Center for Advanced Multimodal Mobility

Solutions and Education

Project ID: 2019-16

EFFECTS OF INCORPORATING CONNECTED VEHICLE TECHNOLOGIES INTO NO-NOTICE EMERGENCY EVACUATION DURING WINTER WEATHER (PHASE I)

Final Report

by

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August 2020

ACKNOWLEDGEMENTS

This project was funded by the Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE @ UNC Charlotte), one of the Tier I University Transportation Centers that was selected in this nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT), under the FAST Act. The authors are also very grateful for all the time and effort spent by the transportation professionals to provide the data that was critical for the successful completion of this study. Special thanks go to Dr. Guojing Hu at Jackson State University for her efforts in applying Intelligent Driver Model in Connected Vehicles and Dr. Yaqin He and Zhiqian Li at Wuhan University of Science and Technology for their assistance in DTA.

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EXECUTIVE SUMMARY

The goal of this CAMMSE project was to preliminarily model the microscopic and macroscopic effects of incorporating CV technologies into emergency evacuation during typical winter weather in the Pacific Northwest. First of all, an appropriate WSDOT highway corridor close to a metropolitan area was selected and the relevant data were collected. The characteristics of the transportation model in winter weather were identified. Sensitivity analysis of winter driving behavior was carried out. Model parameters were calibrated and validated. The calibration results of desired speed distribution and driving behavior were obtained. Subsequently, the impact of varying CV Market Penetration (MP) levels on travel time was investigated with Intelligent Driver Model (IDM) and Platoon Model (PLM) function. The traffic simulation has revealed that increasing CV utilization rate would enhance traffic mobility. An integrated model was then developed that incorporates the effects of winter weather and CVs into the evacuation routing simulation. Traffic simulations were then conducted to examine the synergistic effects of winter weather and CV penetration on emergency evacuation. Dynamic Traffic Assignment (DTA) was applied to simulate the effects of different levels of CV on evacuation clearance time under a hypothetical earthquake scenario.

Two scenarios of winter weather (no snow and snow) and four scenarios of CVs (no CV, 30% CV, 60% CV and 100% CV) were compared to identify the impact of market penetration level of CV technology on the evacuation performance of a chosen road network under winter weather. The traffic simulation has revealed that increasing CV utilization rate would enhance traffic mobility. The average vehicle delay declines with the increase of the market penetration level of CVs, and vice versa. The trend lines under each scenario overlap during warm-up and evacuation periods as expected. Both scenarios show the overall same trends except that the vehicles with a higher CV percentage recorded higher delays in several time intervals in which they became aware of upcoming congestion and changed their speeds and lane choices accordingly. The CVs lane-changing caused some levels of slowdown within the entire network. Clearance time was obtained for all pathways and specific measurement detectors in the network. The double directions of freeway I-5 facilitated the majority evacuation traffic from other communities and accounted for the greatest traffic demand of evacuating vehicles.

Chapter 1. Introduction

1.1 Introduction

In the northern states and other cold-climate regions, winter weather can disrupt reliability and mobility of the roadway system and further complicate emergency evacuation operations. Data modeling and analytical tools are much needed to optimize passenger and freight movements under such scenarios, as the roadway network is exposed to the impacts of winter weather as well as the different levels of market penetration by connected/automated vehicles (CAVs). The effects of winter weather could be particularly problematic during earthquake evacuation.

Increased introduction of CAV technologies on U.S. roads in recent years has played a disruptive role in increasing the roadway capacity, altering the conventional composition and characteristics of traffic flow and ushering in new models of traffic operations and mobility management. Yet, when implemented appropriately, CAV technologies may significantly improve traffic flow and reduce congestion and time delays in the roadway system, which is highly desirable for effective and efficient evacuation transportation. The mobility effects of such enabling technologies, however, remain underexplored and need to be investigated and quantified.

It is the intent of this study to lay the foundational work for modeling the microscopic and macroscopic effects of incorporating connected vehicle (CV) technologies into no-notice emergency (e.g., earthquake) evacuation during winter weather typically seen in the Pacific Northwest, with the first case study conducted on Washington highways. In Phase I, we identified an appropriate WSDOT highway corridor and metropolitan area and collect the relevant data before simulating the non-evacuation and evacuation traffic under a few selected winter weather scenarios and under different levels of CV market penetration. The main methodology will then entail the development of an integrated scenario-simulation planning framework.

1.2 Problem Statement

Existing studies in evacuation transportation (Papazoglou & Christou, 1997; Chen et al., 2006; Mitchell & Radwan, 2006; Liu et al., 2008; Stepanov & Smith, 2009; Wang et al., 2016) have mainly focused on how to respond to natural or man-made hazards/disasters under non-winter weather conditions such as floods, hurricanes, wildfires, security threats, and chemical spills. Yet, winter weather (slippery road surface conditions, poor visibility, etc.) can further complicate emergency evacuation operations in northern states and other cold-climate regions. Winter weather presents unique mobility challenges such as reduced pavement friction, traffic speed and roadway capacity, and increased crash risk, as well as the need for road weather information that is timelier and of better spatial resolution for travelers in route or before their trip. At the microscopic level, winter weather can affect the travel choices of individuals (e.g., travel mode choice) and driver behaviors (distance headways, lane changing, vehicle speed and trajectory, etc.) (Lie et al., 2015; Fu et al., 2015). At the macroscopic level, winter weather can affect traffic volume, traffic density, average traffic speed, average travel time, highway capacity, etc. (Maze et al., 2015; Kwon et al., 2013). These will in turn affect the choice of evacuees' spacetime paths and optimum (e.g., most time-efficient) evacuation route of the given population to safe areas, for instance, during the case of earthquake emergency evacuation.

Increased introduction of CAV technologies on U.S. roads in recent years has played a disruptive role in increasing the roadway capacity (Tientrakool et al., 2011; Bierstedt et al., 2014; Sundquist, 2016), altering the conventional composition and characteristics of traffic flow, and ushering in new models of traffic operations and mobility management (Hendrickson & Samaras, 2017; FHWA, 2016; UK DOT, 2016). Studies have focused on simulated scenarios to capture the impact of CAV technologies on travel time, travel delay, density, volume, throughput, and level of service (LOS) improvement for various transportation facilities (Schaffers et al., 2011; Shi & Prevedouros, 2016). Data modeling and analytical tools are widely employed to optimize passenger and freight movements under various scenarios of emergency evacuation, but existing ones generally fail to account for the impacts of winter weather as well as the different levels of market penetration (in the present time and in the future) by CVs.

The mobility effects of such enabling technologies, however, remain underexplored and need to be investigated and quantified. Such understanding would better inform evacuation decision making and related policies and facilitate enhanced resilience of the roadway network. The absence of such understanding, on the other hand, would make the evacuation routing models limited in their ability to simulate/capture actual scenarios or provide useful guidance in formulating emergency response strategies, as the CV technologies increasingly penetrate the market and are adopted into practice. These limitations drive a critical need for this project.

1.3 Objectives

The goal of this CAMMSE project was to preliminarily model the microscopic and macroscopic effects of incorporating CV technologies into emergency evacuation during typical winter weather in the Pacific Northwest. To meet this goal, the following objectives will be addressed: (1) identifying an appropriate WSDOT highway corridor close to a metropolitan area and collecting the relevant data including: one candidate area for simulation, emergency evacuation objectives and path choices, current practices of evacuation transportation; (2) collecting sensor data at the selected WSDOT highway corridor and metropolitan area and characterizing the changes in traffic patterns due to winter weather; (3) simulating the effects of different levels of CV traffic on evacuation clearance time under a hypothetical earthquake scenario, and; (4) developing an integrated model that incorporates the effects of winter weather and CVs into the evacuation routing simulation.

Note that this CAMMSE project aims to lay the foundation to address much needed research in the area of optimizing winter mobility during emergency evacuation using historical data and assuming no significant changes to the conventional WRM operations or existing traffic signal infrastructure.

1.4 Report Overview

The remainder of this report is organized as follows. Chapter 2 presents a comprehensive review of the state-of-the-art and state-of-the-practice literature on the effect of winter weather and CV on emergency evacuation. Chapter 3 describes the methodology used in this exploratory study, including the procedures used to collect and process the relevant data and the approach of developing and evaluating simulation models. Chapter 4 and Chapter 5 present the effect of winter weather and connected vehicles on traffic mobility, respectively. Chapter 6 develops an integrated model of emergency evacuation. Finally, Chapter 7 concludes this report with a summary and a discussion of the directions for future research.

Chapter 2. Literature Review

2.1 Introduction

This chapter provides an up-to-date overview of the microscopic effects of winter weather and connected vehicles technology on emergency transportation evacuation and helps identify gaps that may exist in the current knowledge domain.

2.2 Emergency Transportation Evacuation

2.2.1 **Evacuation Strategy**

A reliable transportation system is crucial, particularly in times of emergency. In response to hazardous events (such as earthquake, flood, hurricane, wildfire, heavy snowstorm, or chemical spill), the transportation system provides essential access for rescue teams and equipment to reach the locations of interest and to fix other lifelines. In response to hazardous events, largescale evacuation and transfer of people is often necessary. The sudden changes in traffic operational conditions and increase in traffic volume, in turn, will disrupt the balance in the operating roadway network and re-distribute traffic flow. It is very important to develop reliable evacuation routing models based on the defined emergency evacuation conditions and priorities, as such models can provide useful guidance on how to respond to future hazardous events that may occur abruptly. A comprehensive evacuation plan should include an optimized evacuation route, the total time of evacuation routing, and the choice and planning of evacuation shelters that result in timely evacuation and safety of local or regional populations who are exposed to the hazard. The suitable evacuation strategy may vary because of the density and composition of at-risk populations, geographical characteristics of the area, the characteristics of traffic flow, and other factors (Lovas, 1998). The emergency transportation evacuation should focus on where and how many people to transfer, which mode of transportation to use, and how to best allocate the transportation resources to achieve the optimum outcome of evacuation (Mahmassani, 2001). Often, multiple and somewhat conflicting objectives are set for the transportation evacuation thus a multiobjective optimization approach may be needed for the emergency response (Papazoglou & Christou, 1997; Stepanov & Smith, 2009; Wang et al., 2016).

2.2.2 **Impact of Winter Weather**

Inclement weather, such as blowing snow, black ice, and freezing rain can significantly impact and disrupt the reliability, mobility, and safety of passenger, commercial, and public vehicles. The impact of winter weather (and winter roadway operations) on traffic mobility, safety, economy and society is apparent in the Pacific Northwest—and the cost of shutting down the highways in severe wintery weather conditions is not affordable. According to the American Highway Users Alliance (2014), a one- day major snowstorm can cost a state $300 to $700 million if considering both direct and indirect costs. For instance, the closure of I-90 over Snoqualmie Pass in Washington State was estimated to cost $700,000 per hour (Daily Record, 2008). In addition to reducing the safety performance of a transportation system, snowy and icy conditions can have a significant impact on accessibility and mobility by preventing or delaying people and businesses from reaching their desired services, activities and opportunities (Shahdah & Fu, 2010). The mobility on winter roadways are affected by snow event characteristics (duration, amount, severity, etc.), traffic characteristics, driver behaviors, and pavement conditions that are affected not only by winter weather but also by winter road maintenance (WRM) operations.

2.2.3 **Impact of CV Technology**

Both winter weather and CV technologies can complicate emergency evacuation operations by inducing substantial changes in driver behaviors and traffic flow characteristics in the roadway network. But CV data could also be utilized to enhance evacuation strategies by supplementing or complementing current roadway sensing components to improve the effectiveness of the system operations to react to changing road weather and traffic conditions. CVs can communicate with nearby traffic signals via dedicated short-range communications (DSRC) to relay information about current and planned green-signal phases for driving decisions and can also communicate with other DSRC-equipped vehicles, infrastructures, and smartphones. However, the potential mobility benefits of CV technologies are largely dependent on their level of market penetration. The USDOT has estimated that combined vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) systems may potentially reduce travel time by up to 27%, travel time reduction for emergency vehicles by up to 23%, and up to 42% on freeways when cooperative adaptive cruise control and speed harmonization are optimized for the environment (Najafi et al., 2016). The benefits of CVs on roadway mobility are likely to be more significant during adverse weather conditions, and mobile data collected may also improve the situation awareness in emergency evacuation routing (Oxendine et al., 2012). CV technologies will enable traffic managers to deliver road weather advisories directly to a vehicle onboard unit as a visual display to drivers (Chapman & Drobot, 2012). The real-time, microlevel road weather condition information can be communicated to the general public, encouraging them to slow down, choose a different route, or stay home in light of inclement weather. Local governments could introduce adaptive and connected traffic signals to substantially improve traffic flow, e.g., giving priority to high-occupancy vehicles such as buses, or specific types of vehicles (e.g., emergency vehicles). Vehicles communicating desired routes will enable traffic signals to better accommodate flows and reduce delays. WRM operations, especially the more proactive tactics (e.g., anti-icing), can benefit greatly from receiving better information from the mobile data collection platform of CVs (Dey et al., 2015; FHWA, 2014). Bahaaldin et al. (2016) suggested that using communication capabilities of Connected Vehicles (CVs) can improve the overall traffic performance during a no-notice evacuation. The presence of 30% CVs on roadways could significantly reduce evacuation traffic delays compared to a scenario with no CVs. Overall, the utilization of CV technology can improve traffic operations during a no-notice evacuation and increasing the CV penetration rate can contribute to better traffic performance. The benefit of such implementation was correlated proportionally with the factor of time.

2.3 Traffic Simulation Model

2.3.1 **Evacuation Model**

Traffic simulation modeling has been extensively used to aid in planning and response operations during emergency evacuation situations (Moriarty et al., 2007). Signal setting optimization is often incorporated with a path choice model for the purpose of emergency evacuation (Marcianò et al., 2015). Existing strategies used to reduce evacuation time include dynamic routing, network/route optimization, car following techniques, priority signal control, etc. (Bahaaldin et al., 2017). Existing studies in evacuation transportation have mainly focused on how to respond to natural or man-made hazards/disasters under non-winter weather conditions. For instance, Chen et al. (2006) conducted microsimulations to assess the vulnerability of the Florida Keys area to a hurricane strike in terms of the minimum clearance time needed to evacuate all residents and how many residents would need to be accommodated if the evacuation route became impassable. Mitchell and Radwan (2006) evaluated several heuristic strategies and the effect of population density (or total number of trips) on the overall evacuation clearance times for a given presentative roadway network. Liu et al. (2008) presented “a corridor-based emergency evacuation system and an example application of the system for the Washington, D.C., metropolitan area under a hypothetical emergency scenario.” Zhang et al. (2015) presented a model that aims to optimize “both total network productivity and outflow rate” and examined regional evacuation transportation out of the New Orleans metropolitan area. Wang et al. (2016) presented a model that addresses the challenges of shelter allocation and emergency routing while maximizing “the total reliability of routes connecting residential communities and shelters and those connecting shelters.” The modeling study used both “storm surge scenario simulation data and real-world community and infrastructure data from Pingyang County, China.”

