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Designing a critical peak pricing scheme for the profit maximization objective considering price responsiveness of customers

S.C. Park [a], Y.G. Jin [b,*], H.Y. Song [a], Y.T. Yoon [a]

[a] Department of Electrical Engineering and Computer Science, Seoul National University, Gwanak-ro 599, Gwanak-gu, Seoul 151-742, Republic of Korea
[b] Wind energy Grid-Adaptive Technology Research Center, Chonbuk National University, Jeonju 561-756, Republic of Korea

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A B S T R A C T

A deregulated market environment in power industries offers utilities or load serving entities the chance to make profit by pursuing a suitable operational strategy. However, the volatility of the real-time market clearing price raises a price risk issue because the load serving entity sells electricity to customers at a relatively frozen retail rate. One method to hedge price risk is to implement various dynamic pricing schemes in the retail sector in order to reflect the volatility of the real-time market clearing price to the retail rate. This paper presents several analyses for designing one such pricing scheme, namely critical peak pricing for a profit-maximizing load serving entity. Specifically, how the parameters of critical peak pricing affect profit based on the price responsiveness model of customers is analyzed. In this process, a method for solving the events scheduling problem is used as a tool for the analyses. Furthermore, we offer intuitive guidelines and rules for selecting those parameters that maximize the profit of the load serving entity. Finally, the suitability and practicality of the presented analyses are verified by numerical simulations with forecasted data on the real-time market clearing price and demand.

1. Introduction

Utilities, or load serving entities (LSEs), are entities that supply electricity to retail customers. The traditional role of them was regarded as reliably serving contracted customers based on the secure operation of the transmission network [1]. Accordingly, demand response (DR) programs, which enable customers to participate in the operation of the power system by changing their consumption pattern, aim to enhance the efficiency of the system operation by reducing peak demand [2]. Deregulation in power industries, however, has allowed DR programs to be implemented in an electricity market setting [3] in such a way that market participants may take appropriate actions or responsibilities [4]. The responsibilities of LSEs include offering customers a variety of products and services at time-varying rates as well as support for necessary technologies [4]. Thus, in a deregulated environment, LSEs can establish profit maximization as their main goal in return for their efforts to provide benefits to customers [5].

A wholesale real-time market determines prices for a specified time interval (e.g., every 5 min) based on the generation cost and demand. In a market environment, an LSE is able to profit by purchasing electricity at this real-time market clearing price (RTMCP) and then reselling it to customers at its own retail rate. The greatest risk to the profits of the LSE thus lies in the contrast between the volatility of RTMCPs and the relatively fixed retail rate [6]. As such, an LSE is naturally exposed to price risk in a deregulated market [7]. Indeed, when the RTMCP is skyrocketing, the loss suffered by an LSE becomes significant because of the large gap between the RTMCP and the retail price. The bankruptcy of Pacific Gas and Electric Company (PG&E), which is an LSE that provides natural gas and electricity in the United States, during the California electricity crisis is clear evidence that price risk affects the survival of LSEs and compromises the secure operation of power systems [8].

There are several risk hedging strategies that may be employed to address this problem. One method is to take advantage of derivatives, such as options and futures, in the financial market [9]. However, as electricity prices feature extreme variations and seasonal autocorrelation, these instruments may not be as effective as they are in other commodity markets [10]. The other method is to form long-term supply contracts with generation companies through the forward or bilateral markets [11]. Some have proposed

* Corresponding author. Tel.: +82 2 880 9144; fax: +82 2 885 4958.
E-mail address: ygjin93@snu.ac.kr (Y.G. Jin).

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Nomenclature

Variables

S_k	net benefit of customers in period k
$B(q_k)$	benefit of customers from consuming
q_k	amount of electricity in period k
R_k	revenue of a load serving entity in period k
C_k	cost of a load serving entity in period k
PI_k	profit index in period k
q_k	consumption of customers in period k
$q_{0,k}$	consumption of customers in period k when a critical event is not triggered
$q_{CPP,k}$	consumption of customers in period k when a critical event is triggered
$q_{RTP,k}$	consumption of customers in period k under a real-time pricing scheme
ρ_k	electricity price in period k
$\rho_{CPP,k}$	price rate of a critical peak pricing scheme in period k
ρ_{base}	base rate of a critical peak pricing scheme
ρ_{peak}	peak rate of a critical peak pricing scheme
$\rho^*_{peak,k}$	optimal peak rate of the critical peak pricing scheme in period k
ρ^*_{peak}	optimal peak rate of the critical peak pricing scheme throughout the time periods [1,N]
$\rho_{RTMCP,k}$	real-time market clearing price in period k
$\rho_{RTP,k}$	price rate of a real-time pricing scheme in period k
ρ_U	price rate of a uniform pricing scheme
α_k	design parameter of real-time pricing in period k
β_k	price elasticity of customers in period k
u_k	binary decision variable for the critical event in period k
N_{CPP}	maximum number of critical events
N^{min}_{CPP}	minimum number of critical events
D_{CPP}	maximum event duration
H_{CPP}	maximum total event time
Δk	minimum interval between successive critical events
k^*	element of the optimal solution to the events scheduling problem
OS^*	optimal solution to the events scheduling problem
N	scheduling time horizon of the events scheduling problem
x	variable to be forecasted in autoregressive moving average model
c, ϕ, θ	constants in the autoregressive moving average model
ε	zero-mean white noise

List of abbreviations

ANN	artificial neural network
AR	autoregressive
ARIMA	autoregressive integrated moving average
ARMA	autoregressive moving average
CPP	critical peak pricing
DR	demand response
LSE	load serving entity
PG&E	Pacific Gas and Electric Company
PJM	Pennsylvania-New Jersey–Maryland Interconnection
RTMCP	real-time market clearing price
RTP	real-time pricing
TOU	time-of-use

a decision-making framework for the LSE based on stochastic programming where the optimal level of procurement from the forward and pool markets would be determined in such a way as to maximize profit for a specified risk [12]. Another method is to reflect the volatility of the RTMCP to the retail rate through a dynamic pricing scheme as a type of DR program [13], which is the subject discussed in this study.

The dynamic pricing schemes include real-time pricing (RTP), in which fluctuating prices that reflect the RTMCP are charged to customers; time-of-use (TOU), in which different blocks of time carry different rates; and critical peak pricing (CPP), which entails charging higher rates when the RTMCP is high or a contingency situation occurs [2]. Regardless of which scheme is employed, its design will play a crucial role in hedging against LSEs' price risks and thereby their ability to maximize their profits. Accordingly, there have been many studies on the methodologies used to design dynamic pricing schemes for the profit maximization. In Ref. [14], a customer price response model is developed and an agent-based iterative learning method is used to determine the optimal day-ahead real-time prices based on the proposed response model. In Ref. [5], the optimal day-ahead real-time prices are determined through an optimization process that uses nonlinear programming; additionally, this model takes various constraints into account, such as the customers' responses to prices, the minimum and maximum demand limits, and the operating conditions of a distribution network. The interaction between the LSE and their customers, who are optimizing their own objectives, is explored in Ref. [15], where the real-time prices during a scheduling horizon are obtained by solving the profit maximization problem with a simulated-annealing-based price control algorithm. Another study, which assumes a deregulated market environment similar to that in Spain, optimally designs various types of TOU schemes with two, three, and six prices through quadratic nonlinear programming [16]. The study in Ref. [17] proposes a procedure for designing the rates and duration of TOU blocks and finds that a properly designed TOU scheme can improve both the profit of a distribution company and the saving of customers. Furthermore, in Ref. [18], it is shown that both the provider and the consumers may benefit from TOU pricing. Ref. [18] also details the conditions under which this win–win situation may occur and outlines how the optimal TOU rate may be determined. For the design of CPP, a recent research proposes a method to determine the optimal peak rate simultaneously with the optimal triggering schedule of critical events considering variable wind power generation [19].

