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Linear Formulation for Short-Term Operational Scheduling of Energy Storage Systems in Power Grids

Yong-Gi Park [1], Jong-Bae Park [2,*], Namsu Kim [3] and Kwang Y. Lee [4]

[1] Research Center for Innovative Electricity Market Technology, Konkuk University, 120 Neungdong-ro, Gwangjin-gu, Seoul 05029, Korea; draco98@konkuk.ac.kr
[2] Department of Electrical Engineering, Konkuk University, 120 Neungdong-ro, Gwangjin-gu, Seoul 05029, Korea
[3] Department of Mechanical Design and Production Engineering, Konkuk University, 120 Neungdong-ro, Gwangjin-gu, Seoul 05029, Korea; nkim7@konkuk.ac.kr
[4] Department of Electrical and Computer Engineering, Baylor University, Waco, TX 76798, USA; Kwang_Y_Lee@baylor.edu
* Correspondence: jbaepark@konkuk.ac.kr; Tel.: +82-2-450-3483

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Abstract: This paper presents linear programming (LP) formulations for short-term energy time-shift operational scheduling with energy storage systems (ESSs) in power grids. In particular, it is shown that the conventional nonlinear formulations for electric bill minimization, peak shaving, and load leveling can be formulated in the LP framework. New variables for the peak and off-peak values are introduced in peak shaving and load leveling model, and the historical peak value for demand charge are considered in the electric bill minimization model. The LP formulations simplify computation while maintaining the accuracy for including linear technical constraints of ESSs, such as the state-of-charge, charging/discharging efficiency, output power range, and energy limit considering the life cycle of ESS. Proposed LP formulations have been implemented and verified in practical power systems and a large-scale industrial customer using historical data.

Keywords: electric bill minimization; energy arbitrage; energy storage systems (ESSs); linear programming (LP); load-leveling; peak-shaving; short-term optimal operational scheduling

1. Introduction

Energy storage systems (ESSs), both mechanical types, such as pumped-hydro energy storage (PHES), compressed-air energy storage (CAES) and flywheels, and battery types, such as Li-ion, NaS and lead-acid, are given opportunities to enter into power systems to supplement conventional generators as they show technological advances and price competitiveness. The ESSs can be applied for frequency regulation, energy arbitrage, peak-shaving, renewable resource integration, transmission congestion relief, demand response, and the energy management of end-user or micro grid [1,2]. This paper is focused on developing optimal operational scheduling models of an ESS for short-term (minutes or hour basis) energy time-shift applications based on various objectives in a power grid as described in Table 1.

Strategies of ESS for energy arbitrage are determined in response to energy market prices, either in an investor or owner perspective [3]. Moreover, in [4–8], the energy arbitrage of ESS is also tested for power systems with renewable resources. These linear formulated energy arbitrage models of ESSs can be flexibly applied in a transaction model with renewables considering uncertainty [4], operation problems of microgrid with other DERs [5–7], and the optimal size determination models of ESS considering the installed renewable resources [8]. The production cost minimization model of

ESS can be expressed in a form that the energy arbitrage model is included in the unit commitment problem by a system (or market) operator, and it can be effectively formulated as mixed integer linear programming (MILP) [9,10]. Other applications of ESSs, except the energy arbitrage, are often solved by heuristic algorithms. Peak-shaving and load-leveling problems of ESSs are also tested in power grids from the interest of a system operator using dynamic programming in [11–13]. The electric bill minimization problem in the customer side is formulated with nonlinear model considering both demand charge and energy charge, where dynamic programming, Markov decision processes, and particle swarm optimization are used in [14–17], respectively.

Table 1. Short-term energy time-shifting applications of ESSs in power systems.

Entities	Objectives
System Operator	Peak-shaving Load-leveling Production Cost Minimization
Owner or Investor of ESS	Energy Arbitrage Energy Arbitrage with Renewable Resources
End-user	Demand Charge Saving (Peak-shaving) Energy Charge Saving (Energy Arbitrage) Total Electric Bill Minimization

Assuming that demand or renewable resource production is perfectly forecasted, the objective functions are defined with respect to the applications of an ESS, while technical constrains of ESS are commonly contained in the optimization model. The solution technique for an optimization problem is determined according to the type of the formulated problem. Often optimization problems of ESS have been formulated as non-linear problems and solved with heuristic and evolutionary algorithms, except the energy arbitrage for short-term optimal operation scheduling model of an ESS. The main disadvantage of these algorithms is to end up with suboptimal solutions. In contrast, if the same problem can be formulated with linear model without approximation, we can find the optimum solution efficiently and accurately using linear programming (LP) [18].

The objective of this paper is to develop linear expressions of optimal operational scheduling models of an ESS for all time-shifting applications in power grids. It was demonstrated that the energy arbitrage model from the investor or owner perspective as a price-taker in electricity market can be simply expressed in a linear formulation, as mentioned in the above literatures. Therefore, in this paper, we will first develop linear optimization models, which will ensure simplification as well as accuracy for peak-shaving and load-leveling in the system operator perspective. Moreover, we will develop a novel linear model for the electric bill minimization of end-users. Thus, we can find all optimum solutions for the time-shifting applications of ESSs listed in Table 1 using LP.

This paper is composed as follows: Section 2 presents the linear expression of general technical constraints of ESS. Section 3 presents linearly expressed objective functions and additional necessary conditions with respect to the energy-shifting applications of ESS. Proposed linear models are tested in Section 4 and conclusions are drawn in Section 5.

2. Linear Expression of ESS Technical Constraints

This section presents linear expression for constraints in the optimization problem by considering general technical characteristics of an ESS. The major constraints of an ESS are charging/discharging efficiency, limits of power output and the state-of-charge (SOC). Additionally technical constraints on the cumulated energy used during the operation period are included to consider the aging effect of an ESS.

2.1. Charging/Discharging Efficiency

$$\eta_j^c \cdot ep_{j,t}^c = EP_{j,t}^c,\ \forall t,\ \forall j \tag{1}$$

$$ep_{j,t}^d = \eta_j^d \cdot EP_{j,t}^d,\ \forall t,\ \forall j \tag{2}$$

where η_j, $ep_{j,t}$ and $EP_{j,t}$ respectively are efficiency, AC power and DC power in MW; t and j represent the t-th time interval and the j-th EES unit; and superscripts c and d respectively represent charging and discharging.

Energy loss occurs when an ESS are under charging or discharging. Constraints (1) and (2) ensure charging and discharging power of ESS-j considering AC/DC and DC/AC conversion efficiencies, respectively.

