Carbon Capture and Storage Investment and Management in an Environment of Technological and Price Uncertainties

Joachim Geske, Johannes Herold

April 12, 2010

Abstract

We have conducted a dynamic stochastic investment analysis of carbon capture, transport and storage (CCTS) retrofitting in an environment of CO₂ price and technology uncertainty. It includes the option to invest in, and to use or shut down, the CCTS unit. While modeling certificate price uncertainties is standard, stochastic processes including diminishing increments are implemented for thermal efficiency and investment cost improvements. Following a careful quantification of parameters, the optimal investment strategies are derived and used in Monte Carlo simulations to produce results on aggregate investment decision and resulting profits. All simulation data were presented graphically from a low optimal strategy level to an aggregated expected value level. Our results show, that the main determinate for the application of CCTS is the certificate price. However, realized technology learning results in an earlier application of the technology by electricity producers and also acts as an insurance against the low carbon prices which prohibit profitable CCTS operation.

JEL classification: G30; O30; Q40

Keywords: Carbon capture and storage; real options; technology learning
1 Introduction

The political willingness to avoid the global external effects of CO$_2$ emissions has led - or most likely will lead - to a substantial regulatory introduction of CO$_2$ emission costs. Such costs must be absorbed in part by electricity producers which use fossil fuel technologies. Profitable electricity generation from those fuels therefore enters into a stress-ratio between factor- and emission-costs which forms new requirements towards the way electricity is produced. Coal emits the highest amount of CO$_2$ per MWh$_{el}$. However, it is also the fossil resource with large reserves, guaranteeing future fuel availability at reasonable costs. To accommodate coal under a stringent climate policy, technologies to capture and store CO$_2$ emitted by power plants are under development or will reach market maturity within the next years. Carbon Capture, Transport and Storage (CCTS) describes the methods by which CO$_2$ from large point sources, is captured, compressed, transported, and stored underground. Three technology concepts are competing to reach the market: pre-combustion capture, the oxy-fuel process and retrofitable post-combustion capture technology (see e.g. Ansolabehere et al. [2007] for more information about the CCTS technologies).

In this paper we focus on post-combustion capture, examining the option of retrofitting an existing power plant as in Abadie and Chamorro [2008], who analyze the option to invest in a CO$_2$ capture unit under electricity and carbon price uncertainty in the Spanish market. They find that high volatility in carbon prices is the main barrier to firms’ adoption of CCTS.

In addition to legal questions about transport and storage, the costs and performance of CCTS are also high barriers to an early CCTS application. For example, continued funding is critical to support current R&D efforts to scale up the new CCTS technology for application to existing plants (WCI, 2007). As is typical for innovative technologies, CCTS comes with significantly higher capital cost for plants and high efficiency losses in generation. Some studies indicate that the cost of electric generation could almost double [Fischedick et al., 2008], which electricity generation cost could almost double in the beginning. Hence, high carbon prices are needed to attract investment in and bring down the costs of future technological development.

Technology learning was first described in airplane manufacturing, where labor time requirements decreased the more experience workers as workers gained experience [Wright, 1936]. A study undertaken in 1972 by the Boston Consulting Group [1972] concludes that experience curves are widely observable along industries: learning rates, shown as constantly decreasing costs each time cumulated output doubles are in a range of 10 to 25% (see Appendix A for a formal description of the concept of learning). In this paper, we consider two types of technological learning, since the standard assumption of decreasing capital costs alone would neglect the importance of efficiency improvements for energy technologies:

1. Learning-by-doing: unit costs decline with the number of units sold as a consequence of experience gained in production and economies of scale. Examples in the energy sector are the flue gas desulphurization or catalytic NO$_x$ reduction. The unit costs of these technologies, although first increasing due to changes in the technology, declined at a rate of 11% and 12% after application on a larger scale [Rubin et al., 2007].

2.
2. Learning-by-innovating: subsequent technology development and incremental innovation. It takes time to adjust new technologies or components to a firm’s specific process, or new materials or components lead to a better performance of the whole system. Therefore, we assume that the efficiency of the first CCTS plant will be lower compared to subsequent plants.

