Title

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Environmental Energy Technologies Division

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(Submitted to Energy Journal: November 2, 2003)

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Acronyms and Abbreviations

Btu	British Thermal Unit
CERTS	Consortium of Electricity Reliability Technology Solutions
DCF	Discounted Cash Flow
DG	Distributed Generation
DR	Demand Response
Dt	Dekatherm
EIA	Energy Information Administration
EMCS	Energy Management Control Systems
EMM	Electricity Market Module
GBM	Geometric Brownian Motion
HR	Heat Rate
HVAC	Heating, Ventilation, and Air Conditioning
ISO	Independent System Operator
I/C	Interruptible/Curtailable
kWh	Kilowatt-hour
LBNL	Lawrence Berkeley National Laboratory
MW	Megawatt
MWh	Megawatt-hour
NEMS	National Energy Modeling System
NYISO	New York Independent System Operator
O&M	Operations and Maintenance
OTC	Over-the-counter
RTP	Real-time Prices
TES	Thermal Energy Storage

Abstract

As electricity markets deregulate and energy tariffs increasingly expose customers to commodity price volatility, it is difficult for energy consumers to assess the economic value of investments in technologies that manage electricity demand in response to changing energy prices. The key uncertainties in evaluating the economics of demand-response technologies are the level and volatility of future wholesale energy prices. In this paper, we demonstrate that financial engineering methodologies originally developed for pricing equity and commodity derivatives (e.g., futures, swaps, options) can be used to estimate the value of demand-response technologies. We adapt models used to value energy options and assets to value three common demand-response strategies: load curtailment, load shifting or displacement, and short-term fuel substitution—specifically, distributed generation. These option models represent an improvement to traditional discounted cash flow methods for assessing the relative merits of demand-side technology investments in restructured electricity markets.

1. Introduction

The restructuring of the U.S. electricity markets has created new opportunities for customers to partner with utilities or retail energy suppliers to alter their demand in response to electric system reliability needs or high prices. There are significant benefits to the electric system if customers are willing to curtail their loads and/or be dispatched by independent system operators (ISO) or utilities during emergencies or high price situations (Boisvert and Neenan 2003; Borentein et al. 2002; Neenan et al. 2003).[1] Consumer participation in wholesale energy markets tends to increase electricity system reliability, reduce price volatility, and lower average electricity prices paid by consumers.

In order to increase the price elasticity of market demand, an increasing number of large industrial or commercial electricity customers are being exposed to real-time prices (RTP) in their default service tariff rates offered by utilities, particularly in states that have adopted retail competition (e.g., New Jersey, Maryland, New York). A number of utilities also offer optional RTP-based tariffs targeted at larger customers. In addition, ISOs and many utilities are implementing demand response (DR) programs in which customers bid load curtailments into day-ahead or real-time markets.[2] Under such programs and tariffs, customers experience the variability of wholesale market prices. This trend is highlighted in Table 1, where key features of ISO demand response programs and utility RTP tariffs are summarized. These programs or tariffs are typically targeted to large industrial or commercial customers through various program requirements (e.g., customers must have interval meters) or size thresholds (e.g., minimum summer peak demand of 500 kW).

Customers that want to take advantage of these programs and tariffs can achieve demand response through various strategies: (1) load curtailment, in which customers reduce discretionary energy demand during periods with high electricity prices; (2) load displacement, in which peak-hour electricity use is shifted to off-peak hours; or (3) short-term fuel substitution that includes distributed generation (DG) or end use technologies that substitute natural gas for electricity (e.g., dual-fuel chillers).

When evaluating these DR strategies, two simplified discounted cash flow methods are often used by energy consultants and practitioners. In the first method, benefits are estimated using a long-term forecast of future prices, which does not account for the stochastic variability of these prices. This approach tends to underestimate the value of demand responsiveness because of the static view of future prices. In the second method, benefits are estimated using historical hourly or daily prices; this captures price variability but does not incorporate market information about the future (including forward and option prices). Depending on the period of historical data that is used, one gets a wide range of values for the same DR strategy.

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[1] Since the late 1980s, many utilities have offered interruptible/curtailable (I/C) rates to large customers with low outage costs, in an attempt to defer capacity expansion and decrease emergency power pool purchases. See Woo and Pupp (1992) for a summary of approaches used to estimate the costs of service disruptions to electricity consumers.

[2] If the customer's bid price is lower than a competing generation resource, the ISO or utility schedules the load curtailment and the customer is paid for their curtailment at a specified price (e.g., the higher of their bid price or the locational market clearing price).

Table 1. "Economic" demand response and real time pricing (RTP) programs

Administrator	Number of Customers	Subscribed Demand Response Potential (MW)	Notice
ISO DR Programs			
New York ISO Day-Ahead Demand Response Program	~25	200	Day-ahead
ISO-New England Real Time Price Response Program [a]	~150	111	Day-ahead to several hours in advance
PJM Economic Load Response Program [b]	221	711	Day-ahead (Day-Ahead Program) or same-day (Real-Time Program)
Selected Utility DR Programs [c]			
Ameren Customer Energy Exchange	126	272	Same day
BPA Demand Exchange Pilot	18	395	Two days ahead to same-day
Cinergy Power Share Program	731	603	Day-ahead (call option), or one hour ahead (quote option)
Commonwealth Edison	3000	540	One-hour ahead
Kansas City Power and Light Voluntary Load Reduction Program	143	107	None
Pacificorp Energy Exchange Program	380	350	Day-ahead
Portland General Electric Buyback Program	26	230	Day-ahead
Selected RTP Programs [e]			
Alliant (Interstate Power & Light – Iowa)	21	79	Day-ahead
American Electric Power (Public Service Company of Oklahoma)	41	400	Day-ahead
Central and Southwest Corporation	43	NA	Day-ahead
Cinergy	140	NA	Day-ahead
Duke Power [d]	53	600 [d]	Day-ahead
FirstEnergy	45	100-200	Day-ahead
Georgia Power	~1650	~5000	Day-ahead and hour-ahead options
Niagara Mohawk	150	~550	Day-Ahead
Pacific Gas & Electric	~45	~100	Same day 10 am
Pennsylvania Power & Light	12	75	Day-ahead
Progress Energy	85	NA	Day-ahead

a. ISO New England Load Response Statistics
b. PJM Demand Response Working Group
c. Goldman et al. 2002
d. Schwarz et al. 2002
e. Barbose et al. 2004

A more comprehensive approach is to view the operational decisions involved in curtailment, load shifting, and fuel-substitution as real options. On any given day or in any given hour, a facility operator or manager has the *right* but not the *obligation* to alter the operating schedule for loads. Thus, the value of the option to choose to alter demand can be established using methodologies designed for evaluating options in financial and energy markets. Option pricing methodologies were originally developed for the equity and commodity markets and later applied to stock indices, currencies, and futures contracts (for example, see Hull 1997). As energy markets – first natural gas and then electricity – were restructured, many energy-trading companies began offering options on energy commodities. As a result of this new activity, option valuation methodologies customized for energy markets were developed (see Kaminski et. al. 1999 and Clewlow and Strickland 2000). A key complication in evaluating options in electricity markets is that electricity, unlike other commodities, cannot be stored.

