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Speed Selection During Winter Road Conditions

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1. INTRODUCTION

The unpredictability of weather conditions may have direct or indirect impacts on traffic operations and driver behaviors (e.g. speed, headway, and gap). The impacts may occur during or after the weather events, be of short- or long-term duration, and include direct and indirect effects. Adverse winter storms, flooding, or hurricanes may cause major delays in traffic operations and cost millions of dollars (FHWA, 2006). The rain, fog, and snow can result in serious impacts on roadway systems and well-being of the road users. About 24 percent of all reported motor vehicle crashes in the United States are related to weather conditions. They result in more than 673,000 injuries and about 7,400 fatalities per year (Pisano, et al., 2009).

A study of crash rates along Wyoming I-80 corridor was conducted by the University of Wyoming in 2006 (Tomasini, 2006) indicated that the segments between Laramie and Rawlins had the highest crash rates for the years 1995 to 2005 due to high wind, blowing snow, and icy road surface conditions. Road closure is one potential measure to mitigate adverse weather conditions' however other solutions are also necessary. Recent studies showed that average road closure time between Laramie and Rawlins was eight hours per closure resulting in a conservative estimate of economic impact of about \$8–\$12 million in delay costs per one road closure (Young & Liesman, 2007). Another study found that crashes during winter are 2.82 times higher than the number of summer crashes (Young, et al., 2012). Therefore, better understanding of adverse weather condition might be helpful to reduce crashes and improve safety on traffic operations.

Adverse winter weather may affect driver behavior because of the worsened driving conditions it can create. Road conditions become more hazardous during such conditions, which force individual drivers to react accordingly to handle the situations by modifying their individual headway and speeds. Every driver chooses an individual speed according to their own perception of the weather severity, which leads to increases in speed variations and, in turn, result in increases in crash frequencies (Garber & Gadirau, 1988). The weather has a tremendous impact on the transportation system, so it should be taken seriously by the agencies responsible for traffic operation to make roadways safer.

The application of Intelligent Transportation System (ITS) technology such as Road Weather Information System (RWIS), speed detectors, cameras, weather/traffic data, and advanced roadway forecasting methods help in analyzing the impacts of adverse winter weather to improve safety and mobility of roadway users. This will help Weather Responsive Traffic Management strategies (WRTMs) to mitigate weather impacts on the traffic operations. As part of the Federal Highway Administration (FHWA), the Road Weather Management Program (RWMP) has developed strategies to encourage agencies to work effectively to improve traffic operations and safety during adverse weather conditions (WRTM Program). The WRTMs is a new approach aimed to improve traffic safety and mobility on the traveling public during adverse weather conditions. WRTM strategies incorporate the implementation of traffic control and treatment strategies with weather forecasting to provide proactive advisories to road users. This system provides information in advance about road conditions, modification of traffic signal, automated decision systems, and speed limits. Figure 1-1 shows the framework of WRTM program. The RWMP has developed a complete set of different approaches. These approaches help state DOTs and traffic safety agencies to reduce the impacts of adverse winter weather on traffic operatrions. The primary components of the WRTM are (Gopalakrishna, et al., 2011):

- Data Collection and Integration (Traffic and Weather data): Analysis of weather and traffic parameters will enable transportation agencies to make better informed and effective decisions.
- Traffic Analysis (Modeling and Simulation): Modeling and simulation of the actual conditions help to determine impacts of weather and provide tools to make better decisions in advance to road users.
- Human Factors: To assess the issues related to driver behavior (such as lane changing, car-following, and gap acceptance).
- Safety Evaluation: Knowing the performances after the implementation of WRTM strategies.

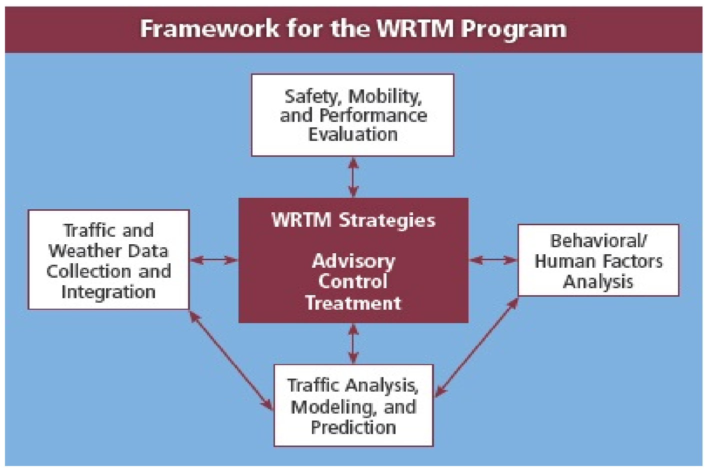

Figure 1.1 Framework of Weather Responsive Traffic Management Strategies (Gopalakrishna, et al., 2011)

This report presents the speed behavior of vehicles during adverse weather conditions to provide guidance for calibration of microscopic simulation analysis of traffic flow. In addition, this study will help address the knowledge gap in defining the relationship between weather conditions (e.g. precipitation, visibility, surface temperature, relative humidity, and gust wind speed) and driver behavior. The operational characteristics of roadways in Wyoming during the winter season are inconsistent due to frequent and often harsh weather conditions. Maintenance crews can observe the conditions through web cameras and weather-monitoring sensors and dispatch snow removal crews. Wyoming Department of Transportation (WYDOT) has established application of sand-salt mixture and snow plowing based on the Average Daily Traffic (ADT) the highways carry. Higher ADT roadways are plowed first followed by medium and low volume roadways.

Variable Speed Limit (VSL) system is an ITS strategy and has been adopted by urban and rural areas worldwide. VSL systems in urban areas are typically used for congestion reduction where in rural areas VSL are typically used to address traffic safety. VSL systems along a rural corridor can be effective in addressing speeding-related safety problems either by helping drivers to choose appropriate speed limits based on road conditions or any incident occurred downstream. VSL systems were implemented by WYDOT for the first time in February 2009 on the Elk Mountain Corridor along I-80. The system was installed along the freeway to improve the traffic safety during winter road conditions by providing real-time information about road conditions. Research performed in the analysis of safety effectiveness in Wyoming Elk Mountain Corridors found that the implementation of VSL system was expected to decrease crash frequency by around 0.75 crashes and road closure frequency by around 0.39 per seven days (Saha, 2015).

1.1 Problem Statement

Winter seasons in Wyoming are usually long, uncertain, and frequently severe. To develop guidelines for adapting microsimulation traffic models for weather conditions, corridors from Wyoming along I-80 will be considered because of frequent adverse weather conditions. This will also help minimize the effects of roadway geometry, particularly horizontal and vertical alignment, and merging and diverging behavior. The development of simulation models to reflect adverse weather condition on microsimulation, I-80 corridors in Wyoming is more appropriate due to severe weather conditions. The developed models may help to identify the relationship between weather conditions and driver behavior. Interstate was selected as the roadway type due to its high design standards and relative uniformity in geometries in order to minimize these effects on the analysis. A better understanding of the relationship between adverse weather conditions and drivers behavior on rural roadways are the main focus of this study.

Ideal road conditions are not always present on roadways, even though this is the underlying assumption for most of the traffic analysis. There are various types of weather events that change the roadway conditions from ideal to non-ideal. The reduction in visibility and reduced pavement friction may lead to degrading the performance of traffic operations. In addition, snow and heavy rain may result decrease in average traffic speed (Ibharim, 1994). Understanding of the impact of adverse winter conditions on traffic operations requires analysis of paired data at the same time with both observed traffic speeds and particular weather parameters. Therefore, weather parameters should be collected nearby the test site to know the impact of a storm event in the considered section.

The report describes the methodology for selection of the Wyoming and Colorado corridors but limits the analysis of data to the Wyoming corridors.

1.2 Objectives and Goals

The main goal of this study is to analyze the impacts of adverse winter weather conditions on speed selection behavior and other driver parameters by using a microsimulation modeling tool. A model will be developed to better understand the relationship between them. It will help to identify the impacts of weather on speed behavior. Moreover, micro-simulation tool will be utilized to develop a microsimulation model based on observed data during different storm events for model calibration. This research will help in addressing the following research questions:

1. What are the impacts of weather parameters on the selection of speed behavior during adverse winter weather conditions?
2. How the change in speed behavior reflects the microscopic behavior: headways and gaps (spacing) during the adverse winter weather conditions?
3. What are the implications of different speed behavior on the operation of the weather-responsive traffic management strategies?

The main objectives of the research are:

1. To address the knowledge gap in explaining the impacts of weather parametres on speed selection behavior on rural interstate facilities during adverse winter weather conditions.
2. To know the impacts on microscopic behavior such as headways and gaps (spacing) due to change in speed behavior during adverse winter weather conditions.

3. To identify how sensitive the change in weather-related simulation model parameters on traffic operations during adverse weather conditions are.

In order to analyze the speed selection behavior during adverse winter road conditions, interstate corridors in Wyoming were considered with a high percentage of freight vehicles. From this study, it is expected to identify the relationship between different weather parameters and speed behavior during adverse weather conditions. The obtained results from the models will help to support weather-responsive traffic management system to create more efficient mitigation techniques.

1.3 Report Organization

The organization of the report is as follows: Chapter 1 provides an introduction, problems, general description and impacts of adverse weather conditions on traffic operations. It also describes the effectiveness of VSL systems along I-80 corridors. Chapter 2 presents the relevant literature review, including uses of VSL systems, different statistical modeling techniques to know the impact of adverse weather conditions on driver behavior. The chapter also reviews the microsimulation modeling on identifying how sensitive the change in weather related parameters on traffic operations. Chapter 3 presents the description of the project areas, roadway segment selection process, and collection of project data. Chapter 4 describes the methodology used for this study. Chapter 5 discusses modeling methodology used for this study. Chapter 6 contains a development of microscopic simulation models base and adjusted models. The sensitivity analysis was carried out by adjusting base models according to observed data during different storm events. Chapter 7 provides a summary of the research findings, conclusions, and identifies future recommendations.

2. LITERATURE REVIEW

In order to further understand and perceive impacts of adverse weather conditions on traffic operations a comprehensive literature review was done in this chapter. The chapter begins with existing studies on the relationship between adverse weather conditions and traffic operations. Second and third sections focus on the microscopic behaviors and microscopic modeling during adverse weather conditions. The forth section includes evaluating the effectiveness of weather responsive traffic management strategies. A study on weather related driver behavior and speed selection model were reviewed in the fifth and sixth sections. Finally, seventh section concludes with the summary of literature review.

2.1 Impact of Adverse Weather Conditions on Speed Selection

Ibharim, A.T., and F.L. Hall (1994) studied the impact of adverse winter weather conditions on traffic speed on a freeway in Canada and observed certain speed reduction. Traffic and weather data were collected and analyzed to get the effect of different weather conditions, rain, and snow (light rain versus heavy rain and light snowfall versus heavy snowfall). Different traffic operation parameters were observed by researchers for each type of weather condition. The following reductions in free-flow speed were found:

- Light rainfall caused a reduction of 2 km/h
- Light snowfall caused a reduction of 3 km/h
- Heavy rainfall caused a reduction of 5 to 10 km/h
- Heavy snowfall caused a reduction of 38 to 50 km/h

Shah analyzed weather effects on roadway sections in metropolitan Washington, D.C., 18 of the selected sections were freeways and 15 were major arterials almost covering 239 miles. Different weather variables were included such as, rainfall (no, light and heavy), snow (no, light and heavy), wind speed (<30 mph or >30 mph), visibility distance (<0.25 miles or ≥0.25 miles), and slippery pavement conditions (dry, snowy, wet, or icy). Two-step regression analysis method was used to anticipate travel time increase due to reduction in speed under adverse winter weather conditions (Shah, 2002). First, travel times data were regressed with selected weather data and second, the regression models were reduced to predict normal travel time with the increased travel time because of adverse weather. Twelve percent and 48 percent increase in arterial travel time was observed during a two-hour and a day, off-peak period respectively (Shah, 2002).

A Federal Highway Administration (FHWA, 1977) study found the economic impacts on each type of weather condition and the interstate speed reduction in adverse winter weather. Table 2.1 illustrates the average percent decreased in speed for different weather conditions.

Table 2.1 Percent of speed reduction due to inclement weather (FHWA, 1977)

Roadway Condition	Speed Reduction
Dry	0%
Wet	0%
Wet and Snowing	13%
Wet and Slushy	22%
Slushy in Wheel Paths	30%
Snowy and Sticking	35%
Snowy and Packed	42%

Research conducted by Hawkins on UK's M1 roadways in Nottinghamshire shows that there is a direct relationship between vehicle speed and weather conditions (Hawkins, 1988). Weather conditions were divided into nine major conditions with visibility and dry pavement as the base condition. The study showed that there was a reduction in speed due to poor visibility; the lesser the visibility the higher the speed reduction. There was a 25–30 percent speed reduction with 328 feet visibility. A higher percentage of speed reduction was seen due to snow or slush, where speed reduction was 18.6 mph–24.9 mph respectively. In addition, light and steady or heavy rain caused speed to be decreased by 2.5 mph on the slow and center lanes and approximately 3.7 mph on the fast lane (Hawkins, 1988).

Also, 24 curved road sections of rural two-lane highways were studied by Lamm for dry and wet conditions to investigate the impacts of adverse weather on traffic speed. Results showed there was no statistical difference in operations between those two conditions (Lamm, et al., 1990).

Chapter 22 in the Highway Capacity Manual (FHWA, 2000) gives information regarding speed and suggests that the free flow speed is decreased by 2 percent to 14 percent and 5 percent to 17 percent due to light and heavy rains, respectively. The reduction value raise up to 3 percent to 10 percent and 20 percent to 35 percent because of light and heavy snow conditions. The manual fails to illustrate the precipitation range for these categories to such reductions.

Thomas studied the effects of adverse weather in three predominant traffic variables; traffic demand, traffic safety, and traffic flow relationship (Thomas, et al., 2006) . The study found an important impact on all three predominant traffic variables because of weather and intensity of precipitation. The roadway traffic volume was reduced by less than 5 percent during rainstorms and 7–80 percent during snowstorms. Crash rates increased by 13 times during moderate-intensity snowstorms and by 25 percent in high-intensity snowstorms (high winds and low visibility). In addition, heavy rains with more than 0.25 in/h and snow with more than 0.5 in/h reduced freeway capacity by an average of 14 percent and 22 percent respectively. Table 2.2 illustrates the impact of adverse weather on transportation systems (Pisano & Goodwin, 2002).

Table 2.2 Weather impacts on roadways and traffic operations (Pisano & Goodwin, 2002)

Weather Events	Impacts on Roadways	Impacts on Traffic Operation
Rain, Snow, Ice, Sleet, Hail, and Flooding	Reduced vehicle performance	Reduced roadway capacity and speed
	Infrastructure damage	Increased delay and speed variability
	Reduced visibility	Increased accident risk
	Lane obstruction and submersion	Road restriction and closures
High Winds	Reduced visibility due to blowing snow/dust	Increased delay and crash risk
	lane obstruction due to wind-blown debris and drifting snow	Reduction in traffic speed
	Reduced vehicle performance	Road restriction and closures
Fog, Smog, and Smoke	Reduced visibility	Reduced speed and increase speed variability
		Increase delay and crash risk
Lightning and Extreme Temperatures	Infrastructure damage	Traffic control device failure
		Loss of power/ communication system

Adverse weather and traffic demand are inversely proportional to each other; if severity of the adverse weather is raised then traffic demand decreases. Research conducted on I-35 in northern rural Iowa resulted in traffic volume reduction on snowy days with low and high wind. There was a 20 and 80 percent reduction respectively (Maze, et al., 2005). Rakha showed there was reduction on capacity by 10–11 percent (Rakha, et al., 2008). Perrin and Agbolosu-Amison analyzed the impacts of snowy conditions and found that the maximum reduction of saturation flow was 21 percent for snowy conditions (Perrin, 2001) (Agbolosu-Amison, et al., 2004). Many researchers have shown the impacts of adverse weather on traffic flow, but none have analyzed the underlying complexity of speed selection behavior during adverse road conditions. This study shows the impacts of different weather variables on traffic operations during adverse winter conditions and addresses the relationship and impacts of such conditions on speed behavior. For this analysis, the VISSIM microsimulation modeling tool willl be used. Table 2.3 shows the impact on microscopic behaviors during adverse weather conditions.

Table 2.3 Microscopic level impacts on traffic operations (Agbolosu-Amison, et al., 2004)

Typical Impact	Weather Event	
	Rain	Snow
Lost startup time	+7.6 % ~ +31.5 %	+18.5 % ~ +65.2 %
saturation headway	+2.5 % ~ +13.2 %	+4.4 % ~ +30.9 %
Free-flow speed	-7.6 % ~ -31.5 %	-3 % ~ +36 %

2.2 Microscopic Behaviors

In additional to speed behavior, adverse winter weather road conditions cause drivers to adopt their own driving behavior to overcome the situation including: car-following, lane-changing, and gap-acceptance behavioral decisions.

2.2.1 Driver Car-Following Behavior

The first car-following model was developed by (Chandler, 1958) based on a simple linear model. The model equation can be expressed as:

$$a_n(t) = \alpha \,\triangle V_n^{front}(t-\tau_n) \tag{1}$$

Where,

$a_n(t)$ = Acceleration or deceleration at time (t)

α = Sensitivity coefficient

$V_n(t-\tau_n)$ = Speed of vehicle

$V_n^{front}(t-\tau_n)$ = Leading vehicle speed

τ_n = Reaction Time

A major limitation of the model above is the assumption of a constant sensitivity for all situations. The model was modified by (Gazi, 1961) by incorporating the space headway between two vehicles in sensitivity terms. The model equation is:

$$a_n(t) = \frac{\alpha}{\triangle \mathrm{Xn}\,(t-\tau_n)} \triangle V_n^{front}(t-\tau_n) \tag{2}$$

Where,

$a_n(t)$ = Acceleration or deceleration at time (t)

$\triangle Xn(t-\tau_n)$ = Space headway

$\triangle V_n$ = Speed of vehicle

Microscopic data were collected to estimate the model from car-following experiments in the Lincoln Tunnel, Holland Tunnel, and at the General Motors test track. Certain parameters, such as α and τ, were predicted for each driver of each data set by using correlation analysis.

Newell (1961) proposed the new model following the relationship between the speed and headway without using sensitivity-stimulus. The model equation is:

$$V_n(t) = G_n \triangle Xn(t-\tau_n) \tag{3}$$

Where,

G_n = Function that determines the specification of the car-following models.

$\triangle Xn(t-\tau_n)$ = Space headway

$\triangle V_n(t)$ = Speed of vehicle

Different microscopic speed flow-density relationship can be obtained from this model, but no quantitative result was reported for validation of the model.

2.2.2 VISSIM Car-Following Behavioral Models

The car-following algorithm in VISSIM was developed by Wiedemann in 1974 (PTV, 2007). It adjusts the change in vehicle speeds with respect to the performance of those leading vehicle speeds. Figure 2.1 has been developed to identify individual vehicle parameters such as relative distance and speed between lag and lead vehicles. There are four stages of the model, recognized by (Fellendorf, 2001) as follows;

1. Free driving
2. Approaching
3. Following
4. Braking

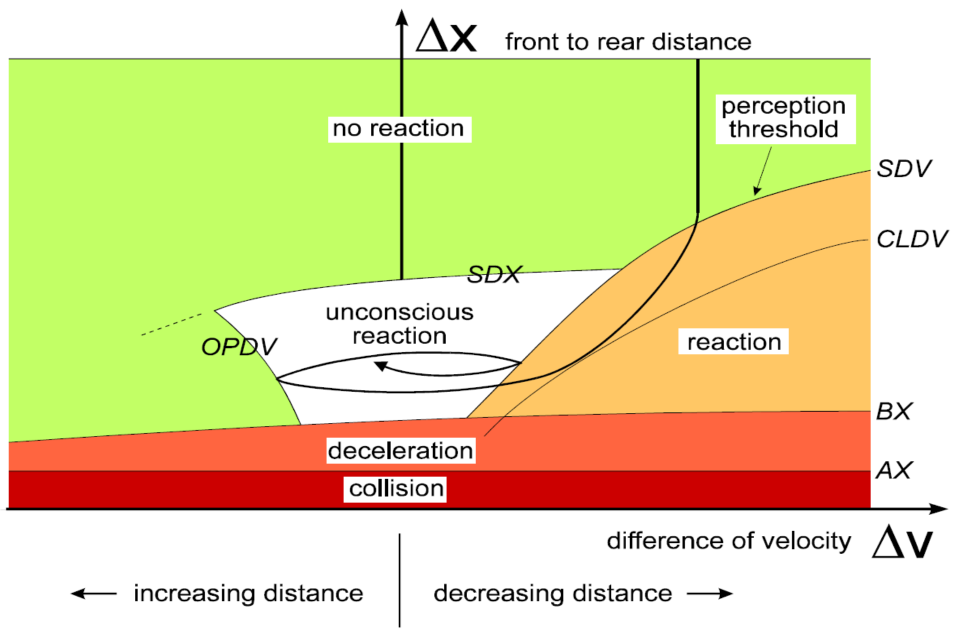

Figure 2.1 Car-Following Model by Wiedemann (AG, 2007)

Where,

$\triangle$X = Change in distance between the lead and lag vehicle and

$\triangle$Y = Change in velocity between the lead and lag vehicle

SDV = Point in road segment where a driver feels that they have approached a slower car. Increase in speed difference increases SDV

OPDV = At point when following driver observed that he/she is slower than leading vehicle and starts acceleration. The variation of OPDV is large.

SDX = Perception threshold for modeling the maximum following distance about 1.5 – 2.5 times ABX

In VISSIM microsimulation software, two algorithm exist for representing driver behavior in the Wiedemann car following mode. They are:

Wiedemann 74 Model

The wiedemann 74 car-following algorithm was developed by Wiedemann in 1974 and is one of the two implementations of car-following algorithms available in VISSIM microsimulation software. This model defines the driver perception thresholds and regimes developed by these thresholds. The model contains a standstill distance, plus additive, and multiplicative parameters to the safety element of the equation and is now applied to urban and arterials traffic. Figure 2.1 illustrates driver behavior in a car-following process. The Wiedemann 74 equation is:

The desired minimum following distance is the function of AX, BX and the speed

$$\text{Distance} = AX + BX \tag{4}$$

Where,

AX = is the standstill distance (m)

$BX = (BX\_add + BX\_Multi * Z) * \sqrt{v}$

Where,

BX_add = is the minimum desired following distance

BX_Multi = is the calibration parameters of the safety distance

Z = is a value of range 0, 1 which is normally distributed around 0.5 with a standard deviation of 0.15.

v = is the vehicle speed [m/s]

Widemann 99 Model

The Wiedemann 99 model is the second implementation of the VISSIM car-following model and is similar to Wiedemann 74 car-following model in many ways, except some of the thresholds in the 99 car-following model are defined in a different and better format for modeling the freeway and motorway parameters. The wiedemann 99 car-following model contains 10 calibration components and shows a more complex representation of the car following than Widemann 74 car-following model. The calibration parameters and a short description of calibration component are tabulated in Table 2.4.

Table 2.4 Calibration parameters of Wiedemann 99 model (Lowness & Machemehl, 2006)

Calibration Component Number	Calibration Component Description
CC0	Distance between rear bumper-to-front bumper of stopped vehicles.
CC1	The following vehicle wishes to keep the safe distance with lead vehicle (Headway Time)
CC2	Longitudinal oscillation during following condition
CC3	Thresholds for Entering
CC4	Controls speed difference during closing process
CC5	Controls speed difference during opening process
CC6	Speed dependency of oscillation during following condition
CC7	Acceleration during oscillation in a following process
CC8	Stopped condition acceleration
CC9	Acceleration when at 80 km/hr

2.2.3 Gap Acceptance Behavior

The gap acceptance model developed between the 1960s and 1970s was based on estimation on distribution of the critical gap length. Fitzpatric and Golias studied the critical gap length model and found that the critical gap length of an individual driver was impossible to measure (Fitzpatric, 1991) and (Golias & Kanellaidis, 1990). Another study conducted at intersections showed that the gaps observed will illustrate only a range of values between the gap length, driver rejected and accepted (Hewitt, 1983).

The Highway Capacity Manual (HCM, 1985) defined the critical gap as the median of all accepted gap lengths. The upgraded version of HCM 1994 defined critical gap as the maximum observed rejected gap length in seconds. After all, the HCM defines the critical gap as "the shortest time between the major and minor street vehicles where minor street vehicles make a movement" (HCM, 2000). Other researchers have their own thoughts regarding critical gap, and defined the critical gap as the gap accepted by a few number of drivers (Greenshields, et al., 1947). In contrast, Pant wrote that critical gap cannot be calculated exactly (Pant & Balakrishnan, 1994).

Microscopic traffic simulation studies individual driver performance on the gap acceptance behavior. Past research used 30 exponential drivers to record driver's variability and determine human factors that impact the driver gap acceptance behavior (Ashworth & Bottom, 1977). The study resulted that the driver's behavior changes drastically according to the real conditions of the roadway.

Kita used a binary logit model for estimating the gap acceptance behavior in the merging area from freeway on-ramp and found an effect on driver's gap-acceptance behavior was due to relative speed and the remaining distance of the acceleration lane (Kita, 1993). Another researcher Cassidy elaborated the binary logit unit for calculating the critical gap length (Cassidy & Yang , 1995). They developed an independent event for each gap event with respect to time (t) and observed a gap sequence for each driver, reject acceptable gaps many times and only accept one gap event (Cassidy & Yang , 1995).

Various factors affect gap acceptance driver behavior, as follows:

- Driver's age
- Delay of number of rejected gaps
- Conflict type
- Driver gender
- Speed of following vehicle
- Type of opposing vehicle
- Opposing traffic volume
- Type of maneuver
- Time of day
- Other factors

Although, the large number of research on gap acceptance behavior have been completed, there still remains a lack of information regarding driver's choice to reject or accept the gap.

Earlier research conducted by Kaisy & Durbin suggested that time headways under five seconds should capture all following (platooned) vehicles, but different researchers illustrate different headways (Kaisy & Durbin, 2009). Figure 2.2 shows different headways threshold values.

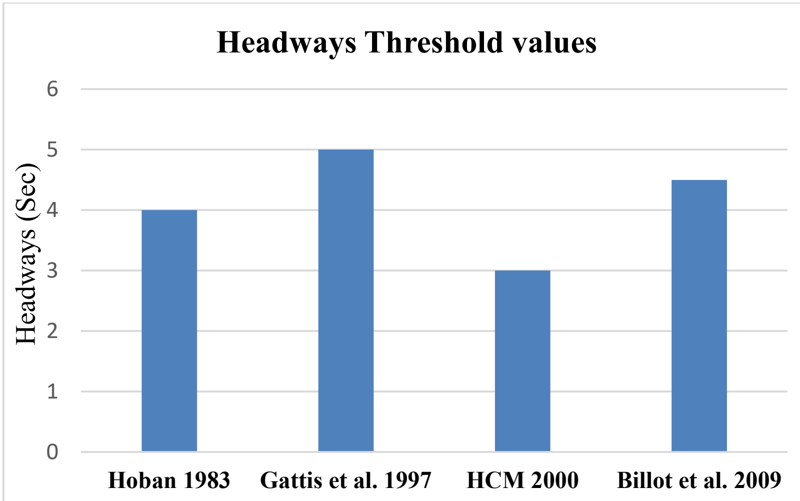

Figure 2.2 Headway Threshold Values of Free Flow/Platooned Vehicles (Rahman & Lowness, 2012)

2.3 Microscopic Traffic Simulation Models and Weather Conditions

To represent the effect of adverse weather conditions in a traffic simulation environment, different traffic characteristics and simulation parameters must be adjusted. Parameters that are included in the traffic characteristics are AADT, vehicle distributions, saturation flow rates. Simulation parameters include driver behavior parameters bserved during weather events.

Research was done on a southeastern Wisconsin highway and a segment of Interstate 43 and 94 (I-43 and I-94) between Howard Avenue and Mitchell Street, to explore the effect of rain on multivehicle crash frequency and severity. Microsimulation modeling was also developed for model validation (Jung, et al., 2011). In this study, different weather data such as wind speed and direction, temperature, rainfall intensity, traffic data, and road geometry data were used to estimate the deficiency of car-following distances and water film depth. The weather data estimation method was used to reflect the actual impact of rainfall on traffic operation and also to learn the microscopic behavior of traffic during the time of crash. VISSIM software was used to develop a traffic simulation model to reflect the impact of rainy weather conditions on traffic operation. Five scenarios were analyzed based on weather-sensitive parameters. The parameters are speed distribution, vehicle deceleration function, and headways. The first task was to simulate rainy weather with the observed traffic volume under the default VISSIM parameter setting as a base condition, which is scenario 5. Further simulation modeling was done by adjusting weather-sensitive parameters. The five scenarios are as follows (Jung, et al., 2011):

Scenario 1: adjustment of desired speed distribution only;
Scenario 2: adjustment of desired speed distribution and vehicle decelerate rate function;
Scenario 3: adjustment of desired speed distribution and headway time value only;
Scenario 4: adjustment of desired speed distribution, vehicle deceleration rate function, and headway time simultaneously; and
Scenario 5: Change nothing.

VISSIM calibration provided similar traffic operations observed in rainy weather conditions when adjustments were made to the desired deceleration rate and desired speed distribution. Traffic speeds and occupancy were used to compare the simulation and observed results.

Another study done by Ambolosu-Amison measured the effect of adverse weather conditions on traffic operation and weather-responsive signal timing by using CORSIM simulation software in an arterial segment of Burlington, Vermont with eight signalized and two un-signalized intersections (Agbolosu-Amison, et al., 2004). The analysis was done for clear weather and for weather-responsive signal timing during inclement weather. The inclement weather was classified into five different road weather categories (wet, wet and snowing, wet and slushy, wheel path slush, and snowy and sticking). A 30-hour videotape data for saturation headways and start-up lost time were collected and analyzed. The study shows that inclement weather conditions have a significant effect on saturation headways, but start-up lost time values were not significantly affected by inclement weather. Among five different weather categories, wet and slushy, wheel path slush, and snowy and sticking have the greater impact on saturation flow rate (Agbolosu-Amison, et al., 2004).

Further study done by Zang used the CORSIM simulation tool to test sensitivity of various simulation parameters to model the effect of different weather conditions. The models were performed using default values (road geometry and volume) and then changing the values according to produce actual driver behavior during adverse weather conditions. The study found that car-following, lane changing, and free-flow speed parameters for road segment have different level of sensitivity (medium to high impacts) on the measure of effectiveness (MOEs) and also found that the lane change parameters have little or no effect on the MOEs (Zhang, et al., 2004).

2.4 Weather Responsive Traffic Management Strategies

Road weather information can be disseminated to roadway passengers through radio, mobile devices, internet, roadside variable message signs, etc. It was found that implementation of weather warning VMSs during adverse weather conditions were effective in reducing average speed and speed variance, which resulted in increased traffic safety and reliability (Louma, et al., 2000).

A study done by Kim shows the development and implementation of methodologies to support WRTM strategies, developing a model called Traffic Estimation and Prediction System (TrEPS). Figure 2.3 shows the framework of implementing and evaluating WRTMs for adverse winter weather conditions and identifies three time horizons (Kim, et al., 2013):

1. Long-term strategic planning
2. Short-term tactical planning
3. Real-time operations

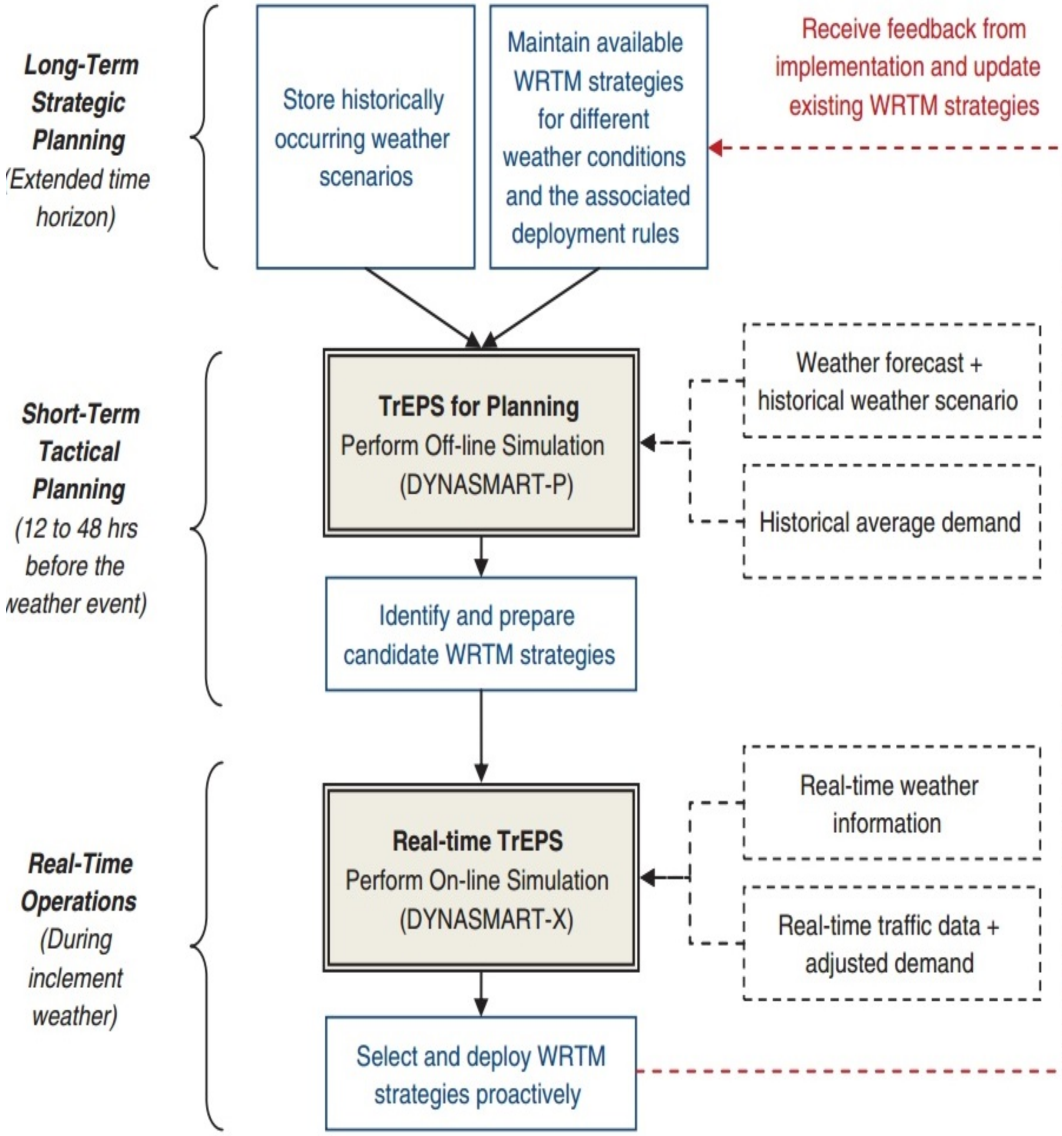

Figure 2.3 TrEPS Support WRTMS Framework (Kim, et al., 2013)

TrEPS is a simulation-based decision support tool that provides necessary information during adverse weather conditions, which fall under short-term planning and real-time operation category (Kim, et al., 2013). If an adverse weather is predicted to occur, TMC managers initiate short-term tactical planning, which helps them to curtail the available WRTM strategies to function in a right way for the predicted weather and roadway conditions. During adverse weather conditions, TMC managers execute real-time TrEPS operations — an online simulation tool. This will help to relay realtime simulation of the roadway and analyses historical data with road sensor information for developing control measures.

2.5 Statistical Analyses of Weather Related Driver Behavior

Chakrabartya (2013) studied an Indian roadway to analyze human responses during inclement weather conditions. Individual drivers' reactions during adverse weather conditions data were collected. V-box with cameras were used to collect the individual driver performances, drivers' reaction time, road conditions, and eye movements. For the analysis, an ANOVA (Analysis of Variance) for the impact of weather condition on driver behavior was performed. Driver behavior factors were classified into the following six categories, and all which are measured in seconds (Chakrabartya & Guptab, 2013):

1. Searching and other Non-driving movements for inside objects
2. Searching and other non-driving movements for outside
3. Yawning time
4. Talking time mobile phone
5. Talking to co-passengers
6. Use of seatbelt while driving

For the research, weather conditions were classified into four categories: clear, cloudy, rain, and foggy days. It was observed that the search time categories were higher on rainy days and lowest on foggy days. The search moment durations were lowest during foggy days, likely because of low visibility and the drivers were more cautious while driving. The analysis showed statistically significant differences (p-value<0.01) between time factors and different human responses driving through inclement weather conditions.

An effect of weather conditions on free-flow speeds study was conducted by DO (2003) on the national highway in Korea. In this study, they considered weather parameters and also road geometry to provide proper speed information to the driver to achieve safety. Four road sections were considered for the data collection process. Speed data were collected with video recorder under free flow conditions and rainfall data from the Flood Control Centers. A significance test of speed difference was done by using ANOVA. When the speed distribution and variance data were tested using ANOVA on clear days and rainy days, it showed that all road sections were statistical significance in the 1 percent significance level (DO, et al., October, 2003).

2.6 Speed Selection Behavior

An ordered probit model was used by Kang in Korean micro data for the speed selection behavior (Kang, 1999). Many other studies showed how road and vehicle characteristics impact speed selection behavior but this study used other factors (e.g. personal characteristics, safety features, etc.) including parameters such as: trip characteristics, vehicular, and attitudinal factors. The measured speed was classified in three, ordered categories. Four types of data were used for the analysis: speed data, road geometry, characteristics of vehicles, and trip purpose. Speed sensor was used for collecting speed data. whereas interviews were taken by stopping vehicles at the intersection for additional data. A model estimated that male drivers with higher income tend to select higher speeds than female drivers. Vehicles with more safety features traveled at a lesser speed than vehicles with less safety features. Trip distance was found to be an important factor for speed selection behavior, as was speed limit (Kang, 1999).

2.7 Summary of Literature Review

This chapter demonstrated the impacts of adverse weather conditions on traffic operation and driver behavior. It also outlined use of microsimulation tools to identify weather-related parameters and their effects on speed selection behavior. In addition, development of WRTM strategies in rural areas helps us understand the impacts of weather variables on speed selection behavior. Furthermore, implementation of strategies and tools to mitigate such impacts could be helpful in achieving road safety to a maximum level during adverse weather conditions.

No specific studies on speed selection during adverse weather conditions were found. However, some guidance was provided by the above literature.

3. ROADWAY SEGMENT AND PROJECT DATA

The roadway segments for this study were selected from Colorado and Wyoming Interstates. These states have significant adverse weather conditions in winter and provide a broad range of traffic volumes in terms ADT and truck percentages. As stated previously, the main objective of this study is to address the relationship and impact of weather conditions on driver behavior, and traffic speed.

This chapter describes the procedure for selecting the roadway segments, the corridors, and data collection for the selected corridors.

3.1 Roadway Segment Selection Process

The primary criteria for data collection in this research was interstate freeway corridors. The interstate freeway corridors from Colorado and Wyoming were selected because they have similar adverse weather conditions and a broad range of traffic volume. Only interstate freeway is considered to limit the geometric design factors that affect driver behavior.

The secondary criteria was availability of weather and speed data during adverse weather conditions. Furthermore, interstate freeway segments away from highly urbanized areas were considered to minimize the influence of traffic congestion.

Based on above mentioned criteria, interstate freeway corridors along Interstate 80 (I-80) in Wyoming and Interstate 25 (I-25) and Interstate 76 (I-76) in Colorado were chosen. This study includes selection criteria of the corridors from Colorado, but analysis is limited only to the Wyoming corridors. The study corridors are all four-lane rural interstate with posted speed limits of 75 mph.

3.2 Wyoming Corridors

In Wyoming, Variable Speed Limit (VSL) corridors were selected for the study due to the availability of data and frequent severe weather conditions. The VSL corridors in Wyoming are located along I-80, which is a major transcontinental corridor for passenger cars and freight trucks crossing southern Wyoming. There are approximately 400 miles of I-80 in Wyoming. Individual vehicle speeds data were collected for different storm events from three corridors: Elk Mountain, Laramie-Cheyenne, and Green River-Rock Spring corridors, respectively. Figure 3.1 shows the locations of the corridors. A description of the corridors follows.

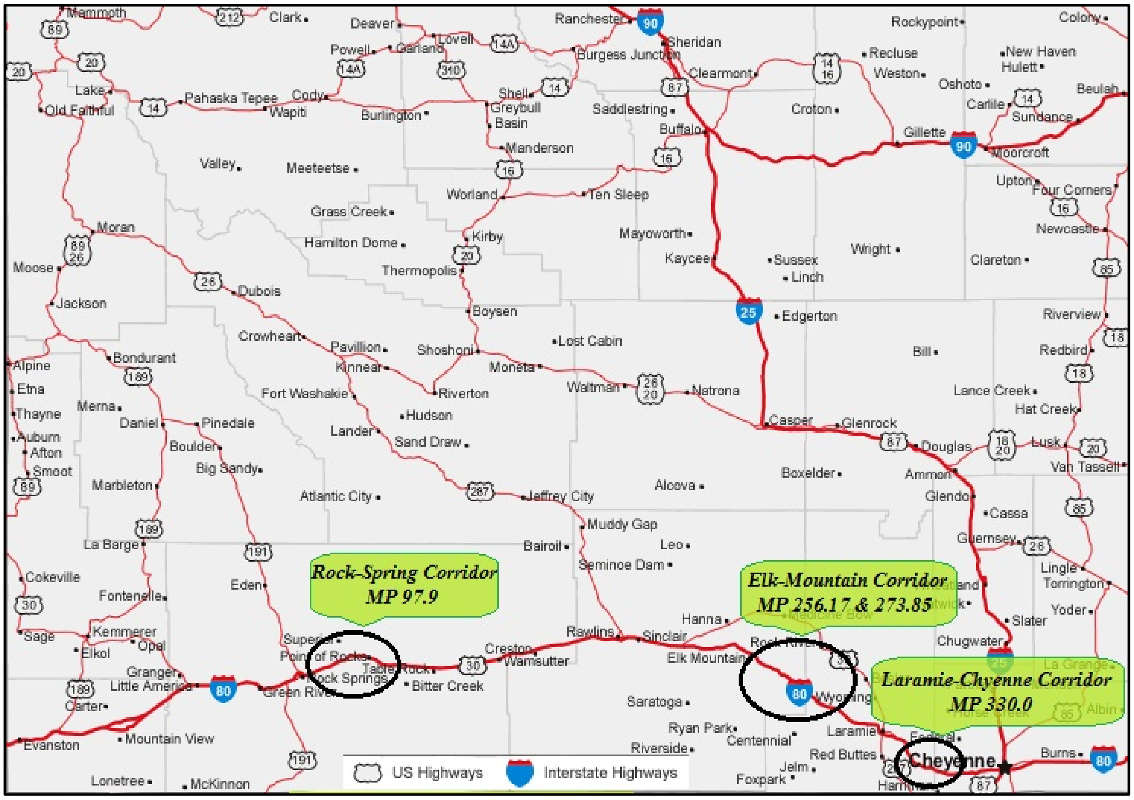

Figure 3.1 Location of the Study Sites in Wyoming

3.2.1 Elk Mountain Corridor

The Elk Mountain Corridor lies in the southeastern part of Wyoming between the towns of Laramie and Rawlins. Laramie is located in Albany Country and Rawlins in Carbon Country. The corridor is located in WYDOT District 1. The length between Laramie and Rawlins is approximately 100 miles and the project corridor extends from mile marker (MM) 256.17 to MM 273.8. The entire corridor is a four-lane rural interstate with a speed limit of 75 mph. The AADT and truck percentages of the corridor are shown in Table 3.1 and Table 3.2.

