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Assessing Mobility under Inclement Weather Using VISSIM Microsimulation - A Case Study in U.S.

Ying Huang[1*], Melika Ansarinejad[1], and Pan Lu[2]
[1]Department of Civil, Construction, and Environmental Engineering, North Dakota State University
Fargo, ND, USA, 58102
[1]Department of Transportation, Logistics, and Finance, North Dakota State University
Fargo, ND, USA, 58102
*Corresponding author: ying.huang@ndsu.edu

Abstract **-** Extreme weather conditions have shown significant impacts on drivers' behaviors. Under deverse weather conditions or inclement weather conditions, the drivers of a motorvehicle behave significantly different, resulting in significant difference in traffic mobility in deverse weather conditions. Thus, it is of interest to understand how extreme weather conditions would influence the mobility of trffic. This study uses microsimulation software VISSIM to investigate how deverse weather conditions influence mpbility. Such a study can be used for further assessment and management of traffic flow.

Keywords**:** Pipeline safety, weather impact, temperature distribution

1. Introduction

Adverse weather events characterized by precipitation, high winds, reduced visibility, and extreme temperatures can influence driving behavior, particularly regarding speed selection and maintaining appropriate headway distances [1], [2]. Driving simulators and video recording data are the predominant methodologies and sources for exploring individual driver responses to adverse weather conditions [3]. By Analyzing traffic data of Florida and Washington freeways from SHRP2 naturalistic driving study (NDS) and Road Information Database (RID), Mohamed M. Ahmed and Ali Ghasemzadeh. 2017 [4] investigated the lane-keeping behavior of drivers under heavy rain and found that the number of lane changes is higher in clear weather compared to heavy rain; however, the speed has higher variability during heavy rain compared to clear weather, which could be a sign of increased safety risk. They also examined the acceleration-deceleration behavior and observed a wider range and higher average acceleration in heavy rain than in clear weather, while higher average deceleration was observed in clear weather.

Mohamed M. Ahmed and Ali Ghasemzadeh. 2017 [2] identified a significant difference in vehicle performance and driving behavior between clear and rainy weather conditions of SHRP2 trips; with drivers maintaining longer headway times and reducing the speed by more than 5 km/h below the posted speed limit in both light rain and heavy rain. Weng et al. 2013 [5] evaluated the changes in the traffic flow characteristics of an expressway in Beijing under various snow intensities. They concluded that heavy snow causes a 15%-40% decline in the vehicle speed depending on the level of traffic flow, and under heavy snow average speed is about 28% lower than clear weather. Additionally, the time gap between vehicles, known as headway time, was found to be increased by 2 to 4 seconds, and the road's capacity decreased by approximately 33%. Druta et al. 2020 [6] mined weather-related crashes and near-crash events from the SHRP2 dataset and presented that drivers tend to drive more cautiously in snow than in the rain. Khan et al. 2020 [1] assessed the drivers' speed selection behavior under near fog and distant fog by using the same dataset, concluding that the average speed in foggy weather is significantly lower than in clear conditions, with a greater speed reduction observed in near fog compared to distant fog scenario. Zolali et al. 2021[7] , as a part of their driving simulator study, examined how drivers' average speed is affected by various weather conditions, road geometry, and driver characteristics and concluded that adverse weather conditions have the most impact on driving behavior with foggy weather lead to a reduction of the mean speed by 40%. While several studies have focused on the detrimental influence of inclement weather on road transport and traffic flow characteristics (capacity, free-flow speed, average speed, and saturation flow rate), only a limited number of them utilized the trajectory-level data from sources like SHRP2-NDS [8]–[10] or driving simulators [11], [12] to comprehensively study the drivers' behavior at microscopic level to develop weather-dependent microsimulation models and assessing traffic flow across a wide range of driving scenarios.

