FRAMEWORK FOR ESTIMATING NETWORK-WIDE SAFETY IMPACTS OF INTELLIGENT TRANSPORTATION SYSTEMS

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ABSTRACT

The paper presents a safety model that is based on US national crash statistics. The model computes the crash risk for 14 different crash types as a function of the facility speed limit and a time-dependent measure of exposure. The use of a time-dependent measure of exposure allows the model to capture differences in the crash risk that result from differences in the network efficiency. The model also computes the vehicle damage and level of injury to the passengers involved in the crash based on the vehicle's instantaneous speed. The use of the instantaneous speed means that the crash damage and injury level is responsive to the level of congestion. Consequently, the model can capture the safety impacts of operational-level alternatives including Intelligent Transportation Systems (ITS's).

A field and simulation application of the model indicates that it produces results that are consistent with the General Estimates System national database. Furthermore, the results indicate that the model can be applied to evaluate the safety impacts of alternative traffic-flow improvement projects, like for example re-timing traffic signals.

INTRODUCTION

During the period of 1988-96 over 58 million crashes were reported in the United States (U.S. DOT). In 1996 alone the total number of reported crashes was approximately 6.8 million, which was significantly higher than what was reported in the previous four years (1992-95). Furthermore, even though the total number of crashes remained almost the same from 1988 to 1994, the number of fatal crashes was not. Consequently, there is a need for a tool that can systematically evaluate the safety impacts of different traffic-flow improvement projects.

Transportation engineers have utilized existing accident/crash databases to evaluate the safety impacts of Intelligent Transportation Systems (ITS). However, there has not been a systematic approach to develop a safety model that is sensitive to ITS. This paper describes a safety model that was developed to address this unique problem. Specifically, the model that is described is sensitive to the facility's speed limit, the level of congestion on the facility, and the vehicle's instantaneous speed. The model computes the crash risk for 14 types of crashes, the level of damage incurred to the vehicles in the crash, and the maximum level of injuries to the people involved in the crash.

Objectives of Paper

The objectives of the paper are twofold. First, the paper describes a safety model that was developed for evaluating the safety impacts of ITS alternatives. The unique features of the model are its sensitivity to vehicle-to-vehicle and vehicle-to-control interaction. Second, the paper demonstrates the feasibility of the model within a simulation environment and its direct application to field data.

Paper Layout

The crash rate as a function of the facility speed limit is computed as the ratio of the number of crashes to the Vehicle Kilometers Traveled (VKT) (more commonly referred to as Vehicle Miles Traveled (VMT)), as illustrated in Figure 1. The VKT in turn, is the product of the traffic volume on the roadway network and the length of the roadway network.

Consequently, in terms of the paper layout, the first section provides a brief background of the available national crash databases and the typical highway statistics in the US. Section 3, describes how the crash data were extracted from the national crash database and how the VKT was computed. In addition, Section 3 describes how the number of crashes and the VKT were utilized to develop the safety model, while Section 4 provides a limited application of the safety model for the evaluation of the safety impacts of traffic signal coordination. Finally, Section 5 provides the conclusions of the paper together with suggestions for further research.

BACKGROUND

A number of national crash databases are available for public usage, including the General Estimates System (GES), the Fatality Analysis Reporting System (FARS), the Highway Statistics Database, the Highway Safety Information System (HSIS), and the Crashworthiness Data System (CDS). The GES database is the largest and the most complete of these databases and thus was utilized for the model development. This section provides a brief overview of the GES database, typical US highway statistics and the current state-of-the-art in safety modeling.

The General Estimates System Database

The General Estimates System (GES) database was developed in 1988 by the National Center for Statistics and Analysis and is operated by the National Highway Traffic Safety Administration (NHTSA) (USDOT, 1996). GES data are obtained from a nationally representative probability sample selected from all police-reported crashes. The primary objectives for the development of this system were the identification of traffic safety problem areas and for usage as a basis for benefit/cost analyses of traffic safety initiatives.

The level of exposure makes GES, the largest crash database available in the United States. Due to its level of exposure, DOT agencies, lawyers, doctors, researchers and insurance companies use it extensively. By using the database one can estimate different crash frequencies (number of vehicle crashes).

For a crash to be eligible for the GES sample, it has to meet a number of criteria including: (a) a Police Accident Report (PAR) must be completed, (b) it must involve at least one motor vehicle traveling on a traffic way, and (c) the result must be property damage, injury or death. GES data collectors perform weekly visits to approximately 400 police jurisdictions in 60 sites across the United States. The GES 1996 file that was used for the purposes of developing the safety model included approximately 56,000 Police Accident Reports (PAR's).

The crashes in the database are classified in a variety of ways, for example by a typical speed limit, crash severity, time-of-day and vehicle type. A statistical model that the database utilizes enables the user to extract national statistics on crash frequencies.

There are three main files (Statistical Analysis Data Sets) in the GES database that include all the variables. The first of these files, the accident file, contains information describing environmental conditions and roadway characteristics at the time of the crash. It also includes information such as the time the crash occurred, the manner of collision and speed limit of the facility on which the crash occurred. The second file, the vehicle/driver file contains information describing the vehicles involved in the crash and their drivers. It also includes information about the model/make of the vehicle, the model year of the vehicle, the driver's maneuver to try and avoid the crash, and the reason for the driver distraction. The third file, the person file, contains general information describing all persons involved in the crash. These include the drivers, passengers, pedestrians, pedalcyclists and non-motorists who were involved in the crash. The file also includes information about the age, sex and injury severity of each of the persons involved in the crash.

Highway Statistics

The computation of the crash rate from the frequency of crashes requires a unit of vehicle exposure, which is typically the VKT. This section briefly describes some of the data available for computing VKT for different facility types.

The Federal Highway Administration (FHWA) and the Office of Highway Management publish the Highway Statistics publication once a year. The Highway Statistics provides information on highway mileage and VKT. Most of the data are divided into urban and rural tables according to the population and Federal-aid legislation definition and are presented primarily on a State-by-State basis.

The Highway Statistics indicates that the United States transportation network is the largest network in the world. Specifically, in 1996, the U.S. transportation system served 265 million people and supported 7.04 trillion passenger kilometers (BTS, 1997). Many factors influence the expansion and growth of this network such as population increase, economy expansion, higher consumer incomes and vehicle availability.

According to the Bureau of Transportation Statistics (BTS, 1997) the public roads in the US transportation network in 1996 included a total of 6,271,120 kilometers (3,919,450 miles) of roads, as summarized in Table 1. Five facility types categorize these highway kilometers. Almost 134 million vehicles (passenger cars and motorcycles) existed in the system during 1996, as opposed to less than 93 million in the 70's (BTS, 1997). In terms of vehicle kilometers, these increased from 1.76 trillion VKT in the 70’s, to approximately 4.0 trillion VKT in 1996, as demonstrated in Table 1.

State-of-the-Art in Safety Modeling

Many researchers have attempted to find the independent variables most highly associated with crashes. For example, Bernardo and Ivan (1997) attempted to establish the relationship between the number of crashes versus the crash rate using Poisson regression. In their study, small data sets for several intersections were utilized while applying different representations of traffic exposure and intersection effects as independent variables. Bernardo and Ivan (1997) suggested that the Poisson distribution allows for the relationship between exposure and crashes to be more accurately modeled as opposed to the linear relationship assumed in crash rate prediction. However, this study was limited to a rather small sample of localized intersections.

