A bottom-up method to develop pollution abatement cost curves for coal-fired utility boilers

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ABSTRACT

This paper illustrates a new method to create supply curves for pollution abatement using boiler-level data that explicitly accounts for technology cost and performance. The Coal Utility Environmental Cost (CUECost) model is used to estimate retrofit costs for five different NOx control configurations on a large subset of the existing coal-fired, utility-owned boilers in the US. The resultant data are used to create technology-specific marginal abatement cost curves (MACCs) and also serve as input to an integer linear program, which minimizes system-wide control costs by finding the optimal distribution of NOx controls across the modeled boilers under an emission constraint. The result is a single optimized MACC that accounts for detailed, boiler-specific information related to NOx retrofits. Because the resultant MACCs do not take into account regional differences in air-quality standards or pre-existing NOx controls, the results should not be interpreted as a policy prescription. The general method as well as NOx-specific results presented here should be of significant value to modelers and policy analysts who must estimate the costs of pollution reduction.

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1. Introduction

Energy models exploring future scenarios of technological change in the electric sector must quantify the economic trade-off between the cost to retrofit existing coal-fired power plants with control technologies and the cost to build newer, cleaner electric power plants. Often, a challenge for energy modelers is to develop marginal abatement cost curves (MACCs) of pollution. MACCs represent the estimated cost of abatement as a function of the emissions level and are an important tool for energy modeling and environmental policy analysis. However, MACCs are often generated using economic techniques that do not include explicit technological considerations, which can lead to an inaccurate characterization of abatement cost. This paper sets out to answer the following question: can detailed technology cost and performance data be used to create MACCs from the bottom up? We present a new method to create MACCs that applies a unit-level engineering-economic assessment tool to determine retrofit costs and abatement levels associated with specific NOx controls on a large subset of US coal-fired utility boilers. The boiler-level retrofit data is then used as input into an integer linear program (Murty, 1995), which determines the optimal distribution of retrofits across all boilers as a function of the NOx abatement level. The result is a MACC that reflects the minimum system-wide cost to achieve a particular level of NOx reduction.

We chose to demonstrate the new method by building an abatement cost curve for NOx emissions. NOx formation is complex and abatement costs depend, in part, on a complex combination of coal type, coal composition, boiler design, plant size, and plant utilization factor. In addition, several mature NOx retrofit technologies exist for coal-fired utility boilers. The focus on NOx emissions provides a rich decision space in which marginal abatement costs depend on complex technical details. Since the analysis presented here does not account for pre-existing controls, state or federal air-quality standards, the need to apply tighter controls in air-quality hot spots, or existing markets for emissions trading, the MACCs developed here should not be treated as a policy prescription, but as an illustration of a novel methodology for developing bottom-up, technology-based MACCs.

While changes in the electric power sector will likely be driven by a future climate policy, the timing and extent of new capacity installations in the electric sector will depend in part on the pollution control retrofits that may need to be installed on existing coal-fired power plants in response to increasingly stringent air pollution regulations. Emissions of nitrogen oxides (NOx) have been associated with various environmental and
public health impacts, such as an increase in drinking water nitrate, eutrophication, acid rain, formation of ground-level ozone, degraded visibility and regional haze, and the formation of secondary fine particles in the atmosphere (Molina and Molina, 2002; Price et al., 1997). In 2007, a total of 17 million tons of NOx was emitted in the US (EPA, 2009). The transportation sector was the largest contributor (~57%) to total NOx emissions, followed by the industrial (~22%) and electric utility (~20%) sectors. Fig. 1 shows the contribution to US NOx emissions from various sources in 2007. The electric utility industry was responsible for emitting about 4.7 million tons of NOx, of which about 87% came from the combustion of coal. Because coal-based power generation currently accounts for roughly half of total US electricity production, it is the single largest stationary source category in the US, contributing about one-fifth to total NOx emissions.

In the following section, we discuss several existing methods used to construct MACCs. Since our method for creating MACCs from the bottom up depends strongly on retrofit cost and performance, Section 3 provides useful technical information regarding currently available NOx abatement technologies. Sections 4 and 5 describe the data sources, tools, and methods employed for this study. Section 6 presents an analysis of the resultant MACCs. Finally, Section 7 draws conclusions and suggests future work related to the development of bottom-up MACCs.

