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Identifying Freeway Locations Prone to High-risk Crashes

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By

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Professor Michael Cassidy, Chair
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Abstract

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The crashes that cause fatalities and serious injuries typically occur at high speeds. Although the Federal Highway Administration (FHWA) asserts a need to identify the most dangerous locations on a roadway system, FHWA promotes a screening practice that fails to reveal these high-speed (high-risk) locations. In fact, the current practice obscures the most dangerous locations by conflating high-speed crashes with low-speed (low-risk) ones. The current practice supported by FHWA has two problems. Firstly, it analyzes crashes in uncongested and congested conditions together, without distinction. Secondly, it uses Vehicle Miles Traveled (VMT) as the measure of traffic exposure which cannot capture the vehicles' extra time spent traveling in slow-moving congestion. These problems arise when the current practice is applied to freeways that see their fair share of congestion: the current practice tends to mistakenly identify locations with large numbers of low-speed (low-risk) crashes in congestion as if they were the most dangerous locations. The reason is that crash rates inside congestion are much higher than those occurring in uncongested traffic conditions.

To remedy these problems with current practice, the present study analyzes crashes in a disaggregated fashion based upon the vehicle occupancies measured by the nearest freeway loop detector at the time of the crash. High-speed crashes in uncongested conditions are analyzed separately from low-speed crashes in congested conditions. Crash counts for both traffic conditions were normalized by Vehicle Hours Traveled (VHT), rather than the commonly used Vehicle Miles Traveled (VMT), to capture vehicles' extra exposure inside congestion. The data used for this research came from a 6-month period in 2016 on a 10-mile stretch of the northbound Interstate 880 freeway in Alameda County, California. Crash records collected by state police and traffic data measured by the site's loop detectors were also used as inputs.

The results show that by using the proposed method, one can better identifies the type of crashes, (uncongested and/or congested), that make some locations stand out as problematic. From there analysts can narrow down the set of these outliers to be the ones driven predominantly by uncongested crashes and are therefore the ones of the greatest safety con-

cern. Additionally, one can rank uncongested outliers based on their magnitudes and focus on the highest ranked ones. For the reasons mentioned above, the proposed approach allows traffic agencies to focus their resources on these most dangerous locations and help improve the overall safety on the transportation system.

The amount of data used for this study is limited. But the findings are very promising. Future research to advance the proposed method and to answer questions that are yet unresolved are discussed.

I dedicate this dissertation to my family and all the people that have helped me along this journey.

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Acknowledgments

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Chapter 1

Introduction

Sections 1.1 and 1.2 describe the motivation for the present study; section 1.3 provides an overview of the present study and section 1.4 describes the structure of this dissertation.

1.1 Traffic Crashes and Vision Zero Initiative

Traffic crashes are one of the world's largest public-health problems. Crashes can result in serious injuries, deaths and cause significant economic loss for society. In the US, according to National Highway Traffic Safety Administration (NHTSA), an estimated 42,915 people died in motor vehicle crashes in 2021 (National Center for Statistics and Analysis, 2022). Across California, around 3600 fatalities were caused by traffic crashes each year for the period 2017-2021, which showed an increase of nearly 20% compared to that of 2012-2016 (Transportation Injury Mapping System, 2022).

The crashes that cause fatalities and serious injuries are often high speed crashes (Joksch, 1993). This is because the energy dissipated during a crash is directly proportional to the square of the travel speed at the time of the crash. This fact has led to a worldwide initiative called Vision Zero, which originated in Sweden in 1997 (Johansson, 2009) and was adopted in the US in the early 2010s. Vision Zero targets the elimination of all traffic fatalities and serious injuries. As a first step to achieve this lofty goal, traffic agencies need to identify freeway locations that stand out in terms of high-speed (high-risk) crashes.

1.2 Shortcomings of the Current Screening Method

Despite acknowledging the need to pinpoint the most dangerous locations on a roadway network, the Federal Highway Administration (FHWA) endorses a screening practice that falls short of this objective. Presently, this practice conceals the most dangerous locations by merging high-speed and low-speed crashes during screening. The practice suffers from two primary drawbacks. Firstly, it combines crashes from both congested and uncongested traffic conditions without distinguishing between them. Secondly, the practice relies on Vehicle Miles Traveled (VMT) as the measure of traffic exposure, failing to capture vehicles' increased exposure in slower-moving congested traffic. These deficiencies become apparent when applying the current practice to freeways that exhibit significant periods of congested traffic. Crash rates within congested areas significantly surpass those in uncongested conditions. As a result, the current practice often mistakenly designates locations with numerous crashes to be the most perilous ones, when most of those crashes occurred in low-speed, congested traffic.

To counter this misidentification, FHWA mistakenly suggests focusing only on crashes that cause fatalities or serious injuries. But this suggestion omits those high-speed crashes that fortuitously did not result in fatalities or serious injuries. This is problematic because these omitted crashes are still rich in information that can help traffic agencies identify the most dangerous, high-risk locations.

1.3 Overview of the Present Study

Given the limitations of the current screening practice, the present study employs a different approach. It categorizes crashes based on vehicle occupancies determined by the closest freeway loop detector at the time of the crash. Hence the proposed approach is able to separate high-speed (low-occupancy) crashes occurring in uncongested conditions from low-speed (high-occupancy) crashes happening in congested situations. To ensure a more precise analysis, crash counts for both traffic conditions were normalized using Vehicle Hours Traveled (VHT) rather than the conventional measure of Vehicle Miles Traveled (VMT). This is because VHT can capture vehicles' increased exposure within congested traffic conditions. In congestion, vehicles travel at slow and varied speeds and thus spend greater and more varied travel times per unit distance.

The data utilized for this study were obtained from a 6-month duration in 2016 on a 10-mile segment of the northbound Interstate 880 freeway in Alameda County, California. Crash records sourced from state police and traffic data derived from loop detectors were employed for analysis as well.

The findings illustrate that the proposed approach enables us to discern the specific type of crashes (whether occurring in uncongested or congested conditions) that make particular locations problematic. Subsequently, we are able to narrow down the group of outliers to be the ones that are predominantly comprised of uncongested (high-risk) crashes, since they represent the greatest safety concerns. Moreover, we can prioritize these uncongested outliers based on their severity, focusing on the locations ranked highest. As previously noted, the proposed approach empowers traffic agencies to concentrate their resources on these critical locations, thereby enhancing the overall safety of the roadway system.

1.4 Dissertation Structure

The structure of this dissertation is as follows. Chapter 2 discusses the concepts and implementation of the Vision Zero initiative and the problems of the current FHWA-recommended screening practice. Chapter 3 describes the study site and data collection. Chapter 4 discusses the data processing used in the present study. Chapter 5 details the analysis and findings. Chapter 6 discusses future work.

Chapter 2

Literature Review

In this chapter, we review the literature to describe the Vision Zero initiative and to illustrate why the federally-promoted screening practice obscures the most dangerous locations on a roadway network.

2.1 Vision Zero

The Vision Zero initiative seeks the elimination of traffic fatalities and serious injuries by designing safer roadway infrastructure and vehicles and via better education and policy enforcement (Fleisher et al., 2016). This idea originated in Sweden in 1997, when the Road Traffic Safety Bill founded on Vision Zero was passed by a large majority in the Swedish parliament (Tingvall and Haworth, 1999). In that year, Sweden's fatality rate from roadway crashes was about 6 deaths/100,000 inhabitants. After the implementation of Vision Zero, the rate in 2006 dropped to 4.7 deaths/100,000 inhabitants, a decrease of 22% (Johansson, 2009). Since its implementation and favorable outcomes in Sweden, the Vision Zero initiative has been adopted by many other countries, including the Netherlands, Germany, the UK, Australia and elsewhere (Mendoza et al., 2017).

The initiative has gained momentum in the US since the 2010s. In 2014, New York (Mammen et al., 2020) and San Francisco (Vision Zero SF) launched their versions of Vision Zero. In 2015, the American Association of Highway and Transportation Officials (AASHTO) and the US Department of Transportation (USDOT) instituted a zero death initiative for traffic safety called Toward Zero Deaths. Also in 2015, the Vision Zero Network was launched to help cities develop and share best practices for all road users. As of 2016, 16 US cities have adopted Vision Zero (Ahangari et al., 2016).

