Optimizing Ground-Level Ozone Control Strategies with Mixed Integer Nonlinear Programming

Wei-Che Hsu[a], Jay M. Rosenberger[a], Victoria C.P. Chen[a], Melanie L. Sattler[b], Aditya Koppikar[a]

[a]Department of Industrial & Manufacturing Systems Engineering, The University of Texas at Arlington, P.O box 19017 Arlington, TX 76019, USA

weiche.hsu@mavs.uta.edu

[b]Department of Civil Engineering, The University of Texas at Arlington, P.O. Box 19308 Arlington, TX 76019, USA

Abreact We present a nonlinear statistical model for ground-level ozone prediction and then study various mixed integer nonlinear programming (MINLP) models for optimizing ozone control strategies for the Dallas Fort-Worth region, so as to comply with the State Implementation Plan (SIP) development requirements with minimum cost. Supplemental control strategies are introduced into the optimization since the models were infeasible. Nonlinear transformations are applied when linear modeling assumptions are violated. Piecewise linear functions are used to estimate ozone concentration for selecting targeted ozone control strategies. Three MINLP models, a static model, a sequential model, and a dynamic model are studied in this research. These different models are optimized to present different sets of targeted control strategies based on various scenarios. Moreover, supplemental control strategies are considered to provide further ozone or emission reduction in the optimization for enabling a feasible solution. The most effective targeted control strategies are selected in each model for controlling ozone, and the most critical supplemental controls in certain time periods and locations for reducing ozone are identified.

Keywords: mixed integer nonlinear programming, ground-level ozone, piecewise linear optimization, linear regression transformation

1. Introduction

Ground-level ozone (O_3) is one of six common air pollutants monitored by the U.S Environmental Protection Agency (EPA). High-level ground-level ozone concentration can lead to a variety of health problems, and it also damages vegetation and ecosystems [1]. In 1990, the Clean Air Act (CAA) required the EPA to set National Ambient Air Quality Standards (NAAQS) for six common air pollutants considered harmful to public health and the environment. The ultimate goal is for each state to comply with the NAAQS and thereby reduce the criteria pollutants and improving air quality. The US government has acted to improve America's air quality significantly by designing, developing, and implementing national programs in order to reduce air emissions. For example, in 2009, ozone concentrations were 30 percent lower than in 1990 based on an annual 4^{th} maximum 8-hour average [2]. However, ground-level ozone continues to present challenges in many areas of the country. In 2008, ground-level ozone was still considered a harmful air pollutant of the six common pollutants that exceeded the NAAQS [3]. Therefore, we have to study more effective targeted strategies for ground-level ozone control since more stringent air quality standards have been made to reduce pollution further.

Ground-level ozone is a secondary pollutant produced by its precursors, oxides of nitrogen (NO_x) and volatile organic compounds (VOC). It is not emitted into the air directly. In fact, it is formed by a complex series of chemical reactions mainly from NO_x and VOC in the sunlight and heat [4]. As sunlight is one of the main catalysts for ozone formation, ozone is also called the "summertime air pollutant" [5]. Common sources of NO_x include automobiles, trucks, marine vessels, construction equipment, power generation, industrial processes, and natural gas furnaces. Major source of VOCs include organic chemicals that vaporize easily, such as those found in gasoline and solvents [6].

To perform modeling for the eight-hour ozone demonstration, the Comprehensive Air Quality Model with Extensions (CAMx) is used in this study to determine concentrations of air pollutants by simulating processes associated with emissions, transport, chemical reactions, and deposition. CAMx could also be used to estimate how emissions from individual source areas and regions that affected the predicted ozone concentrations over space and time. EPA has proved that CAMx would be appropriate to simulate eight-hour ozone concentrations in urban areas and it is currently being used for attainment demonstrations in areas that have violated the NAAQS for ozone.

Ground-level ozone control has been a very challenging issue not only in urban areas of the United States but also in many cities all around the world. Therefore, the first critical task is to predict ozone concentrations accurately. There are numerous research papers of various statistical modeling approaches that have been studied for air quality forecasting. These include multiple linear regression [7, 8, 9, 10], neural networks [11, 12, 13, 14], fuzzy systems [15, 16, 17], generalized additive models [18, 19, 20], nonlinear regression [21, 22], and others.

A secondary pollutant, such as ozone, is formed by a series of complex nonlinear reactions of its precursors. An effective control strategy implementation could target reduction of either one or both of the precursors. Moreover, a control strategy could be implemented on the targeted region where the pollutant is produced. A targeted control strategy can also be applied in the certain time periods, especially in the high ozone concentration hours. However, the traditional control strategy for ground-level ozone control is to apply emission reductions across-the board, i.e., across the entire region and the entire 24 hours per day [23, 24, 25, 26].

1.1 Background on Targeted Control Strategy for Ground-Level Ozone Control

A targeted control strategy is targeted by location, such as a particular county, and time, such as the morning rush hour time period. The ultimate objective of targeted decision-making is to determine the most cost effective control strategies and the most critical supplemental control strategies in the optimization models. The concept of targeted decision-making for ground-level ozone has been studied by Sule et al. [27], Yang et al. [28, 29], and Hsu et al. [30].

In this section, we summarize the targeted control strategy optimization approach in Sule et al. [27] and Hsu et al. [30]. The methods in this research include advanced photochemical modeling, statistical modeling, and optimization. The targeted control strategy is comprised of four phases: (1) Initialization, (2) Mining, (3) Metamodeling, and (4) Optimization.

1.1.1 Initialization

The first step in the initialization process is to identify critical monitors in the region of interest and a potential list of 32 ozone control strategies and then to categorize emission sources into three types--point sources, area sources, and line sources. Next, the control time periods are designated based upon the types of emission sources. The control regions are classified as the counties since control strategies are often implemented differently in different counties. After that, the monitor time periods and regions are identified. Finally, a list of potential control strategies is categorized according to emission types, time periods, and location.

1.1.2 Mining

Data mining is conducted to identify all emission variables, specified by location and time period, that affect the 8-hour ozone maximums. Only significant emissions variables that affect the 8-hour ozone maximums are considered as predictor variables in the metamodeling phase.

1.1.3 Metamodeling

Only linear regression is used for approximating relationships between ozone concentration and predictor variables, such as of emissions and prior ozone variables. The predictor variables for the metamodels include emission sources from current and previous time periods and also 8-hour maximum ozone concentrations from previous time periods. Stepwise regression is conducted for model selection so as to further reduce the numbers of predictor variables.

1.1.4 Optimization

Three mixed integer linear programming (MILP) models were studied in the optimization phase to select the most cost-effective set of control strategies for ground-level ozone control in Hsu et al. [30]. These different MILP models allow decision-makers to study how the selection of control strategies varies under different circumstances. In addition, given that the DFW case study was infeasible, these MILP models also identify the best regions and time periods for supplemental control. Three types of the supplemental control strategies are included in the MILP for further reduction on ozone and emissions because the current set of control strategies cannot satisfy the allowable upper bound on ozone concentration.

