Weight-based Traffic Safety Risk Management On
Hazy/Foggy Weather Conditions

Final report

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ABSTRACT

The characteristics and car-following behavior of traffic flows are the fundamental knowledge in the investigation of traffic safety risk assessment. The data driven approach, with the risk assessment techniques, are used in this project to carry out the investigation of the weight-based traffic safety risk management on hazy/foggy weather conditions.

Firstly, a high fidelity driving simulator is used for conducting some experiments to investigate the impacts of the hazy/foggy weather conditions on driving behaviors. The scenarios with clear and haze weather conditions and two driving simulator fidelities are set up for the investigation, for which the weather conditions are defined by the visibilities. The impacts of the hazy/foggy weather conditions and the fidelity of driving simulators on the driving behavior are investigated and the associated car-following models are set up.

Secondly, on the basis of amount of empirical Weigh-in-motion (WIM) traffic data, this project proposes novel weight- and TTC-based traffic safety risk indicators, integrating the load information. The relationships between the loading characteristics and the traffic risk are investigated.

Thirdly, based on the car-following model and the weight-based traffic safety risk indicators, the Cellular Automaton (CA) is presented for traffic load modeling. The key critical sections like bridge and tunnels along the
roads are selected for the application of the proposed traffic safety risk model.

The main conclusions of this project includes, a) a novel tool incorporating the traffic load information into the traffic safety risk analysis has been proposed; b) a set of tools of weight-based traffic safety risk assessment on hazy/foggy weather conditions have been set up; c)a dynamic traffic safety risk contour for the case study sections along the roads is determined.

The proposed traffic safety risk management in this project help improve traffic safety on hazy/foggy weather conditions.

**Keywords:** Load characteristics, Driving behaviors, Traffic safety risk assessment, Cellular automata simulation, Hazy/Foggy Weather Conditions
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1. Introduction

According to the World Health Organization (WHO), more than a million people are killed on the world’s roads each year\[1\]. The problem is all the more acute because the victims are typically healthy prior to their crashes. Thus, over the past few decades, road traffic safety has been upheld as an important research topic and attracted increasing attentions. China, a region with complex topography and strongly influenced by Asian monsoon circulation, is especially vulnerable to frequent weather and climate disasters. In recent years, China has suffered from increased severe haze events that have had strong impacts on society, the ecosystem, human health, and transportation systems. For example, hazy/foggy weather, occurred in Northeast China on October 21, 2013, led to high levels of casualties, severe accidents, etc. The main reason is that the visibility in hazy/foggy weather condition is fairly low, normally less than 100m. As a consequence, most freeways in the haze weather affected area are closed to prevent traffic accidents, which however had negative impacts on travel efficiency. On 6 November, 2016, Shanghai suffered a heavy hazy/foggy weather condition, which lasted for at least six hours with visibility of less than 200 meters. Nine people were killed and another 43 injured in two accidents involving multiple vehicles along an expressway. Increasing attentions have been paid to the issue of haze/fog by both the public sectors and the general public.
On the one hand, from the public sectors’ perspective, alert systems of traffic safety risk on hazy/foggy weather conditions should be prepared for managing their trips; one the other hand over the past few decades, heavy vehicles and overloading are gaining momentum, having become one of leading causes of road traffic crashes. Overloading traffics is becoming the main cause of traffic safety (especially in China) \(^2\). The studies of the influence of the vehicles’ loading characteristics on road traffic safety are still limited. One of the main reasons is the difficulty in collecting the information of heavy vehicle and overloading. The development of Weigh-in-Motion (WIM) technology provides the empirical traffic data for the research of vehicles’ weight and overloading. Through the embedded coil and pressure sensor in the pavement, a series of information about the vehicles can be detected (contains: the speed, axle weight and gross weight of each vehicle, and the time headway, traffic volume, etc.). The characteristics and car-following behavior of traffic flows are the fundamental knowledge in the investigation of traffic risk assessment. The weight-based traffic safety risk management on hazy/foggy weather conditions will enhance the traffic safety level. Amount of traffic safety studies focused on the characteristics of traffic flow and the simulation of driving behaviors (through which some safety indicators like TTC, DRAC, DTS, etc. were used). The studies of the influence of the vehicles’ loading characteristics on road traffic safety are
still limited. One of the main reasons is the difficulty in collecting the information of heavy vehicle and overloading.
2. Methodology

The traditional traffic safety risk management do not take the effects of the traffic load into account, thus it is difficult to capture the real traffic safety risk situation. Furthermore, the weather condition is an important factor impacting the traffic safety risk. Therefore, it is necessary to conduct the weight-based traffic safety risk management on hazy/foggy weather conditions. Based on the simulated data and empirical data, the weight based traffic safety risk indicators and the associated risk management can be determined.
2.1 Driving Simulation based on the High Fidelity Driving Simulator

2.1.1 Apparatus

Fidelity is an intrinsic element of driving simulators, influencing the validity and credibility of simulation results\textsuperscript{[3]}. It is noted that fidelity of driving simulator actually influences the driving behavior during experiments\textsuperscript{[3, 4]}. High-level driving simulator with high fidelity is preferential if possible. The study was conducted using high fidelity Tongji Driving Simulator System shown in Figure 1(a). The simulator system consists of a fully instrumented actual car (Renault MeganeIII) housed inside a dome and high fidelity visual system. A front view of 250 degrees horizontally and 40 degrees vertically is produced by a 5-projector immersive cylindrical projection system. This simulator has an 8-DoF motion system (6-DoF + lateral movements across a 5*20 meter grid) which could provide immersive forces during driving. The SCANeR\textsuperscript{TM} studio software is used to set up experimental scenarios and manipulate all aspects of the system\textsuperscript{[4]}.

2.1.2 Scenarios

The scenarios are set up to simulate different visibility environment in daytime under different weather conditions including clear weather (CW)
and hazy weather (HW) conditions. The visibility denotes the longest distance from which the driver can recognize the existence of target object (vehicle) under specific haze concentration. The visibility under clear weather is larger than 1000m (Figure 1 (b)) and that under hazy weather condition is 80m (Figure 1 (c)) which is a representative visibility under thick-foggy weather according to the classification of hazy weather levels in China. The SCANeR™ studio software is equipped to simulate the low visibility under hazy weather conditions. However, the set visibility in SCANeR™ is not the same as real visibility that drivers experience in simulator. For instance, the set visibility in SCANeR™ is 200m, but the real visibility in simulator is about 50m actually. Thus, a calibration process is executed to ensure that the real visibility in simulator under hazy weather condition is 80m.

The experimental roads in scenarios are bidirectional four-lane highway (two lanes in one direction) with a speed limit of 110km/h. The trajectory of lead vehicle is preset according to research purposes and set to be longitudinal driving including three car-following stages (acceleration, steady and deceleration) without lane changes as Figure 1 (d) shows. The trajectory is guaranteed to be in line with actual driving behavior avoiding unreasonable acceleration, deceleration or other aggressive driving.
behaviors. An example of speed as a function of time slots of lead vehicle and experimental vehicle during experiment is illustrated in Figure 1 (d). Traffic flows around experimental vehicle are set as illustrated in Figure 1 € to simulate the road environment. The vehicle in black circle is the experimental vehicle manipulated by experimenters. The vehicle in red circle is the lead car with preset trajectory. The vehicle in yellow circle has the same trajectory as the lead car in red circle and followed by vehicles in green rectangle which are controlled by SCANeR™ studio software automatically with a safe headway of 3 second. The vehicle in blue circle is set to follow the experimental vehicle automatically with a safe headway of 3 second. The vehicles in yellow rectangle are set to simulate the traffic flow in the opposite way. The participants manipulated experimental vehicle and were required to follow the lead vehicle without lane change.

(a) High fidelity driving simulator in Tongji University
2.1.3 Procedure, Date Collection and Participants

The experiment procedure includes four steps: 1) inform and train the drivers how to use the driving simulator; 2) the drivers use the driving simulator on a specific highway for about 5 minutes to get familiar with the simulator; 3) take a break for few minutes and execute the CF
experiments under clear weather conditions; 4) take a break for few minutes and execute the CF experiments under hazy weather conditions. To eliminate the influence of experiment order, half of the participants conducted experiments under the hazy weather first and then under clear weather condition. The duration of each scenario is about six minutes.

The variables of the driving behaviors including the speed, acceleration rates of the following and lead vehicles, spacing, the throttle force and the brake pedal force were recorded at the frequency of 10HZ by the simulator system automatically during experiments.

20 participants (eighteen males and two females) were initially recruited from the population of licensed drivers in Shanghai. The average age of experiments is 39.8 with a range from 36 to 44. On average they have a driving experience of 9.4 years, ranging from 6 to 13 years. It can be seen in Figure 1 (d) that each experimenter’s trajectory under each weather condition contains several CF stages. Taking advantage of the abundant trajectory data, we extracted three acceleration stages, three deceleration stages and three steady stages from the whole trajectory of each experimenter under each weather condition to enlarger the samples. Thereby, the sample of every CF stage under each weather condition is 60(3*20). To insure the veracity of identification of different CF stages,
all the extracted process are accomplished manually since the formerly proposed mechanism to identify different regimes\textsuperscript{[5, 6]} of car-following were tested to be not as reliable as manual identification.

2.2 WIM Technology and the Data Acquisition Process

2.2.1 WIM Technology

Figure 2 illustrates the layout of a typical WIM system. In particular, the load of a moving vehicle is estimated based on the dynamic tire force measurement by the coil and pressure sensor embedded on the pavement surface. Therefore, series of synchronized vehicular speed, gross vehicle weight, and vehicle class data can be recorded. The data used for traffic analysis in the proposed study are obtained from highways in Guangdong Province, China. This highway is a principal gate connecting Guangzhou and the surrounding cities and has been in service for over 10 years.

![Figure 2 WIM scale in place](image)
WIM is the process of measuring the dynamic tire forces of a moving vehicle and estimating the corresponding tire loads of the static vehicle. The performance of any WIM system is dependent on road conditions, road geometry, and vehicle condition. Quantifying the accuracy of a WIM system is more difficult than assigning an accuracy to a static scale. With a static scale, the axle, axle group, or vehicle is placed on the scale. The force of that axle, axle group, or vehicle is constant while it is motionless on the scale. The only factor affecting the accuracy of the determined weight is the scale itself. With repeated testing and calibration, an accuracy level for every vehicle can be determined.

One of the purposes behind the development of WIM technology was the ability to measure the actual loads being applied to a roadway by a moving truck. It was felt that this would more accurately represent what the pavement is subjected to than a static weight. However, the calculated static weight is still the value used in evaluating accuracy and in recording traffic information. Although there is a definite relationship between static weights and applied loads, there are many other factors introduced.

