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## Analyzing the effects of L.E.D. traffic signals on urban intersection safety

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ANALYZING THE EFFECTS OF L.E.D. TRAFFIC SIGNALS  
ON URBAN INTERSECTION SAFETY

Thesis

Submitted to

The School of Engineering of the

UNIVERSITY OF DAYTON

in Partial Fulfillment of the Requirements for

The Degree

Master of Science in Civil Engineering

By

Valerie Elizabeth Griffin

UNIVERSITY OF DAYTON

Dayton, Ohio

November 2007

ANALYZING THE EFFECTS OF L.E.D. TRAFFIC SIGNALS ON URBAN  
INTERSECTION SAFETY

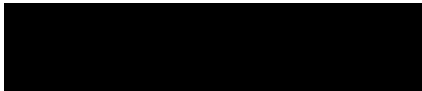
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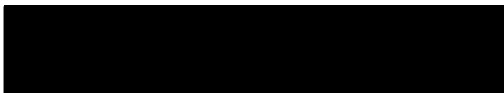
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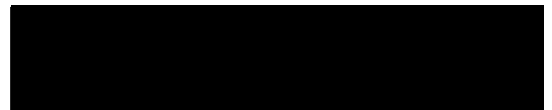
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## ABSTRACT

### ANALYZING THE EFFECTS OF L.E.D. TRAFFIC SIGNALS ON URBAN INTERSECTION SAFETY

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The use of light emitting diodes (LED's) in traffic signals has become widespread over the past decade. Energy efficiency and long service life are the often-cited reasons for converting from incandescent bulbs to LED's, but could improved safety be another, less obvious benefit? LED's appear to be more visible than traditional bulbs, possibly providing the driver with more time to appropriately respond to the traffic control devices and avoid a potential collision.

The objective of this research is to evaluate crashes at signalized urban intersections to determine whether or not crashes were reduced after the installation of LED traffic signals. A before-and-after analysis was conducted for eight intersections using empirical Bayes estimation. Data used for the "before" period was collected when the intersection operated with conventional incandescent bulbs. Each of the treatment sites were retrofitted with LED fixtures of the same size, and data was collected for the "after" period. Two additional sites which had not received the treatment were chosen as

comparison sites in the analysis. The comparison sites were carefully selected based on traffic characteristics, geometry, and driver traits similar to those exhibited at the treatment sites.

The empirical Bayes analysis revealed inconclusive results about the reduction of crashes after the installation of LED traffic signals. The study was limited to a small number of intersections, some with atypical traffic trends, and data from only two comparison sites. Additional studies should be conducted using a more broad range of treatment sites and a greater number of comparison sites to determine the long-term safety benefits associated with LED use in traffic signals.

## ACKNOWLEDGEMENTS

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I would also like to thank the Dayton Area Graduate Studies Institute for giving me the opportunity to pursue a graduate degree, and the University of Dayton Research institute for allowing my participation in traffic safety research, which influenced this text considerably.

Finally, special thanks go to my parents, whose contributions to my education are so numerous that they can never be fully recognized, and to my husband, whose continuous support has allowed me to grow to be a better engineer and a better person.

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## LIST OF SYMBOLS & ABBREVIATIONS

AADT - average annual daily traffic

ADT – average daily traffic

AASHTO - American Association of State Highway and Transportation Officials

Caltrans - California Department of Transportation

CEM – Crash Estimation Model

GIS – geographic information system

LED – light emitting diode

ITE – Institute of Transportation Engineers

UPS – uninterruptible power supply

# CHAPTER I

## INTRODUCTION

### Problem Statement

Signalized urban intersections present increased opportunity for disaster when it comes to roadway safety. The driver is expected to visually detect traffic control devices, react to the devices accordingly, make decisions about their own destination and route, and change direction, if necessary, all while considering the actions of other drivers and trying to avoid conflict. Too often, a driver misses one of these crucial steps and a conflict cannot be avoided. The design of an intersection and the traffic control devices therein directly affect driver behavior and resulting crash frequencies.

In 2002, there were 1,299,000 crashes at signalized intersections in the United States (Rodegerdts et al., 2004). These crashes account for approximately 21% of total crashes and about 24% of all fatal and injury collisions. The social and financial impact of this number of collisions is substantial. The Federal Highway Administration and other agencies have recognized the detrimental effects of intersection crashes on our society, and continue to fund research that will lead to a decrease in crash frequency. Numerous countermeasures have been tested for their potential to reduce

crashes. Infrastructure improvements such as the construction of left turn lanes, the removal of unwarranted signals, and improvement of drainage through intersections have all proven to be effective at reducing crashes (Antonucci et al., 2004). Improving the visibility of traffic signals has also been cited as an important safety measure (Thomas et al., 2001). Many intersection improvements are prohibitively expensive to implement---a drainage upgrade may cost in excess of \$20K, and new turn lanes may exceed \$40K. Financial impact of a countermeasure is always an important consideration to decision-makers who are charged with the responsibility of allocating resources effectively. Low-cost safety countermeasures have become highly desirable as funding for transportation projects becomes more limited.

LED's have been used in various applications since their invention more than forty years ago (Merkel, 2004). As the new style of lighting gained popularity in other disciplines, engineers began to recognize the potential for LED's in traffic applications. Traffic signal bulbs account for approximately 90% of the total energy usage at a typical intersection. By converting incandescent bulbs to LED, energy consumption can be decreased by about 80%. The California Department of Transportation (Caltrans) was one of the first agencies to realize large-scale cost saving by using LED's. In 2003, Caltrans saved taxpayers \$10 million per year by converting state-operated signals to LED (Iwasaki, 2003). LED use became more widespread in the traffic industry as other government entities became aware of the potentially massive energy

savings, eventually leading to the adoption of standard specifications and Federal energy requirements for traffic signal modules.

Conversion to LED's has triggered other benefits besides the well-known energy reduction. They do not burn or distort lens covers, they may help preserve intersection wiring by drawing less power, and they appear brighter than conventional signals (City of Little Rock, 2003). All of these advantages also lead to an impact in another sector of traffic engineering---intersection safety. Visibility of LED's seems to be superior, which could positively effect driver behavior. Reduced maintenance on the fixtures decreases the exposure of workers to traffic and the total number of work zones required at intersections. Also, the minimal energy usage allows for the use of battery back-up systems to operate the intersection during a power outage. Could all of these factors combined improve overall intersection safety?

### Objectives of the Research

The objective of this research is to use empirical Bayes estimation to determine whether or not a noticeable decrease in crashes was experienced at signalized intersections that have been converted to LED signals.

### Organization of Thesis

Chapter 2 describes literature and research on safety estimation methodologies and LED implementation. Chapter 3 explains the use of LED's in

the traffic industry. Chapter 4 outlines the methodology and data collection used in this study. Chapter 5 describes the analysis and contains a discussion of the results. Chapter 6 presents the conclusions and recommendations of the study.

## CHAPTER II

### REVIEW OF RELATED RESEARCH AND LITERATURE

This chapter provides a review of various methodologies commonly used in traffic safety studies as well as a discussion of findings in the field of traffic safety. Since similar research on the specific safety effects of LEDs in traffic signals could not be identified, the literature review will focus primarily on the types of analyses available and the importance of traffic signal visibility in general.

Numerous methodologies have been used over the years in traffic safety evaluations. Choosing the appropriate analysis type based on the available data and desired output, can be a challenging feat. Several approaches were considered before the empirical Bayes method was ultimately chosen. Hirst et al (2003) illustrates the positives and negatives of using simple before-and-after studies, with and without a comparison group. The comparison groups can help identify background effects such as changes in traffic flow and regression-to-mean. The same is true for the empirical Bayes approach using comparison sites, but the sites must be carefully selected to avoid site-specific changes which may skew the overall background effects. They conclude that simple before-and-after studies are unlikely to produce reliable estimates due to



error produced by regression-to-mean. Empirical Bayes analysis, however, requires substantially more data and greater effort.

A classical before-and-after study was conducted at Iowa State University to evaluate the change in crashes after altering four-lane roadways (Stout, 2005). Comparison sites were chosen using several criteria to help account for temporal and site-specific influences. After a large-scale decrease in total crashes was identified, the researchers performed additional analyses to adjust the treatment site crash data to reflect the overall trends.

Normalizing data in before-after studies is discussed in research by Lum and Wong (2003), in which the authors performed a study on red-light running violations after the installation of red-light cameras. Traffic volume, speed, red-light violations, and the status of the traffic signal data were collected at each intersection. Normalization was then done to actual violation counts using the number of vehicles per lane, per cycle, with the following equation:

$$T = \frac{p_1 - p_2}{\left[ \sqrt{p(1-p)} \right] \times \left[ \sqrt{\frac{1}{n_1} + \frac{1}{n_2}} \right]}$$

Where:

T = test statistic

$p_1$  = proportion of violations in each lane with respect to lane volume in the "after" period

$p_2$  = proportion of violations in each lane with respect to lane volume in the "before" period

$p$  = pooled estimate of the proportions

$n_1$  and  $n_2$  = lane volumes "after" and "before," respectively

This computation was thought to add more significance to the values based on the opportunity for a violation to occur at any given time.

The Bayesian approach has been utilized in many road safety studies. Four Bayesian models are discussed in an analysis done to identify hazardous roadways (Ossenbruggen and Linder, 2005). Two simple models and two hierarchical models were compared in an effort to minimize subjectivity in the analytical process. The study concludes that the model producing the most useful results is the hierarchical model with an informative prior. This model incorporates all the known data for similar sites and provides a compromise between raw data values and average known values.

Although the empirical Bayes method can be quite complex, there are guidelines to aid researchers in employing the statistical approach. One such tutorial is written by Powers and Carson (2004). A step-by-step procedure is presented, beginning with the building of a multivariate statistical model. A multiple linear regression equation for a roadway segment is established using average annual daily traffic volume (AADT) and segment length as follows:

$$SPF_i = \beta_0 + \beta_1(L_i) + \beta_2(AADT_i)$$

Where:

- SPF<sub>i</sub> = crashes per time period for roadway section, i
- β<sub>0</sub>, β<sub>1</sub>, β<sub>2</sub> = regression coefficients
- L<sub>i</sub> = length of segment, i
- AADT<sub>i</sub> = annual average daily traffic volume for road segment, i

Other variables were considered in the model but did not result in any correlation. Next, a negative binomial distribution is tested by determining the overdispersion parameter. They decided to use individual overdispersion parameters for each roadway segment, as the different lengths of each were thought to affect the values. This was done using the equation:

$$\phi_i = \phi \times L_i^B$$

Where:

- $\phi_i$  = overdispersion parameter for segment, i
- $\phi$  = overall overdispersion parameter for all segments combined
- $L_i$  = length of segment, i
- $B$  = a constant representing differences between the segment, i, and the other segments

The relative weight is then calculated with the following formula:

$$\alpha_i = \frac{1}{1 + SPF_i / \phi_i}$$

Where:

- $\alpha_i$  = relative weight applied to segment, i, and other variables are as previously defined.

The weight is applied to each test site, and the expected number of crashes is then estimated by the formula:

$$\pi_i = (\alpha_i \times SPF_i) + (1 - \alpha_i)\lambda_i$$

Where:

- $\pi_i$  = expected number of crashes on segment, i
- $\lambda_i$  = actual number of crashes on segment, i

The variance of the data is established and used to calculate the index of effectiveness as follows:

$$\theta_i = \frac{(\lambda_i / \pi_i)}{1 + (\sigma_i^2 / \pi_i^2)}$$

Where:

$\theta_i$  = index of effectiveness  
 $\sigma_i^2$  = variance

They then provide instruction for using an empirical Bayes spreadsheet and interpreting the results.

Hauer, (2001) presents another tutorial about the empirical Bayes method to aid researchers in adopting the method as standard practice. The procedure is explained using the simplified formula:

Estimate of Expected Crashes = Weight x Crashes expected at similar sites + (1-Weight) x Count of crashes at this site

Where the weight is between 0 and 1

Hauer explains from a practical standpoint that safety studies done without regression-to-the-mean corrections produce exaggerated results for the effectiveness of the countermeasure. Decision-makers who are ultimately the end users of studies rely on the results to make knowledgeable decisions about safety mitigation. Erroneous studies can give rise to anticipation of successful safety programs that do not pan out. Hauer illustrates the method by performing numerical examples of an abridged procedure and a full empirical Bayes procedure, explaining each step so that a user could learn and apply this methodology to any before-after safety analyses.

Another statistical approach that was found in related research is the full Bayes method, as opposed to the empirical Bayes method. A study by Miranda-Moreno and Fu (2006) directly compares the two. The full Bayes approach is considered superior due to modeling flexibility and better treatment of uncertainties, but much more effort is required to establish the framework of the model. In studies using small data sets the full Bayes estimation was better, but when studies were done using comprehensive data sets the two approaches resulted in similar performance. The full Bayes method is gaining popularity as more user-friendly computer software packages become available. The empirical Bayes method is still the most popular of the Bayesian models for the typical user due to its extensive use and acceptance in the field of traffic engineering.

The most comprehensive presentation of the empirical Bayes approach can be found in Hauer's book, *Observational Before-After Studies in Road Safety* (Hauer, 1997). In-depth instruction is provided on most every aspect of the method, from assessing measurable and immeasurable variables to using Meta Analysis to combine results of several studies into one application. This particular book has been referenced in numerous empirical Bayes studies, and continues to be an invaluable reference to those employing the method.

Various studies were examined to identify the differences and similarities in the application of empirical Bayes estimation. One such study used the approach to investigate photo-red enforcement and crash occurrence in Fairfax

County, Virginia (Miller et al., 2006). The authors of this study decided to use the empirical Bayes method because it would correct for regression-to-the-mean and produce more credible results, since the method is widely accepted. The following Crash Estimation Model was developed using several variables:

$$C = \alpha_y (ADT)^b (Speed)^c (YellowDiff)^d (Trucks)^e (LeftLanes)^f$$

Where: b, c, d, e, f, and  $\alpha_y$  = model parameters

C = expected crashes per year

ADT = average daily traffic on the major road

Speed = posted speed limit

YellowDiff = a calculation comparing the yellow time to the ITE recommended yellow time

Trucks = percent trucks on the major road

LeftLanes = sum of the left turn lanes on the major road

Miller et al. (2006) note that missing traffic volume data presented a problem that was overcome by averaging data from adjacent years. A sensitivity analysis was performed to compare this strategy with using the minimum volume available, using the maximum volume available, and discarding the site. It was determined that none of these caused much difference in the overall results. After the model was created and used to estimate crashes, the actual crashes were compared to the predicted ones. In conclusion, they note that similar end results were obtained by using both the empirical Bayes method and a before-after analysis, but the empirical Bayes method was much more comprehensive because it included several independent variables in the analysis.

