DEVELOPMENT OF FREEWAY CRASH PREDICTION MODELS USING DISAGGREGATE DATA: EFFECTS OF FLOW STATE INFORMATION FROM DIFFERENT SOURCES AND DATA CORRELATION

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ABSTRACT

Transportation safety has always been an intensively researched topic with the goal of better understanding why crashes occur and how different variables affect the occurrence of crashes. Traffic flow conditions, which frequently change with time, can have a significant impact on crash occurrence. Traditional traffic safety analyses of crash frequency or crash rate usually focus on highly aggregated cross-sectional data. Crash analysis methods customarily use annual average daily traffic (AADT) as an exposure measure, which may be too aggregate to capture the effects of variations in traffic flow and operations that occurs throughout the day. Flow characteristics such as variation in speed and level of congestion play a significant role in crash occurrence and are not currently accounted for in the AASHTO Highway Safety Manual (HSM). As a practical matter, relationships between traffic crashes and traffic flow parameters are inherently difficult to establish due to limitations in available traffic data sources. This difficulty is exacerbated by the random nature of crash occurrence and the quality of available crash and traffic data. The restrictions of the current safety prediction methodology limited the evaluation of operational and safety effects of the Active Traffic Management (ATM) system on Interstate 66 in Northern Virginia. The ATM system included advisory variable speed limits (AVSLs), lane use control signals (LUCS), and dynamic hard shoulder running (HSR). The results of the study showed that much of the benefit from the system were tied to the implementation of dynamic HSR as opposed to the AVSL or LUCS. Locations with HSR had a statistically significant reduction of nearly 25% for total crashes. Although crash modification factors could be generated, they may be biased since the system is not active throughout the entire day. As a result, Virginia's AADT-based safety performance functions failed to capture the true dynamic nature of the system.

This research developed a methodology for creating crash prediction models using traffic, geometric, and control information that is provided at sub-daily aggregation intervals. Evaluating how the use of disaggregate geometry and traffic flow data affects crash modeling compared to the current practice of using only aggregated volume data was one major focus of the research. Hourly data from 110 rural 4-lane segments and 80 urban 6-lane segments were used. The volume data used in this study comes from detectors that collect data ranging from continuous counts throughout the year to only a couple of weeks every other year (short counts). Speed data was collected both from point sensors and probe data provided by INRIX. While developing disaggregated models, the difference in data availability and quality from these sources can be a potential source of error. Hence, evaluating the change in performance of prediction models with changes in volume data availability and speed data source was another objective for this research.

The spatial and temporal correlation present in disaggregated data and their influence on crash prediction was also investigated.

The results showed that the best models include a combination of average hourly volume, selected geometric variables, and speed related parameters. Average hourly aggregation of data was found to be the appropriate level of disaggregation to address the variation in volume and speed throughout the day without compromising model quality. Urban segments experience a 20% improvement in mean absolute deviation (MAD) for total crashes and a 9% improvement for injury crashes when models using average hourly volume, geometry, and flow variables were compared to the AADT based model. Corresponding improvements for rural segments were 11% and 9%. Average hourly speed, standard deviation of hourly speed, and differences between speed limit and average speed had statistically significant relationships with crash frequency. For all models, prediction accuracy was improved across all validation measures of effectiveness (MOE)s when the speed components were added relative to performance without speed measures. For example, for urban segments, MAD improved by 11% for total crashes and 5% for injury crashes when speed was added in different forms. Rural segments experienced similar improvement as well. The positive effect of flow variables was true irrespective of the data source for speed. Further investigation revealed that the improvement achieved in model prediction by using a more inclusive and bigger dataset was larger than the effect of accounting for spatial/temporal data correlation. Models using only continuous count station data were contrasted with the models using both short count and continuous count stations. For rural hourly models, MAD improved by 52% when short counts were added in comparison to the continuous count station only models. The respective value for urban segments was 58%. This means that using short count stations as a data source does not diminish the quality of the developed models. A combination of different volume data source with good quality speed data can lessen the dependency on volume data quality without compromising performance. When comparing the models accounting for correlation to the models that used the same dataset but no correlation, MAD improved by 14% for rural segments and 21% for urban segments. While accounting for correlation improved model performance, it provided smaller benefits than inclusion of the short count data in the models.

This research shows that it is possible to develop a broadly transferable crash prediction methodology using hourly level volume and flow data that are currently widely available to transportation agencies. These models have a broad spectrum of potential applications that involve assessing safety effects of events and countermeasures that create recurring and non-recurring short-term fluctuations in traffic characteristics. The models developed in this dissertation will help to close the gap in existing practice and will also ensure the best use of available resources in future research and applications that examine the relationships between operations and safety.

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

To support the vision of zero deaths and serious injuries on the Nation's highways, the Federal Highway Administration (FHWA) is committed to performance-driven highway safety management practices and promoting deployment of innovative safety countermeasures. States have also begun to more aggressively seek ways to improve safety. For example, the 2017-2021 Virginia Strategic Highway Safety Plan sets a fatality target for the state of zero [1]. To achieve this goal of saving lives and reducing motor vehicle crashes and injuries, the state aims to expand the use of data-driven, systemic safety management approaches. Even with this focus, there were an estimated 1.17 fatalities per 100 million vehicle miles traveled nationally in 2017, reinforcing the importance of continuing the effort to understand why crashes occur and how different variables affect the occurrence of crashes [2]. Crashes are complicated events that are influenced by multiple factors, including roadway geometry, drivers' behavior, traffic conditions, and environmental factors. The influence of those factors on traffic crashes cannot be fully understood without detailed information not only on crash itself, but also on its surrounding circumstances.

The Highway Safety Manual (HSM) was first published by the American Association of State Highway and Transportation Officials (AASHTO) in 2010 and serves as the first national resource that provides standard scientific techniques and knowledge to help transportation officials make educated decisions regarding road safety [3]. One of the most integral parts of the HSM is the predictive methodology for determining the expected number of crashes for various facility types. The core of this methodology is the use of safety performance functions (SPFs). A SPF is a mathematical relationship that models the frequency of crashes by severity and accounts for geometric and traffic control factors that impact crashes on specific types of roads. For practical reasons, base SPFs often use a very concise form and include only limited numbers of variables (such as annual average daily traffic (AADT) and segment length).

The HSM provides professionals with a much-needed resource where current knowledge, techniques, and methodologies to estimate future crash frequency and severity are presented. Despite that, there are some limitations of using the SPFs recommended in the HSM. One drawback of using AADT for predicting crashes is that it can be interpreted as a quantity measure, but it cannot be used to assess the quality of flow. Quality of flow is related to the variation in flow parameters such as speed or density on a much shorter time interval, such as hours or minutes, as compared to the yearly variation in volume used for SPF development. Besides that, there are issues with using the AADT as the exposure measure in the SPF. The AADT is the average number of vehicles per day over one year, which means that hourly, daily, and seasonal variations in traffic volume are averaged out. It is generally perceived that crash rates on highways vary with flow state. However, the relationship between flow, speed, and crashes is not simple. The customary means of including annual traffic volumes in safety analysis is too aggregate to capture all the variation in the flow that may impact the occurrence of highway crashes. For example, it does not consider the possibility that the number of crashes during a specific time of day is related to the prevailing flow rate at that time and that this relationship between the prevailing flow rate and the number of crashes varies by time of day.

1.2 MOTIVATION

The motivation for this research emerged from the limitations encountered while evaluating the Active Traffic Management (ATM) system on I-66 in Northern Virginia [4]. The goal of that system was to improve safety and operations on I-66 without physically expanding the existing roadway. The ATM system included advisory variable speed limits (AVSLs), lane use control signals (LUCS), and dynamic hard shoulder running (HSR). All of these components were activated as needed in order to manage congestion based on current traffic or roadway conditions. The results of the study showed that the I-66 ATM system was able to create significant operational and safety improvements along a very congested corridor, although much of the benefit appears to be tied to the implementation of dynamic HSR as opposed to the AVSL or LUCS. Locations with HSR had a statistically significant reduction of nearly 25% and 32% for total crashes (all severity) and fatal and injury crashes, respectively. Prior to the activation of the ATM, the right shoulder on I-66 was open to travel using static hours from 5:30 to 11:00 AM eastbound and 2:00 to 8:00 PM westbound. After the activation, the shoulders were still open during those times of the day, but could also be dynamically opened and closed outside of those times whenever congestion formed, increasing capacity on I-66. One major limitation of this study was that the safety evaluation was carried out using Virginia specific SPFs that used AADTs as an exposure measure. A number of challenges and limitations are associated with conducting a predictive safety analysis of part-time shoulder use with AADT-based freeway models, including their inability to differentiate between a general-purpose lane and the shoulder, inability to explicitly account for the dynamic nature of the use of the HSR, and lack of ability to account for how the HSR changed flow state on the road.

This affects overall crash prediction, especially in cases where traffic control varies with time, such as the part-time shoulder use. Due to these limitations, the safety evaluation failed to capture the true dynamic nature of the system.

The restrictions of current safety prediction methodology served as a motivation to explore new methodologies that could better account for changing flow conditions throughout the day. A study of the relationship of crashes and flow state requires reliable information on crashes, hourly traffic flow data, and factors that influence highway capacity. The reason why this type of analysis hasn't been done in detail previously is because obtaining reliable, temporally disaggregate data about crashes and traffic flow state broadly across the highway system is not a trivial task. Adequate detector coverage and quality of available data are a major issue in most states, making it difficult to acquire widespread information on quality of flow. Review of current practice reveals that the reason behind using aggregated volume is that AADT is the most widely available format of volume data. Volume data is collected by each state from both a limited set of continuous count stations which collect data continuously throughout the year or more broadly using short count stations that collects data periodically for shorter time intervals. The quality of continuous count data is very high, even though the total numbers of stations are limited. On the other hand, the short count stations have a broader network but the quantity of data available from them is much less. Both of these issues can be crucial since current crash models depends on volume data.

One way to address this concern is to add other variables in the modeling process that captures the variation in traffic, such as speed. Private sector probe data theoretically provides 24-hour temporal coverage and broad network coverage spatially. As availability and reliability of observed traffic data significantly affect the accuracy of crash predictions, using probe data, which has better network coverage, might be useful to improve the availability of data. If a relationship could be developed between crash frequency and speed data along with different levels of volume aggregation, then the quality of volume data can be adjusted. This might help transportation agencies make better use of their resources since they could use the short volume count stations along with broadly available probe data.

Most of the research available for disaggregated studies focused on selected segments of a particular facility and didn't consider the roadway system as a whole. Another important issue in crash modeling with multiple years of data is presence of spatial and temporal correlation. The HSM recommended methodology does not acknowledge correlation in data. This issue is even more acute while using disaggregated data.

Based on the gap in current practices, there are multiple research needs this dissertation seeks to address:

- Assessment of whether inclusion of flow state variables improves crash prediction models.
- Examination of whether using different levels of data disaggregation (raw data, 15-minute average, hourly average, annual) impacts model performance.
- Evaluation of whether sub-annual models are impacted by the level of availability of volume data from different sources (continuous count data vs. short count data).
- Identifying whether the sources of speed data (probe data or sensor data) impacts model performance.
- Assessment of the effects of incorporating spatial and temporal correlation in crash prediction models.

If these gaps can be overcome, crash predictions models that could be broadly applied to sub-daily data could become available that would produce much finer grained results than the ones in broad usage today. These more disaggregate models could be extremely useful in examining countermeasures or traffic flow changes that occur as a result of time-varying operational measures, which cannot be reasonably assess using current methods.

1.3 RESEARCH OBJECTIVES

This research sought to achieve five main objectives:

1. Determine whether sub-daily crash predictions models can provide better safety predictions than AADT models, and what time interval works best for predictions.
2. Determine if inclusion of traffic state variables improves predictions.
3. Evaluate different sources for speed data and change in quality of crash prediction models based on data sources. This has implications for how whether models that rely on speed can be deployed widely.
4. Investigate whether the data from non-continuous count stations can be used to generate quality predictions. This has implications on whether continuous volume data is required to generate sub-annual predictions, which could affect whether models can be applied widely.
5. Investigate whether including spatial and temporal correlations creates significant improvements in the models.

The scope of this research was limited to two lane directional segments of rural basic freeway segments and three lane directional segments of urban basic freeway segments. These cross sections were selected because they are the most common freeway segment type in Virginia.

1.4 EXPECTED CONTRIBUTIONS

The restrictions of current crash prediction models and limitations related to available quality of volume data are acknowledged among researchers and professionals, and methods seeking to develop sub-daily crash predictions methods is an emerging research area nationally. There is ongoing research to develop quantitative tools to evaluate safety performance of freeways where part-time shoulder use is allowed based on a function of temporal, operational, and other conditions [5]. Another research project seeks to estimate the expected crash frequency and severity of a range of freeway facilities with HOV or HOT lanes with various geometric and traffic volume characteristics since the HSM currently does not address this [6]. NCHRP 19-21 is conducting a research effort for developing a predictive methodology for rural two-lane, two-way highways incorporating speed measures (or surrogates for speed measures) to estimate crash frequency and severity [7]. Another proposed research statement by NCHRP is going to explore the development of short-term crash prediction models to estimate the safety performance of roads for specific geometric, operational, and exposure characteristics [8]. As a result, there is currently a great deal of national interest in the topics addressed in this dissertation, and no accepted methods to address the problems investigated currently exist. The work performed in this dissertation will provide valuable knowledge in this developing area of research.

1.5 ORGANIZATION OF REPORT

The remainder of this report is organized as follows:

- Chapter 2: Literature review
  - This chapter summarizes existing research findings, and further elaborates on the gaps in prior research briefly discussed in this chapter.

- Chapter 3: Safety and Operational Effects of the Interstate 66 Active Traffic Management System. *ASCE Journal of Transportation Engineering, Part A: Systems*. Volume 145 (3), December 2018.
  - This paper provides the motivation for research and identifies research needs this dissertation can address.

- Chapter 4: Developing Rural Four Lane Freeway Crash Prediction Models Using Hourly Flow Parameters. *International Association of Traffic and Safety Sciences (IATSS) Research*. Submitted on December 2018 (Under Review). Presented at *Transportation Research Board 98th Annual Meeting*, January 2019.
    - This paper investigated the effect of including geometric features and hourly flow parameters. Models were developed using both raw hourly data and average hourly and contrasted against AADT-based models. This paper addresses research objective 1 and 2.

- Chapter 5: Improving Freeway Segment Crash Prediction Models by Including Disaggregate Speed Data from Different Sources. *Accident Analysis and Prevention.* Submitted on December 2018 (Minor Revisions Under 2nd Review). Presented at *Transportation Research Board 98th Annual Meeting*, January 2019.
    - This paper evaluated the relationship between crashes and quality of flow both at 15 minute and hourly levels of aggregation using different geometric and traffic variables. Models were first developed using speed data from continuous count stations, and then these models were repeated using the probe data from INRIX. A comparison between these two data sources in terms of prediction accuracy is one of the major objectives of this paper. Objective 1, 2 and 3 were examined in this paper.

- Chapter 6: Assessment of the Impacts of Spatial and Temporal Correlation and Incomplete Volume Data on Freeway Hourly Crash Prediction Models. *(To be submitted to Accident Analysis and Prevention)*
    - The objectives of this paper are to define the relationship between average hourly crash frequency on freeways and explanatory variables that vary with time and geography using data commonly available to transportation agencies over a broad network. The volume data used in this study comes from detectors that often did not collect data continuously, so the research sought to determine if positive results previously obtained with continuous count station data were transferable to locations with lower volume data availability. Hence, evaluating the change in performance of prediction models with changes in volume data availability and accounting for the presence of correlation in data were examined as a way to

broaden the applicability of these models to transportation agencies. This paper covers research objectives 4 and 5.

- Chapter 7: Conclusions and Recommendations:
    - ➢ This chapter describes the importance of the research and the expected contribution of the developed methodology. It also provides a short case study to illustrate the possible use of the developed models in practice.
- Publications and Presentations

1.6 REFERENCES

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CHAPTER 2: LITERATURE REVIEW

Although the papers included in this dissertation include separate literature reviews, paper length limitations sometimes prohibit a deeper discussion of past work. As a result, this chapter provides a longer and more integrated discussion of past research relevant to this dissertation, including discussions of the gaps in prior work that this dissertation seeks to address.

Crash prediction models are very useful tools in highway safety, given their potential for determining both the frequency of crash occurrence and the contributing factors that could then be addressed by transportation policies or site interventions. In addition, these models can also assist with the development of generalized theories concerning road safety. Numerous statistical models have been developed to predict the expected number of crashes on roads as well as to identify the various factors associated with the occurrence of crashes. These factors can be categorized into human factors, traffic flow characteristics (e.g. volume, speed), roadway characteristics (e.g. geometric designs and pavement conditions), and environmental conditions (e.g. weather and surface conditions). This chapter highlights some existing research on the disaggregated studies and discusses the issue associated with data availability and correlation.

2.1 CURRENT PRACTICE FOR TRAFFIC DATA COLLECTION

Traffic data plays an important role in establishing traffic characteristics of roadways. Accurate and reliable measurements of traffic counts, speed, and vehicle classification are critical for traffic monitoring, planning, and traffic design. The reliability and accuracy of this data is greatly dependent on the number and placement of data collection sites (e.g., continuous count, short count, weigh stations, etc.) throughout the system. Sensor data collection sites are limited resources, so the deployment needs to be optimized given locational and budgetary restrictions. According to the FHWA's Traffic Monitoring Guide, the primary objective of a statewide continuous count program is to develop daily, hourly, or seasonal factors from volume data in addition to collecting speed and vehicle classification data [1]. The above time varying factors help to compute short duration counts, such as ADT and area wide coverage counts.

The Virginia Department of Transportation's (VDOT) traffic data collection program includes more than 100,000 traffic roadway segments where data are collected and traffic estimates produced. There are more than 400 continuous count stations across the state, 140 of which are on the Interstates [2]. The continuous count stations collect data 24 hours a day, 365 days a year. They provide volume and classification data, as well as data needed to calculate the adjustment factors to apply to short-term counts. VDOT also has short-duration count stations throughout the state in an effort to ensure that at least some data exist for all roads maintained by the agency, even if it's not real time. Short-count durations range from 48 hours to longer periods less than a year. Even though the data derived from these stations are of high quality, it is also restricted to the location of these stations. On the other hand, the short count stations have a broader network but the quantity of data available from them is less. Each state has its own traffic data collection needs, priorities, budgets, geographic, and organizational constraints. These differences cause agencies to select different equipment for data collection and use different data collection plan.

2.2 RELATIONSHIP BETWEEN CRASHES AND HOURLY EXPOSURE

Studies of relationships between crashes and traffic characteristics can be divided into two categories: aggregated studies, in which the units of analysis represent counts of crashes or crash rates for specific time periods (typically months or years) and disaggregated analysis, where the units of analysis are the crashes themselves and traffic flow is represented by parameters of the traffic flow at the time and place of each crash. Disaggregate studies are relatively new and typically use data based on average hourly observations of crash rates and traffic flow.

Ivan et.al concluded that there is evidence that the hourly volume explains much of the variation in highway crash rates. They focused on actual hourly exposure values of seventeen rural, two-lane highway segments in Connecticut, with varying land-use patterns [3]. Single-vehicle and multi-vehicle crashes were modeled separately. Time of day was significant for both types of crash, but in different ways. Single-vehicle crashes occurred most often in the evening and at night. On the other hand, multi-vehicle crashes were more likely to occur under daylight conditions at midday and during the evening peak period. This is when traffic volumes are the heaviest, and there are more discretionary trips than in the morning peak period.

Persaud and Dzbik developed crash prediction models at both the macro level (in crashes per unit length per year), and micro level (in crashes per unit length per hour) using the generalized linear modeling approach with negative binomial error structure [4]. Crash, road inventory, and traffic data for approximately 500 freeway sections in Ontario was obtained for 1988 and 1989. Microscopic models showed a decreasing slope in regression lines, as hourly volume increased, perhaps capturing the influence of decreasing speed. This is in contrast to the macroscopic model, which showed increasing slopes. The afternoon congested period had a higher crash risk than the morning rush period, but the difference was only significant for the express system.

Perhaps the most extensive evaluation of this subject was a 1967 to 1975 study of eight sections of four-lane interurban road in Israel [5] . Single-vehicle rates were extraordinarily high for flow rates below 250 vph. The multiple vehicle rates were more diverse, with half the sites showing a substantial increase in rates for flow rates greater than about 900 vph, and the remaining sites exhibiting little change with increases in hourly traffic volumes. When the two crash types were combined, the results were dominated by the data for multiple-vehicle crashes. More specifically, those study sections that encompassed a broad range of traffic volumes had a U-shaped relationship when crash rates were plotted as a function of hourly volume; the minimum rate occurred near 500 vph. The remaining four sites, three of which did not have hourly volumes in excess of 1,000 vph, did not show an increase in crash rates as hourly volumes increased.

2.3 EFFECT OF ROADWAY GEOMETRY ON CRASH PREDICTION MODELS

A large number of studies have examined the impact of various geometric factors on safety, and their influence is well documented. For example, Khan et al. developed prediction models for total crashes and fatal or injury crashes for rural horizontal curves on undivided roads using a data set of 11,427 rural horizontal curves on Wisconsin state trunk network roads [6]. The result shows that as the difference between posted and advisory speed limit on the curve increases, more crashes are expected. The tangent length upstream of a curve was used as a categorical variable where the base condition was a tangent length greater than 2,600 feet (approx. 0.5 miles). The results show that compared with base conditions, less crashes are expected as tangent length decreases which points to possible driver expectancy issues as they approach the first horizontal curve after a long tangent section.

Another study was performed to determine the horizontal curve features which affect safety and traffic operations and to quantify the effects on crashes of various curve-related improvements [7]. The data base included the cross-sectional data base of nearly 5,000 miles of roadway from 7 states. Based on statistical analyses and model development, it was found that curve flattening is expected to reduce crashes by up to 80%, depending on the amount of flattening. Widening lanes or shoulders on curves can reduce curve crashes by as much as 33%, while adding spiral transitions on curves was associated with a 5% crash reduction.

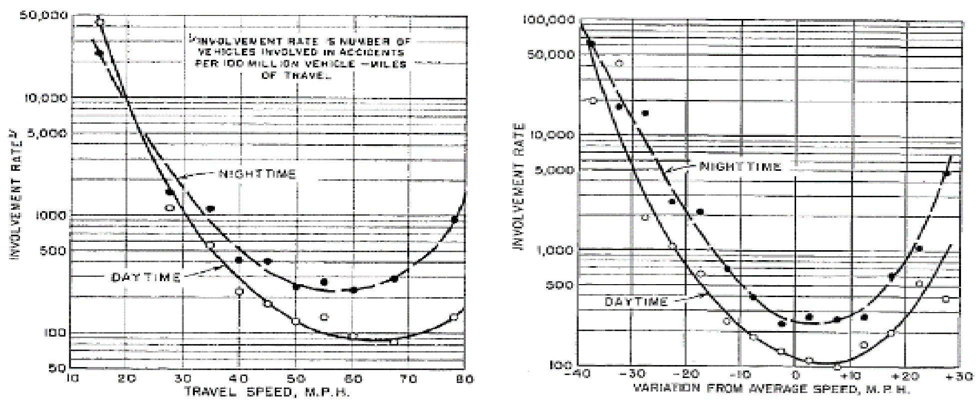
Milton and Mannering examined the association between various geometric features and crash frequency while controlling for traffic exposure [8]. The primary data sources were the Washington State Department of Transportation's database for geometric and traffic information and the Washington State Patrol's accident database for accident information from 1992 and 1993. The researchers found that more crashes are expected on sharper and longer horizontal curves. Sharp curves with more space between them tend to increase the crash probability for collectors in Western Washington but decrease the probability for collectors in Eastern Washington. It was also found that vertical grade greater than 2.5% tends to increase crash probability for principal arterials in Washington. Another analysis of a 61 km portion of I-90 in Seattle showed that grade has a strong positive effect on crash frequency [9]. In comparison to those sections with grades less than 2%, those with maximum grades exceeding 2% experienced a significant increase in crash frequency.

A NCHRP report that summarizes median related crashes indicated that wider medians generally will have more crashes [10]. Even though wider median causes more crashes, fewer of them would be severe. The crash analysis also shows that cross median crashes would keep decreasing, and rollover crashes would keep increasing continuously as the median width increases. Another study in Illinois also looked into the effect of geometry on crashes [11]. Illinois Department of Transportation provided traffic, geometric and crash information from 2002 to 2005. The traversable, curbed, and painted medians would increase the expected crash frequency when compared to segments with no median. The unprotected median causes a reduction in crash frequency compared to segments with no median.

2.4 RELATIONSHIP BETWEEN CRASHES AND FLOW PARAMETERS

When considering the flow of traffic along a freeway, three parameters are of considerable significance. Speed and density; which describe the quality of service experienced by the stream, and volume; which measures the quantity of the stream and the demand on the highway facility. Similar flows could be attributed to different combinations of density and speed, leading to different levels of safety. Speed is an important descriptor of traffic operations that has an effect on crash severity and frequency, but this variable is difficult to accurately capture in aggregate models that use AADT to predict annual crashes. The speed distribution may also play an important role since variance in speed is higher for lower traffic flows than for more congested conditions. That is why it is not enough to just consider volume and segment length as only variables while predicting crashes on freeways. By introducing parameters such as speed, density, or v/c in addition to traffic volume, crash analysis takes into account the effect on traffic operations of both roadway characteristics, and traffic characteristics.

In 1964 the Federal Highway Administration (FHWA) published a report by David Solomon in which he studied of the relationship between crashes on 2-lane and 4-lane roadways and a number of factors [12]. From an analysis of 10,000 crashes, Solomon concluded that crash severity increased rapidly at speeds in excess of 60 mi/h, and the probability of fatal injuries increased sharply above 70 mi/h. He found a relationship between vehicle speed and crash incidence that is illustrated by a U-shaped curve in Figure 1. Crash rates were lowest for travel speeds near the mean speed of traffic, and increased with greater deviations above and below the mean. Solomon's work is often cited as the source of the 85th percentile speed rule for setting speeds.



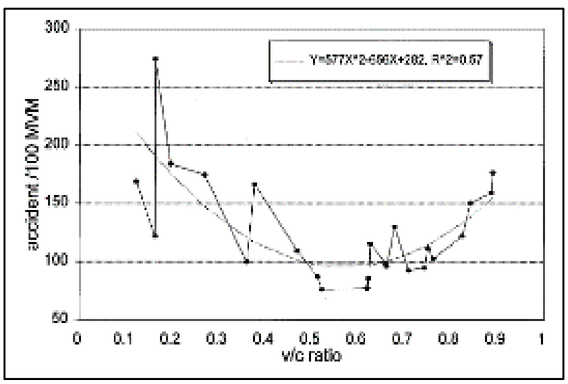
(a) (b)

FIGURE 1: Relationship between crash rates and (a) travel speed, (b) variation from average speed [12]

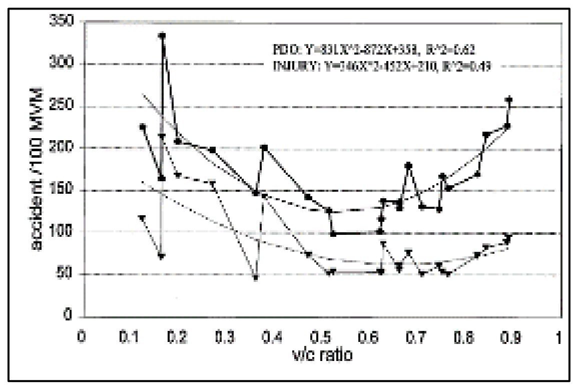
Harkey, Robertson, and Davis also replicated the U–shape relationship between speed and crashes on urban roads [13]. The researchers compared the police–estimated travel speed of 532 vehicles involved in crashes over a 3–year period to 24–hr. speed data collected on the same section of non–55–mi/h roads in mostly built–up areas of Colorado and North Carolina. To partially address the concerns of earlier studies and make the crash and speed data more comparable, their analysis was limited to non–intersection, non–alcohol, and weekday crashes.

Empirical examination of the relationship between flow–density, speed, and crash rate on selected freeways in Colorado by Kononov et. al. suggested that as flow–density increases, the crash rate initially remains constant until a certain critical threshold combination of speed and density is reached [14]. Once this threshold is exceeded, the crash rate rises rapidly. The rise in crash rate may be caused by flow compression without a notable reduction in speed; resultant headways are so small that drivers find it difficult or impossible to compensate for error and avoid a crash. The researchers calibrated performance functions for corridor-specific safety that relate crash rate to hourly volume–density and speed.

Zhou and Sisiopiku examined the general relationships between hourly crash rates and hourly traffic volume/capacity (v/c) ratios using a 16-mile segment of Interstate I-94 in the Detroit area [15]. The v/c ratios were calculated from average hourly traffic volume counts collected in 1993 and 1994 from three permanent count stations. The correlation between v/c values and crash rates followed a general U-shaped pattern. U-shaped models also explain the relationship between v/c and crash rates for weekdays and weekend days, multivehicle and property-damage-only crashes. On the other hand, single-vehicle, and crashes involving injury and fatality follow a generally decreasing trend with increasing v/c ratio (Figure 2).



(a) Total Crashes (Weekdays & Weekends)



(b) PDO & Injury Crashes.

FIGURE 2: Relationship between & crash rate & v/c ratio investigated by Zhou et.al. [15]

Lord et. al. developed predictive models from data collected on freeway segments from Montreal, Quebec [16]. The study period covered 5 years from 1994 to 1998 inclusively. Various traffic flow characteristics were obtained from permanent and temporary count stations. For rural segments, as density and V/C increased, the number of single-vehicle crashes decreased and the number of multi-vehicle crashes increased. The data showed that crashes become less severe with an increasing v/c ratio, but did not seem to be affected by the density. The results also show that predictive models that use traffic volume as the only explanatory variable may not adequately characterize the crashes on freeway segments. Functional forms that incorporate density and v/c ratio offer a richer description of crashes occurring on these facilities.

Imprialou et al. re-examined crash–speed relationships by creating a new crash data aggregation approach that enables improved representation of the road conditions just before crash occurrences [17]. Using Strategic Road Network of England in 2012, development of an alternative data aggregation concept (condition based approach) was developed that defines the pre-crash traffic and geometric conditions as the crash aggregating factors. Compared to the approaches that assign crashes into groups based on their spatial relationship with road entities (link based approach), the new method addresses the inherent problem of over aggregation of time-varying traffic variables and relevant information losses that may affect the modelling outcomes. Speed has been found to be a significant contributory factor for the number and the consequences of crashes when the data are modelled with the condition-based approach. In contrast to that, according to the results of the link-based model speed has a negative relationship with crash occurrences for all severity types. From a methodological point of view, the difference in the results of these approaches reveals that the data aggregation method is an important decision before conducting a crash data statistical analysis.

Evaluation of freeway safety as a function of traffic flow by Golob et al. revealed that the highest crash rates (6.3 crashes per million vehicle miles traveled (VMT)) occurred during the morning peak period with heavily congested flow, corresponding to low mean speeds, low speed variation, low flows, and low flow variation. In contrast, the lowest crash rates (0.6 per million VMT) were characterized by high speeds and low speed variation [18].

Yu et al. investigated the impacts of data aggregation approaches based on traffic data from Shanghai's urban expressway system [19]. Crash frequency analyses with a segment-based approach and a scenario-based approach were conducted first, and then crash risk analyses were developed at the individual crash level. It was found that during the congested period, an increase in operating speed would reduce crash likelihood. For medium operating speeds, the changes in operating speed do not have substantial effects on crash occurrence probability. For free-flow periods, increases in operating speed would further increase the probability of crashes.

Garber and Earhart analyzed the effect of speed, flow, and geometric characteristics on crash rates for different types of Virginia highways [20]. The data were obtained from Virginia Department of Transportation (VDOT) and from police accident reports from January 1993 to September 1995. Based on this study, all of the models show that under most traffic conditions, the crash rate tends to increase as the standard deviation of speed increases. The effect of the flow per lane and mean speed on the crash rate varied with respect to the type of highway.

A recent study by Wang et al developed different models to estimate crash frequency using annual daily traffic and annual hourly traffic [21]. The study segments were from three expressways in Orlando, Florida and included basic freeway segments, merging segments and weaving segments. It was found the logarithm of volume, the standard deviation of speed, the logarithm of segment length, and the existence of a diverge segment were significant in the models. Weaving segments experienced higher daily and hourly crash frequencies than merge and basic segments.

2.5 EFFECT OF CORRELATION ON CRASH PREDICTION MODELS

Statistical methods that incorporate panel data structure have gained popularity due to their capacity to address both time-series and cross-sectional variations. McCarthy employed fixed-effects negative binomial models to examine fatal crash counts using 9 years of panel data for 418 cities and 57 areas in the U.S. [22]. A negative binomial regression with cross sectional data using the same dataset couldn't capture the interaction among crashes and variables properly. Noland used fixed- and random-effects negative binomial models to investigate the effects of roadway improvements on traffic safety using 14 years of data for all 50 U.S. states [23]. Random effects negative binomial model (RENB) was found to be more suitable than the conventional NB model. In the RENB model, the joint effects of the unobserved variables are assumed to follow certain distributions along the spatial and temporal dimensions.

Another popular methodology that has been advocated in recent years is random parameters negative binomial (RPNB) model. Three years of crash data (2005–2007) were obtained from the Florida Department of Transportation for two-lane two-way urban roads in Florida to quantitatively examine the variations in effect of road-level factors on crash frequency across different regions [24]. A Poisson lognormal model, hierarchical random intercept model, and hierarchical random parameter were built for the purpose of comparison. The result shows that the hierarchical random parameter model out-performs the Poisson lognormal model and the hierarchical random intercept model. Compared to the RENB model, rather than treating the intercept term as the only random component, the RPNB model allows each estimated parameter to vary across individual observations, including the unobserved heterogeneity along the spatial and temporal dimensions.

A study by Li et al. used a mixed-effect negative binomial (MENB) regression model and BPNN neural network model to consider bus crashes [25]. The performance of MENB model results shows that it is advantageous to use a mixed-effects modeling method to predict accident counts in practice because it can take into account the effects of specific factors. Another analysis on urban road segments in Turin, Italy also favored the use of mixed effect models [26]. Data from 2006 to 2012 were used and traffic flows and weather station data were aggregated in 5 minutes intervals for 35 minutes across each crash event. Two different approaches, a back-propagation neural network model and a mixed effect model, were used. The researchers concluded that the mixed model not only performed well but was also easier to interpret. The mixed effect models combine two popular methodologies for modeling repeated measurements of crash data – fixed effects and random effects models. They are also widely accepted for their ability to handle both spatial and temporal correlation in data.

2.6 GAPS IN EXISTING LITERATURE

Studies of relationships between crashes and traffic characteristics can be divided into two categories: aggregated studies, in which the units of analysis represent counts of crashes or crash rates for specific time periods (typically months or years) and disaggregated analysis, where the units of analysis are the crashes themselves and traffic flow is represented by parameters of the traffic flow at the time and place of each crash. Prior research has not compared the performance of models based on different level of disaggregation, however [3-5]. This dissertation developed sub-daily crash predictions models and compared them with AADT models and determined what aggregation interval produced the best predictions.

There has been considerable research conducted in recent years into establishing relationships between crashes and various traffic flow characteristics for freeway segments. Despite that, there are several major gaps in existing research that this study intends to fill. Most of the research has focused on determining the relationship between crashes and highway traffic volumes, while little attention has been focused on the relationships of vehicle density, level of service (LOS), v/c ratio, and speed distribution [3,6,7,9]. Most researchers only focused on selected segments of a particular facility and didn’t consider the roadway system as a whole while exploring the relationship between crash rates and flow parameters [14-17]. This dissertation used rural 4 lane and urban 6 lane freeway segments from across the Virginia interstate system and explored relationship between crash frequency and different speed parameters.

