EVALUATING ROUTE DIVERSION AS A STRATEGY FOR REDUCTION OF REAL-TIME CRASH RISK ON FREEWAYS USING MICROSCOPIC SIMULATION

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ABSTRACT: The objective of this study is to evaluate route diversion as a strategy for reducing crash risk on freeways using Microsimulation. Traffic simulation environment provides the 'loop detector data' which in turn are the inputs to the models used for real-time crash risk estimation. It has been found that rear-end crashes are more accurately described as occurring within one of two distinct traffic regimes. Hence, the crash risk estimates for rear-end crashes belonging to Regime 1 and Regime 2 are output posterior probabilities from two different models which are not directly comparable. A method was proposed to transform the output from the two models into a single measure of rear-end crash risk, which can be used to assess the crash risk during simulation environment even when traffic conditions change from Regime 1 to 2 or vice versa. Using the information obtained from simulation package the crash risk estimates for the base case (No route diversion) and cases with route diversion(s) were compared. Route diversion was found to decrease the overall rear-end and lane-change crash risk on the freeway sections with free-flow conditions to low levels of congestion. However, a crash migration phenomenon was observed at higher levels of congestion.

INTRODUCTION

The field of transportation engineering focuses on ensuring the movement of people and goods as efficiently and safely as possible. As the world's population continues to grow and cities become more and more crowded, engineers need to apply new technologies to enhance people's *mobility*, the ease in which they can move from one place to another. Intelligent Transportation Systems (ITS) can be used to increase throughput during congestion (Chu et al, 2004) and provide users with more information about the current state of the transportation network so they can make more informed decisions (Abdel-Aty and Abdalla, 2004). However, these same technologies can also be applied to improve traffic *safety*. This study examines one such ITS strategy, route diversion, for reducing the risk of a crash on an urban freeway. The analysis involves application of models using traffic information provided by loop detectors to estimate crash risk on the freeway. In a simulation environment the measure of crash risk obtained from these models can be used to evaluate route diversion (or any other type of ITS measure). The measure achieving most reduction in crash risk over base case (applying no ITS strategies) may be considered for field implementation in real-time.

MEASURES OF SAFETY

Traditionally, traffic safety studies have used historical crash data at one or many locations to determine problematic areas that need to be addressed. A typical example is a study that has been done that takes historical red-light running crash data for a period of four years and analyzes trends in the data to determine possible mitigation strategies (Retting et al, 1999). The usefulness of these types of studies is not being questioned as these aggregate crash studies are important in the field of traffic safety. However, the strategies adopted by these types of studies are reactive to historical data and typically do not consider temporal fluctuations in the traffic stream. For example, one type of strategy may be extremely useful for light flow conditions but increase the risk of a crash when flow becomes moderate or congested. If these studies only use AADT as a measure of the traffic intensity, the crash prevention measures that are implemented from the study might not be as successful if traffic patterns change. Additionally, studies such as these rely on crashes as measurement of safety. Since traffic collisions are typically rare events, this means that data needs to be collected over long periods of time and, for this reason, the effectiveness of any measure will not be known for some time. Simulation will be of no use if the measure of safety is crashes since most simulation software cannot model the complex nature of traffic crashes.

Instead of performing studies by only using crash data itself, another method is to use a surrogate measure of safety. A surrogate measure of safety is a directly measurable variable that has a known relationship with traffic crashes. Historical crash data can be used to determine a surrogate measure of safety and, once known, this measure can replace actual collisions to either determine the effective of crash prevention measures in the field or model the effectiveness of the measure using simulation. Typical surrogate measures of safety include speed, speed variance, time to collision, or post encroachment time (Gettman and Head, 2003). Some researchers have also developed statistical models that use directly measurable values (e.g. speed) to assess the risk of a collision occurring. One simple example is a model that compares the safe following distance of a vehicle with the actual following distance (Park and Yadlapati, 2003). This model uses both a vehicle's speed and distance away from another vehicle and transforms it into a value that assesses whether or not the vehicle is following too closely. Since following a vehicle too closely has a known relationship with rear-end crashes, this measure can be used as a surrogate measure of safety for rear-end crashes.

Another, more complex, measure of safety are models created by Abdel-Aty et al (2005) which describes the risk of a crash occurring on an urban freeway using logistic regression. This model uses data obtained from induction loop detectors embedded in the freeway which makes it possible to estimate the risk of a crash in real-time. This can be extremely useful in practice because if the state of traffic safety on the freeway can be obtained in real-time, measures can be implemented (or turned off) based on how likely it is for a crash to occur on the freeway. For measures that adversely affect the mobility of vehicles on the freeway, this is invaluable since they can be turned off if the risk of collision is low in order to increase throughput on the freeway. A major drawback to the models created by Abdel-Aty et al (2005) is that the measures of risk is obtained based on within stratum matched sampling procedure. Therefore, the model includes no geometric or spatial input variables and the crash risk cannot be compared across locations. This means that there is no way of determining which location on the freeway has the highest risk of a crash.

