A Cost-Effectiveness Analysis of Alternative Ozone Control Strategies: Flexible Nitrogen Oxide (NOx) Abatement from Power Plants in the Eastern United States

by

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Submitted to the Engineering Systems Division
in Partial Fulfillment of the Requirements for the Degrees of

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ABSTRACT

Ozone formation is a complex, non-linear process that depends on the atmospheric concentrations of its precursors, nitrogen oxide (NOx) and Volatile Organic Compounds (VOC), as well as on temperature and the available amount of sunlight. The dependence of ozone formation on meteorology makes the timing of emissions important, suggesting the need for a temporally differentiated regulation for NOx emissions. Such a flexible NOx regulation policy, so-called "smart trading", which is designed to target ozone episodes by reducing NOx emissions prior to and during forecasted episodes, has the potential for reducing the compliance cost and helping to solve the persistent ozone non-attainment problem in the Eastern United States. However, the total compliance cost of this new policy depends critically on the accuracy of ozone forecasting.

This thesis aims to address the question of whether a NOx trading program that differentiates across emissions by time could reduce ozone concentrations more cost-effectively than the conventional command-and-control method in the Eastern U.S. given the uncertainty in ozone forecasting. A cost-effectiveness analysis is conducted to compare the average cost for achieving a certain amount of ozone reduction under the proposed smart trading plan and the command-and-control policy. The probability distribution of the compliance cost under a smart trading policy is simulated using a stochastic decision model based on the simulated electricity generation and air quality data. This study demonstrates the scientific and economic feasibility of a time-differentiated trading scheme. I explore whether such a regulatory design is justifiable with respect to ozone forecast accuracy by conducting sensitivity analysis of ozone prediction errors and discover that uncertainty in ozone forecasting may not be a major limiting factor for the feasibility of a time-differentiated NOx cap-and-trade program.

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I want to thank Elena and Dave for offering me many valuable suggestions and ideas along the journey. I cannot possibly offer enough thanks to Yo and Gary for their assistance with the CAMx modeling and post-processing, and for always being so responsive and patient with my technical problems, which are mostly stupid. I still remember that Yo taught me hand-on-hand every detail of Lagragian process analysis and how to use PAVE when I visited Texas.

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L. S.
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Chapter 1. Introduction

Epidemiological and toxicological studies, including controlled human exposure studies, have linked short-term, or acute, ozone exposure (i.e. exposure that lasts less than 8 hours) to health problems for concentrations of ozone at or above 0.08 parts per million (ppm) or 80 parts per billion (ppb). The associated health problems include coughing or wheezing, headaches, nausea, and throat and lung irritation. In particular, these problems impact children, people with lung disease, and active adults. Besides, ozone also damages agriculture, materials, and ecosystems [U.S. EPA 2006a, Feltzer *et al*, 2005].

Tropospheric ozone (O_3) is an oxidant formed from photochemical oxidation of Volatile Organic Compounds (VOC), Nitrogen Oxides (NOx) and Carbon Monoxide (CO) in the presence of sunlight [Seinfeld and Pandis, 2006]. NOx compounds are primarily emitted by electric power plants and on-road vehicles; while VOC emissions come from biogenic sources such as trees, on-road vehicles, and petrochemical plants. Sometimes, NOx and VOCs are co-emitted from the same sources [Martin, 2008; Ryerson *et al.*, 2003]. In addition to ozone formation, NOx itself is associated with respiratory problems and also serves as a precursor for fine particulate matter (PM); and many VOCs are human toxins [Martin, 2008]. Thus ozone regulation also has ancillary benefits through the reduction of other harmful pollutants.

In 1997, U.S. EPA announced the National Ambient Air Quality Standards (NAAQS) for eight-hour averaged ground level ozone to be 80 ppb[1]. EPA uses the average of the annual 4th highest 8-hour daily maximum concentrations from each of the last three years of air quality monitoring data to determine a violation of the ozone standard. In 2008, EPA further lowered the 1997 standard to 75 ppb.

[1] Within the context of this thesis, 8-h ozone concentration (or level) will be used to represent the average concentration of ground level ozone over the previous eight hours.

Emission cap-and-trade programs have drawn great research attention over the past two decades by promising an economically efficient mechanism for reducing air pollution [Tietenberg, 1998]. Such a program is designed so that facilities that emit below their assigned emission allowances can sell allowances in a market, while facilities that wish to emit above their allowances must buy additional allowances. Lowering the number of allowances (the cap) over time thus leads to the total reduction of emissions. Such cap-and-trade programs for NOx emissions have been planned or implemented in several ozone non-attainment areas. Examples are California's Regional Clean Air Incentives Market (RECLAIM) since 1994[2]; the East Coast's NOx Budget Program since 1999[3]; and Texas's Emissions Banking and Trading of Allowances (EBTA) program[4]. Similar programs for Highly Reactive VOC (HRVOC) also exist in areas that have identified the need for significant VOC reductions, such as Houston and surrounding areas in Texas [Wang *et al.*, 2007][5].

Many areas of the U.S. have found it particularly difficult to achieve the ozone standard. As shown in Figure 1, almost all major urban and industrial areas in the U.S. fall into the non-attainment category. The Eastern U.S., especially the counties surrounding Philadelphia and Baltimore are typical examples of areas that suffer from persistent ozone non-attainment problems (see Figure 2). In 2005 EPA adopted Clean Air Interstate Rule (CAIR) to provide a federal framework to limit the emission of SO_2 and NOx from the 28 eastern states and the District of Columbia with declining caps in an initial Phase 1 (2009 for NOx and 2010 for SO_2), and a subsequent Phase 2 (2015 for both SO_2 and NOx) in order to reduce the concentrations of ozone and Particulate Matters (PM) in the affected (downwind) states. However, the EPA's air quality modeling shows that further decreases in the seasonal cap on NOx emissions from stationary sources in 2009 and 2015 will not guarantee that all areas of the

[2] Detail information see http://www.aqmd.gov/reclaim/reclaim.html
[3] Detail information see http://www.epa.gov/airmarkt/progsregs/nox/sip.html
[4] Detail information see http://www.tceq.state.tx.us/implementation/air/banking/ebta_sb7_program.html
[5] Detail information see http://www.tceq.state.tx.us/implementation/air/banking/hrvoc_ept_prog.html

Eastern U.S. attain the ozone air quality standards by 2015 (Martin 2008, cite U.S. EPA 2006b). One potential reason for the persistency is that ozone formation depends not only on the quantities of precursor emissions but on their timing and location, indicating an urgent need for a carefully designed policy that considers the complicated ozone formation mechanism.

The federal court in 2008 issued an opinion that vacated the CAIR and the associated NOx cap-and-trade program (*State of North Carolina v. Environmental Protection Agency*, No. 05-1244, slip op. (2008)), finding that the regional framework of the CAIR "does not prohibit polluting sources within an upwind state from preventing attainment of NAAQS in downwind states". The federal court's decision will significantly affect NOx and SO_2 allowance trading markets in the future. Whether a replacement regulation of CAIR that preserves some vestiges of the old regime will be developed in the near future is still unknown. However, this certainly opens up the discussions of designing a NOx regulation to help the downwind states of Eastern U.S. achieve ozone attainment goals.

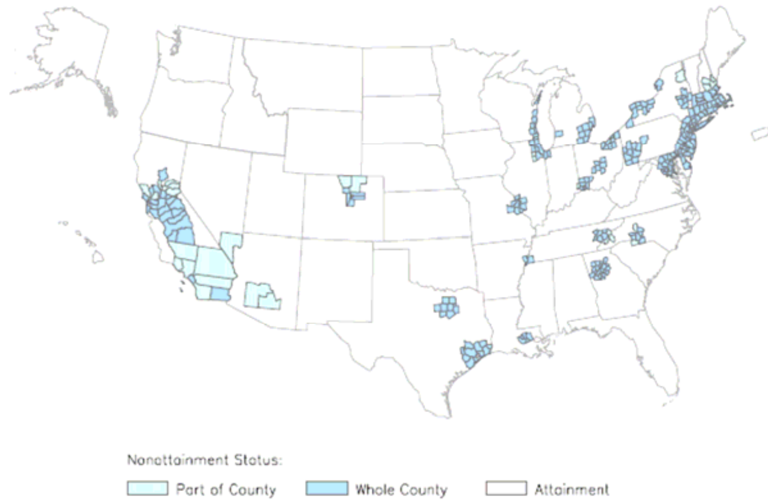

Figure 1: Map of non-attainment areas in the United States for the 8-hour ozone standard in 2008.

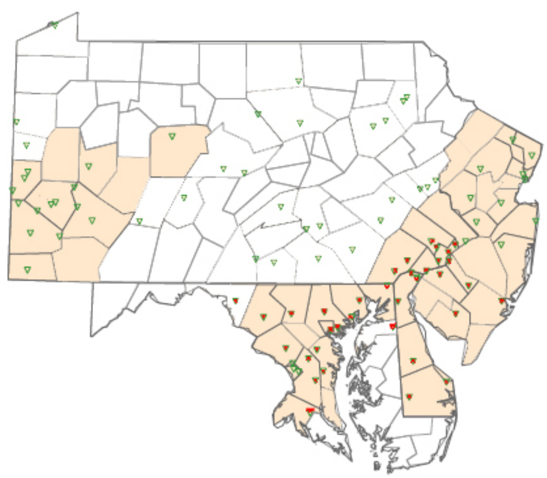

Figure 2: Map of the Classic PJM area (District of Columbia, Delaware, Maryland, New Jersey, or Pennsylvania) with the locations of ozone monitors and ozone non-attainment sites up to December 2008.

Pink shaded area: 8-hour ozone non-attainment counties (52 counties in total)

Green triangles: locations of ozone monitoring sites

Red triangles: 37 ozone monitoring sites used in this study

Source: US EPA Office of Air and Radiation, AQS Database

1.1 Background Information on Ozone Exceedence in the Eastern U.S.

Tropospheric ozone, as an urban pollutant, is not directly emitted from industrial sources; instead, its formation and transport is a complicated, highly nonlinear process. The most important factors affecting photochemical ozone formation are sunlight intensity, absolute and relative concentrations of VOC and NOx, "reactivity" of VOC, temperature, and humidity [Seinfeld and Pandis, 2006]. All of these factors vary in time and by location. Past research has revealed that ozone formed by the same amount of NOx could vary by a factor of five under different meteorological conditions [Mauzeral, 2005]. Additionally, winds transport NOx and VOC emissions and cause ozone formation to be displaced in time and space from the original source. In the meanwhile, precipitation and soil moisture exert a strong control on ozone deposition rates. As a result, ozone concentrations downwind of NOx, CO and VOC emission sources also depend on wind speed, wind direction, precipitation, humidity and soil moisture, which further complicate the problem [Mauzeral, 2005].

Ground-level ozone is a pervasive regional problem in the eastern United States, with frequent exceedences of the 8-hour ozone NAAQS occurring during hot summer days. Scientific studies have uncovered a rich complexity in the interaction of meteorology and topography with ozone formation and transport. In the eastern United States, the worst ozone pollution episodes usually occur when slow-moving, high-pressure systems develop in the summer. This is the time with the greatest amount of daylight, when solar radiation is most direct and air temperatures become quite high. These two prerequisites for abundant ozone formation are further compounded by a circulation pattern favorable for pollution transport over large distances. In the worst cases, the high-pressure systems stall over the eastern U. S. for days, creating ozone episodes of strong intensity and long duration. High ozone episodes are often terminated by the passage of a front that brings cooler, cleaner air to the region [NRC, 1991].

Many areas in the Eastern U.S. have been shown to be sensitive to NOx emissions and insensitive to VOC emissions, making NOx control the major option for reducing ozone concentrations [Martin, 2008]. Anthropogenic NOx emissions are caused by incomplete fossil fuel combustion and are mainly from two sources: on-road and off-road vehicles, and electricity generating units (power plants). Also, all northeastern states are covered under a single airshed, the so-called ozone transport corridor (OTC), and the long-range transport of NOx and ozone from states in the Eastern U.S. such as Pennsylvania and New Jersey greatly contribute to the ozone exceedences in northeastern states such as Massachusetts. Thus, reducing NOx emissions from mobile vehicles and from power plants in the upwind states of the northeastern U.S. are two major options for helping the whole area to achieve ozone standards.

1.2 NOx "Smart trading" Policy

The dependence of ozone formation and transport on meteorology makes the timing and location of precursor emissions important, suggesting the need for a temporally and spatially differentiated regulation for NOx and VOC emissions. It is politically difficult to implement spatially differentiated NOx regulation, i.e. to target specific facilities for application of control technologies/emissions reductions, because it is generally difficult to establish broadly acceptable criteria to do so. In order to address the dependency of ozone formation on meteorology, some NOx emission trading programs are limited within a geographic region that is relatively homogenous in meteorology patterns; and trading between regions is prohibited [Martin, 2008]. For example, the former version of the East Coast's NOx budget program-- the OTR budget program initially allocated different allowances to three different zones; and RECLAIM limits trading between coastal and inland areas [Nobel 2001, cite Farrell, 1999 and Zerlauth, 1999]. On the other hand, temporally differentiated NOx regulations do not suffer from this problem. Therefore, this study focuses on time-differentiated NOx regulations, in particular, time-differentiated NOx cap-and-trade programs, but will pay special attention to the environmental impact and the problem of "hot-spot" formation or "wrong-way trades" as a result of this program.

The proposed time-differentiated NOx cap-and-trade program, so called "smart trading", which is designed to target ozone episodes by reducing NOx emissions prior to and during forecasted high ozone episodes, has the potential for reducing the compliance cost and for solving the persistent ozone non-attainment problem in the Eastern United States. Hypothetically, if the proposed "smart trading" scheme is to be implemented, the price of NOx allowance could be determined by the local administrative agency one day in advance, so that NOx polluters, mainly electricity generating facilities, could adjust their production for the next day.

One way for power plants to achieve short-term NOx reduction is through redispatching, or changing which particular generating units fill electricity demand at a given time. The "dispatch" normally causes the lowest cost generating units to be used first to fill demand, provided that network constraints and other system requirements are met. In the case of NOx cap-and-trade, NOx allowance price changes the relative costs of generating units due to differences in their NOx emission rates. Therefore, a higher NOx price[6] would shift the NOx emissions from those units with higher NOx emission rates to those with lower rates. In this way, the total NOx emissions are reduced while the system's electricity demand is still satisfied.

There are other ways to achieve short-term NOx reductions other than electricity redispatch. For example, instead of producing less electricity, a power plant operator might choose to adjust the air-to-fuel ratio or change the combustion environment in the furnaces to lower NOx emission rates, given an economic incentive. However, unlike the costs for electricity redispatch, the incremental costs associated with these operational changes are difficult to estimate and only limited data is available. For this

[6] If a differentiated cap-and-trade program is to be implemented, number of NOx allowances will vary from day to day, instead of "NOx price". Here, we are using "NOx price" as a convenient way to measure the cost of such a differentiated trading program.

study, operational responses are not modeled; i.e., we assume that the NOx emission rate of each EGU cannot change, and that the only decision a power plant operator could make is whether to dispatch electricity generation or not given the NOx allowance price. The NOx emission changes under electricity redispatch therefore provides a conservative estimate of the cost-effectiveness of a time-differentiated regulation for NOx emissions from point sources.

The main reason why smart trading could help lower ozone concentration at a lower cost than a policy requiring additional control technology is that it targets lowering NOx emissions only on ozone episode days. Different ozone concentrations can result from the same NOx emissions depending on the meteorology. As a result, greater ozone reductions can be achieved by NOx emission reductions during high ozone days. Therefore, compared with reducing NOx emissions during high ozone days, reducing NOx emissions during low ozone days is not only less important in terms of public health, but also less cost-effective in lowering ozone concentrations. However, in order for such a flexible regulation to be implemented, weather and atmospheric chemistry forecasting must be able to predict the conditions conducive to ozone formation with sufficient accuracy and lead-time (24-48 hours) to influence decision-making.

However, whether this goal can be achieved as expected is uncertain and in fact depends on the accuracy of the day-ahead ozone forecasting. Specifically, false positive events (a forecasted high ozone day turns out to be a low ozone day) increase the unnecessary cost on non-ozone days; while false negative events (a forecasted low ozone day turns out to be a high ozone day) decrease the amount of ozone that could otherwise be reduced. The costs of unnecessary reductions and the costs of failing to comply with the NAAQS must be included into the decision analysis when evaluating this new policy.

Although more than 60% of NOx emissions in U.S. are from mobile sources (EPA

AIRDATA[7], see Figure 4 and 5), this work focuses on a differentiated NOx regulation for stationary sources rather than for mobile sources, because fewer data are available that describe the variation of mobile source emissions in time and by location. Stationary anthropogenic sources of NOx, including power plants, industrial boilers, and other industrial facilities, contributed 22% of the total 2005 NOx emissions in Eastern States [Martin, 2008, cite U.S. EPA 2006b], with about 97% of this contribution from power plants. Past research has shown that it is technically feasible, in terms of the ability to redispatch even at high electricity demand times, for power plants to respond to a differentiated regulation with short-term NOx reductions according [Martin 2008]. My research advances the discussion of to what extent ozone regulations could make use of scientific information about the importance of the timing to improve the cost-effectiveness of the regulation of NOx emissions from power plants and how this policy is limited by the advances of modeling techniques; i.e., prediction errors.

1.3 Motivation

It is important to conduct cost-effectiveness analysis for the proposed smart trading policy. Smart trading does not require additional NOx control technology; rather, it provides flexibility to power plant operators to decide whether it is economically preferable to reduce electricity generation to reduce NOx emissions or to generate electricity, and, if necessary, buy NOx permits from other plants. Thus the electricity generation is re-dispatched on ozone conducive days among the electricity generating units within an electrical network so that the electricity generation is shifted to those "cleaner" plants that emit less NOx than others. In this way, the NOx emissions and ozone concentrations in the whole area are reduced with lower cost than installing NOx control technologies such as Selective Catalytic Reduction (SCR) and Selective Non-Catalytic Reduction (SNCR), while still satisfying the total electricity demand in the area. Over time, if the cost of reducing NOx emissions through dispatching

[7] http://www.epa.gov/oar/data/

electricity generation within an electrical network becomes too expensive, NOx control technologies could become a cost-effective strategy for some generators. In other words, smart trading can also provide an incentive for power producers to adopt NOx control technologies. I do not model here this second multi-year decision by power producers. As a first step, it is essential to compare the cost of reducing NOx emissions and ozone concentrations under both smart trading policy designs and under a pollution control technology policy design in order to determine the circumstances under which each policy design would out-perform the other.

Compelling scientific and economic arguments support the use of a differentiated regulation rather than further reductions in the undifferentiated annual or seasonal cap, but there are challenges to implementation. One major challenge is that the time-differentiated regulation requires a reliable, highly accurate ozone forecasting system. The forecasting system must be able to provide prediction of the daily maximum ozone level at least 24-48 hours ahead with enough accuracy in order to influence generator dispatch decisions. The uncertainty in ozone forecasting will add to the compliance cost for achieving a certain ozone mitigation goal under this approach. In particular, a false positive event, or false-alarm of high ozone forecast, would lead to resource misuse and additional cost; while a false negative event would allow high ozone concentrations and continued ozone non-attainment (which imposes other costs on states and localities). Under extreme conditions where ozone forecast is especially inaccurate, a time-differentiated NOx control policy can cost more and reduce less ozone than either a conventional command-and-control policy or an undifferentiated cap-and-trade program. This suggests that there exists a threshold for both the Type I (false positive) and Type II (false negative) errors above which the smart trading policy would not be an effective policy design.

Three-dimensional atmospheric chemistry and transport models (CTM) are widely used by the U.S. EPA and state administrative agencies for ozone attainment demonstrations. These models simulate the photochemical reactions, atmospheric transport, diffusion, advection, and deposition of ozone and its precursors on a three-dimensional grid covering the air-shed of interest, and provides a reliable method for modeling ozone concentration as responses of emissions of ozone precursors and meteorology. Typical examples of such models are Comprehensive Air quality Model with extensions (CAMx) [Environ, 2009] and Community Multi-scale Air Quality model (CMAQ) [Byun, 2006]. However, there is significant uncertainty in ozone modeling using these models, mainly due to uncertainties in model structure, parameters, and inputs. The uncertainty in model structure can be reduced by adding more grid cells, explicitly resolving more physical and chemical processes rather than relying on parameterizations, and/or improving model algorithms. Uncertainties in the input data and parameters mainly include uncertainties in emission inventories of NOx and VOC, estimates of reaction rates and meteorology forecasts. For example, some studies report the uncertainty in the biogenic emission estimates of VOC inventory for the United States to be of the order of 300% [Roselle, 1994]. Improvements in emission inventories of NOx and VOC, and in meteorology forecasts would lower uncertainties in this category.

It is important to determine the threshold type I and type II errors, or the tolerance range for the forecast errors, because it is critical to the evaluation of a flexible regulation plan that relies on accurate ozone forecasting, such as the "smart trading" policy modeled here. If the required forecast accuracy is currently available using current modeling methodologies, further investigation of this regulatory approach is warranted. If the required forecast accuracy is currently not achievable, this analysis could also provide guidelines for the EPA to estimate the potential value of improving their models, improving emission inventories, and increasing computational capacity.

This study will evaluate the validity and technical and economic feasibility of a smart trading policy plan by conducting cost effectiveness analysis. This study will also try to answer the question of whether a temporally more "targeted" reduction plan would help solve the persistent non-attainment at a lower cost than a policy requiring additional pollution control equipment.

1.4 Research Goals and General Approaches

This work aims to provide economic justifications for a time-differentiated NOx cap-and-trade program. The central question I aim to address is whether it is economically more cost-effective to lower ozone concentration through NOx smart trading compared with the traditional command-and-control policies, and whether the implementation of this program is likely to be limited by the uncertainty in ozone modeling and the advances of modeling techniques in the near future.

