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Risk Assessment of Driving Safety in Long Scaled Bridge under Severe Weather Conditions

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by

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Dedication

Dedicated to my Parents.

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Abstract

Weather conditions have certain impacts on roadway traffic operations, especially traffic safety. Bridges differ from most surface streets and highways in terms of their physical properties and operational characteristics. This research assess the driving risk under different weather conditions through focus group firstly, then it develops a multi-ordered discrete choice model that is used to analyze and evaluate driving risks under both single and dual weather conditions. The data is derived from an extensive questionnaire survey in Shanghai. And the questionnaire includes those factors related to roadway, drivers, vehicles, and traffic that may have significant impacts on traffic safety under severe weather conditions.

Considering the actual situation these variables except driver's gender are selected as independent variables of risk evaluation. As a result, different risk levels and corresponding probability are calculated, which are very important to optimize emergency resource allocation and make reasonable emergency measures. Moreover, in order to reduce severe bridge-related crashes, the research develops an ordered probit model to analyze those factors contributing to bridge-related crash severity and to predict probabilities of different severity levels under rainy conditions.

Chapter 1 Introduction

1.1 Background

Long-scale bridges usually built over a river are an important section of the roadway network. They may improve traffic conditions of the road network, save travel time, decrease fuel consumption, and reduce environmental pollution through reducing travel distance. This research is based on the Sutong Changjiang Highway Bridge, which is the longest scaled bridge in the world. The Sutong Highway Bridge, over the Chang Jiang River, is located between the cities of Nantong and Changshu in Jiangsu Province, connects the four intercity freeways, and is a key part of the national interstate freeway. It is also one of the most important sections of the road network in Jiangsu Province, which is shown in Figure 1.

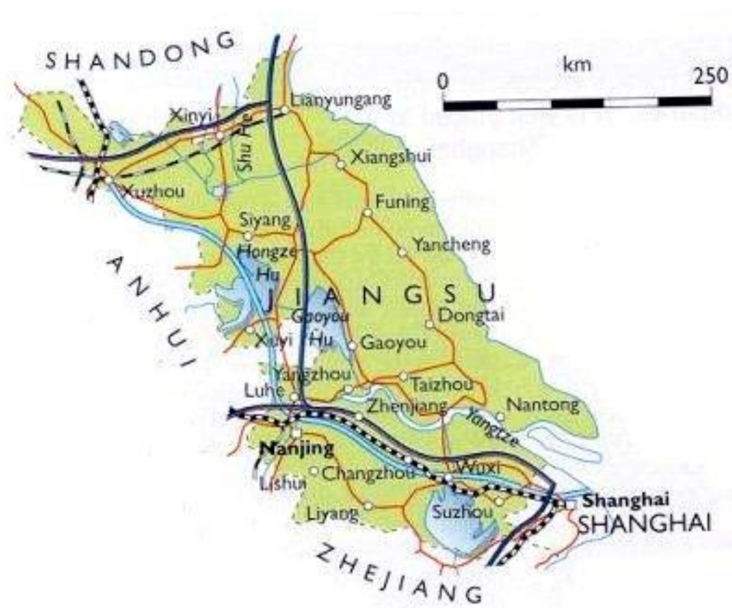

Figure 1 Geographic Location of Sutong Yangzi Bridge

Because of the importance of its geographic position, the traffic conditions on the Sutong Highway Bridge become significant. The bridge can obviously reduce the distance between the cities on the both sides of the Chang Jiang River, but if the bridge is forced to close because of severe weather or emergency cases, the resulting traffic jam may spread to the adjacent cities or the whole Jiangsu province, and even the national interstate freeway.

Bridges differ from most surface streets and highways in terms of their physical properties and operational characteristics. In recent years, bridge-related crashes have become more and more frequent in China. For example, crash data from Nanchang Bridge in Jiangxi Province shows that the number of vehicle crashes on the bridge in 2009 was1180, which is equal to 3.2 crashes per day. Sometimes, bridge-related crashes may result in catastrophic consequences. Examples of events that led to severe loss of life and property include the following:

(1) At 6:12 AM on December 28, 2009, because of heavy fog and icy pavement, more than 50 vehicles were involved in rear-end crashes at Poyang Lake Bridge in Jiangxi Province, resulting in 13 deaths and 19 injuries.

(2) At 2:00 AM on March 29, 2010, at the main deck of Yangpu Bridge in Shanghai, a taxi vehicle was collided with a van running in opposite direction. This crash caused four deaths and one serious injury. Figure 2 shows a picture of the van after the crash.

(3) At 4:00 PM on June 22, 2011, at Zhoushan Bridge in Zhejiang Province, a passenger car hit the bridge guardrails and deformed severely.

Figure 2 Photo of Van after Collision

Bridge-related crashes have their own characteristics, different from other roadway facilities. Although studies of crash severity on highways and freeways have reached important conclusions and recommendations, only a few studies focus on the severity of bridge-related traffic crashes, and limited information has been published regarding the subject. Thus, it is relevant to identify factors contributing to bridge-related crash severity. Results from such a study could help bridge managers to take effective measures to improve traffic safety on bridges.

In China, transportation safety researchers have begun to pay more and more attention to highway safety as quickly-developed highways have become the locations of abnormal fatalities in China. One of the leading causes is adverse weather conditions. The weather conditions around a bridge area can be quite complicated, including strong wind, rainfall, fog, snow, ice, and high temperatures. The traffic operation on the Sutong Bridge is clearly impacted by such disastrous weather conditions. With the global climate changing, severe weather conditions have occurred frequently all over the world. For example, Hurricane Katrina caused a large area to flood. The economic loss exceeded $80 billion (US) due to the lack of risk analysis. Risk assessment and early warnings of severe weather conditions are now given more and more exclusive attention. Compared to a normal highway, accidents that happen on a highway bridge may create more destructive results, such as water pollution and bridge structure damage, which may result in a longer time and more money to recover. Moreover, when there is serious accident in a bridge, it may be more difficult for emergency rescue and traffic dispersion because of the limited access of the bridge. Thus, there is a need to conduct research related to severe weather conditions to evaluate risks for traffic operations on highway bridges.

Risk is commonly defined as a combination of the probability and severity of adverse effects. Risk level is not simply equated to crash rate; higher risk level does not mean a larger crash rate. The task of risk analysis is to study the possible consequences of severe weather conditions and their probability. If we simply consider risk as a product of probability and the severity of consequence, we might get the same results for both low-probability catastrophic and high, frequently less severe accidents. However, there are two challenging questions for operational managers: How safe is safe enough, and what is an acceptable risk? Modern managers and decision makers are often more concerned with low-probability catastrophic events than with more-frequently-occurring but less-severe accidents. The unaccepted risk predicted before a catastrophe happens plays a significant role in transportation safety operation.

The quantitative risk analysis method is usually applied in natural disaster risk analysis. The quantitative analysis method has two primary branches: the probability risk assessment method and the fuzzy risk evaluation method. The common approach to the probability risk assessment method is to determine the empirical distribution of risk events or factors by historical data.

1.2 Problem Statement

In the case of rainfall, for instance, when it is raining, a driver's visibility may be affected, meaning that safety performance of the roadway may be discounted. In addition, rainy weather can result in a reduction in pavement skid resistance and vehicular stability (such as braking stability and steering operation), which may cause a reduction in traffic operational speed. The combined impacts from roadway, vehicle, traffic control, and driver behavior conditions under rainy weather conditions could increase the potential for safety problems and traffic crashes.

In recent years, some research studies have concluded that impacts from rainy weather conditions on traffic operations and safety cannot be ignored. Table1 presents traffic crash data under different weather conditions with original crash data provided from a previous study. In the table, 1,085 traffic crashes during 1998–1999 on the Ji-Qing Freeway in Shandong Province are analyzed to reflect traffic safety risk for different weather conditions. Risk index (which is equal to the percentage of accidents divided by the percentage of days in a corresponding weather category) is used to indicate the diving safety risk under each weather condition. It can be seen that snowy and rainy conditions (with a risk index of 1.75 and 1.57, respectively) are ranked #1and #2, meaning that driving under snowy or rainy conditions could be much more risky compared with other weather conditions. If an average daily accident (crash) rate is used, it is found that Ji-Qing Freeway had an average daily accident rate of 5.20 and 4.68 for snowy and rainy conditions, respectively, which results in the same conclusions as concluded by risk indices.

Table 1 Risk Index Analysis for Ji-Qing Freeway under Different Weather Conditions

Weather Conditions		Sun	Rain	Fog	Cloud	Snow	Strong Wind
Annual Accident Distribution	Numbers of Accidents	794	117	111	32	26	5
	Percentage (%) of Accidents	73.18	10.78	10.23	2.95	2.40	0.46
Annual Weather Distribution	Number of Days	273	25	42	16	5	4
	Percentage (%) of Days	74.79	6.85	11.51	4.38	1.37	1.09
Average Daily Accident Rate		2.91	4.68	2.64	2.00	5.20	1.25
Risk Index		0.98	1.57	0.89	0.67	1.75	0.42

Another similar analysis was performed to analyze risk indices under different weather conditions with crash data provided from another study. In the analysis, 50,000 traffic accidents from 1999 to 2002 in Changchun City in Liaoning Province were analyzed to calculate risk indices and average daily crash rates under different weather conditions. Table2 summarizes the analysis results. It can be concluded that fog and rainy weather conditions have higher risk indices compared with other weather conditions, and similar conclusions can be obtained if average daily crash rates are used.

In summary, whether it is average daily crash rate or risk index, rainy weather may have significant impacts on the safe operation of road traffic. However, such an impact could involve the combined effects from the driver, vehicle, roadway, and traffic conditions. It is meaningful to study and evaluate the combined effects of these factors under rainy weather conditions. Results from such studies could enhance traffic emergency management and optimize emergency source allocation.

Table 2 Risk Index Analysis for Roadways in Changchun City under Different Weather Conditions

Weather Conditions	Rain	Snow	Mist	Fog	Strong Wind	Cloud	Sleet	Sun	Ave.
Percentage (%) of Days	4.63	3.93	1.18	0.27	3.18	26.3	0.21	60.3	12.5
Percentage (%) of Accidents	4.86	3.83	1.05	0.31	2.87	26.59	0.19	60.8	12.5
Average Daily Accidents	40.24	37.34	34.43	44.97	28.75	38.79	33.65	38.69	38.64
Risk Index	1.05	0.97	0.89	1.15	0.90	1.01	0.90	1.01	1.00

In summary, whether it is average daily crash rate or risk index, rainy weather may have significant impacts on the safe operation of road traffic. However, such an impact could involve the combined effects from the driver, vehicle, roadway, and traffic conditions. It is meaningful to study and evaluate the combined effects of these factors under rainy weather conditions. Results from such studies could enhance traffic emergency management and optimize emergency source allocation.

In the past, many research projects have studied the impacts of rainy weather conditions on traffic safety, and most of them have concluded that adverse weather could negatively impact traffic operations and safety. However, there are two basic issues that have not been well understood:

(1) Most of past studies have been based on historical crash data with limited consideration given to roadway users' perceptions or opinions. Many places, such as areas in China, may not have the capability to accumulate traffic crash data for modeling purposes. Thus, it is very difficult to conduct crash analyses.

(2) Under adverse weather conditions, other factors related to user, vehicle, road, traffic, and control conditions play important roles in vehicle operations and safety. The significance of these factors in modeling driver safety perceptions has not been well studied and understood.

1.3 Research Subjective

There are lots of disaster weather conditions in the world, 6 types of severe weather conditions most often occur and impact the traffic operational safety in Sutong Bridge including rainy, snowy, icy, fog, strong wind and high temperature.

(1) Rain

Rain causes wet pavement which reduces vehicle traction, visibility distance and maneuverability. For example, if vehicle has sudden start, sharp turn or emergency stop, it is easy to cause lateral slide or vehicle control loss even roll-over accidents. In practice, the friction coefficient in wet pavement may be less than half of that in dry pavement. The brake distance increasing is harmful to the traffic safety, shown in figure. Heavy rain also may cause structure damage. These impacts prompt drivers to travel at lower speeds causing reduced roadway capacity and increased delay.

In addition, because of the existence of soil or other pollutant, the impact of light rain could not be ignored. This is because that pavement will be covered a layer of wet soil while light rain. At this moment, the pavement has the lowest friction coefficient shown in Figure 4. Many drivers do not recognize the danger of this wet layer. Accidents may happen if they do not reduce the speed.

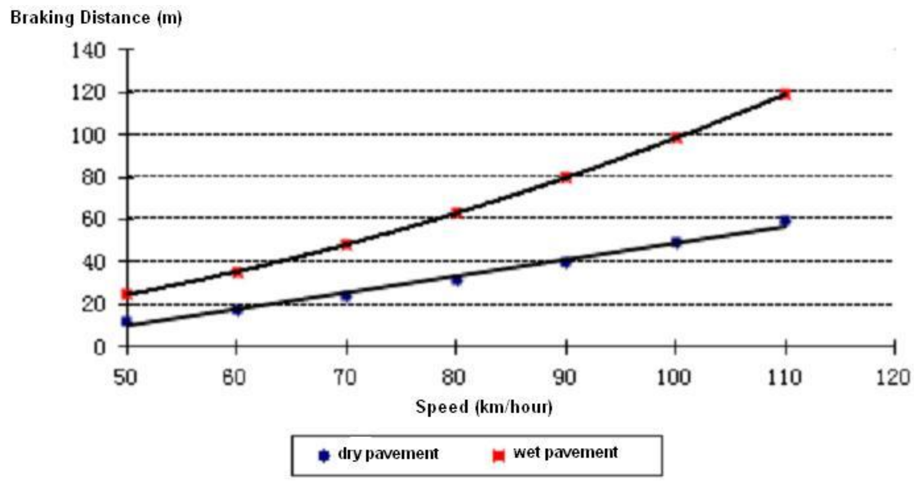

Figure 3 Braking Distance Comparison in Dry and Wet Pavement

As stated above, the influence caused by rain can be summarized as: friction coefficient, visibility, driver error (headway, signs, wet level and so on), and bridge location.

(2) Fog

The most explicit disadvantage of fog is low visibility, which may cause drivers misjudging. Under discontinuous fog, the sudden change of visibility may cause fear for drivers. Moreover, due to the geographic situation, the moisture in Sutong Bridge is usually much higher under fog. The probability of accident will increase, if drivers do not pay enough attention.

(3) Strong Wind

Generally the impacts by light wind for traffic safety can be ignored. The definition of strong wind is the wind whose grade is larger than level 6. The strong wind is usually classified into three categories: downwind, upwind and crosswind. Crosswind causes most negative impacts on traffic safety, and downwind causes the least.

(4) Ice

Ice reduces pavement friction. As shown in Figure 5, the friction coefficient in icy pavement is even lower than that in wet pavement, meaning ice could more harmful than rainfall to traffic safety. The glare produced while strong light in the icy pavement will degrade the drivers' eyesight. It is generally recognized that drivers will be highly alert while pavements all covered by ice. The probability of serious accident is very low due to low speed. But it is likely that minor accidents will happen. However, while pavement freezes partly drivers may neglect the icy conditions leading to misjudge.

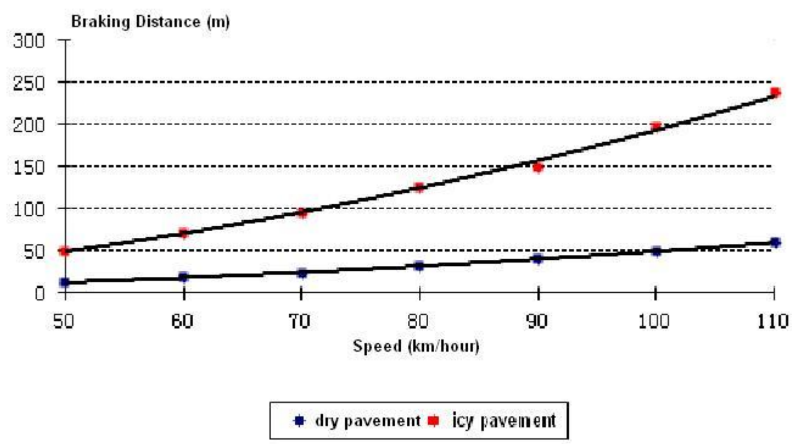

Figure 4 Braking Distance Comparison in Dry and Icy Pavement

(5) Snow

Snow reduces the drivers' visibility and friction coefficient of pavement. The friction coefficient will decrease extremely due to snow-covered pavement rolled by vehicles again and again. The influence by light snow depends on the level of recognition by drivers which could not be ignored. Moderate snow can form snow-covered pavement, snowy pavement may become icy pavement which will be more dangerous for traffic safety.

(6) High temperature

High temperature can be defined as the temperature higher than 30℃. It increases failure rate of vehicle, the probability of fire disaster. Pavement bleeding by high temperature may damage the pavement structure. It also can impact the drivers' physical and psychological states which increases the drivers' perception reaction time. Additionally, the risk of hazard material transport grows up, especially flammable and explosive materials like liquefied petroleum gas.

A series of risk evaluation index could be determined through analyzing the disaster mechanism of each adverse weather event including strong wind, ice, snow, rain, fog and high temperature. Figure 8 shows the traffic accident chain under single weather risk factor.

1.4 Research Objective

The primary objective of this research study is to evaluate the driving risk level of highway traffic under severe weather conditions. With these research results, an early warning system by a bridge operations department can be addressed. More specifically, this study has five major objectives, as follows:

(1) To identify the risk weather factors through analyzing disaster mechanisms of each risk source, including both single events and multiple combinations.

(2) To quantify the influence of the contributing risk factors according to their impacts on traffic operation and safety.

(3) To design reasonable surveys for data collection with limited sources of data.

(4) To develop statistical models to calculate the probability of traffic operation safety on Sutong Bridge under each adverse weather condition.

(5) To classify the level of risk to describe the relationship between risk probability and risk level, which is a tool to support an early warning system for the Sutong Bridge operations department and help officials make decisions.

Statistical methods, statistical tests and risk predictive models were applied in this study. Based on the results, it would be a plausible way to help a highway operations department take effective measures to improve traffic safety on a bridge, which can be very important for optimizing emergency resource allocations and taking reasonable emergency measures.

1.5 Research Approach

Previous studies were reviewed, and a methodology to evaluate the risk level was selected. To achieve the research purposes, the following tasks were developed to obtain rational conclusions. Existing methods and technologies were gathered to reach the goals of the research. Possible applications were identified in different research areas. After summarizing these potential measurements, useful methods from previous studies were selected and detailed developments were conducted. These methods and developments need to be feasible to perform and practice. The analysis process should be correct and reasonable. The results based on this study can be applied to other highway bridge operations. In this study, 4steps containing 10main tasks were categorized to organize the research procedures in an efficient way, as follows:

(1) Step 1:

a. Task 1: Literature Review

b. Task 2: Disaster Mechanism Analysis

c. Task 3: Risk Source Identification and Classification

(2) Step 2:

d. Task 4: Weather and Traffic Data Collection

e. Task 5 Survey Design for Subjective Data Collection

f. Task 6: Risk Filter and Classification

(3) Step 3:

g. Task 7: Data Analysis

h. Task 8: Model Development

(4) Step 4:

i. Task 9: Conclusions and Discussions

j. Task 10: Results and Final Report

Step 1, containing the first three tasks, mainly focused on reviewing past safety performance measures and methods, determining the possibility of potential applications, building up study purposes, and arranging work plans. Step 2, tasks 4 to task 6, included gathering historical data and subjective data and arranging them for the further analysis.

This step was difficult and tedious because the Sutong Bridge came into service in 2009, so there are few historical weather and crash data.

Table 3 Time Schedule of Research Study

Task/Month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Task 1	x	x	x													
Task 2		x	x													
Task 3			x	x												
Task 4			x	x	x											
Task 5						x	x									
Task 6								x	x							
Task 7										x	x					
Task 8											x	x	x	x		
Task 9														x	x	x
Task 10														x	x	x

All the related data needed to be identified and gathered, and subjective data through surveys were collected to get reasonable results. Step 3 applied the main approaches to conduct risk evaluations procedures for all kinds of disaster weather conditions, and two case studies focused only on rainy situations. Step 4 concluded the research findings and summarized the research study in the final report prior to completing this dissertation. These four steps contained all the needed tasks for this research study and have been proved successfully in past research projects.

Table 3 shows the time schedule for this research study.

Chapter 2 Literature Review

Previous studies and findings regarding the risk performance of weather-related traffic operations are reviewed and summarized in this chapter. Many previous research studies have been performed to analyze traffic operations and safety under each type of weather condition. Rain and snow are the most-considered weather situations in past studies, as are wind, fog, and high temperatures. These related studies are also reviewed in this chapter.

Bridge-related crashes may have different characteristics from highway accidents. Traffic safety evaluations of bridges are summarized in this chapter.

Risk assessment methods are widely used in complex systems, such as the nuclear industry, the environment, marine engineering, and fire hazard and security science, and have achieved important results. However, they are seldom used for traffic safety performance evaluations, especially related to severe weather conditions. In addition, many statistical modeling approaches have been used to develop statistical models to analyze the impacts of various factors related to users, vehicles, roadways, and control. Previous research on bridges focused primarily on the areas of bridge construction safety, structure safety, and maintenance. Major statistical methods of risk evaluation are summarized in this chapter.

2.1 Weather-Related Traffic Situations

Chapter 22 of the Highway Capacity Manual 2000 provides information regarding speed and capacity reductions due to rain or snow of light and heavy intensities. The manual recommends 0–15 percent reductions in capacities with2–14 percent and 5–17 percent reductions in speeds for light and heavy rains, respectively. Similarly, it recommends 5–10 percent reductions in capacities with3–10 percent and 20–35 percent reductions in speeds for light and heavy snow conditions. The manual does not describe the precipitation intensity thresholds for these categories, and it is important for freeway operators to know precipitation ranges so they can optimize capacities and operating speeds due to anticipated precipitation (rain and snow) using intelligent transportation system (ITS) devices (e.g., dynamic message signs, ramp metering).

Brilon and Ponzlet investigated the impacts of pavement conditions, darkness, type of day (weekday or holiday), and others on speed-flow relationships for 15 freeway sites in Germany. Traffic volume, traffic mix, and temporal factors were considered as fundamental influencing factors, while changing environmental factors such as daylight, weather conditions, and daily and seasonal variations were the main focus of this research. Based on the analysis of variance (ANOVA) models and separation of different sample data sets, the authors concluded that darkness and wet roadway conditions can cause average speed reductions of about 5km/hour and 10 km/hour, respectively. Lower average speeds were also detected during predominantly leisure traffic, such as on Sundays or during the summer vacation season. Based on the estimated ANOVA model, Brilon and Ponzlet reconstructed speed-flow diagrams for free-flow and partly-dense traffic regimes under varying environmental conditions based on Greenshield’s model.

They found that wet roadway conditions cause a speed reduction of 9.5 km/hr on 4-lane highways and 12km/hr on 6-lane highways. As a result, the authors concluded that freeway capacities were reduced by 350 vehicles per hour (vph) and 500 vph, respectively. However, the study was conducted in Germany, where there are no maximum speed limits on freeways.

Agarwal et al. examined the impacts of adverse weather on freeway capacities and operating speeds on urban freeway segments in the Minneapolis/St. Paul, Minnesota, area using a data set from January 2000–April 2004. Traffic data were obtained from loop detectors for every 30-second interval, and weather data were obtained from automated surface observing systems (ASOS) at nearby airports. The research found that the quality of weather data obtained from Road Weather Information System (RWIS) sensors were not appropriate for the analysis. Speed data, however, must be estimated since only single-loop detectors were installed in the studied network. The authors found that rain and snow events can cause statistically-significant reductions in freeway capacities and operating speeds. The average capacity reduction for trace, light, and heavy rains are 1, 3.5–10, and 10–17 percent, respectively.

Ibrahim and Hall studied the impacts of adverse weather conditions on flow-occupancy and speed-flow relationships. The data used in the analysis were obtained from the Queen Elizabeth Way–Mississauga freeway traffic management system in Canada. Two detector stations that met the following criteria were selected for the study: (a) trap detectors, (b) outside the vicinity of ramp or weaving sections, and (c) satisfactory data quality. However, the authors did not mention any attempt to exclude incident-related impacts on traffic operations. Regression analyses were calibrated to the selected data sets using indicator variables to represent different adverse weather conditions. A quadratic functional form was used to calibrate the flow-occupancy relationship, while a linear functional form was used to estimate the speed-flow relationship. The analyses were conducted using both 30-second and 5-minute aggregated-loop detector data. The results were found to be similar for both intervals except for the rainy conditions, where the difference in slope of the flow-occupancy function was undetectable for the 5-minute aggregated data.

Satterthwaite analyzed the day-to-day variation in the number of accidents on the state highways of California. He found that the weather is a major factor affecting accident numbers. On very wet days, the number of accidents was often double that of corresponding dry days. Single-vehicle accidents were affected more by wet weather than were most other types of accidents studied (pedestrian accidents, head-on collisions, rear-end collisions, and other collisions).

