ADVANCES IN TRANSPORTATION STUDIES
An International Journal

Special Editors: John G. Gaspar & Cara J. Hamann

2020 Special Issue, Vol. 2

Contents

Advances in Transportation Studies an international Journal 2020 Special Issue, Vol. 2

ISBN 978-88-255-3451-1 – ISSN 1824-5463 – DOI 10.4399/97888255345111– pagg. 3-4

Preface:
Special Issue on Road Safety and Simulation

J.G. Gaspar   C.J. Hamann

National Advanced Driving Simulator, University of Iowa,
2401 Oakdale Blvd, Iowa City, IA 52242, United States
email: john-gaspar@uiowa.edu; cara-hamann@uiowa.edu

The 2019 Road Safety and Simulation Conference was held in Iowa City, Iowa. The Road Safety and Simulation (RSS) conference has a history of highlighting the important and dynamic role of simulation in the study of transportation safety. The 2019 meeting brought together an interdisciplinary group of researchers and students to discuss simulation's role in the future of transportation research.

This special issue represents a selected set of papers submitted for RSS 2019. These papers mirror the breadth and quality of the research presented at the meeting.

The articles in this special issue are a reflection of the key topics that emerged from the meeting. RSS 2019 touched on the past, present, and future role of simulation in supporting increased safety in ground surface transportation. The papers included in this special issue highlight four focus areas that emerged from the meeting.

The first is the need to better understand transportation safety from the viewpoint of vulnerable and high-risk populations. These include pedestrians, bicyclists, and younger and older adults. The papers included in this issue highlight the many ways simulation can be used to understand safety issues for these populations.

The second topic of note is the continuing impact of automation and technology on the ground transportation environment. Simulation continues to be a necessary tool to understand issues ranging from in-vehicle interface design to vehicle-pedestrian interaction. The papers included in this issue speak to the creativity with which researchers are applying simulation to address the challenges and opportunities introduced by automation.

Thirdly, more than ever, modeling methods are making a contribution to the road traffic safety. Research is applying a range of different approaches to understand the potential impact of technology and infrastructure changes on traffic safety. This includes the application of approaches in microsimulation to understand issues in connected and automated vehicle environments. These efforts go well beyond what can be accomplished through human-in-the-loop simulation alone and reflect the importance of integrating methodologies to address emerging challenges.

Finally, both the special issue and the conference at large highlighted the evolution of simulation technology. The papers included in this issue demonstrate the technological evolution of simulation, moving from beyond standard driving simulators to pedestrian, all-terrain vehicle, and connected simulation platforms.

We thank the authors for submitting their work for consideration in this Special Edition and for their patience throughout several rounds of review. We also thank the many reviewers who volunteered their time to provide thoughtful feedback on these papers and the larger body of articles submitted to the conference.

Finally, we thank the editors at Advances in Transportation Studies, particularly Editor in Chief Dr. Alessandro Calvi, for the guidance and effort that went into bringing this Special Issue together.

The Guest Editors

Dr. John G. Gaspar and Dr. Cara J. Hamann

Advances in Transportation Studies an international Journal 2020 Special Issue, Vol. 2

ISBN 978-88-255-3451-1 – ISSN 1824-5463 – DOI 10.4399/97888255345112– pagg. 5-18

Exploring the impacts of intersection and traffic characteristics on the frequency and severity of bicycle-vehicle conflicts

B. Russo[1] S. Kothuri[2] E. Smaglik[1] C. Aguilar[3]
E. James[1] N. Levenson[4] P. Koonce[5]

[1]Department of Civil Engineering, Construction Management, and Environmental Engineering, Northern Arizona University, P.O. Box 15600, Flagstaff, AZ 86011,USA.
email: brendan.russo@nau.edu; edward.smaglik@nau.edu; elj52@nau.edu
[2]Department of Civil and Environmental Engineering, Portland State University, USA.
email: skothuri@pdx.edu
[3]Rick Engineering Company, USA
email: caguilar@rickengineering.com
[4]Office of Bicycle and Pedestrian Programs, New York City Department of Transportation, USA.
email: nlevenson@dot.nyc.gov
[5]Bureau of Transportation, City of Portland, OR USA.
email: peter.koonce@portlandoregon.gov

Abstract

In urban locations, intersections are areas where a variety of modes converge, thus leading to an increased potential for conflicts. A common crash type involving bicycles at intersections is the "right/left-hook" where a right/left-turning vehicle collides with a through bicyclist. While geometric treatments and signal control strategies have been used to mitigate right-left/hook conflicts, agencies often face questions about optimal treatments and when to use these treatments at intersections. This exploratory study aims to fill that gap by exploring the safety impacts of split leading bike interval (LBI) and mixing zone treatments to reduce conflicts between bicycles and turning vehicles at intersections using surrogate safety measures with video observations. The surrogate safety measure post encroachment time (PET) was used to classify conflicts by severity based on the magnitude of the value. Next, a negative binomial regression model was estimated to observe the relationship between conflicts, bicycle and motor vehicle volumes. The results revealed that through bicycle and turning motor vehicle volumes, as well as intersection treatment, are significant predictors of conflicts between bicycles and motor vehicles at signalized intersections, which could allow for targeted implementation of safety measures at candidate locations identified through volume analysis. Additionally, a random parameters ordered logit model was estimated to examine factors which impact the severity of bicycle-vehicle conflicts if they occur. It was found that both intersection treatment and time of day were both associated with conflict severities. The results of this study provide guidance for potential improvement of bicycle safety at intersections, which could increase the attractiveness of this mode for possible new cyclists.

Keywords – bicycle safety, bicycle-vehicle conflict, right/Left-hook, surrogate safety measures

1. Introduction

There is notable interest in supporting sustainable and active transportation modes such as bicycling and walking due to the many benefits associated with them, including reduced congestion, lower emissions and improved health [1]. Bicycle trips in the US increased from 0.7% of total trips in 1995 to 1.0% in 2009 [18]. These increases have primarily been driven by growth in bike mode share in cities such as Portland, OR (1.1% to 5.8%) Chicago (0.3% to 1.2%), Washington DC (0.8% to 2.2%), San Francisco (1 % to 3%), Minneapolis (1.6% to 3.9%) and New York City (0.3% to 0.6%) between 1990-2009 [18]. Although the number of bicyclists is increasing, safety remains a top concern and can be a limiting factor in engaging new cyclists [22]. According to the National Highway Traffic Safety Administration, there were 818 bicyclist fatalities in 2015, accounting for 2.3% of all motor vehicle-related fatalities. As a proportion of total crashes, bicyclist fatalities are increasing. Of these, 70% occurred in urban areas and 28% occurred at intersections [14].