These previous studies relied on data from point detectors; hence limiting the coverage. As availability and reliability of observed traffic data significantly affect the accuracy of crash prediction models, using probe data, which has better network coverage, might be useful to improve the availability and quantity and quality of speed data. This research compared different speed data sources and corresponding change in model quality. Whether data from non-continuous count stations can be used to generate quality predictions was also investigated.

A detailed analysis involving a large sample size, representing data from all facility types and a comprehensive analysis of crashes with spatial and temporal correlation are missing from the existing literature. The crash prediction models developed in this dissertation will help to close the gap in that direction and will facilitate the assessment of a facility where conditions are different for different times of day.

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CHAPTER 3

SAFETY AND OPERATIONAL EFFECTS OF THE INTERSTATE 66 ACTIVE TRAFFIC MANAGEMENT SYSTEM

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ABSTRACT

An Active Traffic Management (ATM) system was activated on I-66 in Northern Virginia in September 2015. The ATM system included advisory variable speed limits (AVSLs), lane use control signals (LUCS), and dynamic hard shoulder running (HSR). This paper quantifies the operational and safety effects of the ATM system on I-66 using approximately 2 years of crash and operational data following system activation. The operational analysis showed that off peak hours experienced significant travel time improvement after the ATM system was activated, but peak periods in the peak direction of travel generally did not see improvement. Further analysis revealed that most of these improvements occurred on the HSR sections. The safety evaluation results showed 4%, 4%, and 6% reductions in total (all severity), multiple vehicle (all severity), and rear end (all severity) crashes, respectively, across the entire corridor. Segment-level analysis again showed that the most safety benefits were observed at locations with HSR (31% - 38% crash reductions), and no significant reductions were found on the sections with only AVSLs and LUCS.

INTRODUCTION

An Active Traffic Management (ATM) system has been installed on Interstate 66 (I-66) from Centreville (Exit 52/U.S. 29) to the Capital Beltway (Exit 64/I-495) in Northern Virginia. This project was completed in September 2015 and spans approximately 19.96 kilometers (12.4 miles) in each direction. The goal of the ATM system was to improve safety and operations on I-66 without physically expanding the existing roadway. Twenty-two gantries were installed in each direction at an average spacing of 0.97 kilometers (0.6 miles) to provide continuous delivery of information to drivers. ATM components that were installed on I-66 include:

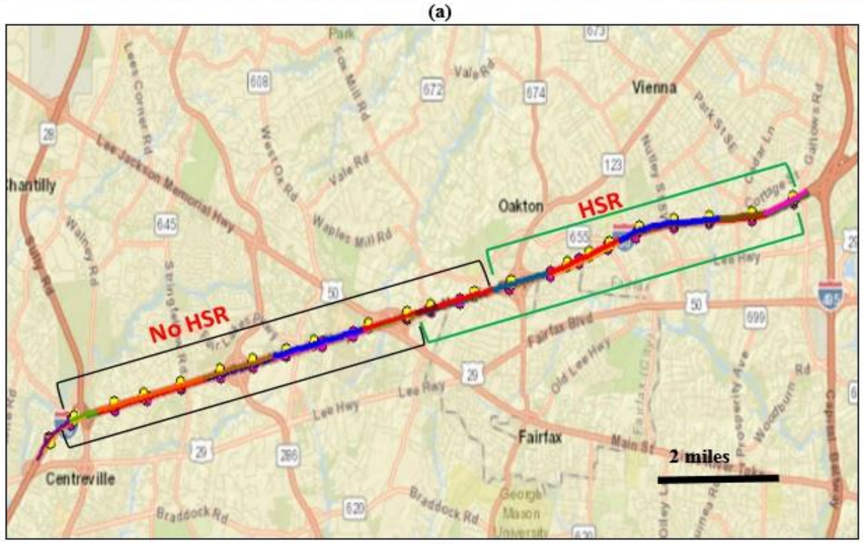
- Advisory variable speed limits (AVSLs) which post dynamic advisory speed limits on overhead gantries above each lane. The normal posted speed limit on I-66 is 24.59 m/s (55 mph), but the AVSL can post speeds between 15.65 m/s (35 mph) and 22.35 m/s (50 mph) based on traffic conditions *(Chun 2016).* An automated algorithm determines the desirable posted speed limit based on observed traffic speeds from sensors, which are then processed, smoothed, and grouped to create transitions into and out of congestion.

- Lane use control signals (LUCS) are also found on the gantries, and they provide information on lane utilization when an incident or work zone are present. Drivers are advised that a lane is open (down green arrow), a lane is closed ahead (diagonal down yellow arrow), or a lane is closed (red X) *(Dutta 2017).*

- Dynamic hard shoulder running (HSR) dynamically opens and closes the shoulder to traffic based on traffic conditions. Prior to the activation of the ATM, the right shoulder on I-66 was open to travel on a static time of day basis during the peak period in the peak direction. After the activation, the shoulders were still open during those times of the day, but could also be dynamically opened and closed outside of those times whenever congestion formed *(Chun 2016).*

These components of ATM have been implemented in different combinations along I-66. Figure 1a shows an example of AVSL activation while the hard shoulder is closed to travel. While the entire ATM corridor had LUCS and AVSLs, Figure 1b shows which sections also had HSR. Table 1 describes the characteristics of the various segments with their respective ATM features.

(a)



(b)

Figure 1: ATM components on I-66 showing (a) AVSL Activation with HSR closed and (b) HSR Locations

Table 1. ATM components on I-66 Corridor

Segment	Location	Approx. Length (mi.)	AADT (2016)	ATM Techniques	Roadway Characteristics
1	US-29 (Exit 52) to VA-28 (Exit 53)	1.3	EB: 67,000 WB: 66,000	AVSL, LUCS	Four lanes in each direction. HOV-2 present in left-most lane. HOV-2 operating hours are 5:30 to 9:30 AM EB and 3:00 to 7:00 PM WB. They are not dynamic.
2	VA-28 (Exit 53) to VA-286 (Exit 55)	1.9	EB: 80,000 WB: 81,000	AVSL, LUCS	
3	VA-286 (Exit 55) to US-50 (Exit 57)	2.6	EB: 64,000 WB: 61,000	AVSL, LUCS	
4	US-50 (Exit 57) to VA-123 (Exit 60)	1.9	EB: 92,000 WB: 92,000	AVSL, LUCS, HSR	Three lanes + shoulder lane in both directions. Right-most shoulder lane is used as travel lane during respective peak hours. Left most lane operates as HOV-2 lane from 5:30 to 9:30 AM EB and 3:00 to 7:00 PM WB. These lanes are not dynamic.
5	VA-123 (Exit 60) to VA-243 (Exit 62)	2.1	EB: 93,000 WB: 86,000	AVSL, LUCS, HSR	
6	VA 243 (Exit 62) to I-495 (Exit 64)	3.2	EB: 81,000 WB: 86,000	AVSL, LUCS, HSR	

OBJECTIVES AND SCOPE

The purpose of this study is to quantify the operational and safety improvements that occurred as a result of the I-66 ATM system, using data from over a year of operation. A previous study provided some preliminary operational results based on the available data after 5 months of operation, but no safety findings could be determined at that point *(Chun 2016)*. Since that evaluation, Virginia Department of Transportation (VDOT) familiarity and comfort with the system has increased, creating changes in operational effectiveness from that earlier preliminary evaluation. Since HSR was manually activated by traffic operations center personnel, there was a learning curve in how the HSR was deployed. Initially, the use was relatively conservative. As the operators gained more experience with the system, they began to use the HSR more aggressively to mitigate congestion. Likewise, enough crash data has accumulated to determine statistically valid results on the safety effects of the system, which was not previously possible. This paper seeks to better characterize the steady-state effectiveness of the system, both in terms of traffic operations and safety.

LITERATURE REVIEW

A number of past studies have examined ATM, and Tables 2, 3, and 4 summarize selected ATM field deployments in the United States, Germany and United Kingdom. Since ATM deployments in the United States are relatively new, most of the evaluation results have been preliminary, however, and are often focused on VSL only applications *(Lucyshyn 2011, Jacobson 2012).* Evaluation results of ATM deployments in Europe have shown improvements in operational measures (throughput, travel times, and reliability) and safety *(Mirshahi 2007)*. Since driving behavior and operational conditions (like the presence of automated speed enforcement) are often different in Europe, those results may be difficult to translate to U.S. applications. Given the limited U.S. experience with ATM and difficulties translating international experience to the U.S., there is still a need to continue to document and evaluate American ATM systems.

Table 2. Summary of the Effects of ATM Deployments in the United States

Location and Reference	ATM Features	Research Design	Operational Effect	Safety Effect	Comments
I-5, Washington *(DeGaspari 2013)*	VSL, QWS	• Total of 8 months before and after period using 19 loop detectors	• Reliability improved by 15 - 31%	N/A	• Used detector data for analysis of entire roadway
I-4, Florida *(Lucyshyn 2011)*	VSL	• Study period from 4PM to 6PM • 21 days of before VSL data and 30 days of after VSL data analyzed	• Speed changes were correlated with changes in occupancy more than changes in the posted speed limit	N/A	• Before and after periods do not match by season • Only focused on peak period
I-27/I-255 in St Louis, Missouri *(Bham 2010)*	VSL	• One year before (2007) and after (2009) data • Crashes examined with Naïve and EB methods	• Average volume improved by 10% after VSL implementation • Public and law enforcement are aware of the system, but were not satisfied with it.	• 11% reduction in total crashes, 3% reduction in rear end crashes. • 6 to 8% reduction in crashes using EB and naïve before and after studies	• Additional outreach and education needed
I-35W and I-94, Minnesota *(Hourdos 2013, Hourdos 2014)*	VSL	• Single loop detectors, video recordings, crash records • 9 months of before VSL data and 17 months of after VSL data for operational analysis • 6 months of before VSL data and 6 months of after VSL data for safety analysis	• During AM peak period, 17% less congestion with the VSL system in operation for speed drop thresholds of 25 mph or more • 7.6 minute less congestion during the average AM peak	• Traffic pattern shows gradual decrease in speeds during the onset of congestion • No change in crash rates	• Used single loop detector data for analysis of entire roadway
I-260 and I-255, Missouri *(Kianfar et al., 2010)*	VSL	Total of 38 miles • Three bottleneck locations	Pre-queue flow decreased by up to 4.5% • Queue discharge flow decreased by up to 7.7% • Average speed fluctuated, but speed variance declined at all bottleneck locations	N/A	• Findings true for bottleneck locations only. Not plausible to conclude that the results apply to the entire roadway.

TABLE 3 Summary of the Effects of ATM Deployments in Europe

Location	ATM Features	Research Design	Operational Effect	Safety Effect	Comments
Germany, A99 *(10)*	VSL	• Used 14 dual-loop detectors to examine 18 bottleneck cases	• Lane utilization was distributed more evenly at the slight cost of capacity • Flow change reduction of 4% when VSL was on and flow change reduction of 3% when VSL was off	N/A	• Used 31 weekdays (25 days when VSL-ON and 6 days when VSL-OFF) for data analysis
Germany, A5 *(11)*	VSL	• No methodology provided	N/A	27% reduction in crashes with heavy material damage and 29% reduction in crashes with personal damage	
U.K., M42 *(12)*	VSL, HSR	• 12 months of before and 12 months of after data analyzed • 1 month of settling in period	• Average capacity increase of 7% • Total flow increases of 6% (NB) and 9% (SB) • Average travel time increase of 9% • Variability of travel time reduced by 22% in both directions	•Preliminary analysis, final analysis shown on next row	• Additional development and construction work between ATM construction phases may reduce ATM benefits
U.K., M42 *(13)*	VSL, HSR	• 36 months of before and 36 months of after data analyzed • 1 month of settling in period	N/A	• Average number of crashes per month reduced from 5.08 to 2.25 after ATM implementation • Monthly mean number of killed or serious injured casualties reduced from 1.15 to 0.19 • Two-way crash rate per billion vehicle miles traveled reduced from 115.92 to 47.98	

Table 4. Summary of the Effects of ATM Deployments in United Kingdom

Location and Reference	**ATM Features**	**Research Design**	**Operational Effect**	**Safety Effect**	**Comments**
U.K., M42 ***(MacDonald 2008)***	VSL, HSR	• 12 months of before and 12 months of after data analyzed • 1 month of settling in period	• Average capacity increase of 7% • Total flow increase of 6% (NB) and 9% (SB) • Average travel time increase of 9% • Variability of travel time reduced by 22% in both directions	•Preliminary analysis, final analysis shown on next row	• Additional development and construction work between ATM construction phases may reduce ATM benefits
U.K., M42 ***(MacDonald 2011)***	VSL, HSR	• 36 months of before and 36 months of after data analyzed • 1 month of settling in period	N/A	• Average number of crashes per month reduced from 5.08 to 2.25 after ATM implementation • Monthly mean number of killed or serious injured casualties reduced from 1.15 to 0.19 • Two-way crash rate per billion vehicle miles traveled reduced from 115.92 to 47.98	

OPERATIONS DATA AND ANALYSIS

Data Sources

INRIX Travel Time Data

Probe-based travel time data from the private company INRIX was used for the operational analysis. INRIX develops travel time estimates using GPS data from truck and passenger vehicles, creating segment travel times based on this probe data. VDOT currently uses INRIX data to support a variety of performance measurement and traveler information applications, and several external and internal evaluations have supported the accuracy of the travel time data for freeways *(Haghani 2009).* The data is reported spatially using Traffic Message Channel (TMC) links, which typically span segments between interchanges. At this study site, there were 14 TMCs with a total length of 19.97 kilometers (12.41 miles) in the Eastbound (EB) direction and 14 TMCs with a total length of 19.86 kilometers (12.34 miles) in the Westbound (WB) direction. The length of each TMC varied from 354 meters (0.22 miles) to 2977 meters (1.85 miles).

INRIX provides confidence scores for each 1-minute interval travel time, with a confidence score of 30 representing real-time data and scores of 10 and 20 representing historic data during overnight and daytime periods, respectively. For the purposes of this analysis, average travel times were determined for every 15-minute interval. Each 15-minute travel time interval had to have an average confidence score of 26.67 or higher for at least 85% of the TMCs composing the analysis section for it to be included in the analysis. The 26.67 value was established by requiring that at least 10 of 15 1-minute intervals had real time speed data. There is a tradeoff between data availability and quality with this threshold. If the threshold was set closer to the "30" value, sometime intervals would be discarded if only 1 or 2 minutes lacked real time data. It was not uncommon to have some gaps in probe data within the 15-minute interval, so this threshold was set in concert with the VDOT business rules for posting travel time data. The INRIX data has been subjected to numerous validation studies in Virginia by the DOT and the I-95 Corridor Coalition, and has been used for travel time messaging since 2010 *(Haghani 2009).* There has been no substantial change in the data quality on high volume urban freeways during the study period.

Traffic Operations Center (TOC) Logs

VDOT TOC logs were reviewed to determine the times when HSR was opened to travel, as well as the time periods when AVSL and LUCS were posted. The TOC logs consisted of information on the sign message, the time stamp when the message was posted, and a location identifier for the sign. Thus, the specific message being displayed on every individual sign could be tracked over time.

Analysis Time Periods and Data Aggregation

The previous analysis of the ATM system used 21 weeks of before-ATM data (Oct 2014 – Feb 2015) and 21 weeks of after-ATM data (Oct 2015 – Feb 2016) for comparison *(Chun 2016)*. While those results provided a preliminary examination of system effectiveness, they may have been influenced by seasonal factors. In this paper, annual data is divided into four parts to be consistent with the seasonal variation in traffic: October-November, December-February, March-May, and June-August. The ATM system was activated on September 15, 2015, so data from the month of September is not used in this paper. Three time periods are considered in this analysis. The Pre ATM period is defined as October 2014- August 2015, ATM year one is defined as October 2015-August 2016, and ATM year two is October 2016- August 2017.

Analysis was segregated by day of the week and time of day. Time of day was defined as AM peak (5:30 AM to 11:00 AM), midday (11:00 AM to 2:00 PM), PM peak (2:00 PM to 8:00 PM), and overnight (8:00 PM to 5:30 AM) for weekdays and daytime peak (10:00 AM to 8:00 PM) and off peak (8:00 PM to 10:00 AM for weekends. These time periods were selected to match the time periods when the static time of day HSR was used in the pre-ATM period (5:30 to 11:00 AM EB and 2:00 to 8:00 PM WB).

Operational Performance Measure Calculation

ATM Utilization

The activation log maintained by the TOC contained detailed records of ATM usage for each individual sign on each gantry. Of the 22 gantries in each direction, 11 gantries were used for HSR in the EB direction and 9 gantries were used for HSR in the WB direction. Average HSR utilization rates were calculated by adding up the total time of HSR activation per gantry then dividing the total by the number of days in the analysis period. This was calculated by direction and for weekdays and weekends.

All 22 gantries were included for the AVSL utilization analysis. AVSL utilization rates were calculated by adding up the total time of AVSL activation per gantry, and then dividing the total by the number of days in the analysis period. All gantries were also included for the LUCS utilization analysis. The utilization rate of LUCS was far less frequent than the activation of AVSL or HSR since they were only activated when there was a lane-blocking incident. Given the lower utilization, LUCS activations are not documented in this paper, but interested readers can consult related work by *Dutta et al (2017).*

Average Travel Times

INRIX travel time data were acquired using a 15-minute temporal aggregation, data quality screening measures were applied to the travel times, and travel times were segregated by segment, day of the week, and time of day. Paired t-tests were conducted at $\alpha = 0.05$ to determine if any changes were statistically significant between the pre-ATM time period and ATM year one and also between pre-ATM and ATM year two. For each day of the week, the 15-minute average times were divided up into time of day for both before-and-after ATM periods to set up the paired t-test. Time periods with incidents were not screened out since those both impact average travel time and reliability. Since ATM is expected to help manage non-recurring events, it was important to include incident impacts in the analysis.

SAFETY DATA AND ANALYSIS

Data Sources

Segment Traffic and Geometric Data

The safety analysis of the I-66 ATM system focused on basic freeway segments only because detailed ramp data was often not available. First, the I-66 corridor was reviewed to ensure compliance with the *Highway Safety Manual* (HSM) base conditions for freeway segments *(HSM 2010).* The eastbound and the westbound directions of the study corridor were sub-segmented into homogeneous sections based on the traffic and geometric characteristics of the roadway and the presence or absence of HSR. Road inventory data for the corridor were obtained from VDOT, and only data from segments outside the interchange area along the corridor were used. An interchange area was defined as an area between gores of entrance/exit ramps *(Kweon 2014).* Additional data collected included length of horizontal curves, lane widths, inside/outside shoulder widths, median widths, and length of median barriers. Traffic data were collected before (2011-2014) and after (2016 and 2017) implementation of the ATM system, and the year of activation was omitted from the analysis. Figure 1 shows the locations with and without HSR.

Crash Data

Crash data for the study were collected between 2011-2014 (before) and 2016-2017 (after) along I-66. Crashes within interchanges areas were not used as part of this study. A count of total (all severities), fatal and injury, and property damage only (PDO) crashes were collected. The analysis was further segregated into crashes involving single vehicles, multiple vehicles, and rear end crashes as shown in Table 5. These types were separated since past studies have shown that ATM is effective in reducing those types of crashes *(Siddiqui 2017, Mudgal 2017, and Aron 2010).* A separate analysis was also done for locations with HSR and locations without HSR to quantify the safety benefit associated with this incremental change over the AVSL and LUCS.

Safety Analysis Methodology

In order to evaluate the safety impacts of ATM on I-66, the empirical Bayes (EB) methodology with safety performance functions (SPFs) described by Gross et al was used *(Gross 2010).* This method is well known for its robustness and ability to calculate statistically defensible crash modification factors (CMFs). It is also able to account for key changes in traffic and geometric conditions that occur during the study period, while also controlling for regression-to-the-mean (RTM) effects, which is a phenomenon that is likely to be present when sites are selected for treatments based on their crash records *(Goh 2012).* Hauer explained SPFs as a representative of the safety performance of a roadway or an intersection, and it is used to correct for RTM bias when calculating the safety effectiveness of a countermeasure *(Hauer 1980)*. It relates crash frequencies, traffic volume, and roadway and land use characteristics. The SPFs include an over dispersion parameter which is developed from a negative binomial model as a measure of precision of the model in predicting crashes that would have occurred at the treatment sites if the treatment had not been implemented. This factor is used in conjunction with the observed crashes before the treatment in the weight computation to predict the expected crashes at each site *(Saito 2011).*

EB Methodology

Virginia statewide SPFs developed by Kweon and Lim for freeway segments with 6 lanes and 8+ lanes were used to develop the CMFs for the I-66 ATM *(Kweon 2014)*. Local SPFs with annual calibration factors from 2011-2017 were used to generate predictions since they better account for jurisdictional and time trends in factors like driving behavior, weather, and reporting thresholds than the national models in the HSM. More generalized SPFs can lead to erroneous computation of the safety effect of the treatment *(Garber 2006).* CMFs for relevant base conditions were computed based on the geometric data collected earlier using equations and coefficients described in the HSM for freeways. These data were used to develop CMFs for site conditions, and they were applied to the Virginia SPF in the EB computation. Coefficients for horizontal curves (HSM Table 18:14), median width (HSM Table 18:17), and median barrier (HSM Table 18:18) were used. Lane width as well as inside and outside shoulder widths met the base conditions, so they were not corrected for in the computation.

The Virginia SPFs developed by Kweon and Lim used in this study were:

$N_{Total\ Crashes,6\ Lanes} = e^{-12.85} AADT_{Directional}^{1.45} Segment\ Length_{Directional}$; $(k = 0.59)$ [Eq. 1]

$N_{Fatal+\ Injury\ Crashes,6\ Lanes} = e^{-15.64} AADT_{Directional}^{1.6} Segment\ Length_{Directional}$; $(k = 0.47)$ [Eq. 2]

$N_{Total\ Crashes,8\ Lanes} = e^{-2.17} AADT_{Directional}^{0.48} Segment\ Length_{Directional}$; $(k = 0.58)$ [Eq. 3]

$N_{Fatal+\ Injury\ Crashes,8\ Lanes} = e^{-5.94} AADT_{Directional}^{0.71} Segment\ Length_{Directional}$; $(k = 0.50)$ [Eq. 4]

Gross et al *(2010)* and Kwigizile et al *(2015)* described the computation of expected crashes without the treatment for a site as follows:

$N_{exp,T,B} = w \times (N_{pred,T,B}) + (1 - w) \times (N_{obs,T,B})$ [Eq. 5]

Where;

$N_{exp,T,B}$ = an estimate of the expected crashes in the before period without the treatment

$N_{obs,T,B}$= observed crash frequency in the before period at the treated sites

$N_{pred,T,B}$ = an estimate of the predicted crashes in the before period from the SPF

w = the weight is based on the over-dispersion parameter (k) from the applicable SPF model and predicted crash frequencies of study before the implementation of the treatment. It is calculated as:

$w = \frac{1}{1+k*\Sigma N_{pred,TB}}$, k = over dispersion parameter [Eq. 6]

Computation of expected crashes after the implementation of the treatment ($N_{exp,T,A}$) is as follows:

$N_{exp,T,A} = (N_{exp,T,B}) \times \left(\frac{N_{pred,T,A}}{N_{pred,T,B}}\right)$ [Eq. 7]

Where;

$N_{pred,T,A}$ = an estimate of the predicted crashes in the after period from the SPF

The variance of the expected number of treatment crashes in the after period is:

$$var(N_{exp,T,A}) = \left[(N_{exp,T,A}) \times \left(\frac{N_{pred,T,A}}{N_{pred,T,B}}\right) \times (1-w)\right] \quad \text{[Eq. 8]}$$

$$CMF = \frac{(N_{Obs,T,A}/N_{exp,T,A})}{\left(1+(var(N_{exp,T,A})/N_{exp,T,A}{}^2)\right)} \quad \text{[Eq. 9]}$$

The standard error is computed from as follows:

$$Standard\ Error = \sqrt{\left(\frac{CMF^2 * \left[\left(\frac{1}{N_{Obs,T,A}}\right)+(var(N_{exp,T,A})/N_{exp,T,A}{}^2)\right]}{[1+(var(N_{exp,T,A})/N_{exp,T,A}{}^2)]^2}\right)} \quad \text{[Eq. 10]}$$

The standard error is used in conjunction with the calculated CMF to determine whether the results are statistically significant.

CMFs for multiple vehicle and rear end crash types were estimated by computing their proportions of the total (all severity) and fatal and injury crashes during the before period. The factors for the proportions (x) were then applied to the sum of the predicted crashes in the before and after period $(x\Sigma N_{pred,TB}, x\Sigma N_{pred,T,A})$ to obtain the predicted crashes for multiple vehicle and rear end crashes. These proportional factors (x) were again applied to the expected crashes $(xN_{exp,T,B}, xN_{exp,T,A})$ to compute the expected number of crashes before and after the ATM activation for the multiple vehicle and rear end crash types.

RESULTS

Operational Analysis

ATM Utilization Analysis

Before ATM was implemented, HSR was only activated on weekdays from 5:30-11:00 AM in the eastbound direction and from 2:00-8:00 PM in the westbound direction. After ATM activation, HSR was dynamically opened in response to congestion, in addition to being opened during the regular peak travel periods. In the EB direction, average weekday HSR utilization increased from 9.4 hours/day/gantry in year one to 10.3 hours/day/gantry in year two. In the WB direction, it decreased from 7.8 hours/day/gantry in year 1 to 7.6 hours/day/gantry in year 2. Weekends followed the same trend where utilization increased slightly from 63 hours/day/gantry in year one to 7.0 hours/day/gantry in year two in the EB direction. In the WB direction, it decreased from 8.5 hours/day/gantry to 6.9 hours/day/gantry. HSR was not used in the pre-ATM period during weekends, so these represent significant changes in operations in those periods.

AVSL utilization rates were also analyzed, but they were used less often than HSR. This system also experienced an increase in usage in the second year. After removing the period from September to December 2015 when the AVSL control algorithm was undergoing calibration, average weekday AVSL utilization was 2.1 hours/day/gantry in the EB direction and 2.7 hours/day/gantry in the WB direction in year 1. Utilization increased in both directions in year 2, with EB usage averaging 2.9 hours/day/gantry and WB usage averaging 3.8 hours/day/gantry. Weekend AVSL utilization was low, but usage increased in year 2 for both directions as well. LUCS utilization followed the same trend as AVSL, but total activations were lower than AVSL.

Average Corridor Travel Times

Figure 2 shows an example of the EB and WB corridor-level average travel time profiles for weekdays and weekends between December and February before and after ATM activation. The analysis was repeated for all the seasons and time periods, and more detail is provided in Table 6.

Improvement in travel times were observed mostly during off peak periods, as seen in Figure 2. The trends seen in Figure 2 were observed in other months as well. The midday period showed slight improvements in travel time in both directions, with the only exception being EB during October and November. Travel time in the midday period improved more in year two compared to year one. All the changes were statistically significant in the WB direction, and a mixed result of significance was observed in the EB direction. For these off peak and midday transition periods when the roadway was not operating at maximum capacity, the dynamic opening of the shoulders may have contributed to faster travel times along the corridor and mitigated any incident and non-recurring congestion impacts.

The ATM system provided much larger improvements on the weekends. The weekend daytime peak period in both directions showed consistent improvement in travel time. A detailed comparison among average travel times and their statistical significance is presented in Table 6. In this case, HSR was not used at all on weekends in the before period, so it provided significant capacity expansion in the after period.

For weekday peak period average travel times, there were statistically significant degradations at $\alpha = 0.05$ between after-ATM and before-ATM average times while traveling in the peak directions (AM for EB, PM for WB). This is true for both year 1 and year 2 after deployment and for all months. This was somewhat expected since HSR as already in use during these time periods before ATM was activated, and I-66 operates far over capacity in these periods. Even though average travel time increased in the peak period, the increase was larger in the 1st year of using the ATM system compared to the second year. This might be an indication that the ATM system may be helping to slow the rate of degradation in travel time, but more data needs to be accumulated before reaching to that conclusion. The differences in trends between weekday peak periods and other times also highlights the ATM system's effectiveness in managing non-recurring congestion that might have occurred during off peak periods if the facility had not been dynamically managed.

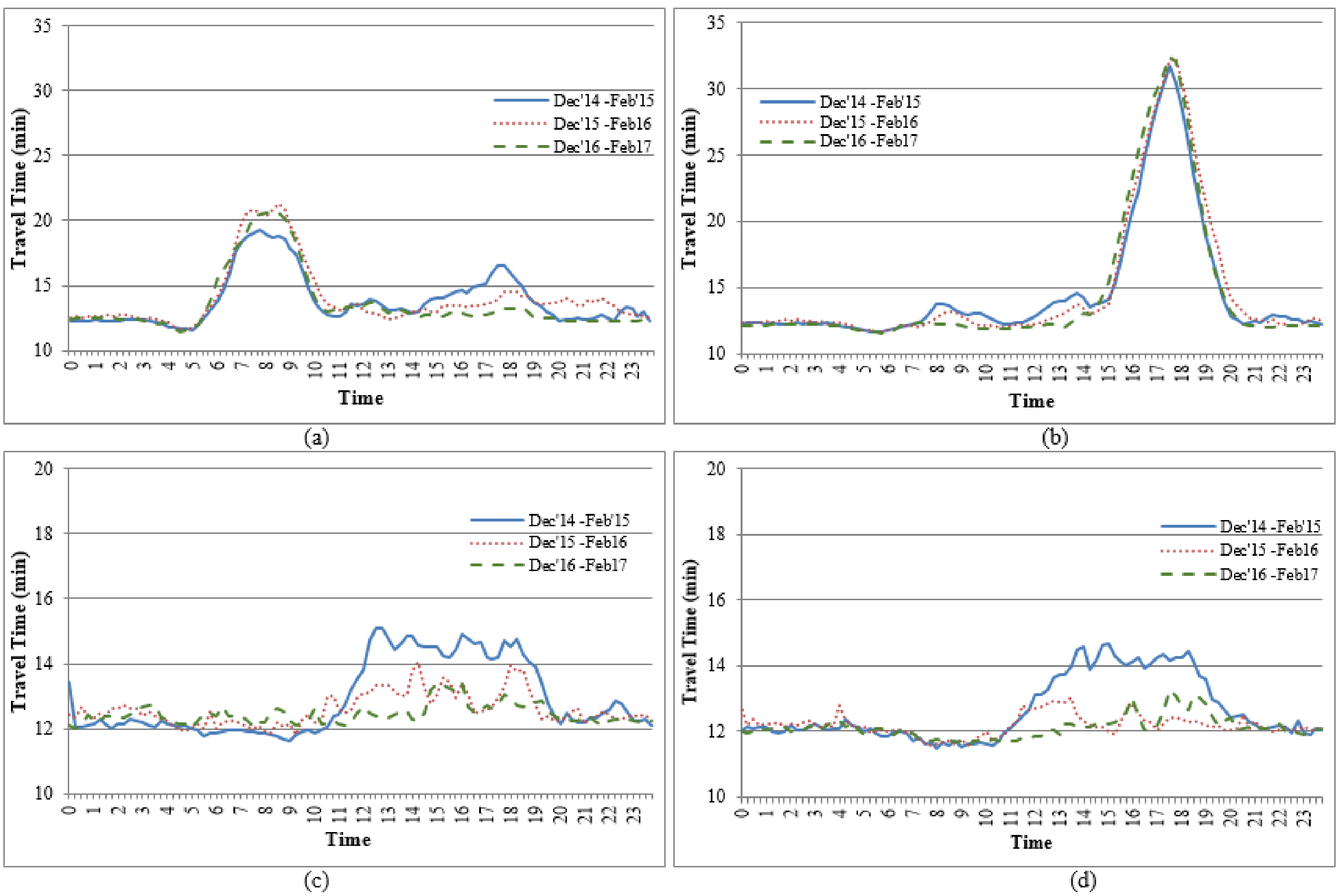


FIGURE 2 Before-and-after average travel time profiles for (a) EB Weekday (b) WB Weekday (c) EB Weekend and (d) WB Weekend

TABLE 5 Changes in Average Travel Time Before and After ATM System Activation

Direction	Time Period	October-November		December-February		March-May		June -August
		Before vs. After Year 1	**Before vs. After Year 2**	**Before vs. After Year 1**	**Before vs. After Year 2**	**Before vs. After Year 1**	**Before vs. After Year 2**	**Before vs. After Year 1**
Eastbound	Weekday AM Peak (5:30 AM - 11AM)	*+0.98 (+5.35%)*	+0.33 (1.80%)	*+1.25 (+7.69%)*	*+ 0.92 (+ 5.66%)*	*+1.07 (+5.85%)*	*+0.33 (+ 1.77%)*	*+0.78 (+4.46%)*
	Weekday Midday (11AM -2PM)	*+0.24 (+ 1.81%)*	*+1.01 (+ 7.56%)*	**-0.41 (- 3.07%)**	- 0.08 (-0.60%)	**-1.05 (-7.31%)**	**-1.41 (- 9.56%)**	**-0.62 (-4.30%)**
	Weekday PM peak (2 PM-8 PM)	**-1.09 (- 7.31%)**	**-1.06 (- 7.08%)**	**-0.83 (- 5.73%)**	**-1.64 (- 11.35%)**	**-1.81 (- 12.37%)**	**-1.99 (-13.65%)**	**-1.36 (-9.34%)**
	Weekday Overnight (8PM-5:30 AM)	*+0.62 (+ 5.15%)*	*+0.20 (+ 1.62%)*	*+0.45 (+ 3.66%)*	**-0.09 (- 0.74%)**	+ 0.03 (+ 0.25%)	**-0.28 (-2.29%)**	**-0.06 (-0.46%)**
	Weekend Peak (10AM-8PM)	**-2.24 (- 14.59%)**	**-0.85 (- 7.05%)**	**-0.97 (- 6.95%)**	**-1.36 (-9.72%)**	**-1.89 (-12.36%)**	**-2.16 (-13.50%)**	**-1.58 (-10.42%)**
	Weekend Off Peak (8PM-10AM)	**-0.21 (-1.77%)**	*+0.26 (+ 1.71%)*	*+0.16 (+ 1.33%)*	*+0.18 (+ 1.44%)*	+0.01 (+ 0.09%)	**-1.53 (12.39%)**	-0.01 (-0.11%)
Westbound	Weekday AM Peak (5:30 AM - 11AM)	- 0.13 (-1.06%)	-0.10 (-0.84%)	**-0.37 (-2.91%)**	**-0.64 (-4.98%)**	**-0.91 (-6.89%)**	-1.27 (-9.44%)	**-0.24 (-1.67%)**
	Weekday Midday (11AM -2PM)	**-0.55 (-4.11%)**	**-0.95 (-7.17%)**	**-0.67 (-5.02%)**	**-1.19 (-8.95%)**	**-1.54 (-10.98%)**	**-1.78 (-12.50%)**	**-2.01 (-11.95%)**
	Weekday PM peak (2 PM-8 PM)	*+0.69 (+ 3.04%)*	*+2.08 (+ 9.10%)*	*+1.00 (+ 4.79%)*	*+ 1.04 (+ 4.99%)*	+ 0.17 (+ 0.78%)	*+ 1.15 (+ 5.25%)*	*+ 1.54 (+6.80%)*
	Weekday Overnight (8PM-5:30 AM)	**- 0.25 (- 1.98%)**	**- 0.24 (- 1.95%)**	*+ 0.13 (+ 1.00%)*	**- 0.19 (- 1.58%)**	**-0.36 (- 2.85%)**	**-0.41 (- 3.28%)**	**-0.47 (-3.26%)**
	Weekend Peak (10AM-8PM)	**-1.92 (- 13.74%)**	**-1.09 (- 7.77%)**	**-1.19 (- 8.78%)**	**-1.28 (- 9.44%)**	**-2.40 (- 16.18%)**	**-2.18 (- 14.06%)**	**-1.90 (-11.49%)**
	Weekend Off Peak (8PM-10AM)	*+ 0.06 (+ 0.47%)*	**-0.03 (- 0.23%)**	*+ 0.07 (+ 0.58%)*	-0.001 (- 0.01%)	+0.02 (+ 0.13%)	-0.07 (-0.54%)	*+0.04 (+0.29%)*

Comparison between HSR and Non-HSR Sections

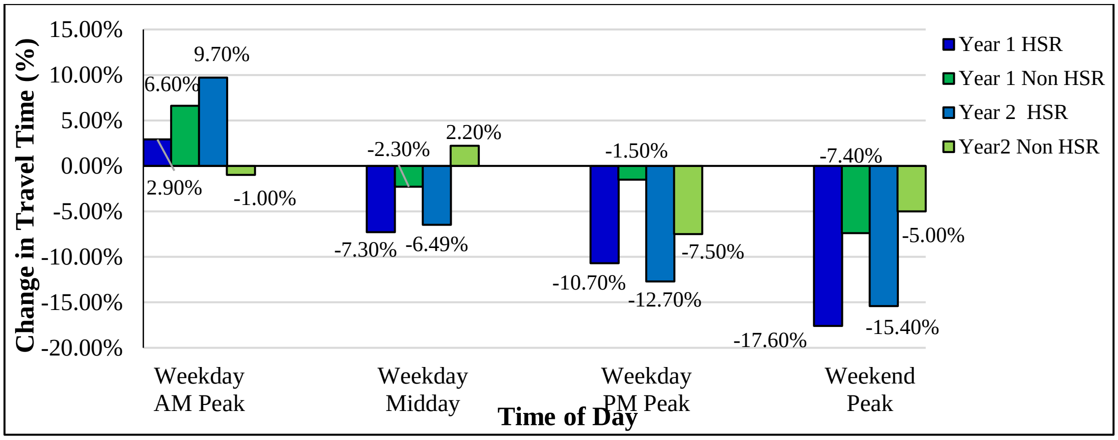
While the corridor-level analysis showed that the ATM system provided some travel time improvements during off peak and weekend operations, it was unclear what role the different ATM elements played in these improvements. Anecdotally, VDOT TOC staff indicated that they believed the addition of dynamic HSR was responsible for the majority of observed benefits. As a result, the operational performance of the sections with HSR, AVSLs, and LUCS was compared to those sections with only AVSLs and LUCs.