SPATIAL AND TEMPORALLY DEPENDENT NEURAL NETWORK MODELS

Newer models have since been created by Pande and Abdel-Aty (2006a, 2006b) which use neural networks and account for geometric and spatial factors as well as the real-time traffic data. These models calculate the risk of rear-end collisions and lane-changing collisions separately which also makes them more appealing than the previous within stratum matched logistic regression models that were generic in nature (not specific by crash type). These models use the 30-second loop data aggregated over 5-minute intervals and across the three lanes of the freeway in order to reduce random noise within the data. The real-time measures considered are average speed, coefficient of variation of speed (the standard deviation divided by the average), standard deviation of speed, average occupancy, standard deviation of occupancy, average volume, and standard deviation of volume all taken either at the station of interest or at locations up to 1 mile upstream or downstream of the station of interest. These values are all calculated for the period of time 5 to 10 minutes before the time of interest. It means that if the models were implemented in real-time they would provide crash risk for a period 5 minutes into the future. This will allow for the implementation of a crash risk alleviation strategy in real-time before a potential crash occurs.

The issues to be resolved before the output of those models could be used for this study emanated from the fact that rear-end crashes were found to occur within two separate traffic regimes (Pande and Abdel-Aty, 2006a). To describe these different regimes, a classification tree model was created that used average speeds at different locations around the station of interest as the input. The result of the classification tree model was a set of simple if-then statements that used the speed variables to classify the data into seven distinct "leaves" on the tree. Each of these leaves had a different percentage of regime 1 and regime 2 crashes and this probability was used to define the traffic conditions as either regime 1 or regime 2. If a particular leaf had a percentage of regime 1 crashes that was greater than 0.50, then that leaf was assumed to represent regime 1 conditions. Likewise, if the percentage of regime 1 crashes was less than 0.50, then the leaf was said to denote regime 2 conditions. The classification tree is given in Figure 1.

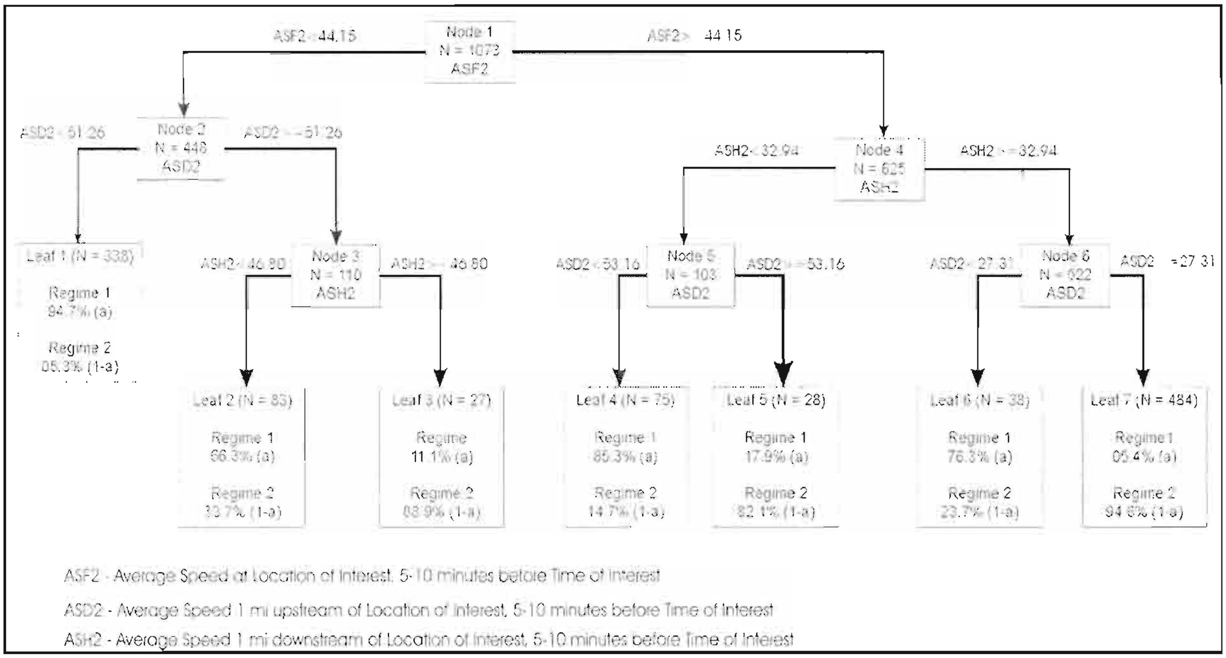

Figure 1. Classification Tree to Determine Regime Conditions for Traffic Data (Pande, 2005)

As seen from Figure 1, regime 1 conditions are generally lower speed conditions that represent congestion on the freeway. Regime 2 conditions are generally higher speeds and represent less congested traffic flow. Also, note that the typical value of "a" (see Figure 1) for a leaf is not close to 0.50. This shows that the classification tree does a good job of partitioning the data into one of the two traffic regime conditions. Traffic data obtained prior to crashes and random (non-crash) traffic data were run through the classification tree model to determine the percentage of crashes that occur within each regime and the percentage of time that traffic condition belonged to each regime, respectively. 45.8% of rear-end crashes were found to occur within regime 1 conditions while this state is only prevalent 6.3% of the time. This leads to the belief that regime 1 conditions are more crash prone than regime 2.