2.3.2 **Parameters Calibration and Algorithms**

The parameters of a microscopic simulation model need to be calibrated to minimize the difference between simulation results and field data. Sterzin (2004) applied an aggregate calibration approach in a Microscopic Traffic Simulator (MITSIMLab)) and used this approach to refine and enhance existing driving behavior models with additional explanatory variables. Asamer et al. (2012) calibrated the parameters of the car-following model in the microscopic simulator VISSIM for snowy road conditions and applied a brute force search method, saturation flow rate and start-up delay estimation from each simulation run. Lu et al. (2016) proposed a video-based approach to incorporate direct measurements of car-following parameters into the process of the VISSIM model calibration that included desired speed, desired acceleration, and safe following distance. They applied the Golden section search algorithm to find the optimal value that would minimize the difference in an average saturation headway between simulation outputs and field observations. Karakikes et al. (2016) described a systematic calibration process based on travel time measurements that is associated with the application of an optimization algorithm (Genetic Algorithm, Memetic Algorithm, Metaheuristic Algorithm, Simultaneous Perturbation Stochastic Approximation algorithm, or others) to determine the optimum parameter set.

2.4 Summary

This chapter has provided an overview of the current knowledge on: emergency transportation evacuation (including evacuation strategy and impacts of winter weather and CV technology); traffic simulation model (including evacuation model and parameters calibration and algorithms).

Chapter 3. Methodology

3.1 Introduction

This chapter presents a demonstration of the methodology developed to evaluate the effects of winter weather and CVs on emergency evacuation. The remaining sections are organized as follows. Section 3.2 provides a description of the procedures used to collect and process the data, Section 3.3 describes driving behavior, and Section 3.4 presents the simulation and modeling process.

3.2 Data Collection and Analysis

3.2.1 **Data collection from practitioners**

To gather relevant data, the research team worked with the Washington State Department of Transportation (WSDOT) stakeholders, especially those in the traffic engineering division and Intelligent Transportation Systems (ITS) group. as well as the Seattle Office of Emergency Management. Data included candidate highway corridors connected to the city of Seattle, population of at-risk residents and tourists, participation rate/behavior patterns, related evacuation objectives/priorities and path choices, emergency evacuation traffic management plan, destination selection behavior of evacuees, and traffic management controls within the existing evacuation plan. This planning effort helped the research team identify an appropriate highway corridor close to the Seattle metropolitan area (e.g., I-5) to serve as the case study in the subsequent tasks, based on the availability and quality of key data elements required by this CAMMSE project. The case study area was identified through close consultation with transportation operation engineer and city emergency manager, leveraging their firsthand experience in planning for real-time operations of evacuation transportation.

To address potential data gaps and learn from other similar transportation agencies or case studies, the team conducted a comprehensive literature search on the effects of winter weather and CV technologies on evacuation transportation, microsimulation studies of evacuation transportation. The team also surveyed the identified practitioners or agencies to gather information about their use of microsimulation models for planning and response operations during emergency evacuation. The topics of interest included: typical evacuation strategies and modeling software/approach, Measures of Effectiveness (MoEs) of evacuation, model inputs and outputs, selection or development of route choice models, driver behavior of evacuees, methods of model calibration/validation, etc., as well as the likely changes in traffic characteristics and behavior patterns induced by CV technologies. The team conducted follow-up interviews by phone, as needed, with survey respondents who did not provide sufficient detail or clarity in their responses.

3.2.2 **Collection and analysis of non-evacuation data from loop detectors**

Once the case study area is selected in Task 1, the team collected and analyzed the non-evacuation WSDOT data from loop detectors in that area, followed by the characterization of changes in traffic patterns due to winter weather. Automatic vehicle detectors are embedded in the interstates of some cities in the state of Washington and are based on single inductive loops from which data on traffic volumes (i.e., vehicle counts) and occupancy (i.e., proportion of time during which the loop is occupied) are available for 20 or 30 second observational periods. This data is accessible via DRIVE Net (http://wsdot.uwdrive.net) and can provide the team valuable information on traffic patterns such as traveling speed and volume. DRIVE Net "adopts digital roadway maps as the base and provides data layers for integrating multiple data sources (e.g., traffic sensor, incident, accident, and travel time) for data sharing, visualization, modeling and analysis" (Ma et al., 2011). The historical data from the selected roadway network under four levels of winter weather (none, light, moderate, and heavy snowfall, respectively) were analyzed to obtain the traffic characteristics on individual links (distribution of vehicle arrival, traffic volume/composition/density, average vehicle speed, capacity) and at intersections (free-flow speeds, delays, saturation volume rate). These were then used to develop the impedance functions of various routes in the roadway network. When necessary, the team also examined historical weather data from WSDOT road weather information systems (RWISs), and road surface condition data from patrol reports and cameras and create an MS Access database to facilitate data processing/analysis.

We employed a microsimulation software (e.g., VISSIM) to model the roadway network, the driving behaviors, and overall non-evacuation traffic under the four levels of winter weather, given a specific time of the day. The model was built, calibrated, and validated for studying the performance of non-evacuation traffic as a function of winter weather. For model calibration, dozens of iterations (adjustments of speed distributions) were conducted until average travel times (calculated from aggregated loop detector data) are within one percent of the actual collected travel times.

3.2.2.1 Distribution of Traffic Flow Data

The statistics of the average speed and average volume per lane per hour are shown in Figure 1.

(a) (b)

Figure 3.1 Statistics of (a) average speed and (b) average volume per lane per hour

3.2.2.2 Vehicle Volume Input by Time Interval

The team obtained traffic volume and speed data from the installed detectors loops and traffic monitoring systems in Washington State. The loop detector data collected every five minutes was obtained from UWDRIVE (http://uwdrive.net/STARLab). The information contained traffic information such as speed and volume per lane per hour, speed and volume per hour for all lanes, and average daily frequency of congestion.

Table 3.1 Vehicle Volume Input

TIMEINT	Vol NONE	Vol LIGHT	Vol MODERATE	Vol HEAVY
0-300	2700	2268	2808	1224
300-600	2628	2304	3564	1152
600-900	2520	2556	3312	1368
900-1200	3060	2340	3348	1188
1200-1500	3240	2592	3060	1008
1500-1800	2844	2376	3492	1116
1800-2100	2700	2412	3312	864
2100-2400	2484	2196	3636	576
2400-2700	2772	2124	3276	540
2700-3000	2988	1872	2952	828
3000-3300	2196	1620	3456	1548
3300-MAX	2556	1908	3492	1152

3.3 Driving Behavior Modeling

3.3.1 **Car Following Model**

The car following model followed the one used in the VISSIM 4.1 User's Manual, as shown in Figure 3.2.

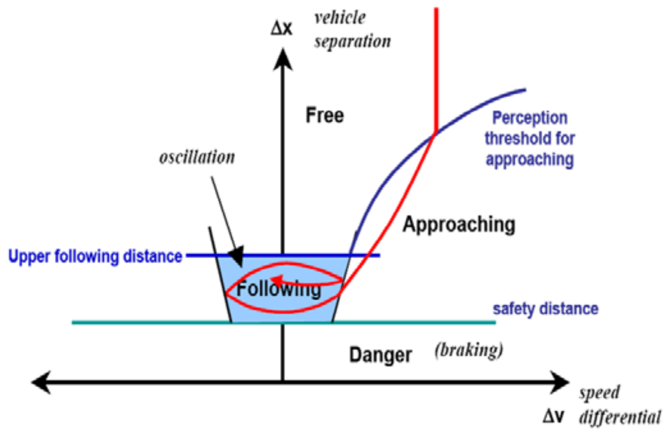


Figure 3.2 Wiedemann Car Following Logic

Source: VISSIM 4.1 User's Manual

3.3.2 **Wiedemann 99 Parameters**

The Wiedemann 99 parameters used are provided in the table below.

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/s2
	CC8	Standstill Acceleration: Desired acceleration starting from standstill	11.48 ft/s2
	CC9	Acceleration at 50 mph: Desired acceleration at 50 mph	4.92 ft/s2

3.4 Simulation and Model Development

3.4.1 **Simulating the effects of varying CV penetration on emergency evacuation**

In this task, the research team developed a CV modeling platform to simulate the effects of varying levels of CV in the vehicle stream (from 0% - 40%), on the no-notice evacuation clearance time under a hypothetical earthquake scenario, assuming that the earthquake has not yet damaged the essential roadway network. The specific simulation scenarios were based on the findings from Task 1 in terms of the population of at-risk residents and tourists, participation rate/behavior patterns, related evacuation objectives/priorities and path choices. We leveraged the simulation software package VISSIM and loaded the evacuation traffic in addition to the non-evacuation traffic into the roadway network. In the model, the behavior of CVs vs. conventional vehicles was coded differently. CVs could enhance the performance of roadway networks and reduce congestion on the evacuation routes “by exchanging real-time information about the traffic conditions downstream” (Bahaaldin et al., 2017). Some assumptions were explored such as CV technologies that can facilitate transportation during evacuations by “identifying and managing the state of the evacuation routes and directing the responders and evacuees to the desired routes” (Bahaaldin et al., 2017; Kantowitz & LeBlanc, 2007; Rizvi et al., 2007; Mohandas et al., 2009), or “using cloud-based data system to manage and distribute evacuees to optimize the network capacity” (Bahaaldin et al., 2017; Alazawi et al., 2012). The calibrated model was employed using VISSIM, which supports modeling CV communications using its Component Object Model (COM) interface. The evacuation modeling effort built on the real-world community, infrastructure, and traffic data (e.g., trip origin/destination matrices, driver behaviors, traffic characteristics, and signal timing) from Task 2, with a focus on capturing the CV effects on driver behaviors (lane changing and car following) and aggregated traffic flow characteristics in the mix environment (with both CVs and conventional vehicles).

3.4.2 **Integrated model of earthquake evacuation with CVs under winter weather**

Building on the outcomes of preceding tasks, the research team developed an integrated model of no-notice earthquake evacuation with CVs under winter weather typically seen in the Pacific Northwest. Task 2 developed and calibrated a model that simulates the effects of four levels of winter weather on the performance of the roadway network of the case study area involving non-evacuation traffic. Task 3 developed a model that simulates the effects of varying levels of CVs on the performance of the roadway network of the same area involving both non-evacuation and evacuation traffic. In task 4, these models were further improved and integrated and the problem areas/bottlenecks in the roadway network identified. For the evacuation traffic management study, the synergistic effects of winter weather and CVs on the network clearance time, total delay, average speed, and travel times were investigated in an effort to illustrate how they redistributed the traffic and altered the overall earthquake evacuation process, considering the likely changes in driver behavior (distance headways, lane changing, vehicle speed, etc.). In Phase I, the model did not incorporate contraflow design, staged evacuation, adaptive signal timing, or enhanced WRM operations due to introduction of CVs.

3.5 Summary

This chapter has described the methodology explored in this exploratory study, including approaches to the data collection from practitioners and from loop detectors, driver behavior, traffic simulation and model development.

Chapter 4. The Impact of Winter Weather on Traffic Mobility

4.1 Introduction

As a result of winter weather (e.g., no-snow, light-snow, moderate-snow, and heavy-snow/ice conditions), the average traffic speed and traffic volume on highways tends to decrease. The characteristics of transportation model in winter weather was calibrated and validated. The rest of this chapter is organized as follows: Section 4.2 provides a brief review of the location of the study freeway corridor; Section 4.3 presents the sensitivity analysis of driving behavior; Section 4.4 presents the parameters calibration and validation, and; Section 4.5 discusses the calibration results of desired speed distribution and driving behavior.

4.2 Study Site

An OpenStreetMap and Aerial map of the study corridor is shown in Figure 4.1, indicating the location of the freeway segment. The selected freeway segment is inside the red circle and is a mainline segment of I-5 freeway eastbound in the south of the Seattle metropolitan area. It has a total length of 3.3 miles including an on-ramp and off-ramp.

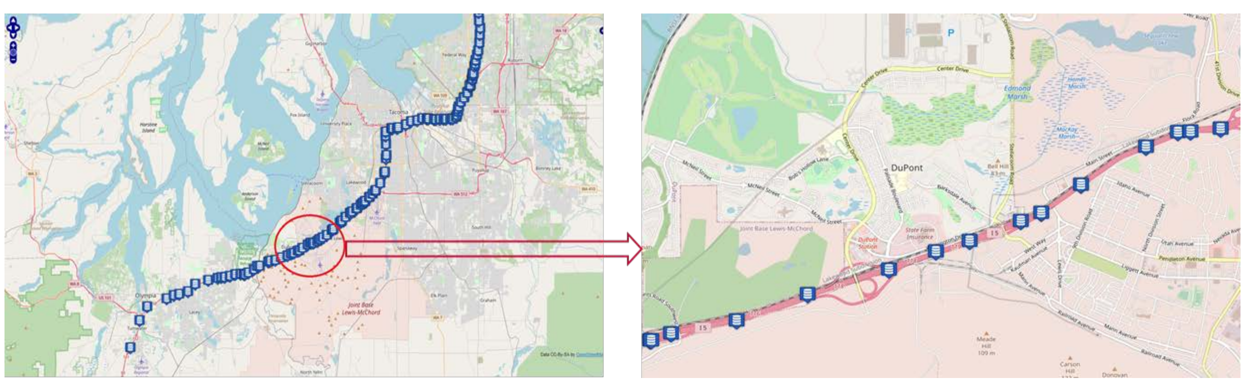


Figure 4.1 OpenStreetMap and Aerial Map of study corridor

4.3 Driving Behavior Sensitivity Analysis

Sensitivity analyses were conducted on selected driving behavior parameters to determine which parameters have the greatest impact on traffic mobility. Analyses were conducted on car following behavior, necessary lane changing, lane changing distance, and maximum look-ahead distance parameters.

4.3.1 Wiedemann 99 Car Following Model

The research team conducted a sensitivity analysis on the Wiedemann 99 car following model parameters to determine which parameters have the most influence on traffic mobility of the interstate I-5 freeway segment.

