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Conjunctive Use of Models to Design Cost-Effective Ozone Control Strategies

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ABSTRACT

The management of tropospheric ozone (O_3) is particularly difficult. The formulation of emission control strategies requires considerable information including: (1) emission inventories, (2) available control technologies, (3) meteorological data for critical design episodes, and (4) computer models that simulate atmospheric transport and chemistry. The simultaneous consideration of this information during control strategy design can be exceedingly difficult for a decision-maker. Traditional management approaches do not explicitly address cost minimization. This study presents a new approach for designing air quality management strategies; a simple air quality model is used conjunctively with a complex air quality model to obtain low-cost management strategies. A simple air quality model is used to identify potentially good solutions, and two heuristic methods are used to identify cost-effective control strategies using only a small number of simple air quality model simulations. Subsequently, the resulting strategies are verified and refined using a complex air quality model. The use of this approach may greatly reduce the number of complex air quality model runs that are required. An important component of this heuristic design framework is the use of the simple air quality model as a screening and exploratory tool. To achieve similar results with the simple and complex air quality models, it may be necessary to "tweak" or calibrate the simple model. A genetic algorithm-based optimization procedure is used to automate this tweaking process. These methods are demonstrated to be computationally practical using two realistic case studies, which are based on data from a metropolitan region in the United States.

IMPLICATIONS

State and local agencies have faced the challenges of designing cost-effective strategies of tropospheric O_3 management. It is exceedingly difficult for a decision-maker to simultaneously consider emission inventories, available control technologies, meteorological data for critical design episodes, and computer models that simulate atmospheric transport and chemistry during control strategy design. The proposed approach applies several optimization methods using both simple and complex air quality models conjunctively to obtain cost-effective designs. The general approach potentially applicable using different combinations of simple and complex models for a wide range of air quality management problems. The approach can be applied not only in the development of more efficient O_3 control strategies, but also in the development of control strategies for other pollutants, such as fine particulate matter, visibility, and acid deposition.

INTRODUCTION

The management of tropospheric ozone (O_3) has been a challenging problem facing the nations of the world during the past several decades and continues to be an important issue in the 21st century. Simplified approaches are often taken to facilitate the process of designing management plans. One simplified management approach involves reducing the same percentage of pollutants across-the-board. Across-the-board strategies, however, may be impractical to implement and generally do not explicitly consider control costs. Another approach for designing control strategies is to focus controls only on the largest emission sources. This approach ignores the issue of control equity and may also lead to a higher cost than necessary, because it ignores potentially cost-effective controls on smaller sources. In the past few decades, researchers have reported various studies that describe methods for developing cost-effective control strategies for the emission least cost (ELC) and the ambient least cost (ALC) control problems.[1–11] These studies are based on a number of traditional optimization techniques, such as dynamic programming, integer programming, linear programming (LP), and mixed-integer programming (MIP). There is considerable difficulty, however, when these techniques are used for problems with pollutants that exhibit nonlinear atmospheric chemistry. Although air quality models represent nonlinear atmospheric chemistry and transport as explicit functions, their complexity and nonlinearity make them exceedingly difficult to incorporate them into a computationally practical optimization model. Simplified air quality models and regression models,[12,13] however, can more readily be incorporated.

Heuristic global search techniques, such as genetic algorithms (GAs)[14] and simulated annealing (SA),[15] are alternative optimization approaches and have been applied to O_3 control problems.[16] Unlike the case with traditional optimization approaches, a complex air quality

Table 1. The summary of past studies for O_3 control strategy using optimization techniques.

Researcher	Year	Air Quality Model	Optimization Technique
Burton and Sanjour	1970	Gaussian plume model	IP
Kohn	1971	Rollback model	LP
Seinfeld and Kyan	1971	Gaussian plume model	DP
Trijonis	1974	Empirical chemical mode	Graphic nonlinear model
Kyan and Seinfeld	1974	Empirical chemical mode	DP
Atkison and Lewis	1974/1976	Gaussian plume model	LP
Gipson et al.	1975	Gaussian plume model	IP; LP
Harley et al.	1989	Receptor-based modeling	MIP
Sich and Baugh	1995	EKMA	Linear regression
McBride et al.	1997	Box model[a]	MIP
Heyes et al.	1997	Source receptor	Nonlinear regression
Loughlin	1999	EKMA	GA

[a]Used complex model to verify VOC's reactivity of some sources.

simulation model can be incorporated directly into the optimization process. An inherent disadvantage of using GA or SA techniques, however, is that they may be computationally intractable, because they may require thousands of runs of a simulation model, and the simulation model itself may be computationally demanding for a single run.[16] Also, these techniques cannot guarantee, within a finite number of iterations, convergence to the global optimal solution.

A summary of past studies on developing O_3 control strategies using optimization procedures is provided in Table 1. One feature, in particular, is evident from these studies. None of them combines a complex air quality model with an optimization technique. The simple air quality models or regression models used in these previous studies for predicting air quality are not, however, sufficiently accurate to justify policy decisions.

Alternative approaches are needed to address the complexity of these problems. One approach, which was examined as preliminary work for this study, is to formulate a nonlinear programming model with gradient information derived from automatic differentiation of FORTRAN.[17] It was determined, however, that the computer memory requirements were very large when it generated a number of differentiated matrices including sensitivity coefficients of photochemical indicators species, such as the ratio of O_3 to the difference of NO_x and volatile organic compounds (VOC). The resulting run times of a differentiated version of the model are several times greater than those of the original model. During the preliminary investigation, it was concluded that the computational burden associated with generating the differential model precluded its practical application at this time. Another disadvantage is that, because it is a nonlinear local search procedure, the quality of the final solution relies on the starting point of the search.

