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DEVELOPING AN ACTIVE TRAFFIC MANAGEMENT SYSTEM FOR I-70 IN COLORADO

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16. Abstract

The Colorado DOT is at the forefront of developing an Active Traffic Management (ATM) system that not only considers operation aspects, but also integrates safety measures. In this research, data collected from Automatic Vehicle Identification (AVI), Remote Traffic Microwave Sensors (RTMS) and Real-Time weather data were utilized to incorporate safety within the ATM system. Preliminary investigation of crashes along 20-miles of I- 70 revealed that the mountainous terrain and adverse weather during the winter season may increase crash likelihood. A traditional automatic incident detection system is a reactive approach to mitigating the effects of crashes without attempting to avoid primary incidents. To reduce the risk of primary incidents, a more proactive approach that identifies locations where a crash is more likely to happen in real-time can be implemented.

The results from the research study suggest that there is a clear demand to incorporate real-time weather conditions and roadway geometric characteristics within the development of the ATM system. Remote Traffic Microwave Sensors, AVI, weather data, and road geometry information were collected and utilized to develop a real-time risk assessment system. Data Mining (DM) techniques were also used to reveal important data relationships and improve prediction accuracy. Based on the data and DM techniques, models were tested and their performances were compared. Results show that the Full Model which incorporates AVI, RTMS data, weather data, and geometric information outperforms other models by identifying about 89% of crash cases in the validation dataset with only 6.5% false positive.

Implementation
This model has the potential to be an accurate component of a proactive traffic management strategy to provide reliable and timely information to drivers under various adverse environments. This work could serve as the basis for a future Variable Speed Limit algorithm to be deployed on I-70.

17. Keywords
Variable Speed Limits (VSL), Automatic Vehicle Identification (AVI), Remote Traffic Microwave Sensors (RTMS), Data Mining (DM), Real-Time Crash Prediction Models, Mountainous Terrain, Adverse Weather Conditions

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EXECUTIVE SUMMARY

This report documents the first part of the development of an Active Traffic Management system on a 20-mile mountainous freeway section on Interstate 70 in Colorado. A comprehensive database including crashes and archived ITS data have been prepared. Real-time weather and roadway geometrical characteristics were incorporated within the development of the database. Safety problems can be assessed through several approaches that can help in mitigating the crash risk on long and short term basis. Therefore, the main focus in this research project is to provide a framework of risk assessment to promote safety and enhance mobility on freeway. To address safety problems on the roadway section, Safety Performance Functions (SPFs) were developed at the aggregate level using historical crash data and the corresponding exposure and risk factors to identify and rank sites with promise (hot-spots). Additionally, SPFs were developed at the disaggregate level utilizing real-time weather data collected from meteorological stations located at the freeway section as well as traffic flow parameters collected from different detection systems such as Automatic Vehicle Identification (AVI) and Remote Traffic Microwave Sensors (RTMS). These disaggregate SPFs can identify real-time risks due to turbulent traffic conditions and their interactions with other risk factors.

At the aggregate level, Bayesian hierarchical models with spatial and random effects were compared to Poisson models to examine the safety effects of roadway geometrics on crash occurrence along freeway sections that feature mountainous terrain and adverse weather. At the disaggregate level; a main framework of a proactive safety management system using traffic data collected from AVI and RTMS, real-time weather and geometrical characteristics was provided. Different statistical techniques were implemented. These techniques ranged from classical frequentist classification approaches to explain the relationship between an event (crash) occurring at a given time and a set of risk factors in real time to other more advanced models. Bayesian statistics with the capability of the updating approach to update beliefs about the behavior of the parameter with prior knowledge in order to achieve more reliable estimation was introduced. Also a relatively recent and promising Machine Learning technique (Stochastic Gradient Boosting) was utilized to calibrate several models utilizing different datasets collected from mixed detection systems as well as real-time meteorological stations. Based on the results from the machine learning procedure, a framework for real-time risk assessment on the freeway section was provided.

The results from this study suggest that both levels of analyses are important, the aggregate level helps in providing good understanding of different safety problems, and developing policies and countermeasures to reduce the number of crashes in total. At the disaggregate level, real-time safety functions help toward more proactive traffic management system that will not only enhance the performance of the high speed facilities and the whole traffic network but also provide safer mobility for people and goods.

In general, the proposed multi-level analyses are useful in providing roadway authorities with detailed information on where countermeasures must be implemented and when resources should be devoted. The study also proves that traffic data collected from different detection systems could be a useful asset that should be utilized appropriately not only to alleviate traffic congestion but also to mitigate increased safety risks using real-time safety mitigation techniques, e.g. variable speed limit. The overall proposed framework can maximize the benefit of the existing archived data for freeway authorities as well as for road users.

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LIST OF ACRONYMS/ABBREVIATIONS

AADT	Annual Average Daily Traffic
ADT	Average Daily Traffic
ATM	Active Traffic Management
AVI	Automated Vehicle Identification
CART	Classification and Regression Trees
CDOT	Colorado Department of Transportation
DIC	Deviance Information Criterion
FB	Full Bayesian
NB	Negative Binomial
RCI	Roadway Characteristics Inventory
SAS	Statistical Analysis Software
SGB	Stochastic Gradient Boosting
SR	State Road
SSE	Sum of Square Errors
VMT	Vehicle Miles Traveled

CHAPTER 1. INTRODUCTION

1.1 Overview

A significant amount of research in the area of freeway traffic management has been aimed at congestion caused by incidents through their early detection. Automatic incident detection algorithms rely on data available from traffic surveillance apparatus (e.g., radars, loop detectors). The aim is to identify incident conditions from free-flow and/or recurring congestion. However, increase in mobile phone usage and video surveillance technology has diminished the relevance of loop data based incident detection models (FHWA, 2000). Incident detection is essentially a reactive approach and does not attempt to avoid primary incidents. To reduce the risk of primary incidents traffic management authorities may prefer a proactive approach to traffic management. A proactive approach would essentially involve identifying freeway locations where a crash is more likely to occur in real-time instead of trying to assess where the incident *has* occurred.

The approach for developing real-time crash risk assessment models is to analyze historical crashes and traffic surveillance data corresponding to historical crashes and detect patterns that are often observed *before* crash occurrence. If these patterns are repeated in the future on a freeway section, that section may be identified as a real-time “black-spot” with high likelihood of crash occurrence. Variable Speed Limit (VSL) - and ramp metering - strategies which specifically aim at reducing crash risk may be developed for these traffic conditions. While the infrastructure used by automatic incident detection algorithms may be used for implementing the crash risk estimation framework; there are some critical differences in the way results are approached.

In the recent past tremendous growth has been observed in traffic management and information systems. Due to recent advances in the capabilities to collect (and archive) the data through underground and microwave sensors these data are available for many freeways. Availability of these data has inspired a new series of studies in traffic safety in which traffic conditions before historical crashes may be collected and examined to identify patterns that commonly occur before crashes. These studies in the area of traffic safety can lead to the emergence of a new proactive paradigm in traffic management.

Research in freeway traffic management was, and to an extent has been, focused on automatic incident detection. The idea of incident detection involves analysis of patterns in traffic surveillance data observed just after the historical incidents. Since traffic data for the freeway are collected continuously it is possible to develop models using historical incident data and apply them in real-time to examine the traffic data for detecting any incident that might have occurred on the freeway.

This report presents the findings of the first phase of a research effort to develop an active traffic management system for Colorado Department of Transportation (CDOT). This system is envisioned to go beyond other ordinary ATM systems. The CDOT system is expected to incorporate Variable Speed Limits based on advanced algorithms to improve traffic turbulence in real-time and therefore reduce crash risk and improve flow. Since Colorado’s I-70 corridor is mountainous in many of its sections, and weather conditions can be severe, the models developed as part of this project incorporate real-time weather conditions and roadway geometric characteristics in the algorithms in addition of real-time traffic data collected from multiple detection systems e.g. AVI and RTMS, which goes beyond any algorithms that were developed before. Although further research is still in progress, the following objectives have been achieved in this phase:

1. A detailed database has been developed using crashes, and archived ITS data.

2. Real-time weather and geometric were collected and incorporated within the database.

3. A preliminary safety analysis has been conducted to gain more understanding of safety problems on I-70 roadway section.

4. Classical, Bayesian, and Data Mining statistical techniques were developed to link geometry of the roadway section, real-time weather and traffic data to crash risk.

5. Based on the calibrated models, a classification algorithm was developed to differentiate between crash prone and normal conditions on the freeway section.

6. To ensure best prediction accuracy, the final selected models were tested and validated using new data.

7. In order to increase real-time crash prediction, the best models were ensemble to increase even more their performance.

8. Stochastic Gradient Boosting, a recently promising data mining technique was examined with fused geometry, real-time weather and traffic data from multiple sources of detection systems.

9. An overall framework was developed to combine all models in one fused system of real-time risk assessment. Development of a system design capturing all data collected from all infrastructure sources. This would be the basic step in developing a variable speed limit algorithm in the future.

1.2 Research Organization

The report is organized as follows: following this chapter, a summarized literature review on previous studies of freeway crash analysis highlighting the important factors that affect crash frequency as well as discussing the different statistical methodologies used in that area, followed by a detailed review of the real-time crash prediction literature. Chapter 3 presents data, methodology, and finding of the analysis of crash frequency of 20-mile mountainous section in Colorado using Full Bayesian Hierarchical approach. The development of detailed database including crashes, roadway geometry, real-time traffic and weather data is discussed in chapter 4. The preparation of automatic vehicle identification traffic data and crash data, methodologies, and viability of using this data in real-time safety risk analysis are provided in Chapter 5. Chapter 6 discusses the inclusion of geometrical characteristics and weather information in real-time risk assessment. A framework for real-time risk assessment using traffic data from mixed detection systems, real-time weather and geometry is illustrated in Chapter 7. The final chapter of this research, chapter 8 concludes the findings, and discusses future recommendations.

CHAPTER 2. LITERATURE REVIEW

2.1 General

The literature review is divided into two main sections. First section summarizes the studies of aggregate crash analysis on freeway in which the frequency of crashes is the number of crashes occurring in some geographical space (road segments, intersections, or network) over specific time period (months, seasons or years), in these studies the traffic flow parameters are represented by aggregated measures (e.g. AADT and speed limit). This section also shed the light on important factors that affect crash frequency as well as discussing the different statistical methodologies used in that area. Second section provides a comprehensive review of previous disaggregate studies focused on relating real-time traffic data and crash occurrence on freeways in a proactive safety management framework. In these studies the units of analysis are the disaggregate crash events and the traffic flow is represented by the corresponding real-time traffic data at the same time and location of each crash.

2.2 Aggregate Analysis of Crashes

2.2.1 Overview

The aggregate crash frequency analysis has been an effective way to gain better understanding of the contributing factors that affect the likelihood of crashes and identify locations with high crash risk potential for many decades. These studies are important to provide directions to officials for policies and countermeasures to reduce number of crashes. Crash performance functions were conventionally used to establish relationships between the traffic characteristics (e.g. speed limit, ADT, and VMT), roadway geometry (e.g. number of lanes, curvatures, grades, etc.) and environmental factors (weather), driver characteristics and behavior (e.g. gender, age, acceleration, braking and steering information, driver response to stimuli, etc.) and crash occurrence.

Ceder (1982), Garber and Ehrhat (2000), and Yan et al. (2009) established relationships between these variables and crash frequency while Abdelwahab and Abdel-Aty (2002), Al-Ghamdi (2002) and Srinivasan (2002) related these variables to the severity of crashes.

2.2.2 Factors Affecting Crash Frequency

There are many factors that contribute to crash occurrence, two main categories of these factors that affect crash frequency on freeways are; 1) behavioral factors, and 2) non-behavioral factors. The data about behavioral factors are typically not available and hence they are less reported in the literature. Traffic flow characteristics, weather, and geometry were extensively reported in many studies as the main contributing factors that affect crash frequency on freeways.

The association between roadway geometry and crash occurrence is well documented in the literature, Wong and Nicholson (1992), Boughton (1975), National Cooperative Highway Research Program (1997), and the Federal Highway Administration (1982) showed strong association between adverse geometric elements and high crash frequency.

Milton and Mannering (1998) reported that the increase in section length tends to increase crash frequency and the effect of section length on expected crash frequency has an exponential nonlinear form. Their study revealed that vertical grades greater than 1 percent produced higher crash frequencies. Upgrade slopes were found to slow trucks by 15 km/h for significantly long grades and this reduction in speed found to be associated with increased passing and risk taking by faster passenger vehicles and increase in crashes. In contrary, downgrades have the effect of increasing speeds and this increase in speed results in increase in crash rates. Sharp horizontal curves with radii less than 868 m were found to decrease the crash frequency and they explained that by the fact that the drivers may be more likely to drive cautiously.

Chang and Chen (2005) established empirical relationship between freeway crash frequency and highway geometric variables, traffic characteristics, and environmental factors. They compared between Classification and Regression Tree (CART) and Negative Binomial (NB). They concluded that CART model relies more on traffic and environmental variables than geometric and location variables to classify crash frequencies on the freeway sections. According to CART, the study showed that ADT is the best single variable to classify the crash frequency on the freeway having the initial split in node 1 based on the ADT of 20,622 vehicles/lane. This indicates that the increase in ADT over 20,622 may increase crash frequency, this finding also confirmed from their NB model that the increase in ADT tend to increase crash frequency because of the increase of exposure. The second important variable to classify crash frequency was the number of rainy days, more crashes was expected with segments with rainy days more than 81 days, and even more crashes are expected with bus ADT more than 4,677 buses/day. In general, freeway sections with higher traffic volume (ADT/lanes, bus volume, truck volume, and semi-tractor volume), higher precipitation (number of days and amount of rain) are found to be more prone to be classified with higher crash rates. Regarding geometric alignment, they found that grade greater than 3.85% and degree of horizontal curvature greater than 0.4° have greater tendency to be classified with higher crash frequencies. It was indicated from NB model which relied more on geometric variables that the presence of degree of horizontal curvature greater than 8° can significantly reduce the crash likelihood.

Carson and Mannering (2001) estimated three separate models for interstate freeways, principal arterial, and minor arterial state highways to examine the effect of warning signs on ice-accident frequency. They found that spatial factors (e.g. urban), traffic characteristics (e.g. AADT, truck percentage), and geometry (e.g. shoulder width, grade) have significant effect on crash frequency while ice-warning signs do not have a statistically significant impact on the frequency or severity of crashes that involve ice.

Chang (2005) compared the predication performance of NB model and Artificial Neural Network (ANN), the study showed that ANN model is a consistent alternative method to analyze the frequency of freeway crash. From both models, it was concluded that ADT, number of lanes, vertical and horizontal alignments are significantly influence the freeway crash frequency. Accident likelihood increase by increase of each of ADT, number of lanes, sections with steep upgrades (3% or more), and sections with steep downgrades. Sections with level grades, severe horizontal curve (degree of horizontal curve greater than 6°) have reduced crash likelihood. Moreover, the study showed an increase in likelihood of crashes at ramps area because of the impact of merging and diverging maneuvers on crash risk.

In a recent study by Park et al. (2010), the safety effect of geometric design elements for various highway facilities was evaluated. The study revealed that crash frequencies on freeway segments were associated with ADT, on-ramp density, degree of curvature, median width, number of urban freeways lanes, and spatial factors (urban/rural).

2.2.3 Statistical Techniques of Analyzing Crash Frequency

Recently, researches have put many efforts using different statistical techniques in trials of revealing the contributing factors that are associated with crash frequency on roadway segments over certain period of time. Different modeling techniques that have been ranged from conventional regression to data mining techniques such as Artificial Neural Network (ANN) and Classification and Regression Trees (CART), and Bayesian statistical techniques such as Empirical Bayes (EB) and Full Bayesian (FB) were used to analyze crash frequency data.

Lord and Mannering (2010) provided a detailed review of the key issues associated with crash-frequency data as well as an assessment of the strengths and weaknesses of the various methodological approaches that have been used to address these problems. They concluded that despite the fact that many researchers have put great effort in innovative methodological approaches to account for these formidable problems in data characteristics to improve the understanding of the factors that affect crash-frequencies, there is still a room for statistical methodologies that can be introduced to overcome these problems.

The nature of the crash-frequencies of being non-negative count data and the randomness discrete distributional property led to use Poisson and negative binomial models (NB) extensively. Poisson and NB models known also for their easy estimation (Shankar et al. 1995; Hadi et al., 1995; Poch and Mannering, 1996; Abdel-Aty and Radwan, 2000; Savolainen and Tarko, 2005).

However, Poisson and NB models have their own restrict assumptions, Poisson model for example cannot handle over- and under- dispersion while NB can only deal with over- dispersed data. In order to overcome different statistical problems in the count data associated with Poisson and negative binomial models, other alternations were applied to these models such as using zero-inflated (Poisson and negative binomial), and random effect negative binomial (Shankar et al., 1997; Carson and Mannering, 2001; Lee and Mannering, 2002; Shankar et al., 1998; Lord and Mannering, 2010).

Moreover, other non parametric models have been used such as Classification and Regression Tree (CART) and Hierarchical Tree-Based Regression (HTBR) to predict and classify the crash occurrence on freeway (Chang and Chen, 2005; Karlaftis and Golias, 2002).

Unlike Poisson and NB models, CART and HTBR have an advantage of not requiring a specified functional form. However, the CART & HTBR models have their own disadvantages of the risk of over-fitting because of the lack of formal statistical inference procedures and they also lack of handling the interactions between risk factors as explained by Harrel (2001).

Chang (2005) concluded that Artificial Neural Network (ANN) is a consistent alternative of NB for analyzing crash frequency on freeway. Similar to CART and HTBR, ANN does not require assumptions to relate risk factors to crash frequency and it features additional ability of handling the interactions between the predictors. CART, HTBR, and ANN all share another drawback of the difficulty of performing elasticity and sensitivity analyses which is important to provide the marginal effects of the variables on crash frequency.

The Full Bayesian (FB) hierarchical approach has gained momentum recently to better account for spatial correlation between observations (e.g. crashes) among locations (e.g. roadways segments or intersections). The Full Bayesian (FB) has become very common in modeling crash frequency because its capability to account for uncertainty in crash data and to provide more detailed causal inferences and more flexibility in selecting crash count distributions. Moreover, random effects can be easily included with the Full Bayesian (FB) formulation to help address individual site differences and prevent regression to the mean bias. It is concluded also that this methodology is extendable to any type of crash and different roadways.

Tunaru (2002) developed a multiple response FB hierarchical model that could support complex correlation structure. Two different ranking criteria were used to identify hazardous sites using the developed model; ranking by the posterior probability that a site is the worst and ranking by posterior distributions of ranks. He concluded that the first criteria can be used for long term projects while the second can be used for short term projects.

Aguero-Valverde and Jovanis (2007) used Full Bayesian Hierarchical Models with random effects to identify road segments with elevated weather-related crash risk. They examined two different ranking criteria; “the expected excess crash frequency (compared to similar sites) and the relative risk (the ratio of the expected number of crashes at a site divided by the number expected for similar sites)", they found that the results were consistent from the two methods.

Huang and Chin (2009) applied Full Bays (FB) hierarchical approach to identify crash hotspot on Singapore intersection crash data (1997-2006), they showed that the FB hierarchical models have better goodness-of-fit than non-hierarchical models and even more, the hierarchical models perform significantly better in safety ranking than the naïve approach using raw crash count.

2.3 Disaggregate Crash Analysis

2.3.1 Applications of ITS-archived Data in Traffic Safety

Safety performance of a transportation facility can be assessed by crash data analysis as one of the most frequent used tool (Abdel-Aty, and Pande, 2007). Crash performance functions were conventionally used to establish relationships between the traffic characteristics, roadway and environmental conditions, driver behavior and crash occurrence. Although these models are useful to some extent, the aggregate nature of traffic parameters is not capable to identify the real-time locations with high probability of crashes.

On the other hand, real-time crash analysis had the researchers' interest recently in the last one decade since it has the capability of identifying crashes in real time and hence being more proactive in safety management rather being reactive.

Madanat and Liu (1995) used traffic flow and environmental conditions measured by surveillance sensors to estimate the incident likelihood for two types of incidents related to crashes and overheating vehicles. The incident likelihood was estimated to enhance existing incident detection algorithms. Using binary logit model, it was concluded that merging section, visibility and rain are the most significant factors affecting crash likelihood prediction.

Loop detectors data were used by Hughes and Council (1999) to explore the relationship between freeway safety and peak period operations. They found that the variability in vehicle speeds was the most significant measure that affects crash occurrence while macroscopic measures as AADT and hourly volume were poor measures in the analysis of safety. They used data from single milepost location during the peak periods of the day with assistant of snapshots provided by cameras installed on the freeway to examine the changes in system performance as it approaches the time of the crash. They concluded that “design inconsistency” is one of the most important factors of crash causation, they also suggested that “traffic flow consistency” should be considered in future research as perceived by the driver as an important variable that affect human. Moreover, they call for determining of the exact time of crash in order to avoid “cause and effect” fallacy. Also, Feng (2001) suggested that the reduction of speed variance may help in reducing crash occurrence.

Oh et al. (2001) was the first to statistically link real-time traffic conditions and crashes. A Bayesian model was used with traffic data containing average and standard deviation of flow, occupancy, and speed for 10-seconds intervals. It was concluded that the five minutes standard deviation of speed contributes the most in differentiating between pre-crash and non-crash condition. Although there sample size of 53 crashes is small, they showed the potential capability of establishing the statistical relationship. Moreover, the practical application of their finding is questionable, since five minutes before the crash is not adequate time for any remedy actions.

“Crash precursors” were first introduced by Lee et al. (2002), they hypothesized that short-term turbulence of traffic flow is significantly affecting the likelihood of crash occurrence. They used the log-linear approach to model traffic conditions leading to crashes “precursor”, spatial dimension was added by using data from upstream and downstream detectors of the crash location as well as data across the three lanes at the crash location to represent factors such as speed variation along a specific section of the crash location along the roadway and between lanes. Also, traffic density was considered at the instant of the crash in addition to other external controlling factors such as weather, road geometry and time of crash. Moreover, they used speed profile captured by the detectors to estimate the actual crash time instead of using the reported crash time. They refined their analysis in a later study (Lee et al., 2003) and the coefficient of temporal variation in speed was found to have a relatively longer-term effect on crash potential than density while the effect of average variation of speed across adjacent lanes was found to be insignificant.

Golob et al. (2003) in later study developed a software tool FITS (Flow Impacts on Traffic Safety) to predict type of crashes based on the flow conditions being monitored. They used data for more than 1000 crashes from six major freeways in Orange County in California to develop the model and applied the tool in a case study on a section of SR55.

Hourdos et al. (2006) developed on-line crash-prone condition model using 110 live crashes, crash-related traffic events, and other contributing factors visualized from video traffic surveillance system (e.g., individual vehicle speeds and headways) over each lane in different places of the study area. They were able to detect 58% of the crashes successfully with a 6.8 false decision rate (where 6.8% of the crash cases were detected as non-crash cases).

Kockelman and Ma (2004) conducted a study using 55 severe crashes that occurred during January 1998 for the same area analyzed by Golob et al. (2003). Unlike all previous studies that have indicated a relationship between speed variability and crash occurrence, they concluded that speeds measured as 30-second time series and their variations are not capable of predicting crash occurrence. However, their conclusion is suspected due to the small sample size.

Similarly, Ishak and Alecsandru (2005) used data for 116 crashes occurred on Interstate 4 in Orlando, Florida. They found that it is not possible to separate pre-incident, post-incident, and non-incident traffic regimes from each other. Moreover, they indicated that traffic conditions that lead to crash might not be discernible in real-time.

Abdel-Aty and Pande (2005) were able to capture 70% of the crashes using the Bayesian classifier based methodology, probabilistic neural network (PNN) using different parameters of the speed only. They found that the likelihood of a crash is significantly affected by the logarithms of the coefficient of variation in speed at the nearest crash station and two stations immediately preceding it in the upstream direction measured in the 5 minute time slice of 10-15 minutes prior to the crash time.

Park and Ritchie (2004) used individual vehicle trajectories obtained from a state-of-the-art vehicle-signature based traffic monitoring technology to relate the lane-changing behavior and presence of long vehicles within a freeway section and speed variation. They claimed that using section speed variance rather than the point speed variance usually obtained from loop detectors data is more efficient in representing traffic changes. They concluded that these factors are significantly affecting the section speed variability.

2.3.2 Real-Time Analysis Based on Traffic Regimes

Golob et al. (2004) related different traffic regimes to crash occurrence. They used data from the six freeways in Orange County in California. They found that about 76% of all crashes occurred in four regimes out of total eight regimes of traffic flow that exist on these freeways. This indicates that specific regimes of the traffic flow is more correlated with crash occurrence than others and hence the key of crash prediction on urban freeways is distinguishing these patterns of traffic flow in real-time.

Zhang et al. (2005) also established a link between traffic congestion and freeway crashes in different weather conditions. They concluded a U-shaped curve relationship between the "Relative Risk Ratio" (a measure of crash probability) and congestion. Moderate congestion resulted in high relative risk ratio while free flow and heavy congestion found to be related with low relative risk ratio.

Matched case-control was used by Abdel-Aty et al. (2004) to link real-time traffic flow variables collected by loop detectors and crash likelihood. Matched case-control was selected because it has the capability of eliminating the influence of location, time and weather condition. They concluded that the average occupancy at the upstream station along with the coefficient of variation in speed at the downstream station, both during 5-10 minutes prior to the crash, were the most significant factors affecting crash likelihood prediction.

They extended their work in later study (Abdel-Aty et al. 2005); multi-vehicle freeway crashes under high- and low-speed traffic regimes were found to differ not only in terms of severity but also in their mechanism. Therefore, these two different distributions of 5-minute average speeds obtained from the closest station to the location of the crash suggested using different models depending on the freeway operation characteristics. Although, they used similar procedure to build low and high-speed models, the parameters entered in the two models are different. They concluded that low speed crashes mostly occur in persisting congested conditions where queues form and dissipate quite frequently. In contrary, freeway operation was found to be smooth at the high-speed crash location before the crash while they argued that some disruptive conditions originating downstream and the propagating backwards were the causes of drivers' errors and hence increasing the crash potential. Also, they found that more parameters came out to be significant from the downstream stations in high-speed model at time duration 5-15 minutes prior to the time of the crash.

2.3.3 Identification of Type of Crash Using Real-Time Data

A detailed study carried out by Golob and Recker (2001) to analyze patterns in crash characteristics as a function of real-time traffic flow, non-liner canonical correlation analysis (NLCCA) and principal component analysis were used with three different sets of variables. The first set defined lighting and weather condition, the second set defined crash characteristics of collision type, location and severity and the third set consisted of real-time traffic flow variables. It was concluded that some collision types are more common under certain traffic conditions; they found that median speed and variation in speed between the left- and interior lanes is related to the collision type. In addition, the inverse of the traffic volume has more influence than the speed in determining the severity of the crash. Although, the established statistical links between environmental factors, traffic flow, and crash occurrence is sound, their findings are limited by the fact that the speed was estimated using a proportional variable (volume/occupancy) from traffic data that were obtained from single loop detectors. Moreover, their findings are not applicable in a real-time proactive management to separate traffic conditions leading to crash from normal traffic conditions since non-crash data were not included.

Modeling crash types was argued by Kim et al. (2006) to be useful for at least three reasons:

1) Identification of sites with high crash risk of specific crash types that may not be identifiable using total crash types.

2) Countermeasures are likely suitable for only a subset of all crashes.

3) Traffic, road geometry, and environmental factors are usually associated with different crash types.

The importance of crash-type analysis was also highlighted by Pande and Abdel-Aty (2006a), they suggested that the traffic conditions preceding crashes are expected to differ by type of crash and therefore the proactive traffic management should be type-specific. They proposed a step by step approach to analyze loop detector data to identify real-time traffic conditions prone to rear-end crashes. They found that rear-end crashes may be grouped into two distinct cluster based on the average speeds prevailing within 2-mile section around the crash location 5-10 minutes prior to the crash time.

Pande and Abdel-Aty (2006b) continued their analysis with different type of crashes on freeway, they investigated lane-change related crashes on a freeway using classification tree procedure, it was concluded that all sideswipe collisions and the angle crashes that occur on the inner lanes (left most and center lanes) of the freeway may be attributed to lane-changing maneuvers. The results also revealed that average speeds upstream and downstream of the crash location, difference in occupancy on adjacent lanes and standard deviation of volumes and speed downstream of the crash location were the significant variables affecting crash occurrence.

Chris Lee et al. (2006) investigated the real-time traffic factors related to sideswipe crashes using a surrogate measure of lane change called “overall average flow ratio (OAFR)” which accounts for imbalance of lane flow across neighboring lanes during short time periods (5-10 minutes) and compared conditions for sideswipe and rear-end crashes based on those factors. They modified the original expression of “average flow ratio (AFR)” between adjacent lanes that was developed in previous experimental study of lane change by Chang and Kao (1991) by suggesting that a geometric mean of ratios of flows between adjacent lanes can be used to indicate the likelihood of sideswipe crashes. Four year loop detector data from 36.3-mile on I-4 in Orlando were used. They conducted t-test to identify the factors that are contributing more to sideswipe than rear-end crashes by comparing the average values (or percentages) of traffic related factors included average speed, flow and occupancy – lane average of 30-second speed, coefficient of variation of speed, coefficient of variation of flow, and peak/off-peak period and road geometric factor included only the curvature of road section. They found that the OAFR is a good surrogate measure of lane change as they found that the OAFR is generally higher for sideswipe than rear-end crashes at a 95% confidence level in addition to coefficient of variation of flow and peak/off-peak period. Simple logistic regression was used to quantify the relationship between these potential indicators and sideswipe, and rear-end crashes. They concluded that the odds of sideswipe relative to rear-end crashes increases as value of OAFR and coefficient of variation of flow increase and when the time period is off-peak period.

2.3.4 Crash Prediction Using Archived Weather and ITS Traffic Data

Many studies showed strong relationship between weather and speed and safety, the effect of weather may include reduced visibility, stability, and controllability. However, very few studies have investigated crash occurrence using real-time traffic data while controlling for environmental and weather conditions. The study by Golob and Recker (2001) was one of the earlier studies that examined the relationship between the types of freeway crashes and the traffic flow parameters while controlling for weather and ambient lighting conditions.

Abdel-Aty and Pemmanaboina (2006) used Principal Component Analysis (PCA) and logistic regression (LR) to estimate a weather model that determines a rain index based on the rain readings at the weather station in the proximity of the I-4 corridor in Orlando. The archived rain index was used with real-time traffic loop data to model the crash potential using matched case-control logit model. They concluded that the 5-minute average occupancy and standard deviation of volume observed at the downstream station and the 5-minute coefficient of variation in speed at the station closest to the crash, all during 5-10 minutes prior to the crash occurrence along with the rain index were found to be the most significant factors to affect crash occurrence.

Hassan et al. (2010) used real-time traffic data to explore visibility related crashes on I-4 and I-95 freeways in Orlando; the main hypothetical testing was to compare between traffic flow characteristics that lead to visibility related crash with non-crash cases at reduced visibility conditions. Random Forest (RF) was used to identify significant traffic flow factors affecting visibility related crash occurrence. The identified factors were then used to examine the effects of traffic flow characteristics on visibility related crashes using matched case-control logistic regression to control for the effect of other confounding variables such as the geometric design and crash time. They found that the 5-minutes average occupancy observed at the nearest downstream station during 10-15 minutes before the crash along with the average speed measured at the downstream and upstream stations 5-10 minutes before the crash increase the probability of having visibility related crash.

2.3.5 The Viability of Using Automatic Vehicle Identification Data in Real-Time Risk Assessment

Although a great effort has been performed in analyzing real-time data collected from inductive loop detectors in safety framework, few safety studies have been carried out using traffic data from one of the most growing surveillance system; the tag readers on toll roads (AVI).

Ahmed and Abdel-Aty (2011*)* implemented for the first time data collected from AVI in a real-time traffic safety analysis, they found that AVI data are promising in providing a measure of crash risk in real-time. They used AVI data collected from 78-mile on the Central Florida expressway network in Orlando in 2008 and historical crash data obtained for the same period and study area. They concluded that the logarithms of the coefficient of variation in speed at the crash segment during 5-10 minutes prior to the time of the crash is found to be the most significant factor affecting the crash likelihood on a freeway with tag readers spaced 1-mile on average and mostly commuting drivers while the standard deviation of the speed at the crash segment and the average speed at the adjacent downstream segment were found to be the most significant on another freeway section with AVI segments length of an average of 1.5-mile with mixed type of road users. It was concluded also that all speed parameters obtained from AVI systems spaced on average at 3 mi apart or more were found to be statistically insignificant to identify crash-prone conditions, the results suggested that the AVI data could only be useful if the AVI segments are within 1.5 mi on average. The results showed that the likelihood of crashes is statistically related to speed data obtained from the AVI system and the model achieved about 70% accuracy.

In a later study Ahmed et al. (2012) applied Bayesian updating approach to compare between the prediction performance of a single generic model for all crashes and a specific model for rear-end crashes using AVI data. By contrasting AVI data preceding all crashes and rear-end crashes with matched non-crash data, it was found that rear-end crashes can be identified with 72% accuracy while the generic all crash model achieved. The results also indicated that Bayesian updating approach can increase the accuracy of the models.

2.3.6 Transferability of Real-Time Crash Potential Models

Although many studies have been conducted to statistically link real-time crash risk and traffic data collected from loop detectors, few studies addressed how the results from one freeway might transfer to another. Abdel-Aty et al. (2008) used Random Forests and multilayer perception neural network (MPNN) to test the transferability between different freeway corridors. Their model was successfully transferable from I4 in Orlando to Dutch motorways.

Pande et al. (2010) tried to explicitly address the transferability issue in a recent study, using MPNN on loop detector data collected from I-4 and I-95 in Orlando they found that while the model developed for one direction of I-4 eastbound worked reasonably for the I-4 westbound the performance was not acceptable for the I-95 sections concluding that the same model for crash risk prediction may only work for corridors with very similar travel patterns.

2.3.7 Real-Time Crash Risk Prevention

Variable Speed Limit (VSL), ramp metering, and route diversion are the main ITS and traffic management strategies that were used to increase the capacity of freeways and alleviate the congestions without costly lane additions or major redesigns of the geometry. These management strategies have also a potential application in the field of traffic safety for example; using VSL in speed harmonization by reducing speed limits at congested downstream areas helps to maintain better traffic flow and reduce the risk of mainly rear-end collisions.

Park and Yadlapati (2003) used the minimum safe distance equation as a measure of safety to compare the actual following distances with minimum recommended following distance at work zone area; they found that implementing VSL reduces the speed variation between successive vehicles throughout the work zone area and the number of rear-end crashes should be reduced as well.

Lee et al., (2004) proposed the application of the developed log-linear models by estimating real-time crash potential. They focused in this study on how to reduce the crash potential using Advanced Travel Management (ATM) systems through different strategies of variable speed limits (VSL). Microscopic simulation tool PARAMICS was used to mimic responses from the drivers to changes in speed limits. VSL was found to significantly reduce the crash potential of the simulated data.

Abdel-Aty et al. (2006) showed that using VSL helps to reduce the real-time crash risk on freeway when the freeway was operating at high speed conditions.

Allaby et al. (2006) showed that VSL is more beneficial for traffic scenarios that experiencing higher congestion on freeway corridors since VSL helps in reduction in the frequency and severity of shockwaves in the congested traffic (i.e. damping of the stop and go oscillations). However, they concluded that for less congested conditions, areas upstream of VSL response zones are more likely to experience negative relative safety benefits.

Ramp metering is widely used in the U.S. states and European countries to reduce the turbulence caused at on-ramp merge areas where slower moving vehicles try to enter into faster moving traffic stream (Bohenberger and May, 1999) and hence helps to reduce speed variation and the length of queues on the mainline which has remarkable safety potential as well (Abdel-Aty and Dhindsa, 2007).

Lee et al. (2006) investigated the potential of using ramp metering on an urban freeway to reduce crashes. Although their study was limited to only single ramp and the network used was not calibrated using real traffic flow data, they showed that crash prevention could be achieved using ramp metering.

Dhindsa (2006) examined larger network calibrated with real traffic data. The study found that ramp metering used on seven ramps was successful in lowering the overall real-time crash risk along the freeway corridor when operating at low speed conditions and that the safety performance was increased with the number of ramps that were metered.

Abdel-Aty et al. (2007) compared the effects of VSL and ramp metering on traffic safety, concluded that variable speed limit strategies reduced the crash potential under moderate to high speed conditions while ramp metering were found to be effective in reducing the crash potential during the low-speed conditions.

Abdel-Aty and Gayah (2010) showed that ramp metering successfully reduce both rear-end and lane change crash risks along the freeway. They examined two ramp metering strategies to reduce real-time crash risk along urban freeway. Both uncoordinated ALINEA and the coordinated Zone ramp metering algorithms successfully reduced the real-time crash risk and provided good overall safety benefits.

The main idea of route diversion in proactive traffic safety management is diverting vehicles from areas that have a high real-time likelihood of crash occurrence. The diversion will result in reduction in traffic demand in these areas and hence reduce the real-time crash risk.

Abdel-Aty and Gayah (2008) examined the ability of route diversion for reducing the real-time crash risk along urban freeway. On one hand they found that route diversion is an effective active crash prevention strategy during uncongested conditions on freeway which helped to decrease the crash risk between the locations where vehicles were diverted from and where the diverted vehicles re-enter the freeway. However, the crash risk was increased near location where vehicles re-enter the freeway due to the additional volume of merging vehicles. On the other hand route diversion found to be not effective during heavy congestion situations due to excessive crash risk migration to the locations where the diverted vehicles re-enter the freeway.

CHAPTER 3. PRELIMINARY ANALYSIS: SAFETY PERFORMANCE FUNCTIONS FOR MOUNTAINOUS FREEWAY

3.1 Introduction

While rural freeways generally have lower crash rates, interactions between driver behavior, traffic and geometric characteristics, and adverse weather conditions may increase the crash risk along some freeway sections. The analysis presented in this chapter is exploring the safety effects of roadway geometrics on crash occurrence along the 20-mile freeway section (Interstate 70 in Colorado) that features mountainous terrain and adverse weather.

The main objective of this analysis was to gain more understanding of the effects of roadway geometrics and weather on crash frequencies of mountainous freeways. The results from this analysis represent an essential step preceding the development of the real-time crash prediction algorithms.

This research attempted an exploratory safety analysis on this section of the freeway by; 1) examining the effect of mountainous highway geometrics and traffic characteristics in adverse weather on the frequency of crashes, 2) identifying hazardous road segments and crash-prone time periods for more focus within an Advanced Traffic Management strategy.

The section of interest features mountainous road geometry and frequent severe weather. As a result of this mountainous terrain, this section of the interstate highway features steep slopes up to 7%. Moreover, climate with all its aspects of temperature, humidity, precipitation and wind is dramatically impacted by the considerable high elevations. This section experienced relatively higher fatality rate, a 0.48 per 100 million vehicle miles traveled (MVMT), compared to the entire interstate system in 2004 (fhwa.dot). In order to come up with an effective ITS upgrade, it is vital for a preliminary evaluation of the contributing factors to crash occurrence and identification of hot-spots.

To achieve the abovementioned objectives, vehicle crash data from I-70 in the state of Colorado were obtained for 6 years (2000-2005) together with roadway geometry, traffic characteristics, and adverse weather represented in the snow and dry season. A series of Negative Binomial (NB) models were fitted as a preliminary analysis to examine the significant factors that contribute to crash occurrence; the grades and weather were found to significantly affect the crash occurrence on this mountainous freeway. Full Bayesian Hierarchical models with random effect were used to fully account for the uncertainty associated with parameter estimates and provide exact measures of uncertainty on the posterior distributions of these parameters and hence overcome the maximum likelihood methods' problem of overestimating precision because of ignoring this uncertainty (Goldstein, 2003; Rao, 2003). Application of random effects models will help also in pooling strength across sets of related units and hence improve the parameter estimation in spare data (i.e. crash frequency models) (Aguero-Valverde and Jovanis, 2007). Moreover, since the crash risk might be spatially correlated among adjacent roadway segments, Bayesian spatial models were also examined. Finally, Bayesian ranking techniques were used to effectively rank the hazard levels associated with the roadway segments of analysis.

3.2 Description of Roadway Section

3.2.1 General Description

The freeway section under consideration in this report is a 20.13 miles long of I-70 starting at Mile Marker (MM) 205.673 at Silverthorne and ends at MM 225.80 at Silver Plume in Colorado. The section encompasses three main parts; the Eisenhower Memorial Tunnel of 1.69 miles long starting at MM 213.18 and ending at MM 214.87, about 7.5 miles of the west side of the tunnel and 11.60 miles of the east side. The Eisenhower Tunnel is a twin bore tunnel with 26 feet of travel width (two lanes of 13 feet each). The tunnel is the highest point along the interstate highway system with an elevation of 11,158 ft and an average grade of 1.7 percent rising toward the west (Coloradodot.info).

3.2.2 Road Alignment

The section passes through extreme mountainous terrain. The horizontal alignment of this section has relatively several sharp horizontal curves' radii. In addition to the steep grades on the west and east sides of the tunnel, as shown in Figure 3-1, the west side has grades up to about 7% while the east side has grades that vary from 1.3% to 6%.

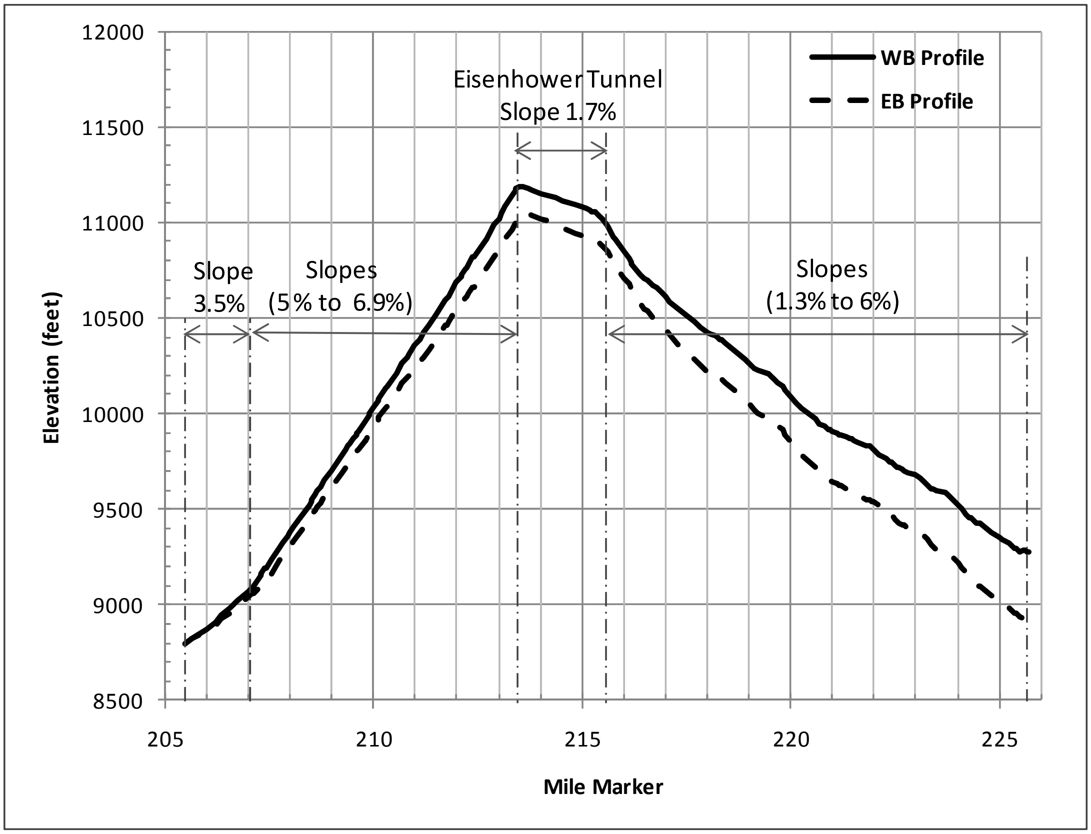


Figure 3-1: Longitudinal Profile

3.2.3 Climate

The section has a quite complex climate compared to most of the U.S. highways. The elevations in the vicinity of the area vary from 8,700 feet to more than 14,000 feet on the highest peaks above the Eisenhower tunnel. The climate within this section is affected by the high altitudes and typically results in variations of all aspect of climate such as temperature, humidity, precipitation and, wind within short distance and time. The crash report identifies the weather and pavement conditions when a crash occurs. The plots of crash frequencies vs. weather and road conditions (see Figure 3-2) conform to the metrological data (climate.colostate.edu), suggesting that there are two main seasons: snow season from October through April and the dry season from May through September which experience small amount of rain, this can explain the small percentage of rain related crashes of 6% that occurred almost exclusively within the dry season. Regarding the distribution of weather-related crashes over the 6 years, 47% of the total crashes occurred within snowy weather where the pavement condition was icy, snowy or slushy, about 6% of the total crashes occurred in rain where the pavement was wet while all other 47% occurred within clear weather and dry pavement conditions. It is worth mentioning that small percentage of snow related crashes occurred within the defined dry season (about 2%) while a negligible number of rain related crashes occurred within the defined snow season (only 2 crashes on WB in the month of October within the 6 years). Classifying the climate into two main seasons will help us understand if there is a significant difference between crashes occurring within seasons that feature snow versus dry and the underlying seasonal effect on the roadway segments. Careful examination of the trends depicted in Figure 3-2 produced these two main seasons. Although, all crashes related to weather and pavement conditions are aggregated within the two seasons to develop the data structure needed for the modeling effort of this study, the likelihood of crash occurrence in normal weather and dry pavement conditions remains constant in both seasons. Moreover, modeling the crash frequency of each specific weather condition (to account for a third rain season) would result in zero inflated problems associated with the short segments of the mountainous road section and the low crash frequency. Thus we were constrained by the data to use 2 main seasons, although more seasons might be possible on other freeways with higher crash frequencies and more distributed crashes per season.

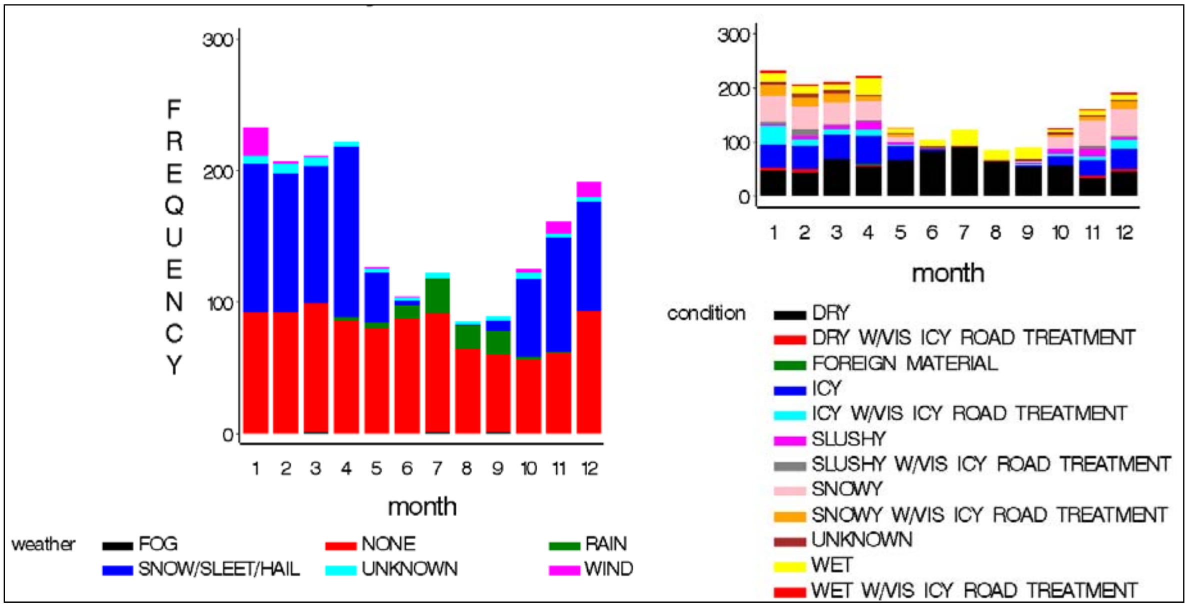


Figure 3-2: Distribution of the Monthly Crashes by Weather and Pavement Conditions for Aggregated 6 Years

3.3 Data Preparation and Preliminary Crash Analysis

There are many factors that contribute to crash occurrence, including driver behavior, traffic and geometric characteristics, weather conditions and interrelationships between these different factors. Unfortunately, the driver behavior factors are usually not available. Therefore, the available roadway, traffic and weather conditions factors were used in this study. There were two sets of data used in the study; roadway data and crash data. The roadway data were collected from CDOT, Roadway Characteristics Inventory (RCI) and Single Line Diagrams (SLD). The crash data were obtained from the road crash database maintained by CDOT.

