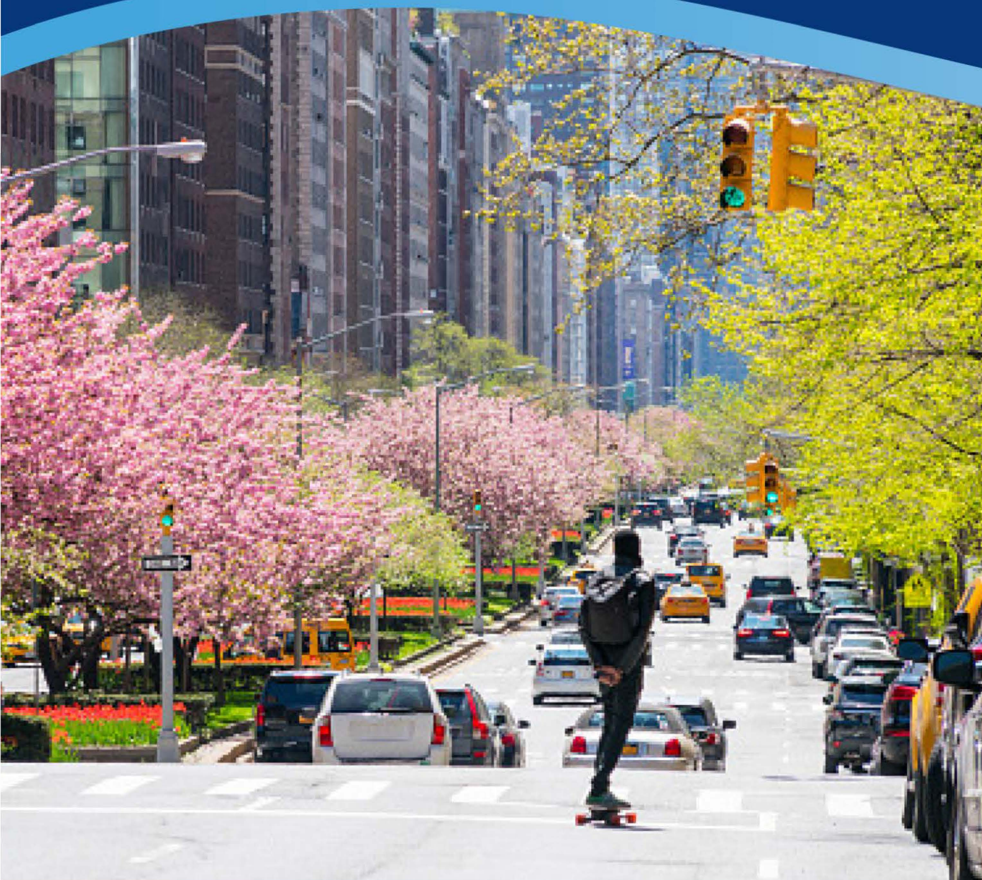
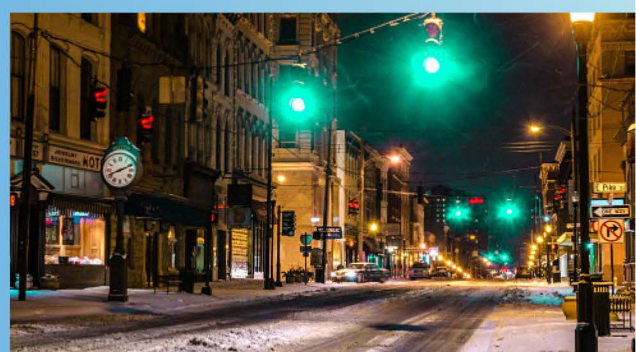
SAFETY PERFORMANCE ANALYSIS OF TSMO: A PRACTICAL APPROACH FOR ASSESSING TRAFFIC SIGNAL COORDINATION EFFECTS ON CRASH PROBABILITY AND SEVERITY





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TECHNICAL DOCUMENTATION PAGE

1. Report No. FHWA-SA-19-043	2. Government Accession No.	3. Recipient's Catalog No.	
4. Title and Subtitle Safety Performance Analysis of TSMO: A Practical Approach for Assessing Traffic Signal Coordination Effects on Crash Probability and Severity		5. Report Date November 2019	
		6. Performing Organization Code	
7.Author(s) Porter, R.J., Gooch, J., and Dunn, M.		8. Performing Organization Report No.	
9. Performing Organization Name and Address Vanasse Hangen Brustlin, Inc (VHB) 940 Main Campus Drive, Suite 500 Raleigh, NC 27606		10. Work Unit No.	
		11. Contract or Grant No. DTFH61-05-D-00024 (VHB)	
12. Sponsoring Agency Name and Address Federal Highway Administration Office of Safety 1200 New Jersey Ave., SE Washington, DC 20590		13. Type of Report and Period Final Report, July 2017 – November 2019	
		14. Sponsoring Agency Code FHWA	
15. Supplementary Notes The contract manager for this report was Jerry Roche, Federal Highway Administration Office of Safety.			
16. Abstract The Federal Highway Administration (FHWA) Office of Safety, in cooperation with the Highway Safety Manual (HSM) Implementation Pooled Fund Study, recently completed a safety analysis needs assessment for TSMO. The safety analysis needs assessment characterized the current state of practice, knowledge, and skills for quantifying the safety performance effects of TSMO. It also identified gaps in the existing body of knowledge and corresponding needs, which will provide the foundation for future research activities and advancements in practice. One group of needs focused on exploring sub-annual safety data collection and analysis methods to address the dynamic conditions under which TSMO strategies operate. This document presents one such sub-annual analysis method: probabilistic models of crash occurrence and severity to estimate how the characteristics of vehicle arrivals in relation to traffic signal timing affect safety performance at a signalized intersection. The analysis method is presented in the context of evaluating the effects of traffic signal coordination on the occurrence and severity of common intersection crash types. Little is known to date on the safety performance impacts of traffic signal timing due to the inability of commonly used annual analysis methods to capture the microscopic variability in traffic signal timing plans, vehicle arrivals, and resulting safety performance over the course of a day. The method in this document is a shorter-term analysis option (e.g., 15-minute time periods). The analysis focuses on rear-end and right-angle crashes, as those are common intersection crash types assumed to be affected by traffic signal timing. The results of the analysis are models that relate the probability of these crash types and their severity on a signalized intersection approach to the characteristics of vehicle arrivals in relation to traffic signal timing on that same intersection approach.			
17. Key Words: traffic signal coordination; safety performance; crash probability; crash severity	18. Distribution Statement No restrictions.		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 42	22. Price

Form DOT F 1700.7 (8-72) Reproduction of completed pages authorized

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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ACRONYMS

AASHTO	American Association of State Highway and Transportation Officials
CMF	crash modification factors
FHWA	Federal Highway Administration
FI	fatal or injury crash
HSM	Highway Safety Manual
MAP-21	Moving Ahead for Progress in the 21st Century
PDO	property-damage only
RA	right-angle crash
RE	rear-end crash
TSMO	Transportation Safety Management and Operations

INTRODUCTION

Moving Ahead for Progress in the 21st Century (MAP-21) defines Transportation Systems Management and Operations (TSMO) as an "integrated set of strategies to optimize the performance of existing infrastructure through the implementation of multimodal and intermodal cross-jurisdictional systems, services, and projects designed to preserve capacity and improve security, safety, and reliability of the transportation system." TSMO offers agencies a wide range of potential strategies for addressing system- and project-level performance needs with cost-effective, tailored solutions. State and local agencies are increasingly recognizing TSMO as a core business area in support of maximizing the performance of their transportation infrastructure and making better use of resources. Some regions in the United States have found it useful to develop TSMO plans to define a common vision for TSMO in the region, develop performance objectives to guide the selection of TSMO strategies, and identify performance measures that will enable a region to track progress towards their objectives. TSMO plans also identify potential policies, services, and projects to make progress towards the performance objectives.

