NATIONAL ENERGY TECHNOLOGY LABORATORY

Conventional Generation Asset Management with Renewable Portfolio Standards Using Real Options

May 24, 2013

DOE/NETL-2013/1619

U.S. DEPARTMENT OF ENERGY

OFFICE OF FOSSIL ENERGY

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Final Report

May 24, 2013

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DOE Contract Number DE-FE0004000

Acknowledgments

This research was funded by the U.S. Department of Energy National Energy Technology Laboratory (U.S. DOE-NETL). Christian Blanco acknowledges additional funding by the National Science Foundation Graduate Research Fellowship Program (NSF GRFP) Grant No. 2011131079.

The authors thank Benoit Morel for helpful comments and suggestions. Christian Blanco wishes to acknowledge insightful discussions with the Engineering and Public Policy doctoral students at Carnegie Mellon University.

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Executive Summary

The transition to a more renewable generation mix under a competitive electricity market will require individual power producers to use sophisticated tools to value conventional generators. Owners will need to understand what market prices signal new investments, temporarily suspending operation, reactivating mothballed generators or permanently abandoning a plant. Net present valuation from a traditional discounted cash flow analysis is limited in capturing the value of generation technologies, and it does not provide an optimal investment criterion. We present and evaluate a closed-form decision support framework using a Spark Spread Real Options approach to value generation assets and to capture optimal market price signals that minimizes financial risks of individual power producers under a transition towards a more renewable energy fleet.

We evaluate the Spark Spread options valuation for capital budgeting without capacity payments. As an example, for a fixed heat rate of 10,000 Btu/kWh and a combined electricity and fuel price annual volatility1 of 58%, the Spark Spread option valuation gives a positive value for a unit of installed generating capacity at electricity prices below $40/MWh. Given the same conditions, a traditional net present value (NPV) cash flow has no value for a unit of installed capacity for electricity prices below $40/MWh. Accounting for the inevitable volatility in electricity and fuel prices can allow firms to see more value in fossil plants than does the traditional approach.

We use a Spark Spread Real Options approach to determine the optimal conditions for investing, reactivating, temporary suspension, and decommissioning power plants from the firm-level perspective. We present numerical results using a closed-form Real Options approach that we have developed, extending the framework of Dixit and Pyndick (1994) to capture the Spark Spread functional form. We evaluate the effect of increased volatility in electricity prices due to market uncertainty and renewable energy policies on investment behavior. We find that new coal and natural gas power plants become harder to justify in the presence of increased volatility. At 15% combined market volatility of coal and electricity prices, a firm would invest in new coal with a capacity factor of 85% only if they expect long-term electricity prices to be at least $80/MWh (the market price signal). With the same combined volatility for natural gas and electricity prices, new investment price signals for natural gas combined cycle generators with a 25% capacity factor is $130/MWh. At 40% combined volatility, new investment price signals for coal and natural gas are $150/MWh and $200/MWh respectively.

On the other hand, we find it may be more economical for conventional generators to delay mothballing with higher volatility. With the same combined volatility, the market price signals for mothballing coal and natural gas are $10/MWh and $40/MWh.

38 states have adopted Renewable Portfolio Standards (Database of State Incentives for Renewables & Efficiency (DSIRE), 2011-2012).

Renewable Portfolio Standards (RPS) require load-serving entities to supply a fraction of their electricity from renewable energy technologies such as wind and solar. In the presence of variable renewable energy generation, we expect a decrease in average prices due to lower

[1] As discussed in the body of the report, volatility is a measure based on the standard deviation in the changes in price of the underlying asset.

marginal cost electricity pricing and an increase in electricity price volatility. We extend the Spark Spread real options model to account for the arrival of a policy.

If a power producer expects average prices to drop by 50% in 10 years due to the introduction of more zero marginal cost generators such as wind, it is more economical to invest early or delay mothball and take advantage of current market prices. The timing and the effect of policy on average prices is important in setting market price signals for individual power producers to invest in enough capacity to maintain a reliable electricity mix.

An option gives the owner the right, but not the obligation to execute a trade.

The Spark Spread Option

Having an asset of installed energy capacity gives the owner the ability to convert fuel into electricity. A cross-commodity derivative is the ability to exchange one risky asset for another in the future (Margrabe, 1978). In the electricity industry, this financial exchange is referred to as the spark spread: the difference between the price of electricity and the cost of converting fuel into electricity. The spark spread option gives the value of owning a unit of installed capacity of an electric generator. Deng, Johnson, & Sogomonian (2001) provides a closed form solution for the value of holding a spark spread option under the assumption that futures prices of electricity and fuel follow either a geometric Brownian motion or a mean reverting process.

In the presence of policies that require more renewable generation, we anticipate a decrease in fossil plant capacity factors, which in turn decrease their profitability. We expect a significant portion of RPS requirements to be fulfilled by variable sources of generation such as wind and solar, which are likely to exhibit more volatility in organized markets. However, conventional generators are needed at times when wind and solar are not able to provide electricity. Given these factors, it is reasonable to ask whether temporarily suspending operation or mothballing is an economical option when market conditions are unfavorable. Our numerical examples illustrate the spark spread options approach with the traditional discounted cash flow. All assumptions for each scenario are documented in Appendix I.

Table 1 Summary of lifetime costs and values in $/kW

	Combined Gas Cycle		IGCC		Coal	
	High Volatility Scenario	Low Volatility Scenario	High Volatility Scenario	Low Volatility Scenario	High Volatility Scenario	Low Volatility Scenario
Overnight Capital Cost (Including Financing)	$1,380	$941	$5,510	$3,870	$5,300	$3,870
Operating Costs	$246	$190	$1,340	$1,320	$1,280	$810
Traditional Cash flow Value	$1,440	$1,060	$6,800	$4,360	$6,900	$4,950
Spark Spread Option Value	$1,630	$1,080	$6,860	$4,360	$7,010	$4,950

In each scenario, the spark spread option value is equal to or greater than the traditional cash flow value. We find three out of the six projects in Table 1are profitable under the spark spread option valuation. On the other hand, we find only two out of the six projects profitable under the traditional cash flow valuation. We further illustrate the rate of increase of an installed generating capacity as a function of electricity prices with different heat rates. For a given heat rate, the spark spread value increases faster as electricity prices increase compared to the traditional cash flow. Figure 1 and Figure 2 are computed at a fuel price of $4.5/MMbtu and a combined electricity and fuel price annual volatility of 58%. Even with a 14,000 Btu/kWh heat rate at electricity prices below $60/MWh, the value of the spark spread option is positive.

Figure 1 Traditional cash flow heat rate sensitivity

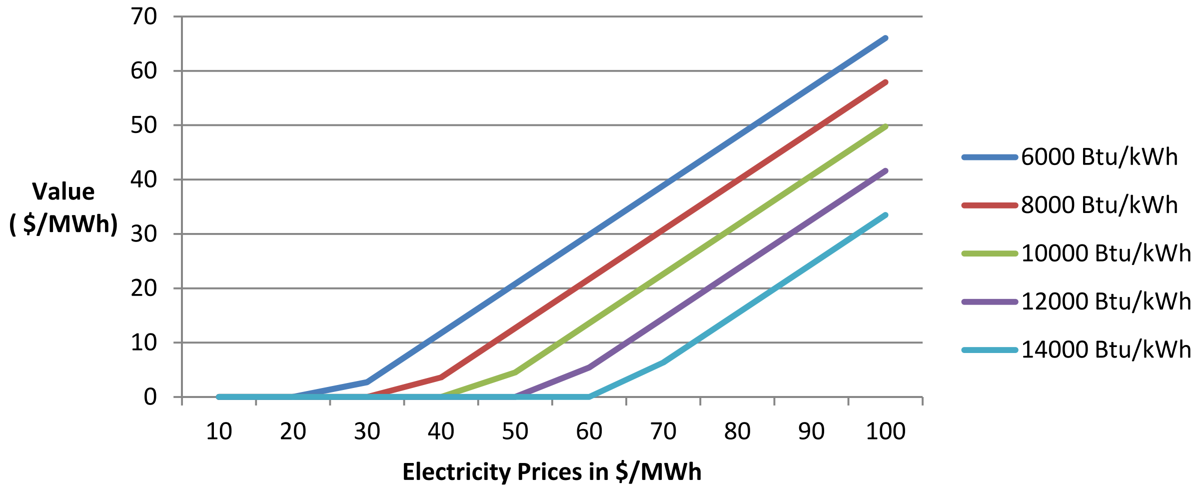
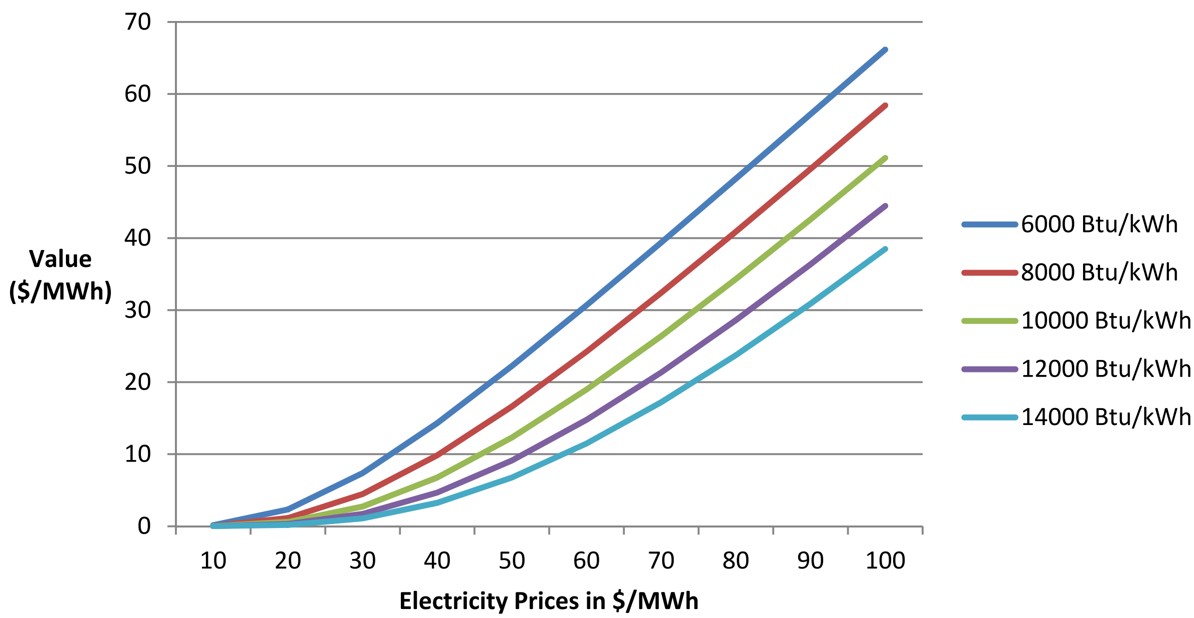


Figure 2 Spark spread options heat rate sensitivity



The Real Options Approach

There are several limitations in using the NPV criterion in capital budgeting and investment decision making. The NPV criterion says if a project has a positive value regardless of its level of profitability, the project should be built. It can be quite puzzling to financial planners that if revenue is $1.001 M and the overnight capital cost is $1 M then according to the NPV criterion the plant must be built since

$NPV = \$1000 \geq 0.$

> The NPV is a now or never approach where the decision to build is based whether current value projections outweigh capital and operation costs.

Although some firms may have higher thresholds for hedging such as increasing the profitability threshold, these methods often times require changing financial parameters to reflect uncertainty that is not accounted in the NPV valuation. Another limitation of the NPV decision process is the lack of the ability to delay an investment due to uncertainty in market conditions. Brennan & Trigeorgis, Project Flexibility, Agency, and Competition (2000) and Dixit & Pindyck (1994) provides a more rigorous treatment on the differences between the NPV and the real options approach in capital budgeting.

Our decision support framework provides firms with tools to help them value projects and to understand the optimal conditions for investing. A numerical example will provide some intuition behind a real options decision process.

We limit our numerical example to a two period decision framework and ignore operating costs. Suppose a coal plant requires $150 Million in overnight capital costs. If the coal plant is built in period 1, the project will receive a stream of revenues through its lifetime of $20 Million a year. In the NPV approach, the firm should build the plant immediately, since the lifetime discounted flow of revenue is $220 M≥ $150 M. Suppose in period two, there are two possible revenue outcomes. The stream of revenues increases to $28 Million with a probability of 50% or revenue drops to $12 Million with a probability of 50%. In the event that the stream of revenues drops below the overnight capital cost, the firm can decide not to build the project. We let the interest rate for discounting be *r* = 10%.

Period 1 | Period 2

$(\sum_{t=0}^{\infty}\frac{\$20\text{ M}}{(1+r)^t})$ -$150 M = $70 M

50% → $.5((\sum_{t=1}^{\infty}\frac{\$28\ M}{(1+r)^t}) - \frac{\$150\text{ M}}{(1+r)^1})$ = $72 M

50% → Do not build the project = $0 M

In period 1, the firm receives $20 Million throughout the lifetime of the project. In period 2, if market conditions improve, the firm receives $28 Million a year. On the other hand, if market conditions worsen, the firm may not decide to build the project if the stream of revenue drops to $12 Million. In expectation, the firm gets $72 Million in the second period, which is larger than the returns from investing in period 1. In this example, it is better for the firm to delay the project and build the coal plant in the second period. We can extend this logic to N periods and apply a similar thought process, but one can imagine that the size of the problem gets bigger as we go out further in time. In the next section, we characterize the value of waiting; we later introduce dynamic programming techniques to provide closed-form solutions in solving waiting functions and plant valuation. We also use dynamic programming to value a plant in mothball stage (temporary shutdown) and solve for optimal conditions for reactivation and permanent abandonment. We illustrate the optimal decision criterion with two graphs below. If long-term electricity prices are above the investment threshold line in Figure 3, it is optimal to invest in a new coal plant. If long-term electricity prices are below the investment threshold, it is better to delay the investment until electricity prices increase. Figure 4 provides investment threshold values for reactivation, mothball, and abandonment. If long-term electricity prices are above the mothball threshold values, it is optimal to delay mothballing. If long-term average electricity prices fall below the mothball threshold, it is better to mothball the plant future possibility of abandonment.

Figure 3 Coal investment threshold as a function of volatility

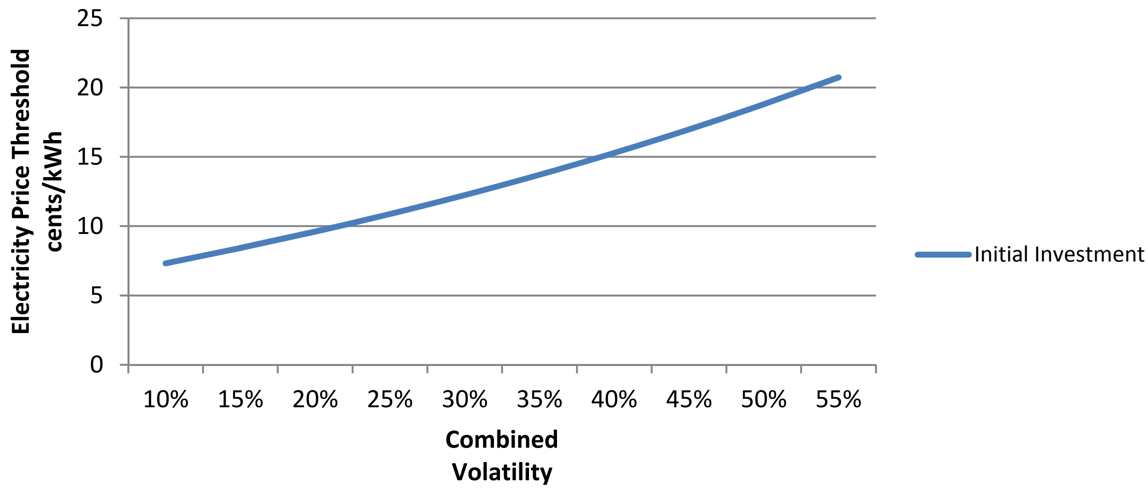
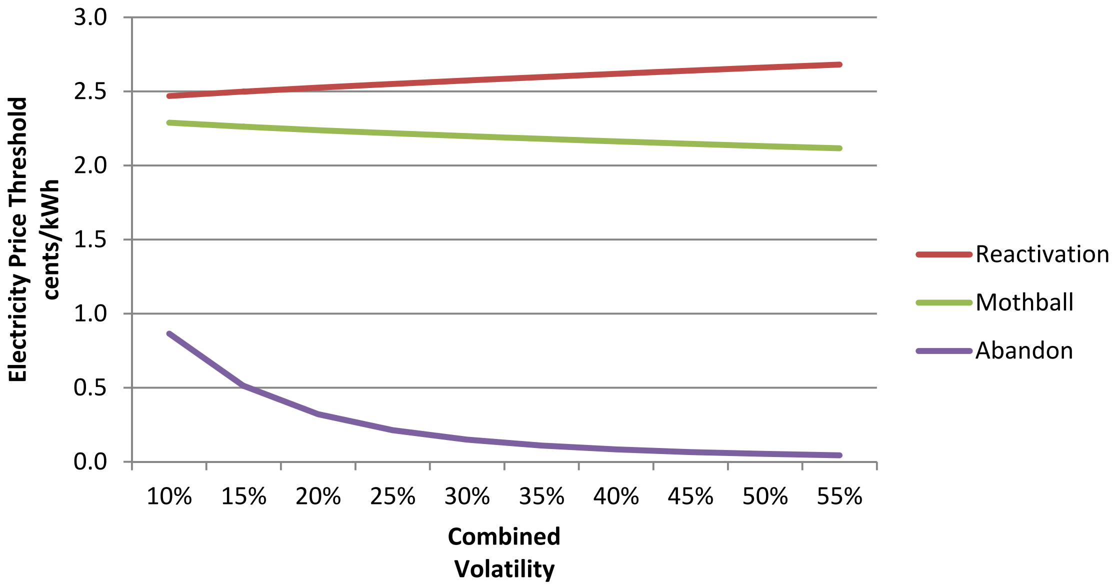


Figure 4 Coal market price thresholds as a function of volatility

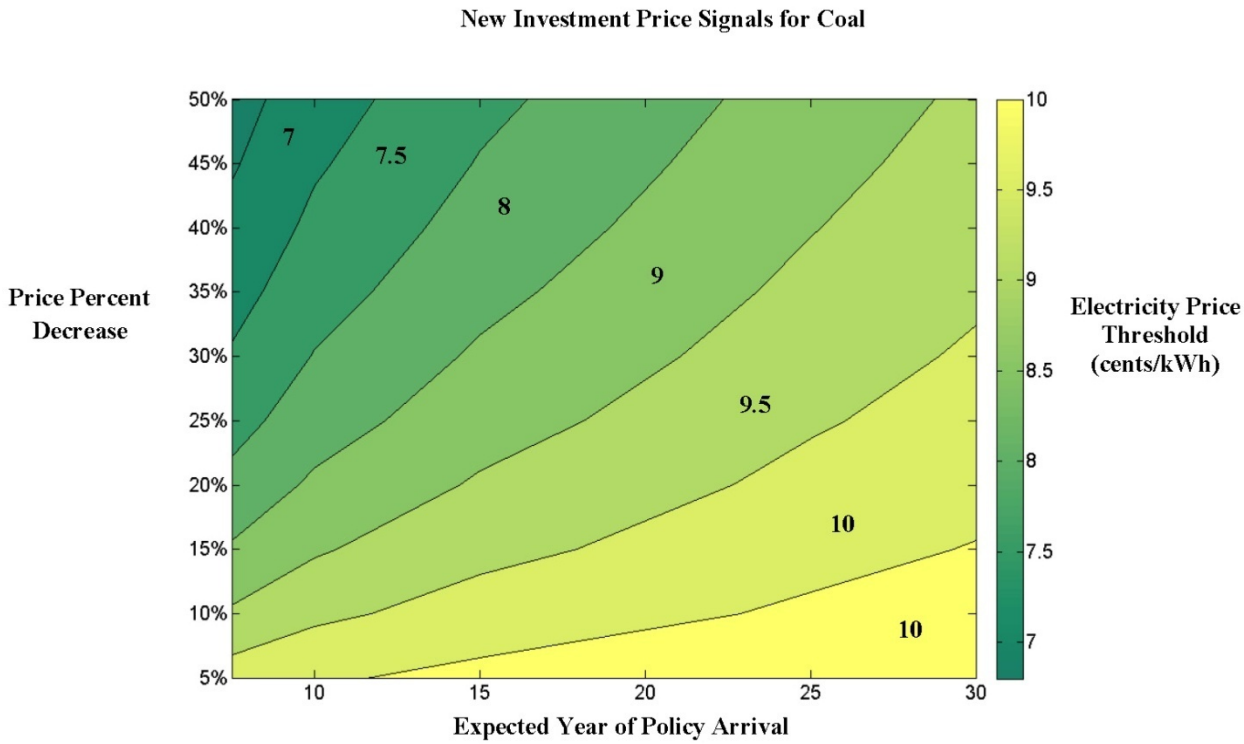


Policy Implications for Investment Behavior

In addition to financial uncertainty, the Spark Spread Real Options can be extended to investigate investments implications of policy uncertainty. We refer to the strength of the policy as the percentage decrease in electricity prices due to more renewable energy penetration. Timing and strength of renewable policy greatly influences investment and operational decisions by individual power producers. Policy timing and strength have important implications in relating market price signals and incentivizing generation for a reliable energ mix. If we expect more wind in our system, it is better to invest early before prices are affected by large penetration of wind or solar in the system. Furthermore, under the real options approach, systems with higher volatility has lower mothballing thresholds. Existing conventional generators are valued more in higher volatility systems.

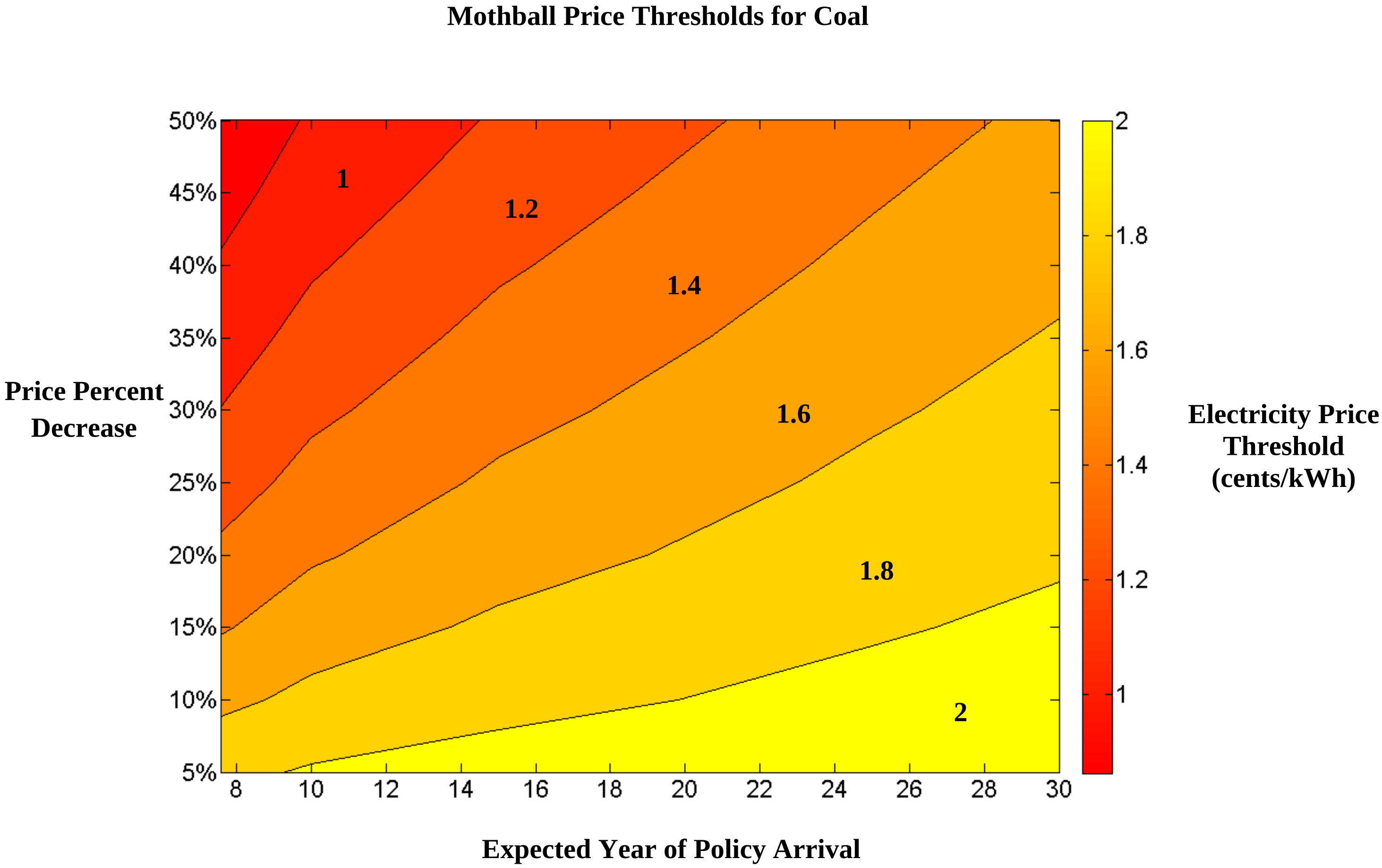
In Figure 5, the colorbar represents the optimal threshold for investing in a coal plant. Fixing our policy arrival at 10 years, as the policy strength increases the investment threshold values decrease. Our results are the opposite when volatilty increases. The reason for a decrease in the investment thershold is capturing the opportunity to invest early while prices are high and taking advantage of higher profits in earlier years. On the other hand, as the expectation of policy increases from 10 to 20 years, we notice a drop in investment price signals. If we expect a large decrease in prices, $\theta = 50\%$ with an arrival rate of, $\lambda = .05$ (20 years), the price signal for investing is \$80-\$85/MWh. Depending on market conditions, this could happen in the next 5 or 10 years of the investment horizon.

Figure 5 Coal investment threshold with policy strength and timing sensitivity



Our final scenario analysis looks at mothballing threshold for coal power plants with varying policy arrival rates and strength (6). If we fix the policy arrival at 10 years, we notice that a larger decrease in price gives a lower threshold for mothballing. It is economical for the plant owner to take advantage of current market prices and delay mothballing. On the other hand, of the expected decrease is not very significant, the power plant owner might want to minimize losses as early as possible by mothballing at relatively higher price.

Figure 6 Coal mothball threshold with policy strength and timing sensitivity



Both the strength of the policy and the timing of its implementation are crucial for individual power producers. An important dynamics in the real options approach is that it captures the arrival of a policy taking into account its implementation and effect on market conditions have uncertainty. Large power producers are very sensitive to policy and thus it is important to understand how to appropriately implement them in the market to provide appropriate market price signals that may ensure a reliable energy mix.

