# Towards Risk-Based Safety Management: A Pilot Study for Rural Freeways

## *Extended Summary*

**Raul Pineda-Mendez, Qiming Guo, Andrew Tarko**[1]

*Lyles School of Civil Engineering, Purdue University, 550 W Stadium Ave, West Lafayette, IN 47907,* rapinedam@purdue.edu
*Lyles School of Civil Engineering, Purdue University, 550 W Stadium Ave, West Lafayette, IN 47907,* guo512@purdue.edu
*Lyles School of Civil Engineering, Purdue University, 550 W Stadium Ave, West Lafayette, IN 47907,* tarko@purdue.edu

## Abstract

In highway safety management, roadway hazards are identified and addressed to reflect fewer crashes and lower severity of injuries. For this purpose, aggregate count-based crash models, such as negative binomial safety performance functions, have been widely adopted in engineering practice. Meanwhile, time-dependent risk factors, such as weather conditions, road construction, and traffic operations are typically omitted. This study evaluates the potential use of disaggregate safety analysis based on high-resolution data to supplement conventional count-based safety management. First, a methodology is proposed to identify and assess time-dependent risk factors related to weather conditions and operational speed characteristics. This methodology is illustrated in a case study on rural interstate freeways in Indiana. In addition to traditional aggregate crash risk factors, the effect of time-dependent variables on the hourly crash probability and injury severity is estimated. Results from a sequential mixed model describe a significant relationship between aggregate and time-dependent risk factors and the probability of crash and its severity. Finally, risk profiles, an example tool for risk-based safety management, are conceptualized.

Keywords: Highway Safety Management; Disaggregate Crash Model; Sequential Mixed Logit; Rural Freeways.

[1] * Corresponding author. Tel.: +1-765-494-5027;
*E-mail address:* tarko@purdue.edu

## 1. Introduction

Count-based crash models are the most prevailing analytical tool for safety management in current engineering practice. The estimated expected safety performance is compared with the observed long-term crash counts, usually aggregated 3 to 5 years, to determine whether the roadway element requires further inspection. However, the intrinsic data aggregation fails to capture the temporal variability of the crash risk and does not provide cues for the deployment of short-term operational safety countermeasures. In addition, previous research has identified the crash risk variation across space, time, and even data aggregation levels (*1–3*). Hence, risk-based safety management came into place, which uses both static geometric features and time-dependent factors, including traffic volume, operating speed, road construction, and weather conditions to estimate the change of crash risk over time.

With the advancement of high-resolution data collection techniques and big data storage capabilities, time-dependent data has become widely available. Many researchers have estimated the probability and severity of crashes at a disaggregated level using so-called real-time crash prediction models (*4, 5*). Respectively, the methods to identify high-risk conditions have been updated. Probabilistic neural networks (*4*, *6*), case-control logistic regression models (*7*), support vector machine (*8*, *9*), backpropagation neural network (*10*), extreme machine learning (*11*), convolutional neural network (*5*), and deep learning (*12*) have been used.

The listed methods showed promise in capturing crash risk changes over disaggregated time scales. Nevertheless, there are multiple limitations when applying these models in a large-scale highway network, preventing the implementation of risk-based safety management. These limitations include the dependence on heavily instrumented road segments (*13*), the lack of research on the relationship between crash injury severity and the time-dependent factors, overlooking conditions that have a proven impact on driving behavior (*14*), and endogeneity issues caused by the direct connection between crash occurrence and changes in traffic dynamics.

This study aims to assess the effects of time-dependent factors on crash probability and injury severity using widely available high-resolution data. In addition, the potential applications for risk-based safety management are explored. The estimated impacts, including static and time-dependent elements, are meant to create analytical tools for a system-wide safety management system. Risk profiles, an example analytical tool, are illustrated based on results from a case study on rural interstate freeways.

