Exploring the Value of the Option of Postponing an Investment Decision for a Coal-Fired Power Plant in Need of Meeting Air Emissions Standards

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Abstract
Inflexible performance or technology standards targeting CO₂ emissions reductions from existing coal power plants would force investors to either retrofit units with CO₂ emissions control equipment or retire them. However, at present neither retrofit nor replacement technologies are ideal. Investments happening today will reduce demand for breakthrough electricity generation technologies that may be just a few years away from becoming an alternative. What if rather than being compelled to make an immediate decision (i.e. to retrofit or replace) power plant owners could pay a fee to have the option of postponing their decision for a few years? If a breakthrough technology becomes commercially available during the waiting period, investors would have the option of using it and this would lower the overall levelized cost of electricity and cumulative emissions over the lifetime of the plant. This project explores the value that investors should be willing to pay for the option of postponing their investment decision.

This report first provides a brief discussion of the compliance options (including retrofitting the existing power plant and replacement by a NGCC plant) for a hypothetical power generator in need of reducing 30% of emissions from its fleet of three coal-fired power plants.

The second section presents a short literature review of the use of real-options valuation and dynamic programming for the valuation of power generation investments.

The third section describes two models used in the project; a Monte-Carlo Simulation model and a Binomial Lattice-Like model, and presents the analysis performed for choosing the parameters and simulating the random variables representing fuel prices and technological change in the Monte-Carlo model. The Monte-Carlo Simulation model is used to calculate the impacts of compliance fees on the investment decisions which include the timing of the investment and the choice of generation technology. Using this model, two metrics, the 1% Upper Threshold Value Fee (UTVF) and 1% Lower Threshold Value Fee (LTVF) are introduced to measure the impact of compliance fees under different assumptions on the arrival rate of
technological change. The Binomial Lattice-Like model is used to derive the value of flexibility by postponing the investment.

The last section presents results for the hypothetical case discussed. Given the assumptions, there are 14 investment strategies available for the investors in terms of the timing of the investment and choice of technology. Two investment matrices reporting the mean and value-at-risk (VaR) at 5% of the Levelized Cost of Electricity (LCOE) for each of the 14 investment strategies are used to compare the two main compliance approaches, namely, to retrofit one of the three coal plants with CCS or to replace two of the coal plants with NGCC plants. Though the NGCC strategy has a lower expected LCOE, its VaR at 5% of LCOE is higher than the Retrofit (strategy). Thus, the NGCC strategy is better on average, but it can be very expensive when natural gas prices are high.

The value of having the option to invest is affected by uncertainties on fuel prices and technologies. Looking at each source of uncertainty separately and in combination provides insights about the value that investors would be willing to pay to delay investment. For the base-case assumptions of the lattice-like model applied to the hypothetical investor, it is found that the value of postponing investment (i.e. the value of investment flexibility) under 1) technological uncertainty, 2) fuel price uncertainty, 3) and combined technological and fuel price uncertainties is $2.14/MWh, $6.28/MWh, and $7.10MWh respectively.
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1. Introduction

Increasing concentrations of greenhouse gases in the atmosphere has led to climate change\(^1\) that threatens human health and welfare for current and future generations\(^2\). The electricity sector accounted for 32% of U.S. total greenhouse gas emissions in 2012\(^3\) according to United States Environmental Protection Agency (EPA). Federal and state authorities are setting and implementing emissions standards for existing coal power plants\(^4\).

To comply with proposed and future environmental regulations, owners of coal power plants could be forced to develop a plan to reduce carbon emissions. Retrofitting existing plants and building new Natural Gas Combined Cycle (NGCC) plants could be considered as solutions for investors. However, the implementation of both solutions is costly, and the investment is irreversible. Additionally, investors face uncertainties including future fuel price, technological progress, and environmental policy that make the challenge of choosing a solution even harder\(^5\).

One major consideration for analyzing potential power plant investments is fuel cost. The life span of a plant can be as long as 30 years, thus the cumulative fuel cost during the life span is considerable. Total fuel cost is determined by fuel consumption and prices. While consumption is predictable, future fuel prices are determined by commodity markets and are for the most part (see Appendix 1), unknown at the time of the investment decision.

Path-breaking electricity generation technologies may become available in the near future\(^6\), which would reduce investment and/or operating costs and hence imply that postponing investment decisions could be cost effective. Since regulators in charge of controlling CO\(_2\) emissions would allow postponing compliance only if this does not affect environmental protection goals, the option to postpone would be limited for a short number of years, and would require the payment of a fee.

In this master’s project, I explore the effects that a fee payment to delay investment would have on investor’s choices. The exploration is carried out with two models that analyze the hypothetical case of a utility owning a small portfolio of 3 coal-fired power plants in need to reduce CO\(_2\) emissions by 30%. The first model estimates the optimal investment strategy by setting up a dynamic program solved through a Monte-Carlo simulation that incorporates uncertainty on fuel prices and timing of technological improvements. The second model narrows the uncertainty on fuel prices and technological advancements and quantifies the

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\(^1\) Intergovernmental Panel on Climate Change (IPCC), Climate Change 2014 Synthesis Report
\(^2\) United States Environmental Protection Agency (EPA), [http://www3.epa.gov/climatechange/endangerment/](http://www3.epa.gov/climatechange/endangerment/)
\(^3\) United States Environmental Protection Agency (EPA), Source of Greenhouse Gas Emissions, [http://www.epa.gov/climatechange/ghgemissions/sources/electricity.html](http://www.epa.gov/climatechange/ghgemissions/sources/electricity.html)
\(^4\) United States Environmental Protection Agency (EPA), Clean Power Plan Proposed Rule, [http://www2.epa.gov/carbon-pollution-standards/clean-power-plan-proposed-rule](http://www2.epa.gov/carbon-pollution-standards/clean-power-plan-proposed-rule)
\(^6\) Ibid
contribution of each uncertainty to the value of postponing the investment decision. This exploration is useful to shedding the light on the question of how much would real investor pay for the option to delay investment given the current market and regulatory conditions.
2. Literature Review

Dixit and Pindyck (1994) have shown how real options related to the flexibility of investment timing have great value in the face of uncertainties on market conditions, policy environment, and technological change. The option to delay investments – or the option to wait - examined in this project is a real option very valuable to investors (Dixit and Pindyck 1994) and as such can be valued using the methods for real options valuation.

