# The Concept of Proactive Traffic Management for Enhancing Freeway Safety and Operation

**PROACTIVE TRAFFIC MANAGEMENT INVOLVES APPLICATION OF INTELLIGENT TRANSPORTATION SYSTEMS (ITS) STRATEGIES THAT ARE INTENDED TO REDUCE THE RISK OF CRASH OCCURRENCE. IT IS AN EVOLVING PARADIGM FOR MANAGING TRAFFIC ON FREEWAYS THAT IS PROACTIVE COMPARED TO INCIDENT DETECTION, WHICH IS CONSIDERED REACTIVE.**

**BY MOHAMED ABDEL ATY, PH.D., P.E. ANURAG PANDE, PH.D. AND LIANG HSIA, P.E., CGC**

## INTRODUCTION

The ITE *Traffic Safety Toolbox* (1999) defines a freeway as a roadway with four or more lanes, opposing lanes separated by a physical median and full access control (i.e., no at-grade intersections with the mainline). The freeways were intended to be used for high-speed travel over long distances. However, in addition to the recurring congestion during peak hours, freeways are affected by nonrecurring congestion caused by incidents, work zones and weather events. Freeway traffic management authorities attempt to minimize the impact of these sources of recurring and nonrecurring congestion.

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

The approach for developing real-time crash risk assessment models is to analyze historical crashes and traffic surveillance data corresponding to historical crashes and detect patterns that are often observed *before* crash occurrence. If these patterns are repeated in the future on a freeway section, that section may be identified as a real-time "black spot" with high likelihood of crash occurrence. Variable speed limit (VSL) and ramp metering strategies that specifically aim at reducing crash risk may be developed for these traffic conditions. While the infrastructure used by automatic incident detection algorithms may be used for implementing the crash risk estimation framework, there are some critical differences in the way results are approached. In the next section of the paper, we discuss differences between incident detection and real-time crash risk estimation. The section following that discusses the results of the study by the authors that established the link between freeway traffic data and crash occurrence. The following section provides the details of a crash risk estimation framework developed for Interstate 4 in Florida, USA, along with its application for developing proactive VSL/ramp metering strategies. The section following that discusses the current incident management practices and the scope of improvement provided by the proposed proactive approach. It is followed by conclusive remarks in the last section.

## INCIDENT DETECTION AND PROACTIVE TRAFFIC MANAGEMENT

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

Research in freeway traffic management was, and to an extent has been, focused on automatic incident detection. The idea of incident detection involves analysis of patterns in traffic surveillance data observed just *after* the historical incidents. Since traffic data for the freeway are collected continuously, it is possible to develop models using historical incident data and apply them in real time to examine the traffic data for detecting any incident that might have occurred on the freeway. Figure 1 shows, as an example, the drop in speed followed by an incident that may be used to detect an incident. The approach is reactive in nature and attempts to swiftly detect incidents so that a timely clearance could be achieved.

However, due to the information technology revolution, the usage of mobile phones has increased manifold along with the video surveillance of freeway sections. Hence, the information on incidents is immediately available to the traffic management authorities. These advancements have rendered incident detection algorithms (e.g., Cheu and Ritchie, 1995; Abdulhai and Ritchie, 1999) somewhat irrelevant and, despite their availability, the incident detection algorithms are not widely used (FHWA, 2000). Archived and real-time traffic information available for the freeways may be better utilized for developing proactive strategies. These strategies would involve anticipating incidents along with attempts to avoid them, or at least reduce their severity and adverse congestion effects. In this regard, crashes, in general, are more frequent and predictable than incidents such as a flat tire. Therefore, to develop a proactive traffic management strategy traffic data prior to individual historical crashes should be collected and analyzed. Figure 2 exemplifies what patterns would be of interest for such analysis.

Golob et al. (2004) analyzed the patterns similar to the one shown in Figure 2 and developed a software tool called FITS (Flow Impacts on Traffic Safety) for predicting the crash type most likely to occur under traffic conditions being observed at the loop detectors. In their analysis traffic conditions that did not lead to crashes were not accounted for and only patterns observed before crashes were analyzed.

**THE PREMISE OF PROACTIVE TRAFFIC MANAGEMENT IS THAT THERE ARE CERTAIN FREEWAY TRAFFIC PATTERNS THAT ARE ASSOCIATED WITH A HIGH LIKELIHOOD OF CRASH OCCURRENCE AND THAT THEY MAY BE DETECTABLE IN THE LOOP DETECTOR DATA.**

The authors in one of their previous studies argued that the performance of such a system may be enhanced significantly if along with the crash data (representing crash prone conditions) some non-crash cases (i.e., loop detector data corresponding to time and location where no crash is recorded) are also incorporated in the analysis for comparison (Abdel-Aty et al., 2004). In this regard, the authors proposed to set up the problem as a binary classification problem between crash and non-crash categorization.