1.2. Contribution

This paper is an extension to the work of Sule et al. [27] and Hsu et al. [30], particularly in the targeted nature of the emission reductions. Both Sule et al. [27] and Hsu et al. [30] used linear statistical models to predict the ozone concentration and then optimized the control strategies. Instead of using linear regression models for approximating ozone concentration, we use transformed nonlinear models to refine the statistical model in the metamodeling phase. Sule et al. [27] used a trial-and-error method to implement supplemental controls on targeted locations and time periods for enabling feasible solutions. Hsu et al. [30] introduced supplemental control strategies with a considerable penalty cost in the optimization models to obtain technically feasible solutions. In this paper, we consider a more conservative way to include the supplemental control strategy with a penalty cost in piecewise linear optimization.

The contribution of this paper are described as follow: First, this paper demonstrates that statistical models of hourly ozone concentrations required nonlinear relationships between predictor variables in order to capture the ozone behavior accurately. We conducted residual analysis to verify the assumption of all linear regression models and checked the statistical plots to ensure model adequacy. Then we determined the need for model refinement. The transformed nonlinear regression models were used in the metamodels to represent the ozone concentration. Second, we applied piecewise linear functions to approximate the nonlinear function for the refined models and then solved three MINLP models. Third, a considerable penalty cost is applied to the supplemental control strategy in the piecewise linear optimization to ensure a feasible solution.

The remainder of this paper is organized in four sections. Section 2 depicts nonlinear transformations of ozone concentration. Section 3 presents mixed integer nonlinear programming models for targeted ozone control. Section 4 describes computational results of three alternative control strategy models. Finally, Section 5 discusses conclusions and future research.

2. Nonlinear Transformation of Ozone Concentration

Residual analysis can be used to verify the assumptions of linear regression models. For a multiple linear regression model to be reasonable, the residuals must have constant variance, the residuals must be normally distributed, the residuals must be uncorrelated, and there should be few residual outliers. Statistical plots are one of the most useful tools available for verifying model adequacy and determining the need for model refinement.

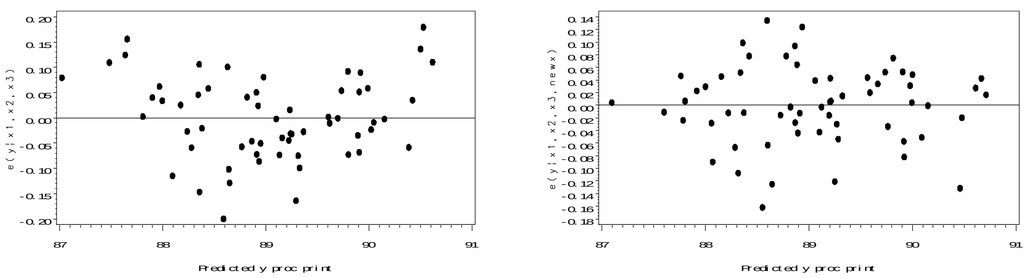
In this paper, residual plots were used to verify model assumptions. Typical residual plots include plots of residuals versus fitted values and residuals versus individual predictor variables. Other plots based on residuals, such as response variables versus individual predictors, predictors versus time series, normal probability plots of residuals, and residuals versus other possible predictor plots, are useful for detecting model inadequacies. Residuals refer to the difference between the observed data values and the corresponding model fits. A plot of residuals versus individual predictor variables is used to check for curvature and a funnel shape. If the residual plot shows curvature in the relationship between the residuals and the predictor variables, then a linear model is inappropriate. Adding a quadratic term or transforming the predictor variables may result in a better model. If the residual plot shows a funnel shape between the residuals and fitted values, then the linear model has nonconstant variance. Performing a variance-stabilizing transformation on the response variable may fix the problem.

After performing residual analysis of the regression models, we found some regression models did not fit the model assumptions. By transforming the response or predictor variables to be nonlinear, the funnel shape and curvature in the residual plots can be eliminated. For example, there is slight curvature in the residual plot in Denton on August 18 from 6 am to12 noon (see Figure 1. (a)). The original linear regression was showed as Equation (1). O_3De12-6a refers to ozone concentration in the Denton monitoring region during 12 midnight to 6 am, O_3Ta12-6a is the ozone concentration in the Tarrant monitoring region during 12 midnight to 6 am, and AJ06-9aN means NO_x emissions from an area source in Johnson County during 6 am to 9 am.

$$y=-0.8(O_3De12\text{-}6a)+2.396(O_3Ta12\text{-}6a)-0.104(AJ06\text{-}9aN)-10.69 \quad (1)$$

$$y=-40.75(O_3De12\text{-}6a)+2.384(O_3Ta12\text{-}6a)-0.096(AJ06\text{-}9aN)+0.314(O_3De12\text{-}6a)^2+1258.32 \quad (2)$$

By adding a squared term from one of the original predictor variables and rerunning the regression model, the problem of curvature was eliminated (see Figure 1. (b)), and the transformed model with the nonlinear regression model is show as Equation (2).



(a) (b)

Figure 1. Plot (a) shows the residuals vs. fitted values for a linear regression model for Denton on August 18 (6 am–12 noon), where curvature is present. Plot (b) depicts a transformed model without curvature.

3. Mixed Integer Nonlinear Programming Models

In this section, we describe the mixed integer linear programming model developed in Hsu et al. [30], which assumed that ozone concentration was a linear function of its predictor variables. However, as described in the Section 2, ozone concentration in certain locations and periods is a nonlinear function of its predictors. We then develop new piecewise linear models to accommodate the nonlinearities.

3.1 Mixed Integer Linear Programming Model

The following describes the mixed integer linear programming model developed in Hsu et al. [30]. Consider the following sets:

Let N be a set of control strategies.

Let I be a set of emissions types (either NO_x or VOC).

Let J be a set of emission sources.

Let $I(j)$ be the set of emission types that are emitted from each emission source $j \in J$.

Let $I(n)$ be the set of emission types that are associated with each control strategy $n \in N$.

Let L be a set locations.

Let T be a set of time periods.

Let D be a set of days that partition the set of time periods T.

Define the following MINLP variables and input parameters:

Let o_{lt} be the ozone concentration on location l during time period t.

Let $d(t)$ be the day in which time period t occurs.

Let $o_{\bullet t}$ be an $|L|$-dimensional variable vector of the ozone concentrations at time period t.

Let $o_{\bullet 0}$ be a vector representing the ozone concentrations before the first day (August 15) of the optimized time horizon.

Let B_{lt} be the maximum allowable ozone concentration in location l during time period t.

Let g_{nijd} be the emission reduction at emission source j of type i on day d due to the implementation of the control strategy n.

Let ε_{ijd} be the maximum emission contributed by emission source j of emission type i on day d.

Let c_{nd} be the expected cost of selecting of control strategy n on day d.

Let s_{lt}^{+}, s_{lt}^{-} be auxiliary variables for supplemental control strategies that can change the ozone concentration at location l during time period t.

Let c_{spen} be the estimated penalty cost of using supplemental control strategies of auxiliary variables s_{lt}^{+}, s_{lt}^{-} for further ozone reduction (typically \$$10^9$).

Let y_{ijd} be an auxiliary variable that can further reduce the remaining emission of emission type i from emission source j on day d.

Let c_{epen} be the estimated penalty cost of using supplemental control strategies of auxiliary variables y_{ijd} for further emission reduction (typically \$$10^8$).