In the Eastern U.S., most power plants that participate in the seasonal NOx cap-and-trade programs also participate in one of three wholesale electricity markets: the New England Power Pool, the New York Power Pool, or the PJM Interconnect [Martin, 2008]. Considering that these systems have similar basic structures and characteristics, PJM is used here to analyze the potential behavior of a typical electrical power system under the proposed time-differentiated NOx cap-and-trade program in the Eastern U.S.. All of these systems have "system operators" who coordinate the balancing of supply and demand; and they could also coordinate the pricing of NOx allowances upon the forecast of a high ozone day under smart trading.

The "Classic" PJM power system is the original Pennsylvania, New Jersey, Maryland power system that included these three states as well as the District of Columbia and Delaware. PJM has since expanded, but in this analysis we restrict attention to the Classic PJM region.

The East Coast's seasonal NOx cap-and-trade programs cap the total emissions from affected stationary sources between May and September each year (the "ozone season"). This analysis uses historical emission inventories of ozone precursors and meteorological data to simulate the hourly ground level ozone concentrations in the

PJM area during June, July and August 2002. The summer 2002 is selected as a case study because it represents a typical summer ozone season with higher ozone occurring in the mid-Atlantic and northeastern urban corridor and the greater Ohio River Valley region. The simulated ozone concentrations will serve as a "test sample" to compare the cost-effectiveness of smart trading and the SNCR case. May and September are not included into this analysis since the meteorological data of the spatial resolution we need are not available for these two months of 2002.

In reality of NOx regulation, states are most likely to impose secondary control technology on the dirtiest plants that run most of the time, such as coal-fired plants. Also, most NOx emissions in the Eastern U.S. are from coal-fired plants; and most of these coal-fired plants have already installed primary control technologies [NESCAUM, 1998]. Thus secondary NOx control technologies are expected to play an important role in controlling point source NOx emissions in the Eastern U.S.. SNCR is one of the most discussed secondary NOx control technologies. Therefore, this study compares the cost-effectiveness of smart trading under different NOx prices with that of installing SNCRs to all coal-fired power plants in PJM.

In this study, I will develop an analysis tool to integrate electrical power system and photochemical modeling into a stochastic decision analysis model (as shown in Figure 3), which will facilitate informed decision-making on NOx control policies under uncertainty in ozone prediction. I will simulate the electricity generation dispatch given different prices of NOx allowances under smart trading, and the resulting NOx emission re-distribution. I will then apply a three-dimensional Atmospheric Chemical and Transport Model--CAMx, which is widely used for ozone attainment demonstrations, to evaluate the impact of NOx emission changes under smart trading on ozone concentrations [Morris 2001, 2003]. I use the summer of 2002 (June, July and August) as a case study for smart trading and develop a two-state Markov Chain model to simulate the occurrence of high ozone days based on the simulation of summer 2002 data. When analyzing the cost and ozone reduction, I incorporate errors in ozone forecasts into the stochastic decision analysis by assuming the modeled world is the real world and that the errors in ozone forecasts occur randomly at a prescribed rate in this modeled world. I then conduct a sensitivity analysis of the mean total cost and mean total reduction of peak ozone of the NOx smart trading policy for different error rates in ozone forecast, and thus determine threshold values for false positive and false negative ozone forecast errors above which the "smart trading" policy is less cost-effective than a command-and-control strategy. In this way, I demonstrate the level of ozone forecast accuracy required for a time-differentiated regulatory design to be effective.

1.5 Overview of Chapters

This thesis is organized as follows:

Chapter 2 examines the anthropogenic sources of ozone precursor emissions, and explains the justifications for policies that limit anthropogenic NOx emissions rather than VOC emissions as the main ozone control strategy in the Eastern U.S..

Chapter 3 reviews the methods and technologies power plants use to control NOx emissions. One of these technologies, Selective Noncatalytic Reduction (SNCR) is used as one example of traditional approach requiring additional emissions reductions through technology to compare with smart trading in terms of the cost-effectiveness in reducing ozone concentrations. The NOx abatement cost of SNCR and smart trading will also be discussed in this chapter.

Chapter 4 turns to the results of potential short-term NOx reductions from power plants under smart trading when assuming that the NOx emission rate is fixed and electricity re-dispatch under higher NOx price is the only response from power plant operators. This chapter will discuss the changes of NOx emissions, as well as the changes of electricity prices as a result of re-dispatch under different NOx prices and compare the results to the case of installing SNCRs to all the coal-fired plants. This chapter will also discuss the daily cost of electricity generation under re-dispatch.

Chapter 5 introduce the 3-dimensional photochemical and transport model used to simulate the ozone concentrations in the PJM area during summer 2002, and the reduction of the 8-hour daily maximum ozone concentrations as a result of electricity redispatch under different NOx prices, and installing SNCRs.

Chapter 6 introduces the framework of decision making about smart trading and SNCR.

Chapter 7 conducts the stochastic decision analysis in conjunction with the 2-state Markov model given prescribed errors in ozone forecasts. This chapter will also conduct sensitivity study of the cost-effectiveness of smart trading on the Type I and Type II errors; as well as the "threshold" Type I and Type II errors on the cost of SNCR. Chapter 7 also discusses the circumstances for rejecting and accepting smart trading, the implications of the results on SNCR, and the estimation of costs of upgrading current atmospheric model.

Chapter 8 discusses the potential political and legal barriers for the implementation of this policy plan. Chapter 9 includes conclusion and future work.

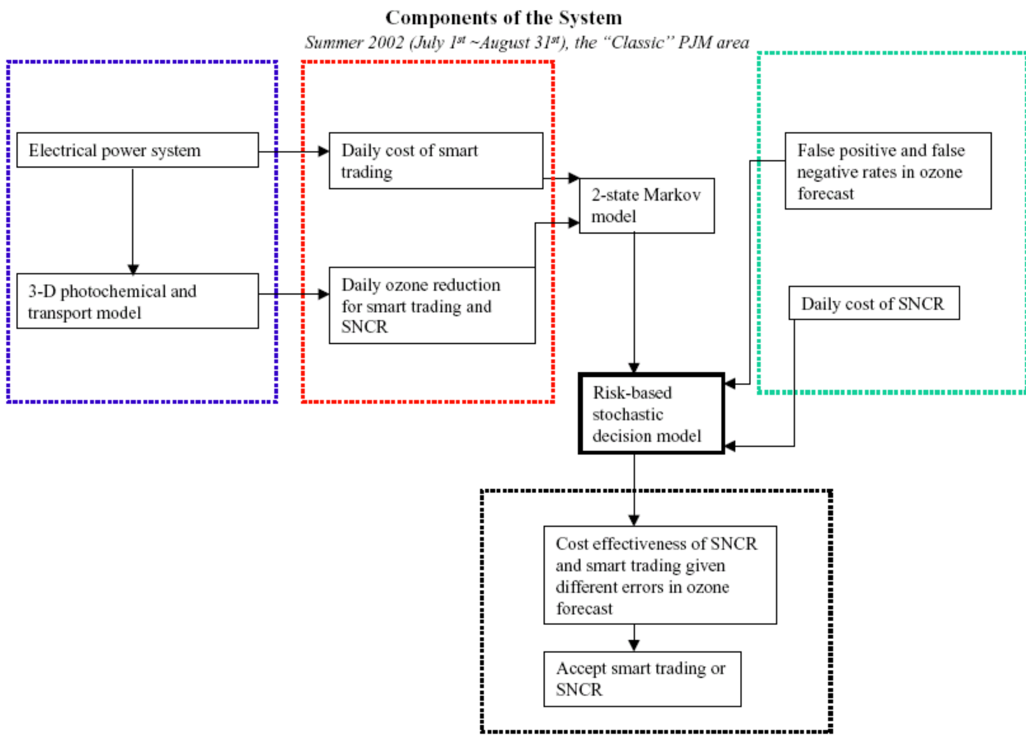

Figure 3: Illustration that shows the components of the system and the flow chart of analysis.

Blue box: the electrical system and photochemical models used to simulate the NOx emissions and resulting ozone concentrations under dispatch. Red box: inputs of the stochastic decision model that varies on the day-to-day basis. Green box: inputs of the stochastic decision model that is constant through each decision analysis. Black box: model outputs.

Chapter 2. Anthropogenic Sources of Ozone Precursors

Daily peak ozone concentrations are nonlinear and non-monotonic functions of VOC, NOx, and the ratio of VOC/NOx. At sufficiently low ratios of VOC/NOx, the conversion of NO to NO_2 and subsequent formation of ozone is limited by the availability of organic compounds (so-called VOC limited or NOx saturated cases), whereas at sufficiently high ratios of VOC/NOx, ozone production is limited by the available amount of NOx. As shown in the ozone isopleths that can be easily found in any atmospheric chemistry textbook [Seinfeld, 2006], reductions of VOC emissions do not change peak ozone levels if ozone formation is NOx-limited. In contrast, reductions of NOx emissions typically increase peak ozone levels if ozone formation is VOC-limited, until a transition to a NOx-limited condition has been achieved, after which further reductions of NOx begin to lower peak ozone levels. Close to the turning points of the ozone isopleths, reducing both NOx and VOC can lead to ozone reduction.

Generally speaking, most ozone pollution problems in the Eastern U.S. can be attributed to either one or the combination of the two main anthropogenic sources of ozone precursors: power plants and urban transportation. These two sources have distinct NOx and VOC compositions and thus lead to different ozone plume characteristics in the downwind area in terms of both ozone production rate and magnitude.

In a typical urban setting, strong sunlight, high temperatures, significant VOC and NOx emissions from mobile sources, and biogenic emissions of reactive VOC from trees, forests and vegetation combine to generate optimal conditions for rapid photochemical ozone production. As shown in Figure 4, mobile vehicles are the biggest contributor to both NOx and VOC emissions in the US---60% and 38%, respectively, in 2002. Co-emissions of NOx and VOC from spatially dispersed sources lead to fast ozone formation and thus elevated ozone concentration in the urban areas diluted somewhat due to the dispersal.

In contrast, electric power plants are the second largest NOx source in the US—22% in 2002, but they have negligible VOC emission compared to their NOx emissions (NOx/VOC~100, from Figure 4). Consequently, VOC/NOx ratios are usually so low that ozone formations in the plumes of air transported away from power plants are initially suppressed. During plume transport, ozone is formed over time as a result of mixing the plume NOx with primarily biogenic reactive VOCs in the environment.

Different ozone control strategies should be applied to different regions in the U.S., depending on the main source types of NOx and VOC, and VOC/NOx; i.e., whether the ozone formation in the region is NOx-limited or VOC-limited. Generally speaking, rural regions have relatively high background biogenic VOC concentrations and limited sources of NOx, while urban regions are the opposite. Thus ozone formation tends to be VOC-limited in urban-core areas of large cities, NOx-limited in rural areas, and less VOC-limited and more NOx-limited in downwind suburban areas. In addition, NOx-limited conditions can also be created within urban plumes where the faster consumption of NOx creates a condition of VOC excess, and by unusually large (and highly reactive) VOC emissions from industrial sources such as found in the Houston, Texas metropolitan area.

NOx reduction may lead to different ozone changes depending on the location of the NOx sources. In the case of the Eastern U.S., most areas are NOx-limited, due to the large amount of trees that produce high levels of VOCs. The main NOx sources in the Eastern U.S. are mobile transportation and fossil fuel combustion in power plants (Figure 5). Thus reducing NOx emissions from power plants is expected to reduce the maximum ozone concentrations. In contrast, most areas in California are VOC-limited. It has been shown that reductions in NOx emissions from diesel trucks not only did not decrease ozone, but actually increased it [Blanchard, *et al.*, 2008]. Thus, more stringent controls on VOCs rather than NOx would be more effective for cutting ozone air pollution there.

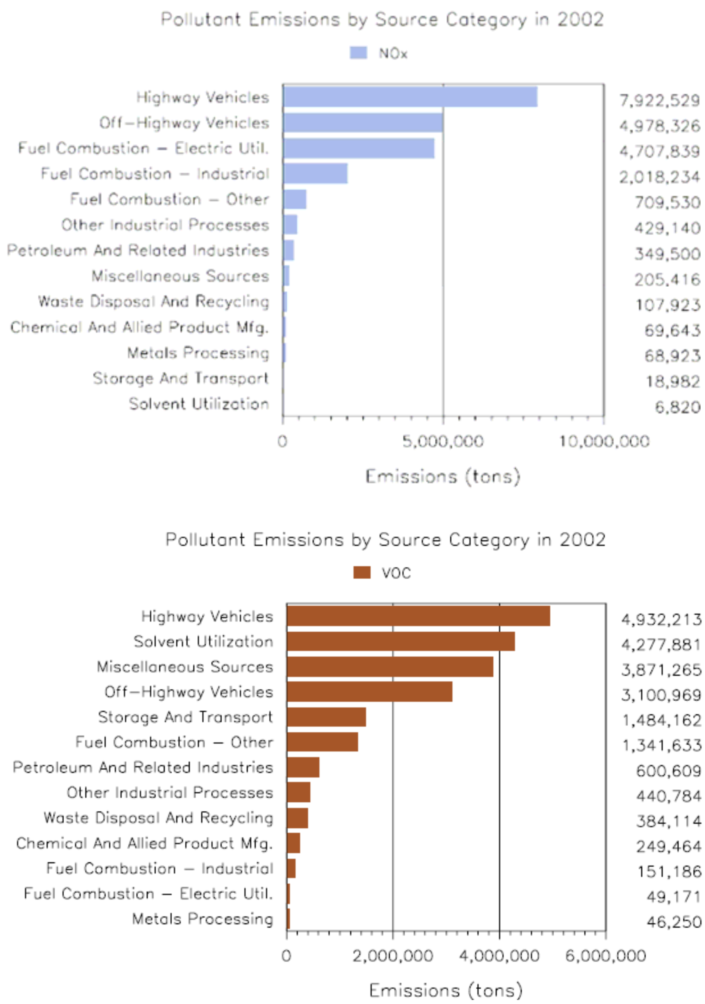

Figure 4: (upper) NOx and (lower) VOC emissions by source category in U.S. in 2002. Source: US EPA Office of Air and Radiation, AQS Database

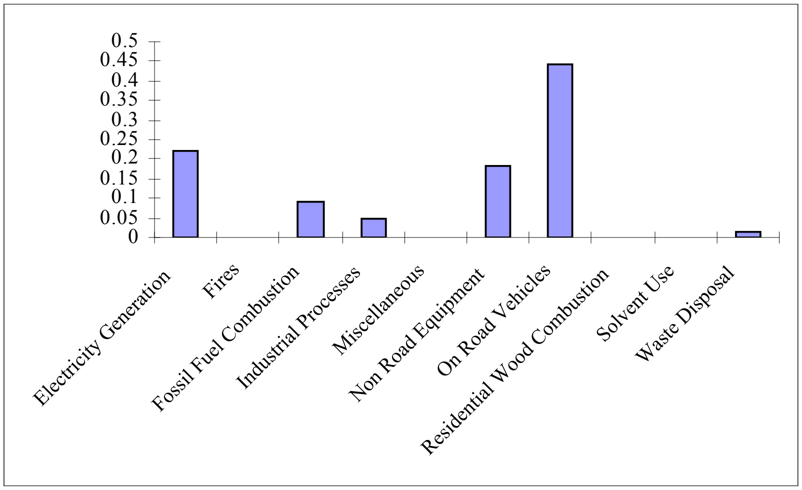

Figure 5: Fraction of anthropogenic NOx emissions by category in the PJM area.

Source: US EPA Office of Air and Radiation, AQS Database

Chapter 3. NOx Control Technologies

The previous chapters discussed three reasons to consider a time-differentiated NOx cap-and-trade program such as smart trading. First, the impact of NOx emissions on ozone formation varies in time and by location. Second, policies that have motivated large reductions in NOx emissions without attention to the timing and location have been shown to be incapable of helping all areas of the Eastern U.S. attain the ozone NAAQS and have been invalidated. Third, a time-differentiated NOx cap-and-trade program can provide an incentive for power producers to adopt NOx control technologies such as Selective Catalytic Reduction (SCR) and Selective Non-Catalytic Reduction (SNCR).

As stated earlier, smart trading does not require additional NOx control technology; rather, it provides flexibility to power plant operators to decide whether it is economically preferable to reduce electricity generation to reduce NOx emissions or to generate electricity. In this way, the NOx emissions and ozone concentrations in the whole area are reduced with lower cost than installing NOx control technologies such as SCR and SNCR. Over time, if the cost of reducing NOx emissions through dispatching electricity generation within an electrical network becomes too expensive, NOx control technologies could become a cost-effective strategy for some generators. Thus it is essential to compare the cost of reducing NOx emissions and ozone concentrations under both smart trading policy designs and under a pollution control technology policy design in order to determine the circumstances under which each policy design would out-perform the other.

This chapter will give an overview of the methods and technologies that are expected to play a significant role in future NOx reductions in Eastern U.S.. One of these technologies, SNCR, is used as one example of traditional approach requiring additional emissions reductions through technology to compare with smart trading in terms of the NOx abatement costs.

3.1 Overview of NOx Control Technologies for Power Plants

The technologies for controlling NOx emissions from power plants can be categorized into primary controls and secondary controls in general. Primary control methods are those that reduce the amount of NOx originally formed in the primary combustion zone of the furnace. Typical examples of primary controls are Ultra Low NOx Burners and combustion modifications, such as adjusting the air-to-fuel ratio, maintaining adequate furnace pressure and biasing the combustion environment in the furnaces. The secondary control methods are those that reduce the NOx concentration of the exhaust gas from the primary combustion zone, including Selective Non-Catalytic Reduction (SNCR), Selective Catalytic Reduction (SCR), Conventional Reburning Technology (Gas and Coal Reburning), Fuel-Lean Gas Reburn™ (FLGR™), hybrid SNCR/SCR, Amine Enhanced Gas Injection (AEGI), Advanced Gas Reburn (AGR) and combinations such as Reburning SNCR. According to a 1998 NESCAUM report [NESCAUM, 1998], in 1996 about 91% of utility boiler NOx is produced by coal-fired power plants and more than 70% of NOx from coal-fired boilers in the OTR was from units that were equipped with Low NOx Burners or Combustion Controls. Thus NOx reduction in the OTR has largely been achieved through the application of primary controls. Thus secondary controls are expected to play an important role in the reduction of NOx from coal-fired facilities in the Eastern U.S..

SCR and SNCR are two popular secondary control methods for reducing NOx emissions from coal-fired power plants [NESCAUM, 1998]. In SCR systems, ammonia vapor is used as the reducing agent and is injected into the flue gas stream, passing over a catalyst. NOx emission reductions of up to 70% can be achieved. The optimal temperature is usually between 300°C and 400°C. In SNCR systems, a reagent is injected into the flue gas in the furnace within an appropriate temperature window. Emissions of NOx can be reduced by 30%~60%, with a typical value of 40%. The NOx and reagent (ammonia or urea) react to form nitrogen and water.

SNCR is generally capable of moderate levels of NOx reduction. It is expected to play a major role in future reductions of NOx from coal-fired plants in the Northeastern U.S., either alone or in combination with other primary or secondary control technologies. A principal advantage of SNCR is its low capital cost relative to most other secondary control approaches, which also makes it very attractive as a seasonal control strategy. In this study, the cost of SNCR and associated reductions of NOx emissions and ozone concentrations will be used to compare with those of smart trading under different NOx allowance prices.

3.2 Cost Analysis of SNCR

Selective Non-Catalytic Reduction (SNCR) is a NOx reduction technology that is highly process dependent. Thus a 40% NOx reduction rate is typically assumed for this technology, because it is in the range of reduction that is typically possible with this technology. The actual level of reduction by SNCR would be determined on a case-by-case basis. Some facilities will not be able to achieve 40% NOx reduction. Others may be capable of greater reductions by SNCR. For simplicity, a 40% reduction of NOx emission rate (from coal-fired power plants) is assumed for this study.

The 1998 NESCAUM report estimated the typical cost, including the O&M costs, for a SNCR system is $0.78-1.05/MWhr for a boiler that has NOx emission rate at 0.45 lb/MMBTU, and is $1.24-1.84/MWhr for a boiler that has NOx rate at 1.00 lb/MMBTU. Considering that the NOx emission rates of all the coal plants in PJM are within the range of 0.04-0.8 lb/MMBTU, $1.23/MWh, which is the average of $0.78/MWh, $1.05/MWhr, $1.24 and $1.84/MWhr, is used to represent the average cost associated with the two types of boilers, and a 20% uncertainty associated with this cost is assumed. The capital cost for both categories of boiler is \$15/KW.[8]

In this analysis, the SNCRs are installed at all coal-fired plants in PJM (98 units in total). The total nameplate capacity for the 98 coal power plants in the PJM region is 25070 MW/h. The average output generation for the 98 plants is estimated to be 17300 MW/h, yielding an average capacity factor of approximately 70%.

Up front capital cost=25070MW*\$15/kW*1000kW/MW=\$376M
Annual net payment=\$40.4 M, assuming a project lifetime of 15 years and a real cost of capital rate of 6.67% (nominal rate of 12% with inflation at 5%).[9]
Monthly average O&M cost=
(Cost/MWhr*25070MW*0.7*24hours/day*365days/year-capital cost)/12
Assuming a 3-month ozone season and no operation outside of the ozone season, the total seasonal cost is the sum of annual capital cost and monthly O&M cost.

If cost/MWhr=\$1.23, monthly average O&M cost=\$12.4 M, total seasonal cost for 3 month=\$40.4 M+\$12.4 M*3=\$77 M, daily average cost=\$0.84 M as shown table 1. These values are estimated in 1998 dollars. Since the daily costs for the "smart trading" are calculated in 2005 dollars, the SNCR cost is converted into 2005 real dollars using a 5% inflation rate in order to compare the cost of SNCR and "smart trading". This yields an average daily cost of 1.2 Million \$/day during the June-July-August ozone season in 2005 dollars.

The results shown in table 1 should be regarded as typical values, and actually cost may be highly uncertain. Since the cost/MWh provided by the 1998 NESCAUM report is \$0.78-1.05/MWhr and \$1.24-1.84/MWhr for two typical types of boilers. A 20% uncertainty is assumed for the estimated daily cost of the SNCR case.

