for DAs, HVAC, and EWH. In the Base Case, the appliances intermittently operate, but generally consume more power when the electricity price is low. Consequently, the total electricity cost is \$4.707. However, the results of Cases I and II show that power consumption is slightly less but more frequent to improve the convenience. As a result, the total power consumption is increased. Moreover, the total costs increase to \$5.217 and \$5.552, respectively.

The electricity cost for the three cases when considering ESS are reduced to \$4.676, \$5.186, and \$5.520, respectively. However, the peak load for all the cases increase because the ESS is mainly charged at times with low prices. From Fig. 18, it can be seen that the impacts of user convenience on AS is similar to the previous results shown in Fig. 17 because the ESS is only used for the cost reduction. Therefore, even when considering ESS, it can be again confirmed that the user convenience should be considered in performing AS for P-DR.

5. Conclusion

This paper proposes a methodology for AS that reflects user convenience based on the usage pattern. Two methods are introduced to model the usage patterns: a copula-based method for DAs and HVAC, and a clustering-based method for EWH. Based on the results of the usage pattern modeling, the discomfort index, DI is formulated to evaluate the degree of user convenience for using appliances. The AS problem are expressed by two terms of cost and DI. In the case study, various AS tasks are performed according to two weighting factors for cost and DI. The results show that the user convenience significantly affects AS, and R-user can make a variety of plans for using appliances the next day depending on the relative importance of user convenience to cost. However, a major issue remains, which is the decision-making problem to select the most preferred one among the diverse schedules. A follow-up study for the decision-making problem are conducting and the proposed methodology would contribute to induce more usefully P-DR participation from R-users.

Acknowledgements

This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(NRF-2017R1A2B1007520).

References

[1] H. Aalami, G. R. Yousefi and M. Parsa Moghadam, “Demand response model considering EDRP and TOU,” *in: IEEE, Trans. and Distr. Conf. and Expo*., Chicago, IL, 21-24 April, 2008.

[2] D. Setlhaolo, X. Xia and J. Zhang, “Optimal scheduling of household appliances for demand response,” *Electric Power Systems Research*, vol. 116, pp. 24-28, Nov. 2014.

[3] J. Kondoh, N. Lu, and D. J. Hammerstrom, “An evaluation of the water heater load potential for providing regulation service,” *IEEE Trans. Power Syst*., vol. 26, no. 3, pp. 1309-1316, Aug. 2011.

[4] C. Vivekananthan and Y. Mishra, “Stochastic ranking method for thermostatically controllable appliances to provide regulation services,” *IEEE Trans. Power Syst*., vol. 30, no. 4, pp. 1987-1996, Jul. 2015.

[5] U. S. Department of Energy, “Energy policy Act of 2005,” section 1252, February 2006.

[6] M. Babar Rasheed, N. Javaid, A. Ahmad, Z. Ali Khan, U. Qasim and N. Alrajeh, “An Efficient Power Scheduling Scheme for Residential Load Management in Smart Homes,” *Applied Sciences*, vol. 5, no. 4, pp.1134-1163, Nov. 2015.

[7] M. Muratori and G. Rizzoni, “Residential Demand Response: Dynamic Energy Management and Time-Varying Electricity Pricing,” *IEEE Trans. Power Syst*., vol. 31, no. 2, pp. 1108-1117, March 2016.

[8] M. Rastegar, M. Fotuhi-Firuzabad and J. Choi, “Investigating the Impacts of Different Price-Based

