Option Valuation Applied to Implementing Demand Response via Critical Peak Pricing

Jhi-Young Joo, Sang-Ho Ahn, Yong Tae Yoon, *Member, IEEE*, and Jong-Woong Choi

Abstract--**The purpose of this paper is to examine the economic and technical perspectives of critical peak pricing plan as an active demand response(DR) program. To implement a good DR program, there are three perspectives to be considered: regulatory, economic, and technical perspectives. This paper will assume that the regulatory perspective of DR is determined as critical peak pricing(CPP) plan and examine the other two. The economic perspective of CPP plan is the incentive of the plan conductor, or the profit of an energy service provider(ESP). The technical perspective is a method to maximize the incentive of CPP plan, or an ESP's profit. An ESP should decide when to call critical peaks within certain constraints to maximize her profit. This is done by predicting the market prices and following a similar method as evaluating a swing option. The numerical example will show the optimal critical peak decisions.**

Index Terms--**power system economics, option valuation, demand response, critical peak pricing**

I. Introduction

DEMAND response(DR) is plans or actions to change electricity demand to respond to variations in electricity prices, especially by instantaneously controlling demand. Nowadays as overall demand grows higher and higher, there is more need for generation capacity. However, it is becoming more expensive to build new power plants due to environmental, political, and other reasons. Therefore, cutting or shifting demand can be a more efficient solution to balancing demand and supply than attempting to meet a high demand with limited capacity of generation. Reducing demand in real-time brings not only stability of the system but an effective use of generation facilities and energy resources.[1],[2],[3]

There are three perspectives to consider when a DR program is to be planned. First, regulatory perspective: it should be decided which program is to be implemented, and by whom in a certain kind of the electricity market structure. Second, economic perspective: what the incentive of the program conductor is, and more particularly how it is formulated mathematically. Lastly, technical perspective: how to maximize the incentive.

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This paper will discuss the economic and technical perspectives of critical peak pricing plan as a DR program. The economic incentive will be formulated as a profit equation of an energy service provider(ESP), who carries out the critical pricing plan. And to maximize the incentive of the critical peak pricing plan, a method to optimize the profit equation will be explored. It will exploit the procedure of evaluating a swing option.

II. Background: Critical Peak Pricing

A. Concept

Critical peak pricing(CPP) plan is one of the tariffs applied to end-use customers.[4],[5] Basically a day is separated into two different sections to have different price charges: peak time(e.g. 11am-6pm) and off-peak time. The price on peak time is more expensive, and it usually coincides with the time where the market prices are more expensive. In addition, CPP has a "critical peak time", which by contract applies extremely higher price than regular peak time for a very short period of time(e.g. 5 minutes). There is also a constraint on how many critical peak times an ESP can call to CPP customers within a certain period: usually 1 month. Another constraint is applied to the minimum interval(e.g. 24 hours) between two different critical peak times, which means ESP must wait for this minimum required time before calling another critical peak time. Customers are given a right to choose whether to use electricity during this critical peak time and pay this high rate, or to shut off electricity for this short period of critical peak time. The default is set to shut off electricity: if a CPP customer wants electricity not to be cut during a certain period of time, they can save the time on a device—usually attached or combined with a meter—which deals with this CPP management. This device is considered to have memory in itself to keep the time when the customer does not want electricity off during a critical peak time. When the ESP announces a critical peak and the signal reaches this device[6],[7], it will see if the time is set not to cut electricity of the customer. If it is, then the device will ignore the critical peak signal and let electricity in. If it is not to block the critical peak signal, it will cut the electricity only during the critical peak time.