## 2. Methodology

### 2.1 Sample

A sample of 133 one-way miles of rural freeways was selected for this study. It consists of approximately 5% of the total mileage of rural interstates in Indiana. These segments were chosen based on their data availability, mainly short-term traffic volumes. The selected road sections were divided into 532 segments with a fixed length of 0.25 miles. This segmentation was chosen for several reasons—first, the ability to reflect sporadic changes in roadway characteristics. Second, on monotonous highways, it has been found that drivers can see as far as 0.28 miles under clear weather conditions. Last, this segmentation permits a quicker transfer of the results to Indiana's current safety management practice.

### 2.2 Data

Information from multiple data sources was gathered and linked to provide a comprehensive dataset for statistical analysis. First, hourly traffic volumes were gathered from permanent traffic count stations. All the sample segments have nearby count stations. Second, operating travel speed characteristics were obtained from the National Performance Management Research Dataset (NPMRDS) provided by INRIX. Third, two weather data sets, Parameter-elevation Relationships on Independent Slopes Model (PRISM) and Multi-sensor Precipitation Estimates (MPE), were provided by Indiana State Climate Office (INClimate). The gridded data has virtual weather stations evenly spaced every 2.5 miles. Fourth, road characteristics were gathered from Google Earth's historical imagery. The collected data includes cross-sectional elements, horizontal alignment, pavement, roadside elements, signing, and road lighting. Such data supplements existing aggregate geometry and traffic data from the Indiana Department of Transportation (INDOT). Finally, crash records were obtained from the Automated Reporting Information Exchange System (ARIES); there were 2,091 crashes assigned to the selected roads between 2014 and

2018. Regarding crash injury severity, 85.8% of crashes were classified as property damage only (PDO), 6.6% as a potential or minor injury, and 7.6% as fatal or incapacitating. On average, each segment reported 3.9 crashes over five years.

Once the data linking process is completed, the resulting modeling dataset is formed by two types of observations: crashes and non-crashes. A 1:30 ratio between the two types of records is enforced via sampling non-crashes based on the number of crashes. Since crash observations are very uncommon compared to non-crashes, this sampling is needed to estimate the effects of contributing factors on hourly crash risk and injury severity. The constant term of the fitted model is later adjusted with an offset variable to represent the original conditions before the sampling.

### 2.3 Statistical Analysis Method

The hourly probability of crash at various injury severity levels is estimated as a function of static roadway characteristics and time-dependent factors. To do so, a sequential mixed logit approach is used. This method fits two consecutive models—first, a model of the hourly crash probability with a crash vs. no-crash binary response. Second, a model of the probability of severe crash (injury or fatal) conditioned on crash occurrence. The later model uses a binary severe vs. not severe outcome. In addition, average marginal effects (AMEs) are calculated to facilitate the interpretation of the results. AMEs represent the crash risk (or injury risk) change from a one-unit increase in a specific predictor variable.