A study comparing crash statistics before and after the installation of roundabouts was done using the empirical Bayes method (Persaud et al., 2000).

This study details the development of the estimation model using different forms of data to determine the best calibrated model. Depending on the data available for each intersection, some models were calibrated using total entering AADT and some used both total AADT and minor road AADT:

$$MODEL1: Crashes = \alpha_y (AADT)^\beta$$

$$MODEL2: Crashes = \alpha_y (AADT)^{\beta_1} (Minor)^{\beta_2}$$

Where:

$\alpha_y$ ,  $\beta$ ,  $\beta_1$  and  $\beta_2$  = model parameters

AADT = total entering AADT

Minor = proportion of AADT on minor road

MODEL2 was applied when possible, as it produced better results. A negative binomial distribution was specified to describe the crashes.

A study done on the development of crash reduction factors also used the empirical Bayes method to predict crashes and compare the prediction to the crashes that actually occurred (Hovey and Chowdhury, 2005). The authors explain the use of SAS computer software to model the analysis and provide crash prediction. Multivariate modeling was utilized, specifically negative binomial regression, using the p-value as an indicator of the significance of individual traits. The model was calibrated with several traits until an acceptable model was formed. This process was repeated to build a different model for each safety countermeasure studied.

A modified empirical Bayes method was used to determine the effects of differential speed limits on roadway safety (Garber et al., 2005). The study

reiterates specific benefits of using the empirical Bayes method, such as the precision of using a negative binomial distribution and the ability to manage trends in the data. Typical empirical Bayes methodology was largely followed--- development of a crash estimation model, calculation of the expected crash frequencies, and comparison between expected and actual crashes after treatment. The variables used in the model were segment length and ADT, though the authors mention that ideally, the model would incorporate other variables which likely affect overall crash statistics. Examples of these variables are changes in enforcement, driver behavior, vehicle condition, and geometric changes.

Numerous studies thus far have indicated the value of employing the empirical Bayes technique to perform safety evaluations. Caution must be used, however, to ensure that the methodology is used correctly in order to produce reliable results. There are key issues that should be considered in the process of the analysis (Persaud et al., 2006). In many crash investigations the type and severity of the crash is essential to draw conclusions about the safety benefits. Red-light running cameras are an example. This safety countermeasure may increase certain crash types and decrease others, resulting in a net increase of crash frequency. The crash severity and economic impact of the reduction in more severe crashes must be analyzed to discover the true effect of the countermeasure, or the result of an empirical Bayes analysis may only be a half-truth. Comparison groups present another opportunity for error in an empirical



Bayes analysis, if not carefully selected. The comparison sites should be representative of the general traffic characteristics of the treatment sites. The traffic volumes, geometric characteristics, and vehicle classifications should be comparable.

In the field of traffic engineering, little research has been published about the safety benefits of increased signal visibility, though it has always been considered inherently beneficial. A study conducted by Thomas et al. (2001) discusses the high reduction in crashes and high cost/benefit ratio for projects that replaced pedestal-mounted signals with more visible mast-arm mounted ones. Improved traffic signal visibility was determined to be a very cost-effective safety strategy.

In *Making Intersection Safer: A Toolbox of Engineering Countermeasures to Reduce Red-Light Running* (ITE, 2003), improved signal visibility is cited as a useful safety measure to be considered for implementation. LED signals are specifically described as being brighter and more conspicuous during inclement weather. Reference is also made to the more evenly-lit surface of the lens that can be achieved with multiple light sources instead of only one light source, as in an incandescent bulb. The longer service life of a LED signal is also thought to improve safety by reducing the frequency of outages and minimizing maintenance exposure. Due to the narrow cone of vision of LED signals, they should be mounted such that they cannot swing out of the driver's view. This is

accomplished through rigid mounting on mast arms or tethering span-wire installations to prevent rotation.

Engineers have begun to utilize LEDs in railroad crossings as a potential safety improvement due to improved visibility and longer life (Coleman et al., 2000). Flashing lights are installed horizontally at approaches to warn drivers of a train. The higher reliability of LEDs has prompted many agencies to use them in place of the existing incandescent bulbs. However, concerns have been raised about the inability of color blind drivers to detect whether or not the signal is active, due to the narrow spectral band in which LEDs emit light.

Minimum traffic signal visibility has been incorporated into standards for traffic signal design for quite some time. The Manual of Uniform Traffic Control Devices (Federal Highway Administration, 2003) requires a larger diameter lens when certain design criteria are met. For example, a twelve-inch lens must be used in place of an eight-inch lens when signals are located more than 120 feet from the stop bar and when minimum sight distance requirements cannot be met. The Manual also encourages using larger signals in areas with a high population of elderly drivers and where signals are unexpected. This suggests that larger lenses are more visible and thus, increase intersection safety.

### CHAPTER III

#### FUNCTIONS OF LED USE

LED's have been transforming the lighting industry since their invention. Scientists have evolved lighting several times over with incandescent, neon, and fluorescent products, seeking to find the most efficient method of lighting. LED's provide just that---efficiency. They produce high light output without wasting energy on heat. Incandescent bulbs use about 90% of their energy intake producing heat instead of light (Merkel, 2004). LED's are lighter, smaller, and more durable than conventional lamps, and offer such flexibility that they can be used in countless real-world applications.

The development of the first viable LED is attributed to Nick Holonyak, Jr. in 1962, as part of research conducted by the General Electric Company (Merkel, 2004). Many improvements have been made since then, resulting in the model that exists today. A LED, or *light emitting diode* is a chip of semiconducting material containing impurities that create a p-n junction, which allows electricity to flow in only one direction. Figure 1 illustrates the structure of the p-n junction:

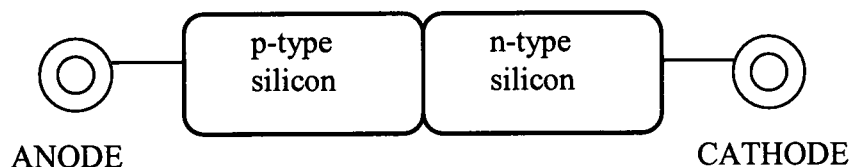


FIGURE 1. PN Junction Structure

The materials forming the p-n junction determine the wavelength of the light emitted. Different materials generate different-colored light. Some of the most common LED's in industry today use the materials shown in Table 1 to produce a variety of colors.

TABLE 1. LED Color Chart (Source: OkSolar, 2007)

Semiconductor Materials	Color
Aluminum gallium arsenide (AlGaAs)	red, infrared
Aluminum gallium phosphide (AlGaP)	green
Gallium arsenide phosphide (GaAsP)	red, orange, yellow
Gallium nitride (GaN)	green, blue
Gallium phosphide (GaAsP)	red, yellow, green
Silicon Carbide (SiC) substrate	blue
Sapphire ( $\text{Al}_2\text{O}_3$ ) substrate	blue
Diamond (C)	ultraviolet

Because LED's produce colored light, they do not use a colored filter that may degrade the light output, like those employed by incandescent fixtures. LED's are packaged in various formats, according to the required function. The packaging material and shape have a significant effect on the light output, as light can be reflected back into the semiconductor if it bounces off the covering. Many applications use a dome-shaped package because the round surface

minimizes reflection. Figure 2 shows various packaging formats used in commercial industry.

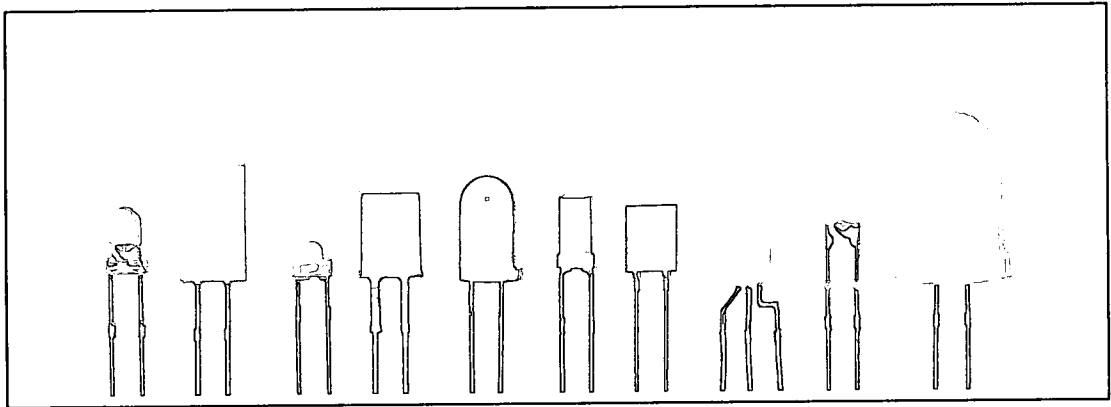


FIGURE 2. LED Packaging Formats (Source: Frank, 2005)

These tiny light sources are only a fragment of the size and weight of an incandescent bulb, making them very versatile for diverse applications. Single LED's are often used as indicators on computer equipment and remote controls, while panels of LED's are used for larger products such as grow lights, street lights, and large illuminated displays. LED's serve as backlighting in LCD televisions, and are growing in popularity as residential Christmas lights. A use for LED's can be identified in nearly every industry as an efficient alternative to conventional lighting.

The traffic industry contains many opportunities to employ LED's. They are used as status indicators in traffic controllers, pedestrian pushbuttons, and various equipment in the controller cabinet. LED's make the most sizeable impact, however, in traffic signal modules. Panels of the lights are constructed to fit inside existing traffic signals much like the customary incandescent bulbs,

illuminating the signal faces with bright, colored light of red, yellow or green.

Pedestrian signals use panels of orange and white LED's, configured into the standard man/hand shapes. Examples of these LED configurations are illustrated in Figure 3.

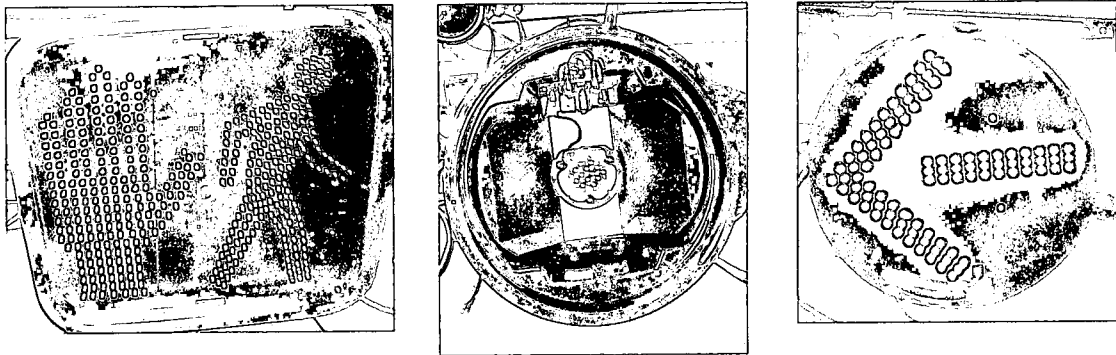


FIGURE 3. LED Traffic Configurations

Traffic signals are complex mechanisms that require many components to work together seamlessly. There is virtually no room for error, due to strict criteria for signal indications. Yellow and all-red clearance times are calculated precisely for each intersection. From the vehicle detectors, to the processor, to the signals, every millisecond counts. The industry is constantly seeking faster, more reliable devices to use in this delicate system. The quick turn-on and shut-off times and lower failure rates of LED's make them a natural choice for traffic signals. A typical LED is rated at 100,000 hours of illumination, or about eleven years (Merkel, 2004). Rating for fluorescent and incandescent bulbs are approximately 30,000 and 1,500 hours, respectively. Though environmental influences like temperature, dust, and vibration may decrease the practical life of

a LED, they still outlast the competition by several years. LED's are ideal for the constant cycling of a traffic signal because they are solid-state and are not degraded by frequently turning on and off.

Another major motive for the use of LED's in traffic signals is the hefty savings to taxpayers that results from reduced energy usage. The California Department of Transportation (Caltrans) pioneered the energy-saving movement by converting to LED's, beginning in 1992 (Iwasaki, 2003). After trials on signals in the Fresno area, Caltrans determined that LED's were viable in traffic signals and could significantly reduce power consumption. Widespread deployment followed in state-operated signals throughout California. Caltrans was recognized for its energy-saving strategy with two prestigious awards in 1995—The California Energy Commission State Energy Award and the U.S. Department of Energy National Energy Award. California taxpayers saved an estimated \$10 million per year just on the state signals converted by Caltrans (Iwasaki, 2003). States and municipalities soon recognized the possibility of converting to LED's as a reality, and many began converting in the mid-1990's.

As energy became a more valuable resource, the Federal government devised regulations requiring manufactures of various goods to be more efficient. The Energy Policy Act of 2005 impacted the traffic industry greatly by requiring traffic signal modules to meet U.S. Energy Star Requirements by 2007 (Behura, 2007). The strict criteria of the U.S. Energy Star Requirements make it nearly

impossible for any conventional traffic signals to be used, with the exception of LED's.

During the past ten years of broad LED implementation, manufacturers have identified many operational deficiencies and have altered their designs for better performance. The Institute of Transportation Engineers (ITE), whose standards are widely accepted in the traffic industry, recognized the need for LED traffic signal standardization. In 2005, ITE Published *Vehicle Traffic Control Signal Heads-Light Emitting Diode Circular Signal Supplement*, commonly referred to as *VTCSH-LED*. This document contains minimum requirements and testing for traffic signal modules. Critical attributes of the LED's are described, such as maximum intensity, luminescence uniformity, resistance to dust and moisture, and turn-on and shut-off times (Behura, 2005). The standard provides for an "ITE Compliant" label to be used on products meeting the requirements, as a guide for buyers.