## ARE CRASH PRONE CONDITIONS DISCERNIBLE?

The premise of the proactive traffic management is that the there are certain freeway traffic patterns that are *associated* with a high likelihood of crash occurrence and that they may be detectable in the loop detector data. It should be noted that the associations automatically do not imply a "cause-effect" relationship between crashes and observed traffic patterns. The premise was initially explored by the authors using crash data from Interstate 4 (in Orlando metropolitan area, Florida, USA) for a four-year period. The traffic information used in the analysis included speed, volume and lane occupancy at the loop detectors surrounding the historical crash location. The geometric characteristics of the freeway were implicitly controlled through a matched study design comparison of crashes and non-crash cases. The binary logistic regression (crash versus non-crash) model, shown in Table 1, indicated that high variation in speed represented by coefficient of variation (=standard deviation/mean) in speed (5–10 minutes before the crash) was the most significant predictor. The other two variables in the model indicated that high average occupancy and low standard deviation in volume (observed 5–10 minutes before the crash) at the station located one-half mile downstream also increase the crash likelihood. The model provided the odds of crash occurrence conditioned on the observed traffic conditions and resulted in 62 percent crash identification (Abdel-Aty and Pande, 2006).

The authors in that study also proposed a rudimentary strategy to "predict" crash occurrences in real time. However, it was observed that the precision of the models may be increased if the historical crash data are segregated by crash type. The disaggregate crash data would also help in providing specific warnings and suggesting specific actions to the motorists on the freeway to avoid specific types of crashes. Having shown that the traffic patterns observed prior to crashes may be differentiated from normal traffic conditions, a detailed framework for proactive traffic management is developed.

## CRASH RISK ASSESSMENT FRAMEWORK FOR INTERSTATE 4 IN FLORIDA

The proactive crash risk estimation framework is based on binary classification problem formulation and has been developed for a 36.25-mile instrumented corridor of Interstate 4 in Orlando, FL (Pande and Abdel-Aty, 2006 a). Historical crash data used for this study included crashes reported for the I-4 corridor dur-

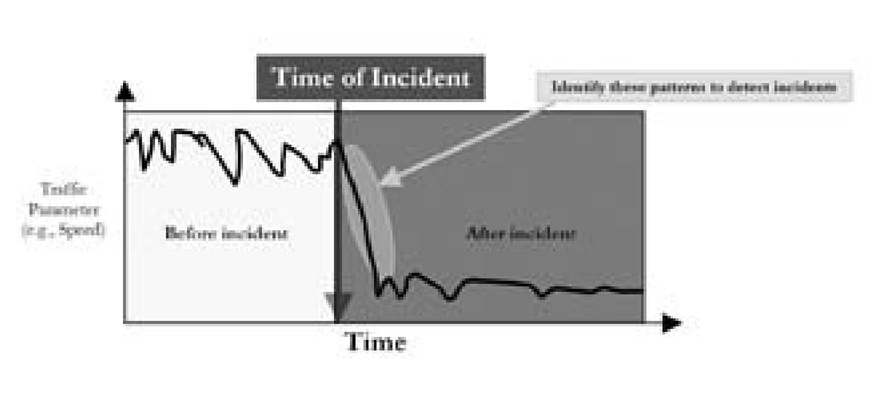


**Figure 1. Approach for incident detection.**

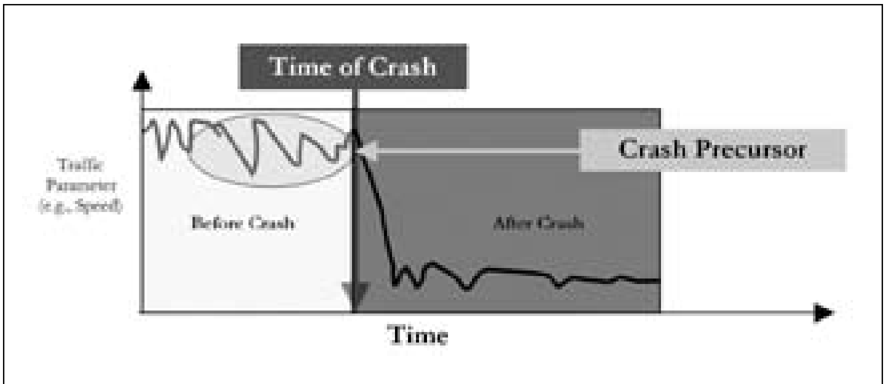


**Figure 2. Approach for proactive traffic management.**

ing the five-year period extending from 1999 through 2004. Out of the total 4,189 crashes, 1,065 crashes had no loop detector data available at all (due to malfunctioning loop detectors). Therefore, the 20-minute loop data observed right before the time of crash were collected for the remaining 3,124 crashes.