The actual load applied by a vehicle includes much more than the weight of the vehicle. As a vehicle travels, the dynamic load applied to the road varies significantly due to the vehicle bouncing, acceleration or
deceleration, and shifting of the load either physically or just in its distribution through the suspension system. The combination of all these loading factors is what is actually measured by a WIM system. In addition to the error in the measuring device which is also present in a static scale, there is a second error due to the dynamic effects of weighing a vehicle at high speeds. Figure 3 illustrates the difference between weighing statically and dynamically.

![Figure 3 Static and Dynamic Weighing](image)

Various techniques are applied to the WIM weights being measured to minimize the effects of vehicle dynamics, but they can not be totally eliminated. Because of the effects of vehicle dynamics, the accuracy level of any WIM system is lower than that for a static scale used for enforcement weighing. It is also not possible to quote an absolute accuracy
for a WIM scale. Therefore, any WIM accuracy is always quoted as a percentage accuracy with a confidence level. The confidence level is typically set at either 68% or 95%. ASTM accuracy uses the 95 % level. This means that 95 % of measured WIM values will fall within the stated accuracy level.

The number of WIM sensors and scales available has increased over the last few years as attempts are made to increase performance and reduce costs. There are three traditional WIM technologies which are the most widely accepted and used in North America [7]:

**Piezoelectric Sensors**

The most common WIM sensor for data collection purposes is the Piezoelectric sensor. The basic construction of the typical sensor consists of a copper strand, surrounded by a piezoelectric material, which is covered by a copper sheath. When pressure is applied to the piezoelectric material an electrical charge is produced. The sensor is actually embedded in the pavement and the load is transferred through the pavement. The characteristics of the pavement will therefore affect the output signal. By measuring and analyzing the charge produced, the sensor can be used to measure the weight of a passing tire or axle group. There are a number of variations on the shape, size and packaging of the sensors produced to
obtain better results, easier installation, and longer life. This discussion will treat piezoelectric sensors as a general group, rather than particular products.

For a complete data collection system, it is common to install two inductive loops and two piezoelectric sensors in each lane which is being monitored. Installation begins by making a relatively small cut in the road into which the sensor will be installed. The size of the cut varies depending on the sensor being installed, but is generally 1”-2” deep and 1” to 2” wide. The sensor is placed in the sawcut and secured in place by a fast curing grout. A complete lane installation consisting of two sensors and two loops can be accomplished in less than a full day, including curing time.

When properly installed and calibrated, a piezoelectric WIM system should be expected to provide gross vehicle weights that are within 15% of the actual vehicle weight for 95% of the trucks measured.

**Bending Plate Scale**

The bending plate scale uses a different approach to determine vehicle weight. The bending plate scale consists of two steel platforms which are each 2’ x 6’, placed adjacent to each other to cover a 12’ lane. The steel plate is instrumented with strain gages at critical points to measure the strain in the plate as a tire or axle passes over. The measured strain is
analyzed to determine the axle load. The Bending Plate scale is typically installed in a lane with two inductive loops and an axle sensor to provide vehicle length and axle spacing information.

There are two basic installation methods for a Bending Plate scale. In concrete roadways of sufficient depth, a shallow excavation is made in the surface of the road. The scale frame is anchored into place using anchoring bars and epoxy. In asphalt roads or thin concrete roads, it is necessary to install a concrete foundation for support of the frame. The roadway is cut and excavated to form a pit of 30” deep by 4’10” wide by 13’10” long. The frame is positioned in place and then is cast into the concrete to form a secure and durable foundation for the scale.

![Figure 4 Staggered bending plate and inductive loops of WIM system](image)

Installing a complete lane of scales, loops and axle sensor can be accomplished in a day using the shallow excavation method and in 3 days
using the concrete vault.

When properly installed and calibrated, Bending Plate WIM system should be expected to provide gross vehicle weights that are within 10% of the actual vehicle weight for 95% of the trucks measured.

**Single Load Cell Scale**

The Single Load Cell Scale consists of two weighing platforms with a surface size of 6’ by 3’2”, placed adjacent to each other to fully cover a normal 12’ traffic lane. A single hydraulic load cell is installed at the center of each platform to measure the force applied to the scale. The load measurements are recorded and analyzed by the system electronics to determine tire and axle loads.

The installation of a single load cell scale requires the use of a concrete vault, as explained earlier for the bending plate scale. The size of vault required is slightly larger, measuring 165” by 58” by 34”.

The Single Load Cell scale is typically installed in a lane with two inductive loops and an axle sensor to provide vehicle length and axle spacing information. Installing a complete lane of scales, loops and axle sensor can be accomplished in 3 days.

When properly installed and calibrated, Single Load Cell WIM system should be expected to provide gross vehicle weights that are within 6% of
the actual vehicle weight for 95% of the trucks measured.

The use of WIM systems to collect truck weight data in the United States can be traced back to the early 1950s. One of the earliest examples was a WIM system developed in 1951 by Norman and Hopkins at the U.S. Bureau of Public Roads \[7-9\]. A Bridge-WIM (B-WIM) system uses the measured responses of a bridge (usually strain) to determine the weight and other characteristics of crossing trucks. B-WIM was first used to measure vehicle weight in the 1970s\[9\]; the data acquisition hardware and software of B-WIM have been continuously developed since then. In the mid-1980s, China began to use the WIM technology in Shanxi Province to detect the coaler, but the accuracy of measurement was quite low. The utility of the earliest WIM systems was severely limited by the sensing, signal conditioning, and data acquisition technologies available at the time.
Modern WIM systems are largely unencumbered by the technology limitations of the past and can effectively capture and record the axle or axle group weights and the GVW while the vehicle is moving at normal highway speeds.

With the advance of indicator accuracy, some researches about the vehicle load (based on WIM technology) were carried out: O’Brien and O’Connor\textsuperscript{[10, 11]} established a model based on the WIM data from a specific location for regional vehicle load assessment; Cremona and Carracilli\textsuperscript{[12]} checked the specification subentry coefficient and the assessment model of the vehicle load; Nowak and Rakoczy\textsuperscript{[9]} established the load model of bridge design using the WIM data from several regions; Enright et al. proved that the parameter errors of the current WIM equipment in different road conditions has reached only $\pm 3\%$ \textsuperscript{[13, 14]}, meeting the requirements of vehicle information research under different conditions.

Thus, the applications of WIM data are limited to traditional mechanical at present, concentrated on the bridge of civil engineering, and short of systematic research about the WIM data from the traffic angle (especially on traffic risk assessment studies).

2.2.2 The Process of the WIM Data

• Speed
Due to the existence of measurement error, there will be several speed values obviously does not conform to the actual situation. We use the allowed maximum instantaneous speed to eliminate the outliers and choose the space average speed to calculate the speed value.

**Time Headway and Vehicle Length**

As the WIM equipment can not only record the car models, speed and other information, but also record the number of axles and weights of each axles for each vehicle. So if the two vehicles get too close, the WIM equipment may “make mistake” and record two vehicles as one; if the wheelbase is too long, the WIM equipment may also make mistake and record one vehicles as multiple vehicles. So we can determine whether the WIM data is error based on the time headway and vehicle length and correct those data.

**Classification and Overloading Criterion**

To reflect the difference between each type of vehicles, we need to group all the data by vehicle characteristics. Considering the two kinds of typical problem in road traffic load effect (asphalt pavement performance and the vehicle load effect of bridge structure), the influences of vehicle’ axle type are both assignable. And to facilitate the data processing, the vehicle data are divided into 5 groups by the axle type. According to the standard of
load limit set out by the Chinese road authority and Highway Capacity Manual (HCM), vehicles can be stratified into five classes, according to the number of axle. Table 1 shows the load limits of different vehicle classes. Define the vehicles having two axles as two-axle vehicles and define the vehicles having three and more axles as multiple-axle vehicles.

<table>
<thead>
<tr>
<th>Vehicle Type</th>
<th>two-axle</th>
<th>3-axle</th>
<th>4-axle</th>
<th>5-axle</th>
<th>6-axle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load Limit/ ton</td>
<td>20</td>
<td>30</td>
<td>40</td>
<td>50</td>
<td>55</td>
</tr>
</tbody>
</table>

**Parameter Definition**

There are two parameters need to define:

*Overloading Ratio (OR)*: Microscopic concept, for a specific vehicle \(i\):

\[
OR_i = \left(\frac{W_i - W_l}{W_l}\right) \cdot 100\%.
\]

Where \(W_i\) is the weight of vehicle \(i\), \(W_l\) is the weight limit of vehicle \(i\), \(OR_i\) is the overloading ratio of vehicle \(i\);

*Average Weight*: Macroscopic concept, the arithmetic mean value of the weights of all vehicles during the time interval;

*Overloading Proportion (OP)*: Macroscopic concept, the proportion of the overload vehicles during the time interval.

**Data pre-processing**

In microscopic traffic risk analysis, we discuss the vehicle weight, the overloading, time headway, speed and micro-risk condition, and
summarize the relationships between these elements. To eliminate the deviation due to some other unrelated conditions, we group the vehicles data by vehicles’ time headway (2s as a group) or speed (10km/h as a group), and reflex the variations of average value of risk indicators under each type. To ensure the sample size, eliminate the groups of less than 5 vehicles.

Yu and Zhang\cite{15} has proved that the most appropriate time interval to demarcate the traffic flow model in a similar traffic condition from the macroscopic angle is 5 minutes, so we choose 5 minutes as the time interval of macroscopic risk analysis. With five-minute-interval grouping, we statistics the average weight, speed, traffic volume, overloading and macro-risk condition, and summarize the relationships between these elements. The study of traffic volume-speed relationships in the US Traffic Capability Handbook\cite{16} found that the rate of change was relatively small over a fairly large flow rate, and this trend continued until traffic volume reached about 1600veh/h \cdot lane^{-1}. Therefore, when the traffic volume is low, the average speed can be used to express the law of macro traffic flow. The specific method is to obtain the situation of average space speed corresponding to the average load and overload rate. To eliminate the discreteness of different time period, grouping the macro
traffic data by average weight (0.5t as a group), OP (10% as a group) or traffic volume (500veh/h · lane⁻¹ as a group), and reflex the variations of average value of risk indicators under each type. Also eliminate the groups of less than 5 vehicles.

