MIXED INTEGER PROGRAMMING MODELS FOR SELECTING GROUND-LEVEL OZONE CONTROL STRATEGIES

by

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ABSTRACT

MIXED INTEGER PROGRAMMING MODELS FOR SELECTING GROUND-LEVEL OZONE CONTROL STRATEGIES

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Under the Clean Air Act (CAA) in 1990, the U.S Environmental Protection Agency (EPA) was required to set National Ambient Air Quality Standards (NAAQS) for six common air pollutants that are considered harmful to public health and the environment. Ground-level ozone was one of the six criteria pollutants monitored by the EPA and considered the most widespread health threat. Two precursors of ground level ozone are nitrogen oxides (NO_x) and volatile organic compounds (VOC) and the common sources of these two precursors include on-road vehicles, non-road engines, area sources, point sources, and biogenic and miscellaneous sources. An area where air pollution levels cannot meet the NAAQS persistently is designated as a "Nonattainment area". A State Implementation Plan (SIP) describes how a state will reduce the emissions of pollutants to satisfy air quality standards in a timely manner. Recently, ozone standards have been revised from a 1-hour to an 8-hour standard by strengthening the threshold from 125 ppb for the previous standard to 85 ppb for the new standard. Due to SIP revision, a total of nine counties are designated as non-attainment for 8-hour ozone standard in the Dallas-Fort Worth (DFW) area, which differed from the original four counties in the earlier 1-hour standard.

The main aim of this research is to study both linear and nonlinear mixed integer programming (MIP) models that seek to select targeted control strategies for the DFW region to reduce emissions, so as to achieve SIP requirements with minimum cost. The list of control strategies, along with the emission reduction and cost for each control strategy was obtained from the Texas Commission on Environmental Quality (TCEQ) and the North Central Texas Council of Governments (NCTCOG). Statistics, data mining, and optimization methods are used to determine a potential set of cost-effective control strategies for reducing ozone. These targeted control strategies are specified by different types of emission sources in various time periods and locations. Three MIP models, a static model, a sequential model, and a dynamic model are studied as both linear and nonlinear models. These different MIP models allow decision-makers to study how the targeted control strategies change under different circumstances. Two types of auxiliary variables are considered as supplemental control strategies in the optimization if the current set of control strategies is unable to reduce ozone to comply with the 8-hour ozone standard. Results from the different models can provide decision-makers with information on how the effectiveness of the control strategies vary with daily emission patterns and meteorology.

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CHAPTER 1

INTRODUCTION

1.1 Background of Ground-Level Ozone

Air is one of the most essential ingredients required for the existence of most life forms. Air is principally composed of nitrogen, oxygen, and argon, which together constitute the major gases of the atmosphere. The remaining gases include water vapor, carbon dioxide, methane, nitrous oxide, and ozone (EPA, 2010a). Today, air in all around the world so as in the States has been polluted. The main causes of air pollution are the industrialization of society, the growth of the population, the introduction of vehicles, and the explosion of the population. These changes in our life are unavoidable factors contributing toward the increasing air pollution problem that can be harmful to humans, plants, animals and property (EPA, 2010b).

Because of the air pollution problem, in 1990 the Clean Air Act (CAA) required the U.S Environmental Protection Agency (EPA) to set National Ambient Air Quality Standards (NAAQS) for six common air pollutants for pollutants considered harmful to public health and the environment. They are particulate matter (PM_{10} & $PM_{2.5}$), ground-level ozone (O_3), carbon monoxide (CO), sulfur oxides (SO_2), nitrogen dioxides (NO_2), and lead (Pb) (EPA, 2010c). These common air pollutants are found all over the United States. These pollutants can affect human health problem, threaten the environment, and cause property damage. Therefore, the EPA called these pollutants “criteria” air pollutants. The CAA also regulated two types of national air quality standards. The set of limits based on public health protection including the health of "sensitive" populations such as asthmatics, children, and the elderly is called primary standards. The other set of limits based on public welfare protection, including protection against decreased visibility, damage to animals, crops, vegetation, and buildings is call secondary standards (EPA, 2010d).

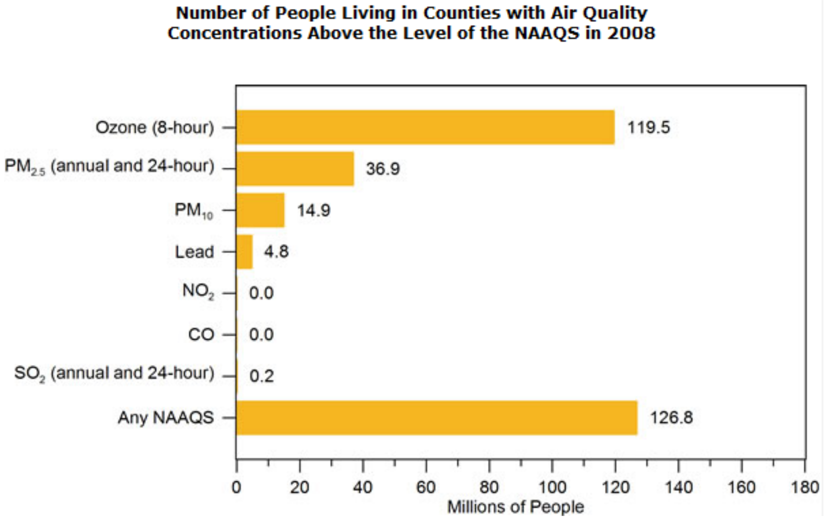


Figure 1.1 Number of people living in counties with air quality concentrations above the level of the primary National Ambient Air Quality Standards in 2008 (EPA, 2010e).

Figure 1.1 shows the number of people living in counties with air quality concentrations exceeding the primary National Ambient Air Quality Standards (NAAQS). There are more than 126.8 million people lived in counties that exceed national air quality standards for six criteria pollutants. Ground-level ozone and fine particle pollution ($PM_{2.5}$) continue to present challenges in many areas of the country. In 2008, about 119.5 million and 36.9 million people lived in counties that exceeded national air quality standards for ozone and $PM_{2.5}$, respectively. In recent years, the US government has acted to significantly improve America's air quality by designing, developing, and implementing national programs so as to reduce air emissions. For example, in 2009, ozone concentrations were 30 percent lower than in 1990 base on annual 4th maximum 8-hour average, and annual $PM_{2.5}$ concentrations were 27 percent lower than in the year 2000 based on seasonally–weighted annual average (EPA, 2010e). The air quality has improved; more importantly, air quality benefits lead to improved human health, plant, and living environment for all Americans. However, the more stringent air quality standards have been made to reduce further pollutions in our life.

A *nonattainment area* is an area where air pollution levels cannot meet the NAAQS persistently, or that leads to ambient air quality in a nearby area that fails to meet standards defined by the Clean Air Act and Amendments of 1990. The EPA normally identifies a nonattainment area only after air quality standards have been exceeded for several consecutive years (EPA, 2010f).

To improve air quality and reduce air pollution is the ultimate goal for each state to comply with the NAAQS for the criteria pollutants in order to be in attainment status. The federal CAA requires states with counties failing to meet national ambient air quality standards to develop a State Implementation Plan (SIP). An SIP is an enforceable plan developed by the state government that explains how the state will reduce the emissions of the pollutants in a timely manner so as to bring the area in attainment to meet the NAAQS (TCEQ, 2010a).

Of the six criteria pollutants, particle pollution and ground-level ozone are the most widespread health threats. Ozone (O_3) is a gas composed of three oxygen atoms. It is not emitted into the air directly. In fact, ground-level ozone is formed by a complex series chemical reaction mainly from oxides of nitrogen (NO_x) and volatile organic compounds (VOC) in the presence of sunlight and heat (Sillman et al., 1995). As sunlight is one of the main catalysts for ozone formation, ozone is also called the “summertime air pollutant” (EPA, 2010g). Ozone is a gas that is formed in the atmosphere when three atoms of oxygen combine. Naturally occurring ozone is found high in the stratosphere surrounding the earth and in ground-level ambient air.

Ozone forms high in the stratosphere popularly called "good ozone." Intense sunlight causes oxygen molecules (O_2) to break up and reform as ozone molecules (O_3). Stratospheric ozone shields people, trees, crops, property, and microorganisms from the harmful effects of the sun's ultraviolet rays. In contrast of stratospheric ozone, ground level ozone is regularly referred to as “bad ozone.” It can cause health problems associated with eyes and the respiratory system and also inhibit plant growth and damage crops and forests.

NO_x is produced as a by-product of high-temperature combustion. The common sources of NO_x include: automobiles, trucks, and marine vessels, construction equipment, power generation, industrial processes, and natural gas furnaces (NCTCOG, 2010a). The major source of VOCs included organic chemicals that vaporize easily, such as those found in gasoline and solvents. They are emitted from many sources, for example: gasoline stations, motor vehicles, airplanes, trains, boats, petroleum storage tanks, and oil refineries. Biogenic or natural emissions from trees and plants are also a major source of VOCs.

Ozone leads to a variety of health problems, including chest pain, coughing, throat irritation, and congestion. It can worsen bronchitis, emphysema, and asthma. Ground-level ozone also can reduce lung function and inflame the linings of the lungs. Repeated exposure may permanently scar lung tissue. Ground-level ozone also damages vegetation and ecosystems (EPA, 2010b).

1.2 Background of Ozone Nonattainment in Dallas/Fort Worth Area

The implementation of the 1-hour ozone standard began in 1990. The ozone threshold value of the 1-hour ozone standard was 125 parts per billion (ppb) and measured by the 1-hour average concentration. An area met this ozone NAAQS if there were no more than three exceedances at any one monitor in the region in a three year period. Four counties in the Dallas-Fort Worth (DFW) region were designated as nonattainment for the 1-hour ozone standard in 1991. Those counties were Collin, Dallas, Denton, and Tarrant (see Figure 1.2). In September 1994, the Texas Commission on Environmental Quality (TCEQ) submitted to the EPA an attainment demonstration SIP revision focused on controlling VOC emissions. The DFW area failed to comply with the 1-hour ozone standard by the November 15, 1996 attainment deadline. The EPA reclassified the four-county area as serious nonattainment on February 18, 1998, and a new deadline, November 15, 1999, was required to demonstrate attainment. In April 2000, the TCEQ adopted a full attainment demonstration including rules to attain the 1-hour standard. That SIP revision considered the importance of local reductions for NO_x emission and the transport of ozone and its precursors (NO_x and VOC) from the Houston-Galveston-Brazoria (HGB) area. The results from the photochemical modeling demonstration showed ozone and precursors transported from HGB affected the DFW area ozone concentrations.

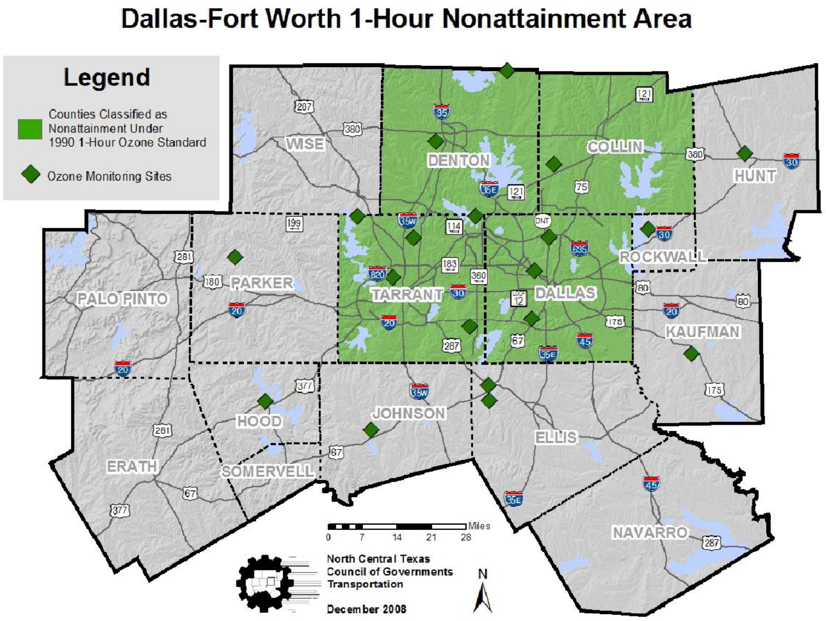
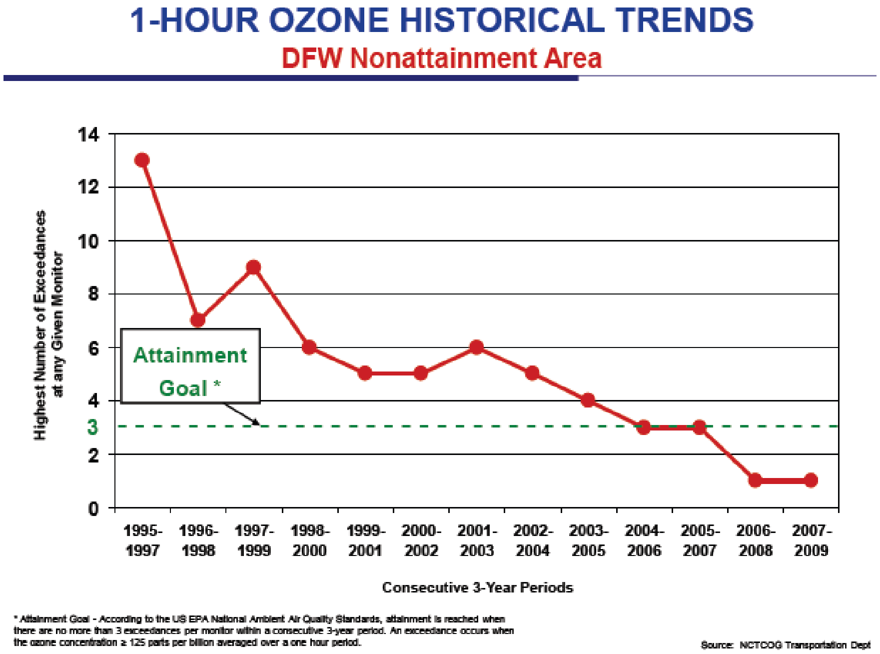


Figure 1.2 Dallas-Fort Worth 1-hour nonattainment area (NCTCOG, 2010b).

In 2006, the control strategies in the 1-hour SIP had improved the ozone pollution in the DFW area, with an 11.4 % decrease in the design value, and also the number of days of exceedances of the 1-hour ozone standard decreased to three which met the ozone NAAQS (see Figure 1.3). The 1-hour design value for the DFW area was 124 ppb, which meant that DFW had come into attainment with the 1-hour standard. On October 16, 2008, the EPA determined that the DFW four-county 1-hour ozone area had attained the 1-hour NAAQS based on verified 2004–2006 monitoring data, further supported by data from 2007 and 2008 (TCEQ, 2010b).



* Attainment Goal - According to the US EPA National Ambient Air Quality Standards, attainment is reached when there are no more than 3 exceedances per monitor within a consecutive 3-year period. An exceedance occurs when the ozone concentration ≥ 125 parts per billion averaged over a one hour period.

Source: NCTCOG Transportation Dept

Figure 1.3 Numbers of days of exceedances of the 1-hour ozone standard in Dallas-Fort Worth nonattainment area (NCTCOG, 2010c).

The EPA announced a revised NAAQS for ground-level ozone in July 1997. The EPA tried to replace the 1-hour standard with an 8-hour standard set at 85 ppb to protect the public health and environment against longer exposure to this air pollutant. On April 15, 2004, EPA began implementing the new 8-hour ozone standard and designated additional five North Central Texas (NCT) counties, which are Ellis, Johnson, Kaufman, Parker and Rockwall into non-attainment, making a total of nine nonattainment counties for the 8-hour ozone standard (see Figure 1.4). The area was classified moderate nonattainment for the standard, with an attainment deadline of June 15, 2010.

The new 8-hour ozone standard differed from the 1-hour standard in several respects. First, the averaging time was extended from 1 hour to 8 hours to reduce prolonged exposure. Second, the ozone standard was dropped from 125 ppb to 85 ppb, which meant that the new standard is more stringent. Attainment for the 1-hour standard was determined by the number of exceedances at a given monitor, whereas attainment for the 8-hour standard was determined by a regional design value. The *design value* is defined as the fourth-highest 8-hour average ozone concentration averaged over a consecutive 3-year period. The region would come in attainment when the design value for all monitors in the region is below 85 ppb. Therefore, design values were used not only in determining attainment versus nonattainment, but also in deciding the severity of nonattainment (NCTCOG, 2010c).

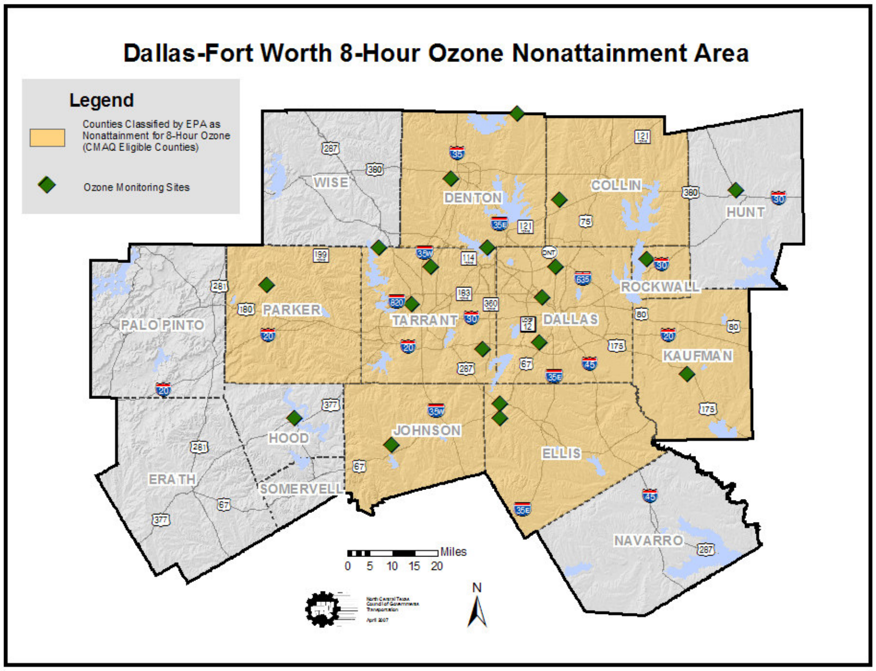
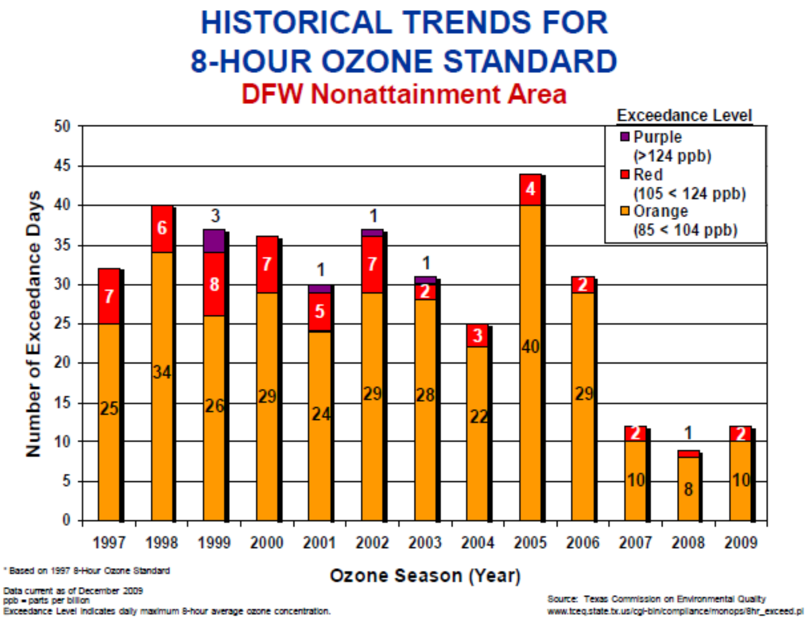


Figure 1.4 Dallas-Fort Worth 8-hour nonattainment area (NCTCOG, 2010e).