Zegeer *et.. al*. (1997) developed motor vehicle crash rates by crash type and roadway class in eight states, including California, Illinois, Maine, Michigan, Minnesota, North Carolina, Utah and Washington. The crash data were extracted from the Highway Safety Information System (HSIS). The most important variables for calculating the crash rates were the urban or rural code, the functional roadway class, number of lanes and divided versus undivided roads. Eight different roadway classes were considered, including urban freeways, urban two-lane highways, urban multi-lane divided non-freeways, urban multi-lane undivided non-freeways, rural freeways, rural two-lane highways, rural multi-lane divided non-freeways, and rural multi-lane undivided non-freeways. The results of this study showed that the most common crash type in most states was the rear end/same direction sideswipe, with angle and turning crashes ranked second. In terms of crash rates produced, these were lower on freeways than any other roadway class. The study showed significant variation in the crash rates, even within common roadway classes. This was justified by the differences in reporting procedures, the nature of the highway system, driving populations and other factors that varied from state-to-state. Severity, light and surface conditions and collision types were also considered, yielding very similar results for all eight states. They concluded that the results from their study were considered reasonable and that the crash rates could be used as a baseline in order to better understand crash trends.

In another study, Mohamedshah and Kohls (1994) developed crash rates using the Highway Safety Information System database for the development of the so-called Interactive Highway Safety Design Model (IHSDM). A crash prediction model was developed to produce average crash rates for different highway crash types. The objective of the study was to determine if the HSIS data could be used to develop a crash prediction model. The results of the study showed that data from a database such as the HSIS could be used to develop a crash prediction model for different roadway types. However, Mohamedshah and Kohls (1994) suggested that the development of average crash rates required judicious manipulation of the data and sound engineering judgement.

Zhou and Sisiopiku (1997) developed crash rates and examined their relationship to volume-to-capacity ratios. Data from Interstate I-94 in Detroit, Michigan were used to examine this relationship. Particular emphasis was given on the development of models to explain the differences between crash rates during weekends and weekdays, rear-end crashes and fixed-object collisions and property damage only crashes versus crashes involving injury and fatality. Zhou and Sisiopiku (1997) concluded that the crash rates were highest at low levels of congestion (low volume-to-capacity ratio (v/c)) and decreased rapidly when the v/c ratio increased. This finding is consistent with the model that is described in this paper, as will be demonstrated later. The final outcome of this study was that the correlation between property damage crash rates and the volume-to-capacity values followed a general U-shaped pattern. Alternatively, the injury and fatality crash rates decreased as the v/c ratio decreased.

Vogt and Bared (1997) developed crash models for two-lane rural segments and intersections. Advanced statistical techniques were used in this study, as well as extensive crash and roadway data. The Highway Safety Information System (HSIS) was used in this study as the main source of data. Models were focused on segments and intersections. Negative binomial and Poisson models were considered for both cases. Vogt and Bared (1997) concluded that the data used for these models offered reasonable representations of the effects of highway variables on crashes. However, the Poisson, negative binomial and logistic models that were used to model crash severities did not produce significant results.

Persaud and Musci (1995) used hourly traffic volumes in regression models for estimating the crash potential on two-lane rural roads. They used data from Ontario, Canada and used different combinations of time periods and geometric characteristics. Single vehicle crashes were particularly studied and the models showed that the crash potential was higher during the night. On the other hand, for multi-vehicle crashes the crash potential was higher during the day. The study also emphasized the importance in differentiating between single and multi-vehicle crashes and day versus night conditions.

In its Special Report 254 (“Managing Speed”), the Transportation Research Board described the relationship between speed and safety. The link between speed and safety was characterized as complex and the researchers emphasized the fact that both speed and speed dispersion are associated with crash involvement. Also in the report, the difficulties of relating the road class with speed-safety are described and it is mentioned that there is a limitation of data to analyze the speed-safety relationships with road class. As will be described below, speed was one of the key variables that were used for the development of the safety model therefore caution must be used when speed and speed limits are associated with safety and crash involvement.

In summary, extensive effort has been devoted to the development of crash risk models, however, these models lack the level of resolution that is required to evaluate the safety impacts of operational-level projects. Namely, they are not sensitive to the level of congestion on the network and/or the smoothness of traffic flow. This paper describes a model that serves as a first step in addressing this unique problem.

DEVELOPMENT OF SAFETY MODEL

As illustrated in Figure 1 the crash rate is computed as the ratio of the crash frequency to the vehicle kilometers traveled. This section describes how the crash frequencies were derived from the GES database as a function of the type of crash, the facility speed limit and the time-of-day of the crash. In addition, this section describes how the crash rates were computed using the GES crash frequencies and the national highway statistics in the US. Finally, the limitations of the model are discussed.

Estimation of Crash Frequencies

The GES database for 1996 was utilized for the development of the safety model because it constituted the latest and most comprehensive crash data that were available at the time of the study. The variables that were considered in the development of the model included the crash type, the time at which the crash occurred, and the facility speed limit on which the crash occurred. Other factors that were considered included the maximum injury to the people involved in the crash and the severity of vehicle damage.

The crash frequencies were extracted based on the speed limit of the facility on which the crash occurred for speed limits ranging from 5 mph to 75 mph, as illustrated in Figure 2. For each roadway speed limit the crash frequencies were further classified by type of crash (14 types in addition to the total number of crashes) and the time-of-day at which the crash occurred (24 hourly periods). The 14 crash types that were considered are summarized in Table 2. These crash types were extracted by considering 80 pre-crash states in the database and then grouping the pre-crash states into 14 categories. Others have typically used the manner of collision variable to compute crash frequencies by crash type, however, in order to capture more crash types the pre-crash state was utilized and merged with the other variables, namely the speed limit and time of crash.

In terms of specific trends, the GES database indicated that the number of fatalities in the US were highest during the PM peak. The data also indicated that the number of crashes were highest on facilities with speed limits in the range of 40 to 72 km/h (25 to 45 mph), as illustrated in Figure 3. The database also indicated a reduction in the total number of crashes for the even numbered speed limits versus the odd numbered speed limits (e.g. 30 versus 35 mph). This difference is a result of a smaller sample size of facilities with even numbered speed limits (i.e. more facilities with a speed limit of 35 mph versus 30 mph).

The database also demonstrated that the angle type of crashes represented the highest frequency (36 percent of all crashes) in terms of crash types followed by rear-end crashes (27 percent), as illustrated in Figure 4. Furthermore, the frequency of rear-end crashes was found to be highest during the AM and PM peaks, as illustrated in Figure 5.

For each crash type, the crash severity was estimated in terms of the vehicle damage and injury to the people involved in the crash. Specifically, five injury severity levels were considered in the database. These included no injuries, possible injuries, non-incapacitating injuries, incapacitating injuries, and fatal injuries. In addition, four vehicle damage levels were considered, including no damages, minor damages, moderate damages, and severe damages. The severity damage was computed as a probability a crash was of a specific level of severity.