Performance analysis helps agencies make sound decisions on which TSMO policies, services, and projects to pursue as part of performance-based planning and programming. A performance analysis of a TSMO strategy might quantify, for example, how the strategy would be expected to affect measures of travel time, travel time reliability, pollutants/air quality, and the number and severity of traffic crashes. An agency could monetize these changes and determine an overall benefit-cost ratio for the investment.

The ability for agencies to quantify the effects of TSMO strategies on the number and severity of traffic crashes is limited when compared to similar abilities for other performance measures (e.g., travel times, vehicle emissions). The Federal Highway Administration (FHWA) Office of Safety, in cooperation with the Highway Safety Manual (HSM) Implementation Pooled Fund Study, recently completed a safety analysis needs assessment for TSMO. While safety and TSMO have clear interrelationships, the needs assessment concluded there is incompatibility between many existing safety performance analysis methods and tools and the characteristics of TSMO. For example, few TSMO strategies have robust crash modification factors (CMFs). In addition, the predictive analysis methods in the First Edition of the American Association of State Highway and Transportation Officials (AASHTO) HSM do not consider daily, hourly, or sub-hourly variations in traffic characteristics and the road environment that are a key part of fully assessing the safety performance of TSMO.(1) The safety analysis needs assessment characterized the current state of practice, knowledge, and skills for quantifying the safety performance effects of TSMO. It also identified gaps in the existing body of knowledge and corresponding needs, which will provide the foundation for future research activities and advancements in practice.

One group of needs focused on exploring sub-annual safety data collection and analysis methods to more effectively address the dynamic conditions under which TSMO strategies operate. This document presents one such sub-annual analysis method: probabilistic models of crash occurrence and severity to estimate how the characteristics of vehicle arrivals in relation to traffic signal timing affect safety performance on a signalized intersection approach. The analysis method is presented in the context of evaluating the effects of traffic signal coordination on the occurrence and severity of common intersection crash types. Little is known to date about the safety performance impacts of traffic signal timing and coordination due to the inability of commonly used annual analysis methods to capture the microscopic variability in traffic signal timing plans, vehicle arrivals, and resulting safety performance over the course of a day. The method in this document is a shorter-term analysis option (e.g., 15-minute time periods).

This document is intended to assist researchers and practitioners interested in exploring and testing probabilistic models of crash occurrence and severity in the traffic signal coordination context. Following an overview of traffic signal coordination and the analysis question, the content covers the data definitions and requirements, analysis steps, supporting tools, and effective practices for reporting the results and documenting assumptions and limitations. The document concludes with a section on other potential TSMO-related safety analysis applications of the method.

SAFETY PERFORMANCE ANALYSIS QUESTION

Traffic signal coordination involves the synchronization of multiple signalized intersections to enhance the operation of one or more directional movements in a system. The synchronization occurs by coordinating traffic signal timing patterns and algorithms.[2] The primary intent of coordinating traffic signals is to improve vehicle flow along the coordinated street by reducing travel times, stops, and delay. Coordination can be a relatively low-cost method for improving the operational performance of a corridor or network. While operational improvements are generally the primary motivation for implementing traffic signal coordination, several studies have explored its potential safety effects.[3,4,5,6,7,8] The results of these studies are mixed and suggest that determining the safety performance effects of traffic signal coordination is a challenging pursuit. One published paper by Li & Tarko noted that crash prediction model development and analysis conducted at the annual level (common to safety performance analysis) cannot capture the microscopic variability of traffic signal timing plans, vehicle arrivals, and resulting safety performance over the course of a day.[9,10] They performed a study that examined 36 coordinated arterial intersections in Indiana and developed probabilistic models of crash occurrence and severity to quantify how the characteristics of vehicle arrivals in relation to traffic signal timing affected safety performance of the intersection approaches.

Based on the work of Li & Tarko, this document outlines a method for analyzing how the characteristics of vehicle arrivals in relation to traffic signal timing affect the safety performance of signalized intersection approaches. The document focuses on two crash types: 1) rear-end crashes involving two or more vehicles on a major street approach and 2) right-angle crashes between a vehicle entering an intersection from a major street and a vehicle entering the intersection from the minor street, regardless of their intended maneuvers at the intersection. These are two intersection crash types assumed to be affected by traffic signal timing and coordination. In incorporating crash severity, the analysis covers four crash type/severity classifications: rear-end fatal or injury crash (FI|RE), rear-end property-damage only crash (PDO|RE), right-angle fatal or injury crash (FI|RA), and right-angle property-damage only crash (PDO|RA). The results of the analysis are models that relate the probability of these crash types and their severity on an intersection approach to the characteristics of vehicle arrivals in relation to traffic signal timing on that same intersection approach. Flexibility exists to extend the analysis method to other crash types that may be affected by the level of traffic signal coordination along a street, such as crashes involving pedestrians and bicyclists.

DATA NEEDS

Access to several datasets is key to performing this analysis. The two most crucial are crash data and traffic signal timing data, including the characteristics of vehicle arrivals. Crash data can come from police records or other similar sources and should be limited to the influence area of the studied intersections. Determining the extent of an intersection's influence area is a subject of ongoing research, but there are several commonly used practices. For example, Harwood et al. used 250 feet as the influence area for urban and suburban arterial intersections when developing predictive methods for the HSM.[11] Any crashes within that distance must have also been coded in the crash report as "at intersection" or "intersection-related" for consideration in their analysis. The crash data should include the date, time, location, intersection approach, type, and severity of the crash as well as any other relevant information. Because these analyses are performed using short time intervals (e.g., 15-minutes) and at the intersection approach level, it is important to verify the reported time of crash is accurate enough for the periods used in the analysis and the location-related information is accurate enough for assignment to a specific intersection approach. The traffic signal timing data should include coordination-related variables like cycle lengths, offsets, and splits. Other variables that may inform the analysis include yellow times, all-red times, and minimum and maximum green times.

It is necessary to collect information on vehicle arrival characteristics for the intersection approaches being studied. The vehicle arrival characteristics of interest are those related to the level of coordination through the corridor. Some data collected and analyzed by Li & Tarko included vehicle arrival rates in the first and second half of the green and red phases, the number of vehicles arriving in the first two seconds of the green and red phases, and the total vehicle arrival rate at the intersection approach. The most desirable way to collect these data is likely through acquiring counts taken by the signal system itself (i.e., detector-based high-resolution traffic data). Using data collected by the traffic signal controller allows for the vehicle arrival characteristics to be easily integrated with the active traffic signal phases for the analysis.

Geometric data, such as the distance between intersections, the number of through and turning lanes, speed limits, and intersection widths, can also be incorporated into the analysis of crash probability and severity. For instance, the presence of dedicated right turn lanes at an intersection may be associated with a decreased probability of rear-end crashes. The distance between intersections is an important factor for developing traffic signal coordination. Table 1 and table 2 contain the notation and definitions of the variables needed for the safety performance analysis. Table 3 shows an example structure of a database for estimating the models described in this document. In this example, one row of the database represents one intersection approach observed for a 15-minute period. The entries of crash type (rear-end, right-angle) and crash severity (FI, PDO) columns indicate whether a crash of the given type or severity occurred on the approach during the 15-minute period (0 indicates a crash of the given type/severity did not occur; 1 indicates a crash of the given type/severity did occur). Analysts applying this method can try different analysis periods (e.g., 30 minutes, 60 minutes) and include vehicle arrival and other intersection variables that are of most interest to their agencies.

Table 1. Notation and definitions for crash probabilities and model functions.