Learning effects for innovative, energy-related technologies have long been identified as a pivotal element for the transformation of the sector and for mitigating climate change (IEA, 2000). Endogenous technology change has been implemented in the models, e.g., MARKAL (Barrete, 2001), MESSAGE (Rao et al., 2006), MERGE (Kypreos, 2005) or POLES (Russ and Criqui, 2007) used to analyze transformation pathways of the sector and the impacts of environmental and technology policy. The literature concludes that learning rates for environmental technologies result in earlier and more rapid reduction in greenhouse gases and the social costs of climate change mitigation.

Literature on real options theory however states that this process can slow or stop if uncertainty is taken into account. The theory is frequently applied to analyze power plant investment in an environment of uncertainty. Yang and Blyth (2007) points to the importance of developing new methods for evaluating the influence of uncertainty in climate policy and factor prices, stating that real options theory results in a better understanding of the impacts of policy and market uncertainty upon investment in the energy sector. The literature describes the impact of regulatory uncertainties (e.g., Blyth et al., 2007), Laurikka (2006), Blyth (2007) or variations in factor prices and commodity prices (e.g., Reedman et al., 2006). Kumbaroglu et al., 2004 evaluate the diffusion of renewable power generation technologies under volatile fuel and electricity prices. Their findings indicate that the option to delay investment requires additional policy instruments, since even under technology learning, the market will not adopt low-carbon alternatives. Murto (2007) considers combined uncertainty on technology and output prices, by modeling decreasing costs for the underlying investment. In this setting, technological uncertainty alone does not significantly delay the optimal investment decision, as long as certain revenues are given. Yet when revenues are also uncertain, increasing technological uncertainty leads to serious delays in investment.

However, there is no such work on combined technological uncertainty, the thermal performance of CCTS plants and the investment costs. In the case of expected high initial learning and announced public demonstration projects, private investors may have an incentive to delay investment in order to benefit from more mature, less costly technology in the future. In contrast to the general finding in the literature on technological change that expected learning effects promote or at least accelerate technological change, from a firm’s perspective may also impede the introduction of new technologies. In the case of CCTS, many demonstration projects are announced by public and private investors (ZEP, 2008). Knowledge gained in those projects spills over to other market players, which benefit from the learning investment and progress made by early adopters. Since, for any particular firm, the number, scope and success of such demonstration projects will remain uncertain, we will model the decrease in capital costs and efficiency improvements of retrofit-able, post-combustion technology as stochastic variables.
We use real options theory to analyze the optimal investment strategy in the presence of exogenous, uncertain technology learning, accounting for uncertainties about CO\textsubscript{2} prices, capital costs and thermal efficiency. The approach is superior because analysis only depends on the parameters of the stochastic processes which reduces the risk of arbitrariness. Standard scenario analysis models decision-makers who are not informed about the sequential resolution of uncertainties and investment timing as a decision variable. We use stochastic dynamic programming and the formulation of uncertainties as stochastic processes to overcome these shortcomings. Our research objective is to examine how an expected technology improvement will alter a firm’s investment decision. The paper is structured as follows: Section 2 presents the stochastic model. The data used is given in Section 3. Section 4 discusses the results for each uncertain parameter alone and in a comprehensive analysis. Section 5 concludes the paper and offers suggestions for further research.

2 Model description

A hypothetical electricity producer has invested in a coal-fired plant. Therefore, our analysis will cover only the sub-decision of retrofitting the existing power plant \textsuperscript{1}. In each period, the plant operator has the option to install a post-combustion capture CCTS technology to reduce CO\textsubscript{2} emissions by 90%; the heat required for solvent regeneration lowers the net energy available for steam and electricity generation. In other words, the high capital expense for the CCTS unit is accompanied by a lower thermal efficiency of the plant. Implicitly we assume that the investment costs of the CCTS technology must be paid at the first time of usage. At a single stage the profit function is:

\[
\pi (s_c, s_e, s_x, tech) = \left( P_e + s_c - \left( C_F + X_{CO_2}((1 - d_r (tech))s_c + C_{TS}) / \eta (tech, s_c) \right) \eta (tech, s_c) \right) L - C_{OM} (tech) - (s_x^0 - s_x^{-1}) C_I (tech) \quad (1)
\]