2.2. Output Power Limits

$$0 \le EP_{j,t}^c \le \overline{EP_j^c},\ \forall t,\ \forall j \tag{3}$$

$$0 \le EP_{j,t}^d \le \overline{EP_j^d},\ \forall t,\ \forall j \tag{4}$$

where $\overline{EP_j^c}$ and $\overline{EP_j^d}$ respectively are the maximum charging and discharging power outputs of ESS-j.

Constraints (3) and (4) respectively represent the bounds on charging and discharging ranges of ESS-j at time interval-t. If an ESS has the minimum power outputs $\underline{EP_j^c}$ and $\underline{EP_j^d}$, constraints (3) and (4) have to be changed as mixed integer linear expressions by introducing binary variables as follows:

$$u_{j,t}^c \cdot \underline{EP_j^c} \le EP_{j,t}^c \le u_{j,t}^c \cdot \overline{EP_j^c},\ \forall t,\ \forall j \tag{5}$$

$$u_{j,t}^d \cdot \underline{EP_j^d} \le EP_{j,t}^d \le u_{j,t}^d \cdot \overline{EP_j^d},\ \forall t,\ \forall j \tag{6}$$

$$u_{j,t}^c + u_{j,t}^d \le 1,\ \forall t,\ \forall j \tag{7}$$

where $u_{j,t}^c$ and $u_{j,t}^d$ respectively represent the binary charging and discharging status of ESS-j at the t-th time interval. Constraint (7) ensures that the status of ESS-j is either under charge, discharge, or idle.

2.3. State-of-Charge

$$SOC_{j,t} = SOC_{j,t-1} + \left(EP_{j,t}^c - EP_{j,t}^d\right) \cdot \Delta t = SOC_j^o + \sum_{k=1}^{t} \left(EP_{j,k}^c - EP_{j,k}^d\right) \cdot \Delta t,\ \forall t,\ \forall j \tag{8}$$

$$SOC_j^{\min} \le SOC_{j,t} \le SOC_j^{\max},\ \forall j,\ t = 1, \ldots, T-1 \tag{9}$$

$$SOC_{j,T}^{lower} \le SOC_{j,T} \le SOC_{j,T}^{upper},\ \forall j \tag{10}$$

where Δt is the time interval in hours, T is the number of time intervals over a decision horizon, $SOC_{j,t}$ is the SOC of ESS-j in MWh at the t-th time interval, $SOC_j^{\max}$ and $SOC_j^{\min}$ respectively are the maximum and minimum SOC limits of ESS-j, SOC_j^o is the initial SOC of ESS-j, and $SOC_{j,T}^{lower}$ and $SOC_{j,T}^{upper}$ respectively are ESS-j's lower and upper bounds of SOC at the final time interval.

Constraint (8) determines the SOC of ESS-j at each time interval-t. Constraint (9) bounds ESS-j's SOC at each time interval-t. It is possible to adjust the range of the final SOC by constraint (10).

2.4. Total Energy Limits

One of the expressions for the lifetime of a battery ESS (BESS) is the cycle-life, which is the expected number of cycles for charging and discharging depending on the depth of discharge (DOD) of a BESS [19], which can be represented by the limited SOC range. When the possible SOC ranges of ESSs are fixed, the excessive number of round-trip operating cycles can be prevented by limiting total charged and discharged energies over an operational period with the following constraints:

$$\sum_{t=1}^{T} EP_t^c \cdot \Delta t \leq \alpha_j^c \cdot \left(SOC_j^{\max} - SOC_j^{\min}\right), \forall j \tag{11}$$

$$\sum_{t=1}^{T} EP_t^d \cdot \Delta t \leq \alpha_j^d \cdot \left(SOC_j^{\max} - SOC_j^{\min}\right), \forall j \tag{12}$$

where α_j^c and α_j^d respectively are positive constants to limit the number of charging and discharging cycles of ESS-j over a decision horizon.

These two constraints are helpful not only for the BESS but also for mechanical ESS (MESS) operational scheduling, because, with them, we can find the least amount of the energy to meet the objectives, and prevent excessive wear and tear by choosing suitable values of α_j^c and α_j^d in the optimization models.

3. Linear Objective Functions for Applications in Power Grid

This section presents linear objective functions for the purpose of short-term ESS applications: energy arbitrage, peak-shaving, load-leveling and minimization of end-user's electricity bill. For energy arbitrage of ESSs from the investor or owner perspective, the existing linear energy arbitrage model as a price-taker in electricity market is already introduced in many existing literatures such as [3–8]. Therefore, in this paper, we develop novel LP expressions, which will ensure simplification and accuracy for the electric bill minimization in an end-user perspective as well as the peak-shaving and load-leveling in the system operator perspective.

3.1. Peak-Shaving

The objective of peak-shaving is focused on reducing maximum load in a decision horizon as shown below:

$$\text{Min} \sum_{t=1}^{T} \max\{D_1', D_2', \ldots, D_T'\} \tag{13}$$

$$D_t\prime = D_t + \sum_{j=1}^{N} \left[ep_{j,t}^c - ep_{j,t}^d\right], \forall t \tag{14}$$

$$D_t\prime \geq 0, \ \forall t \tag{15}$$

where N is the number of ESS, T is a decision horizon, D_t is forecasted load demand at the t-th time interval, D_t' is a modified demand by ESSs at the t-th time interval, $ep_{j,t}^c$ is a charging power of ESS-j from the grid at the t-th time interval, and $ep_{j,t}^d$ is a discharging power of ESS-j injected to the grid at the t-th time interval.

The objective function (13) is a nonlinear function. For a linear formulation, we can modify the objective function (13) as following:

$$\text{Min} \sum_{t=1}^{T} D^{\max} \tag{16}$$

$$D^{\max} \geq D_t', \ \forall t \tag{17}$$

where $D^{\max}$ is a new variable which ensures that the peak value among the modified demands by ESSs is below this level in a decision horizon. Finally we can solve the peak-shaving problem using LP with the objective function (16) subject to ESS technical constraints (1)–(12) and additional constraints (14), (15), and (17).

3.2. Load-Leveling

Strictly speaking, the peak-shaving and load-leveling should be distinguished because the goal of the load-leveling is to make the fluctuating demand flat by increasing the off-peak as well as decreasing the on-peak, while peak-shaving is only focused on the reduction of the peaks [20]. Therefore to formulate as a linear model we can define an objective function of the load-leveling as following:

$$\text{Min} \sum_{t=1}^{T} \left[D^{\max} - D^{\min} \right] \tag{18}$$

$$D^{\min} \leq D'_t, \ \forall t \tag{19}$$

where $D^{\min}$ is a new variable which ensures that the off-peak value among the modified demands by ESSs is above this level in a decision horizon. The linear objective function (18) is to minimize the gap between the on-peak and off-peak demands subject to ESS technical constraints (1)–(12) and additional constraints (14), (15), (17), and (19).