2. Marginal abatement cost curves: a tool for modeling and policy analysis

A MACC provides the cost of reducing an additional unit of pollutant from a given emissions level. Each additional unit of emission reduction generally has incrementally higher cost, leading to the formation of a convex curve with increasingly positive slope. Such curves are a useful tool for modeling, formulation, and analysis of energy and environmental policy because they provide an estimate of the cost to make incremental reductions from a given emissions level. Knowledge of such curves allows analysts to determine economically efficient levels of pollutant reductions. Being able to determine an efficient level of pollution abatement makes it possible to maximize net social benefits (Kwon and Yun, 1999; McKitrick, 1999). At the firm level, a MACC links a firm’s emission levels to the cost of reducing one unit of emissions from the current levels, and therefore can be a key tool for firm related-economics (McKitrick, 1999). Similarly, at the system level, MACCs can be used to determine which sector(s) to focus on to abate emissions in the most cost-effective manner.

In recent years, MACCs for reducing greenhouse gas (GHG) emissions have become a standard tool to estimate and analyze the potential economic impacts of national GHG reductions policies (Johnson, 2002; Klepper and Peterson, 2006). MACCs are a key tool in the study of environmental economics and can be used to identify efficient and practical policy solutions aimed at reducing the net social cost of a policy (Lee, 2005).

Technically, a firm can reduce pollutant emissions by reducing output, or by investing in end-of-pipe (EOP) or change-in-process (CIP) control technologies—options which have very different costs. Selective catalytic reduction (SCR) is an example of an EOP control technology, and combustion modification is an example of a CIP control. In general, methods to estimate abatement costs can be placed in three broad categories: microeconomic theory-based methods, such as the cost function approach (e.g., Gollop and Roberts, 1985) and distance function approach (e.g., Fare et al., 1993), econometric methods (e.g., Becker, 2005; Hartman et al., 1997), and engineering-economic methods (e.g., Beaumont and Tinch, 2004; Karvonen and Johansson, 2003). In the cost function approach, pollution—along with labor, energy, and capital—are treated as an input to the production process, and the marginal cost of emissions reduction is derived by estimating the change in the cost function as the emission level changes. Since firms fail to minimize their production cost in the presence of various regulations, the cost-function approach is likely to underestimate marginal abatement cost (Lee, 2005). Moreover the cost function approach requires a significant amount of information about input costs, which is often not readily available. Fare et al. (1993) have developed an output distance function approach, which has been very widely applied in the recent literature to estimate the marginal abatement cost of ‘bad’ output (e.g., Boyd et al., 1996; Halli and Halli, 2003; Halli and Veeman, 2000; Kwon and Yun, 1999; Lee et al., 2002; Lee, 2005). Using this approach, the marginal abatement cost can be calculated as the shadow price of reducing the pollutant emissions by one unit or the opportunity cost of reducing the level of output by one unit. Two interesting applications of the output distance function approach to the power sector are presented by Coggins and Swinton (1996) and Kwon and Yun (1999). Both papers utilize an output distance function and its relationship to the revenue function to estimate marginal abatement costs.

While the cost function and output distance function methods can roughly indicate the cost of reducing emissions by way of reducing the output, these approaches do not explicitly consider any EOP or CIP control technologies to reduce emissions. For example, Coggins and Swinton (1996) clearly note their inability to incorporate important technology options such as scrubbers to arrive at their estimates of the cost of SO2 allowances from coal-fired utilities. Because these approaches only consider changes in output, a specific EOP or CIP control may have a lower marginal abatement cost than the shadow price estimated using these approaches. Further, the actual opportunity cost of forgoing production may be higher than estimated in a case where plant efficiency decreases with a reduction in the output.