Conclusion

With the introduction of RPS policies, electricity price volatility is likely to increase. In addition, renewable generation is expected to displace coal and lower long-term average electricity prices due to more zero marginal cost generators such as wind and solar. In a competitive market, it is important for individual power producers to capture appropriate market price signals to minimize social welfare losses and to maintain a reliable supply of generation. We modeled and evaluated a spark spread options valuation for capital budgeting and compared it with the traditional cash flow approach. Our numerical examples show it is profitable to build three out of six projects using the spark spread option in capital budgeting even without capacity payments. The traditional cash flow finds only two out of the six projects examined to be profitable.

We extend the use of the spark spread approach in capital budgeting and present a real options approach to understand the optimal conditions for investing, reactivating, mothballing, and permanently abandoning a plant. Under a real options approach, we develop operating and waiting value functions using dynamic programming. We present a closed-form explanation for why real options investment thresholds are higher than those for traditional cash flow valuation. We also show that new investment price thresholds in coal and natural gas will be higher in markets with higher volatility.

The coal industry is projecting an increase in mothballing and decommissioning coal-fired power plants. Although a mothballed plant does not provide energy benefits, there should be a value in holding the option to reactivate the plant in the future to sell energy. We apply the same real options approach to solve for the value of a mothballed plant. Our numerical results show that mothball price signals decrease as volatility increase. In other words, it is better to delay mothballing when electricity price volatility increases. We also show that reactivation costs influence a power plant's decision to mothball.

The timing and strength of policy affects investment and operational decisions. We highlight the effects of increased volatility and a decrease in average prices on investment behavior. The model the arrival of a policy that decreases future average prices incentivizes early investments in coal and gas-fired generators. We conclude that the timing of introduction and implementation will play a key role in providing appropriate market price signals that will provide a reliable mix of generating technologies.

The spark spread approach captures the value in holding the option to convert fuel into electricity in the future. The real options approach gives the optimal threshold value for investment and operational decisions. These tools can help individual power producers capture appropriate market price signals, and avoid under-valuing generation technologies. The real options approach captures the intrinsic value in having installed capacity, thus making several investment decisions profitable even in the absence of capacity payments

1.0 Introduction

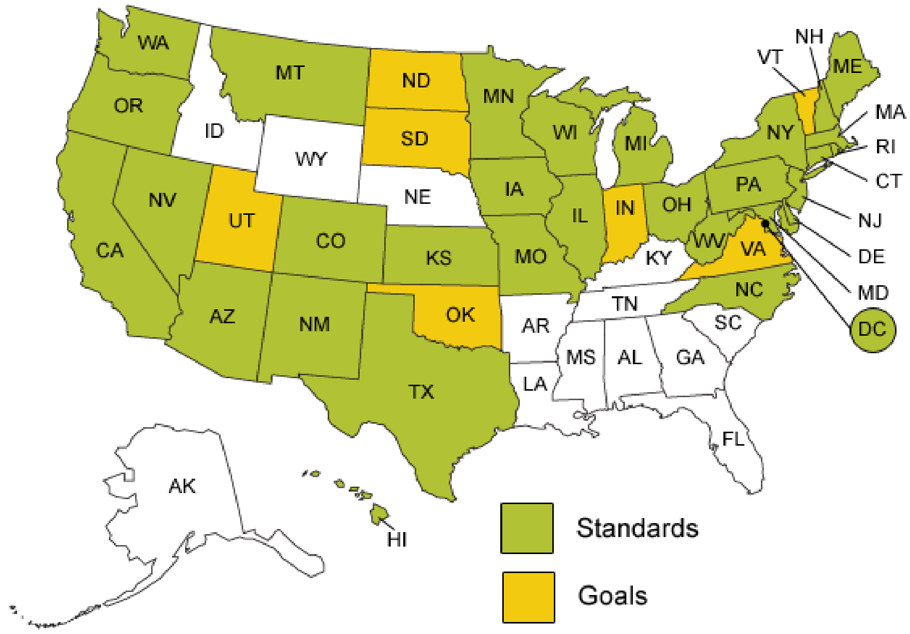
Decisions by operators of coal and natural gas power plants will require increasingly sophisticated investment analysis as renewable penetration increases. Appropriate market mechanisms and market price signals will be crucial in ensuring adequate generation resources as must-run renewables reduce the energy payments to existing fossil generators. Existing and proposed air and water regulations coupled with the reduced energy payments may push firms into making net present value (NPV) decisions to retire fossil plants.

Electricity market and policy uncertainties make timing of investment and operational decisions in conventional generation difficult to assess. In a restructured market with Renewable Portfolio Standards, individual generation asset owners require tools to properly value conventional generators and make timely decisions in investment, temporary suspension, reactivation, and abandonment of power plants. The traditional discounted cash flow valuation of conventional generators does not capture uncertainties such as market volatility of electricity and fuel prices, which may lead to undervaluation of generation assets. A real options approach incorporates both market and policy uncertainty in making investment and operational decisions. Real options analysis works under the assumption of 1) partially or completely irreversible investment decisions, 2) uncertainty in return, and 3) flexibility in the timing of investment decision. This is in contrast to the traditional now-or-never approach of deterministic NPV to value generation assets. Several studies have explored a real options approach in the electricity industry (Dixit & Pindyck, 1994; Fleten & Nasakkala, 2010; Yang & William, 2007).

As illustrated in Figure 7, 38 states have adopted Renewable Portfolio Standards, which requires a fraction of generation come from renewable sources by a target date (Database of State Incentives for Renewables & Efficiency (DSIRE), 2011-2012). Several studies have looked at the implication of these policies on generation mix (Doherty, Outhred, & O'Malley, 2006; Nelosn, et al., 2012). Doherty, Outhred, & O'Malley (2006) argued that that a system with high wind penetration requires fast-ramping technology to better accommodate wind and load variability. Their study suggests the need for appropriate valuation tools to capture market signals that will incentivize the appropriate and reliable mix of generators.

Renewable resources vary by state and geographical location. The optimal generation portfolio will vary across different electricity markets in the US. For instance, PJM has a goal of installing 15 GW (7.3% of installed capacity) of wind capacity by 2015 and 30 GW of wind capacity by 2020 (PJM, 2009). Displacement of conventional generation due to additional wind will vary depending on the current mix of a system. For example, PJM studies suggest that 15 GW of installed capacity from wind will displace an estimated 26,000 GWh (~5%) of coal generation and 13,000 GWh (~22%) of natural gas. A drop in fossil generator capacity factors resulting from increased wind integration requires tools to assess new investments and financial operational decisions of conventional generators.

Figure 7 Renewable portfolio standards



Source: Today in Energy: Most states have Renewable Portfolio Standards (U.S. Energy Information Administration, 2012)

The primary issue we address is the ability of individual power producers to capture appropriate market price signals for investing, temporary suspension, reactivating or permanently abandoning conventional power plants while maintaining a reliable and cost-effective grid in a restructured market. The implication of higher wind penetration on electricity prices is beyond the scope of this report. However, several papers in the academic literature have explored the price implications of wind in electricity markets outside the US (Green & Vasilakos, 2011; Olsina, Roscher, Larisson, & Garces, 2007). While the effort on prices is not easily evaluated, it is widely recognized that polices that prioritize renewable energy generation will cause a drop in capacity factors of conventional generators, thus affecting valuation of conventional generators. Our work focuses on the implication of high wind penetration. Other policies that can affect generation capacity of conventional generators, such as the Environmental Protection Agency (EPA) SO_2 mandate have been studied elsewhere. For example, Patino-Echeverri, Morel, Apt, & Chen (2007) investigated coal plant retrofitting and new investments using a real options approach. Our model allows flexibility in policy assessment since we provide closed-form solutions to our decision support framework.

Recent studies suggest that there will be an increase in retirement of conventional generators under different policy regimes (Electric Power Research Institute, 2011). The Electric Power Research Institute (EPRI) estimates 15 GW of coal plant retirements, 33% of which is expected to be replaced with gas-fired capacity. EPRI is currently conducting a portfolio migration research to assess “long-term outcomes of various utility generation asset portfolio management strategies (Electric Power Research Institute, 2011)”. Coal plant retirement plans have increased in the past three years:

> For 2010-2018, announcements of future coal unit retirements had accelerated from 3.3 GW in spring 2009 to 10.3 GW in autumn 2009 to 15.2 GW by spring 2010 (the date of EPRI’s mid-year

review). Subsequent to EPRI's 2010 mid-year assessment, the pace of announced coal-fired retirements has increased another 10 GW or more.

- *EPRI Generation Portfolio Migration under Market Uncertainty.*

In addition to coal plant retirement, several firms have announced plans to temporarily suspend operation or mothball plants with the possibility of future reactivation. On March 14, 2012, Dunkirk Power LCC submitted their plan to mothball two coal units saying they are not economic to operate (Cassell, Two Dunkirk coal units headed for mothballs, two others getting temporary reprieve, 2012). However, the company has plans for future reactivation and not abandonment. Cayuga Operating Company claims that "current and forecasted wholesale electric prices in New York are inadequate for the Cayuga Facility to operate economically, and, therefore, Cayuga Operating Company intends to place the Cayuga Facility in protective lay-up to limit the costs that are incurred at the facility" (Cassell, Cayuga Operating to mothball over 300 MW of coal capacity by January 2013, 2012). Some firms may decide to mothball to minimize losses, but can later decide to reactive or completely abandon if market conditions do not improve.

Some firms are delaying mothballing and retirement due to large uncertainties in market and policy conditions. Luminant, a Texas-based electric utility, delayed the mothballed of two coal-fired generators, totaling 1,130 MW (Cassell, Luminant delays plan to shut two Monticello coal units, 2012).

We investigate optimal conditions of investment and abandonment as well as other operational decisions such as mothballing and future reactivation from a firm level standpoint. We present a decision support tool to aid individual power producers in evaluating appropriate price signals with market and policy uncertainty. A real option approach provides optimal conditions for hedging strategies in investing and operating large projects with many sources of uncertainties. Our decision support framework is more realistic compared to a now-or-never decision making from traditional NPV in capturing how firms actually manage large assets with varying levels of uncertainty.

1.1 Risk Management

For 70 years of the history of the electricity industry, electric power production was generally considered to be a natural monopoly where utilities and power producers had exclusive geographic rights (Hirsh, 1999). Power plant procurement was done on the basis of reliability requirements in meeting growing demand, and rates were calculated based on the producer's need to cover operating costs as well as capital costs, as opposed to rates that would have been set in a competitive market (Hirsh, 1999). The Public Utilities Regulatory Policy Act (PURPA) of 1978 and the Energy Policy Act of 1992 introduced new market mechanisms that would challenge the traditional natural monopoly principle (Hirsh, 1999). This in turn would shift financial risks of capacity expansion to individual power producers.

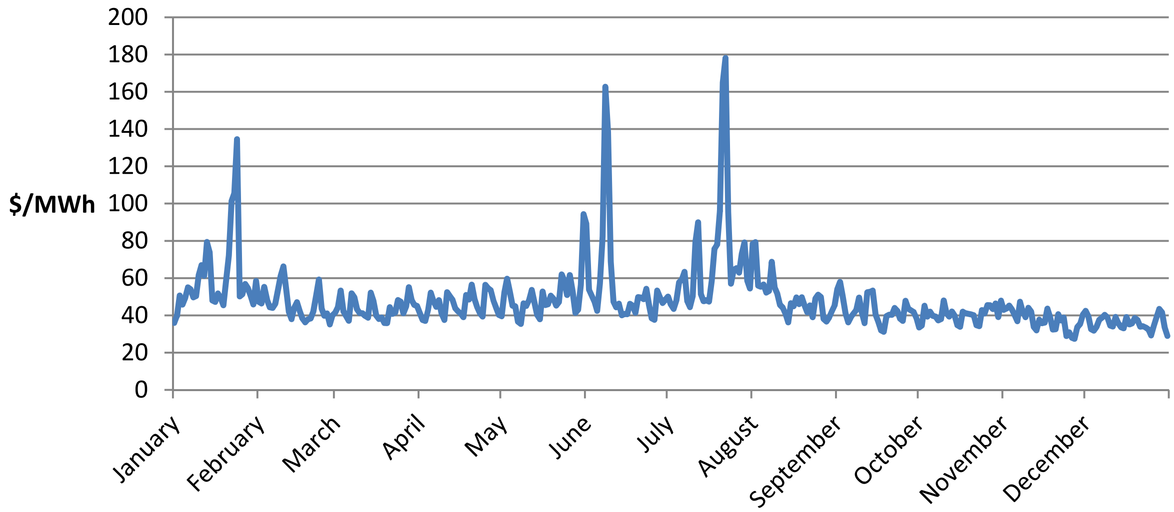
Electricity and fuel prices are volatile, making valuation of electric generation difficult and risky. Our valuation tools focus on market and policy risks. When the price of electricity declines, the value of a unit of installed capacity also decreases. When primary fuel prices increase, the value of a unit of installed capacity decreases because the profit margin from converting fuel to electricity decreases. Uncertainty in demand is also reflected through market prices. Supply and demand must be met on a sub-hourly time scale, which makes it more difficult to balance generation and consumption. A power plant that promised to deliver energy on a certain hour may face unexpected (forced) outages, being unable to deliver energy, which in turn affects other power producers. Power plants have diverse operational characteristics including fuel, heat rate efficiency, and ramping rates thus the cost of providing electricity varies by technology. Coal plants cannot ramp as fast as combined gas cycle turbines, but coal plants can provide energy at a lower rate as long as its power output remains relatively constant. On the other hand, coal cannot respond to quick changes in demand, an important factor in maintaining grid stability. Overnight capital costs also vary by technology. A 500 MW coal plant can cost $1.5 to $2.5 billion, using costs numbers in Lazard (2010).

How should generation assets be managed? Having an asset of installed energy capacity gives the owner the ability to convert fuel into electricity. Derivatives are used to manage tradable commodities including electricity. An electricity derivative is a contract between a buyer and a seller. The seller of energy is typically an independent power producer (IPP), and buyers are often load serving entities (LSEs). Examples of electricity derivatives are forward, futures, and options. An electricity forward contract specifies a fixed amount of electricity to be delivered in the future (often called maturity or expiration date) for a specified forward price, F. The forward contract payoff to the buyer who promises to buy one unit of electricity at time T is:

$$\text{Forward Contract Payoff} = (S_T - F), \tag{1}$$

where S_T is the spot price at time T. The spot prices refer to the real time prices of a commodity on the day it is delivered. The daily spot price is computed by taking the average spot prices between 7:00 AM to 10:00 PM. Figure 8 shows 2011 PJM Day Ahead Average Peak Prices. Forward contracts can have an expiration time in the scale of hours to years. Physical forward contracts with hourly or daily maturity are often traded in electricity markets such as PJM and the California Independent System Operator (Deng & Oren, 2006). Forward contracts are traded over the counter as opposed to future contracts, which are traded in organized exchange markets.

Figure 8 2011 PJM day ahead average peak prices (7:00 AM - 10:00 PM)



Source: Today in Energy U.S. Energy Information Administration (EIA)

Electricity futures were first introduced on the New York Mercantile Exchange (NYMEX) in 1996 (Eydekand & Wolyniec, 2003). Electricity futures are traded exclusively on organized exchanges such as NYMEX while forwards are traded over-the-counter (OTC), typically through bilateral contracts (Deng & Oren, 2006). Futures and forward contracts have very similar characteristics where prices are quoted for delivering a commodity at a certain date and location in the future. Electricity futures provide better market price transparency, trading liquidity, and lower search costs than bilateral contracts (Deng & Oren, 2006). The first two futures contracts traded on NYMEX had a contract size of 736 MWh per month with a rate of 2MW/h for 16 peak hours on 23 peak delivery days (Stoft, Belden, Goldman, & Pickle, 1998). Peak delivery days are Monday through Friday, and the first two delivery locations were California-Oregon Border (COB) and Palo Verde.

Forward contracts face high search costs because buyers and sellers trade over-the-counter. Market price discovery is also more difficult and less transparent, as opposed to price discovery in an exchange where there are several market participants. There is also less trading liquidity in forward contracts since transaction and search costs are higher. An example of forward contract issues is illustrated in the following excerpt:

> …after the collapse of the California power market in the summer of 2000, the California Independent System Operator (ISO) had to discover the price for electricity delivered in the future through lengthy, expensive negotiation, because there was no market price for future electricity deliveries. Second, when the agreed-upon price is far different from the market price, one of the parties may default ("non-perform"). As companies that signed contracts with California for future deliveries of electricity at more than $100 a megawatt found when current prices dropped into the range of $20 to $40 a megawatt, enforcing a "too favorable" contract is expensive and often futile. Third, one or the other party's circumstances might change. The only way for a party to back out of a forward contract is to renegotiate it and face penalties.
>
> *-Derivatives and Risk Management in the Petroleum, Natural Gas, and Electricity Industries 2002*

Electricity futures are not without risks. Stoft, Belden, Goldman, & Pickle (1998) list several entities that have incurred significant losses from participating in electric futures trading. One important feature of the futures market is the convergence to spot prices (Stoft, Belden, Goldman, & Pickle, 1998). We illustrate a simple scenario to show the mechanism of how futures prices converge to spot prices at expiration. This example is adapted from (U.S. Energy Information Administration, 2002). An independent power producer (IPP) who wants to sell electricity in July 2013 can sell electricity futures contracts at 700 MWh per contract to an exchange. A load serving entity (LSE) can buy a July 2013 electricity future from the exchange. Suppose the projected load for July 2013 is 70,000 MWh. If the LSE trader discovers that she no longer needs 7,000 MWh, she can sell a July 2013 electricity futures at the prevailing July 2013 futures price.

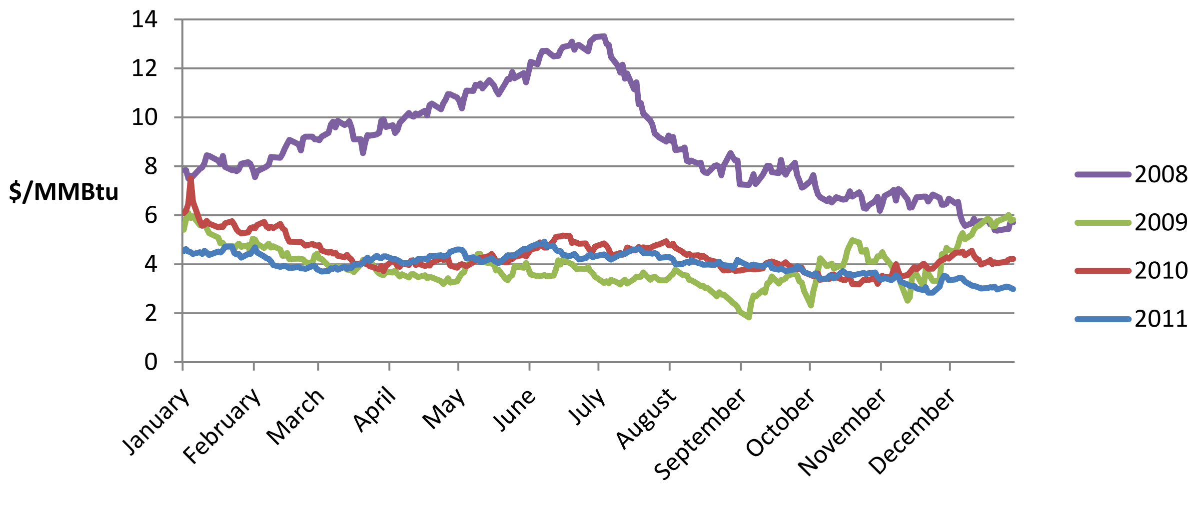
The load serving entity decides to buy 10 contracts of electricity futures at a July 2013 futures price of $45/MWh. There will be no exchange of money in the initial contract other than the initial margin of $2,300 per contract (Capitol Commodity Services, Inc., 2012), which is set by the exchange in case of a default. Between July 2012 and July 2012, the futures price will fluctuate depending on electricity supply and demand. Suppose in October, July 2013 futures price falls to $42/MWh. The LSE trader is required to pay her margin account of $21,000 ($3/MWh * 700 MWh * 10 Contracts). This accounting is referred to as "mark-to-market." In March, July futures prices climb to $44/MWh. Mark-to-market calculations are relative to the most recent futures settlement, and the LSE gets paid $14,000 from the exchange. In May, futures prices increase to $51/MWh, and she receives another $49,000 from the exchange. At the end of June, futures price for July 2013 is exactly the spot price for that month. The LSE trader can either request the delivery of electricity or sell her contract at the spot price. Suppose that she needed all 70,000 MWh of electricity. She pays $51/MWh or $357,000. If the LSE trader decides not to demand electricity, she can keep her trading profit of $42,000. Note that it is not always the case that the trading profit is positive. If she decides to buy at $51/MWh then she effectively pays $45/MWh ([357,000 – 42,000]/ 70,000). In both cases, the initial margin contract cost is returned.

An option specifies an agreement between two parties for a future exchange on a commodity with reference to some price often called the *strike price*. The buyer of the option has the right, not the obligation, to execute the trade. The seller, on the other hand, must fulfill the corresponding obligation on the transaction. The price of an option is the difference between the reference price and the price paid for an underlying asset plus some premium on holding the asset relative to its expiration date. We devote section 1.4 to a brief introduction to the valuation of options. Margrabe (1978) was the first to explore closed form solutions to the valuation of holding an option to exchange one commodity for another. These options are called cross-commodity options; they account for uncertainty in two different commodities. Converting fuel into electricity can be seen as a cross-commodity option. A unit of installed capacity can be seen as buying an option to have the ability to buy fuel and sell it as electricity. We refer to this cross-commodity derivative of converting fuel and selling it as electricity as the *spark spread option*. We explore the options approach in section 1.4 and use it as a tool in capacity valuation.

1.2 Fuel and Electricity Prices

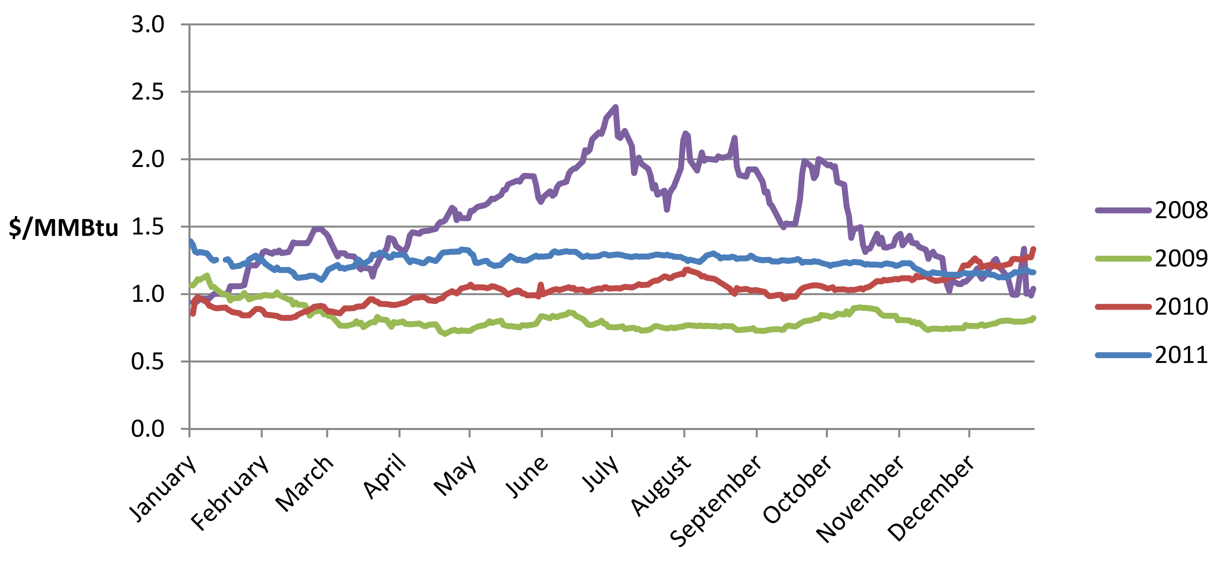
Trends in electricity and fuel prices are crucial in determining a power plant's profitability. This section illustrates market uncertainty and volatility by looking at historical energy prices. In Figure 9, we display not only daily volatility, but also annual shocks to the market. In the 2008 historical data, we observe a shock in fuel prices. Capital budgeting tools should be able to incorporate market trends and volatility. A real options approach considers these risks when solving for optimal conditions in investing in a project. **Error! Reference source not found.** and REF _Ref333557599 \h * MERGEFORMAT **Error! Reference source not found.**show the daily price volatility in historical spot and future prices in natural gas and coal respectively. In contrast, **Error! Reference source not found.** and Figure 12 show the monthly price volatility in historical futures prices in Central Appalachian Coal and Henry Hub respectively.