The model with four lanes mainline section, one lane on-ramp (merging) and one lane off-ramp (diverging) was created in VISSIM. Four separate scenarios were created for each parameter, each with a higher or lower value than the default value. For each scenario, all other parameters were kept at their default values. The average travel time was then collected from VISSIM based on ten simulation runs. The following assumptions were made on the test VISSIM freeway segment:

a) Mainline Dynamic demand volume by 300 second time interval
b) Ramp demand volume = 60 vehicles/hour
c) 5% of vehicles routed to off-ramp
d) 15% trucks in the traffic stream
e) Default vehicle characteristics were used
f) Default free lane selection and Wiedemann 99 car following parameters
g) Simulation time steps of 10 steps/second

Table 4.1 shows the result of the car following sensitivity analysis including travel time and percentage difference over default values. The car following parameters sensitivity analysis indicates that headway time (CC1) has by far the most impact on simulating driver behavior. In addition, standstill distance (CC0) results in a marginal influence on travel time. CC2 ~ CC9 parameters do not impact the overall performance of the transportation mobility.

Table 4.1 Wiedemann 99 Car Following Parameters Sensitivity Analysis

Wiedemann 99 Parameters										Sensitivity Analysis	
CC0	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9	Travel Time (Second)	Difference （%）
*	*	*	*	*	*	*	*	*	*	207.75	-
0.9	*	*	*	*	*	*	*	*	*	206..99	-0.37
1.2	*	*	*	*	*	*	*	*	*	207.53	-0.11
1.8	*	*	*	*	*	*	*	*	*	207.87	0.06
2.1	*	*	*	*	*	*	*	*	*	208.25	0.24
*	0.50	*	*	*	*	*	*	*	*	203.79	-1.91
*	0.60	*	*	*	*	*	*	*	*	204.51	-1.56
*	1.50	*	*	*	*	*	*	*	*	219.99	5.89
*	2.0	*	*	*	*	*	*	*	*	231.94	11.64
*	*	2.5	*	*	*	*	*	*	*	206.83	-0.44
*	*	3.0	*	*	*	*	*	*	*	207.29	-0.22
*	*	5.0	*	*	*	*	*	*	*	207.94	0.09
*	*	5.5	*	*	*	*	*	*	*	208.15	0.19
*	*	*	-4.0	*	*	*	*	*	*	207.05	-0.34
*	*	*	-6.0	*	*	*	*	*	*	207.42	-0.16
*	*	*	-10.0	*	*	*	*	*	*	208.39	0.31
*	*	*	-12.0	*	*	*	*	*	*	208.67	0.44
*	*	*	*	-0.15	0.15	*	*	*	*	207.82	0.03
*	*	*	*	-0.25	0.25	*	*	*	*	207.52	-0.11
*	*	*	*	-0.45	0.45	*	*	*	*	208.43	0.33
*	*	*	*	-0.55	0.55	*	*	*	*	208.35	0.29
*	*	*	*	*	*	6.50	*	*	*	207.12	-0.30
*	*	*	*	*	*	9.00	*	*	*	208.26	0.25
*	*	*	*	*	*	14.00	*	*	*	207.00	-0.36
*	*	*	*	*	*	16.50	*	*	*	208.30	0.26
*	*	*	*	*	*	*	0.05	*	*	207.53	-0.11
*	*	*	*	*	*	*	0.15	*	*	207.31	-0.21
*	*	*	*	*	*	*	0.35	*	*	207.92	0.08
*	*	*	*	*	*	*	0.45	*	*	207.97	0.11
*	*	*	*	*	*	*	*	2.5	*	208.03	0.13
*	*	*	*	*	*	*	*	3.0	*	207.81	0.03
*	*	*	*	*	*	*	*	4.0	*	207.78	0.01
*	*	*	*	*	*	*	*	4.5	*	207.81	0.03
*	*	*	*	*	*	*	*	*	0.5	208.54	0.38
*	*	*	*	*	*	*	*	*	1.0	207.63	-0.06
*	*	*	*	*	*	*	*	*	2.0	207.94	0.09
*	*	*	*	*	*	*	*		2.5	207.92	0.08

4.3.2 Necessary Lane Changing Behavior

A sensitivity analysis was conducted on the necessary lane changing behavior in VISSIM. Keeping the car following headway (CC1) parameter as default, modifications to the maximum deceleration rates for the merging and trailing vehicles were conducted to determine the effect of necessary lane changing behavior. The average travel times were collected in VISSIM using ten simulation runs.

Table 4.2 shows the result of necessary lane changing sensitivity analysis. Travel time and percentage difference over default values are presented.

Table 4.2 Necessary Lane Changing Behavior Sensitivity Analysis

Headway (CC1)	Max Deceleration (m/s2)		Travel Time (Second)	Difference (%)
	Merging	Trailing		
0.9 sec (default)	-4 (default)	-3 (default)	207.75	--
	-4	-4	207.28	-0.23
	-4	-5	206.86	-0.43
	-5	-3	207.08	-0.32
	-5	-4	207.28	-0.23
	-5	-5	206.85	-0.43

Based on the result of the sensitivity analysis, modifying the deceleration rates for the merging and trailing vehicles does not impact travel time of the mainline freeway segment.

4.3.3 Lane Changing Distance

A sensitivity analysis was conducted on lane changing distance in VISSIM, keeping maximum deceleration rates and Wiedemann 99 car following parameters as default. Table 4.3 shows the result of the lane changing distance sensitivity analysis. Travel time and percentage difference over default values are presented.

Table 4.3 Lane Changing Distance Sensitivity Analysis

Lane Changing Distance (m)	Travel Time (Second)	Difference (%)
200 (Default)	207.75	--
100	208.11	0.17
300	207.07	-0.33
400	207.1	-0.31
500	207.09	-0.32
800	207.09	-0.32

Based on the result of the sensitivity analysis, modifying the lane changing distance does not impact travel time of the mainline freeway segment.

4.3.4 Max Look-ahead Distance

A sensitivity analysis was conducted on maximum look-ahead distance in VISSIM, keeping other parameters as default. Table 4.4 shows the result of the maximum look-ahead distance sensitivity analysis. Travel time and percentage difference over default values are presented.

Table 4.4 Max Look-ahead Distance Sensitivity Analysis

Max Look-ahead Distance (m)	Travel Time (Second)	Difference (%)
250 (Default)	207.75	--
200	206.44	-0.63
220	207.66	-0.04
240	207.04	-0.34
260	208.01	0.13
280	206.37	-0.66
300	204.80	-1.42

Based on the result of the sensitivity analysis, modifying maximum look-ahead distance does not impact travel time of the mainline freeway segment.

4.4 Model Calibration and Validation

Based on the analysis of the relevant calibration parameters for freeway modeling in VISSIM, the most important parameters to calibrate for freeway mainline travel time are the desired speed distribution and the Wiedemann 99 car following parameters. Of all the Wiedemann 99 parameters, the headway time (CC1) is the most influential. In addition, modifying the standstill distance (CC0) could make some change to the travel time of the study freeway mainline segment.

4.4.1 Model Calibration

The parameters of a microscopic simulation model need to be calibrated to minimize the difference between simulation results and field data. Figure 4.2 presents a flowchart of the calibration process. The model calibration and validation check steps occur in an iterative loop after the initial validation. After each model calibration step is completed, the output of the simulation model is compared to the field collected data and checked against the validation targets to determine if additional calibration is required. The validation check determines how closely the simulation model replicates the actual study area based on the validation target. If a model meets the validation target, the model is ready to be analyzed for future scenarios and the calibration process is complete. If the validation target is not met, data from the validation check should be reevaluated to determine the best parameters to modify during the next calibration iteration.

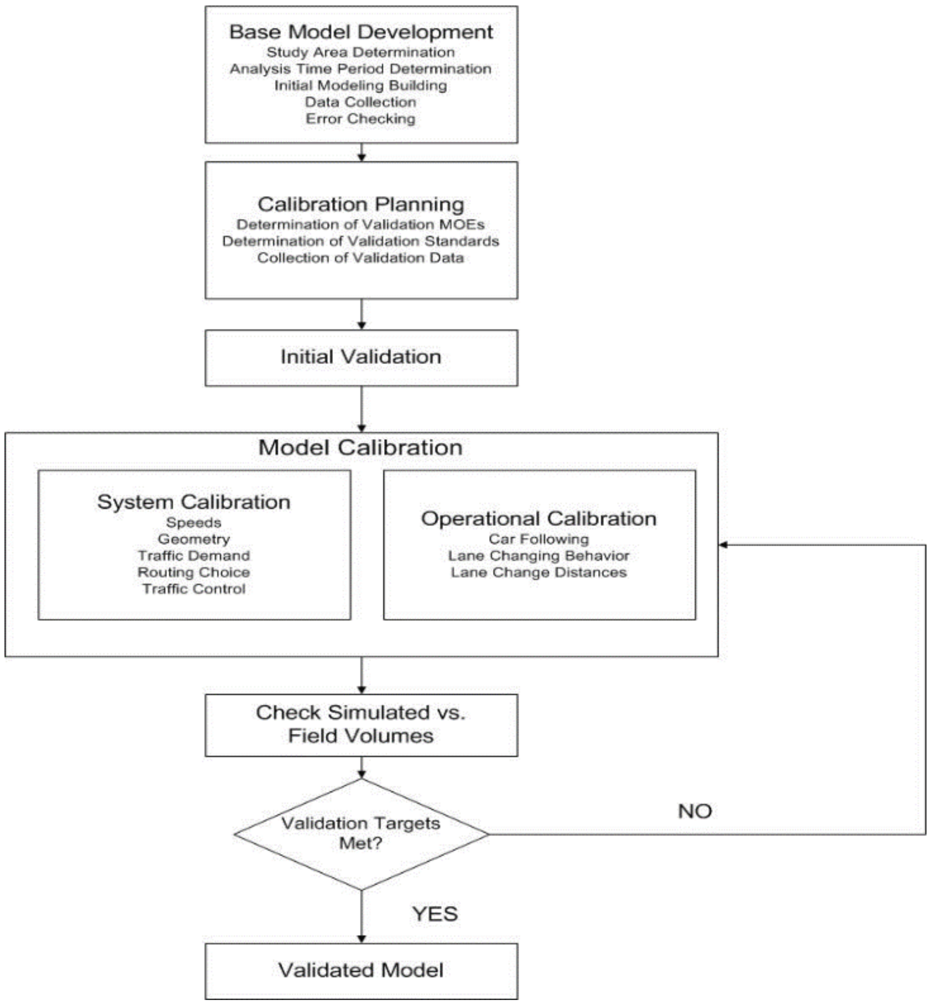


Figure 4.2 Model Calibration Process

The values of simulation outputs were compared with the averaged collected travel times and iterations were continued with new values of the parameters until the model-produced travel times were acceptable. For this model calibration case study, dozens of iterations (adjustments of speed distributions and CC1) were conducted during this calibration process until average modeled travel time was within one percent of the actual collected travel time.

4.4.2 **Model Validation**

Average travel time was collected in the field to conduct statistical analysis to determine the confidence levels. Results showed that the level of confidence is 99.7%. Figure 4.3 presents the statistical analysis of model-produced travel time and actual travel time for non-snowy weather. Figure 4.4 presents the distribution of modeled travel time for different winter weather.

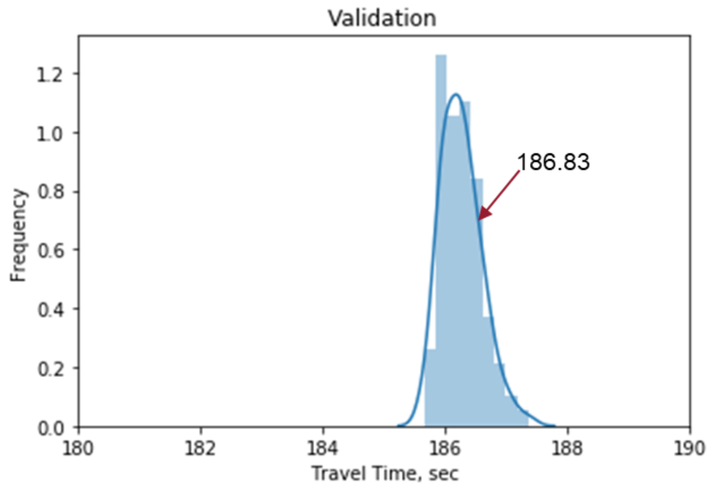


Figure 4.3 Statistical analysis of travel time for non-snowy weather

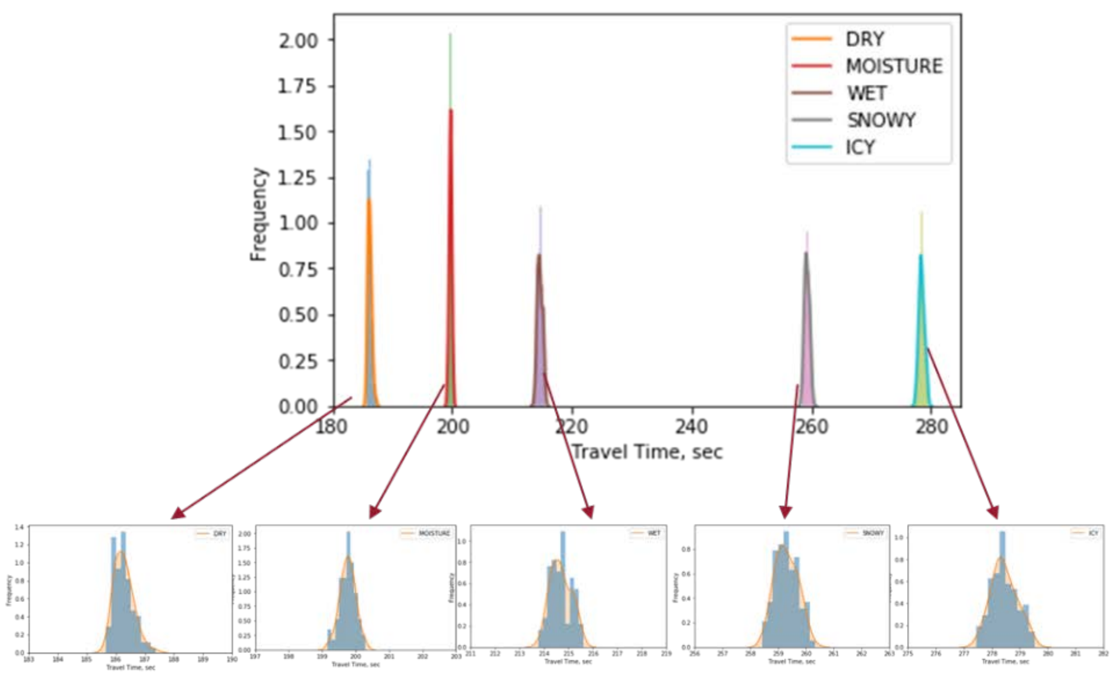


Figure 4.4 Distribution of modeled travel time for different winter weather

In this case study, the difference is less than one percent (Hourdakis et al. 2003) of the actual travel time. Therefore, the model was considered to accurately represent the real world for the scope of the study site I-5 freeway segment.