Separate neural network models were then created for each of the two traffic regimes. These models used variables similar to those used in the classification tree to differentiate between regime 1 and regime 2 conditions. The regime 1 model used traffic data located at the location (loop detector station) of interest only. This was done because in congested situations the traffic conditions do not vary much up to 1 mile upstream or downstream of the location of interest. Therefore, using traffic data from other nearby locations does little to improve the accuracy of the model. In this traffic regime, the average occupancy is the most important variable affecting the rear-end crash risk; higher occupancies increase the risk of such a crash occurring in congestion situations. The regime 2 model uses traffic information at the station of interest as well as up to 1 mile upstream and downstream of that location. In this model, the speed differential is very important as the crash risk is increased when faster moving traffic approaches slower moving traffic. Therefore, average speeds at the location of interest as well as both upstream and downstream of this location are important to determine if there is a large speed differential which would increase the risk of a rear-end collision. Specific information on the modeling process can be obtained from Pande and Abdel-Aty (2006a) and Pande (2006b).

Two separate models provide posterior probabilities of a rear-end crash occurrence given the input traffic and offline (geometric and spatial) factors. A posterior probability of an event (crash) is the conditional probability of the event occurring taking into account the relevant evidence of the dataset used to create the model. Therefore, the output of the regime 1 model is analogous to the probability that a crash will occur for the input conditions given the data used to train the neural network model. This means that the outputs from the two models are not comparable with one another directly. For example, the risk of a regime 2 crash occurring could be determined for two continuous time slices to compare whether or not the crash risk has increased, decreased, or remained the same. However, this assumes that the conditions for the two time slices are both regime 2 conditions. When the traffic conditions change from regime 1 to regime 2 conditions (or vice versa), the output from the models cannot be used to determine whether the crash risk situation has improved or worsened. The lack of comparability between the two model outputs presents a problem for determining the effectiveness of ITS strategies in a simulation environment. The purpose of the simulation will be to test various ITS strategies and their effects on the crash risk. The route diversion strategies tested will change the rear-end crash risk by altering the traffic flow which can (and does) change the traffic conditions from regime 1 to regime 2 or vice versa. It is essential to know how changing the traffic conditions from one regime to another affects the crash risk. If the two models are not comparable, then there is no way of knowing if the implemented procedure is actually increasing or decreasing the risk of a rear-end crash on the freeway.

Methods Used to Compare Model Outputs

Several methods were considered to compare the outputs of the regime 1 and regime 2 rear-end crash risk estimation models. The first was to apply a scale factor to the value outputted by one model to the value outputted by the other. The scale factor was equal to the relative likelihood of observing a crash in regime 1 as opposed to regime 2. This factor was equal to 13.65 ([0.46 / 0.06] / [(1 – 0.46) / (1 – 0.06)]). This method was not useful as the ranges of the risk values obtained from the posterior probability models for regime 1 and regime 2 were not comparable, even when the former was scaled up. The second method was to artificially assign a value of risk if observed conditions were in regime 1 since this regime had such a high percentage of crashes (compared to the percent of time this regime occurred). However, this method assumed that regime 1 conditions were ALWAYS more risky than regime 2 conditions which may not always be the case. This method also treated all regime 1 conditions as the same; however, the output from the Regime 1 model itself shows that there are varying degrees of crash risk within regime 1.

The next method considered was to normalize the outputs of the two models so that they would be on comparable scales. A simple standardization procedure was performed by subtracting from the output of each model the mean of that model's output and dividing by the that output's standard deviation. With this done, the ranges of the normalized outputs were similar and then the values could be directly compared to each other. Comparing these numbers directly when conditions are regime 1 or regime 2 would assume that the traffic conditions (between regime 1 or 2) are absolute. However, based on Figure 1, we see that the classification tree contains a probability of being correct (the value "a" for regime 1 and "1-a" for regime 2). Therefore, the normalized outputs from each model (regime 1 or 2) were weighted by the probability of the traffic conditions belonging to that respective regime. The final expression for the crash risk metric is given below in Eqn 1.

$$RECrashRisk = a(norm\_risk1) + (1-a)(norm\_risk2) \tag{1}$$

where:

a:	probability of traffic conditions belonging to regime 1
1-a:	probability of traffic conditions belonging to regime 2
Norm_risk1:	normalized regime 1 model output
Norm_risk2:	normalized regime 2 model output
RECrashRisk:	rear-end crash risk

The metric for crash risk was then compared for several sample cases (before ITS measures were implemented) to ensure that the actual results are in the expected range. The correlation between *RECrashRisk* and the traffic regime was strong – the value of *RECrashRisk* was typically higher when traffic conditions were in regime 1 but not always so; exactly what is expected. The *RECraskRisk* metric calculated using Eqn 1 was also compared with the other suggested methods (discussed above) and was qualitatively found to more accurately describe the expected crash risk for various situations.