Estimation of Crash Rates

As described in the previous section, the crash frequencies were derived from the GES database as a function of the type of crash, the facility speed limit and the time-of-day of the crash. Unfortunately, the vehicle kilometers traveled along the US highways were available at a more aggregate level of resolution, as indicated in Table 1.

Consequently, the first step in computing the crash rates was to disaggregate the vehicle kilometers traveled to a level of resolution that was consistent with the crash frequency data. Specifically, the vehicle kilometers traveled were disaggregated by roadway speed limit (ranging from 5 to 75 mph at 5 mph increments) and by time-of-day (24 periods), as illustrated in Figure 6.

The disaggregation of vehicle kilometers traveled by speed limit was done using a lookup table that summarized the range of roadway speed limits that were associated with each roadway type, as demonstrated in

Table 3. It was assumed that the vehicle kilometers traveled were equally distributed across the speed limits for a specific facility type. For example, local streets with a speed limit of 25 mph were assumed to contribute one fifth of the local-street vehicle kilometers traveled given the five speed limit levels associated with local streets. In disaggregating the vehicle kilometers traveled by speed limit it was ensured that the sum of the vehicle kilometers traveled for all the speed limits associated with a specific facility type was equal to the facility type vehicle kilometers traveled that were presented in Table 1.

The next disaggregation exercise involved disaggregating the vehicle kilometers traveled by time-of-day. The disaggregation by time-of-day was made consistent with the proportion of daily volume associated with each of the 24 hours of the day. In some cases typical daily volume distributions were generated from field data, as illustrated in Figure 7, while in other cases these distributions were estimated from the literature (TRB, 1994).

Once the vehicle kilometers traveled were disaggregated by time-of-day and by the facility speed limit, the crash rates were computed. For example, Figure 8 illustrates the trend in variation of rear-end crash rates for a 45 mph facility as a function of the time-of-day. Figure 8 was generated by dividing the crash frequencies that are illustrated in Figure 5 by the vehicle kilometers for each time period based on Figure 7. It is interesting to note that the U-shape variation in the crash rate is consistent with other studies (Zhou and Sisiopiku, 1997).

The safety model also indicates that the crash rate decreases as the speed limit increases, as illustrated in Figure 9. Exponential functions were fit to the data with a coefficient of determination ranging from 30 to 80 percent depending on the crash type. The form of the relationship for each of the 15 crash types (including the total number of crashes) is presented in Equation 1. The relationship indicates that the crash frequency in dependent on the speed limit (S_f). The regression coefficients for Equation 1 are summarized in Table 2. The exponential reduction in crash rates as a function of the facility speed limit is consistent with other studies in the literature that have shown that the crash rate on arterial streets is higher than that on freeways for a distance-based unit of exposure.

Finally, by multiplying the distance-based crash rate by the facility free-speed it was possible to estimate a time-based crash rate. The advantage of a time-based crash rate is that the rate level of exposure increases with higher levels of congestion even though vehicles might not necessarily travel longer distances.

$$CrashRate_i = e^{a_1^i \times S_f + a_2^i} \quad \forall\ i = 1,15 \qquad [1]$$

It must be emphasized at this point, that the distance-based crash rate was modeled as a function of posted speed but it did not take into account time-of-day or actual speeds. Because of the fact that the distance-based crash rate depends on observed speeds or level of congestion by multiplying it by the observed speeds it may misrepresent the time-based crash rate.

Estimation of Crash Severity

In addition, the proposed safety model probabilistically computes the level of damage to the vehicles involved in the crash together with the highest level of injury incurred to the passengers involved in the crash. Specifically, Figure 10 illustrates the level of damage relationships that were derived from the GES database. The thin lines indicate the GES estimated probability of each of the four damage levels, while the thick lines represent the third degree polynomial regressed relationships that were derived from the data. The damage level is dependent on the instantaneous speed (*S*), as demonstrated in Equation 2. The values of the regression coefficients are presented in Table 4. The coefficient of determination for these relationships ranged from 55 percent to 69 percent.

In general the relationships indicate a reduction in the no damage crashes with an increase in the other crash damages in the 25 to 45 mph range. The figure does indicate the no damage crashes are the least probable of the different damage levels (less than 10 percent probability).

$$Damage_i = b_1^i + b_2^i \times S + b_3^i \times S^2 + b_4^i \times S^4 \quad \forall\ i = 1,4 \qquad [2]$$

Figure 11 indicates that the injury severity level is fairly constant as a function of the facility speed limit and that the no injury crashes are dominant when compared to the other levels of severity (on average 40 percent probability). The coefficient of determination for these third degree polynomial relationships ranged from 16 percent to 88 percent, as illustrated in Figure 11. As was the case for the damage level, the injury level is dependent on the instantaneous speed (*S*) as demonstrated in Equation 3. The values of the regression coefficients are presented in Table 5.

$$Injury_i = c_1^i + c_2^i \times S + c_3^i \times S^2 + c_4^i \times S^4 \quad \forall\ i = 1,5 \qquad [3]$$

Caveats of the Safety Model

The crash frequencies utilized within the safety model were derived from a national crash database. Clearly, the accuracy of the safety model is governed by the accuracy of the crash database. There are several problems with national databases including, the fact that not all crashes are reported to the police, there are errors in police reporting, and there are sampling errors. In addition, the merging of different files within the GES database results in errors, as was the case in extracting the 14 crash types from the 80 pre-crash states.

Furthermore, the estimation of the crash rates involved certain errors and assumptions. Clearly, there is a level of error associated with the vehicle kilometers traveled that are reported in the literature. Furthermore, in disaggregating the vehicle kilometers traveled, a number of simplifying assumptions were made. First, it was assumed that the vehicle kilometers traveled could be equally distributed to all the speed limits within a facility type. Second, there was a level of error associated with the typical volume profiles that were assumed for each of the facility types. Also, the fact that the GES database did not provide roadway classification for the crashes (it only identifies crashes on interstate highways and National Highway System (NHS) roadways) imposed some limitations to the model. As explained in the literature review the relationship of speed (or speed limit) and crash involvement is complex. Clearly, the GES database did not yield a substantial amount of data for crashes associated with low speed limits, for example 5-25 mph. Consequently, the crash rates that are estimated by the model should be viewed within the context of the caveats that were described.

SAFETY MODEL APPLICATION

The safety model that was described earlier was tested in two ways. First, it was applied to second-by-second floating car field data. Second, the model was incorporated within a microscopic simulation environment and tested on different traffic networks.

This section describes how the model can be applied directly to field data, how it can be utilized within a simulation environment and reasonableness of the estimated crash rates.

Field Application

In order to demonstrate the applicability of the safety model for operational level evaluations, the model was utilized to evaluate the safety impacts of coordinating traffic signals across an inter-jurisdictional boundary. In conducting the analysis, second-by-second speed measurements from floating cars along the study section (9.6-kilometer section of Scottsdale/Rural Road in Phoenix) were gathered prior and after the signal timings were changed.