Vision Zero emphasizes that speed is likely the most critical factor contributing to traffic fatalities (Mendoza et al., 2017). This is because higher traveling speeds are directly and proportionally related to the rise in transferred kinetic energy, which increases the chance of fatalities and serious injuries (Aarts and Van Schagen, 2006). Therefore, analyzing the causes of high-speed crashes is essential in achieving Vision Zero. As a first step, traffic agencies need to identify locations that are rich in high-risk (high-speed) crashes.

At present, the network screening practice recommended by FHWA to find these locations often obscures the most dangerous ones. The reasons will be explained in the two following sections.

2.2 Network Screening

Network screening is a process for reviewing a roadway network to identify and rank locations (i.e., roadway segments, intersections, and ramps) according to some performance measures, (e.g., Crash Rates), where the severity of a crash may or may not be a consideration (National Research Council, 2010; Hauer et al., 2002). Section 2.3 will discuss performance measures in detail. The underlying assumption is that higher ranked locations are more susceptible to being fixed via enhancement to road geometry (such as widening shoulders or implementing superelevation near curves) or traffic control measures (such as signaling, warning signs or speed limits), as advised by investigation teams.

Network screening can be performed by focusing on specific facility types, e.g., two lane rural highways. The selection is based on the objectives of the transportation agencies that perform the analysis. For example, local agencies may only focus on local streets instead of state highways. Network screening can also be performed by focusing on a particular type of crash to formulate and implement a policy or discover roadway characteristics that contribute to this crash type. Examples include: identifying sites with a high number of run-off-the-road crashes can be used to prioritize the replacement of non-standard guardrails (National Research Council, 2010). Wang and Abdel-Aty (2006) focused on rear-end crashes at signalized intersections to show that some intersection characteristics, such as a large number of signed phases per cycle and high speed limits on the main roadway, are correlated with high rear-end crash frequencies. Tay et al. (2008) focused on hit-and-run crashes and found that factors such as night conditions and the driver being a male between the ages of 45 and 69 make hit-and-run crashes more likely. Lee et al. (2006) focused on sideswipe crashes and showed that higher variation of flows across lanes are correlated with higher occurrences of this crash type. In terms of finding the most dangerous sites, FHWA suggests focusing only on crashes that resulted in fatalities and serious injuries. As previously noted, however, this approach overlooks high-risk (e.g., high-speed) crashes that, by good fortune, did not cause fatalities or serious injuries. These crashes still represent a huge risk for roadway users and should therefore be analyzed as such.

Locations of extended physical length, like long segments of a multi-mile freeway, are subdivided into smaller subsections for screening in an effort to pinpoint the most problematic locations. Some options for partitioning these locations are the Sliding Window Method (SWM) and Peak Searching (PS) (Grembek et al., 2012; National Research Council, 2010). Regarding the SWM, a window of a specified length (typically 0.1 to 0.3 miles) is moved along the road segment from beginning to end in increments of a specified length (e.g., 0.1 mile). A selected performance measure is then applied to each window. Of all the windows that pertain to a given segment, the window with the highest-value performance measure is used to represent the entire segment.

For the PS approach, the roadway segment is subdivided into windows in the following iterative fashion: a roadway segment is first divided into 0.1 mile windows and the selected performance measure is applied to each window; then windows of 0.2 mile length are used and window length is iteratively increased until the length of the window is equal to the length of the entire roadway segment. Just as in the SWM, the PS window with the highest-value performance measure is used to represent the entire segment.

2.3 Network Screening Performance Measures

One of the most commonly used performance measures is Crash Rate, by which crash counts are normalized by a measure of traffic exposure, e.g., VMT or VHT. The Federal standard (National Research Council, 2010) suggests that crash counts be normalized by VMT. Yeo et al. (2013) conducted a comparison of crash rates for various traffic conditions. When calculating these crash rates, that study first chose VMT and then VHT as the measure of traffic exposure. That study noticed that for a given VMT, the VHT in congestion was larger than that from free flow and pointed out the reason is that vehicles spend more time in congestion due to lower traveling speeds. Oddly enough, that study primarily emphasized the similarities in the conclusions drawn from using VMT or VHT, without explicitly advocating for VHT as a superior exposure metric in congested scenarios. Goodall (2021) compared the crash rates between different traffic modes, including passenger cars, motorcycles, buses, commercial aircraft and more. That study suggested that VHT is a better measure of exposure than VMT when comparing modes that have very different travel speeds, e.g., buses vs commercial aircraft. But that study did not mention that VHT is a better measure of exposure than VMT when analyzing traffic crashes in congested conditions.

Perhaps these crashes contribute to the problems in current practice. When traffic agencies use Crash Rate as the performance measure on freeways that experience substantial periods of congested traffic, the agencies commit two critical errors. Firstly, agencies fail to analyze crashes in uncongested and congested traffic conditions separately. Secondly, they rely on VMT as the metric for traffic exposure, which cannot capture the additional exposure vehicles face in congestion. Given the slower and more variable speeds in congested traffic, vehicles spend greater and more varied amounts of travel time per unit distance in congestion. Consequently, traffic agencies often erroneously decide that locations with high rates of low-speed (low-risk) crashes in congestion are the most hazardous locations and this is the first limitation of the current practice. The root cause lies in the significantly elevated crash rates within congestion compared to those observed in uncongested conditions. For example, Yeo et al. (2010) discovered that crash rates in either a congested or near congested traffic state are 4-5 times higher than those from free flow states.

As an attempt to overcome this limitation, traffic agencies usually apply a severity filter to help focus on crashes that cause fatalities and serious injuries. They also try to use some other performance measures, such as Equivalent Property Damage Only Average Crash Counts. This measure assigns weighting factors to crashes by severity to develop a combined count. The weighting factors are often calculated relative to Property Damage Only (PDO) crashes so that more severe crashes have higher weights (National Research Council, 2010).

However, a measure like this one has the second limitation: some high-speed crashes that fortunately did not lead to fatalities or serious injuries will be omitted or have lower weights. These crashes are still rich in information that will help traffic agencies identify the most dangerous locations.

All performance measures, when not fixed by Empirical Bayes (EB) method, have the third limitation: they do not account for the Regression-to-the-Mean (RTM) phenomena (De Pauw et al., 2013). Crash frequencies naturally fluctuate up and down over time at any given location. As a result, a short-term average crash frequency may vary significantly from the long-term average crash frequency because of the randomness of crash occurrences.

Ideally the best way to account for the RTM phenomena is to obtain more data, but this is time consuming. Another way to account for the RTM phenomena is using the EB method. This method is based on the recognition that crash counts are not the only clue to the safety of an entity. Another clue is in what is known about the safety of similar entities (Hauer et al., 2002).

Because of these three limitations, the locations identified using the current practice are picked up largely because of high rates of low-speed crashes. Since low speed crashes mostly happen inside congestion and congestion is often caused by downstream bottlenecks, field investigations at the exact crash locations are unlikely to reveal anything that might be viewed as a systematic cause for the clustered crashes (the problems sprouted from bottlenecks downstream). If geometric designs and control measures of a crash location are consistent with the standards, no recommendations for improving traffic safety will be made by the traffic engineers conducting the study. This outcome is then treated as a false positive (Grembek et al., 2012).

The current network screening practice produces an extraordinarily high false positive rate. A Task force was convened by the California Department of Transportation to identify steps that need to be taken to improve dangerous locations detection accuracy (Caltrans Table, 2002). A survey conducted by this task force shows that across California, the rate of proposed improvement locations from 1998 to 2001 was a little more than 10 percent, meaning a false positive rate of nearly 90 percent. The wasted efforts in identifying these false positives does not improve traffic safety for the public and squanders resources and energy.

It seems clear that crashes need to be analyzed in a disaggregated fashion based on their risks. The present study does this for a 10-mile freeway stretch in California. Chapter 3 will provide information on the study area and the collection of its data.

Chapter 3

Study Area and Measured Data

This chapter describes the study area and all the measured data that are used in this research.