MACCs can also be developed by employing econometric methods. These methods utilize extensive plant-level data on capital expenditure and operation and maintenance costs associated with pollution control equipment to derive abatement cost estimates using statistical modeling. There are several pertinent applications of this method in the literature, which rely on data from the US Census Bureau’s Pollution Abatement Costs and Expenditures (PACE) survey (e.g., Becker, 2005; Hartman et al., 1997). The abatement cost estimates thus obtained require a large amount of data collection, but have the same shortcoming as in.
the case of microeconomic theory-based methods: econometric methods cannot attribute abatement costs to specific technological options. Therefore, these methods are able to derive technology-neutral marginal abatement costs but lack the specificity associated with a wide array of available technologies. For example, low NO\textsubscript{x} burners (LNBs) can achieve NO\textsubscript{x} reductions at a lower $/ton cost than selective catalytic reduction (SCR) systems, which can achieve higher abatement levels but also cost more.

The last class of methods to estimate MACCs involves the use of engineering-economic models. Such an approach is made difficult by the requirement for in-depth, plant-specific technical information, hard to find proprietary control technology and cost information, and a sound technical understanding of the construction and operation of the control technologies. Several energy and environmental models (e.g., some versions of MARKAL, and RAINS, the European Union’s acid rain prediction model) explicitly take engineering-economic cost estimates into account—though generally at an aggregated level—and can be used to produce system-wide MACCs. For example, Karvosenoja and Johansson (2003) used actual technical and cost parameters to derive cost curves for SO\textsubscript{2} and NO\textsubscript{x} abatement for Finnish power plants and industry. They combine the emissions of SO\textsubscript{2} and NO\textsubscript{x} into one cost curve, by taking into account their respective acidification potential. They have used costs of EOP control technologies from Finnish national studies, and actual operational characteristics obtained from the utility and industry sectors.

While economic and econometric methods provide useful information for theoretical analysis and policy making, the information is rarely useful to managers or decision-makers at the plant level, as it does not capture plant- and technology-specific details. Likewise, cost engineering tools for individual boilers or plants capture the technology and process details for various abatement options, but cannot be readily used to assess sector-wide costs and tradeoffs among plants.

We bridge this methodological gap by demonstrating a new bottom-up method to create MACCs which, is based on boiler-level data. These bottom-up curves are useful to system analysts who need an accurate and simplified way to estimate the marginal cost associated with a specified emissions reduction. In addition, the MACCs can also be used by plant managers to determine how the retrofit costs and emissions reductions associated with their plants compare with the rest of the system. Like Karvosenoja and Johansson (2003), we start from a hypothetical “no-control” situation for the year 2004.

3. A primer on NO\textsubscript{x} control

Because the technological details of NO\textsubscript{x} control technologies are central to the development of MACCs using our method, we provide a brief overview. There are three principle mechanisms of NO\textsubscript{x} formation during the combustion process: “thermal” NO\textsubscript{x}, which results from the oxidation of molecular nitrogen present in the combustion air; “fuel” NO\textsubscript{x}, which results from the combination of chemically bound nitrogen in the fuel with oxygen, and “prompt” NO\textsubscript{x}, which results from the reaction between molecular nitrogen and hydrocarbon radicals. A detailed discussion of NO\textsubscript{x} types and their formation mechanisms has been well-documented (e.g., Beer, 1996; Beer, 2000; Price et al., 1997; Srivastava et al., 2005).

NO\textsubscript{x} control technologies can be divided into primary control technologies and secondary control technologies. Primary control technologies reduce the amount of NO\textsubscript{x} formed during the combustion process in the primary combustion zone. Low NO\textsubscript{x} burners (LNB) and over-fire air (OFA) are two common primary NO\textsubscript{x} control technologies used in the US. A LNB limits NO\textsubscript{x} formation by controlling the stoichiometric and temperature profiles of the combustion process. This is achieved through design modifications that manipulate the aerodynamic distribution and mixing of the fuel and air to yield one or more of the following conditions: (a) reduced oxygen in the primary flame zone, which limits fuel NO\textsubscript{x} formation; (b) reduced flame temperature, which limits thermal NO\textsubscript{x} formation; and (c) reduced residence time at peak temperature, which limits thermal NO\textsubscript{x} formation. LNBs can typically provide NO\textsubscript{x} reductions up to 50% from uncontrolled levels (Srivastava et al., 2005).