Demand Response Programs on Home Load Management," *Journal of Electrical Engineering & Technology*, vol. 9, no. 3, pp.742-748, May 2014.
[9] Christopher O. Adika and Lingfeng Wang, "Autonomous Appliance Scheduling for Household Energy Management," *IEEE Trans. Power Syst.*, vol. 5, no. 2, pp. 673-682, March 2014.
[10] Vardakas, J.S., Zorba, N. and Verikoukis, C.V. "A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 1, pp. 152-178, 2015.
[11] Liyan Jia and Lang Tong, "Day Ahead Dynamic Pricing for Demand Response in Dynamic Environments," *in IEEE, Decision and Control (CDC) Conf.*, Firenze, Italy, 10-13 Dec. 2013.
[12] D. Kang, S. Park, S. Choi, S. Han, "A Study on Design of Home Energy Management System to Induce Price Responsive Demand Response to Real Time Pricing of Smart Grid," *KIIEE*, vol. 25, no. 11, pp. 39-49, 2011.11.
[13] K. Sou, J. Weimer, H. Sandberg and K. Johansson, "Scheduling smart home appliances using mixed integer linear programming," *in: 50th IEEE, Decision and Control and European Control Conference (CDC & ECC)*, Orlando, FL, USA, 12-15 Dec., 2011.
[14] Pengwei Du and Ning Lu, "Appliance commitment for household load scheduling," *IEEE Trans. Smart Grid*, vol. 2, no. 2, pp.411-419, June 2011.
[15] Jinghuan Ma, Henry Chen, Lingyang Song and Yonghui Li, "Residential Load Scheduling in Smart Grid: A Cost Efficiency Perspective," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp.771-784, March 2016.
[16] Shuhui Li, Dong Zhang, Adam B. Roget and Zheng O'Neill, "Integrating Home Energy Simulation and Dynamic Electricity Price for Demand Response Study," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 779-788, March 2014.
[17] H. Jo, S. Kim, and S. Joo, "Smart Heating and Air Conditioning Scheduling Method Incorporating Customer Convenience for Home Energy Management System," *IEEE Trans. Consumer Electronics*, vol. 59, no. 2, pp.316-322, May 2013.
[18] O. Erdinç, A. Tascıkaraoglu, Nikolaos G. Paterakis, Yavuz Eren and João P. S. Catalão, "End-User Comfort Oriented Day-Ahead Planning for Responsive Residential HVAC Demand Aggregation Considering Weather Forecasts," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 362-372, Jan. 2017.
[19] D.-T Nguyen and L.-B Le, "Joint Optimization of Electric Vehicle and Home Energy Scheduling Considering User Comfort Preference," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp.188-199, Jan. 2014
[20] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 120-133, Sep. 2010.
[21] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "Optimal Residential Load Management in Smart Grids: A Decentralized Framework," *IEEE Trans. Smart Grid*, vol. 7, no. 4, pp. 1836-1845, Sep. 2016.
[22] O. Holub and M. Sikora, "End User Models for Residential Demand Response," *in: IEEE PES Innovative Smart Grid Technologies Europe (ISGT) Conf.*, pp. 1-4, 6-9 October, Copenhagen
[23] M. Tavakoli Bina and Danial Ahmadi, "Stochastic Modeling for the Next Day Domestic Demand Response Applications," *IEEE Trans. Power Syst.*, vol.30, no. 6, pp.2880-2893, Nov. 2015.
[24] Alicja Lojowska, Dorota Kurowicka, Georgios Papaefthymiou and Lou van der Sluis, "Stochastic Modeling of Power Demand Due to EVs Using Copula," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 1960-1968, Nov. 2012.
[25] V. Tavakoli Bina and D. Ahmadi, "Stochastic modeling for scheduling the charging demand of EV in distribution systems using copulas," *Electrical Power and Energy Systems*, vol. 71, pp.15-25, Oct. 2015.
[26] Yi Zhang, Weiwei Chen, Rui Xu and Jason Black, "A Cluster-Based Method for Calculating Baselines or Residential Loads," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2368-2377, Sep. 2016.
[27] Zhi Wu, Suyang Zhou, Jianing Li and Xiao-Ping Zhang, "Real-Time Scheduling of Residential Appliances via Conditional Risk-at-Value," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1282-1291, May 2014
[28] C. Wang, Y. Zhou, J. Wang and P. Peng, "A novel traversal-and-pruning algorithm for household load scheduling," *Applied Energy*, vol. 102, pp.1430-1438, Feb. 2013.

Je-Seok Shin He received the B.S. degrees in 2010, and is currently a Ph.D. candidate in department of Electrical Engineering, Hanyang University, Seoul, Korea. His research interests are demand response, smart energy management system, small and large scale system optimization.

In-Su Bae He received B.S., M.S., and Ph.D. degrees in electrical engineering from Hanyang University, Seoul, Korea, in 1998, 2003, and 2007, respectively. Since 2008, he has been with the department of electrical engineering, Kangwon National University, Samcheok, Korea. His main research interests include power system reliability, planning, and optimization.

Jin-O Kim He received the B.S. and M.S. degrees in electrical engineering from Seoul National University, Seoul, Korea, respectively, and the Ph.D. degree from Texas A&M University, College Station, TX, USA. Currently, he is a Professor with the Department of Electrical Engineering, Hanyang University, Korea. His research interests are power system reliability and economics, smart grid, micro-grid with renewable energy sources.