3.1 Study Area

The selected study area is a 10-mile freeway stretch of the Interstate 880 northbound in Alameda County, California. Figure 3.1 shows the location of this freeway stretch. Pin 1 represents the starting point at postmile 9.90 and pin 2 the ending point at postmile 19.68. This stretch is comprised of segments that are 4, 5 or 6 lanes wide. There are 11 on ramps, 8 off ramps and 29 mainline detectors in this freeway stretch.

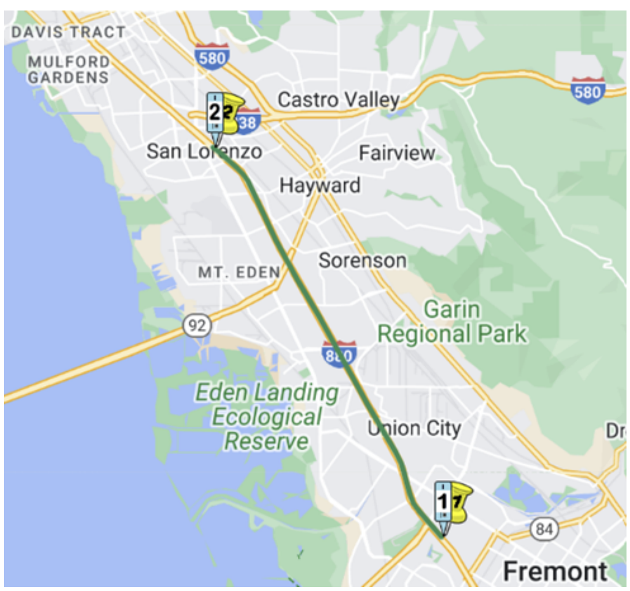


Figure 3.1: Study Area

3.2 Measured Data

There are two types of data used in this research. The first is crash data. Crash data for the study area from January to June 2016 were collected from the Statewide Integrated Traffic Records System (SWITRS). This database, which is maintained by the California Highway Patrol, archives detailed information of each reported crash, including its location, reportedly to within 0.01 mile; its occurrence time, reportedly to within 1 minute (although this precision may be overstated); and its type (e.g., sideswipe, rear-end, etc.). There were in total 287 crashes that occurred in the study area in the 6-month study period.

The second type of data is traffic data. Detectors' occupancy, VMT and VHT data from January to June 2016 were collected from the California Department of Transportation (Caltrans) Performance Measurement System (PeMS). PeMS provides access to real-time and historical freeway traffic data. The data were aggregated in 5 mins intervals.

Additional crash and traffic data were collected for some selected detectors from July to December 2016 to confirm some of our initial findings. These additional data will be used for analysis in chapter 5.

Chapter 4

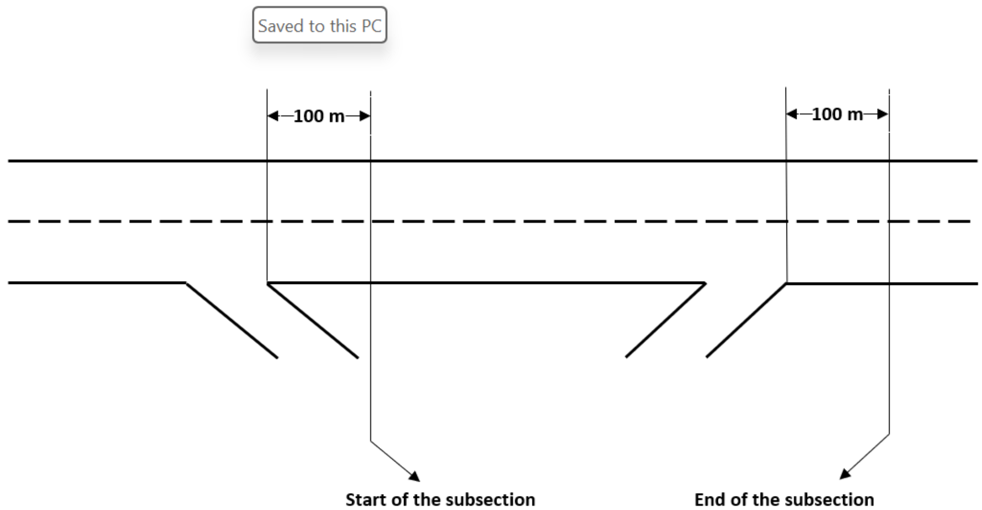
Data Processing

This chapter details the data processing used in present study. Discussion includes how the study area was partitioned into subsections, how uncongested and congested traffic conditions were distinguished using the traffic data measured from PeMS, how the determination was made as to whether a crash happened in uncongested or congested traffic conditions, and how each subsection's VMT and VHT was separately estimated for uncongested and congested traffic conditions.

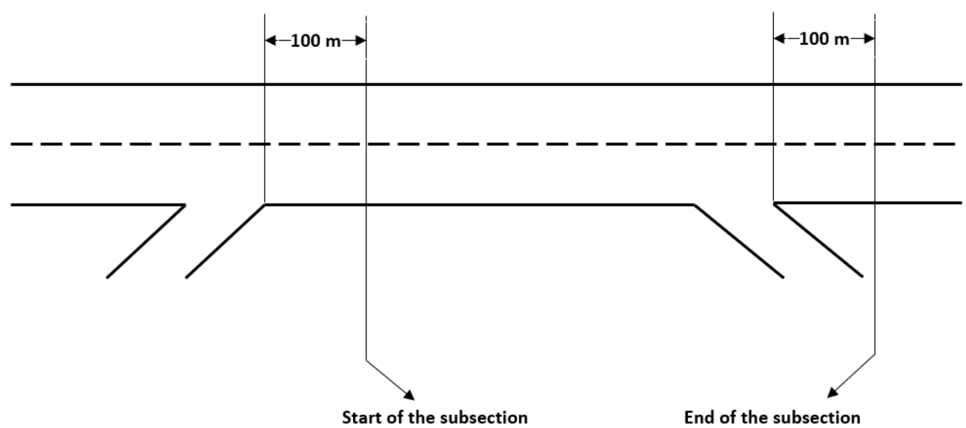
4.1 Segmentation

As explained in chapter 2, traffic agencies typically use a sliding window or peak searching method to partition locations of extended physical lengths into small subsections (of around 0.1 to 0.3 miles) for screening. However, using these small subsections to identify problematic locations is susceptible to mistaking statistical clusters of crashes as if they were caused by systematic factors such as highly localized geometric or traffic control problems. Within a small subsection, a large number of crashes could appear because of the randomness of crashes. A second problem is that some locations that have numerous crashes may not be identified because crashes are uniformly distributed over a longer space.

Given the problems of using small subsections, we instead partitioned the study area into longer contiguous subsections based on geometry, so that each subsection has an on ramp or an off ramp located near its downstream end point. Since subsections are contiguous, the start point of a subsection is the end point of the neighboring upstream subsection. We now describe how the end point of a subsection is determined. There are two cases based on whether the subsection has an on ramp or an off ramp at its downstream end. Figure 4.1a shows an example for a hypothetical subsection that has an on ramp at its downstream end. The end point is 100 meters downstream of the on ramp merge gore with the mainline. If there are auxiliary lanes, then the end point is 100 meters downstream from the end of auxiliary lanes. Figure 4.1b shows an example for a hypothetical subsection that has an off ramp at its downstream end. The end point is 100 meters downstream of the off ramp gore



(a)



(b)

Figure 4.1: Examples of Hypothetical Subsections; (a) when the subsection has an on ramp near its end point; (b) when the subsection has an off ramp near its end point

with the mainline.

This method partitioned our study area into 19 subsections. The lengths across these subsections range from 0.09 miles to 1.13 miles with an average of 0.46 miles. Some of the subsections are not homogeneous because the number of lanes changed within them. If the change in the number of lanes is a geometric feature that results in more crashes, this will presumably be reflected in the number of crashes for that subsection. Since each subsection has a ramp located near its end point, flow is conserved across most of every subsection.

4.2 Distinguishing Uncongested and Congested Traffic Conditions

To determine whether a crash happened under uncongested or congested traffic conditions, we identified a threshold for detector occupancy that separates the two traffic conditions. We found occupancy thresholds that are distinct for 4, 5 and 6 lane freeway sections, with a greater number of lanes producing a smaller threshold. The reason for the distinctions in thresholds could be that more lanes induces more vehicle lane changing maneuvers. A lane changing vehicle might straddle two lanes and thus occupy more than one vehicle space near the detectors. But this vehicle is likely to only be counted once by one detector. This will lead to a lower occupancy threshold for sections with a higher number of lanes.