4.5 Calibrated Parameters for Different Winter Weather

4.5.1 Desired Speed Distribution

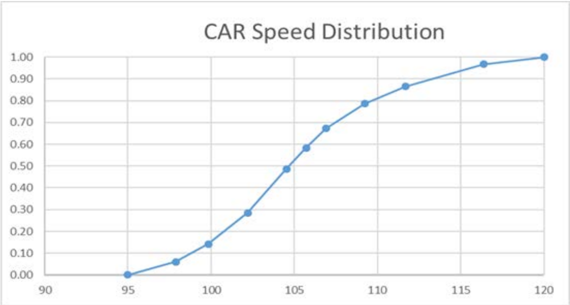
Table 4.5 shows the desired speed distribution range of the traffic models under different winter weather scenarios (non-snowy, moisture, wet, snowy, icy). Figure 4.5(a)-(e) present the desired speed distributions characteristics for different winter weather.

For a non-snowy scenario, the desired speed distribution of cars and trucks ranges from 95 to 120 km/h and 90 to 115 km/h, respectively. For a moisture scenario, the desired speed distribution of cars and trucks ranges from 90 to 110 km/h and 85 to 105 km/h, respectively.

For wet, snowy and icy scenarios, cars and trucks both perform the same desired speed distribution within each scenario. The desired speed distribution range under wet, snowy and icy scenarios are 75 - 105 km/h, 65 - 85 km/h and 60 - 80 km/h, respectively.

Table 4.5 Desired Speed Distribution for Different Winter Weather Scenarios

Vehicle Type	Desired Speed Distribution (km/h)				
	Non-snowy	Moisture	Wet	Snowy	Icy
CAR	95-120	90-110	75-105	65-85	60-80
HGV	90-115	85-105	75-105	65-85	60-80



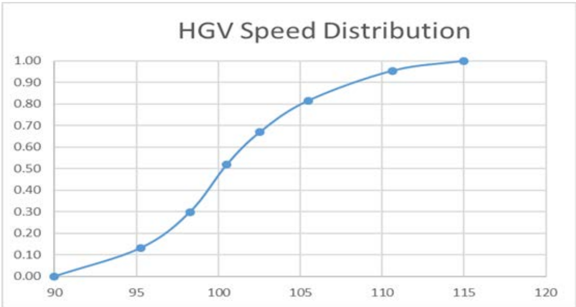


Figure 4.5(a) Desired Speed Distribution of Non-snowy Freeway Condition

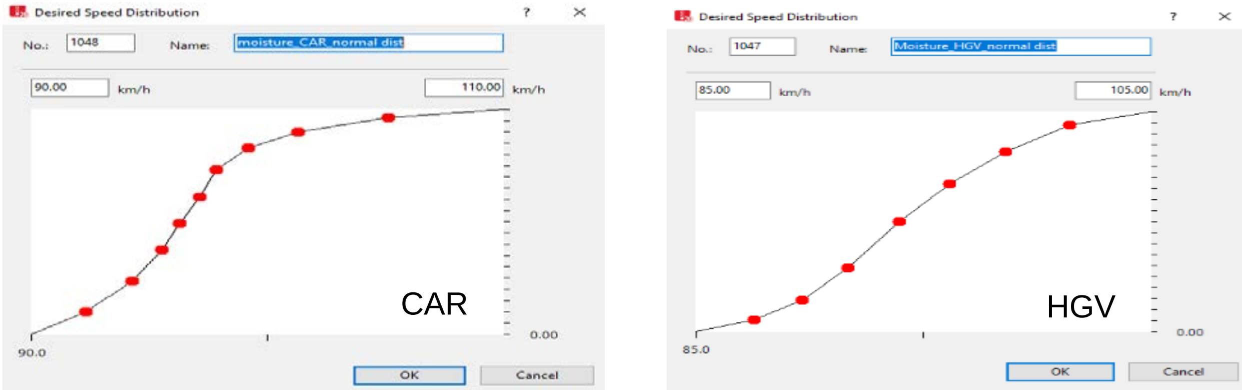
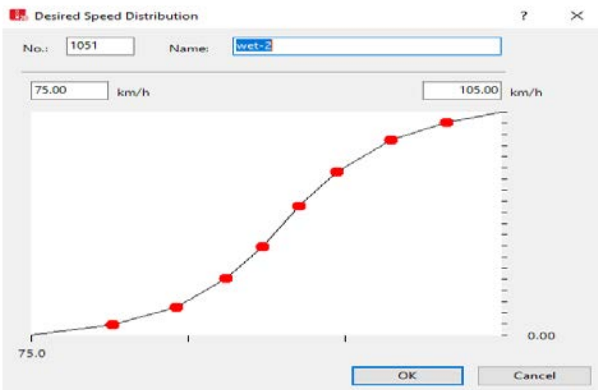
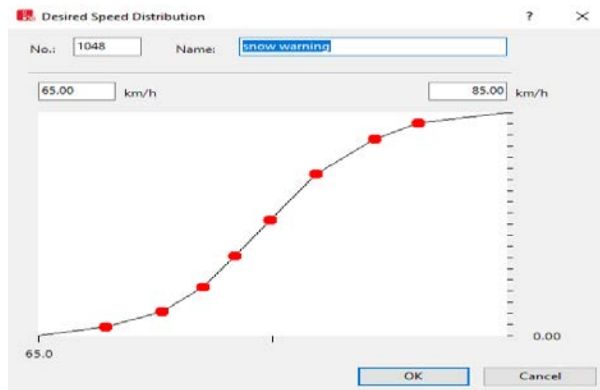


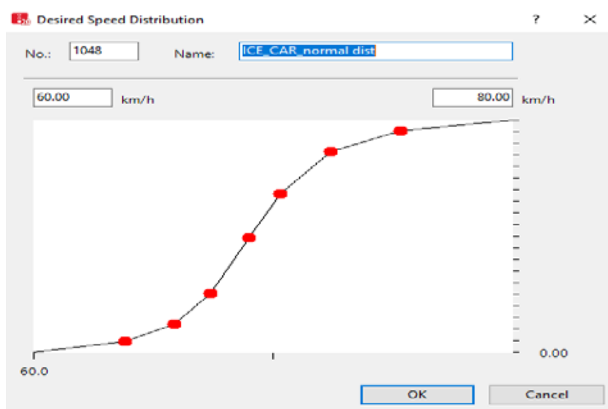
Figure 4.6(b) Desired Speed Distribution of Moisture Freeway Condition



(c)



(d)



(e)

Figure 4.7(c)(d)(e) Desired Speed Distribution of (c) Wet, (d) Snowy and (e) Icy Freeway Condition

4.5.2 Driving Behavior Parameters

Table 4.6 shows the calibration results of the Wiedemann 99 Car Following Model parameters under different winter weather scenarios (non-snowy, moisture, wet, snowy, icy).

Table 4.6 Calibration Results of the Wiedemann 99 Parameters for Winter Weather

Parameters	Non-snowy	Moisture	Wet	Snowy	Icy
CC0 - Standstill Distance (m)	1.5	1.5	2.1	3.0	3.5
CC1 - Headway Time (seconds)	0.9	1.5	1.5	2.0	2.0
CC2 - Following Variation (m)	4.0				
CC3 - Threshold for Entering "Following"	-8				
CC4 - Negative "Following" threshold	-0.35				
CC5 – Positive "Following" threshold	0.35				
CC6 – Speed Dependency of Oscillation	11.44				
CC7 - Oscillation Acceleration (m/s^2)	0.25				
CC8 – Standstill Acceleration (m/s^2)	3.50				
CC9 – Acceleration with 80 km/h (m/s^2)	1.50				

4.6 Summary

This chapter has described a study site, the sensitivity analysis of driving behavior, model calibration and validation, and the calibrated parameters for different winter weather pavement conditions.

Chapter 5. Connected Vehicles Modeling

5.1 Introduction

The improvement of vehicle communication technology is an essential element to assess the impact of CVs on enhancing the traffic flow performance. This chapter investigates the impact of varying CV Market Penetration (MP) levels on travel time for the Intelligent Driver Model (IDM) and Platooning Model (PLM) function embedded in the VISSIM software. The rest of this chapter is organized as follows: Section 5.2 provides a brief overview of the Intelligent Driver Model (IDM) and Section 5.3 demonstrates the impact of varying CVs market penetration level on traffic mobility.

5.2 Intelligent Driver Model (IDM)

In traffic flow modeling, the intelligent driver model (IDM) is a time-continuous car-following model for the simulation of freeway and urban traffic. It was developed by Treiber, Hennecke and Helbing in 2000 to improve upon results provided with other "intelligent" driver models such as Gipps' model, which loses realistic properties in the deterministic limit. As a car-following model, the IDM describes the dynamics of the positions and velocities of single vehicles.

For a simplified version of the model, the dynamics of vehicle μ is described by the following differential equation:

$$IDM\_ac_u = a\left[1 - \left(\frac{v_u}{v_0}\right)^{\delta} - \left(\frac{s^*(v_u, \Delta v_u)}{\Delta x_u - l}\right)^2\right] \quad (1)$$

with $$s^*(v_u, \Delta v_u) = s_0 + \max(0, v_u h + \frac{v_u \cdot \Delta v_u}{2\sqrt{ab}})$$

Table 5.1 shows the notations and values used in this study for IDM.

Table 5.1 Notations and Values Used in the IDM Equation

Notation	Meaning	Parameter value for CVs
a	maximum acceleration	2 m/s^2
b	maximum deceleration	3 m/s^2
l	vehicle length	4 m
s_0	jam spacing	2 m
v_0	desired speed	25 m/s
h	headway time	0.5 s
δ	acceleration exponent	4

v_u	the current speed of vehicle u	--
Δx_u	the bumper-to-bumper distance of vehicle u to the preceding vehicle	--
Δv_u	speed difference of vehicle u with the preceding vehicle	--
$s^*(v_u, \Delta v_u)$	the desired distance of vehicle u from the preceding vehicle	--
IDM_ac_u	acceleration of vehicle u	--

5.3 Impact of CV Market Penetration Level on Traffic Mobility

5.3.1 CVs for IDM

For implementing IDM, vehicle communication behaviors were modeled using the Component Object Model (COM) interface in VISSIM. The IDM process started with writing a Python code to allow for communication of travel speeds, delays, and locations between CVs. To model CVs, a vehicle type "CV" was created in VISSIM. To model a mixed traffic stream in which only CVs can communicate with each other, the COM interface was utilized to exchange required data between "CV" types at every simulation time step. Changing the percentage of these vehicles provides various CV penetration rates in the traffic stream accordingly.

In this section, the impact of the hybrid traffic of Human Vehicles (HV) and CVs on travel time using IDM is investigated by varying the penetration rate of CVs from 0 to 100%. Table 5.2 shows the travel times under different CV market penetration rates for IDM. Figure 5.1 indicates the trend of travel time changes when increasing CV market penetration levels for IDM.

Table 5.2 Travel Times with Different CV Market Penetration Rates for IDM

CV Market Penetration Rate	TRAVTM(ALL)
0%	283.5
10%	269.0
20%	268.0
30%	261.8
40%	261.0
50%	258.3
60%	256.5
70%	255.4
80%	251.2
90%	250.4
100%	247.8

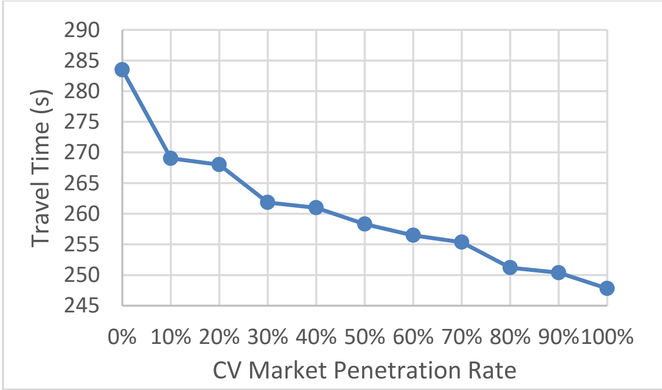


Figure 5.1 The Influence of CV MP Levels on Travel Time for IDM

With the increase of CV market penetration (MP) levels, the performance of traffic flow was enhanced, and vehicle travel time decreased accordingly. There was more impact when MP level was relatively low from 0 to 30%.

5.3.2 CVs for Platoon Model

In this section, a Platoon Model was implemented with the function embedded within VISSIM. The vehicle communication behaviors were modeled to allow the communication of travel speeds, delays and locations between CVs.

Similarly, the impact of the hybrid traffic of Human Vehicles (HV) and CVs on travel time using a Platooning Model is investigated by varying the penetration rate of CVs from 0 to 100%. Table 5.3 shows the travel times under different CV market penetration rates for a Platooning Model. Figure 5.2 indicates the trend of travel time changes when increasing CV market penetration levels for a Platooning Model.

Table 5.3 Travel Time with Different CV Market Penetration Rates for Platoon Model

CV Market Penetration Rate	Travel Time
0%	281.9
10%	274.8
20%	271.6
30%	267.8
40%	265.4
50%	263.6
60%	263.3
70%	261.8
80%	259.9
90%	258.2
100%	256.6

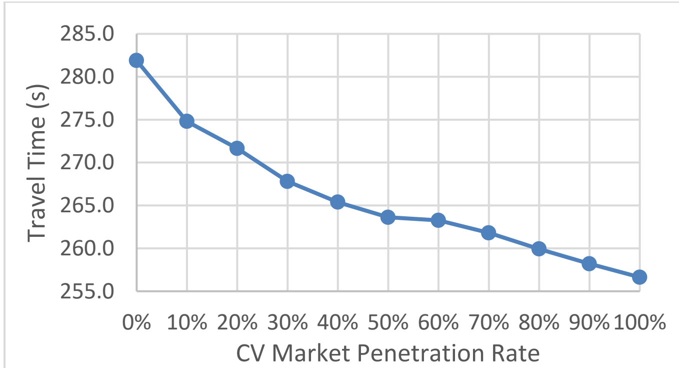


Figure 5.2 The Influence of CV MP Levels on Travel Time for Platoon Model

With the increase of CV market penetration (MP) levels, the performance of traffic flow is enhanced, thus the vehicle travel time decreased accordingly. There was more impact when MP levels were relatively low from 0 to 50%.