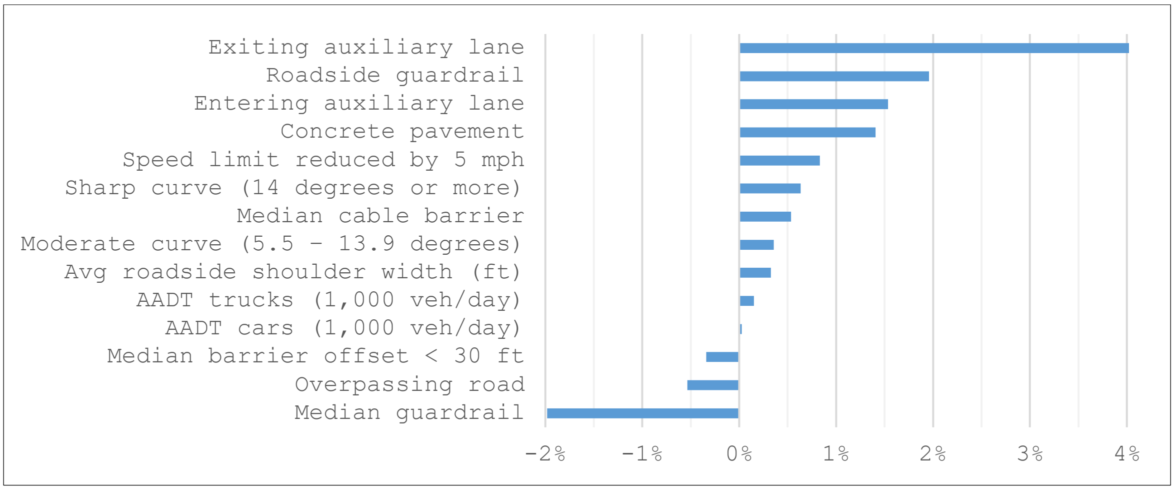
## 3. Results and Discussion

Figure 1 shows the average marginal effects of hourly crash probability and injury severity models. Hourly crash risk is increased by hourly volume, Average Annual Daily Traffic (AADT), horizontal curves, barriers, lower speed limits, the standard deviation of speed, and the interaction of low-intensity rain and freezing temperatures. These findings coincide with previous research (1, 16, 17). Additional factors that increase short-term crash risk include auxiliary lanes, downtrend speeds, and congestion. Conversely, overpassing roads, average speed, and uptrend speeds were found to enhance safety.

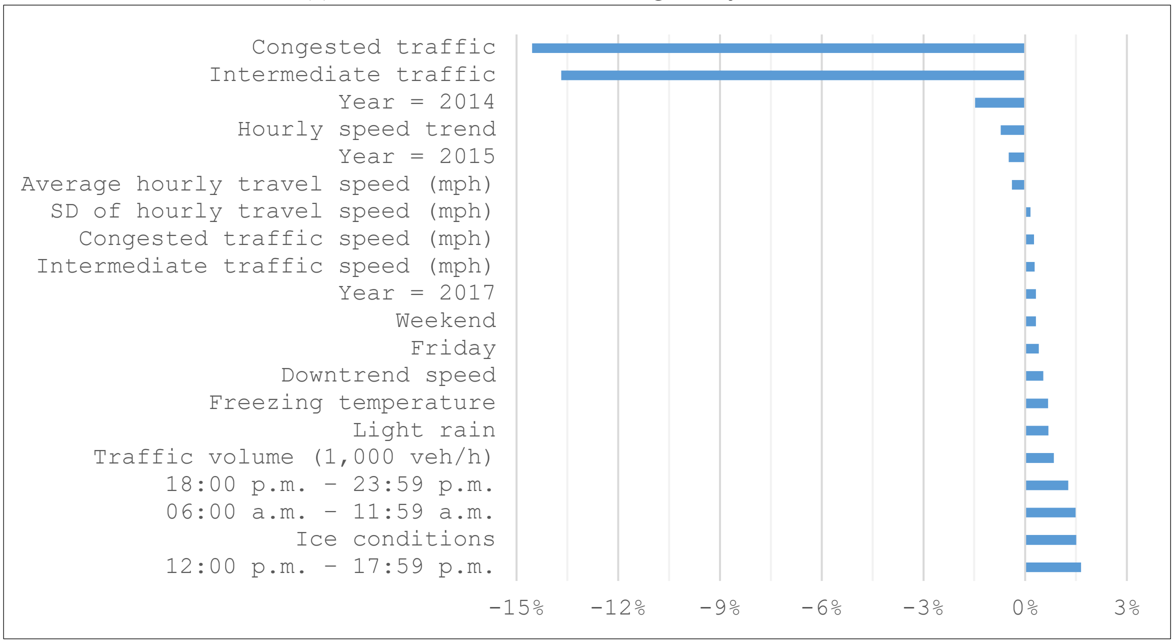
Compared to the crash probability model, fewer predictors affected injury severity. The conditional probability of a severe outcome is increased by the presence of a median guardrail (typical around bridges), mild curves, average speed, the standard deviation of hourly speed, downtrend speeds, and intermediate congestion. In addition, road lighting and lower speed limits reduced crash severity. Interestingly, the presence of icy conditions, and the combination of precipitation and near-freezing temperatures reduced the expected injury severity. The previous may be due to risk compensation as drivers adjust their operating speeds to account for inclement weather conditions. The parameter estimates of hourly temperature and Friday indicator are not discussed since they may reflect local conditions in the sample.