Three Global Positioning System (GPS)-equipped vehicles were driven along the study corridor for three days (Tuesday through Thursday) prior and after changing the signal timings. The GPS runs were conducted during the AM peak (7:00 to 9:00 AM), the off-peak (11:00 to 1:00 PM), and the PM peak (4:00 to 6:00 PM). The GPS unit measured the vehicle's latitude and longitude, its heading, and its speed every second or in some cases every two seconds. The speed was measured based on the shift in the GPS signal (Doppler technology). The vendor stated speed accuracy was 0.1 m/s. It should be noted that the GPS unit did not include any differential correction resulting in a vehicle location accuracy to within 100 meters. However, the relatively low accuracy in locating the vehicle had no bearing on the accuracy of the speed estimates given that they were not computed from the vehicle location.

A total of 141 runs were conducted for the before conditions and a total of 160 runs were conducted for the after conditions, as demonstrated in Table 6. The larger number of runs for the after case versus the before case demonstrates a 12 percent increase in throughput as a result of the improvements in signal timings. Most of the benefits occur during the PM peak (39 percent increase in throughput).

Applying the proposed model to the second-by-second speed measurements resulted in an overall reduction in the crash rate by approximately 8 percent as demonstrated in Table 7. The crash risk was in the range of 25×10^{-6} which translates to a crash rate of approximately 2.5×10^{-6} crashes per million vehicle kilometers (dividing by the trip length of 9.6 kilometers). By conducting an Analysis of Variance (ANOVA) test on the data it was concluded that these results were statistically significant at a 5 percent level of significance. Noteworthy is the fact that the differences in the crash rates are a result of differences in the trip travel times because the facility speed limit was the same for the before and after case. The crash damage and injury level, on the other hand, was directly impacted by the instantaneous speed measurements given that the two independent inputs to the model were the instantaneous speed and the travel time.

A separate study by Science Applications International Corporation (SAIC) investigated the safety impacts of traffic signal coordination by analyzing crash statistics using the ALLIS database at a number of coordinated and uncoordinated traffic signals in the Phoenix area (Carter and St-Onge, 1999). The analysis included a total of 158 traffic signals of which 121 were coordinated and 37 were uncoordinated. Five years of crash data (1993 to 1997) were analyzed which included a total of 345,000 crashes. Annual Average Daily Traffic (AADT) counts that were available for the same time period were utilized to compute the crash rate. The study concluded that the crash rates for coordinated traffic signals were less than those for uncoordinated traffic signals in the range of 14 to 43 percent. Based on these two independent studies it was concluded that the proposed safety model produced results that were reasonable in trend. Furthermore, the absolute value of the crash rates was also found to be reasonable.

Simulation Application

The safety model was also incorporated within the INTEGRATION simulation model (Van Aerde, 1999a and b) and tested on a simple 5-link network. The speed limit along the network was varied from 40 km/h to 120 km/h at increments of 20 km/h. The simulation results indicated that the crash rate decreased from 3.0×10^{-6} crashes per million VKT at a speed limit of 40 km/h to 0.4×10^{-6} crashes per million VKT for a speed limit of 120 km/h. Both the absolute magnitude of the crash rate together the variation in the crash rate as a function of the facility speed limit were found to be consistent with the GES database.

The simulation model was then applied to the same corridor in Phoenix (Scottsdale/Rural Road). Using turning movement and tube counts the O-D demand was calibrated to the field data, which included a total of approximately 130,000 vehicles. The simulated crash rate was approximately 2.6 crashes per million vehicle kilometers traveled. Again, as was the case using the field floating car data, the simulation indicated that by improving traffic signal coordination, the crash risk was reduced by approximately 5 percent.

CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

This paper presented a safety model that is based on US national crash statistics. The model computes the crash risk for 14 different crash types as a function of the facility speed limit and a time-dependent exposure measure. The use of a time-dependent exposure measure allows the model to capture differences in the crash risk as a result of differences in travel times. The model also computes the vehicle damage and level of injury to the passengers involved in the crash based on the vehicle's instantaneous speed. The use of the instantaneous speed means that the crash damage and injury level is responsive to the level of congestion. Consequently, the model can capture the safety impacts of operational-level alternatives including Intelligent Transportation Systems (ITS's).

A field and simulation application of the model indicates that it produces results that are consistent with the GES national database. Furthermore, the results indicate that the model can be applied to evaluate the safety impacts of alternative traffic-flow improvement projects, like for example re-timing traffic signals.

The safety model that was presented in this paper does not consider vehicle-to-vehicle or vehicle-to-control interaction explicitly. Consequently, further research is required to develop safety models that compute the crash risk based on micro-level vehicle interaction parameters. These parameters could include the distance headway and relative speed between following vehicles, the number of lane change maneuvers, and/or the number of path intersecting maneuvers (e.g. the number of left turners that must find a gap in an opposing through movement). While the development of such a micro-level approach is currently underway (Van Aerde and Rakha (1999)), the safety model that is presented in this paper can not only be utilized to evaluate the safety impacts of traffic-improvement alternatives but can also serve as a benchmark for validating such microscopic safety model approaches. Additionally, in a future study, a smaller data set within a corridor can be used for developing a safety model. By doing this instead of assumed data, real data can be used. Such a model can be used to evaluate changes in speed, congestion and other operational characteristics to evaluate the sensitivity of such a model with respect to these changes. In a similar fashion, other databases, such as the Fatality Analysis Reporting System (FARS) can be used for the retrieval of specific data associated with speed limits, time-of-day and crash types.

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Table 1. US Highway Statistics for 1996

Facility Type	Length (km)	Vehicle Kilometers Traveled (VKT)
Interstates	73,658	935,014,000,000
Principal Arterials and Expressways	256,202	1,210,381,000,000
Minor Arterials	362,210	729,515,000,000
Collectors	1,269,166	591,261,000,000
Locals	4,309,885	505,352,000,000
Total	**6,271,120**	**3,971,523,000,000**

Table 2. GES Crash Type Configurations and Safety Model Regression Coefficients

Crash Type	Description	Regression Coeff. (a_1^l)	Regression Coeff. (a_2^l)
1	Single Driver - Right Roadside Departure	-0.021501436	-4.903643188
2	Single Driver - Left Roadside Departure	-0.023559071	-5.013290246
3	Single Driver - Forward Impact	-0.01709544	-4.483434319
4	Same Traffic Way and Same Direction - Rear-end	-0.019589495	-4.283242043
5	Same Traffic Way and Same Direction - Forward Impact	-0.041110596	-6.600147706
6	Same Traffic Way and Same Direction - Sideswipe/Angle	-0.023089944	-5.340775704
7	Same Traffic Way and Opposite Direction - Head-on	-0.026041357	-6.694593649
8	Same Traffic Way and Opposite Direction - Forward Impact	-0.032079684	-5.641286798
9	Same Traffic Way and Opposite Direction - Sideswipe/Angle	-0.020100423	-5.154935427
10	Change Traffic Way and Vehicle Turning – Turn Across Path	-0.020957402	-4.715896567
11	Change Traffic Way and Vehicle Turning – Turn Input Path	-0.019926275	-4.589321771
12	Intersecting Paths – Perpendicular Crash	-0.019976246	-5.073630589
13	Backing Vehicle	-0.014536839	-7.133251805
14	Other or Unknown	-0.017781349	-4.848826862
15	Total Crash Rate	-0.020170247	-2.419018353