5.4 Summary

This chapter has described a simulation study of how various levels of CV market penetration affect traffic mobility, using the Intelligent Driver Model (IDM) and the Platooning Model function embedded in the VISSIM software.

Chapter 6. The Integrated Model on Emergency Evacuation

6.1 Introduction

Traffic simulations were conducted in this chapter to examine the microscopic effects of an integrated model of winter traffic mobility and CVs on emergency evacuation. The rest of this chapter is organized as follows: Section 6.2 provides a methodology of Dynamic Traffic Assignment (DTA); Section 6.3 describes the road network for evacuation; Section 6.4 demonstrates Origin-Destination matrices and model convergence; Section 6.5 evaluates the integrated model on evacuation performance for no snow and snow weather; Section 6.6 concludes the chapter.

6.2 Dynamic Traffic Assignment (DTA)

Dynamic Traffic Assignment is designed to model the route choice behavior of drivers, omitting the creation of static routes and instead using the OD Matrix as flow input. Dynamic Traffic Assignment is to allocate the OD Matrix to the existing road network, and then calculate the traffic flow of each road segment.

In VISSIM, Dynamic Traffic Assignment is carried out through multiple runs of iterative simulation. In each iteration, the best route is found. The travel time and travel cost obtained from the previous simulation step provide the basis for the next route selection. As the number of iterations increases, more alternative paths are obtained. When the convergence criteria are met, the search for optimal path operation is completed. Figure 6.1 shows the flow chart of Dynamic Traffic Assignment. Dynamic assignment was applied in this research, which modeled the choices drivers might make during an evacuation.

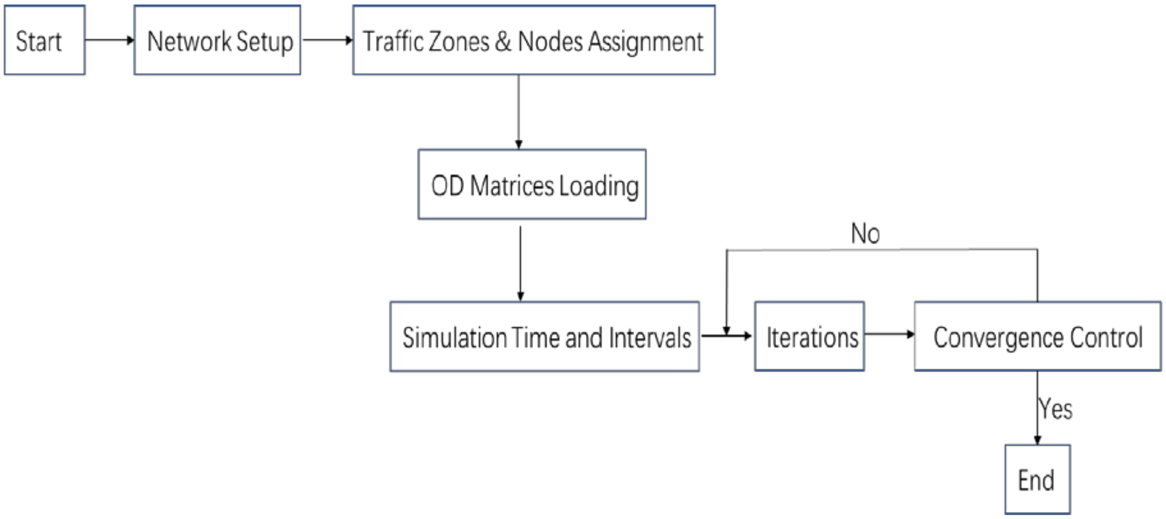
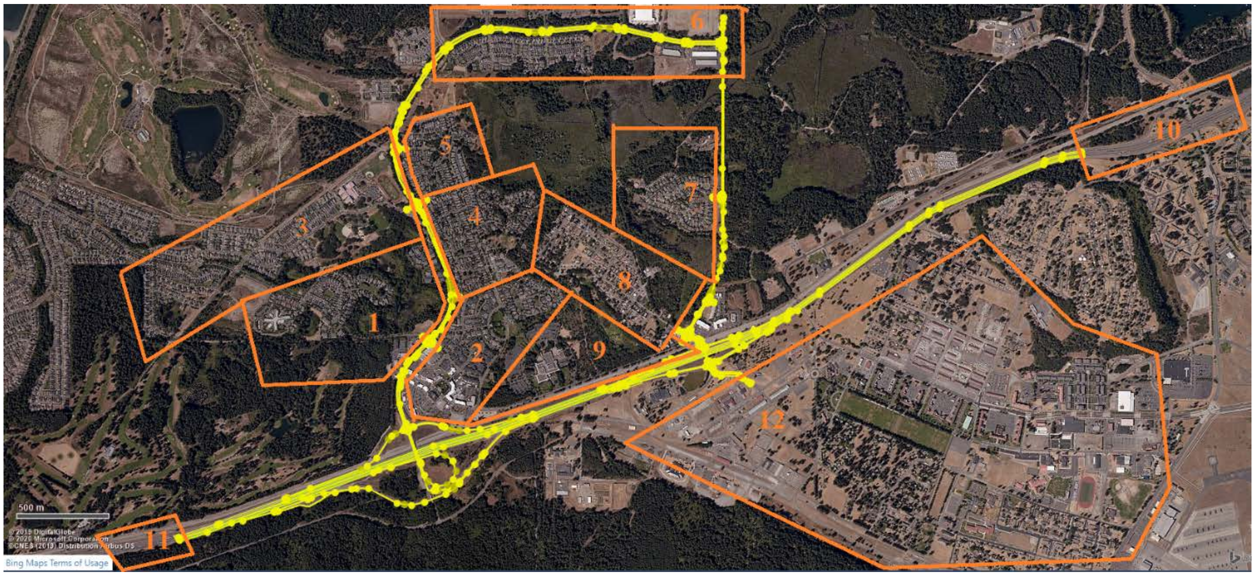


Figure 6.1 The Flow Chart of Dynamic Traffic Assignment

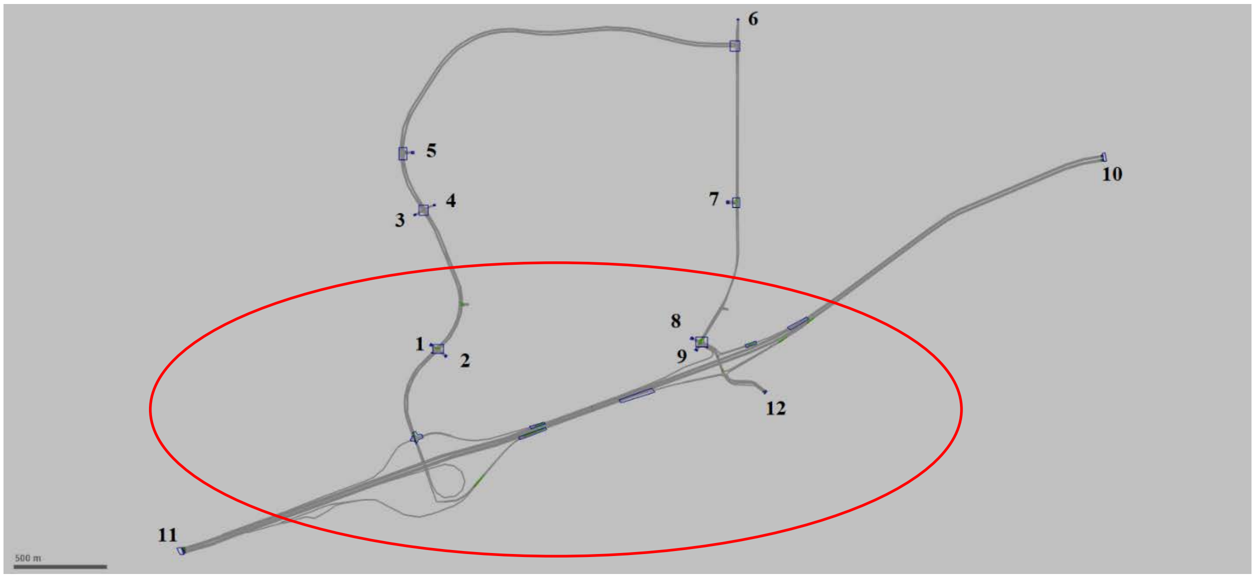
6.3 Road Network

Figure 6.2 illustrates the study area that includes a 4-mile freeway segment within Interstate Corridor I-5, which is located in the center of the network and 12 connected traffic zones (Zone 1 to 9 are origin zones, zones 10, 11 and 12 are destination zones). The I-5 freeway segment was in the geographic center of the other modeled roadways and was assumed to serve as two evacuation destinations (Zone 10 and Zone 11). Zone 12 was the third destination, which is close to an airport that could serve as alternative transportation for further evacuation. In a hypothetical earthquake case, which may occur near the study area (hypothetically at a location of Pacific in the northwest of the study area and not shown in the map), residents in these communities are likely to be affected and evacuation is strongly advised.

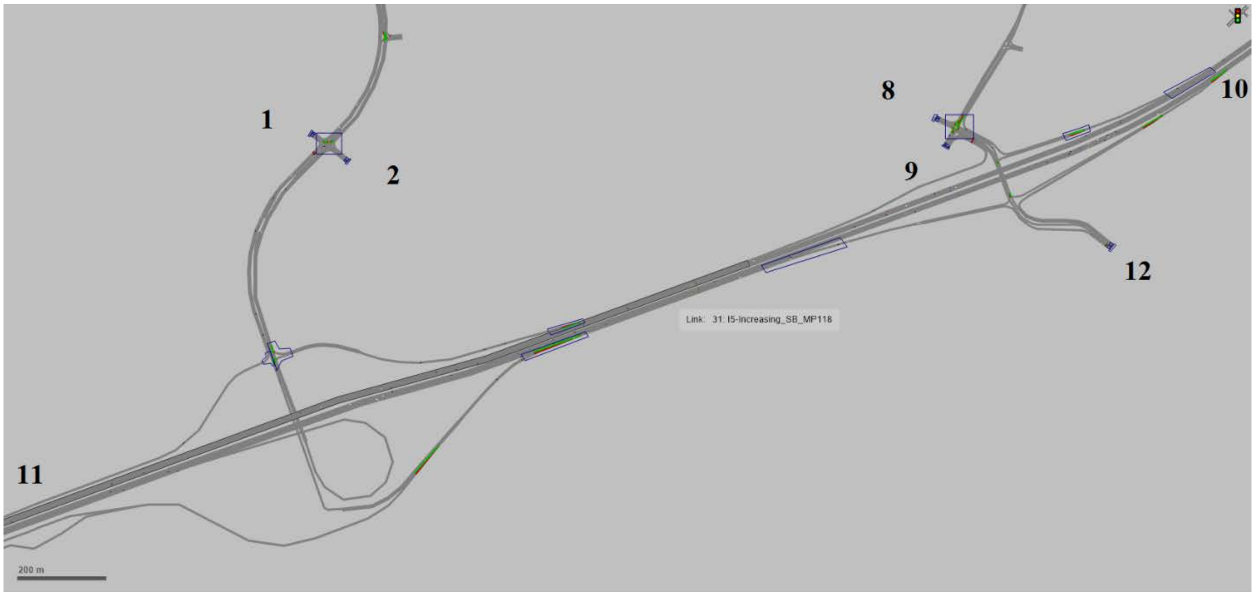
The roadways within the specified area include the I-5 segment and all interchanges that connect the interstates with the local communities. The model network contains a mix of configurations such as freeway, on-ramp, off-ramp, weaving area, cloverleaf and urban roads.



(a) Aerial Photograph of Study Area with Traffic Zones



(b) Abstract Network with Nodes



(c) Abstract Network with Nodes

Figure 6.2 Study Area

6.4 OD Matrices and Model Convergence

The projected evacuation traffic volumes were provided in O-D matrices for dynamic traffic assignment in VISSIM. The two representative O-D matrices represent two types of vehicles: conventional vehicles and connected vehicles. Table 6.1 and 6.2 show the O-D matrices for background traffic and evacuation traffic, respectively.

