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A mixed integer programming model for National Ambient Air Quality Standards (NAAQS) attainment strategy analysis

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A B S T R A C T

The United States federal government establishes National Ambient Air Quality Standards (NAAQS) for six pollutants, including ozone. States with areas designated in nonattainment of the standards are required to develop State Implementation Plans (SIPs) to demonstrate how pollution levels will be reduced to meet the standards. Historically, most states have developed SIPs independently. However, for ozone and other air pollutants, some states have agreed to cooperate to address regional pollution problems. These types of cooperative efforts have the potential to improve pollution control efficiency. We present a mathematical programming model that can help identify potential minimum-cost emissions control strategies that employ regional strategies. We present a series of national-level applications using information from a set of air quality simulations along with spatially and technologically detailed emissions control information. The model quickly evaluates alternative attainment planning scenarios, tests regional strategies, and identifies monitors that potentially have significant influence on attainment strategies.

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1. Introduction

The United States federal government establishes National Ambient Air Quality Standards (NAAQS) for six pollutants, including ozone. Ground-level ozone is predominantly formed from emissions of nitrogen oxides (NO_X) and volatile organic compounds (VOC). Ozone is considered a regional pollutant because it can be transported long distances, including across state and national borders.

Under the Clean Air Act, states with areas designated as in nonattainment with a standard are required to develop State Implementation Plans (SIPs) to demonstrate how pollution levels will be reduced to meet the standard. Historically, many states have developed SIPs independently. However, for ozone and other air pollutants, some states cooperate to better address regional pollution problems.[1] These types of cooperative efforts have the potential for improved pollution control efficiency if states collaboratively determine the least-cost controls within or across regions.

Mathematical programming models can serve as tools for identifying least-cost control strategies for air pollution planning. While many studies have used optimization approaches to model emissions-related issues (Greenberg, 1995; Zhou et al., 2008), here we summarize notable contributions to the literature that employ models that optimize planning decisions regarding source-specific emissions and impacts on ambient air pollution concentrations at receptor locations. The earliest peer-reviewed application of mathematical programming for air quality planning we are aware

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[1] The Ozone Transport Commission (http://www.otcair.org/about.asp), the Lake Michigan Air Directors Consortium (http://www.ladco.org/about/ladco_doc/MOA_2012.pdf), and the Central States Air Resource Agencies (http://censara.org/content/what-does-censara-do) are examples of multi-jurisdictional organizations that engage in cooperative planning on air quality issues.

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of appeared in the 1970s with Kohn's model of particulate matter and sulfur dioxide emissions in the St. Louis, Missouri area (Kohn, 1971). Atkinson and Lewis followed with articles comparing optimization objective functions that reduce emissions at least cost with objective functions that achieve ambient air quality goals at least cost. Atkinson and Lewis also compare the optimization approaches with a "naive" heuristic where emissions reductions are applied uniformly across point sources until federal standards are met, a standard SIP development approach at the time (Atkinson and Lewis, 1974a, 1974b, 1976). Also using data from the St. Louis area, Atkinson and Lewis identify significant efficiency gains from planning under an ambient air quality least cost approach, particularly when compared to standard SIP approaches.

Concerns about the long-range transport of pollution causing acid rain lead to a series of papers from Ellis et al. (1985a; 1985b, 1986) that apply a mathematical programming approach to develop optimal plans for acid rain abatement across eastern parts of North America. These papers examine many of the same issues we examine here, including long-range pollutant transport and attention to both point and non-point emissions. While their first paper focuses on deterministic approaches (Ellis et al., 1985a), the authors' latter two papers explore the uncertainties in the source-receptor relationships using stochastic models (Ellis et al., 1985b, 1986). Altogether, this series of papers represent the most comprehensive and broad-scale analysis of optimization approaches in regional air quality management.

Recent applications focus on ozone planning at local and multi-county scales. Cohan et al. (2006) present an optimization approach to selecting control measures where the cost-effectiveness of the measures are estimated in terms of ozone impacts per dollar spent. These measures are then selected in order of cost-effectiveness until the desired ozone reductions are achieved. This approach is applied in two ways to achieve required ozone reductions in the Macon, Georgia region. Cohan et al. first choose among a restricted set of measures local to Macon and then choose among measures drawn from a statewide inventory. This fosters the ability to examine cost efficiencies from developing more regional emissions control strategies, an important theme we pick up in the case study of this paper. Hsu et al. (2014) apply a suite of control measures to reduce ozone during an eight-day ozone event in the Dallas/Fort Worth area of Texas. First, the measures are chosen and then their cost is minimized within a mixed integer linear programming framework, focusing on the costs and ozone implications of temporally targeting measures. Liao and Hou (2015) present a nonlinear programming model to identify least-cost control strategies to achieve reductions in both ozone and particulate matter ($PM_{2.5}$). Liao and Hou examine the role of regional emissions reductions and estimate the costs of achieving air quality goals in five cities in the United States.

In this paper, we present a mixed integer programming model for identifying least-cost control strategies that analyzes the effectiveness of multistate emissions control strategies. While mathematical programming models are used to develop and evaluate regional ozone control strategies, our model applies the framework nationally to identify efficiencies that may be gained through developing and implementing regional control strategies. Air quality is characterized by a source-receptor matrix estimating the impact of local and regional NO_X and local VOC emissions reductions on ambient ozone concentrations at monitors. Least-cost control strategies are determined by decisions about using specific control measures on specific emissions sources.

This model allows user-defined planning constraints on ozone precursors and emissions locations considered in identifying a least-cost attainment strategy. For example, least-cost NAAQS attainment control strategies can be developed when considering only in-state emissions contributions to ozone formation, the contribution of emissions from multistate regions, or, alternatively, considering emissions from all lower 48 states.

We present a case study of a national-scale application of the model using information from a series of air quality simulations along with the best currently available spatially and technologically detailed emissions control information. We apply the model iteratively to achieve gradually lower ozone goals, from 75 parts-per-billion (ppb) to 65 ppb nationally, in 1 ppb increments. For each goal, we vary the geographic scope of NO_X and VOC emissions reductions targeted to reduce ozone levels in order to achieve alternative goals at all monitors. Varying the geographic scope of emissions reductions enables the measurement of potential efficiency gains or impacts from cooperative ozone planning. We further use solutions of these model runs to examine the relative importance of monitors that have a potential to exert a high level of influence on control strategies. Additionally, we distinguish the ozone level change attributable to within-state and out-of-state emissions reductions. Lastly, we review emissions "co-reductions" of pollutants other than NO_X and VOC resulting from the application of ozone control strategies.

The model presented in this paper advances the optimization and air quality planning and management literature in a variety of ways. First, to our knowledge, this paper represents the first national-level application in the literature, enabling the identification of national-level least cost strategies to attain alternative air quality goals, while retaining important local and regional detail. Second, previous studies generally focus on short episodes or single days of high ozone. This application looks across the April to October period to characterize ozone response on typical high concentration days. We use April through October as the analytic period for the purposes of this analysis because these months represent the bulk of the ozone seasons for most areas of the country. Third, as the case study on the importance of considering regional factors in air quality planning and management demonstrates, the model can be easily adjusted to examine sensitivity to key modeling choices and parameters. Finally, the model is designed to estimate the marginal cost of air quality constraints at individual air quality monitors (e.g. the incremental cost of a 1 ppb change in the ozone target at a monitor), giving planners and managers useful information about the relative importance of individual monitors within the overall air quality system.

We begin by presenting the mathematical formulation of the model. We then describe the model parameters and inputs characterizing the air quality system and emissions controls. Next, we present a case study examining the importance of considering regional factors in developing least-cost attainment strategies. We close with a discussion of caveats and areas for future research.

Our intent is to present the model in sufficient detail such that interested analysts can replicate the model in the software of their choice with data characterizing their air quality management issue of interest. We present a general framework that has the flexibility to incorporate many case-specific details that may be of interest to air quality planners and managers.

2. Mathematical model

We introduce the general optimization framework in three parts. We first describe the model's characterization of the air quality system. Then, we present the characterization of the emissions controls in the model. Subsequently, we present how these combine to form the full mathematical program. We present two formulations of the model. The first formulation assumes a linear response of ozone to emissions reductions. The second formulation presents an approach that approximates in a linear manner the nonlinearity that typically describes the relationship between changes in emissions reductions and ozone concentrations.

2.1. Air quality system

Air quality monitors that measure ozone concentrations are located across the lower 48 states of the United States. We index monitors by $m = 1, \ldots, M$, each with projected future base case ozone levels (called design values in the regulatory context) of dv_m^{base}. Impacts on ozone concentrations at the monitors depend on emissions reductions within local areas, states, and regions. In addition, ozone precursor emissions in one upwind region can contribute to ozone in downwind regions. This relationship is framed in our model as a source-receptor type relationship; as emissions change within a region, ozone concentrations at monitors within the region and elsewhere in the country may change.