In 2005, Chung studied the effect of rain on travel demand measured on the Tokyo Metropolitan Expressway (MEX). Rainfall data monitored by the Japan Meteorological Agency's meson-scale network of weather stations were used. This study found that travel demand decreases during rainy days, and the average frequency of accidents during rainy hours (1.5 accidents/hr) was significantly different from the average frequency at other times (0.85 accidents/hour). It also compared the difference in weekdays and weekend daily trips for rainy and non-rainy days, finding that there is a smaller decrease in daily trips on weekdays (average of 2.9%) than on weekends (7.9% for Saturday,5.2% for Sunday). In other words, Saturday is most sensitive to weather conditions for travel demand decreases, followed by Sunday.

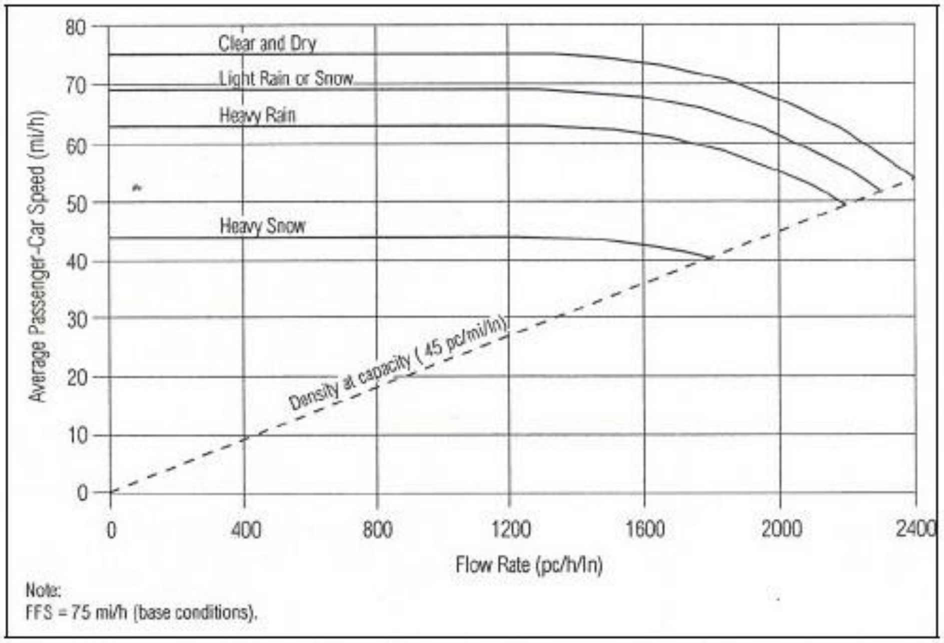

Figure 5 Effect of Different Weather Conditions on Speed-Flow Relationship

In 2007, Balke et al. conducted a study to help the Texas Department of Transportation (TxDOT) develop a structured, systematic approach for managing traffic during weather events. They grouped adverse weather events into five general categories: rain/flooding events, snow/icing events, events that cause low visibility (fog, blowing snow, dust, etc.), high wind events, and severe weather events (hurricanes/tornados). The characteristics and impacts of each of these events that can affect traffic flow on a highway are shown in Figure 5.

After that, a model was developed to assess and quantify the operational (effects on travel speed and capacity) and safety impacts (effects on speed variance) of weather events on freeways. They used a combination of an ANCOVA (analysis of covariance) and a regression model to analyze the weather and environmental impacts on freeway operations.

White and Jeffery reported the effect of fog on the speed and spacing of traffic on motorways. It was shown that in conditions where the visibility distance does not fall below about 150 meters, average traffic speeds are generally sufficiently low to enable most drivers to stop within their visibility distance, but the reduction in speed with reduced visibility is accompanied by an increase in close following, causing an overall increase in risk. Around one-third of all vehicles follow within a 2-second inter-vehicle time gap when driver visibility distances are reduced to 150 meters in day or night-time fog conditions.

Sigbjornsson and Snabjornsson evaluated the probability of vehicle accidents in windy environments using a “safety index approach.” Their methodology can be used to improve the design of roads and highways by pointing out potential accident spots as well as in devising preventive measures to improve traffic safety in windy environments.

Hogema and Van Der Horst studied driving behavior in daytime fog periods using data with detailed visibility measurements from a sensor near the road. Their results showed that drivers reduce their free driving speed in fog, but not sufficiently to avoid a collision when they are confronted with a stationary or much slower lead vehicle. The most critical behavior was displayed in the visibility range between about 40 and 100 meters. Time-to-collisions were seen to increase in fog.

In 2004, Rundmo and Iversen examined the association between risk perception and traffic behavior. Their model tests showed that assessments of the probability of traffic accidents and concern were not significant predictors for self-reported risk behavior. Worry and other emotional reactions related to traffic hazards significantly predicted behavior.

Vaa argued in his paper in 2001 that modeling driver behavior had not reached any kind of consensus because of the lack of common understanding of driver behavior. He concluded that no deep understanding of risk compensation will emerge unless recent developments in cognitive psychology and neurobiology are integrated into the modeling of driver behavior.

2.2 Bridge-Related Traffic Situations

In the 1970s and 1980s, some researchers realized the importance of studying the severity of bridge-related crashes. At that time, crash data had shown that bridge-related crashes, particularly involving severe crashes, were significant percentages of the total crash experience, and the severity of bridge-related crashes was higher than the severity of all crashes. Similarly, Brinkman and Mak also considered that bridge-related crashes constituted a high percentage of all crashes and were approximately twice as likely to result in fatality as a typical crash.

Many studies identified factors affecting traffic safety on bridges, and some of these factors are related to bridge geometric design, such as bridge width and shoulder width. Evan thought the most significant factor that contributes to bridge-related crashes was bridge width. Other similar research can be found. King and Roberts studied the effect of bridge shoulder width on traffic operational characteristics. They considered that a shoulder width of 4–6 ft was adequate for bridge traffic safety. Several other factors about bridge structure, such as bridge guardrail and approach roadway, were studied. Cirillo studied the effect of guardrails on bridge-related crash severity, and results showed that the presence of guardrails reduced the property damage costs of single-vehicle crashes. Turner and Rowan found the average crash rate at bridge ends doubled over a 0.35-mile distance at the approach to a structure. Benham and Laguros analyzed the relationship between crashes and roadway geometrics at bridge approaches, and their results indicated that the degree of curvature was a significant factor affecting the number of crashes. Other studies mostly consider interactions among wind, vehicles, and bridges. These studies basically focused on either wind action on vehicles running on roadways (not on bridges), wind effects on bridges without considering vehicles, or vehicle-bridge interaction analysis without considering wind effects. Only a few works deal with comprehensive vehicle-bridge-wind analysis.

In addition, some researchers developed different methods applied to traffic safety evaluation on bridges. Turner built regression curves to predict bridge-related crashes, given bridge relative width, average daily traffic, and approach roadway width. Gandhi et al. developed an improved safety index model, considering bridge width, length, average daily traffic, and speed, as well as three subjective safety factors—grade continuity, shoulder reduction, and traffic mix. Murthy and Sinha employed a fuzzy set approach for bridge traffic safety evaluation in terms of bridge, roadway approach, and environmental conditions.

2.3 Subjective Data Collection

In 2007, Balke et al. did a study to help TxDOT develop a structured, systematic approach for managing traffic during weather events. They conducted site interviews with operations and maintenance personnel in several TxDOT districts; the survey method had been used to identify and assess the information needs and requirements. The answers were summarized from both a formal survey and an informal discussion.

Questions asked in the surveys included the following:

(1) Which weather events occur in your district and what is the frequency of their occurrence?

(2) Which weather event is most prevalent in your district?

(3) How does this event affect you?

a. Daily roadway operations are affected.

b. Safety of the traveling public is affected.

c. Emergency management procedures are required.

d. Before-event special maintenance and operations measures are required.

e. During-event special maintenance and operations measures are required.

f. Post-event special maintenance and operations measures are required.

(4) How specific must the forecast be to maximize your effectiveness?

(5) What, if any, special information prior to the weather occurrence would assist your district with dealing with this weather event?

In addition to the information obtained from survey, two sources of data were collected for the analysis—traffic data and weather data. Traffic data, including volume, occupancy, speed, and percent truck for trap detectors, were collected by a loop detector. For each loop detector observation, the weather conditions within 30 minutes before and after the detector time stamp were searched, and the nearest weather was recorded. The weather conditions were classified into two major types: normal and irregular. Any combination of weather types was split into a set of single indicator variables.

The survey method is a good alternative data collection method in the case of limited data sources, especially for subjective data collection. It is also a supplement for weather data and traffic data in this research.

2.4 Risk Assessment Methods

2.4.1 Risk Identification and Filtering

Haimes presented Hierarchical Holographic Modeling (HHM) to identify risk, which is good for modeling large-scale and complex systems. Figure 6 shows the framework for identification of sources of risk. The basic concept of HHM is to list all possible factors that may cause negative consequences from all kinds of aspects through brainstorming. Thus, thousands of risk sources can be identified. Then, the risk sources are ranked and filtered according to several guiding principles. In 2004, Leung et al. applied this method to prioritize transportation assets for protection against terrorist events.

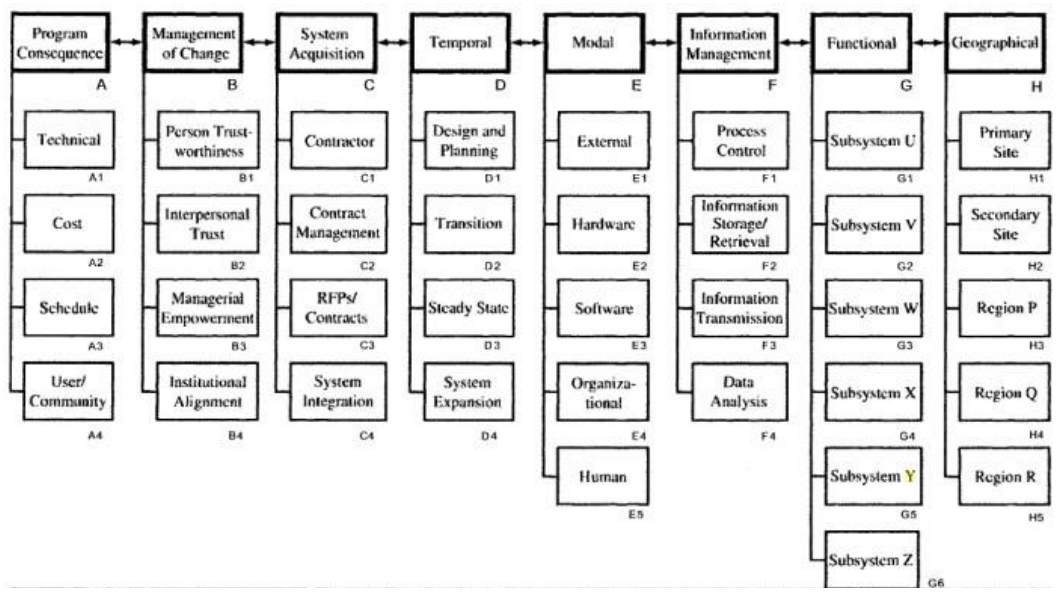

Figure 6 HHM Framework for Identification of Risk Sources

2.4.2 Risk Assessment Statistical Model Review

Statistical modeling approaches have been used to develop statistical models to analyze the impacts of various factors related to users, vehicles, roadways, and control on traffic safety. Hill and Boyle used a logistic regression model to predict traffic fatality and incapacitating injury and concluded that female drivers older than age 54 could have more severe injuries under adverse weather conditions compared to male drivers in the same age group.

Khorashadi et al. used a multinomial Logit model to analyze the severity of track drivers involved in crashes and found that rainy weather was the key factor resulting in an increase in traffic crash injuries. An Ordered Probit model was used by Abdel-Aty to predict drivers' injury severity, and results showed that drivers at signalized intersections could suffer more serious injuries under adverse weather and dark environmental conditions compared to other conditions. In a similar study, an ordinal logistic regression model and a sequential logistic regression model were used to evaluate the impacts of rainfall on single-vehicle crashes in weather conditions and non-weather conditions, and it was concluded that the backward sequential logistic regression model might be the best fit to predict crash severity under rainy weather conditions.

Some researchers developed different methods applied for traffic safety evaluation on bridges. Turner built regression curves to predict bridge-related crashes, given bridge relative width, average daily traffic, and approach roadway width. Gandhi et al. developed an improved safety index model, considering bridge width, length, average daily traffic, and speed, as well as three subjective safety factors—grade continuity, shoulder reduction, and traffic mix. Muthy and Sinha employed a fuzzy set approach for bridge traffic safety evaluation in terms of bridge, roadway approach, and environmental conditions.

Di Pasquale proved that it is more suitable to use a direct loss method rather than a probability method for local hazard risk analysis. Huang developed a possibility-probability method using information allocation theory on the condition of incomplete information on this basis, which many scholars also considered free of internal-external set information and drifted the constrained variables into a probability method of risk assessment. The most applied fuzzy logic risk is fuzzy comprehensive evaluation, which grades the membership degree of risk factors or results. It is described by fuzzy language.

In 2009, Hu et al. used the failure modes and effects analysis (FMEA) to analyze the risks of green components in compliance with the European Union's (EU) Restriction of Hazardous Substance (RoHS) directive in the incoming quality control (IQC) stage, which is based on a case of an OEM/ODM electronic manufacturer in Taiwan. There are three indices of FMEA in his work: 1) an occurrence (O) that can be learned from the testing report; 2) the likelihood of being detected (D) that refers to the difficulty of detection; and 3) the severity (S) that can be quantified from the declaration statement and the frequency of green component used by the project. The fuzzy analytic hierarchy process (FAHP) was applied to determine the relative weightings of four factors; then, a green component risk priority number (GC-RPN) was calculated for each one of the components, which is provided by the suppliers to identify and manage the risks that may be derived from them.

2.5 Summary

Many research projects have studied the impacts of rainy weather conditions on traffic safety, and most of them have concluded that rainy weather can negatively impact traffic operations and safety. However, there are three basic issues that are not well understood:

(1) Most past studies have been based on historical crash data, but many places, such as areas in China, may not have the capability to accumulate traffic crash data for modeling purposes. Thus, the incomplete data may not be enough to conduct crash analysis.

(2) Since the impact of rainy weather conditions has obvious geographical differences, much of the research is not universal.

(3) Traffic risk and traffic accidents are two different concepts. Most past studies use historical accident data to analyze traffic operations under rainy weather conditions, which describe one kind of result, but fewer accidents and low risk levels are not the same. The relationship also depends on driver perception. For example, if drivers are on the alert, the number of accidents may not be increase; they may even decrease.

With the considerations mentioned above, data derived from driver questionnaires is a good choice. However, data from questionnaires have certain limitations, for two reasons:

(1) The content of driver questionnaires may not include data needed for the study.

(2) The data are easily influenced by subjective consciousness. However, a discrete choice model can compensate for these shortcomings to some extent. Based on the structure of Multi ordered Discrete Choice Model

(MDCM),if the probability distribution of non-observable variables is assumed reasonably, impacts mentioned can be weakened to some extent.

This research uses data from driver questionnaires to build a multi-ordered discrete choice model to analyze and evaluate risk levels of roadway traffic under rainy weather conditions. The results include different risk levels and corresponding probabilities, which are helpful and useful for optimizing emergency resource allocation and developing reasonable emergency measures.

Previous studies identified many factors affecting traffic safety on bridges in terms of bridge geometry, bridge structure, and vehicle-bridge-wind interactions, which are very helpful in reducing bridge-related crash rate and severity. Some researchers conducted exploratory works for comprehensive evaluations of traffic safety on bridges, but there are still several problems that need to be considered:

(1) Most studies have focused on the impacts of bridge design on traffic safety on bridges; only a few studies have focused on how operational characteristics and weather conditions affect bridge-related crashes.

(2) Crosswind is not the only factor affecting bridge-related crashes among all meteorological elements, and some other factors, such as temperature, humidity, visibility, etc., may have significant influence on bridge-related crashes.

(3) Many analyses of crash severity do not consider certain characteristics of crashes, such as crash location, crash duration, and crash type, which may have a strong correlation to bridge-related crash severity.

(4) Most studies regarding comprehensive evaluations of traffic safety on bridges are qualitative and subjective.

Chapter 3 Methodology

This chapter describes the selected methodologies that have been applied to this study. The principles for choosing the main methods include what the functions are, whether they are practical or easily applied to the data base, and how the potential results are useful in the risk assessment.

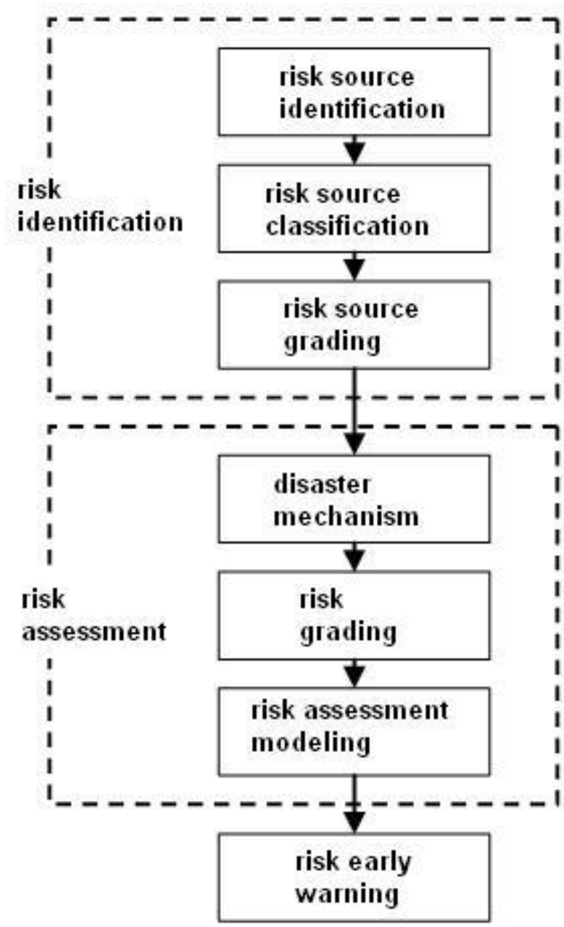

Figure 7 Flow Chart for Risk Assessment Procedure

An emergency rescue management system for operational purposes can be divided into two parts. The first is risk assessment, which predicts the level of risk during severe weather or emergency events. The output of risk assessment from level 1 to level 4 is conveyed to the second part, which optimizes emergency resource allocation and takes reasonable emergency measures. This research focuses on risk assessment under severe weather conditions. The procedure of the methodology is shown in Figure 7 and includes risk source identification, classification and grading. The second part is risk assessment and includes disaster mechanism analysis, risk grading, and risk assessment modeling.

3.1 Risk Source Identification and Classification

3.1.1 Risk Factor Source

Risk source identification is based on analyzing disaster mechanisms for each weather event. The first step of risk factor source identification is to list as many factors as possible through literature review, brainstorming, focus groups, and so on. In this research, a total of 12 types of disaster weather were identified:

(1) Fog

(2) Lightning

(3) Hurricane

(4) Ice

(5) Rain

(6) RIP-Current

(7) Tornadoes

(8) Thunderstorms

(9) Temperatures

(10) Strong Wild

(11) Snow

(12) Wildfires

The corresponding contributions to these risks to the total system were studied thoroughly. According to weather history records of the past 50 years, some low-frequency risk factors were not selected, and some risk factors sharing the same characteristics were grouped. Finally, a total of six risk factors was selected for this research, including fog, rain, snow, ice, strong wind, and high temperature. Then, risk sources for each adverse weather event were classified according to their characteristics and possible consequences.

A series of risk evaluation indices was determined through analyzing the disaster mechanisms of each of the six adverse weather events. Figure 8 shows the traffic accident chain under a single weather risk factor.

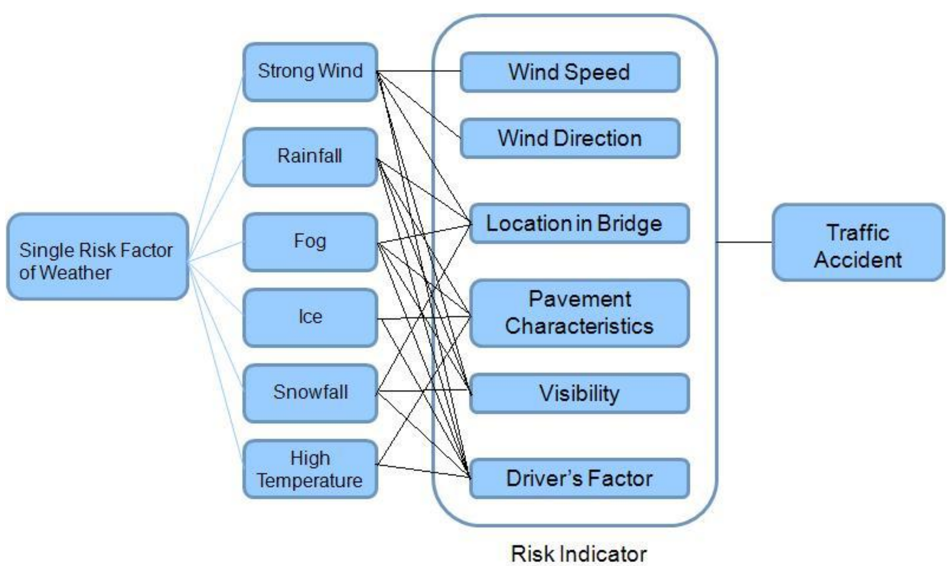

Figure 8 Traffic Accident Chain under Single Weather Risk Factor

Based on the mechanism of each adverse weather condition, there was a need to classify the risks reasonably to improve risk management and early warning when severe weather conditions occur. Table 4 indicates the classification of each risk factor and its description.

Table 4 Risk Factor Classification and Description

Rainfall Classification	
Light rain	Visibility 200~500m
Moderate rain	Visibility 100~200m
Heavy rain	Visibility 50~100m
Rainstorm	Visibility ＜50m
Snowfall Classification	
Rain and snow	Visibility 200~500m
Moderate snow	Visibility 100~200m
Heavy snow	Visibility 50~100m
Snowstorm	Visibility ＜50m
Fog Classification	
Light fog	Visibility 200~500m
Moderate fog	Visibility 100~200m
Heavy fog	Visibility 50~100m
Dense fog	Visibility＜50m
Discontinuous fog	Partial Fog
Ice Classification	
Partial coverage	Partial pavement covered by ice
Full coverage	All pavement covered by ice
Wind Classification	
Light wind	Less than Grade 6
Moderate wind	Grade 6-10
Heavy wind	Larger than Grade 10
High Temperature Classification	
High temperature	Temperature higher than 30℃

3.1.2 Dual Risk Source

Multiple risk factors are the challenge for risk assessment. We list all the combination of dual weather conditions and erase the impossible combination such as high temperature and snow. Then rank the severity of risk factors including both single factor and combination of dual weather conditions through focus group, respectively. The severity is considered through possible serious consequences and urgency of recover or other factors. The less the rank is, the low the importance is. Rank No 1 means the most significant risk problem in Sutong Bridge. Only high rank combination of dual weather conditions will be discussed in this research shown in Table 5 and Table 6.

Table 5 Single Risk Factor Ranking

Number	Single Risk Factor	Rank
1	Snowstorm	1
2	Icy pavement	2
3	Dense fog	3
4	Continuous strong wind	4
5	Strong cross wind	5
6	Rainstorm	6
7	Moderate snow	7
8	Hailstone	8
9	Light Fog	9
10	High Temperature	10

Table 6 Dual Risk Factors Ranking

Number	Dual Risk Factors	Rank
1	Hazard materials leakage/fire	1
2	Snowstorm/Freeze	2
3	Fog/Freeze	3
4	Strong wind/Freeze	4
5	Heavy Wind/Rainstorm	5

According to the rank of dual risk combination, several combinations of dual weather conditions will be considered in this research including: snow and wind, fog and ice, and wind and rainfall.

3.2 Risk Identification and Classification

Identifying adverse weather is not enough because it is the consequences that are undesirable. Different adverse weather conditions may involve more or less severe consequences. The following potential outcomes are general in nature and can be further subdivided in a more detailed analysis: accident, injury, fatality, environmental destruction, and financial loss. A dependable and efficient ranking of identified risk elements can be a step toward systemic risk reduction.

Table 7 Risk Grading and its Description

Severity	**Influence Description**		**Value**
	Traffic Safety	***Traffic Situation***	
Slight Risk (Blue Alarm)	• 1–2 persons light injury OR • Financial loss less than 1000 RMB	• Slight delay • Speed is about 70km/h	1
General Risk (Yellow Alarm)	• 1–2 persons heavy injury or more than 3 persons light injury OR • Financial loss <30,000 RMB	• General traffic same • Speed about 50km/h • Jam can be cleared in 30 mins	2
Serious Risk (Orange Alarm)	• 1-2 person fatality or more than 3–9persons heavy injury OR • Financial loss >30,000 RMB and <60,000 RMB	• Serious traffic jam • Speed <25 km/h • Jam cannot be cleared in 30 mins	3
Catastrophic Risk (Red Alarm)	• 3+ persons fatality or > 11 persons heavy injury OR • Financial loss >60,000 RMB	• Extreme traffic jam • Speed <10 km/h • Jam cannot be cleared in several hrs	4

The risk can be filtered by some multi-criteria evaluation, as follows.

(1) Undetectability

(2) Uncontrollability

(3) Multiple paths to failure

(4) Irreversibility

(5) Duration of effects

(6) Cascading effects

(7) Operating environment

(8) Wear and tear

Table 7 indicates the four levels of risk for an early warning system: Slight Risk, General Risk, Serious Risk, and Catastrophic Risk.