Among the multitude of microsimulation platforms and traffic models available, PTV VISSIM has demonstrated effectiveness and capability to simulate driving behavior under inclement weather conditions, making accurate capture and analysis of the impact of different weather conditions on the traffic flow and transportation network possible. In the pursuit of refining traffic simulation accuracy and developing weather-dependent simulations, previous researchers examined the psycho-physical car-following models "Wiedemann 99" and "Wiedemann 74," as well as the lane change model within the widely used traffic simulation tool, PTV VISSIM to identify parameters representing changes in behavior under the various weather condition and modified default parameters to weather-specific values. For the calibration of weather-dependent car following and lane-change models in the PTV VISSIM, some studies considered different weather conditions in tandem with their respective levels of intensities. In these studies, researchers defined distinct adversity levels corresponding to each of these weather conditions [7, 8, 10]. For instance, Chen et al. 2019 [11] designed eleven distinct weather scenarios under three different traffic flow states, encompassing a clear-sky scenario, four levels of fog, four levels of rain, and two levels of snow within a driving simulator, then all ten parameters of the Wiedemann 99 car-following model (CC0-CC9) along with the desired speed under each weather scenario were suggested based on collected data from driving simulator to analyze traffic flow and road capacity. The simulations output indicated a significant average speed reduction of 19.2%-45.6% during snowy weather, and a noticeable decrease in average speed between 7.6-27.5% in other extreme weather (Heavy Dense Fog, Heavy Rain, and Extremely Heavy Rain). Lower densities in snowy conditions were interpreted by larger headways that drivers tend to maintain due to reduced visibility and road friction to avoid rear-end crashes. Additionally, the road capacity exhibited a substantial decrease of 43.7%-71.1% under snow and a noticeable reduction of 11.1% to 20.5% in other extreme weather conditions. In another study, Hammit et al. 2019 [9] identified optimal parameter values for the W99 model and desired velocities for different weather conditions using the SHRP2 NDS dataset. They then simulated traffic flow scenarios under baseline, fog, snow, and rain (from very light to heavy). VISSIM simulations showed no capacity changes between very light and light rain compared to clear sky conditions. However, the capacity improved in moderate and heavy rain. Speed increased by 22% in fog, very light rain, and light rain, while it decreased by 11% in moderate rain, heavy rain, and snow.

Anik Das, and Mohamed M. Ahmed. 2022 [8] updated the necessary- and free- lane change parameters for seven weather conditions, including clear weather, two levels of rain, two levels of snow, and two levels of fog according to lane-change events of the SHRP2 NDS to assess traffic safety and operation under adverse weather. The results of weather-specific simulations revealed that the total number of simulated conflicts, including lane changes and rear-end conflicts, increased in extremely adverse weather conditions, underscoring the negative impact of inclement weather on driver behavior and performance. Jiaqi Ma et al. 2020 [13] designed three weather scenarios: normal/clear, snowy, and severe weather as representatives for varying winter weather conditions of I-80 in Wyoming for a connected vehicles weather-responsive management application. Ten parameters of Wiedemann 99 model (CC0-CC9) in VISSIM were calibrated for each of three weather scenarios to simulate improving roadway conditions after the deployment of snowplow trucks at key roadway segments ahead of inclement weather events. Golshan Khavas.et al.2017 [14] calibrated nine key input parameters of VISSIM for three weather conditions (Icy, Dry, and Wet) based on loop detector and weather data for I-694 in the Twin Cities, Minnesota to assess the influence of the adverse weather on traffic stream.

The objective of this paper is to understand how the deverse weather conditions influence the traffic mobility and use a case study in United State to demonstrate the influcences. Such an understanding can help the traffic engineers to assist a better traffic management.

2. Setting up MiscroSimilation Using VISSIM

Microscopic traffic simulation has gained significant popularity in transportation planning, design, and analysis due to its ability to deliver cost-effective, risk-free, and high-speed benefits. There are several commercial traffic micro-simulation tools, and each one is intended to simulate a range of network configurations, problems, and solutions.

The Verkehr In Städten - SIMulationsmodell (VISSIM) is one of the most popular micro-simulation tools, created in 1992 by the German business PTV Vision (Planung Transport Verkehr). The VISSIM program does not use the traditional method of modeling a road network using a specific graph of vertices (nodes) and edges (segments). The road network is instead constructed using segments joined together by connectors. With this method, any road system can be modeled. Moreover, it focuses on discrete time steps and relies on behavior-based modeling to simulate traffic in urban and rural areas, and pedestrian movements. Users of the VISSIM micro-simulation software package can customize the lane shift, gap acceptance, and car-following model settings based on different scenarios. It is a comprehensive software that combines traffic flow model that incorporates both car-following and lane-changing models [15]. The car-following models in VISSIM are based on the psycho-physical perception model created by Wiedemann in 1974 and enhanced throughout the years, with the most recent update in 1999. Unlike simpler models that assume constant speed and a deterministic automobile following logic, the fundamental idea behind the Wiedemann model is that as a driver of a faster-moving vehicle reaches his perception threshold of a slower-moving vehicle, is not able to precisely assess the speed of that vehicle, so the driver begins to slow down and will accelerate again when crosses another perception threshold. In practice, VISSIM utilizes this intricate traffic flow model to simulate the movement of driver-vehicle units within the network. Every driver with his specific behavior characteristics is assigned to a specific vehicle. Consequently, the driving behavior corresponds to the technical capabilities of his vehicle. This integration of individual driver behavior and vehicle characteristics makes VISSIM a potent software for simulating real-world traffic scenarios with a high degree of accuracy [15].

