Impact of Optimally Minimizing Delay Times on Safety at Signalized Intersections in Urban Areas, Case Study: The City of Virginia Beach

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Abstract:
Optimally minimizing delay times at signalized intersections can significantly improve both traffic flow and safety. However, most traffic flow optimizing tools do not measure the effect on safety. This study uses nonlinear programming (NLP) algorithms to optimally minimize delay times and employs both Safety performance functions (SPFs) and empirical Bayes (EB) before-after methodology to measure the impact on safety presented as a Crash Modification Factor (CMF). A crash modification factor (CMF) is a multiplicative factor used by transportation practitioners to compute the expected number of crashes at specific study site(s) after a countermeasure has been proposed or is implemented. Using 2013 traffic data from seventeen signalized intersections located in Virginia Beach, the results show that optimally minimizing intersection delay times can result in a safety improvement of approximately 26.46% that is a CMF of 0.735. This result is not conclusive, but the significance of the findings shows the need for further investigations and potential inclusion in the future editions of the Highway Safety Manual (HSM).

Keywords: Safety; crash modification factors; delay; safety performance functions; empirical bayes

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1. Introduction

Minimizing delays at signalized intersections can significantly improve traffic flow as well as safety. According to the Highway Capacity Manual [HCM, 2010], delay is one of the indexes used to evaluate the level of service (LOS), and determining of traffic signal timings at signalized intersections. Both LOS and signal timing are measures of traffic flow effectiveness at signalized intersections. Optimally minimized delays can be associated with efficient traffic progressions, reducing the number of necessary stoppages, traffic congestion and the likelihood of accidents. Objective analysis to validate this presumption is lacking and even though the HSM (2010) states that treatments such as cycle length modification and improved signal coordination have unknown effects on accidents [Stevanovic, Stevanovic, and Kergaye, 2013].

It is demanding to decisively measure the influence of delay on safety at a signalized intersection because of: (1) the influence of other major accident causing factors such as geometrical, human, and weather factors that overshadow the delay effects; (2) the difficulty incurred capturing and recording accident data; and (3) often transportation practitioners work with only a subset of all accidents, usually those reported by enforcement officials and not all the accidents that occurred.

The introduction of the HSM has prompted increased attention to safety studies and different ways to measure and quantify safety [Gross, Persaud, and Lyon, 2010; Hauer, et al, 2012; Tegge, Jo, and Ouyang, 2010]. The need to objectively quantify safety using CMFs continues to attract research and may result in further understanding of the factors that influence safety on roadways. This study investigates the concept at selected signalized intersections by using NLP algorithms, an optimizing mathematical process used to find a feasible extremum delay and the EB before-after methodology to estimate its effect on safety represented as a CMF.

In practice, some improvements in safety measures such as (e.g. reducing the number of conflicts) may reduce traffic flow efficiency [Stevanovic, Stevanovic, and Kergaye, 2013]. To investigate the effect of optimally minimizing delay at signalized intersections, this study also considers cycle length and LOS, because they are traffic flow parameters directly related to intersection delay.

The two main objectives of this study are to:

1. Optimally minimize the delay times at the selected signalized intersection, and
2. Calculate the resultant CMFs.

To achieve these objectives, this study uses statistical models to relate the number of accidents per year to corresponding delay time attribute. The significance of an attribute is based on a user-identified level-of-significance, α [Tegge, Jo and Ouyang, 2010], that measures the plausibility of the null hypothesis [Navidi, 2008] and usually ranges from 0.01 to 0.10 [Hauer, 1996]. A smaller α shows it is more difficult to declare an attribute significant. Accidents are very important and therefore a larger α is usually used so as to include more attributes in the model. The value of α is usually set to 0.10 [Tegge, Jo, and Ouyang, 2010].

2. Literature Review

Delay is estimated as the sum of the approach uniform delay, the overflow plus random delay, and the initial queue delay. Literature Review It reflects driver discomfort, frustration, fuel consumption, and lost travel time [HSM, 2010]. Traffic signal coordination and optimization are the most desirable cost effective [Park, Messer, and Urbanik II, 1999] means of reducing delay. In transportation engineering, optimization pertains to the use of traffic or mathematical models to effectively minimize delay times. Criteria for model selection include "realistic traffic representation, adequate capacity to incorporate most traffic management features, and ability to represent system variability" [Rouphail, Park, and Sacks, 2000]. Some transportation software that meet these requirements include CORSIMTM, VISSIMTM, Synchro® and TransModeler®. The traditional mathematical model used for optimization is the NLP because of its ability to minimize readily quantifiable objectives, coordinate and accurately handle the process of nonlinearities and interactions, and its systematic ways of dealing with processing constraints [Biegler, and Rawlings, 1991].