Figure 9 Historical daily Henry Hub/ NYMEX natural gas spot prices (2008 – 2011)



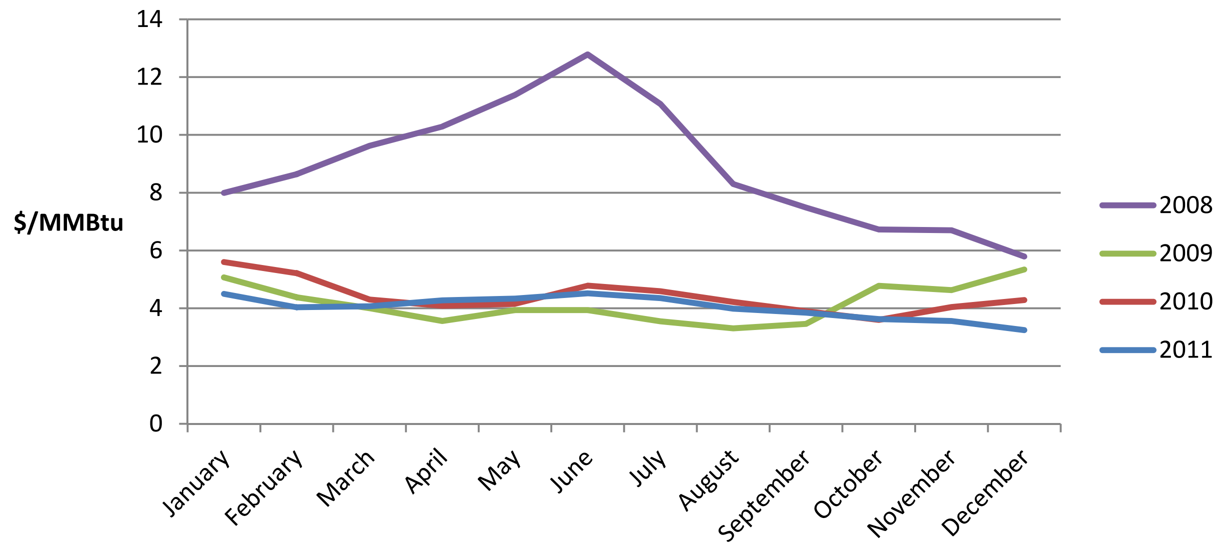
Source: US Energy Information Administration

Figure 10 Historical daily Central Appalachian / NYMEX coal futures (2009-2011)



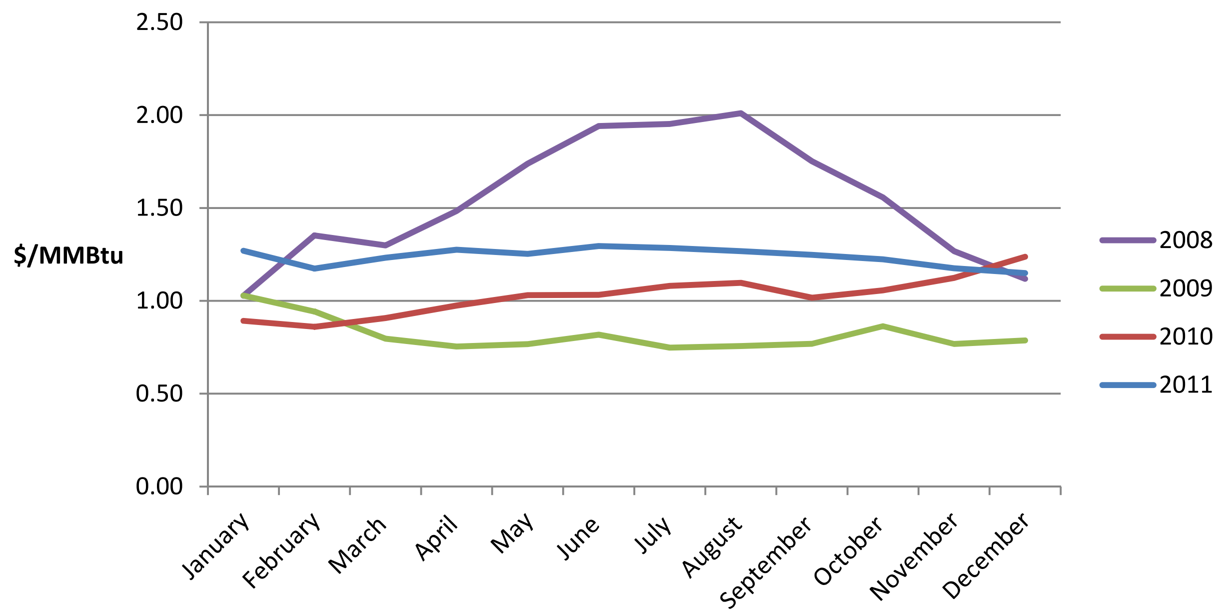
Source: US Energy Information Administration
(http://www.eia.gov/coal/nymex/html/nymex_historical.html)

Figure 11 Monthly Henry Hub historical futures prices (2008 - 2011)



Source: US Energy Information Administration

Figure 12 Historical monthly Central Appalachian / NYMEX coal futures (2008 - 2011)



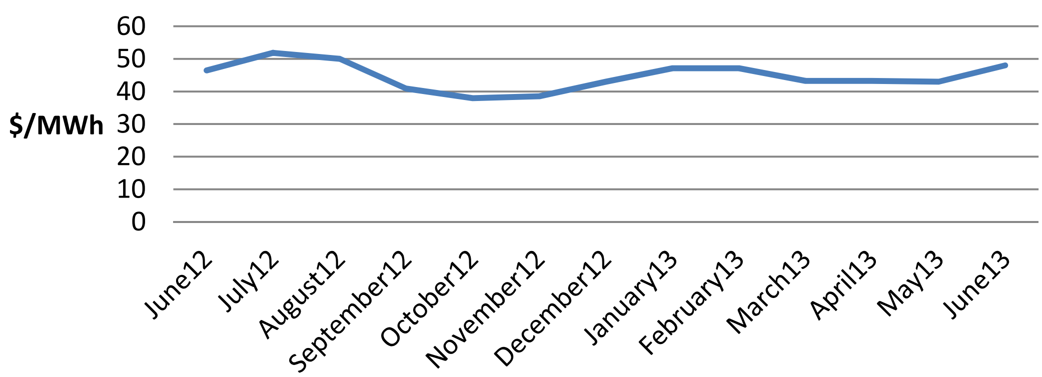
Source: US Energy Information Administration

The Henry Hub is a distribution hub for natural gas that is traded on the New York Mercantile Exchange (NYMEX). Central Appalachian bituminous coal is also traded on NYMEX. The historical futures prices in Figure 11 and 12 show the price of natural gas and coal a calendar month from the trade date. The difference between the spot and the futures market is the time when prices are determined. The first NYMEX natural gas futures contract was traded on April

3, 1990 (Budzik). NYMEX started trading Central Appalachian Coal futures on July 12, 2001 (U.S. Energy Information Administration).

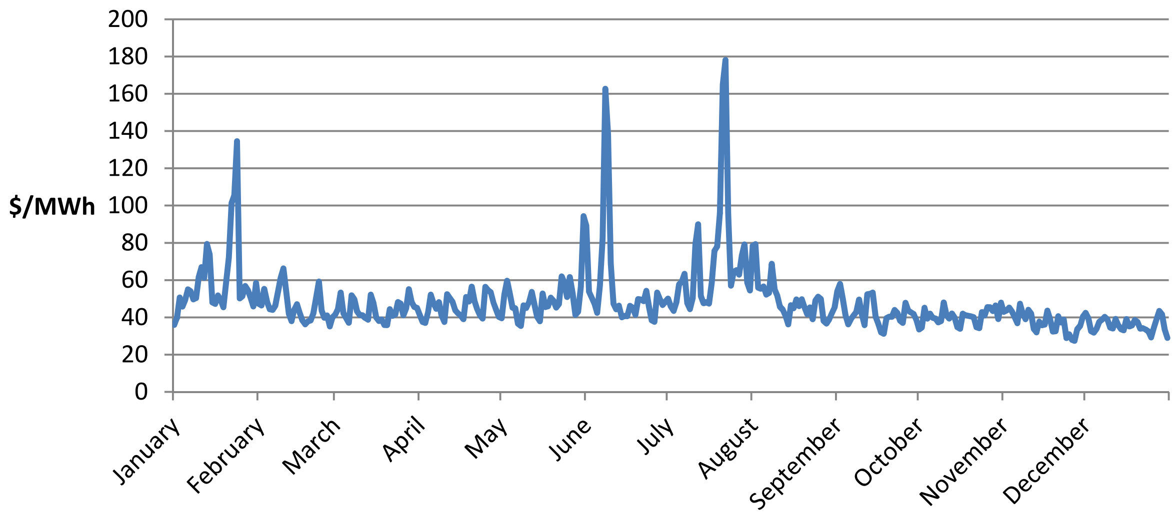
The transfer of energy must follow physical network constraints, and large quantities of electricity cannot be stored economically with current technology. Locational marginal pricing (LMP) is a method of determining real time spot prices in the energy market. Electricity spot prices are more volatile than other storable goods such as oil, gold, and rice (Eydekand & Wolyniec, 2003). **Error! Reference source not found.** and **Error! Reference source not und.** show monthly electricity futures and 2011 historical day ahead aggregate locational marginal prices in PJM respectively. Historical electricity futures data is proprietary therefore we do not include them in this report. Shawky, Marathe, & Barrett (2003) used empirical tests to compare spot and future electricity markets. Their findings show that electricity spot price volatility is 2 to 15 times higher compared to futures price volatility (Shawky, Marathe, & Barrett, 2003). This has significant implications for using future versus spot prices on the valuation of power plants. As we will explain in greater detail in further chapters, an options approach valuation of generator asset is very sensitive to volatility parameters.

Figure 13 NYMEX PJM futures electricity prices



Source: TradingCharts.com Inc. (recorded on May 18, 2012)

Figure 14 Historical day ahead aggregate locational marginal prices in PJM



Source: Monthly Locational Marginal Pricing (PJM, 2012)

1.3 Modeling Stochastic Price Processes

There is extensive literature on modeling electricity and fuel prices as a stochastic differential equation (Pindyck, 1999; Schwartz, 1997; Weron, Bierbrauer, & Truck, 2004). This section provides a brief introduction to mathematical modeling of electricity and fuel prices. We combine several price forecast studies and calibrate our time-continuous stochastic model. We end the section with key assumptions and limitations of the geometric Brownian motion (GBM) and the Ornstein – Uhlenbeck (mean-reverting) process.

1.3.1 Geometric Brownian Motion

A stochastic process, X, is called a geometric Brownian motion if it exhibits the following property:

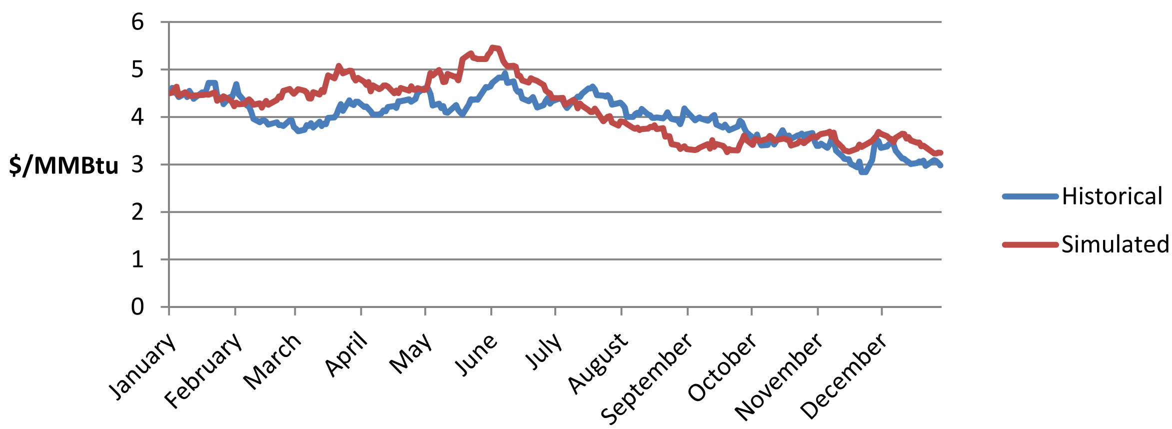
$$dX = \alpha X dt + \sigma X dz \tag{2}$$

$$\mathrm{E}[x_{t+1} | x_t, x_{t-1}, \dots, x_0] = \mathrm{E}[[x_{t+1} | x_t] \tag{3}$$

where dz is called a Weiner process and $dz = \mathcal{N}(0,1)\sqrt{t}.$ $\mathcal{N}(0,1)$ is the notation for a standard normal distribution. The economic interpretation of normality comes from the stylized fact that daily changes in returns are normally distributed (Weron R. , 2006). α (alpha) and σ (sigma) are drift and volatility parameters respectively. The drift, α, accounts for the growth or decline of average prices over time. dt is the time step size, which can be calibrated either daily, monthly or yearly, depending on the relevant time step for the investment decision problem. The volatility, σ, characterizes the step size randomness in the GBM, which is derived by computing the standard deviation of the changes of the logged prices (also called logged returns) of a time series. An inherent mechanism of the geometric Brownian motion is that volatility increases linearly over time. This fits the economic intuition that there is greater uncertainty in forecasting further in time. Equation (2) characterizes the Markov property where future states are dependent on only the previous state. The next four figures qualitatively compare historical prices with simulated prices using MATLAB®**.**

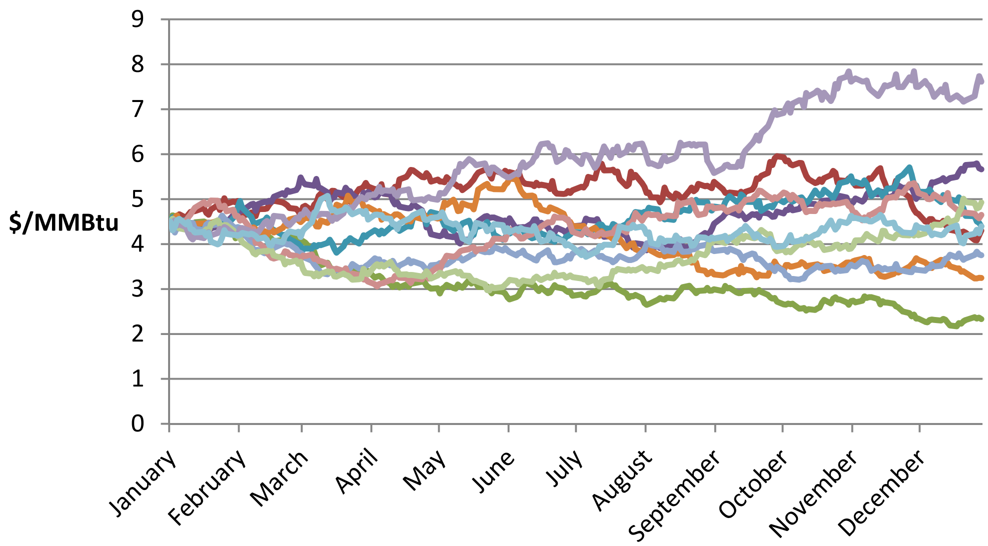
In Figure 15, we plot a geometric Brownian simulation of Daily Spot Prices (252 trading days) with an annual drift of 2% and annual volatility of 30% against 2011 historical daily spot prices. In Figure 16, we plot 10 simulations of the geometric Brownian with the same drift and volatility parameters. Figure 17 contrasts historical NYMEX futures electricity prices and a geometric Brownian simulation with an annual drift of 2% and annual volatility of 35%. Figure 18 shows 10 simulations of the geometric Brownian motion with the same drift and volatility parameters. These plots qualitatively indicate that GBM can produce reasonable simulations of the observed prices.

Figure 15 2011 Daily Henry Hub/ NYMEX natural gas spot prices and MATLAB® geometric Brownian simulation



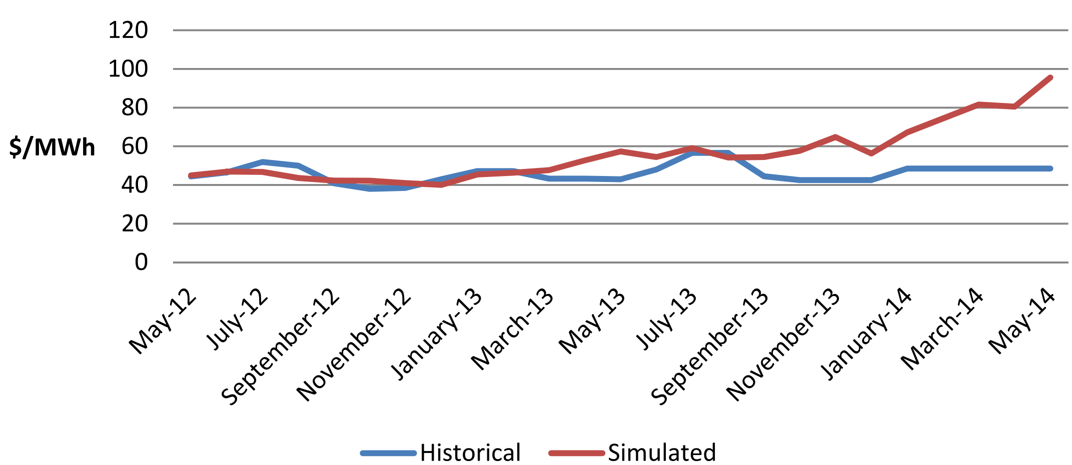
Source: US Energy Information Administration

Figure 16 10 MATLAB® simulations of geometric Brownian natural gas prices



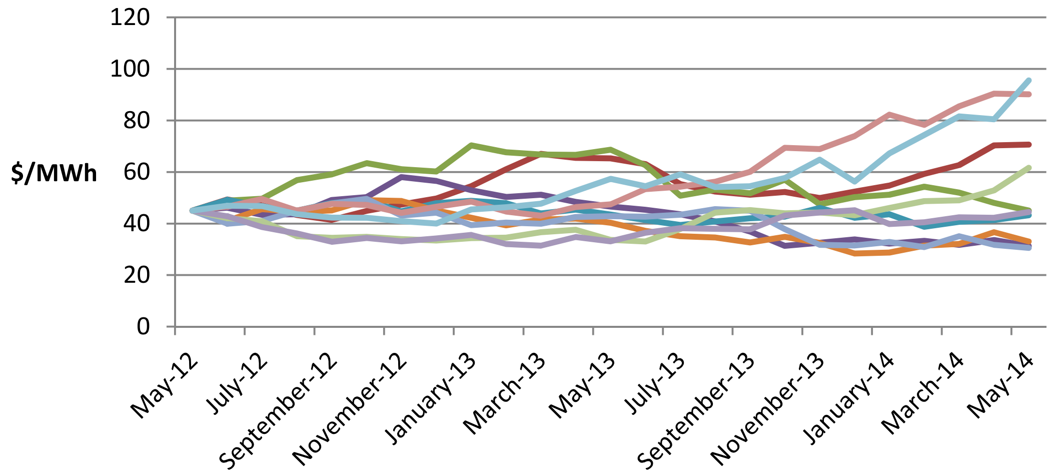
10 Simulations with the same annual drift, $\alpha = 2\%$ **and annual volatility,** $= 30\%$ **.**

Figure 17 2011 NYMEX futures electricity prices and MATLAB® geometric Brownian simulation



Source: TradingCharts.com Inc. (recorded on May 18, 2012)

Figure 18 10 MATLAB® geometric Brownian simulations of 2011 NYMEX futures electricity prices



10 Simulations with the same annual drift, $\alpha = 2\%$ and annual volatility, $\sigma = 35\%$

The expectation and variance of the GBM at time, *t*, is given by (4) and (5).

$$\mathrm{E}(x_t) = x_0 e^{\mu t} \tag{4}$$

$$\mathrm{Var}(x_t) = x_0^2 e^{2\mu t}\left(e^{\sigma^2 t} - 1\right) \tag{5}$$

We can also model two correlated time series that follow geometric Brownian motion. Suppose that dx and dy are two correlated GBM then we have an added property $E\left[dz_x dz_y\right] = \rho dt$ where ρ is the correlation between x and y.

1.3.2 Ornstein-Uhlenbeck / Mean-reverting Process

The Ornstein-Uhlenbeck is another stochastic process often used in modeling energy prices. A stochastic process, *X*, is called an Ornstein-Uhlenbeck or mean-reverting process if it satisfies the following stochastic differential equation:

$$dX = \theta(\mu - X)Xdt + \sigma X dz \tag{6}$$

$$\mathrm{E}[x_{t+1}|x_t, x_{t-1}, \ldots, x_0] = \mathrm{E}[[x_{t+1}|x_t] \tag{7}$$

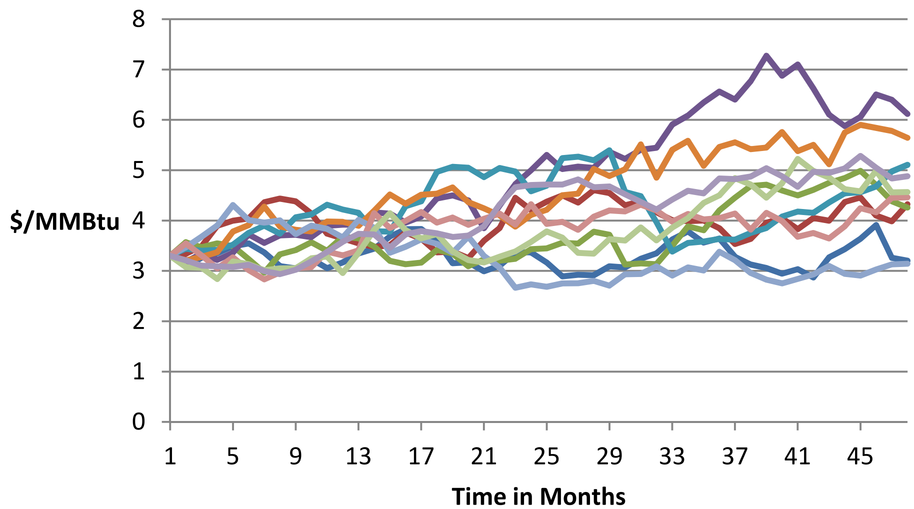
where, *dz,* is the same Weiner process in (2). The economic interpretation of the parameter θ is the rate of reversion to the long-run expectation, μ. Condition (7) is the same Markov property as the geometric Brownian motion. The Ornstein-Uhlenbeck process will keep reverting to the expected mean, while the long-run expectation of the GBM will increase over time. The variance of GBM also increases log-linearly over time, but the variance of the mean-reverting process converges to a single variance. The expectation and variance of (6) at time, *t* is given by equations (8) and (9) respectively.

$$\mathrm{E}[x_t] = \mu + (x_0 - \mu)e^{-\eta t} \tag{8}$$

$$\mathrm{Var}\,[x_t] = \frac{\sigma^2}{2\theta}(1 - e^{-2\eta t}) \tag{9}$$

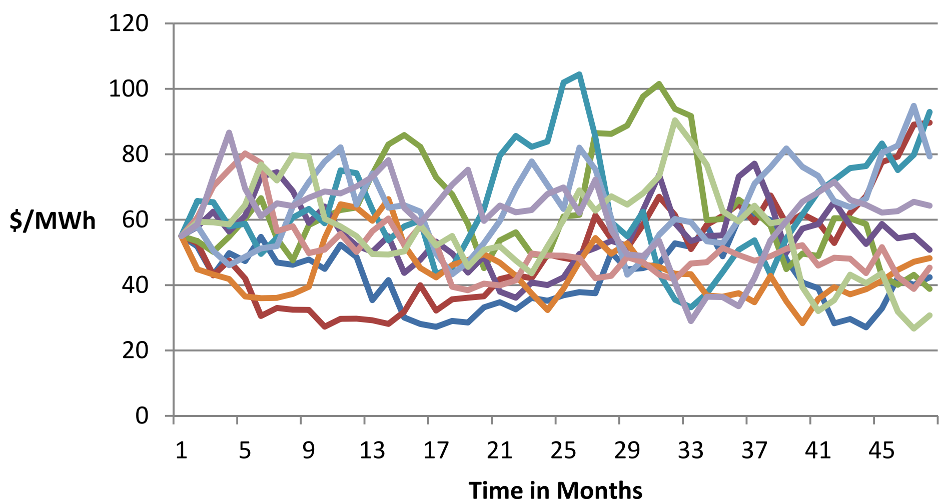
Figure 19 shows 10 mean-reverting simulations of natural gas futures prices with a reversion rate of 40%. The long-run expectation, $\mu = \$3.5$/MMBtu, and volatility, $\sigma = 40\%$, is fixed for the 10 simulations. In Figure 20, we show 10 mean-reverting simulations of electricity price futures with a reversion rate of 10%. We fix the long-run expectation and volatility at $55/MWh and 90 respectively.

Figure 19 10 MATLAB® mean-reverting simulations of natural gas prices



10 mean-reverting simulations with the same parameters: $\eta =$ 40%, $\mu = 3.5, \sigma =$ 40%

Figure 20 10 MATLAB® mean-reverting simulations of electricity prices



10 mean-reverting simulations with the same parameters: η= 10%, μ=55, σ= 90%

1.3.3 Jump Process

In 2008, natural gas and coal prices were very high compared to the followings years. A sudden drop and increase in long-term prices of fuel or electricity can be easily incorporated with a stochastic diffusion process. These sudden long-term drop or increase in price expectations is called a jump. A jump diffusion is modeled as a Poisson arrival process with a parameter, λ, which characterizes the expected time of the drop or rise in long-term trends. In section 4.1.4, we discuss in greater detail the implications of policy on prices and how we can incorporate policy on valuation and investment strategies.

Let q be a Poisson process with parameter λ. The economic interpretation of λ quantifies the expected arrival time of an event such as a policy that will lead to a decrease in average electricity prices. Suppose we expect a 10% decrease in average prices in 20 years, but our forecast is not with full certainty. It is possible that this policy may be delayed by 2 to 3 years. The uncertainty in the policy arrival is captured by the Poisson process. In other words, the probability of the decrease happening in some time interval, dt is λdt. Adding the Poisson process to equation (2) we get:

$$dX = \alpha X dt + \sigma X dz + X dq$$

$$dq = \begin{cases} 0 \text{ with probability } 1 - \lambda dt \\ \theta \text{ with probability } \lambda dt \end{cases}$$

The geometric Brownian motion and mean-reverting process provides us with computationally tractable tools to characterize forecasts with market and policy uncertainty. Although they are powerful tools in characterizing uncertainty, they face a couple of limitations in fully capturing electricity industry trends. It is a stylized fact that electricity prices follow seasonal trends. Electricity prices tend to be higher during summer and winter peak hours compared to fall and spring. Weron R. (2006) has explored how to incorporate seasonality with the GBM process.

Price spikes are often observed in the electricity market. In Figure 15, we notice several price spikes reaching $120/MWh. Geometric Brownian motion and mean-reverting processes does not account for price spikes. There are several challenges in modeling spikes such as understanding the magnitude and frequency of spikes. We acknowledge the presence of price spikes in the electricity industry, but for closed-form tractability we limit our model to geometric Brownian without spikes.

1.4 Spark Spread Options Theory

Spot prices refer to market prices for commodities exchanged in real time. The strike price, K, (or exercise price) is the fixed price at which the underlying commodity is bought. For example, suppose that company X bought commodity A, with some expiration time, T, for K = $3.50. An option refers to the ability of the owner to sell (not sell) if the spot price, S, is higher (lower) than the strike price at time T. The payoff of holding a particular option that expires at time, *T is*:

$$\pi(S_T, K, T) = \text{Max}\ (S_T - K, 0) \tag{10}$$

A cross-commodity derivative is the ability to exchange one risky asset for another in the future (Margrabe, 1978). In the electricity industry, this financial exchange is referred to as the spark spread, the difference between the price of electricity and the cost of converting fuel into electricity. Given the futures price of electricity, F_e, the futures price of fuel, F_f, and the heat rate of a generator, *H*, the economic value of a unit of installed capacity is given by:

$$\pi\left(F_e^T, F_f^T, H, T\right) = \text{Max}\ \left(F_g^T - H\ F_f^T, 0\right) \tag{11}$$

Subject to:

$$dF_e = \alpha F_e dt + \sigma F_e dz \tag{12}$$

$$dF_g = \alpha F_g dt + \sigma F_g dz \tag{13}$$

The spark spread gives us a value of owning a unit of installed capacity of an electric generator. Deng, Johnson, & Sogomonian (2001) provides a closed form solution for the value of holding a spark spread option under the assumption that futures prices of electricity and fuel follow either a geometric Brownian motion or a mean reverting process.