The North Central Texas Council of Governments (NCTCOG) used new the 8-hour ozone standard to monitor the ozone exceedance days per year. Since 8-hour ozone data began to be monitored, ozone exceedance days have decreased from 32 days in 1997 to 12 days in 2009 (see Figure 1.5). In addition, the design value decreased from 102 ppb in 1999 to 86 ppb in 2009 (see Figure 1.6). This demonstrated that SIP had a positive effect on reducing prolonged ozone episodes for the 8-hour ozone standard. A study showed that that despite rapid population growth, increased economic development and increased vehicles miles travelled, ozone emissions did not increase (TCEQ, 2007).


HISTORICAL TRENDS FOR
8-HOUR OZONE STANDARD
DFW Nonattainment Area

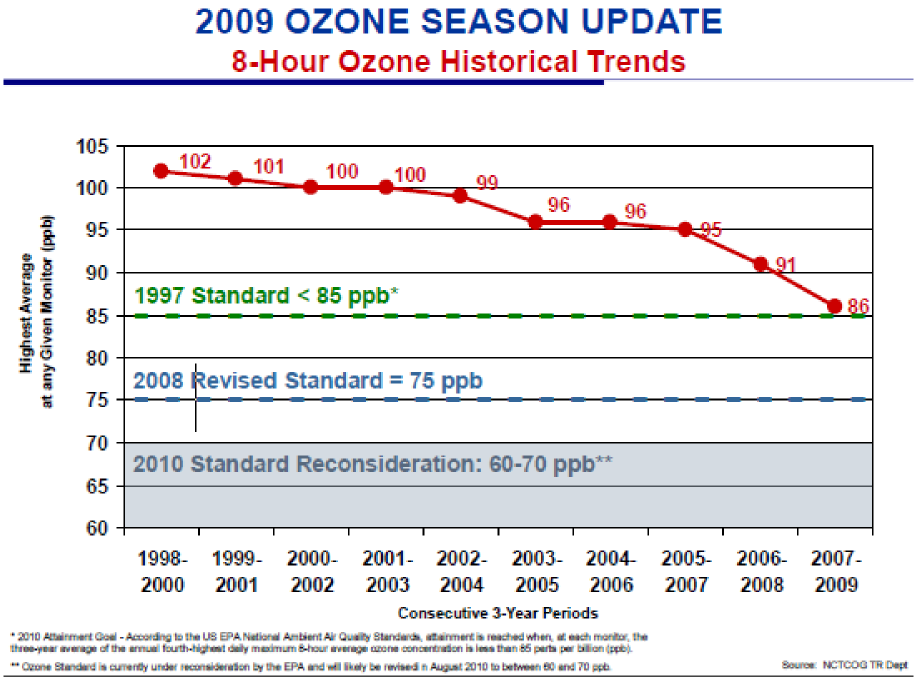
* Based on 1997 8-Hour Ozone Standard

Data current as of December 2009
ppb = parts per billion
Exceedance Level indicates daily maximum 8-hour average ozone concentration.

Source: Texas Commission on Environmental Quality
www.tceq.state.tx.us/cgi-bin/compliance/monops/8hr_exceed.pl

Figure 1.5 Historical 8-Hour Exceedance Days in Dallas-Fort Worth nonattainment area (NCTCOG, 2010f).

According to the SIP Revision for the 8-hour ozone standard, the NO_x baseline emissions in the DFW nine non-attainment counties decreased from 746 tons per day (tpd) in 1999 to 423 tons per day (tpd) for 2009. The VOC baseline emissions also decreased from 442 tons per day (tpd) for 1999 to 343 tons per day (tpd) for 2009 (TECQ, 2010e). The TCEQ had conducted a CAMx sensitivity analysis using the 2009 future case inventory and found that ozone reductions were more effective to reduce NO_x to reduce ozone than VOC. Therefore, the TCEQ considered a wide variety of point, area, non-road mobile, and on-road mobile source control strategies to implement in order to attain the 8-hour ozone standard in the DFW area. The TCEQ also worked in conjunction with the North Central Texas Council of Governments to develop an additional control strategy catalog for the DFW area (TCEQ, 2007).



* 2010 Attainment Goal - According to the US EPA National Ambient Air Quality Standards, attainment is reached when, at each monitor, the three-year average of the annual fourth-highest daily maximum 8-hour average ozone concentration is less than 85 parts per billion (ppb).

** Ozone Standard is currently under reconsideration by the EPA and will likely be revised n August 2010 to between 60 and 70 ppb.

Source: NCTCOG TR Dept

Figure 1.6 8-Hour Ozone trendline in Dallas-Fort Worth nonattainment area (NCTCOG, 2010g).

1.3 Research Motivation

The current ozone standard is 85 ppb for an 8-hour averaging time for both the primary and secondary standard. This standard is more stringent than the earlier 1-hour standard. Under the 1-hour standard, four counties (Dallas, Denton, Tarrant and Collin) were designated as nonattainment. Based on the EPA's review of the 1-hour ozone standard, the agency determined that the 1-hour ozone standard did not fully protect public health, so they replaced the previous ozone standard by an 8-hour ozone standard. Moreover, five more counties (Ellis, Johnson, Kaufman, Parker and Rockwall) were also designated as nonattainment for the 8-hour ozone standard in the North Central Texas region. Since DFW is designated as “moderate non-attainment,” it has a period of 6 years to demonstrate attainment from its designation date. The Texas Commission on Environmental Quality (TCEQ) and the North Central Texas Council of Governments (NCTCOG) have developed a new SIP for the 8-hour ozone standard to demonstrate attainment by 2010 (NCTCOG, 2010h). The Comprehensive Air Quality Model with extensions (CAMx) sensitivity run conducted by TCEQ for 2009 future case emission inventory with 423 tpd of NO_x emissions and 343 tpd of VOC emissions. In order to bring DFW area into attainment for the 8-hour ozone standard, 198.8 tpd (47%) of NO_x emission reductions, or 181.9 tpd (43%) of NO_x emission and 188.7 tpd (55%) of VOC emission combined reduction is required. The results from sensitivity runs also indicated NO_x emission reductions were more effective than VOC emission reductions (Breitenbach, 2006). Therefore, this is the essential motivation for this research to study if the current control strategies proposed by SIP would be able to bring DFW area into attainment for 8-hour ozone standard.

1.4 Research Objective

The main aim of the research is to use decision-making for evaluating and optimizing the targeted ozone control strategies. The latest baseline case, a 10-day episode in August 1999, from the conducted CAMx runs was obtained from TCEQ. The list of control strategies, along with the emission reduction and cost for each control strategy was obtained from TCEQ and NCTCOG. This dissertation studies different linear and non-linear Mixed Integer Programming (MIP) models based on the different scenarios in the optimization. The targeted decision-making will use statistics, data mining, and optimization methods to demonstrate a potential set of control strategies, in order to find the cost-effective combination of control strategies so as to bring DFW area into attainment for the 8-hour ozone standard. Furthermore, the results from the different models can provide decision-makers information on how the effectiveness of control strategies vary with daily emission patterns and meteorology.

1.5 Research Organization

This research is organized in five chapters. Chapter 1 describes background, motivation, and the objective of the study. Chapter 2 reviews the previous research on ground-level ozone control, the decision making framework for controlling ground level ozone, and dealing with infeasible problems in MIP. Chapter 3 presents the linear Mixed Integer Programming models, the definitions of the variables, computational results from three linear

MIP models, and discussions. Chapter 4 presents alternative nonlinear MIP models, computational results of three alternative control strategy models, and discussions. Finally, Chapter 5 discusses conclusions and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In recent years, ground-level ozone control has been a very challenging issue in urban areas. One key task for studying ozone control is the development of accurate tools for predicting ozone concentrations. These involve both advanced photochemical models that are based on the theoretical properties of the airshed and statistical models based on real data. In Section 2.2, some empirical ozone prediction models are described. There is a vast amount of literature on this topic, but it is not the focus of this dissertation. Rather this dissertation focuses on the less studied issue of optimizing the selection of control strategies. Sections 2.3 and 2.4 survey the literature related to this topic. In particular, the methods in this dissertation are based on the work of Sule (2009), which employs advanced photochemical modeling, statistical modeling, and optimization, where Chapters 3 and 4 improve and extend the statistical modeling and optimization components. Section 2.5 provides a detailed description of the work of Sule (2009). Finally, Section 2.6 reviews optimization methods related to those used in this dissertation, and Section 2.7 describes this dissertation's contribution.

2.2 Empirical Ozone Prediction Modeling

In this section, we describe some of the literature on ozone prediction modeling. However, this review is not comprehensive and is only a sample from an enormous body of research. Hubbard et al. (1998) used a multiple linear regression model to predict daily domain-peak ground-level ozone concentration in order to support ozone forecasting and episodic air pollution control initiatives in the Louisville, KY metropolitan area. They also found that transformation of both the predictor variables and the response variable improved the regression significantly. Cobourn et al. (1999) proposed an enhanced ozone forecasting model by using nonlinear regression and an air mass trajectory parameter. The forecasting model performed significantly better in predicting daily maximum 1-hour ozone concentrations during a five-year model calibration period (1993-1997) than their previous reported regression model.

Pires et al. (2008) used multiple linear regression and principal components regression selection methods with meteorological and environmental data as predictor variables for forecasting ozone concentration. Abdul-Wahab et al. (2005) employed data on the concentrations of seven environmental pollutants and meteorological variables to predict the concentration of ozone by using both multiple linear and principal component regression methods. Barrero et al. (2006) conducted multiple linear regression with a forward stepwise method for the prediction of daily ozone concentration, and the results showed this model is easy to implement in association with automated pollution monitoring station systems.

Spellman (1999) used a multilayer perceptron neural network and considered surface meteorological variables as predictors to estimate summer ozone concentrations for five locations in the United Kingdom. Heo and Kim (2004) used a supervised learner with backward-propagating learning rules in the multilayer perceptron neural network system to forecast the daily maximum concentration of ozone on the following day at four monitoring sites in Seoul, Korea. Sousa et al. (2007) proposed a new methodology based on feedforward neural networks using principal components as inputs to predict the next day hourly ozone concentrations in Oporto, Portugal. Cai et al. (2009) categorized traffic, background concentrations, meteorological and geographical influential factors as inputs to the neural networks to predict hourly CO, NO_2, PM_{10} and O_3 concentrations on roadsides near an arterial in Guangzhou, China.

2.3 Air Quality Control for Ground-Level Ozone

Previous studies have been done for optimizing the total cost of control strategies for ground-level ozone air quality control. However, the air quality model, study episode, time horizon, and optimization techniques are different from each other. Some of the previous research is described as follows.

Shih et al. (1998) developed a local linear approximation to the nonlinear relationship between photochemical pollutants and their precursors (NO_x and VOCs). A mathematical programming model was used for optimizing control of photochemical pollutants. The model minimizes the net present value of precursor emission control costs from various emission sources subject to meeting ambient air quality goals for different pollutants and locations over the planning time period. A two-stage approach was proposed in this research. In the first stage, the response surface of pollutant concentration as a function of precursor emissions was generated by using an air quality simulation model. In the second stage, a linear approximation of the nonlinear relationship between photochemical pollutants and their precursors was prepared for the optimization. An assumption was considered in the optimization, which is the reduction in NO_x and VOCs emissions from each of the source categories were spatially uniform. Then a mixed integer nonlinear programming model was used to incorporate the approximated relationship into a decision making model for optimal control of photochemical pollutants. A case study of photochemical smog in Los Angeles was demonstrated using the air quality management model. The results from the model allowed decision makers to find the least cost control path to reduce the precursors from various emission sources as well as to meet the ambient air quality standards.

Fu et al. (2006) presented a simple air quality model that is used conjunctively with a complex air quality model to obtain low-cost management strategies. The simple air quality model is an Empirical Kinetic Modeling Approach (EKMA), while the complex air quality model, an Urban Airshed Model (UAM), is used for designing cost-effective strategies. The first step was to perform multiple UAM runs and the base-case inventory of emissions with four scenarios of across-the-board reductions used for a 3-day simulation. These scenarios were used to identify preliminary control targets and provide initial and boundary condition inputs for the

EKMA simulations. The outputs of the first 2 days were not used. The third day outputs of the UAM runs were used for inputs to EKMA. The second step was to calibrate the EKMA model so as to improve the performance of EKMA in duplicating UAM results. A genetic algorithm-based approach called EKMA-GA was used in the optimization procedure to automate this tweaking process. The cost of different control strategies for ozone management was quantified by the emission least cost (ELC) model. The MIP-ELC was solved to obtain cost isopleths for different NO_x and VOC reductions. Two heuristic methods, an Isopleths Refinement Method and a Cost Ranking Method, were used to find the most cost-effective control measures with a small number of EKMA runs.

2.4 Targeted Decision-Making for Ground-Level Ozone Control

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 (Gao and Niemeier, 2008; Guariso et al., 2004; Sanhueza et al., 2003; Schopp et al., 1999). A targeted control strategy is targeted by location, such as a particular county, and time, such as the morning rush hour time period. The concept of targeted decision-making for ground-level ozone has been studied by Sule et al. (2008), Sule (2009), Yang et al. (2007), and Yang et al. (2009). Conventional across-the-board reductions reduce emissions uniformly throughout the region and the day. By contrast, targeted control optimization seeks to reduce cost and the total amount of emission reductions by tuning the reductions of different emission sources by time and location.

Yang et al. (2007) proposed a decision-making framework (DMF) based on stochastic dynamic programming. A dynamic programming approach requires representation of how the states of the system, in this case the ozone pollution system, transitions through time. Because state transitions for ozone related variables are complex, they focused on the development of the Atmospheric Chemistry Module to represent changes in ozone concentrations. For an Atlanta case study, the Atmospheric Chemistry Module used design and analysis of computer experiments (Chen et al., 2006; Sacks et al., 1989) to collect and model data from an advanced photochemical model called the Urban Airshed Model. To create targeted controls, five time periods were defined, starting at 4am and ending at 7pm, and 25 regions were defined in a 5×5 grid over the Atlanta metropolitan area. Point sources were controlled individually, area sources were controlled by grid region, and both could be adjusted separately in the different time periods. In the Urban Airshed Model, area sources included on-road and non-road sources. The analysis for the Atmospheric Chemistry Module was composed of two phases, a data mining phase and a metamodeling phase. The data mining phase identified those point sources and grid regions that influenced maximum ozone concentrations at four photochemical assessment monitoring stations. The metamodeling phase focused on only 15 (out of 109) point sources and the 25 grid regions to develop regression models for predicting maximum ozone at the four stations for each time period. These regression models represent the ozone transition functions in the larger DMF. Yang et al. (2009) completed this work by formulating and solving the stochastic dynamic program, and then demonstrating the cost-effectiveness of targeted control strategies for the Atlanta case study.

Sule et al. (2008) and Sule (2009) developed a DMF for assessing a specific list of control strategies for ground level ozone in the DFW region. In particular, one goal was to enable the consideration of targeted controls. The optimization in this work was solved by an integer programming (IP) approach. The main purpose of the IP optimization was to select a combination of targeted control strategies that achieves the SIP requirements for attainment and reduces region-wide emissions at a minimum cost.

The computer experiments methods of Yang et al. (2007) were similarly employed by Sule (2009) to develop metamodels for predicting ozone within the optimization. The work of Yang et al. (2009) was different from Sule (2009) in following aspects. First, the Atlanta study used the Urban Airshed Model, while the DFW case study used CAMx. Both are advanced photochemical models that are approved by the U.S. EPA. Second, the Atlanta study did not study any actual potential control strategies, whereas the DFW study selected from a specific list of potential control strategies provided by the Texas state government. Third, only one day was studied in the case of Atlanta, while the DFW case involved ten days with a different meteorology for each day. Finally, the Atlanta study did not separate on-road and non-road sources, while the DFW study separately controlled point, (non-road) area, and (on-road) line sources.

Sule (2009) did not complete the optimization component of his DMF, in part, because he discovered that the list of control strategies was not adequate to enable a feasible IP solution. The research in this dissertation refines and completes the work of Sule (2009). In the following subsection, details from Sule (2009) are presented.

2.5 Targeted Control Strategy Selection

Sule (2009) developed a DMF to evaluate and optimize the selection of control strategies, possibly targeted by location and time period. The ultimate goal was to choose the control strategies that as a set were most cost-effective in bringing the region into attainment with the 8-hour ozone standard. The DMF was tested on a 2009 future case episode of the Dallas Fort-Worth region and the baseline case was based on a 10-day episode from August 13-22, 1999. By separately optimizing each day of the episode, different sets of selected control strategies in each day could be compared. A list of potential control strategies for the DFW region was provided by NCTCOG as a case study. TCEQ and NCTCOG provided the estimated daily costs and estimated daily emission reductions for each of the control strategies. The DMF of Sule (2009) is comprised of four phases: initialization, mining, metamodeling, and optimization, which are described below for the DFW case study. Unfortunately, Sule (2009) determined that the provided list of control strategies was inadequate for bringing the DFW region into attainment. Although, Sule (2009) did implement supplemental control strategies to achieve attainment, the attempt was adhoc. This motivated the need for the research presented in this dissertation.

2.5.1 Initialization

The purpose of initialization is to define the parameters of the DMF. The initialization process starts by identifying critical monitors in the region of interest (e.g., DFW) and a potential list of control strategies for ozone control and then categorizing emission sources into the three types (point, area, line). Next, the control time periods and regions are determined based on the emission sources. After that, the monitor time periods and regions are identified. Finally, a list of potential control strategies needs to be categorized according to emission types, time periods, and location.

The critical monitoring stations in the DFW region were obtained from TCEQ, and a list of potential control strategies were obtained from TCEQ/NCTCOG. In Sule (2009), the NO_x and VOC control strategies are separately listed, creating 43 strategies; however, for the current dissertation, it was observed that in practice these cannot be separated, so the proper list of 32 control strategies is provided in Chapter 3. The emission sources were identified as point, area (including non-road), and line (on-road). These emission sources were also categorized by different control regions and control time periods, and emission controls varied for different regions and time periods. With this setup, the control strategies can be targeted by location and time; however, it is also possible to study across-the-board type strategies

The monitoring regions are based on the monitors, and the minimum grid size of the grid is 4 km; thus, according to the EPA guidelines, the array of nearby grid cells is 7×7 (EPA, 2005). Maximum 8-hour ozone was observed over multiple monitoring time periods for each monitoring region. The ozone non-attainment monitoring regions, by county, are as follows: (1) Collin, (2) Dallas, (3) Denton, (4) Ellis, (5) Tarrant, (6) Kaufman and Rockwall, and (7) Johnson and Parker. For each of these 7 regions, the 8-hour maximum ozone concentrations were monitored over 5 time periods which are 12 midnight – 6 am, 6 am – 12 noon, 12 noon – 3 pm, 3 pm – 7 pm, and 7 pm– 12 midnight. The 4-km domain is used in CAMx modeling for DFW areas. The control regions are classified as the counties, since control strategies are often implemented differently in different counties. Control time periods are designated as appropriate for the type of source. Point sources were controlled separately in 4 time periods: 12 midnight – 6 am, 6 am – 12 noon, 12 noon – 7 pm, and 7 pm – 12 midnight. In particular, the 12 midnight – 6 am and 7 pm – 12 midnight time periods were used to explore the impact of shifting 50% of day-time production from EGUs to these time periods. The points sources are additionally categorized into 7 types, which are brick kilns, EGUs, Industrial, Commercial and Institutional (ICI) boilers medium size (40-80 MMBtu/hr) and large size (> 100 MMBtu/hr), lime kilns, process heaters, and Midlothian cement kilns. These point source categories are selected because the control measures for most of them are listed in the final control strategy list. Area sources and line sources were controlled separately in 3 time periods: 6 am – 9 am, 9 am – 3 pm, and 3 pm – 7 pm, except for weekend line sources, which were controlled separately in 2 time periods: 6 am – 3 pm and 3 pm – 12 midnight.