For this, the corridor level data was divided into segments that have a HSR section and the segments that do not. The change in travel time was analyzed for both sections to assess whether benefits were uniformly distributed. A paired t-test was conducted to check if the change is significant or not.

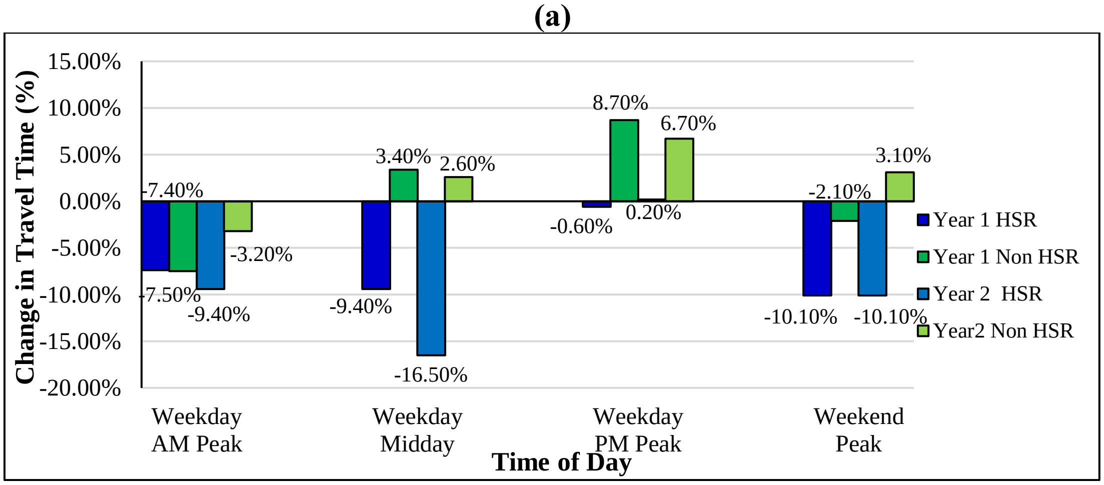
Figure 3 shows the percentage change in travel time in year 1 and 2 compared to the pre-ATM period for HSR and non-HSR. Non-HSR sections usually continued to show degradation in travel times during weekday periods in both directions, while HSR sections showed some improvements, especially in the WB direction. Weekends experienced more drastic improvements in both directions on the HSR sections, as seen in Figure 3.

Before ATM was implemented, HSR was only activated on weekdays from 5:30-11:00 AM in the eastbound direction and from 2:00-8:00 PM in the westbound direction. After ATM activation, HSR usage mostly occurred during daytime periods. Figure 3 shows that most improvements were observed during off peak periods on weekdays and daytime peaks on weekends in the EB direction. These time frames showed even better improvement in the second year. The weekend peak showed the most statistically significant improvement in the HSR section, where travel time was reduced by 11.20 % in year 1 and 13.50 % in year 2 compared to the pre-ATM condition. All other results were statistically significant except for the weekday PM peak results for non-HSR sections for both years.

The change was more prominent in the WB direction, where almost all the HSR sections experienced some improvement. Other than the AM peak period, travel time for all the non-HSR sections deteriorated in both years, with the worst time period being the PM peak. Most of these increases in travel times were statistically significant. In the WB direction, the midday period during weekdays showed the highest improvement, with travel time reduced by 12.60 % in year 1 and 15.10 % in year 2. The results were significant for all time periods on HSR sections except for the weekday PM peak period on year 1. For non HSR sections, the findings were significant for both years during AM peak, midday, PM peak and weekend peak on year one. For year two, results for weekend peak travel time was not significant for the non-HSR sections.



(a)



(b)

FIGURE 3 Comparison between change in travel time in HSR and Non HSR sections for (a) EB and (b) WB

Safety Analysis

Empirical Bayes Results

Table 7 summarizes the results of the EB analysis of the effect of the ATM system. CMFs for total and fatal + injury crashes were calculated for the following crash types:

- All crash types
- Multiple vehicle crashes

- Rear end crashes

Given the results of the operational analysis, the safety effects were further broken down into HSR and non-HSR sections. Since operations generally improved more on the HSR sections, the question was whether the improved flow offset any safety concerns related to the removal of the emergency shoulder for use as a travel lane.

The results showed positive safety improvements when the entire corridor was examined as a whole. There was a 4% reduction in total (all severity) and 4% reduction in fatal/injury crashes, when the entire corridor was examined. These reductions were not statistically significant at a 95% confidence level, however. Multiple vehicle crashes had 4% and 5% reductions for total (all severity) and fatal/injury crashes, respectively, after the implementation of the ATM. These reductions were also not statistically significant at a 95% confidence level. Rear end crashes had the largest reductions for total (all severity) and fatal/injury crashes, with reductions of nearly 6% and 6%, respectively. These reductions were again not statistically significant at the 95% confidence level. The comparatively large reductions in rear end crashes correlate well with the improved traffic flow discussed earlier.

Much like the operational results, it appears that the safety benefits were concentrated in the sections with HSR present. Locations with HSR had a reduction of nearly 31% and 32% for total (all severity) and fatal and injury, respectively, which was statistically significant at α=0.05. Likewise, HSR locations had a 35% and 36% reduction in total (all severity) and fatal and injury multiple vehicle crashes, respectively, which was again statistically significant at α=0.05. Rear end crashes at HSR locations had about 38% and 35% reductions in total (all severity) and fatal/injury crashes, respectively. These reductions were once again statistically significant at α=0.05. The study did not show improvement in safety at locations without HSR. This is in contrast to prior VSL deployments that documented safety improvements, and may reflect the lack of automated speed enforcement at the I-66 site.

These safety results imply a direct correlation between safety and operational improvements. The large reductions in rear end crashes on HSR sections would seem to be correlated with the improved flow at those locations. No statistically significant safety improvements were seen on the non-HSR sections, which also experienced less change operationally. The non-HSR sections experienced increasing crashes during the two years of observation. These sections only had LUCS and advisory VSLs, and there was no obvious trend in crash causation that would relate to these treatments. It was not possible to conclude from this research whether this change was somehow affected by site-specific trends, small sample sizes, or broader behavioral changes in the driving population. While a more detailed study of these crash trends is warranted, the ATM gantries were removed from this section of I-66 due to an ongoing construction project in early 2018. Future deployments of HSR should carefully examine crash trends on adjacent sections to determine if these results occur in the future.

TABLE 5 Empirical Bayes Results for I-66 corridor

Location	Crash Type	Severity	Observed Before Crashes/Year (2011-2014)	Observed After Crashes/Year (2016)	Expected Before Crashes/Year (2011-2014)	Expected After Crashes/Year (2016)	CMF	Standard Error
Entire Corridor	All	All	379.25	380.00	384.27	393.76	0.964	0.043
		Fatal and Injury	121.75	113.50	124.26	117.73	0.962	0.076
	Multiple Vehicle	All	344.00	342.50	348.20	356.89	0.959	0.045
		Fatal and Injury	110.50	100.50	111.96	106.03	0.946	0.08
	Rear End	All	276.25	268.00	278.98	285.86	0.937	0.049
		Fatal and Injury	94.00	84.00	94.39	89.39	0.937	0.086
HSR Sections	All	All	203.50	146.00	205.62	212.48	0.686*	0.047
		Fatal and Injury	67.75	45.00	68.44	65.42	0.686*	0.082
	Multiple Vehicle	All	186.25	127.50	188.06	194.29	0.655*	0.047
		Fatal and Injury	61.00	37.50	61.20	58.51	0.639*	0.084
	Rear End	All	153.5	99.00	154.67	159.79	0.619*	0.05
		Fatal and Injury	53.0	33.00	52.75	50.45	0.651*	0.091
Non-HSR Sections	All	All	175.75	234.00	178.65	181.29	1.289	0.076
		Fatal and Injury	54.00	68.50	55.82	52.31	1.304	0.14
	Multiple Vehicle	All	157.75	215.00	160.14	162.60	1.32	0.082
		Fatal and Injury	49.5	63.00	50.76	47.53	1.319	0.148
	Rear End	All	122.75	169.00	124.30	126.07	1.338	0.094
		Fatal and Injury	41.00	51.00	41.64	38.94	1.302	0.161

*Significant improvement at 95% confidence level **

CONCLUSIONS

The results of this study showed that the I-66 ATM system was able to create significant operational and safety improvements along a very congested corridor, although much of the benefit appears to be tied to the implementation of dynamic HSR as opposed to the AVSL or LUCS. Average travel times generally improved on weekends and during off peak weekday times, but often continued to degrade during peak periods from pre-ATM conditions. Since HSR was active on a static basis during the peak period in the before period, no additional capacity was added during those periods, however. Further investigation showed that operational improvements tended to occur disproportionately on dynamic HSR sections.

Crash analysis of freeway segments mirrored the operational findings, with some benefits accruing with multivehicle and rear end crashes for the entire corridor. Once again, crash reduction benefits occurred primarily on the HSR sections, indicating that improved flow offset concerns about the removal of the refuge area.

The results of this analysis make a strong case for the net benefit of HSR in locations where capacity expansion is not viable. While this study showed that freeway segments experience safety improvements with HSR, HSR may have differing effects in the vicinity of interchange merge and diverge areas. The crash trends in the non-HSR sections did not show any improvements, suggest that continued monitoring is warranted to ensure that crashes have not migrated further downstream due to capacity improvements created by HSR. While further analysis of this trend cannot be performed on I-66 due to ongoing construction, it does indicate that future ATM studies focus on adjacent non-HSR sections for any future part time shoulder implementation to see if similar results occur.

FUTURE RESEARCH AND LIMITATIONS

While all the available data was examined for both the operational and safety analysis, there are several limitations to the analysis. For the operational analysis, it was not possible to isolate the effects of each ATM component since they were deployed in combination. The change in travel time represents the effect of the ATM system as a whole.

The paper focuses on high-level trends in operational performance. Previous work on this topic used the data to discuss impacts on travel time reliability, which gets at the variability of the data *(Chun 2016).* INRIX reports travel time data as the average speed of all of vehicles on a link during a specific time period. Since individual vehicles' speed data were not available, it was not possible to study speed and speed variance for individual vehicles. While some data from

Wavetronix sensors are available, there is a noticeable undercounting of vehicles that occurs as the roadway becomes congested. These undercounts were exacerbated on lanes far from the sensor due to occlusion. As a result, the point sensor data was not used in the analysis since it appeared to contain biases that varied as a function of flow state. Future research is needed to examine individual vehicle speeds and subsequent analysis on speed variance.

This study also could not conduct crash analysis to determine the impact of the ATM system within an interchange area due to limited availability of ramp traffic data. Therefore, an area for future research is crash analysis within interchange areas where HSR is present. Another challenge that was encountered in the safety analysis is that Virginia SPFs were developed using standard freeway cross sections of 6 or 8 lanes. In the ATM system, the roadway cross section changes as shoulder lanes are opened or closed to travel. The safety analysis was performed using the SPF for the base number of lanes since no standard methodology exists in the HSM for dynamically managed facilities. These methodological limitations may also be responsible for some of the safety results obtained on the non-HSR sections. Additionally, SPFs for rear end and multiple vehicle crashes did not exist, so the HSM methods using crash proportions had to be employed. Using SPFs for specific crash types might improve analysis accuracy in the future.

Despite these limitations, this research does offer new data on the operational and safety benefits of ATM systems in the United States. The results show that U.S. AVSL systems may not attain the benefits seen in international deployments, but that HSR offers potential safety and mobility benefits.

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CHAPTER 4

DEVELOPING RURAL FOUR LANE FREEWAY CRASH PREDICTION MODELS USING HOURLY FLOW PARAMETERS

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ABSTRACT

Most past crash prediction research has examined the relationship between crashes, traffic volumes, and other factors at the annual level, due to the rare and random nature of crash occurrence and data availability. For example, the current functional form of safety performance functions in the Highway Safety Manual is based on annual average daily traffic (AADT). Less attention has been given to explicitly modeling the safety effects of vehicle density, volume-to-capacity ratio, and speed distribution at a sub-daily level. This research used continuous count station data from 4 lane rural freeway segments in Virginia and developed crash prediction models using traffic and geometric information provided at hourly aggregation intervals. The results showed that using average hourly volume along with average speed and selected geometric variables improved predictions compared to models that used AADT. When comparing an AADT-based model to an average hourly volume model, the mean absolute prediction error improved by 15% for total crashes. This value improved by 20% after including geometric variables, and by 30% after adding speed to the volume and geometry model. Similar improvements were observed for injury crashes. These results provide a strong indication that crash predictions could be improved using more disaggregate data and justifies further exploration of these relationships using larger datasets and other statistical methodologies. The findings from this research also indicate that inclusion of quality of flow variables, like speed, could create improvements in the quality of crash prediction models.

Keywords: Safety performance, traffic flow parameters, negative binomial

BACKGROUND

Crashes are complex events that are influenced by multiple factors, including roadway geometry, driver behavior, and traffic conditions. The Highway Safety Manual (HSM) provides professionals with a much-needed resource where current knowledge, techniques, and methodologies to estimate future crash frequency and severity are presented *(1).* While the HSM has improved the statistical rigor of safety analysis, the safety performance functions (SPFs) recommended in the HSM have several limitations. For practical reasons, base SPFs are often produced in a very concise form and include only limited numbers of variables (such annual average daily traffic (AADT) and segment length). AADT has been used as the measure of exposure due to its widespread availability, but it does not explicitly indicate the quality of flow on a facility throughout the day. Quality of flow is related to the variation in flow parameters such as speed or density on a much shorter time interval (such as hours or minutes), as compared to the yearly variation in volume used in HSM SPFs. Mensah and Hauer cite two key problems of averaging associated with using aggregated data – argument averaging and function averaging. Argument averaging relates to the use of average traffic flow data, rather than data measuring traffic conditions at the time of the accident. The second problem, function averaging, is caused by using the same functional relationship for all types of collisions under all conditions (e.g., day or night, dry or wet weather) *(2).* For example, a freeway with an intense flow during peak periods would clearly have a different crash potential than a freeway with the same AADT but with flow more evenly spread throughout the day. The use of annual AADT data may also affect overall crash prediction in cases where traffic control varies with time of day, such as with part-time shoulder use, active traffic management strategies, or arterial signal timings.

When real-time sensor data are available, it may be possible to explicitly consider the safety effect of quality of flow on crash likelihood. Quality of flow can be defined in several ways. For example, while volume measures the quantity of the stream and the demand on the facility, speed and density describe the quality of service experienced by the stream. Freeway operating conditions are also often evaluated using level-of-service (LOS) and volume to capacity (v/c) ratio. The Highway Capacity Manual (HCM) defines the levels of service of freeway sections based on density and designates quality of flow with a letter from A to F, with A representing the best operating conditions and F the worst *(3).* It is expected that crash risk varies in a non-linear fashion with exposure since traffic flow is a function of vehicle density and speed *(1).* Hence, similar flows could be attributed to different combinations of density and speed, leading to different levels of safety. As traffic flow increases, the vehicles travel at a lower speed, which could reduce crash severity during those conditions. Consequently, the likelihood for a conflicting situation to arise between vehicles may be different as density changes. Volume, speed, and density are related to each other, and together they play a role in the congestion level of a roadway as measured by v/c ratio.

To address limitations in AADT-based models, this paper examines whether crash predictions could be improved by using information on hourly traffic characteristics. The focus of this initial investigation is rural four-lane freeways in Virginia, since they represent a relatively homogeneous data set.

RESEARCH OBJECTIVE

While most researchers have focused on establishing relationships between crashes and AADT, relatively little work has been done on developing crash prediction models that use more disaggregated traffic data. This paper seeks to investigate the relationship between hourly traffic data and crashes on rural freeway segments in Virginia. Crash prediction models including geometric features and hourly flow parameters will be contrasted against AADT-based models to determine if consideration of more disaggregate traffic data could improve the quality of crash predictions.

LITERATURE REVIEW

Exploring relationships between crash frequency and traffic and geometric variables has been of interest for a long time *(4,5,6)*. Most prior research has focused on determining the relationship between crashes and highway traffic volumes, while less attention has been given to the relationship between crashes and density, level of service (LOS), v/c ratio, and speed distribution. Obtaining reliable data about traffic flow state across a broad set of sites has historically been a difficult task. This issue lead to limited work in this direction, and, in what research does exist, researchers often had to modify their methodology to accommodate data limitations. For example, most researchers only focused on a few selected segments of a specific facility while exploring the relationship between crash frequency and flow parameters. Table 1 below summarizes selected studies that dealt with the relationship between crashes, flow parameters, and disaggregated traffic volume.

TABLE 1 Selected Past Research that Incorporated Hourly Flow Data into Crash Prediction Models

Author(s)	Research Objective	Data & Methodology	Comment/Findings
Solomon, (1964) *(7)*	Examined relationship between crashes, speed, driver and vehicles on rural highways.	10,000 crashes on 2-lane and 4-lane rural roadways from Arizona, California, Connecticut, Iowa, Minnesota, Missouri, Montana, New Jersey, North Carolina, Oregon, and Virginia.	Accident-involvement, injury, and injury severity are highest at very low speeds, lowest at about the average speed of all traffic, and increase again at very high speeds, particularly at night. Thus, the greater the variation in speed of any vehicle from the average speed of all traffic, the greater its chance of being involved in an accident.
Persaud and Dzbik (1993) *(8)*	Developed crash prediction models at both the macro and micro level.	• Highway 401 in Toronto, Canada • Macroscopic: AADT and segment length. • Microscopic: Hourly volume and segment length.	Congestion is associated with a higher risk of accidents than high-volume uncongested operation. The afternoon congested period had a higher accident risk than the morning rush period
Zhou and Sisiopiku (1997) *(9)*	Examined the general relationships between hourly crash rates and hourly traffic volume/capacity (v/c) ratios.	• 16-mile segment of Interstate I-94 in the Detroit area. • Average weekday and weekend hourly volume data from three permanent count stations.	The correlation between v/c values and crash rates followed a general U-shaped pattern for weekdays and weekend days for multivehicle and property-damage-only crashes.
Garber and Ehrhart (2000) *(10)*	Analyzed the effect of speed, flow, and geometric characteristics on crash rates for different types of Virginia highways.	• Roadways within Virginia with speed limits of 55 or 65 mph. • The data were obtained from Virginia Department of Transportation (VDOT) and from police accident reports from January 1993 to September 1995.	Based on this study, all of the models show that under most traffic conditions, the crash rate tends to increase as the standard deviation of speed increases. The effect of the flow per lane and mean speed on the crash rate varied with respect to the type of highway.
Golob et. al. (2003) *(11)*	Evaluated freeway safety as a function of traffic flow.	• Crash and nearby single-loop detector data for all crashes reported along six freeways in California's Orange County in 1998. • Speed variation was defined as the difference between the 90th and 50th percentile values of speed estimates during the 27.5 minutes preceding each crash.	The highest crash rates (6.3 crashes per million vehicle miles traveled (VMT) occurred during the morning peak period with heavily congested flow, corresponding to low mean speeds, low speed variation, low flows, and low flow variation. In contrast, the lowest crash rates (0.6 per million VMT) were characterized by high speeds and low speed variation.

Ivan et al. (2000) *(12)*	Predicted both single and multi-vehicle highway crash rates as a function of traffic density, land use, and time of day.	• Seventeen rural, two-lane highway segments. • Hourly Volume, v/c ratio, and land use data were used.	Single-vehicle crashes occurred most often in the evening and at night. On the other hand, multi-vehicle crashes were more likely to occur under daylight conditions at midday and during the evening peak period.
Lord et. al. (2005) *(13)*	Investigated how flow parameters influenced crashes on rural and urban freeway segments.	• Highway A-40 between Ontario and Montreal. • Analysis was done for weekdays and weekends separately using hourly Volume, density, and v/c ratio.	Functional forms that incorporated density and V/C ratio offered a richer description of crashes occurring on these facilities compared to the volume only models.
Kononov et al. (2011) *(14)*	Examined the relationship between flow–density, speed, and crash rate.	• Four-lane freeways and a segment of Interstate 70 in Denver, Colorado • Hourly volume, operating speed, and free-flow speed data from 2001 to 2006.	As flow–density increases, the crash rate initially remains constant until a certain critical threshold combination of speed and density is reached. Once this threshold is exceeded, the crash rate rises rapidly.
Wu et. al. (2013) *(15)*	Explored the association between traffic safety and geometric design consistency based on vehicle speed metrics.	• Geometric design, roadway inventory, crash, and operating speed data were collected along U.S. 322 and PA 350 in central Pennsylvania. • Design consistency was referred to as the difference between operating speed and inferred design speed.	A statistically significant positive association between geometric design consistency and safety was found. Design consistency surrounding the study elements was also found to increase the expected crash frequency in the study element.
Vayalamkuzhi and Amirthalingam (2016) *(16)*	Focused on analyzing the influence of geometric design characteristics on traffic safety using bi-directional data on a divided roadway.	• The study was carried out on a four-lane divided inter-city highway in India with plain and rolling terrain. Crash history was collected from 2009 to 2012.	Operating speed, access points, median opening and horizontal curvatures (inverse radius) were identified as the significant factors influencing crashes. It was found that a 10 km/h increase in operating speed increases the crash rate by 40% and a 0.1/km decrease in horizontal curvature reduces the crash rate by 1.40% only.

DATA AND METHODOLOGY

Data Preparation

In Virginia, traffic volume data are collected both at fixed continuous count stations and using short-term counts that are performed throughout the state on a rotating basis. This research relied on traffic volume data from permanent count stations because of their high level of quality control and ability to produce accurate volume counts over the entire study period. For this research, only 4 lane rural basic freeway segments free from ramps or interchanges were considered. Segments were identified using the detector database maintained by the Virginia Department of Transportation (VDOT) Traffic Engineering Division and the VDOT GIS integrator *(17, 18).* Segments used for analysis had no entry/exit ramps within 0.5 miles of the start or end of the segment. This produced a total of 31 continuous count stations on rural freeways from around the state. It was important for this analysis to define a segment surrounding each count station where it could be assumed that homogeneous flow conditions were present for the entire length. If the station was on a link with homogeneous geometric characteristics that was greater than 2 miles in length, a buffer of a maximum 2 miles around the actual location of the detector (1 mile upstream and downstream) was created. Number of lanes, lane and shoulder width, speed limit, median type and median width were used to define the geometric homogeneity of segment. Since this research focuses on interaction between geometry and flow parameter's and how they define safety instead of a design focused approach, Horizontal and vertical curvature was not used to define the segment, instead they were used as variables to identify their interaction with flow. Generally speaking, horizontal and vertical curvature was not significant on these segments since they were located on interstates with high geometric design standards.

Hourly volume and speed data were collected for each segment from 2011 to 2017. As mentioned before, this research used only continuous count data that had passed VDOT internal quality checks for consistency and validity. If recorded data did not pass quality checks, it was discarded from the dataset. Only the time periods where both volume and speed data meet the quality threshold set by VDOT were included in the dataset, resulting in a total of 1.3 million site-hours of data points after screening.

The VDOT Highway Traffic Records Information System was used to extract all available geometric and operational information for the segments used in this analysis *(19)*. Crash data for all the sections were obtained from the VDOT Roadway Network System *(20)*. The VDOT Statewide Planning System was used to obtain the capacity for each study site *(21)*. The volume and speed data were then used to compute v/c ratio and density for each period. Table 2 summarizes the properties of the study segments respectively.

TABLE 2 Descriptive Statistics of Study Segments

Total Mileage (mile)	Variable	Mean	Std. Deviation	Min	Max
57.21	AADT	21360	7926	4420	34200
	Hourly Volume (vph)	825	659	1	3822
	Average Hourly Speed (mph)	69.95	3.73	3.29	90.66
	Segment Length (mile)	1.60	0.66	1.00	3.17
	Lane Width (ft)	12.00	0.00	12.00	12.00
	Right Shoulder Width (ft)	6.47	4.93	0.00	10.00
	Left Shoulder Width (ft)	3.88	4.77	0.00	10.00
	Median Width (ft)	114.18	53.63	34.00	220.00
	Percentage of Heavy Vehicles (%)	2.69%	1.53%	0.00%	100.00%
	Radius of Horizontal Curvature (mile)	1.51	0.88	0.00	3.61
	Length of Horizontal Curvature (mile)	0.34	0.18	0.00	0.78
	Grade (%)	-0.22	0.93	-1.67	2.59
	Speed Limit (mph)	69.12	1.96	55.00	70.00
	Speed (mph)	69.53	4.11	3.29	90.66
	Density	11.77	9.13	0.01	148.28
	Volume-Capacity Ratio	0.17	0.13	0.00	0.80

Development of Crash Prediction Models

Selection of Variables

The variables investigated in this research were volume, segment length, heavy vehicle percentage, horizontal curvature, vertical curvature, median width, speed, density, and v/c ratio. Volume was expressed in three ways:

- AADT
- Raw hourly volume, as observed each day at the site
- Average hourly volume, expressed as an average volume for each hour of the day for each site over each year.

Quality of flow variables for the hourly measures was summarized using a similar definition in each case. The hourly models were compared to each other and with the AADT model to determine how the hourly model predictions differed from a typical HSM-like model.

VDOT provided a database containing horizontal and vertical curvature information for each segment. The start and end mile marker position for these segments were used to match them with the selected freeway segments for this analysis. The vertical curvature (VC) data was calculated using the difference in slope and length of curve and expressed in the form of percent grade. Horizontal curvature (HC) was expressed using a variety of variables, including length of the curve, presence of curve as a percentage of segment length, and radius of curve. Length and radius of curve for each segment were directly available in the dataset. Heavy vehicle percentage was calculated directly from the volume data, using FHWA standard classifications *(22)*. Any vehicle above class 3 was considered as heavy vehicle. Other flow parameters such as density and v/c were also calculated from the detector data.

Selection of Model Form

Poisson and negative binomial regression are the most popular methods to model count data. In the Poisson distribution, the mean and variance are considered to be equal. However, the variance of crash data has been found to frequently exceed the mean, which is termed over dispersion. Negative binomial models are widely used as an alternative to Poisson models in crash modeling due to their ability to handle over dispersed data *(6,8,9, 10,23,24),* so this study used negative binomial regression. Since the dataset is disaggregated to an hourly level, that significantly increases the occurrences of zero crash observations. As a result, zero inflated negative binomial regression was also evaluated as a possible model form. The statistical software, R, was used for modeling.

In a negative binomial regression model, the probability of roadway entity (segment, intersection, etc.) i having y_i crashes per some time period (where y_i is a non-negative integer) is given by:

$$\boldsymbol{P(y_i) = \frac{exp(-\lambda_i) * \lambda_i^{y_i}}{y_i\,!}} \tag{1}$$

Where $P(yi)$ is the probability of roadway entity i having yi crashes per time period and λ_i is defined as:

$$\boldsymbol{\lambda_i = exp(\beta X_i + \varepsilon_i)} \tag{2}$$

Where exp (ε_i) is a gamma-distributed error term with mean 1 and variance α *(25).* The addition of this term allows the variance to differ from the mean as:

$$\textbf{VAR } (\boldsymbol{yi}) = \textbf{E } (\boldsymbol{yi}) \; [1+ \boldsymbol{\alpha}\textbf{E } (\boldsymbol{yi})] = \textbf{E } (\boldsymbol{yi}) + \boldsymbol{\alpha}\textbf{E } (\boldsymbol{yi})^{\mathbf{2}} \tag{3}$$

The parameter α is often referred to as the over dispersion parameter. Negative binomial regression has become the most common method for developing SPFs and is also the recommended modeling approach in the HSM *(1)*.

Another type of regression model frequently used by the transportation safety community is the zero-inflated model. Zero inflated models have been developed to handle data characterized by a significant number of zeros or more zeros than one would expect in a traditional Poisson or negative binomial/Poisson-gamma model *(25, 26)*. These models operate on the principle that the excess zero density that cannot be accommodated by a traditional count structure is accounted for by a splitting regime that models a crash-free versus a crash prone propensity of a roadway segment *(25,26)* . If the probability of a data point being zero is π and probability of it being non-zero is (1 – π), then, the probability distribution of the ZINB random variable y_i can be written as:

$$\boldsymbol{P_r(y_i = j) = \begin{cases} \pi_i + (1 - \pi_i) g(y_i = 0) & if\ j = 0 \\ (1 - \pi_i) g(y_i) & if\ j > 0 \end{cases}} \tag{4}$$

Where πi is the logistic link function and g(yi) is the negative binomial distribution given by:

$$\boldsymbol{g(y_i) = P_r(Y = y_i |\, \mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i + 1)} \left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}} \left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i}} \tag{5}$$

Since its inception, the zero-inflated model (both for the Poisson and negative binomial models) has been popular among transportation safety analysts *(24,27)*.

Generalized linear models (GLMs) are extensions of traditional regression models that allow the mean to depend on the explanatory variables through a link function, and the response variable to be any member of the exponential family (e.g., Normal, Poisson, Binomial, Zero Inflated) *(28)*. There are three components to any GLM. The *Random Component* refers to the probability distribution of the response variable (Y) (e.g., negative binomial distribution). The second part, the *Systematic Component,* specifies the explanatory variables in the model and the

Link *Function*, specifies how the expected value of the response relates to the linear predictor of explanatory variables.

In a generalized linear model, each outcome Y of the dependent variables is assumed to be generated from a particular distribution in the exponential family. The mean, $\boldsymbol{\mu}$, of the distribution depends on the independent variables, X, through:

$$\boldsymbol{E(Y) = \mu = g^{-(X\beta)}} \tag{6}$$

Where E(Y) is the expected value of Y; Xβ is the *linear predictor*, a linear combination of unknown parameters $\boldsymbol{\beta}$; g is the link function. The unknown parameters, β, are typically estimated with maximum likelihood, maximum quasi-likelihood, or Bayesian techniques.

The likelihood is the occurrence probability that the data observed will actually be comprehended under the given parameter estimates. The higher the log-likelihood value, the better the model. For a negative binomial regression model, the likelihood function can be described as:

$$\boldsymbol{L\,(\lambda_i) = \prod_i \frac{\Gamma\,(y_i+\left(\frac{1}{\alpha}\right))}{y_i!\,\Gamma\left(\frac{1}{\alpha}\right)} \cdot \left[\frac{\alpha\lambda_i}{1+\alpha\lambda_i}\right]^{y_i} \cdot \left[\frac{1}{1+\alpha\lambda_i}\right]^{1/\alpha}} \tag{7}$$

Where Γ(x) is the gamma function, and y_i is number of crashes per period for roadway segment i *(28)*.

Vuong Test

Since both the negative binomial and zero-inflated negative binomial models were evaluated, it was necessary to compare the performance of the two model forms. The Vuong test statistic (V) has been proposed for non-nested models to compare the fitness of zero inflated models versus regular count models *(29):*

$$\boldsymbol{V = \frac{\overline{m} * \sqrt{N}}{S_m}} \tag{8}$$

Where, $m_i = \log[\frac{f_1\,(y_i)}{f_2\,(y_i)}]$

N = number of observations

$\overline{m}$ = Mean of m_i

S_m= Standard deviation of m_i

f_1, f_2 = Two competing models

V has a standard normal distribution, and has three possible outcomes:

- If the absolute value of V is less than 1.96 for a 0.95 confidence level, then neither model is preferred by the test result.
- V is a large positive value, then model 1 is preferred.
- V is a large negative value, then model 2 is preferred.

This test was used to select which model form is appropriate for the dataset.

Model Selection and Validation

A popular method for model selection is the Akaike information criterion (AIC) *(30)*. AIC is an estimator of the relative quality of statistical models for a given set of data. It offers an estimate of the relative information lost when a given model is used to represent the process that generated the data. AIC is computed based on the equation given below:

$$\mathbf{AIC} = -2LL + 2p \tag{9}$$

Where p is the number of estimated parameters included in the model. A lower value of AIC indicates a better model.

It is important to note that an objective assessment of the predictive performance of a particular model can be made only through the evaluation of several goodness of fit (GOF) criteria. The GOF measures used to conduct external model validation included mean prediction bias (MPB), mean absolute deviation (MAD), and mean squared prediction error (MSPE) *(25)*.

Since AADT based models predict annual crashes while hourly volume models predicted hourly crashes, the summation of hourly predictions was used to generate annual predicted numbers of crashes for the GOF calculations. The average hourly volume data was computed by averaging data for each available hour for each site, so there were always 24 hours of data available for each year and each site for validation. For the validation of raw hourly data, high quality volume and speed data was not always available for all 24 hours of every single day. To deal with this issue, crash predictions were calculated using all hours with valid data. The hour-by-hour predictions produced by these valid hours were then averaged and multiplied by 365 to convert predictions to an annual value for each hour of the day. This essentially assumed that missing hours have the value of the average hourly crash prediction for that hour at that site and provides a consistent basis for comparison between the model forms. Data from the years 2011 to 2015 was used to build the models, and data from 2016 and 2017 were used for validation.