Table 3.1 AADT and trucks percentage for MP 256.17

YEAR	AADT	TRUCKS (%)
2005	5,890	55.69%
2006	5,290	58.03%
2007	5,420	58.30%
2008	5,130	57.31%
2009	5,140	50.82%
2010	5,155	51.83%
2011	5,012	53.31%

Table 3.2 AADT and trucks percentage for MP 273.85

YEAR	AADT	TRUCKS (%)
2005	5,400	58.89%
2006	5,320	58.08%
2007	5,450	58.35%
2008	5,130	57.12%
2009	5,140	50.70%
2010	5,155	51.72%
2011	5,012	53.19%

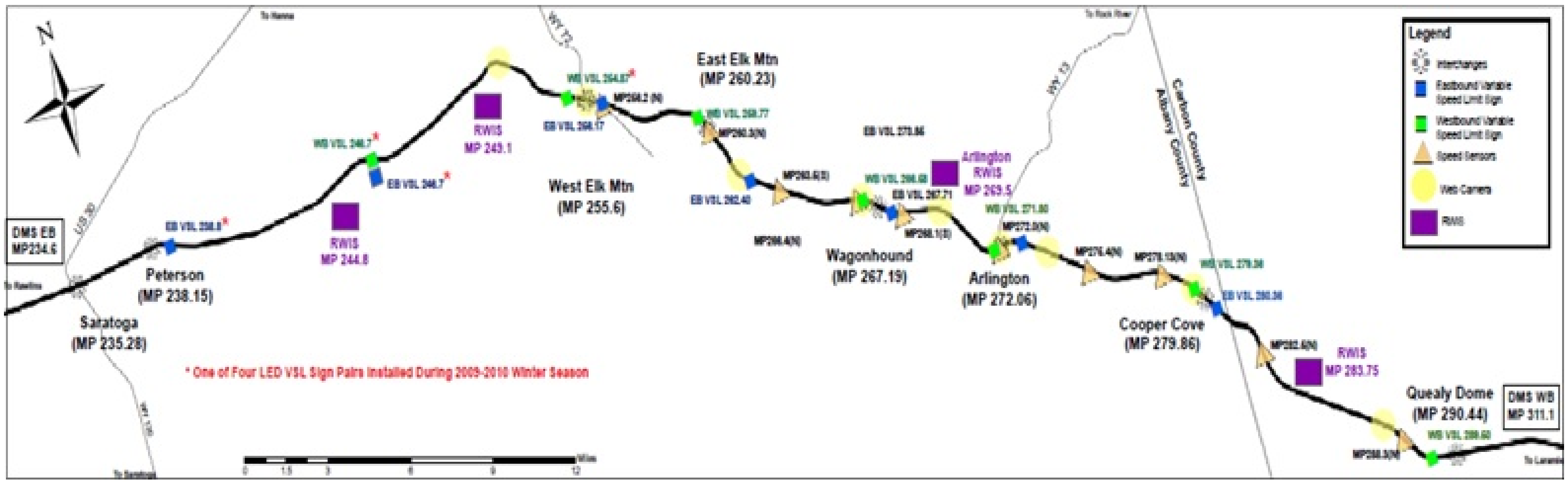

Figure 3.2 Elk Mountain Corridor

3.2.2 Laramie–Cheyenne Corridor

The Laramie–Cheyenne corridor lies on I-80 between the towns of Laramie and Cheyenne in south-eastern Wyoming in the counties of Laramie and Albany. The corridor is operated and maintained by WYDOT District 1. The VSL signs were first implemented in February 2009. The corridor is approximately 45 miles long and is a four-lane rural interstate. The speed limit for the westbound direction around milepost 320 (an area called Telephone Canyon) has a maximum speed limit of 65 mph because of road geometry (steep downhill grades and horizontal curve). The rest mileposts have a maximum speed limit of 75 mph. The 65 mph section was not considered in this study due to its geometric conditions. The AADT and trucks percentage of the corridor are shown in Table 3.3.

Table 3.3 AADT and truck percentage of MP 330

YEAR	AADT	TRUCKS (%)
2005	6,220	48.07%
2006	6,400	46.56%
2007	6,560	46.34%
2008	6,270	46.57%
2009	6,283	43.20%
2010	6,302	44.18%
2011	6126	46.53%

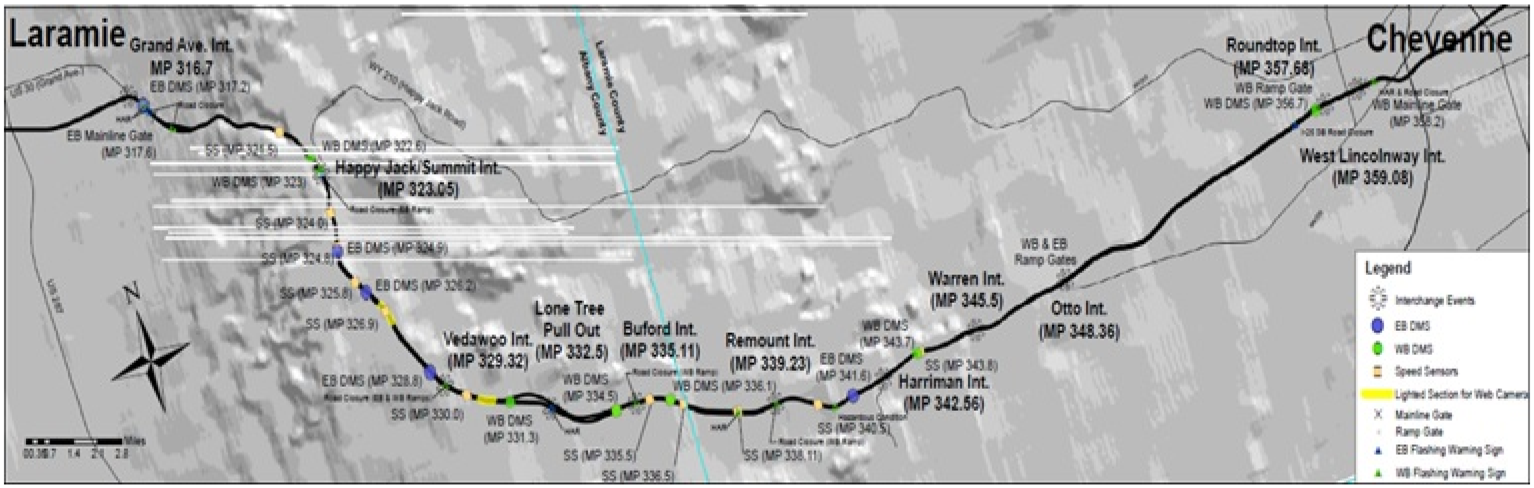

Figure 3.3 Laramie−Cheyenne Corridor

3.2.3 Green River−Rock Springs Corridor

The Green River−Rock Springs Corridor lies between the towns of Green River and Rock Spring in south-central Wyoming in Sweetwater County. The corridor is operated and maintained by WYDOT District 3. The VSL system began its operation on the corridor from February 2011. The entire corridor is a four-lane rural interstate and is approximately 13 miles. 75 mph is the maximum speed limit for the corridor, except in the region around a twin-bore tunnel mile post 90.2. The 65 mph section was not considered in this study. The AADT and Truck Percentage of the corridor are given in Table 3.4.

Table 3.4 AADT and truck percentage of MP 97.9

YEAR	AADT	TRUCKS (%)
2005	10,450	34.35%
2006	12,810	35.13%
2007	12,800	35.39%
2008	12,070	30.90%
2009	12,154	27.03%
2010	12,069	27.22%
2011	11,791	27.86%

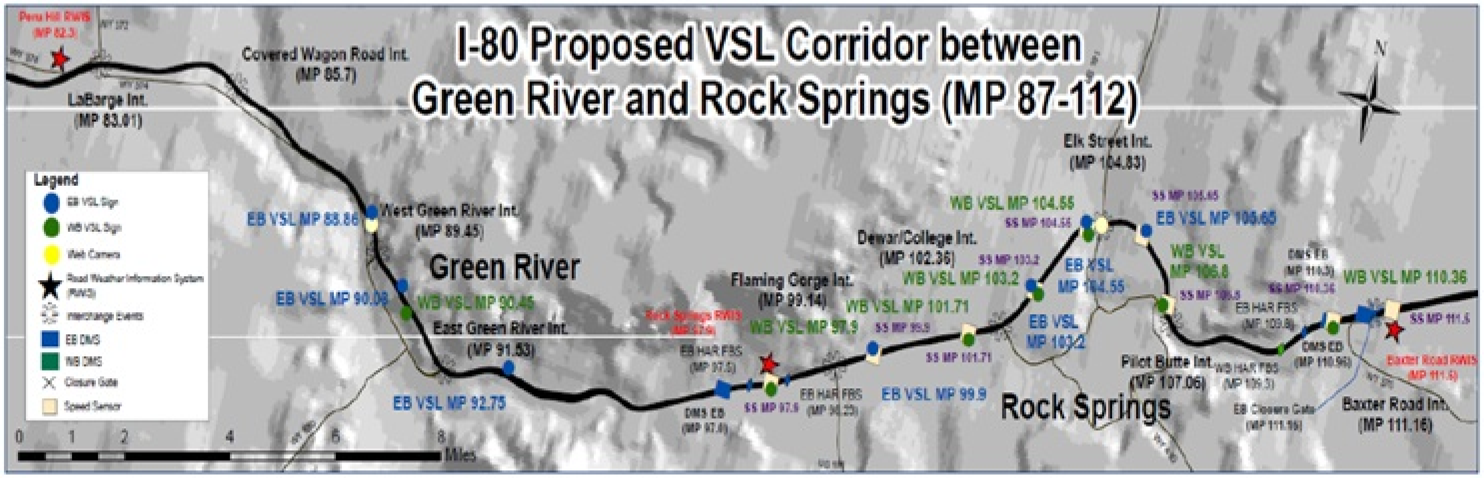

Figure 3.1 Green River−Rock Spring Corridor

3.3 Colorado Corridors

Corridors from I-25 and I-76 were selected for the study in Colorado for reasons cited earlier in this chapter. I-25 runs through Colorado from north to south for approximately 305 miles. It passes through Colorado Springs, Denver, Fort Collins, Loveland, and Pueblo. I-76 runs from interstate 70 from Arvada, Colorado, to the east and an intersection with I-80 near Big Spring, Nebraska. There is about 184.86 miles of I-76 in Colorado. These freeways are implemented with ITS components.

3.4 Summary of Selected Roadway Segments

Corridors outside of urban areas in Colorado and Wyoming were chosen for this study to represent a broad range of traffic volumes and truck percentages. Two states were chosen for this study because both experienced similar weather during winters but have a significant range of traffic volume and truck percentage. The corridors were chosen in such a way to limit the effects of road geometry. Therefore, the challenging geometries of mountainous corridors were excluded from the study. To meet the above criteria, corridors in Colorado along I-25 and I-76, and the I-80 corridor in Wyoming were considered. The analysis of speed selection behavior was done only for Wyoming corridors under free flow subjected to adverse weather conditions. The analysis for Colorado corridors were beyond the scope of this report.

3.5 Project Data Collection

This section involves the description of data sources. Roadside speed sensors provide individual vehicle speeds, timestamp, lane classification, vehicle length and class data. Road Weather Information Systems (RWIS) located beside the freeway provide weather data.

3.5.1 Traffic data

The individual vehicle speeds data were collected from the Wavetronix radar detectors installed along the corridors. The captured data is transmitted to a central server in Cheyenne at the WYDOT Traffic Management Center (TMC). The TMC operator use aggregated speed data for their current decision-making processes. To extract data from radars, it must be taken into offline mode from the TMC's system. This restricts the duration of data collection periods. Setting the speed sensors offline during data extraction impact TMC's speed mapping system. To reduce the impact, only a few speeds sensors were considered on each corridor to extract speed data for specific storm events. The data format includes:

- Date and time
- Vehicle length (feet)
- Type of lane (lane 01, lane 02, lane 03, and lane 04)
- Class
- Range
- Direction (West Bound, WB and East Bound, EB)
- Mile post (MP)

An example of unprocessed individual speed data can be found in Appendix A.

Figure 3.5 Wavetronix Speed Sensor

3.5.2 Weather Data

Weather data was collected by Road Weather Information Systems (RWIS) stations for selected corridors. WYDOT TMC computer was used by remote access to collect weather data from RWIS. RWIS collected the weather data of surrounding environment and pavement conditions every five minutes with the following parameters:

- Date and time
- Surface Temperature (degree F)
- SfStatus: Pavement Surface Conditions (category)
- Air temperature (degrees F)
- Relative humidity (RH) (%)
- Dew point (degrees F)
- Average wind speed (mph)
- Gust wind speed (mph)
- Wind direction (category)
- Precipitation accumulation
- Precipitation rate
- Visibility (feet)

Surface temperature provides the pavement surface temperature. The SfStatus is the status of the pavement surface conditions including dry, trace moisture, wet, chemically wet, ice, ice warning, ice watch, or error. Air temperature represents atmospheric readings at the RWIS site. Relative humidity (RH) is the percentage of moisture in the air. The moisture presence in the air is high if the RH value is higher. Dew point is the temperature at which the air becomes saturated as it cools. The RWIS measures the average wind speed, wind direction, and wind gust speed. Average wind speed is the average wind speed during five-minute periods. It also shows direction of the wind. The maximum wind speed measured during five-minute intervals is known as gust wind speed. Visibility is the atmospheric visibility of the environment. Visibility distance is reduced according to weather conditions. The visibility might decrease either due to blowing snow, fog, or heavy precipitation.

Figure 3.6 RWIS Station

3.6 Existing ITS Applications

The chosen corridors have a significant installation of ITS components such as speed sensors, road weather information systems (RWIS), Dynamic Message Sings (DMS), Variable Speed Limit (VSL) systems, and Pan-Tilt-Zoom (PTZ) cameras. WYDOT installed a VSL system along the Elk Mountain corridor in February 2009. The VSL systems consist of variable speed limit with scrolling film technology. The speed limits of 75, 65, 60, 55, 50, 45, 40, and 35 mph are printed on the rotating film. These signs are shown on the left-hand side of Figure 3.7.

Figure 3.7 VSL Signs, Scrolling Film Technology (left) and LED Technology (right)

All VSL signs were placed at required heights for driver to see the speed limit clearly and were installed in pairs on the median and shoulder. The VSL signs are equipped with flashing beacons and are activated when the speed limit is reduced. WYDOT implemented a newer VSL sign with LED display technology on other corridors in Wyoming and on the extension road section of the Elk Mountain in 2009–2010. The LED VSL signs also use flashing beacon. The LED VSL signs are shown on the right side of Figure 3.7.

3.7 Merged Datasets

The RWIS data were merged with individual speed data using Microsoft Excel. Some RWIS stations had insufficient data. In such conditions, weather data from the closest RWIS was used. After data was merged into a single file, weather data was used to identify the ideal and non-ideal periods. Ideal and non-ideal conditions are based on SfStatus, wind speed, and visibility (Buddemeyer, et al., 2010). Non-ideal conditions are at when SfStatus changed into any other condition than dry. Gust wind speed greater than 45 mph and visibility value less than or equal to 500 feet were also considered as non-ideal periods (Buddemeyer, et al., 2010). Visibility value greater than 500 feet, SfStatus in dry condition, and gust wind speed less than 45 mph are considered an ideal.

The ideal and non-ideal observations were extracted from each storm event data set and compiled into a single data set. The ideal was used to establish a baseline traffic speed during normal condition. The non-ideal data set was used to know the impacts of adverse weather on traffic operations.

Analysis was done by considering three different types of data during adverse weather conditions: weather variables, pavement surface conditions, and driver behavior. Data were collected during different storm events from different mile posts. Table 4.1 illustrates detail about data collection periods. The objective of this project was to identify impacts of weather parameters in speed selection behavior during adverse weather. The above-mentioned weather parameters will be used to develop a model.

4. DATA ANALYSIS

The “ideal” and “non-ideal” individual speeds obtained under ideal and non-ideal weather conditions were used to analyze the performance of traffic operations. Vehicle speeds were obtained for each direction — WB and EB — for ideal and non-ideal weather conditions. For this research, WB and EB directions were combined, since the research locations had roadway geometry that limited the directional differences.

Statistical analyses were done using observed speeds, driver behavior, and weather conditions. The analysis might be helpful to address the knowledge gap when explaining impacts of adverse weather conditions. This chapter describes the statistical analysis on traffic operations during ideal and non-ideal periods.

4.1 Data Description

The individual vehicle speed and weather data collected along I-80 corridors were used to know the impacts on traffic performance. Four different corridors were considered for further analysis to identify the relationship and impacts of adverse weather conditions. Measuring the effectiveness of VSL systems along rural interstate corridors during adverse weather conditions is also a major task.

4.1.1 Wyoming Data

The data consists of ideal periods data before and after the storm event. Data is collected on the basis of storm prediction. Speed and weather data was collected from three different locations on I-80 in year 2010 and 2011: Elk Mountain (Elk Mountain Corridor), Green River (Green River – Rock Spring Corridor), and Vedawoo (Laramie-Cheyenne Corridor) corridors. Data was collected at four different mile posts. Two mile posts from Elk mountain corridor, one each from Green River-Rock Spring and Laramie-Cheyenne corridor. Three different storm event data were collected for every mile post. The collected data contained the storms’ start and end time. The mile posts considered for data collection are illustrated as follows:

- Green River- Rock Springs Corridor
    - Mile post 97.5
- Elk Mountain Corridor
    - Mile post 256.17
    - Mile post 273.85
- Laramie-Cheyenne Corridor
    - Mile post 330

Table 4.1 shows data collected for different storm events at different mile posts. It contains the number of observations under ideal and non-ideal conditions.

Table 4.1 Summary of individual data collection from different storm events

Start Time	End Time	Mile post	# Observations		Storm Event Number
			Ideal	Non-Ideal	
12/29/2010 7:01:19	1/4/2011 18:59:34	256.17	25,649	20,420	1
1/8/2011 17:39:23	1/9/2011 19:18:34	256.17	5,848	2,317	2
1/18/2011 15:02:10	1/24/2011 14:04:20	256.17	22,709	21,177	3
12/29/2010 7:05:07	1/4/2011 18:59:16	273.85	22,704	24,071	4
1/8/2011 17:37:01	1/9/2011 19:19:14	273.85	4,713	3,587	5
1/18/2011 15:14:10	1/24/2011 14:05:29	273.85	8,107	35,973	6
12/29/2010 7:08:21	1/4/2011 19:00:20	97.5	100,769	1,797	7
1/8/2011 17:40:33	1/9/2011 19:20:04	97.5	15,695	140	8
1/18/2011 15:03:04	1/24/2011 14:04:59	97.5	85,402	24,144	9
11/16/2010 14:01:00	11/17/2010 9:56:55	330	-	1,167	10
12/19/2010 19:58:15	12/19/2010 21:18:26	330	-	162	11
12/29/2010 11:24:58	12/31/2010 2:00:07	330	-	3,829	12

Tables 4.2 and 4.3 show the summary statistics of different weather parameters for 12 storm events. There are seven weather parameters and one categorical parameter for pavement surface conditions included in this research: surface temperature, relative humidity, gust wind speed, precipitation accumulation, precipitation rate, and visibility.

Table 4.2 Summary statistics of different weather parameters (Storm Event 1 to 6)

Statistics	SfTemp	Relative Humidity	Gust Wind Speed (Mph)	Precipitation Accumulation	Visibility (Feet)	Remarks
Storm Event 1						
Mean	15.06	77.09	31.64	0.082	5,553.7	Snow event with cold temp. and high wind speed
Mode	17.4	82	40	0	6,560	
Std. Dev.	10	9.98	11.86	0.071	1,678.4	
Minimum	-1.5	41	2	0	761	
Maximum	47.7	96	61	0.25	6,560	
Storm Event 2						
Mean	26.75	79.07	24.67	0.046	6,466.5	Snow event but high temp. & low wind speed & clear visibility
Mode	27	76	32	0.04	6,560	
Std. Dev.	8.26	7.22	9.52	0.038	459.74	
Minimum	9.1	59	1	0	3,172	
Maximum	49.3	94	42	0.12	6,560	
Storm Event 3						
Mean	23.66	77.64	30.67	0.18	6,043.5	Snow event with high temp. & high wind speed. clear visibility
Mode	27	77	37	0.17	6,560	
Std. Dev.	6.81	11.72	13.2	0.18	1,287.5	
Minimum	12.2	41	1	0	551	
Maximum	41.7	98	63	0.61	6,560	
Storm Event 4						
Mean	15.04	75.9	35.83	0.09	5,376.9	Snow event with low temp., high wind speed & high Precip. Accumulation
Mode	12.4	84	37	0	6560	
Std. Dev.	10.32	12.78	14.08	0.07	1,823.9	
Minimum	-3.5	40	1	0	640	
Maximum	43.5	99	65	0.21	6,560	
Storm Event 5						
Mean	27.77	79.4	27.93	0.02	6,459.3	Snow event with high temp., low wind speed & clear visibility
Mode	26.4	72	35	0.02	6,560	
Std. Dev.	9.85	8.3	8.9	0.012	500.2	
Minimum	4.1	64	6	0	1,981	
Maximum	50	97	44	0.04	6,560	
Storm Event 6						
Mean	22.2	79.3	35.61	0.28	5,654.9	Snow event with high temp., but high wind speed & high Precip. Accum. with bad visibility
Mode	24.4	96	37	0.15	6,560	
Std. Dev.	6.83	14.2	14.2	0.26	1,691.9	
Minimum	9.7	43	1	0.02	456	
Maximum	41.9	100	68	0.82	6,560	

Table 4.3 Summary statistics of different weather parameters (Storm Event 6 to 12)

Statistics	SfTemp	Relative Humidity	Gust Wind Speed (Mph)	Precipitation Accumulation	Visibility (Feet)	Remarks
Storm Event 7						
Mean	15.42	79.5	12.61	0.06	6,377.6	Snow event
Mode	18.7	88	9	0	6,560	but low temp.
Std. Dev	8.7	10.61	7.9	0.08	672.9	& low wind
Minimum	0.9	47	0	0	2,316	speed & clear
Maximum	31.6	98	35	0.29	6,560	visibility
Storm Event 8						
Mean	24.2	79.7	13.31	0.02	6,556.2	Snow event
Mode	31.1	94	6	0	6,560	but high temp.
Std. Dev	6.32	10.94	7.21	0.019	82.81	& low wind
Minimum	9.1	56	0	0	5,110	speed & clear
Maximum	34.2	96	27	0.05	6,560	visibility
Storm Event 9						
Mean	29.9	67.96	21.01	0.02	6,560	Snow event
Mode	30.7	65	24	0	6,560	but high temp.
Std. Dev	7.2	9.75	9.09	0.02	0	& low wind
Minimum	15.6	46	1	0	6,560	speed & clear
Maximum	48	97	48	0.06	6,560	visibility
Storm Event 10						
Mean	24.86	82.48	29.52	0.32	5,642.5	Snow event
Mode	23.4	99	34	0.18	6,560	with moderate
Std. Dev	5.52	15.53	7.8	0.28	1,842.5	temp., high
Minimum	12.9	44	7	0.02	430.2	RH & high
Maximum	42.3	99	47	0.92	6,560	Precip. Accum
Storm Event 11						
Mean	31.46	94.2	19.89	0.02	6,560	Snow event
Mode	27	99	16	0	6,560	but high temp.
Std. Dev	5.03	6.46	3.13	0.018	0	& low wind
Minimum	25	76	3	0	6,560	speed & clear
Maximum	47.1	99	38	0.06	6,560	visibility
Storm Event 12						
Mean	18.77	93.75	19.38	0.05	6,277.3	Snow event
Mode	23.7	99	16	0	6,560	but low temp.
Std. Dev	10.14	5.92	10.68	0.08	672.9	& low wind
Minimum	-0.8	82	4	0	2,316	speed & clear
Maximum	34.3	89	50	0.28	6,560	visibility

An analysis of individual speed data was performed on merged data set and for every storm event. For the analysis, several indicator factors were developed for each storm event, which are as follows:

1. **Mile Post (MP):** MP is the specific point along a freeway t;l.o mark distance by miles and where the individual traffic data was collected from.
2. **Truck:** The factor helps to identify vehicle class. Trucks and cars are separated according to the length of vehicles. Vehicles less than or equal to 24 feet were considered as cars and greater than 24 feet were considered as trucks.
3. **Headways:** The time interval between the front bumper of the leading and front bumper of the following vehicle at a specific test point along a stated lane of the road is known as headway. Headway is usually measured in seconds.
4. **Spacing (Gap):** Spacing or gap is defined as the distance between the rear bumper of the leading and front bumper of the following vehicle at a specific test point along a specified lane. Spacing is usually measured in feet.

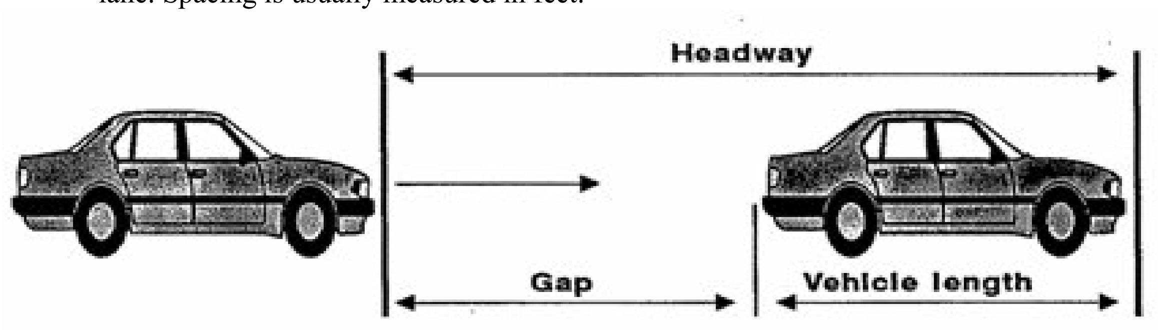

Figure 4.1 Gap and Headway Illustration

4.2 Descriptive Statistics of Vehicle Speeds

A descriptive statistics was consequently done to numerically summarize the data and learn what impacts storm events had on vehicle speed. Tables 4.4 and 4.5 show the descriptive statistics of vehicle speeds for 12 storm events. Data included in the table shows that drivers choose individual speed selection behavior during different types of storm events. Each storm event has its own impact on speed selection behavior. The impacts on traffic operation during adverse weather conditions depend on severity of the storm.

Table 4.4 Descriptive statistics of individual speed for storm event one to six

Parameters	Storm Events					
	1	2	3	4	5	6
# of Observation	46,069	8,165	43,886	46,775	6,037	32,917
Mean	60.38	68.11	60.85	62.31	69.06	58.91
Median	60.3	67.4	62	62.2	69	60.6
Mode	57.3	66.1	64.8	62.4	69.8	67.1
Standard Deviation	10.85	6.4	10.45	10.74	6.14	11.64
Kurtosis	-0.14	1.54	0.13	0.04	3.33	-0.16
Skewness	-0.06	0.07	-0.35	-0.06	-0.18	-0.42
Range	85.9	78.3	95	105.4	79.6	92.2
Minimum	13.6	18.2	12.8	10.4	32	9.4
Maximum	99.5	96.5	107.8	115.8	111.6	101.6

Table 4.5 Descriptive statistics of individual speed for storm event seven to 12

Parameters	Storm Events					
	7	8	9	10	11	12
# of Observation	44,327	7,912	48,400	2,096	335	3,620
Mean	67.46	71.07	71.2	46.68	72.78	66.09
Median	68	70.8	71.1	47.2	73.4	66
Mode	66.4	66.2	66.3	53.6	77.6	65.7
Standard Deviation	9.24	6.25	6.61	11.64	7.11	8.7
Kurtosis	1.49	0.57	0.87	-0.25	0.53	1.53
Skewness	-0.88	-0.09	-0.21	-0.16	-0.36	-0.11
Range	92.2	68.1	81.8	70.2	44.4	89.5
Minimum	11.4	28.4	25.3	9.4	47.9	28.6
Maximum	103.6	96.5	107.1	79.6	92.3	118.1

Table 4.5 shows that storm event 10 had a higher impact on operating speed. The average speed is 46.68 mph with a higher variation of 11.64 mph. The reason behind this might be due to high accumulation of snow on the roadway or poor visibility. There could be impact of other weather parameters too. Statistical modeling will estimate the actual cause, which will be discussed in the following chapter. Storm event 11 did not have much impact on average traffic speed possibly due to clear visibility. The average speeds under different storm events are in the following order: storm event 6, 1, 3, 12, 7, 2, 5, 8, 9, and 11 respectively.

4.2.1 Vehicle Speed Baseline

To determine winter weather impact on driver behavior and resulting vehicle speed, it is necessary to establish baseline speed. The "ideal" data obtained from individual storm events were combined into a single ideal dataset (as described in Chapter 3) and used to develop baseline speed along the corridor. The baseline speed provides understanding about how drivers choose their individual speed during ideal conditions. Figure 4.2 shows the combined average speeds for all vehicles, cars, and trucks during ideal conditions for all 12 storm events (see Table 4.1). All vehicles represent the overall vehicle speeds without separating car and truck. The average speed for all vehicles during ideal periods was 69.76 mph. Average speed for cars and trucks were also analyzed separately. As expected, it was found that cars are traveling at a higher speed than trucks, on average. The average speed for cars was 71.83 mph while trucks were 67.76 mph.

Figure 4.3 shows speed distribution of all vehicles under ideal weather conditions. The variation in speed and the speed distribution is skewed towards higher speeds.

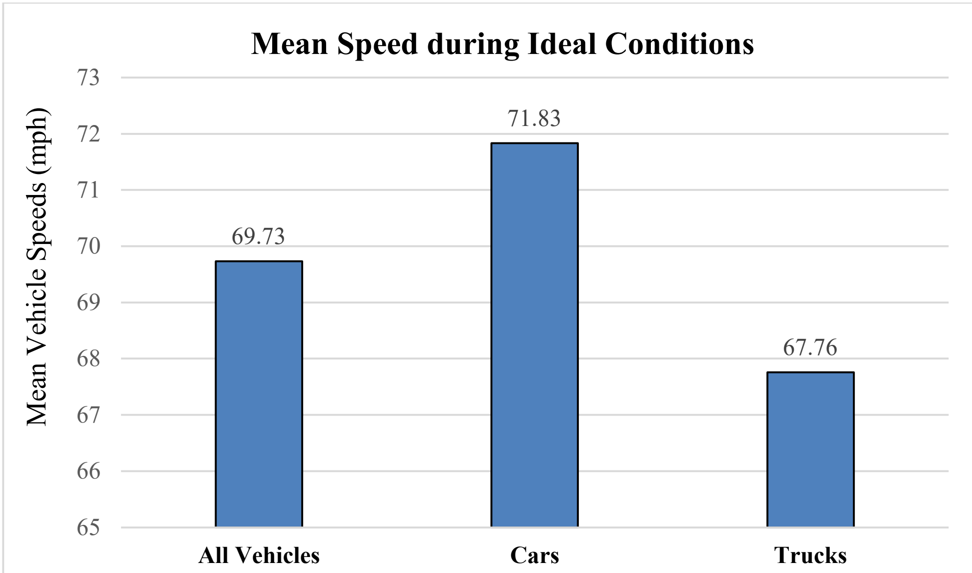

Figure 4.2 Mean Speed for Ideal Weather Conditions

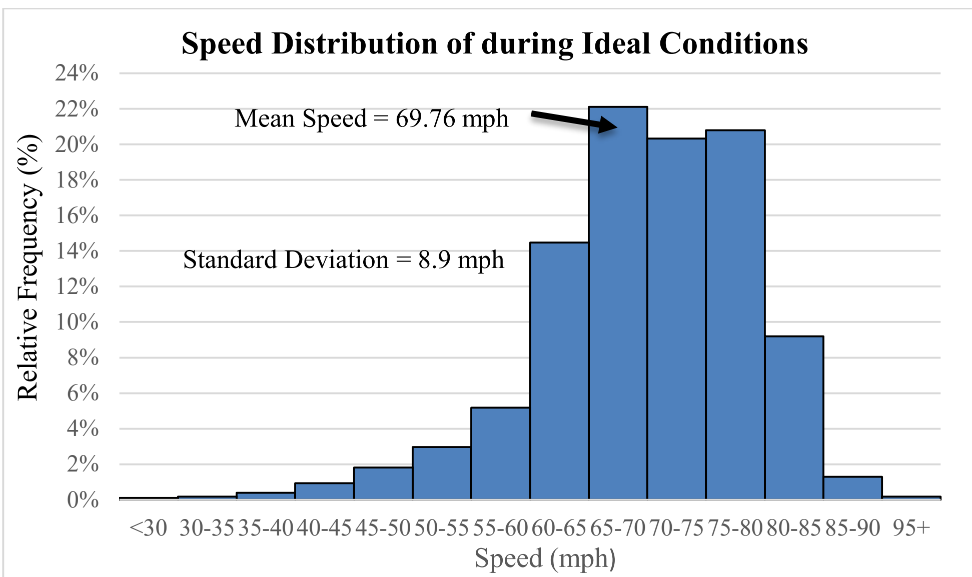

Figure 4.3 Speed Distribution of All Vehicles during Ideal Conditions

Table 4.6 shows the summary statistics for baseline speed. The variability in speed may be due to merging individual speed observations from different storm events and at different mile posts.

Table 4.6 Baseline speed summary statistics for all vehicles during ideal conditions

Speed (MPH)				
Mean	**Median**	**Minimum**	**Maximum**	**Standard Deviation**
69.76	70.4	30	95	8.9

4.2.2 Traffic Speed

The average speed was calculated from observed data at 15 minute intervals. This helped to provide an overview of speed behavior during different storm events. Figure 4.4 illustrates the comparison of speed behavior during different storm events at mile post 256.17. The graph shows that vehicles' speed during ideal periods was similar to speed during the different storm events. The speed behavior during the ideal periods represents the baseline speed of the corridor. The speed selection suddenly changes when the road condition changes from ideal to non-ideal. Steep reduction of average speed was observed when the storm event one worsened the road conditions into a more stable "non-ideal" period. The graph of speed behavior in different storm events at different mile post can be found in Appendix A.

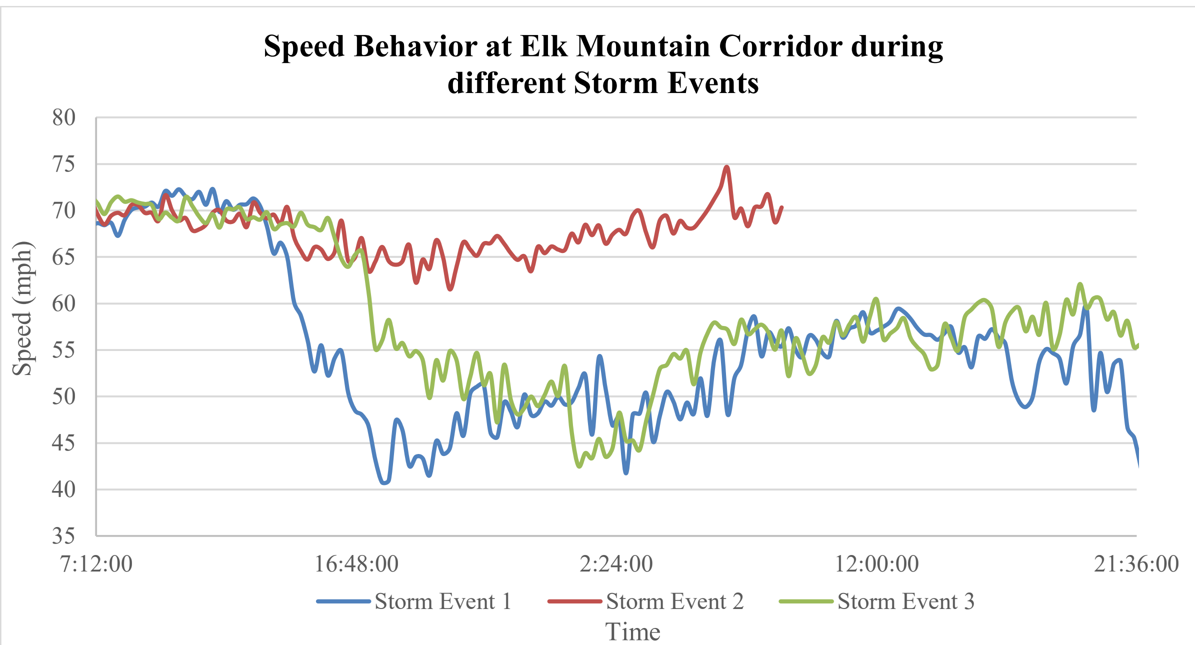

Figure 4.4 Observed 15 Minutes Average Speeds on Elk Mountain, MP 256.17

Figure 4.4 shows the 15-minute aggregate speeds during different storm events, a general trend was that different storm events have differing impacts on speed selection behavior. To plot all three storm event speeds into a single chart was difficult because each storm event has its own duration. To plot them, a 24-hour time format was developed and set to a common time period that initiates from zero. Storm event 1 has a sharper reduction in speed than storm events 2 and 3 when storm changed from ideal to non-ideal periods. Figure 4.4 shows storm event 2 had relatively higher speeds than others with a low variation at 6.40 mph.

4.2.3 Vehicle Speeds During Non-Ideal Periods

In this section, individual vehicle speed was analyzed under non-ideal weather conditions. The change in average speed and speed variation were observed due to adverse winter weather conditions. The ideal data set contains individual speed observation during ideal periods (as described in Chapter 3). The non-ideal data set contains individual speed observation during non-ideal periods. Figure 4.5 shows that there was a reduction in an average speed of all vehicles, cars, and trucks when road conditions changed from ideal to non-ideal. Decrease in average speed during non-ideal periods impacts the microscopic behavior of traffic operations, gaps, and headways (Billot, et al., 2009). The impact of weather events on microscopic behavior will be discussed in the following sections. There was a higher reduction on trucks average speed by 9.22 mph and cars by 5.49 mph.

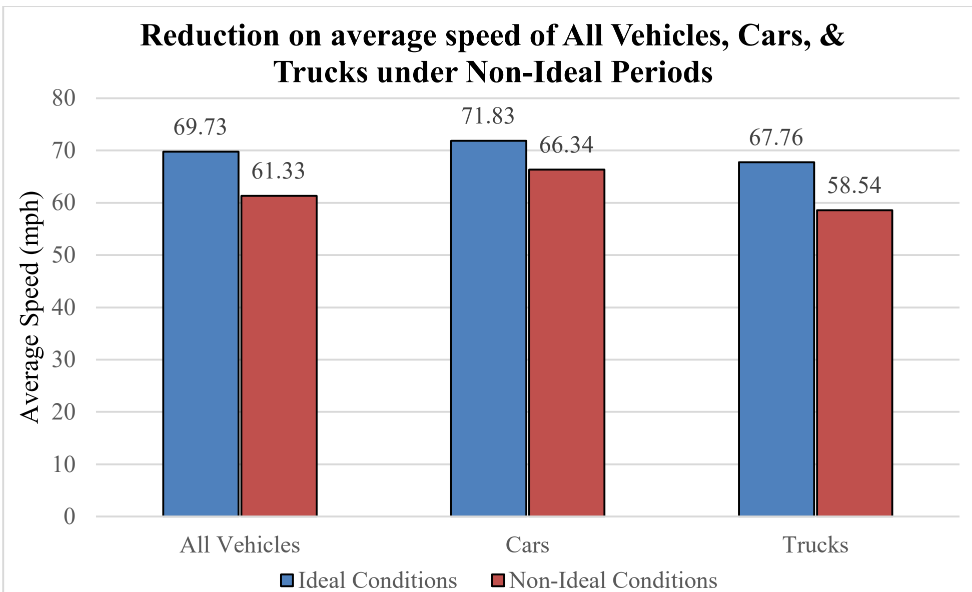

Figure 4.5 Mean Speed Difference under Ideal and Non-Ideal Weather Conditions

A z-test was performed at a 95% confidence interval between two means of ideal and non-ideal conditions and found statistically significant (p-value <.0001). A z-test for the speed gave a z-statistic of 299.78 — greater than the z-critical value (1.95) which illustrates that average speed is higher during ideal periods. Table 4.7 shows a summary of vehicle average speeds, difference in average speed, and speed variations during ideal and non-ideal weather conditions.

Table 4.7 Summary of ideal and non-ideal weather conditions vehicle speeds

Vehicle Classifications	Ideal Conditions Mean Speed (Mph)	Non-Ideal Mean Speed (Mph)	Difference in Mean speeds (Mph)	Ideal conditions Standard Deviation (Mph)	Non-Ideal Standard Deviation (Mph)
Cars	71.83	66.34	-5.49	9.81	12.37
Trucks	67.76	58.54	-9.22	7.78	10.78
All Vehicles	69.73	61.33	-8.43	9.05	12.26

4.2.4 Speed and Cumulative Distributions

It is accepted worldwide that adverse winter weather conditions can affect driver behavior on selection of traffic speeds (Rahman & Lowness, 2012). Reduction on speeds depends on the severity of weather conditions. To learn the impacts of adverse weather conditions on traffic operations, traffic speeds should be analyzed at a microscopic level. Figure 4.6 shows speed distribution of all vehicles during ideal and non-ideal road conditions.

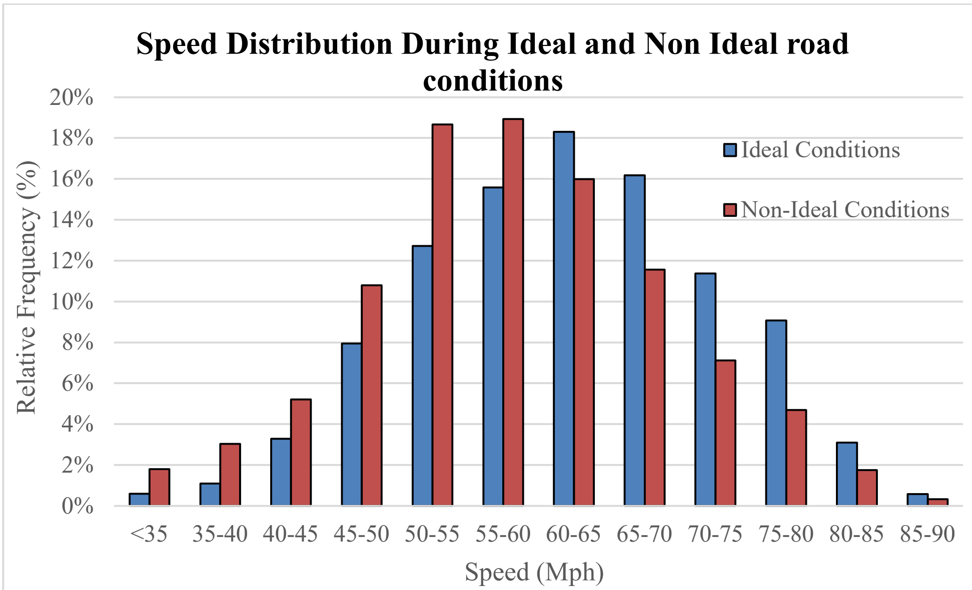

Figure 4.6 Speed Distribution of All Vehicles during Ideal and Non-Ideal Conditions

The speed distribution developed shows occurance of speed versus relative frequency. This analysis showed there was a reduction in frequencies during non-ideal conditions. The speed on x-axis shifted slightly toward the lower range as the road condition changed from ideal to non-ideal conditions. In almost all road sections, the speed distributions during non-ideal periods learned more toward left on the x-axis (lower speed ranges) than during ideal periods. Speeds are high during ideal periods (section 4.2.3) and gradually decrease during non-ideal periods. Moreover, cumulative frequency from merged data set was plotted to know the operating speeds. Figure 4.7 clearly shows that the cumulative distributions are entirely different during ideal and non-ideal periods. Maximum operating speeds were observed during ideal periods with lower speed variation. In contrast, during non-ideal periods, lower operating speeds were observed with higher speed variations. A statistical test was done by using individual speed data of ideal and non-ideal periods to learn the impact of weather conditions on speed selection behavior.

