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계통연계형 신재생 에너지 시스템을 위한 주거용 에너지 스케줄링 기법

Residential Energy Scheduling Scheme for Grid-Connected Renewable Energy Systems

中央大學校　大學院

컴퓨터工學科 컴퓨터네트워크 專攻

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1. Introduction

Thanks to the convenience, electricity has been widely used as an energy resource. However, in the last few decades, global electricity consumption has dramatically increased and has become drastically fluctuating as well. In addition, electricity production and consumption should be done at the same time, because it is difficult to store the electricity. Therefore, electric power plants which has a fast response speed must be operated to cope with the variability of demand, however it has a disadvantage, poor energy efficiency.

The solutions to these problems are smart grid system which is envisioned as future power system. Smart grid system can reduce electricity peak load and induce effective electricity consumption through real-time electricity pricing model, demand response systems (DR), and energy storage units in order to optimize electricity usage in an intelligent fashion [4, 14].

Demand response (DR) is one of the technologies to enable smart grid, and it can distribute electricity tasks in response to electricity price. In other words, their tasks can be either delayed or temporarily suspended in high demand periods. However, this system has a tendency to change an operating time of appliances, and it can cause serious inconvenience to consumers in practice [6].

With this current problem of demand response systems, there is a strong

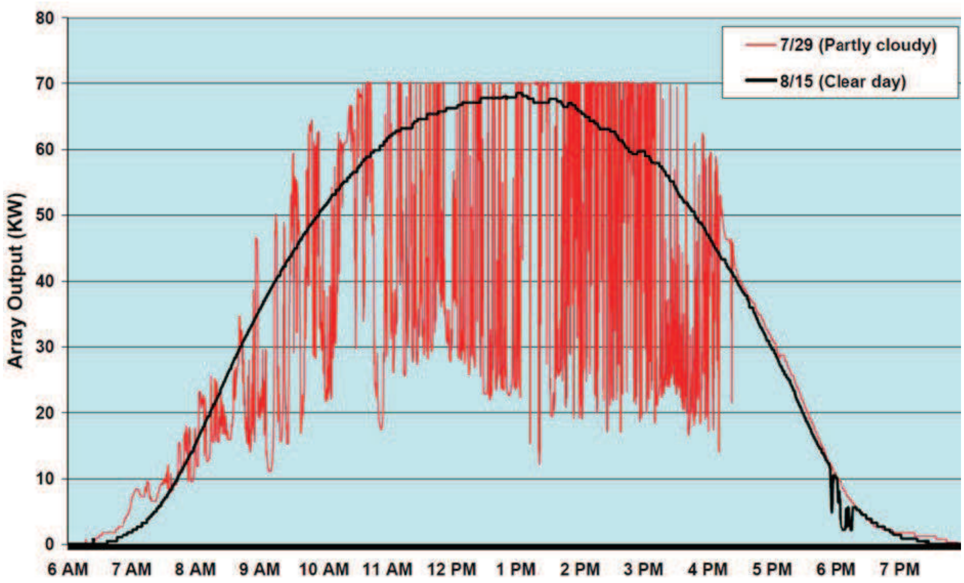

Figure 1.1: Solar power generation under the influence of cloud.

demand for energy storage systems (ESS) for the residential smart grid systems. In this system, energy can be stored in advance and there is no necessity to delay or suspend some tasks in high demand periods [1, 3]. Furthermore, ESS can store and consume the renewable energy freely such as solar photovoltaic energy, wind energy, etc. This helps reduce not only electricity prices for consumers but also peak load for suppliers.

Grid-connected renewable energy system is one of the techniques using energy storage units, and it can use both energy harvested from natural environment and the one purchased from the electrical grid. In general, this system consumes energy from the grid in case of energy shortage in the storage units.

However, the amount of harvested renewable energy can fluctuate depending on the environment factor, and it is also difficult to predict the amount of harvested energy. As shown in the Figure 1.1, amount of the solar photovoltaic energy varies according to the weather. When the stored energy is insufficient, consumers have to utilize electricity from the power grid, and power demand is much higher. In that case, high demand tends to push up the electricity prices. Consequently, affordable prices cannot be guaranteed for consumers, and it causes consumers' inconvenience.

In this regard, it is necessary to propose an energy scheduling schemes considering energy storage systems, and schemes have to be designed in terms of reducing electricity prices and users' inconvenience. A large variety of energy scheduling schemes for consumers have been proposed. Existing scheduling schemes have taken into account reducing electricity price or improving users' satisfaction or sustaining the energy storage units. We can classify the prior energy scheduling schemes into the following categories: (1) approaches considering only electricity prices without storage units, (2) approaches considering both electricity prices and user convenience without any storage units, and (3) approaches considering both of them with energy storage units.

In this paper, we proposed residential energy scheduling schemes considering both electricity prices and user convenience for grid-connected renewable energy system. The rest of this paper is organized as follows. In Section II, related work are presented, and we introduce the system architecture and model in Section III. Energy scheduling schemes for energy storage systems are given and the optimization problems are formulated in Section IV. Simulation results are given in Section V. Conclusions are drawn in Section VI.

Energy scheduling schemes for energy storage systems are given and the optimization problems are formulated in Section IV. Simulation results are given in Section V. Conclusions are drawn in Section VI.

2. Related Work

By the taxonomy mentioned in section 1, Chen *et al.* [7] proposed a scheme considering electricity bill only for large-scale Internet data centers in smart grid environment via stochastic optimization approach. The goal of this scheme is minimizing electricity bill by shifting electricity usage for each appliance. Parvania *et al.* [22] proposed an scheduling scheme considering only electricity prices by two-stage stochastic approach. Firstly, scheduling manager calculates electricity prices for each appliance, and predicts total electricity bill in the residential system. However, considering only electricity bill may cause significant concentration of diverse appliance schedules on a certain period of time, which results in blackout.

There also exist approaches considering an electricity price [26,28,33]. Li *et al.* [17] asserted that if most of consumers use demand response scheduling system which is aiming at affordable electricity prices, it may make a rebound peak. Their objective of scheme is to reduce the rebound peaks using multiple approaches for each home. Samadi *et al.* [27] proposed a residential energy scheduling scheme based on consumption uncertainty. They take into account different types of constraints on the operation of different appliances such as must-run appliances, interruptible appliances, and non-interruptible appliances. By running a centralized algorithm, a control unit determines the optimal operation schedule of each appliance and sets power constraint. Logenthiran *et al.* [18] proposed an optimization algorithm aiming at the final consumption curve as close to the objective consumption curve as possible. Their objective of scheme is to maximize the economic benefit and reducing the peak load demand. Xiao *et al.* [30] proposed a minMax scheduling algorithm focusing on the electricity usage of consumers. This algorithm assigns the tasks with the largest energy consumption instead of longest processing time, and estimates which timeslot can be assigned in ther range that meets the deadline. After that, system assigns the task within the lowest-cost timeslots. Koutsopoulos *et al.* [14] considered the problem of scheduling power demand tasks for minimizing long-term average operational cost. Each task has own deadline, generation time, power consumption, duration, and using these information, threshold-based approaches are proposed for balancing power consumption. However, considering electricity bill and peak load may cause sacrificing user convenience.