The proposed traffic management framework is essentially a proactive extension of the traditional approach used for incident detection. The traffic data used in the study were obtained from the loop detector stations located approximately every half-mile throughout the corridor. The information corresponding to each historical crash is derived from five loop detector stations: the station nearest to the crash location (referred to as Station F), two stations upstream of Station F (referred as Stations D and E) and two stations downstream of station F (Stations G and H). The 5-minute average and standard deviations of speed, volume and lane occupancy measured at 5-minute levels were calculated for four time slices (total 20-minute period before the crash). A range of classification models for identifying conditions prone to rear-end (Pande and Abdel-Aty, 2006 a) and lane-change-related crashes (Pande and Abdel-Aty, 2006 b) were developed using the traffic information from these stations. These models were the components of the real-time crash risk estimation framework. It is worth repeating that traffic parameters found significant in these models (based on historical crashes) do not automatically imply their causal relationship with crash occurrence. Such relationships are only inferred by relating the freeway traffic conditions represented by analysis as crash prone with possible crash mechanisms. For example, as discussed later in detail, speed differential between an upstream and downstream station can create conditions prone to rear-end crash at freeway section in between those stations within 5–10 minutes.

*Risk Assessment Models for Rear-End Crashes*

Rear-end crashes made close to 51 percent of the crash data for which some corresponding loop data were available (1,620 crashes). To develop a crash risk assessment system for rear-end crashes the distributions of 5-minute average speeds observed over the 5–10 minute period prior to historical rear-end crashes were examined. The speed data were collected from the five aforementioned stations (referred to as stations D through H) surrounding the crash location. Based on these distributions, rear-end crashes were grouped into two distinct clusters. The first cluster consisted of crashes that occur under extended congestion on the freeway, while the average speeds were relatively higher before the second cluster of rear-end crashes. The traffic speed conditions corresponding to the former group are referred to as Regime 1 and those corresponding to the later were called Regime 2. Simple "if-then" rules consisting of average traffic speeds at the aforementioned stations were formulated (based on classification tree methodology) to separate the traffic conditions belonging to the two regimes in real-time. These rules and the complete procedure to formulate these rules may be found in (Pande and Abdel-Aty, 2006 a). It was found that the Regime 1 conditions are very rare on the freeways (about 6.27 percent of the time) while the "exposure" of Regime 2 was much higher (about 93.73 percent of the time). Among the rear-end crashes, however, Regime 1 crashes makeup about 45.80 percent of the total 1,620 rear-end crashes while 54.20 percent of crashes occurred under Regime 2 conditions. The break up of two groups of rear-end crashes and random non-crash cases by traffic regime are provided in Figure 3.

Based on these observations, it was inferred that it would be reasonable to issue a warning for a rear-end crash if conditions belonging to traffic Regime 1 are encountered. It will identify nearly half of the rear-end crashes with a very small number of warnings. For crashes belonging to Regime 2, two classes of neural network-based classification models [multilayer perceptron (MLP) and normalized radial basis function (NRBF) neural networks] were estimated. The strategy of combining traffic regime information with neural network-based classification has been shown to have the potential to

| Variable | Parameter Estimate | Standard Error | Chi-Square | Pr > ChiSq |
|---|---|---|---|---|
| ***Coefficient of Variation*** in speed at station ***nearest to crash location*** | 1.21405 | 0.15548 | 60.9729 | <.0001 |
| ***Average occupancy*** at the station location ***½ mile d/s of crash location*** | 0.02466 | 0.00571 | 18.6747 | <.0001 |
| ***Standard deviation of volume*** at the station location ***½ mile d/s of crash location*** | –0.19124 | 0.04569 | 17.5216 | <.0001 |

**Table 1. Logistic regression model for identifying crash prone conditions (Abdel-Aty and Pande, 2006).**

identify 75 percent of rear-end crashes with reasonable false alarm rate.