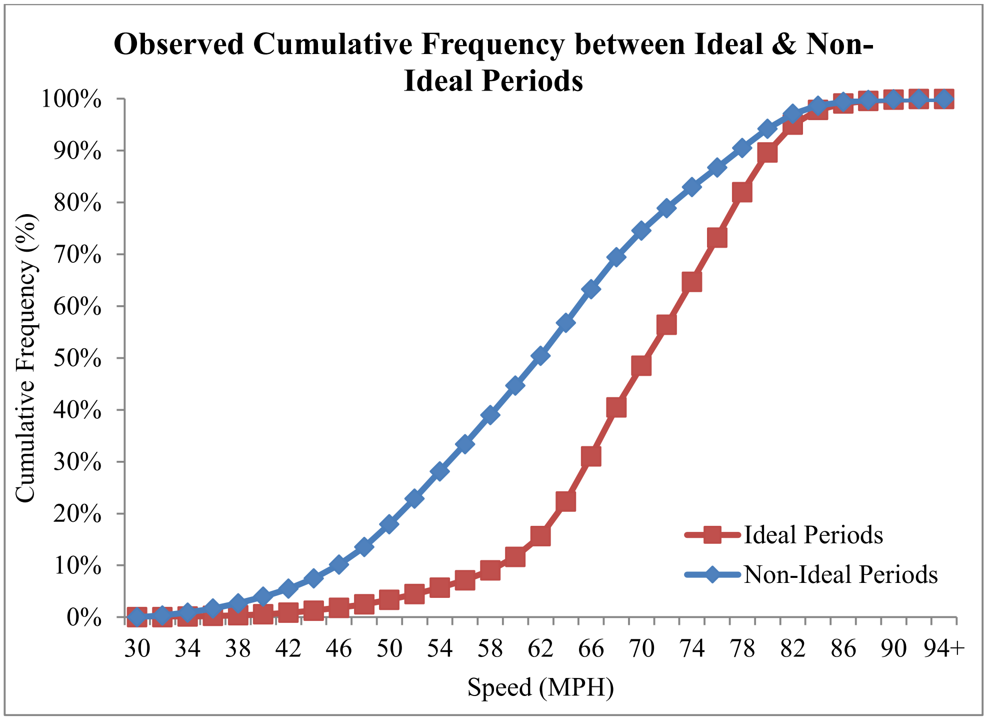

Figure 4.7 Cumulative Percentage of Individual Speeds during Ideal and Non-Ideal Periods

A t-test was done assuming unequal variance at a 95% confidence level between ideal and non-ideal speeds. A test was run for every storm event and for a merged data set. The results showed a statistical significance difference in individual speeds between ideal and non-ideal periods. Ideal periods have higher speeds in all storm events. A statistical test of speed data (ideal and non-ideal) for storm events 9, 10, and 11 was not possible because during those storm events, we were unable to collect before and after ideal period data.

Further analysis of individual vehicle speeds was performed according to vehicle classification to determine speed behavior between each other. It was separated by using truck factor. The 15-minute average speeds were calculated and graphed for each storm event for cars and trucks. Traffic speed observation was analyzed at microscopic levels to learn the difference in speed behavior between cars and trucks. Figure 4.8 shows speed behavior of cars and trucks during storm event 5. The speed behavior of cars and trucks for other storm events can be found in Appendix A.

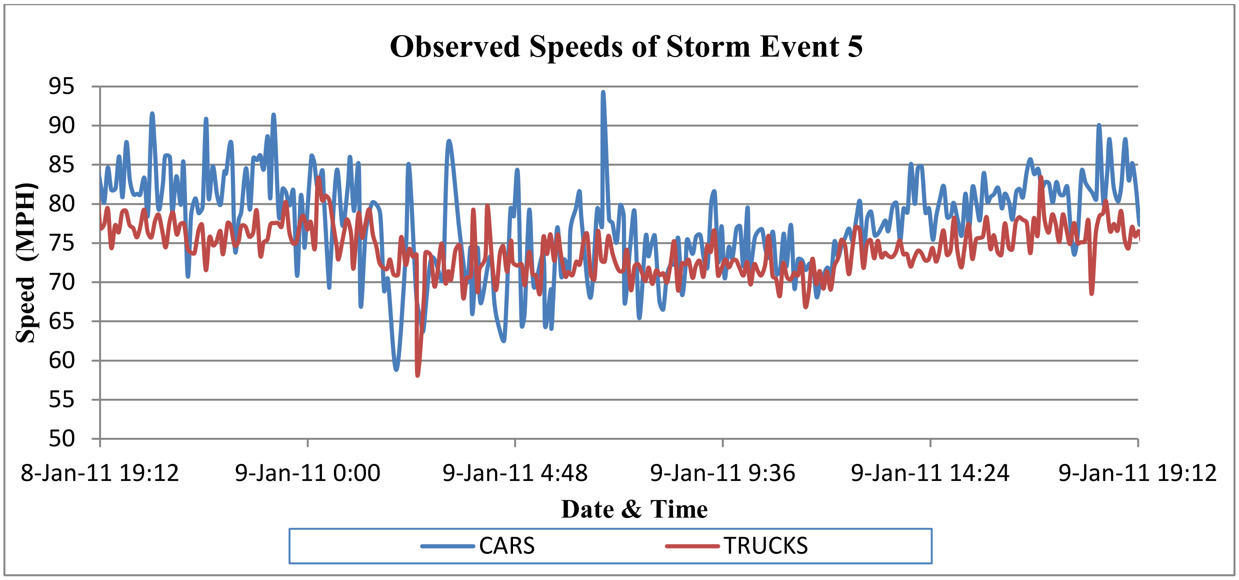

Figure 4.8 Observed 15 Minutes Average Speed

From the above graph, it was observed that the speed of cars is higher than truck speed. To prove this observation, a statistical t-test for mean assumed unequal variance was done at 95% confidence interval for all storm events. The results obtained from the test found that there was a statistical significant difference ($p<0.001$) in speed between cars and trucks. Cars had greater speeds than trucks for every storm event. Table 4.8 shows a t-test between cars and trucks during different storm events.

Table 4.8 Statistically significant difference of individual speed between cars and trucks

Storm Events	Statistically Significant difference at 95% Confidence	Higher Speed	P-Value
1	Yes	Cars	<0.001
2	Yes	Cars	<0.001
3	Yes	Cars	<0.001
4	Yes	Cars	<0.001
5	Yes	Cars	<0.001
6	Yes	Cars	<0.001
7	Yes	Cars	<0.001
8	Yes	Cars	<0.001
9	Yes	Cars	<0.001
10	Yes	Cars	<0.001
11	Yes	Cars	<0.001
12	Yes	Cars	<0.001

4.2.5 Standard Deviation

The standard deviations were calculated from individual vehicle speeds to learn the effects of non-ideal weather conditions on speed selection behaviors and also to determine the significant difference in the standard deviation of speed between cars and trucks. An increase in standard deviation indicates a high variability on vehicle speeds. The standard deviation data obtained from car and truck speeds were compared using F-test, which assumed independent variables and unequal variance at a 95% confidence level for all cases (all 12 storm events). Results in Table 4.9 illustrate statistical significance standard deviation between cars and trucks. Cars statistically proved to have a larger standard deviation than trucks at almost all storm events, except storm event 10.

Table 4.9 Statistical significance in standard deviation between cars and trucks

Storm Events	Statistically Significant at 95% Confidence	Std. Deviation (Cars)	Std. Deviation (Trucks)	Higher Std. Deviation	P-Value
1	Yes	11.27	9.79	Cars	<0.001
2	Yes	7.22	5.39	Cars	<0.001
3	Yes	11.17	9.80	Cars	<0.001
4	Yes	11.04	9.58	Cars	<0.001
5	Yes	7.43	6.14	Cars	<0.001
6	Yes	12.75	11.64	Cars	<0.001
7	Yes	10.13	9.24	Cars	<0.001
8	Yes	6.07	6.25	Trucks	0.004
9	Yes	5.95	6.61	Trucks	0.001
10	No	11.20	11.64	Trucks	0.061
11	Yes	5.31	6.60	Trucks	0.003
12	Yes	9.11	8.70	Cars	0.001

Further analysis of standard deviation was done on merged data sets by categorizing the observation into two periods: ideal and non-ideal. Observations under ideal and non-ideal periods were classified according to RWIS data (as described in Chapter 3). Speed during ideal periods was high and decreased when weather conditions become non-ideal. In contrast, standard deviation during ideal periods is expected to be low and increase as the weather conditions become worse.

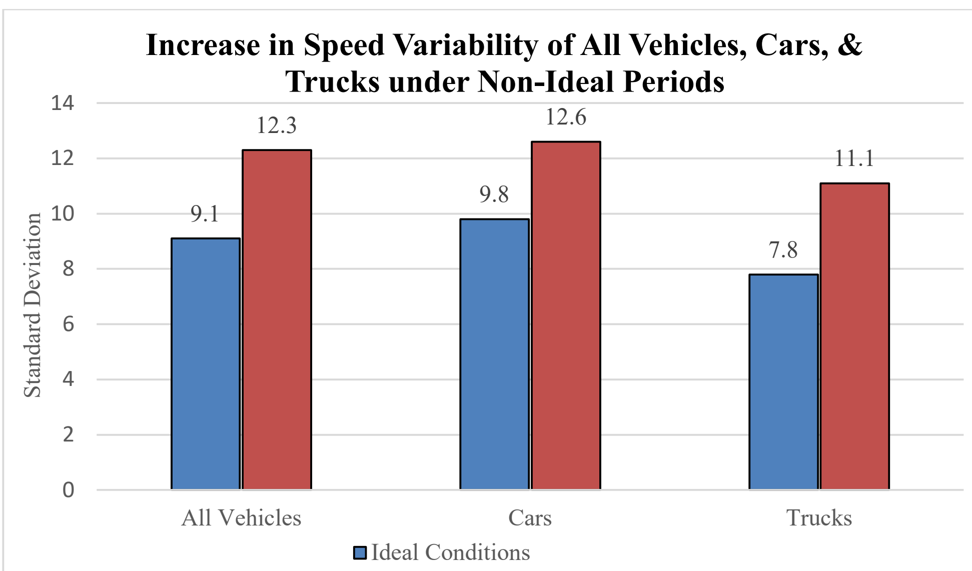

Figure 4.9 Standard Deviation for Individual Vehicle Speeds

As we know, drivers tend to reduce speeds under non-ideal conditions, which increases variations in speed. Figure 4.9 shows the standard deviation of all vehicles, cars, and trucks are increased significantly when compared to baseline speed conditions. The cars' standard deviation is increased by 2.8 mph and trucks by 3.3 mph respectively. An F-test was run for speed variation between ideal and non-ideal conditions at 95% confidence level and was found to be statistically significant.

4.3 Headways and Gap Analyses

It is anticipated that weather events affect the headway between vehicles as drivers react to roadway conditions. During adverse weather road conditions, driver choose their individual speed behavior, which increases speed variation, gap distances, and headway time intervals. Headways can be described as either time headways (sec) or space headways (feet). Time headways for this project were calculated from the same individual vehicle speed observation dataset as used in the previous speed analysis. Headway is defined as distance between the front bumper of the lead vehicle and front bumper of the following vehicle passing at a specific point and a specific lane.

The dataset contains time-stamp observations for all vehicles that pass the radar sensor location and lane classifications, which help to categorize observations. Subtracting time periods between lead and following vehicles in the same lane provides the vehicle headway in seconds. Figure 4.10 shows the time headway distribution of eight storm events during ideal and non-ideal periods. Observed time headways ranged from 0 seconds to more than 2 minutes given the rural nature of the interstate. Small time headway observations less than 0.5 seconds and more than 12 seconds were frequently found during the analysis and were neglected for the further analysis. It is assumed that they were considered to be well outside the range of values for car-following mode. As described in Chapter 2, previous research used different threshold values for car-following headway values, but no single value is accepted for defining car-following mode. Headway time for non-ideal periods was assumed to be higher than ideal periods because it was anticipated that the driver might feel uncomfortable driving in adverse weather conditions. Headway distributions were chosen from specific storm events because the sample size of ideal and non-ideal datasets were not equal.

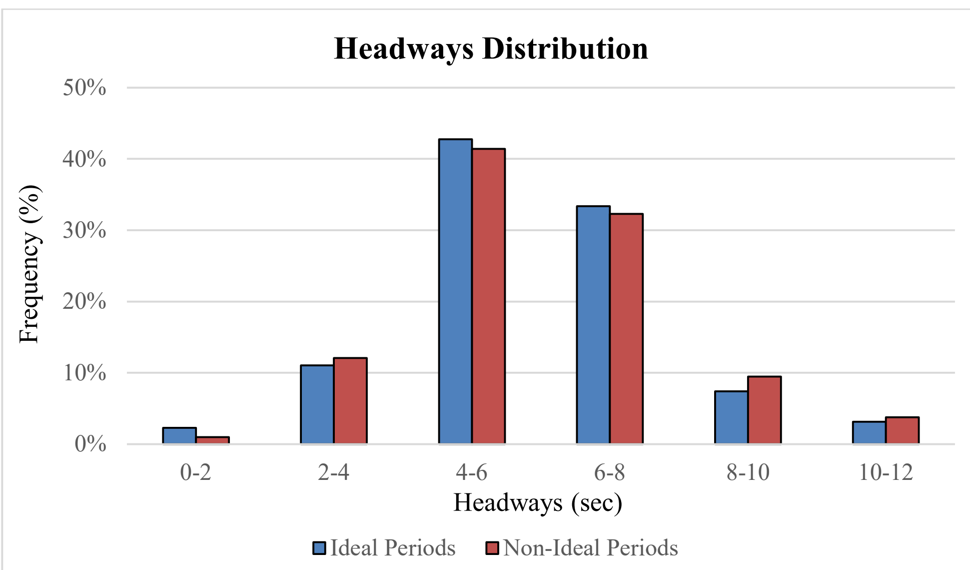

Figure 4.10 Headways Distributions during Ideal and Non-Ideal Periods

From the above headway distribution graphs, calculated headways are classified according to relative frequency of the headways intervals. Figure 4.10 shows a decrease in shorter headways between 0 to 2 seconds by 1.3% under non-ideal weather conditions and an increase of the headway between 2 to 4 seconds and 8 to 10 seconds by 1% and 2.1% respectively. A decrease in headway distribution is observed between 4 to 6 and 6 to 8 seconds by 1.3% and 1.1%. It clearly exhibits the impact of adverse weather conditions on driver behavior. Drivers tend to reduce their speed and increase headway time. Increase in headway time increases spacing between vehicles. Headways and spacing are directly proportional to each other. The driver tries to adopt longer spacing to meet safe driving maneuvers. Figure 4.11 clearly illustrates that an increase in headway goes with an increase in spacing and is statistically analyzed.

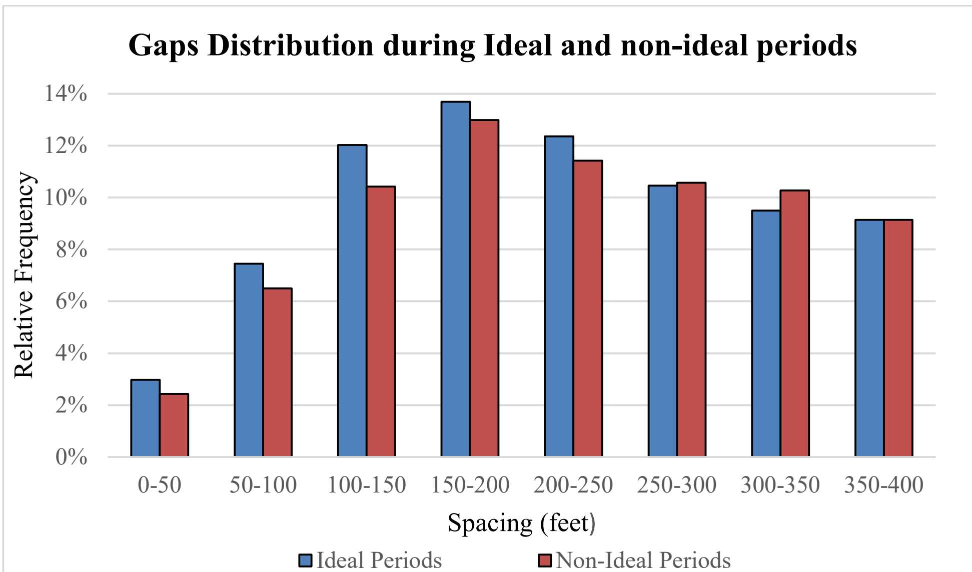

Figure 4.11 Frequencies of Different Spacing Categories

Spacing or gap between two vehicles was calculated to learn microscopic behavior of individual vehicles during ideal and non-ideal periods. Figure 4.11 clearly shows that there is a decrease in the frequency of spacing under non-ideal weather conditions. Indeed, a decrease of more than 14% of the spacing between 0 to 50 feet was observed. The frequency of spacing between 250 to 300 and 300 to 350 feet was increased during non-ideal periods. The statistical significance between spacing in ideal and non-ideal conditions was analyzed by applying z-test at a 95% confidence interval. A z-test for a spacing gave a z-value of -7.918 and is lower than z-critical value of 1.959, which indicated that the mean spacing is greater in non-ideal weather conditions. A Q-Q plot is a graphical representation for comparing two distributions and is drawn and shown in Figure 4.12. A Q-Q plot of spacing clearly represents that the spacing lies above the reference line, illustrating that spacing or gaps are higher during non-ideal winter weather conditions.

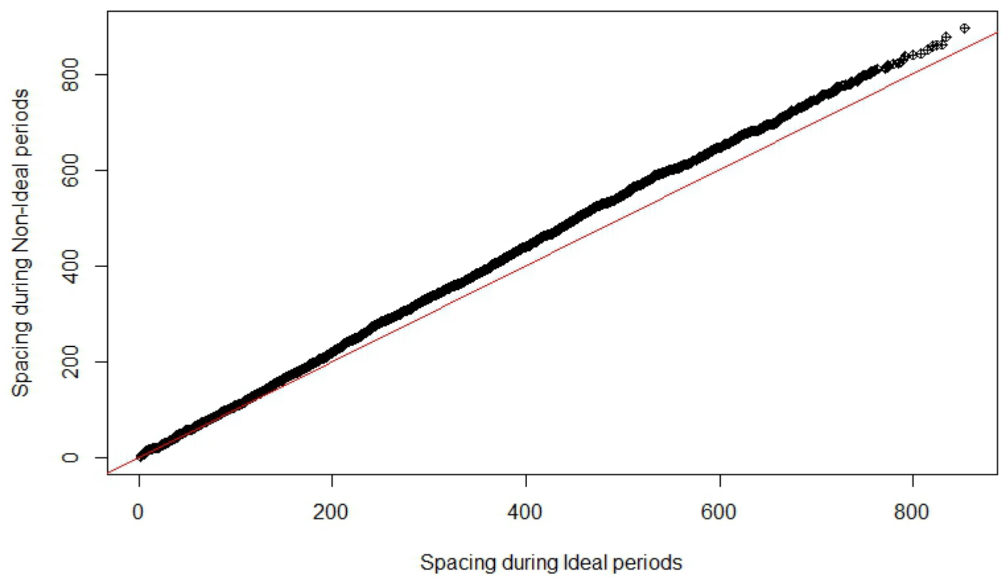

Figure 4.12 Q-Q Plot of Spacing between Ideal and Non-Ideal Conditions

In summary, we can conclude that adverse winter weather conditions have a direct impact on speed selection behavior. Due to adverse weather conditions, drivers tend to reduce their average speed and select higher average spacing than ideal periods. Additional statistical models are done in Chapter 5 to learn the impact of different weather variables in speed selection behavior.

4.4 Comparison Between Ideal Periods and Storm Events

From the above speed analysis (Table 4.8 and Table 4.9), it was found that speed difference between cars and trucks for each storm event were confirmed by variations analysis. In addition, variation analysis also showed that speed difference between ideal and non-ideal was significant at a 5% confidence level. Table 4.10 indicates that the statistical test for speed data between ideal conditions and storm events. A t-test was run at a 95% confidence level and was found to be significant for all cases.

Table 4.10 Statistical significance in speeds between ideal periods and storm events

Storm Events	Statistically significant difference	t-value	p-value	Higher Standard Deviation
Milepost: 256.17				
1	Yes	168	<0.001	Storm Event
2	Yes	21.84	<0.001	Ideal
3	Yes	161.5	<0.001	Storm Event
Milepost: 273.85				
4	Yes	135.4	<0.001	Storm Event
5	Yes	-7.04	<0.001	Ideal
6	Yes	144.02	<0.001	Storm Event
Milepost: 97.9				
7	Yes	50.55	<0.001	Storm Event
8	Yes	-2.29	0.02	Ideal
9	Yes	-16.42	<0.01	Ideal
Milepost: 330				
10	Yes	111.4	<0.001	Storm Event
11	Yes	-7.84	<0.001	Ideal
12	Yes	6.99	<0.001	Storm Event

The individual vehicle speeds data were further analyzed for cars and trucks for each storm event. Microsoft Excel was used to calculate the mean, standard deviation, and number of observation for cars and trucks. The cars and trucks speed were separate from each storm event. The merged ideal periods data and separated cars and trucks data from each storm event were analyzed separately. The analysis was done to learn significance at a microscopic level. The statistical (t-test) test was run at a 95% confidence interval for all cases and Table 4.11 shows the results obtained from the test.

Table 4.11 Statistical significance of observed speeds between ideal periods and storm events for cars and trucks

Storm Event	Cars		Trucks	
	t-statistic	P-Value	t-statistic	P-Value
1	70.97	0.000	18.99	0.000
2	-12.18	0.000	40.96	0.000
3	46.47	0.000	172.86	0.000
4	44.38	0.000	158.4	0.000
5	-24.23	0.000	8.19	0.000
6	31.95	0.000	158.65	0.000
7	-37.44	0.000	45.76	0.000
8	-96.63	0.000	-17.98	0.000
9	-223.62	0.000	-38.67	0.000
10	67	0.000	90.31	0.000
11	-16.57	0.000	0.64	0.261
12	-12.33	0.000	24.92	0.000

Cars speeds were statistically significant for all storm events. Trucks speeds were also found to be significant, except for storm event 11. However, speed analysis concluded that each storm event showed a statistical difference. Therefore, further analysis was needed to know the actual speed difference.

The values in each row and column of Table 4.12 show the significant difference in speed between two storm events. All 12 storm events are statistically significant from other storm events. This shows that each storm event does had its own impacts on speed selection behavior. The storm event had its own effect depending on severity of different weather parameters. The effect of weather variables could be different. The drivers became extremely cautious in their driving and slowed their speed with an increase in variation. Therefore, statistical modeling was necessary to address the impacts of these weather parameters into speed selection behavior. The model selection and analysis are described in the following chapter.

Table 4.12 Statistical comparison of individual speeds between different storm events

Events	Storm 1	Storm 2	Storm 3	Storm 4	Storm 5	Storm 6	Storm 7	Storm 8	Storm 9	Storm 10	Storm 11	Storm 12
Storm 1	-	-88.76 (<0.001)	-6.49 (<0.001)	-27.2 (<0.001)	-109.63 (<0.001)	-3.48 (<0.001)	-62.43 (<0.001)	-77.28 (<0.001)	-154.04 (<0.001)	62.52 (<0.001)	-31.64 (<0.001)	-73.28 (<0.001)
Storm 2		-	83.84 (<0.001)	67.02 (<0.001)	-21.15 (<0.001)	81.09 (<0.001)	21.87 (<0.001)	-14.14 (<0.001)	-29.34 (<0.001)	97.73 (<0.001)	-11.84 (<0.001)	-6.83 (<0.001)
Storm 3			-	-20.83 (<0.001)	-104.96 (<0.001)	2.49 (0.006)	-57.45 (<0.001)	-73.73 (<0.001)	-148.19 (<0.001)	64.84 (<0.001)	-30.47 (<0.001)	-69.51 (<0.001)
Storm 4				-	-88.79 (<0.001)	21.58 (<0.001)	-40.83 (<0.001)	-61.97 (<0.001)	-126.1 (<0.001)	72.1 (<0.001)	-26.73 (<0.001)	-57.03 (<0.001)
Storm 5					-	101.3 (<0.001)	42.20 (<0.001)	2.1 (0.017)	-2.77 (0.002)	107.4 (<0.001)	-6.31 (<0.001)	10.1 (<0.001)
Storm 6						-	-56.29 (<0.001)	-73.1 (<0.001)	-136.7 (<0.001)	63.18 (<0.001)	-30.9 (<0.001)	-68.82 (<0.001)
Storm 7							-	-30.5 (<0.001)	-55.3 (<0.001)	86.91 (<0.001)	-17.4 (<0.001)	-24.05 (<0.001)
Storm 8								-	-4.31 (<0.001)	98.24 (<0.001)	-6.87 (<0.001)	6.59 (<0.001)
Storm 9									-	113.6 (<0.001)	-5.78 (<0.001)	13.59 (<0.001)
Storm 10										-	-57.58 (<0.001)	-95.36 (<0.001)
Storm 11											-	9.45 (<0.001)
Storm 12												-

Note: Numbers in the parentheses () represent the p-value and others are t-value

5. STATISTICAL MODELING

Two different model specifications were used for further analysis: order probit model and log-logistic distribution model. Brief descriptions of the two models are illustrated in the following sections. It was assumed that change in speed behavior during adverse weather conditions directly reflected on microscopic behavior headways and spacing. Detailed statistical analysis is provided in the following two sections.

5.1 Ordered Probit Model for Speed Selection Behavior

To analyze the impact of winter weather conditions on speed selection behavior, ordered probit models were estimated to examine the likelihoods of driver behavior on I-80 corridors. A previous study conducted by Kang in Korea used this model for speed selection behavior based on the characteristics of roads, vehicles, and trip purposes (Kang, 1999). This model was selected for analysis because it provides analysis with more than two outcomes and for its ability to analyze an ordinal dependent data. Similarly, ordered logit model provides similar results but it treats ordinal dependent variables as nominal and loses efficiency due to information being neglected. The ordered probit model recognizes the difference in ordinal dependent variables and also that errors are distributed normally, and is more likely to be valid.

The ordered probit model analyzes in a latent and continuous underlying measures of response. This will help discover the relationship between weather variables and speed selection behavior during winter weather conditions. The general formula of this model is:

$$\boldsymbol{y_i = x_i\beta + \epsilon} \qquad \text{Equation 1}$$

Where,

y_i = a latent and continuous dependent variable
x_i = a vector of independent variables
β = a vector of estimated parameters;
$\in$ = the random error term assumed to be normally distributed

The dependent variable y_i is an integer representing speed selection, which has four categories.

Individual vehicles speed is used for the cut-points. The observed speeds are classified in order:

- 3 = speed below 45 mph ($y_i \leq \mu_1$)
- 2 = speed between 45 to 55 mph ($\mu_1 < y_i \leq \mu_2$)
- 1 = speed between 55 to 65 mph ($\mu_2 < y_i \leq \mu_3$)
- 0 = speed greater than 65 mph ($y_i > \mu_3$)

Where,

μ_i's represent thresholds to be estimated

The ordered probit model analyzed the impact of weather variables on speed selection behavior. The dependent variable is speed, which represents speed selection behavior and is classified into four cut-points and coded as mentioned above. The probabilities associated with the coded response with the normal distribution are as follows:

Prob[y = 3] = Φ (μ - βx_i)
Prob[y = 2] = Φ (μ_1 - βx_i) – Φ (μ - βx_i)
Prob[y = 1] = Φ (μ_2 - βx_i) – Φ (μ_1 - βx_i)
Prob[y = 0] = 1- Φ (μ_3 - βx_i)

Where Φ is the standard normal cumulative distribution function. The interpretation of the ordered probit model is based on primary parameter β.

5.1.1 Descriptive Statistics

Individual vehicle speeds collected during different storm events were distinguished according to mile post and merged to learn the speed selection behavior during different storm events at different mile post. Speeds were categorized and ordered into four different groups, as mentioned above. Overall, 139,841 speeds were measured during 12 storm events. Passenger cars accounted for 34.39% and trucks were 65.61% of the data. Figures illustrated below (Figure 5.1 to Figure 5.4) show speed selection classification at a different mile post during different storm events.

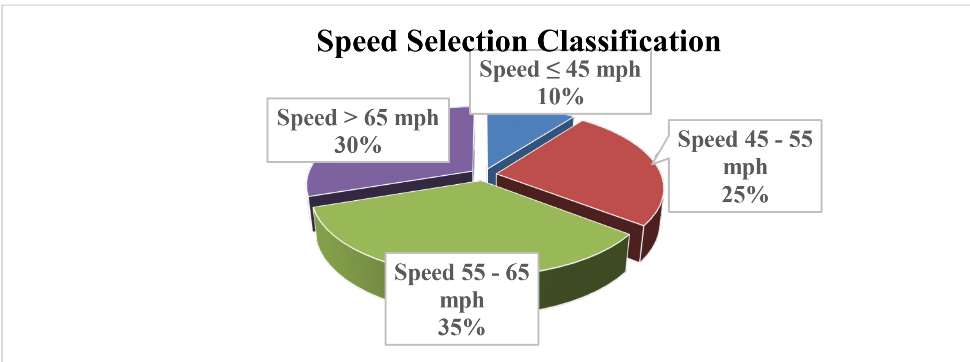

Figure 5.1 Speed Selection Behavior Classification at MP 256.17

From Elk Mountain, storm events 1, 2, and 3 from mile post 256.17 and storm events 4, 5, and 6 from mile post 273.85 were merged into a single dataset assuming the effect of weather conditions on driver behavior to be similar for homogenous geometric considerations. Figure 5.1 shows different speed selection behavior during different storm events at mile post 256.17 and 273.85 respectively.

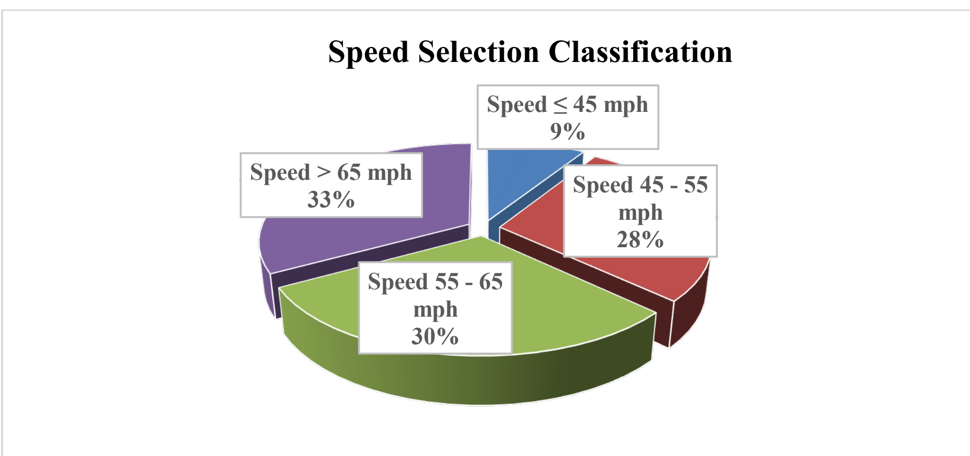

Figure 5.2 Speed Selection Behavior Classification at MP 273.85

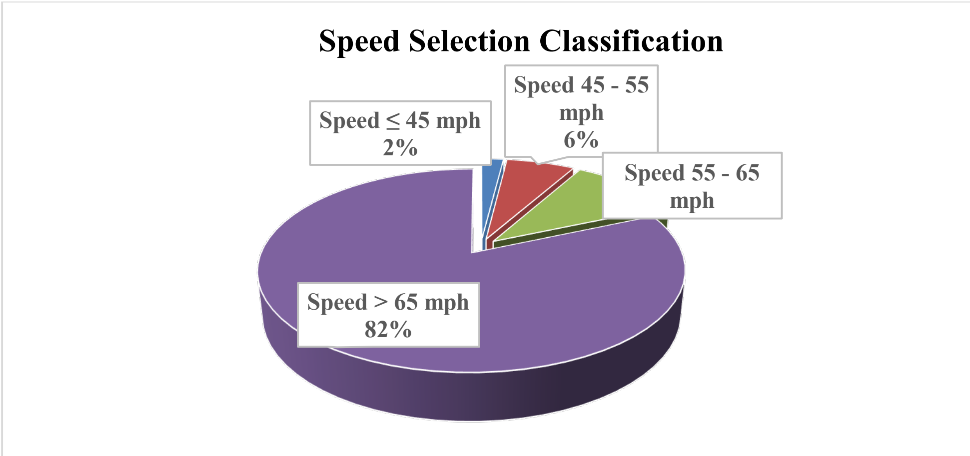

Figure 5.3 Speed Selection Behavior Classification at MP 97.5

Storm events 7, 8, and 9 from Green River−Rock Spring Corridor at mile post 97.5 and storm event 10, 11, and 12 from Laramie−Cheyenne at mile post 330 were also merged. Figure 5.3 and Figure 5.4 speed selection shows the different driver behavior during different storm events at mile post 97.5 and 330 respectively.

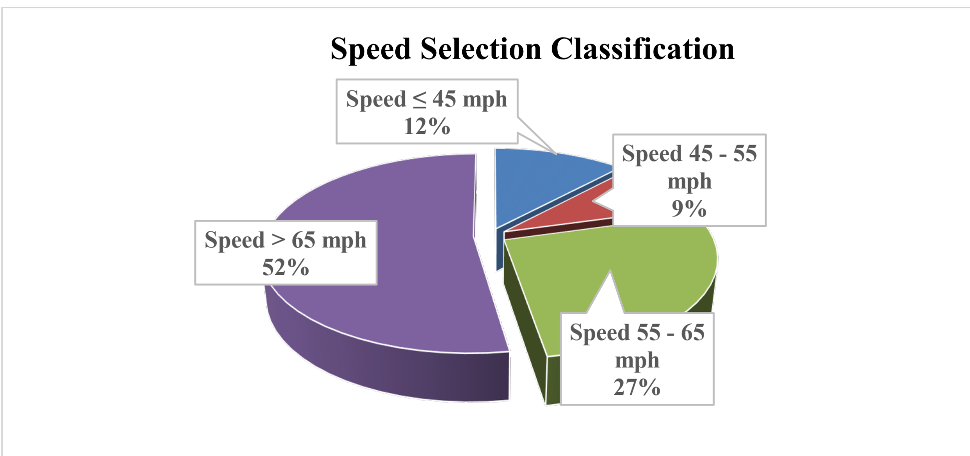

Figure 5.4 Speed Selection Behavior Classification at MP 330.0

The dependent variable was vehicle speeds, which represent speed selection behavior. An exploratory data analysis was done to summarize data and learn the relationship between traffic speed, weather conditions, and driver behavior during adverse weather conditions.

A correlation analysis was done among the independent variables before proceeding into model estimation to determine extent of the multi-collinearity between the variables. A high correlation existed between some of the weather variables like air temperature and has a significant correlation with dew point and gust wind speed with average wind speed. To address this, dew point and average wind speed were neglected for further analysis. Since it was determined that surface temperature and gust wind-speed best-captured roadway conditions. The correlation analysis can be found in Appendix B. Table 5.1 illustrates the list of all independent variables considered for further analysis. Detailed descriptive statistics can be found in Table 4.2 and Table 4.3.

Table 5.1 Independent variables for the speed selection model

Variables	Definitions
Surface Temperature (SfTemp)	Temperature of the pavement surface
Air Temperature (degree F)	Atmospheric temperature
Relative Humidity (RH)	Percentage of moisture in the air
Gust Wind Speed	Maximum wind speed measured during an evaluation cycle
Precipitation Accumulation	Rainfall amount or snowfall
Visibility (feet)	The distance at which an object can be clearly seen
Surface Status	Conditions of the pavement surface
Dry Chemically Wet Ice Warning Ice Watch Snow Watch Trace Moisture Wet	1 when surface status is dry, 0 otherwise 1 when surface status is Chemically Wet, 0 otherwise 1 when surface status is Ice Warning, 0 otherwise 1 when surface status is Ice Watch, 0 otherwise 1 when surface status is Snow Watch, 0 otherwise 1 when surface status is Trace Moisture, 0 otherwise 1 when surface status is Wet, 0 otherwise
Precipitation Rate	Average precipitation rate computed every minutes
Number of Trucks	Percentage of trucks
Speed Limit	Posted speed limits

Table 5.1 contains a simple description that describes the weather variables used for modeling. The pavement surface status contains the categorical variables and dry status is considered as the base condition. The different categorical variables are converted into a dummy variable, which is equal to 1 when specific surface status appears, 0 otherwise. Table 5.1 shows the pavement surface status parameters and its coded dummy variable.

5.1.2 Model Estimation Results

This section shows the results obtained from an ordered probit regression model for speed selection behavior during different storm events. Individual vehicle speed during different storm events is considered an ordered dependent variable. The statistical software program SAS, Version 9.4, with the probit procedure, was used to estimate the maximum likelihood probability function.

This section discusses the five different models developed based on weather information and evaluates whether the information provided by RWIS correlated to speed selection behavior. Separate models were developed for each mile post. A combined model merging all storm events was also developed to identify whether the impact of weather variables on speed selection behavior is similar or not. The combined model gives an over-all representation and is more reasonable than a specific model. The results obtained from statistical analysis using ordered probit model for the speed selection behavior of I-80 at different corridors are shown in Table 5.2. The models show impact of various weather variables and pavement surface conditions on drivers speed selection behavior. In addition, more variables such as truck percentage and VSL speed limit were also included in the model. The SAS analysis output for the first and final iteration of every model are placed in Appendix C.

The intercept represents the threshold of response variable in ordered probit regression. The threshold estimate is the cut point value between individual vehicle speeds. The variables that had higher p-values were removed for further analysis until all the other variables had a p-value below 0.05. The coefficient estimates for the models are located in Appendix C and the final estimates are illustrated in Table 5.2.

Table 5.2 Ordered probit model for speed selection behavior at different mile posts

Parameters	Mile Posts							
	97.9		256.17		273.85		330	
	Estimates	P-Value	Estimates	P-Value	Estimates	P-Value	Estimates	P-Value
Surface Temperature	0.078	<.0001	0.074	<.0001	0.081	<.0001	0.367	<.0001
Air Temperature	0.034	<.0001	-0.045	<.0001	-0.050	<.0001	-0.235	<.0001
Relative Humidity	-0.037	<.0001	-0.051	<.0001	-0.043	<.0001	-0.275	<.0001
Gust Wind Speed	-0.051	<.0001	-0.020	<.0001	-0.019	<.0001	-0.045	<.0001
Precipitation Accumulation	-16.101	<.0001	1.016	<.0001	-0.568	<.0001	-	-
Precipitation Rate	-	-	-	-	-	-	-	-
Chemically Wet	-	-	-2.038	<.0001	-	-	-	-
Ice warning	-	-	-0.312	<.0001	-0.553	<.0001	-	-
Ice watch	-	-	-1.984	<.0001	-2.306	<.0001	-	-
Snow watch	-	-	-0.999	0.0373	-0.529	<.0001	-	-
Trace Moisture	-	-	-0.148	0.0291	-0.324	<.0001	-	-
Wet	-	-	-0.588	<.0001	-0.692	<.0001	-	-
Truck Percentage	-	-	-1.512	<.0001	-1.066	<.0001	-1.190	<.0.001
VSL Speed	-	-	0.117	<.0001	0.103	<.0001	-	-

Table 5.3 Parameter coefficients for combined model

Combined Model				
Parameter	**Estimate**	**Standard Error**	**Chi-Square**	**P-Value**
Surface Temperature	0.076	0.003	604.61	<.0001
Air Temperature	-0.051	0.003	361.32	<.0001
Relative Humidity	-0.045	0.002	540.62	<.0001
Gust Wind Speed	-0.012	0.001	75.55	<.0001
Precip Accumulation	0.219	0.094	5.42	0.0199
Chemically Wet	-1.884	0.234	64.92	<.0001
Ice Warning	-0.250	0.040	39.43	<.0001
Ice Watch	-1.866	0.120	241.82	<.0001
Snow Watch	-0.523	0.044	143.8	<.0001
Wet	-0.497	0.159	9.8	0.0017
Truck Percentage	-1.064	0.090	140.89	<.0001
VSL Speed	0.109	0.002	2643.79	<.0001

Table 5.2 shows variables statistically significant for each corridor. Table 5-3 shows results obtained from the combined model. In the following section, the relationship between each significant variable on the speed selection behavior is interpreted.

5.1.2.1 Pavement Surface Temperature

Surface temperature was statistically significant for all five models. It has a positive coefficient, which shows that a higher temperature on the pavement surface increases the speed selection behavior toward a higher category. As the temperature on the pavement surface increases, it might be due to improvement on pavement surface conditions. This could be the reason drivers choose a higher speed when the road surface condition is dry. In contrast, it is assumed that pavement surface conditions could become poor due to lower surface temperature and may decrease pavement friction. However, the impact of this factor is relatively small. One unit increase in surface temperature, raised the observed speed selection behavior towards a higher category.

5.1.2.2 Weather Variables

Table 5.2 and Table 5.3 show that various weather parameters are significant at different corridors. Air temperature, relative humidity, and gust wind speed were found to be statistically significant for all five models at a 5% significance level. Precipitation accumulation was found to be significant for four single models and for the combined model. In contrast, precipitation rate was found to be insignificant for all models.

Air temperature had a negative effect on speed selection behavior for all models except for mile post 97.9, which had a positive effect. The reason behind this could be due to improvement on pavement surface conditions. The other possible reason could be a lower percentage of traffic on the corridor or clear visibility. This will help drivers choose acceptable higher speeds during winter weather conditions. For remaining models, air temperature had a negative effect. The relationship seems unreasonable, as the opposite was expected. The negative effect on speed behavior may have been caused due to worsening of pavement surface conditions due to an increase in air temperature. An increase in air temperature increases temperature of the surrounding environment, which ultimately melts accumulated snow and makes road surfaces wet. This leads to a decrease in pavement surface friction, might make drivers cautious about the roadway conditions and lead them to choose a lower speed category to be safe. Furthermore, the reason might be due to a higher number of vehicles following each other.