Suppose electricity futures, F_e follows a geometric Brownian motion with some drift and volatility $\alpha_e$and σ_e respectively. We also let fuel futures, F_f, follow GBM with drift α_f and volatilityσ_f. We add an interest rate parameter, *r*, to discount the value of owning the asset in the beginning of the year. The value of holding a unit of generating capacity with an electricity and fuel future that expires in one year is given by:

$$V\left(F_e^T, F_f^T, H\right) = e^{-r}(F_e \Phi(d1) e^{\alpha_g} \ - HF_f\ \Phi(d2) e^{\alpha_f}) \tag{14}$$

$$d1 = \frac{\left(\text{Ln}\left(\frac{F_e}{HF_f}\right) + \frac{1}{2}\sigma^2\right)}{\sigma} \tag{15}$$

$$d2 = d1 - \sigma \tag{16}$$

$$\sigma = \sqrt{\sigma_e^2 + \sigma_f^2 - 2\rho\sigma_e\sigma_f} \tag{17}$$

Equation (17) is the parameter that characterizes both electricity and fuel price volatility. We refer to this parameter as the combined volatility parameter. $\Phi(x)$ is the notation for a standard cumulative distribution.

2.0 Capital Budgeting

Since 1996, the energy industry has experience significant restructuring in many states. In restructured markets there is free entry and exit of firms. In theory, free entry and exit incentivizes firms to compete for profitability driving their prices down until they sell at or close to their marginal costs. Several concerns have been raised regarding maintaining reliability in restructured markets (Oren, Generation Adequacy via Call Options Obligations: Safe Passage to the Promised Land, 2005; Oren, Ensuring Geenration Adequacy in Competitive Electricity Markets, 2003).

In the presence of policy that requires more renewable generation, we anticipate a decrease in fossil plant profitability. Furthermore, we expect a significant portion of Renewable Portfolio Standards (RPS) to be fulfilled by variable and intermittent source of generation such as wind and solar. Conventional generators are needed at times when wind and solar are not able to provide electricity. Given these factors, it is reasonable to ask whether temporarily suspending operation or mothballing is an economical option when market and conditions are unfavorable. Similarly, what are the optimal economic conditions when a fossil plant should be permanently decommissioned? We begin addressing these questions by examining traditional capital budgeting decisions without capacity payments (section 2.3). In the Section 3 we introduce the real options approach and present our decision support tools to address market price signals and optimal decisions under high intermittent penetration scenarios.

In this section we compare and contrast the traditional cash flow valuation of investment projects and the spark spread options approach of generation valuation. We assume a competitive industry where individual power plants are price takers and there is freedom in entry and exit in the market. In our valuation calculation, we ignore capacity payments, and we derive the value of the generating asset strictly from providing electricity services.

2.1 Traditional Cash Flow Value

Justifying the construction of new power plants is difficult because of capital cost and profitability uncertainty. An intuitive way to value power plants is to compute the expected return from buying fuel and converting it to electricity over the lifetime of the plant. Plants that have low capacity factors such as shoulder and peak generators may find it more difficult to justify their profitability compared to base load plants such as coal. Capacity payments are fixed income for generating technologies regardless of their energy production. We present a traditional cash flow valuation in the absence of capacity payments. We use energy production as the only source of revenue. We illustrate our traditional valuation with a simple numerical example.

Suppose the price for a December electricity future is \$42/MWh and the price for a December fuel future is \$4.5/MMBtu. If the heat rate of the plant is 9000 Btu/kWh (9MMBtu/MWh), then the expected profit in December is:

$$V(F_e, F_g, H) = \text{Electricity Future Price} - \text{Heat rate} * \text{Fuel Future Price} \tag{18}$$

$$V(F_e, F_g, H) = \$1.5/\text{MWh} \tag{19}$$

If the 1MW plant operates for 300 hours (15 peak hours * 5 days a week * 4 weeks) in December, then the value of a MW of installed capacity is \$450 (\$1.5/MWh * 300 hours). If we introduce an interest rate, $r = 10\%$, we get a discount factor of e^{-r}. We can also incorporate the drift in prices over time in the traditional cash flow valuation. If we have a drift, $\alpha = 3\%$, we expect the prices to grow by e^{α} at the end of the year. We compute the present value of holding 1 MW of generating capacity in the beginning of the year, and we get ~ \$430/MW (\$4,500$e^{.03-.10}$). If the plant has a lifetime of 20 years with an annual capacity factor of 40% then the lifetime discounted value of the project is \$55,000/MW ($1.5 * 8760 * .40 \int_0^{19} e^{(.03-.10)t} \; dt$).

2.2 Spark Spread Valuation

The traditional cash flow valuation ignores price volatilities. One way to incorporate volatility is to do a sensitivity scenario by enumerating several electricity and fuel prices with some weighted probabilities to reflect their volatilities. Although it may sound computationally expensive, modern computers can perform thousands of these valuations in seconds. However, there is a better and more elegant solution. Exotic option valuation of conventional generators is explored in Deng, Johnson, & Sogomonian (2001) and Hsu (1998). We can use the closed form solutions derived by Deng, Johnson, & Sogomonia (2001) to value the spark spread option in equation (13). We note that this functional form is very similar to equation (12). The significant difference is that we account for electricity and fuel volatility. We assume the same electricity and fuel futures prices of \$42/MWh and \$4.5/MMBtu using the same heat rate of 9000 Btu/kWh. Suppose the annual volatility of electricity and fuel prices are $\sigma_e = \ 50\%$ and $\sigma_f = 30\%$ respectively. We also calibrate electricity and fuel price correlation to $\rho = 0.3$. The value of a unit of MW installed capacity using the spark spread options approach (14) – (17) is ≈ \$9/MWh. In this example, the spark spread value is 6 times higher than the traditional discounted cash flow. If the plant operates in December for 300 hours then the value of holding a unit of installed capacity to convert fuel into electricity is \$2700/MW (\$9 * 300 Hours). If we assume similar interest and drift rates, capacity factor, and operating life time as in the earlier example, the lifetime discounted value of the plant is \$330,000/MW. The value of the spark spread is significantly higher compared to the traditional cash flow valuation.

2.3 Project Decisions without Capacity Payments

The two numerical examples of asset valuation previously discussed illustrate the difference between the traditional cash flow and the spark spread. We extend our valuation to capital budgeting examples for Gas Combined Cycle, Integrated Gasification Combined Cycle (IGCC), and Coal Plants. We provide high and low price and plant characteristic parameters. All detailed assumptions and calculations for each scenario are found in Appendix 1. The **Error! Reference ource not found.** and Table 3 below show the lifetime summary statistic for the decision to build a 1 kW plant project. All units are in \$/kW unless stated otherwise.

Table 2 Price parameters

	Value		Unit
	(High)	(Low)	
Electricity Price	70	50	$/MWh
Natural Gas Price	5.5	3.4	$/MMBtu
Coal Price	2	1.5	$/MMBtu
Electricity Volatility	70%	45%	N/A
Natural Gas Volatility	40%	35%	N/A
Coal Volatility	30%	20%	N/A
Electricity and Gas Correlation	0.3	0.3	N/A
Electricity and Coal Correlation	0.2	0.2	N/A
Electricity Drift	3.0%	0.0%	N/A
Natural Gas Drift	2.0%	0.0%	N/A
Coal Drift	1.0%	0.0%	N/A

Table 3 Summary lifetime costs and values in $/kW

	Combined Gas Cycle		IGCC		Coal	
	(High)	(Low)	(High)	(Low)	(High)	(Low)
Overnight Capital Cost (Including Financing)	$1,380	$941	$5,510	$3,870	$5,300	$3,870
Operating Costs	$246	$190	$1,340	$1,320	$1,280	$810
Traditional Cash flow Value	$1,440	$1,060	$6,800	$4,360	$6,900	$4,950
Spark Spread Value	$1,630	$1,080	$6,860	$4,360	$7,010	$4,950

The decision to build a project is given by the following net present value (NPV) criterion:

$$\text{Present Value} - \text{Present Operating Costs} - \text{Overnight Capital Costs} \geq 0. \qquad (20)$$

We have a binary decision to either build the project or not depending on whether the NPV is greater than zero. The limitation of the now-or-never NPV approach ignores the ability to wait and delay investments. In addition, the traditional NPV criterion ignores volatility. We contrast the various decisions making under our high and low assumption cases with the traditional cash flow and the spark spread valuation. The parameters and assumptions used for the scenarios are found in Appendix 1. We do a comparative static analysis for various price, cost, and plant parameters in the next section.

Table 4 Construction decision summary

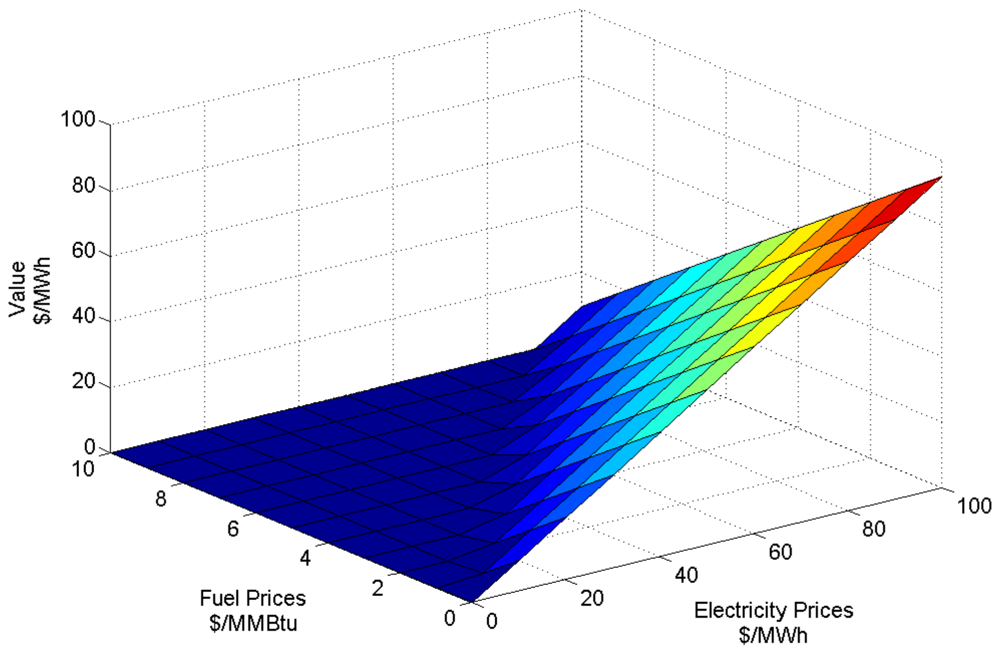
	Combined Gas Cycle		IGCC		Coal	
	(High)	(Low)	(High)	(Low)	(High)	(Low)
Traditional Cash Flow	Don't Build	Don't Build	Don't Build	Don't Build	Build	Build
Spark Spread	Build	Don't Build	Don't Build	Don't Build	Build	Build

In the construction summary Table 4, three out of the six projects are profitable using the spark spread valuation in capital budgeting. In the traditional Cash Flow, only two out of the six projects are found to be profitable.

2.4 Comparative Statics

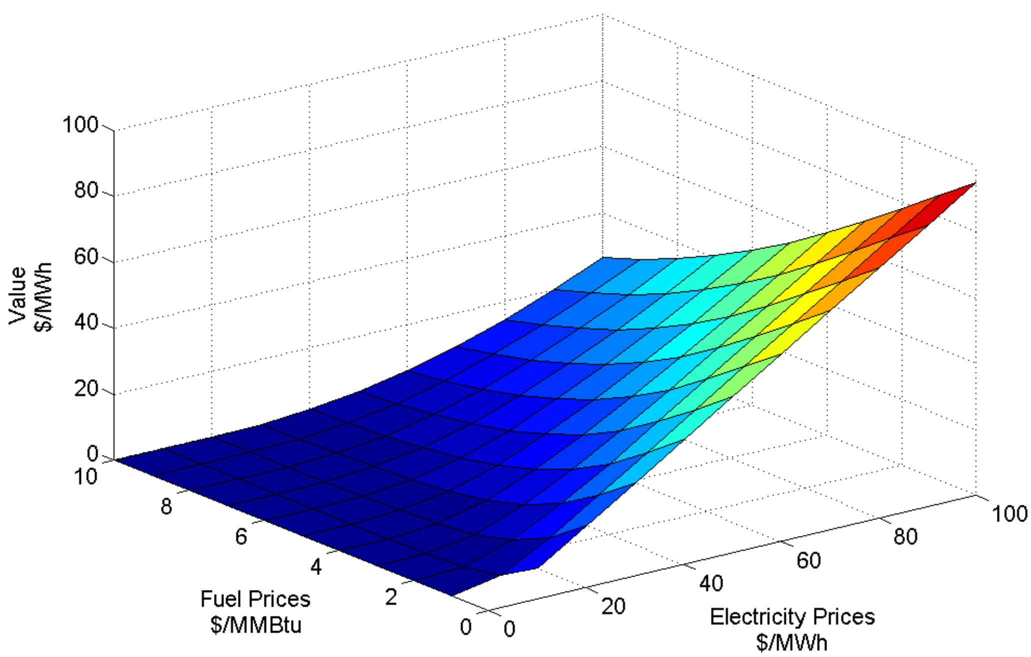
Error! Reference source not found. and **Error! Reference source not found.** show the value n $/MWh of a unit of installed capacity from a generic technology using the traditional discount cash flow and the spark spread option valuation respectively. Capacity factors are not yet included in this valuation. The spark spread captures the value of holding the option to convert fuel to energy in the future. We assume that the option expires exactly one year from when it was purchased and we discount the option value to present terms. We have set the drift values to zero in both cases, and set the interest rate, $r = 5\%$. The spark spread rises much faster in value as electricity prices increase compared to the traditional cash flow. Similarly, as fuel prices decrease, the value increases non-linearly compared to the traditional approach.

Figure 21 Traditional cash flow



Heat rate = 9,000 Btu/kWh

Figure 22 Spark spread valuation



Heat rate = 9,000 Btu/kWh

Figure 23 and Figure 24show the difference in valuation as heat rate increases. For a given heat rate, the spark spread value increases faster as electricity prices increase compared to the traditional cash flow. The two examples depicted below are fixed at a fuel price of $4.5/MMbtu and a combined volatility of 58%. Even with a 14,000 Btu/kWh (14 MMBtu/MWh) heat rate at electricity prices below $60/MWh, the value of the spark spread option is positive.

Figure 23 Traditional cash flow heat rate sensitivity

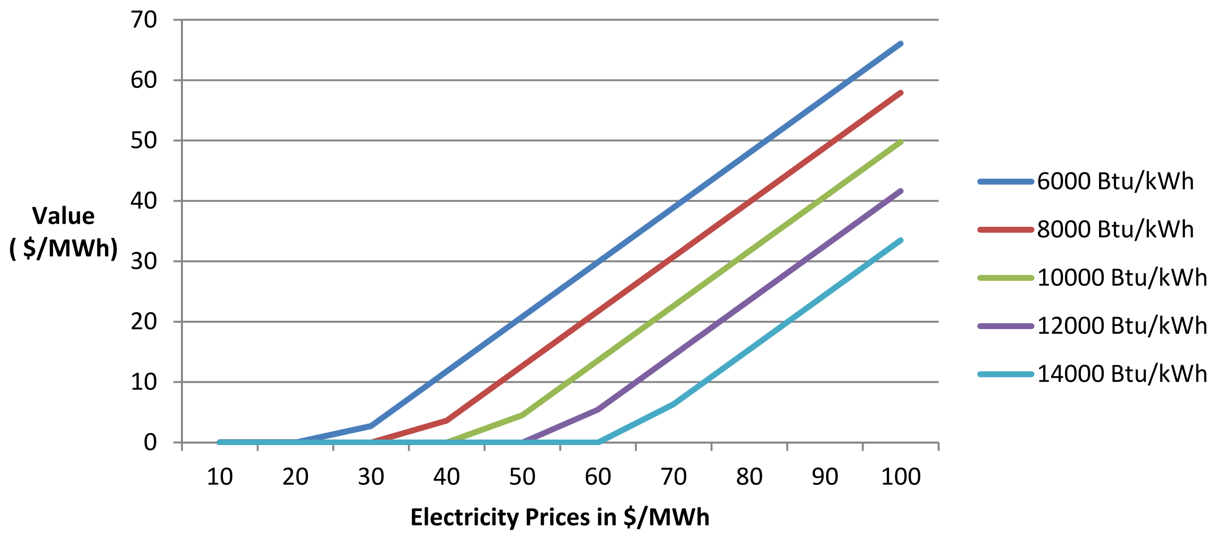
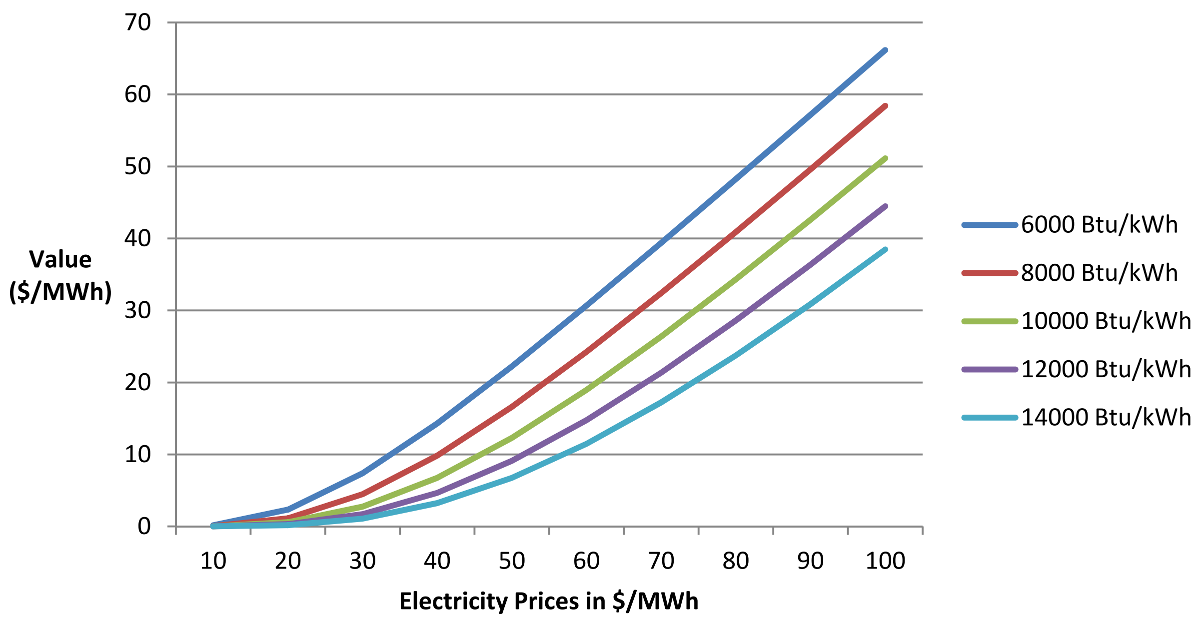


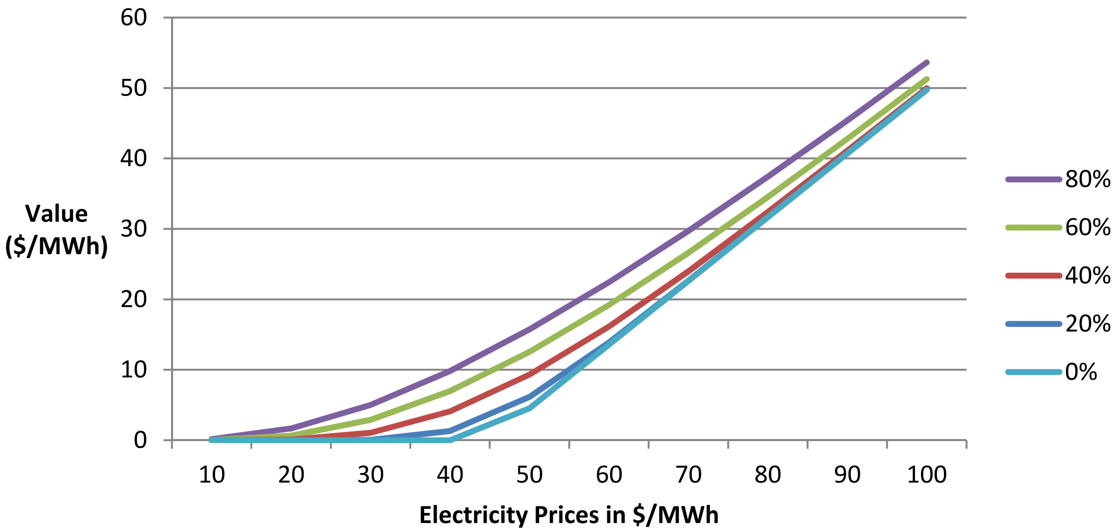
Figure 24 Spark spread options heat rate sensitivity



Error! Reference source not found. shows the sensitivity of the generator value when combined volatility increases. We assume a fixed heat rate of 10,000 Btu/kWh and fuel price of $4.5/MMBtu. We let the interest rate $r = 5\%$ and set electricity and fuel price drift rate $\alpha_x =$

$\alpha_y = 0$. A combined volatility of 0% converges to the traditional cash flow value. We observe that the spark spread options approach increases the value of the underlying asset as volatility increases. In a forward contract, the payoff is a linear function (equation 1). In an options contract, the payoff is non-linear (equation 16). The forward contract is a better approach if there is no significant volatility; however, an options contract is more valuable in the presence of higher volatility.

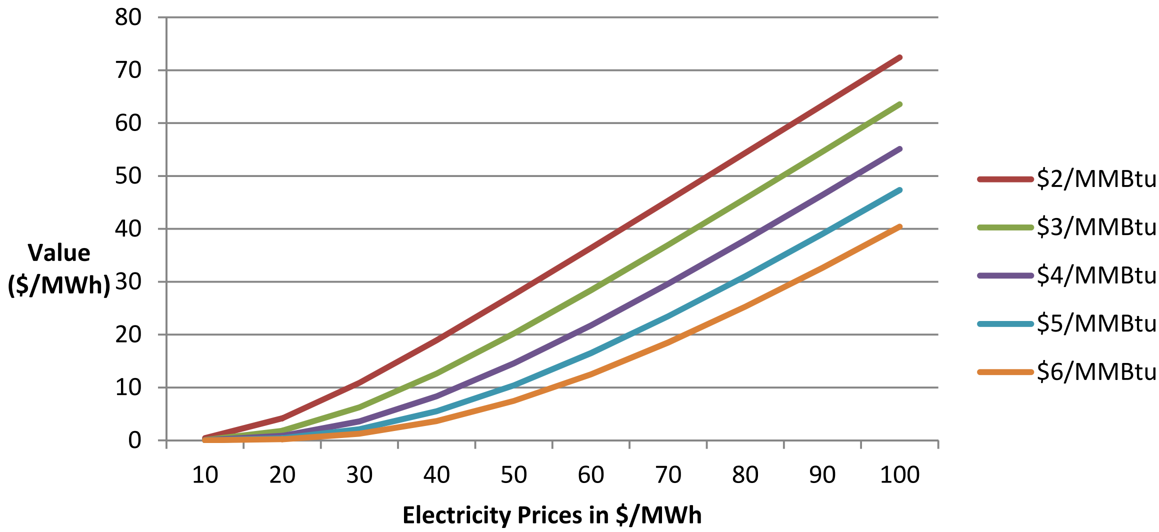
Figure 25 Spark spread options sigma sensitivity



In order to evaluate the changes in the value of the spark spread option with increased fuel prices, we assume the same plant characteristics and interest rate as in the previous scenario. In this scenario, we fix volatility at 58% and run simulations for different fuel prices. The graph below (Figure 26) illustrates that as fuel prices decrease, the spark spread option value increase. At electricity prices above $40/MWh, the added value of going from $3/MMBtu to $2/MMBtu is at most $9/MWh. In a traditional cash flow with a fixed heat rate, H, the added value of a unit decrease in fuel prices is exactly $H/MWh. The value of the option does not rise as fast as the traditional cash flow when fuel prices decrease. A more detailed numerical investigation of this behavior is detailed in Appendix I, Table 25.

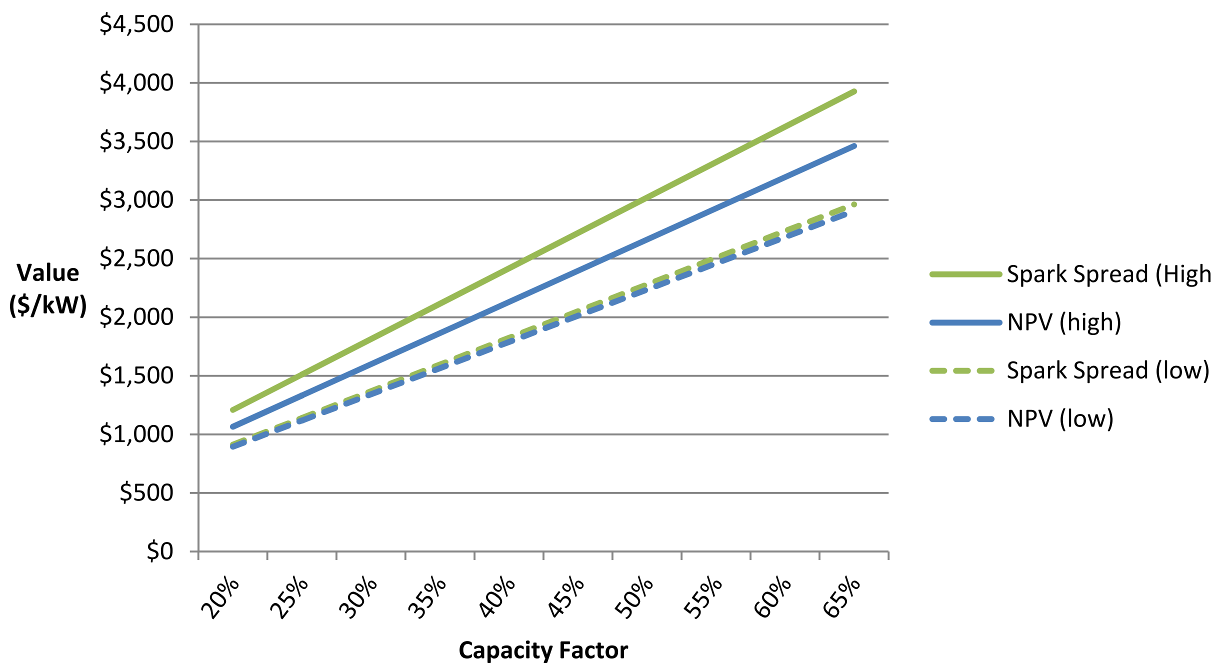
Table 25.

Figure 26 Spark spread option fuel sensitivity



The capacity factor is the ratio of the actual energy output by the plant (kWh per year) to the theoretical nameplate capacity in kW times the number of hours in a year. The more the generator operates, the higher the value. The generator value is a linear function of capacity factor as illustrated in Figure 27. In this scenario, we calculate the lifetime value of 1 kW of gas combined cycle. We assume a fixed heat rate of 7200 for the high and low price scenarios. We use 5% for both electricity and fuel convenience yield. The two solid lines show the value of a unit of installed capacity for a high price scenario with electricity and fuel prices fixed at 7 cents/kWh and $5.5/MMBtu respectively. Assumptions for **Error! Reference source not found.** an be found in Appendix I, Table 24. With the implementation of RPS requirements, we expect renewable generators to displace coal and natural gas generation. A lower capacity factor implies a lower value for conventional generators.