Let a_{nijd} be the fraction of the reduction of emission type i from source j on day d due to the implementation of control strategy n, where $a_{nijd} = \left(\frac{g_{nijd}}{\varepsilon_{ijd}}\right)$.

Let $\hat{f}_{lt}$ be a statistical model estimating the ozone concentration at location l during time period t.

Let x_{ijd} be the fraction of the remaining emission of emission type i from emission source j on day d.

Let u_{ind} be a binary decision variable representing whether control strategy n is selected on day d for emission type i.

Let z_{nd} be the binary decision variable representing whether control strategy n is selected on day d.

Let c_{nd} be the daily estimated cost of the selected control strategy n on day d.

The MILP model formulation is given by:

$$\min \sum_{n\in N}\sum_{d\in D} c_{nd} z_{nd} + c_{spen}\sum_{l\in L}\sum_{t\in T}\left(s_{lt}^{+} + s_{lt}^{-}\right) + c_{epen}\sum_{i\in I(j)}\sum_{j\in J}\sum_{d\in D} y_{ijd} \tag{3}$$

s.t.

$$\hat{f}_{lt}\left(o_{\bullet 0}, o_{\bullet 1}o_{\bullet 2}, \cdots, o_{\bullet t-1}o_{\bullet d(t)}\right) - s_{lt}^{+} + s_{lt}^{-} = o_{lt} \qquad \forall l \in L, t \in T, \tag{4}$$

$$o_{lt} \le B_{lt} \qquad \forall l \in L, t \in T, \tag{5}$$

$$x_{ijd} + y_{ijd} + \sum_{n\in N} a_{nijd} u_{nid} = 1 \qquad \forall i \in I(j), j \in J, d \in D, \tag{6}$$

$$z_{nd} \geq u_{nid} \qquad \forall i \in I(n), n \in N, d \in D, \quad (7)$$

$$s_{lt}^{+}, s_{lt}^{-}, o_{lt} \geq 0 \qquad \forall l \in L, t \in T, \quad (8)$$

$$x_{ijd}, y_{ijd} \geq 0 \qquad \forall i \in I(j), j \in J, d \in D, \quad (9)$$

$$z_{nd}, u_{nid} \in \{0,1\} \qquad \forall i \in I(n), n \in N, d \in D, \quad (10)$$

The objective (3) is to minimize the total cost of the set of targeted control strategies and the penalty cost of applying supplemental control strategies necessary to bring the region into attainment for the 8-hour ozone standard. Constraint set (4) estimates the ozone concentration in a certain time period and location which could be either linear or nonlinear regressions. In Hsu et al. [30], the $\hat{f}$ functions were assumed to be linear. Constraint set (5) ensures the ozone concentration in each time period and location does not exceed its mandated limit. Constraint set (6) ensures that the fraction of remaining emissions plus the fraction of emission reduction sums to one. Constraint set (7) specifies linking constraints for the reduction of NO_x and VOC emissions due to the same control strategy. Constraints (8) and (9) represent standard lower bounds, and constraint set (10) represents integrality restrictions on the decision variables.

Hsu et al. [30] defined three variant MILP models as follows:

- Static model: Optimize a static control strategy across the entire episode. This results in a single set of selected control strategies that is implemented on every day of the episode.
- Sequential model: Optimize a set of control strategies separately for each day in a sequential order. This results in possibly different sets of selected control strategies on each day of the episode.
- Dynamic model: Optimize a set of dynamic control strategies in which the selected control strategies can vary from day to day. This optimization over the entire episode was conducted simultaneously. This enables the decision-maker to see how the ideal set of control strategies varies with daily emission patterns and meteorology.

3.2 Mixed Integer Linear Programming Model

In this research, an MINLP model formulation is constructed by including piecewise linear functions to the MILP (3) – (10) from Hsu et al. [30]. In the MINLP, the emission variable x_{ijd} and estimated ozone concentration o_{lt} could be considered as both linear and nonlinear terms in the MINLP models.

3.2.1 Piecewise Linear Functions

A piecewise linear function is a separable function that is represented by a set of linear functions with constraints on the variables. Any arbitrary continuous function of one variable can be approximated by a piecewise linear function [31]. However, the quality of the approximation is controlled by the number of the linear segments. With more linear segments in the piecewise linear function; the approximation can be made more accurate. In this research, four equally spaced linear segments were created for each of the nonlinear functions. Since the range of the transformed response (ozone concentration) variable and each transformed predictor variable are typically very small, sometimes the range between the minimum and maximum ozone is less than 1 part per billion (ppb). A piecewise linear function with four equally spaced linear segments is often specified by giving a set of four slopes, a set of breakpoints at which the slopes change, and the approximated value of the liner functions at a given point. Therefore, piecewise linear programming is an optimization method that allows nonlinear programming problems that consist of separable functions to be approximated by linear functions. The resulting piecewise linear program can subsequently be solved as a mixed-integer linear program.

To formulate a transformed ozone concentration variable using a piecewise linear function, consider the following. To simplify notation, we ignore the subscripts l and t for location and time period, respectively.

Let o be the ozone concentration.

Let $\hat{f}$ be the nonlinear transformation of ozone concentration.

Let o^k be the ozone concentration if segment k of the piecewise linear function used.

Let w_k be the binary decision variable indicating the ozone concentration uses segment k on the piecewise linear function.

Also consider the following parameters in the piecewise linear function:

Let b^{k-1}, b^k be the break points corresponding to the segment k.

Let p_k be the slope of segment k.

Let q_k be intercept of segment k.

The piecewise linear function formulation is given by:

$$o = \sum_{k \in K} o^k \tag{11}$$

$$\hat{f} = \sum_{k \in K} p_k o^k - q_k w_k \tag{12}$$

$$b^{k-1} w_k \le o^k \le b^k w_k \qquad \forall k \in K, \tag{13}$$

$$\sum_{k=1}^{K} w_k = 1 \qquad \forall k \in K, \tag{14}$$

$$w_k \in \{0,1\} \qquad \forall k \in K, \tag{15}$$

Constraint set (11) indicates that a given ozone variable equals the ozone concentration approximated by one of the segments. Constraint set (12) represents the linear approximation of the transformed ozone concentration. Constraint set (13) represents the lower and upper bounds of ozone concentration approximated by segment k. Constraint sets (14) and (15) ensure that only one segment is used. Although equations (11)-(15) present an example of a piecewise linear function for a nonlinear transformation of ozone, a similar set of constraints can be used to transform an emission variable.

3.2.2 Penalized Cost of Supplemental Control Strategy in MINLP Models

The linear MILP models for the DFW case study were infeasible [27, 30], so supplemental control strategies with considerable penalized cost were introduced into the optimization model to enable feasible solutions. However, the MINLP models consisted of nonlinear terms in the regression models. It is challenging to penalize the estimated cost of the transformed ozone variable when supplemental control is required because the different dimension between the linear and nonlinear terms. For example, consider an increasing piecewise linear function with four segments within the minimum (min) and maximum value (B) of the break points as shown in Figure 2. (The minimum and maximum ozone concentration in a region and a period was obtained from observing 60 CAMx runs.) If the estimated ozone concentration falls within any one of the segments, we can determine the needs for supplemental control based upon the linear approximation of the segments.