Table 6.1 Non- evacuation O-D Matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1	0	5	15	19	12	22	13	19	7	23	23	5
2	5	0	17	13	15	16	15	6	25	23	23	5
3	14	10	0	13	11	22	12	23	18	29	29	5
4	5	15	7	0	11	12	13	12	15	14	14	5
5	4	8	11	12	0	21	19	14	13	25	25	5
6	10	4	28	22	11	0	13	14	22	46	46	5
7	10	8	5	3	10	8	0	5	10	23	23	5
8	3	11	6	9	14	8	12	0	16	23	23	5
9	6	14	17	22	12	24	13	9	0	22	22	5
10	15	15	15	15	15	15	15	15	15	0	1500	10
11	15	15	15	15	15	15	15	15	15	1500	0	10
12	5	5	5	5	5	5	5	5	5	30	30	0

Table 6.2 Evacuation O-D Matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0	0	0	0	0	0	0	0	81	81	30
2	0	0	0	0	0	0	0	0	0	82	82	30
3	0	0	0	0	0	0	0	0	0	93	93	30
4	0	0	0	0	0	0	0	0	0	62	62	30
5	0	0	0	0	0	0	0	0	0	78	78	30
6	0	0	0	0	0	0	0	0	0	110	110	30
7	0	0	0	0	0	0	0	0	0	55	55	30
8	0	0	0	0	0	0	0	0	0	64	64	30
9	0	0	0	0	0	0	0	0	0	83	83	30
10	0	0	0	0	0	0	0	0	0	0	1500	15
11	0	0	0	0	0	0	0	0	0	1500	0	15
12	0	0	0	0	0	0	0	0	0	30	30	0

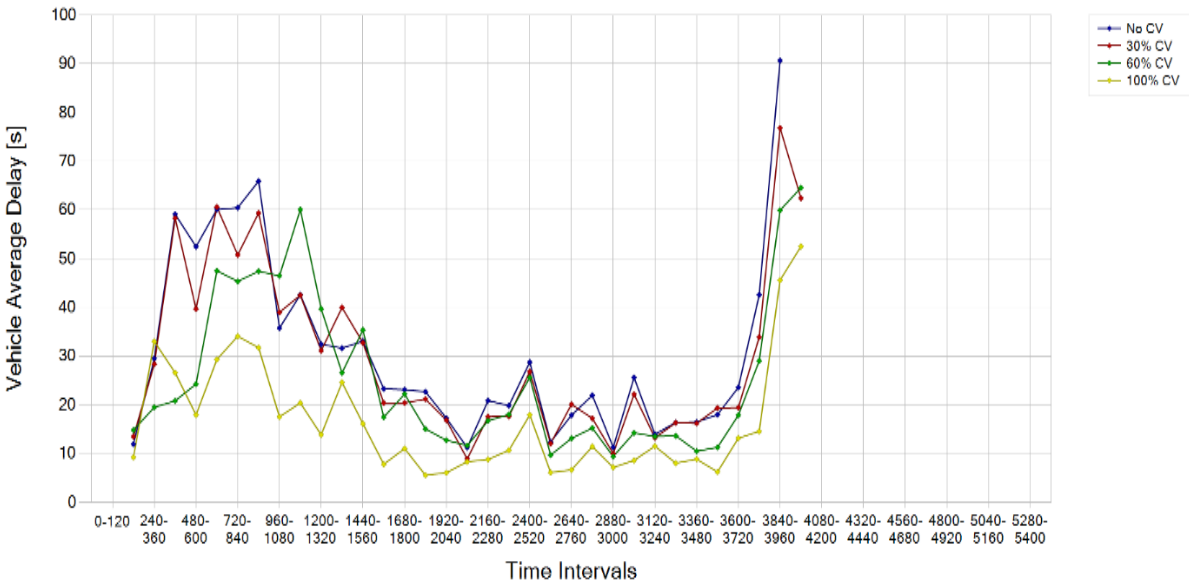
The evacuation traffic was loaded after 20 minutes from simulation start to allow vehicles to completely distribute to every part of the road network. The evacuation traffic was then mixed with the background traffic that remained on the roadways. In this case study, a value of 15% was chosen as the model convergence criteria. The convergence was obtained by running the simulation with more than 20 iterations.

6.5 Evacuation Performance Analysis

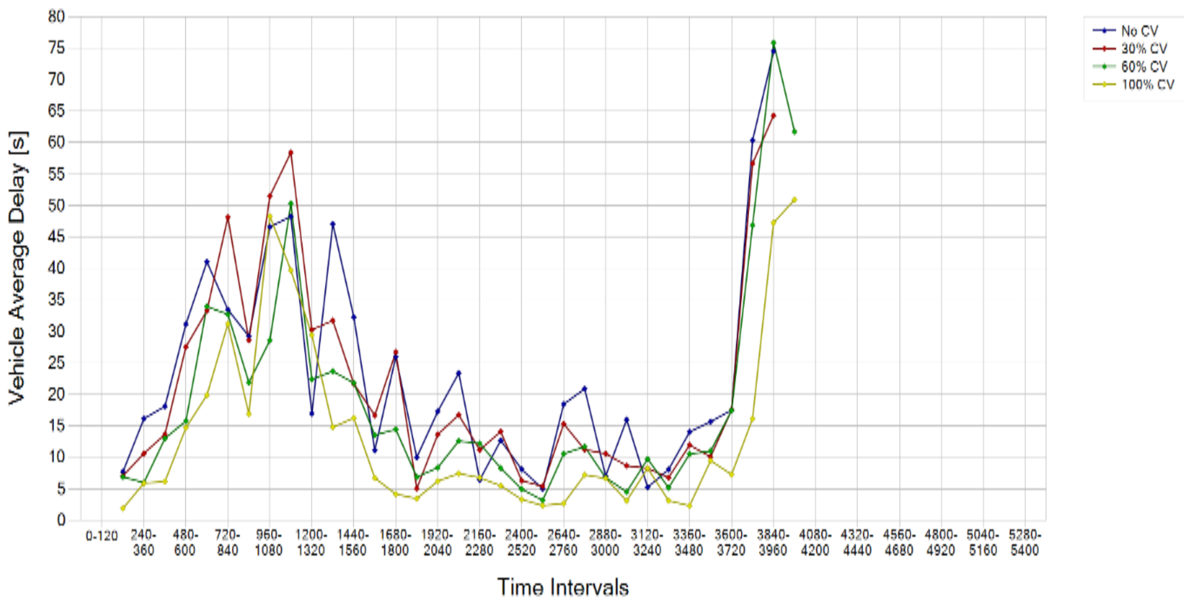
Two scenarios of winter weather (no snow and snow) and four scenarios of CVs (no CV, 30% CV, 60% CV and 100% CV) were compared to identify the impact of market penetration level of connected vehicles technology on evacuation performance under winter weather.

6.5.1 **Vehicle Delay Analysis**

Vehicle delay analysis was conducted for four pathways, which includes zone 10 to zone 11, zone 11 to zone 10, zone 2 to zone 11, and zone 9 to zone 11. Figure 6.3 to 6.6 indicate the average vehicle delay distribution with different time intervals of the four pathways under clear and snow winter weather scenarios.