MEASURE OF EFFECTIVENESS

Using the aforementioned crash risk models, a value of the rear-end and lane-change crash risk is determined for every 5-minute period at every location along the freeway for each of the simulation runs. When multiple different scenarios are simulated, plots of the crash risk vs. time and crash risk vs. location can be created in order to assess the scenario that has the lowest real-time crash risk value. However, graphical comparisons are not efficient at determining the best strategy so numerical measures of effectiveness are also used to help determine the strategies that reduce the crash risk the most.

The first two measures of effectiveness (MOE's) used in this study are the Overall Risk Change index (ORCI) and the Lane-Changing Risk Change Index (LCRCI). They denote the change in the rear-end and lane-change crash risk, respectively, between any particular test case (with Route diversion strategies) and the base case (without Route diversion strategies). These MOE's are calculated in the following manner. First, the crash risk is calculated for each 5-minute period at every location. Second, the crash risk at each location is averaged over the entire simulation length (3-hour simulation = 36x5-minute crash risk values) at every location. Next, a plot of the average crash risk value vs. location is created for the base case and the test case. The area between the two rear-end crash risk curves represents the ORCI while the area between the lane-change crash risk curves is the LCRCI. This measure is shown more clearly in Equation 2. A negative value of the ORCI (or LCRCI) indicates that the overall change across the freeway segment is an increase in the crash risk while a positive value shows a decrease in the crash risk (improved safety conditions).

$$ORCI = \sum_{l}\left[\frac{1}{T}\sum_{t=1}^{T}(Risk\_profile)_{tl}\right]_{Base} - \sum_{l}\left[\frac{1}{T}\sum_{t=1}^{T}(Risk\_profile)_{tl}\right]_{Test} \qquad (2)$$

Where, $(\text{Risk\_profile})_{t\,l}$ = the average rear-end crash risk at time t and station l; T = the number of time periods in the simulation run (36)

ROUTE DIVERSION ANALYSIS

The diversion route used in this study is located in the downtown Orlando area and is depicted in Figure 1. This route was chosen to influence the traffic flow around the Interstate-4 / SR 408 Interchange. At this interchange a large volume of vehicles enter Interstate-4 in an uncontrolled fashion from SR 408 which causes heavy congestion and possibly increased crash risk. The route is comprised of two decision points, DP-1A and DP-1B. A decision point is defined as a location where a vehicle is faced with the choice of whether or not to divert from its natural route defined by PARAMICS. At DP-1A, vehicles that would traditionally enter I-4 via the Orange Blossom Trail (OBT) on-ramp have the option to instead travel further northbound on OBT until they reach DP-1B. At DP-1B, the diverted vehicles have the choice between traveling east on Anderson Street to access I-4 through the Anderson Street ramp or traveling further north, then east on Colonial Drive to enter I-4 at the Colonial Drive ramp. The vehicles that enter on Anderson Street were diverted a total of 2 miles while the vehicles entering on Colonial Drive were diverted 3 miles from the initial entry location on I-4. This diversion route forces vehicles that entered just upstream of the I-4 / SR 408 Interchange to bypass the freeway and enter downstream of the interchange.

The evaluated diversion route kept vehicles from entering I-4 on the Orange Blossom Trail entry ramp and instead diverted them downstream to enter the freeway on either the Anderson Street or Colonial Drive on-ramp. The Orange Blossom Trail on-ramp has a high ramp volume of about 1020 veh/hr during the PM peak period (the duration of the simulation). The Anderson Street on-ramp has a low volume of about 300 veh / hr and the Colonial Drive on-ramp has a much higher volume of about 970 veh / hr. Diverting too many vehicles to any of the on-ramps would increase the ramp volume beyond capacity and cause the ramp traffic to back up onto the surrounding surface streets. This fact was taken into consideration when examining the results of route diversion to ensure that operational capacity was not exceeded in order to improve the safety on the roadway.