3.3. End-User Electricity Bill Minimization

The customer electric bill is composed of demand charge and energy charge. The demand charge is paid to the utility which operates and plans transmission and distribution network, and is based on the highest average load for 15 min during the billing period. To determine the demand charge, some electricity retail markets consider the historical peak loads within a specified period. For example, non-residential customers are served at the regulated time-of-use (TOU) rate by Korea Electric Power Corporation (KEPCO) in Korea, i.e., they are required to pay the demand charge for the highest load between the peak load during current billing month and the peak load of July-September and December-February during the prior 11 months [21]. Energy charge is calculated for the amount of electricity consumption. Generally a customer have a right to choose an appropriate time-varying pricing among TOU, critical peak price (CPP), real-time-pricing (RTP), etc.

Therefore we can formulate the optimization model for electric bill minimization with ESSs in the end-user perspective as follows:

$$\text{Min} \left\{ R^D \cdot D^{\max} + \sum_{t=1}^{T} R_t^E \cdot D'_t \cdot \Delta t \right\} \tag{20}$$

where R^D is the demand charge rate imposed on peak $D^{\max}$ of the end-user, and R_t^E is the energy charge rate at the t-th time interval. The linear objective function (20) is subject to constraints (14), (15), (17), and ESS technical constraints (1)–(12). We can solve this model by LP because all of objective functions and constraints are expressed in linear forms.

If historical peak load $D^{\max,o}$ is necessarily considered to calculate the demand charge, $D^{\max}$ in the first term of the objective function (20) can be replaced with $\max(D^{\max,o}, D^{\max})$, then the objective function can be changed as following:

$$\text{Min} \left\{ R^D \cdot \max(D^{\max,o}, D^{\max}) + \sum_{t=1}^{T} R_t^E \cdot D'_t \cdot \Delta t \right\} \tag{21}$$

By defining $D^{\max,g} = \max(D^{\max,o}, D^{\max})$, the optimization model for end-user's electric bill minimization with ESS can be generalized as the following linear formulation:

$$\text{Min} \left\{ R^D \cdot D^{\max,g} + \sum_{t=1}^{T} R_t^E \cdot D'_t \cdot \Delta t \right\} \tag{22}$$

$$D^{\max,g} \geq D'_t, \ \forall t \tag{23}$$

$$D^{\max,g} \geq D^{\max,o} \tag{24}$$

where the linear objective function (22) is subject to constraints (14), (15), (17), (23), (24), and ESS technical constraints (1)–(12).

As mentioned above, the constant $D^{\max,o}$ is the historical peak load during a billing period. In this generalized model, we can consider peak-load reduction or the energy-cost reduction, as priority, by setting $D^{\max,o} = 0$ or $D^{\max,o} = \infty$ (a large positive constant), respectively. In the peak-load reduction priority mode, the ESS charges when energy prices are low and discharges first when the loads are on-peak, then discharges extra charged energy at the other times when energy prices are high. On the other hand, ESS charges when energy prices are low and discharges when the prices are high in the energy-cost reduction priority mode.

4. Case Studies

Assuming that all estimation data are perfectly known, the proposed linear short-term optimal scheduling problems for the use of an ESS have been tested in this section. Peak-shaving and load-leveling in a system operator perspective are tested on a 500 MW/4000 MWh PHES. Since the round-trip efficiency of PHES is 0.75 in [2], we assume that the each of pumping and generating efficiencies is set to $\sqrt{0.75}$. The electric-bill minimization is implemented in a large industrial customer with a 4 MW/8 MWh Li-ion BESS, for which conversion efficiencies on charging and discharging are equally set to 0.95 [2]. The proposed linear models are implemented in IBM CPLEX 12.6, which gives robust solutions for optimization problems [22].

4.1. Case-I: Peak-Shaving and Load-Leveling with PHES

Figure 1 is the demand for a week provided from the Korea Power Exchange (KPX) during 2–8 August 2010 [23], which is described in Table A1 and it has 3707 MW of off-peak and 6273 MW of on-peak demand. The leveled demand pattern corresponding to the time of energy prices shown in Figure 2 is obtained from the historical data from Korea, forecasted and posted by KPX [23]. The energy prices are described in Table A2.

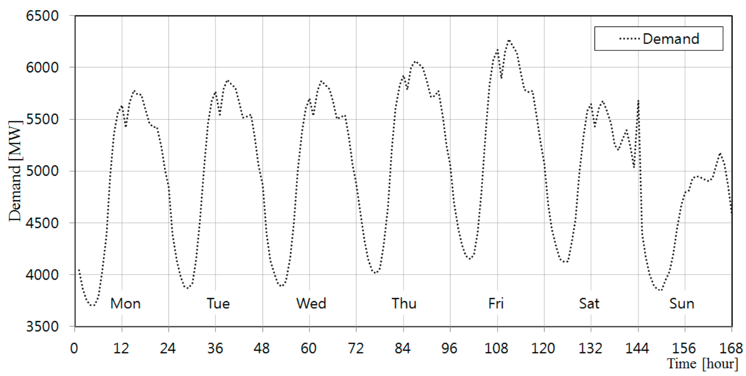


Figure 1. Demand for a week.

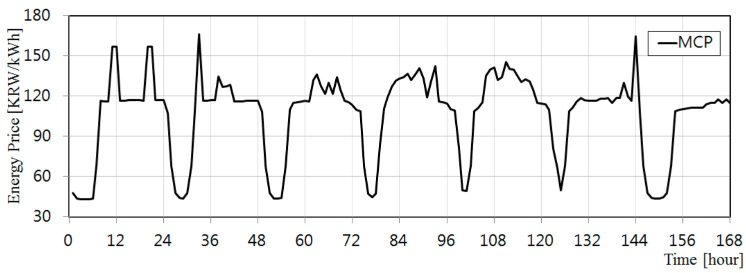


Figure 2. Hourly energy prices for a week (2–8 August 2010).

When the ESS is scheduled for peak-shaving and/or load-leveling, the adjusted on-peak $D^{\max}$ and off-peak D^{mim} need to be determined, which would result from the allowed maximum charging and discharging energy over a given planning horizon as defined in (11) and (12). Figure 3 shows an experimental result of on-peak $D^{\max}$, off-peak D^{mim}, and the differences between them ($D^{\max} - D^{\text{mim}}$) according to α_j^c and α_j^d for the weekly operation mode, where both α_j^c and α_j^d in (11) and (12) are set to the same value α in this case study. The optimization models are solved by weekly operation mode where each of the initial and final state of reservoir is set to 12.5% of the PHES capacity. In the figure, the adjusted on-peak $D^{\max}$ and the difference ($D^{\max} - D^{\min}$) are becoming constant when the values of α are 1.02 and 2.62, respectively, and these values are used for the peak-shaving and load-leveling models because full peak-shaving and load-leveling with the PHES can be most efficiently solved by weekly operation mode when the values of α are 1.02 and 2.62, respectively.