In urban locations, intersections are areas where a variety of modes converge, thus leading to an increased potential for conflicts. A common crash type involving bicycles at intersections is the "right/left-hook" where a right/left-turning vehicle collides with a through bicyclist. Right/left-hook crashes typically occur in one of two ways. First, they can occur during the onset of the green indication due to the failure of the motorist to notice and yield to the bicyclist. The second scenario occurs at least several seconds after the onset green indication (sometimes termed as "stale green"), and may happen when either a faster bicyclist overtakes a slower vehicle or a faster vehicle overtakes a slower cyclist. In either case, the vehicle executes a turn in front of the bicyclist [6]. Various studies have investigated causal factors for right-hook crashes between bicycles and motor vehicles. Primary causal factors are a motorist's failure to look for the bicyclist prior to turning, motorist's incorrect assumption about right-of-way, bicyclist inattention, especially on familiar routes, and a bicyclist's inaccurate assumption regarding motorist-yielding behavior [19]. Recent work by Hurwitz and Monsere [6] confirmed a number of these factors using a driving simulator.

Various mitigation treatments have been employed to reduce and/or eliminate the probability for a right/left-hook crash to occur. Geometric treatments including advance stop lines or bike boxes have been used in some cities as a treatment, and there is some evidence showing a reduction of right/left-hook conflicts at the onset of the green indication due to their use [2]. Other treatments that have been used include signage (static or dynamic), colored pavement markings highlighting potential conflict areas, tighter curb radii, mixing zones, the use of pocket bike lanes at intersections, and protected intersections. While protected intersections are designed to slow turning motorists with tighter turn radii and improve sight lines, extensive geometric modifications at the site are needed [9]. Mixing zones have been used by agencies as an alternative to excusive bicycle signal phases and are designed to minimize conflicts with turning vehicles at intersections [13]. A mixing zone is an area where the turning vehicles are expected to yield and cross paths with a bicyclist in advance of an intersection [11]. Agencies often choose mixing zones as a treatment to minimize impacts to traffic operations and site geometry in addition to a safety benefit.

Signal timing treatments to improve safety and prevent right/left-hook crashes include the provision of bicycle specific signals, exclusive bicycle phases and leading bike intervals (LBI). Exclusive bicycle phases stop all motor vehicle traffic while allowing bicyclists to proceed through the intersection. Leading Bike Intervals (LBI) are similar to Leading Pedestrian Intervals (LPI) and provide a lead interval for the bicyclists to proceed through the intersection. Following the lead interval, the operation reverts to concurrent phasing, where the turning vehicles are expected to yield to the through bicyclists. Recently, New York City has adopted the use of split LBI, which is similar to the LBI treatment, except that the through non-conflicting motor vehicles are also allowed to proceed during the lead interval along with the through bicyclists. The City of Portland, Oregon has also experimented with an active warning sign that lights up and reminds turning vehicles to yield to bicyclists when a bicyclist is detected [15].

Agencies often face questions regarding which optimal treatment to use at intersections to minimize bicycle-vehicle conflicts and when to use this treatment. A scan of the literature reveals little to no research that can help answer this question. This exploratory study aims to fill that gap by exploring the safety impacts of split LBI and mixing zone treatments to reduce conflicts between bicycles and turning vehicles at intersections using surrogate safety measures with video observations. The surrogate safety measure post encroachment time (PET) was used to classify conflicts by severity based on the magnitude of the value. Next, a negative binomial model was estimated to observe the relationship between conflicts, bicycle and motor vehicle volumes. The results revealed that through bicycle and turning motor vehicle volumes are significant predictors of right/left-hook conflicts between bicycles and motor vehicles at signalized intersections, which could allow for targeted implementation of safety measures at candidate locations identified through volume analysis. Additionally, an analysis of conflict severity through development of a random parameters ordered logit model indicated both intersection treatment and time of day were associated with conflict severity. Using results such as these in providing guidance for improving bicycle safety at intersections could increase the attractiveness of this mode for potential new cyclists.

1.2. Background

The decision of when to separate bicycle and motor vehicle movements in time using signalization is a question that is faced by many agencies. Significant factors that can drive this decision often include safety considerations. Quantification of safety has traditionally been performed using crash data, which is a reactive approach and has several limitations such as limited sample size, improper records, missing information about causal factors, and randomness associated with crashes. To replace the need for crash data, surrogate safety measures (SSM) have been developed as a more proactive approach based on an observable non-crash event that is related to crashes and can further be converted into a corresponding crash frequency or severity.

Traffic conflict technique (TCT) is a systematic method of observing and measuring crash potential, where conflicts are defined as the occurrence of evasive vehicular actions and characterized by braking and/or weaving measures. A number of surrogate safety measures have been developed, and among those, time to collision (TTC) and post encroachment time (PET) have been widely used [8]. While TTC requires the two users to be on a collision path, PET can be used to measure conflicts between users that are not on a collision course [8]. In the context of this paper, the PET measure is defined as the time between the departure of the encroaching cyclist from the potential collision point (at the intersection of the two trajectories) and the arrival of the first vehicle at the potential collision point at the intersection, or vice versa [4].

A few studies have used PET to assess the safety of bicycle infrastructure. Zangenehpour et al. [26] used video data from intersections with and without cycle tracks with automated techniques to obtain bicyclist and motor vehicle trajectories and interactions [26]. Using PET as the surrogate safety measure, Zangenehpour et al. [26] estimated ordered logit models with random effects and found that intersection approaches with cycle tracks on the right were safer than those approaches with cycle tracks on the left [26]. Their results also revealed that the likelihood of a cyclist being involved in a dangerous interaction increases with increasing turning vehicle flow and decreases as the size of the cyclist group arriving at the intersection increases, demonstrating the safety in numbers effect [26]. However, these cycle tracks did not have mixing zones or bicycle-specific signals [26]. Kassim et al., 2014 [7]used automated techniques to measures PET for motor vehicle and bicyclist conflicts at signalized intersections and studied the differences in measurement techniques [7].