To model the source-receptor relationship, we split the country into R emissions regions, $r = 1, \ldots, R$.[2] In our model, we define a region as an area where emissions reductions within that area relate to ozone impacts at each monitor across the contiguous U.S. via a unique air quality transfer (source-receptor) coefficient, $a_{r,m}$. The transfer coefficient measures the impact of emissions reductions in region r on ozone concentrations at monitor m in terms of parts-per-billion (ppb) per ton emissions reduction. For now, we assume the response of ozone at monitors is linear with emissions reductions, an assumption we relax later.

Emissions reductions within each region r, written as er_r, are multiplied by the transfer coefficients associating each region to each monitor to obtain a revised ozone level dv_m^{new} at each monitor, or:

$$dv_m^{new} = dv_m^{base} + \sum_{r=1}^{R} a_{r,m} er_r \text{ for all } m. \tag{1}$$

The estimation of emissions reductions in each region is more fully explained below, in the section on emissions controls. For simplicity, we present the model with a single emitted pollutant.[3] Note that since we define the regions as the same for each source in a region, some information of the spatial relationship between sources and monitors is likely lost.

Air quality managers and regulators seek to reduce ozone concentrations by reducing emissions of ozone precursors. Policy scenarios then require air pollutant ambient concentrations at each monitor to be reduced to or below an ozone goal, dv_m^{goal}, written:

$$dv_m^{new} \le dv_m^{goal} \text{ for all } m. \tag{2}$$

Note that the goal can vary across monitors in the model.

2.2. Emissions controls

Each region contains a set of up to S emissions sources, $s = 1, \ldots, S$ that can potentially be controlled by control measures. For many sources, there may be multiple applicable control measures. Different control applications may yield different emissions reductions at the source for different costs than other control measures. Decisions whether to control emissions at these sources are defined by a vector of binary decision variables, $x_{s,t}$, where s indexes the source and t indexes the applicable emissions control measure for that source. The variable equals one if the control is applied, zero otherwise. There are as many binary decision variables as there are applicable control measures per controllable source.[4] In this application, the source can only be controlled by a single measure, the sum of the $x_{s,t}$ must not exceed one, or:

$$\sum_{s=1}^{S} \sum_{t=1}^{T} x_{s,t} \le 1. \tag{3}$$

The vector of annualized costs associated with each application of these control measures is identified by $c_{s,t}$.

Achieving an ozone target might require more emissions reductions than can be specified with the list of control measures within the emissions control measure database.[5] We model the emissions reductions resulting from the application of unspecified emissions controls as a backstop measure within each region with a user-defined cost per ton of reduction. In this paper, we describe these reductions as being produced by backstop technologies. We model each region-specific backstop measure as a non-zero, positive continuous decision variable $\widehat{x}_r$ indicating the amount of emissions reductions from backstop technologies needed in region r. Similarly, the cost of emissions reductions from employing backstop technologies is modeled as $\widehat{c}_r$. The total annual cost, TC, of the air quality program is the sum of the costs of decisions over specified and backstop technologies:

$$TC = \sum_{s=1}^{S} \sum_{t=1}^{T} c_{s,t} x_{s,t} + \sum_{r=1}^{R} \widehat{c}_r \widehat{x}_r. \tag{4}$$

An emissions reduction of $e_{r,s,t}$ (specified in terms of tons of emissions reduced per year) is associated with the application of control measures.[6] To obtain total emissions reductions within each region, er_r, the emissions reductions from application of control measures are added to the reductions produced by backstop technologies, which are obtained from the decision vector $\widehat{x}_r$:

$$er_r = \sum_{s=1}^{S} \sum_{t=1}^{T} e_{r,s,t} x_{s,t} + \widehat{x}_r \text{ for all } r. \tag{5}$$

Emissions reductions within a region are limited by physical constraints. For example, it is not possible to reduce emissions in a region more than the level recorded in the region's anthropogenic emissions inventories. These limits on emissions reductions are entered into the model as the constraint:

$$er_r \le er_r^{\max} \text{ for all } r. \tag{6}$$

[2] In the case study that follows, regions largely but do not exclusively follow state borders. In the model, however, regions may be defined as areas within states such as counties, entire states, or groups of states, depending on the specific planning scenario being modeled.

[3] In this paper, we model the transformation of both NO_X and VOC into ozone. We treat the impacts of these two pollutants on a monitor as additive and do not account for nonlinear interactions between NO_X and VOC.

[4] Depending on the source and type of emissions, more than one measure may be feasibly applied to the source, though for simplicity, here we limit the control application to a single control.

[5] This issue is discussed extensively in U.S. EPA (2015b). The need for control measures beyond the well-defined set of technologies is also noted in Sule et al. (2011) and Hsu et al. (2014) in their work on the Dallas-Fort Worth area.

[6] While we do not index emission control measures by region, the emissions reductions produced through the applications of controls belong in regions. This is equivalent to saying each application of a control produces reductions within the region of its source, but not in other regions.

2.3. Complete model: with linear ozone response to emissions reductions

In the case of linear ozone response to emissions reductions, the equations discussed above are combined into the optimization model:

$$\begin{aligned}
&\min_{x_{s,t},\hat{x}_r} TC = \sum_{s=1}^{S}\sum_{t=1}^{T} c_{s,t}x_{s,t} + \sum_{r=1}^{R}\hat{c}_r\hat{x}_r \\
&\text{subject to :} \\
&\quad dv_m^{base} + \sum_{r=1}^{R} a_{m,r}er_r \le dv_m^{goal} \text{for all } m \\
&\quad er_r \le er_r^{\max} \quad \text{for all } r \\
&\quad x_{s,t} \in 0,1 \quad \text{for all } s \text{ and } t \\
&\quad \sum_{s=1}^{S}\sum_{t=1}^{T} x_{s,t} \le 1 \\
&\quad \hat{x}_r \ge 0 \quad \text{for all } r \\
&\text{where :} \\
&er_r = \sum_{s=1}^{S}\sum_{t=1}^{T} e_{r,s,t}x_{s,t} + \hat{x}_r \quad \text{for all } r.
\end{aligned} \tag{7}$$

This model chooses emission control and backstop technologies to achieve ozone targets at all monitors in the system, while meeting the various constraints and minimizing total annual cost.

2.4. Approximating non-linear ozone response to emissions reductions in model

In the case of ozone, the responsiveness of ozone to NO_X reductions is not typically linear and the degree of nonlinearity generally increases for larger emissions reductions (Cohan et al., 2005). As planners and managers may want to examine policy scenarios with large emissions reductions, we approximate the nonlinearity by segmenting the response of ozone concentrations to emissions reductions into multiple coefficients or "impact step" functions that depend upon the amount of reduction already obtained.

To incorporate the impact steps, we begin by indexing the multiple impact steps in each region by $n = 1, \ldots, N$. The transfer coefficient is then additionally indexed by the air quality steps, $a_{r,m,n}$, which encodes the impact of emissions reduction in region r on monitor m using air quality step n. Equations (3) and (4) are now indexed and summed across n, the details of which will be represented below in the restatement of the complete model to incorporate the air quality steps.

Analysis in U.S. EPA (2015b) shows that ozone responds more strongly to deeper NO_X reductions. Therefore, a set of constraints must be introduced to prevent the model from reducing tons from upper (and higher ozone impact) steps before exhausting tons in lower steps. To ensure the proper ordering of the multiple response steps within the model, we drew upon the "volume discounting" example in McCarl and Spreen (2007), where the marginal cost of inputs declines as production levels increase as a result of input costs being increasingly discounted as more are purchased. In that example, the buyer cannot purchase inputs at a discounted cost until a sufficient quantity of the inputs have already been purchased. The increasingly nonlinear response of ozone to deeper emissions reductions is analogous to this method in that planners cannot obtain the emissions reductions with a higher air quality impact (the higher ozone responses consistent with deeper reductions) until sufficient reductions with relatively lower air quality impacts are obtained.

To illustrate the volume discounting approach to modeling the air quality steps, each region r has multiple air quality response steps, $n = 1, \ldots, N$. Following McCarl and Spreen, each step within each region is associated with a set of binary decision variables, $d_{r,n}$. Emissions reductions belonging to each step are denoted by $er_{r,n}$, while the tons of reductions needed before moving from one step to the next are denoted by $\overline{er}_{r,n}$. A first set of N constraints is written:

$$er_{r,n} - \overline{er}_{r,n}d_{r,n} \le 0 \quad \text{for all } r \text{ and } n. \tag{8}$$

In the model solution, the binary variable associated with each step will be equal to one if the reductions belonging to that step are needed to help meet air quality targets and zero otherwise. This set of constraints also requires that if an air quality step is used, the quantity of tons of emissions reductions applied to that step cannot exceed the allowable reductions for that step, else the left hand side of the constraint is greater than zero, a violation of the constraint.