\text{tech} \in \{CCTS, retrofittable\}

\eta (tech, s_c) = \begin{cases} s_c & \text{tech = CCTS} \\ s_c^* & \text{tech = retrofittable} \end{cases}

\begin{align*}
\text{s_c} &= \text{stochastic carbon price} \\
\text{s_c} &= \text{thermal efficiency} \\
\text{s_x} &= \text{CCTS technology is not yet installed } \in \{0, 1\} \\
\text{P_e} &= \text{electricity price} \\
\text{X_{CO_2}} &= \text{carbon emission factor} \\
\text{C_F} &= \text{fuel costs} \\
\text{C_{TS}} &= \text{transport and storage costs} \\
\text{C_{OM}} &= \text{O&M costs} \\
\text{C_I} &= \text{investment costs} \\
\text{d_r} &= \text{deposition rate } \in [0, 1] \\
\text{L} &= \text{load}
\end{align*}

Profit consists of the revenues of electricity production, reduced by operational costs, fuel costs, and CO\textsubscript{2} emission costs. The CO\textsubscript{2} emission costs depend

\text{\textsuperscript{1}This is not a severe restriction, as long as net present value is positive; the investment is profitable in all of our simulations.}
on the efficiency of the plant $\eta$. Efficiency $\eta$ itself depends on the technology used and the stage of efficiency reached for CCTS. We assume that the innovative CCTS technology bears a high potential for efficiency improvement, as shown in [Fischedick et al. 2008]. Nevertheless, the efficiency improvements of subsequent periods remain uncertain to the plant operator. We model them as a stochastic process with decreasing increments and an upper bound, because the development of the efficiency of the fossil fuel technologies is restricted by thermodynamics. For the stochastic decrease of investment costs, the process is limited by a lower bound. A multinomial lattice which is used in finance for the numerical approximation of Wiener processes does not have this quality. To model stochastic processes that approach a saturation upper bound, we use the discrete time stochastic process $X_t$. We have independent Bernoulli distributed random variables $Z_t \in \{0, 1\}$. $P(Z_t = 1) = p, t = 1, 2, \ldots$

The process is defined by the initial value $X_0$ and the recursion formula:

$$X_t - X_{t-1} = \beta e^{-\alpha \sum_{k=1}^{t} Z_k} \quad t \geq 1$$

The bound of the process $\overline{X}_t$ and the limit $\overline{X}$ is for $Z_k = 1$:

$$\overline{X}_t = X_0 + \beta \frac{1 - e^{-\alpha t}}{e^\alpha - 1}$$

$$\overline{X} = X_0 + \beta \left( \frac{1}{e^\alpha - 1} \right)$$

Equation 4 derives the equivalence of $\beta$ and the upper bound $\overline{X}$. The process could therefore be parametrized via $\alpha$ and $\overline{X}$. Equation 3 and 4 imply under the condition $X_0 = 0$:

$$\ln \frac{\overline{X}_t - \overline{X}_{t/2}}{\overline{X}_t} \sim -\alpha t.$$  

Thus, $\alpha$ is a measure for the speed by which the process approaches the upper (in case of thermal efficiency) or the lower (in case of investment costs) bound. $\alpha$ and $\beta$ influence the structure of the lattice while $p$ only accounts for the relative frequency of the states reached in the lattice. 1 shows that from an initial starting point the process increases with probability $p$ and rests on the initial level with probability $1 - p$. The increments are decreasing with time such that the upper bound is not exceeded. With time passing the distribution approaches a normal distribution on a nonlinear transformed scale (the process is described in more detail in Appendix B).

The fact that CO$_2$ caps are significantly influenced by policies allows us to imitate a structure instead of than having to rely on the available (short) records of certificate prices (see Seifert et al. 2008). The authors state that the immaturity of the EU ETS allows large players to exert market power. Further, the expectation that builds up due to annually published emission reports and the break between the trading periods can explain the price spikes and high volatility. We account for the uncertainty in CO$_2$ prices by applying a simple binomial lattice using parameters presented in Section 3.