Due to many valuable findings in the previous works, several design methods of dynamic pricing schemes are available for the LSE maximizing the profit. Among the pricing schemes, CPP has several advantages over RTP and TOU. For instance, although RTP is the most effective at hedging against price risk, its complexity resulting from the need for continuous response prevents small residential customers from participating in a RTP program [20]. TOU is easy to implement because there are only a few block rates announced to customers in advance; its main detraction lies in its inability to deal with sudden increases in the RTMCP. Thus, CPP provides a reasonable alternative to RTP for residential customers and can be used in conjunction with TOU to dynamically apply the peak price in a critical situation [20]. Despite its clear advantages and relevancy, especially in light of the current developing status of smart grids, CPP has received far less attention than either RTP or TOU in the literature. Furthermore, there have been few studies that examined how the parameters in CPP other than the peak rate affect profit of the LSEs, and even fewer that employed an analytical approach to factor in consumer responses. Consequently, this study presents several such analyses. First, we analyze how the CPP parameters which include the peak rate, the number of critical events, and the duration of each critical event affect profit by considering the responses of customers. Second, intuitive guidelines and rules for selecting the CPP parameters such that the LSE may maximize its profit are suggested. In the development of analyses, a price response model in Ref. [21] is used to quantify the reduction in electricity consumption, and the optimal schedule of critical events is determined using the dynamic programming [22].

The remainder of this paper is organized as follows. Section 2 provides background information, such as a model of customers' price responsiveness, the formulation of the events scheduling problem, and a method for forecasting prices and demand. Section 3 describes how to design the CPP parameters and how these parameters affect profit based on the assumed price responsiveness model of customers. Section 4 runs numerical simulations using forecasted market data on the RTMCP and demand in order to demonstrate the suitability and practicality of the presented analyses. Finally, conclusions are drawn in Section 5.

2. Backgrounds

2.1. Price responsiveness model with the CPP scheme

If a group of customers consumes an amount of electricity, q_k, in period k, their net benefit at that time, denoted by S_k, can be presented as [21]

$$S_k = B(q_k) - \rho_k q_k \tag{1}$$

where $B(q_k)$ is the benefit derived from electricity consumption and ρ_k is the price of electricity in period k. If customers behave strategically in a competitive environment, they are likely to maximize their net benefits. Thus, $\partial S_k/\partial q_k$ should equal zero given ρ_k at the optimal point, and the following relation can thus be obtained:

$$\frac{\partial B(q_k)}{\partial q_k} = \rho_k \tag{2}$$

The relation in (2) suggests that reasonable customers tend to consume the amount of electricity for which the marginal benefit of consumption equals the electricity price. Such a benefit function is often assumed to take the following quadratic function form [23]:

$$B(q_k) = B_{0,k} + \rho_{0,k}\left(q_k - q_{0,k}\right)\left(1 + \frac{q_k - q_{0,k}}{2\beta_k q_{0,k}}\right) \tag{3}$$

where $B_{0,k}$, $q_{0,k}$, and $\rho_{0,k}$ are the nominal values of the benefit, demand, and price in period k, respectively. β_k is the elasticity constant of demand and is defined as [24]

$$\beta_k = \frac{\rho_k}{q_k}\frac{dq_k}{d\rho_k} \tag{4}$$

The variable β_k has a negative value because a price increase reduces demand. For example, β_k becomes -0.01 when demand decreases by 1% following a 100% increase in price. Indeed, the empirical results of the Statewide Pricing Pilot program showed that β_k ranges from -0.044 to -0.027 under CPP [25].

Then, after differentiating (3) with respect to q_k and substituting (4) in, the resulting equation can be arranged for q_k as

$$q_k = q_{0,k}\left\{1 + \frac{\beta_k(\rho_k - \rho_{0,k})}{\rho_{0,k}}\right\} \tag{5}$$

This equation implies that reasonable consumers who have a demand elasticity of β_k change consumption from $q_{0,k}$ to q_k when the price shifts from $\rho_{0,k}$ to ρ_k.

To derive a price responsiveness model in the case of a CPP scheme, we first define a specific form of CPP in period k as

$$\rho_{CPP,k} = u_k\rho_{peak} + (1 - u_k)\rho_{base} \tag{6}$$

where u_k is an event decision variable that takes on a value of 1 if the critical event is triggered in period k and zero otherwise. The parameters ρ_{peak} and ρ_{base} are defined as the peak and off-peak rates, respectively. Normally, ρ_{base} is lower than the uniform price and ρ_{peak} is much higher than the uniform price, which is applied to customers who do not participate in CPP. Under the CPP scheme, customers change consumption when a critical event is triggered or when the price moves from ρ_{base} to ρ_{peak}. Then, assuming demand elasticity is constant at β, the modified consumption for the critical event triggered in period k can be determined by replacing $\rho_{0,k}$ and ρ_k in (5) with ρ_{base} and ρ_{peak}, respectively,

$$q_{CPP,k} = q_{0,k}\left\{1 + \beta\left(\frac{\rho_{peak}}{\rho_{base}} - 1\right)\right\} \tag{7}$$

Eq. (7) shows that customers with demand elasticity β reduce their consumption linearly to ρ_{peak}/ρ_{base}. In the real world, however, nominal demand $q_{0,k}$ does not occur when consumption changes to $q_{CPP,k}$. Thus, $q_{0,k}$ should be interpreted as forecasted consumption, regardless of whether critical events have been triggered.

2.2. Events scheduling problem

An events scheduling problem is an optimization problem that seeks to determine when critical events should be triggered in order to maximize or minimize a certain value. The events scheduling problem can be formulated in several different ways. For example, a profit-maximizing schedule of critical events can be developed by using dynamic programming deterministically based on the forecasted price and demand [22] or stochastically based on the probability distributions of the price and temperature [26]. The events scheduling problem can be solved by integer programming to maximize the total benefit of both LSEs and customers [27]. Alternatively, one study proposed using stochastic, nonlinear mixed-integer programming to solve the events scheduling problem in such a way that would minimize the total operational cost [19].

In order to develop a design methodology for the CPP in this study, the deterministic dynamic programming for maximizing profit of an LSE based on the forecasted price and demand in Ref. [22] is taken to solve the events scheduling problem. Then, the events scheduling problem can be formulated as

$$\max_{u_k} \sum_{k=1}^{N}\{R_k - C_k\} \tag{8}$$

where N is the scheduling time horizon of the problem and R_k and C_k are the revenue and cost of the LSE in period k, respectively, and are defined as

$$R_k = u_k\rho_{peak}q_{CPP,k} + (1 - u_k)\rho_{base}q_{0,k} \tag{9}$$

$$C_k = u_k\rho_{RTMCP,k}q_{CPP,k} + (1 - u_k)\rho_{RTMCP,k}q_{0,k} \tag{10}$$

The variable $\rho_{RTMCP,k}$ is the forecasted RTMCP in period k.

The constraints on the events scheduling problem consist of conditions related to the maximum number of events, maximum event duration, maximum total event hours, and the minimum interval between successive events. These constraints are imposed in order to avoid inconveniencing customers and interrupting consumption by frequently issuing events. The specific descriptions of these constraints are presented next.

