EXPLORING WEATHER-RELATED CONNECTED VEHICLE APPLICATIONS FOR IMPROVED WINTER TRAVEL IN THE PACIFIC NORTHWEST

FINAL PROJECT REPORT

by

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16. Abstract

The objectives of this project were to investigate how connected vehicle (CV) data could be integrated with existing infrastructure data, and how the integrated data could be utilized to improve decision-making for highway operations and to enhance traveler information during inclement winter weather events. Because of some unforeseen difficulties, this PacTrans project was unable to pilot test the CV solution on DOT vehicles or during winter weather. Instead, the project laid the foundation to address the innovative use of CV technologies for improving winter travel mobility. We started from a literature review and a national survey of transportation agencies to understand \ current practices and the needs of using CVs for improving winter travel, followed by the development of a vision (e.g., operational scenarios). Then we focused on the development of a road surface friction analysis and visualization platform. This methodology was based on time-aware recurrent gated neural networks. The RCM-411 friction sensing data were selected as the model input. Finally, we simulated the operational enhancement of highways through the deployment of vehicle communication technology during inclement weather by using a modified Intelligent Driver Model (IDM) to incorporate the effects of CVs in a mixed traffic scenario. For high market penetration of CVs (60 percent), the model showed less speed perturbation along the roadway, leading to stable traffic movement.

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SI* (Modern Metric) Conversion Factors

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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Acknowledgments

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List of Abbreviations

ABMS	Agent-based modeling and simulation
ABS	Automatic braking system
API	Application programming interface
AVL	Automatic vehicle
CA	Cellular automaton
CAN-Bus	Controller area network bus
CCTV	Closed-circuit television
CAV	Connected autonomous vehicle
CF	Cooperative following
CV	Connected vehicle
C-V2X	Cellular vehicle to everything
DMS	Dynamic message sign
DOT	Department of transportation
DRIVE Net	Digital Roadway Interactive Visualization and Evaluation Network
DSRC	Dedicated short-range communications
ESS	Environmental sensor station
GPRS	General Packet Radio Service
GPS	Global Positioning System
HCM	Highway Capacity Manual
HV	Human-operated vehicle
IDM	Intelligent Driver Model
IMO	Integrating Mobile Observations
ITS	Intelligent transportation systems
LOS	Level of service
LSTM	Long-short-term memory
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MAS	Multi-agent system
MDSS	Maintenance decision support system
MP	Market penetration

MSE	Mean square error
NWS	National Weather Service
OBU	On-board unit
RBF	Radial basis function
RCM	Road Condition Monitor
RF	Random forest
RNN	Recurrent neural network
RWIS	Road weather information station/system
SVR	Support vector regression
TSM	Two-state, safe-speed model
V2I	Vehicle to infrastructure
V2V	Vehicle to vehicle
VDT	Vehicle data translator
VMS	Variable message sign
WITS	Washington Incident Tracking System
WRM	Winter road maintenance

Executive Summary

Winter weather poses negative impacts on the safety, mobility, and economic productivity of surface transportation systems. Snow and ice on roads reduce friction and visibility, contribute to accidents and injuries, and decrease traffic speed and roadway capacity. Connected vehicle (CV) technology is well-suited to address multiple safety and mobility impacts of winter weather. Accurate and real-time road weather information is essential for road maintenance decision-making and a to provide high level of service to road users.

The objectives of this project were to investigate how CV data could be integrated with data from road weather information system (RWIS) stations and other existing infrastructure, and how the integrated data could be utilized to improve decision-making for highway operations and to enhance traveler information during inclement winter weather events. Note that during the course of the project, some unforeseen difficulties occurred, preventing the research team from pilot testing the CV solution on department of transportation (DOT) vehicles or during winter weather. Instead, the research team focused on the development of a road surface friction analysis and visualization platform. This PacTrans project laid the foundation to address the innovative use of CV technologies to improve winter travel mobility. Future phases of this project may expand the scope into more road weather-related mobility applications of CV technologies.

Part I of this project focused on understanding the current practices and needs related to using CV technology to improve winter travel, followed by the development of a vision. A nationwide survey of maintenance departments conducted as part of this work assessed the application of CV technologies to improve safety and mobility during the winter. All respondents had positive attitudes toward the potential of using CV technology to improve winter travel, but they also had some concerns about system performance in poor weather, vehicle and system security, and increased driver distraction. This work presents the potential application of CV technology under operational scenarios to improve winter travel. Maintenance departments would use mobile road weather-related, route-specific data to determine maintenance strategies in advance; subsequently, they would provide the travel alerts and advisories to road users.

Part II of this project focused on the development of a road surface friction analysis and visualization platform. This methodology was based on time-aware, recurrent, gated neural networks. RCM-411 friction sensing data were selected as the model input. To evaluate the

predictive effectiveness of the proposed method, several baseline prediction and imputation models were employed for comparison purposes. In addition to evaluating prediction performance, the impact of missing rates, learning efficiency, and learned decay rates were also analyzed. This study was meant to improve the effectiveness of prediction models in handling missing values to mitigate the impacts of road surface conditions on road traffic safety and mobility. The models could also be used to visualize road surface friction on the DRIVE Net platform to show results intuitively.

Part III of this project focused on simulating operational enhancements to highways through the deployment of vehicle communication technology during inclement weather. While many studies have already looked at ways to mitigate congestion during adverse weather, no study has yet demonstrated how the CV technology can be applied to better manage traffic network during such an event. The potential traffic performance benefits associated with the emergence of vehicle communication technology, and the lack of tools to evaluate those benefits, were the impetus behind this project. The Oregon State University team developed a modified Intelligent Driver Model (IDM) to incorporate the effects of CVs in a mixed traffic scenario. The developed methodology was implemented into a simulation framework, and detailed analysis was conducted to evaluate how CV data can improve vehicle movement during adverse weather. Results showed that a high market penetration of CV (60 percent) produced less speed perturbation along the roadway, leading to stable traffic movement.

Part I. Background, Current Practices, and Vision

1. Background

Winter weather negatively affects the safety, mobility, and economic productivity of road transportation. Snow and ice on roads reduce friction and visibility, leading to accidents, injuries, and death. Nationally, snowy, slushy, or icy pavement conditions are present in about 27 percent of weather-related crashes, or over 300,000 crashes annually (FHWA 2018a). Many studies have demonstrated increased accidents and fatalities during winter in general and icy/snowy conditions in particular, with some noting increased severity at the beginning of winter (Andersson 2010, Saha 2016, Dey 2015). However, drivers actually tend to drive slower during winter weather, reducing crash severity, and become more focused and conservative during the winter season (Pisano 2008). The consequences of slower, safer driving during winter weather are reduced mobility and economic impacts. The mobility impacts of winter weather on the road transportation system include decreased traffic speed, flow, volume, and capacity and increased car-following distances, travel time, and start-up delays (Pisano 2017, Strong 2010). The economic impacts of winter weather range from indirect costs associated with crashes, traveler delays, and the environmental impacts of winter road maintenance, to the direct costs of plowing, material applications, and consequent corrosion impacts to infrastructure and vehicles.

Winter road maintenance activities are necessary and can significantly reduce the deleterious impacts of winter weather. One major benefit item associated with winter road maintenance operations is improved mobility, which has been the subject of many studies (Shahdah 2009, Shahdah 2010). Another major benefit associated with winter road maintenance operations is safety of the traveling public. For Washington state, “crash frequency in the presence of snow was five times higher than the rate under clear conditions.” A comparison of crash rates between winter and summer revealed that January had 12 times as many accidents as July (Goodwin 2003). In recent years, there has been a transition from mostly deicing to anti-icing wherever suitable (O’Keefe 2005, Cui 2015). As a proactive approach, anti-icing hinges on reliable weather forecasts and nowcasts for its success. Therefore, accurate and timely road weather information is essential for winter road maintenance.

Road weather information system (RWIS) stations at fixed locations and manual patrolling are widely adopted by departments of transportation (DOTs) for understanding current weather conditions and for forecasting winter weather and making pavement predictions for optimal winter road maintenance activities (plowing, deicing, anti-icing, etc.). However, it must be noted that pointwise RWIS data are inadequate for predicting surface conditions along the road network (Drobot 2010, Shi 2007). Therefore, there is an interest in "filling in the gaps" between RWIS stations by using mobile sensors mounted onto patrol vehicles and plows (Nordin 2013).

The broad availability of road weather data from an immense fleet of mobile sources could vastly improve the ability to detect and forecast road weather and pavement conditions (Hill 2013). Connected vehicle (CV) technologies can provide connectivity and communication between data from mobile sensors such as vehicle probes and data from fixed RWIS stations (Dey 2015). The combination of vehicle probe data and RWIS data may have the potential to provide meteorological and transportation agencies with a highly detailed temporal and spatial data set of road and atmospheric conditions (Fehr 2015). Road weather data collection could be improved by utilizing weather sensors in CVs and by transferring collected data through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, which has been demonstrated in the European WiSafeCar project (Sukuvaara 2012). The Connected Vehicle Reference Implementation Architecture (CVRIA) developed by FHWA (Fehr 2015) has defined how CVs will contribute to road weather management data collection and information dissemination. The enhanced road weather condition information could be communicated to the general public to allow them to slow down, choose a different route, or stay home in light of inclement weather.