A computationally efficient heuristic approach to designing cost-effective air quality management strategies for the ALC problem is presented here. It is called the conjunctive use approach (CUA), because it is based on the use of both a simple and a complex air quality model. The simple air quality model used in this work is the Empirical Kinetic Modeling Approach (EKMA), developed by Gery and Crouse.[18] The complex model used is the Urban Airshed Model (UAM) developed by Scheffe and Morris.[19] The purpose of using both types of models is to reduce the number of runs that would be required using the complex model alone for designing cost-effective strategies. A computationally efficient approach is presented below.

THE CUA

The CUA incorporates both simple and complex models with optimization methods to find lower cost control strategies. The overall framework for the CUA is shown in Figure 1 and is described in the next subsection. The CUA approach includes a step to solve the ELC problem for different emissions control combinations for NO_x and VOC. For each emissions control combination, the least cost control strategy is determined by solving a MIP formulation. The next step is to use the simple model, EKMA, to estimate the resulting peak O_3 concentrations for each solution. Then, the least cost value and peak O_3 concentration for each solution are used to construct a set

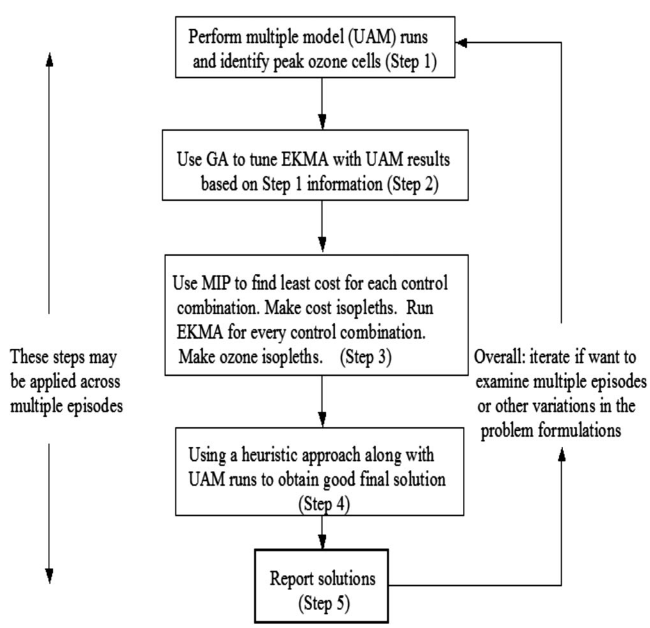

Figure 1. Schematic diagram of the proposed approach.

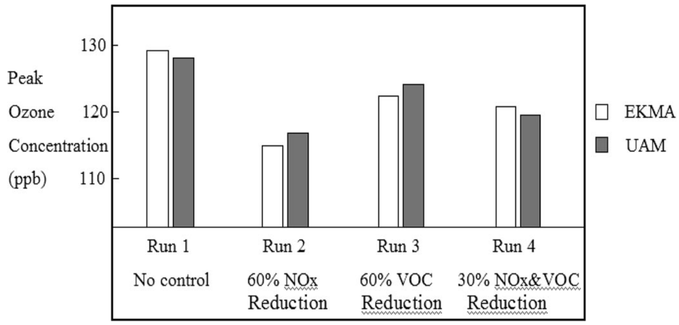

Figure 2. Comparisons of the EKMA and the UAM results.

of isopleths for both cost and O_3. These isopleths are then used to identify the combinations of reductions in the NO_x and VOC emissions that would meet target O_3 levels and have relatively low cost. Then, the final step is to use one of the two heuristics described below to refine the analysis to identify a cost-effective solution that meets the O_3 target when evaluated using the more complex UAM model. The solution is cost effective in the sense that it meets the O_3 target, and the resulting emissions levels are obtained at the least cost. The approach is a heuristic for solving the ALC problem, because the solution obtained is not expected to be optimal with respect to cost while meeting O_3 targets.

Step 1: Perform Base Case Runs Using UAM

In this study, the two models used were the complex grid model, UAM, and the simple box model, EKMA. The first step was to perform multiple UAM runs, in this case, 3-day simulations using the base-case inventory of emissions with four combinations of across-the-board reductions. The four scenarios used in this work examined the following cases: (1) no reduction at any source, (2) 60% reduction across the board of NO_x emissions, (3) 60% reduction across the board of VOC emissions, and (4) 30% reduction across the board of both NO_x and VOC emissions.

These scenarios were used to identify preliminary control targets and to provide initial and boundary condition inputs for the EKMA simulations. To minimize the effects of initial conditions, the outputs of the first 2 days were not used. The third day outputs of UAM runs were used for inputs to EKMA. Parameters needed for EKMA include the peak O_3 concentrations, the third day early morning (6:00 to 9:00 a.m.) NO_x and VOC concentrations, hourly NO_x and VOC emissions, VOC/NO_x ratio, fraction of NO_2 emissions, NO_x and VOC ratios of source emissions, mixing height, and temperature.

Step 2: Tune EKMA Using a GA to Best Duplicate UAM Results

The initial and boundary conditions used in or obtained from the UAM model runs described above were used to provide consistent meteorological and emissions inputs to the EKMA model. To calibrate the EKMA model parameters, an inverse approach was used. This procedure is intended to improve the performance of EKMA in duplicating UAM results. Values of the EKMA model parameters described in the previous step were changed and optimized to duplicate the O_3 concentrations produced by the UAM model using a GA-based approach called EKMA-GA. During this process, values for model parameters are identified such that the predictions of O_3 concentrations by EKMA and UAM are closely matched. The similarity between EKMA-GA and UAM results is shown in Figure 2.