There is limited research on the safety impacts of a mixing zones, which is an area where turning vehicles are expected to yield and cross paths with a bicyclist in advance of an intersection [11]. This treatment is intended to minimize conflicts with turning vehicles at intersections and can be considered as an alternative to an exclusive bike signal phase [13]. However, there is a tradeoff related to lower comfort as compared to the separated bike lane, since bicyclist and motor vehicles have to share the space. This treatment can reduce motor vehicle speed in the turn lane and reduce the risk of right/left-hook conflicts at intersections and is typically used in locations where there is not enough space to include a right-turn lane and a bicycle lane at the intersection, or at locations where a right/left-turn lane is present with a bike lane, but there is risk of conflicts between turning vehicles and bicyclists. The merge point is recommended to be located as close to the intersection as possible, so that vehicular speeds are lower in that area [11]. Monsere et al. [12] studied five designs for protected bike lanes at intersections, which included mixing zones at intersections without bike signals [12]. Video analysis for the mixing zones with yield markings revealed that while 93% of the turning vehicles used the lane as intended, only 63% of the observed bicycles correctly used the mixing zone. Additionally, their findings also revealed that 1% to 18% of vehicles at mixing zones also turned from the wrong lane. Monsere et al. also found that the perception of safety for cyclists appeared to be more heavily influenced by the volume of turning motor vehicle traffic than the correct turning movements of motorists [12]. One item to note is that goal of any of the above treatments is to improve safety and/or comfort for bicycles, the implementation of any treatment is highly dependent upon vehicular volumes and movements.

The Federal Highway Administration (FHWA) issued an interim approval for the optional use of bicycle signal faces in 2013 [3]. Since then, some jurisdictions have adopted the use of bicycle signals and strategies (LBI, split LBI, exclusive phases) to improve bicyclist safety at intersections. While the interim approval allows bicycle signals to be used in some capacities, it is rather restrictive in that it prohibits bicycle signals to be used along with the pedestrian hybrid beacon, for controlling bicycle movements that share a lane with motor vehicle traffic and for exclusive bicycle phases that permit scramble phases [3]. In both LBI's and split LBI's, bicyclists are provided with a leading interval which allows an early start to establish themselves in the intersection (and in the driver's visual field), thereby reducing the probability of a conflict at the onset of green. A lead interval may provide at least three to ten seconds of green time for bicycles prior to the green phase for the concurrent vehicle traffic [11]. While all vehicular traffic is stopped during the leading interval with an LBI, only conflicting turn movements are stopped with a split LBI. Motorized traffic delays at the intersection are lower with the split LBI than the LBI treatment [8]. It is important to note that both the LBI and split LBI require that motor vehicles comply with right-turn-on-red restrictions. However, level of compliance for obeying right-turn-on-red restrictions varies depending on the activity of the area and understanding of risk [17]. Advances in regulatory signage have helped reduce these conflicts [17], but the need for this restriction when using LBI and split LBI treatments remains. There has been no published research on the safety impacts of bicycle specific signal control strategies. In addition, there is limited guidance available on when to separate the bicycle and motor vehicle movements using signalization. The Mass DOT Bikeway Design Guide recommends that bicycle and motor vehicle movements be separated in time when the right-turn vehicle volumes exceed 150 vph with a one-way bike lane, and 100 vph with a two-way bike lane [11]. These thresholds were developed based on engineering judgement. Table 1 shows the guidance regarding when to consider time-separated turning movements between bicycles and motor vehicles [11].

Tab. 1 - Guidance on the use of bicycle signals based on bicycle and vehicle volumes
(Source: Mass DOT Bikeway Design Guide [11])

Separated Bike Lane Operation	**Motor Vehicle per Hour Turning Across Separated Bike Lane**			
	Two-way Street			One-way Street
	Right Turn	Left Turn across One Lane	Left Turn across Two Lanes	Right or Left Turn
One-way	150	100	50	150
Two-way	100	50	0	100

Given that the perception of safety is influenced by the magnitude of motor vehicle volume and its proximity, the objective of this paper is to explore the relationship between bicycle and vehicle volumes and bicycle-vehicle conflicts at locations with split LBI and mixing zone treatments.

2. Methodology

2.1. Study site descriptions

Five intersections were chosen for analysis, four in New York City – 1st Ave and 61st St, 2nd Ave and 74th St, 6th Ave and 23rd St, and 1st Ave and 63rd St, and one in Portland, Oregon – NE Grand Ave and NE Multnomah St. These intersections were chosen because they had the desired treatment (either Split LBI or mixing zone). Video data were collected at each of these intersections and mined to derive PET values for bicycles and motor vehicle movements in conflict. It should be noted that the video data were collected at 30 frames per second. Overhead satellite views of each study intersection are shown in Figure 1, and descriptions of each study site location are as follows:

<u>1st Avenue and 61st Street (Split LBI example)</u>

1st Avenue and 61st Street are both one-way streets. 1st Avenue has one buffered bike lane with median separation near the intersection, one vehicle left-turn lane, three vehicle through lanes, and one "Bus Only" lane. 61st Street has two through lanes and one through right-turn lane. The outside lanes on 61st Street can be used for parking, so in general most vehicles will travel down the center through lane. This intersection was analyzed after the implementation of a split leading bike interval (split LBI) on March 16, 2017, from 10:30 a.m.to 7:30 p.m. The cycle length was 90 seconds, and the lead interval for the Split LBI was 10 seconds.

<u>6th Avenue and 23rd Street (Split LBI example)</u>

6th Avenue is a one-way street and 23rd Street is bidirectional. 6th Avenue has one bike lane, one vehicle left-turn lane, four vehicle through lanes, and one vehicle right-turn lane. 23rd Street has two northwest bound lanes and two southeast bound lanes, each direction with one vehicle through lane and one "Bus Only" lane. Following the implementation of a split LBI, the intersection was analyzed on Feb. 20, 2017, from 7 a.m. to 6 p.m. The cycle length was 90 seconds, and the lead interval for the Split LBI was 7 seconds.

<u>2nd Avenue and 74th Street (Mixing Zone example)</u>

2nd Avenue and 74th Street are both one-way streets. 2nd Avenue has one buffered bike lane, one vehicle left-turn lane/mixing zone, three vehicle through lanes, and one "Bus Only" lane. 74th Street has one vehicle through lane with street parking on both sides of the street. This intersection was analyzed after the implementation of a mixing zone on May 18, 2017 from 8 a.m.to 7 p.m. The cycle length was 90 seconds.