In this context, there is an urgent need to identify and demonstrate the operational scenarios in which CV technology can be employed to improve winter road surface condition monitoring and traveler information and to enhance the decision-making of winter maintenance operations.

The objectives of this project were to investigate how CV data could be integrated with data from RWIS stations and other existing infrastructure, and how the integrated data could be utilized to improve decision-making for highway operations and to enhance traveler information during inclement winter weather events. The main approach for this project was formulated as follows:

1. Actively engage regional agencies and industry partners/stakeholders to develop operational scenarios for CVs to improve winter road operations and traveler information service;

2. Demonstrate the proof-of-concept of selected operational solutions at the UW test-bed;
3. Develop the CV solution for winter road surface condition monitoring and traveler information;
4. Pilot test the CV solution on selected road segments in the Pacific Northwest, conduct preliminary analyses, and make recommendations for implementation.

Note that during the course of the project, some unforeseen difficulties occurred, preventing the research team from pilot testing the CV solution on DOT vehicles or during winter weather. Instead, the research team focused on the development of a road surface friction analysis and visualization platform. This PacTrans project laid the foundation to address the innovative use of CV technologies to improve winter travel mobility. Future phases of this project may expand the scope into more road weather-related mobility applications of CV technologies.

2. A Review of Relevant Literature

Numerous vehicle-based technologies have been developed to achieve improvements in winter maintenance efficiency, mobility, and safety (Ye 2012). Among them, automatic vehicle location (AVL) is conceptually most integrated with other technologies, especially surface temperature sensors, freezing point and ice-presence detection systems, snowplow blade position sensors, and application rate sensors. Smart snowplows featuring AVL and other sensors have been increasingly used as mobile data collection platforms for enhanced winter road maintenance (WRM) operations. If these sensors are working properly, then both vehicle operators and maintenance managers can have more precise information about current roadway conditions, resulting in better winter maintenance decisions.

Integration is also a key consideration for the maintenance decision support system (MDSS). MDSS is a software application that integrates information from a variety of sources, such as RWIS and weather service forecasts, to provide recommendations for road treatment. With many mobile data collection technologies being introduced and integrated into an AVL platform (Ye 2009), MDSS helps improve winter maintenance decisions, and its benefits significantly outweigh its costs.

Recent advances in mobile sensing and data collection technologies have provided new opportunities for road weather management strategies such as Weather-Savvy Roads (FHWA 2019a). The Weather-Savvy Roads program has been developed by the FHWA through round four of Every Day Counts (EDC-4) and provides two distinct strategies that allow state and local agencies to be proactive in managing the surface transportation system in advance of and during adverse weather events. The Pathfinder and Integrating Mobile Observations (IMO) strategies can help agencies manage road systems and inform travelers during heavy rain, snow, and other weather events, all of which can have noteworthy impacts on the safety, mobility, and productivity of road users (FHWA 2019b).

CV data could be utilized to enhance existing intelligent transportation system (ITS) strategies by supplementing or complementing current roadway sensing components, thereby improving the effectiveness of the system operations to react to changing road weather conditions.

A summary of existing research of CV technology applications for winter travel is shown in table 2-1.

Table 2-1. Summary of relevant CV technology for winter travel

Categories	CV Application	Results	Ref
Weather and road condition assessment	Slippery road condition assessment	Proposed data from weather stations and friction data from fleets of connected cars can be used to predict the slippery road conditions.	(Panahandeh 2017)
	Road pavement condition estimation	Proposed using crowdsourcing with numerous probe vehicles and sensors installed on vehicles and smartphones for collecting pavement condition information.	(Dennis 2014)
	Slippery road detection and evaluation	Proposed Droid smartphone app (DataProbe) to collect data to estimate slippery road condition.	(Robinson 2012)
	Winter road condition monitoring	Demonstrated a smart phone based system was capable of providing reliable results in comparison with the current method of patrol reporting for route-level monitoring of winter road conditions.	(Linton 2015)
	Road surface condition assessment	Demonstrated vehicle-based image data combined with RWIS data and machine-learning models to improve accuracy of smartphone-based road surface condition	(Linton 2016)
	Road condition imagery	Iowa DOT uses plow dashboard-mounted mobile phones and an app to take images of road surface and provides images to maintenance managers and the general public on a web service (Track a Plow).	(Hirt 2017)
	Road weather and condition	The FHWA Every Day Counts program Integrating Mobile Observations (IMO) is working with 23 state DOTs. IMO involves collecting weather and road condition data from government fleet vehicles, such as snowplows. The focus is on supplemental data from ancillary sensors installed on the vehicles, such as pavement temperature sensors, and includes native vehicle data such as windshield wiper status and anti-lock brake or traction control system activation. The data provides maintenance managers with an extremely detailed view of the weather and road conditions along the road network.	(Pisano 2017)
Road weather advisories	Integrating Snowplow Camera Images into	MnDOT installed network video dash cameras and ceiling-mounted cameras on 226 snowplows. The cameras were integrated with the onboard MDC/AVL equipment and	(Hirt 2017)

Categories	CV Application	Results	Ref
for Travelers	Traveler Information System	automatically captured snapshots of road conditions during plowing. Images were sent to MnDOT's server and then imported in near-real-time to the MnDOT travel information website and MnDOT 511 mobile app for up-to-the-minute use by the traveling public.	
	Using Clarus Data for Disseminating Winter Road Weather Advisories and Alerts	New York State 511 system combines the road weather information from Clarus and other weather data sources to generate various weather alerts pertaining to snow, ice, winds, and other severe weather conditions, and posts these alerts on the 511NY website.	(Alfelor 2012)
		Western States One-Stop Shop project creates a user-friendly website that integrates and displays weather and road condition information for a four-state region from Clarus, CCTV, National Weather Service (NWS) and other data.	
	The Road Weather Management Program	IntelliDrive's Dynamic Mobility Applications capitalize on vehicle-infrastructure connectivity by using data from vehicle probes and other real-time data sources, and enable TMCs to manage mobility between and across modes more effectively while providing information to travelers to support dynamic decision making.	(Alfelor 2011)
CV technology	Rural Variable Speed Limit Corridors	A research vehicle was equipped with connected vehicle technology and vehicle data were collected during storm events along a rural VSL corridor. Also tested NCAR's Pikalert system and suitability of CV data for VSL decision-making algorithms.	(Hammit 2015)
	WYDOT CV Pilot Deployment Program	The Wyoming pilot will specifically use V2V and V2I technology to reduce the impact of adverse weather on truck travel in the I-80 corridor in Wyoming.	(Gopalakrishna 2015)
	Weather Responsive Traffic Management	FHWA, Michigan DOT, Minnesota DOT, and Nevada DOT joined to work under the Integrated Mobile Observations (IMO) project and develop an architecture that provides efficient Weather Responsive Traffic Management (WRTM) strategies and advanced data collection and analysis.	(Belzowski 2016)

Although many researchers and transportation communities have worked to explore how to capitalize on CV technologies to enhance safety and mobility, few studies have been specifically geared toward improved winter travel. The Wyoming Department of Transportation (WYDOT) CV Pilot deployment program presented concept of operations for seven applications focusing on travel alerts and advisories regarding inclement weather, emergency situations, and work zones, but not referring to winter travel such as winter road maintenance (Gopalakrishna 2015). Winter-specific topic areas worth noting are winter road maintenance and road weather advisories/warnings for travelers. Hence, this work focused on those two significant aspects.

2.1. National Survey of Road Maintenance Departments

This work entailed the design of a survey to gather information from winter roadway maintenance professionals on their relevant experience and insights. The objective of the survey was to explore the use of CV technology applications for improved winter travel, including CV application situations, needs, and potential uses for winter travel. The survey questionnaire was distributed online to several state DOTs and maintenance departments. Meanwhile, the research team brought this survey to attendees of the 2018 Pacific Northwest Snow Fighters Conference. In total, the research team collected 51 effective responses, including 30 paper-based survey and 21 online responses. The respondents were basically distributed over the entire Northern areas (figure 2-1).

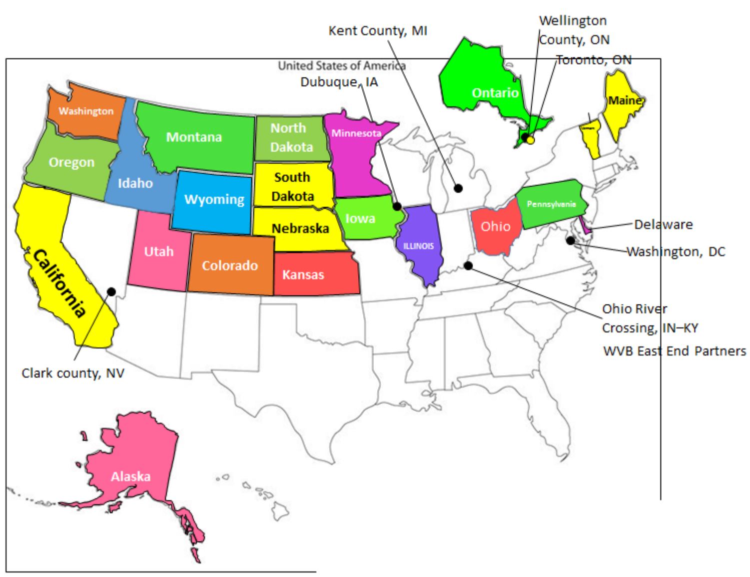


Figure 2-1. Distribution of survey respondents

Agency website, 511, and dynamic message signs were most used by these state and local DOTs to provide road weather information for public. These state and local DOTs mainly used road a weather information system (RWIS) (88.24 percent) and manual patrols (84.31 percent) to collect road weather data. A maintenance decision support system (MDSS) was rarely adopted (29.41 percent) (figure 2-2). They reported that most road weather data could be gathered easily by present methods except a few road weather parameters such as friction and solar radiation. In addition, the majority of respondents thought they could gather these road weather data in near real time by RWIS and cameras. However, the present methods have many limitations, and cost is the greatest problem. Furthermore, for RWIS and fixed cameras, spatial resolution is also a great deficiency. For manual patrols, time and labor create high barriers.