2.2.3 Traffic Safety Risk Assessment

The characteristics and car-following behavior of traffic flows are the fundamental knowledge in the investigation of traffic safety assessment. A common measure used in assessing traffic safety is to set up methods for observing conflicts between vehicles. Based on the hypothesis of constant speed or space headway, WIM data can reflect the traffic flow behavior and the conflicts between vehicles with the influence of traffic load. Some safety indicators are used to evaluate the risks of traffic or a specific vehicle (from macroscopic to microcosmic levels), such as time headway, time to collision (TTC), time to accident, post encroachment time, deceleration to safety Time, deceleration rate to avoid crash [17-21]. Among which TTC and its derivatives are the most widely used indicators. When operating a vehicle, the driver is continuously faced with the task of avoiding collisions with other vehicles, pedestrians, and various obstacles that may lie in the path of travel. To prevent potential collisions, the driver may initiate steering or braking actions or a combination of
these. Appropriate regulation of the timing and control of such actions requires the driver to anticipate the time of the impending collision. This time remaining before the collision, often termed Time To Collision (TTC), is critical information for the driver in enabling prospective control of braking or steering behavior. When vehicles are closer to each other or drive at a higher speed the risk of a crash will increase. In case of an evacuation, the way drivers steer or break (driving behavior) is different to normal traffic conditions. Thus, it is expected that the driving behavior may have a significant impact on TTC. On the basis of the characteristics of traffic flows from the WIM data, the risk assessment TTC-based indicator system of traffic load can be set up. The research can greatly benefit the application of more advanced tools for managing traffic safety risk due to hazy/foggy weather conditions and the design of more effective scheme for risk reductions in hazy/foggy weather diversion area.

TTC refers to the duration of time before two (or more) vehicles collide with initial certain conditions such as speeds, relative positions, etc. It’s an important time-based safety indicator for detecting rear-end conflicts in road traffic risk assessments. Considering a steadily car-following in traffic flow, if the speed of following vehicle is higher than the first-arrive vehicle and drivers don’t take any measures, the collision would happen.
We defined this period of time from data detecting to the ‘hypothetical collision’ happening as TTC. TTC is based upon physical relationships between consecutive vehicles, either in the same lane or adjoining lanes. As defined originally by Hayward\textsuperscript{[22]}, the TTC for a following vehicle can be calculated with Eq. (1)

\[
TTC_i = \frac{X_{i-1}(t) - X_i(t) - l}{\dot{X}_i(t) - \dot{X}_{i-1}(t)} \quad \forall \dot{X}_i(t) > \dot{X}_{i-1}(t) \quad (1)
\]

Where \(X_{i-1}\) is the position of the lead vehicle, \(X_i\) is the position of the following vehicle. \(l_i\) is the length of the following vehicle. \(\dot{X}_{i-1}\) is the speed of the lead vehicle. \(\dot{X}_i\) is the speed of the following vehicle. All values are taken at the same moment in time (t).

Horst and Hogema\textsuperscript{[23]} redefined \(\dot{X}_{i-1}\) as the free speed of the lead vehicle, measured at the point of detection on the freeway, and assumed constant until the detection of the following vehicle with speed \(\dot{X}_i\). Thus, the measurement times of \(\dot{X}_i\) and \(\dot{X}_{i-1}\), are now different. As it’s not easy to get the space headway via the WIM-detected data. So we adopt this assumption to modify the formula for TTC. The modified equation is described in Eq. (2).

\[
TTC_i = \begin{cases} 
\frac{\dot{X}_i(t)ht_i - l_i}{\dot{X}_i(t) - \dot{X}_{i-1}(t)}, & \dot{X}_i(t) > \dot{X}_{i-1}(t) \\
\infty, & \dot{X}_i(t) \leq \dot{X}_{i-1}(t)
\end{cases} \quad (2)
\]
Where \( h_{t_i} \) is the time headway of the two vehicles. The two vehicles’ speeds are measured via the same section using WIM equipment.

In this way, we can obtain the TTC value of the following vehicle through the WIM data of the immediately proximate vehicles.

TTC can be assessed to identify whether the interaction between vehicles is a conflict and how serious this conflict is. In general, a lower TTC-value indicates a higher probability of a conflict. To distinguish whether the interaction between vehicles is a conflict or a relatively safer situation, a critical or threshold value for this safety indicator should be chosen. The threshold value of TTC is not only related to the vehicles’ braking performance and drivers’ characteristics, but also influenced by the road traffic condition.

For general roadway, Hirst and Graham \(^{24}\) reported that a threshold of TTC as 4 seconds results in too many false alarms and thus proposed 3 seconds reducing this number of alarms. Hogema and Jassen \(^{25}\) suggested a minimum TTC value of 2.6 seconds for drivers on a basis of a driving simulator experiment. Minderhoud and Bovy \(^{21}\) concluded that different values are used for critical TTC in different studies. Lu et al.\(^{26}\) studied different accident risk classes based on three critical TTC values at junctions. TTC with a value lower than 1 second is considered as high risk,
with a value between 1 and 1.5 second as moderate risk and with a value between 1.5 and 2 second as low risk. Van der Horst \[^{23}\] concluded that TTC value should be less than 2.5 seconds and Archer \[^{27}\] reported even a lower critical TTC value, less than 1.5 second. As for freeway, Gao et al. \[^{20}\] suggested 6.0 seconds as the threshold value in freeway work zone. Wang et al. \[^{28}\] proposed that TTC thresholds of the freeway lane change warning system in the relative distance of 0-20, 20-40, 40-60, >60m should be set as 3.3, 3.8, 5, 6.5 seconds, respectively. However, the threshold value of TTC based on multi-axle vehicles is still unknown. Considering the aforementioned factors, we choose 5s as the following threshold values of TTC.

Minderhoud and Bovy \[^{21}\] defined two additional situation-specific metrics based on the threshold TTC value:

See TET (Time Exposed Time-to-Collision) as the duration of exposition to the threshold values of TTC over specified time duration H. This means that the lower the TET is, the less time that the vehicle is in a conflict situation and thus the safer the situation is.

A disadvantage of the TET indicator is that any TTC value that is lower than the critical value is not included in the calculation. As an example, let us take a situation (Figure 6) in which a critical \(TTC'\) of 3 seconds has
been set: a TTC that has a value of 1 second for a period of 3 seconds has the same weighting in the calculation of the TET indicator as a TTC that has a value of 2 seconds for a period of 3 seconds. The first situation is more dangerous than the second situation. In order to properly reflect the impact of the TTC value, the TIT indicator was developed.

TIT = Time Integrated Time-to-Collision as the integral of the time-to-collision profile of drivers over specified time duration H. TIT reflects the variation in safety levels of different TTC values below the threshold value, which TET does not take into account. This is expressed as the formula:

\[ TIT_i = \int |TTC' - TT'C_i(t)| \]  

Figure 6 TET and TIT

Compared the damage caused by a traffic accident, certainly a truck is more dangerous than car. By the relationship between traffic risks and
accidents, even with the same frequency of conflict, the traffic risk must be different between heavy vehicles and light vehicles. Therefore, the load factor must be taken into consideration in traffic risk analysis.

The definition of TET and TIT are based on continuous traffic flow, since WIM system can only detect the traffic data of specific section, these metrics have some limitation in practical use.

Dijkstra and Drolenga\cite{29} introduced the Potential Collision Energy (PCE) to reflect the impact of a conflict. This indicates how much energy is released in the event of a collision between the vehicles that are in conflict with each other. The potential collision energy is built up from the weights and speeds of the vehicles involved and the way in which they collide: the type of conflict.

\begin{figure}[h]
\centering
\includegraphics[width=0.8\textwidth]{conflict_types.png}
\caption{Figure 7 several conflict types}
\end{figure}

\textit{Longitudinal (rear-end) conflict:}

In order to calculate the potential impact energy $PCE_i(t)$ at point in time $t$ in the event of a longitudinal conflict between vehicle $i$ and vehicle $i - 1$, the kinetic energy of one vehicle is deducted from that of the other. This is expressed as the formula:
\[ PCE_i(t) = \frac{1}{2} \left[ m_i \cdot \dot{X}_i^2(t) - m_{i-1} \cdot \dot{X}_{i-1}^2(t) \right] \]  \hspace{1cm} (5)

Where \( m_i \) is the mass of the following vehicle. \( m_{i-1} \) is the mass of the lead vehicle. \( \dot{X}_i \) is the mass of the following vehicle. \( \dot{X}_{i-1} \) is the mass of the lead vehicle.

**Frontal conflict and transverse conflict:**

In order to calculate the potential impact energy \( PCE_i(t) \) at point in time \( t \) in the event of a frontal or transverse conflict between vehicle i and vehicle k, the kinetic energy of one vehicle is added to that of the other. This is expressed as the formula:

\[ PCE_i(t) = \frac{1}{2} \left[ m_i \cdot \dot{X}_i^2(t) + m_{i-1} \cdot \dot{X}_{i-1}^2(t) \right] \]  \hspace{1cm} (6)

Where \( m_i \) is the mass of the following vehicle. \( m_{i-1} \) is the mass of the lead vehicle. \( \dot{X}_i \) is the mass of the following vehicle. \( \dot{X}_{i-1} \) is the mass of the lead vehicle.

**Converging conflict:**

In order to calculate the potential impact energy \( PCE_i(t) \) at point in time \( t \) in the event of a converging conflict between vehicle i and vehicle k, the kinetic energy of one vehicle is added to that of the other and correct the result by a factor to take into account the angle \( (45^\circ) \) between the vehicles.
This is expressed as the formula:

$$PCE_i(t) = \frac{1}{2} [m_i \cdot \dot{X}_i^2(t) + m_{i-1} \cdot \dot{X}_{i-1}^2(t)]$$  \hspace{1cm} (7)$$

Where $m_i$ is the mass of the following vehicle. $m_{i-1}$ is the mass of the lead vehicle. $\dot{X}_i$ is the mass of the following vehicle. $\dot{X}_{i-1}$ is the mass of the lead vehicle.

Only consider longitudinal (rear-end) conflict. According to the definition of $PCE$, the influence of load is considered, but it can’t reflect the risk of immediately proximate vehicles (the time headway or space headway cannot be reflected). Besides, since the $PCE$ may be negative value, in some extreme cases the risk judgment will be diametrically opposite (e.g. lead: 10t/60km; following: 20t/50km compare with lead: 20t/50km; following: 10t/60km).

In view of the fact that the traditional detection device cannot provide the load characteristic information, the rear-end risk indicator TTC and its related indicators mentioned in the past don’t take the load characteristic factors into account. And the superiority of WIM data is that it can provide the traffic flow data including load information. In this report, the WIM data can be used to improve the traditional rear-end risk indicator TTC and its related indicators for the lack of load characteristic. However, the WIM equipment is usually placed on the front section of the bridge to
prevent overweight. Therefore, according to the characteristics of the equipment and the necessity of the risk assessment, the tunnel or bridge is chosen as the object of the traffic safety risk assessment model considering the load characteristics.

