Estimating Future Costs of CO_2 Capture Systems Using Historical Experience Curves

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Abstract

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 in CO_2 capture technologies applied to four types of electric power systems: pulverized coal (PC) and natural gas combined cycle (NGCC) plants with post-combustion CO_2 capture; coal-based integrated gasification combined cycle (IGCC) plants with pre-combustion capture; and coal-fired oxyfuel combustion for a new PC plants. We assess the rate of cost reductions achieved by other process technologies in the past, and by analogy with capture plant components estimate future cost reductions that might be achieved by power plants employing CO_2 capture. Effects of uncertainties in key parameters on projected cost reductions also are evaluated via sensitivity analysis.

Keywords: CO_2 capture, cost estimates, experience curves, technology innovation, PC plants, IGCC plants, NGCC plants, oxyfuel plants

Introduction

Given the growing worldwide interest in CO_2 capture and storage (CCS) as a potential option for climate change mitigation, the expected future cost of CCS technologies is of significant interest. Most studies of CO_2 capture and storage costs have been based 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 long-term competitiveness of CO_2 capture systems in different applications, and the overall role of CCS as a climate mitigation strategy. To address this problem, most large-scale energy-economic models used to assess global climate change mitigation policies and strategies assume some degree of technological improvement over time. While models (and modellers) differ in the approach used to represent technological change (for example, endogenous vs. exogenous rates of improvement), there is currently little empirical data to support assumptions regarding future CO_2 capture costs for power plants and other industrial processes. The objective of the present study is to develop projections of future cost trends based on historical observations for other technologies relevant to CO_2 capture systems.

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_2 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 and operating and maintenance (O&M) cost of each technology. To estimate future cost trends for plants with CO_2 capture, we first decompose each of the 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_2 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_2 capture. We also quantify the effect of uncertainties in component learning rates and other key parameters. Although technologies and costs for CO_2 transport and storage are outside the scope of this study, these components clearly are critical to a complete CCS system. The following sections provide additional details of the study methodology and results obtained.

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. 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 [1].

Table 1 summarizes the learning rates for capital and O&M cost for the seven technologies examined. Results for three of the technologies (FGD, SCR and GTCC) are based on previous studies [2–4], while the remaining four (Figure 1) are newly derived. Detailed descriptions and discussions of each technology are presented elsewhere [5]. All learning rates derived in this study fall within the range reported in the literature for an array of energy-related technologies [6]. Factors contributing to 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. Summary of learning rates for capital and O&M costs, and whether a cost increase was observed during the early stages of commercialization.

Technology	Learning Rate*		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	0.07-0.30	n/a**
LNG production	0.14	0.12	Yes
Oxygen production	0.10	0.05	n/a
Hydrogen production (SMR)	0.27	0.27	n/a

*Fractional reduction in cost for each doubling of total production or capacity. **n/a=not available.

Table 1 also indicates that four of the seven technologies displayed an increase in cost during the early stages of commercialization, as illustrated in Figure 1(a) and Figure 2. 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.