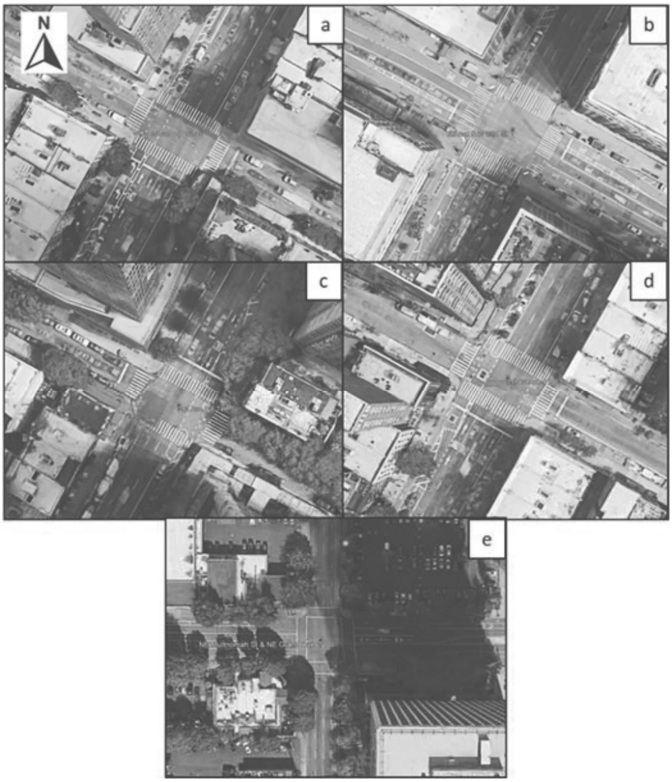

Fig. 1 - Satellite views of study intersections: a) 1st Avenue and 61st Street, b) 6th Avenue and 23rd Street, c) 2nd Avenue and 74th Street, d) 1st Avenue and 63rd Street, and e) NE Grand Avenue and NE Multnomah Street (Source: Google Earth)

1st Avenue and 63rd Street (Mixing Zone example)

1st Avenue and 63rd Street are both one-way streets. 1st Avenue has one buffered bike lane with median separation near the intersection, one vehicle left-turn lane, four vehicle through lanes, and one "Bus Only" lane. 63rd Street has two through lanes and one through/right-turn lane. This intersection was analyzed after the implementation of a mixing zone on March 16, 2017, from 9:00 a.m.to 7:30 p.m., though only the first two hours of data were extracted due to time constraints. The cycle length was 90 seconds.

NE Grand Avenue and NE Multnomah Street (Mixing Zone Example)

Grand Avenue is a one-way street and Multnomah Street is bidirectional. Grand has one vehicle left through lane, two vehicle through lanes, and one vehicle through right lane that is shared with the Portland Streetcar. Multnomah Street has varying geometries for each direction. Westbound, Multnomah Street has one vehicle left-turn lane, one vehicle through lane, and one vehicle right-turn lane that is shared with a bicycle lane. Eastbound, Multnomah Street has one vehicle left-turn lane, and one vehicle right through lane that is shared with a bicycle lane. This intersection was analyzed after the implementation of a mixing zone on July 10, 2017, from 7 a.m. to 7 p.m. The westbound direction, which included the mixing zone was analyzed. The average cycle length was 90 seconds.

2.2. Post Encroachment Time (PET) conflict description

Post-encroachment time (PET) was used to analyze bicycle-vehicle conflicts throughout the various treatments at each intersection. The PET measure is defined as the time between the departure of the encroaching cyclist from the potential collision point (at the intersection of the two trajectories) and the arrival of the first vehicle at the potential collision point at the intersection, or vice versa (14).

$$PET = t_v - t_b \quad (1)$$

where,

t_v = arrival/departure time of the encroaching cyclist from potential collision point, and

t_b = arrival/departure time of the first vehicle at the potential collision

This metric gives a measure of how closely a collision was avoided in the final stage of an encounter [24]. The lower the PET, the more likely a collision would have been. For cyclists, PET values (for each cyclist) are separated into four categories [26]:

- PET ≤ 1.5 s
- 1.5 s < PET ≤ 3s
- 3s < PET ≤ 5s
- PET > 5s

A value of “0” for a PET value indicates the bicycle went around the car. The lower the PET value, higher is the potential for collision. However, lower PET values do not mean that a collision is imminent. Rather, the thresholds themselves may indicate a comfort level for the cyclist and the PET values may vary depending on the environment and the prevailing traffic culture. For example, in New York City, bicyclists and drivers may be willing to accept closer gaps (lower PET values) due to higher density and mix of users compared to other cities. Speed along with PET values may provide an indicator of the potential for conflicts.

In order to calculate the PET, a video analysis was done using software that had the ability to advance frame by frame with video resolution less than one second. As each bicycle or vehicle entered the frame, a time stamp was recorded along with a specification of bicycle or vehicle. Once the next type of vehicle entered the frame, a time difference was calculated between the two types of candidates for an event. It should be noted that more than one bicycle may be associated as a potential event with only one vehicle, therefore one motor vehicle may count as multiple events. The same may be said for multiple vehicles and one bicycle. If the time difference between interacting users was less than five seconds, the event was classified as an “incident.”

To calculate the speed of each bicycle or vehicle, two monuments were identified and the distance between them recorded. Field measurements were preferred, but when unavailable Google Maps was used. The elapsed time between the arrival of a candidate at monument one and the arrival of the same candidate at monument two was noted. The difference was recorded. The speed was calculated by dividing the distance between the two monuments by the elapsed time. Additionally, the time since bicycle green was measured and recorded. For concurrent phasing, if the signals were visible in the video, the difference in time between the green and the time stamp was subtracted. If the signals were not visible in the video, the movement of the vehicles in the through lanes was taken, added to 1.5 seconds for perception/reaction time, and then the time stamp was subtracted.

In order to calculate the PET, the area of potential collision was defined as the intersection of the bicycle lane (or its extension through the intersection as if it was continuously marked) and the motor vehicle's footprint as it travels across the bicycle lane. The time between one candidate leaving an area of potential collision and the arrival of the next was noted. It was also noted whether the bicycle slowed, swerved, changed lanes, or otherwise maneuvered to avoid collision with a motor vehicle. An evasive movement was recorded if the bicyclist went around the vehicle with no abrupt stop or movement. Near misses were recorded when a bicycle or vehicle had to make an abrupt/last second stop or maneuver to avoid a collision. Those interactions with PET times of less than 3 seconds were identified as critical conflicts for further analysis based on thresholds used in previous literature [23; 16; 20] for the frequency analysis.

2.3. Conflict frequency and severity statistical modeling

In order to identify factors associated with the hourly number of critical vehicle-bicycle conflicts at each study intersection, a statistical model was developed using hourly vehicle volumes, hourly bicycle volumes, and site characteristics. Given the discrete non-negative nature of hourly conflict frequency data (similar to annual traffic crash frequency data), Negative Binomial (NB) regression was considered for this analysis. This modeling framework is appropriate for this type of count data [25] and has been employed in numerous previous studies analyzing traffic crash frequency [20] as well as traffic conflict frequency [25; 10]. NB regression is a generalization of Poisson regression, and in the context of this study, the probability of intersection i experiencing y_i conflicts during one hour is given by [25]:

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!} \tag{2}$$

where:

$P(y_i)$ = probability of intersection i experiencing y_i conflicts during a one hour period, and

λ_i = Poisson parameter for intersection i, which is equal to the intersection's expected number of conflicts per hour, $E[y_i]$.