The aforementioned schemes are based on electricity prices without storage units. Approaches considering only electricity bill may cause significant concentration of diverse appliance schedules on a certain period of time, which results in blackout. Furthermore, they may cause sacrificing user convenience.

Agnetis *et al.* [2] proposed an approach can be applied to situations where electrical tasks have to be scheduled over a limited time horizon. Since the problem is NP-hard, a heuristic algorithm has been proposed to derive suboptimal solutions within a limited computational time. Mohsenian-Rad *et al.* [19] proposed energy consumption scheduling scheme which tries to achieve a desired trade-off between minimizing the electricity cost and minimizing the waiting cost for each appliance. Since the waiting cost increases as an appliance is assigned at later time slots, this scheme can improve the consumers' convenience. Qian *et al.* [23] designed a real-time scheduling scheme aiming at two goals: The first one is to maximize whole satisfaction as a way of meeting all appliances' deadline, and the second one is to minimize electricity bill payment. For balancing the two objectives, each user can adjust their parameter. Du *et al.* [9] proposed an appliance commitment algorithm that considering both payment and user comfort. However, user comfort is estimated using only hot water management in this paper. Consequently, user convenience considering all appliances cannot be calculated.

There also exist approaches considering both electricity price and user convenience. Yi *et al.* [31] proposed an opportunistic scheduling scheme in the manner of stopping rule for each appliance. There scheme determines the best time for each appliance to balance electricity bill and user discomfort occurred by delay. This scheme is not suitable for those who want to complete their task by deadline because user cannot set a preferred deadline for each appliance. The scheduling schemes proposed by Tsui *et al.* [29] minimize an characteristic function which measures: 1) the total cost of using the all appliances and 2) the user inconvenience calculated by delay time of each appliances. They assume that the home is equipped with interruptible appliances, uninterruptible appliances, and battery-assisted appliances. When it comes to battery-assisted appliances, some of appliances has an internal battery, and it can harvest any possible renewable energy. There is a distinct difference that any appliances can utilize shared energy storage units in our proposed scheme.

The above scheduling approaches considering both user convenience and electricity prices have a tendency to estimate user convenience based on delayed time. However, consumers prefer to operate task within their own schedule. In this regard, user preferred time have to be taken into account for each appliance.

Last of all, the approaches based on energy storage systems have proposed for a few years [24,25]. Chen *et al.* [5] considered a scheduling problem of delay tolerant tasks with the renewable energy to reduce the residential electricity bill. They try to minimize the total energy drawn from the external grid. However, they assumes infinite energy storage unit. Moser *et al.* [20] proposed a Lazy Scheduling Algorithm (LSA) that handles constraints from both energy and time domain without deadline violations. Since this scheme is based on energy harvesting sensor nodes, it cannot be operated on residential system operating multiple tasks. Yu *et al.* [32] established a scheduling optimization problem to minimize the price, and then incorporate the peak power use into the problem considering the electrical facilities. They also expanded the optimization problems with a harvesting system and an energy storage. EL Ghor *et al.* [10] proposed scheduling framework called earliest deadline with energy guarantee (Edeg). It is the extension of the earliest deadline as late as possible (EDL) scheduler and earliest deadline as soon as possible (EDS) scheduler. This approach considers both energy storage system, however it is based on the off-the-grid power system and they assume that multiple tasks cannot be operated simultaneously.

The above scheduling schemes cannot forecast amount of harvesting energy in common, and consumers cannot fully utilize energy storage units even if charging rate is high. When the stored energy is insufficient, electricity prices is generally more expensive than the one of any other time of day. In this respect, scheduling schemes prevent consumers from purchasing expensive energy from the electrical grid.

Consequently, we propose a scheduling algorithm to improve ESS utilization, and our objective function is to reduce the electricity bill payment and user' inconvenience. In order to forecast battery level of energy storage, we utilize confidence interval technique according to external factors. In this respect, scheduling schemes prevent consumers from purchasing expensive energy from the electrical grid.

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3. System Model

In this section, we provide a system architecture for grid-connected renewable energy system. We assume that smart home is equipped with a renewable energy charger, energy storage units, and demand response manager, and smart home is connected to power grid in case of insufficient storage. And the electricity price is known from the day-ahead price of the power utilities. Users are able to set an operating time, a preferred starting time, a deadline, and a priority for each appliance using their smartphone or IHD.

As shown in the Figure 3.1, there are mainly four parts in the smart home system: Scheduling Manager, Load Controller, Energy Storage System (ESS), and Database (DB). The scheduling manager has a significant role in this scheduling system. It collects a time-based pricing information and a weather forecast information on the Internet. We also assume that it has an energy consumption control (ECC) unit capable of scheduling and adjusting the household energy consumption. It manages detail configuration for each appliance such as operating time, preferred starting time, deadline, and priority. Taking these information into consideration, the scheduling manager can calculate the expected battery level of storage and make a schedule for each device. According to the scheduling result, the load controller switch a power source of each device between electrical grid and energy storage. In

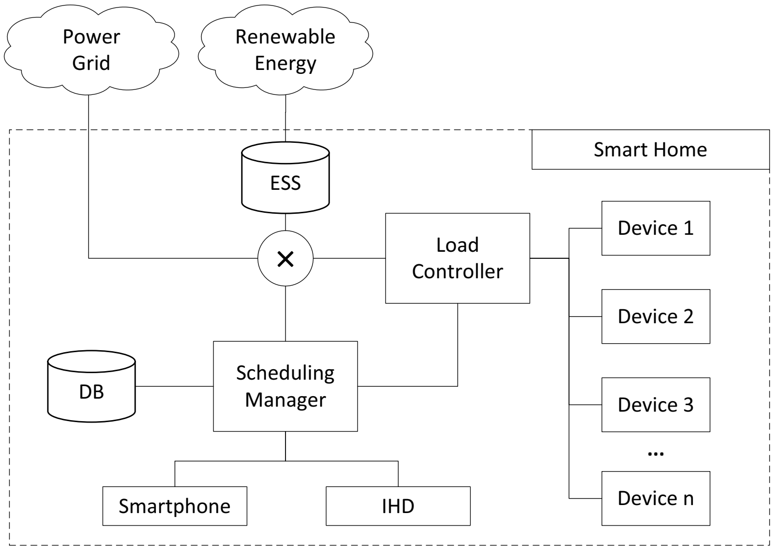

Figure 3.1: System model of residential energy storage systems.

addition to switching power source, it measures actual energy consumption in real-time and communicates with the scheduling manager. In the energy storage system, renewable energy from the solar photovoltaic or the wind turbine is charged whenever possible, and charging record is stored in the DB. The energy usage record is also stored in the DB. Devices are embedded with communication modules (e.g.,WiFi, ZigBee) to manage the information about energy consumption.