3.3 Focus Group

A focus group is a form of qualitative research in which a group of people is asked about their perceptions, opinions, beliefs, and attitudes towards a product, service, concept, advertisement, idea, or packaging. Questions are asked in an interactive group setting where participants are free to talk with other group members. The results accuracy of focus group depends on the practical experiences of each group member. The focus group member could be individual or groups; in this study, 10 transportation area faculties, 20 graduate students, and 10 transportation researchers or engineers were selected. This research used a weighted score method to calculate the final score, which has high reliability and is widely used. The focus group questions for rainy conditions were designed as shown in Table 8.

The weight values of event are determined by the Analytical Hierarchy Progress (AHP) method in this research. Figure 9 shows the procedure of determining index weight by AHP.

The first step of every AHP analysis is to define the structure of hierarchy of the study. Thus, the first step was to model the problem as a hierarchy containing the decision goal, the alternatives for reaching it, and the criteria for evaluating the alternatives, as shown in Figure 10.

Table 8 Questions for Rainy Conditions by Focus Group

Please grade the severity of traffic conditions under rainy conditions, from 0 to 10, the higher score means more severe.					
Rainy	Events	Light Rain (Visibility 200~500m)	Moderate Rain (Visibility 100~200m)	Heavy Rain (Visibility 50~100m)	Rainstorm (Visibility <50m)
	Longer Braking Distance				
	Lower Friction				
	Unclear Signs				
	Weak Illumination				
	Pavement Reflection				
	Drivers' Psychological Effects				

It is difficult to accurately determine the corresponding weights for a set of attributes simultaneously. The AHP method helps the decision makers to derive relative values for each attribute using their judgment or data based on a standard scale.

Step 2 is to establish priorities among the elements of the hierarchy by making a series of judgments based on pairwise comparisons of the elements. The experts' judgments are reflected in as o-called Matrix of Pairwise Comparison (MPC). In an MPC, a decision maker specifies a judgment by inserting the entry a_{ij} ($a_{ij}>0$), stating that how much more important attribute "i" is than attribute "j". An MPC is defined as.

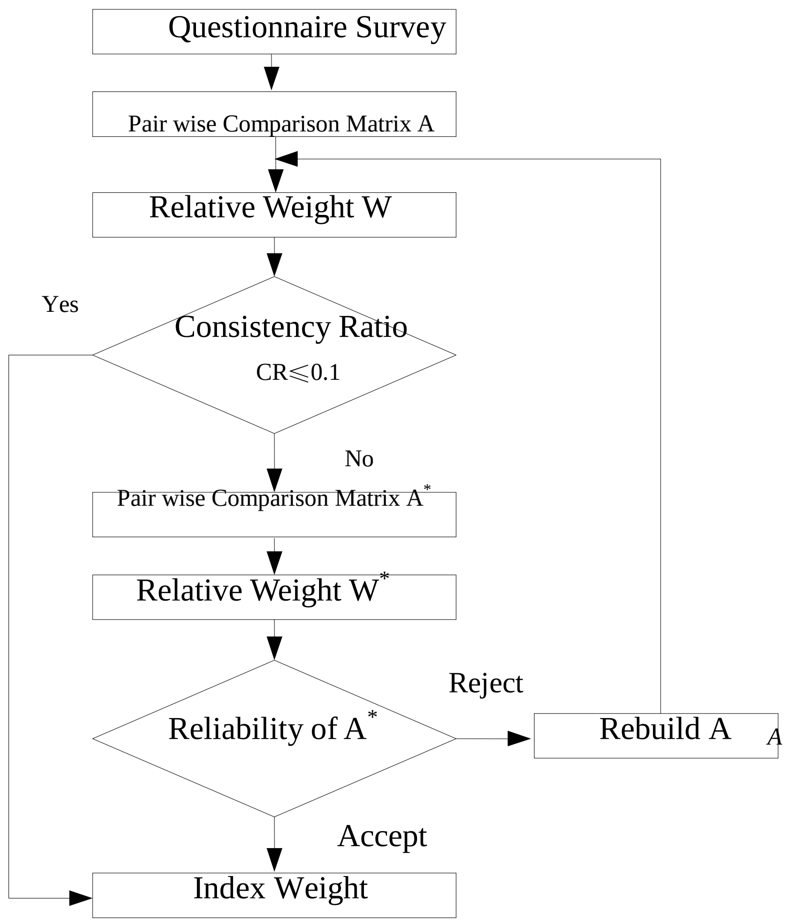

Figure 9 Procedure of Index Weight Determination Using AHP

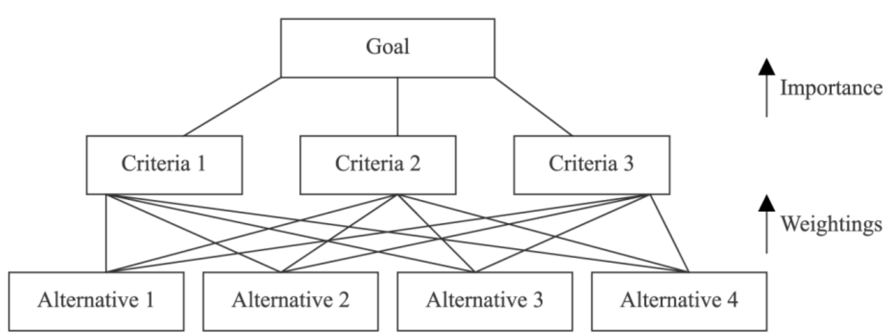

Figure 10 A Simple AHP Hierarchy

$$A = \left(a_{ij}\right)_{nxn} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} \qquad (1)$$

In this respect, the MPC would be a square matrix, A embracing n number of attributes has relative weights of$w_1,\ldots,w_n$, respectively. In this matrix, the weights of all attributes are measured with respect to each other in terms of multiples of that unit. The comparison of the values is expressed in Equation 2:

$$a_{ij} = \frac{w_i}{w_j} \qquad (2)$$

Table 9 Comparison Scale for the MPC in the AHP Method

Relative Importance of Attribute a_{ij}	Definition
1	Equal importance
3	Moderate importance of one over another
5	Essential or strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values between the two adjacent judgments
Reciprocals	When activity "i" compared with "j" is assigned one of the above numbers, then activity "j" compared with "i" is assigned its reciprocal, $a_{ji}=1/a_{ij}$,

Step 3 is to synthesize these judgments to yield a set of overall priorities for the hierarchy. Saaty recommended that equivalent scores from 1 to 9 be used as a basis to solve the problem in this study. The score description is shown in Table 9.he weights for w_1, w_2, …w_n can be calculated using Equation 3:

$$w_k = \frac{1}{n}\sum_{j=1}^{n}\left(\frac{a_{kj}}{\sum_{i=1}^{n} a_{ij}}\right) \tag{3}$$

Checking the consistency of the judgments was the fourth step. The decision maker may need to make tradeoffs within the attribute values in a compensatory way if the inconsistencies calculated exceed 10 percent. The calculated priorities are plausible only if the comparison matrices are consistent or near consistent. The approximate ratio of consistency can be obtained using Equation (4):

$$CR = \frac{CI}{RI} \tag{4}$$

where,

CR=Consistency Ratio

CI= Consistency index

RI=Random index for the matrix size, n

The value of RI depends on the number of attributes under comparison. This can be taken from Table 10, as given by Saaty:

Table 10 Average Random Index Values

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45

The consistency index, CI, is calculated from the following equation:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{5}$$

where, λ max is the principal eigen value of a nxn comparison matrix A.

After obtaining weight w, the score can be reached by Equation 6:

$$S = \sum_{i=1}^{n} S_i W_i \tag{6}$$

where, i is the event or index to be evaluated, S_i is the score of the event, and W_i means its weight value.

Then the risk level is obtained through the Risk Level Criterion shown in Table 11. Thus, the final results of risk level by focus group can be obtained.

Table 11 Risk Criterion Under Severe Weather Conditions

Weighted Grade	[0，2.5]	(2.5，5]	(5，7.5]	(7.5，10]
Risk Level	Slight	General	Serious	Catastrophic

3.4 Statistical Model for Risk Assessment

Multi-ordered discrete choice models originally began use in economics but have been widely used in modeling the choice selection of individual behavior. Such models have the following characteristics: (1) dependent variables are discrete, and independent variables are observable or non-observable; (2) the main difference between multi-ordered discrete choice models and other discrete choice models is that the former should have a dependent variable with at least three discrete levels; and (3) non-observable variables are assumed to fit some probability distributions, and different distributions can have significant impacts on modeling qualities. According to the modeling structures, multi-ordered discrete choice models are an adequate choice for the modeling purpose in this study.

3.4.1 Variables Selection

In this study, the major data come from questionnaire surveys. A questionnaire survey should not only consider multiple characteristics related to drivers and vehicles, but also characteristics of roadways, traffic volume, and severity of the rainy situation. Roadway segment types are divided into type A (level and straight road segments), type B (level segments with some obstructions on road sides), and type C (segments with horizontal and vertical curves).Because a driver may have difficulty correctly estimating the volume on the road, traffic volume is processed in definitely; there are only descriptions of low volume or high volume. In the example of a rainy situation, the rain levels include light rain, moderate rain, heavy rain, and rainstorm. The risk levels are defined considering accident severity and vehicle speed.

For modeling purpose, all variables in the questionnaire should be quantified and analyzed. All dummy variables used in the modeling process and their statistical indicators need to be defined. The variables of driver age and driving age are defined based on the actual age (years) and years of driving experience, respectively. However, to avoid variables producing heteroscedasticities, roadway segment types are divided into two categories with two dummy variables in each category. The correlation tests are used to determine the association among all the variable pairs.

For comparison of continuous variables the Pearson *r* was calculated. Pearson devised a very common way of measuring correlation, often called the Pearson Product-Moment Correlation. It is used when both variables are at least at interval level and data is parametric and is calculated by dividing the covariance of the two variables by the product of their standard deviations, as shown in Equation 7.

$$r = \frac{SUM\left[(x_i - \overline{x})(y_i - \overline{y})\right]}{(n-1)*s_n*s_y} \tag{7}$$

where, x and y are the variables, x_i is a single value of x, x bar is the mean of all x's, n is the number of variables, and s_x is the standard deviation of all x's. r may also be considered as being:

r^2 = explained variation / total variation

where, variation is calculated as the Sum of the Squares, SS. In other words, it is the proportion of variation that can be explained. A high explained proportion is good, and a value of 1is a perfect correlation.

For continuous-discrete pairs, the Spearman correlation was calculated. The Spearman correlation coefficient is a statistical measure of the strength of a monotonic relationship between paired data. It is defined as the Pearson correlation coefficient between the ranked variables. For a sample of size *n*, the *n* raw scores X_i, Y_i, are converted to ranks x_i,y_i, and ρ is computed from Equation 8:

$$\rho = \frac{\sum_i (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_i (x_i - \overline{x})^2 \sum_i (y_i - \overline{y})^2}} \tag{8}$$

Finally, for discrete variable pairs, the phi coefficient, φ, was calculated. In statistics, the phi coefficient is a measure of association for two binary variables. This measure is similar to the Pearson correlation coefficient in its interpretation. In fact, a Pearson correlation coefficient estimated for two binary variables will return the phi coefficient. The square of the phi coefficient is related to the chi-squared statistic for a 2×2 contingency table.

$$\phi^2 = \frac{\chi^2}{n} \tag{9}$$

where, n is the total number of observations. Two binary variables are considered positively associated if most of the data falls along the diagonal cells.

For the modeling purpose, it is very important to select independent variables scientifically. In general the relationship of independent variables should be linear independently. In contrast, there is a strong correlation between independent variables and dependent variables.

3.4.2 Latent Variable

As mentioned, driver safety risk level (y_i) is considered a dependent discrete variable in the modeling with y_i ranged from slight risk, general risk, serious risk, and catastrophic risk, and I representing the i^{th} driver surveyed. Observable independent variables include driver age, driving age, gender, vehicle type, roadway segment type, traffic demand, and rainy weather severity level. As a general practice, a non-observable ε_i is assumed to calculate a continuous latent variable y_i^*:

$$y_i^* = \sum_j^J x_{ij}\beta_{ij} + \varepsilon_i, \qquad y_i = 1, 2, ..., M \tag{10}$$

where, ε_i is assumed to be independently distributed, J is the number of observable independent variables, M is the number of dependent levels (M=4 in this research), β_{ij} is the parameter for the j^{th} variable, and the dependent variable y_i has the following relationship with the latent variable y_i^*:

$$y_i = \begin{cases} 1 & if \quad y_i^* \le c_1 \\ 2 & if \quad c_1 < y_i^* \le c_2 \\ 3 & if \quad c_2 < y_i^* \le c_3 \\ \vdots & \quad \vdots \\ M & if \quad c_{M-1} < y_i^* \end{cases} \tag{11}$$

where, c_k (k = 1, 2, …, M-1) are threshold values to satisfy: $c_1 < c_2 < ... < c_{M-1}$ 。

3.4.3 Probability Distributions of the Non-Observable Variable

It is important to select a probability distribution format for the non-observable variable. In transportation fields, logit and probit distributions are often used. Another important distribution format called Extreme Value distribution is another alternative. Generally, if middle values of independent variables are selected, probit and logit models may produce similar probabilities. However, if small values of independent variables are selected, the logit model and Extreme Value model have a similar probability range, but they may tend to give relatively larger probability values as compared to the probit model. If large values of independent variables are selected, the probit model and Extreme Value model have a similar probability range, but they would give relatively large probability as compared to the logit model. In general, the Extreme Value model produces probability values between the logit model and probit model.

Estimation for parameters in development of multi-ordered discrete choice models includes the estimation of parameters β_{ij} for independent variables and threshold values c_k (k = 1, 2, …,M-1), with β_{ij} and c_i defined previously. The following gives the example based on the logit, probit, and Extreme Value modeling process, respectively.

If ε_i shown in Equation (12) follows Extreme Value distribution, according to Equations (10) and (11), then:

$$P(y_i = 1) = P(y^* \le c_1) = P(\sum_{j=1}^{J} \beta_{ij} x_{ij} + \varepsilon_i \le c_1) = \exp\left[-e^{(c_1 - \sum_{j=1}^{J} \beta_{ij} x_{ij})} \right]$$

$$P(y_i = 2) = P(c_1 < y^* \le c_2) = P(c_1 < \sum_{j=1}^{J} \beta_{ij} x_{ij} + \varepsilon_i \le c_2) = \exp\left[-e^{(c_2 - \sum_{j=1}^{J} \beta_{ij} x_{ij})} \right] - \exp\left[-e^{(c_1 - \sum_{j=1}^{J} \beta_{ij} x_{ij})} \right]$$

$$\cdots\cdots$$

$$P(y_i = M) = P(y^* > c_{M-1}) = P(\sum_{j=1}^{J} \beta_{ij} x_{ij} + \varepsilon_i > c_{M-1}) = 1 - \exp\left[-e^{(c_{M-1} - \sum_{j=1}^{J} \beta_{ij} x_{ij})} \right] \tag{12}$$

If ε_i shown in Equation (10) follows logit distribution, according to Equations (10) and (11), then:

$$P(y_i = 1) = P(y^* \le c_1) = P(\sum_{j=1}^{J} \beta_{ij} x_{ij} + \varepsilon_i \le c_1) = \frac{1}{1 + e^{-[c_1 - \sum_{j=1}^{J} \beta_{ij} x_{ij}]}}$$

$$P(y_i = 2) = P(c_1 < y^* \le c_2) = P(c_1 < \sum_{j=1}^{J} \beta_{ij} x_{ij} + \varepsilon_i \le c_2) = \frac{1}{1 + e^{-[c_2 - \sum_{j=1}^{J} \beta_{ij} x_{ij}]}} - \frac{1}{1 + e^{-[c_1 - \sum_{j=1}^{J} \beta_{ij} x_{ij}]}}$$

$$\cdots\cdots$$

$$P(y_i = M) = P(y^* > c_{M-1}) = P(\sum_{j=1}^{J} \beta_{ij} x_{ij} + \varepsilon_i > c_{M-1}) = 1 - \frac{1}{1 + e^{-[c_{M-1} - \sum_{j=1}^{J} \beta_{ij} x_{ij}]}} \tag{13}$$

3.4.4 Model Parameter Estimation

For Equation (12), its likelihood function is:

$$L = \prod_{i=1}^{n} \prod_{m=0}^{M} \left[P\left(y_i = m\right) \right]^{d_{im}} = \prod_{i=1}^{n} \prod_{m=0}^{M} \left\{ \exp\left[-e^{(c_m - \sum_{j=1}^{J} \beta_{ij} x_{ij})} \right] - \exp\left[-e^{(c_{m+1} - \sum_{j=1}^{J} \beta_{ij} x_{ij})} \right] \right\}^{d_{im}} \tag{14}$$

If Log function is applied to both sides of Equation (14), then:

$$\ln L = \sum_{i=1}^{n}\sum_{m=0}^{M} d_{im} \ln\left[P\left(y_i = m\right)\right] = \sum_{i=1}^{n}\sum_{m=0}^{M} d_{im} \ln\left\{\exp\left[-e^{(c_m - \sum_{j=1}^{J}\beta_{ij}x_{ij})}\right] - \exp\left[-e^{(c_{m+1} - \sum_{j=1}^{J}\beta_{ij}x_{ij})}\right]\right\} \tag{15}$$

where, d_{im} = 1, meaning the i^{th} individual selects the m^{th} risk level, and d_{im} = 0, meaning the i^{th} individual does not select the m^{th} risk level.

If a partial derivative is taken for Equation (15) and let

$$\frac{\partial \ln L}{\partial \beta} = 0 \tag{16}$$

Then the maximum likelihood of all parameters can be obtained. Similar procedures can be applied if logit and probit distributions are applied.

3.4.5 Model for Crash Severity

Ordered probit models are widely used for analyzing crash severity. Hutchinson built an ordered probit model to study occupants' injury severity of single-vehicle crashes. In this research, an ordered probit model was select to measure the crash level.

For an ordered probit model, crash severity level (y_i) as dependent variable is considered discrete with y_i ranged from slight crash, general crash and severe crash, and i representing a severity level of a crash. Observable independent variables (x_{ij}) are factors contributing to bridge-related crash severity in this study. Non-observable variables (ε_i) are factors that are difficult to measure, such as driver behavior, which is assumed to fit standard normal distribution in the model. Thus, a continuous latent variable y_i^* can be expressed as follow.

$$y_i^* = \sum_{j}^{J} x_{ij}\beta_j + \varepsilon_i, \qquad y_i = 0,1,2 \tag{17}$$

where, J is the number of observable independent variables, β_j is a parameter for the j^{th} variable, and the dependent variable y_i has the following relationship with the latent variable y_i^*:

$$y_i = \begin{cases} 0 & if \quad y_i^* \le c_1 \\ 1 & if \quad c_1 < y_i^* \le c_2 \\ 2 & if \quad c_2 < y_i^* \end{cases} \tag{18}$$

where, c_1, c_2 are threshold values to satisfy: $c_1 < c_2$.

In the model, the method of maximum likelihood estimation is used to calculate all parameters including β_j and c_1, c_2. Then, the probability of every severity level can be obtained as follows:

$$P(y_i = 0) = P(y^* \le c_1) = P(\sum_{j=1}^{J} \beta_j x_{ij} + \varepsilon_i \le c_1) = \Phi(c_1 - \sum_{j=1}^{J} \beta_j x_{ij})$$

$$P(y_i = 1) = P(c_1 < y^* \le c_2) = P(c_1 < \sum_{j=1}^{J} \beta_j x_{ij} + \varepsilon_i \le c_2) = \Phi(c_2 - \sum_{j=1}^{J} \beta_j x_{ij}) - \Phi(c_1 - \sum_{j=1}^{J} \beta_j x_{ij})$$

$$P(y_i = 2) = P(y^* > c_2) = P(\sum_{j=1}^{J} \beta_j x_{ij} + \varepsilon_i > c_2) = 1 - \Phi(c_2 - \sum_{j=1}^{J} \beta_j x_{ij}) \tag{19}$$

where, $\Phi(\cdot)$ is a probability distribution function of standard normal distribution.

3.4.6 Measure of Fitness

EViews (Econometric Views) is a statistical package for Windows used mainly for time-series oriented econometric analysis (see Figure 3.5). EViews can be used for general statistical analysis and econometric analyses, such as cross-section and panel data analysis and time series estimation and forecasting. EViews combines spreadsheet and relational database technology with the traditional tasks found in statistical software and uses a Windows GUI. This is combined with a programming language that displays limited object orientation. The survey results and Ordered Choice modular are applied to EViews 6.0 software packages. The Quadratic Hill Climbing algorithm in EViews was used. Then, the maximum likelihood of all parameters can be obtained. The corresponding probability of a certain risk level can also be calculated.

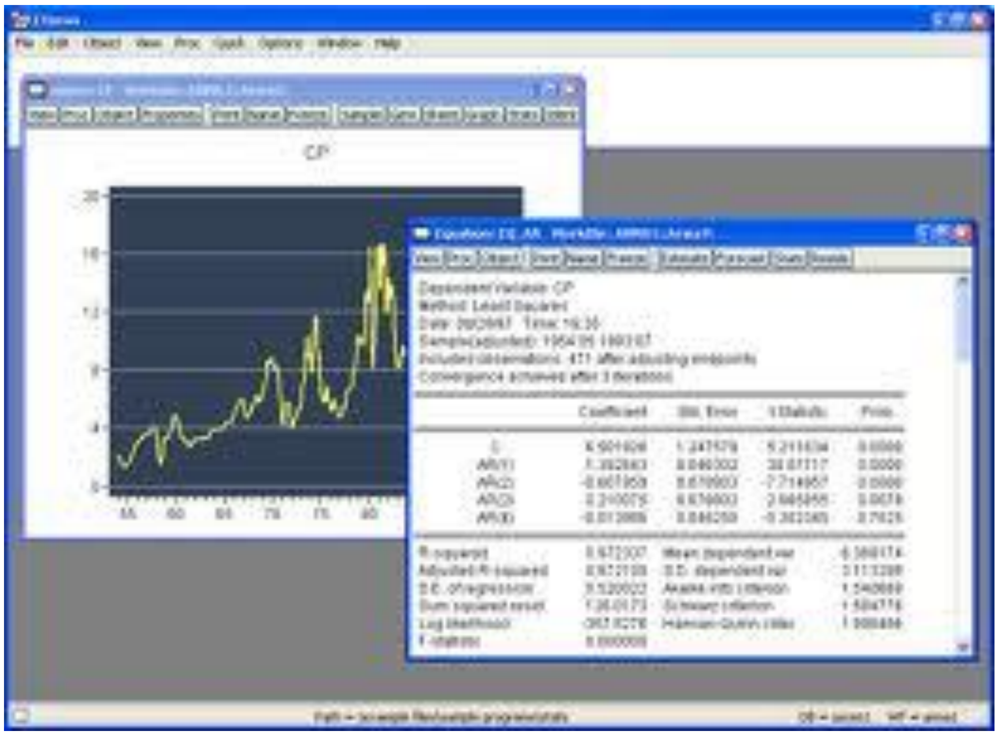

Figure 11 Interface of EViews 6.0

In the Eviews software package, four default measurement of fitness may be used:

(1) *Pseudo R-squared* is the ratio of calculated likelihood, and this index is similar to R^2 value used in regression model. As model fitness gets better, this index gets larger. The following is the often used equation for the index:

$$\mathrm{R}^2 = 1 - \left(\frac{\ln L_0}{\ln L}\right)^{2/n} \tag{20}$$

where, L is the maximum likelihood function, L_0 is the maximum likelihood value when $\beta_1 = ... = \beta_k = 0$, and n is number of samples.

(2) *Akaike Information Criterion (AIC):* Equation (21) is used to calculate AIC:

$$AIC = -\frac{2L}{n} + \frac{2k}{n} \tag{21}$$

where, *L* is the maximum likelihood value, *n* is number of samples, and *k* is number of parameters to be estimated. Small AIC value means better modeling results.

(3) *Schwarz Criterion (SC):* Equation (22) is used to calculate SC, and similar definitions for *L*, *n*, and *k* used in Equation (21) can be applied.

$$SC = -\frac{2L}{n} + \frac{k \ln n}{n} \tag{22}$$

From Equations (21) and (22), *SC* has the similar implication as *AIC* has. Thus, smaller *SC* value means better modeling results.

(4) *Log Likelihood (L): L* is the statistical value from maximum likelihood estimation. Generally, smaller residual errors could mean a larger *L* value. Thus, a larger *L* value could mean the model has better accuracy. However, smaller residual errors also are contributed by more independent variables. This means more independent variables could also result in a larger *L* value.

Chapter 4 Data Collection

This chapter describes the procedure of data collection and reduction. The Sutong Bridge opened to traffic in May 2008, there are total 569 accidents reported, however the number of major accidents is only 9, so crash data were limited and may not reflect the traffic operation and safety situation of the bridge well. Such few amount of crash is not enough to complete modeling purpose. Due to such limitations of data acquisition, questions were designed for officials in the Sutong Bridge Operation Department and for drivers to collect more subjective information through a survey. Other two types of data needed to be collected: weather data and traffic data. Weather data, including temperature, moisture, and wind speed, were gathered by a detector device built in to the Sutong Bridge; other data, such as rainfall and snowfall information, were collected from a weather forecast center. Crash data were provided by the Sutong Bridge Department.