The calculation of these measures was based on the following equations:

$$\boldsymbol{Mean\ Absolute\ Deviation\ (MAD)} = \frac{\sum_{i=1}^{n}|Y_{model} - Y_{observed}|}{n} \tag{10}$$

$$\boldsymbol{Mean\ Absolute\ Prediction\ Error\ (MAPE)} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_{observed} - Y_{model}}{Y_{observed}}\right| \tag{11}$$

$$\boldsymbol{Mean\ Squared\ Prediction\ Error\ (MSPE)} = \frac{\sum_{i=1}^{n}(Y_{model} - Y_{observed})^2}{n} \tag{12}$$

Where:

Y_{model} = Predicted Crash Frequency

$Y_{observed}$ = Observed Crash Frequency

n = Sample Size

RESULTS AND DISCUSSION

Three separate regression model forms were explored:

- Volume and length models
- Volume, length, and geometry models
- Volume, length, geometry, and flow state models.

For each model type, both negative binomial and zero inflated negative binomial regression methods were evaluated. Models using AADT data were also created for the first two model forms so that model performance could be compared using the same datasets. To be consistent with the HSM, length was used as an offset variable in the models.

For the Vuong test results, the test statistic is adjusted using the Akaike (AIC) and Schwarz (BIC) penalty terms, based on the complexity of the two models. Sometimes, the test statistics for these two corrected terms lead to different results. For those cases, AIC corrected statistics are preferred for small sample sizes and BIC corrected statistics are preferred for large sample sizes. Results from the Vuong test are summarized in Table 3. For each of these models, model 1 represents negative binomial models and model 2 represents zero inflated negative binomial models.

TABLE 3 Results from Vuong Test

Total Crashes				
	Model	AIC Corrected	BIC Corrected	Result
Raw Volume	Volume and length models	-0.2544	4.9891	model 1 > model 2
	Volume, length, and geometry models	0.0873	5.4982	model 1 > model 2
	Volume, length, geometry, and flow state models.	0.5405	5.3307	model 1 > model 2
Average Hourly Volume	Volume and length models	0.8507	6.2367	model 1 > model 2
	Volume, length, and geometry models	0.3286	4.7197	model 1 > model 2
	Volume, length, geometry, and flow state models.	0.9133	5.6069	model 1 > model 2
Injury Crashes				
	Model	AIC Corrected	BIC Corrected	Result
Raw Volume	Volume and length models	-2.9275	-2.0836	model 2 > model 1
	Volume, length, and geometry models	-2.9044	-2.0478	model 2 > model 1
	Volume, length, geometry, and flow state models.	1.8011	8.6905	model 1 > model 2
Average Hourly Volume	Volume and length models	2.9655	1.1918	model 1 > model 2
	Volume, length, and geometry models	3.9216	16.9734	model 1 > model 2
	Volume, length, geometry, and flow state models.	3.1259	13.6353	model 1 > model 2

In general, negative binomial models performed better than the zero inflated ones with respect to AIC value, variable significance, and sign of estimated coefficients. The Vuong test results supported negative binomial models for all categories except for injury crash models using raw hourly volume. To maintain consistency in model form, negative binomial models were selected for both total and injury crashes.

The first set of models used only traffic volume and segment length, and both parameters were significant for all levels of volume aggregation for total crashes. Similar results were found for injury crashes as well. Table 4 shows the best performing models using the negative binomial form.

TABLE 4 Parameter Estimates for Volume and Length Model

	Total Crashes								
	Raw Hourly Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-11.68	0.279	<2e-16	-6.79	0.341	<2e-16	-6.32	1.120	1.7e-08
log (Volume)	0.39	0.042	<2e-16	0.53	0.051	<2e-16	0.65	0.114	1.2e-08
AIC	12211			3589			853		
	Fatal and Injury Crashes								
	Raw Hourly Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-12.22	0.467	<2e-16	-7.73	0.559	<2e-16	-9.38	1.734	6.3e-08
log (Volume)	0.31	0.070	1e-05	0.50	0.082	1.1e-09	0.83	0.175	2.1e-06
AIC	4475			1631			553		

Next, geometric variables were added to the model using manual stepwise variable selection to identify significant variables. The results for this step are summarized in Table 5. Variables representing median width, horizontal curvature, and vertical curvature were all found to be significant. Lane and shoulder width were not significant factors, likely due to the limited range of these variables in the data set.

For total crashes, the results indicated that wider medians generally had more crashes. This is consistent with previous research, even though it largely depends on crash type *(31, 32)*. Cross median crashes tend to decrease with increasing median width, whereas rollover crashes tend to increase. Analysis by type of median crashes was outside of the scope of this study, however. For vertical curvature, positive grades did not have any significant effect on crash frequency based on this data set. The radius of horizontal curvature had a negative parameter, indicating larger radii are associated with fewer crashes. These findings were similar irrespective of the volume disaggregation level and also align with the results from previous research *(33, 34).*

For injury crashes, only volume and segment length were significant for hourly volume models and no relationship between geometric variables and crash frequency were present. This might be due to the significantly lower number of injury crashes when disaggregated at the hourly level. The same data, when averaged over each year, showed that median width was a significant variable, similar to total crashes. Variables for the AADT-based model followed the same trend as raw hourly and average hourly volume. The only exception was horizontal curve radius, which was not significant for this model for total crashes.

TABLE 5 Parameter Estimates for Volume and Geometry Based Models

	Total Crashes								
	Raw Hourly Volume			Average Hourly Volume			AADT		
	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)
Intercept	-12.53	0.452	<2e-16	-7.75	0.501	<2e-16	-5.78	1.803	0.001348
log (Volume)	0.31	0.046	1.07e-11	0.50	0.057	<2e-16	0.49	0.186	8.07e-04
Median Width									
≤ 60 ft	0.67	0.251	0.0941	0.45	0.265	0.0895	0.55	0.237	0.1210
> 60 ft to ≤ 120 ft	1.04	0.251	3.34e-05	0.79	0.257	0.0019	1.11	0.229	1.27e-06
> 120 ft to ≤ 180 ft	1.05	0.239	1.04e-05	1.06	0.246	1.78e-05	0.83	0.209	7.23e-05
>180 ft	0.76	0.232	0.0011	0.81	0.239	7.96e-04	0.74	0.206	3.133-04
Grade of VC									
≤ -1.0%	0.31	0.309	0.3272	0.08	0.317	0.8039	0.27	0.348	0.4387
≥ -1.0% to <-0.5%	0.59	0.292	0.0437	0.42	0.302	0.0163	0.40	0.349	0.2471
≥ -0.5% to < 0%	0.87	0.289	0.0027	0.55	0.297	0.0063	0.42	0.338	0.2156
≥ 0% to < 0.5%	0.16	0.297	0.5815	0.11	0.308	0.7154	0.28	0.344	0.4201
≥ 0.5%	0.22	0.302	0.4599	0.35	0.311	0.2567	0.12	0.389	0.7564
Radius of HC	-0.06	0.029	0.0243	-0.007	0.047	0.0087	-0.03	0.039	0.0042
AIC	12170			3563			838		
	Fatal and Injury Crashes								
	Raw Hourly Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)
Intercept	-12.21	1.023	<2e-16	-7.71	0.783	<2e-16	-7.29	2.720	7.30e-06
log (Volume)	0.19	0.117	8.89e-04	0.42	0.090	3.43e-06	0.54	0.282	4.68e-04
Median Width									
≤ 60 ft	0.34	0.571	0.5439	0.31	0.435	0.4747	0.64	0.358	0.0717
> 60 ft to ≤ 120 ft	0.73	0.567	0.1968	0.55	0.418	0.1898	0.38	0.362	0.2970
> 120 ft to ≤ 180 ft	0.67	0.531	0.2071	1.04	0.392	0.0023	0.95	0.293	0.0012
>180 ft	0.52	0.518	0.3183	0.82	0.379	0.0034	0.78	0.283	0.0055
Grade of VC									
≤ -1.0%	-0.22	0.676	0.7504	-0.68	0.488	0.1612	-0.34	0.509	0.5011
≥ -1.0% to <-0.5%	0.14	0.625	0.8277	0.17	0.455	0.7074	0.22	0.501	0.6625
≥ -0.5% to < 0%	0.46	0.621	0.4531	0.09	0.443	0.8359	0.43	0.486	0.3781
≥ 0% to < 0.5%	-0.59	0.629	0.3501	-0.76	0.486	0.1182	-0.22	0.506	0.6646
≥ 0.5%	-0.34	0.633	0.5941	-0.32	0.476	0.4962	-0.04	0.572	0.7005
Radius of HC	-0.29	0.115	0.7251	-0.07	0.081	0.9350	-0.04	0.056	0.5136
AIC	4735			1623			551		

Finally, models were created by adding flow parameters such as v/c, speed, and density to the models selected in the previous step. The percentage of heavy vehicles was also considered as a variable, but it did not have any significant effect on crash frequency in this dataset. AADT based models were not developed for this alternative since average speed over a year showed little variability.

Initially, speed, density, and v/c ratio were all tested in the model. While developing models, it was found that v/c ratio was often an unreliable indicator of traffic flow state since incidents, work zones, or other events might restrict flow at the site. This created a situation where observed speeds may be low, but the corresponding v/c was also low. Inclusion of the v/c often resulted in counterintuitive parameter signs, so it was removed from further consideration.

After examining different combinations of volume, speed, and density variables, it was observed that speed and density only have a logical and statistically significant relationship when they are used one at a time with volume or when they are both used in the same model, but no volume component is added. This finding is not surprising since traffic flow theory indicates that all three variables are related, so their presence in the same model affects the performance. Since volume was deemed to be an important measure of exposure and speed is more widely available than density, models that used volume in conjunction with speed were selected as the best alternative.

Table 6 shows the final models that include speed parameters. For all models, speed was negatively related to crashes, meaning that lower average speed is correlated with higher crash frequency. Lower average speeds indicate the presence of congestion, so this relationship is intuitive. For these models, radius of horizontal curve and vertical grade were not significant. Median width had a mixed effect. This indicates that on hourly level, flow parameters may play a more significant role in crash prediction than geometric variables, at least on rural freeways. Rural freeways in this data set did not exhibit substandard features, so this finding may be explainable due to the high level of design present and limited geometric variability at these specific sites.

The negative relationship with speed and injury crashes seems counter intuitive since higher speeds are generally associated with more severe injuries. This result could be due to how injury was defined, and the type of data used for modeling. Fatal and injury crashes were combined in this category and range from a crash being fatal to a minor injury that does not require any doctor or hospital visit. Separating fatal and severe injury crashes from minor injury crashes might shed some light on the relationship. Unfortunately, that level of detail was out of scope for this analysis. This relationship also might be specific to this particular dataset. This analysis was based on rural continuous count station data where the max hourly volume observed was 3822 vph across two lanes. Thus, these results may be driven by the fact that this dataset is dominated by locations that are often traveling near free flow and a broader variation in traffic speed is not expected.

TABLE 6 Parameter Estimates for Volume, Geometry and Flow Based Model

	Total Crashes					
	Raw Hourly Volume			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)
Intercept	-2.63	0.512	2.8e-07	-2.09	0.875	<2e-16
log (Volume)	0.44	0.045	<2e-16	0.53	0.054	<2e-16
Median Width						
≤ 60 ft	0.62	0.237	0.1685	0.15	0.244	0.5398
> 60 ft to ≤ 120 ft	0.31	0.223	0.0086	0.02	0.222	0.9426
> 120 ft to ≤ 180 ft	0.28	0.210	0.0183	0.63	0.208	0.0026
>180 ft	0.26	0.198	0.1929	0.48	0.197	0.0014
Grade of VC						
≤ -1.0%	0.02	0.324	0.9475	0.44	0.315	0.1603
≥ -1.0% to < -0.5%	0.15	0.318	0.6313	0.09	0.308	0.7705
≥ -0.5% to < 0%	0.28	0.307	0.3546	0.03	0.300	0.9236
≥ 0% to < 0.5%	0.25	0.323	0.4337	0.09	0.317	0.7758
≥ 0.5%	0.11	0.327	0.7568	0.09	0.302	0.7635
Radius of HC	-0.01	0.047	0.8115	-0.07	0.047	0.4172
Speed	-0.14	0.004	<2e-16	-0.07	0.009	1.41e-13
AIC	11166			3399		
	Fatal and Injury Crashes					
	Raw Hourly Volume			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)
Intercept	-0.32	2.408	0.0098	-1.89	1.164	0.0013
log (Volume)	0.38	0.141	0.0071	0.46	0.082	1.68e-08
Median Width						
≤ 60 ft	0.49	0.733	0.4983	0.58	0.411	0.1538
> 60 ft to ≤ 120 ft	0.41	0.679	0.5478	0.31	0.362	0.3872
> 120 ft to ≤ 180 ft	0.24	0.659	0.7115	0.38	0.341	0.2643
>180 ft	0.43	0.666	0.5182	0.45	0.337	0.1833
Speed	-0.19	0.033	1.94e-08	-0.084	0.013	1.05e-10
AIC	4529			1527		

Model Comparison

Next, the performance of the raw hourly and average hourly models was contrasted to the AADT-based models. For all models, data from 2016 and 2017 was used as the validation dataset. Table 7 shows the comparison among these models. The AADT models didn't include speed as a variable because averaging hourly speed over a year did not capture the effect of speed on traffic conditions and crashes on an hourly level. For comparison purposes, the volume, flow, and geometry model were compared to the AADT based volume and geometry models.

For both the raw and average hourly volume models, prediction accuracy consistently improved as geometric and then speed variables were added. This improvement was higher in magnitude across all validation MOEs when the speed component was added to the model, although this may be due to the use of rural freeways for this analysis. The geometric variables, even though they vary from site to site, had variation within a small range. Since geometric factors were relatively uniform across the sites, there may not have been enough variation in geometry for the geometry models to create substantial improvements to the models over a volume only form.

The raw hourly models gave a mixed result in comparison to the AADT based model. For these models, both the volume only model and volume and geometry model performed worse than the AADT model in terms of MAD and MSPE. Similar results were found for injury crashes for raw hourly models as well. This result is likely influenced by the missing data in the raw volume dataset. Ideally, all sites would have 100% hourly data availability. Unfortunately, 23% of the raw hourly data in the validation dataset did not meet quality control standards, and thus was not used to generate predictions. As noted earlier, averages of available data in each hour were used to impute crash prediction estimates for missing hours, so this likely influenced the results.

The prediction accuracy improved significantly for both total and injury crashes when average hourly data is used. In this case, the average volume calculation helped to smooth out the discrepancies created by missing raw hourly data. The average hourly data also followed the same trend of improved model quality as geometric and speed variables were added. This model consistently performed better than the AADT based model for all MOEs. For the volume only models, MAD, MSPE, and MAPE improved by 10%, 15% and 12% respectively for total crashes and 6%, 12%, and 11% respectively for injury crashes. For the geometry models, improvements were even better for total crashes where MAD, MSPE and MAPE improved by 12%, 20%, and 21% respectively. Corresponding improvements for these parameters were 10%, 12%, and 13% respectively for injury crashes. In general, the flow parameter models showed the highest improvement for all MOEs compared to AADT based model with volume, length and geometric variables. MAD, MSPE and MAPE decreased by 13%, 31%, and 38% respectively for total crashes and 10%, 16%, and 25% respectively for injury crashes.

The comparison results reinforce the importance of selecting an appropriate disaggregation level. Due to the random nature of crash occurrence, the raw hourly data was heavily influenced by 0 crash observations and missing volume data, which negatively impacted the ability to generate useful models. Similarly, aggregated models that rely on AADT may fail to capture variations traffic flow that could influence safety. Finding a proper disaggregation level as well as significant variables that influence crash frequency is one of the major concerns in the area of crash prediction modeling.

TABLE 7 Comparison of Model Performance*

	Total Crashes								
	Hourly Volume			**Average Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	3.97 (+1.0%)	72% (-13.0%)	37.17 (+9.0%)	3.52 (-10.0%)	70% (-15.0%)	29.89 (-12.0%)	3.92	85%	34.06
Volume, length, and geometry models	3.87 (+2.0%)	69% (-9.0%)	31.46 (+3.0%)	3.31 (-12.0%)	58% (-20.0%)	24.28 (-21.0%)	3.78	78%	30.60
Volume, length, geometry, and flow state models. **	3.77 (-0.3%)	61% (-17.0%)	28.98 (-5.3%)	3.29 (-13.0%)	47% (-31.0%)	18.98 (-38.0%)	–	–	–
	Fatal & Injury Crashes								
	Hourly Volume			**Average Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	2.24 (+83.6%)	55% (-7.0%)	3.19 (+0.6%)	1.15 (-5.7%)	50% (-12.0%)	2.83 (-10.7%)	1.22	62%	3.17
Volume, length, and geometry models	2.15 (+85.3%)	53% (-6.0%)	2.53 (+3.3%)	1.04 (-10.3%)	47% (-12.0%)	2.12 (-13.5%)	1.16	59%	2.45
Volume, length, geometry, and flow state models. **	1.14 (-1.7%)	52% (+9.0%)	2.04 (+16.7%)	1.04 (-10.3%)	43% (-16.0%)	1.84 (24.9%)	–	–	–

** Value in the parentheses represents the change compared to respective AADT based models.*

*** These models were compared to the AADT based volume, length, and geometry models.*

CONCLUSIONS AND FUTURE RESEARCH

This study developed a general relationship that accounts for both hourly speed and volume on rural freeway segments in Virginia. The results indicated that inclusion of quality of flow variables, like speed, could create improvements in the quality of crash prediction models. If speed is explicitly included in a model, it creates an opportunity to better assess the safety impacts of a variety of operational improvements that might improve flow on a facility but might otherwise be difficult to examine.

Currently, there is no existing methodology for safety assessment of facilities with dynamic traffic control or geometry such as part time shoulder use or variable speed limits *(35, 36)*. The crash prediction models developed in this study serve as a strong proof of concept for further research in this direction. For example, AADT-based models cannot capture variations in safety created by the use of a dynamic use of the shoulder as a travel lane, as found during the evaluation of the I-66 active traffic management system in Virginia *(35).* In that case, flow improved along the road because the shoulder was dynamically opened as a travel lane, even though the overall AADT did not change significantly. AADT-based methods would not be able to accurately evaluate safety effects of changes in shoulder operation since variations were occurring on at a sub-daily level. Another possible application is assessing work zone safety. Since work zone lane closures and configurations may only be present for a portion of the day, methods are needed to better account for how the timing of lane closures impacts safety. The HSM provides crash modification functions that account for the effects of project length and duration on crash frequency but do not allow for explicit comparisons of safety effects of daily lane closures *(37).*

As seen with the raw hourly data models, a major challenge in developing and applying models that rely on hourly data is data availability. Continuous count stations are often present on a relatively small proportion of the roadway network. They are also strategically placed on less congested parts of the system to ensure counts are accurate. Even though the data derived from these stations are of high quality, this data does not exist on a broad network. Apart from continuous count stations, most DOTs collect short-duration counts throughout the state periodically. These short duration count stations often do not record speed data, but real-time speed data for many of these locations are available through probe data providers like INRIX or the Federal National Performance Measures Research Data Set *(38).* This research showed that average hourly volume profiles could be coupled with hourly speed to generate better crash predictions. It is possible that average hourly volume distributions derived from short-term counts could be combined with probe data to make the methodology developed in this paper more broadly applicable.

As a first step, this paper focused on selecting an appropriate disaggregation level using cross sectional data from the rural segments only. Future work could focus on urban segments as well. Additionally, year to year correlation in the data was not addressed in this work but could be incorporated into future modeling. Likewise, performance might be improved further by using seasonal average hourly volumes rather than annual averages.

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CHAPTER 5

IMPROVING FREEWAY SEGMENT CRASH PREDICTION MODELS BY INCLUDING DISAGGREGATE SPEED DATA FROM DIFFERENT SOURCES

Accident Analysis and Prevention (2nd review following minor revisions).
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ABSTRACT

Traditional traffic safety analyses use highly aggregated data, typically annual average daily traffic (AADT) and annual crash counts. This approach neglects the time-varying nature of critical factors such as traffic speed, volume, and density, and their effects on traffic safety. This paper evaluated the relationship between crashes and quality of flow at different levels of temporal aggregation using continuous count station data and probe data from 4 lane rural freeway and 6 lane urban freeway segments in Virginia. The performance of crash prediction models using traffic and geometric information at 15-minute, hourly, and annual aggregation intervals were contrasted. This study also assessed whether inclusion of speed data improved model performance and examined the effects of using speeds from physical sensors versus speed estimates from private-sector probe speed data. The results showed that using average hourly volume along with average speed and selected geometric variables improved predictions compared to annual models that did not use speed information. When comparing an AADT-based model to an average hourly volume model for total crashes, the mean absolute prediction error improved by 11% for rural models and 20% for urban models. This result was based on volume and speed data from continuous count stations. When private sector probe speed data was used, the rural model performance improved by 10% and urban models by 20%. This trend was consistent for all crash types irrespective of level of injury or number of vehicles involved. Even though models using private sector data performed slightly worse than the ones based on continuous count data, they were still far better than AADT based models. These results indicate that probe-based data can be used in developing crash models without harming prediction capability.

1. INTRODUCTION

Transportation safety research has sought to gain a better understanding of how different variables such as roadway geometry, driver behavior, traffic conditions, and environmental factors affect crash occurrence. The influence of those factors on traffic crashes cannot be fully understood without detailed information not only on crash itself, but also on its surrounding circumstances.

The Highway Safety Manual (HSM) provides standard scientific techniques and knowledge to help transportation officials make educated decisions regarding road safety (AASHTO, 2010). The safety performance functions (SPF) recommended in the HSM relate crash occurrence to annual average daily traffic (AADT). A difficulty with this approach is that a freeway with an intense flow during rush periods would clearly have a different crash potential than a freeway with the same AADT but with flow more evenly spread throughout the day. The customary means of using AADT in safety analysis may be too aggregate to capture all the variation in traffic flow that occurs throughout the day and could mask safety effects of operational improvements on a roadway. When considering the flow of traffic along a freeway, three parameters are of considerable significance. Speed and density describe the quality of service experienced by the stream, while volume measures the quantity of the stream and the demand on the highway facility. Drivers change or adapt their driving behavior according to the level of traffic present on the road. They may become more alert as traffic increases, but small driver errors may be more likely to result in collisions if traffic is congested. As traffic flow increases, the vehicles may travel at a lower speed, which could reduce crash severity during those conditions. Likewise, several past studies have indicated that speed variance may play a role in crash likelihood (Choudhary et al., 2018; Garber, 1989; Garber, 2000; Quddus, 2013; Solomon, 1964; Tanishita and Van Wee, 2017).

There has been considerable research conducted in recent years into establishing predictive crash relationships for freeway segments. Despite overall progress, there is still no clear understanding about how different traffic flow characteristics that represent quality of flow affect safety. This paper addresses the limitations of current SPFs by developing crash prediction models using traffic and geometric information that is provided at sub-daily aggregation intervals for urban and rural freeway segments.

2. RESEARCH OBJECTIVE

As a practical matter, relationships between traffic crashes and traffic flow parameters are inherently difficult to establish due to limitations in matching crash data with available traffic data sources. It is further restricted by the random nature of crash occurrence and the quality of available crash and traffic data. For this reason, there is considerable interest in surrogate measures such as speed, standard deviation of speed, density, or volume to capacity (*v/c)* ratios that may help in identifying problems.

This paper seeks to evaluate the relationship between crashes and quality of flow both at 15 minute and hourly levels of aggregation for freeway segments using data from Virginia. Using different geometric and traffic variables, predictive models were developed for both urban and rural freeway segments and for different crash types. The goal is to identify how traffic flow variables are related to crash occurrence and if disaggregate traffic data could improve the quality of crash predictions over AADT-based models. This paper also evaluates the possibility of using private sector probe speed data as an alternate source for speed data. Models were first developed using speed data from continuous count stations, and then these models were repeated using the probe data from INRIX. A comparison between these two data sources in terms of prediction accuracy is one of the major objectives this paper wanted to address since probe data is widely available on freeways at a much lower per-mile cost than sensor data.

3. LITERATURE REVIEW

Crashes are complex events and are influenced by many factors such as road geometric design, traffic volume and composition, speed differentials between vehicles, and so on. This paper addresses two major topics that have been of interest in the field of traffic safety research: (a) geometric and traffic variables influencing the frequency of crashes and (b) disaggregated analysis, where exposure is defined by sub-daily data instead of AADT.

Horizontal curvature, grade, median width, lane width, and shoulder width are some of the significant factors influencing road crashes on freeway segments. Crash frequency has been shown to decrease as curve radius increases (Khan et al., 2013; Shaw-pin, 1994; Tegge et al. 2010). Prior research has also demonstrated that steeper vertical grades are associated with higher crash rates (Geedipally et al., 2017; Tegge et al., 2010). These effects of horizontal curve radius, horizontal curve length, and percent grade are included in the HSM in the form of crash modification functions (CMF) based on studies by Zegeer et al. (Zegeer et al., 1990) and Harwood et al. (Graham et al., 2014). Crashes also tend to increase with wider medians, even though it largely depends on crash type. Cross median crashes tend to decrease with increasing median width, whereas rollover crashes tend to increase (Khan et al., 2013; Shaw-pin, 1994).

Speed and speed variation are widely believed to be key issues in the understanding of traffic crashes. In 1964 the Federal Highway Administration (FHWA) published a report by Solomon that studied the relationship between crashes on 2-lane and 4-lane roadways and a number of factors (Solomon,1964). From an analysis of 10,000 crashes, it was concluded that crash rates were lowest for travel speeds near the mean speed of traffic and increased with greater deviations above and below the mean. Solomon's work is often cited as the source of the 85th percentile speed rule for setting speeds. Imprialou et al. re-examined crash–speed relationships by creating a new crash data aggregation approach that enables improved representation of the road conditions just before crash occurrences (Imprialou et al., 2016). Crashes from Strategic Road Network of England in 2012 were aggregated according to the similarity of their pre-crash traffic and geometric conditions, forming an alternative crash count dataset termed as a condition-based approach. The results showed that high speeds trigger crash frequency. But the speed–crash relationship is negative regardless of crash severity. Empirical examination of the relationship between flow–density, speed, and crash rate on selected freeways in Colorado by Kononov et. al. suggested that as flow–density increases, the crash rate initially remains constant until a certain critical threshold combination of speed and density is reached (Kononov et al., 2012). Once this threshold is exceeded, the crash rate rises rapidly. Lord et. al. developed predictive models from data collected on freeway segments from Montreal, Quebec. For rural segments, as density and V/C increased, the number of single-vehicle crashes decreased, and the number of multi-vehicle crashes increased. The data showed that crashes become less severe with an increasing v/c ratio but did not seem to be affected by density (Lord et al., 2005).

Persaud and Dzbik developed crash prediction models at both the macro level (in crashes per unit length per year), and micro level (in crashes per unit length per hour) using the generalized linear modeling approach with a negative binomial error structure (Persaud and Dzbik, 1993). Microscopic models showed a decreasing slope in regression lines as hourly volume increased, perhaps capturing the influence of decreasing speed. This is in contrast to the macroscopic model, which showed increasing slopes. Evaluation of freeway safety as a function of traffic flow by Golob et al. revealed that the highest crash rates (6.3 crashes per million vehicle miles traveled (VMT)) occurred during the morning peak period with heavily congested flow, corresponding to low mean speeds, low speed variation, low flows, and low flow variation. In contrast, the lowest crash rates (0.6 per million VMT) were characterized by high speeds and low speed variation (Golob et al., 2004). Ivan et.al concluded that there is evidence that the hourly volume explains much of the variation in highway crash rates. They focused on actual hourly exposure values of seventeen rural, two-lane highway segments in Connecticut, with varying land-use patterns (Ivan et al., 2000). Single-vehicle crashes occurred most often in the evening and at night. On the other hand, multi-vehicle crashes were more likely to occur under daylight conditions at midday and during the evening peak period. Yu et al. investigated the impacts of data aggregation approaches based on traffic data from Shanghai's urban expressway system (Yu et al., 2018). Crash frequency analyses with a segment-based approach and a scenario-based approach were conducted first, and then crash risk analyses were developed at the individual crash level. It was found that during the congested period, an increase in operating speed would reduce crash likelihood. For medium operating speeds, the changes in operating speed do not have substantial effects on crash occurrence probability. For free-flow periods, increases in operating speed would further increase the probability of crashes.

The study of the relationship of crashes and traffic flow state is largely constrained by the difficulty in acquiring widespread information on quality of flow. Each agency has a different strategy regarding whether the roads are maintained at the state level or city/county level, which can also limit the ability to collect consistent crash and traffic detector data. Limited research focuses on different levels of data disaggregation, considers temporal traffic flow characteristics, compares different model forms and modeling techniques, and goes through vigorous model validation. A recent study by Wang et al. shed some light on this area (Wang et al., 2018). They developed different models to estimate crash frequency using annual daily traffic and annual hourly traffic. The study segments were from three expressways in Orlando, Florida and included basic freeway segments, merging segments and weaving segments. It was found the logarithm of volume, the standard deviation of speed, the logarithm of segment length, and the existence of a diverge segment were significant in the models. Weaving segments experienced higher daily and hourly crash frequencies than merge and basic segments.

This work discussed in this paper addresses similar concerns as those described by Wang et al., but the scope of these two papers are different in terms of dataset used and research objective. In this study, focus was on establishing a relationship between traffic flow variables and crashes using disaggregate traffic data over a broad statewide network. This paper also evaluates whether widely available probe data could serve as a substitute for loop detector data, which could broadly expand the applicability of crash prediction models that use speed as an input factor.

4. DATA COLLECTION AND PREPARATION

Volume and speed data were collected for 2-lane directional rural freeway segments and 3-lane directional urban freeway segments in 15-minute increments from 2011 to 2017 using the Virginia Department of Transportation (VDOT) Traffic Management System. A total of 31 continuous count station were identified from rural 2 lane segments and 24 from urban 3 lane segments as shown in Figure 1.

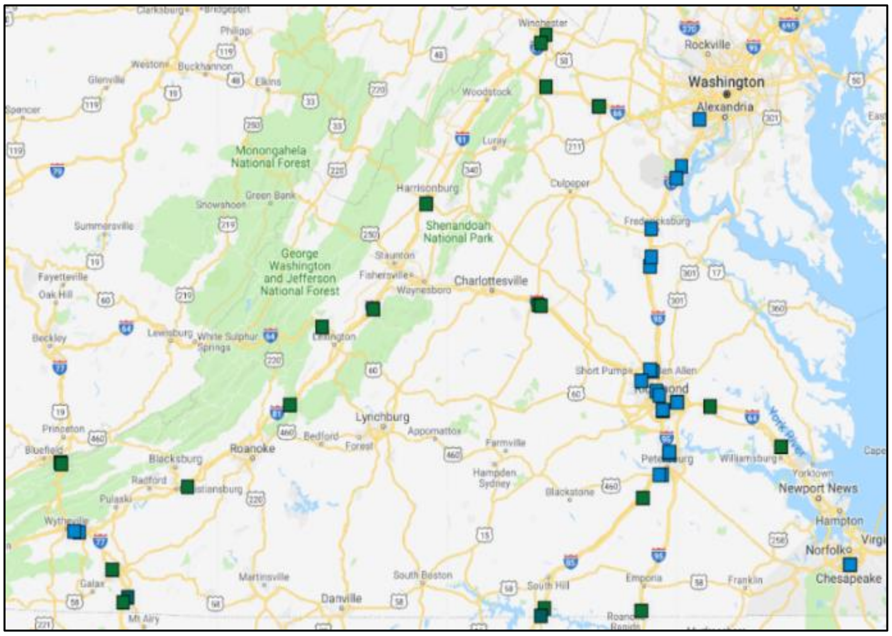

FIGURE 1 Continuous Count Stations on Freeway Segments Used in This Research (Green squares represent rural stations; blue station represents urban stations)

4.1 Volume and Speed Data

In Virginia, traffic volumes are determined using both continuous count stations and short-term counts conducted throughout the state on a rotating basis. This study relied on data from the continuous count stations only because of their high level of quality control and their ability to produce accurate volume counts over the entire study period. Only time periods where both volume and speed data meet a quality threshold set by VDOT were included in the dataset used for this research.

As an alternate data source, speed data was also obtained from the private sector travel time data provider INRIX for both 15-minute and hourly interval. INRIX is a private company that processes GPS probe data to estimate speeds, which are reported spatially using traffic message channel (TMC) links. TMC links are spatial representations developed by digital mapping companies for reporting traffic data and consist of homogeneous segments of roadways. VDOT currently uses INRIX data to support a variety of performance measurement and traveler information applications, and several external and internal evaluations have supported the accuracy of the travel time data for freeways (Haghani et al., 2009). INRIX provides confidence scores for each 1-minute interval travel time, with a confidence score of 30 representing real-time data and scores of 10 and 20 representing historic data during overnight and daytime periods, respectively. For the purposes of this analysis, no threshold was set for the confidence scores and both real time and historic speed data was used in model development.

While continuous volume data is available only at a discrete number of locations with sensors installed, INRIX speed data is broadly available across the roadway network in Virginia. Use of INRIX data in crash modeling will help to overcome the difficulties associated with using only continuous count station data.

4.2 Geometry Data

The VDOT Highway Traffic Records Information System (HTRIS) was used to extract all geometric and traffic control information used for this analysis. Using this database, information such as number of lanes, speed limit, shoulder width, median type, rural/urban designation, etc. was gathered for the study segments. The vertical curvature (VC) data are expressed in the form of percent grade, with positive grades indicating uphill segments and negative grades indicating downhill segments. Horizontal curvature (HC) was expressed using a variety of variables, including length of the curve, presence of curve as a percentage of segment length, and radius of curve. Length and radius of curve for each segment were directly available in the dataset.

4.3 Crash Data

Crash data for all the sections were obtained from VDOT as well (Roadway Network System, Virginia Department of Transportation.). The data included detailed information on crash location and date, crash type, severity, number of vehicles involved, etc. For all the segments, crash information was also collected between 2011 and 2017.