The real options approach has been used for valuing power generation investments, and to examine the impact of different sources of uncertainty, in a number of studies. For example, Yang, Blyth, Bradley, Bunn, Clarke, and Wilson (2008) examined the impacts of environmental policy risks on power generation investments, concluding that policy risk is significant when a time gap between the investment decision and the environmental policy event is small. Fuss and Szolgayova (2009) found that uncertainty on technological advancement of renewable energy technologies would cause investment delays. Takashima and Oda (2012) evaluated market and policy uncertainties on the timing of power generation investments and confirmed that high carbon taxes create strong incentives to invest in low carbon emission power generation.

The optimal timing of technology adoption under uncertainty on technological progress has also been the focus of several studies. Farzin, Huisman, and Kort (1998) studied the optimal timing of technological adoption using a dynamic programming approach, and found that uncertainty of technological change (including the arrival rate of new technology and extent of efficiency improvements) increased the value of the option to wait and hence postponed investments. Doraszelski (2004) modeled the optimal timing of technological adoption by introducing innovation and improvements. The author concluded that the adoption time lags the technology innovation due to the need for engineering refinement (or improvement), and that both innovation and improvement of such innovation are likely to defer the investment decisions by a firm. On the other hand, Murto (2007) assumed the arrival rate of technological change follows Poison process, and different from Farzin, Huisman, Kort (1998),

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7 Ibid
9 Yang, M., Blyth, W., Bradley, R., Bunn, D., Clarke, C., Wilson, T., 2008, Evaluating the Power Investment Options with Uncertainty in Climate Policy, Energy Economics
11 Takashima, R., Oda, J., 2012, Effect of power generation mix and carbon emission tax on investment timing, handbook of CO2 in power system
14 Murto, P., Timing of investment under technological and revenue-related uncertainties, Journal of Economic and Dynamics and Control 31
and Dorazelshi (2004) considered market condition uncertainties in the decision making process.

Dynamic programming and contingent claims are two methods used to value real options. Dynamic programming is an optimization tool that breaks a complex problem into a sequence of decisions consisting of two components, immediate decision and remaining decisions. In a finite time horizon, the optimization process can be solved backwards from the final period (or stage) to the initial stage. Once the decision at each stage is derived, an overall solution to the complex problem can be determined by the sequence of decisions. The solution of a dynamic program can be estimated using the Bellman equation or through a Monte Carlo simulation. Takshima, Oda (2012), and Murto (2007) solved a dynamic program to identify optimal investment strategies by solving the Bellman Equation (partial differential equations). In contrast Fuss, Szolgayova (2009), Yang, Blyth, Bradley, Bunn, Clarke, and Wilson (2008) solved the dynamic program through Monte Carlo simulation. In this project I set up a dynamic program and solve it through Monte Carlo simulation as described in the next section.

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15 Insley, M.C., Wirjanto, T.S., 2008, Contrasting two approaches in real options valuation: contingent claims versus dynamic programming

3. Method

In order to explore the value to investors of having the option to delay compliance decisions, I set up the hypothetical example of one power producer that owns 3 coal-fired power plants and build two different models to identify the investment strategy that minimizes capital and operational costs over the life-time of the 3 plants. The investment decision is evaluated under technological and fuel price uncertainties and found using a dynamic programming approach.

I assume that a company with a portfolio of 3 subcritical coal-fired power plants is required to reduce its CO2 emissions by 30%. One option to achieve this carbon emission reduction target is to retrofit one of the three coal-fired power plants with Carbon Capture and Sequestration (CCS). The alternative is to replace two of the three coal-fired power plants with NGCCs. A third alternative is to postpone the investment for up to 3 years by paying a fee – hereafter called the compliance fee. During the 3 years that the investment could be postponed there could be a technological breakthrough.

With three time periods and three alternative compliance options, the decision of whether to invest or wait at year 0 becomes a complex decision consisting of 4 stages of sub-decisions across different years that can be represented as a dynamic program. The cost of waiting to invest must be compared to the cost of the alternative strategies at each decision making stage. However, the cost of waiting at year t depends on the optimal strategy at year t+1. Without knowing which the optimal strategy at year t+1 is, the optimal strategy in year t cannot be determined. Thus, using backward induction is appropriate. In this case the cost of the optimal option in year 3 is calculated first, and used to then move backward to year 0. Once a sequence of sub-decisions are made, the optimal investment strategy is identified.

Solving this dynamic program allows exploring the effect of different values of the required compliance fee on the timing and technology chosen. Because the characterization of the uncertainty on fuel prices and technological advancement has an enormous impact on the decision we set up two models described below. The first model uses a Monte-Carlo approach to solve the dynamic program. This model is used to estimate the lower and upper bounds of the compliance fee. A second model has different representation of the uncertainty that allows separating the effects of different values of the fee from the effects of technological advancement or fuel prices.

3.1 Monte-Carlo Simulation Model

The Monte-Carlo model is used to calculate the impacts of option fee on the investment decision which includes the timing of the investment and choice of generation technology. The investment decision in the context depends on the cost of power generation which is determined by fuel price, environmental policy, technological progress, investment capital cost, and operation & maintenance costs. Unlike the traditional Discount Cash Flow (DCF) method that assumes point estimates for the parameters (e.g. fuel prices), the Monte-Carlo method considers their uncertainty as represented by a probability distribution. This model generates
thousands of simulations for each of the random variables affecting the Levelized Cost of Electricity (LCOE) used as a criteria for the investment decision. LCOE is a standard metric of electricity cost that is not affected by the type or size of plant and hence allows a fair comparison of fossil-fired, baseload alternatives. In this context, the LCOE is a function of random variables including fuel prices, compliance fees, and technological change, and represents the annualized capital and operating and maintenance costs per unit of electricity generated (given in $/MWh).

The two functions below:

\[ LCOE_{\text{Retro}} = f(P_{\text{coal}}, \text{Compliance fees}, \text{Technology Change}) \]

\[ LCOE_{\text{NG}} = f(P_{\text{coal}}, \text{PriceRatio}, \text{Compliance fees}, \text{Technology Change}) \]

represent cost functions for the retrofit alternative (i.e. retrofitting one coal plant and leaving 2 coal-fired power plant without CCS) and the NGCC alternative (i.e. replacing 2 coal plants with 2 new NGCC plants and leaving 1 coal-fired power plant as is) respectively. The variable \textit{PriceRatio} in the function of LCOE\textsubscript{NG} above is the price ratio of natural gas to coal (included to avoid having to include 2 different values for coal and gas prices).