The neural network modeling was repeated in three steps. In the first step, the independent variables included were the off-line factors (such as distances to the nearest ramps, milepost, time of day and so forth) and the traffic parameters (5-minute average/standard deviation of speeds, volume and occupancy) measured only at the station nearest to the crash location (Station F). In the next step, traffic parameters were included from three stations, the station of the crash and one station each in the upstream (Station E) and downstream (Station G) direction. In the third step traffic parameters were included from five stations [i.e., the station of the crash and two stations each in the upstream (Stations D and E) and downstream direction (Stations G and H)].

Multiple neural network models of each of the two classes were examined for their classification performance at each of the three stages. The best model was identified for each of three stages, and these three models required data from one, three and five stations, respectively. The model using data from five loop detector stations was better than the best models from other two stages (using traffic data from one or three loop detector stations). However, it required that none of the five loop detector stations surrounding the freeway location under surveillance be malfunctioning.

*Models for Lane-Change-Related Crashes*

Based on the findings from Lee et al. (2006) and an extensive review of crash reports, it was concluded that sideswipe crashes and the crashes classified as "angle crashes" on inner lanes of the freeway may be attributed to faulty lane-changing maneuvers. These crashes were about 16 percent of the crash data and were referred to as lane-change-related crashes (Pande and Abdel-Aty, 2006 b). The classification models utilized traffic parameters from the stations located immediately upstream and downstream of the historical crash locations as inputs. The same classes of neural network models (i.e., MLP and NRBF) were explored for lane-change-related crashes. The best models in the two classes were MLP, with four hidden neurons, and NRBF, with three hidden neurons. The hybrid model with these two models as its constituents was recommended for the real-time application.

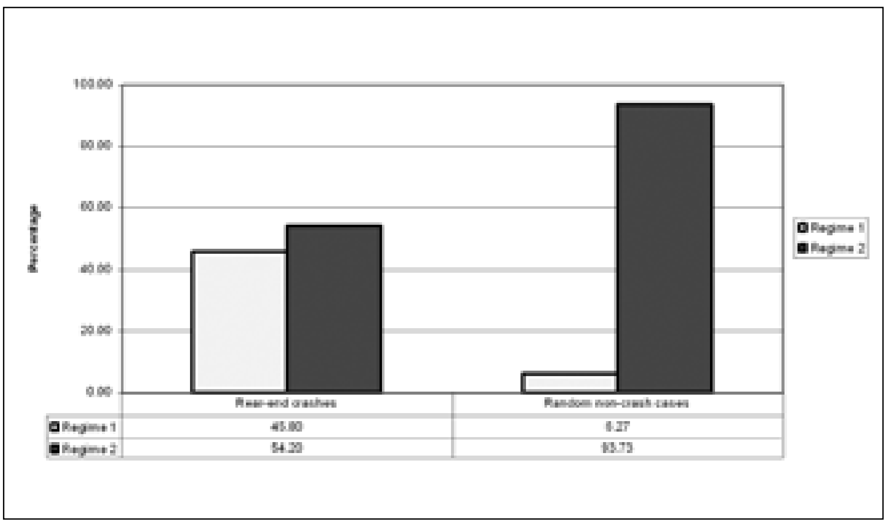


**Figure 3. Relative frequency of traffic regimes in rear-end crashes and a random sample of non-crash cases.**

*Framework for Real-Time Application*

The output of the neural network models discussed in the last two section (for any observation) is the posterior probability (0<posterior probability<1) of the event of interest (a rear-end crash or lane-change related crash). A higher (i.e., closer to 1) output would indicate that corresponding observation is more crash prone. Appropriate threshold on posterior probability may be used for separating potential crash warnings (positive decisions) versus normal traffic conditions. The models may be applied on the real-time traffic data as they become available from the loop detectors and warnings may be issued if the conditions are classified as crash prone. The framework proposed for real-time application of these models is provided in Figure 4.

In the proposed real-time application framework, the models developed for rear-end and lane-change-related crashes are applied in parallel. Hence, the locations would be flagged for rear-end crash independent of the flag for a lane-change-related crash. It is therefore possible for any freeway section to be flagged for a rear-end crash or a lane-change-related crash or both. For rear-end crashes the application first starts by applying the classification tree model for identification of traffic regime (Regime 1 or Regime 2). If the patterns belong to Regime 1, a rear-end crash warning is issued for the location without any further application. If the patterns belong to Regime 2, then we need to apply the neural network based