A first but essential step in data preparation is road segmentation. Given the variation of road geometry, a major criterion employed for segmentation in this study was homogeneity in roadway alignment. According to the RCI data, both horizontal and vertical alignments were scrutinized. Moreover, a minimum-length criterion was set to 0.1 mile to avoid the low exposure problem and the large statistical uncertainty of the crash rate per short segment (Miaou 1994). Segments shorter than 0.1 mile were combined with adjacent segment with similar geometrical characteristics as much as possible. For example, a 0.021 mile long straight segment was combined with the preceding segment with smooth curve of 39755 feet radius, rather than the subsequent sharp-curved segment with 1813 feet radius. With this approach, 20 less-than-0.1mile segments from 104 homogeneous segments were combined with their adjacent segments, resulting in 84 segments for each direction. Table 3-1 illustrates the definitions and descriptive statistics of traffic, road geometrics, and weather characteristics for the segments.

Segment length and AADT are multiplied to estimate daily VMT to reflect the crash exposure for each segment. Among risk factors, of most interest are road alignment factors. The longitudinal grades are defined as a categorical variable with 8 categories gradually from upgrade (being positive) to downgrade (being negative), categorizing grades within 2% according to the American Association of State Highway and Transportation Officials (AASHTO 2004) classification would help in reducing the number of short segments by combining the segments that share all other geometrical characteristics and fall within the same grade range and hence avoiding excessive zero frequency within short segments without losing interpretable useful information about grades. For segments with multiple grades, the equivalent grade for those segments was calculated in accordance with the Highway Capacity Manual (HCM 2000) (Highway Capacity Manual 2000). Specifically, an overall average grade was calculated in case of no single portion of the grade is steeper than 4 percent or the total length of the grade is less than 0.75 mile. For some sub segments steeper than 4 percent, the HCM (2000)

(Highway Capacity Manual 2000) composite grade procedure was used to determine an equivalent grade.

Defining variables for horizontal alignment is more complicated. The basic parameters, including curve radius, deflection angle, and degree of curvature, are parameterized for the curve contained in each segment. The curve direction is also monitored as safety effect may be different between left-side and right-side curves. Other variables speed limit, median width, shoulder width, number of lanes, and truck percentage, are also included as control variable although there are no much variation for these factors at the 20-mile freeway section.

Table 3-1: Summary of Variables Descriptive Statistics

Variables	Description	Mean	Stdev	Min	Max
Response Variable					
Crash Frequency	Frequency of all crashes per segment	5.45	7.37	0	55
Exposure Variables					
Segment Length	Length of the road segment (mile)	0.24	0.16	0.099	0.92
AADT	Average Annual Daily Traffic	27626	1889	25500	29300
Daily_VMT	Daily Vehicle Mile Traveled	6582	4419	2267	23409
Risk Factors					
Season	Rainy = 0, Snowy = 1	-	-	-	-
Grade	Longitudinal grade, eight categories: Upgrade: 0-2%=1, 2-4%=2, 4-6%=3, 6-8%=4; Downgrade: 0-(-2)%=5, (-2)-(-4)% =6, (-4)-(-6)% =7, (-6)-(-8)% =8	-	-	-	-
Curve Radius	Curve radius (ft)	4396	6356	1348	39755
Deflection Angle	Deflection angle of curve	21.07	13.43	1.02	48.90
Degree of Curvature	Degree of the curve per segment with curves	2.39	1.13	0.14	4.25
Curve Length	Length of the curve per segment with curves	0.17	0.09	0.01	0.48
Curve Length Ratio	Percentage of curve length to total segment length	0.53	0.46	0	1
No of Lanes	Number of lanes: 2 lanes=0, 3 lanes =1	-	-	-	-
Median Width	Width of median (ft)	20.67	15.88	2	50
Outside Shoulder	Outside shoulder width (ft)	6.80	3.20	1	20
Inside Shoulder	Inside shoulder width (ft)	3.99	1.83	0	12
Speed Limit	Posted speed limit	60.95	4.8547	50	65
Truck Percentage	Percentage of Trucks	10.35	0.39	10	10.8

In the study area, a total of 1877 crashes were reported over 6 years of the study period (2000-2005), 804 and 1057 crashes occurred on the East and West bounds, respectively. Sixteen crashes were not assigned to any of the East or West directions and they were excluded from this study. Four Hundred were rear end crashes, 234 turn over crashes and 370 were collision with guard rail or median barrier while the side swipe crashes were 223 on the mainline. Twenty five percent of the crashes occurred on curves with steep grades, about 60% occurred on straight segments with steep grades and the remaining 15% occurred on either curve or straight with flat grades.

Figures 3-3 and 3-4 depict a preliminary crash distribution for east and west bound respectively. In the figures, each of the east and west bound sections are divided into 3 miles long sub-sections. Each of these sub-sections has different number of homogenous segments according to roadway geometry as explained above (e.g. first section at MM 207 has 13 homogenous segments, starts at MM 206 and ends at MM 208).

As shown in Figure 3-3, although the section that starts at MM 215 and ends at MM218 at the east bound has the second least number of 9 segments, it has the highest mean of the crash frequency of 6 and 18 for dry and snowy seasons, respectively. It is worth mentioning that the sub-section at MM 216 on east bound is located after the tunnel with average downgrade of 6.5%.

Generally, west bound has higher crash frequency within the 3 miles sub-sections than the east bound in both seasons. Similarly, the 3 miles section centered at MM 216 has the highest mean of the crash frequency of 5.56 followed by the sub-section at MM 213 having 5.30 in dry season while the sub-section at MM 213 experienced a mean of the crash frequency of 18 in the snow season.

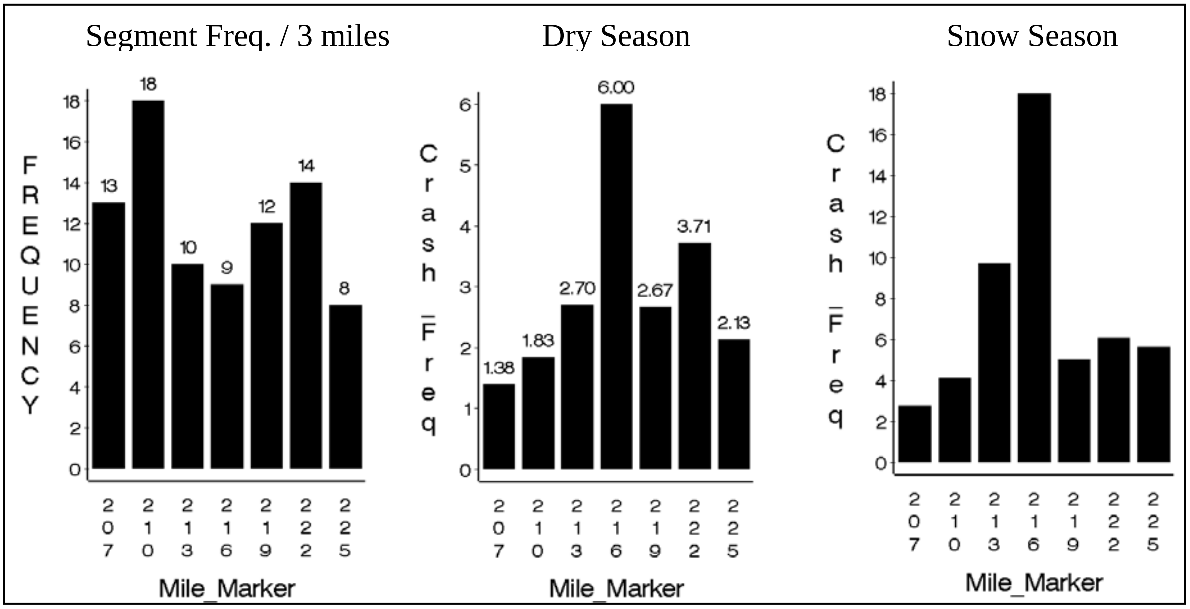


Figure 3-3: East Bound Crash Frequencies in Dry and Snowy Seasons

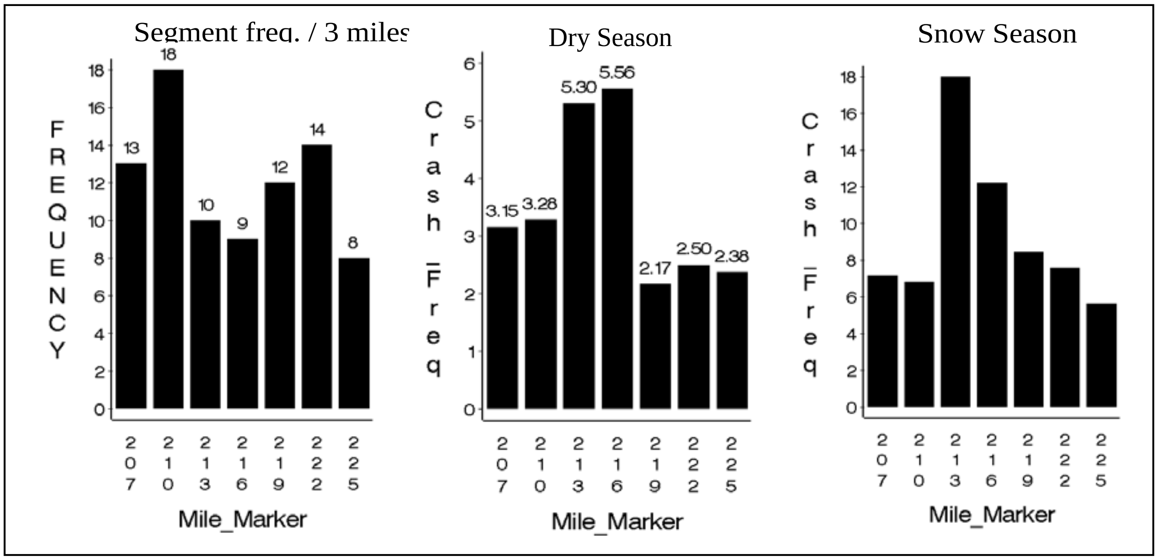


Figure 3-4: West Bound Crash Frequencies in Dry and Snowy Seasons

3.4 Bayesian Hierarchical Approach

The factors affecting the occurrence of crashes could be conceptually categorized into two groups, associated with crash exposure and crash risk, respectively.

$$\text{Crashoccurrence} \sim \text{Crashexposure} \times \text{Crashrisk}$$

While exposure factors account for the amount of opportunities for crashes which traffic systems or drivers experience, the risk factors reflect the conditional probability that a crash occurs given unit crash exposure. Statistically, the stochastic crash occurrence is rationally assumed to be Poisson process, which justifies the popular use of the Poisson distribution to model crash frequencies (Jovanis and Chang, 1986).

$$\begin{aligned} &\mathrm{y}_{it} \mid \lambda_{it} \sim \text{Poisson } (\lambda_{it}) = \text{Poisson } (\mu_{it} e_{it}) \\ &\qquad \log \lambda_{it} = \log e_{it} + \mathbf{X}_{\mathbf{it}}^{'} \boldsymbol{\beta} \end{aligned} \tag{3.1}$$

in which, y_{it} is the crash count at segment i (i = 1,…,168(84 segments on each direction)) during season t (t = 1 for dry season, 2 for snow season) with the underlying Poisson mean λ_{it}. μ_{it} and e_{it}, contributing to λ_{it}, denote risk factors (covariates $\mathbf{X}_{\mathbf{it}}$ and the coefficients $\boldsymbol{\beta}$) and exposure factors, respectively. Based on parameter estimation, the Incidence Rate Ratio (IRR) is generally computed to more conveniently understand the impact of covariates, say k, on the expected crash frequency for one unit change of continuous variables or binary effect for dummy variables (Haque et al., 2010).

$$IRR_k = \frac{E(y_{it} \mid \mathbf{X_{it}}, x_k + 1)}{E(y_{it} \mid \mathbf{X_{it}}, x_k)} = \exp(\beta_k) \tag{3.2}$$

In this current study, daily VMT, the product of AADT and length of road segment, is employed to reflect crash exposure associated with each road segment. Moreover, a time exposure coefficient (1 for dry season, log(5/7) for snow season) is used to offset the unbalanced design of seasons (5 month for dry season and 7 month for snow season). As shown in Table 1, risk factors include road alignment (grade and curve), road design (number of lanes, median width, and shoulders), traffic characteristics (speed limit and truck percentage), and the environmental factor (season).

In regard to model structure, given the “variance = mean” constraint of Poisson model, the Negative Binomial model (NB), a parent model of Poisson model, has been extensively employed to deal with the over-dispersion problem, which is generally observed in crash data (Miaou and Song, 2005; Persaud et al., 1997, 2001; Harwood et al., 2000; Hauer et al., 2002; Hovey and Chowdhury, 2005; Shankar et al., 1995). Nevertheless, as ordinary NB models only provides a blind account for individual heterogeneity, numerous techniques have recently been proposed to more specifically accommodate for various crash data features, for example, zero-inflation model for excess zeros (Shankar et al., 1997; Carson and Mannering, 2001; Lee and Mannering, 2002; Lord et al., 2005,2007), a two-state Markov switching count-data model to overcome the drawbacks of the traditional zero-inflated Poison (ZIP) and zero-inflated negative binomial (ZINB) (Malyshkina et al., 2009), spatial and time series model for spatiotemporal data (Aguero-Valverde and Jovanis, 2006; Quddus, 2008a, 2008b, Huang et al., 2010), hierarchical model for multilevel data structure (Huang and Abdel-Aty, 2010). Furthermore, the use of variable dispersion parameters in negative binomial models have been reported useful to improve the model-fitting (Heydecker and Wu, 2001; Miaou and Lord, 2003; Miranda-Moreno et al., 2005; El-Basyouny and Sayed, 2006; Mitra and Washington, 2007; Lord and Park, 2008). Multivariate count models have also been applied to jointly model crash frequency at different levels of injury severity (Tunaru, 2002; Park and Lord, 2007; Ma et al., 2008; Ye et al., 2009; Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a). More recently, a more flexible random parameter modeling approach, including random intercept and/or random slope, is emerging in the literature, in which model parameters are allowed to vary from site to site (Li et al., 2008; Anastasopoulos and Mannering, 2009; Huang et al., 2008, 2009; El-Basyouny and Sayed, 2009b; Huang and Chin, 2010). Lord and Mannering (2010) provided a detailed review of the key issues associated with crash-frequency data as well as an assessment of the strengths and weaknesses of the various methodological approaches that have been used to address these problems.

Despite the availability of various statistical model selection measures, selection of appropriate crash prediction models should be dependent on the characteristics of the specific crash data. Specifically, we have three basic observations for the current crash data: (a) Over-dispersion: the data may be highly over dispersed as the overall mean and variance equal to 5.45 and 54.32, respectively, as shown in Table 3-1; (b) Site-specific structure: each segment has two observations; crash count during each of the dry and the snow seasons. Hence, random effects may be appropriate to account for the global site-specific effects; (c) Spatial distribution: as road segments are mutually connected, spatial heterogeneities, resulting from spatial confounding factors, may exist for adjacent segments.

Based on these observations, two alternative models are suggested, i.e. random effect model (also called hierarchical Poisson model) and spatial model, both of which are modified from the basic Poisson model.

Random effect model:
$$\log \lambda_{it} = \log e_{it} + \mathbf{X}_{\mathbf{it}}^{'}\boldsymbol{\beta} + \theta_i \tag{3.3}$$
$$\exp(\theta_i) \sim \text{gamma}(a, a)$$
$$\text{overdispersion parameter}: k = 1/a$$

Spatial model:
$$\log \lambda_{it} = \log e_{it} + \mathbf{X}_{\mathbf{it}}^{'}\boldsymbol{\beta} + \theta_i + \phi_i \tag{3.4}$$
$$\theta_i \sim \text{normal}(0, 1/\tau_h)$$
$$\phi_i \sim \text{normal}\,(\overline{\phi}_i, 1/\tau_i) \text{ with } \overline{\phi}_i = \frac{\sum_{i \neq j} \phi_j \omega_{ij}}{\sum_{i \neq j} \omega_{ij}} \text{ and } \tau_i = \frac{\tau_c}{\sum_{i \neq j} \omega_{ij}}$$
$$\alpha = \frac{sd(\phi)}{sd(\theta) + sd(\phi)}$$

Clearly, the random effect model is actually a slight modification of the ordinary NB model, in which the two observations associated with one same segment share an equal extra error component. In the spatial model, the extra variance component consists of two parts, θ_i for site-specific random effects, denoting the global extra-Poisson variability, and ϕ_i for spatial correlation with the Gaussian Conditionally Autoregressive prior (CAR model, Besag, 1974). It is noted that θ_i is assumed to be Normal distribution rather than the Gamma distribution in the random effects model. This is because the multivariate normal distribution is more convenient computationally while combining with the Gaussian spatial component (ϕ_i) than the multivariate version of Gamma distribution (Huang et al. 2010), This also is suggested by the literature that Poisson Lognormal PLN was found to provide the best statistical fit for the spatial model (Milton et al. 2008; Anastasopoulos and Mannering, 2009; Li et al., 2008; El-Basyouny and Sayed 2009a). Regarding ω, the proximity matrix, a 0-1 adjacency weight is employed. In other words, each segment is specified an equal weight to its adjacent segment(s). With the model specification, α denotes the proportion of variability in the random effects that is due to spatial heterogeneity, in which, sd is the empirical marginal standard deviation function.

Although the most common CAR model is employed in this study to model spatial effects, there are other techniques available in the literature such as Simultaneous Autoregressive (SAR), Moving Average (MA) (Congdon, 2007), and Multiple Membership (MM) (Goldstein, 1995; Goldstein et al., 1998; Langford et al., 1999). El-Basyouny and Sayed (2009c) compared CAR, MM and Extended Multiple Membership (EMM) to the traditional PLN model, they concluded that EMM provided the best fit with a little better performance than CAR and both EMM and CAR outperformed the MM and PLN.

The candidate models could be estimated conveniently by Bayesian inference using the freeware WinBUGS package (Lunn et al., 2000). The CAR model is embedded in the function "car.normal" in GeoBUGS, an add-on to WinBUGS that fits spatial models. The DIC, a Bayesian generalization of AIC, is used to measure the model complexity and fit (Spiegelhalter et al., 2003). DIC is a combination of the deviance for the model and a penalty for the complexity of the model. The deviance is defined as $-2\log(\text{likelihood})$. The effective number of parameters, pD, is used as a measure of the complexity of the model, $\text{pD} = \text{Dbar} - \text{Dhat}$, where Dbar is the posterior mean of the deviance, and Dhat is a point estimate of the deviance for the posterior mean of the parameters. DIC is given by DIC = Dhat + 2 pD. In addition, a R^2 -type Bayesian measure is developed to evaluate the model fitting,

$$R^2_{Bayes} = 1 - \frac{\sum_{\forall i,t}(y_{it} - \lambda_{it})^2}{\sum_{\forall i,t}(y_{it} - \bar{y})^2} \qquad (3.5)$$

which estimates the proportion of explained sum of squares to total sum of squares. It could be regarded as a global model-fitting measurement.

3.5 Results and Discussion

3.5.1 Model Estimation and Diagnostics

In model estimation, with no prior knowledge of the likely range of values of the parameters for mountainous freeway section, non-informative priors were specified for parameters. For each model, three chains of 20,000 iterations were set up in WinBUGS based on the convergence speed and the magnitude of the dataset. All the models were converged reasonably through visual inspection on the history plots and confirmed by the Brooks-Gelman-Rubin (BGR) convergence diagnostics (Brooks and Gelman, 1998). After ensuring the convergence, first 10,000 samples were discarded as adaptation and burn-in. To reduce autocorrelation, only every tenth samples of the rest were retained for parameter estimation, calculation of DIC and Bayesian R^2, as well as site rankings.

Exploratory modeling indicated that the crash frequencies are not significantly associated with *Speed Limit, Truck Percentage, Percentage of Curve Length* in all the three models. This was expected since there is a little variation in those variables between segments; the speed limit and the truck percentage are almost identical along the considered section and hence they were excluded from the final models. Results of model estimation with the remaining factors are summarized in Table 3-2.

Comparisons among the three candidate models imply very interesting findings. On one hand, the over-dispersion observed in crash data is confirmed by the extra variance components of the random effect model and the spatial model. Specifically, significant dispersion parameter is identified in the random effect model (k = 0.418, 95%CI (0.305, 0.561)). In the spatial model, variance components from spatial correlation and site-specific random effects are 0.469 (95%CI(0.297, 0.710)) and 0.584 (95%CI(0.481, 0.686)), respectively, which apparently indicate the proportion of the over-dispersion accounted by the spatial clustering is 44.1% (α=0.441, 95%CI(0.330, 0.560)). Moreover, model diagnostic measures confirmed that the random effect and spatial models outperform the Poisson model by accounting for over-dispersion. Specifically, DIC is substantially reduced from 1903 in Poisson to 1456 in the random effect model and 1468 in the spatial model. The Bayesian R^2 is increased from 0.61 to 0.88.

On the other hand, however, while all the parameters are significant in the Poisson model except of *Degree of curvature*, some of them come out to be insignificant in the random effect model (*Grade(4)*, and *Median Width*). This phenomenon becomes more remarkable especially in the spatial model where almost all the variables turn out to be insignificant despite having the same sign as in the basic Poisson model. Another interesting observation from the parameter coefficients is that the safety effects of most of the geometry-dependant factors fade away gradually from Poisson through the other two, e.g. *Grade*, *Degree of curvature*, and *Percentage* *of Curve Length* etc. But the non-geometry-dependant factor (*Season*) remains constant (0.600 in Poisson, random effect model and spatial model).

Furthermore, based on estimation of pD (the number of effective variables in Bayesian model) and R^2, we found that, compared to the random effect model, the spatial model has equal R^2 (0.88) and has only an increase of 5 effective variables (pD from 117.3 to 122.3). With all these observations, we argue that the spatial model does not actually outperform the random effect model. This may be reasoned that the spatial heterogeneity mostly depends on road geometries among adjacent segments, which have been accommodated for by the well-defined geometry-dependent factors in the models. In other words, with explicit consideration for various road geometric factors in the model, the specification for spatial effect becomes redundant and hence, may reduce the significance of the geometric factors instead. We further confirmed this argument by calculating an R^2 which does not include residual terms for crash expectations (i.e. λ_{it}), as shown by R^2 (without error terms) in Table 3-2. Clearly, results indicate that the inclusion of error terms reduced the model-fitting proportion explained by the risk factors, especially in the spatial model.

In summary, the over-dispersion problem in Poisson model is effectively addressed by the random effect and spatial models, but the spatial model may have the problem of redundantly accounting for geometry-dependant effect. Therefore, the random effect model, which has the least DIC, is selected for further model inference and site ranking. The adequacy of the random effects assumption may be assessed with lack-of-fit statistics, although these statistics test the fit of the model as a whole rather than the specific random effects assumption. This random effects assumption may be made less restrictive if θ is allowed to vary with specific site effects.

Season was found to significantly affect crash occurrence (β = 0.600, 95%CI (0.499, 0.702)), the Incident Rate Ratios (IRR) are obtained by exponentiation of the regression coefficients exp[β]. IRR value shows that the risk of crashes during snow season was approximately 82% higher than the crash risk in dry season, given all other variables constant. The increased crash risk within the snow season may be explained by the confounding effect of the snowy, icy, or slushy pavement conditions during the snow season, and exacerbated by the steep slopes. This finding is important for officials to pay more attention and devote more resources during snow season than in dry season for traffic management.

Table 3-2: Parameters Estimates

Model	**Poisson**			**Random Effect**			**Spatial**		
		Credible interval			Credible interval			Credible interval	
	Mean	2.5%	97.5%	Mean	2.5%	97.5%	Mean	2.5%	97.5%
Season [snow]	0.600	0.501	0.698	0.600	0.499	0.702	0.600	0.498	0.710
Season [dry] (reference)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Grade[1]	-1.302	-1.538	-1.072	-1.287	-1.797	-0.778	-1.041	-1.950	-0.097
Grade[2]	-0.855	-1.026	-0.685	-0.870	-1.322	-0.422	-0.458	-1.400	0.534
Grade[3]	-0.786	-0.949	-0.617	-0.907	-1.285	-0.516	-0.316	-1.251	0.679
Grade[4]	-0.530	-0.735	-0.328	-0.297	-0.845	0.277	0.237	-0.745	1.286
Grade[5]	-1.193	-1.421	-0.981	-1.167	-1.674	-0.657	-0.663	-1.374	0.047
Grade[6]	-0.888	-1.084	-0.704	-0.857	-1.322	-0.386	-0.434	-1.095	0.244
Grade[7]	-0.698	-0.884	-0.515	-0.672	-1.175	-0.185	-0.281	-0.886	0.342
Grade[8] (reference)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Degree of curvature	-0.032	-0.066	0.003	-0.048	-0.131	0.035	-0.050	-0.132	0.029
Three road lanes	-0.484	-0.620	-0.346	-0.509	-0.846	-0.157	-0.435	-1.119	0.321
Median width	-0.007	-0.010	-0.003	-0.006	-0.015	0.003	-0.012	-0.027	0.002
k (dispersion parameter)	-	-	-	0.418	0.305	0.561	-	-	-
Sd(Φi): Spatial correlation	-	-	-	-	-	-	0.469	0.297	0.710
Sd(θi): site-specific random effect	-	-	-	-	-	-	0.584	0.481	0.686
α	-	-	-	-	-	-	0.441	0.330	0.560
pD: no of effective variables	11.9	-	-	117.3	-	-	122.3	-	-
DIC	1903	-	-	1456	-	-	1468	-	-
R^2 (with error terms)	0.61	0.59	0.62	0.88	0.86	0.90	0.88	0.86	0.90
R^2 (without error terms)	-	-	-	0.52	0.32	0.60	0.39	0.02	0.56

3.5.2 Interpretation of Risk Factors

Road alignment factors, i.e. slope and curve, are the other key variables of interest. Preliminary analysis on the data indicates that more than 85% of the total crashes occurred on steep grades (Grade <-2% or >2%). Steep grades are often considered implausible in design, and all design manuals recommend avoiding or keeping minimal the use of steep slopes. Nevertheless, this is not the case with mountainous terrain highways since the steep grades cannot be easily avoided.

Longitudinal slope comes out to be significant as indicated in Table 3-2. The effects of various slopes are compared to *Grade[8]* (reference condition, steep slope ranges from -6% to -8%). Figure 3-5 shows the slope coefficients and their 95% credible intervals, it can be noted that in order, *Grade[8]* is the most hazardous slope followed by *Grade[4]*, *Grade[7], Grade[2], Grade[6], Grade[3], Grade[5] then Grade[1]*.Generally, trends in the results indicate that the steeper the slope, the higher the crash risk; and segments with upgrade slope are safer than corresponding downgrades in the same slope range. These results are consistent with the preliminary analysis and complementary to existing findings that the steep grades may increase the likelihood of crash occurrence (Shankar et al., 1995; Chan and Chen 2005).

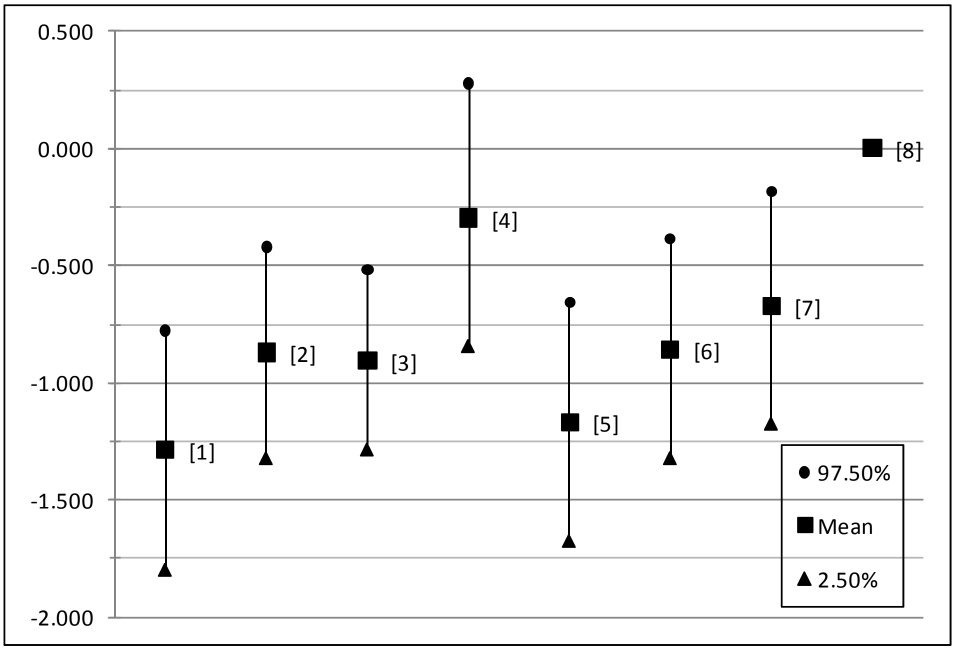


Figure 3-5: Grade Coefficients

In regard to the curve effect, although not statistically significant, the result implies that a unit increase in *Degree of Curvature* (β = -0.048, 95%CI(-0.131,0.035), IRR = 0.95) is associated with a 5% decrease in the crash risk, with all other factors equal. Actually, it is not uncommon that high degree of curvature was found to be associated with decrease in crash likelihood (Shankar et al., 1995; Anastasopoulos et al., 2008; Change and Chen, 2005). Previous studies argued that the feeling of danger along sharp curves might make the drivers compensate by driving more cautiously, leading to lower crash rate instead.

Other variables included in the models are *Number of Lanes* and *Median Width.* Results revealed that segments with three lanes (β =-0.509, 95%CI(-0.846, -0.157), IRR = 0.6) are 40% less in crash risk than two-lane segments, with all other factor being equal. This finding conforms to the study by Park et al. (2010). The increase of safety due to the increase in number of lanes is plausible since this freeway has a high percentage of trucks which could be confined to the 2 right lanes providing more space for other vehicles, contributing to easier maneuvers and less speed variance. Median width is associated with a tiny positive effect (β = -0.006, 95% CI (-0.015, 0.003), IRR = 0.99), which is only significant in the Poisson model. The increasing safety associated with wide median is well known as median works as division for traffic in opposite directions and a recovery area for out-of-control vehicles (Anastasopoulos et al., 2008; Shankar et al., 1998).

3.5.3 Ranking of Sites

The ranking of sites is important to enable officials to pay more attention to those sites with high crash risk. Sites can be ranked by the probability that a site is the worst or by posterior distribution of ranks (Tanaru, 2002). The separate rankings for dry and snow seasons were produced based on the estimation on λ_{it} , the estimated rankings are presented graphically in Figures 3-6 and 3-7. The results confirmed that sites with steep grades are drastically affected during snow season and those segments received significantly higher risk ranks than in the dry season. Moreover, an overall site ranking is developed by rating the weighted average of crash expectations in the two seasons (λ_{i1} for dry season and λ_{i2} for snow season), i.e.,

$Safety\_Site_i = 0.42 \times \lambda_{i1} + 0.58 \times \lambda_{i2}$ to offset the unbalanced design of seasons (5 month for dry season and 7 month for snow season) as explained in the model specification section.

For illustration, the overall site rankings for the 84 segments are plotted on the longitudinal profile for eastbound and westbound, as shown in Figures 3-6 and 3-7, respectively. Sites with high rank values are more dangerous while sites with low rank values are safer. The results appear to be in good agreement with results from the preliminary analysis that the steep downgrade sections received the high risk ranks in general. The segments at Eisenhower tunnel seem to be safer in both east and west bounds. However, the segments just before and after the tunnel received relatively high rank on the eastbound. On the westbound, the downgrade segments received most of the high ranks.

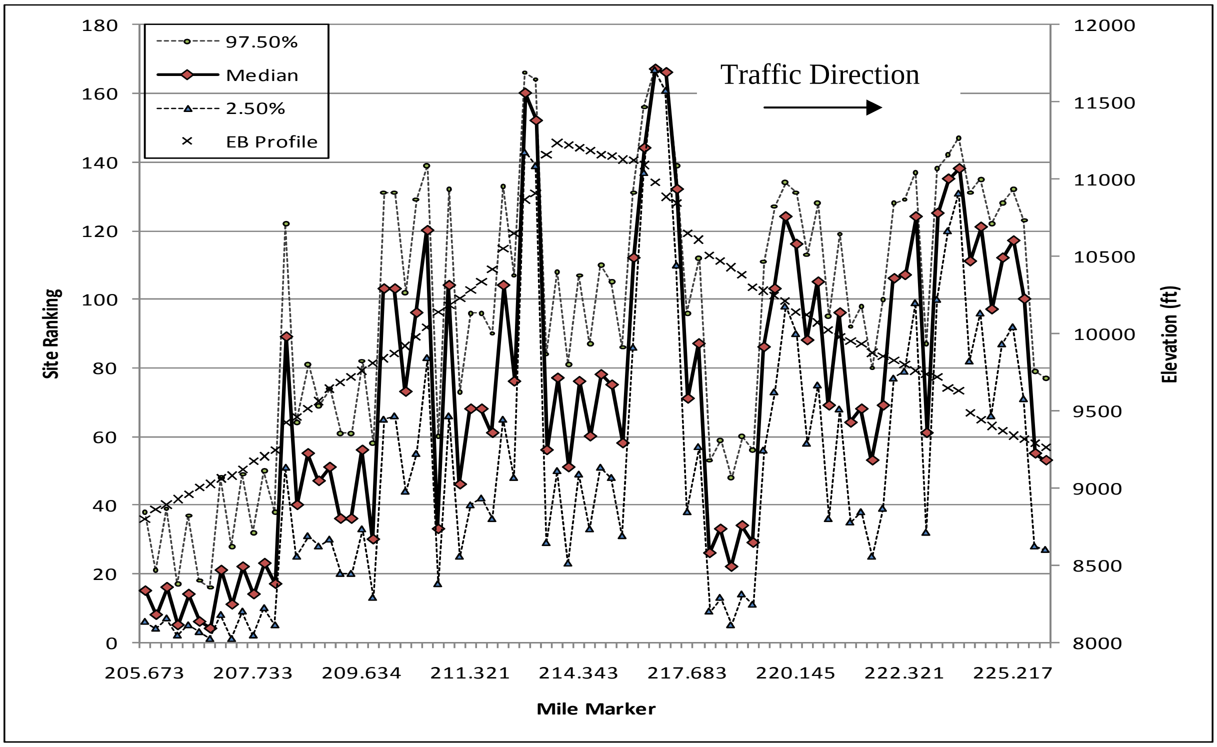


Figure 3-6: East-Bound Segment Ranking

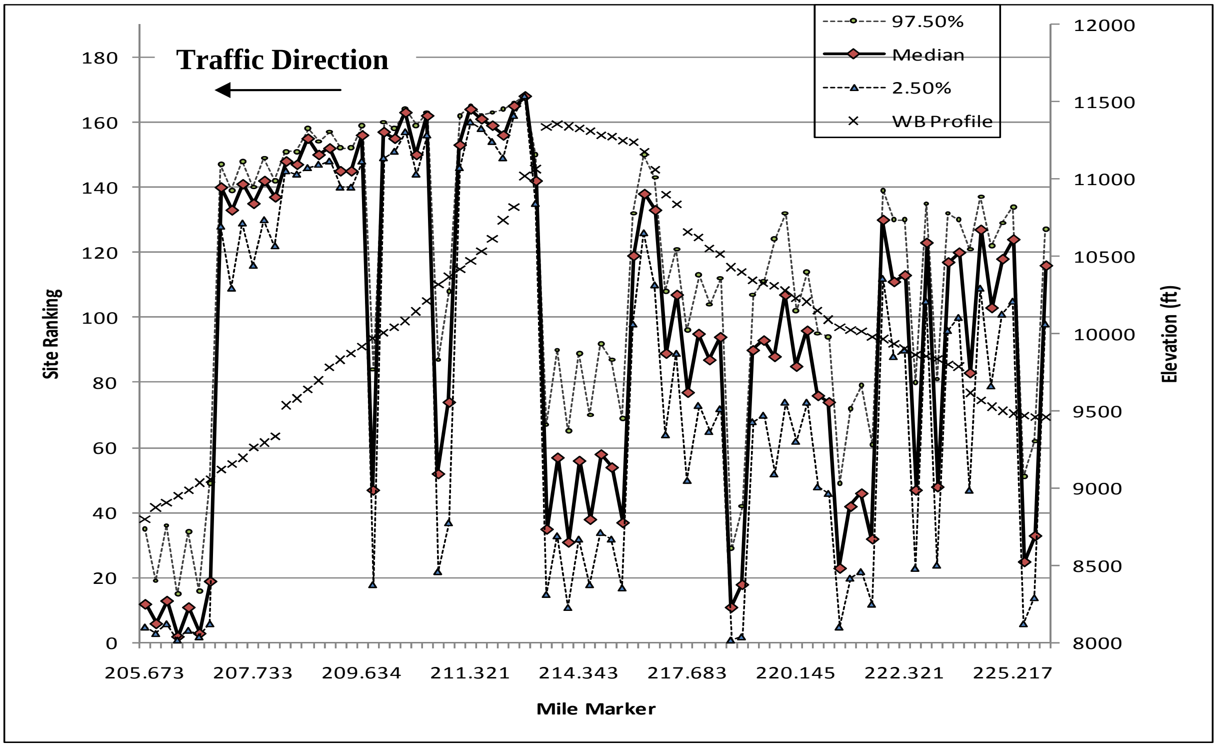


Figure 3-7: West-Bound Segment Ranking

3.6 Conclusion

This chapter presents an exploratory investigation of the safety problems of a mountainous freeway section of unique weather condition. Hierarchical Full Bayesian models were developed to relate crash frequencies with various risk factors associated with adverse weather, road alignments and traffic characteristics. Using the calibrated model, the sites were ranked in term of crash risk for further safety diagnostics and mitigation.

In modeling, it was found that while the random effect and spatial models outperform the Poisson model, the spatial model may have the problem of redundantly accounting for the geometry-dependant effect. Therefore the random effect model is selected for model inference.

Crash risk during snow season was estimated to be approximately 82% higher than the crash risk in dry seasons. Results also identified clear trends associated with the effect of slopes, i.e. the steeper the slope, the higher the crash risk; and segments with upgrade slope are safer than downgrades in the same slope range. The degree of curvature is negatively correlated with crash risk, which is consistent with previous studies that some visual variation of the road alignment may help with drivers' alertness increase and hence decrease crash risk. Median width and number of lanes also showed to be effective in affecting crash risk. Segments with three lanes are 40% less in crash risk than two-lane roads.

Based on site ranking, segments succeeding the tunnel in both east and west bounds received the highest rank of hazardous sites. These segments feature steep slopes and reduction in number of lanes for the east bound. In particular sites with steep slopes should receive more attention from officials and decision makers during snow season to control the excess of crash rate during this season. Also, the identified sites could be included in the strategy for choosing the location of future Variable Speed Limits.

CHAPTER 4. DEVELOPING THE DATABASE

As mentioned earlier that the main goal of this research is to develop a framework to utilize all ITS archived data as well as geometry and weather data into a predictive system for crash occurrence on I-70 roadway section. All real-time traffic and weather data were collected and collated to the previously extracted geometry data to develop the main database that will be used for the development of the crash prediction algorithms.

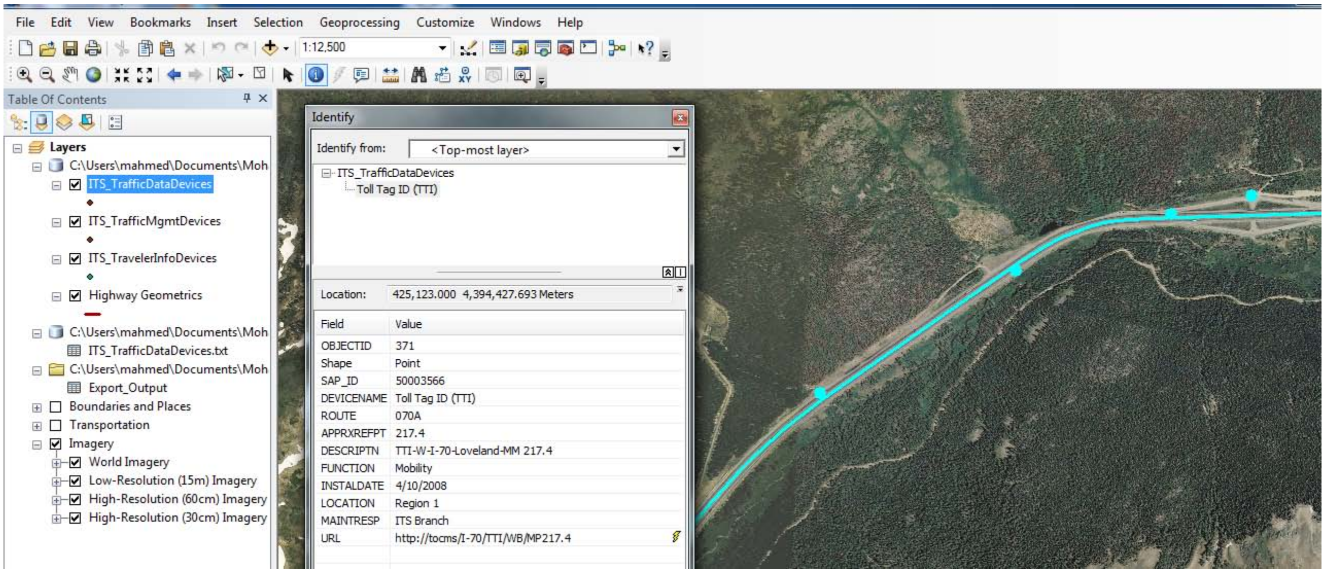
4.1 Data Description

Access to VPN-Portal TOC and SQL server was granted to query and download data needed for this project. Active Traffic Management (ATM) concept of operation report and existing travel time estimation algorithm were provided. Additional information also were provided in a document file to describe speed and travel time estimation algorithm using different data collected from AVI, RTMS, RM, Doppler., etc.

Crash data for the study roadway section on I-70 (MP 205 – 220) were provided for years 2000 through 2010. CDOT suspect that number of crashes in 2009 and 2010 are short due to a problem with the Department of Revenue rejecting records sent to them by the State Patrol that should be accepted. They estimate that they have approximately 3/4 of the records that they should for this section of I-70 for the years 2009 and 2010. The other years (2001-2008) look to be satisfactory as far as completeness. Revenue and the state patrol were working on correcting this problem; however this report was based on the original crash data as they were received. The missing crash cases should not affect the modeling results since those cases were rejected on a consistent basis.

4.2 Detection Devices Data

GIS files were collected from CDOT FTP site. The data contains rich information about all traffic management devices of AVI tag readers, remote traffic microwave system, variable speed limit signs, lane control signs, ramp metering, variable message signs, CCTV, blank out signs, etc.



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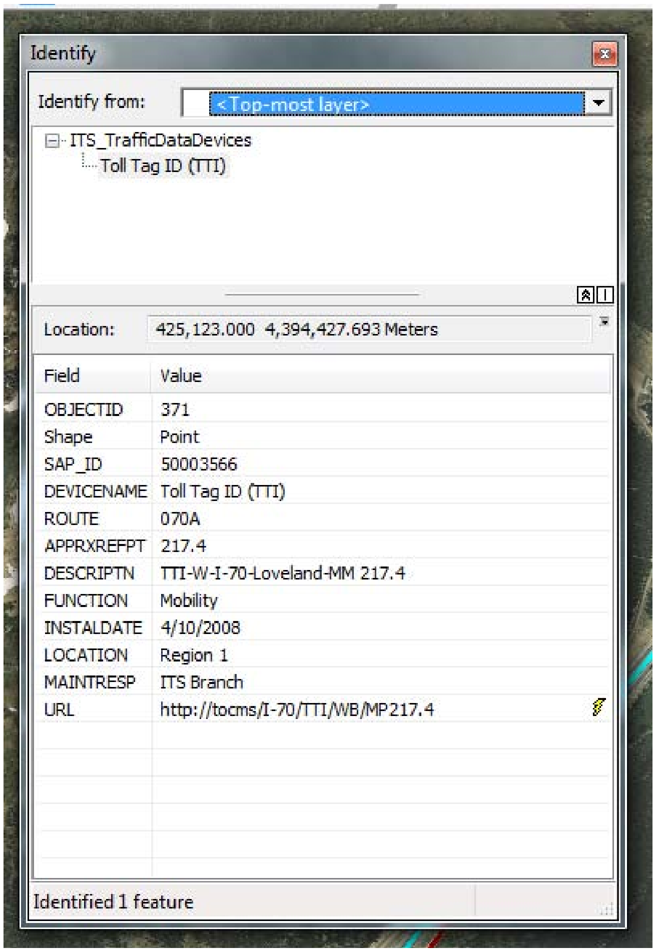
ITS_TrafficDataDevices
Toll Tag ID (TTI)

Location: 425,123.000 4,394,427.693 Meters

Field	Value
OBJECTID	371
Shape	Point
SAP_ID	50003566
DEVICENAME	Toll Tag ID (TTI)
ROUTE	070A
APPRXREFPT	217.4
DESCRIPTN	TTI-W-I-70-Loveland-MM 217.4
FUNCTION	Mobility
INSTALDATE	4/10/2008
LOCATION	Region 1
MAINTRESP	ITS Branch
URL	http://tocms/I-70/TTI/WB/MP217.4

4-1: Tag Readers Locations on GIS Map



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ITS_TrafficDataDevices
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FUNCTION	Mobility
INSTALDATE	4/10/2008
LOCATION	Region 1
MAINTRESP	ITS Branch
URL	http://tocms/I-70/TTI/WB/MP217.4

Identified 1 feature

4-2: Detection Devices Information

4.3 Verification of RTMSs Locations

The Remote Traffic Microwave Sensor (RTMS) is a traffic sensor that uses microwave signals to detect vehicles, unlike other sensors which use the Doppler effect, RTMS modulates the transmitted frequency continuously and therefore can detect stationary objects. In order to determine the location of each RTMS, two series of histograms were generated showing the frequency of the observed traffic flow parameters (Volume, Speed and Occupancy) at each RTMS location for combined lanes and for each lane separately as shown in Appendix 1. For example, the frequency of the observations reported in the downloaded RTMS data for

September 2010 at each RTMS location is shown in Figure A-1; RTMS's are located at mile posts 208, 208.7, 210.8, 213.3, 216.7, 217.85, 219.7, 239.5, 242, 243, 243.35, 250.5 and 205.7, 207.1, 208.9, 209.79, 210.6, 211.8, 217.4, 218.1, 221.1, 222.36, 223, 234.6, 246, 253.6 for eastbound and westbound respectively. It can be seen that while some locations have more than 45000 observations at east bound and more than 130000 observations at west bound, others have zero or less than 1500 observations which indicates that these locations might be disconnected during the whole month or at different time periods. It should be noted that RTMS reports traffic parameters each 20 second which means that each RTMS location should have 24hr*60min.*3times/min.*30days = 129600 observations. It is not quite clear why eastbound has two thirds less observations than westbound. Moreover, it can be noted that there is a slight difference in the location of the RTMSs as illustrated in the Table 2 throughout the 7 month time period.

