Analyzing the Effects of LEDTraffic Signals on Urban Intersection Safety

THE USE OF LIGHT EMITTING DIODES (LEDS) 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 LEDS, BUT COULD IMPROVED SAFETY BE ANOTHER, LESS OBVIOUS BENEFIT?

BY DEOGRATIAS EUSTACE, PH.D., P.E., PTOE, VALERIE GRIFFIN AND PETER HOVEY, PH.D.

BACKGROUND

In 2002, there were 1,299,000 crashes at signalized intersections in the United States.[1] These crashes account for approximately 21 percent of total crashes and about 24 percent of all fatal and injury collisions. The social and financial impact of this number of collisions is substantial. The Federal Highway Administration (FHWA) 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.[2] Improving the visibility of traffic signals has also been cited as an important safety measure.[3] Many intersection improvements are prohibitively expensive to implement—a drainage upgrade may cost in excess of $20,000, and new turn lanes may exceed $40,000. The 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.

Light emitting diodes (LEDs) have been used in various applications since their invention more than 40 years ago.[4] As the new style of lighting gained popularity in other disciplines, engineers began to recognize the potential for LEDs in traffic applications. Traffic signal bulbs account for approximately 90 percent of the total energy usage at a typical intersection. By converting incandescent bulbs to LEDs, energy consumption can be decreased by about 80 percent. The California Department of Transportation (Caltrans) was one of the first agencies to realize large-scale cost saving by using LEDs. In 2003, Caltrans saved taxpayers $10 million per year by converting state-operated signals to LED.[5] 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 LEDs 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.[6] All of these advantages may also lead to an impact in another sector of traffic engineering—intersection safety. Visibility of LEDs seems to be superior, which could positively affect 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 backup systems to operate the intersection during a power outage. Could all of these factors combined improve overall intersection safety? The objective of this study was to use empirical Bayes estimation to determine whether there was a noticeable decrease in crashes at signalized intersections that have been converted to LED signals.

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 by Thomas et al. 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.[7] Improved traffic signal visibility was determined to be a cost-effective safety strategy.

The Institute of Transportation Engineers cites improved signal visibility as a useful safety measure to be considered for implementation.[8] LED signals are specifically described as being brighter and more conspicuous during inclement weather. Engineers have begun to utilize LEDs in railroad crossings as a potential safety improvement due to improved visibility and longer life.[9] Flashing lights are installed horizontally at approaches to warn drivers of a train.

METHODOLOGY AND DATA COLLECTION

Data Collection

Data was collected for 10 urban signalized intersections in the city of Middletown, Ohio, USA. Of the 10 intersections studied, eight were converted to LED signals between 2003 and 2005. Summary data for the study intersections are provided in Table 1. For each intersection, the average daily traffic (ADT) was also broken into approach ADT for both intersecting roadways. For the year of conversion, crash and ADT data were broken down into the month of conversion or the proportion of the year that falls into the "before" and "after" periods. The lengths of the "before" and "after" periods varied from site to site depending on the availability of crash and ADT data.

Variables considered for use in the analysis include road classification, number of lanes, lane width, total entering ADT, entering ADT of the major and minor roads, the number of police officers patrolling each year, and year. 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 two sites that were chosen experience very similar traffic flow as the treatment sites, as they are located on the same arterials.

Methodology

After considering the numerous statistical methods available for crash estimation, the empirical Bayes (EB) method was chosen for this study. Findings in the literature suggest that the empirical Bayes method is appropriate for this type of analysis and is a widely accepted method in the field of traffic safety.[10–12] 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 and successfully used in the past to model and evaluate various transportation safety projects.[13–22] On the contrary, 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.[23] Empirical Bayes estimation is employed to estimate the number of crashes 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 change in safety at the converted intersection is given as shown in Equation 1:

$$\Delta\ safety = B - A$$

Where:

$\Delta\ safety$ = change in the number of crashes

Table 1. Crash and ADT Data for Signalized Intersections Studied

Site	INTERSECTION		1999		2000		2001		2002		2003		2004		2005		2006		2007*	
			Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
1	Roosevelt & Wicoff																			
		Crash Counts***			11		15		7		9	4		5		13		14		2
		ADT			28620		27190		26950			26120		26690		27260		27830		28910
2	Breiel & Bonita																			
		Crash Counts	18		14		7		2				4		8	4		9		4
		ADT	14350		14680		15010		15340		15670		16000			16450		16910		17360
3	Central & Sutphin																			
		Crash Counts							6		6		4	2		0		3		4
		ADT			15700		15470		15230		15000			14910		14810		14720		14620
4	Breiel & Central																			
		Crash Counts											8		12	4		12		8
		ADT					35040		35020		36010		37000			35930		34870		33800
5	Breiel & Batsey																			
		Crash Counts					6		1		5		1		0	2		4		2
		ADT					25060		23950		22830		21720			20600		20870		21140
6	Breiel & Shopping Center																			
		Crash Counts					9		10		6		2		1	0		1		3
		ADT					23060		23070		23080		23100			23110		23300		20905
7	Breiel & Lewis																			
		Crash Counts					13		8		5		9		8	3		10		0
		ADT					23030		23550		24070		24580			25100		26140		27210
8	Breiel & N. Lefferson																			
		Crash Counts							6		14		8		4	3		5		8
		ADT					10000		14010		18020		22030			26040		34060		25270
9	University & Woodlawn**																			
		Crash Counts											5		6		5		1	
		ADT			22200		25700				18990		19180		19370		19560		19760	
10	Breiel & Forset Hills**																			
		Crash Counts											2		5		2		2	
		ADT					27890		27800		27710		27620		27530		27440		27350	

Notes

* For 2007, data were collected for only between 4–8 months.

** These are control sites, i.e., sites that were not converted (treated)

*** Crash counts include all types of crashes

Shaded cells indicate the year for which each site was converted

B = expected number of crashes in the after period without the improvement
A = actual number of crashes reported in the after improvement period

After site selection, the next step in the study was the development of the crash estimation model (CEM). The CEM is simply a multivariate regression model used to estimate the mean and variance of the annual number of crashes that would be expected at each intersection site.

Various multivariate models were tested through an iterative process by fitting the available traits using SAS (version 9.1) software in order to form a suitable CEM. The GENMOD procedure in SAS allows the specification of a negative binomial distribution by fitting a generalized linear model to the data by maximum likelihood estimation of the parameter vector β. The p-value was used as an indicator of the significance of the individual traits. The traits that produced a statistically sound model include the average daily traffic (ADT) for the major street, ADT for the minor street and the data year (i.e., the actual year for which the data were collected). The resulting CEM was in the form shown in Equation 2:

$$P = \alpha_{\lambda} (ADT_{Maj})^{\hat{\beta}_1} (ADT_{Min})^{\hat{\beta}_2} e^{\hat{\beta}_3 (Year)} e^{\hat{\beta}_0}$$

Where:
P = expected (mean) total number of crashes/year at an intersection site
ADT_{Maj} = average daily total entering traffic for the major street (vehicles/day)
ADT_{Min} = average daily total entering traffic for the minor street (vehicles/day)
$Year$ = actual year of the crash data
α_{λ}, $\hat{\beta}_i$ = model parameters

The model parameters and the overdispersion parameter (ϕ) 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, ϕ, is commonly used in the calculation of the variance as shown in Equation 3:[24]

$$variance = mean^{*} \left(1 + \frac{mean}{\phi}\right)$$

THE EXPECTED MEAN CRASHES/YEAR FROM THE CEM CALCULATION WAS USED TO PROJECT THE NUMBER OF CRASHES FOR POST-TREATMENT YEARS, HAD THE TREATMENT NOT OCCURRED.

In the SAS software, however, the calculation is slightly different as in equations 4a and 4b:

Equation 4a:

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

Equation 4b:

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

The calculations in this study compensated 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 crash 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 that are likely to affect overall crash frequencies along with the study treatment. In 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 remainder of this section outlines step by step the method used in the empirical Bayes (EB) estimation.