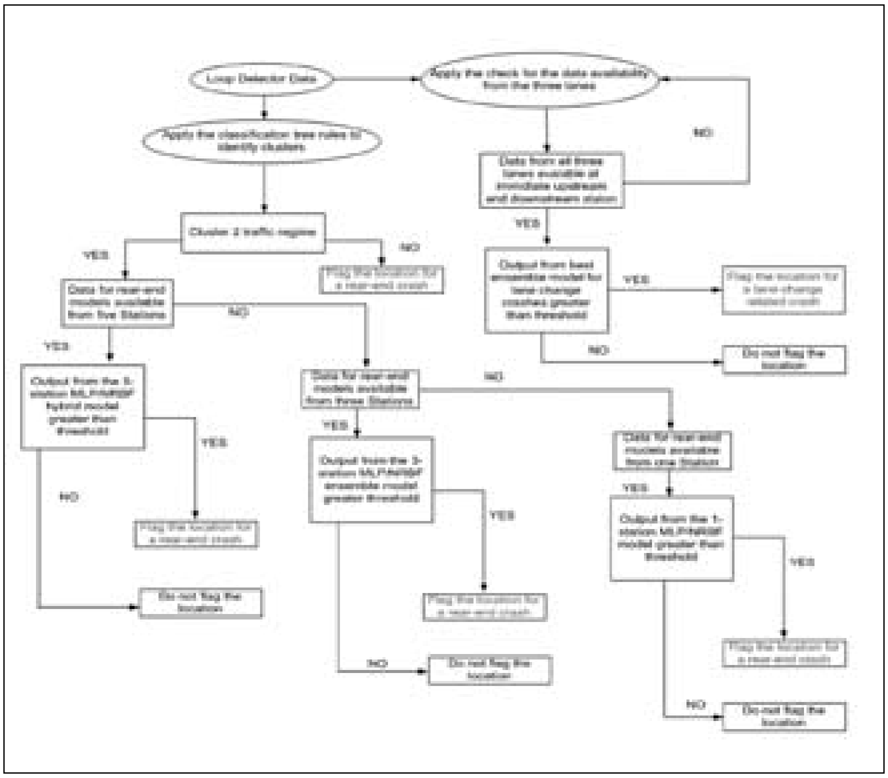


**Figure 4. A real-time application framework for the models developed to assess risk of the more frequent types (rear-end and lane-change related) of freeway crashes.**

models. As mentioned earlier, the model using traffic data from five loop detector stations provided optimal crash identification over the validation dataset and hence is preferred over other models.

Therefore, in the next step a check for data availability over five stations is applied. If data from five stations are available then the data are subjected to the corresponding model. The posterior probability output obtained from the model is then compared with the threshold. If the output is greater than the threshold value then the location may be flagged for a rear-end crash. If data from five stations are not available due to intermittent loop failures, a data availability check is applied for three stations. If data are not available from three stations then the best individual one-station model may be applied for assessing the risk of a Regime 2 rear-end crash.

The decision process to flag (or not to flag) the location is identical to the one used when data from five stations were available. To assess the risk of a lane-change-related crash, a check for data availability is first applied. If detectors at all three lanes of the upstream station are functioning then the input parameters are subjected to the corresponding neural network model. If the output posterior probability is greater than the threshold then warning for a lane-change-related crash may be issued. Note that the proposed framework shown in Figure 4 not only accounts for the classification performance of various models but also involves checks on data availability. The framework directs toward application of a more tolerant model (in terms of data requirements) if the requisite data are not available (due to malfunctioning loop detectors) for application of the preferred model. Note that such a framework may be developed and applied for any instrumented freeway corridor and does not require any more sophisticated data than series of single or dual loop detectors. Further details of the framework may be found in Pande and Abdel-Aty (2007).

## FORMULATION OF CRASH-PREVENTION STRATEGIES

The crash data have been analyzed so far to make a reliable assessment of traffic conditions on freeways for their crash potential. The objective is to be able to proactively manage traffic in such a way that reduces the estimated crash potential. This section provides an example of the notion behind developing such strategies. It specifically addresses rear-end crashes in medium- to high-speed traffic conditions (Regime 2). Figure 5 depicts the spatio-temporal patterns of the effect of average speeds on risk of rear-end crashes under medium- to high-speed traffic regime. The effect of average speed is derived using binary logistic regression while controlling the effect of freeway location related characteristics (Pande, 2005).