For efficient scheduling, we assume in this paper that the appliances can be classified as following types: *Must-Run Appliances* and *Controllable Appliances*.

1. Must-Run Appliances have to start working immediately. For instance, we can classify PC and TV as must-run appliances. The users are definitely free to turn on or turn off the PC whenever they want without

any interference. However, operation of must-run appliances affects an existing task scheduling. If the energy storage is not sufficient for a new must-run appliance, the scheduling manager makes a decision immediately either utilizing an energy from grid or suspending an existing task already assigned.

2. Controllable Appliances can be delayed if necessary. Each of them has a configuration information about preferred starting time, deadline, priority, and operating time. We assume that once their operation becomes active, they must remain active until the end of their operation. Plug-in electric vehicle (PEV), dish washer, and washing machine are examples of controllable appliances, respectively.

The proposed schemes consist of two operation modes: *Global Scheduling Mode* and *Local Scheduling Mode*. In the global scheduling mode, the scheduling manager make a day-ahead schedule based on configuration of each device which is set in advance. Firstly, it expects hourly ESS battery level using both weather forecast information and charging record stored in database. And the electricity price is known from the day-ahead price of the power utilities. With those information, the objective function of global scheduling is to minimize both electricity prices and user inconvenience where the battery level of ESS is sufficient at all times. In addition, the scheduler makes best-effort to fully utilize the energy storage. In this manner, the whole schedule of all appliances is made a day ahead.

However, if there is a change in expected battery level, the local scheduling make a renewed schedule, and it is also necessary when receiving a new operation request of must-run appliances. It measures a current battery level of energy storage, and by using that information, calculates an expected battery level again. The objective of local scheduling is also to minimize both electricity prices and user inconvenience, but it can only push back the existing task. The objective of local scheduling is also to minimize both electricity prices and user inconvenience, but it can only push back the existing task.

4. Problem Formulation and Algorithm Description

In this section, we present problem formulation and algorithm description. The main objective of scheduling optimization is to minimize the electricity bill and minimize users' inconvenience by managing the load of appliances. Since our main focus is on single household scenario, we simply assume that the price function is a day-ahead pricing model provided by national power exchange.

Conceptually, we shall minimize an objective function which measures: 1) the total cost of using the appliances and 2) the user inconvenience, subject to the operating constraints of the appliances. More precisely, if $P_a(d_a)$ is the electricity bill of appliance a, then the total cost is given by $g_a \sum_{a \in \mathcal{A}} P_a(d_a)$. Also, if the users' discomfort of appliance $a \in \mathcal{A}$ is expressed by $U_a(d_a)$ and λ is the adjustable control parameter, then the optimization problem can be written as

$$\begin{aligned} \underset{\mathcal{D},\mathcal{G}}{\text{minimize}} \quad & g_a \sum_{a \in \mathcal{A}} P_a(d_a) + \lambda \sum_{a \in \mathcal{A}} U_a(d_a) \\ \text{subject to} \quad & \text{operating constraints.} \end{aligned} \tag{4.1}$$

In order to formulate an objective function, we simply define the variables as following Table 4.1.

Table 4.1: Variables of the Model

Variable	Description
$\mathcal{A}$	A set of household appliances.
$\mathcal{T}$	A set of time slots.
e_a	Required energy consumption of appliance a during its operation.
g_a	Indicator function of appliance a where g_a is 1 if appliance a utilizes energy from the power grid ; 0 if it utilizes renewable energy charged in ESS.
d_a	The total number of delayed time slots of appliance a.
s_a	The scheduled starting time slot of appliance a.
T_a	The total number of required time slots to operate appliance a.
w_a^t	The number of non-overlapping time slots with intended operating time given that appliance a starts at time slot t.
$p(t)$	Electricity price at time slot t.
$c(t)$	The average charging amount of renewable energy at time slot t.
$\hat{c}(t)$	The lower endpoint of confidence interval about charging amount at time slot t.
$P_a(d_a)$	Electricity price function of appliance a given that operating time of appliance is delayed d_a time slots.
$U_a(d_a)$	User inconvenience function of appliance a given that operating time of appliance is delayed d_a time slots.
α	A significance level for estimating confidence interval of $c(t)$
λ	Adjustable control parameter for balancing electricity bill and user discomfort.
$[\alpha_a, \beta_a]$	Preferable operating interval of appliance a between timeslots α_a and β_a.
$ESS(t)$	Battery level of energy storage system at time slot t.
ESS_{max}	Maximum battery level of energy storage system.

Let a $\mathcal{T}$ denotes the set of time slots and a $\mathcal{A}$ denotes the set of household smart appliances such as washer, refrigerator, dish washer, air conditioner, and PHEV. We assume that each appliance $a \in \mathcal{A}$, a time slot $t \in \mathcal{T} = \{1, \ldots, T_{max}\}$, and $T_{max} = 1440$ because time-varying price is generally changed for a minute. We also assume that appliance a consumes time invariant energy e_a during its operation time. T_a denotes the total number of required time slots to operate appliance a. We assume that the user want appliance a to operate within a user's preferred time period $[\alpha_a, \beta_a] \subseteq \mathcal{T}$.

In this scheme, there are two choices to operate appliances: *from-grid* and *from-ESS*. For that reason, we assume that g_a is an indicator function expressing either appliance a should utilize the grid energy or renewable energy from ESS. If appliance a utilizes energy from the power grid, g_a is equal to 1, otherwise it is equal to 0. Also, the total number of delayed time slots of appliance a which is occurred by scheduling can be expressed d_a.

$$0 \leq d_a \leq T_{max} - (T_a + \alpha_a - 1) \tag{4.2}$$

The electricity price at time slot t is denoted by $p(t)$, and Figure 4.1 is an example of electricity price given by electrical grid. And the scheduled starting time slot of appliance a which is s_a is equal to $\alpha_a + d_a$. Therefore, $P_a(d_a)$ which is the electricity price of appliance a can be calculated as

$$P_a(d_a) = e_a \sum_{t=s_a}^{s_a+T_a-1} p(t), \qquad s_a = \alpha_a + d_a \tag{4.3}$$

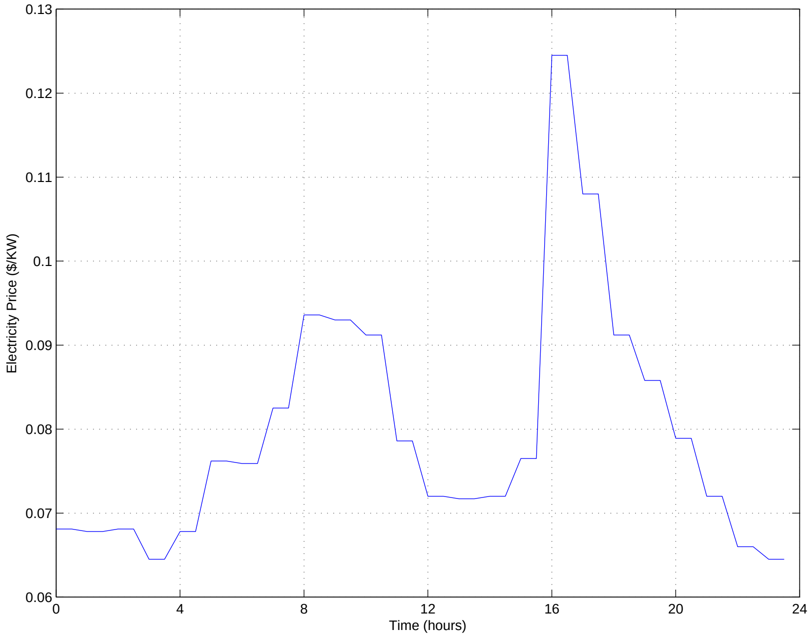

Figure 4.1: The example of day-ahead electricity pricing model.