2.5.2 Mining

Data mining was conducted to identify those emission variables, specified by location and time period, that impact the 8-hour ozone maximums, so as to reduce the number of predictor variables. As in Yang et al. (2007), a design and analysis of computer experiments approach was employed. Data collected based on an efficient Latin hypercube experimental design (Chen et al., 2003; Chen et al., 2006; Mason et al., 2003) was used an to obtain various scenarios specifying the control of NO_x and VOC emissions ranging from 1 to 0.1; 1 refers to 0% reduction and 0.1 refers to 90% reduction from the emission sources. This experimental design not only provided a range of the emissions in different scenarios but also considered the nonlinearity of the ozone chemistry. The shifted production is considered during evening and overnight on the point sources due to the increased emissions. A 30-point Latin hypercube experimental design corresponding to 30 scenarios from CAMx runs was generated. Sule (2009) wrote a C-code to develop the implementation in each scenario for the 2009 future case emission inventory for point, area, and line sources before preprocessing files using Emission

Preprocessing System Version 3 (EPS3) to create “CAMx-ready” files for each day. This output from EPS3 was considered the input for CAMx in each day of the 2009 future case to obtain the 8-hour maximums for 7 monitoring regions and 5 monitoring time periods.

Multivariate adaptive regressions splines (MARS) (Friedman, 1991), decision trees (Breiman, et al., 1984; Huo, et al., 2005), and multiple testing based on false discovery rate (Benjamini and Hochberg, 1995) were utilized to evaluate 612 emission sources in the different time periods and locations and 28 time-lagged 8-hour maximum ozone concentrations (4 time lags and 7 monitoring regions), for a total of 640 predictor variables. Those variables that were selected by at least one of these methods were maintained for future work, while others were eliminated from further study.

The total number of emission variables was reduced from 612 per day to a maximum of 126 on one day. The number of important variables varied from 82 to 126 in each day of the episode. Following this, an additional 30 CAMx runs, again based on a Latin hypercube, were conducted to focus on the selected emission variables.

2.5.3 Metamodeling

Linear regression is useful for approximating relationships between ozone concentration and predictor variables that consist of emissions and prior ozone variables. Model selection is conducted by performing stepwise regression. The set of linear regressions over the 60 CAMx runs is used to construct metamodels for predicting the 8-hour maximum ozone concentration within each monitoring time period and monitoring region. The optimization phase will use the metamodels to efficiently represent linear inequality ozone constraints bounded by the maximum allowable ozone concentration (see Section 2.5.4).

The predictor variables for the metamodels included emission sources from current and previous time periods and also 8-hour maximum ozone concentrations from previous time periods. Then the linear regression metamodels were constructed as follows. First, the variables selected by data mining were used to specify the set of predictor variables. Next, a stepwise regression method at a significance level (α) of 0.1 for each monitoring region and time period was used to select the best model (using a subset of the predictor variables). The stepwise regression not only further reduced the number of predictor variables, but also selected a model that included variables with significant impact on ozone formation.

2.5.4 Optimization

The objective of the optimization was to select the most cost-effective set of control strategies for ground-level ozone control. Integer programming (IP) was employed because the decision variables were set up to “toggle on and off” the different control strategies. IP is a special case of Mixed Integer Programming (MIP) in which there are no continuous decision variables. The objective of IP is to minimize the total estimated cost of the selected control strategies subject to control limit upper bound linear inequality constraints of emission reduction and control strategy selection. IP was used as an optimization method to obtain a realistic and reasonable solution because it forces decision variables to be integer, or in this case, binary.

EPA recommended a “Modeled Attainment Test” (MAT) to demonstrate attainment by simulating current and future air quality using air quality models (EPA, 2005). This test uses baseline and future design values for ozone. A design value based on the 8-hour ozone standard is calculated by taking the fourth highest 8-hour daily maximum in each year of the 3-year design value period, and then averaging over the 3 years. The baseline observed design value (DVB) for a specific monitor is calculated as the average of that monitor’s design values for the 3 design value periods including the baseline year, For DFW, the baseline year is 1999, so the 3 design value periods are 1997-1999, 1998-2000, and 1999-2001, and the average of the design values from each these periods provides the baseline observed design value for each monitor.

The estimated future design value (DVF) for a specific monitor was calculated via a relative reduction factor (RRF) for that monitor. The relative reduction factor (RRF) was calculated by Equation (1).

$$\text{RRF}=\frac{\text{mean}\left(\text{highest modeled 8-hour daily max. } O_3 \text{ for each episode day}\right)_{\text{future}}}{\text{mean}\left(\text{highest modeled 8-hour daily max. } O_3 \text{ for each episode day}\right)_{\text{baseline}}} \qquad (1)$$

The baseline mean value of the highest modeled 8-hour daily maximum ozone was taken over the study episode excluding ramp-up days. Then the future design value of the highest modeled 8-hour daily maximum ozone at a monitor was estimated by multiplying the RRF and DVB. DVF is given by Equation (2).

$$\text{DVF}=\text{RRF}*\text{DVB} \qquad (2)$$

To demonstrate attainment, the DVF throughout the non-attainment region must be less than or equal to 84 ppb. Since DVB and the denominator of RRF are known, by plugging 84 for DVF, we can solve for the numerator of the RRF equation for each critical monitor. These values are used to derive the upper bound on the ozone constraints in each region. The IP optimization was carried out to incorporate the metamodels, control strategies, and relative reduction factors. Three types of the supplemental control measure were considered in the optimization since the current set of control strategies cannot satisfy the allowable upper bound on ozone concentration. The set of control strategies was optimized separately for each day in sequential manner, where the final ozone of each day was passed on to initialize the next day. The first five days from August 15 to 19 of the episode were optimized to demonstrate applicability of the DMF.

2.6 Optimization Methods for Targeted Decision-Making

2.6.1 Mixed Integer Programming

Linear programming (LP) is a mathematical method that seeks the best outcome, such as maximizing the profits or minimizing costs. It is a technique for optimizing a linear objective function, subject to linear equality and linear inequality constraints. Linear programming can be applied to various fields of study. It is used most extensively in business and economics, but can also be utilized for many engineering problems. Industries that use linear programming models include transportation, energy, telecommunications, and manufacturing (Wikipedia, 2010). It has proved useful in modeling diverse types of problems in planning, routing, scheduling, assignment, and design. If some of the variables are required to be integer then it is considered as mixed integer programming (MIP). MIP problems are in general more difficult to solve than linear programming problems.

Mixed Integer Nonlinear Programming (MINLP) refers to mathematical programming with continuous and discrete variables and nonlinearities in the objective function and/or constraints. MINLP have been used in various applications, including industrial engineering, financial engineering, management science, and operations research.

2.6.2 Handling Infeasibility

Atlihan and Schrage (2008) presented some generalized filtering algorithms for debugging linear, mixed integer and nonlinear infeasible programs. They used algorithms to identify a minimal subset of these constraints that are inconsistent in a given set of constraints that are infeasible or inconsistent. The algorithms combine existing filtering algorithms with a binary-search based on a divide-and-conquer approach to improve search speed. They also gave some computational results to show the speed of the algorithms on various problem types.

Fischetti and Lodi (2008) introduced and analyzed a hybrid algorithm that uses the feasibility pump method to provide an initial possibly infeasible solution with very low computational cost to the local branching procedure. The overall procedure is reminiscent of Phase I of the two-phase simplex algorithm, in which the original LP is augmented with artificial variables that make a known infeasible starting solution feasible, and then the augmented model is solved to iteratively reduce that infeasibility by driving the values of the artificial variables to zero. Their approach can also used to find a minimum-cardinality set of constraints, whose removal converts an infeasible MIP into a feasible one, which is a very important piece of information in the analysis of infeasible MIP models. They proposed to integrate two algorithms for general purpose MIPs called feasibility pump and local branching, which were originally proposed to separately cope with the issues of finding an initial feasible solution and improve it.

Guieu and Chinneck (1999) developed the basic algorithms for isolating infeasibility in mixed integer and integer linear programming (MILP). They used an approach to isolate an irreducible infeasible set (IIS) of constraints for infeasible linear programs. That means a subset of the constraints defining the overall linear program that is itself infeasible, but for which any proper subset is feasible. Isolating an IIS from the larger model speeds the diagnosis and repair of the model by focusing the analytic effort. They also described and tested some algorithms for finding small infeasible sets in infeasible MILP to prove those possible small sets are IISs.

2.7 Contribution

In this dissertation, we study both linear and nonlinear MIP models to find an optimal set of control strategies. Three different optimization models, specifically static, sequential, and dynamic models, were considered in both linear and nonlinear MIP models to obtain sets of targeted control strategies. Results of the control strategies selection in different models can be useful information for understanding the benefit of the controls. Finally, to address the infeasibility issue, we identify the most effective supplemental controls for further reduction of emissions and ozone in specific regions and time periods.

CHAPTER 3

OPTIMIZATION MODELS FOR TARGETED OZONE CONTROL

3.1 Introduction

Given a list of potential control strategies, possibly targeted by time and location, the Optimization Phase of Sule (2009) selects the set of control strategies that is most cost-effective in satisfying constraints on ozone based on the EPA's Modeled Attainment Test (MAT) for the 8-hour standard. The decision variables are binary for this optimization, i.e., either the control strategy is selected or it is not, however, ozone variables are continuous. Hence, the optimization is formulated as a mixed integer programming (MIP) problem. The optimization constrains ozone based on MAT, as described in Chapter 2 and shown in Appendix B, where the linear regression ozone metamodels from Sule (2009) are used to calculate ozone concentrations. Note: Corrected versions of the metamodels are provided in Appendix A. As mentioned in Chapter 2, Sule (2009) represented NO_x and VOC controls separately, yielding 43 control strategies. In practice, the same control strategy, e.g., building a bike path cannot be separately implemented to reduce NO_x vs. VOC, so it is more practical to consider the list as 32 control strategies (see Table 3.1). All control strategies are also categorized into three types of sources, which are on-road, non-road, and point, and each strategy can address one or both of two types of pollutants, which are NO_x and VOC.

Table 3.1 Summary of control strategies, emission reductions and cost (Environ, 2006).

Line/On-road Sources					
No.	Control Strategies	Emissions Affected	Amount of Emission Reduction (tons/day) and Cost ($/day)		
			NO_x	VOC	Cost
1	Bicycle and Pedestrian Programs	9 counties	0.070	0.040	2,448.37
2	Clean Fleet Vehicle Procurement Policy/Clean	9 counties	5.000		37,500.00

Table 3.1 – *Continued*

	Fleet Program (only weekdays)				
3	Freeway and Arterial Bottleneck Program	9 counties	0.250	1.010	3,768.72
4	Higher Vehicle Occupancies	9 counties	0.270	0.280	25,961.54
5	Idle Reduction Infrastructure	9 counties	0.060		547.95
6	Intelligent Transportation Systems	9 counties	4.870	1.990	8,342.31
7	Additional Taxi Fleet Emission Testing	9 counties	0.001		109.59
8	Traffic Signal Improvement	9 counties	1.110	3.070	14,807.69
9	Transit	9 counties	0.070	0.070	11,441.10
10	Fare-Free Transit, System-Wide on Ozone Action Days	9 counties	0.710	0.720	597,000.00
11	ETR-Vanpool Program	9 counties	0.023	0.026	5,920.37
12	ETR-Best Workplaces Program	9 counties	0.104	0.107	241.57
13	ETR-Carpooling Programs	9 counties	0.020	0.020	83.16
14	ETR-Transit Subsidy Programs	9 counties	0.370	0.380	1,538.35
Area/Non-road Sources					
15	Freight Rail Infrastructure Improvement	9 counties	0.350		18,169.90
16	Emission Reduction Contract Incentives with Public Funding	9 counties	1.100		14,300.00
17	Limitation on Idling of Heavy Duty		0.750		16,500.00
18	Rail Efficiency	9 counties	1.900		1,881.00
19	Stationary IC Engines	9 counties	6.290		16,627.62
20	Lawn Mower Replacement Program	9 counties		0.422	2,743.00
21	Architectural & Industrial Coatings	9 counties		9.600	126,720.00
22	Cold Cleaning Regulations	9 counties		0.710	986.90
23	Commercial and Consumer Products Requirements	9 counties		11.100	53,280.00
24	Fuel Hose Permeation	9 counties		0.063	945.00
25	Glycol Dehydrators	9 counties		0.420	178.15
Point Sources					
26	Brick Kilns	Denton & Parker	0.13		176.15
27	ICI Boilers #7	Dallas, Denton, Ellis, Kaufman & Tarrant	0.38		1,489.60
28	ICI Boilers #9	Dallas, Kaufman & Tarrant	0.12		503.40
29	Lime Kilns	Johnson	2.20		7,414.00
30	Refinery Boilers and Heaters	Dallas & Tarrant	0.41		3,860.15
31	EGU	All counties except Rockwall	5.97		35,820.00
32	Midlothian Cement Kilns	Ellis	17.40		71,340.00

Quantitative evaluations were conducted by ENVIRON for the list of control strategies (TCEQ 2010d). The estimated emission reductions of on-road vehicles control strategies vary widely, however, some of the more significant NO_x reduction control strategies include implementation of the clean fleet program and intelligent transportation systems. The most significant NO_x reduction among area control strategies is stationary IC engines, and the most significant VOC reductions among non-road control strategies are architectural & industrial coatings and commercial & consumer products requirements. Most of the control strategies in the list are not targeted in structure. The DMF of Sule (2009) handles the general case of targeted control strategies, but also handles typical controls that are not targeted. The allowable maximum ozone concentration for each monitoring region and time period was calculated by relative reduction factors of MAT recommended by the EPA (see Appendix B).

Because Sule (2009) found that the MIP models for the DFW case study were infeasible, supplemental control strategies with considerable penalized cost were introduced into the optimization to enable technically (but perhaps not practically) feasible solutions. This is the primary motivation for the work in this dissertation. As mentioned in Chapter 2, Sule (2009) implemented adhoc supplemental controls on specific emission sources. A comprehensive approach is employed in this dissertation. There are two types of supplemental controls applied in this research. The first type allows further reduction on emissions. It is more practical to first consider implementing further reductions on emission sources than trying to reduce ozone directly. The second type allows further reduction directly on ozone targeted by time period and location. These cannot be directly implemented in practice; however, this information enables decision-makers to identify which are the key ozone levels, targeted by time and location that need to be reduced. These supplemental controls have very high penalty costs in order to force the optimization to first consider the set of 32 control strategies.

Three MIP models, static, sequential, and dynamic, are studied:

- 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 allows different sets of selected control strategies on each day of the episode. However, each day is optimized separately, although the resulting ozone level at the end of one day is passed on to initialize the next day. Sule (2009) partially implemented the sequential model.
- Dynamic model: Optimize a set of dynamic control strategies in which the selected control strategies can vary from day to day. This conducts simultaneous optimization over the entire episode, like the static model, but the sets of control strategies may be different for each day. This enables the decision-maker to see how the ideal set of control strategies varies with daily emission patterns and meteorology.

It is recognized that the static policy is the only practical approach at this time, but as a research tool, we can learn about how to improve control strategies by studying an ideal dynamic set. The sequential model is suboptimal relative to the dynamic model; however, we have modeled it fully in order to complete the work of Sule (2009). The main aim of the Optimization Phase of the DMF of Sule (2009) was to identify the most cost effective (targeted) control strategies that would bring the region into attainment for 8-hour ozone standard. These different MIP 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 MIP models also identify the best regions and time periods for supplemental control.

The following assumptions with respect to emission reductions and emission sources were specified for implementing the optimization:

1. No more than a 90% reduction in emissions was allowed by any control strategy. This assumption was applicable if the emission reduction estimated by NCTCOG/TCEQ was greater than the total emissions, because a 100% reduction would mean removing the source entirely.
2. VOC emissions for point sources were not controlled because no control strategies for point sources in the control strategy list were provided by NCTCOG/TCEQ.

To create control strategies that are targeted by control time period (Table 3.2) and control region (see Section 2.5.1), the following assumptions were made to partition the estimated total emission reductions and costs in Table 3.1 to the different control time periods and control regions:

1. Emission reductions are uniform across the 9 control regions and across the 24 hours of a day.
2. The average emission reduction and the average cost are listed in Table 3.1 for each control strategy, although the original documentation from NCTCOG/TCEQ may have used a range on the estimated emission reduction and cost (TCEQ 2010c).

The control strategies were permitted to be implemented separately in the affected counties (see Table 3.1). For line or area source control strategies, all nine counties are affected, while for point sources, the specific subset of affected counties is listed in Table 3.1. Furthermore, the control strategies were all permitted to be controlled separately by the control time periods in Table 3.2, even if it was not practical. For example, for area source control strategy #15 (Freight Rail Infrastructure Improvement), the total NO_x emission reduction of 0.35 tons per day would first be divided by 24 hours and divided by nine counties to obtain the reduction per hour per county. Then this is multiplied by the number of hours in a specific control time period. For the 6am–9am time period, this is three hours, and the NO_x emission reduction is estimated to be 0.0049 tons per county in the 6am–9am time period. For point source control strategy #30 (Refinery Boilers and Heaters) only Dallas and Tarrant counties are affected. Hence, to estimate the NOx emission reduction in Dallas County during the 12 – 6 am control time period, the total reduction of 0.41 tons per day was divided by 24 hours and divided by two counties, then multiplied by six hours to yield 0.05125 tons of NO_x emission reduction.

Table 3.2 Control time periods by type of source (Sule 2009).

Source Category	Types of emission sources	Control time periods
Point source (Monday – Sunday)	7	12 midnight – 6 am 6 am – 12 noon 12 noon – 7 pm 7 pm – 12 midnight
Area (Monday – Sunday)	1	6 am – 9 am 9 am – 3 pm 3 pm – 7 pm
Line (Monday – Thursday)	1	6 am – 9 am 9 am – 3 pm 3 pm – 7 pm
Line (Friday)	1	6 am – 9 am 9 am – 5 pm 5 pm – 12 midnight
Line (Saturday – Sunday)	1	6 am – 3 pm 3 pm – 12 midnight

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 emission source j, let $I(n)$ be the set of emission types that are associated with control strategy n, let L be a set locations, let T be a set of time periods, and let D be a set of days that partition the set of time periods T.

Define the following MIP variables and input parameters:

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

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 optimization.

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 l location 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 l location 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 vector representing whether control strategy n is selected on day d *for* emission type i.

Let cs_{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 MIP model formulation is given by:

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

s.t.

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

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

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

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

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

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

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

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, using the linear regression models from Sule (2009). Constraint set (5) ensures the ozone concentration in each time period and location does not exceed its mandated limit based on the EPA's MAT. Constraint set (6) ensures that the fraction of remaining emissions plus the fraction of emission reduction sums to one. Constraint set (7) specifies link constraints for the reduction of NO_x and VOC emissions due to the same control strategy. The decision rule of this idea is similar to disjunction of Boolean operations. For example, if a certain control strategy can help NO_x and/or VOC emission reduction for ozone control, then the estimated cost of the selected control strategy would be counted only once. Constraints (8) and (9) represent standard lower bounds, and constraint set (10) represents integrality restrictions on the decision variables.