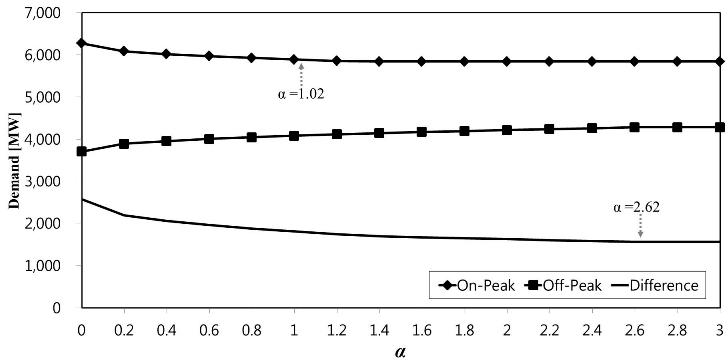
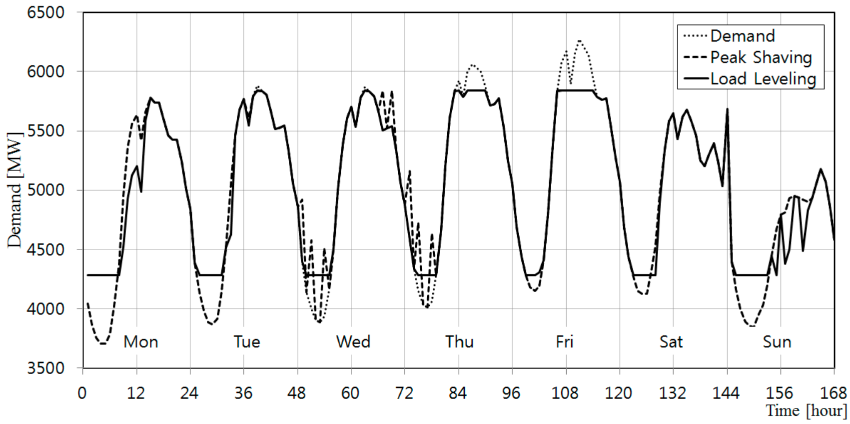


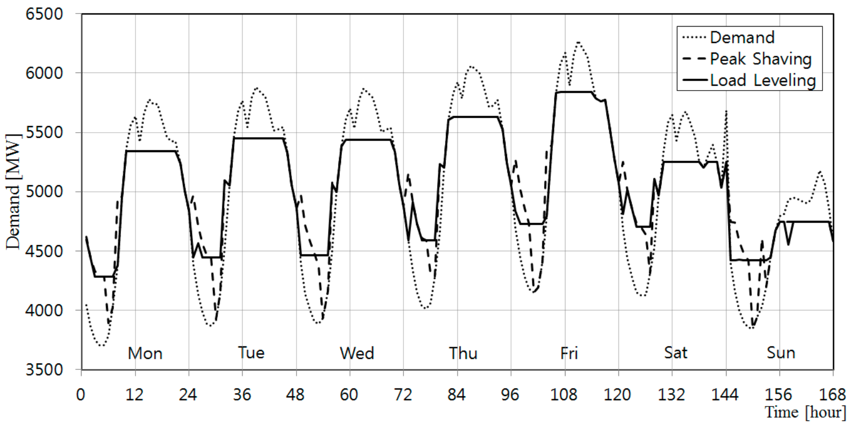
Figure 3. Adjusted on-peak $D^{\max}$ and off-peak $D^{\min}$ while increasing α for the weekly operation mode.

Dashed line and solid line shown in Figure 4a are the results of peak-shaving and load-leveling with the PHES, where the values of α are set to 1.02 and 2.62, respectively, in the optimization models for peak-shaving and load-leveling solved by weekly operation mode. Both peak-shaving and load-leveling have reduced the on-peak to 5840 MW. Moreover the load-leveling has raised the off-peak to 4284 MW while peak-shaving still remains at 3707 MW. Therefore, the load-leveling can reduce the demand range more than the peak-shaving. On the other hand, the advantage of the peak-shaving model is that the energy required to reduce the peak is smaller than the load-leveling energy, even though it cannot control the off-peak. As the a result, cumulated charged (pumping) energies including energy losses from the grid for a week are 4108 MWh and 10589 MWh for peak-shaving and load-leveling, respectively, and cumulated discharged (generated) energies delivered to the grid are 3081 MWh and 7942 MWh, respectively. Each value is 0.75 of cumulated charged energy which is the round-trip efficiency of PHES as assumed above.

Since load forecasting necessarily has error caused by uncertainties, the operator can decide an alternative strategy of scheduling period to take consideration of the forecasting error. To reduce forecasting error, operating period should be shorter and scheduling cycle should be more frequent. If the optimization is solved by daily operation mode, we can get the results as shown in Figure 4b. In this case, for a week, total charged energies as the results of peak-shaving and load-leveling respectively are 24,172 MWh and 24,421 MWh including the losses, and total discharged energies to the grid are 18,129 MWh and 18,316 MWh, where α is set to 6.00 for the peak-shaving and to 6.06 for the load-leveling. These are minimal cumulated energy requirements which respectively can contribute to full peak-shaving and full load-leveling with the PHES.



(**a**) Weekly operation mode



(**b**) Daily operation mode

Figure 4. Adjusted demands for a week by peak-shaving and load-leveling models of the ESS.

4.2. Case-II: Electric Bill Minimization of a Customer with Li-ion BESS

The proposed linear electric bill minimization model was tested for a large industrial customer being served with the time-of-use (TOU) rate from KEPCO. The customer is charged with the demand rate of 7380 KRW/kW and the energy rate (KRW/kWh) adjusted on seasonal and hourly basis as shown in Figure 5 and described in Table A3 [21]. As mentioned above, the peak-load applied to demand charge by KEPCO is determined as the maximum value during prior 12 months including the current month. As described in Figure 6 and Table A4, the customer load data in summer, assuming that it is constant for each hour, has different daily pattern, but has a recursive tendency on a weekly basis. The minimum and maximum values of the load are 0.66 MW and 15.15 MW, respectively. In addition, daily on-peaks in the weekend are larger than those in weekdays.