4.1 Weather Data Collection

4.1.1 Temperature Data Collection

Temperature data were collected by means of the equipment (Temperature Detector WS040100) previously built into the Sutong Bridge. The temperature testing duration was from January to December 2009.The actual number of days tested was 333. The device recorded the temperature every hour of each day, resulting in a total of 24 records. Several kinds of data were collected, including average temperature (℃),highest temperature (℃), and lowest temperature (℃) for each day. To reflect the temperature situation more clearly, this information was statistically analyzed.

High temperatures impact traffic operational safety mostly only in summer (June, July and August), and low temperatures, which also can affect traffic safety, occurred in winter (January, February and December). The statistical results of 12 months (January–December 2009) of daily average temperature, summer highest temperature, and winter lowest temperature for the Sutong Bridge are shown in Figure 12, Figure 13, and Figure 14, respectively.

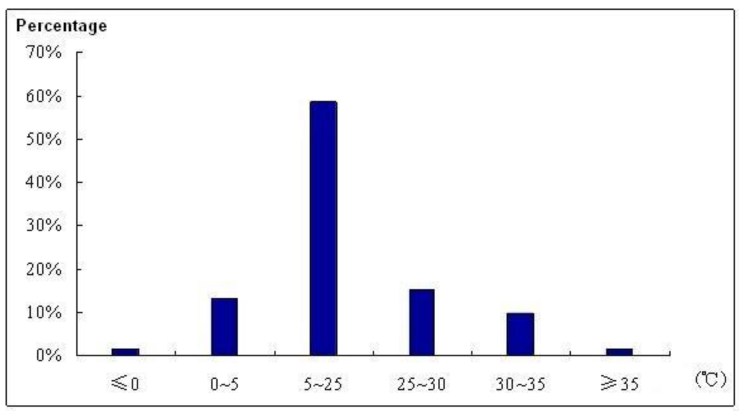

Figure 12 Daily Average Temperature Distribution,Sutong Bridge, January–December 2009

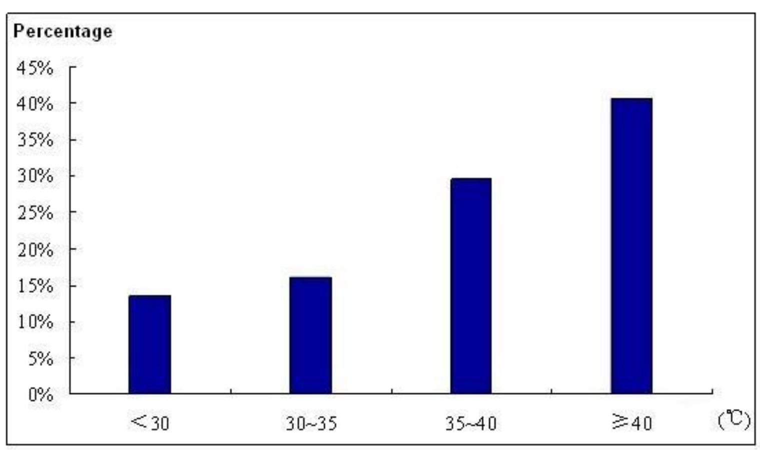

Figure 13 Daily Highest Temperature Distribution, Sutong Bridge, June–August 2009

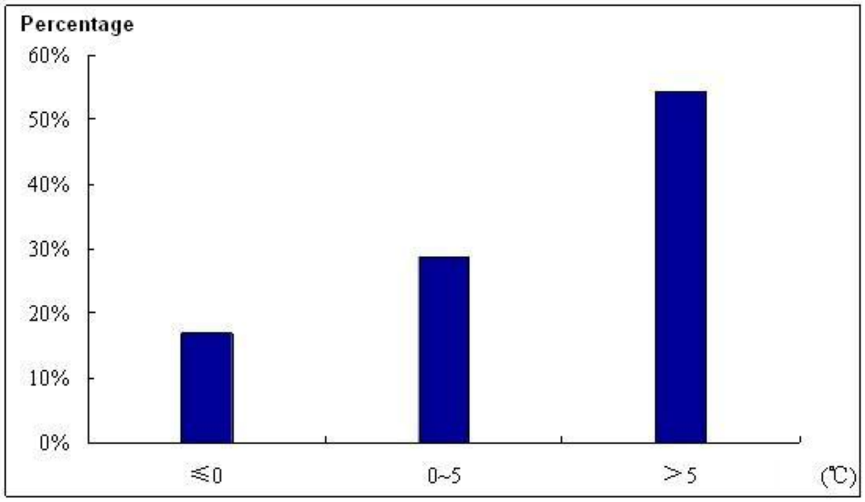

Figure 14 Daily Lowest Temperature Distribution, Sutong Bridge, January, February, December 2009

From the statistical results, the temperature characteristics of the Sutong Bridge were obtained. There were70 days when the temperature was higher than 30℃; the average temperature was 40.82℃. The percentage of high temperatures for summer and for one year was 86 percent and 37.43 percent, respectively. For temperatures higher than 40℃, the number of days was33,or 18.17 percent for the year, and 41 percent for summer, respectively. The highest temperature was 44.099℃and occurred on July 20, 2009, which is higher than the average high temperature.

There were25 days when the temperature was lower than 0℃; the average temperature was -2.19℃. The percentage of low temperatures for winter was 28 percent. The lowest temperature was -6.44℃and occurred on January 6, 2009. The lowest temperatures generally occur in January.

This analysis indicated that high temperatures should be paid more attention for traffic safety, and low temperatures cannot be ignored, especially in January.

4.1.2 Wind Data Collection

Wind speed information was collected by a wind speed detector, FS040101, which can record wind speed only. Daily average, highest, and lowest wind speeds were recorded, but, generally, only high winds impact traffic safety. The highest wind speed level distribution for the Sutong Bridge from January–August 2009 is shown in Figure 15.

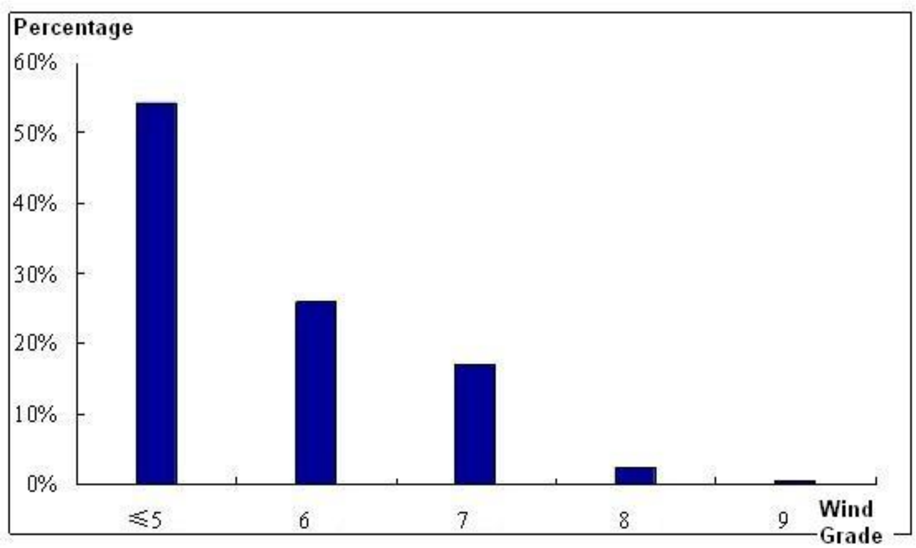

Figure 15 Highest Wind Speed Distribution, Sutong Bridge,January–August 2009

Strong winds occurred every month and are one of the most important risk factors for traffic safety. Although the probability of extreme wind speed is very low, only 0.52 percent, the probability of level 6 or more wind is 45.75 percent.

4.1.3 Rain and Snow Data Collection

No device is built into the Sutong Bridge that can record rainfall data directly. Through local weather forecasts, the data were obtained, but the results maybe different from the actual rainfall amount. Rainy weather can be classified into seven conditions: No Rainfall, Shower, Light Rain, Moderate Rain, Heavy Rain, Rain Storm, and Extreme Rain Storm, and the percentages of these are54.4, 27.2, 12.1, 1.9, 1.6, 1.6, and 1.2 percent, respectively. Figure 16 shows rainfall at the Sutong Bridge from May 2008 to October 2010. To allow for analysis of the relationship between traffic accidents and rainfall, rainfall type distribution for each month in 2009 was determined, as shown in Figure 17.

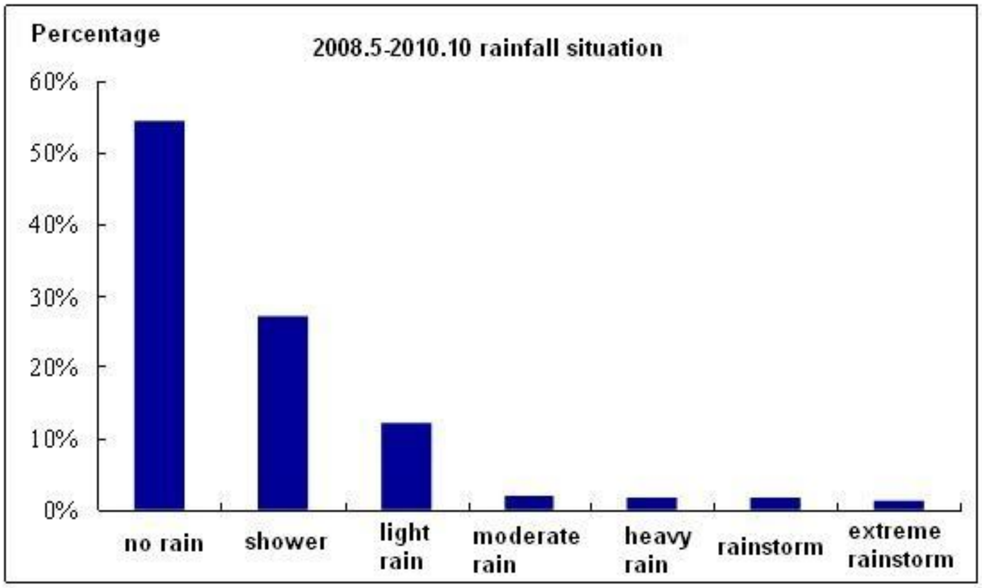

Figure 16 Rainfall Distribution, May 2008 to Oct 2010

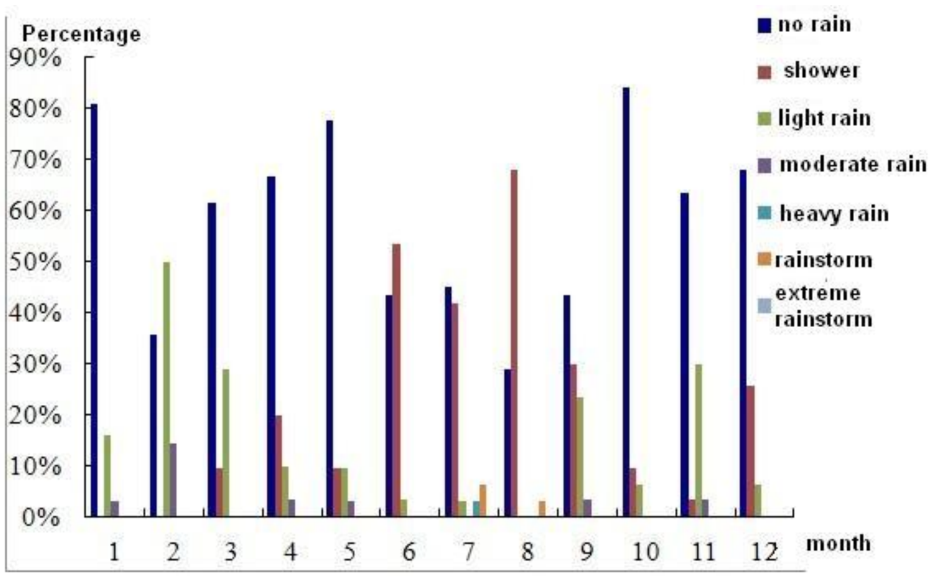

Figure 17 Rainfall Type Distribution, 2009

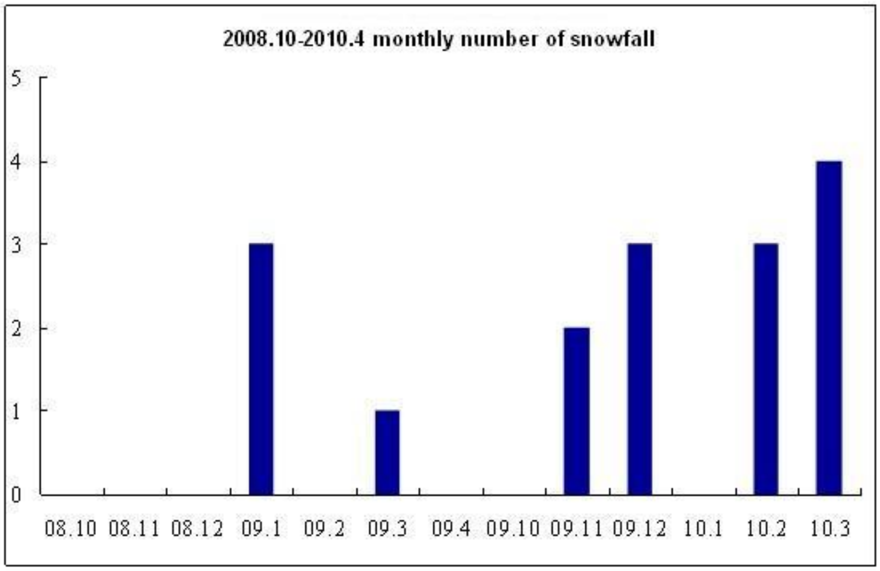

Figure 18 Amount of Snowfall for Each Month, October 2008 to April 2010

Figure 18 shows the amount of snowfall in each month from October 2008 to April 2010.

4.1.4 Fog Data Collection

Low temperatures or large temperature differences combined with high moisture easily form fog, which can cause significant impacts on traffic safety. Figure 4.8 shows the average temperature and moisture points for Sutong Bridge from January–August 2009. The red line is the tendency line of moisture. It can be seen that, when temperatures increase, moisture also generally increases.

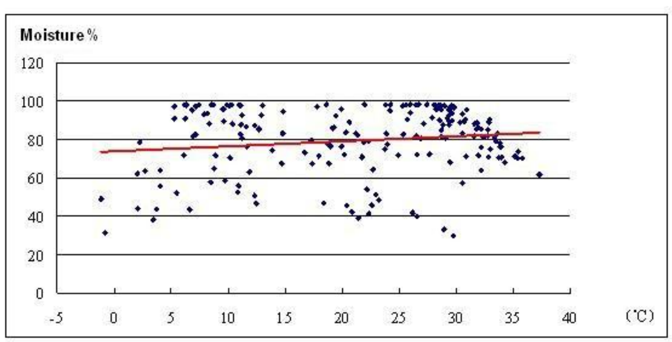

Figure 19 Average Daily Temperature and Moisture, January–August 2009

4.1.5 Ice Data Collection

Figure 20 shows the lowest temperature and rainfall, and Figure 21 shows the lowest temperature and snowfall from December 2008 to January 2010 for the Sutong Bridge. When temperatures are below 0℃ and there are high amounts of rainfall and snowfall, it is easy for bridge pavement to freeze.

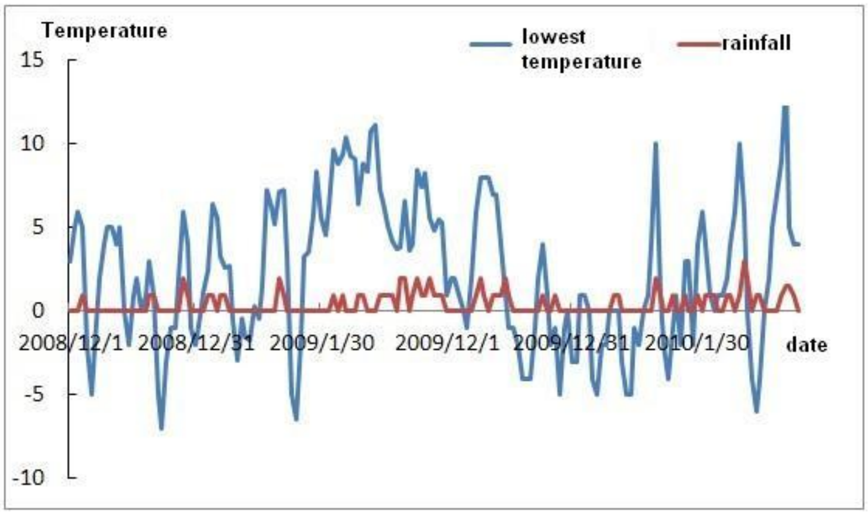

Figure 20 Lowest Temperatures and Rainfall, Sutong Bridge, December 2008–January 2010

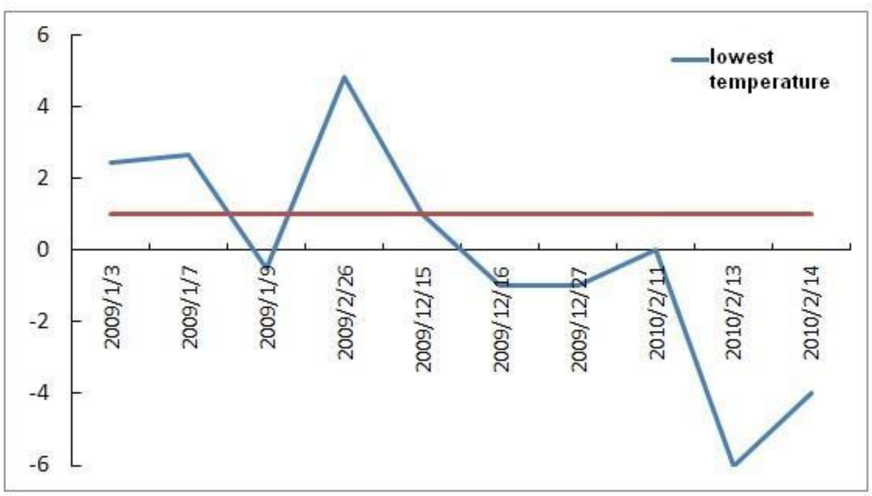

Figure 21 Lowest Temperatures and Snowfall, Sutong Bridge, January 2009–February 2010

4.2 Traffic Data Collection

All traffic data for this research were collected from the Sutong Bridge, which is located between Suzhou and Nantong in the Jiangsu Province. It is operated and managed by the Sutong Bridge Co., Ltd. Its length is about 32.4 km in total, which consists of the bridge crossing the river (8146 m), the north-line (15 km), and the south-line (9.2 km). The main span of the bridge has a length of 1088 m and is a steel stayed-cable bridge with double towers and chains. Figure 4.11is ageneral view of the Sutong Bridge.

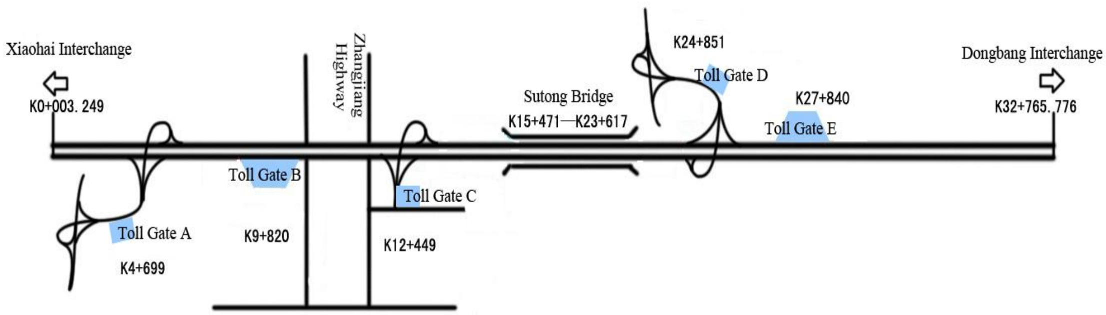

Figure 22 General View of Sutong Bridge

There were 459 crashes on the Sutong Bridge from May 2008 to June 2010, including 455 minor accidents, 9 moderate accidents, and 5 major accidents. Based on accident information recorded by the Sutong Bridge Operations Department, the distribution of accidents by month, week, and hour were obtained, as shown in Figure 23, Figure 24 and Figure 25, respectively.

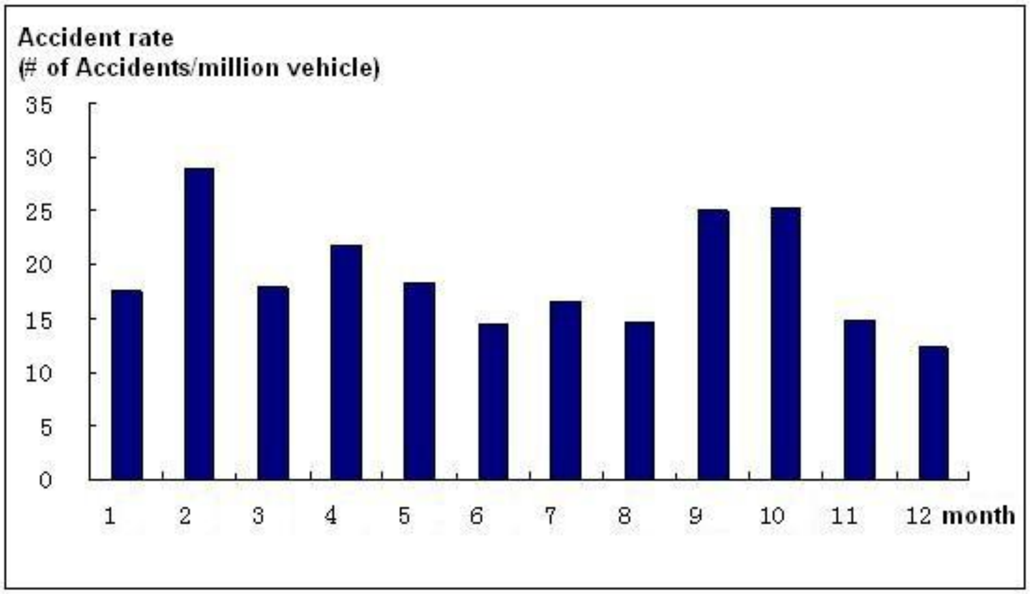

Figure 23 Accident Distribution for Sutong Bridge, Year

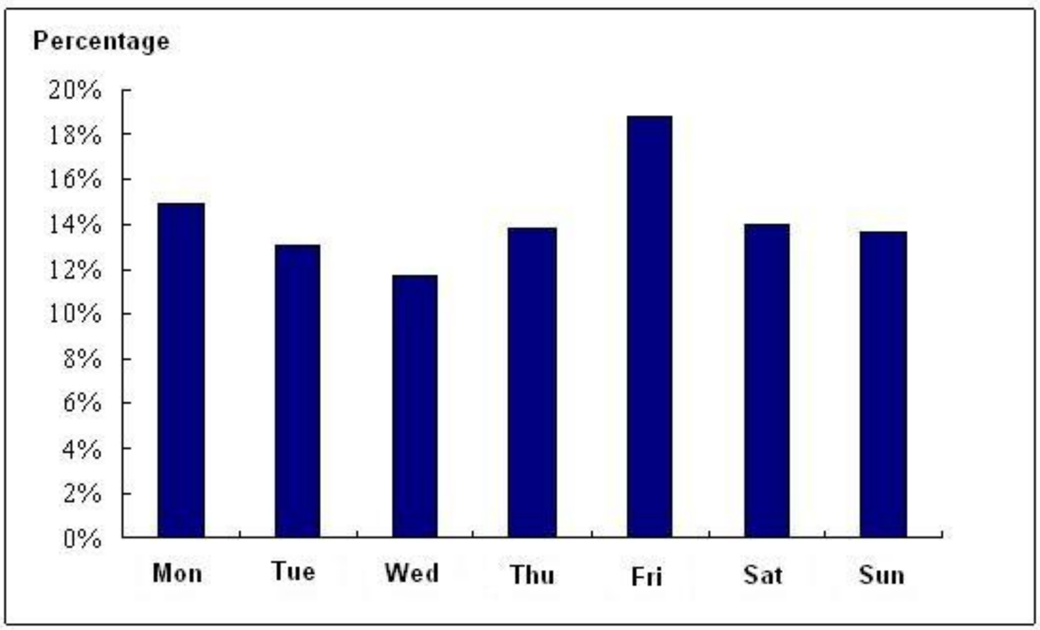

Figure 24 Accidents Distribution for Sutong Bridge, Week

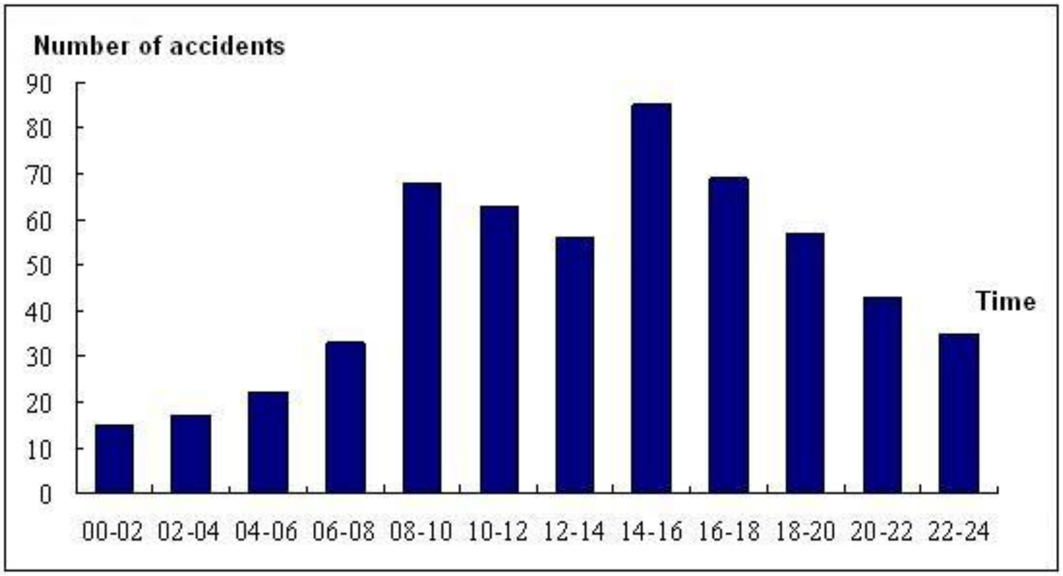

Figure 25 Accidents Distribution for Sutong Bridge, Hour

Statistical data gathered provide an accident comparison between the Sutong Bridge and a normal highway, as shown in Figure 26. As can be seen, hitting the guiderail and rear-end crashes are most common type of accident on the bridge, with percentages of 30.4and 37.77, respectively. The number of collision the bridge is higher than that of a normal highway.