Several other advantages have surfaced since the implementation of LED's in traffic signals. A study done by the City of Little Rock, Arkansas (2003) reported that low power consumption could help preserve intersection wiring, and that minimal heat output of LED's does not burn the lens coverings, as is common with incandescent bulbs. The extended service life reduces the frequency of relamping and minimizes worker exposure to traffic. Work zones are often complicated at signalized intersections. Driver confusion and vulnerability of a technician in an aerial bucket over traffic can create serious



safety risk. Minimizing this type of operation is highly desirable in the traffic industry.

Another intrinsic value of LED's is their ability to be used with a battery back-up system, or "uninterruptible power supply" (UPS). Power outages are common in cities experiencing regular lightning storms, power shortages, or errant drivers crashing into transformers. A dark intersection is an unexpected and difficult situation for the driver. Often police officers are deployed to direct traffic, their safety becoming uncertain in the middle of traffic flow. A UPS system provides an alternate power source that is available instantaneously upon failure of the primary power supply. The systems use batteries to power the traffic signal for a short time until primary power is restored. Traditional signals draw such a large amount of energy that the batteries in a UPS system are depleted too quickly to justify their purchase. The low power consumption of LED's, however, allows the batteries to last for a few hours. This makes UPS systems a cost-effective safety measure that can reduce collisions and liability during power outages.

## CHAPTER IV

### METHODOLOGY AND DATA COLLECTION

#### Methodology

After considering the numerous statistical methods available for crash estimation, the empirical Bayes method was chosen for this study. Findings in the literature suggest that the empirical Bayes method is appropriate for this type of analysis, and that it is widely accepted in the field of traffic safety. The correction for regression-to-the-mean and the use of negative binomial distribution are two chief reasons for the success of empirical Bayes estimation. Negative binomial distribution has been established by researchers as a more accurate description of yearly crash variation between sites. Poisson distribution was formerly used as the probability distribution for crash frequency, but inconsistencies in model predictions have led to widespread use of negative binomial distribution (Hauer, 1997). Empirical Bayes estimation is employed to estimate the crash rates before the improvement. These "before" estimates are then used to project the number of crashes that could be expected to occur at a certain intersection, during a specified year, without the safety improvement. The general format of the study, then, is outlined below:

$$\Delta\text{Safety} = B - A$$

Where:

$\Delta\text{Safety}$  = Change in crash frequency

B = Expected number of crashes without the improvement  
(determined by the model)

A = Actual number of crashes after the improvement

Treatment sites and comparison sites were selected carefully, based on several criteria, which are illustrated in Figure 4:

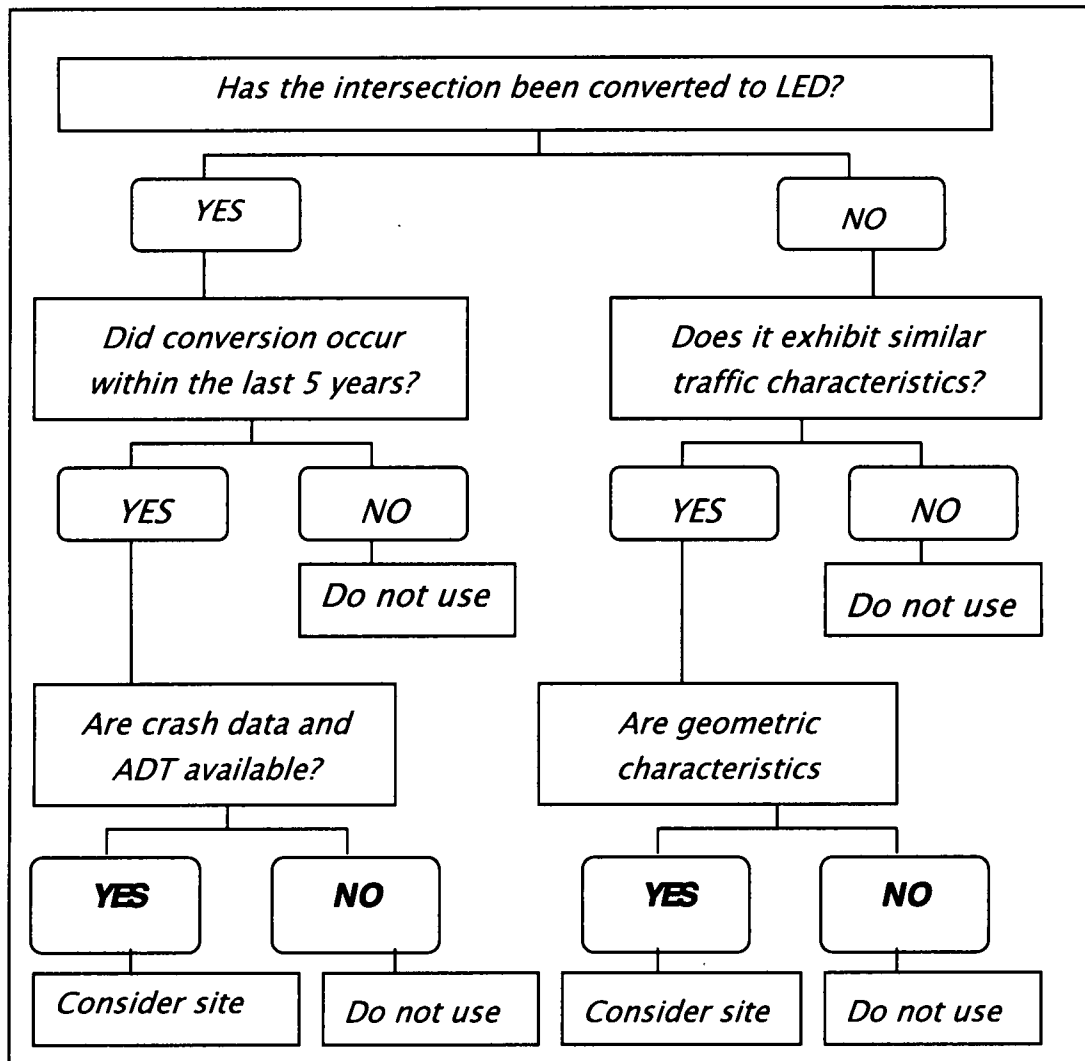


FIGURE 4. Site Selection Flowchart

Comparison sites are a critical component of the analysis because they help establish the mean trend for crash rates at sites without improvement in both the “before” and “after” periods of the treatment sites. The sites that were chosen experience very similar traffic flow as the treatment sites, as they are located on the same arterials. Physical characteristics of the intersections were also considered and found to be consistent with those of the treated intersections.

After site selection, the next step in the study was the development of the Crash Estimation Model (CEM). The CEM is used to estimate the mean and variance of crash frequency. The basic formula that has been widely used for intersection analyses, using the negative binomial distribution, is in the form shown below (Hauer, 1997):

$$E(m) = \alpha F_1^{\beta_1} F_2^{\beta_2}$$

Where:

$E(m)$  = expected mean of the crashes

$\alpha$  = relative weight

$F_1$  and  $F_2$  = variables

$\beta_1$  and  $\beta_2$  = model parameters

The relative weight for the empirical Bayes model,  $\alpha$ , is calculated by the equation:

$$\alpha = \frac{\mu_\lambda}{(\mu_\lambda + \sigma_\lambda^2)}$$

Where:

$\mu_\lambda$  = the mean

$\sigma_\lambda$  = the variance

Multiple variables were considered for use in the analysis, including land use, road classification, number of lanes, lane width, total entering traffic volume, traffic volumes of the major and minor roads, and year. Ideally, any variable that could cause a change that may affect crash frequency should be incorporated into the model. This is not possible, however, because some operation changes are often impossible to quantify. Researchers are often limited to the availability of data. Another variable that was considered was the number of police officers patrolling each year. This variable was not ultimately used because a strong correlation with the crash data was not evident. The model for this study was created through an iterative process by fitting the available data using SAS (version 9.1) software. The GENMOD Procedure in SAS fits a generalized linear model to the data by maximum likelihood estimation of the parameter vector  $\beta$ . The p-value was calculated in SAS for each proposed model to find the best fit. The variables that have the highest correlation to the crash data produce the lowest p-value, and are more significant to the model. The variables that produced a statistically sound model include the average daily traffic (ADT) for the major street, ADT for the minor street, and year. The resulting model was in the form shown in the equation below:

$$\hat{E}(m) = \alpha (ADTMaj)^{\hat{\beta}_1} (ADTMin)^{\hat{\beta}_2} e^{\hat{\beta}_3 (Year)} e^{\hat{\beta}_0}$$

The model parameters ( $\beta$ 's), and the overdispersion parameter ( $\phi$ ), were outputs of the GENMOD procedure. The overdispersion parameter is a measure

of the extra variation in the negative binomial distribution compared to the Poisson distribution. The overdispersion parameter,  $\phi$ , is commonly used in the calculation of the variance as follows:

$$Variance = mean(1 + \frac{mean}{\phi})$$

In the SAS software, however, the calculation is slightly different:

$$k = (\frac{1}{\phi})$$

$$Variance = mean(1 + k * mean)$$

The calculations in the remainder of the analysis compensate for this difference. Using the parameters and data, the expected number of crashes was estimated for each site, had there been no improvement made.

Assumptions of the CEM include the use of negative binomial distribution as an accurate descriptor of the crash variation and the absence of random sampling. In a perfect controlled experiment, treatment sites and control sites would be selected at random from the population, or eligible intersections, such that each site has the same probability of being selected during sampling. This would reduce the possibility of deliberately choosing sites with high crash frequencies. Random sampling is difficult for roadway improvements, however, because the high expense of improvements limits application to sites with high accident counts. Also, the struggle to attain historical crash data and the limited

number of sites having the same characteristics limits the size of the population. It is also difficult to control for the particular safety improvement being tested; many intersection projects involve several infrastructure upgrades which are likely to affect overall crash frequencies along with the study treatment. During the next steps the empirical Bayes method corrects possible regression to the mean caused by the bias of selecting sites with high crash rates for the improvement.

The expected mean crash rates from the SAS calculation are used to project crash rates for post-treatment years, had the treatment not occurred. In order to get the projected rates, several variables need to be calculated. Normalization of the crash frequencies for each year,  $C_y$ , is accomplished by dividing the expected crashes from the CEM,  $ptotal_i$ , by the expected crashes for the base year,  $ptotal_b$ , for each site. This figure is later used to determine the projected count. The variance of the expected count,  $V(p)$  is calculated using the overdispersion parameter in the following equation:

$$V(p) = (1 + \phi \times ptotal_i) \times ptotal_i$$

Next, the relative weight,  $\alpha$ , is calculated as follows:

$$\alpha = \frac{ptotal_i}{V(p)}$$

Actual crash counts,  $A$ , are used in the next step to determine the variance,  $V(EB)$ , using the equation:

$$V(EB) = (1 - \alpha)[A + \alpha(ptotal_i - A)]$$

The baseline projected count,  $PC_b$ , can then be found by dividing the weight by the normalized crash rate before treatment, as follows:

$$PC_b = \frac{\Sigma V(EB)}{\Sigma C_y}$$

Projected crash rates are determined by multiplying the normalized crash rate,  $C_y$ , by the baseline projected count,  $PC_b$ . The variance of the projected count,  $V(PC)$  is calculated by:

$$V(PC) = \frac{\Sigma V(EB)}{\Sigma C_y^2}$$

The overall index of effectiveness,  $\theta$ , is then calculated by comparing the projected crash rates to the actual crash rates as follows:

$$\theta = \frac{\Sigma A}{\Sigma PC}$$

The unbiased estimate of  $\theta_u$  is found with the equation:

$$\theta_u = \frac{\theta}{\left[ 1 + \frac{\Sigma V(PC)}{\Sigma (PC^2)} \right]}$$

Therefore, the percent change in crashes due to the treatment can be represented by:

$$\Delta Crashes(\%) = (1 - \theta_u) \times 100$$



If the treatment causes crashes to be reduced,  $\theta_u$  will be positive and  $\Delta Crashes$  will be a positive value significantly different from 0.

This basic procedure was applied to the data for ten treatment sites, using three comparison sites. A discussion of the analysis can be found in Chapter 5, Data Analysis.

#### Data Collection

Data was collected from ten urban signalized intersections in the city of Middletown, Ohio. A map of the site locations within the City is provided in Figure 5, with the eight treatment sites represented by blue circles and the two comparison sites represented by red circles.