t	$\cdots$	417	418	419	420	421	422	423	424	425	426	$\cdots$
w_a^t	$\cdots$	0	0	0	0	1	2	3	4	5	6	$\cdots$
		$\uparrow$ α_a			$\uparrow$ β_a							

Figure 4.2: The example of using a paramter w_a^t .

We can evaluate user inconvenience using w_a^t which is the number of non-overlapping time slots with intended operating time given that appliance a. As shown in the Figure 4.2, the preferable operating interval of appliance a is equal to $[417, 420]$, and the shaded areas show the scheduled operating interval given that four time slots are delayed. For each appliance a, w_a^t can

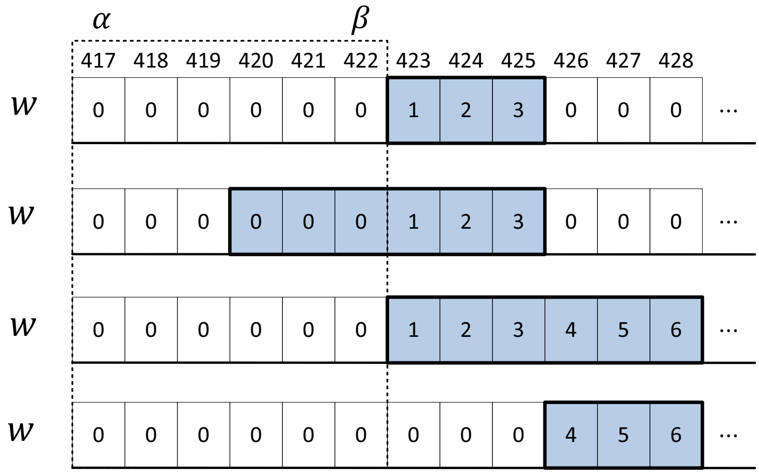

Figure 4.3: The examples of task scheduling for comparing the inconvenience for each appliance.

be expressed in three cases:

$$w_a^t = \begin{cases} \alpha_a - t, & t < \alpha_a \\ 0, & \alpha_a \le t \le \beta_a \\ t - \beta_a, & \beta_a < t. \end{cases} \tag{4.4}$$

Using the parameter w_a^t, a sum of valid w_a^t can be expressed by w_a. For example, if user wants appliance a to operate between 06:57 and 07:00, α_a is 417 and β_a is 420. In this case, as you can see in the Figure 4.2, we can calculate a parameter w_t^a for each time slots. Therefore, we can evaluate w_a which is user inconvenience of appliance a using the summation of w_a^t.

$$w_a = \sum_{t=s_a}^{s_a+T_a-1} w_a^t, \qquad s_a = \alpha_a + d_a \tag{4.5}$$

However, in this case, the longer the operation time of an appliance, the higher the users' inconvenience. In the Figure 4.3, there are four appliances a, b, c, and d which user set up under the same preferred time duration $[\alpha, \beta]$. The shaded areas on the Figure 4.3 show the scheduled result of appliance a, b, c, and d. In this case, the total inconvenience degree caused by appliance c can be calculated as 21, and the degree of appliance d is 15. However, user feels much more uncomfortable caused by appliance d because the starting time and ending time of appliance d are postponed longer than those of appliance c. On the other hand, in case of appliance a and b, both of them has a same dissatisfaction degree. However, scheduling result of appliance b is more convenient for user to follow in practice. For this reason, we divide total inconvenience degree w_a by the operating time of appliance T_a, and we call this *per-slot inconvenience.* Using the per-slot inconvenience, we can estimate that the inconvenience of appliance $a = 2, b = 1, c = 3.5$, and $d = 5$ and the task of appliance b causes a least inconvenience relatively. Consequently, $U_a(d_a)$ which is the user inconvenience function of appliance a can be expressed as

$$U_a(d_a) = \frac{\sum_{t=s_a}^{s_a+T_a-1} w_a^t}{T_a}, \qquad s_a = \alpha_a + d_a \tag{4.6}$$

In order to forecast battery level of energy storage, we use a way to estimate a confidence interval with a confidence level. We denotes α as a significance level, and the confidence level is the complement of respective level of significance. For example, 95% confidence interval reflects that a significance level α is equal to 0.05 [8]. The average charging amount of renewable energy at time slot t is denoted by $c(t)$, and it is calculated using a sample taken from the database which stores whole charging record. The desired level of confidence is set by the user using the significance level α. Before estimating the confidence interval, we only consider the lower endpoint of confidence interval in terms of maintaining energy storage units. In that case, the confidence interval meets following equation (4.7) and equation (4.8) in the normal distribution.

$$P(-z \leq Z \leq \infty) = 1 - \alpha \tag{4.7}$$

$$P(\hat{c}(t) \leq c(t)) = 1 - \alpha \tag{4.8}$$

The battery level of energy storage system at time slot t is denoted by $ESS(t)$, and it can be expected using the lower endpoint of confidence interval. Using the lower endpoint which is denoted by $\hat{c}(t)$, sustainability of energy storage system can be improved within certain confidence level. We use g_a which is an indicator function expressing either appliance a should utilize the grid energy or renewable energy from ESS. In case that appliance a should utilize ESS battery, g_a has to be equal to 0. In order to express $ESS(t)$, we denote e_a^t firstly, where $s_a = d_a + \alpha_a$.