Table 5.2 and Table 5.3 show that relative humidity played a significant role in speed selection behavior in all five models and had a negative effect. This illustrates that a rise in relative humidity is more likely to have a lower category of speed selection behavior. The presence of moisture in the air could be a factor in this. A relative humidity of 0% represents that air contains no moisture and 100% shows that air is fully saturated and cannot absorb moisture any more. A rise in relative humidity might contribute to making atmospheric air denser and could degrade visibility.

As expected, gust wind speed was found to had a statistically significant effect on speed selection behavior in all five models. The relationship between wind and vehicle speed seems reasonable. The higher the wind speed, a decrease in speed toward the lower category was observed. However, the impact of this variable is somewhat small, as drivers might became perceptive to overturning vehicles.

Precipitation accumulation had a significant effect in speed selection category for all models except for a single model at mile post 330, which was observed to be insignificant. It had a negative coefficient for mile post 97.9 and mile post 273.85 models but had a positive coefficient for mile post 256.17 and combined models. This relationship looks somehow counterintuitive as the positive effect might be attributed to improvement of pavement surface conditions or due to error in data. The results of four models clearly showed the significance of precipitation accumulation in speed selection behavior during adverse weather conditions.

5.1.2.3 Pavement Surface Status

Table 5.3 shows that chemically wet, ice warning, ice watch, snow watch, and wet pavement surface conditions for the combined model were statistically significant with a negative coefficient. However, for the single models, only some of the variables were significant. Pavement surface condition variables were insignificant for the mile post 97.9 and mile 330 models. However, for mile post 256.17 and mile post 273.85 models all the variables were significant with negative coefficient except chemically wet for mile post 273.85 model. Statistically insignificant was noticed. The variables that were insignificant at the mile post 97.9 and mile post 330 models might be due to error in data or may be due to a fewer number of non-ideal data during the storm event. In addition, trace moisture was significant with a negative coefficient in two models but was insignificant for three models. Trace moisture (a thin or spotty film moisture) on the pavement surface above freezing temperature (32^0 F or 0^0 C) might be the reason for a decrease in pavement friction, which leads drivers to decrease their speed. In the mile post 273.85 model, speed selection behavior greatly decreased toward a lower category when the pavement surface status was ice watch (-2.306). This was the highest reduction on speed category among the single models. In the combined model, higher negative impacts on speed selection category were observed due to chemically wet. The results showed that ice watch and chemically wet variables of pavement surface status implies a higher negative effect on degrading speed selection toward a lower category. The reason could be the driver was being too cautious or due to the presence of black ice on the pavement surface. This might reduce pavement friction between vehicle tires and the road surface. Another reason may be speed limit control. Among all pavement surface variables, ice warning tends to have a lower negative effect.

5.1.2.4 Truck Percentage

The main purpose of this project was not to include non-weather-related variables with speed selection behavior but had to add this parameter to the model because of its importance. I-80 in Wyoming is a major corridor for freight vehicles and consists of more than 50% AADT. The model presents that the effect of truck percentage was similar to weather parameters. It was found to be statistically significant and had negative coefficients for all models except for the mile post 97.9 model. The result at mile post 97.9 model is stunning and could be due to a lower percentage of trucks during a specific storm event. As mentioned in Chapter 3, the truck percent is lower than the other mile post. The results from rest of the models seem identical. According to results obtained from these models, the higher the truck percentage, the lower the observed speed selection behavior. The presence of big trucks on rural highways during adverse weather conditions could cause difficulty driving. The reason could be their size, which is far larger than any other vehicle, or it could be the visibility. The size and mass of big trucks produces moisture in the air through tire compaction during adverse weather conditions. This might reduce visibility for seeing lane markings and cause driving difficulty. In such conditions, drivers select comfortable average speed toward the lower category. The maximum negative effects were noticed in Elk Mountain corridor. The truck percentage in this corridor is about 60 percent. The results clearly showed that the higher the number of trucks, the lower the speed selection category.

5.1.2.5 VSL Speed Limit

Evaluating effectiveness of VSL systems in speed selection behavior during adverse weather conditions was one of the major focuses for this study. VSL system is a device used to display speed limits according to weather conditions. TMC collects weather information from the nearby road-side RWIS and further analyze to determine appropriate speed limit during such conditions. Implementation of the VSL system had a statistical significance and a positive effect at mile post 256.17, mile post 273.85 and at the combined models. The higher the VSL speed limit, the more there will be an increase on speed selection category. As expected, a 5 mph increase on VSL signs had a faster speed because drivers felt comfortable driving with a posted speed limit. Another reason could be the change in road conditions from non-ideal to ideal. This indicated that there was compliance with speed limits posted by VSL systems. The implementation of VSL signs during inclement weather condition reduced speed and speed variations (Yanfei, 2013). The VSL system was insignificant at mile post 97.9 and mile post 330 models. This may be due to driver attitude toward VSL implementation. Drivers with aggressive natures will not change their speeds, which could lead to an increase in speed variation and may be potentially dangerous.

The result obtained from this study is that weather parameters, visibility and precipitation rate were found to be statistically insignificant for all models.

5.2 Log-Logistic Distribution Model for Vehicle Headway

The log-logistic distribution model is a continuous probability distribution for modeling a non-negative random variable. This model is basically used for analyzing parametric data whose flow goes up initially and goes down in time. Many other leading models for headway distribution exist and log-logistic is one of them. It is similar to log-normal distribution but has heavier tails. The log-normal distribution model is known to be a convenient model representing time headway for uncongested traffic flow with higher number of vehicles and is more appropriate for urban conditions. Many other headway distributions models were not fit for the dataset. Finally, the log-logistic distribution model was taken into consideration for further analysis. The log-logistic distribution model is expressed as:

$$\boldsymbol{F}\,(\boldsymbol{x}) = \left[\boldsymbol{1} + \left(\frac{\boldsymbol{\alpha}}{\boldsymbol{x}-\boldsymbol{\gamma}}\right)^{\boldsymbol{\beta}}\right]^{-\boldsymbol{1}} \qquad \text{Equation 2}$$

Where,

α = shape parameter > 0
β = scale parameter > 0
γ = location parameter

Parameter estimation of headway distribution must be properly estimated. The conventional Maximum Likelihood Estimates (MLEs) technique is used in this study to develop the best-unbiased estimates. The MLE approach is found to be the perfect unbiased estimators (Guohui, et al., 2007). Furthermore, goodness of fit test for the model by the Kolmogorov-Smirnov (K-S) statistic (Shengchao, et al., 2009). The K-S test is nonparametric and has benefits of not making any assumption about the distribution of data. It fits the cumulative distribution point by point and is the most stable. The K-S test is appropriate only for continuous distributions. The two-tails and one-tail K-S tests were done to learn the significant difference in headways during ideal and non-ideal periods. The critical value $D_{Critical}$ of K-S test was calculated using the equation below:

$$\boldsymbol{D_{Critical}} = \boldsymbol{1.36}\sqrt{\frac{(\boldsymbol{n1}+\boldsymbol{n2})}{(\boldsymbol{n1}*\boldsymbol{n2})}} \qquad \text{Equation 3}$$

Where n1 and n2 are the sample sizes and 1.36 is a value for a significance level at 95 % confidence interval. The calculated value $D_{Calculated}$ greater than $D_{Critical}$ implies that there is a significant difference between the two datasets.

5.2.1 Descriptive Statistics

Individual vehicle speeds collected during different storm events were captured with the timestamp, vehicle speed, vehicle length and lane classifications (Chapter 3). The headways and gaps were calculated for each mile post for each lane and for ideal and non-ideal periods (Chapter 4). The calculated headways and gaps of each lane for different storm events were merged. Data were selected from eight out of 12 storm events for further analysis based on the availability of ideal and non-ideal headways. Only westbound direction is considered for the analysis assuming homogenous segments. Data was merged into a single dataset because the corridors were chosen to limit the effects of road geometries. The challenging geometric conditions of mountain corridors were excluded from the study (Chapter 3). Data were chosen from eight storm events based on the availability of ideal and non-ideal headways. The calculated headways were found between 0 sec to more than 2 minutes and could be due to low traffic volume. The smaller and longer headways were removed for the further analysis considering the car-following approach (Chapter 2). Table 5 shows the descriptive statistics of time headways (sec) during ideal and non-ideal weather conditions.

Table 5.4 shows an increase in mean headways by 0.15 sec (2.89 %) from ideal to non-ideal road weather conditions. The increase in mean headway illustrates that spacing increases with the change in weather conditions from ideal to non-ideal conditions. In addition, standard deviation increased from ideal to non-ideal by 0.08 sec (4.32 %). This proved that there is slightly more high-speed variation during non-ideal periods than ideal periods. The reason could be drivers choosing their individual speed during non-ideal periods.

Table 5.4 Fundamental statistics of collected headways during ideal and non-ideal periods

Parameters	**Ideal**	**Non-ideal**
# Observation	1366	2020
Mean	5.81	5.96
Standard Error	0.05	0.04
Median	5.7	5.8
Mode	6	5.8
Standard Deviation	1.85	1.93
Kurtosis	1.06	0.54
Skewness	0.27	0.42
Minimum	0.1	0.2
Maximum	11.9	12

A z-test was performed at a 95% confidence interval to observe the difference between mean headways during ideal and non-ideal periods. The test shows that there is a significant difference between means of ideal and non-ideal conditions. The calculated value of z-statistic is -2.31, which is less than z-critical value 1.959. This indicates that mean headway is longer during non-ideal periods than ideal periods. A Kolmogorov-Simonov (K-S) two-sided test is performed with the null hyporeport to know whether the ideal and non-ideal datasets differ significantly between each other or not. $D_{Calculated} = 0.367$, which is greater than $D_{Critical} = 0.047$ (section 5.2), and proved that there is a significant difference in headway distributions during ideal and non-ideal periods.

5.2.2 Model Estimation Results

This section will discuss results obtained from a model that was performed to analyze headway distribution during ideal and non-ideal periods. Headways samples were calibrated using log-logistic distribution model and a set of three parameter estimates were obtained to compare between ideal and non-ideal periods.

Ideal Periods

Figure 5.5 shows a histogram of the headways and its fitted distributions during ideal periods. The histogram shows that the headways are centered between 4.5 and 6.5 seconds with high density. The density of the headway less than 6 seconds is higher. There is low density of headways below 4 seconds. The reason may be due to the low traffic volume in the roadway segment (rural freeway). Table 5.7 shows that headway variability during ideal conditions was more stable with an average standard deviation of 1.85 seconds. The plotted pattern of headway distribution represents that driver behaviors and traffic operations on the freeway were less consistent during ideal conditions. This might be either due to the presence of larger number of truck or the effect of different weather parameters. Table 5.5 shows the goodness of fit and parameter estimation for the fitted headway distributions during ideal periods.

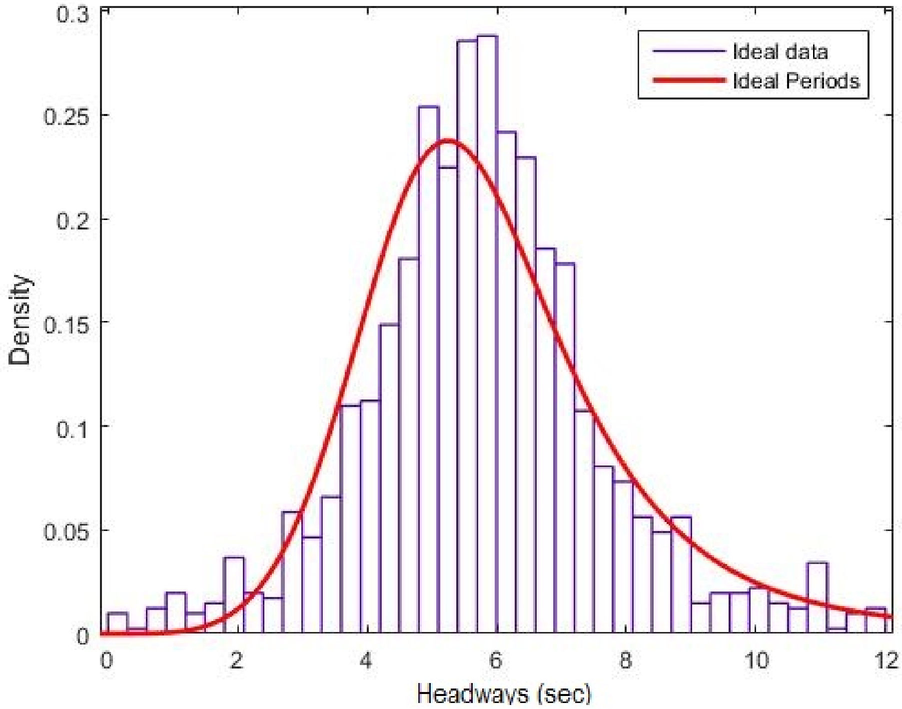

Figure 5.5 Histogram and Density Plot during Ideal Periods

The p-value of K-S test is higher than 0.05, which proved that the data are normally distributed. Detail statistics is placed in Appendix B.

Table 5.5 Parameter estimators for the fitted distribution during ideal periods

Fitted Distribution at α = 0.05	Estimated parameters	K-S Test P-Value
Log-Logistic Distribution	α = 28.05	0.131
	β = 28.14	
	¥ = -22.38	

Non-ideal Periods

The histogram of headways frequency and fitted distribution during non-ideal periods is illustrated in Figure 5.6 The histogram shows that the headways are centered around 5 and 7 seconds, which is an incremental direction towards x-axis than the ideal periods. This implies that there is an increase in longer headways during non-ideal periods. The density of headways less than 6 seconds is also lower than the ideal periods. The density of headways becomes larger with the increase in adverse weather events from headways of about 7.5 to 12 seconds. During adverse weather conditions, the smaller headways (less than 4 seconds) were decreased during non-ideal periods. This shows that during non-ideal conditions, reduction on average speed during non-ideal periods reflects on-time headways.

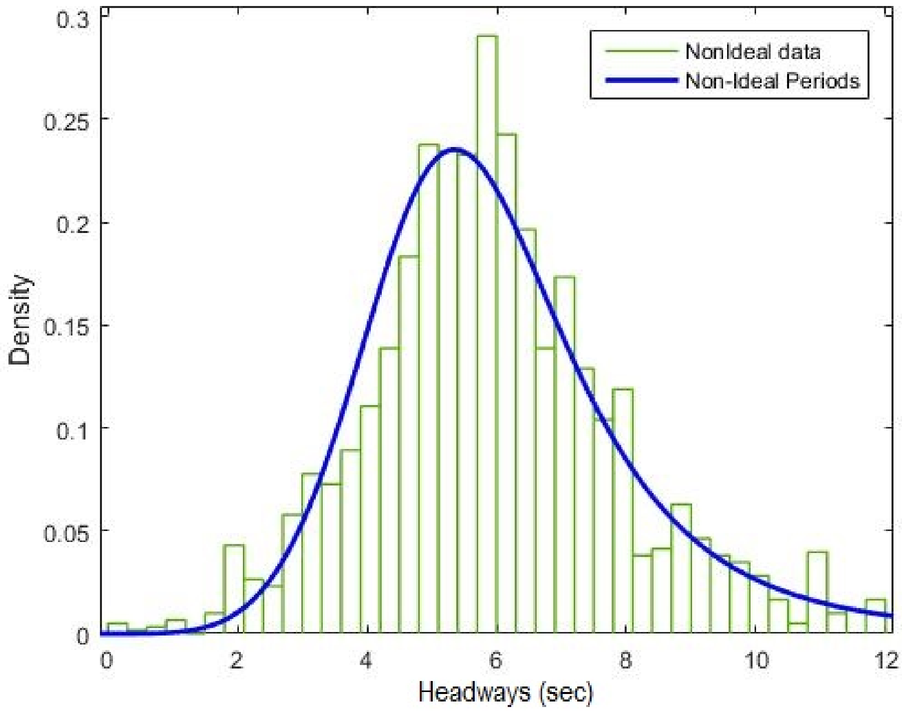

Figure 5.6 Histogram and Density Plot during Non-Ideal Periods

The driver chooses a longer headway, which is directly proportional to spacing. An increase in headways will increase in spacing, as described in Chapter 4. Table 5.6 shows the goodness of fit and parameters estimation for the fitted headways during non-ideal weather conditions.

Table 5.6 Parameter estimators for the fitted distribution during non-ideal periods

Fitted Distribution at α = 0.05	**Estimated parameters**	**K-S Test P-Value**
Log-Logistic Distribution	α = 13.3	0.068
	β = 14.08	
	¥ = -8.24	

5.2.3 Comparison Between the Results

The obtained density function graphs in Figures 5.5 and 5.6 confirm the results with histogram plots — shorter headways decrease during non-ideal periods. The density of headway is below 6 seconds during ideal periods and lower during non-ideal road conditions. The density of headway becomes higher after 7 seconds during non-ideal periods and expands to more than 12 seconds. The log-logistic distribution model confirms there is longer headway during inclement weather conditions, as confirmed by the z-test in section 5.2.1. Figure 5.7 shows the combined line graph of log-logistic density function between ideal and non-ideal conditions. The average density was decreased by 3.49% when the weather changed from ideal to adverse winter weather. This proves there is a decrease in shorter headways during non-ideal periods. As mentioned in Chapter 4, during inclement weather conditions, drivers tend to reduce their speed to be safe and increase their headways, which directly reflects on spacing.

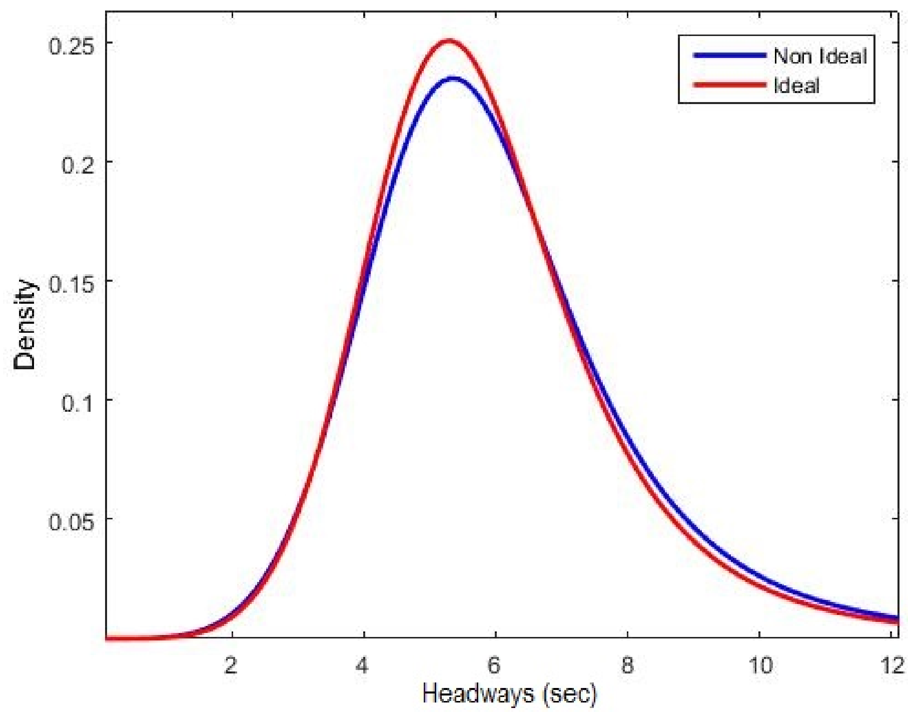

Figure 5.7 Density Function between Ideal and Non-Ideal Periods

The comparison between estimated parameters between ideal and non-ideal weather events are shown in Table 5.7. The parameter estimators demonstrated a decrease in value from ideal to non-ideal weather conditions. The mean headway was increased by 0.15 second and speed variations increased by 0.08 second when weather conditions changed from ideal to non-ideal. All these results show the characteristics of traffic operations and impacts on driver behavior during non-ideal weather events when compared with ideal periods.

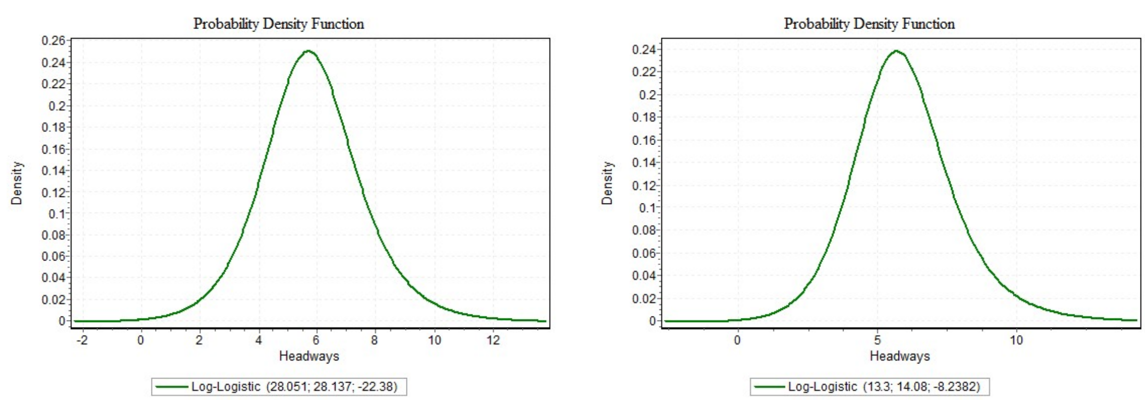

Figure 5.8 Probability Density Function with Parameter Estimations

Table 5.7 Comparison of estimated parameters

Parameters	Estimated parameters	
	Ideal	Non Ideal
Log-Logistic Distribution at α = 0.05	α = 28.05	α = 13.3
	β = 28.14	β = 14.08
	¥ = -22.38	¥ = -8.24
Mean	5.81	5.96
Standard Deviation	1.85	1.93

The empirical cumulative distribution function is drawn between ideal and non-ideal headways data illustrated in Figure 5.9. The graph shows that the headways lower than 11 seconds cover the distribution for ideal conditions, whereas the distribution function for non-ideal periods are somehow slower than ideal periods. This also shows that during non-ideal weather conditions, drivers choose a safer speed with a longer headway time. Chapter 4 clearly explained that the frequency of shorter headway and spacing decreased during non-ideal periods and is statistically proved in this chapter. Decreases in headways and spacing is clearly mentioned in the previous chapter.

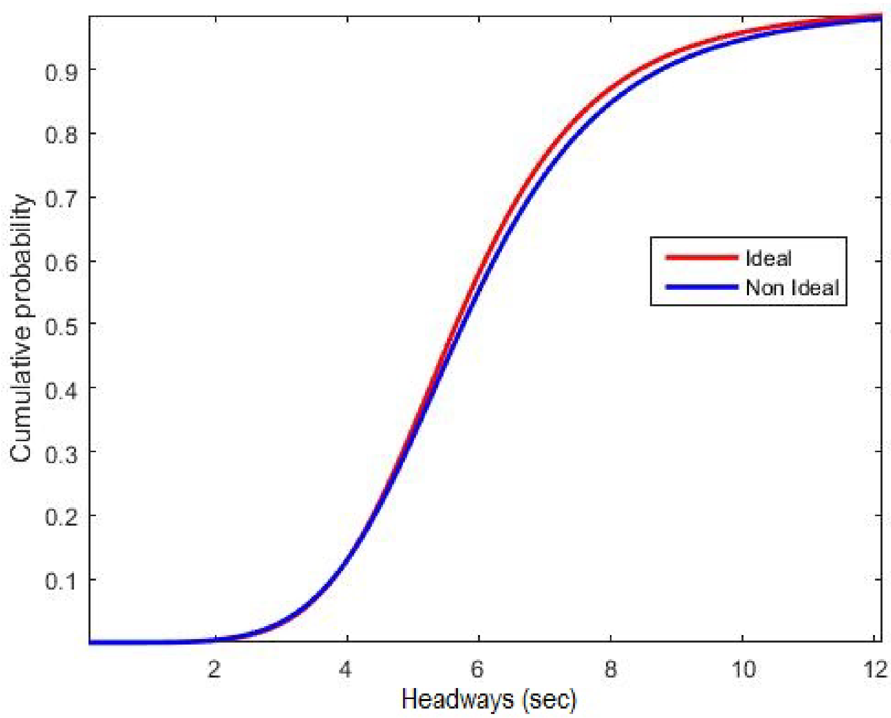

Figure 5.9 Cumulative Distribution Functions between Ideal and Non-Ideal Periods

In summary, from the statistical analysis, it can be concluded that adverse winter weather conditions have a fine impact on speed selection behavior. The impact of non-ideal weather conditions is reflected on driver behavior such as reduction in average speed, a decrease of shorter headways and spacing. The log-logistic distribution model was used to appropriately fit the empirical headways distributions.

6. MICROSCOPIC SIMULATION

Adverse weather conditions cause various impacts on the ground transportation system. Changes in weather conditions from ideal to non-ideal could increase driving risk and lead to higher crashes. Microscopic analysis of traffic parameters describes the individual behavior of vehicles. Analysis of individual vehicle speed, time headway, and gap during different weather conditions can give an extensive understanding of traffic operations and drivers' behavior. A microscopic model would be useful as a decision- making tool for a weather-responsive traffic management center. It helps to develop more efficient policies to provide necessary information about road conditions to road users in advance. Microsimulation modeling tools are becoming the industry standard for analyzing impacts of different factors on traffic operations. For them to be useful in testing WRTMs, they need to adequately model traffic flows during weather events. There are few studies in microsimulation modeling under adverse weather conditions. The study done by Zhang used CORSIM traffic microsimulation model to identify the effect of weather events on traffic operations (Zhang, et al., 2004). It was based on theoretical data and found that driver behavior had medium to high sensitivity on different measures of effectiveness (MOEs) (Zhang, et al., 2004).

In this chapter, the VISSIM microsimulation tool is used to develop simulation models. The different weather-related simulation model parameters were selected in VISSIM for calibration process. The model will help analyze how sensitive the change in weather-related traffic parameters is on traffic operations during different storm events. Observed data during different storm events will be used for adjustment on the base model to reflect the actual storm event and calibrate to verify sensitivity of the models. The following sections describe more about base and modified models. Figure 6.1 shows a flow chart of the analysis approach and steps involved for calibration.

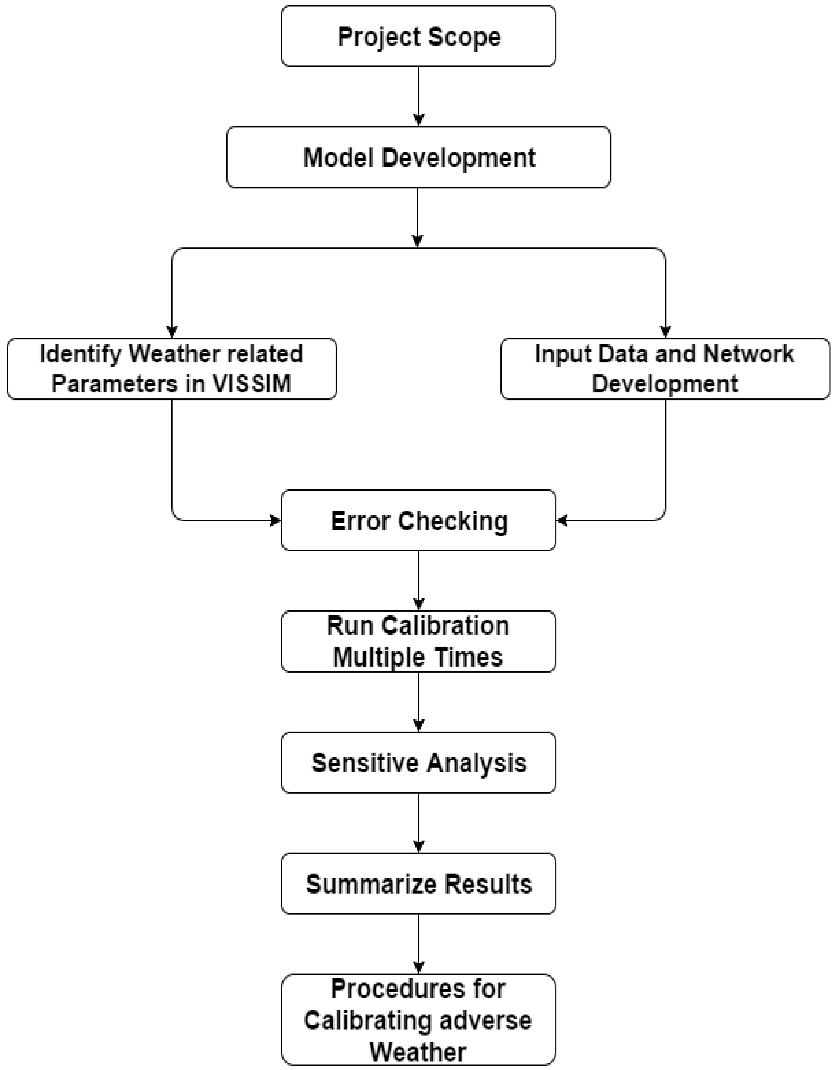

Figure 6.1 Flow Chart for Project Approach

6.1 Base Model

The simulation model of the study area includes approximately 3.17 miles of a freeway along I-80 in Wyoming. The area was considered assuming homogenous segments in order to limit the effect of road geometry. The ideal data obtained from individual storm events were combined into a single ideal dataset (as described in Chapter 3) and used to develop a base model for the study. The development of the base model helped to identify a baseline speed of the corridors during ideal conditions.

Traffic volume information is coded into VISSIM in vehicles per hour. The observed field data during the ideal period is used to develop a base model. The simulation model parameters such as vehicle input, vehicle distribution, headways, and vehicle compositions were assigned to reflect the actual traffic operations under ideal conditions. The considered simulation model parameters were based on previous studies (described in Chapter 2) and engineering judgments. The model was run 10 times. Each run model used random seeds and probability distributions for the numbers of traffic flow, which gave slightly different results. The model was run for 3,600 seconds to analyze for one full hour. The obtained results are more reliable because it is calculated with the multiple runs of the model. Table 6.1shows the assigned value for simulation model parameters for base model and Figure 6.2 shows the vehicle speed distribution during ideal period.

Table 6.1 Simulation parameters values for base model

Models	Vehicles per hour	Headways(Sec)	Vehicle Composition (%)	
			Cars	Trucks
Base Model	500	5.64	0.46	0.54

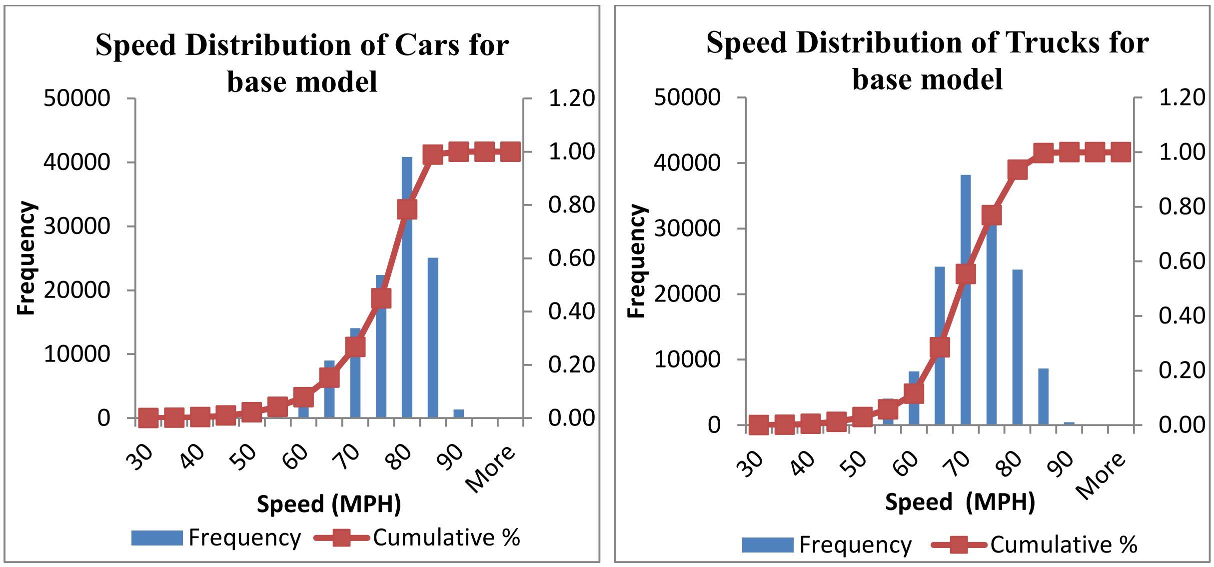

Figure 6.2 Speed Distribution of Cars and Trucks for Base Model

6.2 Adjusted Models

The base model was adjusted according to 12 storm events to represent the actual traffic operations during different storm events. The adjusted base models were used for calibrating different storm events. As mentioned in the previous section, the observed field data during 12e storm events were used to assign in adjusted models. Table 6.2 shows the assigned value for simulation model parameters for 12 storm events and Figure 6.3 shows the vehicle speed distribution for storm event 1. Vehicle speed distributions of cars and trucks for other storm events of the adjusted models is illustrated in Appendix D.

Table 6.2 Modified simulation parameters for adjusted models

Models	Vehicles per hour	Headways(Sec)	Vehicle Composition (%)	
			Cars	Trucks
Storm Event 1	500	5.82	0.42	0.58
Storm Event 2	500	6.3	0.29	0.71
Storm Event 3	500	5.98	0.26	0.74
Storm Event 4	500	4.26	0.4	0.6
Storm Event 5	500	4.75	0.27	0.73
Storm Event 6	500	4.63	0.25	0.75
Storm Event 7	500	5.71	0.57	0.43
Storm Event 8	500	5.87	0.5	0.5
Storm Event 9	500	5.46	0.55	0.45
Storm Event 10	500	5.82	0.41	0.59
Storm Event 11	500	6.55	0.44	0.56
Storm Event 12	500	6.07	0.53	0.47

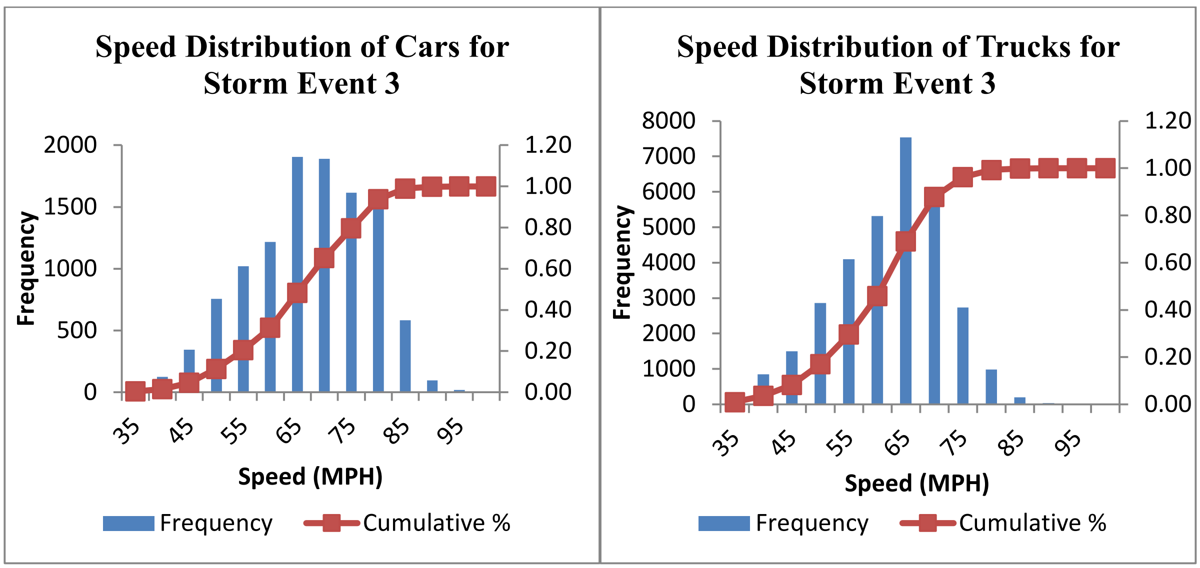

Figure 6.3 Speed Distribution of Storm Event 3 of Cars and Trucks for Adjusted Model

6.3 Model Calibration

The purpose of the model calibration in VISSIM was to obtain the best values between model output and field observations to determine the model parameters in an acceptable range. The VISSIM microsimulation software tool has numerous parameters (e.g. driver behavior, speed distribution, vehicle composition, etc.) that help the traffic analyst to better fit the model according to project scope and objectives. The selection of required model parameters are necessary to understand the possible factors according to specific conditions that may impact the measures of effectiveness (MOEs). Therefore, the model calibration includes the choice of known simulation model parameters to identify how a change in simulation model parameter impacts the MOEs. The calibration is done multiple times for output and compared with filed observation to determine the best match. Data collection measurements and vehicle network performance were selected for capturing individual vehicle performances for the calibration outputs.

For the model validation, the root-mean-square percent error was used to learn the overall error of the simulation and is shown below (Jung, et al., 2011):

$$RMSPE = \left[\frac{1}{N}\sum_{1}^{n}\frac{(Ysim-Yobs)^2}{(Yobs)^2}\right]^{0.5} \qquad \text{Equation 4}$$

Where,

Ysim = simulation traffic performance estimates
Yobs = observed traffic performance estimates
N = total number of observation

From the previous research, it was found that the difference between simulation output and field observed data should fall within a 15% range of the observed field data, which is greater than 85% of the total observations (Dowling, et al., 2004). A similar approach is used for the model validation for this project. Table 6-3 shows the RMSPE values for different storm events and all fall in the above-mentioned range. This implies that the obtained results can use for model validation.

Table 6.3 RMSPE values for 12 storm events

Storm Events	Average observed speed	Average simulated Speed	RMSPE
Storm Event 1	60.38	59.51	0.0006
Storm Event 2	68.11	67.81	0.0002
Storm Event 3	60.85	60.29	0.0004
Storm Event 4	62.31	61.54	0.0006
Storm Event 5	69.06	69.86	0.0005
Storm Event 6	58.91	60.10	0.0009
Storm Event 7	67.46	68.80	0.0009
Storm Event 8	71.07	73.41	0.0015
Storm Event 9	71.2	74.00	0.0018
Storm Event 10	46.68	48.87	0.0021
Storm Event 11	73.4	71.63	0.0011
Storm Event 12	66.09	67.99	0.0013

6.4 Sensitivity Analysis

Sensitivity analysis helps to determine how sensitive the change in weather-related traffic parameters on traffic operations during different adverse weather conditions are. Weather-related traffic parameters, such as speed distribution and car-following parameters in VISSIM, are assigned according to the field observation to learn impacts on driver behavior during different storm events. The values of other parameters were not changed and remained as defaults. The sensitivity analysis illustrated how these parameters impacted the traffic operations on a rural freeway. The sensitivity analysis started with a base model created using ideal weather conditions. Earlier research used default values for the base model (Billot, et al., 2009). However, for this study, the traffic parameters collected during ideal weather conditions were used for the base model development. Identified weather-related parameters were coded according to the field observation on adjusted models during different storm events to generate the MOEs. The comparison of obtained MOEs between base and adjusted models result how sensitive the change in weather-related parameters are. Table 6.2 and Table 6.3 show the sensitivity of free-flow speed and spacing when comparing ideal conditions with different storm events.

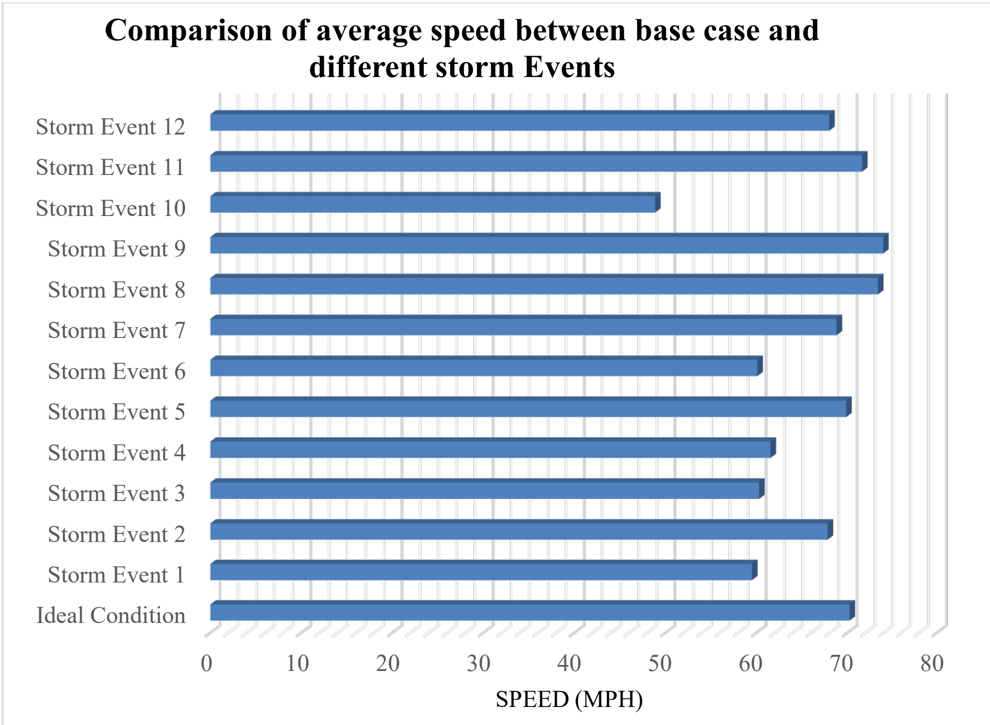

Figure 6.4 Average Speed Illustration for Sensitivity Test

Average speeds were compared between ideal conditions and different storm events. Average speed for each storm event was found to be highly sensitive. Storm event 10 was found to be highly sensitive followed by storm event 3 and storm event 6 respectively. Percentage differences from the base case are illustrated in Table 6.2. A t-test assuming unequal variance at 98% confidence interval was done and found to have statistically significant difference for all storm events.