Widemann 99 model has ten parameters (CC0-CC9). CC0, CC1, and CC3 play the most important role in car following behavior of vehicles in VISSIM software, in particular in case of high traffic demand. CC1 and CC2 stand out as parameters, significantly affecting simulated vehicles' safety and operational aspects. CC3 exclusively affects safety without any influence on operations, while CC4 and CC5 have a moderate impact on the safety and operations of simulated vehicles. Understanding the definition of each parameter is essential for their proper adjustments to develop a smooth simulation run: The initial set of parameters (CC0 - CC3) pertain to maintaining a safe distance between vehicles, the next three parameters (CC4 - CC6) are related to the speed of the following vehicle. The last group of parameters (CC7 - CC9) focuses on the acceleration involved in the process of following a proceeding vehicle [16]. we adjusted the parameters of the Wiedemann 99 car-following model (CC0-CC9) by substituting the default parameter values suggested by the PTV VISSIM Group with weather-specific values. These adjustments were made to accurately reflect driving behaviors across each of the earlier mentioned weather scenarios. After conducting an extensive review of the literature that suggested weather-responsive values for car-following parameters, subjecting the parameter values to rigorous evaluation by running validation simulations, we selected the values provided by Chen et al. 2019 [11] as the most suitable representation of driving behaviors and traffic flow dynamics within the context of our modeled intersection, our vehicle type and weather scenarios.

As extensively documented in the literature review chapter, Chen et al. 2019 conducted a comprehensive investigation into the variations in traffic flow characteristics under a wide spectrum of adverse weather conditions and suggested values for simulating car-following behavior of vehicles under different road types and driving conditions in PTV VISSIM. Out of the 11 weather scenarios examined by Chen et al. 2019, we opted to focus on four prevalent weather conditions in our project site for this study. These selected scenarios aim to serve as the basis for modeling driving performance under adverse weather conditions. Table 1 displays the visibility distances, the levels of precipitation and the friction reduction percentage for each of these chosen weather scenarios, offering a comprehensive view of the severity of the weather conditions included in our research.

Table 1. Characteristics of different weather scenarios

Weather Condition	Road Friction	Precipitation Intensity (mm/h)	Visibility Distance(m)
Clear Sky	100%	N/A	10,000
Heavy Dense Fog	100%	N/A	50
Rain	75%	(10.0–24.9) mm/24 h	800
Snow	45%	(2.5–4.9) mm/24 h	500

Furthermore, Table 2 displays the values recommended by VISSIM, along with the chosen parameters for the simulation of drivers' behavior in four distinct weather scenarios in this study.

Table 2. Adopted values for the W99 car-following model for human-driven vehicles [11]

W99 Parameters Human-Driven	Definition	VISSIM Default	Clear	Rain	Heavy Dense Fog	Snow
CC0 (m)	Standstill Distance	1.5	4.45	1.06	1.6	2.33
CC1(s)	Headway Time	0.9	0.87	1.67	1.26	3.93
CC2 (m)	Following Variation	4	5.28	9.67	19.4	16
CC3 (s)	Threshold for Entering Following	-8	-7.92	-7.24	-5.37	-7.01
CC4 (m/s)	Negative Following Threshold	-0.35	-1.52	-0.64	-0.83	-0.59
CC5 (m/s)	Positive Following Threshold	0.35	1.52	0.64	0.83	0.59
CC6 (-)	Speed Dependency of Oscillation	11.44	0.71	0.56	0.25	0.64
CC7 (m/s2)	Oscillation Acceleration	0.25	0.31	0.35	0.34	0.38
CC8 (m/s2)	Standstill Acceleration	3.5	1.03	1.34	1.18	1.37
CC9 (m/s2)	Acceleration at Speed of 80 km/h	1.5	0.33	0.38	0.26	0.32