EKMA is only appropriate for those regions that have both a clearly defined urban core and a simple trajectory to the point of the peak downwind O_3 level. The EKMA and UAM models contain the most detailed and up-to-date photochemical Carbon Bond-IV mechanism (CB-IV) including 86 reactions and 35 species. In this study, the box of the EKMA model moves toward the peak O_3 grid in the UAM domain. EKMA also simulates a single day when the peak O_3 occurred in the UAM domain. Being a simple box model, it is very computationally efficient, requiring a run time of ~2 sec on a low-end UNIX work station for a typical model run for the domain of Charlotte, NC. UAM, in contrast, represents the preferred approach to O_3 air quality modeling but takes 3–4 hr to run a comparable 3-day simulation. Therefore, by calibrating, or tuning, EKMA over the same time period, it is possible to use it to provide quick estimates of the O_3 responses for many emissions reduction programs as part of the heuristic process. This calibration is only intended to produce simulation results as similar as possible to those expected using UAM. Traditional calibration and verification issues would be expected to be considered as part of the overall UAM modeling process and are not considered here.

Step 3: Construct Cost and O_3 Isopleths

Construct Cost Isopleths Using ELC Solutions. To quantify the cost of different control strategies for O_3 management, the ELC model is used to minimize the total cost of an emissions control strategy while constraining total reductions to meet a given set of targets for NO_x and VOC emission reductions. This is repeated for different combinations of NO_x and VOC levels.

The ELC model can be expressed as follows:

$$\text{Minimize TC} = \sum_{i}^{N} \sum_{j}^{M} [E_i \times c_{i,j} \times e_{i,j} \times X_{i,j}] \qquad (1)$$

subject to

$$\sum_{i}^{N}\left[E_i \times \sum_{j}^{M}[(1 - e_{i,j}) \times X_{i,j}]\right] \leq T \text{ (for NOx or VOC emissions)} \quad (2)$$

$$\sum_{j}^{M} X_{i,j} = 1 \text{ for all } i = 1, \text{N and all } j = 1, \text{M} \quad (3)$$

where i is the source index; j is the control technology index; N is the number of sources; M is the number of control technology; $c_{i,j}$ is the cost per unit of emissions removed using control technology j at *source* i; E_i is the initial emissions from controllable source i; $e_{i,j}$ is the control efficiency of technology j at source i; $\chi_{i,j}$ is a binary variable, which equals 1 when control technology j at source i is used and equals 0 when control technology j at source i is not used.

Equation 1 represents the TC of the strategy, which is minimized over all of the sources in the modeled domain for an emissions target, T. The control cost functions used in eq 1 were obtained from U.S. Environmental Protection Agency (EPA) Emission Reduction and Cost Analysis Model (ERCAM)-NO_x[20] and ERCAM-VOC.[21]

The analyst selects a target (T) limit on the total quantity of NO_x or VOC emissions from the controllable sources. If targets are set for both NO_x and VOC emissions, then two such constraints are used with a value of T for each. A T value is calculated based on the overall requirement using the following equation:

$$T = BE \times (1 - FRC) - UE \quad (4)$$

where BE is the base inventory emissions including controllable and uncontrollable emissions; FRC is the overall desired fraction of reduction of NO_x or VOC emissions for the region; and UE is the quantity of uncontrollable emissions in the inventories. Equation 3 is based on the assumption that control options are mutually exclusive and that no more than one control option can be applied at each source.

The MIP-ELC formulation was solved using the commercial optimization software package CPLEX,[22] a MIP and LP solver. The ELC solutions that were obtained for various combinations of targets were used to produce cost isopleths.

Construct Peak O_3 Concentration Isopleths of Control Strategies. At the heart of the problem of designing a cost-effective control strategy is the need to take into account the emissions-air quality relationship and to ensure that the O_3 ambient standard is met. The next step in the methodology is to determine the air quality effects that would result from the alternative target levels of precursor controls used in the ELC solutions. The tuned EKMA model was used to estimate the peak O_3 level for each of the different combinations of target levels of VOC and NO_x. After EKMA runs were carried out and ELC solutions were obtained, these O_3 levels and cost levels were used, for example, to plot the isopleths as shown by the solid and fine lines in Figure 3.

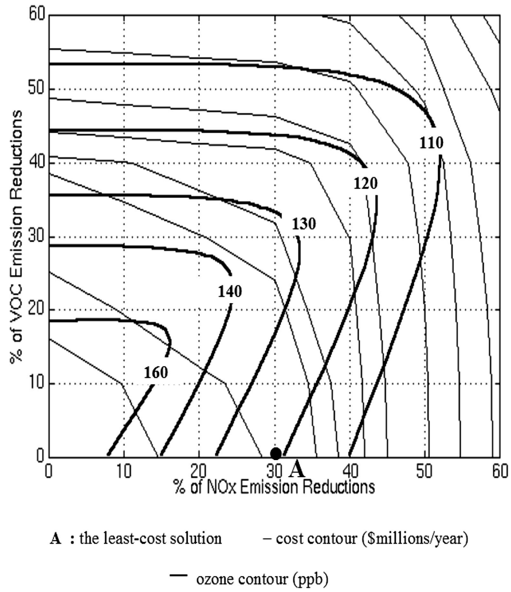

Figure 3. The best solution (point A) that meets 124-ppb standard.