To find these distinct occupancy thresholds, we picked one section from each freeway category based on its number of lanes and used that section as a representative for all the other sections in that category. The process of finding the occupancy threshold is described below.

- We first pick a detector that at times is immediately downstream of an active bottleneck that creates congestion so that we can measure uncongested flows and near capacity flows. The detector is also at times visited by spill over queues downstream so that we can also measure flows in congestion at the detector. Then we plot flow vs occupancy for that detector using a week's worth of data. Here we use a detector located at postmile 12.30 in a 4 lane freeway section and the plot is shown in Figure 4.2.

- The occupancy at the intersection of the uncongested and congested branch (see Figure 4.2) is the occupancy threshold we are looking for. To find this threshold, we eliminated data from the congestion branch and only kept the data points with occupancies less than 30% (see Figure 4.3). The reason is that data points with occupancies higher than 30% are far from the intersection of the branches that we seek.

- To obtain the best fit line for the congested branch, we define for each congested data point, a pseudo-speed as flow divided by occupancy. This recognizes that occupancy and density are related by an average of the vehicle lengths (Cassidy and Coifman, 1997). We then plot 8 radial lines, as shown in Figure 4.3. These lines collectively span the range of occupancies used for the congested branch. The slope of each radial line increases by 40 units of pseudo-speed from its neighbor to the right. To counter the scatter of data in the congested branch, we find the median of the data points between two radiant lines, again as shown in Figure 4.3, and then find the best fit line through the locus of these median points, as shown in Figure 4.4.

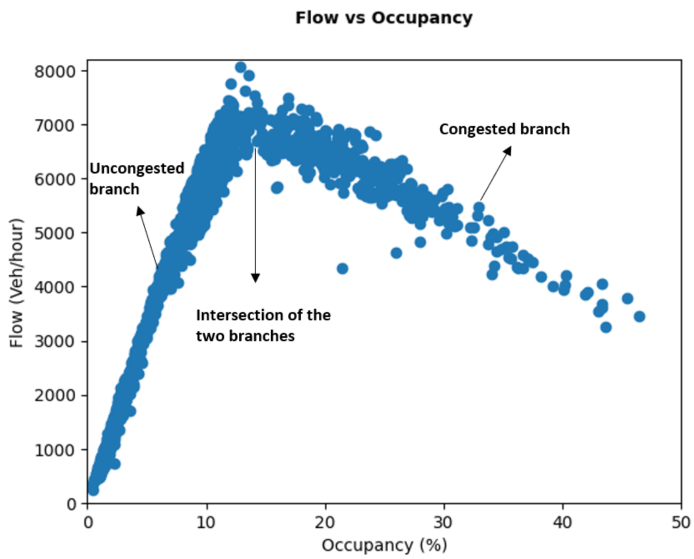


Figure 4.2: Detector Flow vs Occupancy Plot

- For the uncongested branch of the flow vs occupancy scatter plot, we find the best fit line through those data points using linear regression. We then extrapolate the best fit line for the congested branch until it intersects with the best fit line for the uncongested branch. The occupancy at the intersection of these two lines is the occupancy threshold that we seek. For the example of a 4-lane section shown in Figures 4.2 - 4.4, the occupancy threshold is 12.3%. We repeat the same process for detectors located in 5 and 6 lane sections separately, and the corresponding occupancy thresholds are 11.6% and 8.9% respectively.

4.3 Determining Traffic Condition for Each Crash

With the occupancy threshold as described in section 4.2, we next determine whether a crash happened in uncongested or congested traffic conditions. For each crash, we first find the detector that is located closest to the crash location. Then the detector occupancy at the time of crash (to the nearest 5 mins interval) is used to determine whether traffic conditions for the crash were uncongested or congested. If the detected occupancy is higher than the threshold, then this crash is labeled as a congested crash. If lower, then it is labeled as an uncongested crash.

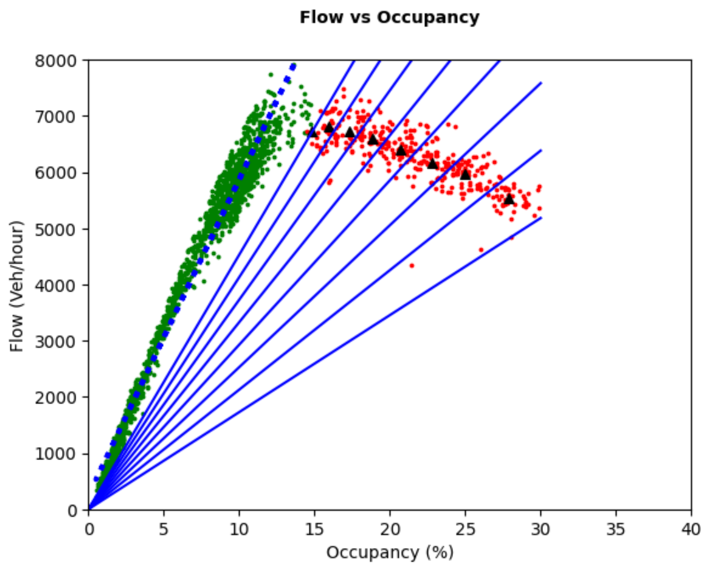


Figure 4.3: Detector Flow vs Occupancy Plot with Uncongested Branch and Congested Branch Separated

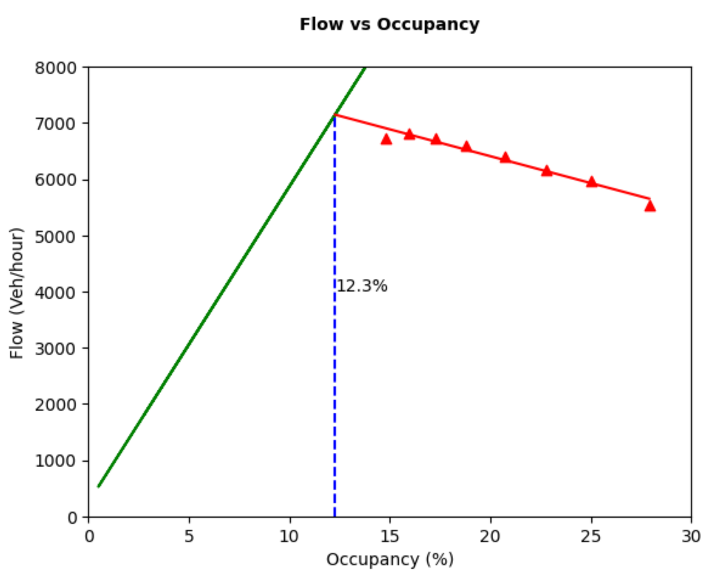


Figure 4.4: Detector Flow vs Occupancy Plot with Occupancy Threshold

4.4 Estimating VMT and VHT for Subsections

For each subsection, we next estimate, over the 6-month study period, each subsection's traffic exposure data, i.e., VMT and VHT for uncongested and congested conditions. As explained earlier in chapter 2, VMT and VHT data will be used to calculate the two variants of the Crash Rate performance measure. To be used as a baseline for comparison, we use VMT as the measure of traffic exposure for the current practice. We then use VHT for our proposed approach.

To come up with VMT and VHT for each of our subsection, we started by using VMT and VHT data from PeMS estimated by detectors. For each detector, VMT and VHT data were estimated inside its detector zone. Figure 4.5 shows an example of a hypothetical freeway lane. The start point of Detector 2's detector zone is the midpoint between Detector 2 and its neighboring upstream detector, i.e., Detector 1. The end point of this detector zone is the midpoint between Detector 2 and its neighboring downstream detector, i.e., Detector 3. L_2 represents the detector zone for Detector 2.

