Incorporating Technological Learning in the Coal Utility Environmental Cost (CUECost) Model: Estimating the Future Cost Trends of SO_2, NO_x, and Mercury Control Technologies

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Executive Summary

Reductions in the cost of technologies as a result of learning-by-doing, R&D investments and other factors have been systematically observed over many decades. This project uses historical experience curves observed for a range of energy technologies, especially flue gas desulphurization (FGD) technology for SO_2 control and selective catalytic reduction (SCR) technology for NO_x control, as the basis for estimating future cost trends of four pollution control technologies, including limestone forced oxidation (LSFO, or wet FGD), lime spray dryer (LSD, or dry FGD), SCR, and mercury sorbent injection control technologies applicable to U.S. coal-fired utility plants. The methodology developed in the study will be incorporated in Coal Utility Environmental Cost (CUECost). CUECost has been developed by the Office of Research and Development, U.S. Environmental Protection Agency, which prodives rough-order-of-magnitude (ROM) cost estimates (+/-30% accuracy) of the installed capital and annualized operating costs for air pollution control (APC) systems installed on coal-fired power plants to control emissions of sulfur dioxide, nitrogen oxides (NO_x), and particulate matter.

Average "learning rates" are derived for capital costs and operating and maintenance (O&M) costs of wet-FGD and SCR based on historical cost estimates reported in the literature and current cost estimates by CUECost. The learning rates represent the fractional reduction in cost associated with each doubling of cumulative total capacity of the technology. The learning rates for these technologies were applied for the case study technologies to make projections for future cost reductions by 2020 based on estimates of the additional capacity of each technology expected as a result of recent environmental regulations. The projections of future mercury control technology take into account the uncertainties associated with early commercialization. Previous studies suggest costs of initial commercial plants are often higher than those estimated in pre-commercial studies. We assume that the learning rates will only be applied after a certain amount of initial Hg sorbent injection system capacity has been installed, at which point costs will start to decline. The estimated capital and O&M costs learning rates and projected cost reductions by 2020 for these technologies are summarized in Table ES-1.

Table ES-1. Summary of learning rates for capital and O&M costs and projected cost reductions by 2020 for the case study technologies.

Technology	**Learning rate (LR)**		**Projected Cost Reductions by 2020 (Best Estimate)**	
	Capital Cost	O&M Cost	Capital Cost	O&M Cost
Wet FGD (LSFO)	0.17	0.37	9.9%	22.7%
SCR	0.08	0.17	7.4%	15.8%
Dry FGD (LSD)	0.17	0.37	20.4%	42.9%
Active Sorbent Injection	0.17	0.37	28.72%	0%

This study projects higher capital cost reductions for less mature technologies. Sorbent injection for mercury control is the least mature of the four technologies considered, with the highest projected capital cost reduction within the next 15 years. SCR has the lowest projected capital cost reductions among the technologies examined here due to the low learning rate for the capital costs. In contrast, the lowest O&M cost reduction was found for the mercury control sorbent injection system. This is because we took into account the possibility of cost increases for technologies at the early commercialization stage and assumed that the learning rates will only apply after a certain amount of initial Hg sorbent injection system capacity has been installed (7.4 GW for capital cost and 42.5 GW for O&M cost, based on the wet FGD studies), at which point costs will start to decline. The capital costs of an Hg sorbent injection system are expected to decrease at a large rate by 2020 after the technology exceeds the estimated learning threshold after 2015. Based on the case studies examined and reviewed here, the study suggests

that higher learning rates were observed for the O&M costs for FGD and SCR systems. More studies, however, are needed to examine the underlying factors contributing to the higher learning rates observed for O&M costs compared to capital costs.

Uncertainty analysis is used to explore a range of cost projections associated with different assumptions regarding the experience curve. Our analysis focuses on the uncertainty of learning rates and the uncertainty associated with technology at early commercialization. An uncertainty factor of ±50% is applied to all the learning rates estimated in this study. Contingency factors are applied to the upper bound uncertainty estimates of Hg sorbent injection technology capital and O&M cost estimates. The contingency factor is intended to illustrate the possibility of cost increases at the beginning of commercialization, but it by no means represents the upper bound of possible cost increases.

Projections based on the experience curves developed in this report provide no guarantee of future performance. Nonetheless, they offer an *empirically*-grounded basis for estimating or bounding expected rate of progress in various technological domains.

Keywords: mercury control, cost estimates, experience curve, technological learning, coal power plant, uncertainty.

Acknowledgement

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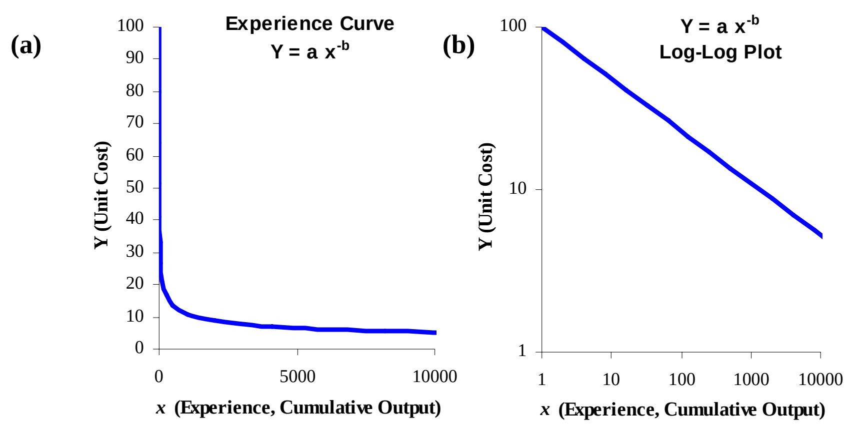
1. Introduction

The importance of technological innovation and its contributions to increased productivity, lower production costs, and economic growth are widely recognized (Yeh et al. 2007; McDonald and Schrattenholzer 2002; van der Zwaan and Seebregts 2004; Dutton and Thomas 1984; Argote 1999; Boston Consulting Group 1968). Retrospective studies often have been used to characterize the historical pattern of cost reductions associated with increased level of production in a variety of industries—a phenomenon commonly called learning-by-doing (Wright 1936; Dutton et al. 1984; Boston Consulting Group 1968). In most cases, cumulative output or capacity is used as a measure of experience to quantify overall cost reductions resulting from economies of scale, learning-by-doing, capital deepening[1] (Sinclair et al. 2000), and expenditures for research and development (Grubler and Gritsevskyi 2002), as well as other factors that influence cost trends, such as changes in market structure, organizational forgetting, variations in knowledge transferability, and government regulations (Hewlett 1996; Komanoff 1981; Argote and Epple 1990; Taylor et al. 2003). Various theories have been proposed to explain observed reductions in unit cost as cumulative output increases. Generally, they fall into three categories: (1) costs fall due to changes in production that include process innovations, worker familiarity in the use of tooling, improved management, and economies of scale; (2) costs fall due to changes in the product itself, including product innovations, redesign, and standardization; and (3) costs fall due to changes in input prices.

The notion of technological learning is often expressed through the use of an "experience curve," which was first proposed by Wright (1936) for airplane production and later reaffirmed by various pioneering scholars in this field. The experience curve has the following functional form:

$$Y = ax^b \qquad \text{(Equation 1)}$$

where Y is the estimated average cost per unit for the first x units; a is the cost needed to make the first unit; and b $(b<0)$ is a parametric constant. Learning rate (LR), $1-2^{-b}$, is the rate of cost reduction for every doubling of cumulative output, while progress ratio (PR) equals 1-LR. For example, an 80 percent "progress ratio" implies 20 percent reduction of cost for every doubling of cumulative output, in which case the exponent b equals -0.32. In a linear-scale figure, the curve shows steep cost reductions at the beginning of the curve and slower cost improvements toward the end of the curve as the technology becomes mature and the improvement in cost becomes smaller in absolute terms (Figure 1a). In a log-log space, the curve is a straight line representing constant rate of cost reduction associated with increased production (Figure 1b).



[1] Capital deepening is the increases in the amount of capital equipment available per unit of production.

Figure 1. Illustrative plots of the experience curve (Equation 1) in a (a) linear-scale plot and (b) log-log graph.

Previous studies have observed technological learning in a wide range of industries and products (Arrow 1962), including ship production (Argote and Epple 1990; Argote et al. 1990), airplane production (Alchian 1963; Benkard 1999; Garg and Milliman 1961), electronics, chemicals and consumer goods, and energy and pollution control technologies (IEA/OECD 2000; McDonald and Schrattenholzer 2001; Rubin, Taylor et al. 2004). Figure 2 shows that the observed learning rates are typically in the range of 0 – 40%, with few outliers in both sides of the distribution (negative learning rate implies cost increases with increased production). Figure 3 shows the observed experience curves for selected electricity generation technologies (IEA/OECD 2000).