Maximum number of events (N_{CPP}): The number of critical events can be determined by counting the number of times u_k changes from zero to one. Then, by assuming that $u_k = 0$ for $k \le 0$, this constraint can be presented as

$$\sum_{k=1}^{N} u_k(1-u_{k-1}) \le N_{CPP} \tag{11}$$

Maximum event duration (D_{CPP}): Once a critical event has been triggered, its duration should be no longer than a specified interval. Thus, the number of times $u_k = 1$ within the time window of $D_{CPP}+1$ should be less than or equal to D_{CPP}. This condition has to hold for all moving time windows; this can be expressed as

$$\sum_{i=k}^{k+D_{CPP}} u_i \le D_{CPP}, \quad \forall k \in \{1,2,\cdots,N-D_{CPP}\} \tag{12}$$

Maximum total event time (H_{CPP}): The maximum total event time during the scheduling horizon can be given regardless of N_{CPP} and D_{CPP}. In other words, if this constraint is not explicitly provided, H_{CPP} is naturally equal to N_{CPP} times D_{CPP}. If it is given, H_{CPP} should be less than or equal to N_{CPP} times D_{CPP}, and the total number of times $u_k = 1$ during the scheduling horizon should satisfy the following relationship:

$$\sum_{k=1}^{N} u_k \le H_{CPP} \tag{13}$$

Minimum interval between successive events (Δk): In contrast to the maximum number of events constraint, the count of the interval should start just after u_k changes from one to zero. In addition, u_k should not change again during the subsequent interval of Δk. Thus, by assuming that $u_k = 0$ for $k \le 0$, this constraint can be presented as

$$u_{k-1}(1-u_k)\sum_{i=k}^{k+\Delta k-1} |u_i - u_{i+1}| = 0, \quad \forall k \in \{1,2,\cdots,N-\Delta k+1\} \tag{14}$$

Solving the events scheduling problem is identical to computing the optimal events schedule OS^*, for the set of time periods, k^* s, such that u_{k^*} s are the solutions to (8) by satisfying all the constraints (11)–(14). Similar to previous studies, the optimal solution is available by using dynamic programming [22,26] or integer programming [27].

2.3. Forecasting demand and price

The profit of the LSE is realized at the end of the scheduling time horizon for the actual RTMCP and demand. The design of a CPP scheme and calculation of the associated solution to the events scheduling problem, however, should be conducted before the information on the actual RTMCP and demand is available. Thus, in the design process of a CPP scheme, the RTMCP and demand need to be forecasted in advance for all time periods in the scheduling time horizon.

Various methods have been presented for using time series to forecast prices and demand [28–31]. Several types of autoregressive (AR) and autoregressive moving average (ARMA) models are investigated in terms of the performance of the models in forecasting prices [28], and the autoregressive integrated moving average (ARIMA) model has been used to forecast next-day prices in Ref. [29]. It has been pointed out, though, that different time-series analyses, such as a dynamic regression model or a transfer function model, may be able to forecast next-day prices more accurately and efficiently by addressing the correlation problem [30]. The AR, ARMA, and ARIMA models have all been used to forecast demand as well [31]. Several studies have employed extended methods based on the basic structure of artificial neural networks (ANNs) to forecast prices and demand [32–36]. The study in Ref. [32] proposes implementing a similar days technique to select suitable input factors in order to more accurately forecast day-ahead prices with a simplified ANN model. Yet another study put forth a computationally efficient ANN-based method that used a decoupled extended Kalman filter for price forecasting [33]. Multiple ANNs, which together are called a committee machine, may be used to improve price predictions [34]. The ANN approach may also be used to forecast demand in relation to the temperature [35], though some argue that a weather compensation ANN model [36], could yield more accurate predictions.

More detailed and comprehensive descriptions of these methodologies are beyond the scope of this study. Instead, the autoregressive moving average (ARMA) model is briefly introduced because it is used in the numerical simulation presented later. The ARMA(p,q) model is expressed as [28].

$$x_k = c + \sum_{i=1}^{p} \phi_i x_{k-i} + \varepsilon_k + \sum_{j=1}^{q} \theta_j \varepsilon_{k-j} \tag{15}$$

where c, ϕ_i, and θ_j are constant terms, x_k is the variable to be forecasted, ε_k is zero-mean white noise, and p and q are the orders of the ARMA model.

3. Implementation of CPP scheme for LSE

3.1. Profit index

As a tool for the analysis, we define a profit index for the LSE. Suppose that the maximum event duration is equal to one. Then, the profit index, PI_k, for each period, k, is defined as

$$PI_k = \sum_{i=k}^{k+D_{CPP}-1} q_{CPP,i}\left(\rho_{peak}-\rho_{RTMCP,i}\right) - q_{0,i}\left(\rho_{base}-\rho_{RTMCP,i}\right) \tag{16}$$

The profit index in (16) represents the additional profit that the LSE will receive from the triggering of a critical event in period k. The objective function, or the profit of the LSE, in (8), (9), and (10) can be arranged by using the definition of PI_k in (16) such that

$$\begin{aligned}\sum_{k=1}^{N}\{R_k - C_k\} &= \sum_{k=1}^{N}\left\{u_k PI_k\left(\rho_{peak}\right) + q_{0,k}\left(\rho_{base}-\rho_{RTMCP,k}\right)\right\} \\ &= \sum_{k=1}^{N} u_k PI_k\left(\rho_{peak}\right) + \sum_{k=1}^{N} q_{0,k}\left(\rho_{base}-\rho_{RTMCP,k}\right)\end{aligned} \tag{17}$$

The second term in (17) is constant given the forecasted price and demand. Additionally, in a period without critical event, there is no change in demand such that $q_{CPP,k}$ and $q_{0,k}$ in (16) are equal and PI_k become zero. Therefore, one may maximize the profit of the LSE by maximizing the summation of the profit indexes for the periods with critical events. Furthermore, it can be seen from (16) and (17) that this summation depends on the CPP parameters, such as the optimal peak rate (ρ_{peak}), the number of critical events (N_{CPP}), and the event duration (D_{CPP}). Consequently, by using the profit index, the effects of the parameters on the profit of the LSE can be analyzed and the method to select the suitable values of the parameters for the profit maximization can be devised, which are presented in the next subsections.

3.2. Selection of optimal peak rate

Suppose that $N_{CPP} = 1$ and $D_{CPP} = 1$. Then, the substitution of (7) into the profit index in (16) results in a quadratic function of ρ_{peak} as

$$PI_k\left(\rho_{peak}\right) = a_{2,k}\left(\rho_{peak}\right)^2 + a_{1,k}\rho_{peak} + a_{0,k} \tag{18}$$

where

$$a_{2,k} = \frac{q_{0,k}\beta}{\rho_{base}}, \quad a_{1,k} = q_{0,k}\left(1 - \beta - \beta\frac{\rho_{RTMCP,k}}{\rho_{base}}\right), \quad a_{0,k} = q_{0,k}\left(\beta\rho_{RTMCP,k} - \rho_{base}\right) \tag{19}$$

Because β is negative, $a_{2,k}$ is also negative. Then, because PI_k in (18) is a convex function, there exists the optimal peak rate for period k that maximizes PI_k, which is denoted as $\rho^*_{peak,k}$. As the derivative of (18) with respect to ρ_{peak} must be equal to zero, the value of $\rho^*_{peak,k}$ is determined from

$$\frac{\partial PI_k\left(\rho_{peak}\right)}{\partial\rho_{peak}} = 2a_{2,k}\rho_{peak} + a_{1,k} = 0 \tag{20}$$

Then, $\rho^*_{peak,k}$ for $k\in\{1,2,\cdots,N\}$ can be found by solving (20) and substituting the expression in (19) as

$$\rho^*_{peak,k} = -\frac{a_{1,k}}{2a_{2,k}} = \frac{\rho_{base}}{2}\left(1 - \frac{1}{\beta}\right) + \frac{\rho_{RTMCP,k}}{2} \tag{21}$$