To simplify the comparison of cost among scenarios the following assumptions are made:

1. All investments are built overnight
2. The full capital costs is paid for in the investment period
3. The investments are compared on the basis of capital costs and 30 years’ worth of operating expenses from power generation. For example, when investing in NGCC immediately (i.e. at year 0), the lifespan of the new power plants is assumed to be 30 years. But, if the investment in NGCC occurs at year 3, the operating expenses and the capital costs of the new NGCCs are only paid for 27 years while the costs of operating the original replaced coals plant are paid during the first 3 years. As a result, the total cost of electricity for each scenario refers to the expected net present value of costs over a 30-year period.

The decision tree presented in Figure 1 illustrates the different alternatives between year 0 and year 3. Three investment alternatives are available between year 0 and 2 including 1) retrofitting a coal-fired plant (called “retrofit strategy/alternative”), 2) building 2 new NGCC plants (called (“NGCC strategy/alternative”), and 3) waiting. However, at year 3, waiting is no longer possible and the only alternatives are to 1) retrofit the coal-fired plant and 2) to build 2 new NGCCs.
The optimal investment strategy is the one with the lowest Levelized Cost of Electricity (LCOE). However as a function of random variables, LCOE is in itself a random variable and hence it is not possible to say which investment strategy has the lowest LCOE. Rather, we assume a risk-neutral investor and assume the optimal strategy is the one with the lowest expected value of LCOE. The expected value is estimated as the average of thousands of realizations of LCOE where the random variables for fuel prices and technological advancements are simulated using a Monte-Carlo approach.

The first step to solve this investment problem is to find the strategy with the lowest expected LCOE (explained in section 4.2) between Retrofit and NGCC alternatives, $\text{Min} (\text{LCOE}_{NG,t}, \text{LCOE}_{Re,t})$. In addition, the investor needs to understand whether it is worth to pay K dollars as a compliance fee to postpone the investment for a year. The next step is to compare the expected value of the cost of waiting $\text{LCOE}_{\text{wait},t}$ with the minimum of the expected cost of investment $\text{Min}(\text{LCOE}_{NG,t}, \text{LCOE}_{Re,t})$. In order to derive the cost of waiting the method of dynamic programming is applied. This method calculates backward starting from the last period.

Where,

$LCOE_{NG,t}$: the average LCOE of NGCC strategy during power plant lifetime when investment occurs in year $t$

$LCOE_{Re,t}$: the average LCOE of Retrofit strategy during lifetime when investment occurs in year $t$

$LCOE_{\text{wait},t}$: the average LCOE during power plant lifetime when investor choose to wait in year $t$

$$LCOE_{NG,t} = \frac{2 * (\sum_{T=t+1}^{T} \frac{C_{NG,\tau}}{(1 + r)^{T-\tau}} + \sum_{a=0}^{t} \frac{C_{\text{Coal},a} + K}{(1 + r)^a}) + \sum_{a=0}^{T} \frac{C_{\text{Coal},a}}{(1 + r)^a}}{2 * (P_{NG} * (T - t) + P_{\text{coal}} * t) + P_{\text{coal}} * T}$$
\[
LCOE_{Re,t} = \frac{\sum_{t=1}^{T} \frac{C_{Re,t}}{(1+r)^{t-t}} + \sum_{a=0}^{t} \frac{C_{Coal,a} + K}{(1+r)^a} + 2 \sum_{a=0}^{T} \frac{C_{Coal,a}}{(1+r)^a}}{P_{Re} * (T-t) + P_{coal} * t + 2 * P_{coal} * T}
\]

Where, \( C_{NG,t} \) is the total cost of NGCC incurred in year \( t \)

\( C_{Re,t} \) is the total cost of Retrofit plant incurred in year \( t \)

\( C_{coal,t} \) is the total cost of coal – fired power plant incurred in year \( t \)

\( P_{NG} \) is the net power output of the NGCC plant

\( P_{Re} \) is the net power output of the Retrofit plant

\( P_{coal} \) is the net power output of the Coal – fired plant

\( K \) is the annual alternative compliance payment for delaying investment

\[ 0 \leq t \leq 3, \quad 0 \leq a \leq t, \quad t < \tau \leq T \ (T = 30) \]

At year 3, the investor has to choose the lower cost technology between Retrofit and NGCC, 
\( (LCOE_{NG,3}, LCOE_{Re,3}) \). The next step is to find cost of waiting at \( t=2 \),

\[ LCOE_{wait,2} = \text{Min}(LCOE_{NG,2}, LCOE_{Re,2}) \]

Invest if \( \text{Min}(LCOE_{NG,2}, LCOE_{Re,2}) < LCOE_{wait,2} \)

Wait, if \( \text{Min}(LCOE_{NG,2}, LCOE_{Re,2}) \geq LCOE_{wait,2} \)

Similarly, we can calculate cost of waiting at year 1 and 0.

\[ LCOE_{wait,t} = (LCOE_{NG,t}, LCOE_{Re,t}, LCOE_{wait,t+1}) \text{ where } t = 0, 1 \]

3.2 Binomial Lattice-like Model

Similar to the method described in section 3.1, a decision tree is constructed to represent the investment alternatives and to calculate the value of flexibility derived from the alternative of paying a compliance fee.

The problem analyzed with this model is the same as in the previous one: the investor can either retrofit one of the three coal-fired power plants or to replace two of them with NGCC plants, or can postpone the investment for up to 3 years by paying the compliance fee. However, the uncertainty on fuel prices and technological advancement is characterized differently. Rather than assuming a continuous stochastic process for fuel prices and simulating them accordingly, this model uses the Energy Information Admiration (EIA) projections. Also, instead of simulating the number of technological advancements within 3 years as a poison process, it assumes each year has the same chances of seeing one technological advance. So
while under the first representation the number of technological advancements can be any non-negative value, in the second model, the number of advancements can be at most 3 (i.e. the number of years, assuming there is one advance each year). Finally, another difference between both models is that while the first uses the joint random realizations of fuel prices and technological change to generate each of the thousands of paths analyzed to estimate the expected LCOE, the second model represents each source of uncertainty separately.

Due to the complexity of the decision tree diagram, a simplified two-period decision tree is displayed in Figure 2. In the first period, the investor has 3 alternative choices including NGCC, Retrofit, and Waiting. If the investor chooses to Wait (i.e. to postpone the investment decision), the decision tree is divided into 2 branches based on the status of the technological change, and then there are 3 branches for different fuel price projections. If the investor chooses NGCC or Retrofit, the investment decision tree terminates.