A summary of all the data sources are included in Table 1. Figure 2(a) shows a sample of the data format for a segment and figure 2(b) provides explanation of the data format.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	LinkID	Year	Hour	Volume	HV	Total	Speed	Std	Length	Percent HC	L_HC	Radius_HC	Grade_VC	Mwidth	Speed Limit	Delta
2	10148	2011	0	203.13	39.80	0	48.88	4.21	1.78	12.92	0.23	0.78	0.32	40	70	21.12
3	10148	2011	1	157.27	42.23	0	48.31	3.98	1.78	12.92	0.23	0.78	0.32	40	70	21.69
4	10148	2011	2	144.88	41.00	0	48.69	3.43	1.78	12.92	0.23	0.78	0.32	40	70	21.31
5	10148	2011	3	124.67	43.19	1	48.44	3.71	1.78	12.92	0.23	0.78	0.32	40	70	21.56
6	10148	2011	4	135.88	41.30	0	48.93	3.2	1.78	12.92	0.23	0.78	0.32	40	70	21.07
7	10148	2011	5	181.82	38.49	0	50.03	3.44	1.78	12.92	0.23	0.78	0.32	40	70	19.97
8	10148	2011	6	289.33	30.31	0	52.2	3.1	1.78	12.92	0.23	0.78	0.32	40	70	17.8
9	10148	2011	7	438.81	24.57	0	53.23	3.13	1.78	12.92	0.23	0.78	0.32	40	70	16.77
10	10148	2011	8	590.53	21.40	1	53.24	3.56	1.78	12.92	0.23	0.78	0.32	40	70	16.76
11	10148	2011	9	738.24	18.93	0	52.93	3.98	1.78	12.92	0.23	0.78	0.32	40	70	17.07
12	10148	2011	10	892.68	17.21	1	52.58	4.17	1.78	12.92	0.23	0.78	0.32	40	70	17.42

2 (a)

Column	Explanation
LinkID	Identifier for Segments
Year	Year
Hour	Hour
Volume	Average Hourly Volume (vph)
HV	Heavy Vehicle Percentage (%)
Total	Hourly Total Crashes
Speed	Average Hourly Speed (mph)
Std	Standard Deviation of Speed
Length	Length of Segment (mile)
Percent HC	Percent of Horizontal Curve Presence (%)
L_HC	Length of Horizontal Curve (mile)
Radius_HC	Radius of Horizontal Curve (mile)
Grade_VC	Grade of Vertical Curve (%)
Mwidth	Median Width (ft)
SL	Speed Limit (mph)
Delta	Difference between Speed Limit & Speed (mph)

2 (b)

FIGURE 2: Sample Data (a) Data Format, (b) Data Explanation

TABLE 1: **Summary of data**

Type of Data	Source (Maintaining Agency)	Data Format	Data Elements
Traffic Volume	Continuous Count Stations on Virginia Freeways (VDOT)	Data was extracted for every 15-minute interval for the entire study period. This raw data was then converted to an average 15-minute volume and average hourly volume for each year. AADT data was directly available from the source.	• Average 15-minute Volume • Average Hourly Volume • AADT
Speed	Continuous Count Stations on Virginia Freeways (VDOT) Probe data from private data source (INRIX)	Data was extracted for every 15-minute interval for the entire study period. The raw data was then converted to average 15-minute speed and average hourly speed for each year using the two different data sets.	• Average 15-minute Speed (Count Station and INRIX) • Average Hourly Speed (Count Station and INRIX)

Roadway Geometry	Highway Traffic Records Information System (VDOT)	Comprehensive inventory on detailed geometric data for Virginia. The data is provided for each roadway link in the state.	• Number of lanes • Horizontal & Vertical Curvature • Median Type & Width • Shoulder Width • Speed Limit
Crashes	Roadway Network System (VDOT)	Detailed information on time, location, crash type, injury and road condition. The crash models predicted either crashes/15 min or crashes/hour depending on the time resolution under study. During validation, predicted number of crashes were summed to create yearly numbers to compare with AADT based crash models that predict crashes/year.	• Total Crashes • Fatal and Injury Crashes • Property Damage Crashes • Single Vehicle Crashes • Multiple Vehicle Crashes

4.4 Selection of freeway segment

For this research, only basic freeway segments free from ramps or interchanges were considered. This was done using the detector database maintained by the Traffic Engineering Division at VDOT and the VDOT GIS integrator. The GIS integrator stores layers of different elements such as mile markers, exits and traffic count stations. All these elements contain direction and location information that helped to define the segments in a way that there is no entry/exit ramp within 0.5 miles of start/end of the segment.

It was important for this analysis to define a segment surrounding each count station where it could be assumed that homogeneous flow conditions were present for the entire length. If the station was on a link with homogeneous geometric characteristics that was greater than 2 miles in length, a buffer of a maximum 2 miles around the actual location of the detector (1 mile upstream and downstream) was created.

The number of lanes, lane and shoulder width, speed limit, median type, and median width were used to define the geometric homogeneity of segment. Generally speaking, horizontal and vertical curvature was not significant on these segments since they were located on interstates with high geometric design standards. Since this research focuses on interaction between geometry and flow parameters and how they define safety instead of a design focused approach, horizontal and vertical curvature was not used to define the segment, instead they were used as variables to identify their interaction with flow. Table 2 summarizes the properties of the study segments.

TABLE 2: Summary of the descriptive statistics of freeway study segments

Type of Segment	Total Mileage (mile)	Variable	Mean	Std. Deviation	Min	Max
Rural 4 Lane Segments	57.21	AADT	21360	7926	4420	34200
		Average Hourly Volume (vph)	855	600	29	2754
		Average Hourly Speed (mph)	69.36	4.19	48.31	75.72
		Segment Length (mile)	1.85	0.41	1.06	2.00
		Lane Width (ft)	12.00	0.00	12.00	12.00
		Right Shoulder Width (ft)	6.47	4.93	0.00	10.00
		Left Shoulder Width (ft)	3.88	4.77	0.00	10.00
		Median Width (ft)	115	54	34	220
		Horizontal Curvature Radius (mile)	2.10	1.47	0.00	5.31
		Horizontal Curvature Length(mile)	0.37	0.23	0.00	0.99
		Grade (%)	-0.27	0.96	-1.67	2.69
		Speed Limit (mph)	69	1.70	65	70
		Annual Total Crashes	7.00	7.00	1.00	13.00
		Annual Fatal & Injury Crashes	2.00	3.00	0.00	5.00
		Annual Property Damage Crashes	5.00	5.00	0.00	8.00
		Annual Single Vehicle Crashes	4.00	2.00	0.00	9.00
		Annual Multiple Vehicle Crashes	3.00	4.00	0.00	4.00
Urban 6 Lane Segments	38.67	AADT	43840	15754	20137	80656
		Average Hourly Volume (vph)	1717	1209	69	5243
		Average Hourly Speed (mph)	63.96	7.31	19.92	74.71
		Segment Length (mile)	1.59	0.41	0.81	2.21
		Lane Width (ft)	12.00	0.00	12.00	12.00
		Right Shoulder Width (ft)	5.38	5.19	0.00	12.00
		Left Shoulder Width (ft)	4.77	5.39	0.00	12.00
		Median Width (ft)	66.35	51.62	5	220
		Horizontal Curvature Radius (mile)	1.51	0.88	0	3.61
		Horizontal Curvature Length(mile)	0.35	0.19	0	0.78
		Grade (%)	-0.18	1.09	-2.58	2.20
		Speed Limit (mph)	63.05	4.19	55	70
		Annual Total Crashes	16.00	17.00	0.00	74.00
		Annual Fatal & Injury Crashes	4.00	5.00	0.00	34.00
		Annual Property Damage Crashes	12.00	13.00	0.00	60.00
		Annual Single Vehicle Crashes	5.00	4.00	0.00	32.00
		Annual Multiple Vehicle Crashes	11.00	15.00	0.00	64.00

5. METHODOLOGY

A series of crash prediction models were developed using a variety of variables including volume, segment length, heavy vehicle percentage, horizontal curvature, vertical curvature, median width, median type, and speed. Speed was expressed in a variety of ways, including average speed, standard deviation of speed, and difference between speed limit and average speed. Volume and segment length are already used in the HSM SPFs.

Previous research by the authors indicated that crash prediction models using raw hourly volume and speed data as observed on each site perform worse than the AADT based model (Dutta & Fontaine, 2018) With raw hourly data, data errors and availability can create issues and imputation of missing values can be problematic and increase errors. The same research also showed that use of the average volume calculation helped to smooth out the discrepancies created by missing raw hourly data. Based on this previous experience, volumes in this research were expressed in the form of AADT, average 15-min volume, and average hourly volume for each site over each year. Quality of flow variables were summarized using a similar definition in each case. The disaggregated models were compared to each other and with the AADT model to determine how the predictions vary from typical HSM-like models. Three different regression model forms were evaluated as part of this research:

1. Models using volume and segment length only
2. Models using volume, segment length, and geometric variables
3. Models using volume, segment length, geometric variables, and traffic flow parameters

For each model, volumes were expressed as AADT (to be consistent with the current HSM SPFs), average 15-min volume, and average hourly volume. Both negative binomial and zero inflated negative binomial regression methods were evaluated. Models using AADT data were created for the first two model forms so that model performance could be compared using the same datasets. To be consistent with the HSM, length was used as an offset variable in the models. One additional step for the third model was that it was developed twice. First a model was selected for each crash type using volume, geometry and flow parameters based on data from continuous count station. Once the models are finalized, they were regenerated by keeping the same form but using speed data from INRIX. For this iteration, volume data was still generated by the continuous count stations, but speed components were coming from probe based INRIX data.

5.1 Selection of Model Form

There are a wide variety of statistical methods that researchers have been using to model crash frequency over the years. Although Poisson models have served as a starting point for crash analysis, they are often criticized for its inability to handle over- and under-dispersed data (Lord and Mannering, 2010). The negative binomial regression model is an extension of the Poisson model that helps overcome possible over dispersion in the data. Negative binomial regression has become the most common method for developing SPFs, and is also the recommended modeling approach in the HSM (Highway Safety Manual, 2010). In a negative binomial regression model, the probability of roadway entity i having yi crashes per time period is defined as:

$$\boldsymbol{P(y_i)} = \frac{\boldsymbol{exp(-\lambda_i) * \lambda_i{}^{y_i}}}{\boldsymbol{y_i\,!}} \tag{1}$$

$$\boldsymbol{\lambda_i = exp(\beta X_i + \varepsilon_i)} \tag{2}$$

Where exp (ε_i) is a gamma-distributed error term with mean 1 and variance α (Simon et al., 2010). The addition of this term allows the variance to differ from the mean as:

$$\textbf{VAR}\ \boldsymbol{(yi)} = \textbf{E}\ \boldsymbol{(yi)}\ [1+ \boldsymbol{\alpha}\textbf{E}\ \boldsymbol{(yi)}] = \textbf{E}\ \boldsymbol{(yi)} + \boldsymbol{\alpha}\textbf{E}\ \boldsymbol{(yi)^2} \tag{3}$$

Since crashes are random events, researchers are often left with a dataset that is characterized by a significant number of zeros. As the data becomes more disaggregated, zero crashes become more common for the selected interval (hour or 15-minute). Zero inflated models have been developed to handle data characterized by a significant number of zeros or more zeros than the one would expect in a traditional Poisson or negative binomial/Poisson-gamma model. These models operate on the principle that the excess zero density that cannot be accommodated by a traditional count structure is accounted for by a splitting regime that models a crash-free versus a crash prone propensity of a roadway segment (Lord and Mannering, 2010; Simon et al., 2010). If the probability of a data point being zero is π and probability of it being non-zero is (1 – π), then, the probability distribution of the ZINB random variable y_i can be written as:

$$\boldsymbol{P_r(y_i = j)} = \begin{cases} \boldsymbol{\pi_i + (1 - \pi_i)g(y_i = 0)} & \boldsymbol{if\ j = 0} \\ \boldsymbol{(1 - \pi_i)g(y_i)} & \boldsymbol{if\ j > 0} \end{cases} \tag{4}$$

Where πi is the logistic link function and g(yi) is the negative binomial distribution given by:

$$\boldsymbol{g(y_i) = P_r(Y = y_i |\, \mu_i, \alpha)} = \frac{\boldsymbol{\Gamma(y_i + \alpha^{-1})}}{\boldsymbol{\Gamma(\alpha^{-1})\Gamma(y_i+1)}} \left(\frac{\boldsymbol{1}}{\boldsymbol{1+ \alpha\mu_i}}\right)^{\boldsymbol{\alpha^{-1}}} \left(\frac{\boldsymbol{\alpha\mu_i}}{\boldsymbol{1+ \alpha\mu_i}}\right)^{\boldsymbol{y_i}} \tag{5}$$

5.2 Selection of Modeling Technique

Generalized linear models are extensions of traditional regression models that allow the mean to depend on the explanatory variables through a link function, and the response variable to be any member of a set of distributions called the exponential family (e.g., Normal, Poisson, Binomial) (McCullagh & Nelder,1989). In a generalized linear model (GLM), each outcome Y of the dependent variables is assumed to be generated from the exponential family. The mean, $\boldsymbol{\mu}$, of the distribution depends on the independent variables, X, through:

$$\boldsymbol{E(Y) = \mu = g^{-(X\beta)}} \tag{6}$$

Where E(Y) is the expected value of Y; Xβ is the *linear predictor*, a linear combination of unknown parameters $\boldsymbol{\beta}$; g is the link function. The unknown parameters, β, are typically estimated with maximum likelihood. This method estimates model parameters by selecting those that maximize a likelihood function that describes the underlying statistical distribution assumed for the regression model. For a negative binomial regression model, the likelihood function can be described as -

$$\boldsymbol{L\,(\lambda_i) = \prod_i \frac{\Gamma\,(y_i+\left(\frac{1}{\alpha}\right))}{y_i!\,\Gamma\left(\frac{1}{\alpha}\right)} \cdot \left[\frac{\alpha\lambda_i}{1+\alpha\lambda_i}\right]^{y_i} \cdot \left[\frac{1}{1+\alpha\lambda_i}\right]^{1/\alpha}} \tag{7}$$

Where Γ(x) is the gamma function, variance is α, λ is the mean and y_i is number of crashes per period for roadway segment i.

5.3 Vuong Test

The Vuong test statistic (V) has been proposed for non-nested models to compare the fitness of zero inflated models versus regular count models (Vuong, 1989) *:*

$$\boldsymbol{V = \frac{\overline{m} * \sqrt{N}}{S_m}} \tag{8}$$

Where, $m_i = \log[\frac{f_1\,(y_i)}{f_2\,(y_i)}]$

N = number of observations

$\overline{m}$ = Mean of m_i

S_m= Standard deviation of m_i

f_1, f_2 = Two competing models

V has a standard normal distribution, and has three possible outcomes:

- If the absolute value of V is less than 1.96 for a 0.95 confidence level, then neither model is preferred by the test result.
- V is a large positive value, then model 1 is preferred.
- V is a large negative value, then model 2 is preferred.

This test was used to select which model form is appropriate for the dataset.

5.4 Model Selection and Validation

While comparing the models, it is important to have a consistent methodology to select a model from a series of models that has been developed for each technique. A popular method for model selection is the Akaike information criterion (AIC)(Akaike, 1974) . AIC offers an estimate of the relative information lost when a given model is used to represent the process that generated the data.

$$\mathbf{AIC = -2LL + 2p} \tag{9}$$

Where p is the number of estimated parameters included in the model. A lower value of AIC indicates a better model. It should be noted that the values of AIC are only relevant to that particular disaggregation level. Different levels of data aggregation lead to very different total numbers of data points in all these models, and the interaction among variables changes for different levels of disaggregation as well. As a result, AIC values should not be compared across different data aggregation levels.

It is important to note that an objective assessment of the predictive performance of a particular model can be made only through the evaluation of several goodness of fit (GOF) criteria. The GOF measures used to conduct external model validation included mean prediction bias (MPB), mean absolute deviation (MAD), and mean squared prediction error (MSPE) (Washington et al.,2010.)

Since AADT based models predict annual crashes while hourly volume models predicted hourly crashes, the summation of hourly predictions was used to generate annual predicted numbers of crashes for the GOF calculations. The average hourly volume data was computed by averaging data for each available hour for each site, so there were always 24 hours of data available for each year and each site for validation. A similar methodology was followed for average 15 min data as well. Data from the years 2011 to 2015 was used to build the models, and data from 2016 and 2017 were used for validation. The calculation of these measures was based on the following equations:

$$\boldsymbol{Mean\ Absolute\ Deviation\ (MAD) = \frac{\sum_{i=1}^{n}|Y_{model} - Y_{observed}|}{n}} \tag{10}$$

$$\boldsymbol{Mean\ Absolute\ Prediction\ Error\ (MAPE) = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_{observed} - Y_{model}}{Y_{observed}}\right|} \tag{11}$$

$$\boldsymbol{Mean\ Squared\ Prediction\ Error\ (MSPE)} = \frac{\sum_{i=1}^{n}(Y_{model} - Y_{observed})^2}{n} \quad (12)$$

Where –

Y_{model} = Predicted Crash Frequency

$Y_{observed}$ = Observed Crash Frequency

n = Sample Size

Figure 3 below provides an overview of the methodology followed in this research. Figure 4 provides a sample flowchart for all the tasks under a particular model. Other models were developed by performing same tasks with added variables.

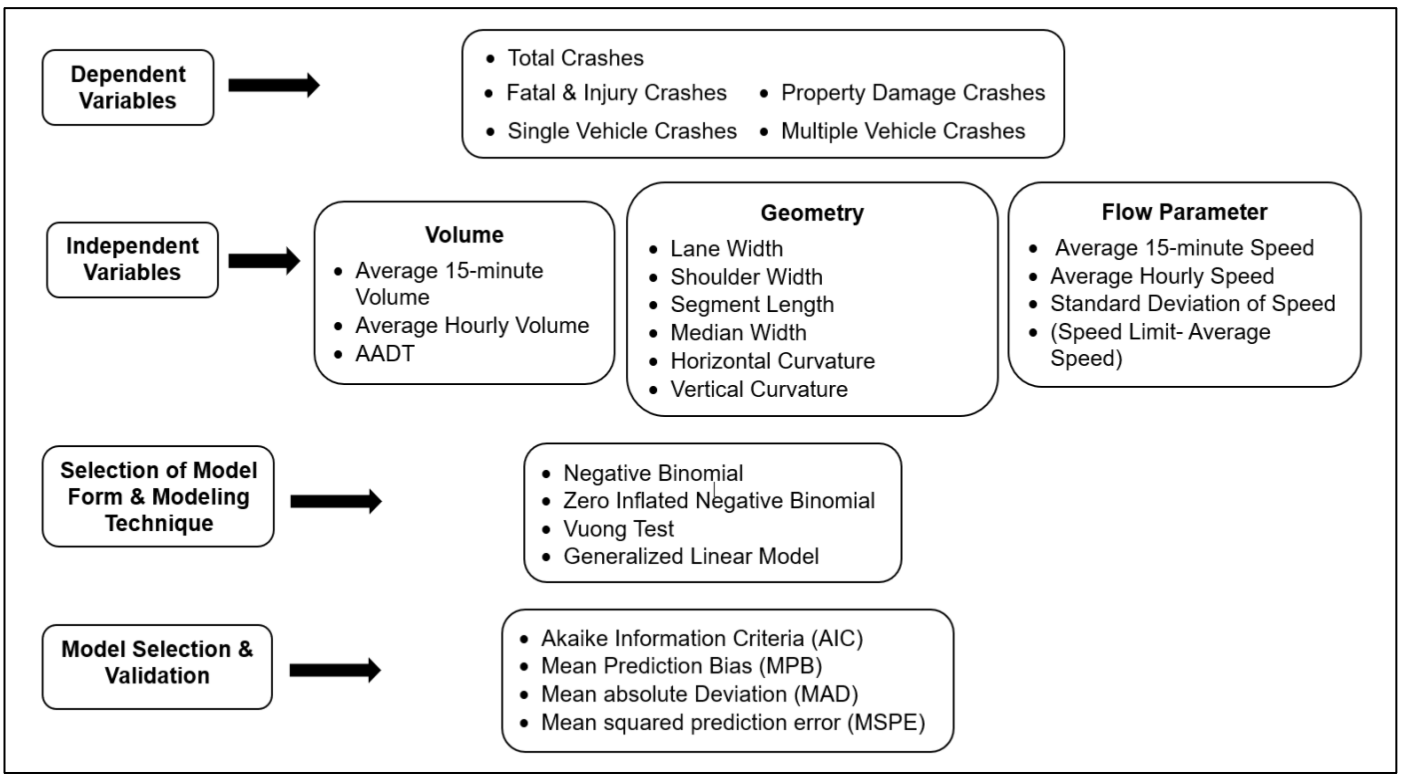

FIGURE 3: Summary of Methodology

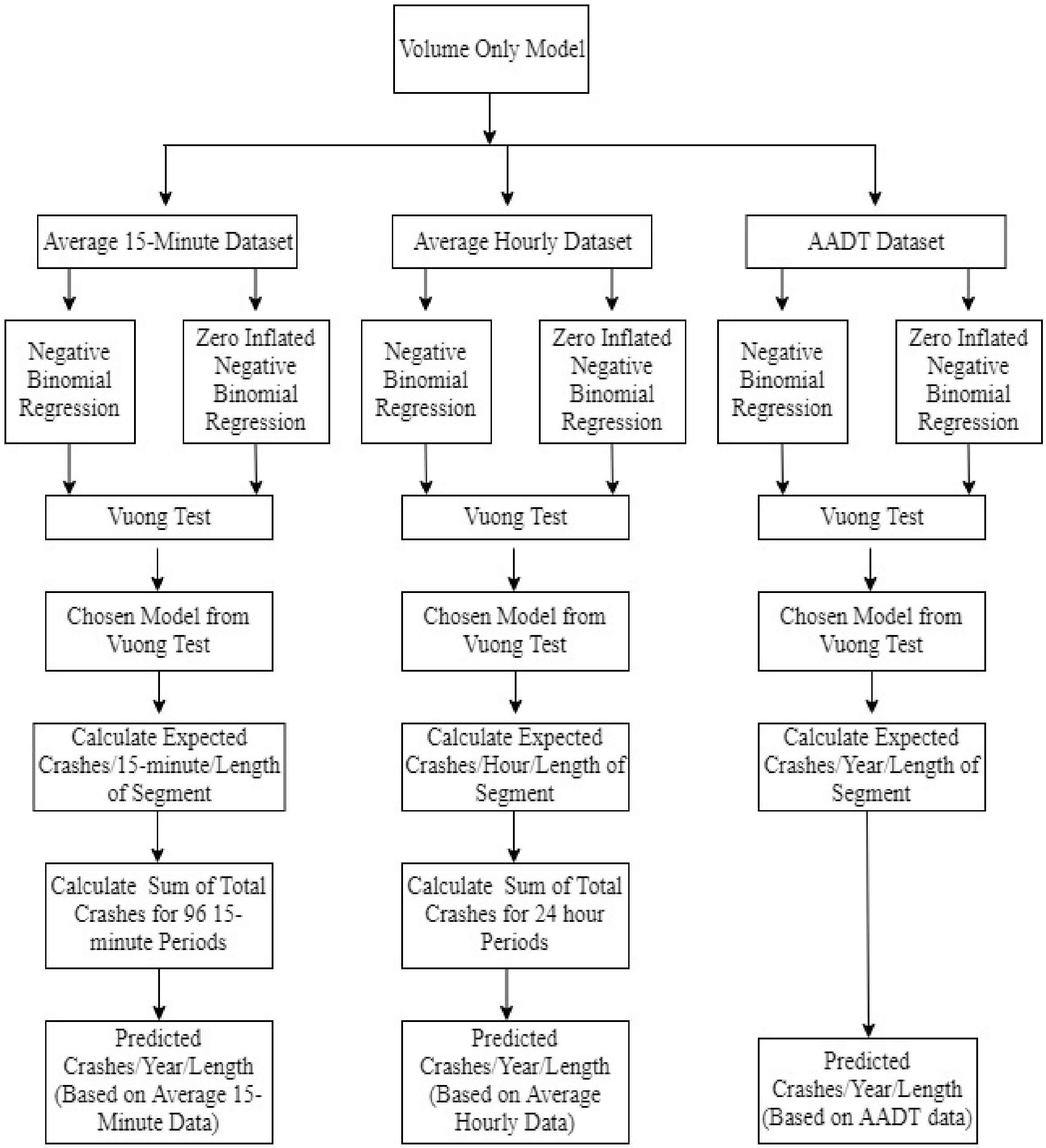

FIGURE 4: Flowchart of Modeling Tasks

6. RESULTS AND DISCUSSION

6.1 Vuong test

The Vuong test results showed that, in general, negative binomial models performed better than the zero inflated ones with respect to AIC value, variable significance, and sign of estimated coefficients. For the 15-minute volume dataset, the volume and geometry model for single vehicle crashes on urban segments and fatal and injury crashes for rural segments were the only two categories where the Vuong test results preferred the zero inflated model over the negative binomial form. The results supported negative binomial model for all other cases. For hourly data, negative binomial models outperformed the zero inflated models for both rural and urban segments, irrespective of crash type. To maintain consistency in model form, negative binomial models were used for both total and injury crashes, and those results are documented in the remainder of this paper.

6.2 Volume and Length Model

For the first set of models, volume was significant for all levels of aggregation for all types of crashes. This model is consistent with the current HSM SPFs in terms of variables used but differs in how volume is being used. This serves as the basic model, and more variables are added in subsequent steps to increase the complexity of the models. Sample results are summarized in Table 3 and 4 for the volume only models for rural and urban segments respectively.

TABLE 3 Parameter Estimates for Volume Only Models for Rural 4 Lane Freeway Segments

	Total Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-7.59	0.255	<2e-16	-7.21	0.338	<2e-16	-6.32	1.120	2E-08
log (Volume)	0.55	0.047	<2e-16	0.59	0.049	<2e-16	0.65	0.114	1E-08
AIC	6027			3924			853		
	Injury Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-8.68	0.448	<2e-16	-8.06	0.564	<2e-16	-9.38	1.734	6E-08
log (Volume)	0.54	0.083	8E-11	0.54	0.083	5E-11	0.83	0.175	2E-06
AIC	2425			1764			553		
	Single Vehicle Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-6.3	0.288	<2e-16	-5.45	0.363	<2e-16	-2.47	1.085	0.0023
log (Volume)	0.20	0.055	3E-04	0.23	0.055	2E-05	0.18	0.110	0.001
AIC	3953			2741			656		

TABLE 4 Parameter Estimates for Volume Only Models for Urban 6 Lane Freeway Segments

	Total Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-10.05	0.301	<2e-16	-7.51	0.359	<2e-16	-19.71	1.951	<2e-16
log (Volume)	1.06	0.047	<2e-16	0.74	0.048	<2e-16	1.95	0.184	<2e-16
AIC	8941			5571			825		

	Injury Crashes								
	Average 15 Minute Volume			Average Hourly Volume			AADT		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-10.43	0.499	<2e-16	-9.04	0.556	<2e-16	-23.06	2.420	<2e-16
log (Volume)	0.92	0.078	<2e-16	0.76	0.073	<2e-16	2.14	0.225	<2e-16
AIC	3687			2594			548		
	Single Vehicle Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-5.65	0.326	<2e-16	-4.31	0.406	<2e-16	-9.41	2.125	10E-06
log (Volume)	0.15	0.054	8E-03	0.13	0.056	0.0177	0.89	0.199	9E-06
AIC	3927			2763			621		

6.3 Volume, Length and Geometry Model

Next, geometric variables were added to the volume only model discussed previously. Due to limited variability in lane width and shoulder width for this particular data set, they were not significant in the modeling process. Other geometric variables such as median width, horizontal curvature, vertical curvature was evaluated. Horizontal curvature was included in the models as length of curvature and percentage of curvature (ratio of curve length and segment length) variables. Vertical curvature was categorized as positive and negative grades.

For urban segments, the only statistically significant geometric variable was median width for all levels of aggregation and crash types. The segments with curve presence were mostly comprised of long, gentle horizontal curves that almost resemble a tangent section. There was little variability in vertical grades for these segments as well. Median width was negatively associated with crash frequency, indicating wider medians in urban segments reduce the total number of crashes. Previous research indicated that median width between 20 and 30 ft generally shows a mixed effect on crashes and median width of 60 to 80 ft has decreasing effect on crashes (Chang and Xiang, 2003; Knuiman et al., 1993). About 55% of the urban dataset had median widths within this range so the negative relationship between median width and crashes is intuitive. Table 5 summarizes some sample models for this step. The geometric variables that were significant are a function of the data set available for modeling, and these models may not reflect variation that would be seen across a broader cross section of sites.

TABLE 5: Parameter Estimates for Volume and Geometry Based Models for Urban Segments

	Total Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)
Intercept	-9.65	0.301	<2e-16	-6.91	0.359	<2e-16	-17.36	2.401	4.81E-13
log (Volume)	0.97	0.051	<2e-16	0.70	0.048	<2e-16	1.75	0.236	1.07E-13
Median Width	-0.13	0.032	4E-09	-0.11	0.063	<2e-16	-0.21	0.001	0.0043
AIC	8868			5520			742		
	Injury Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)
Intercept	-9.99	0.499	<2e-16	-8.56	0.563	<2e-16	-23.12	2.805	<2e-16
log (Volume)	0.82	0.083	<2e-16	0.75	0.073	<2e-16	2.19	0.272	7.55E-16
Median Width	-0.11	0.541	6E-06	-0.32	0.423	1E-09	-0.15	0.001	5.97E-07
AIC	3964			2559			469		
	Single Vehicle Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(> |z|)	Estimate	Std. Error	Pr(> |z|)
Intercept	-5.32	0.335	<2e-16	-3.74	0.427	<2e-16	-6.87	2.604	0.00833
log (Volume)	0.09	0.059	3E-04	0.11	0.057	0.0571	0.67	0.256	8.59E-03
Median Width	-0.12	0.025	4E-04	-0.21	0.001	9E-11	-0.01	0.321	0.00272
AIC	3909			2721			550		

For rural segments, 71% of the data came from segments with median widths greater than 80 ft and no median barrier. The results indicated that wider medians generally had more crashes. This is contradictory to the urban segments, but consistent with previous research (Shankar et al., 2004; Graham et al., 2014). The relationship between median width and crashes largely depend on type of facility, crash type, and also presence and type of median barrier. Cross median crashes tend to decrease with increasing median width, whereas rollover crashes tend to increase. For vertical curvature, presence of grade (both positive and negative) increases the probability of any types of crash. For injury crashes and single vehicle crashes, only negative grades had a statistically significant affect. These findings were similar irrespective of the volume disaggregation level, and also align with the results from previous research (Graham et al., 2014; Shankar et al., 2004; Watson et al., 2014). Table 6 includes final selected models from this step.

TABLE 6: Parameter Estimates for Volume and Geometry Based Models for Rural Segments

	Total Crashes								
	Average 15 Minute Volume			Average Hourly Volume			AADT		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|	Estimate	Std. Error	Pr(>|z|)
Intercept	-8.41	0.307	<2e-16	-8.04	0.385	<2e-16	-9.04	1.289	2E-12
log (Volume)	0.56	0.051	<2e-16	0.57	0.0524	<2e-16	0.87	0.131	2E-11
Median Width	0.43	0.138	5E-06	0.51	0.315	3E-09	0.65	0.902	0.0153
Grade of VC									
Negative	0.42	0.092	5.E-06	0.48	0.098	8.E-07	0.55	0.106	3E-07
Positive	0.38	0.133	0.00465	0.33	0.143	2E-02	0.41	0.161	0.0102
Percent of HC	0.05	0.001	6E-11	0.06	0.009	9E-11	0.06	0.008	3E-14
Length of HC	-2.74	0.472	4E-09	-3.15	0.515	8E-10	-3.82	0.476	1E-15
AIC	5977			3864			796		
	Injury Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-9.29	0.532	<2e-16	-8.46	0.629	<2e-16	-11.07	2.125	2E-07
log (Volume)	0.51	0.087	8E-09	0.47	0.086	3E-08	0.95	0.216	1E-05
Median Width	0.24	0.711	1E-03	0.36	0.667	2E-05	0.29	0.201	0.0255
Grade of VC									
Negative	0.35	0.161	3E-02	0.36	0.161	0.0248	0.49	0.167	3E-03
Positive	0.16	0.243	0.4989	0.03	0.255	0.8909	0.36	0.267	0.1784
Percent of HC	0.05	0.015	8E-04	0.04	0.016	9E-03	0.041	0.014	4E-03
Length of HC	-2.59	0.855	2E-03	-2.61	0.936	5E-03	-2.70	0.807	8E-04
AIC	2416			1745			544		
	Single Vehicle Crashes								
	Average 15 Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-7.09	0.374	<2e-16	-6.11	0.433	<2e-16	-4.03	1.309	2.E-03
log (Volume)	0.23	0.059	1E-04	0.22	0.058	2E-04	0.28	0.135	3E-02
Median Width	0.33	0.612	4E-03	0.41	0.125	2E-06	0.22	0.311	0.0122
Grade of VC									
Negative	0.54	0.131	3E-05	0.44	0.124	4E-04	0.61	0.125	1E-06
Positive	0.37	0.175	0.0351	0.14	0.179	0.4419	0.36	0.192	0.0602
Percent of HC	0.04	0.012	6E-04	0.06	0.012	9E-07	0.05	0.009	3E-07
Length of HC	-2.32	0.654	4E-04	-3.47	0.672	2E-07	-2.99	0.556	7E-08
AIC	3934			2699			624		

6.4 Volume, Geometry and Flow Parameter Models

The final sets of models were created by adding flow parameters to the models selected in the previous step. Average speed, standard deviation of speed, and the difference between speed limit and average speed (called the delta speed hereafter) were selected to represent traffic flow. AADT based models were not developed for this alternative since average speed over a year showed little variability. These models were developed twice; first with speed data from the continuous count stations and then repeating the same model with speed data from INRIX. This was done to compare the quality of data between these sources and how they affect the model fit.

Table 7 shows the rural models that include speed parameters. For total crashes, speed was negatively related to crashes, meaning that lower average speed is correlated with higher crash frequency. Lower average speeds indicate the presence of congestion, so this relationship is intuitive for rural sites. These models also show that as standard deviation of hourly average speeds or 15-minute average speed increases, probability of crashes also increases.

For models based on level of injury, it was found that standard deviation is positively related to crashes for both injury and PDO crashes. The variable delta speed had a negative relationship for both types of crashes. Delta speed is defined as the difference between posted speed limit and average speed. A positive value of delta would mean average speed is lower than the speed limit, indicating congestion. A negative value, on the other hand, would represent free flow conditions. A negative relationship between this variable and property damage crashes means that this type of crashes increases when congestion increases. This is a logical relationship since during congestion, speed is lower so the probability of the crash being an injury crash is lower. The negative relationship between delta speed and injury crashes seems counter intuitive since higher speeds are generally associated with more severe injuries. This result could be due to how injury was defined, and the type of data used for modeling. Fatal and injury crashes were combined in this category and range from a crash being fatal to a minor injury that does not require any doctor or hospital visit. Separating fatal and severe injury crashes from minor injury crashes might shed some light on the relationship. Even though this issue was not explicitly addressed in this paper, it could be an interesting area for future research. This relationship also might be specific to this particular dataset. This analysis was based on rural continuous count station data where the maximum hourly volume observed was 3822 vph across two lanes. Thus, these results may be driven by the fact that this dataset is dominated by locations that are often traveling near free flow and a broader variation in traffic speed is not expected.

For crashes involving single vehicle, average speed and standard deviation both were significant and followed an intuitive relation showing that as speed increases, single vehicle crashes increase. Increase in average speed means there is no congestion, which also means fewer vehicles on the road. As the number of vehicles on the road increases and speed decreases, the probability of multiple vehicles being involved in a crash also increases. Multiple vehicle crash models for rural segments showed this relationship as well.

The AIC value for models using INRIX speeds were worse than the continuous count station-based models. This is expected since continuous count station data is based on speeds of all traffic, whereas the probe data estimates link speed based on a sample of vehicles less than the entire population. While the AIC values for the INRIX models were lower than the count station models, the goal here was to evaluate if inclusion of the INRIX data could improve crash prediction models as compared to models without traffic speed parameters. The prediction accuracy is discussed in the model validation section below. For all the models, parameters for speed related variables didn't vary much between two data sources. Since these two models essentially had the same data other than the speed component, this is an indication that the speed data from these two sources are not significantly different than each other in terms of their effect on the model.