The frequency histograms by lane revealed that more observations are archived for mostly outer lanes for the 2 and 3 lanes roadway sections (MM205, MM216.7, MM217.4, MM217.85, MM218.1, MM218.7 and MM221.1). While other locations at 3 lanes roadway sections seemed to have more observations in the middle lane (MM208, MM 208.7, MM 209.79, and MM210.8) which can be explained by the locations of the access points on the road. It is not quite clear if the few or missing observations is due to the malfunction of the RTMS's or failure of the archiving system, more investigation to identify the different problems in the RTMS data is provided in section 2.

Collected data indicate the location of RTMS stations and travel lanes they cover as shown in Table 4-1.

Table 4-1: RTMS Location and Number of Monitored Lanes

Mile Marker	**Number of the monitored RTMS lanes**	**Number of Through lanes**	**RTMS location**
205.7	4	4	Roadside W
207.1	3	6	Roadside W
208	3	6	Median E
208.7	3	6	Median E
208.9	3	6	Roadside W
209.79	6	6	Roadside W
210.6	3	6	Roadside W
210.8	3	6	Roadside E
211.8	6	6	Roadside W
213.3	5	5	Roadside E
216.7	4	4	Roadside E
217.4	4	4	Roadside W
217.85	4	4	Roadside E
218.1	4	4	Roadside W
218.7	4	4	Roadside W
219.7	2	4	Median E
219.7	2	4	Median W
221.1	4	4	Roadside W
222.36	4	4	Roadside W

The RTMS can be used to count vehicles and their speed in either a side-fired or forward-looking setup. The installed RTMS’s along the 15-mile section are installed in a side-fired setup. In the side-fired position, RTMS’s can be installed on the roadside or in the median. If installed on the side of the road, one sensor can monitor up to eight lanes of both direction, however, if installed in the median, one sensor can monitor only one direction of the road. In order to determine the side of each of the RTMSs using the downloaded data, another series of speed profiles were generated for randomly selected different morning and afternoon hours for each traffic lane. The following sample figures show that the traffic lanes with lower speeds are the outer lanes while the traffic lanes with higher speeds are the inner lanes. Figure 4-3 shows an example of RTMS located in the median where only 3 lanes of one traffic direction are monitored, S1 (speed at lane 1, counted from the sensor) is the highest speed followed by S2 (middle lane) and then S3 (outer lane) with the lowest speed among the three lanes. While Figure 4-4 illustrates a speed profile for RTMS that is located on the side of the road where 5 lanes of east and west bounds are monitored, S1 and S5 (speed at outer lanes 1 and 5) have the lowest speeds and S2 and S4 (speed at inner lanes 2 and 4) have the highest speeds. These findings were confirmed from the CDOT provided Excel file shown in Table 4-1.

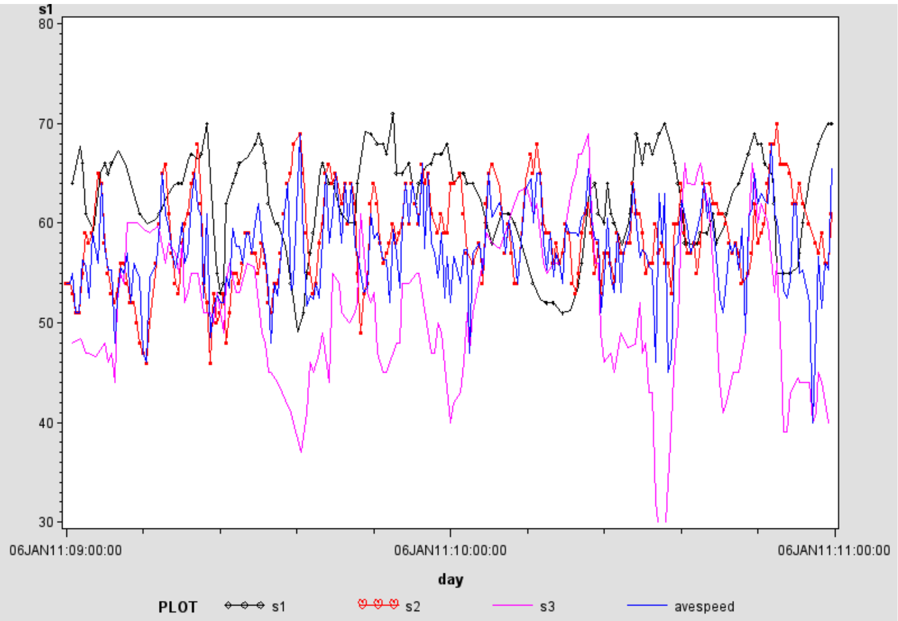


Figure 44-3: Speed profile for MM208 eastbound

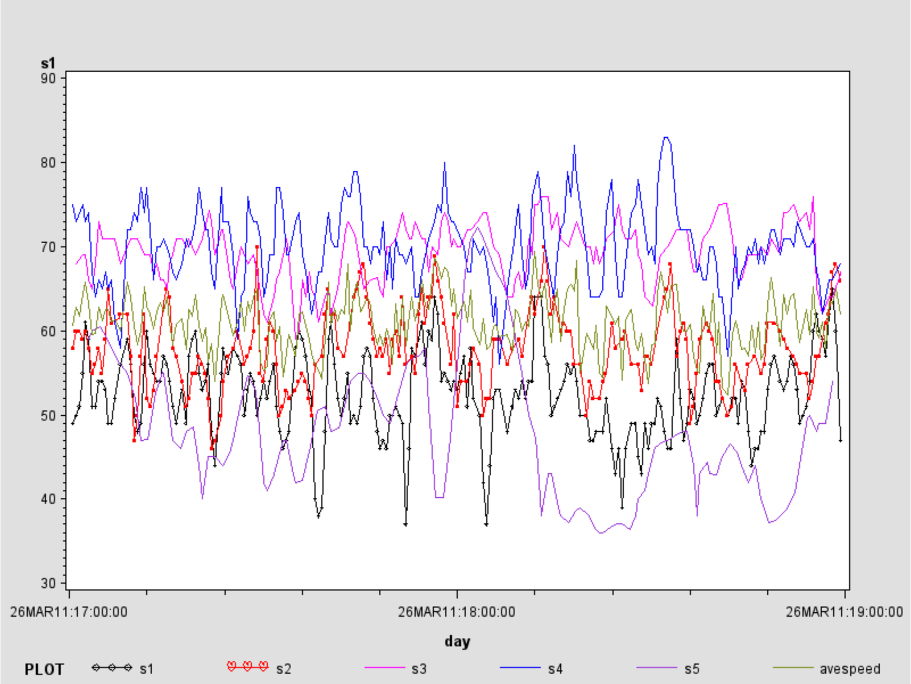


Figure 4-4: Speed profile for MM213.3 eastbound

Table 4-2 shows the RTMS locations and spacing for the 15-mile roadway section along the eastbound and westbound of I-70 in Colorado. The RTMSs are spaced on average of 1.19 mile with standard deviation of 0.82 mile and 0.77 mile for eastbound and west bound respectively.

Table 4-2: RTMS Station Segments

	Eastbound Segment			Westbound Segment		
	Starting RTMS Station	Ending RTMS Station	Segment Length (mi)	Starting RTMS Station	Ending RTMS Station	Segment Length (mi)
1	205.7	208	2.3	205.7	207.1	1.4
2	208	208.7	0.7	207.1	208.9	1.8
3	208.7	209.79	1.09	208.9	209.79	0.89
4	209.79	210.8	1.01	209.79	210.6	0.81
5	210.8	211.8	1	210.6	211.8	1.2
6	211.8	213.3	1.5	211.8	213.3	1.5
7	213.3	216.7	3.4	213.3	216.7	3.4
8	216.7	217.4	0.7	216.7	217.4	0.7
9	217.4	217.85	0.45	217.4	217.85	0.45
10	217.85	218.1	0.25	217.85	218.1	0.25
11	218.1	218.7	0.6	218.1	218.7	0.6
12	218.7	219.7	1	218.7	219.7	1
13	219.7	221.1	1.4	219.7	221.1	1.4
14	221.1	222.36	1.26	221.1	222.36	1.26
	Average Segment Length		1.19	Average segment length		1.19
	Minimum Segment Length		0.25	Minimum segment length		0.25
	Maximum Segment Length		3.4	Maximum segment length		3.4
	Standard Deviation of Segment Length		0.82	Standard Deviation of Segment Length		0.77

4.4 RTMS Data Availability and Reliability

One important aspect in any successful advanced traffic management system is the availability and accuracy of the reported data. Since checking 7-month (October 2010 through April 2011) of RTMS data for 3 lanes at each direction is an overwhelming procedure. The availability and accuracy of RTMS data were checked for crash cases only to get an overall idea of how the system is performing. There were only 188 crashes that had occurred in October 2010 through April 2011, a series of speed profiles were generated for each crash case for the nearest, upstream and downstream RTMS. Out of the 188 crashes 87 did not have any RTMS data available and other crash cases had partial data available which indicates that RTMS failed to report more than 46% of the speed related data, as mentioned earlier some of the RTMS has no data for a whole month or has few observations at other time periods.

Other problems can be illustrated by the provided samples of the speed profiles below; Figure 4-6 indicates that there are partial missing speed data between 12:40 and 13:00.

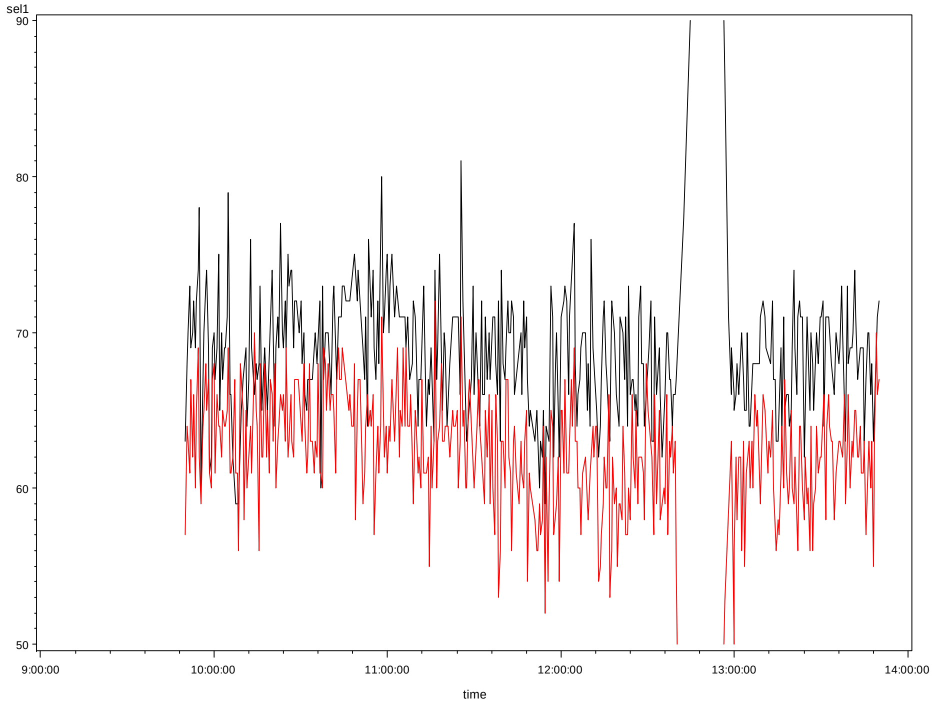


Figure 4-5: Speed Profile for Nearest RTMS, Crash Time 11:50

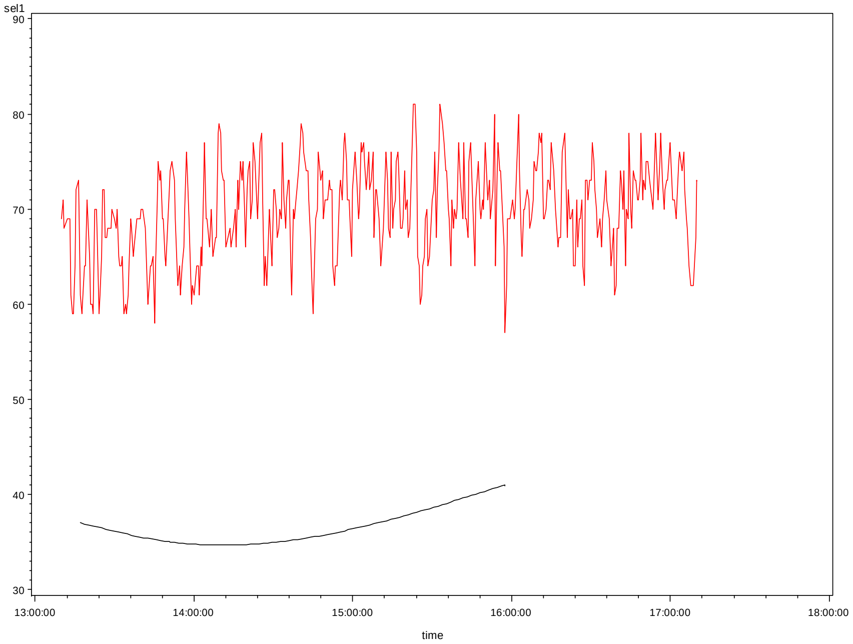


Figure 4-6: Speed Profile for downstream RTMS, Crash Time 15:10

Figure 4-7 shows that the reported speed data for the outer lane for 2 lane section has unreasonable values between 13:20 to 16:00 and missing values for the other times.

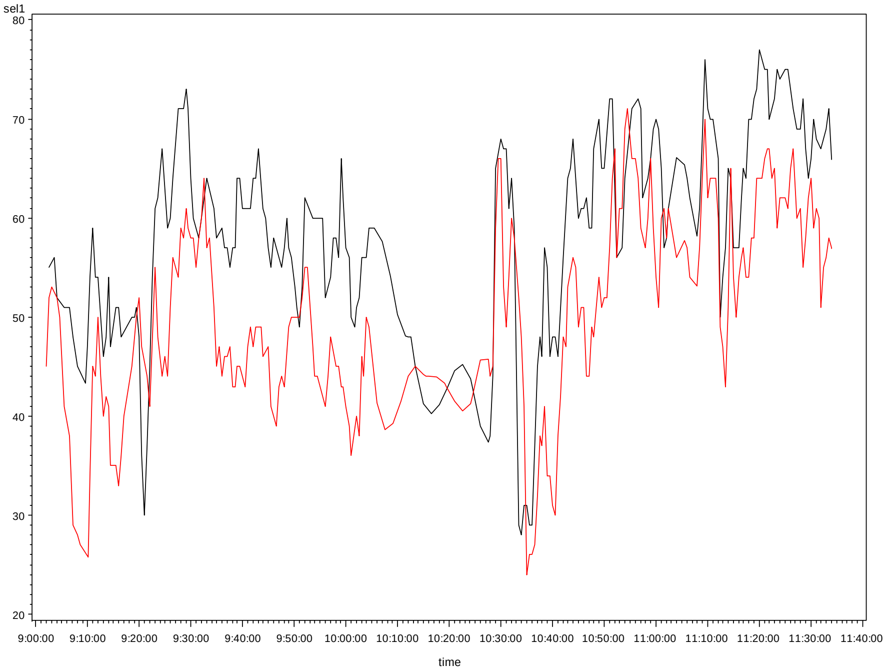


Figure 4-7: Speed Profile for nearest RTMS,Crash Time 9:34

Others have normal speed profile with partial missing observations, speed profiles were generated for four hours, 2 hours before the crash time and 2 hours after. As shown in Figures 4-8 and 4-9, the speed data were available only for less than half an hour before the crash time at the nearest RTMS as well as the downstream one.

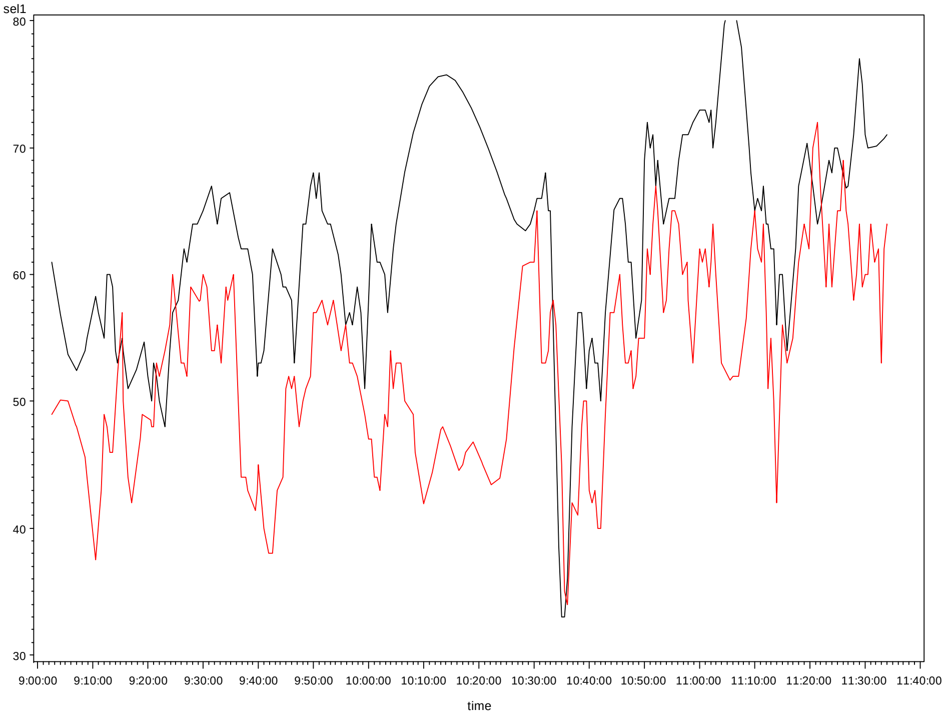


Figure 4-8: Speed Profile for downstream RTMS, Crash Time 9:34

Figures 4-10 to 4-15 show normal full speed profile data for the nearest, downstream and upstream of two different crash cases, it can be seen that the speed profiles are slightly different for each case which may be explained by the severity level or the location of the crash.

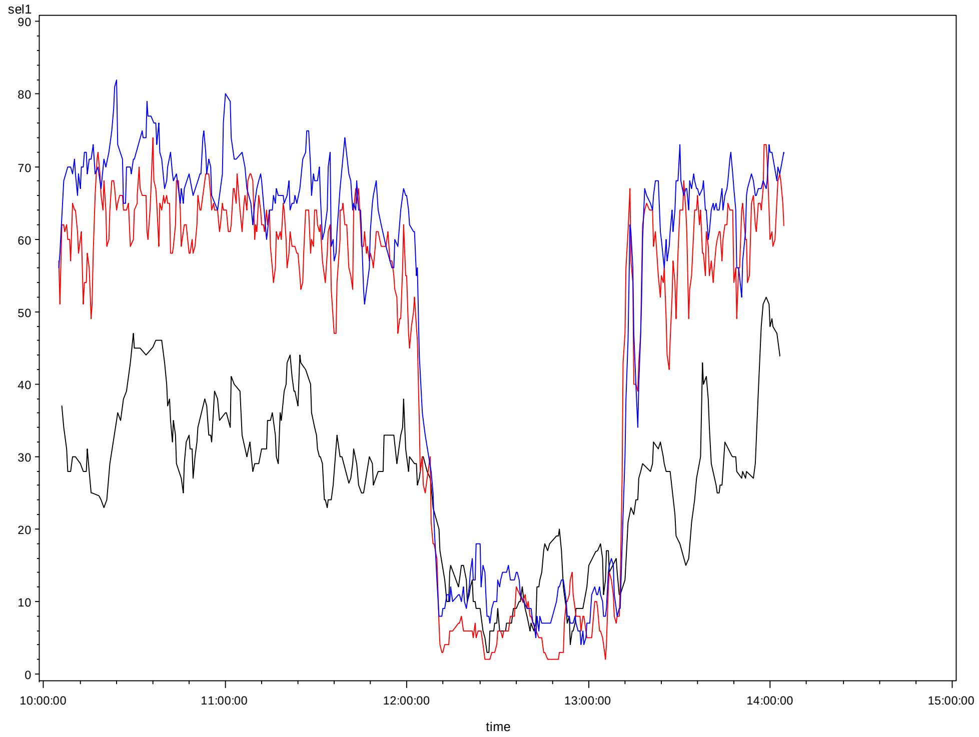


Figure 4-9: Speed Profile for nearest RTMS, Crash Time 12:05

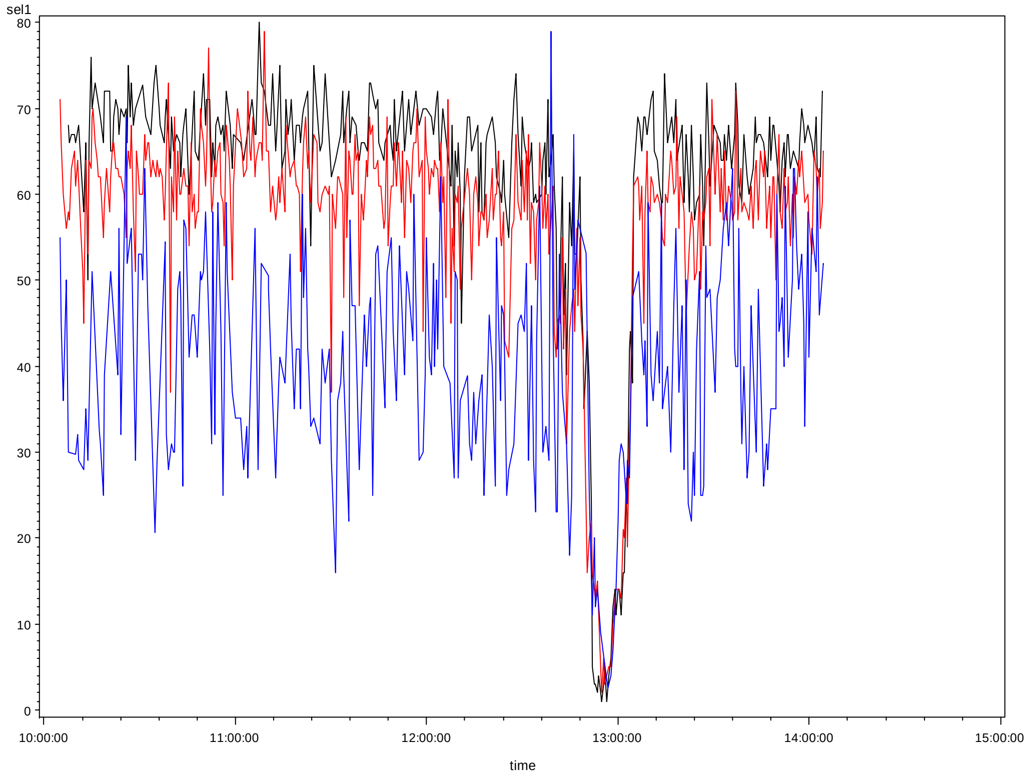


Figure 4-10: Speed Profile for upstream RTMS, Crash Time 12:05

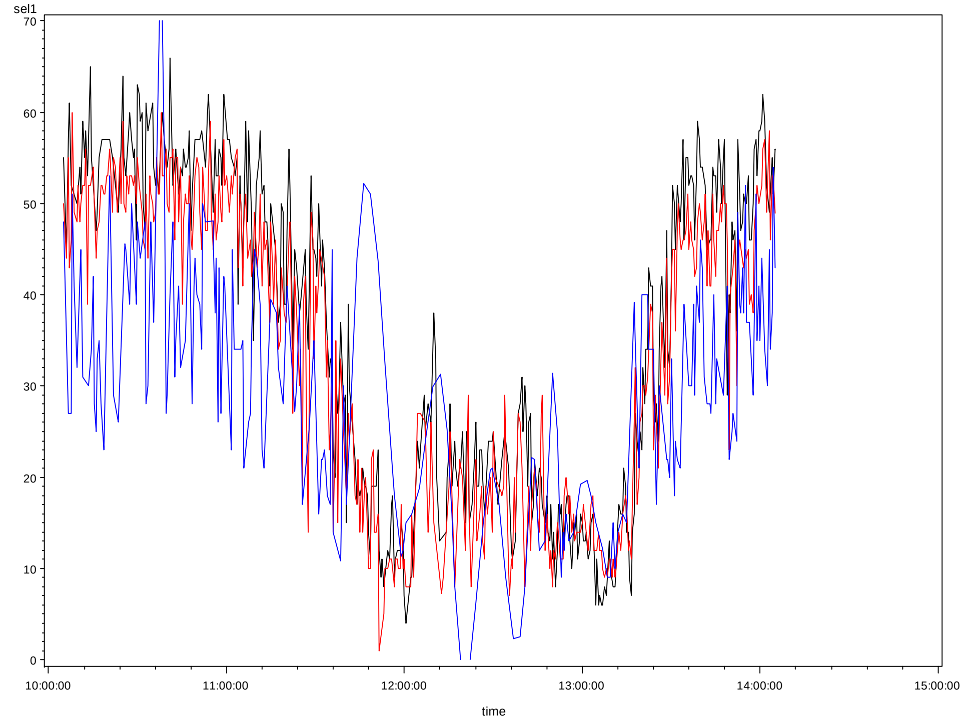


Figure 4-11: Speed Profile for downstream RTMS, Crash Time 12:05

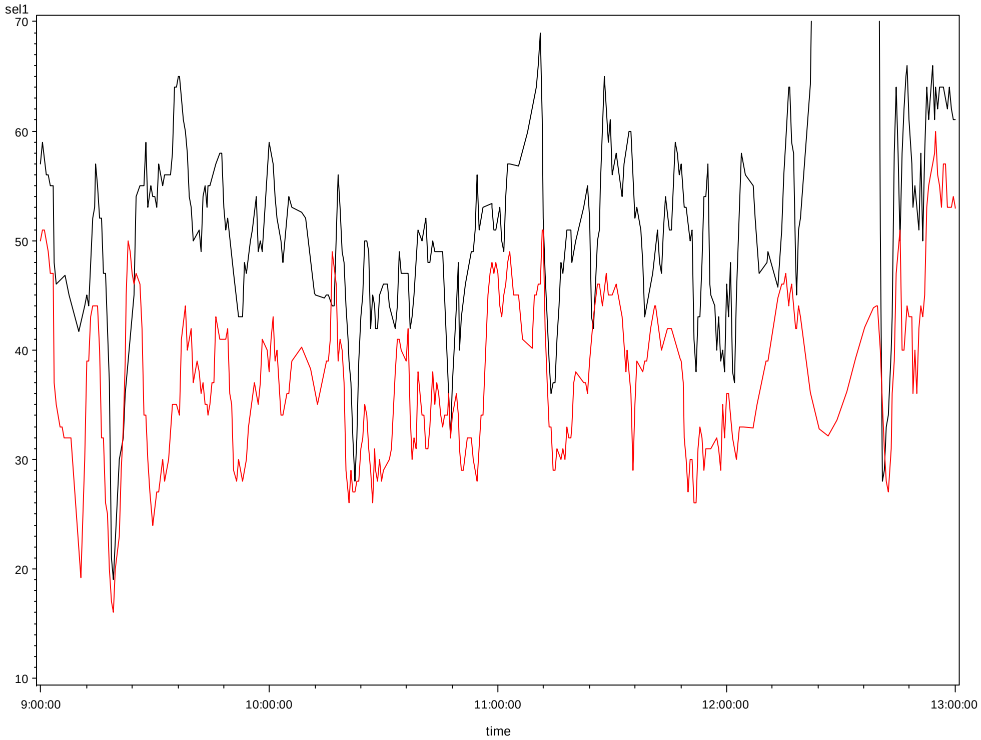


Figure 4-12: Speed Profile for nearest RTMS, Crash time 11:00

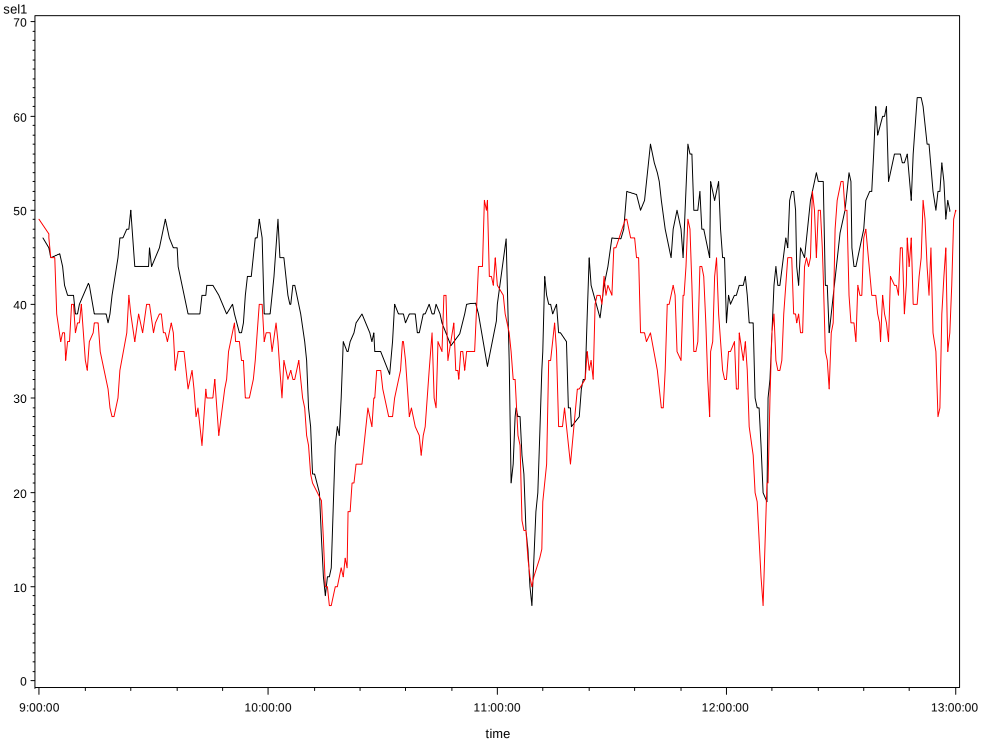


Figure 4-13: Speed Profile for upstream RTMS, Crash time 11:00

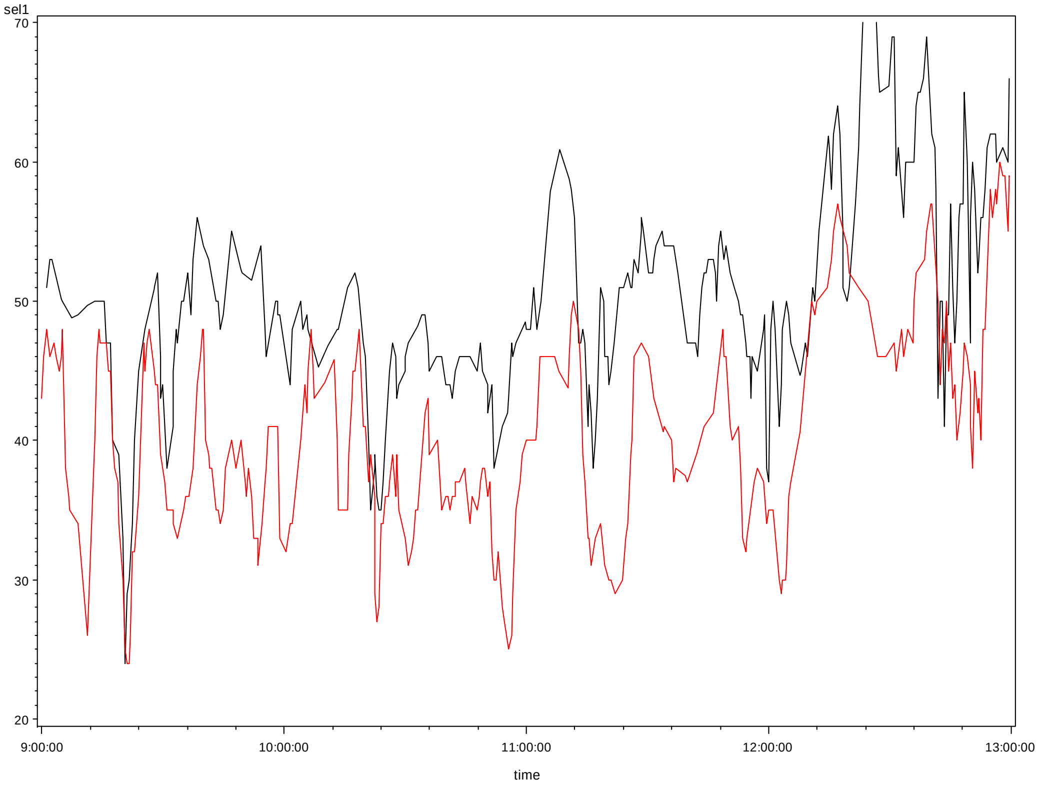


Figure 4-14: Speed Profile for downstream RTMS, Crash time 11:00

4.5 Preliminary Analysis of RTMS Data

The meteorological and weather data suggest that there are two main seasons: snow season from October through April and the dry season from May through September. Therefore, preliminary analysis of RTMS data was conducted for the main traffic flow parameters (speed, volume and occupancy) collected from the RTMS for snow and dry seasons from October 2010 to September 2011.

Figure 4-18 to 4-21 represent the 24-hour average occupancy by day corresponding to snow and dry seasons along eastbound and westbound. The data are aggregated over the whole season and the average is plotted on a daily basis. For example, in Figure 4-18 the solid line represents the hourly occupancy of Monday averaged over all Mondays in the snow season for eastbound. In comparison with the occupancy by day; it was found that weekend had the highest traffic occupancies during the peak hours while occupancies were almost similar during the off-peak hours in both dry and snow seasons, Sunday has the highest average occupancy for eastbound, while Friday and Saturday have relatively high occupancy for westbound in both seasons. Occupancy was found to have similar distribution during weekdays.

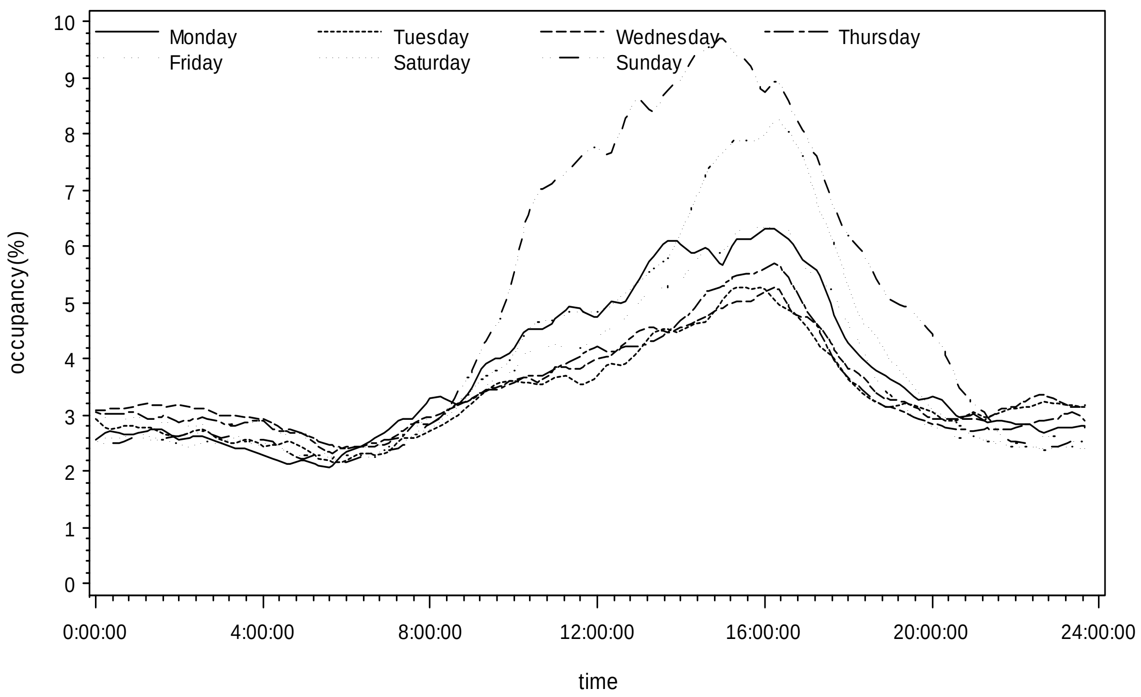


Figure 4-15: Eastbound Occupancy (Snow Season)

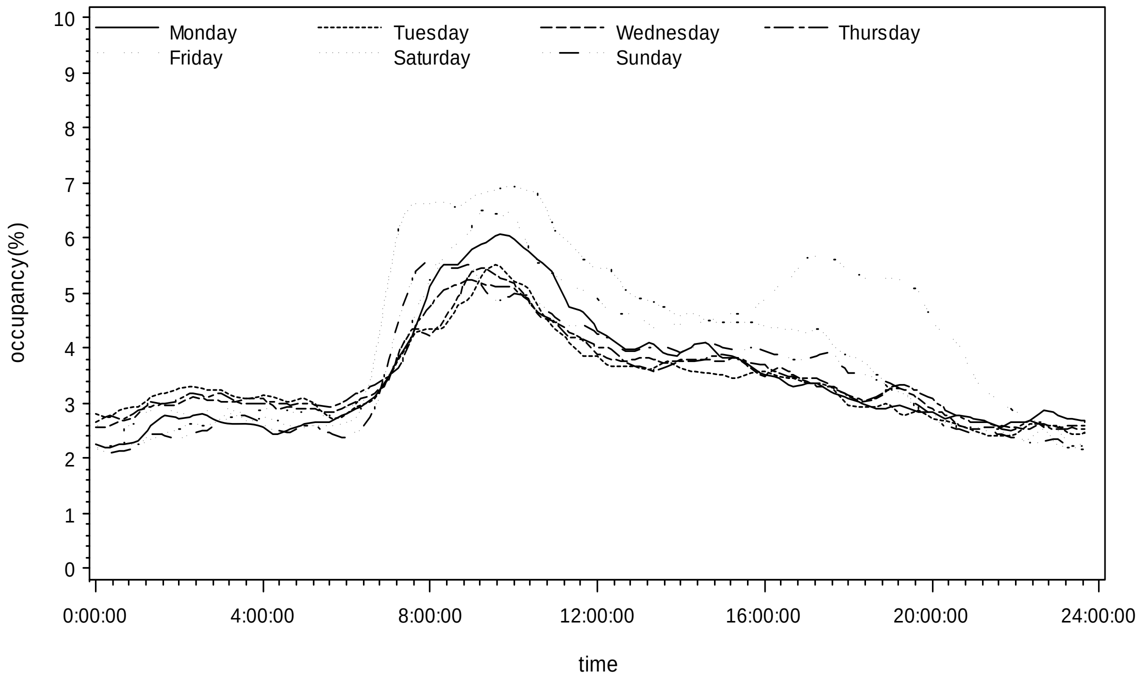


Figure 4-16: Westbound Occupancy (Snow Season)

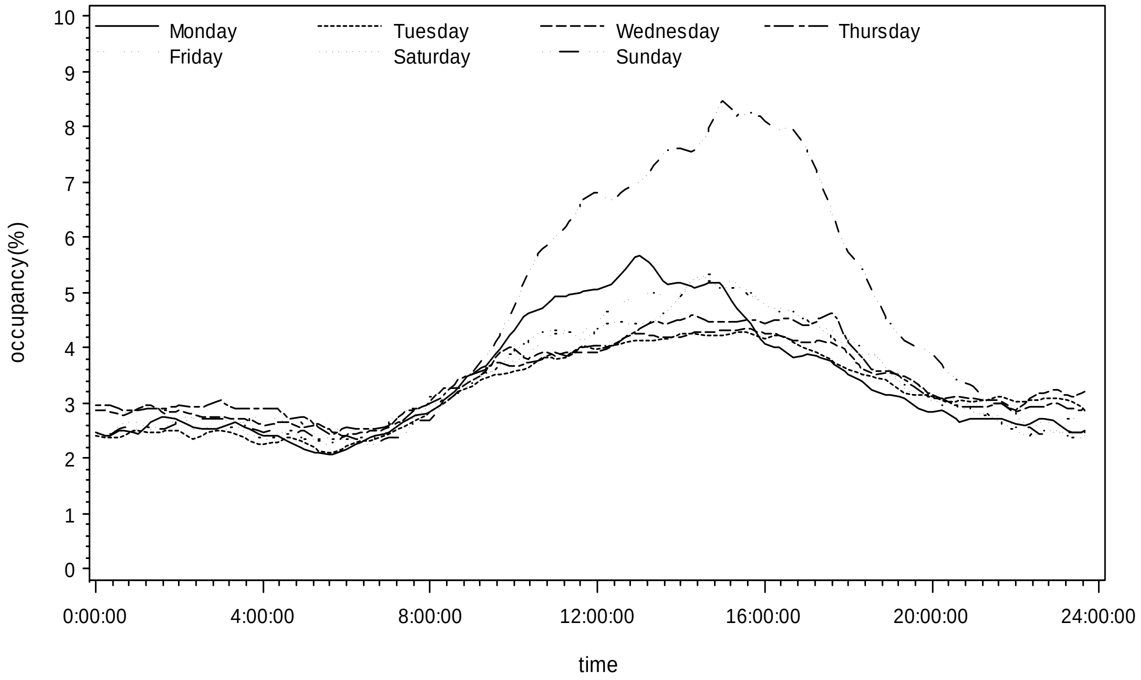


Figure 4-17: Eastbound Occupancy (Dry Season)

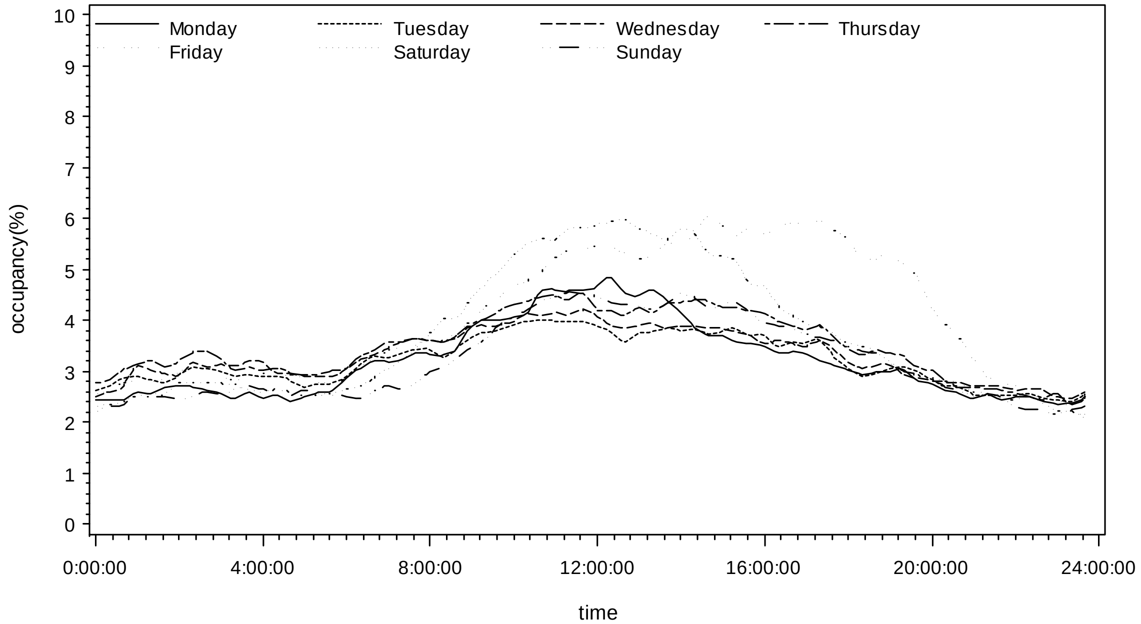


Figure 4-18: Westbound Occupancy (Dry Season)

Same findings were depicted from the hourly volumes distributions by day during snow and dry seasons as shown in Figures 4-22 to 4-25, weekdays except Fridays have more uniform pattern of hourly volumes during the day while weekends and Fridays have high volumes during the peak-hours. Snow season has relatively higher volumes than dry season that peak on Sundays to reach an average of 3000 vehicle per hour (vph) on eastbound and 2800 vph on westbound. It can be noticed that during weekends Eastbound has more flat peak-hours that extend from 9:00AM to 17:00PM while westbound has two morning and evening peaks.