State transitions are stochastic and take previous decisions into account. The decision variable is $d_t$ with the possible values: $d^1 = 1$ use CCTS technology, and $d^0 = 0$ omit CCTS technology usage. $s_x$ works as a memory if the CCTS
technology has already been used. As described above, if used for the first time, the generator must spend the cost of investment. State transitions are described by:

\[ s^t_e = s^{t-1}_e + \beta e^{-\alpha} \sum_{k=1}^{z^t_e} \]

\[ s^t_c = s^{t-1}_c + z^t_c d + (1 - z^t_c) u \]

\[ s^t_x(d^t, s^{t-1}_x) = \begin{cases} 
  s^{t-1}_x & d^t = 0 \\
  1 & d^t = 1 
\end{cases} \]

where \( z^t_e \) and \( z^t_c \) are independent Bernoulli distributed random variables with probabilities \( P(z^t_e = 1) = p_e \) and \( P(z^t_c = 0) = p_c \). Initial conditions of the processes are \( s^0_e, s^0_c \) and \( s^0_x = 0 \).

The stage profit, the stage transitions and the discount rate \( r \) give the following stochastic dynamic program in recursive definition:

\[
V (s^t_e, s^t_c, s^t_x) = \max_{d^t \in \{0,1\}} d^t \pi (s^t_e, s^t_c, s^t_x, CCTS) + (1 - d^t) \pi (s^t_e, s^t_c, s^t_x, rf) + \frac{1}{1 + r} E_{d^t} (V (s^{t+1}_e, s^{t+1}_c, s^{t+1}_x(d^t, s^t_x)))
\]

The program is solved using a recursive formulation in Mathematica.

3 Data

Technology parameters are taken from the comprehensive literature review (Matisen et al., 2007). Table 1 summarizes the values we use in our simulations. As investment costs for CCTS remain uncertain until the first large-scale demonstration plants are built, we estimate a cost of 1,100,000 €/MW for a lignite plant without retrofitted CCTS post-combustion technology, and 800,000 €/MW for the retrofitted CCTS unit.
The price for electricity, 55 €/MW, is based on the average price for baseload at the European Energy Exchange (EEX), and includes a stochastic component of 25 €/tCO\textsubscript{2} for the price for the CO\textsubscript{2} certificate.

**Table 1: Parameter values**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Standard Value</th>
<th>CCTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity price</td>
<td>( P_e )</td>
<td>55 [€/MWh]</td>
<td></td>
</tr>
<tr>
<td>Fuel cost</td>
<td>( C_f )</td>
<td>5 [€/MWh]</td>
<td></td>
</tr>
<tr>
<td>Efficiency</td>
<td>( s_e )</td>
<td>0.45%</td>
<td>33%</td>
</tr>
<tr>
<td>Certificate price</td>
<td>( s_c )</td>
<td>25 [€/tCO\textsubscript{2}]</td>
<td></td>
</tr>
<tr>
<td>( CO_2 )Emissions factor</td>
<td>( X_{CO_2} )</td>
<td>0.39 [t/MWh\textsubscript{th}]</td>
<td>0.039 [t/MWh\textsubscript{th}]</td>
</tr>
<tr>
<td>Load</td>
<td>( L )</td>
<td>7000 [h/a]</td>
<td>7000 [h/a]</td>
</tr>
<tr>
<td>Operation cost</td>
<td>( C_{om} )</td>
<td>28,000 [€/MW]</td>
<td>56,000 [€/MW]</td>
</tr>
<tr>
<td>Investment cost CCTS</td>
<td>( C_i )</td>
<td>1,100,000 [€/MW]</td>
<td>800,000 [€/MW]</td>
</tr>
<tr>
<td>Interest rate</td>
<td>( r )</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>Plant life</td>
<td>( T )</td>
<td>50 [a]</td>
<td></td>
</tr>
<tr>
<td>Period length</td>
<td>( t_P )</td>
<td>2 [a]</td>
<td></td>
</tr>
</tbody>
</table>

Plant efficiency is 33% initially, and stochastically increases due to learning by doing for the CCTS plant. We do not model the learning process as a function of the installed capacity or the production of electricity but assume that there is a certain probability \( p \) that an efficiency improvement is realized, thus increasing efficiency at a decreasing given rate. The process parameters are shown in Table 2.

As discussed above, the certificate price process is assumed to reflect political uncertainties about future CO\textsubscript{2} caps. Since the process structure is unclear due to lack of data, we assume a binomial lattice with parameters \( u, d \) and then probability \( p_c \). It is generally agreed that the estimated certificate price will be 55 €/tCO\textsubscript{2} in 2030 (see e.g., Prognos, 2009), which means that the price doubles. The probability \( p_c \) is calibrated to reproduce a doubling of the expected value of the certificate price process during this period. The value \( u = 1.05 \) is set and \( d \) is derived by the standard assumption \( ud = 1 \).