A complementary set of constraints is then introduced:

$$\overline{er}_{r,n}d_{r,n+1} - er_{r,n} \le 0 \quad \text{for all } r \text{ and } n = 1, \ldots, N-1. \tag{9}$$

In this second set of constraints, the binary decision variable for the next higher step is chosen to be equal to one when the emissions reductions belonging to the lower step are fully used and reductions from the higher step also need to be used to meet the air quality targets.[7] By combining these two sets of constraints, the model is required to consume the air quality steps fully and in the correct order. The cumulative reduction within a region also functions as the upper limit on the quantity of emissions that can be reduced within a region, so we eliminate the need for Equation (6).

2.5. Complete model: with linear approximation of non-linear ozone response to emissions reductions

We now restate the full model to account for the non-linear approximation of ozone response to emissions reductions:

$$\begin{aligned}
&\min_{x_{s,t},\hat{x}_r} TC = \sum_{s=1}^{S}\sum_{t=1}^{T} c_{s,t}x_{s,t} + \sum_{r=1}^{R}\sum_{n=1}^{N}\hat{c}_{r,n}\hat{x}_{r,n} \\
&\text{subject to :} \\
&\quad dv_m^{base} + \sum_{r=1}^{R}\sum_{n=1}^{N} a_{r,m,n}er_{r,n} \le dv_m^{goal} \quad \text{for all } m \\
&\quad er_{r,n} \le \overline{er}_{r,n} \quad \text{for all } r \text{ and } n \\
&\quad x_{s,t} \in 0,1 \quad \text{for all } s \text{ and } t \\
&\quad \sum_{s=1}^{S}\sum_{t=1}^{T} x_{s,t} \le 1 \\
&\quad \hat{x}_{r,n} \ge 0 \quad \text{for all } r \text{ and } n \\
&\text{where :} \\
&\quad er_{r,n} = \sum_{t=1}^{T} e_{t,r,n}x_{s,t} + \hat{x}_{r,n} \quad \text{for all } r \text{ and } n.
\end{aligned} \tag{10}$$

This model minimizes total annual cost by choosing emissions control and backstop technologies to achieve ozone targets at all monitors in the system, while meeting the various constraints, including the correct ordering of the air quality steps.

3. Parameters, data inputs, and software

3.1. Base case ozone concentrations at monitors

We used a combination of measured and modeled air quality data to project ozone concentrations and responses in the year

[7] Note this set of constraints has been written differently to make clear there are N - 1 constraints of this type, as the constraint for the highest step per region is not needed.

Table 1
Anthropogenic NO_X emissions by state, 2025 projected levels (in short tons).

States	NO_X emissions (2025 projected)	States	NO_X emissions (2025 projected)	States	NO_X emissions (2025 projected)
Alabama	153,000	Maine	34,000	Oklahoma	253,000
Arizona	102,000	Maryland	83,000	Oregon	68,000
Arkansas	99,000	Massachusetts	73,000	Pennsylvania	320,000
California	419,000	Michigan	240,000	Rhode Island	13,000
Colorado	197,000	Minnesota	144,000	South Carolina	95,000
Connecticut	36,000	Mississippi	86,000	South Dakota	27,000
Delaware	13,000	Missouri	181,000	Tennessee	149,000
D.C.	4000	Montana	63,000	Texas	843,000
Florida	263,000	Nebraska	120,000	Utah	110,000
Georgia	177,000	Nevada	41,000	Vermont	11,000
Idaho	45,000	New Hampshire	17,000	Virginia	147,000
Illinois	284,000	New Jersey	90,000	Washington	118,000
Indiana	266,000	New Mexico	124,000	West Virginia	135,000
Iowa	116,000	New York	221,000	Wisconsin	128,000
Kansas	142,000	North Carolina	173,000	Wyoming	126,000
Kentucky	214,000	North Dakota	128,000	**Contiguous U.S. Total**	**7,531,000**
Louisiana	347,000	Ohio	291,000		

Note: quantities are rounded to the nearest thousand, and sums in table may not total due to independent rounding.

Table 2
Anthropogenic VOC emissions by VOC impact area, 2025 projected levels (in short tons).

VOC region	VOC emissions (2025 projected)	VOC region	VOC emissions 2025 projected)
Baltimore	74,000	Kentucky (Western)	34,000
Beaumont-Port Arthur	65,000	Las Vegas	27,000
California (North)	223,000	Louisiana (South)	159,000
California (South)	243,000	Louisville	99,000
Chicago	389,000	New York/New Jersey/Connecticut	341,000
Cincinnati	122,000	Philadelphia	69,000
Dallas-Fort Worth	217,000	Phoenix	67,000
Denver	283,000	Pittsburgh	109,000
Detroit	139,000	San Antonio	140,000
Houston	236,000	**Total**	**3,035,000**

Note: quantities are rounded to the nearest thousand, and sums in table may not total due to independent rounding.

2025 for 1008 monitors in the contiguous 48 states of the U.S. For this purpose, we used the Comprehensive Air Quality Model with Extensions (CAMx version 6.1), a three-dimensional grid-based Eulerian air quality model using a 12-km grid resolution covering the contiguous 48 U.S. states. CAMx simulates the effects of emissions, meteorology, chemistry, and deposition on gridded hourly air pollutant concentrations (Environ International Corporation, 2014). Details on model inputs and configuration are described in detail in U.S. EPA (2015b).

To project future ozone concentrations, we simulate ozone for a recent year (2011) and for a future year (2025) during the April to October period. Simulations of the two model years are identical except for the emissions inputs, which are developed separately for 2011 and 2025. Emissions projections for 2025 use control and growth assumptions that are documented elsewhere (U.S. EPA, 2015a, b). Federal regulations expected to have a major impact on future emissions are incorporated into the emissions projections (U.S. EPA, 2015a, b). Table 1 and Table 2 summarizes projected 2025 anthropogenic emissions for the two major ozone precursors, NO_X and VOC, respectively.[8]

Hourly measured ozone concentrations are used to calculate a base case ozone design value for each monitor. The design value is the air quality management metric used in determining compliance with the NAAQS. The design values are calculated as the three-year average of the annual fourth highest daily maximum 8 h ozone concentration, measured in parts per billion (ppb) (see Appendix U to 40 CFR Part 50). For this analysis, we projected design values out to 2025 using the methods and tools described in (U.S. EPA, 2015a). The distribution of resulting base case design values is presented in Table 3.

3.1.1. NO_X and VOC air quality transfer coefficients

Air quality transfer coefficients define the relationship between emissions changes in one area and changes in ozone concentrations at monitors in that area and elsewhere. The expected response of ozone (or another pollutant) to changes in model inputs, such as emissions, can generally be derived by one of two techniques: 1) brute force, or 2) instrumented modeling methods such as the higher-order decoupled direct method (HDDM) (Dunker, 1984; Hakami et al., 2003).

Brute force analysis requires running the model simulation multiple times while varying emissions inputs to determine how ozone concentrations change in response to changes in emissions (Hakami et al., 2004; Kelly et al., 2015). The emission inputs can be varied by different magnitudes and from different emissions

Table 3
Distribution of 2025 projected base case design values at monitors.

Design Value	Monitors (no.)	Monitors (percent)
60 ppb or below	574	57%
61 ppb–65 ppb	273	27%
66 ppb–70 ppb	94	9%
71 ppb–75 ppb	35	3%
75 ppb and above	32	3%
Total	**1008**	**100%**

[8] VOC impact areas are defined in Section 3.1.1.

Fig. 1. A) NO_X emissions sensitivity regions with unique region-to-source air quality transfer coefficients (generally defined by state and thinner outlines B) hypothetical ozone regional planning districts implemented in case study (defined by Central, Midwest, Northeast, Southeast, and West state groupings and thicker outlines).

sectors or source regions. HDDM is a tool that uses the governing differential equations within an air quality model to propagate the effects of incremental changes in inputs on resulting ozone concentrations under the specific conditions being modeled. This tool estimates coefficients that can be used to fit a nonlinear response of ozone concentrations to emissions changes and has been used in the past to simulate potential ozone concentrations resulting from meeting the NAAQS (Simon et al., 2013). An additional advantage of this tool is that it allows for tracking the effects on ozone concentrations of the interactions between NO_X and VOC emissions in addition to the impacts of changes to either pollutant alone.

In general, it is preferable to develop the transfer coefficients from a consistent set of future-year brute force or HDDM simulations that tracked ozone response to emissions reductions from a set of fine-resolution source regions covering the contiguous U.S. For the case study in this paper, we leveraged existing model simulations to estimate transfer coefficients. Brute force NO_X emission sensitivity estimates for future year 2025 were available from a series of model simulations, some of which covered multi-state source regions. We combined these estimates with information from available state-level source apportionment modeling[9] to create state-level transfer coefficients in those areas. The set of emissions sensitivity regions for which we derive transfer coefficients is shown in Fig. 1. We provide details of the model simulations and calculation methods in the supplemental information for this paper.