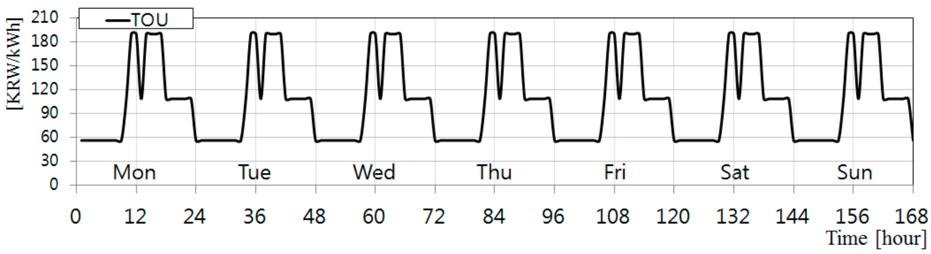


Figure 5. Customer's energy rate (TOU) for a week.

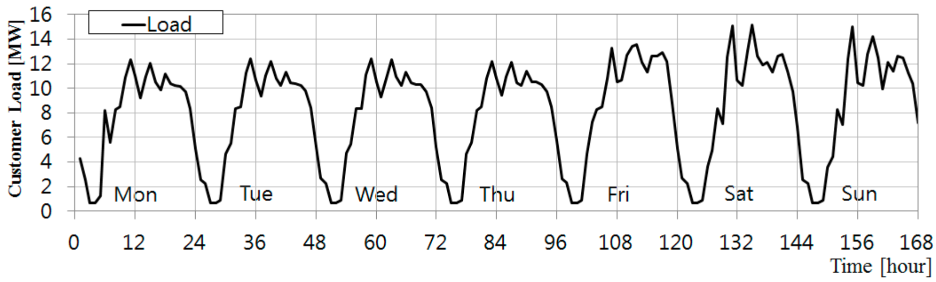


Figure 6. Customer's load profile for a week.

Optimal scheduling results of the Li-ion BESS installed in an industrial customer obtained by the linear electric bill minimization algorithm for weekly operation mode are shown in Figure 7, where both initial and final SOCs of the Li-ion BESS have been set to 5% capacity of the rated energy. To concentrate on saving the bill, α has been set to a large constant. For the weekly operating mode, adjusted on-peak load is decreased to 11.98 MW with the full discharging power, when the optimization is solved to satisfy the objective function (22) without consideration of the historical peak value by setting $D^{max,o} = 0$. Since on-peak loads in the first four days (weekdays) are relatively lower than in the last three days (weekends), charge and discharge of the ESS are focusing on saving the energy cost during weekdays while they are focusing on reducing on-peak loads during the weekends. If the demand charge considers the historical peak-value and it is set to $D^{max,o} = 13$ MW, the customer's on-peak decreases only to 13 MW and the ESS is scheduled to save the energy cost elsewhere. If the demand charge considers the historical peak-value but it is set to $D^{max,o} = 16$ MW, the optimization is solved only to concentrate on saving the energy cost (arbitrage) since $D^{max,o}$ is greater than the peak load during a week. Hourly operating schedules of the ESS according to $D^{max,o}$ are shown in Figure 8.

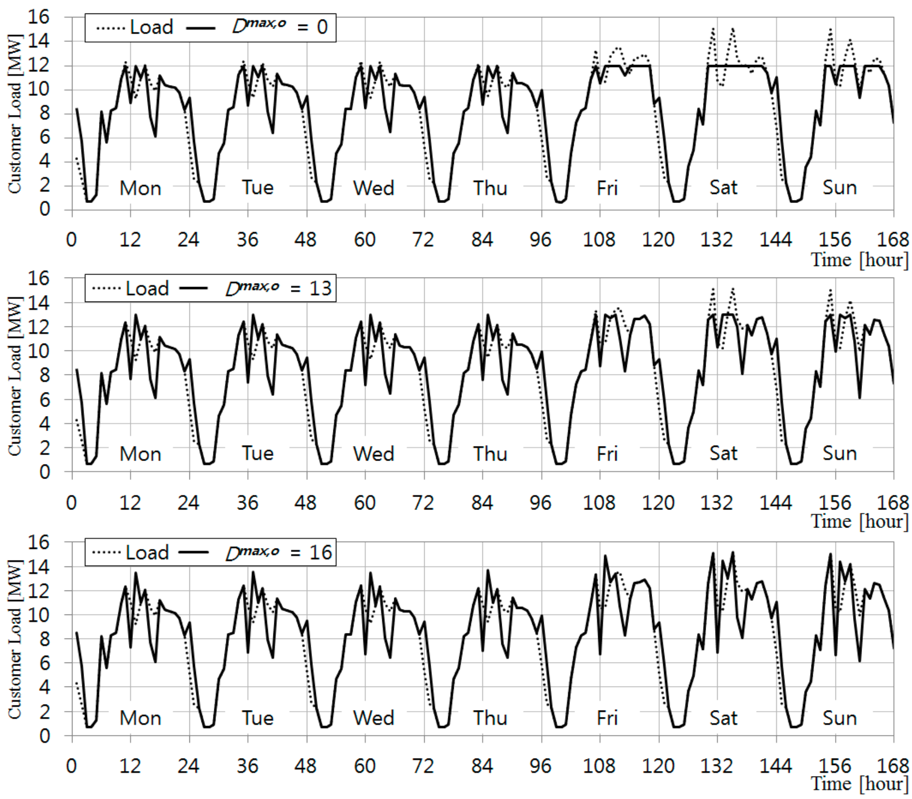


Figure 7. Weekly operation results for the customer electric bill minimization.

