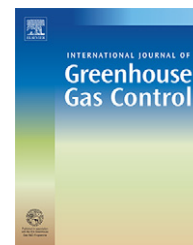


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# Use of experience curves to estimate the future cost of power plants with CO<sub>2</sub> capture

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## ABSTRACT

Given the dominance of power plant emissions of greenhouse gases, and the growing worldwide interest in CO<sub>2</sub> capture and storage (CCS) as a potential climate change mitigation option, the expected future cost of power plants with CO<sub>2</sub> capture is of significant interest. Reductions in the cost of technologies as a result of learning-by-doing, R&D investments and other factors have been observed over many decades. This study uses historical experience curves as the basis for estimating future cost trends for four types of electric power plants equipped with CO<sub>2</sub> capture systems: pulverized coal (PC) and natural gas combined cycle (NGCC) plants with post-combustion CO<sub>2</sub> capture; coal-based integrated gasification combined cycle (IGCC) plants with pre-combustion capture; and coal-fired oxyfuel combustion for new PC plants. We first assess the rates of cost reductions achieved by other energy and environmental process technologies in the past. Then, by analogy with leading capture plant designs, we estimate future cost reductions that might be achieved by power plants employing CO<sub>2</sub> capture. Effects of uncertainties in key parameters on projected cost reductions also are evaluated via sensitivity analysis.

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## 1. Introduction

Given the growing worldwide interest in CO<sub>2</sub> capture and storage (CCS) as a potential option for climate change mitigation, the expected future cost of CCS technologies is of significant interest. Applications to fossil fuel power plants are especially important since such plants account for the major portion of CO<sub>2</sub> emissions from large stationary sources (Metz et al., 2005). While the literature on CCS costs covers a range of applications and technologies, most studies of CO<sub>2</sub> capture and storage for power plants have focused on

currently available technology. This approach has the advantage of avoiding subjective judgments of what may or may not happen in the future, or what the cost will be of advanced technologies still in the early stages of development. On the other hand, reliance on cost estimates for current technology has the disadvantage of not taking into account the potential for improvements that can affect the overall role of CCS as a climate mitigation strategy, and the long-term competitiveness of CO<sub>2</sub> capture systems in different applications.

To address this problem, most large-scale energy-economic models used to assess global climate change mitigation

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policies and strategies assume some degree of technological improvement over time. However, there is currently little empirical data to support the assumptions and models used to calculate future CO<sub>2</sub> capture costs for power plants and related industrial processes. The objective of the present study is to improve the modeling and estimation of future cost trends based on historical observations for other technologies relevant to power plants with CO<sub>2</sub> capture and storage systems.

## 2. Study methodology

In this study, we first develop a set of experience curves characterizing historical cost trends for seven technologies relevant to power plants with CO<sub>2</sub> capture. These are: flue gas desulfurization (FGD) systems, selective catalytic reduction (SCR) systems, gas turbine combined cycle (GTCC) plants, pulverized coal (PC) boilers, liquefied natural gas (LNG) production plants, oxygen production plants, and steam methane reforming (SMR) systems for hydrogen production. Average learning rates are derived for the capital cost as well as the operating and maintenance (O&M) costs of each technology.

To estimate future cost trends for plants with CO<sub>2</sub> capture, we first decompose each of four power plant designs into major process areas or sub-systems that include all equipment needed to carry out certain functions such as power generation, air pollution control, or CO<sub>2</sub> capture. We then apply a learning rate to each sub-system based on judgments as to which of the seven case study technologies offers the best analogue to the power plant process area in question. The cost of the total plant is then calculated as the sum of all process area costs for increasing levels of total installed capacity. A classical learning curve is then fitted to the total cost trend to obtain a learning rate for the overall plant with CO<sub>2</sub> capture. We also quantify the effects of uncertainties in component learning rates and other key parameters. This approach implicitly assumes that technological change occurs via incremental improvements to existing technologies, which historically has been the dominant mode of technology innovation (Alic et al., 2003). While CO<sub>2</sub> transport and storage technologies also are vital components of a complete CCS system, these components are outside the scope of the present

study as they are different in nature from the power plant technologies examined here. The potential impact of transport and storage costs on overall results, however, is discussed later in this paper. The following sections provide additional details of the study methodology and results obtained. Full details are elaborated elsewhere (Rubin et al., 2006).

## 3. Case study results

The experience curves used in this study to characterize cost trends have the form:  $Y = ax^{-b}$ , where,  $Y$  is the specific cost of the  $x$ th unit,  $a$  is the cost of the first unit, and  $b$  ( $b > 0$ ) is a parametric constant. This formulation of a learning curve, first proposed by Wright (1936) to describe productivity improvements in the manufacture of an aircraft, has been widely adopted in the literature and in advanced energy-economic models to describe cost reductions as a function of cumulative production or deployment of a technology (Boston Consulting Group, 1968; Argote and Epple, 1990; McDonald and Schratzenholzer, 2001; Rubin et al., 2004; Riahi et al., 2004). The quantity  $2^{-b}$  is defined as the progress ratio (PR). It implies that each doubling of cumulative production or capacity results in a cost savings of  $(1 - 2^{-b})$ . The latter quantity is defined as the learning rate (LR). Values of PR and LR are commonly reported as a fraction or percentage for each doubling of cumulative installed capacity or production. In this common form of an experience curve, cumulative capacity is a surrogate for all factors that contribute to cost reductions, including expenditures for research and development.