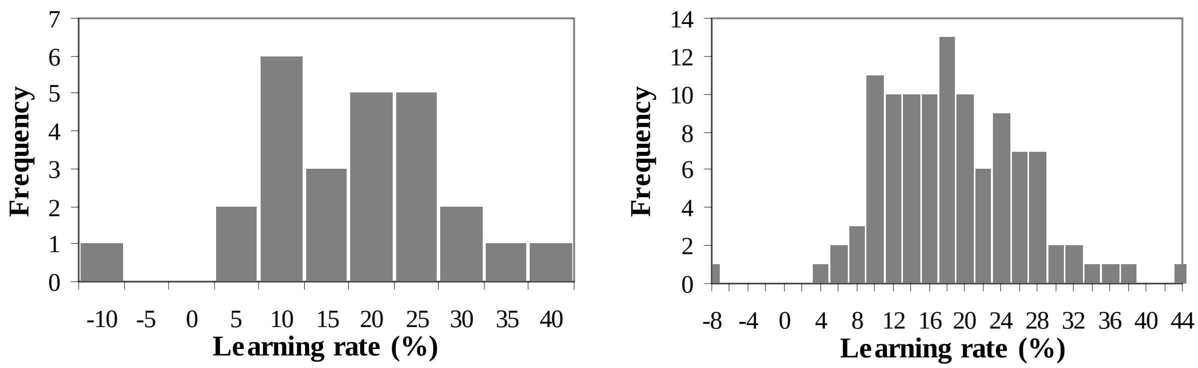


Figure 2. Distribution of observed learning rates for 42 energy technologies (left panel) and 108 manufacturing products (right panel).
Source: Modified from McDonald and Schrattenholzer (2001)

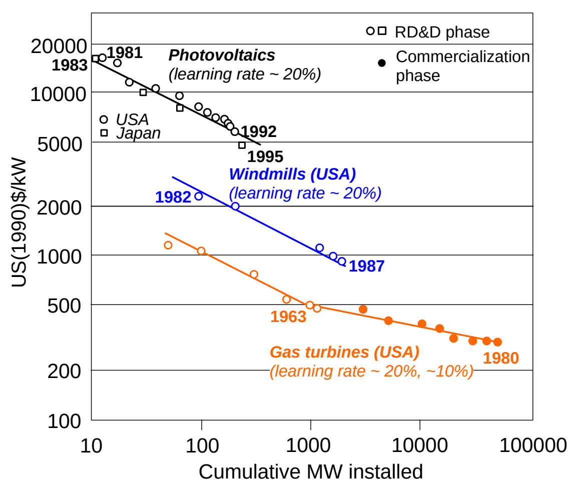


Figure 3. Learning curves for selected electricity generation technologies.
Source: IEA/OECD (2000)

Several studies have examined the technological histories of environmental control technologies and how the level of technological innovations is affected by government policies and regulations worldwide (Taylor, Rubin, and Hounshell 2003; Rubin, Taylor et al. 2004; Yeh et al. 2005; Yeh et al. 2007). These studies have shown that the technological innovations and diffusion of sulfur dioxide (SO_2) (Taylor, Rubin, and Hounshell 2003) and nitrogen oxide (NO_x) control technologies (Yeh et al. 2005) over the past 30 years are affected by government policies, and significant learning has been observed for flue gas desulfurization (FGD) systems and selective catalytic control (SCR) technology (Rubin, Yeh et al. 2004) for coal-fired power plant application.

Recently, an increasing number of studies are using the experience curve approach to make future projections of technology cost (van der Zwaan and Rabl 2003; Claeson Colpier and Cornland 2002; Grubb et al. 2002; Riahi, Rubin, Taylor et al. 2004; Rubin et al. 2007). These studies make projections of future technology costs based on the observed learning rates of the same or similar technologies. Projections based on this type of "learning curve" provide no guarantee of future performance. Nonetheless, they offer an *empirically*-grounded basis for estimating or bounding expected rate of progress in various technological domains (Gumerman and Marnay 2004; Rubin et al. 2007; Riahi, Rubin, and Schrattenholzer 2004).

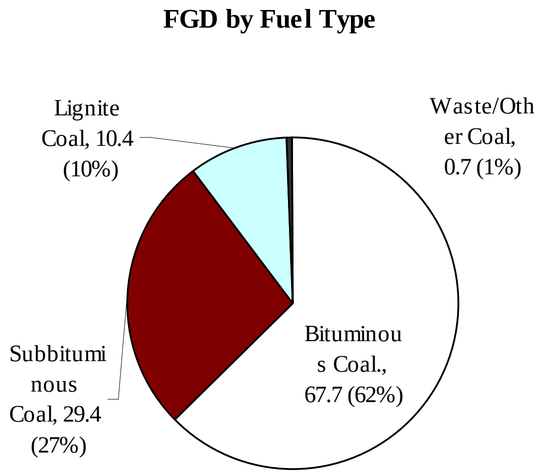
The objective of the project is to develop methodologies to make projections for future costs of environmental control technologies, including limestone forced oxidation (LSFO, wet FGD), SCR, lime spray dryer (LSD, dry FGD), and mercury sorbent injection control technologies in CUECost. These four technologies will be affected by the new U.S. Environmental Protection Agency (EPA) regulations, including the Clean Air Interstate Rule (CAIR) and the Clean Air Mercury Rule, that require substantial SO_2, NO_x, and mercury emission reductions from coal-fired power plants. CUECost workbook produces rough-order-of-magnitude (ROM) cost estimates (+/-30% accuracy) of the installed capital and annualized operating costs for air pollution control (APC) systems installed on coal-fired power plants to control emissions of SO_2, NO_x, particulate matter, and mercury. Previous studies of wet FGD and SCR learning rates will serve as reasonable estimates of future technological progress for the costs of wet FGD, SCR, dry FGD, and mercury sorbent injection control technologies. Uncertainty analysis is conducted to take into account the extrapolation uncertainty (how to extrapolate the learning rate observed in the past to project the future costs of the same technology and/or the future costs of similar technologies) and uncertainty of emerging technology (how to appropriately account for cost uncertainties usually observed for new technologies). The technical reviews of FGD, SCR, and mercury sorbent injection control technologies have been extensively presented elsewhere (e.g., Srivastava and Jozewicz (2001), Srivastava et al. (2004), Srivastava et al. (2006)) and also in CUECost documentation (EPA 2007). Thus the details of these technologies will not be reviewed here.

This report is divided into the following sections. Section 2 briefly describes the current status of FGD, SCR, and mercury control technology (specifically, the active carbon injection (ACI) system) applied in coal-fired power plants in the U.S. and abroad. The future projected installed capacities of these technologies to 2020 are estimated based on available data or an assumed growth rate. Section 3 summarizes previous findings on the experience curves of wet FGD and SCR and the current cost estimates for wet FGD, dry FGD, SCR and ACI from CUECost. The methodology of using the experience curve approach to make future cost projections of the four technologies will be described, and examples will be provided to demonstrate how the applications are incorporated into CUECost. Section 4 will describe how future projections are affected by uncertainties in key assumptions regarding the experience curves, focusing on the learning rates (how fast the technologies learn) and the shape of the curve (the possibility of cost uncertainties during early technology deployment).

2. Current Status and Future Projected Markets for FGD, SCR, and Mercury Control Technologies

2.1. Current Status of FGD

The most common post-combustion SO_2 control technology in the U.S. coal-fired power plants is the flue gas desulfurization (FGD) system or "scrubbing" technology. FGD systems involve contacting the flue gas stream with a base reagent in order to remove SO_2. These systems can be categorized as wet or dry processes. Wet FGD is currently installed in roughly one third of all U.S. capacity, while dry FGD is installed in less than five percent. According to Energy Information Administration Form EIA-767: Steam-Electric Plant Operation and Design Report[2] conducted in 2004, total cumulative FGD installations in U.S. coal-fired utility plants is expected to be 102 GW by 2006 (EIA 2006), of which 96 GW are FGD units using limestone and lime sorbent. The primary coal types where FGD units are installed are bituminous coal and subbituminous coal. Other applications include lignite coal, and others (waste/other coal[3]) are less than 10% of total installation (Figure 4). The predominant FGD type utilized at U.S. coal-fired utility boilers is the wet spray scrubber with limestone reagent. Statistics on FGD types utilized in the U.S. can be seen in Figure 4.



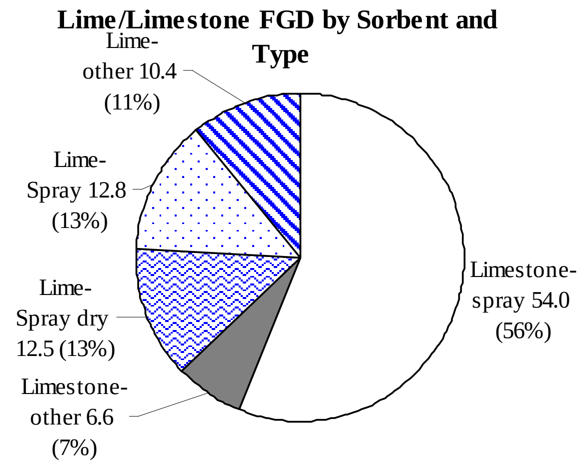
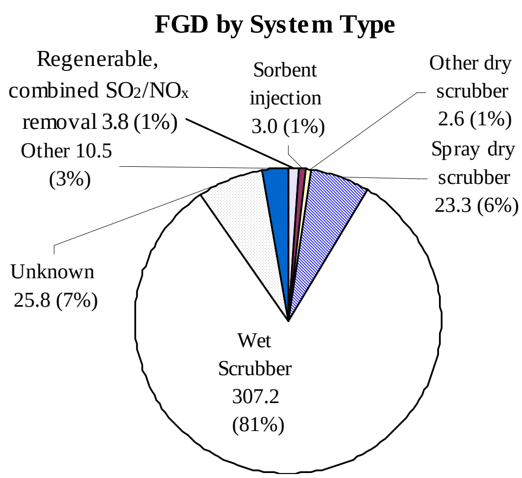
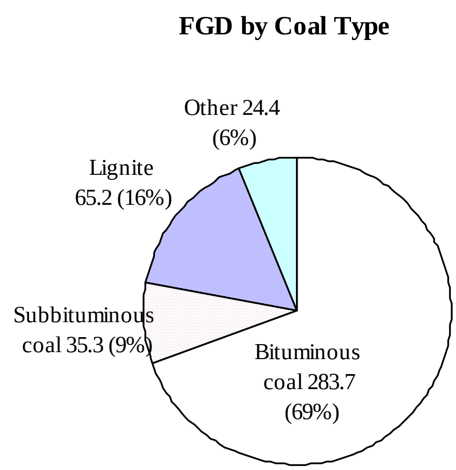


Figure 4. Breakdown of FGD in U.S. coal-fired plants by fuel type (left graph) and by sorbent and type (right graph), 2004. The units are GW and percentage (parenthesis).
Source: EIA (2006)

Figure 5 shows the world market distribution of installed post-combustion SO_2 control technologies in 2005 and Figure 6 shows the world cumulative installed capacity of FGD system by country.





[2] Form 767 is published annually by the Energy Information Agency, U.S. Department of Energy. Form EIA-767 collects information annually from all U.S. plants with a total existing or planned organic-fueled or combustible renewable steam-electric unit that has a generator nameplate rating of 10 megawatts or larger.
[3] This may include: anthracite culm, bituminous gob, fine coal, lignite waste, waste coal.