B. Critical Peak Pricing Plan as Demand Response

Electricity demand is considered very inelastic with respect to price. It means that the customers are not likely to give up

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on using electricity even when the price is very high. Since the marginal cost of electricity grows much higher as supply quantity increases, supply curve of electricity has a very steep slope. Therefore, if the demand quantity is already high and it continues to grow, the speed of price increasing becomes much faster than when the demand was low.[8]

However, when customers are on a CPP plan, they will be more likely to cut their loads due to the high price and the default option. This means that customers will actually "respond" to the price change by not using electricity when the price is extremely high: only the customers that are in great need would be willing to pay the price.[9] This gives a certain degree of elasticity to electricity price, which lowers the supply-demand meeting price. And it will reduce the risk of market power by pivotal players on the supply side.

Since critical peak times happen mostly on peak-load times, or on price spikes, CPP plan also relaxes burden of power system on peak load period. In other words, cutting the peak load reduces the risk of supply-demand imbalance due to lack of supply caused by excessive demand. Therefore, CPP plan prevents the system from becoming unstable and helps maintain the adequate quality and reserve rate of the system.

Critical peak pricing plan, as an active DR program has several advantages over passive DR programs such as mandatory load curtailment programs. First, since the end-use customers had given an option for electricity tariff and basically agreed to cut the load on critical peak times, a system operator can actually cut the load without dissatisfying the end-users. Second, it gives the option not to a system operator but to the end-users, to respond to a price. End-users can buy electricity when cheap and refuse to buy it when not on critical peak times. This gives the demand more elasticity to the market as well, which brings benefits discussed in the previous section. Third, it can draw more participants to a DR program than passive ones because it gives the end-users an incentive: cheaper price.

Critical peak pricing plan has other advantages resulting from its unique strategy. With respect to elasticity of demand, it is expected to be better than real-time pricing(RTP) plan as far as customers such as residential ones are concerned. It is because most end-users cannot simply watch how the electricity price changes and decide whether to buy it or not in real-time. In this sense, CPP is more feasible for obtaining more demand elasticity than RTP.

Another important strong point of CPP plan is that it does not need a calculation of the intangible value: the amount that is under-consumed by an end-user. In many load-bidding DR programs, an operator has to check how much load a participant or end-user actually cut. This is estimated by comparing the load consumption during the program-active time with the average consumption during the same time for the last few cycles. This procedure is relatively more demanding than simply checking how much load a participant has used within a cycle of payment.

C. Conductor of Critical Peak Pricing Plan: Energy Service Provider(ESP)

The designers and providers of critical peak pricing plan, ESP's are defined as the companies that market electricity and related services, or an energy entity that provides service to a retail or end-use customer . Basically, they buy electricity from the markets or by contracts with companies related, and sell it to end-use customers expecting profit. They can either make bilateral contracts with GenCo(generation company)'s and TransCo(transmission company)'s, or make bids in a day-ahead or real-time market to buy the demand they need. To have the purchased electricity reach the end-use customers, ESP's pay network charge to DisCo(distribution company)'s. The overall structure of this procedure from the perspective of an ESP is illustrated in Fig. 1.

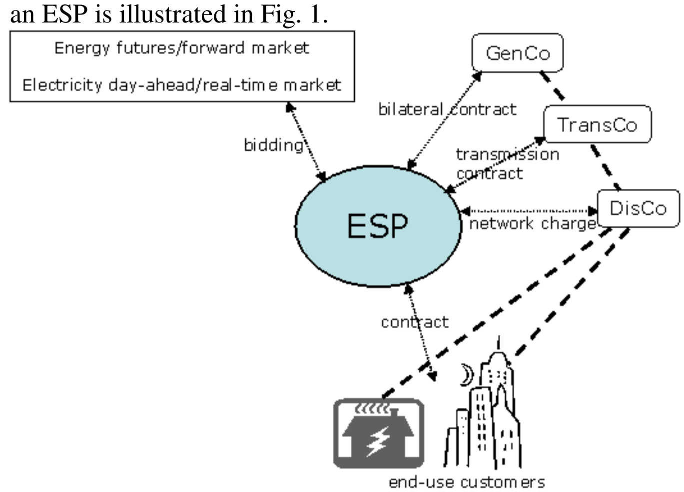

Fig. 1. Overview of the market structure on ESP's perspective.