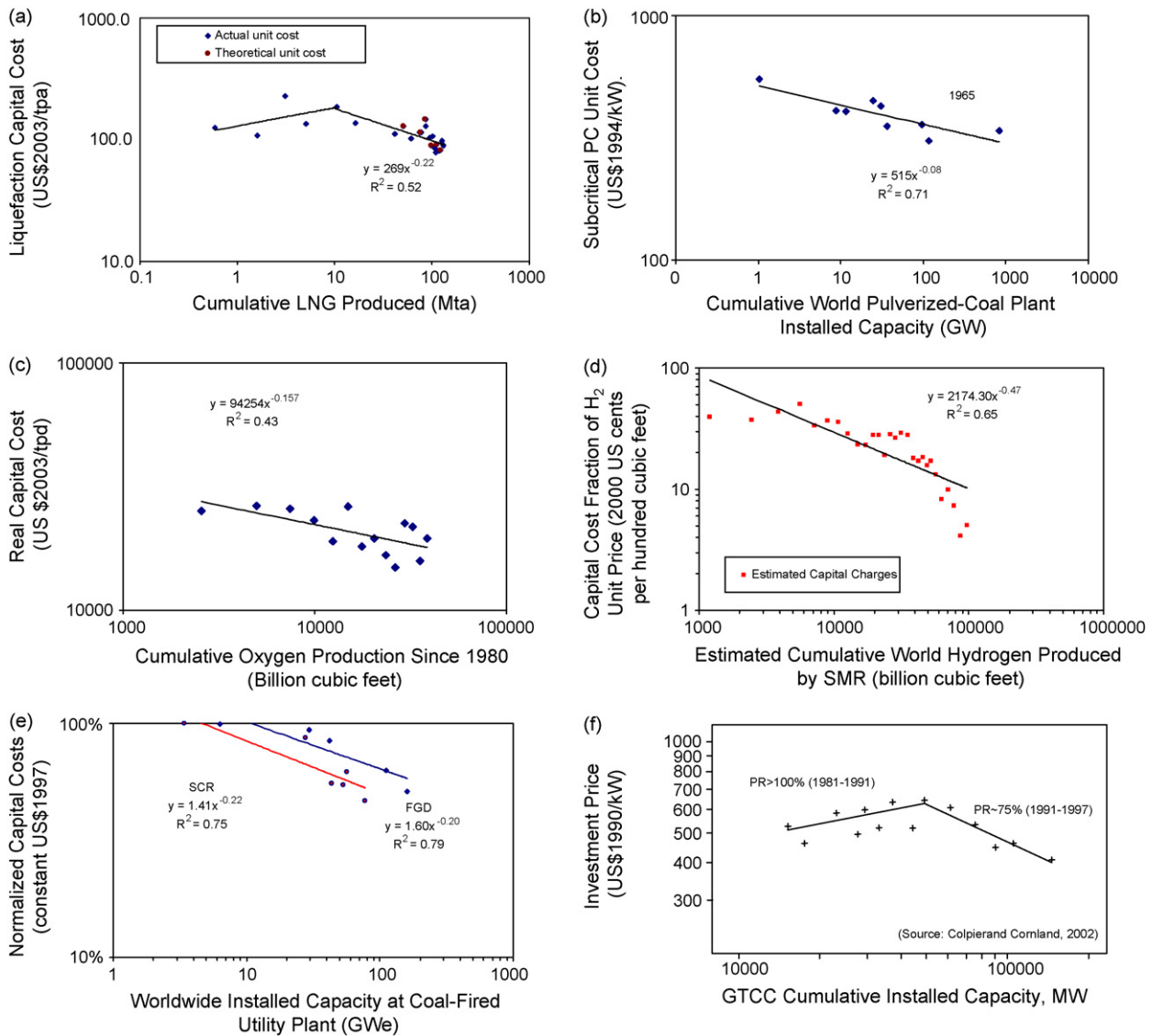
Table 1 summarizes the learning rates for capital cost and O&M cost for the seven technologies examined in this study. The capital cost learning curves are shown graphically in Fig. 1. Results for three of the technologies (FGD, SCR and GTCC) are based on previous work (Rubin et al., 2004; Yeh et al., 2005; Colpier and Cornland, 2002), while the remaining four cases are newly derived. Detailed descriptions and discussions of each technology and their historical cost trends are presented elsewhere (Rubin et al., 2006). All learning rates derived in this study fall within the range reported in the literature for an array of energy-related technologies studied by McDonald and Schratzenholzer (2001), although the learning rates found here for capital cost are systematically smaller than the median rate of 14% found in that study.

**Table 1 – Summary of “best estimate” learning rates for capital and O&M costs from historical case studies, and whether a cost increase was observed during the early stages of commercialization**

Technology	Learning rate <sup>a</sup>		Initial cost increase?
	Capital cost	O&M cost	
Flue gas desulfurization (FGD)	0.11	0.22	Yes
Selective catalytic reduction (SCR)	0.12	0.13	Yes
Gas turbine combined cycle (GTCC)	0.10	0.06	Yes
Pulverized coal (PC) boilers	0.05	0.18	n/a <sup>b</sup>
LNG production	0.14	0.12	Yes
Oxygen production	0.10	0.05	n/a
Hydrogen production (SMR)	0.27	0.27	n/a

<sup>a</sup> Fractional reduction in cost for each doubling of total production or capacity.