The results presented in Figure 1 can be used to supplement crash-based safety management by estimating the short-term crash risk of a target road segment. This estimation may improve the current safety management tasks. Specific applications include risk-based network screening and operational countermeasure evaluation through crash risk visualization tools for safety audits. An example visualization tool that may benefit safety audits is the risk profile. Using historical crash data, one can plot the expected hourly risk and observed crashes against time. The exploration of the time-dependent characteristics that lead to an increment in short-term crash risk may provide useful insights for further field inspection and road safety audits.

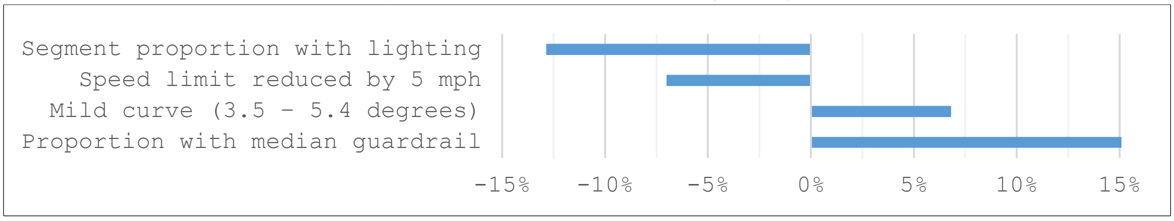
.



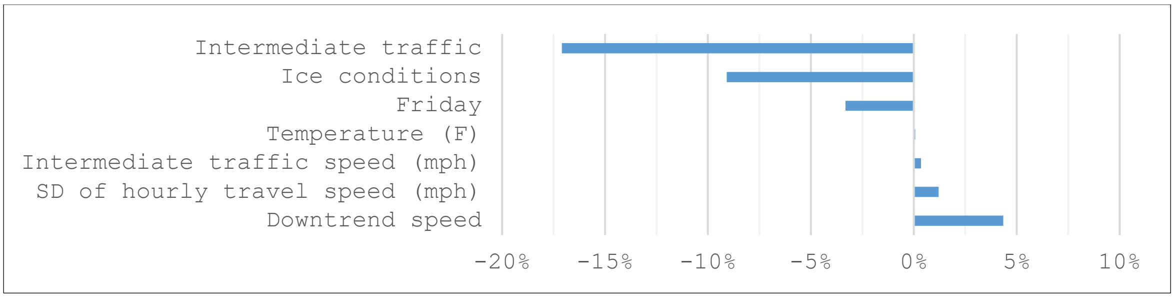

(a) Fixed risk factors influencing hourly crash occurrence.




(b) Time-dependent risk factors influencing hourly crash occurrence.




(c) Fixed risk factors influencing injury severity given crash occurrence.




(d) Time-dependent risk factors influencing injury severity given crash occurrence.

**Figure 1: Average Marginal Effects on Hourly Crash Risk and Injury Severity.**

## 4. Conclusion

The concept of risk-based safety management shows promise. Disaggregate safety analysis can supplement count-based crash models for safety management by estimating the short-term crash risk of a target road segment. A case study on rural interstate freeways in Indiana was used to illustrate the proposed method. The effects of static roadway characteristics and time-dependent factors on short-term crash probability and injury severity were estimated using a sequential mixed logit approach. The estimated impacts, including static and time-dependent elements, can be potentially valuable for multiple safety management tasks. For example, results can be used to perform statistical simulations to identify frequent high-risk situations and estimate the economic benefits of implementing operational countermeasures. Moving forward, numerous challenges emerge when performing disaggregate safety analysis, including addressing endogeneity, ensuring data consistency, conducting data linking, delays in data transfers, and manual extraction of detailed roadway elements. Addressing these challenges is key to ensure the complete implementation of risk-based safety management.