These NO_X emissions sensitivity regions are mainly defined by state boundaries. There are exceptions, including California and Texas, which are broken into sub-state regions, and a multistate region in the Northeast composed of several entire states and a few partial states. We estimate unique coefficients for portions of states that do not belong to the multistate region, such as Pennsylvania and New York. We also developed multiple coefficients or “impact steps” that depend upon the amount of abatement already obtained within the California and the Northeast regions.

In order to create transfer coefficients for VOC, we leveraged a single sensitivity simulation to modeled ozone response with 50 percent reductions in anthropogenic VOC emissions across the contiguous U.S. Since previous work has shown that VOC impacts tend to be localized (Jin et al., 2008), we create 100 km buffer VOC “impact areas” around counties with future-year design values above the ozone concentrations being analyzed. VOC-specific transfer coefficients are estimated for monitors within each VOC impact region using only VOC emissions reductions within that VOC impact region. VOC-specific transfer coefficients are developed for areas that show at least a moderate response to VOC emissions perturbations in the simulation and that have base case design values above 65 ppb. See Fig. 2 for a map of VOC impact areas. Again, ideal inputs for VOC-based transfer coefficients could be developed by running a series of brute force model simulations or by tracking emissions from multiple source regions using HDDM. Since brute force model simulations with simultaneous VOC and NO_X cuts were not available, we were not able to capture any nonlinear interactions from the combined reductions of both pollutants.

3.1.2. *Hypothetical ozone regional planning districts used in the case study*

The hypothetical ozone planning districts used in the case study

[9] Source apportionment modeling tracks contributions to modeled pollutant concentrations from predefined emissions sources but does not explicitly characterize how pollutant concentrations would respond to changes in those emissions sources.

Fig. 2. VOC impact areas.

are based upon the Regional Planning Organizations (RPOs) that work to address regional haze and visibility issues from a regional perspective.[10] Regional designations and the RPO they are based upon are:

- Central: based on states in the Central Regional Air Planning Association
- Midwest: based on states in the Midwest Regional Planning Organization
- Northeast: based on Ozone Transport Region (corresponds to state membership in the Ozone Transport Commission)
- Southeast: based on states in the Visibility Improvement State and Tribal Association of the Southeast
- West: based on states in the Western Regional Air Partnership

These illustrative planning districts can also be seen in Fig. 1, overlaying the emissions sensitivity regions.

3.2. Control measures, emissions reductions, and engineering cost

The control measures and associated costs are primarily drawn from the U.S. EPA's Control Strategy Tool (U.S. EPA, 2014). The Control Strategy Tool (CoST) matches control measures to point, area, and mobile emissions sources and estimates emissions reductions and engineering costs[11] associated with the applications of the control measures. Using CoST, we create a dataset for NO_X and VOC reductions across the contiguous U.S. NO_X control measures are limited to emissions sources that emit more than five short tons per year of NO_X. VOC control measures are limited to emissions sources that emit more than one ton per year of VOC. We include supplementary data on NO_X reductions from selective catalytic reduction (SCR) and selective non-catalytic reduction (SNCR) controls applied to coal-fired electric generating units where the measures are in place but are idle, based upon the regulatory impact analysis reported in U.S. EPA (2015b). An additional set of potential NO_X controls (diesel engine retrofits and rebuilding) is drawn from the analysis performed in U.S. EPA (2015b).

The CoST tool primarily contains “end-of-pipe” or “add-on” control measures. Meanwhile, measures that reduce emissions by increasing use of renewable energy, improving energy efficiency, or substituting fuels may become increasingly important for reducing ozone (Loughlin et al., 2015). These measures are currently not well represented in the CoST control measures dataset. As a result, we are likely underestimating the overall emissions reduction supply available in the model, especially for application to emissions in future years such as 2025.

In instances where the application of a control measure reduces multiple pollutants, the dataset includes reductions of each pollutant. This is important because a single control application might reduce both NO_X and VOC emissions (e.g., emission controls for diesel reciprocating internal combustion engines, possibly leading to non-trivial air quality impacts of the joint reductions. There may also be environmentally important reductions (or increases) in emissions of other pollutants. For these reasons, in addition to NO_X and VOC reductions, the dataset includes changes in $PM_{2.5}$, PM_{10}, carbon monoxide (CO), and sulfur dioxide (SO_2)

[10] For more information, see <http://www3.epa.gov/visibility/regional.html>. Accessed 12/5/15.

[11] The annual engineering cost estimates include the capital, operating, and maintenance costs associated with the application of the emissions control measure.

Table 4
NO_X and VOC emissions reduction potential in the model by region in 2025 (short tons).

NO_X region	NO_X emissions reduction potential (short tons)	NO_X region	NO_X emissions reduction potential (short tons)
Central	228,300	Southeast	113,100
Midwest	108,500	West	117,100
Northeast	93,000	**Total**	**659,900**
VOC region	VOC emissions reduction potential (short tons)	VOC region	VOC emissions reduction potential (short tons)
Baltimore	3800	Kentucky (Western)	1400
Beaumont-Port Arthur	600	Las Vegas	2700
California (Northern)	22,000	Louisiana (Southern)	8300
California (Southern)	18,100	Louisville	4400
Chicago	25,000	New York/New Jersey/Connecticut	24,000
Cincinnati	7000	Philadelphia	6500
Dallas-Fort Worth	9700	Phoenix	4800
Denver	3100	Pittsburgh	7200
Detroit	7300	San Antonio	3600
Houston	10,000	**Total**	**169,500**

Note: In developing this table, for emissions sources with multiple applicable controls, we chose the control that produced the largest emissions reduction, regardless of cost. For VOC abatement potential in areas outside of VOC impact areas, total VOC abatement potential sums to about 440,000 short tons. Additionally, quantities are rounded to the nearest hundred, and sums in the table may not total due to independent rounding.

emissions from the application of the control measures.

Table 4 presents potential NO_X reductions broken down by hypothetical ozone planning districts and potential VOC reductions by VOC impact areas. Over 75,000 possible applications of control measures are specified in the dataset, adding up to potential reduction of about 660 thousand short tons of NO_X emissions per year and 170 thousand tons of VOC emissions per year for the entire U.S. However, the potential emissions reductions in Table 4 are distributed across the lower 48 states and many potential reductions are in areas that reductions are not needed to reduce ozone levels to target levels.

Within the control measures dataset, the most common controls for NO_X emissions include selective catalytic reduction (SCR), non-selective catalytic reduction (NSCR), low emissions combustion, and low NO_X burners. For VOC emissions, the most common measures in the database include process changes or product substitutions such as reformulated architectural, industrial, and traffic coatings, pesticides, and automobile refinishing. A more complete list of measures is included in Table 5.

We excluded control measures that did not have cost information or that are cost savings measures (i.e., measures in which total costs are reduced from their application). Cost saving measures are difficult to model in a cost minimization framework, as they will be adopted regardless of whether an air quality requirement is binding. A more complex behavioral model than what we present here is needed to model adoption of control measures that yield cost savings.

In the case study analysis, some areas may be unable to attain ozone goals using only the control measures specified in CoST. In these areas, it is necessary to assume the application of backstop technologies in order to estimate the full cost of achieving the analyzed ozone goal. We follow the procedure used by the U.S. EPA (U.S. EPA, 2015b) and assume an average annual cost of $15,000 per ton for NO_X or VOC reductions needed beyond the control measures applied.[12] There are likely existing control measures not in our control dataset that may be applied to additional sources and cost less than $15,000 per ton, while newly developed technologies or technologies that may be developed in the future may cost more than this amount.[13] The assumption of an average cost of $15,000 per ton does not reflect an assumption that all controls will be available at this cost. Rather, it reflects a belief that a mixture of less expensive and more expensive controls will lead to an average cost of about $15,000 per ton.[14]

3.3. Planning scenarios analyzed

For the case study presented in Section 4, we apply the model iteratively to analyze gradually lower ozone goals, from 75 ppb to 65 ppb nationally, in 1 ppb increments. For each ozone goal analyzed, we vary the geographic scope of NO_X and VOC emissions reductions that areas target to reduce their ozone levels.[15]. We call these the “state”, “regional”, and “national” planning scenarios. Under the state planning scenario, states focus on emissions reductions within their own state. This mimics states acting individually through their SIPs. In the regional planning scenario, we construct hypothetical planning regions where states work cooperatively to target the most cost-effective emissions reductions within a given region. In the national planning scenario, we choose the least cost solution associated with all states achieving the goal of interest, regardless of the locations of emissions reductions. Varying the geographic scope of emissions reductions enables the measurement of the potential efficiency gains of cooperative ozone planning.