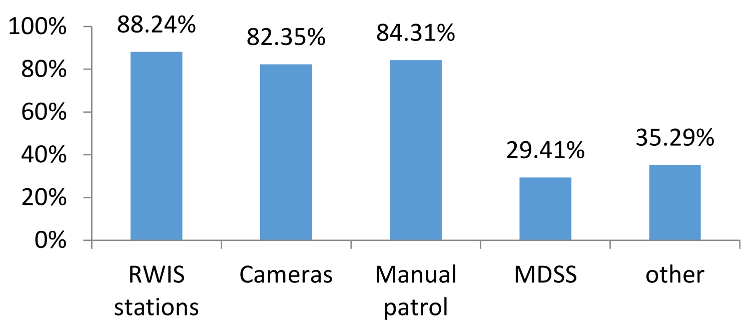


Figure 2-2. Use of data collection methods

Most state DOTs reporting having snowplows that had automatic vehicle location (AVL) and GPS. Basically, the snowplow could report location and monitor air temperature and surface temperature. Few snowplows could report pavement condition, and only one state (Iowa DOT) reported having snowplows with dash cameras mounted on them. The majority of respondents thought the data from snowplows were useful for improving winter road maintenance and travel information. However, the integration of smart snowplow data with RWIS data was not easy.

Although most state DOTs didn't yet have infrastructure to collect data from CVs, they had very positive attitudes toward CV applications for enhancing winter maintenance operations and traveler information (figure 2-3) They thought that the combination of RWIS data and personal CV data or mobile data collected by plows would be beneficial for improving winter maintenance strategies and travel information, particularly the spatial resolution of near real-time road condition reporting and traveler information advisory (figure 2-4). Nevertheless, they thought it was difficult to integrate CV data into RWIS (figure 2-5). Moreover, they were still concerned about the application of CV technologies for winter road maintenance and traveler information. The largest cause of concern was system performance in poor weather (44.19 percent very concerned and 30.23 percent moderately concerned). Vehicle security (from hackers) (30.23 percent very concerned and 32.56 percent moderately concerned) and system security (from hackers) (31.82 percent very concerned and 34.09 percent moderately concerned) were also notable. Also worrying were increased distraction and legal liabilities for drivers, as well as drivers' overreliance on technology (figure 2-6).