However, if the estimated ozone (o') is greater than the maximum allowable ozone concentration (B) then a difference (Δ) exists between the penalized cost (ω) of the nonlinear model and the penalized cost (θ) from the linear extrapolation of last segment. Consequently, we applied supplemental controls on the piecewise linear approximation on ozone (see Equation 16) and the upper bound of the last segment (see Equation 17). Considering that, we ensure that the supplemental cost penalty is more conservative and reasonable. By contrast, we applied the supplemental controls on the piecewise linear approximation on ozone and lower bound of the first segment in a decreasing function.

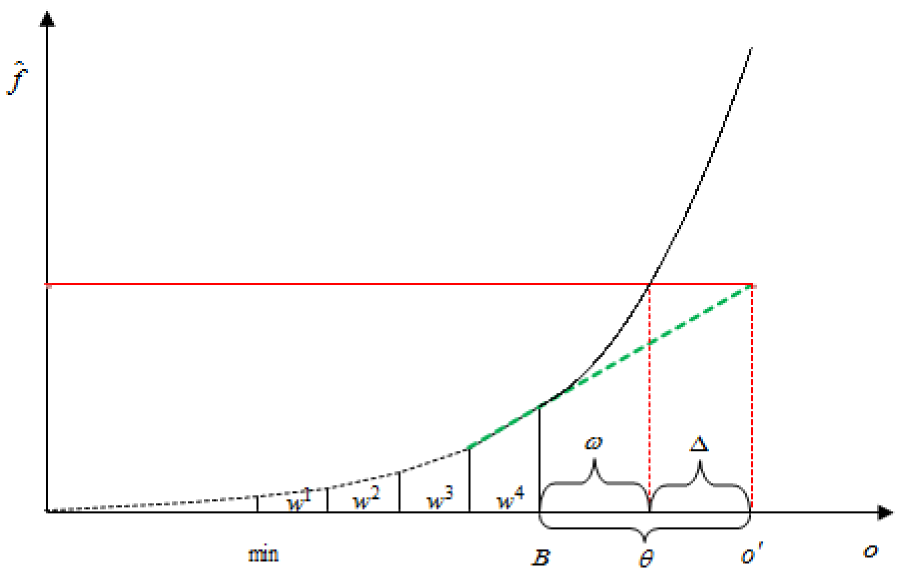


Figure 2. Increasing piecewise linear function

$$\hat{f} - s^{+} \leq B \tag{16}$$

$$b^{|K|-1} w_{|K|} \leq o^{|K|} \leq b^{|K|} w_{|K|} + s^{-} \tag{17}$$

4. Computational Results

The computational results were carried out using FICO Xpress-Mosel optimization software. A total of eight days from August 15 to 22 of the episode were optimized in order to select targeted control strategies and targeted supplemental control strategies for three MINLP models.

4.1 Computational Results of Nonlinear Static Model

In Table 1, the selected control strategy for the static model are shown as follows: X represents that control strategy being selected, X^V represents that only the VOC control was helpful on emission reduction, and X^N indicates that only the NO_x control was helpful on emission reduction. Results show that six control strategies for VOC emissions from on-road sources were selected. Four control strategies for NO_x emissions (control strategy 16-19) from non-road sources were selected. Control strategies for Midlothian Cement Kilns from point sources helped reduce NO_x emissions. The total cost of the selected control strategies and penalty cost is $254.89 billion, and the cost of the selected control strategies over the 8-day episode is $9.57 million. The cost of the selected control strategies is the maximum in the three MINLP models. The same set of control strategies are implemented each day of the episode in order to comply with the maximum allowable ozone concentration in each time period and location. Therefore, the set of control strategies would be implemented exactly the same regardless of the meteorology of the day. This is the reason why the static model yields the most expensive control strategy cost.

Table 1 Nonlinear static optimization model: Selected control strategies.

Control No.	Selected	Control Strategies
1		Bicycle and Pedestrian Programs (NO_x, VOC)
2		Clean Fleet Vehicle Procurement Policy/Clean Fleet Program (NO_x)
3	X^v	Freeway and Arterial Bottleneck Program (NO_x, VOC)
4		Higher Vehicle Occupancies (NO_x, VOC)
5		Idle Reduction Infrastructure (NO_x)
6	X^v	Intelligent Transportation Systems (NO_x, VOC)
7		Additional Taxi Fleet Emission Testing (NO_x)
8	X^v	Traffic Signal Improvement (NO_x, VOC)
9		Transit (NO_x, VOC)
10		Fare-Free Transit, System-Wide on Ozone Action Days (NO_x, VOC)
11		ETR-Vanpool Program (NO_x, VOC)
12	X^v	ETR-Best Workplaces Program (NO_x, VOC)
13	X^v	ETR-Carpooling Programs (NO_x, VOC)
14	X^v	ETR-Transit Subsidy Programs (NO_x, VOC)
15		Freight Rail Infrastructure Improvement (NO_x)

16	X	Emission Reduction Contract Incentives with Public Funding (NO_x)
17	X	Limitation on Idling of Heavy Duty (NO_x)
18	X	Rail Efficiency (NO_x)
19	X	Stationary IC Engines (NO_x)
20		Lawn Mower Replacement Program (VOC)
21		Architectural & Industrial Coatings (VOC)
22		Cold Cleaning Regulations (VOC)
23		Commercial and Consumer Products Requirements (VOC)
24		Fuel Hose Permeation (VOC)
25		Glycol Dehydrators (VOC)
26	X	Brick Kilns (NO_x)
27		ICI Boilers #7 (NO_x)
28		ICI Boilers #9 (NO_x)
29		Lime Kilns (NO_x)
30		Refinery Boilers and Heaters (NO_x)
31		EGU (NO_x)
32	X	Midlothian Cement Kilns (NO_x)

Table 2 Nonlinear static optimization model: Supplemental controls on ozone by day, time period, and county.

Day	Time Period	Counties Requiring Supplemental Control on Ozone
Aug 15	12pm-6am	Johnson & Parker, Tarrant
Aug 16	12pm-6am	Collin, Dallas
Aug 16	6am-12pm	Tarrant
Aug 17	12pm-6am	Dallas
Aug 17	6am-12pm	Denton
Aug 18	12pm-6am	Tarrant
Aug 19	12pm-6am	Johnson & Parker
Aug 19	6am-12pm	Dallas
Aug 20	12pm-6am	Ellis, Johnson & Parker
Aug 20	6am-12pm	Collin, Denton
Aug 21	12pm-6am	Denton
Aug 21	12pm-3pm	Ellis
Aug 22	12pm-6am	Collin, Dallas
Aug 22	6am-12pm	Dallas
Aug 22	3pm-7pm	Ellis

Since the set of 32 control strategies was unable to reduce ozone to comply with the 8-hour ozone standard in the static model, supplemental controls needed to be used. The results of the supplemental control in targeted time periods and locations are shown in Table 2. Most supplementary implementations required further reduction of ozone during the morning busy hours, (12pm-6am and 6-12pm) except Ellis on August 21 and 22. Each day of the episode required at least one supplemental control for reducing ozone. A total of five supplemental controls are applied to Dallas for ozone attainment, which is the largest requirement of the counties. However, Kaufman and Rockwall did not need any supplementary control for ozone attainment. The majority of the supplemental controls are applied in the busy morning hour, which is the same finding for both the linear and nonlinear models. However, the nonlinear model required supplemental control in two time periods (12pm-3pm and 3pm-7pm) in Ellis, which is different from the linear model. Also, the nonlinear model used supplemental controls for five more days than that in the linear model.