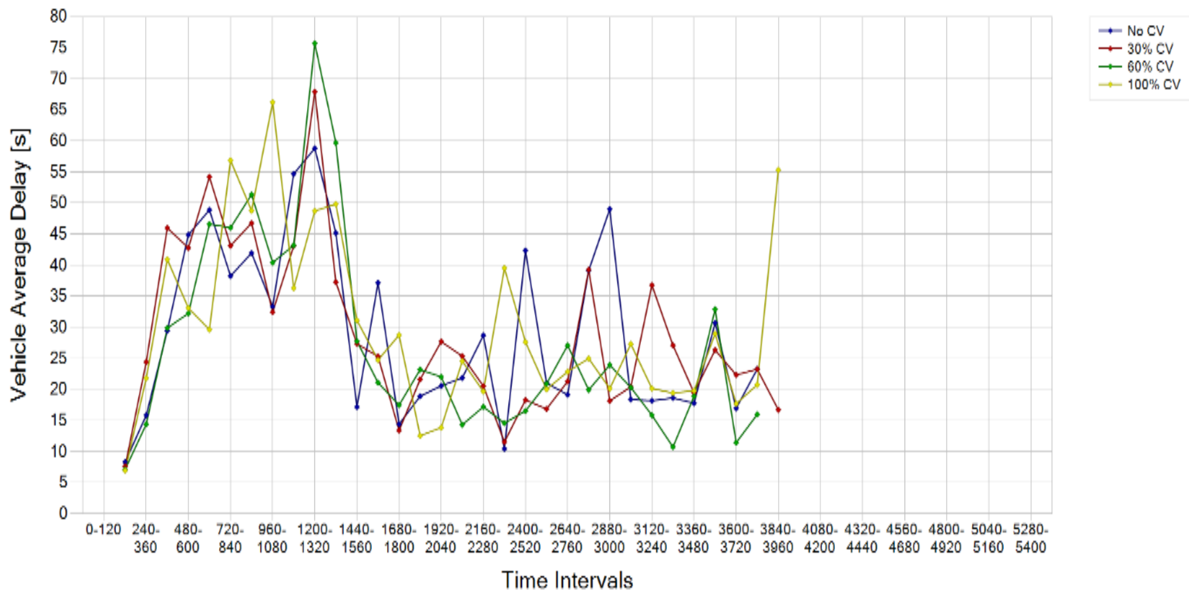


(a) Dry

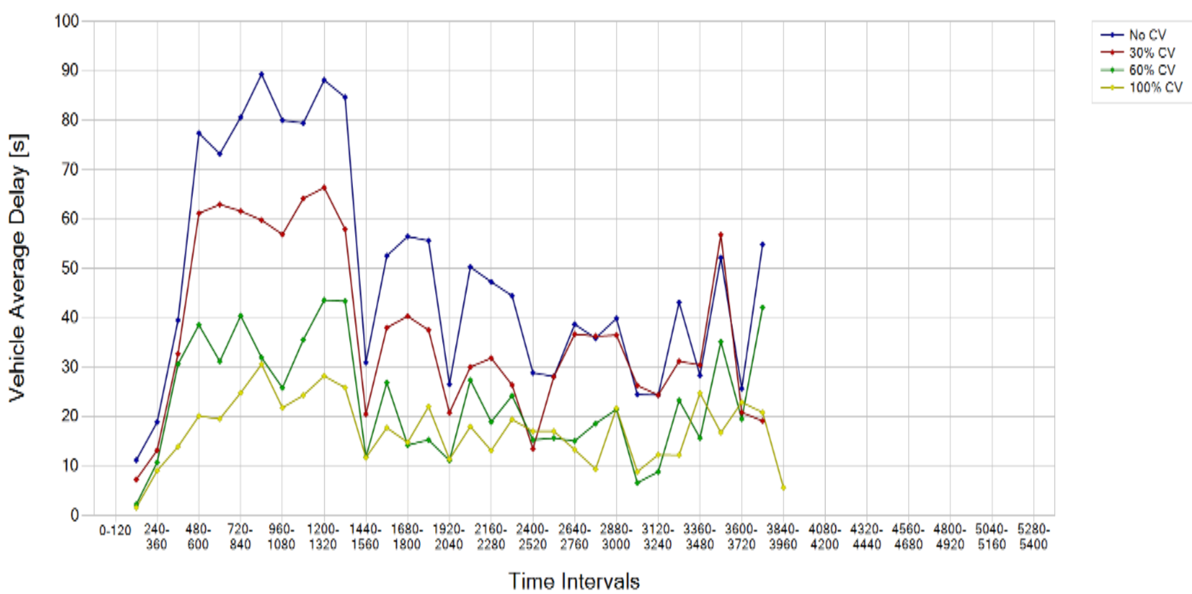


(b) snow

Figure 6.3 Vehicle Average Delay for path of Zone 10 to Zone 11

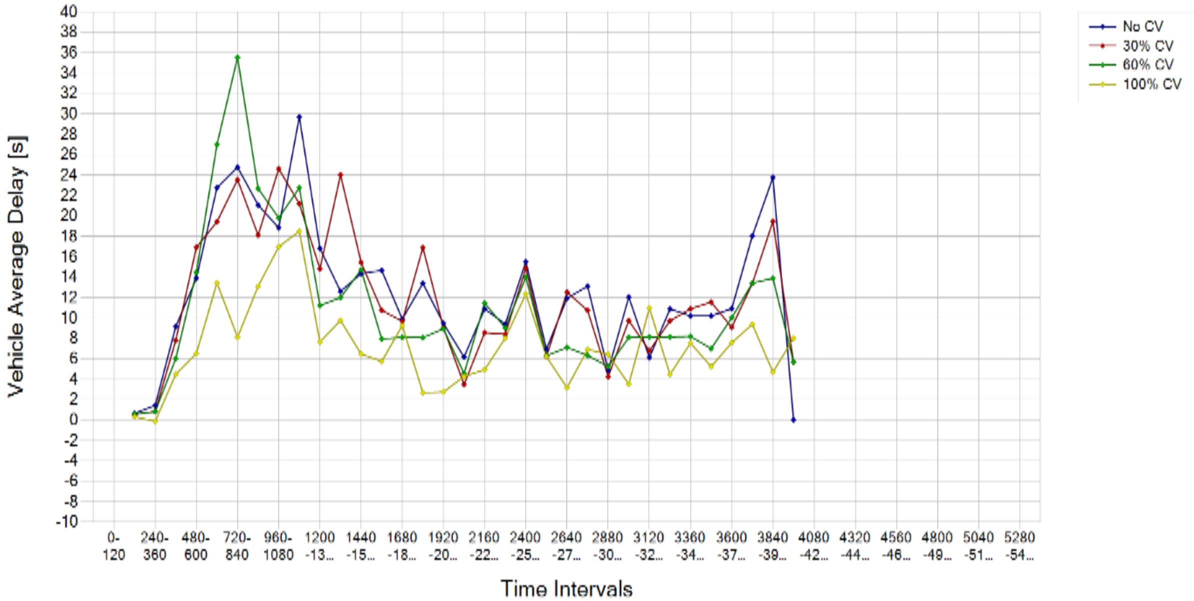


(a) dry

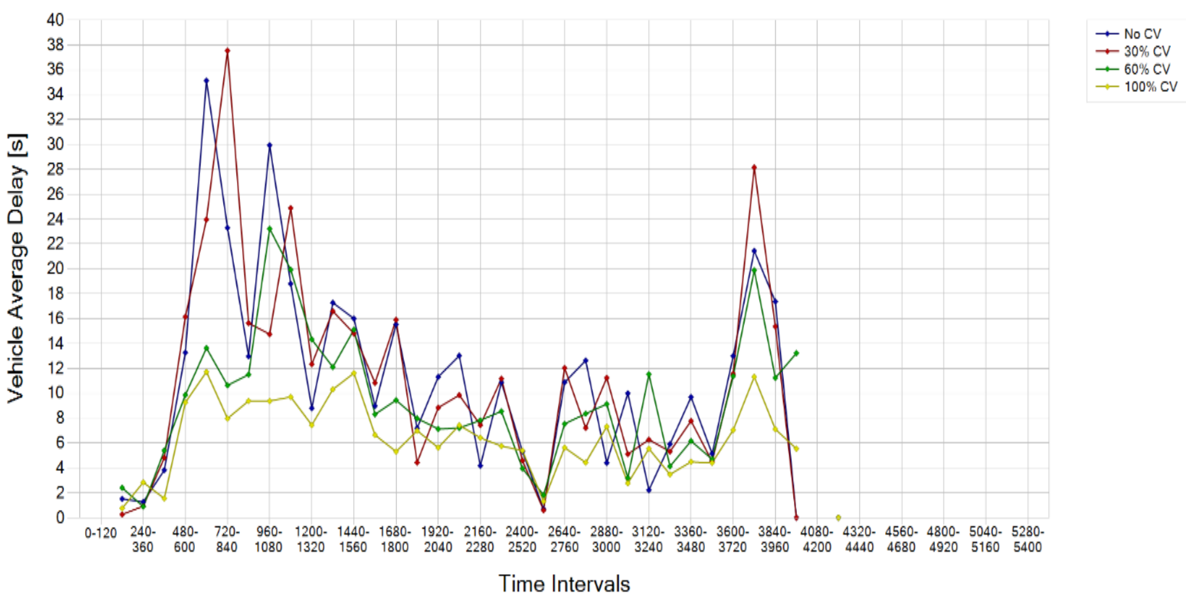


(b) snow

Figure 6.4 Vehicle Average Delay for path of Zone 11 to Zone 10

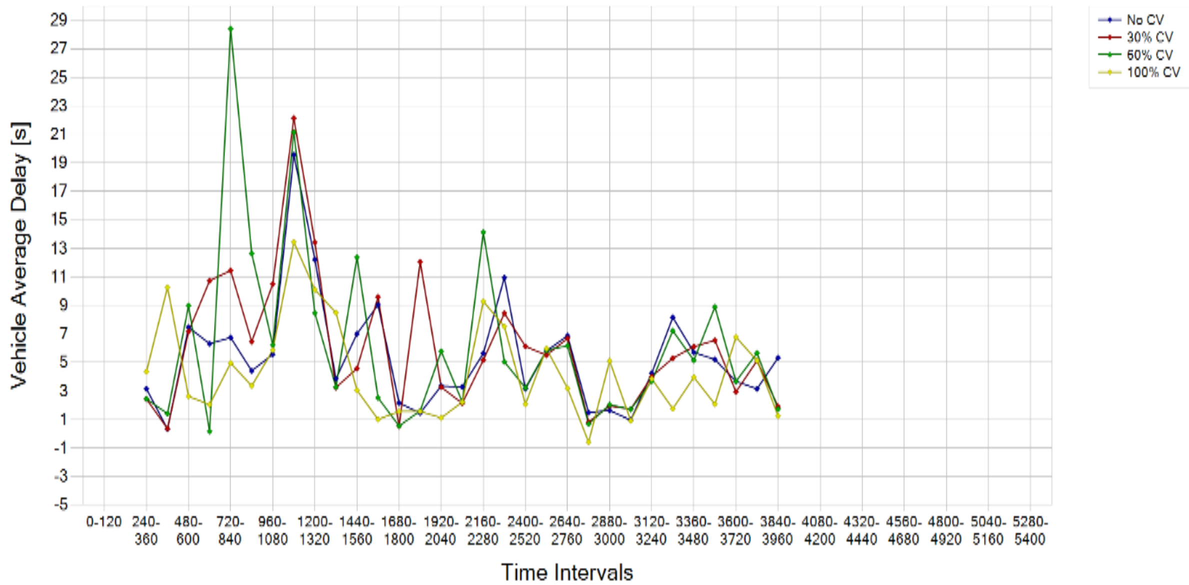


(a) dry

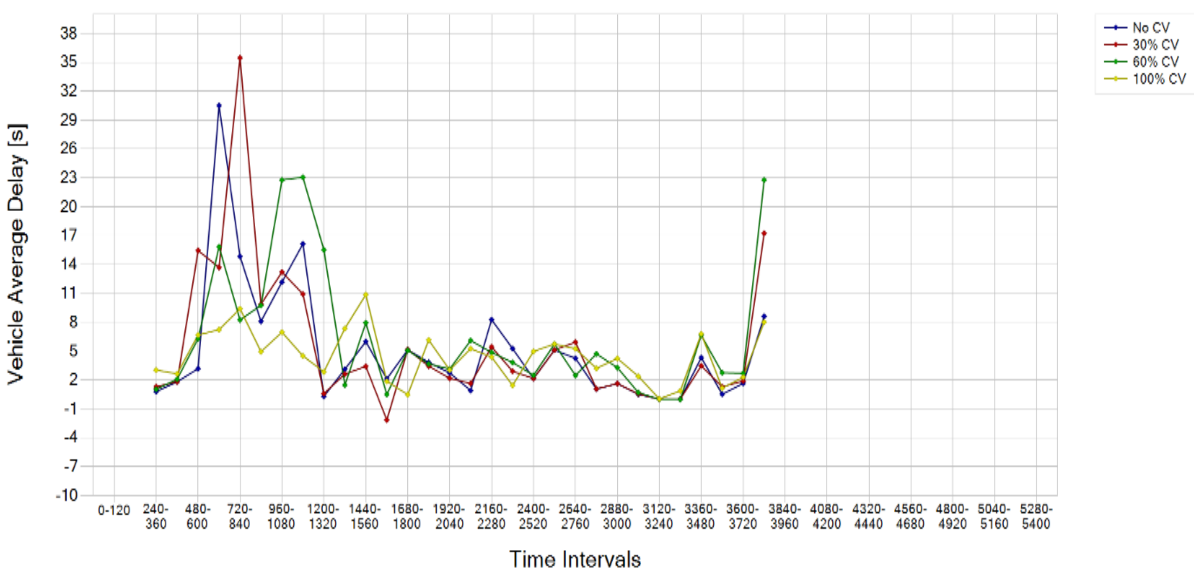


(b) snow

Figure 6.5 Vehicle Average Delay for path of Zone 2 to Zone 11



(a) dry



(b) snow

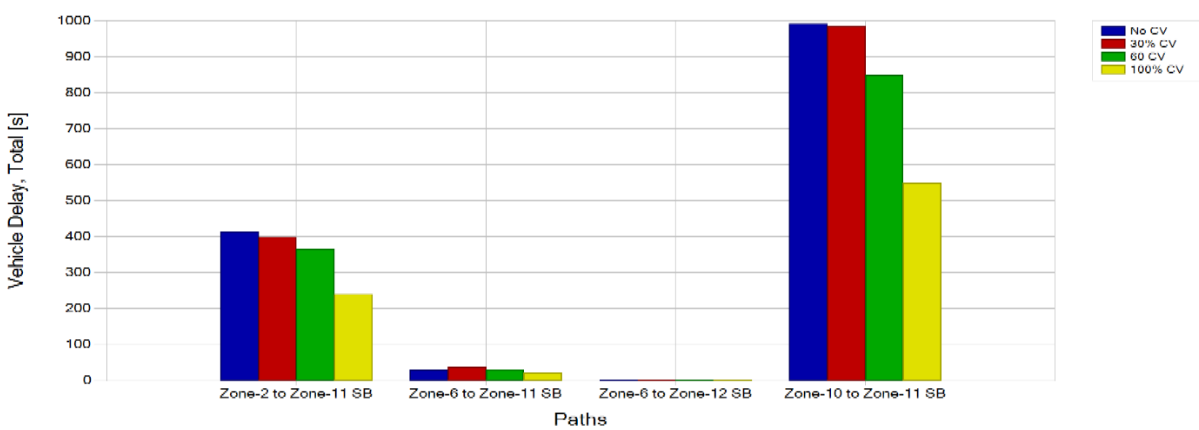
Figure 6.6 Vehicle Average Delay for path of Zone 9 to Zone 11

Figure 6.6 reveals that the trend lines of the four paths under each scenario overlap during warm-up and evacuation period when normal background traffic and evacuation traffic populate the simulated road network, as expected. The delays increase rapidly after the start of the simulation begins due to the addition of the traffic flows.

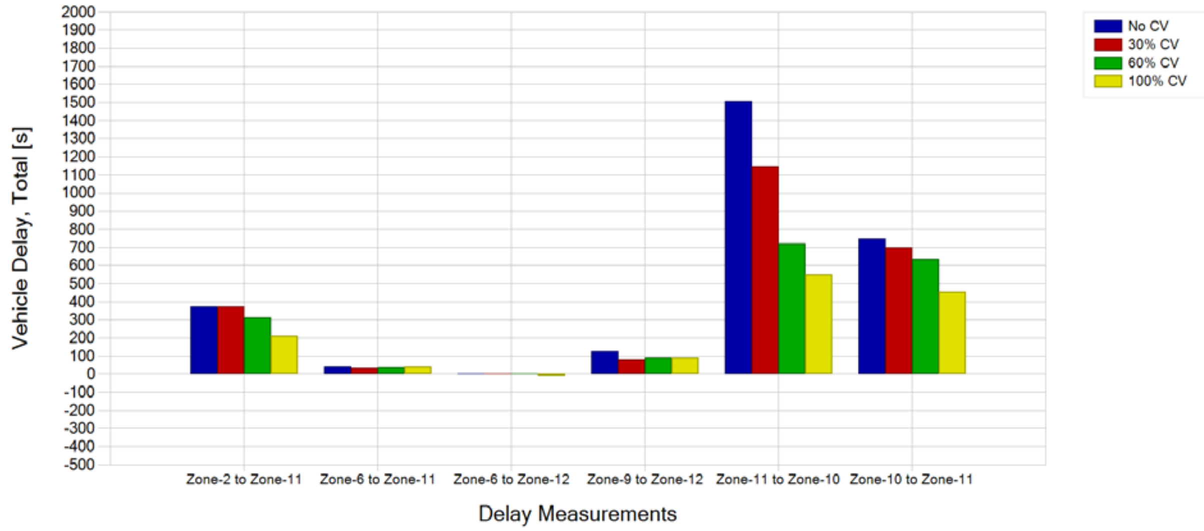
For both dry and snow scenarios, the average vehicle delay declines with the increase of market penetration level of CV, and vice versa. From simulation start to 1200 seconds, the overall vehicle delay is larger than that of the afterwards simulation. It indicates that the background traffic has more delay than evacuation traffic. After 1200 seconds, the change of vehicle delay per time interval is less significant and the trend continues until clearance time.

Both scenarios show the overall same trends except that the vehicles with higher CV percentage recorded higher delay in several time intervals. At that time interval, CVs became aware of upcoming congestion and changed their speeds and lane choices accordingly. The finding suggests that the CVs slowed the entire traffic stream during some time intervals is likely due to their speed reduction and lane choice in response to downstream congestion. The CVs lane-changing caused some levels of slowdown within the network. This slowdown likely affected other vehicles, causing slower albeit steadier traffic operation compared to the low-CV scenarios. The fluctuation during the entire simulation is the result of frequent deceleration and multiple stops caused by traffic congestion.

Figure 6.7 shows the average total vehicle delay of different pathways under clear and snow winter weather scenarios. For both dry and snow scenarios, the total vehicle delay declines when increasing market penetration level of CV, and vice versa.



(a) dry

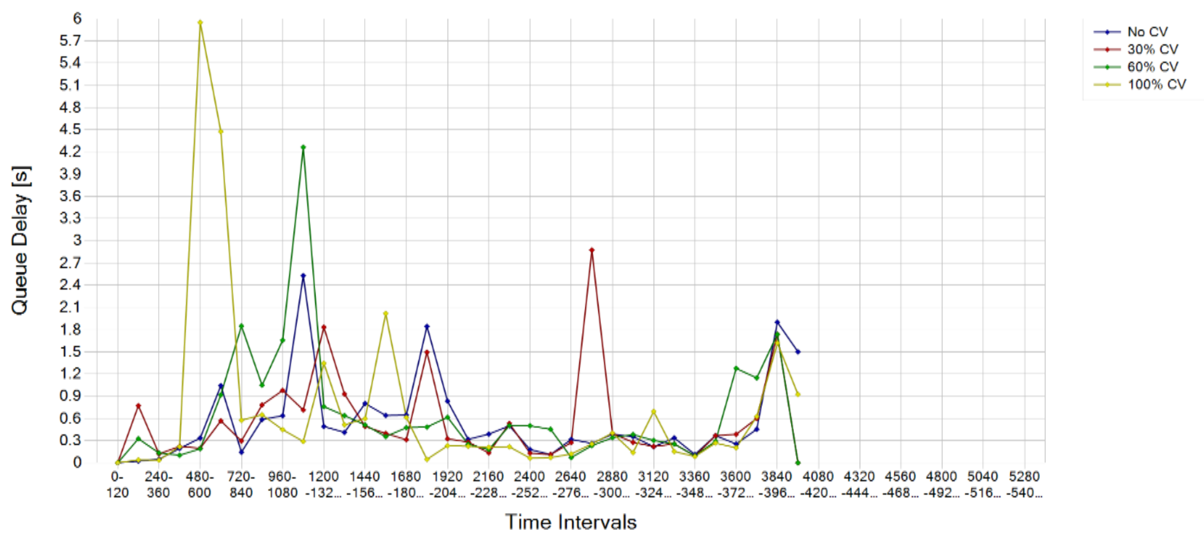


(b) snow

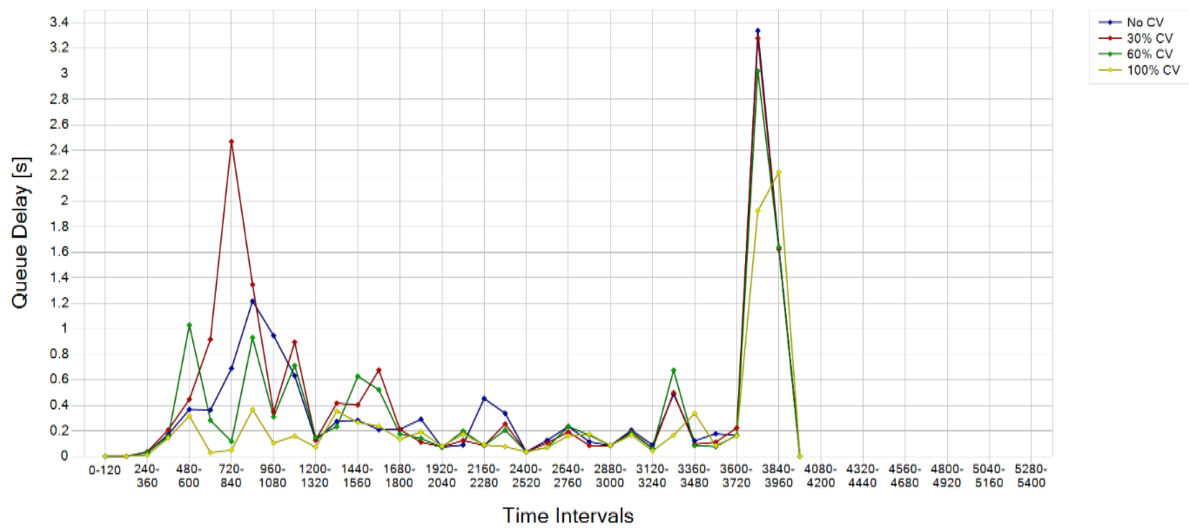
Figure 6.7 Vehicle Total Delay for Different Paths

6.5.2 **Queue Delay Analysis**

Queue delay analysis was conducted for the I-5 north bound pathway under dry and snow weather, respectively. Figure 6.8 indicates the queue delay distribution with different time intervals of the I-5 north bound pathway under dry and snow winter weather scenarios.