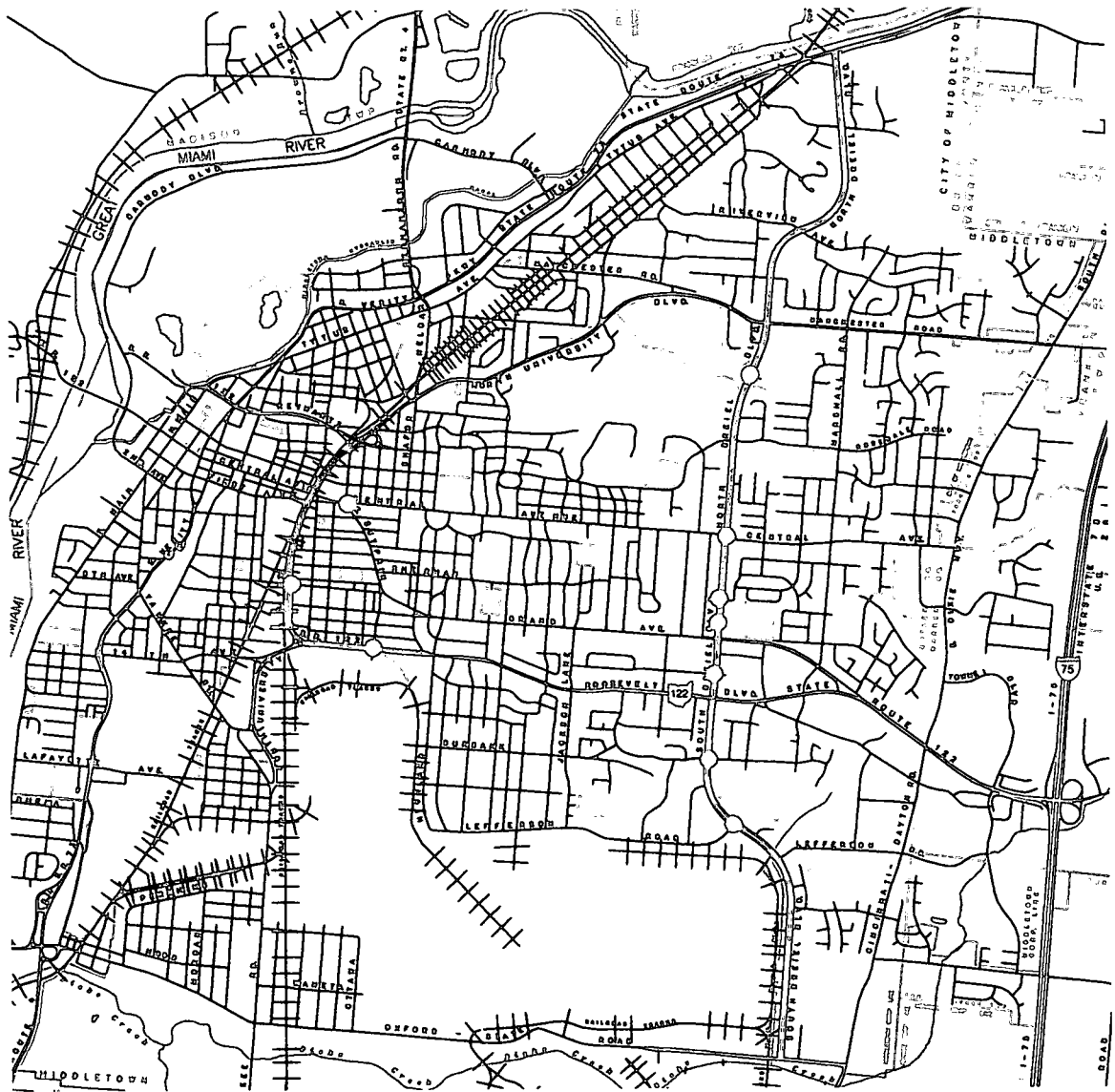


FIGURE 5. Map of Study Sites

Obtaining crash records was the first priority of the data collection process. The City of Middletown Police Records Division retains crash reports for three years, so the past three years of data for each intersection was obtained from Police. Several years of older crash reports have been stored by the City of Middletown's Engineering Department for use in safety studies; these were also

sorted and compiled for use. Next, the crash reports were all checked for errors. A few reports were discarded because of location inaccuracies.

Traffic counts were collected using records from the City of Middletown's Engineering Department, counts obtained from the Ohio Department of Transportation (ODOT), and counts collected using Nu-metrics HI-STAR Traffic Counters, model NC-97. Figure 6 shows a photograph of the type of counter used.

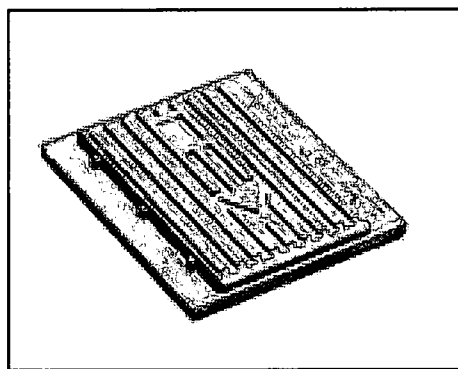


FIGURE 6. HI-STAR Counter (NC-97)

The counters use Vehicle Magnetic Imaging (VMI) to detect vehicle presence, speed, and length. Data is exported into Highway Data Management software, which prepares summary reports and graphs. A sample volume report from the HI-STAR counters is contained in Appendix A.

All other variables, such as intersection geometry, were determined next. Aerial photographs and data from The City of Middletown's Geographic Information System (GIS) were used to find the number and width of lanes at each intersection. Aerial views are provided in Appendix B. The operational characteristics were scrutinized to identify similarities among the sites. Daily flow

traits were noted, as well as the percentage of trucks on each corridor. Also, the number of law enforcement officers over the past several years was collected to determine if enforcement levels impacted crash frequency.

Once intersections were identified as having available data and acceptable characteristics, information about the LED conversion was obtained. Records from the City of Middletown's Electronics Maintenance Department were used to ascertain the date of conversion at some intersections. Test sites along Breiel Blvd. were converted during a capital improvement project; the project files identified the timeline of the traffic signal work. This data was broken down into the month of conversion, or the proportion of the year that falls into the "before" and "after" categories.

Due to incomplete data and the iterative process used to develop the best-fit model, the only data that was used in the analysis was the ADT of the major street, the ADT of the minor street, the number of crashes, with respect to year, and the month of LED conversion. Sample data collected from the intersection of Roosevelt Blvd. and Wicoff St. is shown below in Tables 2 and 3, while the complete data table is provided in Appendix C:

CRASH DATA		
	Before	After
2000	11	
2001	15	
2002	7	
2003*	9	4
2004		5
2005		13
2006		14
2007**		2
* Year of conversion		
** 4 months of data		

TABLE 2. Sample Crash Data

ADT			
	Roosevelt	Wicoff	TOTAL
2000	26120	2500	28620
2003	23620	2500	26120
2006	25005	2828	27833
2007	26322	2591	28913

TABLE 3. Sample ADT Data

## CHAPTER V

### DATA ANALYSIS

Once data collection was completed, all data was entered into a spreadsheet in Microsoft Excel and converted to the format required by SAS. The data sheet is provided in Appendix D. This was imported into SAS and the iterative process was carried out using the GENMOD procedure to build the Crash Estimation Model. As detailed in the Methodology, the resulting CEM is reproduced below:

$$\hat{E}(m) = \alpha (ADTMaj)^{\hat{\beta}_1} (ADTMin)^{\hat{\beta}_2} e^{\hat{\beta}_3(Year)} e^{\hat{\beta}_0}$$

The model parameters, including the overdispersion parameter were also estimated by SAS. The SAS code file and the output file from this procedure can be found in Appendix D.

The expected number of crashes and the overdispersion parameter from SAS were entered into an Excel spreadsheet to calculate the remaining values to attain the projected crash frequencies. These values were all computed according to the equations in the Methodology. Finally, projected counts, *PC*'s, were estimated for the "after" years to represent what the crash rates would have

been in future years without LED conversions. These were compared to the yearly number of counts that actually occurred after conversion to determine the unbiased  $\theta$ , or  $\theta_u$ . The change in crashes,  $\Delta Crashes$ , is calculated as  $(1 - \theta_u) \times 100$ . The value of  $\theta_u$  was expected to be significantly less than zero, but this result was not achieved. Instead,  $\theta_u$  was a positive value much higher than one, 1.681 to be exact. This caused  $\Delta Crashes$  to be a large negative number, -68.012. The results are shown in Table 4 below; a complete table of the analysis results is provided in Appendix E.

	127	127.000	11.269	86.870		75.539	3.811	1.952
				4.853	Theta	1.681		
Dispersion	0.0947			271.194	bias	1.001	Variance	Std Error
				7.934	Unbiased	1.680	0.024	0.155
				0.612				
					<b><math>\Delta Crashes</math></b>			
					=	<b>-68.012</b>		<b>15.518</b>
					Z	-4.383		
					P-value	5.855E-06		

TABLE 4. A Sample of Excel Analysis Results

The results indicate that crashes actually increased after the installation of LED's, but other factors likely contributed to this trend. The analysis of the safety effect of LED's yielded inconclusive results. Several factors may have contributed to the inconclusive results attained. The most substantial of these was likely the small sample size. Only eight treatment sites were used, many along the same corridor. Also, only two comparison sites were used for background data. More comparison sites should have been selected to greatly

improve the analysis. The lack of available data, however, prevented other sites from being eligible. Middletown has been converting traffic signals to LED for over ten years; almost the entire boulevard system is already converted. This presents a problem in choosing un-treated comparison sites that possess the same characteristics as the test sites. Many of the conversions took place more than five years ago, making it difficult to determine the date of conversion and impossible to attain old crash records. Also, different LED specifications were used for older fixtures. The visual qualities are noticeably different from new models. Only conversions done within the past five years were considered for this study, for consistency.

Additionally, a unique traffic situation in Middletown became apparent during the course of the study. Abnormal trends appeared in the traffic counts for a few of the test intersections. For example, the intersection of Breiel Blvd. and Lefferson Road experienced traffic growth of 160% over four years due to development in the southeast quadrant of the City. North Breiel Blvd., however, has undergone a decrease in traffic volumes, with intersections averaging -9% over the past six years, despite the overall traffic growth of the City. These atypical trends illustrate the shifting traffic patterns within the City due to job loss, businesses relocating to the east end of the City, and other business-related dynamics. AK Steel Middletown Works suffered a year-long lockout in 2006 involving over 2,500 employees. An event of this size could have skewed traffic data for the entire year. New housing developments in some areas and



deteriorating housing in other areas of the City have also caused traffic patterns to evolve. So, the changes in both origination points (housing) and destination points (industry/businesses) have shifted traffic throughout the City.

## CHAPTER VI

### CONCLUSIONS

The objective of this study was to evaluate the safety benefits of LED traffic signals. The development and use of LED's was discussed to identify additional impacts to safety that may not be fully recognized. An investigation of appropriate analytical methods resulted in the selection of the empirical Bayes method for the statistical evaluation.

Though the analysis produced inconclusive results, additional testing may confirm a change in crash frequency. Safety benefits will be easier to quantify in future years when the full benefits of LED's are realized by widespread implementation of battery back-up systems at traffic signals, and relamping operations are reduced to 20% of the typical rate.

Additional study is recommended, preferably using a larger sample size and more comparison sites. The Crash Estimation Model could likely be improved with the inclusion of more variables that help account for changing traffic patterns.

LED traffic signals have become the national standard. They are less expensive to maintain and provide more reliability than traditional incandescent

bulbs. Future studies may show that the benefits of LED's are just beginning to be understood.

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## APPENDIX A – VOLUME REPORT FOR HI-STAR COUNTER

### Date/Time/Volume/Average Speed/Temperature Report

Hi-Star ID: 8118	Begin: 06/27/2007 03:30 PM	End: 06/28/2007 03:30 PM
Street: Sutphin	Lane: SB thru	Hours: 24:00
State: OH	Oper: VEG	Period: 15
City: Middletown	Posted: 35	Raw Count: 4458
County: Butler	AADT Factor: 1	AADT Count: 4458

NC97				
Date & Time Range	Count	Avg Speed	Temp	Wet/Dry

#### 06/27/2007

[03:30 PM-03:45 PM]	107	25 mph	114 F	Dry
[03:45 PM-04:00 PM]	75	25 mph	113 F	Dry
[04:00 PM-04:15 PM]	77	23 mph	113 F	Dry
[04:15 PM-04:30 PM]	98	22 mph	114 F	Dry
[04:30 PM-04:45 PM]	95	24 mph	114 F	Dry
[04:45 PM-05:00 PM]	69	25 mph	113 F	Dry
[05:00 PM-05:15 PM]	84	24 mph	113 F	Dry
[05:15 PM-05:30 PM]	89	24 mph	113 F	Dry
[05:30 PM-05:45 PM]	90	23 mph	113 F	Dry
[05:45 PM-06:00 PM]	100	24 mph	113 F	Dry
[06:00 PM-06:15 PM]	79	24 mph	111 F	Dry
[06:15 PM-06:30 PM]	65	25 mph	109 F	Dry
[06:30 PM-06:45 PM]	85	23 mph	110 F	Dry
[06:45 PM-07:00 PM]	68	25 mph	108 F	Dry
[07:00 PM-07:15 PM]	64	22 mph	106 F	Dry
[07:15 PM-07:30 PM]	69	23 mph	105 F	Dry
[07:30 PM-07:45 PM]	68	25 mph	104 F	Dry
[07:45 PM-08:00 PM]	65	24 mph	102 F	Dry
[08:00 PM-08:15 PM]	67	25 mph	100 F	Dry
[08:15 PM-08:30 PM]	56	24 mph	98 F	Dry
[08:30 PM-08:45 PM]	59	26 mph	95 F	Dry
[08:45 PM-09:00 PM]	48	24 mph	95 F	Dry
[09:00 PM-09:15 PM]	54	25 mph	93 F	Dry
[09:15 PM-09:30 PM]	51	24 mph	93 F	Dry
[09:30 PM-09:45 PM]	37	22 mph	92 F	Dry
[09:45 PM-10:00 PM]	39	26 mph	92 F	Dry
[10:00 PM-10:15 PM]	38	24 mph	92 F	Dry
[10:15 PM-10:30 PM]	38	25 mph	91 F	Dry
[10:30 PM-10:45 PM]	34	25 mph	91 F	Dry
[10:45 PM-11:00 PM]	20	26 mph	91 F	Dry
[11:00 PM-11:15 PM]	17	26 mph	89 F	Dry
[11:15 PM-11:30 PM]	23	23 mph	88 F	Dry
[11:30 PM-11:45 PM]	13	26 mph	88 F	Dry
[11:45 PM-12:00 AM]	12	24 mph	87 F	Dry

#### 06/28/2007

[12:00 AM-12:15 AM]	15	25 mph	87 F	Dry
[12:15 AM-12:30 AM]	15	21 mph	86 F	Dry
[12:30 AM-12:45 AM]	14	27 mph	86 F	Dry
[12:45 AM-01:00 AM]	5	25 mph	86 F	Dry
[01:00 AM-01:15 AM]	7	23 mph	86 F	Dry