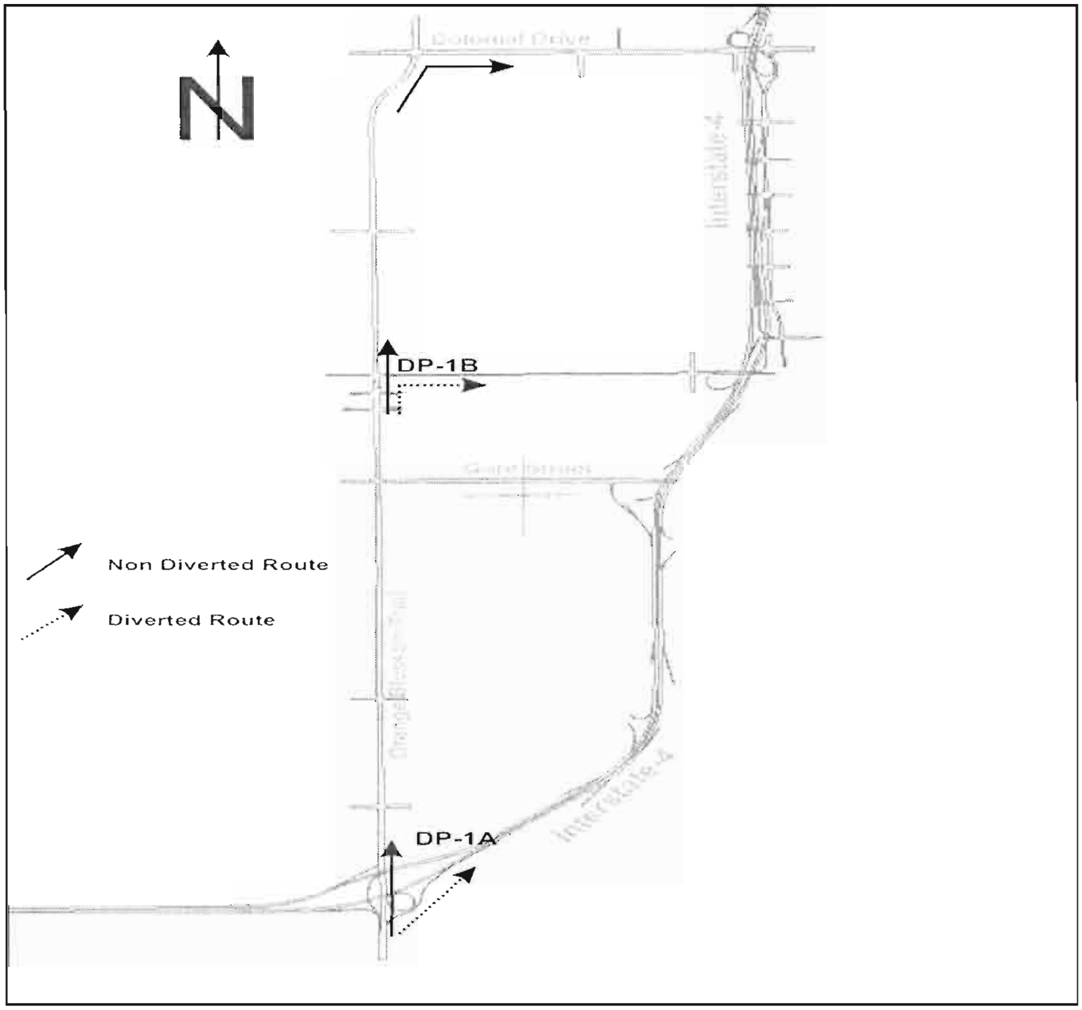

Figure 2. Location of Diversion Route and Decision Points.

EXPERIMENTAL DESIGN

The experimental design for this study consisted of a total of 60 runs created to test different levels of diversion for the two diversion routes at different network loading conditions. This factorial design tested all combinations of different levels of network loading conditions (60, 80, 90, and 100 percent of the OD matrix to represent varying conditions – uncongested to congested), percent diversion from DP-1A (20, 40, 60, 80, and 100 percent), and percent diversion from DP-1B (0, 50, and 100 percent). The percent of vehicles diverted from DP-1A controls how many vehicles were diverted from using their preferred entry location and the percent of vehicles diverted from DP-1B controls how far these diverted vehicles traveled before re-entering the freeway traffic stream.

For each test case a minimum of 10 simulation runs were performed using different random number seeds to ensure variation within the traffic data. Using multiple runs helped to ensure that the results that are found were based on the route diversion and not simply an effect of using a specific starting number seed. After 10 runs were performed, the variation in the crash risk was calculated and, if it was too high, more runs were added in order to reduce the variation to within acceptable limits. A 90% significance level was assumed along with an allowable error of 0.1 in the average crash risk (which corresponded to 2% of the range of crash risks found). Based on this method, the maximum number of runs that were needed to be performed for any scenario was 20. Once the runs for a particular test case were completed, the values of the crash risk at each similar time period and location were averaged together which created a single crash risk profile that represented the particular test case.

The experimental design was created in order to answer the following questions: 1) does route diversion serve to reduce the crash risk more during times of free flow conditions or heavy congestion; 2) does diverting more vehicles increase the safety benefits along the freeway; and 3) does diverting vehicles further away have a greater safety impact than diverting them to nearby on-ramps?