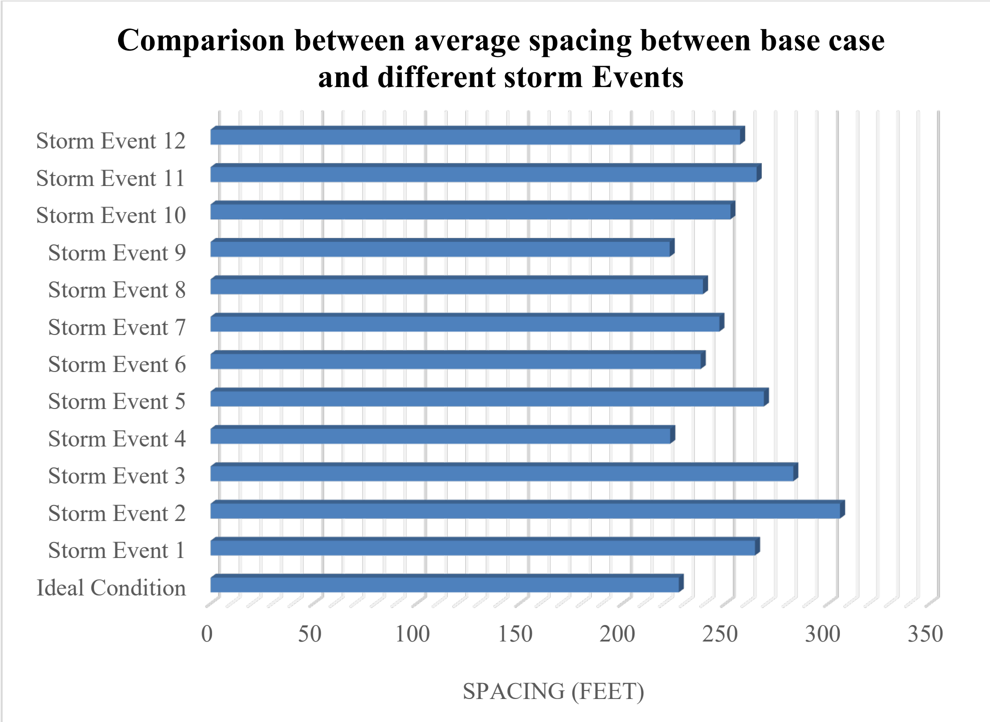

Figure 6.5 Average Spacing Illustration Sensitivity Test

Average spacings were also compared between base case and different storm events to learn how sensitive the weather-related parameters in VISSIM are. The change in weather-related parameters according to storm events showed sensitivity in spacing between ideal conditions and different storm events. Storm event 2 showed a high sensitivity followed by storm events 3 and 5. A detailed sensitive test is illustrated in Table 6.4. A t-test assuming unequal variance between the ideal condition and different storm events was done at 95% confidence interval and found statistically significant.

Table 6.4 Average speed and headways sensitivity test

Weather Events	Average Speed	Spacing (feet)
Storm Event 1	-24.39%	+16.28%
Storm Event 2	-8.84%	+34.44%
Storm Event 3	-31.25%	+24.47%
Storm Event 4	-18.61%	-1.84%
Storm Event 5	-4.01%	+18.19%
Storm Event 6	-30.09%	+4.68%
Storm Event 7	-5.84%	+8.67%
Storm Event 8	6.03%	+5.15%
Storm Event 9	8.53%	-1.93%
Storm Event 10	-40.14%	+11.03%
Storm Event 11	-1.81%	+16.63%
Storm Event 12	-6.56%	+13.08%

The main idea of sensitivity analysis is to learn sensitivity of the weather-related parameters in VISSIM. There are other many MOEs in VISSIM but for this study only free-flow speed and spacing were considered. According to the available field observations, speed distributions and average headways were assigned for different storm events and found to be sensitive. It was observed that average speed was found to be more sensitive than spacing. The model was calibrated on a homogeneous topography without congestion, at free-flow speed. The change in weather-related parameters value represented different driver behaviors during different storm events. The change in MOEs between ideal case and different storm events determined the level of sensitivity. The percentage difference between observed and simulated average speed for individual vehicles during different storm events are illustrated in Figure 6.6, Figure 6.7, and Figure 6.8.

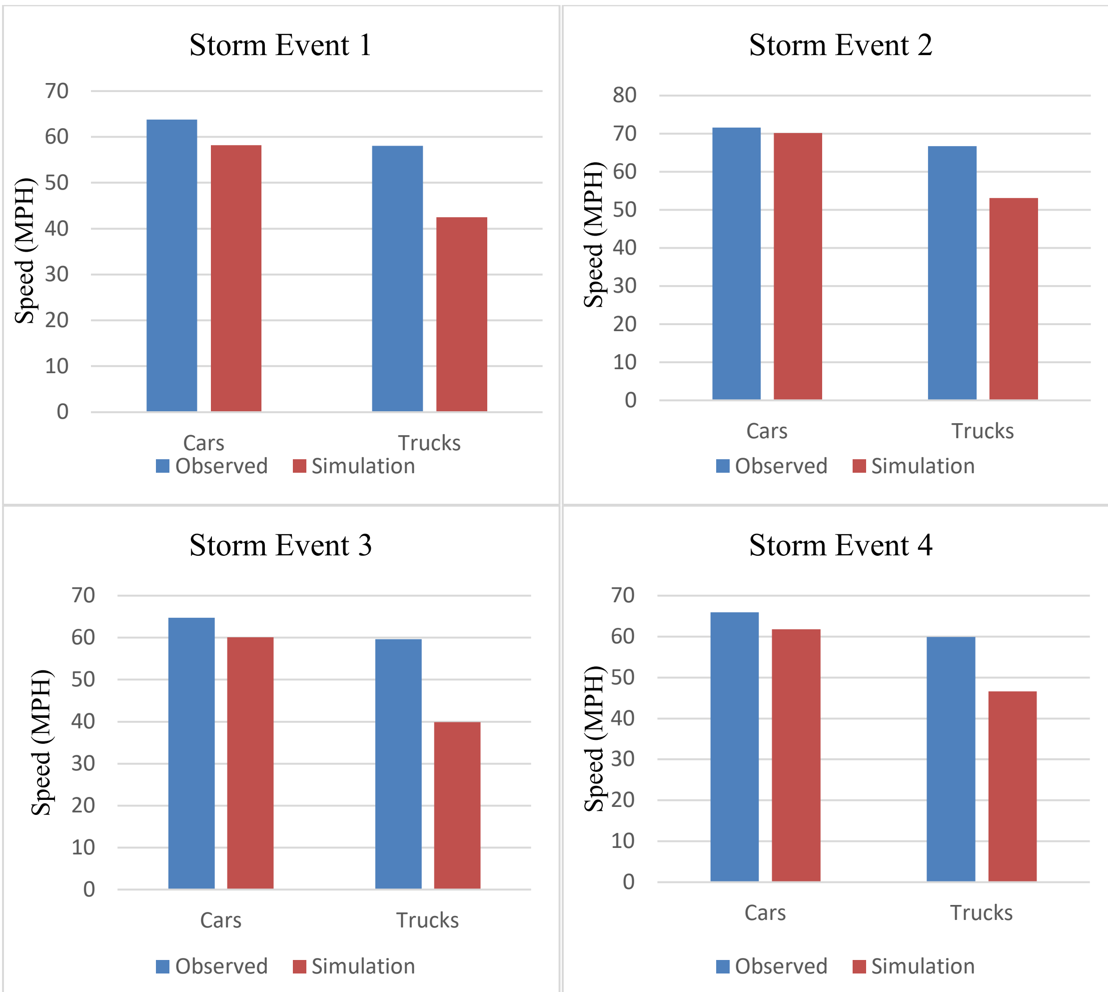

Figure 6.6 Average Speed between Observed and Simulated for Storm Events 1 to 4

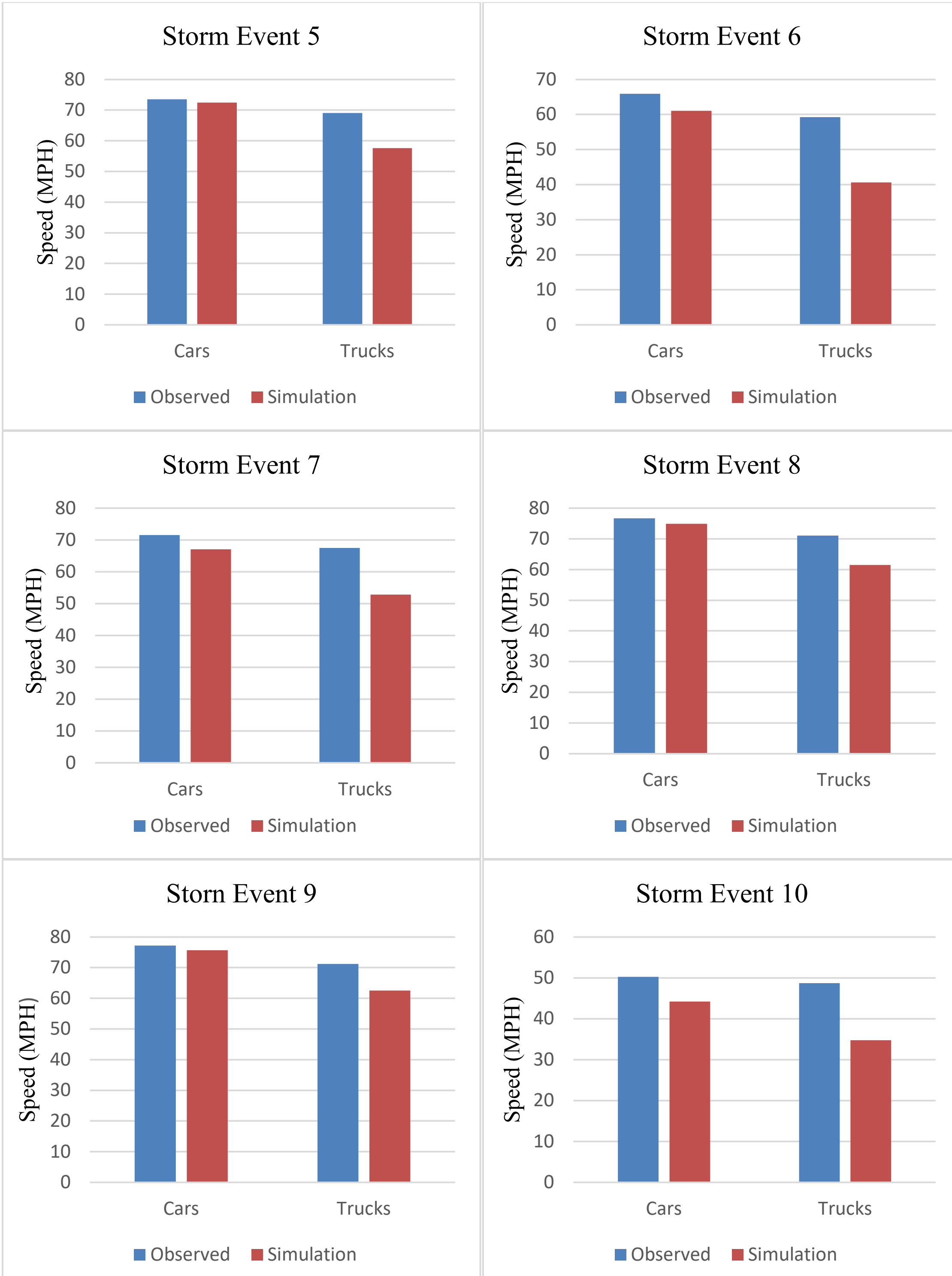

Figure 6.7 Average Speed between Observed and Simulated for Storm Events 5 to 10

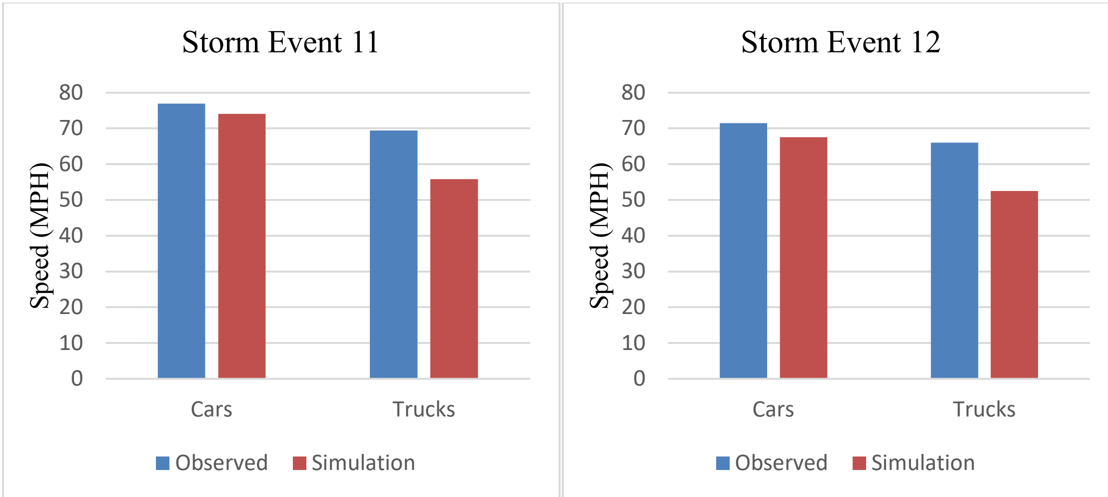

Figure 6.8 Average Speed between Observed and Simulated for Storm Events 11 and 12

6.5 Procedures for Calibrating Adverse Weather Conditions in VISSIM

This section provides procedures for modeling the impacts of adverse weather conditions on surface transportation using VISSIM. Procedures depend on the project scope and objectives. For this study, modeling was done on VISSIM during different storm events at rural freeways in free flow condition.

Figure 6.9 shows the stepwise procedure for calibrating adverse weather conditions in VISSIM. In this study, field observation data were used to calculate speed distributions and headways. Many other weather-related parameters exist in VISSIM for calibrating weather events. For every project, the traffic analyst must choose the appropriate parameters in VISSIM to reflect the real scenario and MOEs according to project needs and objectives.

The procedures presented here are based on the Traffic Analysis Toolbox Volume XI: Weather and Traffic Analysis, Modeling and Simulation (Byungkyu "Brian", et al., December 2010) and Identifying and assessing Key Weather Related Parameters and Their Impacts of Traffic Operations Using Simulation (Zhang, et al., 2004).

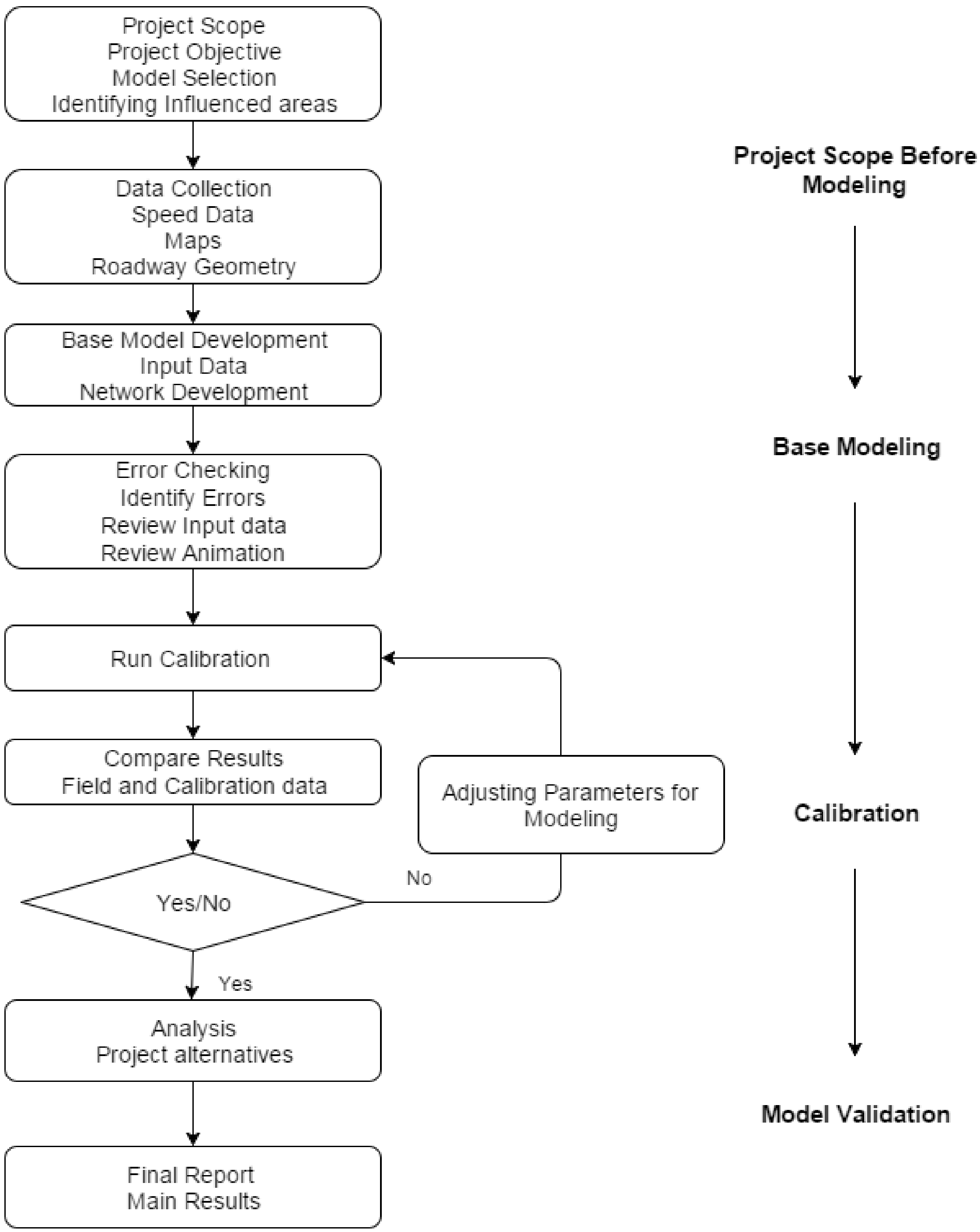

Figure 6.9 Flow Chart to Calibrate Adverse Weather Conditions in Microsimulation

Step 1: Objectives of the Project

The purpose and use of a microsimulation model (VISSIM) is to know the impacts of adverse weather conditions and are described with additional questions such as:

1. Is VISSIM the right tool for modeling adverse weather conditions?
2. What are the weather-related parameters that can be adjusted in the model?
3. Does it reflect the real adverse weather conditions throughout the simulation period?
4. What types of transportation modes and networks will be evaluated?
5. What are the measures of effectiveness (MOEs) for decision-making process to Weather Responsive Traffic Management Center?

These are the important questions that should be addressed before implementation of the project. If answers to these questions are yes, then it might be helpful to know the effects of adverse weather conditions on traffic operations using a VISSIM microsimulation tool.

Step 2: Data Preparation

This section provides guidance on collecting and preparation of datasets required to develop a microsimulation model for a specific project. It is very important to collect the actual roadway conditions in the field. The input data required for simulation depends on the project scope and modeling application. Data required for microsimulation modeling are as follows:

- Roadway geometrics (such as number of lanes, width, lengths, curvature etc.)
- Traffic volume and speed
- Vehicle compositions
- Signal timing data
- Transit, bike, and pedestrian data
- Calibration data/MOEs like speed, delays, capacities, travel time etc.
- Aerial photographs

To model adverse weather conditions on microsimulation, it is important to collect traffic data during weather events. Previous research and sensitivity analysis recognized the impacts of weather conditions on driver behaviors such as free-flow speed, car-following, gap acceptance, discharge headways, delays, demand (Zhang, et al., 2004).

Step 3: Base Model Development

In this step, a microsimulation model was developed by coding the required data obtained from the field observation (step-2). Stepwise model development in VISSIM is presented in the above section. There are two driver behavior parameters in VISSIM tool: car following and lane changing models. In this research only car-following model is considered. Car following mode consists of two models:

- Wiedemann 74 model
- Wiedemann 99 model

Either can be used depending on the project scope. To include weather events in model calibration, different traffic parameters should be identified that are impacted by the adverse weather conditions. They can be found by sensitivity analysis, previous studies, observed data, and sometimes by engineering judgment. The following steps will discuss more in detail about VISSIM parameters that are being impacted by adverse weather conditions. Weather-related parameters found by the study done by Zhang were used for calibrating driver behavior such as free-flow speed and car-following parameters (Zhang, et al., 2004). Table 6.5 shows the VISSIM parameters impacted by different storm event and Table 6.6 shows the details parameters included in Wiedemann 99 car-following behavior.

Table 6.5 VISSIM parameters impacted by storm events

Category	VISSIM Code	Description
Roadway Geometry Parameters		
Number of Lanes	Number of lanes	Number of lanes can be reduced according to the storm events
Lane Width	Lane Width	Can only assign the lane width but cannot change according to the visibility of lane marking
Traffic Parameter		
Vehicle Demand	Entering volume in the link	Vehicle input can be adjusted according to field observation during adverse weather conditions.
Driver Behavior		
Free-Flow Speed	Desired Speed Distribution	For any particular vehicle, the speed distribution is an important variable that has a significant impact on capacity and achievable travel speed and can be adjusted according to a storm event.
Car-Following	CC0 to CC9	Detail in Table 6.2

Many other parameters in VISSIM tool can be adjusted according to the project scope and data availability. Details of VISSIM parameters impacted by adverse weather conditions is presented in Appendix D. The traffic analyst would choose the network performance parameters according to the needs and objectives of the project. It is a known fact that drivers reduce their vehicle speed during adverse weather conditions. According to the observed impacts, the traffic engineer would choose MOEs to recognize specific parameters in VISSIM that need to be changed according to the storm events.

Few studies have been done to model impacts of adverse weather conditions based on field observation or by an assumption. It is not always possible to get values for some parameters (e.g. look ahead distance, lane-changing, etc.), the estimated value of the parameters could be assigned according to past research or by engineering judgment. It is sometimes difficult to get empirical values for all the parameters. Based on previous research, the following traffic parameters have been known (Byungkyu "Brian", et al., December 2010):

- Free-flow speed
- Car-following behavior
- Discharge headway and lost time at intersection
- Traffic demand during adverse weather conditions

In this study, base model was developed according to observed data in the field during ideal road conditions.

Table 6.6 Car-following parameters in VISSIM impacted by storm events

Category	VISSIM Code	Description	Default Value
Thresholds for Dx	CC0	**Standstill distance:** Desired distance between lead and following vehicle at v = 0 mph	4.92 ft
	CC1	**Headway Time:** Desired time in seconds between lead and following vehicle	0.90 sec
	CC2	**Following Variation:** Additional distance over safety distance that a vehicle requires	13.12 ft
	CC3	**Threshold for Entering 'Following' State:** Time in seconds before a vehicle starts to decelerate to reach safety distance (negative)	-8.00 sec
Thresholds for Dv	CC4	**Negative 'Following' Threshold:** Specifies variation in speed between lead and following vehicle	0.35 ft/s
	CC5	**Positive 'Following Threshold':** Specifies variation in speed between lead and following vehicle	0.35 ft/s
	CC6	**Speed Dependency of Oscillation:** Influence of distance on speed oscillation	11.44
Acceleration Rates	CC7	**Oscillation Acceleration:** Acceleration during the oscillation process	0.82 ft/s^2
	CC8	**Standstill Acceleration:** Desired acceleration starting from standstill	11.48 ft/s^2
	CC9	**Acceleration at 50 mph:** Desired acceleration at 50 mph	4.92 ft/s^2

Step 4: Error Checking

After coding the observed data into the microsimulation VISSIM network, the model was run for error checking. Error checking is important for identifying errors so analysts can fix the mode coding errors. Error checking is important for the model calibration because the coding errors can distort the model calibration process and provide incorrect results for the analysis. Error checking in the networks involves a review of vehicle movements, turning movement vehicles, any conflicts present, signal timing, and any other coded inputs so the calibration model reflects the actual driver behavior with the real traffic conditions.

Step 5: Model Calibration

The main goal of model calibration in VISSIM is to obtain the best value between calibration results and the observed data. Model calibration checks against the accepted region to determine if further calibration is needed. It is difficult to adjust weather-related parameters to a suitable value that represent actual weather conditions. Previous studies done used a three-step calibration process and are (Byungkyu "Brian", et al., December 2010):

1. Identifying calibration parameters
2. Determining an appropriate range for sampling
3. Verifying the determined ranges

Calibration parameters are adjustments in values during modeling that reflect the actual field conditions. MOEs is needed to compare between the outputs. It is necessary to have MOEs in the field during different storm events. In this study, a base model is developed for ideal weather conditions in the VISSIM tool to compare its MOEs to the observed MOEs observed during different storm events. Only weather-related parameters were adjusted to reflect the actual adverse weather conditions.

Step 6: Model Validation

Model validation is the final step in the calibration process. The model validation determines the actual difference between observed and simulation outputs. It also helps to recognize how closely the model is reflecting the real scenario. The validation target for a project depends on the project scope and objectives. If the simulation model outputs fall in the range of the validation target, further analysis is accepted. If the outputs do not fall in the acceptable range, necessary adjustments must be coded in the model for further calibration process.

7. SUMMARY AND CONCLUSIONS

The main goal of this report was to address the relationship and impacts of adverse weather conditions on traffic speed and driver behaviors on rural interstate corridors. Evaluating the effectiveness of VLS systems to improve the performance of traffic operations was also a major concern. Furthermore, sensitivity analysis on different weather-responsive simulation parameters in the VISSIM model to identify how sensitive the change in values impacts MOEs. Finally, procedure guidelines for calibration of rural interstate facilities in VISSIM during different adverse storm events is recommended. This section documents the major results obtained and conclusion of this project.

7.1 Summary of Findings

The data considered for the analysis were taken from the storms occurring during 2010 and 2011. Results obtained from the analysis are summarized in this section with the conclusion of the project.

7.1.1 Analysis of Speed

The statistical analysis on vehicle speeds during “ideal” and “non-ideal” weather conditions were computed on corridors along I-80 (Rock Spring-Green River, Elk Mountain, and Laramie-Cheyenne). Results suggest there was a decrease in average speed with an increase in standard deviation during non-ideal periods. Ideal conditions were described when the pavement surface condition is dry, gust wind speed less than 45 mph, and visibility greater than 500 feet. The ideal data set was used for analyzing baseline speed to determine the understanding of how drivers choose their speed during ideal conditions. An ideal period is one that appears prior to a storm events. The average speed of all vehicles during ideal periods was 69.76 mph. As expected, on average, cars were traveling at higher speed than trucks. The average speed for cars and trucks during ideal periods were 71.83 mph and 67.76 mph respectively.

Vehicle speeds were averaged into 15-minute time intervals during different storm events to plot a graph. The plotted graph Figure 4.4 describes the speed selection behavior during different storm events. A general trend was observed. Different storm events have their own impact on speed selection behavior. The driver chooses individual speed depending on the nature of storm events. The change in average vehicle speed and speed variations were observed when road condition changed from ideal to adverse. The average speed of trucks and cars were found to be reduced by 9.22 mph and 5.49 mph respectively. A z-statistic performed between average of ideal and non-ideal conditions illustrated that average speed during ideal periods were higher than non-ideal periods.

The speed and cumulative graph, Figure 4.6 and Figure 4.7 clearly show speed distribution during ideal and non-ideal periods. Speeds were higher during the ideal periods and seem to be normally distributed. Maximum operating speeds were observed during ideal conditions with lower speed variations. Whereas during non-ideal conditions, a decrease in vehicle speed with wide distribution was observed and suggested an increase in speed variation. It was also found that (Table 4.8) operating speeds of cars were higher than trucks for every storm event. The graph plotted (Figure 4.9) indicates a significant increase in standard deviation during non-ideal periods when compared to baseline speed conditions. The cars variation increased by 2.8 mph and trucks variation increased by 3.3 mph.

7.1.2 Impacts of Adverse Weather Condition on Traffic Operations

It is well known adverse weather conditions have an impact on traffic operations. The impact might be reduction in average speed, higher delays, an increase on travel time, gap acceptance at the intersection, and driver behavior etc. However, identifying the relationship between adverse weather conditions and traffic parameters could help to understand the cause of a storm event on degrading traffic performances.

A storm event affects traffic operations according to its strength and in multiple ways such as reduction in visibility, pavement surface conditions other than dry degrade in performance of traffic operations. It was clearly observed that different storm events had an impact on traffic speed which reduced traffic flow. The average speed of trucks was highly reduced compared to cars under non-ideal periods. Statistical analysis (t-test) on the observed data during different storm events proved that cars physically traveled at higher speeds than trucks with greater speed variations. In addition, statistical test son average speeds illustrated that speed is higher during ideal conditions.

An ordered probit model was considered because it provides analysis with more than two outcomes and it has an ability to analyze an ordinal dependent data. In addition, it also helps to recognize the difference between ordinal dependent variables. Errors are distributed normally and are more likely to be valid. An ordered probit statistical model was developed for speed selection behavior with the observed vehicle speeds and different weather parameters during different storm events. The dependent variable, speed, is an integer representing speed selection, which has four categories and is classified in order:

- 3 = speed below 45 mph
- 2 = speed between 45 to 55 mph
- 1 = speed between 55 to 65 mph
- 0 = speed greater than 65 mph

Out of five models developed, four were based on mile post whereas one combined model was developed by merging all storm events. The combined model was developed to identify if the impact of weather variables on speed selection behavior was similar or not. This model will provide an over-all representation and is more reasonable than a specific model. Estimation results from models showed that different weather parameters have their own impact on speed selection behavior. Pavement surface temperature variable was found to be statistically significant for all five models with a positive coefficient. This illustrates that higher temperature on the pavement surface will tend to increase the speed selection behavior towards higher category. The rationale behind this could be due to improvement on pavement surface conditions.

Weather variables such as air temperature, relative humidity (RH), gust wind speed had a significant impact on traffic operations. Air temperature had a negative effect on speed selection behavior, which seems unreasonable as the opposite was expected. Raise in air temperature will increase temperature of surrounding environment and ultimately melts snow accumulated along roadways and makes pavement surface wet. This might lead to a decrease in pavement friction and could might make drivers cautious about the roadway conditions and choose lower speed category. In addition, RH was also found to have a negative impact on speed selection behavior for all five models. Increase in RH will increase moisture in the air which may make surrounding denser and reduces visibility. The relationship between wind speed and vehicle speed seems reasonable. Higher the wind speed, the lower the average speed selection category. The impact is somehow small as drivers are perceptive overturning of vehicles. The precipitation accumulation variable was significant for all models but was insignificant for a single model at mile post 330. The relationship between precipitation accumulation and vehicle speed showed somewhat counterintuitive. Although negative impact was expected. Two models showed a positive impact, which could be attributed to the improvement of pavement surface conditions or might be due to an error in RWIS sensor during data collection.

Pavement surface status like chemically wet, ice warning, ice watch, snow watch, and wet, had a higher negative impact on speed selection behavior. The reason might be drivers being overly cautious or due to the presence of moisture which decreases the pavement friction. The results obtained from the models illustrated that ice watch and chemically wet pavement surface conditions tend to have a higher negative effect on degrading speed selection towards lower category.

Along with weather variables, truck percentage was also included in the model because of its important impact. I-80 in Wyoming is a major corridor for freight vehicles and consists of an AADT more than 50%. The impact of truck percentage coefficient is similar to weather parameters and was found to be statistically significant with a negative coefficient. Based on the results obtained from the models, we concluded that a higher number of trucks on rural highways during adverse weather conditions tends to decrease average speed selection behavior toward lower speed category. The reason might be their size and mass. The big trucks produce moisture in the air through tire compaction, which makes visibility poor and creates difficulty in seeing lane markings and driving on.

Furthermore, a VSL system was included in the model to measure the effectiveness of WRTMs during inclement weather conditions. From the model, implementation of VSL system improved in speed selection behavior with a positive coefficient. One unit increase in the VSL posted speed limit tends to have increased in speed category toward a higher range. The reason may be either due to VSL posted speed limit or a change in road conditions from non-ideal to ideal. The strange thing is that visibility and precipitation rate were found to be statistically insignificant for all models.

7.1.3 Impacts of Adverse Weather Condition on Microscopic Indicators

It was assumed that during inclement weather conditions drivers chose a safer speed and longer headways. A log-logistic distribution statistical model was developed to illustrate the impact of adverse weather conditions on microscopic behavior. The reduction on average speeds directly reflects on microscopic behavior of traffic parameters headways and spacing. The descriptive statistic (Table 5.5) showed that mean headway was increased during non-ideal periods by 0.15 second, which is 2.89 % greater than ideal periods. In addition, standard deviation was also increased by 0.08 seconds during non-ideal periods. The density function graphs (Figure 5.5 and Figure 5.6) confirmed that the shorter headways decreased during non-ideal periods. The average density decreased by 3.49 % when the weather changed from ideal to adverse weather conditions. Hence, during adverse weather conditions, drivers tend to reduce their speed to be safe and increase their headways. Headways are directly proportional to spacing. Therefore, increase in headways ultimately increases spacing between the vehicles. Drivers reduce their speeds and increase headways during adverse weather conditions to meet safe driving maneuvers. The shorter spacing between 0-50 feet was decreased by 14% during non-ideal conditions.

In summary, it can be concluded that inclement weather conditions have a significant impact on speed selection behavior, which reflects directly on driver behavior such as reduction in speed, a decrease of shorter headways and spacing. All the results obtained show the characteristics of traffic operations and impacts on driver behavior during non-ideal weather events when compared with ideal periods.

7.1.4 Sensitivity Analysis on Weather Responsive Simulation Model Parameters

The model calibration in VISSIM microsimulation was done to obtain the best values between calibration results and field observation to determine the outputs within an acceptable range. Root-mean-square percent error (RMSPE) was used to find out overall error of the simulation for further model validation. Different parameters in VISSIM help to better fit the model according to project scope and objectives. Data collection measurements and network performances were selected for capturing individual vehicle performance and model were run for 3,600 seconds to get one full hour of simulation outputs.

The main purpose of sensitivity analysis is to determine degree of sensitivity of the change in weather-related traffic parameters on traffic operations during different storm events in VISSIM microsimulation tool. Speed distribution and car-following parameters were assigned in VISSIM according to the field observation during different storm events and other parameters remained at defaults. The model was calibrated at homogeneous topography without congestion, at free flow speed giving the nature of rural interstate. The change in weather-related parameters in the simulation model represents different driver behavior during different storm events. The sensitivity analysis was done with the base model developed using ideal observed data. The obtained MOEs between ideal model and MOEs of different storm events showed the sensitivity of the change in weather-related parameters (Figure 6.4 and Figure 6.5). Average speeds were found to be more highly sensitive than spacing. Storm event 10 was found to be highly sensitive and is similar to the observed field data. The average speed was decreased by 40.14%. There are some other different weather-related parameters in VISSIM microsimulation tool and can be chosen according to the project scope and needs. For this project, driver behavior such as average speed, headways, and spacing were considered.

7.1.5 Procedure Guidelines for Calibrating Adverse Weather Conditions in VISSIM

The procedure guidelines for calibrating adverse weather conditions in VISSIM was created on the basis of sensitivity analysis on VISSIM parameters. The procedures are based on Traffic Analysis Toolbox Volume XI: Weather and Traffic Analysis, Modeling and Simulation (Byungkyu "Brian", et al., December 2010) and Identifying and Assessing Key Weather-related Parameters and Their Impacts on Traffic Operations Using Simulation (Zhang, et al., 2004). The procedure develops a general idea of microsimulation models in VISSIM during different storm events. The field observation is a need for different storm events to code in VISSIM to reflect the real conditions.

7.2 Conclusions

The objectives of this project were to identify the relationship and impacts of different weather variables on driver behavior and traffic speed during adverse winter weather conditions. During ideal weather conditions, drivers maintain their operating speeds according to the posted speed limits but ultimately change their driving behavior when road conditions fall into non-ideal. To harmonize the speed selection during adverse weather conditions on the rural freeways, implementation of different WRTMs are needed. For example, VSL systems provide a safe speed that vehicles should follow and help to reduce vehicle speed and speed variations.

The overall goal of this project is to measure the effectiveness of WRTMs and know the relationship and effects of different weather variables on traffic operations by including traffic speeds and weather parameters in an engineering model to develop strategies to mitigate or manage traffic operations during adverse winter weather conditions. More advanced WRTMs strategies should be developed in future which help to predict the effects of different weather variables on traffic operations and develop plans to resolve or mitigate the impact of such weather conditions.

The results obtained from this study is the starting point to identify the relationship between speed selection behavior and weather parameters during inclement weather conditions. There are many other factors that may impact on speed selection behavior such as road geometry, ramp density, weaving zones etc. These all factors should be included in the model in the model to understand the actual speed selection behavior and weather parameters.

7.3 Recommendation and Future Research

Based on the results and conclusion of this study, the following recommendations are put forward to identify the relationship between speed selection behavior, headways, and weather variables and also to measure the effectiveness of WRTMs to mitigate the impact of adverse weather conditions on rural freeways.

1. More data should be acquired during ideal and non-ideal periods on the same segments on rural freeways for further analysis of non-ideal data with reference to ideal data.
2. Further implementation of WRTMs as an important tool for TMC to implement its strategy during adverse weather conditions.
3. Road geometry, safety measures, weaving zones, and ramp density is also key elements in the selection of speeds during adverse weather conditions in rural freeways. Therefore, further research focusing on these elements along with weather variables could be beneficial in identifying driver behaviors.
4. Further research should be conducted, possibly on predicting impacts of adverse winter weather conditions on driver behavior by simulating different weather-related model parameters in microsimulation tool to determine the cause and develop different decision-support tools.

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APPENDIX A: DATA FORMAT AND GRAPHS

Sample Data format obtained from Wavetronix radar and RWIS

Wavetronix radar speed data along I-80 MP 256.17

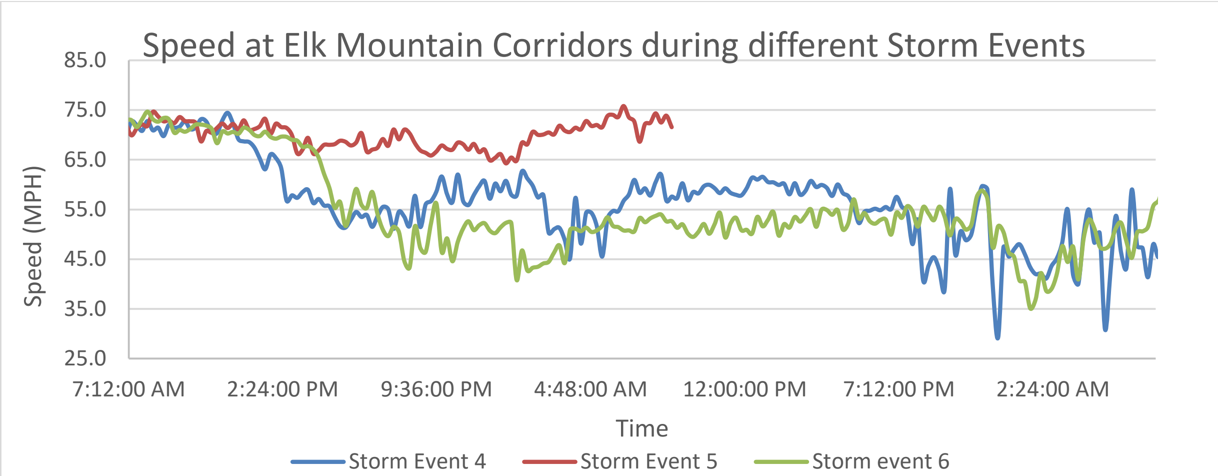
```
DATE          : January 08, 2011
SERIAL NUMBER: SS125 U100002704
DESCRIPTION   : SS125 ITS Radar
LOCATION      : I80 EB MP 256.17
ORIENTATION   : North
```

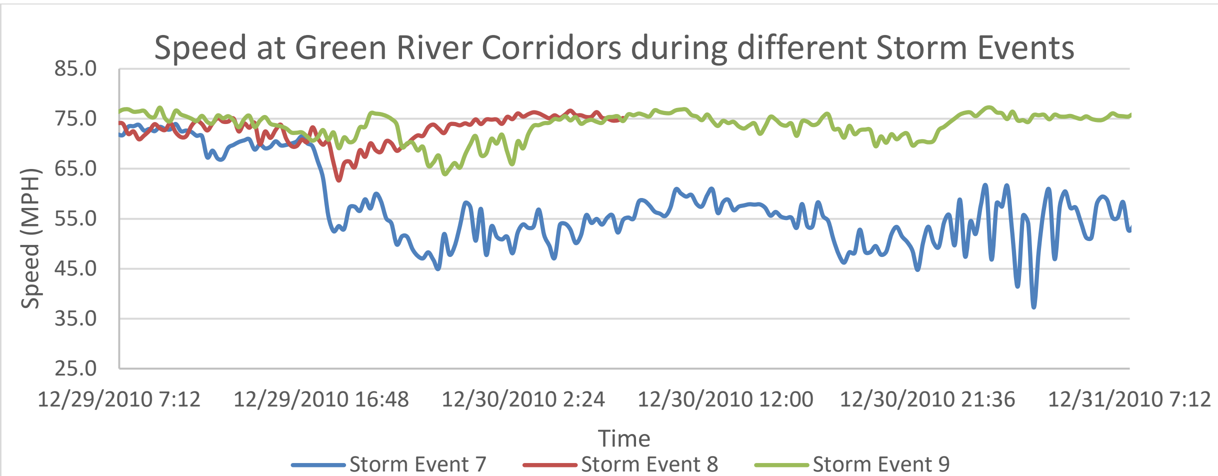
LANE	LENGTH	(MPH)	CLASS	RANGE	SENSOR TIME YYYY-MM-DD HH:MM:SS.sss
LANE_03	6		1	222	2011-01-08 17:39:23.257
LANE_04	63	63.3	5	240	2011-01-08 17:39:23.412
LANE_04	73	67.5	5	240	2011-01-08 17:39:26.031
LANE_04	6		1	240	2011-01-08 17:39:29.293
LANE_01	70	66.6	5	83	2011-01-08 17:39:29.349
LANE_01	86	70.6	6	83	2011-01-08 17:39:35.181
LANE_01	21	77.0	2	84	2011-01-08 17:39:39.333
LANE_01	21	77.4	2	84	2011-01-08 17:39:40.362
LANE_01	15	76.4	2	82	2011-01-08 17:39:45.473
LANE_04	66	63.6	5	240	2011-01-08 17:39:46.226
LANE_01	75	72.9	5	82	2011-01-08 17:39:50.246
LANE_02	18	75.7	2	96	2011-01-08 17:39:53.428
LANE_01	78	73.7	5	82	2011-01-08 17:39:56.070
LANE_01	73	69.5	5	82	2011-01-08 17:40:05.197
LANE_04	15	80.2	2	242	2011-01-08 17:40:06.035
LANE_03	17	76.5	2	230	2011-01-08 17:40:12.189
LANE_04	25	73.4	3	240	2011-01-08 17:40:13.386
LANE_03	12	81.3	2	230	2011-01-08 17:40:15.482
LANE_01	17	83.1	2	82	2011-01-08 17:40:19.272
LANE_04	31	60.8	3	241	2011-01-08 17:40:23.061
LANE_04	71	66.6	5	242	2011-01-08 17:40:36.345
LANE_04	19	79.6	2	242	2011-01-08 17:40:58.152
LANE_04	79	68.8	5	240	2011-01-08 17:41:20.070
LANE_04	67	68.6	5	241	2011-01-08 17:41:32.129
LANE_04	7		1	240	2011-01-08 17:41:34.373
LANE_01	77	65.1	5	83	2011-01-08 17:41:34.461
LANE_02	18	76.3	2	96	2011-01-08 17:41:35.118
LANE_03	22	74.1	2	229	2011-01-08 17:41:56.208
LANE_04	83	69.6	5	242	2011-01-08 17:41:57.271
LANE_04	77	70.2	5	238	2011-01-08 17:41:59.144
LANE_01	77	67.7	5	82	2011-01-08 17:42:01.014
LANE_01	75	65.4	5	83	2011-01-08 17:42:04.237
LANE_02	75	66.3	5	96	2011-01-08 17:42:07.474
LANE_04	22	67.6	2	242	2011-01-08 17:42:08.097
LANE_01	15	59.3	2	82	2011-01-08 17:42:08.139
LANE_01	80	59.9	5	82	2011-01-08 17:42:12.083
LANE_02	78	66.0	5	90	2011-01-08 17:42:12.163
LANE_04	22	69.1	2	242	2011-01-08 17:42:14.458
LANE_03	19	78.3	2	229	2011-01-08 17:42:16.004
LANE_04	27	68.5	3	242	2011-01-08 17:42:17.117
LANE_01	18	79.0	2	82	2011-01-08 17:42:23.445
LANE_02	19	76.3	2	91	2011-01-08 17:42:27.101
LANE_01	80	63.9	5	82	2011-01-08 17:42:30.480
LANE_02	64	64.7	5	96	2011-01-08 17:42:31.437
LANE_03	23	70.7	2	230	2011-01-08 17:42:33.147
LANE_04	72	64.7	5	240	2011-01-08 17:42:35.084
LANE_03	64	73.0	5	230	2011-01-08 17:42:37.404
LANE_03	23	74.8	2	230	2011-01-08 17:42:38.416
LANE_04	32	69.6	3	242	2011-01-08 17:42:45.146
LANE_04	21	74.3	2	241	2011-01-08 17:42:47.441
LANE_01	74	62.6	5	84	2011-01-08 17:42:48.357
LANE_02	6	64.1	1	92	2011-01-08 17:42:48.360
LANE_01	16	76.4	2	84	2011-01-08 17:43:05.270
LANE_01	75	71.1	5	84	2011-01-08 17:43:11.057
LANE_04	78	71.2	5	240	2011-01-08 17:43:27.329
LANE_01	18	76.3	2	84	2011-01-08 17:43:29.297
LANE_04	63	66.2	5	242	2011-01-08 17:43:43.390
LANE_04	71	65.4	5	241	2011-01-08 17:43:47.434