Although some studies have shown that there is a trade-off between delay and safety at signalized intersections

[Zhang, and Prevedouros, 2003], efficient intersection traffic flow designs can considerably enhance both, especially in congested urban settings [Wong, Sze, and Li, 2007]. For example, if left-turning vehicles are permitted to make a turn, they may experience shorter delays, but have higher chances of an accident with the opposing traffic as they try to find a gap to negotiate the left-turn. Alternatively, if the left-turning vehicles are protected by signal timing the likelihood of accidents decrease, but they may experience longer delays [Zhang, and Prevedouros, 2003]. Wong et al [2007] states that efficient design of traffic flow elements like signal phasing leads to equalization of traffic delays at different approaches, resolves conflicts between different streams, and can accommodate for variations in traffic volumes, thus enhancing safety.

Previously, practitioners applied crash reduction factors (CRF) to estimate the safety benefits of certain countermeasure(s). Currently, the HSM [2010] encourages the use of CMFs instead. The manual also recognizes that although important, the safety effects of traffic flow parameters like delay and signal timing are not yet well understood. CMFs for before and after conditions are usually found by applying observational before and after studies, such as comparison group studies, and EB studies.

In comparison studies, sample sets are taken from untreated site(s) and compared to similar, but treated site(s). Both samples are assumed to be equal in all aspects of crash causing factors except the treatment being studied. The CMF is then found by determining the ratio of the observed number of accidents in the after period to those in the before period. The number of accidents in the before period at the treatment site(s) is multiplied by this ratio to determine the expected accidents at the treatment group had there been no treatment applied. However, comparison studies have a setback; such studies assume that both treated and untreated sites have the same attributes, and that there are no other safety mitigating factors affecting beyond the treatment. Realistically, this is difficult to achieve. Additionally, treated sites are likely to be associated with higher number of accidents in the before period than untreated sites, hence benefit overestimation referred to as regression-to-the-mean (RTM) bias [Shahdah, Frank Saccomanno, and Persaud, 2014].

In the past 30 years, EB models have been used successfully by other researchers to perform this type of evaluation [Elvik, 2008]. The EB studies use a more complex application that corrects for RTM the bias associated with comparison group studies by expressing the expected number of accidents before the treatment as a weighted function of the observed and predicted accidents at the treated sites in the before period with the assumption that the traffic volumes and geometric features are similar [Gross, Persaud, and Lyon, 2010; Hauer, 1995; Srinivasan, et al, 2008]. The predicted number of accidents is determined using Safety Performance Functions (SPFs) that relate the accidents to the traffic and geometrical features used. Studies show that the best SPF distributions to be Poisson regression and negative binomial (NB) [Lord and Mannering, 2010; Persaud, and Lyon, 2007; Stamatiadis et al, 2008] because of their ability to deal with crash data characteristics.

3. Methodology

This section employs both delay optimization and resultant CMF assessment to measure safety impacts. NLP algorithms are used to analyze delay optimization and EB before-after studies to determine the resultant CMF. The flowchart in Figure 1 shows a step-by-step procedure in the delay optimization and the CMF development.

Optimization

The theory of optimization is an essential principle for evaluating of many complex decisions or allocation of problems. In its operational simplicity, optimization gives a certain degree of philosophical elegance that is hard to dispute [Luenberger, and Ye, 2010]. Here, a complex problem involving analysis of given interrelated variables is solved by focusing on a single objective function specifically designed to quantify performance, and measure the quality of the determined results. The objective function is either maximized or minimized subject to the given constraints.

Finding the optimal values of decision variables x_1, x_2, …, x_n in an NLP, can generally be expressed as follows:

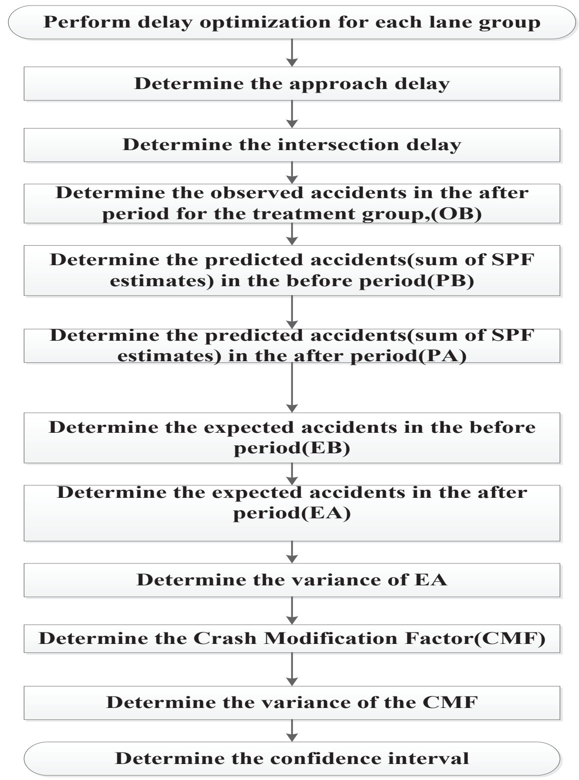


Figure 1. Delay optimization and CMF development procedure

$$\begin{aligned}
&\max(\min) z = f(x_1, x_2, \ldots, x_n)\\
&\text{subject to } g_1(x_1, x_2, \ldots, x_n)\ (\le, =, \text{or} \ge)\ b_1\\
&\text{subject to } g_2(x_1, x_2, \ldots, x_n)\ (\le, =, \text{or} \ge)\ b_2\\
&g_m(x_1, x_2, \ldots, x_n)\ (\le, =, \text{or} \ge)\ b_m
\end{aligned} \tag{1}$$

Where $f(x_1, x_2, \ldots, x_n)$ or z is the NLP's objective function, and $g_1(x_1, x_2, \ldots, x_n)\ (\le, =, \text{or} \ge)\ b_1$, $g_m(x_1, x_2, \ldots, x_n)\ (\le, =, \text{or} \ge)\ b_m$ are the NLP's constraints.

The feasible region for the NLP in equation 1 is the set of points $(x_1, x_2, \ldots, x_n)$ that fulfills the m constraints of the equation. Any point that is in the feasible region is taken as a feasible point, those outside are in-feasible. Any point $\bar{x}$ in the feasible region for which $f(\bar{x}) \ge f(x)$ when maximizing or $f(\bar{x}) \le f(x)$ when minimizing holds for all points x in the feasible region is an optimal solution to the NLP [Winston, 2004].

Crash Modification Factors

A crash modification factor (CMF) is a multiplicative factor used by transportation practitioners to compute the expected number of crashes at specific study site(s) after a countermeasure has been proposed or is implemented. The countermeasure can be positive (improve safety) or negative (degrade safety) [HSM, 2010]. This study uses the EB before-after methodology to determine the resultant CMF because it has the ability to account for: (a) RTM effects due to sites experiencing randomly high short-term crash counts selected for treatment and show reduction in crashes afterwards, when the counts regress towards their true long-term mean and vice versa; (b) changes in traffic volumes, and (c) time trends in crash occurrence due to changes over time in factors like weather, human habits, and crash reporting practices [Gross, Persaud, and Lyon, 2010], and bias in site selection [Lan et al, 2009].

In the EB before-after evaluation of a treatment effect, the change in crashes at a basic freeway segment is given by the sum of predicted estimates (P_B) combined with the sum of the observed accidents (O_B) in the 'before' period to obtain the expected number of accidents (E_B) before the treatment, expressed as:

$$E_B = w * P_B + (1 - w)\frac{O_B}{n} \tag{2}$$

where n is the time period of observation and w is the weight factor estimated as

$$w = \frac{1}{1 + k\sum_{n=1}^{N} P_n} \tag{3}$$

where k is the dispersion parameter of the NB distribution that is assumed for the crash counts used in estimating the SPF, and P_n is the predicted number of accidents for period of time n. k is estimated from the SPF calibration procedure.

As discussed previously, SPF is part of the EB methodology and is used to determine the predicted number of accidents. SPF is regression statistical models relating observed or actual accident counts to their causing factors. There are several SPFs, but the two most accurate and common types are Poisson and NB models [Elvik, 2008]. Accident data are discrete, non-negative, and sporadic; the Poisson regression model is the natural first choice for modeling [Poch and Mannering, 1996]. However, the Poisson model has a key limitation, which is the variance of the dependent variable is constrained to be nearly or equal to it's meanwhile the variance of accident and traffic data is likely to be over dispersed and differ significantly from the mean [Tegge, Jo and Ouyang, 2010]. Hence, the correct model in such analysis is the NB distribution formulated as follows:

$$P(y_i) = \frac{\Gamma\left(y_i + \frac{1}{k}\right)}{y_i!\,\Gamma\left(\frac{1}{k}\right)}\left(\frac{k\mu_i}{1+k\mu_i}\right)^{y_i}\left(\frac{1}{1+k\mu_i}\right)^{\frac{1}{k}} \quad (4)$$

Where P (y_i) is the 'predicted' number of accidents, Γ is the gamma function, μ is the NB mean, and k is the dispersion parameter. The NB model allows the mean to differ from the variance such that

$$\operatorname{var} n_i = E(n_i)[1 + \alpha E(n_i)] \quad (5)$$

where α is the measure of the dispersion and can be estimated using the standard maximum likelihood techniques. The appropriateness of the NB relative to the Poisson model is determined by the statistical significance of α. If α is not statistically different from zero, the NB simply reduces to Poisson regression with $varn_i$=E(ni). If α is significantly different from zero, then the NB is adopted and the Poisson regression is inappropriate.

