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

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ABSTRACT

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

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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