The values of $\rho^*_{peak,k}$ and the associated profit indexes, $PI_k(\rho^*_{peak,k})$, can be computed using (21) and (18). Similarly, for the extended case where $N_{CPP} = 1$ but $D_{CPP} > 1$, $\rho^*_{peak,k}$ for $k \in \{1,2,\cdots,N-D_{CPP}+1\}$ can be derived by following the procedures in (18)–(21) as

$$\rho^*_{peak,k} = \frac{\rho_{base}}{2}\left(1 - \frac{1}{\beta}\right) + \frac{\sum_{i=k}^{k+D_{CPP}-1}\rho_{RTMCP,i}q_{0,i}}{2\sum_{i=k}^{k+D_{CPP}-1}q_{0,i}} \tag{22}$$

The associated profit indexes, $PI_k(\rho^*_{peak,k})$, in the extended case also can be computed from (22) and (18). Because $N_{CPP} = 1$ is assumed, a critical event should be triggered when $PI_k(\rho^*_{peak,k})$ is greatest, regardless of whether is $D_{CPP} = 1$ or $D_{CPP} > 1$. Consequently, the optimal peak rate $\rho^*_{peak,k}$ can be determined for a time period in which a critical event occurs. It should be noted that neither the second term in (21) nor that in (22) change with respect to β. In addition, the magnitude of β is very small. As a result, it can be stated that ρ^*_{peak} is approximately inversely proportional to $|\beta|$. In other words, when customers are less responsive to critical events (i.e., when $|\beta|$ is small) the optimal peak rate, ρ^*_{peak}, should be set at a high value in order to maximize the profit of the LSE.

When $N_{CPP} = 1$, ρ^*_{peak} can be analytically determined in a simple form of (21) or (22). However, in the general case where N_{CPP} and D_{CPP} are both greater than one, on the other hand, the summation of the profit indexes must be calculated for each combination of N_{CPP} numbers of elements among the set of time periods or $k\in\{1,2,\cdots,N\}$. For example, if $N = 10$ and $N_{CPP} = 2$, then ${}_{10}C_2 = 45$; thus, 45 combinatorial profit indexes should be computed without other constraints. In order to derive an analytical form of the optimal peak rate for $N_{CPP} > 1$, let us assume that the optimal events schedule is determined as OS^*. Then, the summation of profit indexes for the determined N_{CPP} numbers of critical events can be expressed as

$$\sum_{k\in OS^*} PI_k\left(\rho_{peak}\right) = \sum_{k\in OS^*}\left\{a_{2,k}\left(\rho_{peak}\right)^2 + a_{1,k}\rho_{peak} + a_{0,k}\right\} \tag{23}$$

As in the case where $N_{CPP} = 1$, the optimal peak rate, ρ^*_{peak}, is determined by the following condition

$$\frac{\partial}{\partial\rho_{peak}}\sum_{k\in OS^*} PI_k\left(\rho_{peak}\right) = \sum_{k\in OS^*}\frac{\partial PI_k\left(\rho_{peak}\right)}{\partial\rho_{peak}} = \sum_{k\in OS^*}\left\{2a_{2,k}\rho_{peak} + a_{1,k}\right\} = 0 \tag{24}$$

By using (19), the solution of (24) can be rearranged for the analytical form of the optimal peak rate as

$$\rho^*_{peak} = \frac{\rho_{base}}{2}\left(1 - \frac{1}{\beta}\right) + \frac{\sum\limits_{k\in OS^*}\sum_{i=k}^{k+D_{CPP}-1}\rho_{RTMCP,i}q_{0,i}}{2\sum\limits_{k\in OS^*}\sum_{i=k}^{k+D_{CPP}-1}q_{0,i}} \tag{25}$$

Because the second term in (25) is not dependent on $|\beta|$, it can be also stated that ρ^*_{peak} is approximately inversely proportional to $|\beta|$ in this case as well. Furthermore, the numerator and denominator of the second term both include $q_{0,i}$, and the numerator is the sum of demand weighted by the $\rho_{RTMCP,i}$ s. Thus, if the $\rho_{RTMCP,i}$ s in periods with critical events are not unreasonably different from each other, then ρ^*_{peak} will not significantly change as N_{CPP} increases as compared to the value when $N_{CPP} = 1$. When $|\beta|$ is small, the first term in (25) is large and, thus, the change in the second term with respect to N_{CPP} may be negligible. This, therefore, implies that the number of critical events has little impact on the optimal peak rate, and that the optimal peak rate for $N_{CPP} = 1$, which may be easily calculated, can be safely used even when $N_{CPP} > 1$.

3.3. Selection of number of events

Under a CPP scheme, the off-peak rate, ρ_{base}, should be less than the uniform price, ρ_U, in order to attract customers because, otherwise, there would be no reason for them to sign a CPP contract. Therefore, in the absence of a critical event, an LSE should receive less profit under a CPP scheme than it would under a uniform pricing scheme. However, this reduction in profits during normal time periods may be offset by increased profit during the periods with critical events. It therefore follows that there is the minimum number of critical events that must be triggered for a CPP scheme to be more profitable than a uniform pricing scheme.

The profit of LSEs when they sell electricity at price ρ_U can be expressed as

$$\sum_{k=1}^{N}\left[q_{0,k}\left(\rho_U - \rho_{RTMCP,k}\right)\right] \tag{26}$$

In order not to lose profit from the application of a CPP scheme, the profit of the LSE in (17) with the optimal peak rate should be greater than or equal to (26). This condition can be represented after some arrangements as

$$\sum_{k\in OS^*} PI_k\left(\rho^*_{peak}\right) \geq \sum_{k=1}^{N} q_{0,k}\left(\rho_U - \rho_{base}\right) \tag{27}$$

The term on the right side is the loss in profit incurred by instituting CPP instead uniform pricing during normal time periods. Thus, (27) explicitly shows that the sum of the profit indexes for critical events should be greater than or equal to said loss in order to make CPP a reasonable option. The number of elements in OS^* is equal to the number of critical events, N_{CPP}, and the profit of the LSE always rises as N_{CPP} increases. As a result, the minimum number of events required to satisfy the minimum profit condition of the LSE, denoted as $N_{CPP}^{\min}$, can be found. Because N_{CPP} is a nonnegative integer, it is difficult to represent $N_{CPP}^{\min}$ in an analytical form. Thus, $N_{CPP}^{\min}$ can be determined through an iterative procedure in which N_{CPP} is incrementally increased and then checked to determine whether it satisfies the condition in (27)

When $N_{CPP} = 1$ and $D_{CPP} = 1$, the profit index with the optimal peak rate can be determined with (18), (19), and (21) such that

$$PI_k\left(\rho^*_{peak,k}\right) = -\frac{q_{0,k}\rho_{base}\left(1-\rho_{RTMCP,k}/\rho_{base}\right)^2}{4}\cdot\beta - \frac{q_{0,k}\rho_{base}}{4}\cdot\frac{1}{\beta} + \frac{q_{0,k}}{2}\left(\rho_{RTMCP,k}-\rho_{base}\right) \tag{28}$$

As $|\beta|$ is significantly smaller than one, changes in β dramatically impact the second term in (28) which includes $1/\beta$ unless $\rho_{RTMCP,k}$ is much greater than ρ_{base}. Additionally, because β is negative, it can be stated that the profit index decreases as $|\beta|$ increases, i.e., as the price responsiveness of customers becomes higher. It can be inferred from (28) that this trend in PI_k with respect to $|\beta|$ will be present in the general cases where $D_{CPP} > 1$ because the summation is a simple linear operation. The profit index means the compensation for the reduced profit with a critical event. Consequently, $N_{CPP}^{\min}$ increases as the price responsiveness of customers increases. Intuitively, if customers are less responsive to price changes, their demand will remain fairly constant when prices increase for the periods with critical events, thus resulting in a large profit index and a small $N_{CPP}^{\min}$. In contrast, if they are highly responsive, demand will decrease significantly during the periods with critical event, which leads to a small profit index and a large $N_{CPP}^{\min}$.