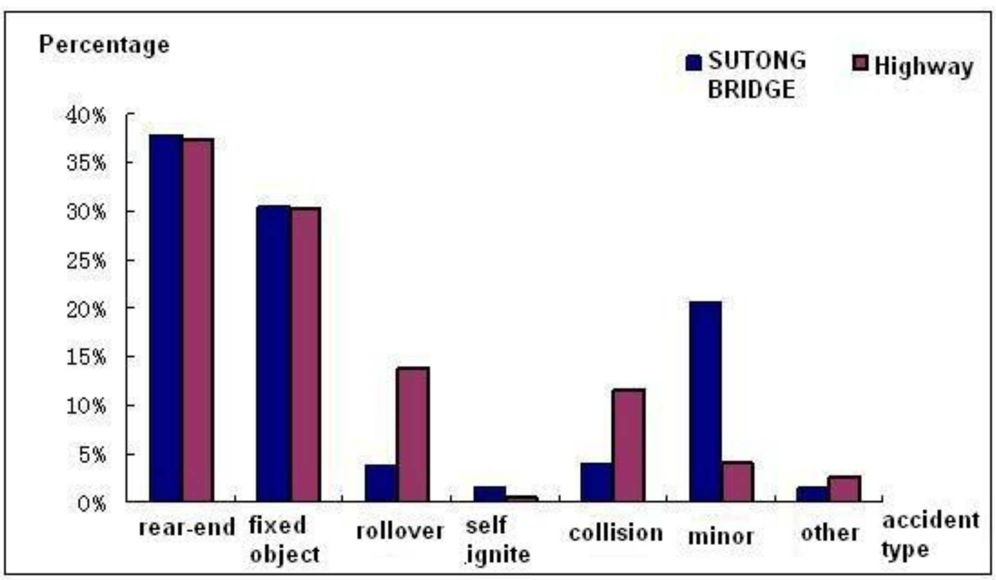

Figure 26 Accident Comparison, Sutong Bridge and Normal Highway

Accident duration is also an important indicator for determining risk level. Figure 27 shows accident duration distribution in 2009; 30–60 minutes is most the common accident duration.

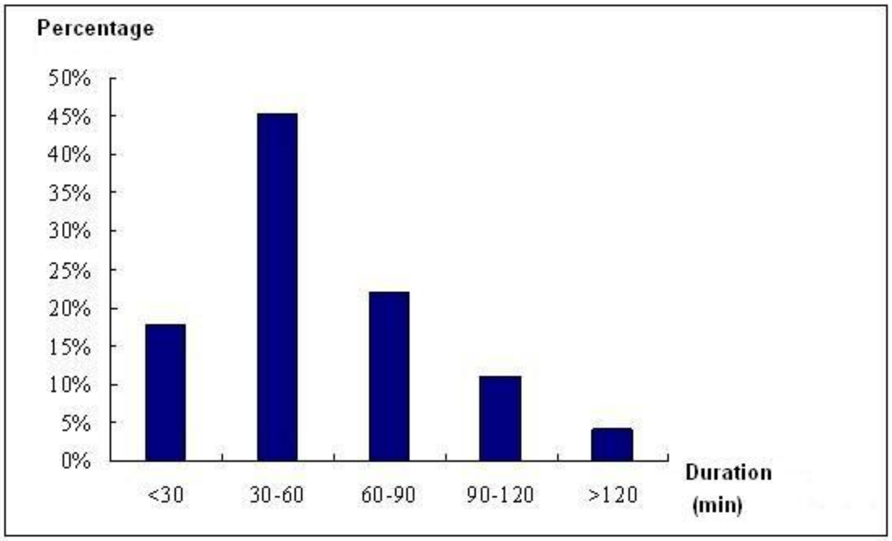

Figure 27 Accident Duration Distribution, Sutong Bridge

4.3 Questionnaire Survey Data Collection

The questionnaire surveys are designed for both officials in bridge management department and the drivers. The questionnaire survey for drivers should consider multiple characteristics related to drivers, vehicles, roadways, traffic, and severity of rainy situation. Since rain is most common situation, we only consider rainfall condition, two parts of the survey were considered: driver information and drivers' risk assessment when driving under rainy weather conditions. Table 12 presents the survey form for rainfall situation.

Table 12 Survey Form for Drivers' Perception of Safety Risk, Rainy Conditions

Driver Information Survey
Age ( ) Gender ( ) Driving Age ( ) Vehicle Type ( )
(A) Light-duty Vehicle: Bus of 19-seats or Less and Track of Carrying Capacity 0.9-1.8 Mg (B) Medium-weight Vehicle: Bus of 19-seats or More and Track of Carrying Capacity 1.8-6.3 Mg (C) Oversize Vehicle: Track of Carrying Capacity 6.3-12.7 Mg (D) Trailer: Track of Carrying Capacity Greater Than 12.7 Mg
Survey on Driving Risk Levels under Rainy Weather Conditions
1. Rain Severity Levels:
(1) Light Rain: Visibility of 200-500 Meters, Daily Rainfall Less Than 10Millimeters (2) Moderate Rain: Visibility of 100-200 Meters, Daily Rainfall between 10 and 25 Millimeters (3) Heavy Rain: Visibility of 50-100 Meters, Daily Rainfall between 25 and 50 Millimeters (4) Rainstorm: Visibility Less Than 50 Meters, Daily Rainfall More Than 50 Millimeters
2. Driving Risk Levels:
(1) Slight: may cause 1 to 2 people minor injuries, or property damage with cost less than 1000 RMB, or slight traffic congestion, about 65 km/h driving speed, and surrounded by cars.
(2) General: may cause 1 to 2 people serious injuries, or 3 or more people minor injuries, or property damage with cost less than 30000 RMB, or normal traffic congestion, and about 50 km/h driving speed.
(3) Serious: may cause 1 or 2 people to death, or 3 to 10 people serious injuries, or property damage with cost between 30000 RMB and 60000 RMB, or serious traffic congestion, less than 35 km/h driving speed.
(4) Catastrophic: may cause 3 or more people to death, or 11 or more people serious injuries, or 1 people to death and 8 or more people serious injuries, or 2 people to death and 5 or more people serious injuries, or property damage with cost more than 60000 RMB, or extreme traffic congestion, less than 20 km/h driving speed.
3. Based on conditions listed below, give your ratings on driving safety risk levels: (catastrophic=4, serious=3, general=2, slight =1)
(1) Level and Straight Road Segments (Type A), with Low Traffic Demand
Light Rain ( ) Moderate Rain ( ) Heavy Rain ( ) Rainstorm ( )
(2) Level Segments with Some Obstructions on Road Sides (Type B), with Low Traffic Demand
Light Rain ( ) Moderate Rain ( ) Heavy Rain ( ) Rainstorm ( )
(3) Segments with Horizontal and Vertical Curves (Type C), with Low Traffic Demand
Light Rain ( ) Moderate Rain ( ) Heavy Rain ( ) Rainstorm ( )
(4) Level and Straight Road Segments (Type A), with High Traffic Demand
Light Rain ( ) Moderate Rain ( ) Heavy Rain ( ) Rainstorm ( )
(5) Level Segments with Some Obstructions on Road Sides (Type B), with High Traffic Demand
Light Rain ( ) Moderate Rain ( ) Heavy Rain ( ) Rainstorm ( )
(6) Segments with Horizontal and Vertical Curves (Type C), with High Traffic Demand
Light Rain ( ) Moderate Rain ( ) Heavy Rain ( ) Rainstorm ( )

Table 13 Survey Form for Drivers' Perception of Safety Risk, Snowy Conditions

Survey on Driving Risk Levels under Snowy Weather Conditions
1. Snow Severity Levels:
(1) Light Snow: Visibility of 200-500 Meters (2) Moderate Snow: Visibility of 100-200 Meters (3) Heavy Snow: Visibility of 50-100 Meters (4) Snowstorm: Visibility Less Than 50 Meters
2. Driving Risk Levels:
(1) Slight: may cause 1 to 2 people minor injuries, or property damage with cost less than 1000 RMB, or slight traffic congestion, about 65 km/h driving speed, and surrounded by cars.
(2) General: may cause 1 to 2 people serious injuries, or 3 or more people minor injuries, or property damage with cost less than 30000 RMB, or normal traffic congestion, and about 50 km/h driving speed.
(3) Serious: may cause 1 or 2 people to death, or 3 to 10 people serious injuries, or property damage with cost between 30000 RMB and 60000 RMB, or serious traffic congestion, less than 35 km/h driving speed.
(4) Catastrophic: may cause 3 or more people to death, or 11 or more people serious injuries, or 1 people to death and 8 or more people serious injuries, or 2 people to death and 5 or more people serious injuries, or property damage with cost more than 60000 RMB, or extreme traffic congestion, less than 20 km/h driving speed.
3. Based on conditions listed below, give your ratings on driving safety risk levels: (catastrophic=4, serious=3, general=2, slight =1)
(1) Level and Straight Road Segments (Type A), with Low Traffic Demand
Light Snow ( ) Moderate Snow ( ) Heavy Snow ( ) Snowstorm ( )
(2) Level Segments with Some Obstructions on Road Sides (Type B), with Low Traffic Demand
Light Snow ( ) Moderate Snow ( ) Heavy Snow ( ) Snowstorm ( )
(3) Segments with Horizontal and Vertical Curves (Type C), with Low Traffic Demand
Light Snow ( ) Moderate Snow ( ) Heavy Snow ( ) Snowstorm ( )
(4) Level and Straight Road Segments (Type A), with High Traffic Demand
Light Snow ( ) Moderate Snow ( ) Heavy Snow ( ) Snowstorm ( )
(5) Level Segments with Some Obstructions on Road Sides (Type B), with High Traffic Demand
Light Snow ( ) Moderate Snow ( ) Heavy Snow ( ) Snowstorm ( )
(6) Segments with Horizontal and Vertical Curves (Type C), with High Traffic Demand
Light Snow ( ) Moderate Snow ( ) Heavy Snow ( ) Snowstorm ( )

Table 14 **Survey Form for Drivers' Perception of Safety Risk, Fog Conditions**

Survey on Driving Risk Levels under Fog Weather Conditions
1. Fog Severity Levels:
(1) Light Fog: Visibility of 200-500 Meters (2) Moderate Fog: Visibility of 100-200 Meters (3) Heavy Fog: Visibility of 50-100 Meters (4) Dense Fog: Visibility Less Than 50 Meters
2. Driving Risk Levels:
(1) Slight: may cause 1 to 2 people minor injuries, or property damage with cost less than 1000 RMB, or slight traffic congestion, about 65 km/h driving speed, and surrounded by cars.
(2) General: may cause 1 to 2 people serious injuries, or 3 or more people minor injuries, or property damage with cost less than 30000 RMB, or normal traffic congestion, and about 50 km/h driving speed.
(3) Serious: may cause 1 or 2 people to death, or 3 to 10 people serious injuries, or property damage with cost between 30000 RMB and 60000 RMB, or serious traffic congestion, less than 35 km/h driving speed.
(4) Catastrophic: may cause 3 or more people to death, or 11 or more people serious injuries, or 1 people to death and 8 or more people serious injuries, or 2 people to death and 5 or more people serious injuries, or property damage with cost more than 60000 RMB, or extreme traffic congestion, less than 20 km/h driving speed.
3. Based on conditions listed below, give your ratings on driving safety risk levels: (catastrophic=4, serious=3, general=2, slight =1)
(1) Level and Straight Road Segments (Type A), with Low Traffic Demand
Light Fog ( ) Moderate Fog ( ) Heavy Fog ( ) Dense Fog ( )
(2) Level Segments with Some Obstructions on Road Sides (Type B), with Low Traffic Demand
Light Fog ( ) Moderate Fog ( ) Heavy Fog ( ) Dense Fog ( )
(3) Segments with Horizontal and Vertical Curves (Type C), with Low Traffic Demand
Light Fog ( ) Moderate Fog ( ) Heavy Fog ( ) Dense Fog ( )
(4) Level and Straight Road Segments (Type A), with High Traffic Demand
Light Fog ( ) Moderate Fog ( ) Heavy Fog ( ) Dense Fog ( )
(5) Level Segments with Some Obstructions on Road Sides (Type B), with High Traffic Demand
Light Fog ( ) Moderate Fog ( ) Heavy Fog ( ) Dense Fog ( )
(6) Segments with Horizontal and Vertical Curves (Type C), with High Traffic Demand
Light Fog ( ) Moderate Fog ( ) Heavy Fog ( ) Dense Fog ( )

Table 15 **Survey Form for Drivers' Perception of Safety Risk, Windy Conditions**

Survey on Driving Risk Levels under Windy Weather Conditions
1. Windy Severity Levels:
(1) Light Wind: Less than Level 6 (2) Moderate Wind: Level 6-Level 10 (3) Strong Wind: More than Level 10
2. Driving Risk Levels:
(1) Slight: Driver may feel the existence of wind resistance, but no offset. The large size vehicle need to reduce the speed while segments with Horizontal and Vertical Curves (Type C).
(2) General: Slight offset, but usually drivers can adjust properly. Drivers need to pay attention to the speed especially while segments with Horizontal and Vertical Curves (Type C).
(3) Serious: Obvious offset or side rolling, usually vehicle drives in low speed or park in the emergency lane. Bus or large size truck has the very high risk.
(4) Catastrophic: Vehicle may occur side rolling even rollover, vehicles cannot run normally
3. Based on conditions listed below, give your ratings on driving safety risk levels: (catastrophic=4, serious=3, general=2, slight =1)
(1) Level and Straight Road Segments (Type A), with Low Traffic Demand
Light Wind ( )   Moderate Wind ( )   Strong Wind ( )
(2) Level Segments with Some Obstructions on Road Sides (Type B), with Low Traffic Demand
Light Wind ( )   Moderate Wind ( )   Strong Wind ( )
(3) Segments with Horizontal and Vertical Curves (Type C), with Low Traffic Demand
Light Wind ( )   Moderate Wind ( )   Strong Wind ( )
(4) Level and Straight Road Segments (Type A), with High Traffic Demand
Light Wind ( )   Moderate Wind ( )   Strong Wind ( )
(5) Level Segments with Some Obstructions on Road Sides (Type B), with High Traffic Demand
Light Wind ( )   Moderate Wind ( )   Strong Wind ( )
(6) Segments with Horizontal and Vertical Curves (Type C), with High Traffic Demand
Light Wind ( )   Moderate Wind ( )   Strong Wind ( )

Table 16 **Survey Form for Drivers' Perception of Safety Risk, Icy Conditions**

Survey on Driving Risk Levels under Icy Weather Conditions
1. Icy Severity Levels:
(1) Partial Freeze (2) Fully Freeze
2. Driving Risk Levels:
(1) Slight: may cause 1 to 2 people minor injuries, or property damage with cost less than 1000 RMB, or slight traffic congestion, about 65 km/h driving speed, and surrounded by cars.
(2) General: may cause 1 to 2 people serious injuries, or 3 or more people minor injuries, or property damage with cost less than 30000 RMB, or normal traffic congestion, and about 50 km/h driving speed.
(3) Serious: may cause 1 or 2 people to death, or 3 to 10 people serious injuries, or property damage with cost between 30000 RMB and 60000 RMB, or serious traffic congestion, less than 35 km/h driving speed.
(4) Catastrophic: may cause 3 or more people to death, or 11 or more people serious injuries, or 1 people to death and 8 or more people serious injuries, or 2 people to death and 5 or more people serious injuries, or property damage with cost more than 60000 RMB, or extreme traffic congestion, less than 20 km/h driving speed.
3. Based on conditions listed below, give your ratings on driving safety risk levels: (catastrophic=4, serious=3, general=2, slight =1)
(1) Level and Straight Road Segments (Type A), with Low Traffic Demand
Partial Freeze ( ) Fully Freeze( )
(2) Level Segments with Some Obstructions on Road Sides (Type B), with Low Traffic Demand
Partial Freeze ( ) Fully Freeze( )
(3) Segments with Horizontal and Vertical Curves (Type C), with Low Traffic Demand
Partial Freeze ( ) Fully Freeze( )
(4) Level and Straight Road Segments (Type A), with High Traffic Demand
Partial Freeze ( ) Fully Freeze( )
(5) Level Segments with Some Obstructions on Road Sides (Type B), with High Traffic Demand
Partial Freeze ( ) Fully Freeze( )
(6) Segments with Horizontal and Vertical Curves (Type C), with High Traffic Demand
Partial Freeze ( ) Fully Freeze( )

Table 17 Survey Form for Drivers' Perception of Safety Risk, Windy/Rainy Conditions

Survey on Driving Risk Levels under Windy/Rainy Weather Conditions
1. Windy and Rainy Severity Levels:
(1) Moderate Wind and Moderate Rain: Less than Wind Level 6, Visibility of 200-500 Meters (2) Moderate Wind and Heavy Rain: Less than Wind Level 6, Visibility Less than 200 Meters (3) Strong Wind and Moderate Rain: More than Wind Level 6, Visibility of 200-500 Meters (4) Strong Wind and Heavy Rain: More than Wind Level 6, Visibility Less than 200 Meters
2. Driving Risk Levels:
(1) Slight: may cause 1 to 2 people minor injuries, or property damage with cost less than 1000 RMB, or slight traffic congestion, about 65 km/h driving speed, and surrounded by cars.
(2) General: may cause 1 to 2 people serious injuries, or 3 or more people minor injuries, or property damage with cost less than 30000 RMB, or normal traffic congestion, and about 50 km/h driving speed.
(3) Serious: may cause 1 or 2 people to death, or 3 to 10 people serious injuries, or property damage with cost between 30000 RMB and 60000 RMB, or serious traffic congestion, less than 35 km/h driving speed.
(4) Catastrophic: may cause 3 or more people to death, or 11 or more people serious injuries, or 1 people to death and 8 or more people serious injuries, or 2 people to death and 5 or more people serious injuries, or property damage with cost more than 60000 RMB, or extreme traffic congestion, less than 20 km/h driving speed.
3. Based on conditions listed below, give your ratings on driving safety risk levels: (catastrophic=4, serious=3, general=2, slight =1)
(1) Level and Straight Road Segments (Type A), with Low Traffic Demand
Moderate Wind and Moderate Rain ( ) Moderate Wind and Heavy Rain ( ) Strong Wind and Moderate Rain ( ) Strong Wind and Heavy Rain ( )
(2) Level Segments with Some Obstructions on Road Sides (Type B), with Low Traffic Demand
Moderate Wind and Moderate Rain ( ) Moderate Wind and Heavy Rain ( ) Strong Wind and Moderate Rain ( ) Strong Wind and Heavy Rain ( )
(3) Segments with Horizontal and Vertical Curves (Type C), with Low Traffic Demand
Moderate Wind and Moderate Rain ( ) Moderate Wind and Heavy Rain ( ) Strong Wind and Moderate Rain ( ) Strong Wind and Heavy Rain ( )
(4) Level and Straight Road Segments (Type A), with High Traffic Demand
Moderate Wind and Moderate Rain ( ) Moderate Wind and Heavy Rain ( ) Strong Wind and Moderate Rain ( ) Strong Wind and Heavy Rain ( )
(5) Level Segments with Some Obstructions on Road Sides (Type B), with High Traffic Demand
Moderate Wind and Moderate Rain ( ) Moderate Wind and Heavy Rain ( ) Strong Wind and Moderate Rain ( ) Strong Wind and Heavy Rain ( )
(6) Segments with Horizontal and Vertical Curves (Type C), with High Traffic Demand
Moderate Wind and Moderate Rain ( ) Moderate Wind and Heavy Rain ( ) Strong Wind and Moderate Rain ( ) Strong Wind and Heavy Rain ( )

Table 18 Survey Form for Drivers' Perception of Safety Risk, Windy/Snowy Conditions

Survey on Driving Risk Levels under Windy/Snowy Weather Conditions
1. Windy and Snow Severity Levels:
(1) Moderate Wind and Moderate Snow: Less than Wind Level 6, Visibility of 200-500M (2) Moderate Wind and Heavy Snow: Less than Wind Level 6, Visibility Less than 200M (3) Strong Wind and Moderate Snow: More than Wind Level 6, Visibility of 200-500M (4) Strong Wind and Heavy Snow: More than Wind Level 6, Visibility Less than 200M
2. Driving Risk Levels:
(1) Slight: may cause 1 to 2 people minor injuries, or property damage with cost less than 1000 RMB, or slight traffic congestion, about 65 km/h driving speed, and surrounded by cars.
(2) General: may cause 1 to 2 people serious injuries, or 3 or more people minor injuries, or property damage with cost less than 30000 RMB, or normal traffic congestion, and about 50 km/h driving speed.
(3) Serious: may cause 1 or 2 people to death, or 3 to 10 people serious injuries, or property damage with cost between 30000 RMB and 60000 RMB, or serious traffic congestion, less than 35 km/h driving speed.
(4) Catastrophic: may cause 3 or more people to death, or 11 or more people serious injuries, or 1 people to death and 8 or more people serious injuries, or 2 people to death and 5 or more people serious injuries, or property damage with cost more than 60000 RMB, or extreme traffic congestion, less than 20 km/h driving speed.
3. Based on conditions listed below, give your ratings on driving safety risk levels: (catastrophic=4, serious=3, general=2, slight =1)
(1) Level and Straight Road Segments (Type A), with Low Traffic Demand
Moderate Wind and Moderate Snow ( ) Moderate Wind and Heavy Snow ( ) Strong Wind and Moderate Snow ( ) Strong Wind and Heavy Snow ( )
(2) Level Segments with Some Obstructions on Road Sides (Type B), with Low Traffic Demand
Moderate Wind and Moderate Snow ( ) Moderate Wind and Heavy Snow ( ) Strong Wind and Moderate Snow ( ) Strong Wind and Heavy Snow ( )
(3) Segments with Horizontal and Vertical Curves (Type C), with Low Traffic Demand
Moderate Wind and Moderate Snow ( ) Moderate Wind and Heavy Snow ( ) Strong Wind and Moderate Snow ( ) Strong Wind and Heavy Snow ( )
(4) Level and Straight Road Segments (Type A), with High Traffic Demand
Moderate Wind and Moderate Snow ( ) Moderate Wind and Heavy Snow ( ) Strong Wind and Moderate Snow ( ) Strong Wind and Heavy Snow ( )
(5) Level Segments with Some Obstructions on Road Sides (Type B), with High Traffic Demand
Moderate Wind and Moderate Snow ( ) Moderate Wind and Heavy Snow ( ) Strong Wind and Moderate Snow ( ) Strong Wind and Heavy Snow ( )
(6) Segments with Horizontal and Vertical Curves (Type C), with High Traffic Demand
Moderate Wind and Moderate Snow ( ) Moderate Wind and Heavy Snow ( ) Strong Wind and Moderate Snow ( ) Strong Wind and Heavy Snow ( )

4.4 Survey Data Reduction

The questionnaire survey for driver was performed through both on site survey and online survey. The survey sites selected in on site survey are parking lots and shopping malls. Online survey methods include emails, vehicle driving forums, and web site specialized in survey (http://www.diaochapai.com/survey536523), etc.

The total number of questionnaires received from one site is 1080. The study selects 286 samples randomly among them. Comparing with the population, the ratio of large vehicle and female drivers in the sample is slightly smaller. But the consistency between the sample and the population can be accepted. The factual statistics were shown that drivers' age was distributed from 21 to 55, driving age ranged from 1 to 20 years with a mean of 8 years, the ratio of male to female is 1.47:1; the ratio of passenger cars to large vehicle was 1.4:1. Note that, based on the national specifications JTG B01-2003; this research combines middle size vehicles, two-axle large trucks, and multi-axle large tracks to form one type (large vehicle type).