The expected mean crashes/year from the CEM calculation was used to project the number of crashes for post-treatment years, had the treatment not occurred. In order to get the projected crashes the first step was to select a base year from the before period from which the annual number of crashes for all other years were normalized to. For each intersection site, the base year was chosen to be the first year for which the before data was available. Normalized mean number of crashes for year y, denoted by C_y, was calculated by using Equation 5:

$$C_y = \frac{P_y}{P_b}$$

Where, P_y and P_b are the predicted total number of crashes from the CEM for year y and base year, respectively for each intersection site. The projections of the annual number of crashes are independent of the choice of the base year.[25] This value was later used to determine the projected number of crashes. The variance of the expected number of crashes, *Var(P)* was calculated using the overdispersion parameter as shown in Equation 6:

$$Var(P) = (1 + \phi * P) * P$$

Next, the relative weight, α, was calculated as shown in Equation 7:

$$\alpha = \frac{P}{Var(P)}$$

Actual site crash counts, K, were used in the next step to determine the EB estimates of the mean and variance of the number of crashes for a site, *EB* and *Var(EB)*, using equations 8a and 8b, respectively:

(8a) $EB = \alpha * P + (1-\alpha) * K$

(8b) $Var(EB) = (1-\alpha) * EB$

The projection of the expected "after" treatment number of crashes was based on the weighted average of the EB estimates of number of crashes of all "before" treatment (conversion to LED) years. First, the estimate of the baseline mean and variance of number of crashes, PC_b and $Var(PC_b)$, were required and determined, as shown in equations 9a and 9b, respectively:

(9a) $$PC_b = \frac{\sum_{before} EB}{\sum_{before} C_y}$$

(9b) $$Var(PC_b) = \frac{\sum_{before} Var(EB)}{\left(\sum_{before} C_y\right)^2}$$

It is noteworthy to mention that the comparison sites were also used in the development of the CEM and in the computations of equations 5–9 because they are regarded as "before" period data as no conversion took place at those sites. Then the projected number of crashes for the treated (converted) intersection sites in the "after" conversion period were determined by multiplying the normalized number of crashes/year, C_y, by the baseline projected number of crashes, PC_b. The mean and variance of the projected crash count in the "after" conversion period for year *y*, *B* and *Var(B)*, were calculated by equations 10a and 10b:

(10a) $B = C_y * PC_b$

(10b) $Var(B) = C^2_y * Var(PC_b)$

The overall index of effectiveness, θ, was then calculated by comparing the total projected number of crashes (*B*) in the after period to the total actual number of crashes (*A*) in the after period by using Equation 11:

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

The unbiased estimate, θ_u, was then determined by the use of Equation 12:

$$\theta_u = \frac{\theta}{1 + \frac{\Sigma Var(B)}{(\Sigma B)^2}}$$

Lastly, the percent change in total crashes due to the treatment was calculated by Equation 13:

$$\Delta\ crashes(\%) = (1 - \theta_u) * 100$$

If the treatment causes crashes to be reduced, θ_u will be significantly less than one and Δ*crashes* will be a positive value significantly different from zero. In other words, if the treatment increases crashes, θ_u will be significantly larger than one and Δ*crashes* will be a negative value significantly lower than zero. This basic procedure was applied to the data that included eight treatment sites and two comparison sites.

RESULTS

The expected number of crashes as estimated by the CEM and the overdispersion parameter from SAS were entered into an Excel spreadsheet to compute all values according to the equations (5–13) discussed in the methodology section. Table 2 presents the CEM parameters from a SAS output, which were significant at α = 0.05. The resulting CEM equation is presented by Equation 14. The projected total crash counts, *B*s, were estimated for the "after" years to represent what the number of crashes would have been in future years without LED conversions. These were compared to the yearly number of total crash counts that actually occurred after conversion to determine the unbiased overall index of effectiveness, θ_u. The value of θ_u is expected to be significantly less than zero if the conversion reduced the crashes. The results are shown in Table 3 and θ_u is 1.7066, which is significantly higher than zero.