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[8] Capital costs are assumed for a ~200 MW or smaller boiler. \$/KW for capital is expected to be lower for larger boilers.
[9] The average age of boilers in the Eastern U.S. is about 30 years. The unusually high age of boilers in this region makes a shorter lifetime more appropriate for this study.

Table 1 Summary of Approximate Costs of SNCR

Capacity	Average Capacity Factor	Capital Cost		Annual Control		3 month Seasonal Control (June-July-August)		
MW	%	\$/KWh	M\$/year	\$/MWhr	M\$	M\$	M\$/day (1998 \$)	M\$/day (2005 \$)
25070	70	15	40	1.23	189	77	0.84	**1.2**

3.3 Cost of Smart Trading

Assume that the only response a power plant operator has upon the forecast of high ozone days is whether to dispatch electricity generation or not given the NOx allowance price. Then the cost of smart trading is estimated using the cost of electricity redispatch, which is the increased variable cost of electricity generation under higher NOx price relative to the base price. The increased cost of electricity generation for an individual EGU is takes into account of the generator's output level, heat rate, the cost of fuel, NOx emission rate and the price of NOx allownce.

In the Classic PJM simulations, the variable costs of the power plants are represented by linear cost curves, in which NOx emissions are incorporated as an additional fuel cost:

c_i (\$/MWh) = $H_i(p_{fi} + p_{ni}N_i) + O\&M_i$

where, for each generating unit *i*, H_i is its heat rate (mmBTU/MWh), p_{fi} is the price of fuel (\$/mmBTU), p_{ni} is the price of NOx permits (\$/ton), N_i is the unit's NOx emission rate (tons/mmBTU), and $O\&M_i$ is the unit's variable Operation and Maintenance costs ($/MWh).

The increased cost of electricity generation under higher NOx price relative to the base price for each generating unit *i* at a given hour is then $C_i^{'}$:

$C_i^{'}=c_i\ u_i(\text{higher NOx price})-\ c_i\ u_i(\text{base NOx price})$

where u_i is the unit's output in MWh.

The increased daily cost of smart trading is then the summation of $C_i^{'}$ across over each hour of the day and over all EGUs in PJM. The cost analysis of smart trading will be discussed in detail in the later chapters.

Chapter 4. Flexible NOx Reductions through Power Plant Redispatch in Classic PJM

Past research has shown an urgent need for a flexible and targeted regulation of NOx emissions, which could provide incentives to reduce the environmentally most damaging emissions. Electricity generators contribute to about 20% of total anthropogenic NOx emissions in the U.S. and about 22% in the PJM area in 2002 (EPA only released this information up to 2002, from the EPA AIR website; see Figures 4 and 5). One example of a flexible regulation is to reduce NOx emissions from power plants through electricity re-dispatch upon the forecast of upcoming ozone episodes 24-48 hours in advance, shifting some of the electricity generation from units with high NOx emission rates to those with low rates[10].

Previous analysis [Martin, 2008] has shown that flexibility exists in the PJM system to reduce NOx emissions through redispatch because (1) even during the hours of the highest demand, there is reserve generating capacity that is not actually generating electricity; (2) there is heterogeneity in the NOx emission rates across generators and the low NOx generation is underutilized, and (3) transmission constraints do not prevent redispatching and, in some cases, actually relieves congestion. Redispatching could occur between natural gas burning units and coal burning units, or between units of the same fuel type with different NOx rates. This means that achieving NOx reductions through re-dispatch is technically feasible. However, questions remain in order to test the feasibility of this regulatory concept, including:

1) Do changes in NOx emissions from redispatching actually lower ozone concentrations, especially during high ozone episodes?

[10] There are other ways of achieving short-term NOx reduction other than electricity redispatch. The system being modeled in this study is a simplified model that assume the NOx emission rate of each EGU can not change, so that the only decision a power plant operator could make is whether to dispatch electricity generation or not given the NOx allowance price.

2) How would the electricity prices change with increasing NOx price, considering the inelasticity of electricity demand?
3) Is the electricity generation redispatch likely to move large amounts of NOx emissions into one area (and thus lead to the formation of "hot spots")?

These questions will be addressed in this and the next chapter. Considering that other Eastern U.S. power systems share key characteristics with Classic PJM, the results presented in this chapter is likely to hold generally for other power systems in the Eastern U.S..

4.1 Description of Methods

The "Classic" PJM power system is the original Pennsylvania, New Jersey, Maryland power system that included these three states as well as the District of Columbia and Delaware. PJM has since expanded, but in this analysis we restrict attention to the Classic PJM region (PJM for short).

The electricity generation re-dispatch under different NOx prices, which determine the NOx emission changes from individual power plants, is modeled using the *PowerWorld* Simulator[11]. Optimal Power Flow (OPF) mode is used to simulate the potential magnitude of reductions in NOx emissions that can be achieved as a consequence of redispatch while meeting electricity demand in PJM. In OPF mode the network constraints (e.g., line limits) were enforced. Only network contingencies are considered in this study, but not security contingencies.

The PJM Financial Transmission Rights (FTR) base-case power flows is used to simulate Classic PJM [Martin, 2008]. It contains nodal loads and power injections for representative levels of demand at different times. Two scaled cases of FTR are used in this study to simulate the hourly electricity redispatch: the "high utilization" case and the "July average" case. The "high utilization" case scaled the FTR base case

[11] Available from http://www.powerworld.com/downloads/general.asp

according to the July peak demand; while the "July Average" case is based on the PJM FTR July (average demand) load flow. The hourly electricity generation is scaled from either one of the two base cases depending on whether the hourly demand is closer to the average or peak demand.

In the Classic PJM simulations, NOx emissions and NOx allowance prices are incorporated into the variable costs of the power plants as an additional fuel cost. For each level of demand and NOx price, the units are "dispatched" in order of least cost according to these cost curves. By explicitly including the emissions cost in the generator's supply cost curve, we are able to endogenize the generator's response to changing NOx stringency. The NOx price is applied uniformly to all units in PJM with $2k/ton reproduces the policy as of 2002 (which I define as the base case). Smart trading policy scenarios within the context of this study consist of increasing the base case NOx price to $30k, 50k, 100k and 125k/ton.

Data on the average delivered cost of fuel for natural gas, coal, petroleum products, and petroleum coke delivered to the electricity sector from the EIA's Electric Power Monthly for August 2005, as well as fuel types and heat rates from the EPA's EGRID[12] database, are used to generate the cost curves. The cost curves are calibrated to reproduce several solved load-flow cases for representative hours. We constrained the generation from all initially operating units to be at least 20% of their capacity and units could generate up to 100% of their summertime rated capacities. We also held the generation from all units outside Classic PJM and imports and exports constant.

4.2 NOx Emission Changes

Figure 6 shows the level of NOx reduction for the aggregate PJM region that result from different NOx prices. Prices of $30k, 50k, 100k and 125k/ton NOx result in

[12] EGRID: http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html

approximately 23%, 30%, 41% and 42.5% NOx emission reduction, respectively, through electricity re-dispatch. In comparison, installing SNCRs at the 98 coal electricity generation units in the Classic PJM leads to ~34% NOx emission reduction in aggregate. Estimated from Figure 6, the maximum NOx emission reduction that can be achieved through electricity re-dispatch is around 43%. The incremental NOx reduction from $125k relative to $100k /ton NOx is less than 2%. Therefore, this analysis only considers electricity re-dispatch with NOx prices up to $100k/ton.

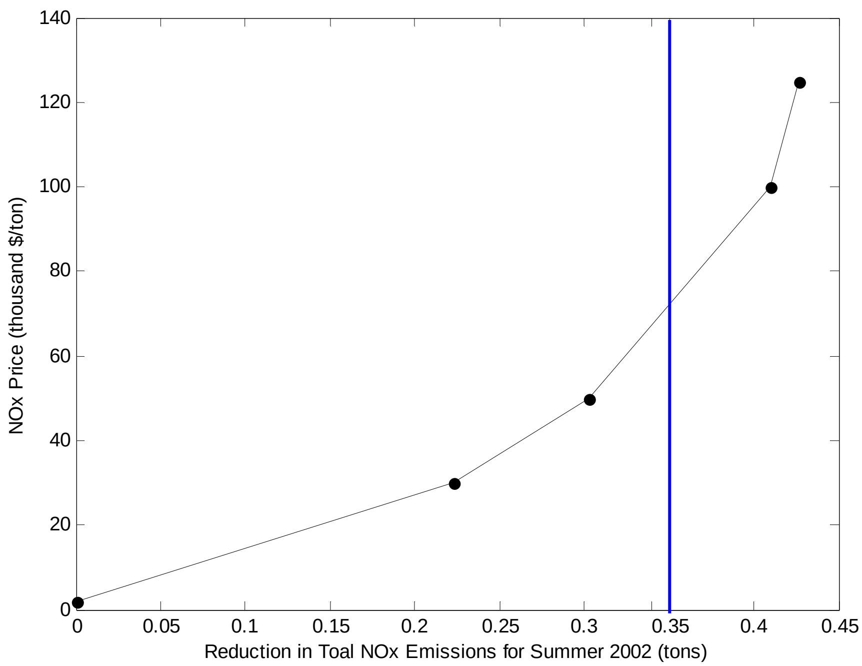


Figure 6: The fraction of total NOx reduction over the whole PJM network during June 1st ~August 31st, 2002. Vertical line: fraction of total NOx reduction if install SNCR to all coal plants.

Figure 7 shows the time series of total NOx emissions from the Classic PJM through electricity re-dispatch under NOx prices of $2k and 100k/ton. It is shown that hourly NOx emissions have the diurnal cycle with peak in the afternoon and minimum value in the night. The maximum hourly NOx emission rate in aggregate is around 42 tons, the minimum rate is around 7 tons, and the mean rate is around 22 tons; and the rate does not have strong episodic feature.

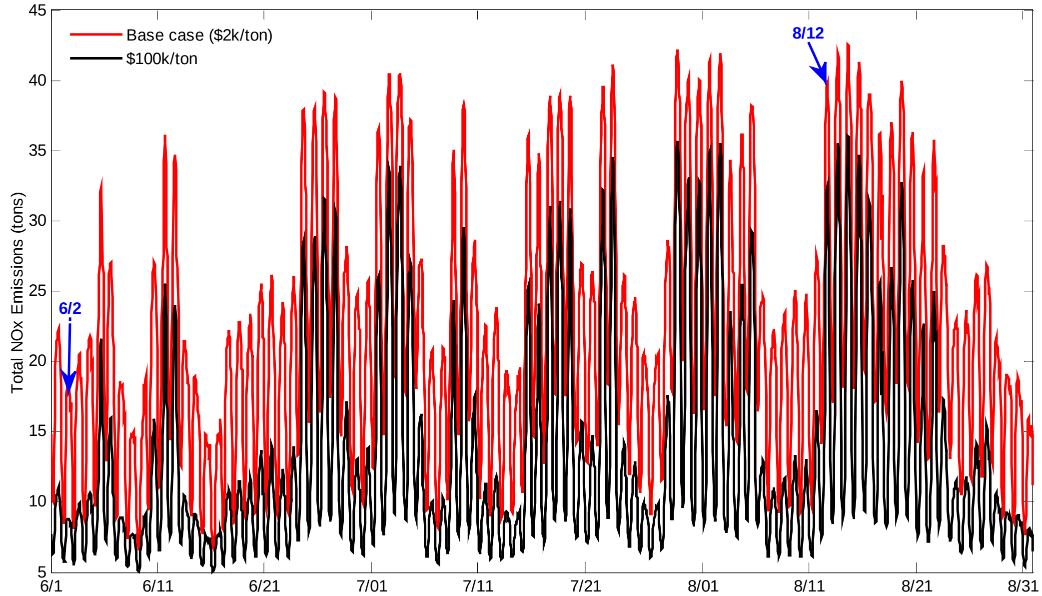
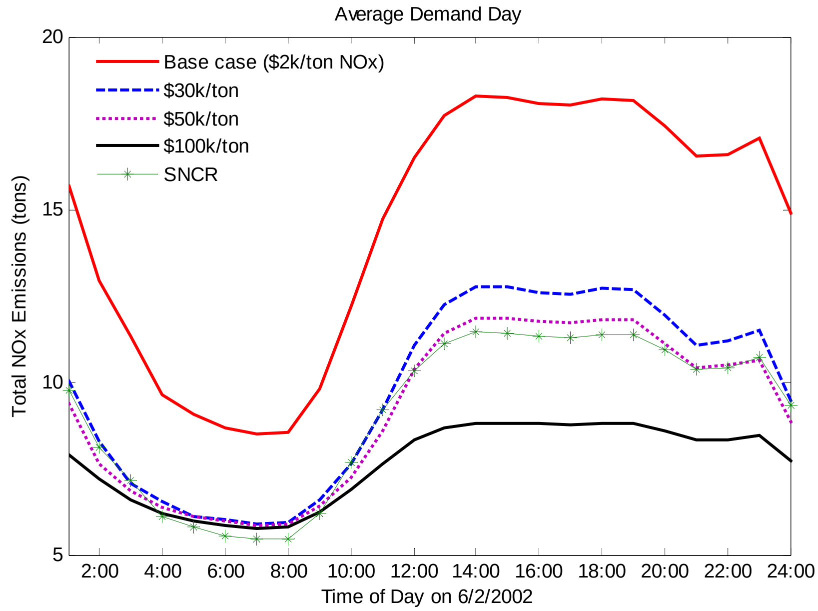


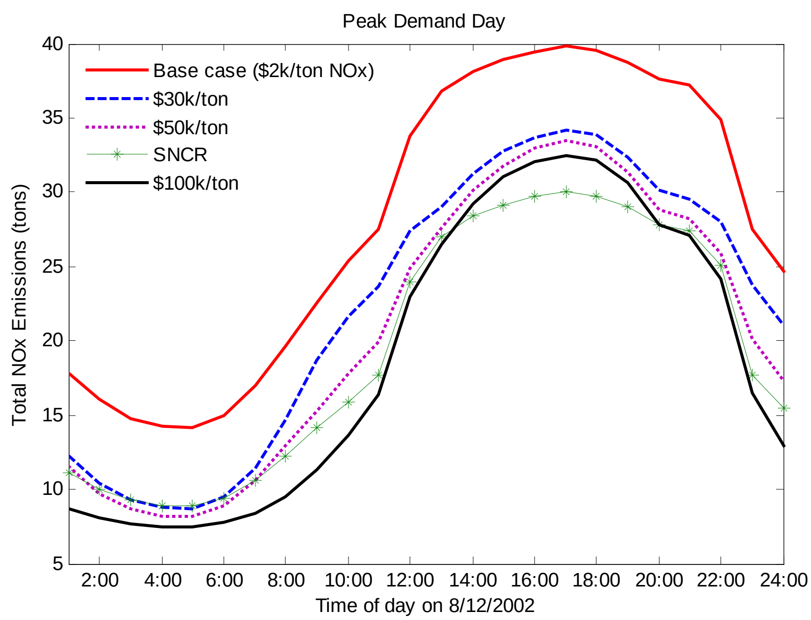
Figure 7: Time series of total NOx emissions across the Classic PJM system during June 1st~ August 31st 2002 with the NOx price to be $2k and 100k/ton.

Figure 7 shows that electricity redispatch would likely lead to more NOx reductions during an average or low demand hour than during a peak demand hour. To illustrate this feature more clearly, the diurnal cycle of NOx emissions as modeled for June 2nd and August 12th are shown in shown in Figure 8 (a) and (b). Considering that the peak electricity demand for PJM is roughly 48000 MW, June 2nd 16:00 (16:00 in Central Time; 15:00 in Eastern Time) with a demand of ~26500 MW represents an average demand hour, and August 12th 16:00 with a demand of ~46700 MW, represents a peak demand hour.

From Figure 8, it can be seen that even during peak demand hours, re-dispatch is still able to reduce NOx emissions, although the amount reduced is smaller during the higher demand hour in terms of percentage (but not tons). In peak demand hours (e.g., afternoon of August 12th, as shown in Figure 8b), installing SNCRs at all coal power plants is likely to reduce more NOx than through re-dispatch, even at a NOx price of $100k/ton; while during an average (e.g., afternoon of June 2nd) or low demand hour (e.g., night or early morning of June 2nd) the SNCR case is likely to reduce a similar amount of NOx as achieved by re-dispatch with a NOx price of $50k/ton.



(a)



(b)

Figure 8: Time series of total NOx emissions on (a) June 2 and (b) August 12, 2002 if different NOx price are applied ($2k, 30k, 50k and 100k/ton) and installing SNCR on all coal units.

The fact that less NOx reduction can be achieved during the peak demand hours than during average demand hours does not diminish the value of smart trading at all. Peak electricity demand usually happens in the early afternoon. However, scientific research shows that morning emissions are more potent ozone precursors than emissions later in the day [Thompson, 2009]. Power plants release large amounts of NOx, but no VOC, so that ozone formed gradually, rather than instantaneously, when NOx from power plants reacts with the VOCs in the environment during its transport to the downwind areas. Hence reducing NOx emissions in the morning is crucial in reducing the ozone concentration of the downwind areas in the early afternoon. Considering that ozone formation is significantly driven by temperature and the amount of sunlight, reducing NOx emissions in the morning is then crucial in reducing the daily maximum ozone concentrations in the downwind areas of power plants. Due to the same reason, some policies have attempted to control the morning release of ozone precursor emissions. For example, regulations have been proposed in Texas to limit the morning construction and commercial lawn and garden activity during the ozone season [Thompson 2009]. Therefore, the NOx emission reductions during average demand hours, instead of peak demand hours, are most important in evaluating the alternative ozone control technologies.

Figure 9[13] shows the aggregate percentage NOx reductions as a result of electricity re-dispatch given NOx prices of $30k, 50k and 100k/ton and as a result of installing SNCRs in all coal-fired power plants (assuming a 40% of reduction of NOx emissions from these units) versus hourly electricity demand. This figure shows that during the lowest and highest demand hours NOx emission reduction that is achievable through redispatch are similar for the three NOx prices, and that the SNCR case could reduce more NOx than the three cases of redispatch. The former phenomena is caused by the fact that during the lowest demand hours electricity generation is so low that the costs of NOx emissions do not drive re-dispatch as much as during high demand hours.

[13] The hourly electricity generation is scaled from either the average or peak demand base case. The percentage NOx reductions in the middle region of the average and peak demand hours are linearly interpolated.

Considering that the aggregate hourly NOx emissions during the low demand hours are below 10 tons, controlling NOx emissions during these hours have negligible effects in reducing the occurrence of high ozone episodes. The latter phenomena is caused by the fact that during the peak demand hours a majority of units are at their full capacities so that the flexibility of dispatching NOx emissions is significantly limited. From Figure 9, within the middle range of electricity demands (or average demand hours), the order of NOx reduction for the four cases are: \$100k case > SNCR similar or slightly more than \$50k case > \$30k case.

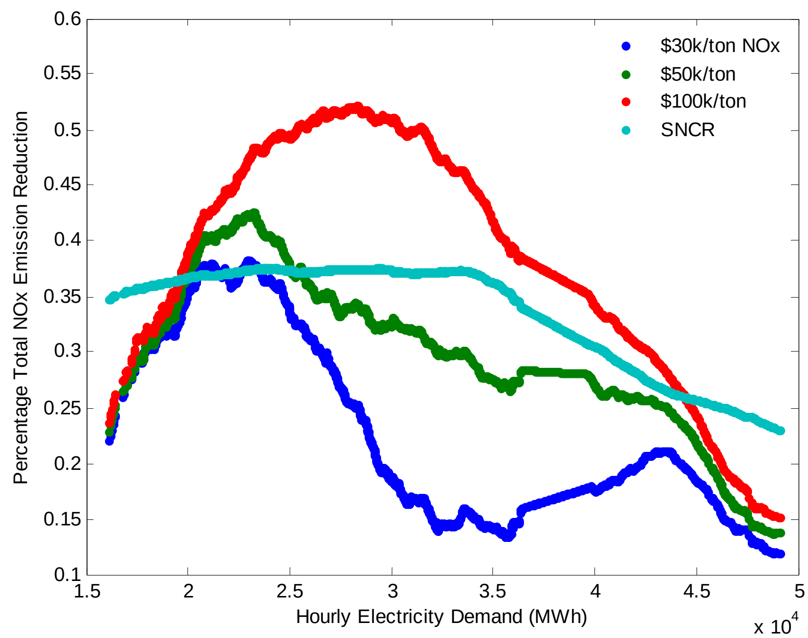


Figure 9: Percentage decreases of total hourly NOx emissions across all the power plants in the Classic PJM network for (a) \$30k (b) \$50k (c) 100k and (d) SNCR relative to the \$2k/ton NOx base case versus hourly electricity demand for PJM.

The comparison of the magnitudes of NOx reductions between the three trading cases and the SNCR case are based on average demand hours (20,000~44,000 MWh) due to the following two reasons. First, 84% of the PJM hourly demands in 2002 are within this range, with 15% of demands are smaller than 20,000 MWh and only 2% of demands are higher than 44,000 MWh[14]. Second, as stated earlier, NOx reductions that occur in the morning are more important in reducing the daily peak ozone level than in the afternoon or nighttime. And the electricity demands during the morning hours, even on a peak demand day, fall within the range of average demands.