<sup>b</sup> n/a: not available.



**Fig. 1 – Capital cost experience curves derived in this study for (a) LNG production, (b) PC boilers, (c) oxygen production, (d) hydrogen production via steam methane reforming, (e) power plant FGD and SCR systems; also, (f) gas turbine combined cycle (GTCC) plants (from Colpier and Cornland, 2002). All costs are in constant dollars adjusted using the Handy-Whitman Cost Index for PC boilers and the Chemical Engineering Cost Index for all others. See Rubin et al. (2006) for additional details.**

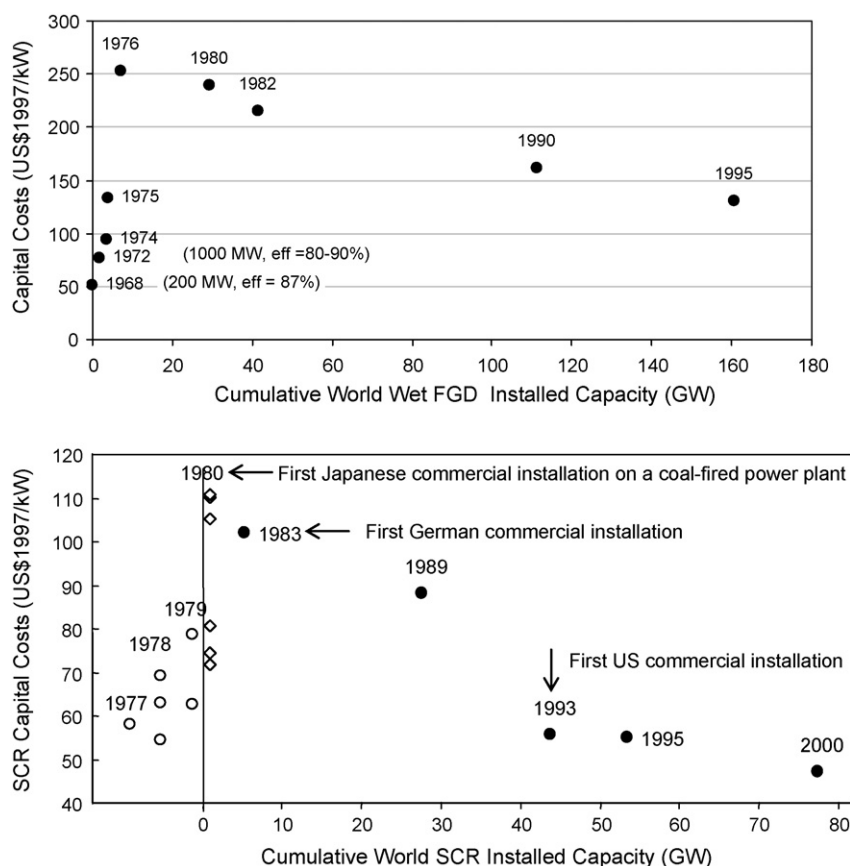
Factors contributing to real long-term declines in capital and O&M costs included improvements in technology design, materials, product standardization, system integration or optimization, economies of scale, and reductions in input prices.

Table 1 also indicates that four of the seven technologies displayed an increase in cost during the early stages of commercialization, as illustrated in Figs. 1 and 2. While a number of factors contributed to cost increases, the predominant causes were shortfalls in performance and reliability of early system designs (Rubin et al., 2006). Such cost increases relative to pre-commercial estimates often are not reflected in the long-term learning rates reported in the literature. In the context of the current study, the potential for

costs to rise before they fall is an important finding affecting projections of future cost trends, as elaborated below.

#### 4. Application to power plants with CO<sub>2</sub> capture

A number of recent studies have estimated the cost of CO<sub>2</sub> capture at power plants (Metz et al., 2005). The prevailing design for PC and NGCC plants employs post-combustion capture using commercial amine-based absorption systems. IGCC plants typically employ a water-gas shift reactor plus a commercial (e.g., Selexol) absorption system for CO<sub>2</sub> capture. Oxyfuel combustion designs for PC plants employ commercial



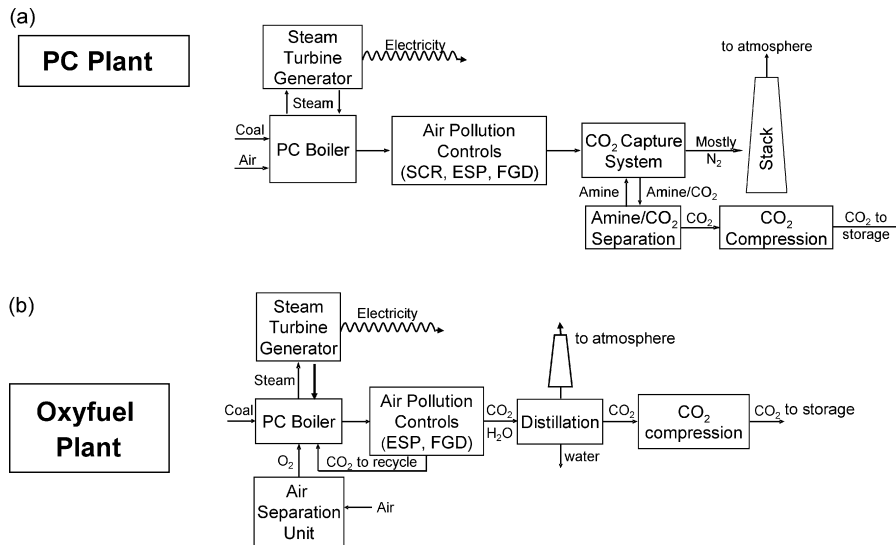
**Fig. 2 – Details of capital cost trends for wet limestone FGD systems and selective catalytic reduction (SCR) systems at a new coal-fired power plant in the U.S. (500 MW, 90% SO<sub>2</sub> capture, 80% NO<sub>x</sub> reduction), including cost studies conducted during (FGD) or prior to (SCR) the period of early commercial applications. Estimated O&M costs for both technologies also increased significantly during this period. In both cases the cost increases were due to poor performance with early designs. See Rubin et al. (2006) for additional details.**