Figure 27 Capacity factor sensitivity



3.0 Real Options Approach

So far we have presented a literature review of the Spark Spread Options approach in valuing conventional generators. In this section, we present a novel Real Options approach in capturing optimal conditions for investing, mothballing, reactivating, and abandoning a power plant. We begin the section with a comparison of the NPV and the Real Options investment criterion. We later present numerical results using a closed-form Real Options approach that we have developed, extending the framework of Dixit and Pyndick (1994) to capture the Spark Spread functional form.

There are several limitations in using the NPV (equation 20) criterion in capital budgeting and investment decision making. The NPV criterion is a now or never approach: the decision to build is based on whether current value projections outweigh capital and operation costs. The NPV simply says if a project has a positive value regardless of its level of profitability, the project should be built. It can be quite puzzling to financial planners that if revenue is \$1.001 M and the overnight capital cost is \$1 M then according to the NPV criterion the plant must be built since $NPV = \$1000 \geq 0$. Some firms may have higher thresholds for hedging such as increasing the profitability threshold, but these methods are arbitrary and often require changing internal financial parameters to reflect uncertainty that is not accounted for in the NPV valuation. Another limitation of the NPV decision process is the lack of the ability to delay an investment due to uncertainty in market conditions. We refer to the reader to Brennan & Trigeorgis, Project Flexibility, Agency, and Competition (2000) and Dixit & Pindyck (1994) for a more rigorous treatment on the differences between NPV and the real options approach in capital budgeting. Our decision support framework provides firms with tools to help them value projects and to understand the optimal conditions for investing. A numerical example will provide some intuition behind a real options decision process.

We limit our numerical example to a two period decision framework and ignore operating costs. Suppose a coal plant requires \$150 Million in overnight capital costs. If the coal plant is built in period 1, the project will receive a stream of revenues through its lifetime of \$20 Million each year. Note that in the NPV approach, we should build the plant immediately since the lifetime discounted flow of revenue is \$220 M≥ \$150 M. Suppose in period two, there are two possible revenue outcomes. The stream of revenues increases to \$28 Million with a probability of 50% or revenue drops to \$12 Million with a probability of 50%. In the event that the stream of revenues drops below the overnight capital cost, the firm can decide not to build the project. We let the interest rate for discounting be *r* = 10%.

Period 1		Period 2	
$\left(\sum_{t=0}^{\infty} \frac{\$20\text{ M}}{(1+r)^t}\right) - \$150\text{ M} = \$70\text{ M}$	50% →	$.5\left(\left(\sum_{t=1}^{\infty} \frac{\$28\ M}{(1+r)^t}\right) - \frac{\$150\text{ M}}{(1+r)^1}\right) = \$72\text{ M}$	(21)
	50% →	Do not build project = \$0 M	

In period 1, the firm receives \$20 Million throughout the lifetime of the project. In period 2, if market conditions improve, the firm receives \$28 Million a year. On the other hand, if market conditions worsen, the firm may not decide to build the project if the stream of revenue drops to \$12 Million. In expectation, the firm gets \$72 Million in the second period, which is higher than investing in period 1. In this example, it is better for the firm to delay the project and build the coal plant in the second period. We can extend this logic to N periods and apply a similar thought process, but one can imagine that the size of the problem gets bigger as we go out further in time. In the next section, we characterize the value of waiting and later introduce dynamic programming techniques to provide closed-form solutions in solving waiting functions and plant valuation. We also use dynamic programming to value a plant in mothball stage (temporary shutdown) and solve for optimal conditions for reactivation and permanent abandonment.

3.1 The Value of Waiting

We develop different value functions following the framework of Dixit and Pindyck (1994) and extending it to include the Spark Spread functional form. The real options approach provides a different threshold for investment. In equation (21) even though the project is profitable in period 1, it is more optimal to delay investment and build the plant in the second period. Note that once a decision to delay investment has been made, the firm can no longer go back in time to reconsider rebuilding at an earlier period. Our valuation and decision tools should be able to compute the value of the investment opportunity at each period and compare them recursively. Let F_t denote the value of holding the option to invest the project at time *t*. *F* represents the value of waiting or how much the firm should be willing to pay to hold the option to invest in the future. In example (21), if revenue drops to \$12 Million per year, $F_1 = 0$ since there is no value in holding the option when the investment project is not profitable. On the other hand, if revenue goes to \$30 Million per year then F_1 = \$72 Million. The problem is solving for the value of F_0 or similarly solving for the value of holding the option to invest in the future. In our example we are able to solve for F_1 since we were able to characterize all possible outcomes. Let *I* be the overnight capital cost. We use *p* to denote the probabilities of each scenario and V_{high} and V_{low} to denote the high and low revenue outcomes respectively. To summarize F_1 succinctly we have:

$$\mathrm{E}[F_1] = p \max[V_{high} - I, 0] + (1-p)\max[V_{low} - I, 0] \tag{22}$$

Now we work our way back to period 1 and compare the value of investing immediately or waiting. Let V_0 be the revenue stream from investing in period 1. The optimal decision is given by F_0 in equation (23).

$$F_0 = \max\left\{ V_0 - I, \frac{1}{1+r}\mathrm{E}[F_1] \right\} \tag{23}$$

We can extend this to multiple periods and perform a series of binary questions of investing now or delaying. If the firm decides to invest in a project at any period, the firm will receive an irreversible stream of profits and pay the capital cost up front. We can denote the stream of profits minus the overnight capital cost as the termination pay-off:

$$\Omega_\mathrm{t} = \max\{V_t - I, 0\}. \tag{24}$$

How do we characterize the added value of having the option to wait? F_0 - Ω_0 gives us the added value of waiting in period 1. If the value of holding the option is exactly the same as the termination pay-off then it is optimal to invest right away. In our example, the added value of waiting is $2 Million ($72-$70). Dynamic programming provides us with appropriate tools to solve optimal conditions in infinite horizon cases. The next section generalizes this recursive decision making and provides a brief introduction to dynamic programming theory.

3.2 Dynamic Programming

Dynamic programming is a technique developed by Richard Bellman to solve a class of problems in optimization. In this section, we present a generalized Bellman equation that characterizes our decision framework. We setup our decision framework with a Bellman equation to solve for optimal conditions for initial investment, mothballing, reactivation, and permanent abandonment of a plant. This section will cover general aspects of the Bellman equation in conjunction with the stochastic price process explored in section 1.3. Later sections will define each component of the Bellman equation with respect to the decision process the firm is currently facing.

Let *x* be our state variable that evolves over time. For conservation of notation we leave out time from our state variable *x*, but we emphasize that *x* evolves over time and we denote the previous state as *x'*. Since our stochastic processes are Markov, all relevant information is contained in the previous state variable *x'*. The right term in the maximization problem in equation (27), $\pi(x) + \frac{1}{1+r}E[x'|x]$ is called the continuation value. The termination pay-off , $\Omega(x)$, is the value the firm receives if it decides not to continue. If the firm is facing an initial investment problem, the termination pay-off will be defined as the stream of profits for the life of the project and the continuation function will simply capture the value of waiting. Equation (23) can be generalized to a continuous optimal stopping dynamic programming problem:

$$F(X) = \max\ \{\Omega(X), \pi(X) + \frac{1}{1+r}\mathrm{E}[F(X'|X)]\ \}, \tag{25}$$

where F is the value function that needs to be solved. $\pi(x)$ is the profit generated while in operation. In dynamic programming theory, equation (27) is referred to as the Bellman equation. We will refer back to the Bellman equation for each decision process (initial investment, mothballing, reactivation and permanent abandonment) and define each term depending on the firm's decision stage.

We say that the firm decides to continue (delay investment or continue operation depending on the decision stage) if $\Omega(x) \leq \pi(x) + \frac{1}{1+r}\mathrm{E}[F(x'|x)]$. At each time period we can compare $\Omega(x)$ and $\frac{1}{1+r}\mathrm{E}[F(x'|x)]$ and the point $x*$ where the two values meet will provide us the optimal threshold where we are indifferent between stopping and continuing. This is called the value-matching condition. Our class of problems results in free boundary problems where $\Omega(x^*)$ itself is unknown. We require that the first-order conditions also meet at the boundary, namely $\Omega(x^*) = F(x^*)$.

Lastly, we extend equation (27) in continuous time to account for the evolution of electricity and fuel prices characterized by the stochastic differential equation (2). We convert the dynamic programming problem to a binary decision, u of continuing or terminating, and rewrite the termination pay-off and smooth-pasting criteria as boundary conditions. We wish to optimize our decision while accounting for the evolution of electricity and fuel prices given by dX and dY respectively. This problem is summarized by equation (28).

$$rF(X,Y,H) = \max_{\mathrm{u}} \{\ \pi(X,Y,H,u) + \frac{1}{dt}\mathrm{E}[dF]\ \} \tag{26}$$

Subject to:

$$dX = \alpha_x X dt + \sigma_x X dz$$

$$dY = \alpha_y Y dt + \sigma_y Y dz$$

$$\Omega(\mathrm{X}^*, Y^*, H) = F(X^*, Y^*, H)$$

$$\Omega_{\mathrm{x}}(\mathrm{X}^*, Y^*, H) = F_x(X^*, Y^*, H)$$

$$\Omega_{\mathrm{y}}(\mathrm{X}^*, Y^*, H) = F_y(X^*, Y^*, H)$$

The equation above is the general form for our real options spark spread framework, and we will refer back to this equation in the next sections.

3.3 Optimal Conditions for Investing Using Spark Spread

Pindyck (1999) explores long-term trends in energy prices including coal and natural gas. He explores both geometric Brownian motion as well as mean-reversion of energy prices. We explored both random-walk and mean-reverting processes, however we focus primarily on geometric Brownian motion (GBM). Modeling prices as GBM provides closed-form solutions to optimal conditions in investment. Pindyck argues that variance ratio tests suggest that prices exhibit mean-reversion, but if the rate of reversion is slow enough, a geometric Brownian motion can be used to treat energy price commodities for investment decision purposes (Pindyck, 1999).

Sections 2.1 and 2.2 illustrate the difference between the traditional cash flow (TCF) and the spark spread valuation. In this section we explore solving the real options approach using the spark spread functional form to gain insights on the optimal conditions for investing in a new power plant. We note that we refer to the dynamic programming as the real options spark spread since we use the assumption that dx and dy follows a geometric Brownian motion and the functional form of the firm profit is given by $x - yH$. For now we ignore operational costs, and solve for the investment threshold. We recall the NPV criterion and rewrite them in equation (29) including the drift parameters. We define $\delta_x = \mu_x - \alpha_x$ as the convenience yield of electricity prices where μ_x and α_x are the risk-adjusted discount rate and drift for electricity. We define δ_y = $\mu_y - \alpha_y$ the same way for fuel convenience yield. Suppose dx and dy are two correlated geometric Brownian motions then the value-matching and smooth-pasting conditions give us equation (30). All derivations and proofs are deferred to Appendix III.

$$I + \frac{y}{\delta_y} = \frac{x}{\delta_x} \tag{27}$$

$$(I + \frac{y}{\delta_y})(\frac{\beta_1}{\beta_1 - 1}) = \frac{x}{\delta_x} \tag{28}$$

β_1 is the positive root of the fundamental quadratic used in solving for *F(X,Y,H)* in the dynamic programming problem. The derivation of the β_1 parameter is technical, and we defer on its technical treatment in the Appendix III. What is important to note is the economic interpretation of the β_1 parameter. In Appendix III, we show that $\beta_1 > 1$ and this implies the term $\left(\frac{\beta_1}{\beta_1 - 1}\right) > 1.$ Now we can directly compare the investment thresholds (27) and (28). We can see that the real options approach increases the investment threshold. This is due to the fact that we account for uncertainty and the ability to delay to make sure the investment is deep-in-the-money. Equation (28) only gives us a heuristic for an initial investment problem. *F(X,Y,H)* in equation (29) captures what the firm should be willing to pay to hold the option of investing in the future. In turn, this cost of holding the option is added to the investment costs.

In the range, $[0,\bar{x}_h]$, the closed-form solution to (27) in the initial investment problem is

$$F(X, Y, H) = yHA_1 \left(\frac{x}{yH}\right)^{\beta_1}, \tag{29}$$

where $\bar{x}_h$ is the initial investment threshold to be solved together with some constant $A_1 > 0.$ We will return to the waiting value function when we solve for investment, mothballing, reactivation, and decommissioning thresholds simultaneously.

3.4 The Value of an Operational Plant Using Dynamic Programming

In previous sections we have ignored operational costs. Operations and maintenance (O&M) costs play an important role in capital budgeting, and they cannot be fully ignored. In the previous section, we illustrate that the real options approach will always give a higher investment threshold (assuming volatility > 0) compared to the traditional NPV. Going back to the Bellman equation in (26) we now solve for the value of an operating plant. We replace *F* with V_1 to keep track that we are solving for the value of an operational plant. In this scenario, $\pi \geq 0$ since the plant is now in operation. In the range $[\bar{x}_m,\infty)$, the closed form solution for (26) from the perspective of a fully operational plant is:

$$V_1 = yHB_2 \left(\frac{x}{yH}\right)^{\beta_2} + \frac{x}{\delta_x} - \frac{y}{\delta_y} - \frac{C}{r}\ . \tag{30}$$

We have excluded the case where electricity prices are 0, and this value function is defined only for a threshold $\bar{x}_m > 0$. Appendix IV contains the full mathematical derivation of equation (32). The economic interpretation of this condition is that there will be no value in holding the option to mothball when prices go below some threshold $\bar{x}_m$. At prices below $\bar{x}_m$, the firm should be deciding whether to permanently abandon the plant or wait in mothball stage. δ_x and δ_y is defined the same way as the parameters in equation (27). We have introduced a new parameter *C*, which is the annual O&M cost. Note that we have used the notation β_2 instead of β_1. In equation (28) we called β_1 the positive root of the fundamental quadratic, β_2 is the negative root of the fundamental quadratic. So we have $\beta_2 < 0.$ The first term in $V_1$is the option value to suspend operation, $yHB_2\left(\frac{x}{yH}\right)^{\beta_2}$. B_2 is a constant that will be solved for together with other value functions. Note that as x increases the option value to mothball decreases.

3.5 The Value of a Plant in Mothball Using Dynamic Programming

In Section 3.3, F is regarded as the value function of holding the option to build a project in the future. In this scenario, the plant is currently mothballed and it does not currently provide a stream of revenues for the firm, but there should still be value in holding the option to reactivate the plant in the near future. We refer back to the Bellman equation in (26) to solve for the value of a power plant in mothball stage. However, we replace $F(X,Y,H)$ with V_m. We also note the behavior of V_m in the limit is different compared to F_0 and V_1. The reader can find the derivation of V_m in Appendix V. The closed-form solution for the value of a plant in mothball is:

$$V_m = yH\left(D_2\left(\frac{x}{yH}\right)^{\beta_1} + D_2\left(\frac{x}{yH}\right)^{\beta_2}\right) - \frac{M}{r} \quad . \tag{31}$$

The mothball function V_m is defined in the interval $[\ \bar{x}_s, \bar{x}_r]$, which are abandonment and reactivation thresholds respectively. We have introduced a new term, M, which is the annual maintenance cost the firm must pay in order to keep the power plant in a stage that can be reactivated in the near future. Maintenance costs include, but are not limited to, physical upkeep, security, logistical personnel, and other asset costs during mothball. The first term $D_2\left(\frac{x}{yH}\right)^{\beta_1}$ captures the value to reactivate and the second term $D_2\left(\frac{x}{yH}\right)^{\beta_2}$ captures the option value of abandoning the project. For a more rigorous mathematical treatment of the value function of mothballing we direct the reader to Appendix V.

3.6 Optimal Investment, Mothball, Reactivation, and Decommissioning

Now that we have value functions for waiting, an operational plant, and a mothballed plant, F, V_1, V_m respectively, the natural question to ask is what are the optimal threshold values, $\bar{x}_h, \bar{x}_m, \bar{x}_r, \bar{x}_s$, for initial investment, mothballing, reactivation, and abandonment? We introduce parameters R, E_m and E_s for lump-sum cost of reactivation, mothballing, and decommissioning of a plant respectively. R is a single cost that needs to be paid to reactivate a plant in mothball stage. E_m should not be confused with M, which is the annual mothball maintenance cost. For example, some generators that are put into mothball require a nitrogen blanket. The application of the nitrogen blanket is considered a lump-sum cost of going into mothball stage. On the other hand, the maintenance and security crew that is employed for the years the plant is in mothball is considered an annual mothball cost. E_s, the lump-sum cost of permanent abandonment or decommissioning, can either take a positive or negative value. It is what the firm gets when they decide to decommission a plant. If the plant can be recycled for its metal scraps, then the abandonment parameter can take a negative value. On the other hand, if the owner of the plant needs to pay for environmental costs such as returning to the land to a green field, E_s takes a positive value. Note that we denote a positive E_s to signify cost and a negative E_s refer to a net gain from permanent abandonment.

Solving for the value matching conditions (34) – (37) and the smooth pasting conditions will give us the thresholds.

$$F(x_h) = V_1(x_h) - I \tag{32}$$

$$V_1(x_m) = V_m(x_m) - E_m \tag{33}$$

$$V_m(x_r) = V_1(x_r) - R \tag{34}$$

$$V_m(x_s) = F(x_s) - E_s \tag{35}$$

We elaborate on equation (34). We direct the reader to Appendix VI for the smooth pasting conditions and formal derivations and rigorous economic treatment of the value matching conditions. Equation (34) is a very similar formulation on how we derived equation (32). The only significant difference is that we have written the value of the operating firm as V_1, which includes operating costs, C, and the added value of the option, $yHB_2\left(\frac{x}{yH}\right)^{\beta_2}$, to temporarily suspend the plant if market conditions are unfavorable. Note that with the added value of the option to mothball, the firm might find it reasonable to delay even if market conditions are not favorable. The waiting function adds to the investment cost, which is the same formulation we have emphasized on "bumping" up the initial investment threshold. Individual effects of various parameters are discussed in the next section.

4.0 Results

The four value matching conditions and four smooth pasting conditions give a system of non-linear equations. We exploit large-scale solvers for non-linear systems in GAMS (General Algebraic Modeling System) using the solver CONOPT. Although our problem formulation is not a traditional NLP (non-linear program), we exploit commercial generalized reduced gradient (GRG) solvers with CONOPT. The non-commercial version of GAMS software can solve up to 300 variables. Although our optimal conditions are given in closed form, due to the high non-linearity in the terms, it is difficult to perform analytical sensitivity analysis. We revert to numerical simulations by perturbing individual parameters to see how a particular parameter affects the optimal conditions for investment, reactivation, mothballing, and abandonment. The next paragraph will guide the reader on how to interpret and analyze our results.

In the figures that illustrate section 5, the Y-axis gives the optimal condition in cents/kWh. The blue line shows the threshold values for an initial investment. If future prices are at or above this line, the investment should be executed. The red line gives the market price signal for when a mothballed plant should reactivate. The red line is the market price signal for a mothballed plant to reactivate. If future prices remain below this threshold, it is not economical for the firm to reactivate the plant. The green line is the mothball threshold for a currently operating plant deciding when to suspend operation due to unfavorable market conditions. If prices go below the green line, it is economical to mothball with future possibility of reactivation. The last threshold value is the decommissioning or permanent abandonment conditions. If prices fall below this threshold, the owner should consider decommissioning the plant since it is not economical for the firm to temporarily suspend the project. It is important to know how various parameters such as costs, prices, volatility, and policy timing affect the threshold values.

4.1 Financial parameters and plant characteristics in Tables 5, 6, 7, 8, 9 and 10 are derived from Lazard (2011) and various inquiries with power companies. Gas Combined Cycle Optimal Conditions

The assumptions for the sensitivity graphs are in Table 5 and Table 6. For each subsection we use the same assumptions and perturb a single parameter then solve for the optimal price signal in cents/kWh. For computational tractability, we normalize costs to cents/kWh. These units refer to 1 kW installed capacity of a gas combined cycle plant.

Table 5 Gas combined cycle characteristics and financial parameters

Plant Characteristics and Financial Parameters	Value
Capacity Factor	25%
Life Time	40 Years
Heat Rate	7200 Btu/Kwh
Electricity Drift	3%
Natural Gas Drift	2%
Electricity Volatility	30%
Natural Gas Volatility	30%
Correlation	.3
Interest Rate	6%
Risk Adjusted Rate for Electricity	7%
Risk Adjusted Rate for Natural Gas	8%
Electricity Convenience Yield	4%
Natural Gas Convenience Yield	6%

Table 6 Gas combined cycle cost parameters

Cost Parameters	Value	Unit
Natural Gas Price	$5.5	$/MMBtu
Annual Operating Costs (Fixed and Variable)	15	$/kW
Overnight Capital Cost	1300	$/kW
Annual Blended Cost of Capital	86	$/kW
Annual Mothball Maintenance Cost	10	$/kW
Lump Sum Cost of Mothballing	1	$/kW
Lump Sum Cost of Reactivating	.001	$/kW
Lump Sum Decommissioning Cost *	0	$/kW

** Lump sum decommissioning cost is a combination of the cost to return the land to either a brown or green field as well as selling recyclable metal and scrap. From some of our industry inquiries, we gathered a cost around $10-$100 per kW, but none of our sources provided estimates for scraping and recycling of metal and other reusable machinery. For our simulations we use a net $0/kW for our decommissioning costs.*

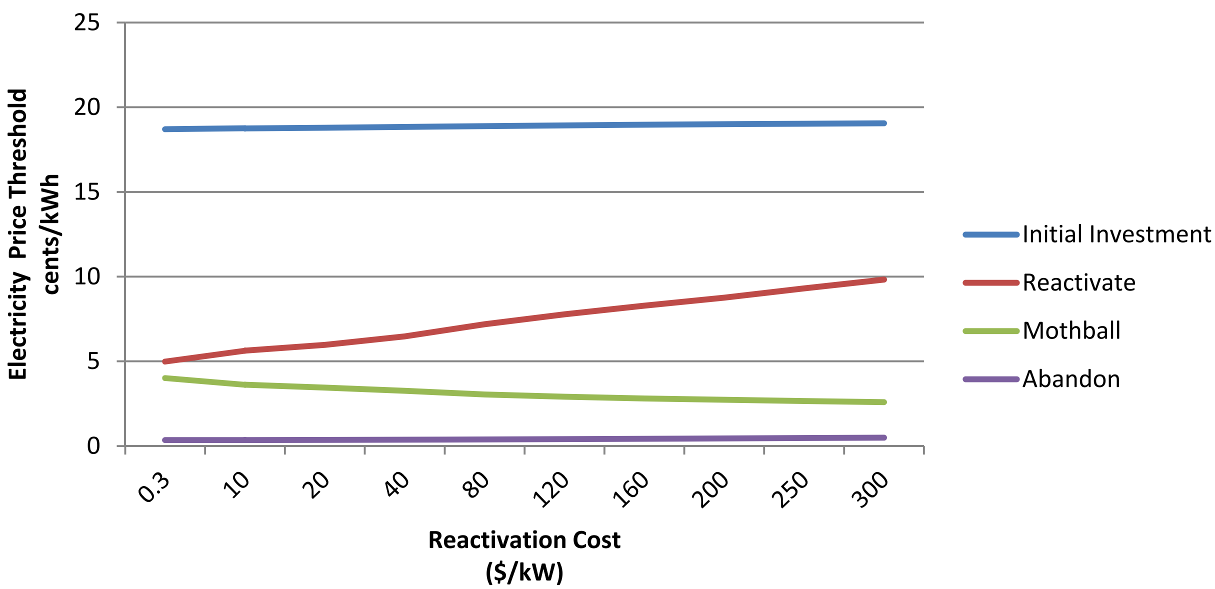
4.1.1 Reactivation and Mothball Costs

We refer to reactivation cost as the lump sum cost of reactivating the plant. Initial investments decisions are not sensitive to reactivation costs since the decision to reactivate is only significant if the owner is currently in mothball stage or contemplating temporary suspension. Figure 28 and

Figure 29 show the optimal investment and operational decisions with increasing reactivation cost. As the reactivation costs increase, the threshold for mothballing decreases. An owner should consider the trade-off of continuing operation either at the profit margin or close to a loss versus mothballing. When a plant is mothballed, it does not generate revenue, but maintenance costs are significantly lower compared to O&M in full operation ($M < C$). A real options approach captures this trade-off between incurring a loss over time versus mothballing and requiring paying reactivation costs in the future. If the value of the plant during unfavorable market conditions is greater than the value of holding the option to reactivate during mothball, it is better for the plant owner to remain operational even if it operates close to its profit margins. From the graph below, if reactivation costs are high, it is better to delay mothballing. On the other hand, if reactivation costs are low, then a firm may find it more economical to mothball for a short time period when market conditions are unfavorable and reactivate when price signals are appropriate.

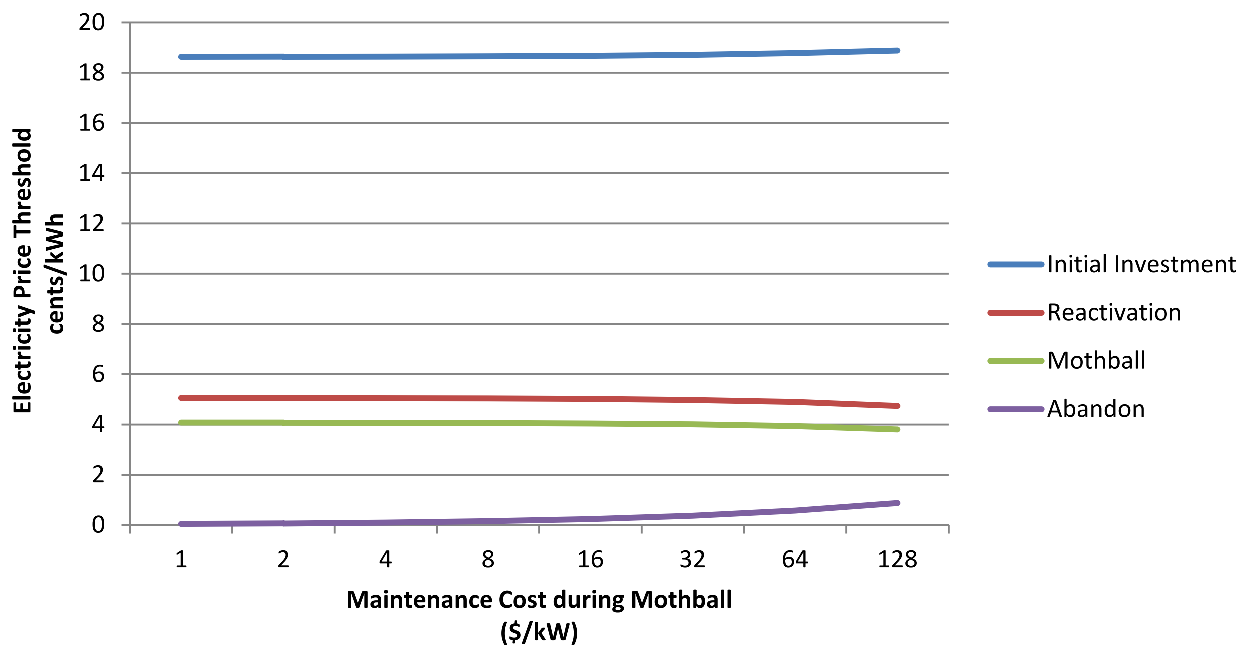
We now examine the graph from the perspective of a currently mothballed plant debating when to reactivate. A higher reactivation costs increases the threshold for reactivating. The firm needs to ensure that the lump sum cost of reactivating is recouped during the remainder of the plant's operational lifetime.