Figure 10 shows the changes in NOx emissions under the $50k/ton NOx scenario (relative to the $2k baseline) plotted against the NOx emission rates for all the dispatchable units in PJM that have non-zero NOx emissions during an average demand hour (6/2 16:00). Each point in the scatterplots represents the change in emissions and emissions rate for one EGU during that hour. Positive Y-values represent the NOx emission reductions for those EGUs, while negative values represent increases in NOx increases in tons. Different units for the positive and negative Y-values are used here, which makes it easier to tell whether large amounts of NOx emissions are shifted to individual units. We want to compare the percentage NOx reduction that can be achieved through redispatch and by installing the SNCRs. However, if the percentage NOx reduction are used as the uniform unit for all the Y-values, quite often we will encounter a NOx increase of 50 or 100 times more than in the base case, but we could not find out the magnitude of the increase from such a plot. Figure 10 shows that the EGUs in PJM can be classified into three groups in general: the first group of units (black box) are those that have high NOx emission rates (higher than 0.25 ton/MWh in this case) and reduces more than 40% of NOx emissions as a result of redispatch under the NOx price of $50k/ton. It would be more cost-effective for these units to reduce NOx emissions through re-dispatch than installing SNCR. The second group of units (purple box) are those that reduce zero or small percentage of NOx emissions (0 or <40%) as a result of redispatch. The third group of units (green box) are those that have low NOx emission rates (lower than 0.15 ton/MWh in this case) and increases NOx emissions as a result of redispatch. Figure 10 clearly shows the shifts of NOx emissions from the units with higher NOx

[14] During summer 2002 (June 1st~August 31st, the fraction of low, average and peak demand hours are approximately 8%, 84% and 8%, respectively.

emission rates to those with lower NOx rates, or, from the first group to the third group. The shifting of NOx emissions happens both between coal burning units and non-coal units, and between units of the same fuel type with different NOx rates. The changes of electricity prices as a result of redispatch will be used to help explain the difference of the three groups in the next section.

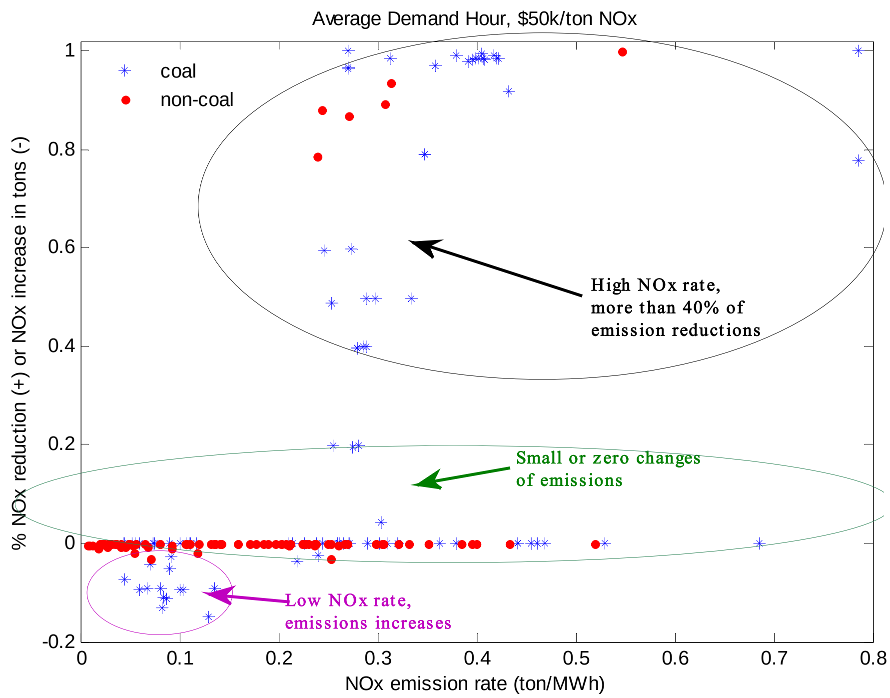


Figure 10: Changes of NOx emissions between \$50k and base case versus NOx emission rates during one average demand hour (June 2nd, 4pm) Positive part of the y-axis represents the percentage reduction of NOx emissions; and the negative part of the y-axis represents the amount of NOx increases in tons.

Black box: Group 1 of units that have high NOx emission rates and reduces more than 40% of NOx emissions. Purple box: Group 2 of units that could not reduce much of NOx emissions (0 or <40%). Green box: Group 3 of units that have low NOx emission rates and increases NOx emissions.

As shown in Figure 10, the maximum increase of the NOx emissions with a NOx price of \$50k/ton during an average hour is smaller than 0.2 ton, indicating that electricity generation redispatch is unlikely to move large amounts of NOx emissions into one or several units and form "hot spots". In the next chapter, the changes of ozone concentrations as a result of redispatch will be examined using an atmospheric chemistry and transport model to further test this hypothesis.

4.3 NOx Abatement Costs Associated with Redispatch

The real-time and day-ahead wholesale electricity markets in the Eastern U.S. use the dispatch auction mechanisms that yield locational prices for electricity. Locational Marginal Price (LMP) is used here to study the changes of electricity prices resulting from the redispatch. According to the definition of LMP, it represents the marginal cost to the system of electricity generation at each generating unit, accounting for transmission constraints.

As shown in Figure 11, the average electricity price across all generating units increases dramatically during high demand hours. Also, the base electricity price shifts from \$40/MWh (or 4 cents/KWh), which is generally consistent with the LMPs available from the PJM website, to \$100/MWh (or 10 cents/KWh) when NOx allowance price increases from \$2k/ton to \$100k/ton.

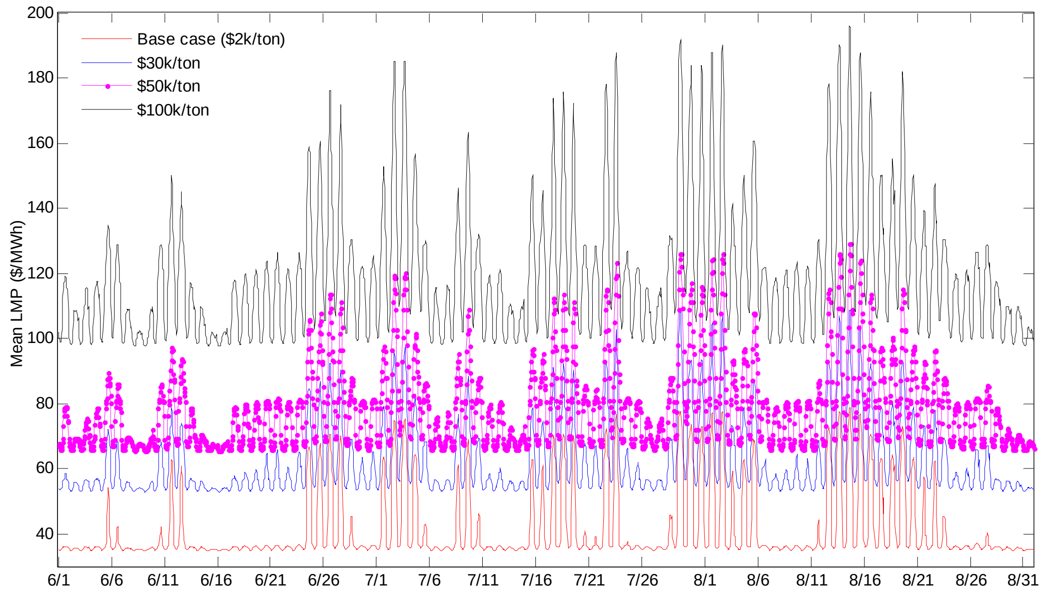


Figure 11: Time series of mean electricity price across all dispatchable (fossil) generation units (464 EGUs in total) for the $2k, 30k, 50k and 100k/ton of NOx case scenarios.

Figure 12 shows the changes in LMP under the $50k/ton NOx scenario (relative to the $2k baseline) plotted against the NOx emission rates for all the dispatchable units in PJM that have non-zero NOx emissions during an average demand hour (6/2 16:00). Each point in the scatterplots represents the change in LMP and emissions rate for one EGU during that hour. The three groups of units defined in the last section are shown in different colors. Combined with results shown in Figure 10, the first group contains units that reduce NOx emissions through redispatch with approximately $100/MWh increase in LMP. The second group contains units that hardly reduce NOx emissions while the inelasticity of electricity demand forces the LMP to increase. From Figure 9, the increases of LMP for these units approximately follow a linear relationship with the units' NOx rates, so that the costs of NOx allowances almost completely determine the increases of electricity prices. The third type of units contains those that have low NOx emission rates and that increase NOx emissions with higher NOx price. NOx emissions are usually shifted to these units from the first group, with smallest magnitude of increase in LMP compared with the other two groups. From Figure 12, the first group of units tend to fall below the diagonal while the third group of units tend to fall above the diagonal. The existence of the second group of units is likely to be due to location and congestion, which will be tested more thoroughly in the future work.

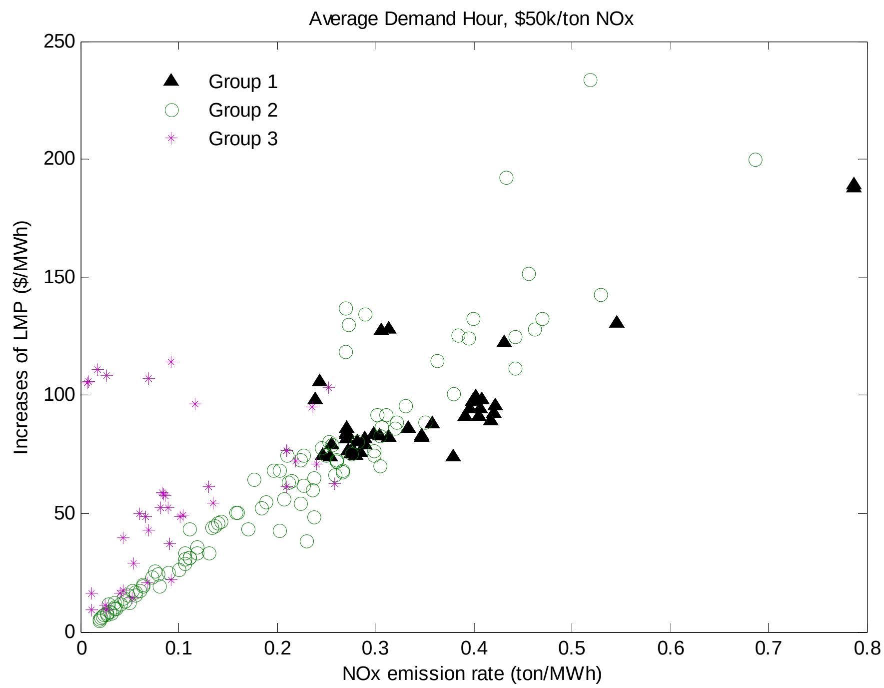


Figure 12: Increases of Locational Marginal Price (LMP) for all the dispatchable EGUs that have non-zero NOx emissions versus NOx emission rate with NOx prices increase from $2k/ton to $50k/ton during a typical average demand hour.

As defined in section 3.3, NOx abatement costs through re-dispatch are modeled as the increased variable costs of electricity generation as NOx price increases from $2k/ton to a higher value (e.g., $30k, $50k and $100k/ton). Time series of daily NOx abatement costs through electricity re-dispatch for the three NOx prices are plotted in Figure 13. For comparison between the NOx cap-and-trade cases and the SNCR control case, the estimated average daily cost of installing SNCR in all coal power plants in PJM is also shown (the horizontal blue line).

Figure 13 shows the high abatement costs of NOx re-dispatch on peak demand days. The daily abatement cost for the $100k/ton NOx case rises to $6M on the highest peak demand day. This is due to the high cost in dispatching electricity generation during the high demand hours and the inelasticity in electricity demand. However, once time-differentiation is introduced, the average daily abatement cost of re-dispatch will be significantly lowered. This analysis will be presented in chapters 7 and 8.

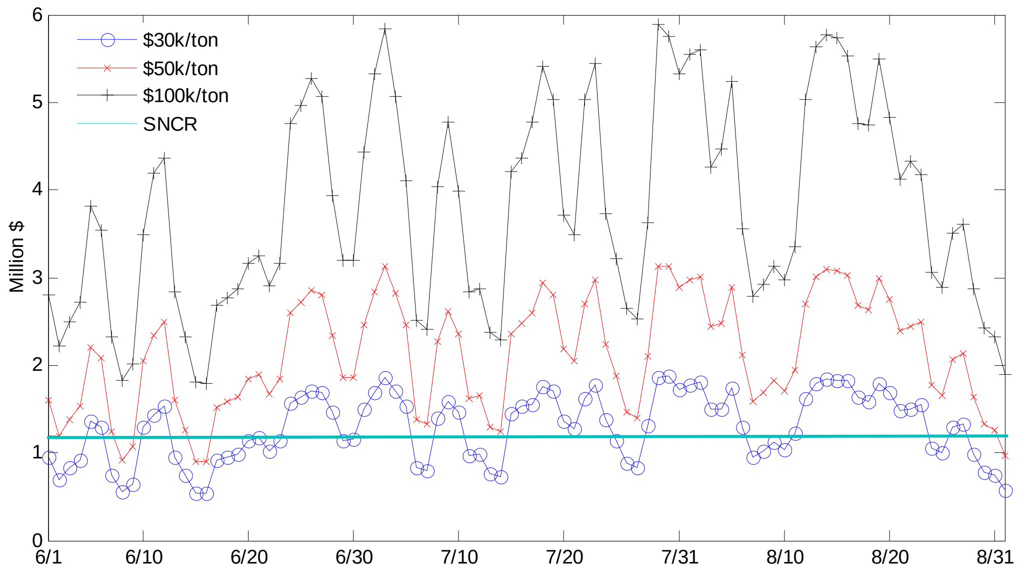


Figure 13: Time series of increased daily electricity generation cost associated with the NOx prices of $30k, 50k and 100k/ton relative to the base case under electricity redispatch, as well as the estimated daily cost of SNCR relative to the base case.

Chapter 5. Impact of NOx Emission Changes on Ozone Concentrations

The previous chapter discussed the shifting of NOx emissions from units with NOx emission rates to those with lower NOx rates as a result of redispatch under higher NOx prices. This chapter will examine the occurrence of ozone exceedences in a typical ozone season, and whether the changes in NOx emissions from redispatching actually lower ozone concentrations, especially during high ozone episodes. The formation of a "hot-spot" as a result of the re-distribution of ozone concentrations will also be studied in this chapter.

5.1 Ozone Concentrations Modeling

Photochemical 3D grid modeling provides a quantitative and objective way to forecast ozone levels, given NOx and VOC emissions, meteorological forecasts, and other relevant physical, chemical and geological parameters. The Comprehensive Air Quality Model with Extensions (CAMx) [Environ, 2009] is one such 3D grid model that determines concentrations of air pollutants by simulating processes associated with emissions, transport, chemistry, and dry or wet deposition. It is currently being used by the U.S. EPA and state administrative agencies for attainment demonstrations [Morris, 2001 and 2003] in areas that have violated the NAAQS for ozone. CAMx simulates the emission, dispersion, chemical reaction, and removal of pollutants in the troposphere by solving the pollutant continuity equation for each chemical species on a system of nested three-dimensional grids.

CAMx modeling is very demanding in time and computational resources and was performed for this study in collaboration with researchers at the University of Texas, Austin. The two nested modeling domains are shown below. The coarse domain includes the eastern United States and has a 36 km resolution; the fine (nested) domain covers the PJM area, and has a 12 km resolution. A sub-grid scale

Plume-in-Grid (PiG) module is used to treat the chemistry of large point source plumes.

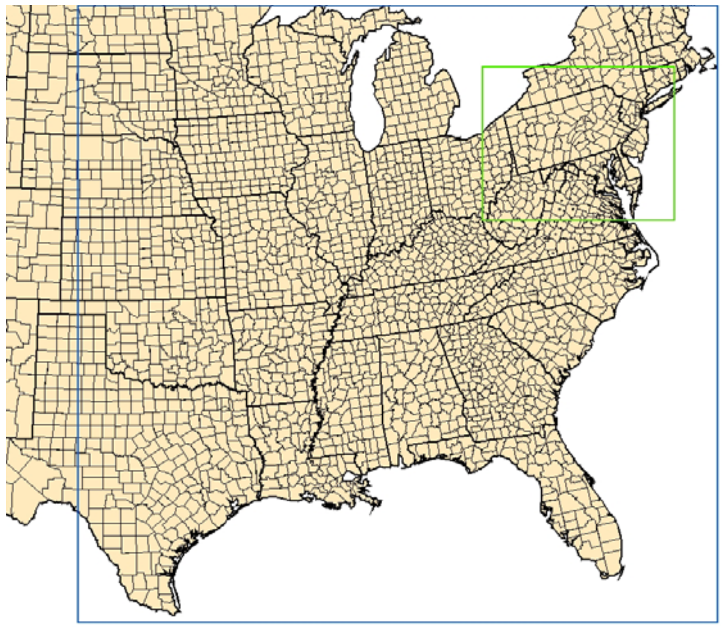


Figure 14: Modeling domains with colored rectangles shows nested grids: blue for 36 km domain and light green for 12 km domain.

5.2 Simulated Ozone Concentrations in the Base Case

This study focuses on the period June 1st through August 31st of the year 2002 (92 days). CAMx is used to simulate the ozone concentration changes associated with each NOx prices under NOx smart trading, as well as the SNCR case during this period. The comparison of ozone level changes between different policy scenarios is based on the simulated 8-hour daily maximum ozone concentrations at the 37 ozone monitoring sites in the Philadelphia/Baltimore region (as shown in Figure 1). The 37 simulated 8-hour daily peak ozone levels are averaged and plotted in Figure 15, which shows that there are 5-6 major high ozone episodes during the 92-day period. This figure also shows that the 8-hour ozone standard is violated episodically and that the daily 8-h ozone concentration exhibits strong autocorrelation. In other words, a randomly selected day is more likely to be a high ozone day if the previous day is a high ozone day, and vice versa. This is because the occurrence of ozone exceedence is driven by specific meteorological patterns, which occur episodically and disappear gradually.

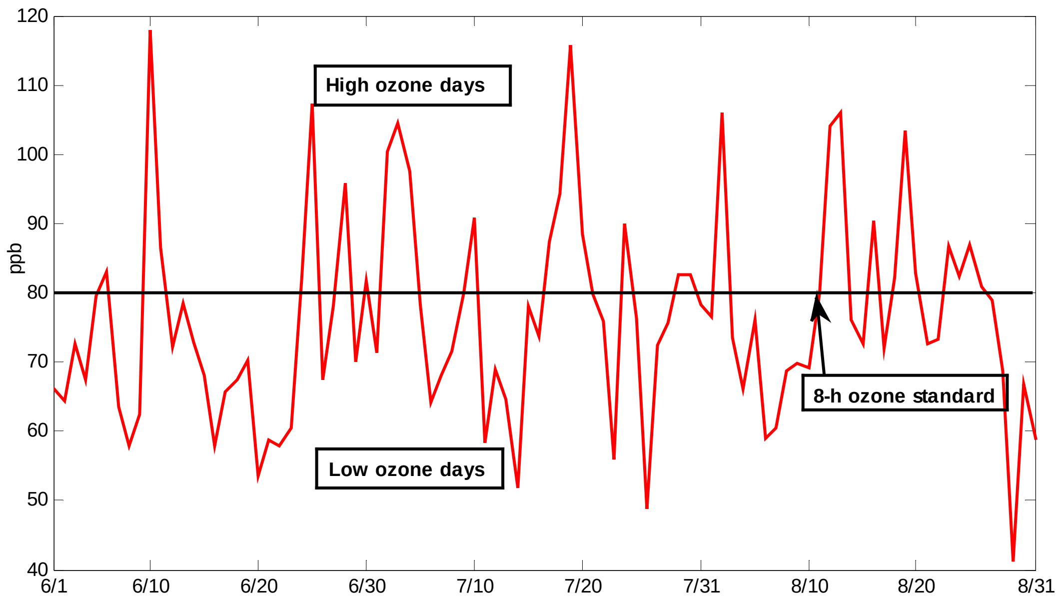


Figure 15: Daily 8-hour maximum ozone concentration average over all the 37 ozone monitoring sites in the Philadelphia/Baltimore area from June 1st to August 31st, 2002.

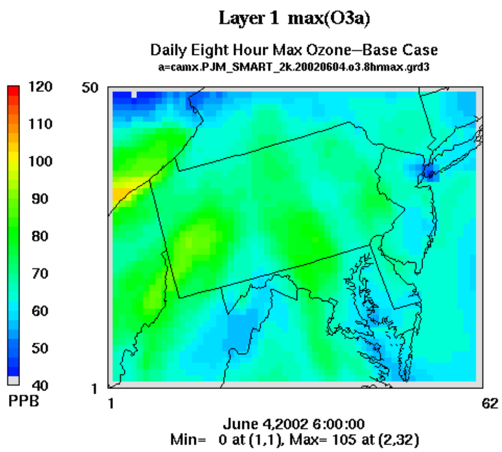
5.3 Changes of Ozone Concentrations associated with Smart Trading and SNCR

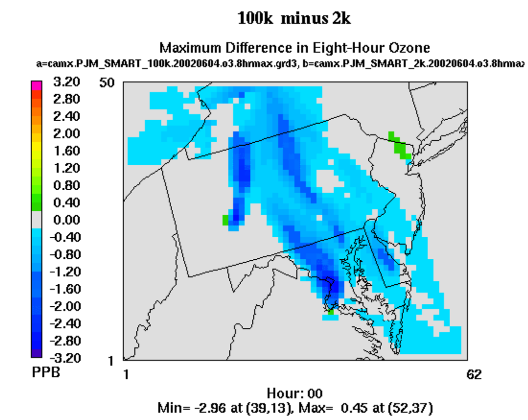
Based on the simulated eight-hour averaged ozone concentrations, the difference in the daily maximum ozone concentrations between the base case and each of the policy scenarios is calculated for each grid cell for each day. Ozone difference maps are generated that show, for each grid cell, the differences in the daily maximum ozone concentrations. These maps display the spatial scale and magnitude of air quality impacts associated with changes in NOx emissions between the scenarios.