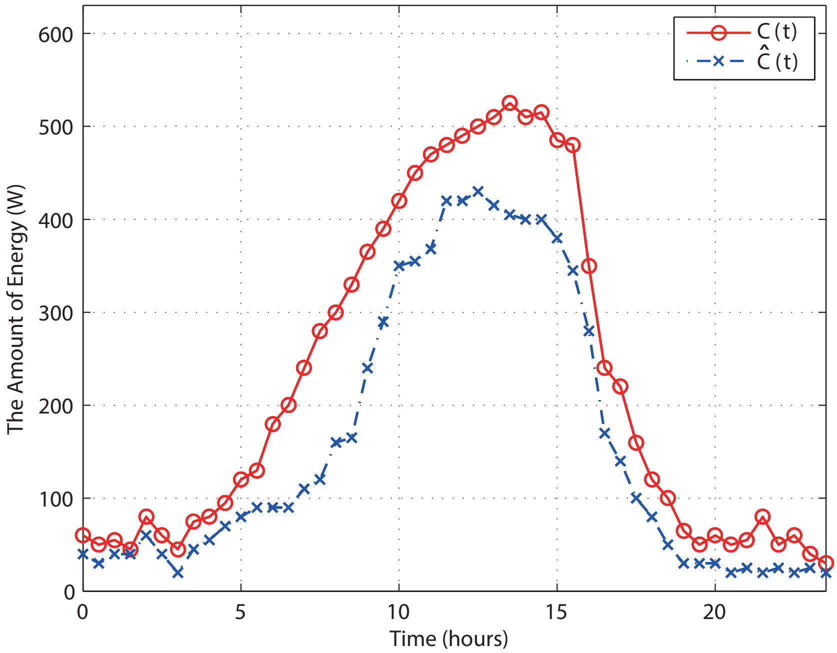

Figure 4.4: The amount of charged energy during a day.

$$e_a^t = \begin{cases} e_a, & s_a \le t < s_a + T_a \\ 0, & otherwise \end{cases} \tag{4.9}$$

The total energy consumption using energy storage can be calculated as $\sum_{a \in \mathcal{A}} (1 - g_a) \cdot \sum e_a^t$. In addition, the total energy charging amount can be calculated as $\sum(\hat{c}(t))$. Consequently, we can expect the battery level of ESS at time slot k which is denoted by $ESS(k)$, and we assume that the maximum battery level of ESS is equal to ESS_{max} and initial battery level is denoted by $ESS(0)$.

$$\begin{aligned} ESS(k) =& ESS(0) + \sum_{t=0}^{k} \hat{c}(t) - \sum_{a \in \mathcal{A}} (1 - g_a) \sum_{t=0}^{k} e_a^t, \\ \text{where} \quad & s_a = \alpha_a + d_a, \\ & k \in \mathcal{T} = \{1, \dots, T_{max}, \} \\ & 0 \le ESS(k) \le ESS_{max}, \forall k. \end{aligned} \tag{4.10}$$

We shall minimize an objective function which measures: 1) the total cost of using the appliances and 2) the user inconvenience, subject to the operating constraints of the appliances. The detail operating constraints for energy storage systems are as follows:

- The expected battery level is greater or equal to 0 for all $t \in \mathcal{T}$.
- The expected battery level shall not exceed the maximum battery level of ESS which is ESS_{max}.
- The indicator parameter g_a has either 0 or 1 to express which energy source the appliance a uses.
- The number of delayed time slots should be less than or equal to $T_{max} - (T_a + \alpha_a - 1)$.
- The number of preferable operating interval of appliance a is larger than or equal to the one of required time slots to operate appliance a.

Using the objective function, the system find the number of delayed time slots (d_a) and the indicator parameter (g_a) for each appliance a. We assume that a set of the paramter d_a is expressed by $\mathcal{D}$ and a set of g_a is expressed by $\mathcal{G}$. Overall, we define the objective function as follows:

$$
\begin{aligned}
\underset{\mathcal{D},\mathcal{G}}{\text{minimize}} \quad & g_a \sum_{a \in \mathcal{A}} P_a(d_a) + \lambda \sum_{a \in \mathcal{A}} U_a(d_a) \\
\text{subject to} \quad & 0 \leq ESS(t) \leq ESS_{max}, \;\; t \in \mathcal{T} \\
& 0 \leq d_a \leq T_{max} - (T_a + \alpha_a - 1), \;\; a \in \mathcal{A} \\
& 0 < T_a \leq \beta_a - \alpha_a + 1, \;\; a \in \mathcal{A} \\
& g_a \in \{0, 1\}
\end{aligned}
\tag{4.11}
$$

4.1 Complexity Issues

In this subsection, we show the computational complexity of our proposed scheduling problem (RESS). To this aim, we show the simplified scheme (S-RESS) is NP-hard, implying that our scheme is NP-hard, too. In S-RESS, the time horizon is composed of only two time slots, only schedulable loads exist, and there is an only energy storage units. We assume that maximum energy usage from the storage, say W, during each slot. Let n be the number of schedulable loads, and let e_k, for $k = 1, \ldots, n$, be the required energy of each appliance k when it is operated in a time slot. We also assume that the total required energy of appliances is equal to $2W$ and the total number of required time slots of appliance is equal to 1. In other words, one of two slots should be utilized for operating an appliance, and the other one is for idle state. Since the total required energy of appliances is equal to $2W$, the decision problem consists in determining if it is possible to switch on each device in one slot, in such a way that the energy drawn from the ESS in each time slot does not exceed W.

We show that the S-RESS which is simplified version is equivalent to the NP-complete problem PARTITION [11]. Given a set B of n items $\{1, \ldots, n\}$ and an integer value b_j associated to each item $j \in B$, PARTITION consists in determining whether a partition of B into two sets B_1 and B_2 exists, such that $\sum_{j \in B_1} b_j = \sum_{j \in B_2} b_j$. Identifying the schedulable appliances with the items of the set B, it is clear to note that the simplified scheme has a feasible solution if and only if a partition of B exists such that $\sum_{j \in B_1} b_j = \sum_{j \in B_2} b_j$. Therefore, the decision form of S-RESS is NP-complete. Since simplified problem is a particular case of our proposed scheme, the following theorem follows.

Theorem 4.1.1. *The proposed scheduling problem (RESS) is NP-hard.*

4.2 Scheduling Algorithm

In this subsection, we propose a Residential Energy Scheduling Scheme (RESS) for optimizing the objective function. Since our scheduling problem is NP-hard problem, we suggest a heuristic scheme that can diminish the number of schedulable appliances. There are two major parts for this scheduling algorithm: (1) Reduction procedure of $\mathcal{G}$ vector from the objective problem and (2) Decision procedure of delay time ($\mathcal{D}$) for each appliance.