Figure 5. World market distribution of post-combustion SO_2 control technologies in 2005, by system type (left graph) and by fuel type (right graph). The units are GW and percentage (parenthesis). The sum of FGD units by fuel type is greater than the total installation since many plants use multiple types of fuels. Source: (IEA Clean Coal Centre 2005)

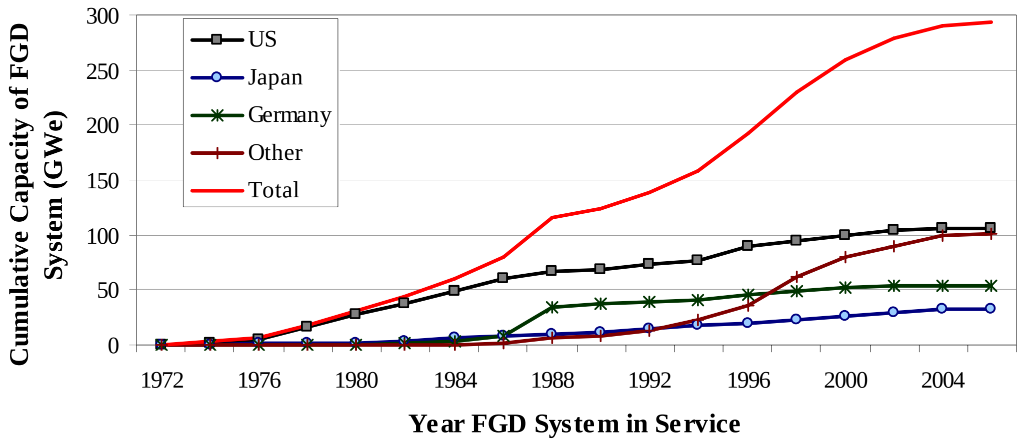


Figure 6. Cumulative FGD installed capacity (GW) by country.
Source: (IEA Clean Coal Centre 2005)

Lime spray dryer (LSD), or dry FGD, has been used commercially with low-sulfur coals in Europe and in the U.S. with an SO_2 removal efficiency of 70 to 90 percent. Unlike wet FGD, where flue gas reacts with sprayed water slurry to form calcium sulfate in the spray tower/absorber, a calcium hydroxide slurry is atomized in a dry FGD system and injected into a spray dryer tower to react with SO_2 in the flue gas. The resulting dry by-product is collected in the bottom of the spray dryer and in the particulate removal equipment. Dry FGD has lower SO_2 removal efficiency than wet FGD and is suited to plants burning low- and medium- sulfur coal (1% to 2% S). Applications of LSD in high sulfur coal (up to 4.5 percent) have been demonstrated, but more testing is required for large scale commercial applications (World Bank 1995). The installed capacity of dry FGD was estimated to be 14.4 GW and 11.0 GW in the U.S. and abroad, respectively (Srivastava et al. 2001; Maller and Hollinden 2000).

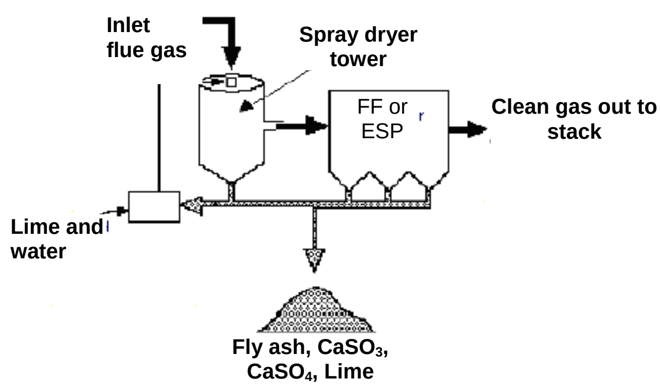


Figure 7. Illustration of a typical dry FGD system in a coal-fired power plant.
Source: World Bank (1995)

2.2. Current Status of SCR

Nitrogen oxides (NO_x) emissions have been associated with a wide variety of health and environmental impacts, including an increase in ground-level O_3, the formation of fine particles in the atmosphere, acid rain, the acidification of aquatic systems, and, more recently, global warming effects. In response to government regulations, NO_x control technology has been passing through various phases as the regulatory and commercial climates have changed. NO_x regulations prior to 1990s can easily be met with low-cost control technologies with relatively low removal efficiencies, such as combustion modification, low NO_x burner, or selective noncatalytic reduction (SNCR). After the 1990 Clean Air Act Amendment (CAAA), a series of regulations stemming from CAAA including the Title I (National Ambient Air Quality Standards) and Title IV (Acid Rain Control) established stringent NO_x emission regulations that would required SCR control in many coal-fired power plants in order to meet the new emission limits established by the new regulations (Yeh et al. 2005). The first coal-fired SCR was installed in the U.S. in 1993, by which time Japan, Germany and the rest of the world already had 44 GW cumulative installations of coal-fired SCR (Yeh et al. 2005). However, with the legislation including the 1998 Title I: NO_x State Implementation Plan (SIP) Call and the NO_x Budget Trading Program (NBTP) implemented in 2003, U.S. capacity of SCR systems was expected to grow to at least 100 GW by 2004 [2, 5, 11] and exceed other countries (Yeh et al. 2005)(Figure 8). In the U.S., 76% of SCR are installed at coal plants whose primary fuel type is bituminous coal, and the remaining 24% are installed at coal plants burning sub-bituminous coal.[4]

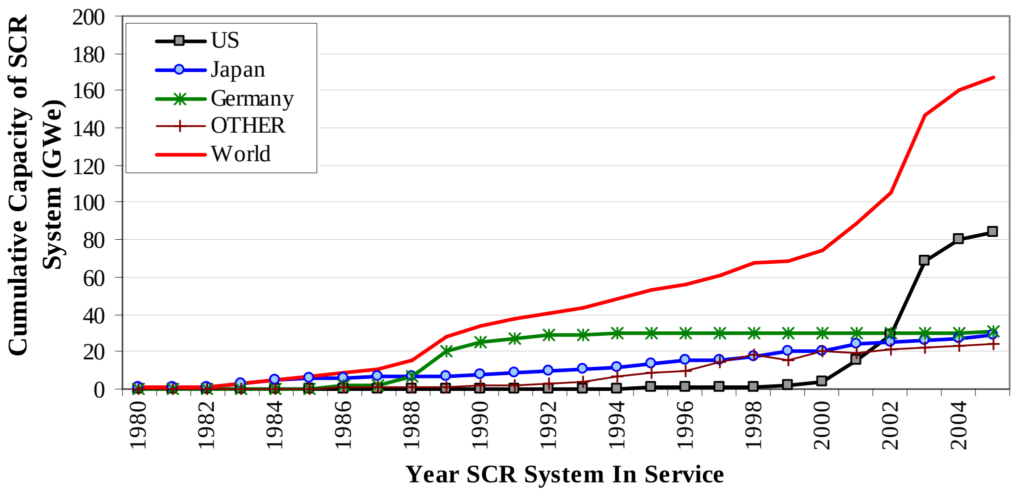


Figure 8. Cumulative SCR installed capacity (GW) by country.

Though SCR is only installed on a small fraction of the coal-fired units today, they are responsible for a much larger share of electric generation. A recent study published by the U.S. EPA examining the progress of NBTP suggests that although coal-fired units with NO_x emission controls (i.e., post-combustion controls and/or combustion controls) represent less than 30 percent of the total number of electric generating units within the affected region, they represent almost 80 percent of total electric generation (U.S. EPA 2006). It was observed that units with NO_x emission controls are deployed more often for longer periods of time (U.S. EPA 2006).

[4] SCR systems also have been deployed at some power plants burning oil or natural gas, including gas turbine plants used for peak power generation. Previous analysis of SCR learning experience on coal-fired units excludes the SCR installations in oil and gas units, as these units have very different operating conditions and thus are not considered to contribute to the same learning experience at coal-fired units. In 1997, retrofit SCR systems in the U.S. were in operation on 5.5 GW of gas-fired utility boilers, 7.8 GW of gas turbines, and less than 2 GW of coal-fired units. The projected short- to medium-term new SCR retrofits in gas-boilers are roughly the same as projected SCR-retrofits in coal-fired units.

2.3. Future Projections of FGD and SCR Applications

On March 10, 2005, EPA issued the Clean Air Interstate Rule (CAIR), which permanently caps emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_x) in the eastern United States. When fully implemented, CAIR is expected to reduce SO_2 emissions in these states, which include 28 states in the eastern United States and the District of Columbia, by over 70 percent and NO_x emissions by over 60 percent from 2003 levels. The Office of Air and Radiation of the U.S. EPA (U.S. EPA 2006) projects significant growth of SCR and FGD under the new CAIR rule. The total coal-fired capacity in the U.S. is currently 305 GW, and the number is projected to increase to about 321 GW by 2020. It is projected that by 2020, about 79% of CAIR-affected coal-fired capacity will install at least one of the following air pollution control devices: SCR/SNCR for NO_x, FGD for SO_2, activated carbon injection (ACI) for mercury (U.S. EPA 2006). The projected cumulative capacity with existing controls; controls projected to be retrofitted under the NO_x SIP Call, New Source Review (NSR) settlements, State-enacted programs, and CAA Title IV; and controls projected to be retrofitted with CAIR/Clean Air Mercury Rule (CAMR) / Clean Air Visibility Rule (CAVR) are shown in Figures 9 and 10 for FGD and SCR, respectively (U.S. EPA 2006).