# Date/Time/Volume/Average Speed/Temperature Report

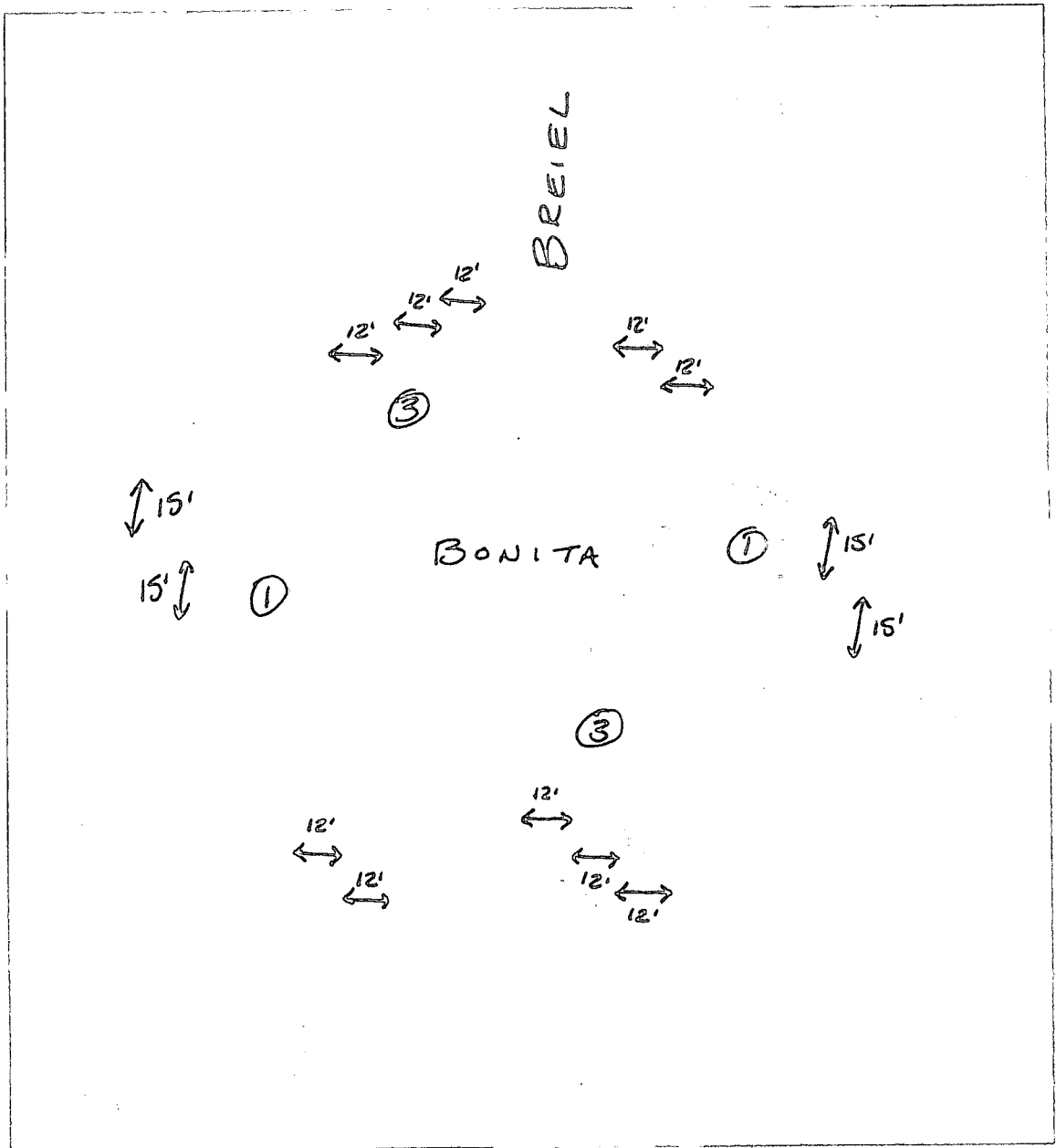
NC97				
Date & Time Range	Count	Avg Speed	Temp	Wet/Dry
06/28/2007				
[01:15 AM-01:30 AM]	4	25 mph	85 F	Dry
[01:30 AM-01:45 AM]	5	29 mph	85 F	Dry
[01:45 AM-02:00 AM]	5	22 mph	85 F	Dry
[02:00 AM-02:15 AM]	1	23 mph	84 F	Dry
[02:15 AM-02:30 AM]	6	26 mph	84 F	Dry
[02:30 AM-02:45 AM]	3	29 mph	84 F	Dry
[02:45 AM-03:00 AM]	2	18 mph	84 F	Dry
[03:00 AM-03:15 AM]	3	33 mph	84 F	Dry
[03:15 AM-03:30 AM]	4	24 mph	84 F	Dry
[03:30 AM-03:45 AM]	5	27 mph	84 F	Dry
[03:45 AM-04:00 AM]	6	32 mph	83 F	Dry
[04:00 AM-04:15 AM]	3	28 mph	82 F	Wet
[04:15 AM-04:30 AM]	2	26 mph	82 F	Dry
[04:30 AM-04:45 AM]	4	22 mph	82 F	Dry
[04:45 AM-05:00 AM]	6	24 mph	82 F	Dry
[05:00 AM-05:15 AM]	8	27 mph	82 F	Dry
[05:15 AM-05:30 AM]	13	26 mph	82 F	Dry
[05:30 AM-05:45 AM]	15	26 mph	82 F	Dry
[05:45 AM-06:00 AM]	15	25 mph	82 F	Dry
[06:00 AM-06:15 AM]	13	27 mph	81 F	Dry
[06:15 AM-06:30 AM]	15	27 mph	81 F	Dry
[06:30 AM-06:45 AM]	25	27 mph	81 F	Dry
[06:45 AM-07:00 AM]	24	29 mph	81 F	Dry
[07:00 AM-07:15 AM]	20	28 mph	82 F	Dry
[07:15 AM-07:30 AM]	22	29 mph	82 F	Dry
[07:30 AM-07:45 AM]	43	27 mph	82 F	Dry
[07:45 AM-08:00 AM]	65	26 mph	82 F	Dry
[08:00 AM-08:15 AM]	42	26 mph	82 F	Dry
[08:15 AM-08:30 AM]	58	25 mph	83 F	Dry
[08:30 AM-08:45 AM]	41	28 mph	83 F	Dry
[08:45 AM-09:00 AM]	64	26 mph	84 F	Dry
[09:00 AM-09:15 AM]	57	23 mph	85 F	Dry
[09:15 AM-09:30 AM]	47	26 mph	87 F	Dry
[09:30 AM-09:45 AM]	51	24 mph	88 F	Dry
[09:45 AM-10:00 AM]	47	25 mph	88 F	Dry
[10:00 AM-10:15 AM]	46	26 mph	89 F	Dry
[10:15 AM-10:30 AM]	51	24 mph	93 F	Dry
[10:30 AM-10:45 AM]	50	24 mph	92 F	Dry
[10:45 AM-11:00 AM]	56	24 mph	89 F	Dry
[11:00 AM-11:15 AM]	70	23 mph	89 F	Dry
[11:15 AM-11:30 AM]	55	26 mph	91 F	Dry
[11:30 AM-11:45 AM]	57	26 mph	93 F	Dry
[11:45 AM-12:00 PM]	72	24 mph	95 F	Dry
[12:00 PM-12:15 PM]	76	23 mph	95 F	Dry
[12:15 PM-12:30 PM]	69	24 mph	95 F	Dry
[12:30 PM-12:45 PM]	60	24 mph	97 F	Dry
[12:45 PM-01:00 PM]	64	24 mph	98 F	Dry

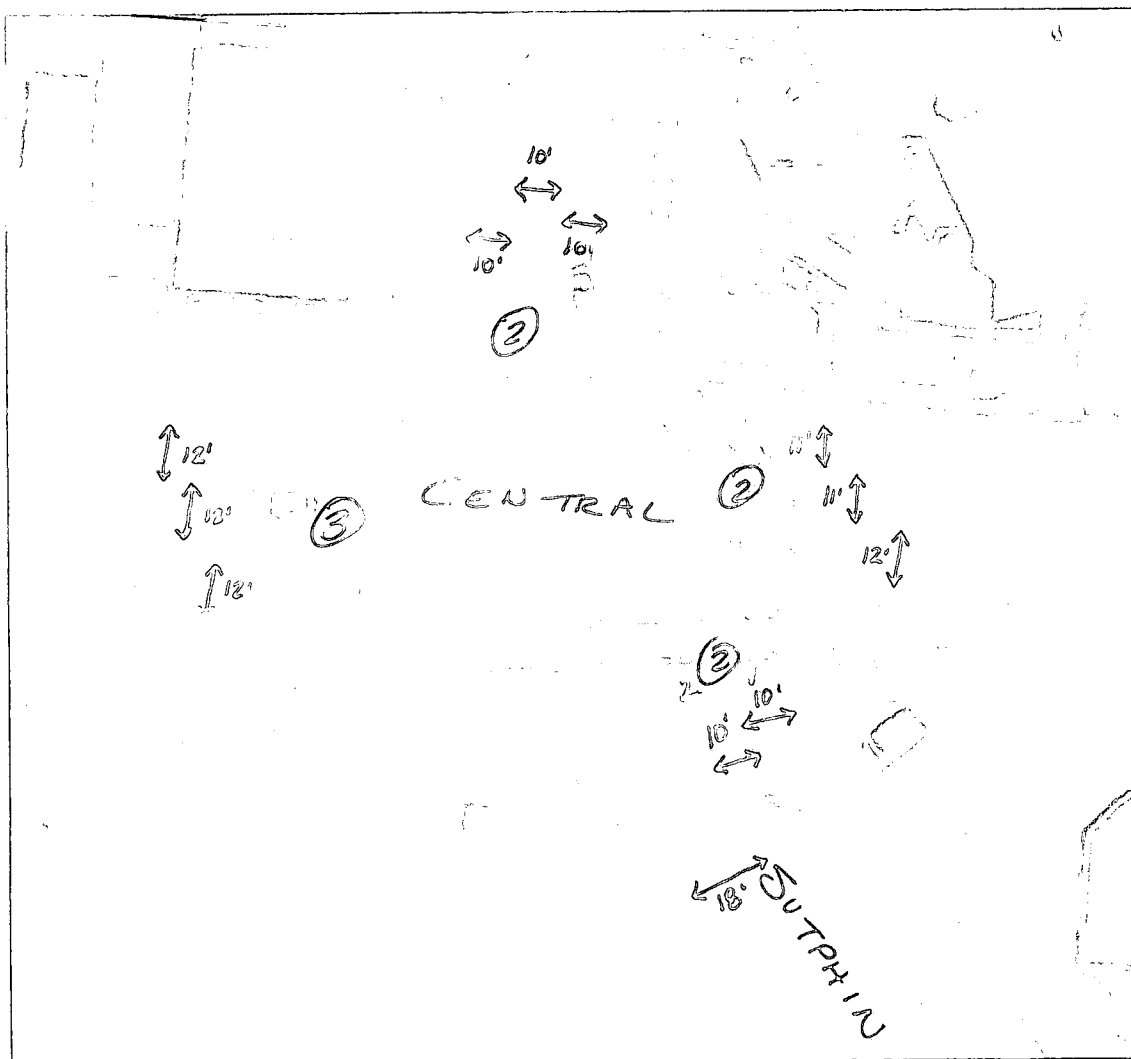
Page: 2

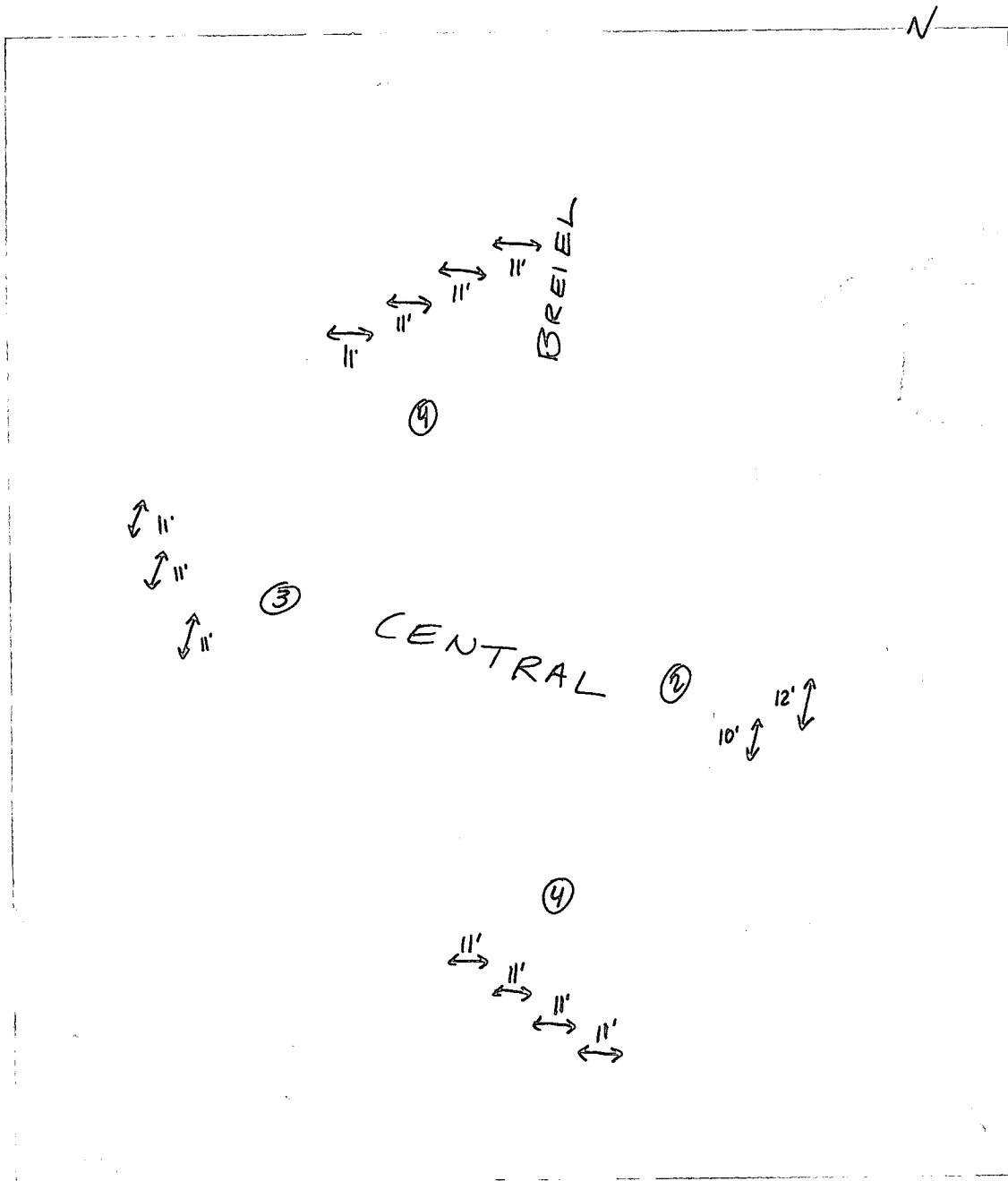
# Date/Time/Volume/Average Speed/Temperature Report