Analysis of generation and transmission project investments has demonstrated the accuracy of these customized option valuation techniques for electricity markets. Deng et. al. (2001) and Hsu (1998) show that a generating asset can be viewed as a strip of natural gas/electricity spread options. Deng et al. (2001) also demonstrate that transmission assets can be modeled as a strip of spread options on locational electricity prices. These analyses assume that an individual market participant cannot alter the market prices. Keppo and Lu (2003) derive a real option model for a large generator making optimal investment decisions in an environment where the investor can alter market prices. In our analysis, we assume that demand-side participants are small and market prices are not affected by their actions.

In this article, we demonstrate that similar techniques can be used to value demand response capability. Our main objective is to present analytic methods that end-users can use to evaluate the benefits of participating in day-ahead and real-time energy markets either through RTP tariffs or DR programs and assess alternative demand-side technology investments under different pricing and operating regimes. We assume that in the future an increasing number of large end users will be exposed to RTP either in their retail tariffs or through DR programs administered by ISOs or utilities. Thus, we do not focus on assessing the societal benefits of RTP or on specific DR or RTP tariff design issues, which have been analyzed conceptually by others Boisvert and Neenan 2003; Borentein et al. 2002; Braithwait 2003). Chao et al. (1986), Chao and Wilson (1987), and Kamat and Oren (2002) discuss issues related to the design and valuation of demand response tariffs, such as interruptible rates.[3]

Our examples focus on end users that have the metering and communications capability to observe day-ahead market hourly prices and decide at that point either to take action the next day or not. The actions involve load shifts or curtailments during on-peak hours. Specific examples could include increasing space cooling temperature set-points by a few degrees, reducing lighting levels by 10%, shifting production to off-peak hours, stopping production for the day, operating thermal energy storage overnight for use the next day, and running micro-turbine generators the next day.

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[3] Chao et al. (1986) develop a customer value model for both the supplier and consumer for selecting optimal pricing structures, specifically, interruptible-type service. Kamat and Oren (2002) present the design and pricing for both supply and procurement of interruptible electricity service.

The remainder of this article is organized as follows. In the next section, we describe the approach used to construct a forward view of energy prices and interest rates. This view includes forward curves for electricity (on-peak and off-peak) and natural gas prices, the volatility term structure for these prices, and the correlation between these prices. In section three, we describe options models used to assess and value three DR strategies (load curtailment, load shifting, and fuel substitution) and present results from stylized examples. These examples demonstrate how options modeling approaches can help customers and load aggregators assess the potential benefits of operating and/or investing in technologies that facilitate demand response. For the evaluation of the fuel substitution strategy, we demonstrate the benefits of using options valuation methods over traditional discounted cash flow methods. In section four, we summarize key findings and suggest areas in which these modeling techniques could be improved in order to create enhanced decision support tools both for customer operations optimization and investment analysis.

2. Constructing a Forward View of Energy Prices and Interest Rates

In this section, we describe the key financial components used in our options-valuation models: forward curves of energy prices, price volatility, correlation between prices, and interest rates. To build these views of future financial conditions, we use data from Energy Information Agency (EIA) forecasts, wholesale prices from the New York Independent System Operator (NYISO), and Gas Daily price index for natural gas. We locate our illustrative case study in New York because the state has developed programs that use the two demand participation mechanisms of interest for our analysis – real-time pricing tariffs and demand bidding in wholesale electricity markets.

2.1 Energy Price Forward Curves

Private investors develop forward curves of energy prices, typically drawing upon the futures and forward prices of power and natural gas traded in liquid markets.[4] The near-term of a forward curve is built based on futures prices traded in financial exchanges. For the mid-term (18 months to about five years), over-the-counter (OTC) market prices, which are available from brokers and traders, are often used. Generation expansion and dispatch models are typically used to forecast prices far into the future. The forward curves used in our analysis represent the price that would be established today to provide electricity or natural gas at a designated future date.

We rely on a simplified approach to model future electric price levels, using only publicly available data sources based upon prices from the EIA Annual Energy Outlook 2002 (2001).[5] We use EIA forecasts of spot prices as if they were forward prices.[6] Because the standard data sets published by the EIA do not list on-peak and off-peak electricity prices separately, we obtained wholesale spot price forecasts from Aniti (2002) and used them to derive on-peak and off-peak price forecasts for the New York region, as shown in Figure 1.[7]

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[4] Natural gas and electricity contracts are traded in the New York Mercantile Exchange. Gas contracts are liquid up to 3 years and electricity contracts are liquid up to 18 months.

[5] Methods based on futures and forward contract prices are the preferred approach to develop forward curves of energy prices. Note that the results based on commercially available or EIA models are forecasts of future spot prices. Forward prices tend to be different from future spot prices when natural buyers and natural sellers are not evenly distributed. We assume that the simulated spot prices are unbiased estimators of forward prices in our analysis.

[6] The forecast of electricity prices is a key input assumption for computing the option values. The EIA prices used in this analysis simply serve as an example. In real life, customers must have access to simple methods of forecasting prices. Other approaches for constructing forward curves in electricity markets are described in Fleten and Lemming (2003); Avsar and Goss (2001); Bessembinder and Lemmon (2002) and Woo, Olson, and Orans (2004) analyze electricity market forward curves and discuss their limitations.

[7] These forecasts came from the National Energy Modeling System (NEMS) Electricity Fuel Dispatching sub-module of the Electricity Markets Module (EMM). EMM represents hourly electricity demand as 18 separate load duration curves corresponding to six seasons (January/February, December/March, April/May, June/September, July/August, and October/November); each season is divided into daytime, nighttime, and shoulder "intra-day" periods. This treatment of demand means that, for each region, dispatch and prices are determined only for the 18 designated periods, and the hourly detail is lost. However, it is possible to develop price duration curves for each season and intra-day period, from which on-peak and off-peak prices are calculated by region and month (period).