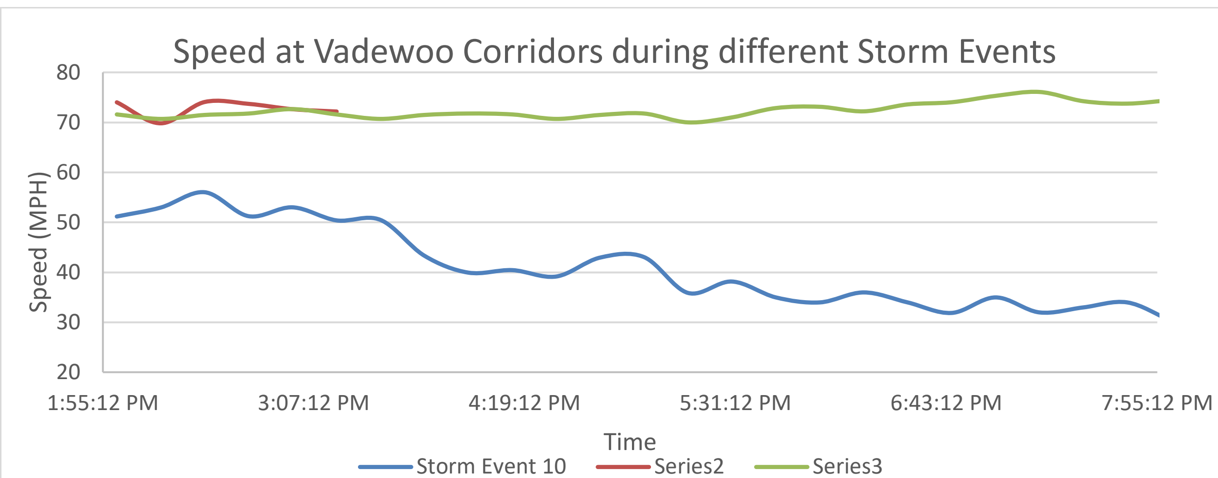
RWIS Weather Data

Date/Time (MDT)	SfStatus	SfTemp	PrecipType	AirTemp	RH	Dewpoint	Barometric	AvgWindSpeed	GustWindSpeed	Wind Direction	PrecipType	Precip Intensity	Precip Accumulation	Precip Rate	Visibility
12/29/2010 12:25	Dry	43.2	None	30	68	21	22	37	51	S	None	None	0	0	6560
12/29/2010 12:30	Dry	43	None	30	69	21	22	35	47	S	None	None	0	0	6560
12/29/2010 12:35	Dry	42.3	None	29	69	21	22	36	47	S	None	None	0	0	6560
12/29/2010 12:40	Dry	43	None	29	69	20	22	36	43	S	None	None	0	0	6560
12/29/2010 12:45	Dry	43	None	30	69	21	22	35	45	S	None	None	0	0	6560
12/29/2010 12:50	Dry	42.3	None	30	69	21	22	34	45	S	None	None	0	0	6560
12/29/2010 12:55	Dry	42.6	None	30	68	21	22	32	45	S	None	None	0	0	6560
12/29/2010 13:00	Dry	43.2	None	30	68	21	22	35	46	S	None	None	0	0	6560
12/29/2010 13:05	Dry	42.4	None	30	68	21	22	37	46	S	None	None	0	0	6560
12/29/2010 13:10	Dry	42.3	None	30	66	20	22	36	44	S	None	None	0	0	6560
12/29/2010 13:15	Dry	41.5	None	30	67	20	22	35	44	S	None	None	0	0	6560
12/29/2010 13:20	Dry	41.4	Snow	30	67	20	22	34	44	S	Snow	Slight	0	0	6560
12/29/2010 13:25	Dry	41.4	Snow	29	71	21	22	34	44	S	Snow	Slight	0	0	6560
12/29/2010 13:30	Dry	41	Snow	29	72	21	22	34	44	S	Snow	Slight	0	0	6560
12/29/2010 13:35	Dry	39.7	Snow	29	75	22	22	34	44	S	Snow	Slight	0	0	6560
12/29/2010 13:40	Trace Moisture	36.9	Snow	28	78	22	22	32	40	S	Snow	Slight	0	0	6560
12/29/2010 13:45	Wet	35.6	Snow	28	78	22	22	32	44	S	Snow	Slight	0	0	6560

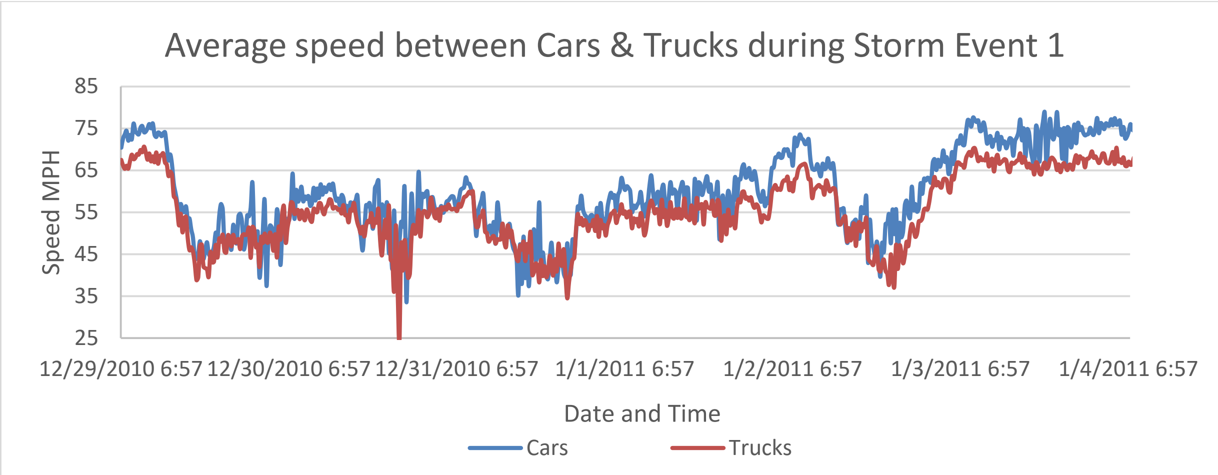
Graphical representation of traffic speeds during different Storm Events

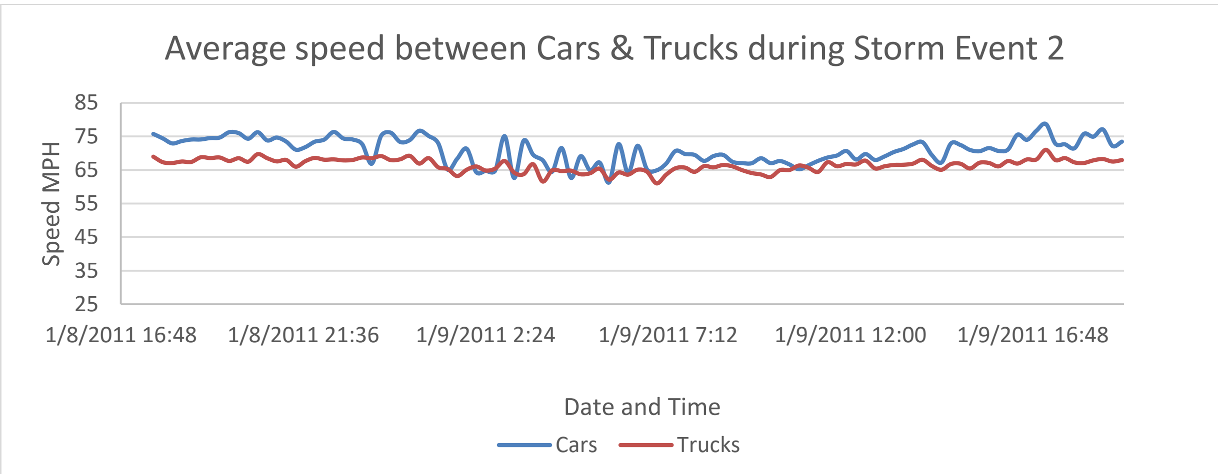


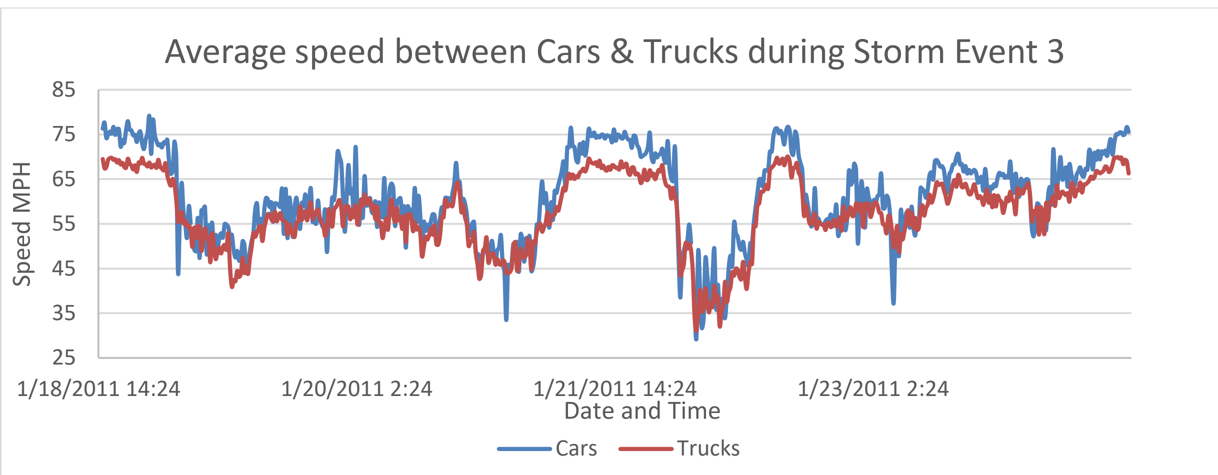


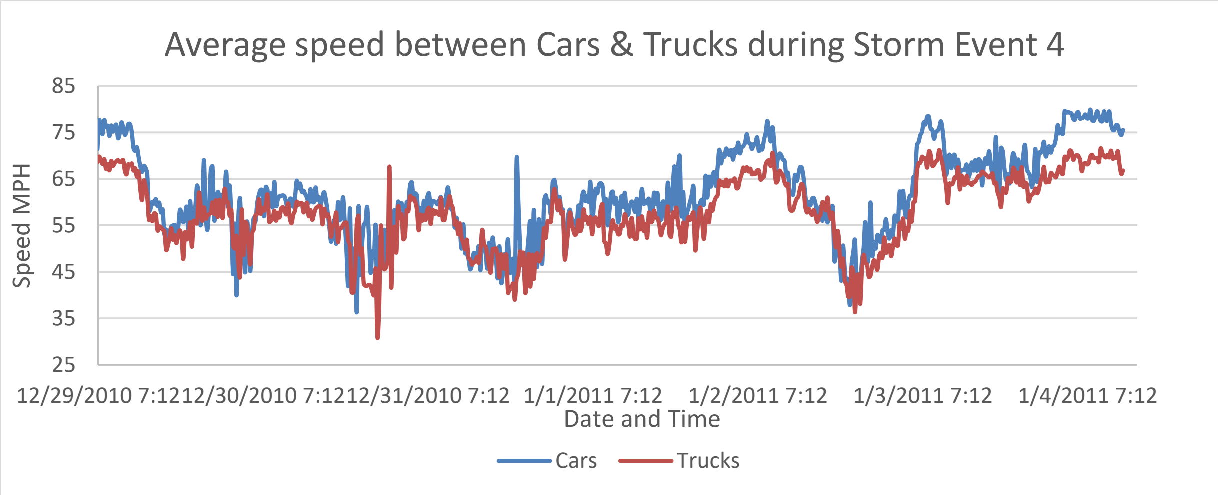


Graphical representation of observed average speeds between cars and Trucks during different storm events

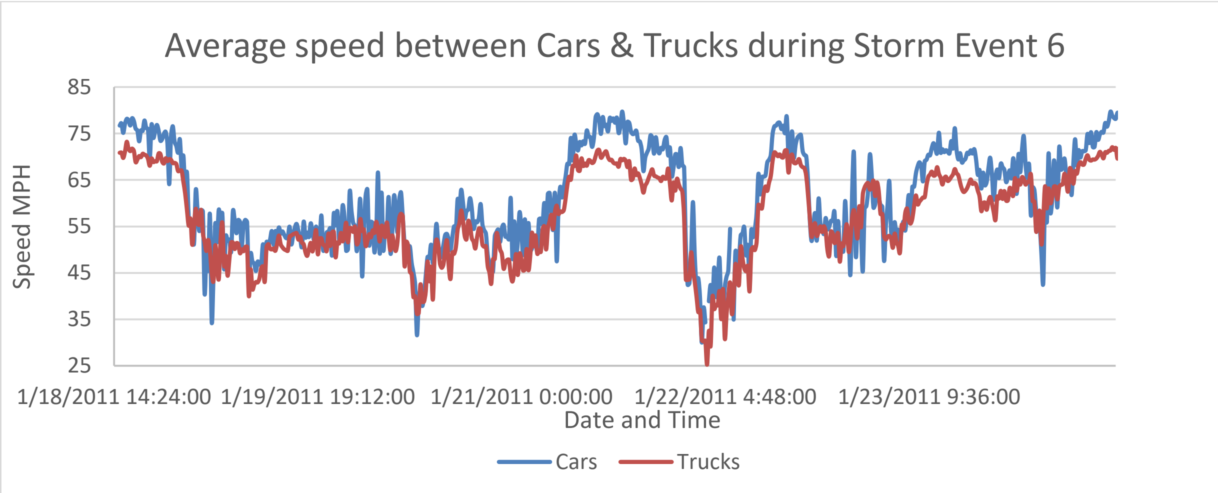




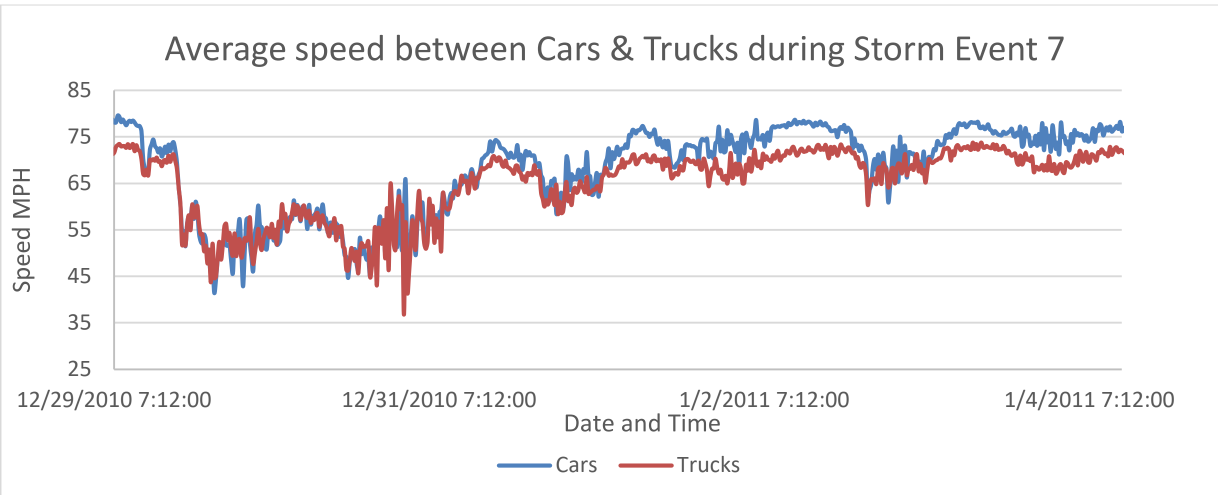




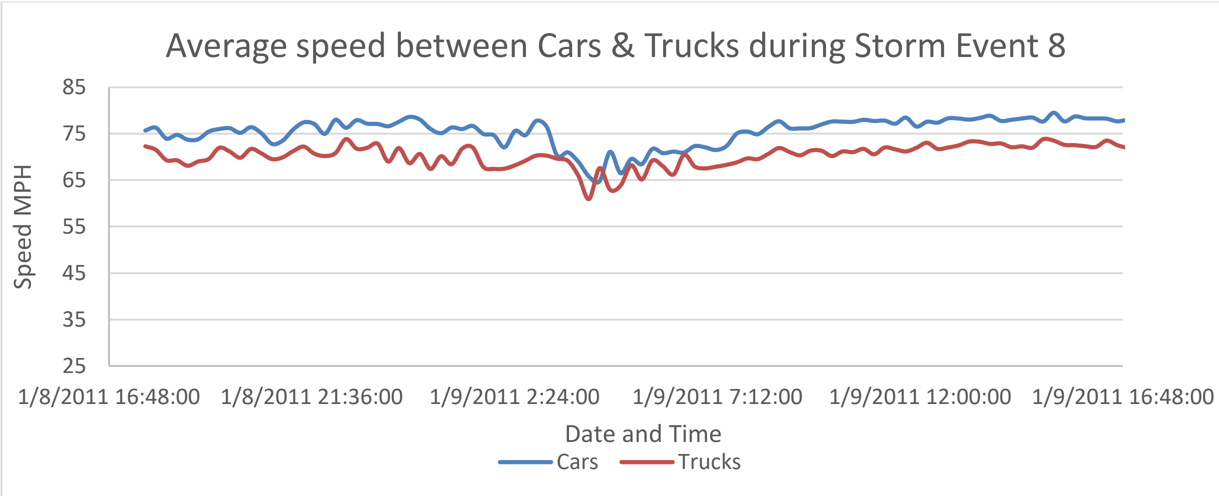
Average speed between Cars & Trucks during Storm Event 4
Speed MPH
85
75
65
55
45
35
25
12/29/2010 7:12
12/30/2010 7:12
12/31/2010 7:12
1/1/2011 7:12
1/2/2011 7:12
1/3/2011 7:12
1/4/2011 7:12
Date and Time
Cars
Trucks

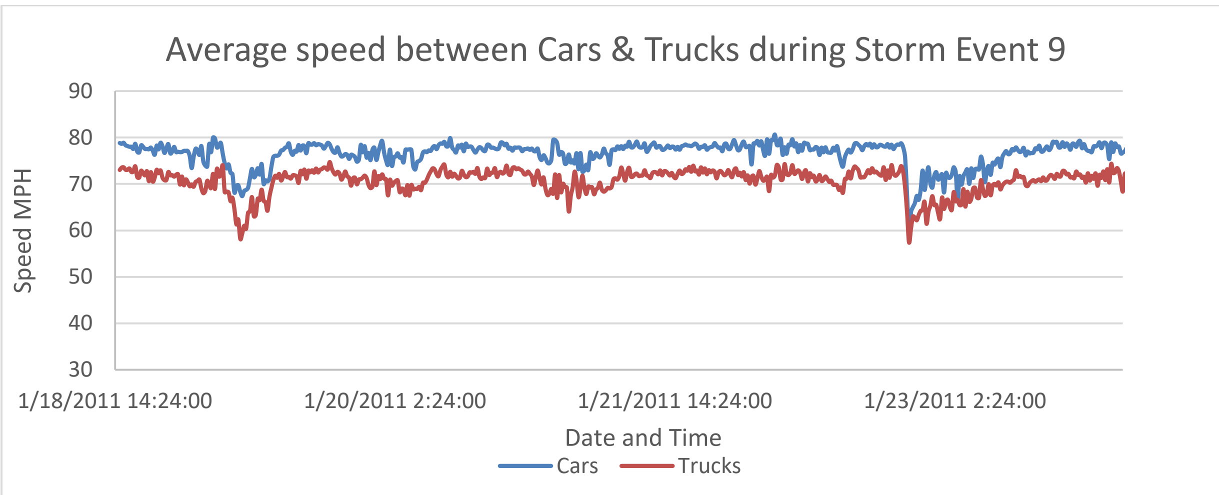


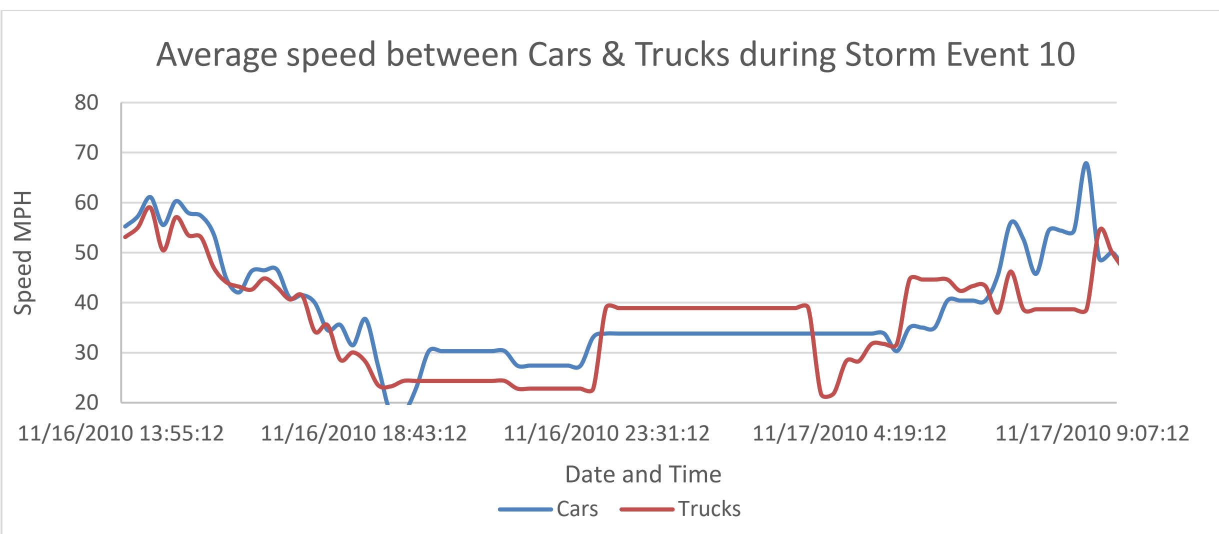
Average speed between Cars & Trucks during Storm Event 6
Speed MPH
85
75
65
55
45
35
25
1/18/2011 14:24:00
1/19/2011 19:12:00
1/21/2011 0:00:00
1/22/2011 4:48:00
1/23/2011 9:36:00
Date and Time
Cars
Trucks

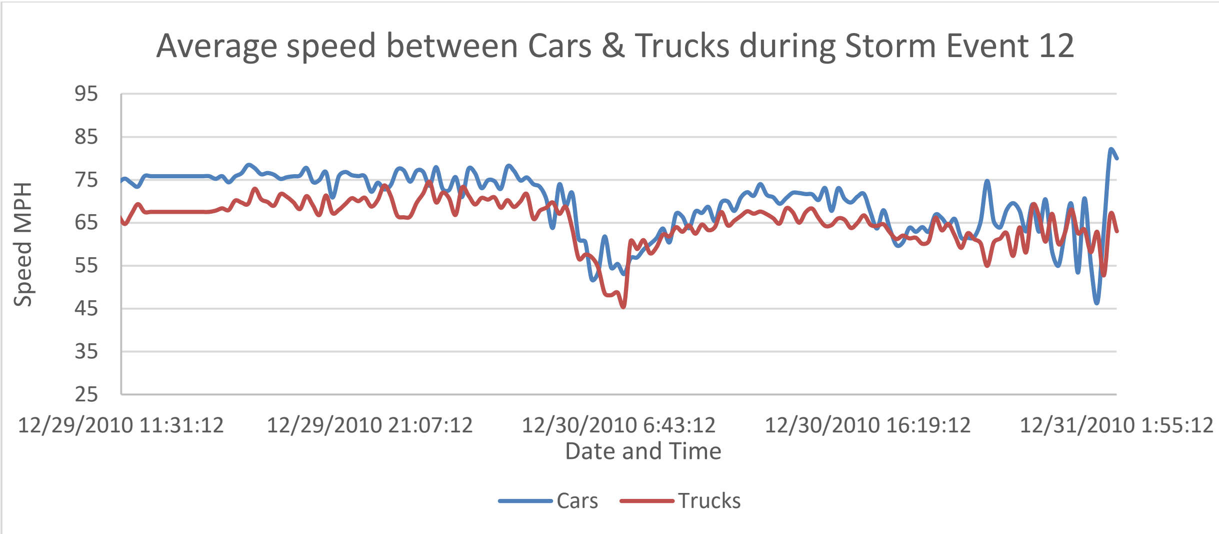


Average speed between Cars & Trucks during Storm Event 7
Speed MPH
85
75
65
55
45
35
25
12/29/2010 7:12:00
12/31/2010 7:12:00
1/2/2011 7:12:00
1/4/2011 7:12:00
Date and Time
Cars
Trucks

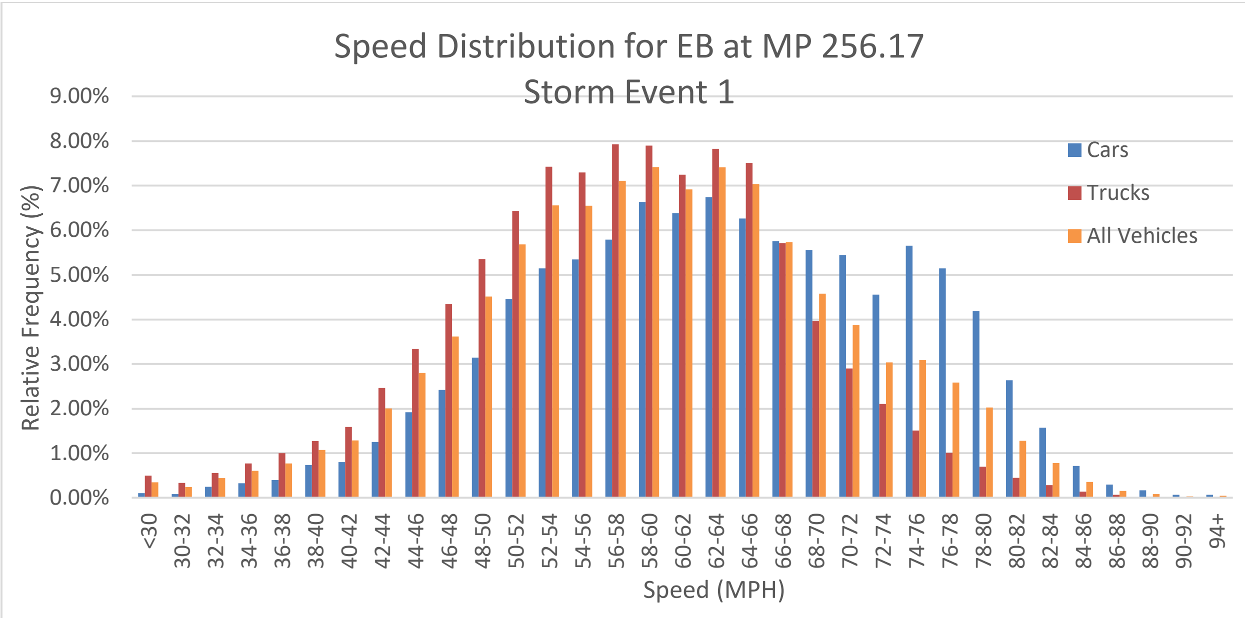

Average speed between Cars & Trucks during Storm Event 8
Speed MPH
85
75
65
55
45
35
25
1/8/2011 16:48:00
1/8/2011 21:36:00
1/9/2011 2:24:00
1/9/2011 7:12:00
1/9/2011 12:00:00
1/9/2011 16:48:00
Date and Time
Cars
Trucks

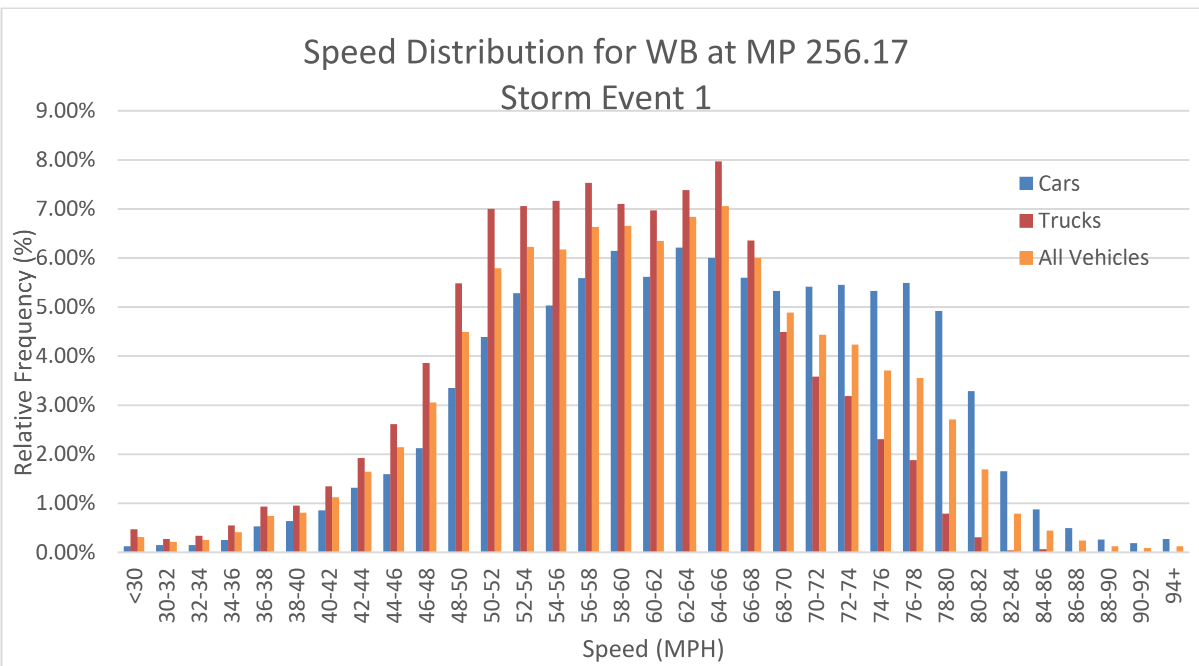

Average speed between Cars & Trucks during Storm Event 9
Speed MPH
90
80
70
60
50
40
30
1/18/2011 14:24:00
1/20/2011 2:24:00
1/21/2011 14:24:00
1/23/2011 2:24:00
Date and Time
Cars
Trucks

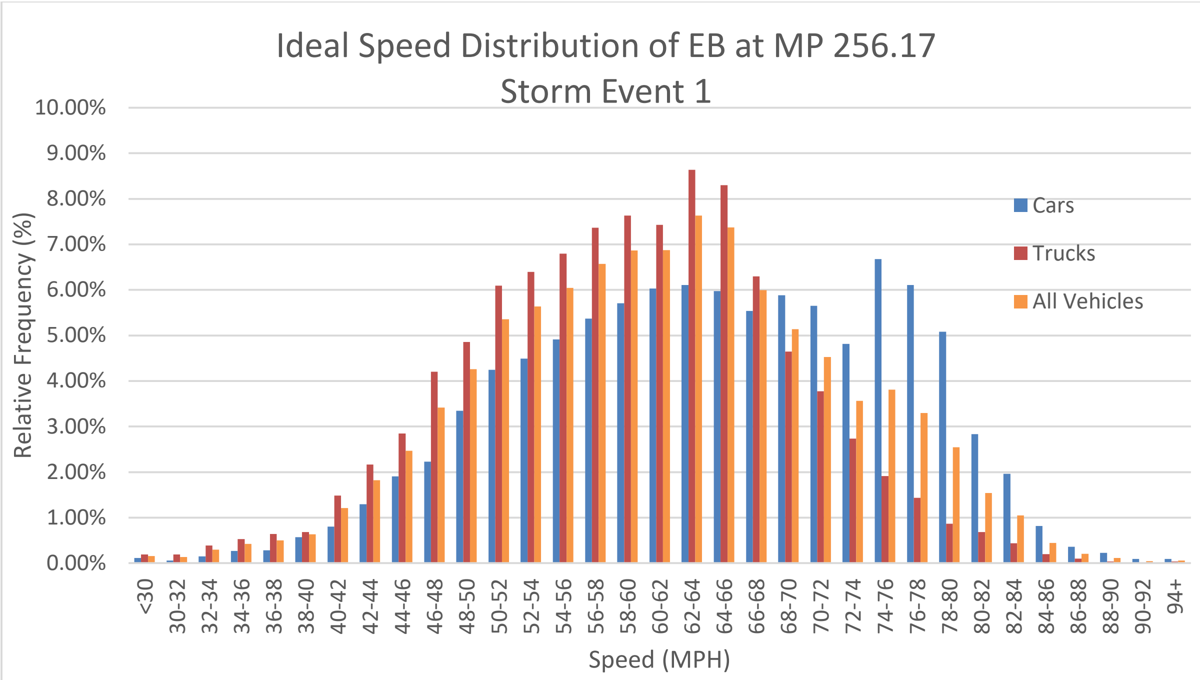

Average speed between Cars & Trucks during Storm Event 10
Speed MPH
80
70
60
50
40
30
20
11/16/2010 13:55:12
11/16/2010 18:43:12
11/16/2010 23:31:12
11/17/2010 4:19:12
11/17/2010 9:07:12
Date and Time
Cars
Trucks

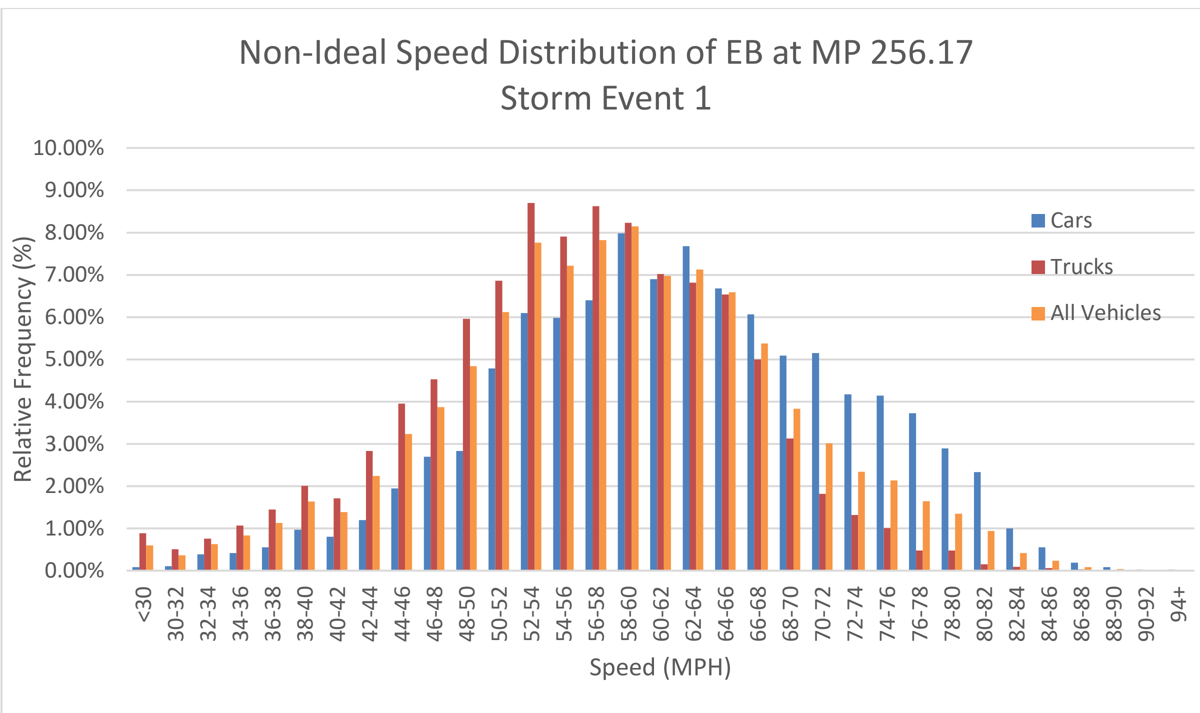

Average speed between Cars & Trucks during Storm Event 12
Speed MPH
95
85
75
65
55
45
35
25
12/29/2010 11:31:12
12/29/2010 21:07:12
12/30/2010 6:43:12
12/30/2010 16:19:12
12/31/2010 1:55:12
Date and Time
Cars
Trucks

Speed Distribution






Ideal Speed Distribution of EB at MP 256.17
Storm Event 1
Relative Frequency (%)
10.00%
9.00%
8.00%
7.00%
6.00%
5.00%
4.00%
3.00%
2.00%
1.00%
0.00%
Cars
Trucks
All Vehicles
<30
30-32
32-34
34-36
36-38
38-40
40-42
42-44
44-46
46-48
48-50
50-52
52-54
54-56
56-58
58-60
60-62
62-64
64-66
66-68
68-70
70-72
72-74
74-76
76-78
78-80
80-82
82-84
84-86
86-88
88-90
90-92
94+
Speed (MPH)