4.2 Computational Results of Nonlinear Sequential Model

The set of selected control strategies from the sequential model in each day are shown in Table 3. On August 15, nine control strategies of on-road VOC emission sources and one control strategy of NO_x emission point sources were selected. On August 16, two control strategies for NO_x emission point sources were selected. No control strategies were selected on August 17. On August 18, 14 control strategies of on-road NO_x emission sources, all control strategies of non-road NO_x and VOC emission sources and two control strategies of NO_x emission point sources were selected. On August 19, all 14 control strategies of on-road NO_x and VOC emission sources, all five control strategies of non-road NO_x emission sources, and one control strategy of a NO_x emission point source were selected. On August 20, ten control strategies of on-road VOC emission sources, all five control strategies of non-road sources of NO_x, and two control strategies of NO_x emission point sources were selected. On August 21, all five control strategies of non-road NO_x emission sources and two control strategies of NO_x emissions from point source were selected. Only one control strategy of NO_x emissions from a point source was selected on August 22. From the results, we found that on-road control strategies were more effective at reducing ozone than non-road control strategies. Point emissions from Brick Kilns, ICI Boilers #9, and Refinery Boilers and Heaters were helpful in reducing NO_x emissions throughout the episode. The total cost of the selected control strategies and penalty cost is $255.1 billion, and the total the cost for selected control strategies is $2.73 million.

Table 3 Nonlinear sequential optimization model: Selected control strategies by day.

Control No.	Sun Aug 15	Mon Aug 16	Tue Aug 17	Wed Aug 18	Thu Aug 19	Fri Aug 20	Sat Aug 21	Sun Aug 22	Control Strategies
1	X^V			X^N	X	X^V			Bicycle/Pedestrian Programs (NO_x, VOC)
2				X	X				Clean Fleet Vehicle Procurement Policy/Clean Fleet Program (NO_x)
3	X^V			X^N	X	X^V			Freeway/Arterial Bottleneck (NO_x, VOC)
4	X^V			X^N	X	X^V			Higher Vehicle Occupancies (NO_x, VOC)
5				X	X				Idle Reduction Infrastructure (NO_x)
6	X^V			X^N	X	X^V			Intelligent Transportation Sys (NO_x, VOC)
7				X	X				Additional Taxi Fleet Emission Testing (NO_x)
8	X^V			X^N	X	X^V			Traffic Signal Improvement (NO_x, VOC)
9	X^V			X^N	X	X^V			Transit (NO_x, VOC)
10	X^V			X^N	X				Fare-Free Transit, System-Wide on Ozone Action Days (NO_x, VOC)
11				X^N	X	X^V			ETR-Vanpool Program (NO_x, VOC)
12	X^V			X^N	X	X^V			ETR-Best Workplaces (NO_x, VOC)
13				X^N	X	X^V			ETR-Carpooling Programs (NO_x, VOC)

14	X^{V}			X^{N}	X	X^{V}			ETR-Transit Subsidy (NO_x, VOC)
15				X	X	X	X		Freight Rail Infrastructure Improvement (NO_x)
16				X	X	X	X		Emission Reduction Contract Incentives with Public Funding (NO_x)
17				X	X	X	X		Limitation on Idling of Heavy Duty (NO_x)
18				X	X	X	X		Rail Efficiency (NO_x)
19				X	X	X	X		Stationary IC Engines (NO_x)
20				X					Lawn Mower Replacement (VOC)
21				X					Architectural & Industrial Coatings (VOC)
22				X					Cold Cleaning Regulations (VOC)
23				X					Commercial and Consumer Products Requirements (VOC)
24				X					Fuel Hose Permeation (VOC)
25				X					Glycol Dehydrators (VOC)
26				X			X	X	Brick Kilns (NO_x)
27	X								ICI Boilers #7 (NO_x)
28		X			X	X			ICI Boilers #9 (NO_x)
29									Lime Kilns (NO_x)
30						X	X		Refinery Boilers and Heaters (NO_x)
31				X					EGU (NO_x)
32		X							Midlothian Cement Kilns (NO_x)

The set of 32 control strategies was unable to reduce ozone to comply with the 8-hour ozone standard in the sequential model. Therefore, supplemental controls need to be considered in the optimization. The results of the supplemental control in targeted time periods and locations are shown in Table 4. Supplemental control was required throughout the episode from August 15 to 22. Most supplemental controls required further reduction on ozone during the morning busy hours (12pm-6am and 6am-12pm). Dallas required the most supplemental control for controlling ozone concentration. However, Kaufman and Rockwall did not need any supplementary control to further reduce ozone. This result is very similar to that of the static model. The only slight change was in Tarrant, which time period 6am-12pm was removed while the time period 12pm-6am was added. The dissimilarities between the linear and nonlinear model are two supplemental controls applied after 12 noon in Ellis and five more supplemental controls are required in the nonlinear model for further reduction of ozone.

Table 4 Nonlinear sequential optimization model: Supplemental controls on ozone by day, time period, and county.

Day	Time Period	Counties Requiring Supplemental Control on Ozone
Aug 15	12pm-6am	Johnson & Parker, Tarrant
Aug 16	12pm-6am	Collin, Dallas
Aug 17	12pm-6am	Dallas
Aug 17	6am-12pm	Denton
Aug 18	12pm-6am	Tarrant
Aug 19	12pm-6am	Denton, Johnson & Parker
Aug 19	6am-12pm	Dallas
Aug 20	12pm-6am	Ellis, Johnson & Parker
Aug 20	6am-12pm	Collin, Denton

Aug 21	12pm-6am	Denton
Aug 21	12pm-3pm	Ellis
Aug 22	12pm-6am	Collin, Dallas, Tarrant
Aug 22	6am-12pm	Dallas
Aug 22	3pm-7pm	Ellis

4.3 Computational Results of Nonlinear Dynamic Model

Table 5 depicts the set of selected control strategies from the dynamic model. On August 15, eight control strategies of on-road VOC emission sources and two control strategies of NO_x emission point sources were selected. On August 16, only one control strategy of NO_x emissions from a point source was selected. On August 17, three control strategies of NO_x emissions from point sources were selected. On August 18, 14 control strategies of on-road NO_x emission sources, all of the control strategies of non-road NO_x and VOC sources, and two control strategies of NO_x emissions from point sources were selected. On August 19, four control strategies of non-road sources from NO_x emissions and one control strategy for NO_x emissions from a point source were selected. On August 20, ten control strategies for on-road NO_x and VOC emission sources, all five control strategies of non-road NO_x emission sources, and three control strategies of NO_x emissions from point sources were selected. On August 21, five control strategies of non-road sources from NO_x emissions, and four control strategies of NO_x emissions from point sources were selected. On August 22, only one control strategy of NO_x emissions from point sources was selected. From the results, we found that on-road control strategies were helpful in reducing ozone on August 15, 18, and 20. Non-road control strategies were helpful in reducing ozone on August 18, 19, 20, and 21. Furthermore, non-road control strategies of NO_x emissions were more helpful in reducing ozone than VOC emissions in these four days. Point sources from Brick Kilns, Refinery Boilers and Heaters, and Midlothian Cement Kilns were more helpful on NO_x emission reduction than other point sources throughout the episode. The total cost of the selected control strategies and estimated penalty cost is $254.3 billion, which is the minimum total cost of the three models. This result is consistent with the linear models in which the dynamic linear model yields the least total estimated cost among the three linear models. Considering that the dynamic models allow different implementations of control strategies in each day of the episode, initial conditions of the previous day's ozone can be manipulated, and optimization is in a single general model, the dynamic models have greater capability to reduce the ozone concentration in order to satisfy constraints. This is the reason why the dynamic models yield the minimum estimated total cost of the selected control strategies and the supplemental controls. The estimated cost for selected control strategies is $2.20 million.