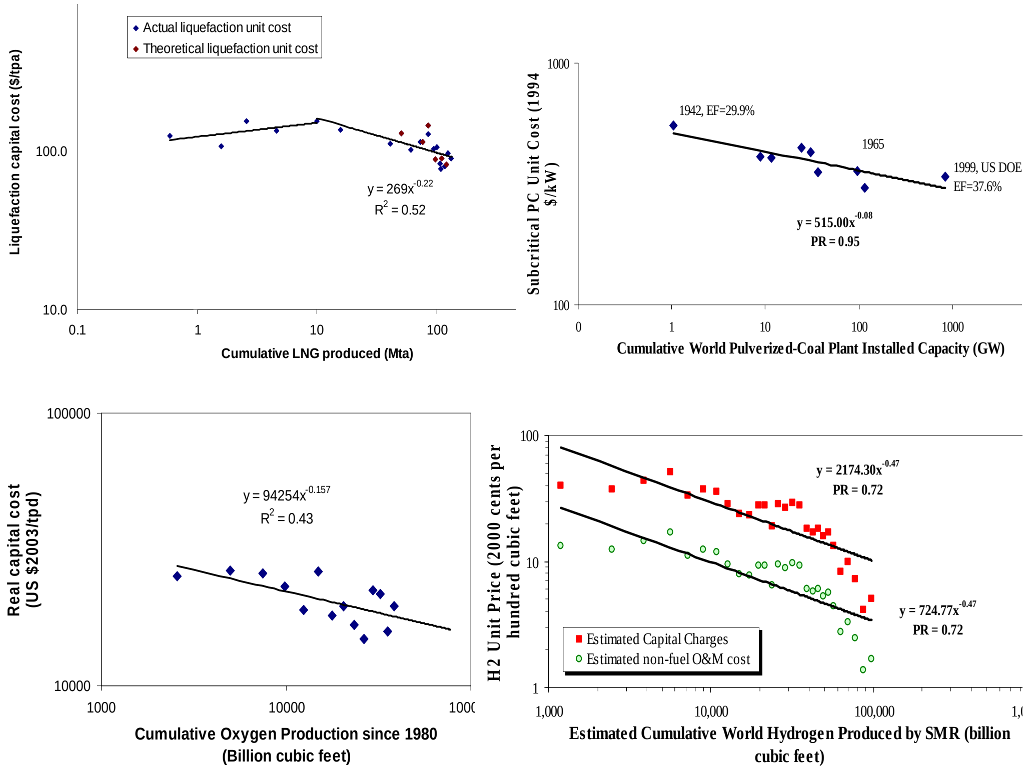

Figure 1. Capital cost experience curves derived in this study for four processes: (a) LNG production, (b) PC boilers, (c) oxygen production, and (d) hydrogen production via steam methane reforming.

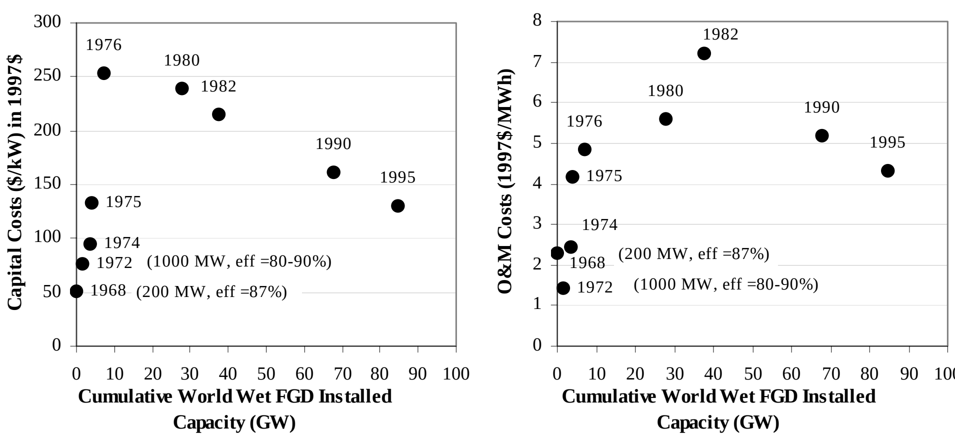

Figure 2. Capital and O&M cost trends for wet limestone FGD systems at a new coal-fired power plant in the U.S. (500 MW, 90% SO_2 capture), including cost studies conducted during the period of early commercial applications.

Application to Power Plants with CO_2 Capture

A number of recent studies have estimated the cost of CO_2 capture at power plants [7]. Here we use the Integrated Environmental Control Model (IECM) developed at Carnegie Mellon University [8] to estimate the current cost of four plant types (PC, NGCC, IGCC and oxyfuel). IECM costs are comparable to other reported costs under similar assumptions. In this study, plants are assumed to have a net output of approximately 500 MW, a levelized capacity factor of 75%, and a capture system that removes 90% of the CO_2 produced and compresses it to 13.8 MPa.