At time 0, the investor has to choose a strategy among NGCC (node H), Retrofit (node I), and Waiting (node J). The investor can choose NGCC or Retrofit for immediate investment if the strategy is more cost-effective than waiting. If the investor chooses waiting (node J), the decision would be postponed to the next year with an advantage of gaining more information for decision making. There are two layers of uncertainties in the valuation. First uncertainty is the technological change. Given the investor chooses to wait at time 0, we assume that one technological breakthrough in year 1 has a probability p of success which would lead to a heat rate improvement of D1% and D2% for NGCC and retrofitted coal plant respectively. On the other hand, there is a probability of 1-p that there would be no change in the heat rate (i.e. there would be no technological advancement). The second uncertainty is regarding the path that fuel prices will take. At year 1, fuel prices have 1/3 chance of following the trajectory of high prices predicted by EIA under its high prices scenarios, another 1/3 chance of following the EIA’s reference trajectory, and a 1/3 chance of following the low price trajectory. At year 1, the investor selects NGCC (node B), or Retrofit (node A) given that the technological breakthrough succeed and fuel prices follow a high trajectory. As displayed in the graph, the cost of investment depends on the status of technology and fuel price path. The combinations of two uncertainties create many different scenarios.

Same as with the Monte Carlo model described above, backward calculation is used to derive the cost of waiting at each period for the comparison of costs. This method starts the calculation from the last period to time 0. In this illustrated 2-period diagram, we first calculate all possible cost outcomes for NGCC and Retrofit at year 1 and derive the cost of waiting (node J). For example, the cost at node C is the lower cost of node A and B. Next step is to derive the cost at node F, which is weighted average cost of node C, D, and E. Finally, the cost of waiting (Node J) is the weighted average cost of node F and G. The value of flexibility is the difference between cost of waiting and minimum cost of NGCC (node I) and Retrofit (node H).
Similarly, we expand the decision tree to 4 periods (year 0, 1, 2, and 3). We start the cost of each strategy from year 3 and derived backward to calculate the cost of waiting and value of flexibility.
3.3 Parameters Modeling
The Monte-Carlo model requires simulating fuel prices ratio, and technological change. Then, these simulated data are used to derive results. On the other hand, the binomial lattice-like model does not require simulations but does require the estimation of the probabilities for each possible outcome at each node.

In the Monte Carlo model, the random variables fuel cost, and heat rate (resulting from technological renovation) need to be simulated. The following sections describe how their uncertainty is characterized.

3.3.1 Monte Carlo Method
Fuel Price
A key factor in the power plant investment evaluation is fuel cost, which is derived from the fuel price and quantity of the fuel consumption during the lifetime of the power plants. However, fuel prices are a time-varying random variable denoted as:

\[ P_{\text{Coal},t} \quad \text{coal price at year } t \]
\[ P_{\text{NG},t} \quad \text{natural gas price at year } t \]

We assume that \( P_{\text{Coal},t}, P_{\text{NG},t} \) follow a Geometric Brownian Motion (GBM), which means that

\[
dP_t = \mu P_t \, dt + \sigma P_t \, dB(t) \\
\frac{d \ln(P_t)}{} = \left( \mu - \frac{1}{2} \sigma^2 \right) dt + \sigma dB(t)
\]

And hence, future fuel prices can be simulated with GBM as:

\[ P_t = P_0 e^{(\mu - \frac{1}{2} \sigma^2) t + \sigma B(t)} \]

Where \( \mu \) is the mean of growth rate of price, and \( \sigma \) is the volatility of percentage change.

According to historical data, there is a correlation\(^{17}\) (see Appendix 2) between \( P_{\text{Coal},t}, P_{\text{NG},t} \), so instead of simulating both coal and natural gas prices, our model generates coal prices and price ratios of natural gas to coal, denoted by \( \bar{R}_t \). Once we take random draws of the two variables \( P_{\text{Coal},t} \) and \( R_t \), the natural gas price can be derived by the product of coal price and ratio.

\[
P_{\text{coal},t} = P_{\text{coal},0} \times e^{(\mu - \frac{1}{2} \sigma^2) t + \sigma B(t)} \\
\bar{P}_{\text{NG},t} = P_{\text{coal},t} \times \bar{R}_t
\]

\[ \mu = E \left[ \ln \left( \frac{P_{\text{Coal},t+1}}{P_{\text{Coal},t}} \right) \right], \quad t \geq 0 \]

\[ \sigma = \sqrt{ \frac{1}{N} \sum_{t=1}^{N} \left[ \ln \left( \frac{P_{\text{Coal},t+1}}{P_{\text{Coal},t}} \right) - \mu \right]^2 } \]

**Ratio**

The histogram and cumulative distribution function (CDF) plot of ratio change in percentage from January 2002 to July 2012 are shown in Figure 3. According to the graphs, it appears that the ratio percentage change follows a normal distribution. Shapiro-Wilk normality test (P value = 0.4554 > 0.05) also shows that the percentage ratio change is normally distributed (see Appendix 3).

**Figure 3**

The Ornstein and Uhlenbeck (O-U) model is used to simulate the ratio of natural gas to coal prices. The advantage of the Ornstein and Uhlenbeck model over the GBM model is that the former is a mean-reverting process which results in simulated ratios that tend to move toward a long term mean.

As discussed above, the percent changes of fuel price ratio follow a normal distribution. In other words, the price ratio follows a lognormal distribution. Thus, the exponential Ornstein and Uhlenbeck model must be used rather than the standard Ornstein and Uhlenbeck model. Another advantage of this modified model is to avoid the negative simulated price ratio. The
exponential Ornstein and Uhlenbeck model can be applied in two steps. The first step is to calculate the logarithm of the ratio for all the historical data. The next step is to use this logarithm in the Ornstein and Uhlenbeck model to simulate price ratios.

The Ornstein and Uhlenbeck equation is the following,

\[ dx_t = \theta (\mu - x_t) dt + \sigma dw_t \]

Where \( x_t \) is the percentage change of price ratio at time \( t \); \( \mu \) is the long-term mean of the percentage change of price ratio; \( \theta \) is the rate of mean reversion; \( \sigma \) is the volatility; \( w_t \) indicates the wiener process.