Individual primary control technologies have been implemented very widely in the US. These technologies have been able to achieve high reduction efficiencies for certain fuel-boiler type combinations. However, for many coal-boiler combinations, primary controls may not be able to achieve the desired reductions. Secondary control technologies can help such boilers reach higher reduction levels, either alone or in combination with primary control technologies. Reburning, where a secondary fuel is injected above the main combustion zone to produce a fuel-rich reburn zone, falls under the category of secondary controls. Natural gas reburning (NGR) uses natural gas as a secondary fuel for the reburn. Coal may also be used as a reburn fuel. While it is possible to estimate the cost of NGR retrofits to existing coal boilers using CUECost, we have not included NGR in this analysis due to the high natural gas price volatility observed in the recent past (EIA, 2009).

Selective non-catalytic reduction (SNCR) and selective catalytic reduction (SCR) are the two most common secondary post-combustion NO\textsubscript{x} control technologies. SNCR uses a reagent (ammonia in gaseous form or urea injected as an aqueous solution) to convert NO\textsubscript{x} into N\textsubscript{2} and water. SCR also uses ammonia as a reagent; however, in SCR the flue gases pass through a layer of catalysts where ammonia and NO\textsubscript{x} react to form N\textsubscript{2} and water. NO\textsubscript{x} reduction reactions in SCR take place at a much lower temperature than in SNCR. Generally, SCR can achieve much higher reduction efficiencies, ranging from 80% to more than 90% in some cases, as compared to 35–60% for SNCR (ICAC, 2000).

In this analysis, we have assumed stand-alone primary (LNB) and secondary technologies (SNCR; SCR), and their feasible combinations (LNB+SNCR; LNB+SCR), resulting in a total of five possible control measures for each boiler. The list of control technology options and their control efficiencies are shown in Table 1.

Note that, in general, the feasibility of implementing a specific control technology may depend on several factors, such as plant size, location, and coal type. For simplicity, we have not taken into account some of the second-order factors, such as regional differences in the cost of material and labor, the cost differential resulting from different building codes for regions with high seismic activity, and the retrofit difficulty factor. In the next

<table>
<thead>
<tr>
<th>Control measure</th>
<th>Control efficiency (%)</th>
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<tbody>
<tr>
<td>Primary control (PC)</td>
<td>Low NO\textsubscript{x} burner (LNB) 30–45</td>
</tr>
<tr>
<td>Secondary controls (SC)</td>
<td>Selective catalytic reduction (SCR) 90</td>
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<tr>
<td></td>
<td>Selective non-catalytic reduction (SNCR) 35–60</td>
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<td></td>
<td>LNB+SNCR 75–80</td>
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<td>LNB+SCR 90–95</td>
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Table 1: NO\textsubscript{x} control measures and their control efficiency.
section we describe the data sources and methods used to develop the MACCs.

4. Data and tools

Coal Utility Environmental Cost (CUECost) is a publicly available engineering cost and performance spreadsheet model that employs several algorithms to relate technical characteristics of a plant to the cost of abatement for various control technologies (EPA, 2000; Keith et al., 1999). CUECost incorporates commercially proven and established retrofit technologies to reduce air pollutants from coal-fired utility boilers ranging from 100 to 2000 MWe. Specifically, it can estimate the cost of control technology retrofits for the abatement of particulate matter (PM), sulfur oxides (SOx), and nitrogen oxides (NOx). The budgetary retrofit cost estimates provided by CUECost are ±30% accurate. For this study, we used the latest version of CUECost, which can be obtained by request. Note that an advanced beta version of CUECost (currently under review) will also be able to estimate the cost of retrofitting a plant to reduce CO2 emissions.

CUECost can be used to estimate abatement cost for a boiler if detailed technical data about the boiler are known, for example: size, plant factor, coal type, coal characteristics, bottom type (wet or dry), firing type (tangential, wall, or cyclone), and uncontrolled emission rate for pollutants. We created a database of all the existing US coal-fired, utility-owned boilers in 2004 with the detailed plant characteristics required as input for CUECost. We used data available from the Energy Information Administration (EIA) of the U.S. Department of Energy and the U.S. Environmental Protection Agency (EPA). Primary data sources were EIA’s Form 767 (EIA, 2005a), Form 860 (EIA, 2005b), Form 906 and 920 (EIA, 2005c), and EPA’s NEEDS database (EPA, 2005). Information about monthly fuel consumption and fuel quality—particularly coal type, heat content, sulfur and ash content—was obtained from the FERC-423 database maintained by the EIA (Scott, 2005). We then automated a process to mine the characteristic data for each boiler and used this data as input to CUECost, which estimated the cost of various NOx control retrofits. We did not take into account any pre-existing controls due to the inadequate data regarding controls on each boiler.