**Table 2: Parameter values of stochastic processes**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper bound CCTS plant efficiency</td>
<td>( s_e )</td>
<td>0.45%</td>
</tr>
<tr>
<td>Initial CCTS plant efficiency</td>
<td>( s_{e0} )</td>
<td>0.45 - 0.12 = 0.33%</td>
</tr>
<tr>
<td>Limit expected value / Max value</td>
<td>( p_c )</td>
<td>0.5</td>
</tr>
<tr>
<td>Process growth parameter</td>
<td>( \alpha )</td>
<td>0.1</td>
</tr>
<tr>
<td>Bernoulli probability</td>
<td>( p_c )</td>
<td>Value</td>
</tr>
<tr>
<td>&quot;up&quot;-factor</td>
<td>( u )</td>
<td>1.05</td>
</tr>
<tr>
<td>&quot;down&quot;-factor</td>
<td>( d )</td>
<td>( d = 1/u )</td>
</tr>
</tbody>
</table>
4 Results

In four scenarios we analyze the optimal investment and management strategy of the CCTS unit by combining case and aggregate analysis of Monte Carlo simulations with 10000 randomly drawn paths (Table 3). Optimal decisions are presented in dependence of the states reached, time-dependent moments of the decision, and the distribution of the discounted profits. These distributions reveal the effects of the investment decisions on profits.

Table 3: Scenario description

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Plant efficiency</th>
<th>Investment cost</th>
<th>Certificate price</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>constant</td>
<td>deterministic</td>
<td>stochastic</td>
</tr>
<tr>
<td>S2</td>
<td>stochastic</td>
<td>constant</td>
<td>constant</td>
</tr>
<tr>
<td>S3</td>
<td>constant</td>
<td>stochastic</td>
<td>constant deterministic</td>
</tr>
<tr>
<td>S4</td>
<td>stochastic</td>
<td>stochastic</td>
<td>stochastic</td>
</tr>
</tbody>
</table>

4.1 Scenario 1 (S1): Carbon price uncertainty

We start by focusing only on carbon price uncertainty. The stochastic certificate price is parameterized as:

\[
s_{c0} = 25\text{€/CO}_2
\]

\[u = 1.1\]

\[d = 1/u\]

\[p_{uc} = 0.58\]

Thermal efficiency is at 33% and investment costs for the CCTS unit are 800,000 €. Figure 2 shows the optimal investment and management decision; the meaning of the colors is explained in Table 4.

Table 4: Visualization of state transitions

<table>
<thead>
<tr>
<th>CCTS Capacity</th>
<th>Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>installed</td>
<td>not installed</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The left side of Figure 2 shows that carbon prices of at least 45 €/tCO₂ are needed to start investment in the CCTS technology. In the range of 20
to 45 €/tCO₂ it is optimal to operate a once-installed unit (green area in the middle). If carbon prices fall below 20 €/tCO₂ (the lower blue area), it would even be optimal to shut the once-installed unit. The price level of 45 €/tCO₂ is not reached before period 7. The threshold level rises as the amortization period shortens from period 17. There is no further investment after period 15, because states colored in red can no longer be reached from green states. The right side of Figure 2 shows the optimal investment and operation strategy under a deterministic efficiency path reaching 0.40% in 2052. The optimal CCTS investment and operation strategy changes when:

1. lower carbon prices still allow for profitable operation of a once installed CCTS unit.

2. the threshold for investment and usage drops to 35 €/tCO₂. Therefore investment takes place earlier.

Figure 3: Investment decision for stochastic certificate prices by Monte Carlo simulation

To aggregate decisions and to derive the distributions of stage profits we use Monte Carlo Simulations with 10000 iterations. We record management decisions for every state if a CCTS technology is used in this state (run or invested). States colored in red (upper area) indicate 100% usage and states colored in blue (lower area) indicate no usage. The right side of Figure 3 shows the probability of reaching these states. A light-colored area indicates a high probability and dark areas a low probability. We observe an average CCTS utilization of 27%. The low utilization is based on two facts: first, under the

---

2This process consists of expected efficiencies of the process used in Section 4.2
assumptions of the carbon price process, the expected price value in average rises only to a level of 37 €/tCO₂; second, since we only look at retrofitting an existing plant, the amortization time of an investment matters. With respect to the distribution of profits, we observe a shift to higher profits in later periods for the CCTS unit. Since the electricity price is driven by the carbon price, we do not observe negative profits for the standard plant.