NC97				
Date & Time Range	Count	Avg Speed	Temp	Wet/Dry
06/28/2007				
[01:00 PM-01:15 PM]	76	22 mph	100 F	Dry
[01:15 PM-01:30 PM]	95	22 mph	102 F	Dry
[01:30 PM-01:45 PM]	64	24 mph	104 F	Dry
[01:45 PM-02:00 PM]	63	24 mph	103 F	Dry
[02:00 PM-02:15 PM]	86	22 mph	104 F	Dry
[02:15 PM-02:30 PM]	64	23 mph	108 F	Dry
[02:30 PM-02:45 PM]	75	25 mph	108 F	Dry
[02:45 PM-03:00 PM]	78	23 mph	104 F	Dry
[03:00 PM-03:15 PM]	98	23 mph	104 F	Dry
[03:15 PM-03:30 PM]	182	23 mph	104 F	Dry

## APPENDIX B – AERIAL VIEWS OF INTERSECTIONS







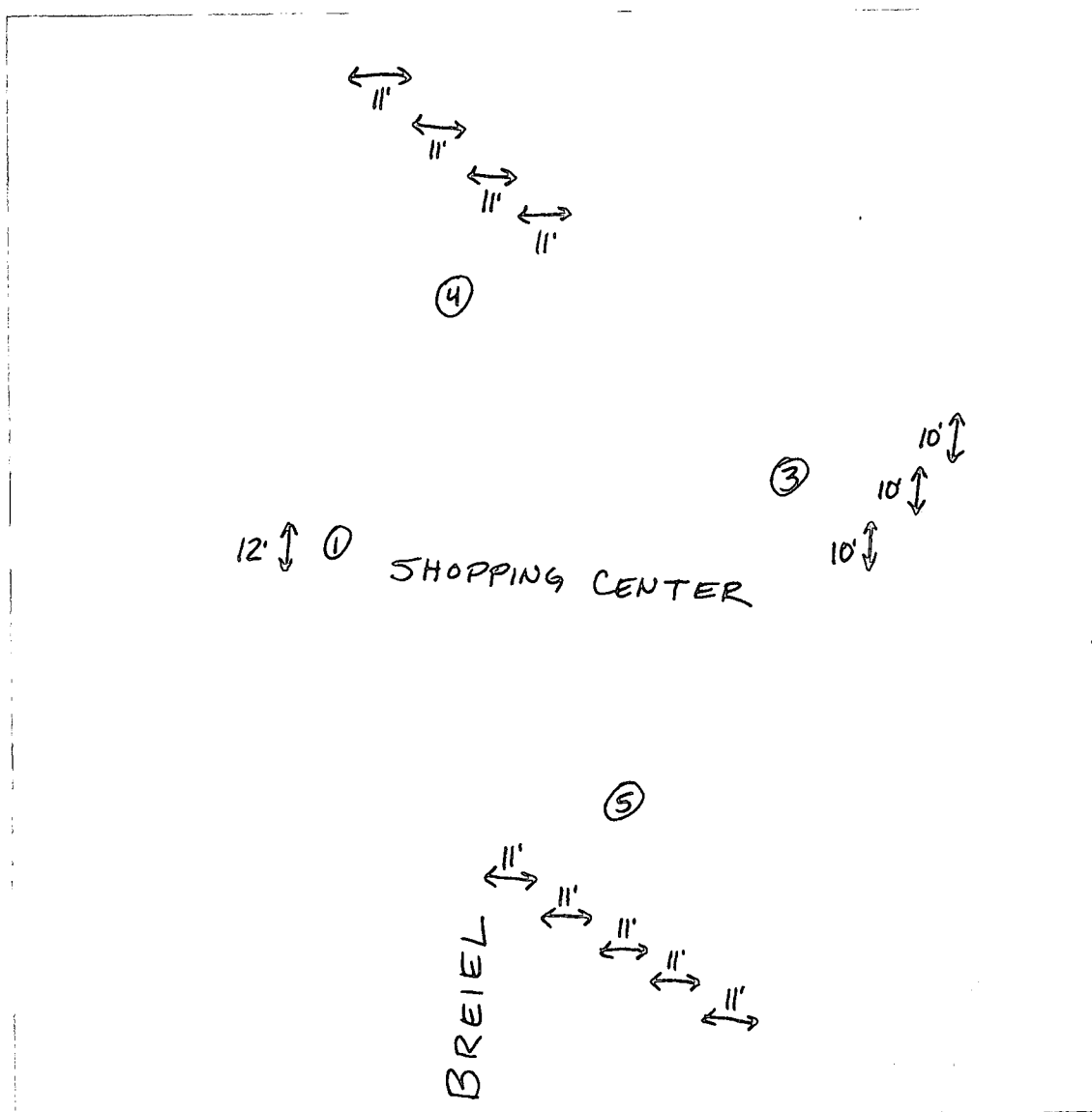
$\parallel''$   $\parallel''$   $\parallel''$   $\parallel''$  BREIEN  
 ④

12'  $\updownarrow$  ①

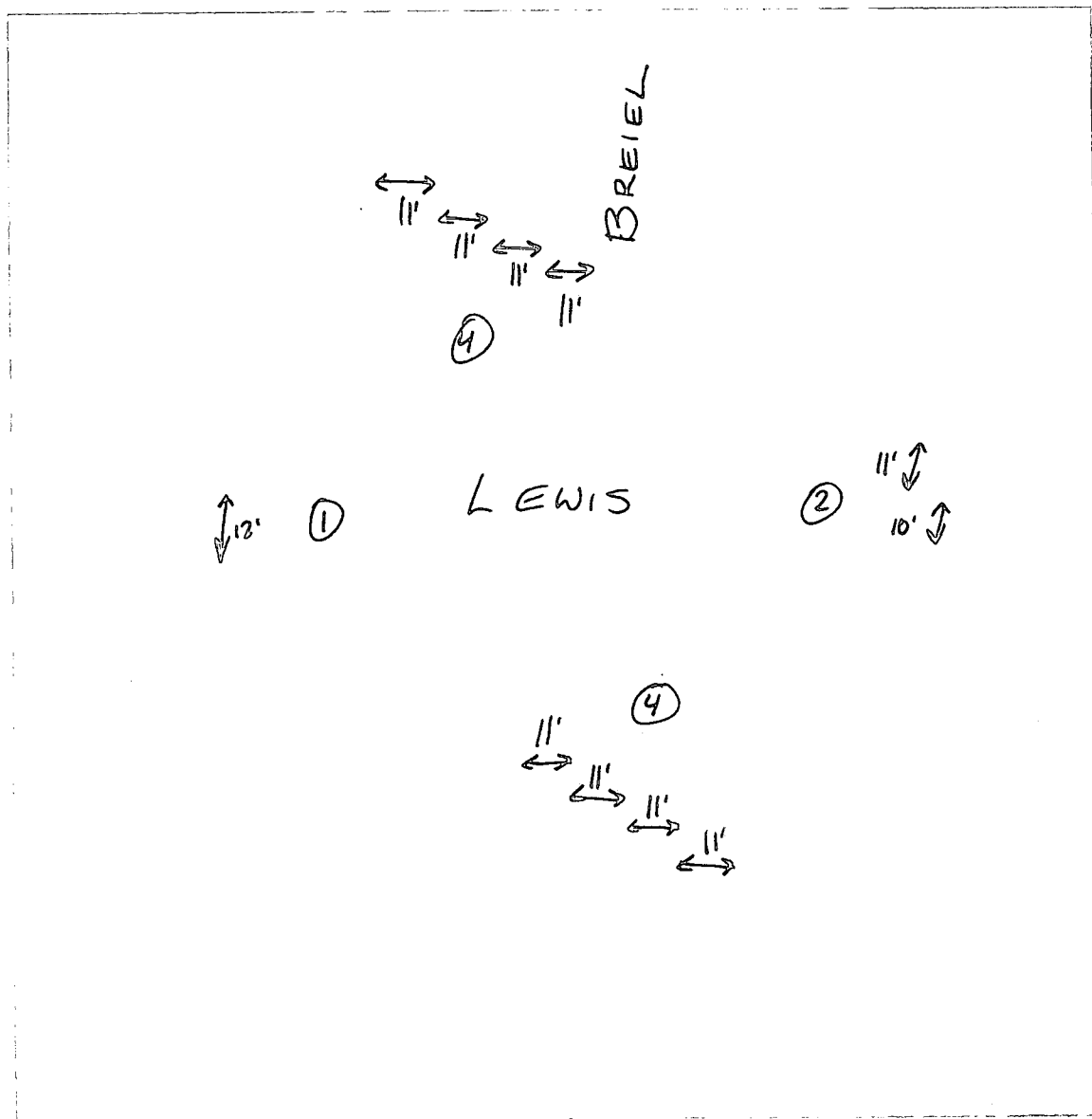
BATSEY ① 12'  $\updownarrow$

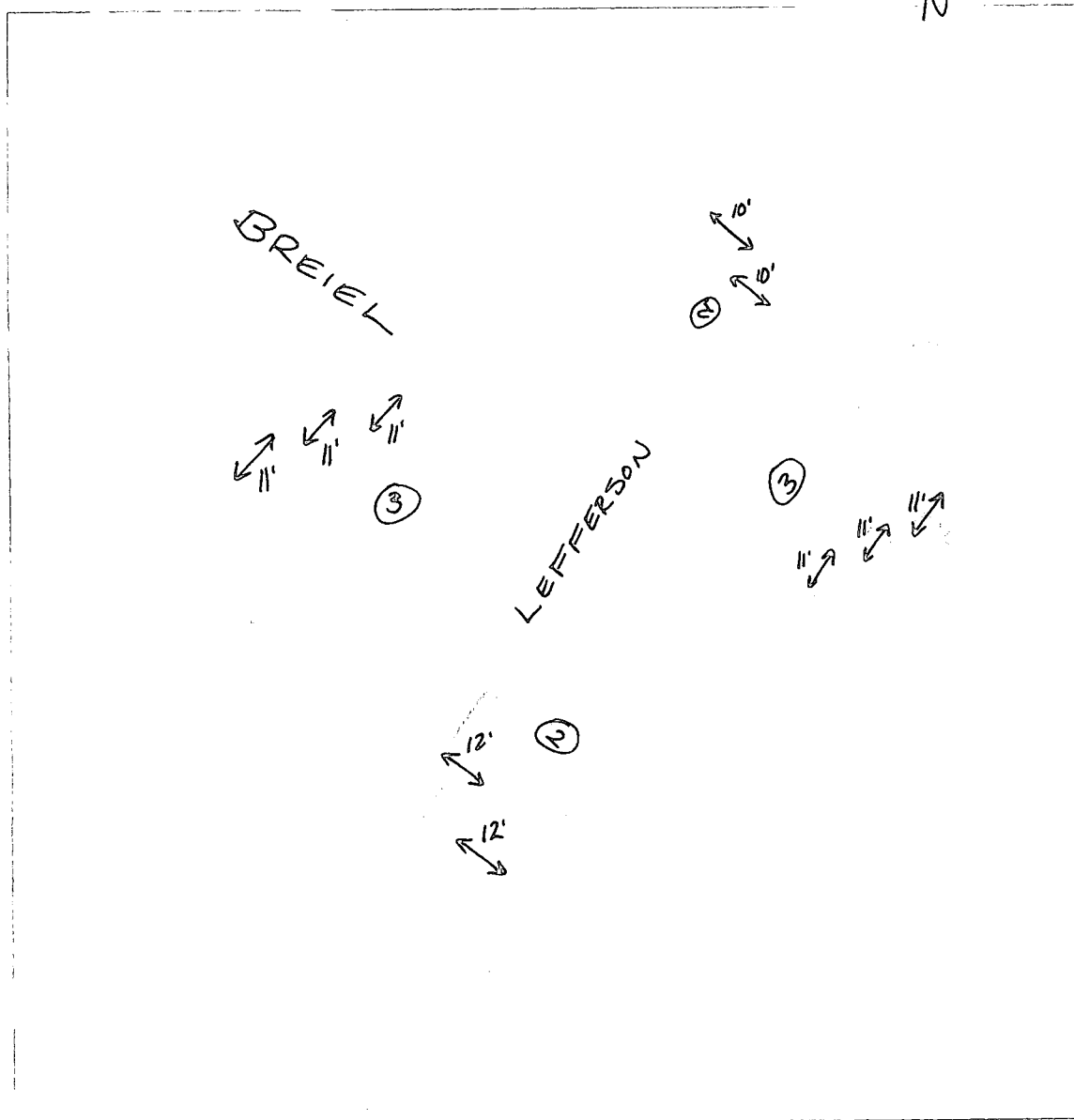
④

$\parallel''$   $\parallel''$   $\parallel''$   $\parallel''$

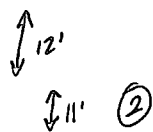
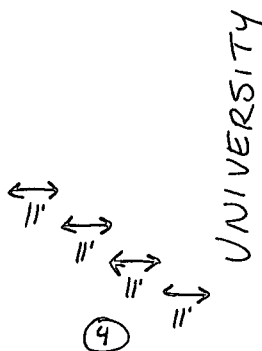