The maximum number of critical events is limited not by the profit of the LSE but by the constraint on the maximum total event time, H_{CPP}. The value of H_{CPP} must be selected with care because it affects convenience of customers and the attractiveness of a CPP scheme in a competitive environment. Consequently, H_{CPP} places an upper bound on N_{CPP} due to the trade-off between the profit of the LSE and the convenience of customers.

3.4. Selection of event duration

The number of events (N_{CPP}) and the event duration (D_{CPP}) are not independent parameters because of the constraint on maximum total event time (H_{CPP}) in (13). Moreover, it is obvious from (16) that the profit of the LSE increases as D_{CPP} increases until the constraint on H_{CPP} is satisfied. Therefore, for a given N_{CPP}, D_{CPP} is resultantly determined from (13) as follows

$$D_{CPP} = \lfloor H_{CPP}/N_{CPP} \rfloor \tag{29}$$

where $\lfloor x \rfloor$ is the floor function that gives the largest integer not greater than x.

On the other hand, a combinatorial selection of both N_{CPP} and D_{CPP} should be performed with the constraint on H_{CPP} when N_{CPP} is also a variable. This combinatorial selection problem can be qualitatively solved by the following reasoning. Suppose a simple example where $H_{CPP} = 3$, the demand is constant throughout the time periods, and the market prices are those given as in Fig. 1. When $D_{CPP} = 1$ and $N_{CPP} = 3$, profit is greatest when critical events are triggered in periods $k_{A,2}$, $k_{B,2}$, and $k_{C,2}$. In contrast, when $D_{CPP} = 3$ and $N_{CPP} = 1$, the profit is maximized if critical events are triggered in periods $k_{C,1}$, $k_{C,2}$, and $k_{C,3}$. The profit indexes for $k_{A,2}$ and $k_{B,2}$ are greater than that for $k_{C,2}$. However, the profit indexes around $k_{A,2}$ and $k_{B,2}$ are smaller than those for $k_{C,1}$ and $k_{C,3}$ around $k_{C,2}$. As a result, the constraint that $D_{CPP} = 3$ requires that $k_{C,1}$, $k_{C,2}$, and $k_{C,3}$ be the periods with critical events. This example clearly shows that D_{CPP} hinders the optimal selection of time periods for critical events, and becomes a factor reducing the degrees of freedom for the selection. Therefore, it is a reasonable choice to set $D_{CPP} = 1$ and $N_{CPP} = H_{CPP}$ in order to avoid a case-by-case evaluation of each combination of N_{CPP} and D_{CPP}.

In addition, because of the constraint on the minimum interval between successive events (Δk), the largest profit indexes may not be chosen even with $D_{CPP} = 1$ if their time periods are too close together. As a result, there is no choice but to calculate the profit of the LSE for all combinations of N_{CPP} and D_{CPP} in order to find that which yields the greatest profit. While this initially appears to be a decidedly time-consuming task, N_{CPP} and D_{CPP} possess several useful characteristics that allow us to reduce the number of combinations. First, both N_{CPP} and D_{CPP} are positive integers, and profit is maximized not when N_{CPP} times D_{CPP} is less than H_{CPP}, but when N_{CPP} times D_{CPP} is exactly equal to H_{CPP}. This greatly limits the number of possible combinations because the combination of positive integers with the product of them being equal to H_{CPP} is limited. Second, as described in Section 3.3, N_{CPP} should fall within the range of $N_{CPP} \geq N_{CPP}^{\min}$. This condition on N_{CPP} may achieve an additional reduction of the number of combinations.

4. Numerical simulation

The data on the RTMCP and demand are forecasted from actual historical data on the Pennsylvania-New Jersey-Maryland Interconnection (PJM), which is one of the regional transmission organizations in the United States, for one month (May 2013) [37] by using the ARMA model in (15). The orders and constant terms of the ARMA models are determined by using the SPSS tool [38]. Specifically, ARMA(3,0) and ARMA(5,9) are chosen as the most suitable models for the RTMCP and demand, respectively. The forecasted values of the RTMCP and demand in comparison with the actual values are shown in Fig. 2(a) and Fig. 2(b), respectively. The interval of each time period is assumed to be 1 h, meaning that the scheduling time horizon is $N = 744$. The values of ρ_{base} and H_{CPP} are set at 0.050 $/kWh and 12 h/month, respectively.

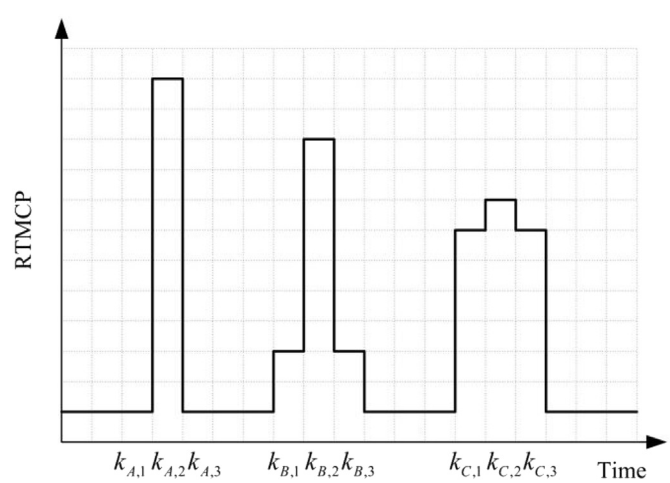

Fig. 1. Imaginary market prices used in the example.

4.1. Events scheduling problem and profit index

In order to show the usefulness of the proposed profit index, the events scheduling problem is solved for $\beta = -0.02$, $\rho_{peak} = 1.900$ $/kWh, $D_{CPP} = 1$, $N_{CPP} = 3$, and $\Delta k = 24$ hours. The solution is obtained as $OS^* = \{354, 474, 714\}$ with the increased profit of $26.421 million from CPP. The periods with critical events are represented as stars in Fig. 3 with the profit indexes over the scheduling time horizon. It seems that the highest three profit indexes provide the solution to the events scheduling problem. In this simulation, however, PI_{712}=$2.201 million is greater than PI_{354}=$2.158 million, but the constraint $\Delta k = 24$ results in the selection of $k = 354$ as the time period for a critical event. This result demonstrates that when the constraint on Δk is imposed, critical events cannot always occur in the periods with the highest profit indexes. Nonetheless, $k = 474$ and $k = 714$, the periods with the greatest and second greatest profit indexes, are still selected. Consequently, it seems that the profit indexes, which can be calculated more simply and faster than the solution to the events scheduling problem, can offer an approximate picture of the operational strategy under a CPP scheme.

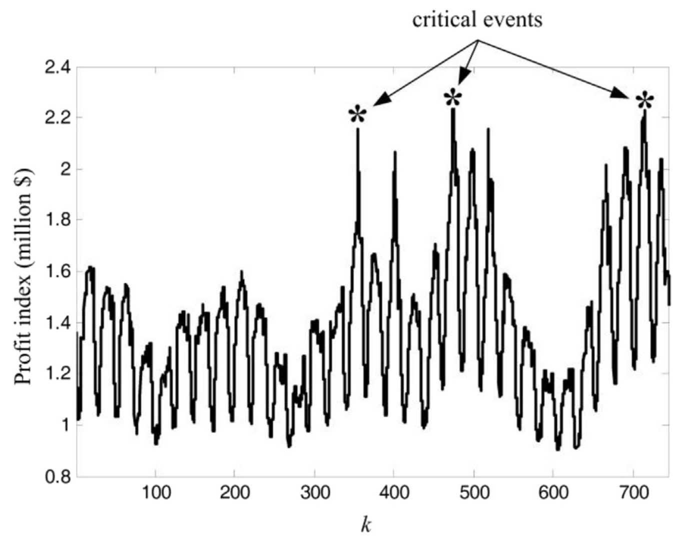

Fig. 3. Profit indexes for the scheduling time horizon.