RESULTS

Summary values of the first two measures of effectiveness (ORCI and LCRCI) were calculated for each test case values are presented in Table 1. Looking at these summary measures gives an indication of the effects of route diversion on the crash risk throughout the network corridor. From this table it can be seen that as the percent of vehicles that were diverted from DP-1A (the total number of vehicles diverted) increases the values of the ORCI and LCRCI increase as well. This means that diverting more vehicles tends to increase the safety benefits realized on the freeway. Maximum safety benefits are realized when 100 percent of the vehicles are diverted from DP-1A (100 percent of the vehicles are diverted from entering at the Orange Blossom Trail on-ramp).

Diverting vehicles to the further on-ramp (having a higher percentage of vehicles using DP-1B) also serves to increase the safety benefits on the freeway corridor. As shown in Table-1, the values of the ORCI and LCRCI tend to increase with higher percentages of vehicles using DP-1B. The most notable exceptions are the values of LCRCI at the 60 percent loading scenario which decrease as more vehicles are diverted to the further on-ramp. The reason for this is because at the low (60 percent) loading scenario diverting more vehicles to the Colonial Drive on-ramp (which already has a high traffic volume) significantly increases the occupancy in the right most lane of the freeway near the re-entry location. Although the overall effect of the diversion is to reduce the lane-change crash risk, the higher differential between the lane occupancies on adjacent lanes caused by diverting more vehicles to the Colonial Drive on-ramp causes the magnitude of the safety benefits to be reduced compared to when the diverted vehicles used the less traveled on-ramp. This phenomenon is not realized at the higher (80 percent or greater) loading cases, however. The reason for this is that the traffic flow on the freeway is already so high that the difference in the lane occupancies across adjacent lanes does not become significant enough to cause reduced values of LCRCI when the further re-entry ramp is used.

Looking at the ORCI and LCRCI values in Table 1, it can be seen that route diversion seems to have a positive impact on the rear-end crash risk at the 60, 80, and 90 percent loading conditions as well as a positive impact on the lane-change crash risk at all loading cases. However, while the summary statistics show the overall change in the crash risk throughout the corridor, a more in-depth look at how the crash risk changes across the different locations along the freeway is needed to understand the true effects of route diversion; even though the summary statistics show a positive change in the risk there is still the chance that route diversion is not applicable in some situations.

Table 1 Summary Statistics

MOE	Loading Considered (%)	% Diverted from DP-1B	% Diverted from DP-1A 20	40	60	80	100
Rear-End Crash Risk Change (ORCI)	60	0	0.6305	0.9213	1.7876	2.0213	2.8737
		50	0.397	1.232	1.91	2.55	3.224
		100	0.418	1.299	2.085	2.777	3.666
	80	0	0.788	1.211	1.779	1.893	2.651
		50	0.666	1.173	1.901	2.613	3.391
		100	0.899	1.39	2.026	3.105	4.069
	90	0	0.144	0.135	0.866	0.622	2.096
		50	0.535	-0.754	-0.155	0.704	1.021
		100	0.113	0.07	1.995	4.188	6.746
	100	0	-0.318	-0.206	-0.385	-0.523	-0.179
		50	-0.198	-0.421	-0.312	-0.531	-0.676
		100	-0.558	-0.795	-0.572	0.413	1.763
Lane-Change Crash Risk Change (LCRCI)	60	0	0.1453	0.4137	1.0798	1.544	2.3687
		50	0.1549	0.3844	0.8631	1.3271	2.0104
		100	0.1713	0.4029	0.8503	1.1939	1.7599
	80	0	-0.2765	0.624	1.134	1.3718	2.0311
		50	0.3977	0.6216	0.9969	1.3087	2.3167
		100	0.3809	0.6411	0.8872	1.5085	2.3923
	90	0	-1.646	-0.8402	-0.3415	-1.0547	0.1982
		50	1.0137	0.4761	0.9333	1.7692	2.1639
		100	0.9293	1.2258	2.9725	4.6942	7.2035
	100	0	0.4027	1.0147	1.4612	3.1549	4.7468
		50	1.5103	1.7742	2.9133	4.4731	5.5983
		100	0.7432	2.3237	5.0834	6.6753	8.3067