TABLE 7: Parameter Estimates for Volume, Geometry and Flow Parameter Based Models for Rural Segments

	Models with Detector Speed						Models with INRIX Speed					
Total Crashes	**Average 15 Minute Volume**			**Average Hourly Volume**			**Average 15 Minute Volume**			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-1.31	1.770	<2e-16	-6.91	0.394	<2e-16	-1.66	1.760	<2e-16	-5.95	0.413	<2e-16
log (Volume)	0.42	0.052	6E-16	0.45	0.054	<2e-16	0.36	0.058	3E-10	0.34	0.061	2E-08
Grade of VC												
Negative	0.31	0.098	0.0016	0.33	0.098	0.0003	0.24	0.096	0.014	0.36	0.094	0.0002
Positive	0.17	0.137	0.2164	0.07	0.149	0.3004	0.09	0.139	0.476	0.03	0.135	0.8272
Percent of HC	0.05	0.008	2E-10	0.04	0.009	1E-09	0.05	0.007	3E-09	0.04	0.007	2E-06
Length of HC	-2.66	0.496	8E-08	-2.21	0.463	7E-09	-2.21	0.471	2E-06	-2.13	0.439	1E-06
Average Speed	-0.09	0.026	0.0001	0.06	0.012	3E-05	-0.09	0.026	8E-04	0.07	0.017	2E-05
Std of Speed	0.13	0.022	2E-09	0.17	0.024	3E-10	0.15	0.022	2E-11	0.17	0.021	3E-07
AIC	5805			3708			5903			3826		
Injury Crashes	**Average 15 Minute Volume**			**Average Hourly Volume**			**Average 15 Minute Volume**			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-5.15	0.678	<2e-16	-7.25	0.612	0.0002	-8.19	0.902	<2e-16	-6.33	0.691	<2e-16
log (Volume)	0.37	0.086	2E-05	0.36	0.093	0.0001	0.32	0.097	9E-04	0.26	0.101	0.001
Percent of HC	0.04	0.015	0.0033	0.17	0.057	0.0618	0.04	0.014	0.006	0.21	0.053	0.001
Length of HC	-1.88	0.826	0.0023	-0.59	0.334	0.0066	-1.60	0.797	0.045	-0.68	0.329	0.037
Std of Speed	0.11	0.039	0.0035	0.19	0.042	7E-07	0.12	0.041	0.004	0.17	0.035	3E-06
Delta	0.15	0.044	0.0002	0.07	0.024	0.0003	0.16	0.039	6E-05	0.07	0.029	0.011
AIC	2368			1681			2399			1741		
Property Damage Crashes	**Average 15 Minute Volume**			**Average Hourly Volume**			**Average 15 Minute Volume**			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-2.73	0.132	0.008	-7.77	0.463	<2e-16	-8.04	0.406	<2e-16	-6.72	0.492	<2e-16
log (Volume)	0.44	0.063	2E-12	0.52	0.07	<2e-16	0.37	0.069	1E-08	0.38	0.071	1E-07
Grade of VC												
Negative	0.38	0.122	0.0017	0.42	0.156	1E-05	0.35	0.112	2E-04	0.43	0.111	0.0001
Positive	0.26	0.168	0.1052	0.12	0.173	0.0504	0.23	0.163	0.158	0.19	0.156	0.2272
Percent of HC	0.06	0.011	2E-08	0.06	0.011	5E-08	0.05	0.009	2E-08	0.05	0.008	3E-07
Length of HC	-2.83	0.595	2E-06	-2.51	0.592	6E-08	-2.66	0.542	1E-06	-2.41	0.501	1E-06
Std of Speed	0.14	0.027	1E-07	0.16	0.027	7E-08	0.18	0.026	2E-12	0.17	0.023	7E-12
Delta	0.07	0.028	0.008	0.05	0.015	3E-06	0.03	0.018	0.058	0.09	0.019	1E-08
AIC	4406			2910			4493			2995		

Single Vehicle Crashes	Average 15 Minute Volume			Average Hourly Volume			Average 15 Minute Volume			Average Hourly Volume		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-7.04	0.374	<2e-16	-12.23	1.47	<2e-16	-9.69	1.38	2E-12	-13.28	1.53	<2e-16
log (Volume)	0.21	0.062	0.0015	0.11	0.06	0.0008	0.14	0.069	0.052	0.07	0.069	0.0005
Grade of VC												
Negative	0.55	0.132	3E-05	0.36	0.126	0.0004	0.53	0.129	6E-05	0.42	0.121	0.0005
Positive	0.33	0.177	0.0731	0.06	0.186	0.7654	0.36	0.181	0.047	0.08	0.173	0.658
Percent of HC	0.04	0.012	0.0003	0.04	0.012	2E-06	0.04	0.011	5E-04	0.04	0.009	8E-05
Length of HC	-2.66	0.682	9E-05	-2.93	0.678	6E-05	-2.42	0.642	2E-04	-2.91	0.589	6E-07
Average Speed	0.03	0.015	0.0263	0.11	0.021	4E-06	0.06	0.021	0.006	0.13	0.024	3E-08
Std of Speed	0.06	0.031	0.0073	0.13	0.035	0.0022	0.07	0.035	0.039	0.12	0.031	0.0002
AIC	3855			2575			3918			2684		
Multiple Vehicle Crashes	**Average 15 Minute Volume**			**Average Hourly Volume**			**Average 15 Minute Volume**			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-3.53	0.609	<2e-16	-3.94	0.893	<2e-16	-1.29	2.066	0.005	-1.42	0.283	0.0005
log (Volume)	0.99	0.103	<2e-16	1.05	0.107	<2e-16	0.92	0.105	<2e-16	0.95	0.111	<2e-16
Percent of HC	0.05	0.011	1E-05	0.04	0.013	0.001	0.04	0.01	2E-05	0.02	0.011	0.0506
Length of HC	-2.15	0.701	0.0021	-1.76	0.806	0.0029	-1.73	0.623	0.006	-1.57	0.681	0.004
Average Speed	-0.12	0.033	0.0003	-0.12	0.041	8E-05	-0.15	0.031	2E-06	-0.14	0.034	3E-05
Std of Speed	0.22	0.029	8E-15	0.19	0.034	4E-06	0.22	0.028	4E-15	0.19	0.029	1E-10
Delta	0.14	0.031	1E-05	0.16	0.037	9E-06	0.17	0.029	5E-09	0.18	0.033	4E-07
AIC	3020			2005			3071			2053		

Table 8 shows that the speed parameters showed consistent results for urban segments as well. Standard deviation of speed always had an increasing effect on crash frequency for all crash types. For total crashes, another significant flow parameter was delta speed. The models showed that crashes on urban segments increase as congestion increases.

For injury models, only standard deviation of speed was a statistically significant flow parameter. For property damage crashes, models indicated that crashes increase as average speed decreases, which is again a logical finding.

For crashes involving a single vehicle, urban segments showed similar results as rural segments where single vehicle crashes showed increasing trends with increases in average speed. A reverse trend was observed between congestion and multi vehicle crashes, where crash frequency increased with increasing congestion.

Similar to the rural models, these relationships were consistent irrespective of the level of aggregation. The model parameters for volume, geometry, and flow models based on continuous count data and the corresponding models based on INRIX data were very close to each other. The AIC value for INRIX models were worse than the detector data-based models, which is again consistent with the findings from rural segments. In this case also, the main focus was to identify whether this drop-in quality in models make a significantly lower prediction quality or not.

TABLE 8: Parameter Estimates for Volume, Geometry and Flow Parameter Based Models for Urban Segments

	Models with Detector Speed						Models with INRIX Speed					
Total Crashes	**Average 15 Minute Volume**			**Average Hourly Volume**			**Average 15 Minute Volume**			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-10.59	0.755	<2e-16	-4.87	0.347	<2e-16	-7.64	0.665	<2e-16	-4.81	0.338	<2e-16
log (Volume)	0.55	0.051	<2e-16	0.34	0.048	9E-13	0.58	0.052	<2e-16	0.32	0.048	9E-12
Median Width	-0.21	0.167	<2e-16	-0.22	0.366	<2e-16	-0.15	0.208	<2e-16	-0.28	0.278	<2e-16
Std of Speed	0.08	0.009	<2e-16	0.13	0.012	<2e-16	0.11	0.013	<2e-16	0.16	0.111	<2e-16
Delta	0.11	0.013	<2e-16	0.05	0.006	<2e-16	0.03	0.011	0.0002	0.02	0.009	1.4E-05
AIC	7709			4264			8407			4887		
Injury Crashes	**Average 15 Minute Volume**			**Average Hourly Volume**			**Average 15 Minute Volume**			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-11.14	1.34	<2e-16	-6.62	0.594	<2e-16	-8.07	1.16	<2e-16	-6.07	0.539	<2e-16
log (Volume)	0.51	0.089	1E-08	0.36	0.079	6E-07	0.44	0.088	6E-07	0.32	0.072	8E-06
Median Width	-0.13	0.128	1E-10	-0.25	0.123	<2e-16	-0.17	0.146	2E-06	-0.19	0.135	<2e-16
Std of Speed	0.07	0.017	2E-05	0.17	0.013	<2e-16	0.12	0.018	3E-10	0.15	0.009	<2e-16
AIC	3274			2059			3515			2328		
Property Damage Crashes	**Average 15 Minute Volume**			**Average Hourly Volume**			**Average 15 Minute Volume**			**Average Hourly Volume**		
	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-11.07	0.857	<2e-16	-3.22	0.497	<2e-16	-8.59	0.764	<2e-16	-3.58	0.617	5E-09
log (Volume)	0.57	0.059	<2e-16	0.31	0.055	2E-08	0.64	0.061	<2e-16	0.33	0.052	3E-10
Median Width	-0.17	0.112	<2e-16	-0.16	0.011	1E-14	-0.13	0.011	<2e-16	-0.22	0.068	<2e-16
Average Speed	-0.06	0.013	6E-13	-0.07	0.052	5E-10	-0.11	0.012	<2e-16	-0.03	0.085	2E-06
Std of Speed	0.08	0.011	9E-14	0.15	0.523	5E-10	0.09	0.012	0.0001	0.16	0.0118	<2e-16
AIC	6288			3556			6869			4159		

Single Vehicle	Average 15 Minute Volume			Average Hourly Volume			Average 15 Minute Volume			Average Hourly Volume		
Crashes	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-8.75	1.131	<2e-16	-3.46	0.467	<2e-16	-7.19	1.05	7E-13	-2.94	0.449	<2e-16
log (Volume)	0.11	0.062	0.0007	0.47	0.066	5E-05	0.13	0.056	2E-05	0.49	0.065	8E-07
Std of Speed	0.06	0.018	0.0006	0.05	0.022	2E-06	0.08	0.016	0.0003	0.07	0.018	8E-06
Average Speed	0.09	0.022	2E-06	0.02	0.008	0.0003	0.07	0.018	3E-06	0.03	0.015	0.00009
AIC	3694			2411			3898			2681		
Multiple Vehicle	**Average 15 Minute Volume**			**Average Hourly Volume**			**Average 15 Minute Volume**			**Average Hourly Volume**		
Crashes	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)	Estimate	Std. Error	Pr(>|z|)
Intercept	-13.94	0.988	<2e-16	-7.79	0.486	<2e-16	-11.06	0.867	<2e-16	-7.74	0.464	<2e-16
log (Volume)	1.02	0.077	<2e-16	0.64	0.065	<2e-16	1.07	0.574	<2e-16	0.63	0.064	<2e-16
Std of Speed	0.09	0.107	<2e-16	0.15	0.014	3E-08	0.13	0.118	4E-14	0.19	0.013	<2e-16
Delta	0.11	0.602	4E-11	0.15	0.006	6E-06	0.15	0.472	<2e-16	0.11	0.011	2E-06
AIC	5619			3092			6204			3689		

6.5 Model Comparison

Tables 9 and 10 shows the comparison of performance among the models developed. The AADT models didn't include speed as a variable because averaging hourly speed over a year did not capture the effect of speed on traffic conditions and crashes. For comparison purposes, the volume, flow, and geometry model were compared to the AADT based volume and geometry models. Model comparison was important for multiple reasons. First, it provided a check on whether adding geometric and then flow parameters really improve model performance as expected. Second, it showed how different levels of data aggregation affect the performance. Finally, it shows whether the model performance is significantly different depending on the source of speed data. For all models, irrespective of type of facility, type of crash, or level of data aggregation, prediction accuracy consistently improved as geometric and then speed variables were added. This improvement was higher in magnitude across all validation MOEs when the speed component was added to the model.

The average 15-minute volume models gave a mixed result in comparison to the AADT model. Even though it did perform better than the AADT based model most of the time, there were certain models (injury models for urban segments, single vehicle models for rural segments) when the model could not outperform the AADT models. It is possible that at a 15-min level data is too noisy to capture the true relationship between crashes and flow parameters. Likewise, inaccuracies in time stamps of crash reports could influence results at that level. The prediction accuracy improved significantly for all models when average hourly data was used. In this case, the aggregation interval was not too disaggregated to capture the random nature of crashes, also not too aggregated to lose the variation in traffic. These models consistently performed better than the AADT based model for all MOEs.

For the rural hourly volume, geometry, and flow models, MAD, MAPE, and MSPE improved by 11%, 33% and 29% respectively while using continuous count station as speed data source and 10%, 28%, and 17% respectively when INRIX speed data was used. For the urban models, similar trends were observed where MAD, MAPE and MSPE improved by 20%, 22%, and 38% respectively for detector data and 20%, 19% and 32% for INRIX data. In both cases, these models were compared to AADT based volume and geometry models. This trend was consistent for all other models as well. Even though models using INRIX data performed slightly worse than the ones based on continuous count data, they were still far better than AADT based models.

The comparison results reinforce the importance of selecting an appropriate disaggregation level. Due to the random nature of crash occurrence, the 15 min data had too much variability to generate useful models. Similarly, aggregated models that rely on AADT may fail to capture variations traffic flow that could influence safety. Finding a proper disaggregation level as well as significant variables that influence crash frequency is one of the major concerns in the area of crash prediction modeling. Another very important finding is that speed variables played a significant role in model performance irrespective of their source. This essentially opens up the possibility to extend the analysis to sections without a continuous count station. Since current models only rely on volume, quality of volume data dictates the quality of model. This research showed that INRIX data can be used as an alternate source for speed data without reducing the quality of crash prediction models. Models developed using INRIX data performed very similarly to the continuous count station data during model validation. For all crash types and model categories, INRIX models consistently outperformed AADT models. This indicates that it may be possible to use INRIX data along with historic volume distributions from short duration count stations (where only volume data is collected intermittently) to run this analysis on a larger scale.

TABLE 9: Model Comparison for Urban Segments *

	Total Crashes								
	Average 15 min Volume			**Average Hourly Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	8.22 (-5%)	58% (-1%)	152.42 (-18%)	8.19 (-5%)	54% (-5%)	140.59 (-24%)	8.65	59%	185.38
Volume, length, and geometry models	8.13 (-5%)	52% (0%)	140.56 (-23%)	7.72 (-9%)	40% (-12%)	120.92 (-34%)	8.52	52%	181.91
Volume, length, geometry, and flow state models **	7.87 (-8%)	45% (-7%)	129.97 (-29%)	6.81 (-20%)	30% (-22%)	112.47 (-38%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	8.11 (-5%)	40% (-12%)	138.81 (-24%)	6.82 (-20%)	33% (-19%)	124.35 (-32%)	–	–	–
	Fatal & Injury Crashes								
	Average 15 min Volume			**Average Hourly Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	2.81 (+1%)	39% (+8%)	18.85 (+4%)	2.65 (-5%)	28% (-3%)	12.13 (-33%)	2.79	31%	18.21
Volume, length, and geometry models	2.77 (+3%)	36% (+7%)	15.14 (+1%)	2.56 (-4%)	21% (-8%)	10.83 (-28%)	2.68	29%	14.94
Volume, length, geometry, and flow state models **	2.53 (-6%)	29% (0%)	12.68 (-15%)	2.44 (-9%)	19% (-10%)	8.61 (-42%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	2.67 (0%)	31% (+2%)	12.73 (-15%)	2.34 (-13%)	24% (-5%)	9.71 (-35%)	–	–	–

	PDO Crashes								
	Average 15 min Volume			Average Hourly Volume			AADT		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	6.53 (-5%)	47% (-2%)	90.4 (-15%)	6.36 (-7%)	49% (0%)	80.97 (-24%)	6.85	49%	106.72
Volume, length, and geometry models	6.41 (-5%)	44% (-3%)	86.56 (-17%)	6.18 (-9%)	42% (-5%)	71.72 (-31%)	6.78	47%	104.29
Volume, length, geometry, and flow state models **	6.23 (-8%)	41% (-6%)	77.76 (-25%)	5.83 (-14%)	37% (-10%)	63.14 (-39%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	6.11 (-10%)	37% (-10%)	81.09 (-22%)	5.95 (-12%)	38% (-9%)	68.41 (-34%)	–	–	–
	Single Vehicle Crashes								
	Average 15 min Volume			**Average Hourly Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	2.79 (+3%)	59% (+2%)	13.79 (+13%)	2.71 (0%)	55% (-2%)	11.3 (-7%)	2.72	57%	12.19
Volume, length, and geometry models	2.63 (+0%)	53% (-2%)	11.31 (-3%)	2.59 (-2%)	47% (-8%)	9.94 (-15%)	2.64	55%	11.72
Volume, length, geometry, and flow state models **	2.46 (-7%)	42% (-13%)	10.88 (-7%)	2.44 (-8%)	39% (-16%)	6.64 (-43%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	2.61 (-1%)	51% (-4%)	11.00 (-6%)	2.47 (-6%)	43% (-12%)	9.01 (-23%)	–	–	–
	Multiple Vehicle Crashes								
	Average 15 min Volume			**Average Hourly Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	6.66 (-1%)	44% (0%)	95.51 (-31%)	6.63 (-2%)	42% (-2%)	82.56 (-40%)	6.76	44%	137.63
Volume, length, and geometry models	5.58 (-12%)	42% (-2%)	63.57 (-52%)	5.66 (-11%)	33% (-11%)	71.08 (-47%)	6.37	44%	133.06
Volume, length, geometry, and flow state models **	5.51 (-14%)	35% (-9%)	60.17 (-55%)	4.94 (-22%)	26% (-18%)	57.81 (-57%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	5.54 (-13%)	38% (-6%)	63.01 (-53%)	5.37 (-16%)	33% (-11%)	69.18 (-48%)	–	–	–

** Value in the parentheses represents the change compared to respective AADT based models.*
*** These models were compared to the AADT based volume, length, and geometry models.*

TABLE 10: Model Comparison for Rural Segments *

	Total Crashes								
	Average 15 min Volume			Average Hourly Volume			AADT		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	3.58 (-9%)	58% (-27%)	30.63 (-10%)	3.52 (-10%)	70% (-15%)	29.89 (-12%)	3.92	85%	34.06
Volume, length, and geometry models	3.47 (-4%)	58% (-18%)	27.88 (-1%)	3.45 (-5%)	58% (-18%)	25.24 (-10%)	3.62	76%	28.18
Volume, length, geometry, and flow state models **	3.37 (-7%)	54% (-22%)	23.77 (-16%)	3.21 (-11%)	43% (-33%)	20.11 (-29%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	3.35 (-7%)	59% (-17%)	22.07 (-22%)	3.24 (-10%)	48% (-28%)	23.5 (-17%)	–	–	–
	Fatal & Injury Crashes								
	Average 15 min Volume			**Average Hourly Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	1.31 (+7%)	47% (-15%)	2.97 (-6%)	1.15 (-6%)	50% (-12%)	2.83 (-11%)	1.22	62%	3.17
Volume, length, and geometry models	1.31 (+9%)	41% (-14%)	2.86 (-3%)	1.13 (-6%)	40% (-15%)	2.23 (-24%)	1.2	55%	2.94
Volume, length, geometry, and flow state models **	1.17 (-3%)	39% (-16%)	2.47 (-16%)	1.09 (-9%)	33% (-22%)	1.72 (-41%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	1.17 (-3%)	37% (-18%)	2.83 (-4%)	1.1 (-8%)	38% (-17%)	1.85 (-37%)	–	–	–

	PDO Crashes								
	Average 15 min Volume			**Average Hourly Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	2.89 (-6%)	67% (-26%)	19.2 (-19%)	2.99 (-3%)	59% (-34%)	22.45 (-6%)	3.07	93%	23.79
Volume, length, and geometry models	2.75 (-6%)	64% (-23%)	17.46 (-23%)	2.87 (-2%)	55% (-32%)	18.4 (-19%)	2.92	87%	22.7
Volume, length, geometry, and flow state models **	2.65 (-9%)	58% (-29%)	12.84 (-43%)	2.77 (-5%)	52% (-35%)	17.45 (-23%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	2.7 (-8%)	60% (-27%)	16.23 (-29%)	2.74 (-6%)	58% (-29%)	17.1 (-25%)	–	–	–
	Single Vehicle Crashes								
	Average 15 min Volume			**Average Hourly Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	2.15 (+5%)	85% (+2%)	9.79 (+47%)	2.09 (+2%)	71% (-12%)	6.08 (-9%)	2.05	83%	6.68
Volume, length, and geometry models	1.92 (-3%)	72% (-5%)	6.43 (0%)	1.88 (-5%)	62% (-15%)	5.85 (-9%)	1.98	77%	6.42
Volume, length, geometry, and flow state models **	1.89 (-5%)	65% (-12%)	6.27 (-2%)	1.79 (-10%)	57% (-20%)	5.8 (-10%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	1.92 (-3%)	58% (-19%)	6.38 (-1%)	1.83 (-8%)	60% (-17%)	5.64 (-12%)	–	–	–
	Multiple Vehicle Crashes								
	Average 15 min Volume			**Average Hourly Volume**			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume and length models	2.44 (-4%)	49% (-12%)	15.13 (+1%)	2.51 (-1%)	53% (-8%)	14.31 (-5%)	2.53	61%	15.05
Volume, length, and geometry models	2.31 (-4%)	47% (-7%)	13.26 (+3%)	2.23 (-7%)	43% (-11%)	12.87 (0%)	2.41	54%	12.93
Volume, length, geometry, and flow state models **	2.19 (-9%)	44% (-10%)	11.25 (-13%)	2.03 (-16%)	34% (-20%)	11.31 (-13%)	–	–	–
Volume, length, geometry, and flow state models (INRIX) **	2.23 (-7%)	41% (-13%)	10.03 (-22%)	2.19 (-9%)	39% (-15%)	12.09 (-6%)	–	–	–

***** *Value in the parentheses represents the change compared to respective AADT based models.*
****** *These models were compared to the AADT based volume, length, and geometry models.*

7. CONCLUSIONS AND FUTURE RESEARCH

Crash prediction models have been a major focus for researchers in the field of traffic safety. Past research examining the influence of traffic speed relied on data from point detectors, hence limiting the coverage. This study developed a general relationship that accounts for both hourly speed and volume on freeway segments in Virginia. The results indicated that inclusion of variables, like speed, standard deviation, and difference in speed could create improvements in the quality of crash prediction models. As availability and reliability of observed traffic data significantly affect the accuracy of the study, using probe data, which has better network coverage, might be useful to improve the availability and quality of data. This research showed that average hourly volume profiles could be coupled with hourly speed to generate better crash predictions even when the speed data does not come from a continuous count station. This finding is important since INRIX data has been used in numerous studies related to traffic operations so far, but their application in safety research has been limited.

Future research could use average hourly volume distributions derived from short-term counts in combination with probe data to make the methodology developed in this paper more broadly applicable. Future work in this direction would consider year to year correlation in the data that was not addressed in this paper.

Additionally, models that assess safety when traffic control and cross section are changed dynamically have not been estimated previously**.** Currently, there is no existing methodology for safety assessment of facilities with dynamic traffic control or geometry such as part time shoulder use or variable speed limits (Dutta et al., 2018; Gonzales et al., 2018). Another gap in current research is in the area of work zone safety. Work zones are only active for a portion of the day, and it is important to know how the timing of lane closures impacts safety. The HSM provides crash modification functions that account for the effects of project length and duration on crash frequency but do not allow for explicit comparisons of safety effects of daily lane closures (Kweon et al.,2014). Further extension of the approaches developed in this paper could enable more proactive analysis of work zone impacts while the traffic management plans are in the planning stage.

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CHAPTER 6

ASSESSMENT OF THE IMPACTS OF SPATIAL AND TEMPORAL CORRELATION AND INCOMPLETE VOLUME DATA ON FREEWAY HOURLY CRASH PREDICTION MODELS

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ABSTRACT

Transportation safety has always been an intensively researched topic, with the goal of better understanding why crashes occur and how different variables affect the occurrence of crashes. Traffic and geometric conditions have a significant impact on crash occurrence. Traditional traffic safety analyses of crash frequency usually focus on highly aggregated cross-sectional data and ignores the time-varying nature of some critical factors. In an effort to address the issue, this research focused on the presence of spatial and temporal correlation in disaggregated datasets. Hourly data from 110 rural 4-lane segments and 80 urban 6-lane segments were used from 2011 to 2017. To properly account for the over-dispersion of data and unobserved heterogeneity, generalized linear mixed effect models (GLMM) were developed and contrasted against negative binomial (NB) models. The volume data used in this study comes from detectors that collects data ranging from continuous counts throughout the year to only a couple of weeks every other year (short counts). While developing disaggregated models, the difference in data availability from these sources can be a potential source of error. Hence, evaluating the change in performance of prediction models with changes in volume data availability was another focus for this research. The results showed that the best models include a combination of hourly volume, selected geometric variables, and speed related parameters. Further investigation revealed that the positive effect of using a more inclusive and bigger dataset was larger than the effect of accounting for data correlation. This showed that using short count stations as a data source does not diminish the quality of the developed models, thus indicating that these methods could be broadly applied across agencies, even when volume data is relatively sparse.

1. INTRODUCTION

Investigating factors contributing to freeway crashes play a crucial role in identifying effective safety countermeasures. With advancements in data collection and modeling methodologies, an increasing number of safety factors are better understood and new safety improvement measures are being implemented. However, crashes are complex events that involve a large variety of factors with multifaceted interactions, making it challenging to fully understand them. Roadway characteristics, such as geometric design elements, traffic control measures, and traffic conditions contribute to about 30% of all crashes, either alone or in combination with human, vehicular, or environmental factors (Sabey and Taylor, 1980).

Most prior research efforts focused on studying crash counts that are highly aggregated over a particular time period, usually a year or even several years. The safety performance functions (SPFs) recommended in the Highway Safety Manual (HSM) are limited to relating crash occurrence to annual average daily traffic (AADT) (American Association of State Highway Transportation Officials, 2010). A disadvantage of using AADT in safety analysis is that it does not capture all the variation in traffic flow that occurs throughout the day and could mask safety effects of operational changes on a roadway. Flow characteristics such as variation in speed and level of congestion play a significant role in crash occurrence and are not currently accounted for in the HSM. Several past studies have indicated the importance of including geometric and flow variables in crash prediction models (Choudhary et al., 2018; Garber, 2000; Geedipally et al., 2017; Shankar et al., 1995; Tanishita and van Wee, 2017).

Previous research by the authors showed that using average hourly volume along with average speed and selected geometric variables from high quality continuous count station data improved predictions compared to models that used AADT and no other traffic state information (Dutta and Fontaine, 2019a, 2019b). The researchers also evaluated private sector probe data from the vendor INRIX data as an alternate source for speed data and concluded that probe speed can be used in lieu of detector speed data without reducing the quality of crash prediction models. These results were based only on continuous count stations that collect quality data but are often widely spaced on state road systems. Most states collect short duration counts (which could range from 2 days to multiple months) on a broader geographic footprint of their roadway network than continuous count data. While these short count stations are much more broadly available, they do not provide as complete of a picture of true average travel as the continuous count stations. Given that the prior work showed that crash predictions could be improved by using more disaggregate data at continuous count stations, this paper sought to determine if those trends could extend to short count stations where data availability is more limited, potentially broadening application of these methods.

Additionally, this study incorporates consideration of temporal and spatial variation in the crash prediction models. With hourly data collected from multiple years and from different parts of the state, correlation problems may exist among the records in both the spatial and temporal domains. As pointed out by several researchers, if the correlation is not appropriately addressed in the model, inconsistent parameters estimation would occur, and erroneous inferences would be made consequently (Lord and Mannering, 2010; Mannering and Bhat, 2014; Washington et al., 2010).

2. RESEARCH OBJECTIVE

The objectives of this paper are to define the relationship between average hourly crash frequency on freeways and explanatory variables that vary with time and geography using data commonly available to transportation agencies over a broad network. For this paper, data representing crashes that occurred on rural 2-lane and urban 3-lane freeway directional segments in Virginia were collected for a seven-year period on an hourly level. The dataset contains information pertaining to the traffic conditions, geometry, and volume. Using different geometric and traffic variables, predictive models were developed for both urban and rural freeway segments and for different severities. The volume data used in this study comes from detectors that often did not collect data continuously, so the research sought to determine if positive results previously obtained with continuous count station data were transferable to locations with lower volume data availability. Hence, evaluating the change in performance of prediction models with changes in volume data availability and accounting for the presence of correlation in data were examined as a way to broaden the applicability of these models to transportation agencies.

3. LITERATURE REVIEW

Numerous statistical models have been developed to predict the expected number of crashes on roads as well as to identify the various factors associated with the occurrence of crashes. These factors can be categorized into human factors, traffic flow characteristics (e.g. volume, speed), roadway characteristics (e.g. geometric designs and pavement conditions), and environmental conditions (e.g. weather and surface conditions).

Researchers found that geometric factors such as horizontal curve length, the degree of curvature, and vertical curvature contributes to crash likelihood (Jianming Ma and Kockelman, 2006; Khan et al., 2013; Miaou, 1994; Tegge et al., 2010; Zegeer et al., 1990). Milton and Mannering examined the association between various geometric features and crash frequency while controlling for traffic exposure. For example, more crashes are expected on sharper and longer horizontal curves.(Milton and Mannering, 1996). Vertical grade also appears to have a strong effect on crash frequency (Cafiso et al., 2010; Geedipally et al., 2017; Tegge et al., 2010). A previous study indicated that in comparison to sections with grades less than 2%, those with maximum grades exceeding 2% will experience a significant increase in crash frequency (Shankar et al., 1995). A study of median crashes indicated that cross-median crashes are reduced with wider medians; but median-related crashes increase as the median width increases (Graham et al., 2014; Knuiman et al., 1993)

Speed is an important descriptor of traffic operations that has an effect on crash severity and frequency, but this variable is difficult to accurately capture in aggregate models that use AADT to predict annual crashes. Researchers have found that with increase in flow, crash rate initially remains constant until a certain critical threshold combination of speed and density is reached, and then rises rapidly (Golob et al., 2004; Imprialou et al., 2016; Kononov et al., 2012; Lord et al., 2005; Solomon, 1964). Researchers who developed models using macroscopic or hourly level models also often ignored the correlation that exists in disaggregated data and used generalized linear models (GLM) to develop predictions (Ivan et al., 2000; Persaud and Dzbik, 1993; Yu et al., 2018). To develop crash risk models at the disaggregated level requires overcoming some technical challenges, such as correlations by sharing unobserved effects among multiple observations generated from the same road segments and/or time period (Lord and Mannering, 2010; Shankar et al., 1998; Ulfarsson and Shankar, 2003).

In earlier work, Dutta and Fontaine used continuous count station data from 4 lane rural freeway segments in Virginia and developed crash prediction models using traffic and geometric information. They used both raw hourly volume (as observed each day at the site) and average hourly volume (expressed as an average volume for each hour of the day for each site over each year). The results showed that using average hourly volume along with average speed and selected geometric variables performed better than the raw volume format, due to the influence of missing time intervals. When comparing an AADT-based model to an average hourly volume model, the mean absolute prediction error improved by 20% for total crashes after including geometric variables, and by 30% after adding speed to the volume and geometry model. These results provide a strong indication that crash predictions could be improved using more disaggregate data and justifies further exploration of these relationships using larger datasets (Dutta and Fontaine, 2019a).

Subsequent research by same authors evaluated models using traffic and geometric information at 15-minute, hourly, and annual aggregation from 4 lane rural freeway and 6 lane urban freeway segments in Virginia. This study also examined the effects of using speeds from physical sensors versus speed estimates from private-sector probe speed data. The mean absolute prediction error improved by 11% for rural models and 20% for urban models when average hourly volume, speed and geometry models were compared to AADT based models. When private sector probe speed data was used, the rural model performance improved by 10% and urban models by 20% relative to the AADT based models. These results indicate that probe based data can be used in developing crash models without harming prediction capability (Dutta and Fontaine, 2019b). Both these studies only used high quality volume data from continuous count stations and ignored the spatial and temporal correlation that exists in a disaggregated dataset.

Statistical methods that incorporate panel data structure have gained popularity due to their capacity to address both time-series and cross-sectional variations. McCarthy employed fixed-effects negative binomial models to examine fatal crash counts using 9 years of panel data for 418 cities and 57 areas in the U.S. (Mccarthy, 1999). Noland used fixed- and random-effects negative binomial models to investigate the effects of roadway improvements on traffic safety using 14 years of data for all 50 U.S. states (Noland, 2003). A random effects negative binomial model (RENB) was used by many researchers who found it to be more suitable than the conventional NB model (Caliendo et al., 2007; Hausman et al., 1984; Shankar et al., 1998). In the RENB model, the joint effects of the unobserved variables are assumed to follow certain distributions along the spatial and temporal dimensions. Another popular methodology that has been advocated in recent years is random parameters negative binomial (RPNB) model (Anastasopoulos and Mannering, 2009; Han et al., 2018; Venkataraman et al., 2013). Compared to the RENB model, rather than treating the intercept term as the only random component, the RPNB model allows each estimated parameter to vary across individual observations, including the unobserved heterogeneity along the spatial and temporal dimensions.

Random effects negative binomial (RENB) models and random parameters negative binomial (RPNB) models were developed to investigate the factors contributing to freeway crashes in China (Hou et al., 2018). The analysis revealed a large number of crash frequency factors, including several interesting and important factors rarely studied in the past, such as the safety effects of climbing lanes. Moreover, the RENB and RPNB models were found to considerably outperform the NB model. Chin and Quddus investigated the relationship between crash occurrence and the geometric, traffic and control characteristics of signalized intersections in Singapore using the random effect model (Chin and Quddus, 2003). The results showed that total approach volumes, the numbers of phases per cycle, the presence of an uncontrolled left-turn lane, and the presence of a surveillance cameras were among the variables that were the highly significant. Another study my Ma et al. on the relationship between crash frequency and potential influence factors on an expressway in China also showed preference for the random effect model in comparison to the traditional negative binomial model (Ma et al., 2017). A study by Li et al. used a mixed-effect negative binomial (MENB) regression model and BPNN neural network model to consider bus crashes (Li et al., 2018). The results show that the safety benefits are more significant when providing bus priority measures. The performance of MENB model results shows that it is advantageous to use a mixed-effects modeling method to predict accident counts in practice because it can take into account the effects of specific factors. Another analysis on urban road segments in Turin, Italy also favored the use of mixed effect models (Mussone et al., 2017). Data from 2006 to 2012 were used and traffic flows and weather station data were aggregated in 5 minutes intervals for 35 minutes across each crash event. Two different approaches, a back-propagation neural network model and a mixed effect model, were used. The researchers concluded that the mixed model not only performed well but was also easier to interpret.

The mixed effect models combine two popular methodologies for modeling repeated measurements of crash data – fixed effects and random effects models. They are also widely accepted for their ability to handle both spatial and temporal correlation in data. This research adopted a mixed effect modeling approach for developing crash prediction models.

4. DATA COLLECTION AND PREPARATION

Volume, speed and geometry data were collected for 2-lane directional rural freeway segments and 3-lane directional urban freeway segments from 2011 to 2017 using Virginia Department of Transportation (VDOT) data systems. The data was collected on an hourly level and the segments came from different VDOT construction districts.

For this research, only basic freeway segments free from ramps or interchanges were considered. These segments were identified using the detector database maintained by the VDOT Traffic Engineering Division and the VDOT GIS integrator. Both of these sources contain direction and location information that helped to define the segments in a way that there was no entry/exit ramp within 0.5 miles of the start/end of the segment. It was important for this analysis to define a segment surrounding each count station where it could be assumed that homogeneous conditions were present for the entire length. If the station was on a link with homogeneous geometric characteristics that was greater than 2 miles in length, a buffer of a maximum 2 miles around the actual location of the detector (1 mile upstream and downstream) was created. The number of lanes, lane and shoulder width, speed limit, median type, and median width were used to define the geometric homogeneity of segment. Since this research focuses on interaction between geometry and flow parameters and how they define safety instead of a design focused approach, horizontal and vertical curvature was not used to define the segment, instead they were used as variables to identify their interaction with flow.