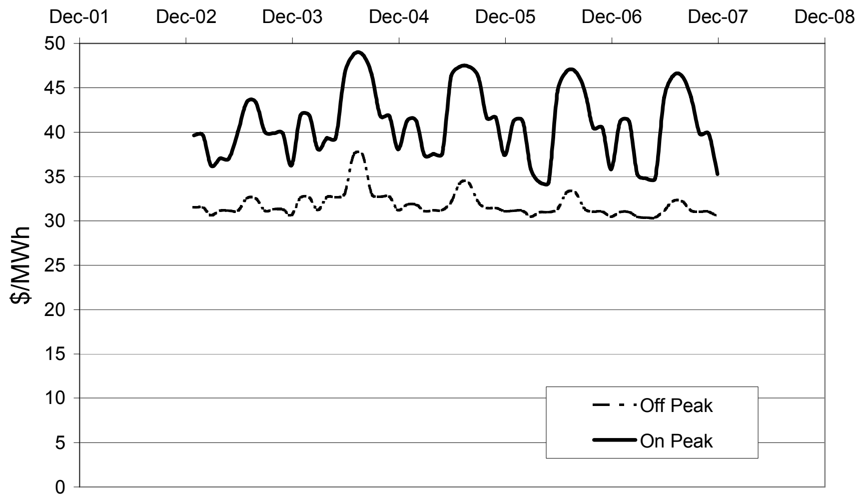

Figure 1. Power Price Forward View

The wholesale electricity prices shown in Figure 1 include marginal energy costs, reliability costs and taxes that are considered variable. In states with retail competition where utility rates have been unbundled, end users also pay rates set by tariff to the regulated local utility for distribution service charges, and possibly surcharges that recover costs associated with the transition to retail competition (e.g., "competitive transition charges") or support "public benefit" programs. These regulated charges often represent a significant portion of the total cost that customers pay for electricity (e.g., 30-50%) and are typically passed onto customers as a customer or demand charge. In our analysis, we include only the variable portion of electricity prices in evaluating demand-response investments, rather than the fixed rate charge elements. For utilities that utilize bundled tariffs that do not separate transmission and distribution costs from variable cost of electric commodity service, the methodologies described here could be used, with modifications to forward curves, volatilities, and strike prices.

Our gas forward price view, shown in Figure 2, is derived from the 2002 New York State Energy Plan (2002). These prices are for Transco Zone 6 and can be viewed as city-gate prices for the utility, which do not include gas utility system distribution charges. Treatment of distribution charges in modeling will be covered later in Section 3.3.

2.2 Volatility and Correlation

Volatility of energy prices is another major component in our option valuation models. Volatility is a measure of price variability; the exact definition depends on the specific options model. However, several features of volatilities that are common to the three models are described in this section. Correlations between different price streams are a measure of how closely these prices track each other and are needed in cases where more than one price stream is relevant to the evaluation of a DR strategy.

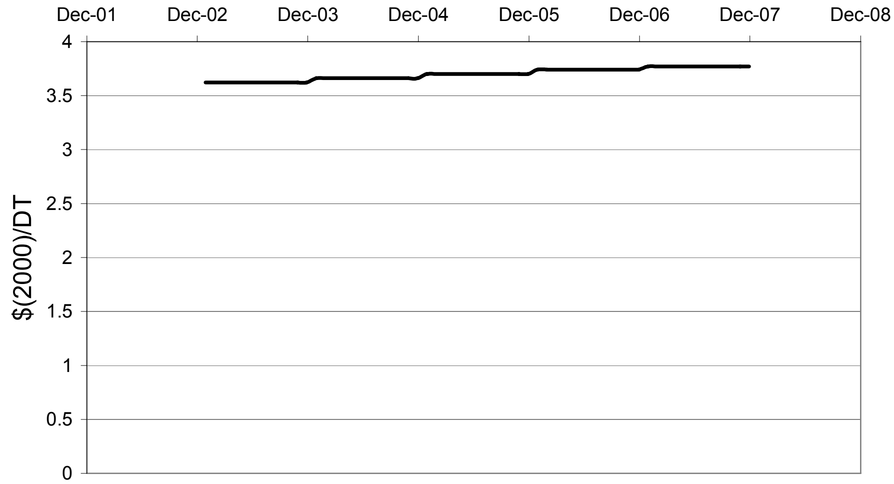

Figure 2. Natural Gas Price Forward View

Volatility, unlike price, is not directly observable in the market. It needs to be derived from prices that can be observed in the market. The most obvious sources of data for characterization of volatility are historical spot prices. We estimate future volatilities of and correlations between spot prices using historical price data for the New York Region. Figure 3 shows historical day-ahead on-peak market electricity prices for New York City as obtained from the NYISO, while Figure 4 shows historical gas prices in the New York area as obtained from Gas Daily.

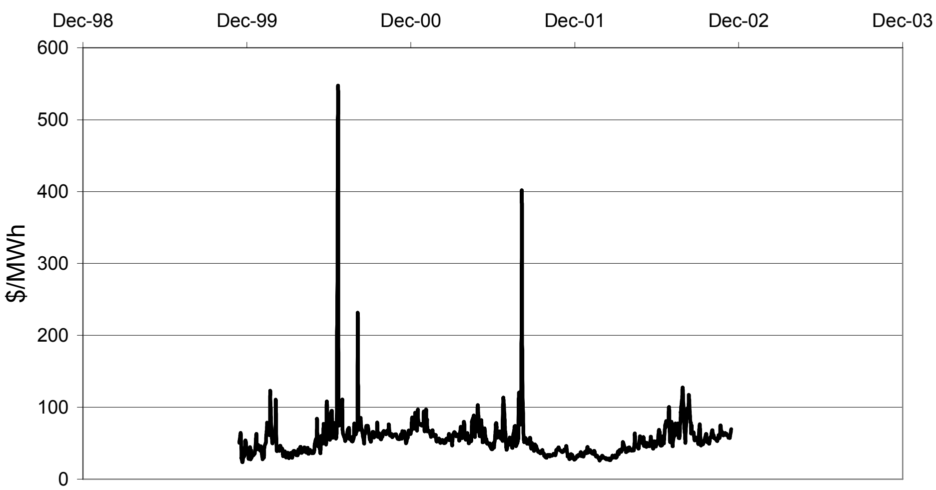

Figure 3. NYISO Day-Ahead Market Prices (On-Peak)

In characterizing price volatility, we must recognize that volatility has a term structure. The volatilities corresponding to different prices in the forward price curve form the volatility curve (i.e., referred to as the term-structure of volatilities). A volatility curve is typically a declining curve as volatilities of spot prices and prices for nearby forward contracts are higher than the volatilities for longer-dated contracts. The reason is that weather-related events and supply interruptions affect near-term prices much more than long-term prices.