Regression models are estimated by specifying $\boldsymbol{\lambda_i}$ (the expected number of conflicts per hour) as a function of explanatory variables taking the form $\boldsymbol{\lambda_i = EXP(\beta X_i)}$, where X_i is a vector of explanatory variables and β is a vector of estimable parameters [25]. The NB model then allows the mean and variance of the distribution to differ. The NB model is derived by rewriting the Poisson parameter for each intersection i as $\boldsymbol{\lambda_i = EXP(\beta X_i + \varepsilon_i)}$, where $\boldsymbol{EXP(\varepsilon_i)}$ is a gamma-distributed error term with mean 1 and variance α [25]. The α term is also known as the over-dispersion parameter in NB regression modeling.

To examine factors associated with conflict severity, an ordered logit model was developed, given the discrete, ordered nature of conflict severity data (i.e. PET≤1.5 sec, PET 1.5-3 sec, PET 3-5 sec). Note that conflicts with PET >5sec were not considered in this analysis. In the ordered logit model, a latent variable z is specified which is used as the basis for modeling the ordinal ranking of the conflict severity data such that [25]:

$$Z = \beta X + \varepsilon \tag{3}$$

where:

X: vector of variables determining the discrete ordering for each occupant injury severity observation

β: vector of estimable parameters

ε: disturbance term

With this specification, the observed ordered data, y, for each conflict observation is defined as [25]:

$$y = 0\ (PET > 3\text{-}5\ sec) \quad if\ z \le \mu_0,$$
$$y = 1\ (PET > 1.5\text{-}3\ sec) \quad if\ \mu_0 < z \le \mu_1, \qquad (4)$$
$$y = 2\ (PET \le 1.5\ sec) \quad if\ z > \mu_1,$$

where:

μ_i : estimable threshold parameters that define y, which corresponds to the ordered conflict severity categories.

The μ thresholds are parameters which are estimated jointly with the model parameters β. It should be noted that the first threshold (i.e. μ_0) is set to 0 without loss of generality, and the error term, ε, is assumed to be logistically distributed across observations. Setting the lower threshold, μ_0, equal to zero then results in the outcome probabilities, $P(y = i) = \Phi(u_i - \beta X) - \Phi(u_{i-1} - \beta X)$ where μ_i and μ_{i-1} represent the upper and lower thresholds for injury severity i [25]. To account for unobserved heterogeneity (e.g. unobservable differences between study sites), random parameters (RP) were incorporated in the ordered logit model by allowing the constant term to vary across observations. Further details regarding the incorporation of random parameters in this type of model can be found elsewhere [5; 25].

3. Analysis and results

3.1. Data summary

Table 2 shows the summary statistics from the five locations in this study. The number of incidents shown in Table 2 are total interactions between bicycles and motor vehicles. The potential number of collisions that would have occurred if the bicyclist or the driver did not swerve or change their path is noted in Table 2, as well the ratio of evasive actions taken to total incidents which varied from 5.3% to 66.7%.

The magnitudes of PET values were used to classify the interactions into four categories at each location. Table 3 shows the distribution. The highest proportion of PET ≤ 1.5s interactions occur at the 1st Avenue and 61st Street intersection, followed by 1st Avenue and 63rd Street. Proportion of interactions with 1.5s ≤ PET ≤ 3s were highest at the 2nd Avenue and 74th Street location. While a buffer is present between the left turn lane and through vehicle lane at the intersection of 1st Ave and 61st St, it is absent between the turn lane and the bike lane. This design places the vehicles next to bicycles and may have a bearing on the low PET values that were observed.

Tab. 2 - Summary of the video analysis

Parameter	**1st Ave and 61st St**	**6th Ave and 23rd St**	**2nd Ave and 74th St**	**1st Ave and 63rd St**	**Grand Ave and Multnomah St**
Number of Hours (Video) Analyzed	9	11	11	2	12
Number of Incidents	445	221	253	27	76
Number of Collisions if No Evasive Action Taken	197	46	57	18	4
Evasive actions as a % of Incidents	44.3%	20.8%	22.5%	66.7%	5.3%

Tab. 3 - Distribution of PET by site

Severity	1st Ave and 61st St		6th Ave and 23rd St		2nd Ave and 74th St		1st Ave and 63rd St		Grand Ave and Multnomah St	
	# of Incidents	% of Total Incd.	# of Incidents	% of Total Incd.	# of Incidents	% of Total Incd.	# of Incidents	% of Total Incd.	# of Incidents	% of Total Incd.
PET ≤ 1.5s	272	61.1%	94	42.5%	95	37.5%	15	55.6%	22	28.9%
1.5s< PET ≤ 3s	142	31.9%	51	23.1%	93	36.8%	11	40.7%	22	28.9%
3s < PET ≤ 5s	29	6.5%	58	26.2%	54	21.3%	0	0.0%	25	32.9%
PET > 5s	2	0.4%	18	8.1%	11	4.3%	1	3.7%	7	9.2%

3.2. Conflict frequency modeling results

The results of the NB hourly vehicle-bicycle conflict models are presented in Table 4. The model results are interpreted such that a positive parameter, β, indicates that variable is associated with an increase in vehicle-bicycle conflicts, and vice versa for a negative β estimate. As shown in Table 4, the variables which were found to be statistically significantly associated with vehicle-bicycle conflict frequency are the hourly volume of through bikes and the hourly volume of turning vehicles. Further discussion on the results of the conflict frequency model are provided in subsequent sections.

3.3. Conflict severity modeling results

The results of the RP Ordered logit conflict severity model are presented in Table 5. The model results are interpreted such that a positive parameter, β, indicates that variable is associated with an increase in probability of the most severe conflict (i.e. PET ≤1.5sec), and vice versa for a negative β estimate. As shown in Table 5, the variables which were found to be statistically significantly associated with vehicle-bicycle conflict severity were the presence of a mixing zone and the pm peak hour. Additionally, the marginal effects for severe conflict are included in Table 5 which represent the percent change in probability of a severe conflict associated with each variable. Further discussion on the results of the conflict severity model are provided in subsequent sections.

4. Discussion

Based on the results of the NB conflict frequency model presented in Table 4, the hourly volume of through bikes and the hourly volume of turning vehicles were associated with conflict frequency while the hourly volume of turning bicycles and hourly volume of through vehicles were not significant predictors of conflict frequency.