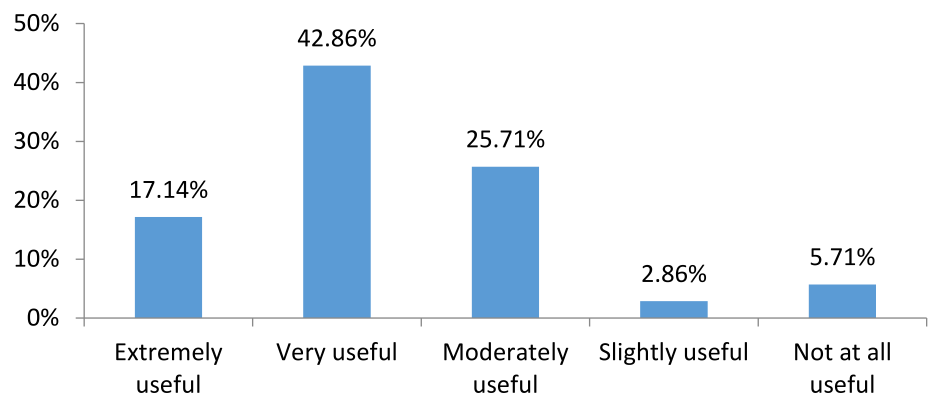


Figure 2-3. Degree of expected usefulness of CV data

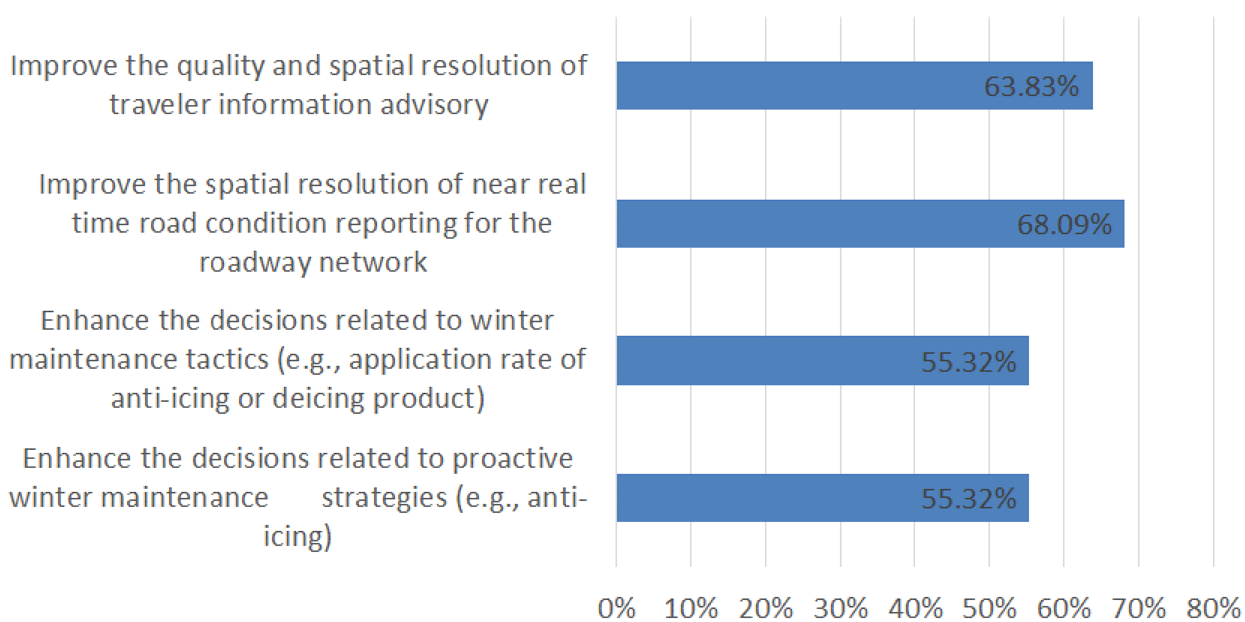


Figure 2-4. The beneficial scenarios of supplemental CV data

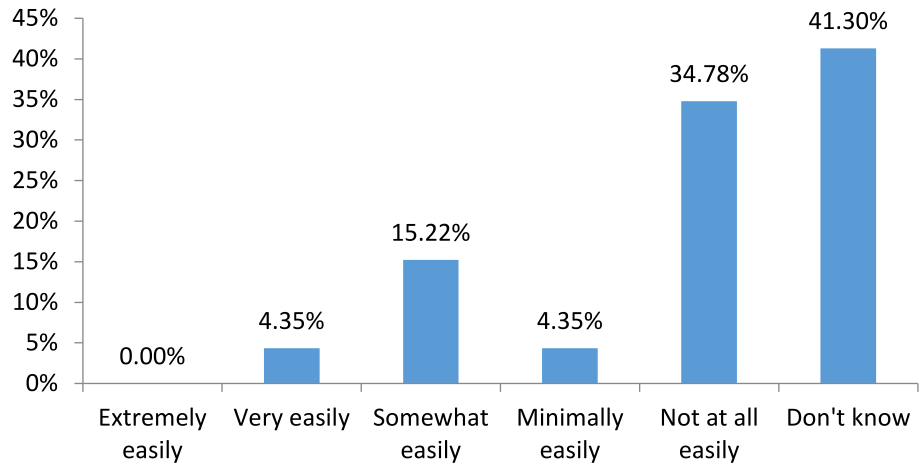


Figure 2-5. Degree of ease in integrating CV data into RWIS

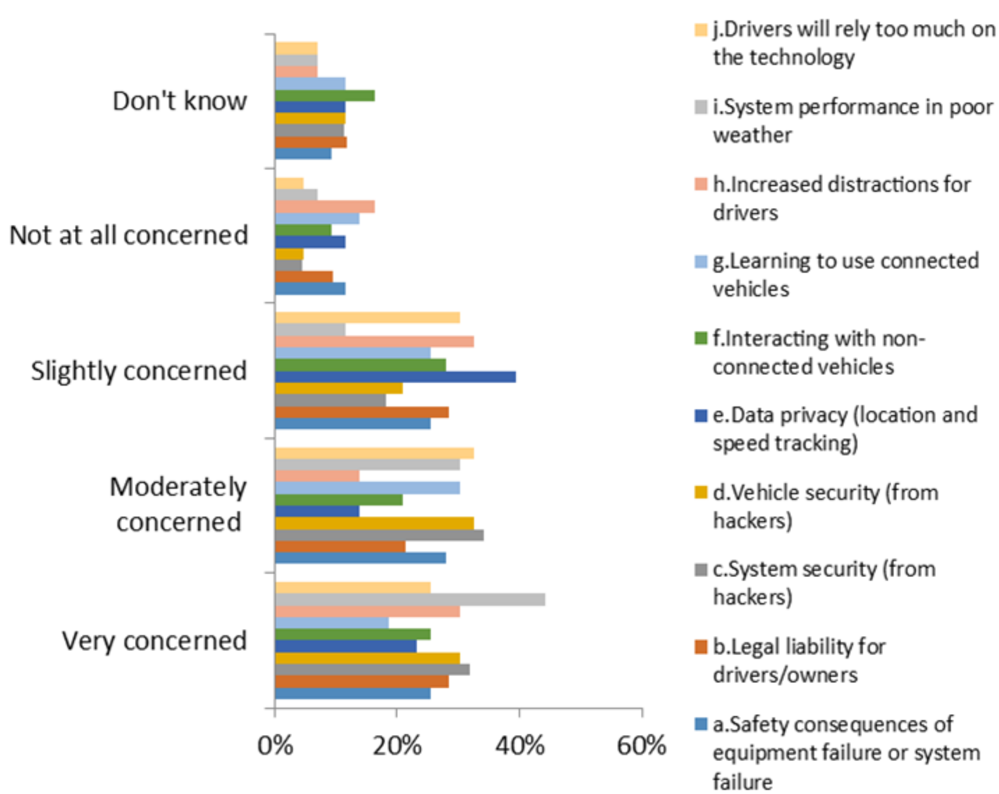


Figure 2-6. Concerns about CV application

Finally, the respondents made free comments about challenges related to and suggestions for the application of CV technologies to winter road maintenance and traveler information. They pointed out that the application of CV technologies for improving winter travel had lots of potential but suggested that researchers should focus on CV data collection, integration and quality, and communication, as well as applications in rural road networks when CV technologies are implemented in actual road network environments.

3. A Vision of CV Application for Improving Winter Travel

3.1. Description of the Concept for CV Application

State and local transportation departments are required to process huge amounts of of road weather information and to handle multiple tasks when facing winter weather events. Whether for maintenance decision-making or traveler information distribution, gathering accurate and real-time road weather data is the key. RWISs are extremely useful for collecting road weather data, including pavement temperature, pavement condition, wind speed, precipitation amount, and more. However, fixed RWISs only gather point-specific road weather data. Route-specified road weather data, which are more important for identifying road weather conditions on a network, are hardly collected.

The application of CV technologies for improving winter travel concept will change this situation by providing expanded road weather data through sensors available on connected vehicles. Mobile road weather-related data and traffic flow data will be collected from CV technology-enabled snowplows, maintenance trucks, city fleet vehicles, and private vehicles through CAN-Bus, AVL, and sensors mounted on the vehicles. These route-specific data will be transmitted to a remote data analytics center through various wireless communication technologies. They will then be combined with point data obtained from an RWIS and traffic cameras. After data processing and analysis, real-time road segment weather information will become available to the road maintenance department and traffic management center. Advanced maintenance strategies, such as what material to put on which roads and how much of it, will be obtained by the maintenance decision-making support system on the basis of the route-specified road weather information. Such strategies will be communicated to snowplow operators and drivers of maintenance trucks through existing wireless networks, e.g., dedicated short-range communication (DSRC) or cellular networks. Meanwhile, road segment weather information will be aggregated and transferred to the traffic management center, which will further process those data using advanced algorithms/models and then generate and transmit short-term travel alerts and medium/long-term travel advisories to road users through a smartphone app, websites, and social media. These alerts and advisories will enable road users to select better trip behavior (trip times, trip modes, trip routes, etc.), which would be impossible without the proposed CV-based solution. Figure 3-1 provides a schematic of how the application could operate.

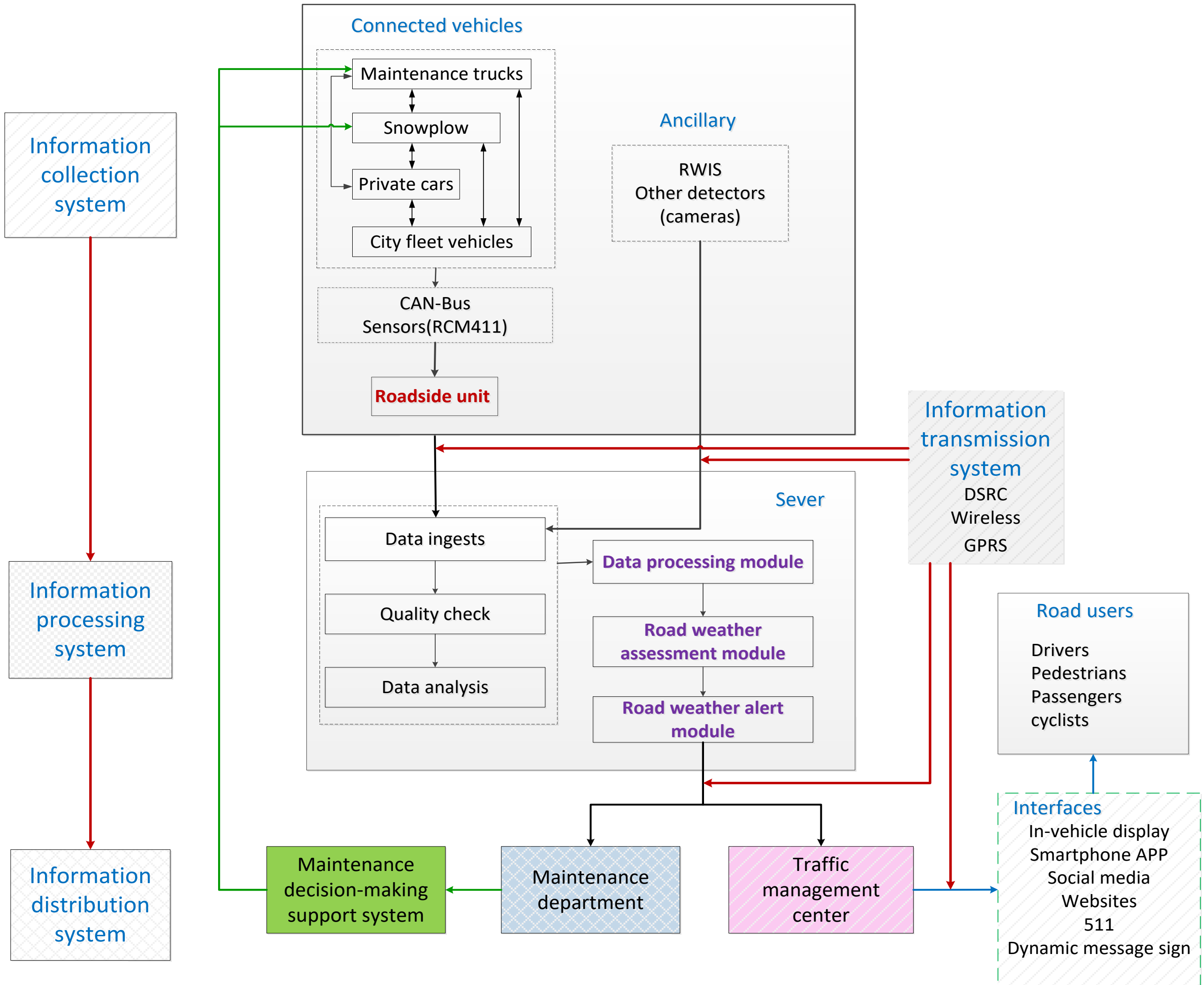


Figure 3-1. Schematic of CV application in winter travel

3.2. <u>CV Application Subsystems</u>

The proposed CV-based solution to improving winter travel requires various subsystems, i.e., data collection, data processing (and aggregation), information generation, data transmission, and user interfaces, as shown in figure 3-1.

3.2.1. Information Collection System

The information collection subsystem includes all the necessary hardware and/or software to collect winter travel-related information. It consists of the connected vehicles, RWIS, other detection equipment (such as cameras, sensors), and roadside units.

Connected vehicles. The connected vehicles involved in the system are mainly snowplows, maintenance trucks, city fleet vehicles, and voluntary private vehicles that contribute data from their controller area network bus (CAN-Bus), as well as the road weather sensors mounted on them. As the size of raw sensor data tends to be very large, these data need to be pre-processed locally on individual vehicles before they are transmitted (Chen 2019). In fact, the on-board units (OBU) available on connected vehicles can process these data in real time and transmit the processed data to nearby vehicles and/or roadside units (Su 2017). As these vehicles move on public roads, continuous data (or a stream of data) are generated, providing a more comprehensive view of the monitored road segments. The information obtained on connected vehicles can be categorized into two groups:

- Data collected from CAN-Bus and GPS/AVL: average vehicle speeds, location, automated braking system (ABS) activation events, vehicle stability, traction control activation events, windshield wiper blade speed, headlight status and other basic safe messages.
- Data collected by external road weather sensors mounted on vehicles: road surface condition, coefficient of friction, water layer thickness, and surface temperature.