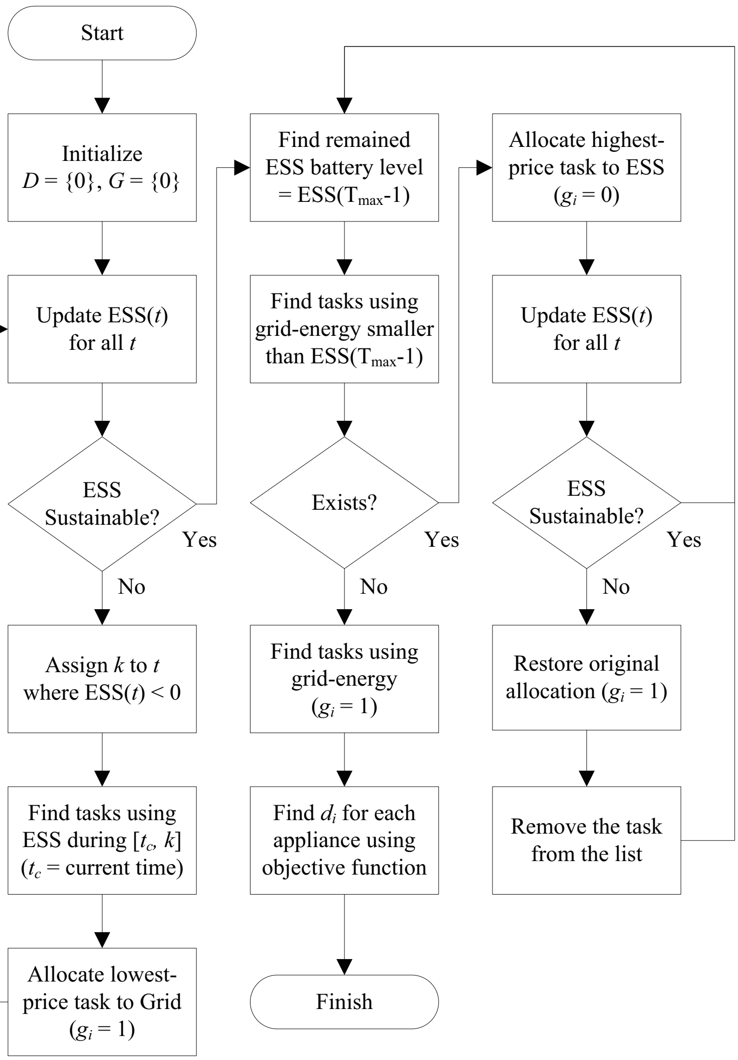

Figure 4.5: The flow chart of the proposed algorithm.

First and foremost, the scheduler assigns all appliances to use ESS considering only preferable time interval. After that it computes an expected battery level of ESS, and finds the first time slot on which the battery level is less than 0. If the time slot exists, the scheduler finds tasks which is operated before that time slot, and assigns the task to use power grid in lowest-price order. In that way, the scheduler accomplish the initial task placement in respect of power-grid. However, since the remaining battery level of ESS can be higher than a required energy of certain task, the scheduler assigns the task consuming the energy less than remaining battery to utilize ESS. After that, the scheduler calculates a delay time of each appliance using objective function. Since the variable g_i is determined by the prior procedure, the delay time of each appliance can be calculated independently in polynomial time. As shown in the Figure 4.5, the scheduler is able to handle whole task of appliances. In addition, since the expected battery level of ESS is calculated using the concept of confidence interval, the probability of sustaining ESS is the same as confidence level configured by user. The pseudo code of proposed algorithm and the flow chart are as follows:

Algorithm 1 Proposed scheduling algorithm

Input: $\mathcal{A} = \{a_1, \ldots, a_i\}, p(t), \hat{c}(t)$
Output: $\mathcal{D} = \{d_1, \ldots, d_i\}, \mathcal{G} = \{g_1, \ldots, g_i\}$
Initialize scheduling vectors $\mathcal{D}, \mathcal{G}$ to zero;
while $t \in \mathcal{T}$ **do**
if $ESS(t) < 0$ **then**
$temp \leftarrow \infty$
for $a \in \mathcal{A}$ **do**
if $g_a == 0$ **and** $s_a \leq t$ **and** $P_a(d_a) < temp$ **then**
$temp \leftarrow P_a(d_a)$
$id \leftarrow a$
end if
end for
$g_{id} \leftarrow 1$
else
$t \leftarrow t + 1$
end if
end while
for $a \in \mathcal{A}$ **do**
if $g_a == 1$ **and** $e_a < ESS(T_{max} - 1)$ **then**
Add a task a to the set $GridTask$ in electricity price order;
end if
end for
for $a \in GridTask$ **do**
$g_a \leftarrow 0$
for $t \in \mathcal{T}$ **do**
if $ESS(t) < 0$ **then**
$g_a \leftarrow 1$
Delete the task a from the list $GridTask$;
break;
end if
end for
end for
for $a \in \mathcal{A}$ **do**
if $g_a == 1$ **and** $e_a < ESS(T_{max} - 1)$ **then**
Add a task a to the set $GridTask$ in electricity price order;
end if
end for
for $a \in GridTask$ **do**
Compute a delay time d_a using eqation (4.11);
end for

5. Simulation Result

In this section, we conduct simulations to verify our optimization problem. The proposed scheme is implemented by Java console program, and simulation result is drawn by MATLAB graphical tool. In order to efficient simulation, we assume that a time slot is 30 minutes long and the user has 18 schedulable appliances in residential energy storage system. The appliance task list is obtained from the jeju smart grid demonstration project. The detail configuration of simulation parameters is shown in the following Table 5.1. Comparing to the proposed scheme, there are two greedy scheduling schemes, and detail descriptions of them are as follows.

- The first scheme is an existing scheduling scheme for energy storage system. In this scheme, the appliances are operated by the energy from

Table 5.1: Simulation Parameters

Parameters	Value
Number of appliances	18
Number of time slots	48
Total energy consumption	10 kW
Total stored energy	5 kW
Energy storage capacity	3 kW
Initial battery level	0 kW

the storage. When the storage is not sufficient, the remaining appliances should be operated by the energy from the power grid regardless of real time price. We call this scheduling scheme*ESS-AMAP (ESS As Much As Possible)*.

- The other greedy scheme is an advanced scheduling scheme considering electricity prices. If the energy storage is sufficient or the electricity price is too expensive, this scheme tries to utilize the energy from the battery regardless of current price. In addition, if the total energy consumption of remaining tasks is larger than the remaining energy of ESS, it utilizes the energy storage in the same manner as the ESS-AMAP scheme. However, it uses electrical grid in the circumstance which meets two conditions: insufficient storage and inexpensive electricity price. It also utilizes inexpensive grid-energy to prepare the expensive electricity price in the future. This scheduling scheme is called *PB-ESS (Price Based ESS)*.

Since these two scheduling schemes are based on delay-intolerant tasks, for better comparison, we classify our proposed scheduling scheme into three schemes: RESS (Delay-Intolerant), RESS (Delay-Tolerant), and RESS (Lowest Price).