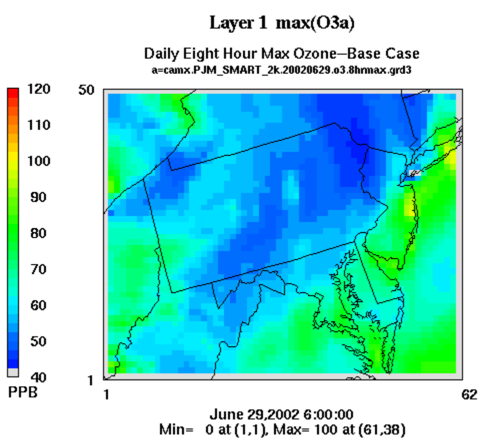
The impact of NOx emission changes on ozone level changes is complicated and greatly depends on meteorology. Figure 16 shows the base case daily eight-hour maximum ozone concentrations along with the differences in daily eight-hour maximum ozone concentrations between the $100k/ton trading case and the base case over the PJM area on 7 representative days: June 4, June 25, June 29, July 1, Aug 2, Aug 12, and August 29. It can be seen that the redispatching of NOx emissions across the PJM area leads to reductions in daily maximum 8-hour ozone concentrations of approximately 3 ppb to 12.4 ppb, and the ozone reduction varies greatly from day to day. Results in Figure 16 illustrate the strong influence of transport during different synoptic flow patterns on the downwind area and how they moderate decreases in maximum 8-h ozone due to the NOx point source emissions reductions. Typical flow patterns are: southerly (June 4), northerly (June 29), westerly/southwesterly (July 1) flow regimes, and stagnant regimes (June 25, August 2 and August 12). The stagnant regime cases experienced the slowest wind flows, so the most notable decreases in maximum 8-h ozone are primarily confined close to the point sources rather than extending downwind and therefore result in larger ozone reductions. Nevertheless, the westerly/ southwesterly flow case (July 1) show a more pronounced area of ozone reduction extending downwind of the point sources to the northeastern corridor and enhanced the benefits of the NOx reductions.

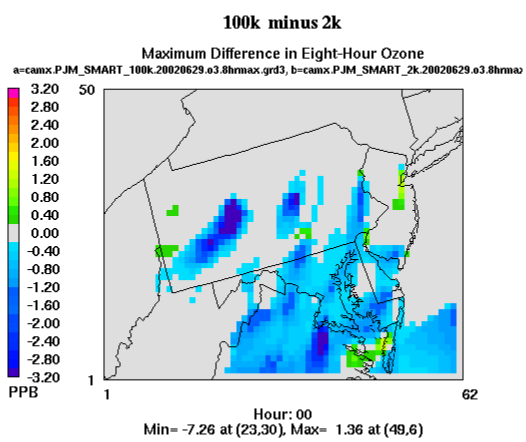
The impact of NOx emissions (e.g., the $100k case results in approximately a 41% NOx reduction across all EGUs in the PJM system) is shown to be greater on high ozone days, such as June 25, August 2 and August 12, than days during which the ozone levels are relatively lower, such as June 4th, June 29th and July 1st. On low ozone days NOx reductions could even increase ozone levels in the area, such as on August 29. This suggests that a carefully designed control strategy that considers the temporal variability and the role of meteorology into ozone mitigation could more effective at reducing peak ozone concentrations.

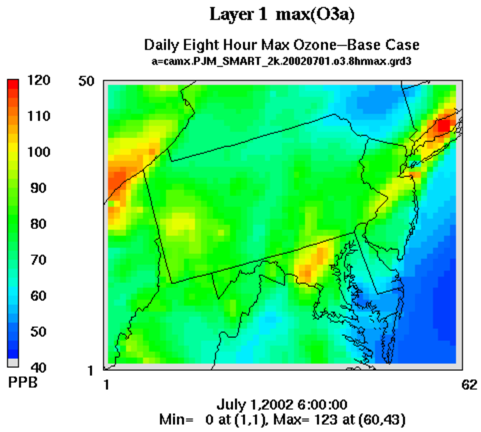
June 25th, August 2nd and August 12th represent typical high ozone episode days during summer 2002, during which the eight hour ozone standard is violated for almost all the areas within the modeling domain, with areas around Baltimore and Philadelphia having maximum ozone concentrations over 120 ppb. Although ozone reductions are pervasive during these days, we do see small areas where daily eight-hour maximum ozone level increases by up to 3 ppb. These small areas are often located outside or downwind of regions where ozone concentrations are the highest within the whole PJM area. This could be due to the redispatch of NOx emissions from units with higher NOx emission rates to those with lower rates; or associated with NOx reduction dis-benefit, as in the case of August 29th.

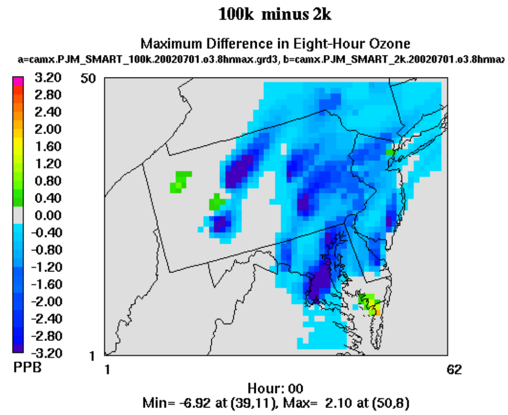


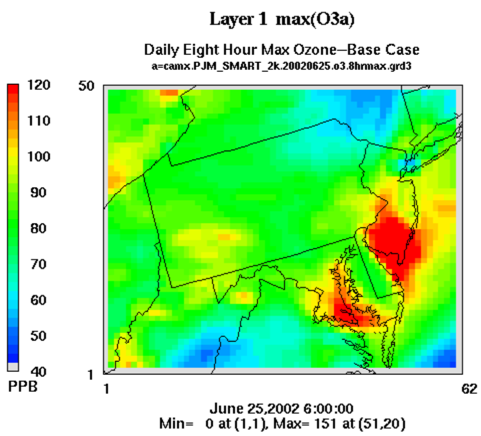


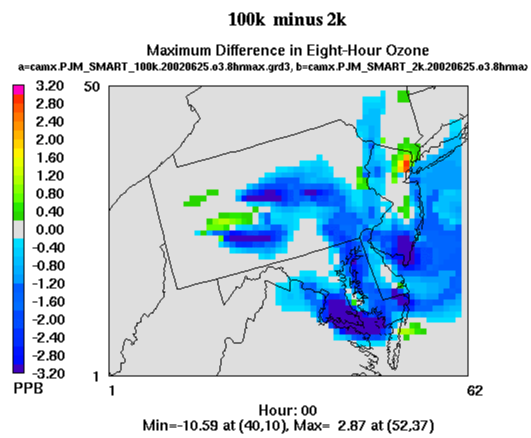


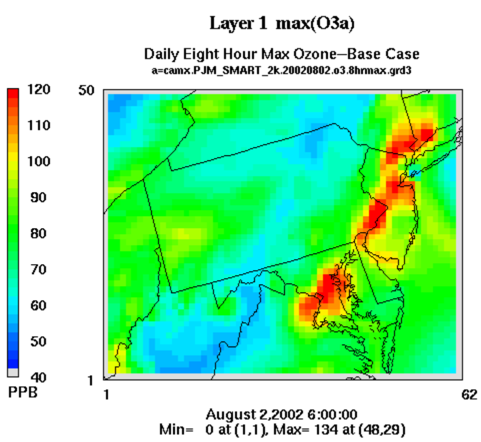


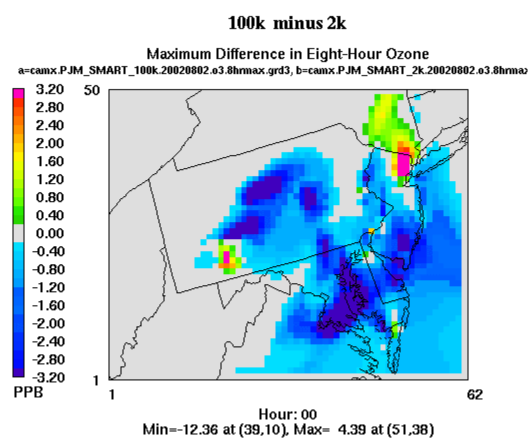

Layer 1 max(O3a)
Daily Eight Hour Max Ozone–Base Case
a=camx.PJM_SMART_2k.20020701.o3.8hrmax.grd3
120
110
100
90
80
70
60
50
40
PPB
50
1
1
62
July 1,2002 6:00:00
Min= 0 at (1,1), Max= 123 at (60,43)


100k minus 2k
Maximum Difference in Eight-Hour Ozone
a=camx.PJM_SMART_100k.20020701.o3.8hrmax.grd3, b=camx.PJM_SMART_2k.20020701.o3.8hrma
3.20
2.80
2.40
2.00
1.60
1.20
0.80
0.40
0.00
-0.40
-0.80
-1.20
-1.60
-2.00
-2.40
-2.80
-3.20
PPB
50
1
1
62
Hour: 00
Min= -6.92 at (39,11), Max= 2.10 at (50,8)


Layer 1 max(O3a)
Daily Eight Hour Max Ozone–Base Case
a=camx.PJM_SMART_2k.20020625.o3.8hrmax.grd3
120
110
100
90
80
70
60
50
40
PPB
50
1
1
62
June 25,2002 6:00:00
Min= 0 at (1,1), Max= 151 at (51,20)


100k minus 2k
Maximum Difference in Eight-Hour Ozone
a=camx.PJM_SMART_100k.20020625.o3.8hrmax.grd3, b=camx.PJM_SMART_2k.20020625.o3.8hrma
3.20
2.80
2.40
2.00
1.60
1.20
0.80
0.40
0.00
-0.40
-0.80
-1.20
-1.60
-2.00
-2.40
-2.80
-3.20
PPB
50
1
1
62
Hour: 00
Min=-10.59 at (40,10), Max= 2.87 at (52,37)


Layer 1 max(O3a)
Daily Eight Hour Max Ozone–Base Case
a=camx.PJM_SMART_2k.20020802.o3.8hrmax.grd3
120
110
100
90
80
70
60
50
40
PPB
50
1
1
62
August 2,2002 6:00:00
Min= 0 at (1,1), Max= 134 at (48,29)


100k minus 2k
Maximum Difference in Eight-Hour Ozone
a=camx.PJM_SMART_100k.20020802.o3.8hrmax.grd3, b=camx.PJM_SMART_2k.20020802.o3.8hrma
3.20
2.80
2.40
2.00
1.60
1.20
0.80
0.40
0.00
-0.40
-0.80
-1.20
-1.60
-2.00
-2.40
-2.80
-3.20
PPB
50
1
1
62
Hour: 00
Min=-12.36 at (39,10), Max= 4.39 at (51,38)

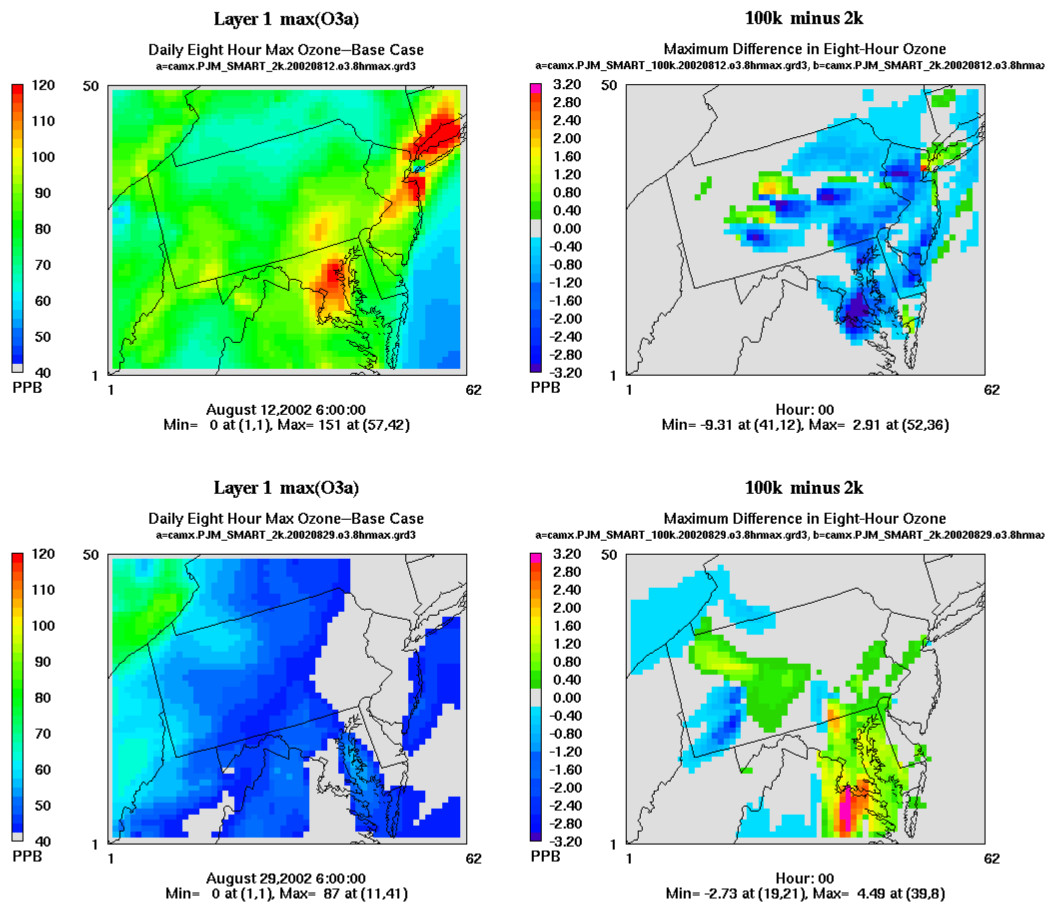


Figure 16: Tile plots of the daily maximum eight-hour ozone concentrations for the base case and the difference of the daily maximum eight-hour ozone concentrations between the 100k trading case scenario and the base case on selected dates (June 4, June 25, June 29, July 1, Aug 2, Aug 12, and August 29)[15].

[15] Time label of 6:00 and 0:00 are all system defaults and does not mean the actual time when the maximum ozone concentration happens.

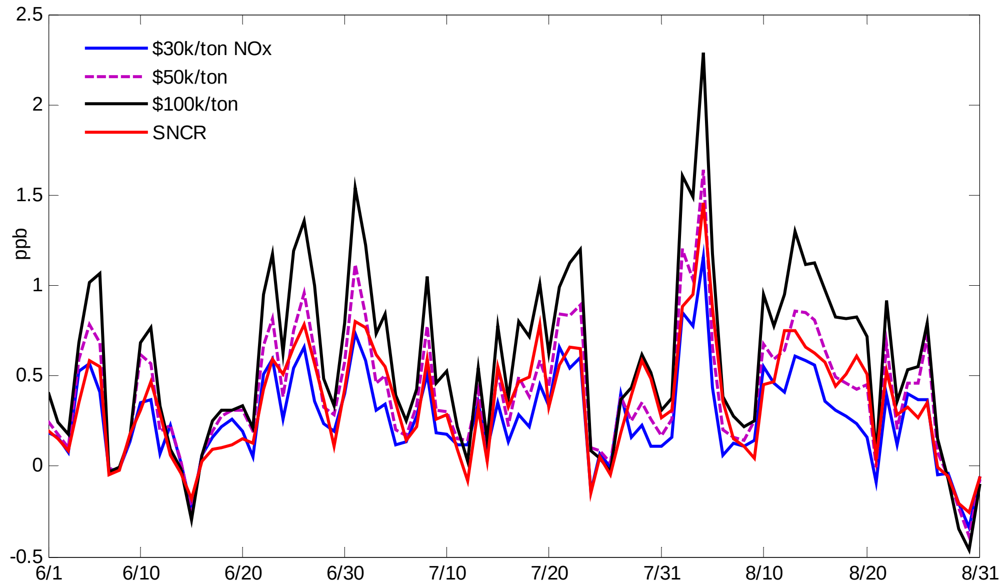


Figure 17: Time series of ozone reduction amount (ppb) averaged across the 37 ozone monitoring sites under $30k, 50k and 100k/ton of NOx smart trading and SNCR.

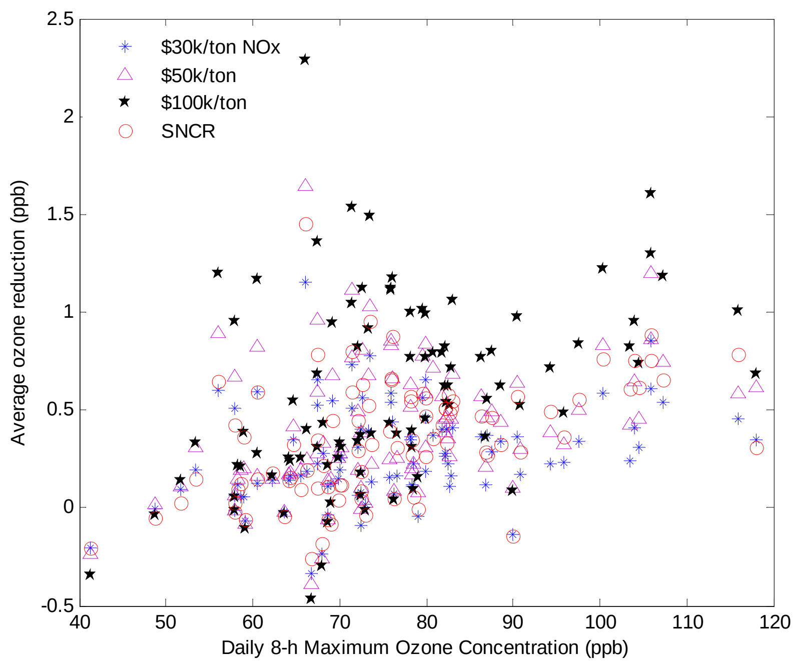


Figure 18: Average ozone reduction amount (ppb) across the 37 ozone monitoring sites versus the average daily 8-h maximum ozone concentrations across the 37 sites.

Figure 17 shows the total differences in the 8-hour daily maximum ozone concentrations between the base case and each of the policy scenarios (3 trading cases and the SNCR case) for the 37 ozone monitoring sites for each day during summer 2002. The average reduction of daily 8-h maximum ozone across over the 37 sites during the 92 days are calculated to be 0.27, 0.41, 0.59 and 0.35 ppb, respectively, for the $30k, 50k, 100k and the SNCR case scenarios. Recall from Chapter 4, the aggregate NOx reductions in PJM for the four case scenarios are ordered as: 100k case> SNCR case> 50k case > 30k case. The aggregate NOx reductions during the peak demand hours (i.e. peak hours of NOx emissions) for the four case scenarios are ordered as: SNCR case> 100k case> 50k >30k. The relative magnitudes of the NOx emissions reductions and ozone reductions for the 50k and 100k case and the SNCR case are not the same. This is because during the early morning hours the achievable NOx reductions under the 50k case are greater than or close to the SNCR case, and the NOx reductions made during these earlier hours are the most important in reducing the daily maximum ozone concentrations.

Another notable result is that greater decreases in daily maximum 8-h ozone occur at higher concentrations. Figure 18 shows the scatter plot of average reduction of the daily 8-hour maximum ozone concentrations (in ppb) across the 37 sites versus the average daily 8-hour maximum ozone concentrations across the 37 sites for the three trading cases and the SNCR case. Each group of points in Figure 18 represent one day. The correlation between ozone concentration and ozone reduction suggests that the ozone reduction is more likely to be achieved on high ozone days. And reducing NOx emissions during low ozone days is less likely to be effective in reducing ozone concentrations. This further supports the cost-effectiveness of smart trading, which aims to focus on NOx emissions during high ozone days.

The results presented in this and the previous chapter strongly support the effectiveness of smart trading in reducing NOx and ozone concentrations compared with the technology based control strategies such as SNCR. A common assumption prior to this study was that the high electricity demand during the peak demand hours would limit the dispatching of NOx emissions and thus limit the capability of smart trading in lowering ozone concentrations. However, this is not necessarily true. First, the high flexibility of dispatching NOx emissions in the PJM during morning hours (average and low-average demand hours) yields significant NOx emission reductions, even greater than under the SNCR case, and NOx reductions during these hours are most effective in reducing the daily maximum ozone concentrations. Although the NOx reductions are not as much under smart trading as the SNCR case during the actual peak demand hours (e.g., 3 or 4pm), the ozone reductions are actually larger from redispatching. Second, ozone reductions are more likely to be achieved on high ozone days, so that reducing NOx emissions on low ozone days is not only less important in terms of public health, but also less effective in reducing the daily maximum ozone concentrations, and bringing regions into compliance with the NAAQS.

Chapter 6. A Stochastic Decision Model for Cost-Effectiveness Analysis of Ozone Regulatory Design

Specific combinations of precursor emission levels, sunlight, and wind occasionally produce periods of high ozone concentrations, called ozone episodes, which typically last for a few days. Recall from Chapter 1, the occurrence of ozone is usually associated with the passage of specific weather patterns, such as a Bermuda High. Thus the occurrence of high ozone days exhibits episodic behavior. As the public health impacts and environmental damages from ozone exposure worsen with increasing concentration, it is these episodes that are of particular importance in air quality policy. Further, the legal/policy structure is framed around an ozone NAAQS that is based on whether the observed daily maximum 8-hour average ozone concentration exceeds 80ppb. Although the 8-hour standard became 75 ppb in 2008, this study aims to provide a proof of concept of ozone control strategy based on 2002 data, so that 80 ppb, instead of 75 ppb is used as the 8-h ozone standard. The results in Chapter 4 showed that applying a higher NOx price (e.g., $50k/ton), and assuming reductions come only from redispatching of EGUs, throughout the entire ozone season would be more costly than simply installing pollution control equipment. A hypothesis is that if a higher NOx price can be applied only during the high ozone episodes, it might be more cost-effective than a technology-based approach. This chapter and the next will test this hypothesis.

The exploration of the cost-effectiveness of a time-differentiated approach requires the prospective simulation of future (uncertain) ozone episodes and uncertain ability to forecast those episodes. In this chapter, I describe the stochastic decision model I have developed that integrates the results from the electrical power system model and photochemical model, and use it to explore the potential for time-differentiated NOx control policies under uncertainty in ozone prediction. I use the summer of 2002 (June, July and August) in the Classic PJM region as a case study, and develop a two-state Markov Chain model to simulate the occurrence of high ozone days based on the simulation of summer 2002 data.