3.2 Static Model

For this optimization model, a single set of static control strategies will be implemented across the entire episode from August 15 to 22. The selected targeted control strategies of each day of the episode are the same, which means the same control strategy will be implemented everyday ($cs_{n1} = cs_{n2} = \cdots = cs_{n8}$).The total estimated cost of each static control strategy is the daily estimated cost from NCTCOG/TCEQ multiplied by 8 days. There are 284 emission variables (x_{ijd}) specified by emission sources and control time periods used for a weekday (Monday-Thursday), 284 emission variables used on Friday, and 266 emission variables used for weekend days (Saturday and Sunday). Therefore, a total of 1952 emission variables in the specific time periods and locations and a set of 32 control strategies were considered in optimization. The ending ozone concentration of each day is considered as an ozone variable (o_{lt}) to link to the beginning ozone concentration of next day. For example, the last time period (7 pm-12 midnight) ozone concentrations on August 15 will carry over to the first time period (12 midnight – 6 am) ozone concentrations on August 16. The first two days (August 13 and 14) of the episode were considered ramp-up days for the air quality model simulation, therefore, the previous day's ozone concentrations in specific control regions on August 15 were obtained from the CAMx results. This static model results in a single set of selected control strategies that is implemented on every day of the episode. In this research, the selected control strategies will be implemented throughout the study episode from August 15 to 22. In terms of the practicability, the implementation of a static model is currently how control strategies are implemented by the government.

3.3 Sequential Model

For this model, the set of targeted control strategies is optimized each day separately in a sequential manner. The selection of control strategies is allowed to differ from day to day, which means the selected control strategy ($cs_{n1}, cs_{n2}, \cdots, cs_{n8}$) does not need to be same on each day of the episode. Consequently, the daily estimated cost of the selected control strategies can be different. The total estimated cost of the targeted control strategies is calculated by summing up the daily estimated costs for the strategies selected from each day of the episode. The number of emission variables (x_{ijd}) used in each day varied from August 15 to August 22 (266, 284, 284, 284, 284, 284, 266, 266). The ending ozone concentration of each day was calculated by the optimization then carried over to the beginning ozone concentration of next day. For example, we can obtain the ozone concentration of the last time period on August 15 by optimizing the first day of the episode. If the past ozone concentration was considered in the first time period on August 16, then the calculated ozone concentrations on August 15 would be used in the metamodels representing the previous day's ozone concentration. The first two days (August 13 and 14) of the episode were considered ramp-up days for the air quality model simulation. Hence the previous day's ozone concentrations on August 15 were obtained from the CAMx results. The sequential model results in eight different sets of selected control strategies that will be implemented separately from August 15 to 22.

3.4 Dynamic Model

This model is like the sequential model, in that the set of targeted control strategies can vary by day. However, it is different from the sequential model because these daily sets are simultaneously optimized across all eight days. The emission reduction of certain emission variables (x_{ijd}) and selected control strategies ($cs_{n1}, cs_{n2}, \cdots, cs_{n8}$) can be vary from day to day. Therefore, 1952 plus 266 equals to 2218 emission variables used in the dynamic model. The set of 32 control strategies is multiplied by 8 to enable separate implementation on each of the 8 days, making a total of 256 decision variables in the optimization. The final ozone concentration of each day is considered as an ozone variable (o_{l_t}) to link to the beginning ozone concentration of the next day. Although it is not currently practical to implement different sets of control strategies on different days, these results enable the decision-maker to see how the best set of control strategies varies with daily emission patterns and meteorology.

3.5 Computational Results

The computational results were carried out using FICO Xpress-Mosel optimization software. Except for the first two ramp-up days of the CAMx simulation, a total of eight days (from August 15 to 22) of the episode were optimized in order to select targeted control strategies for the three distinct MIP models. In Tables 3.3, 3.5 and 3.7, selected control strategies are marked by "X." For control strategies that reduce both NO_x and VOC, the optimization additionally identifies if only one type of emission reduction was needed, where X^v indicates when only the VOC reduction was helpful, and X^N indicates when only NO_x reduction was helpful. By considering constraint (8) in section 3.1, the optimization has the ability to specify the different emission reductions (NO_x or VOC) due to the same selected control strategy.

3.5.1 Computational Results of Static Model

The set of selected control strategies for the static model are implemented everyday throughout the episode. Results in Table 3.3 show that seven control strategies associated with VOC emissions from on-road sources were selected. Four control strategies associated with NO_x emissions (control strategies #16-19) from non-road sources were selected. Control strategies for Brick Kilns and EGU point sources were selected to reduce NO_x emissions.

Table 3.3 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)

Table 3.3 – *Continued*

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	X	EGU (NO_x)
32		Midlothian Cement Kilns (NO_x)

Since the set of 32 control strategies was unable to reduce ozone to comply with the 8-hour ozone standard in static model, three auxiliary variables ($s_{lt}^{+}, s_{lt}^{-}, x_{ijd}$) need to be considered as the supplemental controls in the optimization. The results of the supplemental control in targeted time periods and locations are shown in Table 3.4. All supplementary implementations required further reduction of ozone during the morning busy hours (12-6am and 6-12pm). Each day of the episode required at least one supplemental control for controlling ozone except August 18. A total of four supplemental controls are applied in Denton for ozone attainment, which is the largest requirement of the counties. By contrast, Ellis and Kaufman and Rockwall did not need any supplementary control for ozone attainment. The total cost of the selected control strategies plus penalty cost was $6.1 billion, where the portion of the cost that was only due to the selected control strategies over the eight-day episode was $7.3 million.

Table 3.4 Static optimization model: Supplemental controls on ozone by day, time period, and county.

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

3.5.2 Computational Results of Sequential Model

The results of the set of selected control strategies for the sequential model in each day are shown in Table 3.5. On August 15, nine control strategies for on-road VOC emission sources and two control strategies for NO_x emission point sources were selected. On August 16, only one control strategy for a NO_x emission point source was selected. No control strategies are selected on August 17. On August 18, 14 control strategies for on-road NO_x emission sources, all control strategies for non-road associated with NO_x and VOC emission sources and two control strategies for NO_x emission point sources were selected. On August 19, all 14 control strategies for on-road NO_x and VOC emission sources, all five control strategies for non-road sources associated with NO_x emission source, and one control strategy for a NO_x emission point source were selected. On August 20, ten control strategies for on-road VOC emission sources, all five control strategies for non-road sources associated with NO_x, and two control strategies for NO_x emission point sources were selected. On August 21, only two control strategies for NO_x emissions from point source were selected. No control strategies were selected on August 22.

From the results, we found that on-road control strategies of NO_x emissions were similar on August 18 and 19. On August 19, 14 options of NO_x and VOC were all selected. However, the control strategies of NO_x emissions were removed on August 20, and only control strategies of VOC emissions were selected. The selected control strategies of VOC emissions were very similar on August 15 and 20. Non-road control strategies were more effective on weekdays then on weekends throughout the episode. All five options of non-road control strategies of NO_x were selected on August 18, 19, and 20, which were weekdays. An additional six options of non-road control strategies of VOC emissions were selected on August 18. Point emissions control strategies for ICI Boilers #7 and ICI Boilers #9 were helpful in reducing NO_x emissions throughout the episode.

Table 3.5 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			Freight Rail Infrastructure Improvement (NO_x)
16				X	X	X			Emission Reduction Contract Incentives with Public Funding (NO_x)
17				X	X	X			Limitation on Idling of Heavy Duty (NO_x)
18				X	X	X			Rail Efficiency (NO_x)
19				X	X	X			Stationary IC Engines (NO_x)

Table 3.5 – *Continued*

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					Brick Kilns (NO_x)
27	X						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 controls in targeted time periods and locations are shown in Table 3.6. Supplemental controls were required throughout the episode from August 15 to 22. All supplemental controls required for further reduction of ozone occurred during the morning busy hours (12-6am and 6-12pm). Denton required the most supplemental control for controlling ozone concentration. However, Kaufman and Rockwall did not need any supplementary control to reach attainment. The total cost of the sets of selected control strategies from each day of the episode and the penalty cost due to the implementation of supplemental control strategies was $6.3 billion, and the total the cost for only the selected control strategies was $2.7 million. Because the sequential model allows different sets of control strategies to be implemented in each day of the episode, a control strategy would be applied only when emission reduction is helpful in reducing ozone. This is the reason why the estimated cost of the sequential model is lower than that of the static model.

Table 3.6 Sequential optimization model: Supplemental controls on ozone by day, time period, and county.

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

3.5.3 Computational Results of Dynamic Model

Like the sequential model, the set of selected control strategies from the dynamic model could vary day by day (see Table 3.7). On August 15, nine control strategies for on-road VOC emission sources and two control strategies for NO_x emission point sources were selected. On August 16, only one control strategy for NO_x emissions from a point source was selected. On August 17, three control strategies for NO_x emissions from point sources were selected. On August 18, 14 control strategies for on-road NO_x emission sources, all control strategies for non-road sources of NO_x and VOC, and five control strategies for NO_x emissions from point sources were selected. On August 19, all five control strategies for non-road sources associated with 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 VOC emission sources, all five control strategies for non-road sources of NO_x emissions, and four control strategies for NO_x emissions from point sources were selected. On August 21, nine control strategies for on-road NO_x and VOC emission sources, all six control strategies for non-road sources of VOC emissions, and three control strategies for NO_x emissions from point sources were selected. On August 22, no control strategies were selected.

From the results, we found that on-road control strategies were helpful for ozone reduction on August 15, 18, 20, and 21. Non-road control strategies were helpful for ozone reduction on August 18, 19, 20, and 21, and control strategies for NO_x emissions were more effective on weekdays than on weekend days. Point source control strategies for ICI Boilers #7, ICI Boilers #9, and Refinery Boilers, and Heaters were more helpful than other point source control strategies throughout the episode.

Table 3.7 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^V			X^N		X^V	X		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^V	X		Freeway/Arterial Bottleneck (NO_x, VOC)
4	X^V			X^N		X^V			Higher Vehicle Occupancies (NO_x, VOC)
5				X			X		Idle Reduction Infrastructure (NO_x)
6	X^V			X^N		X^V	X		Intelligent Transportation Sys (NO_x, VOC)
7				X					Additional Taxi Fleet Emission Testing (NO_x)
8	X^V			X^N		X^V	X		Traffic Signal Improvement (NO_x, VOC)
9	X^V			X^N		X^V			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^V			ETR-Vanpool Program (NO_x, VOC)
12	X^V			X^N		X^V	X		ETR-Best Workplaces (NO_x, VOC)
13				X^N		X^V	X		ETR-Carpooling Programs (NO_x, VOC)
14	X^V			X^N		X^V	X		ETR-Transit Subsidy (NO_x, VOC)
15				X	X	X			Freight Rail Infrastructure Improvement (NO_x)
16				X	X	X			Emission Reduction Contract Incentives with Public Funding (NO_x)
17				X	X	X			Limitation on Idling of Heavy Duty (NO_x)
18				X	X	X			Rail Efficiency (NO_x)
19				X	X	X			Stationary IC Engines (NO_x)
20				X			X		Lawn Mower Replacement (VOC)
21				X			X		Architectural & Industrial Coatings (VOC)
22				X			X		Cold Cleaning Regulations (VOC)
23				X			X		Commercial and Consumer Products Requirements (VOC)
24				X			X		Fuel Hose Permeation (VOC)
25				X			X		Glycol Dehydrators (VOC)
26			X	X					Brick Kilns (NO_x)
27	X			X		X	X		ICI Boilers #7 (NO_x)
28				X	X	X			ICI Boilers #9 (NO_x)

Table 3.7 – *Continued*

29			X				X		Lime Kilns (NO$_x$)
30	X			X		X	X		Refinery Boilers and Heaters (NO$_x$)
31				X		X			EGU (NO$_x$)
32		X	X						Midlothian Cement Kilns (NO$_x$)

Table 3.8 Dynamic optimization model: Supplemental controls on ozone by day, time period, and county.

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

Three auxiliary variables need to be considered to represent supplemental controls 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 3.8. All supplemental controls occurred during the morning busy hours (12-6 am and 6-12 pm). Denton used supplemental controls on August 17, 19, 20, and 21 to do further reduction for controlling ozone, which required the most compared with other counties. Ellis and Kaufman and Rockwall did not need any supplementary control for ozone attainment. The results of supplemental control strategies were similar across the three MIP models; nevertheless, the amount of emission reduction that was applied varied for the selected supplemental controls. The penalty cost of the supplemental controls of dynamic model was the smallest among three models. Since the dynamic model allows different control strategies to be implemented in each day of the episode, previous day's ozone considered an ozone variable, and the entire episode is optimized in one general model, the dynamic model yields the minimum penalty cost of the supplemental controls. The total cost of the selected control strategies and the penalty cost was $6.1 billion, where the portion due only to the selected control strategies was $1.7 million. The dynamic model's total cost is the smallest of the three MIP models. This is because the dynamic model simultaneously optimizes the sets of controls on the different days. Unlike the sequential model, the dynamic model has the capability to adjust the selection of control strategies and/or auxiliary variables to reduce ozone concentrations in early time periods/days, which reduces the cost to achieve the 8-hour ozone standard in later time periods/days.

CHAPTER 4

NONLINEAR OTIMIZATION MODELS FOR TARGETED OZONE CONTROL

4.1 Introduction

Linear regression models were applied in chapter 3 to forecast ozone concentration in each region and time period and incorporated with optimization, and MIP optimization selected targeted control strategies and supplemental controls for ground level ozone control. Residual analysis can be used to verify the assumptions of the linear regression models. For the current 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.

4.2 Transformation in Linear Regression Model

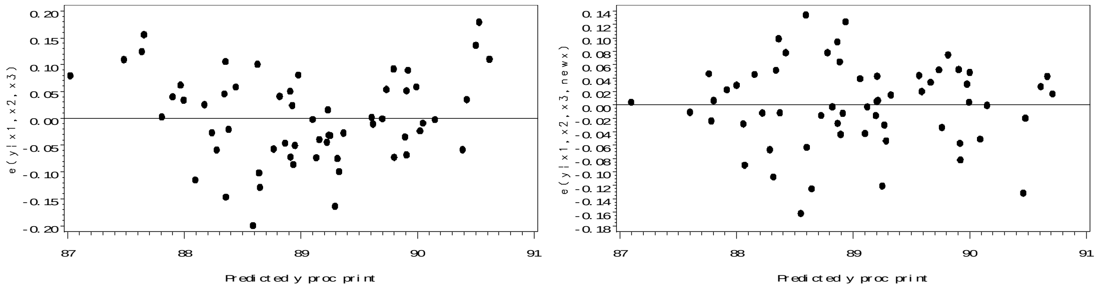
In this research, residual plots were used to verify the model assumptions. Typical residual plots include plots of residuals versus fitted values and residuals versus individual predictor variables. Other plots based on residuals, such as response variables versus individual predictors, predictors versus 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. The results of the regression models with funnel shape and curvature are summarized in Appendix C. The author acknowledges the significant help from Industrial and Manufacturing System Engineering Master students Aditya Koppikar to complete this important work. 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 4.1 (a)). The original linear regression was showed as Equation (12).

$$y=-0.8(O_3De12\text{-}6a)+2.396(O_3Ta12\text{-}6a)-0.104(AJ06\text{-}9aN)-10.69 \quad (12)$$

$$y=-40.75(O_3De12\text{-}6a)+2.384(O_3Ta12\text{-}6a)-0.096(AJ06\text{-}9aN)+0.314(O_3De12\text{-}6a)^2+1258.32 \quad (13)$$

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 4.1 (b)), and the transformed model with the nonlinear regression model is show as Equation (13). The list of the transformed models is summarized in Appendix D.



(a) (b)

Figure 4.1 Original (a) versus transformed (b) residuals vs. fitted value plot in Denton on August 18 (6 am–12 noon).

4.3 Piecewise Linear Function

A piecewise linear function is a separable function that could be 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 (Nemhauser and Wolsey 1998). For example, Figure 4.2 depicts a piecewise linear function. 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 (Figure 4.3). Therefore, piecewise linear programming is an optimization method that allows nonlinear programming problems that consist of separable functions to be approximated by a linear function. The resulting piecewise linear program can subsequently be solved as a mixed-integer linear program.

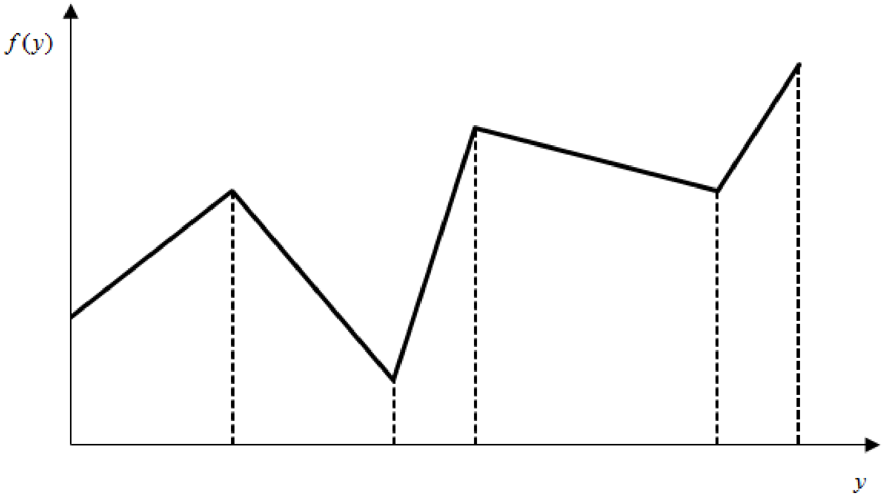


Figure 4.2 Piecewise linear function.

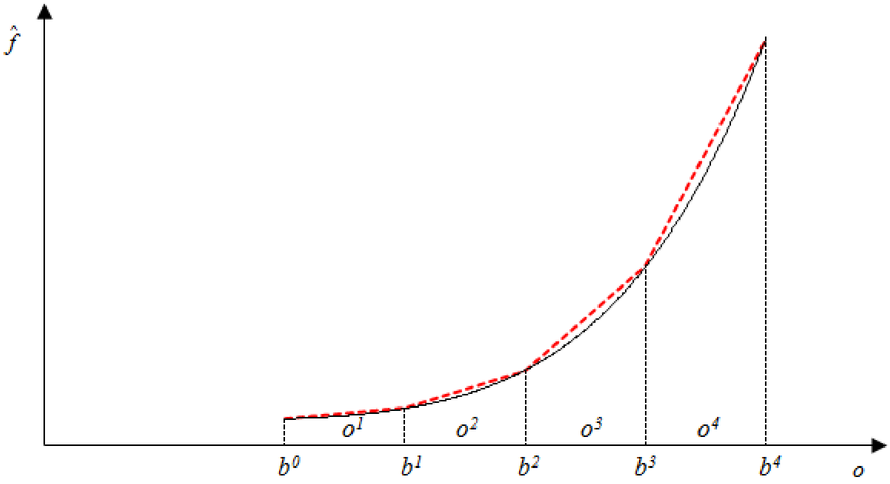


Figure 4.3 Piecewise linear function with four equally spaced linear segments.

To formulate a transformed ozone concentration variable using a piecewise linear, 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:

$$o = \sum_{k=1}^{4} o^k \tag{11}$$

$$\hat{f} = \sum_{k=1}^{4} p_k o^k - q_k w_k \tag{12}$$

$$b^{k-1} w_k \le o^k \le b^k w_k \qquad \forall k = 1, \cdots, 4, \tag{13}$$

$$\sum_{k=1}^{4} w_k = 1 \tag{14}$$

$$w_k \in \{0,1\} \qquad \forall k = 1, \cdots, 4. \tag{15}$$

Constraint set (11) indicates that a given ozone variable equals the ozone concentration approximated by one of the four segments. Constraint set (12) represents the linear approximation of the transformed ozone concentration. Constraint set (13) represents the lower and upper bound 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 with four equally spaced linear segment for a nonlinear transformation of ozone, a similar set of constraints can be used to transform an emission variable.