Figure. 5.1 shows the battery level of energy storage per hour. Because the ESS-AMAP scheme considers only current battery level of ESS, it utilizes the storage as much as possible regardless of electricity prices. Otherwise,

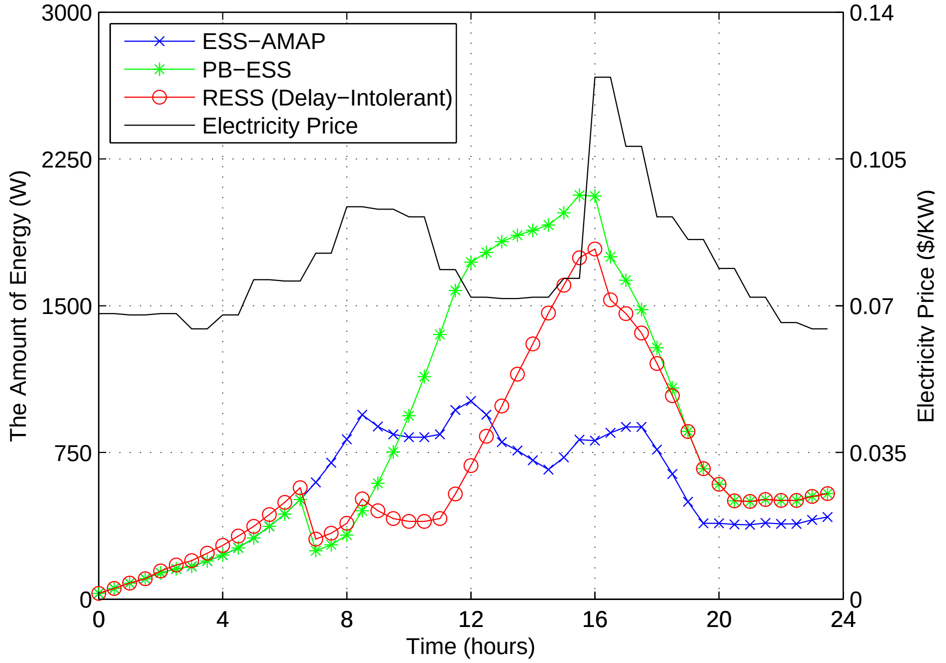

Figure 5.1: The battery level of energy storage per hour.

the PB-ESS scheme tries to save the energy storage during the low-price interval, and consequently it can utilize the ESS stroage when the electricity prices are high. However, if there is a few task when the price is high, this scheme can cause serious waste in terms of ESS utilization. The proposed scheme, RESS, tries to save the energy storage only if the scheduler predicts the insufficiency of battery because the charging prediction technique of storage units is used.

Figure. 5.2 shows that the energy consumption from the electrical grid. Since the ESS-AMAP scheme does not consider electricity price, it consumes the grid energy despite the expensive electricity price. As shown in the Fig-

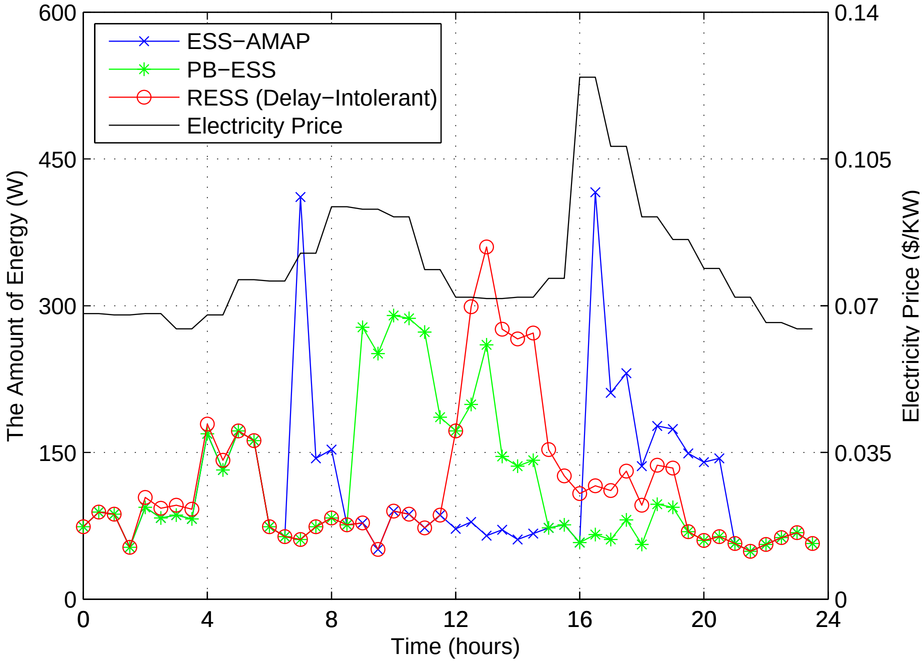

Figure 5.2: The energy consumption from the electrical grid.

ure. 5.2, the appliance spending lots of grid energy at 5 pm in that scheme. However, the proposed RESS scheme and the PB-ESS scheme mostly consume the grid energy during low-price interval.

As shown in the Figure. 5.3, the proposed scheme can utilize ESS when the electricity price is high. In addition, the amount of energy consumption from the ESS is larger than one of other schemes until 12 o'clock because of the charging prediction technique. Even if the present amount of the ESS is smaller than total required energy, it can calculate expected battery level of the ESS in the near future. For that reason, it can fully utilize the ESS even though the present battery level is low. Especially, if there are lots of

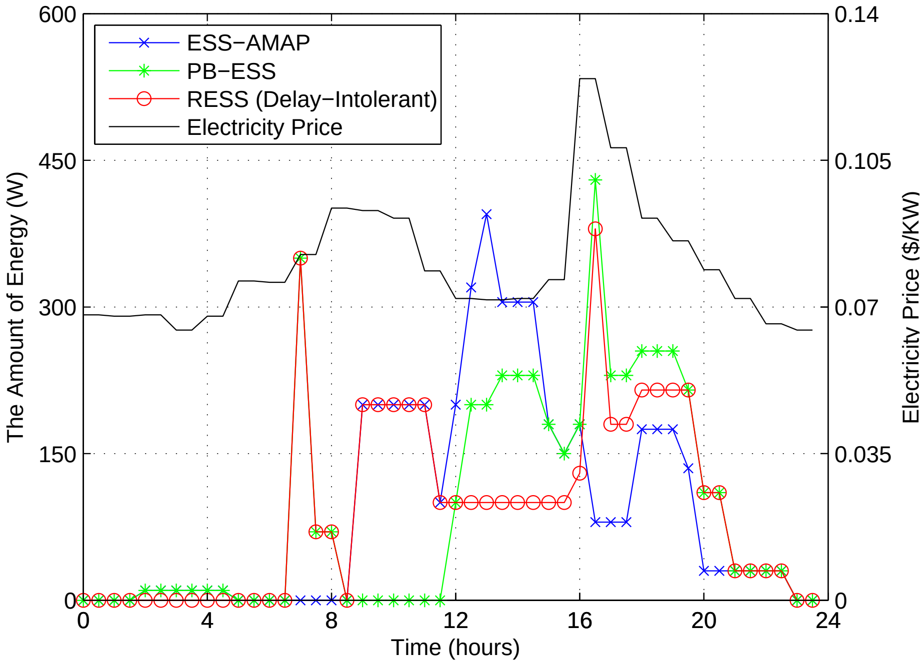

Figure 5.3: The energy consumption from the energy storage units.

task during a day, this scheme can utilize the ESS actively.