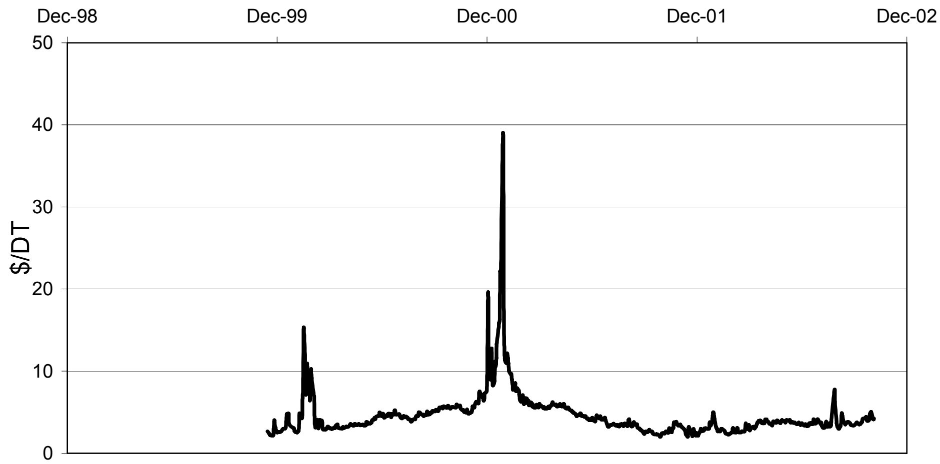

Figure 4. Gas-Daily Natural Gas Price Index (New York Transco Zone 6)

For near-term volatilities, there may be traded options in the market from which volatilities can be computed, assuming a stochastic model for the movement of the underlying price. Long-term volatilities are difficult to obtain as long-term options are usually not traded in markets. One solution is to run a capacity expansion and dispatch model under different scenarios or assumptions on driving factors to generate a reasonable distribution for future spot prices. In this study, we develop the volatility of near-term prices using historical day-ahead prices. Based on our prior experience with volatility term structures, we assume that the volatility developed for the near-term diminishes to one-third of the original level for a 5-year forward contract. As such, this volatility curve is suitable for valuing daily on-peak and off-peak options that is the subject matter of this paper. When option prices are available, one typically obtains monthly volatilities from the prices of monthly options. These monthly volatilities are blended with the short term volatilities mentioned above to obtain the term structure of volatilities that are used to evaluate daily options.

2.3 Interest Rates

The third major component of options valuation models is the term structure of risk-free interest rates. Because forward curves used in our analysis are expressed in real terms (2000$), we use risk-free real interest rates, which can be estimated from U.S. Treasury Bond prices. Table 2 shows interest rates on Treasury bonds of varying maturities and inflation estimates used by the federal government for lease and procurement activities. Risk-free real interest rates are calculated from the inflation rate and the yield-to-maturity of treasury bonds.

2.4 Analysis Period

We report the expected savings over a five-year analysis period, which is the sum of the monthly option values for five years of operation. This permits investors to evaluate decisions in relation to five-year paybacks on investment, which is at the upper end of acceptable hurdle rates for many large industrial and commercial customers for energy efficiency investments.

Table 2. Treasury Yield Curve and Inflation Assumptions (September 2002)

Maturity	Yield to Maturity (%)	Estimated Inflation Rate (%)
1 month	1.5	1.5
3 months	1.5	1.5
6 months	1.75	1.5
2 years	1.75	1.5
5 years	2.75	1.5
10 years	3.9	1.7
30 years	5.0	1.9

3. Evaluating Demand Response Investments

In this section, we describe the specific options models used to assess and value the three DR strategies. An option is specified by a payoff agreement and this payoff is a function of one or more underlying prices for which there are liquid market (or some other way, like a published index) that establishes the level of those prices objectively at the expiration/exercise time of the option.

The first step in valuing an option is characterizing the underlying prices as a stochastic process. Black and Scholes have shown that one can calculate the value of an option by changing the probability measure for this price stochastic processes to a risk-neutral measure, simulating this new process to generate realizations of prices in the future (using Monte Carlo methods), calculating payoffs, discounting these payoff values using the risk free rate, and averaging the values calculated for each realization of prices (Hull 1997).[8] Black and Scholes also provided closed form solutions for the option values for certain price processes, including Geometric Brownian Motion (GBM), which allows us to derive results directly without doing Monte Carlo type simulations. In this study, we assume that the prices follow GBM and use closed form option value calculations for the three DR strategies. It should be noted that GBM assumes that volatility, which represents the price variability, is constant over time. However, we know that the volatility of electricity prices has a seasonal pattern and term structure, which we account for in our analysis method (see section 3.1). [9]

3.1 Load Curtailment

Load curtailment involves reducing electricity usage during a given time period without causing demand to increase during another period. For example, an industrial customer might be willing to shut down or halt a production process without rescheduling. Similarly, commercial or institutional customers may be willing to reduce the consumption of end uses such as lighting and heating, ventilation, and air conditioning (HVAC) services in response to high prices or electric system emergency. For a customer on a RTP tariff, they can exercise the option to curtail load during hours when the prices exceed the cost of curtailing. Alternatively, for a customer that participates in an ISO day-ahead market DR program, they typically bid the duration of time that they are willing to curtail load and their "strike price." In our stylized analysis, we assume that the curtailment time period is defined as the block of weekday on-peak hours.[10] The benefit to the customer of curtailing electricity use on a given day is the difference between their hourly RTP prices (or ISO day-ahead market prices) and the cost of curtailment.

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[8] This approach eliminates the need to consider risk preferences of participants to the market.

[9] Each option that is associated with the time periods under consideration can be viewed as a separate option with its specific volatility that is read from the term structure. This volatility happens to be the average volatility from the beginning of the analysis period to the specific date. Therefore the model is accurate to the extent the volatility term structure is accurate.

[10] Note that this analysis could also be performed for a subset of on-peak hours (e.g., 2-5 pm), although forward price curves and volatility term structures would have to be developed for these shorter time periods. This is a more difficult process because futures prices and options contracts are generally for on-peak and off-peak blocks and at this point in time the market for derivatives for smaller time windows is not liquid.

3.1.1 Load Curtailment Options Model

The ability to curtail electricity usage can be viewed as the equivalent of owning a strip of options, one for each time period during which load could be reduced. These options can be viewed as European options that can only be exercised at the expiration date as opposed to American options that can be exercised any time until the expiration date. In either case, the analysis approach is similar and estimates the value of the option to curtail under various conditions and bidding strategies.