Step 4: Search for the Best Control Strategy among Potential Strategies

Once the O_3 concentration and cost isopleths are obtained, one of the following heuristic approaches is used to identify a cost-effective control strategy.

Heuristic Approach 1: Isopleth Refinement Method. The cost and O_3 isopleths are combined as shown, for example, in Figure 3. Using such as figure, a region of cost-effective combinations of NO_x and VOC control levels can be identified. For this example, if the target O_3 level is 124 ppb, the most cost-effective combination appears to be in the subregion near point A. A small number of UAM runs are then used to determine more refined isopleths for such a subregion. This iterative refinement can be carried out to the extent desired to obtain a control strategy that is cost effective and that meets the O_3 target as described in the case studies.

Heuristic Approach 2: Cost Ranking Method. In this approach, ELC solutions for discrete NO_x and VOC reduction levels are ranked by cost. Their corresponding peak O_3 concentrations are obtained using the tuned EKMA model. Based on a target range of O_3 values, candidate solutions are identified. For instance, for the range 120 ± 0.5 ppb, potential solutions that meet this requirement are first identified. The strategy that has the lowest cost among this subset of strategies is examined first using UAM to determine the O_3 target that would be met. If the resulting O_3 concentration does meet the standard, then that strategy is considered to be a relatively cost-effective control strategy. The next lower cost strategy, which has lower emissions targets, would also need to be checked to see if it meets the O_3 standard when evaluated using the more complex UAM model. If the initial strategy does not meet the standard, the next higher cost strategy, which

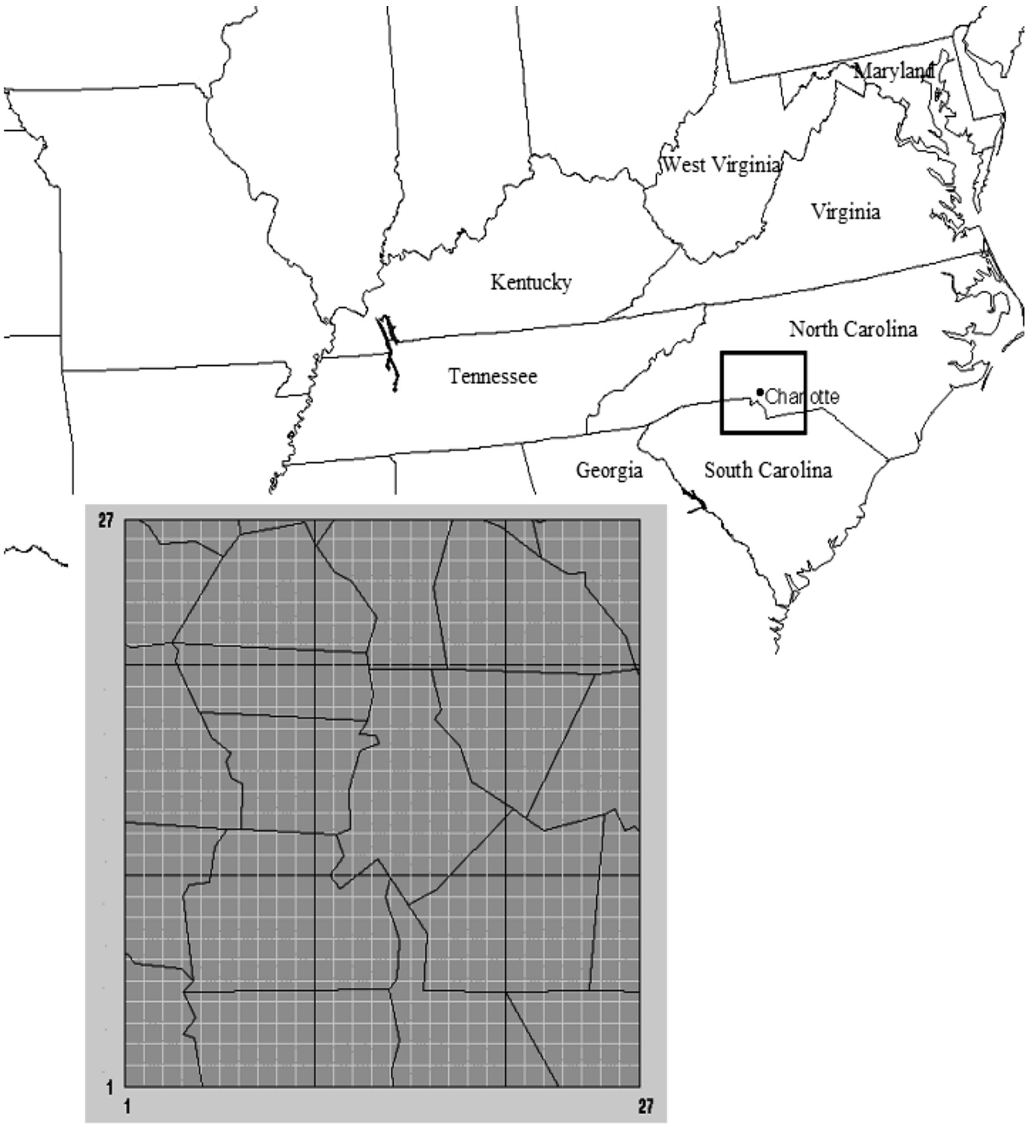

Figure 4. The modeling domain and grid in the area near Charlotte, NC.

has higher emission targets, must be checked. The iterative examinations are continued until the best solution that meets the air quality standard when evaluated using the UAM model is obtained.