Figure 28 Gas combined cycle market price signals as a function of reactivation cost in $/kW



Maintenance cost, M, while in mothball refers to the annual cost the firm needs to pay to physically maintain the plant for future reactivation. This is not to be confused with the lump sum cost to mothball, which is a one-time cost the firm incurs to go into temporary suspension. The base case assumes no added financial cost or mortgage in the mothball maintenance cost, but we perform a sensitivity analysis to see what happens to threshold values when this cost increases due to physical or financial reasons. Figure 29 below shows the optimal threshold conditions as mothball maintenance cost per kW increase. Note that initial investment is not significantly affected by this number. Reactivation and mothball threshold values are not sensitive to the annual maintenance cost, but abandonment threshold increases significantly as maintenance cost per kW increase. As the cost of remaining in mothball increases it is more favorable for the firm to abandon the plant and avoid further loses than to wait for market conditions to improve.

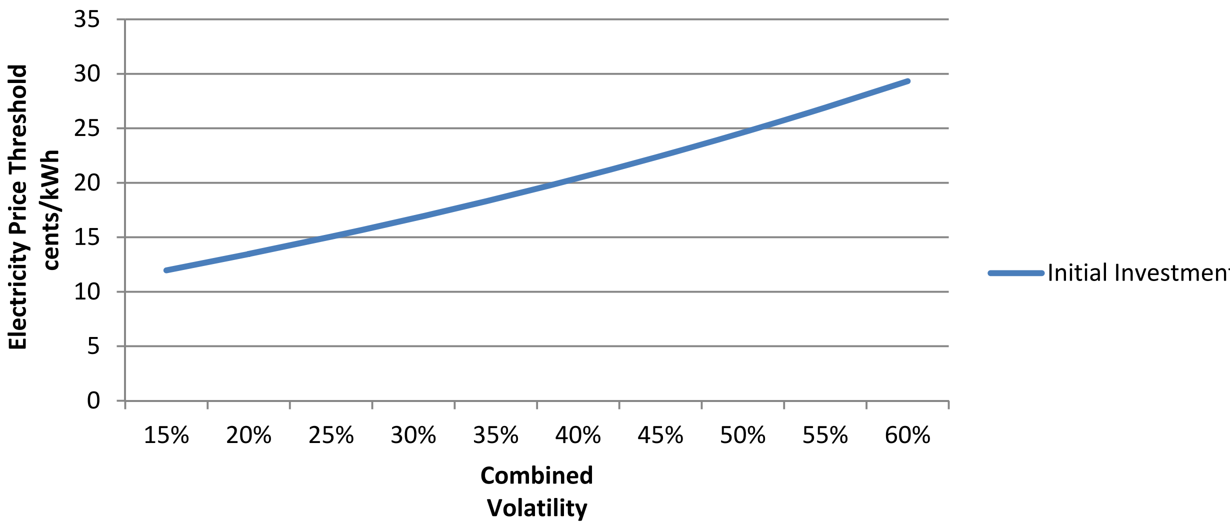
Figure 29 Gas combined cycle market price signals as a function of mothball maintenance cost



4.1.2 Volatility

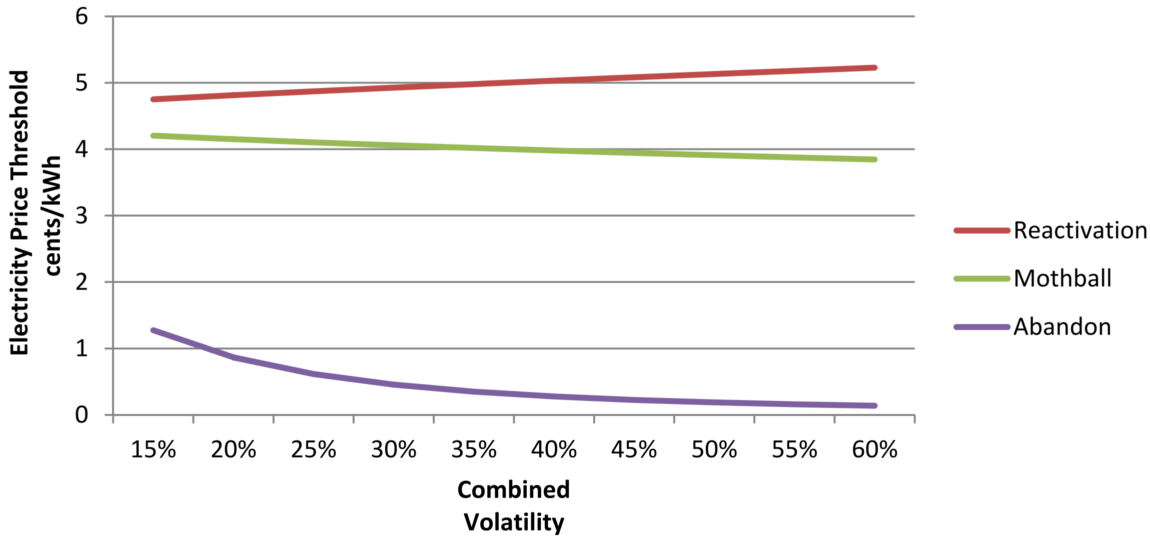
The difference between the traditional NPV and the spark spread real options approach is that the latter accounts for volatility. Figure 30 shows investment thresholds as combined volatility (equation 19) of electricity and fuel prices increase. With an increased fraction of variable renewable energy in the system, we can expect an increase in electricity price volatility due to shifts in the supply curve at times when there is no wind. At low volatility values, the investment decision threshold for natural gas combined cycle is also low. Although $120/MWh is quite high, natural gas combined cycle operates mostly at peak. In addition, capacity factor assumptions for natural gas combined cycles are low (25%), so they must operate at higher electricity prices to recover investment costs. In contrast, coal has a higher capacity factor and it operates as base load. Market price signals for coal will be lower compared to natural gas combined cycle.

Figure 30 Gas combined cycle investment threshold as a function of combined volatility



Volatility also affects mothball, reactivation, and abandonment thresholds. In an initial investment, the threshold for investing increases as volatility increases. This is due to the added cost of holding the option to wait and do the investment in the future. Higher volatility means higher uncertainty in returns. Thus, the firm should hedge the investment project by ensuring the project is deep in the money. A similar argument can be made when the firm is deciding to reactivate the plant. However, mothballing thresholds decrease as volatility increases. It is economical for the firm to delay mothballing even if market conditions are not favorable. The trade-off between mothballing early is foregoing profits that could have been made in the volatile market. A higher volatility leads to a higher value of holding the option to delay mothballing. A plant's value during operation is influenced by prices and O&M costs, but not overnight capital costs. Similarly, a plant in mothball will have a value influenced by prices, O&M, and reactivation costs. The value of a mothball plant is the combined option value to reactive or decommission the plant in the future. With higher volatility, there is more value in delaying abandonment.

Figure 31 Gas combined cycle market price signals for reactivation, mothball, and abandonment as a function of combined volatility

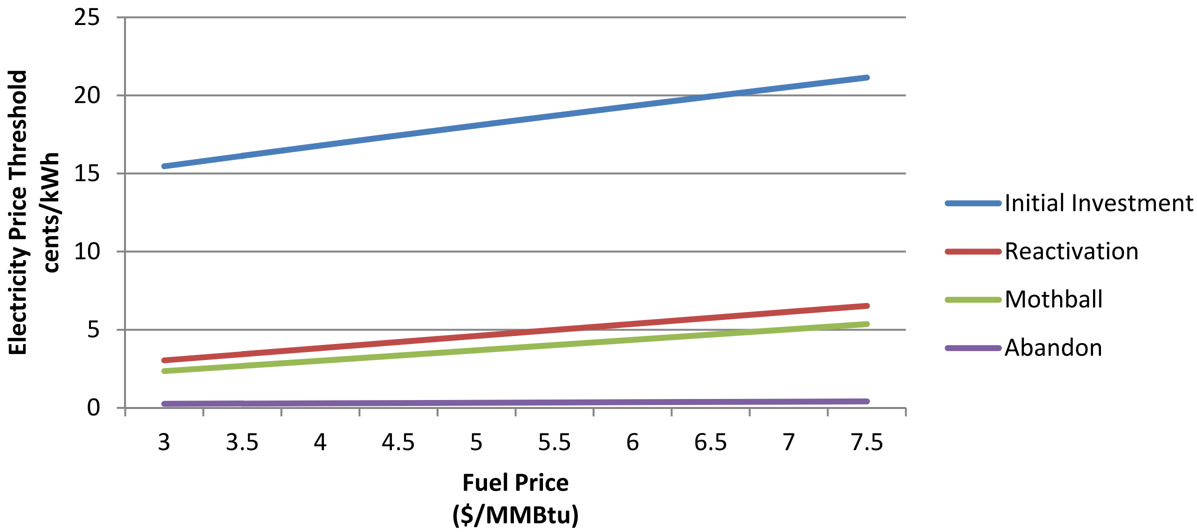


Accounting for volatility in the optimal conditions for mothballing and abandonment have significant implications when there is more wind in the system. We associate high wind penetration with an increase in electricity price volatility. As illustrated by Figure 31, the real options approach may lead to better reliability in the electricity industry. The real options approach gives us insights on why it is economical to delay mothballing and abandoning generators even when there is more intermittent generation. On the other hand, it makes future investments in coal and natural gas more difficult to justify. Electricity and fuel volatility is a crucial financial parameter to individual power plant owners.

4.1.3 Fuel Prices

The spark spread approach allows us to model fuel prices stochastically. The closed form solution of the value of operating and mothballing the plant includes a ratio of electricity price and the fuel price times the heat rate: $\left(\frac{x}{yH}\right)^{\beta_i}$ for $i = 1,2$. We refer to this term as the spark margin. When we solve for optimal values of electricity prices, we fix the fuel price, y and solve for the optimal electricity price thresholds. Figure 32 shows how fuel prices affect optimal thresholds for the real options approach. Although the spark margin is non-linear, there are other terms in the value-matching conditions that are linear. The linear terms for this scenario analysis dominate the non-linear contribution of fuel prices in the spark margin, thus the linear increase in the optimal thresholds. We can see a similar linear trend when we increase O&M costs.

Figure 32 Gas combined cycle market price signals as a function of fuel price

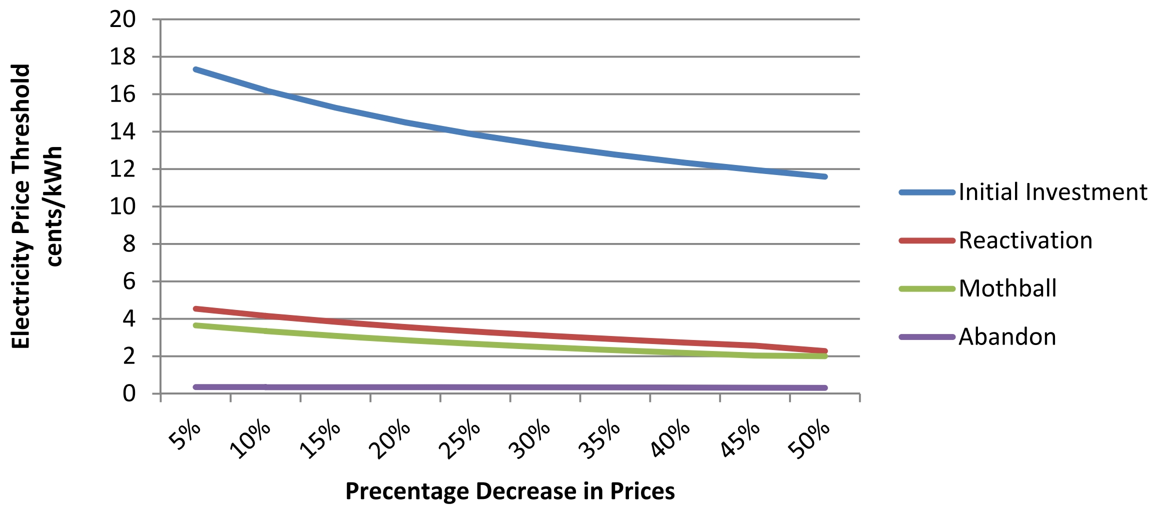


An important result of this sensitivity analysis is the contribution of volatility and fuel prices to the optimal threshold. We note that price threshold values as a function of volatility increases non-linearly as shown in investment thresholds in Figure 30. However, electricity price thresholds for initial investment thresholds increase linearly as a function of fuel prices.

4.1.4 Policy Arrival

In section 1.3.3, we showed how we can incorporate a jump in our stochastic process. We run scenario analyses on the effect of a policy that leads to a decrease in price on investment and operational thresholds. In this scenario, we use a Poisson process to model the arrival of an RPS in 2022. We calibrate the arrival rate of $\lambda = .1$. With the penetration of more variable, renewable energy we expect average electricity prices to drop due to lower marginal-cost electricity pricing and volatility to increase. Figure 30 summarized the implications of higher volatility on the optimal thresholds. In contrast, Figure 33 shows a decrease in initial investment threshold when we expect larger drops in price in 10 years. This result may sound counterintuitive, but it means that it is more favorable for the firm to invest earlier to take advantage of higher prices as opposed to wait and face lower prices in the future. The value of holding the option to invest in the future decreases when we expect a significant drop in prices in the future.

Figure 33 Gas combined cycle policy sensitivity



4.2 Integrated Gasification Combined Cycle Optimal Conditions

The IGCC plant characteristics and financial parameters are on Table 7 and cost parameters are on Table 8. We perform sensitivity analysis for Integrated Gasification Combined Cycle Optimal Conditions (IGCC). We note that the general shape and direction of these sensitivity analysis are the same for natural gas combined cycle, IGCC, and coal. The difference will come in the actual threshold price in cents/kWh since capacity factors, O&M, overnight capital costs and other parameters are different for each technology. It is more important to understand the direction and rate of increase or decrease on the optimal conditions when we perturb a particular parameter.

Table 7 IGCC characteristics and financial parameters

Parameter	Value
Capacity Factor	75%
Life Time	40 Years
Heat Rate	10500 Btu/Kwh
Electricity Drift	3%
Coal Drift	0%
Electricity Volatility	30%
Coal Volatility	10%
Correlation	.7
Interest Rate	6%
Risk Adjusted Rate for Electricity	8%
Risk Adjusted Rate for Natural Gas	5%
Electricity Convenience Yield	5%
Natural Gas Convenience Yield	5%

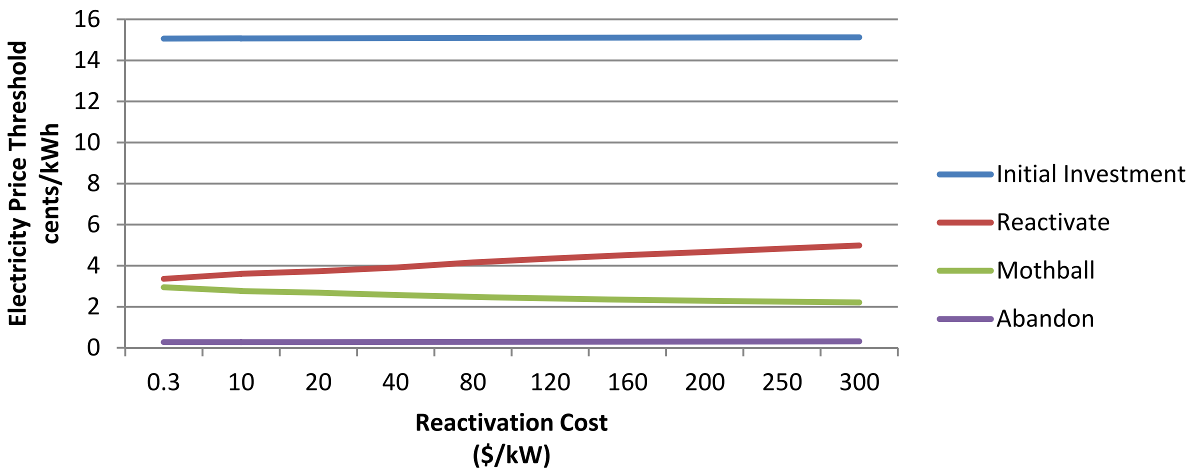
Table 8 IGCC cost parameters

Parameter	Value	Unit
Coal Price	2	$/MMBtu
Annual Operating Costs (Fixed and Variable)	84	$/kW
Overnight Capital Cost	5200	$/kW
Annual Blended Cost of Capital	346	$/kW
Annual Mothball Maintenance Cost	10	$/kW
Lump Sum Cost of Mothballing	1	$/kW
Lump Sum Cost of Reactivating	.001	$/kW
Lump Sum Decommissioning Cost	0	$/kW

4.2.1 Reactivation

We start with a familiar sensitivity graph for IGCC: Figure 34. We note that the directions of the optimal conditions are similar to Figure 28 when reactivation cost per kW increases. The only difference is the absolute value of initial investment, mothballing, reactivation, and abandonment thresholds. The rate of change of increase or decrease is also slightly difference, but its behavior is not significantly different for natural gas combined cycle reactivation graphs.

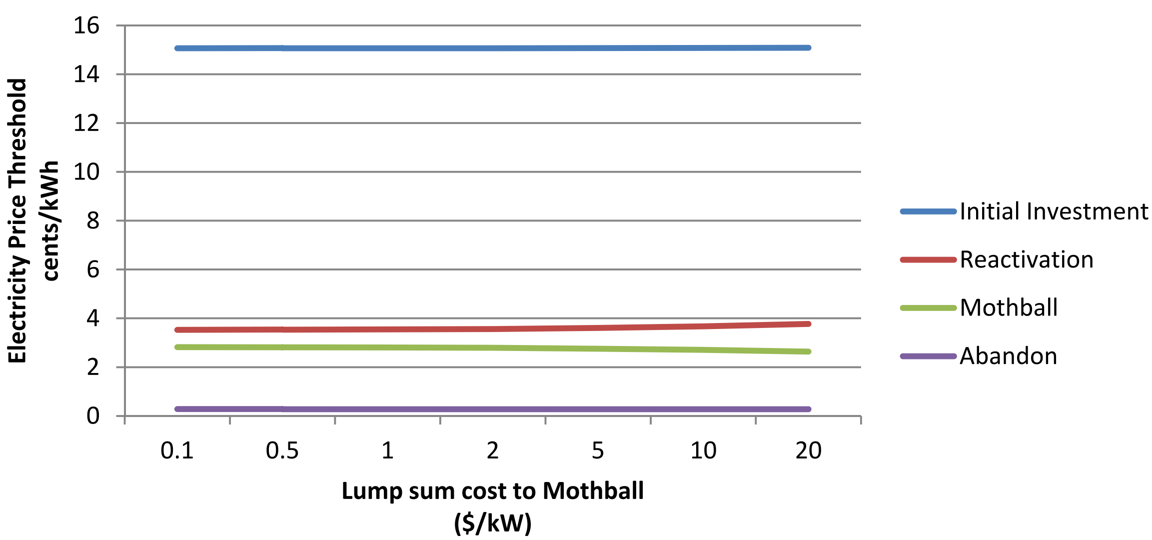
Figure 34 IGCC reactivation sensitivity



4.2.2 Lump Sum Cost to Mothball

Lump sum cost to mothball (Figure 35) are not significantly financially limiting compared to reactivation costs and mothball maintenance costs (Figure 34 and Figure 29). We note that the lump sum costs we have explored for mothballing are not large enough to make significant changes in the optimal conditions.

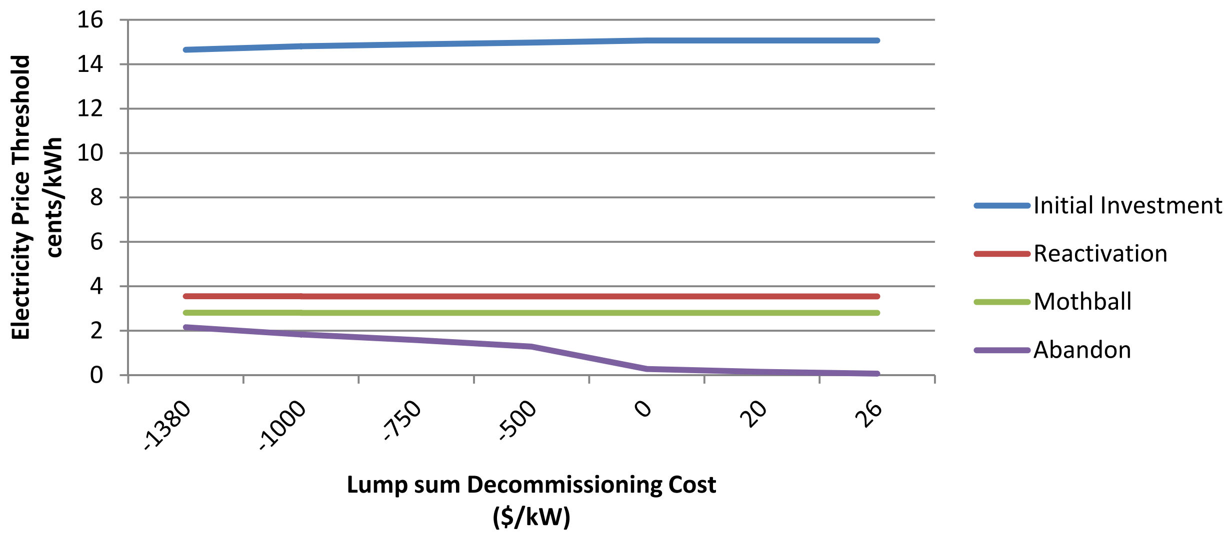
Figure 35 IGCC lump sum cost to mothball sensitivity



4.2.3 Decommissioning Cost and Scrap Value

When a plant is decommissioned, the firm faces cost to return the land to either brown or green field. A firm may also face other environmental or legal costs when they decide to abandon a plant. On the other hand, the firm can also gain scarp value from recycling metal and other materials. A net negative decommissioning cost implies the scrap value is larger than the cost of abandoning the plant. Intuitively, the firm might find it more profitable to abandon early if there is positive scarp value. However, if the decommissioning costs are greater than or equal to zero, it is more economical for the firm to stay in mothball stage and delay abandonment with plans of future reactivation. Figure 36 shows as lump cost decreases, it is better to delay permanent abandonment.

Figure 36 IGCC lump sum decommissioning cost sensitivity



4.3 Coal

Table 9 and Table 10 provide plant characteristics and financial parameters. We turn to our last generation type: supercritical coal. The introduction of variable and intermittent renewable energy will displace conventional generators. This raises several concerns about maintaining a reliable mix of generation. We note that our valuation tools do not incorporate capacity payments; we have looked at valuation of conventional generators from an energy-only perspective. The real options approach captures the intrinsic value in having installed capacity, thus making several investment decisions profitable even with the absence of capacity payments. The spark spread approach captures the value in holding the option to convert fuel into electricity in the future. The real options approach gives the optimal threshold value for investment and operational decisions.

Table 9 Coal characteristics and financial parameters

Parameter	Value
Capacity Factor	85%
Life Time	40 Years
Heat Rate	10000 Btu/Kwh
Electricity Drift	3%
Natural Gas Drift	0%
Electricity Volatility	30%
Coal Volatility	10%
Correlation	.7
Interest Rate	6%
Risk Adjusted Rate for Electricity	8%
Risk Adjusted Rate for Natural Gas	5%
Electricity Convenience Yield	5%
Natural Gas Convenience Yield	5%

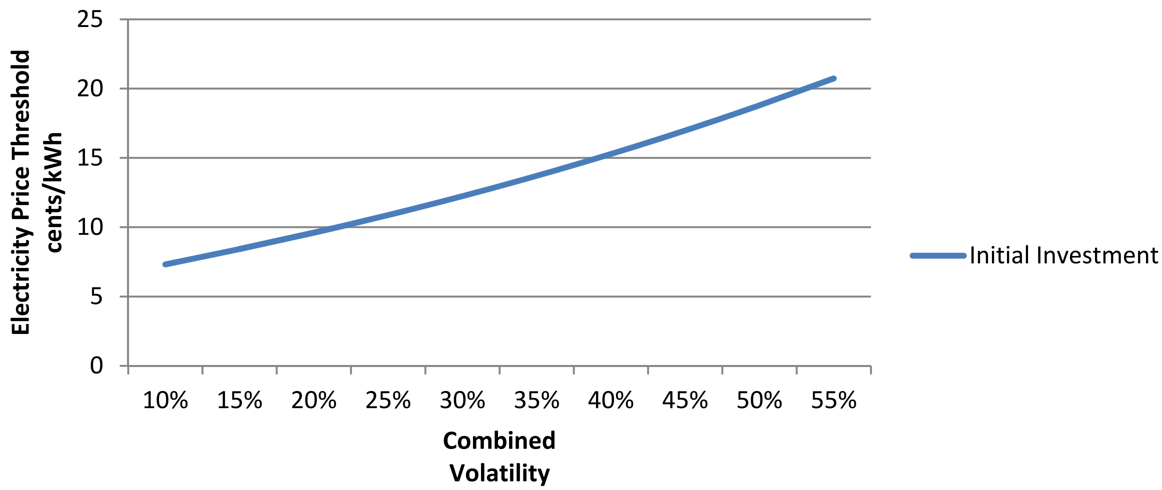
Table 10 Coal cost parameters

Parameter	Value	Unit
Coal Price	$1.5/MMBtu	Coal Price
Annual Operating Costs (Fixed and Variable)	80	$/kW
Overnight Capital Cost	4000	$/kW
Annual Blended Cost of Capital	266	$/kW
Annual Mothball Maintenance Cost	10	$/kW
Lump Sum Cost of Mothballing	1	$/kW
Lump Sum Cost of Reactivating	.001	$/kW
Lump Sum Decommissioning Cost *	0	$/kW

4.3.1 Volatility (Sigma) Sensitivity

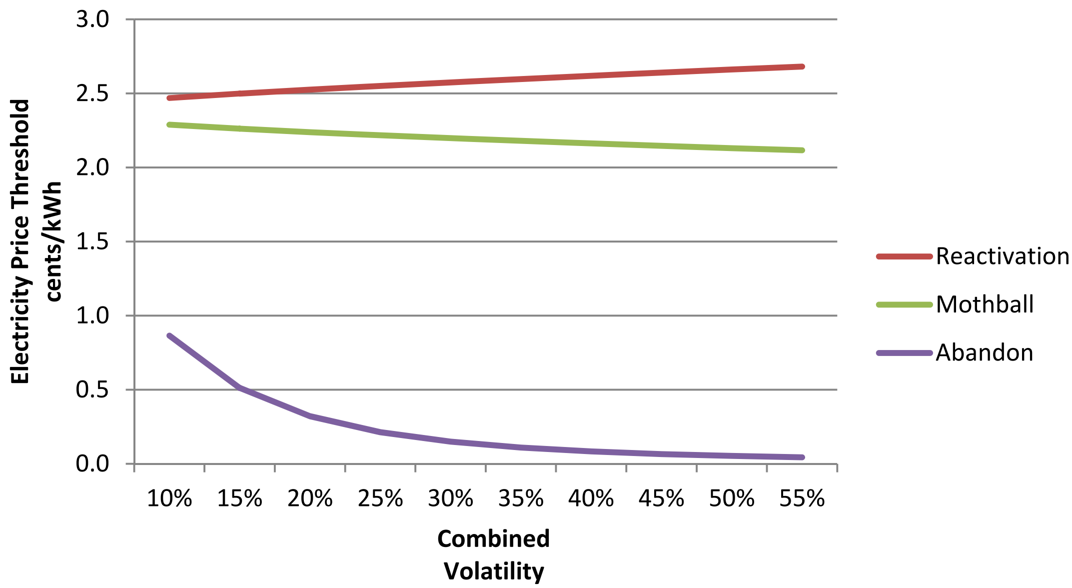
Coal prices are much less volatile than natural gas prices, but we expect more electricity price volatility in the presence of more variable renewable generation. We have seen in previous sections that move volatility increases the threshold for an initial investment. The price thresholds for coal (Figure 37) are lower compared to natural gas combined cycle due to difference in capacity factors, operating and overnight capital costs. At combined volatility of coal and electricity prices below 25%, it is economical for coal to invest even if prices are below $100 /MWh, but if volatility rises above 25%, price hurdles for coal investments rise above $100/MWh.