Techniques for estimating the parameters of the O-U include the least square regression and maximum likelihood\(^\text{18}\). In this project, the least square regression method is used to derive the parameters, \( \mu \), \( \theta \), and \( \sigma \).

\[ X_t = X_{t-1} e^{-\theta \Delta t} + \mu \left( 1 - e^{-\theta \Delta t} \right) + \sigma \sqrt{\frac{1 - e^{-2\theta \Delta t}}{2\theta}} dW_t \]

We build a linear regression with dependent variable \( X_t \) and independent variable \( X_{t-1} \),

\[ X_t = a + b X_{t-1} + \epsilon_t \]

and then derive the O-U parameters by calculating:

\[ \theta = \ln b / \Delta t \]
\[ \mu = a / (1 - b) \]
\[ \sigma = sd(\epsilon) \sqrt{\frac{-2 \ln b}{\Delta t(1 - b^2)}} \]

**Technological Change**

Path-breaking technologies could result in economic benefits for investors. If a disruptive technology is under development and is likely to become commercially available soon, then waiting to invest could lead to great cost reductions. For the simplicity of the model, we assume any upgrade of new technology would reduce the heat rate of retrofitted coal plant and NGCC by \( D_1 \% \) and \( D_2 \% \) respectively, and model the arrival of improvements as a Poisson jump process.

The model assumes the technological progress \( X(t) \) follows a Poisson process, and \( dx \) represents the number of technological changes during a given time interval. Hence \( dx \) follows a Poisson

\(^{18}\) Smith, W., Feb 2010. On the Simulation and Estimation of the Mean-Reverting Ornstein-Uhlenbeck Process
distribution with parameter $\lambda$ (the expect value of number of technological changes). Given the assumption that the investor is allowed to postpone investment for up to 3 years, only the break-through technologies that are successful within 3 years are valuable, and any new technologies that arrive later than 3 years are worth nothing. Thus, we simulate the number of the technological changes within the first three years only.

Murto (2007) simulated the technological change using a Poisson process to evaluate cost of power plant investment. In our model, the Poisson process is used to simulate the power plant heat rate resulting from technological change:

$$HR_t = HR_0 * D^N, \quad D \in [0, 1)$$

Where $HR_t$ is heat rate at year $t$, $HR_0$ is the current heat rate. $(1 - D)$ is percent-based reduction of heat rate due to a technology advancement. $N$ follows Poisson process with arrival rate of innovation $\lambda$.

$$E[HR_t] = HR_0 * e^{-\lambda(1-D)}$$

In the Monte-Carlo model, we randomly simulate the number of technological upgrades by Poisson distribution during year 1, year 2, and year 3 respectively.

### 3.3.2 Binomial Lattice-like Method

The fuel price projections (for both coal and gas) for years 2015 to 2044 that are used in the binomial lattice-like model are provided by the U.S. Energy Information Administration (EIA) in the Annual Energy Outlook report of 2014. The forecast by EIA includes three scenarios, high, reference, and low price levels. In the model used here, fuel prices are assumed to jump from and to these three different paths (high, low, and reference) at each time period with 1/3 of probability. Also, it is assumed that during years 4 to 30, the prices trajectories are the same as the fuel price scenario at year 3. The arrival rate of technological innovation is modeled by assuming at each time period there is a probability $p$ of a technological change calibrated to achieve consistency with the expected value of arrivals over the 3 year-long time period.

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19 Murto, P., Timing of investment under technological and revenue-related uncertainties, Journal of Economic and Dynamics and Control 31
4. Parameters calibration

The parameter values in Table 1 are taken from the IECM model developed by Carnegie Mellon University and NETL.\(^2\)

\(\text{Table 1}\)

<table>
<thead>
<tr>
<th>Parameters for Power Plants</th>
<th>Coal</th>
<th>Retrofit</th>
<th>NGCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nameplate Capacity (MW)</td>
<td>500</td>
<td>500</td>
<td>540.9</td>
</tr>
<tr>
<td>Net Electricity Output (MW)</td>
<td>481.9</td>
<td>409.4</td>
<td>530.1</td>
</tr>
<tr>
<td>Capacity Factor</td>
<td>75%</td>
<td>75%</td>
<td>75%</td>
</tr>
<tr>
<td>Heat Rate (Btu/kWh)</td>
<td>9017</td>
<td>13100</td>
<td>6780</td>
</tr>
<tr>
<td>Heating value (Btu/lb)</td>
<td>13260</td>
<td>13260</td>
<td>22480</td>
</tr>
<tr>
<td>Energy Efficiency</td>
<td>37.84%</td>
<td>26.04%</td>
<td>50.33%</td>
</tr>
<tr>
<td>Fuel Consumption (ton/hr)</td>
<td>163.9</td>
<td>202.3</td>
<td>79.92</td>
</tr>
<tr>
<td>Emission Rate – CO2 (ton/hr)</td>
<td>443.2</td>
<td>55.27</td>
<td>211.4</td>
</tr>
<tr>
<td>Total O&amp;M ($M)</td>
<td>20.58</td>
<td>46.71</td>
<td>9.127</td>
</tr>
<tr>
<td>Investment – Annualized ($M)</td>
<td>N/A</td>
<td>105</td>
<td>92.98</td>
</tr>
</tbody>
</table>

Discounting Factor

The simulated fuel prices, capital costs, and operation and maintenance costs are expressed as 2012 dollar value. The discount rate for capital of cost using in the IECM model is 10.3%.

Fuel Prices

Monte-Carlo Method

Coal prices are simulated using a Geometric Brownian Motion model. Mean and volatility of coal price percentage change are required to generate the coal price paths. The mean and volatility of the coal price percentage change derived from Annual Energy Outlook (AEO) 2014\(^2\) forecasted fuel prices (2011 – 2040) data are 1.23% and 1.49% respectively (see Appendix 4). The natural gas to coal price ratio is simulated by the Ornstein and Uhlenbeck (O-U) model. Similarly, the parameters for the O-U model are calculated from the AEO 2014 forecasted fuel prices.

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The long-term mean $\mu$, mean reversion rate $\theta$, volatility $\sigma$ are 0.8009, 0.0947, 0.2122 respectively.

Figure 4 show the average, 5% and 95% percentile of simulated coal and natural gas prices, along with the 3 scenarios of EIA forecasted fuel prices for the reference, low, and high levels. It appears from the graph the simulated average of coal prices is close to the EIA forecasted reference level. The 5% and 95% percentile of coal prices fall between the low and high scenarios projected by EIA. Though simulated average gas prices do not perfectly match the EIA reference levels, their prices are relative close. The 95% percentile of simulated gas prices fall below the EIA high projection in the long run; and the 5% percentile path almost overlaps with the EIA low projection.

