Optimization of Scheduling for Home Appliances in Conjunction with Renewable and Energy Storage Resources

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Abstract

In this paper, for efficient energy consumption through the residential demand response in the smart grid, an optimization algorithm, which can provide a schedule plan for the home appliance usages, is proposed. In order to minimize the average electricity price based on the time-varying electricity price in conjunction with the peak hourly load, which decides the capacity of the electric supply facilities, we establish a mixed integer linear programming problem considering various energy consumption patterns of home appliances. In addition, a photovoltaic system and an energy storage are added to the residential side to achieve further efficient schedule plans. By measuring the power consumptions of the home appliances with respect to the time, we constructed the power consumption patterns of each appliance and numerically analyzed the performance of our algorithm by using a real time-varying electricity price and the solar cell power profile obtained through a mathematical model.

Keywords: *Mixed binary linear program, schedule plan, smart grid, time-varying electricity price, home appliance*

1. Introduction

Because of rapid and continuous increases in the electric power demand, the electricity distribution systems are confronted with numerous difficulties in the power grid. Developing the smart grid is embedding intelligence into the power grid and provides benefits to the customers as well as the electric power providers [1]. The demand response (DR) can make an important contribution to enabling the smart grid. DR is changes in electric power usage by the customers from their normal consumption patterns in response to changes in the electricity price over time, or incentive payments prepared to induce the lower consumption at times [2].

Under the time-varying electricity price structures, such as the time of use (TOU) pricing, the customers in the residential side can reduce their electricity bills by changing the usage patterns. In this paper, we focus on the schedule plan of home appliances based on the TOU pricing system. In order to reduce the residential electricity bill, several research works have been conducted. Kumaraguruparan *et al.*, [3] classified the home appliances depending on the power controllability and conducted minimizations of the residential electricity bill by using the multiple knapsack method. Chen *et al.*, [4] considered a scheduling problem of delay tolerant tasks with the renewable energy to reduce the residential electricity bill. On the other hand, Zhu *et al.*, [5] formulated a min-max problem to reduce the peak power demand based on the mixed binary linear program (BLP). Note that the mixed BLP can manage further

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general types of optimization problems especially for the scheduling problem than the case of the Knapsack method. Hence, we employ the mixed BLP technique to solve an optimization problem of scheduling the home appliances to reduce the residential electricity bill.

In this paper, for the purpose of minimizing the residential electricity bills under the TOU pricing or tariff system, we formulate several optimization problems to obtain good schedule plans of the home appliances in the form of the mixed BLP. We first establish a scheduling optimization problem to minimize the price, and then incorporate the peak power use into the problem considering the electrical facilities. We then expand the optimization problems with a photovoltaic system and an energy storage. We measure the power consumption patterns of the home appliances and classified them into three classes depending on the control types as in [3] and [5]. By using a TOU pricing and simulated locally-generated power from the photovoltaic system, the optimizations are performed and the results are compared.

2. Residential Power Management

In this section, in a similar manner as in [1, 3] and [5], we observe the power consumption patterns of widely used home appliances and then classify the types of appliances, which can be controlled based on DR to reduce the residential electricity bill.

Let a set $\mathbf{A}$ be defined as $\mathbf{A} \coloneqq \{1, \ldots, N\}$, of which elements indicate N appliances, respectively, and let a vector $\mathbf{x}_i$, which denotes the *schedule plan* of the *i*-th appliance, be defined as

$$\mathbf{x}_i \coloneqq \left(x_{i,1}, \ldots, x_{i,24}\right) \in \mathbf{R}^{24}, \text{for } i \in \mathbf{A} \quad \textbf{(1)}$$

where $x_{i,j} \geq 0$. Consider a set $\mathbf{H}$, which implies 24 slots of hours for one day, and define the set as $\mathbf{H} \coloneqq \{1, \ldots, 24\}$. For a particular time slot j in $\mathbf{H}$, $x_{i,j}$ is the scheduling variable, which means the power consumption of the *i*-th appliance in kilowatt-hour (kWh). We now classify the types of the power consumption patterns as follows.