RWIS. Road weather information systems are an aggregation of advanced sensors and communication technologies designed to gather weather information (Kwon 2014). They are mainly mounted along a road at a fixed location, and they only obtain road weather data for those particular points, including air temperature, barometric pressure, dew point, pavement temperature, surface condition, wind speed, and precipitation.

Other equipment. Other equipment (e.g., cameras and sensors) that is deployed on the road for different purposes can be leveraged to observe road weather conditions or traffic conditions at the location where the equipment is installed. Through advanced image processing algorithms, it is possible to derive the current weather condition. By counting the number of vehicles passing through a certain location, the current traffic volume, speed, and condition can be estimated as well.

Roadside units. Roadside units are deployed along roads to facilitate the wireless communication and data transmission of connected vehicles. These include infrastructure that can receive data from and transmit them to connected vehicles, other infrastructure, and servers by using dedicated short range communication. Roadside units are also a good candidate for implementing data aggregation and data processing algorithms (Chen 2019), which eliminate the burden of transmitting all data to a remote data center. As data are processed on roadside units that are close to the data generator, the system's latency is significantly reduced. In addition, less network bandwidth is required, and better data privacy protection is offered.

3.2.2. Information Processing System

The information processing subsystem is a unit that accepts data from connected vehicles, RWIS, and other detectors; analyzes and processes data; and then outputs route-specified road weather information to road maintenance departments and traffic management centers. Data cleansing and data aggregation are carried out on this unit. It includes the following modules.

Road weather data processing module. This module handles mobile data gathered from the CAN-Bus and external sensors on connected vehicles. The data are timestamped, ingested, quality checked, and matched (aggregated) to a road segment using GPS location (Young 2019). As massive amounts of data are processed by this module, efficient data processing and aggregation mechanisms are employed. Data from other sources such as RWIS and other detectors are also aggregated to corresponding road segments.

Road weather risk assessment module. This module uses some algorithms/models to determine the risk of each road segment on the basis of data provided by the road weather data processing module. For example, precipitation is forecasted on the basis of precipitation type, precipitation density, and air temperature, as well as vehicle-based data (wiper blade speed, travel speed, headlight status). Road surface condition is estimated on the basis of precipitation outputs, pavement temperature, surface condition reported from RWIS, and ABS/traction activation information. It can be classified into bare, partly snow covered, and fully snow covered. Visibility is also assessed on the basis of precipitation outputs, humility, headlight status, vehicle speed, and RWIS visibility.

Road weather alert module. This module transforms the outputs generated from the road weather risk assessment module to actual travel alerts or advisories. Particular travelers may be more concerned with the overall road weather condition than conditions of each section of the road. Hence, in this module, the overall road weather condition is obtained to generate an alert or travel advisory for individual travelers.

3.2.3. Information Communication System

Connected vehicle data are communicated to roadside units via DSRC or cellular vehicle-to-everything (C-V2X) (Yang 2010). The data are transferred to data severs through the existing wireless network, e.g., General Packet Radio Service (GPRS).

3.2.4. Information Distribution System

Various user groups can access the travel alerts and advisories through a series of interfaces, such as 511, smartphone apps, websites, in-vehicle displays, dynamic message signs (DMS), and social media. In addition, snowplow operators and drivers of maintenance trucks can receive maintenance strategies through the driver-vehicle interface. Users (or information consumers) can communicate with information providers through a publisher and subscriber mode (Yang 2016). In this system, users select and subscribe their interested topics, e.g., road condition information; the server then automatically pushes newly generated information to corresponding users. As the information is contributed and consumed by different users, trust relationships between vehicles can be established, which facilitate the efficient delivery of more relevant information to users.

3.3. Operation Flow of the CV Application

The operation flows of the CV application for improving winter travel are as follows:

Step 1: Connected vehicles collect road weather data and broadcast those data to other vehicles equipped with-vehicle devices within the V2V communication area and to roadside units by using DSRC. Then the data are transferred to a server.

Step 2: Wireless or wired communications are sent from the RWIS, cameras, and other sensors to the server.

Step 3: Algorithms/models in the server process the data.

Step 4: The server ingests the data, executes a quality check, and generates route-specified road weather information, and then transfers outputs to the traffic management center and road maintenance department.

Step 5: The route-specified road weather information is input to a maintenance decision-making support system to generate optimal winter maintenance strategies on the basis of some forecast algorithms/models. And then, the optimal maintenance strategies are disseminated to an in-vehicle display in snowplow and maintenance trucks. Then the operators of snowplow and maintenance trucks implement the actions.

Step 6: Travel alerts and advisories are generated by some algorithms/models in the traffic management center on the basis of the route-specified road weather information and are distributed to road users such as passengers, drivers, pedestrians and cyclists through an information distribution system.

3.4. Operational Assumptions and Constraints

The effectiveness of this application is based on the availability of CV road weather data. That means that sufficient snowplows, maintenance trucks, city fleet vehicles, and private cars are equipped with sufficient onboard or external equipment. Appropriate roadside units are also required. Additional research is needed to identify the required levels of CV penetration and the appropriate spatial resolution of the roadside units. Finally, this application supposes road maintenance departments and traffic management departments would like to deploy connected vehicle devices and other external sensors into the vehicles.

Server data processing requires additional research to improve algorithm precision. Poor quality data or poorly functioning algorithms will yield inadequate route-specific road weather information and only hinder decision support for road maintenance personnel. As stated, the concept assumes the development of new algorithms to quickly analyze the road weather data to produce short-time travel alerts and medium- and long term advisories for road users. Users can access the advisories and alerts through a variety of means, including public websites, phone hotlines, and smartphone apps.

The development of suitable interfaces will be required to adapt the existing systems. Lack of training and knowledge for various involved personnel will also result in limited use of CV road weather information.

Regarding deployment coverage, an adequately dense network of roadside units with appropriate geographic coverage is required to collect connected vehicle road weather data. This is especially important in areas of complex terrain or where information on short roadway segments is desired.

3.5. Analysis of the Application of CV Technologies for Improving Winter Travel

3.5.1. Benefits

The improvements expected from implementing the proposed CV application mainly focus on the accuracy and timeliness of road weather data from CV technologies in comparison to existing road weather data acquisition methods. The anticipated advantages include the following.

Sharing advanced road weather information with drivers, passengers, pedestrians, and cyclists will enable road users to make better trip plans, such as selecting trip modes, trip times, trip routes, or cancelling trips to improve mobility and safety. A travel survey on winter weather events, organized by the Utah DOT and National Weather Service (NWS), showed that 83 percent of respondents gathered information from multiple sources and 66 percent individuals changed their trip plans, such as changing trip time (62 percent), trip route (26 percent), not traveling (13 percent), or using transit (6 percent). Travelers who adopt appropriate measures on the basis of the received information will probably experience safer trips and overall improved mobility (FHWA 2018b). Similar results were also found in an investigation of the provision of winter snowstorm information to road users (Takechi 2012).

Generating accurate, location-specific, real-time information about weather and road conditions for maintenance departments, in combination with maintenance decision-making support systems, will produce better maintenance strategies and reduce materials and cost. A case study by the Utah DOT with its nationally unique Weather Operations showed that improved weather information could reduce winter maintenance costs and enhance the level of service of the roadway system (Drobot 2009). Moreover, according to an analysis of the MDSS of the New Hampshire DOT, total resource consumption was reduced by 15 percent, saving about $1.18 million annually (Strong 2008).

Enhancing the efficiency of maintenance departments can be accomplished by improving reporting and saving time spent relaying information. The results of a benefit-cost analysis of MDSS showed that the labor and equipment costs were expected to be reduced with reduced materials usage (Ye 2009). It is estimated that the Michigan DOT saved $680,000 annually through staff time saved by automatic system reporting (FHWA 2018b).

3.5.2. Limitations and Challenges

It will be necessary to increase the density of road units and the market penetration (MP) of connected vehicles equipped with onboard equipment and additional sensors by encouraging more private cars engaged in the CV network to gather mobile data, which will not only assist maintenance departments in obtaining sufficient road weather data to generate more accurate information on road weather and traffic conditions, but will also dispel concerns about interacting with non-connected vehicles.

It will be critical to improve server capabilities and performance to be able to handle the data processing requirements and to develop appropriate algorithms to transform raw connected vehicle data and other road weather and traffic data into timely and actionable information. In order to address the heterogeneity of the data format, reporting intervals, transmission rates, and more, special and improved software modules will be required to improve data processing. The vehicle data translator (VDT) (Drobot 2011), developed by the National Center for Atmospheric Research (NCAR) in collaboration with the U.S. Department of Transportation, can be used to ingest, parse, process, and quality check mobile data along with ancillary weather data. Moreover, the Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net) (Ma 2011) provides a practical method for facilitating data retrieval and integration to enhance data usability.

It will be important to enhance the user interface to distribute the actionable information to connected vehicle drivers conveniently, without distracting drivers.

It will be important to improve network transmission encryption technology, firewall technology, and other security means to prevent hacking attacks and to protect the vehicles' privacy.

4. Conclusions

This work provided the current state-of-the-art of CV technology for winter road maintenance and traveler information, the results of a CV application survey, and development of a Concept of Operations for improving winter road maintenance and travel advisories. The significant findings include the following:

Winter road condition assessments using CV technology, particularly AVL and automated plow-mounted cameras, have been demonstrated and will likely be more widely implemented by state DOTs for two purposes: improving winter road maintenance decision-making and providing traveler information and advisories.