4.2. Optimal peak rate

For the CPP scheme with $N_{CPP} = 3$, $D_{CPP} = 1$, $\beta = -0.02$, and $\Delta k = 0$, the optimal peak rate can be determined from (25), which leads to $\rho^*_{peak} = 1.305$ $/kWh. In order to examine the improvement in profit under the optimal peak rate, the profits for $\rho^*_{peak} = 1.305$ $/kWh and $\rho_{peak} = 1.900$ $/kWh are compared. At a glance, $\rho_{peak} = 1.900$ $/kWh seems to be better because a higher peak rate might be considered to lead to greater profit. However, the profit for $\rho_{peak} = 1.900$ $/kWh is $26.464 million, which is lower than that for $\rho^*_{peak} = 1.305$ $/kWh ($28.348 million) because a higher peak rate may result in an over-reduction of consumption by customers.

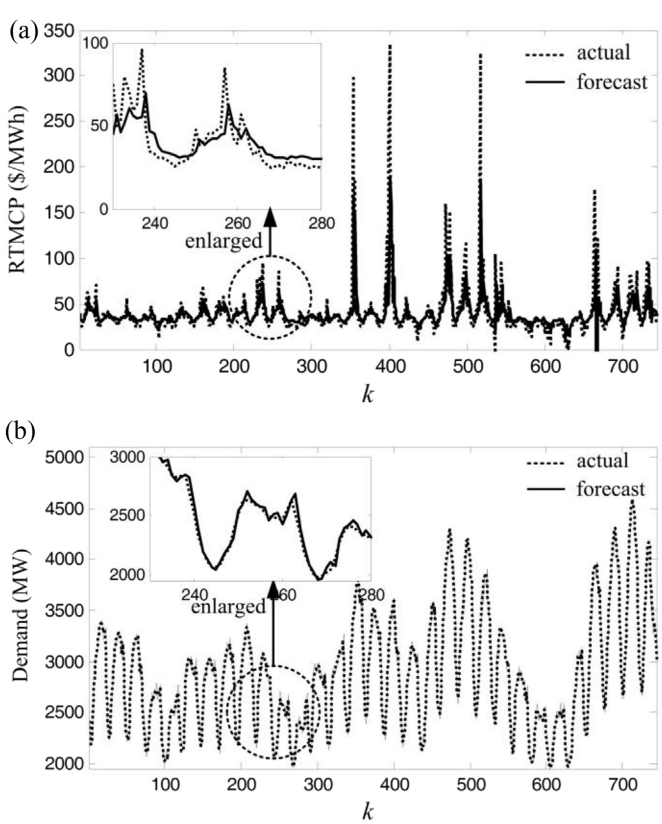

Fig. 2. Forecasted and actual data on (a) the RTMCP and (b) demand.

The optimal peak rate is calculated for various combinations of β and N_{CPP}, as shown in Fig. 4. From Fig. 4(a), it can be seen that ρ^*_{peak} is approximately inversely proportional to $|\beta|$. The result suggests that it is better to select a lower peak rate for customers that have high price responsiveness than for those that have low price responsiveness. Although Fig. 4(a) shows a decreasing pattern with respect to $|\beta|$, these patterns are not monotonically decreasing functions of $|\beta|$. For example, when the section around $|\beta| = 0.05$ is enlarged, as shown as a subfigure in Fig. 4(a), it can be seen that the optimal peak rate for $N_{CPP} = 1$ rises. This is because the optimal schedule of critical events may change as $|\beta|$ changes, and the values of $\rho_{RTMCP,k}$ for the modified event schedule may cause an increase in ρ^*_{peak}. After such an increase, however, ρ^*_{peak} decreases again with respect to $|\beta|$, which shows that $|\beta|$ remains the dominant factor affecting ρ^*_{peak}.

Fig. 4(b) shows the difference between each N_{CPP}'s ρ^*_{peak} value and that for the case where $N_{CPP} = 1$. From this figure we can see that N_{CPP} has little effect on ρ^*_{peak}, especially when $|\beta|$ is small. Specifically, the range of the difference in ρ^*_{peak} s for $|\beta| = 0.02$ is 0.004 $/kWh, which is 0.31% of $\rho^*_{peak} = 1.305$ $/kWh for $N_{CPP} = 1$. In contrast, the range in ρ^*_{peak} s for $|\beta| = 0.05$ is 0.037 $/kWh, which is 6.00% of $\rho^*_{peak} = 0.617$ $/kWh for $N_{CPP} = 1$. Therefore, it may be a practical choice to use ρ^*_{peak} for $N_{CPP} = 1$ even in other cases when $N_{CPP} > 1$, particularly if customers are less responsive to price changes, that is, $|\beta|$ has a small value.

The effect of the minimum interval between successive events on profit of the LSE is now analyzed for various values of Δk when $\beta = -0.02$, $D_{CPP} = 1$, $N_{CPP} = 3$ and $\rho^*_{peak} = 1.305$ $/kWh. The results are presented in Table 1. Profit tends to decrease as Δk increases because a larger value of Δk prevents better time periods from being selected.

4.3. Number of events

Fig. 5 shows the profit of the LSE for various values of N_{CPP} with respect to $|\beta|$ when ρ^*_{peak} is applied and $D_{CPP} = 1$. This figure clearly shows that, given β or price responsiveness of customers, profits rise as N_{CPP} increases. In addition, it can also be seen from Fig. 5 that the interval between the profits for different N_{CPP} s is larger when

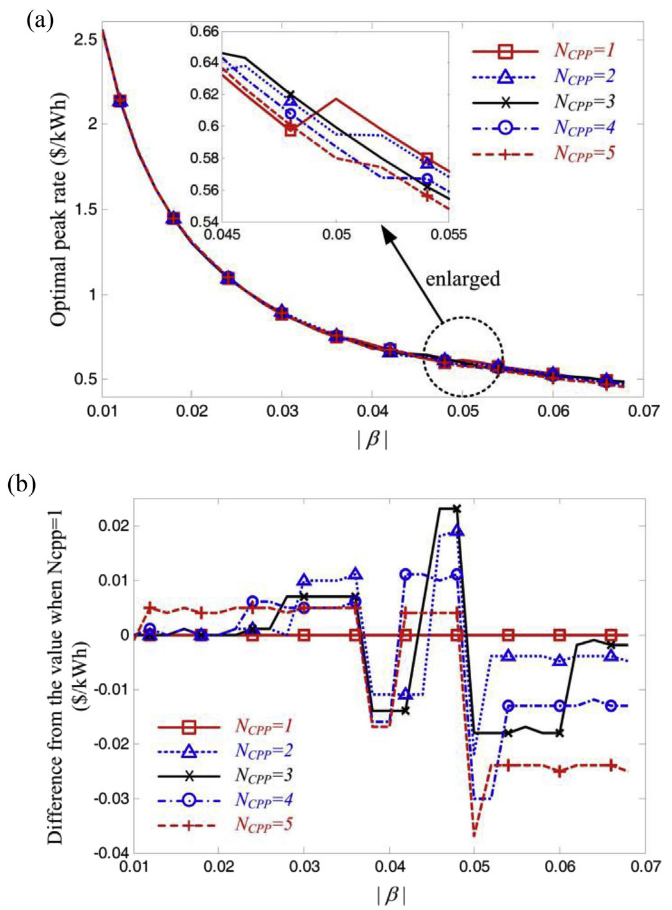

Fig. 4. Simulation results of (a) Optimal peak rate for various values of N_{CPP} and (b) Difference in the optimal peak rate for each N_{CPP} as compared to $N_{CPP} = 1$.