2.1. Power-Shiftable Appliances

For the *power-shiftable appliances*, such as the water boiler and the plug-in electric vehicle (PEV) chargers, the scheduling optimization can arrange flexible power usages in several hours while ensuring the total energy supplies. Let $\mathbf{P}(\subset \mathbf{A})$ denote the set of indexes of the power-shiftable appliances, and for $i \in \mathbf{P}$ let positive constants δ_i denote the total daily energy requirements for the *i*-th appliances, respectively. For the power-shiftable appliances with a standby power $\alpha_{i,j}(\geq 0)$ and a maximum working power $\beta_{i,j}(\leq 0)$, which can describe a possibly preferred working period, the consumption constraints, for $i \in \mathbf{P}$, can be written as

$$\alpha_{i,j} \leq x_{i,j} \leq \beta_{i,j}, \forall j, \text{and } \mathbf{1}^T \mathbf{x}_i = \delta_i \quad \textbf{(2)}$$

where $\mathbf{1} \coloneqq (1, \ldots, 1) \in \mathrm{R}^{24}$.

2.2. Time-Shiftable Appliances

The *time-shiftable appliances*, such as the washing machine, dish washer, electric rice cooker, and iron, can shift the power consumption time within a preferred working period. Let $\mathbf{T}(\subset \mathbf{A})$ denote the set of indexes of the time-shiftable appliances, and for $i \in \mathbf{T}$ define the fundamental power consumption pattern as $\left(\epsilon_{i,1}, \ldots, \epsilon_{i,24}\right)$, where $\epsilon_{i,j} \geq 0$. The *i*-th time-shiftable appliance can then have 24 possible patterns, which are obtained by circular shifting the fundamental pattern. In order to select one of them for optimization, Zhu *et al.* [5] used the BLP technique. For the switch control, a binary integer vector $\mathbf{s}_i$ is defined as $\mathbf{s}_i \coloneqq (s_{i,1}, \dots, s_{i,24}) \in \{0,1\}^{24}$. In the vector $\mathbf{s}_i$, there is only one non-zero element that is equal to one. For $i \in \mathbf{A}$, this constraint can be written as

$$\mathbf{1}^T \mathbf{s}_i = 1, \text{ and } \mathrm{s}_{i,j} \in \{0,1\}, \text{ for } j \in \mathbf{H}. \tag{3}$$

By using $\mathbf{s}_i$, the schedule plan $\mathbf{x}_i$ of the time-shiftable appliances can be written as

$$\mathbf{x}_i = E_i^T \mathbf{s}_i, \qquad \text{for } i \in \mathbf{T}, \tag{4}$$

where the columns of the 24×24 matrix E_i are the circular shifts of the fundamental pattern $(\epsilon_{i,1}, \dots, \epsilon_{i,24})$ as

$$E_i \coloneqq \begin{pmatrix} \epsilon_{i,1} & \cdots & \epsilon_{i,24} \\ \vdots & \ddots & \vdots \\ \epsilon_{i,24} & \cdots & \epsilon_{i,23} \end{pmatrix}.$$

2.3. Non-Shiftable Appliances

The *non-shiftable appliances*, which cannot shift their working time to any time slot, have fixed power requirement, operation period, and have to ensure continuous supply of power. For example, the fridge, TV, and the heater belong to the non-shiftable appliances. Suppose that the complement set $\mathbf{A} \setminus (\mathbf{P} \cup \mathbf{T})$ implies the non-shiftable appliances. For the schedule plan $\mathbf{x}_i$ of the non-shiftable appliances, the hourly power requirements are fixed constants during their working periods.

3. Scheduling Optimizations

In this section, for the TOU pricing environment, we suppose that the energy is only provided from the grid and then formulate optimization problems to achieve a lower electricity bill in the residential side based on the mixed BLP.

3.1. Minimization of the Residential Electricity Bill

We define the vector $\mathbf{c}$, which represents the time-varying electric price rate for a day, as $\mathbf{c} \coloneqq (c_1, \dots, \mathrm{c}_{24}) \in \mathbf{R}^{24}$. Here, the non-negative constants $\mathbf{c}_j$, for $j \in \mathbf{H}$, are the price rates, which are given in dollars per kWh (dollars/kWh). We call the summation $\sum_{i \in A} x_{i,j}$, which implies the required power of the all appliances for the time slot ($j \in \mathbf{H}$), the *hourly load*. Then, the cost for the hourly load of load j is $\mathrm{c}_j \sum_{i \in A} x_{i,j}$ and the total cost a day is given by

$$\sum_{j \in \mathbf{H}} \mathrm{c}_j \sum_{i \in \mathbf{A}} x_{i,j} = \sum_{i \in \mathbf{A}} \mathbf{c}^T \mathbf{x}_i \tag{5}$$

which implies the residential electricity bill per day. We can now formulate the consumption scheduling mechanism based on the mixed BLP, which aims to minimize the bill of (5) with respect to the schedule plan $\mathbf{x}_i$ in (1), as follows.