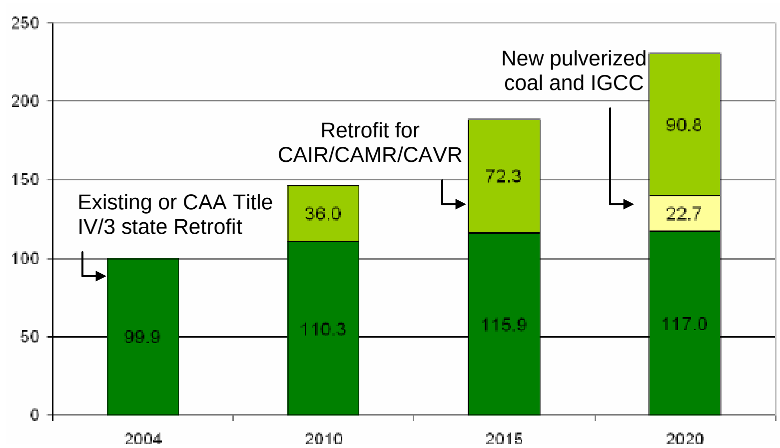


Figure 9. Projected coal-fired capacity with scrubbers (GW) by 2020. Source: U.S. EPA (2006)

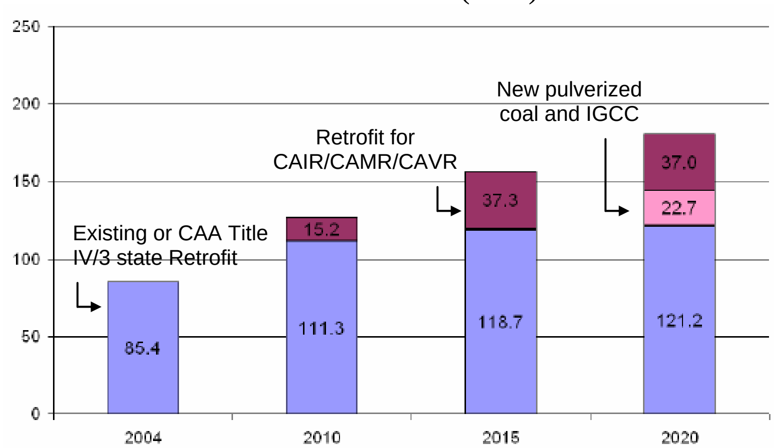


Figure 10. Projected coal-fired capacity with SCR (GW) by 2020. Source: U.S. EPA (2006)

There is currently no reliable data available on projected future world FGD and SCR installations, thus this data will be estimated. The International Energy Outlook of 2006 (EIA 2006) estimates that the worldwide installed coal-fired generating capacity will increase by 42% from 1,119 GW in 2003 to 1,590 GW in 2020. Most of the growth will come from China (292 GW) and India (73GW). In China, only limited numbers of FGDs are in operation today, mostly in the Southwest region where the coal sulfur content is around 4 percent, or 5-10 times the level typical throughout most of north and east China (Martinot 2001). Recent regulatory actions to control sulfur pollution in China prompted many coal-fired power plants to switch to low-sulfur coal. However, few power plants or industrial coal users have adopted specific sulfur-emission control technologies (Guttikunda et al. 2004). Studies suggest that there will be significant sulfur emission controls in Asia due to significant economic growth in the next two to three decades, and these emission reductions are expected to come from a combination of emission controls. Most emission reductions are expected to occur after 2020 (Smith 2005), though no direct numbers on projected FGD units have been provided in any studies we have reviewed so far. Similar to China, local and regional pollution are major problems in Russia and India and airborne emissions of NO_x, SO_2, and particulates are among the highest in the world (IEA 2004). Aggressive emission controls for SO_2 and NO_x emissions in these regions are also expected to occur after 2020 (Smith 2005; Qi et al. 1995) (Figure 11). Roughly half of the sulfur emission reductions shown in Figure 11 are expected to come from the electric sector through a combination of advanced electric generating technologies, efficiency improvement, and emission control technologies. Though no actual numbers have been proposed, it is likely that dry FGD will be more popular in developing countries due to its relatively low cost, simple operation, and high removal efficiency for plants burning low-sulfur coal. The interest to control NO_x emissions in developing countries primarily focuses on low-NO_x burner technology (Martinot 2001), thus no significant SCR installations are foreseen for China, India or Russia.

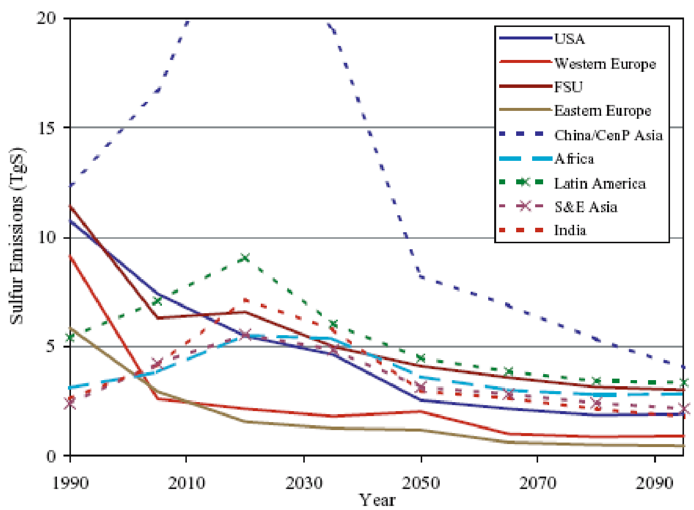


Figure 11. Projected sulfur dioxide emissions (TgS) for selected world regions.
Source: Smith (2005)

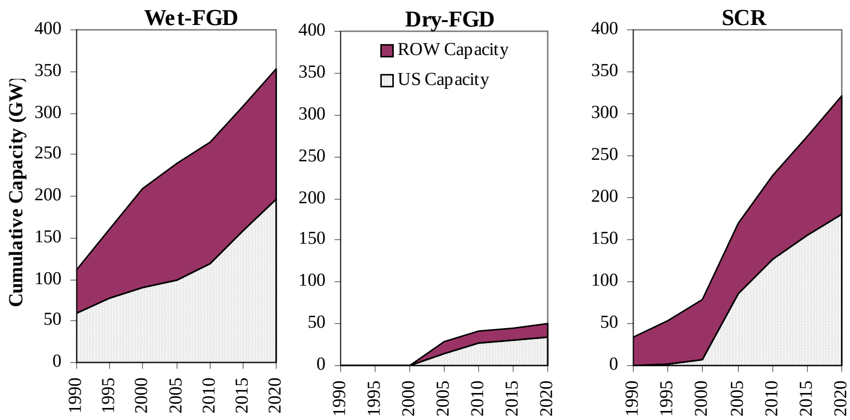
In Europe, NO_x and SO_2 emissions from electricity production have fallen by 44% and 60%, respectively, from 1990 to 1999, despite a 16% increase in the amount of electricity produced (European Environment Agency 2002). A large percentage of the reduction came from flue gas treatment at coal-fired power plants using FGD and SCR technologies. The remaining decrease, for both NO_x and SO_2, was due to fuel switching to natural gas or low sulfur coal, improved efficiency, and an increased share of nuclear and renewables (European Environment Agency 2002). The National Emission Ceilings Directive (NECD) and the Large Combustion Plant Directive passed in 2001 set SO_2 and NO_x emission targets for each EU Member State and for all new and existing plants of 50MW or larger are expected to reduce these emissions even further. Though no projected FGD or SCR installations can be found in the published peer-reviewed literature, the CoalPower5 database published by the IEA Clean Coal Centre (IEA Clean Coal Centre 2005) contains data on the existing and *planned* FGD and SCR installations up to 2010. The planned installations in CoalPower5 will be used for our estimates of the world's (excluding the U.S.) future FGD and SCR installations to 2010. This number should be considered as the lower-bound estimate, as it only captures planned units reported to the IEA Clean Coal Centre before 2005.

Table 1 summarizes the cumulative wet FGD, dry FGD and SCR installed capacities from 1990 to 2005 and the projected U.S. and world installations by 2020. Since the projection in Figure 9 does not make a distinction between wet FGD and dry FGD installations, the proportion between wet/dry FGD in 2010-2020 is assumed to be the same as in 2005.

Table 1. Historical and projected coal-fired FGD (wet/dry) and SCR cumulative capacity (GW) to 2020.

	Wet FGD			**Dry FGD**			**SCR**		
	US	ROW	World	US	ROW	World	US	ROW	World
1990	59.9	51.5	111.4					33.8	33.8
1995	77.7	82.9	160.6				1.2	52.0	53.4
2000	89.5	120.1	209.6				7.2	70.8	78.0
2005	99.9	139.9	239.8	14.4	13.9	28.8	85.4	84.0	169.4
2010	119.2	145.0	264.2	27.1	14.4†	54.1	126.5	99.5*	226.0
2015	158.0	150.3*	308.2	30.3	15.5†	60.5	156.0	118.0*	274.0
2020	197.1	155.7*	352.8	33.4	16.0†	66.9	180.9	139.9*	320.8

ROW: Rest of the world
* Assumes the same growth rate as the previous period
† Assumes the same growth rate as wet FGD-ROW for the same time period.



Source: (EIA 2006; U.S. EPA 2006, 2005; Srivastava and Jozewicz 2001; IEA Clean Coal Centre 2005)

2.3 Mercury Control via Active Sorbent Injection (ASI)

Mercury is one of the natural elements in Earth's crust. It exists in rocks and coals, and it can also be found in air, water, and soil. Coal-burning power plants release mercury into the air during combustion, which contributes to over 40 percent of all domestic anthropogenic mercury in the U.S. On March 15, 2005, EPA issued the Clean Air Mercury Rule, which creates performance standards and establishes permanent, declining caps on mercury emissions. Though some mercury emissions can be captured via conventional environmental control technologies, such as electrostatic precipitator (ESP) and fabric filter (FF) for PM control, FGD and SCR, the capture efficiencies vary. It is expected that for some areas the total co-benefits from these conventional control technologies will not be sufficient to meet the more stringent mercury standard (Srivastava et al. 2006). Thus the installation of pollution control technologies to remove mercury from flue gas will be needed. One of the most promising technologies to control mercury emissions from coal-fired power plants is the active sorbent injection (ASI), especially the active carbon injection (ACI). Similar to dry FGD, mercury can be controlled via the injection of sorbent materials into the flue gas stream upstream of the existing PM control device. Typically, ASI injects powered sorbent into the flue gas upstream of the existing PM control device (ESP or FF). (Figure 12). The sorbent is then collected in the downstream PM control device, which effectively segregates the fly ash and injected sorbent. Detailed review of the mercury control technologies and the co-control benefits with other pollutant control technologies can be found elsewhere (Srivastava et al. 2006; U.S. EPA 2005).