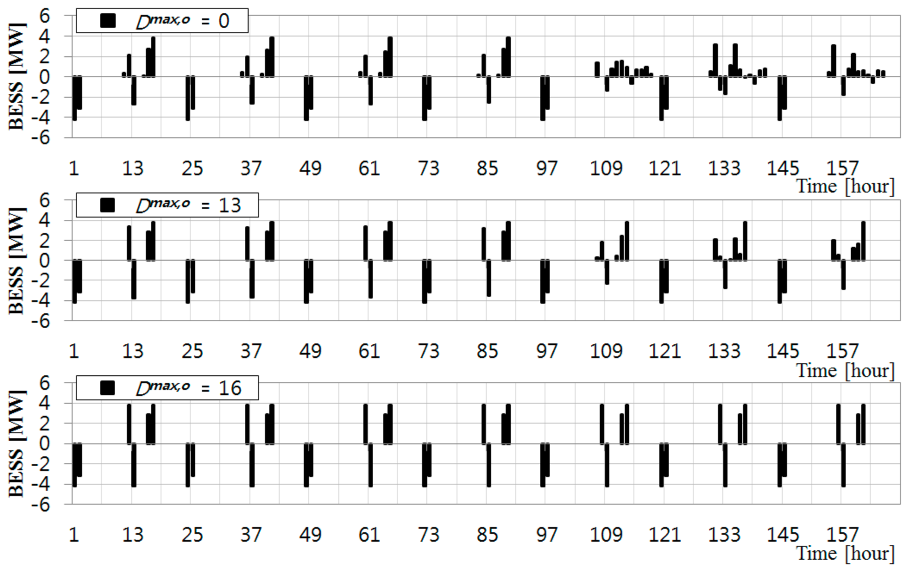
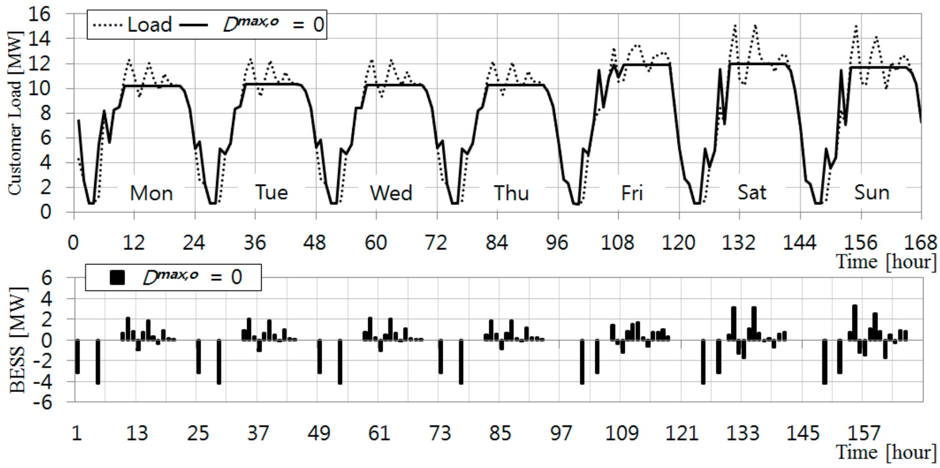


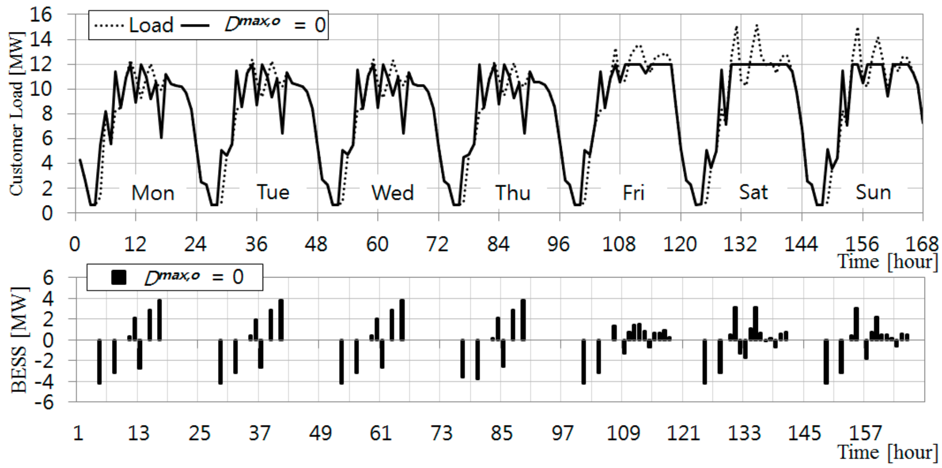
Figure 8. Weekly schedules of ESS for the customer electric bill minimization.

The results for the daily operation mode are shown in Figures 9 and 10. Compared with the weekly mode, if the demand charge does not consider the historical peak value by setting $D^{\max,o} = 0$ on the first day of billing month, the ESS is scheduled to concentrate on reducing daily peak and $D^{\max,o}$ is increasingly updated every day during the first week as shown in Figure 9a. The ESS is scheduled to reduce daily peak to 11.98 MW and to save the energy cost elsewhere on the day during remaining three weeks as shown in Figure 9b since the values of $D^{\max,o}$ are equally set to 11.98 MW until the end of the billing month. If the demand charge considers the historical peak-value for the daily operation mode and it is set to $D^{\max,o}$ = 13 MW and $D^{\max,o}$ = 16 MW, the schedules of ESS are similar with those of the weekly operation mode while the used energies of ESS are equal to 74.12 MWh and 81.05 MWh.



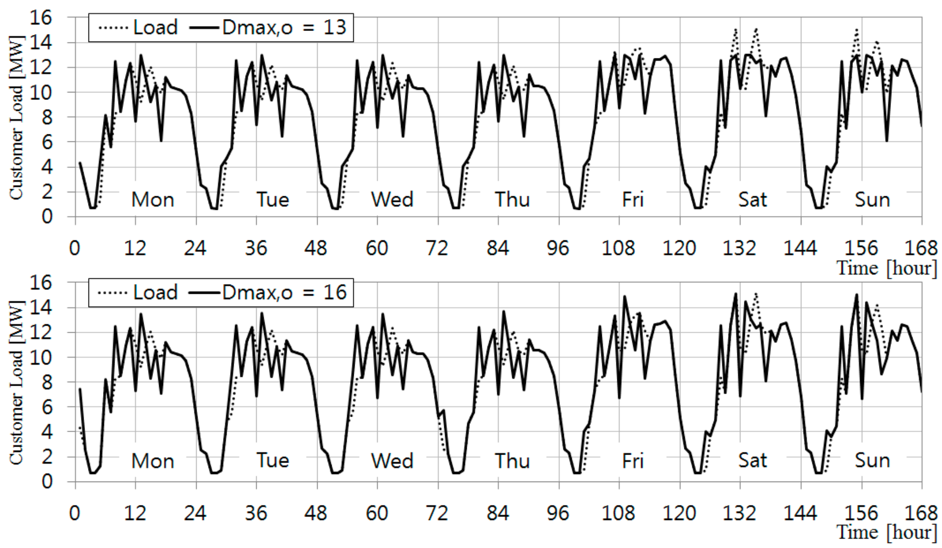
(**a**) The 1st week

Figure 9. *Cont.*

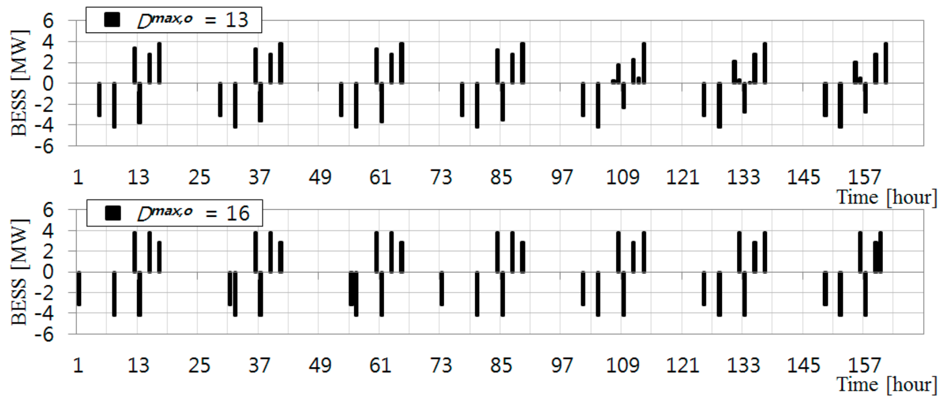


(**b**) The other weeks (2nd–4th weeks)

Figure 9. Daily operation results for the customer electric bill minimization which does not consider the historical peak-value.