Table 1 shows a summary of data used in this research and their sources. Each of these data elements is discussed in more detail below.

TABLE 1: **Summary of data**

Type of Data	Source (Maintaining Agency)	Data Format	Data Elements
Traffic Volume	Count Stations on Virginia Freeways (VDOT)	Data was extracted for every hour for the entire study period. This raw data was then converted to an average hourly volume for each year. AADT data was directly available from the source.	• Average Hourly Volume • AADT
Speed	Probe data from private data source (INRIX)	Data was extracted for every hour for the entire study period. The raw data was then converted to average hourly speed for each year.	• Average Hourly Speed
Roadway Geometry	Highway Traffic Records Information System (VDOT)	Comprehensive inventory on detailed geometric data for Virginia. The data is provided for each roadway link in the state.	• Number of lanes • Horizontal and Vertical Curvature • Median Type and Width • Shoulder Width • Speed Limit
Crashes	Roadway Network System (VDOT)	Detailed information on time, location, crash type, injury and road condition. The crash models predicted crashes/hour. During validation, predicted number of crashes were summed to create yearly numbers to compare with AADT based crash models that predict crashes/year.	• Total Crashes • Fatal and Injury Crashes

4.1 Volume Data

In Virginia, traffic volumes are collected both at permanent count stations on a continuous basis and using short-term counts conducted throughout the state on a rotating basis. The continuous count stations also record speed and usually maintain a high level of data quality. The short count stations are more common, but they do not collect data on a continuous basis and may have a lower level of data quality. Previous research by Dutta and Fontaine evaluated the potential for using speed information from a private sector probe data provider (INRIX) in combination with continuous count volume data, and validated that INRIX data performed very similarly to the continuous count station speed data (Dutta and Fontaine, 2019b). As a result, the count stations were only used to generate traffic volume data.

A total of 110 count stations were used for rural segments (31 continuous count, 79 short count); for urban segments, the total number of stations were 80 (24 continuous count, 56 short count). For all the continuous count stations, only the time periods where volume data meet the quality threshold set by VDOT were included in the dataset, resulting in a total loss of 16% data for the rural segments and 9% of data for urban segments after screening. The short count stations collect data periodically, so average volumes were determined using less than an entire year's worth of data. The average hourly volume data was computed by averaging data for each available hour for each site, so there were always 24 hours of data available for each year and each site for the final dataset, even though the number of days used to compute averages varied among sites.

4.2 Speed Data

Speed data was obtained from the private sector travel time data provider INRIX at an hourly interval. INRIX is a private company that processes GPS and fleet probe data to estimate speeds, which are reported spatially using traffic message channel (TMC) links. TMC links are spatial representations developed by digital mapping companies for reporting traffic data and consist of homogeneous segments of roadways. Using the detector location information from VDOT and the latitude and longitude information from INRIX, it was possible to match the location of selected segments and corresponding TMCs. VDOT currently uses INRIX data to support a variety of performance measurement and traveler information applications, and several external and internal evaluations have supported the accuracy of the travel time data for freeways (Haghani et al., 2009). INRIX provides confidence scores for each 1-minute interval travel time, with a confidence score of 30 representing real-time data and scores of 10 and 20 representing historic data during overnight and daytime periods, respectively. About 73% of the data for rural segments and 71% of the data for urban segments had a confidence score of 30. For the purposes of this analysis, no threshold was set for the confidence scores and both real time and historic speed data was averaged for use in model development. Similar to the volume data, average hourly speed was also computed by averaging data for each available hour for each site.

4.3 Geometry Data

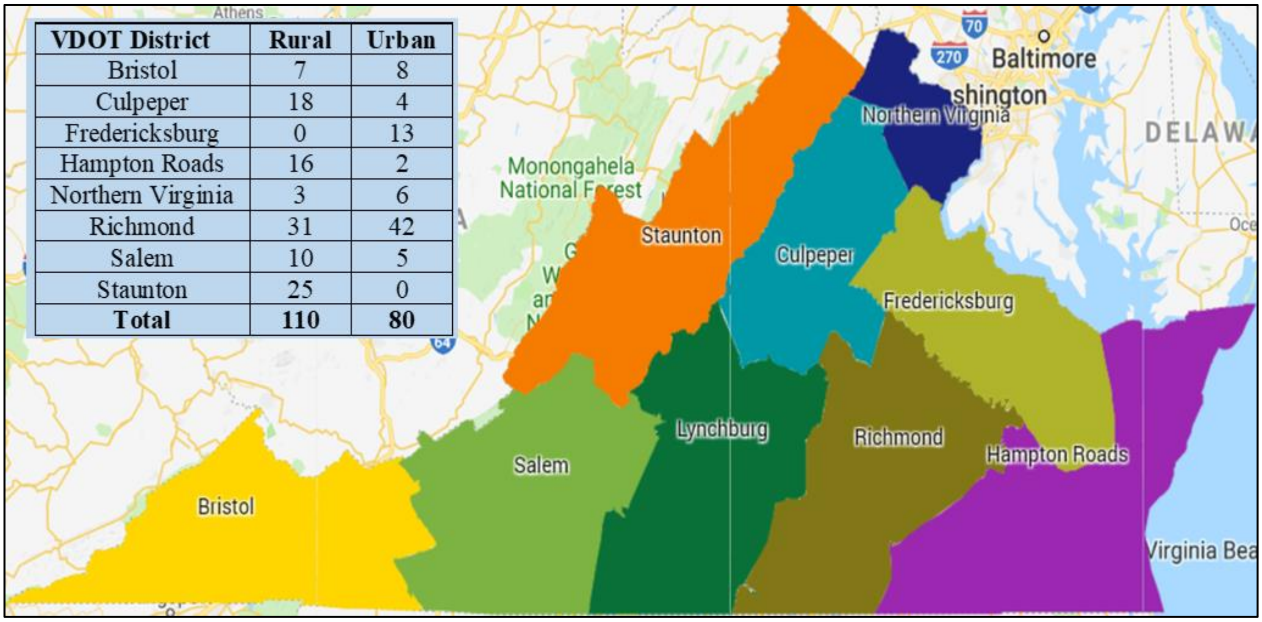
The VDOT Highway Traffic Records Information System (HTRIS) was used to extract all geometric and traffic control information used for this analysis. Using this database, information such as number of lanes, speed limit, shoulder width, median type, rural/urban designation, etc. was gathered for the study segments. The vertical curvature (VC) data were collected in the form of percent grade, with positive grades indicating uphill segments and negative grades indicating downhill segments. Horizontal curvature (HC) was expressed using length of the curve, presence of curve as a percentage of segment length, and radius of curve.

4.4 Crash Data

Crash data for all the sections were obtained from the VDOT Roadway Network System (RNS) . The data included detailed information on crash location and date, crash type, severity, number of vehicles involved, etc. For all the segments, crash information was also collected between 2011 and 2017. For this analysis, the researchers examined total crashes as well as fatal and injury crashes.

4.5 VDOT Districts

In Virginia, VDOT Construction Districts have been frequently tied with variations across the state from a traffic safety perspective due to differences in driving population, terrain, and traffic conditions. For example, Interstates in the Salem, Staunton, and Bristol Districts are predominantly rural and travel through mountainous terrain while the Northern Virginia and Hampton Roads districts experience significant recurring congestion. This research used districts as a grouping variable to account for the differences in driving behavior and environment in different parts of Virginia. Figure 1 shows the locations of the districts and the number of study segments on each district.



VDOT District	Rural	Urban
Bristol	7	8
Culpeper	18	4
Fredericksburg	0	13
Hampton Roads	16	2
Northern Virginia	3	6
Richmond	31	42
Salem	10	5
Staunton	25	0
Total	**110**	**80**

FIGURE 1: VDOT district map and number of study sites from each district (Lynchburg District does not contain any Interstates)

Figure 2 shows the distribution of crashes over the study period by year, and Table 2 summarizes the properties of the study segments.

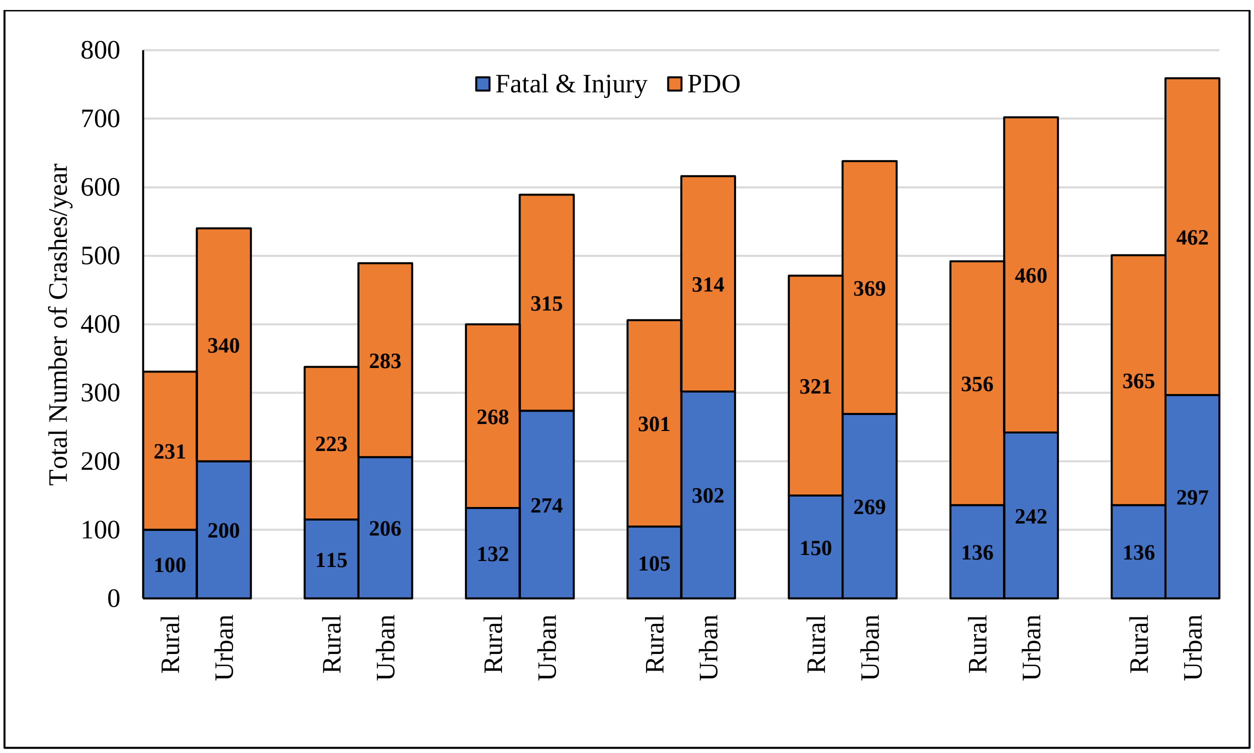


FIGURE 2: Distribution of Total Number of Crashes for All Study Segments

TABLE 2: Summary of the descriptive statistics of freeway study segments

Type of Segment	Total Mileage (mile)	Variable	Mean	Std. Deviation	Min	Max
Rural 4 Lane Segments (110 Segments)	195.07	AADT	18702	6225	4059	34728
		Average Hourly Volume (vph)	787.30	530.09	12.00	3064.00
		Average Hourly Speed (mph)	67.83	3.10	48.31	75.72
		Segment Length (mile)	1.79	0.29	1.00	2.00
		Lane Width (ft)	12.00	0.00	12.00	12.00
		Median Shoulder Width (ft)	3.93	2.03	0.00	10.00
		Right Shoulder Width (ft)	5.24	5.08	0.00	12.00
		Median Width (ft)	107.8	59.35	4.00	334.00
		Horizontal Curvature Radius (mile)	2.00	1.58	0.00	5.92
		Horizontal Curvature Length (mile)	0.76	0.59	0.00	2.00
		Grade (%)	-0.26	0.80	-3.17	1.58
		Speed Limit (mph)	69.00	2.64	55.00	70.00
		Annual Total Crashes	5.19	5.13	0	48
		Annual Fatal & Injury Crashes	1.53	1.91	0	19
Urban 6 Lane Segments (80 Segments)	125.42	AADT	40731	17667	10931	76207
		Average Hourly Volume (vph)	1690.71	1186.88	38.75	4960.50
		Average Hourly Speed (mph)	66.13	3.11	40.46	72.60
		Segment Length (mile)	1.60	0.43	0.66	2.00
		Lane Width (ft)	12.00	0.00	12.00	12.00
		Median Shoulder Width (ft)	7.08	3.07	2.00	12.00
		Right Shoulder Width (ft)	4.88	5.12	0.00	12.00
		Median Width (ft)	103.78	86.97	0.00	363
		Horizontal Curvature Radius (mile)	1.83	1.00	0.00	4.62
		Horizontal Curvature Length (mile)	0.93	0.53	0.00	2.00
		Grade (%)	-0.29	0.98	-2.69	2.67
		Speed Limit (mph)	64.42	4.59	55	70
		Annual Total Crashes	12.25	11.47	0	81
		Annual Fatal & Injury Crashes	3.31	2.98	0	19

5 METHODOLOGY

In this paper, a series of crash prediction models were developed using a variety of variables related to volume, geometry, and traffic flow parameters. The modeling process started with a simple volume and geometry model and then more complex models were developed by adding traffic variables to it.

Previous research by the authors indicated that when crash prediction models use a data format that is too disaggregated, data errors and imputation of missing values can be problematic and increase errors (Dutta and Fontaine, 2019a, 2019b). Based on this previous experience, volumes in this research were expressed as AADT (to be consistent with the current HSM SPFs) and as average hourly volume. To be consistent with the HSM, length was used as an offset variable in the models.

5.1 Spatial and Temporal Correlation

A very common phenomenon in crash data is overdispersion, meaning that the variance of the data exceeds the mean. Overdispersion is usually attributed to unobserved heterogeneity. In general, motor vehicle crashes are highly complex processes influenced by various contributing factors such as roadway geometrics, traffic characteristics, environmental conditions, and human elements. It is nearly impossible to collect all the data that describe factors that contribute to a crash and its resulting injury severity. As a result, the impacts of these unobserved factors on the likelihood of a crash cannot be adequately captured by the explanatory variables in the model, leading to the unobserved heterogeneity problem (Lord and Mannering, 2010; Mannering and Bhat, 2014).

Traditionally, most crash frequency models use a cross sectional data format. Cross sectional data are observed at a single point of time for several study sites. While using this data format, the interest lies in modeling how particular sites are performing at a certain point of time (Frees, 2003). Since this format overlooks the correlation between crashes and their contributing factors over time, it is not suitable for studies where multiple years of data are available for study sites. Panel data permits identification of variations across individual roadway segments and variations over time. Accommodation of observation-specific effects also mitigates omitted-variables bias by implicitly recognizing segment-specific attributes that may be correlated with control variables. The time-series nature of multiyear data as used in this study presents serial correlation issues. In a similar vein, there can be correlation over space because roadway entities that are in close proximity may share unobserved effects. This again sets up a correlation of disturbances among observations and results in the associated parameter-estimation problems.

Both overdispersion and serial correlation need to be addressed in a modeling framework to produce efficient estimates. Negative binomial (NB) regression has become the most common method for developing SPFs and is also the recommended modeling approach in the HSM (American Association of State Highway Transportation Officials, 2010). It should be noted that the regular NB model, while accounting for overdispersion, will not allow for location-specific effects or serial correlation over time for clustered crash counts. In recent years, mixed effect models have gained popularity among researchers due to their ability to handle both overdispersion and correlation. They are usually called Generalized Linear Mixed Models (GLMM) because they use the common distributions associated with the generalized linear model (GLM) such as Poisson, negative binomial, or zero inflated models and also account for data structures in which observations cluster within larger groups (Hausman et al., 1984).

5.2 Generalized Linear Mixed Model

There are a number of statistical methods available to predict the number of crashes on roadway segments. As crashes are non-negative and characterized by over dispersion (the variance is greater than the mean), negative binomial regression has become the most common method for developing SPFs and is also the recommended modeling approach in the HSM (American Association of State Highway Transportation Officials, 2010; Lord and Mannering, 2010; Milton and Mannering, 1996). In a negative binomial regression model, the probability of roadway entity i having y_i crashes per time period is defined as:

$$\boldsymbol{P(y_i) = \frac{exp(-\lambda_i) * \lambda_i^{y_i}}{y_i\,!}} \quad (1)$$

$$\boldsymbol{\lambda_i = exp(\beta X_i + \varepsilon_i)} \quad (2)$$

where y_i is the number of crashes for segment i in year t, β is a vector of the estimable parameters, X_i is a vector of the explanatory variables, and exp (ε_i) is a gamma-distributed error term with mean 1 and variance α (Simon et al., 2010). The addition of this term allows the variance to differ from the mean as:

$$\mathbf{VAR}\ (\boldsymbol{y_i}) = \mathbf{E}\ ((\boldsymbol{y_i})\ [1+ \boldsymbol{\alpha}\mathbf{E}(\boldsymbol{y_i})\ ] = \mathbf{E}(\boldsymbol{y_i}) + \boldsymbol{\alpha}\mathbf{E}(\boldsymbol{y_i})^{\mathbf{2}} \quad (3)$$

Another popular method for modeling disaggregated data are zero inflated models. Zero inflated models have been developed to handle data characterized by a significant number of zeros or more zeros than the one would expect in a traditional Poisson or negative binomial/Poisson-gamma model. These models operate on the principle that the excess zero density that cannot be accommodated by a traditional count structure is accounted for by a splitting regime that models a crash-free versus a crash prone propensity of a roadway segment (Lord and Mannering, 2010; Simon et al., 2010).

The most frequently used modeling technique for crash data is the generalized linear modelling (GLM) methodology. Generalized linear models are extensions of traditional regression models that allow the mean to depend on the explanatory variables through a link function, and the response variable to be any member of a set of distributions called the exponential family (e.g., Normal, Poisson, Binomial) (McCullagh and Nelder, 1991). The traditional NB model can account for over-dispersion in crash data, but does not allow for location specific effects or time-serial correlations. The dataset for this study is comprised of multiple segments for both rural and urban highways where data has been collected on average hourly basis for seven years. That introduces correlation in the data that came from a combination of spatial considerations (data from different districts of VDOT within Virginia) and temporal considerations (average hourly data for seven years).

The motivation for the random effects model is that this model can introduce random location-specific or time specific effects into the relationship between the expected numbers of crashes and the covariates of an observation unit i in a given time period t (Hausman et al., 1984).

The GLMM model structure is:

$$\boldsymbol{y_i|b \approx Distr\left[\mu_i, \frac{\sigma^2}{w_i}\right]} \tag{4}$$

$$\boldsymbol{g(\mu) = \beta X + bZ + \delta} \tag{5}$$

Where y_i = dependent variable, b = random effects vector, Distr = a specified conditional distribution of y given b, μ= the conditional mean of y given b, μ_i is its i-th element, σ^2 = the variance or dispersion parameter, w = the effective observation weight vector (w_i = the weight for observation i), g(μ) = link function that defines the relationship between the mean response μ and the linear combination of the predictors, X = fixed effects design matrix (of independent variables), β = fixed-effects vector, Z = random-effects design matrix (of independent variables), and δ = residuals (Mussone et al., 2017) . The model for the mean response μ is

$$\boldsymbol{\mu = g^{-1}(\hat{\eta})} \tag{6}$$

Where g^{-1} = inverse of the link function g(μ), and $\hat{\eta}$ = linear predictor of the fixed and random effects of the generalized linear mixed-effects model.

In the simplest term, the mixed effect model used in this research can be defined as –

$$Y = \overbrace{\text{Volume} + \text{Geometric Variables} + \text{Flow Variables}}^{\text{Fixed Effect}} + \underbrace{(1|\text{District}) + (1|\ \text{Year}) + (1|\text{Hour})}_{\text{Random Effect}}$$

Y is the dependent variable (number of crashes), the fixed effect part defines the relationship between different variables and total crashes, and the random effect part clusters data by VDOT districts (to account for spatial correlation) and by year and hour (to account for temporal correlation). The format "(1|x)" means that the model calculates the variance in intercepts that is different for each group for the random effect "x". This effectively resolves the non-independence that stems from having multiple responses by the same subject. It is also possible to estimate the random effect for each variable separately. For example, Volume|District would essentially estimate intercept for each district and also a separate random effect parameter for volume for each district. Considering separate parameters for both spatial and temporal effects and for all the correlated variables creates a very complicated model and additional difficulty in interpretation and application. As a result, this research focuses on the variances between intercepts for each random effect.

The "glmmTMB" package built for Generalized Linear Mixed Models using Template Model Builder in the R statistical software was used for the modeling. The package fits linear and generalized linear mixed models with various extensions, including zero-inflation. The models are fitted using maximum likelihood estimation. Random effects are assumed to be Gaussian on the scale of the linear predictor and are integrated using the Laplace approximation (Bolker, 2019; Brooks et al., 2017).

5.3 Model Selection and Validation

In order to measure the model, fit, the ρ_c^2 statistic is used based on the loglikelihood of the selected model and the constant only model:

$$\boldsymbol{\rho_c^2 = 1 - \frac{LL(\beta)}{LL(C)}} \tag{7}$$

Where $L(\beta)$ is the log-likelihood at convergence and $LL(\mathrm{C})$ is the log-likelihood with constant only model. A perfect model has a likelihood equal to one. The closer the value is to one, the more variance the estimated model is explaining (Washington et al., 2010).

An ANOVA test comparing the NB and ZINB models was used to test which distribution fits the model better. The test, which is readily available on R, gives a list of AIC, BIC, log likelihood, difference in degrees of freedom and chi-square test statistics and associated p-value.

While comparing the models, it is important to have a consistent methodology to select a model from a series of models that has been developed for each technique. A popular method for model selection is the Akaike information criterion (AIC)(Akaike, 1974) . AIC offers an estimate of the relative information lost when a given model is used to represent the process that generated the data.

$$\mathbf{AIC = -2LL + 2p} \quad (8)$$

Where p is the number of estimated parameters included in the model. A lower value of AIC indicates a better model.

Bayesian Information Criterion (BIC) is a criterion for model selection among a finite set of models. It is based in the part on the likelihood function and it is closely related to the Akaike's Information Criterion (AIC). The BIC also uses a penalty term for the number of parameters in the model. The penalty term is larger in BIC than in AIC.

$$\mathbf{BIC = -2lnL + k*ln(n)} \quad (9)$$

Where n= number of observations, k=the number of free parameters to be estimated, and L= the maximized value of the likelihood function for the estimated model (Schwarz, 1978).

It is important to note that an objective assessment of the predictive performance of a particular model can be made only through the evaluation of several goodness of fit (GOF) criteria. The GOF measures used to conduct external model validation included mean absolute prediction error (MAPE), mean absolute deviation (MAD), and mean squared prediction error (MSPE)(Washington et al., 2010). Additionally, cumulative residual (CURE) plots were examined to check the functional form of the model. CURE plots are figures that show how well a model fits the data. Residuals are defined as the "differences between the observed and fitted values of the response" and, when plotted cumulatively, demonstrate the suitability of a regression model. The data in the CURE plot are expected to oscillate about 0. Any large jumps between residuals indicate areas where there may be outliers in the data.

Since AADT based models predict annual crashes while hourly volume models predicted hourly crashes, the summation of hourly predictions was used to generate annual predicted numbers of crashes for the GOF calculations. The average hourly volume data was computed by averaging data for each available hour for each site, so there were always 24 hours of data available for each year and each site for validation. Model building used a random selection of 70% of the available data and the remaining 30% was used for testing and validation. The calculation of these measures was based on the following equations:

$$\boldsymbol{Mean\ Absolute\ Prediction\ Error\ (MAPE)} = \frac{\mathbf{100\%}}{\boldsymbol{n}} \sum_{i=1}^{n} \left| \frac{Y_{model} - Y_{observed}}{Y_{observed}} \right| \quad (10)$$

$$\boldsymbol{Mean\ Absolute\ Deviation\ (MAD)} = \frac{\sum_{i=1}^{n} |Y_{model} - Y_{observed}|}{n} \quad (11)$$

$$\boldsymbol{Mean\ Squared\ Prediction\ Error\ (MSPE)} = \frac{\sum_{i=1}^{n} (Y_{model} - Y_{observed})^2}{n} \quad (12)$$

Where –

Y_{model} = Predicted Crash Frequency

$Y_{observed}$ = Observed Crash Frequency

n = Sample Size

5.4 Check for Data Availability and Correlation

This research is an extension of previous work by the authors where they developed crash prediction models using only continuous count stations without accommodating for the data correlation (Dutta and Fontaine, 2019a, 2019b). This paper used a larger dataset that came from both continuous count and short count stations. While the quantity of data available for modeling increased overall, the availability and quality of data at the short count stations was lower than that used in the prior study. This new dataset is more broadly representative of average data quality and availability present on freeway facilities nationally. The mixed effect methodology used in this paper addresses the spatial and data correlation. Since both the data set used for modeling and the way that correlation was addressed changed from prior work, the final models selected from the GLMM method were re-run using GLM that doesn't account for correlation. This was done to isolate the effect for correlation only versus changes in the data set. Both of these models were then contrasted against the models developed using just the continuous count stations previously (Dutta and Fontaine, 2019b). This step ensured that the effect of using a broader dataset (short and continuous count) compared to a smaller one (continuous count only) have been checked without treating for the correlation.

6 RESULTS AND DISCUSSION

The interpretation of GLMMs is similar to GLMs; however, there is an added complexity because of the random effects. The output of a mixed model lists some measures of model fit, parameter estimates for the fixed effect part and the variance between groups for the random effect part. If the variance is indistinguishable from zero, then the correlation within a group is not strong. In the mixed model, one or more random effects are added to the fixed effects. These random effects essentially give structure to the error term "ε". For this research, random effects for "district", "year" and "hour" were considered.

6.1 Selection of Model Form

The comparison between negative binomial and zero inflated negative binomial distribution for the same model showed that, in general, negative binomial models performed better with respect to AIC value, BIC value, variable significance, and ANOVA test. Each model form was checked with both distributions. Since the negative binomial model outperformed the zero inflated ones for most crash types for both rural and urban segments, only the results from the negative binomial mixed effect models are documented in this paper. Table 3 shows the model comparison between these two forms for total crashes; similar results were obtained for fatal and injury crashes.

TABLE 3: **Comparison between NB and ZINB Model**

	Rural Segments						
	AIC		**BIC**		**ANOVA (NB, ZINB)**	**Critical Chi-Square**	**Preferred Model**
	NB	ZINB	NB	ZINB			
Volume, length, and geometry models	10783	10833	10870	10895	4.77	7.79	NB
Volume, length, geometry, and flow models	10679	10687	10795	10811	2.46	4.61	NB
	Urban Segments						
	AIC		**BIC**		**ANOVA (NB, ZINB)**	**Critical Chi-Square**	**Preferred Model**
	NB	ZINB	NB	ZINB			
Volume, length, and geometry models	10218	10229	10312	10333	5.08	6.25	NB
Volume, length, geometry, and flow models	10186	10199	10293	10311	6.87	7.79	NB

6.2 Volume, Length and Geometry Models

A combination of volume and different geometric variables such as median width, horizontal curvature, vertical curvature was used to develop initial models. Due to limited variability in lane width and shoulder width for this particular data set, they were not found to be significant in the modeling process.

For urban segments, median width, radius and length of horizontal curvature, and grade were significant variables. For total and injury crashes, the radius of horizontal curve was negatively associated with crash frequency. A larger radius indicates a flatter curve, so this relationship is intuitive. On a similar note, increases in length of horizontal curve increases the probability of a cash. This finding is also consistent with previous research (Khan et al., 2013; Zegeer et al., 1990).

Vertical grade, which ranges from -3% to +3% (negative grade means downgrade, and positive grade means upgrade), was found to be significant for total crashes, but only negative grades had a statistically significant relationship. This result indicates that for total crashes, steeper negative grade causes more crashes. Since speed usually increases while driving downhill, this finding is logical.

Median width indicated that wider medians in urban segments reduce the total number of crashes. Previous research indicated that median widths between 20 and 30 ft generally show a mixed effect on crashes and median widths of 60 to 80 ft have decreasing effect on crashes (Chang and Xiang, 2003; Knuiman et al., 1993). About 65% of the urban dataset had median widths within this range, so the negative relationship between median width and crashes is intuitive. Table 4 summarizes the models developed for this step.

TABLE 4 Parameter Estimates for Volume and Geometry Models for Urban Freeway Segments

	Total Crashes					
	Average Hourly Volume			AADT		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-6.68	0.372	<2e-16	-5.55	0.919	1.5E-09
log (Volume)	0.67	0.047	<2e-16	0.65	0.085	4.5E-15
Radius of Horizontal Curve (mile)	-0.09	0.033	0.0032	-0.14	0.044	1.1E-03
Grade						
Positive Grade	-0.04	0.052	0.39928	–	–	–
Negative Grade	0.22	0.071	0.00173	–	–	–
Length of Horizontal Curve						
≤ 0.5	0.04	0.179	0.8147	0.26	0.245	3.0E-01
>0.5 ~≤ 1.0	0.45	0.177	0.0112	0.6	0.243	1.3E-02
> 1.0 ~ ≤ 1.5	0.61	0.181	0.0007	0.94	0.253	2.2E-04
> 1.5	0.26	0.182	0.0154	0.44	0.249	7.7E-02
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.129 (0.071)			0.173 (0.054)		
Year	0.576 (0.087)			0.215 (0.083)		
Hour	0.618 (0.145)			–		
AIC	10217.9			1538		
BIC	10311.7			1576.8		
$\boldsymbol{\rho_c^2}$	0.15			0.10		
	Injury Crashes					
	Average Hourly Volume			**AADT**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-8.62	0.587	<2e-16	-7.75	1.422	4.8E-09
log (Volume)	0.71	0.058	<2e-16	0.71	0.129	3.6E-09
Radius of Horizontal Curve (mile)	-0.12	0.051	0.01971	–	–	–
Length of Horizontal Curve						
≤ 0.5	0.94	0.393	0.01707	0.72	0.358	4.3E-02
>0.5 ~≤ 1.0	1.32	0.388	0.0007	0.93	0.35	7.7E-03
> 1.0 ~ ≤ 1.5	1.46	0.4	0.0003	1.15	0.37	9.0E-04
> 1.5	1.13	0.398	0.0046	0.81	0.35	2.2E-02
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.132 (0.053)			0.137 (0.256)		
Year	0.242 (0.085)			0.267 (0.032)		
Hour	0.529 (0.057)			–		
AIC	4600.3			1015.5		
BIC	4687.4			1054.2		
$\boldsymbol{\rho_c^2}$	0.14			0.10		

For rural segments, 71% of the data came from segments with median widths greater than 80 ft and no median barrier. The results indicated that wider medians generally had more crashes. This is contradictory to the urban segments, but consistent with previous research (Chayanan et al., 2004; Graham et al., 2014). The relationship between median width and crashes largely depend on type of facility, crash type, and also presence and type of median barrier. Cross median crashes tend to decrease with increasing median width, whereas rollover crashes tend to increase. Radius of horizontal curve had a similar relationship as urban segments where crashes decrease with increase in curve radius. increases the probability of any types of crash. For rural segments, presence of horizontal curve as a % of total segment length had more significant effect on total crashes than length of curve. As this % increases, crash occurrence also increases. Table 5 documents the results for rural segments.

TABLE 5 Parameter Estimates for Volume and Geometry Models for Rural Freeway Segments

	Total Crashes					
	Average Hourly Volume			**AADT**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-7.04	0.401	<2e-16	-9.98	1.14	<2e-16
log (Volume)	0.67	0.062	<2e-16	1.11	0.11	<2e-16
Radius of Horizontal Curve (mile)	-0.05	0.019	0.00875	–	–	–
Median Width (ft)	0.21	0.005	2.72E-05	–	–	–
% of Horizontal Curve Length						
Less than 25%	0.53	0.111	1.39E-06	0.28	0.106	0.0077
>25% ~≤ 50%	0.24	0.092	0.009	0.13	0.094	0.0028
>50% ~ ≤ 75%	0.46	0.088	2.02E-07	0.27	0.099	0.0065
> 75%	0.09	0.099	0.338	0.16	0.104	0.8737
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.182 (0.047)			0.198 (0.028)		
Year	0.465 (0.105)			0.317 (0.049)		
Hour	0.538 (0.241)			–		
AIC	10782.9			2324.3		
BIC	10870.1			2361.3		
$\boldsymbol{\rho_c^2}$	0.21			0.19		
	Injury Crashes					
	Average Hourly Volume			**AADT**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-7.13	0.464	<2e-16	-11.81	1.46	4.9E-16
log (Volume)	0.54	0.069	1.80E-14	0.67	0.114	7.7E-16
Median Width	0.14	0.001	9.90E-03	–	–	–
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.132 (0.055)			0.065 (0.048)		
Year	0.297 (0.017)			0.193 (0.025)		
Hour	0.419 (0.047)			–		
AIC	4777.3			1485		
BIC	4828.2			1505.5		
$\boldsymbol{\rho_c^2}$	0.11			0.07		

6.3 Volume, Geometry and Flow Parameter Models

The next set of models were created by adding flow parameters to the models selected in the previous step. Average speed, standard deviation of speed, and the difference between speed limit and average speed (called the delta speed hereafter) were selected to represent traffic flow. If the delta speed is negative, average speed is higher than the speed limit, meaning a free flow condition exists (represented by Delta 1 in models). When this value is positive, speed limit is higher than average speed, meaning the segment is congested (represented by Delta 2 in models). AADT based models were not developed for this alternative since average speed over a year showed little variability.

Table 6 shows the rural models that include speed parameters. Average hourly speed was positively related to total crashes, meaning that higher average speed is correlated with higher crash frequency. Standard deviation of speed was significant for all crash types and indicated that as more variation in hourly speeds are observed over a year, the frequency of crashes increases. The variable delta that represents difference between speed limit and average speed was significant for all crash types as well. It was observed that injury crashes increase during free flow conditions (Delta 1) and decreases during congestion (Delta 2). This is a logical relationship given the relative velocities during collision.

TABLE 6: Parameter Estimates for Volume, Geometry and Flow Based Models for Rural Segments

	Total Crashes			**Injury Crashes**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-8.61	0.971	<2e-16	-6.73	0.375	<2e-16
log (Volume)	0.54	0.076	1.5E-12	0.41	0.055	4.0E-14
Radius of Horizontal Curve (mile)	-0.06	0.019	0.00443	–	–	–
% of Horizontal Curve Length						
Less than 25%	0.53	0.107	6.60E-07	–	–	–
>25% ~≤ 50%	0.11	0.096	0.000025	–	–	–
>50% ~ ≤ 75%	0.41	0.093	1.20E-05	–	–	–
> 75%	0.13	0.099	0.19522	–	–	–
Speed	0.03	0.012	0.00974	–	–	–
Standard Deviation	0.17	0.017	<2e-16	0.16	0.024	2.0E-11
Delta						
Delta 1	0.31	0.068	9.05E-06	1.29	0.095	<2e-16
Delta 2	0.04	0.067	0.57048	-0.29	0.117	0.0014
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.182 (0.017)			0.174 (0.035)		
Year	0.212 (0.045)			0.111 (0.013)		
Hour	0.508 (0.003)			0.263 (0.092)		
AIC	10679			5716.8		
BIC	10795.1			5782.1		
$\boldsymbol{\rho_c^2}$	0.29			0.18		

Table 7 shows that the speed parameters showed consistent results for urban segments as well. Standard deviation of average speed always had an increasing effect on crash frequency for all crash types. The variable delta was significant for all crash types for urban segments as well. During free flow conditions (Delta 1), total crashes and injury crashes increase. This relationship is intuitive and consistent with rural segments.