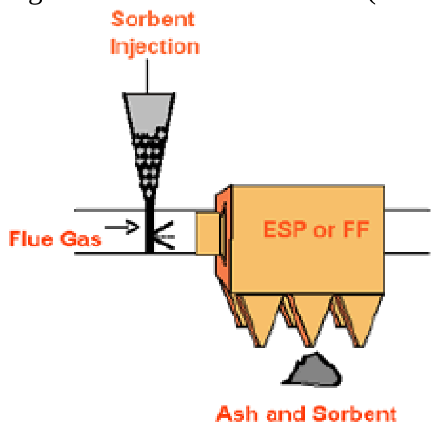


Figure 12. Schematic of Activated Carbon Injection for Mercury Control.
Source: www.epa.gov/mercury/control_emissions/fig3.gif

A study conducted by the EPA (U.S. EPA 2006) predicts that future installation of mercury control technologies, specifically ACI, in coal-fired power plants under the new Clean Air Mercury Rule (CAMR) will require roughly 10.9 GW of ACI installations by 2020 (Figure 13). These ACIs are predicted to be installed in plants with dry and wet FGDs (U.S. EPA 2005). Since the U.S. is the first country in the world to regulate mercury emissions from coal-fired power plants, we do not expect there will be other ACI installations in the world within the next 10-15 years.

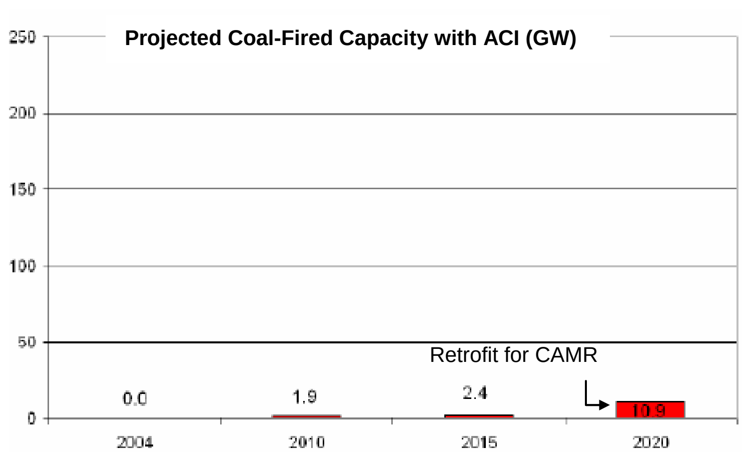


Figure 13. Projected coal-fired capacity with ACI control technology (GW) by 2020.
Source: (U.S. EPA 2006)

3. Experience Curves and Projections for Future Cost Estimates

3.1 Limestone Forced Oxidation, LSFO

It is expected that at least 70% of coal-fired capacity will utilize installed scrubbers (most of them wet scrubbers) by 2020 (Figure 9). Previous studies suggest that the capital costs of FGD were reduced by more than 50% from 1976 to 2005, and more than 50% from 1982 to 2005 for the O&M costs (Figures 14 and 15) (Rubin, Yeh et al. 2004; Taylor, Rubin, and Hounshell 2003) and are expected to continue to decrease in the future (Burtraw et al. 2005; Carlson et al. 2000). Many process improvements contributed to lowering the capital costs, especially improved understanding and control of process chemistry, improved materials of construction, simplified absorber designs, and other factors that improved reliability.

The updated experience curve of wet FGD (LSFO) is calculated by fitting to the historical capital cost data reported in previous studies (Taylor, Rubin, and Hounshell 2003; Rubin et al. 2003) and the 2005 value estimated using CUECost. A retrofit factor of 1.3, the default retrofit factor in CUECost, is used to convert the capital cost estimates for new units previously reported, to the capital costs of retrofit units. The data series is fitted to a log-linear experience curve function: $Y = ax^b$ (Equation 1). Extra weight is given for the value estimated by CUECost, to force the regression line to pass through CUECost estimate. The fitted curve is shown in Figure 14. All capital costs were adjusted to $2005 using the Chemical Engineering Plant Cost Index (CEPCI).

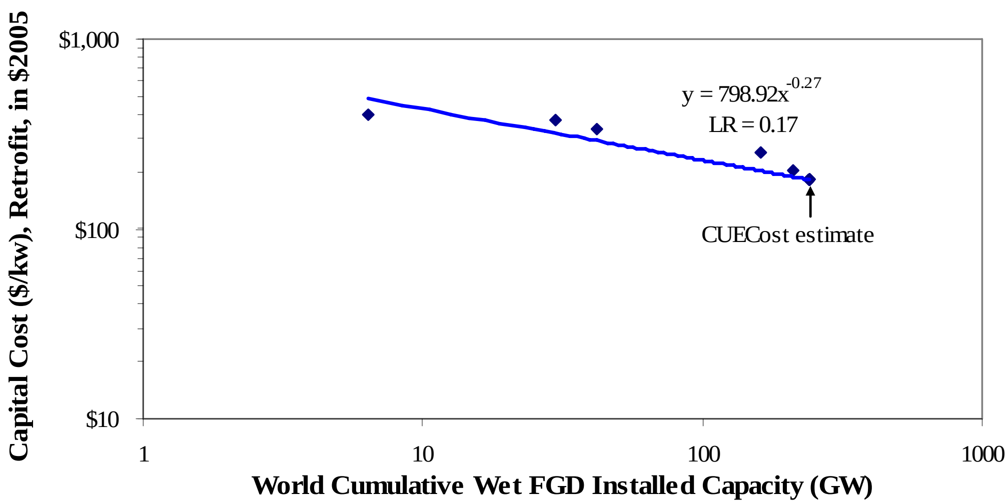


Figure 14. Experience curve of wet FGD capital costs.
(500 MW, 3.5% sulfur coal, 90% SO_2 removal, retrofit factor 1.3, 2005 dollars)

The fitted experience curve for wet FGD capital cost is $Y = 798.92x^{-0.27}$ (Figure 14)[5]. In other words, we estimate that the capital cost of wet FGD has been reduced by 17% for every doubling of cumulative capacity. Assuming that the same learning pattern will continue at least to 2020, the experience curve is extrapolated to make future cost projections. The experience curve approach assumes that the *rate* of cost reduction is constant as cumulative installed capacity increases, though the *absolute* changes in cost become smaller as the technology matures (see Figure 1). Appendix 1 provides a detailed example of how the calculations are implemented in CUECost.

The calculation of O&M cost projections follows the same methodology. The experience curve of LSFO O&M cost is calculated by fitting to the historical O&M cost estimates reported in previous studies (Taylor, Rubin, and Hounshell 2003; Rubin et al. 2003) and the 2005 value estimated using CUECost, again adjusted to a common basis. Extra weight is given for the value estimated by CUECost to force the

[5] The learning rate estimated here (16%, b = -0.26) is higher than our earlier estimate (13%, b = -0.20) reported in Rubin et al. (2006), since we try to fit the experience curve through the 2005 CUECost estimate. The discrepancy will be addressed using uncertainty analysis in Section 4.

regression line to pass through CUECost estimate. The fitted O&M experience curve is shown in Figure 15.

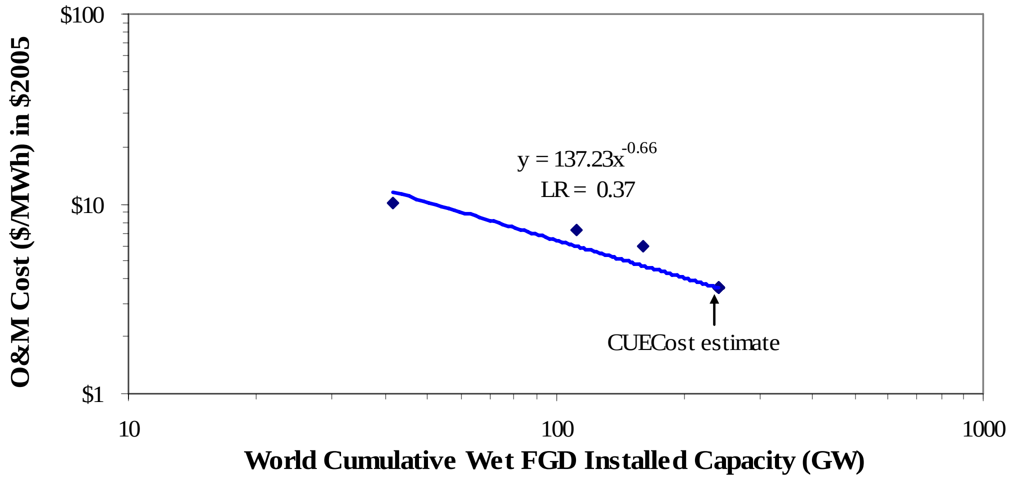


Figure 15. Experience curve of wet FGD O&M costs
(500 MW, 3.5% sulfur coal, 90% SO_2 removal, retrofit factor 1.3, 2005 dollars)

Figure 16 shows the historical wet FGD capital and O&M costs, CUECost 2005 estimates, and projected future capital and O&M costs in the reference case (the assumptions for the reference case are defined in Figures 14 and 15). Overall, the capital and O&M costs of LSFO units are projected to fall by 9.9% to 162.8$/kW and by 22.7% to 2.6$/MWh, respectively, between 2005 and 2020. Assuming a fixed charge factor of 13.3% (used to annualize capital costs), and an annual average capacity factor of 65% the levelized total cost of the FGD system will be reduced by 15.6% between 2005 and 2020.