For the plants where more than one boiler was affiliated with one generator, we attributed the generation capacity among all the boilers, proportional to their generation in the year 2004. To estimate the levelized cost of control, we assumed for simplicity a uniform 20-year service life for all the retrofit equipment. We realize that some of these plants may not have a remaining life of 20 years, whereas some newer plants may have a life-span longer than 20 years. A 7% percent discount rate is applied to all investments, consistent with the guidelines for benefit-cost analysis suggested by the U.S. Office of Management and Budget (OMB, 1992).

This analysis includes all US electric utility-owned coal boilers with capacities over 100 MWe and with plant utilization factors greater than 50% in order to target the boilers that would most likely be retrofitted. For consistency, we also removed boilers using multiple fuels from our analysis. Fig. 2 presents a histogram of nameplate capacity for the coal-fired units included in this analysis. The majority of the boilers are smaller than 500 MWe and only a handful are larger than 1000 MWe.

Three different NOx controls were considered: LNB, SCR, and SNCR. In addition, we considered the following feasible combinations of the primary and secondary controls: LNB+SCR and LNB+SNCR (see Table 1). Although it is possible to combine SCR and SNCR, in practice it is rarely done; therefore, we did not include this combination of control measures. Due to its ease of transport and handling, we assumed that the reagent used in SNCR was urea. CUECost was used to calculate the emission reduction and mitigation cost ($/ton of NOx reduced) associated with each of these control measures on each boiler.

5. Constructing the marginal abatement cost curves

Once the cost of all five NOx control measures for each boiler in the database was estimated using CUECost, we built a series of technology-specific MACCs. To do so, the emissions reduction associated with each retrofit on each boiler was divided by the total system-wide uncontrolled emissions to obtain the relative incremental abatement for a particular retrofit and boiler combination. Then, for each retrofit option, the boilers were sorted from least to greatest abatement cost. Plotting the abatement cost versus the cumulative NOx emissions reduction yields a series of technology-specific MACCs, as shown in Fig. 3.

Next, we used an integer linear program to construct an optimal marginal abatement cost curve that considers all retrofits on all boilers simultaneously. The model minimized the total system cost by choosing a single optimal retrofit or no control for each boiler, subject to a system-wide NOx emissions constraint.
Each retrofit option was treated as a binary variable, subject to the constraint that one and only one option could be selected per boiler. The model was built in the General Algebraic Modeling System (GAMS) and solved using CPLEX®. The optimization was performed in 1% increments of NOx abatement from the uncontrolled level.

Note that the MACCs developed in this analysis include the cost of retrofits for a few select technologies, and do not take into account the possibility of reducing emissions by reducing the output, which is also an option for plant operators. We also did not take into account regional differences in ambient temperatures, construction cost, or different levels of abatement required by local regulations. Also, difficulty in the ability to retrofit a plant with primary or secondary control was assumed to be moderate for all the boilers in this analysis. While the retrofit difficulty can vary and may affect the plant-specific retrofit costs, it is unlikely to affect the overall shape of the MACC. More accurate plant-specific costs would require a detailed on-site engineering analysis, which is beyond the scope of this paper.