Table 3. Facility Types and Assumed Corresponding Speed Limits

Facility Type	Speed Limit (mph)
Locals	5-25
Collectors	30-35
Minor Arterials	40-45
Principal Arterials & Interstates	50-75

Table 4. Vehicle Damage Level Regression Coefficients

Damage Level (i)	b_1^i	b_2^i	b_3^i	b_4^i
1	-0.239700394	0.020748326	-0.000456083	3.07144E-06
2	1.880157356	-0.115168621	0.002713999	-1.98096E-05
3	-0.408725633	0.053370557	-0.001282669	9.55118E-06
4	-0.361429514	0.044930641	-0.001113984	8.48361E-06

Table 5. Maximum Injury Level Regression Coefficients

Injury Level (i)	c_1^i	c_2^i	c_3^i	c_4^i
1	0.684906791	-0.018349016	0.000404226	-2.93146E-06
2	0.061498825	0.001148376	8.36568E-05	-1.31214E-06
3	0.381316662	-0.011131083	0.000156714	-7.44377E-07
4	-0.330753659	0.030304057	-0.00069379	5.08542E-06
5	-0.033918500	0.002760289	-6.63681E-05	5.31696E-07

Table 6. Classification of GPS Before and After Runs and Safety Results

	Northbound			**Southbound**			**Total**
	AM Peak	**Midday**	**PM Peak**	**AM Peak**	**Midday**	**PM Peak**	
Before	26	26	17	27	27	18	141
After	29	27	26	27	26	25	160
Total	55	53	43	54	53	43	301

Table 7. GPS Floating Car Safety Results (Crashes $\times 10^{-6}$) – (Model Predictions)

	Northbound				**Southbound**			
	AM Peak	**Midday**	**PM Peak**	**Average**	**AM Peak**	**Midday**	**PM Peak**	**Average**
Before	24.780	25.650	28.960	26.463	23.670	24.040	37.350	28.353
After	23.540	24.450	27.350	25.113	23.300	24.800	29.910	26.003
Difference	**5.00%**	**4.68%**	**5.56%**	**5.10%**	**1.56%**	**-3.16%**	**19.92%**	**8.29%**

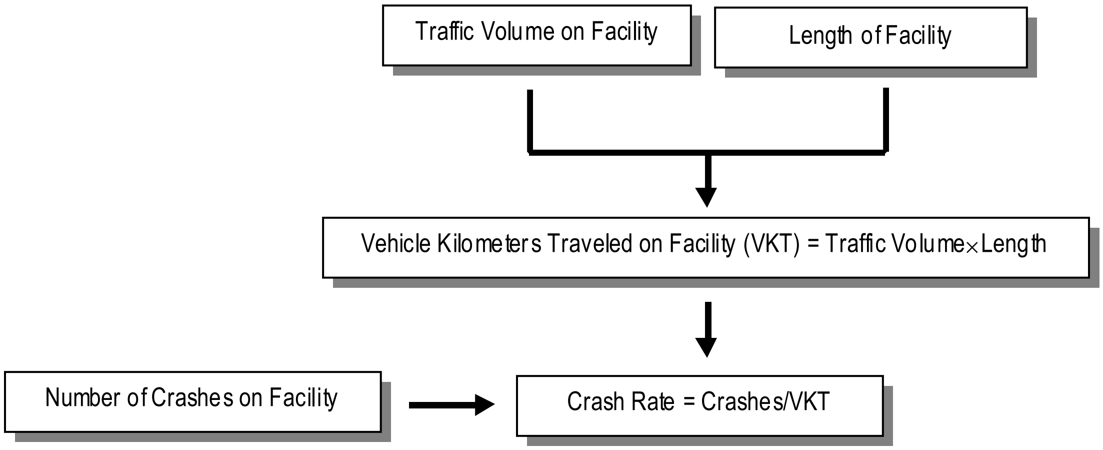

Figure 1. Schematic of Crash Risk Computation

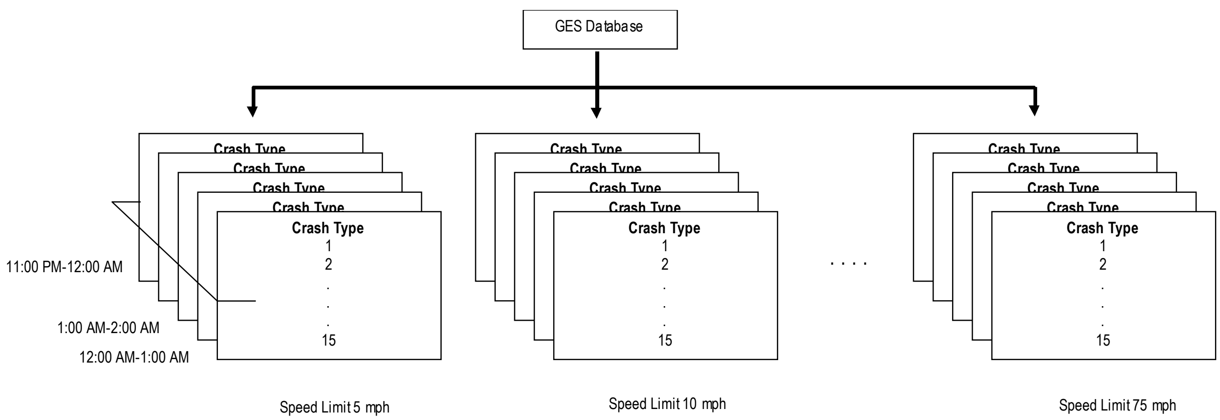

Figure 2. Crash Frequency Grouping

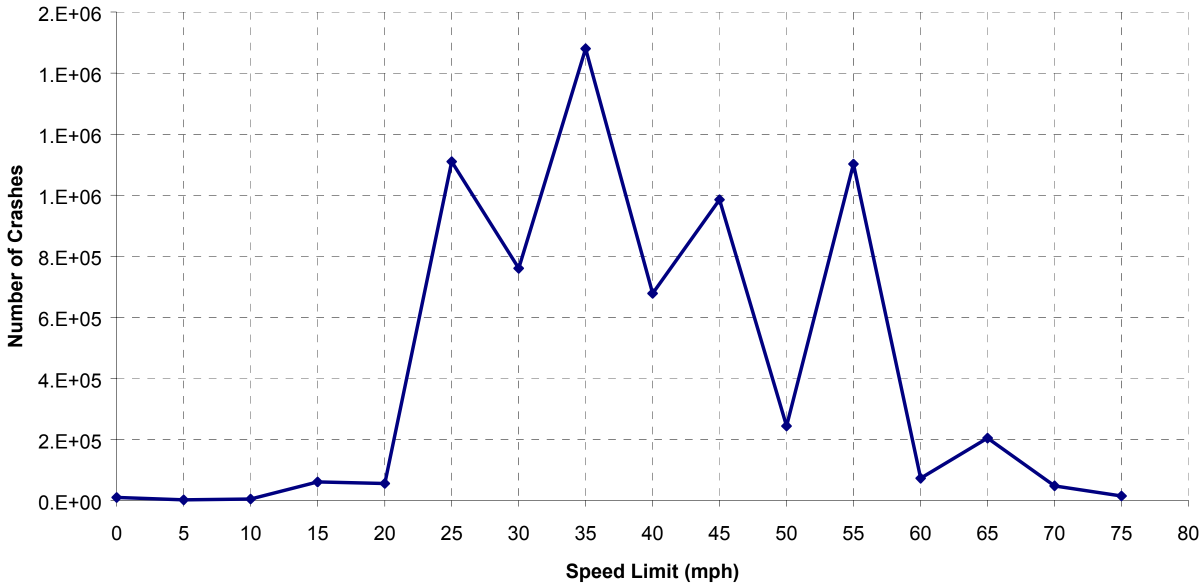

Figure 3. Number of crashes as a Function of Speed Limit (Based on GES 1996 Data)