4.4 Penalized Cost of Supplemental Control Strategy in Nonlinear Model

The linear MIP models for the DFW case study were infeasible, so supplemental control strategies with considerable penalized cost were introduced into the optimization model to enable feasible solutions. However, the nonlinear MIP models consisted of nonlinear terms in the regression models. It is very difficult to penalize the estimated cost of the transformed ozone variable when the 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 and maximum value of the break points (see Figure 4.4). The minimum and maximum value was obtained from checking a total of 60 CAMx runs and then determining the range of the ozone concentration in the certain region and time period. 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 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 the supplemental controls on the piecewise linear approximation on ozone (see Equation 17) and the upper bound of the last segment (see Equation 18). 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 last segment in a decreasing function.

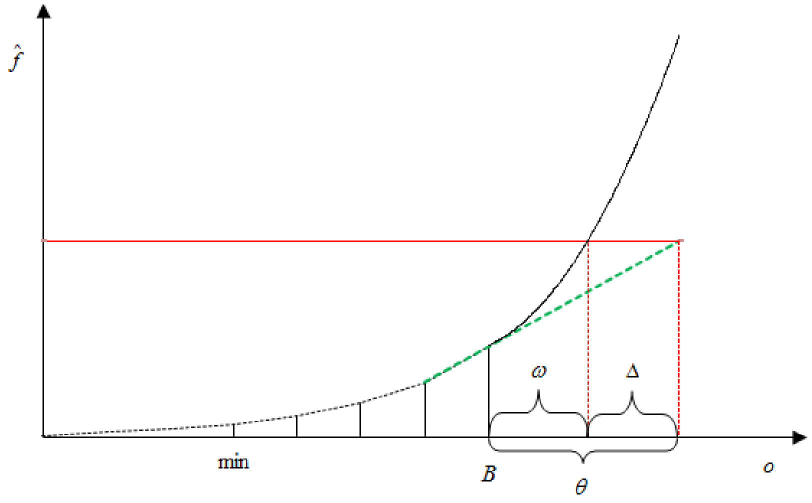


Figure 4.4 Increasing piecewise linear function

$$\sum_{k=1}^{4} p_k b^{k-1} - q_k w_k - s^{+} \le B \tag{17}$$

$$b^3 w_4 \le o^4 \le b^4 + s^{-} \tag{18}$$

4.5 Nonlinear MIP Model

The nonlinear MIP model formulation is constructed based on Equations (3)-(10) in Chapter 3.1, in addition to the formulations of the piecewise linear functions as in Equations (11)-(18). Note that emission variable x_{ijd} and estimated ozone concentration o_{lt} could be considered as both linear and nonlinear terms in the nonlinear MIP models. The list of 32 control strategies, assumptions with respect to emission reductions and emission sources for implementing the optimization, assumptions to partition the estimated total emission reductions, and costs from Chapter 3 are used in the nonlinear MIP models as well.

Three non linear MIP models--static, sequential, and dynamic models--are studied. Recall from Chapter 3, we defined these 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.

4.6 Computational Results

The computational results were carried out using FICO Xpress-Mosel optimization software. A total of 8 days from August 15 to 22 of the episode were optimized in order to select targeted control strategies for three various MINLP models. The supplemental control strategies with considerable penalized cost were introduced into the optimization model to encourage feasibility.

4.6.1 Computational Results of Nonlinear Static Model

In Table 4.1, 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 represents that only the NO_x control was helpful on emission reduction. Results show 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 MIP models. The same set of control strategies are implement 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 strategy would be implemented the exactly same emission reduction in the different meteorology of each day in the entire episode. This is the reason why the static model yields the most expensive cost of selected control strategies.

Table 4.1 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)

Table 4.1 – *Continued*

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 4.2 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	12-6am	Johnson & Parker, Tarrant
Aug 16	12-6am	Collin, Dallas
Aug 16	6am-12pm	Tarrant
Aug 17	12-6am	Dallas
Aug 17	6am-12pm	Denton
Aug 18	12-6am	Tarrant
Aug 19	12-6am	Johnson & Parker
Aug 19	6am-12pm	Dallas
Aug 20	12-6am	Ellis, Johnson & Parker
Aug 20	6am-12pm	Collin, Denton
Aug 21	12-6am	Denton
Aug 21	12pm-3pm	Ellis
Aug 22	12-6am	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 need to be considered in the optimization. The results of the supplemental control in targeted time periods and locations are shown in Table 4.2. Most supplementary implementations required further reduction of ozone during the morning busy hours (12-6am and 6-12pm) except Ellis on August 21 and 22. Each day of the episode required at least one supplemental control for controlling 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 linear model.

4.6.2 Computational Results of Nonlinear Sequential Model

The set of selected control strategies from the sequential model in each day are shown in Table 4.3. On August 15, nine control strategies of on-road VOC emission sources and two control strategies 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 $256.7 billion, and the total the cost for selected control strategies is $2.74 million.

Table 4.3 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	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 4.4. 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 (12-6am and 6-12pm). 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 12-6am 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 4.4 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	12-6am	Johnson & Parker, Tarrant
Aug 16	12-6am	Collin, Dallas
Aug 17	12-6am	Dallas
Aug 17	6am-12pm	Denton
Aug 18	12-6am	Tarrant
Aug 19	12-6am	Denton, Johnson & Parker
Aug 19	6am-12pm	Dallas
Aug 20	12-6am	Ellis, Johnson & Parker
Aug 20	6am-12pm	Collin, Denton
Aug 21	12-6am	Denton
Aug 21	12-3pm	Ellis
Aug 22	12-6am	Collin, Dallas, Tarrant
Aug 22	6am-12pm	Dallas
Aug 22	3pm-7pm	Ellis

4.6.3 Computational Results of Nonlinear Dynamic Model

Table 4.5 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 matches the optimization on the linear models from Chapter 3 in which the dynamic model yields the least total estimated cost among three 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 to be manipulated, and optimization in a single general model, the dynamic models have more capability to manipulate the ozone concentration in advance in order to satisfy other 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 4.5 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 4.6. Most supplemental controls occurred during the morning busy hours (12-6am and 6-12pm). Denton and Dallas used supplemental controls during four time periods to further reduce ozone, which were the most of all of the counties. Kaufman and Rockwall did not need any supplementary control for ozone attainment. The results of the supplemental control 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 (12-6am) 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 4.6 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	12-6am	Johnson & Parker, Tarrant
Aug 16	12-6am	Collin, Dallas
Aug 17	12-6am	Dallas
Aug 17	6am-12pm	Denton
Aug 18	12-6am	Tarrant
Aug 19	12-6am	Johnson & Parker
Aug 19	6am-12pm	Dallas
Aug 20	12-6am	Ellis, Johnson & Parker
Aug 20	6am-12pm	Collin, Denton
Aug 21	12-6am	Denton
Aug 21	12pm-3pm	Ellis
Aug 22	12-6am	Tarrant
Aug 22	6am-12pm	Dallas
Aug 22	3pm-7pm	Ellis

CHAPTER 5

CONCLUSIONS AND FUTURE RESEARCH

5.1 Conclusion

Optimizing the selection of the cost effective control strategies for ground-level ozone has been a continuing challenge for air quality research. The struggle to improve air quality has lasted for decades. Although the air quality for many U.S. cities is cleaner today than it was couple decades ago, air pollution, such as ground-level ozone, continues to be a serious environmental challenge that would benefit from closer cooperation between environmental science, government decision makers, and operations research. This dissertation addressed this need by formulating and studying MIP models from operations research to complete the decision-making framework developed in environmental engineering Sule (2009) and the optimization of DFW control strategies provided by NCTCOG and TCEQ. This dissertation studied both linear and non-linear MIP applied to three different optimization models. In particular, the MIP models for the DFW case study were infeasible, making it necessary to introduce supplemental control strategies with considerable penalized cost to enable feasible solutions. Results from these different MIP models allow decision-makers to study how the selection of control strategies varies under for different circumstances. Furthermore, given that the DFW case study was infeasible, these MIP models also identify the best regions and time periods for supplemental control. The findings are as follows:

1. Dynamic optimization models for both linear and nonlinear formulations yielded the minimum total estimated cost for control strategy and supplemental control implementation. This is because of a dynamic model not only allows flexibility from day to day, but conducts simultaneous optimization across all the days, so as to fully capture the downstream impacts of emissions.

2. All models required supplemental control to enable feasible solutions for the DFW case study. Dallas and Denton required the most supplemental control for controlling ozone and Dallas and Tarrant required the most supplemental control for reducing emission. However, Kaufman and Rockwall did not apply any supplemental control for further ozone reduction.
3. For the static optimization models, the same control strategies for on-road and non-road emissions were selected by both the linear and nonlinear models. For point source emissions, only one control strategy was different between linear and nonlinear models.
4. For the sequential optimization models, the same control strategies were selected on August 15, 17, 18, 19, and 20 by both the linear and nonlinear models. On August 16, one control strategy was different between the linear and nonlinear models. On August 21, five more non-road control strategies of NO_x were selected by the nonlinear model, and point source control strategy was different selected by the nonlinear model, but not by the linear model.
5. For the dynamic model, the same control strategies were selected on August 17 by both the linear and nonlinear models. One on-road VOC control strategy was removed by the nonlinear model on August 15. One point source control strategy was added by the nonlinear model on August 16. One point source control strategy was removed by the nonlinear model on August 18. One non-road NO_x control strategy was removed by the nonlinear model on August 19. An additional ten on-road NO_x control strategies were selected by the nonlinear model and one point source control strategy was different n between the linear and nonlinear models on August 20. On August 21, nine on-road NO_x control strategies were removed by the nonlinear model, seven on-road VOC control strategies were removed by the nonlinear model, non-road control strategies of NO_x emissions were selected in the nonlinear model, however VOC emissions were selected in the linear model, and one point source control strategy was

different between the linear and nonlinear models. Finally, one point source control strategy was selected by nonlinear model on August 22, but not by the linear model.

5.2 Future research

Some possible directions for future research based on the results of this study include the following:

1. In this research of the dissertation, the ozone prediction models were regression models with emission and prior ozone concentration as predictor variables. Meteorological data such as wind speed, wind direction, maximum daily temperature, could help to refine these regression models.
2. The baseline case of 2006 episode is currently in development. The methodology in this dissertation could be applied to select control strategies for this future case based on this 2006 episode.
3. No interaction terms were considered in the regression metamodels in this research or in Sule (2009). This choice was made to simplify the optimization formulations. 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 metamodels in this research.
4. Piecewise linear approximations were used to approximate nonlinear functions resulting from the refinement of the metamodels conducted to better satisfy regression model assumptions. In this dissertation, 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 approximation 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.

APPENDIX A

SUMMARY OF METAMODELS FOR AUGUST 15 - 22

Collin

August 15

12 midnight – 6 am
- 0.008 (P2Jo 12-6aN) + 0.162 (P3Da 12-6aN) + 0.015 (P3De 12-6aN) - 0.0013 (P4Da 12-6aV) + 0.102 (P6Da 12-6aN) + 51.75 ≤ 68.09

6 am – 12 noon
0.877 (O_3Co 12-6a) + 0.296 (O_3KR 12-6a) + 0.091 (P4Ta 12-6aV) + 7.56 ≤ 68.09

12 noon – 3 pm
1.1 (O_3Co 6-12n) - 0.706 (O_3Co 12-6a) + 0.005 (O_3Ta 6-12n) - 0.007 (O_3Da 6-12n) + 26.13 ≤68.09

3 pm – 7 pm
- 0.197 (P2Jo 6-12nN) + 0.407 (P4Da 12-7pN) - 0.187 (P6Da 6-12nN) + 53.73 ≤ 68.09

7 pm – 12 midnight
0.008 (O_3Da 3-7p) + 0.0021 (LRo 3-12mN) - 0.014 (P1Pa 6-12nV) + 0.002 (P3Da 7-12mV) - 0.0004 (P3El 6-12nV) - 0.006 (P3El 12-7pV) - 0.005 (P4Ka 12-7pN) + 0.002 (P5Ta 6-12nV) - 0.004 (AEl 6-9aN) - 0.003 (LJo 6-3pN) - 0.01 (P6Da 6-12nV) + 41.74 ≤ 68.09

Dallas

August 15

12 midnight – 6 am
0.532 (P3Ka 12-6aN) - 0.422 (P3Ka 12-6aV) - 0.242 (P4Da 12-6aV) - 0.102 (P4Ta 12-6aV) + 0.433 (Prev.day O_3KR 7-12mn) + 0.083 (P4Da 12-6aN) - 0.460 (P6Ta 12-6aN) + 32.86 ≤ 74.09

6 am – 12 noon
1.90 (O_3Da 12-6a) - 0.539 (O_3Ta 12-6a) - 0.553 ≤ 74.09

12 noon – 3 pm
0.557 (O_3Co 6-12n) + 0.834 (O_3Da 6-12n) - 0.947 (O_3Da 12-6a) - 0.167 (P7El 6-12nV) + 0.431 (O_3Ta 6-12n) - 0.433 (O_3Ta 12-6a) + 9.79 ≤ 74.09

3 pm – 7 pm
-1.272 (O_3Co 6-12n) + 2.462 (O_3Co 12-3p) + 0.326 (P5Ka 12-7pN) – 12.40 ≤ 74.09

7 pm – 12 midnight
1.369 (O_3Co 3-7p) - 22.63 ≤ 74.09

Denton

August 15

12 midnight – 6 am
- 0.464 (P4Ka 12-6aN) – 0.118 (P4Ta 12-6aN) - 0.091 (P6Da 12-6aN) + 0.178 (Prev.day O_3Ta 7-12mn) +46.21 ≤ 84.91

6 am – 12 noon
0.505 (O_3Co 12-6a) + 0.849 (O_3Da 12-6a) - 1.018 (O_3De 12-6a) + 2.579 (O_3Ta 12-6a) - 78.66 ≤ 84.91

12 noon – 3 pm
-0.221 (O_3Co 6-12n) + 0.702 (O_3Da 6-12n) – 1.017 (O_3Da 12-6a) + 1.094 (O_3De 6-12n) – 0.782 (O_3De 12-6a) + 50.25 ≤ 84.91

3 pm – 7 pm
0.253 (O_3Da 12-3p) – 0.534 (O_3De 6-12n) +0.869 (O_3De 12-3p) – 0.143 (O_3Da 12-6a) + 0.389 (O_3De 12-6a) + 7.54 ≤ 84.91

7 pm – 12 midnight
1.279 (O_3Co 3-7p) + 0.272 (O_3Da 3-7p) - 42.44 ≤ 84.91

Ellis

August 15

12 midnight – 6 am
- 0.217 (P3Da 12-6aN) + 0.171 (P3Ta 12-6aV) - 0.162 (P4Da 12-6aN) + 0.197 (P7El 12-6aV) - 0.302 (P7El 12-6aN) + 49.86 ≤ 71.10

6 am – 12 noon
2.678 (O_3El 12-6a) - 63.98 ≤ 71.10

12 noon – 3 pm
0.673 (O_3El 6-12n) - 0.427 (P3Ta 6-12nN) - 0.497 (P1De 6-12nN) + 20.22 ≤ 71.10

3 pm – 7 pm
0.152 (P2Jo 12-7pV) + 55.44 ≤ 71.10

7 pm – 12 midnight
- 0.089 (P1De 12-6aV) + 46.41 ≤ 71.10

Johnson & Parker

August 15

12 midnight – 6 am
0.379 (P3El 12-6aN) + 0.45 (P3El 12-6aV) + 0.753 (P6Ta 12-6aN) + 0.111 (Prev.day O_3Da 7-12mn) + 48.33 ≤ 71.07

6 am – 12 noon
1.694 (O_3JP 12-6a) - 16.12 ≤ 71.07

12 noon – 3 pm
0.191 (O_3Co 6-12n) + 0.172 (O_3El 6-12n) + 0.925 (O_3JP 6-12n) - 0.208 (O_3JP 12-6a) + 0.159 (LKa 6-3pV) - 8.44 ≤ 71.07

3 pm – 7 pm
0.164 (O_3El 6-12n) + 0.487 (O_3El 12-3p) + 0.445 (O_3JP 12-3p) - 8.68 ≤ 71.07

7 pm – 12 midnight
0.037 (O_3El 6-12n) + 0.341 (O_3El 12-3p) + 0.055 (O_3TA 3-7p) + 24.846 ≤ 71.07

Kaufman & Rockwall

August 15

12 midnight – 6 am
0.060 (P4Da 12-6aV) - 0.073 (P2Jo 12-6aV) + 0.131 (P6Da 12-6aN) + 46.40 ≤ 66.54

6 am – 12 noon
0.008 (Ade 6-9aN) - 0.0046 (P1De 6-12nN) - 0.0004 (P2Jo 12-6aV) - 0.0065 (P3De 12-6aV) - 0.00011 (P3El 12-6aN) - 0.0023 (P4Da 12-6aN) + 0.00083 (P4Ta 12-6aN) + 0.0028 (P5Ta 6-12nV) - 0.0011 (P6Da 12-6aN) + 0.0071 (P6Ta 12-6aN) + 62.53 ≤ 66.54

12 noon – 3 pm
- 0.017 (Lda 6-3pN) - 0.178 (LDa 6-3pV) + 0.01 (P1De 6-12nN) + 0.015 (P2Jo 12-6aV) - 0.02 (P3Ta 12-6aN) - 0.016 (P5Co 6-12nV) - 0.008 (Lro6-3pV) + 0.015 (LTa 6-3pV) - 0.013 (P4Da 6-12nN) - 0.007 (P4Da 12-6aN) + 62.22 ≤ 66.54

3 pm – 7 pm
0.635 (KR12-3p) + 18.62 ≤ 66.54

7 pm – 12 midnight
1.146 (KR6-12n) - 24.28 ≤ 66.54

Tarrant

August 15

12 midnight – 6 am
0.19 (P3De 12-6aV) + 0.455 (P3Ka 12-6aN) - 0.16 (P6Da 12-6aN) + 0.033 (P6Da 12-6aV) + 0.127 (Prev.day O_3Ta 7-12mn) + 50.15 ≤ 76.22

6 am – 12 noon
0.892 (O_3Da 12-6a) - 1.84 (O_3De 12-6a) + 3.691 (O_3Ta 12-6a) - 72.38 ≤ 76.22

12 noon – 3 pm
0.493 (O_3Da 6-12n) - 0.717 (O_3Da 12-6a) - 0.610 (O_3De 12-6a) - 0.180 (LTa 6-3pV) + 1.035 (O_3Ta 6-12n) +29.11 ≤ 76.22

3 pm – 7 pm
0.554 (O_3El 12-3p) + 0.533 (P7El 12-7pN) + 0.188 (O_3Ta 12-3p) +11.38 ≤ 76.22

7 pm – 12 midnight
- 0.64 (P7El 7-12mN) - 0.493 (P5Ka 12-7pN) + 51.09 ≤ 76.22

Collin

Aug 16

12 midnight – 6 am
- 0.503(P3Ka 12-6aV) + 0.377(Prev.day O_3Da 7-12mn) + 42.634 ≤ 89.61

6 am-12 noon
1.305 (O_3Da 12-6a) - 0.358 (P4Ta 6-12mN) + 3.623 (O_3Co 12-6a) - 1.353 (O_3De 12-6a) - 0.296 (P4Da 12-6aV) + 0.383 (P5Ka 6-12nN) - 124.116 ≤ 89.61

12 noon-3 pm
0.251 (O3Da6-12n) + 0.705 (O_3Co 6-12n) - 0.161(O_3Da 12-6a) - 0.057 (O_3El 6-12n) - 0.580 (O_3De 12-6a) + 0.072 (LEl 9-3pN) + 48.97 ≤ 89.61