DESCRIPTION OF THE CASE STUDIES

The U.S. Supreme Court upheld the EPA new 8-hr O_3 standard on February 27, 2001,[23] and ruled in 2003. The previous O_3 standard was 0.12 ppm for the 1-hr standard. The previous standard is still implemented at the state level and was used in the case studies presented here.

The case studies were carried out for the Charlotte, NC, metropolitan area, including Mecklenburg and Gaston counties (see Figure 4). The area was in violation of the 0.12-ppm standard during the 3-yr period from 1987 through 1989. During this period, O_3 levels reached 0.167 ppm at one location, and the area was classified as a moderate O_3 nonattainment area by EPA. The North Carolina Department of Environment and Natural Resources (NCDENR) has been developing state implementation plans to reduce the ambient O_3 concentrations to meet and to maintain the standard for at least a 10-yr period. The NO_x and VOC emissions inventories used in the case studies were projected 1999 emissions calculated by applying growth factors to the 1990 and 1991 emissions inventories provided by NCDENR for the study region. The emissions inventory files list VOC, CO, and NO_x pollutant-emitting sources with emissions >10 tons per year, 100 tons per year and 100 tons per year, respectively. For each source, every pollutant-emitting process is listed separately in the inventory.

Information about NO_x and VOC control options available for each type of process was obtained from the EPA cost manual. These programs group sources by classification code into pods of processes that are subject to the same control options. The cost manual also provides the removal efficiency and a cost function for each control option. The cost function gives a cost per ton of NO_x and VOC emissions removed. In these studies, only control technologies currently available for the existing emission sources were considered. Of the 759 NO_x-emitting processes in the modeled domain, only 546 NO_x sources,

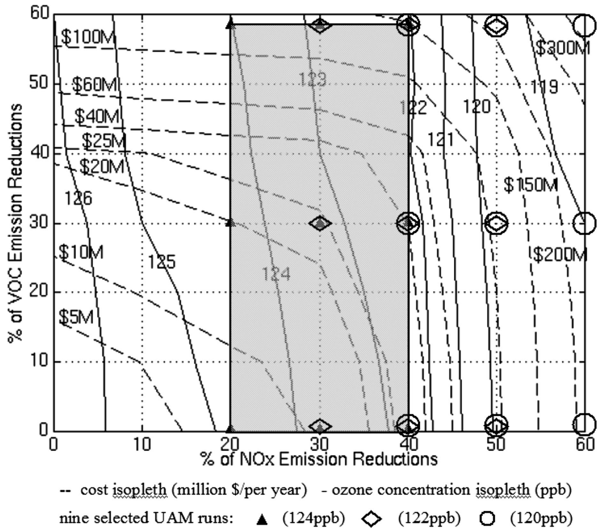

Figure 5. Isopleths of peak O_3 concentrations using EKMA and costs (case 1).

which collectively emit a total of 95,280 tons of NO_x per year, have control options available. The remaining 213 NO_x sources emit a total of 5230 tons of NO_x per year. Of the 1487 VOC-emitting processes in the domain, only 1174 sources, which emit a total of 37,100 tons of VOC per year, can be controlled. The remaining 313 sources emit a total of 4720 tons of VOC per year.

Cost isopleths were developed based on 49 combinations of overall reduction levels for NO_x and VOC; specifically, each reduction level could take on the value of 0, 10, 20, 30, 40, 50, or 60%. For each combination, the ELC solution was obtained by solving an MIP model. The solutions were used to produce the cost isopleths shown by the dashed lines in Figure 5.

The following case studies use a meteorological episode during which the Charlotte area experienced exceedances of the O_3 standard and which represents days when high O_3 concentrations are likely to occur.

Case Study 1: The Original Meteorological Episode

The historical photochemical smog episode, which occurred on July 19–21, 1987, represents a stagnant condition in which there was little transport from outside of the modeled domain and very light wind flow within the domain. The boundary conditions for the Charlotte area were obtained from UAM runs carried out for the North Carolina domain.

Case Study 2: The Original Meteorological Episode with Modified Boundary Conditions

For case study 1, VOC emission controls were observed to be ineffective in reducing O_3 levels in the Charlotte area resulting in a NO_x-limited case due to the dominance of biogenic emissions in the region. The biogenic VOC, in general, was transported to the study area. To test the general applicability of the proposed methodology, a hypothetical case that is representative of areas other than a NO_x-limited area was developed such that both NO_x and VOC controls would be necessary.

A hypothetical set of boundary conditions was defined as follows based on the original episode: all VOC concentrations, including the species ETH, OLE, PAR, TOL, XYL, FORM, ALD2, MEOH, ETOH, and ISOP in the UAM input file, described in Table 5.3 of UAM User's Guide,[24] were reduced by 80%, and all of the NO_x concentrations, including the NO and NO_2 species, were increased by 15%. Boundary O_3 concentrations were increased by 10% to increase overall O_3 concentrations.

CASE STUDY RESULTS

In the case studies, only feasible control technologies for current emission sources were considered, resulting in maximum overall NO_x and VOC reductions of 60% and 58%, respectively. The 49 assumed combinations of levels of reductions were used to formulate ELC problems that were solved using MIP. For the Charlotte example, the cost varies from 0 for no control to (U.S.)$450 million per year for maximum reduction levels. The cost isopleths shown in Figure 5 were developed for the case studies using the 49 ELC solutions. O_3 isopleths were determined by using the EKMA model to determining the peak O_3 level for each of the 49 solutions.