The hourly payoff of an option at the expiration date is:

$$payoff = max\ [price - strike,\ 0] \qquad (1)$$

This formula expresses the option payoff as the maximum of (1) the difference between the price received if the option is exercised and the strike price, or (2) zero. In this example, the "price" is the amount the customer receives/saves for curtailing, which is the day-ahead market price. If the customer is operating under a real-time-price tariff, the payoff is the savings for not consuming the energy that would otherwise be used minus the "strike price", which reflects the customer's costs that would be incurred because of the curtailment. Note that the payoff is for a 1MW curtailment capability that can be scaled to the actual capability of the customer. If the customer is participating in a demand-bidding program, we assume that it first pays the local distribution company the otherwise applicable tariff rate for its baseline. However, it gets paid the day-ahead market price for the amount of load curtailed. Compared to the case where it does not curtail, the payoff is the day-ahead price minus the curtailment cost.[11]

$$Option\ Value_t = e^{-rt}[P_t\ N(d) + Strike\ N(d - \sigma\sqrt{t})] \qquad (2)$$

$$d = \frac{\ln(P_t / Strike) + 0.5\ \sigma^2\ t}{\sigma\sqrt{t}}$$

$$P_t = forward\ \ price\ of\ \ power$$

$$r = risk\ \ free\ discount\ rate$$

$$\sigma = Black - Scholes\ volatility$$

$$Strike = strike\ \ price$$

$$N(.) = normal\ \ distribution\ \ function$$

The option value for a 1MW curtailment capability for a one hour period, under the assumption of GBM for the on–peak day-ahead prices, is as follows:

The time stamp t is in terms of years from the beginning of the analysis period (e.g., t for six months into the analysis period would be 0.5). The strike price is the customer's bid price, which should be at least equal to the costs that the customer would incur as a result of curtailing electricity usage. To determine the option value for the entire period, we multiply this hourly

[11] The otherwise applicable tariff does not come into the picture because the customer needs to pay that amount if it participated that day or not.

value by the total number of on-peak hours during the month to find the monthly option value and add the monthly values during the analysis period to calculate the total option value.

3.1.2 Modeling Assumptions for Load Curtailment

The following inputs and assumptions are used in modeling the value of load curtailment:

1. Forward price curve for on-peak electricity is shown in Figure 1.
2. Volatilities of wholesale prices were derived from historical day-ahead prices for the NYISO (see Figure 5). The volatilities shown are the standard deviations (SD) of daily price returns. For each day the price return is:

Returns = {[price(t+1)-price(t)]/price(t)} (3)

The SD of such returns for the period 15 days before through the period 15 days after a given day gives the 30-day rolling price volatility.[12]

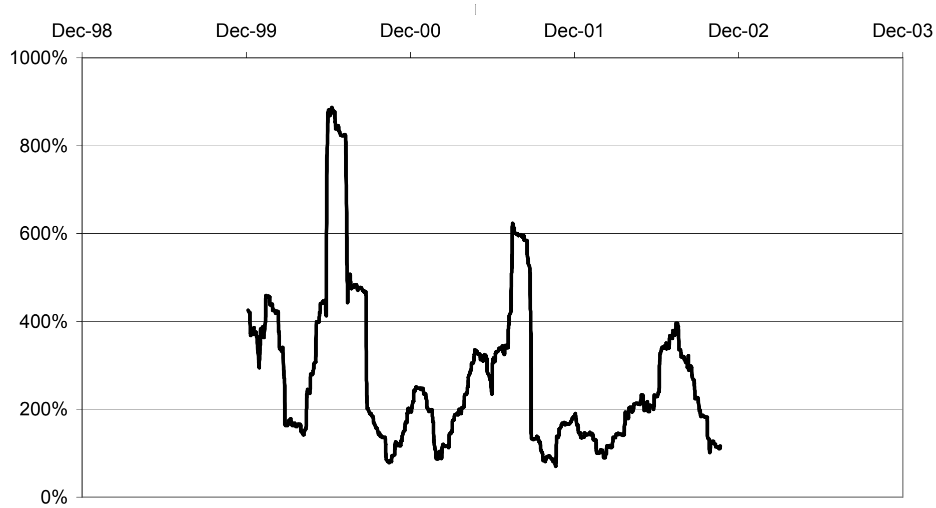

Figure 5. Volatility of On-Peak Power (30-day Rolling Annualized)

As noted previously, the Black-Scholes model assumes that volatility is constant over time. However, the volatility of on-peak prices clearly exhibits a distinct seasonal pattern (see Figure 5). For example, the volatility of on-peak period prices in the New York market tends to be higher during the summer months compared to fall (e.g., October and November). Moreover, over time, the on-peak price volatilities in spring and summer months appear to trend downwards (e.g., from 400-600% in 2000/01 to 200-400% in 2002). During periods or times of low demand, on-peak short term (intra-day) price volatility ranges between 80-120%. In our analysis, we assumed a short-term value for on-peak electric price volatility of 90%. We assume a term structure such that this 90% volatility diminishes linearly to 30% by the fifth year.

The customer's strike price is assumed to include the customer's variable operating expenses and/or revenue losses. Strike Price ranges from \$100/MWh to \$300/MWh for this analysis and is

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[12] This daily volatility of price returns is annualized by multiplying it by the square root of 250 (the number of days in a year that there is price data for).

facility specific.[13] For example in industrial facilities, end users can estimate the cost of stopping production by estimating reduced revenues. In buildings, during a curtailment event, end users typically reduce service levels and it is up to the facility manager to quantify the effect of this reduction on occupant productivity and comfort.

Customer constraints are intended to reflect the range in customer's willingness to accept load curtailments that reflects both the frequency and duration of load curtailment. We specify monthly maximum curtailment periods from 5 to 20 days per month in order to represent a range of customer constraints (e.g., a customer willing to curtail load for five days each month must be willing and able to curtail if market prices exceed their strike price on five days).

3.1.3 Results: Load Curtailment Option

We calculate option values for a customer that is willing to curtail 1 MW of load, depending on their strike price and business/facility constraints. Results of this analysis are summarized in Table 3. To interpret these results, note that customers that offer 20 days per month of load curtailment are willing to reduce load between the hours of 7am to 11pm each of the 20 weekdays of the month. This is a very high degree of flexibility. A customer with that level of flexibility, and a strike price of $100/MWh ($0.10/kWh) would generate $70,000 in savings for a 1 MW load curtailment in the day-ahead market for New York city during the five-year period of the analysis. If the customer is only willing to curtail at much higher prices (e.g., a strike price of $300/MWh), then expected benefits would decrease to about $6,000.[14] Based on market research and existing program experience, many businesses are willing to curtail some of their load for fewer days each month (e.g., 5 days). For these customers, the expected savings are about $18,000 if they are willing to curtail load at a strike price of $100/MWh.