Tab. 4 - Results of the NB hourly vehicle-bicycle conflict frequency model

	Negative Binomial Model		
Parameter	**β**	**Std. Error**	**p-value**
Constant	0.5292	0.2745	0.0539
Thru Bikes	0.0088	0.0013	<0.0001
Turning Vehicles	0.0124	0.0015	<0.0001
Mixing Zone Indicator	-0.3320	0.1401	0.0178
Overdispersion	0.0342		
Log-Likelihood	-133.40		
AIC	276.8		

Tab. 5 - Results of the RP ordered logit conflict severity model

	RP Ordered Logit Model			
Parameter	**β**	**Std. Error**	**p-value**	**Marginal Effect for PET <1.5 sec.**
Constant	1.9497	0.1632	<0.0001	N/A
Std. Dev.	*1.0027*	*0.0750*	*<0.0001*	*N/A*
Mixing Zone Indicator	-0.6810	0.1513	<0.0001	-0.1683
PM Peak (3-6pm)	0.3009	0.1528	0.0489	0.0751
Threshold	1.9049	0.0973	<0.0001	N/A
Restricted Log-Likelihood	-996.93			
Log-Likelihood (RP model)	-979.80			
AIC	1969.6			

In addition to traffic volume parameters, an indicator variable for mixing zone presence exhibited a negative effect on vehicle-bicycle conflicts as compared with the split LBI sites, indicating that the mixing zone sites examined in this study were associated with a lower rate of bicycle-vehicle conflicts. However, due to relatively small sample of sites in this study (three sites with mixing zones and two sites with split LBI), it's unclear if this result is truly the isolated effect of mixing zone presence and further research is warranted.

Using the numerical NB model results presented in 4, vehicle-bicycle conflicts can be predicted given hypothetical hourly through bike and turning vehicle volumes using the following formula:

$$N_{predict\_conflicts} = exp[0.5292+(0.0088*ThroughBikes)+(0.0124*TurningVeh)+(-0.3320*0or1\ for\ mixing\ zone)] \quad (5)$$

Using this formula, predicted hourly vehicle-bicycle conflicts were estimated over a range of through bike and turning volumes, and the results are shown graphically in Figure 2. As can be seen in Figure 2, the relationship between number of conflicts and through bike/turning vehicle volumes is generally exponential in nature.

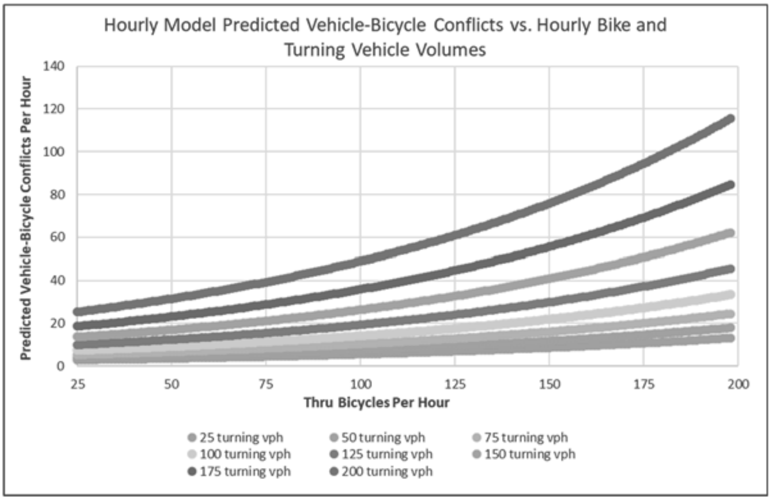

Fig. 2 - Hourly model-predicted vehicle-bicycle conflicts

Additionally, a qualitative analysis of Figure 2 shows that the rate of increase in conflicts starts to markedly increase at through bicycle volumes greater than 100 bikes/hr and/or turning vehicle volumes greater than 100 veh/hr. To the authors' knowledge, this is the first analysis linking both bicycle and vehicle volumes to number of vehicle-bicycle conflicts. The volume thresholds provided here agree with previous guidance on when to separate the bicycle and vehicular movements in time [11]. This provides important guidance for practitioners as to the number of vehicle-bicycle conflicts to expect at a certain location as a surrogate measure of safety, and may be useful in identifying sites in need of safety and/or operational treatments.

Turning to the results of the conflict severity model presented in Table 5, it was found that presence of a mixing zone decreased the probability of a severe conflict by 16.8% as compared to an LBI. This result may be due to certain road user behaviors (such as situational awareness or cautiousness) at mixing zones, however further research is needed to fully explore the reasons for this finding. Additionally, a conflict being observed during PM peak hours (3-6pm) was associated with a 7.5 increase in probability of severe conflict compared with other times of day. This result may be due to increased volumes during this time period and possibly more aggressive road user behavior during this congested time period. Surprisingly, neither bicycle or vehicle speed were significant predictors of conflict severity, and further research is needed to examine this effect as well the effect of other intersection characteristics and/or treatments on conflict severity.

5. Conclusions

This study presents an exploratory analysis aimed at linking traffic parameters (bicycle and vehicle volumes) to vehicle-bicycle conflicts as a surrogate measure of safety. Critical vehicle-bicycle conflicts (with PET times 3 seconds or less) were analyzed at a total of five signalized intersections in New York City, NY and Portland, OR. All sites contained treatments aimed at improving bicycle operations; two sites had leading bicycle intervals and three sites had mixing zones. Predictive models were developed using NB regression and it was found that hourly through bicycle volumes and hourly turning vehicle volumes are significantly associated with the frequency of critical vehicle-bicycle conflicts. Furthermore, the relationship between these traffic volume parameters and conflicts was found to be exponential in nature, and significant increases in conflicts are expected at through bicycle volumes greater than 100 bikes/hr and/or turning vehicle volumes greater than 100 veh/hr. Additionally, mixing zone sites examined in this study were associated with a lower rate of bicycle-vehicle conflicts. Conflict severity was also examined and mixing zones were associated with lower probabilities of the most severe conflicts (PET≤1.5sec). However, due to relatively small sample of sites in this study, it's unclear if these findings are truly the isolated effect of mixing zone presence.

Using conflicts as a surrogate measure of safety can be advantageous as it allows practitioners to be more proactive in safety management, rather than reactive to past crash experience. Past research has linked vehicle-vehicle conflicts to crash frequency and found a 0.8% increase in predicted collisions for each 1% increase in predicted conflicts with TTC's of 1.5 sec or less [21]. However, the link between vehicle-bicycle conflicts and crashes has not been firmly established. The results of this study provide a critical first step in establishing a framework to quantitatively predict vehicle-bicycle conflicts and link them to crash risk. This would allow practitioners to make more informed decisions as to bicycle infrastructure decisions in the design phase or when considering retrofitting or redesigning existing facilities. In addition to safety, bicyclist comfort should also be considered.