The two heuristic search approaches described in section 2 were each used to determine a cost-effective control strategy for each case study. These procedures were carried out for three different standards for the peak O_3 concentration, 124, 122, and 120 ppb, for each case.

Case Study 1: The Original Meteorological Episode

The O_3 isopleths generated by applying EKMA are shown in Figure 5. These isopleths show that the peak O_3 level is not sensitive to VOC reductions, as is characteristic, in general, of O_3 levels in the Charlotte area for this episode. Each of the heuristic approaches was then applied to identify a cost-effective control strategy.

Heuristic Approach 1. The isopleths for peak O_3 and cost, shown in Figure 5, were used to identify a subregion for further evaluation. For the 124 ppb case, nine points were examined; these points correspond with combinations of 20, 30, and 40% reductions in NO_x and 0, 30, and 58% reductions in VOC. The UAM model was used to calculate the peak O_3 values at these nine points, and interpolation was used to draw the refined isopleths for peak O_3 concentrations. Along the 124 ppb iso-line, the best solution corresponds with a 30% reduction in NO_x and a 0% reduction in VOC. The peak O_3 concentration, estimated using UAM, associated with this strategy is 123.9 ppb. Thus, this strategy meets the 124-ppb standard, and it has a cost of (U.S.)$10.6 million per year.

Along the 122 ppb iso-line, nine points were examined; these points correspond with combinations of 30, 40, and 50% reductions in NO_x and 0, 30, and 58% reductions in VOC. The UAM model was used to calculate the peak O_3 values at these nine points. The best solution corresponds with a 40% reduction in NO_x and a 30% reduction in VOC. The peak O_3 concentration, as estimated using UAM, associated with this strategy is 122 ppb. This strategy has a cost of (U.S.)$40.19 million per year. For a 120-ppb standard, nine points were examined; these points correspond with

Table 2. Peak O_3 concentration (EKMA and UAM) and cost of various ELC strategies for two case studies.

			Case Study 1		Case Study 2	
No.	**Strategy**	**Cost (U.S.$million/yr)**	**Concentration 1[a]**	**Concentration 2[b]**	**Concentration 1[a]**	**Concentration 2[b]**
1	n0v0	0.00	126.7		125.6	124.3
2[c]	n0v10[c]	1.79	126.9		124.7	**123.6**[c]
3	n10v0	3.34	125.5		124.8	123.8
4	n10v10	5.13	125.3		**123.9**	↑ 122.8
5	n20v0	6.97	124.9	125.7	124.4	
6	n0v20	6.97	126.7		124.2	
7[c]	n20v10[c]	8.76	124.8	125.3	122.7	**121.8**[c]
8	n10v20	10.31	125.2		123.1	
9[c]	n30v0[c]	10.60	**123.7**	↑ **123.9**[c]	123.2	
10	n30v10	12.4.	123.6		**122.0**	↑ 121.2
11	n0v30	12.77	126.6		124.0	
12	n20v20	13.94	124.7		122.4	
13	n10v30	16.10	125.0		122.9	
14	n30v20	17.57	123.4		121.6	
15	n20v30	19.74	124.5		122.1	
16	n0v40	21.28	126.2		123.7	
17	n30v30	23.37	123.2		121.4	120.6
18	n10v40	24.61	124.7		122.5	
19	n40v0	27.42	122.8		122.0	
20	n20v40	28.25	124.3		121.8	
22	n40v10	29.21	122.7	122.2	121.3	120.8
22	n30v40	31.88	123.0		121.1	120.2
23[c]	n40v20[c]	34.39	122.6	122.1	121.2	**120.0**[c]
24[c]	n40v30[c]	40.19	**122.5**	↑ **122.0**[c]	120.5	119.9
25	n40v40	48.69	123.1		120.2	119.7
26	n0v50	66.00	126.1		123.2	
27	n10v50	69.34	124.6		122.1	
28	n20v50	72.97	124.2		121.3	
29	n30v50	76.61	122.9		120.8	
30	n50v0	92.97	**119.9**	↓ 121.2	121.7	
31	n40v50	93.42	122.2	121.7	**119.3**	↑ 119.6
32	n50v10	94.76	119.8		120.5	
33	n50v20	99.94	119.7	120.8	120.2	
34	n50v30	105.74	119.5	120.7	120.0	
35	n50v40	114.24	119.4	120.5	119.7	
36	n0v58	129.34	126.0		122.8	
37	n10v58	132.68	124.5		121.8	
38	n20v58	136.31	124.0		120.9	
39	n30v58	139.96	122.8		120.2	
40	n40v58	156.76	122.1		118.9	
41	n50v50	158.97	119.3	120.4	118.5	
42[c]	n60v0[c]	212.09	119.2	**118.9**[c]	119.8	
43	n60v10	213.89	119.2		119.1	
44	n60v20	220.86	119.1		118.9	
45	n50v58	222.31	119.2		118.0	
46	n60v30	233.63	119.0		118.3	
47	n60v40	254.90	118.8		118.2	
48	n60v50	320.91	118.7		118.0	
49	n60v58	450.25	118.6		117.9	

[a]EKMA peak O_3 concentration; [b]UAM peak O_3concentration; [c]The best strategies for different standards are marked.

combinations of 20, 30, and 40% reductions in NO_x and 0, 30, and 58% reductions in VOC. The UAM model was used to calculate the peak O_3 values at these nine points. The best solution obtained corresponds with a 60% reduction in NO_x and a 0% reduction in VOC. The peak O_3 concentration, as estimated using UAM, is 118.9 ppb, and the cost is (U.S.)$212.09 million per year. In this case, the standard is met by >1 ppb, so additional refinement could be used to seek a lower-cost solution by reducing the target for NO_x reductions. For instance, examination of Figure 5 suggests an NO_x target of 55%, because the 120-ppb UAM isopleth would be met at that point.