Variable	Description
U_{RE}	Function that can be used to calculate the probability of a rear-end crash
U_{RA}	Function that can be used to calculate the probability of a right-angle crash
P_{RE}	Probability that a rear-end crash will occur within a 15-minute interval on the approach
P_{RA}	Probability that a right-angle crash will occur within a 15-minute interval on the approach
P_{Other}	Probability that neither a right-angle nor rear-end crash will occur within a 15-minute interval on the approach
P_{FI}	Probability that a right-angle or rear-end crash will result in a fatality or injury
$P_{FI\|RE}$	Probability that a rear-end crash will result in at least one fatality or injury
$P_{PDO\|RE}$	Probability that a rear-end crash will not result in a fatality or injury
$P_{FI\|RA}$	Probability that a right-angle crash will result in at least one fatality or injury
$P_{PDO\|RA}$	Probability that a right-angle crash will not result in a fatality or injury

Table 2. Notation and definitions for traffic signal timing and other intersection variables.

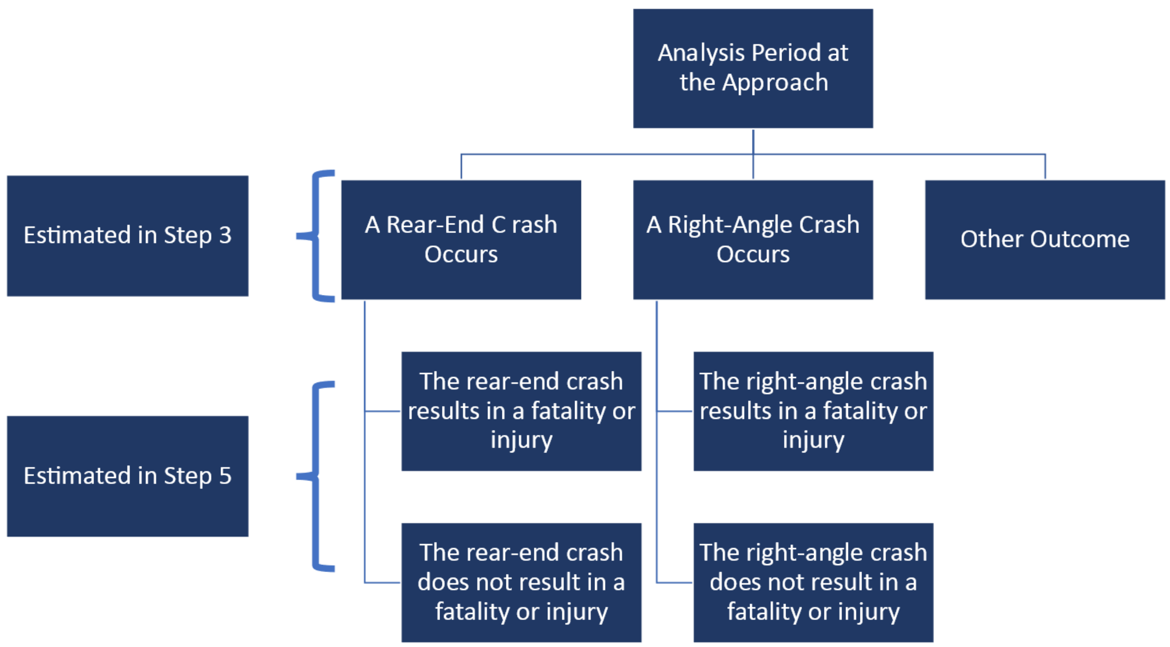
Variable	Description (Units)
R_1	Indicator variable for whether more than 25 percent of traffic on an intersection approach arrives in the first half of the red phase (1 if true; 0 otherwise) (unitless)
$BRVol_{Max}$	The number of vehicles arriving on the approach in the first two seconds of the red phase (vehicles)
$BGVol_{Max}$	The number of vehicles arriving on the approach in the first two seconds of the green phase (vehicles)
$Wint$	Indicator variable for winter (observation is in January, February, November, December) (1 if true; 0 otherwise) (unitless)
AM	Indicator variable for morning (observation is before noon) (1 if true; 0 otherwise) (unitless)
RL	Indicator variable for right-turn lane on approach (1 if present; 0 otherwise) (unitless)
PSL	Posted speed limit on the approach roadway (miles per hour)
$TrTimeLt_{15}$	Indicator variable if the travel time from the upstream intersection is less than 15 seconds (1 if true; 0 otherwise) (unitless)
$TrTimeGt_{40}$	Indicator variable if the travel time from the upstream intersection is greater than 40 seconds (1 if true; 0 otherwise) (unitless)
G_2	Indicator variable for whether more than 25 percent of traffic on an intersection approach arrives in the second half of the green phase (1 if true; 0 otherwise) (unitless)
CPH	The average number of cycles per hour at the intersection (cycles per hour)
x_i	Covariates describing the intersection approach during a fifteen-minute period, including traffic and signal conditions (units vary)
a, b_i	Regression constant (a) and coefficients corresponding to each covariate (b_i) (unitless)
Vol_{Total}	Total approach volume rate (vehicles per hour per lane)
Y_{Short}	Indicator variable noting if the yellow interval on the approach is shorter than what is recommended by the Manual on Uniform Traffic Control Devices (MUTCD)[12] (1 if true; 0 otherwise) (unitless)
$SR135$	Indicator variable noting if the approach was at an intersection along State Route 135 (1 if true; 0 otherwise) (unitless)
$SR431$	Indicator variable noting if the approach was at an intersection along State Route 431 (1 if true; 0 otherwise) (unitless)

Table 3. Example data structure for estimating the effects of vehicle arrival characteristics in relation to signal timing on rear-end and right-angle crash probability.

Observation ID	Approach	Start Time	End Time	Date	Primary Road	Secondary Road	Posted Speed Limit [MPH]	Rear-End Crash	Right-Angle Crash	FI	PDO	Distance to Upstream Intersection [Miles]	R_1	G_2
158497	NB	6:30 AM	6:45 AM	6/7/2018	Route 1	Route 146	45	0	0	0	0	0.10	0	1
158498	NB	6:45 AM	7:00 AM	6/7/2018	Route 1	Route 146	45	0	0	0	0	0.10	1	0
158499	NB	7:00 AM	7:15 AM	6/7/2018	Route 1	Route 146	45	0	0	0	0	0.10	0	1
158500	NB	7:15 AM	7:30 AM	6/7/2018	Route 1	Route 146	45	0	0	0	0	0.10	0	1
158501	NB	7:30 AM	7:45 AM	6/7/2018	Route 1	Route 146	45	0	0	0	0	0.10	1	0
158502	NB	7:45 AM	8:00 AM	6/7/2018	Route 1	Route 146	45	1	0	0	1	0.10	1	1
158503	NB	8:00 AM	8:15 AM	6/7/2018	Route 1	Route 146	45	0	0	0	0	0.10	1	0

SAFETY PERFORMANCE ANALYSIS STEPS – ESTIMATING EFFECTS OF TRAFFIC SIGNAL COORDINATION

This section describes a five-step procedure for estimating the probability of a crash (for different crash types and severities) on an intersection approach as a function of vehicle arrival characteristics and traffic signal timing. The analysis is performed at the approach level for individual 15-minute periods. Each 15-minute period has five potential outcomes, as shown in figure 1.



Source: FHWA.

Figure 1. Graphic. Potential outcomes for a 15-minute period on a signalized intersection approach.

1. Collect intersection data.

Identify signalized arterial intersections with a range of traffic and signal timing characteristics. Collect traffic counts, signal timing plans, vehicle arrival characteristics, geometrics, and crash data for the intersection approaches of interest at these study intersections. Combine the data into a database with a structure like that in table 3, where one row represents one intersection approach observed for a 15-minute period. The "Data Needs" section of this document provides additional detail.