Total 816 survey forms were returned online. A preliminary screening processing was conducted to filter out unacceptable survey forms, such as the ones with too fast answering time (less than 300 seconds) and the ones with obviously repeated answers. Finally, 552 survey forms out of the 816 survey forms were accepted (about 68% accept rate).

Chapter 5 Data Analysis and Results

The research result of this project is a tool to support an early warning system during decision making. This chapter summarizes the data analysis from the focus group and from survey answers. The weight in the model was calculated from subjective data collected from a survey of drivers. Finally, risk assessment results under rainy weather conditions are presented and then applied to all other severe weather conditions.

5.1 Focus Group Data Analysis

To define the structure of the hierarchy of risk assessments, six alternatives were selected in this research and priorities among all six elements were established. The judgment matrix for rainy weather conditions is shown in Table 19.

Table 19 Judgment Matrix for Rainy Conditions

Event	X1	X2	X3	X4	X5	X6
X1(Longer Braking Distance)	1	3	7	8	9	5
X2(Lower Friction)	1/3	1	5	6	7	3
X3(Unclear Signs)	1/7	1/5	1	2	3	1/3
X4(Weak Illumination)	1/8	1/6	1/2	1	1/2	1/4
X5(Pavement Reflection)	1/9	1/7	1/3	2	1	1/3
X6(Drivers' Psychological Effects)	1/5	1/3	3	4	3	1

From this analysis, we can obtain weight value through calculation,

W_i=(0.474, 0.261, 0.067, 0.036, 0.045, 0.117), CR==0.023341<0.1

Applying the weight value to Equation 6, the weighted scores of driving risk under rainy weather conditions are shown in Table 20. According to the risk criteria shown in Table 11, the risk level can be obtained.

A similar procedure can be applied to other severe weather conditions. Risk assessment results under all severe weather conditions through focus group are shown in Table 21.

Table 20 Weighted Score by Focus Group under Rainy Conditions

Event	Slight Rain	Moderate Rain	Heavy Rain	Rainstorm
X1(Longer Braking Distance)	2.79	3.67	5.64	7.76
X2(Lower Friction)	3.06	4.39	5.33	7.36
X3(Unclear Signs)	0.36	1.06	2.06	2.88
X4(Weak Illumination)	0.97	2.30	3.12	5.33
X5(Pavement Reflection)	1.73	3.39	4.39	5.06
X6(Driver Psychological Effects)	1.24	3.91	4.33	5.73
Weighted Score	2.404	3.650	5.020	6.884
Risk Level	Slight	General	Serious	Catastrophic

5.2 Preliminary Survey Data Analysis

To understand the impacts of rainfall levels, roadway segment types, and traffic demand on driving safety risk levels, the 552 survey forms were analyzed to conduct preliminary analysis results, as shown in Figure 28. In Figure 28, frequency, representing the Y-axis, refers number of drivers who selected corresponding answers.

From Figure 28, it can be seen that rainfall levels have obvious and regular effects on driving safety risk levels: the Light Rain level has the largest probability of resulting in Slight risk; the Moderate Rainfall level has the largest probability of resulting in General risk; the Heavy Rain level has the largest probability of resulting in Serious risk; and the Rainstorm level has the largest probability of resulting in Catastrophic risk. In general, the higher the rainfall level, the higher the risk level.

Table 21 Risk Assessment Results under All Severe Weather Conditions by Focus Group

Weather Condition		Score	Risk Level
Rain	Light Rain	2.404	Slight
	Moderate Rain	3.650	General
	Heavy Rain	5.020	Serious
	Rainstorm	6.439	Serious
Snow	Light Snow	1.830	Slight
	Moderate Snow	2.783	General
	Heavy Snow	3.744	General
	Snowstorm	5.069	Serious
Fog	Light Fog	2.190	Slight
	Moderate Fog	3.222	General
	Heavy Fog	5.151	Serious
	Dense Fog	7.513	Catastrophic
Icy	Partial Freeze	4.551	General
	Full Freeze	5.042	Serious
Windy	Slight Wind	0.190	Slight
	Moderate Wind	1.702	Slight
	Strong Wind	3.292	General
High Temperature	High Temperature	2.374	Slight
Windy and Rainy	Moderate Wind/Rain	1.563	Slight
	Moderate Wind/Heavy Rain	3.506	General
	Moderate Wind/Rainstorm	5.370	Serious
	Strong Wind/Moderate Rain	4.004	General
	Strong Wind/Heavy Rain	5.112	Serious
	Strong Wind/Rainstorm	6.797	Serious
Windy and Snowy	Moderate Wind/Moderate Snow	1.614	Slight
	Moderate Wind/Heavy Snow	3.666	General
	Moderate Wind/Snowstorm	5.605	Serious
	Strong Wind/Moderate Snow	4.008	General
	Strong Wind/Heavy Snow	5.148	Serious
	Strong Wind/Snowstorm	7.531	Catastrophic
Ice and Fog	Partial Freeze/Slight Fog	4.829	Serious
	Partial Freeze/Heavy Fog	6.092	Serious
	Partial Freeze/Dense Fog	7.055	Serious
	Fully Freeze/Slight Fog	5.018	Serious
	Fully Freeze/Heavy Fog	6.180	Serious
	Fully Freeze/Dense Fog	7.409	Serious
	Fully Freeze/Agglomerate Fog	7.840	Catastrophic

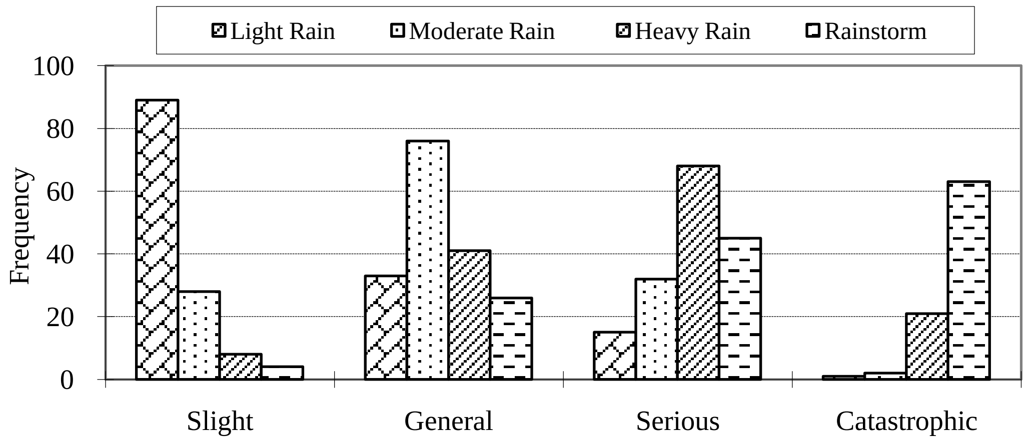

Figure 28 Survey Data Analysis for Various Rainy Weather Conditions

Figure 29 presents the relationship between roadway segment types and driving safety risk levels. For type A segments, the frequencies for Slight risk level and General risk level are similar, but frequencies for Serious risk level and Catastrophic risk level get lower and lower. On type B segments, the level of General risk has the highest probability, the level of Serious risk has the second highest probability, and the level of Catastrophic risk has the lowest probability. On type C segments, the probability ranks from Serious risk level to General risk level, then to Catastrophic risk level, and finally to Slight risk level.

The impact of traffic demand on driving safety risk levels was also analyzed. From Figure 30, it can be seen that given low traffic demand, drivers may perceive a general safety risk or a slight safety risk under rainy weather conditions. But under high traffic demand situations, drivers may perceive serious or general safety risk. In general, driving in high traffic demand could have a high driving safety risk when it is raining.

From Figure 28, it can be seen that rainfall levels have obvious and regular effects on driving safety risk levels: a Light Rainfall level has the largest probability of resulting in Slight risk; a Moderate Rainfall level has the largest probability of resulting in General risk; a Heavy Rainfall level has the largest probability of resulting in Serious risk; and a Rainstorm has the largest probability of resulting in Catastrophic risks. In general, the higher the rainfall level, the higher the risk level.

Figure 29 presents the relationship between roadway segment types and driving safety risk levels. On type A segments, the frequencies for the Slight risk level and the General risk level are similar, but frequencies for the Serious risk level and the Catastrophic risk level get lower and lower. On type B segments, the level of General risk has the highest probability, the level of Serious risk has the second highest probability, and the level of Catastrophic risk has the lowest probability. On type C segments, the probability goes from the Serious risk level to the General risk level, then to the Catastrophic risk level, and finally to the Slight risk level.

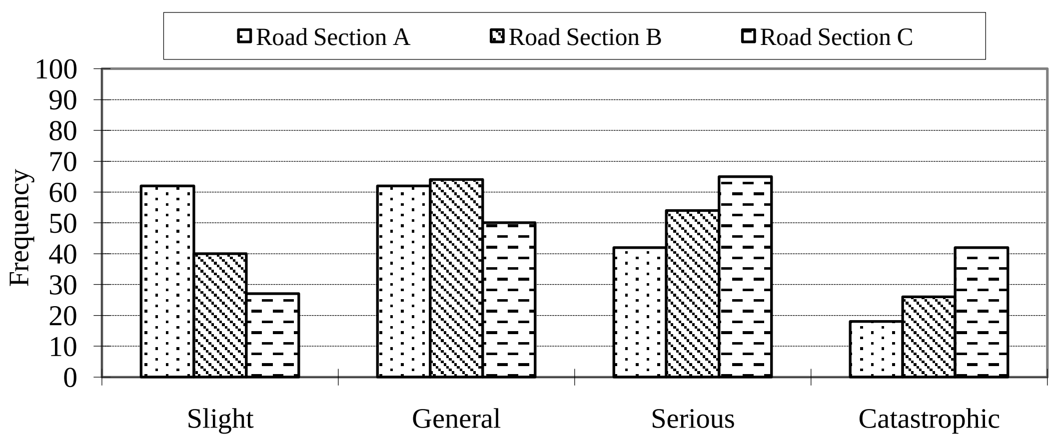

Figure 29 Survey Data Analysis under Different Road Segment Type Conditions

Impacts of traffic demand on driving safety risk levels were also analyzed. From Figure 30, it is clearly shown that given low traffic demand, drivers may perceive general safety risk or slight safety risk under rainy weather conditions. But in high traffic demand situations, drivers may perceive serious or general safety risk. In general, driving in high traffic demand could have high driving safety risk when it is raining.

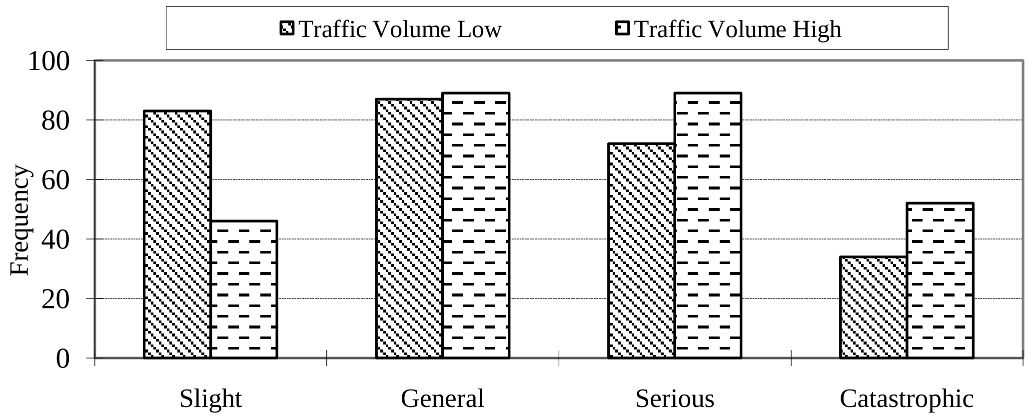

Figure 30 Survey Data Analysis under Different Traffic Volume Conditions

In summary, the frequency analysis results in preliminary conclusions on the impacts of rainy weather, roadway types, and traffic demand on traffic safety risk levels. However, such analysis results do not contain information about quantified statistical impacts and may reflect only subjective perception from the drivers who were surveyed. With such considerations, statistical models need to be developed to predict the perceived safety risk levels in given weather, roadway, and traffic conditions.

Table 22 Definitions of Real Variables and Dummy Variables

<table>
<tr><th colspan="5">Quantitative Variables</th></tr>
<tr><th>VariableName</th><th>Definition of Variables</th><th>Mean</th><th>Standard Deviation</th><th>Min~Max</th></tr>
<tr><td>Age</td><td>Actual Years</td><td>34</td><td>9.585</td><td>21~55</td></tr>
<tr><td>Driving Age</td><td>Actual Years</td><td>8</td><td>5.894</td><td>1~20</td></tr>
<tr><th colspan="5">Qualitative Variables</th></tr>
<tr><th>VariableName</th><th>Definition of Variables</th><th>Frequency</th><th>%</th><th>Cumulative %</th></tr>
<tr><td rowspan="2">Gender</td><td>Male=1</td><td>238</td><td>59.50</td><td>59.50</td></tr>
<tr><td>Female=0</td><td>162</td><td>40.50</td><td>100.00</td></tr>
<tr><td rowspan="2">VehicleType</td><td>Large Vehicle=1</td><td>167</td><td>41.75</td><td>41.75</td></tr>
<tr><td>Small Vehicle=0</td><td>233</td><td>58.25</td><td>100.00</td></tr>
<tr><td rowspan="4">RainLevel</td><td>Rainstorm=4</td><td>100</td><td>25.00</td><td>25.00</td></tr>
<tr><td>Heavy=3</td><td>97</td><td>24.25</td><td>49.25</td></tr>
<tr><td>Moderate=2</td><td>103</td><td>25.75</td><td>75.00</td></tr>
<tr><td>Light=1</td><td>100</td><td>25.00</td><td>100.00</td></tr>
<tr><td rowspan="2">SegmentCategory1</td><td>Type B=1</td><td>129</td><td>32.25</td><td>32.35</td></tr>
<tr><td>Others=0</td><td>271</td><td>67.75</td><td>100.00</td></tr>
<tr><td rowspan="2">SegmentCategory2</td><td>Type C=1</td><td>141</td><td>35.25</td><td>32.25</td></tr>
<tr><td>Others=0</td><td>259</td><td>64.75</td><td>100.00</td></tr>
<tr><td rowspan="2">TrafficVolume</td><td>HighTraffic Demand=2</td><td>192</td><td>48.00</td><td>48.00</td></tr>
<tr><td>Low Traffic Demand=1</td><td>208</td><td>52.00</td><td>100.00</td></tr>
<tr><td rowspan="4">RiskLevel</td><td>Catastrophic=4</td><td>76</td><td>19.00</td><td>19.00</td></tr>
<tr><td>Serious=3</td><td>113</td><td>28.25</td><td>47.25</td></tr>
<tr><td>General=2</td><td>122</td><td>30.50</td><td>77.75</td></tr>
<tr><td>Slight=1</td><td>89</td><td>22.25</td><td>100.00</td></tr>
</table>

5.3 Modeling Results

All variables for the questionnaire were quantified and analyzed. Table 22 presents all dummy variables used in modeling process and their statistical indicators. The variables of Driver Age and Driving Age were defined based on the actual age (years) and years of driving experience, respectively. However, to avoid variables producing heteroscedasticities, roadway segment types were divided into two categories with two dummy variables in each category, as shown in Table 22.

Prior to building the model, the association of the variables discussed in Table 23, including the response variable, was investigated by determining the correlation among the variable pairs. At the 0.05 significance level, the response variable risk level is associated with Gender, Vehicle Type, Rain Level, Segment Category 2, and Traffic Volume. The relationships between risk level and these variables, except Gender, are positive. That is to say, a female driver with a large vehicle may have a higher risk levelin those segments with horizontal and vertical curves when the traffic volume is large, which would be expected. At the same time, the table shows that Age, Driving Age and Gender are all relative, but Age and Driving Age are not associated with risk level. This is not an error, because the relationship between Age and Driving Age is not completely linear.

Table 23 Correlation Tests of All Variables from Questionnaire Survey

	Age	**Driving Age**	**Gender**	**Vehicle Type**	**Rain Level**	**Segment Category 1**	**Segment Category 2**	**Traffic Volume**	**Risk Level**
Age	—								
Driving Age	**0.751**	—							
Gender	**0.475**	**0.478**	—						
Vehicle Type	**0.236**	**0.378**	**0.335**	—					
Rain Level	-0.003	0.044	0.054	0.050	—				
Segment Category 1	-0.023	-0.041	-0.042	-0.029	0.023	—			
Segment Category 2	-0.011	-0.021	-0.027	0.011	0.054	-0.509	—		
Traffic Volume	0.032	0.040	0.038	0.022	0.088	-0.031	0.014	—	
Risk Level	0.036	-0.019	**-0.198**	**0.184**	**0.604**	0.071	**0.259**	**0.125**	—

Note: In each cell, the numbers give the correlations respectively. Boldfaced numbers represent significant correlations when the significance level is 0.05.

For modeling purposes, it was very important to select independent variables scientifically. In general, the relationship of independent variables should be linear independently. In contrast, there is a strong correlation between independent variables and dependent variables. Thus, Driver Gender, Vehicle Type, Rain Level, Segment Category 2,and Traffic Volume were selected as the independent variables of the model.

Thus, five variables are selected in the model, and relevant parameters were estimated using maximum likelihood value. As mentioned in Chapter 3, the Ordered Choice modular in the Eviews software package and the Quadratic Hill Climbing algorithm were used in the modeling process to obtain all parameters for all variables and the threshold values for non-observable error terms.

The modeling results based on Multi-ordered Logit Model approach are presented in Table 24. The model output included the coefficients of the five variables, standard error, z-statistic value， pseudo R-squared, and the associated *p*-value. The coefficients of variables and the associated *p*-value are important parameters. The relationship between dependent variables and independent variables was decided by the coefficients of variables and tested by the *p*-value.

In Table 24, the *p*-value means good correlation between dependent variables and independent variables. The pseudo R-squared value is not very close to 1 because of impacts of non-observable variables; however, it can be accepted in general. Besides, only Driver Gender has a negative impact on risk level considering the coefficients of variables. The influence degree of five independent variables sorted in descending order is Rain Level, Vehicle Type, Driver's Gender, Segment Category 2,and Traffic Volume.

Table 24 Parameter Estimation of First Multi-ordered Logit Model

Variable	Coefficient	Std. Error	z-Statistic	*p*-Value
Gender	-1.296516	0.244768	-5.296927	0.0000
Vehicle Type	1.387561	0.251217	5.523355	0.0000
Rain Level	1.473376	0.115059	12.80542	0.0000
Segment Category 2	1.179286	0.210046	5.614406	0.0000
Traffic Volume	0.888443	0.200028	4.441587	0.0000
Limit Points	Value	Std. Error		z-Statistic
C1	3.288257	0.874228		0.0000
C2	5.023610	1.130002		0.0000
C3	6.726702	1.301396		0.0000
Pseudo R-squared	0.352546	*p*-Value (LR statistic)		0.0000

The model output included the coefficients of the five variables, standard error, z-statistic value, pseudo R-squared, and the associated *p*-value. The coefficients of the variables and the associated *p*-value are important parameters. The relationship between dependent variables and independent variables is decided by the coefficients of variables and tested by the *p*-value.

With the application of Equation11 and the parameters and thresholds presented in Table 24, the final model has the following form:

$$\mathrm{Y}^{*} = -1.2965x_1 + 1.3875x_2 + 1.4733x_3 + 1.1792x_4 + 0.8884x_5$$

$$Y = \begin{cases} 1 \quad if & Y^{*} \leq 3.2882 \\ 2 \quad if & 3.2882 < Y^{*} \leq 5.0236 \\ 3 \quad if & 5.0236 < Y^{*} \leq 6.7267 \\ 4 \quad if & 6.7267 < Y^{*} \end{cases} \qquad (23)$$

5.4 Model Evaluation

For the purpose of model evaluation, the Prediction-Evaluation modular in the Eviews software package was used to calculate the outputs (risk levels) of the multi-ordered discrete choice model shown in Equation 23 and zero-assumption model (with all parameters equal to zero) under different combined conditions. Outputs were compared with survey results, and the comparison summaries are presented in Table 25. Estimated Equation presents the model-fitting quality with the Dependent Value representing the driving safety risk level, Observations representing number of observations, Correct and Incorrect representing number of correct estimations and number of incorrect estimations, respectively, and %Correct representing the percentage of correct estimations. Constant Probability Spec. presents the model fitting quality with the use of zero-assumption model. According to Table 25, the multi-ordered discrete choice model has a correct estimation rate of 66.304 percent, and the zero-assumption model has a correct estimation rate of 31.341 percent, meaning that the Multi-ordered Discrete Choice model has an improvement rate of 50.923 percent over the zero-assumption model. Statistically, the evaluation through this process proves that the model developed in the study has good quality to fit drivers' perception to driving safety risk levels.

Table 25 shows the magnitudes of all parameters estimated in the modeling process. From the table, it is known that Gender has negative parameters, meaning gender has negative impacts on safety risk levels (larger values of Gender mean fewer safety risks), and other variables (Vehicle Type, Raining Severity Level, Roadway Segment Type, and Traffic Demand) have parameters with positive signs, meaning they have positive impacts on safety risk levels (larger values of Vehicle Type, Raining Severity Level, Roadway Segment Type, and Traffic Demand mean higher safety risks). The following discusses the implication of these variables.

Table 25 Prediction Evaluation of Multi-ordered Discrete Choice Model

Estimated Equation				
Dependent Value	***Observations***	***Correct***	***Incorrect***	***% Correct***
1	128	89	39	69.531
2	173	105	68	60.694
3	159	101	58	63.522
4	92	71	21	77.174
Total	552	366	186	66.304
Constant Probability Spec.				
Dependent Value	***Observations***	***Correct***	***Incorrect***	***% Correct***
1	128	0	128	0.000
2	173	173	0	100.000
3	159	0	159	0.000
4	92	0	92	0.000
Total	552	173	379	31.341

The variable of Gender has a parameter with a negative sign, indicating it has a negative impact on safety risk levels. This conclusion basically indicates that male drivers, when driving under rainy weather conditions, could have less safety risk as they may have better capabilities in making decisions and taking actions when facing driving difficulties as compared to female drivers.

The variable of Vehicle Type has a positive parameter, meaning larger vehicles could have higher driving risks when it is raining. In fact, larger vehicles have relatively poor dynamic characteristics as compared to smaller vehicles. When it is raining, larger vehicles need to take much longer braking distance to slow down or stop.

Rainy weather would decrease driver visibility and pavement skid resistance. As rain gets more severe (rain level gets higher), driver visibility gets poorer and skid resistance becomes smaller, meaning drivers may lose their control capability, resulting in more potential in traffic crashes.

Roadway segment types have positive impacts on safety risk levels, meaning when roadway geometrics and other conditions get worse, driving under rainy conditions could have more safety risks.

Table 26 Risk Assessment Results for Long-Scaled Bridge under Rainy Weather Conditions

Rain Level	Geometric	Traffic Volume	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
Light Rain	Segment Category 1	Low	**0.96**	0.04	0.00	0.00
Moderate Rain			**0.71**	0.28	0.01	0.00
Heavy Rain			0.19	**0.71**	0.10	0.01
Rainstorm			0.02	0.42	**0.48**	0.08
Light Rain	Segment Category 1	High	**0.88**	0.12	0.00	0.00
Moderate Rain			0.41	**0.55**	0.04	0.00
Heavy Rain			0.06	**0.64**	0.27	0.03
Rainstorm			0.01	0.18	**0.59**	0.23
Light Rain	Segment Category 2	Low	**0.80**	0.19	0.01	0.00
Moderate Rain			0.28	**0.65**	0.06	0.00
Heavy Rain			0.04	**0.54**	0.38	0.05
Rainstorm			0.00	0.11	**0.54**	0.34
Light Rain	Segment Category 2	High	**0.54**	0.44	0.02	0.00
Moderate Rain			0.10	**0.70**	0.18	0.02
Heavy Rain			0.01	0.26	**0.58**	0.15
Rainstorm			0.00	0.03	0.32	**0.65**

The parameter for the Traffic Demand variable has a positive sign. This indicates that driving safety risk under rainy weather conditions could increase as traffic demand increases. In fact, the increase in traffic demand results in an increase in traffic density, which could increase the number of interactions between vehicles. When it is raining, such increase in traffic interactions could result in more driving safety risks.

5.5 Risk Assessment Results

The risk probability of rainy weather conditions is shown in Table 26.The bold value indicates the highest probability under such conditions. Similar procedures can be applied to all the other severe weather conditions.