Heuristic Approach 2. This approach is based on sorting the control strategies by cost as shown in Table 2. Peak O_3 concentrations, based on EKMA runs, are also shown.

Three O_3 standards were used to test this approach for the first case study. For the O_3 standard of 124 ppb, an interval of ±0.5 ppb was used for selecting the initial strategy using the EKMA results. The initial solution is strategy 9, which is estimated to have a peak O_3 level of 123.7 ppb based on the EKMA results. Using UAM, the peak O_3 concentration was evaluated as 123.9 ppb, which meets the O_3 standard of 124 ppb. In this case, the next lower cost solutions with peak O_3 levels <125 ppb, based on EKMA results, are strategies 7 and 5. They were also evaluated using UAM, but their peak O_3 levels exceed the 124-ppb standard. The best solution obtained, therefore, is strategy 9, which requires an NO_x reduction of 30% at a cost of (U.S.)\$10.6 million per year marked in Table 2. This is the same solution obtained using Heuristic approach 1.

For an O_3 standard of 122 ppb, strategy 24 was selected as the initial solution, because it had the lowest cost of solutions, yielding O_3 levels within the range of 121.5–122.5 ppb. Using UAM, the peak O_3 concentration was evaluated as 122 ppb. The next lower cost solutions with peak O_3 levels <123 ppb, estimated based on EKMA results, are strategies 23 and 21. They were also evaluated with UAM, but their peak O_3 levels exceed the 122-ppb standard. The best solution obtained is strategy 24; it requires a 40% reduction in NO_x and a 30% reduction in VOC at a cost of (U.S.)\$40.19 million per year (Table 2). This is also the same solution obtained using Heuristic approach 1.

For an O_3 standard of 120 ppb, strategy 30 was selected as the initial solution. Based on the EKMA results, the peak O_3 concentration is 119.9 ppb but the UAM result was 121.2 ppb, which does not meet the 120-ppb standard. In this case, more costly strategies (strategies 31, 33, 34, 35, 41, and 42) were selected judgmentally and evaluated using UAM. Strategy 42 is the best solution identified. It has a peak O_3 level of 118.9 ppb, and it requires a 60% NO_x reduction and a 0% VOC reduction at a cost of (U.S.)\$212.09 million per year. This is also the same solution obtained using Heuristic approach 1. As discussed, a lower cost solution might be obtained by refining the analysis. In addition, Table 2 indicates that several strategies, such as 35 and 41, nearly meet the 120-ppb standard with substantially lower costs.

Case Study 2: The Original Meteorological Episode with Modified Boundary Conditions

The peak O_3 isopleths generated using EKMA results are shown in Figure 6. Unlike those in the first case study, these isopleths exhibit regimes of relative sensitivity to both NO_x and VOC reductions. Both heuristic approaches were applied to identify cost-effective control strategies for the same three O_3 standards.

Heuristic Approach 1. Using the peak O_3 and cost isopleths shown in Figure 6, a region was selected for obtaining a strategy that meets a 124-ppb standard. Control strategies correspond with combinations of 0, 10, and 30% reductions in NO_x, and 0, 30, and 58% reductions in VOC were considered. The resulting UAM isopleths of peak O_3 concentration were constructed. Along the 124-ppb iso-line, the best solution corresponds with 0% reduction in NO_x

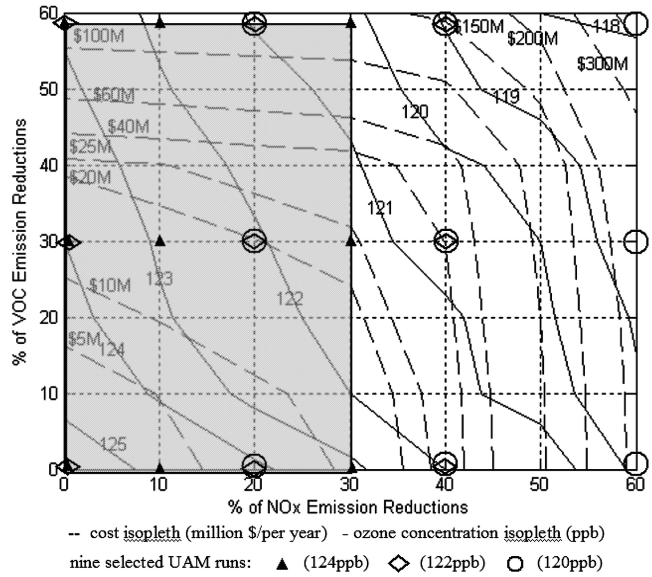

Figure 6. Isopleths of peak O_3 concentrations using EKMA and costs (case 2).

and 10% reduction in VOC. The peak O_3 concentration, estimated using UAM, is 123.6 ppb, and the strategy has a cost of (U.S.)\$1.79 million per year (Table 2). Because the standard being considered is 124 ppb, further refinement could be used to seek a lower cost solution by reducing the target VOC reduction.