2. **Estimate the crash probability model.**

   Develop a model that predicts the probability that either a rear-end crash occurs, a right-angle crash occurs, or another outcome occurs in a 15-minute period given vehicle arrival, signal timing, and other intersection approach characteristics within that same 15-minute period.

   Multinomial logistic regression can be used for this step of the analysis because of the three possible outcomes for a 15-minute period. A multinomial logistic regression model is used to estimate the probabilities of different categorical outcomes occurring when there are more than two possible outcomes.[13]

   Estimating a multinomial logistic regression model produces functions (i.e., equations) for all outcomes except for a base outcome that is selected by the analyst. In this analysis, the base outcome is the "other outcome" that neither a rear-end or right-angle crash occurs. Figure 2 and figure 3 are examples of functions associated with the two crash types.

$$U_{RE} = f(signal\ phasing, traffic\ volumes, intersection\ geometry)$$

Figure 2. Equation. Function associated with a rear-end crash occurring on the approach within a 15-minute analysis period.

$$U_{RA} = f(signal\ phasing, traffic\ volumes, intersection\ geometry)$$

Figure 3. Equation. Function associated with a right-angle crash occurring on the approach within a 15-minute analysis period.

It is worth noting the work from Li & Tarko used as an example focuses solely on crashes involving two or more motor vehicles; a vehicle-pedestrian or vehicle-bicycle crash would be considered an "other" outcome. However, the method proposed in this guide can be used for any crash type. Agencies considering coordination on corridors with significant pedestrian or bicycle volumes should consider explicitly incorporating the probability of pedestrian and bicyclist crashes as an outcome into the multinomial logit model. In this case, there could be four possible outcomes: 1) a rear-end crash occurs, 2) a right-angle crash occurs, 3) a pedestrian or bicyclist crash occurs, or 4) another outcome occurs.

The multinomial logistic regression model provides a high level of flexibility in terms of model specification, allowing exploration of various possible crash probability relationships such as:

- Certain intersection and signal timing characteristics impacting the probability of one crash type, but not impacting others.
- Certain intersection and signal timing characteristics increasing (or decreasing) the probability of one crash type, while having the opposite effect on another crash type.

The main disadvantage of the multinomial logistic regression model is that it is characterized by the independence of irrelevant alternatives (IIA) assumption, meaning that it may not appropriately handle scenarios with two or more outcomes that are close substitutes. One example could be two crash type outcomes that are sometimes difficult to distinguish, such as same direction sideswipe versus rear-end crashes of major-road, through moving vehicles with minor-road, right-turning vehicles.

As with any statistical method, analysts should be aware of how to assess the analysis dataset for accuracy and sample size, including whether there are adequate numbers of the different outcomes being modeled occurring in the dataset. Analysts should also be familiar with how to specify models, assess the model goodness of fit, test the model against model assumptions (like the IIA assumption), and validate the model by testing its predictive performance on different datasets than that used to develop the model. Multinomial logistic regression is one of several approaches available to analyze more than two discrete outcomes. Other alternatives include nested logit regression, classification and regression trees, or a series of binary logistic regression models of one of the outcomes versus all others (e.g., a binary logistic regression model of rear-end crash probability versus all other outcomes; a second binary logistic regression model of right-angle crash probability versus all other outcomes.

3. **Predict the probability of the different crash outcomes as a function of vehicle arrival and signal timing characteristics.**

The equations in figure 4 through figure 6 illustrate how to calculate probabilities using the functions produced by multinomial logistic regression. For any set of covariates, the sum of probabilities across all three outcomes is one. Note that the functions used to calculate probability (U_{RE} and U_{RA}) produce very small results in this particular context of predicting crash occurrence during a short time period. As such, the denominators of these probability functions are virtually one (i.e., $1 + U_{RE} + U_{RA} \approx 1$), resulting in probabilities (P_{RE} and P_{RA}) which are nearly equal to the respective function results (U_{RE} and U_{RA}).

$$P_{RE} = \frac{U_{RE}}{1 + U_{RE} + U_{RA}}$$

Figure 4. Equation. Probability of a rear-end crash on the approach within a 15-minute analysis period.

$$P_{RA} = \frac{U_{RA}}{1 + U_{RE} + U_{RA}}$$

Figure 5. Equation. Probability of a right-angle crash on the approach within a 15-minute analysis period.

$$P_{Other} = \frac{1}{1 + U_{RE} + U_{RA}}$$

Figure 6. Equation. Probability that neither a right-angle nor rear-end crash occurs on the approach within a 15-minute analysis period.

Example – Steps 1 through 3

To demonstrate the application of the method outlined in this document, this example adopts the probabilistic models of crash occurrence and severity reported by Li & Tarko to quantify how the characteristics of vehicle arrivals in relation to traffic signal timing affected safety performance at a sample of intersection approaches in Indiana.[9,10]

Table 4 provides the multinomial logistic regression model output from Li & Tarko. Figure 7 and figure 8 are examples of how the model output translates to the functions associated with each crash type. It is important to note the addition of two indicator variables in Li & Tarko's model ($SR135$, $SR431$) that signify whether an intersection approach was on a specific route. For example, the variable $SR135$ has a value equal to one when the intersection approach is on State Route 135. It has a value equal to zero if the intersection approach is on any other route. These types of variables can be explored when a significant number of intersection approaches in the dataset (e.g., 10 percent or more) are from a series of signalized intersections along the same route. These types of variables are intended to capture the effects of characteristics common to these routes and locations, but not captured in the models (e.g., surrounding land use, driver population). They help in obtaining more accurate estimates of the traffic signal timing and vehicle arrival effects.

Table 4. Multinomial logistic regression results from Li & Tarko.[9]

Variable	Rear-End Coefficient	Rear-End Standard Error	Rear-End t-Statistic	Right-Angle Coefficient	Right-Angle Standard Error	Right-Angle t-Statistic
$SR135$	-2.35	0.345	-7.34	-0.831	0.407	-2.04
$SR431$	0.864	0.359	2.41	-1.261	0.460	-2.74
$R_1 * BRVol_{Max}$	0.0280	0.00813	3.45	0.0334	0.0197	1.69
$BGVol_{Max}$	0.0384	0.0110	3.50	0.0370	0.0258	1.44
$Wint$	-0.290	0.121	-2.41	-	-	-
AM	-0.291	0.122	-2.39	-0.559	0.279	-0.559
RL	-2.75	0.321	-8.56	-1.15	0.339	-1.145
PSL	0.158	0.0305	5.17	0.159	0.0394	0.159
$TrTimeLt_{15}$	-0.764	0.202	-3.78	-0.668	0.381	-0.668
$TrTimeGt_{40}$	0.861	0.163	5.27	-	-	-
G_2	-0.215	0.122	-1.77	-0.471	0.301	-1.57
CPH	-0.0444	0.0157	-2.82	-	-	-
$Constant$	-11.2	1.61	-6.94	-14.00	1.82	-7.70

$$U_{RE} = f(signal\ phasing, traffic\ volumes, intersection\ geometry)$$
$$= \exp(-2.35 * SR135 + 0.864 * SR431 + 0.0280 * R_1 * BRVol_{Max} + 0.0384 * BGVol_{Max} - 0.290 * Wint - 0.291 * AM - 2.75 * RL + 0.158 * PSL - 0.764 * TrTimeLt_{15} + 0.861 * TrTimeGt_{40} - 0.215 * G_2 - 0.0444 * CPH - 11.2)$$

Figure 7. Equation. Example function associated with a rear-end crash occurring on the approach within a 15-minute analysis period.

$$U_{RA} = f(signal\ phasing, traffic\ volumes, intersection\ geometry)$$
$$= \exp(-0.831 * SR135 - 1.261 * SR431 + 0.0334 * R_1 * BRVol_{Max} + 0.0370 * BGVol_{Max} - 0.559 * AM - 1.15 * RL + 0.159 * PSL - 0.668 * TrTimeLt_{15} - 0.471 * G_2 - 14.00)$$

Figure 8. Equation. Example function associated with a right-angle crash occurring on the approach within a 15-minute analysis period.