The form of the model equation for NB regression is the same as that of Poisson regression. The log of the outcome is predicted with a linear combination of the predictors' variable as:

log(crash) = intercept + b_1*(delay) +* b_2*(major AADT) +* b_3 *(minor AADT)* *(6)*

This implies that:

$$accidents = exp^{(intercept + b1(delay) + b2(major\ AADT) + b3(minor\ AADT))} \quad (7)$$

The expected accident frequency found in Equation 3 is used in the development of CMFs as published in the FHWA guide for developing CMF (4). The development of CMF is presented in several steps. In the initial step, the expected number of accidents in the 'after' period in the treatment group that would have occurred without treatment, (E_A) is

$$E_A = E_B * \left(\frac{P_A}{P_B}\right) \quad (8)$$

where E_B, and P_B are as previously defined, and P_A, is the predicted number of crashes or sum of SPF estimates in the 'after' period. The variance of E_A is estimated as

$$(E_A) = E_A * \left(\frac{P_A}{P_B}\right) * (1 - w) \quad (9)$$

Finally, the CMF is approximately equal to the 'after' period accident counts divided by the E_A. It is an approximate because of a small adjustment based on E_A and with the variance expressed as

$$CMF = \frac{\left(\frac{O_A}{E_A}\right)}{1 + \left(\frac{var(E_A)}{{E_A}^2}\right)} \quad (10)$$

$$var_{CMF} = CMF^2\left[\frac{\left((1/O_A) + (varE_A/E_A^2)\right)}{\left(1 + (varE_A/E_A^2)\right)^2}\right] \quad (11)$$

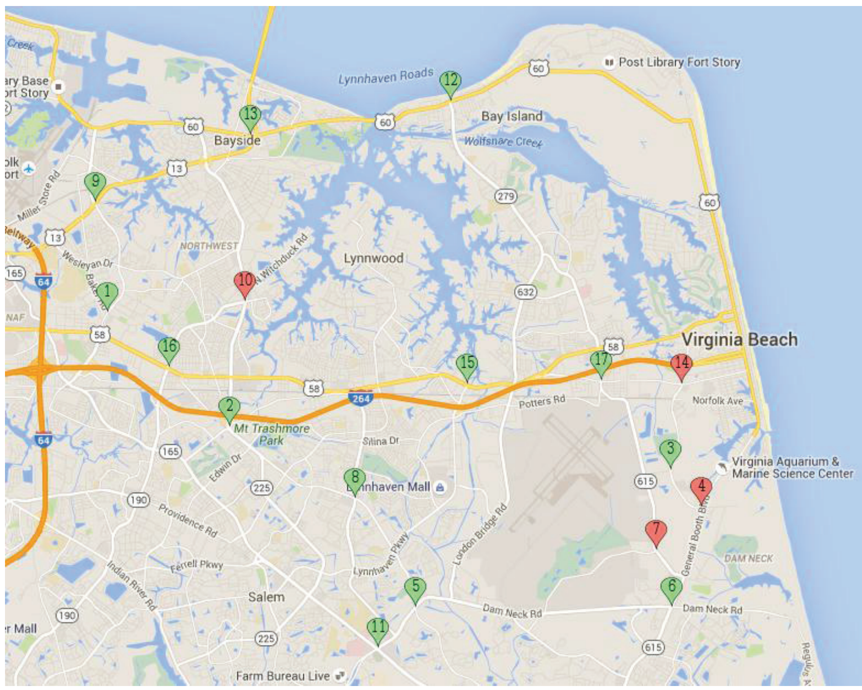
Where O_A is the sum of the observed number of accidents in the 'after' period for the treatment sites and E_A is as previously described.

Data Analysis and Result Interpretation

This study analyzes a set of seventeen signalized intersections located in Virginia Beach to estimate a CMF for optimally minimized delays. These seventeen study sites and their geographical locations are presented in Figure1. In Figure 1, thirteen intersections are marked in green and four in red. As this study will show later, the optimized delay times for those in green are less than the city's operational delay times while those marked in red are higher.

The intersections in figure 1 are numbered from 1 to 17. The identities of these intersections are presented in figure 1 together with their corresponding numbers.

Both the major and minor entering ADTs presented in table 1 were obtained from the city of Virginia Beach's traffic count database. Also obtained from the city were the signal delay times per vehicle in seconds, and the number of observed/reported accidents per year. The before and after delay optimization conditions are first established by this study before finally measuring its impact on safety.