Starting with the estimated current cost, we use the historical learning rates reported in Table 1 to project the future costs of major power plant sub-systems (Table 2) as new plant capacity is built. 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. Component costs are then summed to obtain the total plant cost as a function of total installed capacity. From this, a learning curve of the form $Y = ax^{-b}$ is derived for the overall plant. One drawback of this approach is that it does not explicitly include potential cost increases that may arise when integrating components that have not yet been proven for the application and/or scale assumed. For example, no IGCC power plant has yet combined CO_2 capture with a gas turbine fired by a H_2-rich fuel gas at a scale of 500 MW. Nor has an oxyfuel combustion plant compressing concentrated CO_2 yet been demonstrated at a commercial scale. Since there is no easy or reliable method to quantify potential cost increases during early commercialization (a common phenomenon also seen in several of the case studies), we instead assume that any such costs 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, the higher plant costs incurred initially are gradually reduced (via learning-by-doing and continued R&D). The cumulative capacity at which the total plant cost equals the currently estimated cost (C_{min}, a parameter of the analysis) is when learning (cost reduction) is assumed to begin. Similarly, a capacity parameter C_{max} defines the end point of the projected learning curve. Other variables in the analysis are the current (initial) capacity of each plant sub-system, and a set of multipliers to reflect additional experience from continued deployment of plant components in applications other than power plants with CO_2 capture (sometimes called cluster learning). Full details of all assumptions and calculation procedures are described in Ref. [5].

Table 2. Sub-systems for each of the power plants analyzed.

NGCC Plant	PC Plant	Oxyfuel Plant	IGCC Plant
GTCC system CO_2 capture system CO_2 compression Fuel use	Boiler/turbine area Air pollution controls CO_2 capture system CO_2 compression Fuel use	Air separation unit Boiler/turbine area Air pollution controls CO_2 distillation CO_2 compression Fuel use	Air separation unit Gasifier area S removal/recovery CO_2 capture system CO_2 compression GTCC system Fuel use

Results for CO_2 Capture Plants

Table 3 shows the overall learning rates for the total levelized cost of electricity (COE) for each plant from the onset of learning (a variable in the study) to a future point where the total installed capacity of each system reaches 100 GW worldwide. The nominal values reflect a set of base case assumptions for each plant sub-system, while the ranges reflect uncertainty in the component-level learning rates. The nominal learning rates show a 3–5% decrease in COE for each doubling of capacity; with uncertainty the range is 1–8%. Based on these rates, Table 4 shows the overall change in COE. The largest cost reduction (18%) is seen for the IGCC system and the smallest (10%) for the oxyfuel system. The results with learning rate uncertainties show a broader range of COE reductions, from 3–26%. The sensitivity of results to other parameters is shown in Table 5, which displays projected trends in capital cost as well as COE. Overall ranges are slightly greater than those in Table 4. Combustion-based plants, whose cost is dominated by relatively mature components, show generally lower learning rates than gasification-based plants. For similar reasons, the cost of CO_2 capture (defined as the cost difference between plants with and without capture at any point in time) declines faster than the total cost of generation (a reduction of 13–40% across the four plant types, as compared to 10–18% for COE) [5].

Table 3. Learning rates for total cost of electricity (excluding transport & storage costs)

Technology	Learning Rates for Total Plant COE (excl transport/storage)		
	Nominal	r^2	Range
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

Table 4. Overall change in cost of electricity after 100 GW of capture plant capacity

Technology	Cost of Electricity (excl 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

Table 5. Summary of additional sensitivity study results

NGCC Sensitivity Case	Capital Cost ($/kW) Learning Rate	Initial Value	Final Value	% Change	COE ($/MWh) Learning Rate	Initial Value	Final Value	% Change
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%