Figure 4: CCTS participation and profit distribution for stochastic certificate price

4.2 Scenario 2 (S2): Thermal efficiency uncertainty

Figure 5: CCTS investment and management for stochastic efficiency without and with certificate price trend

We set the carbon price to 32 €/tCO₂, because the value guarantees the existence of the inner invest/not-invest dividing line shown in Figure 5. Investment first starts after 4 efficiency improvements at a level of 37%. If this value is reached after period 8, the remaining amortization time is too short to justify CCTS investment given the reached efficiency level. The structure of the stochastic process allows investment up to period 13. The comparison with the introduction of a deterministic certificate price trend (from 32 to 37 €/tCO₂) shows that the impact of a modest certificate price trend is much stronger than
the full efficiency trend. The right side of Figure 6 shows the optimal decisions. 
The deterministic rise in certificate prices works in two directions:

1. since certificate prices will definitely rise the amortization interval shrinks for a fixed efficiency level. The investment windows opens up to earlier and later periods.

2. it lowers the efficiency threshold to invest. It is optimal to invest at efficiency levels in later periods that would not have sufficed in earlier periods.

Thus, the impact of the certificate price trend dominates the impact of the efficiency trend.

The results of Monte Carlo simulation are presented in Figure 6. The participation rate of CCTS is around 57% without the deterministic carbon price trend and reaches almost 100% with the price trend.

**Figure 6: CCTS participation and profit distribution for stochastic learning**

4.3 Scenario 3 (S3): Investment price uncertainty

This scenario analyzes uncertainty on investment costs. The process is defined by:

\[ X_{0t} = 800,000[\text{€/MW}] \]
\[ \bar{X}_t = 500,000[\text{€/MW}] \]
\[ \alpha_t = 0.3 \]
\[ p_{dt} = 0.5 \]

Absent certificate price and efficiency learning trend there is almost no CCTS investment. We thus introduce deterministic trends for the certificate price and learning effects resulting from the time series of expectations of the processes:
The certificate price trend results in an increase from 25 to 37 € over 40 years. Efficiency is expected to rise by 21%, from 0.33 to 0.4%. Investment takes place in periods 14 and 15 after investment costs have undergone the threshold of 620,000 € (Figure 7).

**Figure 7: CCTS investment and management for stochastic investment costs with certificate and efficiency trend**

We see from Figure 8 that CCTS participation is lowest under investment price uncertainty. We take this as an indication for the limited influence of the investment costs compared to the influence of the certificate price and the thermal efficiency.

**Figure 8: CCTS participation and profit distribution for stochastic investment costs with certificate and efficiency trend**
4.4 Scenario 4 (S4): Combined efficiency and certificate price uncertainty

We now combine the stochastic processes and analyze the optimal investment and management decisions of the CCTS unit.

The state-time space now turns three-dimensional. We thus present optimal decisions as two-dimensional state samples for periods 5, 10, 15 and 20 in Figure 9 in which realization of the stochastic processes are shown as a sequence of arrows. The actual state is marked by a white point, and the not yet realized states by dotted arrows.

Figure 9: Stochastic learning and certificate price uncertainty; \( t = 5, 10, 15, 20 \)

In Period 5 (Figure 9-1), investment is only profitable if efficiency has reached at least 35.5\% and the certificate price exceeds 33 €. For the realization in this example, no investment would take place (white point in green area without having reached red states before).

In Period 10 (Figure 9-2), the decision space has expanded and more states are reachable. The colored rectangle extends to higher efficiency levels and higher certificate prices. Now there is an almost constant certificate price of 37
for every efficiency level that allows profitable investment. In this example, realization has reached a red area: investment takes place.

Five periods later (Figure 9-3), investment thresholds have not changed their values substantially. The specific realization is still located in the red area. The previously installed capacity operates profitably.