TABLE 7: Parameter Estimates for Volume, Geometry and Flow Based Models for Urban Segments

	Total Crashes			**Injury Crashes**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-5.8	0.351	<2e-16	-6.79	0.459	<2e-16
log (Volume)	0.44	0.044	<2e-16	0.37	0.057	3.9E-11
Radius of Horizontal Curve (mile)	-0.08	0.029	0.00563	-0.09	0.043	0.00408
Length of Horizontal Curve						
≤ 0.5	0.76	0.174	1.4E-05	0.89	0.233	0.00013
>0.5 ~≤ 1.0	1.06	0.171	6.4E-10	1.2	0.229	1.5E-07
> 1.0 ~ ≤ 1.5	1.16	0.175	3.6E-11	1.34	0.244	4.4E-08
> 1.5	0.75	0.177	2.1E-05	0.85	0.236	0.00034
Standard Deviation	0.11	0.007	<2e-16	0.12	0.011	<2e-16
Delta						
Delta 1	0.14	0.059	2.1E-04	0.98	0.088	<2e-16
Delta 2	0.03	0.058	0.58262	-0.21	0.103	0.00438
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.137 (0.007)			0.152 (0.022)		
Year	0.326 (0.181)			0.254 (0.159)		
Hour	0.546 (0.032)			0.324 (0.092)		
AIC	10185.9			6025.2		
BIC	10293.1			6119.2		
ρ_c^2	0.23			-0.24		

Figure 3 shows the CURE plots for average hourly volume from the volume, flow and geometry models. CURE plots are not only a reflection of the functional form of the particular explanatory variable, but also whether other relevant explanatory factors have been included in the model in an appropriate form. Figure 3 shows that for both rural and urban segments, the CURE plot for hourly volume are within the limit of 2 standard deviation. It reinforces the suitability of volume, flow and geometry models and also shows that inclusion of volume in average hourly level form is not inaccurate.

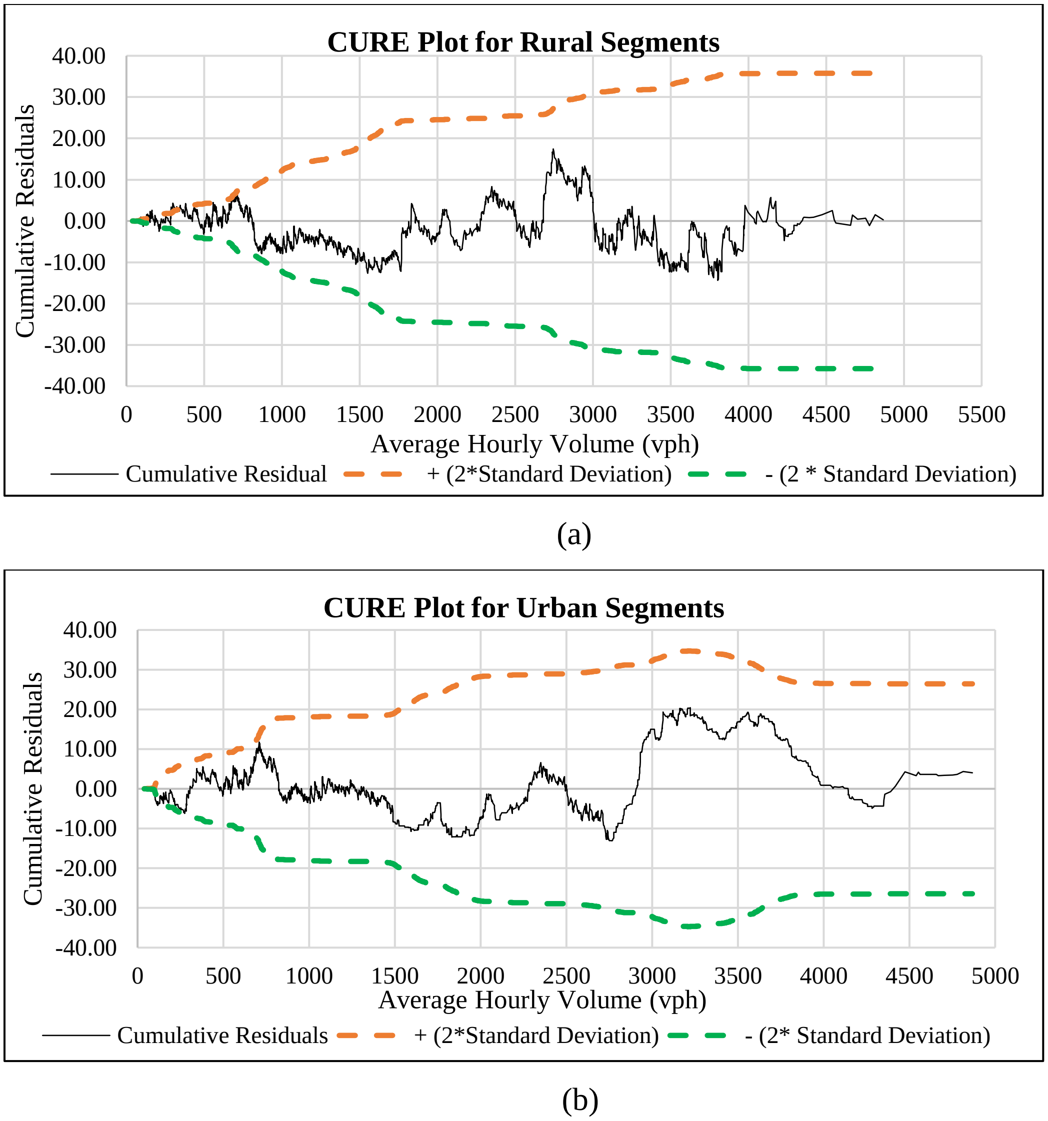


FIGURE 3: Hourly Volume CURE Plot for (a) rural segments (b) urban segments

6.4 Effect of Correlation

This research focused on developing models that have both spatial and temporal random effect variables. The spatial correlation is represented by "District". For all models, the intercept and standard deviation for this group reveals that even though a correlation is present between segments that belong to same district, in general, the spatial correlation is weaker than the temporal one. For all categories, the variance is much smaller for districts than it is for year or hour. This is due to the fact that the sample size among districts are not equally distributed, as seen on Figure 1. A larger dataset where all the districts are equally represented could shed more light on the spatial correlation.

The temporal correlation was modeled using year and hour since the dataset consists of hourly data for seven years. For both urban and rural models, the temporal correlation was stronger than the spatial one, but still the variance in data explained by yearly correlation was smaller than the hourly one. The total crashes vary between years and total sample size while considering hourly correlation is higher as well. Having more segments in both rural and urban category could produce a model where stronger temporal correlation have been defined.

6.5 Model Comparison

6.5.1 Comparison between Mixed Effect (GLMM) Models

Tables 8 and 9 shows the comparison of performance among the models developed. For both rural and urban segments and for both crash types, prediction accuracy improved when speed variables were added. Models using average hourly data showed better predictive capability compared to AADT models. While using hourly data, the aggregation interval was not too disaggregated to capture the random nature of crashes, also not too aggregated to lose the variation in traffic. The AADT models didn't include speed as a variable because averaging hourly speed over a year did not capture the effect of speed on traffic conditions and crashes. For comparison purposes, the volume, flow, and geometry model were compared to the AADT based volume and geometry models.

For the rural hourly volume, geometry, and flow models, MAD, MAPE, and MSPE improved by 64%, 26% and 62% respectively for total crashes and 39%, 20%, and 40% respectively for injury crashes as compared to AADT models. For the urban models, similar trends were observed where MAD, MAPE and MSPE improved by 51%, 18%, and 53% respectively for total crashes and 45%, 18% and 59% for injury crashes as compared to AADT models.

All the models discussed in the prior section were developed using mixed effect modeling methodology, so the relative performance quantifies the effect of data aggregation and variable selection. The comparison results reinforce the importance of selecting an appropriate disaggregation level. Aggregated models that rely on AADT may fail to capture variations traffic flow that could influence safety. Hourly aggregation showed better performance compared to the AADT models. Another very important finding is that speed variables played a significant role in model performance. Currently, traffic volume is widely used as a measure of exposure. The same traffic flow occurring on road sections with different capacities creates different operating conditions, and, therefore, different probabilities for crashes. That is why it is not enough to just consider volume and segment length as only variables while predicting crashes on freeways. Understanding the real traffic behavior requires quantification of some of the basic traffic flow characteristics. Since current models only rely on volume, quality of volume data dictates the quality of model. This research showed that speed data from INRIX coupled with volume data with mixed data quality can significantly improve model performance compared to AADT models.

TABLE 8: Model Comparison for Rural Segments *

	Total Crashes					
	Average Hourly Volume			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume, length, and geometry models	1.16 (-63%)	55% (-14%)	2.92 -57%	3.1	69%	6.87
Volume, length, geometry, and flow state models. **	1.11 (-64%	43% (-26%)	2.59 (-62%)	–	–	–
	FI Crashes					
	Average Hourly Volume			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume, length, and geometry models	0.73 (-33%)	33% (-15%)	1.58 (-32%)	1.09	48%	2.33
Volume, length, geometry, and flow state models. **	0.66 (-39%)	28% (-20%)	1.39 (-40%)	–	–	–

** Value in the parentheses represents the change compared to respective AADT based models.*

*** These models were compared to the AADT based volume, length, and geometry models.*

TABLE 9: Model Comparison for Urban Segments *

	Total Crashes					
	Average Hourly Volume			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume, length, and geometry models	1.92 (-36%)	35% (-12%)	47.92 (-40%)	2.98	47%	79.43
Volume, length, geometry, and flow state models. **	1.45 (-51%)	29% (-18%)	36.95 (-53%)	–	–	–
	FI Crashes					
	Average Hourly Volume			**AADT**		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume, length, and geometry models	1.09 (-36%)	12% (-14%)	4.58 (-48%)	1.69	26%	8.82
Volume, length, geometry, and flow state models. **	0.93 (-45%)	8% (-18%)	3.63 (-59%)	–	–	–

** Value in the parentheses represents the change compared to respective AADT based models.*

*** These models were compared to the AADT based volume, length, and geometry models.*

6.5.2 Effects of Correlation and Volume Source

The model comparison in previous section showed that the best models for this dataset were the volume, geometry and flow model. Similar results were found when researchers compared continuous count station models without any data correlation (Dutta and Fontaine, 2019b).

To isolate the effects of using the broader dataset comprised of continuous count stations and short count stations and the effect of correlation, three types of volume, geometry and flow models were compared. Model 1 was developed using only continuous count station data (31 rural segments, 23 urban segments) and negative binomial regression. The results are used directly from previous research by Dutta and Fontaine (add ref). Model 3 is the model discussed on section 7.4 and developed using a combination of short and continuous count data (110 rural segments, 80 urban segments) and mixed effect generalized linear model. Model 2 was developed by re-running model 3 without any correlation. This model used data from model 3 and negative binomial regression from model 1. A comparison of all three models is shown in Table 10 based on total crashes. Table 10 shows how performance changes from using smaller dataset without correlation to the broader dataset with correlation. In each case, model 1 was used as base model for comparison. As mentioned before, the AADT models are based on volume and geometry only.

TABLE 10: Model Comparison to Check for Data Quality and Correlation *

	Rural Segments			
	Data Source	Correlation	MAD	MSPE
Model 1	Continuous Count Only	No	3.24	23.5
Model 2	Continuous and Short Count	No	1.56 (-52%)	6.63 (-72%)
Model 3	Continuous and Short Count	Yes	1.11 (-66%)	2.59 (-89%)
	Urban Segments			
	Data Source	Correlation	MAD	MSPE
Model 1	Continuous Count Only	No	6.82	124.35
Model 2	Continuous and Short Count	No	2.89 (-58%)	90.54 (-27%)
Model 3	Continuous and Short Count	Yes	1.45 (-79%)	36.95 (-70%)

**** Value in the parentheses represents the change compared to Model 1.***

The results show that for both rural and urban segments, inclusion of the short count stations in Model 2 had a large beneficial impact on model performance compared to Model 1.

Acknowledging data correlation also had a positive effect as seen on MOEs for Model 3, although the incremental improvement was lower than that from the inclusion of the short count stations. For rural hourly models, MAD and MSPE improved by 52% and 72% respectively for Model 2 in comparison to Model 1. The improvement in model performance can be attributed to the size of the dataset. The MAD and MSPE further improved by 66% and 89% between Model 1 and Model 3. The improved performance for model 3 was due to the more appropriate methodology acknowledging correlation and also using a broader dataset. The urban segments showed similar results as well.

Since current models like those in the HSM only rely on volume, the quality of volume data dictates the quality of model. The analysis showed that using short count stations as a data source does not diminish the quality of developed models if speed related variables are used in the model. This means that a combination of different volume data sources with good quality speed data can lessen the dependency on volume data quality without compromising performance. Since short count stations are more common, this finding also ensures making the best use of available resources in future research and application.

7 CONCLUSIONS AND FUTURE RESEARCH

The relationship between traffic flow parameters and safety has important implications for the philosophy and policy of transportation planning, highway design criteria, and freeway management. The results from this study provide a better understanding of the impact of geometric and traffic variables on safety and how crash frequency varies over the course of a day. These findings will be useful for estimating the safety performance of the roadway systems, especially when examining how operational changes on a facility impact safety. The models that includes speed related variables in combination with volume and geometry provided superior predictions to ones that did not include speed variables. Availability of adequate detector coverage and quality of available data are a major issue in applying disaggregate models, but this paper shows that using available volume data to estimate hourly average volumes and probe data can be used to generate quality predictions.

The essential requirement for establishing relationship between crashes and flow state on a disaggregate level is reliable information on crashes, hourly traffic flow data, and factors that influence highway capacity. The reason why this type of analysis hasn't been done in detail previously is because obtaining reliable data about crashes and traffic flow state is not a trivial task. It has often been difficult to acquire consistent and good quality traffic flow information in a reasonable amount of time. Adequate detector coverage and quality of available data is a major issue in most states, making it difficult to acquire widespread information on quality of flow. From that perspective, this research sheds light on using various data sources to create a dataset of mixed quality volume data and good quality speed data.

The random effect part of the modeling showed that the spatial correlation between districts were weaker than the temporal correlation. The variance in data between years and hours were small as well. This finding was reinforced during model validation where having a broader and more inclusive dataset (irrespective of continuous volume data availability) had a greater impact than data correlation.

Suitability of average hourly models opens up the possibility to a more accurate safety assessment of facilities with dynamic traffic control or geometry. Treatments such as part time shoulder use or variable speed limits are not active throughout the day but current practice of AADT based SPFs cannot capture the true nature of operation for these systems. Using the methodology proposed in this paper, it would be possible in future to evaluate these facilities for the hours when they are active. The findings from this research can also be used for analysis of work zones since traffic impacts and configuration can also vary by hour. Aggregation of similar districts to have a better sample size in each category could be a logical step in future.

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CHAPTER 7: CONCLUSIONS AND FUTURE WORK

Investigating the relationship between crash characteristics (e.g. occurrence, type, and severity) and traffic characteristics has been a prime focus in the field of traffic operations and safety. However, despite substantive progress in predicting road safety, most past studies are limited by their use of temporally aggregated traffic and/or crash data. This can be a critical limitation for locations where some explanatory variables experience considerable variations temporally (e.g., inclement weather, rush hours, and capacity reduction). This research explored how to effectively quantify highway safety on a short-term basis to overcome these limitations of current methods to provide better crash predictions. Major contributions of this research, applications of the developed techniques, and future research are summarized in this chapter.

7.1 SUMMARY OF MAJOR FINDINGS AND CONCLUSIONS

This research was conducted using volume, speed, and geometry data from 4-lane rural freeway segments and 6-lane urban freeway segments from 2011 to 2017 using Virginia Department of Transportation (VDOT) data systems. Major findings across the papers in this dissertation are summarized below:

- Development of crash prediction models using non-annual data:
  - ➢ Models using raw hourly data were found to be inferior to other levels of aggregation. The raw hourly models were influenced by the missing data in the dataset. About 23% of the raw hourly data in the validation dataset did not meet quality control standards, and thus could not be used to generate predictions. These models did not have a better prediction capability in comparison to the AADT model.

  - ➢ Using averages of available data in each hour or each 15-minute improved the model performance significantly over AADT models. The average volume calculation helped to smooth out the discrepancies created by missing raw hourly data. Models based on average 15-minute data did not always perform better than AADT models. For both rural and urban segments, models based on average hourly data outperformed the AADT based models across all MOEs. For total crashes on urban segments, models using hourly volume, geometry, and flow variables showed 20%, 22%, and 38% improvement in MAD, MAPE, and MSPE, respectively, as compared to the AADT based model. Corresponding improvements for rural segments were 11%, 33%, and 29%.

- Due to the random nature of crash occurrence, the raw hourly data was heavily influenced by 0 crash observations and missing volume data, which negatively impacted the ability to generate useful models. Similarly, aggregated models that rely on AADT failed to capture variations traffic flow that could influence safety. Average hourly aggregation of data was the appropriate level of disaggregation to address the variation in volume and speed throughout the day without compromising model quality.

- Inclusion of traffic flow state parameters:
    - Initially multiple flow parameters were investigated such as heavy vehicle percentage, v/c, speed, and density. Heavy vehicle percentage was not a significant variable. It was found that v/c ratio was often an unreliable indicator of traffic flow state since incidents, work zones, or other events might restrict flow at the site and these conditions are not always documented in agency databases. Speed and density only had a logical and statistically significant relationship when they are used one at a time with volume or when they are both used in the same model, but no volume component is added. Since volume was deemed to be an important measure of exposure and speed is more widely available than density, models that used volume in conjunction with speed were selected as the best alternative.

    - Speed was used in the models in the form of average hourly speed, standard deviation of average speed, and difference between speed limit and average speed. Average hourly speed was positively related to total crashes, meaning that higher average speeds are correlated with higher crash frequency. Standard deviation of average speed was significant for all crash types. This indicated that as more variation in hourly speeds are observed over a year, the frequency of crashes increases.

    - The variable that represents difference between speed limit and average speed was significant for all crash types as well. It was observed that during free flow conditions, total crashes, injury crashes, and single vehicle crashes increase while PDO and multi vehicle crashes decrease. During congestion, a reverse scenario was observed where single vehicle injury crashes decrease and multi vehicle and PDO crashes increase. This is a logical relationship since there is a higher probability of having more than one vehicle involved in a crash during congestion. During free flow conditions, fewer vehicles are on the road so average speed is higher. Higher average speed increases the probability of injury crashes.

  - For all models, prediction accuracy was improved across all validation MOEs when the speed components were added relative to performance without speed measures. For example, for urban segments, MAD improved by 11% for total crashes and 5% for injury crashes when speed was added in different forms. Rural segments experienced similar improvements as well.

- Effects of using sensor data and probe data for speed measures:
  - First, the volume, geometry, and flow models used speed and volume data from continuous count stations. Later, INRIX data was used in combination with detector volume while maintaining the same model format. For all the models, parameters for speed related variables didn't vary much between two data sources. Since these two models essentially had the same data other than the speed component, this is an indication that the speed data from these two sources are not significantly different than each other in terms of their effect on the model.

  - When comparing an AADT-based model to an average hourly volume model for total crashes, the mean absolute prediction error improved by 11% for rural models and 20% for urban models. This result was based on volume and speed data from continuous count stations. When private sector probe speed data was used, the rural model performance improved by 10% and urban models by 20%. This trend was consistent for all crash types irrespective of level of injury or number of vehicles involved. Given that model performance was similar and probe data is more widely available, probe data offers a way to significantly expand the application of models that include speed measures.
- Evaluation of model performance with non-continuous volume count stations:
  - Models using only continuous count station data were contrasted with the models using both short count and continuous count stations. For rural hourly models, MAD and

MSPE improved by 52%, and 72% respectively when short counts were added in comparison to continuous count only models. The respective values for urban segments were 58% and 51%.

  - The results show that for both rural and urban segments, inclusion of the short count stations had a large, beneficial impact on model performance. Thus, using average hourly volumes can be coupled with averages of real-time speed data to generate models that offer substantially improved predictions over AADT-based models.

- Effects of spatial and temporal correlation:
  - Results show that the spatial correlation effect is weaker than the temporal one. For all categories, the variance is much smaller for districts than it is for year or hour. This is due to the fact that the sample size among districts is not equally distributed. Even though the temporal correlation was stronger than the spatial one, the variance in data explained by yearly correlation was smaller than the hourly one. The total crashes vary between years and total sample size while considering hourly correlation is higher as well.

  - While comparing the models accounting for correlation to the models that used the same dataset but no correlation, the MAD, MAPE, and MSPE improved by 14%, 1%, and 17% respectively for rural segments and 21%, 1%, and 0.19% respectively for urban segments. While accounting for correlation improved model performance, it provided smaller benefits than inclusion of the short count data in the models.

7.2 POTENTIAL APPLICATIONS

A major gap in existing literature as pointed out repeatedly in this dissertation is the absence of an existing methodology for safety assessment of facilities with dynamic traffic control or geometry. This is true for recurring situations that deviate from average conditions (e.g., day and night, peak periods) as well. The crash prediction models developed in this study close the gap in these areas and will facilitate the assessment of a facility where conditions are different for different times of day. Some possible examples of the application of the models developed in this research include:

- Work Zones: The temporary traffic control strategies at work zone generally affect both traffic safety and operations and are often only implemented during off peak periods. An important issue with work zone safety assessment is that work zones typically occur during off peak periods, particularly if lane closures are used. The HSM provides crash modification functions that account for the effects of project length and duration on crash frequency but do not allow for explicit comparisons of expected safety performance among different work or closure types, nor do HSM CMFs account for the time of day when the work zone is active *(1).* The methods developed in this dissertation would allow engineers to explicitly look at expected tradeoffs in safety created by using different work hours or lane closure configurations.

- Managed Lanes: The HSM does not address freeway facilities with high-occupancy vehicle (HOV) lanes, high-occupancy toll (HOT) lanes, or other managed-lane strategies [1]. Ideally, the managed lanes operate at higher speeds than general purpose lanes during peak period. Since both HOV and HOT facilities are time varying in nature, the methodology described in this study could be extended to estimate safety for managed vs. general purpose lanes or to evaluate potential safety impacts of changes in operating hours.

- Part-time Shoulder Use: Part-time shoulder use is an increasingly popular strategy for both reducing freeway congestion and improving travel time and reliability. FHWA published a guide on part-time shoulder use in February 2016, and the lack of tools for quantifying the safety impact of part-time shoulder use was identified as a major research gap by the guide's authors [2]. Quantitative safety analysis of the part-time shoulder use operations can be an excellent application of the methodology developed in this study.

- Variable Speed Limits: This research can also be helpful in evaluating a variable speed limit operation by separating the hours when the VSL is active as opposed to using an aggregated model without hourly variation. To improve safety on the I-77 corridor, the Virginia Department of Transportation has been using variable speed limits (VSLs) that change the posted speed based on current weather conditions, including fog, high winds, snow, and ice [3]. Since VSLs only post reduced speeds during fog events, traditional safety analyses would have difficulty estimating crash modification factors for this countermeasure. This research can also help evaluating that system or any other ATM system in future.

7.2.1 Case Study: Work Zone Application

To illustrate the application of the developed models, a case study was carried out using data from four ongoing work zones on I-81 in the VDOT Staunton and Salem District. All these sites have a rural 4 lane freeway cross section, and work zones were active from 8 PM to 6 AM on weekdays. Each project involved roadway paving, and lane closures that created congestion were present during at least a portion of the work zone activities. The earliest start date for these projects was May 2018 and latest end date was August 2018, although all of these projects had different durations within this timeframe. Volume data was collected from detectors that cover these sites. The location information of detectors was matched with the start and end points of TMCs from INRIX. Hourly volume data was downloaded from those detectors from VDOT and speed data was downloaded from INRIX. Geometry data was available from HTRIS. Properties for these sites are shown in Table 1.

Table 1: Description of Work Zone Sites (During Work Zone Hours)

	Total Work Days	Total Crashes	Length (mile)	AADT	Average Hourly Volume	Average Hourly Speed (mph)	Speed Limit (mph)
Site 1	20	2	2.00	31860	625	49.47	60
Site 2	26	2	1.51	31492	686	50.79	60
Site 3	27	3	2.00	26699	581	60.72	70
Site 4	19	2	1.60	29115	610	62.65	70

The rural models for total crashes developed in this research were used to evaluate the safety effect during the hours work zone was active at these sites. Hourly predictions were calculated for the hours when work zone was active and the predictions were then summarized to generate annual predicted numbers of crashes during active hours.

Annual predicted number of crashes was also predicted using the Virginia-specific SPF for 2 lane rural interstates that uses AADT and segment length [4]. The predicted crashes from the AADT SPF were multiplied by a factor for each site data to focus on total number of days and hours when the work zone was active. The first part of the factor is a ratio of total hourly volume during work zone hours to total AADT. The second part is a ratio of total number of days to 365.

It was assumed that crash distribution will follow the same distribution as volume during active hours. This factor helps to take into account the crash experience in short duration rather than whole year.

$$Factor = \frac{\sum_{8PM}^{6AM} Hourly\ Volume}{AADT} * \frac{Total\ Number\ of\ Workdays}{365}$$

The results from both models were compared to check which model captures the safety effect of work zone better. MAD, MAPE, and MSPE were used as measure of effectiveness. Table 2 shows the result. The hourly model developed in this research performed better than the current SPF used for Virginia freeways for all sites. Since work zones are only active certain hours a day, it is difficult to estimate safety using an AADT based model. The AADT based model also does not allow inclusion of speed related variables. Even though the annual predicted crashed were converted to annual crashes during work zone hours, that conversion was not enough to capture the variation in flow and associated safety effects of work zone. The MAD, MAPE, and MSPE improved by 36%, 27% and 33% on an average for the research models in comparison to Virginia SPF.

Table 2: Model Comparison

	Developed Model			Virginia Model		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Site 1	1.29 (-34%)	51% (-32%)	1.55 (-31%)	1.96	83%	2.25
Site 2	1.04 (-38%)	53% (-30%)	1.35 (-36%)	1.67	83%	2.10
Site 3	0.98 (-34%)	50% (-21%)	1.39 (-30%)	1.48	71%	1.99
Site 4	1.25 (-36%)	51% (-24%)	1.40 (-35%)	1.96	75%	2.15
Overall	1.14 (-36%)	51% (-27%)	1.42 (-33%)	1.77	78%	2.12

This case study highlights how the models can be used to assess safety for a short duration activity. The result of this study proves that the models developed in this research has better capability to assess safety than current SPFs for work zone application or any other application that is not active 24 hours a day.

7.3 RESEARCH CONTRIBUTIONS

- While previous studies have defined relationships between crashes and geometric and environmental characteristics, there is a lack of robust research examining the relationship between crash frequency and severity and speed and flow characteristics. A few states like North Carolina and California have developed additional SPFs that includes design speed or speed limit as variables in addition to AADT [5,6]. Even though they included additional variables, these AADT based SPFs don't capture the variation in actual flow since no measure to capture actual traffic speed is present. The models developed in this research as documented in Chapters 4, 5 and 6 address this limitation in current literature. These models identified how interactions between flow parameters and crash frequency changes based on crash types and facilities. Such detailed analysis is currently not present especially for state level SPFs. The developed models will allow explicit consideration of the impact of traffic flow state on safety.

- Despite the importance of the relationship between speed and safety, predictive models generally do not yet include speed measures, partially due to the lack of widespread speed data from point detectors. This research showed that private sector probe data (INRIX) could be successfully used in place of detector data for models that utilizes speed to generate predictions. Many states including Virginia already use INRIX data to support a variety of performance measurement and traveler information applications. Despite the availability of highly disaggregated speed data and broader spatial coverage, integrating probe data with data from loop detectors for safety modeling is not common. Chapter 5 shows the comparison between sensor data and INRIX data and proves that INRIX is a suitable alternative for speed data while developing crash prediction models. These findings will be helpful in closing the gap in existing practices and promote use of probe data in safety analysis.

- Inclusion of speed related variables can help reduce the dependence on volume data alone. The quality of current crash prediction models is directly related to the quality of volume data used. As discussed repeatedly in this dissertation, access to adequate volume data may be a significant barrier to developing crash prediction models. The developed models include flow variables that come from verified alternate data sources, thus providing an opportunity to both improve model quality and help to balance the influence of volume data. Even though the problems associated with reliance on volume data only are widely acknowledged, very little research focused on examining this topic. Chapter 5 and 6 documents how this dissertation explored different speed related variables and proved their superiority over volume-based model for different levels of aggregation and crash type.

- The larger impact of using an extensive dataset proved that using short count stations as data source does not diminish the quality of developed models if speed related variables are used in the model. As documented in Chapter 6, this means that a combination of different volume data source with good quality speed data can lessen the dependency on volume data quality without compromising performance. Since the use of short counts did not degrade the models, this shows that states with limited continuous count stations could still apply average hourly volumes from short counts to generate similar models. For example, there are only 70 continuous count stations available for the roadway network maintained by North Carolina DOT [7]. On the other hand, VDOT maintains around 2900 count stations located on the interstates, around 150 of which are continuous counts [8]. The findings from this dissertation show that similar average hourly models could be generated nationally and do not rely on robust continuous data.

- Accounting for correlation in developing SPFs is currently not very common. Spatial correlation for multilane highways is addressed by developing separate models for separate district. The models in chapter 6 used district as a grouping variable to capture overall correlation among districts without developing separate models. It also accounts for the temporal correlation by using year and hour as grouping variable.

7.4 FUTURE RESEARCH

While this research made significant progress in developing disaggregate SPFs that could be broadly applied to freeway segments, several possible avenues for future research have been identified. Possible future research has been organized based on whether it is a near-term to long-term research need.

7.4.1 Near-Term Research

A very interesting future research topic using the developed methodology would be to explore other facility types such as arterials. This research focused on rural 4 lane and urban 6 lane freeway segments because they are the most common freeway cross sections in Virginia. The methodology developed in this dissertation can be extended to other facility types in the future. It would be interesting to see how this methodology can improve crash prediction models for arterials and signalized intersections in particular. The nature of operations on an arterial is different than freeways and investigating how that changes the models would be interesting. This will be particularly useful in places where time of day (TOD) based signal timing plans are used. Hourly models will help isolate the effect of these signal timings and accurately assess the safety effectiveness. This is a logical next step to evaluate the methodology developed in this dissertation and check its broader transferability.

Further examination of the spatial and temporal correlation another way to refine the developed model. VDOT districts have been used to define spatial correlation in this dissertation. The results showed that there is indeed spatial correlation among districts, even though it is very low. This was largely due to the sample size in each district. Since neighboring districts might share some similar characteristics, grouping them together will increase sample size in each category and also simplify the modeling process. The current SPF for multilane highways in Virginia has different models for different district groups, and the grouping was done through an iterative process [4]. A similar approach could be adapted for future research. It is also possible to modify these models to capture the seasonal variability in data or even the difference in traffic trends between weekdays and weekends. This temporal disaggregation can help to capture the difference in driving behavior and also incorporate the effect of weather through the seasonal variable. Further exploration of the data correlation can be an immediate step for these models.

In addition to different facilities, parallel efforts could be made to explore different crash types as well. This research primarily focused on total and injury crashes. Even though PDO, single vehicle, or multivehicle crashes were considered initially, they were not included in the final models. It would also be interesting to see how different crash types such as rear end or roadway departure crashes for freeways and head-on crashes or sideswipe crashes for intersections would be affected by more disaggregate predictions. It is also possible to extend this work to investigate bicycle or heavy vehicle crashes.

7.4.2 Medium-Term Research

Future research could also focus on developing default values for parameters that are hard to predict for future years. For example, knowing the standard deviation of hourly speeds for a future year may be hard to identify. Research in this direction could focus on how to estimate the parameters for future use so that developed models could be used more accurately for prediction as well as safety assessment.

The cost of collecting accurate, high-quality volume data with traditional infrastructure sensors can be high, which is why real-time volume data remains relatively sparse and of varying quality on the majority of the freeway and major arterial networks. Data analytics companies such as Streetlight now provide probe data-based estimate of volume to leverage existing count stations, and these data products are expanding. The volume estimates from these sources still need to checked for accuracy, but quality is expected to improve in coming years, especially with the inclusion of connected and automated vehicles in the traffic stream. Probe volume estimates could be explored as a way to further extend these models as the data streams mature.

7.4.3 Long-Term Research

With the emergence of connected and automated vehicles, the available data on crash contributing factors could change significantly. It is expected that the CV-AV environment will change the quality, quantity, and type of data available for safety assessment. Connected Vehicles (CV) can provide data such as instantaneous driving behavior, maneuvers, trajectory, individual origin and destination, and traffic data which previously were not obtainable. Currently, lane by lane speed data is sparse. In a connected vehicle environment, it would be possible to get speed data for each individual vehicle instead of an average value for the whole traffic stream at a certain time. That would ensure more accurate calculation of speed variance and detailed lane by lane analysis. The role of speed variance may be even bigger during transitional mixed automated and human-driven traffic periods, and it would be interesting to assess how different rates of market penetration and differences in speed changes affect safety in those scenarios.

In a traditional traffic environment, data regarding the type of crash, time, location, and driver information is collected by law enforcement officers at the scene. All this information is collected after the crash already happened. In a connected vehicle environment, high-resolution trajectory and vehicle status data will become more available. These trajectory data can not only provide rich and timely traffic flow information, but also capture the exact location before, during, or after a crash for all the vehicles involved.

In a human driven vehicle, the driver makes the decisions on vehicle operation based on his own perception of the driving environment. A connected vehicle is equipped with technologies that gives the driver additional information on the surroundings and also the traffic conditions ahead of them. Knowledge about how the drivers use this information, how they maneuver in traffic, and what kind of behavior leads up to a crash can open up a possible path of future research. Connected vehicles will help us get more information on questions that has huge impact on crashes but is not available currently. Questions regarding the seatbelt use on drivers involved in crashes (or in general as well), driving patterns before crash (risk taking behavior, aggressive driving, too frequent lane changing etc.), variance in speed between the vehicles involved in crash and the traffic stream, etc. insights into the chain of events that lead to a crash.

The improvement in data quality and availability of different types of data in future would enable a detailed analysis of safety. For example, the accuracy of crash data from police reports have always been a source of concern. Using connected vehicles, it will be possible to get the exact time and location of crashes, and the movement of all the involved vehicles before, during and immediately after a crash; significantly improving the currently available crash databases. This will also improve how we develop the crash models. Currently, the driver level information is not used for crash modeling. It is possible that in addition to geometry and traffic flow, driving behavior related information could also be included in the modeling process. This will be particularly useful for models based on level of injury and types of crashes.

Availability of data for each individual vehicle will be particularly useful for safety assessment of managed lanes. The managed lanes operate at higher speeds than general purpose lanes during peak period. Since both HOV and HOT facilities are time varying in nature, methods to estimate safety for managed vs. general purpose lanes or ways to evaluate potential safety impacts of changes in operating hours will be an interesting topic to explore.

With an increasing rate of penetration of connected and automated vehicles in the near future, the models developed in this research would require revision to properly incorporate the effect of new technology and new data sources. It is expected that the interaction between the selected variables in the developed models and also the variables itself will change in that environment. More research is required in this direction to conclude on a direction of change.

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