oxygen plants plus flue gas recycle, with differing configurations for flue gas treatment systems. Because plant costs depend on a wide range of technical and economic factors and assumptions, comparisons across technologies require a systematic framework for analysis. In this study, we use the Integrated Environmental Control Model (IECM) developed at Carnegie Mellon University (IECM, 2005) to estimate the current cost of the four plant types (PC, NGCC, IGCC and oxyfuel) on a consistent basis. IECM costs are benchmarked against other recent studies, and are comparable to other reported costs when based on similar assumptions (Rubin et al., 2005). Figs. 3 and 4 show schematics of the nominal plant designs with CO<sub>2</sub> capture employed in this study. All plants are assumed to have a net power output of approximately 500 MW, a levelized capacity factor of 75%, and a capture system that removes 90% of the CO<sub>2</sub> produced and compresses it to a pressure of 13.8 MPa. Table 2 summarizes the nominal cost estimates for each system based on a U.S. location with coal plants using bituminous coal with 2.1% sulfur. As with all preliminary cost estimates, the absolute cost of each system can vary with alternate design assumptions and power plant locations (as illustrated later in the paper). As discussed below, the reliability of cost estimates for plants with CCS is most uncertain since none of these systems have yet been built and

operated at the scale of a modern power plant. Of particular relevance to the present study, however, is the percentage contribution of each sub-section to the total costs of construction and operation. These percentages are typically more robust for a given plant design.

Starting with current cost estimates, we use the historical learning rates reported in Table 1 to project the future costs of each major power plant sub-system (Table 3) as a function of cumulative plant capacity (which is proportional to power output at a given capacity factor). This approach allows the cost of different plant sections to change at different rates, reflecting differences in the technological maturity of each plant type and sub-system. It also reflects the contribution of each component to the total capital cost and total O&M cost of the plant. Improvements in overall plant efficiency due to improved component designs and/or improved plant integration also is reflected in a learning rate for fuel use per kWh of electricity generated. Component costs are then summed to obtain the total plant cost as a function of total installed capacity. From this result, a learning curve of the form  $Y = ax^{-b}$  is fitted to the overall cost trend for each plant type.

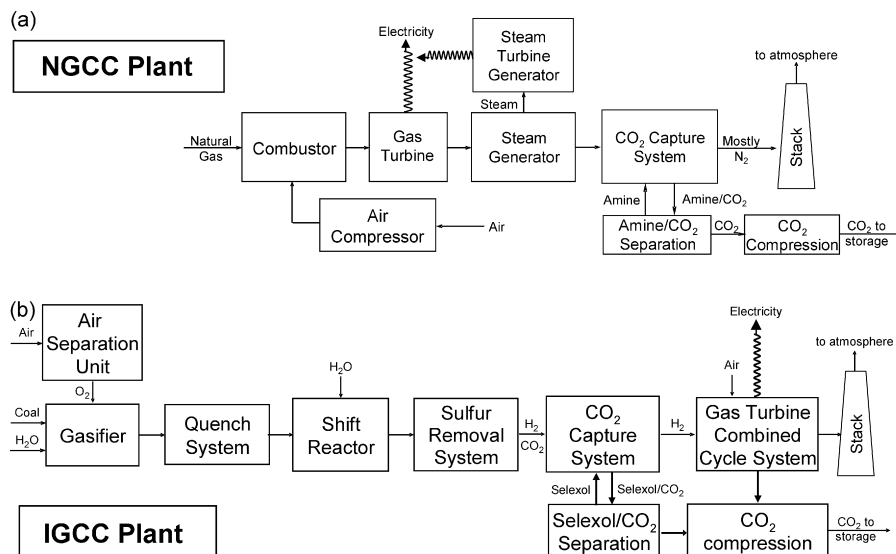
One drawback of this approach is that it does not explicitly include potential cost increases that may arise when building or combining components that have not yet been proven for