Figure 5 compares the fuel prices for all three types of power plant in terms of per unit electricity (MWh) generated for one realization. The graphs shows that per unit of electricity generated by NGCC are the most expensive in most of time, followed by retrofitted coal-fired power plant as the second. Fuel cost for the original coal-fired power plant is the lowest.
Figure 5

Fuel cost for three plants ($/MWh)

Coalplant
Retrofit
NGCC

Year

Price ($/MWh)

0 5 10 15 20 25 30
15
20
25
30
35
40
45
50
55
60

Figure 6

Ratio

NG/Coal price ratio

Year

0 5 10 15 20 25 30
1
1.5
2
2.5
3

Empirical CDF

X

F(X)

0 0.5 1.0
-0.03 -0.02 -0.01 0 0.01 0.02 0.03
-0.03 -0.02 -0.01 0 0.01 0.02 0.03

Percentage Change of Ratio
Figure 6 shows the simulated natural gas to coal price ratio during a 30-year period. The bottom plot of Figure 6 displays the Cumulative Probability Distribution Function (CDF) of percentage change of Ratio. The red line in the plot is the CDF of a normal distribution which is compared to the CDF of a simulated logarithm ratio (blue). The comparison of the two CDFs suggests that the simulated data loosely follows a normal distribution as originally assumed.

**Binomial Lattice-like Method**
The coal and gas prices for 2015 to 2044 in this model are those projected by the Energy Information Administration (EIA) in 2014. The time frame of the EIA forecasted fuel prices is from 2010 to 2040. Thus, we assume the fuel prices between 2040 and 2044 are the same.

**Technological change**
A new power generation technology developed by NET POWER (an energy company located in Durham, NC, USA) would increase the efficiency of coal-fired power plants from 39% to 49% and the efficiency of the NGCC from 50% to 53% (Patino-Echeverri 2014)\(^{22}\). We take this information as a proxy for the maximum efficiency improvements (i.e. reductions in heat rate) that could occur if there is a technological breakthrough either in NGCC or retrofit technologies for coal. Hence we assume the reduction of heat rate is 20.4% and 5.7% for coal-fired retrofitting plant and NGCC respectively if a technological change occurs.

**Arrival rate of technological change**
In the Monte-Carlo model, the expected arrival rate between technological changes is a model input that can be adjusted (e.g. 3 years or 5 years). In the binomial lattice-like model, the expected time between arrivals of technological change (or time until the first arrival) is assumed to be 5 years.

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5. Results

5.1 Investment Strategies

Table 2

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Year 0</th>
<th>Year 1</th>
<th>Year 2</th>
<th>Year 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Retrofit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Retrofit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Retrofit</td>
<td>Retrofit</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Retrofit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>NGCC</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>NGCC</td>
<td>NGCC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>NGCC</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>NGCC</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Retrofit New</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Retrofit New</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>NGCC New</td>
<td>Retrofit New</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>NGCC New</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>NGCC New</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>NGCC New</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In the two models, 14 investment strategies exist as shown in Table 2. If break-through technologies do not succeed between year 0 and year 3, the investor has 8 strategies with the combinations of technology types and timing of the investment. On the other hand, if technological innovation becomes true, the investor could choose between a new type of retrofit and a new NGCC between year 1 and year 3, which results in another 6 strategies.

5.2 Investment Matrix

In the Monte-Carlo model, we calculate the Mean and Value at Risk (VaR) from each strategy. The mean is the average LCOE incurred for each investment strategy. The Value at Risk (VaR) is a metric commonly used to measure volatility (or dispersion) of the random variable. The combination of these two estimates provide information on the investment cost for each strategy. Given a technological arrival rate of $\lambda = 0.2$ we compare the mean and VaR (at 5%) of LCOE between the NGCC and Retrofit strategies. In addition, the trend of the mean and VaR is analyzed as the value of the compliance fee changes. Mean and VaR at 5% for both NGCC and Retrofit technologies are plotted when the compliance fee takes the values of $0M, $200M, $800M respectively. At all three levels of the compliance fee, Figure 7 shows that the mean of NGCC strategy is slightly lower than the mean of the Retrofit strategy for each of the three years considered. However, Figure 7 illustrates that VaR at 5% of NGCC strategy is higher than Retrofit strategy for all scenarios. The results indicate that the NGCC strategy is risker due to
the possibilities of high natural gas prices. In addition to the choice of technology, the value of the compliance fee affects the timing of investment. Higher compliance fees shift the investment to the beginning of investment time frame. Figure 7 shows that the immediate investment (at year 0) costs the least with an option fee at $800M. In contrast, immediate investment costs (at year 0) the most with an option fee at $0.
Figure 8 and Figure 9 show the distribution of LCOE for the retrofit, NGCC, and waiting alternatives at year 0. Two scenarios under different levels of compliance fees are studied. Figure 8 shows the histogram of LCOE when a $0 fee is charged for postponing investment. Based on the shape of histograms, the LCOE of NGCC appears to be more spread out. In contrast, LCOE of Retrofit appears to be concentrated around the mean. The histogram of LCOE for the Waiting strategy is shifted to the left and thus the LCOE of Waiting on average is lower than the LCOE of the NGCC and Retrofit strategies at year 0. Therefore, Waiting is a rational choice at year 0 when the option fee is low (or none). Figure 9 shows the histogram of LCOE when $800 million option fee is charged for postponing investment. In this plot, the histogram of Waiting moves right to the middle. Thus, the mean of LCOE for waiting seems higher than the mean of LCOE for the NGCC and Retrofit. Waiting is not favorable choice at year 0 when the option fee is high.
5.3 Estimating bounds for the compliance fee

The Monte-Carlo model allows assessing the impact of different compliance fees on the investment decision. In order to evaluate the impact of the compliance fees on the investment decision, we define the 1\% Upper Threshold Value Fee (UTVF) and 1\% Lower Threshold Value Fee (LTVF) as follows:

1\% LTVF: The Lower Threshold Value Fee is the fee at which 1\% or less of the simulations result in investment occurring at the end of year 3. The approach to find 1\% significance level is to use the Monte-Carlo method to simulate 2000 runs and count the number of paths for which investing occurs before the end of year 3. This fee value is adjusted until the number of investments before the end of year 3 is less than or equal to 20.