The sign of the coefficient in front of each variable indicates the direction of the correlation between the variable and the outcome's probability. A positive coefficient indicates that increases in the variable result in increases in the probability of that outcome; negative coefficients indicate increases in the variable result in decreases in probability of that outcome. For example, the models estimated by Li & Tarko show the following associations between vehicle arrival characteristics and crash probabilities:

- Higher concentrations of vehicles arriving in the first half of the red signal, especially during the first two seconds ($R_1 * BRVol_{Max}$) were associated with higher probabilities of both the rear-end and right-angle crash outcomes, as shown by the positive coefficients of 0.0280 and 0.0334 in table 4.
- Higher concentrations of vehicles arriving in the first two seconds of the green signal ($BGVol_{Max}$) were associated with higher probabilities of both the rear-end and right-angle crash outcomes, as shown by the positive coefficients of 0.0384 and 0.0370 in table 4.
- Higher concentrations of vehicles arriving during the second half of the green signal (G_2) were associated with lower probabilities of both the rear-end and right-angle crash outcomes, as shown by the negative coefficients of -0.215 and -0.471 in table 4, respectively.

If an agency were to develop an arterial coordination strategy around these Li & Tarko models in order to reduce the probability of crashes, the plan would seek to minimize arrival rates during the red phase and the very beginning of the green phase, encouraging platooned arrivals towards the second half of the green phase. When the proportion of vehicles arriving in the second half of the green phase exceeds 0.25, the Li & Tarko models suggest a 19.3 percent reduction in the probability of a rear-end crash and a 37.6 percent reduction in the probability of a right-angle crash.

To demonstrate a possible application of these example models, assume that city engineers are interested in coordinating traffic signals along an arterial that leads to the city center during the AM peak period (6 AM to 10 AM). One of the signalized intersections along the arterial is a known safety hot-spot, consistently ranked as a top crash location in the city. City officials are interested in whether coordination will affect safety performance at this intersection and to what degree.

To develop inputs for the model, the engineers observed vehicle arrivals at the main intersection approach of interest during the AM peak over a period of a few weeks. They collected vehicle and signal data in fifteen-minute increments. The data were averaged; the results are provided in table 5.

Traffic engineers for the city then developed a proposed signal coordination plan for the arterial corridor. Based on a series of calibrated microsimulations, they were able to estimate average inputs for the intersection approach of interest under the proposed coordination plan during the AM peak period. The goal of coordination was to synchronize vehicle arrivals at each intersection to encourage smooth vehicle flow along the corridor. These inputs are summarized in table 6. This proposed coordination plan adjusts the signal timing so that fewer than 25 percent of vehicles are predicted to arrive during the first half of the red phase and fewer vehicles arrive in the first two seconds of the red and green phases (a reduction of 2 vehicles and 7 vehicles every 15 minutes, respectively).

Table 5. Average model inputs under existing conditions at the approach.

Variable	Description	Average
R_1	Indicator variable for whether more than 25 percent of traffic on an intersection approach arrives to the approach in the first half of the red phase (1 if true; 0 otherwise) (unitless)	1
$BRVol_{Max}$	The number of vehicles arriving on the approach in the first two seconds of the red phase (vehicles)	4
$BGVol_{Max}$	The number of vehicles arriving on the approach in the first two seconds of the green phase (vehicles)	13
$Wint$	Indicator variable for winter (interval is in January, February, November, December) (1 if true; 0 otherwise) (unitless)	0
AM	Indicator variable for morning (interval is before 12:00 noon) (1 if true; 0 otherwise) (unitless)	1
RL	Indicator variable for right-turn lane on approach (1 if present; 0 otherwise) (unitless)	1
PSL	Posted speed limit on the approach roadway (miles per hour)	35
$TrTimeLt_{15}$	Indicator variable if the travel time from the upstream intersection is less than 15 seconds (1 if true; 0 otherwise) (unitless)	0
$TrTimeGt_{40}$	Indicator variable if the travel time from the upstream intersection is greater than 40 seconds (1 if true; 0 otherwise) (unitless)	0
G_2	Indicator variable for whether more than 25 percent of traffic on an intersection approach arrives to the approach in the second half of the green phase (1 if true; 0 otherwise) (unitless)	0
CPH	The average number of cycles per hour at the intersection (cycles per hour)	40
Vol_{Total}	Total approach volume rate (vehicles per hour per lane)	470
Y_{Short}	Indicator variable noting if the yellow interval on the approach is shorter than what is recommended by the MUTCD (1 if true; 0 otherwise) (unitless)	0

Table 6. Average model inputs under proposed conditions at the approach.

Variable	Description	Average
R_1	Indicator variable for whether more than 25 percent of traffic on an intersection approach arrives to the approach in the first half of the red phase (1 if true; 0 otherwise) (unitless)	0
$BRVol_{Max}$	The number of vehicles arriving on the approach in the first two seconds of the red phase (vehicles)	2
$BGVol_{Max}$	The number of vehicles arriving on the approach in the first two seconds of the green phase (vehicles)	6
$Wint$	Indicator variable for winter (interval is in January, February, November, December) (1 if true; 0 otherwise) (unitless)	0
AM	Indicator variable for morning (interval is before 12:00 noon) (1 if true; 0 otherwise) (unitless)	1
RL	Indicator variable for right-turn lane on approach (1 if present; 0 otherwise) (unitless)	1
PSL	Posted speed limit on the approach roadway (miles per hour)	35
$TrTimeLt_{15}$	Indicator variable if the travel time from the upstream intersection is less than 15 seconds (1 if true; 0 otherwise) (unitless)	0
$TrTimeGt_{40}$	Indicator variable if the travel time from the upstream intersection is greater than 40 seconds (1 if true; 0 otherwise) (unitless)	0
G_2	Indicator variable for whether more than 25 percent of traffic on an intersection approach arrives to the approach in the second half of the green phase (1 if true; 0 otherwise) (unitless)	1
CPH	The average number of cycles per hour at the intersection (cycles per hour)	40
Vol_{Total}	Total approach volume rate (vehicles per hour per lane)	470
Y_{Short}	Indicator variable noting if the yellow interval on the approach is shorter than what is recommended by the MUTCD (1 if true; 0 otherwise) (unitless)	0

Using the inputs in table 5 and table 6, the city engineers calculate the probability of a rear end crash or a right-angle crash occurring with and without coordination on the intersection approach. A sample of these calculations is provided below.