$$\text{minimize} \sum_{i \in \mathbf{A}} \mathbf{c}^T \mathbf{x}_i \tag{6}$$

The minimization of (6) is achieved by changing the parameters on the power-shiftable and time-shiftable appliances under the constraints of (2), (3) and (4). Hence from the optimization of (6), we can obtain an optimal schedule plan of $\mathbf{x}_i$, which yields the minimal bill of (5).

3.2. Residential Electricity Bill Considering the Peak Hourly Load

Since the scheduling optimization of (6) minimizes the residential electricity bill, the power-shiftable and time-shiftable appliances converge on low cost time slots. This convergence yields increased energy consumption at a particular time slot, and demands further extension of the electrical facilities. Such an extension also increases the basic charge for the usage of the electric power. Hence, in optimizing the appliance schedule plan, we may consider the *peak hourly load* [5], which is the maximal hourly load among the hourly loads. Let a constant L denote the peak hourly load. The constraint regarding the peak hourly load is then given $\sum_{i\in\mathbf{A}} x_{i,j} \leq L$, for $j \in \mathbf{H}$. We now modify the optimization problem in (6) by adding the constraint on the peak hourly load L as

$$\text{minimize} \sum_{j\in\mathbf{H}} \mathbf{c}^T\mathbf{x}_i + \lambda L \tag{7}$$

$$\text{subject to} \sum_{i\in\mathbf{A}} \mathbf{c}^T x_{i,j} \leq L, \text{for } j \in \mathbf{H}$$

In (7), a positive constant λ implies a contribution portion of the peak hourly load to the total cost and the value λL is concerned with the basic electricity price.

4. Scheduling Optimizations with a Photovoltaic System and an Energy Storage

By using the locally-generated power system and the energy storage battery, the customer can harvest and store the electric energy, and more efficiently optimize the schedule plan to minimize the residential electricity bill. In this section, we formulate the scheduling optimization problems by incorporating a photovoltaic system and an energy storage.

4.1. Residential Electricity Bill with a Photovoltaic System

We consider a photovoltaic system as a locally-generated power. Depending on weather conditions, the photovoltaic system can produce electricity for particular time slots. Letting the vector $\mathbf{g}$ imply the hourly energy generation, $\mathbf{g}$ is defined as $\mathbf{g} \coloneqq (g_1, \dots, g_{24}) \in \mathbf{R}^{24}$, where $g_j \geq 0$. The generated energy g_j for a given time slot $j(\in \mathbf{H})$ can reduce the energy, which is required from the grid for the time slot. If the locally-generated power is greater than the power for appliances in the specific time slot, then the total hourly load can be negative. The negative hourly load implies that the locally-generated power is surplus, and it can be sold or thrown away. Depending on how to manage the surplus energy, we can formulate two types of optimization problems.

If we have no energy storage such as a battery to save the surplus energy or cannot sell it to the grid due to the systematic problem from the metering system or grid operation policies, then we cannot utilize the surplus energy and inevitably throw it away. The scheduling optimization for reducing the residential electricity bill is then written as follows

$$\text{minimize} \sum_{j \in \mathbf{H}} c_j\, a_{1,j} \tag{8}$$
$$\text{subject to } a_{1,j} - a_{2,j} = \left(\sum_{i \in \mathbf{A}} x_{i,j} - g_j\right), \text{for } j \in \mathbf{H},$$
$$a_{1,j}, a_{2,j} \geq 0, \text{for } j \in \mathbf{H}.$$

In (8), the positive variables $a_{1,j}$ and $a_{2,j}$ imply the hourly load and the surplus energy, respectively, for the *j*-th time slot.