As one may observe from Figure 5, the effect of speeds at the downstream of the crash site (speeds at Station G and H) is negative (lower speeds increase the crash risk) while the effect for the upstream average speed (speed at Station D) is positive (higher speed increase the risk) for all four time slices (20-minute period). The effect of average speeds at Stations E and F was not found to be statistically significant. Based on the contour plot it may be inferred that under relatively free-flow traffic conditions, speed differential between upstream (Station D) and downstream stations (Stations G and H) increases the risk of a rear-end crash on the freeway section in between (i.e., vicinity of Station F). A possible explanation may be that the drivers under medium- to high-speed traffic conditions are caught unaware of the congestion that had been building up downstream as suggested by low average speeds at stations G and H prior to the time of crash.

The interpretation that spatial speed differential in the direction of travel contributes significantly to rear-end crash risk may be used to devise variable speed limit (VSL) strategies that may be effective in reducing the crash risk on freeways. An example of a potential VSL strategy that relies on this interpretation would be as follows: If the average speeds downstream of a freeway section are measured to be less than the speeds at station one mile upstream, then a decrease in speed limit upstream and an increase in speed limit at the downstream section may help in reducing the speed differential. It, in turn, would reduce the crash risk at the freeway section (in between the stations) that was experiencing a higher risk of rear-end crashes.

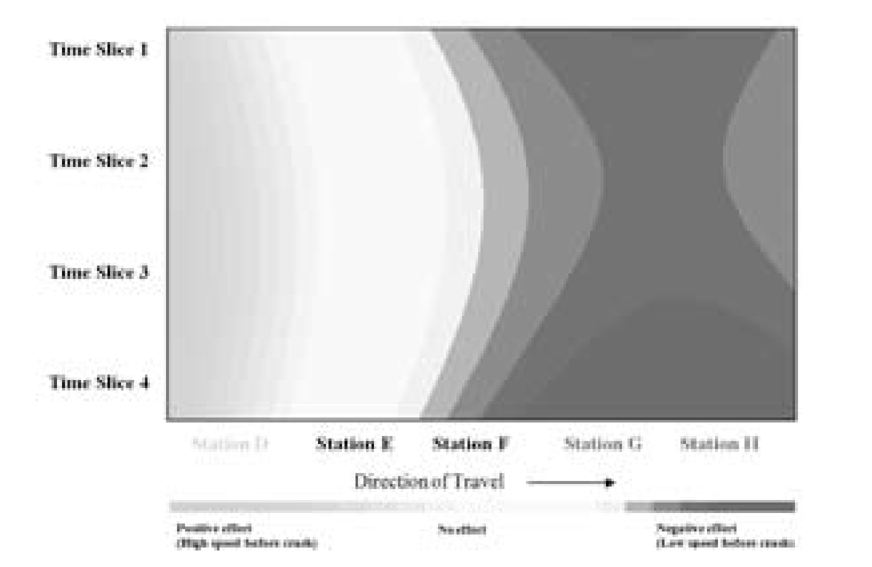


**Figure 5. Spatio-temporal pattern of the effect of average speeds on rear-end crashes under medium to high speed traffic regime.**

It is worth mentioning that the similar traffic speed differentials were not found to be significant before rear-end crashes that occur under extended congested conditions. Hence, crashes under low-speed traffic regime (Traffic Regime 1) may require different in telligent transportation system (ITS) strategies. Indeed, it was observed that while VSL is an effective strategy under medium- to high-speed traffic regime ramp metering (RM) is more effective under low-speed regime (e.g., Abdel-Aty et al., 2006, 2007). The specific ITS strategies, VSL, RM and a combination of the two were evaluated using a model of the Interstate 4 corridor in microscopic traffic simulation environment. These studies were able to quantify the benefits of the proactive approach in terms of reduced crash risk.

In those studies the authors have demonstrated significant benefits of using ITS strategies in a simulation environment (Abdel-Aty et al., 2006, 2007). The microscopic simulation tool PARAMICS was used to evaluate these strategies. By simulating their effects using PARAMICS, various strategies were tested to estimate the improvement over the simulated base case (with no VSL and/or ramp metering). Ramp metering and/or VSL strategies currently deployed in metropolitan areas around the USA primarily aim at reducing congestion or responding to a weather event. The strategies proposed by Abdel-Aty et al. (2006, 2007) specifically aim at reducing crash risk in real time as estimated by the proactive framework discussed in this study. The results obtained by these studies need to be integrated with the traffic management centers' existing strategies dealing with congestion.