Non-Ideal Speed Distribution of EB at MP 256.17
Storm Event 1
Relative Frequency (%)
10.00%
9.00%
8.00%
7.00%
6.00%
5.00%
4.00%
3.00%
2.00%
1.00%
0.00%
Cars
Trucks
All Vehicles
<30
30-32
32-34
34-36
36-38
38-40
40-42
42-44
44-46
46-48
48-50
50-52
52-54
54-56
56-58
58-60
60-62
62-64
64-66
66-68
68-70
70-72
72-74
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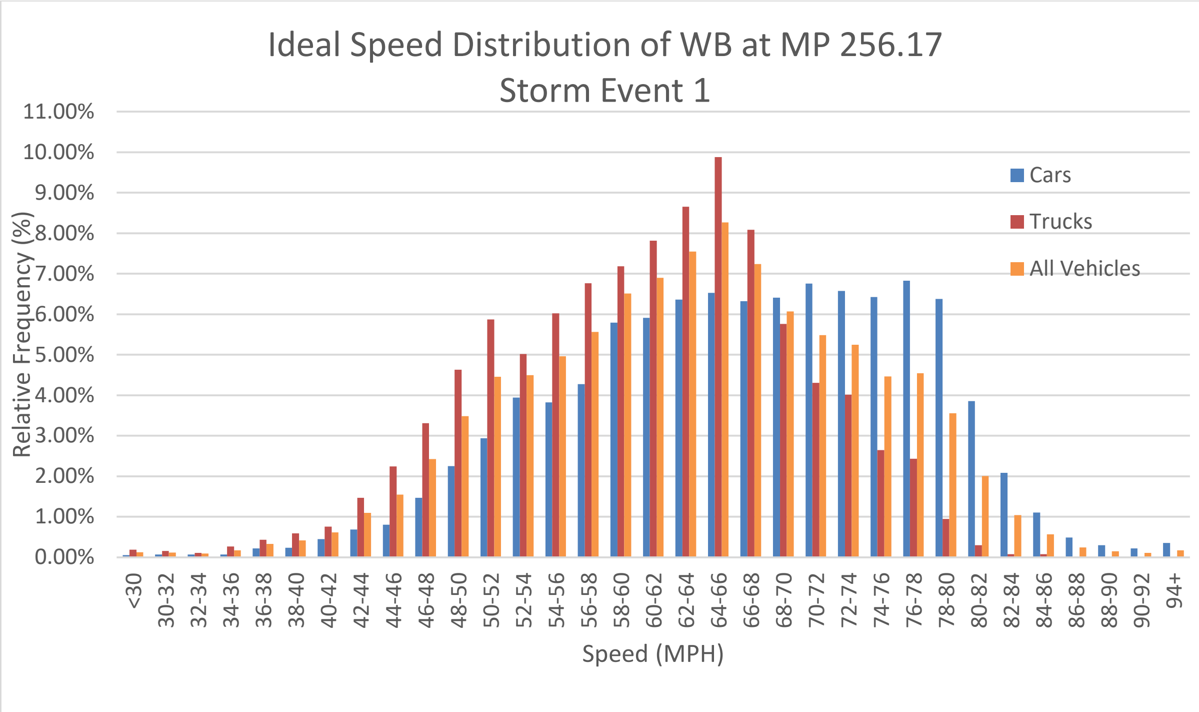
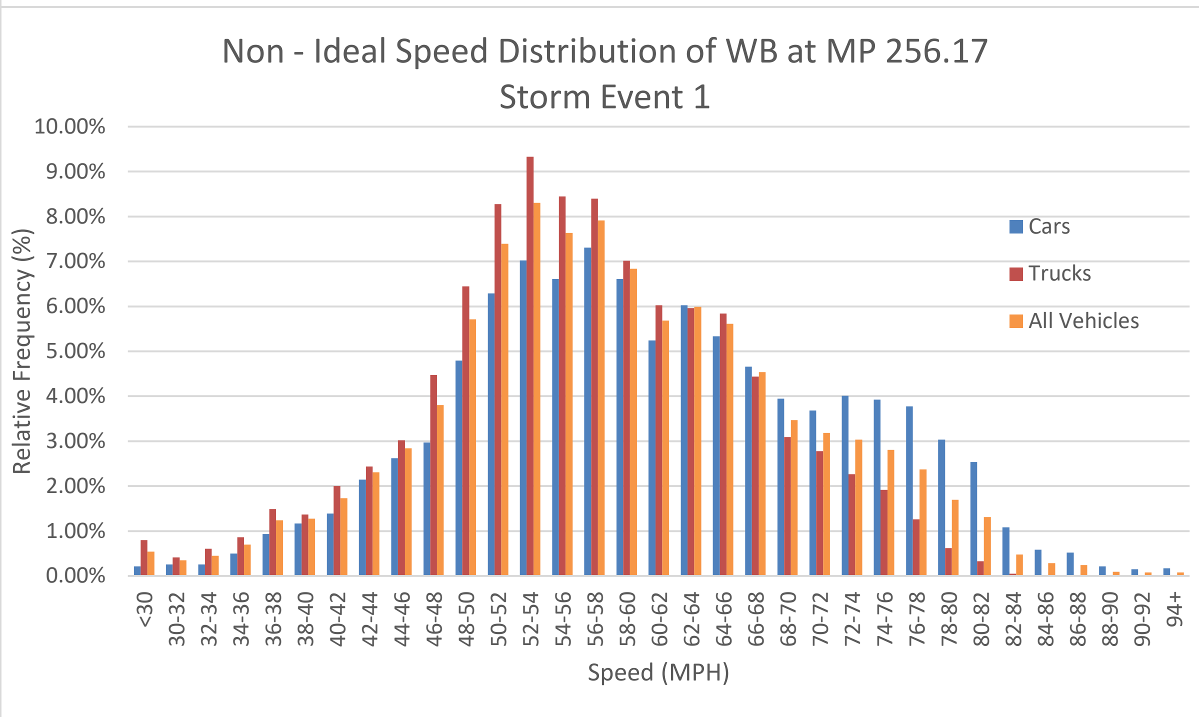
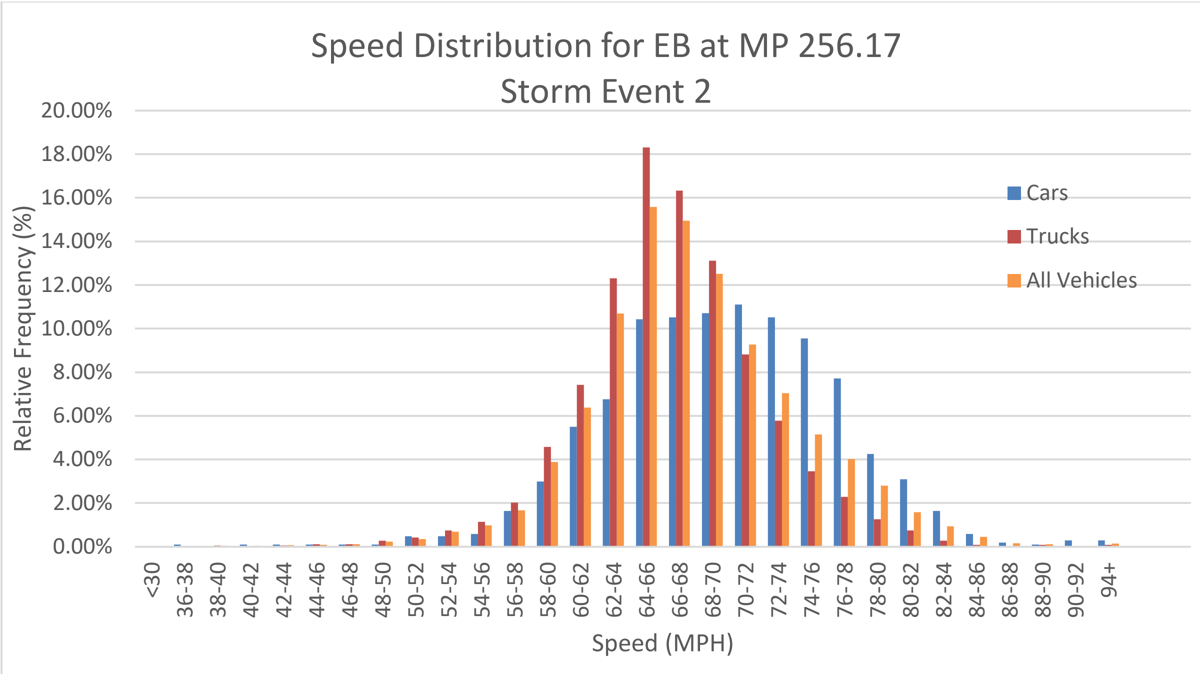
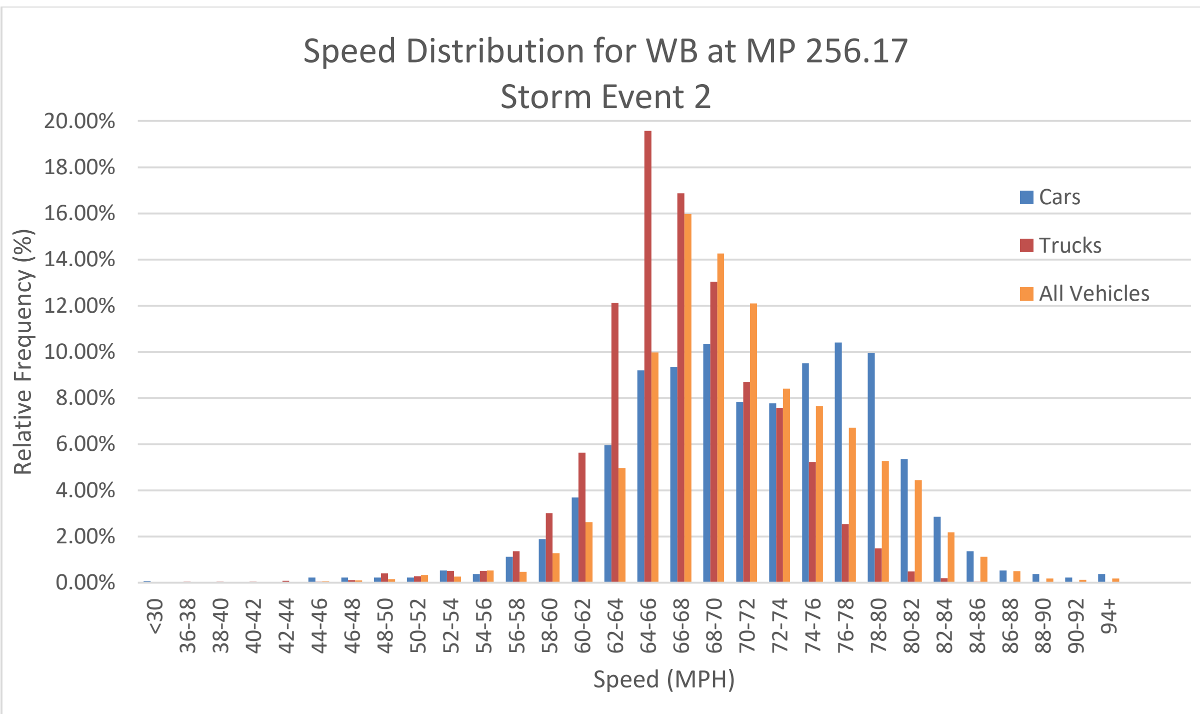
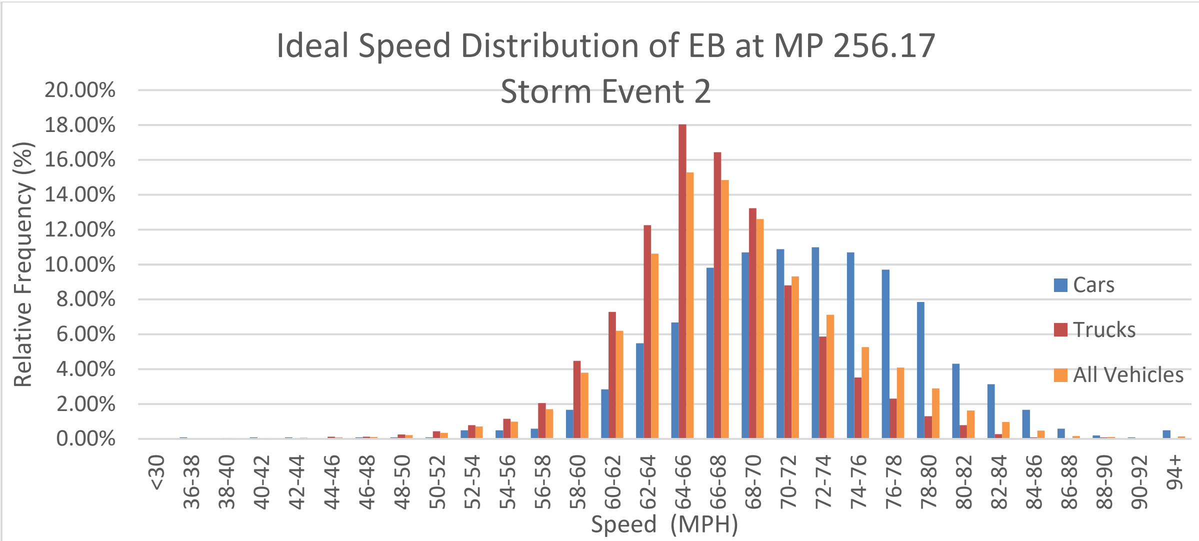
82-84
84-86
86-88
88-90
90-92
94+
Speed (MPH)

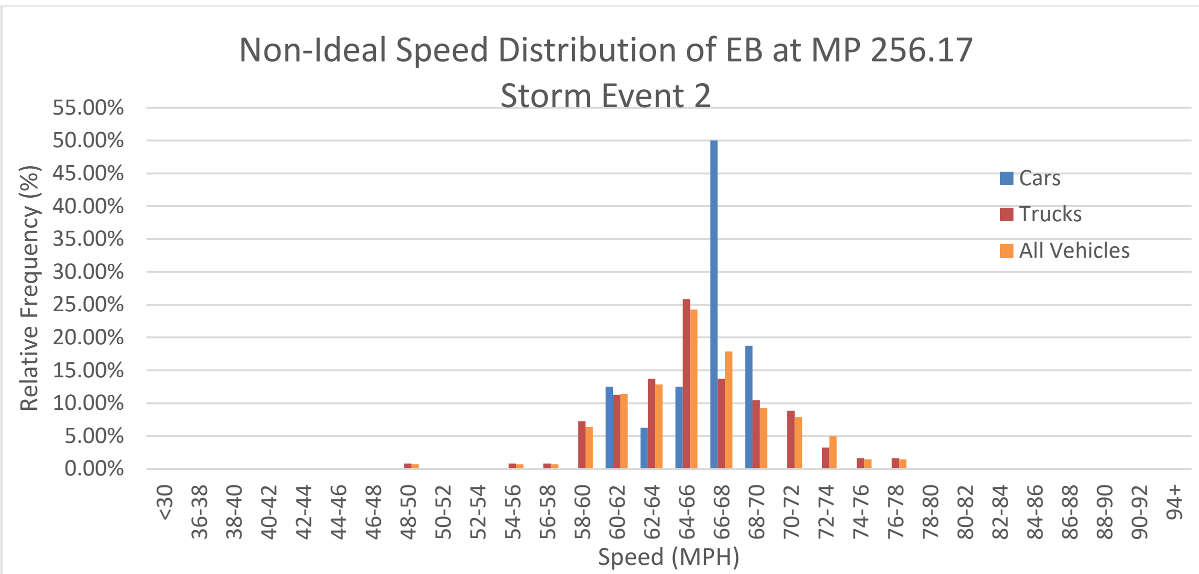

Ideal Speed Distribution of WB at MP 256.17
Storm Event 1
Relative Frequency (%)
Speed (MPH)
Cars
Trucks
All Vehicles

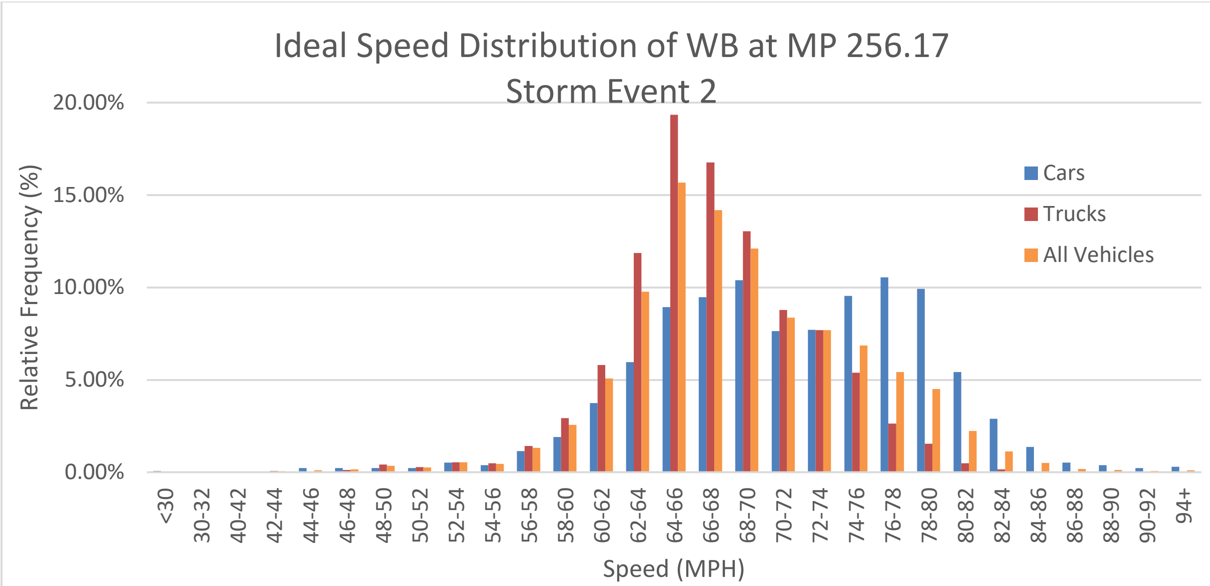

Non - Ideal Speed Distribution of WB at MP 256.17
Storm Event 1
Relative Frequency (%)
Speed (MPH)
Cars
Trucks
All Vehicles

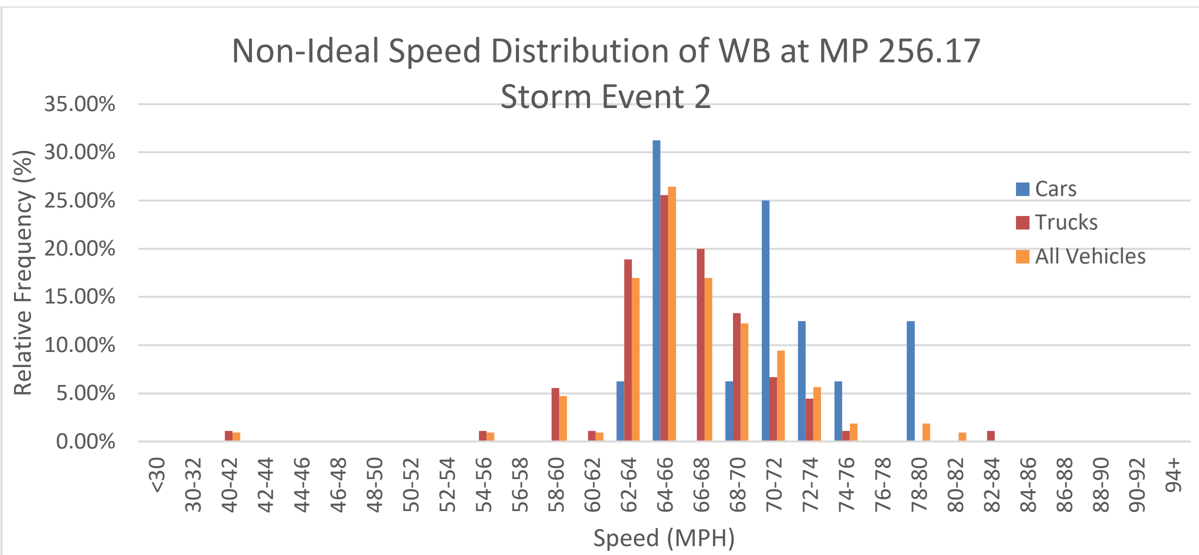

Speed Distribution for EB at MP 256.17
Storm Event 2
Relative Frequency (%)
20.00%
18.00%
16.00%
14.00%
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
Cars
Trucks
All Vehicles
<30
36-38
38-40
40-42
42-44
44-46
46-48
48-50
50-52
52-54
54-56
56-58
58-60
60-62
62-64
64-66
66-68
68-70
70-72
72-74
74-76
76-78
78-80
80-82
82-84
84-86
86-88
88-90
90-92
94+
Speed (MPH)

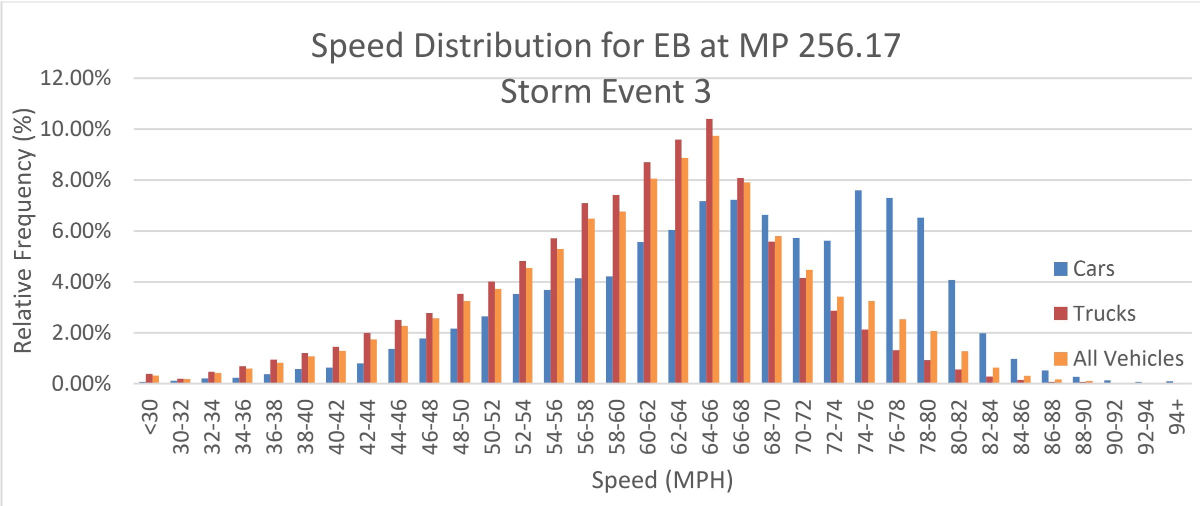

Speed Distribution for WB at MP 256.17
Storm Event 2
Relative Frequency (%)
20.00%
18.00%
16.00%
14.00%
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
Cars
Trucks
All Vehicles
<30
36-38
38-40
40-42
42-44
44-46
46-48
48-50
50-52
52-54
54-56
56-58
58-60
60-62
62-64
64-66
66-68
68-70
70-72
72-74
74-76
76-78
78-80
80-82
82-84
84-86
86-88
88-90
90-92
94+
Speed (MPH)

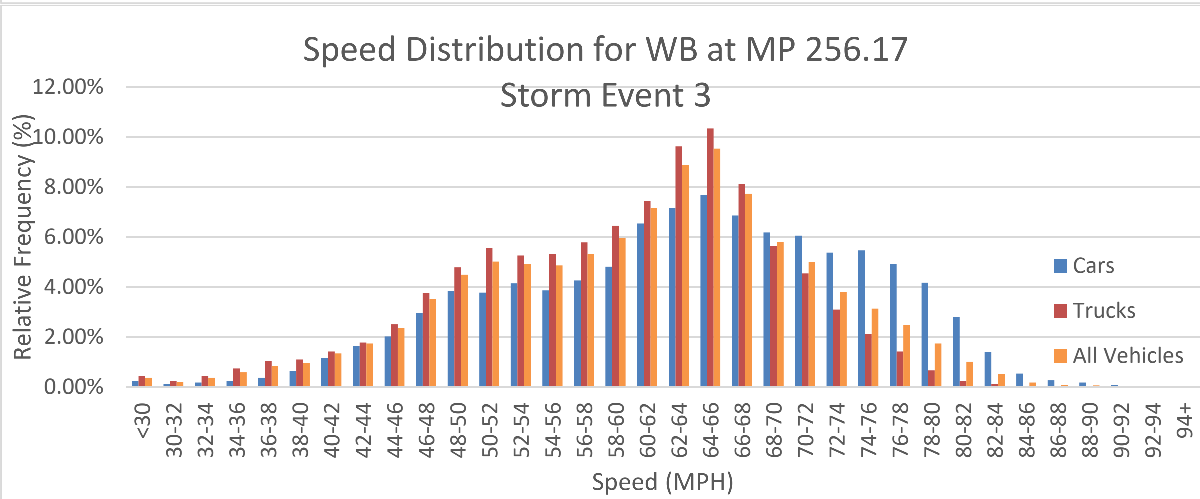

Ideal Speed Distribution of EB at MP 256.17
Storm Event 2
Relative Frequency (%)
20.00%
18.00%
16.00%
14.00%
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
<30
36-38
38-40
40-42
42-44
44-46
46-48
48-50
50-52
52-54
54-56
56-58
58-60
60-62
62-64
64-66
66-68
68-70
70-72
72-74
74-76
76-78
78-80
80-82
82-84
84-86
86-88
88-90
90-92
94+
Speed (MPH)
Cars
Trucks
All Vehicles

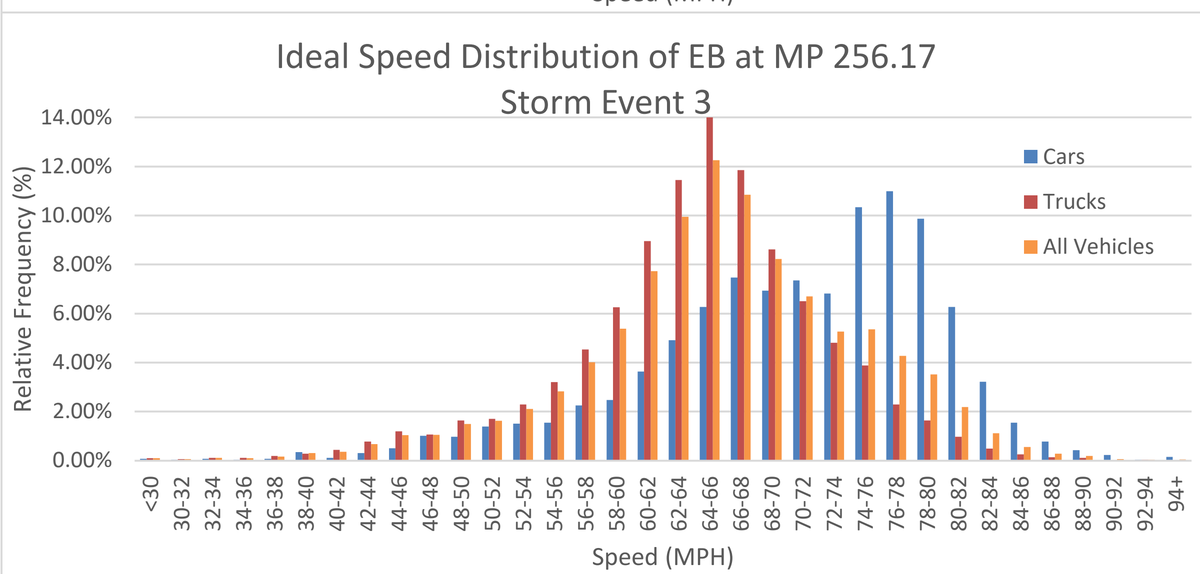

Non-Ideal Speed Distribution of EB at MP 256.17
Storm Event 2
Relative Frequency (%)
55.00%
50.00%
45.00%
40.00%
35.00%
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
<30
36-38
38-40
40-42
42-44
44-46
46-48
48-50
50-52
52-54
54-56
56-58
58-60
60-62
62-64
64-66
66-68
68-70
70-72
72-74
74-76
76-78
78-80
80-82
82-84
84-86
86-88
88-90
90-92
94+
Speed (MPH)
Cars
Trucks
All Vehicles

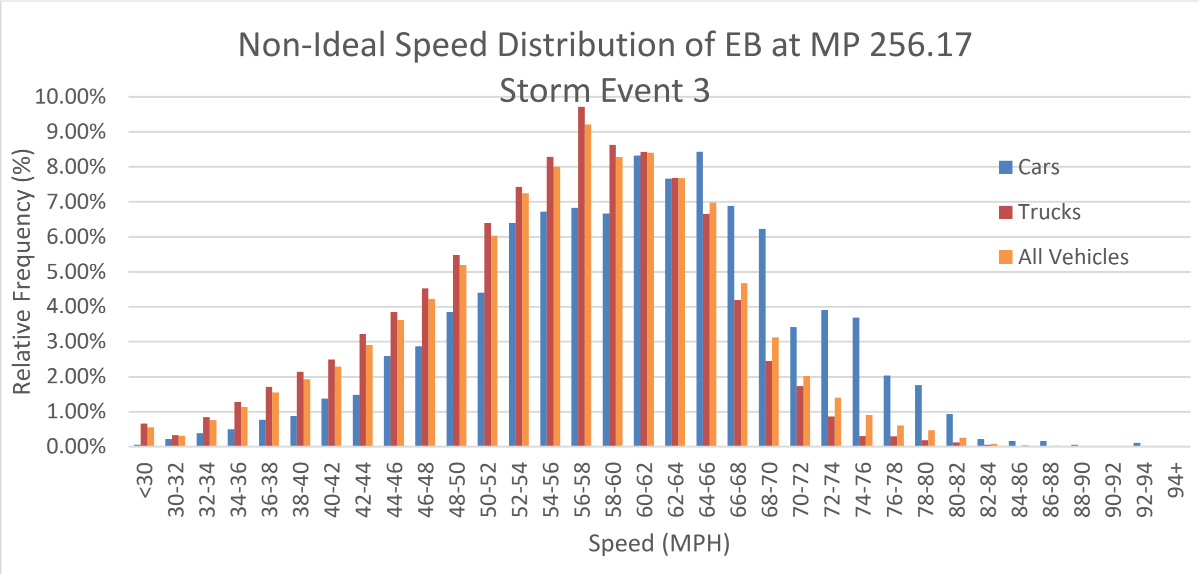

Ideal Speed Distribution of WB at MP 256.17
Storm Event 2
Relative Frequency (%)
20.00%
15.00%
10.00%
5.00%
0.00%
<30
30-32
40-42
42-44
44-46
46-48
48-50
50-52
52-54
54-56
56-58
58-60
60-62
62-64
64-66
66-68
68-70
70-72
72-74
74-76
76-78
78-80
80-82
82-84
84-86
86-88
88-90
90-92
94+
Speed (MPH)
Cars
Trucks
All Vehicles

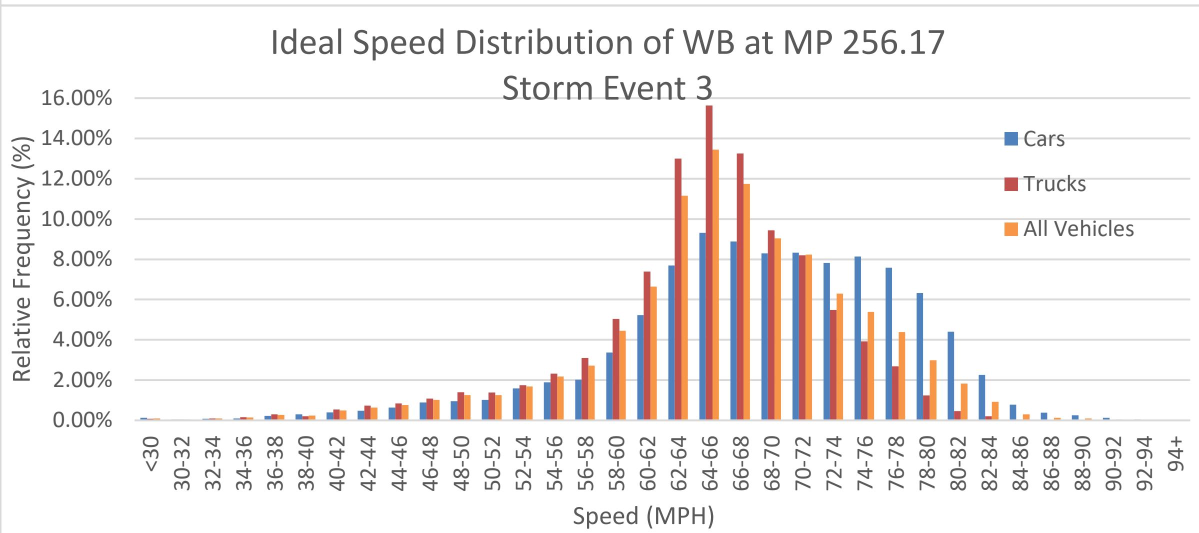

Non-Ideal Speed Distribution of WB at MP 256.17
Storm Event 2
Relative Frequency (%)
35.00%
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
<30
30-32
40-42
42-44
44-46
46-48
48-50
50-52
52-54
54-56
56-58
58-60
60-62
62-64
64-66
66-68
68-70
70-72
72-74
74-76
76-78
78-80
80-82
82-84
84-86
86-88
88-90
90-92
94+
Speed (MPH)
Cars
Trucks
All Vehicles

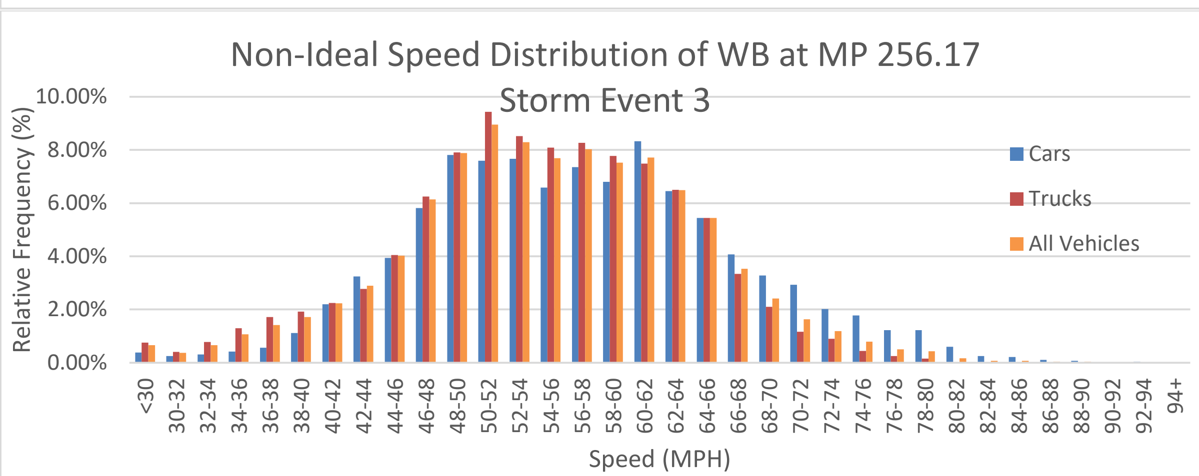

Speed Distribution for EB at MP 256.17
Storm Event 3
Relative Frequency (%)
Speed (MPH)
Cars
Trucks
All Vehicles


Speed Distribution for WB at MP 256.17
Storm Event 3
Relative Frequency (%)
Speed (MPH)
Cars
Trucks
All Vehicles


Ideal Speed Distribution of EB at MP 256.17
Storm Event 3
Relative Frequency (%)
Speed (MPH)
Cars
Trucks
All Vehicles


Non-Ideal Speed Distribution of EB at MP 256.17
Storm Event 3
Relative Frequency (%)
Speed (MPH)
Cars
Trucks
All Vehicles


Ideal Speed Distribution of WB at MP 256.17
Storm Event 3
Relative Frequency (%)
Speed (MPH)
Cars
Trucks
All Vehicles


Non-Ideal Speed Distribution of WB at MP 256.17
Storm Event 3
Relative Frequency (%)
Speed (MPH)
Cars
Trucks
All Vehicles

APPENDIX B: STATISTICAL TESTS

T-test between Ideal data and Cars/Trucks for every Storm Events

	Ideal Data	*Storm 1 (Cars)*	*Ideal Data*	*Storm 1 (Trucks)*
Mean	69.73373392	63.79180041	69.73373392	58.09181454
Variance	81.95850477	125.7808495	81.95850477	92.91154712
Observations	151942	19440	151942	26486
Hypothesized Mean Difference	0		0	
df	22795		35112	
t Stat	70.97096508		182.9948596	
P(T<=t) one-tail	0		0	
t Critical one-tail	1.644920476		1.644897025	
P(T<=t) two-tail	0		0	
t Critical two-tail	1.96006806		1.96003155	

	Ideal Data	*Storm 2 (Cars)*	*Ideal Data*	*Storm 2 (Trucks)*
Mean	69.73373392	71.56779661	69.73373392	66.69958656
Variance	81.95850477	52.26273529	81.95850477	29.45612664
Observations	151942	2360	151942	5805
Hypothesized Mean Difference	0		0	
df	2475		7100	
t Stat	-12.1772239		40.49608594	
P(T<=t) one-tail	1.79125E-33		0	
t Critical one-tail	1.645469523		1.645068271	
P(T<=t) two-tail	3.5825E-33		0	
t Critical two-tail	1.960922939		1.960298163	

	Ideal Data	*Storm 3 (Cars)*	*Ideal Data*	*Storm 3 (Trucks)*
Mean	69.73373392	64.7676783	69.73373392	59.65732817
Variance	81.95850477	121.8823501	81.95850477	92.99499563
Observations	151942	11203	151942	32532
Hypothesized Mean Difference	0		0	
df	12338		45619	
t Stat	46.47297654		172.8603818	
P(T<=t) one-tail	0		0	
t Critical one-tail	1.644977138		1.64488703	
P(T<=t) two-tail	0		0	
t Critical two-tail	1.960156277		1.960015988	

	Ideal Data	*Storm 4 (Cars)*	*Ideal Data*	*Storm 4 (Trucks)*
Mean	69.73373392	66.02104342	69.73373392	59.9192775
Variance	81.95850477	121.8415121	81.95850477	91.79236966
Observations	151942	18861	151942	27820
Hypothesized Mean Difference	0		0	
df	22122		37475	
t Stat	44.37711241		158.4024573	
P(T<=t) one-tail	0		0	
t Critical one-tail	1.64492251		1.644894289	
P(T<=t) two-tail	0		0	
t Critical two-tail	1.960071226		1.960027289	

	Ideal Data	*Storm 5 (Cars)*	*Ideal Data*	*Storm 5 (Trucks)*
Mean	69.73373392	73.55824127	69.73373392	69.05901938
Variance	81.95850477	55.15880805	81.95850477	37.71122621
Observations	151942	2263	151942	6037
Hypothesized Mean Difference	0		0	
df	2363		7121	
t Stat	-24.2302126		8.190497366	
P(T<=t) one-tail	2.5043E-116		1.52898E-16	
t Critical one-tail	1.645498727		1.645067637	
P(T<=t) two-tail	5.0086E-116		3.05796E-16	
t Critical two-tail	1.960968414		1.960297178	

	Ideal Data	*Storm 6 (Cars)*	*Ideal Data*	*Storm 6 (Trucks)*
Mean	69.73373392	65.8077309	69.73373392	58.90682018
Variance	81.95850477	162.543978	81.95850477	135.545932
Observations	151942	11163	151942	32917
Hypothesized Mean Difference	0		0	
df	12003		41948	
t Stat	31.94897354		158.6505165	
P(T<=t) one-tail	2.4307E-215		0	
t Critical one-tail	1.644980586		1.644889953	
P(T<=t) two-tail	4.8613E-215		0	
t Critical two-tail	1.960161644		1.960020539	

	Ideal Data	Storm 7 (Cars)	Ideal Data	Storm 7 (Trucks)
Mean	69.73373392	71.52982709	69.73373392	67.4611546
Variance	81.95850477	102.6506212	81.95850477	85.39587786
Observations	151942	58239	151942	44327
Hypothesized Mean Difference	0		0	
df	95895		70999	
t Stat	-37.435007		45.76473175	
P(T<=t) one-tail	0		0	
t Critical one-tail	1.644869517		1.644875089	
P(T<=t) two-tail	0		0	
t Critical two-tail	1.959988723		1.959997398	

	Ideal Data	Storm 8 (Cars)	Ideal Data	Storm 8 (Trucks)
Mean	69.73373392	76.69132904	69.73373392	71.0645728
Variance	81.95850477	36.79885563	81.95850477	39.09454933
Observations	151942	7923	151942	7912
Hypothesized Mean Difference	0		0	
df	9862		9726	
t Stat	-96.6335697		-17.9767962	
P(T<=t) one-tail	0		2.08047E-71	
t Critical one-tail	1.645008151		1.645010312	
P(T<=t) two-tail	0		4.16095E-71	
t Critical two-tail	1.96020456		1.960207925	

	Ideal Data	Storm 9 (Cars)	Ideal Data	Storm 9 (Trucks)
Mean	69.73373392	77.21408596	69.73373392	71.20257025
Variance	81.95850477	35.43951031	81.95850477	43.72112069
Observations	151942	61146	151942	48400
Hypothesized Mean Difference	0		0	
df	169008		110866	
t Stat	-223.618632		-38.6705235	
P(T<=t) one-tail	0		0	
t Critical one-tail	1.644862643		1.644867371	
P(T<=t) two-tail	0		0	
t Critical two-tail	1.959978021		1.959985382	

	Ideal Data	Storm 10 (Cars)	Ideal Data	Storm 10 (Trucks)
Mean	69.73373392	49.29926308	69.73373392	46.68053435
Variance	81.95850477	125.4600142	81.95850477	135.4373011
Observations	151942	1357	151942	2096
Hypothesized Mean Difference	0		0	
df	1372		2130	
t Stat	67.009662		90.31347189	
P(T<=t) one-tail	0		0	
t Critical one-tail	1.645965001		1.645569325	
P(T<=t) two-tail	0		0	
t Critical two-tail	1.961694546		1.961078349	

	Ideal Data	Storm 11 (Cars)	Ideal Data	Storm 11 (Trucks)
Mean	69.73373392	76.93133333	69.73373392	69.42216216
Variance	81.95850477	28.23236734	81.95850477	43.60803878
Observations	151942	150	151942	185
Hypothesized Mean Difference	0		0	
df	150		185	
t Stat	-16.5667845		0.641009311	
P(T<=t) one-tail	5.30256E-36		0.261154954	
t Critical one-tail	1.6550755		1.653131869	
P(T<=t) two-tail	1.06051E-35		0.522309907	
t Critical two-tail	1.975905331		1.972869946	

	Ideal Data	Storm 12 (Cars)	Ideal Data	Storm 12 (Trucks)
Mean	69.73373392	71.50214872	69.73373392	66.08599448
Variance	81.95850477	82.99975148	81.95850477	75.62560926
Observations	151942	4142	151942	3620
Hypothesized Mean Difference	0		0	
df	4367		3808	
t Stat	-12.3277217		24.91770705	
P(T<=t) one-tail	1.18957E-34		2.1756E-127	
t Critical one-tail	1.64520263		1.645253874	
P(T<=t) two-tail	2.37915E-34		4.3512E-127	
t Critical two-tail	1.960507359		1.96058715	

T-test between Ideal data and Storm Events

	IDEAL (MPH)	*STORM EVENT 1 (MPH)*
Mean	69.73373392	60.38483579
Variance	81.95850477	117.7967172
Observations	151942	46069
Hypothesized Mean Difference	0	
df	66655	
t Stat	168.0095828	
P(T<=t) one-tail	0	
t Critical one-tail	1.644876488	
P(T<=t) two-tail	0	
t Critical two-tail	1.959999575	

	IDEAL (MPH)	*STORM EVENT 2 (MPH)*
Mean	69.73373392	68.10668708
Variance	81.95850477	40.91324778
Observations	151942	8165
Hypothesized Mean Difference	0	
df	10010	
t Stat	21.83962468	
P(T<=t) one-tail	1.2308E-103	
t Critical one-tail	1.645005866	
P(T<=t) two-tail	2.4617E-103	
t Critical two-tail	1.960201003	

	IDEAL (MPH)	*STORM EVENT 3 (MPH)*
Mean	69.73373392	60.84609898
Variance	81.95850477	109.2405826
Observations	151942	43886
Hypothesized Mean Difference	0	
df	64096	
t Stat	161.4973924	
P(T<=t) one-tail	0	
t Critical one-tail	1.644877401	
P(T<=t) two-tail	0	
t Critical two-tail	1.960000996	

	IDEAL (MPH)	*STORM EVENT 4 (MPH)*
Mean	69.73373392	62.31238268
Variance	81.95850477	115.284037
Observations	151942	46775
Hypothesized Mean Difference	0	
df	68478	
t Stat	135.4031868	
P(T<=t) one-tail	0	
t Critical one-tail	1.644875879	
P(T<=t) two-tail	0	
t Critical two-tail	1.959998628	

	IDEAL (MPH)	*STORM EVENT 5 (MPH)*
Mean	69.73373392	70.28573494
Variance	81.95850477	46.47716484
Observations	151942	8300
Hypothesized Mean Difference	0	
df	9970	
t Stat	-7.04512597	
P(T<=t) one-tail	9.87731E-13	
t Critical one-tail	1.645006477	
P(T<=t) two-tail	1.97546E-12	
t Critical two-tail	1.960201954	

	IDEAL (MPH)	*STORM EVENT 6 (MPH)*
Mean	69.73373392	60.65443512
Variance	81.95850477	151.3856765
Observations	151942	44080
Hypothesized Mean Difference	0	
df	58593	
t Stat	144.0297701	
P(T<=t) one-tail	0	
t Critical one-tail	1.644879633	
P(T<=t) two-tail	0	
t Critical two-tail	1.960004473	

	IDEAL (MPH)	*STORM EVENT 7 (MPH)*
Mean	69.73373392	65.89383731
Variance	81.95850477	90.98012874
Observations	151942	17395
Hypothesized Mean Difference	0	
df	21141	
t Stat	50.55274045	
P(T<=t) one-tail	0	
t Critical one-tail	1.644925707	
P(T<=t) two-tail	0	
t Critical two-tail	1.960076203	

	IDEAL (MPH)	*STORM EVENT 8 (MPH)*
Mean	69.73373392	70.00007163
Variance	81.95850477	36.08230025
Observations	151942	2792
Hypothesized Mean Difference	0	
df	3029	
t Stat	-2.295429133	
P(T<=t) one-tail	0.010888287	
t Critical one-tail	1.645356842	
P(T<=t) two-tail	0.021776573	
t Critical two-tail	1.960747479	

	IDEAL (MPH)	STORM EVENT 9 (MPH)
Mean	69.73373392	70.52368879
Variance	81.95850477	36.69082024
Observations	151942	20668
Hypothesized Mean Difference	0	
df	34699	
	-	
t Stat	16.41947309	
P(T<=t) one-tail	1.17271E-60	
t Critical one-tail	1.644897542	
P(T<=t) two-tail	2.34541E-60	
t Critical two-tail	1.960032354	

	IDEAL (MPH)	STORM EVENT 10 (MPH)
Mean	69.73373392	47.70967275
Variance	81.95850477	133.1152135
Observations	151942	3453
Hypothesized Mean Difference	0	
df	3549	
t Stat	111.3947047	
P(T<=t) one-tail	0	
t Critical one-tail	1.645283091	
P(T<=t) two-tail	0	
t Critical two-tail	1.960632642	

	IDEAL (MPH)	STORM EVENT 11 (MPH)
Mean	69.73373392	72.78447761
Variance	81.95850477	50.60305175
Observations	151942	335
Hypothesized Mean Difference	0	
df	336	
	-	
t Stat	7.835482206	
P(T<=t) one-tail	3.10362E-14	
t Critical one-tail	1.64940126	
P(T<=t) two-tail	6.20725E-14	
t Critical two-tail	1.967049384	

	IDEAL (MPH)	STORM EVENT 12 (MPH)
Mean	69.73373392	68.9761917
Variance	81.95850477	86.85190571
Observations	151942	7762
Hypothesized Mean Difference	0	
df	8526	
t Stat	6.994882926	
P(T<=t) one-tail	1.42759E-12	
t Critical one-tail	1.645032367	
P(T<=t) two-tail	2.85518E-12	
t Critical two-tail	1.960242263	

Correlation analysis between Independent variables

	SfTemp	AirTemp	RH	Dew point	Barometric	Avg Wind Speed	Gust Wind Speed	Precip Accumulation	Precip Rate	Visibility	Accumulation	Precip Rate
SfTemp	1.000											
AirTemp	0.769	1.000										
RH	-0.037	-0.346	1.000									
Dewpoint	0.804	0.965	-0.090	1.000								
Barometric	0.755	0.848	-0.272	0.827	1.000							
AvgWindSpeed	-0.069	0.077	-0.170	0.051	0.219	1.000						
GustWindSpeed	-0.022	0.163	-0.264	0.116	0.254	0.975	1.000					
PrecipAccumulation	-0.118	-0.190	0.375	-0.100	-0.025	-0.275	-0.340	1.000				
PrecipRate	-0.049	-0.003	-0.062	-0.018	0.009	0.022	0.016	0.064	1.000			
Visibility	0.286	0.243	0.078	0.275	0.232	-0.082	-0.067	-0.153	-0.122	1.000		
Accumulation	-0.211	-0.353	0.311	-0.304	-0.316	-0.099	-0.130	0.167	-0.026	-0.010	1.000	
PrecipRate	0.024	0.049	-0.022	0.049	-0.041	0.054	0.076	-0.057	0.097	-0.092	0.050	1.000

Log-Logistic (3P) [#36]					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	1366 0.03144 0.13142 2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.02903	0.03309	0.03674	0.04107	0.04408
Reject?	Yes	No	No	No	No
Anderson-Darling					
Sample Size Statistic Rank	1366 1.5154 4				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	Yes	No	No	No	No

Log-Logistic (3P) [#36]					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	2020 0.02886 0.06773 3				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.02387	0.02721	0.03022	0.03378	0.03624
Reject?	Yes	Yes	No	No	No
Anderson-Darling					
Sample Size Statistic Rank	2020 1.3333 2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No

APPENDIX C: MODEL RESULTS

SAS Analysis Results

<u>The SAS analysis results for MP 97.9 (Green River – Rock Spring Corridor)</u>

The SAS System

The Probit Procedure

Model Information		
Data Set	WORK.IMPORTED_EXCEL	
Dependent Variable	SpeedSelection	SpeedSelection
Number of Observations	3621	
Name of Distribution	Normal	
Log Likelihood	-986.7249924	

Number of Observations Read	3896
Number of Observations Used	3621
Missing Values	275

Class Level Information		
Name	Levels	Values
SpeedSelection	4	0 1 2 3

Response Profile		
Ordered Value	SpeedSelection	Total Frequency
1	0	3031
2	1	354
3	2	213
4	3	23

PROC PROBIT is modeling the probabilities of levels of SpeedSelection having LOWER Ordered Values in the response profile table.