On the other hand, we can sell the surplus energy to the grid in general. We suppose that the selling price of the surplus energy is equal to the time-varying electricity price at the corresponding time slot. Then, the money, which is obtained by selling the energy, is given by $c_j a_{2,j}$ in (8), and the optimization problem of (8) can be simplified as follows.

$$\text{minimize} \sum_{i \in \mathbf{A}} \mathbf{c}^T \mathbf{x}_i - \mathbf{c}^T \mathbf{g}, \tag{9}$$

where $\sum_{i \in \mathbf{A}} \mathbf{c}^T \mathbf{x}_i - \mathbf{c}^T \mathbf{g}$ is the total cost in the residential side.

4.2. Residential Electricity Bill with a Photovoltaic System and an Energy Storage

In order to efficiently utilize the time-varying electric price rates and the energy from the locally-generated power, we may consider to add an energy storage. The battery can store the electric energy from the grid when the price is low, and discharge the energy when the price is high.

We formulate a simple battery model for charging and discharging in conjunction with the levelized cost of storage use. Let the vector **b**, which represents the battery charge pattern, be defined as $\mathbf{b} \coloneqq (b_1, \dots, b_{24}) \in \mathbf{R}^{24}$, where b_j are non-negative constants and denote the stored energy level of the battery at the 24 time slots, respectively. Let a positive constant γ denote the maximal capacity of the battery in kWh. In other words, in each time slot, the minimal and maximal power capacities are zero and γ, respectively, hence a constraint on the maximal battery capacity is given by

$$0 \leq b_j \leq \gamma, \text{for } j \in \mathbf{H}. \tag{10}$$

The battery can store energy from the grid and can provide the energy to the home appliances. However, the charging or the discharging speed is restricted to ensure the battery life. In order to describe such a restriction, we consider the charge or discharge amount for a time slot as follows. In the *j*-th time slot, let the constants $b_{1,j}$ and $b_{2,j}$ imply the charge and discharge amounts, respectively, and define the vectors $\mathbf{b}_1$ and $\mathbf{b}_2$ in $\mathbf{R}^{24}$, as $\mathbf{b}_1 \coloneqq (b_{1,1}, \dots, b_{24})$ and $\mathbf{b}_2 \coloneqq (b_{2,1}, \dots, b_{2,24})$. Here, the battery charge pattern **b** should satisfy $\mathrm{b_j} = \sum_{k=1}^{j} (\mathrm{b_{1,k}} - \mathrm{b_{2,k}})$, for $j \in \mathbf{H}$. Let a positive constant μ denotes the C-rate and thus $\mu\gamma$ implies the maximally charge/discharge energy capacity for a time slot. Hence, we can have a constraint on the charging and discharging speed as

$$0 \leq b_{1,j}, b_{2,j} \leq \mu\gamma, \text{for } j \in \mathbf{H} \tag{11}$$

Here, the C-rate is typically given by $\mu = 0.2$.

If the energy storage is employed, then the total cost should include the utilization cost of the battery. In this section, we add a notion of the levelized cost on the battery usage. Let a positive constant δ denote the levelized cost in dollars per kWh per cycle (dollars/kWh/cycle). The cost, which is produced only by the battery charging and discharging, can then be expressed as $(\delta/2)\mathbf{1}^T(\mathbf{b}_1 + \mathbf{b}_2)$. Hence, the total price is given by

$$\sum_{i\in\mathbf{A}} \mathbf{c}^T\mathbf{x}_\mathrm{i} + \mathbf{c}^T(\mathbf{b}_1 - \mathbf{b}_2 - \mathbf{g}) + \frac{\delta}{2}\mathbf{1}^\mathrm{T}(\mathbf{b}_1 + \mathbf{b}_2). \tag{12}$$

Considering the energy storage battery, the minimization of (12) under the constraints of (10) and (11) can be solved by the following optimization problem:

$$\begin{aligned} &\text{minimize } \sum_{i\in\mathbf{A}} \mathbf{c}^T\mathbf{x}_\mathrm{i} + \mathbf{c}^T(\mathbf{b}_1 - \mathbf{b}_2 - \mathbf{g}) + \frac{\delta}{2}\mathbf{1}^\mathrm{T}(\mathrm{b}_1 + \mathrm{b}_2) \\ &\text{subject to } 0 \le b_j = \sum_{k=1}^{j}(b_{1,j} - b_{2,j}) \le \gamma, \text{for } j \in \mathbf{H}, \\ &\qquad 0 \le b_{1,j}, b_{2,j} \le \mu\gamma, \text{for } j \in \mathbf{H}. \end{aligned} \tag{13}$$