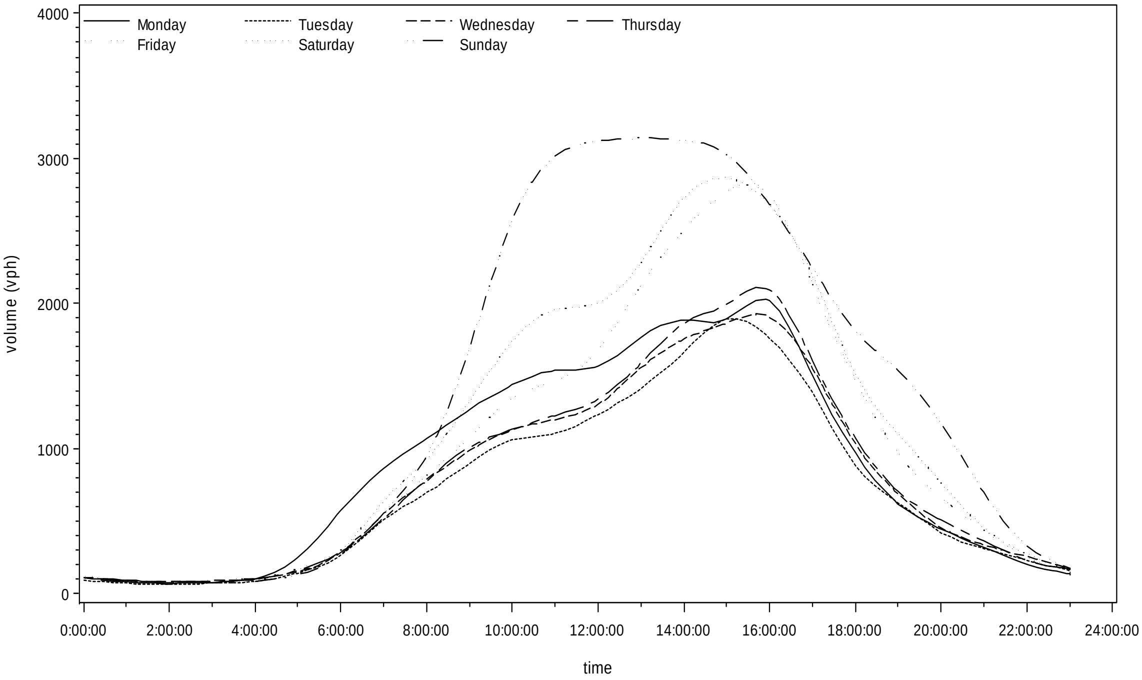


Figure 4-19: Eastbound Volume (Snow Season)

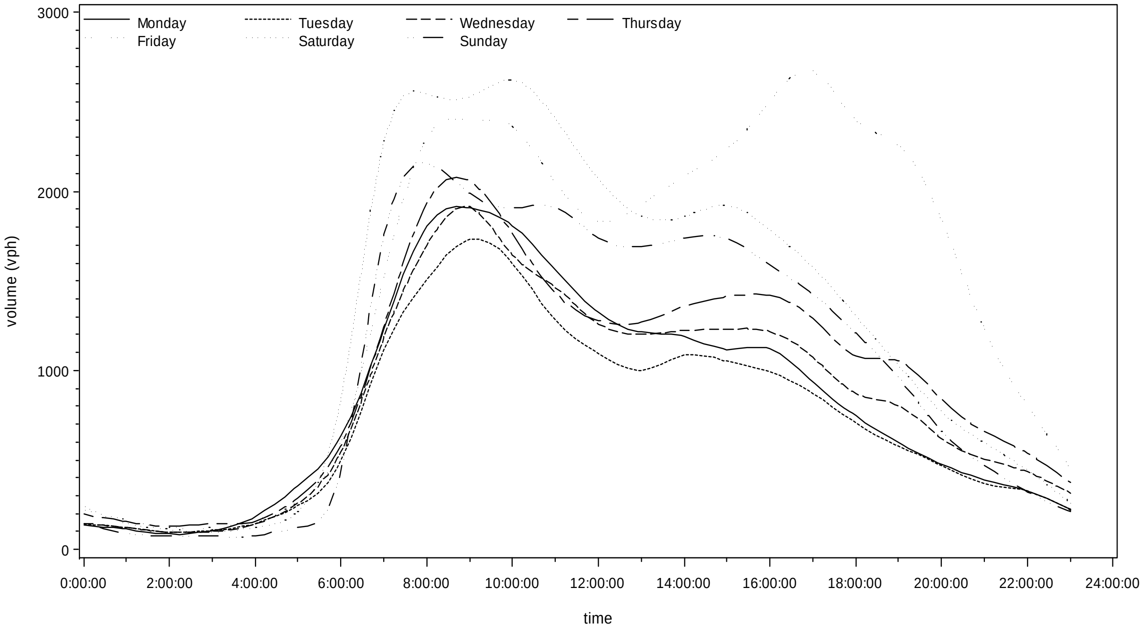


Figure 4-20: Westbound Volume (Snow Season)

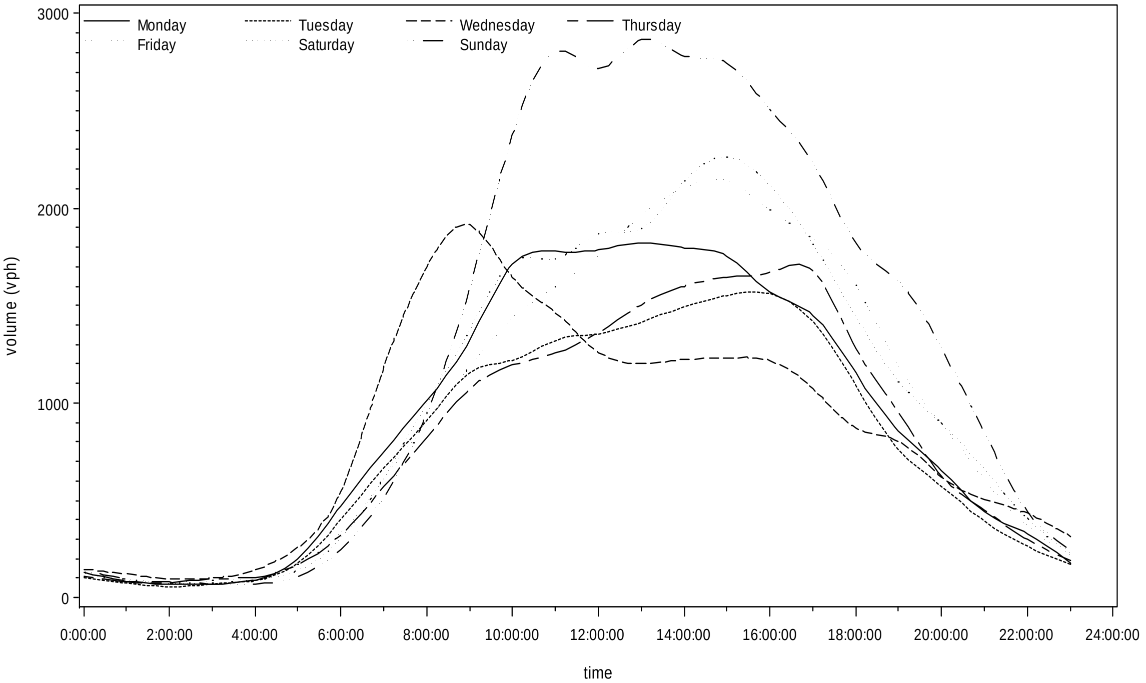


Figure 4-21: Eastbound Volume (Dry Season)

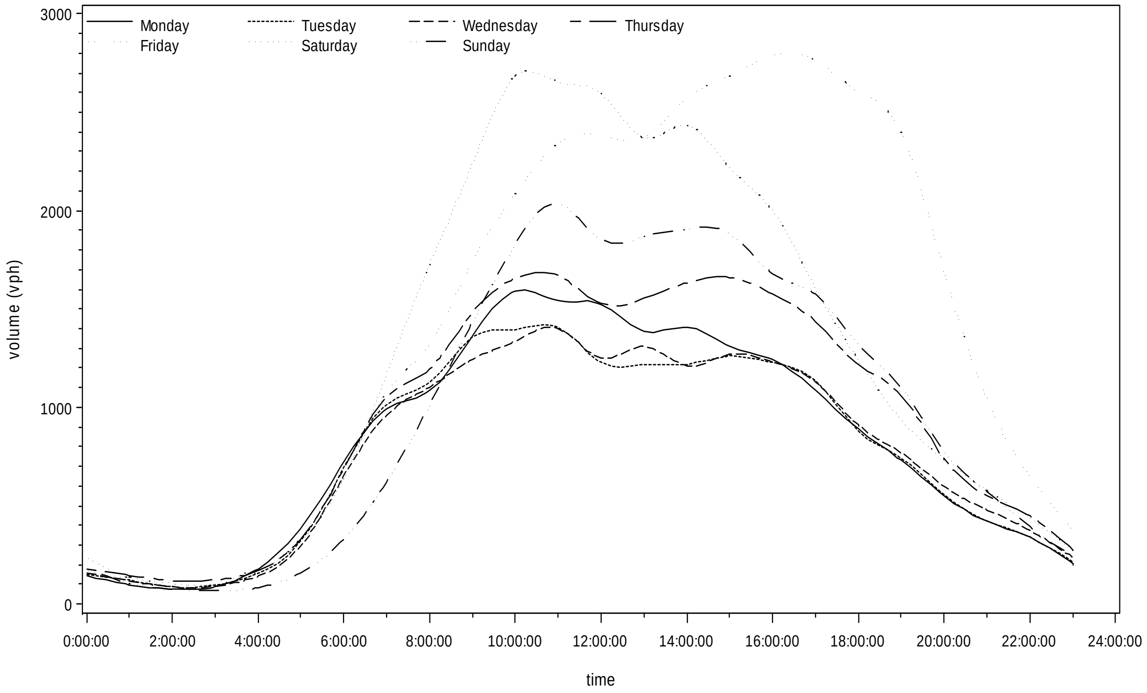


Figure 4-22: Westbound Volume (Dry Season)

Figures 4-26 to 4-34 show the average speed along the 17-mile study roadway section, each line denotes the average speed aggregated over 4-hour time interval. It can be concluded from the parallel lines that the aggregated 4-hour average speeds follow same distributions along the roadway sections throughout the weekdays and weekends for eastbound and westbound. It is worth mentioning that different speed limits are applied along the roadway section as shown in Table 4-3.

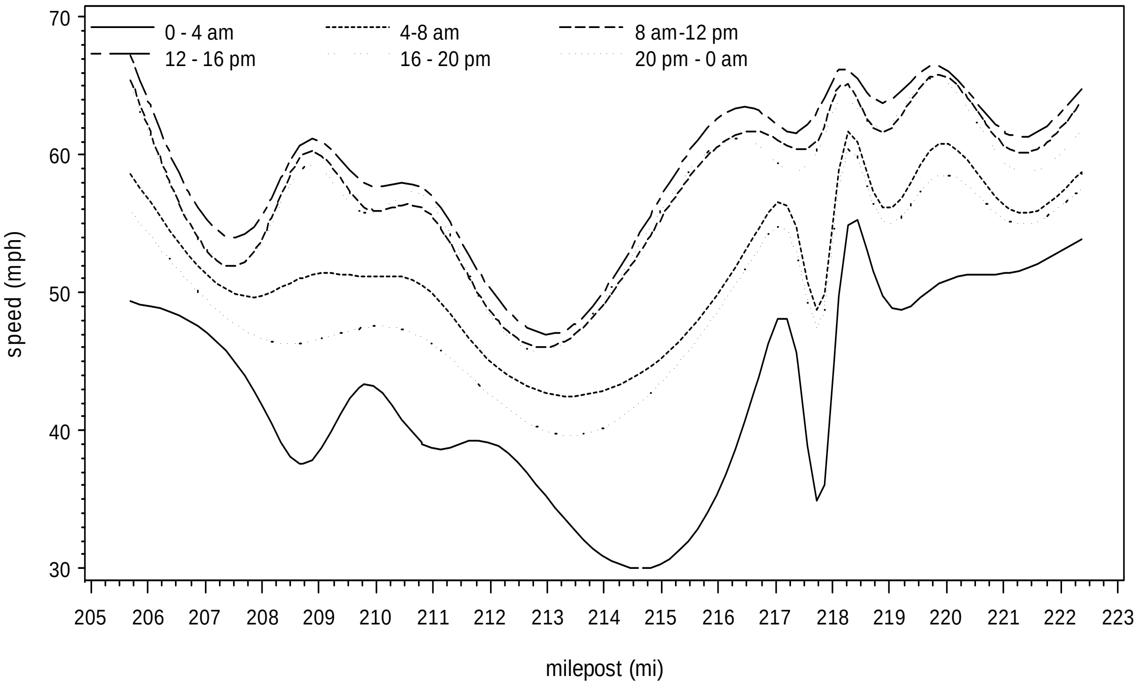


Figure 4-23: Weekdays Eastbound Speed (Snow Season)

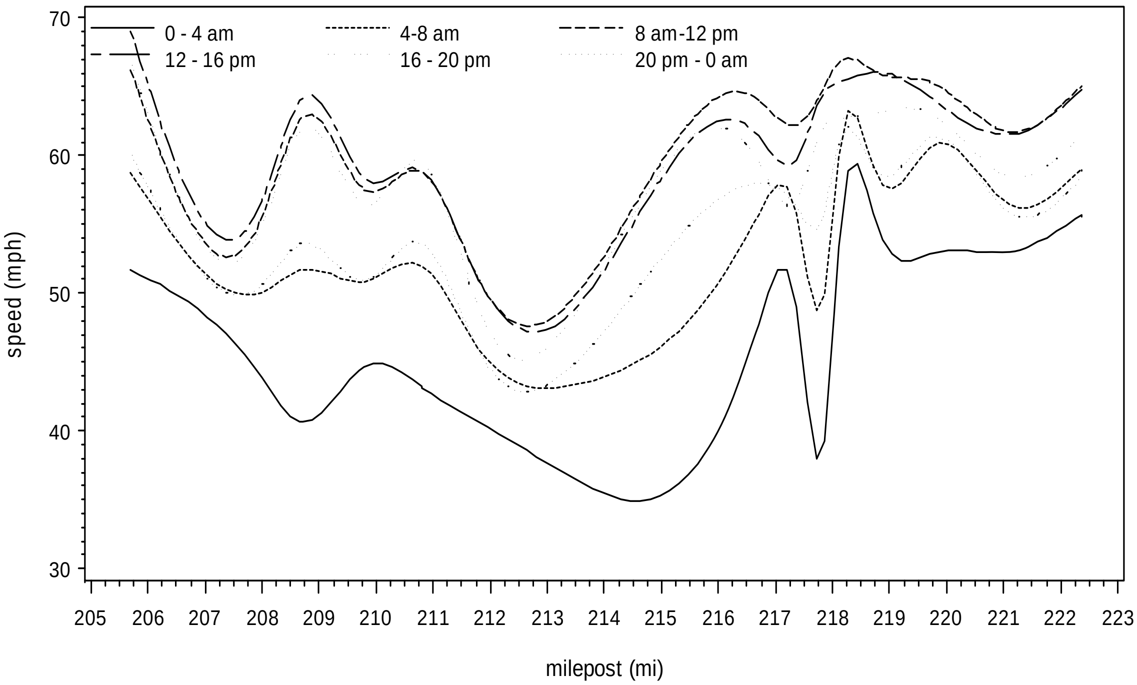


Figure 4-24: Weekends Eastbound Speed (Snow Season)

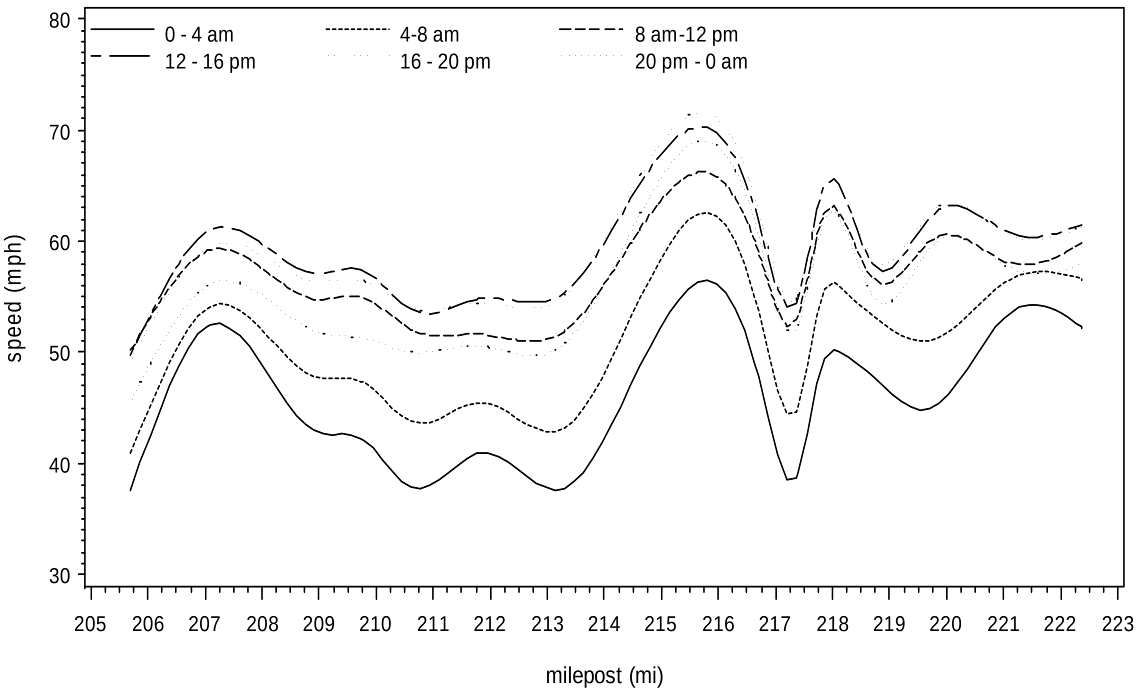


Figure 4-25: Weekdays Westbound Speed (Snow Season)

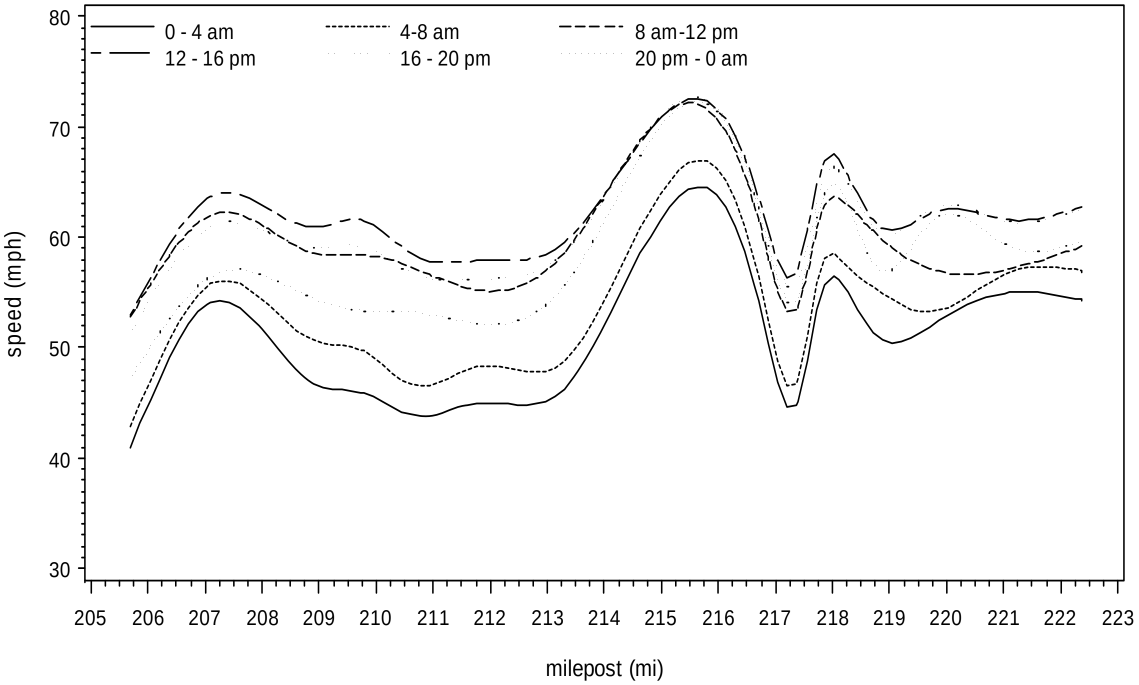


Figure 4-26: Weekends Westbound Speed (Snow Season)

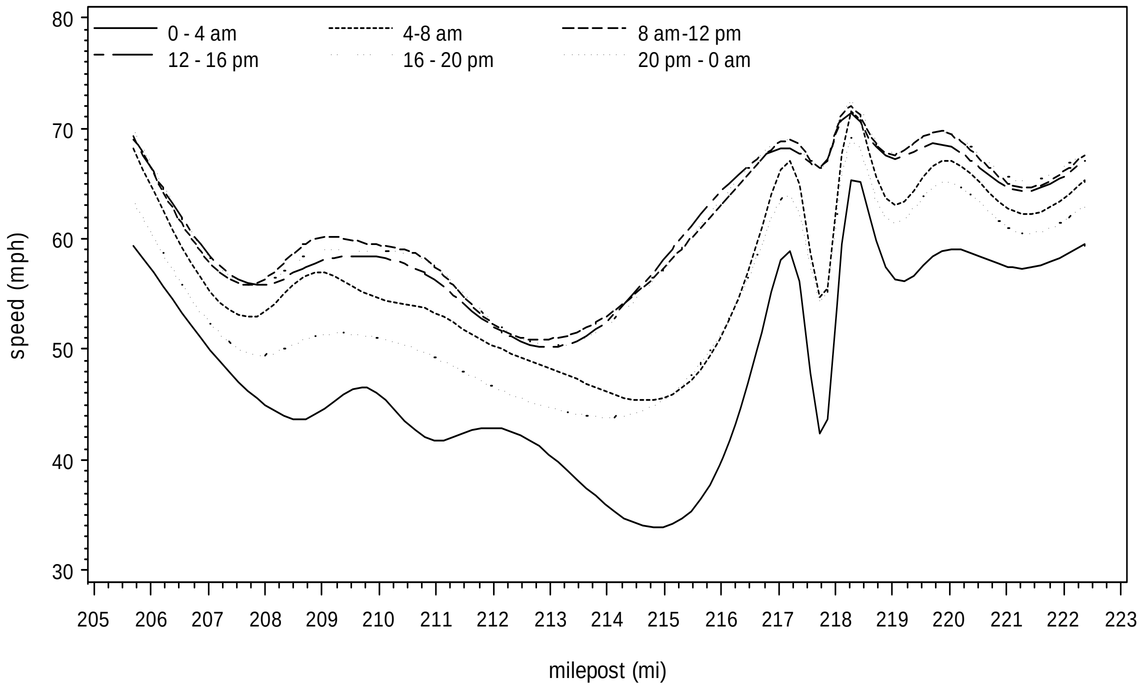


Figure 4-27: Weekdays Eastbound Speed (Dry Season)

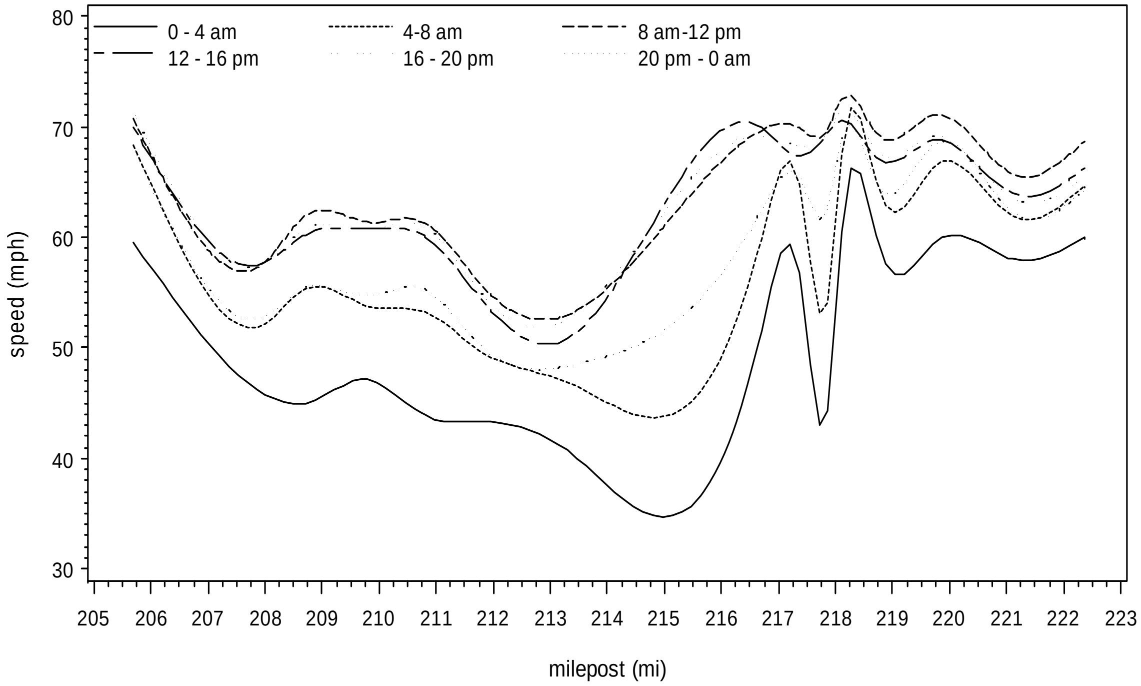


Figure 4-28: Weekends Eastbound Speed (Dry Season)

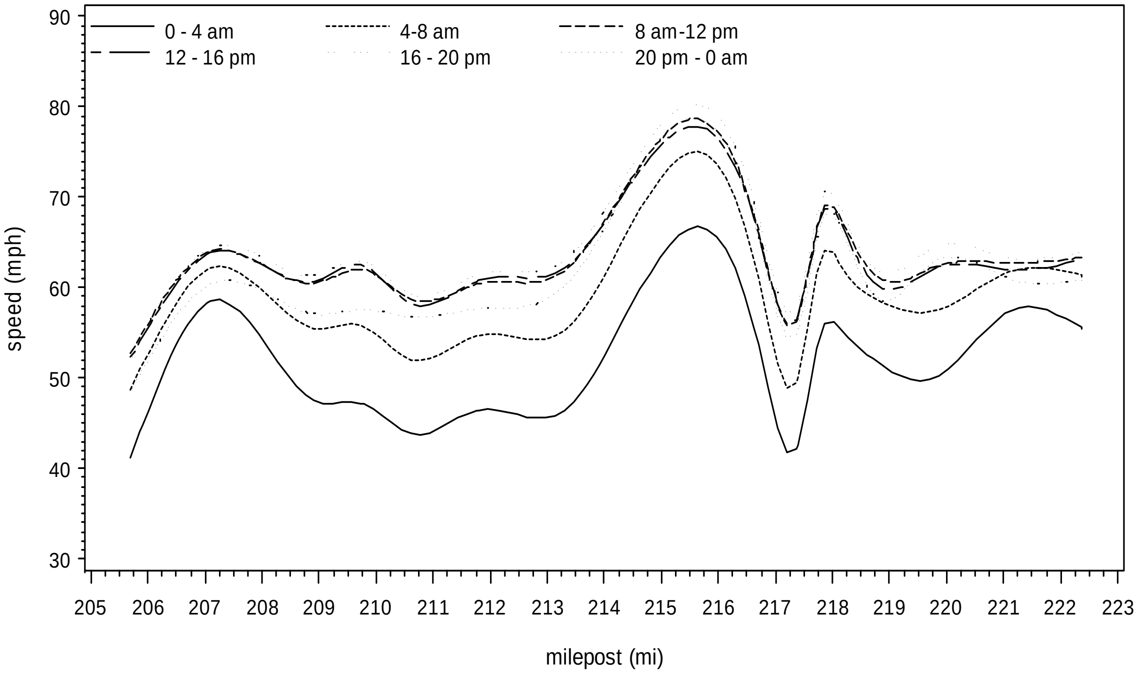


Figure 4-29: Weekdays Westbound Speed (Dry Season)

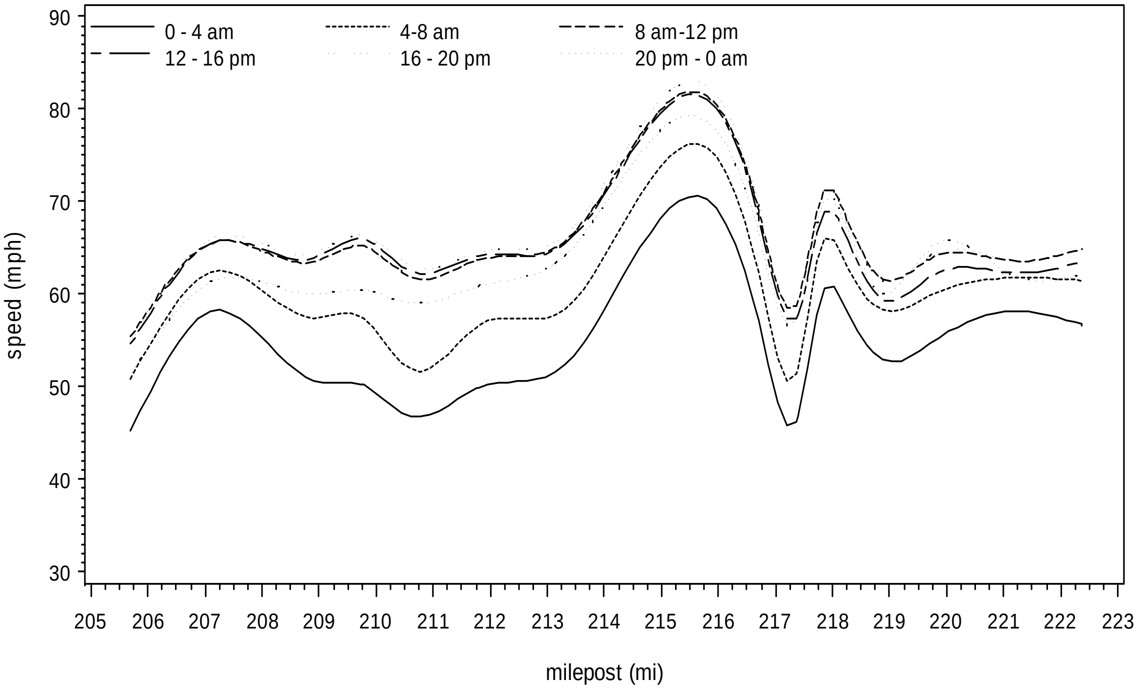


Figure 4-30: Weekends Westbound Speed (Dry Season)

Table 4-3: Speed Limits

Roadway Milepost(mi)	Speed limit (mph)
205-213	60
213-215.77	50
215.77-220	65

Therefore standard deviations of the speeds are generated as a safety measure along the 17-mile roadway section during the two seasons (by weekdays and weekends) for eastbound and westbound. It can be concluded from Figures 4-34 to 4-41 that westbound has relatively milder standard deviation of the speeds than the eastbound in both snow and dry seasons during both weekdays and weekends. Moreover, it is found that standard deviation of the speeds have double peaks at milepost 208 to 212 for eastbound of more than16 mph during weekdays and weekends for the snow season while these peaks are more flat during dry season of about 10 mph. The standard deviation of the speeds is higher during the peak-hours for eastbound in the snow season for weekdays and weekends with relatively higher values during the weekends. Westbound experienced flatter standard deviation along the roadway section in general; during the snow season during 8:00AM to 12:00PM the highest standard deviation followed exists by 4:00AM to 8:00AM while in dry season higher standard deviation of the speed is between 12:00AM to 8:00AM followed by 20:00PM to 12:00AM.

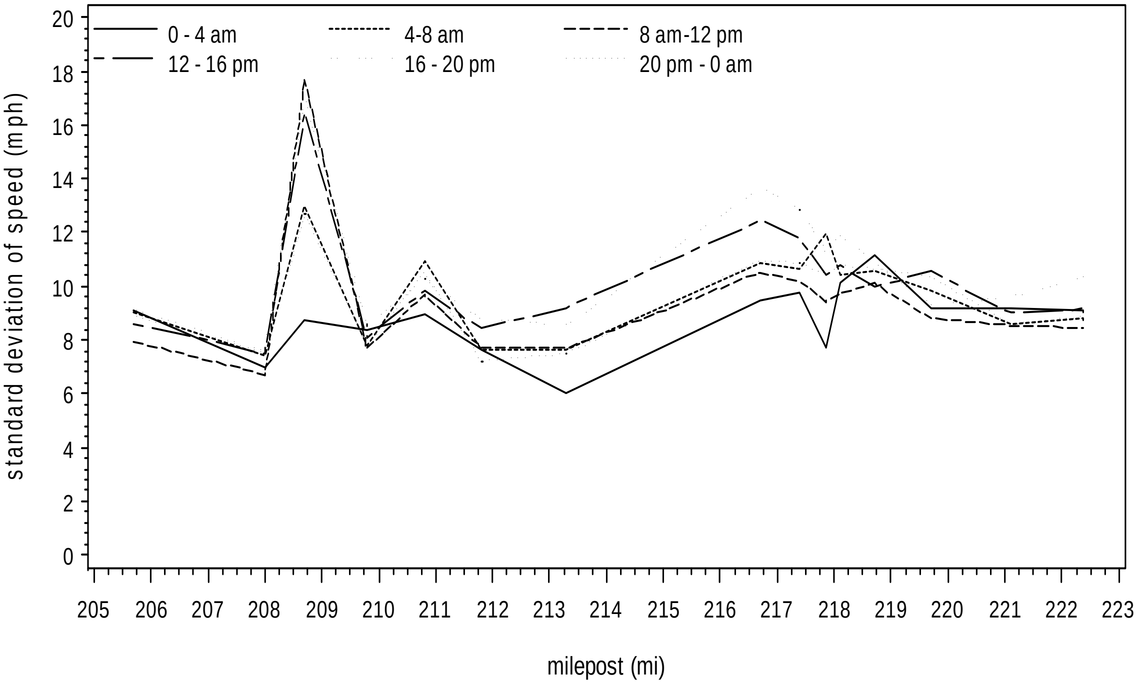


Figure 4-31: Weekdays Speed Standard Deviation (Eastbound -Snow Season)

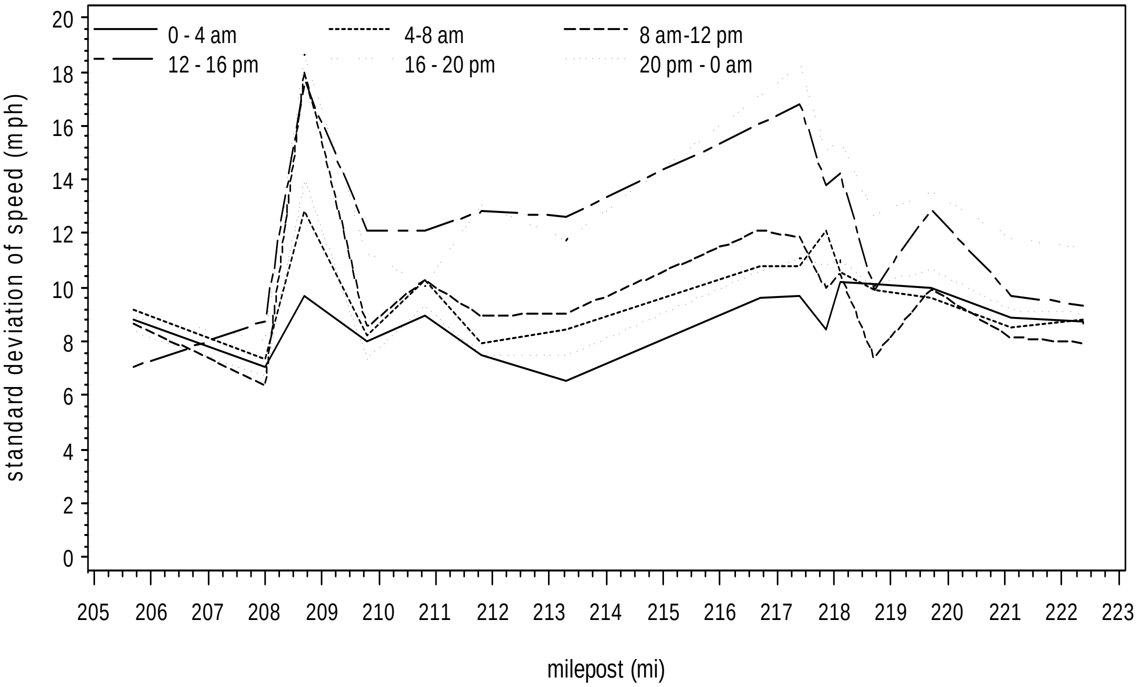


Figure 4-32: Weekends Speed Standard Deviation (Eastbound -Snow Season)

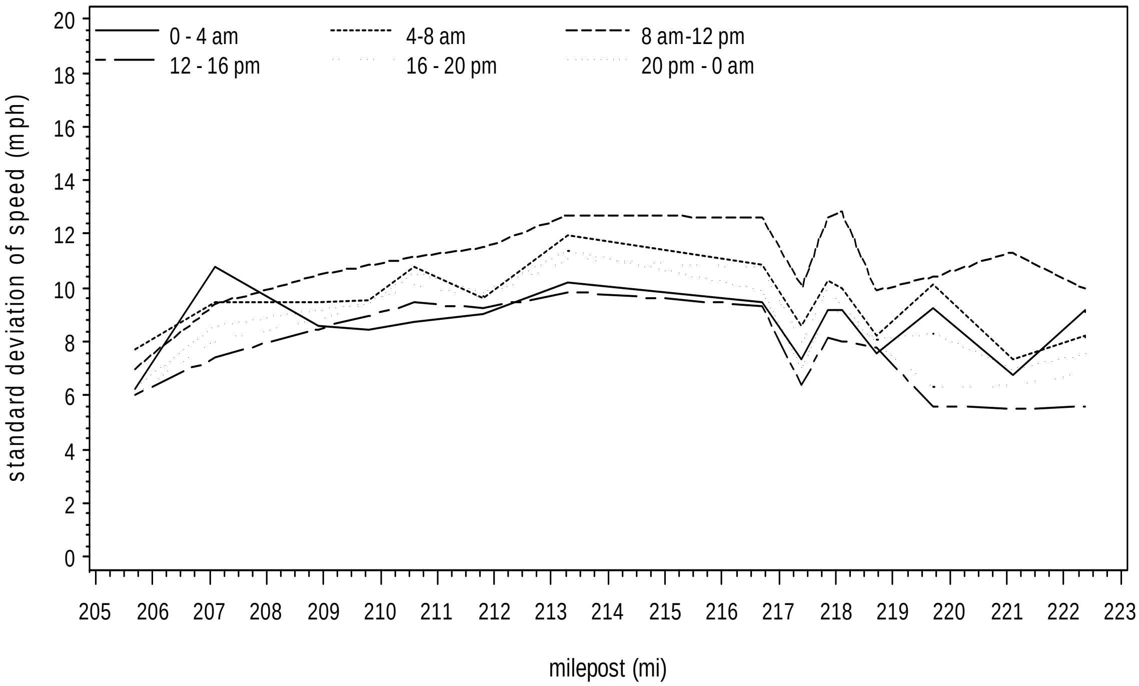


Figure 4-33: Weekdays Speed Standard Deviation (Westbound -Snow Season)

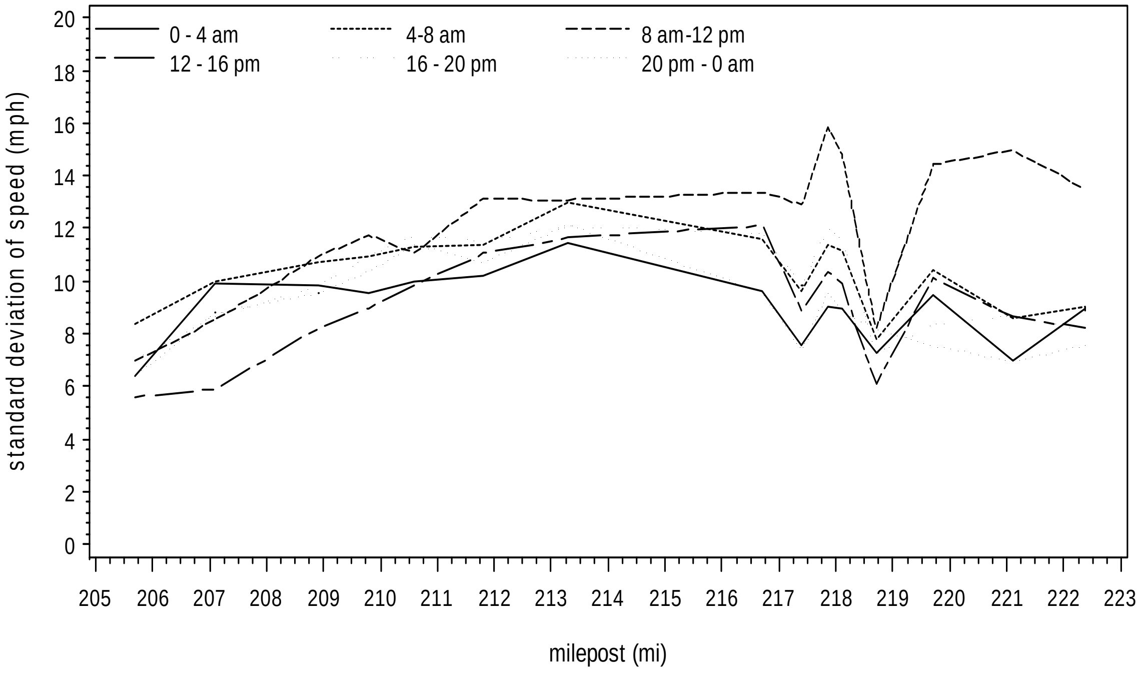


Figure 4-34: Weekends Speed Standard Deviation (Westbound -Snow Season)

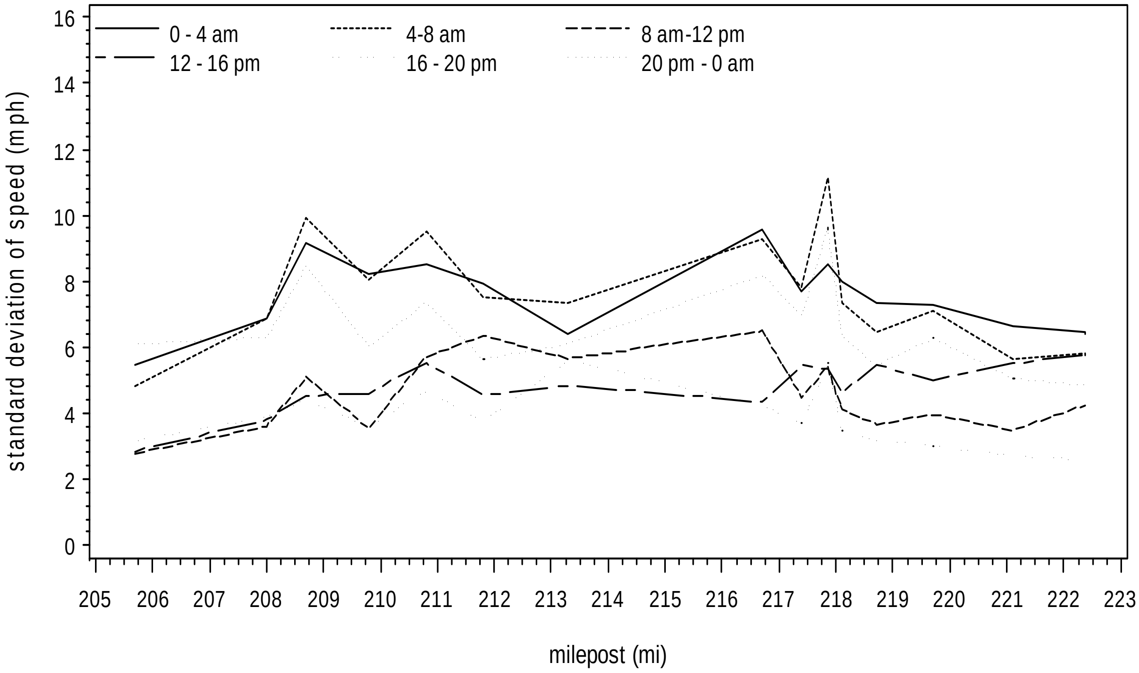


Figure 4-35: Weekdays Speed Standard Deviation (Eastbound -Dry Season)

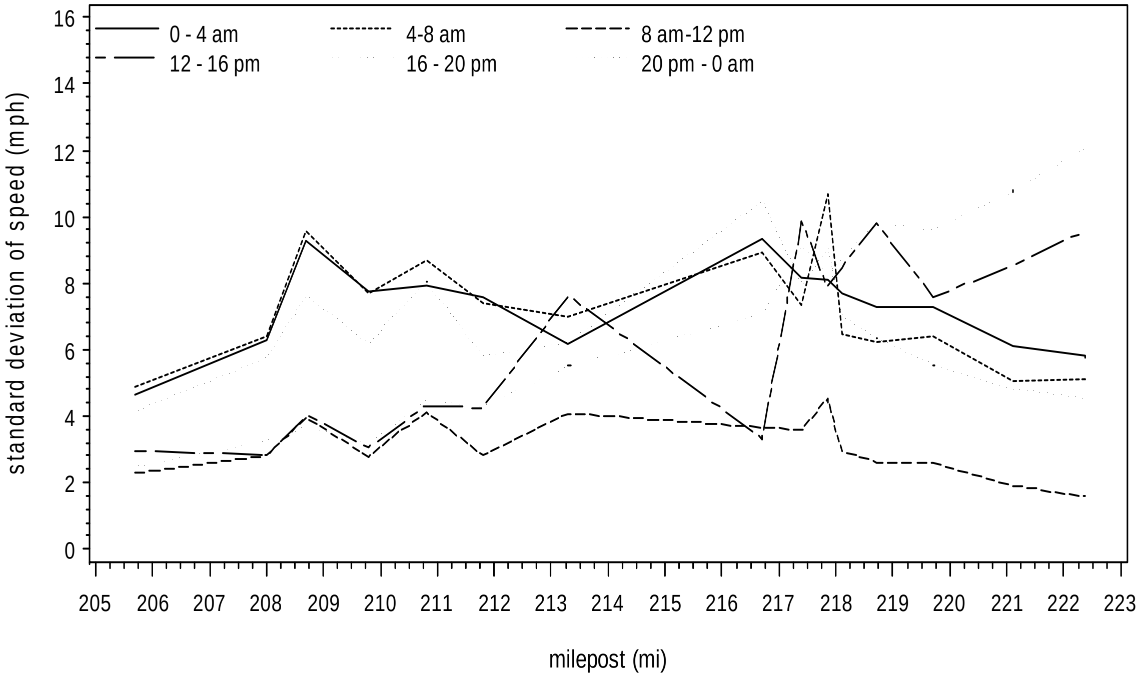


Figure 4-36: Weekends Speed Standard Deviation (Eastbound -Dry Season)

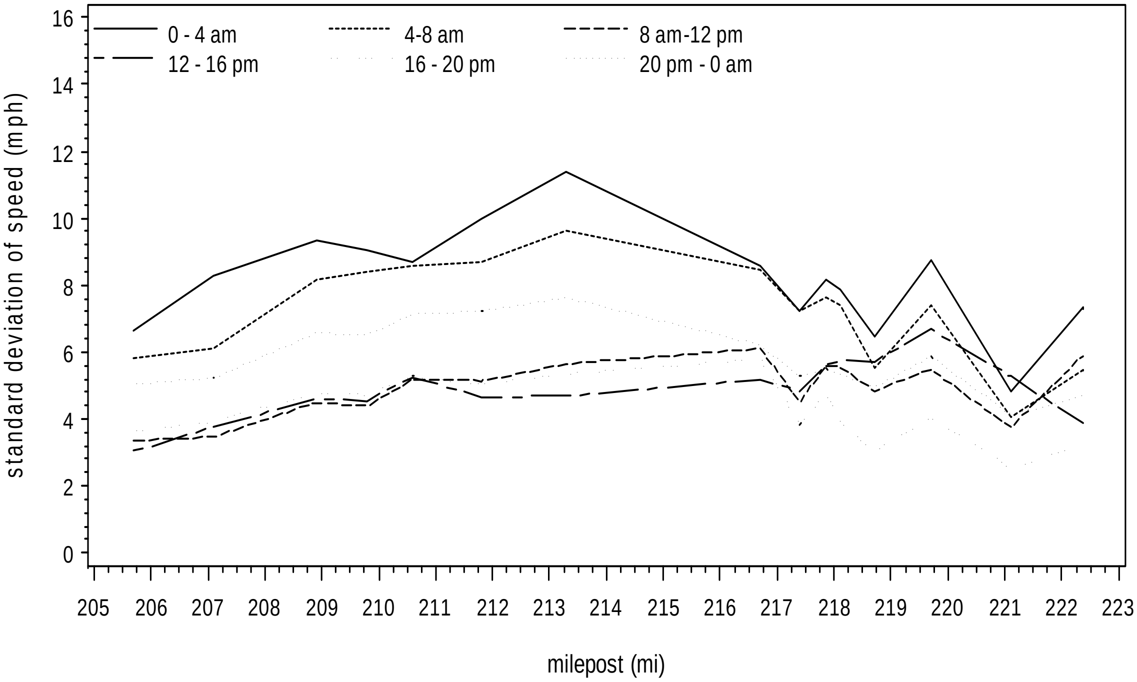


Figure 4-37: Weekdays Speed Standard Deviation (Westbound -Dry Season)

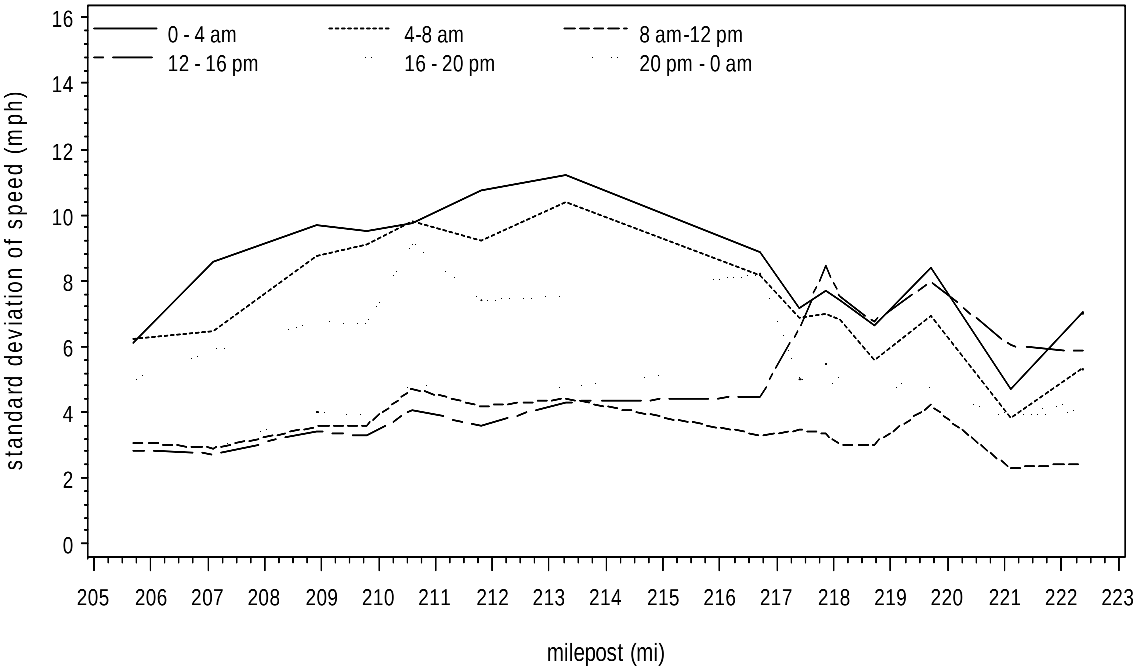


Figure 4-38: Weekend Speed Standard Deviation (Westbound -Dry Season)

4.6 Exploratory Comparison of the AVI and RTMS Data

Interstate-70 in Colorado is equipped with both Automatic Vehicle Identification (AVI) System and Remote Traffic Microwave Sensor (RTMS) System as part of the Intelligent Transportation System (ITS). Data from AVI are mainly used for toll collection and travel time estimation. It provides information about the space-mean-speed. RTMS is mostly used as a tool for operation and incident detection. It offers more detailed information on fundamental traffic parameters as time-mean-speed, volume and occupancy of each travel lane on the roadway.