SOURCE: Google Maps

Figure 1. Study site geographical locations

Table 1. Study site identities and average daily traffic (ADT) volumes for 2013

ID	INTERSECTION			Major Ent. ADT	Minor Ent. ADT
1	Baker Rd	and	Newtown Rd	41,115	13,159
2	Baxter Rd	and	Independence Bl	76,058	23,287
3	Bells Rd	and	Birdneck Rd	16,067	5,487
4	Birdneck Rd	and	General Booth Rd	30,522	12,289
5	Dam Neck Rd	and	Holland Rd	42,644	26,569
6	Dam Neck Rd	and	General Booth Rd	54,333	33,504
7	Harpers Rd	and	Oceana Bl	32,407	10,440
8	Holland Rd	and	Rosemont Rd	39,815	21,688
9	Northampton Bl	and	Diamond Springs Rd	63,658	28,247
10	Pembroke Bl	and	Independence Bl	52,242	10,374
11	Princess Anne Rd	and	Dam Neck Rd	46,957	42,644
12	Shore Dr	and	Great Neck Rd	33,878	8,458
13	Shore Dr	and	Northampton Bl	25,318	23,474
14	Virginia Beach Bl	and	Birdneck Rd	32,771	13,002
15	Virginia Beach Bl	and	Lynnhaven Rd	41,214	21,106
16	Virginia Beach Bl	and	Witchduck Rd	46,785	38,751
17	Virginia Beach Bl	and	First Colonial Rd	39,230	29,665

Ent. = entering
Rd = road, Bl = boulevard, Dr = drive

Before Delay Optimization Period

The before period, describes the actual operational conditions at the study intersections prior to the optimization of delay times. Table 2 presents the cycle lengths, delay times and level of services for these intersections prior to delay time optimization.

Intersections with LOS F (delay times ≥ 80 s/veh) are not considered for analysis by this study because in this state, the roadway is considered to be failing [Roess, Prassas, and McShane, 2011]. In this state, there is a breakdown in vehicular flow, the arrival flow rate temporally exceeds the departure rate hence the limitation to mathematically describe the operational conditions.

Using the actual delay times and number of accidents (before the optimization period), NB regression analysis was performed and the resulting parameters are presented in table 3.

Column 1 of Table 3 shows each of the variables used in the analysis. Column 2 shows the NB regression coefficients for each of the variables along with their related standard errors, Wald chi-square values, and p-values for each of the coefficients in columns 4, 5, 6, and 7 respectively. All the variables are statistically significant at a 0.05 level. The coefficients indicate that as the delay (s/veh), major entering ADT, and minor entering ADT increase, the number of accidents increase too.

Table 2. Study site operational conditions in the before period

ID	INTERSECTION			C (s)	D (s)	LOS
1	Baker Rd	and	Newtown Rd	160	51.6	D
2	Baxter Rd	and	Independence Bl	160	45.6	D
3	Bells Rd	and	Birdneck Rd	90	12.9	B
4	Birdneck Rd	and	General Booth Rd	90	22.9	C
5	Dam Neck Rd	and	Holland Rd	160	63.4	E
6	Dam Neck Rd	and	General Booth Rd	160	68.6	E
7	Harpers Rd	and	Oceana Bl	160	18.5	B
8	Holland Rd	and	Rosemont Rd	160	57	E
9	Northampton Bl	and	Diamond Springs Rd	160	41.2	D
10	Pembroke Bl	and	Independence Bl	160	26.7	C
11	Princess Anne Rd	and	Dam Neck Rd	160	47.5	D
12	Shore Dr	and	Great Neck Rd	160	17.5	B
13	Shore Dr	and	Northampton Bl	160	19.7	B
14	Virginia Beach Bl	and	Birdneck Rd	120	21.6	C
15	Virginia Beach Bl	and	Lynnhaven Rd	180	38.9	D
16	Virginia Beach Bl	and	Witchduck Rd	160	41.4	D
17	Virginia Beach Bl	and	First Colonial Rd	140	57.8	E

C = cycle length, D = delay, LOS = level of service

Table 3. Negative binomial parameter estimates in the before delay optimization period

Parameter	B	Standard Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	*p*-value
Intercept	0.02	0.5984	-1.153	1.199	0.001	1	0.000
Delay	0.033	0.0078	0.018	0.048	17.899	1	0.000
Major entering ADT	3.42E-07	5.79E-06	-1.10E-05	1.18E-05	0.003	1	0.001
Minor entering ADT	4.38E-07	8.05E-06	-1.53E-05	1.62E-05	0.003	1	0.008
NB dispersion	0.098	0.045	0.009	0.187			

Dependent Variable: Accidents / yr.
Model: (Intercept), Delay, Major entering ADT, Minor entering ADT

This is reasonable because increased delay together with increased volumes may lead to increased queues and conflicts, hence the higher chances of accidents/ incidences.