At the 60 percent loading case the effect of route diversion is to reduce the crash risk at all locations between where vehicles are diverted from and where they re-enter I-4. At the 80 percent loading case, a phenomenon known as crash risk migration starts to appear. Crash-risk migration is the reduction of the crash-risk at one location coupled with the increase of the crash risk immediately downstream. This is shown graphically in Figure 2 which is a plot of how the crash risk changes for the various route diversion test cases compared to the base case. The locations along the freeway make up the vertical axis while the percent of vehicles diverted from DP-1B (or where the vehicles are diverted to) is shown on the horizontal axis. Note that on the vertical axis each loop detector station is represented twice. The suffix 0 denotes the risk value calculated for the area just upstream of the detector location while the suffix 1 represents the crash risk just downstream of the loop detector. On Figure 2, the location of the ramp where vehicles are diverted from is marked as a solid horizontal line while the location of where vehicles are diverted to is marked as a dashed horizontal line. In this figure, the dark colored areas represent locations where the rear-end crash risk is increased in the test case as compared to the base case, the medium shades represent areas of no crash risk change, and the light areas represent a rear-end crash risk decrease. For the 80 percent loading case, the rear-end crash risk is reduced between the locations where the vehicles are diverted from and where the vehicles are diverted to. The crash risk migration occurs where the diverted vehicles are reinserted back onto the freeway. This occurs because as large numbers of vehicles re-enter the freeway they increase the traffic volume near that area and cause added congestion which increases the crash risk. The area affected by crash risk migration in Figure 2 is very small and is confined to just the few stations located immediately downstream of the vehicle re-entry ramps.

However, for the 90 and 100 percent loading cases the results are significantly different. The change in the crash risk due to route diversion at the 90 and 100 percent loading cases are shown in Figure 2 as well. First, the area of effect of route diversion is much larger for these cases than the area of effect for the 80 percent loading case. This occurs because at higher loading cases there is much more traffic volume and congestion on the freeway. The effect of diverting vehicles, therefore, is to reduce the lengths of the large queues that form in the downtown area. These large areas of congestion extend upstream for miles and when vehicles are diverted the queues become shorter. This causes a reduction in the crash risk at the upstream end of the original queuing area. As this area that was typically congested in the base case suddenly becomes less congested, the rear-end crash risk decreases. Second, the number of locations that experience an increase in the rear-end crash risk (crash risk migration) increases significantly. At the 80 percent loading scenario, between 15 and 19 locations showed a crash risk decrease while 2 to 4 locations experienced a risk increase. However, at the 90 percent loading scenario, 16 to 22 locations showed a crash risk decrease while 6 to 12 locations experienced increased crash risk. At the 100 percent loading scenario, this is even further exaggerated as 10 to 18 locations showed reduced crash risk while 13 to 16 locations showed increased crash risk. As shown, the number of locations that show crash risk decrease remains relatively constant regardless of the network loading conditions. However, at higher loading scenarios the number of locations that experience negative safety benefits (crash risk migration) increases significantly. This furthers the evidence that implementing route diversion at high loading scenarios has a negative effect on the crash risk along the freeway.

Another reason that route diversion is not ideal at higher loading scenarios is the re-entry ramp volume. As previously mentioned, the first diversion route diverted vehicles from a ramp with a peak volume of about 1020 veh/hr to either a ramp volume of about 300 veh/hr or another with a 970 veh/hr vehicular demand. At the 90 percent loading scenario, diverting all vehicles to the nearer re-entry ramp increased the ramp volume to about 1200 veh/hr while diverting to the further ramp increased the volume to 1800 veh/hr. These are extremely high ramp volumes and in the simulation this causes queues to form on the ramps which extend onto the surface streets and disrupt the background traffic flow. This is unacceptable from an operations perspective and helps to rule out route diversion as a real-time crash prevention strategy at high levels of traffic flow.