Table.5 Nonlinear dynamic optimization model: Selected control strategies by day.

Control No.	Sun Aug 15	Mon Aug 16	Tue Aug 17	Wed Aug 18	Thu Aug 19	Fri Aug 20	Sat Aug 21	Sun Aug 22	Control Strategies
1				X^N		X			Bicycle/Pedestrian Programs (NO_x, VOC)
2				X					Clean Fleet Vehicle Procurement Policy/Clean Fleet Program (NO_x)

3	X^V			X^N		X			Freeway/Arterial Bottleneck (NO_x, VOC)
4	X^V			X^N		X			Higher Vehicle Occupancies (NO_x, VOC)
5				X					Idle Reduction Infrastructure (NO_x)
6	X^V			X^N		X			Intelligent Transportation Sys (NO_x, VOC)
7				X					Additional Taxi Fleet Emission Testing (NO_x)
8	X^V			X^N		X			Traffic Signal Improvement (NO_x, VOC)
9	X^V			X^N		X			Transit (NO_x, VOC)
10	X^V			X^N					Fare-Free Transit, System-Wide on Ozone Action Days (NO_x, VOC)
11				X^N		X			ETR-Vanpool Program (NO_x, VOC)
12	X^V			X^N		X			ETR-Best Workplaces (NO_x, VOC)
13				X^N		X			ETR-Carpooling Programs (NO_x, VOC)
14	X^V			X^N		X			ETR-Transit Subsidy (NO_x, VOC)
15				X		X	X		Freight Rail Infrastructure Improvement (NO_x)
16				X	X	X	X		Emission Reduction Contract Incentives with Public Funding (NO_x)
17				X	X	X	X		Limitation on Idling of Heavy Duty (NO_x)
18				X	X	X	X		Rail Efficiency (NO_x)
19				X	X	X	X		Stationary IC Engines (NO_x)
20				X					Lawn Mower Replacement (VOC)
21				X					Architectural & Industrial Coatings (VOC)
22				X					Cold Cleaning Regulations (VOC)
23				X					Commercial and Consumer Products Requirements (VOC)
24				X					Fuel Hose Permeation (VOC)
25				X					Glycol Dehydrators (VOC)
26			X	X			X	X	Brick Kilns (NO_x)
27	X								ICI Boilers #7 (NO_x)
28					X	X			ICI Boilers #9 (NO_x)
29			X				X		Lime Kilns (NO_x)
30	X					X	X		Refinery Boilers and Heaters (NO_x)
31				X			X		EGU (NO_x)
32		X	X			X			Midlothian Cement Kilns (NO_x)

Supplemental controls need to be considered in the optimization since the set of 32 controls was unable to reduce ozone to comply with the 8-hour ozone standard. The results of the supplemental controls in targeted time periods and locations are shown in Table 6. Most supplemental controls occurred during the morning busy hours (12pm-6am and 6pm-12pm). Denton and Dallas used supplemental controls during four time periods to reduce ozone further, which were the most of all of the counties. Kaufman and Rockwall did not need any supplementary control for ozone attainment. The resulting supplemental control strategies are very similar to those of the sequential model. The slight difference was that the dynamic model used one fewer supplemental control during the time period (12pm-6am) in each of Collin and Dallas. The nonlinear dynamic model required that three more time periods use the supplemental controls for reducing ozone than in linear dynamic model used.

Table 6 Nonlinear dynamic optimization model: Supplemental controls on ozone by day, time period, and county.

Day	Time Period	Counties Requiring Supplemental Control on Ozone
Aug 15	12pm-6am	Johnson & Parker, Tarrant

Aug 16	12pm-6am	Collin, Dallas
Aug 17	12pm-6am	Dallas
Aug 17	6am-12pm	Denton
Aug 18	12pm-6am	Tarrant
Aug 19	12pm-6am	Johnson & Parker
Aug 19	6am-12pm	Dallas
Aug 20	12pm-6am	Ellis, Johnson & Parker
Aug 20	6am-12pm	Collin, Denton
Aug 21	12pm-6am	Denton
Aug 21	12pm-3pm	Ellis
Aug 22	12pm-6am	Tarrant
Aug 22	6am-12pm	Dallas
Aug 22	3pm-7pm	Ellis

4.4 Differences between Linear and Nonlinear Models

Predicting hourly ground-level ozone concentration is a very important task for the ozone control strategy optimization. It not only accounts for the nonlinear relationship between pollutant and its precursors but also improves the accuracy of the statistical prediction model. This research addresses this need by building nonlinear statistical models to represent the hourly ozone concentration in different time periods and regions. Then we study three MINLP models to obtain three different sets of optimal control strategies. Furthermore, three supplemental control strategies are introduced into the optimization models since the DFW case study was infeasible. These models can provide decision-makers information on how the best set of control strategies changes under different scenarios. The selection of the supplemental controls also specifies the most critical time periods and regions that require further reductions either on ozone concentration or emissions. In this remainder of this section, we discuss the differences in the solutions when optimizing with the linear prediction models versus the nonlinear prediction models.

Table 7 compares the solutions found using the linear and nonlinear static optimization models. The same control strategies for on-road and non-road emissions were selected by both models. For point source emissions, one control strategy was different between the two models.

Table 7 Selected control strategy comparison of static linear and nonlinear models.

	On-road emissions		Non-road emissions		Point emissions
	NO_x control strategies	VOC control strategies	NO_x control strategies	VOC control strategies	NO_x control strategies
Linear model	None	3,6,812,13,14	16,17,18,19	None	26,31
Nonlinear model	None	3,6,812,13,14	16,17,18,19	None	26,32

Table 8 shows the solutions for the sequential optimization models, and the two solutions were very similar on all but one day during the horizon. The same control strategies were selected on August 17, 18, 19, and 20 by both the linear and nonlinear models. On August 15, the nonlinear model selected one fewer point source emission control strategy than the linear model selected. By contrast, on August 16 and 22, the nonlinear model used one more point source emission control strategy than the linear model used. However, on August 21, the two solutions were quite different. Specifically, the nonlinear model chose five non-road NO_x control strategies, while the linear model selected none; and while both models used two point source control strategies, they chose different ones.

Table 8 Selected control strategy comparison of sequential linear and nonlinear models.