The variable delay has a coefficient of 0.033, which shows that for each one-unit increase in delay, the expected log count of the number of accidents increases by 0.033. The dispersion coefficient, which does not include zero (0.098), suggests that the NB model form is appropriate than Poisson. An estimate larger than zero suggests over-dispersion (variance larger than the mean) and an estimate less than zero indicates under-dispersion.

After Delay Optimization Period

Having established the before period conditions, the next step involves establishing the after conditions. The after period conditions describe the projected accidents and the predicted accidents after delay optimization.

To determine the observed accidents (O_A) in the after period, a relationship between delay (s/veh) and number of accidents is established by conducting a simple linear regression using both accident and delay data from thirty-nine signalized intersections for the year 2013. Twenty-eight observations from Virginia Beach and eleven observations from Chesapeake both cities located in the Hampton Roads metropolitan region. The resulting correlation relationship is presented in figure 4 and shows that as the delay times (s/veh) increases, the number of accidents increases too. This is reasonable because an increase in traffic flow may also increase the chances of accidents occurring.

As presented in figure 2, the relationship between the number of accidents and delay can be expressed as No. of Accidents / yr. = (0.1508*Delay) – 0.9136. The strong relationship implied by the fitted line plot is supported by is an R-square value of 85.4% correlation between the number of accidents and delays at the study sites.

To determine the optimal minimum delay time, each lane group delay was evaluated separately and then weighted progressively as presented in the HCM (2010) to determine the overall intersection delay using NLPs as discussed in the methodology section. Using these found delay times and the number of accidents found from the linear regression evaluation, NB regression analysis was performed and the resulting parameters are presented in table 4 as follows:

Column 1 of Table 3 shows each of the variables used in the analysis. Column 2 shows the NB regression coefficients for each of the variables along with their related standard errors, Wald chi-square values, and p-values for each of the coefficients in columns 4, 5, 6, and 7 respectively. All the variables are statistically significant at a

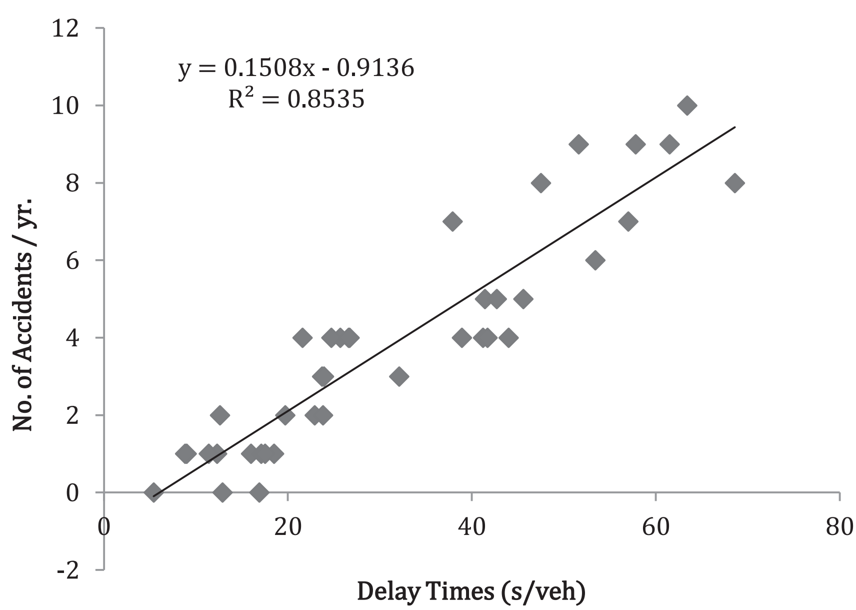


Figure 2. Fitted line plot for accidents per year and delay (s/veh)

Table 4. Negative binomial parameter estimates in the after delay optimization period

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	*p*-value
Intercept	-0.003	0.050	-1.005	0.937	0.005	1	0.009
Major entering ADT	5.97E-06	1.08E-05	-1.52E-05	2.73E-05	3.05E-01	1	0.007
Minor entering ADT	4.59E-06	1.51E-05	-2.51E-05	3.43E-05	0.092	1	0.009
Delay	0.033	0.009	0.015	0.051	12.788	1	0.000
NB dispersion	0.039	2.01E-04	0.038	0.039			

Dependent Variable: Crashes
Model: (Intercept), Major entering ADT, Minor entering ADT, Delay (s/veh)

0.05 level. The coefficients indicate that as the delay (s/veh), major entering ADT, and minor entering ADT increase, the number of accidents increase too. This is reasonable because increased delay together with increased volumes may lead to increased queues and conflicts, hence the higher chances of accidents/incidences.