**Fig. 3 – Schematics of nominal plant designs for pulverized coal combustion systems with (a) post-combustion CO<sub>2</sub> capture and (b) oxyfuel combustion with capture.**

the application and/or scale assumed. For example, no IGCC power plant has yet combined CO<sub>2</sub> capture with a gas turbine fired by a hydrogen-rich fuel gas at a scale of 500 MW. Nor has an oxyfuel combustion plant producing and compressing a concentrated stream of CO<sub>2</sub> yet been demonstrated at a commercial scale. There are no easy or reliable methods, however, to quantify the magnitude of potential cost increases commonly observed during early commercialization of large-scale technologies (Merrow et al., 1988), and also seen in several of the current case studies. Thus, we instead assume that any such cost increases effectively delay the onset of learning until later generations of the plant or process are designed, deployed and operated for a period of time. With additional experience, higher plant costs that might be incurred initially are gradually reduced

via learning-by-doing and continued R&D. The cumulative capacity at which the total plant cost finally equals the current cost estimate ( $C_{min}$ , a parameter of the analysis) is when learning (cost reduction) is assumed to begin. Based on the case study data and judgments about the relative maturity of current CCS power systems, we assumed nominal values of  $C_{min}$  to be 3, 5, 7 and 10 GW for NGCC, PC, IGCC and oxyfuel plants, respectively. A sensitivity case assumes earlier learning if the first full-size plant is indeed deployed at the costs shown in Table 2. Another cumulative capacity parameter,  $C_{max}$ , defines the end point of the projected learning curve. The nominal value for this study is 100 GW—equivalent to roughly the first 25 years of experience for NO<sub>x</sub> and SO<sub>2</sub> capture systems at coal-fired power plants (Fig. 2).



**Fig. 4 – Schematics of nominal plant designs for combined cycle systems based on (a) natural gas with post-combustion CO<sub>2</sub> capture and (b) coal gasification with pre-combustion capture.**

**Table 2 – Case study cost estimates for current power plants with CO<sub>2</sub> capture (excluding transport and storage costs; see legend for reference plant costs without capture)**

Plant type and technology	Total plant costs (\$ 2002)					
	Capital cost		Total O&M cost <sup>a</sup>		Total COE <sup>b,c</sup>	
	\$/kW	% Total	\$/MWh	% Total	\$/MWh	% Total
NGCC plant <sup>d</sup>	916	100	38.5	100	59.1	100
GTCC (power block)	660	72	2.2	6	17.1	29
CO <sub>2</sub> capture (amine system)	218	24	2.4	6	7.3	12
CO <sub>2</sub> compression	38	4	0.2	0	1.0	2
Fuel cost	0	0	33.6	87	33.6	57
PC plant <sup>e</sup>	1962	100	29.3	100	73.4	100
PC boiler/turbine-generator area	1282	65	5.7	19	34.5	47
AP controls (SCR, ESP, FGD)	241	12	4.1	14	9.5	13
CO <sub>2</sub> capture (amine system)	353	18	7.2	25	15.2	21
CO <sub>2</sub> compression	86	4	0.4	1	2.3	3
Fuel cost	0	0	11.9	41	11.9	16
IGCC plant <sup>f</sup>	1831	100	21.3	100	62.6	100
Air separation unit	323	18	1.7	8	8.9	14
Gasifier area	494	27	3.7	17	14.8	24
Sulfur removal/recovery	110	6	0.6	3	3.1	5
CO <sub>2</sub> capture (WGS/selexol)	246	13	1.6	7	7.1	11
CO <sub>2</sub> compression	42	2	0.3	1	1.2	2
GTCC (power block)	616	34	2.0	9	15.8	25
Fuel cost	0	0	11.6	54	11.6	19
Oxyfuel plant <sup>g</sup>	2417	100	24.4	100	78.9	100
Air separation unit	779	32	3.1	13	20.6	26
PC boiler/turbine-generator area	1280	53	5.6	23	34.4	44
AP controls (ESP, FGD)	132	5	2.7	11	5.7	7
CO <sub>2</sub> distillation	160	7	1.4	6	5.0	6
CO <sub>2</sub> compression	66	3	0.5	2	1.9	2
Fuel cost	0	0	11.2	46	11.2	14

Source: IECM version 5.0.2. The cost of reference plants with similar net output and no CO<sub>2</sub> capture are: NGCC = \$ 563/kW, \$ 43.3/MWh; PC = \$ 1229/kW, \$ 44.9/MWh; IGCC = \$ 1327/kW, \$ 46.8/MWh.

<sup>a</sup> Based on levelized capacity factor of 75% for all plants.

<sup>b</sup> COE is the levelized cost of electricity.

<sup>c</sup> Based on fixed charge factor of 0.148 for all plants.

<sup>d</sup> NGCC plant = 432 MW (net); 517 MW (gross); two 7FA gas turbines; gas price = 4.0 \$/GJ.

<sup>e</sup> PC plant = 500 MW (net); 719 MW (gross); supercritical boiler; Pittsburgh #8 coal; price = 1.0 \$/GJ.

<sup>f</sup> IGCC plant = 490 MW (net); 594 MW (gross); three GE gasifiers + two 7FA gas turbines; Pgh #8 coal; price = 1.0 \$/GJ.

<sup>g</sup> Oxyfuel plant = 500 MW (net); 709 MW (gross); supercritical boiler; Pittsburgh #8 coal; price = 1.0 \$/GJ.

Other variables in the analysis are the current (initial) capacity of each plant sub-system (estimated in Table 3 in terms of equivalent power plant capacity), and a set of multipliers to reflect additional experience from continued deployment of plant components in applications other than power plants with CO<sub>2</sub> capture (sometimes called cluster learning). The latter parameter is employed in the sensitivity studies presented later in the paper. Details of all assumptions and calculation procedures are given in Rubin et al. (2006).