It's important to note there were some limitations in this study, all of which should be considered as directions for future research. First, the study sites used in this analysis were equipped with either LBIs or mixing zones. Future research should include sites with no specific bicycle treatment, as well as other bicycle treatments beyond LBIs and mixing zones to determine if there are varying effects on vehicle-bicycle conflicts. Second, the impact of pedestrian volumes was not considered in this analysis as pedestrian volumes were not available from the collected videos. It's possible high pedestrian volumes may impact intersection operations and have an effect on vehicle-bicycle conflicts, and future studies should consider this. Third, the impact of a PET value on user safety/comfort may vary greatly between jurisdictions. A 2.0s PET in New York City may be routine and a result of motorists yielding to pedestrians and congestion, while a similar interaction could be great cause for concern in a less dense environment. The typically slower speeds in a congested environment such as New York City along with drivers conditioned to yield to many users may further distort the difference of a 2.0s PET value in this environment from that in a suburban environment with higher speeds and a driver expectation of not having to yield. Fourth, in instances where the PET value is 0, a future analysis should consider which user is the lead participant. Typically, if the bicycle is behind the vehicle, this is a safer interaction than vice versa. Lastly, vehicle classifications (e.g. passenger vehicles, trucks, busses, etc.) were not recorded for this study. Future research should consider the possible impact of volumes of different vehicle classifications on conflicts and investigate if the cross product of turning vehicle and through bicycle volumes would be appropriate to model the relationship between traffic characteristics and right/left-hook conflicts. Also, the impact of signal green times on conflicts should also be investigated.

Acknowledgments

The National Institute for Transportation and Communities funded part of this study. The authors are also grateful to Carl Sundstrom from the New York City Department of Transportation for his assistance and to Bill Schultheiss for his valuable comments. The authors would also like to thank Andrew Schrope and Kelly White from Portland State University and Shota Furugen from Northern Arizona University for their assistance.

References

1. de Hartog J, Boogaard M, Nijland H, Do Hoek G. Do the health benefits of cycling outweigh the risks? Environ Health Perspect. 2010;118 (8):1109–1116.
2. Dill, J., Monsere, C. and N. McNeil. Evaluation of Bike Boxes at Signalized Intersections. Accident Analysis and Prevention, No. 44, pp. 126-134, 2012.
3. Federal Highway Administration, 2013. https://mutcd.fhwa.dot.gov/resources/interim_approval/ia16/
4. Gettman, D., and L. Head. "Surrogate Safety Measures from Traffic Simulation Models." Transportation Research Record: Journal of the Transportation Research Board, No. 1840, pp. 104-15, 2003.
5. Greene, W. H., and D. A. Hensher. Modeling ordered choices: a primer. Cambridge University Press, New York, New York, 2010.
6. Hurwitz, David, Mafruhatul Jannat, Jennifer Warner, Christopher Monsere, and Ali Razmpa. 2015. Towards Effective Design Treatment for Right Turns at Intersections with Bicycle Traffic. Final Report prepared for the Oregon Department of Transportation, SPR 767, 2015.
7. Kassim, A., Ismail, K., and Hassan, Y. Automated Measuring of Cyclist-Motor Vehicle Post Encroachment Time at Signalized Intersections. Canadian Journal of Civil Engineering, Vol 41 (7), July 2014.

8. Kothuri, S., Kading, A., Schrope, A., White, K., Smaglik, E., Aquilar, C., and W. Gil. Addressing Bicycle-Vehicle Conflicts with Alternate Signal Control Strategies. Final Report, National Institute for Transportation and Communities, 2018.
9. Madsen, T., and H. Lahrmann. Comparison of Five Bicycle Facility Designs in Signalized Intersections Using Traffic Conflict Studies. Transport Research Part F, Vol. 46, 2017, pp. 438-450.
10. Mannering, F. L., and C.R. Bhat. Analytic methods in accident research: Methodological frontier and future directions. Analytic Methods in Accident Research, 1, pp. 1-22, 2014.
11. Massachusetts Department of Transportation (MassDot). Separated Bike Lane Planning and Design Guide. 2015.
12. Monsere, C., N. Foster, J. Dill, and N. McNeil. User Behavior and Perceptions at Intersections with Turning and Mixing Zones on Protected Bike Lanes. Transportation Research Record: Journal of the Transportation Research Board, No. 2520, Transportation Research Board, Washington, D.C., pp. 112–122, 2015.
13. National Association of Street Transportation Officials (NACTO). Urban Bikeway Design Guide, Second Edition, 2014.
14. National Highway Traffic Safety Administration (NHTSA), 2015.
15. Paulsen, Kirk, William Farley, Todd Mobley, Michael Ard, and Peter Koonce. "Analysis of Active Warning Sign to Address Potential Bicycle 'Right Hook' Conflict at Signalized intersections." Transportation Research Board 95th Annual Meeting, 2016.
16. Pin, C., Sayed, T., and M.H. Zaki. Assessing Safety Improvements to Pedestrian Crossings Using Automated Conflict Analysis. Transportation Research Record: Journal of the Transportation Research Board, No. 2514, pp. 58-67, 2015.
17. Preusser, D. F., Leaf, W.A., DeBartolo, K.B., and R. Blomberg. The Effect of Right-Turn-On-Red on Pedestrian and Bicyclist Accidents. USDOT, 1981.
18. Pucher, J., R. Buehler, and M. Seinen. Bicycling renaissance in North America? An update and re-appraisal of cycling trends and policies. Transportation Research Part A: Policy and Practice, Vol. 45, No. 6, pp. 451-475, 2011.
19. Räsänen, M., and H. Summala. Attention and expectation problems in bicycle–car collisions: an in-depth study. Accident Analysis & Prevention, Vol. 30, No. 5, pp. 657-666, 1998.
20. Sacchi, E., and T. Sayed. Bayesian Estimation of Conflict-Based Safety Performance Functions. Journal of Transportation Safety and Security, Vol. 8, 2016a, pp. 266-279.
21. Sacchi, E. and T. Sayed. Conflict-Based Safety Performance Functions for Predicting Traffic Collisions by Type. Transportation Research Record: Journal of the Transportation Research Board, No. 2583, pp. 50-55, 2016b.
22. Sanders, R. "Examining the Cycle: How Perceived and Actual Bicycling Risk Influence Cycling Frequency, Roadway Design Preferences, and Support for Cycling among Bay Area Residents." Accident Analysis & Prevention No. 75, pp. 26-34, 2013.
23. Sayed, T., and S. Zein. Traffic Conflict Standards for Intersections. Transportation Planning and Technology, Vol. 22, 1999, pp. 309–323.
24. Van der Horst, ARA. A time based analysis of road user behaviour in normal and critical encounters. Publication no. HS-041 255. Transport and Road Research Laboratory (TRRL). 1990.
25. Washington, S., Karlaftis, M., and F. Mannering. Statistical and Econometric Methods for Transportation Data Analysis (2nd ed.). Boca Raton, FL.: Chapman and Hall/CRC, 2011.
26. Zangenehpour, S., Strauss, J., Miranda-Moreno, L., and N. Saunier. Are Signalized Intersections with Cycle Tracks Safer? A case Control Study Based on Automated Surrogate Safety Analysis Using Video Data. Accident Analysis and Prevention, Vol 86, pp. 161-172, 2015.