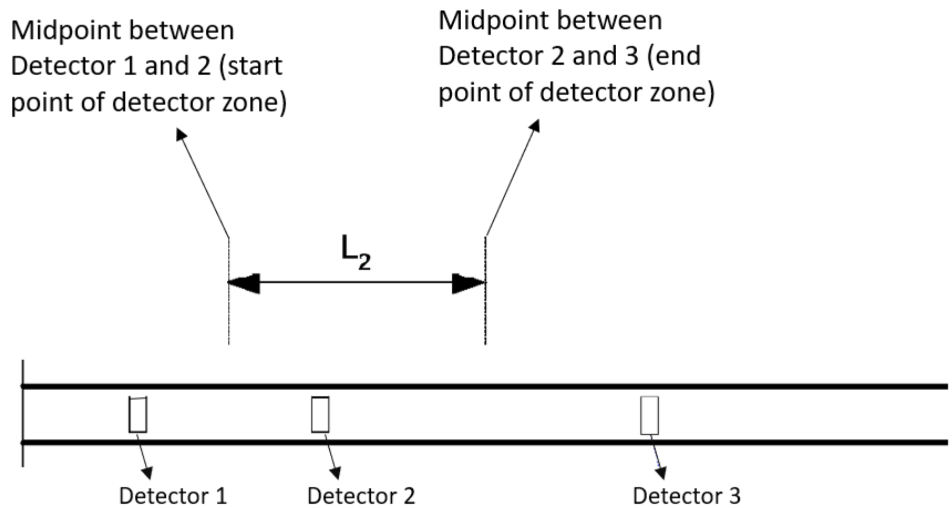


Figure 4.5: Detector Zones

The detector zones are not spatially aligned with our subsections. So, each detector zone is divided into contiguous spatial intervals of 0.01 mile length. Then each detector zone's VMT and VHT are equally distributed into each 0.01-mile interval. After that, based on the start and end points for each subsection (for example, see Figure 4.5), we aggregate VMT and VHT across all the 0.01 mile intervals inside this subsection to get estimates of its VMT and VHT. Once processed in the ways described in this chapter, all the data are used for analysis in the next chapter.

Chapter 5

Analysis and Findings

In this chapter, we will present the analysis and findings for our proposed approach and compare them with those from the current practice. Recall that our proposal is to first separate crashes in uncongested traffic from those in congestion. Then we use VHT instead of VMT for capturing traffic exposure, i.e., we normalize crash counts with VHT and thus obtain a variant of Crash Rate as the performance measure that is different from what is currently used (crash counts normalized by VMT) for the network screening process. Although we are not the first to use VHT as the measure of traffic exposure while calculating Crash Rate (Yeo et al., 2013; Goodall, 2021, have both used VHT as the traffic exposure measure, see again section 2.2), we seem to be the first to point out that VHT is better than VMT as the exposure metric for congested freeway traffic since the former can capture the vehicles' extra exposure in slow-moving congestion.

The proposed approach enables us to identify whether crashes occur in uncongested or congested conditions. Then we can understand the type of crashes (uncongested and/or congested) that cause certain locations to be problematic. Subsequently, we can narrow down the set of outliers, to focus on those predominantly influenced by uncongested crashes that represent the most critical safety concerns. Furthermore, we can prioritize these uncongested outliers based on their magnitudes and concentrate our efforts on addressing the highest ranked ones. In the following sections, we will use the results from our study area to further illustrate these ideas. Section 5.1 presents the findings using the current practice and discusses its problem. Section 5.2 presents the findings using the proposed approach and describes how our proposed approach can address the problem with the current practice. Section 5.3 provides a summary of the findings.

5.1 Findings Using Current Practice

The current practice first groups study locations based on road geometry (e.g., number of lanes) and geographic settings (e.g., rural, or urban). We do not group our subsections, however, for three reasons. Firstly, our study area only has 19 subsections. Hence the data are limited and we do not have enough subsections to be partitioned into multiple groups. Secondly, the purpose of grouping is unclear to us, since crashes are normalized by a measure of traffic exposure, in this case, VMT. Lastly, recall that section 4.1 reports that current practice uses a small spatial window (0.1 to 0.3 miles) to partition locations of extended physical length. This means of partitioning leads to two problems. First, problematic locations are susceptible to statistical clusters of crashes not caused by systematic factors. Second, some locations that have numerous crashes may not be identified because the crashes are uniformly distributed over a longer space. Because of these two problems, our proposed approach divides the study area based on road geometry and the subsections we thus obtain are longer than the aforementioned small windows. As a result, some of the subsections are not geometrically homogeneous because the number of lanes changed within them. Therefore, we cannot group subsections based on geometry. Comparisons between current practice and the proposed approach therefore occur without groupings.

The current practice also finds a base average crash rate for each group to find the outlier locations. The definition of this base rate is vague: it is determined by looking at all crashes in the study time period. Based on this vague definition, we have two interpretations. The first is that base rate is calculated by dividing the total number of crashes from all the locations combined by the total VMT from all the locations combined. The second interpretation is that base rate is determined by finding the best fit linear regression line through all the data points where each data point represents a subsection's total number of crashes plotted against VMT. In the latter interpretation, the slope of the best fit line is the base rate. We separately followed both interpretations for our study area. Since zero traffic exposure should be corresponded with zero crash, both linear models do not have intercepts. We found that the R squared value for the first interpretation is -0.033. That the R squared value is negative means that the regression line from the first interpretation is worse than using a horizontal line located at the average number of crashes for which the R squared value would be 0. Note that the R squared value could be negative because our models do not have intercepts. The R squared value for our second interpretation is 0.018, which is higher than -0.033 indicating the linear regression line fits the data better. Hence we use linear regression to find the base crash rate. Since we want to compare the results from the current practice with our proposed approach, we also use linear regression to find the base rate when our proposed approach is used in the later sections of this chapter.

Outcomes for our study area using our best interpretation for the current practice are shown in Figure 5.1. The Y axis displays the number of total crashes that occurred in the subsections for all traffic conditions combined, i.e., both uncongested and congested crashes. The X axis displays the VMT that accumulated on that subsection over the 6-month study period. The subsection from which comes each data point is identified by its postmile. These are annotated in the figure. There are 19 data points in total representing the 19 subsections. The linear regression for the best fit line through all the data points is shown as a solid line in Figure 5.1. A two-standard-deviation upper bound is shown as a dash line in the figure. Five subsections emerge as outliers. The crash and VMT data from these outliers are represented as solid circles and are labeled a through e in Figure 5.1.

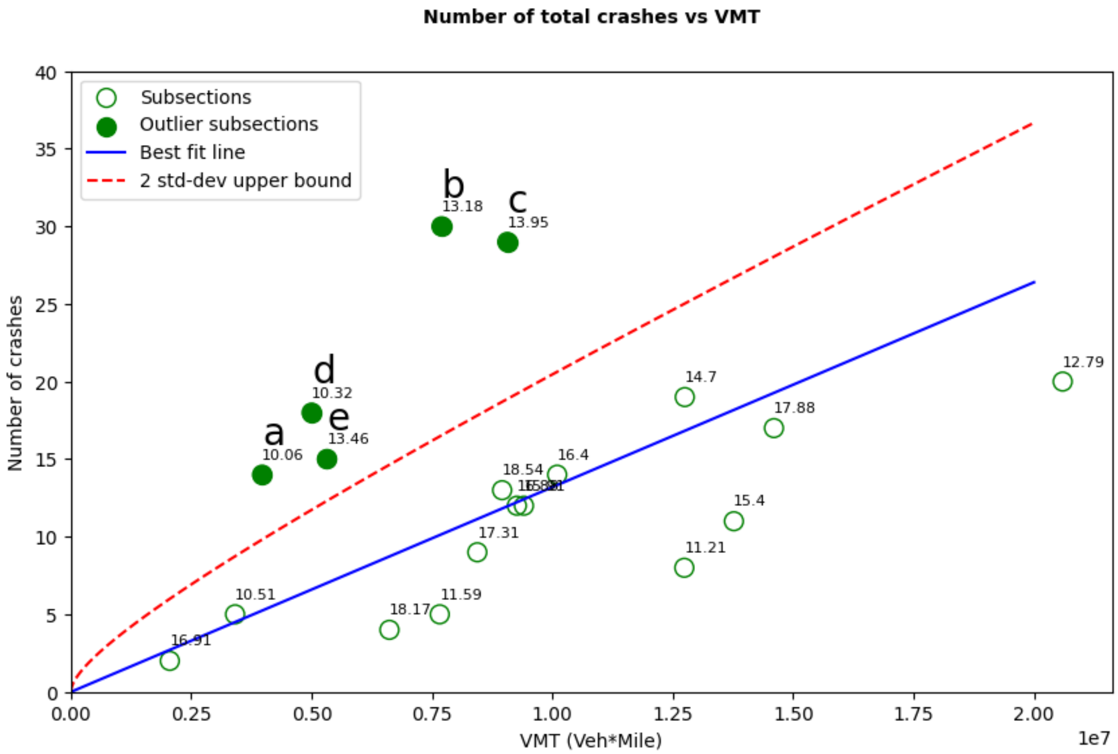


Figure 5.1: Number of Total Crashes vs VMT for All Subsections

Since uncongested crashes are the most dangerous and congested crashes are often Property Damage Only (PDO), the main problem with the current practice is that traffic agencies do not know the type of crashes that make some locations outliers. Some locations are outliers because of large number of uncongested crashes; some because of congested crashes, and others because of both. As a result, traffic agencies are not able to focus on the most dangerous locations, i.e., those that are outliers because of high-risk uncongested crashes. In section 5.2, we will show that with our proposed approach, we can address this problem.