## 5. Results for plants with CO<sub>2</sub> capture

Fig. 5 gives an example of the projected changes in component and total plant capital cost for the case of the PC plant. Similar curves were derived for the O&M costs and total levelized cost of electricity (COE) for each of the four plant types. Table 4 summarizes the resulting learning rates for total plant capital cost, O&M cost, and COE from the onset of learning ( $C_{\min}$ ) to a point when the worldwide capacity of each system reaches

100 GW. The nominal (“best estimate”) learning rates for plant COE show a 3–5% decrease for each doubling of CCS plant capacity based on the assumptions shown earlier. Note that these learning rates for CCS plants as a whole are smaller than the individual component rates, largely because many of the components begin from a much larger base of experience than the overall CCS plant, and thus undergo smaller reductions in cost for each doubling of CCS plant capacity. Table 5 shows the overall changes in COE based on the learning rates in Table 4. The largest COE reduction (18%) is seen for the IGCC system and the smallest (10%) for the oxyfuel system. The sensitivity of these results to key assumptions of the analysis is explored next.

## 6. Sensitivity analysis

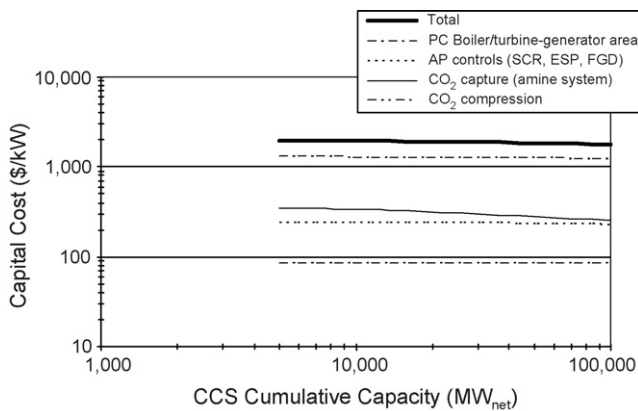
Here, we examine the sensitivity of our results to uncertainties or variability in a number of factors. First, Table 4 shows the range of learning rate results for plant-level COE for a change

**Table 3 – Sub-systems for each of the power plants analyzed**

Plant components	Current GW <sub>equiv</sub>
<b>NGCC plant</b>	
GTCC system (G)	240
CO <sub>2</sub> capture system (F)	10
CO <sub>2</sub> compression (N)	10
<b>IGCC plant</b>	
Air separation unit (O)	50
Gasifier area (L)	10
S removal/recovery (F)	50
CO <sub>2</sub> capture system (F)	10
CO <sub>2</sub> compression (N)	10
GTCC system (G)	240
<b>PC plant</b>	
Supercritical boiler/turbine (B)	120
Air pollution controls (F, S)	230
CO <sub>2</sub> capture system (F)	10
CO <sub>2</sub> compression (N)	10
<b>Oxyfuel plant</b>	
Air separation unit (O)	50
Supercritical boiler/turbine (B)	120
Air pollution controls (F)	230
CO <sub>2</sub> distillation (L)	10
CO <sub>2</sub> compression (N)	10

The letter in parenthesis indicates the case study learning rates (Table 1) assumed for each component (B = PC boiler, F = FGD system, G = GTCC system, L = LNG plant, N = no change, O = oxygen production, and S = SCR system). In addition, the fuel cost component for each plant assumes a learning rate of 4% to reflect plant-wide efficiency gains that reduce fuel use per unit of net plant output. Estimates of current component capacity reflect the experience base on which new CCS plants build, expressed in terms of equivalent electric power plant capacity.

in the component-level learning rates of approximately plus or minus 50% of the nominal values derived from the historical case studies. Compared to the nominal values in Table 4, the range of learning rates for the COE of the four plant types broadens to 1–8% for each doubling of CCS plant capacity. The corresponding reductions in COE after 100 GW of experience (Table 5) broaden to a range of 3–26% below the initial COE.



**Fig. 5 – Capital cost projection for the supercritical PC plant with post-combustion CO<sub>2</sub> capture assuming cost reductions begin after 5 GW of installed capacity.**

**Table 4 – Learning rates for total plant capital cost, O&M cost and cost of electricity (excluding CO<sub>2</sub> transport and storage costs). r<sup>2</sup> values reflect goodness of fit**

Technology	Nominal	r <sup>2</sup>	Range
<b>Capital cost</b>			
NGCC plant	0.022	0.96	0.012–0.036
PC plant	0.021	0.97	0.011–0.035
IGCC plant	0.050	0.99	0.025–0.076
Oxyfuel plant	0.028	0.97	0.014–0.044
<b>O&amp;M cost</b>			
NGCC plant	0.039	1.00	0.004–0.055
PC plant	0.057	0.99	0.020–0.083
IGCC plant	0.048	1.00	0.012–0.073
Oxyfuel plant	0.035	0.99	0.007–0.060
<b>Cost of electricity (COE)</b>			
NGCC plant	0.033	1.00	0.006–0.048
PC plant	0.035	0.98	0.015–0.054
IGCC plant	0.049	0.99	0.021–0.075
Oxyfuel plant	0.030	0.98	0.012–0.049

Here, the smallest reduction is for the NGCC plant while the greatest reduction again is for the IGCC system.