The purpose of an ESP's business is to make the maximum profit. The ESP will try to make profit also through critical peak pricing plan. Therefore, the incentive of critical peak pricing plan is the ESP's profit through critical peak pricing plan, which will be formulated in the next chapter.

III. Economic Perspective: Formulation

In this chapter, an equation to estimate how profitable critical peak pricing plan will be to an ESP is established. Assuming that the billing period is one month(30 days), the total profit by CPP customers can be formulated as follows. The meanings of the variables defined and notations are shown in Table I.

$$\pi = \sum_{n=d_j}^{N_{CP}} R_{d_j} - \sum_{k=1}^{24\times 30} \rho^{DA}[k]\cdot Q_{mkt}[k] - \sum_{t=1}^{12\times 24\times 30} \rho^{RT}(t)\cdot Q_{mkt}(t) \qquad (1)$$

$$\text{where} \quad R_{d_j} = \sum_{k=1}^{24\times 30} \rho^{non-CP}[k]\cdot Q_{d_j}[k] + \sum_{t=1}^{12\times 24\times 30} \rho^{CP}\cdot Q_{d_j}(t)$$

The following are the assumptions made for the profit equation.

1. The billing period is 1 month, or 30 days.
2. Every variable is defined within one period.
3. The real-time market is run by 5 minutes, and the day-ahead market by 1 hour.

4. The prices on non-critical peak times are paid by an hour, and the price on critical peak times by 5 minutes.

TABLE I
VARIABLES AND NOTATIONS USED IN THE PROFIT EQUATION

k	time on day-ahead market (unit: 1 hour)
t	time on real-time market (unit: 5 minutes)
d_j	index for a critical peak pricing customer (demand)
Q_{mkt}	quantity an ESP bought from a market
Q_{d_j}	quantity of electricity demand by customer d_j
R_{d_j}	revenue from customer d_j
u_t	1 if a critical peak signal called by ESP at time t 0 otherwise
τ_i	time when i th critical peak signal is called
N_{CPP}	number of critical peak pricing customers
$\rho^{DA}[k]$	electricity price of day-ahead market
$\rho^{RT}(t)$	electricity price of real-time market
ρ^{CP}	price of critical peak pricing for critical peak times
ρ^{non-CP}	price of critical peak pricing for non-critical-peak times
$N_{\max}$	maximum number of critical peaks allowed
Δt_R	minimum interval allowed between two consecutive critical peaks (refraction period)

The objective is to maximize the profit, which is expressed in (1). Critical peak pricing plan has constraints on the number of critical peak calls by ESP and the interval between two consecutive critical peaks. These work as constraints of the problem of maximizing the objective function: profit. Therefore, the problem can be formulated as follows:

$$\max \ \pi = \sum_{n=d_j}^{N_{CPP}} R_{d_j} - \sum_{k=1}^{24\times 30} \rho^{DA}[k]\cdot Q_{mkt}[k] - \sum_{t=1}^{12\times 24\times 30} \rho^{RT}(t)\cdot Q_{mkt}(t)$$

$$\text{subject to} \quad 0 \le \sum_{t=1}^{12\times 24\times 30} x_t \le N_{\max}$$

$$\tau_{i+1} - \tau_i \ge \Delta t_R \quad \text{for} \quad 0 \le i \le N_{\max} - 1$$

N_{CPP}, ρ^{CP}, ρ^{non-CP}, $N_{\max}$, and Δt_R are the values that are defined in or can be obtained from a contract between an ESP and customers. $\rho^{DA}[k]$ and $\rho^{RT}(t)$ mean prices that an ESP pays for electricity that she buys from a day-ahead and real-time market respectively.