Whether an emissions reduction in a region contributes to ozone at a monitor is governed by the whether there is a non-zero relationship in the matrices of transfer coefficients. To vary the geographic scope of the tons that contribute to ozone changes, we simply zero out the relevant transfer coefficients, for both NO_X and VOC. For example, in the state planning scenario, if there is a relationship between out-of-state emissions reductions and ozone levels at in-state monitors, we set that transfer coefficient to zero. We perform an analogous operation in the regional planning

[12] This value also functions as an upper limit on the per ton cost of control measures from the database that will be used in the least cost solution.

[13] The use of a constant dollar-per-ton for backstop technologies implies that CoST-based control measures above that per-ton cost will not be used, implicitly defining a cost cutoff.

[14] While we use an average cost per ton to estimate the costs of the emissions reductions beyond control measures specified in the database, this does not imply that marginal abatement costs are not upward sloping in emissions reductions. The average cost per ton is assumed to capture total costs associated with the abatement of the emissions reductions from backstop technologies, not the marginal cost.

[15] VOC emission reductions only influence ozone concentrations with the same VOC impact region, so scenarios only affect availability of VOC emissions reductions when VOC impact regions cross state or hypothetical planning district boundaries.

Table 5
NO_X and VOC control measures in database.

NO_X reduction measures	VOC reduction measures
Biosolid Injection Technology	Gas Recovery in Landfills
Diesel Retrofits & Engine Rebuilds	Incineration (Thermal, Catalytic, etc) to Reduce VOC Emissions
Ignition Timing Improvements	Low Pressure/Vacuum Relief Valves in Gasoline Storage Tanks
LNB (Low NO_X Burner Technology)	Low VOC Adhesives and Improved Application Methods
LNB + Flue Gas Recirculation	Low VOC Materials Coatings and Add-On Controls
LNB + Over Fire Air	Permanent Total Enclosure (PTE)
LNB + SCR	Petroleum Wastewater Treatment Controls
LNB + SNCR	Process Modification to Reduce Fugitive VOC Emissions
LNB Water Heaters	Reduced Solvent Utilization
Low Emission Combustion	Reformulation to Reduce VOC Content
Natural Gas Reburn	Solvent Recovery System
NSCR (Non-Selective Catalytic Reduction)	Solvent Substitution, Non-Atomized Resin Application Methods
OXY-Firing	Work Practices, and Material Reformulation/Substitution
SCR (Selective Catalytic Reduction)	
SNCR (Selective Non-Catalytic Reduction)	
Ultra LNB	

Note: Measures are listed in alphabetical order.

scenario. However, since interstate ozone planning is performed in the Ozone Transport Region, we do not eliminate transfer coefficients in the analogous Northeast study region for either the state or the regional planning scenarios.

In addition to determining possible efficiency gains from cooperative emissions reduction planning, we use the solutions of these model runs to examine the relative importance of certain monitors in the system. These monitors, often called controlling monitors, may be difficult-to-control monitors that just meet the ozone goals after application of a control strategy, while other monitors in the region may be reporting emissions below the ozone goal. Additionally, in an example national planning scenario, we draw out the ozone level change attributable to in-state versus out-of-state emissions reductions. This provides insights, at the monitor-level, to the locations of the potentially cost-effective reductions under alternative planning strategies. Lastly, we review emissions "co-reductions" of pollutants other than NO_X and VOC that result from multipollutant emissions control applications.

We should note that the model solutions across planning scenarios are hypothetical in nature and do not account for transaction costs associated with interstate coordination. Additionally, it may not be possible to implement a least cost solution in practice, as technical and administrative challenges may lead to alternative control strategies that diverge from least cost. With these caveats in mind, the results discussed in the next section should be viewed as lower cost boundary solutions for the ozone goals and planning scenarios under examination.

3.4. Software used and algorithmic initial solutions

The models are implemented using the General Algebraic Modeling System (GAMS) version 23.8 with the CPLEX 12 solver, which uses a branch and cut algorithm to solve mixed integer programming models.[16] Data inputs are drawn from a Microsoft Excel 2013 workbook using the GAMS GDX data exchange facility. Model outputs are also saved into an Excel workbook.

It is important to note that current solution approaches to mixed integer problems do not guarantee exact solutions. Results can also be sensitive to starting values. Because the problems solved in the case study are relatively large, we introduce starting values to facilitate the branch and cut algorithm in finding improved solutions. For each ozone goal, we first solve the state planning scenario absent initial values, and then use the state planning solution as the initial solution for the regional planning scenario. Subsequently, we use the regional planning solution as the initial solution to the national planning scenario.

4. Results

4.1. Emissions reductions and total costs

Table 6 presents the number of monitors exceeding 75 ppb, 70 ppb, and 65 ppb ozone goals in the 2025 base case across hypothetical ozone regional planning districts, which is useful in interpreting the result that follow. Only the western hypothetical planning district has monitors exceeding 75 ppb in the base case. Under the 70 ppb ozone goal, all hypothetical planning districts have monitors in excess of 70 ppb in the base case. About 22 percent (or 15 of 67 monitors) of the monitors above 70 ppb in the base case are outside of the western hypothetical planning district. As the ozone goal is lowered to 65 ppb, roughly half of the monitors (80 of 161) are outside the western hypothetical planning district.

Under the least cost solutions, the national-level NO_X and VOC emissions reductions required across planning scenarios are shown in Fig. 3. The emissions reductions associated with achieving ozone goals of 75 ppb–70 ppb are similar, if not equivalent, across planning scenarios, as the least cost solution for the scenarios do not heavily rely upon regional or national emissions reductions. This results from a relatively limited number of monitors with base case design values above 70, few of which require reductions beyond their state boundaries.

As the goal is decreased from 70 ppb to 65 ppb, more monitors require reductions and the high ozone monitors need additional reductions. As a result, the model increasingly draws on out-of-state emission reductions in order to reduce ozone levels to the constraints in a cost-effective manner. It is important to look at the NO_X and VOC results in tandem. The state planning scenario generally requires fewer NO_X than the regional and national planning scenarios, but also requires substantially more VOC reductions than the other planning scenarios. This substitution of NO_X reductions for VOC reductions when moving from the state planning scenario to the regional and national planning scenarios primarily results from the ability of the model to find more cross-border NO_X reductions that are more cost-effective than in-state VOC reductions. To a lesser degree, the same applies to the comparison of the regional and national planning scenarios, as the regional

[16] For technical details on the CPLEX 12 solver, please see GAMS Development Corporation, 2015. GAMS-The Solver Manuals: Washington DC.

Table 6
Number of monitors exceeding ozone goals in 2025 base case across hypothetical regional ozone planning districts.

	75 ppb	74 ppb	73 ppb	72 ppb	71 ppb	70 ppb	69 ppb	68 ppb	67 ppb	66 ppb	65 ppb
Central	0	1	2	3	5	6	8	16	24	30	39
Midwest	0	0	0	0	0	1	3	4	7	10	14
Northeast	0	0	0	2	4	7	10	10	12	14	19
Southeast	0	0	0	0	0	1	1	2	5	6	8
West	32	35	39	43	45	52	60	62	65	75	81
Total	**32**	**36**	**41**	**48**	**54**	**67**	**82**	**94**	**113**	**135**	**161**

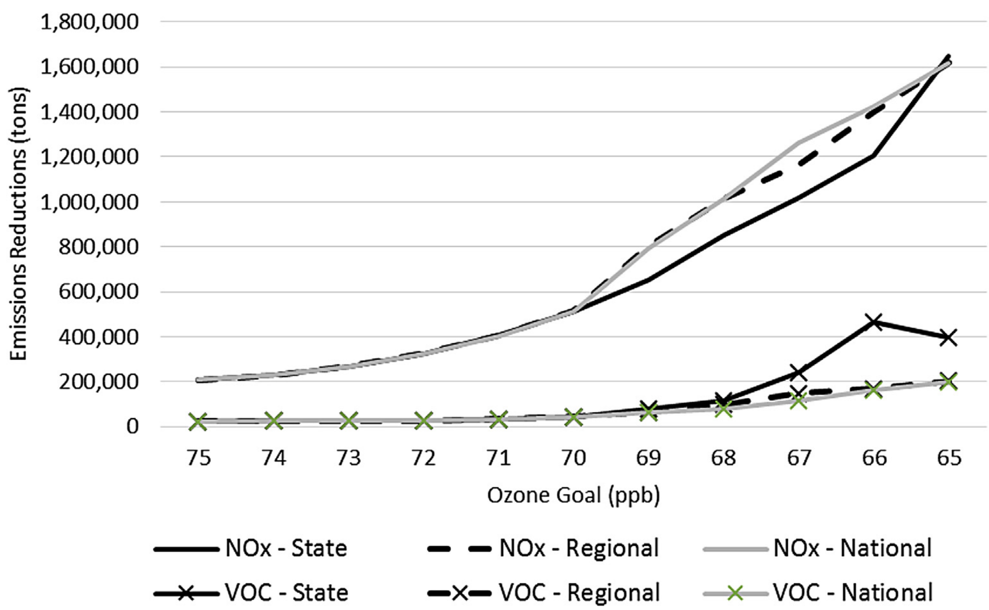

Fig. 3. Total NO_X and VOC emissions reductions in 2025 by ozone goal and planning scenario.

planning scenario generally requires fewer NO_X reductions but more VOC reductions than the national planning scenario.