Figure 37 Coal investment threshold with volatility



We come to an important threshold value for coal with our support decision tools. We've seen the general shape of mothballing and reactivation thresholds when volatility increases. Increased volatility implies a greater option value for delaying temporary suspension. The firm is valuing the trade-off between temporary shutdowns to minimize losses or continued operations, but the firm could also miss some gains from a volatile market. The real options approach captures the value in delaying mothballing with higher volatility. The same argument can be made for abandonment thresholds. On the other hand reactivation thresholds increase as volatility increases. In the case of coal, these threshold values are between $25 -$35/MWh (Figure 38).

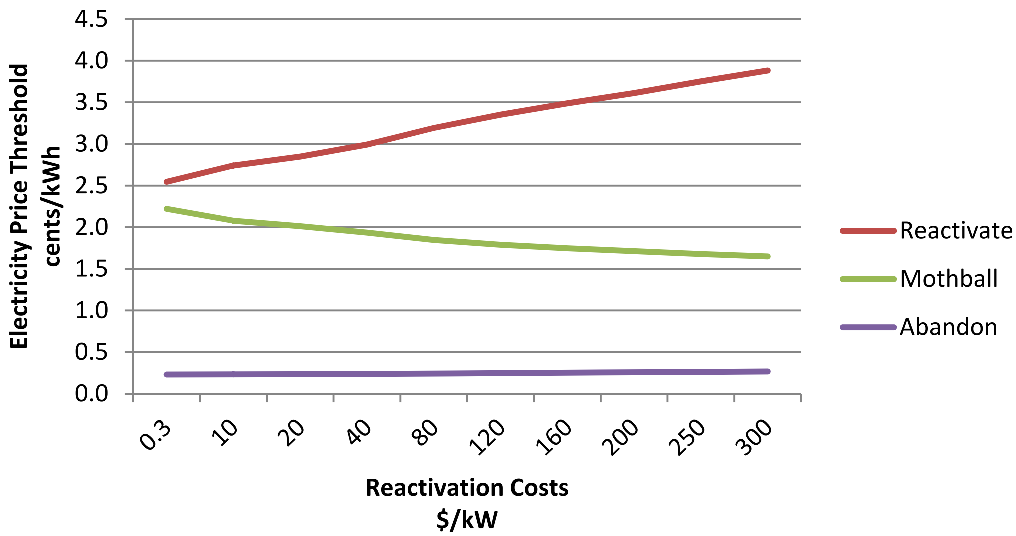
Figure 38 Coal combined volatility sensitivity



4.3.2 Reactivation Sensitivity

In the current state of the coal industry, several firms are either mothballing or retiring coal-fired generators. Some firms have decided to delay either mothballing or retirement due to market and policy uncertainty. The real options approach provides individual power producers some insights on how to value either an operational or mothballed plant with the option to mothball or reactivate. For example, as long as reactivation costs are low, \$0.3 - \$40/kW, it will be optimal for the firm to reactivate even at prices below \$30/MWh (Figure 39). On the other hand if prices go below \$25/MWh, it is more economical for coal plants to mothball. In our model, coal plants should be decommissioned if they can no longer lock in prices higher than \$5/MWh.

Figure 39 Coal reactivation sensitivity

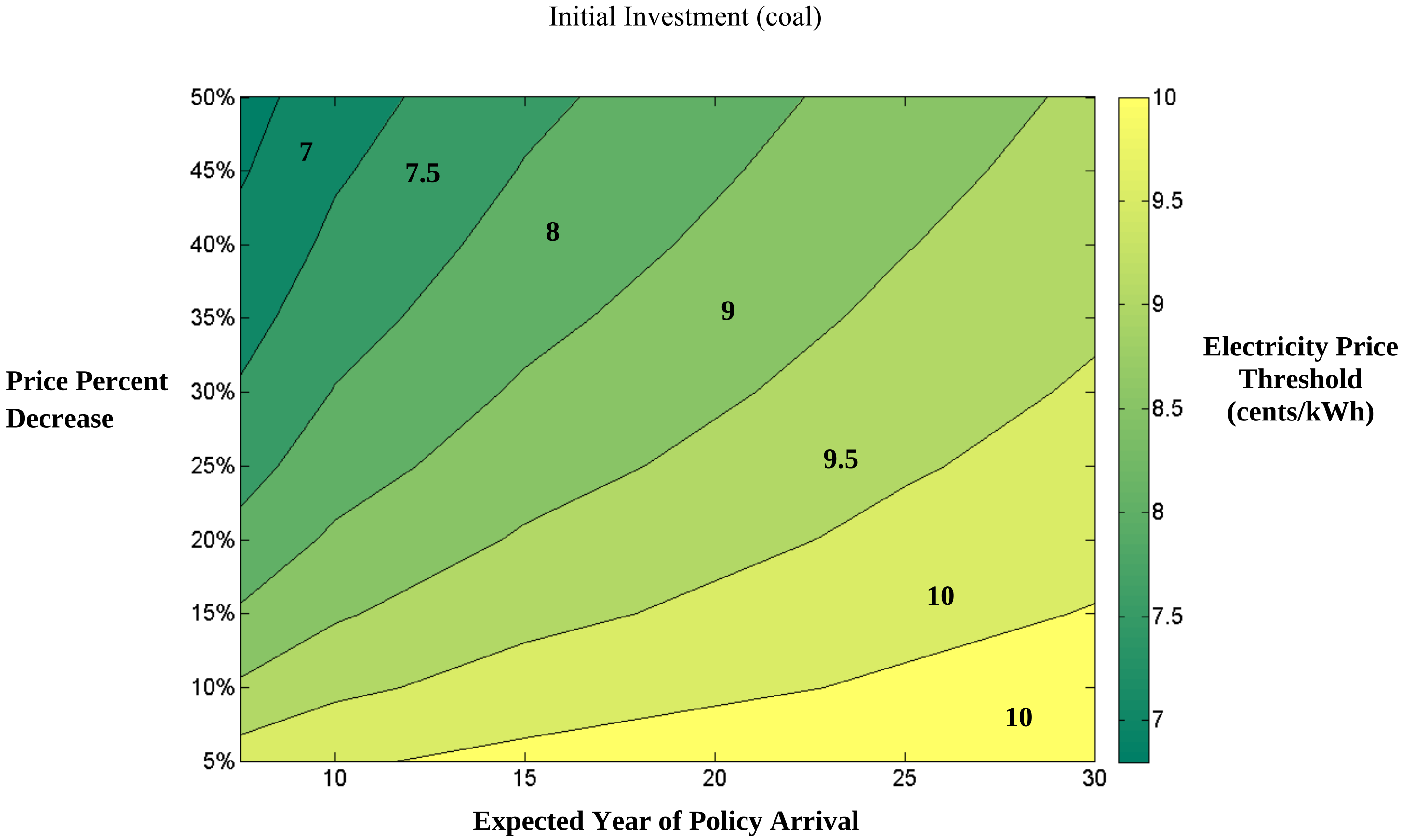


In the past few years we have observed coal plant retirements even though electricity prices are not below the abandonment threshold. There are several reasons for current decommissioning. We have assumed very long lifetimes for our plants and constant capacity factors through its lifetime. Most coal plant retirements today are due to age or strict environmental standards. This is not the subset of plants we consider in our study. The scenarios we have emphasized are investment and operational decisions from market and RPS policy uncertainty.

4.3.3 Policy Timing and Strength

Timing of renewable policy greatly influences investment and operational decisions by individual power producers. Several papers have looked at the effects of more renewable energy generation such as wind and solar on electricity prices (Green & Vasilakos, 2011; Olsina, Roscher, Larisson, & Garces, 2007; Saenz de Miera, del Rio Gonzalez, & Vizcaino, 2008). We refer to the strength of the policy as the percentage decrease in electricity prices due to more renewable energy penetration. We perform scenario analyses by calibrating the jump process by looking at various timing, λ, and strength, θ, parameters in equation 11.

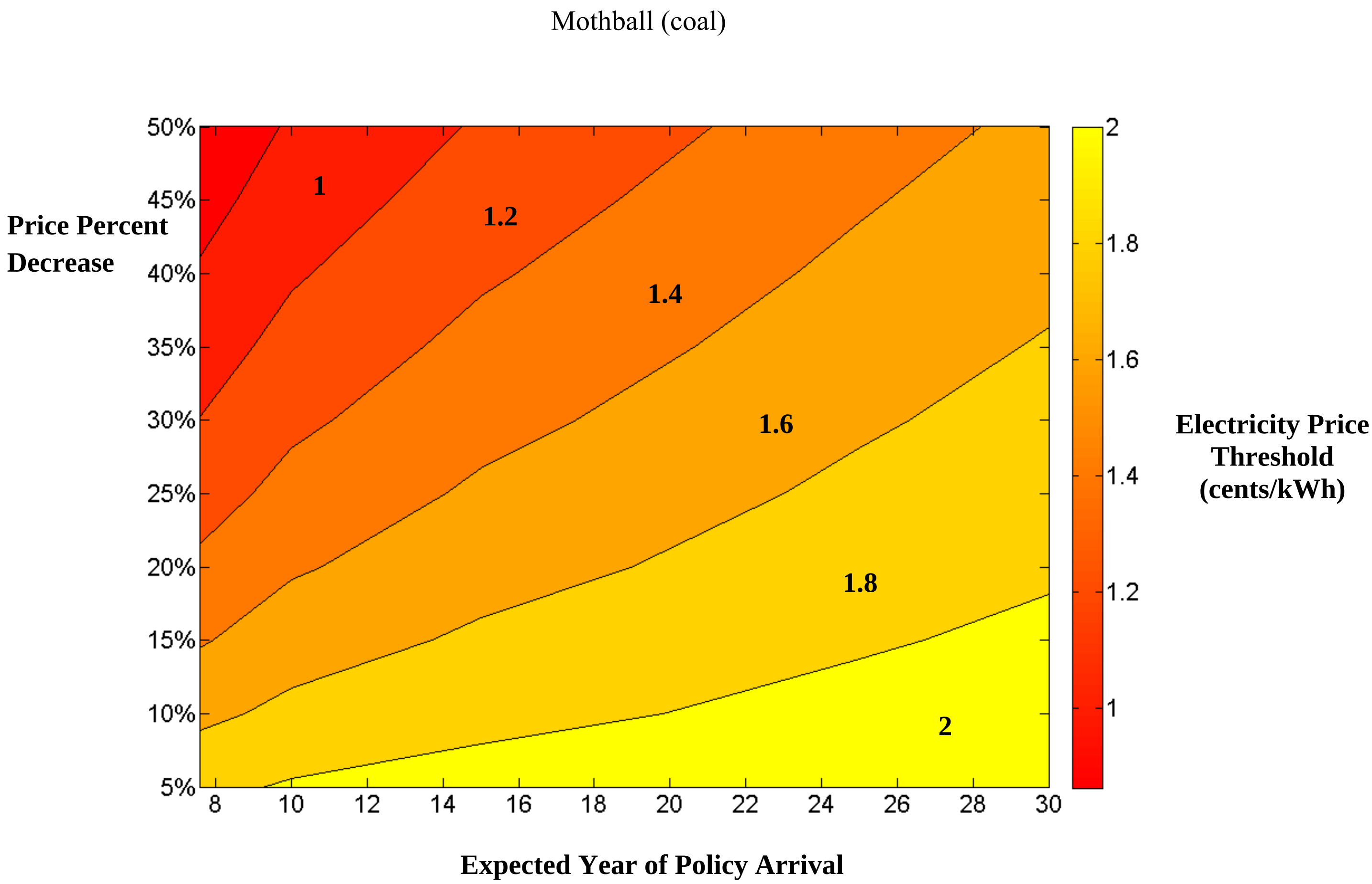
Figure 40 Coal investment threshold with policy strength and timing sensitivity



In Figure 40, the colorbar represents the optimal threshold for investing in a coal plant. Fixing our policy arrival at 10 years, as the policy strength increases the investment threshold values decrease. Our results are quite the opposite when volatilty increases. The reason for a decrease in the investment thershold is capturing the opportunity to invest early while prices are high and taking advantage of higher profits in earlier years. On the other hand, as the expectation of policy increases from 10 to 20 years, we notice a drop in investment price signals. If we expect a large decrease in prices, $\theta = 50\%$ with an arrival rate of $\lambda = .05$ (20 years), the price signal for investing is \$80 – \$85/MWh. Depending on market conditions, this could happen in the next 5 or 10 years of the investment horizon.

Policy timing and strength has very important implications in relating market price signals and incentivizing generation for a reliable energ mix. If we expect more wind in our system, it is better to invest early before prices are affected by large penetration of wind or solar in the system. Furthermore, under the real options approach, systems with higher volatility has lower mothballing thresholds. Existing conventional generators are valued more in higher volatility systems.

Figure 41 Coal mothball threshold with policy strength and timing sensitivity



Our last scenario, Figure 41, analysis looks at mothballing threshold for coal power plants with varying policy arrival rates and strength. If we fix the policy arrival at 10 years, we observe that a larger decrease in price gives a lower threshold for mothballing. It is economical for the plant owner to take advantage of current market prices and delay mothballing. On the other hand, if the expected decrease is not very significant, the power plant owner might choose to minimize losses as early as possible by mothballing at relatively higher price.

The last two figures (Figure 40 and Figure 41) summarize the influence of policy expectation on investments and operational decisions. Both the strength of the policy and the timing of its implementation are crucial for individual power producers. An important dynamic in the real options approach is that it captures the arrival of a policy. Although there is an expectation of its arrival, its implementation and effect on market conditions are uncertain. An example of this is the recent delay of EPA rules in 2011 and the delay of RPS rules in various states. California's 2010 targets were met only in 2012. Large power producers are very sensitive to policy and thus it is important to understand how to appropriately implement them in the market to provide appropriate market price signals that will ensure a reliable energy mix.

5.0 Summary and Conclusions

With the introduction of RPS policies, we expect electricity price volatility to increase. In addition, renewable generation is expected to displace coal and natural gas. competitive markets, it is important for individual power producers to react appropriately to market price signals to minimize social welfare losses by maintaining a reliable supply of generation. We modeled and evaluated a spark spread options valuation for capital budgeting and compared it with the traditional cash flow approach. Our numerical examples show it is profitable to build 3 out of 6 projects examined using the spark spread option in capital budgeting even without capacity payments. The traditional cash flow finds only 2 out of these 6 projects to be profitable.

We extend the use of the spark spread approach in capital budgeting and present a real options approach to understand the optimal conditions for investing, reactivating, mothballing, and permanently abandoning a plant. Under a real options approach, we develop operating and waiting value functions using dynamic programming. We present a closed-form explanation for why real options investment thresholds are higher compared to traditional cash flow valuation. The economic reason behind an increase in the threshold is due to the added cost of holding the option to delay the investment and execute the project at a later date when market conditions are better and risks are minimized. We also show that new investment price thresholds in coal and natural gas will be higher in markets with higher volatility.

The coal industry is experiencing and projecting an increase in mothballing and decommissioning coal-fired power plants. Although a mothballed plant does not provide energy benefits, there should be a value in holding the option to reactivate the plant in the future to sell energy. We apply the same real options approach to solve for the value of a mothballed plant. Our numerical results show that mothball price signals decrease as volatility increase. In other words, it is better to delay mothballing when electricity price volatility increases. We also show that reactivation costs influence a power plant’s decision to mothball.

The timing and strength of policy affects investment and operational decisions. This is crucial for policy makers when designing the timing and strength of a policy. We highlighted the effects of increased volatility and a decrease in average prices on investment behavior. The arrival of a policy that decreases future average prices incentivizes early investments in coal and gas-fired generators. There is a trade-off between increased volatility and lower average prices in the future in incentivizing new generation when we expect more intermittent, renewable energy. Therefore the timing of introduction and implementation will play a key role in providing appropriate market price signals that will provide a reliable mix of generating technologies.

The spark spread approach captures the value in holding the option to convert fuel into electricity in the future. The real options approach gives the optimal threshold value for investment and operational decisions. These tools can help individual power producers capture appropriate market price signals, and avoid under-valuing generation technologies. The real options approach captures the intrinsic value in having installed capacity, thus making several investment decisions profitable even with the absence of capacity payments.

Appendix I

Table 11 Gas combined cycle valuation assumptions

Gas Combined Cycle Valuation Assumptions			
	Value		Unit
	(High)	(Low)	
Electricity Risk Adjusted Discount Rate	8.0%	5.0%	N/A
Natural Gas Risk Adjusted Discount Rate	7.0%	5.0%	N/A
Interest Rate	6.0%	4.5%	N/A
Electricity Convenience Yield	5.0%	5.0%	N/A
Fuel Convenience Yield	5.0%	5.0%	N/A
Plant Life Time	40	40	Years
Annual Operating Costs	15	10	$/kW
Annual Mortgage	86	49	$/kW-year

Table 12 Gas combined cycle costs and characteristics

Gas Combined Cycle Costs and Characteristics			
	Value		Unit
	(High)	(Low)	
Overnight Capital Costs	1300	900	$/kW
Heat Rate	7200	6800	Btu/kWh
Capacity Factor	30%	25%	N/A
Yearly Operational Hours	2628	2190	Hours/Year
Fixed O&M	6.2	5.5	$/kW-yr
Variable O&M	3.5E-03	2.0E-03	$/kWh
Reactivation Cost	0.3	0.2	$/kW
Mothball Cost	1.0	0.4	$/kW
Annual Mothball Maintenance	10	6	$/kW
Decommissioning Cost	100	10	$/kW

Table 13 Integrated gasification combined cycle valuation assumptions

Integrated Gasification Combined Cycle Valuation Assumptions			
	Value		Unit
	(High)	(Low)	
Electricity Risk Adjusted Discount Rate	8.0%	5%	N/A
Coal Risk Adjusted Discount Rate	6.0%	5%	N/A
Interest Rate	6.0%	5%	N/A
Electricity Convenience Yield	5.0%	5%	N/A
Fuel Convenience Yield	5.0%	5%	N/A
Plant Life Time	40	40	Years
Annual Operating Costs	84	69	$/kW
Annual Mortgage	346	201	$/kW-year

Table 14 Integrated gasification combined cycle costs and characteristics

Integrated Gasification Combined Cycle Costs and Characteristics			
	Value		Unit
	(High)	(Low)	
Overnight Capital Costs	5200	3700	$/kW
Heat Rate	10520	8800	Btu/kWh
Capacity Factor	88%	75%	N/A
Yearly Operational Hours	7709	6570	Hours/Year
Fixed O&M	28	26	$/kW-yr
Variable O&M	7.3E-03	6.5E-03	$/kWh
Reactivation Cost	0.3	0.2	$/kW
Mothball Cost	1.0	0.4	$/kW
Annual Mothball Maintenance	10	6	$/kW
Decomissioning Cost	100	10	$/kW

Table 15 Coal plant valuation assumptions

Coal Plant Valuation Assumptions			
	Value		Unit
	(High)	(Low)	
Electricity Risk Adjusted Discount Rate	8.0%	5.0%	N/A
Coal Risk Adjusted Discount Rate	5.0%	5.0%	N/A
Interest Rate	6.0%	4.5%	N/A
Electricity Convenience Yield	5.0%	5.0%	N/A
Fuel Convenience Yield	5.0%	5.0%	N/A
Plant Life Time	40	40	Years
Annual Operating Costs	80	42	$/kW
Annual Mortgage	332	163	$/kW-year

Table 16 Coal plant costs and characteristics

Coal Plant Costs and Characteristics			
	Value		Unit
	(High)	(Low)	
Overnight Capital Costs	5000	3000	$/kW
Heat Rate	12000	8750	Btu/kWh
Capacity Factor	95%	85%	N/A
Yearly Operational Hours	8322	7446	Hours/Year
Fixed O&M	30	20	$/kW-yr
Variable O&M	6.0E-03	3.0E-03	$/kWh
Reactivation Cost	0.3	0.2	$/kW
Mothball Cost	1.0	0.4	$/kW
Annual Mothball Maintenance	10	6	$/kW
Decommissioning Cost	100	10	$/kW

Table 17 1 kW of gas combined cycle flow sheet (high scenario)

1 kW of Gas Combined Cycle Flow Sheet (High Scenario)				
Year	**Operating Costs**	**Net Present Value**	**Spark Spread Value**	**Investment Costs**
0	$15.40	$79.89	$90.64	$86.40
1	$14.53	$76.09	$86.32	$81.51
2	$13.70	$72.46	$82.21	$76.90
3	$12.93	$69.01	$78.29	$72.54
4	$12.20	$65.73	$74.57	$68.44
5	$11.51	$62.60	$71.02	$64.56
6	$10.85	$59.62	$67.63	$60.91
7	$10.24	$56.78	$64.41	$57.46
8	$9.66	$54.07	$61.35	$54.21
9	$9.11	$51.50	$58.42	$51.14
10	$8.60	$49.05	$55.64	$48.25
11	$8.11	$46.71	$52.99	$45.51
12	$7.65	$44.49	$50.47	$42.94
13	$7.22	$42.37	$48.07	$40.51
14	$6.81	$40.35	$45.78	$38.21
15	$6.43	$38.43	$43.60	$36.05
16	$6.06	$36.60	$41.52	$34.01
17	$5.72	$34.86	$39.54	$32.09
18	$5.39	$33.20	$37.66	$30.27
19	$5.09	$31.62	$35.87	$28.56
20	$4.80	$30.11	$34.16	$26.94
21	$4.53	$28.68	$32.53	$25.42
22	$4.27	$27.31	$30.98	$23.98
23	$4.03	$26.01	$29.51	$22.62
24	$3.80	$24.77	$28.10	$21.34
25	$3.59	$23.59	$26.76	$20.13
26	$3.38	$22.47	$25.49	$18.99
27	$3.19	$21.40	$24.28	$17.92
28	$3.01	$20.38	$23.12	$16.90
29	$2.84	$19.41	$22.02	$15.95
30	$2.68	$18.49	$20.97	$15.04
31	$2.53	$17.60	$19.97	$14.19
32	$2.39	$16.77	$19.02	$13.39
33	$2.25	$15.97	$18.12	$12.63
34	$2.12	$15.21	$17.25	$11.92
35	$2.00	$14.48	$16.43	$11.24
36	$1.89	$13.79	$15.65	$10.60
37	$1.78	$13.14	$14.90	$10.00
38	$1.68	$12.51	$14.19	$9.44
39	$1.59	$11.92	$13.52	$8.90
	Life Time Operating Costs	**Life Time Value**	**Life Time Value**	**Investment Costs**
	$246	$1,439	$1,633	$1,378

Table 18 1 kW of gas combined cycle flow sheet (low scenario)

1 kW of Gas Combined Cycle Flow Sheet (Low Scenario)								
Year		Operating Costs		Net Present Value		Spark Spread Value		Investment Costs
0		$9.88		$58.87		$59.67		$48.91
1		$9.45		$56.06		$56.83		$46.80
2		$9.05		$53.39		$54.12		$44.79
3		$8.66		$50.85		$51.54		$42.86
4		$8.28		$48.43		$49.09		$41.01
5		$7.93		$46.12		$46.75		$39.25
6		$7.59		$43.93		$44.53		$37.56
7		$7.26		$41.84		$42.40		$35.94
8		$6.95		$39.84		$40.39		$34.39
9		$6.65		$37.95		$38.46		$32.91
10		$6.36		$36.14		$36.63		$31.49
11		$6.09		$34.42		$34.89		$30.14
12		$5.83		$32.78		$33.23		$28.84
13		$5.58		$31.22		$31.64		$27.60
14		$5.33		$29.73		$30.14		$26.41
15		$5.11		$28.32		$28.70		$25.27
16		$4.89		$26.97		$27.33		$24.18
17		$4.67		$25.68		$26.03		$23.14
18		$4.47		$24.46		$24.79		$22.15
19		$4.28		$23.30		$23.61		$21.19
20		$4.10		$22.19		$22.49		$20.28
21		$3.92		$21.13		$21.42		$19.41
22		$3.75		$20.12		$20.40		$18.57
23		$3.59		$19.17		$19.43		$17.77
24		$3.44		$18.25		$18.50		$17.01
25		$3.29		$17.38		$17.62		$16.27
26		$3.15		$16.56		$16.78		$15.57
27		$3.01		$15.77		$15.98		$14.90
28		$2.88		$15.02		$15.22		$14.26
29		$2.76		$14.30		$14.50		$13.65
30		$2.64		$13.62		$13.81		$13.06
31		$2.52		$12.97		$13.15		$12.50
32		$2.42		$12.35		$12.52		$11.96
33		$2.31		$11.77		$11.93		$11.44
34		$2.21		$11.21		$11.36		$10.95
35		$2.12		$10.67		$10.82		$10.48
36		$2.03		$10.16		$10.30		$10.03
37		$1.94		$9.68		$9.81		$9.60
38		$1.85		$9.22		$9.34		$9.18
39		$1.78		$8.78		$8.90		$8.79
		Life Time Operating Costs		**Life Time Value**		**Life Time Value**		**Investment Costs**
		$190		$1,061		$1,075		$941