IV. TECHNICAL PERSPECTIVE: METHODOLOGY

The technical perspective of CPP plan implies a method to maximize the economic perspective, or an ESP's profit. According to the profit equation of an ESP obtained before, we find out that an ESP should know when to call critical peaks to maximize her profit given the market prices. This requires a good prediction of market prices followed by a critical peak decision based on the prices predicted. This paper will explore methods to predict the market price effectively and make critical peak decisions based on these prices.

A. Price prediction

There are certain factors which decide the electricity prices such as temperature and meteorological influences, demand, etc. In this study, price prediction is based on demand, or load.

The relationship between price and load from historical data is obtained to forecast market prices in the future. Therefore, load and price data on the same period of time in a certain area is collected to find the relationship. Least-squares estimation[10] was used to define it, and forecasted load data is applied to this relationship to predict the corresponding prices. While obtaining a certain deterministic relationship between load and price, the randomness of the prices must be taken into consideration as well.[11] To see how volatile the prices will change, the price prediction will be based on three methods widely used to predict variable prices in financial engineering: random walk, mean reversion, and jump diffusion with mean reversion(simply denoted as 'jump diffusion' in this thesis) methods.

1) Price-load relationship

When least-squares estimation applied, load and logarithm of price shows a good fit to a first-order polynomial function. It is noticeable that real-time market price deviates from the regression line more than day-ahead market price, as can be expected.

From this relationship, we can formulate a general load and price relationship equation[12],

$$\ln \rho_n = aL_n + b$$

where ρ_n and L_n denote the price and load at time step n respectively, a the slope of the regression line from the load-price relationship, and b the intercept of the line.(Fig. 2.)

2) Price process with randomness

Basically, price prediction is estimating a time-varying random variable having a tendency and randomness together. This trait of variable price can be well represented by a generalized Wiener process[13]. A random variable x which follows a generalized Wiener process over time variable can be defined as

$$dx = a'\,dt + b'\,dz \qquad (2)$$

where x is a variable which follows a Wiener process and a', b' constants. Here the constant a' can be interpreted as the tendency, or the drift of the price. And by one of the properties of a Wiener process, $\Delta z = \varepsilon\sqrt{\Delta t}$ for a small period of time Δt where ε has a standardized normal distribution with mean 0 and standard deviation 1.

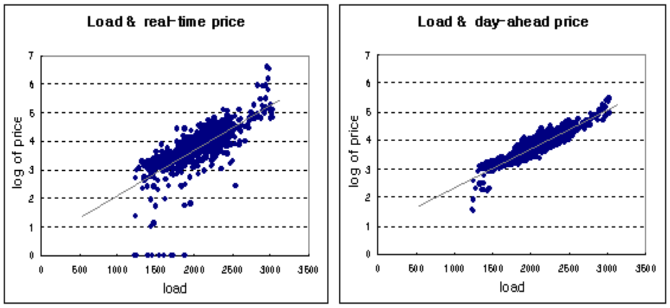

Fig. 2. Load and real-time market/day-ahead market relationship. (August 2006 load and day-ahead, real-time price data from PJM [14])

Although the Brownian motion model could fairly well reflect how the price evolves, other various models were developed to compensate for the flaws of the generalized Wiener process model. Noting the property of the evolution of a price that it eventually reverts to a certain point or range after some drift and randomness, a mean-reversion model was developed. And to include the effect of price spikes that occasionally occur especially in energy markets such as electricity, jump diffusion model is more efficient. The equations of these three different models will be explained in detail in the next section. The meanings of the variables and notations used in the equations can be referred to in Table II.