5.2 Findings Using the Proposed Approach

In this section, we will present the findings from screening crashes via our proposed approach. Section 5.2.1 presents the findings for congested crashes and 5.2.2 for uncongested crashes. We shall see that: points labeled a and b in Figure 5.1 come from subsections that are outliers because of high crash rates in both uncongested and congested traffic; points labeled d and e come from subsections that are outliers because of high crash rates in congested condition and the point labeled c comes from a subsection that is an outlier because of high crash rates in uncongested conditions. Hence, the proposed approach enables traffic agencies to

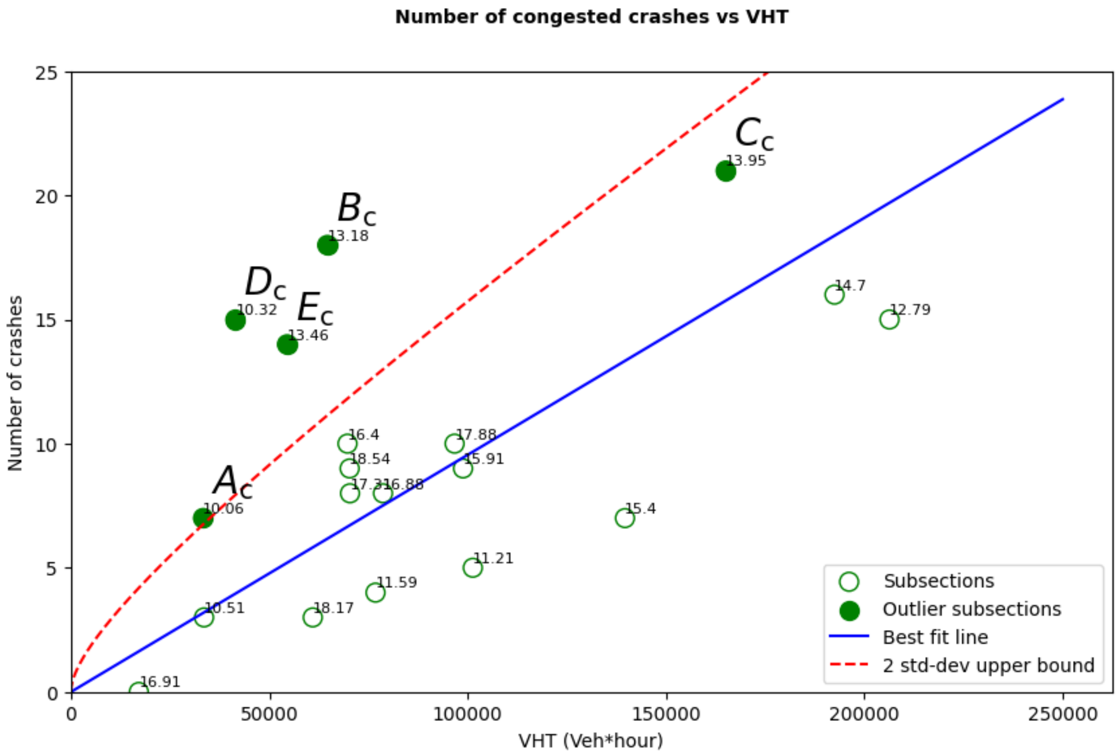


Figure 5.2: Number of Congested Crashes vs VHT for All Subsections

understand the type of crashes, (uncongested and/or congested), that make some locations outliers and then to focus on uncongested outliers as they are of the greatest safety concerns.

5.2.1 Findings Using the Proposed Approach for Congested Crashes

The data points in Figure 5.2 display the number of low-risk crashes that occurred in low-speed congested traffic. All 19 subsections are represented. These low-risk crashes are plotted against VHT. Recall that we use VHT as the normalizer instead of VMT because the former does a better job of capturing a vehicle's extra exposure in congestion. The reason is that in congestion, vehicles travel at slow and varied speeds and thus spend greater and more varied time traveling per unit distance.

We first use R squared values to compare the two linear regression models obtained from the current practice and from our proposed approach. The model based on congested VHT yields a higher R squared value (0.222) than the VMT-based model (-0.090) indicating that VHT provides a better fit and thus a better measure of traffic exposure in congestion for the assumed linear relationship. Recall that the negative R squared value for the VMT-based model means that the regression line provides an even worse fit than using a horizontal line located at the average number of congested crashes. Further recall since both models do not have intercepts, negative R squared values are possible.

We choose the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) as additional measures to compare the two linear regression models. AIC and BIC are statistical measures widely used in model selection (Vrieze, 2012). The two are computed based on the likelihood function of the model and the number of its independent variables. The distinction between these two measures of fit lies in BIC's stronger penalty for the inclusion of more independent variables. A lower value for either AIC or BIC signifies a better fit. The VHT-based model yields a lower AIC value (123.607) than that of the VMT-based model (130.346). The VHT-based model also yields a lower BIC value (124.603) than that of the VMT-based model (131.342). These outcomes are consistent with what we concluded using the R squared value: VHT indeed provides a better fit and thus a better measure of traffic exposure in congestion for the assumed linear relationship.

The five outlier subsections previously represented by data points labeled a through e in Figure 5.1 are now represented by data points labeled A_c through E_c in Figure 5.2. The subscript c represents congested traffic conditions. Note that points a, b, d and e in Figure 5.1 now labeled A_c, B_c, D_c and E_c in Figure 5.2 remain outliers. This indicates that they come from subsections where congested crash rates are concerning, i.e., high congested crash rates are at least one reason that these subsections are outliers. In contrast, point c in Figure 5.1 is no longer an outlier (see the point labeled C_c in Figure 5.2) indicating that it comes from a subsection where congested crash rates are not concerning. Other than these 5 subsections labeled A_c through E_c, all of the other 14 subsections are still not outliers, as Figure 5.2 makes clear.

Given that the study period is only 6 months, we explore possible problems regarding the RTM phenomena by collecting another set of 6-month data (from 07/01/2016 to 12/31/2016) for the 5 subsections from which come the data points labeled A_c through E_c in Figure 5.2. We take an average of the original 6-month data and the new data and plot these data in Figure 5.3. The original 6-month data are represented as lightly shaded circles, the new data as hollow circles, and the averages as larger, darker shaded circles. Then we find a new best-fit line through data points from all the 19 subsections because of the addition of the new data. This new best-fit line is shown as a solid line in Figure 5.3. A new 2-standard-deviation upper boundary is shown as a dash line in this figure. Notice that the other 14 subsections are not plotted in this figure to make it more readable. For the 4 previously identified outliers, A_c, B_c, D_c and E_c in Figure 5.2, their averages are labeled A'_c, B'_c, D'_c and E'_c in Figure 5.3. They all remain as outliers. Further note that point C_c in Figure 5.2 is still not an outlier (see the point labeled C'_c in Figure 5.3). Since the new data points do not qualitatively change our findings, this shows that the RTM phenomena is not an issue in our congested crash data.