Except that RTMS system keeps record of other traffic parameters that AVI system does not. It is also crucial to recognize that two types of speed differ with each other naturally. AVI measures space-mean-speed, which means that it reflects the average speed of all the vehicles occupying the detected road segment over a given time period (basically 2 min interval). RTMS measures time-mean-speed, the arithmetic mean of the speed of vehicles passing a point during specific time slice (normally 30 sec).

Moreover, due to that the speed data from AVI are aggregated together without considering for inner or outer lanes, further attention should be paid on the potential difference between AVI speed data and RTMS speed data. For example, the outer lanes are more often travelled by trucks that could result in significantly lower average speed value for outer lane than inner lanes. However, this distinction could not be seen from the AVI speed data.

Therefore it is of great importance as well as interest for us to look into the data and check on the comparability of these two types of data. If they are comparable, then we may come up with a useful alternative data source when either one of them is not available.

Data are recorded at each RTMS station and each AVI segment. Besides the table for RTMS stations already given, a table for AVI stations is developed. Table 5 shows that AVI segments have similar average length as the RTMS system, namely 1.16 mile and 1.15 mile for east and west bounds but a little bit smaller standard deviation. Also, a majority of the starting and end points of AVI segment and RTMS stations are located at the same or close milepost. The spatial distribution of these stations facilitates us to compare speed data from RTMS stations to those collected from corresponding AVI segments.

Table 4-4: AVI Station Segment

	Eastbound			Westbound		
	Starting AVI Station	Ending AVI Station	Segment Length (mi)	Starting AVI Station	Ending AVI Station	Segment Length (mi)
1	205.05	207	1.95	205.7	205	0.7
2	207	208	1.0	207.1	205.7	1.4
3	208	208.7	0.7	208.9	207.1	1.8
4	208.7	208.79	0.09	209.79	208.9	0.89
5	209.79	210.8	1.01	210.6	209.79	0.81
6	210.8	211.8	1.0	211.8	210.6	1.2
7	211.8	213.4	1.6	213.4	211.8	1.6
8	213.4	215.3	1.9	215.3	213.4	1.9
9	215.3	216.7	1.4	216.57	215.3	1.27
10	216.7	217.85	1.15	217.4	216.57	0.83
11	217.85	218.7	0.85	218.1	217.4	0.7
12	221.1	222.4	1.3	218.7	218.1	0.6
13				219.7	218.7	1.0
14				221.1	219.7	1.4
	Average Segment Length		1.16	Average Segment Length		1.15
	Minimum Segment Length		0.09	Minimum Segment Length		0.6
	Maximum Segment Length		1.95	Maximum Segment Length		1.9
	Standard Deviation of Segment Length		0.52	Standard Deviation of Segment Length		0.42

Three scenarios are used to compare the data from these two sources.

1. Normal condition;

2. Crash with property damage only;

3. Crash with injury or fatality

For each case, an AVI segment is selected and the RTMS stations within this segment are also included. RTMS data are processed according to each lane at each station. Two-hours' records are studied.

1. Normal condition

Normal condition is defined as the traffic without interruption of crashes. Figure 4-42 represents a typical normal traffic flow condition. Though having variation, the speed curves are mild and without values sudden dropping or raising. The RTMS data give more detailed description about the speed distribution on each lane. From the figure below it shows that at the same station, speed on inner lanes are higher than that on outer lanes. Trucks travelling on outer lanes at lower speed serve as the explanation. The AVI and RTMS give two different types of speed. Therefore we do not focus on the direct comparison of the speed profiles. However, from Figure 4-42 it is clear that their patterns are alike.

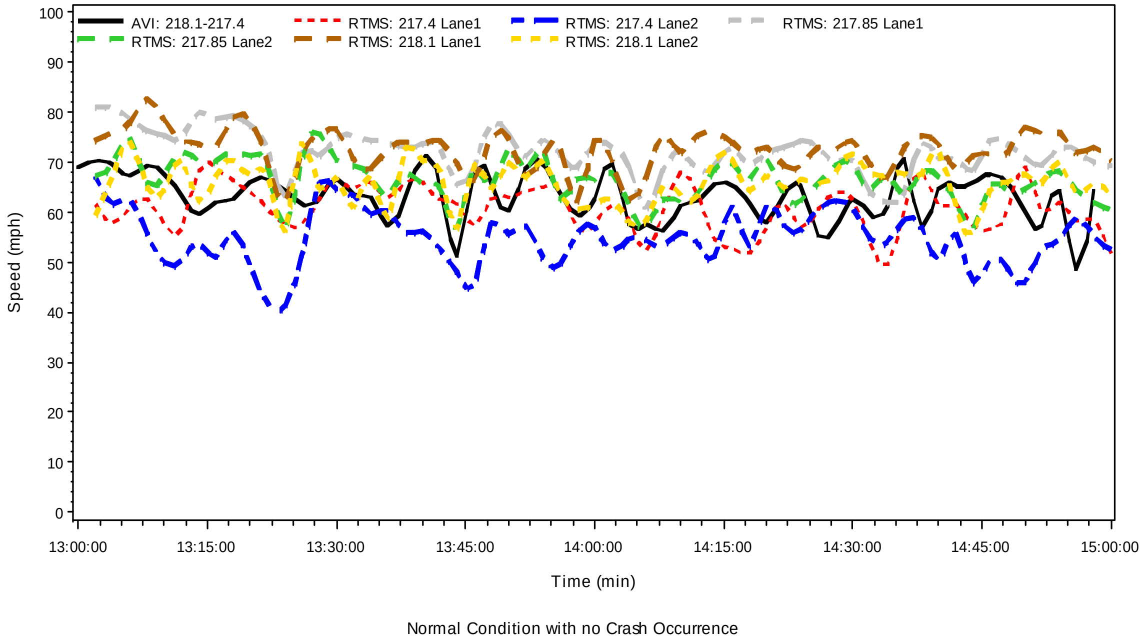
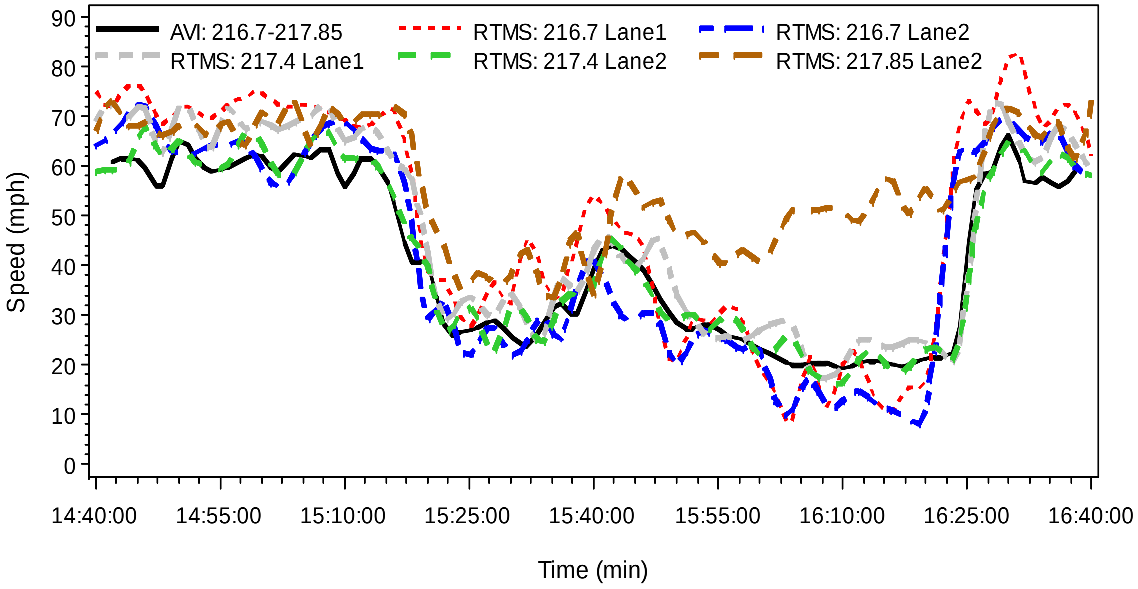


Figure 4-39: Westbound Dry Season Normal Condition

2. Crash with property damage only

Figure 4-43 shows the occurrence of property-damage-only crash. Speed profile is from one hour before the crash to one hour after the crash. The figure is straight forward. When a crash happens on road, temporary congestion will be generated. And vehicles upstream to the crash location have to slow down. Once they pass the site, the speed will recover to some extent. So no significant change in speed from RTMS stations downstream after the crash happens shown in the figure has been expected. Figure 4-43 also demonstrates that speed from stations upstream can experience sudden rise, due to the removal of the vehicles involved in crash from the roadway. In this scenario, the AVI and RTMS give very comparable speed profile.

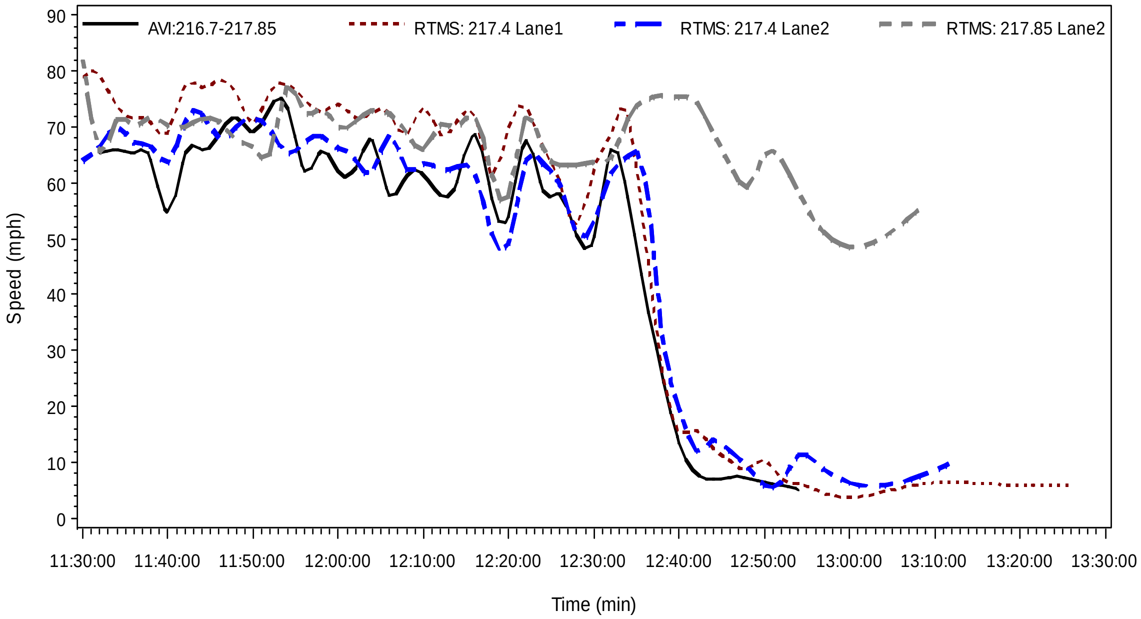


Crash Location: Milepost 217.7

Figure 4-40: Snow Season Eastbound PDO Crash

3. Crash with injury or fatality

When more severe crash occurs, as in Figure 4-44, both AVI and RTMS data show that the speed drops deeply. Different from the case of property damage only crash, when injury or fatality result from traffic crashes, it take longer time for the traffic flow to recover. In this crash happened at 12:30 pm on milepost 217.5, the congestion caused by it lasts more than one hour. Similar with PDO crash, AVI and RTMS still represent consistent pattern of speed.



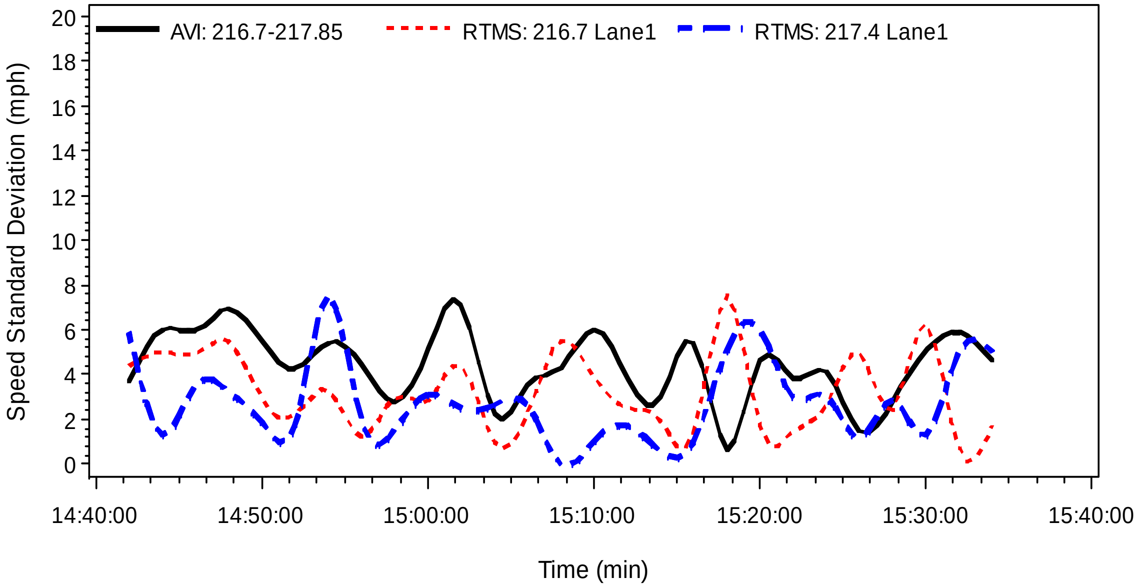
Crash Location: Milepost 217.5

Figure 4-41: Dry Season Eastbound INJ/FATAL Crash

1) Comparison of Speed Variation

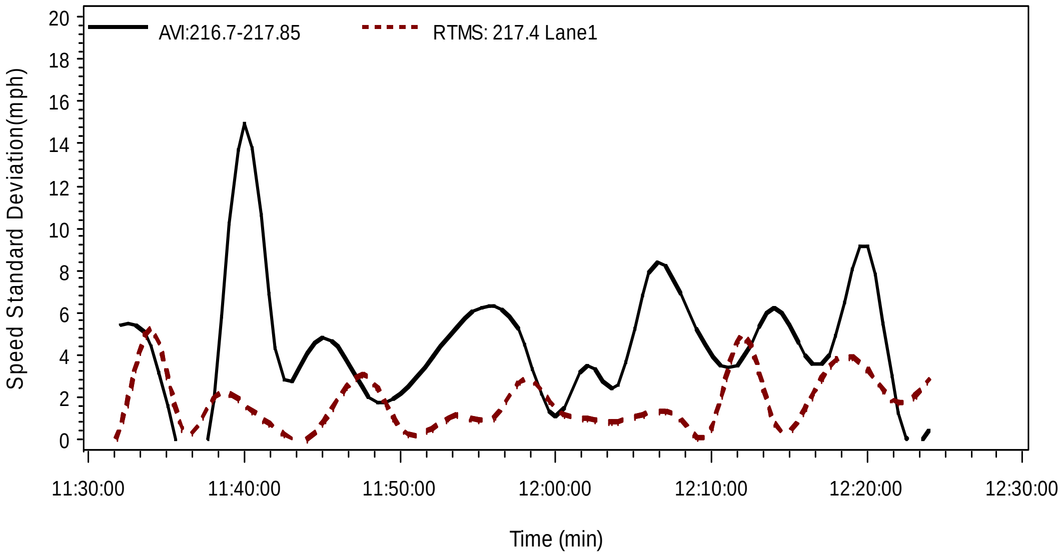
With the comparability of these two types of speed data in mind, we also explored the variation of the speed that AVI and RTMS system record. From Figure 4-45 and 4-46, we can see the existence of significant turbulence in speed prior to the occurrence of traffic crash on road. In order to get better insight about these two types of data, we believe it is necessary for us to look into the standard deviation of speed before the crash happens. The 5 minutes' data adjacent to the crash are disregarded to the potential bias of the recorded crash time. The speed standard deviation is determined on 2 minutes' interval basis from 1 hour to 5 minutes before the reported crash time. And only the inner lanes of RTMS stations upstream to the crash location are studied.

Profiles of speed standard deviation indicate that AVI system records relatively higher speed variation than RTMS system. Looking more closely to the 20 minutes period prior to crash, AVI data still keeps higher variation.



Crash Location: Milepost 217.7

Figure 4-42: Speed Variation in Crash with Property Damage Only



Crash Location: Milepost 217.5

Figure 4-43: Speed Variation in Crash with Injury/ Fatality

4.7 Basic Statistical Analysis

In order to shed light on the evolution of the macroscopic traffic flow parameters under meteorological variation for crash and non-crash cases as well as between snow and dry seasons, a series of statistical tests were conducted. F-test showed that the crash and non-crash cases have equal variance and hence t-tests for equal variance were used. The results showed that there is a significant difference between all the average speed related variables indicated in Table A-1 of crash cases and non-crash cases; non-crash cases have higher average speed compared to crash cases. Similar results were drawn for all variance of occupancy at the nearest RTMS in upstream and downstream, crash cases were found to have higher variance of occupancy than non-crash cases. Moreover, the mean of the estimated visibilities one hour before the non-crash cases was found to be higher than crash cases, the mean of the estimated visibility for non-crash cases was found to be 1.61 miles while it was found to be 1.32 miles for crash-cases.

CHAPTER 5. LINKING CRASH OCCURRENCE TO ROADWAY GEOMETRY, WEATHER CONDITION, AND AVI TRAFFIC DATA

5.1 Introduction

In previous studies, weather data were estimated from crash reports for crash cases and from airports weather stations in the vicinity of the freeway section for non-crash cases (Abdel-Aty and Pemmanabonia, 2006; Hassan and Abdel-Aty, 2010). It should be noted that none of these studies had access to actual weather information on the roadway section itself. In this chapter, real-time weather data are gathered by weather stations installed on the roadway solely for the purpose of collecting real-time information about the adverse weather conditions. Moreover, roadway geometrics were considered in few studies (Abdel-Aty and Abdalla, 2004; Abdel-Aty et al., 2007), and their effects were controlled for by a matched case-control framework in other studies (Abdel-Aty et al. 2004, 2005, 2007, 2008; Abdel-Aty and Pande, 2004, 2005; Pande and Abdel-Aty 2006a, 2006b; Hassan and Abdel-Aty, 2010; Ahmed and Abdel-Aty, 2011). These studies were mostly conducted on freeways/expressways that feature normal roadway geometry and hence the traffic flow parameters were found to be the most dominant factors that contribute to crash occurrence. Since the roadway section under study features mountainous terrain of relatively steep grades and sharp horizontal curves' radii, the geometrical characteristics were considered to examine how the interaction between all these factors contributes to crash occurrence. This chapter investigates the identification of freeway locations with high crash potential using traffic data collected from AVI, real-time weather information and geometric features.

According to the Federal Highway Administration (Goodwin, 2002), weather contributed to over 22% of the total crashes in 2001. This means that adverse weather can easily increase the likelihood of crash occurrence. Several studies, in fact, concluded that crashes increase during rainfall by 100% or more (Brodsky and Hakkert, 1988; National Traffic Safety Board, 1980), while others finding more moderate (but still statistically significant) increase (Andreescu and Frost, 1998; Andrey and Olley, 1990).

Automatic Vehicle Identification (AVI) system has been widely used in real-time travel time estimation (Tam and Lam, 2011; Dion and Rakha, 2006). While few studies used traffic data from AVI in real-time traffic safety application (Ahmed and Abdel-Aty, 2011; Ahmed et al. 2012a, 2012b), in this study, AVI data, real-time weather data, and roadway geometry are implemented to assess the safety risk on a freeway section that features mountainous terrain.

5.2 Data Preparation

This study involves four datasets; roadway geometry data, crash data, and the corresponding AVI and weather data. The crash data were obtained from CDOT for a 15-mile segment on I-70 for three years (2007 to 2009). Traffic data consists of space mean speed captured by 20 AVI detectors located on each east and west bounds along I-70. We obtained from CDOT the processed 2-minute space mean speed and the estimated average travel time for each AVI segment. Although the tag readers have the capability of collecting lane by lane data, the processed and archived AVI data included only the combined travel time and space mean speed for all lanes. It is worth mentioning that ATIS was developed and implemented without consideration for safety applications. Weather data recorded by three automated weather stations along I-70 for the same time period were also provided by CDOT. The roadway data were collected from Roadway Characteristics Inventory (RCI) and Single Line Diagrams (SLD).

AVI data corresponding to each crash case were extracted in the following process; the location and time of occurrence for each of the 301 crashes were identified. Since the space mean speeds were archived on 2-minute intervals, the speeds were aggregated to different aggregation level of 2, 4, and 6-minute level to obtain averages and standard deviations and to investigate the best aggregation level that will give better accuracy in the modeling part. Six-min aggregation level was found to provide better fit. Three time slices of the 6-minute prior the crash time were extracted. For example if a crash happened on Sep 16, 2007 (Sunday) at 14:00, at the milepost of 205.42. The corresponding 18-min window for this crash of time intervals (13:42 to 14:00) recorded by AVI segment 34 (Mile marker starts at 200.8 and ends at 205.55). Time slice 1 was discarded in the analysis since it would not provide enough time for successful intervention to reduce crash risk in a proactive safety management strategy. Moreover, the actual crash time might not precisely be known. Golob and Recker (2004) discarded the 2.5 minutes of traffic data immediately preceding each reported crash time to avoid uncertainty of the actual crash time. In general with the proliferation of mobile phones and CCTV cameras on Freeways, crash time is almost usually immediately identified. One-hour speed profiles were also generated (about 30 minutes before and 30 minutes after the crash time) to verify the reported crash time. The modeling procedure required non-crash data, a random selection from the whole remaining AVI dataset where there was no crash within 2-hour before the extraction time was utilized in the study to represent the whole population of different traffic patterns, weather conditions and roadway characteristics.

Similarly, weather data for crash cases and non-crash ceases were extracted. Automated weather stations monitor the weather conditions continuously and the weather parameters are recorded according to a specific change in the reading threshold and hence they do not follow a specific time pattern. The stations report frequent readings as the weather conditions change within short time; if the weather conditions remain the same the station would not update the readings. However, these readings were aggregated over certain time periods to represent the weather conditions. For example; precipitation described by rainfall amount or snowfall liquid equivalent for ten minutes, one hour, three hours, six hours, twelve hours and twenty-four hours and the estimated average hourly visibility which provides an hourly measure of the clear distance in miles that drivers can see. Visibility in general can be described as the maximum distance (in mile) that an object can be clearly perceived against the background sky, visibility impairment can be result of both natural (e.g., fog, mist, haze, snow, rain, windblown dust, etc.) and human induced activities (transportation, agricultural activities, and fuel combustion). The automated weather stations do not directly measure the visibility but rather calculate it from a measurement of light extinction which includes the scattering and absorption of light by particles and gases.

A total number of 301 crashes and 880 non-crashes were finally considered in the analysis in which 70 and 231 crashes and their randomly selected 256 and 624 non-crashes occurred during the dry and the snow seasons, respectively.

5.3 Preliminary Analysis and Results

From the preliminary analysis, it can be found that the environmental conditions have a strong effect on crash occurrence within that section. According to the meteorological data, the study section has two distinct weather seasons; dry season from May through September which experience small amount of rain, and snowy season from October through April. The crash frequencies during the snowy season months were found to be more than double the frequencies during the dry season months. Figure 6-1 shows the 3-year aggregated crash frequency by month and weather for the 15-mile freeway section.

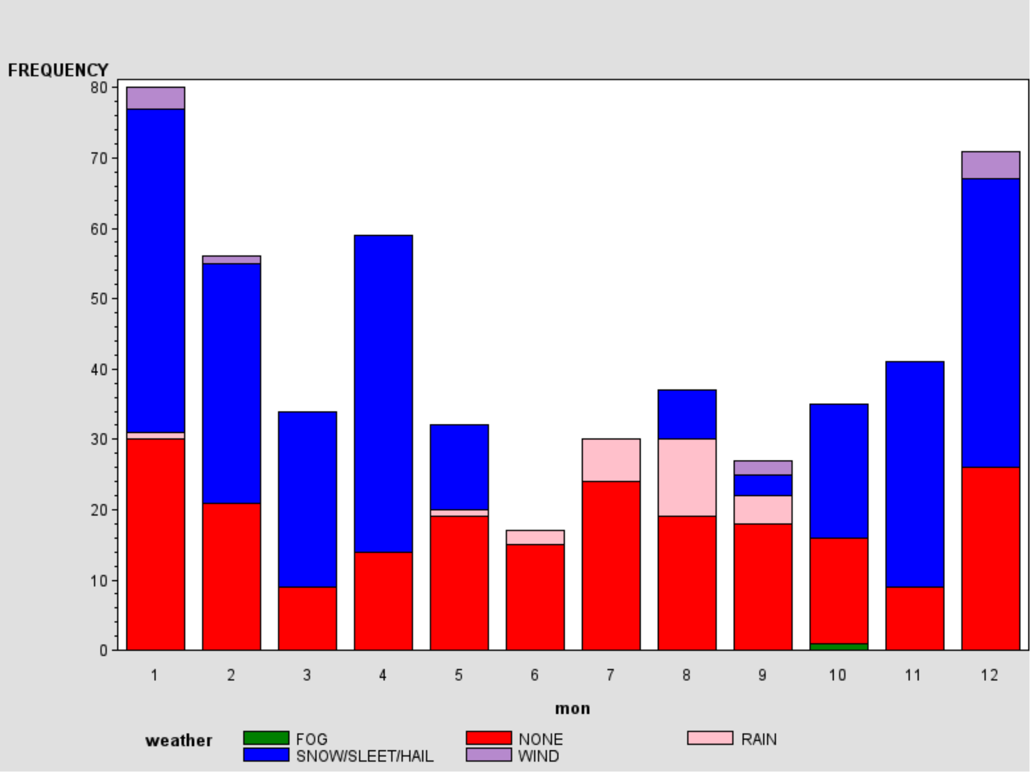


Figure 5-1: Crash Frequency by Month

To compare between the traffic and environmental factors for crash and non-crash cases as well as between snow and dry seasons, a series of statistical tests were conducted. F-test showed that the crash cases and non-crash cases have equal variance and hence t-tests for equal variance were used. The results showed that there is a significant difference between each of the mean of the average speed and the mean of the average 1-hour visibility of crash-cases and non-crash cases. For example, the 6-min average speed 6-12 min prior to the crash cases for both the snowy and the dry seasons was found to be 48.21 mph while it was found to be 55.71 mph prior to the non-crash cases with a resulted t-test p-value of 6.7×10-8. The mean of the estimated visibilities one hour before the crash cases/non-crash cases was found to be significantly higher for non-crash cases than crash-cases, the mean of the estimated visibility for non-crash cases was found to be 1.22 miles while it was found to be 0.95 mile for crash-cases. These results depicts that there is a significant difference between the crash-cases and non-crash cases at the 95% confidence level for the speed and different weather related factors. Similarly, t-tests were used to evaluate weather condition factors in different seasons (dry and snow). The t-test results showed that the dry season had a higher visibility and significantly lower precipitation rate. For visibility, the dry season had a visibility of 1.29 miles while the snow season has 1.09 miles; for ten-minute precipitation, the dry season had a precipitation only as 0.000543 inch while the snow season had 0.057 inch. Average speed for different seasons has also been compared; t-test result shows that in the dry season the average speed is significantly higher than the snow season and with a smaller standard deviation. These observations also suggest that different active traffic management strategies should be implemented for each season.

5.4 Bayesian Logistic Regression

The study utilized a Bayesian logistic regression approach to estimate the probability of crash occurrence in each of the dry and the snow seasons. Bayesian logistic regression has the formulation of a logistic equation and can handle both continuous and categorical explanatory variables. The classical logistic regression treats the parameters of the models as fixed, unknown constants and the data is used solely to best estimate the unknown values of the parameters. In the Bayesian approach, the parameters are treated as random variables, and the data is used to update beliefs about the behavior of the parameters to assess their distributional properties. The interpretation of Bayesian inference is slightly different than the classical statistics; the Bayesian derives updated posterior probability of the parameters and construct credibility intervals that have a natural interpretation in terms of probabilities. Moreover, Bayesian inference can effectively avoid the problem of over fitting that occurs when the number of observations is limited and the number of variables is large.

The Bayesian logistic regression models the relationship between the dichotomy response variable (crash/no-crash) and the explanatory variables of roadway geometry, real-time weather and traffic. Suppose that the response variable y has the outcomes y=1 or y=0 with respective probability p and 1-p. The logistic regression equation can be expressed as:

$$\log\left(\frac{p}{1-p}\right)=\beta_0+\beta X \tag{6.1}$$

where β_0 is the intercept, β is the vector of coefficients for the explanatory variables, and X is the vector of the explanatory variables,. The logit function relates the explanatory variables to the probability of an outcome y=1. The expected probability that y=1 for a given value of the vector of explanatory variables X can be theoretically calculated as:

$$p(y=1) = \frac{exp\ (\beta_0 + \beta X)}{1 + exp\ (\beta_0 + \beta X)} = \frac{e^{\beta_0 + \beta X}}{1 + e^{\beta_0 + \beta X}} \tag{6.2}$$

One advantage of the Bayesian approach over the classical model is the applicability of choosing the parametric family for prior probability distributions. There are three different priors that can be used; 1) informative prior distributions based on the literature, experts' knowledge or explicitly from an earlier data analysis, 2) weak informative priors that do not supply any controversial information but are strong enough to pull the data away from inappropriate inferences, or 3) uniform priors or non-informative priors that basically allow the information from the likelihood to be interpreted probabilistically. In this study, uniform priors following normal distribution with initial values for the estimation of each parameter from the maximum likelihood method was used. Different types of prior distributions using the results from this study as prior could be considered for further research once more data become available to update the estimated models.

As discussed earlier in the preliminary section that Colorado has two distinct weather seasons and hence two models for the snow and dry seasons were considered, these models were estimated by Bayesian inference using the freeware Winbugs (Lunn et al., 2000). For each model, three chains of 10,000 iterations were set up in Winbugs based on the convergence speed and the magnitude of the dataset. The Deviance Information Criterion DIC, a Bayesian generalization of Akaike Information Criterion AIC, is used to measure the model complexity and fit. DIC is a combination of the deviance for the model and a penalty for the complexity of the model. The deviance is defined as $-2\log$ (likelihood). The effective number of parameters, pD, is used as a measure of the complexity of the model, $\mathrm{pD} = \mathrm{Dbar} - \mathrm{Dhat}$, where Dbar is the posterior mean of the deviance, and Dhat is a point estimate of the deviance for the posterior mean of the parameters. DIC is given by DIC = Dhat + 2 pD (Spiegehalter et al., 2003). Moreover, receiver operating characteristic (ROC) curve analysis was used to assess the prediction performance.

5.5 Results and Discussion

5.5.1 Model 1 (Dry Season)

The dry season model was estimated using real-time weather, AVI data and roadway geometry for crashes that occurred during May to September for years 2007 through 2009 and the randomly selected non-crashes with their corresponding data. Before drawing inferences from posterior sample, the trace, autocorrelation and density plots were examined visually to ensure that the underlying Markov chains have converged. Following Brooks-Gelman-Rubin (BGR) convergence diagnostics (Brooks and Gelman, 1998), the mixing in the chains was found to be acceptable with no correlation for all included variables in the final model. After ensuring the convergence, first 2,000 samples were discarded as adaptation and burn-in. Table 1 provides the estimates of beta coefficients, credible interval, hazard ratio and fit statistics for the (Dry Season) model; all included roadway alignment factors, i.e. median width, longitudinal grade and horizontal curve were found to be significant. Preliminary analysis on the data indicates that more than 85% of the total crashes occurred on steep grades (grade <-2% or >2%). Steep grades affect the operation and the braking of the vehicles on both upgrade and downgrade, the results indicates that the crash likelihood increases as the grade increases, the effect of various grades are compared to Grade[Flat] (reference condition, flat grade ranges from 0% to ±2%). It can be noted that in order, Grade[Very Steep] (grade (>6% to 8%)and(<-6% to -8%)) is the most hazardous followed by Grade[Steep] (grade (>4% to 6%) and (<-4% to -6%)), and Grade[Moderate] (grade (>2% to 4%) and (<-2% to -4%)). Generally, trends in the results indicate that the steeper the grade, the higher the crash risk. Table 6-1 shows the hazard ratio for the significant variables. Hazard ratio is the exponent of the beta coefficient and it represents an estimate of the expected change in the risk ratio of having crash versus non-crash. The interpretation of the hazard ratio depends upon the measurement scale of the explanatory variable; for interval variables it represents the change in the risk ratio per unit change in the corresponding factor while for categorical variables it represents the change in the risk ratio compared to the base case, e.g. the hazard ratio of 5.63 for the categorical variable Grade[Very Steep] means that the likelihood of a crash at very steep grades is 5.63 times the likelihood at the base case of flat grades Grade[Flat].

A binary variable Grade Index was created to represent the direction of the grade at the crash segment, [1=upgrade] as a reference and [2=Downgrade], the grade index was found to be significant at the 90% credible interval with a positive coefficient which implies that the positive road grades are slightly safer than the negative ones. These results are consistent with the finding from the aggregate models in the literature that the steep grades may increase the likelihood of crash occurrence (Shankar, 1995; Chang and Chen, 2005; Ahmed et al., 2011).

The results imply that the Degree of curvature (β=-0.246, 95%CI(−0.484,-0.024), hazard ratio = 0.78) is significantly associated with crash risk, a unit increase in degree of curvature is associated with 22% decrease in crash likelihood, with all other factors remain constant. High degree of curvature was found to be associated with decrease in crash likelihood in previous studies, it may be explained that the discomfort feeling along sharp curves might make the drivers compensate by driving more cautiously, leading to lower probability of involvement in a crash (29,30,31,32). Median width (β=-0.046, 95%CI(−0.075,-0.019) has a negative coefficient meaning that a wider median is safer since it works as a recovery area for out-of-control vehicles.

The 6-minute average speed of the crash segment during 6-12 minutes prior the crash time as well as the average visibility during the last hour before the crash time were found to be significant during the dry season. Both variables have negative beta coefficients, which mean that the odds of a crash increase as the average speed decreases at the segment of the crash at 6-12 minutes before crash occurrence and the average visibility decreases during one hour prior the crash time. The hazard ratio of 0.926 means that the risk for a crash increases 7.4 percent for each unit decrease in the six minutes average speed, and the hazard ratio of 0.211 means that the risk for a crash increases 79% for each unit mile decrease in the average Visibility measured over one hour before the crash time.

Table 5-1: Parameters and Hazard Ratio Estimates (Dry Season Model)

Variables	**Parameters Estimates**				**Hazard Ratio**			
	Credible interval				Credible interval			
	Mean	S.D.	2.5%	97.5%	Mean	S.D.	2.5%	97.5%
Intercept	2.070	1.37	-0.599	4.830	-	-	-	-
Grade[Flat (0-2)%](reference)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Grade[Moderate >2-4%]	0.510	0.554	-0.565	1.640	1.950	1.210	0.568	5.150
Grade[Steep >4-6%]	1.120	0.485	0.201	2.120	3.470	1.860	1.220	8.330
Grade[Very Steep >6-8%]	1.540	0.604	0.373	2.740	5.630	3.840	1.450	15.600
Grade Index[1=Upgrade](ref.)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Grade Index[2=Downgrade]	0.658	0.354	-0.023	1.350	2.060	0.755	0.977	3.860
Degree of curvature	-0.246	0.116	-0.484	-0.024	0.787	0.091	0.616	0.976
Median width	-0.046	0.014	-0.075	-0.019	0.955	0.014	0.928	0.981
Average Speed	-0.076	0.020	-0.115	-0.037	0.926	0.019	0.891	0.964
Visibility	-1.750	0.636	-3.070	-0.568	0.211	0.141	0.046	0.566
pD: no of effective variables	9.803	-	-	-	-	-	-	-
DIC	297.762	-	-	-	-	-	-	-
ROC	0.783	-	-	-	-	-	-	-
Sensitivity	75.71	-	-	-	-	-	-	-

Summary statistics (Mean, S.D.): Degree of curvature (1.33, 1.49), Median Width (ft) (25.96, 15.11), Average Speed (mph) (56.4, 7.94), and Visibility (mi) (1.29, 0.95).

5.5.2 Model 2 (Snow Season)

Another model was estimated for crash no-crash cases in the snow season to examine whether the same variables have the same effect on crash likelihood as in the dry season. Comparisons between the two models imply very interesting findings. On the one hand, same geometric variables came out to be significant; on the other hand, it is noticeable that all the coefficients increased yielding to the fact that the hazard ratios increase due to the interaction between the snowy, icy, or slushy pavement conditions during snow season, and exacerbated by the steep grades. The hazard ratio for Grade[Very Steep] (grade (>6% to 8%)and(<-6% to -8%)) during snow season increased to 9.67 compared to 5.63 in the dry season which means that the change in risk ratio almost doubled during the snow season. Similar findings were concluded for Degree of Curvature and Median Width. Another interesting observation from the parameter estimate for Grade Index is that the hazard ratio decreased and the variable became insignificant which may indicate that steep grades become hazardous during snow season in both the upgrade and downgrade directions.

While only the 1-hour Visibility was significant in the dry season model, in the snow season model both 1-hour Visibility and the ten-minute Precipitation described by rainfall amount or snowfall liquid equivalent came out to be significant. These results are consistent with the preliminary analysis that the precipitation rates are significantly higher during the snow season than in the dry season, one unit increase in the Precipitation increases the risk of the crash by 165%. Moreover, it can be implied from the results that one unit decrease in the Visibility during the snow season increases the crash likelihood by 88% compared to 79% in the dry season.

Logarithm of the coefficient of variation in speed at the crash segment at time slice 2 (6-12 minutes before the crash) came out to be significant. Log COV Speed has positive beta coefficient, which means that the risk of a crash increases as the variation of the speed increases. The increase in the standard deviation coupled with the decrease in the average speed 6-12 minutes before the crash (since the coefficient of variation of speed includes the standard deviation as the nominator and the average speed as the denominator) may increase the likelihood of crash occurrence.

Table 5-2: Parameters and Hazard Ratio Estimates (Snow Season Model)

Variables	**Parameters Estimates**				**Hazard Ratio**			
	Credible interval				Credible interval			
	Mean	S.D.	2.5%	97.5%	Mean	S.D.	2.5%	97.5%
Intercept	1.596	0.510	0.600	2.541	-	-	-	-
Grade[Flat (0-2)%](reference)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Grade[Moderate >2-4%]	0.820	0.354	0.147	1.533	2.420	0.905	1.158	4.631
Grade[Steep >4-6%]	0.927	0.341	0.279	1.612	2.691	0.952	1.261	4.951
Grade[Very Steep >6-8%]	2.203	0.361	1.533	2.928	9.671	3.730	4.634	18.69
Grade Index[1=Upgrade](ref.)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Grade Index[2=Downgrade]	0.009	0.188	-0.369	0.381	1.031	0.191	0.688	1.456
Degree of curvature	-0.301	0.067	-0.434	-0.175	0.742	0.049	0.648	0.839
Median width	-0.053	0.008	-0.069	-0.038	0.948	0.008	0.933	0.963
Precipitation	0.881	0.418	0.149	1.774	2.652	1.268	1.161	5.892
Visibility	-2.207	0.342	-2.862	-1.533	0.117	0.041	0.057	0.216
Log COV Speed	0.501	0.225	0.056	0.944	1.693	0.388	1.058	2.576
pD: no of effective variables	9.506	-	-	-	-	-	-	-
DIC	802.028	-	-	-	-	-	-	-
Area under ROC Curve	0.84	-	-	-	-	-	-	-
Sensitivity	80.09	-	-	-	-	-	-	-

Summary statistics (Mean, S.D.): Degree of curvature (1.39, 1.52), Median Width (ft) (24.50, 15.45), Visibility (mi) (1.09, 0.47), Precipitation (in) (0.05, 0.29), and Log COV Speed (0.24, 0.38).

In order to implement the estimated model in real-time application, sensitivity analysis is conducted. Tables 6-3 and 6-4 show sensitivity and the specificity for the dry and snow models respectively. Sensitivity is the proportion of crashes that are correctly identified as crashes while specificity is the proportion of non-crashes that are correctly identified as non-crashes by the estimated Bayesian logistic regression models (Agresti, 2002). The sensitivity was found to be 75.71% and 80.09% while the models achieved specificity of 66.41% and 67.79 at cutoff points equal to 0.20 and 0.25 for the dry and the snow seasons, respectively. The cutoff was chosen for each model to reduce the false positive rate; about 33.59% and 32.21% for the dry and snow seasons were classified incorrectly as crashes, respectively.

As mentioned earlier that different classification accuracy can be obtained by changing the threshold depending on the management strategy. The threshold should be chosen carefully for application; large number of false alarms might affect the drivers' compliance to the system and hence reduce the effectiveness of the system. Nevertheless, Advanced Traffic Management (ATM) objectives of reducing turbulence to improve operation can still be achieved even with high percentage of false alarms. False alarm conditions are still non ideal, and reducing the flow turbulence could lead to operation benefits although it might not have lead to a crash. As discussed earlier, ITS strategies such as variable speed limits could be introduced without the drivers' knowledge of false alarm or not.

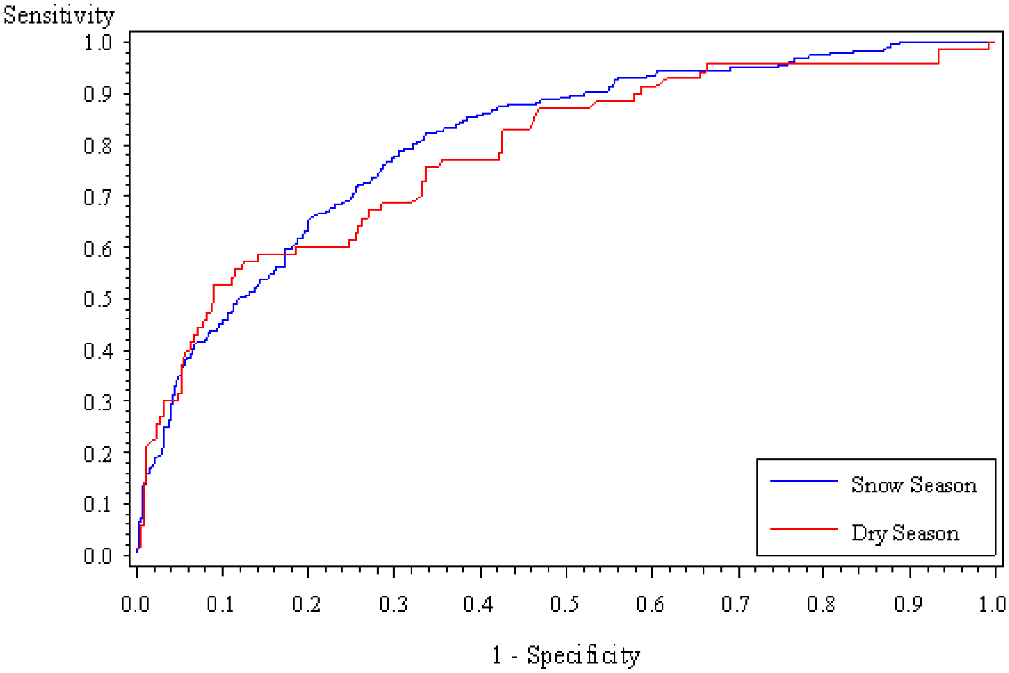


Figure 5-2: Receiver Operating Characteristic (ROC) (Dry and Snow Seasons Models)

The Receiver-Operating Characteristic (ROC) curves were also generated as another way to assess the models' performance. The area under the ROC curve shows how well the model is discriminating between the crash (y=1) and no-crash (y=0) cases in the response variable. This is similar to the misclassification rate, but the ROC curve calculates sensitivity (true positive rate) and 1-specificty (false positive rate) values for many cutoff points. The exact areas under the ROC curves were found to be 0.783 and 0.840 for the dry and the snow seasons, respectively which indicate that the models can provide good discrimination.

Table 5-3: Classification Results (Dry Season Model)

		Dry Season Model		
Frequency Percent Row Percent Column Percent		**Predicted**		**Total**
		0 (Non-Crash)	**1 (Crash)**	
Actual	**0 (Non-Crash)**	170 52.15 **Specificity 66.41** 90.91	86 26.38 **False Positive Rate 33.59** 61.87	256 78.53
	1 (Crash)	17 5.21 **False Negative Rate 24.29** 9.09	53 16.26 **Sensitivity 75.71** 38.13	70 21.47
Total		187 57.36	139 42.64	326 100.00

Table 5-4: Classification Results (Snow Season Model)

		Snow Season Model		
Frequency Percent Row % Column%		**Predicted**		**Total**
		0 (Non-Crash)	**1 (Crash)**	
Actual	**0 (Non-Crash)**	423 49.47 **Specificity 67.79** 90.19	201 23.51 **False Positive Rate 32.21** 52.07	624 72.98
	1 (Crash)	46 5.38 **False Negative Rate 19.91** 9.81	185 21.64 **Sensitivity 80.09** 47.93	231 27.02
Total		469 54.85	386 45.15	855 100.00

5.6 Conclusion

Real-time crash prediction models that depend only on traffic parameters are useful for freeways with normal geometry and at locations that do not encounter severe weather conditions. Most of the previous studies found that the traffic turbulence (e.g., speed variance) defined by the traffic parameters is more dominant to discriminate between crash and non-crash cases and hence the matched case-control design was an adequate technique to account for the small variability in roadway geometry and weather. In this study we illustrate that the same traffic turbulence could affect the driver differently on roadway sections with special geometry and at different weather. Mountainous roadway geometry and adverse weather could exacerbate the effect of traffic turbulence and hence the inclusion of these factors is vital in the context of active traffic management systems.

Although all previous studies used loop detectors data (which provide time mean speed, flow and lane occupancy) we showed in this study that traffic data collected from AVI and real-time weather data were found to provide good measure of crash risk in real-time.

Preliminary analysis on the data and findings discussed in earlier study (Ahmed et al., 2011) indicate that the crash risk during snow season is 82% higher than the crash risk in dry season and hence two models were considered in this study to examine the effect of the interaction between geometric features, weather and traffic data on crash occurrence. While all included geometric factors were significant in the dry and snow seasons, the coefficient estimates indicate that the crash likelihood could be doubled during the snow season because of the interaction between the snowy, icy, or slushy pavement conditions during snow season and the steep grades.

The hazard ratio for the very steep grades (grade (>6% to 8%) and (<-6% to -8%)) during snow season increased to 9.71 compared to 5.63 in the dry season. Same conclusion can be implied for the visibility, reduction of one unit in the visibility was found to increase the crash risk by 88% in the snow season compared to 79% in the dry season. The 10-min. precipitation prior the time of the crash was significant in only the snow season model; one unit increase in the precipitation increases the risk of the crash by 169%. The logarithms of the coefficient of variation in speed at the crash segment during 6-12 minutes prior to the time of the crash is found to be significant in the snow season while the 6-minute average speed at the crash segment 6-12 minutes prior to the crash time was found to be significant in the dry season.

The results from this study suggest that the inclusion of roadway and weather factors in real-time crash prediction models is essential; in particular with roadways that feature challenging roadway characteristics and adverse weather conditions. Also, different active traffic management strategies should be in place during these two distinctive seasons and more resources should be devoted during the snow season.