3. Case Study and Results

The site of this study is located at the intersection of two principal five-lane arterials, Redwood Road (a north-south road) and Pioneer Crossing (an east-west road) in Saratoga Springs, Utah, USA, as detailed in Figure 1. Table 3 illustrates the results of traffic flow analysis under four different weather scenarios by focusing on the average number of stops, average delay time, and average speed of passenger vehicles during ten simulation runs. The most significant increase in the number of stops and the delay times, compared to the baseline scenario (Clear Sky), happens in snowy weather conditions. During this condition, drivers show the utmost caution, exhibiting slower perception and reaction time in comparison to rainy and clear weather while selecting significantly lower speeds for their travel. On average, snowy weather results in a 2.5-fold increase in delay time and a 7.5-fold increase in the number of stops. Following snowy conditions, heavy dense fog becomes the next most influential weather condition regarding its impact on traffic flow. It contributes to a significant rise in both the number of stops (1.83 times more) and delay time (about 3 times more) when compared to clear weather. This change can be attributed to a shift in driving behavior from a normal approach to a more cautious driving conduct. Due to the impaired visibility, drivers exhibit the lowest degree of reaction and perception, their speed decreases significantly and varies significantly in this scenario.

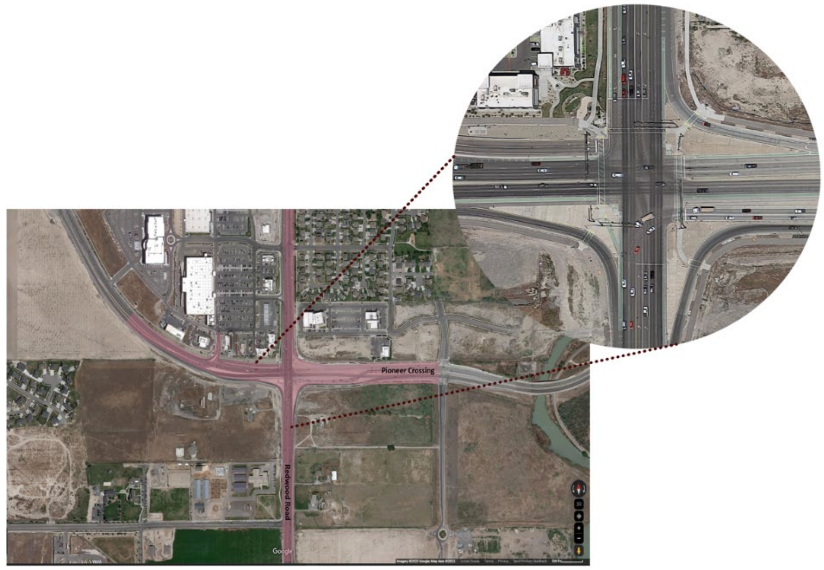

Figure1. Project Site, Saratoga Springs, UT, USA

Rainy weather takes the third spot in terms of its impact on altering normal driving behavior and impacting the number of stops and delay times when contrasted with other weather conditions. In this weather scenario, delay times increase by 1.3 times, and the average number of stops rise 2.4 times compared to clear weather. Although the effect is less noticeable than in snowy and foggy circumstances, drivers still behave differently, with their average speed being approximately 22% lower than in clear weather, resulting in more stops and delays. As expected, in clear weather, drivers show the lowest degree of caution translating to the fewest number of stops and shortest delay time in this scenario.

Table 3. Results of traffic flow in a traditional network under different weather scenarios

Weather Scenarios	Clear	Rain	Heavy Dense Fog	Snow
Average Delay (s)	440.42	565.27	808.21	1113.73
Average Stop (-)	23.71	56.25	70.66	176.76
Average Speed (km/h)	62.38	48.86	35.08	23.11

4. Conclusions and future work

Inclement weather conditions encompassing instances of Snowfall, Heavy Dense Fog, and Rain manifest a significant impact on driving behavior and the flow of traffic. Snowy weather has the most effect on traffic flow, causing a 2.5-fold increase in delay times and a 7.5-fold increase in the number of stops compared to clear weather. Heavy dense fog following snowy weather, is the second most influential adverse weather condition. It causes significant increases in the number of stops (1.8 times more) and delay times (2.9 times more) compared to clear weather. While less impactful than snowy and foggy conditions, rainy weather resulted in a 1.3-fold increase in delay times and a 2.37-fold increase in the number of stops compared to clear weather. The practical implications of this study are that traffic engineers should consider the impact of extreme weather conditions on traffic mobility. Further research is needed to investigate the environmental impacts of the deverse weather conditions.

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