Special CV applications for winter travel have undergone limited development and pilot testing.

State DOTs and maintenance departments generally have positive attitudes toward the potential of CV technology to improve winter road maintenance operations, but they have some concerns regarding the integration of CV data and RWIS data, system performance, privacy safety, driver distraction, and cost.

This work developed the concept of applying CV technologies for improving winter travel as follows. Mobile road weather-related data will be collected from CV technology-enabled snowplows, maintenance trucks, city fleet vehicles, and private vehicles through CAN-Bus, AVL, and sensors mounted on vehicles. These route-specific data will be combined with point data from RWIS and traffic cameras. After data processing and analysis, road segment weather information will be analyzed by a maintenance decision-making support system to provide optimal maintenance strategies. Meanwhile, the information will also be further processed in a traffic management department to provide road users with travel alerts and advisories through a series of means to allow them to better select appropriate trip behavior (trip time, trip modes, trip routes, etc.).

Part II: Proof-of-Concept Demonstration

5. Introduction: Developing a Road Surface Friction Prediction and Visualization System

Road surface condition has a great impact on road traffic mobility and safety(Ye *et al.*, 2012; Chen, et al., 2017; Pisano, 2017) . Especially in the winter season, terrible road surface conditions could result in more traffic crashes and a low level of service (LOS). The United States spends $2.3 billion annually to keep highways clear of snow and ice; in Canada, winter highway maintenance costs more than $1 billion (Shi, 2011). Improving road surface condition monitoring systems and operations could result in fewer crashes, higher LOS, improved mobility, better fuel economy and sustained economic productivity (Rita, 2018). As one of the direct measurements of road surface condition, road surface friction has a strong correlation with traffic accident risk (Wallman and Åström, 2001). Therefore, in order to mitigate the impact of road surface condition on traffic safety and mobility, an efficient and cost-effective road surface friction prediction methodology is needed.

Road surface friction is defined as the resistance to motion between vehicle and road surface, which strongly affects the distance required for a vehicle to decelerate and a driver's safety when a vehicle must brake to avoid a collisions (Mayora and Piña, 2009). In the winter season, road surface friction decreases substantially with decreases in temperature, which increases the risk for car accidents dramatically (El Esawey *et al.*, 2019). FHWA has reported that, in the United States, the majority of traffic accidents happened during wet or icy road conditions, as 73 percent of accidents occurred on wet pavements, and 17 percent on snow or sleet ((FHWA), 2005). In addition, existing studies have indicated that intelligent systems that have the capacity to share timely road condition-related information can potentially increase traffic safety (Panahandeh, et al., 2017). Therefore, given that road surface friction is a directly quantifiable measurement of road surface condition, an efficient and cost-effective road surface friction prediction and visualization system would help improve traffic safety.

The primary objective of this work was to develop a road surface friction prediction and visualization system that relyies on the data collected by sensing devices on connected vehicles. The remainder of Part II is organized as follows. Chapter 6 presents a literature review on relevant topics. Chapter 7 introduces a system design for the data analysis and visualization platform and the proposed methodology for road surface friction prediction. Chapter 8 shows the experimental results, and Chapter 9 discusses a demonstration of the system through a case study in Washington state. Part II concludes with Chapter 10, a summary of the research findings and future research.

6. Literature Review

6.1. Road Weather Information System

Road weather information systems (RWIS) are a platform used to collect, process, and broadcast road weather and condition information. Road maintenance departments use RWIS to improve road safety in severe weather and to make operational decisions. Many North American transportation agencies have invested millions of dollars to deploy RWIS stations to improve their information about winter road conditions. The design of these networks usually varies from region to region (Biswas et al., 2019).

The component of an RWIS that collects weather data is the environmental sensor station (ESS). The ESS is a set of sensors used to collect and transmit road and weather data. The sensors measure weather-related data including road temperature and condition (wet, dry). These data are transmitted to an automatic warning system. For drivers, predictions developed from these data can increase road safety.

In the past, RWIS were used by state and local transportation maintenance departments to make better operational decisions. The collected weather data enables jurisdictions to make winter route plans effectively. While state and local transportation agencies now share weather data with more data users, researchers can also use these data to help improve road management (Vavrik et al., 2016).

Many different sensors provide weather-related data from RWIS. Thermometers measure temperature and pavement conditions. Anemometers measure wind speed. Wind vanes measure wind direction. Visibility sensors detect fog and smoke. Rain gauges measure precipitation.

6.2. Sensing Devices on Connected Vehicles

Several sensing technologies have been developed for winter road surface condition monitoring. DSC-111 and DST-111 sensors are two remote optical sensors developed by the Vaisala company (of Transportation, 2008; Ye *et al.*, 2012; Ewan, et al., 2013). DSC-111 can provide the road surface state (dry, moist, wet, icy, snowy/frosty, or slushy) on the basis of backscattered signals of infrared light and can measure the friction level of the road surface, and DST-111 can present the pavement surface temperature, air temperature, and relative humidity through long-wave infrared radiation detection (Pilli-sihvola *et al.*, 2006). Previous studies have demonstrated that DSC-111 can provide accurate surface state measurement, but the friction detection of DST-111 is not precise (of Transportation, 2008). The Road Condition Monitor

(RCM) 411 is an optical instrument equipped with a transmitter to send a probe light pulse and a detector to measure backscattered light, which can be easily installed into a passenger vehicle (Haavasoja, et al., 2012). Previous studies and experiments have demonstrated that the RCM-411 is accurate for temperature, water thickness, and road surface status detection (Haavasoja, et al., 2012; Maenpaa *et al.*, 2013; Fay, et al., 2018). For friction detection, even when the detected friction value does not always accurately match the actual friction, it still can be calibrated to provide the actual friction value (Haavasoja, et al., 2012). Such sensing technologies have already been employed for real-time road monitoring, e.g., RWIS in the U.S., (Maenpaa *et al.*, 2013; Saarikivi, 2012; Karsisto and Nurmi, 2016; Singh *et al.*, 2017). However, each sensing technology has its own disadvantages, e.g., a fixed sensor can only cover a fixed area, and using mobile sensors is time and energy consuming. Therefore, determining how to utilize the data collected by such sensing technologies to expand the ability to predict road surface conditions would be valuable for improving the effectiveness and efficiency of the whole system.

6.3. Road Surface Friction Prediction Methods

Most previous models for predicting road condition-related parameters have been developed on the basis of laboratory tests. Shao et al. (1996) proved that ice hazards only happen under both conditions, based on field test data from seven countries (Shao *et al.*, 1996). They also tried to predict ice conditions on the basis of air temperature, wind speed, and precipitation. However, the results showed great differences on different roadways. Samodurova (no date) pointed out that the ice point varies in terms of pavement types. Most ice prediction models have been developed on the basis of laboratory tests, and many significant factors have been found to be related to ice generation. For example, Mohseni and Symons (Contact and Symons, 1995), and Diefenderfer et al. (2006) both regressed the relationship between pavement temperature and various environmental conditions, such as illumination, air temperature, longitude, latitude, etc., but the impact of those factors was still unmeasurable. Therefore, given the existing models that were built through laboratory tests, precise road surface conditions are hard to predict.

By utilizing the data collected by existing sensing technologies, several researchers have developed data-driven models for predicting road surface condition-related parameters. Liu et al. (2018) developed a road surface temperature prediction model based on a gradient extreme learning machine boosting algorithm. Sokol et al. (2017) developed a road surface temperature prediction model based on energy balance and heat conduction models. In addition, some researchers have developed road surface condition recognition algorithms based on computer vision technologies (Cnn, no date; Sukuvaara and Nurmi, 2012; Jonsson, et al., 2014; Linton and Fu, 2016). However, previous studies have had several disadvantages in terms of prediction effectiveness. For example, those methodologies can only regress the current road surface condition on the basis of current environmental measurements, e.g. air temperature, etc. They are not able to predict future road surface conditions. Moreover, past studies have demonstrated the existence of the time-series features of road surface condition (Kangas, et al., 2015). However, only a few studies have looked at time-series prediction model development. Therefore, a prediction method that considers the time-series features of road surface condition is needed.

A long-short-term memory (LSTM) neural network (NN)is a kind of computational intelligence approach for dealing with time-series data (Hochreiter and Urgen Schmidhuber, 1997). Several studies have demonstrated that LSTM is more accurate for short-term prediction problems—e.g. traffic flow prediction, patient visitation frequency prediction—than other approaches, such as random forest (RF) and support vector regression (SVR), because of its ability to handle both long-term and short-term dependencies. Given the above considerations, the primary objective of this study was to develop a road surface friction prediction model based on the LSTM NN model and using historical data. RCM-411 friction sensing data were selected as the historical data set because of their accuracy. To evaluate the predictive effectiveness of the proposed method, several other prediction models were employed for comparison purposes. In addition to the overall prediction performance, the influence of the number of time-lags, the influence of the time interval between each time-step, and the influence of adding features were also evaluated.

Basically, the inputs to these models is a set of historical road surface condition measurements with a fixed temporal resolution for each time step. The output of the forecasting model is the same road surface condition parameter in the next time step. For example, if the model aims to predict the road surface condition tomorrow, then the measurements of each time step in the input data set should have one-day time intervals between each other. However, having data points at every time stamp cannot be guaranteed because of weather, cost, or other issues, e.g., road monitoring may be provided by vehicles equipped with on-vehicle sensors, but those vehicles cannot be guaranteed to travel the road every single day. Therefore, it is highly possible for the input data set to have missing values that cannot be handled by the existing prediction models. Such missing data could affect the accuracy and effectiveness of existing models, thereby influencing decision-making.