If ozone forecasts were 100% accurate, time-differentiated NOx regulations would have clear advantages over permanent control technology approaches. However, there are significant errors in day-ahead ozone forecasts, which will partly determine whether a time-differentiated approach is in fact cost-effective. When analyzing the cost and ozone reduction, I incorporate the errors in ozone forecasts into the stochastic decision analysis, and determine threshold values for false positive and false negative ozone forecast errors above which the “smart trading” policy is less cost-effective than a technology-based strategy. In this way, I demonstrate the level of ozone forecast accuracy that is required for a time-differentiated regulatory design to be cost-effective. This chapter will describe the methods used for the stochastic analysis, and the results are given in Chapter 7.

6.1 Prospective Ozone Simulations: A Two-State Markov Chain Model

As shown in the previous chapter, strong autocorrelation is apparent in the time series of daily 8-h maximum ozone concentrations averaged across the 37 ozone monitoring sites. Considering that the average ozone lifetime in the eastern U.S. is roughly two days, this analysis simulates the occurrences of ozone exceedences as a two-state Markov process (Figure 19). For this analysis, I use the 2002 observations of ozone concentrations in PJM to define the population distribution for sampling future ozone episodes.

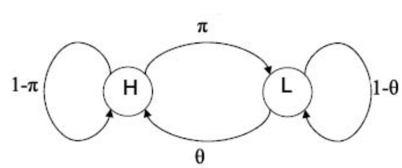


Figure 19: Illustration of using a two-state Markov Chain model to simulate the behavior of high ozone days. State H represents high ozone days, and state L represents low ozone days.

As defined earlier, a high (or low) ozone day is defined as a day in which the average eight-hour ozone concentration across the 37 ozone monitoring sites is higher (or lower) than 80 ppb (using the 2002 regulatory standard, consistent with the emissions and costs modeled in this case study). π represents the probability that a randomly chosen day is a low ozone day, given that the previous day was a high ozone day. 1-π represents the probability that a randomly chosen day is a high ozone day, given that the previous day is a high ozone day. Similarly, θ represents the probability that a randomly chosen day is a high ozone day given that the previous day is a low ozone day, and 1-θ represents the probability that a randomly chosen day is a low ozone day given that the previous day is a low ozone day. Among the simulated ozone concentrations under the base case during the 92 days (June 1st~August 31st, 2002), there are 32 high ozone days and 60 low ozone days. Within the 32 high ozone days, there are 18 days whose ozone level in the day before is also high. Among the 60 low ozone days, there are 45 days whose ozone level in the day before is also low. The transition probability matrix for the 2-state Markov Chain is estimated as[16]:

$$P = \begin{array}{c} \\ \mathrm{H} \\ \mathrm{L} \end{array} \begin{array}{c} \begin{array}{cc} \mathrm{H} & \mathrm{L} \end{array} \\ \begin{bmatrix} 1-\pi & \pi \\ \theta & 1-\theta \end{bmatrix} \end{array} = \begin{bmatrix} 0.56 & 0.44 \\ 0.24 & 0.76 \end{bmatrix}$$

6.2 Risk-based Decision Analysis

There is significant uncertainty associated with the forecasting of ozone levels. A forecasted high ozone day might end up being a low ozone day, making it a false positive event; and a forecasted low ozone day might end up being a high ozone day, making it a false negative event. Table 2 illustrates the conditions.

---

[16] June 1st is a low ozone day, so that there are only 59 low ozone days in total when estimating θ. θ is estimated to be (59-45)/59~0.24.

Table 2: Type I and Type II Errors in the Forecast of Ozone Concentrations.

		Actual condition	
		Low ozone day (L)	High ozone day (H)
Ozone level forecast	Low ozone day (L)	True Negative	False Negative ***Type II error***
	High ozone day (H)	False Positive ***Type I error***	True Positive

The uncertainty in ozone forecasting is critical when comparing different ozone control policies. In the design of smart trading, or any similar flexible NOx regulation that aims to target the high ozone days, the system operator needs to make the decision about the next day's NOx price based on the forecasted ozone level for the next day. If a high ozone level is forecasted for the next day, a high NOx price ($30k, 50k or 100k/ton) will be announced for the next day. If the next day turns out to be a low ozone day (i.e., if the forecast was a false positive one), the decision to raise the NOx price will lead to unnecessary costs. Similarly, if a low ozone level is forecasted, the NOx price will not be raised for the next day. If the next day turns out to be a high ozone day (i.e., if the forecast was a false negative one), the decision to maintain the default NOx price will lead to continued ozone non-compliance, which could have been reduced if the forecast had been accurate. In this study, the false positive (Type I error) and false negative (Type II error) forecast rates are incorporated into the decision analysis.

The utility function for the decision model is defined as the ratio of the incremental costs (Δcost) to the incremental reductions of daily maximum ozone concentrations at the 37 ozone monitoring sites in the Philadelphia/ Baltimore region (ΔO_3), relative to the base case. In the context of this thesis, Δcost and ΔO_3 indicate the increased cost and the reduction in the 8-h daily maximum ozone level for the policy case relative to the base case ($2k/ton). When high ozone days are forecast, the high NOx price is triggered. Δcost is measured as the increased cost of electricity generation resulting from redispatching to lower emitting but more clostly generating units, relative to the base case. ΔO_3 will be positive unless the forecast is a false alarm. In the case of forecast low ozone days, the base case NOx price is maintained, so that Δcost and ΔO_3 are, by definition, 0. If the forecast low is a false negative, ozone mitigation on this particular day is not achieved. The decision tree for this process is shown in Figure 20.

I define p and q to be the rates of false positive and false negative events, respectively. From the definition of Type I and Type II errors:

Type I error= False positive= Pr [Forecast H | Actual L]=p (1)

True negative=Pr [Forecast L | Actual L]=1-p (2)

Type II error= False negative= Pr [Forecast L | Actual H]=q (3)

True positive=Pr [Forecast H | Actual H]=1-q (4)

in which H (or L) represents a high (or low) ozone day.

The probabilities that a randomly chosen day is a high and low ozone day are defined to be a and 1-a, respectively. From Table 2, on each day, there are four possible outcomes associated with smart trading: the day is forecasted to be a high ozone day and is actually a high ozone day; the day is forecasted to be a high ozone day and is actually a low ozone day; the day is forecasted to be a low ozone day and is actually a high ozone day; and the day is forecasted to be a low ozone day and is actually a low ozone day. I define the probability for the above four outcomes are p_1, p_2, p_3 and p_4, respectively. Applying Bayes' theorem to equations (1)-(4) , p_1, p_2, p_3 and p_4 can be obtained by:

p_1=Pr[Actual H ∩ Forecast H]= Pr[Actual H]*Pr[Forecast H | Actual H]=$a(1-q)$ (5)

p_2=Pr[Actual L ∩ Forecast H]= Pr[Forecast H | Actual L] * Pr[Actual L]= $(1-a)p$ (6)

p_3=Pr[Actual H ∩ Forecast L]= Pr[Forecast L | Actual H] * Pr[Actual H]= aq (7)

p_4=Pr[Actual L ∩ Forecast L]= Pr[Forecast L | Actual L] * Pr[Actual L]= $(1-a)(1-p)$ (8)

In reality, there are 4^N outcomes associated with smart trading during an N-day ozone season, as illustrated in Figure 20. Ideally, one would want to perform a Monte Carlo simulation on the meteorological model, sampling values for its parameters and boundary conditions, to generate many sample meteorological fields. Then, with the uncertainties in meteorology and in NOx emissions propagated through CAMx, the ozone concentrations would stochastically vary. Since the MM5 and CAMx models used in this study (like all 3-D meteorology and photochemical models) are computationally demanding prohibiting the above approach, I apply the 2-state Markov model as a simple and feasible way to illustrate the concepts. The decision analysis is performed here by repeating the one-day decision analysis for N sample days, as shown in Figure 20.

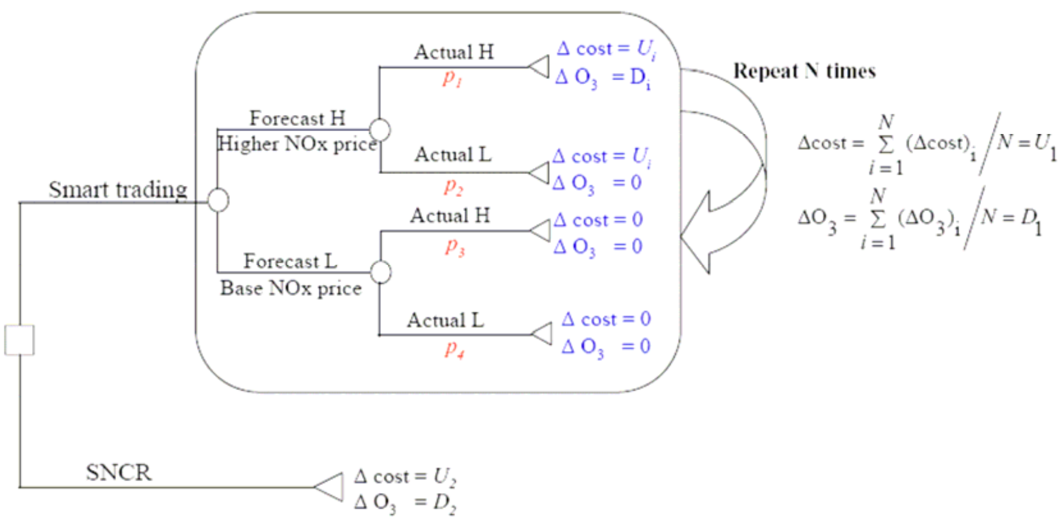


Figure 20: Framework for deciding whether to choose smart trading or SNCR as the ozone control policy in the presence of risks in ozone forecasts during an N-day period. H and L represent a high ozone day and a low ozone day, respectively.

We assume that the occurrence of high or low ozone days approximately follow a 2-state Markov process (as described in section 6.1) and that false positive and false negative events occur randomly with given rates of p and q. Assume U_i and D_i are the increased cost of electricity generation under a higher NOx price on the i^{th} day of the N-stage decision-making process and the associated reduction in the daily maximum 8-h ozone concentration, respectively. Then from (5)-(6), on the i^{th} day, the expected daily cost and the associated ozone reduction are:

$$(\Delta\text{cost})_i = (p_1+p_2)U_i = [a(1-q)+(1-a)p]U_i \tag{10}$$

$$(\Delta O_3)_i = p_2 D_i = a(1-q)D_i \tag{11}$$

where a is a function of the transition matrix of the 2-state Markov model, and of the initial state of the model.

The mean and probability distribution of Δcost/ΔO_3 associated with each smart trading case can be simulated by conducting the above decision analysis for a large number of sample days; In this analysis, I use a sample size of N=10,000 days. Denote the mean Δcost and ΔO_3 generated by the Monte Carlo method are U_1 and D_1, respectively, and the Δcost and ΔO_3 of the SNCR case as U_2 and D_2, respectively. Because U_2 and D_2 are not a function of p and q, the values for U_1/D_1 obtained by the stochastic decision model will be used to compare to the deterministic U_2/D_2. The rule for accepting smart trading is defined as:

Δcost/ΔO_3(smart trading)> Δcost/ΔO_3(SNCR), or accept smart trading if:

$$U_1/D_1 > U_2/D_2, \tag{9}$$

and reject smart trading otherwise.

The results of this analysis are given in the next chapter.

Chapter 7. Cost-Effectiveness Analysis of Smart Trading vs. SNCR Under Uncertainty in Ozone Forecasting

In the previous chapters, smart trading through electricity redispatching has been shown to have potential advantages in reducing ozone concentrations during high ozone episodes when compared to an SNCR-based command-and-control policy, and assuming there is no error in ozone forecasts. This chapter will explore the cost-effectiveness of smart trading in reducing ozone concentrations in the presence of ozone forecast uncertainty. Because the accuracy of ozone forecasting is not precisely known and will likely change in the future, I conduct sensitivity analysis of cost-effectiveness to the ozone forecast error rates. The stochastic decision model is described in Chapter 6. All results are obtained by simulating with a sample size of 10,000 days.

7.1 Comparison of NOx Abatement Costs and Ozone Abatement Costs between SNCR and Smart Trading Cases without Forecast Errors

I begin by presenting the results of Monte Carlo simulation of ozone concentrations and abatement costs using the two-state Markov chain described in chapter 6, and assuming no ozone forecast errors. The number of high ozone days within a 92-day ozone season is approximately normally distributed with a mean of 32.38 days and a standard deviation of 6.39 days. Over a three month ozone season, the probability that a randomly chosen day is a high ozone day is 35.2%±6.9%. If the ozone forecast were 100% accurate, the chance of a random day triggering smart trading is therefore also 35.2%±6.9%. Similarly, the abatement costs of smart trading under different NOx prices can be simulated using the same stochastic decision model. The average daily abatement costs for $30k, 50k and 100k/ton NOx, assuming a perfectly accurate forecast, would be: $0.56M ± 0.11M, $0.92M±0.18M and $1.67M±0.33M, respectively. These uncertainty ranges would narrow if the population size (currently only 2002 season) of the Markov model were increased by including additional ozone season observations.

The average daily abatement costs for the three trading cases are plotted against the NOx price with error bars ($\pm\sigma$) representing the uncertainty in the occurrence of high ozone events, which equals the uncertainty in triggering high NOx price assuming a 100% accurate forecast (see Figure 21). The solid horizontal line indicates the estimated daily cost of the SNCR case ($ 1.2M) and the dotted lines represents a 20% uncertainty in the estimation. Note that the uncertainty in the costs of the three trading cases are perfectly correlated, not independent, because these errors are a function of the uncertainty in the number of high ozone days in a season. In reality, the daily operational costs of SNCR would vary with actual daily levels of electricity generation and NOx emissions, but we omit this variability in this study and consider the daily cost of the SNCR case as a constant.

As shown in chapter 4, applying a higher NOx price (e.g., $50k/ton) and inducing redispatching throughout the entire ozone season would be more costly than simply installing pollution control equipment. However, Figure 21 shows that the cost of lowering NOx emissions through redispatch only on high ozone days with a NOx price of $50k/ton is likely to be lower than the estimated daily cost of SNCR. Further, because the $50k/ton case leads to a greater ozone reduction, lowering daily maximum ozone concentrations through smart trading with a NOx price of $50k/ton is more cost-effective than the SNCR case. Although the $100k case has a higher cost than installing SNCRs, it leads to more NOx and ozone reduction. Comparing the $100k case to installing SCRs, which have higher (~70% NOx reductions) would be a more appropriate comparison, and is beyond the scope of this study.

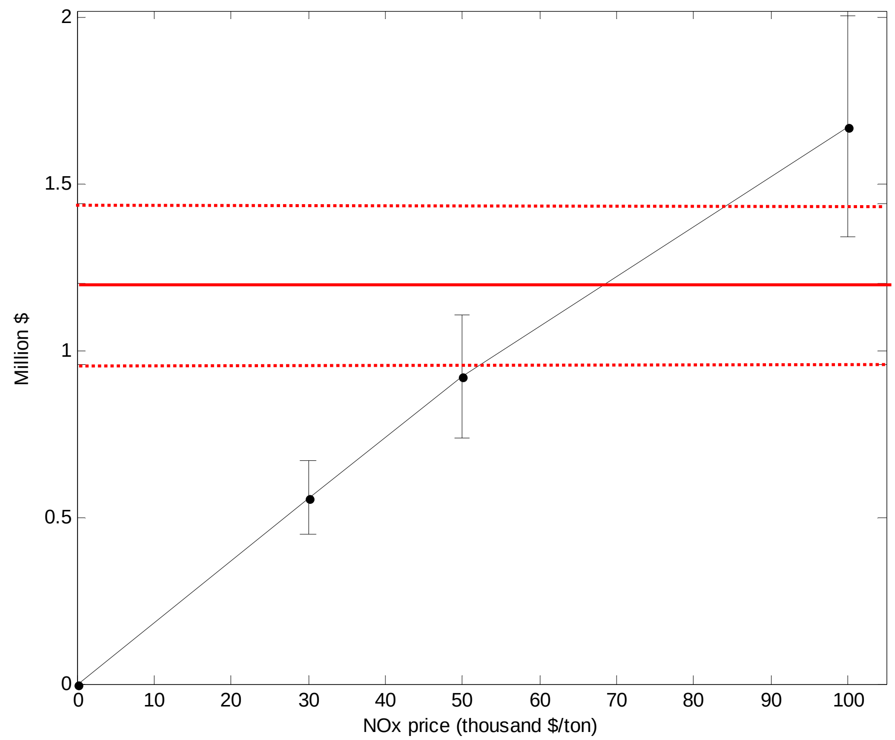


Figure 21: Average daily cost of smart trading versus NOx price. Error bars ($\pm\sigma$) represent uncertainty in the occurrence of high ozone events. The solid horizontal line indicates the estimated daily cost of the SNCR case scenario, and the dotted line indicates 20% uncertainty associated with the estimated cost.

Assuming that there is no forecast error, the average daily costs of smart trading and SNCR compared with the average reduction in the daily 8-h maximum ozone concentrations over the 37 monitoring sites are plotted in Figure 22. Error bars ($\pm\sigma$) except the one on the SNCR cost represent uncertainty in the occurrence of high ozone events. The error bars on the SNCR cost represent uncertainty of the cost provided by the 1998 NESCAUM report.

As shown in Figure 22, assuming no error in ozone forecasting, the lines connecting 0, 30k, 50k and 100k cases form a cost-effectiveness frontier for ozone reductions. An ideal regulatory design would have zero cost and maximum ozone reductions, and would be located in the lower right corner. The frontier describes the trade-offs across the cost-effective options modeled; one can achieve greater ozone reductions, but only at an increased cost. Most notably in this figure, the SNCR alternative is dominated, even within the uncertainty bounds. Without ozone forecast error, one would almost never prefer the SNCR approach to any of the smart trading approaches.

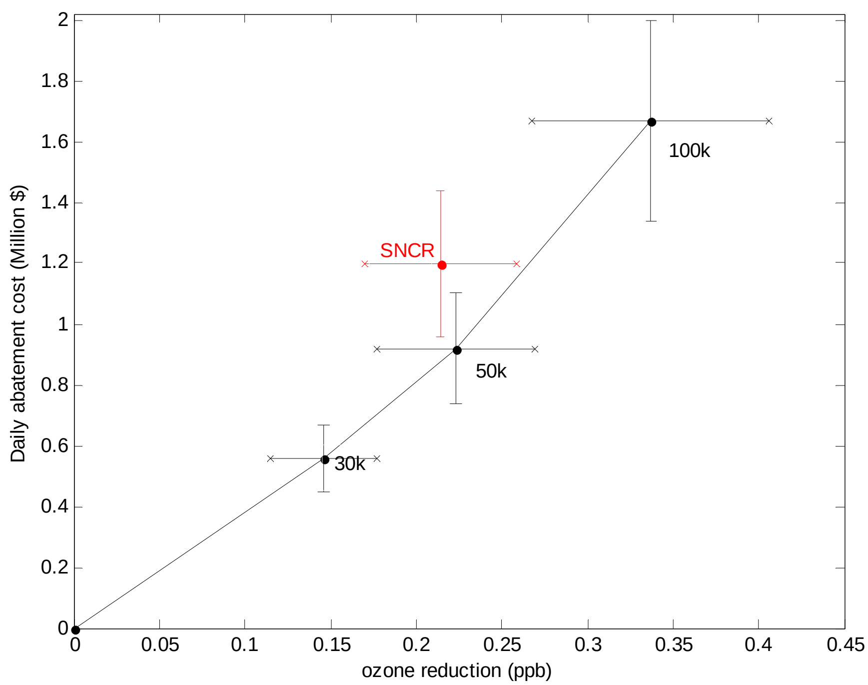


Figure 22: Average daily cost of smart trading and SNCR versus average reduction of daily 8-h maximum ozone concentrations across over the 37 monitoring sites. Error bars ($\pm\sigma$) except the one on the SNCR cost represent uncertainty in the occurrence of high ozone events. The error bars on the SNCR cost represent uncertainty in the estimation of the cost provided by the 1998 NESCAUM report.

As discussed previously, the daily NOx abatement cost (Δcost) and the daily ozone reduction (ΔO_3) have strong correlation and vary dependently with each other. I therefore will use the increased cost for reducing one ppb of daily 8-h maximum ozone (Δcost/ΔO_3) as the criterion to compare the cost-effectiveness of smart trading with NOx prices of $30k, 50k and 100k/ton, with the SNCR case under uncertainty in ozone forecasting in the next section.

7.2 Sensitivity Analysis of Forecast Errors

One important feature of smart trading is that its cost-effectiveness is dependent on the accuracy of ozone forecasts. Type I errors (false positive) lead to unnecessary costs, and Type II errors (false negative) lead to fewer ozone reductions and to extra penalty costs. This section will examine the dependence of cost-effectiveness of the three smart trading scenarios and the threshold false positive and false negative error rates above which the SNCR case becomes more cost effective than smart trading.

As one estimate of the accuracy in ozone forecasting, the observed daily maximum 8-h ozone concentrations at the 37 EPA ozone monitoring sites (from EPA AIRSNOW) during summer 2002 in the Philadelphia/Baltimore region are plotted against the simulated daily maximum 8-h ozone concentrations for the grid cells where the ozone monitoring sites locate (see Figure 23). Each point in the scatterplot represents the observed and simulated ozone concentration at one site on one day. Most data points appear to scatter along the 45-degree line, indicating moderate accuracy in the modeled ozone levels. According to the definition in Table 2, the upper left, points in the upper left and lower right quadrants then represent "false negative" and "false positive" forecasts, respectively. According to equations (1) and (3), the rate of false positives (*p*) is estimated as the ratio of the number of points in the lower right quadrant to the total number of points below the horizontal line (all actual low ozone days), which equals 7.2%. Similarly, the rate of false negatives (*q*) is estimated to be the ratio of the number of points in the upper left quadrant to the total number of points above the horizontal line, which equals 31.8%. This is a conservative estimate of the currently achievable level of accuracy in ozone forecasting, because only two levels of nested grids are used in this modeling, the spatial resolution we used is at 12 km, and the model simulates the entire ozone season rather than forecasting each day based on the previous days observations as initial conditions.