6. Analysis of the resulting MACCs

Inspection of Fig. 3 indicates that no specific retrofit technology is clearly the best choice for all levels of reduction. In general, the higher cost retrofits reduce NOx emissions more than lower cost options. Low plant utilization results in smaller amounts of marginal mitigation cost of 500 $/ton NOx system-wide abatement at a given mitigation cost. For example, a still relatively low. Each retrofit option buys a different level of the lower bound on the plant utilization factor is 50%, which is indicated by the steep part of each MACC results from boilers with low plant utilization factors. For inclusion in our boiler database, the lower bound on the plant utilization factor is 50%, which is still relatively low. Each retrofit option buys a different level of system-wide abatement at a given mitigation cost. For example, a marginal mitigation cost of 500 $/ton NOx buys a 0% reduction using SNCR; a 28% reduction using SCR; a 36% reduction using LNB–SCR; a 38% reduction using LNB; and a 40% reduction using LNB–SNCR. Even though SCR can achieve deep reductions in NOx emissions, a marginal mitigation cost of 500 $/ton NOx is too low to be applied widely, so SCR retrofits at that cost are limited to a small subset of the existing boilers.

Because Fig. 3 did not yield a dominant retrofit technology across all abatement levels, we decided to optimize the choice of retrofits across all boilers in order to minimize system-wide cost, subject to a constraint on total NOx emissions. In this optimization framework, the boiler-specific choice of an optimal retrofit depends on the overall desired level of emissions abatement. The optimization routine minimizes the total cost of retrofits subject to a NOx emissions constraint by choosing the optimal retrofit (or no retrofit) for each boiler. The optimization is performed under NOx emissions constraints ranging from 0% to 94% below the uncontrolled level, in increments of 1%. Note that reductions in NOx emissions above 94% are infeasible because even the most advanced technologies cannot produce such large reductions across a range of boilers. The share of optimal retrofit technologies across all boilers as a function of the abatement level is shown in Fig. 4. Emissions reductions of less than 35% only require primary controls (i.e., LNB) to meet the abatement target. As the emissions reductions increase above 35%, secondary controls are required to meet the constraint. With the required abatement level at 50%, LNB still plays a significant role in achieving the target level of reduction, but SNCR, LNB+SNCR, and LNB+SCR also enter the optimal solution set. At a 60% abatement level, the combination of LNB+SNCR plays a dominant role. As the abatement level increases further, SCR and LNB+SCR achieve an increasingly larger share in the optimal solution set.

Using the results from the integer linear program, an optimized MACC was created, as shown in Fig. 5A. Note that the abatement cost increases at a higher rate for emissions reductions above 80% because the optimal solutions are dominated by SCR and LNB+SCR, which are significantly more expensive than the other options, and because boilers with lower utilization factors are retrofitted. A total abatement cost curve (Fig. 5B) indicates the total cost of retrofit to achieve a target level of abatement of NOx. While Fig. 5 cannot be validated in the context of existing US policy, they do provide a general indication of the total NOx abatement cost from large coal-fired boilers, which can be compared to mitigation options in other sectors.

Fig. 4. Relative proportions of optimal retrofits to meet the specified NOx reduction targets. The 0% system-wide NOx reduction on the left-hand side represents the case where there is no NOx control. Note that LNB dominates the choice of retrofit at lower reduction levels up to 50% and is increasingly coupled with secondary controls to achieve higher emissions reductions.
or EOP technologies, the MACCs presented here are based on the technical details associated with specific boiler configurations, coal characteristics, and retrofit technologies. Both the general method and specific application to NOx abatement should be of significant value to energy and integrated assessment modelers, whose models often do not have enough resolution to represent the engineering specifics related to pollution control, but nonetheless require fairly accurate characterization of abatement costs. The bottom-up method presented here can easily be applied to create MACCs for other pollutants.

In addition, both the technology-specific and optimized MACCs created with this method provide detailed information regarding the application of control technologies to achieve a given system-wide reduction. Because specific points on the MACC are directly tied to particular boiler- or plant-level configurations, it is possible for decision-makers to assess how changes in an emissions cap may affect specific plants as well as the system-wide distribution of controls. For example, inspection of Fig. 4 indicates that at a NOx reduction of ≤50%, LNB is the dominant control technology. As the abatement level increases, the distribution of control shifts to more expensive retrofits such as SCR and LNB+SNCR, which also have higher removal efficiencies than LNB.

In this paper, we have done a “green-field” analysis, assuming no existing controls on the power plants, whereas many of the US power plants already have primary and secondary NOx controls installed to meet with the Clean Air Act (CAA) and State Implementation Plans (SIP) requirements. Furthermore, the regional requirements to control NOx vary greatly depending on how sensitive the ozone formation process for that particular region is to the airshed. In this analysis, NOx is treated as a uniformly mixing pollutant. A more sophisticated analytical tool can be developed to estimate region-specific MACCs that take into account regional differences and existing controls on the power plants.