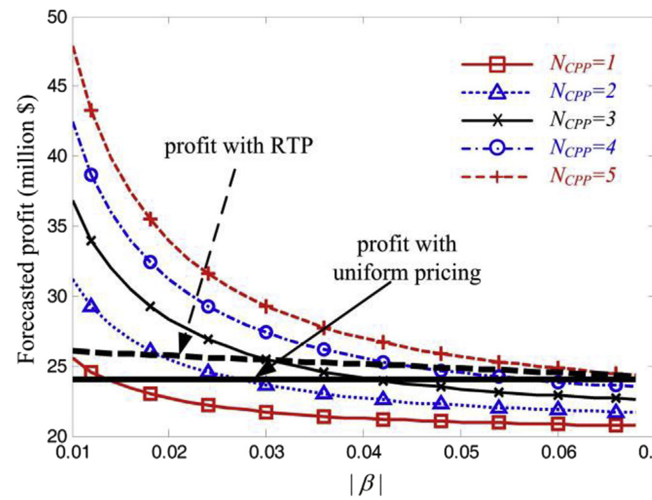

Fig. 5. Profit of the LSE for various values of N_{CPP} with respect to $|\beta|$.

$|\beta|$ is smaller. For example, when N_{CPP} increases from 2 to 3, PI_{713}=\$2.835 million is added to the profit level for $|\beta| = 0.02$, whereas PI_{474}=\$1.009 million is added to the profit level for $|\beta| = 0.06$. As described in Section 3.3, the demand remains fairly constant during the periods with critical events if customers are less responsive to price changes. Thus, the profit index, or the additional profit from the increase in N_{CPP}, will be large. In contrast, demand will fall sharply if customers are sensitive to price increases; this will, in turn, yield a small profit index. Therefore, Fig. 5 explicitly verifies this property of the profit index with respect to N_{CPP} and $|\beta|$.

The profit of the LSE for the CPP with various values of N_{CPP} is examined in comparison with the uniform pricing. Suppose that the uniform price, ρ_U, is 0.052 \$/kWh, which is 4% higher than ρ_{base}; the profit of the LSE in this situation is represented by the solid line in Fig. 5. Clearly, the profit under a uniform pricing scheme does not change with respect to $|\beta|$. The minimum number of events below which the LSE loses profit, $N_{CPP}^{\min}$, can also easily be checked with Fig. 5. The results for $N_{CPP}^{\min}$ in a uniform pricing scheme are presented in Fig. 6, which shows that $N_{CPP}^{\min}$ increases as $|\beta|$ increases. In a CPP scheme, the reduced profit that results from ρ_{base} being less than ρ_U should be offset by the profit indexes for critical events; thus, more critical events are necessary when the profit indexes are small. In other words, $N_{CPP}^{\min}$ is large when $|\beta|$ is high because the profit index for a high $|\beta|$ is small. Consequently, the results of $N_{CPP}^{\min}$ in Fig. 6, represented by a solid line, agree with this reasoning of $N_{CPP}^{\min}$ with respect to $|\beta|$.

The profit of the LSE for the CPP with various values of N_{CPP} is compared also with another dynamic pricing of the RTP scheme. The price in the RTP scheme, denoted as $\rho_{RTP,k}$, can be expressed as [39].

$$\rho_{RTP,k} = \rho_{RTMCP,k} + \alpha_k \tag{30}$$

Table 1
Effects of the optimal peak rate and minimum interval between successive events on forecasted profit of the LSE.

Minimum event interval (hour)	Forecasted profit (million dollar)	Profit change (%)
0	28.348	−0.000
24	28.075	−0.963
48	28.075	−0.963
72	28.075	−0.963
96	28.075	−0.963
120	27.963	−1.358
144	27.891	−1.612

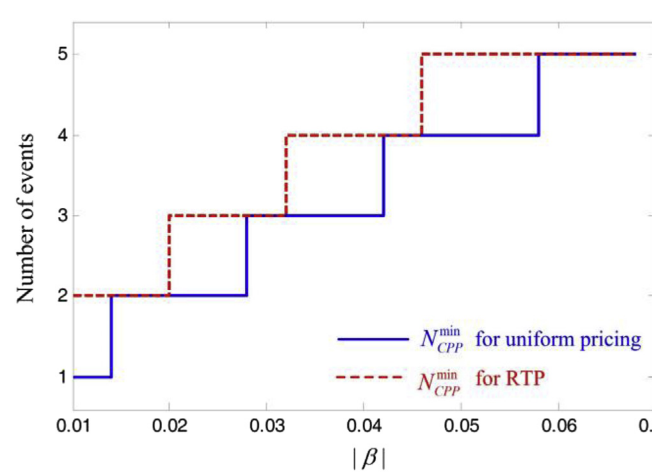

Fig. 6. Minimum number of events with respect to $|\beta|$.

where α_k is a design parameter that accounts for the objective, such as the profit of the LSE given various constraints. The profit of the LSE under the RTP scheme in (30) can be written

$$\sum_{k=1}^{N}\{R_k - C_k\} = \sum_{k=1}^{N} q_{RTP,k}(\rho_{RTP,k} - \rho_{RTMCP,k}) = \sum_{k=1}^{N} q_{RTP,k}\alpha_k \tag{31}$$

where $q_{RTP,k}$ is the demand, which is adjusted by $\rho_{RTP,k}$. Therefore, the RTP scheme completely hedges against price risk because $\rho_{RTMCP,k}$ is canceled out and α_k is a parameter that determines the profit of the LSE. Though a more sophisticated RTP scheme design based on α_k would be of great interest and importance, it is beyond the scope of this study. Consequently, a simple but reasonable RTP scheme is composed for the comparison purposes in the simulation, which is given as

$$\rho_{RTP,k} = \rho_{RTMCP,k} + \begin{cases} 70 & \text{if } \rho_{RTMCP,k} \ge \rho_U \\ 5 & \text{otherwise} \end{cases} \tag{32}$$

where $\alpha_k = 70$ and $\alpha_k = 5$ are selected such that the profit under RTP is approximately equal to that under uniform pricing for customers with $|\beta| = 0.07$. The profit of the LSE with the RTP is also shown as a dashed line in Fig. 5. It can be seen from Fig. 5 that, as intended in the design in (32), the profit with the RTP is close to the profit with the uniform pricing when $|\beta| = 0.07$. For customers with the same $|\beta|$, the profit under CPP is not necessarily greater than that under RTP, and vice versa. Nevertheless, $N_{CPP}^{\min}$ associated with the RTP can be also determined, and the results are shown by a dashed line in Fig. 6. As $|\beta|$ increases, both the profit under RTP and the profit index of the CPP decreases. Therefore, the $N_{CPP}^{\min}$ associated with RTP tends to increase as $|\beta|$ increases. In addition, the $N_{CPP}^{\min}$ for RTP is greater than that for uniform pricing because RTP is designed to yield greater profit than uniform pricing within the range of $|\beta|$ in the simulation. However, Fig. 6 demonstrates that there are some regions of $|\beta|$ in which the $N_{CPP}^{\min}$ s associated with RTP and uniform pricing are equal to each other. This occurs because $N_{CPP}^{\min}$ is a positive integer determined by a ceiling function.