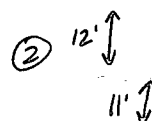




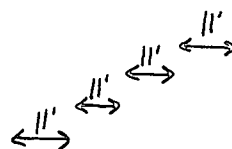
University + Woodlawn

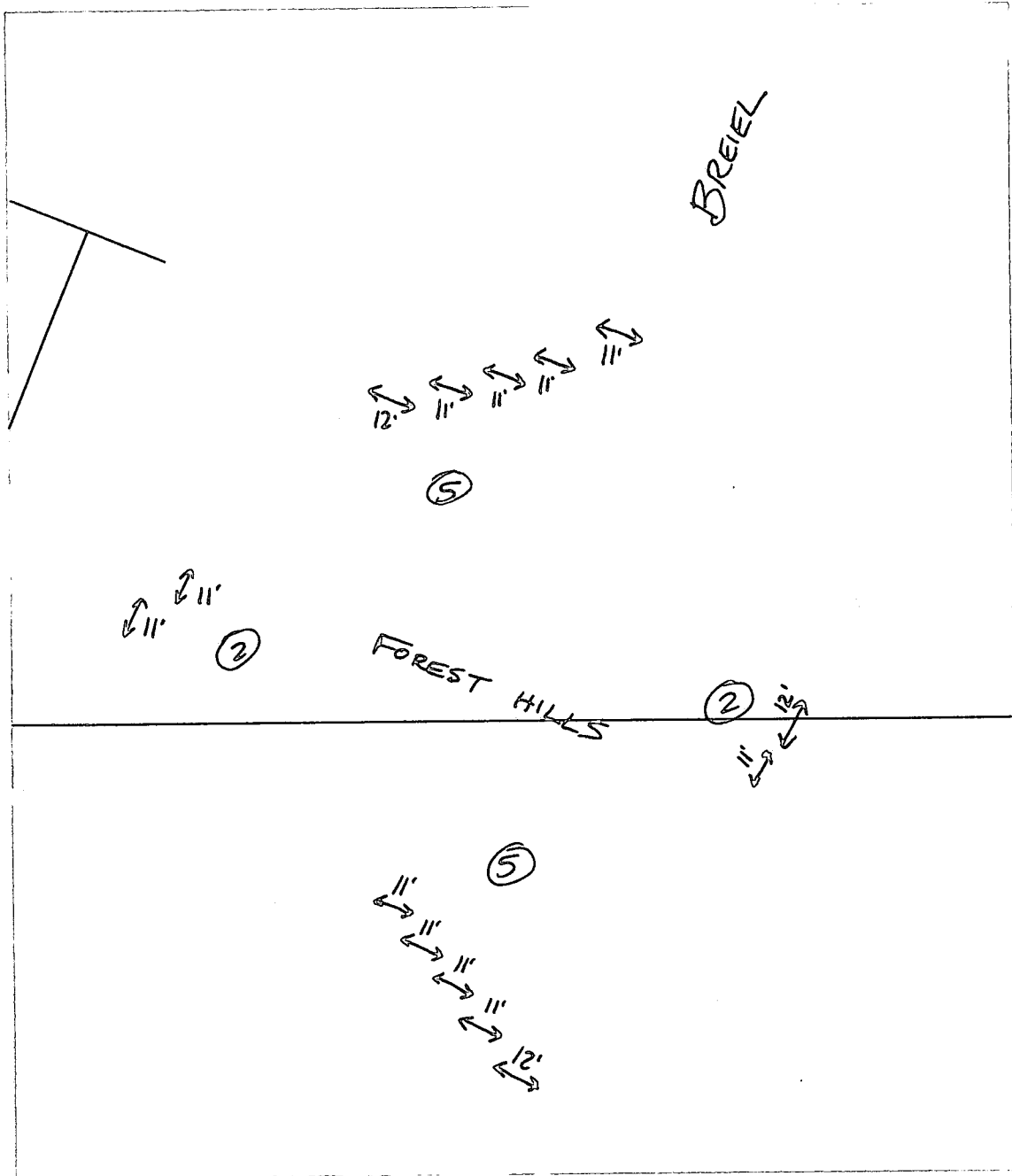


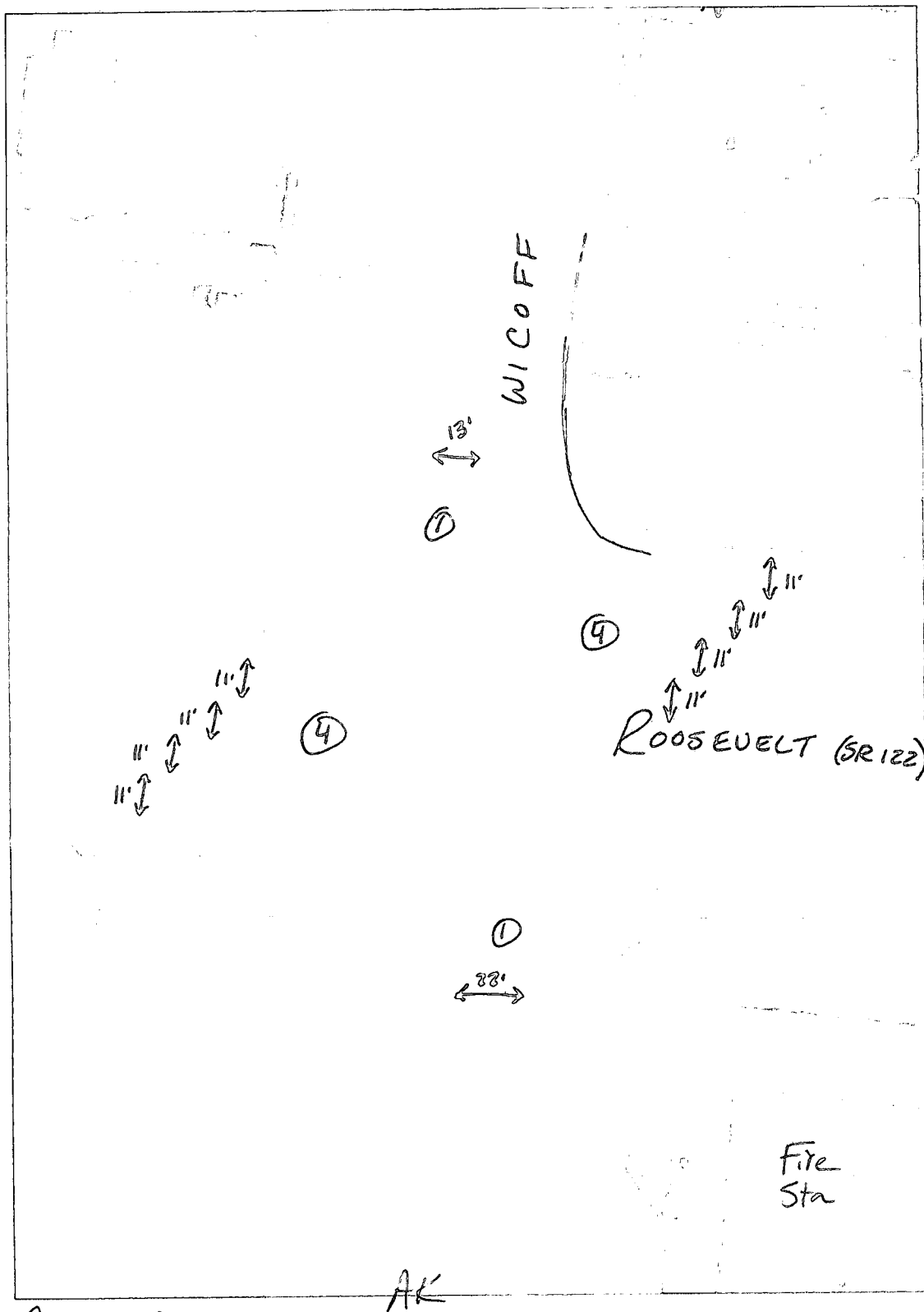
WOODLAWN



④







## APPENDIX C – COMPETE DATA TABLE

YEAR		1999		2000		2001		2002		2003	
LOCATION		B	A	B	A	B	A	B	A	B	A
1	<b>Roosevelt &amp; Wicoff</b>										
	Collisions			11		15		7		9	4
	ADT			28620						26120	
2	<b>Breiel &amp; Bonita</b>										
	Collisions	18		14		7		2			
	ADT					15010					
3	<b>Central &amp; Sutphin</b>										
	Collisions							6		6	
	ADT			15700						15000	
4	<b>Breiel &amp; Central</b>										
	Collisions										
	ADT					35040					
5	<b>Breiel &amp; Batsey</b>										
	Collisions					6		1		5	
	ADT					25064					
6	<b>Breiel &amp; Shopping Center</b>										
	Collisions					9		10		6	
	ADT					23056					
7	<b>Breiel &amp; Lewis</b>										
	Collisions					13		8		5	
	ADT					23030					
8	<b>Breiel &amp; N. Lefferson</b>										
	Collisions							6		14	
	ADT					10000					
9	<b>University &amp; Woodlawn</b>										
	Collisions										
	ADT			22200		25700				18988	
10	<b>Breiel &amp; Forest Hills</b>										
	Collisions										
	ADT					27890					

<b>YEAR</b>	<b>2004</b>		<b>2005</b>		<b>2006</b>		<b>2007*</b>		<b>* portion of the year</b>
<b>LOCATION</b>	<b>B</b>	<b>A</b>	<b>B</b>	<b>A</b>	<b>B</b>	<b>A</b>	<b>B</b>	<b>A</b>	
<b>Roosevelt &amp; Wicoff</b>									
Collisions		5	13		14		2		4
ADT					27833		28913		months
<b>Breiel &amp; Bonita</b>									
Collisions	4		8	4	9		4		6
ADT	16000						17362		months
<b>Central &amp; Sutphin</b>									
Collisions	4	2	0		3		4		7
ADT							14622		months
<b>Breiel &amp; Central</b>									
Collisions	8		12	4	12		8		8
ADT	37000						33798		months
<b>Breiel &amp; Batsey</b>									
Collisions	1		0	2	4		2		6
ADT				20599			21140		months
<b>Breiel &amp; Shopping Center</b>									
Collisions	2		1	0	1		3		6
ADT				23,110			20905		months
<b>Breiel &amp; Lewis</b>									
Collisions	9		8	3	10	0	0		6
ADT				25100			27212		months
<b>Breiel &amp; N. Lefferson</b>									
Collisions	8		4	3	5		8		8
ADT				26042			25269		months
<b>University &amp; Woodlawn</b>									
Collisions	5		6		5		1		6
ADT							19756		months
<b>Breiel &amp; Forest Hills</b>									
Collisions	2		5		2		2		8
ADT							27350		months



## APPENDIX D – SAS INPUT AND OUTPUT

Int	Yn_No	Year	Wt	lnWt	Crashes	BA	C_F_P	F1	F2	F	LnF1	LnF2	LnF
1	2	2000	1	0	11	0	11	26120	2500	28620	10.170	7.824	10.262
1	3	2001	1	0	15	0	15	25287	2500	27787	10.138	7.824	10.232
1	4	2002	1	0	7	0	7	24453	2500	26953	10.105	7.824	10.202
1	5	2003	0.5	0.6931	9	0	9	24037	2500	26537	10.087	7.824	10.186
1	5	2003	0.5	0.6931	4	1		23620	2500	26120	10.070	7.824	10.170
1	6	2004	1	0	5	1		24082	2609	26691	10.089	7.867	10.192
1	7	2005	1	0	13	1		24543	2719	27262	10.108	7.908	10.213
1	8	2006	1	0	14	1		25225	2828	27833	10.136	7.947	10.234
1	9	2007	0.33	1.1087	2	1		26322	2591	28913	10.178	7.860	10.272
2	1	1999	1	0	18	0	18	8667	5683	14350	9.067	8.645	9.572
2	2	2000	1	0	14	0	14	9333	5347	14680	9.141	8.584	9.594
2	3	2001	1	0	7	0	7	10000	5010	15010	9.210	8.519	9.616
2	4	2002	1	0	2	0	2	10667	4673	15340	9.275	8.450	9.638
2	6	2004	1	0	4	0	4	12000	4000	16000	9.393	8.294	9.680
2	7	2005	0.7	0.4005	8	0	8	12430	3872	16302	9.428	8.262	9.699
2	7	2005	0.3	1.1087	4	1		12645	3809	16454	9.445	8.245	9.708
2	8	2006	1	0	9	1		13291	3617	16908	9.495	8.193	9.736
2	9	2007	0.33	1.1087	4	1		13936	3426	17362	9.542	8.139	9.762
3	4	2002	1	0	6	0	6	8700	6533	15233	9.071	8.785	9.631
3	5	2003	1	0	6	0	6	8700	6300	15000	9.071	8.748	9.616
3	6	2004	0.5	0.6931	4	0	4	8170	6783	14953	9.008	8.822	9.613
3	6	2004	0.5	0.6931	2	1		7640	7266	14906	8.941	8.891	9.610
3	7	2005	1	0	0	1		8232	6579	14811	9.016	8.792	9.603
3	8	2006	1	0	3	1		9198	5519	14717	9.127	8.616	9.597
3	9	2007	0.58	0.5447	4	1		10164	4458	14622	9.227	8.402	9.590
4	3	2001	1	0	10	0	10	24000	10040	34040	10.086	9.214	10.435
4	4	2002	1	0	12	0	12	24000	11027	35027	10.086	9.308	10.464
4	5	2003	1	0	10	0	10	24000	12013	36013	10.086	9.394	10.492
4	6	2004	1	0	8	0	8	24000	13000	37000	10.086	9.473	10.519
4	7	2005	0.8	0.2877	12	0	12	23227	12973	36200	10.053	9.471	10.497
4	7	2005	0.3	1.3863	4	1		22969	12964	35933	10.042	9.470	10.489
4	8	2006	1	0	12	1		21938	12927	34865	9.996	9.467	10.459
4	9	2007	0.67	0.4005	8	1		20907	12891	33798	9.948	9.464	10.428
5	3	2001	1	0	6	0	6	23814	1250	25064	10.078	7.131	10.129
5	4	2002	1	0	1	0	1	22745	1203	23948	10.032	7.093	10.084
5	5	2003	1	0	5	0	5	21675	1157	22832	9.984	7.054	10.036
5	6	2004	1	0	1	0	1	20606	1110	21716	9.933	7.012	9.986
5	7	2005	0.8	0.2877	0	0	0	19803	1075	20878	9.894	6.980	9.946