Table 27 Risk Assessment Results for Long-Scaled Bridge under Snowy Weather Conditions

Snow Level	Geometric	Traffic Volume	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
Light Snow	Segment Category 1	Low	**0.84**	0.15	0.01	0.00
Moderate Snow			0.43	**0.50**	0.06	0.01
Heavy Snow			0.10	**0.55**	0.29	0.06
Snowstorm			0.02	0.20	**0.49**	0.30
Light Snow	Segment Category 1	High	**0.68**	0.30	0.02	0.00
Moderate Snow			0.23	**0.60**	0.14	0.02
Heavy Snow			0.04	0.39	**0.44**	0.13
Snowstorm			0.01	0.09	0.39	**0.51**
Light Snow	Segment Category 2	Low	**0.62**	0.35	0.03	0.00
Moderate Snow			0.19	**0.61**	0.17	0.03
Heavy Snow			0.03	0.34	**0.47**	0.16
Snowstorm			0.01	0.07	0.35	**0.57**
Light Snow	Segment Category 2	High	0.40	**0.52**	0.07	0.01
Moderate Snow			0.09	**0.53**	0.31	0.06
Heavy Snow			0.01	0.18	**0.49**	0.32
Snowstorm			0.00	0.03	0.20	**0.76**

Table 28 Risk Assessment Results for Long-Scaled Bridge under Fog Weather Conditions

Fog Level	Geometric	Traffic Volume	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
Light Fog	Segment Category 1	Low	**0.90**	0.09	0.01	0.00
Moderate Fog			**0.64**	0.32	0.03	0.00
Heavy Fog			0.26	**0.58**	0.15	0.02
Dense Fog			0.00	0.05	0.37	**0.58**
Light Fog	Segment Category 1	High	**0.73**	0.24	0.02	0.00
Moderate Fog			0.10	**0.51**	0.34	0.05
Heavy Fog			0.02	0.21	**0.56**	0.21
Dense Fog			0.00	0.05	0.37	**0.58**
Light Fog	Segment Category 2	Low	**0.71**	0.27	0.03	0.00
Moderate Fog			0.08	**0.49**	0.37	0.06
Heavy Fog			0.02	0.19	**0.56**	0.24
Dense Fog			0.00	0.05	0.34	**0.61**
Light Fog	Segment Category 2	High	0.42	**0.49**	0.08	0.01
Moderate Fog			0.03	0.26	**0.55**	0.17
Heavy Fog			0.01	0.07	0.42	**0.51**
Dense Fog			0.00	0.01	0.15	**0.84**

Table 29 Risk Assessment Results for Long-Scaled Bridge under Icy Weather Conditions

Icy Level	Geometric	Traffic Volume	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
Partial Icy	Segment Category 1	Low	0.30	**0.63**	0.06	0.01
Fully Icy			0.05	**0.58**	0.33	0.04
Partial Icy	Segment Category 1	High	0.04	**0.51**	0.40	0.06
Fully Icy			0.00	0.13	**0.55**	0.33
Partial Icy	Segment Category 2	Low	0.05	**0.59**	0.31	0.04
Fully Icy			0.01	0.18	**0.57**	0.24
Partial Icy	Segment Category 2	High	0.00	0.13	**0.55**	0.31
Fully Icy			0.00	0.02	0.20	**0.79**

Table 30 Risk Assessment Results for Long-Scaled Bridge under Windy Weather Conditions

Wind Level	Geometric	Traffic Volume	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
Light Wind	Segment Category 1	Low	**0.94**	0.06	0.00	0.00
Moderate Wind			**0.50**	0.45	0.05	0.00
Strong Wind			0.06	**0.46**	0.42	0.06
Light Wind	Segment Category 1	High	**0.75**	0.24	0.02	0.00
Moderate Wind			0.16	**0.61**	0.22	0.02
Strong Wind			0.01	0.16	**0.58**	0.25
Light Wind	Segment Category 2	Low	**0.77**	0.21	0.02	0.00
Moderate Wind			0.18	**0.61**	0.20	0.02
Strong Wind			0.01	0.18	**0.59**	0.22
Light Wind	Segment Category 2	High	0.39	**0.53**	0.08	0.01
Moderate Wind			0.04	0.37	**0.50**	0.09
Strong Wind			0.00	0.04	0.36	**0.60**

Table 31 Risk Assessment Results for Long-Scaled Bridge under High Temperature Conditions

High Temperature	Geometric	Traffic Volume	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
High Temperature	Segment Category 1	Low	**1.00**	0.00	0.00	0.00
	Segment Category 1	High	0.09	**0.91**	0.00	0.00
High Temperature	Segment Category 2	Low	0.45	**0.55**	0.00	0.00
	Segment Category 2	High	0.00	**0.55**	0.45	0.00

Table 32 Risk Assessment Results for Long-Scaled Bridge under Windy/Snowy Weather Conditions

Wind/Snow Level	Geometric	Traffic Vol	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
Moderate Wind/Snow	Segment Category 1	Low	**0.84**	0.15	0.01	0.00
Moderate Wind/Heavy Snow			0.21	**0.65**	0.13	0.01
Strong Wind/Moderate Snow			0.07	**0.57**	0.31	0.05
Strong Wind/Heavy Snow			0.01	0.15	**0.53**	0.31
Moderate Wind/Snow	Segment Category 1	High	**0.63**	0.35	0.02	0.00
Moderate Wind/Heavy Snow			0.08	**0.58**	0.30	0.04
Strong Wind/Moderate Snow			0.02	0.34	**0.51**	0.13
Strong Wind/Heavy Snow			0.00	0.05	0.35	**0.59**
Moderate Wind/Snow	Segment Category 2	Low	**0.53**	0.43	0.03	0.00
Moderate Wind/Heavy Snow			0.05	**0.51**	0.38	0.06
Strong Wind/Moderate Snow			0.02	0.26	**0.54**	0.18
Strong Wind/Heavy Snow			0.00	0.04	0.28	**0.68**
Moderate Wind/Snow	Segment Category 2	High	0.27	**0.63**	0.10	0.01
Moderate Wind/Heavy Snow			0.02	0.27	**0.54**	0.17
Strong Wind/Moderate Snow			0.01	0.10	**0.48**	0.41
Strong Wind/Heavy Snow			0.00	0.01	0.12	**0.87**

Table 33 Risk Assessment Results for Long-Scaled Bridge under Windy/Rainy Weather Conditions

Wind/Rain Level	Geometric	Traffic Vol.	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
Moderate Wind and Moderate Rain	Segment Category 1	Low	**0.95**	0.05	0.00	0.00
Moderate Wind and Heavy Rain			0.25	**0.69**	0.06	0.00
Strong Wind and Moderate Rain			0.15	**0.74**	0.10	0.01
Strong Wind and Heavy Rain			0.02	0.42	**0.48**	0.09
Moderate Wind and Moderate Rain	Segment Category 1	High	**0.84**	0.16	0.00	0.00
Moderate Wind and Heavy Rain			0.08	**0.72**	0.18	0.02
Strong Wind and Moderate Rain			0.05	**0.65**	0.28	0.03
Strong Wind and Heavy Rain			0.00	0.17	**0.57**	0.26
Moderate Wind and Moderate Rain	Segment Category 2	Low	**0.82**	0.18	0.00	0.00
Moderate Wind and Heavy Rain			0.07	**0.71**	0.20	0.02
Strong Wind and Moderate Rain			0.04	**0.62**	0.31	0.04
Strong Wind and Heavy Rain			0.00	0.15	**0.56**	0.29
Moderate Wind and Moderate Rain	Segment Category 2	High	**0.55**	0.44	0.02	0.00
Moderate Wind and Heavy Rain			0.02	**0.47**	0.44	0.07
Strong Wind and Moderate Rain			0.01	0.33	**0.54**	0.12
Strong Wind and Heavy Rain			0.00	0.04	0.35	**0.60**

Table 34 Risk Assessment Results for Long-Scaled Bridge under Icy/Fog Weather Conditions

Ice/Fog Level	Geometric	Traffic Vol.	Slight Risk	General Risk	Serious Risk	Catastro Risk
Partial Ice/Light Fog	Segment Category 1	Low	0.36	**0.56**	0.08	0.01
Partial Ice/ Heavy Fog			0.11	**0.59**	0.26	0.04
Partial Ice/ Dense Fog			0.02	0.30	**0.52**	0.15
Full Ice/Light Fog			0.05	**0.48**	0.40	0.07
Full Ice/Heavy Fog			0.01	0.15	**0.53**	0.31
Full Ice/Dense Fog			0.00	0.07	0.42	**0.51**
Partial Ice/Light Fog	Segment Category 1	High	0.16	**0.63**	0.19	0.02
Partial Ice/ Heavy Fog			0.04	0.40	**0.46**	0.10
Partial Ice/ Dense Fog			0.01	0.13	**0.52**	0.34
Full Ice/Light Fog			0.02	0.26	**0.54**	0.18
Full Ice/Heavy Fog			0.00	0.06	0.37	**0.57**
Full Ice/Dense Fog			0.00	0.03	0.22	**0.75**
Partial Ice/Light Fog	Segment Category 2	Low	0.14	**0.62**	0.21	0.03
Partial Ice/ Heavy Fog			0.03	0.37	**0.49**	0.11
Partial Ice/ Dense Fog			0.01	0.12	**0.50**	0.38
Full Ice/Light Fog			0.02	0.23	**0.55**	0.21
Full Ice/Heavy Fog			0.00	0.05	0.34	**0.61**
Full Ice/Dense Fog			0.00	0.02	0.20	**0.78**
Partial Ice/Light Fog	Segment Category 2	High	0.05	**0.47**	0.41	0.07
Partial Ice/ Heavy Fog			0.01	0.17	**0.54**	0.27
Partial Ice/ Dense Fog			0.00	0.04	0.31	**0.64**
Full Ice/Light Fog			0.01	0.09	**0.47**	0.44
Full Ice/Heavy Fog			0.00	0.02	0.16	**0.82**
Full Ice/Dense Fog			0.00	0.01	0.08	**0.91**

Chapter 6 Case Study

This chapter describes two case studies focusing on rainy weather conditions. The first case develops another Multi-ordered Discrete Choice model to improve the previous model in Chapter 5. The second case studies crash severity using an ordered probit model.

6.1 Modified MDCM under Rainy Condition

As discussed in Chapter 5, the model was developed by putting the five variables into the Multi-ordered Discrete Choice model in this research. Even though this research has derived some important factors from original questionnaires, they are not completely suited for risk evaluation under rainy weather conditions. For example, driver gender cannot be controlled by road managers, but traffic volume, vehicle type, and road choice can. Therefore, this case study selected Vehicle Type, Rain Level, Segment Category 2, and Traffic Volume as the independent variables. Another MDCM was built, and its parameters are shown in Table 35. All *p*-Values are less than the confidence level of 0.01, which are acceptable statistically.

Even though the parameters of this model are reasonable statistically, its precision was still tested and verified. A Prediction-Evaluation sheet may be adequate to test the fitting effect of the model. It puts the data of four independent variables into the second MDCM to calculate risk levels in different conditions and compares the results with the risk levels from the questionnaires.

Table 35 Parameter Estimation of the Case Study Multi-ordered Logit Model

Variable		Coefficient	Std. Error	z-Statistic	*p*-Value
x_1	Vehicle Type	0.938233	0.232200	4.040619	0.0001
x_2	Rain Level	1.422050	0.112270	12.66632	0.0000
x_3	Segment Category 2	1.141149	0.207098	5.510196	0.0000
x_4	Traffic Volume	0.808460	0.196316	4.118151	0.0000
Limit Points		***Value***	***Std. Error***	***z-Statistic***	***p-Value***
C1		3.416659	0.426172	8.017091	0.0000
C2		5.569498	0.484118	11.50442	0.0000
C3		7.617166	0.552054	13.79785	0.0000
Pseudo R-squared		0.325994	*p*-Value (LR statistic)		0.0000

As a result, the total percentage of correct estimations using the model is 73.5 percent, which has good quality to fit driver perception of driving safety risk levels. Therefore, valuating driving risks of roadway traffic under rainy weather conditions using a MDCM is reasonable and scientific.

Table 36 Prediction-Evaluation of New Multi-Ordered Discrete Choice Model

Dependent Value	Observations	Correct	Incorrect	% Correct
1	89	60	29	67.416
2	122	86	36	70.492
3	113	89	24	78.761
4	76	59	17	77.632
Total	400	294	106	73.500

Table 36 includes the number of observations, number of correct estimations and incorrect estimations, and percentage of correct estimations.

A determined function can be received if the parameters are input into the model, and based on the formula, risk levels and corresponding probability in different conditions can be calculated, as shown in Table 37. Bold values mean the largest probability in the same conditions.

$$Y^* = 0.9382x_1 + 1.4221x_2 + 1.1411x_3 + 0.8085x_4$$

$$Y = \begin{cases} 1 \quad if & Y^* \le 3.4167 \\ 2 \quad if & 3.4167 < Y^* \le 5.5695 \\ 3 \quad if & 5.5695 < Y^* \le 7.6172 \\ 4 \quad if & 7.6172 < Y^* \end{cases} \tag{24}$$

Table 37 Risk Levels and Corresponding Probability in Different Conditions

Rain Level	Vehicle Type	Seg.Category 2	Traffic Volume	Slight Risk	General Risk	Serious Risk	Catastrophic Risk
1	0	0	1	**0.79**	0.18	0.03	0.00
1	1	0	1	**0.59**	0.34	0.06	0.01
1	0	1	1	**0.54**	0.37	0.08	0.01
1	1	1	1	0.32	**0.48**	0.17	0.03
1	0	0	2	1.00	**0.62**	0.31	0.06
1	1	0	2	0.39	**0.46**	0.13	0.02
1	0	1	2	0.34	**0.48**	0.15	0.03
1	1	1	2	0.17	**0.47**	0.29	0.07
2	0	0	1	0.41	**0.45**	0.12	0.02
2	1	0	1	0.21	**0.49**	0.25	0.05
2	0	1	1	0.18	**0.48**	0.28	0.06
2	1	1	1	0.08	0.35	**0.42**	0.15
2	0	0	2	0.23	**0.49**	0.23	0.05
2	1	0	2	0.10	**0.40**	0.38	0.11
2	0	1	2	0.09	0.37	**0.41**	0.14
2	1	1	2	0.04	0.21	**0.47**	0.29
3	0	0	1	0.17	**0.47**	0.29	0.07
3	1	0	1	0.07	0.34	**0.43**	0.16
3	0	1	1	0.06	0.30	**0.45**	0.19
3	1	1	1	0.02	0.16	**0.45**	0.37
3	0	0	2	0.08	0.36	**0.42**	0.14
3	1	0	2	0.03	0.20	**0.47**	0.30
3	0	1	2	0.03	0.17	**0.46**	0.34
3	1	1	2	0.01	0.08	0.34	**0.57**
4	0	0	1	0.04	0.25	**0.47**	0.24
4	1	0	1	0.02	0.12	0.41	**0.45**
4	0	1	1	0.01	0.10	0.38	**0.50**
4	1	1	1	0.01	0.04	0.23	**0.72**
4	0	0	2	0.02	0.13	**0.43**	0.42
4	1	0	2	0.01	0.06	0.28	**0.65**
4	0	1	2	0.01	0.05	0.25	**0.69**
4	1	1	2	0.00	0.02	0.12	**0.85**

Note: (1) Rain Level: 1= Light Rain; 2= Moderate Rain; 3=Heavy Rain; 4= Rainstorm;(2) Vehicle Type: 0= Small Vehicle; 1= Large Vehicle;(3) Segment Category 2: 1= segments with horizontal and vertical curves; 0=others;(4) Traffic Volume: 1=Low Traffic Demand; 2=High Traffic Demand

Considering the coefficients of independent variables, the four variables all have a positive impact on risk levels of roadway traffic. Their influence degree, sorted in descending order, is Rain Level, Segment Category 2, Vehicle Type, and Traffic Volume. The following discusses the implication of these variables.

(1) Rainy weather would decrease driver visibility and pavement skid resistance. As rain gets more severe (rain level gets higher), driver visibility gets poorer and skid resistance becomes smaller, meaning that drivers may lose their control capability, resulting in potentially more traffic crashes.

(2) Roadway segment types have positive impacts on safety risk levels, meaning that when roadway geometrics and other conditions get worse, driving under rainy conditions could have more safety risks.

(3) The variable of Vehicle Type has a positive parameter, meaning that larger vehicles could have higher driving risks when it is raining. In fact, larger vehicles have relatively poor dynamic characteristics as compared to smaller vehicles. When it is raining, larger vehicles would need to a much longer braking distance to slow down or stop.

(4) The parameter for the Traffic Demand variable has a positive sign. This indicates that driving safety risk under rainy weather conditions could increase as traffic demand increases. In fact, the increase in traffic demand results in an increase in traffic density, which could increase the number of interactions between vehicles. When it is raining, such increase in traffic interactions could result in more driving safety risks.

In addition, risk levels and corresponding probability in different conditions are very important for road operation and risk management. First, road managers must know which risk level is most likely to occur. If a timely message can be released, drivers will be more careful, which means fewer accidents. Second, the results can help optimize emergency resource allocation. This means to spending less time for rescue and reducing accidents losses. Finally, the results can help managers take reasonable emergency measures. Based on differences in risk levels, they can determine effective measures to reduce driving risk. However, the probability of some risk levels is not different. The reason may be insufficient data from the sample. Increasing the number of the sample is considered a method to solve the problem.

6.2 Bridge-Related Crash Severity under Rainy Conditions

Crash data from of 459 crashes (May 2008–June 2010) were available, with specific information related to crash characteristics (crash time, crash duration, crash location, crash vehicle type, crash type and crash severity), meteorological elements (average, maximum and minimum temperature, average and maximum humidity, and average and maximum of wind speed) and traffic conditions (daily volume at five toll gates, daily volume of cross-bridge and noncross-bridge).

Bridge-related crash severity is divided into three categories: Slight Crash, General Crash, and Severe Crash, with the definitions based on:

(1) damage to bridge and roadway

(2) injury to occupant

(3) debris of vehicle

(4) occupancy of lane

(5) leak of hazardous goods

Table 38 shows a summary and definitions of all variables. In Table 38, many crash characteristics of the Sutong Bridge can be found. Most crashes happened from 8:00–20:00 because there were more vehicles on the bridge during those times. Crash duration varied in a large range, with mean and standard deviationof78.1 min and 138.24 min, respectively. About half of the crashes happened at toll gates.

Among all types of vehicles involved in the crashes, small-size vehicles had the highest percentage, followed by middle-size vehicles and large-size vehicles. There are three main crash types: Fixed-Object Crashes, Rear-End Crashes, and Scrape Collisions, with slight crashes being the majority and severe crashes being about 14 percent. It is noted that three variables in Table 1—CL, CVT, and CT—are all categorical variables.

In theory, for example, the variable Crash Location should be coded as three different dummy variables instead of 1, 2, 3, 4.If this kind of data processing is adopted, it is impossible to estimate parameters of the Ordered Probit model. So, based on the number of accidents, the three variables were coded as 1, 2, 3, 4 or 1, 2, 3. That is to say, categorical variables are meaningful and logical statistically in view of the number of crashes. The results of the model show that this kind of process is acceptable.

As shown in Table38, many factors related to bridge-related crashes were collected. These factors include the categories of Crash Characteristics, Meteorological Elements, and Traffic Conditions.

Table 38 Summary and Definitions of All Variables

Continuous Variables				
Variable Title	***Units***	***Mean***	***Std.Deviation***	***Min~Max***
Crash Duration	min	78.10	138.24	2~1371
Mean Temperature	℃	18.01	9.05	-2.00~35.32
MAX Temperature	℃	22.35	10.19	0.00~44.98
MIN Temperature	℃	14.43	9.05	-9.00~30.00
Mean Humidity	%rh	76.73	15.63	29.80~165.00
MAX Humidity	%rh	90.58	10.11	50.92~160.00
Mean Wind Speed	m/s	3.97	1.97	0.00~10.91
MAX Wind Speed	m/s	7.71	3.20	0.00~23.90
Daily Volume	1000pcupd	15.999	6.861	1.132~31.776
Discrete Variables				
VariableTitle	***Definition of Variables***	***Frequency***	***Percent %***	***Cumulative percent %***
Crash Time	(00:01~04:00)=1	27	5.9	5.9
	(04:01~08:00)=2	56	12.2	18.1
	(08:01~12:00)=3	99	21.5	39.6
	(12:01~16:00)=4	115	25.1	64.7
	(16:01~20:00)=5	106	23.1	87.8
	(20:01~24:00)=6	56	12.2	100.0
Crash Location	BridgeTower=1	32	7.0	7.0
	Approach =2	62	13.5	20.5
	Roadway=3	131	28.5	49.0
	Toll Gate=4	234	51.0	100.0
Crash Vehicle Type	Small-size V=1	317	56.9	56.9
	Middle-size V=2	198	35.6	92.5
	Large-size V=3	42	7.5	100.0
Crash Type	Fixed-object Crash=1	157	34.1	34.1
	Rear-end Crash=2	155	33.6	67.7
	Scrape Collision =3	118	25.6	93.3
	Others=4	31	6.7	100.0
Crash Severity	Slight Crash=0	226	49.2	49.2
	General Crash=1	169	36.8	86.0
	Severe Crash=2	64	14.0	100.0

In the past, for crashes that occurred on bridges, no specific evidence showed that these factors had good correlations with crash severity. Practically, there may be multi-collinearity among these independent variables, which is against the hypothesis of the ordered probit models.

Thus, it was necessary to select appropriate independent variables without significant multi-collinearity. To analyze the correlativity among continuous variables, the Pearson *r* should be used. For the same purpose, the Spearman correlation analysis should be used to analyze the correlativity between continuous-discrete pairs and between discrete pairs. Based on Pearson *r* calculations and Spearman analysis results, correlation coefficients for all variables are listed in Table 39. In the table, boldfaced numbers represent the variable pairs with significant correlations if the significant level 0.05 is used.

The table can be divided into four areas, with each area indicating useful information, summarized as follows:

(1) There are strong correlations among the variables such as Mean Temperature, Maximum Temperature, and Minimum Temperature. Similarly, the variables Mean Humidity and Maximum Humidity have a strong correlation, and the variables Mean Wind Speed and Maximum Wind Speed have a strong correlation. Meanwhile, there are weak correlations among Temperature, Humidity, and Wind Speed.

Table 39 Correlation Coefficients for All Variables

	CD	MET	MAT	MIT	MEH	MAH	MEWS	MAWS	DV	CTI	CS	CVT	CT	Severity
CD	1	0.028	0.017	0.048	0.014	0.042	0.047	-0.045	0.117	0.148	0.097	0.027	0.114	**0.337**
MET		1	**0.979**	**0.966**	0.078	0.061	**-0.357**	**-0.364**	0.124	0.060	0.007	0.100	0.075	**0.208**
MAT			1	0.914	0.194	0.135	**-0.354**	**-0.328**	0.113	0.069	0.019	0.131	0.085	**0.247**
MIT				1	0.053	0.096	**-0.294**	**-0.379**	0.119	0.078	0.007	0.075	0.058	**0.166**
MEH					1	**0.911**	0.000	0.036	0.039	0.086	0.098	-.021	0.138	**-0.160**
MAH						1	-0.066	0.051	0.077	0.050	0.093	0.030	**0.171**	0.013
MEWS							1	**0.826**	0.027	0.077	0.037	0.143	**0.161**	0.028
MAWS								1	0.057	0.106	0.036	0.034	**0.158**	**-0.169**
DV									1	0.093	**0.259**	**0.249**	0.020	**0.164**
CTI										1	**0.156**	0.061	0.114	-0.043
CL											1	**0.318**	**0.304**	**-0.341**
CVT												1	**0.190**	**-0.243**
CT													1	**-0.267**
Severity														1

(2) Humidity and wind speed influence on bridge-related crashes. Some similar conclusions were obtained in the past. In research by Khattak et al., it was found that single-vehicle and rear-end crashes were more likely to occur than two-vehicle and sideswipe crashes on wet roads. In another study by Baker, it was found that for the Leyland Atlantean bus, overturning crashes were much more likely to occur than other types of crashes in strong crosswinds.

(3) Crash location, vehicle type, and crash type influence each other. For example, in strong wind situations, middle-size vehicles are more likely to be involved in rollover crashes near bridge towers.

(4) Crash severity is associated with crash duration, temperature, mean humidity, maximum wind speed, daily volume, crash location, vehicle type, and crash type. Considering strong correlations among temperature factors, only one variable should be selected. In fact, the Sutong Bridge has a subtropical monsoon climate and there are very few days with low temperature below 0℃. Thus, Maximum Temperature was selected as an independent variable.

In conclusion, this study selected 8 independent variables out of 13 variables. These variables have good correlation with bridge-related crash severity, with no significant correlations among them. The eight independent variables are: Crash Duration, Maximum Temperature, Maximum Wind Speed, Mean Humidity, Daily Volume, Vehicle Type, Crash Location, and Crash Type.

The eight variables selected in the previous analysis were put into an ordered probit model, and the method of maximum likelihood estimation was used to calculate all parameters in the model. Estimation results are presented in Table 40. From the table, it is indicated that with a significance level of 0.05, coefficients of all variables, thresholds, and log likelihood ratios are significant. Meanwhile, a goodness-of-fit statistic, pseudo R-squared is equal to 0.208544, which is generally acceptable. In other words, the Ordered Probit model is adequate if these statistical indicators are considered.

The Ordered Probit model was also used to predict crash severity levels. Prediction results show that percentages of the correct prediction of slight crashes and severe crashes are higher than those of general crashes, which are 80.1and 76.6 percent, respectively. The overall percentage of correct prediction is about 75.2 percent. It can be seen that the fitness between the prediction results and original data are good and the model is acceptable.