The MACCs developed in this analysis do not take into account endogenous technical learning (ETL) and its impact on the cost of retrofitting a plant with EOP or CIP controls. Generally, MACCs represent the state of control technologies and abatement options at a single point in time. However, expectation of learning and the associated reduction in cost can have a significant impact on the strategic decision by firms to install controls. At a system level, different technological learning rates can impact the shape of the MACC over time and create potential path dependencies. Future work should include the effects of endogenous technological learning, such that cost and performance of retrofits in the future are contingent upon the number of similar prior retrofits. In addition, the shapes of the MACCs created using our bottom-up approach are sensitive to embedded assumptions regarding technology cost and performance. Future work should include a parametric sensitivity analysis to determine how sensitive the MACCs and their function forms are to specific input parameters, such as cost of capital, technology lifetime, and capital cost.

Finally, given the importance of climate change mitigation, the method developed here can be applied to develop a MACC for carbon capture and sequestration retrofits to existing coal-fired power plants. Such a result would provide a valuable quantitative benchmark for policy analysis.

**Fig. 5.** Optimized abatement cost curves for NOx emissions from coal-fired US utility boilers with plant utilization factor ≥ 50% and capacity ≥ 100 MWe. (A) Marginal abatement costs and (B) total abatement costs. Both curves are well-represented by a third-order polynomial.

An interesting result from Fig. 4 is the large share of LNB+SNCR in the optimal control mix when the system-wide NOx constraint is between 60–80%. This is contrary to the observed implementation of secondary NOx controls in the US, which are dominated by SCR. The higher share of SCR in practice most likely results from regional differences in emissions limits. For example, only 22 states are included under Phase II of EPA’s NOx Budget Trading Program, all focused in the eastern half of the US (EPA, 2009). Techno-economic factors such as load-following capability and NOx removal efficiency of SNCR for large boilers (Srivastava et al., 2005) may also play a role in the model preference for SNCR.

**7. Conclusions**

Given the importance of technology characteristics in determining pollution abatement costs, this paper presents a new method to build marginal abatement cost curves from the bottom up using detailed technology cost and performance data. Unlike conventional economic methods that do not include specific CIP or EOP technologies, the MACCs presented here are based on the technical details associated with specific boiler configurations, coal characteristics, and retrofit technologies. Both the general method and specific application to NOx abatement should be of significant value to energy and integrated assessment modelers, whose models often do not have enough resolution to represent the engineering specifics related to pollution control, but nonetheless require fairly accurate characterization of abatement costs. The bottom-up method presented here can easily be applied to create MACCs for other pollutants.

In addition, both the technology-specific and optimized MACCs created with this method provide detailed information regarding the application of control technologies to achieve a given system-wide reduction. Because specific points on the MACC are directly tied to particular boiler- or plant-level configurations, it is possible for decision-makers to assess how changes in an emissions cap may affect specific plants as well as the system-wide distribution of controls. For example, inspection of Fig. 4 indicates that at a NOx reduction of ≤50%, LNB is the dominant control technology. As the abatement level increases, the distribution of control shifts to more expensive retrofits such as SCR and LNB+SNCR, which also have higher removal efficiencies than LNB.

In this paper, we have done a “green-field” analysis, assuming no existing controls on the power plants, whereas many of the US power plants already have primary and secondary NOx controls installed to meet with the Clean Air Act (CAA) and State Implementation Plans (SIP) requirements. Furthermore, the regional requirements to control NOx vary greatly depending on how sensitive the ozone formation process for that particular region is to the airshed. In this analysis, NOx is treated as a uniformly mixing pollutant. A more sophisticated analytical tool can be developed to estimate region-specific MACCs that take into account regional differences and existing controls on the power plants.

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Finally, given the importance of climate change mitigation, the method developed here can be applied to develop a MACC for carbon capture and sequestration retrofits to existing coal-fired power plants. Such a result would provide a valuable quantitative benchmark for policy analysis.

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References