Advances in Transportation Studies an international Journal 2020 Special Issue, Vol. 2

ISBN 978-88-255-3451-1 – ISSN 1824-5463 – DOI 10.4399/97888255345113– pagg. 19-32

Analysis, modeling and simulation framework for performance evaluation of the Wyoming connected vehicle pilot deployment program

G. Yang[1] M.M. Ahmed[1,2]

[1]Department of Civil and Architectural Engineering, University of Wyoming, 1000 E. University Avenue, Dept. 3295, Laramie, WY82071
[2]Office of Safety Research & Development, Federal Highway Administration, U.S. Department of Transportation, Turner-Fairbank Highway Research Center, 6300 Georgetown Pike, McLean, VA 22101
email: mahmed@uwyo.edu

Abstract

Wyoming was selected as one of three sites to develop, test, and deploy a suite of Connected Vehicle (CV) applications on a 402-mile of Interstate 80. It is expected that after full deployment of the technology, the pilot will improve safety and mobility by creating new ways to communicate road and travel information to both drivers and fleet managers. One of the key tasks of this pilot is to evaluate the performance of the Wyoming CV system. This paper presents a framework of using microsimulation modeling for performance evaluation of the Wyoming CV Pilot. It describes the opportunities of using microsimulation modeling for performance evaluation, procedure of model calibration and data needs for model calibration, challenges due to data acquirement process specific to the deployment and solutions to the expected challenges. It was concluded that microsimulation modeling is a low-cost approach for assessing the performance of CV systems, particularly when testing various CV strategies and/or CV penetration rates. Nevertheless, the accuracy of the simulation results highly depends on the calibration of microsimulation models. Ultimately, lessons learned from the Wyoming CV Pilot performance evaluation effort will provide added insights to states and transportation professionals that embark on similar initiatives.

Keywords - Wyoming connected vehicle pilot; Analysis, Modeling, and Simulation (AMS) framework; microsimulation modeling; surrogate measure of safety, model calibration

1. Introduction

The Interstate 80 (I-80) in Wyoming is a major freight corridor connecting the east and west in the U.S. Commercial truck volume makes up 30 to 55 percent of the total annual traffic volume and can comprise as much as 70 percent of the seasonal traffic flow on I-80 [1]. Furthermore, its elevation is all above 6,000 feet, with the highest point reaching 8,640 feet (2,633 m) above sea mean level. Being affected by the Wyoming's adverse winter weather conditions such as the notorious strong winds, low visibility and icy road surface from blizzard conditions, and the presences of work zones, there have been remarkable traffic crash records along I-80 in Wyoming, which resulted in fatalities, extended closures, and significant economic loss [1].

To improve traffic safety and mobility of the 402-mile I-80 corridor in Wyoming, the U.S. Department of Transportation (USDOT) selected the Wyoming Department of Transportation (WYDOT) to deploy a Connected Vehicle (CV) Pilot Program along the corridor. The main objectives of the Wyoming CV Pilot Deployment Program include the following [2]: 1) Deploy about 75 roadside units (RSUs) with Dedicated Short-Range Communication (DSRC) that are able to transmit advisories and alerts to equipped vehicles along I-80. 2) Develop several CV applications that utilize vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) and infrastructure-to-vehicle (I2V) DSRC technologies. 3) Equip and operate a set of vehicles that are expected to be regular users of I-80, with on-board units (OBU) with DSRC connectivity.CV technology will enable communication of alerts and advisories regarding various road conditions to drivers. These CV applications mainly include: Forward Collision Warning (FCW), Distress Notification (DN), Situation Awareness (SA), Work Zone Warning (WZW), and Spot Weather Impact Warning (SWIW). Figure 1 illustrates the existing communication and traffic control devices along the Wyoming I-80 corridor, and the DSRC locations that will be deployed on the corridor.

Systems and applications developed within the Wyoming CV Piot Deployment Program will enable CV drivers to have improved awareness of potential hazards and of situations they cannot see. Specifically, this pilot expects to improve operations on the corridor especially during periods of adverse weather and when work zones are present. Through the anticipated outcomes of the pilot, fleet managers will be able to make better decisions regarding their freight operations on I-80, truckers will be made aware of conditions downstream and will be provided guidance on parking options as they travel the corridor. Moreover, automobile travelers will receive improved road condition and incident information through various existing and new information outlets. The expected benefits of the project revolve around objectives of improving safety, mobility and productivity of the users of I-80 in Wyoming [3]. These benefits are directly dependent on the CV applications that will be developed during the Wyoming CV Pilot. Table 1 summarized the expected benefits of the CV applications to various users of the Wyoming CV system.

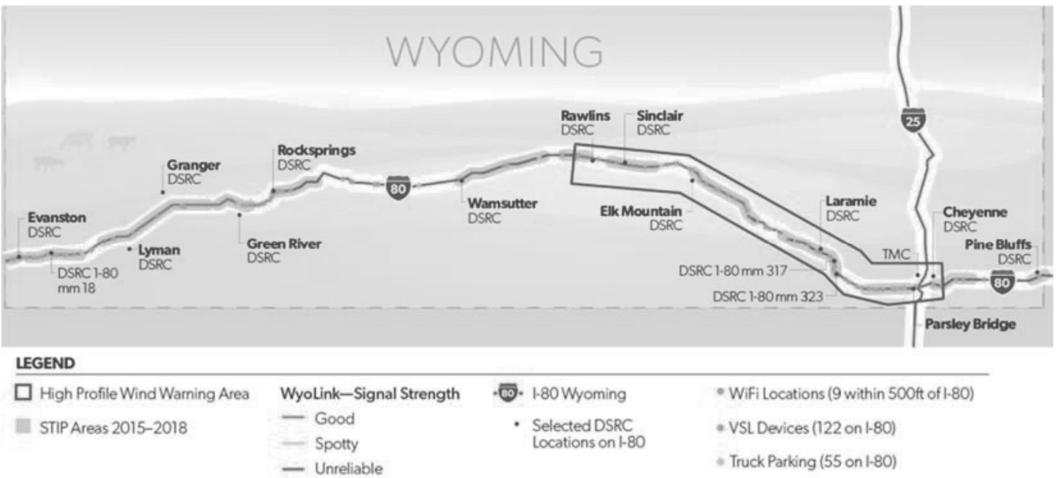

Fig. 1 - Scope of Wyoming CV pilot deployment program [1]