If we consider the peak hourly load in minimizing the total cost of (12), we should know the hourly load on the grid side. Charging the battery increases the hourly load. Discharging the battery however decreases the hourly load. Furthermore, the solar energy can also decrease hourly load. Therefore, the constraint regarding the hourly load can be rewritten as

$$\text{minimize } \sum_{i\in\mathbf{A}} \mathbf{c}^T\mathbf{x}_\mathrm{i} + \mathbf{c}^T(\mathbf{b}_1 - \mathbf{b}_2 - \mathbf{g}) + \frac{\delta}{2}\mathbf{1}^\mathrm{T}(\mathrm{b}_1 + \mathrm{b}_2) \tag{14}$$

With the constraint of (14), the overall scheduling optimization problem in conjunction with the peak hourly load is summarized as follows.

$$\begin{aligned} &\text{minimize } \sum_{i\in\mathbf{A}} \mathbf{c}^T\mathbf{x}_\mathrm{i} + \mathbf{c}^T(\mathbf{b}_1 - \mathbf{b}_2 - \mathbf{g}) + \lambda L + \frac{\delta}{2}\mathbf{1}^\mathrm{T}(\mathbf{b}_1 + \mathbf{b}_2) \\ &\text{subject to} \sum_{i\in\mathbf{A}} x_{i,j} + b_{1,j} - b_{2,j} - g_j \le L, \text{for } j \in \mathbf{H}, \\ &\qquad 0 \le b_j = \sum_{k=1}^{j}\left(b_{1,j} - b_{2,j}\right) \le \gamma, \text{for } j \in \mathbf{H}, \\ &\qquad 0 \le b_{1,j}, b_{2,j} \le \mu\gamma, \text{for } j \in \mathbf{H}. \end{aligned} \tag{15}$$

5. Experimental Results

In this section, we numerically simulate the scheduling optimizations and compare their results. We first measure the power consumptions of the home appliances every second, and then construct the power patterns with respect to the time slot. Figure 1 illustrates an example of the power consumption curve of the washing machine and a refined power pattern, which is designated as `work'. The power pattern implies the energy curve with respect to the time slot for the washing machine. In the simulation, we use five appliances ($N = 5$), the fridge, heater 1, heater 2, washing machine, and iron and summarize their power pattern in Table 1.

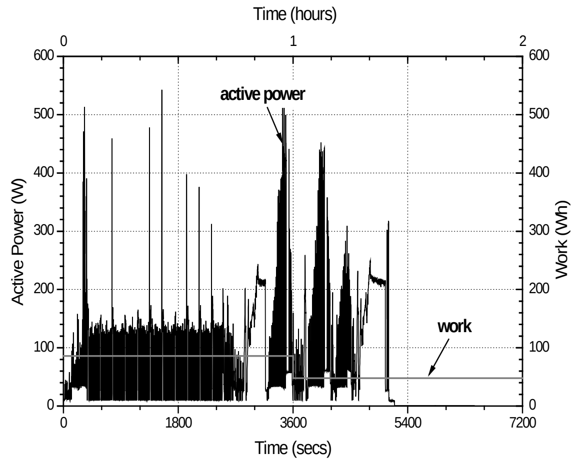


Figure 1. Example of the Power Consumption Curve (`active power') of the Washing Machine and a refined Power Pattern (`work') with Respect to the Time Slot

Table 1. Appliances and Power Consumption Patterns

Appliances	Type	Power consumption patterns
1.Fridge	Non-shiftable	Operating 24hrs 1-2am: 120Wh, 3am-22pm: 80Wh, 23-24pm: 120Wh
2. Heater 1	Power-shiftable	Preferred hour: 8am – 21pm Daily requirement: 1kWh
3. Heater 2	Power-shiftable	Preferred hour: 1am – 7pm, 22-24pm Daily requirement: 270Wh
4. Washing machine	Time-shiftable	Operating 2hrs, once per day First hour: 85Wh, second hour: 45Wh
5. Iron	Time-shiftable	Operating 2hrs, once per day 85Wh for the first hour