In addition to these findings, there remains a question to be answered: which, if any of the 4 outlier subsections from which come data points labeled A_c, B_c, D_c and E_c in Figure 5.2, will remain outliers when only high-risk uncongested crashes are considered? Furthermore, for the subsection from which comes data point labeled as C_c in Figure 5.2, we shall confirm

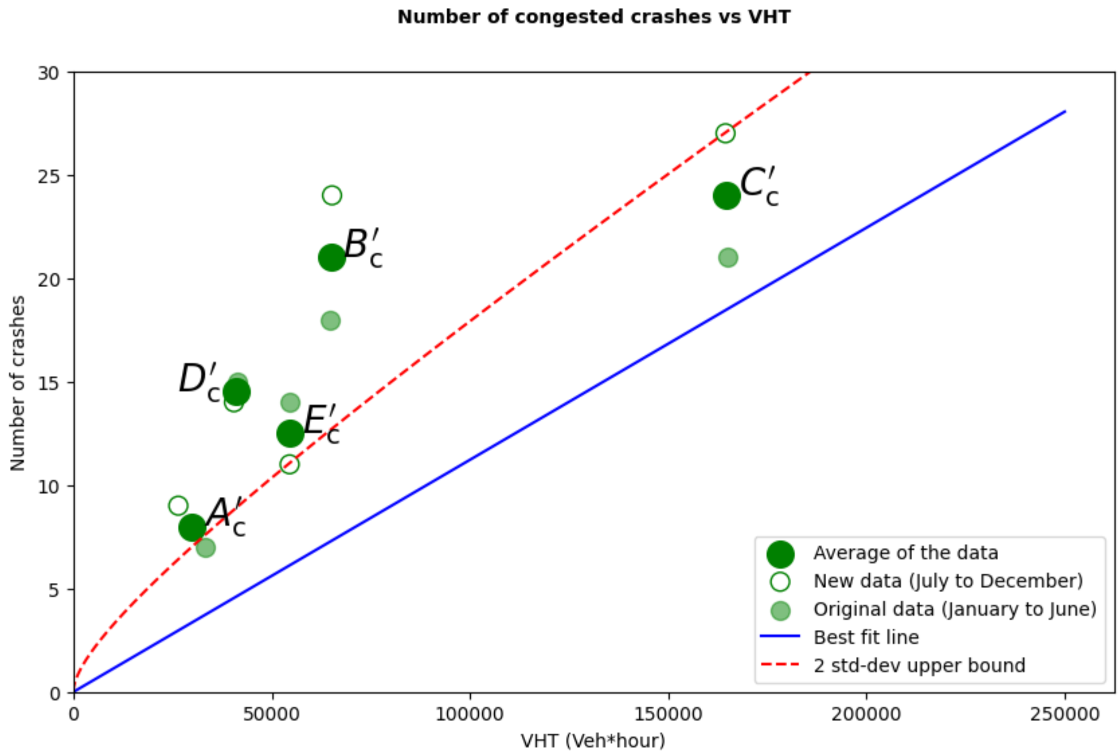


Figure 5.3: Number of Congested Crashes vs VHT for Data Points Labeled A'_c through E'_c

that it will become an outlier if only uncongested crashes are considered. To attend to these matters, we now present our findings using the proposed approach for uncongested crashes.

5.2.2 Findings Using the Proposed Approach for Uncongested Crashes

The data points in Figure 5.4 display the number of high-risk crashes that occurred in high-speed uncongested traffic. Note that these high-risk crashes are plotted against VHT. Even though in uncongested traffic, VHT and VMT are linearly related and will produce the same results, we use VHT here for uncongested crashes to achieve symmetry with the analysis in section 5.2.1.

Recall that the data points labeled D_c and E_c in Figure 5.2 were previously identified as coming from outlier subsections when only congested crashes were considered. In Figure 5.4, they are now labeled D_u and E_u. The subscript u represents uncongested traffic conditions. These two subsections are no longer outliers. They instead reveal themselves to have come from subsections where the high-risk uncongested crash rates are not high enough for these two to constitute problems. Therefore, points labeled d and e are outliers for the current

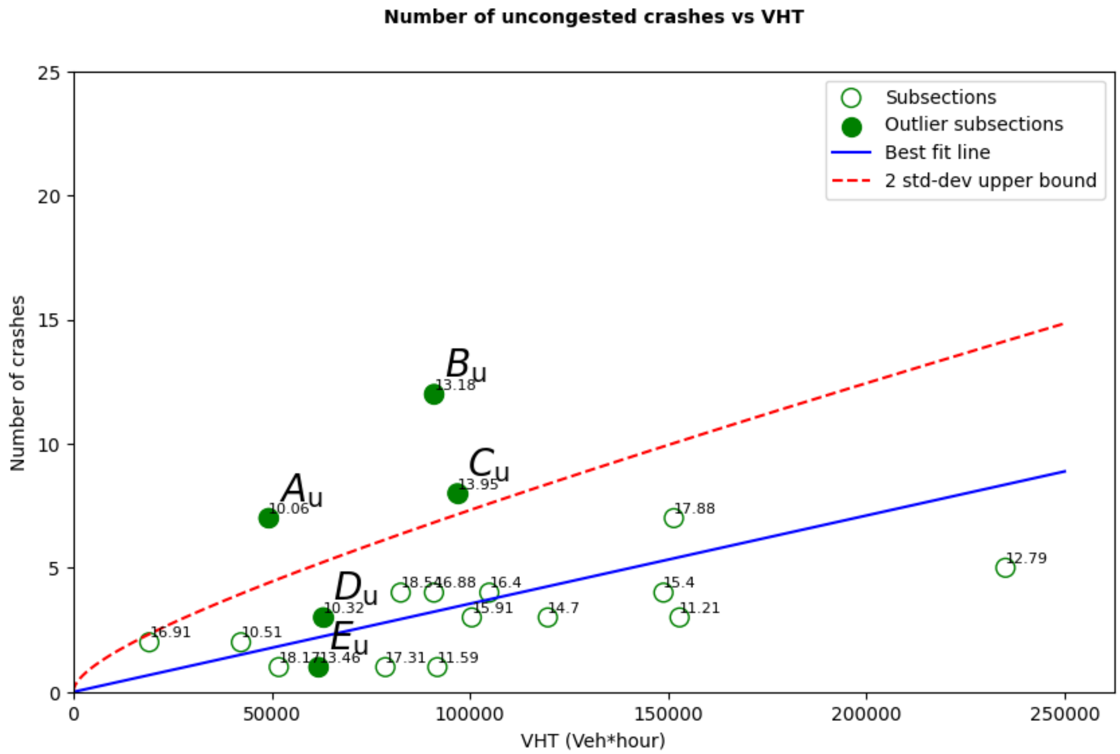


Figure 5.4: Number of Uncongested Crashes vs VHT for All Subsections

practice, (see again Figure 5.1), because of the influence of the high crash rates in congested, slow-moving traffic.

In contrast, note that data points labeled A_c and B_c in Figure 5.2 now labeled A_u and B_u in Figure 5.4 remain as outliers, indicating that these two data points come from subsections where the high-risk uncongested crash rates are substantial. Recall that these two data points are also outliers when only congested crashes are considered. This indicates that the data points labeled a and b are outliers for the current practice, (see again Figure 5.1), because of high crash rates in both uncongested and congested traffic. The data point labeled C_c, which is not an outlier in Figure 5.2, is now labeled C_u in Figure 5.4 and returns to be an outlier. This is as expected because point c was an outlier for the current practice (see again Figure 5.1). This indicates that this data point comes from a subsection where the high crash rates in uncongested traffic are the reason for this subsection to be an outlier. Hence, the three subsections from which come the data points labeled in Figure 5.4 as A_u, B_u, and C_u should be investigated as potential high-risk locations. In contrast, the two subsections from which come data points labeled as D_u and E_u should be given low priority when the focus is to reduce the number of high-risk uncongested crashes. Other than these 5 subsections, all of the other 14 subsections are still not outliers, as Figure 5.4 makes clear.