Table 3. Option Value of Load Curtailment for 5 Years of Operation

Monthly Limit (days)	Strike Price ($/MWh)		
	100	200	300
5	$18,000	$4,000	$2,000
10	$35,000	$9,000	$3,000
20	$70,000	$17,000	$6,000

Note: Prices are in year 2000 dollars/MW.

The two dimensions of the matrix in Table 3 (monthly limit and strike price) characterize the flexibility of an end-user. An investment in an enabling technology typically moves the end-user to a lower strike price—making it cheaper to exercise the option (see Kintner-Meyer et al. 2003). To determine the economic feasibility of an investment in a load-curtailment enabling technology, we compare the value of the customer optionality before and after the investment with the cost of the demand-side investment. For example, a commercial building facility manager may consider investing and upgrading their existing energy management control system (EMCS). Let us assume that the investment in automated control equipment allows this

[13] Woo and Pupp (1992) report that industrial outage costs can easily exceed $1000/MWh.
[14] Even though the higher strike price produces more revenue for the customer for any hour in which these loads are scheduled, the number of hours scheduled is significantly reduced; thus total revenues decline.

customer to reduce their operating expenses necessary to implement a load curtailment from \$200/MWh to \$100/MWh. Table 3 indicates that the facility manager should be willing to invest up to \$26,000 per 1MW of curtailment capability for that DR technology (i.e., \$35,000 minus \$9,000), assuming a 5-year payback criterion and a customer that is willing to curtail for 10 days each month. For comparison, the installed costs of various DR enabling technologies range from \$7,000 to \$250,000 per MW of curtailment capability as described by Nexant (2001).

3.2 Load Shifting/Displacement

Load shifting or displacement entails customers moving usage from one period to another – typically from on-peak to off-peak hours. Thermal energy storage technologies are probably the best known example of this DR strategy. These technologies generate heat or cooling during off-peak hours and store it to be used during on-peak hours. We assume that the customer's RTP tariff offers prior day notice of hourly prices and that this provides sufficient time for the customer to decide whether to operate their thermal storage system and for the system to be fully charged before the next day's on-peak hours. We also assume that the customer will operate their thermal storage system if the differential between on-peak and off-peak electricity prices is large enough to cover thermal losses and incremental variable costs resulting from use of the energy storage system.

3.2.1 Load Shifting Options Model

A customer's decision to operate a thermal energy storage system is a real option; that is, the equipment owner has the right but not the obligation to run the system.

The hourly payoff function for the load shifting option (savings per unit (MWh) of shifted on-peak power) is:

$$payoff = \max\left\{P_{on-peak}(t) - \frac{1}{\eta}P_{off-peak}(t) - K, 0\right\} \tag{4}$$

where, η is the thermal efficiency of the storage system, and K, the strike price, is the variable cost of producing a unit (MWh) of on-peak power. We are assuming that if the system is operated, the payoff to the customer per unit of shifted on-peak power is:

$$P_{on-peak}(t) - \frac{1}{\eta}P_{off-peak}(t) - K \tag{5}$$

If the payoff is positive, the operator will run the thermal storage system on the following day. The above payoff shows that a load shifting option can be valued as an option on the spread between on-peak and off-peak power prices.

We assume that the on-peak and off-peak prices can both be characterized using GBM and that these price processes are correlated with each other. Under these assumptions, the value of an option (of size 1MW) for operating the system at any given hour t in the future is:[15]

[15] This formula is an approximation, but is reasonably accurate for the expected range of on-peak and off-peak prices. The computation of the exact spread-option value involves evaluation of a complicated one-dimensional integral. See Boyle et al. (1989) for details.

$$Option \;\; Value_t = e^{-rt}\left[P_{on-peak}\;\; N(d_1) - \left(\frac{1}{\eta} P_{off-peak} + K\right) N(d_2)\right] \tag{6}$$

$$d_1 = \frac{\ln a}{\sigma \sqrt{t}} + \frac{\sigma \sqrt{t}}{2}$$

$$d_2 = d_1 - \sigma \sqrt{t}$$

$$a = \frac{P_{off-peak}}{P_{off-peak} + \eta K}$$

$$\sigma = \sqrt{\sigma^2_{on-peak} + a^2 \sigma^2_{off-peak} - 2a\rho\sigma_{on-peak}\;\sigma_{off-peak}}$$

where,

$P_{on-peak} = forward\;\; price\; of\;\; on-peakpower$

$P_{off-peak} = forward\;\; price\; of\;\; off-peakpower$

$r = risk\;\; free\; discount\; rate$

$\sigma_{on-peak} = Black-Scholes\; volatility\; of\;\; on-peak\;\; power$

$\sigma_{off-peak} = Black-Scholes\; volatility\; of\;\; off-peak\;\; power$

$\rho = on-peak/off-peak\;\; power-price\; correlation$

$K = strike\;\; Price$

$N(.) = normal\;\; distribution\;\; function$

Every time period is a separate option. The total value of the strategy is the sum of the values of each time period throughout the lifetime of the equipment.

3.2.2 Load Shifting Modeling Assumptions

The following inputs and assumptions are used in modeling the value of load shifting.

- Forward Price Curves for on-peak and off-peak electricity are shown in Figure 1.
- Volatilities and Correlations involve treating on-peak and off-peak hours as separate commodities. These volatilities are developed as described in the previous section on load curtailment. The correlation between on-peak and off-peak prices is developed using the time series of daily price returns for on-peak and off-peak hours. For the correlation calculations for a given day, a 30-day period is considered (15 days before and 15 days after). Volatilities and correlations of on-peak/off-peak electricity prices are shown in Figure 6.

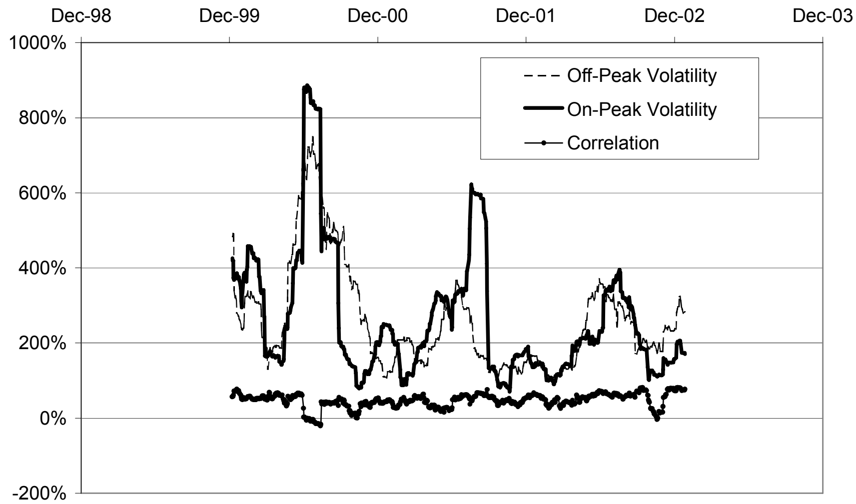

Figure 6. On-Peak/Off-Peak Power: Volatilities and Correlation

For on-peak periods, we used 90% volatility for the near term and this is assumed to diminish to 30% in 5 years. For off peak, we used 80% volatility for the near term that reduced to one-third that level in 5 years. We also assumed a 50% correlation that stayed constant through the analysis period.