For a 122-ppb standard, nine points were examined; these points correspond with combinations of 0, 20, and 40% reductions in NO_x and 0, 30, and 58% reductions in VOC. The UAM model was used to calculate the peak O_3 values at these nine points. The best solution corresponds with a 20% reduction in NO_x and a 10% reduction in VOC. The peak O_3 concentration estimated using UAM is 121.8 ppb, and the cost is (U.S.)\$8.76 million per year (Table 2). For a 120-ppb standard, nine points were examined; these points correspond with combinations of 20, 40, and 60% reductions in NO_x and 0, 30, and 58% reductions in VOC. The UAM model was used to calculate the peak O_3 values at these nine points. The best solution for the 120-ppb standard obtained corresponds with a 40% reduction in NO_x and a 20% reduction in VOC. The peak O_3 concentration is 120 ppb, and the cost is (U.S.)\$34.39 million per year (Table 2). For both the 122- and 120-ppb standards, further refinement might lead to a lower-cost solution.

Heuristic Approach 2. The control strategies were sorted by cost as shown in Table 2. O_3 concentrations, obtained based on EKMA results are also listed. As discussed below, this heuristic approach led to the same best solution as the first heuristic for the three values of the O_3 standard.

For an O_3 standard of 124 ppb, strategy 4 was selected as the initial solution, because it closely meets the standard, with a 123.9-ppb value based on EKMA results. The peak O_3 concentration was shown to be 122.8 ppb, however, using UAM. Thus, the next lower cost solutions (strategies 3, 2, and 1) were also evaluated using UAM. Strategy 2 was then identified as the one that meets the standard at lowest cost. It requires a 10% reduction in

Table 3. Number of UAM runs required for different cases using heuristic approaches.

	Case Study 1			Case Study 2		
O_3 Standard (ppb)	120	122	124	120	122	124
Heuristic approach 1	9	9	9	10	10	10
Heuristic approach 2	7	3	3	6	2	4

VOC at a cost of (U.S.)$1.79 million per year (Table 2). The peak O_3 concentration, estimated using UAM, is 123.6 ppb.

For an O_3 standard of 122 ppb, strategy 10 was selected as the initial solution, because its peak O_3 level is 122 ppb based on the EKMA result. The peak O_3 concentration determined using UAM to be 121.2 ppb. In this case, strategy 7 was selected judgmentally for evaluation, and its O_3 concentration is 121.8 ppb. This strategy was the best obtained. It specifies a 20% reduction in NO_x and a 10% reduction in VOC at a cost of (U.S.)$8.76 million per year (Table 2). For the 120-ppb standard, strategy 31 was picked first because it has an EKMA estimate of 119.3 ppb. The UAM level is 119.6 ppb. In this case, strategies 25, 24, 23, 22, and 21 were selected judgmentally and evaluated with UAM, and strategy 23 was the best obtained. It specifies a 40% reduction in NO_x and a 20% reduction in VOC at a cost of (U.S.)$34.39 million per year (Table 2). Its peak O_3 level is 119.6 ppb.

EVALUATION OF THE HEURISTIC APPROACHES

To evaluate the performance of the heuristic approaches, the ELC strategies for all 49 combinations of emissions reduction levels were evaluated using UAM. The resulting O_3 concentration isopleths were developed, and the best solution for each of O_3 standards (i.e., 124, 122, and 120 ppb) was identified and shown to be the same as the results obtained using each of the two heuristic approaches.

To compare the savings in the number of UAM runs by using each heuristic approach, the number of UAM runs required in each case by each approach is shown in Table 3. The various heuristic applications required from 2 to 10 UAM runs as opposed to the 49 required for enumeration. (In practice, of course, one would not need to enumerate all 49 cases if a good solution has been obtained that dominates others not yet checked.) It is also observed that heuristic approach 2 requires fewer UAM runs than the first approach. Also, using either approach, additional UAM runs would be required to further refine the optimal solution. Nevertheless, the numbers of runs required to obtain cost-effective solutions for the case studies can be carried out by an analyst on a single work station.

The case studies considered are of practical complexity and, therefore, the conjunctive approach should be applicable to many other urban locations. Milford et al.[25] and Winner et al.[26] showed that 45 and 64 different control combinations, respectively, could be evaluated on a parallel computing system within a reasonable time frame. Although these two studies did not consider cost effectiveness, they do provide insights about the computational problem. The CUA, which relies on many runs of a simple air quality model to reduce the number of runs required of a complex model, has been demonstrated to be practical when implemented on a single workstation or personal computer.

CONCLUSIONS

Two heuristic approaches that are simple and practical to use were presented. They use an implementation of the EKMA model, which was "tuned" using a GA to represent the outputs from the more complex UAM model. The EKMA model was used to quickly identify an approximate combination of NO_x and VOC emissions reduction levels, and these results were refined using UAM to identify a cost-effective solution. The various heuristic applications required from 2 to 10 UAM runs as opposed to the 49 required for enumeration in general.

These heuristics approaches were demonstrated using two realistic, but hypothetical, case studies for the Charlotte metropolitan region in North Carolina. This work presents for the first time a series of methods for determining cost-effective emissions control strategies that explicitly consider cost and air quality and that require a small and practical number of UAM simulations.

The procedures presented here are based on and illustrated using UAM as the complex air quality modeling system. They can, however, be easily modified to incorporate other air quality modeling systems, such as the EPA third-generation air quality modeling system, called the Community Multi-Scale Air Quality Modeling System,[27] and the CAMx model developed by ENVIRON Corporate. The CUA is potentially applicable using different combinations of simple and complex models for a wide range of air quality management problems. Future research could focus on such applications for reducing particulate matter and visibility problems.

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