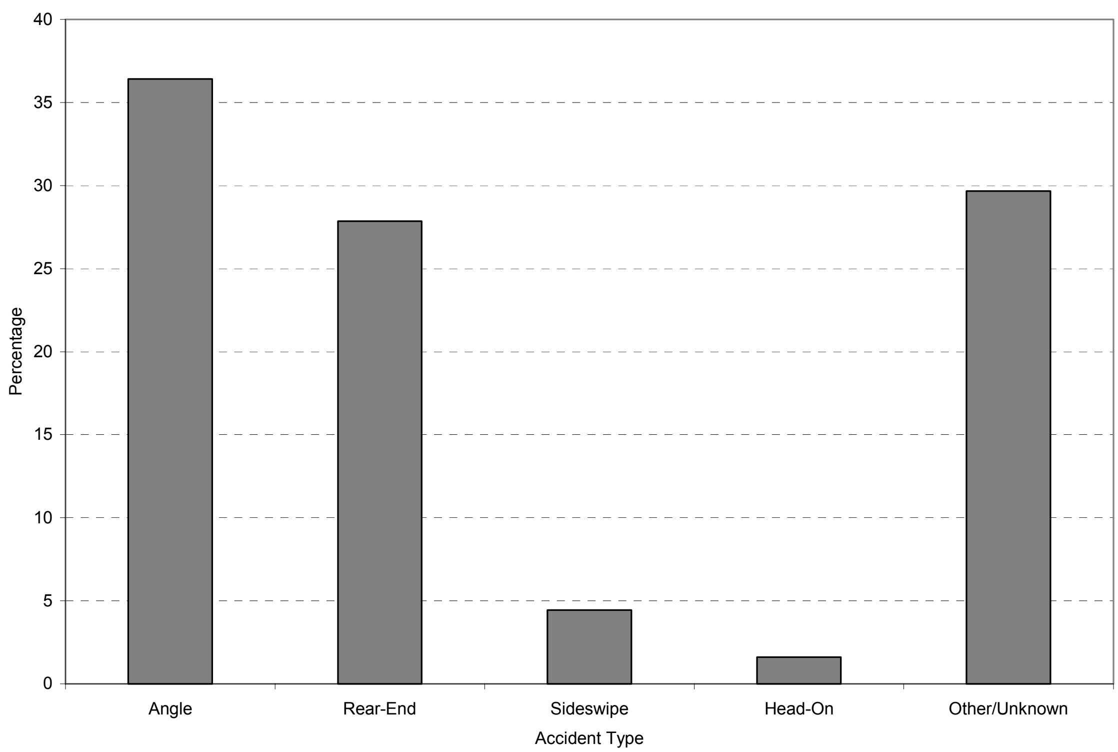

Figure 4. Crash Type Distribution

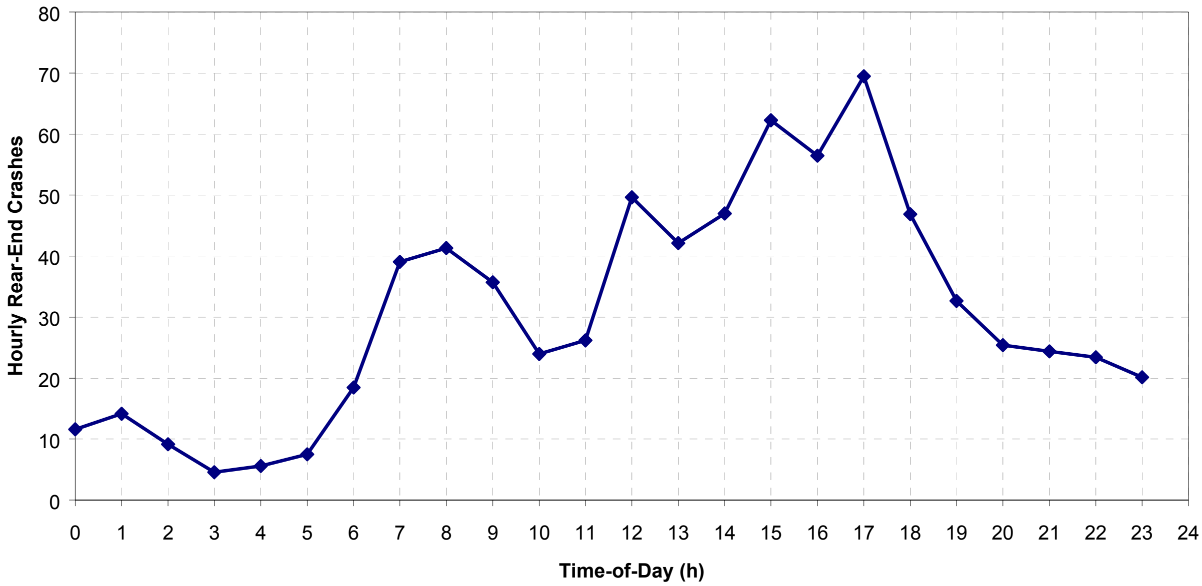

Figure 5. Variation in Rear-End Crashes as a Function of Time-of-day (45 mph Speed Limit)