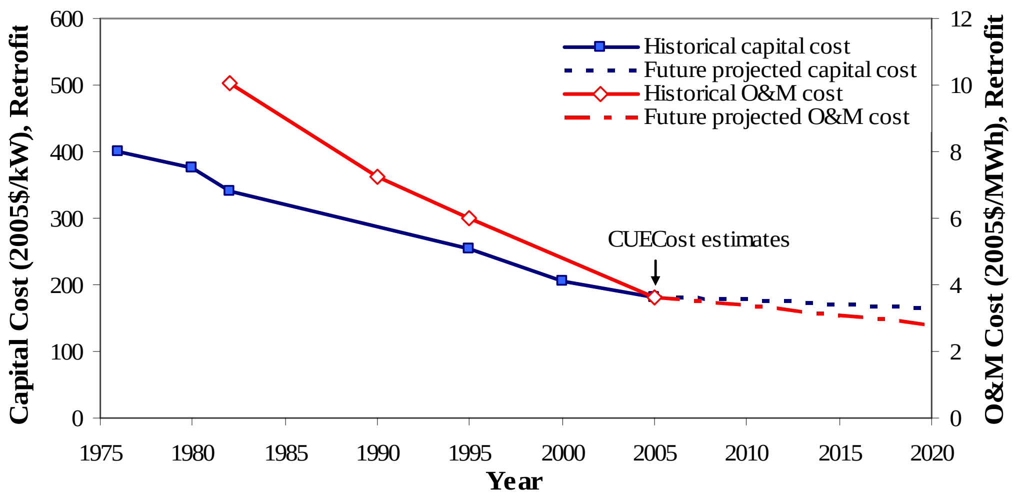
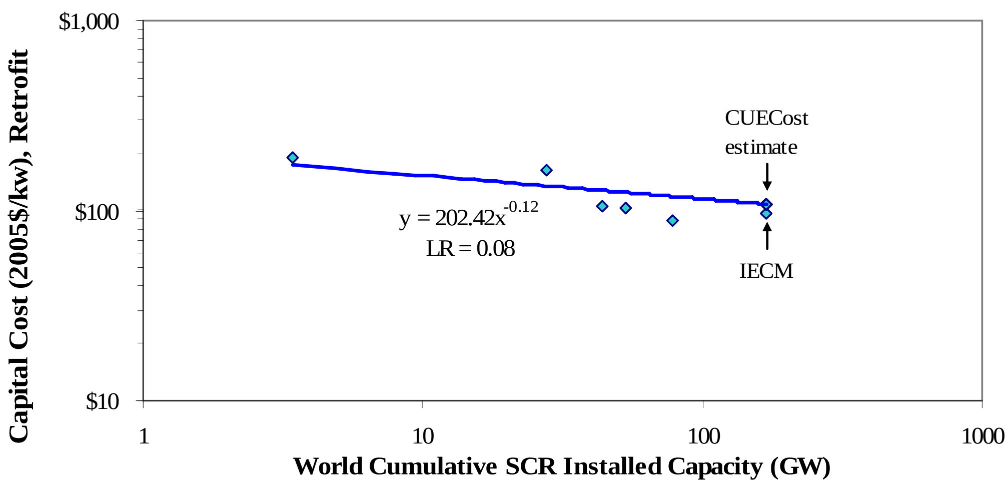


Figure 16. Wet FGD capital and O&M costs: historical values, CUECost 2005 estimates, and projected future values in the reference case.
(500 MW, 3.5% sulfur coal, 90% SO_2 removal.)

3.2 Selective Catalytic Reduction, SCR

A detailed review of the history of NO_x regulation in the U.S. and abroad, technological innovations, and experience curves of SCR capital and O&M costs can be found in Yeh et al. (2005). Overall, the estimated capital and O&M costs of a new SCR unit were reduced by 15% and 44%, respectively, between 1993 and 2000. A number of technological improvements contributed to the reduction of capital cost, such as efficient catalyst designs that reduced the size and cost of the support structures, sophisticated catalyst management practices, and advanced flow modeling that allowed uniform gas flow and lower NH_3/NO_x ratios, which reduced the required catalyst volumes. Improvement to both catalyst geometry and composition led to cost reductions as compared with earlier generations of these products. The single dominant factor contributing to SCR O&M cost declines has been the cost of replacement catalyst: 50% reduction of the catalyst unit cost between 1994 and 2000 (due to economy of scale and market competition), increased catalyst lifetime and improved catalyst management plans.

The historical capital and O&M costs of SCR and the cost estimates from CUECost are fitted to the log-linear experience curve function: $Y = ax^b$ (Equation 1). A retrofit factor of 1.5, the default SCR retrofit factor in CUECost, is used to convert the cost estimates for new plants reported in Yeh et al. (2005) to retrofit units. Extra weight is given for the value estimated by CUECost, to force the regression line to pass through CUECost estimate.[6] Figure 17 shows the estimated regression lines for SCR capital and O&M costs. Examples of the projected future capital and O&M costs are illustrated in Figure 18 based on the projected new capacity estimates shown earlier.



[6] Note that forcing the regression lines to pass through the cost estimates by CUECost resulting lower (i.e. more conservative) learning rates in the SCR case. The implications of learning rate uncertainties will be discussed in Section 4.

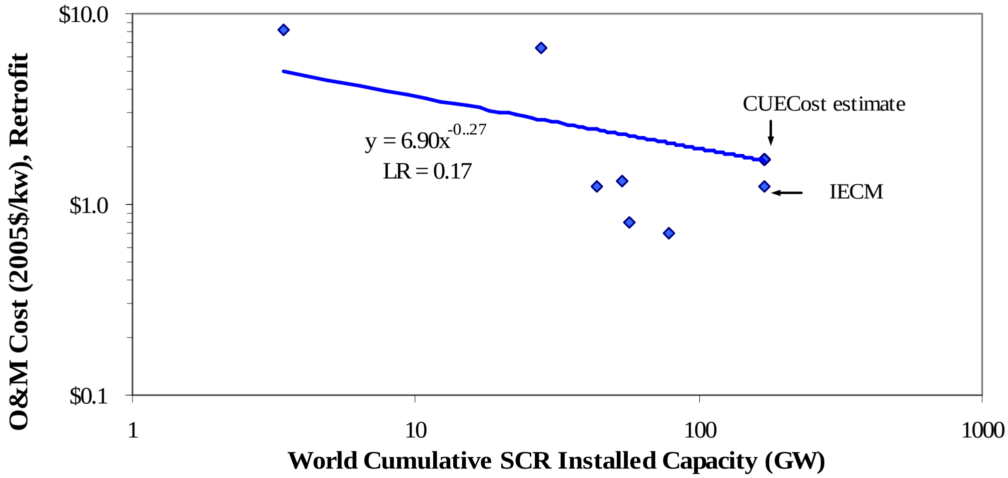


Figure 17. Estimated experience curves for SCR capital costs (top figure) and O&M costs (bottom figure) at a standard U.S. coal-fired power plant
(500 MWe, medium sulfur coal, 0.6 lb/MBtu inlet NO_x, 80% NO_x removal, retrofit factor =1.5).

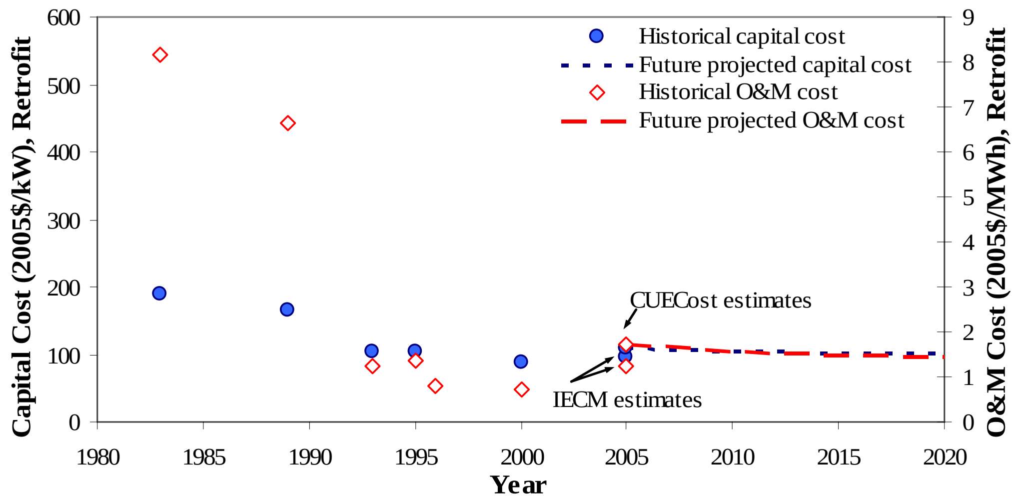


Figure 18. Historical, current, and projected retrofit SCR capital and O&M costs to 2020 at a standard coal-fired power plant.
(500 MWe, medium sulfur coal, 0.6 lb/MBtu inlet NO_x, 80% NO_x removal, retrofit factor =1.5.). IECM: Integrated Environmental Control Model.[7]

The historical SCR capital and O&M costs have observed learning rates of 0.08 and 0.17, respectively. Using the experience curve approach, it is projected that the future capital and O&M costs for a retrofit SCR at a standard coal-fired plant in 2020 are expected to be 100.7 $/kW(2005$) and 1.47 $/MWh, respectively (Figure 18). The capital, O&M costs of a retrofit SCR unit are projected to fall by 7.4% and 15.8%, respectively, between 2005 and 2020.

[7] IECM is a computer-modeling program that performs a systematic cost and performance analysis of emission control equipment at coal-fired power plants. It is developed for the U.S. Department of Energy by Carnegie Mellon University and is available at http://www.iecm-online.com (accessed October 8, 2006).

The learning rates of the O&M costs for both wet FGD and SCR are at the higher end of the range of reported learning rates for the capital costs of energy technologies (Figure 2). Most studies in the learning literature do not report the learning rates of the O&M costs. This is most likely because estimation of O&M costs is subject to more variations and uncertainties, thus imposing significant challenges to estimating the associated learning rate. One of the few case studies is that of photovoltaic (PV) technology. We found the learning rate of the PV module price is estimated to have been 0.20 between 1968 and 1998 (Harmon 2000), while the cost of electricity produced by PV has an estimated LR of 0.35 between 1985 and 1995 (IEA/OECD 2000). PV module price (capital cost) is estimated to be around 40-50% of the total system cost, which in addition to module price also includes costs for site preparation, permits, system design and engineering, installation labor and O&M (Harmon 2000). This suggests that a large cost reduction was gained through overall system design and operation. A recent study examining the history of pulverized coal-fired (PC) boilers also found higher cost reductions for O&M costs compared to the capital cost (LR= 0.06 vs. 0.3 for capital cost and O&M cost, respectively) (Yeh and Rubin 2007). In our studies of the experience curves of FGD, SCR, and PC boilers, we applied consistent methodologies to compare the capital cost and O&M costs, and we found higher LRs for the O&M costs in all three technologies. These case studies provide anecdotal evidence suggesting that higher learning rates were observed for the O&M costs, but more studies are needed to examine the underlying factors contributing to learning in capital vs. O&M costs.