Table 7 presents emissions reductions across planning scenarios and ozone goals of 75 ppb, 70 ppb, and 65 ppb, broken down by hypothetical planning districts. In order to present more detail, we do not present results for all scenarios. Under the 75 ppb ozone goal, California is the only state that does not meet the ozone goal in the base case, and as California resides in the western hypothetical district, reductions under the 75 ppb ozone goal are entirely from the West region. For the 70 ppb ozone goal, emissions reductions come from all hypothetical planning districts, although relatively few are needed in the Midwest and Southeast as a single monitor in each exceeds 70 ppb in the baseline. As the ozone goal is reduced to 65 ppb, the emissions reductions needed become more balanced across hypothetical planning districts. Also, note that the reliance on backstop technologies decreases as the spatial restrictions in regional control strategy development are loosened from the state to regional to national planning scenarios.

The total costs across planning scenarios are shown in Fig. 4. As with emissions reductions, the total costs associated with achieving ozone goals of 75 ppb–70 ppb are similar across planning scenarios, as the least cost solution for the scenarios does not heavily rely upon regional or national emissions reductions. This similarity may partially be due to the relatively isolated nonattainment areas above 70 ppb.

As described above, as the ozone goal is decreased, the ability to obtain out-of-state emissions reductions becomes increasingly important. The relative cost of achieving the ozone goals increases most steeply under the state planning scenario, while costs under the national planning scenario are the lowest. The difference between the costs shown in Fig. 4 is a measure of the potential gains (in this case, reductions in cost) from collaborative planning as the planning domains converge toward a single national domain.

Fig. 5A and B depict the share of emissions reductions (Fig. 5A) and the share of total costs (Fig. 5B) in percentage terms attributable to types of NO_X and VOC emissions controls measures. The figures present these percentage shares across planning scenarios and ozone goals (note the figures do not present reductions and costs in absolute terms). With respect to emissions reductions, the share attributable to control measures rises as the ozone goal is decreased to 69 ppb, but then decreases as backstop technologies, particularly VOC emission reductions from backstop technologies, assume a larger proportion of the total reductions. The regional and national planning scenarios rely on a larger percentage of control measures than the state planning scenario and the national planning scenario uses a larger proportion of control measures than the regional planning scenario. In terms of cost, regardless of planning scenario or level, the large majority of costs in this case study are attributable to backstop technologies.

The interpretation of these results follows. First, as the model becomes less restricted in its spatial search for cost-effective control measures, it can increasingly rely on control measures in the dataset with costs lower than the assumed $15,000 per ton of NO_X or VOC backstop abatement. About 89 percent of the NO_X and VOC emissions sources specified in the dataset as incrementally controllable have an applicable control that costs less than this

Table 7
Emissions reduction (in 1000s of short tons) in 2025 by hypothetical regional planning district and emissions type for 75 ppb, 70 ppb, and 65 ppb ozone goals.

	75 ppb			70 ppb			65 ppb		
	State	Reg.	Natl.	State	Reg.	Natl.	State	Reg.	Natl.
Central									
NO_X Control	–	–	–	76	76	76	98	207	303
Backstop NO_X Technology	–	–	–	51	51	50	244	225	210
NO_X Total	**-**	**-**	**-**	**128**	**128**	**126**	**342**	**433**	**513**
VOC Control	–	–	–	10	10	10	10	10	11
Backstop VOC Technology	–	–	–	–	–	–	–	–	–
VOC Total	**-**	**-**	**-**	**10**	**10**	**10**	**10**	**10**	**11**
Midwest									
NO_X Control	–	–	–	7	7	7	140	174	172
Backstop NO_X Technology	–	–	–	–	–	–	150	165	97
NO_X Total	**-**	**-**	**-**	**7**	**7**	**7**	**290**	**339**	**269**
VOC Control	–	–	–	8	8	8	34	32	28
Backstop VOC Technology	–	–	–	–	–	–	203	–	–
VOC Total	**-**	**-**	**-**	**8**	**8**	**8**	**237**	**32**	**28**
Northeast									
NO_X Control	–	–	–	100	100	100	145	146	147
Backstop NO_X Technology	–	–	–	3	3	2	245	162	87
NO_X Total	**-**	**-**	**-**	**103**	**103**	**102**	**391**	**308**	**234**
VOC Control	–	–	–	1	1	1	29	29	35
Backstop VOC Technology	–	–	–	–	–	–	–	94	86
VOC Total	**-**	**-**	**-**	**1**	**1**	**1**	**29**	**123**	**120**
Southeast									
NO_X Control	–	–	–	9	9	9	24	67	128
Backstop NO_X Technology	–	–	–	–	–	–	221	71	31
NO_X Total	**-**	**-**	**-**	**9**	**9**	**9**	**245**	**139**	**159**
VOC Control	–	–	–	1	1	1	–	–	3
Backstop VOC Technology	–	–	–	–	–	–	–	–	0
VOC Total	**-**	**-**	**-**	**1**	**1**	**1**	**-**	**-**	**3**
West									
NO_X Control	30	30	30	39	39	39	62	92	138
Backstop NO_X Technology	179	179	179	228	228	228	319	306	303
NO_X Total	**209**	**209**	**209**	**266**	**266**	**266**	**381**	**399**	**441**
VOC Control	24	24	24	24	24	24	31	31	31
Backstop VOC Technology	–	–	–	–	–	–	90	7	5
VOC Total	**24**	**24**	**24**	**24**	**24**	**24**	**121**	**37**	**36**
Total									
NO_X Control	30	30	30	231	231	231	470	687	888
Backstop NO_X Technology	179	179	179	282	282	279	1178	930	728
NO_X Total	**209**	**209**	**209**	**513**	**513**	**510**	**1648**	**1617**	**1616**
VOC Control	24	24	24	44	44	44	105	102	107
Backstop VOC Technology	–	–	–	–	–	–	293	100	91
VOC Total	**24**	**24**	**24**	**44**	**44**	**44**	**397**	**203**	**197**

Note: quantities are rounded to the nearest thousand, and sums in table may not total due to independent rounding.

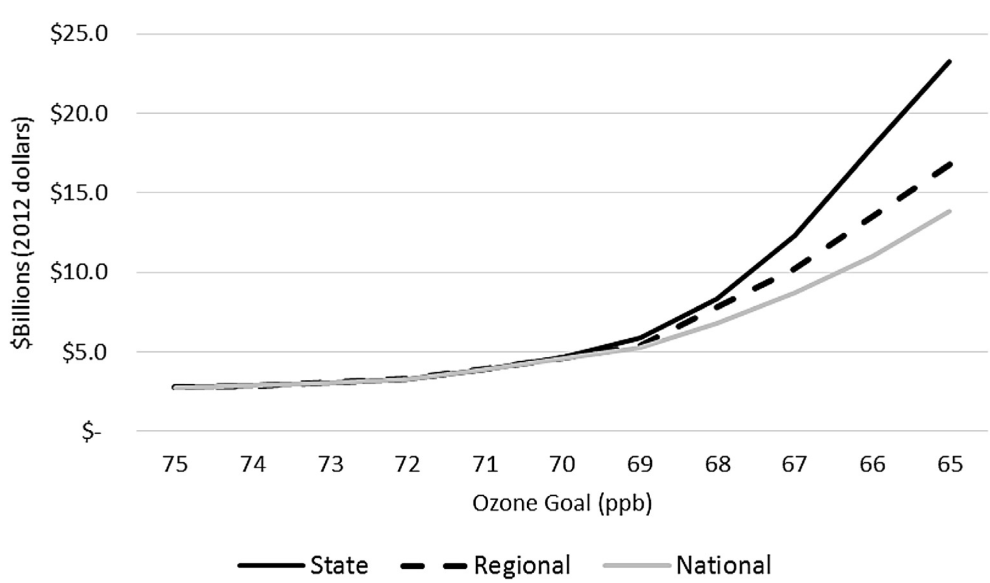

Fig. 4. Total annual cost in 2025 by ozone goal analyzed and planning scenario (2012 dollars).