TABLE II
VARIABLES AND NOTATIONS USED IN THE PRICE PROCESS EQUATIONS

ρ_n	price at time step n
L_n	load at time step n
a	slope of the least-squares estimation on load and logarithmic price
σ	volatility; error degree of the linear regression on load and logarithmic price
Δt	interval of the time step (1 hour)
α	mean reversion rate
l	long run mean
η	indicator variable on price spike (1: spike, 0: not spike)
κ	multiplier of "mean-of-spike-size" with respect to average non-spike price size
δ	standard deviation of price spike size

a) Random walk model

A random walk model is simply a Brownian motion or a Wiener process model. Price evolution model can be decomposed into a drift component and a random component as explained earlier in (2).

To include the effect of load on price determination, however, deterministic price prediction value will be first obtained. From the relationship of the price and load, we can get deterministic value of the price at time n, ρ_n from the values of load and price from the previous time step $n-1$, L_{n-1} and ρ_{n-1} respectively and predicted load L_n. If we subtract two equations of load-price relationship with only different time steps $\ln\rho_n = aL_n + b$ and $\ln\rho_{n-1} = aL_{n-1} + b$, we obtain

$$\ln\rho_n = \ln\rho_{n-1} + a(L_n - L_{n-1})$$

where the intercept of the linear regression b will be. Now the random component $\sigma\sqrt{\Delta t}$ is added to complete the random walk model including the randomness of the price.

$$\ln\rho_n = \ln\rho_{n-1} + a(L_n - L_{n-1}) + \sigma\sqrt{\Delta t}$$

b) Mean reversion model

A mean reversion model generally determines a drift by mean reversion rate and long run mean[15]. In this study, the model basically follows a random walk process, and the mean reversion component is simply added to the whole random walk process in order to maintain the load effect in the drift component. This yields the mean reversion model equation

$$\ln\rho_n = \ln\rho_{n-1} + a(L_n - L_{n-1}) + \alpha(L_n - L_{n-1}) + \sigma\sqrt{\Delta t}\ .$$

A long run mean, or mean reversion level is a value where the evolving price reaches in the long run, as the name implies. It is calculated as an intercept estimate of the linear regression of two price value groups: a price at a time step and the corresponding price change from the previous step, divided by the mean reversion rate. A mean reversion rate, or mean reversion speed indicates how quickly the price reverts to the long run mean. It is mathematically defined as the negative of the slope obtained from the regression line of a price at a time step and the corresponding price change from the previous step[15].

c) Jump diffusion model

Jump diffusion model takes price spikes into consideration for price prediction[16]. In this study, price spike components are added to a mean reversion process. Therefore, it gives a mean-reversion jump diffusion process which is defined as

$$\ln\rho_n = \ln\rho_{n-1} + a(L_n - L_{n-1}) + \alpha(L_n - L_{n-1}) + \sigma\sqrt{\Delta t} + \eta(E[\ln\rho_{n-1}](\kappa + \delta))$$
.

It is determined by a jump frequency and a jump size respectively whether the current price will have a spike and how high the spike will be if it does. And these spike parameters are obtained from historical price data. With a criteria of a 'spike' defined beforehand—e.g. prices straying over 5 times a standard deviation from the mean, we sift through the whole historical price data to find out the spikes. Jump frequency simply becomes the number of the prices classified as spikes divided by the total number of prices in the data. For jump size parameters, mean and standard deviation of the spikes are calculated and standardized with respect to the mean of non-spike prices or the total prices.

To implement jump instances according with the jump frequency in a program code, a random variable having a value between 0 and 1 with a uniform distribution can be generated. And if the variable randomly generated is less than or equal to the jump frequency, it can be regarded as a jump instance.

B. Swing option methodology

A swing option is a kind of an exotic option that is used in energy markets. Its value depends on the trade quantity of energy, which must be between a minimum and maximum level. Also, there is usually a limit on the number of times the option holder can change the rate at which the energy is consumed, and a limit on the time interval between consecutive exercises of options. Therefore, the option holder must make most profitable decisions on when to exercise the options within these limits.