3 pm-7 pm
- 0.429 (O_3Da 6-12n) + 0.139 (O_3Co 6-12n) + 0.399 (O_3Da 12-3p) + 0.129 (O_3Da 12-6a) + 0.274 (O_3De 12-3p) + 0.132 (P5Ka 6-12nN) - 0.060 (O_3Ta 6-12n) + 29.02 ≤ 89.61

7pm -12 midnight
0.01 (LJo 6-9aV) - 0.0164 (P5Co 12-7pN) - 0.0136 (ACo 9-3pN) + 0.005 (P5Da 6-12nN) + 38.76 ≤ 89.61

Dallas

Aug 16

12 midnight-6 am
- 0.19 (P2Jo 12-6aV) - 0.422 (P4Da 12-6aN) + 0.316 (P4Da 12-6aV) + 0.039 (P4Ta 12-6aV) + 61.11 ≤ 89.77

6 am-12 noon
2.788 (O_3Da 12-6a) - 1.861 (P4Ta 6-12nN) – 81.497 ≤ 89.77

12 noon -3pm
1.397 (O_3Da 6-12n) - 0.693 (O_3Co 6-12n) - 0.271 (O_3Da 12-6a) + 0.163(P3El 12-6aN) + 41.470 ≤ 89.77

3 pm-7pm
- 0.534(O_3Da 6-12n) + 0.983 (O_3Da 12-3p) - 0.322 (O_3Da 12-6a) + 0.098 (O_3El 6-12n) – 0.215(P7El 12-7pV) + 41.374 ≤ 89.77

7-12m
- 0.070 (P2Jo 12-6aN) + 46.140 ≤ 89.77

Denton

Aug 16

12 midnight-6 am
- 0.382 (P3Ka12-6aV) + 61.99 ≤ 93.60
6 am-12 noon
1.368 (O_3Da 12-6a) + 1.18(O_3Co 12-6a) - 58.45 ≤ 93.60

12 noon -3pm
0.532(O_3Da 6-12n) - 0.272(O_3Da 12-6a) + 0.137 (O_3Ta 6-12n) + 50.03 ≤ 93.60

3 pm-7 pm
- 0.422 (O_3Da 6-12n) + 0.477 (O_3Da 12-3p) + 0.40 (O_3De 12-3p) + 0.185 (O_3Ta 6-12n) + 0.208 (O_3Da 12-6a) - 0.033 (O_3El 6-12n) - 0.058 (P5Jo 12-7pV) + 7.987 ≤ 93.60

7 pm-12 midnight
- 0.086 (O_3KR 3-7p) + 0.020 (LKa 9-3pN) - 0.015 (P1De 12-6aN) - 0.021 (P4Da 6-12nN) + 0.035 (AKa 9-3pN) + 0.013 (ARo 3-7pV) + 0.053 (LDe 9-3pV) + 0.020 (LTa 6-9aV) + 43.89 ≤ 93.60

Ellis

Aug 16

12 midnight-6 am
0.115 (P1De12-6aN) + 0.105 (P2Jo 12-6aN) - 0.022 (P3El 12-6aN) - 0.07 (P3El 12-6aV) - 0.161 (P4Ta 12-6aN) + 54.18 ≤ 78.19

6 am-12 noon
1.42 (O_3Da 12-6a) - 1.621 (P4Ta 6-12nN) - 9.672 ≤ 78.19

12 noon-3 pm
2.229 (O_3El 12-6a) - 0.890 (P3Ta 6-12nN) - 47.596 ≤ 78.19

3 pm-7 pm
1.351 (O_3El 12-6a) + 0.248 (P6Ta 12-6aN) - 11.904 ≤ 78.19

7 pm-12 midnight
0.016 (APa 9-3pN) + 0.014 (LRo 3-7pN) - 0.005 (LRo 9-3pN) - 0.019 (P3Da 12-7pN) + 0.003 (P3De 12-7pV) + 39.42 ≤ 78.19

Johnson & Parker

Aug 16

12 midnight-6 am
- 0.310 (P3Da 12-6aN) + 50.353 ≤ 76.06

6 am-12 noon
1.441 (O_3El 12-6a) + 1.167(O_3JP 12-6a) - 68.654 ≤ 76.06

12 noon-3 pm
0.979 (O_3JP 6-12n) - 0.252 (O_3JP 12-6a) + 13.874 ≤ 76.06

3 pm-7 pm
0.646 (O_3JP 12-3p) + 21.196 ≤ 76.06

7 pm-12 midnight
0.275 (O_3JP 3-7p) - 0.801 (O_3JP 6-12n) + 1.034 (O_3JP 12-3p) - 0.080 (LCo 6-9aV) + 21.613 ≤ 76.06

Kaufman & Rockwall

Aug 16

12 midnight-6 am
$0.044(P4Da\ 12\text{-}6aV) - 0.043\ (Prev.day\ O_3JP7\text{-}12mn) - 0.107(P4Ta\ 12\text{-}6aV) + 55.53 \leq 75.93$

6 am-12 noon
$1.522(O_3JP\ 12\text{-}6a) - 14.440 \leq 75.93$

12 noon-3 pm
$0.60\ (O_3KR\ 6\text{-}12n) - 0.047\ (P1De\ 12\text{-}6aV) - 0.036\ (ADa\ 9\text{-}3pN) + 24.387 \leq 75.93$

3 pm-7 pm
$0.014\ (P3De\ 6\text{-}12nV) - 0.014\ (P5Co\ 12\text{-}7pN) + 54.656 \leq 75.93$

7 pm-12 midnight
No significant variables from data mining

Tarrant

Aug 16

12 midnight-6 am
$0.538\ (Prevday\ O_3De7\text{-}12mn) + 34.264 \leq 87.01$

6 am-12 noon
$1.223\ (O_3Da\ 12\text{-}6a) - 0.952\ (LJo\ 6\text{-}9aN) - 1.190\ (P2Jo\ 12\text{-}6aN) + 1.806\ (P7El\ 6\text{-}12nN) + 17.818 \leq 87.01$

12 noon-3 pm
$0.119\ (O_3Da\ 12\text{-}6a) - 0.284\ (O_3De\ 12\text{-}6a) + 0.227\ (O_3El\ 6\text{-}12n) + 0.756\ (O_3Ta\ 6\text{-}12n) + 11.909 \leq 87.01$

3 pm-7 pm
$-\ 0.235\ (O_3Da\ 12\text{-}3p) + 0.408\ (O_3El\ 6\text{-}12n) + 0.265\ (O_3Ta\ 12\text{-}3p) + 34.679 \leq 87.01$

7 pm-12 midnight
$0.479\ (O_3El\ 3\text{-}7p) - 0.228\ (P7El\ 7\text{-}12mN) + 18.64 \leq 87.01$

Collin

Aug 17

12 midnight-6 am
- 0.25 (Prev.day O_3Da7-12mn) + 0.327 (Prev.day O_3De7-12mn)+ 61.885 ≤ 85.93

6 am-12 noon
2.105 (O_3Da 12-6a) + 2.698 (O_3KR 12-6a) - 186.717 ≤ 85.93

12 noon-3 pm
0.8 (O_3Co 6-12n) + 0.129 (O_3Da 6-12n) + 0.121 (LEl 9-3pN) -0.0552 (O_3Ta 6-12n) + 9.335 ≤ 85.93

3 pm-7 pm
0.35 (O_3Da 12-3p) - 0.606 (O_3Ta 6-12n) + 0.485 (O_3Ta 12-3p) + 51.371 ≤ 85.93

7 pm-12 midnight
0.068 (LKa 9-3pN) - 0.006 (P1De 12-6 aN) - 0.066 (P2Jo 12-6aV) - 0.016 (P2Jo 12-7pN) - 0.003 (P3De 12-6 aV) + 0.047 (ADa 6-9 aV) + 0.024 (LKa 3-7pN) + 0.008 (P3Ka 6-12nV) + 0.049 (P5Pa 12-7pN) + 46.93 ≤ 85.93

Dallas

Aug 17

12 midnight-6 am
- 0.475 (P4Ka 12-6aN) + 57.77 ≤ 92.67

6 am-12 noon
1.350 (AE16-9 aV) + 4.20 (O_3Da 12-6a) + 3.37 (O_3Ka 12-6a) - 349.426 ≤ 92.67

12 noon-3 pm
- 0.215 (O_3Co 6-12n) + 1.2 (O_3Da 6-12n) - 0.125 (O_3Ta 6-12n) - 0.192 (P4Ta 12-6aN) + 10.851 ≤ 92.67

3 pm-7 pm
0.43 (O_3Da 12-3p) - 0.031 (O_3De 6-12n) + 0.028 (O_3De 12-3p) + 1.17 (O_3Co 12-3p) - 1.258 (O_3Co 6-12n) + 44.935 ≤ 92.67

7 pm-12 midnight
0.022 (AEl 3-7pV) + 0.488 (O_3KR3 3-7p) + 22.346 ≤ 92.67

Denton

Aug 17

12 midnight-6 am
- 0.027 (P3Da 12-6aN) + 0.016 (P3De 12-6aV) - 0.011 (p3e1 12-6aN) + 0.024 (Prev.day O_3JP 7-12mn) - 0.029 (P7El 12-6aN) + 0.006 (Prev.day O_3Ta 7-12mn) + 53.29 ≤ 91.03

6 am-12 noon
- 2.884 (AEl 6-9aV) + 0.595 (O_3Da 12-6a) + 65.33 ≤ 91.03

12 noon-3 pm
0.62 (O_3De 6-12n) + 0.319 (O_3Ta 6-12n) + 6.666 ≤ 91.03

3 pm-7 pm
0.923 (O_3Da 12-3p) - 0.042 (O_3De 12-3p) + 0.157 (O_3Ta 6-12n) - 0.251 (O_3Co 12-3p) + 12.076 ≤ 91.03

7 pm-12 midnight
0.28 (O_3De 3-7p) + 0.225 (O_3Ta 3-7p) - 0.807 (O_3El 6-12n) + 0.717 (O_3El 12-3p) + 0.374 (O_3El 3-7p) - 0.159 (P7El 7-12mN) - 8.137 ≤ 91.03

Ellis

Aug 17

12 midnight-6 am
- 0.271 (P3El12-6aN) + 49.901 ≤ 78.01

6 am-12 noon
0.661 (O_3 KR12-6a) + 1.178 (P1De 12-6aV) + 0.832 (P7El12-6aV) + 35.774 ≤ 78.01

12 noon-3 pm
0.986 (O_3E1 6-12n) + 0.176 (P3El 6-12nV) - 0.607 ≤ 78.01

3 pm-7 pm
0.216 (O_3El 12-3p) - 0.285 (P1Pa 6-12nV) - 0.446 (ACo 9-3pN) + 47.191 ≤ 78.01

7 pm-12 midnight
0.042 (P5El 6-12 nV) + 45.889 ≤ 78.01

Johnson & Parker

Aug 17

12 midnight-6 am
- 0.65 5(P2Jo12-6 aN) + 55.737 ≤ 79.62

6 am-12 noon
72.12 + 0.282 (P1Pa 6-12nV) + 0.306 (P4Ta 6-12 nV) + 0.075 (APa 6-9 aN) – 0.648(P1De 6-12 nV) ≤ 79.62

12 noon-3 pm
1.099 (O_3JP 6-12n) - 0.111 (LJo 9-3pN) – 6.815 ≤ 79.62

3 pm-7 pm
-1.346 (O_3JP 6-12n) + 2.239 (O_3JP 12-3p) + 3.812 ≤ 79.62

7 pm-12 midnight
0.303 (LTa 9-3 pN) + 57.833 ≤ 79.62

Kaufman & Rockwall

Aug 17

12 midnight-6 am
- 0.318 (P3Ka 12-6aN) + 60.407 ≤ 82.77

6 am-12 noon
1.399 (O_3KR 12-6a) + 0.215 (AJo 6-9 aN) + 0.210 (P4Da 6-12nV) + 0.380 (P5Ka 6-12nN) - 8.366 ≤ 82.77

12 noom-3 pm
1.044 (O_3KR 6-12n) - 0.653 (O_3KR 12-6a) + 30.088 ≤ 82.77

3 pm-7 pm
0.043 (AKa 9-3 pN) + 62.917 ≤ 82.77

7 pm-12 midnight
- 0.005 (P5El 12-7pN) + 53.616 ≤ 82.77

Tarrant

Aug 17

12 midnight-6 am
0.075 (P4Da 12-6aN) - 0.673 (Prev.day O_3De 7-12mn) - 0.032 (Prev.Day O_3J P 7-12mn) + 82.15 ≤ 88.60

6 am-12 noon
3.245 (O_3Da 12-6a) + 1.156 (P4Da 6-12nV) - 89.738 ≤ 88.60

12 noon-3 pm
- 0.16 (O_3Co 6-12 n) + 0.182 (O_3Da 6-12 n) + 0.977(O_3Ta 6-12 n) - 1.713 (O_3De 12-6 a) + 93.3925 ≤ 88.60

3 pm-7 pm
-1.418 (O_3Co 6-12n) + 1.169 (O_3Da 6-12n) - 0.072 (O_3De 12-3p) + 0.860 (O_3Co 12-3p) - 0.520 (P1Pa 12-7pN) + 31.123 ≤ 88.60

7 pm-12 midnight
- 0.109 (AKa 9-3pV) + 0.336 (O_3E1 3-7p) - 0.083 (LKa 6-9aV) + 35.432 ≤ 88.60

Collin

Aug 18

12 midnight – 6 am
- 0.267 (P7El 12-6aN) + 0.241 (Prev.day O_3Ta 7-12mn) + 46.758 ≤ 91.45

6 am – 12 noon
- 3.882 (O_3De 12-6a) + 0.168 (LJo 6-9aN) + 4 (O_3Ta 12-6a) + 91.146 ≤ 91.45

12 noon – 3 pm
1.019 (O_3Co 6-12n) + 0.423 (O_3De 12-6a) + 0.129 (O_3Ta 6-12n) - 0.431 (O_3Ta 12-6a) + 0.024 (O_3Da6-12n) - 13.950 ≤ 91.45

3 pm – 7 pm
-1.459 (O_3Co 6-12n) + 2.047 (O_3Co 12-3p) + 0.365 (O_3De 6-12n) - 1.371 (O_3Ta 6-12n) + 1.133 (O_3Ta 12-3p) + 14.017 ≤ 91.45

7 pm – 12 midnight
0.320 (ADa 9-3pN) - 0.496 (ACo 9-3pN) + 0.232 (P3De 12-6aV) - 0.250 (P6Ta 12-7pN) + 47.977 ≤ 91.45

Dallas

Aug 18

12 midnight – 6 am
0.378 (Prev.day O_3De 7-12mn) + 35.979 ≤ 92.95

6 am – 12 noon
0.565 (O_3Da 12-6a) + 60.268 ≤ 92.95

12 noon – 3 pm
0.90 (O_3Da 6-12n) - 0.124 (O_3Da 12-6a) - 0.217 (O_3KR 6-12n) + 0.115 (O_3Ta 6-12n) + 22.743 ≤ 92.95

3 pm – 7 pm
0.223 (O_3Da 6-12n) + 0.419 (O_3Da 12-6a) +1 (O_3KR 12-3p) - 1.545 (O_3KR 12-6a) - 0.335 (LEl 9-3pN) + 36.151 ≤ 92.95

7 pm – 12 midnight
0.416 (O_3Co 12-6a) + 0.173 (O_3El 3-7p) + 15.119 ≤ 92.95

Denton

Aug 18

12 midnight – 6 am
0.262 (P3Ka 12-6aN) + 0.030 (P4Da 12-6aV) + 0.124 (P4Ta 12-6aN) + 0.084 (P3Ta 12-6aN) - 0.194 (P4Da 12-6aN) - 0.156 (P6Ta 12-6aN) - 0.037 (Prev.day O_3De 7-12mn) + 65.24 ≤ 93.10

6 am–12 noon
- 0.80 (O_3De 12-6a) + 2.396 (O_3Ta 12-6a) - 0.104 (AJo 6-9aN) - 10.69 ≤ 93.10

12 noon– 3 pm
- 0.019 (APa 6-9aV) + 0.037 (O_3Co 6-12n) + 0.974 (O_3De 6-12n) + 0.06 (O_3Ta 6-12n) - 6.423 ≤ 93.10

3 pm– 7 pm
0.095 (O_3Co12-3p) + 0.644 (O_3De 12-3p) - 0.238 (O_3De 12-6 a) + 0.204 (O_3Ta 12-3p) + 0.023 (O_3Da 12-3p) + 0.053 (LJo 9-3pN) + 11.997 ≤ 93.10

7 pm– 12 midnight
0.316 (O_3Ta 3-7p) + 0.089 (O_3KR 3-7p) - 0.273 (P7El 7-12mN) + 21.994 ≤ 93.10

Ellis

Aug 18

12 midnight – 6 am
$- 0.334 (P3Ta\ 12\text{-}6aN) + 50.277 \leq 69.20$

6 am – 12 noon
$0.931 (P3De\ 6\text{-}12nN) + 1.188 (ADe\ 6\text{-}9aN) + 1.031 (LRo\ 6\text{-}9aN) + 66.808 \leq 69.20$

12 noon– 3 pm
$0.967 (O_3El\ 6\text{-}12N) + 0.098 (P3De\ 6\text{-}12nN) - 0.105 (P7El\ 6\text{-}12nN) + 0.733 \leq 69.20$

3 pm– 7 pm
$0.208 (O_3El\ 12\text{-}3p) - 0.394 (LDa\ 9\text{-}3pN) + 41.550 \leq 69.20$

7 pm– 12 midnight
$- 0.098 (AC0\ 9\text{-}3pN) + 0.05 (O_3E13\text{-}7p) - 0.037 (P3Da\ 6\text{-}12nN) + 0.158 (ADa\ 9\text{-}3PV) - 0.170 (P1De\ 12\text{-}6aV) + 33.33 \leq 69.20$

Johnson & Parker

Aug 18

12 midnight– 6 am
$0.005 (Prev.day\ O_3JP\ 7\text{-}12mn) + 54.47 \leq 66.75$

6 am – 12 noon
$0.035 (P1Pa\ 6\text{-}12nN) + 65.305 \leq 66.75$

12 noon – 3 pm
$0.037 (O_3Ta\ 6\text{-}12n) - 0.068(O_3Ta\ 12\text{-}6a) + 65.736 \leq 66.75$

3 pm– 7 pm
$1.622 (O_3JP\ 12\text{-}3p) - 43.839 \leq 66.75$

7 pm– 12 midnight
$0.939 (O_3JP\ 3\text{-}7p) - 5.812 \leq 66.75$

Kaufman & Rockwall

Aug 18

12 midnight– 6 am
0.123 (Prev.day O_3De 7-12mn) + 49.720 ≤ 82.45

6 am– 12 noon
-1.546 (O_3C0 12-6a) + 4.862 (O_3KR 12-6a) - 92.706 ≤ 82.45

12 noon– 3 pm
- 0.056 (O_3Da 12-6a) + 1.093 (O_3KR 6-12n) - 0.529 (O_3KR 12-6a) + 0.114 (LEl 9-3pN) + 21.129 ≤ 82.45

3 pm -7 pm
0.063 (O_3Da 6-12n) + 0.551 (O_3KR 12-3p) - 0.336 (O_3KR 12-6a) + 0.298 (LEl 9-3pN) – 0.207 (P5Da 12-7pN) + 33.306 ≤ 82.45

7 pm– 12 midnight
0.031 (ACo 6-9aN) + 0.022 (LEl 6-9LV) - 0.058 (P3Ta 7-12mV) - 0.028 (ACo 9-3pN) - 0.021 (ADa 6-9aV) + 53.77 ≤ 82.45