Similar to what we did for congested crashes (see section 5.2.1) to investigate potential issues associated with the RTM phenomena, we also collected additional 6-month data for the 5 subsections from which come the data points labeled A_u through E_u in Figure 5.4. We take an average of the original 6-month data and the new data and plot these data in Figure 5.5. The initial 6-month data are depicted as lightly shaded circles, the new data as hollow circles, and their respective averages as darker shaded circles. Subsequently, a revised best-fit line is calculated across all 19 subsections, incorporating the newly added data points. This updated best-fit line is illustrated as a solid line in Figure 5.5. Additionally, a new upper boundary, delineated by 2-standard deviations, is displayed as a dash line in this figure. Notably, to enhance readability, the other 14 subsections are omitted in this figure. We also reduced the range of the X-axis in Figure 5.5 to ensure clearer separation between data points. For the 3 previously identified outliers, A_u, B_u and C_u in Figure 5.4, their averages are labeled A'_u, B'_u and C'_u in Figure 5.5. They all remain as outliers. Further notice that points labeled D_u and E_u in Figure 5.4 are still not outliers (see the points labeled D'_u and E'_u in Figure 5.5). As the inclusion of the new data points does not qualitatively alter our conclusions, it demonstrates that the RTM phenomena does not pose a concern in our analysis of uncongested crash data.

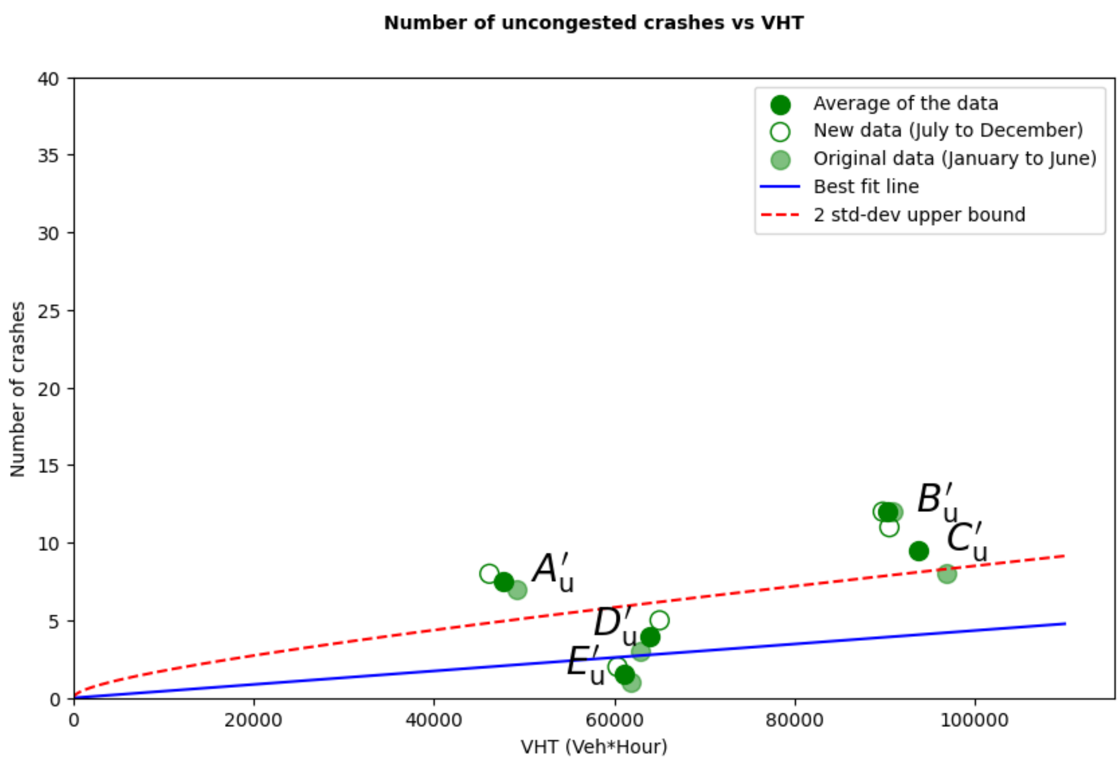


Figure 5.5: Number of Uncongested Crashes vs VHT for Data Points Labeled A'_u through E'_u

5.3 Summary

The findings in this chapter illuminate the specific crash types, (uncongested and/or congested), that single out certain locations as problematic. Consequently, we can narrow down this set of outliers to focus primarily on those influenced by riskier uncongested crashes. In our example, points a and b in Figure 5.1 are outliers because of high crash rates in both uncongested and congested traffic. Point c is an outlier because of high crash rates in uncongested traffic. Points d and e are outliers because of high crash rates in congested conditions. So, the three subsections from which come data points labeled a, b and c should be investigated as potential high-risk locations. In contrast, the two subsections from which come data points labeled d and e should have low priority.

Additionally, based on the uncongested outliers' relative deviations from the 2 standard-deviation upper boundary in Figure 5.4, we can rank uncongested outliers and focus on the highest ranked ones. In this case the ranking order is B_u followed by A_u followed by C_u. Point B_u should have a much higher priority than C_u since its relative deviation in Figure 5.4 is much bigger than that of C_u's. However, if the current practice is used for ranking as shown in Figure 5.1, then the ranking order would be b, c, d, a and e where b and c have similar priorities. Another issue with the ranking order from the current practice is that since d and e are outliers only because of high crash rates in congested conditions, they should have low priority when the focus is on reducing the most dangerous uncongested crashes. For the reasons mentioned above, the proposed approach allows traffic agencies to focus their resources on these more dangerous locations and help improve the overall safety on the roadway system.

Chapter 6

Future Work

In this chapter, we will discuss some research questions that can be explored in the future related to this study.

6.1 Further Testing for the Proposed Approach

In this research, we focused the analysis on a 10 mile freeway stretch for a 6 month study period. This small scale study shows that our proposed approach holds promise to find out what type of crashes (uncongested/congested) make some locations stand out as problematic and narrow down the set of these outliers to the ones that are caused by uncongested crashes. This method needs further testing on more freeways and with longer study periods. Further study should include freeways in other districts in California and elsewhere in the country. These freeways should come from urban or suburban areas that are subject to congestion. On any freeway without congestion, the proposed approach will produce the same outcomes as the current practice. The study periods should also span multiple years.

With these additional data, we may be able to show that dangerous locations which otherwise would be overlooked by the current practice will emerge using the proposed approach. We can also check if the proposed approach can help reduce the high false positive rate that plagues the current practice, see again Chapter 2. This can be done by checking how often outliers identified by the proposed approach have identifiable problems such as geometric design or control problems. Even in cases where there are no such problems, traffic agencies can experiment to see if some additional control methods can help reduce the number of high-risk crashes. Some possible control methods include reducing the speed limit, adding sobriety check points and using video cameras to detect driving speeds.

To enhance our proposed method, further work is also needed to explore other explanatory variables that may have impacts on the occurrences of high-risk crashes. Some examples for these explanatory variables are daylight or nighttime conditions, weather conditions (dry or wet), freeway width, and driver demographics (different states and age groups). For example, if the outcomes show that under wet conditions, high-risk crashes happen more often, then improving the drainage system or using pavement materials that provide more friction may help reduce the number of high-risk crashes. If high-risk crashes happen more often at nighttime, then implementing more police patrols or better illumination may also help reduce high-risk crashes.

6.2 Automate Data Collection, Processing, and Analysis

For the present study, the collection, processing, and analysis of data are being done in a semi-automated fashion using Python scripts. Realistically speaking, if this proposed approach is to be used by traffic agencies, we need to fully automate all the aforementioned processes and develop more user-friendly software. This software could include three stages. The first of which is data collection. During this stage, the user would select the study freeway and study period and the software would start collecting both traffic and crash data from the relevant data archives, e.g., PeMS and SWITRS in California.

The second stage is data processing. In this stage, the software would first partition the study freeway into contiguous subsections. Then it would determine whether each crash happen in uncongested or congested traffic and estimate VHT for each subsection.

The third stage is data analysis. The software would plot the number of uncongested crashes vs VHT for each subsection and pick the top-ranked outliers. These outliers will be provided to the user as potentially dangerous locations for investigation.

With further testing and the development of more user-friendly software, the proposed approach can be used by traffic agencies across the country to identify what are potentially the most dangerous freeway locations more accurately. This will give agencies the ability to better allocate their resources by focusing on these dangerous locations to improve overall safety for all users.

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