The problem of a swing option holder to decide when to exercise options is analogous to that of an ESP to decide when a critical peak time should be called. As described in Section 2.3, a CPP plan includes limits on the maximum number of critical peak times and on the minimum time interval between two consecutive critical peak times—named as ‘refraction period’ in this thesis, as in a swing option problem. Therefore, a problem of an ESP deciding on when to call critical peak decisions can be solved in a way that a swing option valuation problem is solved. The two problems are also similar in the sense that they both have to predict the value of the product related ahead of time to make decisions in a longer run. And the three price process methods can be utilized to predict the price of electricity. The overall procedure of making critical peak decisions is shown in Fig. 3.

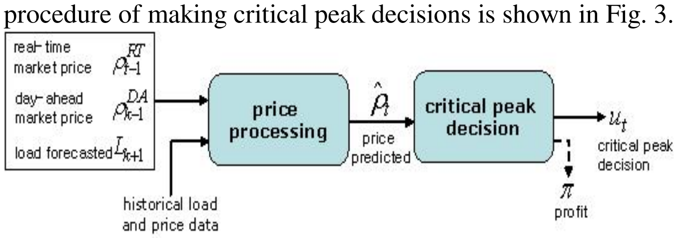

Fig. 3. Overall procedure of making critical peak decisions

Swing options can be priced through a so-called “binomial/trinomial forest”, which is a multi-layer tree extension of the traditional binomial/trinomial tree dynamic-programming approach.[17] In a problem of swing options valuation, the dynamic programming procedure starts from the expiration date of the options and works backward in time to value the instrument in three dimensions: price; number of exercise rights left; and usage level of the commodity traded. However, in a critical peak decision problem, it is excluded since a critical peak only has a choice of on or off. The dynamic programming thus should be solved in only two dimensions: price and number of call rights left.

Each layer of a binomial forest for a critical peak decision problem represents a number of call rights left which is denoted by s. The dots—different prices are lined up in a column which represents a time step. Here, the prices are evolving through the solid lines on the same layer, and there are two possibilities of how price may evolve: up or down. When a critical peak is called, the price evolves in the same way but only with the layer changed. This procedure is drawn by partially dotted lines connecting the prices on the different layers. At each node, the state—price and number of call rights left combined determines the profit of an ESP as a swing option’s value is determined. As the forest is completed with every possible layer, price, and time step, the dynamic programming can be started from the last time step on the bottom layer(with $s = 0$), estimating the profit at each price node and working backward to find the optimal, or most profitable path. This will lead to an optimal decision of critical peak calls on a period.

V. Numerical Example

In this chapter, an example is simulated based on the methods explored so far. Using a sample of historical data of price and load, prices are predicted in three different ways: random walk, mean reversion, and jump diffusion method. Using these data and swing option methodology, a critical peak decision problem is solved.

Load and price(real-time and day-ahead) data for August, 2006 in an area denoted as DUQ are obtained from PJM website, which are used as the input data.[14]

A. Price processes

The overall procedure of price process by three different methods are discussed in the last chapter. From a linear regression of historical price and load data, drift and volatility are obtained which are used in all of the three methods. A long run mean and a mean reversion rate for mean reversion process, and a jump frequency and size for jump diffusion process are obtained from the historical data as well. With all these parameters and forecasted load data in addition, three different price evolution forms are obtained from each of the processes.

Drifts and volatilities obtained from real-time and day-ahead data from the linear regression of the load and logarithm of price are shown in Table III, and the regression graph which was shown before is in Fig. 2.; the regression lines are expressed as solid gray lines. These parameters are used in all of the three processes. As can be expected, the drift and volatility from real-time prices are higher than those of day-ahead data. Especially, the volatility is very high, which can be inferred from the linear regression plots as well. This will give very different results for price predictions, as will be shown shortly.

B. Critical peak decision

For critical peak decision, the price predicted by the three methods will be used as an input. Then the swing option methodology explored in the previous chapter will be used to decide the optimal critical peak call points. The price predicted will be exactly the nodes on the swing forest, and each node will incur its own profit, which is determined by the price on the nodes and whether a critical peak call is available regarding the constraints.