## IMPACT ON INCIDENT MANAGEMENT PRACTICES

The issue that remains to be addressed is how the current traffic management practices may be adjusted to include the proactive traffic management paradigm. FHWA (2000) defines incident management as the process of managing multi-agency responses to highway traffic disruptions. Efficient and coordinated management of incidents is directed at reducing their adverse impacts on public safety, traffic conditions and the local economy. While incident detection is a critical part of the incident response; FHWA (2000) documented that cellular phone-based incident detection is generally the most efficient method for the same with detection times of less than a minute. For example, even back in the year 2000, close to 80 percent of the incidents in the Seattle, Washington, USA, metropolitan area were detected using cell phones (FHWA, 2000). It was also reported that automated incident detection algorithms are available but not widely used since system data requirements demand significant equipment investment and maintenance. Due to advances in recent information technology not only are more and more incidents are reported by cell phones, but the capabilities to collect, store and analyze data have increased manifold. In this regard, the proactive approach proposed by the authors could be very attractive to traffic management authorities.

The automated incident detection systems need to be replaced with a proactive framework, such as the one shown in Figure 4, for assessing the real-time traffic conditions on freeways. The models constituting the proactive framework could enable traffic management authorities to be prescient about the location where a crash is likely to occur. The warnings from a proactive system may play an advisory role for the drivers so that they can be more vigilant while driving under crash-prone conditions. Incidents avoided using such a system would result in significant benefits through reduced vehicle delays and enhanced safety to motorists through the reduction of crash frequency or severity. Moreover, the results from this proactive system would also be helpful in managing the incidents that do occur. The information available from these models may also be used to improve response and clearance times, which is one of the stated incident management goals of the Federal Highway Administration (FHWA, 2000) and state-level agencies. For example, response times have also been recognized as a metric by Florida Department of Transportation (FDOT) to assess traffic incident management performance in the short-term (CUTR, 2005).

Freeway locations under high risk of crash occurrence according to the proactive framework may be monitored using closed-circuit television (CCTV) cameras. Video monitoring may provide important details about the incident, in case it does occur. This timely verification would result in optimum response based on accurate and rapid verification since verification and response time are large components of the overall clearance time. For the proposed proactive approach, primary crash rates would be a long-term performance measure along with the secondary crash rates. It is worth mentioning that while this new proactive approach has a significant potential to save lives and/or avoid delays, there is no substitute for having better coordination between transportation agencies, law enforcement and service patrols while managing freeway traffic. The responding agencies prepared with interagency response action plans tailored for various incident scenarios and supported by shared data are still desirable to improve operations on the freeway (FHWA, 2000).

**IT IS WORTH MENTIONING THAT THE PROACTIVE FRAMEWORK IS EXPECTED TO DETECT CRASH-PRONE CONDITIONS AND NOT NECESSARILY PREDICT INDIVIDUAL EVENTS (CRASHES).**

## CONCLUSIONS

In conclusion, it is worth mentioning that the proactive framework is expected to detect crash-prone conditions and not necessarily predict individual events (crashes). Therefore, while the approach adopted here is somewhat similar to incident detection in terms of analysis of the historical data, the two applications would differ significantly. The objective exactly analogous to incident detection algorithms would have been to *predict* crashes. It should be acknowledged that the term prediction is not really applicable here. The objective is to identify conditions under which, based on historical data, the drivers are more likely to make errors, which in turn lead to crashes.

Also, false alarms are not as detrimental to the present application as they would be for incident detection algorithms. In fact, the ultimate goal of this research would, or at least should be, to achieve a false alarm every time a crash warning is issued. The goal would be based on the expectation that with some form of proactive real-time countermeasure or warnings to the motorists, potential crashes may be avoided. Such countermeasures are obviously a matter of further investigation but even without the countermeasures it is neither improbable nor unacceptable to have these false alarms. Crash-prone traffic conditions identified by the framework proposed here would not always result in crash occurrence even though a significant proportion of historical crashes did occur under those conditions. These conditions are worth warning the drivers. In other words, drivers need to be more attentive under such traffic conditions, even if they do not culminate in a crash every time.

The justification or inevitability of false alarms does not mean that an unlimited number of warnings could be issued, especially if the information based on the framework is being transferred to the motorists. It should be ensured that the drivers do not perceive the warnings to be "too many" and become immune to them. Examination of drivers' reaction to real-time information about crash-prone conditions is a much needed avenue for future research. ■


## ACKNOWLEDGMENTS

The authors wish to thank the Florida Department of Transportation for funding this work.


*References*


Abdel-Aty, M., Dilmore, J., and Hsia, L. (2006), Applying Variable Speed Limits and the Potential for Crash Migration. *Transportation Research Record*, 1953, pp. 21–30.