No Coordination

$$U_{RE,No\ Coordination} = \exp(0.0280 * R_1 * BRVOL_{Max} + 0.0384 * BGVOL_{Max} - 0.290 * Wint - 0.291 * AM - 2.75 * RL + 0.158 * PSL - 0.0764 * TrTimeLt_{15} + 0.861 * TrTimeGt_{40} - 0.215 * G_2 - 0.0444 * CPH - 11.2)$$
$$= \exp(0.0280 * 1 * 4 + 0.0384 * 13 - 0.290 * 0 - 0.291 * 1 - 2.75 * 1 + 0.158 * 35 - 0.0764 * 0 + 0.861 * 0 - 0.215 * 0 - 0.0444 * 40 - 11.2)$$
$$= 5.14 * 10^{-5}$$

Figure 9. Equation. Example calculation of function of rear-end crash with no signal coordination.

$$U_{RA,No\ Coordination} = \exp(0.0334 * R_1 * BRVOL_{Max} + 0.0371 * BGVOL_{Max} - 0.559 * AM - 1.15 * RL + 0.159 * PSL - 0.668 * TrTimeLt_{15} - 0.471 * G2_{Max} - 14.00)$$
$$= \exp(0.0334 * 1 * 4 + 0.0371 * 13 - 0.559 * 1 - 1.15 * 1 + 0.159 * 35 - 0.668 * 0 - 0.471 * 0 - 14.00) = 7.28 * 10^{-5}$$

Figure 10. Equation. Example calculation of function of right-angle crash with no signal coordination.

$$P_{RE,No\ Coordination} = \frac{U_{RE,No\ Coordination}}{1 + U_{RE,No\ Coordination} + U_{RA,No\ Coordination}}$$
$$= \frac{5.14 * 10^{-5}}{1 + 5.14 * 10^{-5} + 7.28 * 10^{-5}} = 5.14 * 10^{-5}$$

Figure 11. Equation. Example calculation of probability of rear-end crash with no signal coordination.

$$P_{RA,No\ Coordination} = \frac{U_{RA,No\ Coordination}}{1 + U_{RE,No\ Coordination} + U_{RA,No\ Coordination}}$$
$$= \frac{7.28 * 10^{-5}}{1 + 5.14 * 10^{-5} + 7.28 * 10^{-5}} = 7.28 * 10^{-5}$$

Figure 12. Equation. Example calculation of probability of right-angle crash with no signal coordination.

$$P_{Other,No\ Coordination} = 1 - P_{RE,No\ Coordination} - P_{RA,No\ Coordination} = 1 - 5.14 * 10^{-5} - 7.28 * 10^{-5} = 0.99987$$

Figure 13. Equation. Example calculation of probability of other outcome with no signal coordination.

Coordination

$$U_{RE,Coordination} = \exp(0.0280 * 0 * 2 + 0.0384 * 6 - 0.290 * 0 - 0.291 * 1 - 2.75 * 1 + 0.158 * 35 - 0.0764 * 0 + 0.861 * 0 - 0.215 * 1 - 0.0444 * 40 - 11.2) = 2.83 * 10^{-5}$$

Figure 14. Equation. Example calculation of function of rear-end crash with signal coordination.

$$U_{RA,No\ Coordination} = \exp(0.0334 * 0 * 2 + 0.0371 * 6 - 0.559 * 1 - 1.15 * 1 + 0.159 * 35 - 0.668 * 0 - 0.471 * 1 - 14.00) = 3.07 * 10^{-5}$$

Figure 15. Equation. Example calculation of function of right-angle crash with signal coordination.

$$P_{RE,Coordination} = \frac{2.83 * 10^{-5}}{1 + 2.83 * 10^{-5} + 3.07 * 10^{-5}} = 2.83 * 10^{-5}$$

Figure 16. Equation. Example calculation of probability of rear-end crash with signal coordination.

$$P_{RA,Coordination} = \frac{3.07 * 10^{-5}}{1 + 2.83 * 10^{-5} + 3.07 * 10^{-5}} = 3.07 * 10^{-5}$$

Figure 17. Equation. Example calculation of probability of right-angle crash with signal coordination.

$$P_{Other,Coordination} = 1 - 2.83 * 10^{-5} - 3.07 * 10^{-5} = 0.99994$$

Figure 18. Equation. Example calculation of probability of other outcome with signal coordination.

The crash probabilities are summarized in table 7. As shown in the right-side column, the proposed coordination plan reduces the probability of a rear-end crash on the approach by almost 45 percent and a right-angle crash by almost 58 percent.

Table 7. The probability of a crash within an average 15-minute period with and without coordination.

	Probability with No Coordination	Probability with Coordination	Percent Change in Probability
Rear-End	$5.14 * 10^{-5}$	$2.83 * 10^{-5}$	-44.9
Right-Angle	$7.28 * 10^{-5}$	$3.07 * 10^{-5}$	-57.9
Other	0.99987	0.99994	$+6.52 * 10^{-5}$

While the individual probabilities seem negligible, one must consider their aggregated effect. The probability represents a single fifteen-minute period on one approach; within the four hours representing the AM peak period, there are 16 fifteen-minute periods every weekday. With five weekdays per week and 52 weeks per year, there are 4,160 fifteen-minute periods per year during which this coordination plan will be active. Assuming that no more than one crash occurs on the approach during the analysis period, this probability can be converted to an expected number of crashes. Summing this number of crashes over the 4,160 potential periods, the engineers expect 0.21 rear-end crashes and 0.30 right-angle crashes without coordination, while they expect 0.12 rear-end crashes and 0.13 right-angle crashes with coordination.

Given that probabilistic models of crash occurrence over short time periods are relatively new to their agency, the city engineers decide to compare the results to adjusted predictions from the predictive methodology for urban and suburban four-leg signalized intersections in the HSM for a check of reasonableness. They use the HSM to develop an annual crash frequency prediction under the following assumptions:

- Major road has 3 lanes in each direction.
- Hourly volume per lane (470 vehicles from table 5) represents 8 percent of total daily traffic volume and is equal to the traffic volume in the opposite direction, resulting in an annual average daily traffic volume of 35,250 vehicles per day.
- Exclusive left-turn lanes on both the major and minor approaches.
- Left turns are protected on the major approaches and protected/permitted on the minor approaches.

- Minor road daily traffic volume equals 24,000 vehicles per day.

The HSM predictive methodology produces a predicted number of crashes for one year at the intersection. This prediction can be converted to rear-end and right-angle crash frequency by applying the default crash type distribution for this facility type. These assumptions produce an annual crash frequency of 3.4 rear-end crashes per year and 2.0 angle crashes per year. To convert these to an estimate of AM peak period crashes on one major road approach on weekdays, the city engineers applied the following additional assumptions:

- The frequency was multiplied by 5/7 to adjust for the ratio of weekdays to number of days in the week.
- The frequency was then multiplied by 25 percent, assuming the AM peak period represented 1/4 of crashes during weekdays.
- The frequency was multiplied by 35 percent, assuming this major road approach accounted for 35 percent of AM peak period crashes at the intersection.

These assumptions resulted in predictions of 0.21 rear-end crashes and 0.13 angle crashes during AM peak periods at this approach on weekdays over the course of a year. These values estimated using the HSM methodology are similar in general magnitude to the predicted number of crashes estimated using the probability-driven approach described in this guide. This confirms that the individual probabilities over 15-minute periods aggregate to reasonable annual predictions.

4. **Estimate crash severity models and predict severity probabilities.**

The next step of the analysis consists of estimating binary logistic regression models to predict the probability that right-angle and rear-end crashes that occur result in a fatality or injury (FI) or property-damage only (PDO).

Binary logistic regression can be used to model dependent variables with two possible outcomes (e.g., a crash results in at least one fatality or injury or it does not). (13) The resulting model predicts the probabilities of the binary outcomes occurring as a function of variables that affect the probabilities. In this case, the probability being predicted is the probability of a right-angle or rear-end crash resulting in at least one fatality or injury, while the predictive variables describe traffic conditions, vehicle arrivals, and signal timing on the approach.

Figure 19 illustrates the form of the binary logistic regression model describing the probability of a fatality or injury given that a rear-end crash occurs ($P_{FI|RE}$).

$$P_{FI|RE} = \frac{e^{(a+b_1x_1+b_2x_2+\cdots+b_nx_n)}}{1+e^{(a+b_1x_1+b_2x_2+\cdots+b_nx_n)}}$$

Figure 19. Equation. Probability that a rear-end crash will result in at least one fatality or injury.