TABLE III
REGRESSION PARAMETERS OF PRICE PROCESSES

parameter / *price*	slope	volatility

real-time	0.0075	0.2767
day-ahead	0.0014	0.0067

To recall the swing option evaluation method, a value of a plain option at a particular time is determined as either the value or the price of the commodity at the time subtracted by the strike price if positive, or 0 if not. In this example, the break-even point of critical peak profit analogous to the strike price is set at the initial price. If the price goes higher than the initial price, its value is positive and otherwise, zero. Then at each price node, the value of the option or the profit is easily calculated. Starting from the last time step, the value of each node is calculated and is added up with its probability to every possible node connected in the previous time step. When there are multiple branches which means choices from a node, the optimal one(s) is(are) selected as the optimum so far, and the procedure continues until it reaches the first time step.

This example is solved as a problem with a period of one month, or 31 days from the historical data used in price process. The time unit is one hour, thus there are in total 744 time steps for the problem. Prices predicted are discretized in 5 nodes for one decision. Decisions are denoted as Y or N meaning a critical peak signal on or off respectively. The refraction period is 24 (hours) and the number of maximum call rights is 3, which means an ESP can call at most 3 critical peak times and the two consecutive calls should be at least 24 hours apart from each other.

The state variable has to be a combination of three individual variables: number of possible call rights, hours remained to be able to call the next critical peak, and price, denoted by x_i, x_t, and ρ. Since x_i and x_t are related with each other, possible combinations (x_t, x_i) can be written as in Fig. 4. The total number of the state variable combinations can be formulated as $(N_{\max} - 1) \times \Delta t_R + 2$, and the value is 50 in this case. The first state variable x_t of the combination at the bottom is 1 but it does not actually mean the time remained for the next critical peak time is 1 hour since all the possible call rights are used up($x_i = 0$). The reason why it is given 1 is merely due to convenience in programming and it can rather be considered as a dummy notation.

Solving the backward dynamic programming, the solution of whether to exercise the critical peak is obtained. And by the prices predicted, an ESP can see approximately when to exercise the next critical peak right since a critical peak time exercised at a higher price will apparently profit more. The swing option algorithm is set up and simulated for the three price process methods based on the most probable single price on each time step. The results are shown in Fig. 5., 6., and 7. with the prices predicted expressed as smooth curves and the critical peak calls as bullets on solid lines. These coincide with the inference that the critical peaks will be the most profitable on the highest prices. The expected profits are 163.77, 123.14, 529.96 for random walk, mean reversion, and jump diffusion respectively.

Although the result is given for the whole one month, this will not be permanent throughout the month. As the real-time market price data continuously becomes updated, these price values can be taken as the input when solving the critical peak decision problem. Therefore, the ESP would solve a critical peak decision problem at the beginning of a month, and keep updating the new price data until the end of the month. The window of the calculation will continue to decrease within the same month since the profit-making period is given as a month.