In order to conduct the scheduling optimization based on the time-varying price system, a TOU pricing, which is designed based on the price pattern of Korea Electric Power Corporation (KEPCO), is used for **c** as

$$\mathbf{c} = \{\ 0.05, 0.05, 0.05, 0.05, 0.05, 0.05,0.05, 0.05, 0.09, 0.13, 0.13, 0.09,$$

$$0.09, 0.09, 0.09, 0.09, 0.13, 0.13, 0.13, 0.09, 0.09, 0.13, 0.05, 0.05\ \},$$

of which elements are given in dollars. Regarding the solar energy, the hourly energy generation **g** is obtained from a simulated solar panel with 400Wp, and is given by

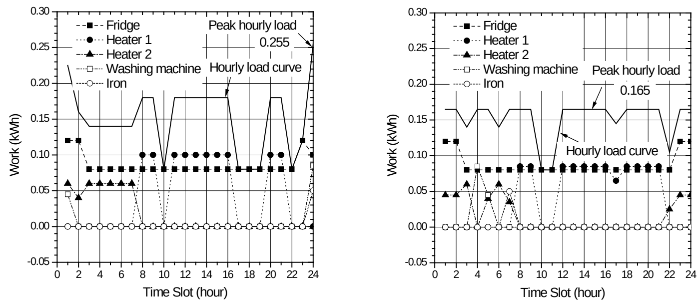
$$\mathbf{g} = \{\ 0.00, 0.00, 0.00, 0.00, 0.00, 0.00,13.0, 54.8,10,223,289,321,$$

$$309,257,178,90.3,28.5,0.64, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00\},$$

of which elements are given in Wh. Here, we can see that the energy is generated from 5 am through 7 pm.

5.1. Scheduling Optimization Results

The minimized residential electricity bill from the optimization of (6) is given by 0.287 dollar. An optimal schedule plan is shown in Figure 2(a). We can observe the peak hourly load



(a) (b)

Figure 2. Optimized Schedule Plan obtain by the Problems of (6) and (7). (a) Residential Electricity Bill is Minimized in (6). The Total Bill is 0.287 Dollar and the Peak Hourly Load is 0.255kWh. (b) Peak Hourly Load is considered in (7), where $\lambda = 1.0$. The Total Bill is 0.295 Dollar and the Peak Hourly Load is decreased to 0.165kWh

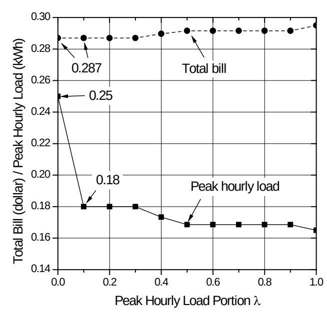
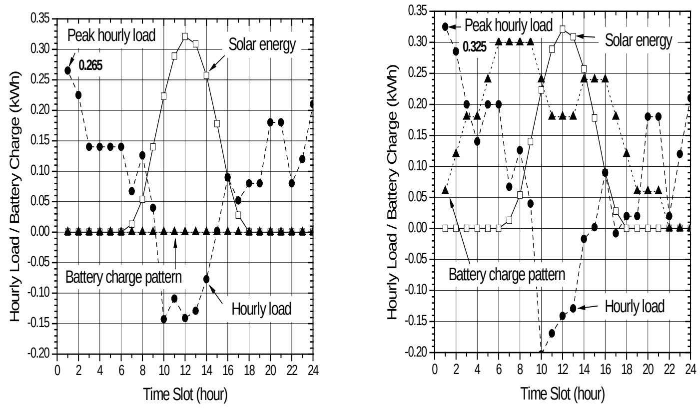


Figure 3. Curves of the Total Bills and the Peak Hourly Loads for the Different values of λ in the Optimization of (7) in Conjunction with the Peak Hourly Load

0.255kWh at the time slot $j = 24$ in Figure 2(a). A worst bill, which is a maximized bill under the same constraints of the (6) case, is 0.326 dollar, the optimized bill is reduced from the worst case by 12.0%. We then simulate the optimization of (7) considering the peak hourly load when $\lambda = 1.0$, and depict the scheduling result in Figure 2(b). The optimized peak hourly load is 0.165kWh and the total bill, which is defined as (5), is 0.295 dollar. We can notice that the peak hourly load is significantly reduced by 35.3% even though the total bill is slightly increased by 2.79%. Compared to the Figure 2(a) case, considering the peak hourly load can efficiently distribute the electric power usages to the time slots as shown in the hourly load curve of Figure 2(b). Figure 3 depicts the curves of the total bills and the peak hourly loads for different values of λ. We can notice that as λ increases the peak hourly load quickly decreases whereas the total bill slightly increases. Hence, even for $\lambda = 0.1$, we can obtain a quite low peak hourly load compared to the conventional case of (6).