(a) dry



(b) snow

Figure 6.8 Vehicle Total Delay for Midway I-5 north bound

It shows that the trend lines under each scenario overlap during warm-up and evacuation periods when normal background traffic and evacuation traffic populate the simulated road network, as expected. For both dry and snow scenarios, the queue delay declines with the increase of market penetration level of CV, and vice versa.

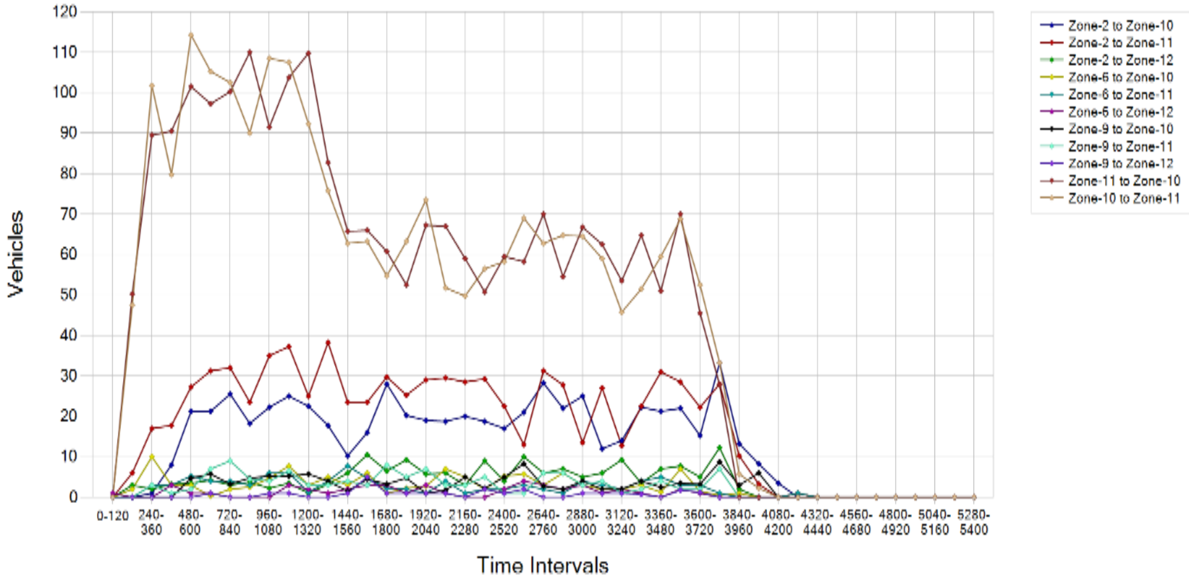
The fluctuation during the entire simulation is the result of frequent deceleration and multiple stops caused by traffic congestion. From simulation start to 1200 seconds, the overall queue delay was larger than that of the afterwards simulation. It indicates that the background traffic experienced more delay than evacuation traffic. After 1200 seconds, the change of queue delay per time interval was less significant and the trend continued until clearance time.

Both scenarios show the overall same trends except that the vehicles with higher CV percentages recorded higher queue delays in the first several time intervals under dry weather condition. In this case, CVs became aware of upcoming congestion and changed their speeds and lane choices accordingly. The speed reduction and lane choice of CVs in response to downstream congestion are likely to lead to the slowdown of the traffic stream during some time intervals. The CVs lane-changing caused some levels of slowdown within the entire network. This slowdown consequently affected other vehicles, including both conventional vehicles and CVs.

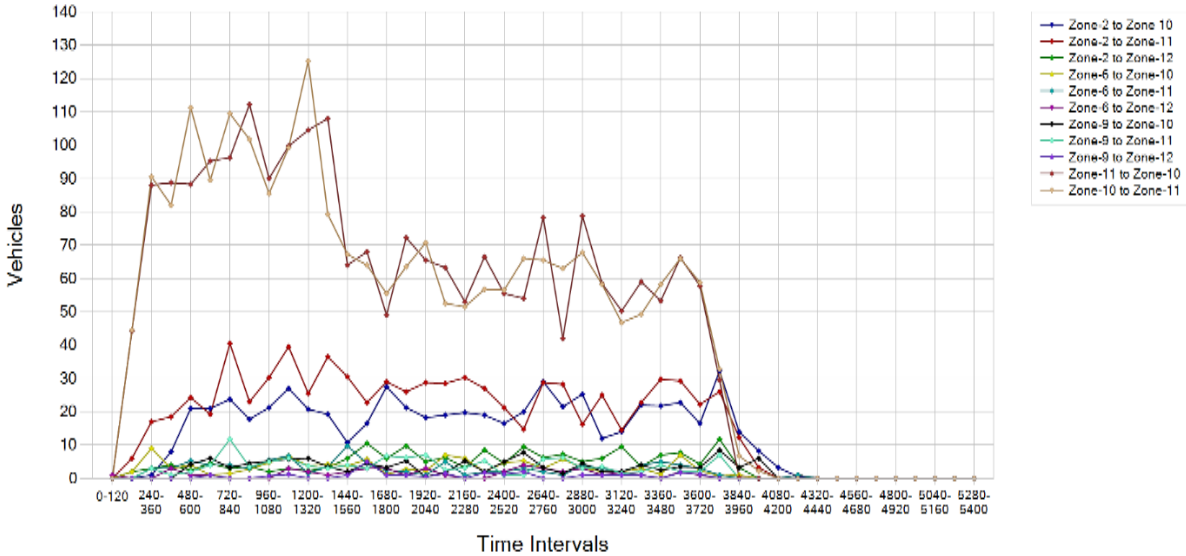
6.5.3 **Clearance Time Analysis**

The vehicle count data was recorded during simulation and was used to determine clearance time of each route and each detector. Evacuation was considered complete when vehicle volume dropped to zero. Clearance time was obtained for all pathways and specific measurement detectors in the network under dry and snow weather, respectively. The following line charts show the volume against time on all evacuation routes and detector locations.

Figure 6.9 indicates the change of vehicles for each pathway by different time intervals under dry and snow winter weather scenarios.



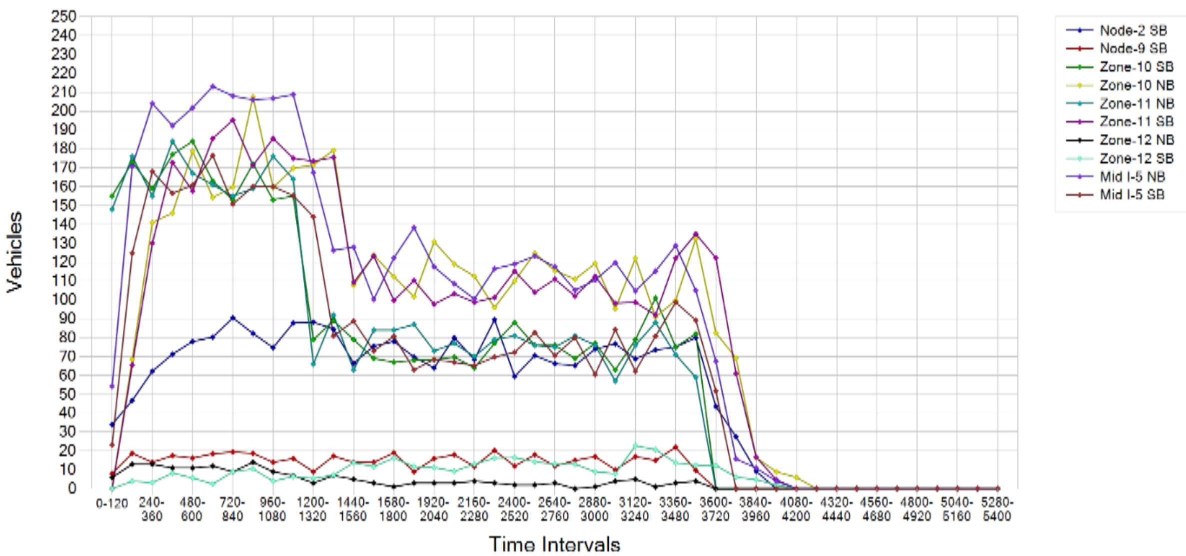
(a) dry



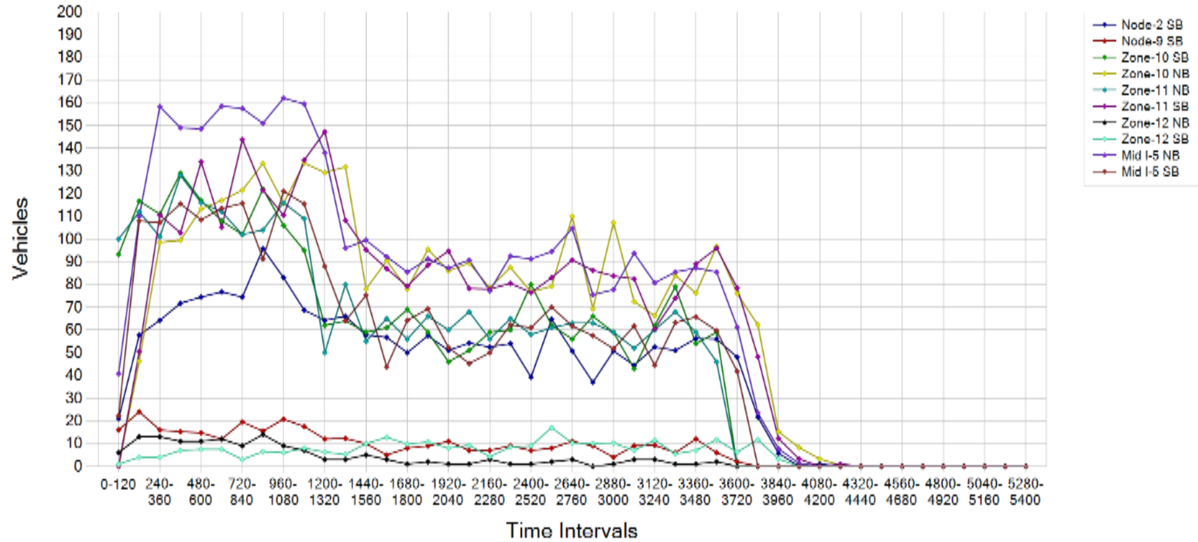
(b) snow

Figure 6.9 Clearance Time of Different Paths

Figure 6.10 shows the change of vehicles for each measurement detector by different time intervals under dry and snow winter weather scenarios.



(a) dry



(b) snow

Figure 610 Clearance Time of Different Measurement Detectors

The road network condition during the evacuation can be easily determined from the above charts. All the routes cleared up prior to simulation end (5400 seconds). The clearance time ranges from 3720 to 4320 seconds for both dry and snow scenarios. The double directions of freeway I-5 (routes between zone 10 and zone 11 in figure 6.9, Mid I-5 NB & SB in figure 6.10) served as two evacuation destinations and facilitated the majority of evacuation traffic from other communities.

The I-5 freeway segment accounted for the greatest traffic demand of evacuating vehicles. Figure 6.9 demonstrates that the evacuation route of I-5 south bound experienced peak values of 115 vehicles in 480-600 seconds under dry weather and 125 vehicles in 1200-1320 seconds under snow weather. Figure 6.10 indicates that the mid-point of I-5 freeway north bound experienced peak values of 215 vehicles in 600-720 seconds under dry weather and 160 vehicles in 960-1080 seconds under snow weather. Heavy congestion was also observed on roads that experienced a sudden peak in on-ramp, off-ramp, and weaving areas. This is potentially the reason for the fluctuating trend.

6.6 Summary

This chapter has described an integrated model to account for the effects of both winter weather and CVs on emergency evacuation, using the Dynamic Traffic Assignment to model the route choice behavior of drivers. For the chosen road network, the O-D matrices and model convergence were discussed, followed by the analysis of evacuation performance in terms of vehicle delay, queue delay and clearance time.

Chapter 7. Conclusion

7.1 Key Findings

An appropriate WSDOT highway corridor close to a metropolitan area was selected and the relevant data were collected. The characteristics of the transportation model in winter weather were identified. Driving behavior sensitivity analysis was carried out. Model parameters were calibrated and validated and the calibration results of desired speed distribution and driving behavior were obtained. Subsequently, the impact of varying CV Market Penetration (MP) levels on travel time was investigated with Intelligent Driver Model (IDM) and Platoon Model (PLM) function. The traffic simulation has revealed that increasing CV utilization rate would enhance traffic mobility.

An integrated model was then developed that incorporates the effects of winter weather and CVs into the evacuation routing simulation. Traffic simulations were then conducted to examine the synergistic effects of winter weather and CV penetration on emergency evacuation. Dynamic Traffic Assignment (DTA) was applied to simulate the effects of different levels of CV on evacuation clearance time under a hypothetical earthquake scenario.

Two scenarios of winter weather (no snow and snow) and four scenarios of CVs (no CV, 30% CV, 60% CV and 100% CV) were compared to identify the impact of market penetration level of CV technology on the evacuation performance of a chosen road network under winter weather. The average vehicle delay declines with the increase of the market penetration level of CVs, and vice versa. The trend lines under each scenario overlap during warm-up and evacuation periods as expected. Both scenarios show the overall same trends except that the vehicles with a higher CV percentage recorded higher delays in several time intervals in which they became aware of upcoming congestion and changed their speeds and lane choices accordingly. The speed reduction and lane choice of CVs in response to downstream congestions are likely to lead to the slowdown of the traffic stream during some time intervals. The CVs lane-changing caused some levels of slowdown within the entire network. This slowdown consequently affected other vehicles, including both conventional vehicles and CVs. The fluctuation during the entire simulation is the result of frequent deceleration and multiple stops caused by traffic congestion.

The vehicle count data was recorded during simulation and was used to determine clearance time of each route and each detector. Evacuation was considered complete when vehicle volume dropped to zero. Clearance time was obtained for all pathways and specific measurement detectors in the network under dry and snow weather, respectively. The double directions of freeway I-5 facilitated the majority of evacuation traffic from other communities and thus accounted for the greatest traffic demand of evacuating vehicles.

7.2 Direction for Future Research

In the next phase of this project, one should further enhance the model developed in Phase I and incorporate the effects of CV technologies on WRM operations and adaptive/connected traffic signals, and possibly integrate real-time data into evacuation operations. We will seek support from stakeholders such as the state DOTs to develop a coherent and comprehensive traffic simulation model that is customized to the needs of emergency evacuation for the Pacific Northwest. This scope is directly relevant to the CAMMSE theme of “developing data modeling and analytical tools to optimize passenger and freight movements” as well as that of “Smart Cities”.

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