The last time slice of period 20 (Figure 9-4) shows the process realization in the green area, which means the installed capacity is additionally profitable in usage. The investment threshold has risen to 95 €. The CCTS capacity will run only one period, so the amortization period is extremely short and profitable investment requires extremely high certificate prices and efficiency levels.

Throughout the simulation the frontier between the red and green shaded areas remains almost horizontal. This indicates that the certificate price dominates the improvement in thermal efficiency in terms of the investment decision. However, a higher efficiency acts as an insurance against too-low carbon prices and increases the range of profitable CCTS operation. Nevertheless comparison with certificate price uncertainties and deterministic efficiency trend shows that the participation rate has increased to 50% (Figure 10). E

Figure 10: Stochastic learning and certificate price uncertainty

4.5 Stochastic learning, investment cost and certificate price uncertainty

\[
\begin{align*}
X_{0L} &= 0.45 - 0.12 \\
X_{0I} &= 800,000[\text{€/MW}] \\
\bar{X}_L &= 0.45 \\
\alpha_L &= 0.1 \\
p_{ul} &= 0.5 \\
\alpha_I &= 0.3 \\
p_{dl} &= 0.5 \\
s_{0I} &= 25[\text{€/tCO}_2] \\
u &= 1.1 \\
d &= 1/u \\
p_{uc} &= 0.58
\end{align*}
\]

We have shown that each uncertainty incorporates investment threshold levels that are modulated by the deterministic trend components of other uncertainties. In Section 4.4 the combination of stochastic certificate price and
stochastic learning was dominated by the price development. That means certificate price threshold was only slightly modulated by different efficiency levels. We now add up the investment cost uncertainty; Figure 11 shows the results.

Figure 11: Stochastic learning, investment cost and certificate price

CCTS participation further increases by introducing investment cost uncertainty from 60% to 65%. Profit distribution appears almost the same, although the standard deviation of profits has increased.

5 Conclusion

We have conducted a dynamic stochastic investment analysis of CCTS retrofitting in an environment of CO$_2$ price and technology uncertainty. It includes the option to invest in, and to use or shut down, the CCTS unit. While modeling certificate price uncertainties is standard, stochastic processes including diminishing increments are implemented for thermal efficiency and investment cost improvements. Following a careful quantification of parameters, the optimal investment strategies are derived and used in Monte Carlo simulations to produce results on aggregate investment decision and resulting profits. All simulation data were presented graphically from a low optimal strategy level to an aggregated expected value level.

In the case of isolated technology uncertainties we found that CCTS unit offers the opportunity to benefit from positive efficiency and capital cost developments. The option value of waiting shows in the delayed and per se limited investment activity. Isolated certificate uncertainties with a trend of expected rises promoted a very strong investment activity within the first 10 periods after four periods of investment delay. The combination of all three uncertainties shows aspects of both previous optimal investment strategies, while the impact of certificate prices dominates aggregate investment and profit structure. In all three simulations cases, not using a once-installed CCTS unit is either not optimal or shows only in very unlikely cases. An important finding is that the model predicts an initial investment delay that is due to the possibility to extract valuable information about future development. Additional profits can be
generated by conditioning investment decision on the initial realizations of the stochastic processes.

As shown in Scenario 4, technology policy complements a pollution controlling policy which is the driver for technology change. The combination of high CO\textsubscript{2} prices and technology development results in an earlier and more likely adoption of CCTS by a firm. Many studies show that a rapid adoption of CCTS on a large scale is evidence for the reduction of carbon emission required to comply with the 2°C goal (Knopf and Edenhofer (2009) or Gerlagh (2006)). The following three policy instruments, which can help to achieve this target, are deduced from our analysis:

1. All new build coal power plants must be build as capture ready. This ensures that technologies will be compatible and CCTS can be retrofitted at least cost. With the urgent need for fossil-fired capacity replacement in developed countries (Fischedick et al., 2008), and even more fossil capacity planned or under construction in developing countries within the next decade, the success of CCTS will depend on compatibility as much as on costs and performance.

2. Long-term reliable and stable carbon prices are needed on a level high enough to incentivize investment in CCTS. As carbon caps and the resulting prices are now set more or less arbitrarily, the resulting volatility and uncertainty significantly delays investment. Given the long capital turn-over and life of a CCTS investment, plant owners need to be sure that their investment in CCTS technology will pay off.