## 5. References


1. Dutta, N., and M. D. Fontaine. Improving Freeway Segment Crash Prediction Models by Including Disaggregate Speed Data from Different Sources. *Accident Analysis and Prevention*, 2019. https://doi.org/10.1016/j.aap.2019.07.029.
2. Mohammadnazar, A., I. Mahdinia, N. Ahmad, A. J. Khattak, and J. Liu. Understanding How Relationships between Crash Frequency and Correlates Vary for Multilane Rural Highways: Estimating Geographically and Temporally Weighted Regression Models. *Accident Analysis & Prevention*, Vol. 157, 2021, p. 106146.
3. Yuan, J., M. Abdel-Aty, J. Fu, Y. Wu, L. Yue, and N. Eluru. Developing Safety Performance Functions for Freeways at Different Aggregation Levels Using Multi-State Microscopic Traffic Detector Data. *Accident Analysis & Prevention*, Vol. 151, 2021, p. 105984.
4. Oh, C., J.-S. Oh, S. Ritchie, and M. Chang. Real-Time Estimation of Freeway Accident Likelihood. 2001.
5. Yu, R., Y. Wang, Z. Zou, and L. Wang. Convolutional Neural Networks with Refined Loss Functions for the Real-Time Crash Risk Analysis. *Transportation research part C: emerging technologies*, Vol. 119, 2020, p. 102740.
6. Oh, C., J.-S. Oh, and S. G. Ritchie. Real-Time Hazardous Traffic Condition Warning System: Framework and Evaluation. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 6, No. 3, 2005, pp. 265–272.
7. Abdel-Aty, M., N. Uddin, F. Abdalla, and A. Pande. Predicting Freeway Crashes Based on Loop Detector Data Using Matched Case-Control Logistic Regression. CD-ROM. *Transportation Research Board. National Research Council. Washington, DC*, 2004.
8. Xiao, J., and Y. Liu. Traffic Incident Detection Using Multiple-Kernel Support Vector Machine. *Transportation research record*, Vol. 2324, No. 1, 2012, pp. 44–52.
9. Wang, L., M. Abdel-Aty, J. Lee, and Q. Shi. Analysis of Real-Time Crash Risk for Expressway Ramps Using Traffic, Geometric, Trip Generation, and Socio-Demographic Predictors. *Accident Analysis & Prevention*, Vol. 122, 2019, pp. 378–384.
10. Cheng, X., W. Lin, E. Liu, and D. Gu. Highway Traffic Incident Detection Based on Bpnn. *Procedia Engineering*, Vol. 7, 2010, pp. 482–489.
11. Li, L., X. Qu, J. Zhang, and B. Ran. Traffic Incident Detection Based on Extreme Machine Learning. *Journal of Applied Science and Engineering*, Vol. 20, No. 4, 2017, pp. 409–416.
12. Huang, T., S. Wang, and A. Sharma. Highway Crash Detection and Risk Estimation Using Deep Learning. *Accident Analysis & Prevention*, Vol. 135, 2020, p. 105392.
13. Hossain, M., M. Abdel-Aty, M. A. Quddus, Y. Muromachi, and S. N. Sadeek. Real-Time Crash Prediction Models: State-of-the-Art, Design Pathways and Ubiquitous Requirements. *Accident Analysis & Prevention*, Vol. 124, 2019, pp. 66–84.
14. Yu, R., and M. Abdel-Aty. Analyzing Crash Injury Severity for a Mountainous Freeway Incorporating Real-Time Traffic and Weather Data. *Safety Science*, Vol. 63, 2014, pp. 50–56. https://doi.org/10.1016/j.ssci.2013.10.012.
15. Tarko, A. P., Q. Guo, and R. Pineda-Mendez. *Using Emerging and Extraordinary Data Sources to Improve Traffic Safety*. Joint Transportation Research Program, West Lafayette, 2021.
16. Roshandel, S., Z. Zheng, and S. Washington. Impact of Real-Time Traffic Characteristics on Freeway Crash Occurrence: Systematic Review and Meta-Analysis. *Accident Analysis & Prevention*, Vol. 79, 2015, pp. 198–211.
17. Zou, Y., and A. Tarko. Performance Assessment of Road Barriers in Indiana. 2016.