(**a**) Load profiles



(**b**) BESS Schedule

Figure 10. Daily operation results for customer electric bill minimization which considers the historical peak-value.

The operation results and customer's cost savings for the two operation modes are summarized in Table 2. In both modes, the modified peak values for demand charge are the same as 11.98 MW, 13 MW, and 16 MW when $D^{\max,o} = 0$, $D^{\max,o} = 13$ MW, and $D^{\max,o} = 16$ MW, respectively. Compared with the weekly mode, the used energy for the daily operation mode decreases 1.42%, but total cost savings is 1.38 million KRW smaller due to the lower energy savings when $D^{\max,o} = 0$. On the other hand, the used energies and cost savings for the daily mode are equal to those for the weekly mode when $D^{\max,o} = 13$ MW and $D^{\max,o} = 16$ MW. Total cost savings from the ESS can be expected to be 45.27 million KRW, which is the sum of demand charge savings of 15.89 million KRW and energy charge savings of 29.38 million KRW, and 5.57% reduction from the total electric bill without ESS when $D^{\max,o} = 13$ MW. Only energy savings of 31.12 million KRW can be expected due to no reduction of the peak value when $D^{\max,o} = 16$ MW. As a result from the schedule of weekly operation mode, reduced cycle-life of ESS is calculated to 38.21 cycles, 40.24 cycles, and 44.00 cycles during four weeks when each $D^{\max,o}$ is set to 0 MW, 13 MW, and 16 MW, respectively. Reduced cycle-life from the schedule of daily operation mode is calculated to 37.67 cycles, 40.24 cycles, and 44.00 cycles when each $D^{\max,o}$ is set to 0 MW, 13 MW, and 16 MW, respectively.

Table 2. Customer's cost savings for the electric bill minimization during four weeks.

Classification	**Weekly Operation Mode**			**Daily Operation Mode**		
Consideration of Historical Peak-value	No	Yes	Yes	No	Yes	Yes
$D^{\max,o}$ (MW)	0	13	16	0	13	16
Used Energy of BESS (MWh)	281.53	296.47	324.21	277.53	296.47	324.21
Applied Peak wihout BESS (MW)	15.15	15.15	16	15.15	15.15	16
Applied Peak wih BESS (MW)	11.98	13	16	11.98	13	16
Reduction of Applied Peak (MW)	3.17	2.15	0	3.17	2.15	0
Demand Charge Savings (million KRW)	23.39	15.89	0	23.39	15.89	0
Energy Charge Savings (million KRW)	25.94	29.38	31.12	24.56	29.38	31.12
Total Savings (million KRW)	49.34	45.27	31.12	47.94	45.27	31.12
Savings Rate	6.07%	5.57%	3.80%	5.90%	5.57%	3.80%
Reduced Cycle-life (cycles)	38.21	40.24	44.00	37.67	40.24	44.00

5. Conclusions

This paper presented linear programming models for short-term optimal operational scheduling of ESSs as the energy time-shifting application in a power system. As a follow-up to the existing linear energy arbitrage model in an ESS owner perspective, we developed linear programming framework for peak-shaving and load-leveling from the aspect of system operator, and for electric bill minimization model from the perspective of end users. The proposed linear models have been implemented and verified in a practical power system and a large-scale industrial customer using historical demand and energy prices. Under the forecast data, they can effectively solve the short-term operational scheduling problem of ESSs, promising that they can also be applied in other operational problems. The proposed linear peak-shaving and load-leveling problems can give a system operator an effective tool to secure the system reliability by making use of the operational scheduling models of grid-scale ESSs while existing energy arbitrage model can be included in traditional unit commitment problem solved by ISO. Moreover, the electric bill minimization model can be also applied in the energy management system for a grid-connected microgrid consisting of ESSs as well as other distributed resources to minimize production cost for industrial or commercial customers. Developing short-term operational scheduling models of the ESS considering stochastic linear formulation will be our future works.

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Nomenclature

Indices

t	Index of time intervals in a decision horizon T, $t \in T$
j	Index of energy storage systems, $j \in N$

Variables

$D_t\prime$	Adjusted demand by charging and discharging of ESSs at time interval-t
$D^{\max}$	The maximum demand with charging/discharging operation of ESSs during operating period (or the highest load to impose the demand charge in an end-user perspective)
$D^{\max,o}$	End-user's historical maximum load
$D^{\max,g}$	The larger value between $D^{\max,o}$ and $D^{\max}$
$D^{\min}$	The minimum demand with charging/discharging operation of ESSs
$ep^c_{j,t}$	Charging power of ESS-j from the grid at time interval-t
$ep^d_{j,t}$	Discharging power of ESS-j injected to the grid at time interval-t
$EP^c_{j,t}$	Charging power in ESS-j at time interval-t
$EP^d_{j,t}$	Discharging power from ESS-j at time interval-t
$SOC_{j,t}$	State-of-charge of ESS-j at time interval-t
$u^c_{j,t}$	Binary variable which is equal to 1 if ESS-j is under charge at time interval-t
$u^d_{j,t}$	Binary variable which is equal to 1 if ESS-j is under discharge at time interval-t

Constants

α^c_j	A positive constant to limit the number of charging cycles of ESS-j during the operation period
α^d_j	A positive constant to limit the number of discharging cycles of ESS-j during the operation period
D_t	Estimated demand at time interval-t
$\underline{EP^c_j}$	Minimum charging power of ESS-j
$\overline{EP^c_j}$	Maximum charging power of ESS-j
$\underline{EP^d_j}$	Minimum discharging power of ESS-j
$\overline{EP^d_j}$	Maximum discharging power of ESS-j
P^{re}_t	Power production of renewable resource at time interval-t
R^E_t	Energy price at time interval-t
R^D	Demand price imposed on $D^{\max}$ of end-user
SOC^o_j	Initial state-of-charge of ESS-j
$SOC^{\max}_j$	Maximum state-of-charge limit of ESS-j
$SOC^{\min}_j$	Minimum state-of-charge limit of ESS-j
$SOC^{lower}_{j,T}$	Lower bound of the state-of-charge of ESS-j at final time interval-T
$SOC^{upper}_{j,T}$	Upper bound of the state-of-charge of ESS-j at final time interval-T
η^c_j	Charging efficiency of ESS-j
Δt	The time interval unit in hours
η^d_j	Discharging efficiency of ESS-j

Appendix A

Table A1. Forecasted demand for peak-shaving/load-leveling (MW) [23].