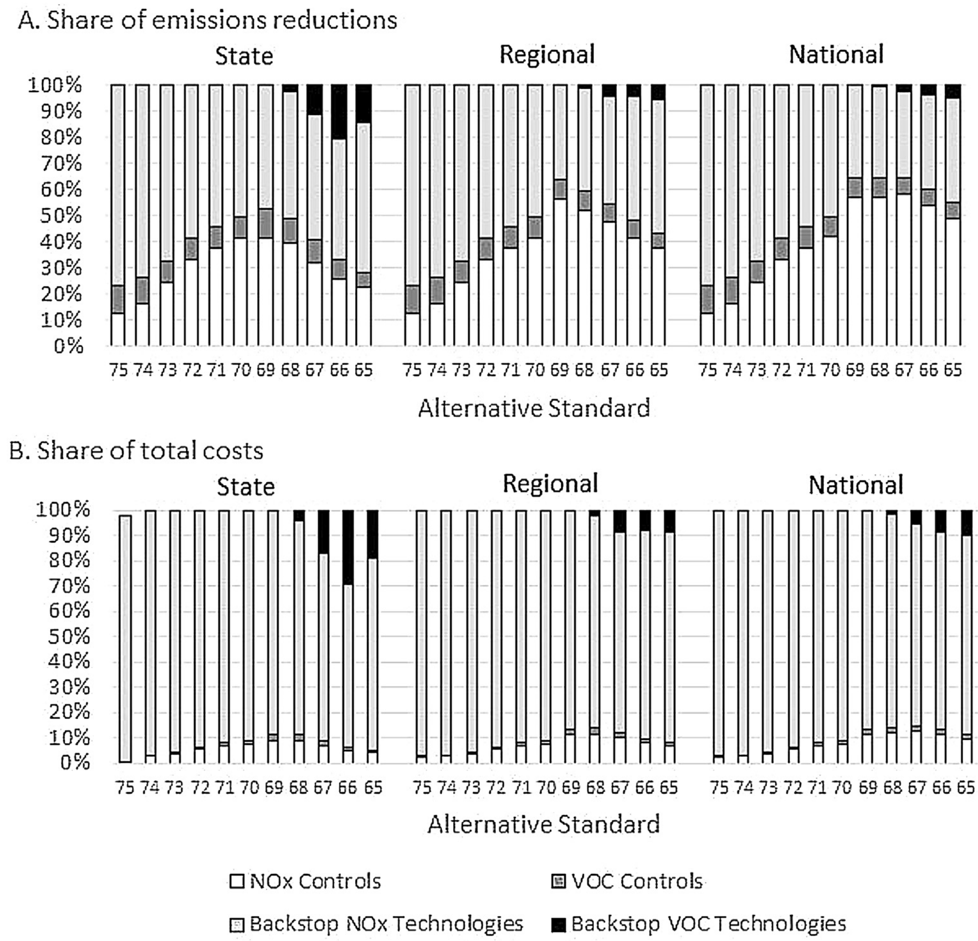

Fig. 5. A). Percentage of emissions reductions by planning scenario, type of emissions reduction, and ozone goal. B.) Percentage of total costs by planning scenario, type of emissions reduction, and ozone goal.

amount. Consequently, in the regional and national planning scenario, the model can substitute more cost-effective out-of-state emission control measures for less cost-effective in-state. Second, although the share of reductions generated by control measures peaks at 69 ppb, control measures are not exhausted; however, due to cost effectiveness, backstop technologies (measures with an average annual cost of more than $15,000 per ton) are adopted at a greater rate than control measures as the ozone goal is lowered.

4.2. *Using marginal value of air quality constraints to identify high-influence monitors*

In constrained optimization, the marginal value (sometimes referred to as the shadow value or shadow price) of a constraint at the solution indicates how the value of the objective function reacts to a slight change in the level of the constraint. If the constraint is not binding, the marginal value is zero. In the current case, the marginal values of the air quality constraint, or the ozone design values that monitors are required to achieve, provide useful information about which monitors exert a high degree of influence within the least-cost control strategy. High influence monitors are monitors whose air quality levels in the solution just meet (or are bound by) the air quality constraint. These monitors are often referred to as "controlling monitors". While a region may have multiple monitors with ozone levels that exceed the goal in the base case, regional emissions reductions may improve air quality metrics at multiple monitors simultaneously. The controlling monitor is the monitor(s) whose air quality indicators just meet the ozone goals and thus have a non-zero marginal value at the air quality constraint.

To demonstrate this concept, Table 8 presents marginal values of high-influence monitors in the state, regional, and national planning scenarios. For simplicity, this analysis presents results for the 75 ppb, 70 ppb, and 65 ppb ozone goals. The marginal values in the table indicate how much total costs decrease (increase) with a 1 ppb increase (decrease) in the air quality constraint at that monitor (and only at that monitor).

At 75 ppb, there are two controlling monitors in California in all three of the planning scenarios. It should be noted that no monitors outside of California are projected to have base case design values greater than 75 ppb. In the 70 ppb case, these California monitors continue to be controlling, while a single monitor in New York and another in Texas become controlling in each of the three planning scenarios. As discussed earlier, as the ozone goal is lowered to 65 ppb, more monitors have base case design values exceeding 65 ppb. As a result, more monitors exert a relatively high degree of influence on the least-cost control strategy. In addition, the list of controlling monitors changes across planning scenarios.

4.3. *Impact of in-state versus out-of-state reductions in regional and national planning scenarios*

Analysis of the model's solution also allows us to compare the relative effect of with-in state emissions reductions to the effects of

Table 8
High influence monitors within least-cost solutions for 75 ppb, 70 ppb, and 65 ppb ozone goals (in millions 2012 dollars).

Monitor No.	County	State	Base case ozone levels (ppb)	75 ppb			70 ppb			65 ppb		
				State	Reg.	Nat.	State	Reg.	Nat.	State	Reg.	Nat.
40,131,004	Maricopa	AZ	69	–	–	–	–	–	–	70	70	60
60,190,242	Fresno	CA	81	–	–	–	–	–	–	–	60	60
60,710,005	San Bernardino	CA	100	50	50	50	50	50	50	50	40	40
60,195,001	Fresno	CA	83	$100	$100	$100	$100	$100	$100	–	–	–
80,590,006	Jefferson	CO	72	–	–	–	–	–	–	–	$140	$140
80,690,011	Larimer	CO	71	–	–	–	–	–	–	$150	–	–
180,550,001	Greene	IN	68	–	–	–	–	–	–	$350	–	–
211,110,067	Jefferson	KY	72	–	–	–	–	–	–	–	–	$170
211,451,024	McCracken	KY	69	–	–	–	–	–	–	$430	$430	–
240,251,001	Harford	MD	73	–	–	–	–	–	–	–	$200	$200
261,630,019	Wayne	MI	70	–	–	–	–	–	–	$350	$330	$280
260,050,003	Allegan	MI	70	–	–	–	–	–	–	$370	–	–
320,030,043	Clark	NV	69	–	–	–	–	–	–	–	$210	$210
320,031,019	Clark	NV	68	–	–	–	–	–	–	$820	–	–
360,810,124	Queens	NY	72	–	–	–	–	–	–	–	$720	$720
361,030,002	Suffolk	NY	73	–	–	–	$420	$420	$420	–	–	–
390,610,006	Hamilton	OH	70	–	–	–	–	–	–	$380	$320	–
420,031,005	Allegheny	PA	71	–	–	–	–	–	–	–	$140	$140
482,011,039	Harris	TX	75	–	–	–	$580	$580	$580	$580	$580	$550
551,170,006	Sheboygan	WI	71	–	–	–	$470	$470	–	$470	$420	$400

Note: quantities are rounded to the nearest ten million dollars.

out-of-state emissions reductions on ozone levels at a given monitor. This is accomplished by zeroing out in-state emissions reductions from the solution vector of regional emissions reductions and multiplying the adjusted vector by the matrix of transfer coefficients. This procedure yields an adjusted post-strategy design value that estimates the share of reductions in ozone concentrations due to out-of-state emissions reductions. The difference between this adjusted design value and the final post-strategy design value reflects the share of ozone concentration reductions due to out-of-state emissions versus in-state emissions reductions. Note that this does not imply anything about contributions of in-state vs out-of-state emissions to 2025 base case design values, but rather indicates what fraction of the ozone *decreases* come from out-of-state emissions reductions under the hypothetical least-cost control strategy that is dependent upon the parameters of this case study.

Table 9 presents a comparison of the share of least-cost strategy ozone impacts from in-state and out-of-state NO_X and VOC emissions reductions. For brevity, we focus the analysis on the single model solution for the 65 ppb national planning scenario.

As Table 9 shows, there are 161 monitors in 16 states with projected design values above 65 ppb in the base case. The table shows the average ppb reduction by state for design values at these monitors and the share of this average reduction due to in-state versus out-of-state emissions reductions (in ppb and percentage terms).