2.2.4 Traffic Safety Risk Management

Establish weight-based indicators including WRT (Weigh Based Risk Level of Time-to-collision) and WIRT (Weigh based Integrated Risk Level of Time-to-collision). Since the WIM traffic data is section-based, it is difficult to obtain the trajectories of the vehicles along the roads. Establish time-space traffic safety risk field by using weight-based cellular automata simulation model considering weather conditions. The key critical sections like bridge and tunnels along the roads will be selected for the application of the proposed traffic safety risk model. The dynamic time-space weight-based traffic safety risk contour on the critical sections will be illustrated and determined. The weight-based traffic safety risk management is a multi-factors driven model. Therefore, the risk factors will be predicted and the prediction model for the traffic safety risk contour can be set up.
3. Driving Behaviors under Haze Weather Condition

3.1 Car-following Model Calibration

Two typical CF models from engineering perspective are adopted: Helly\textsuperscript{[30]} model and GIPPS\textsuperscript{[31]} model. The two models are shown in Eqn.\textsuperscript{(8)}.

\begin{equation}
\text{Helly: } a_n(t) = \begin{cases} 
C_1\Delta V_n(t-\tau_n) + C_2[\Delta X_n(t-\tau_n) - \Delta X_n(t-\tau_n)] \\
\Delta X_n(t-\tau_n) = a + b\#V_n(t-\tau_n)
\end{cases} \\
\text{GIPPS: } V_n(t) = \min \left\{ \frac{V_n(t-\tau_n) + 2.5a_{\text{max}}\tau_n(1-V_n(t-\tau_n)/V_{\text{drive}})(0.025+V_n(t-\tau_n)/V_{\text{drive}})^2}{b_{\text{max}}\tau_n + \sqrt{b_{\text{max}}^2\tau_n^2 - b_{\text{max}}[2(\Delta X_n(t-\tau_n) - S_{n-1}) - V_n(t-\tau_n)\tau_n - V_{\text{drive}}(t-\tau_n)^2]}} \right\} \tag{8}
\end{equation}

Where \( a_n(t) \) is the acceleration rate of vehicle \( n \) at time \( t \); \( \tau_n \) is the reaction time; \( C_1 \) and \( C_2 \) are the drivers’ sensitivity parameter of reaction to changes in relative speed and spacing respectively; \( a \) and \( b \) are estimated coefficient of desired spacing; \( V_{n-1}(t-\tau_n) \), \( V_n(t-\tau_n) \) and \( \Delta V_n(t-\tau_n) \) are respectively the speed of vehicle \( n-1 \), the speed of vehicle \( n \) and the speed difference of vehicle \( n-1 \) and \( n \) at time \( t-\tau_n \); \( V_{\text{drive}} \) is the desired speed of the following vehicle; \( \Delta X_n(t-\tau_n) \) and \( \Delta X_n(t-\tau_n) \) are the actual and desired spacing separately; \( a_{\text{max}} \) and \( b_{\text{max}} \) are separately the desired maximum acceleration and deceleration rates of following vehicle; \( S_{n-1} \) is the minimum spacing at a standstill situation and set to be 6.5m\textsuperscript{[31]}; \( b_{\text{max}} \) is the estimate of deceleration applied by the lead vehicle.

The calibration of parameters in CF model is actually an optimization problem to find a set of parameters that minimize the difference between
simulated and observed values of certain variable. In this study, the Genetic Algorithm (GA) was implemented to search the optimum set of parameters. GA is a widely used calibration tool in microscopic traffic model research and proved to be appropriate for calibration of CF models by several researchers\cite{32, 33}. Technically, the speed, speed difference, acceleration or spacing are all feasible variables to be used in the objective function of optimization process\cite{34}. Whereas it is note that the spacing is preferred and recommended in calibration of CF models\cite{32, 35}. Punzo and Montanino\cite{35} indicated that calibration on spacing is more robust than calibration on speed or acceleration. For optimization of the parameters, it also needs an objective function as quantitative measure of the error. Referring to \cite{32, 36}, the Root Mean Squared Percent Error (RMSPE) is adopted as the objective function (see Eqn.(9)).

\[
\text{RMSPE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \frac{S_{i}^{\text{obs}} - S_{i}^{\text{sim}}}{S_{i}^{\text{obs}}} \right)^2} \tag{9}
\]

Where: \(S_{i}^{\text{obs}}\) and \(S_{i}^{\text{sim}}\) denote the observed and simulated values of spacing at time \(i\) respectively; \(N\) is the amount of observed data.

GA Toolbox in MATLAB was applied to execute the calibration process. Regarding the relevant parameters in GA, the population size is 100 and the maximum number of iterations is set to be 500. The stall generation is 50. When the weighted average relative change in the fitness function over
stall generation is less than function tolerance, the calculation stops. The function tolerance is set to extremely small (1e-150), so that every calculation can reach the maximum iteration for the sake of better fitness. Due to the randomness of GA, there existed slight differences between solutions in each optimization. Hence, the optimization process is repeated 10 times and the result with minimum error (RMSPE) is selected. The scales of parameters are determined referring to several high-quality relevant literatures\cite{37-39} and keep in reasonable ranges (see Table 2) to improve the reliability and efficiency of calibration.

<table>
<thead>
<tr>
<th>Model</th>
<th>Parameters</th>
<th>Range (lower bound- upper bound)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Helly</td>
<td>$C_1$ : the drivers’ sensitivity parameter of reaction to changes in relative speed (SPORS)</td>
<td>0~1.5</td>
</tr>
<tr>
<td></td>
<td>$C_2$ : the drivers’ sensitivity parameter of reaction to changes in spacing (SPOS)</td>
<td>0~0.4</td>
</tr>
<tr>
<td></td>
<td>$a$ and $b$ : estimated coefficient of desired spacing</td>
<td>0<del>30 and 0</del>3</td>
</tr>
<tr>
<td>GIPPS</td>
<td>$a_{max}$ : the desired maximum acceleration rates of following vehicle (DMAR) (m/s²)</td>
<td>0~3.5</td>
</tr>
<tr>
<td></td>
<td>$b_{max}$ : the desired maximum deceleration rates of following vehicle (DMDR) (m/s²)</td>
<td>-6~1</td>
</tr>
<tr>
<td></td>
<td>$V_{desire}$ : the desired speed of following vehicle (DS) (km/h)</td>
<td>20~150</td>
</tr>
<tr>
<td></td>
<td>$b_{pmax}$ : the estimate of the deceleration rate of the lead vehicle (DROLV) (m/s²)</td>
<td>-6 ~1</td>
</tr>
</tbody>
</table>

The action point could be described as the relationship of speed difference and spacing between the following and the leading vehicle, when the following vehicle consciously starts to accelerate or decelerate responding to changes of the leading vehicle\cite{40}. The methods for AP identification
have been proposed by researchers\textsuperscript{[41-43]} based on kinematic principles. For instance, the AP of acceleration is a trace while spacing and speed difference increasing, changes to spacing increasing and speed difference decreasing. The kinematically identified APs are viewed as \textit{candidate action points} by Pariota and Bifulco\textsuperscript{[44]}. The point where drivers actually take action is generally a bit earlier than \textit{candidate action point}. Taking the acceleration AP for example, the point when the driver begins to continuously tread the throttle is the actual point that the driver want to react (\textit{actual action point}). It takes a while for the following vehicle to get a larger acceleration and reach \textit{candidate action point} with speed difference decreasing. The \textit{actual action point} is more precise to depict the point the driver react than \textit{candidate action point}\textsuperscript{[44]}. Therefore, we take advantages of the collected data in this study with throttle force and baking pedal force to identify the \textit{actual action point}. The AP of acceleration is where the throttle force and acceleration rate both begin to increase sharply, keeps in a high level (acceleration rate $>0.5\text{m/s}^2$) and lasts for at least 3 second. The AP of deceleration is where the baking pedal force and deceleration rate both begin to increase dramatically, keeps in a high level (deceleration rate $<-0.5\text{m/s}^2$) and lasts for at least 3 second.
Due to the drivers’ heterogeneity or preferences in driving behavior and various situations in the actual car following, the parameters or variables in models should virtually be treated as a random variable rather than a constant\textsuperscript{37}. Therefore, when comparing the differences of variables under clear and hazy weather conditions, not only is the regular parametric test implemented to identify the discrepancy of average values, but also nonparametric test Kolmogorov-Smirnov(KS) test is used to compare the differences of the distributions. It is found in this study that the distributions of most parameters do not follow normal distributions and this do not satisfy the basic assumption of statistical tests like T-test. However, for experiments whose sample size is over 30 (The sample size of every CF stage under each weather condition is 60), the Z-test can free from the assumption and consequently is employed for parametric test.

To clearly show distributions of parameters, the probability density distribution of each studied variable is drawn. The kernel density estimation is used to fit the probability density distribution as well. Examples of the results can be seen in Figure 2(a). The results of clear (white bars) and hazy (gray bars) weather conditions are demonstrated above and below the X-axis respectively. The fitness curve of clear weather is illustrated by the point line and that of hazy weather is
demonstrated by the triangle line. For the convenience of comparing the distributions under different weather conditions, the kernel density estimation fitness curve under hazy weather condition is copied as a symmetry curve from below the X-axis to above the X-axis. The cumulative probability distributions of variables are also illustrated. The left Y-axis denotes the probability density and the right Y-axis stands for cumulative probability.

### 3.2 Acceleration CF Stage

In acceleration CF stage, the studied variables are the drivers’ sensitivities of reaction to changes in relative speed (SPORS) \( c_1 \) and spacing (SPOS) \( c_2 \), the desired maximum acceleration rate (DMAR) \( a_{\text{max}} \) and the desired speed (DS) \( v_{\text{desire}} \). Figure 8 illustrates the results and Table 3 demonstrates the mean value, coefficient of variation, relative difference of above variables. The Z-test and KS test (\( \alpha=5\% \) and \( \alpha=10\% \)) are performed for all the behavioral variables to investigate the significance of the impacts of weather conditions.

The differences in mean values of SPORS \( c_1 \) and SPOS \( c_2 \) caused by different weather conditions ((HW-CW)/CW) are -29.3% and -33.1% respectively. Table 3 presents the test results, from which it can be seen that the hazy weather conditions does have significant impacts on the two
parameters. It indicates that given the same changes of speed differences or spacing, the acceleration reaction that drivers adopt under HW conditions is smaller than that in CW conditions.