3. With high uncertainty in the costs and performance of the first CCTS plants and high knowledge spillover in the energy sector, we suggest that part of the initial learning investment should be provided by the public to compensate for the knowledge market failure. Society could benefit from this investment, because CCTS is considered a promising hedge against high carbon prices, and will allow for reliable and affordable baseload electricity production in the future.

Most of the literature on learning effects focuses on the decrease in capital costs. Our analysis, however, indicates that the influence of efficiency improvements in thermal plants plays an important role, too. We therefore suggest a stronger emphasis on this technology learning in the future to help achieve a more realistic modeling not only for the CCTS investment and management decision.

Our basic model covers uncertainty only for thermal efficiency, investment costs and certificate price uncertainty. We suggest that future models should incorporate fuel and electricity prices for a more comprehensive investment analysis.

References


6 Appendix A: The concept of learning

The standard expression for modeling the learning effect take the form of a single factor experience curve, e.g., given in [Barreto (2001)]:

\[ \text{Cost}_t = \text{Cost}_0 \times (\frac{1}{2})^{t/t_0} \]

where \( \text{Cost}_t \) is the cost at time \( t \), \( \text{Cost}_0 \) is the initial cost, \( t_0 \) is the time it takes to reach half the initial cost, and \( t \) is the time elapsed.
\[ UC_t(\text{CC}_t) = a \ast \text{CC}_t^{-b} \]  

(9)

with

\( UC_t \) = Unit costs
\( \text{CC}_t \) = Cumulative capacity
\( b \) = Learning-by-doing elasticity
\( a \) = \( \frac{UC_0}{CC_0} \)

A more common way to express technology’s movement along the learning curve is by means of the progress ratio instead of an experience curve. The progress ratio gives the rate at which costs (efficiency) improve if cumulative capacity (output) doubles. A progress ratio of 80\% corresponds to a cost reduction or learning rate of 20\% each time cumulative capacity doubles:

\[ pr = 2^{-b} \]  

(10)

### 7 Appendix B: Stochastic process

We can further deduce the expected value and variance of a stage as:

\[ E[\beta e^{-ak}Z_{k+1}] = \beta e^{-ak} p \]  

(11)

\[ Var[\beta e^{-ak}Z_{k+1}] = \beta^2 e^{-2ak} p(1 - p). \]

Independency gives us the following expressions for expected value and variance:

\[ E[X_t] = X_0 + p\beta \frac{1 - e^{-at}}{e^\alpha - 1} \]  

(12)

\[ Var[X_t] = p(1 - p) \beta^2 \frac{1 - e^{-2at}}{1 - e^{-2\alpha}} \]

with its limits:

\[ \lim_{t \to \infty} E[X_t] = X_0 + p\beta \frac{1}{e^\alpha - 1} \]  

(13)

\[ \lim_{t \to \infty} Var[X_t] = p(1 - p) \beta^2 \frac{1}{1 - e^{-2\alpha}}. \]

We can now derive the following interesting and interpretable relation:

\[ E[X_t] - X_0 = p (\bar{X}_t - X_0) \]  

(14)

\[ \lim_{t \to \infty} E[X_t] - X_0 = p (\bar{X} - X_0). \]

The following three nonlinear equations offer an attractive way to calibrate the parameter \( \alpha, \beta \) and \( p \) of the process:

\[ p : p = \lim_{t \to \infty} E[X_t] - X_0 \]  

(15)

\[ \alpha : 1 - e^{-\alpha} \frac{X_{t+1} - X_t}{\bar{X}_t - X_0} = (X_{t+1} - X_0)/(X_t - X_0) \]  

(16)

\[ \beta : \beta = \frac{1}{\bar{X} - X_0} (e^\alpha - 1). \]

We can thus derive \( \alpha, \beta \) and \( p \) from potential limit \( \bar{X} \), the limit of the expected value and the actual average growth rate \( \frac{X_{t+1} - X_t}{X_t - X_0} \).
8 Appendix B: Figures

Figure 12: Investment decision for stochastic efficiency by Monte Carlo simulation

Figure 13: Investment decision for stochastic investment costs by Monte Carlo simulation