1\% UTVF: The Upper Threshold Value Fee is the fee at which 1\% or less of the simulations result in investment occurring at the beginning of year 1. To find this value we simulate 2000 runs and count the number investments after year 1. We keep adjusting the compliance fee until the number of investments after year 1 is less than or equal to 20.

We find the LTVF and UTVF under three scenarios: 1) base case (λ =0.2), 2) high technology arrival rate (λ =0.3), and 3) low technology arrival rate (λ =0.1). In the base case, a $115 million/year Lower Threshold Value Fee (LTVF) is required to have investment to occur at the end of year 3 with probability of 1\% or less. In contrast, to make the chance of investment occurring after the beginning of year 1 be 1\% or less, the Upper Threshold Value Fee (UTVF) reaches $1210 Million/year.
Furthermore, the effect of arrival rate of technological change on investment decision is examined by comparing the three scenarios. The results from Table 3 show that UTVF positively correlates with the arrival rate of technological change. For example, the high arrival rate (\(\lambda =0.3\)) has greater UTVF than the other 2 scenarios with lower arrival rates. Immediate investment is economically reasonable only when the cost of waiting (including compliance fees and annualized capital cost) exceeds the potential fuel cost savings resulting from efficiency improvements due to technological change. Hence, the potential for fuel cost savings increases with the likelihood of the technological breakthrough. If the annualized capital cost is unchanged and the potential for fuel cost savings increases, then the compliance fee has to increase to make immediate investment more appealing.

On the other hand the LTVF shows an opposite trend. Table 4 shows that the LTVF negatively correlates to the arrival rate of technological change. The scenario with high arrival rate (\(\lambda =0.3\)) has the lowest LTVF, $105M. This means that 99% of investors would wait to invest to the end of the third year to take advantage of the potential fuel cost savings. If technological change occur sooner (e.g. in year 1 and 2), the investors may invest before year 3 rather than waiting more time for nothing and having to pay the compliance fee. As the odds of technological advancement increases, some investors are more likely to invest sooner unless a lower option fee is makes it worth to keep postponing the investment.

Table 3 also indicates that as expected, the LCOE negatively correlates with the arrival rate of technology change. The expected LCOE decreases as arrival rate of technology change increases.

Furthermore, a higher arrival rate of technological change achieves slightly lower carbon emissions reductions when the investor is charged the UTVF. Table 3 shows that the percentage
of carbon emissions reduction for UTVF decreases with arrival rate of technological change. Even though a 30% carbon emissions reduction can be achieved by both the NGCC and Retrofit strategies, according to the ICEM data, a portfolio of 2 NGCC with 1 coal-fired power plant (866 ton/hour) emits less CO2 than a combination of 2 coal-fired power plant and coal-fired plant with CSS technology (941.67 ton/hour). Table 3 also shows the ratio of NGCC to retrofit in terms of number times to be selected as the optimal strategy in the 2000 simulations. Retrofit is more likely to be the optimal solution as the technological arrival rate (or option fee) increase. The decreasing reduction rate of CO2 emission results from the shift from NGGC to retrofitting.

In contrast, LTVF shows a different trend. A higher arrival rate of technological change mitigates more carbon emissions when the compliance fee is equal to the LTVF. Table 3 shows that the percentage of carbon emission reduction for LTVF increases with the arrival rate of technological change. Lower fuel consumption due to technological change leads to more CO2 mitigation (higher CO2 reduction rate). Also, the adoption of NGCC or retrofit as optimal strategies, is also affected by the rate of technological change.

5.4 Value of postponing the investment decision
The value of flexibility in the investment process comes from 2 uncertainties: fuel prices and technology. The lattice-like model is used to study 3 cases to identify the contribution of each uncertainty to the value of flexibility.

- Case 1: the value of flexibility under technological uncertainty
- Case 2: the value of flexibility under fuel prices uncertainty
- Case 3: the value of flexibility under both technological and fuel prices uncertainties
The lattice-like model finds that the value of flexibility for the 3 cases ranges from $2.14/MWh to $7.10/MWh and the contribution from each source of uncertainty to the value of flexibility is different.

In case 1, the Net Present Value (NPV) when the option to postponing investments does not exist is $57.87/MWh and the optimal value when the real option to wait exists (ROA) is $55.73/MWh. The value of flexibility is the difference between NPV and ROA values, $2.14/MWh. In case 2, the NPV is $57.87/MWh, and the optimal value when the option to wait exists is $51.59/MWh. The value of flexibility is the difference between NPV and ROA values, $6.28/MWh. In case 3, the NPV when the option to wait does not exist is $57.87/MWh, and optimal value accounting for the value of the real option to wait (ROA) is $50.77/MWh. The value of flexibility is the difference between NPV and ROA values, $7.10/MWh.

5.5 Sensitivity Analysis
Since the results discussed before are dependent on many assumptions, sensitivity analysis are performed to explore the relationship between inputs and outputs. Three sensitivity analysis are constructed in response to the changes of probability of technological change success, heat rate, and cost of retrofitting coal-fired power plant.
Probability of technological change success

In previous section, the arrival rate of technological change is assumed to happen once every 5 years. Equivalently, the probability of Net Power’s technology success is 20%. To better understand the relationship between the value of flexibility and the probability of technological breakthrough, we explore the trend of value of flexibility, under technological uncertainty alone and under both technological and fuel prices uncertainties, in response to the probability ranging from 10% to 30%. Figure 10 shows that the value of flexibility increases as the probability of a breakthrough in technology increases.

![Figure 10](image)

Heat Rate

The heat rate of the retrofit and NGCC plants would decrease if the technological change occurs. It has been assumed that the new heat rates are 94.34% and 79.59% the original heat rates for the NGCC and retrofitted coal plants respectively after the arrival of technological change. To analyze the impact on the value of investment flexibility from different heat rate improvements, we assume scenarios where the heat rate improvement deviates from the expected mean by 20% in both up and down directions. The results from the binomial lattice model show that the value of flexibility increases as the heat rate improvement increases (see Figure 11 below).
Cost of retrofitting a coal-fired power plant