The results show a great deal of variation across the states with California and Nevada at either end of the spectrum. Virtually all (98 percent) of California's impacts are due to in-state reductions, while all of Nevada's ozone reductions are due to out-of-state emissions reductions. The results also indicate that, with the exception of Nevada, the least cost control solution tends to rely on out-of-state reductions in the eastern states more than in western states.

We should note that these results reflect emissions reductions under a least-cost solution and do not represent a unique solution to achieving the analyzed ozone goals. For example, Nevada has abatement opportunities that are not used in the least-cost solution

Table 9
Share of control strategy impacts in 2025 due to in-state versus out-of-state NO_X and VOC emissions reductions (based upon states with monitors exceeding 65 ppb in base case and results from 65 ppb national planning scenario).

State	No. of monitors over 65 ppb in base case	Average impact of control strategy (ppb)	Average impact due to in-state reductions (ppb)	Average impact due to out-of-state reductions (ppb)	Share of impact due to in-state reductions (%)	Share of impact due to out-of-state reductions (%)
California	63	−20.8	−20.4	−0.3	98%	2%
Texas	37	−9.4	−9.1	−0.3	96%	4%
Colorado	9	−5.9	−5.5	−0.4	93%	7%
Kentucky	8	−7.1	−4.6	−2.5	64%	36%
New York	6	−12.1	−1.2	−10.8	10%	90%
Michigan	6	−5.5	−2.3	−3.1	43%	57%
Ohio	5	−7.8	−4.5	−3.3	58%	42%
Nevada	5	−7.8	0.0	−7.8	0%	100%
Pennsylvania	4	−9.6	−3.8	−5.7	40%	60%
Connecticut	4	−13.2	−1.2	−12.0	9%	91%
Arizona	4	−3.4	−2.6	−0.8	77%	23%
New Jersey	3	−13.6	−0.3	−13.3	2%	98%
Louisiana	2	−2.1	−0.9	−1.1	46%	54%
Wisconsin	2	−6.5	−4.4	−2.1	67%	33%
Maryland	2	−15.9	−0.3	−15.6	2%	98%
Indiana	1	−5.5	−2.2	−3.3	40%	60%
Total	**161**	**−13.4**	**−11.2**	**−2.2**	**84%**	**16%**

Note: sums may not total due to independent rounding.

for the 65 ppb national planning scenario. Achievement of the ozone goal in Nevada in this particular simulation is a spillover effect from emissions reductions elsewhere.

4.4. Co-reductions of $PM_{2.5}$, PM_{10}, and CO emissions

As mentioned earlier, a single control application might also lead to important reductions (or increases) in emissions of other pollutants. Based on the information in our control measures dataset, the control measures and strategies specified in the case study are estimated to lead to the following changes in $PM_{2.5}$, PM_{10} and CO emissions. Table 10 presents estimates of the co-reductions of emissions of these pollutants.

As would be expected, co-reductions of $PM_{2.5}$, PM_{10} and CO emissions increase as the ozone goal examined is lowered. The co-reduction estimates are based upon the application of multi-pollutant control measures from the CoST database, whereas the application of backstop technologies have no effect on other pollutants. As seen above, in the regional and national planning scenarios, where control measures make up a larger proportion of the least-cost control strategies, co-reduction estimates are generally higher than in the state planning scenarios.

4.5. Caveats and limitations

Because the models do not account for transaction costs associated with interstate coordination and technical or administrative inefficiencies that may result from real-world implementation of control strategies, the results discussed in this paper should be viewed as lower cost boundary solutions for the ozone goal and planning scenarios under examination. This case study is a proof of concept, and is additionally limited by the specificity of the transfer coefficients matrix and by the completeness of the data on emissions controls. More spatially-detailed transfer coefficients will improve the accuracy of the model, as will additional control measures and related cost information.

The methodology we use to estimate transfer coefficients relies on several simplifying assumptions, which are necessary due to the limited number of photochemical model simulations available for this analysis. First, across-the-board emissions reductions within a region are used to derive the transfer coefficients. We therefore assume that every ton of NO_X or VOC reduced within each region (or VOC impact area) results in the same ozone response regardless of where the emissions reductions are located within the region. The source apportionment modeling is used to reduce this uncertainty by creating transfer coefficients at a finer spatial resolution than was achievable with the brute force simulations alone. However, transfer coefficients that delineated the impact of emissions from even smaller regions would provide a more precise answer than was achieved in this application. Second, we treat NO_X and VOC responses as being additive. The impact of interactions between NO_X and VOC reductions is expected to be small compared to the impact of the reductions themselves. Third, at each monitor we treat the response of ozone concentrations to emissions reductions from multiple regions as additive. Since emissions perturbations in each of the photochemical model simulations used to estimate transfer coefficients were performed independently, we do not have any information on nonlinear interactions between emissions reductions from multiple regions. Fourth, we assume that ozone response within each of these sensitivity simulations is linear (i.e., the first ton of NO_X reduced results in the same ozone response as the last ton of NO_X reduced), except in regions where we have multiple emissions sensitivity simulations (i.e., California and the Northeast). For these regions, we approximate the nonlinearity by segmenting the response into multiple linear impact steps. In addition, in regions without multiple levels of emissions perturbations, response to NO_X reductions greater than 50 percent must be extrapolated beyond the modeled emissions reductions.

The case study is additionally limited by the completeness of the data on emissions controls. The application of backstop technologies does not mean that control measures that would reduce these emissions are currently not commercially available or do not exist. Backstop technologies or measures can include existing controls or measures for which we do not have sufficient data to estimate engineering costs. We assume that the emission control measures in our dataset will provide the same amount of emission reduction in 2025, as they do currently, and that the emission control costs will not change. Finally, the control measures in the CoST database do not include exhaustive abatement possibilities from energy efficiency measures, fuel switching, input or process changes, or other abatement measures that are non-traditional in the sense that they are not the application of an end-of-pipe control.

5. Conclusions

This paper presents a mathematical programming model for identifying least-cost control strategies incorporating the potential for multistate control strategy development. Air quality is characterized by a source-receptor matrix estimating the impact of regional NO_X and local VOC emissions reductions on ambient ozone concentrations at monitors. Least-cost control strategies are determined by evaluations of the specific control measures used on specific emissions sources. This model allows users to select which

Table 10
$PM_{2.5}$, PM_{10}, and CO emissions co-reductions in 2025 from NO_X and VOC control strategies (in short tons) across ozone goals and planning scenarios.

Ozone goal (ppb)	State			Regional			National		
	PM_{10}	$PM_{2.5}$	CO	PM_{10}	$PM_{2.5}$	CO	PM_{10}	$PM_{2.5}$	CO
75	80	60	6220	80	60	6220	80	60	6220
74	80	60	6220	80	60	6220	80	60	6220
73	80	60	6220	80	60	6220	80	60	6220
72	150	130	7470	150	130	7470	150	130	7470
71	170	150	7710	170	150	7710	170	150	7710
70	170	150	7720	170	150	7720	170	150	7720
69	290	260	10,350	280	250	10,000	280	250	10,000
68	310	270	11,490	400	350	13,220	370	320	11,980
67	380	350	12,500	410	360	14,270	400	350	13,400
66	400	360	12,720	450	400	14,250	510	460	15,520
65	400	360	13,190	490	430	14,850	510	460	15,520

Note: While for some controls, the control measures dataset contains information on SO_2 emissions reductions, none of the controls applied in the case study changed emissions of this pollutant. Quantities are rounded to the nearest ten.

ozone precursors and emissions locations to consider in developing a least-cost attainment strategy.

The case study demonstrates that multi-state planning can lead to more cost-effective emissions control strategies. This case study is a proof of concept, but is limited by the specificity of the source-receptor matrix and by the completeness of the data on emissions controls. More refined information about the responsiveness of ozone concentrations to emissions reductions and additional emissions control measure cost information will improve the accuracy of the model.

The model presented in this paper advances the optimization and air quality planning and management literature in a variety of ways. First, to our knowledge, this paper represents the first national-level application in the literature, enabling the identification of national-level least cost strategies to attain alternative ozone goals, while retaining important local and regional detail. Second, previous studies have generally focused on short episodes or single days of high ozone. This application looks across the April to October period to characterize ozone response on typical high days consistent with how the U.S. EPA projects future ozone concentrations in their regulatory assessments. Third, as the case study on the importance of considering regional factors in air quality planning and management demonstrates, the model can easily be adjusted to examine sensitivity to key modeling choices and parameters. Finally, the model is designed to estimate the marginal cost of air quality constraints at individual air quality monitors, giving air quality planners and managers useful information about the relative importance of individual monitors within the overall air quality system.

Beyond improving the inputs for the current ozone-focused application, future work with the model will seek to incorporate the ability to evaluate more than one ambient air quality goal. While extending the model to other pollutants, such as $PM_{2.5}$, might require some modification due to pollutant-specific dynamics, the current model is generally structured to layer in the additional information needed to perform multipollutant air quality analysis.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2017.01.008.

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