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	4042	4389	4397	4586	4695	4688	4398
2	3864	4132	4141	4339	4439	4441	4161
3	3756	3984	4003	4152	4281	4273	4004
4	3707	3886	3904	4033	4183	4154	3895
5	3707	3866	3885	4014	4153	4125	3855
6	3787	3915	3934	4063	4193	4125	3845
7	4024	4153	4161	4281	4411	4312	3943
8	4380	4518	4507	4656	4796	4529	4031
9	4956	5054	5001	5201	5391	4966	4198
10	5361	5459	5386	5607	5836	5343	4445
11	5559	5677	5604	5835	6074	5580	4673
12	5638	5766	5703	5924	6173	5649	4793
13	5418	5546	5534	5785	5894	5430	4812
14	5657	5794	5782	6004	6153	5619	4931
15	5777	5884	5872	6065	6273	5680	4951
16	5737	5835	5833	6035	6203	5590	4941
17	5738	5805	5794	5995	6143	5461	4921
18	5608	5666	5664	5875	5954	5251	4900
19	5459	5517	5504	5716	5784	5201	4931
20	5428	5527	5523	5725	5763	5299	5057
21	5427	5545	5541	5773	5772	5397	5177
22	5237	5327	5333	5525	5554	5239	5069
23	5012	5060	5065	5246	5277	5032	4862
24	4845	4863	4879	5050	5070	5684	4585

Table A2. Energy prices for peak shaving and load leveling (KRW/kWh) [23].

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	47.61	107.38	108.24	110.12	110.53	113.8	108.25
2	43.89	68.20	68.2	108.71	109.41	109.67	68.21
3	43.39	47.55	47.57	67.91	81.53	80.76	47.58
4	42.97	43.93	43.92	47.45	49.77	66.60	44.24
5	42.97	43.73	43.92	44.74	49.59	49.66	43.89
6	43.42	47.55	44.17	47.45	67.83	68.02	43.74
7	68.30	68.20	68.20	83.30	109.01	108.66	44.53
8	116.47	109.45	109.95	110.68	111.27	111.38	47.58
9	116.31	166.42	114.91	119.27	115.53	115.92	68.21
10	116.31	116.37	115.60	127.04	135.38	118.47	108.62
11	157.06	116.62	116.17	131.60	140.13	117.02	109.94
12	157.06	117.11	116.35	133.27	141.37	116.86	110.34
13	116.53	117.11	116.12	133.96	132.38	116.86	111.05
14	116.53	134.78	132.21	136.75	134.39	116.77	111.22
15	117.32	127.10	136.08	131.89	145.79	117.98	111.65
16	117.32	127.53	127.66	136.10	140.57	118.17	111.65
17	117.32	128.68	121.64	141.06	139.94	118.55	111.65
18	117.32	116.12	130.11	133.22	134.49	115.10	114.21
19	116.37	116.15	121.64	118.97	130.72	118.70	115.15
20	157.06	116.30	133.94	131.64	132.79	118.70	115.20
21	157.06	116.47	124.92	142.26	131.34	130.29	117.78
22	116.99	116.47	116.49	116.04	125.12	119.78	115.20
23	116.99	116.47	115.63	115.41	115.12	116.82	117.77
24	116.99	116.47	113.4	114.68	114.66	164.46	114.84

Table A3. TOU rate of Industrial (B), high-voltage (B), and Option-II by KEPCO [21].

Demand Charge	**7380 (KRW/kW)**			
	Time Period	**Summer**	**Spring/Fall**	**Winter**
Energy Charge (KRW/kWh)	Off-peak	56.2 (23:00~09:00)	56.2 (23:00~09:00)	63.2 (23:00~09:00)
	Mid-peak	108.5 (09:00~10:00, 12:00~13:00, 17:00~23:00)	78.5 (09:00~10:00, 12:00~13:00, 17:00~23:00)	108.5 (09:00~10:00, 12:00~17:00, 20:00~22:00)
	On-peak	189.7 (10:00~12:00, 13:00~17:00)	108.8 (10:00~12:00, 13:00~17:00)	164.7 (10:00~12:00, 17:00~20:00, 23:00~23:00)

Effective date: 21 November 2013.

Table A4. Forecasted load of an industrial customer (MW).

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	4.29	2.54	2.70	2.58	2.64	2.68	2.58
2	2.56	2.27	2.27	2.27	2.31	2.30	2.30
3	0.69	0.69	0.68	0.69	0.68	0.69	0.69
4	0.68	0.66	0.66	0.67	0.66	0.70	0.68
5	1.28	0.90	0.90	0.91	0.88	0.89	0.91
6	8.19	4.67	4.70	4.69	4.69	3.64	3.58
7	5.60	5.54	5.49	5.58	7.27	4.98	4.42
8	8.27	8.35	8.38	8.20	8.28	8.37	8.29
9	8.47	8.53	8.38	8.47	8.48	7.15	7.08
10	10.92	11.26	11.07	10.80	10.83	12.53	12.43
11	12.32	12.40	12.39	12.18	13.31	15.10	15.01
12	11.06	10.69	10.49	10.84	10.52	10.69	10.47
13	9.24	9.33	9.30	9.45	10.66	10.25	10.22
14	10.99	11.01	10.80	10.99	12.72	13.06	12.74
15	12.07	12.23	12.36	12.14	13.41	15.15	14.19
16	10.55	10.82	10.95	10.46	13.54	12.63	12.46
17	9.90	10.23	10.25	10.22	12.11	11.89	9.92
18	11.18	11.34	11.35	11.43	11.31	12.13	12.14
19	10.41	10.48	10.43	10.53	12.63	11.29	11.38
20	10.27	10.37	10.30	10.53	12.66	12.62	12.60
21	10.16	10.22	10.29	10.33	12.93	12.75	12.51
22	9.73	9.77	9.75	9.74	12.21	11.42	11.26
23	8.32	8.41	8.39	8.53	8.81	9.72	10.35
24	5.12	5.26	5.21	5.74	5.13	6.82	7.22

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