Where:
$P_{FI|RE}$ = the probability of at least one fatality or injury given that a rear-end crash occurs.
x_i = covariates describing the traffic and signal conditions. Example covariates include traffic volume (Vol_{Total}), duration of the yellow interval (Y_{Short}), and vehicle arrival rate in the second half of the green phase (G_2).
a, b_i = regression coefficients.

Similarly, figure 20 illustrates the form of the binary logistic regression model describing the probability of a fatality or injury given that a right-angle crash occurs ($P_{FI|RA}$)

$$P_{FI|RA} = \frac{e^{(a+b_1x_1+b_2x_2+\cdots+b_nx_n)}}{1+e^{(a+b_1x_1+b_2x_2+\cdots+b_nx_n)}}$$

Figure 20. Equation. Probability that a right-angle crash will result in at least one fatality or injury.

Where:

$P_{FI|RA}$ = the probability of at least one fatality or injury given that a right-angle crash occurs.

x_i = covariates describing the traffic and signal conditions. Example covariates include traffic volume (Vol_{Total}), duration of the yellow interval (Y_{Short}), and vehicle arrival rate in the second half of the green phase (G_2).

a, b_i = regression coefficients.

Analysts can consider the same variables and variable combinations used for the multinomial logit models in Step 2. The databases used for each severity model are specific subsets of the full database previously used for model estimation in Step 2 and illustrated in table 3. The database for estimating the severity model for rear-end crashes will only include the rows from the full database where the entry for the rear-end crash column equals one (i.e., a rear-end crash occurred in that 15-minute period). Similarly, the database for estimating the severity model for right-angle crashes will only include the rows from the full database where the entry for the right-angle crash column equals one (i.e., a right-angle crash occurred in that 15-minute period). Table 8 provides an example for the rear-end crash severity model.

Binary logistic regression is a relatively robust and informative method for modeling dependent variables with two possible outcomes. Model results are straight forward to interpret. Researchers have applied binary logistic regression in multiple contexts in the TSMO-related literature.[9,14,15,16]

As with multinomial logistic regression, analysts should be aware of how to assess the analysis dataset for accuracy and sample size, including whether there are adequate numbers of the rarer of the binary outcomes being modeled occurring in the dataset (e.g., higher severity crashes in this case). Analysts should also be familiar with how to specify models, assess the model goodness of fit, and validate the model by testing its predictive performance on different datasets than that used to develop the model. Binary logistic regression is one of several approaches available to analyze binary outcomes. Other alternatives include probit regression, classification and regression trees, and rare event logistic regression.

Table 8. Example data structure for estimating the rear-end severity model.

Observation ID	Approach	Start Time	End Time	Date	Primary Road	Secondary Road	Posted Speed Limit [MPH]	Rear-End Crash	Right-Angle Crash	FI	PDO	Distance to Upstream Intersection [Miles]	R_1	G_2
723609	NB	6:30 AM	6:45 AM	6/7/2018	Route 1	Route 146	45	1	0	1	0	0.10	1	0
231584	SB	7:15 AM	7:30 AM	6/19/2018	Route 12	Route 13	35	1	0	0	1	0.20	1	0
153851	SB	6:00 AM	6:15 AM	6/22/2018	Route 361	Route 14	55	1	0	0	1	0.12	1	1
125201	NB	8:15 AM	8:30 AM	6/24/2018	Route 28	Route 61	55	1	0	0	1	0.40	0	0
974845	SB	7:30 AM	7:45 AM	6/26/2018	Route 1	Route 111	35	1	0	1	0	0.18	0	0
315467	NB	6:45 AM	7:00 AM	6/29/2018	Route 91	Route 808	45	1	0	0	1	0.61	1	1
188874	NB	8:00 AM	8:15 AM	6/31/2018	Route 12	Route 146	25	1	0	1	0	0.45	0	1

The equations in figure 19 and figure 20 can be used to estimate the probability that a rear-end or right-angle crash will result in a fatality or injury. Figure 21 and figure 22 show how to estimate PDO probability given these FI probabilities.

$$P_{PDO|RE} = 1 - P_{FI|RE}$$

Figure 21. Equation. Probability that a rear-end crash will not result in a fatality or injury.

$$P_{PDO|RA} = 1 - P_{FI|RA}$$

Figure 22. Equation. Probability that a right-angle crash will not result in a fatality or injury.

5. Predict the combined crash type and crash severity probabilities.

Finally, the equations presented in Step 3 and Step 5 can be used to compute the probabilities of five outcomes:

1. A rear-end crash with at least one fatality or injury occurs ($P_{RE} * P_{FI|RE}$).
2. A rear-end crash without a fatality or injury occurs ($P_{RE} * P_{PDO|RE}$).
3. A right-angle crash with at least one fatality or injury occurs ($P_{RA} * P_{FI|RA}$).
4. A right-angle crash without a fatality or injury occurs ($P_{RA} * P_{PDO|RA}$).
5. No rear-end or right-angle crash occurs (P_{Other}).

Example – Steps 4 through 5

In continuing the example application, Table 9 and table 10 show the model coefficients estimated by Li & Tarko for the crash severity models for rear-end and right-angle crashes, respectively.

Table 9. Example binary logistic regression model of crash severity for rear-end crashes estimated by Li & Tarko. [9]

Variable	Coefficient	Standard Error	t-Statistic
$SR431$	-0.726	0.270	-2.69
Vol_{Total}	-0.00129	0.0005	-2.65
G_2	0.520	0.273	1.90
$Constant$	-0.538	0.305	-1.76

Table 10. Example binary logistic regression model of crash severity for right-angle crashes estimated by Li & Tarko. [9]

Variable	Coefficient	Standard Error	t-Statistic
Y_{Short}	1.720	0.562	3.06
$Wint$	-1.250	0.634	-1.97
G_2	-1.485	0.660	-2.25
$Constant$	-0.538	0.305	-1.76

As with the multinomial logit models in Step 2, coefficients in table 9 and table 10 represent the associations between each covariate and the probability of an FI crash. A positive coefficient indicates that increases in the variable increase the probability of a crash resulting in a fatality or injury; a negative coefficient indicates that increases in the variable decrease the probability of a crash resulting in a fatality or injury. For example, the model presented in table 9 shows that the probability that a rear-end crash results in a fatality or injury increases if more than 25 percent of vehicles arrive in the second half of the green phase (G_2) with a coefficient of 0.520, while, with a coefficient of -0.00129, the probability decreases as total volume on the approach increases (Vol_{Total}). The negative coefficient for $SR431$ (-0.726) implies that rear end crashes on approaches along that route are less likely to result in a fatality or injury than the other routes used to develop the model.

Figure 23 and figure 24 include example models from Li & Tarko for the probability of an injury or fatality given that either a rear-end or right-angle crash occurs.

$$P_{FI|RE} = \frac{exp(-0.538 - 0.726 * SR431 - 0.00129 * Vol_{Total} + 0.520 * G_2)}{1 + exp(-0.538 - 0.726 * SR431 - 0.00129 * Vol_{Total} + 0.520 * G_2)}$$

Figure 23. Equation. Probability that a rear-end crash will result in at least one fatality or injury.

$$P_{FI|RA} = \frac{\exp(-0.538 + 1.720 * Y_{Short} - 1.250 * Wint - 1.485 * G_2)}{1 + \exp(-0.538 + 1.720 * Y_{Short} - 1.250 * Wint - 1.485 * G_2)}$$

Figure 24. Equation. Probability that a right-angle crash will result in at least one fatality or injury.

Having already calculated the change in probability of rear-end and right-angle crashes, the engineers wanted to consider the potential change in the severity of these crashes. Example applications of the models in table 9 and table 10 are provided below.