Algorithm converged.

ype III Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
SfTemp	1	53.6065	<.0001
AirTemp	1	16.0334	<.0001
RH	1	67.5435	<.0001
GustWindSpeed	1	125.1039	<.0001
PrecipAccumulation	1	847.8201	<.0001

Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	3.9985	0.3682	3.2769	4.7201	117.95	<.0001
Intercept2	1	1.4267	0.0715	1.2865	1.5668	398.27	<.0001
Intercept3	1	3.0844	0.1222	2.8448	3.3239	636.63	<.0001
Surface Temp**erature**	1	0.0784	0.0107	0.0574	0.0994	53.61	<.0001
Air Temp**erature**	1	0.0338	0.0084	0.0172	0.0503	16.03	<.0001
Relative **H**umidity	1	-0.0367	0.0045	-0.0455	-0.0280	67.54	<.0001
Gust Wind Speed	1	-0.0509	0.0046	-0.0598	-0.0420	125.10	<.0001
Precip Accumulation	1	-16.1005	0.5530	-17.184	-15.016	847.82	<.0001

The SAS analysis results for MP 256.17 (Elk Mountain Corridor)

The SAS System

The Probit Procedure

Model Information		
Data Set	WORK.IMPORTED_EXCEL	
Dependent Variable	SpeedSelection	SpeedSelection
Number of Observations	3428	
Name of Distribution	Normal	
Log Likelihood	-2380.149713	

Number of Observations Read	3805
Number of Observations Used	3428
Missing Values	377

Class Level Information		
Name	Levels	Values
SpeedSelection	4	0 1 2 3

Response Profile		
Ordered Value	SpeedSelection	Total Frequency
1	0	1081
2	1	1117
3	2	915
4	3	315

PROC PROBIT is modeling the probabilities of levels of SpeedSelection having LOWER Ordered Values in the response profile table.

Algorithm converged.

Type III Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
SfTemp	1	268.4453	<.0001
AirTemp	1	131.9102	<.0001
RH	1	244.0060	<.0001
GustWindSpeed	1	66.4010	<.0001
PrecipAccumulation	1	23.8760	<.0001
ChemicallyWet	1	66.0432	<.0001
IceWarning	1	17.0158	<.0001
IceWatch	1	109.9730	<.0001
SnowWatch	1	175.4742	<.0001
TraceMoisture	1	4.3372	0.0373
Wet	1	4.7634	0.0291
TruckPercentage	1	135.3601	<.0001
VSLSpeed	1	1327.5291	<.0001

Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-2.6240	0.3372	-3.2849	-1.9630	60.54	<.0001
Intercept2	1	1.9874	0.0531	1.8833	2.0914	1402.58	<.0001
Intercept3	1	3.9309	0.0779	3.7782	4.0837	2544.90	<.0001
SfTemp	1	0.0737	0.0045	0.0649	0.0825	268.45	<.0001
AirTemp	1	-0.0454	0.0040	-0.0532	-0.0377	131.91	<.0001
RH	1	-0.0508	0.0032	-0.0571	-0.0444	244.01	<.0001
Gust Wind Speed	1	-0.0200	0.0025	-0.0248	-0.0152	66.40	<.0001
Precip Accumulation	1	1.0155	0.2078	0.6082	1.4228	23.88	<.0001
Chemically Wet	1	-2.0384	0.2508	-2.5300	-1.5468	66.04	<.0001

Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	95% Confidence Limits		Chi-Square	Pr > ChiSq
Ice Warning	1	-0.3124	0.0757	-0.4609	-0.1640	17.02	<.0001
Ice Watch	1	-1.9838	0.1892	-2.3546	-1.6130	109.97	<.0001
Snow Watch	1	-0.9987	0.0754	-1.1464	-0.8509	175.47	<.0001
Trace Moisture	1	-0.1476	0.0709	-0.2866	-0.0087	4.34	0.0373
Wet	1	-0.5875	0.2692	-1.1152	-0.0599	4.76	0.0291
Truck Percentage	1	-1.5120	0.1300	-1.7668	-1.2573	135.36	<.0001
VSL Speed	1	0.1170	0.0032	0.1107	0.1232	1327.53	<.0001

The SAS analysis results for MP 273.85 (Elk Mountain Corridor)

The SAS System

The Probit Procedure

Model Information		
Data Set	WORK.IMPORTED_EXCEL	
Dependent Variable	SpeedSelection	SpeedSelection
Number of Observations	3808	
Name of Distribution	Normal	
Log Likelihood	-2653.308688	

Number of Observations Read	3895
Number of Observations Used	3808
Missing Values	87

Class Level Information		
Name	**Levels**	**Values**
SpeedSelection	4	0 1 2 3

Response Profile		
Ordered Value	**SpeedSelection**	**Total Frequency**
1	0	1371
2	1	1186
3	2	977
4	3	274

PROC PROBIT is modeling the probabilities of levels of SpeedSelection having LOWER Ordered Values in the response profile table.

Algorithm converged.

Type III Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
SfTemp	1	328.8001	<.0001
AirTemp	1	161.7442	<.0001
RH	1	269.5458	<.0001

Type III Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
GustWindSpeed	1	80.5677	<.0001
PrecipAccumulation	1	24.9013	<.0001
IceWarning	1	67.7945	<.0001
IceWatch	1	190.6278	<.0001
SnowWatch	1	48.9891	<.0001
TraceMoisture	1	22.5763	<.0001
Wet	1	10.9691	0.0009
TruckPercentage	1	65.4631	<.0001
VSLSpeed	1	1095.5314	<.0001

Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	-2.0501	0.3241	-2.6853	-1.4149	40.02	<.0001
Intercept2	1	1.8604	0.0478	1.7667	1.9542	1513.45	<.0001
Intercept3	1	3.7483	0.0700	3.6111	3.8854	2869.15	<.0001
SfTemp	1	0.0809	0.0045	0.0721	0.0896	328.80	<.0001
Air Temp	1	-0.0496	0.0039	-0.0572	-0.0419	161.74	<.0001
RH	1	-0.0430	0.0026	-0.0481	-0.0379	269.55	<.0001
Gust Wind Speed	1	-0.0186	0.0021	-0.0226	-0.0145	80.57	<.0001
Precip Accumulation	1	-0.5675	0.1137	-0.7904	-0.3446	24.90	<.0001
Ice Warning	1	-0.5529	0.0671	-0.6845	-0.4213	67.79	<.0001
Ice Watch	1	-2.3058	0.1670	-2.6331	-1.9785	190.63	<.0001
Snow Watch	1	-0.5294	0.0756	-0.6777	-0.3812	48.99	<.0001
Trace Moisture	1	-0.3240	0.0682	-0.4577	-0.1904	22.58	<.0001
Wet	1	-0.6916	0.2088	-1.1008	-0.2823	10.97	0.0009
Truck Percentage	1	-1.0660	0.1318	-1.3242	-0.8078	65.46	<.0001
VSL Speed	1	0.1027	0.0031	0.0966	0.1087	1095.53	<.0001

<u>The SAS analysis results for MP 330.00 (Laramie – Cheyenne Corridor)</u>

The SAS System

The Probit Procedure

Model Information		
Data Set	WORK.IMPORTED_EXCEL	
Dependent Variable	SpeedSelection	SpeedSelection
Number of Observations	473	
Name of Distribution	Normal	
Log Likelihood	-191.963045	

Number of Observations Read	724
Number of Observations Used	473
Missing Values	251

Class Level Information		
Name	**Levels**	**Values**
SpeedSelection	4	0 1 2 3

Response Profile		
Ordered Value	**SpeedSelection**	**Total Frequency**
1	0	304
2	1	119
3	2	33
4	3	17

PROC PROBIT is modeling the probabilities of levels of SpeedSelection having LOWER Ordered Values in the response profile table.

Algorithm converged.

Type III Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
SfTemp	1	109.2275	<.0001
AirTemp	1	87.4586	<.0001
RH	1	172.0394	<.0001

Type III Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
GustWindSpeed	1	10.7841	0.0010
TruckPercentage	1	10.1851	0.0014

Analysis of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	95% Confidence Limits		Chi-Square	Pr > ChiSq
Intercept	1	20.9194	1.6025	17.7786	24.0602	170.42	<.0001
Intercept2	1	2.6801	0.2675	2.1559	3.2043	100.42	<.0001
Intercept3	1	3.9412	0.3206	3.3128	4.5695	151.14	<.0001
Sf Temp	1	0.3669	0.0351	0.2981	0.4357	109.23	<.0001
Air Temp	1	-0.2347	0.0251	-0.2839	-0.1855	87.46	<.0001
RH	1	-0.2745	0.0209	-0.3155	-0.2334	172.04	<.0001
Gust Wind Speed	1	-0.0445	0.0135	-0.0710	-0.0179	10.78	0.0010
Truck Percentage	1	-1.1897	0.3728	-1.9204	-0.4591	10.19	0.0014

The SAS analysis results for Combined Model (All Corridors)

The SAS System

The Probit Procedure

Model Information		
Data Set	WORK.IMPORTED_EXCEL	
Dependent Variable	SpeedSelection	SpeedSelection
Number of Observations	7236	
Name of Distribution	Normal	
Log Likelihood	-5227.767685	

Number of Observations Read	12320
Number of Observations Used	7236
Missing Values	5084

Class Level Information		
Name	**Levels**	**Values**
SpeedSelection	4	0 1 2 3

Response Profile		
Ordered Value	**SpeedSelection**	**Total Frequency**
1	0	2452
2	1	2303
3	2	1892
4	3	589

PROC PROBIT is modeling the probabilities of levels of SpeedSelection having LOWER Ordered Values in the response profile table.

Algorithm converged.

Type III Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
SfTemp	1	604.6090	<.0001
AirTemp	1	361.3195	<.0001
RH	1	540.6247	<.0001

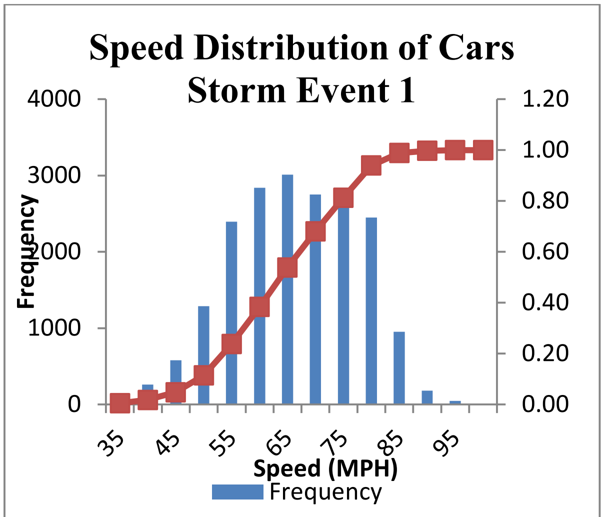
Type III Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
GustWindSpeed	1	75.5473	<.0001
PrecipAccumulation	1	5.4198	0.0199
ChemicallyWet	1	64.9177	<.0001
IceWarning	1	39.4277	<.0001
IceWatch	1	241.8206	<.0001
SnowWatch	1	143.8017	<.0001
Wet	1	9.7996	0.0017
TruckPercentage	1	140.8904	<.0001
VSLSpeed	1	2643.7889	<.0001

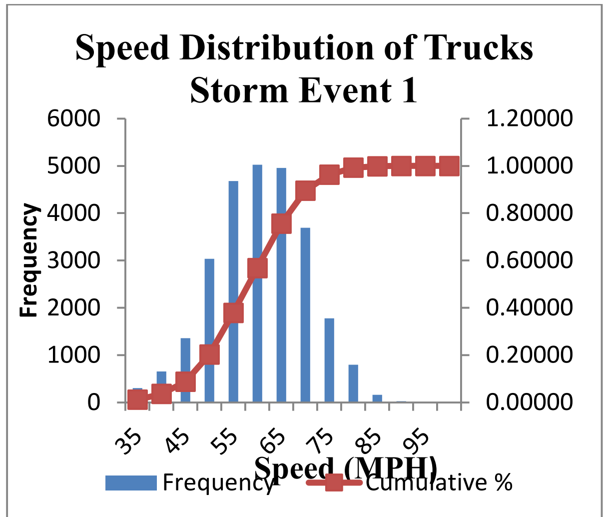
Analysis of Maximum Likelihood Parameter Estimates							
Parameter	**DF**	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Chi-Square**	**Pr > ChiSq**
Intercept	1	-2.8239	0.2236	-3.2621	-2.3856	159.51	<.0001
Intercept2	1	1.8340	0.0338	1.7677	1.9002	2945.96	<.0001
Intercept3	1	3.6834	0.0496	3.5861	3.7807	5504.84	<.0001
SfTemp	1	0.0755	0.0031	0.0694	0.0815	604.61	<.0001
AirTemp	1	-0.0514	0.0027	-0.0567	-0.0461	361.32	<.0001
RH	1	-0.0449	0.0019	-0.0486	-0.0411	540.62	<.0001
GustWindSpeed	1	-0.0123	0.0014	-0.0151	-0.0096	75.55	<.0001
PrecipAccumulation	1	0.2191	0.0941	0.0346	0.4035	5.42	0.0199
ChemicallyWet	1	-1.8841	0.2338	-2.3424	-1.4258	64.92	<.0001
IceWarning	1	-0.2497	0.0398	-0.3277	-0.1718	39.43	<.0001
IceWatch	1	-1.8656	0.1200	-2.1007	-1.6304	241.82	<.0001
SnowWatch	1	-0.5233	0.0436	-0.6089	-0.4378	143.80	<.0001
Wet	1	-0.4967	0.1587	-0.8077	-0.1857	9.80	0.0017
TruckPercentage	1	-1.0637	0.0896	-1.2393	-0.8880	140.89	<.0001
VSLSpeed	1	0.1089	0.0021	0.1047	0.1130	2643.79	<.0001

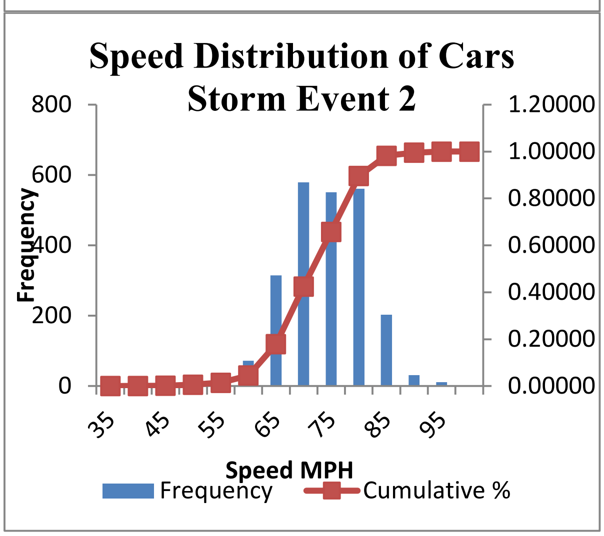
APPENDIX D: VISSIM OUTPUT RESULTS

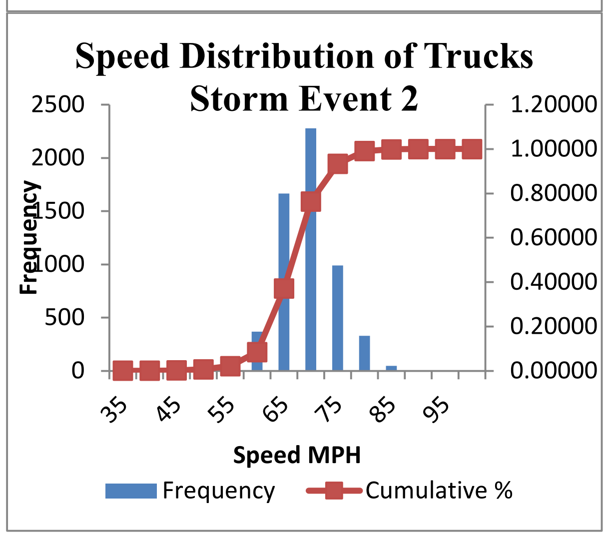
Cumulative Distribution for adjusted model and Obtained Results from VISSIM

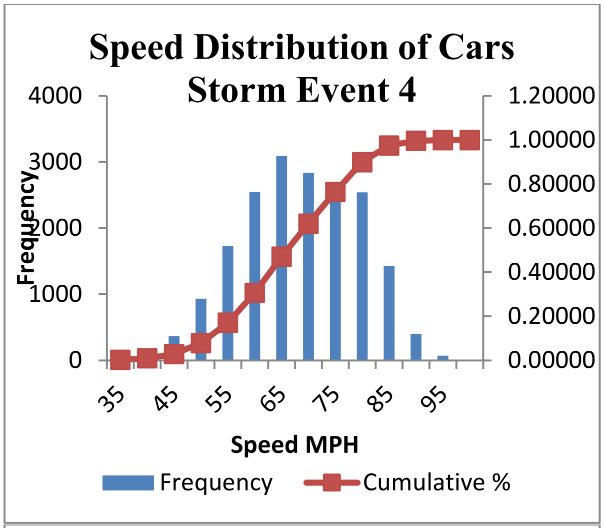
<u>**Cumulative Distribution of Cars and Trucks during different Storm Events used for Adjusted Model in VISSIM microsimulation tool.**</u>



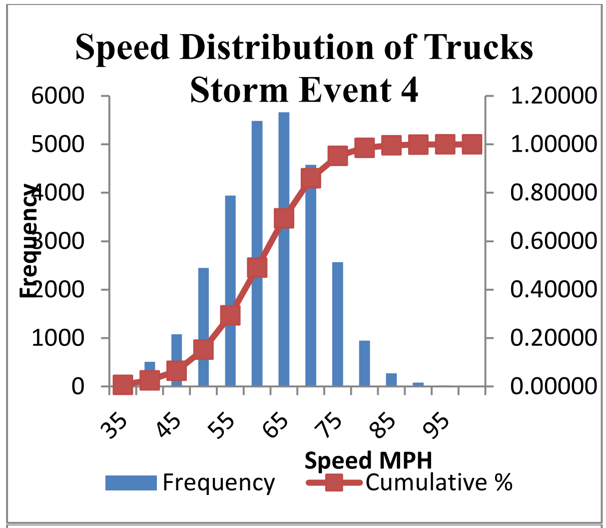




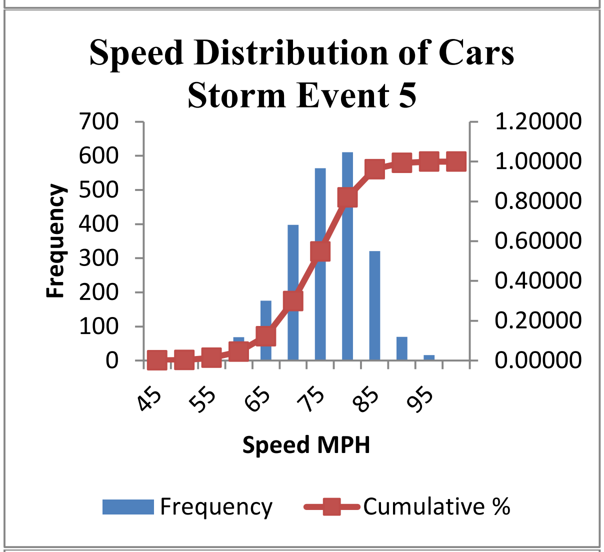




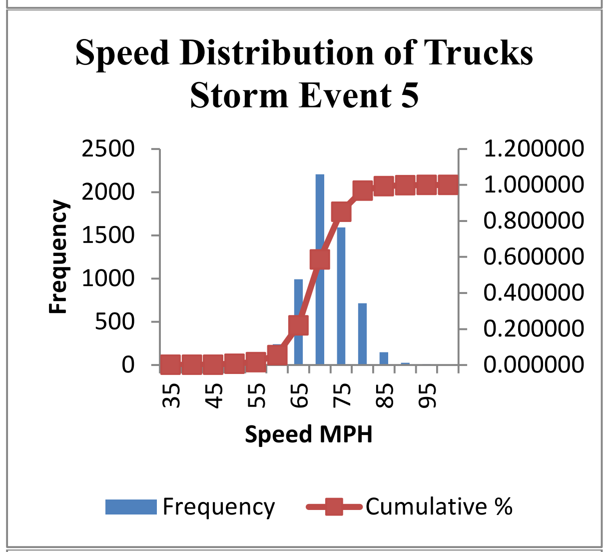
Speed Distribution of Cars
Storm Event 4
Frequency
Speed MPH
Frequency
Cumulative %



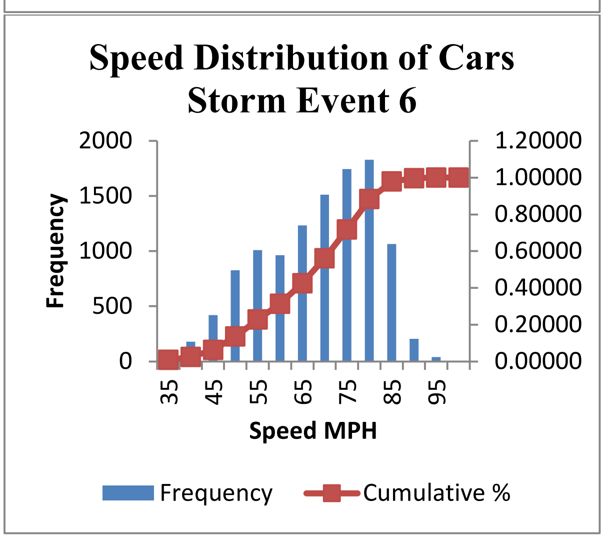
Speed Distribution of Trucks
Storm Event 4
Frequency
Speed MPH
Frequency
Cumulative %



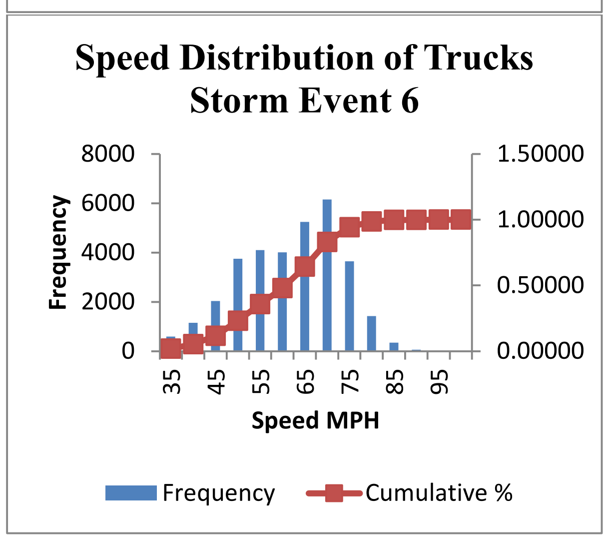
Speed Distribution of Cars
Storm Event 5
Frequency
Speed MPH
Frequency
Cumulative %



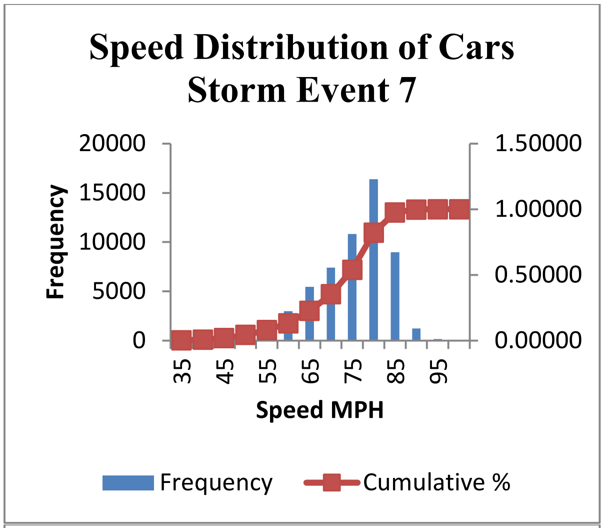
Speed Distribution of Trucks
Storm Event 5
Frequency
Speed MPH
Frequency
Cumulative %

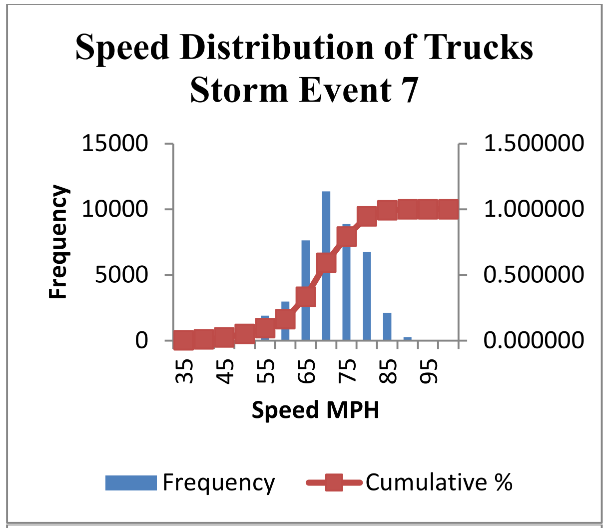


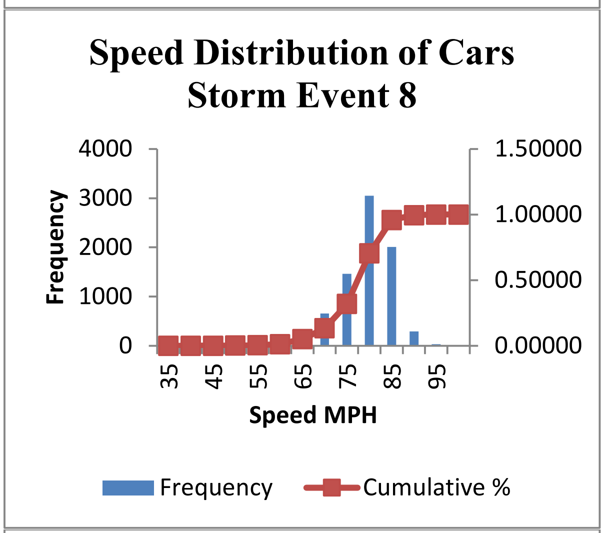
Speed Distribution of Cars
Storm Event 6
Frequency
Speed MPH
Frequency
Cumulative %

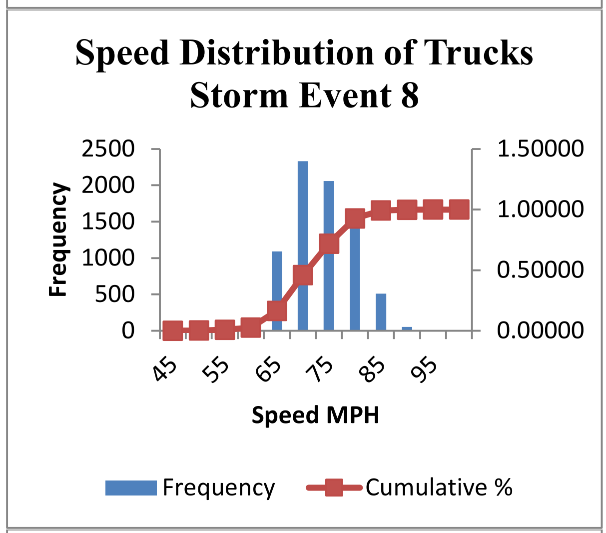


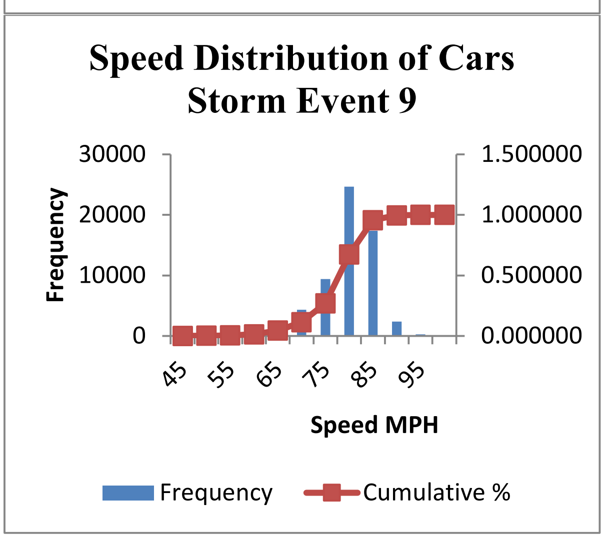
Speed Distribution of Trucks
Storm Event 6
Frequency
Speed MPH
Frequency
Cumulative %

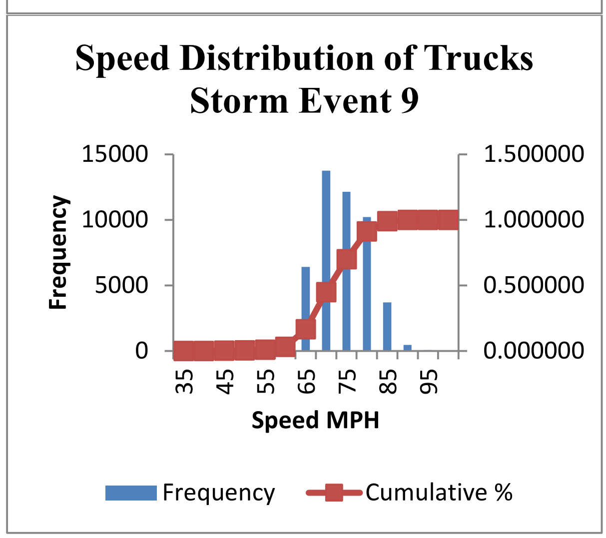

Speed Distribution of Cars
Storm Event 7
20000
15000
10000
5000
0
1.50000
1.00000
0.50000
0.00000
Frequency
35
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %

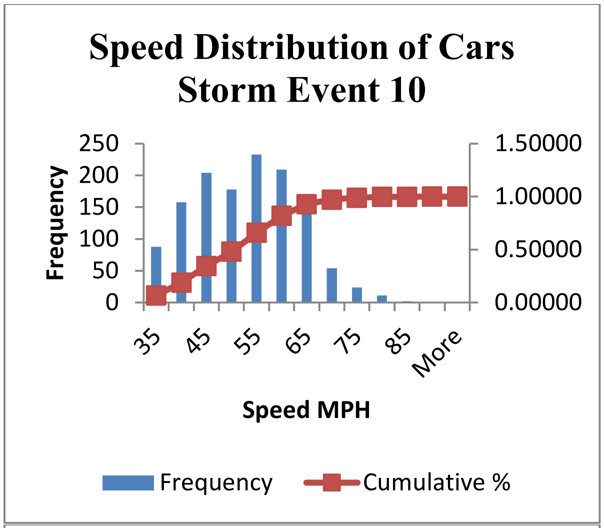

Speed Distribution of Trucks
Storm Event 7
15000
10000
5000
0
1.500000
1.000000
0.500000
0.000000
Frequency
35
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %

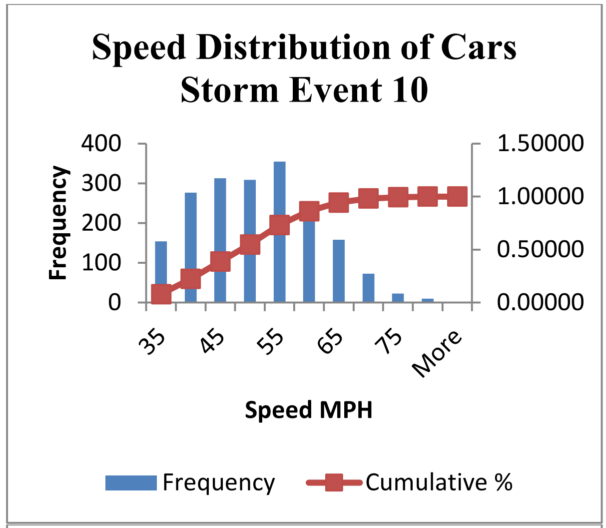

Speed Distribution of Cars
Storm Event 8
4000
3000
2000
1000
0
1.50000
1.00000
0.50000
0.00000
Frequency
35
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %

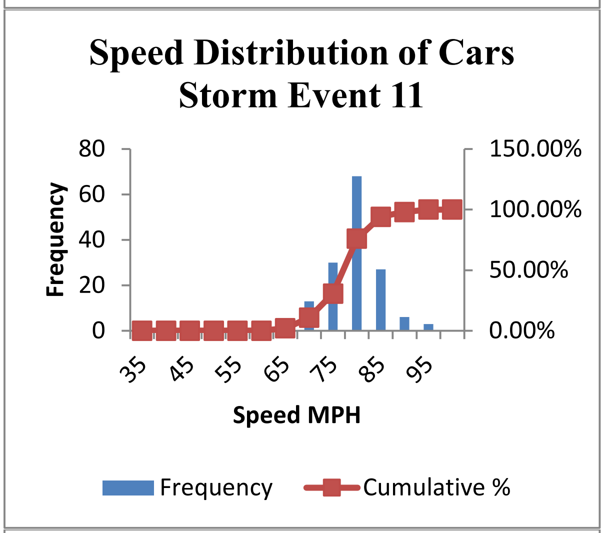

Speed Distribution of Trucks
Storm Event 8
2500
2000
1500
1000
500
0
1.50000
1.00000
0.50000
0.00000
Frequency
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %

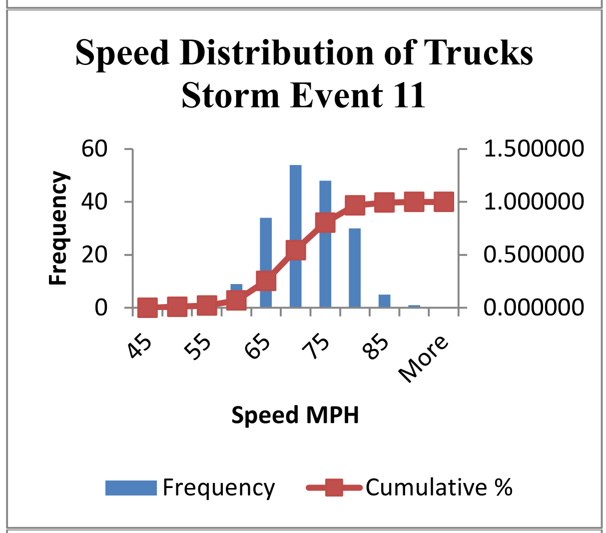

Speed Distribution of Cars
Storm Event 9
30000
20000
10000
0
1.500000
1.000000
0.500000
0.000000
Frequency
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %

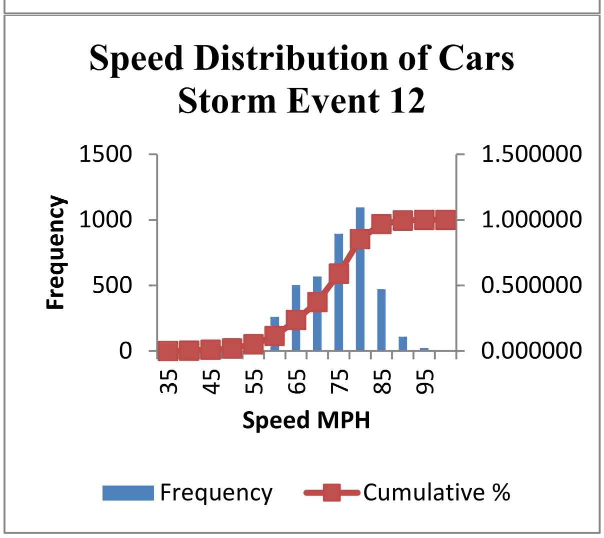

Speed Distribution of Trucks
Storm Event 9
15000
10000
5000
0
1.500000
1.000000
0.500000
0.000000
Frequency
35
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %

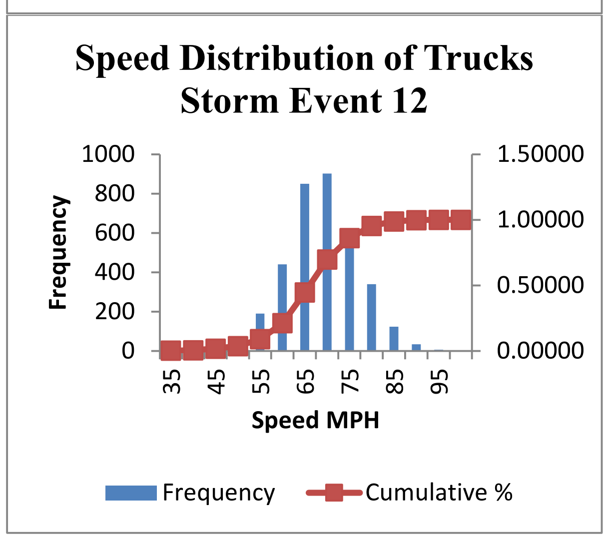

Speed Distribution of Cars
Storm Event 10
Frequency
250
200
150
100
50
0
1.50000
1.00000
0.50000
0.00000
35
45
55
65
75
85
More
Speed MPH
Frequency
Cumulative %


Speed Distribution of Cars
Storm Event 10
Frequency
400
300
200
100
0
1.50000
1.00000
0.50000
0.00000
35
45
55
65
75
More
Speed MPH
Frequency
Cumulative %


Speed Distribution of Cars
Storm Event 11
Frequency
80
60
40
20
0
150.00%
100.00%
50.00%
0.00%
35
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %


Speed Distribution of Trucks
Storm Event 11
Frequency
60
40
20
0
1.500000
1.000000
0.500000
0.000000
45
55
65
75
85
More
Speed MPH
Frequency
Cumulative %


Speed Distribution of Cars
Storm Event 12
Frequency
1500
1000
500
0
1.500000
1.000000
0.500000
0.000000
35
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %


Speed Distribution of Trucks
Storm Event 12
Frequency
1000
800
600
400
200
0
1.50000
1.00000
0.50000
0.00000
35
45
55
65
75
85
95
Speed MPH
Frequency
Cumulative %

VISSIM Outputs
$VISION
* File: \\warehouse\cae_trans\VISSIM Model\Base Model\Base Model 1.inpx
* Comment:
* Date: 3/1/2016 5:11:23 PM
* PTV Vissim: 7.00 [06]
*
* Table: Vehicles In Network
*
* SIMSEC: Simulation second [s]
* ACCELERATION: Acceleration [ft/s2]
* DESSPEED: Desired speed [mph]
* DESLANE: Desired lane
* FOLLOWDIST: Following distance [ft]
* HDWY: Headway [ft]
* SAFEDIST: Safety distance [ft]
* SIMRUN: Simulation run
* SIMSEC: Simulation second [s]
* SPEED: Speed [mph]
* SPEEDDIFF: Speed difference [mph]
* VEHTYPE: Vehicle type
* NEXTLINK\VEHRECACT: Next link\Vehicle record active
*
$VEHICLE:SIMSEC;ACCELERATION;DESSPEED;DESLANE;FOLLOWDIST;HDWY;SAFEDIST;SIMRUN;SIMSEC;SPEED;SPEEDDIFF;VEHTYPE;NEXTLINK\VEHRECACT
30.80;0.00;68.40;;820.21;0.00;95.21;2;30.80;68.40;0.00;100;
30.90;0.00;68.40;;820.21;0.00;95.21;2;30.90;68.40;0.00;100;
31.00;0.00;68.40;;820.21;0.00;95.21;2;31.00;68.40;0.00;100;
31.10;0.00;68.40;;820.21;0.00;95.21;2;31.10;68.40;0.00;100;
31.20;0.00;68.40;;820.21;0.00;95.21;2;31.20;68.40;0.00;100;
31.30;0.00;68.40;;820.21;0.00;95.21;2;31.30;68.40;0.00;100;
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31.50;0.00;68.40;;820.21;0.00;95.21;2;31.50;68.40;0.00;100;
31.60;0.00;68.40;;820.21;0.00;95.21;2;31.60;68.40;0.00;100;
31.70;0.00;68.40;;820.21;0.00;95.21;2;31.70;68.40;0.00;100;
31.80;0.00;68.40;;820.21;0.00;95.21;2;31.80;68.40;0.00;100;
31.90;0.00;68.40;;820.21;0.00;95.21;2;31.90;68.40;0.00;100;
32.00;0.00;68.40;;820.21;0.00;95.21;2;32.00;68.40;0.00;100;
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32.40;0.00;68.40;;820.21;0.00;95.21;2;32.40;68.40;0.00;100;
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