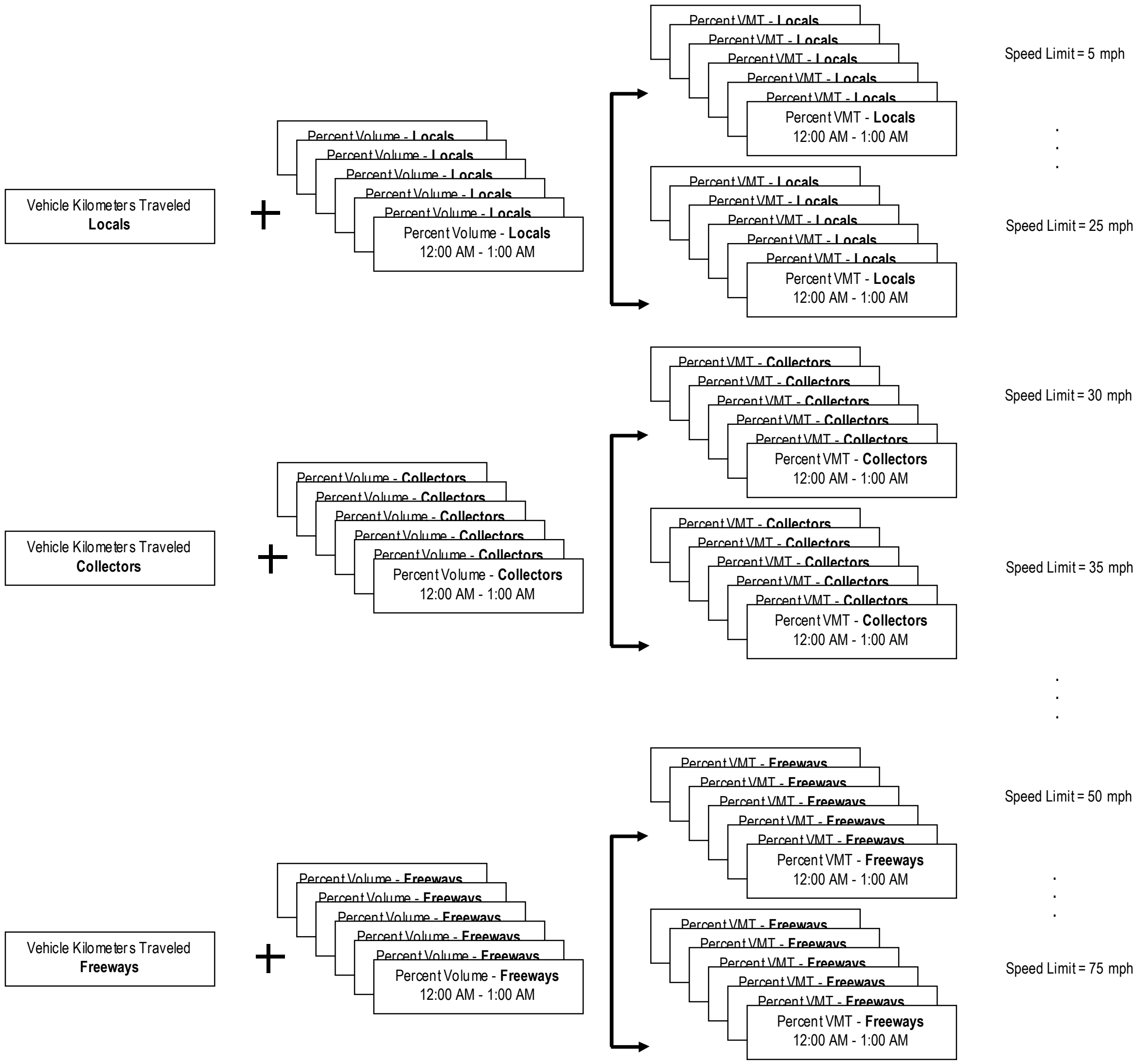

Figure 6. Vehicle Kilometers Traveled Grouping

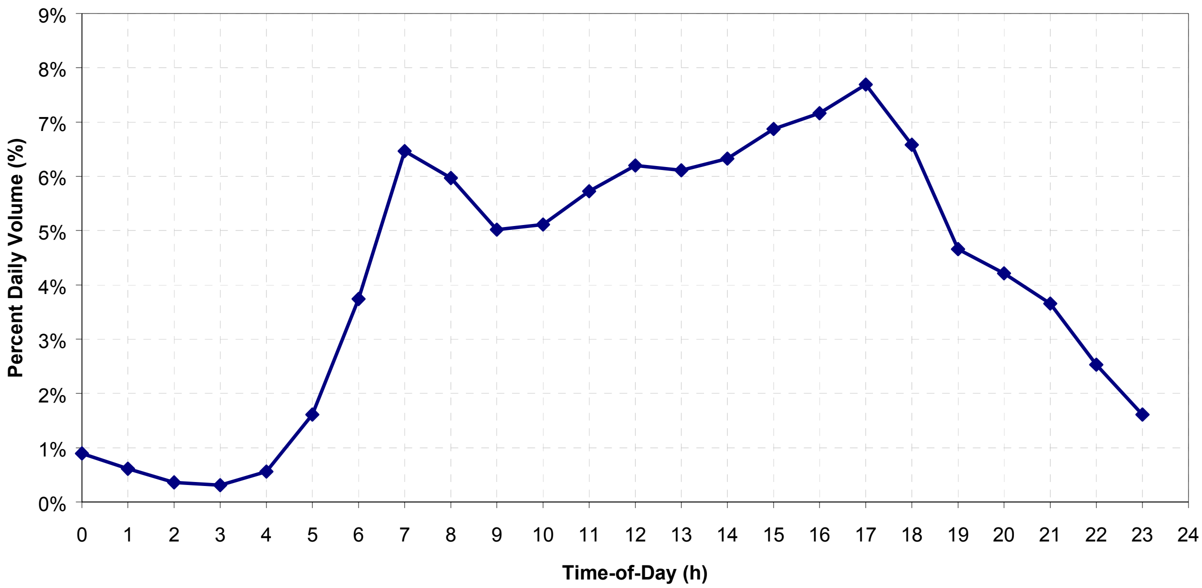

Figure 7. Scottsdale/Rural Road Tube Counts as a Function of Time-of-Day (45-mph Speed Limit)

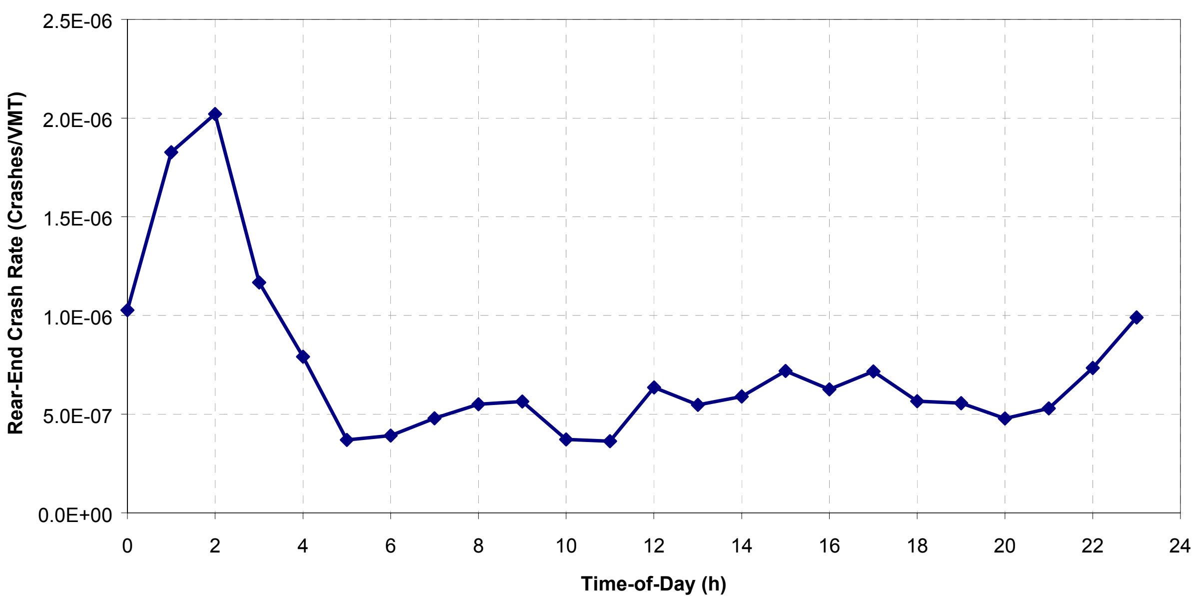

Figure 8. Rear-End Crash Rate as a Function of Time-of-Day (45 mph Speed Limit)