The variable delay has a coefficient of 0.033, which shows that for each one-unit increase in delay, the expected log count of the number of accidents increases by 0.033. The dispersion coefficient, which does not include zero (0.039), suggests that the NB model form is appropriate than Poisson.

With the actual accidents in the before period and calculated accidents in the after period determined, the next task was to determine the predicted accidents for both periods. As discussed in the methodology section, the predicted accidents for both periods are determined using SPFs. The SPFs for both periods were found using NB distributions shown in tables 3 and 4. The determined predicted accidents for both periods are presented in table 5.

Table 5. Actual, calculated, and predicted accidents for both before and after periods

ID	INTERSECTION			Before Opt.		After Opt.	
				Act. Acc/yr.	SPF Acc/yr.	Cal. Acc/yr.	SPF Acc/yr.
1	Baker Rd	and	Newtown Rd	9	5.7	5.0	4.9
2	Baxter Rd	and	Independence Bl	5	4.8	4.1	5.2
3	Bells Rd	and	Birdneck Rd	0	1.6	0.9	1.7
4	Birdneck Rd	and	General Booth Rd	2	2.2	3.8	3.5
5	Dam Neck Rd	and	Holland Rd	10	8.5	7.6	9.3
6	Dam Neck Rd	and	General Booth Rd	8	10.1	9.3	14.9
7	Harpers Rd	and	Oceana Bl	1	1.9	2.1	2.4
8	Holland Rd	and	Rosemont Rd	7	6.8	5.3	5.5
9	Northampton Bl	and	Diamond Springs Rd	4	4.1	3.8	4.7
10	Pembroke Bl	and	Independence Bl	4	2.5	4.3	4.5
11	Princess Anne Rd	and	Dam Neck Rd	8	5.1	4.6	5.4
12	Shore Dr	and	Great Neck Rd	1	1.8	0.3	1.6
13	Shore Dr	and	Northampton Bl	2	2.0	1.2	2.0
14	Virginia Beach Bl	and	Birdneck Rd	4	2.1	3.0	3.0
15	Virginia Beach Bl	and	Lynnhaven Rd	4	3.8	4.7	4.8
16	Virginia Beach Bl	and	Witchduck Rd	5	4.1	4.4	5.1
17	Virginia Beach Bl	and	First Colonial Rd	9	7.1	6.9	7.9
			TOTAL Acc/yr.	**83**	**74.3**	**71.2**	**86.5**

Opt. = optimization, Act. = Actual, Acc = Accidents, SPF = safety performance functions, Cal. = calculated

Table 5 shows actual, calculated and predicted accidents at each intersection for both periods. The total for each of the four categories are also presented. In 2013, the total actual accidents that occurred in the before period is 83, the SPF predicted accidents is 74, the calculated accidents that occurred in the after period is 71, and the SPF predicted accidents is 87.

Crash Modification Factor – Empirical Bayes Before-After

Using the results presented in table 5, and following the steps presented in the methodology section, the corresponding CMF is estimated and presented in table 6. Table 6 also presents the dispersion factor, weight factor, E_B, the ratio of the after SPF to the before SPF accident estimates, E_A, and its variance. These are important values used to estimate the CMF.

Table 6. Crash Modification Factors for minimized delays at signalized intersections

Parameter	Value
k	0.098
w	0.121
EB	82.143
Pa/Pb	1.165
Ea	95.707
var (Ea)	100.587
CMF	**0.735**
Variance of CMF	0.012
CMF standard error	0.110
95% Confidence	
$0.846 \pm 1.645*0.110$	0.520 to 0.950

As shown in Table 6, the EB estimated CMF is 0.735 with a standard error of 0.012. The standard error (square root of the variance) is used to assist in CMF certainty check. At 95% confidence interval, the CMF expected range is 0.520 to 0.950. At 95% confidence level it can be interpreted that the number of accidents will reduce by approximately 26.46% (1 – 0.735) when the delays at the study sites are optimally minimized.

4. Conclusions and Recommendations

This study has estimates a CMF for optimally minimized delays at signalized intersections and has also to show that there is a need for such CMFs. This study, therefore concludes that at signalized intersections: (1) traffic flow parameters, such as delays may have significant influence on both traffic flow efficiency and safety, and (2) by optimally minimizing delay times may improve safety by approximately 26.46%.

The models presented are specific; they have been used before, and are appropriate to be used elsewhere. This study recommends that the sample size be increased to find more accurate and appropriate results. Furthermore, although this study provides the estimated safety factor for optimally minimizing delay, more research is needed to precisely understand how delay affects roadway safety. As technology for counting vehicles and recording traffic incidences becomes more familiar and improved, appropriate CMFs should be developed. As a result, this may lead to the potential inclusion of traffic flow SPFs and CMFs in future HSM editions.