This study also depicts that traffic management authorities can benefit from the AVI and real-time weather data not only to ease congestion and enhance the operation but also to mitigate increased safety risk.

CHAPTER 6. CRASH PREDICITON USING DATA MINING TECHNIQUES

6.1 Introduction

Different Data Mining (DM) techniques have been used for real-time crash prediction using available roadway geometry, weather condition and AVI traffic data. DM can be defined as the process that extracts the information and knowledge from the massive, incomplete, noise, fuzzy and random data. The information and knowledge is implicit in these data, but is potentially useful. Data Mining (DM) techniques are known for their capabilities of generating accurate and robust prediction models; they can quickly reveal important data relationships that could remain hidden using other classical analytical tools. SAS Enterprise Miner 6.1 is used to implement the data mining process of Selecting, Exploring, Modifying, Modeling, and Assessing (SEMMA) the large amounts of roadway geometry, weather and AVI traffic data to uncover previously hidden patterns preceding a crash from those preceding non-crashes.

Different Data mining techniques such as Decision Trees, Artificial Neural Network, Memory Based Reasoning, Boosting, Bagging and Ensemble were built, in addition to classical logistic regression for comparison purposes. Real-time crash predication can be made of one or more DM models and also from ensembles. When several DM models have high performance, an ensemble of those models can result in better accuracy due to generalization. All data mining models were found to outperform the classical ones. Artificial Neural Network and decision trees were found to provide the best accuracy in terms of the area under the ROC curve, lift chart and misclassification error for both validation and test datasets. Moreover, using DM ensemble technique to combine the results from the best 3 models enhanced the prediction accuracy.

The following sections illustrate the procedures of preparing the data, modeling techniques, rational of modeling technique selection, evaluation for these different models and the conclusions.

6.2 Data Preparation

Crash data for three years 2007 through 2009 were assigned using GIS in order to later combine the corresponding AVI, and weather data. These different datasets were merged for further processing and analysis in SAS Enterprise Miner 6.1.

Many ways of cleansing, variable transformation, data imputation, random sampling, partitioning, and variable selection techniques were attempted with keeping tracking of the performance of the fitted models. Partitioning provides mutually exclusive data sets; two or more mutually exclusive data sets share no observations with each other. Partitioning is needed for DM models to have part of the data set for training in order to fit preliminary model and find the best model weights using this training data set, and since DM techniques have the capacity for overtraining, validation data set will be used to retreat to a simpler fit than to calibrate the model based only on the training dataset. Moreover, validation part of the original data set is used for DM models fine-tuning to assess the prediction accuracy of each model. Also, part of the data will be partitioned to provide test dataset that is used for final assessment of the model.

The data have been partitioned into 50% for training, 30% for validation and 20% for test using random sampling, in random sampling every observation in the data set has the same probability of being written to the sample. For example, the 50% of the population that is selected for the training data set, then each observation in the input data set has a 50% chance of being selected.

6.3 Imputation and Transformation

Since the percentages of the missing values are relatively low for the entire interval and class variables, the distributions would not be affected by the imputation process. In view of the fact that most of the traffic data have relatively skewed distributions, a statistic that is less sensitive to extreme values should be used for imputation. The values of missing interval variables were replaced by the median of the non-missing values which is preferred over the mean and midrange for the mentioned reason. The values of missing class variables were imputed using predicted values from a decision tree; in such for each class variable a decision tree is built using surrogate splitting rules with that variable as the target and the other input variables as predictors.

Once all missing values have been taken care of, the distribution and linearity of the interval variables were further examined to perform the required transformation to stabilize variance, remove nonlinearity, and counter non-normality. Transformations are known to be useful in DM applications to improve the fit of the models by adjusting the scale of the input variables and make them more informative than that on which they were originally collected.

6.4 Modeling

SAS Enterprise Miner 6.1 may be conveniently used to create, compare and ensemble multiple models. Modeling techniques include classical logistic regression and DM such as decision trees, artificial neural network, memory based reasoning, boosting, bagging and ensemble. The final DM process flow diagram from SAS EM is shown in Figure 42. The theoretical details of these tools may be found in any standard data mining text. The three trees were grown using different splitting criterion, namely, the chi-square test, entropy reduction and gini measure of impurity reduction while the neural network models were built using two architectures of the Normalized Radial Basis Function (NRBF) and Multilayer Perceptron (MLP). As explained in the literature that an MLP structure with one hidden layer and nonlinear activation functions for the hidden nodes can implement any function of practical interest. Other DM techniques were considered to evaluate their performance in comparison with ANN and decision trees such as the memory based reasoning and gradient boosting; memory based reasoning uses k-nearest neighbor algorithms to classify the binary target variable of crash/no-crash. The basic idea of the gradient boosting is to create a series of simple decision trees that together form a single predictive model. Each tree in the series is fit to the residual of the prediction from the earlier trees in the series. Each time the data is used to grow a tree, the accuracy of the tree is computed. The successive samples are adjusted to accommodate previously computed inaccuracies. The posterior probabilities from models with the highest accuracy and less misclassification rates were further combined to form ensemble model, ensemble models were found to enhance the classification accuracy.

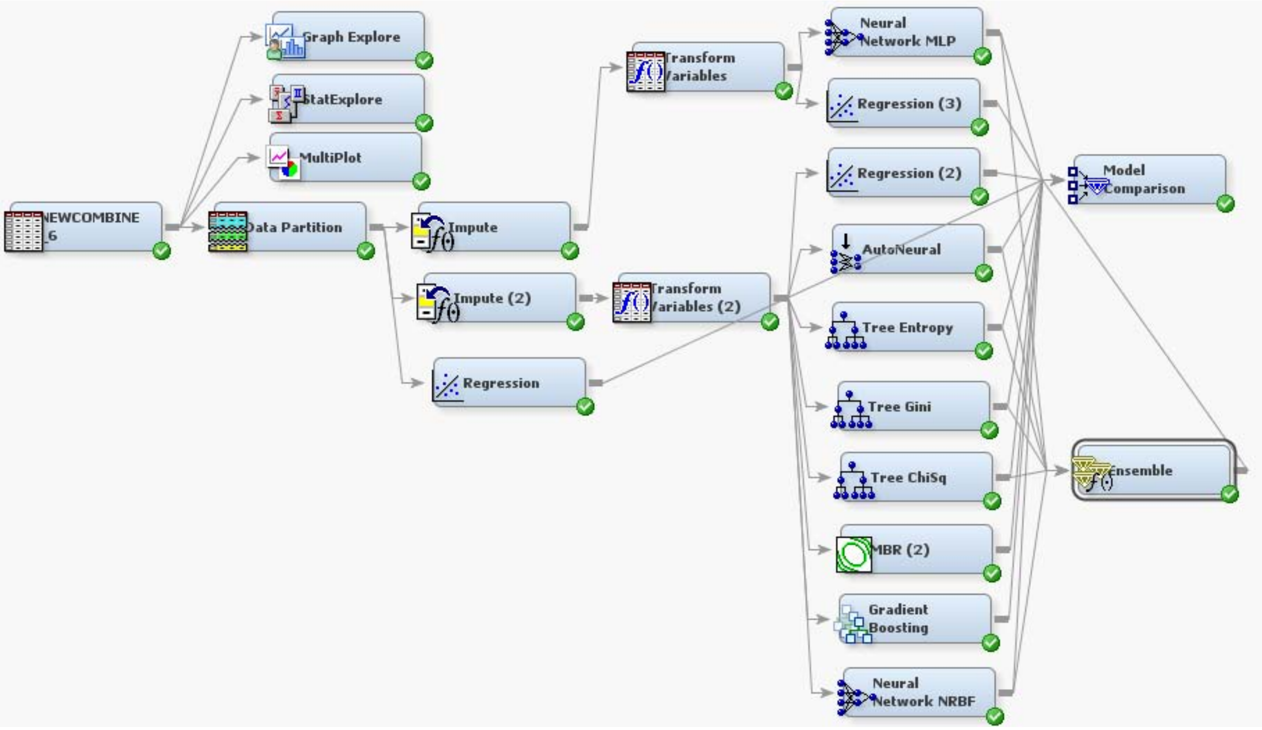


Figure 6-1: SAS Enterprise Miner Flow Chart

6.5 Models Comparison

Selection of the best model is subjective and depends on different criteria; misclassification rate and the area under the Receiver Operating Characteristics (ROC) were used as the main performance criteria in this analysis. The area under the ROC curve shows how well the model is at discriminating between the crash and non-crash cases in the target variable. This is similar to the misclassification rate, but the ROC curve calculates sensitivity and 1 – specificity values for many cutoff points. However the misclassification rate mentioned earlier has been calculated using the default cutoff point of 0.5. The area under the curve seems to be large for the best selected model in brown color (ensemble model) as shown in Figure 43. The exact area under the ROC curve found to be 0.936 and 0.950 for the validation and test datasets respectively.

Generally, all DM techniques outperformed the classical logistic regression models as shown in Table 6 and Figure 33. ROC curves are divided into 2 main groups; the classical logistic regression group that give area below 78% and the DM group that achieved area above 88% and hit 95% for the ensemble model. In terms of accuracy and misclassification rate, also DM techniques outperformed the classical logistic regression of achieving 90% accuracy vs. 77%. Ensemble was found to provide the highest accuracy and it is marginally performed better than the MLP neural network of misclassification rate of 11.4% and 10% for the validation and test datasets respectively.

Table 6-1: Misclassification Rate

Model	**Train:** **Misclassification**	**Validation:** **Misclassification Rate**	**Test:** **Misclassification**
Ensemble	0.086	0.114	0.100
Neural Network	0.037	0.152	0.116
Auto Neural	0.078	0.135	0.133
Neural Network	0.101	0.146	0.141
Decision Tree Gini	0.135	0.161	0.150
Decision Tree	0.136	0.165	0.158
Decision Tree Chi-	0.137	0.122	0.161
Gradient Boosting	0.172	0.237	0.208
MBR	0.204	0.161	0.225
Logistic	0.246	0.237	0.225
Logistic	0.253	0.254	0.25
Logistic	0.246	0.250	0.258

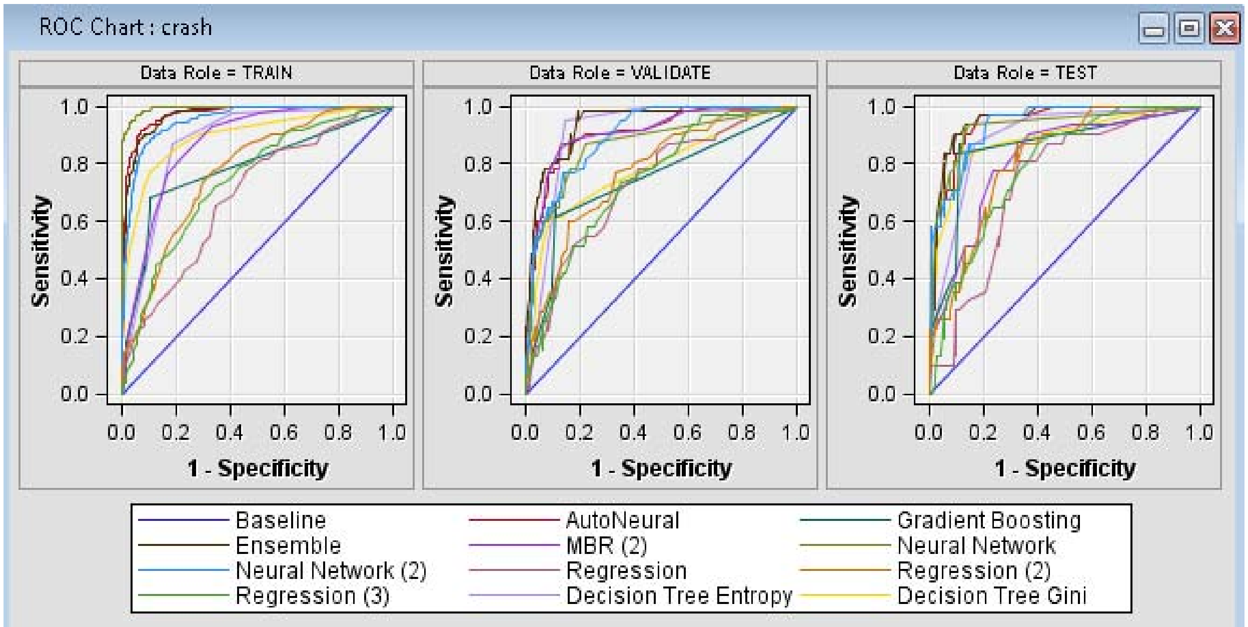


Figure 6-2: ROC Chart

6.6 Conclusion

An assessment of the interaction between the mountainous roadway geometry, weather condition and AVI traffic data on crash occurrence was conducted. Different Data Mining techniques were compared to the classical logistic to link a total of 301 crash occurrences on I-70 in Colorado with the real-time space mean speed collected from the Automatic Vehicle Identification (AVI) system, real-time weather and roadway geometry data. It was set up as a binary classification problem in which traffic, geometry, and weather variables are used as independent variable to identify crashes. It was found that DM techniques outperformed the classical logistic regression models in terms of the accuracy and the area under the ROC curve. Although DM results are not easy to interpret, they may be implemented in real-time traffic safety management for their high accuracy with conjunction of classical statistical models that have the capabilities of interpreting and explaining the different variables that are associated with increased hazardous on freeways.

CHAPTER 7. A DATA FUSION FRAMEWORK FOR REAL-TIME RISK ASSESSMENT ON FREEWAYS

7.1 Introduction

Accurate and reliable estimation of increased risk of crashes is critical to the success of proactive safety management strategies on freeways. In recent years, the advances in electronics have had a tremendous impact on enhancing and improving detection systems, new non-intrusive traffic detection devices are in use more these days because of their easiness of installation and maintenance in addition to their accuracy and affordable cost. Moreover, some freeways have multiple non-intrusive detection systems in place such as the Automatic Vehicle Identification (AVI) and Remote Traffic Microwave Sensors (RTMS). AVI is used mainly for toll collection and for travel time estimation purposes along freeways while RTMS are used mostly for operation and incident management. Research in the field of freeway traffic management has extensively utilized traffic data collected from inductive loop detectors in real-time proactive traffic management (Oh et al., 2001; Abdel-Aty et al., 2004; Abdel-Aty and Pande, 2005; Pande and Abdel-Aty, 2006a, 2006b; Hourdos et al., 2006). Recently, the usefulness of the collected traffic data from AVI has been investigated in real-time safety assessment (Ahmed and Abdel-Aty, 2011; Ahmed et al., 2011, 2012a, 2012b).

Traffic data from AVIs and RTMSs as well as weather data are collected on 15-mile of mountainous Interstate-70 in Colorado to provide roadway users with important information about travel time, congestion, adverse weather conditions and lane closure due to occasional avalanche danger, maintenance on the road and/or road crashes. This information is provided as a part of an Intelligent Transportation System (ITS) and is dynamically disseminated in real time to road users via Dynamic Message Signs (DMS). This system utilizes AVI to estimate the segment travel time by monitoring the successive passage times of vehicles equipped with electronic tags at designated locations. Main traffic flow parameters are collected using RTMS. It is worth mentioning that the AVIs and RTMSs are providing different measures of speeds; AVIs measure space-mean-speed (SMS), which is defined by Gerlough and Huber, 1975 as "the mean of the speeds of the vehicles traveling over a given length of road and weighted according to the time spent traveling that length", whereas RTMSs measure time-mean-speed (TMS) which is the arithmetic mean of the speed of vehicles passing a point during a given time interval. Hence, TMS only reflects the traffic condition at one specific point. On the other hand, SMS is the average speed of all the vehicles occupying a given stretch of the road over some specified time period (there are several definitions of SMS depending on how it is calculated (Hall, 1996); the definition in this research is the best to describe the AVI's SMS).

Weather condition is considered one of the most important factors that can contribute to crash occurrence. In previous studies weather data are always estimated from crash reports, in this study real-time weather data are gathered by weather stations located on the roadway section.

Although in previous chapters, it was found that classical statistical models provide interpretable models and acceptable accuracy of crash prediction using AVI and real-time weather data (Ahmed et al. 2011, 2012a); in this study a framework was proposed to augment even more traffic data from multiple sources, weather and geometry data using an advanced machine learning (ML) technique. Machine learning methods are known for their superior performance over the classical statistical ones. In order to enhance the accuracy and increase the reliability of the real-time crash prediction, Stochastic Gradient Boosting (SGB), a recent and promising machine learning technique is attempted to uncover previously hidden patterns preceding a crash relative to non-crash conditions from the large amounts of roadway geometry, weather and AVI and RTMS traffic data.

An overall framework was developed to combine all models in one fused system of real-time risk assessment. The following sections illustrate the procedures of preparing the data, modeling technique, interpretation and evaluation, risk assessment framework and the conclusions.

7.2 Data Description and Preparation

There were five sets of data used in this study; roadway geometry data, crash data, and the corresponding AVI, RTMS and weather data. The crash data were obtained from CDOT for a 15-mile segment on I-70 for 13 months (from October 2010 to October 2011). Traffic data consists of space mean speed captured by 12 and 15 AVI detectors located on each east and west bounds, respectively along I-70. Volume, occupancy and time mean speed are collected by 15 RTMSs on each direction. AVI estimates SMS every 2-minute while RTMS provides traffic flow parameters every 30-second. Weather data were recorded by three automated weather stations along the roadway section for the same time period. The roadway data were extracted from Roadway Characteristics Inventory (RCI) and Single Line Diagrams (SLD).

In a previous study (Ahmed and Abdel-Aty, 2011), it was found that crash occurrence was mostly related to the AVI crash segment, one segment in the upstream and another segment in the downstream directions and therefore these AVI segments and their respective RTMS stations were considered in the data extraction process and modeling parts. The crashes have been assigned to the AVI segment and to the closest RTMS station; upstream and downstream AVI segments as well as 3 RTMSs in the upstream and downstream were identified to extract their corresponding traffic data. The upstream, crash, and downstream segments were named U, C and D, respectively while the upstream and downstream RTMSs were named US and DS respectively and assigned numbers in order from the closest to the farthest ones. It is worth mentioning also that most of the RTMSs are located exactly at the same location of the AVIs' tag readers. The arrangement of RTMS and AVI segments and their spacing are illustrated in Figure 7-1.

AVI and RTMS data corresponding to each crash case were extracted in the following process; the location and time of occurrence for each of the 186 crashes were identified. Traffic data were aggregated to 6-minute level to obtain averages, standard deviations, and logarithm of coefficient of variations (standard deviation divided by the average of the traffic parameters) of 2-minute space mean speed obtained from AVIs and 30-second time mean speed, volume, and occupancy raw data obtained from RTMSs. The 6-minute aggregation level was chosen to have consistent time periods between AVIs and RTMSs.

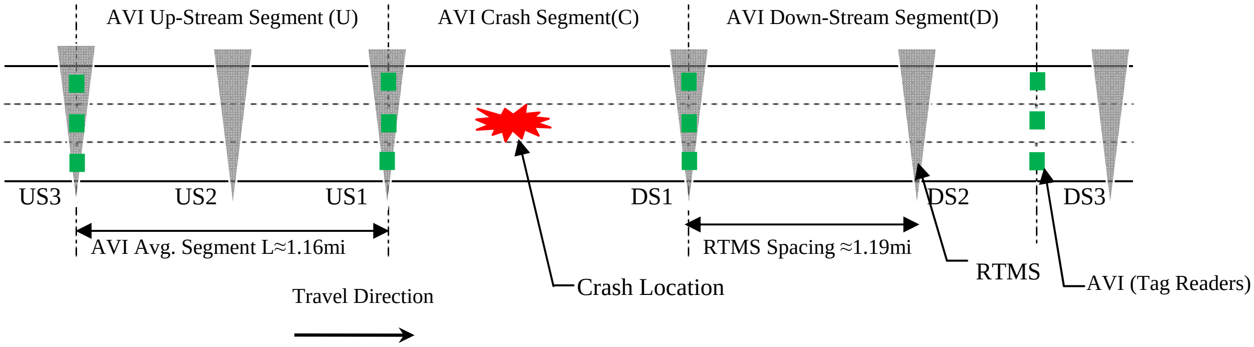


Figure 7-1: Arrangement of RTMS and AVI Segments

Three time slices of the 6-minutes prior to the crash time were extracted. For example if a crash happened on Sep 16, 2010 (Sunday) at 14:00, at the milepost of 210.1 EB. The corresponding 18-min window for this crash of time intervals (13:42 to 14:00) recorded by AVI segment 6 (Mile marker starts at 209.79 and ends at 210.60), upstream AVI segment 5 and downstream AVI segment 7 as well as 3 RTMSs in the upstream and 3 in the downstream were extracted. Time slice 1 was discarded in the analysis since it would not provide enough time for successful intervention to reduce crash risk in a proactive safety management strategy.

Moreover, the actual crash time might not precisely be known. Golob and Recker, 2004 discarded the 2.5 minutes of traffic data immediately preceding each reported crash time to avoid uncertainty of the actual crash time. In general with the proliferation of mobile phones and CCTV cameras on Freeways, crash time is almost usually immediately identified. One-hour speed profiles were also generated (about 30 minutes before and 30 minutes after the crash time) to verify the reported crash time. The modeling procedure required non-crash data, a random selection from the whole remaining AVI and RTMS datasets where there was no crash within 2-hour before the extraction time was utilized in the study to represent the whole population of different traffic patterns, weather conditions and roadway characteristics. A total of 18 (3 parameters x 3 AVI segments x 2 time slices) and 108 (9 parameters x 6 RTMSs x 2 time slices) input variables are prepared from AVI and RTMS raw data respectively.

Similarly, weather data for crash cases and non-crash ceases were extracted. Automated weather stations monitor the weather conditions continuously and the weather parameters are recorded according to a specific change in the reading threshold and hence they do not follow a specific time pattern. The stations report frequent readings as the weather conditions change within short time; if the weather conditions remain the same the station would not update the readings. However, these readings were aggregated over certain time periods to represent the weather conditions. For example; precipitation described by rainfall amount or snowfall liquid equivalent for ten minutes, one hour, three hours, six hours, twelve hours and twenty-four hours and the estimated average hourly visibility which provides an hourly measure of the clear distance in miles that drivers can see. Visibility in general can be described as the maximum distance (in mile) that an object can be clearly perceived against the background sky, visibility impairment can be the result of both natural (e.g., fog, mist, haze, snow, rain, windblown dust, etc.) and human induced activities (transportation, agricultural activities, and fuel combustion). The automated weather stations do not directly measure the visibility but rather calculate it from a measurement of light extinction which includes the scattering and absorption of light by particles and gases.

The basic parameters that define the geometrical characteristics of the roadway section for each crash and non-crash cases were considered in this study, these parameters include longitudinal grade, curve radius, deflection angle, degree of curvature, number of lanes, and width of median.

Multiple Stochastic Gradient Boosting models were calibrated for each dataset separately as well as for fused data from all sources. Each of these data were partitioned into 70% for training, 30% for validation using random sampling, in random sampling every observation in the data set has the same probability of being written to the sample. For example, the 70% of the population that is selected for the training data set, then each observation in the input data set has a 70% chance of being selected. Partitioning provides mutually exclusive datasets; two mutually exclusive datasets share no observations with each other. Partitioning is needed for machine learning (ML) models to have part of the data set for training in order to fit a preliminary model and find the best model weights using this training data set, and since ML techniques have the capacity for overtraining, validation data set will be used to retreat to a simpler fit than to calibrate the model based only on the training dataset. Validation part of the original data set is used for ML models fine-tuning to assess the prediction accuracy of each model. A total number of 186 crashes and 744 non-crashes were finally considered in the analysis.

Exploratory analysis and comparison of RTMS and AVI speed data reveals that they are highly comparable in recording the speed trends in normal traffic condition, crash with property damage only and more hazardous conditions involving injury and fatality. The data collected from each system could strengthen one another's credibility when traffic data are missing. RTMS system provides more detailed information in respect of speed. Lane by lane information is provided by

RTMS while AVI in its current archiving system provides lane aggregated speed data. On the other hand, AVI system is more sensitive to higher speed variation, which has been attributed as a factor to the occurrence of crash. The examination of two systems suggests that combining them together in the modeling process might help with more accurate crash prediction.

7.3 Stochastic Gradient Boosting

The Stochastic Gradient Boosting (SGB) is a machine learning technique that was introduced by (Friedman, 2001). This technique which is also known under other names such as Multiple Additive Regression Trees (MART), and TreeNet is technically suitable to be used for all data mining problems including regression, logistic regression, multinomial classification and survival models. The general idea of boosting is to create a series of simple learners known as “weak” or basic learners, i.e. a classifier that has a slightly lower error rate than random guessing. Most of the boosting algorithms use binary trees with only two terminal nodes as the basic learner (Hastie et al., 2001). Boosting these simple trees forms a single predictive model. The gradient boosting trees method has been proposed as a recent advancement in data mining that combines the advantages of the non-parametric tree-based methods and the strengths of boosting algorithms. It showed outstanding prediction performance in different fields including; real-time credit card fraud detection and terrorism culpability. The fraud detection application has some similarity to real-time crash prediction; with thousands of credit, debit and online transactions taking place every minute; the probability of a fraud transaction is very small and the variables space is relatively high, the mechanism that is deployed to monitor all transactions in real-time may be adopted in traffic safety applications.

Some of the key features of Stochastic Gradient Boosting are its ability of handling large number of mixed predictors (quantitative and qualitative) without preprocessing of rescaling or transformation which allows real-time traffic and weather data to be directly fed into the SGB algorithms without any time consuming processes. Moreover, by using CART as the basic learner, SGB can automatically handle the missing values which can still yield an accurate prediction in case of missing one of the important variables with no need to consider prior data imputation (Breiman et al, 1983). SGB has the capability of resisting the outliers in predictors and it can perform well with partially inaccurate data, therefore any erroneous traffic data can be handled easily without cleaning. Additional advantage of tree-based models is the robustness of variable selection; tree models have the capability of excluding irrelevant input variables. The main disadvantage however of single tree models is instability and poor predictive performance especially for larger trees which can be mitigated by other techniques that can improve model accuracy such as boosting, bagging, stacking, model averaging and ensemble which merges results from multiple models. Stochastic gradient boosting is uniquely advantageous over other merging techniques because it follows sequential forward stagewise procedure. The process of boosting is an optimization technique to minimize a loss function by adding a new simple learner (tree) at each step that best reduces the loss function, first tree is selected by the algorithm that maximally reduces the loss function. The residuals are the main focus for each following step by performing weighted resampling to boost the accuracy of the model by giving more attention to observations that are more difficult to classify. As the model enlarges, the existing trees are left unchanged; however, fitted value for each observation is to be re-estimated at each new added tree. The sampling weight is adjusted at the end of each iteration for each observation with respect to the accuracy of the model result. Observations with correct classification receive a lower sampling weight while incorrectly classified observations receive a higher weight. In the next iteration, a sample with more misclassified observations would be drawn.

SGB was used for classification in which, traffic, weather, and geometry variables are used as independent variables x to identify the binary crash $\mathrm{y} \in \{-1,1\}$, by using a “training” sample $\{\mathrm{y_i}, \mathrm{x_i}\}_1^{\mathrm{N}}$ of known (y, x) values. The goal of estimating the function that maps the traffic, weather and geometry features to crashes is to be used for prediction of the increased risk for future observations, where only x is known. As explained in Friedman (2001) we need to obtain an approximation $F(x)$ of the function $F^*(x)$ linking x to y, that minimize the expected value of a loss function $\Theta(y, F(x))$ over the joint distribution of all (y, x) values

$$F^*(x) = \arg\ \min_{F(x)} E_{y,x}\Theta(y, F(x)) \qquad (7.1)$$

As mentioned earlier, the boosting idea is to build an additive model on a set of basic functions (weak classifier). In case of using a single tree as the individual classifier, the boosted tree model will be a sum of many simple trees:

$$f_T(x) = \sum_{m=1}^{M} T_m(x;\ \gamma_m, R_m) \qquad (7.2)$$

where

$$T_m(x;\ \gamma_m, R_m) = \sum_{i}^{I_m} \gamma_{mi} I(x \in R_{mi}) \qquad (7.3)$$

where $R_{mi}, i = 1,2, \dots, I_m$ are disjoint regions that collectively cover the space of all joint values of X. γ_{mi} is a constant that is assigned to each such region. $R_{mi}$is the i^{th} terminal node in tree m with fitted value of γ_{mi}. Ideally, γ_{mi} and $R_{mi}$are fitted by minimizing a loss function;

$$\min_{\{\gamma_m\ R_m\}_1^M} \sum_{j-1}^{N} \Theta\ (y_j, \sum_{m=1}^{M} T_m\big(x_j;\ \gamma_m, R_m\big)) \tag{7.4}$$

Commonly used loss function for classification is given by;

$$\Theta\big(y, \hat{F}\big) = 2\text{log (1+ exp (-2}y\hat{F}\text{))} \tag{7.5}$$

Where,

$$F(x) = \frac{1}{2}\ \log\ \left[\frac{\Pr\ (Y=1|x)}{\Pr(Y=-1|x)}\right] \tag{7.6}$$

The solution can be approximated by iteratively adding a single tree at each step without adjusting the parameters of the existing trees as mentioned earlier. Therefore, by adding tree k+1, the following equation can be minimized

$$\sum_{j=1}^{N} \Theta\ (y_j, \sum_{m=1}^{K} T_m\big(x_j;\ \gamma_m, R_m\big) + T_{k+1}(x_j; \gamma_{k+1}, R_{k+1})) \tag{7.7}$$

as a function of γ_{k+1} and R_{k+1}, holding γ_1,…, γ_k and R_1,…, R_k fixed. After M iterations (7.7) will achieve (7.4).

7.4 Results and Discussion

7.4.1 Model Estimation, Interpretation and Diagnostics

This section explains how the calibration, interpretation and evaluation processes were performed.

In this study, Stochastic Gradient Boosting models were fitted in SAS Enterprise Miner 6.1. The SGB was iterated 50 times with different random samples in the validation dataset to stabilize the error rate. The optimization parameters were set at SAS default values; shrinkage (learn rate) =0.1, train proportion (different training observations are taken in each iteration) =60, maximum branch=2 (binary tree), and the maximum depth (number of generation) =2.

In machine learning applications, the data may include easily hundreds of variables; a key question therefore whether or not all these variables actually lead to true information gain? The answer is obviously, no, since there are a lot of redundant variables that may increase the performance of the learning data set but they do not necessarily increase the performance on the actual validation dataset which can be easily controlled for by keeping an eye on the over-fitting. Many data mining techniques such as neural networks, near-neighbor, kernel methods, and support vector machines perform worse when extra irrelevant predictors are added, and therefore variable selection technique should always precede the modeling. On the other hand tree-based models are highly resistant to the inclusion of irrelevant variables; tree-based models perform automatic variable subset selection.

One of the main advantages of tree-based models is their simple interpretability. Single tree model can be graphically illustrated by two-dimensional figure that is easily interpreted. On the other hand, boosted trees are formed of linear combination of many trees (hundreds and in some cases thousands of trees), and therefore forfeit this important feature. The main two components of interpretation are identifying the variables importance and understanding their effect on the classification problem which is provided in all conventional regression models.

Fortunately, unlike other black-box machine learning techniques, SGB can be summarized and interpreted. Relative importance of predictor variables can be conveniently calculated, the variable importance is based on the number of times a variable is selected for splitting rule and weighted by the squared improvement to the model as a result of each split, and averaged over all trees as explained in Friedman and Meulman (2003). Table 7-3 provides the selected variable subsets and their relative importance for each of the calibrated models. The input variables characterized by a relative importance smaller than 25% have been discarded in the SGB models.

Stochastic Gradient Boosting models were estimated for four different datasets; Model-1 was calibrated using all available data collected from AVI, RTMS and weather stations as well as geometrical characteristics for crash/non-crash cases. In order to examine the prediction accuracy that can be achieved depending only on one dataset at a time and to account for any interruption of the data flow from any source, another three models were calibrated; Model-2 based only on RTMS data, Model-3 based only on AVI data, and Model-4 based on real-time weather data.

It may be observed from Model-1 results that the most important variables are traffic data collected from RTMS such as Average occupancies from US2 and US3 sensors during time slice two and three respectively (time slice 2: 6-12 minutes before the crash and time slice 3: 12-18 minutes before the crash), followed by logarithm of the coefficient of variation of speed from AVI crash segment at time slice 2 and average speed from AVI downstream segment at time slice 2, other RTMS and AVI variables were selected but with less relative importance. Weather related variables are relatively important; 1-hour visibility is shown at the top of the list just after some traffic variables. The ten-min precipitation variable was also selected among the important variables. Other site-related variables came out to be important including longitudinal grade, number of lanes, absolute degree of curvature and width of median.

Comparison between models performance is subjective and depends on different criteria; misclassification rate and the area under the Receiver Operating Characteristics (ROC) were used as the main performance criteria in this analysis. The area under the ROC curve shows how well the model is discriminating between the crash and non-crash cases in the target variable. This is similar to the misclassification rate, but the ROC curve plots sensitivity vs. 1 – specificity values for many cutoff points. The area under the curve seems to be large for the best selected model in red color (model) as shown in Figure 7-7. The exact areas under the ROC curves for all models validation datasets are listed in Table 7-4.

Table 7-1: Variable Importance

Model-1		Model-2		Model-3		Model-4	
Variables	**Variable Importance**	**Variables**	**Variable Importance**	**Variables**	**Variable Importance**	**Variables**	**Variable Importance**
Avg. Occ. Upstream1_Time Slice _2	1.000	Avg. Occ. Upstream 2_Time slice_3	1.000	Log. Coef. of Var. of Speed Crash Segment Time Slice_2	1.000	1-Hour Visibility	1.000
Avg. Occ. Upstream 2_Time slice_3	0.887	Log. Coef. of Var. of Speed Upstream 1_Time Slice_2	0.997	Avg. Speed Downstream Segment Time Slice_2	0.899	10-Minute Precipitation	0.459
Log. Coef. of Var. of Speed Crash Segment Time Slice_2	0.798	Avg. Speed Upstream 2_Time Slice_2	0.804	Avg. Speed Downstream Segment Time Slice_3	0.741	1-Hour Precipitation	0.324
Avg. Speed Downstream Segment Time Slice_2	0.742	S.D. Occ. Upstream 2_Time Slice 2	0.541	Avg. Speed upstream Segment Time Slice_2	0.537		
1-Hour Visibility	0.684	Avg. Speed Downstream 1_Time Slice_2	0.457				
Grade	0.661	Avg. Speed Downstream 2_Time Slice_2	0.391				
S.D. Occ. Upstream 3_Time Slice 2	0.642	Avg. Occ. Upstream1_Time Slice _2	0.374				
No. of Lanes	0.521	Avg. Occ. Upstream2_Time Slice _2	0.348				
Avg. Speed Upstream 1_Time Slice_2	0.519	Log. Coef. of Var. of Volume Downstream 2_Time Slice_2	0.249				
Avg. Speed Downstream Segment, Time Slice_3	0.431						
Abs. Deg. of Curve	0.337						
10-Minute Precipitation	0.335						
Log. Coef. of Var. of Volume Downstream 2_Time Slice 3	0.334						
Log. Coef. of Var. of Speed Upstream Segment_Time Slice 3	0.329						
Med. Width	0.278						

Generally, Model-1 is consistently superior in term of classification accuracy and area under the ROC curve. Model-2 and Model-3 are relatively ranked lower than Model-1 but still providing satisfactory performance. Model-4 is ranked the lowest on these measures. Area under the ROC curves as shown in Figure 7-7 and listed in Table 7-4 was found to be 0.946 for Model-1 validation dataset, 0.762 and 0.721 for Model-2 and Model-3, respectively while Model-4 achieved only ROC of 0.675 all for the validation datasets.

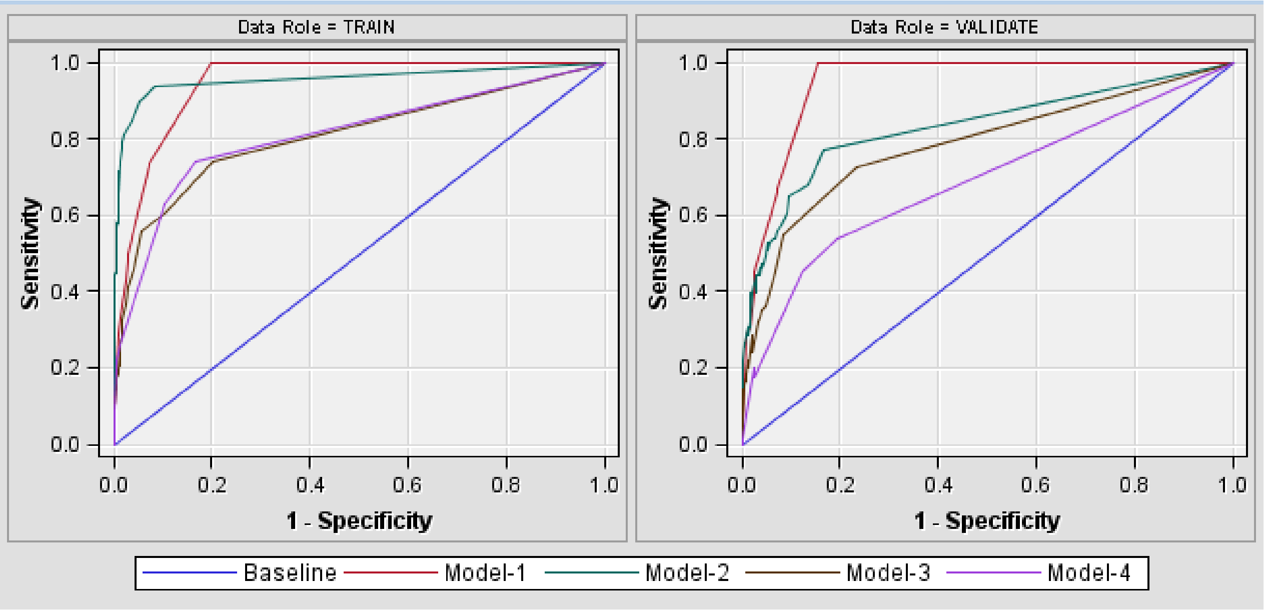


Figure 7-2: Receiver Operating Characteristics Chart

Unlike previous studies that only reported accuracy and misclassification rate at one cutoff value, in this study the accuracy and misclassification rates are graphically illustrated for many cutoff values as shown in Figures 7-8 to 7-11. In terms of accuracy and misclassification rate, also Model-1 outperformed all other individual models in all classification measures. Sensitivity analysis is important for the implementation of the proposed system in real-life application; while the overall classification rate can provide some insight of the model performance, sensitivity which is defined as the proportion of crashes (event cases) that are correctly identified as crashes (known also as true positive rate) is usually the most important measure of accuracy. Other measure that may affect drivers' compliance to the management system and should be kept as minimum as possible is the proportion that is incorrectly classified as crashes (false positive rate). As shown in Figures 7-8 to 7-11 that different false positive rates can be obtained by changing the cutoff value. In order to fairly compare across the four calibrated models, cutoff values have been chosen that achieve the highest possible sensitivity while preserving false positive rates at low values ranging between 5 to 8 percent, specificity (the proportion of correctly identified non-crashes) and overall classification. As illustrated in Figures 7-8 to 7-11 and summarized in Table 7-4 for the chosen cutoff values, Model-1 identified about 89% of crashes correctly while only about 6.5% of non-crash cases were incorrectly identified as crashes; Model-1 also achieved the highest overall accuracy of about 92%. Model-2 and Model-3 ranked the second in term of overall accuracy with Model-2 performed slightly better than Model-3 to the respect of true positive rate and area under ROC curve as mentioned earlier. Model-4 achieved the lowest overall accuracy and true positive rate in the same range of false positive rate defined above.

Table 7-2: Validation: Classification Rates and ROC Index

Model	Model Description	Overall Classification Rate	True Positive Rate	False Positive Rate	True Negative Rate	ROC Index
Model-1	All Data	92.157%	88.889%	6.481%	93.519%	0.946
Model-2	RTMS	87.879%	73.333%	7.154%	92.845%	0.762
Model-3	AVI	87.653%	70.192%	6.393%	93.607%	0.721
Model-4	Weather	84.364%	55.714%	5.854%	94.146%	0.675

Although Model-4 (weather only based model) performed not as good as the other 3 models, inclusion of weather information is essential in risk assessment framework; drivers need to have localized real-time information especially during adverse weather, including pavement conditions, visibility level, lane closure, snow, heavy rain and fog. The weather information would be more relevant if provided at segment level rather than regional level. According to the Federal Highway Administration (Goodwin, 2002), weather contributed to over 22% of the total crashes in 2001. This means that adverse weather can easily increase the likelihood of crash occurrences. Several studies, in fact, concluded that crashes increase during rainfall by 100% or more (Brodsky and Hakkert, 1988; NTSB, 1980), while others founnd more moderate (but still statistically significant) increases (Andreescu and Frost, 1998; Andrey and Olley, 1990). Model-4 may provide an adequate measure of risk in scenarios where weather information is only available and may help toward more weather responsive traffic management.

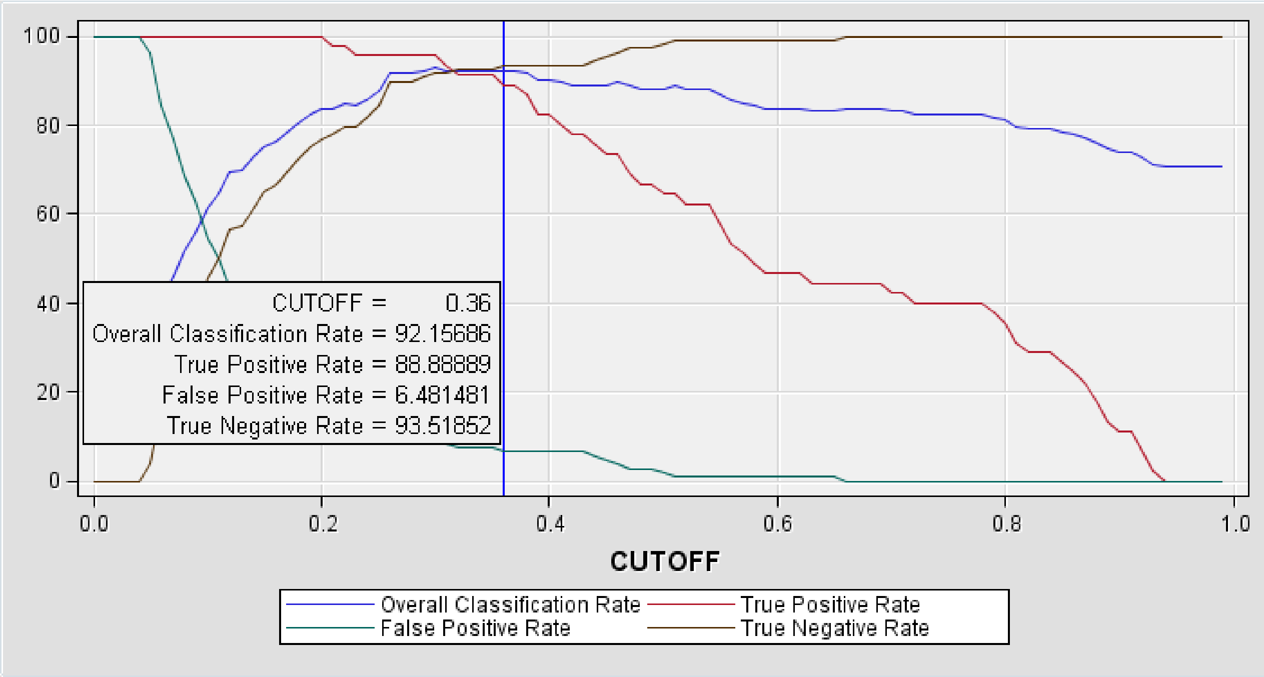


Figure 7-3: Model-1 Classification Rates

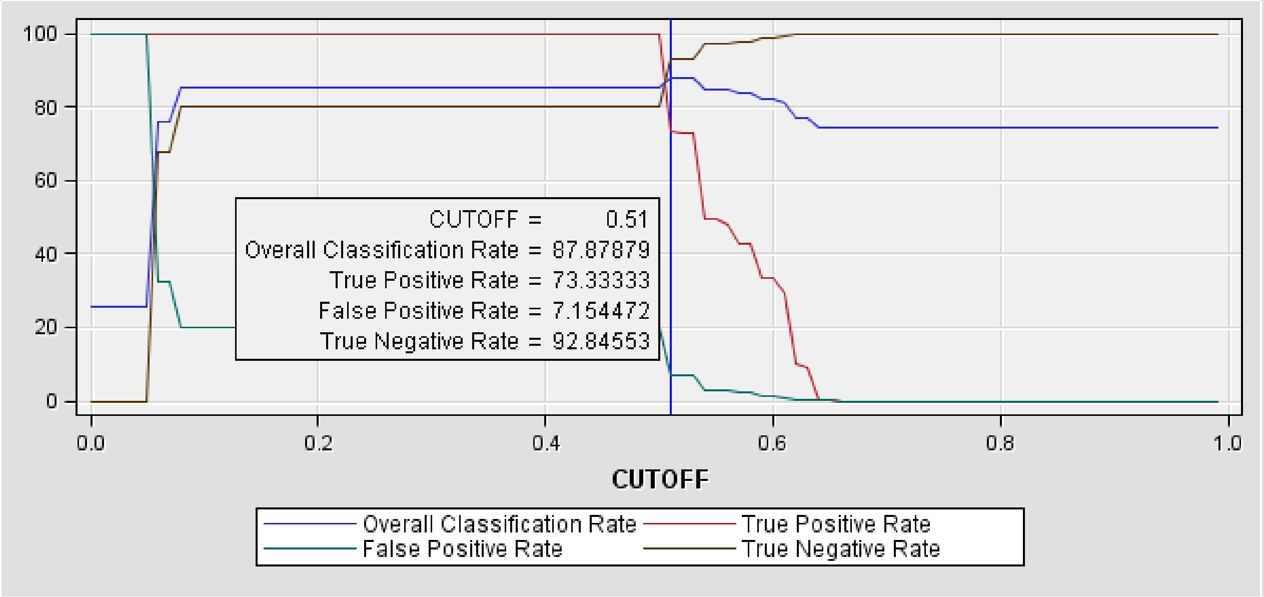


Figure 7-4: Model-2 Classification Rates

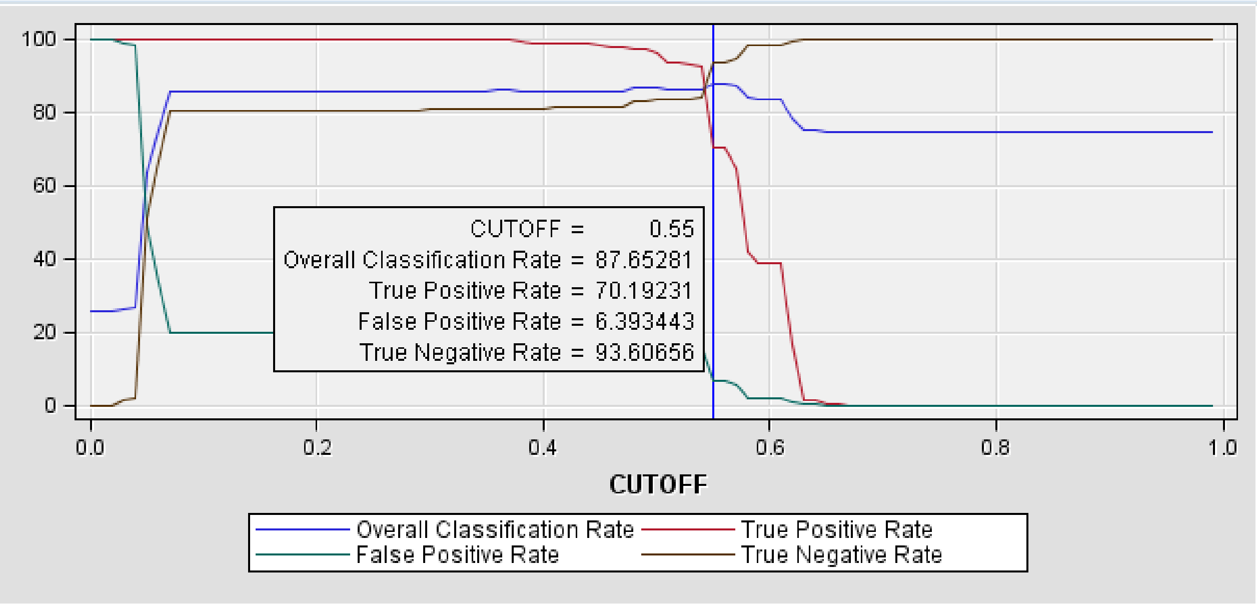


Figure 7-5: Model-3 Classification Rates

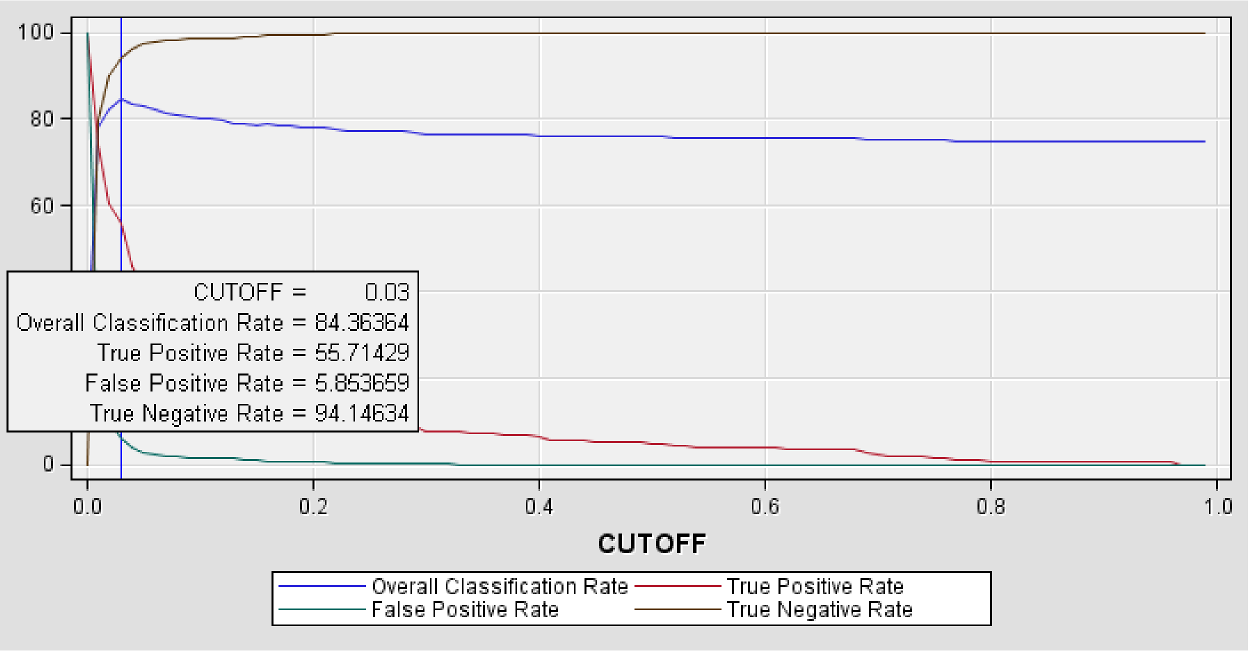


Figure 7-6: Model-4 Classification Rates

7.5 Risk Assessment Framework

The collected data on the study roadway section is one of the greatest assets that should be utilized appropriately to maximize the benefit for the roadway authority as well as for the road users. Buried within this vast amount of data is useful information that could make significant difference in how these roads are managed and operated. Figure 7-12 illustrates a framework to assess the increased real-time risk depending on the availability of on-line data. The idea behind the proposed framework based on the fact that although the traffic detection and meteorological stations became advanced enough to overcome hardware failures and malfunctions, the challenging weather conditions may interrupt the flow of the data in real-time at some point. Therefore, a reliable and robust framework should be in place at all times. Moreover, another issue that was discussed but not explicitly addressed in previous studies is how different the prediction accuracy of traffic data that are collected from different sources at the same location in identifying hot spots on freeway sections in real-time.