		On-road emissions		Non-road emissions		Point emissions
		NO_x control strategies	VOC control strategies	NO_x control strategies	VOC control strategies	NO_x control strategies
Aug 15	Linear model	None	1,3,4,6,8,9,10,12,14	None	None	27,30
	Nonlinear model	None	1,3,4,6,8,9,10,12,14	None	None	27
Aug 16	Linear model	None	None	None	None	32
	Nonlinear model	None	None	None	None	28,32
Aug 17	Linear model	None	None	None	None	None
	Nonlinear model	None	None	None	None	None
Aug 18	Linear model	1,2,3,4,5,6,7,8,9,10,11,12,13,14	None	15,16,17,18, 19	20,21,22,23,24,25	31
	Nonlinear model	1,2,3,4,5,6,7,8,9,10,11,12,13,14	None	15,16,17,18, 19	20,21,22,23,24,25	31
Aug 19	Linear model	1,2,3,4,5,6,7,8,9,10,11,12,13,14	1,3,4,6,8,9,10,11,12,13,14	15,16,17,18, 19	None	28
	Nonlinear model	1,2,3,4,5,6,7,8,9,10,11,12,13,14	1,3,4,6,8,9,10,11,12,13,14	15,16,17,18, 19	None	28
Aug 20	Linear model	None	1,3,4,6,8,9,11,12,13,14	15,16,17,18, 19	None	28,30
	Nonlinear model	None	1,3,4,6,8,9,11,12,13,14	16,17,18,19	None	28,30
Aug 21	Linear model	None	None	None	None	27,28
	Nonlinear model	None	3,6,812,13,14	None	None	26,32
Aug 22	Linear model	None	None	None	None	None
	Nonlinear model	None	None	None	None	26

Table 9 shows the differences in the solutions from the dynamic models. No control strategies were selected on August 17 by either the linear and nonlinear models. One additional on-road

VOC control strategy was selected by the linear model on August 15. By contrast, one additional point source control strategy was selected by the nonlinear model on August 16. Three more point source control strategies were used by the nonlinear model on August 18. One non-road NO_x control strategy was removed by the linear model on August 19. An additional ten on-road NO_x control strategies were selected by the nonlinear model, and one fewer point source control strategy was selected by the nonlinear model on August 20. As in the sequential model results, there were significant differences in the solutions of the models on August 21. Specifically, the linear model selected nine on-road NO_x control strategies and seven on-road VOC control strategies, while the nonlinear model used five non-road control strategies of NO_x emissions and one additional point source control strategy. Finally, one point source control strategy was selected by the nonlinear model on August 22, but not by the linear model.

Table 9 Selected control strategy comparison of dynamic linear and nonlinear models.

		On-road emissions		Non-road emissions		Point emissions
		NO_x control strategies	VOC control strategies	NO_x control strategies	VOC control strategies	NO_x control strategies
Aug 15	Linear model	None	1,3,4,6,8,9,10,12,14	None	None	27,30
	Nonlinear model	None	3,4,6,8,9,10,12,14	None	None	27
Aug 16	Linear model	None	None	None	None	32
	Nonlinear model	None	None	None	None	28,32
Aug 17	Linear model	None	None	None	None	None
	Nonlinear model	None	None	None	None	None
Aug 18	Linear model	1,2,3,4,5,6,7,8,9,10,11,12,13,14	None	15,16,17,18, 19	20,21,22,23,24,25	26,27,28,30,31
	Nonlinear model	1,2,3,4,5,6,7,8,9,10,11,12,13,14	None	15,16,17,18, 19	20,21,22,23,24,25	26,31
Aug 19	Linear model	1,2,3,4,5,6,7,8,9,10,11,12,13,14	None	15,16,17,18, 19	None	28
	Nonlinear model	1,2,3,4,5,6,7,8,9,10,11,12,13,14	None	16,17,18, 19	None	28
Aug 20	Linear model	None	1,3,4,6,8,9,11,12,13,14	15,16,17,18, 19	None	27,28,30,31
	Nonlinear model	1,3,4,6,8,9,11,12,13,14	1,3,4,6,8,9,11,12,13,14	16,17,18,19	None	28,30,32
Aug 21	Linear model	1,2,3,5,6,8,12,13,14	1,3,6,812,13,14	None	None	27,29,30
	Nonlinear model	None	None	15,16,17,18,19	None	26,29,30,31
Aug 22	Linear model	None	None	None	None	None
	Nonlinear model	None	None	None	None	26

To determine the cost effectiveness between the MINLP models and the MILP models in Hsu [30], we fixed the targeted control strategies of the MILP in the MINLP and resolved it to determine the emissions, ozone, and costs in the nonlinear objective function. The total cost of the targeted control strategies and supplemental control strategies of three MINLP models are less than the MINLP models fixed with MILP solutions, which indicates that the selection of the control strategies of the nonlinear models are more effective than the linear models (see table 10, 11, and 12). Moreover, the costs of the selected control strategies of the three MINLP models are surprisingly more than those of the linear solutions. Therefore, the three MINLP models are able to select targeted control strategies that are a little more expensive but reduce the need for excessive supplemental reduction of emissions and ozone.

Table 10 Cost comparison of dynamic optimization models.

Optimization Model	Total cost $ 10^{11}$	Cost of selected controls $\$10^6$	Penalty cost of s_{lt}^{+} $\$10^{11}$	Penalty cost of s_{lt}^{-} $\$10^{10}$	Penalty cost of y_{ijd} $\$10^9$
MINLP	2.54315	2.20188	2.28183	2.43214	1.80903
MINLP with Linear Solutions	2.54382	1.74548	2.28271	2.43586	1.75044

Table 11 Cost comparison of sequential optimization models.

Optimization Model	Total cost $ 10^{11}$	Cost of selected controls $\$10^6$	Penalty cost of s_{lt}^{+} $\$10^{11}$	Penalty cost of s_{lt}^{-} $\$10^{10}$	Penalty cost of y_{ijd} $\$10^9$
MINLP	2.55076	2.73270	2.30156	2.32085	1.70906
MINLP with Linear Solutions	2.55162	2.62037	2.30278	2.32327	1.64827

Table 12 Cost comparison of Static optimization models.

Optimization Model	Total cost $ 10^{11}$	Cost of selected controls $\$10^6$	Penalty cost of s_{lt}^{+} $\$10^{11}$	Penalty cost of s_{lt}^{-} $\$10^{10}$	Penalty cost of y_{ijd} $\$10^9$
MINLP	2.54886	9.57482	2.28442	2.43718	2.06300
MINLP with Linear Solutions	2.54911	7.30154	2.28394	2.43816	2.12799

5. CONCLUSIONS AND FUTURE RESEARCH

In this research, we presented three nonlinear models for selecting ground-level ozone control strategies in order to more accurately capture the nonlinear relationships between precursors and pollutants. We showed that the MINLP models are superior to MILP models in Hsu [30] in terms of cost effectiveness. Some possible directions for future research based on the results of this study include the following. In this research, no interaction terms were considered to predict ozone concentration in the statistical models. However, interactions between NO_x and VOC emissions could potentially be important in accurately predicting ozone and could be considered in the future refinement of the statistical models in this research. Piecewise linear approximations were used to approximate nonlinear functions resulting from the refinement of the statistical models conducted to better satisfy regression model assumptions. In this research, four equally spaced linear segments were created for each transformed response variable and each transformed predictor variable. It could be beneficial to create unequally spaced linear segments of piecewise linear approximations for each nonlinear transformation so as to obtain a more precise approximation for the transformed response or predictor variables. Moreover, the piecewise linear function could yield a better approximation by increasing the number of the segments.