Improved knowledge on this topic could lead to efficient traffic planning and control of present and future transportation facilities, hence improving safety by: (1) better understanding of what facilities and conditions that are safer for drivers, (2) determining how other variables such as road surface condition, human behavior, and weather conditions may influence roadway safety, and (3) better understanding of the already identified variables.

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6. References

- AASHTO (2010) "Manual, highway safety ", Washington, DC 529.

- Biegler, L. T. and Rawlings, J. B. (1991) "Optimization approaches to nonlinear model predictive control

(No. ANL/CP-72735)", Argonne National Lab., IL (USA).

- Elvik, R. (2008) "The predictive validity of empirical Bayes estimates of road safety", Accident Analysis and Prevention, 40, No. 6, pp. 1964-1969.

- Gross, F., Persaud, B. and Lyon, C. (2010) "A guide to developing quality crash modification factors (No. FHWA-SA-10-032)", Federal Highway Association.

- Hauer, E. (1995) "On exposure and accident rate", Traffic Engineering and Control, Vol. 36, No. 3, pp. 134-138.

- Hauer, E. (1996) "Statistical test of difference between expected accident frequencies", Transportation Research Record: Journal of the Transportation Research Board, 1542, pp.24-29.

- Hauer, E., Bonneson, J., Council, F., Srinivasan, R. and Zegeer, C. (2012) "Crash modification factors: foundational issues", Transportation Research Record: Journal of the Transportation Research Board, 2279, pp.67-74.

- Lan, B., Persaud, B., Lyon, C. and Bhim, R. (2009) "Validation of a full Bayes methodology for observational before–after road safety studies and application to evaluation of rural signal conversions". Accident Analysis and Prevention, Vol. 41, No. 3, pp.574-580.

- Lord, D. and Mannering, F. (2010) "The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives", Transportation Research Part A: Policy and Practice, Vol. 44, No. 5, pp. 291-305.

- Luenberger, D. G. and Ye, Y. (2008) "Linear and nonlinear programming", Vol. 116, Springer Science and Business Media.

- Navidi, W. C. (2008) "Statistics for engineers and scientists", McGraw-Hill Higher Education.

- Park, B., Messer, C. and Urbanik, T. (1999) "Traffic signal optimization program for oversaturated conditions: genetic algorithm approach", Transportation Research Record: Journal of the Transportation Research Board, (1683), pp.133-142.

- Persaud, B. and Lyon, C. (2007) "Empirical bayes before–after safety studies: lessons learned from two decades of experience and future directions", Accident Analysis and Prevention, Vol. 39, No. 3, pp. 546-555.

- Poch, M. and Mannering, F. (1996) "Negative binomial analysis of intersection-accident frequencies". Journal of Transportation Engineering, Vol. 122, No. 2, pp. 105-113.

- Roess, R. P., Prassas, E. S. and McShane, W. R. (2011) "Traffic engineering", Transportation Research Board.

- Rouphail, N. M., Park, B. B. and Sacks, J. (2000). "Direct signal timing optimization: Strategy development and results". In In XI Pan American Conference in Traffic and Transportation Engineering.

- Shahdah, U., Saccomanno, F. and Persaud, B. (2014) "Integrated traffic conflict model for estimating crash modification factors", Accident Analysis and Prevention, 71, pp.228-235.

- Srinivasan, R., Council, F., Lyon, C., Gross, F., Lefler, N. and Persaud, B. (2008) "Safety effectiveness of selected treatments at urban signalized intersections", Transportation Research Record: Journal of the Transportation Research Board, (2056), 70-76.

- Stamatiadis, N. (2009) "Impact of shoulder width and median width on safety (Vol. 633)", National Academies Press.

- Stevanovic, A., Stevanovic, J. and Kergaye, C. (2013) "Optimization of traffic signal timings based on surrogate measures of safety", Transportation Research Part C: Emerging technologies, 32, pp.159-178.

- Tegge, R. A., Jo, J. H. and Ouyang, Y. (2010) "Development and application of safety performance functions for Illinois", Illinois, Illinois Center for Transportation.

- Transportation Research Board (2010) "Highway capacity manual", Washington, DC.

- Winston, W. L. and Goldberg, J. B. (2004) "Operations research: applications and algorithms (Vol. 3)". Boston: Duxbury press.

- Wong, S. C., Sze, N. N. and Li, Y. C. (2007) "Contributory factors to traffic crashes at signalized intersections in Hong Kong". Accident Analysis and Prevention, Vo. 39, No. 6, pp. 1107-1113.

- Zhang, L. and Prevedouros, P. (2003) "Signalized intersection level of service incorporating safety risk". Transportation Research Record: Journal of the Transportation Research Board, (1852), pp.77-86.