PC Sensitivity Case	Capital Cost ($/kW) Learning Rate	Initial Value	Final Value	% Change	COE ($/MWh) Learning Rate	Initial Value	Final Value	% Change
Nominal Base Case Assumptions	0.021	1,962	1,783	9.1%	0.035	73.4	62.8	14.4%
Learning Starts with First Plant	0.013	1,962	1,764	10.1%	0.024	73.4	60.8	17.2%
Learning up to 50 GW	0.018	1,962	1,846	5.9%	0.031	73.4	66.0	10.1%
Current Capture Capacity = 0 GW	0.026	1,962	1,744	11.1%	0.042	73.4	60.9	17.1%
Non-CSS Exp. Multipliers = 2.0	0.029	1,962	1,723	12.2%	0.068	73.4	60.4	17.8%
Coal Price = $1.5/GJ	0.021	1,965	1,786	9.1%	0.035	79.6	68.2	14.3%
FCF = 11%, CF = 85%	0.021	1,963	1,785	9.1%	0.039	57.2	48.2	15.7%

IGCC Sensitivity Case	Capital Cost ($/kW) Learning Rate	Initial Value	Final Value	% Change	COE ($/MWh) Learning Rate	Initial Value	Final Value	% Change
Nominal Base Case Assumptions	0.050	1,831	1,505	17.8%	0.049	62.6	51.5	17.7%
Learning Starts with First Plant	0.029	1,831	1,448	20.9%	0.032	62.6	48.6	22.4%
Learning up to 50 GW	0.044	1,831	1,610	12.1%	0.045	62.6	54.9	12.2%
Current Gasifier Capacity = 1 GW	0.057	1,831	1,460	20.3%	0.055	62.6	50.2	19.7%
Above + H2-GTCC = 0 GW	0.088	1,831	1,285	29.8%	0.078	62.6	45.9	26.6%
Non-CSS Exp. Multipliers = 2.0	0.062	1,831	1,432	21.8%	0.054	62.6	49.5	20.8%
Coal Price = $1.5/GJ	0.050	1,834	1,507	17.8%	0.048	68.4	56.6	17.3%
FCF = 11%, CF = 85%	0.048	1,832	1,516	17.2%	0.047	47.2	39.2	16.9%

Oxyfuel Sensitivity Case	Capital Cost ($/kW) Learning Rate	Initial Value	Final Value	% Change	COE ($/MWh) Learning Rate	Initial Value	Final Value	% Change
Nominal Base Case Assumptions	0.028	2,417	2,201	9.0%	0.030	78.8	71.2	9.6%
Learning Starts with First Plant	0.013	2,417	2,160	10.7%	0.017	78.8	68.6	12.9%
Learning up to 50 GW	0.023	2,417	2,291	5.2%	0.025	78.8	74.3	5.8%
Current Boiler Capacity = 0	0.054	2,417	2,008	16.9%	0.056	78.8	65.1	17.5%
Non-CSS Exp. Multipliers = 2.0	0.038	2,417	2,122	12.2%	0.044	78.8	68.8	12.7%
Coal Price = $1.5/GJ	0.028	2,421	2,204	9.0%	0.030	84.7	76.4	9.8%
FCF = 11%, CF = 85%	0.028	2,418	2,202	9.0%	0.031	58.8	53.0	9.9%

Concluding Remarks

Projections of technological change are a critical factor in analyses of alternative futures, and the impacts of policy interventions to address issues such as global climate change. In this context, the results of this study can be used to help project and bound estimates of future cost trends for power plants with CO_2 capture based on historical rates of change for similar technologies.

A study of this nature also has 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 [9]. 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, and then gradually slow again [1,9]. Alternative representations of technological learning, including models that account for additional factors such as R&D spending, are a subject of on-going research, and future developments in this area may provide insights beyond the scope of the present study. We also note that this study is based on incremental improvements to existing technologies, which historically has been the dominant mode of technology innovation [10]. However, if radically new CO_2 capture technologies were to be developed the resulting cost reductions could be greater than those estimated here.

Within the current framework, a more extensive set of sensitivity analyses could provide a more detailed picture of how alternative assumptions influence reported results. Extensions of the current analysis also could incorporate the costs of CO_2 transport and storage technologies and their projected trends, as well as improvements in CO_2 capture efficiency and its impact on future cost. Such analyses could advance our understanding of potential improvements in the cost-effectiveness of CO_2 capture and the cost of CO_2 avoided. Software included with the current study [5] can be used to further analyze such options.

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