3.3 Lime Spray Dryer, LSD

The application of LSD began in the early ‘80s, and the performance of LSD technology has been improved significantly over the years. The designed SO_2 removal efficiencies have improved from a median of 82% in the 1980s to 90% in the 1990s (Srivastava and Jozewicz 2001). An earlier publication using an earlier version of CUECost (Srivastava and Jozewicz 2001) estimated that the capital cost of LSD for a 250 MWe plant operating with a heat rate of 10,500 Btu/kWh and firing coal with a heating value of 11,900 Btu/lb (2.77×10^7 J/kg) is roughly \$200/kW for a plant using 1% S lignite coal (in 1998 dollars), and close to \$250/kW for a plant using 4% S bituminous coal.[8] Using the same set of assumptions (90% S removal), the current CUECost estimates the capital costs of LSD at \$166/kW and \$197/kW (in 2005 dollars) for plants burning 1% S lignite and 4% S bituminous coal[9], respectively.

There are no learning rates for LSD technology in the literature; thus we apply the same learning rates we found for wet FGD capital and O&M costs and use these to make projections for future costs of LSD. Since LSD is considered a simpler technology than wet FGD, it is likely that the learning rates of dry FGD capital and O&M costs will be lower than those of wet FGD. Though studies have found the existence of learning in technologies with simple as well as complex designs, some studies observed that experience curves became flat (exhibiting “level-off”) with sufficiently large cumulative output. They believed this was probably due to limitations imposed by a given set of tooling, and the level-off point seemed to occur sooner for processes exhibiting steeper learning rates and for simpler technologies (Yeh et al. 2007). Nevertheless, it is difficult to speculate how much lower, if at all, the learning rates of dry FGD will be, compared to wet FGD. Thus the learning rates we found for wet FGD capital and O&M costs will be applied.

The historical, current and projected capital and O&M cost estimates for LSD are shown in Figure 19. The 2000 estimates are based on the previous study (Srivastava, Jozewicz, and Singer 2001) using the previous version of CUECost. 2005 cost estimates based on the IECM also are shown for comparison, and agree well with CUECost 2005 estimates. The projection uses the same methodology and learning rates described for LSFO in Section 3.1. The annualized cost values employ the same assumptions given earlier for LSFO. The capital costs and O&M costs are projected to be reduced by 20.4% and 42.9%,

[8] A capacity factor of 90% was used in the study.
[9] More precisely, ND lignite: 7,500 Btu/lb, 0.94% S, 5.9% ash; and Illinois No. 6: 10,100 Btu/lb, 4% S, 16% ash.

respectively, from 2005 to 2020 based on the default learning rates and future projected installed capacity estimated in Table 1.

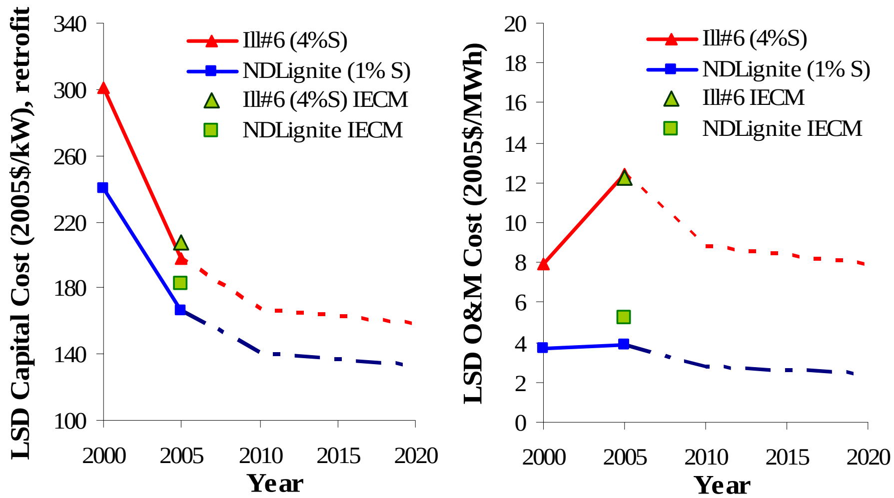


Figure 19. LSD capital cost (left) and O&M cost (right) costs – past and current estimates based on CUECost with projections to 2020.
(250MW, 90% S removal efficiency, retrofit factor = 1.3.)

3.4 Active Sorbent Injection, ASI

There is currently no commercial operation of ASI in coal-fired power plants, except in a few demonstration plants sponsored by the U.S. DOE. Detailed review of mercury control technologies, performance, and future improvements can be found elsewhere (Srivastava et al. 2006; U.S. EPA 2005). Table 2 provides examples of the estimated capital and O&M costs of an ACI system from CUECost.

Table 2. Estimated costs of ACI control systems using CUECost.

APC Configuration	Capital Cost (2005$/kW)	O&M Cost (2005$/MWh)	Hg Removed by Sorbent Injection (lb/yr)	Control Cost (2005$/lb Hg removed)
ACI +Cold-side ESP	19.41	4.06	240.7	53,380
ACI +Cold-side ESP + Wet FGD System	19.41	4.06	188.9	68,013
ACI+ Dry Scrubber + Fabric Filter	3.17	0.32	290.7	3,844

500 MW, Wyoming Powder River Basin (PRB) coal, active carbon injections, capacity factor = 65%, 80% Hg removal.

Since there is currently no commercial operation of mercury control systems at any coal-fired power plant, making future projections of mercury control systems imposes special challenges. Previous studies suggest that costs of initial commercial plants are often higher than those estimated in pre-commercial studies (Merrow et al. 1988; Yeh et al. 2007). Such increases are typically linked to shortfalls in performance and/or reliability that result from insufficient data or experience for scale-up and detailed design, or from new problems that arise during full-scale construction and operation. For example, cost increases during pre-commercial or early-commercial stages have been observed for FGD and SCR (Yeh et al. 2007). In the case of FGD, the "technological optimism" of process developers tended to maximize process potential and minimize problem areas such as corrosion, scaling, solids disposal, sulfite oxidation, mist elimination, gas reheat, operational turndown, and pH control. The earliest cost estimates of SCR were based on the extrapolation of Japan's and Germany's technology assumptions; differences in plant operating conditions and fuel characteristics (such as sulfur and heavy metals content) were noted, but not factored into these early cost estimates. Figure 20 shows the observed cost increases during early-commercialization (or pre-commercialization) of wet FGD, SCR, liquefied natural gas (LNG) production (Rubin et al. 2007), and combined cycle gas turbine (CCGT).

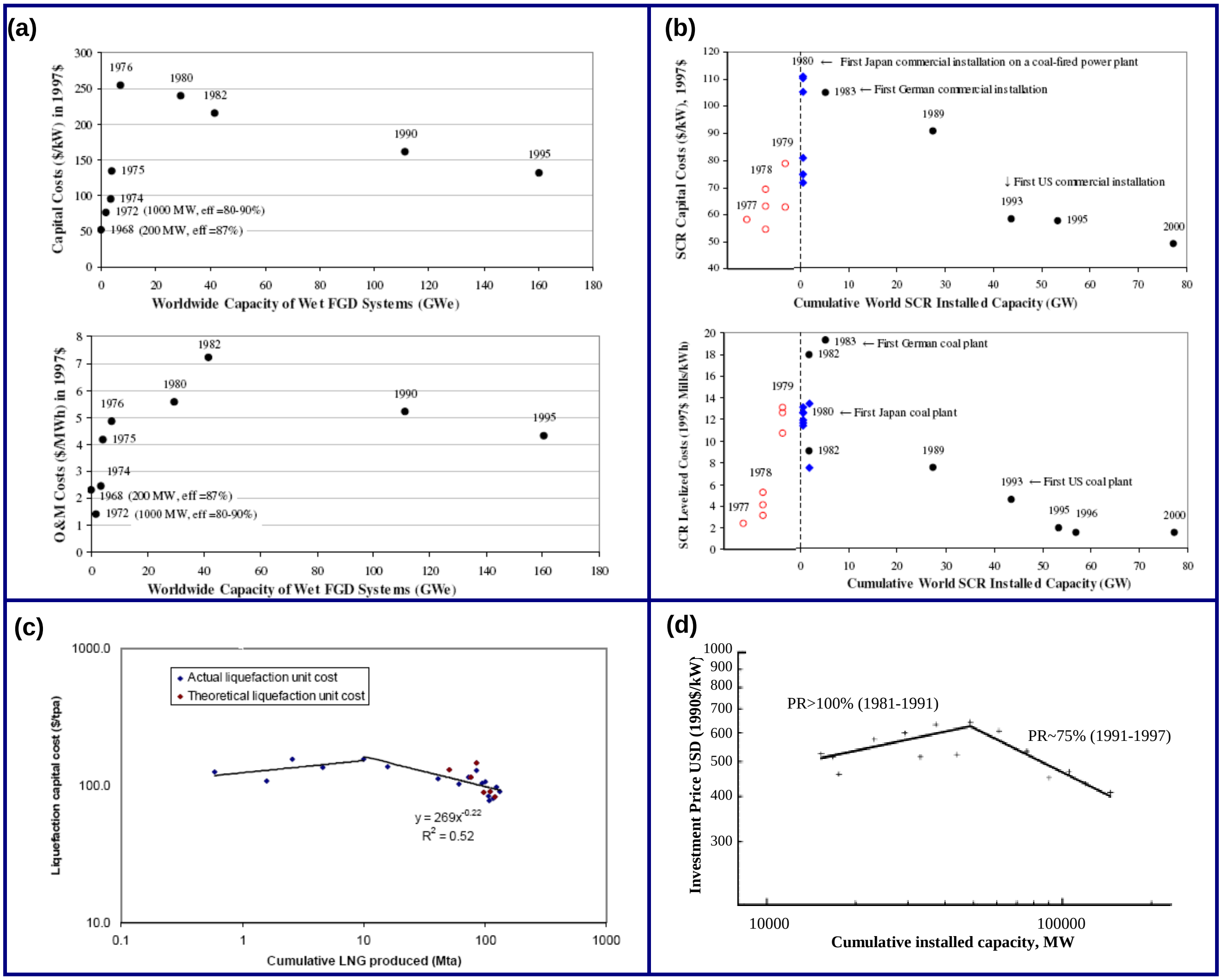


Figure 20. Observed cost trends during early commercialization of technologies:
(a) Wet FGD capital and O&M costs; (b) SCR capital and total levelized costs; (c) liquefaction unit cost for LNG production; (d) capital costs of combined cycle gas turbine (CCGT).