Equation 14:

$$P = 0.972172 * e^{406.0598} * e^{-0.2046*Year} * ADT^{0.2979}_{Maj} * ADT^{0.3424}_{Min}$$

DISCUSSION OF RESULTS

The empirical Bayes results indicate that crashes actually increased after the installation of LEDs by about 71 percent. The analysis of the safety effect of LEDs in this study show that they did not yield safety benefits. However, when interpreting the results of the current study several limitations have to be considered. First, the most substantial of these is the small sample size used. Only eight treatment sites were used, many along the same corridor. Also, only two comparison sites (untreated) were used. More comparison sites should have been selected to

Table 2. The Crash Estimation Model Parameters from SAS Output

Parameter	Estimate	Standard Error	Z	Pr > |Z|
β_0 (Y-intersept)	406.0598	84.7436	4.79	< 0.0001
β_1 (ADT Major road)	0.2979	0.1066	2.79	0.0052
β_2 (ADT Minor road)	0.3424	0.1167	2.93	0.0034
β_3 (Year)	–0.2046	0.0423	–4.84	< 0.0001
Overdispersion	0.0947	0.0607		
α_λ	0.972172			

Table 3. Results of the EB Estimation

Parameter	Value
Total Crash Counts (ΣA) for the "After" Period	129
Projected Total Crash Counts (ΣB) for the "After" Period (Standard Deviation)	75.539 (1.952)
Overall Unbiased Index, θ_u (Standard Deviation)	1.7066 (0.156)
Overall Percent Reduction in Crashes (%)	–70.66
Z-value	–4.515
p-value	< 0.00001

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 10 years; almost the entire boulevard system is already converted. This presents a problem in choosing untreated 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 find out the date of conversion and impossible to get old crash records. Also, different LED specifications were used for older fixtures. The visual qualities of the old ones 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 study intersections. For example, the intersection of Breiel Boulevard and Lefferson Road experienced traffic growth of 160 percent over four years due to development in the southeast quadrant of the City. North Breiel Boulevard, however, has undergone a decrease in traffic volumes, with intersections averaging –9 percent 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 more than 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 unusual traffic patterns to evolve. So, the changes in both origination points (housing) and destination points (industry/businesses) have shifted traffic throughout the city.

CONCLUSIONS

The objective of this study was to evaluate the safety benefits of LED traffic signals. The development and use of LEDs 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.

The empirical Bayes results have shown that the total number of crashes increased after the installation of LEDs by about 71 percent. The analysis in this study reveals that the safety deteriorated at intersections that had LED signals installed.

Additional studies are recommended, preferably using larger sample sizes of both converted and comparison sites. The CEM could also 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. However, with all these benefits if they deteriorate the intersection safety, they will be undesirable. This study was an exploratory one, so future studies are required to expand from this one to investigate further and determine the long-term safety benefits associated with LED use in traffic signals. ■

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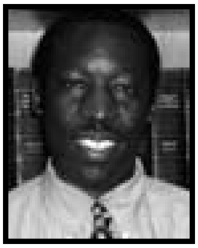

DEOGRATIAS EUSTACE,
Ph.D., P.E., PTOE is an assistant professor of civil engineering at the University of Dayton, where he is the director of the Transportation Engineering Laboratory (TEL). He received a B.Sc. (Eng) and M.Sc. (Eng) from the University of Dar-Es-Salaam, Tanzania, and a Ph.D. from Kansas State University. His research interests include traffic safety, travel demand modeling, non-motorized transport, and traffic operations. He is a member of ITE.

VALERIE E. GRIFFIN
is the city traffic engineer for Middletown, Ohio, where she is responsible for design, operation and management of the signal system. She received both a B.S. and M.S. in civil engineering from the University of Dayton. Her research focuses on traffic safety and ITS. She is a member of ITE.

PETER W. HOVEY,
Ph.D. is an associate professor in the Department of Mathematics at the University of Dayton. His experience includes collaborative research in areas as diverse as chemometrics, bioengineering, environmental engineering and aerospace engineering. He has recently worked with civil engineering graduate students helping them to use empirical Bayes estimation to help evaluate the effectiveness of various road improvement projects on Ohio roadways. He received a B.S. in mathematics from the University of Dayton and a Ph.D. in mathematical statistics from the University of Kentucky.