There are 4 main models calibrated in the proposed framework; Model-1 based on all available data collected from AVI, RTMS, weather stations and roadway geometry, Model-2 based only on RTMS data, Model-3 based only on AVI data, and Model-4 based on real-time weather data. As shown in the flowchart in Figure 7-12, in case of the availability of all traffic and weather data at the same time, these data would be fused together to provide the most comprehensive data and then Model-1 can be calibrated. If a hazardous traffic condition is detected, this section would be flagged, otherwise, the section would be operated under normal condition. The other 3 models are calibrated for each data separately to examine how each model performs and to substitute the full model in case of absence of other data as mentioned earlier. Based on Model-2, a roadway section can be flagged if unsafe traffic condition was encountered otherwise Model-4 needs to be checked. If a critical visibility or adverse weather encountered from Model-4 then an advisory/warning messages have to be issued to inform drivers about the situation. It should be noted that some specific traffic regimes would not be affected by inclined weather; however, drivers may still need some advisory messages to help them in selecting the safe operating speed. In case that the real-time weather is not available, advisory messages can be issued depending on the forecasted weather. The same logic can be followed by Model-2 using data collected from AVI.

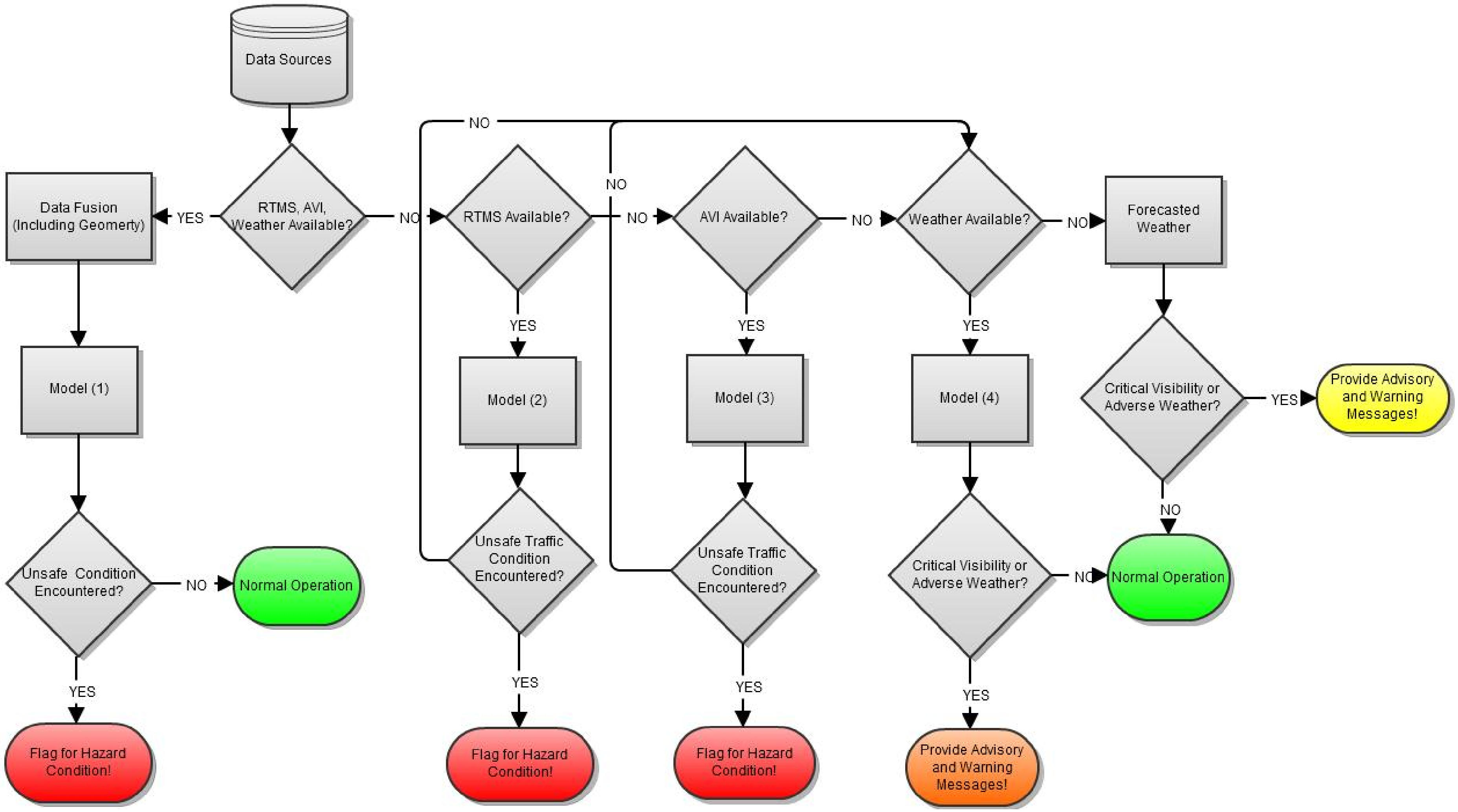

Data Sources
RTMS, AVI, Weather Available?
YES
Data Fusion (Including Geomerty)
Model (1)
Unsafe Condition Encountered?
NO
Normal Operation
YES
Flag for Hazard Condition!
NO
RTMS Available?
YES
Model (2)
Unsafe Traffic Condition Encountered?
YES
Flag for Hazard Condition!
NO
NO
AVI Available?
YES
Model (3)
Unsafe Traffic Condition Encountered?
YES
Flag for Hazard Condition!
NO
NO
Weather Available?
YES
Model (4)
Critical Visibility or Adverse Weather?
YES
Provide Advisory and Warning Messages!
NO
Normal Operation
NO
Forecasted Weather
Critical Visibility or Adverse Weather?
YES
Provide Advisory and Warning Messages!
NO

Figure 7-7: Framework of the Real-Time Risk Assessment

7.6 Conclusion

The recent advances in data collection technologies for traffic and weather on freeway sections provided valuable asset that should be utilized properly to increase safety and mobility and maximize the benefit for highway authorities as well as for road users. These valuable data can be utilized to provide a framework for real-time risk assessment on freeways and expressways.

By fusing data from two different detection systems (AVI and RTMS), real-time weather and geometrical characteristics, the database created in this analysis are by far the most comprehensive database created for a real-time crash prediction study.

In this chapter, a relatively recent machine learning technique known under different names such as Stochastic Gradient Boosting (SGB), Multiple Additive Regression Trees (MART), and TreeNet was used to analyze 186 crashes that had occurred on a 15-mile mountainous freeway section (I-70) in Colorado. The analyses were set up as a binary classification problem in which traffic, geometry, and weather variables are used as independent variables to identify crashes in real-time. The proposed learning machine methodology seems to provide all advantages that are needed in a real-time risk assessment framework. The Stochastic Gradient Boosting inherited all key strengths from tree-based models for their ability in selecting relevant predictors, fitting appropriate functions, accommodating missing values without the need for any prior transformation of predictor variables or elimination of outliers while overcoming the unstable prediction accuracy of single tree models. Boosting is considered unique among other popular aggregation methods; while ensemble, bootstrap or bagging, bagged trees and random forest can improve single tree model's performance. Bagged trees and random forest can reduce variance more than single trees, however unlike boosting; they cannot achieve any bias reduction (Prasad et al., 2006).

The proposed methodology has brought considerable advantage over classical statistical approaches. In particular, it has provided outstanding performance. On the other hand, machine learning techniques are being argued against for being black boxes; there are no *P* values to indicate the relative significance of model coefficients and there is no simple model with fewer variables. The proposed methods of interpretation (variable importance) and evaluation (ROC and classification) can be regarded as functional equivalence to many conventional regression techniques, thus addressing the criticisms against machine learning techniques.

Another issue that has been explicitly addressed in this study is how different the prediction accuracy of traffic data that are collected from different sources at the same location in identifying hot spots on freeway sections in real-time; the results showed that crash prediction from AVI is comparably equivalent to RTMS data. Moreover, the accuracy of the main model that is augmenting information from multiple traffic detectors (AVI and RTMS), weather, and geometry performed the best in terms of classification rate and area under the ROC curve. The overall model (Model-1) identified about 89% of crash cases in the validation dataset with only 6.5% false positive.

This study proposed a framework for real-time risk assessment using data from multiple sources that can achieve reliable and robust prediction performance under different scenarios of data availability. The results depict that traffic management authorities as well as road users can benefit from the wealth of collected data from multiple sources not only to alleviate traffic congestion but also to mitigate increased safety risk.

CHAPTER 8. DEVELOPMENT OF A SYSTEM DESIGN DOCUMENT

As discussed in previous chapters of this report that the accuracy and reliability to estimate the increased risk of crashes is critical to the success of proactive safety management strategies on freeways, there is a need of a robust system to collect, validate, and archive traffic and weather data and then feed these data into the developed algorithms. Depending on the results from these algorithms, different dynamic messages and variable speed limits can be displayed to motorists. The roadway section studied in this report is equipped with multiple detection systems (Automatic Vehicle Identification and Remote Traffic Microwave Sensors) and weather stations. Although AVIs and RTMSs are providing different measures of speeds; AVI data as well as RTMS data were proven to be promising in providing a good measure of crash risk in real time. Moreover, by fusing all these data together, superior crash prediction can be achieved as illustrated in the previous chapter.

It is worth mentioning that the structure of the non-intrusive detection systems and the availability of a monthly based data on this section enabled the UCF team to investigate the differences between data collected form AVI and RTMS as explained in Chapter 3. The location of AVI and RTMS, data availability, quality of data (in terms of erroneous readings and/or missing data) were checked on a monthly basis to ensure that all needed parameters are collected and archived appropriately.

Figure 8-1 shows the system design capturing data collected from all infrastructure and database design items. The collected RTMS data would be aggregated into 5-min level (RTMSs report traffic data every 30-sec) to calculate averages, standard deviations and coefficient of variations of speeds, volumes, occupancy at each station, data collected from AVI would be aggregated into 6-min level (AVIs report traffic data every 2-min) to obtain averages, standard deviations and coefficient of variations of speeds for each AVI segment. Weather information would be prepared in similar way including all important variables of precipitation, visibility, etc. These data will be fed continuously into the developed safety risk algorithms to compute the hazard ratios at each location. This would be the basic step in developing a variable speed limit algorithm in the future. Utilizing micro-simulation, different scenarios of VSL can be attempted to examine their impact on the measure of crash risk.

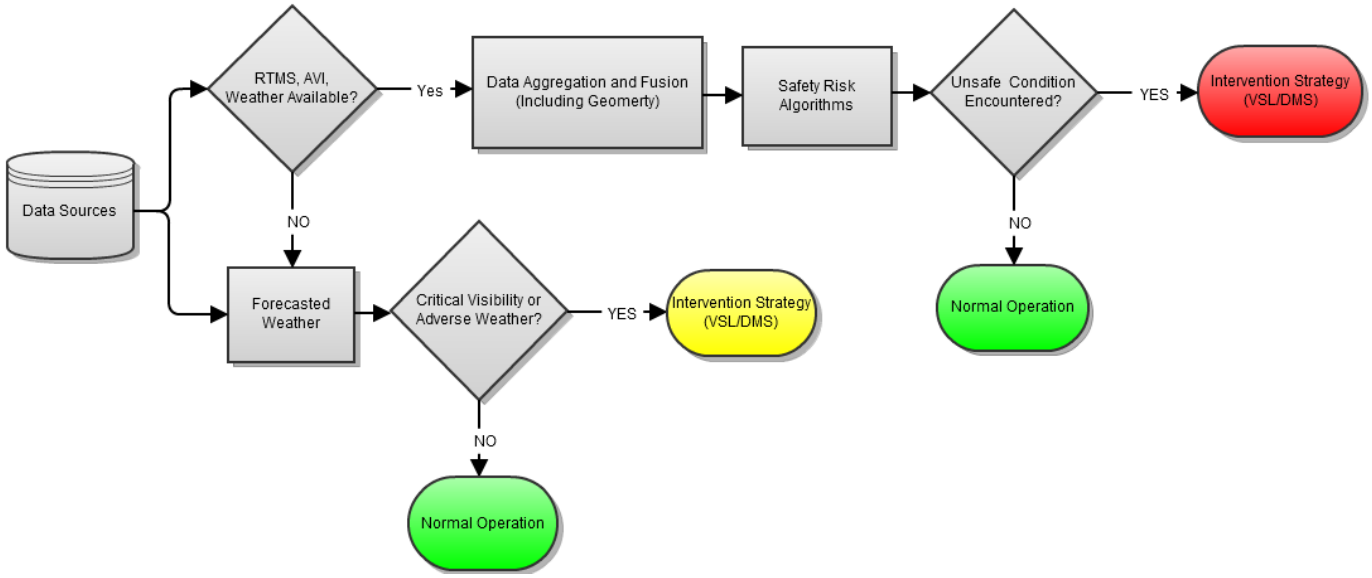

Data Sources
RTMS, AVI, Weather Available?
Yes
Data Aggregation and Fusion (Including Geomerty)
Safety Risk Algorithms
Unsafe Condition Encountered?
YES
Intervention Strategy (VSL/DMS)
NO
Forecasted Weather
Critical Visibility or Adverse Weather?
YES
Intervention Strategy (VSL/DMS)
NO
Normal Operation
NO
Normal Operation

Figure 8-1: System Design

CHAPTER 9. CONCLUSIONS AND RECOMMENDATIONS

9.1 General

This project is the first step toward developing an active traffic management (ATM) system that not only considers operation aspects but also integrates safety measures. Traffic parameters collected by different detection systems (AVI and RTMS), real-time weather data collected from weather stations along the roadway section, and the freeway geometric characteristics were all utilized to develop an overall framework for real-time crash prediction and mitigation on I-70 in Colorado. The main objectives of the first part of the development of the ATM were 1) to assess constant hazards (site-specific static risks) as well as 2) to identify real-time risks due to turbulent traffic conditions and interactions with other risk factors. To achieve these objectives, SPFs were developed at the aggregate level using historical crash data and the corresponding exposure and risk factors in which the unit of analysis was the crash frequency. Additionally, other SPFs were developed for individual crashes at the disaggregate level to identify crash prone conditions in real-time. Both levels of aggregate and disaggregate analyses were found to be important, the first helped in providing good understanding of different safety problems, ranking the hazardous sites, and developing policies and countermeasures to reduce the number of crashes in total. Also, hazardous sites (hot spots) were identified and hence resources can be allocated more appropriately. In order to assess and enhance the performance of freeways and expressways in real-time, the SPFs based on the disaggregate level can be implemented.

In this research, the most comprehensive data were prepared. These datasets comprise of historical crash data, roadway geometrical characteristics, real-time weather and traffic data. The traffic flow parameters were collected from various types of advanced detection systems such as Automatic Vehicle Identification (AVI) and Remote Traffic Microwave Sensors (RTMS).

9.2 Bayesian Hierarchical Approach for Developing SPFs

The safety effects of roadway geometrics on crash occurrence along a freeway section that features mountainous terrain and adverse weather were explored using Poisson models, Bayesian hierarchical models with spatial and random effects were developed to efficiently model the crash frequencies for six years at the roadway section. Furthermore, a Bayesian ranking technique was implemented to rank the hazard levels of the roadway segments. It was found that while the random effect and spatial models outperform the Poisson model, the spatial model may have the problem of redundantly accounting for the geometry dependent effect. Therefore the random effect model was selected for model inference. Estimation of the model coefficients indicates that roadway geometry is significantly associated with crash risk; segments with steep downgrades were found to drastically increase the crash risk. Moreover, this crash risk could be significantly increased during the snow season compared to dry season as a confounding effect between grades and pavement condition. Additionally, sites with higher degree of curvature, wider medians and an increase of the number of lanes appear to be associated with lower crash rate. Based on Bayesian ranking technique; the results confirmed that segments with steep downgrades are more crash prone along the study section. These identified sites should receive more attention from officials and decision makers especially during the snow season. This aggregate level of analysis provided good understanding of the effects of roadway geometrics and weather on crash frequencies on mountainous freeways. Furthermore, the results depict that this step should be considered before proceeding to disaggregate level analysis.

In the future, the Bayesian Hierarchical approach could be extended to utilize informative prior employing real-time traffic and weather data. Instead of using aggregate traffic measure (e.g. ADT and speed limit), and aggregate weather information (e.g. number of rainy days), the mean and the distribution of the archived real-time traffic characteristics of volume, speed and occupancy and real-time weather of visibility, precipitation and temperature could be implemented to provide more certain prior information. Furthermore, with the availability of more crash and risk factors data, the analysis could be expanded to analyze specific crash types (e.g. single-vehicle crashes and multi-vehicle crashes) and different severity levels (e.g. property damage only, injury and fatal crashes). This can shed more light on the different mechanisms for each crash type and identify the different factors that affect different severity levels.

In segment-based SPFs studies, it is believed that crashes are not randomly distributed, but are usually associated with underlying geometrical characteristics, environmental and traffic conditions. In this study a homogeneous segmentation method was adopted, it is worth to investigate different segmentation methods and compare across them to better understand how the segmentation method can affect the analysis results.

9.3 The Viability of Using AVI Data in Real-Time Risk Assessment

Real-time individual crash analysis captured the researchers' interest in the last decade since it has the capability of identifying crashes in real time and hence being more proactive in safety management rather than being reactive. The real-time risk assessment research attempted the use of data from inductive loop detectors; however, no safety analysis has been carried out using traffic data from an increasingly prevalent non-intrusive surveillance system; the tag readers on toll roads known as Automatic Vehicle Identification (AVI). In this research, for the first time, the identification of freeway locations with high crash potential has been examined. AVI data were found to be promising in providing a good measure of crash risk in real time. The operation-based management of freeways can benefit from the collected AVI traffic data not only to ease congestion and enhance the operation but also to provide warnings of increased risk situations to promote safety on freeways and expressways.

9.4 Incorporating Roadway Geometry and Weather in Real-time Risk Assessment

The effect of the interaction between roadway geometric features, and real-time weather and traffic data on the occurrence of crashes on the mountainous freeway section was investigated. The Bayesian logistic regression technique was used to link a total of 301 crash occurrences on I-70 in Colorado with the real-time space mean speed collected from the Automatic Vehicle Identification (AVI) system, real-time weather and roadway geometry data. The results suggest that the inclusion of roadway geometrics and real-time weather with AVI data in the context of active traffic management systems is essential, in particular with roadway sections characterized by mountainous terrain and adverse weather. The modeling results showed that the geometric factors are significant in the dry and the snow seasons and the crash likelihood could double during the snow season because of the interaction between the pavement condition and steep grades. The 6-minute average speed at the crash segment during 6-12 minutes prior to the crash time and the 1-hour visibility before the crash time were found to be significant in the dry season while the logarithms of the coefficient of variation in speed at the crash segment during 6-12 minutes prior to the time of the crash, 1-hour visibility as well as the 10-minute precipitation prior to the time of the crash were found to be significant in the snow season. The results from the two models suggest that different active traffic management strategies should be in place during these two distinctive seasons.

9.5 A Framework for Real-Time Risk Assessment Using Mixed Detection Systems

The increased deployment of non-intrusive detection systems such as automatic vehicle identification (AVI) and remote traffic microwave sensors (RTMS) provided an access to real-time traffic data from multiple sources. The data that are collected from such systems is one of the greatest assets that should be utilized appropriately to maximize the benefit for the roadway authority as well as for the road users. Buried within this vast amount of data is useful information that could make a significant difference in how these roads are managed and operated. Data mining and Machine Learning techniques are known for their capability of extracting the useful hidden information from the massive archived data as well as their superior performance in classification and prediction. Stochastic Gradient Boosting (SGB), a relatively recent and promising machine learning technique was used to calibrate several models utilizing different datasets collected from mixed detection systems as well as real-time meteorological stations (collected on I-70 in Colorado). The results showed that crash prediction from AVI is comparably equivalent to RTMS data, crash prediction model utilizing RTMS data only identified 73% of crash cases with 7% false positive while AVI only model identified 70% with about 6.5% false positive rate. Moreover, the accuracy of the full model that is augmenting information from multiple traffic detectors (AVI and RTMS), weather, and geometry performed the best in terms of classification rate and area under the ROC curve. The full model identified about 89% of crash cases in the validation dataset with only 6.5% false positive.

Based on the results from the machine learning procedure, a framework for real-time risk assessment on freeways was proposed. The proposed framework assesses the increased real-time risk depending on the availability of on-line data. The idea behind the proposed framework based on the fact that although the traffic detection and meteorological stations became advanced enough to overcome hardware failures and malfunctions, the challenging weather conditions may interrupt the flow of the data in real-time at some point. Therefore, a reliable and robust framework should be in place at all times. The proposed framework is considered a good alternative for real-time risk assessment on freeways because of its high estimation accuracy, robustness and reliability.

Overall, the proposed multi-level analyses are useful in providing roadway authorities with detailed information on where countermeasures must be implemented and when resources would be devoted. The study also proves that traffic data collected from different detection systems could be a useful asset that should be utilized appropriately to not only alleviate traffic congestion but also to mitigate increased safety risk in order to maximize the benefit of an existing archived data for freeways/expressways authorities as well as for road users.

9.1 Future Scope

The multi-level safety analyses (aggregate and disaggregate) demonstrated in this project are considered as the primary element of a proactive traffic management system. The secondary but vital element would be the traffic control techniques (proactive intervention systems) that will be used to achieve the safer operation conditions. Route diversion, ramp metering, Variable Speed Limit (VSL), and Dynamic Message Signs (DMS) can be used as intervention strategies. Among those strategies, VSL systems are proven to reduce recurrent congestion and speed variation, and maintain higher operating speeds on freeways. Integrating VSL and dynamic safety messages based on the estimated risk level within existing Advanced Traveler Information Systems (ATIS) would be a cost-effective added value to these systems. A good message at the right time is the key to gaining drivers' trust and compliance of the system which in return will improve the reliability of the system and increase the flow. Micro-simulation could be used to evaluate different scenarios of route diversion, ramp metering, and VSL. In order to come up with the most appropriate dynamic message(s), based on the findings from the statistical models, tailored sets of messages have to be tested at different traffic and weather conditions. Driving simulator and user preference survey could be used as an effective way to achieve such target.

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APPENDIX 1

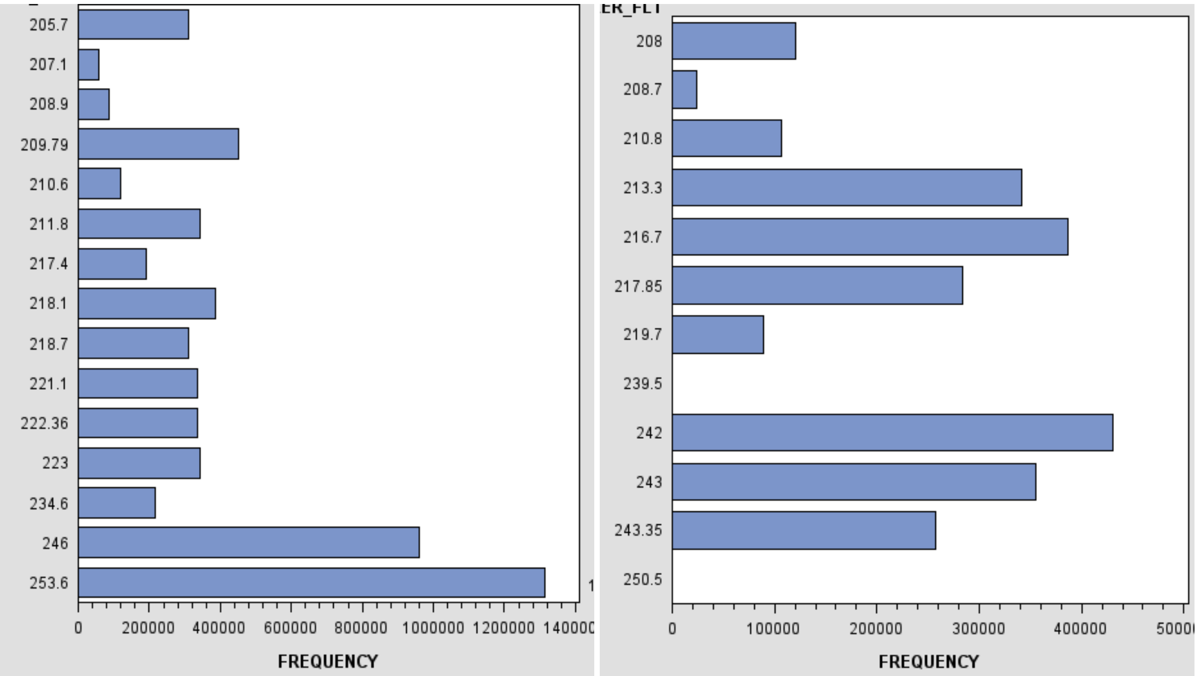

Figure A-1: RTMS locations histogram for September 2010 (Eastbound, Westbound)

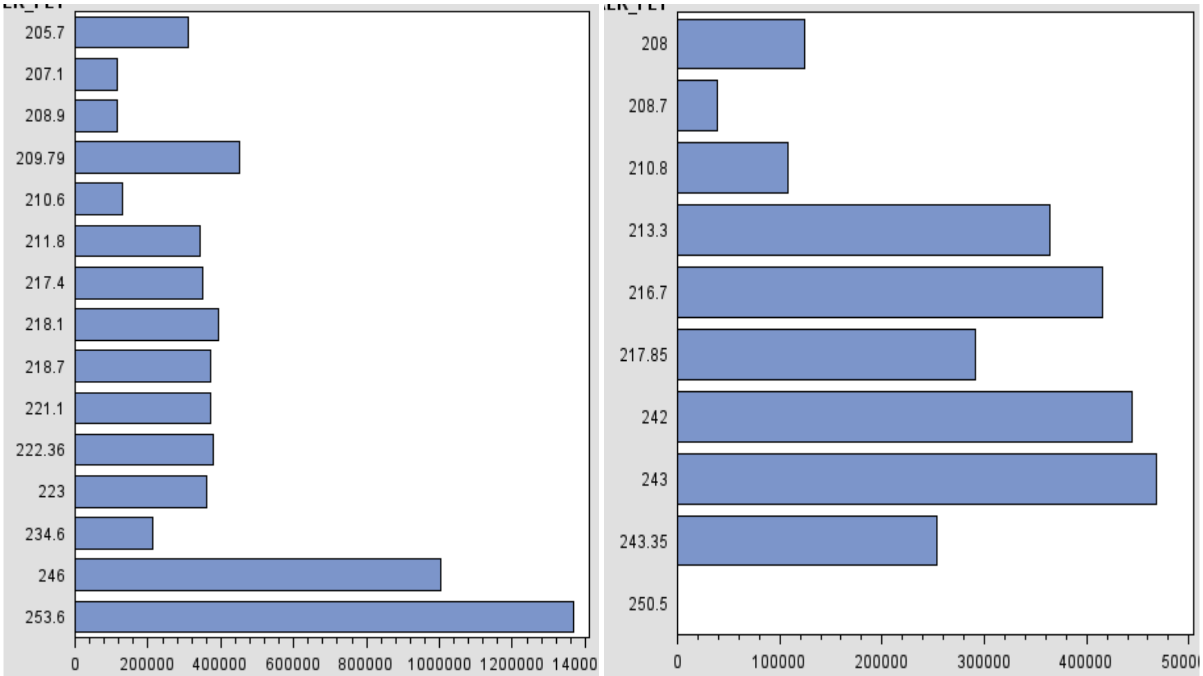

Figure A-2: RTMS locations histogram for October 2010 (Eastbound, Westbound)

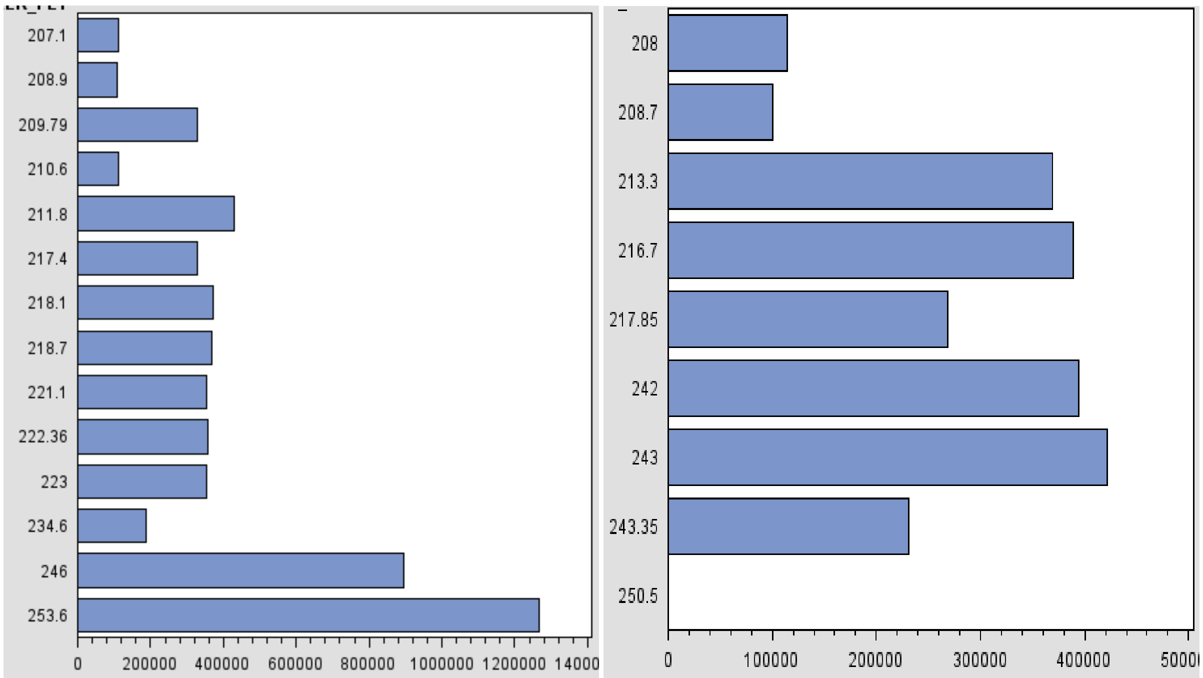

Figure A-3: RTMS locations histogram for November 2010 (Eastbound, Westbound)

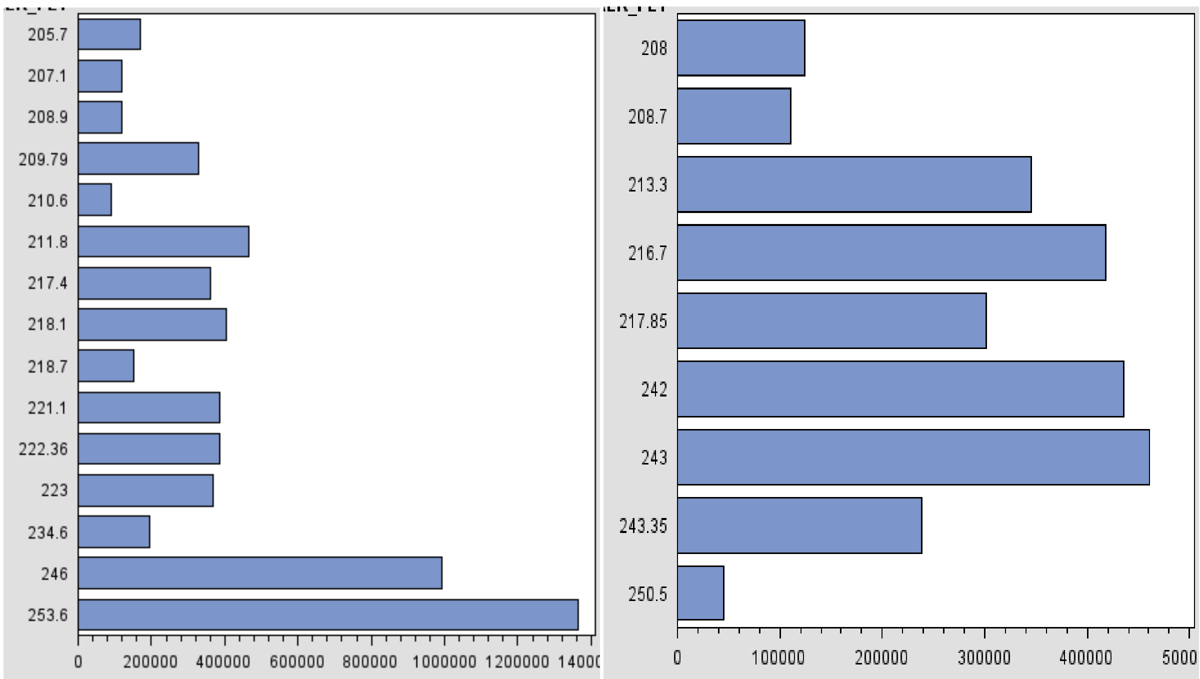

Figure A-4: RTMS locations histogram for December 2010 (Eastbound, Westbound)

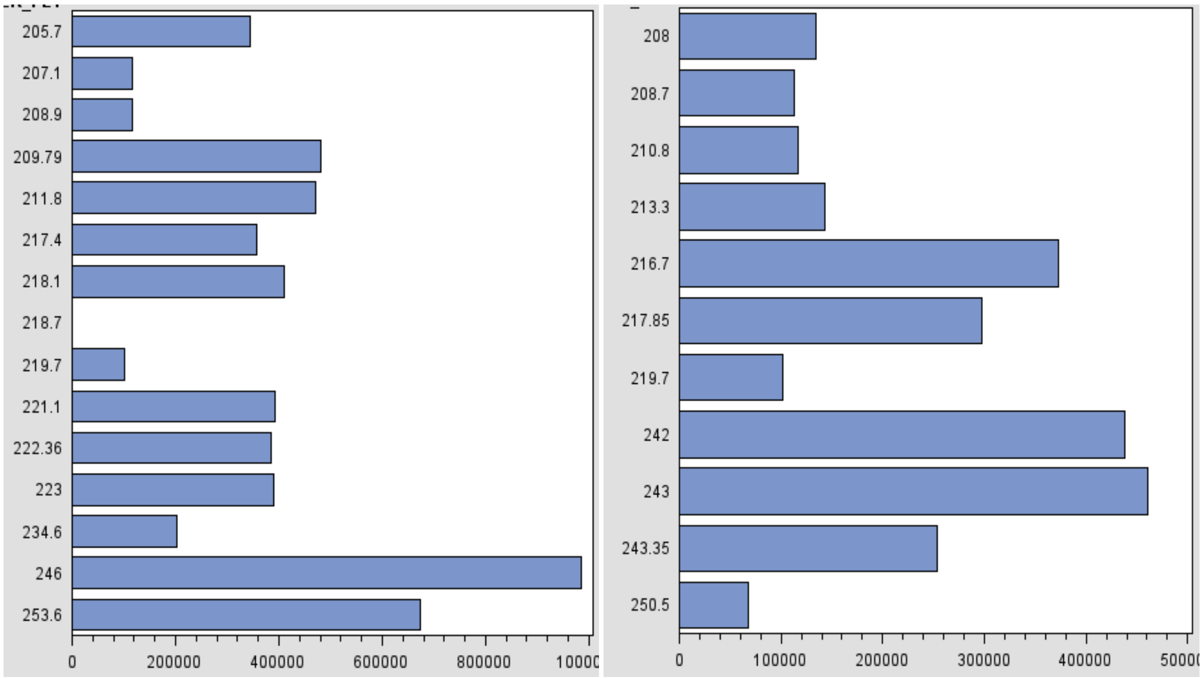

Figure A-5: RTMS locations histogram for January 2011 (Eastbound, Westbound)

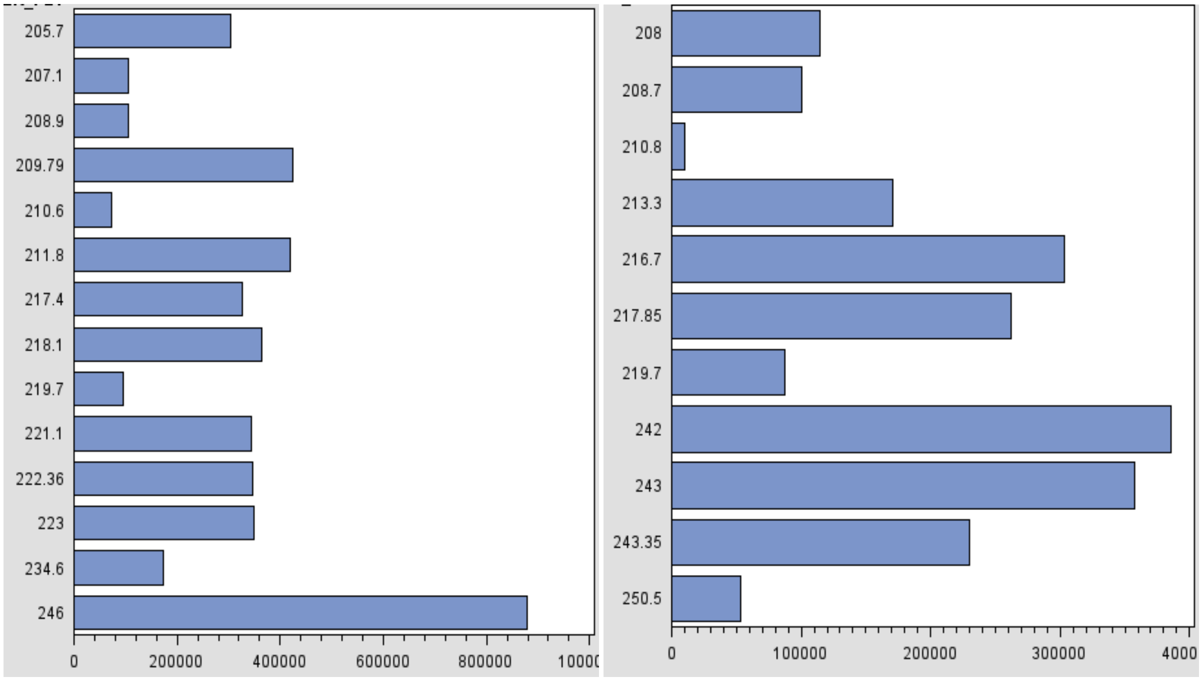

Figure A-6: RTMS locations histogram for February 2011 (Eastbound, Westbound)

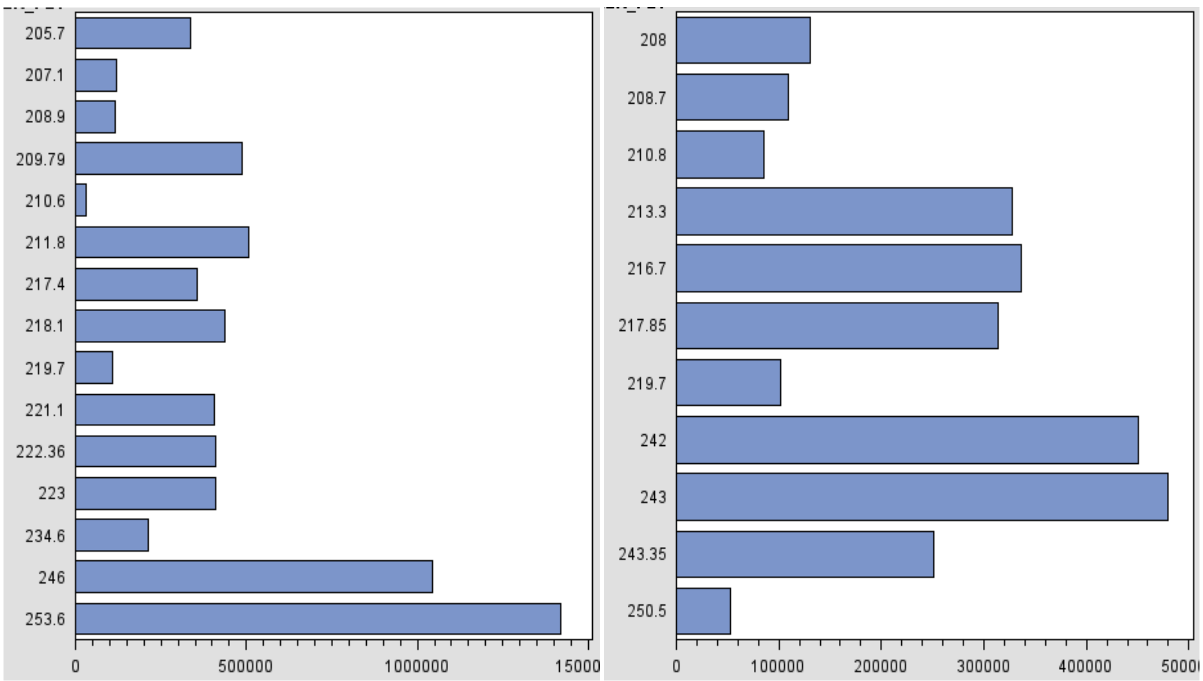

Figure A-7: RTMS locations histogram for March 2011 (Eastbound, Westbound)

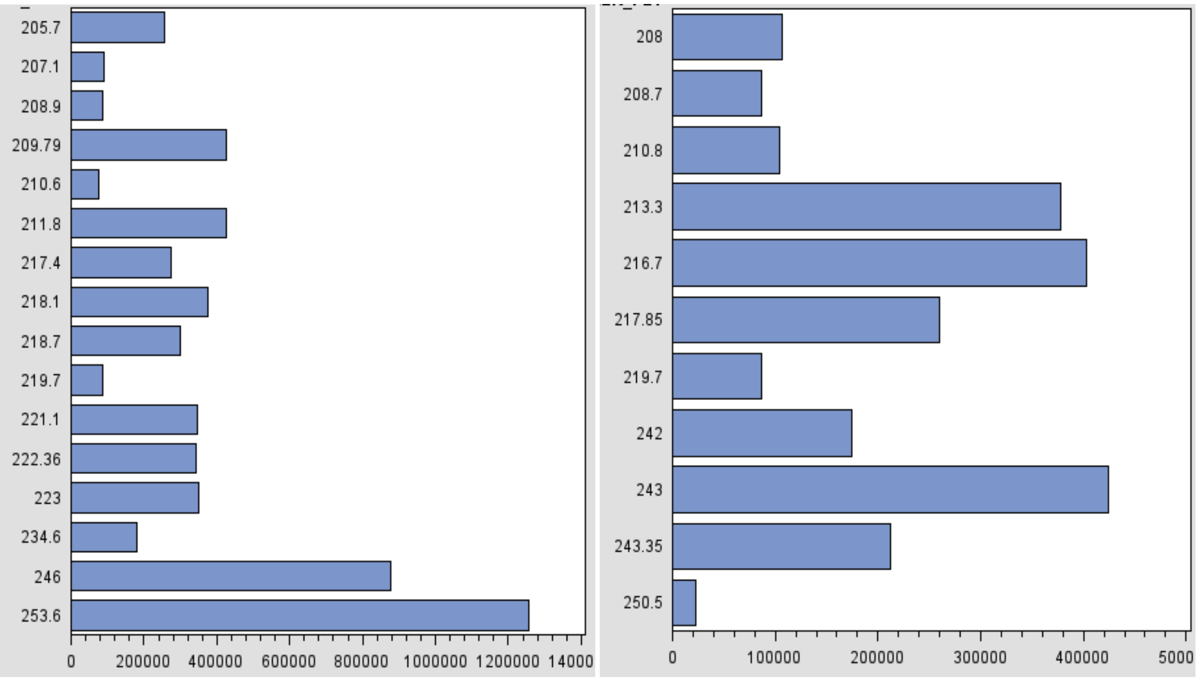

Figure A-8: RTMS locations histogram for April 2011 (Eastbound, Westbound)