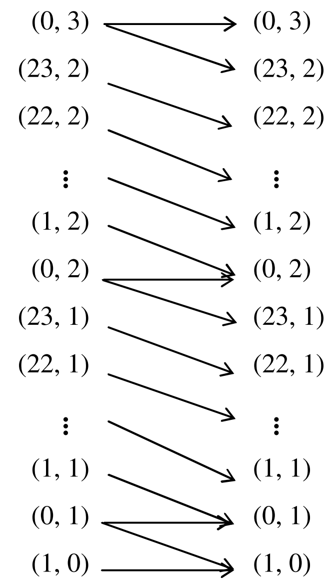

Fig. 4. State variables of a critical peak decision example

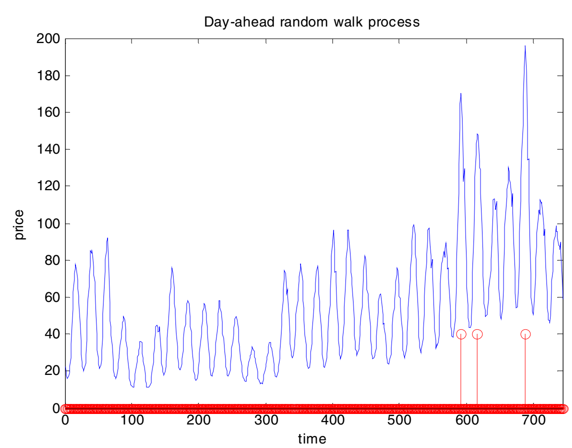

Fig. 5. Critical peak decision with random walk process ($a = 0.0014, \sigma = 0.0668$)

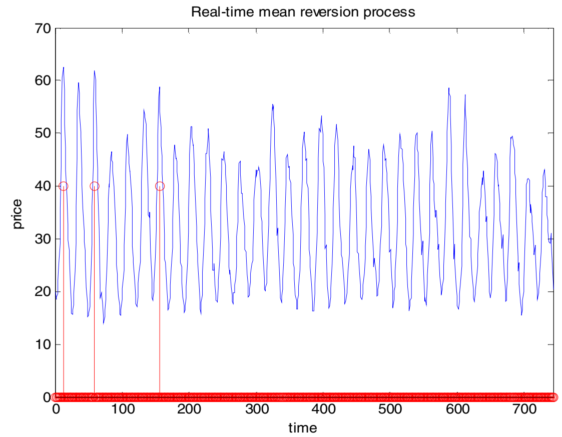

Fig. 6. Critical peak decision with mean reversion process ($a = 0.0016, \sigma = 0.277, l = 39.187, \alpha = 0.257$)

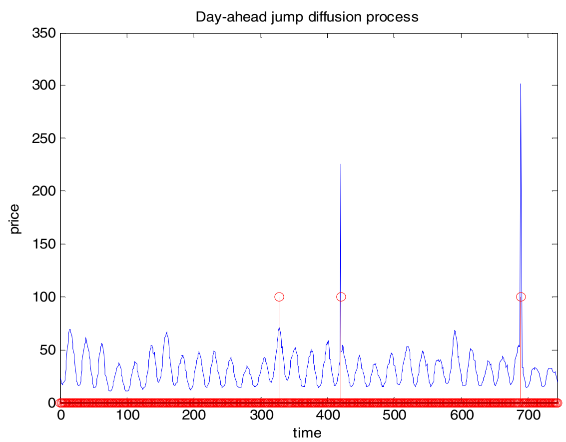

Fig. 7. Critical peak decision with jump diffusion process ($a = 0.0014, \sigma = 0.0668, l = 39.620, \alpha = 0.0461$ and jump frequency 0.0054, mean of jump size 4.723)

VI. Conclusion

This paper mainly discussed the two perspectives on demand response program: critical peak pricing(CPP) plan. On an economic perspective, the incentive of a critical peak pricing plan will be the profit of an energy service provider(ESP). To technically maximize this incentive of CPP plan, we explored a method to optimize the profit equation of an ESP. Through three different price processing methods to predict market prices and a method similar to that of evaluating a swing option, we could get a decision on whether to call a critical peak signal to end-use customers. It also turned out that the profit-maximizing time points for an ESP were the points where the price is expected to rise the highest.

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VIII. Biographies

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Yong Tae Yoon was born in Korea on April 20, 1971. He received his B.S. degree, M.Eng. and Ph.D. degrees from M.I.T., USA in 1995, 1997, and 2001, respectively. Currently, he is an Assistant Professor in the School of Electrical Engineering and Computer Science at Seoul National University, Korea. His special field of interest includes electric power network economics, power system reliability, and the incentive regulation of independent transmission companies.

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