Table 3 Impacts of Low Visibility under Hazy Weather on Variables in Case of Acceleration Car-following Stage

<table>
<thead>
<tr>
<th>Variable Scenarios</th>
<th>C₁ Mean (COV)</th>
<th>C₂ Mean (COV)</th>
<th>aₘₐₓ Mean (COV)</th>
<th>Vᵋᵣᵉₛᵋᵉ Mean (COV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CW</td>
<td>0.669 (58.1%)</td>
<td>0.148 (79.0%)</td>
<td>1.105 (39.1%)</td>
<td>103.9 (23.6%)</td>
</tr>
<tr>
<td>HW</td>
<td>0.473 (59.8%)</td>
<td>0.099 (102.8%)</td>
<td>0.913 (56.1%)</td>
<td>96.7 (25.9%)</td>
</tr>
<tr>
<td>HW - CW</td>
<td>29.3% (2.9%)</td>
<td>33.1% (30.1%)</td>
<td>17.4% (43.4%)</td>
<td>5.6% (11.1%)</td>
</tr>
<tr>
<td>CW VS HW</td>
<td>sig.** (p=0.004)</td>
<td>sig.** (p=0.029)</td>
<td>sig.** (p=0.042)</td>
<td>not sig. (p=0.148)</td>
</tr>
<tr>
<td>(Z-test)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CW VS HW</td>
<td>sig.** (p=0.003)</td>
<td>sig.** (p=0.000)</td>
<td>sig.** (p=0.004)</td>
<td>sig.** (p=0.024)</td>
</tr>
<tr>
<td>(KS test)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ** and * denote significant in the confidence level of 95% and 90% respectively. COV denotes coefficient of variation. These go for other tables as well.

Figure 8 Results of acceleration car-following stage: probability distributions under clear (white bars) and hazy weather (gray bars); kernel density estimation curves under clear (point line) and hazy weather (triangle line); cumulative probability distributions under
The difference in DMAR $a_{\text{max}}$ due to the different weather conditions ((HW-CW)/CW) is -17.4\%. The distributions of DS $v_{\text{desire}}$ under CW and HW conditions have significant differences with the confidence level of 95\%, according to the KS test. It can be seen in Figure 8(d) that the DS $v_{\text{desire}}$ under HW conditions keeps in lower level. However, the difference of mean value is not significant in Z-test because of large variation. Large variations are observed in studied variables under both weather conditions. Furthermore, coefficients of variations of the four variables under HW conditions are larger than those under CW conditions. This indicates that there exist larger heterogeneities in drivers’ acceleration CF behavior due to the low visibility under hazy weather conditions.

### 3.3 Deceleration CF Stage

The variables involved in deceleration CF stage are SPORS $c_1$, SPOS $c_2$, the desired maximum deceleration rate (DMDR) $b_{\text{max}}$ and the estimate of the deceleration rate of the lead vehicle (DROLV) $b_{\text{pmax}}$. The DROLV $b_{\text{pmax}}$ reflects the drivers’ caution for the lead vehicle’s sudden deceleration. The larger the (DROLV) $b_{\text{pmax}}$ is, the more cautious the drivers are for collision. The results are demonstrated in Table 4 and Figure 9.

In deceleration CF stage, the mean value of SPORS $c_1$ under HW
conditions is 31.7 % larger than that under CW conditions and the
difference is significant in both Z-test and KS test (α=5%). It implies that
the drivers bake harder under HW conditions for changes in speed
difference. The difference in SPOS $c_2$ caused by different weather
conditions ((HW-CW)/CW) is -32.1% and significant in the confidence
level of 95%, which indicates that drivers under HW condition react more
smoothly to changes of spacing.

Table 4 Impacts of Low Visibility under Hazy Weather on Variables in Case of Deceleration

| Variable Scenario | $C_1$ (Mean (COV)) | $C_2$ (Mean (COV)) | $|b_{max}|$ (Mean (COV)) | $|b_{pmax}|$ (Mean (COV)) |
|-------------------|--------------------|--------------------|--------------------------|--------------------------|
| CW                | 0.548 (50.1%)      | 0.234 (86.2%)      | 2.30 (45.2%)             | 2.03 (46.4%)             |
| HW                | 0.714 (42.5%)      | 0.161 (93.3%)      | 2.71 (42.3%)             | 2.36 (35.4%)             |
| HW - CW/CW        | 31.7% (-15.2%)     | -32.1% (8.2%)      | 17.8% (-6.4%)            | 16.3% (-23.7%)           |

Larger DMDR $b_{max}$ and DROLV $b_{pmax}$ are observed under HW conditions.

The differences in average absolute values of DMDR $b_{max}$ and DROLV
$b_{pmax}$ under different weather conditions((HW-CW)/CW) are 17.8% and
16.3% separately. The difference is significant in Z-test (α=10%) and KS
test (α=5%). Again, large variations in variables are observed on account
of heterogeneity. The coefficient of variation of SPORS $c_1$, DMDR $b_{max}$

40
and DROLV $b_{\text{max}}$ under HW conditions are 15.2%, 6.4%, 23.7% smaller compared to those in CW conditions, which implies the heterogeneities of relevant driving behavior decrease under HW conditions.

![Graphs showing sensitivity parameters](image)

(a) Sensitivity parameter of changes in relative speed  
(b) Sensitivity parameter of changes in spacing

(c) Desired maximum acceleration rate  
(d) Estimated deceleration of leading vehicle

Figure 9 Results of deceleration car-following stage: probability distributions under clear (white bars) and hazy weather (gray bars); kernel density estimation curves under clear (point line) and hazy weather (triangle line); cumulative probability distributions under clear (dashed line) and hazy weather (solid line)

3.4 Steady CF Stage

Table 5 and Figure 10 present the results in the steady CF stage. The relative difference of mean value in SPORS $c_1$ influenced by different weather conditions $((\text{HW-CW})/\text{CW})$ is 41.6% and test results in Table 5 show the difference is significant ($\alpha=5\%$). There are no differences in
SPOS \( c_2 \) under different weather conditions. The mean value of DMAR \( a_{\text{max}} \) under HW condition reduced by 19.9\% in contrast to that under CW condition and the difference is significant in confidence level of 90\%. It can be clearly seen from Figure 10 (c) that the probability of DMAR \( a_{\text{max}}>1.5 \) under HW condition is smaller. For DS \( v_{\text{desire}} \), no significant differences exist in both average value and distributions under different conditions. Above results indicate that drivers under HW condition prefer smaller DMAR and avoid taking drastic acceleration (\( a_{\text{max}}>1.5 \)), but hold the similar desired speed in comparison to CW conditions. The mean absolute value of DMDR \( b_{\text{max}} \) and DROLV \( b_{p\text{max}} \) decreases by 13.2\% and increases by 13.9\% respectively under HW conditions.

**Table 5 Impacts of Low Visibility under Hazy Weather on Variables in Case of Steady Car-following Stage**

<table>
<thead>
<tr>
<th>Variable Scenario</th>
<th>CW</th>
<th>HW</th>
<th>HW - CW</th>
<th>CW VS HW</th>
<th>CW VS HW</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_1 ) Mean (COV)</td>
<td>0.457 (86.2%)</td>
<td>0.647 (65.8%)</td>
<td>41.6% (-23.7%)</td>
<td>sig** (p=0.021)</td>
<td>sig ** (p=0.008)</td>
</tr>
<tr>
<td>( C_2 ) Mean (COV)</td>
<td>0.106 (124.5%)</td>
<td>0.094 (129.4%)</td>
<td>-12.8% (3.9%)</td>
<td>not sig (p=0.656)</td>
<td>not sig (p=0.521)</td>
</tr>
<tr>
<td>( a_{\text{max}} ) Mean (COV)</td>
<td>1.148 (65.4%)</td>
<td>0.919 (46.2%)</td>
<td>-19.9% (-29.4%)</td>
<td>sig* (p=0.085)</td>
<td>not sig (p=0.270)</td>
</tr>
<tr>
<td>( v_{\text{desire}} ) Mean (COV)</td>
<td>89.3 (21.9%)</td>
<td>95.4 (18.7%)</td>
<td>6.8% (-14.6%)</td>
<td>not sig (p=0.110)</td>
<td>not sig (0.317)</td>
</tr>
<tr>
<td>(</td>
<td>b_{\text{max}}</td>
<td>) Mean (COV)</td>
<td>2.689 (42.2%)</td>
<td>2.333 (46.4%)</td>
<td>-13.2% (9.9%)</td>
</tr>
<tr>
<td>(</td>
<td>b_{p\text{max}}</td>
<td>) Mean (COV)</td>
<td>2.286 (40.5%)</td>
<td>2.443 (41.7%)</td>
<td>13.9% (2.9%)</td>
</tr>
</tbody>
</table>

Figure 10 (e) shows that DMDR \( b_{\text{max}} \) under HW conditions is
comparatively smaller. However, no significant difference for the two variables are found in statistical tests on account of large heterogeneity as observed. The coefficients of variation of SPORS $c_1$, DMDR $b_{\text{max}}$ and DROLV $b_{\text{pmax}}$ under HW conditions are slightly larger, whereas those of SPOS $c_2$, DS $V_{\text{desire}}$ and DMAR $a_{\text{max}}$ are 23.7%, 14.6% and 29.4% smaller separately compared to CW conditions.

Figure 10 Results of steady car-following stage: probability distributions under clear (white bars) and hazy weather (gray bars); kernel density estimation curves under clear (point line) and hazy weather (triangle line); cumulative probability distributions under clear (dashed lines), and hazy weather (dashed-dotted lines).
3.5 Action Points of Acceleration and Deceleration

Figure 11(a) illustrates the action points (AP) of acceleration under clear and hazy weather conditions. The APs scatter discretely due to the drivers’ heterogeneities. Exponential function is implemented to fit the perceptual threshold curve. It is observed that the perceptual threshold curve under HW condition is lower than that under CW conditions which demonstrates that drivers take earlier acceleration reaction. To identify the distinction in spacing and relative speed of APs, the Figure 11 (b) and (c) demonstrate the cumulative probabilities of relative speed and spacing at APs referring to Hoogendoorn\cite{38}. The Figure 11 (b) shows that the relative speeds of APs under HW conditions are smaller with significance in 95% confidence level by KS test. The Figure 11 (c) illustrates that the spacing of APs under HW conditions are smaller to some degree albeit the difference is not significant. The results indicate that while the lead vehicle is going away, the APs under HW conditions have smaller relative speed and slightly smaller spacing than those under CW conditions.