5	7	2005	0.3	1.3863	0	1	19536	1063	20599	9.880	6.969	9.933	
5	8	2006	1	0	4	1	19619	1251	20870	9.884	7.132	9.946	
5	9	2007	0.5	0.6931	2	1	19702	1438	21140	9.888	7.271	9.959	
6	3	2001	1	0	9	0	9	22006	1050	23056	9.999	6.957	10.046
6	4	2002	1	0	10	0	10	22032	1038	23070	10.000	6.945	10.046
6	5	2003	1	0	6	0	6	22058	1025	23083	10.001	6.932	10.047
6	6	2004	1	0	2	0	2	22084	1013	23097	10.003	6.921	10.047
6	7	2005	0.7	0.4005	1	0	1	22101	1004	23105	10.003	6.912	10.048
6	7	2005	0.3	1.1087	0	1	22110	1000	23110	10.004	6.908	10.048	
6	8	2006	1	0	1	1	22162	1141	23303	10.006	7.040	10.056	
6	9	2007	0.5	0.6931	3	1	19700	1205	20905	9.888	7.094	9.948	
7	3	2001	1	0	13	0	13	20030	3000	23030	9.905	8.006	10.045
7	4	2002	1	0	8	0	8	20548	3000	23548	9.931	8.006	10.067
7	5	2003	1	0	5	0	5	20165	3000	23165	9.912	8.006	10.050
7	6	2004	1	0	9	0	9	21583	3000	24583	9.980	8.006	10.110
7	7	2005	0.7	0.4005	8	0	8	21929	3000	24929	9.996	8.006	10.124
7	7	2005	0.3	1.1087	3	1	22100	3000	25100	10.003	8.006	10.131	
7	8	2006	1	0	10	1	23135	3000	26135	10.049	8.006	10.171	
7	9	2007	0.5	0.6931	0	1	24240	2972	27212	10.096	7.997	10.211	
8	4	2002	1	0	6	0	6	9101	4910	14011	9.116	8.499	9.548
8	5	2003	1	0	14	0	14	12201	5810	18011	9.409	8.667	9.799
8	6	2004	1	0	8	0	8	15302	6730	22032	9.636	8.814	10.000
8	7	2005	0.7	0.4005	4	0	4	17369	7337	24706	9.762	8.901	10.115
8	7	2005	0.3	1.1087	3	1	18402	7640	26042	9.820	8.941	10.167	
8	8	2006	1	0	5	1	24603	9460	34063	10.111	9.155	10.436	
8	9	2007	0.7	0.4005	8	1	18000	7269	25269	9.798	8.891	10.137	
9	6	2004	1	0	5	0	5	14985	4196	19181	9.615	8.342	9.862
9	7	2005	1	0	6	0	6	14981	4391	19372	9.615	8.387	9.872
9	8	2006	1	0	5	0	5	14978	4587	19565	9.614	8.431	9.881
9	9	2007	1	0	1	0	1	14974	4782	19756	9.614	8.473	9.891
10	6	2004	1	0	2	0	2	20995	6625	27620	9.952	8.799	10.226
10	7	2005	1	0	5	0	5	20363	7167	27530	9.921	8.877	10.223
10	8	2006	1	0	2	0	2	19732	7708	27440	9.890	8.950	10.220
10	9	2007	1	0	2	0	2	19100	8250	27350	9.857	9.018	10.216

1

## The GENMOD Procedure

## Model Information

Data Set	SASUSER.DE02		
Distribution	Negative Binomial		
Link Function	Log		
Dependent Variable	C_F_P	C_F_P	
Offset Variable	lnWt	lnWt	

Number of Observations Read	72
Number of Observations Used	45
Missing Values	27

## Class Level Information

Class	Levels	Values
Intersection	10	1 2 3 4 5 6 7 8 9 10
Yn_No	9	1 2 3 4 5 6 7 8 9

## Parameter Information

Parameter	Effect
Prm1	Intercept
Prm2	Year
Prm3	LnF2
Prm4	LnF1

## Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	41	53.5046	1.3050
Scaled Deviance	41	53.5046	1.3050
Pearson Chi-Square	41	54.1344	1.3204
Scaled Pearson X2	41	54.1344	1.3204
Log Likelihood		308.5923	

Algorithm converged.

## The GENMOD Procedure

## Analysis Of Initial Parameter Estimates

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	406.0598	83.4157	242.5681	569.5516	23.70	<.0001
Year	1	-0.2046	0.0420	-0.2868	-0.1224	23.78	<.0001
LnF2	1	0.3424	0.1073	0.1321	0.5526	10.19	0.0014
LnF1	1	0.2979	0.2146	-0.1226	0.7185	1.93	0.1649
Dispersion	1	0.0947	0.0607	-0.0242	0.2136		

NOTE: The negative binomial dispersion parameter was estimated by maximum likelihood.

## GEE Model Information

Correlation Structure	Independent
Subject Effect	Intersection (10 levels)
Number of Clusters	10
Clusters With Missing Values	8
Correlation Matrix Dimension	9
Maximum Cluster Size	6
Minimum Cluster Size	3

Algorithm converged.

Analysis Of GEE Parameter Estimates  
Empirical Standard Error Estimates

Parameter	Estimate	Standard Error	95% Confidence Limits		Z	Pr >  Z
Intercept	406.0598	84.7436	239.9653	572.1543	4.79	<.0001
Year	-0.2046	0.0423	-0.2875	-0.1217	-4.84	<.0001
LnF2	0.3424	0.1167	0.1136	0.5711	2.93	0.0034
LnF1	0.2979	0.1066	0.0889	0.5070	2.79	0.0052

## Wald Statistics For Type 3 GEE Analysis

Source	DF	Chi-Square	Pr > ChiSq
Year	1	23.38	<.0001
LnF2	1	8.60	0.0034
LnF1	1	7.80	0.0052

## APPENDIX E – ANALYSIS RESULTS

Int ID	Year	Duratio n	DY	B/A	ptotal	Cy	Tot al	V(cou nt)	Alpha	EB lambd a	V(EB)	Proje cted Coun t	V(PC)	
1	2000	1	0	B	12.68463	1.000	11	27.922	0.454	11.765	6.420	13.505	2.311	
1	2001	1	0	B	10.23814	0.807	15	20.165	0.508	12.582	6.194			
1	2002	1	0	B	8.260738	0.651	7	14.723	0.561	7.707	3.383			
1	2003	0.5	-0.69315	B	3.348928	0.264	9	4.411	0.759	4.710	1.134			
1	2003	0.5	-0.69315	A	3.331512	0.263	4	4.383	0.760	3.492	0.837	3.547	0.159	
1	2004	1	0	A	5.541923	0.437	5	8.450	0.656	5.355	1.843	5.900	0.441	
1	2005	1	0	A	4.606718	0.363	13	6.616	0.696	7.156	2.174	4.904	0.305	
1	2006	1	0	A	3.836363	0.302	14	5.230	0.734	6.545	1.744	4.084	0.211	
1	2007	0.33	-1.10866	A	1.014063	0.080	2	1.111	0.912	1.100	0.096	1.080	0.015	
2	1999	1	0	B	14.84211	1.000	18	35.703	0.416	16.687	9.750	14.727	2.019	
2	2000	1	0	B	12.11018	0.816	14	25.999	0.466	13.120	7.009			
2	2001	1	0	B	9.852363	0.664	7	19.045	0.517	8.476	4.091			
2	2002	1	0	B	7.992429	0.538	2	14.042	0.569	5.411	2.331			
2	2004	1	0	B	5.21276	0.351	4	7.786	0.670	4.812	1.590			
2	2005	0.67	-0.40048	B	2.844457	0.192	8	3.611	0.788	3.939	0.836			
2	2005	0.33	-1.10866	A	1.400291	0.094	4	1.586	0.883	1.705	0.200	1.389	0.018	
2	2006	1	0	A	3.448247	0.232	9	4.574	0.754	4.815	1.185	3.421	0.109	
2	2007	0.33	-1.10866	A	0.92324	0.062	4	1.004	0.920	1.171	0.094	0.916	0.008	
3	2002	1	0	B	8.435756	1.000	6	15.175	0.556	7.354	3.266	7.903	1.412	
3	2003	1	0	B	6.789868	0.805	6	11.156	0.609	6.481	2.536			
3	2004	0.5	-0.69315	B	2.784961	0.330	4	3.519	0.791	3.039	0.634			
3	2004	0.5	-0.69315	A	2.794912	0.331	2	3.535	0.791	2.629	0.550	2.618	0.155	
3	2005	1	0	A	4.502193	0.534	0	6.422	0.701	3.156	0.943	4.218	0.402	
3	2006	1	0	A	3.571052	0.423	3	4.779	0.747	3.427	0.866	3.346	0.253	
3	2007	0.58	-0.54473	A	1.616364	0.192	4	1.864	0.867	1.933	0.257	1.514	0.052	
4	2001	1	0	B	16.22484	1.000	10	41.154	0.394	12.454	7.544	15.074	2.235	
4	2002	1	0	B	13.65401	0.842	12	31.309	0.436	12.721	7.174			
4	2003	1	0	B	11.45859	0.706	10	23.893	0.480	10.700	5.568			
4	2004	1	0	B	9.594202	0.591	8	18.311	0.524	8.835	4.206			
4	2005	0.75	-0.28768	B	5.803126	0.358	12	8.992	0.645	8.001	2.838			
4	2005	0.25	-1.38629	A	1.92749	0.119	4	2.279	0.846	2.247	0.347	1.791	0.032	
4	2006	1	0	A	6.191872	0.382	12	9.823	0.630	8.339	3.082	5.753	0.326	
4	2007	0.67	-0.40048	A	3.32959	0.205	8	4.379	0.760	4.449	1.067	3.093	0.094	
5	2001	1	0	B	7.932188	1.000	6	13.891	0.571	7.103	3.047	6.678	0.721	
5	2002	1	0	B	6.293451	0.793	1	10.044	0.627	4.317	1.612			
5	2003	1	0	B	4.988776	0.629	5	7.346	0.679	4.992	1.602			
5	2004	1	0	B	3.948395	0.498	1	5.425	0.728	3.146	0.856			
5	2005	0.75	-0.28768	B	2.358913	0.297	0	2.886	0.817	1.928	0.352			
5	2005	0.25	-1.38629	A	0.780127	0.098	0	0.838	0.931	0.726	0.050	0.657	0.007	
5	2006	1	0	A	2.692306	0.339	4	3.379	0.797	2.958	0.601	2.267	0.083	

5	2007	0.5	-0.69315	A	1.152104	0.145	2	1.278	0.902	1.236	0.122	0.970	0.015	
6	2001	1	0	B	7.298808	1.000	9	12.344	0.591	7.994	3.267	7.853	0.808	
6	2002	1	0	B	5.926972	0.812	10	9.254	0.640	7.391	2.657			
6	2003	1	0	B	4.811149	0.659	6	7.003	0.687	5.183	1.622			
6	2004	1	0	B	3.906496	0.535	2	5.352	0.730	3.392	0.916			
6	2005	0.67	-0.40048	B	2.127022	0.291	1	2.555	0.832	1.938	0.325			
6	2005	0.33	-1.10866	A	1.046334	0.143	0	1.150	0.910	0.952	0.086	1.126	0.017	
6	2006	1	0	A	2.705267	0.371	1	3.398	0.796	2.357	0.481	2.911	0.111	
6	2007	0.5	-0.69315	A	1.084412	0.149	3	1.196	0.907	1.263	0.118	1.167	0.018	
7	2001	1	0	B	10.16655	1.000	13	19.955	0.509	11.556	5.669	11.01 3	1.339	
7	2002	1	0	B	8.348616	0.821	8	14.949	0.558	8.195	3.618			
7	2003	1	0	B	6.765768	0.665	5	11.101	0.609	6.076	2.373			
7	2004	1	0	B	5.626621	0.553	9	8.625	0.652	6.799	2.364			
7	2005	0.67	-0.40048	B	3.086865	0.304	8	3.989	0.774	4.198	0.950			
7	2005	0.33	-1.10866	A	1.523919	0.150	3	1.744	0.874	1.710	0.216	1.651	0.030	
7	2006	1	0	A	3.815112	0.375	10	5.193	0.735	5.457	1.448	4.133	0.189	
7	2007	0.5	-0.69315	A	1.571294	0.155	0	1.805	0.870	1.368	0.177	1.702	0.032	
8	2002	1	0	B	7.753372	1.000	6	13.446	0.577	7.011	2.968	8.516	0.998	
8	2003	1	0	B	7.304373	0.942	14	12.357	0.591	10.042	4.106			
8	2004	1	0	B	6.696994	0.864	8	10.944	0.612	7.203	2.795			
8	2005	0.67	-0.40048	B	3.91135	0.504	4	5.360	0.730	3.935	1.064			
8	2005	0.33	-1.10866	A	1.987276	0.256	3	2.361	0.842	2.148	0.340	2.183	0.066	
8	2006	1	0	A	5.757444	0.743	5	8.897	0.647	5.490	1.937	6.324	0.550	
8	2007	0.67	-0.40048	A	2.617182	0.338	8	3.266	0.801	3.686	0.732	2.875	0.114	
9	2004	1	0	B	5.661411		5	8.697	0.651	5.431	1.895			
9	2005	1	0	B	4.685776		6	6.765	0.693	5.090	1.564			
9	2006	1	0	B	3.876019		5	5.299	0.731	4.178	1.122			
9	2007	1	0	B	3.203899		1	4.176	0.767	2.691	0.626			
10	2004	1	0	B	7.3193		2	12.393	0.591	5.142	2.105			
10	2005	1	0	B	6.072173		5	9.564	0.635	5.681	2.074			
10	2006	1	0	B	5.02607		2	7.418	0.678	4.050	1.306			
10	2007	1	0	B	4.152001		2	5.785	0.718	3.545	1.000			



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			SE					
	127	127.000	11.269	86.870		75.539	3.811	1.952
				4.853	Theta	1.681		
Dispersion	0.0947			271.194	bias	1.001	Variance	Std Error
				7.934	Unbiased	1.680	0.024	0.155
				0.612				
					<b>ΔCrashes</b>			
					=	-68.012		15.518
					Z	-4.383		
					P-value	5.855E-06		