Abdel-Aty, M., Dhindsa, A., and Gayah, V. (2007), Considering various ALINEA Ramp Metering Strategies for Crash Risk Mitigation on Freeways under Congested Regime *Transportation Research Part C: Emerging Technologies*, 15(2), pp. 113–134

Abdel-Aty, M., and Pande, A. (2006), ATMS Implementation System for Identifying Traffic Conditions leading to Potential Crashes, *IEEE Transactions on Intelligent Transportation Systems*, 7(1), pp. 78–91.

Abdel-Aty, M., Uddin, N., Abdalla, F., Pande, A., and Hsia, L. (2004), Predicting Freeway Crashes based on Loop Detector Data using Matched Case-Control Logistic Regression, *Transportation Research Record 1897*, pp. 88–95.

Abdulhai, B., and Ritchie, S. (1999), Enhancing the Universality and Transferability of Freeway Incident Detection using a Bayesian-based Neural Network, *Transportation Research Part C: Emerging Technologies*, 7(5), pp. 261–280.

Cheu, R., and Ritchie, S. (1995), Automated detection of lane-blocking freeway incident using artificial neural networks, *Transportation Research Part C: Emerging Technologies*, 3(6), pp. 371–388.

Center for Urban Transportation (2005), Best Practices for Traffic Incident Management in Florida, University of South Florida, Tampa, FL, 2005. Available online at: www.iacptechnology.org/IncidentManagement/BestPracticesFLDOT.pdf. Accessed on February 11, 2008.

Federal Highway Administration (2000), Incident Management Successful Practices: A Cross-Cutting Study, Washington, DC. Available online at: www.itsdocs.fhwa.dot.gov/JPODOCS/REPTS_TE/11484.pdf. Accessed on February 10, 2008.

Golob, T. F., Recker, W. W., and Alvarez, V. M. (2004), Tool to Evaluate the Safety Effects of Changes in Freeway Traffic Flow, *Journal of Transportation Engineering*, 130(2), pp. 222–230.

ITE Traffic Safety Toolbox (1999), A Primer on Traffic Safety, Institute of Transportation Engineers, 1999.

Lee, C., Abdel-Aty, M., and Hsia, L. (2006), Potential Real-Time Indicators of Sideswipe Crashes on Freeways. *Transportation Research Record 1953*, pp. 41–49.

Pande, A. (2005), Estimation of Hybrid Models for Real-Time Crash Risk Assessment on Freeways, Ph.D. Dissertation, University of Central Florida, Orlando, FL.

Pande, A., and Abdel-Aty, M. (2006 a), A comprehensive analysis of the relationship between real-time traffic surveillance data and rear-end crashes on freeways, *Transportation Research Record 1953*, pp. 31–40.

Pande, A., and Abdel-Aty, M. (2006 b), Assessment of freeway traffic parameters leading to lane-change related collisions. *Accident Analysis and Prevention*, 38(5), pp. 936–948.

Pande, A. and Abdel-Aty, M. (2007), A Multi-Model Framework for Real-Time Crash Risk Assessment, *Transportation Research Record*, 2019, pp. 99–107.



**MOHAMED ABDEL-ATY,** *Ph.D., P.E. is a professor of civil engineering at the University of Central Florida (UCF). His main research interest is in the areas of traffic safety, traffic simulation, ITS and travel demand analysis. He has more than 200 published papers. He is an associate editor of* Accident Analysis and Prevention. *He is a co-chair of the TRB ATIS subcommittee, a member of the TRB committee on Safety Data Analysis and Evaluation and committee on User Information Systems, and a member of the Editorial Board of the* ITS Journal. *Dr. Abdel-Aty is the 2003 UCF Distinguished Researcher. He is a registered professional engineer in Florida.*



**ANURAG PANDE,** *Ph.D is assistant professor of civil engineering at the California Polytechnic State University, San Luis Obispo. Pande received the B.Tech. Degree in civil engineering from Indian Institute of Technology (IIT), Mumbai, India, in 2002 and the M.S. and Ph.D. in transportation systems engineering from the University of Central Florida in 2003 and 2005, respectively. His research interests include traffic safety analysis, ITS and traffic simulation along with statistical and data mining applications in transportation engineering.*



**LIANG Y. HSIA,** *P.E. CGC is an engineer administrator with the Florida Department of Transportation (FDOT). He is the FDOT deputy state traffic engineer. He received his bachelor of science degree in architectural engineering from the Chinese Culture University and a master of science degree in construction from the University of Florida with additional graduate studies in computer science, structural engineering, and traffic engineering. He is a member of ITE.*