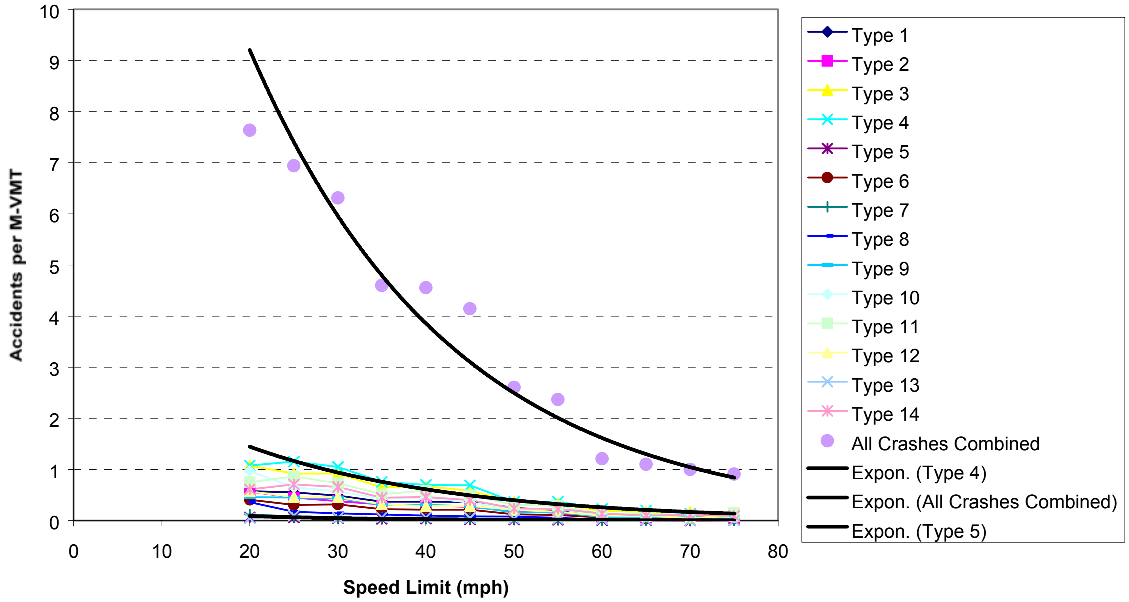

Figure 9. Crash Rate Variation as a Function of Facility Speed Limit

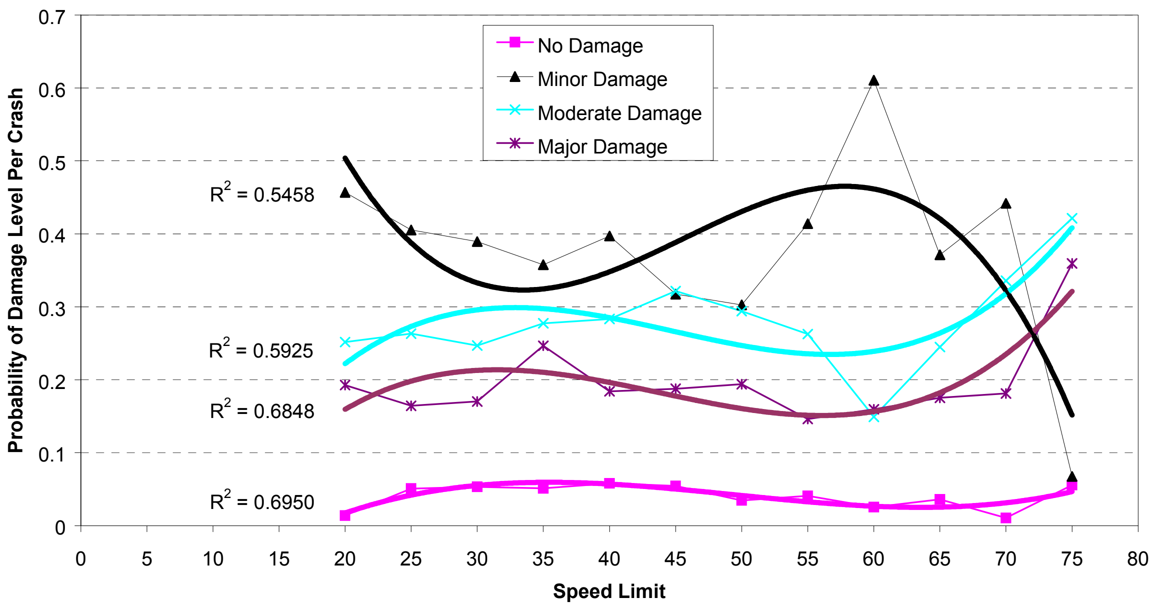

Figure 10. Variability in Damage Level as a Function of Facility Free-speed

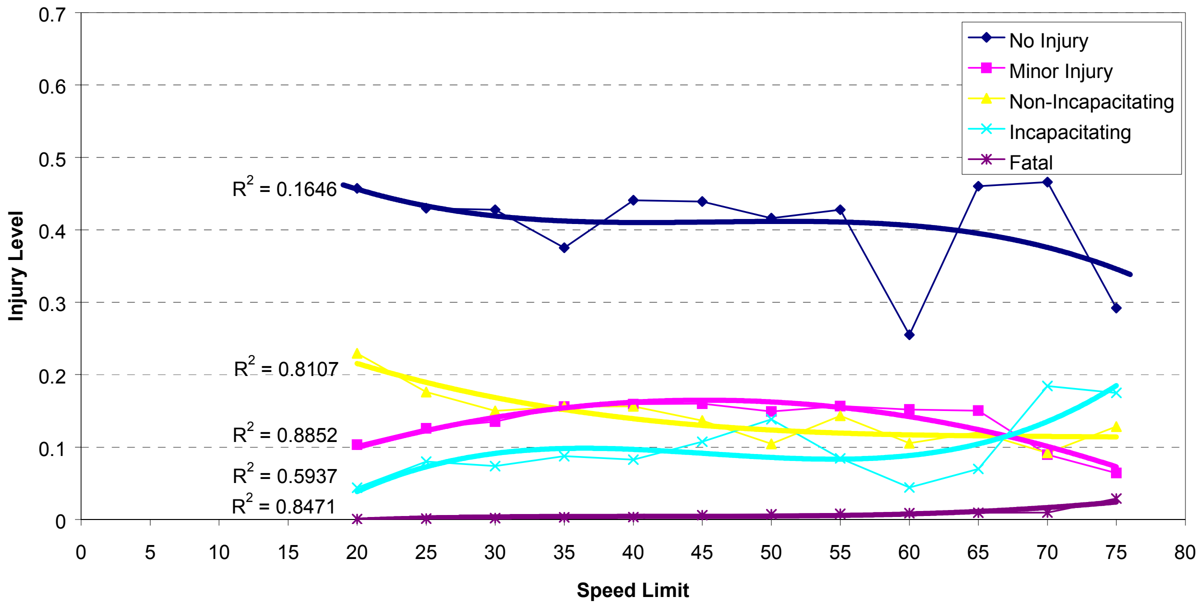

Figure 11. Variability in Injury Level as a Function of Facility Free-speed