Tarrant

Aug 18

12 midnight-6 am
- 0.245 (P3Ka 12-6aV) + 0.205 (P3Ta 12-6aN) - 0.343 (P4Da 12-6aN) - 0.171 (P6Ta 12-6aN) - 0.164 (Prev.day O_3Co 7-12mn) - 0.109 (Prev.day O_3De 7-12mn) + 0.115 (Prev.day O_3JP 7-12mn) + 0.284 (Prev.day O_3Ta 7-12mn) + 53.53 ≤ 84.18

6 am– 12 noon
0.160 (ADe 6-9aV) - 1.044 (O_3El 12-6a) - 0.967 (O_3KR 12-6a) + 0.688 (P1De 12-6aN) - 0.290 (P2Jo 12-6aN) -1.281 (P2Jo 12-6aV) + 0.868 (P5El 6-12nN) + 0.644 (P4Ta 6-12nN) + 190.93 ≤ 84.18

12 noon– 3 pm
- 0.142 (O_3De 6-12n) + 1.171 (O_3Ta 6-12n) - 0.406 (O_3Ta 12-6a) + 23.475 ≤ 84.18

3 pm– 7 pm
0.036 (O_3El 6-12n) + 0.949 (O_3JP 12-3p) + 0.114 (P4Ta 6-12nN) - 1.394 (O_3Ta 6-12n) + 2.105 (O_3Ta 12-3p) + 0.063 (O_3Da 12-3p) - 52.992 ≤ 84.18

7 pm– 12 midnight
- 0.374 (O_3Co 3-7p) - 1.323 (O_3JP 12-3p) + 1.653 (O_3Ta 3-7p) + 1.821 (O_3Ta 6-12n) - 2.715 (O_3Ta 12-3p) + 111.846 ≤ 84.18

Collin

Aug 19

12 midnight-6 am
0.044 (Prev.day O_3De 7-12mn) + 0.406 (Prev.day O_3JP 7-12mn) + 0.089 (Prev.day O_3Ta 7-12mn) + 24.41 ≤ 72.02

6 am-12 noon
0.360 (O_3Co 12-6a) + 0.240 (O_3De 12-6a) + 0.730 (O_3JP 12-6a) + 0.153 ≤ 72.02

12 noon-3 pm
0.596 (O_3Co 6-12n) - 0.068 (O_3Co 12-6a) + 0.003 (O_3JP 6-12n) + 0.208 (O_3JP 12-6a) - 0.005 (ATa 9-3pN) + 19.229 ≤ 72.02

3 pm-7 pm
0.17 (O_3JP 12-6a) + 0.017 (P3Ta 12-6aN) + 0.015 (P4Ka 12-6aN) + 54.106 ≤ 72.02

7 pm-12midnight
No significant variables from data mining

Dallas

Aug 19

12 midnight-6 am
- 0.014 (P4Da 12-6aN) + 0.171 (P1De 12-6aV) + 53.45 ≤ 87.16

6 am-12 noon
0.855 (O_3Da 12-6a) + 45.802 ≤ 87.16

12 noon-3 pm
0.814 (O_3Da 6-12n) + 0.15 (O_3Ta 6-12n) + 1.79 ≤ 87.16

3 pm-7 pm
0.373 (O_3Da 12-3p) - 0.054 (O_3El 6-12n) + 0.087 (O_3Ta 6-12n) + 41.056 ≤ 87.16

7 pm-12 midnight
- 0.013 (LEl 3-7pN) + 0.0287 (AEl 3-7pN) - 0.005 (O_3JP 12-3p) + 0.001(LJo 3-7pN) + 57.57 ≤ 87.16

Denton

Aug 19

12 midnight-6 am
0.166 (Prev.day O_3De 7-12mn) - 0.047 (Prev.day O_3E l7-12mn) + 0.334 (Prev.day O_3JP 7-12mn) + 0.102 (Prev.day O_3Ta 7-12mn) + 24.930 ≤ 70.10

6 am-12 noon
0.105 (O_3De 12-6a) + 1.059 (O_3JP 12-6a) - 0.035 (LKa 6-9aN) + 6.610 ≤ 70.10

12 noon-3 pm
- 0.103 (O_3Co 12-6a) + 0.791 (O_3De 6-12n) - 0.015 (P4Ta 6-12nN) - 0.016 (P5Co 6-12nV) + 18.719 ≤ 70.10

3 pm-7 pm
No significant variables from data mining

7 pm-12 pm
0.002 (AEl 6-9aV) + 0.0002 (O_3Ta 12-6a) + 53.59 ≤ 70.10

Ellis

Aug 19

12 midnight-6 am
- 0.214 (P3De 12-6aV) + 0.287 (Prev.day O_3De 7-12mn) + 36.74 ≤ 103.52

6 am-12 noon
0.567 (P1De 6-12nV) + 1.067 (P1De 12-6aV) - 0.124 (P3Da 6-12nV) + 0.148 (P3El 12-6aN) - 0.894 (P6Da 12-6aN) + 91.86 ≤ 103.52

12 noon-3 pm
1.068 (O_3El 6-12n) – 5.846 ≤ 103.52

3 pm-7 pm
0.355 (O_3Da 12-3p) + 0.434 (O_3El 12-3p) + 0.170(O_3Ta 6-12n) + 0.316 (O_3KR 12-6a) - 17.628 ≤ 103.52

7 pm-12 midnight
0.347(O_3KR 12-3p) + 0.233(O_3Da 3-7p) + 13.533 ≤ 103.52

Johnson & Parker

Aug 19

12 midnight-6 am
0.181(Prev.day O_3JP 7-12mn) + 0.013(Prev.day O_3Ta 7-12mn) + 45.620 ≤ 76.06

6 am-12 noon
- 2.588 (O_3Co 12-6a) + 6.968 (O_3De 12-6a) + 0.451 (AJo 6-9aN) - 161.961 ≤ 76.06

12 noon-3 pm
0.709 (O_3JP 6-12n) + 1.129 (O_3JP 12-6a) + 0.135 (O_3Da 6-12n) + 0.167 (O_3KR 6-12n) - 61.464 ≤ 76.06

3 pm-7 pm
1.169 (O_3De 12-6a) - 0.872 (O_3JP 6-12n) + 1.488 (O_3JP 12-3p) + 0.192 (LEl 6-9aN) - 35.978 ≤ 76.06

7 pm-12 midnight
0.263 (O_3Da 6-12n) + 0.102 (O_3Ta 12-3p) - 0.483 (O_3Da 3-7p) + 0.983 (O_3De 6-12n) + 0.578 (O_3KR 12-6a) - 30.793 ≤ 76.06

Kaufman & Rockwall

Aug 19

12 midnight-6 am
- 0.016 (P3Da 12-6aN) - 0.134 (P3De 12-6aV) + 0.174 (P4Ta 12-6aN) – 0.175 (P6Da 12-6aN) + 0.043 (P1De 12-6aV) + 0.182 (P3El 12-6aV) - 0.545 (Prev.day O_3KR 7-12mn) + 83.44 ≤ 95.86

6 am-12 noon
0.309 (O_3Da 12-6a) + 1.309 (O_3KR 12-6a) - 4.353 ≤ 95.86

12 noon-3 pm
0.782(O_3KR 6-12n) + 16.297 ≤ 95.86

3 pm-7 pm
- 1(O_3Co 6-12n) + 2.986 (O_3Co 12-3p) + 0.060 (O_3JP 12-3p) - 0.655 (O_3JP 12-6a) - 35.777 ≤ 95.86

7 pm-12 midnight
- 0.161 (O_3Co 6-12n) + 0.541 (O_3KR 3-7p) - 0.012(O_3Ta 12-6a) + 30.437 ≤ 95.86

Tarrant

Aug 19

12 midnight-6 am
0.177 (Prev.day O_3De 7-12mn) + 0.349 (Prev.day O_3JP 7-12mn) + 0.086 (Prev.day O_3Ta 7-12mn) + 22.578 ≤ 80.60

6 am-12 noon
0.469 (O_3Da 12-6a) + 9.889 (O_3JP 12-6a) - 483.56 ≤ 80.60

12 noon-3 pm
- 0.217 (O_3Co 6-12n) + 0.106 (O_3Da 6-12n) + 0.904 (O_3Ta 6-12n) + 13.880 ≤ 80.60

3 pm-7 pm
0.27 (O_3Da 6-12n) - 0.287 (O_3Da 12-3p) + 0.371 (O_3Ta 12-3p) + 45.332 ≤ 80.60

7 pm-12 midnight
- 0.014 (LEl 3-7pN) + 0.029 (AEl 3-7pN) - 0.005 (O_3JP 12-3p) + 0.001(LJo 3-7pN) + 57.56 ≤ 80.60

Collin

Aug 20

12 midnight-6 am
- 0.0066 (P7El 12-6aN) + 50.232 ≤ 58.54

6 am-12 noon
0.005 (P3Ka 12-6aN) + 0.0033 (P6Da 12-6aN) + 63.954 ≤ 58.54

12 noon-3 pm
0.0036 (O_3El 6-12n) + 0.5440 (O_3Co 6-12n) - 0.0008 (O_3JP 6-12n) + 25.931 ≤ 58.54

3 pm-7 pm
No significant variables from data mining

7 pm-12 midnight
No significant variables from data mining

Dallas

Aug 20

12 midnight-6 am
$- 0.622 (P4Ka\ 12\text{-}6aN) + 58.266 \leq 69.01$

6 am-12 noon
$1.362 (O_3Da\ 12\text{-}6a) + 1.567 (O_3El\ 12\text{-}6a) - 1.696 (O_3Ta\ 12\text{-}6a) + 1.136 (AEl\ 6\text{-}9aN) + 13.445 \leq 69.01$

12 noon-3 pm
$0.690 (O_3Da\ 6\text{-}12n) + 0.060 (O_3Da\ 12\text{-}6a) + 0.203 (O_3Ta\ 6\text{-}12n) - 5.781 (O_3De\ 12\text{-}6a) + 296.197 \leq 69.01$

3 pm-7 pm
$- 0.595 (APa\ 9\text{-}3pN) - 18.12 (O_3KR\ 12\text{-}6a) + 8.82 (O_3KR\ 6\text{-}12n) - 0.209 (LJo\ 6\text{-}9aV) + 0.134 (P3Da\ 12\text{-}6aV) - 0.293 (P5Da\ 6\text{-}12nN) - 0.082 (P7El\ 12\text{-}7pV) - 0.681 (P5Da\ 6\text{-}12nV) - 0.573 (P5Ta\ 6\text{-}12nV) + 430.09 \leq 69.01$

7 pm-12 midnight
$0.651 (O_3Da\ 3\text{-}7p) + 4.791 \leq 69.01$

Denton

Aug 20

12 midnight-6 am
$0.0063 (P3De\ 12\text{-}6aN) + 50.783 \leq 60.50$

6 am-12 noon
$0.0277 (LDe\ 6\text{-}9aV) - 0.0311 (P1De\ 6\text{-}12nN) + 0.031 (P3De\ 12\text{-}6aN) + 64.470 \leq 60.50$

12 noon-3 pm
$0.942 (O_3De\ 6\text{-}12n) + 3.278 \leq 60.50$

3 pm-7 pm
No significant variables from data mining

7 pm-12 midnight
No significant variables from data mining

Ellis

Aug 20

12 midnight-6 am
0.514 (Prev.day O_3El 7-12mn) + 25.321 ≤ 80.64

6 am-12 noon
1.616 (O_3El 12-6a) - 0.753 (O_3Ta 12-6a) + 1.009 (AEl 6-9aN) + 35.15 ≤ 80.64

12 noon-3 pm
0.523 (O_3Da 6-12n) + 0.654 (O_3El 6-12n) - 0.11 (O_3Ta 12-6a) + 0.304 (P3Ka 12-6aN) - 10.363 ≤ 80.64

3 pm-7 pm
0.332 (O_3Da 6-12n) + 0.237 (O_3El 6-12n) + 17.101 ≤ 80.64

7 pm-12 midnight
0.534 (O_3Da 3-7p) + 5.620 ≤ 80.64

Johnson & Parker
Aug 20

12 midnight-6 am
- 0.452 (P3Da 12-6aN) + 0.597 (Prev.day O_3JP 7-12mn) + 21.055 ≤ 65.23

6 am-12 noon
1.078 (O_3JP 12-6a) + 0.805 (P3Ka 6-12nN) - 0.348 (O_3Da 12-6a) + 38.451 ≤ 65.23

12 noon-3 pm
- 0.091 (O_3JP 12-6a) + 0.997 (O_3JP 6-12n) + 3.15 ≤ 65.23

3 pm-7 pm
0.508 (O_3JP 12-3p) + 25.125 ≤ 65.23

7 pm-12 midnight
0.065 (O_3Da 3-7p) + 0.183 (P6Ta 12-6aN) - 0.255 (P7El 7-12mN) + 42.322 ≤ 65.23

Kaufman & Rockwall

Aug 20

12 midnight-6 am
0.004 (P3De 12-6aN) + 0.0009 (P3Ta 12-6aN) + 0.002 (P4Da 12-6aV) + 0.0002 (P4Ka 12-6aV) - 0.013 (Prev.dayKR 7-12mn) + 51.95 ≤ 72.29

6 am-12 noon
0.8 (O_3KR 12-6a) + 0.0065 (P5Da 6-12nV) + 22.640 ≤ 72.29

12 noon-3 pm
0.804 (O_3KR 6-12n) + 11.068 ≤ 72.29

3 pm-7 pm
- 0.0047 (AJo 3-7pN) + 54.681 ≤ 72.29

7 pm-12 midnight
No significant variables from data mining

Tarrant

Aug 20

12 midnight-6 am
0.013 (P1De 12-6aN) - 0.168 (P3De 12-6aN) - 0.233 (P4Da 12-6aN) + 0.252 (P6Ta 12-6aN) + 0.30 (Prev.dayEl 7-12mn) + 40.18 ≤ 68.45

6 am-12 noon
1.227 (O_3El 12-6a) + 0.983 (AEl 6-9aN) + 13.312 ≤ 68.45

12 noon-3 pm
0.626 (O_3Da 6-12n) - 0.191 (O_3El 6-12n) + 0.461 (O_3Ta 6-12n) - 6.438 (O_3De 12-6a) + 0.107 (LCo 6-9aN) + 0.115 (LJo 6-9aN) + 0.224 (P5Pa 6-12nV) + 332.589 ≤ 68.95

3 pm-7 pm
- 0.037 (LKa 6-9aV) + 0.047 (P1De 12-6aV) - 0.106 (P3De 12-6aN) - 0.136 (P3El 6-12nV) - 0.448 (P3Ka 12-6aV) - 0.35 (P5Co 6-12nV) - 0.137 (P5El 6-12nN) +0.259 (P5Pa 12-7pN) + 0.220 (P3Ka 6-12nN) + 63.03 ≤ 68.45

7 pm-12 midnight
1.231 (O_3Ta 3-7p) - 32.660 ≤ 68.45

Collin

Aug 21

12midnight-6 am
0.0003 (P2Jo 12-6aN) + 0.0001 (P4Ta 12-6aN) + 0.003 (P7El 12-6aV) + 0.002 (P4Ta 12-6aV) + 0.012 (Prev.dayDa 7-12mn) - 0.017 (Prev.dayEl 7-12mn) + 0.002 (Prev.dayTa 7-12mn) + 54.05 ≤ 72.95

6 am-12 noon
0.493 (O_3De 12-6a) + 0.820 (O_3KR 12-6a) - 0.256 (P3Da 6-12nN) - 0.190 (P7El 6-12nV) - 0.315 (O_3Ta 12-6a) + 23.73 ≤ 72.95

12 noon-3 pm
1.247 (O_3Co 6-12n) - 0.026 (O_3Da 6-12n) - 0.180 (O_3KR 12-6a) - 10.81 ≤ 72.95

3 pm-7 pm
0.057 (P5Da 12-7pN) + 60.86 ≤ 72.95

7 pm-12 midnight
0.411 (O_3Co 6-12n) - 0.634 (O_3Co 12-3p) + 0.019 (O_3Da 3-7p) + 0.036 (O_3Da 12-3p) + 0.44 (O_3De 3-7p) + 0.005 (P2Jo 7-12mN) + 0.008 (P5Ka 12-7pN) + 0.0004 (LKa 6-3pN) + 0.019 (P5Da 6-12nN) + 0.018 (P5Da 6-12nV) - 0.002 (P5Ka 6-12nN) - 0.011 (P5Ka 6-12nV) + 36.51 ≤ 72.95

Dallas

Aug 21

12 midnight-6 am
0.285 (P1De 12-6aN) + 0.03 (P3De 12-6aN) + 0.186 (P3El 12-6aN) + 0.107 (P3Ta 12-6aV) - 0.196 (P4Ta 12-6aN) + 0.299 (P7El 12-6aV) + 0.261 (P3El 12-6aV) + 0.129 (Prev.dayDa 7-12mn) - 0.137 (Prev.dayEl 7-12mn) + 55.13 ≤ 76.40

6 am-12 noon
- 26.665 (O_3Co 12-6a) + 0.524(O_3Da 12-6a) + 2.438 (O_3De 12-6a) - 1.178 (O_3Ta 12-6a) + 1415.208 ≤ 76.40

12 noon-3 pm
0.208 (O_3Co 6-12n) + 0.789 (O_3Da 6-12n) + 0.344 (O_3De 6-12n) - 1.041 (O_3De 12-6a) - 0.124 (O_3Ta 6-12n) - 0.081 (LRo 6-3pN) + 37.47 ≤ 76.40

3 pm-7 pm
- 3.231(O_3Co 6-12n) + 3.535 (O_3Co 12-3p) + 54.98 ≤ 76.40

7 pm-12 midnight
0.389 (O_3Da 3-7p) + 0.210 (O_3El 12-3p) + 0.418 (O_3Ta 3-7p) - 6.59 ≤ 76.40

Denton

Aug 21

12 midnight-6 am
- 0.266 (P4Ka 12-6aN) + 57.36 ≤ 84.08

6 am-12 noon
0.575 (O_3Da 12-6a) + 4.713 (O_3De 12-6a) - 0.386 (O_3KR 12-6a) - 0.143 (P7El 6-12nV) - 197.39 ≤ 84.08

12 noon-3 pm
0.535 (O_3Da 6-12n) - 1.003 (O_3De 12-6a) + 0.738 (O_3Ta 6-12n) - 0.192 (O_3Co 6-12n) - 0.256 (O_3Da 12-6a) + 65.05 ≤ 84.08

3 pm-7 pm
- 0.771 (O_3Co 6-12n) + 1.186 (O_3Co 12-3p) - 0.082 (O_3Da 6-12n) - 0.131 (O_3De 12-6a) + 0.083 (P5Da 12-7pN) + 0.041 (O_3Ta 12-3p) + 47.55 ≤ 84.08

7 pm-12 midnight
0.626 (O_3Co 3-7p) – 0.045 (O_3De 3-7p) + 0.013 (P5Ka 12-7pN) + 14.865 ≤ 84.08

Ellis

Aug 21

12 midnight-6 am
0.197 (Prev.dayO_3El 7-12mn) + 42.399 ≤ 68.74

6 am-12 noon
0.504 (O_3El 12-6a) + 43.38 ≤ 68.74

12 noon-3 pm
- 0.072 (AJo 9-3pN) + 0.093 (P3Ka 6-12nN) + 0.460 (O_3El 6-12n) + 1.082 (O_3KR 6-12n) - 35.33 ≤ 68.74

3 pm-7 pm
0.160 (P6Da 6-12nV) + 61.04 ≤ 68.74

7 pm-12 midnight
1.080 (O_3El 3-7p) - 19.244 ≤ 68.74

Johnson & Parker

Aug 21

12 midnight-6 am
0.202 (P3Da 12-6aV) + 0.228 (P3El12-6aV) + 0.115 (P4Ka 12-6aV) + 0.0003 (P6Da 12-6aN) - 0.217 (P4Da 12-6aV) - 0.248 (Prev.day O_3JP 7-12mn) + 64.82 ≤ 74.38