Sorbent injection technologies have been applied commercially to control mercury emissions in industrial facilities in the U.S. and Europe (Presto and Granite 2006). The analysis of technological learning experience on coal-fired units excludes such installations of these technologies in other industrial applications, as these units have very different operating conditions and industrial settings, as well as different scales of operation. Thus, while not explicitly contributing to learning at coal-fired units, they nonetheless represent a level of domestic experience that may benefit power plant applications.

The National Energy Modeling System (NEMS), an energy policy model of the U.S. Department of Energy[10], applies a Technological Optimism Learning (TOL) factor to electricity technologies just beginning commercialization (Gumerman and Marnay 2004). In recognition of the optimism that often surrounds new/emerging technologies, the TOL represents the difference between initial new technology cost estimates and actual first-of–a-kind costs by adding a premium to the first five units built of unproven technologies. Depending on the complexity of technologies, TOL has a value of 1.05 (biomass technology) -1.10 (fuel cells, solar thermal, and photovoltaic) for the first unit, and the value decrease linearly to 1.0 as units two through five are built. However, the data in Figure 20 show that early cost increases can vary considerably among technologies, and that for environmental technologies whose installation is driven by regulatory requirements, considerably more experience than five plants is needed before costs begin to decline (recognizing that initial installations typically employ the same or similar designs without the learning that benefits later generations of the technology).

In this study, to take into account the uncertainties of early cost estimates, we assume that the learning rates will only be applied after a certain amount of initial ACI capacity has been installed, at which point costs start to decline. We nominally assume these capacity values to be 7.4 GW for capital cost and 42.5 GW for O&M cost, based on the historical FGD studies in Figure 20(a). This approach avoids the need to speculate how high the cost might rise initially before it comes down. Examples are shown in Figure 21 based on the use of FGD learning rates once learning begins. The projected capital costs O&M costs in 2020 are estimated to be 28.7% and 0.0%, respectively, lower than the 2005 values based on the default learning rates and future projected installed capacity given in Figure 13.

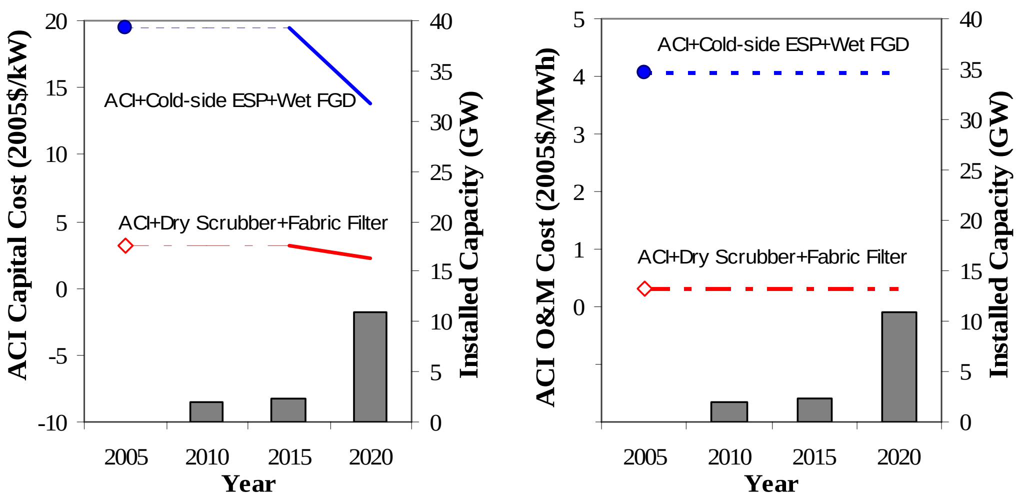


Figure 21. Estimated current and projected capital and O&M costs of ACI in two different plant settings. The bar shows the cumulative installed capacity.
(500 MW, Wyoming PRB coal, capacity factor = 65%, 80% Hg removal.)

4. Characterization of Uncertainties of the Experience Curve

Future costs that are predicted using learning curves are subject to various uncertainties such as learning rate, shapes of the experience curve, and interactions between cost and performance. For example, many studies suggest that the learning curve is not always log-linear, which implies a constant learning rate

[10] NEMS is used by the Energy Information Administration, U.S. DOE to produce their official annual forecast of U.S. energy use, the "Annual Energy Outlook."

throughout the lifetime of the technology. Many other shapes of experience curves, including the S-shape curve and the "level-off" curve when the technology matures, have been suggested in the literature (Gumerman and Marnay 2004; Boston Consulting Group 1968; Claeson Colpier and Cornland 2002). In addition, the experience curves presented above for SO_2, NO_x and Hg control technologies were based on a constant pollutant removal efficiency in order to characterize the cost of doing the same job at different points in time. While improved performance of environmental technologies generally comes at a higher initial cost, subsequent cost reductions are such that a high-efficiency SO_2 scrubber today costs much less than a lower-efficiency system a decade ago. Experience curves reflecting such interactions between performance and cost have not yet been developed to be included in this analysis. Detailed reviews of these sources of uncertainty can be found in several recent studies (Rubin et al. 2007; van der Zwaan and Seebregts 2004; Yeh et al. 2007). Though using the experience curve approach provides a reasonable guide to making future projections, such an approach cannot project future costs with perfect accuracy. Thus, uncertainty analysis is necessary to provide bounding values to the "best estimates" described in the previous section.

The uncertainty we consider in this analysis focuses on learning rate uncertainties. An uncertainty factor of ±50% is applied to all the learning rates estimated in this study. For example, the learning rate of 0.16 for FGD capital cost will have lower bound and upper bound values of 0.08 and 0.25, respectively, when making future projections. In addition, contingency factors similar to the TOL approach by the NEMS model, of 1.1 for 2010, 1.05 for 2015, and 1.025 for 2020 for O&M costs, are applied to the upper bound uncertainty estimates of Hg sorbent injection technology capital and O&M cost estimates. The contingency factor is intended to further illustrate the possibility of cost increase at the beginning of commercialization as a result of technology uncertainties, but it by no means represents the upper bound of possible cost increases. Examples of the future projected cost with these assumed uncertainties are illustrated in Figure 22.

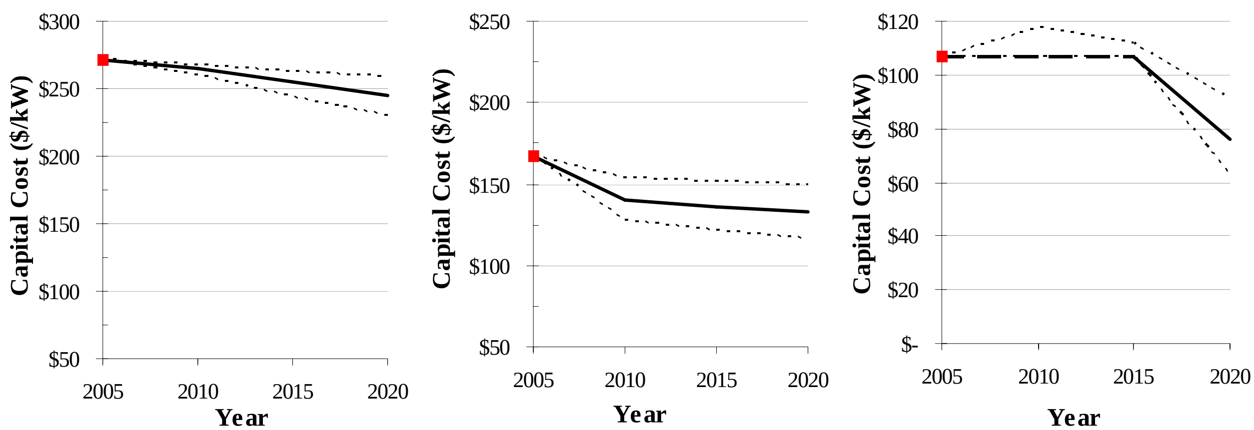


Figure 22. Examples of projected capital costs for LSFO, LSD and ASI with uncertainty estimates.

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Appendix 1.

CUECost allows users to evaluate up to five cases with unique economic and technology assumptions at any given time. Thus, to apply a learning curve to these estimates, the value of *a* in the Equation 1, i.e., the unit cost of the first unit, will need to be changed in each case to reflect the true first unit cost estimates for each technological and financial assumption (such as plant size, coal sulfur content, SO_2 removal efficiency, cost-basis year dollars, discount rate, and contingency factor). The slope of the curve, *b*, remains the same for all cases, as the rate of improvement is the same for all cases. The change in value *a* is necessary to ensure that the effect of learning is evaluated based on consistent assumptions, thus not affected by cost variations due to changes in the assumptions of technological specifications and economic factors not related to learning.

Examples: The current cost estimate for an LSFO control device for a standard plant design (500 MW, 3.5% sulfur coal plant with 90% SO_2 removal efficiency) is estimated to be \$180.99/kW in 2005 dollars using CUECost. The equation of the learning curve is: $Y = 798.92.4x^{-0.27}$ (Figure 14).

Case A. Estimate the cost of LSFO at a 400 MW unit burning low-S (0.37%) Wyoming PRB coal. The LSFO will have 95% removal efficiency. Use 2000 dollars.
Case B. The same assumptions as Case A but use 2005 dollars.

From CUECost the current cost estimate for Case A is \$182/kW (2000 dollars) and \$207/kW for Case B (2005 dollars). Constant *a* for Case A is 798.9 × (182/180.99) = 799.2 and the new experience curve for Case A is $Y = 799.2x^{-0.27}$.
Constant *a* for Case B is 798.9 × (207/180.99) = 908.9 and the new experience curve for Case B is $Y = 908.9x^{-0.27}$.