Table 19 1 kW of IGCC flow sheet (high scenario)

1 kW of IGCC Flow Sheet (High Scenario)								
Year		**Operating Costs**		**Net Present Value**		**Spark Spread Value**		**Investment Costs**
0		$84.27		$377.42		$378.08		$345.60
1		$79.50		$359.45		$360.07		$326.04
2		$75.00		$342.33		$342.93		$307.58
3		$70.76		$326.03		$326.60		$290.17
4		$66.75		$310.51		$311.05		$273.75
5		$62.97		$295.72		$296.23		$258.25
6		$59.41		$281.64		$282.13		$243.63
7		$56.05		$268.23		$268.69		$229.84
8		$52.87		$255.45		$255.90		$216.83
9		$49.88		$243.29		$243.71		$204.56
10		$47.06		$231.70		$232.11		$192.98
11		$44.39		$220.67		$221.05		$182.06
12		$41.88		$210.16		$210.53		$171.75
13		$39.51		$200.16		$200.50		$162.03
14		$37.27		$190.62		$190.96		$152.86
15		$35.16		$181.55		$181.86		$144.21
16		$33.17		$172.90		$173.20		$136.04
17		$31.30		$164.67		$164.95		$128.34
18		$29.52		$156.83		$157.10		$121.08
19		$27.85		$149.36		$149.62		$114.23
20		$26.28		$142.25		$142.49		$107.76
21		$24.79		$135.47		$135.71		$101.66
22		$23.39		$129.02		$129.25		$95.91
23		$22.06		$122.88		$123.09		$90.48
24		$20.81		$117.03		$117.23		$85.36
25		$19.64		$111.45		$111.65		$80.52
26		$18.52		$106.15		$106.33		$75.97
27		$17.48		$101.09		$101.27		$71.67
28		$16.49		$96.28		$96.45		$67.61
29		$15.55		$91.69		$91.85		$63.78
30		$14.67		$87.33		$87.48		$60.17
31		$13.84		$83.17		$83.31		$56.77
32		$13.06		$79.21		$79.35		$53.55
33		$12.32		$75.44		$75.57		$50.52
34		$11.62		$71.84		$71.97		$47.66
35		$10.96		$68.42		$68.54		$44.96
36		$10.34		$65.16		$65.28		$42.42
37		$9.76		$62.06		$62.17		$40.02
38		$9.21		$59.11		$59.21		$37.75
39		$8.68		$56.29		$56.39		$35.62
		Life Time Operating Costs		**Life Time Value**		**Life Time Value**		**Investment Costs**
		$1,344		$6,800		$6,812		$5,512

Table 20 1 kW of IGCC flow sheet (low scenario)

1 kW of IGCC Flow Sheet (Low Scenario)				
Year	Operating Costs	Net Present Value	Spark Spread Value	Investment Costs
0	$68.71	$241.78	$241.78	$201.07
1	$65.75	$230.26	$230.26	$192.41
2	$62.92	$219.30	$219.30	$184.13
3	$60.21	$208.86	$208.86	$176.20
4	$57.61	$198.91	$198.91	$168.61
5	$55.13	$189.44	$189.44	$161.35
6	$52.76	$180.42	$180.42	$154.40
7	$50.49	$171.83	$171.83	$147.75
8	$48.31	$163.64	$163.64	$141.39
9	$46.23	$155.85	$155.85	$135.30
10	$44.24	$148.43	$148.43	$129.47
11	$42.34	$141.36	$141.36	$123.90
12	$40.51	$134.63	$134.63	$118.56
13	$38.77	$128.22	$128.22	$113.46
14	$37.10	$122.11	$122.11	$108.57
15	$35.50	$116.30	$116.30	$103.90
16	$33.97	$110.76	$110.76	$99.42
17	$32.51	$105.49	$105.49	$95.14
18	$31.11	$100.46	$100.46	$91.04
19	$29.77	$95.68	$95.68	$87.12
20	$28.49	$91.12	$91.12	$83.37
21	$27.26	$86.78	$86.78	$79.78
22	$26.09	$82.65	$82.65	$76.35
23	$24.96	$78.72	$78.72	$73.06
24	$23.89	$74.97	$74.97	$69.91
25	$22.86	$71.40	$71.40	$66.90
26	$21.88	$68.00	$68.00	$64.02
27	$20.93	$64.76	$64.76	$61.26
28	$20.03	$61.68	$61.68	$58.63
29	$19.17	$58.74	$58.74	$56.10
30	$18.34	$55.94	$55.94	$53.69
31	$17.55	$53.28	$53.28	$51.37
32	$16.80	$50.74	$50.74	$49.16
33	$16.07	$48.32	$48.32	$47.04
34	$15.38	$46.02	$46.02	$45.02
35	$14.72	$43.83	$43.83	$43.08
36	$14.09	$41.74	$41.74	$41.22
37	$13.48	$39.76	$39.76	$39.45
38	$12.90	$37.86	$37.86	$37.75
39	$12.34	$36.06	$36.06	$36.13
	Life Time Operating Costs	**Life Time Value**	**Life Time Value**	**Investment Costs**
	$1,321	$4,356	$4,356	$3,867

Table 21 1kW of coal flow sheet (high scenario)

1 kW of Coal Flow Sheet (High Scenario)				
Year	Operating Costs	Net Present Value	Spark Spread Value	Investment Costs
0	$79.93	$382.81	$384.31	$332.31
1	$75.41	$364.58	$366.01	$313.50
2	$71.14	$347.22	$348.58	$295.75
3	$67.11	$330.69	$331.98	$279.01
4	$63.31	$314.94	$316.17	$263.22
5	$59.73	$299.94	$301.12	$248.32
6	$56.35	$285.66	$286.78	$234.26
7	$53.16	$272.06	$273.12	$221.00
8	$50.15	$259.10	$260.12	$208.49
9	$47.31	$246.76	$247.73	$196.69
10	$44.63	$235.01	$235.93	$185.56
11	$42.11	$223.82	$224.70	$175.06
12	$39.72	$213.16	$214.00	$165.15
13	$37.48	$203.01	$203.81	$155.80
14	$35.35	$193.35	$194.10	$146.98
15	$33.35	$184.14	$184.86	$138.66
16	$31.46	$175.37	$176.06	$130.81
17	$29.68	$167.02	$167.67	$123.41
18	$28.00	$159.07	$159.69	$116.42
19	$26.42	$151.49	$152.09	$109.83
20	$24.92	$144.28	$144.84	$103.62
21	$23.51	$137.41	$137.95	$97.75
22	$22.18	$130.86	$131.38	$92.22
23	$20.93	$124.63	$125.12	$87.00
24	$19.74	$118.70	$119.16	$82.07
25	$18.62	$113.05	$113.49	$77.43
26	$17.57	$107.66	$108.08	$73.04
27	$16.58	$102.54	$102.94	$68.91
28	$15.64	$97.65	$98.04	$65.01
29	$14.75	$93.00	$93.37	$61.33
30	$13.92	$88.57	$88.92	$57.86
31	$13.13	$84.36	$84.69	$54.58
32	$12.39	$80.34	$80.65	$51.49
33	$11.68	$76.51	$76.81	$48.58
34	$11.02	$72.87	$73.16	$45.83
35	$10.40	$69.40	$69.67	$43.23
36	$9.81	$66.10	$66.35	$40.79
37	$9.26	$62.95	$63.19	$38.48
38	$8.73	$59.95	$60.19	$36.30
39	$8.24	$57.10	$57.32	$34.25
	Life Time Operating Costs	Life Time Value	Life Time Value	Investment Costs
	$1,275	$6,897	$6,924	$5,300

Table 22 1 kW of coal flow sheet (low scenario)

1 kW of Coal Flow Sheet (Low Scenario)				
Year	Operating Costs	Net Present Value	Spark Spread Value	Investment Costs
0	$42.34	$274.57	$274.57	$201.07
1	$40.51	$261.50	$261.50	$192.41
2	$38.77	$249.04	$249.04	$184.13
3	$37.10	$237.18	$237.18	$176.20
4	$35.50	$225.89	$225.89	$168.61
5	$33.97	$215.13	$215.13	$161.35
6	$32.51	$204.89	$204.89	$154.40
7	$31.11	$195.13	$195.13	$147.75
8	$29.77	$185.84	$185.84	$141.39
9	$28.49	$176.99	$176.99	$135.30
10	$27.26	$168.56	$168.56	$129.47
11	$26.09	$160.54	$160.54	$123.90
12	$24.97	$152.89	$152.89	$118.56
13	$23.89	$145.61	$145.61	$113.46
14	$22.86	$138.68	$138.68	$108.57
15	$21.88	$132.07	$132.07	$103.90
16	$20.93	$125.78	$125.78	$99.42
17	$20.03	$119.79	$119.79	$95.14
18	$19.17	$114.09	$114.09	$91.04
19	$18.35	$108.66	$108.66	$87.12
20	$17.56	$103.48	$103.48	$83.37
21	$16.80	$98.56	$98.56	$79.78
22	$16.08	$93.86	$93.86	$76.35
23	$15.38	$89.39	$89.39	$73.06
24	$14.72	$85.14	$85.14	$69.91
25	$14.09	$81.08	$81.08	$66.90
26	$13.48	$77.22	$77.22	$64.02
27	$12.90	$73.54	$73.54	$61.26
28	$12.34	$70.04	$70.04	$58.63
29	$11.81	$66.71	$66.71	$56.10
30	$11.30	$63.53	$63.53	$53.69
31	$10.82	$60.50	$60.50	$51.37
32	$10.35	$57.62	$57.62	$49.16
33	$9.91	$54.88	$54.88	$47.04
34	$9.48	$52.27	$52.27	$45.02
35	$9.07	$49.78	$49.78	$43.08
36	$8.68	$47.41	$47.41	$41.22
37	$8.31	$45.15	$45.15	$39.45
38	$7.95	$43.00	$43.00	$37.75
39	$7.61	$40.95	$40.95	$36.13
	Life Time Operating Costs	**Life Time Value**	**Life Time Value**	**Investment Costs**
	$814	$4,947	$4,947	$3,867

Table 23 Spark spread cash flow support documentation

Spark Spread Cash Flow Support Documentation

Gas Combined Cycle (High)	
	Value
Combined Electricity and Gas Volatility	69%
d1	1.17
d2	0.47
Gas Combined Cycle (Low)	
	Value
Combined Electricity and Gas Volatility	48%
d1	1.85
d2	1.37
IGCC (High)	
	Value
Combined Electricity and Coal Volatility	53%
d1	2.52
d2	1.98
IGCC (Low)	
	Value
Combined Electricity and Coal Volatility	34%
d1	4.07
d2	3.73
Coal (High)	
	Value
Combined Electricity and Coal Volatility	53%
d1	2.27
d2	1.73
Coal (Low)	
	Value
Combined Electricity and Coal Volatility	34%
d1	30.83
d2	30.49

Table 24 1 kW of gas combined cycle heat rate: 7200

1 kW of Gas Combined Cycle Heat Rate: 7200				
	Net Present Value		Spark Spread Present Value	
Capacity Factor	(High Prices)	(Low Prices)	(High Prices)	(Low Prices)
20%	$1,065	$894	$1,208	$912
25%	$1,332	$1,118	$1,511	$1,140
30%	$1,598	$1,341	$1,813	$1,367
35%	$1,864	$1,565	$2,115	$1,595
40%	$2,130	$1,788	$2,417	$1,823
45%	$2,397	$2,012	$2,719	$2,051
50%	$2,663	$2,236	$3,021	$2,279
55%	$2,929	$2,459	$3,323	$2,507
60%	$3,196	$2,683	$3,625	$2,735
65%	$3,462	$2,906	$3,928	$2,963

Electricity Convenience Yield	5.0%
Natural Gas Convenience Yield	5.0%

	(High Prices)	(Low Prices)
Combined Volatility	69%	48%
d1	1.17	1.73
d2	0.47	1.25

Table 25 Spark spread fuel price sensitivity

Electricity Prices in $/MWh	Fuel Prices in $/MMBtu: 2	3	4	5	6
	Spark Spread Value in $/MWh				
10	$0	$0	$0	$0	$0
20	$4	$2	$1	$0	$0
30	$11	$6	$4	$2	$1
40	$19	$13	$8	$5	$4
50	$28	$20	$15	$10	$7
60	$36	$28	$22	$17	$12
70	$45	$37	$30	$23	$19
80	$54	$46	$38	$31	$25
90	$63	$55	$46	$39	$33
100	$72	$64	$55	$47	$40

Appendix II

Ito's Lemma is used to take a derivate of an Ito process. Let F be a function of x_i for $i = 1, \dots, N$ where we have:

$$F(x_1, x_2, \dots, x_N) \tag{36}$$

$$dx_i = a_i(x_1, x_2, \dots, x_N, t)dt + b_i(x_1, x_2, \dots, x_N, t)dz_i \ .$$

We note that dz_i is a Weiner process, and we denote the correlation between two Weiner processes as $\rho_{ij} = \mathrm{E}[dz_i dz_j]$. Ito's Lemma gives us the differential of the function F:

$$\begin{aligned} dF = \Bigg[& \frac{\partial F}{\partial t} + \sum_i a_i(x_1, x_2, \dots, x_N, t)\frac{\partial F}{\partial x_i} + \frac{1}{2}\sum_i b_i^2(x_1, x_2, \dots, x_N, t)\frac{\partial^2 F}{\partial x_i^2} \\ & + \sum_{i \neq j} \rho_{ij} b_i(x_1, x_2, \dots, x_N, t) b_j(x_1, x_2, \dots, x_N, t)\frac{\partial^2 F}{\partial x_i \partial x_j}\Bigg] dt \\ & + \sum_i b_i(x_1, x_2, \dots, t)\frac{\partial F}{\partial x_i} dz_i \ . \end{aligned} \tag{37}$$

Appendix III

In this section, we derive the closed-form of the waiting functions. The stream of profits from converting fuel bought at price,Y, and selling it at electricity price, X, with a fixed heat rate, H, and operating cost, C, is given by:

$$\int_0^\infty \left(xe^{(\mu_i-\alpha_x)t} - yHe^{(\mu_i-\alpha_y)t} - Ce^{rt}\right) dt\,. \tag{38}$$

We can simplify by rewriting $\delta_i = \mu_i - \alpha_i$ for $i = x, y$. Solving the integral above gives us:

$$\frac{x}{\delta_x} - \frac{y}{\delta_y} - \frac{C}{r} \tag{39}$$

Note that our exogenous parameter is μ_i for$i = x, y$. We can choose μ_i to select the appropriate convenience rates δ_x and δ_y . In addition, we must have $\mu_i \geq r$. Similarly we can write this relationship as $\mu_i = r + \phi_i$ for some $\phi_i \geq 0$. In our framework in equation 26, we have converted a discrete dynamic programming model to a continuous time dynamic program that incorporates an Ito process (Appendix II). In an initial investment problem, the idle firm is deciding to build the project or wait. Once the project is built, the firm will receive the stream of profits resulting from building the project. Our termination pay-off from the initial investment perspective is given by the stream of profits minus the overnight capital cost to build the project:

$$\Omega(X, Y, H) = \frac{x}{\delta_x} - \frac{y}{\delta_y} - \frac{C}{r} - I\,. \tag{40}$$

We look at equation (28) form the perspective of an initial investment and note that $\pi(X, Y, H) = 0$ until we invest in the project. This simplifies the continuation equation to be solved to the following equation:

$$r\mathrm{F} = \mathrm{E}[dF] \tag{41}$$

We use Ito's Lemma to expand, dF, in equation (43), and we substitute $\alpha_i = r - \delta_i + \phi_i$ for to get the partial differential equation:

$$\frac{1}{2}\left(\sigma_x^2 x^2 F_{xx} + 2\rho\sigma_x\sigma_y xyF_{xy} + \sigma_y^2 y^2 F_{yy}\right) + (r - \delta_x)xF_x + \left(r - \delta_y\right)yF_y - rF = 0\,. \tag{42}$$

We can choose ϕ_x and ϕ_y such that $\phi_x xFx = -\phi_y yF_y$. This differential equation can also be derived using contingency claim analysis, which has a more intuitive economic interpretation and detailed description of this substitution. We refer the reader to Dixit & Pindyck (1994) chapter 6, section 5 for the derivation of equation (44) using contingency claims analysis.

The solution to the partial differential equation (44) is:

$$yH(A_1\left(\frac{x}{yH}\right)^{\beta_1} + A_2\left(\frac{x}{yH}\right)^{\beta_2}) \tag{43}$$

where $\beta_1$and β_2 are positive and negative roots of the fundamental quadratic equation:

$$\frac{1}{2}\left(\sigma_x^2 - 2\rho\sigma_x\sigma_y + \sigma_y^2\right)\beta(\beta+1) + \left(\delta_x - \delta_y\right) - \delta_y = 0 \, . \tag{44}$$

Function (45) is defined in the domain $x \in [0, x_h], y \in [y_h, \infty)$. As fuel prices approach zero, the value of holding the option increases. On the other hand, if electricity prices go to 0, then the value of the project is 0, and there will be no value in holding the option. Thus we have $F(0, y, H) = 0$, which implies that $A_2 = 0$. This completes the derivation that the value function for waiting is given by:

$$yH(A_1\left(\frac{x}{yH}\right)^{\beta_1}) \tag{45}$$

We use the value-matching, $\Omega(x^*, y^*, H) = F(x^*, y^*, H)$, and smooth-pasting conditions, $\Omega_{\mathrm{x}}(x^*, y^*, H) = F_x(x^*, y^*, H)$ and $\Omega_{\mathrm{y}}(x^*, y^*, H) = F_y(x^*, y^*, H)$, to derive the real options threshold for an initial investment found in equation (30). In our numerical examples, we have fixed the fuel price, y, and solve for the optimal electricity price threshold. We can simply use one of the two smooth-pasting conditions to derive equation (30).

$$yH\left(A_1\left(\frac{x}{yH}\right)^{\beta_1}\right) = \frac{x}{\delta_x} + \frac{yH}{\delta_y} - \frac{C}{r} - I \tag{46}$$

$$\beta_1\left(A_1\left(\frac{x}{yH}\right)^{\beta_1 - 1}\right) = \frac{x}{\delta_x} \tag{47}$$

Putting equations (48) and (49) together we can derive the initial investment criterion in the real options approach.

Appendix IV

This section will provide the mathematical background and derivation to the closed-form solution of the value of an operational plant using dynamic programming. We start with the dynamic programming framework in equation (28) but replace F with V_1 to emphasize we are solving for the value of an operational firm:

$$rV_1(X,Y,H) = \max_{u} \{ \ \pi(X,Y,H,u) + \frac{1}{dt}\mathrm{E}[dV_1] \ \} \tag{48}$$

Subject to:

$$dX = \alpha_x X dt + \sigma_x X dz_x$$

$$dY = \alpha_y Y dt + \sigma_y Y dz_y$$

The firm operates under the condition $\pi(x,y,H) > 0$. The profit function follows our spark spread functional form:

$$\pi(x,y,H) = x - yH - C \tag{49}$$

where $x \sim GBM(\alpha_x, \sigma_x)$ and $y \sim GBM(\alpha_y, \sigma_y)$. In the case that $\pi(x,y,H) \leq 0$, the firm can decide to temporary suspend operations and the value function reverts back to F, which is the value function of a waiting firm. We solve for V_1 Using Ito's Lemma (Appendix II) and substituting $\alpha_i = r - \delta_i + \phi_i$ where we choose ϕ_i such that $\phi_x xFx = -\phi_y yF_y$. We arrive at the following partial differential equation:

$$\frac{1}{2}(\sigma_x^2 x^2 V_{xx} + 2\rho\sigma_x\sigma_y xy\, V_{xy} + \sigma_y^2 y^2 V_{yy}) + (r-\delta_x)xV_x + \left(r-\delta_y\right)yV_y - rV + x - yH - C \tag{50}$$

The solution to this PDE gives us the value of an operating firm:

$$V_1 = \ yH(B_1\left(\frac{x}{yH}\right)^{\beta_1} + B_2\left(\frac{x}{yH}\right)^{\beta_2}) + \frac{x}{\delta_x} - \frac{yH}{\delta_y} - \frac{C}{r} \ , \tag{51}$$

where β_1 and β_2 are the positive and negative roots of the fundamental quadratic (46) respectively. The proof is completed by verifying equation XX satisfies equation YY. The value of an operating plant is defined in the domain $x \in (0,\infty)$ $y \in [0,\infty)$. When electricity prices are high, the value of waiting, $B_1\left(\frac{x}{yH}\right)^{\beta_1}$, should be very small or zero. In this case, we set $B_1 = 0$. We only keep the second term, $B_2\left(\frac{x}{yH}\right)^{\beta_2}$ since there is value in holding the option to mothball the plant in the future when electricity prices drop or fuel prices increase.

Appendix V

This section will provide the mathematical background and derivation to the closed-form solution of the value of a mothballed plant using dynamic programming. . We start with the dynamic programming framework in equation (28) but replace F with V_m to emphasize we are solving for the value of an operational firm:

$$rV_m(X,Y,H) = \max_{\mathrm{u}} \{ \pi(X,Y,H,u) + \frac{1}{dt}\mathrm{E}[dV_1] \} \tag{52}$$

Subject to:

$$dX = \alpha_x X dt + \sigma_x X dz$$

$$dY = \alpha_y Y dt + \sigma_y Y dz \ .$$

The profit function follows our spark spread functional form:

$$\pi(x,y,H) = -M \tag{53}$$

where $x \sim GBM(\alpha_x, \sigma_x)$ and $y \sim GBM(\alpha_y, \sigma_y)$. In mothball stage, the mothballed plant does not earn any stream of revenues, but a maintenance cost, M, is incurred over time. We solve for V_m Using Ito's Lemma (Appendix II) and substituting $\alpha_i = r - \delta_i + \phi_i$ where we choose ϕ_i such that $\phi_x x F x = -\phi_y y F_y$. We arrive at the following partial differential equation:

$$\frac{1}{2}\left(\sigma_x^2 x^2 V_{xx} + 2\rho\sigma_x\sigma_y xy\, V_{xy} + \sigma_y^2 y^2 V_{yy}\right) + (r-\delta_x)xV_x + \left(r-\delta_y\right)yV_y - rV - M \tag{54}$$

The solution to this PDE gives us the value of an operating firm:

$$V_m = \ yH(D_1\left(\frac{x}{yH}\right)^{\beta_1} + D_2\left(\frac{x}{yH}\right)^{\beta_2}) - \frac{M}{r} \ , \tag{55}$$

where $\beta_1$and $\beta_2$are the positive and negative roots of the fundamental quadratic (46) respectively. The proof is completed by verifying equation (57) satisfies equation (56). The value of a mothballed plant is defined in the domain $x \in [x_s, x_r]$ $y \in (0, \infty)$. In this valuation equation, we cannot eliminate either $D_1\left(\frac{x}{yH}\right)^{\beta_1}$or $D_2\left(\frac{x}{yH}\right)^{\beta_2}$. The first term is the value of the option to reactivate, and the second term is the value of the option to abandon the plant. Both have meaningful values, and we cannot eliminate either term in the limit where V_m is defined.

Appendix VI

We recall the value-matching conditions and smooth-pasting conditions in solving our optimal thresholds for initial investment, reactivation, mothballing, and permanent abandonment. We can rewrite our value-matching conditions (34) – (37) using the closed-form functions F, V_1, V_m, presented in sections 3.1, 3.4, and 3.5 respectively.

$$yHA_1\left(\frac{x_h}{yH}\right)^{\beta_1} = yHB_2\left(\frac{x_h}{yH}\right)^{\beta_2} + \frac{x_m}{\delta_x} - \frac{y}{\delta_y} - \frac{C}{r} - I \tag{56}$$

$$yHB_2\left(\frac{x_m}{yH}\right)^{\beta_2} + \frac{x_m}{\delta_x} - \frac{y}{\delta_y} - \frac{C}{r} = yH(D_1\left(\frac{x_m}{yH}\right)^{\beta_1} + D_2\left(\frac{x_m}{yH}\right)^{\beta_2}) - \frac{M}{r} - E_m \tag{57}$$

$$yH\left(D_1\left(\frac{x_r}{yH}\right)^{\beta_1} + D_2\left(\frac{x_r}{yH}\right)^{\beta_2}\right) - \frac{M}{r} = yHB_2\left(\frac{x_r}{yH}\right)^{\beta_2} + \frac{x_r}{\delta_x} - \frac{y}{\delta_y} - \frac{C}{r} - R \tag{58}$$

$$yH\left(D_1\left(\frac{x_s}{yH}\right)^{\beta_1} + D_2\left(\frac{x_s}{yH}\right)^{\beta_2}\right) - \frac{M}{r} = yHA_1\left(\frac{x_s}{yH}\right)^{\beta_1} - E_s \tag{59}$$

In our numerical examples, we have fixed fuel prices and therefore only need one of the two smooth-pasting conditions in equation (28). We use $\Omega_x(x^*, y^*, H) = F_x(x^*, y^*, H)$. The 4 smooth-pasting conditions are:

$$\beta_1 A_1\left(\frac{x_h}{yH}\right)^{\beta_1 - 1} = \beta_1 B_2\left(\frac{x_h}{yH}\right)^{\beta_2 - 1} + \frac{1}{\delta_x} \tag{60}$$

$$\beta_2 B_2\left(\frac{x_m}{yH}\right)^{\beta_2 - 1} + \frac{1}{\delta_x} = \beta_1 D_1\left(\frac{x_m}{yH}\right)^{\beta_1 - 1} + \beta_2 D_2\left(\frac{x_m}{yH}\right)^{\beta_2 - 1} \tag{61}$$

$$\beta_1 D_1\left(\frac{x_r}{yH}\right)^{\beta_1 - 1} + \beta_2 D_2\left(\frac{x_r}{yH}\right)^{\beta_2 - 1} = \beta_2 B_2\left(\frac{x_r}{yH}\right)^{\beta_2 - 1} + \frac{1}{\delta_x} \tag{62}$$

$$\beta_1 D_1\left(\frac{x_s}{yH}\right)^{\beta_1 - 1} + \beta_2 D_2\left(\frac{x_s}{yH}\right)^{\beta_2 - 1} = \beta_1 A_1\left(\frac{x_s}{yH}\right)^{\beta_1 - 1} \tag{63}$$

Equations (58) – (65) gives a system of non-linear equations that will give us the optimal threshold conditions where the variables to be solved are $x_h, x_r, x_m, x_s, A_1, B_2, D_1$, and D_2.

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