Next we analyze the sensitivity of learning rate and cost reduction results to several other key parameters:

- **Learning starts with first plant.** This case assumes that current cost estimates for CCS plants are indeed the true cost of building and operating the first full-size unit, so that subsequent cost reductions begin sooner than in the cases above.
- **Learning up to 50 GW of capacity.** This case extends the learning curve for cumulative capacity of CCS plants to 50 GW instead of 100 GW. The case studies show that this level of deployment occurred over a period of 10–15 years for FGD and SCR systems installed at coal-fired power plants.
- **Lower component capacity estimates.** This case takes a more restrictive (bounding) view of the current capacity estimates in Table 3. Amine systems for post-combustion capture are assumed to have zero experience at a 500 MW power plant; coal gasifier experience for IGCC is reduced to 1 GW<sub>e</sub>; hydrogen-fired GTCC experience at IGCC plants is lowered to zero; and the current capacity of supercritical boilers with oxyfuel combustion and flue gas recycle also is set to zero. Lower capacity estimates cause costs to fall more rapidly.
- **Additional non-CCS experience.** For illustrative purposes, a multiplier of 2.0 is assumed for all components of all plants in lieu of the nominal value of 1.0. This assumes that for every increment of CCS power plant capacity there is an equal increment of other industrial capacity adding to the total cumulative experience for each component.<sup>1</sup>

<sup>1</sup> Arguably, many of the power plant components could have larger multipliers based on a global scenario of future deployment of all technologies, but that is beyond the scope of the present study. The appropriate base of experience for learning curve analyses also is often is ambiguous. For example, had the large experience base of subcritical PC units been added to the base of supercritical experience the learning rates for PC-CCS plants would be even lower that reported here.

**Table 5 – Overall change in cost of electricity after 100 GW of capture plant capacity (excluding transport and storage costs)**

Technology	Cost of electricity (excluding transport/storage)				
	Nominal (\$/MWh)			Range (\$/MWh)	
	Initial	Final	% Change	Range	% Change
NGCC plant	59.1	49.9	15.5	46.1–57.2	3.2–22.0
PC plant	73.4	62.8	14.4	57.8–68.8	6.2–21.3
IGCC plant	62.6	51.5	17.6	46.4–57.8	7.7–25.8
Oxyfuel plant	78.8	71.2	9.7	66.7–75.8	3.9–15.4

All costs in constant US\$ 2002.

- *Higher fuel prices.* This case assumes a natural gas price of \$ 6.00/GJ and a coal price of \$ 1.50/GJ (versus nominal assumptions of \$ 4/GJ and \$ 1/GJ, respectively). The result is a higher estimate of initial COE and a larger contribution of fuel cost to total O&M cost and COE.

- *Lower financing cost and higher utilization.* This case assumes a fixed charge factor of 11% and a levelized plant capacity factor of 85%. These are the assumptions used in recent IEA GHG studies. The result is a lower estimate of total plant COE. However, the percent contribution of plant components to the total capital and O&M costs remains similar to the values shown in Table 2.

Table 6 displays the resulting trends in capital cost as well as COE. Combustion-based plants again show generally lower learning rates than gasification-based plants since a larger portion of their cost is dominated by relatively mature components. In contrast, IGCC plants have yet to realize gains in such areas as reliability and economies of scale (e.g., 1000 MW gasifier units with no spares versus today's 250 MW units with spare gasifiers for reliability) that have been a major source of historical cost reductions for more mature technologies. Opportunities for improved plant integration also can contribute to cost reductions, especially for newer technologies (e.g., IGCC and oxyfuel plants). Table 6 also shows that plant-level learning rates are most sensitive to assumptions