Figure 11 (d) illustrates the APs of deceleration. It is observed that the APs under HW conditions are generally higher and noteworthy heterogeneities are observed again. The fitting exponential function under HW conditions
is higher than that under CW conditions as well. The cumulative probability of relative speed and spacing are demonstrated in Figure 11 (e) and (f). The absolute values of relative speeds at APs under HW conditions are smaller in contrast to those under CW conditions and the differences are significant at 95% confidence level by KS test. Nonetheless, there are no remarkable distinctions in spacing under different weather conditions. It can be deduced that while the following vehicle is approaching the lead vehicle, the APs under HW conditions have smaller relative speed and similar spacing.
(d) Distributions of action points in case of deceleration

(e) Cumulative probability of relative speed spacing

(f) Cumulative probability of

Figure 11 (a) The action points of acceleration, the dashed line with arrow denotes the changes during going away. (b) and (c) are the cumulative probability distributions functions of $\Delta V$ and $\Delta S$ of action points in case of acceleration (d) The action points of deceleration, the dashed line with arrow denotes the changes during approaching. (e) and (f) are the cumulative probability distributions functions of $\Delta V$ and $\Delta S$ of action points in case of deceleration.
4. Weight-Based Traffic Safety Risk Assessment

One of the most commonly used indicators for assessing traffic collision risk is TTC(time to collision) value, which indicates the time duration from the current car following states to collision event, similarly indicates the potential collision risk in the traffic flow. Based on a threshold value of the TTC, Minderhoud presented two new traffic safety indicators, TET (time exposed time to collision) value and TIT (Time Integrated Time to collision) value. TET value indicates the time duration of the condition that the TTC value is smaller than the threshold value, while TIT value is the integration of the TET value in the time domain where TTC is smaller than certain threshold. These two indicators assess traffic collision risk more accurately compared with TTC value. However, the traffic collision risk is not only associated with the probability of the collision event, but also affected by the loss of such event, while the previous indicators can hardly evaluate the loss of the collision event. In specific, the previous indicators of traffic collision risk didn’t take the vehicle load into consideration, which is quite a drawback of the risk assessment as vehicle load has substantial effect on the loss of traffic accident event.

In this part, we study on the traffic flow regularity and safety risk assessment in view of load characteristics. Firstly, analyze traffic flow
regulations considering load characteristics. Based on the WIM measured data from some expressway, analyze the relationships between some load characteristics such as axial type, average load and overload rate and their effects on variables of traffic flow. Results showed that, in the 95% confidence interval, the headways of multi axle vehicles followed the same distributions. But the headway distribution of two axle vehicles was different from that of multi axle vehicles. Traffic flow characteristics of multi axle vehicles were similar to each other but they were significantly different from that of two axle vehicles. Load characteristics have significant effect on free flow speed. With the decrease of average load, free flow speed increased linearly. Secondly, establish a traffic safety risk assessment method considering load characteristics. Based on the risk result measured by PCE(Potential Collision Energy), establish risk assessment indicator set including the load characteristics whose core is WRT (Weigh Based Risk Level of Time-to-collision) and WIRT (Weigh based Integrated Risk Level of Time-to-collision). Do traffic safety risk assessment based on the WIM data measured at cross section. Results showed that the risk indicators WRT considering load characteristics can reflect the time variability of cross section rear-end risk. Finally, combined with the traffic safety risk indicators in view of load characteristics,
establish time-space traffic safety risk field by means of establishing cellular automata simulation model considering the load characteristics. Compared with the traditional conflict indicator to test and verify the validity of traffic risk assessment indicators set.

The result in this Chapter can provide theory basis and technical support for highway especially bridge and tunnel traffic safety risk assessment and early warning.

4.1 Traffic Flow Regularity in View of Load Characteristics

It is of great significance for the traffic flow theory improvement to consider load characteristics in the study of expressway traffic flow regularity. Based on the measured WIM data, we investigate the relationships between the traffic flow variables from macroscopic and microscopic perspectives and discusses the traffic flow regularity considering the load characteristics.

• Microscopic Traffic Flow Regularity in View of Load Characteristics

Based on the WIM data obtained in 2009 and 2013, the relationship between lane choice and traffic load was measured. Table 6 presents the distribution of vehicle type in terms of number of axle. As shown in Table 6, two-axle vehicles were the majority (88% in 2009 and 90% in 2013 respectively).
Table 6 Distribution of Vehicle Type

<table>
<thead>
<tr>
<th>Vehicle Type</th>
<th>two-axle</th>
<th>3-axle</th>
<th>4-axle</th>
<th>5-axle</th>
<th>6-axle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion in 2009 (%)</td>
<td>88.34</td>
<td>4.40</td>
<td>2.80</td>
<td>1.52</td>
<td>2.91</td>
</tr>
<tr>
<td>Proportion in 2013 (%)</td>
<td>89.86</td>
<td>2.09</td>
<td>2.85</td>
<td>0.73</td>
<td>4.47</td>
</tr>
</tbody>
</table>

Table 7 Lane Choice and Vehicle Type

<table>
<thead>
<tr>
<th>Vehicle Type</th>
<th>Proportion in 2009 (%)</th>
<th>Proportion in 2013 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lane 1</td>
<td>Lane 2</td>
</tr>
<tr>
<td>two-axle</td>
<td>72.20</td>
<td>27.80</td>
</tr>
<tr>
<td>3-axle</td>
<td>40.25</td>
<td>59.75</td>
</tr>
<tr>
<td>4-axle</td>
<td>34.26</td>
<td>65.74</td>
</tr>
<tr>
<td>5-axle</td>
<td>39.22</td>
<td>60.78</td>
</tr>
<tr>
<td>6-axle</td>
<td>40.38</td>
<td>59.62</td>
</tr>
</tbody>
</table>

Figure 12. Lane Choice and Vehicle Type

Lane 1 refers to the left hand most lane (right hand driving rule). Table 7 and Figure 12 present the lane choice distributions by vehicle type. As shown in Table 7 and Figure 12, for two-axle vehicles, the proportion of vehicle using the left hand lane (Lane 1 in 2009, and Lanes 1 & 2 in 2013 respectively) was much higher than that of right hand lanes. In contrast, proportion of multiple-axle vehicles using the left hand lane was much
lower than that of right hand lane. No significant difference was observed for the lane choice between different vehicle types of multiple-axle vehicles.

Distributions of time headway, speed and the relationship between the time headway and speed were showed in Figure 13, Figure 14 and Figure 15 respectively. Differences in the microscopic traffic characteristics, in the terms of time headway and speed, between vehicle types were evaluated using Analysis of Variance (ANOVA) approach. Results indicated that the differences in time headway and speed were significant, all at the 5% level. For multiple-axle vehicles, no significant difference could be established at the 5% level. Results were consistent both before and after the major expansion, based on the ANOVA of 2009 and 2013 data. Consistently, results of KS test also indicated that no difference could be established for the distribution of time headway between multiple-axle vehicles, but the differences were significant between two-axle vehicles and multiple-axle vehicles, under free flow conditions, all at the 5% level.

As shown in Table 8, overall vehicular speed increased after the major expansion.
Figure 13 Distribution of Time Headway

Figure 14 Distribution of Speed

Figure 15 The Relationship between Time Headway and Speed
Results of this part showed that from the microscopic perspective, the traffic flow operation characteristics of multiple-axle vehicles were similar. But they were significantly different from the traffic flow operation characteristics of biaxial vehicles.

**Macroscopic Traffic Flow Regularity in View of Load Characteristics**

From the macroscopic perspective, it could be concluded that under free flow condition, Average load was a major factor affecting free-flow traffic speed and free-flow traffic speed. The average load is the main determinant of the speed of traffic flow. The smaller the average load is, the smaller the traffic flow is. The results of the traffic flow regularity considering load characteristics can provide support to the traffic simulation.

The average load of two-axle vehicles was about 3 ton, and the load of multiple-axle vehicles was all above 18 ton in general. No major difference was observed for the average load between the before and after periods of the road expansion. However, as shown in Figure 16, average
traffic volume increased remarkably after the expansion. In particular, the
average hourly traffic volume increased from 3859 veh/h/direction in
2009 to 9591 veh/h/direction in 2013. Considerable increases both in the
directional traffic volume and per lane traffic volume were observed.
The data collected were under the free-flow traffic condition, with traffic
volume of 1000 veh/h or below. The macroscopic traffic characteristics
were measured in the terms of average load, traffic volume and space
mean speed in every 5 minute interval. Vehicle load was stratified into
group using 0.5 ton interval. Figure 17 illustrated the relationship between
average load and mean speed, based on the results of regression, given the
average load of 35 ton or less. As shown in Figure 18, the mean speed
decreases with the average load, with R-square values of 0.9442 and
0.9551 in 2009 and 2013 respectively.

![Figure 16 Time Variability of Average Load and Traffic Volume](image)

(a) 2009  
(b) 2013

Figure 16 Time Variability of Average Load and Traffic Volume
4.2 Weight-Based Traffic Safety Risk Indicators

Time-to-collision (TTC) is a common used indicator for traffic risk analysis, but does not take the load information of vehicles into account. It’s necessary to propose some weight-based TTC indicators for the traffic risk analysis. The WRT indicator expresses the microscopic collision risk by considering collision probabilities and the potential collision energy of two closely following vehicles, and the WIRT indicator reflects the macro-risk (after considering loading characteristics) of the traffic flow. Vehicle-loading characteristics as well as safety-critical probabilities can easily be determined from the developed safety measures. The extended indicators therefore can give a more complete and comprehensive picture of the collision risk under certain conditions. The relationships between the load characteristics and the traffic risk are investigated. The empirical WIM data from Chinese freeways are used for the investigations. The results
show that the novel weight-based TTC approach gains better insight into the traffic risk analysis. The risk indicators WRT/WIRT both increase with an exponential function as the loading increases.

We define the potential risky vehicles as those vehicles whose TTC values are less than the thresholds. The Risky Time-to-collision (RT) is defined as the degree measure of TTC below the threshold:

$$RT_i = TTC^\prime - TTC_i \quad RT = \sum_{i=1}^{N} TTC^\prime - TTC_i$$

(10)

Where $TTC^\prime$ is the threshold value of TTC.

Now, Researchers often use PCE to reflect the impact of load characterize to conflicts. This indicates how much energy is released in the event of a collision between the vehicles that are in conflict with each other. The potential collision energy is built up from the weights and speeds of the vehicles involved and the way in which they collide: the type of conflict. In order to calculate the potential impact energy, at point in time t in the event of a longitudinal conflict between vehicle i and vehicle i-1, the kinetic energy of one vehicle is deducted from that of the other. When vehicles longitudinal conflicts, PCE can be expressed as the formula:

$$PCE_i = \frac{1}{2} (m_i v_i^2 - m_{i-1} v_{i-1}^2)$$

(11)

Where $m_i$ is the mass of the following vehicle. $m_i$ is the mass of the lead
vehicle. $V_i$ is the mass of the following vehicle. $V_{i-1}$ is the mass of the lead vehicle.