Figure 23 shows that the model tends to underestimate the daily maximum ozone concentrations, possibly because the spatial resolution is not high enough so that the extreme ozone concentrations are diluted when averaged over the grid cell. This could explain why the false negative forecasts occur more frequently than the false positive forecasts. The photochemical model used by the EPA and NOAA (National Oceanic and Atmospheric Administration) could have more nested grids, higher spatial resolution, and ozone observation data could be used to modify the ozone model on a day-to-day basis.

We have good reasons to believe that the highest ozone forecasting accuracy that is currently available is better than reported here. From the literature, a false positive rate (p) of 2.06% was achieved in forecasting the daily-eight hour maximum ozone concentration in New England [Kang, 2005]. The Texas Commission on Environmental Quality (TCEQ) publishes their one-day ahead ozone forecasting accuracy on their website[17]. Based on ozone forecasting made by TCEQ from 1994 to 2004 in the nine metropolitan areas in Texas, the false negative rate (q) of their model is estimated to be 29%. Another research group reported that the false negative rate (q) of 10%~30% was achieved by applying their ozone forecasting model in seven Kentucky metropolitan areas during the 2004 and 2005 ozone seasons [Cobourn, 2007]. Although the accuracy of one-day ahead ozone forecasting by the NOAA and EPA is currently unknown, it is reasonable to believe that the accuracy is higher than reported in the literature. Therefore, a false positive rate of 2% and false negative rate of 10% is assumed to represent the highest ozone forecasting accuracy that is currently available in the following analysis.

[17] http://www.tceq.state.tx.us/compliance/monitoring/air/monops/ozonestats.html

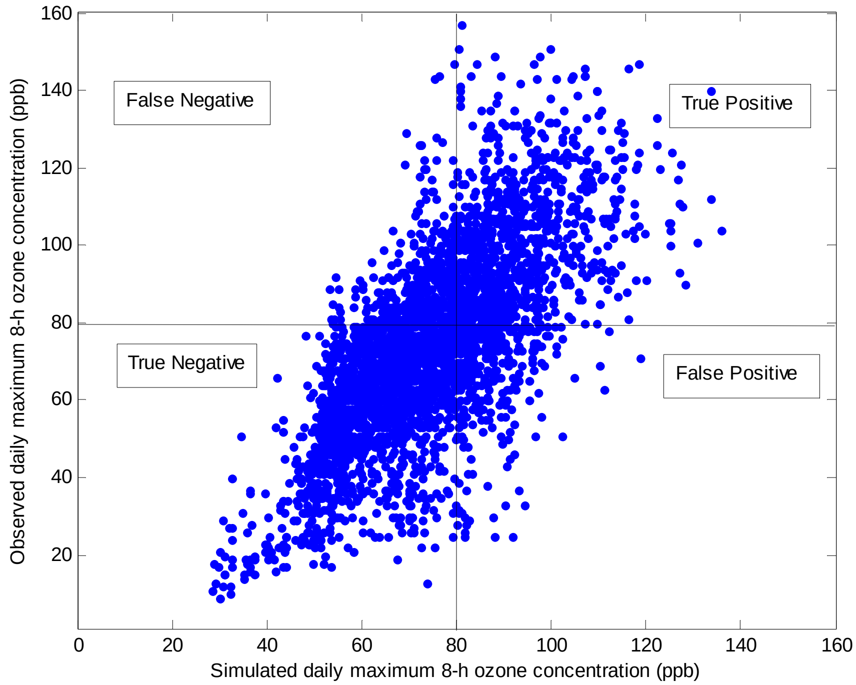


Figure 23: The observed daily maximum 8-h ozone concentrations at the 37 EPA ozone monitoring sites during summer 2002 in the Philadelphia/Baltimore region versus the simulated daily maximum 8-h ozone concentrations for the grid cells where the ozone monitoring sites locate.

As stated earlier, Δcost/ΔO_3 is used to measure the cost-effectiveness of smart trading scenarios and the SNCR scenario. However, both Δcost and ΔO_3 decrease with the false negative rate (q) increases. Thus if we focus exclusively on the ratio Δcost/ΔO_3, we might reach misleading conclusion that smart trading is more cost-effective than the SNCR case even though both Δcost and ΔO_3 under smart trading are very small. Therefore, a modified decision rule is used to conduct the decision analysis here in which a smart trading scenario is considered more cost-effective than the SNCR scenario if it has lower Δcost/ΔO_3 than the SNCR scenario, while reducing at least 70% of ozone under the SNCR scenario.

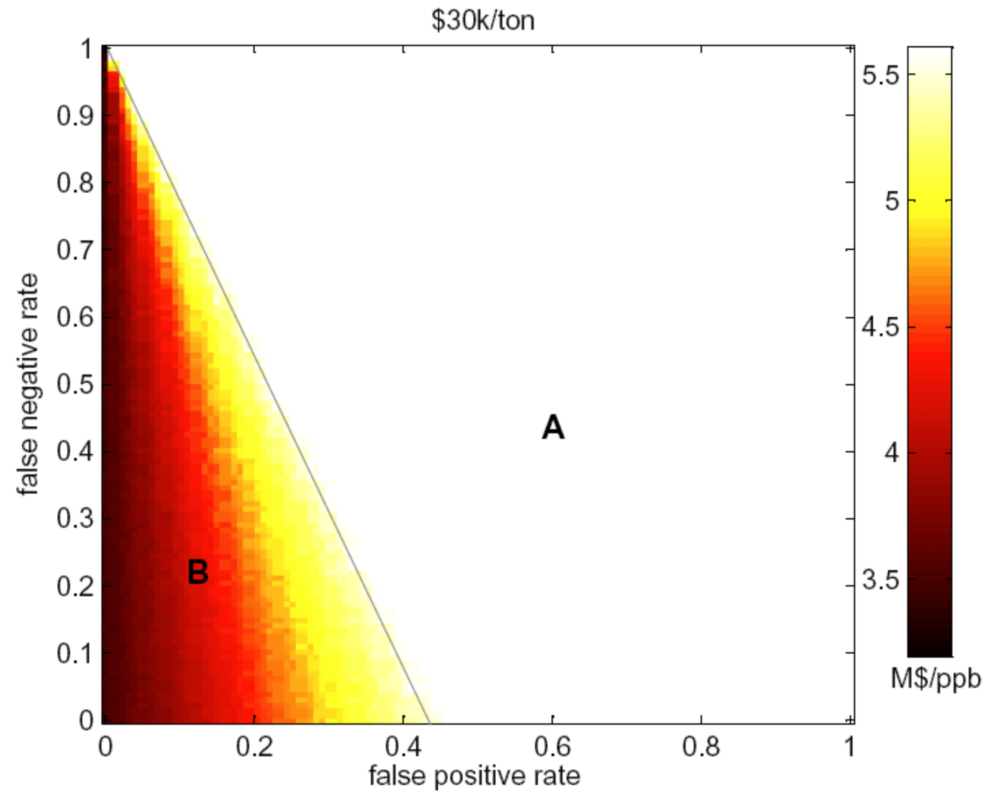
The mean values for the cost-effectiveness measure, Δcost/ΔO_3, under the four scenarios are plotted for different rates of false positive and false negative errors (Figure 24). Different colors represent different values of Δcost/ΔO_3, in the unit of Million \$/ppb. Darker colors indicate lower values of Δcost/ΔO_3, which are more cost-effective. Points with higher Δcost/ΔO_3 than the SNCR scenario are shown in white. The black line indicates the approximate frontier where Δcost/ΔO_3 are equal for SNCR and smart trading. The dotted line indicates the approximate boundary where ΔO_3 for the two case scenarios equals.

Figure 24 shows the range of false positive and false negative errors within which each of the smart trading case scenarios is more cost effective than the SNCR case. The Δcost/ΔO_3 for very low false positive (p) and false negative (q) errors (lower left corner of the plots) under the three trading scenarios are ordered as: 30k < 50k < 100k, although the variability across the three scenarios is not large. Area A indicates that the smart trading case scenario has higher Δcost/ΔO_3 than the SNCR scenario. Area B indicates that the smart trading scenario has higher Δcost/ΔO_3, but reduces less than 70% of ozone than the SNCR scenario (thus is not considered environmentally effective). Area C indicates that the smart trading scenario has lower Δcost/ΔO_3, and reduces at least 70% of ozone than the SNCR scenario, and thus is considered as more cost-effective than the SNCR scenario. Area B in Figure 24 (b) and (c) (\$50k and \$100k scenarios, respectively) are shown in black to distinguish from Area C. Area B in Figure 24 (a) is not shown in black since area C does not exist for the \$30k scenario.

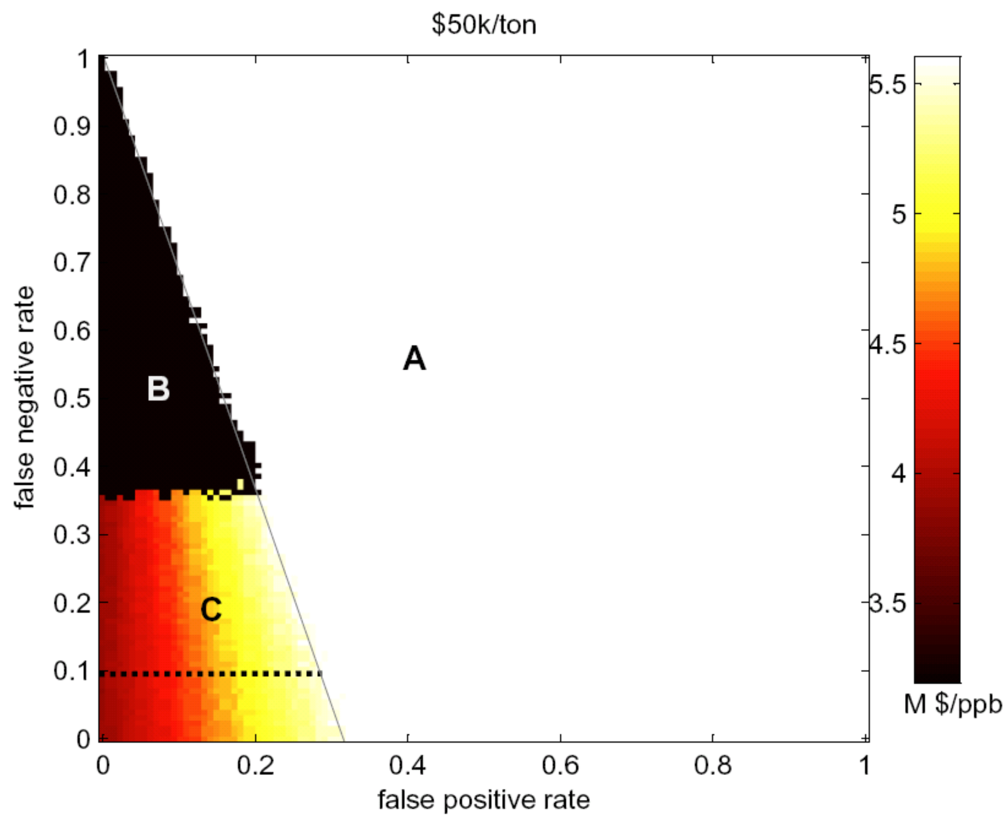
Figure 24 shows not only the threshold values for the false positive and false negatives under which smart trading has lower Δcost/ΔO_3 than the SNCR case scenario, but also the threshold values for the false negatives above which ΔO_3 would be too small. From Figure 24 (a), for example, if the rate of false negative errors (q) was 0.3, the false positive error rates (p) within which smart trading has lower Δcost/ΔO_3 than the SNCR scenario would range from 0 to 0.3 for the \$30k trading case scenario. However, even under 100% forecasting accuracy, the ozone reduction under the 30k trading case scenario is still too low, so that this scenario is not considered as more cost-effective than the SNCR case. From Figure 24 (b) and (c), the threshold *q* values for smart trading at 50k and 100k NOx prices to be more cost-effective than the SNCR case is approximately 0.36 and 0.57, respectively. If *q* is 0.3, the values of *p* for which the 50k and 100k scenarios has are more cost effective than the SNCR scenario range from 0 to 0.25 and from 0 to 0.08, respectively. In general, the higher the NOx price is, the higher the threshold *q* value is to prefer smart trading in the decision analysis. Also, the higher the NOx price is, the more sensitive the cost-effectiveness of smart trading is to the false positive error rate, and the higher is the required level of ozone forecasting accuracy. Besides, for any NOx price level, the higher the false negative rate, the lower is the required rate of false positives for smart trading to still be preferred.

The black dotted line in Figure 24 (b) and (c) represents the *q* values under which the ozone reduction for the smart trading case scenario and the SNCR scenario approximately equals, which are around 0.085 and 0.37 for the \$50k and \$100k case scenarios, respectively. If the currently achievable ozone forecasting accuracy is the same as the highest accuracy from literature (*p*=2%, *q*=10%), smart trading at \$50k/ton is approximately 30% more cost-effective than the SNCR case while resulting in comparable amount of ozone reduction, and smart trading at \$100k/ton is approximately 15% more cost-effective than the SNCR case while resulting in more ozone reduction. Even if the currently achievable ozone forecasting accuracy is what we estimated in this analysis (*p* =7%, *q* =32%), smart trading at \$50k and \$100k/ton NOx prices would still be more cost-effective than the SNCR case.

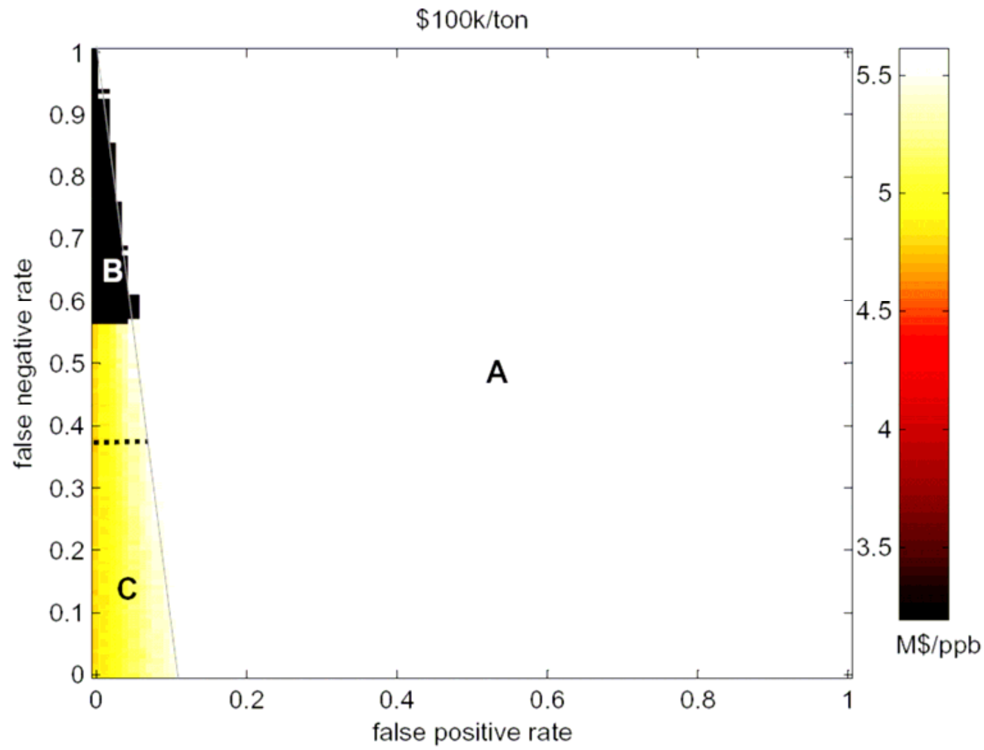
These results suggest that uncertainty in ozone forecasting may not be a major limiting factor for the feasibility of a time-differentiated NOx cap-and-trade program.


$30k/ton
false negative rate
false positive rate
A
B
M$/ppb

(a)


$50k/ton
false negative rate
false positive rate
A
B
C
M $/ppb

(b)



(c)

Figure 24: Δcost/ΔO_3 (Million \$/ppb) of smart trading versus false positive rate and false negative rate for the (a) \$30k, (b) \$50k and (c) \$100k relative to the \$2k/ton NOx case.

Again, although there are ranges of false positive and false negative errors within which the $100k case is more cost effective than installing SNCRs, it would be more appropriate to compare the $100k case to installing SCRs which achieve comparable ozone reductions, but is beyond the scope of this study.

The analysis conducted here does not include a penalty cost for continued non-compliance, which makes the cost-effectiveness much less sensitive to the false negative error than it probably should be. In actual ozone modeling, the false negative rate tends to be higher than the false positive rate. Analysis using an alternative utility function that includes the penalty cost of ozone non-attainment should be explored in the future study.

7.3 Sensitivity Study of the Distribution of Cost-effectiveness of Smart Trading

The previous section examined the dependence of the mean Δcost/ΔO_3 on the ozone forecasting errors for the three smart trading scenarios. This section will investigate the dependence of the full distribution of Δcost/ΔO_3 on false positive and false negative errors. Since smart trading at $50k/ton NOx reduces a comparable amount of NOx and ozone as the SNCR case, frequency counts for Δcost/ΔO_3 under the $50k/ton trading scenario, given four different pairs of false positive and false negative rates (p=1%, q=1%; p=2%, q=10%; p=4%, q=20%; and p=8%, q=30%) are obtained from the stochastic decision model and shown in box-plot in Figure 25. To avoid the problem of infinite Δcost/ΔO_3 when ozone reduction is 0, the monthly sum of Δcost divided by the monthly sum of ΔO_3 is used to construct the distribution of Δcost/ΔO_3. In the first case shown assumes that the ozone forecasting is very accurate, where both p and q equal 1% (column a). The second case assumes that the ozone forecasting errors are the same as the lowest values in literature, where p equals 2% and q equals 10% (column b). The fourth case assumes that the ozone forecasting errors are similar to the values obtained from this analysis, where p equals 7.2% and q equals 31.8% (column d). The third case assumes that ozone forecasting errors are in between the second and the fourth cases (column c). The black horizontal line in the figure indicates the cost-effectiveness measure of the SNCR scenario. The summary statistics obtained from the boxplots are listed in Table 3. Figure 25 shows that Δcost/ΔO_3 has an increasingly long tail as ozone forecasting errors increase. The mean, standard deviation, 25% and 75% quartiles of Δcost/ΔO_3 all increase with error rates in ozone forecasting, and the standard deviation increases more rapidly than mean and quartiles. Under all four assumed pairs of p and q values, the 75% quartiles (Q3) of Δcost/ΔO_3 are below that of the SNCR scenario. There is nearly a 95% probability that the monthly averaged Δcost/ΔO_3 under the $50k/ton scenario is higher than the SNCR scenario if the currently achievable values of p and q are 2% and 10%, respectively. There is still an 80% probability that the monthly averaged Δcost/ΔO_3

under the \$50k/ton scenario is higher than the SNCR scenario if the currently achievable values of p and q are 8% and 30%. These results provide additional evidence that the uncertainty in ozone forecasting is not likely to be a limiting factor for the cost-effectiveness of a time-differentiated NOx cap-and-trade program.

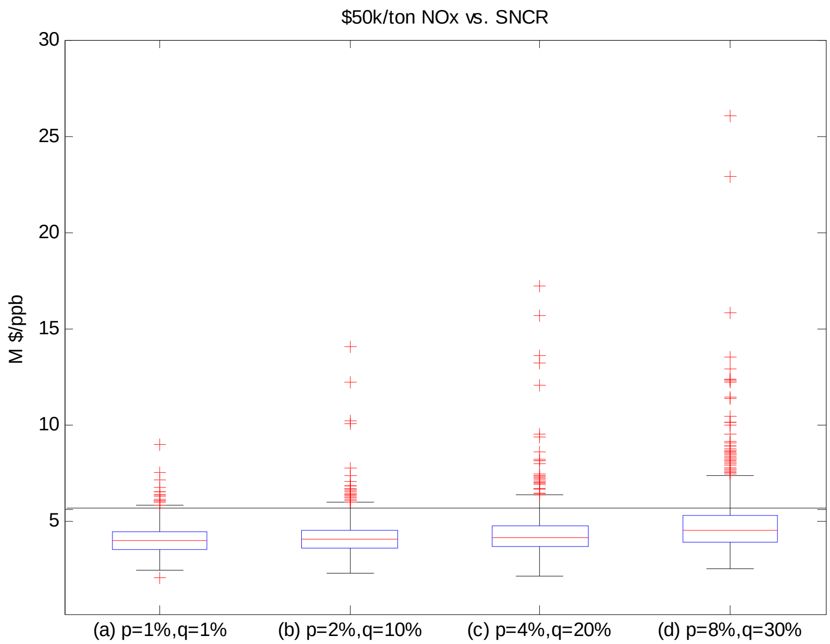


Figure 25: Boxplots of Δcost/ΔO_3 (Million \$/ppb) given (a) false positive (p) = false negative (q) = 1%, (b) p = 2%, q = 10%, (c) p = 4%, q = 20%, (d) p = 8%, q = 30%. Δcost and ΔO_3 are monthly summed. The horizontal black line indicates the Δcost/ΔO_3 for the SNCR scenario.