6 am-12 noon
1.319 (O_3JP 12-6a) - 1.187 (P4Ta 6-12nV) + 4 ≤ 74.38

12 noon-3 pm
0.795 (O_3JP 6-12n) + 13.759 ≤ 74.38

3 pm-7 pm
0.734 (O_3JP 12-3p) + 1.237 (O_3El 12-6a) - 0.126 (O_3JP 6-12n) - 38.281 ≤ 74.38

7 pm-12 midnight
0.292 (O_3El 12-6a) + 0.159 (O_3JP 3-7p) + 0.188 (P3El 6-12nV) + 29.843 ≤ 74.38

Kaufman & Rockwall

Aug 21

12 midnight-6 am
0.038 (P3Ka 12-6aN) + 0.023 (P3De 12-6aV) - 0.012 (P4Ta 12-6aV) + 49.71 ≤ 78.09

6 am-12 noon
- 0.006 (O_3JP 12-6a) + 0.007 (P1De 12-6aN) - 0.002 (P3De 12-6aV) - 0.002 (P4Da 12-6aN) - 0.023 (P6Da 12-6aN) + 66.38 ≤ 78.09

12 noon-3 pm
0.022 (P3Ta 6-12nV) - 0.021 (P1Pa 12-6aN) + 66.43 ≤ 78.09

3 pm-7 pm
0.216 (O_3KR 12-3p) - 0.004 (P2Jo 6-12nN) + 51.94 ≤ 78.09

7 pm-12 midnight
0.005 (O_3KR 6-12n) - 0.0002 (P1De 12-7pN) + 59.32 ≤ 78.09

Tarrant

Aug 21

12 midnight-6 am
- 0.358 (P3Ka 12-6aN) - 0.156 (Prev.day O_3Ta 7-12mn) + 65.95 ≤ 72.42

6 am-12 noon
0.981 (O_3Da 12-6a) + 4.753 (O_3De 12-6a) - 0.412 (P7El 6-12nV) + 0.248 (P4Ka 12-6aV) - 243.487 ≤ 72.42

12 noon-3 pm
14.759 (O_3Co 12-6a) + 0.234 (O_3Da 6-12n) - 1.967 (O_3De 12-6a) + 1.422 (O_3Ta 6-12n) - 0.671 (O_3Ta 12-6a) - 0.232 (O_3Co 6-12n) - 0.323 (O_3Da 12-6a) - 667.72 ≤ 72.42

3 pm-7 pm
0.146 (ADa 3-7pV) + 0.131 (APa 6-9aV) + 0.246 (ARo 9-3pV) + 0.106 (LTa 6-3pN) + 0.089 (P1De 12-7pN) - 0.092 (P5Da 12-7pN) + 0.04 (P6Da 12-6aN) - 0.029 (P6Ta 12-6aV) +63.44 ≤ 72.42

7 pm-12 midnight
1.046 (O_3Da 3-7p) + 0.633 (O_3Ta 3-7p) - 53.58 ≤ 72.42

Collin

Aug 22

12 midnight – 6 am
0.153 (P3De 12-6aV) - 0.109 (P4Da 12-6aV) - 0.014 (P6Da 12-6aN) + 0.29 (P4Ta 12-6aV) + 0.05 (Prev.day O_3JP 7-12mn) + 54.37 ≤ 74.96

6 am-12 noon
2.217(O_3Co 12-6a) - 0.349 (O_3Da 12-6a) - 0.452 (O_3De 12-6a) - 8.781 ≤ 74.96

12 noon-3 pm
1.066 (O_3Co 6-12n) - 0.206 (O_3Co 12-6a) - 0.166 (O_3De 12-6a) - 0.107 (O_3KR 12-6a) + 20.428 ≤ 74.96

3 pm-7 pm
0.291 (O_3Ta 6-12n) - 0.087 (O_3Ta 12-3p) + 0.205(ADe 9-3pV) + 0.190 (O_3KR 6-12n) - 0.117 (O_3Ta 12-6a) +29.92 ≤ 74.96

Dallas

Aug 22

12 midnight-6 am
No significant variables from data mining

6 an-12 noon
$- 2.277 (O_3Co\ 12\text{-}6a) + 3.268 (O_3Da\ 12\text{-}6a) +16.44 \leq 76.49$

12 noon-3 pm
$0.642 (O_3Da\ 6\text{-}12n) + 0.171 (O_3De\ 6\text{-}12n) - 0.063 (O_3El\ 6\text{-}12n) – 0.154 (O_3Ta\ 12\text{-}6a) – 0.143 (O_3De\ 12\text{-}6a) + 30.277 \leq 76.49$

3 pm-7 pm
$- 0.670 (O_3Co\ 6\text{-}12n) +1.172 (O_3Co\ 12\text{-}3p) + 0.136 (O_3Da\ 6\text{-}12n) - 0.094 (O_3Ta\ 12\text{-}3p) +23.695 \leq 76.49$

Denton

Aug 22

12 midnight-6 am
$1.068 (Prev.dayO_3El\ 7\text{-}12mn) + 8.84 \leq 82.43$

6 am-12 noon
$3.513 (O_3Co\ 12\text{-}6a) - 0.770 (O_3De\ 12\text{-}6a) + 0.762 (O_3Ta\ 12\text{-}6a) - 120.794 \leq 82.43$

12 noon-3 pm
$0.140 (O_3Co\ 6\text{-}12n) + 1.035 (O_3De\ 6\text{-}12n) - 0.473 (O_3De\ 12\text{-}6a) + 12.92 \leq 82.43$

3 pm-7 pm
$0.056 (ADa\ 9\text{-}3pV) - 0.667 (O_3Co\ 6\text{-}12n) + 0.833 (O_3Co\ 12\text{-}3\ p) + 0.686 (O_3De\ 12\text{-}3p) - 0.046 (P7El\ 6\text{-}12nV) - 0.09 (O_3Ta\ 12\text{-}6a) + 8.66 \leq 82.43$

Ellis

Aug 22

12 midnight-6 am
0.025 (P3Ta 12-6aN) + 0.0009 (P4Ta 12-6aN) - 0.009 (P6Da 12-6aN) - 0.034 (P3Da 12-6aN) - 0.031 (Prev.day O_3El 7-12mn) + 52.64 ≤ 69.65

6 am-12 noon
-1.91 (O_3KR 12-6a) +132.90 ≤ 69.65

12 noon-3 pm
0.929 (O_3El 6-12n) + 0.363 (O_3KR 12-6a) - 0.412 (P5Ka 6-12nN) - 1.921 (O_3KR 6-12n) +103.39 ≤ 69.65

3 pm-7 pm
0.377 (O_3El 12-3p) +0.419 (P5De 12-7pN) +29.701 ≤ 69.95

Johnson and Parker

Aug 22

12 midnight-6 am
0.046 (P2Jo 12-6aN) + 0.057 (P3Da 12-6aV) - 0.021 (P4Da 12-6aV) + 56.60 ≤ 75.10

6 am-12 noon
2.836 (O_3JP 12-6a) - 90.48 ≤ 75.10

12 noon-3 pm
1.035 (O_3JP 6-12n) - 5.56 ≤ 75.10

3 pm-7 pm
0.953 (O_3JP 12-3p) - 1.64 ≤ 75.10

Kaufman and Rockwall

Aug 22

12 midnight-6 am
0.022 (P1De 12-6aN) + 0.096 (P3De 12-6aV) - 0.069 (P4Ta 12-6aV) + 1.017 (Prev.day O_3Co 7-12mn) + 0.048 (Prev.day O_3El 7-12mn) - 0.113 (Prev.day O_3JP7-12mn) - 2.24 ≤ 73.69

6 am-12 noon
No significant variables from data mining

12 noon-3 pm
- 0.0005 (ADa 6-9aN) - 0.00002 (AKa 9-3pN) - 0.0018 (ATa 6-9aN) + 0.00019 (O_3Da 6-12n) - 0.0025 (LJo 6-3V) + 0.0013 (P2Jo 12-6aV) - 0.001 (P3Da 12-6aN) - 0.002 (P3Da 12-6aV) - 0.001 (P3Ka 12-6aN) + 0.002 (AEl 6-9aV) + 0.0003 (P1Pa 12-6aN) - 0.002 (P2Jo 6-12nN) - 0.0011 (P3De 6-12nV) + 62.25 ≤ 73.69

3 pm-7 pm
- 1.16 (O_3KR 12-3p) + 130.95 ≤ 73.69

Tarrant

Aug 22

12 midnight-6 am
0.170 (prev.day O_3Ta 7-12mn) + 47.91 ≤ 76.66

6 am-12 noon
1.293 (O_3Da 12-6a) - 0.59 (O_3De 12-6a) + 1.90 (O_3Ta 12-6a) - 69.10 ≤ 76.66

12 noon-3 pm
0.307 (O_3Da 6-12n) + 0.948 (O_3Ta 6-12n) - 1.3418 (O_3Co 12-6a) + 57.01 ≤ 76.66

3 pm-7 pm
0.71 (O_3El 12-3p) + 0.16 (O_3Ta 12-3p) + 6.10 ≤ 76.66

APPENDIX B

SUMMARY OF DAILY UPERBOUND CONTRAINTS BY MONITORING REGIONS

Monitoring Region	**0815 1999**	**0816 1999**	**0817 1999**	**0818 1999**	**0819 1999**	**0820 1999**	**0821 1999**	**0822 1999**
Collin	68.09	89.61	85.93	91.45	72.02	58.54	72.95	74.96
Dallas	74.09	89.77	92.67	92.95	87.16	69.01	76.40	76.49
Denton	84.91	93.60	91.03	93.10	70.10	60.50	84.08	82.43
Ellis	71.10	78.19	78.01	69.20	103.52	80.64	68.74	69.65
Johnson & Parker	71.07	76.06	79.62	66.75	76.06	65.23	74.38	75.10
Kaufman & Rockwall	66.54	75.93	82.77	82.45	95.86	72.29	78.09	73.69
Tarrant	76.22	87.01	88.60	84.18	80.60	68.45	72.42	76.66

APPENDIX C

SUMMARY OF RESIDUAL ANALYSIS FROM AUGUST 15 TO 22

RISIDUAL ANALYSIS (15th August)

August 15							
	Collins	**Dallas**	**Denton**	**Ellis**	**Johnson and Parker**	**Kaufman and Rockwall**	**Tarrant**
12mn to 6am	OK	OK	OK	OK	Slight curvature in x2 ,x4	OK	OK
6 am to 12 n	OK	Funnel shape	OK	OK	OK	OK	OK
12 n to 3 pm	OK	OK	OK	OK	OK	OK	OK
3 pm to 7 pm	OK	OK	OK	OK	Slight curvature	Slight funnel	Slight curvature in x3
7 pm to 12 mn	OK	OK	OK	OK	OK	OK	OK

RESIDUAL ANALYSIS (16th Monday)

August 16							
	Collins	**Dallas**	**Denton**	**Ellis**	**Johnson and Parker**	**Kaufman and Rockwall**	**Tarrant**
12mn to 6am	OK	OK	Slight curvature	OK	OK	OK	OK
6 am to 12 n	OK	OK	OK	OK	OK	OK	Funnel
12 n to 3 pm	OK	OK	Slight curvature in e Vs x1	Slight reverse funnel shape	OK	OK	OK
3 pm to 7 pm	Slight reverse funnel	Slight curvature in e Vs x1,x2,x4	Slight curvature in x1,x2	OK	OK	OK	Reverse funnel
7 pm to 12 mn	No curvature /funnel shape but shows bimodal distribution	OK	OK	OK	OK	OK	Reverse funnel

RESIDUAL ANALYSIS (17th Tuesday)

August 17							
	Collins	**Dallas**	**Denton**	**Ellis**	**Johnson and Parker**	**Kaufman and Rockwall**	**Tarrant**
12mn to 6am	OK	Slight funnel shape	OK	OK	OK	OK	OK
6 am to 12 n	Slight funnel	OK	OK	Slight reverse funnel shape	OK	OK	OK
12 n to 3 pm	OK	OK	OK	OK	OK	OK	OK
3 pm to 7 pm	OK	OK	Slight curvature in e Vs x1	OK	OK	OK	OK
7 pm to 12 mn	OK	OK	OK	OK	OK	No curvature/ funnel shape but a bimodal distribution can be seen	OK

RESIDUAL ANALYSIS (18th Wednesday)

August 18							
	Collins	**Dallas**	**Denton**	**Ellis**	**Johnson and Parker**	**Kaufman and Rockwall**	**Tarrant**
12mn to 6am	OK	OK	OK	OK	No curvature or funnel shape but a bimodal distribution can be seen	OK	OK
6 am to 12 n	OK	OK	Slight curvature	OK	OK	OK	OK
12 n to 3 pm	OK	OK	OK	OK	curvature	OK	OK
3 pm to 7 pm	OK	OK	OK	OK	OK	OK	OK
7 pm to 12 mn	OK	OK	OK		OK	OK	OK

RESIDUAL ANALYSIS (19th Thursday)

August 19							
	Collins	**Dallas**	**Denton**	**Ellis**	**Johnson and Parker**	**Kaufman and Rockwall**	**Tarrant**
12mn to 6am	OK	OK	OK	OK	No curvature or funnel shape but a bimodal distribution can be seen	OK	OK
6 am to 12 n	OK	OK	OK	OK	OK	OK	OK
12 n to 3 pm	OK	Slight funnel	OK	OK	OK	OK	Slight funnel
3 pm to 7 pm	OK	OK	OK	Slight curvature in x4	Slight Funnel	OK	OK
7 pm to 12 mn	OK	OK	OK	OK	OK	OK	OK

RESIDUAL ANALYSIS (20th Friday)

August 20							
	Collins	**Dallas**	**Denton**	**Ellis**	**Johnson and Parker**	**Kaufman and Rockwall**	**Tarrant**
12mn to 6am	OK Bimodal distribution	OK	Bimodal distribution	OK	OK	OK Bimodal distribution	OK
6 am to 12 n	OK Bimodal distribution	OK	Bimodal distribution	OK	OK	OK Bimodal distribution	OK
12 n to 3 pm	OK Bimodal distribution	OK	Bimodal distribution	OK	OK	OK Bimodal distribution	OK
3 pm to 7 pm	OK Bimodal distribution	OK	Bimodal distribution	Slight Funnel	OK	OK Bimodal distribution	OK
7 pm to 12 mn	OK Bimodal distribution	OK	Bimodal distribution	Funnel	OK	OK Bimodal distribution	Slight funnel

RESIDUAL ANALYSIS (21st Saturday)

August 21							
	Collins	**Dallas**	**Denton**	**Ellis**	**Johnson and Parker**	**Kaufman and Rockwall**	**Tarrant**
12mn to 6am	OK Bimodal distribution	OK	OK	OK	Slight funnel	OK	OK
6 am to 12 n	OK	OK	OK	Slight funnel	Slight reverse funnel	OK	OK
12 n to 3 pm	OK	OK	OK	Slight funnel	Funnel	OK	OK
3 pm to 7 pm	OK Bimodal distribution	OK	OK	OK	OK	OK Bimodal distribution	OK
7 pm to 12 mn	OK Bimodal distribution	OK	OK	OK	OK	OK Bimodal distribution	OK

RESIDUAL ANALYSIS (22nd Sunday)

August 22							
	Collins	**Dallas**	**Deton**	**Ellis**	**Johnson and Parker**	**Kaufman and Rockwall**	**Tarrant**
12mn to 6am	OK	OK	No model	OK	OK	OK	OK
6 am to 12 n	OK	Curvature and slight funnel	OK	OK	OK	No model	Reverse funnel
12 n to 3 pm	OK	OK	OK	OK	OK	Bimodal distribution	OK
3 pm to 7 pm	OK	Reverse funnel	OK	Funnel	OK	Bimodal distribution	OK
7 pm to 12 mn	No model	No model	No model	No model	No model	No model	No model

APPENDIX D

LIST OF MODELS WHICH NEEDED TRANSFORMATION

Johnson & Parker August 15

12 midnight-6 am
0.25 (P3El 12-6aN) + 5.12 (P3El 12-6aV) + 0.98 (P6Ta 12-6aN) + 0.22 (Prev.day O_3Da 7-12mn) - **4.20 (P3El 12-6aV)^2** + 41.77 ≤ 71.07

3 pm – 7 pm
7.88 (O_3El6-12n) + 0.45 (O_3El 12-3p) + 0.445 (O_3JP 12-3p) - **0.055 (O_3El 6-12n)^2** - 274.49 ≤ 71.07

Tarrant August 15

3 pm-7 pm
0.536 (O_3El 12-3p) + 0.549 (P7El 12-7pN) - 6.69 (O_3Ta 12-3p) + **0.044 (O_3Ta 12-3p)^2** + 281.29 ≤ 76.22

Denton August 16

12 noon-3 pm
- 0.42 (O_3Da 6-12n) - 0.22 (O_3Da 12-6a) + 0.12 (O_3 Ta 6-12n) + **0.005 (O_3Da 6-12n)^2** + 90.51 ≤ 93.60

Ellis August 16

12 noon-3 pm
exp^{y} = 8.145 (O_3El 12-6a) - 3.52 (P3Ta 6-12nN) – 4.34 ≤ 78.19

Denton August 18

6 am-12 noon
- 40.75 (O3De12-6a) + 2.384 (O3Ta12-6a) - 0.096 (AJ06-9aN) + **0.314 (O3De12-6a) ^2** + 1258.32 ≤ 93.10

Johnson & Parker August 18

12 noon-3 pm
- 0.855 (O3Ta6-12n) - 0.065 (O3Ta12-6a) + **0.0052** (**O3Ta6-12n) ^2** + 103.50 ≤ 66.75

Ellis August 20

7 pm-12 midnight
log(y) = 0.12 (O_3Da 3-7p) - 7.50 ≤ 80.64

Tarrant August 20

7 pm-12 midnight
sqrt(y) = 0.539 (O_3Ta 3-7p) - 32.59 ≤ 68.45

Ellis August 21

6 am-12 noon
sqrt(y) = 0.35 (O_3El 12-6a) - 17.03 ≤ 68.74

12 noon-3 pm
-1/sqrt(y) = - 0.05 (AJo 9-3pN) + 0.069 (P3Ka 6-12nN) + 0.338 (O_3El 6-12n) + 1.21 (O_3KR 6-12n) - 104.58 ≤ 68.74

Johnson &Parker August 21

6 am-12 noon
y^2 = 21.54 (O_3JP 12-6a) - 19.40 (P4Ta 6-12nV) - 1059.92 ≤ 74.38

12 noon-3 pm
sqrt(y) = 0.206 (O_3JP 6-12n) - 13.13 ≤ 74.38

Dallas August 22

6 am-12 noon
y^2 = - 29.25(O_3Co 12-6a) + 18.31 (O_3Da 12-6a) +**5.28 (O_3Co 12-6a) ^2** +**2.9938(O_3Da 12-6a) ^2** +22.83 ≤ 76.49

3-7 p
exp^y = - 7.09 (O_3Co 6-12n) +1.18 (O_3Co 12-3p) + 1.78 (O_3Da 6-12n) - 1.12 (O_3Ta 12-3p) - 3.48 ≤ 76.49

Ellis August 22

3 pm-7 pm
-1/sqrt (y) = 0.09 (O_3El 12-3p) +0.10 (P5De 12-7pN) - 6.89 ≤ 69.95

Tarrant August 22

6 am-12 noon
y^2 = 24.06 (O_3Da 12-6a) - 8.71 (O_3De 12-6a) + 24.46 (O_3Ta 12-6a) - 2181.48 ≤ 76.66

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