5.2. Scheduling Optimization Results with a Photovoltaic System and an Energy Storage

In this section, we simulate the optimization problems with a photovoltaic system and an energy storage. We first compare the optimizations of (8) and (9), in which only the solar energy is incorporated. If we are prohibited from providing the surplus energy to the grid as in (8), then the total bill is 0.143 dollar and the peak hourly load is 0.180kWh. However, if we can sell the surplus energy, then the total bill is obviously reduced to 0.0969 dollar even though the peak hourly load increases to 0.265kWh. Note that this increment in the peak



(a) (b)

Figure 4. Comparison of the Hourly Loads and the Battery Charge Pattern for the Different Levelized Costs in the Optimization of (13). (a) $\delta = 0.2$ dollar/kWh/cycle. The Total Bill is 0.0969 Dollar and the Peak Hourly Load is 0.265kWh. (b) $\delta = 0.03$ dollar/kWh/cycle. The Total Bill is 0.0705 Dollar and the Peak Hourly Load is 0.325kWh

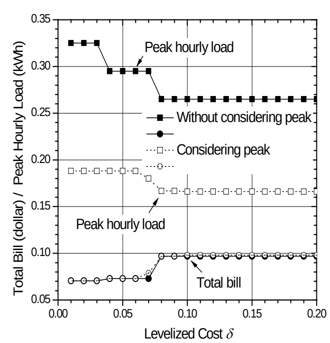


Figure 5. Comparison of the Total Bills and the Peak Hourly Loads for the Different Values of the Levelized Costs in the Optimizations of (13) and (15) when $\lambda = 0.1$

hourly load can be possible since the optimization problems in (8) and (9) do not consider the peak hourly load. We next conduct the optimization of (13), which utilizes energy storage, for different values of the levelized cost δ. As shown in the optimized schedule plan for $\delta = 0.2$ dollar/kWh/cycle of Figure 4(a) the battery is not used at all since the levelized cost is too expensive to be used. Hence, the optimization problem of (13) is equivalent to that of (9). However, if the levelized cost is reduced to $\delta = 0.03$ dollar/kWh/cycle, then the battery is used for scheduling the appliances and six charge and discharge cycles are observed in Figure 4(b). Such usage of battery reduces the total bill to 0.0705 dollar, which is corresponding to 27.2% saving in the residential electricity bill. We finally conduct the proposed optimization in (15) in conjunction with the peak hourly load. In Fig. 5, the curves obtained from the optimizations of (13) and (15) are compared for different levelized costs δ at $\lambda = 0.1$. Similarly to the case of (7), considering the peak hourly load even for a small λ, we can significantly reduce the peak hourly load by slightly increasing the total bill. For example of $\lambda = 0.1$ in Figure 5, the peak hourly load decreases from 0.325kWh of Figure 4(b) to 0.188kWh, which is corresponding to a 42.2% reduction. However, the total bill is not changed from 0.0705 dollar. We can observe that by using the battery we can reduce the total bill efficiently suppressing the peak hourly load.

6. Conclusion

In this paper, in order to minimize the electricity bill in the residential side for the time-varying electricity price, optimization problems, which can provide schedule plans for the home appliance usages, are formulated and numerically simulated. Through a simulation, an optimization under the TOU pricing environment can reduce the residential electricity bill by 12.0% from a worst case. By considering the peak hourly load, we can decrease the peak hourly load by 35.3% when $\lambda = 1.0$ whereas the total bill is slightly increased. In addition, locally-generated power system and energy storage are added to the residential side to achieve further efficient schedule plans in reducing the residential electricity bill. By using the battery, we can find that the advantage from using an energy storage is quite dependent on the levelized cost. When $\lambda = 0.1$ and the levelized cost is $\delta = 0.03$ dollar/kWh/cycle, the peak hourly load is reduced by 42.2% for a fixed total bill.

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