Table 3: Summary statistics of Δcost/ΔO_3 under different values of false positive (*p*) and false negatives (*q*).

p	q	Mean	Standard Deviation	Q1	Q3	$\Pr\{\frac{\Delta\text{cost}}{\Delta O_3}(\$50\text{k}) > \frac{\Delta\text{cost}}{\Delta O_3}(\text{SNCR})\}$
1%	1%	4.087	0.727	3.614	4.450	96.9%
2%	10%	4.182	0.838	3.651	4.598	94.8%
4%	20%	4.344	1.133	3.668	4.772	90.4%
8%	30%	4.940	1.996	3.949	5.362	80.2%

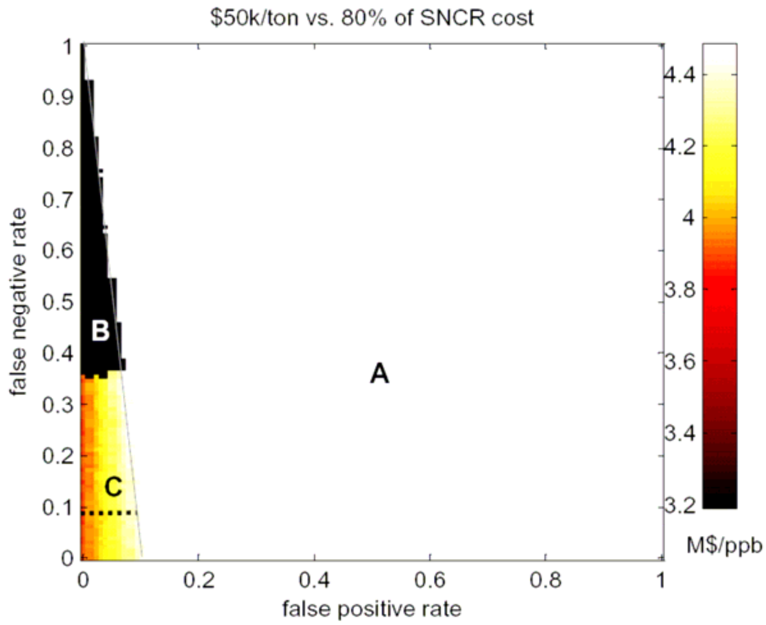
7.4 Sensitivity Study of the SNCR Costs

The previous sections focused on comparing the cost-effectiveness (Δcost/ΔO_3) of the smart trading scenarios to the SNCR scenario. As discussed in chapter 3, the 1998 NESCAUM report estimated the cost/MWh for installing SNCR into coal plants and provided a 20% uncertainty in the estimated cost/MW. Thus \$ 1.2±0.24 M or \$ 0.96~1.44 M is assumed to be the uncertainty range for the SNCR cost.

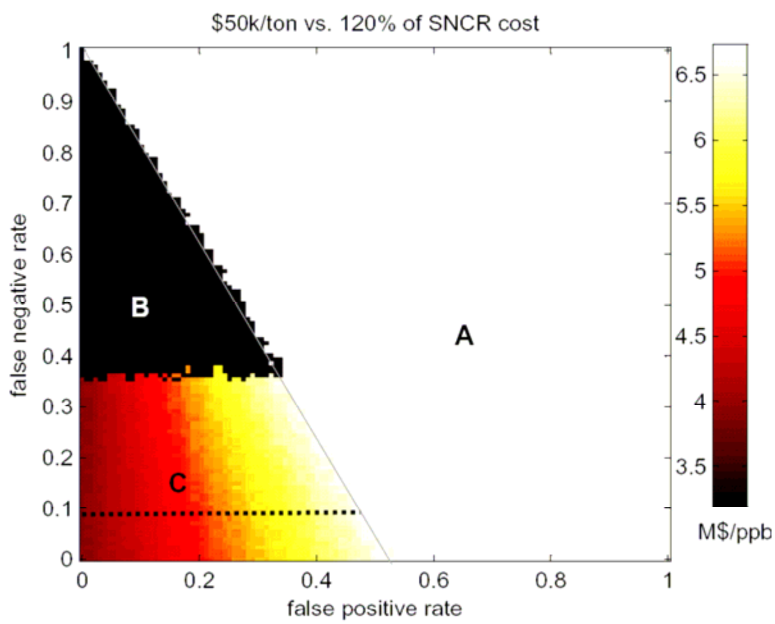
Here, I repeat the sensitivity analysis of false positive (p) and false negative (q) errors from section 7.2 assuming the SNCR cost is either \$ 0.96 or 1.44 M. The results are plotted in Figure 26 in in the same format as Figure 24, but only for the \$50k/ton NOx, because these two cases lead to comparable amounts of NOx and ozone reduction assuming a 100% forecasting accuracy. Similarly, the region for which the Δcost/ΔO_3 of the \$50k/ton scenario is higher than the SNCR scenario is shown in white, and the region for which ΔO_3 is lower than 70% of the SNCR scenario is shown in black. The black line indicates the approximate boundary where Δcost/ΔO_3 for the two scenarios are equal. Area A indicates that the smart trading scenario has lower Δcost/ΔO_3 than the SNCR scenario. Area B indicates that the smart trading scenario has higher Δcost/ΔO_3, but less than 70% of ΔO_3 than the SNCR scenario. Area C indicates that the smart trading scenario has higher Δcost/ΔO_3, and leads to ozone reduction of at least 70% of the SNCR scenario. The dotted line indicates the approximate boundary where ΔO_3 for the two case scenarios equals. From Figure 26, the threshold value of q, which approximately equals 0.36, does not change with the SNCR costs, and is the same as in Figure 24(b). The threshold value of p depends on the value of q. A smaller q will result in a wider tolerance region, yielding a higher threshold value for p. From Figure 26, the threshold values for p assuming daily costs for the SNCR case of \$ 0.96 M and 1.44 M are approximately 0.07 and 0.34, respectively, given a q value of 0.36.

From Figure 26, assuming that the SNCR cost is at the lower end of the uncertainty range, even if the currently achievable ozone forecasting accuracy is the same as what we obtained in this analysis (p=7.2%, q =31.8%), smart trading at $50k/ton NOx price would still be slightly more cost-effective than the SNCR case. If the currently achievable ozone forecasting accuracy is the same as the highest rates from literature (p=2%, q =10%), smart trading at $50k/ton would be approximately 15% more cost-effective than the SNCR case while resulting in comparable amount of ozone reduction.

The sensitivity analysis above is based on cost data from a 1998 NESCAUM report. The cost of SNCRs in 2005 is converted from the cost in 1998 dollars based on an inflation rate of 5%, and the annual capital cost is discounted at a rate of 6.7%. Also, the cost of SNCR depends on the size, boiler type, fuel type, NOx emission rate and other characteristics of the EGUs, so that the actual cost of installing the SNCR on all power plants in PJM and running it during the summer season might be beyond the uncertainty range discussed here. However, as a proof-of-concept study, this sensitivity analysis shows that the cost-effectiveness of smart trading is fairly robust to uncertainty in the costs of SNCR, and the uncertainty in ozone forecasting does not appear to be a major limiting factor for smart trading.



(a)



(b)

Figure 26: Δcost/ΔO_3 (Million $/ppb) of smart trading versus false positive rate and false negative rate for the $50k relative to the $2k/ton NOx case assuming (a) Δcost for the SNCR case is 20% lower than the estimated value and (b) Δcost for the SNCR case is 20% higher than the estimated value.

Chapter 8. Policy Discussion

It has been nearly four decades since the passage of the Clean Air Act and the establishment of the NAAQS for ozone and other criteria pollutants. But due to complexities of implementation and high costs of emissions reductions many regions of the U.S. remain in non-attainment of the ozone standard. As easier, less expensive emissions reductions are made, and additional permanent or annual reductions have even higher marginal costs, it becomes worthwhile to consider time-differentiated approaches. The motivation for this is the concern that if options are restricted to costly technological mandates, further reductions may become politically infeasible, and ozone levels that harm human health could be allowed to persist as they have already for decades.

One of the major technical barriers to a time-differentiated approach is the necessary reliance on weather and atmospheric chemistry forecasting, which is generally perceived to have large uncertainty. The transaction costs of a time-differentiated program would be too high if ozone forecasting is not sufficiently accurate. This thesis demonstrates that current weather and air quality forecasting abilities may already be beyond the needed minimum threshold of accuracy. However, other challenges remain that could impede the implementation of a time-differentiated regulatory design.

There are significant political and legal barriers to the implementation of a differentiated regulation. Programs that temporarily raise the NOx price during ozone episodes could use photochemical modeling to define the high ozone days, if regulators had sufficient information to correctly define these days. However, it could be difficult to establish a generally accepted standard for when to trigger a higher NOx price (or, equivalently, a higher redemption ratio under the cap) in practice. For example, what predicted maximum ozone concentrations for the next day, and with what probability or confidence level, would be required to trigger the rule implementation? Consequently, political and legal disputes are likely to arise over the definitions of high ozone days and rules for permit exchange in such a program, since small changes to this definition could have significant impacts on participants. These affected parties could use political influence or legal disputes over the modeling to shape the details of the regulation and this could limit the regulation's effectiveness if they alter the definitions of when NOx reductions are needed. These disputes could well politicize the scientific uncertainties in ozone modeling.

Additional political and legal disputes could arise if the differentiated program is only time-differentiated but not location-differentiated. The locational variation of ozone concentrations provides a challenge to the implementation of a time-differentiated NOx regulation. Even within a relatively homogeneous region, the ozone concentrations could still vary greatly at different locations, so that a forecasted ozone episode might only happen in Washington D.C. but not in Philadelphia, influenced by the meteorological field. Also, a regulated facility far from a monitor used to determine the high ozone condition could argue that it is unfair for it to be treated the same as a unit closer to that monitor (e.g., in a more urban location). This could result in disputes over claims of unfairness. The ensuing political and legal processes could constrain the effective implementation of a differentiated cap-and-trade program.

The complexity of ozone chemistry also provides further challenges to NOx regulation and could also potentially lead to political and legal disputes, Reducing NOx emissions involves tradeoffs, because reductions in NOx emissions may sometimes increase ozone concentrations. Conversely, increasing NOx emissions, under some circumstances, may decrease ozone concentrations. These problems could amplify the effects of legal disputes toward a time-differentiated regulation.

Another challenge is in defining an appropriate evaluation metric for the impact of a time-differentiated regulation. Using population-weighted compared with purely concentration-based metrics would likely lead to different results. Considering the human population densities in designing the details of the differentiated policy plan provides an additional challenge for the statutory framework for air quality policy, which currently does not allow the EPA to consider the costs and benefits when framing ozone regulations. However, if the human population densities are not to be considered, it might also raise disputes based on fairness.

Finally, the problem of “hot-spot” or “wrong-way trades” is an inevitable problem associated with a cap-and-trade program in the context of a pollutant that is not uniformly mixed. It is almost impossible to eliminate the possibility of NOx allowances being sold from where ozone productivity is low to where it is high. The best that atmospheric modeling could do to address this problem would be to demonstrate that under specific policy scenarios the formations of hot-spots are not a major concern. However, even a 3 ppb increase of ozone increase would lead to disputes of fairness. These political and legal disputes have the potential to significantly reduce or eliminate the benefits of the NO*x* emission trading.

Possible ways to reduce these problems include, but not limited to, increasing the amount and spatial coverage of ozone monitoring sites, increasing the accuracy of ozone forecasting, and validating the accuracy of ozone forecasting by publicizing the forecasting errors on a day-to-day basis. One alternative avenue for implementation that might help mitigate the above problems is to define high ozone days using meteorological parameters and rely less on atmospheric modeling, since high accuracy of one-day ahead weather forecasting is widely acknowledged. Although forecasting ozone concentrations using this method is very likely to result in higher rates of errors than relying explicitly on photochemical models, it could potentially reduce political and legal disputes.

Another possible way to increase the acceptability of a differentiated cap-and-trade program is to combine it with other policy changes to “widen the pie” and buy off support from political parties and industries. For example, a time-differentiated cap-and-trade program could reduce the total amount of NOx abatement required from point sources, since it would not require emission reductions during forecasted low ozone days. Thus if the alternative of a time-differentiated cap-and-trade program is costly annual cap reductions, the time-differentiated program could increase support for the differentiated approach from industry.

Chapter 9. Conclusions and Future Work

The dependence of ozone pollution on meteorology and atmospheris chemistry creates a challenge for environmental regulation. To design an effective NOx (or VOC) regulation to reduce ozone, timing and location have to be incorporated and the impacts of meteorological variability have to be considered. This thesis aims to demonstrate the scientific and technical feasibility of a time-differentiated NOx cap-and-trade program for power plants. I have examined the following technical challenges: Could power plants respond to incentives for short-term NOx reductions that vary over time, how would the reductions of NOx emissions impact the ozone concentrations, how would the cost and ozone reduction of this type of flexible abatement compare to a technology based command-and-control strategy, and what is the threshold level of ozone forecasting accuracy above which this flexible regulation is no longer preferable to a technology-based command-and-control strategy?

9.1 Conclusions

The results presented in this thesis have shown:

- ***It would be difficult to determine the most cost-effective NOx control options for each power plant, which makes abatement decisions under a market-based regulation preferable.*** Results in chapter 4 show that a large heterogeneity exists in the NOx emission characteristics of fossil fuel-fired electric power generators. Some coal generating units are shown to be able to reduce more NOx emissions through redispatching than by adopting NOx control technologies such as SNCR. And for other units, the feasibility of dispatching NOx emissions is limited by congestion and high costs of dispatching electricity generations. This suggests that it would be less costly for the operators of some units to abate NOx emissions through redispatching only on the high ozone days than by adopting

NOx control technologies, and less costly for the operators of other units to abate NOx emissions through control technologies. Smart trading could provide strong incentives to the latter units to adopt NOx control technologies.

- ***The capability of reducing NOx emissions by redispatching is not likely to be limited by network constraints, congestion, and inflexibility of dispatching electricity generation during peak demand hours.*** It was shown that during an average demand hour, which constitutes the majority of hours both in the summer and over the year, redispatch could lead to a typical NOx reduction rate of 35% in aggregate. Even during the peak demand hours, redispatching could still result in a typical NOx reduction rate of 15~20%.

- ***The potential for smart trading to reduce ozone concentrations is not likely to be limited by the inflexibility of dispatching electricity generation during peak demand hours.*** Even if the percentage NOx reduction during a peak demand hour through smart trading is lower than installing the SNCRs, smart trading can still result in the same or lower ozone concentrations as installing SNCRs. The results shown here indicate that NOx reductions during the average demand hours, earlier in the day during ozone episodes, are more important for reducing the daily maximum ozone concentrations than are NOx reductions during the peak demand hours.

- ***Smart trading would likely lead to noticeable environmental benefits in terms of lowering ozone concentrations, particularly during high ozone episodes.*** Results of ozone modeling shows that the NOx reductions as a result of electricity redispatch is capable of lowering the daily maximum 8-hour ozone concentrations by 2~16 ppb given a NOx price of $100k/ton, depending on the meteorology. It is also shown that ozone reduction is more likely to be achieved through NOx emission reductions during high ozone days, which makes smart trading a more cost-effective strategy in ozone mitigation.

- ***Smart trading does not lead to the shifting of large amounts of NOx to one area, the maximum increase of hourly NOx emission at a single unit is below 0.2 ton.***

- ***Although pervasive ozone reductions of 3~12 ppb can be achieved under smart trading at $100k/ton of NOx, we do see small areas where daily eight-hour maximum ozone level increases by up to 3 ppb. These small areas are often located outside or downwind of regions where ozone concentrations are the highest within the whole PJM area.***

- ***The ozone forecasting accuracy that is required for smart trading at $50k/ton of NOx to have lower cost for reducing per unit of ozone than the SNCR case is within the range of published error rates of ozone forecasting and modeling, strongly suggesting that uncertainty in ozone forecasting may not be a major limiting factor for the feasibility of a time-differentiated NOx cap-and-trade program.***

9.2 Future work

There are several areas where this work could be further extended and improved in order to yield additional insights. These areas are:

- The choice of utility functions can greatly influence the decision making about ozone control policies. In future work, other utility functions, such as one that considers a penalty cost for ozone non-attainment should be explored.

- The stochastic decision model used in this study is a simplified model and provides a convenient way to illustrate the dependence of the cost-effectiveness of a time-differentiated NOx regulation on the uncertainty of ozone forecasting. In future analysis, a more advanced Markov model could be built by including a observations from more years into the model, as well as by developing more Markov states. Ideally, a reduced form model of CAMx would be developed to allow the full simulation of the process of the sequential decision making, and to allow the selection of different NOx prices as an option on each day.

- This analysis assumes that the only decision that a plant operator has to react to an increased NOx price is whether to dispatch electricity generation or not. In reality, there are operational adjustments at these facilities, although they come at an incremental cost. In further work, operational modifications that temporarily lower NOx emission rates at a plant should be included. In addition, the decision to adopt NOx control technologies within a multi-year decision analysis could be developed.

- Comparing additional technology-based command-and-control policy scenarios, including scenarios with other control technologies and scenarios with different subsets of units installing controls, with smart trading would likely yield additional insights. For example, installing SCRs at all generating in PJM would likely result in comparable NOx and ozone reductions as smart trading with a NOx price of $100k/ton.

Chapter 10. References

Blanchard, C.L., Tanenbaum, S., Lawson, D.R., **2008**, “Differences between Weekday and Weekend Air Pollutant Levels in Atlanta; Baltimore; Chicago; Dallas–Fort Worth; Denver; Houston; New York; Phoenix; Washington, DC; and Surrounding Areas”, *Journal of Air & Waste Management Association* 58,1598–1615

Byun, D., and K.L. Schere, **2006**, “Review of the Governing Equations, Computational Algorithms, and Other Components of the Models-3 Community Multiscale Air Quality (CMAQ) Modeling System”, Applied Mechanics Reviews, 59, 51-77

Cobourn, W.G.,2007, “Accuracy and reliability of an automated air quality forecast system for ozone in seven Kentucky metropolitan areas”, Atmospheric Environment 41, 5863–5875

ENVIRON, **2009**. User’s Guide Comprehensive Air Quality Model with Extensions (CAMx) version 5.01, ENVIRON International Corporation. Novato, California.

Felzer, B. S., Reilly, J. Melillo, J., Kicklighter, D. W., Sarofim, M., Wang, C., Prinn, R. G., and Q. Zhuang., **2005**, “Future effects of ozone on carbon sequestration and climate change policy using a global biochemistry model”, *Climatic Change*, 73 (3): 345-373.

Kang, D., B.K. Eder, A.F.Stein, G.A. Grell, S.E. Peckham, and J. McHenry, (2005), “The New England Air Quality Forecasting Pilot Program: Development of an Evaluation Protocol and Performance Benchmark,” *Air and Waste Management,* **55**; 1782-96.

Martin, K., **2008**, "Implementing a differentiated cap-and-trade program for ozone: flexible nitrogen oxide abatement from power plants", Ph.D. Dissertation, Massachusetts Institute of Technology, Engineering System Division, Cambridge, MA.

Mauzerall, D.L., Sultan, B., Kim, N. and Bradford, D.F., **2005**. "NOx emissions from large point sources: variability in ozone production, resulting health damages and economic costs," *Atmospheric Environment,* 39, 2851-2866.

Morris R.E., Tai, E., Hersey, C., Fitzner, C., Rodenberg M., Lebeis, M., Pocalujka, L.P., and Wolff, G.T., **2001**, "A Methodology for Quantifying Ozone Transport and Assessing the Benefits of Alternative Control Strategies".
Retrieved from
http://www.camx.com/publ/pdfs/semcog-pap_AWMA_2001.pdf

Morris, R.E., Yarwood, G., Emery, C.A., Koo, B., and Wilson, G.M., **2003**,"Development of the CAMx One-Atmosphere Air Quality Model to Treat Ozone, Particulate Matter, Visibility and Air Toxics and Application for State Implementation Plans (SIPs)". Retrieved from
http://www.camx.com/publ/pdfs/AWMA_AQGuidelines03_Paper9_CAMx.pdf

NESCAUM, **1998**, "Status Report on NOx: Control Technologies and Cost Effectiveness for Utility Boilers—Excecutive Summary", June 1998
Retrieved from
www.nescaum.org/documents/execsum_nox.pdf/

NRC (National Research Council), **1991**, "Rethinking the Ozone Problem in Urban and Regional Air Pollution", National Academy Press, Washington, DC.

Nobel, C.E., McDonald-Buller, E.C., Kimura, Y., and Allen D.T., **2001,** "Accounting for spatial variation of ozone productivity in NO*x* emission trading", *Environmental Science and Technology* 35 (22), 4397-4407

Roselle. S. J., **1994**, "Effects of biogenic emission uncertainties on regional photochemical modeling of control strategies", *Atmospheric Environment*, 28(10):1757-1772.

Ryerson, T. B., Trainer M., *et. al.,***2003, "**Effect of petrochemical industrial emissions of reactive alkenes and NOx on tropospheric ozone formation in Houston, Texas", *Journal of Geophysical Research*, 108(D8), 4249

Seinfeld J. and Pandis S., **2006**. Atmospheric Chemistry and Physics: From Air Pollution to Climate Change, Wiley-Interscience; 2nd edition.

Tietenberg, T. H., **1998**, "Ethical Influences on the Evolution of the US Tradable Permit Approach to Pollution Control." *Ecological Economics* 24(2-3): 241-257

Thompson T., Webber M. and Allen D.T., **2009**, "Air quality impacts of using overnight electricity generation to charge plug-in hybrid electric vehicles for daytime use", *Environ. Res. Lett.* 4, 014002

Wang, L., Thompson T., McDonald-Buller, E.C., Webb, A. and Allen D.T., **2007**, "Photochemical modeling of emissions trading of highly reactive volatile organic compounds in Houston, Texas. 1. Reactivity based trading and potential for ozone hot spot formation", *Environmental Science and Technology* 41(7), 2095

------- (U.S. EPA 2006a), "Air Quality Criteria for Ozone and Related Photochemical Oxidants," Research Triangle Park, NC: Office of Health and Environmental Assessment, Environmental Criteria and Assessment Office; EPA report no. 600/R-05/004aF, February.

-------- (U.S. EPA 2006b), "NOx Budget Trading Program: 2005 Program Compliance and Environmental Results," EPA report no. EPA430-R-06-013, September.