However, there are some problems with the formula. When the vehicle kinetic energy is greater than the kinetic energy of the front vehicle, the value of the formula

$$PCE_i = \frac{1}{2} (m_i v_i^2 - m_{i-1} v_{i-1}^2)$$

is greater than 0, and the collision energy can be calculated according to the formula

$$PCE_i = \frac{1}{2} (m_i v_i^2 - m_{i-1} v_{i-1}^2).$$

When the vehicle kinetic energy is less than or equal to the vehicle kinetic energy, the value of the formula

$$PCE_i = \frac{1}{2} (m_i v_i^2 - m_{i-1} v_{i-1}^2)$$

is less than or equal to 0. When light load vehicle rears heavy load vehicle, calculating according to the formula

$$PCE_i = \frac{1}{2} (m_i v_i^2 - m_{i-1} v_{i-1}^2)$$

is obviously wrong. Assuming that the two cars arrive at the same speed after the collision. According to the non-elastic collision momentum conservation and speed uniform conditions, after the collision, the common speed is:

$$\begin{align*}
\begin{cases}
m_1 v_{1,0} + m_2 v_{2,0} = m_1 v_{1,1} + m_2 v_{2,1} \\
v_1 = v_2
\end{cases} \quad v_{i,1} = v_{2,1} = \frac{m_1 v_{1,0} + m_2 v_{2,0}}{m_1 + m_2} \quad (12)
\end{align*}$$

According to the principle of conservation of mechanical energy, the loss
of kinetic energy in collision process (as the loss of rear-end collision) is:

\[ E = \frac{1}{2} m_i v_{10}^2 + \frac{1}{2} m_2 v_{2,0}^2 - \left( \frac{1}{2} m_1 v_{1,1}^2 + \frac{1}{2} m_2 v_{2,1}^2 \right) = \frac{m_i m_2}{2(m_i + m_2)} (v_{1,0} - v_{2,0})^2 \quad (13) \]

Where \( m_i \) is the mass of the following vehicle. \( m_{i-1} \) is the mass of the lead vehicle. \( V_{2,0} \) is the mass of the following vehicle before the collision. \( V_{1,0} \) is the mass of the lead vehicle before the collision. \( V_{2,1} \) is the mass of the following vehicle before the collision. \( V_{1,1} \) is the mass of the lead vehicle before the collision. All in all, we can modified the definition of PCE:

\[
PCE_i(t) = \begin{cases} 
\frac{1}{2} \frac{m_i \cdot m_{i-1}}{m_i + m_{i-1}} \left[ v_i(t) - v_{i-1}(t) \right]^2 & \left(m_i \cdot v_i^2(t) \leq m_{i-1} \cdot v_{i-1}^2(t)\right) \\
\frac{1}{2} \left[m_i \cdot v_i^2(t) - m_{i-1} \cdot v_{i-1}^2(t)\right] & \left(m_i \cdot v_i^2(t) > m_{i-1} \cdot v_{i-1}^2(t)\right) 
\end{cases}
\quad (14)
\]

Then we give the definition of WRT (Weight based Risk Time-to-Collision) and WIRT (Weigh as Integrated RT). WRT (Weight based RT) is a physical quantity that can describe the risk consequence RT of the rear-end collision and the collision loss (i.e., the potential collision energy).

In general, a higher TTC-value indicates a higher risk of a potential conflict. WIRT (Weigh as Integrated RT) is a physical quantity that can describe the risk consequences which made up of risk degree RT and collision loss of a continuous rear-end. Similar to WRT, the lower the WIRT value, the higher the overall security level on the specified segment.
in this time period. WRT and WIRT can described as the following formula in microscopic and macroscopic respect.

\[ WRT_i = RT_i \times PCE_i(t) \]
\[ WRT = \sum_{i=1}^{N} (TTC' - TTC) \times PCE_i |_{TTC < TTC} \]  

(15)

\[ WIRT_i = \int_{0}^{T} RT_i \times PCE_i \times \tau_{SC} \]
\[ WIRT = \sum_{i=1}^{N} \int_{0}^{T} RT_i \times PCE_i \, dt \]  

(16)

The volumes and proportions of potential risky vehicles of each axial type can be shown in Table 9. We can know that the number of biaxial vehicles are the biggest and the largest percentage of dangerous vehicles are five-axle vehicles.

<table>
<thead>
<tr>
<th>Axial type</th>
<th>2-axle</th>
<th>3-axle</th>
<th>4-axle</th>
<th>5-axle</th>
<th>6-axles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of vehicles</td>
<td>371995</td>
<td>33201</td>
<td>24813</td>
<td>11760</td>
<td>22195</td>
</tr>
<tr>
<td>The number of RT (veh)</td>
<td>33628</td>
<td>3104</td>
<td>2657</td>
<td>1475</td>
<td>2373</td>
</tr>
<tr>
<td>Percentage of dangerous vehicles (%)</td>
<td>9.04</td>
<td>9.35</td>
<td>10.71</td>
<td>12.54</td>
<td>10.69</td>
</tr>
</tbody>
</table>

As Table 10 showed, the difference of vehicle Type potential risky of is obvious. With the number of axle’s increase, dangerous vehicles average WRT is increasing.

<table>
<thead>
<tr>
<th>Axial type</th>
<th>2-axle</th>
<th>3-axle</th>
<th>4-axle</th>
<th>5-axle</th>
<th>6-axle</th>
</tr>
</thead>
<tbody>
<tr>
<td>dangerous vehicles average RT (s)</td>
<td>2.84</td>
<td>3.27</td>
<td>3.25</td>
<td>3.04</td>
<td>2.93</td>
</tr>
<tr>
<td>dangerous vehicles average PCE (MJ)</td>
<td>1.72</td>
<td>2.09</td>
<td>4.47</td>
<td>5.35</td>
<td>6.45</td>
</tr>
<tr>
<td>dangerous vehicles average WRT (MJ·s)</td>
<td>4.00</td>
<td>4.01</td>
<td>7.92</td>
<td>10.54</td>
<td>13.44</td>
</tr>
<tr>
<td>dangerous vehicles total WRT (kJ·s)</td>
<td>134512.0</td>
<td>12447.0</td>
<td>21043.4</td>
<td>15546.5</td>
<td>31893.1</td>
</tr>
</tbody>
</table>
Figure 18 Macroscopic parameters correlation graph

Table 9 Macroscopic parameters correlation

<table>
<thead>
<tr>
<th>Correlation coefficient</th>
<th>Q</th>
<th>V</th>
<th>W</th>
<th>The number of RT</th>
<th>WRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q</td>
<td>1</td>
<td>0.35</td>
<td>0.46</td>
<td>0.88</td>
<td>0.69</td>
</tr>
<tr>
<td>V</td>
<td>0.35</td>
<td>1</td>
<td>0.28</td>
<td>0.40</td>
<td>0.38</td>
</tr>
<tr>
<td>W</td>
<td>0.46</td>
<td>0.28</td>
<td>1</td>
<td>0.36</td>
<td>0.33</td>
</tr>
<tr>
<td>The number of RT</td>
<td>0.88</td>
<td>0.40</td>
<td>0.36</td>
<td>1</td>
<td>0.74</td>
</tr>
<tr>
<td>WRT</td>
<td>0.69</td>
<td>0.38</td>
<td>0.33</td>
<td>0.74</td>
<td>1</td>
</tr>
</tbody>
</table>

As showed in Table 9, macroscopic parameters correlated closely, the number of RT and Q has a strong correlation and its correlation is 0.88; the number of RT and WRT has a strong correlation and its correlation is 0.74.

4.3 Traffic Safety Risk Assessment

From the perspective of traffic safety risk assessment, we can use WIM data and the traffic safety risk indicators to get the traffic safety risk condition of the measured section. The analysis of traffic safety risk RT\ WRT\ WIRT indicators can reflect the risk considering the load
characteristic of detection section. However, from the practical application view, it’s necessary to get the whole road’s risk situation. So we need to performed simulations based on cellular automata and obtained the output data. Then put forward traffic safety risk field, which start from field theory, to distribute the time-space traffic safety risk situation.

Traditional risk field has been raised to assess quantitative the risks in petrochemical enterprises, however, it mainly quantitatively characterizes the space risk condition. Traffic safety risk field, using in our research, is a new kind of time-space model which can quantitatively characterize the degree of traffic safety risk from the field theory. It can reveal the influence of traffic factors such as load characteristics on traffic safety, laying the foundation for predicting the dynamic trend of driving risk. At the same time, the load spectrum, from the perspective of bridge structure safety, is often used to calculate the cumulative damage caused by the typical load on the bridge. Accurate and reasonable traffic load frequency spectrum, i.e., the fatigue load spectrum of bridge, is the basis of fatigue design of bridge structure. The continuous traffic safety risk field can fully and quantitatively characterize the traffic safety risk at every moment and position, which is particularly important for traffic safety management.
The length of the simulation road is 4000 m. Third lane terminates until 2500 m and all the vehicles will change into lane2, as is showed in Figure 19. Based on indicators system and the concept of traffic safety time-space risk field, 5 minutes and 500m-3500m sections of the simulation data were taken as the research object. Each 200m space range and 5 minutes time range was selected as a study section, and the traffic space-time dimension risks were evaluated from the perspective of traffic risk field. Time variety of traffic elements, including speed, traffic composition and volume, is shown in Figure 20, Figure 20, Figure 20 partly.

![Sketch map of the expressway](image)

**Figure 19 Sketch map of the expressway**

![Time variety of the Speed](image)

**Figure 20 Time variety of the Speed**
Figure 19 Time variety of the 2-axle percentage

(a) Time variety of traffic volume  (b) Time variety of speed limitation  
(c) Time variety of average weight

Figure 20 Time Variety of Traffic elements

The result can be proposed that compared with the traditional indicator (TTC), the new indictors (WRT/WIRT) can put load characteristic into the
calculation of risk assessment. Figure 20 shows the traffic safety risk assessment result of one direction (includes three lanes) of an expressway. Figure 20 (a) shows the original time-space traffic risk situation based on WIRT indicator. We can find that the traffic risk, considering traffic loading, is higher ahead of the bottleneck between 5:00 to 10:00, because of it, we should take some measures to avoid the local time-space high risk. We set speed limits for 80km/h between 5:00 to 10:00 on simulated road sections. The traffic condition is improved and the time-space WRT condition is showed as Figure 20 (b). The number of 2-axle vehicle is increasing rapidly between 5:00 to 10:00, as the reason of it, the total traffic speed is rising rapidly which causes lots of traffic conflicts. Our WIRT indicators can reflect the phenomenon and we can solve the problem by taking different speed limitation according to the actual situation.