Reference

[1] Environment Protection Agency (EPA). (2011a). Pollutants in the Ambient Air. http://www.epa.gov/apti/course422/ap2.html. Accessed 25 November 2011.

[2] Environment Protection Agency (EPA). (2011b). Health and Environment. http://www.epa.gov/air/ozonepollution/health.html. Accessed 25 November 2011.

[3] Environment Protection Agency (EPA). (2011c). Air Quality Trends. Retrieved November 25, 2011, from http://www.epa.gov/airtrends/aqtrends.html.

[4] Sillman S. (1995). “The use of NOy, H2O2, and HNO3 as indicators for ozone-NOx-hydrocarbon sensitivity in urban locations.” Journal of Geophysical Research, vol. 100, pp. 14175-14188.

[5] Environment Protection Agency (EPA). (2011d). Technology Transfer Network-NAAQS. Retrieved November 25, 2011, from http://www.epa.gov/ttn/naaqs.

[6] North Central Texas Council of Governments (NCTCOG). (2011a). Ozone Emission Sources. http://www.nctcog.org/trans/air/ozone/sources.asp. Accessed 25 November 2011.

[7] Hubbard, Milton C.and Cobourn, W.Geoffrey (1998). Development of a regression model to forecast ground-level ozone concentration in Louisville, KY. *Atmospheric Environment*, 32(14), 2637-2647.

[8] Abdul-Wahab, S.A., Bakheit, C.S., Al-Alawi, S.M. (2005). Principal component and multiple regression analysis in modelling of ground-level ozone and factors affecting its concentrations. *Environmental Modelling & Software*, 20(10), 1263-1271

[9] Barrero, M.A., Grimalt, J.O., Canton, L., (2006). Prediction of daily ozone concentration maxima in the urban atmosphere. *Chemometrics and Intelligent Laboratory Systems*, 80(1), 67-76.

[10] Pires, J., Martins, F., Sousa, S., Alvim-Ferraz, M., Pereira, M. (2008). Selection and validation of parameters in multiple linear and principal component regressions. *Environmental Modelling and Software*, 23(1), 50-55.

[11] Spellman, Greg (1999). “An application of artificial neural networks to the prediction of surface ozone concentrations in the United Kingdom.” Applied Geography, vol. 19, no. 2, pp. 123-136.

[12] Heo, Jeong-Sook, Kim, Dong-Sool (2004). “A new method of ozone forecasting using fuzzy expert and neural network systems.” Science of The Total Environment, vol. 325, no. 1-3, pp. 221-237.

[13] Sousa, S.I.V., Martins, F.G., Alvim-Ferraz, M.C.M., Pereira, M.C. (2007). "Multiple linear regression and artificial neural networks based on principal components to predict ozone concentrations" Environmental Modelling & Software, vol.e 22, no. 1, pp. 97-103.

[14] Cai, Ming, Yin, Yafeng, Xie, Min (2009). "Prediction of hourly air pollutant concentrations near urban arterials using artificial neural network approach." Transportation Research Part D: Transport and Environment, vol. 14, no. 1, pp. 32-41.

[15] Mintz R., Young B. R., and Svrcek W. Y. (2005). Fuzzy logic modeling of surface ozone concentrations, Computers & Chemical Engineering, Vol. 29, Issue 10, pp. 2049-2059.

[16] Nebot A., Mugica V., and Escobet A. (2008). Ozone prediction based on meteorological variables: a fuzzy inductive reasoning approach, Atmospheric Chemistry and Physics Discussions, Vol. 8, pp 12343–12370.

[17] Domanska D., Wojtylak M. 2012 (2012). Application of fuzzy time series models for forecasting pollution concentrations, Expert Systems with Applications, Vol. 39, Issue 9, pp. 7673-7679.

[18] Davis, J.M. and Speckman, P. (1999). A model for predicting maximum and 8-hr average ozone in Houston. Atmospheric Environment, Vol. 33, pp. 2487-2500.

[19] Schlink, U., Herbarth, O., Richter, M., Dorling, S., Nunnari, G., Gawley, G., Pelikan, E., (2006). Statistical models to assess the health effects and to forecast ground level ozone. Environmental Modelling and Software, Vol. 21, pp. 547-558.

[20] Francisco-Fernandez M., Quintela-del-Rio A., Fernandez-Casal R. (2012). Nonparametric methods for spatial regression. An application to seismic events. Environmetrics, Vol. 23, pp. 85-93.

[21] Cohan, Daniel S., Boylan, James W., Marmur, Amit, Khan, Maudood N. (2007). An Integrated Framework for Multipollutant Air Quality Management and Its Application in Georgia. *Environmental Management*, 40, 545–554.

[22] Bordignon S., Gaetan C. and Lisi F. (2002). Nonlinear models for ground-level ozone forecasting. Statistical Methods and Applications, Vol. 11, p. 227-246

[23] Gao, H. Oliver, Niemeier, Debbie A. (2008). Using functional data analysis of diurnal ozone and NOx cycles to inform transportation emissions control. *Transportation Research Part D*: Transport and Environment, 13(4), 221-238.

[24] Guariso, Giorgio, Pirovano, Guido, Volta, Marialuisa (2004). Multi-objective analysis of ground-level ozone concentration control. *Journal of Environmental Management*, 71(1), 25-33.

[25] Sanhueza, Pedro A., Reed, Gregory D., Davis, Wayne T., and Miller, Terry L. (2003). An Environmental Decision-Making Tool for Evaluating Ground-Level Ozone-Related Health Effects. *Journal of the Air & Waste Management Association*, 53(12), 1448-1459.

[26] Schopp, W., Amann, M., Cofala, J., Heyes, C., Klimont, Z. (1999). Integrated assessment of European air pollution emission control strategies. *Environmental Modelling and Software*, 14, 1-9.

[27] Sule, Neelesh V., Chen, Victoria and Sattler, Melanie (2011). A decision making framework for assessing control strategies for ground level ozone. *Atmospheric Environment*, 45, 4996-5004.

[28] Yang, Z., V. C. P. Chen, M. E. Chang, T. E. Murphy, and J. C. C. Tsai (2007). Mining and Modeling for a Metropolitan Atlanta Ozone Pollution Decision-Making Framework. *IIE Transactions, Special Issue on Data Mining*, 39(6), 607-615.

[29] Yang, Z., V. C. P. Chen, M. E. Chang, M. L. Sattler, and A. Wen (2009). A Decision-Making Framework for Ozone Pollution Control. *Operations Research*, 57(2), 484-498.

[30] Hsu, Wei-Che, Rosenberger, Jay M., Sule, Neelesh V., Sattler, Melanie L., and Chen, Victoria C.P. (2012). Mixed Integer Linear Programming Models for Selecting Ground-Level Ozone Control Strategies. COSMOS Technical Report 12-03. The University of Texas at Arlington. Arlington, TX.

[31] Nemhauser, George L. and Wolsey, Laurence A. (1988). Integer and combinatorial optimization, Wiley-Interscience Series in Discrete Mathematics and Optimization. New York, ISBN 0-471-82819-X.