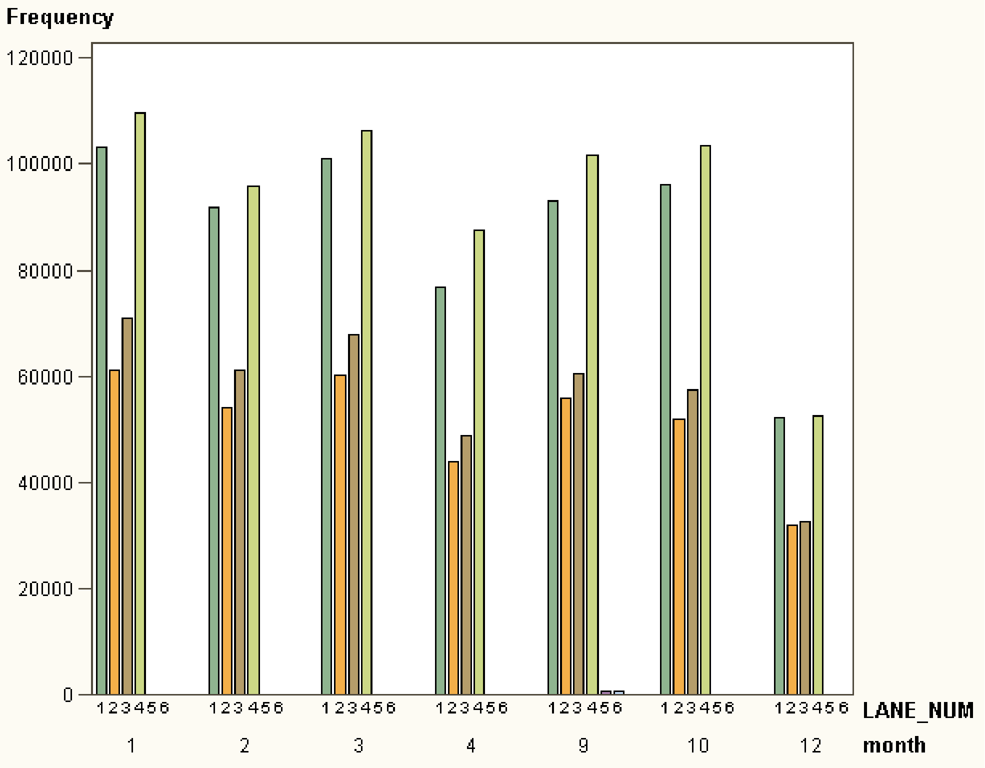

Figure A-9: RTMS at MM205.7 WB/EB Frequency by Lane

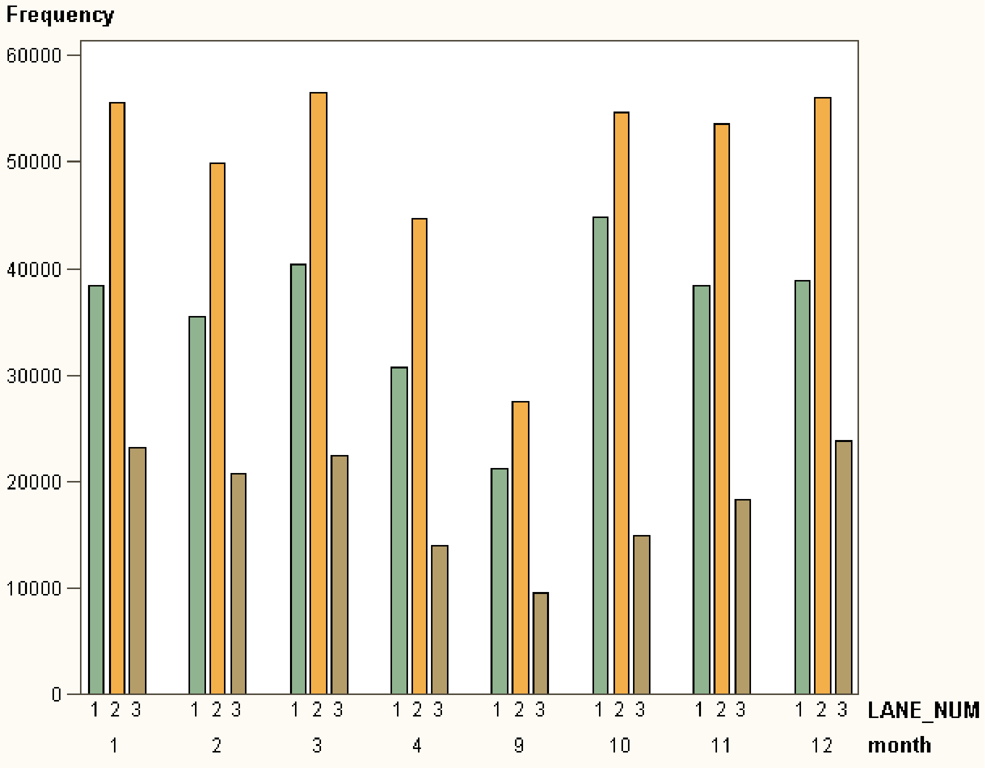

Figure A-10: RTMS at MM207.1 WB Frequency by Lane

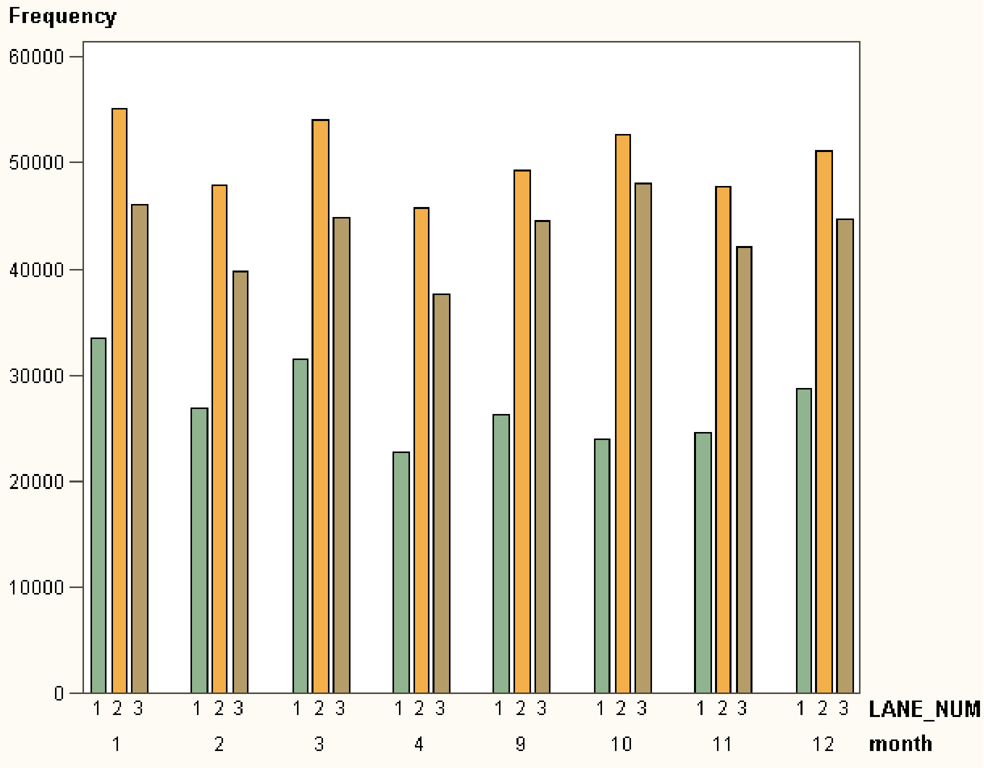

Figure A-11: RTMS at MM208.0 EB Frequency by Lane

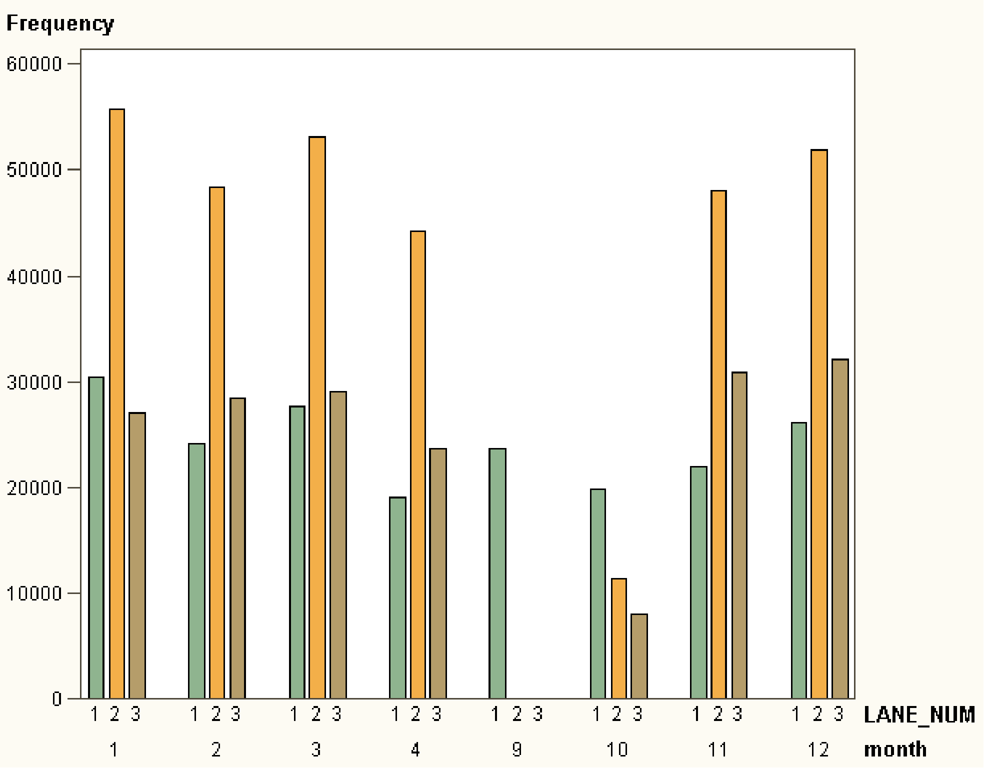

Figure A-12: RTMS at MM208.7 EB Frequency by Lane

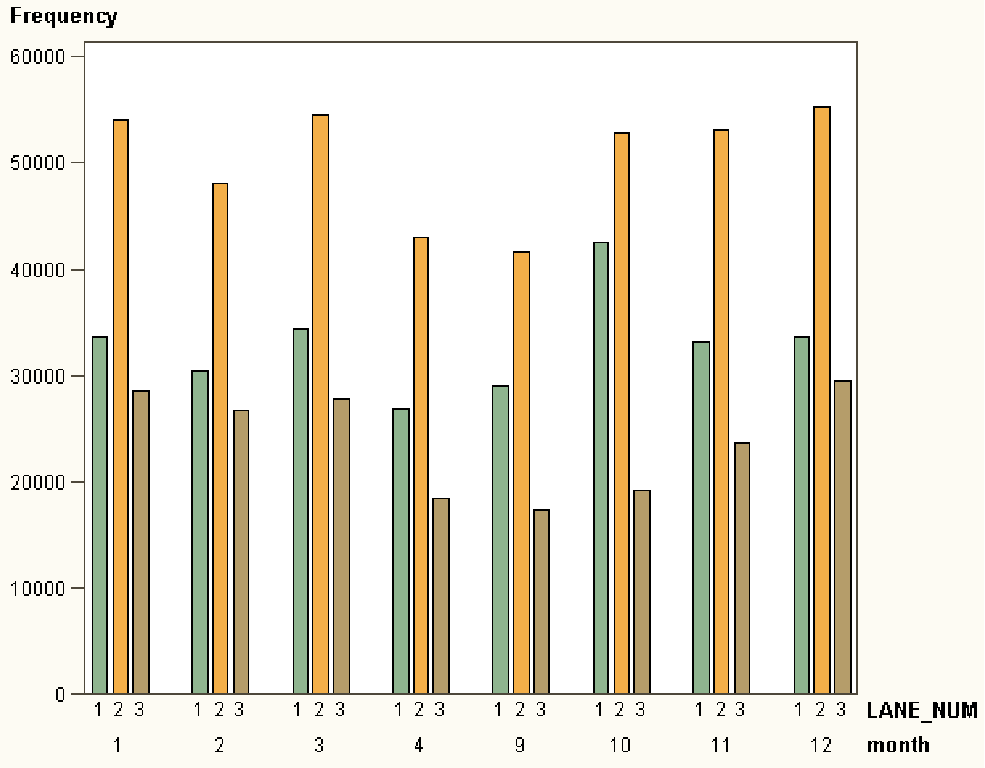

Figure A-13: RTMS at MM208.9 WB Frequency by Lane

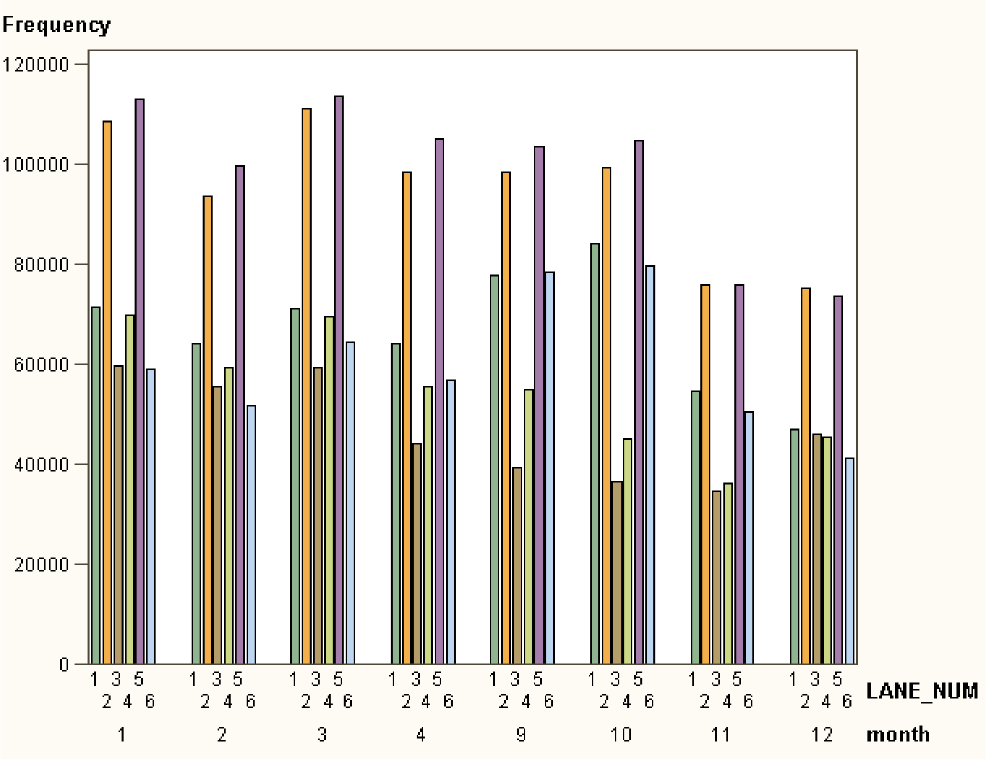

Figure A-14: RTMS at MM209.79 WB/EB Frequency by Lane

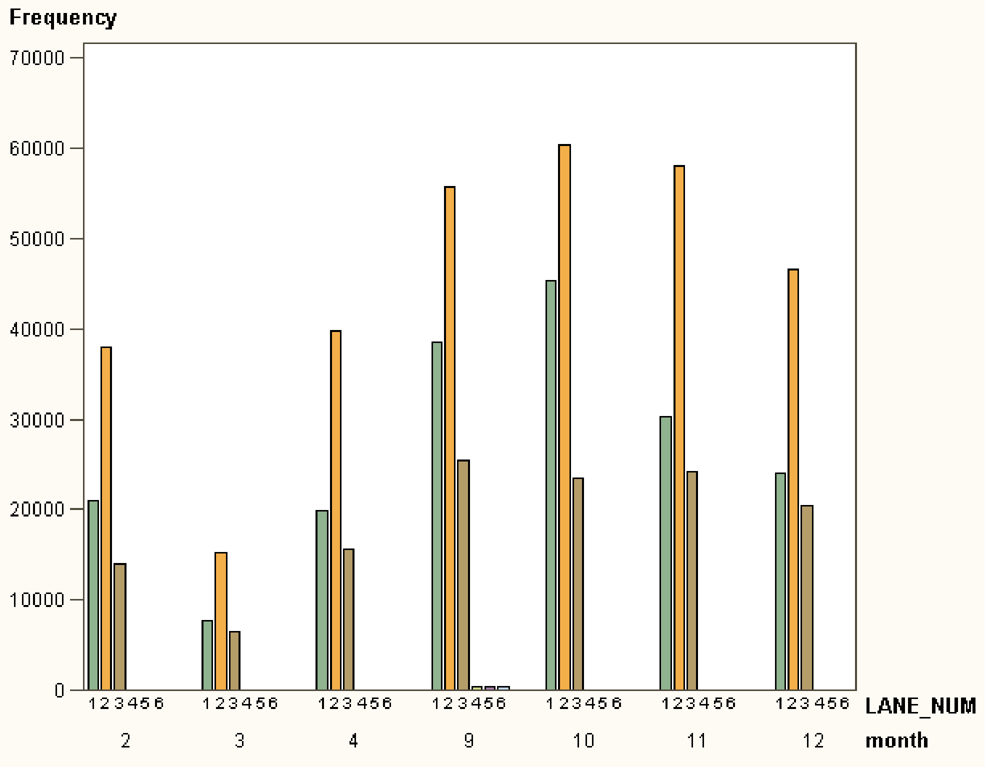

Figure A-15: RTMS at MM210.6 WB Frequency by Lane

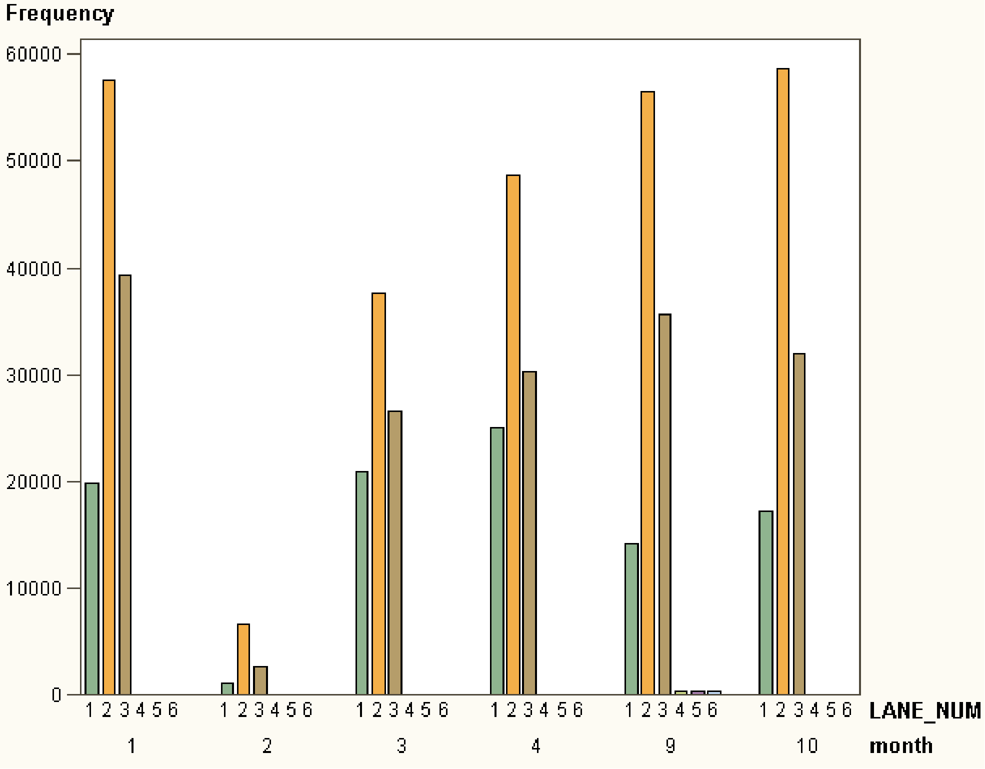

Figure A-16: RTMS at MM210.8 EB Frequency by Lane

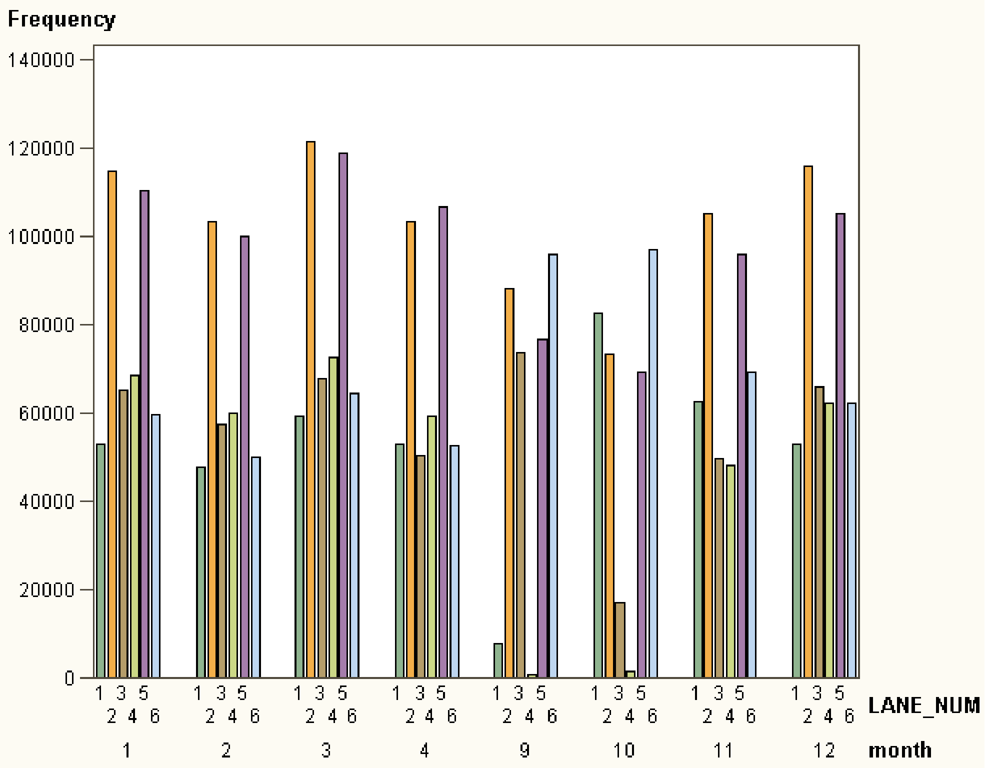

Figure A-17: RTMS at MM211.8 WB Frequency by Lane

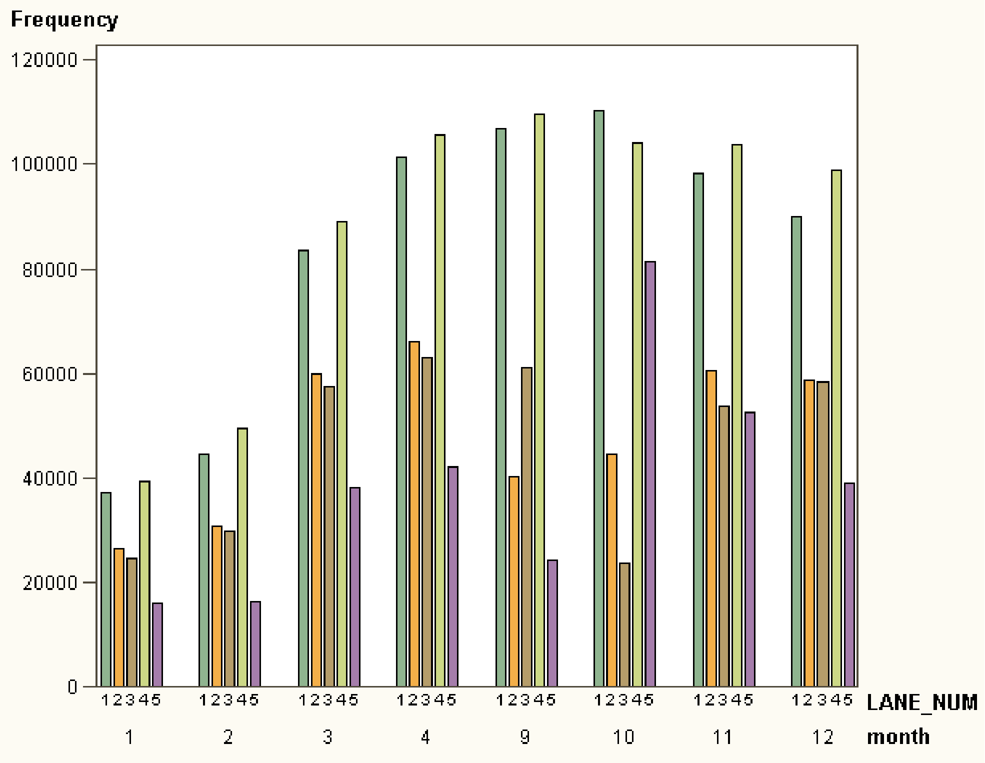

Figure A-18: RTMS at MM213.3 EB/WB Frequency by Lane

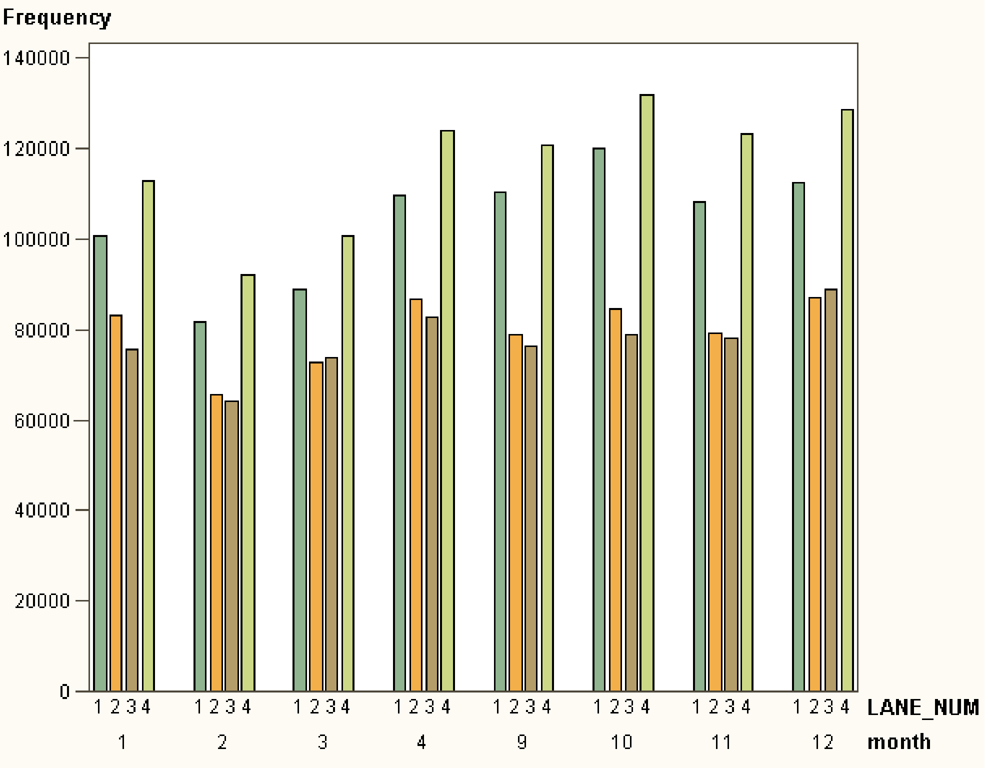

Figure A-19: RTMS at MM216.7 EB/WB Frequency by Lane

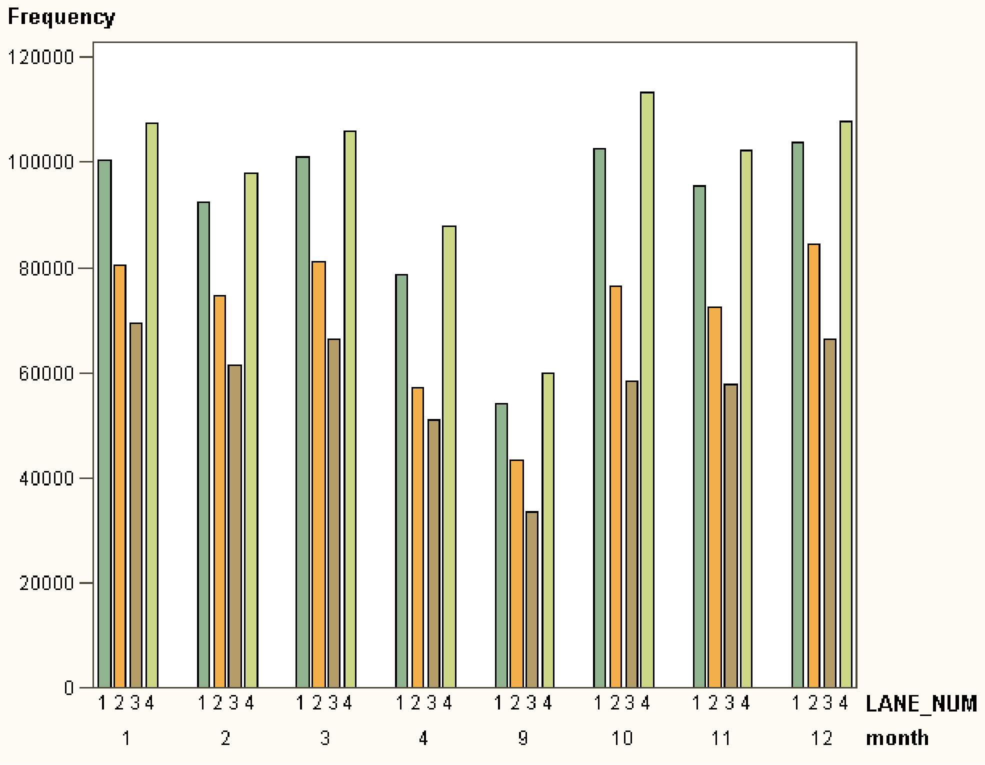

Figure A-20: RTMS at MM 217.4 WB/EB Frequency by Lane

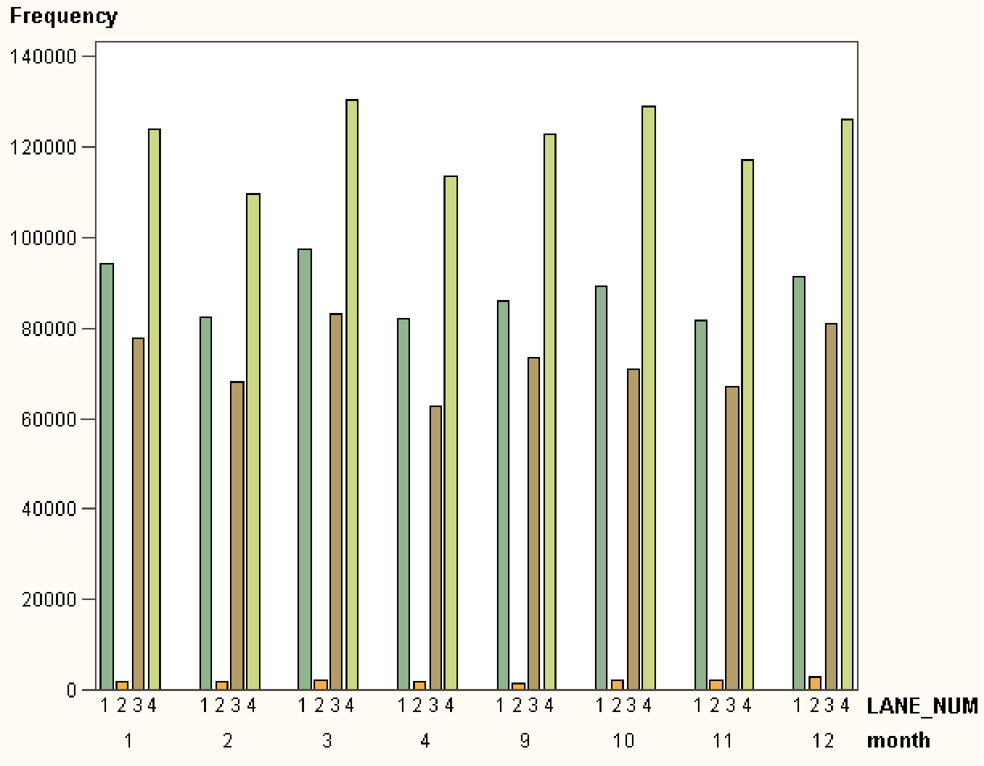

Figure A-21: RTMS at MM 217.85 EB/WB Frequency by Lane

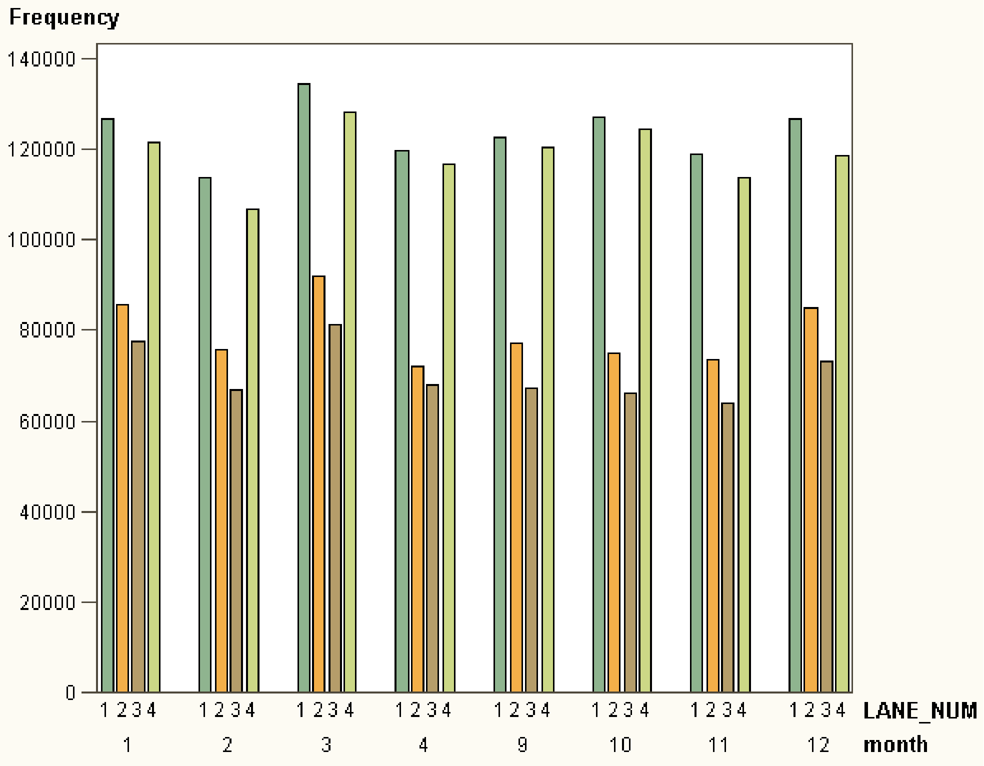

Figure A-22: RTMS at MM 218.1 WB/EB Frequency by Lane

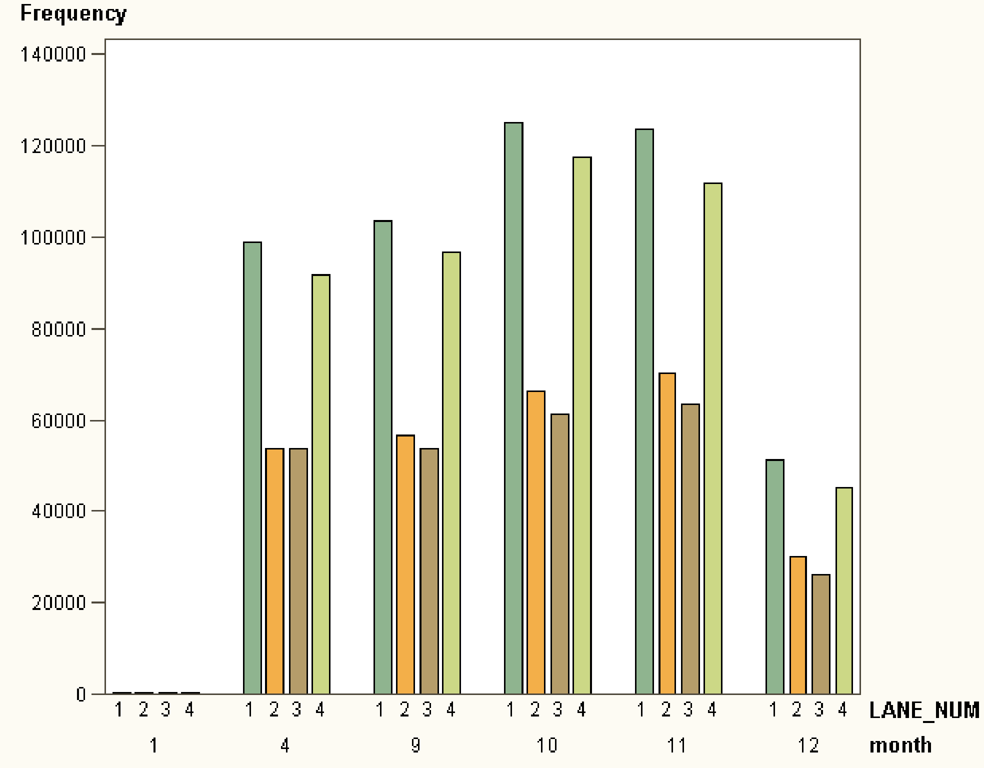

Figure A-23: RTMS at MM 218.7 WB/EB Frequency by Lane

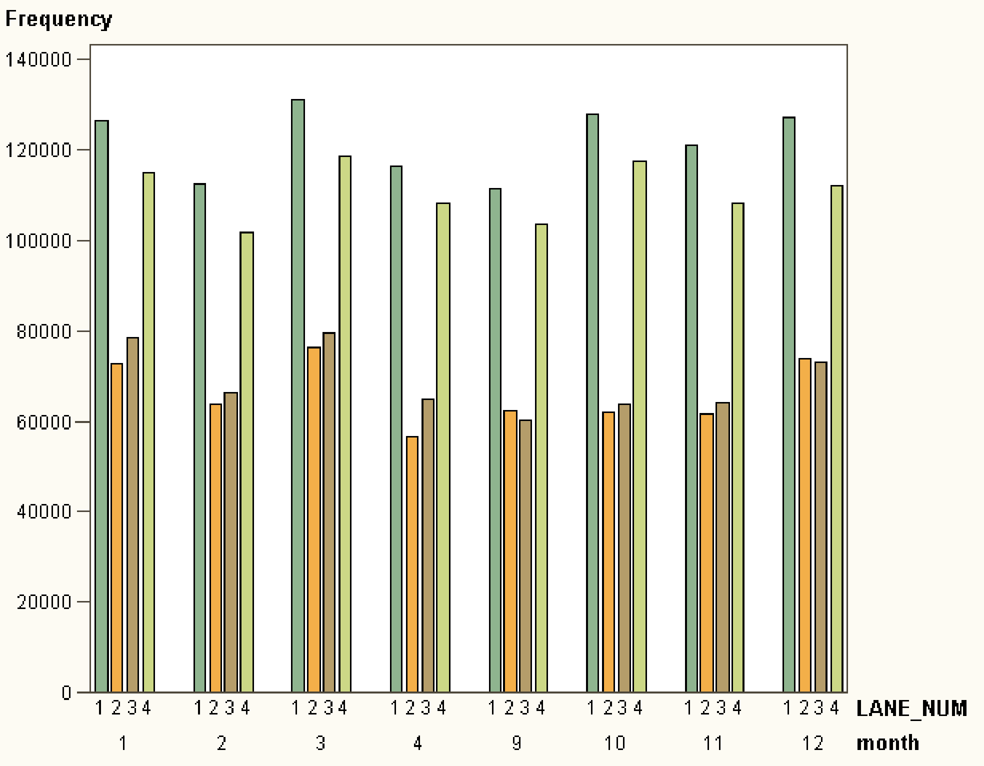

Figure A-24: RTMS at MM 219.7 WB/EB Frequency by Lane

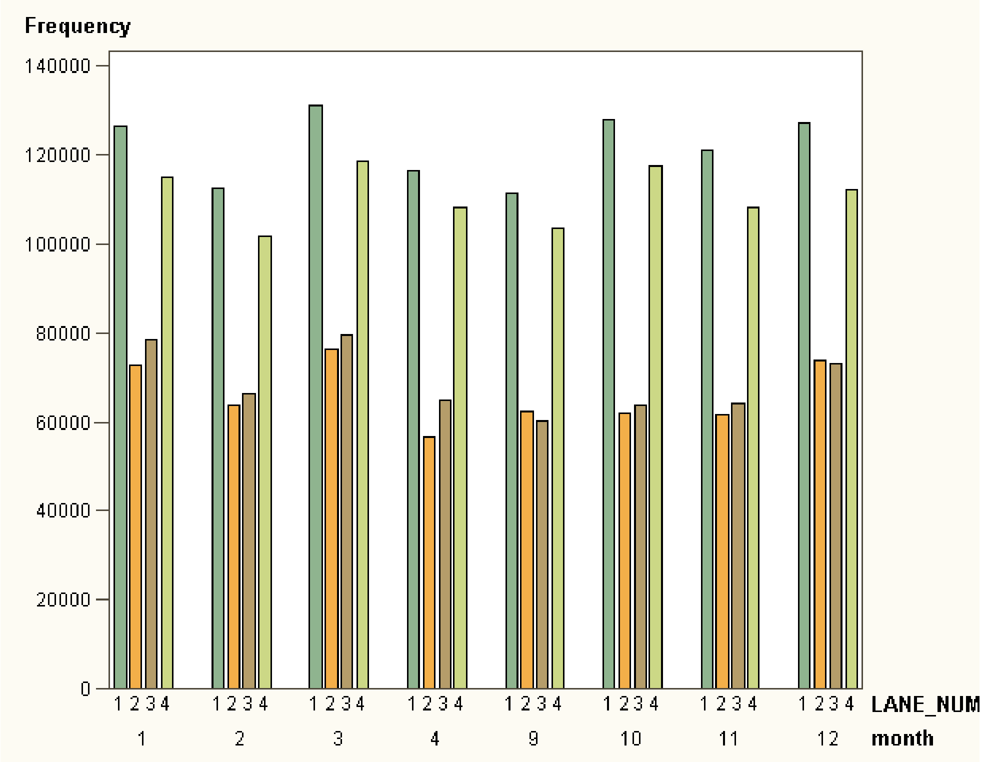

Figure A-25: RTMS at MM 221.1 WB/EB Frequency by Lane

Table A-1: F-test and T-test Results

Variable	Crash	Non-crash	Significant	Equal Variance	Definition
aodli	+		1	1	average occupancy of downstream inner lane
aouli	+		1	0	average occupancy of upstream inner lane
aoulm	+		1	0	average occupancy of upstream medium lane
asdli		+	1	0	average speed of downstream inner lane
asdlm		+	1	1	average speed of downstream medium lane
asdlo		+	1	0	average speed of downstream outer lane
asli		+	1	0	average speed of inner lane
aslm		+	1	0	average speed of medium lane
aslo		+	1	0	average speed of outer lane
asuli		+	1	0	average speed of upstream inner lane
asulm		+	1	0	average speed of upstream medium lane
asulo		+	1	0	average speed of upstream outer lane
avo	+		1	1	average occupancy
avod	+		1	1	downstream average occupancy
avs		+	1	1	average speed
avsd		+	1	1	downstream average speed
avsu		+	1	0	upstream average speed
ddewtemp	+		1	0	downstream dew point temperature
difdo	+		1	1	downstream difference of occupancy between lanes
difds		+	1	0	downstream difference of speed between lanes
difus		+	1	1	upstream difference of occupancy between lanes
occdstd	+		1	1	variance of downstream occupancy between lanes
so	+		1	1	standard deviation of occupancy
sod	+		1	1	downstream standard deviation of occupancy
sodli	+		1	1	downstream standard deviation of inner lane occupancy
sodlm	+		1	1	downstream standard deviation of medium lane occupancy
sodlo	+		1	1	downstream standard deviation of outer lane occupancy
sou	+		1	0	upstream standard deviation of occupancy
souli	+		1	0	upstream standard deviation of inner lane occupancy
soulm	+		1	1	upstream standard deviation of medium lane occupancy
speeddstd		+	1	0	downstream variance of speed between lanes
ssuli	+		1	1	upstream standard deviation of inner speed

udewtemp	+		1	1	upstream dew point temperature
aodlm	+		0	1	average occupancy of downstream medium lane
aodlo	+		0	1	average occupancy of downstream outer lane
aoli	+		0	1	average occupancy of inner lane
aolm	+		0	1	average occupancy of medium lane
aolo	+		0	0	average occupancy of outer lane
aoulo	+		0	0	average occupancy of upstream outer lane
avdli	+		0	0	average volume of downstream inner lane
avdlm	+		0	0	average volume of downstream medium lane
avdlo		+	0	0	average volume of downstream outer lane
avli		+	0	1	average volume of inner lane
avlm		+	0	0	average volume of medium lane
avlo		+	0	1	average volume of outer lane
avou	+		0	0	upstream average occupancy
avuli	+		0	0	average volume of upstream inner lane
avulm		+	0	0	average volume of upstream medium lane
avulo		+	0	0	average volume of upstream outer lane
difdv	+		0	1	downstream difference of volume between lanes
difo	+		0	1	difference of occupancy between lanes
difs		+	0	0	difference of speed between lanes
difuo		+	0	0	difference of volume between lanes
difuv		+	0	0	upstream difference of speed between lanes
difv		+	0	0	upstream difference of volume between lanes
dprecip		+	0	1	downstream precipitation rate
dtemp		+	0	1	downstream temperature
dtenprecip		+	0	1	downstream ten minutes precipitation rate
dvisibility		+	0	0	downstream visibility
occustd		+	0	0	variance of upstream occupancy between lanes
soli	+		0	1	standard deviation of inner lane occupancy
solm	+		0	1	standard deviation of medium lane occupancy
solo	+		0	1	standard deviation of outer lane occupancy
soulo	+		0	0	upstream standard deviation of outer lane occupancy
speedstd		+	0	0	variance of speed between lanes
speedustd		+	0	0	upstream variance of speed between lanes
ss		+	0	1	standard deviation of speed
ssd	+		0	0	downstream standard deviation of speed
ssdli	+		0	0	downstream standard deviation of inner speed
ssdlm	+		0	0	downstream standard deviation of medium speed
ssdlo		+	0	0	downstream standard deviation of outer speed

ssli	+		0	0	standard deviation of inner lane speed
sslm	+		0	0	standard deviation of medium lane speed
sslo		+	0	1	standard deviation of outer lane speed
ssu		+	0	1	upstream standard deviation of speed
ssulm	+		0	0	upstream standard deviation of medium speed
ssulo		+	0	1	upstream standard deviation of outer speed
sumv		+	0	1	volume
sumvd		+	0	0	downstream volume
sumvu	+		0	0	upstream volume
sv	+		0	0	standard deviation of volume
svd	+		0	0	downstream standard deviation of volume
svdli	+		0	0	downstream standard deviation of inner lane volume
svdlm		+	0	0	downstream standard deviation of medium lane volume
svdlo		+	0	0	downstream standard deviation of outer lane volume
svli	+		0	0	standard deviation of inner lane volume
svlm	+		0	0	standard deviation of medium lane volume
svlo		+	0	0	standard deviation of outer lane volume
svu	+		0	0	upstream standard deviation of volume
svuli	+		0	0	upstream standard deviation of inner lane volume
svulm	+		0	0	upstream standard deviation of medium lane volume
svulo		+	0	0	upstream standard deviation of outer lane volume
u1hourprecip	+		0	1	upstream one hour precipitation
uprecip	+		0	1	upstream precipitation
utemp		+	0	1	upstream temperature
utenprecip	+		0	1	upstream ten minutes precipitation
uvisibility		+	0	0	upstream visibility
voldstd	+		0	1	standard deviation of downstream volume
volstd		+	0	0	standard deviation of volume
volustd	+		0	0	standard deviation of upstream volume