In order to better understand the characteristics of CPP, the conditions under which CPP converges to uniform pricing or RTP are investigated. Without binding on the constraints, such as the maximum total event time (H_{CPP}) or the minimum interval between successive events (Δk), critical events are triggered in every time period in order to maximize the profit of the LSE; thus, the CPP scheme becomes equivalent to the uniform pricing scheme such that $\rho_U = \rho^*_{peak}$. When the constraints are imposed for the convenience of the customers, however, the CPP ceases to resemble the uniform pricing scheme. On the other hand, the CPP scheme may be equivalent to the RTP scheme regardless of the constraints. In other words, CPP is the same as the RTP when α_k in (30) is designed as follows

$$\alpha_k = \begin{cases} \rho^*_{peak} - \rho_{RTMCP,k} & \text{if } k \in OS^* \\ \rho_{base} - \rho_{RTMCP,k} & \text{otherwise} \end{cases} \tag{33}$$

However, the RTP scheme with α_k from (33) no longer completely hedges against price risk because $\rho_{RTMCP,k}$ is not canceled out. Consequently, when the RTP scheme is designed to once again hedge against price risk, its prices vary continuously with $\rho_{RTMCP,k}$, thus CPP is differentiated from RTP.

4.4. Event duration

Event duration, D_{CPP}, should be selected by considering total event hours, H_{CPP}, which reflects the degree of inconvenience that customers are willing to accept. Because D_{CPP} cannot be determined independently of N_{CPP}, the profit of the LSE should be evaluated for the combinations of D_{CPP} and N_{CPP} that satisfy the constraints on H_{CPP} in (13).

In this simulation, two scenarios are composed. The first one is to change D_{CPP} for a constant $N_{CPP} = 3$, while the other is to change both D_{CPP} and N_{CPP} for $H_{CPP} = 12$ hours. The results are presented in Table 2 for $\beta = -0.02$, confirming that profit increases as D_{CPP} rises for the constant N_{CPP}. On the contrary, profit rather tends to decrease as D_{CPP} increases even though the differences in profit level are not prominent. In other words, $(D_{CPP}, N_{CPP}) = (1,12)$ is selected as the best parameter because, under the constraint on H_{CPP}, an increase in D_{CPP} reduces the freedom to choose better parameters related to N_{CPP}. As a result, without other reasons for setting $D_{CPP} > 1$, it is desirable to set $D_{CPP} = 1$ for a specified value of H_{CPP}.

Table 2
Effects of the event duration and the number of events on the profit of the LSE.

	Event duration (hour)	Number of the events	Optimal peak rate ($/kWh)	Forecasted profit (million dollar)
Constant N_{CPP}	1	3	1.305	28.348
	2	3	1.305	31.164
	3	3	1.303	36.570
	4	3	1.302	41.806
Constant H_{CPP}	1	12	1.307	52.771
	2	6	1.306	47.439
	3	4	1.307	44.734
	4	3	1.302	41.806
	6	2	1.302	36.071

4.5. Discussion on the benefit of customers

This study focuses on maximizing profit of the LSE; however, it is important to examine the benefits of customers by the designed CPP. These benefits are directly tied to the costs that the customers face. The costs of customers with the CPP for various values of N_{CPP} are shown in Fig. 7 along with the cost under a uniform pricing scheme. Fig. 7 shows that customers who are less responsive to price changes face greater costs under a CPP scheme for all the cases where $N_{CPP} \ge N_{CPP}^{\min}$, that is, where the LSE profits more from a CPP scheme than from a uniform pricing scheme. Therefore, when customers have a small $|\beta|$, only the LSE reaps the benefits from a

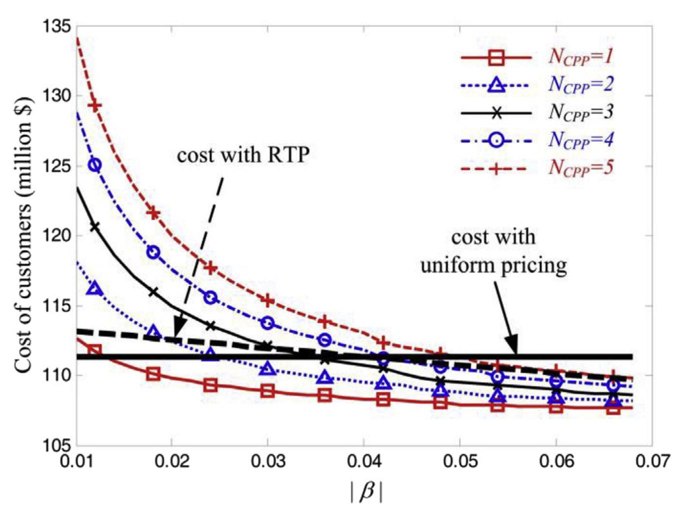

Fig. 7. Cost of the customers for various values of N_{CPP} with respect to $|\beta|$.

CPP scheme as their profits are mostly generated from increased consumer costs.

In contrast, when customers are highly responsive to price changes, the LSE may profit in two ways: one is from a decrease in demand that reduces the purchase cost of electricity and the other is from the cost that customers pay. Additionally, it is possible that customers may reduce their demand enough to actually decrease their costs even under CPP. For example, Figs. 5 and 7 show that when $|\beta| = 0.06$ and $N_{CPP} = 5$, the LSE receives \$0.8 million more in profit (CPP: \$24.85 million, uniform pricing: \$24.05 million), and customers pay \$1 million less (CPP: \$110.29 million, uniform pricing: \$111.29 million) under a CPP scheme as compared to a uniform pricing scheme. Consequently, if $|\beta|$ is sufficiently large, both the LSE and the customers may benefit from CPP.

5. Conclusion

When a CPP scheme is used by LSEs that operate in a deregulated retail sector, it should be appropriately designed to meet the profit maximization objective of such entities. An effective CPP design means selecting parameters such as peak rate, number of events, and event duration. Based on the price responsiveness of customers, how these parameters affect profit was analytically investigated in the present study, allowing us to offer the following three guidelines. First, the optimal peak rate is approximately inversely proportional to price responsiveness of customers. Second, the optimal peak rate changes little as the number of events varies. Third, the optimal peak rate when $N_{CPP} = 1$ can be safely used even when $N_{CPP} > 1$. Fourth, there exists a minimum number of events to avoid losing profit compared the uniform pricing. Finally, it is a reasonable choice to set $D_{CPP} = 1$ and $N_{CPP} = H_{CPP}$ instead of evaluating each combination of N_{CPP} and D_{CPP}. These findings were then verified by using the numerical examples.

In addition to examining the profit maximization of the LSE, we also explored the benefits that a CPP scheme would afford customers. The results showed that CPP could be advantageous to both customers and the LSE if the customers were sufficiently responsive to price fluctuations. It should be emphasized that such a win–win situation may be only achieved if the CPP scheme is properly designed; this, in turn, requires an analysis of the effects of the CPP parameters on profit and a methodology for selecting appropriate parameter values, which were presented in this study. Nevertheless, further study is needed to explore optimal response strategy of customers to a CPP scheme, including the energy management system and the control of smart appliances. Additionally, this study assumed that the LSE was a price-taker and that the change in demand in response to the peak price would not, itself, affect market prices. However, when the change in demand is synchronized, it may be significant enough to influence market prices, which would, in turn, affect the CPP. Such an interaction between the CPP and the market price would be a continuously repeating process, which should be modeled as market dynamics in the form of, e.g., differential equations. Therefore, further research is needed to establish a method for designing a CPP scheme that takes into account the unique dynamics of the market.

Acknowledgement

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