**Table 6 – Summary of additional sensitivity study results**

	Capital cost (\$/kW)				COE (\$/MWh)			
	Learning rate	Initial value	Final value	% Change	Learning rate	Initial value	Final value	% Change
<b>NGCC sensitivity case</b>								
Nominal base case assumptions	0.022	916	817	10.8	0.033	59.1	49.9	15.5
Learning starts with first plant	0.014	916	811	11.5	0.028	59.1	47.0	20.4
Learning up to 50 GW	0.018	916	849	7.3	0.031	59.1	52.0	12.0
Current capture capacity = 0 GW	0.029	916	786	14.2	0.037	59.1	48.8	17.4
Non-CSS exp. multipliers = 2.0	0.030	916	783	14.4	0.036	59.1	49.0	17.1
Natural gas price = \$ 6.0/GJ	0.022	925	826	10.7	0.033	76.1	64.2	15.7
FCF = 11%, CF = 85%	0.022	918	820	10.7	0.034	51.6	43.3	16.1
<b>PC sensitivity case</b>								
Nominal base case assumptions	0.021	1962	1783	9.1	0.035	73.4	62.8	14.4
Learning starts with first plant	0.013	1962	1764	10.1	0.024	73.4	60.8	17.2
Learning up to 50 GW	0.018	1962	1846	5.9	0.031	73.4	66.0	10.1
Current capture capacity = 0 GW	0.026	1962	1744	11.1	0.042	73.4	60.9	17.1
Non-CSS exp. multipliers = 2.0	0.029	1962	1723	12.2	0.044	73.4	60.4	17.8
Coal price = \$ 1.5/GJ	0.021	1965	1786	9.1	0.035	79.6	68.2	14.3
FCF = 11%, CF = 85%	0.021	1963	1785	9.1	0.039	57.2	48.2	15.7
<b>IGCC sensitivity case</b>								
Nominal base case assumptions	0.050	1831	1505	17.8	0.049	62.6	51.5	17.6
Learning starts with first plant	0.029	1831	1448	20.9	0.032	62.6	48.6	22.4
Learning up to 50 GW	0.044	1831	1610	12.1	0.045	62.6	54.9	12.2
Current gasifier capacity = 1 GW	0.057	1831	1460	20.3	0.055	62.6	50.2	19.7
Above + H2-GTCC = 0 GW	0.088	1831	1285	29.8	0.078	62.6	45.9	26.6
Non-CSS exp. multipliers = 2.0	0.062	1831	1432	21.8	0.059	62.6	49.5	20.8
Coal price = \$ 1.5/GJ	0.050	1834	1507	17.8	0.048	68.4	56.6	17.3
FCF = 11%, CF = 85%	0.048	1832	1516	17.2	0.047	47.2	39.2	16.9
<b>Oxyfuel sensitivity case</b>								
Nominal base case assumptions	0.028	2417	2201	9.0	0.030	78.8	71.2	9.7
Learning starts with first plant	0.013	2417	2160	10.7	0.017	78.8	68.6	12.9
Learning up to 50 GW	0.023	2417	2291	5.2	0.025	78.8	74.3	5.8
Current boiler capacity = 0	0.054	2417	2008	16.9	0.056	78.8	65.1	17.5
Non-CSS exp. multipliers = 2.0	0.038	2417	2122	12.2	0.040	78.8	68.8	12.7
Coal price = \$ 1.5/GJ	0.028	2421	2204	9.0	0.030	84.7	76.4	9.8
FCF = 11%, CF = 85%	0.028	2418	2202	9.0	0.031	58.8	53.0	9.9

All costs in constant US\$ 2002, excluding transport and storage costs.



**Table 7 – Percentage reduction in the cost of CO<sub>2</sub> capture after 100 GW of capacity**

Technology	Capital cost	Total cost
NGCC, post-combustion	20	40
PC, post-combustion	15	26
IGCC, pre-combustion	15	20
Oxyfuel combustion	13	13

about when learning begins and the magnitude of current and future experience for major sub-systems. The absolute value of future costs depends more strongly on assumptions about the design and current cost of each technology.

Finally, while the results above focus on total plant costs with CO<sub>2</sub> capture, there is also interest in potential cost reductions for the capture system alone. Here, the cost of CO<sub>2</sub> capture is defined as the cost difference between plants with and without capture at any point in time. This recognizes that the cost of a reference plant without capture does not remain constant, but also tends to decrease with experience. Table 7 shows the percentage reduction in the cost of CO<sub>2</sub> capture after 100 GW of CCS plant capacity based on the nominal assumptions for this study. Compared to the base case results in Table 6, the capital cost and total cost of capture are seen to decline faster than the corresponding costs for the total plant (e.g., a reduction of 13–40% in capture cost versus a 10–18% reduction in COE across all plant types). In large part, this again reflects the differences in maturity of current CO<sub>2</sub> capture systems and the reference plant technologies to which they are applied.

## 7. Caveats and concluding remarks

Projections of technological change are a critical factor in analyses of alternative futures and the impacts of policy interventions to address global climate change. In this context, the results of this study can be useful in projecting and bounding estimates of future cost for power plants with CO<sub>2</sub> capture based on historical rates of change for similar technologies. An important caveat in this regard is to recall that the cost and learning curve estimates in this study do not include the costs of CO<sub>2</sub> transport and storage, which add to the total operating cost of plants with CCS. Because these costs are generally small relative to the cost of the plant with capture (Metz et al., 2005), the impact on results presented here are not likely to be large. However, future study is needed to estimate future cost trends for these components and their impact on overall learning rates for the full CCS system.

A study of this nature also has other important limitations that must be recognized. For one, while the concept of a constant learning rate is a convenient and widely used measure to characterize technological change, often it is an over-simplification of actual cost trends for large-scale technologies (Yeh et al., 2006). For example, several technologies in this study displayed cost increases during early commercialization, followed by subsequent decreases. In other cases, actual cost trends are better represented by an S-shaped curve, in which learning is initially slow, then accelerated, then gradually slow again (Rubin et al., 2006; Yeh

et al., 2006). While sensitivity analysis can help quantify the consequences of variable learning rates, alternative representations of technological learning, including models that account for additional factors such as R&D spending, may in the future provide insights beyond the scope of the present study. Also as noted earlier, technology innovation in this study is based on the historically dominant mode of continuing improvements to existing technologies (especially true in the electric power industry). However, if radically new CO<sub>2</sub> capture technologies or plant designs were to be developed and adopted commercially, the resulting cost reductions could be greater than those estimated here.

Within the current framework, additional sensitivity analyses could provide a more comprehensive picture of how alternative assumptions for various plant design and learning rate parameters influence reported results. Extensions of the current analysis also could incorporate the costs of CO<sub>2</sub> transport and storage technologies and their projected trends, as well as improvements in CO<sub>2</sub> capture efficiency and its impact on future cost. Such analyses could advance our understanding of potential improvements in the cost-effectiveness of CO<sub>2</sub> capture and the cost of CO<sub>2</sub> avoided. Software included with the current study (Rubin et al., 2006) can be used to further analyze such options.

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