![Figure 21 Time-space Risk field based on WIRT](image)

(a) The original situation        (b) Under speed limitation
5. Weight-Based Traffic Safety Risk Management

5.1 Weight-based microscopic traffic simulation

5.1.1 Lattice, Cell’s States and Neighborhoods

In the traffic simulation, any cell has two states, either empty or occupied by the first axle of a vehicle. The cell with a first axle of a vehicle is defined as a vehicle cell. The kinematic evolution of cells’ states is determined by the vehicle cells, while the loading of vehicle sequences is performed by vehicle cells with vehicle axles and their weights fully extended in the detailed positions. Vehicle gaps are detailed as bumper-gap (clear distance between successive vehicles) for vehicle transition and axle-gap (distance between the rear axle of the lead vehicle and the front axle of the following vehicle) for traffic loading. Time steps and velocity evolution can be user-defined and are independent. The four ingredients of lattice, cells, neighborhoods and transition rules in MSCA are redefined as follows.

It is noted that periodic, open, inflow and outflow boundary conditions are typically used in STCA. For bridge loading, however, it is important to present the time-dependent traffic volumes, traffic compositions, and truck proportions, etc. Hence, the outflow boundary condition is applied
here to assume a free road, i.e., the first vehicle in the simulation of each lane accelerates freely until it is taken out of the simulation if it moves to the end of the simulated length.

The lattice contains the global information of the MSCA, as presented in Eq. (2). The simulation length, \( l \), lane numbers, \( n \), cell shape, \( s \), and road information, \( r \), are given by the physical features of the road. Generally, the cells are rectangular and the cell dimensions are determined by the lane numbers: single lane is 1-dimension and multiple lanes are 2-dimension. The road information refers to lane closures, traffic control, forbidden lane-changing, road slope, etc. With vehicle configuration and calculation demand, the cell size, \( Dl \), and time step, \( Dt \), for modeling can be determined. The cell size can be set for any length, but should satisfy the parameters that a cell can be filled with a maximum of a single vehicle to make it simple for the evolution of transition rules. That means the size should be no larger than the distance between the front axles of two consecutive vehicles, and to improve the calculation efficiency, the size should be as large as possible. Consequently, the cell size is recommended as 5 m considering extreme traffic congestion with a minimum axle-gap of 2 m plus a minimum vehicle accumulated spacing of 3 m.

\[
L^d = \{ (l), (n), (s), (r), (\Delta l), (\Delta t), \ldots \} \tag{17}
\]
Cells’ states include information of status, kinematics and load, as indicated in Eq. (3). In MSCA, the status of cells can be represented by parameter sets of \( f \) and \( q \). When \( f \) is equal to 0 or 1, the cell is empty or occupied by a vehicle’s first axle, respectively. Another important parameter set is the location of the first axle in the vehicle cell. It is not fixed in MSCA, but dependent on the vehicle motion, denoted as \( q \) and ranging from 0 to 1 as a length proportion to the cell size. Then, the kinematic state of the vehicle cell is defined as the parameter set \( M \), which is composed of vehicle instantaneous velocity, \( v \), speed limit, \( v_{\text{max}} \), and bumper-gap, \( \text{gap} \). The speed limit is usually determined by the road information and traffic control. Finally, the load information of the vehicle cell is the parameter set \( W \), including gross vehicle weight, \( G \), axle number, \( k \), lengths of the front overhang of and the rear overhang or, axle weights, \( g^1; g^2; \ldots; g^k \), and axle spacings, \( p^1; p^2; \ldots; p^{k-1} \). With \( q \), \( p^1; p^2; \ldots; p^{k-1} \) and \( g^1; g^2; \ldots; g^k \), the precise loading of each vehicle can be determined.

\[
\Sigma = \{(f, (q, (M, (W))\}
\]

\[f = (0,1), q = [0,1), M = (v, v_{\text{max}}, \text{gap}), W = (G, k, (g^1, g^2, \ldots, g^k), (p^1, p^2, \ldots, p^{k-1})\}
\]

5.1.2 Transition rules

GM model was utilized to calculate the acceleration and deceleration rate in the CA model, the acceleration and deceleration rate were calculated by
the following equation:

\[
\Delta v_i(t) \leftarrow \lambda \cdot v_i(t)^m \cdot \frac{v_{i-1}(t) - v_i(t)}{g_s(t-1)}
\]  

(18)

Where the \( g_s \) represents the following distance, \( v_{i-1}(t) \) and \( v_i(t) \) represent the speed of the leading and following vehicle in time instance \( t \), \( \lambda \), \( m \) and \( l \) represent the sensitive parameters in GM model, the values of these sensitive parameters was illustrated by Figure 22.

![Figure 22 Parameter settings of GM model in different CF stages](image)

The speed of each vehicle was updated by the following equation:

\[
v_i(t + \Delta t) = v_i(t) + \Delta v_i(t)
\]  

(19)

After the calculation of the speed of each vehicle, the location of each vehicle in the lattice was updated by the following equation:

\[
x_i(t + \Delta t) \leftarrow x_i(t) + v_i(t) \cdot \Delta t
\]  

(20)

5.2 Weight-based Traffic Safety Risk Management On Hazy/Foggy Weather Conditions

Visibility under hazy weather condition is fairly low compared with clear weather condition and the traffic safety condition will be different under
different weather conditions. It is necessary to analyze risk condition of different kind of the weather. The traffic flow data was collected from 500 m to 3500 m of lane1 to lane3. Table 10 gives the statistical description of traffic safety risk of lane2 under different weather conditions, the mean value, medium value and maximum value of traffic safety risk are higher under hazy weather condition than clear weather condition. The traffic collision risk field of different lanes under clear and hazy weather conditions are illustrated by Figure 23. The traffic safety risk under hazy weather condition is significantly larger than clear weather condition (Figure 23). Compared with hazy weather condition, the traffic safety risk under clear weather condition can be more easily self-eliminated over time. There is a strong demand for traffic managing under hazy weather condition, especially under the circumstance of traffic convergence as the hazy weather condition had negative effects on the driving behaviors adapting to the changing of traffic states.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>WIRT /(MJ*s^2)</th>
<th>Mean value</th>
<th>Medium Value</th>
<th>Maximum value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clear weather condition</td>
<td>1.2×10^6</td>
<td>0.75×10^6</td>
<td>4.1×10^6</td>
<td></td>
</tr>
<tr>
<td>Hazy weather condition</td>
<td>1.8×10^6</td>
<td>2.1×10^6</td>
<td>4.4×10^6</td>
<td></td>
</tr>
</tbody>
</table>

(a) Clear weather condition  (b) Hazy weather condition  
Figure 23 Traffic safety risk field under clear and hazy weather conditions
6. Conclusions

6.1 Major Contributions

Both the driving behavior and the traffic load play an important role in the traffic risk assessment. Yet, their effects on safety risk are lack of investigation. On the basis of the empirical data from the WIM technology and the simulated data from the high fidelity driving simulator, WRT (Weigh Based Risk Level of Time-to-collision) and WIRT (Weigh based Integrated Risk Level of Time-to-collision) incorporating the factors of the traffic load and the driving behavior are considered as the safety risk indicators. These indicators are proposed for traffic safety risk assessment, gaining better insight into the traffic risk analysis.

Based on the car-following model and the weight-based traffic safety risk indicators, the Cellular Automaton (CA) is presented for traffic load modeling. The key critical infrastructure sections like bridges along the roads are selected for the application of the proposed traffic safety risk model. The dynamic temporal-spatial weight-based traffic safety risk contour on the critical sections is illustrated and determined.

This project sets up a set of tools and proposes a novel safety risk concept, the safety risk contour. It explicitly helps improve traffic safety in risk management on hazy/foggy weather conditions. Main findings include:
- A novel tool incorporating the traffic load information into the traffic safety risk analysis;
- A set of tools of weight-based traffic safety risk assessment on hazy/foggy weather conditions;
- A dynamic traffic safety risk contour for the case study sections along the roads;
- 5 related academic papers;
- This project stimulates new ideas in the research field of safety risk and establishes the mutual interests in the research issues for cooperation between both Tongji University and HKPU. This cooperation takes the advantages from both sides in terms of theory, policies, models, algorithms, applications and instruments (simulators, etc.) in the safety risk research.

### 6.2 Future Research

The driving behaviors under haze weather condition, weight-based traffic safety risk assessment, and weight-based traffic safety risk management have been proposed in this project. The combination of these aspects to announcing the law of the traffic safety risk influence by weight and hazy/foggy weather conditions, could be the future work. It is worth further work how to establish a normal application and provide practical decision support for highway management.
7. International Cooperation

The project carried out within 8 months, between February 2017 and September 2017. The simulated data collected at Tongji University using the high fidelity driving simulator and the empirical WIM data obtained from local municipalities, such as Shanxi and Guangdong province.

The research team includes young scholars from Tongji University, Beijing Normal University (BNU), Shanxi Transportation Research Institute (SXTI) and from the Hong Kong Polytechnic University (HKPU), with the background of transport, meteorology, economics and expertizing in traffic safety analysis and risk management. The interdisciplinary research team is of the personnel and technology for the successful implement of the project. Tongji University is fully responsible for the overall organization and implementation of the project, including the outline, coordinating, reporting of the project and attending all the research activities.

SXTI has a long history in participating the planning, design, construction, management of transport infrastructure, and the research team from SXTI collected and processed the WIM traffic data. BNU has a wealth of experience in traffic simulation based on driving behavior, and researcher from BNU built driving behavior model on hazy/foggy weather conditions.
Tongji University attains international reputation in the field of traffic and transportation engineering and has the most advanced national laboratories on road and traffic. HKPU has an international faculty and student community and has developed a global network with more than 440 institutions in 47 countries and regions. Researchers from Tongji University and HKPU expertise in the field of traffic safety assessment & management. Based on the empirical WIM data and simulate model provided by SXTI and BNU, researchers built a weight-based traffic safety risk assessment & management method on adverse weather conditions like hazy/foggy weather conditions.

<table>
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<th>Table 11 Assignments of Key Personnel</th>
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<tbody>
<tr>
<td><strong>Name</strong></td>
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<tr>
<td>Huizhao Tu</td>
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<td>Hao Li</td>
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<td>Fuyu Hu</td>
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<td>Xiao Zhang</td>
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<tr>
<td>Tony Sze</td>
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</table>

In May, 2017, Dr. Tony N.N. Sze visited Tongji University to discuss with the research group of Prof. Tu and dr. Li and gave some advices on risk management and the CA model.

In July, 2017, Prof. Tu had a discussion meeting with Prof. Yang (from BNU) and dr. Zhang (from SXTI) in Shanghai, about the safety risk assessment indicators.
In August, 2017, Prof. Tu and Dr. Li visited HKPU to have solid discussions about the project progress with Dr. Sze. A few joint papers between Tongji University and HKPU will be coming.

In December, 2017, Prof. Tu and PH.D candidate Ms. Ying WANG will attend the 22\textsuperscript{th} HKSTS to have further contacts with Dr. Sze to stimulate new ideas in the research field of safety risk and establish the mutual interests in the research issues for cooperation between both Tongji University and HKPU.
8. Acknowledgments

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