Table 40 Ordered Probit Estimations for Bridge-related Crash Severities

Variable Title	**Coefficient**	**Std. Error**	**z-Statistic**	**p-Value**
CD	0.000524	0.000885	2.981771	0.0030
MAT	0.034805	0.013027	5.671676	0.0000
MEH	-0.008250	0.006293	-2.925955	0.0039
MAWS	0.012271	0.055620	2.320623	0.0134
DV	-0.008727	0.016192	-2.918888	0.0040
CL	-0.315101	0.110463	-9.852529	0.0000
CVT	-0.084700	0.181926	-2.465563	0.0115
CT	-0.216969	0.113231	-2.896192	0.0043
Limit Points	Value	Std. Error	z-Statistic	p-Value
C1	-1.189351	0.852376	-5.395336	0.0000
C2	-0.391517	0.848339	-3.461510	0.0014
Pseudo R-squared	0.208544	p-Value (LR statistic)		0.0001
Dependent Value	***Observations***	***Correct***	***Incorrect***	***% Correct***
0	226	181	45	80.1%
1	169	115	54	68.0%
2	64	49	15	76.6%
Total	459	345	114	75.2%

According to Table 40, the coefficients for three variables (Crash Duration, Maximum Temperature, and Maximum Wind Speed) have positive signs, meaning that these variables have positive impacts on bridge-related crash severity. The remaining five variables have negative impacts on crash severity. The following discusses the implication of these variables.

(1) The variable Crash Duration has a positive sign, meaning that if a crash takes a longer time to be cleared, the crash could be more severe. In a study by Chung, the similar conclusion was obtained.

(2) The variable Maximum Temperature has a positive impact on bridge-related crash severity. Actually, as temperature increases, the possibility of vehicle failure increases as well, and driver physical and psychological conditions may get worse, also. For example, a driver’s reaction time increases by 0.3s when the temperature increases from 23℃ to 27℃. If the speed of the car is

80km/h at this time, the corresponding brake distance increases by 7m, which may significantly increase the severity of the crash when the car is involved in a crash.

(3) The variable Mean Humidity has a negative sign. High humidity often occurs in rainy days. Rainy weather would decrease driver visibility and pavement skid resistance. However, under such conditions, drivers maybe more careful to control their speeds and keep longer spacing between vehicles. Thus, the chance for a severe crash may decrease. Similar research was conducted by Edwards, who found that crash severity decreased significantly in rain as compared with that in good weather condition.

(4) The variable Maximum Wind Speed has a positive impact on bridge-related crash severity. Strong wind could make vehicles sideslip and even lead to rollover crashes. Relevant studies show when the speed of crosswind is higher than 15.5m/s, the middle vehicle begins to sideslip. Particularly in bridge towers, severe crashes are more likely to occur.

(5) The variable Daily Volume has a negative impact on bridge-related crash severity. When traffic volume is large, vehicle speed is low and vehicle spacing is small, which make cars run in a more orderly fashion. Thus, the probability of severe crashes would decrease. A study by Martin found that hourly traffic flow has a negative impact on crash severity for crashes involving three or more vehicles.

(6) The variable Crash Location has a negative sign. Severe crashes are more likely to occur at bridge towers and on the bridge approach. One reason for

this is that the roadway environment close to the bridge approach is more complex, with the impacts of horizontal curves and longitudinal slopes. Shankar at al. also found that the length and number of horizontal curves may have a significant impact to the likelihood of a possible injury crash.

(7) The variable Vehicle Type has a negative parameter. Small-size vehicles are most vulnerable when involved in crashes with heavier vehicles as compared to other vehicle types, which means that occupants in small-size vehicles may get more severe injuries, as compared to occupants in a larger-size vehicle, without other conditions given.

(8) The variable Crash Type also has a negative parameter. Fixed-object crashes could result in severe crashes; rear-end crashes rank second in terms of severity, and scrape collisions would result in the least severity. Shankar at al. also found rear-end crashes and fixed-object crashes both had greater probability of possible injury as compared to property-damage-only crashes. However, they did not explain which type was more severe.

In addition, the Ordered Probit model considers impacts of non-observed variables such as driver behavior, and non-observed variables are assumed to fit standard normal distribution. Thus, the model is not only applied for identifying factors contributing to bridge-related crash severity, but also for predicting probabilities of different severity levels in different conditions. The detail of the model is shown as follows.

$$\begin{aligned} \mathrm{S} = {} & 0.000524 * CD + 0.034805 * MAT - 0.008250 * MEH + 0.012271 * MAWS \\ & - 0.008727 * DV - 0.315101 * CL - 0.084700 * CVT - 0.216969 * CT \end{aligned}$$

$$\begin{cases} \text{Severity\_0} = \Phi(-1.327236\text{-S}) \\ \text{Severity\_1} = \Phi(-0.529402\text{-S}) - \Phi(-1.327236\text{-S}) \\ \text{Severity\_2} = 1 - \Phi(-0.529402\text{-S}) \end{cases} \quad (25)$$

where, $\Phi(\cdot)$ represents a probability distribution function of standard normal distribution, and $\text{Severity\_0}, \text{Severity\_1}, \text{Severity\_2}$ are probabilities of slight, general and severe crashes, respectively. Thus, if the eight variables are put into the model, the corresponding probabilities of different severity levels can be estimated.

It is important to identify those factors that contribute to crash severity for safe and efficient bridge operations. The models to estimate crash severity can help managers develop effective measures to reduce crash severity. Also, prediction of the probabilities of different severity levels can be used to optimize emergency resource allocation.

This case study has identified those factors contributing to bridge-related crash severity and calculated probabilities of different severity levels under different weather conditions. For safe and efficient bridge operations, it is important to quantify the impacts of these factors on bridge-related crash severity. For example, bridge operators may need to predict where and under what weather conditions severe crashes could happen. The following discusses the specific conditions that may cause severe crashes (Severity=2).

First, based on the probability prediction model shown in Equation 25, independent variables are divided into crash information (*X1*) and environment information (*X2*). Crash information (*X1*) includes crash duration, crash location, crash vehicle type, and crash type. Environment information (*X2*) consists of temperature, humidity, wind speed and daily volume. The following equations are used to calculate *X1* and *X2*:

$$
\begin{aligned}
&X1{=}0.034805*MAT-0.008250*MEH+0.012271*MAWS-0.008727*DV \\
&X2=0.000524*CD-0.315101*CL-0.084700*CVT-0.216969*CT
\end{aligned} \tag{26}
$$

Then, it is assumed that severe crashes would happen when the probability of severe crashes is higher than 0.85. The relationship among crash information, environment information, and probability of severe crashes is shown in Figure 31. Figure 32shows the top view of Figure 31. According to Figures 31 and 32, the probability of severe crashes beyond the interface (p=85%) is higher than 0.85. Thus, specific conditions contributing to severe crashes are located in the triangle area in Figure 32. The area can be expressed by *X1* and *X2*.

$$
\begin{cases}
X1+X2\geq 0.507031 \\
X1\leq 0.101634 \\
X2\leq 1.621002
\end{cases} \tag{27}
$$

If the multiple inequalities group can be solved, specific conditions contributing to severe crashes can be obtained. However, it is impossible to calculate the exact solution of the group because there are too many independent variables.

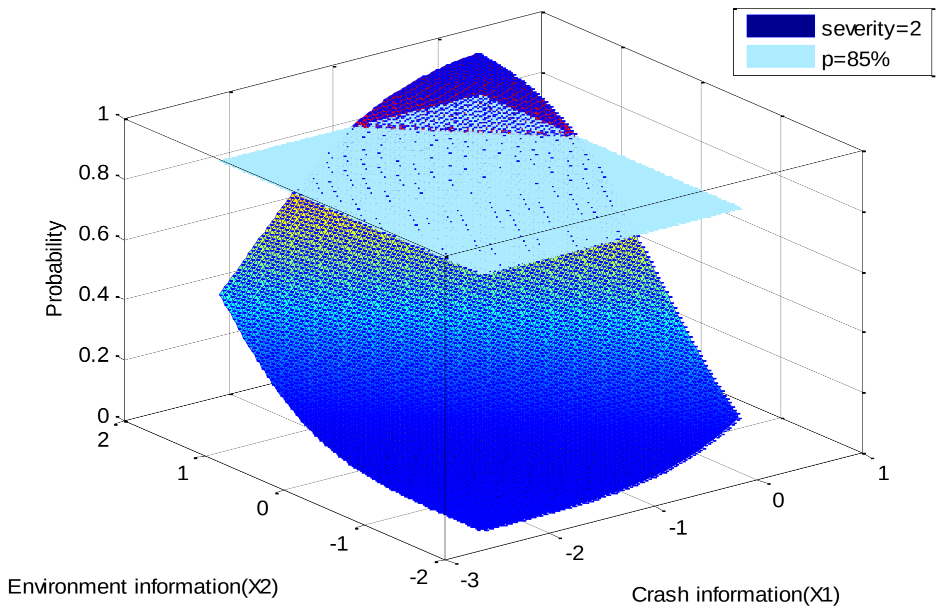

Figure 31 Probability of Severe Crashes and Interface (p=85%)

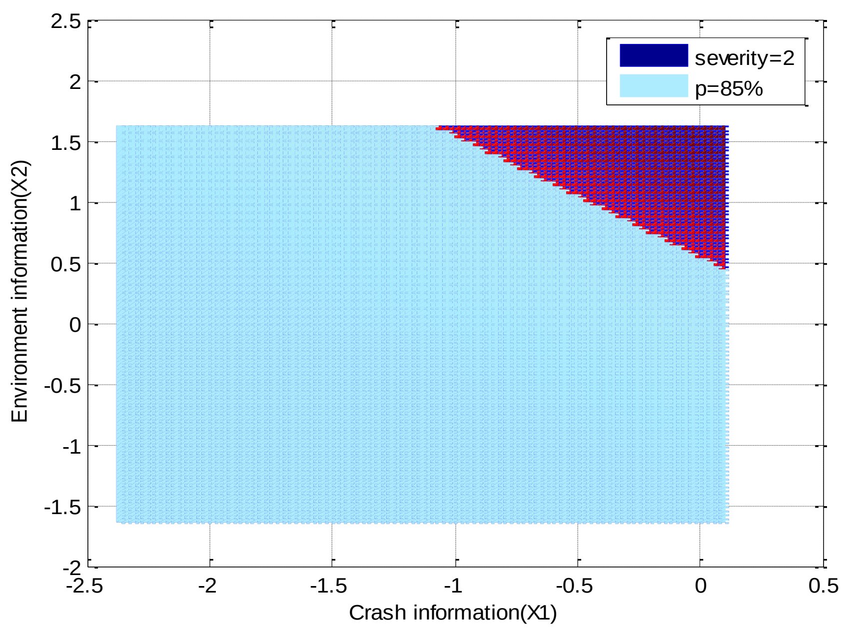

Figure 32 Top View of Figure 31

To solve the problem practically, the iterative method is considered as an alternative method. Based on maximum, minimum, and standard error of the sample, a step-size of every variable can be determined, as shown in Table 41.

Table 41 Step-size of Every Independent Variable

Variable Title	Range	Step-size
CD	0~720min	120min
CS	1,2,3,4	---
CVT	1,2,3	---
CT	1,2,3,4	---
MAT	0~50℃	10℃
MEH	30~120%rh	15%rh
MAWS	0~24m/s	4m/s
DV	1~36 (1000pcupd)	5 (1000pcupd)

The number of iterations of the eight variables is 790,272 ($7\times4\times3\times4\times6\times7\times7\times8=790272$) in total, and there are 14,219 records that meet the multiple inequalities group. Based on distribution of these records, specific conditions resulting in severe crashes can be received. For example, it is found that the value of crash location is not equal to 4, meaning that severe crashes do not occur at toll gates. Figure 33 and 34 represent frequency distribution of crash information and environment information respectively, when severe crashes occur. According to Figures 33 and 34, four variables, including Crash Location, Crash Type, Maximum Temperature, and Mean Humidity, vary in a large range. Thus, they have greater impacts on bridge-related crash severity than the other four variables of Crash Vehicle Type, Crash Duration, Daily Volume, and Maximum Wind Speed. Other important conclusions can be received as follow.

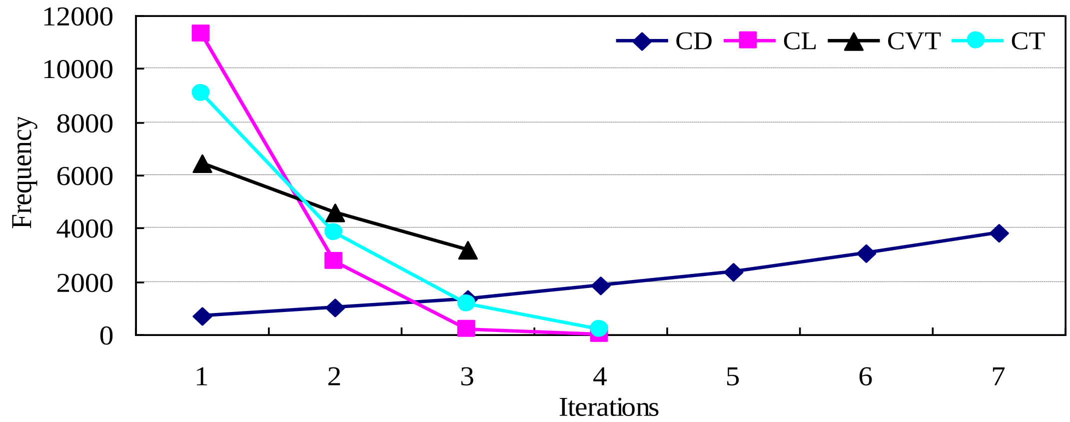

Figure 33 Frequency Distribution of Crash Information

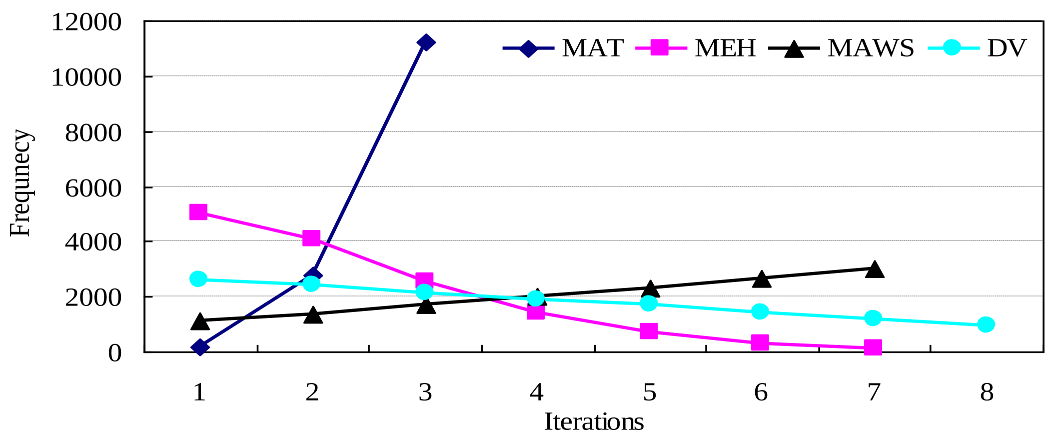

Figure 34 Frequency Distribution of Environment Information

(1) Collisions with fixed-objects and rear-end crashes on basic roadways can result in severe consequences when the maximum temperature is more than 40℃ and the mean humidity is less than 75%rh. Under such conditions, crash duration is a significant factor affecting bridge-related crash severity.

(2) Collisions with fixed-objects, rear-end crashes, and crash collisions at the bridge approach are dangerous and severe when the maximum temperature is more than 30℃ and the mean humidity is less than 105% rh.

(3) A middle-size vehicle is more likely to be involved in severe crashes in bridge tower areas when the maximum temperature and wind speed are more than 30℃ and 16 m/s, respectively.

Chapter 7 Conclusions

In this study, the driving risk of six severe weather conditions and three dual severe weather conditions were evaluated separately. The results may help the Bridge Operations Management Department to predict and warn drivers before severe weather conditions occur and optimize emergency resource allocation when accidents occur. Detailed conclusions are as follows:

The concepts of risk and accident are different. High risk may not result in a high crash rate. If drivers can be informed and pay more attention to their driving behaviors when severe weather conditions occur, accidents, especially serious accidents, can be avoided.

As discussed previously, most past studies related to safety analysis of roadway safety under severe weather conditions have been based on historical crash data, which are difficult to obtain in areas such as China. Evaluating the driving risks of roadway traffic under rainy weather conditions using a Multi-ordered Discrete Choice model could be an alternative to replace current crash analysis approaches.

In addition, a questionnaire survey of subjective data might be a good alternative data collection method when there is a lack of historical data. The accuracy of results depends on the quality of questionnaire survey, and the respond rate of the questionnaire survey is not absolutely associated with results accuracy.

Compared to a normal highway, strong wind contributes more risk probability in a long-scale highway bridge. Wind level in a long-scale highway bridge usually is much higher than that in nearby highway road due to the bridge crossing the river. If strong winds are combined with accidents with vehicles carrying hazardous materials, it may increase the risk level significantly if the wind pulls the hazardous materials into the river.

Fog decreases driver visibility significantly. When foggy and icy conditions occur together, they may lead to the most severe risks among all severe weather conditions.

High temperatures may not create a high level risk, but their negative impacts still cannot be ignored, especially when involved in an emergency event such as an oil leaking accidents.

Bridges differ from most surface streets and highways in terms of their physical properties and operational characteristics. Bridge-related crashes, particularly severe crashes, area significant percentage of the total crash experience, and the severity of bridge-related crashes is higher than the severity of all crashes. Practically, for safe and efficient bridge operations, it is important to know under what conditions severe crashes are more likely to occur, which can aid in the development of effective measures to reduce crash severity and optimize emergency resource allocation.

Chapter 8 Limitations and Future Work

Emergency rescue management for long-scale highway bridges is a complex system research area that involves varied subjects. Some limitations must be considered, and the following study areas could be further investigated:

(1) Only severe weather conditions are studied in this research; they could be combined with other emergency events, such as wind with hazardous materials and high temperatures with oil leaking.

(2) The design of a survey impacts the accuracy of results significantly. Some methods could be added to the questionnaire to improve the quality of the survey, including pretest, behavior coding, or cognitive interviewing.

(3) Weight value in the judgment matrix of the focus group method may change with the development of new technologies. The focus group method in this research considered disaster weather conditions only; traffic volume, location, and time could be integrated in the future.

(4) In this research, driver attributes were not selected as independent variables, and driver attributes are assumed to fit standard normal distribution.

(5) Six types of severe weather conditions are considered in this research. Other types of disaster weather may occur in the future, and their consequences cannot be ignored even if have very low frequency.

References

Abdel-Aty, M., Analysis of Driver Injury Severity Levels at Multiple Locations Using Ordered Probit Models, *Journal of Safety Research*. Vol. 34, No. 5, 2003

Agent,K. R. Crash Associated with Highway Bridge. Presented at the 54th Annual Meeting of the Transportation Research Board, Washington, D.C., 1975.

Agent, K. R., and Deen, R. C. Highway Crashes at Bridges. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 601, Transportation Research Board of the National Academies, Washington, D.C., 1976, pp. 83-85.

Andrey, J. and Yagar, S., A Temporal Analysis of Rain-related Crash Risk, *Journal of Accident Analysis and Prevention*, Vol. 25, 1993, pp. 465-472.

Andrey, J., Mills, B., and Vandemolen, J., *Weather Information and Road Safety*, A Report to the Institute for Catastrophic Loss Reduction, University of Western Ontario, August 2001.

Benham, J., and Laguros, J.G.Crashes and Roadway Geometries at Bridge Approaches. *Public Works*, April, 1973, pp.67-70.

Billot, R., El Faouzi, N.-E., Sau, J. and De Vuyst, F., How Does Rain Affect Traffic Indicators? Empirical Study on a French Interurban Motorway, In *Proceedings of the Lakeside Conference*. Klagenfurt, Austria, 2008.

Brinkman, C. P., and Mak, K. K. Crashes Analysis of Highway Narrow Bridge Sites. In *Public Roads: Journal of the Transportation Research Board*, No. 4, Transportation Research Board of the National Academies, Washington, D.C., 1986, pp.127-133 .

Brodsky, H. and Hakkert, A. S., Risk of a Road Accident in Rainy Weather, *Journal of Accident Analysis and Prevention*, Vol. 20, No. 3, 1988, pp. 161-176.

C.J. Baker. The Quantification of Crash Risk for Road Vehicles in Cross Winds.*J. Wind Eng. Ind.Aerodyn*, Vol. 52, 1999, pp. 93-107.

C.J. Baker. A Simplified Analysis of Various Types of Wind-induced Road Vehicle Crashes.*J. WindEng. Ind. Aerodyn,*Vol. 22, 1986, pp. 69-85.

Codling, P., Weather and Road Accidents, *Journal of Climatic Resources and Economic Activity*, Newton Abbot, England: David and Charles Holdings, 1974, pp. 205-222.

Department of Transportation of China, *Technical Standards for Highway Engineering: JTG B01-2003*, Publisher of China Standards, January 2004.

Eisenberg, D., The Mixed Effects of Precipitation on Traffic Crashes, *Journal of Accident Analysis and Prevention*, Vol.36, No. 4, 2004, pp. 637-647.

Evans, J. Road Crashes Involving Bridges and Culverts. In *Research Report: Journal of the Transportation Research Board*, No. 303, Transportation Research Board of the National Academies, Washington, D.C., 1997,pp. 16.

FHWA, *Road Weather Management Overview*, http://ops.fhwa.dot.gov/weather/overview.htm, 2008.

Goodwin, L. C., *Weather impacts on Arterial Traffic Flow*, Mitretek Systems, Inc., December 2004.

Gunnerson H.E., Narrow Bridge Study, Iowa State Highway Commission, Ames, Iowa, Feb. 1961.

Hill, J. D., and Boyle, L. N., Assessing the Relative Risk of Severe Injury in Automotive Crashes for Older Female Occupants, *Journal of Accident Analysis and Prevention*, Vol. 38, No. 1, 2006, pp. 148-154.

Hollingworth, G. H. Road Crashes at Bridge Sites--Their Nature and Difficulties with Their Prediction. In *Institution of Engrs, Aust Queensland Div Tech Pap: Journal of the Transportation Research Board*, No. 7, 1983, pp.11-18.

Jorgensen. R. *Cost and Safety Effectiveness of Highway Design Elements*. National Cooperative Highway Research Program Report No. 197, Transportation Research Board, National Research Council, Washington, D.C., 1978.

Jung, S., *Modeling Highway Safety and Operational Impacts of Rain*, A Ph.D. Dissertation, University of Wisconsin–Madison, 2010.

Jung, S., Qin, X., and Noyce, D. A., Rainfall Effect on Single-vehicle Crash Severities Using Polychotomous Response Models, *Journal of Accident Analysis and Prevention*, Vol. 42, 2010, pp. 213-224.

Khorashadi, A., Niemerier, D., Shankar, V., and Mannering, F. L., Differences in Rural and Urban Driver-injury Severities in Accidents Involving Large-trucks: an Exploratory Analysis, *Journal of Accident Analysis and Prevention*. Vol. 37, No. 5, 2005, pp. 910-921.597-603.

King, L Ellis, and Plummer, R W. Lateral Vehicle Placement and Steering Wheel Reversalon A Simulated Bridge of Variable Width. In *Highway Research Record: Journal of the Transportation Research Board*, No. 432, Transportation Research Board of the National Academies, Washington, D.C.,1973,pp. 61-69.

Mak, K. K. Effect of Bridge Width on Highways Safety. In *State-of-the-Art Report: Journal of the Transportation Research Board*, No. 6, Transportation Research Board of the National Academies, Washington, D.C., 1987, pp.22-35.

Maze, T. H., Agarwal, M., and Burchett, G., *Whether Weather Matters to Traffic Demand, Traffic Safety, and Traffic Flow.* Center for Transportation Research and Education, Iowa State University. Final General Report [DOT F 1700.7 (8-72)], August 2005.

Palutikof, J. P., Road Accidents and the Weather, *Journal of Highway Meteorology*, London, 1991, pp.163-189.

Qin, L. and Shao, C., Traffic Crash Analysis of Ji-Qing Freeway, *Journal of Shandong Transportation College*, Vol. 11, No. 3, 2003, pp. 23–36.

R.H. Scanlan, and N.P. Jones. Aeroelastic Analysis of Cable-stayed Bridges. In *Structural Engineering: Journal of the Transportation Research Board*, No. 2, Transportation Research Board of the National Academies, Washington, *D.C.*, 1990, pp. 279-297.

Roberts, R. R. Effect of Bridge Shoulder Width on Traffic Operational Character. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 601, Transportation Research Board of the National Academies, Washington, D.C.,1976, pp. 73-75.

Sherretz, L. A., and Farhar, B. C., An Analysis of the Relationship between Rainfall and the Occurrence of Traffic Accidents, *Journal of Applied Meteorology*, Vol. 17, 1978, pp. 711-715.

S. Timoshenko,D.H. Young, and W. Weaver, *Vibration Problems in Engineering (4th Edition).* John Wiley & Sons, New York, 1974.

Smith, K., How Seasonal and Weather Conditions Influence Road Accidents in Glasgow, *Scottish Geographical Magazine*, Vol. 98, 1982, pp. 103-114.

Turner, D. S., and Rowan, N. J. Investigation of Crashes on Alabama BridgeApproach. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 847, Transportation Research Board of the National Academies, Washington, D.C.,1982, pp. 1-6.

Wang, B., Xie, J., and An, H., Analysis of the Impacts of Weather Conditions on Traffic Accidents in Changchun City and Traffic Prediction Systems, *Journal of Jilin Weather*, Vol. 1, 2004, pp. 26 – 29.