The capital cost of retrofitting is a determining factor for investors to choose the optimal investment strategy. In the binomial lattice model, the cost of retrofitting (on existing coal-fired power plant) is assumed to be 1.5 times as the cost of CCS installation in a new power plant. In other words, a 50% cost premium is incurred for an existing power plant to be retrofitted relative to the installation of a new plant with CCS technology. The sensitivity analysis evaluates the impacts of cost of retrofitting on the value of flexibility. Figure 12 shows that 1) for case 1, the value of flexibility under technological uncertainty only increases as the premium of retrofit cost increases from 50% to 100%; the value of flexibility peaks at a retrofit premium of 100%, decreases from 100% to 200% premium of retrofitting cost, and stays flat when the retrofitting premium is above 200%. 2) for case 2 and 3, the value of flexibility, under fuel cost uncertainty only and combined uncertainties of technological and fuel prices, increases as the premium of retrofitting cost from 50% to 150%; the value of flexibility peaks at a retrofit premium of 150%, decreases from 150% to 300% premium of retrofitting cost, and stays flat when the premium of retrofitting cost is above 300%. The non-linear trend of the value of flexibility is due to the increasing retrofitting cost and changing composition of NGCC and Retrofit. The value of flexibility is determined by the value of option to wait (ROA) which is a weighted value deriving from the 258 optimal scenarios as a result of 258 combinations of different uncertainties and investment timing. Many of these optimal scenarios are Retrofit. The higher cost of retrofit leads to a higher value of flexibility by postponing the investment. However, as the cost of retrofitting increases, Retrofit starts to be replaced by lower-cost NGCC as the optimal scenario at each combination of uncertainty and investment timing. Thus, the marginal effect of the cost of retrofitting on value of flexibility is decreasing until it becomes 0.
5.6 Accounting for CO2 prices

It is possible that in the future, power plants might be penalized for any ton of emissions of greenhouse gases. The CO2 emission cost would raise the total cost. In the previous sections it was assumed that if the portfolio of plants complied with the 30% emissions reductions required, then no extra cost would be incurred for the remaining CO2 emissions. This section estimates the value of investment flexibility after incorporating the CO2 emission cost to total cost estimates. Four scenarios for CO2 prices are considered: 1) $0/Ton, 2) $5/Ton, 3) $10/Ton, and 4) $20/Ton. The sensitivity analysis is similar to the one in the last section except that this analysis includes two variables at the time: 1) The probability of technological change and CO2 price, 2) cost of retrofitting and CO2 price.

The probability of technological change and CO2 price

Figure 13 shows 1) under technological uncertainty, the value of flexibility follows a similar trend for CO2 prices at 0, 5, 10, 20 $/ton. At each level of CO2 price, the value of flexibility increases with the probability of technological breakthrough. Given the same probability of technological breakthrough, the value of flexibility increases with the CO2 price. 2) Under the combined technological and fuel price uncertainties, the value of flexibility follows a similar trend.
**Cost of retrofitting and CO2 price**

The value of flexibility after accounting for CO2 cost also shows a non-linear trend in response to the cost of retrofitting. Figure 14 shows 1) under technological uncertainty, the value of flexibility follows a similar trend for CO2 price at 0, 5, 10, 20 $/ton. The value of flexibility initially increases, and then declines, and finally stabilizes as the retrofitting cost increases at all level of CO2 prices. The value of flexibility peaks at 100% premium of retrofitting cost (more than CCS technology in new power plant) for CO2 price at 0, 5, 10 $/ton. However, for CO2 price at 20 $/ton, the value of flexibility peaks at 150% premium of retrofitting cost. Given the same level of premium of retrofitting cost, the value of flexibility increases as the CO2 prices. 2) Under the technological and fuel price uncertainties, the value of flexibility also has a similar trend. The value of flexibility peaks at a retrofit premium of 150% and stabilizes at a 300% retrofit premium for all level of CO2 prices.
6. Conclusion

This master’s project explores the impact that a compliance fee would have on the compliance decision of a power plant operator required to reduce 30% of CO2 emissions from a portfolio of 3 coal plants. Two different models are used to 1) examine the effect of the compliance fee on investment decisions under fuel prices and technological change uncertainties, 2) estimate the lower and upper bounds of a compliance fee, and 3) to estimate the value of waiting to invest by paying a fee.

Although the analysis presented offers valuable information on the effects of a compliance fee on investment, it has a number of limitations. First the models only allow the investor to postpone investment for up to 3 years and only consider two investment strategies (either NGCC or Retrofit). These assumptions are not realistic, so future work should increase the number of investment options, and should extend the investment timing beyond 3 years as well. A better representation of the uncertainty on future CO2 costs should also be included.
Appendix

1. Future fuel prices
While there are some long-term supply contracts between natural gas producers or distributors and power generators, the majority of utilities continue to buy on spot or short-term arrangements. Also, long-term fuel contracts tend to be signed for significantly shorter times than the 30+ years assumed as the economic life of a power plant.

2. Correlation between coal and natural gas
Patiño-Echeverri D., Pratson L., and Haerer D. (2013) explore the relationship between competitiveness of natural gas fired power plant to coal-fired power plant and natural-gas-to-coal-price ratio (NG2CP). They indicate the average of NG2CP is greater than 3.5 between 2002 and 2012, but it is predicted to be less than 2.8 till 2035.

3. Shapiro-Wilk normality test
Shapiro-Wilk test is a test of normality. The null hypothesis of the Shapiro-Wilk test is that the tested data set is normally distributed. If the P value is greater than alpha level (usually 5% or 1%), then the hypothesis that the data set is normally distributed cannot be rejected. In contrast, if the P value is smaller than alpha level, then the tested data does not follow a normal distribution.

4. Fuel prices and price ratio
The volatility of coal price percentage change derived by monthly data from January 2002 to July 2012 is more volatile (6.29%). Thus, the simulated coal price is higher than high price scenario projected by EIA. Instead, Annual Energy Outlook (AEO) 201423 forecasted fuel prices (2011 – 2040) data is used to calculate the parameters including mean and volatility. Simulation with this AEO 2014 data gets more stable results (low volatility). The mean and volatility of the coal price percentage change are 1.23% and 1.49% respectively.

The simulated trajectory of natural gas price (derived by price ratio and coal price) based on the monthly price ratio from 2007 to 2013 is lower than the AEO 201424 forecasted reference trajectory. The low trajectory of ratio is possibly caused by the low natural price between 2009 and 2013 and higher natural gas prices in the future forecasted by EIA. Instead, annual natural gas price data from 2011 to 2040 forecasted by EIA (Annual Energy Outlook 2014) is used to estimate O-U model parameters. The simulated ratio falls into the band between AEO high and low forecasted trajectories. We get $\mu = 0.8009$, $\theta = 0.0947$, $\sigma = 0.2122$ based on AEO 2014 data between 2011 and 2040.

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