Figure. 5.4 shows the scheduling result using the three different version of the proposed scheme: RESS (Delay-Intolerant), RESS (Delay-Tolerant), and RESS (Lowest Price). In the delay-intolerant RESS scheme, there is not a delaying or shifting manner, and it does not cause inconvenience. When we formulate our objective function, we use adjustable control parameter, λ, to determine the acceptable level of delaying task. Using this variable, some tasks of appliance can be delayed if necessary, and this scheme is called delay-tolerant RESS scheme. As shown in the figure, the scheduling result from both RESS-DI and RESS-DT is almost same, and it means the degree

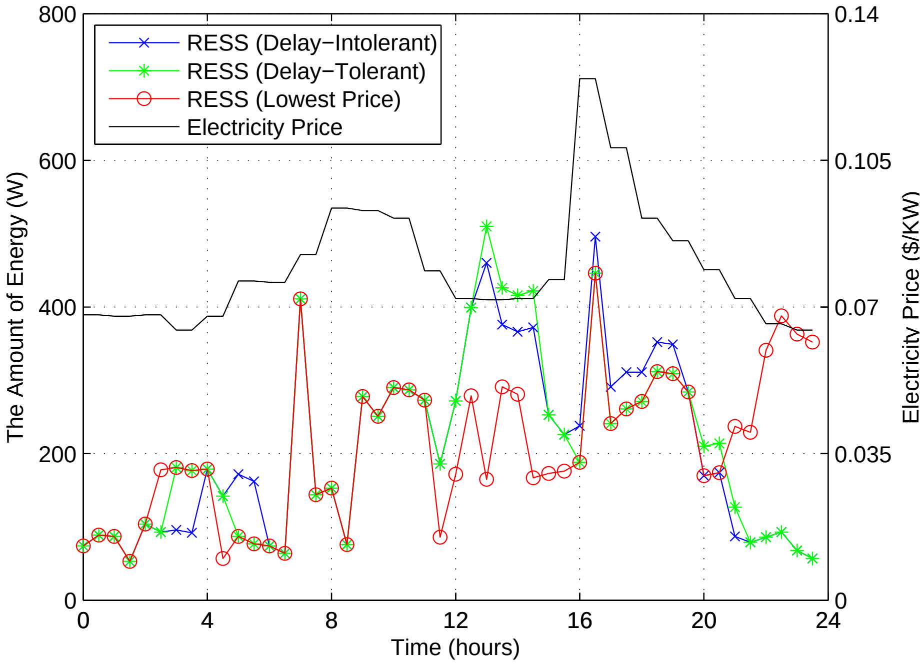

Figure 5.4: The scheduling result using the three different version of the proposed scheme.

of user discomfort is very low. If λ is equal to 0, scheduler considers only electricity price, and it make a schedule which is much more different from the user preferable schedule. In other words, RESS (Lowest Price) policy may make a serious inconvenience for user.

An overall simualtion result is on the following Table 5.2. The ESS-AMAP scheme can consume the largest amount of ESS energy above all. However, the electricity bill of the PB-ESS scheme is cheaper than the one of the ESS-AMAP. Even though our proposed scheme, RESS, and the PB-ESS scheme consume the same energy from the grid, users can cut their electricity bill more using the proposed scheme. If the user sacrify their inconvenience

Table 5.2: A comparision on simulation result

Scheme	ESS Energy Usage (W)	Grid Energy Usage (W)	Electricity Bill ($)	Average Time Delay (m)	Average n of Delayed Task
ESS-AMAP	4580	5420	13.73	0	0
PB-ESS	4460	5540	13.29	0	0
RESS (Delay-Intolerant)	4460	5540	13.08	0	0
RESS (Delay-Tolerant)	4460	5540	12.71	11.6	2
RESS (Lowest Price)	4460	5540	12.44	78.3	9

by postponing appliances' task, the scheduler can provide much affordable electricity price.

6. Conclusion

In this paper, we introduce the system model in the grid-connected renewable energy storage system, and the optimization problem has been proposed. Our objective function is aiming at two goals: The first one is to maximize whole satisfaction as a way of meeting all appliances' preferable time interval, and the second one is to minimize electricity bill payment. In addition, the prediction scheme of energy storage units also has been proposed, and it is utilized as a constraint of optimization problem. Experimental results validate that the proposed scheduling scheme shifts the operation to fully utilize the energy storage and achieves significant saving in the electricity bill as well as improving user convenience.

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국 문 초 록

계통연계형 신재생 에너지 시스템을 위한 주거용 에너지 스케줄링 기법

최근 세계 전력 사용량은 급격하게 증가 추세에 있으며 변동성 또한 날로 커지고 있다. 따라서 전기수요의 변동성에 대응하기 위해 응답속도가 빠른 발전 설비를 갖추거나 전력수요를 정확하게 예측해야 하지만 효율성, 정확성이 매우 떨어지는 문제를 갖는다. 이를 해결하기 위해 에너지 저장 장치를 이용해 전력을 저장하고, 필요할 때 공급하는 에너지 저장 방법이 대두되고 있다. 특히 전력 계통과 신재생 에너지를 복합적으로 이용하는 계통연계형 신재생 에너지 시스템은 자연 환경에서 얻는 신재생 에너지를 저장하여 주로 활용하고, 에너지가 부족한 경우 연결된 전력 계통을 통해 에너지를 공급받을 수 있다.

그러나 신재생 에너지 충전 역시 외부 환경적인 요인에 따라 변동성이 매우 크고, 신재생 에너지가 부족해 지는 현상 또한 특정시간에 사용자들에게 공통적으로 나타나는 특징을 갖는다. 이는 일시적으로 전력 계통에 높은 부하를 가져와 블랙아웃과 같은 위험 상황을 일으키게 된다.

따라서 본 논문에서는 통계적 기법을 통해 에너지 저장 장치의 충전량을 예측하는 기법을 제안하고, 예측 충전량을 통해 소비자의 전력 작업을 최적화 할 수 있는 스케줄링 기법에 대해 제안한다. 특히 스케줄링 문제에서는 실시간 요금과 사용자의 불편도를 다각적으로 고려해, 이용 요금과 불편도를 최소화 하는 기법에 대해 소개한다. 제안하는 알고리즘의 시뮬레이션 결과, 일평균 10KW를 소비하고 5KW 규모의 저장 장치를 갖는 가정에서 약 75%의 에너지를 절약할 수 있었으며, 전력 계통을 통해 수급받는 에너지에 대한 요금도 약 12% 절감할 수 있었다.

Abstract

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Demand response (DR) is one of the technologies to enable smart grid, and it can distribute electricity tasks in response to electricity price. However, the existing systems have a tendency to change an operating time of appliances, and it can cause serious inconvenience to consumers in practice. With this current problem of demand response systems, there is a strong demand for grid-connected renewable energy system which is able to use both energy harvested from natural environment and the one purchased from the electrical grid. However, since the amount of harvested renewable energy can fluctuate depending on the environment factor, it is not easy to schedule whole tasks in advance. In this regard, we proposed a scheduling algorithm and a prediction methodology of energy storage units in this paper. We also designed the objective function considering user inconvenience and electricity bill, and prove it with NP-hard problem. Experimental results validate that the proposed scheduling scheme shifts the operation to fully utilize the energy storage and achieves significant saving in the electricity bill as well as improving user convenience.