7. Road Surface Friction Prediction and Visualization System Development

7.1. System Overview

This chapter describes a system proposed for road surface friction and visualization. A three-layer system architecture was designed, including a data collection and processing layer, a data analysis and data matching layer and a data visualization layer (see figure 7-1). First, real-time road surface friction data collected by the sensing devices on connected vehicles are transmitted to the remote server. Because the raw data may include some erroneous data, duplicated data, and noisy data, the system needs to clean the data and classify all data with different dates separately. Then, the data are saved into the SQL Server database. In the data analysis and matching layer, the data are stored in two databases on the basis of the data type: spatial data and non-spatial data. Data with road surface information are treated as non-spatial data and are stored in the SQL Server. Map data are downloaded from OpenStreetMap and inserted into the PostgreSQL database to show the road surface state on the map. Next, the system calls the data analysis module to predict the road friction. The data analysis module is in charge of predicting future road surface friction on the basis of the proposed methodology, which is introduced in Section 7.2. These predicted results are saved into the SQL Server. In the databases, the system finds the corresponding road ID in the PostgreSQL for each predicted location in the SQL Server. All the predicted data with a road ID will be saved in the SQL Server. Finally, the platform calls the data from the SQL Server to show the predicted results intuitively on the DRIVE Net.

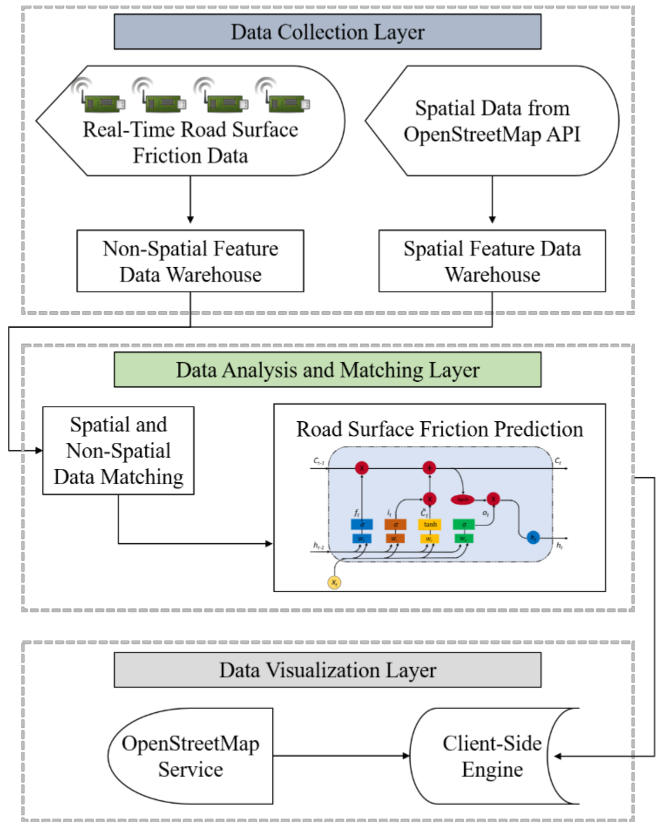


Figure 7-1. The framework of the system

7.2. Road Surface Friction Prediction Based on Long-Short-Term Memory Neural Networks

A long-short-term memory (LSTM) neural network (NN) is proposed to predict short-term road surface friction because of its ability to handle both long-term and short-term dependencies (Bengio, et al., 1994; Sundermeyer, et al., 2012). LSTM NNs share similar architecture with traditional recurrent neural networks (RNN), which are composed of one input layer, one hidden layer, and one output layer. The main difference between LSTM and RNN architecture is the structure of the hidden layer (Gers and Cummins, 1999), which is shown in figure 7-2.

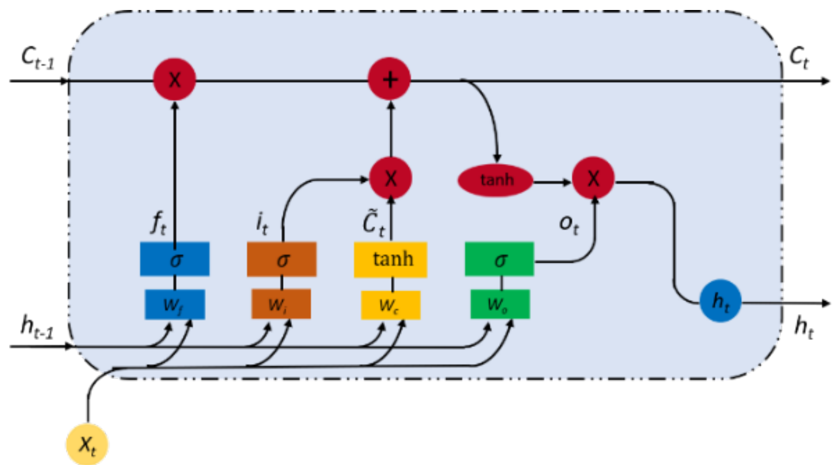


Figure 7-2. Model architecture of the LSTM (The red circles are arithmetic operators and the rectangles in different colors are the gates in the LSTM)

Typically, at each time iteration t, the LSTM cell has the input layer, X_t, the output layer, h_t and the hidden layer, which is called the LSTM cell. By adding a cell state component, the LSTM cell is capable of handling long-term dependencies of sequence data. The previous output cell state, C_{t-1}, and current input cell state, $\tilde{C}$, both influence the current output cell state, C_t. Three gates control the information to flow into and out of the cell state, which are the forget gate, the input gate, and the output gate, denoted as f_t, i_t, and o_t, respectively. The forget gate controls how much information from the previous cell state should be forgotten by the current cell state. The input gate handles how much information from the current input layer flows into the current cell state. The output gate controls how much information from the current cell state would be conveyed into the current output layer. They can be calculated by the following equations,

$$f_t = \sigma_g\left(W_f X_t + U_f h_{t-1} + b_f\right) \tag{1}$$

$$i_t = \sigma_g(W_i X_t + U_i h_{t-1} + b_i) \tag{2}$$

$$o_t = \sigma_g(W_o X_t + U_o h_{t-1} + b_o) \tag{3}$$

$$\tilde{C}_t = tanh(W_C X_t + U_C h_{t-1} + b_C) \tag{4}$$

where W_f, W_i, W_o, and W_C are the weight matrices for mapping the current input layer into three gates and the current input cell state. U_f, U_i, U_o, and U_C are the weight matrices for mapping the previous output layer into three gates and the current input cell state. b_f, b_i, b_o, and b_C are bias vectors for gate and input cell state calculation. σ_g is the gate activation function, which is normally a sigmoid function. $tanh$ is the hyperbolic tangent function, which is the activation function for current input cell state.

Then, the current output cell state and output layer can be calculated by the following equations. Finally, the output of the LSTM prediction model in this study should be the road surface friction in the next time iteration.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Because it is assumed that there is no spatial correlation between road segments, the spatial dimension of the input data is set as $P = 1$. The unit of time-step for road surface friction detection is set as one day, then the data set has 446 time-steps for each road segment. Suppose the number of the time-lag is set as $T = t$ with $L = l$ days between each time-lag, which means the model used the data in previous t consecutive time-steps to predict the road surface friction in the following 1 day time-step. Then the data set is separated into samples with t time-lags and the sample size is $N = 446 - t$. Thus, each sample of the input data, X_t, is a two-dimensional vector with the dimension of $[T, P] = [t, 1]$, and each sample of the output data is a one-dimensional vector with one component. The input of the model for each road segment is a three-dimensional vector, whose dimension are $[N, T, P] = [446 - t, t, 1]$. Before being fed into the model, all samples are randomly divided into three data sets for training, validating, and testing with the ratio 7:2:1.

7.3. Database Design

7.3.1. SQL Server

Database name: CV4WM

Structure: There are two tables in this database, routing and osm_id, shown in tables 7-1 and 7-2. Routing is used to save the historical data and predicted results. Road segment ids searched on OpenStreetMap according to each location point are saved in osm_id. The database structures are as follows.

Table 7-1. Routing

Columns	**Type**
DateTime	Datetime
Friction	nchar(10)
State	nchar(10)
Tsurf	nchar(10)
Water	nchar(10)
Latitude	Varchar(50)
Longitude	Varchar(50)
Serial	nchar(10)

Table 7-2. osm_id

Columns	**Type**
DateTime	Datetime
osm_id	varchar(50)
Friction	nchar(10)
State	nchar(10)
Tsurf	nchar(10)
Water	nchar(10)
Latitude	Varchar(50)
Longitude	Varchar(50)
Serial	nchar(10)

7.3.2. PostgreSQL

Database name: cv4wmmap

Structure: The map data are downloaded from OpenStreetMap. These data are inserted into the PostgreSQL database. There are eight tables in this database: osm_nodes, osm_relations, osm_way_classes, osm_way_types, relations_ways, special_ref_sys, ways and ways_vertices_pgr, shown in figure 7-3.