No Coordination

$$P_{FI|RE,No\ Coordination} = \frac{\exp(-0.538 - 0.00129 * Vol_{Total} + 0.520 * G_2)}{1 + \exp(-0.538 - 0.00129 * Vol_{Total} + 0.520 * G_2)}$$
$$= \frac{\exp(-0.538 - 0.00129 * 470 + 0.520 * 0)}{1 + \exp(-0.538 - 0.00129 * 470 + 0.520 * 0)} = 0.242$$

Figure 25. Equation. Example calculation of probability of a rear-end crash resulting in a fatality or injury with no signal coordination.

$$P_{PDO|RE,No\ Coordination} = 1 - P_{FI|RE,No\ Coordi\ nation} = 1 - 0.242 = 0.758$$

Figure 26. Equation. Example calculation of probability of a rear-end crash resulting in property damage only with no signal coordination.

$$P_{FI|RA,No\ Coordination} = \frac{\exp(-0.538 + 1.720 * Y_{Short} - 1.250 * Wint - 1.485 * G_2)}{1 + \exp(-0.538 + 1.720 * Y_{Short} - 1.250 * Wint - 1.485 * G_2)}$$
$$= \frac{\exp(-0.538 + 1.720 * 0 - 1.250 * 0 - 1.485 * 0)}{1 + \exp(-0.538 + 1.720 * 0 - 1.250 * 0 - 1.485 * 0)} = 0.369$$

Figure 27. Equation. Example calculation of probability of a right-angle crash resulting in a fatality or injury with no signal coordination.

$$P_{PDO|RA,No\ Coordination} = 1 - P_{FI|RA,No\ Coordination} = 1 - 0.369 = 0.631$$

Figure 28. Equation. Example calculation of probability of a right-angle crash resulting in property damage only with no signal coordination.

Coordination

$$P_{FI|RE,Coordination} = \frac{\exp(-0.538 - 0.00129 * 470 + 0.520 * 1)}{1 + \exp(-0.538 - 0.00129 * 470 + 0.520 * 1)} = 0.349$$

Figure 29. Equation. Example calculation of probability of a rear-end crash resulting in a fatality or injury with signal coordination.

$$P_{PDO|RE,Coordination} = 1 - 0.349 = 0.651$$

Figure 30. Equation. Example calculation of probability of a rear-end crash resulting in property damage only with signal coordination.

$$P_{FI|RA,Coordination} = \frac{\exp(-0.538 + 1.720 * 0 - 1.250 * 0 - 1.485 * 1)}{1 + \exp(-0.538 + 1.720 * 0 - 1.250 * 0 - 1.485 * 1)} = 0.117$$

Figure 31. Equation. Example calculation of probability of a right-angle crash resulting in property damage only with signal coordination.

$$P_{PDO|RA,Coordination} = 1 - 0.117 = 0.883$$

Figure 32. Equation. Example calculation of probability of a right-angle crash resulting in property damage only with signal coordination.

Multiplying these probabilities with the crash probabilities produces probabilities of the five potential outcomes for a fifteen-minute period at this intersection approach with and without signal coordination. These probabilities are summarized in table 11.

Table 11. Crash type and severity probability during the average 15-minute period.

Potential Outcome	Equation	Probability with No Coordination	Probability with Coordination	Percent Change in Probability
FI|RE	$P_{RE} * P_{FI\|RE}$	$1.24 * 10^{-5}$	$9.88 * 10^{-6}$	-20.4%
PDO|RE	$P_{RE} * P_{PDO\|RE}$	$3.89 * 10^{-5}$	$1.84 * 10^{-5}$	-52.7%
FI|RA	$P_{RA} * P_{FI\|RA}$	$2.68 * 10^{-5}$	$3.58 * 10^{-6}$	-86.6%
PDO|RA	$P_{RA} * P_{PDO\|RA}$	$4.59 * 10^{-5}$	$2.71 * 10^{-5}$	-41.1%
Other		0.99988	0.99994	0.017%

Aggregating these number over the 4,160 potential 15-minute periods during weekday AM peaks accumulated over one year, the engineers predict 0.05 FI|RE crashes, 0.16 PDO|RE crashes, 0.11 FI|RA crashes, and 0.19 PDO|RA crashes without coordination at the intersection approach of interest. With coordination, they predict 0.04 FI|RE crashes, 0.08 PDO|RE crashes, 0.02 FI|RA crashes, and 0.11 PDO|RA crashes.

SUPPORTING TOOLS

Statistical modeling software is required for estimating the logistic regression models for crash probability and crash severity. Statistical software with regression models can be found for free or at a cost. As previously mentioned, analysts developing the models should have experience in how to assess the analysis dataset for accuracy and sample size, specify models, assess the model goodness of fit, test underlying model assumptions, and validate the models by testing their predictive performance on different datasets than that used to develop the model. The rest of the analysis steps can be executed using Microsoft Excel or another spreadsheet software.

DOCUMENTING ANALYSIS AND REPORTING RESULTS

Consistent documentation of analyses that inform investment decisions improves the transparency and defensibility of those decisions. It helps future officials, planners, and engineers know why and how certain decisions were made and provides data and context for those decisions. Consistent documentation also provides a valuable record in the event of public or legal challenges to a decision and encourages the establishment of a consistent, repeatable analysis process. Documentation of the analysis described in this document should generally include:

- A description of the traffic signal coordination project or program.
- The estimated models developed.
- Descriptive statistics for each model.
- A list of any assumptions, along with justification.
- A summary of the results.

The following information is necessary for this analysis and should form part of the analysis documentation:

- The average traffic arrival characteristics for existing and proposed conditions under the signal coordination plan.
- The average signal phase characteristics for existing and proposed conditions under the signal coordination plan.

In addition, the procedure in this document has the following methodological assumptions:

- The method assumes only one crash can occur within the 15-minute observation period. The possibility of multiple crashes within one 15-minute observation period is not considered.
- The method assumes that characteristics of vehicle arrivals with respect to signal timing can be accurately predicted for a proposed condition.

BROADER APPLICATIONS

This document describes a methodology for estimating the change in safety performance that can be expected after enhancing traffic signal coordination on an arterial. Safety performance effects are estimated by first developing a multinomial logistic regression model of crash outcomes and then developing a binary logistic regression model of crash severity. These same general steps can be used to analyze other TSMO strategies where shorter analysis periods are desired to capture the microscopic variability of TSMO operation, vehicle arrivals and departures, operational conditions, and resulting safety performance over the course of a day. Examples may include variable speed limits, dynamic lane use control, adaptive ramp metering, and adaptive signal control.

When extended to other contexts, analysts should tailor the same general steps of this method to the strategy of interest. When predicting crash outcomes, the prediction should be limited to the times and facilities on which the strategy of interest will have an impact. For example, in the case of ramp metering, required data will include the timing of the ramp metering algorithm, the periods during which it is operational (if it operates dynamically or at set times of day), and the area of analysis should be limited to the road segments in the direct vicinity of the ramps in question. Furthermore, the crash type or types analyzed can be changed based on the TSMO strategy in question. Analysts should review the strategy to identify which crash types will be specifically targeted by the strategy. In the case of the ramp metering example, it may be desirable to predict same-direction sideswipe (or merging) crashes along with rear-end crashes.

In addition to these applications, the use of logistic regression for short-term crash prediction has other potential applications to safety performance analyses of TSMO. A companion noteworthy practice report shows the application of binary logistic regression to estimating changes in the occurrence of secondary crashes due to implementing traffic incident management strategies aimed and reducing primary incident duration.(17) A final report documenting a safety analysis needs assessment for TSMO synthesizes research that used logistic regression to relate traffic operational performance to safety performance.(18)

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FHWA-SA-19-043