Strike Price has as its main component the difference between the variable operations and maintenance costs of a stand-alone HVAC system and those of an HVAC system utilizing thermal energy storage. There is no clear rule that dictates whether this difference will be negative or positive. Usually, there are no additional variable operations and maintenance costs associated with a thermal energy storage system. Therefore, we use a strike price of zero. Thermal efficiency η of the storage unit is assumed to be 70% and a sensitivity analysis is presented for a range from 60% to 80%.

Customer Constraints are typically not an issue under a day-ahead notification regime if the thermal energy storage system can cover the whole building load. Full storage systems are designed to cover the building's entire load for the following day and can be fully charged during the preceding night. We assume that if the system is utilized, it operates throughout the day.

3.2.3 Load Shifting Option Valuation Results

We estimate that the value of having the capability to shift one MW of load from on-peak to off-peak hours for a five year period in the New York City market through operating a thermal storage system ranges from ~$150,000- $240,000, depending on storage efficiency (see Table 4). These expected savings can be compared to the initial investment cost to determine if payback time is acceptable to the customer. Typical thermal energy storage system installations cost around $35/ton-h which translates into about $560,000 per MW shifted (EPRI 1988). These results suggest that savings on electric commodity charges alone would yield a payback time for a Thermal Energy Storage (TES) system investment that ranges from 12-14 years for systems with 80 and 70% storage efficiency respectively.

Table 4. Option Value of a Thermal Energy Storage System for 5 Years of Operation

Monthly Limit (days)	Storage Efficiency (%) 80	70	60
20	$237,000	$199,000	$149,000

Note: Prices are in year 2000 dollars/MW.

3.3 Fuel Substitution

The third demand response strategy involves fuel substitution for electricity.[16] We used a natural gas-driven distributed generation technology to illustrate this DR strategy.[17] In this strategy, we assume that the customer is on a RTP tariff and decides to run their generator the next day if the electricity prices are high enough to cover the expenses for natural gas and any other variable costs. The customer can also bid into an ISO day-ahead DR program, provided the day-ahead gas price quote, which is obtained right before bidding, is binding until the ISO informs the end-user whether it is scheduled to operate for the next day.

3.3.1 Distributed Generation Options Model

Owning a natural-gas generator is equivalent to owning a strip of spread options, one for each time period during which the generator can be deployed. For this analysis, we assumed that the time period of interest is on-peak hours during the weekday. The DG option has an hourly payoff for a unit MW generation capability given by:

$$payoff = max\,[\ (power\ price - HR * gas\ price) - variable\ O\&M\ \ ,\ \ 0] \qquad (7)$$

In the above expression, the term $(power\ price - HR * gas\ price)$ is called the "spark spread" in the energy industry.

To value the DG option, we need to characterize the probabilistic nature of electricity and gas prices. For the current analysis, we used a simplified model where the spread $(power\ price - HR * gas\ price)$ is assumed to have a normal distribution.[18] In this case, volatility is the absolute volatility of the spread, not the standard Black-Scholes definition of volatility used in previous examples.

[16] Examples of this strategy include distributed generation, dual fuel chilling, and other dual fuel equipment.

[17] We did not consider diesel generators because environmental regulations generally prevent diesel-fueled equipment from participating in "economic" DR programs. However, if eligible, diesel generation could be modeled using the methodology described in the curtailment section and embedding diesel fuel prices in the strike price.

[18] It is possible to model DG using an approach similar to that used for thermal energy storage where the underlying prices (natural gas and on-peak electricity) are modeled using two correlated stochastic processes. However, the DG model presented in this study is easier to implement because we only estimate an absolute volatility, rather than two volatility term structures and a correlation. An example of such a methodology, the regression-based approach that uses natural gas prices to forecast the expectation and variance of electricity prices, has been presented by Woo, Olson, and Orans (2004).

$$Option\ Value_t = e^{-rt}[(P_t - HR * G_t - Strike)N(d) + \sigma\sqrt{t}\ n(d)] \qquad (8)$$

$$d = \frac{P_t - HR * G_t - Strike}{\sigma\sqrt{t}}$$

P_t = *forward price of power*

G_t = *forward price of gas*

HR = *heat rate*

r = *risk free discount rate*

σ = *absolute volatility*

Strike = var*iable O & M*

$N(.)$ = *normal distribution function*

$n(.)$ = *normal density function*

Every time period is a separate option. The total value of the distributed generation option is the sum of the values of each time period throughout the lifetime of the equipment. The strike price is mainly composed of the variable operating costs for running the DG equipment. The other key factor in valuing the distributed generation option is the Heat Rate (HR) of the equipment. In this approach, fixed operations and maintenance costs for the DG equipment are not part of the strike price. These costs are bundled with the investment costs for the system and compared to the option value in order to determine whether the investment in this technology is economically feasible or not.

3.3.2 Distributed Generation Modeling Assumptions

The important assumptions in the DG model have to do with specification of the forward curve and volatility, setting of strike prices, and constraints on curtailment bidding imposed by environmental regulations. These are described below.

Forward Curves used for on-peak electricity and natural gas are shown in Figures 1 and 2 respectively. Spark spread values developed from the historical gas and electricity price data shown in Figures 3 and 4 are presented in Figure 7. Volatility of the spread for the last 250 data points of the spark-spread time series shown in Figure 7 is 17.30 dollars. This is absolute volatility; in other words, it is the standard deviation of *spark-spread* over a 250-day window.

Strike Prices, which are equivalent to variable operations and maintenance costs, are typically around \$7/MWh for gas-driven technologies, which is used in our base case analysis that values a DG option. Sensitivity analysis is presented for costs between \$5 and \$10/MWh. The local distribution charges for gas can also be incorporated into the strike price. A local distribution charge of \$0.20/DT increases the strike by about \$2/MWh (heat rate times the local distribution charge). In the analysis presented in this paper, local distribution charges are not directly considered. However, the results for different strike price levels are presented.
Heat Rate (HR) is assumed to be 11,400 British Thermal Units (Btu)/kWh. This corresponds to 30-percent efficiency, which is representative of the more efficient micro-turbines available on the market at present.