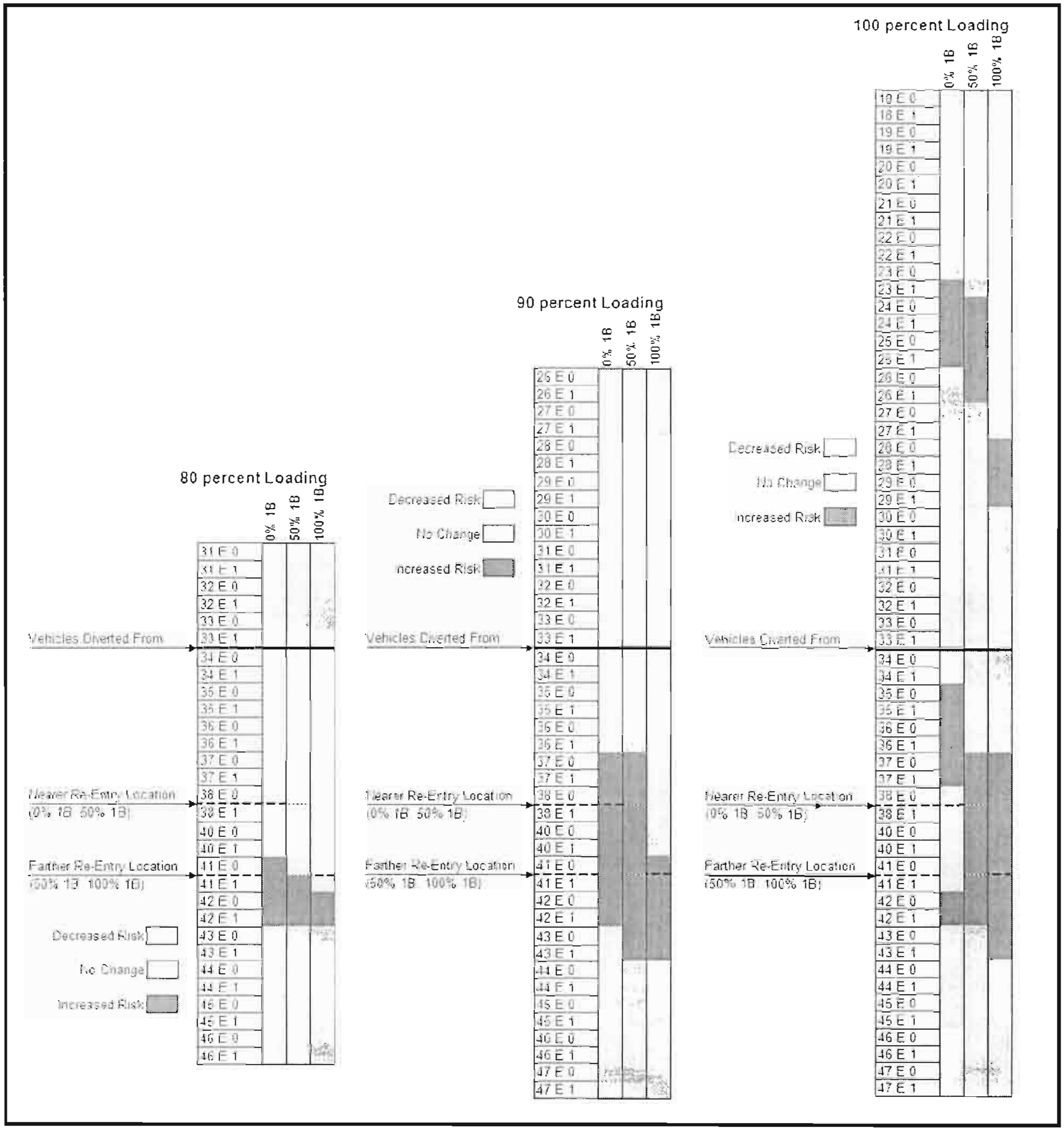

Figure 2 Locations Affected by Route Diversion (Rear-End Risk)

CONCLUSIONS

This paper demonstrates how the crash risk models developed by Pande and Abdel-Aty (2006 a), which calculate the risk of rear-end collisions in two separate traffic regimes, may be combined to form a single metric for rear-end crash risk. By normalizing the risk values and combining them using the probability of the respective traffic regime occurring, one can obtain a single value that represents the crash risk. This measure of crash risk can be compared even if the traffic conditions change (from Regime 1 to Regime 2) as a result of route diversion. Using this combined rear-end crash risk and another model for lane-change crash risk it was found that, in general, route diversion successfully decreases both the rear-end and lane-change crash risk along the freeway during periods in which the freeway is operating at uncongested conditions (represented by 60 and 80 percent network loading). During these times, the primary area of effect of route diversion is between the locations where vehicles are diverted from and where the diverted vehicles are allowed to re-enter the freeway. When route diversion is implemented at higher levels of congestion (when the demand is at or near capacity), the effects of route diversion extend much further upstream and downstream due to the heavy traffic flow. When route diversion is implemented, crash risk migration typically occurs at or near the location where vehicles are reinserted back onto the network from the diversion route. This is caused by the much larger inflow of vehicles onto the freeway compared to the base case when route diversion is not applied. During lower loading scenarios this effect is modest but at the higher loading scenarios the crash risk migration becomes significant. In the higher loading cases, diverting a majority of the vehicles from a particular on-ramp also causes queuing on the re-entry ramp which, if it spills onto the surface streets, can seriously deteriorate the operational capacity of the network as a whole.

Vehicles can be diverted by warning drivers of the high crash risk on the freeway at specific locations. Even if a minority (close to 20%) of vehicles diverts during light traffic situations, the results of this study show that a significant crash risk benefit would be realized. The authors recognize that diverting vehicles from the freeway to nearby surface streets may increase the congestion and/or risk of collisions on the arterials. Although further research is needed in this area to determine if this crash risk increase on the arterials would negate the benefits on the freeway, there are two reasons to believe that this might be acceptable in certain instances. First, route diversion would only be applied during relatively free flow (off-peak) conditions when traffic volumes would be low on the arterials and the arterials should be able to adequately accommodate this additional flow. Second, vehicle speeds on arterials are generally lower than speeds on freeways which would generally lead to less severe crashes on arterials than on the freeways. Still, care needs to be taken about where vehicles are diverted from, where they are diverted to, and how many vehicles are diverted in order to minimize the potential negative impacts.

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