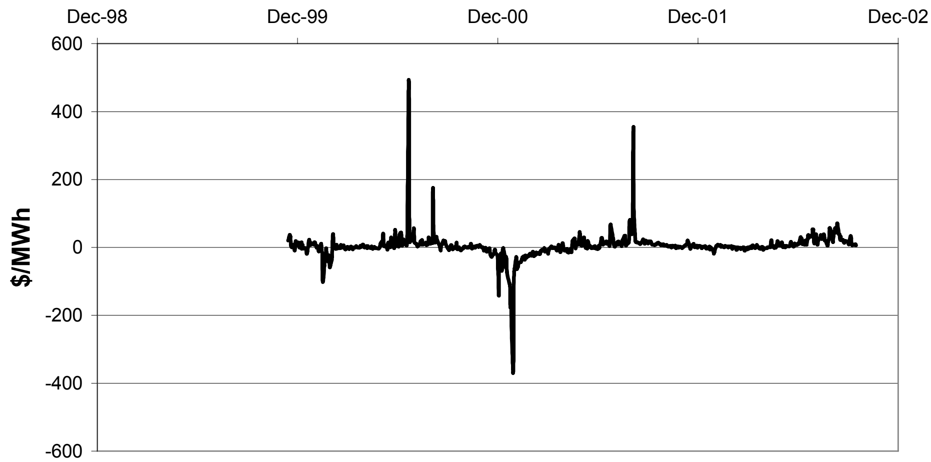

Figure 7. Historical Spark-Spread between Power and Gas Prices

Customer constraints are related to customers' limits on the frequency and duration for running and operating DG equipment, which are typically established by environmental regulations or permits. In this study, we evaluated the value of DG for facilities that can run DG for a maximum number of days of 5 to 20.

3.3.3 Distributed Generation Option Results and Comparisons to Other Methods

The option values calculated for gas-driven DG in power-only application are presented in Table 5 and, for a variable O&M cost of \$7/MWh, range between \$33,000/MW (if dispatchable for five days per month) to about \$130,000/MW (if dispatchable for 20 days per month). According to a recent study, the costs of micro-turbine generators are generally greater than \$1,000,000/MW (Workshop for Analysts 2003). This suggests that payback times for DG in power only applications are likely to be greater than 30 years in the New York region. However, it should be noted that DG technologies with heat recovery applications (e.g., combined heat and power) are likely to have more attractive economics to customers. Also, the generators may be turned on and off during the day that adds to the option value and there may be a transmission deferral benefit to the utility; neither of these potential values are considered in our analysis.

Table 5. Option Value of Gas-Driven Distributed Generation for 5 Years of Operation

Monthly Limit (days)	Variable O&M (\$/MWh)		
	4	7	10
5	\$38,000	\$33,000	\$28,000
10	\$76,000	\$65,000	\$56,000
20	\$151,000	\$130,000	\$111,000

Note: Prices are in year 2000 dollars/MW and heat rate=11.4 MBtu/kWh (30% efficiency)

It is useful to compare the options value results with the two other approximate discounted cash flow (DCF) methods mentioned earlier in evaluating potential investments. The results for the different approaches are summarized in Table 6. DCF Method 1 relies on monthly price forecasts in estimating benefits. If only the forward views presented in Figures 1 and 2 (i.e., monthly on-peak and off-price prices and monthly gas prices) are used to estimate average prices in the future, the present value of future cash streams from running DG would be only $17 instead of $130,000.[19] The main reason for the low value in this instance is the high heat rate and the high strike price associated with the DG unit considered here. It is clear that without taking advantage of the fluctuations in daily prices, especially for small size units, the value of DG is much smaller. Recognizing these limitations, end users may conduct sensitivity analysis using DCF Method 2 in which they take the past price time series for electricity and natural gas and calculate the cash flows during various periods to represent alternative futures. The value generated depends on the section of the time series that is considered (e.g., Dec. 99- Nov. 00 or March 01-Feb. 02). In our example, if one uses different one-year segments for such a calculation, values ranging from $80,000 to $150,000 per MW are obtained. The limitation of this approach is that: (1) historical price levels may not be representative of the future price levels causing the value calculated to be either higher or lower than the actual value, and (2) a wide range of values are obtained depending on the time segment chosen, which the customer must still interpret. Options value methods presented in this article provide a more systematic way of combining forecasts of average prices with price volatility data (obtained from either historical time series or backed out from options market prices) to derive estimated benefits that incorporate all available market information (see Table 6).

Table 6. Comparison of Alternative Methods for the evaluation of DG investments

Method	Inputs	Value ($/MW)
DCF Method 1	Monthly forward prices	$17
DCF Method 2	Historical day-ahead prices	$80,000-150,000
Real Option Valuation	Monthly forward prices, volatility developed from historical day-ahead prices	$130,000

[19] This calculation assumes that DG equipment will be operated during the on-peak hours each month if the average forward price of electricity is more than the forward gas price times the heat rate by at least a margin equal to the $7/MWh (the variable O&M cost).

4. Conclusions and Future Work

This study demonstrates how option-pricing methodologies can be used to value investments in three different kinds of demand-response strategies: load curtailment, load shifting/displacement, and fuel substitution. The models for the three DR strategies can be used to evaluate investment opportunities that facilitate demand responsiveness and to estimate the market value of demand flexibility if the option to be dispatched is being sold to a load aggregator or utility. Our DR examples assume that customers have prior day notice on hourly electricity prices and are capable of and willing to respond during all hours of the on-peak period of a given day.

In the future, we plan to enhance the models and analysis tools in three general areas: (1) by incorporating the option value of intra-day flexibilities for shorter time periods (e.g., hourly, 4 hour blocks), (2) by more customized representation of the actual operational constraints that exist for individual customers at their facilities, (3) by extending the fuel substitution model to include cogeneration, and (4) by developing simple ways to forecast price expectation and volatility, the key input assumption for computing option values.. These enhancements are necessary to better capture the heterogeneity of loads of retail customers that want to participate in wholesale electricity markets or are directly exposed to wholesale electricity market prices. Capturing the full value of customer demand response capability involves developing forward curves for prices and volatilities for shorter time blocks (e.g., 12-4 pm or hourly) rather than the broader on-peak and off-peak periods that we utilized here. This will facilitate inclusion of the hourly texture of customer constraints and opportunities into the models.

Experience with restructuring in the U.S. and other countries demonstrate that price-responsive customer loads are a critical feature of competitive wholesale electricity markets. In order for customers to participate effectively in wholesale electricity markets, we will need continued improvements in enabling technologies and information/analysis tools described in this study. These tools are essential for customers to assess the risks and value of participating in energy markets.

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