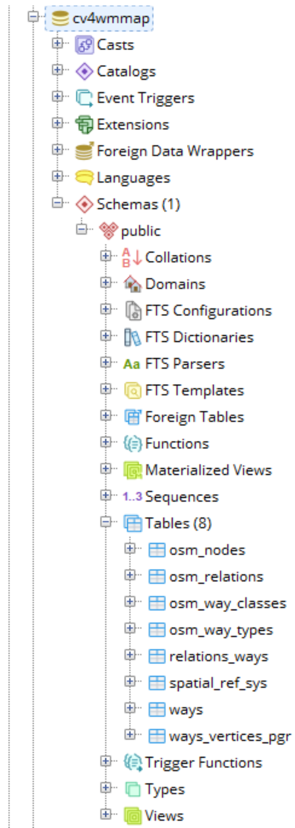


Figure 7-3. Tables in PostgreSQL

In these tables, 'ways' is the most important for this project (figure 7-4). There are 24 columns in 'ways'. They are gid, class_id, length, length_m, name, source, target, x1, y1, x2, y2, cost, reverse_cost, cost_sreverse_cost_s rule, one_way, maxspeed_forward, maxspeed_backward, osm_id, source_osm, target_osm, priority, the_geom.

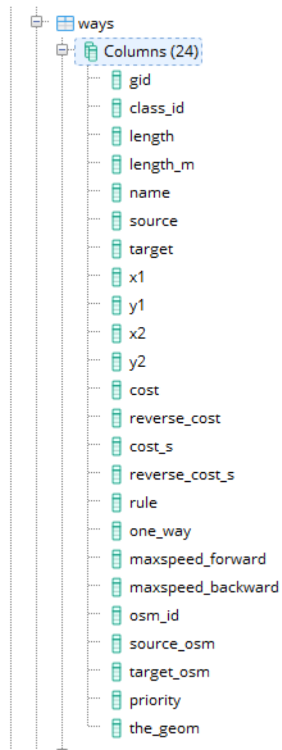


Figure 7-4. Columns in the table ways in PostgreSQL

7.3.3. E-R Diagram

Routing queries the osm_id from ways, according to the column Latitude and Longitude in routing. x2, and y2 represent the latitude and longitude of the end point of the road. Multiple locations may belong to the same road segment. Then the query results are saved into the osm_id table in the SQL Server. Multiple road segments may own multiple road states. Different states can describe different road segments. The logistic relationship between the three tables is as shown in figure 7-5.

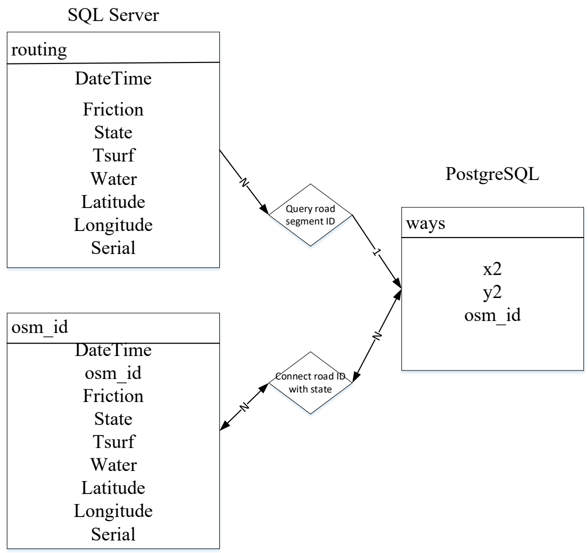


Figure 7-5. E-R diagram for tables

7.4. Data Visualization on DRIVE Net

Each road segment owns the source and the terminal. The terminal state of the point on the road segment is taken as the state of the current road segment. Then then final predicted state on the road is visualized on the Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net).

DRIVE Net is an on-line transportation platform aimed at data sharing, integration, visualization, and analysis. The system provides users with the capability to store, access, and manipulate data from anywhere as long as they have Internet connections. It can achieve the integration and visualization of information needed for decision support. Not only do the research findings include data fusion techniques and database design details, but they can also be delivered in a functioning DRIVE Net archive service capable of collecting detector data from all WSDOT regions and incorporating third party data from both the Washington Incident Tracking System (WITS), the INRIX company, and weather databases. In this system, roadway geometric data are properly stored in an open-sourced geospatial database, PostgreSQL, and seamlessly connect with the SQL Server database (i.e., sensor data, weather data). The platform combines a series of loop data quality control algorithms in the back end. These processed data are used to generate WSDOT's Gray Notebook statistics and are available for WSDOT personnel to visualize and produce their annual and quarterly congestion reports through the DRIVE Net system. A new module named cv4wm on DRIVE Net has been created to visualize the road state. There are six colors for each state level: Dry, Moist, Wet, Slush, Ice and Snow. The model integrates the database, road surface friction prediction methodology, and data processing in the back end.

8. Experimental Design and Numerical Results

8.1. Experimental Design

This chapter describes four independent experiments conducted to evaluate the predictive performance of algorithm structures and investigate their impacts. First, the predictive performance of the proposed LSTM prediction algorithm was evaluated by comparing it with other baseline models. Baseline model selection and performance metrics are presented. The other three experiments were conducted to investigate the impacts of the number of time-lags, the prediction after different numbers of days, and other features related to predicting accuracy. The detailed experimental results are presented in Section 8.2.

8.1.1. Baseline Model Selection

The performance of an LSTM NN in predicting road surface friction was compared to that of many classical baseline models for short-term prediction. Typically, the ARIMA, support vector regression (SVR), fandom forest (RF), Kalman filter, tree-based, and feed-forward NN models have been used to address short-term prediction problems (Wu *et al.*, 2004; Guo, et al., 2014; Yuan-yuan Chen *et al.*, 2016), e.g., traffic speed and travel time prediction (Ma *et al.*, 2015; Cui *et al.*, 2018a; Cui, et al., 2018b). However, the predictive performance of several time-series prediction models has been demonstrated to be less accurate than that of others, e.g., the ARIMA and Kalman filter. On the basis of those previous research results, the SVR, RF, and feed-forward NN models were selected for comparing road surface friction predictions with those of the proposed LSTM NN model. Among these models, the feed-forward NN, also called the Multilayer Perceptron, is popular for precise short-term prediction (Lv *et al.*, 2014). The RF and SVR models are also well known for efficient predictive performance (Wu *et al.*, 2004; Yuan-yuan Chen *et al.*, 2016). For the parameters of model development, the radial basis function (RBF) kernel was deployed in the SVR model. Ten trees were built, and there was no pre-determined limitation for the maximum depth of the trees for the RF model. The feed-forward NN was composed of two hidden layers with 100 nodes in each layer.

8.1.2. Predictive Performance Metrics

Mean absolute error (MAE), mean square error (MSE) and mean absolute percentage error (MAPE) are used as the measurements of predictive performance. The following equations present the measurement formulations.

$$MAE = \frac{\sum_{i=1}^{N}\left|Y_i - \widehat{Y}_i\right|}{N} \tag{7}$$

$$MSE = \frac{\sum_{i=1}^{N}\left(Y_i - \widehat{Y}_i\right)^2}{N} \tag{8}$$

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{Y_i - \widehat{Y}_i}{Y_i}\right| \tag{9}$$

where N is the total number of samples in testing data set, Y_i is the ground truth of the road surface friction that was detected by the RCM 411 sensor in this study, and $\widehat{Y}$ is the predicted road surface friction of the proposed prediction model. Typically, the MAE is used to measure the absolute error associated with a prediction, the MAPE is a measure of the percentage of average mis-prediction of the model, and the MSE measures the relative error for a prediction. A prediction model with smaller values of MAE, MSE, and MAPE performs better.

8.2. Numerical Results

8.2.1. Predictive Performance Evaluation

The proposed LSTM NN model and other baseline models were trained with the same training data set for each road segment separately, and the predictive performance for each model was calculated on the basis of the predicted value and ground truth value. In this step, only road surface friction for the previous time period was used as the model input. The final predictive performance measurements were the averaged value of all road segments. Table 8-1 shows a comparison of the prediction performance of the LSTM with that of the other baseline models. Among the other algorithms, the RF model performed much better than the SVR model and feed-forward NN, with an MAE of 0.166, an MSE of 0.0132, and a MAPE of 16.6 percent, which makes sense because of the majority votes mechanism of the RF model. The feed-forward NN had the worst predictive performance, which was caused by the sparsity of the data. The proposed LSTM model outperformed all the models, with an MAE of 0.0778, an MSE of 0.0112, and a MAPE of 15.16 percent, indicating the best performance in predicting road surface friction while considering only the road surface friction in the previous time period.

Table 8-1. Comparison of the predictive performance of the LSTM with that of other models

Models	MAE (N)	MSE	MAPE (%)
Feed-forward NN	0.1660	0.0132	26.86
SVR	0.2142	0.0174	21.42
RF	0.1660	0.0132	16.60
LSTM NN	0.0778	0.0112	15.16

A further examination of the predictive performance of the proposed LSTM model in a more intuitive way involved a comparison of the predicted values of the LSTM on a randomly selected day for all road segments with ground truth values, which is presented in figure 8-1. For most of road segments, the predicted values were very close to the observed data. Only a few of the road segments showed clear errors in road surface condition prediction. Overall, the LSTM effectively predicted road surface friction on the basis of historical road surface friction data for all road segments.

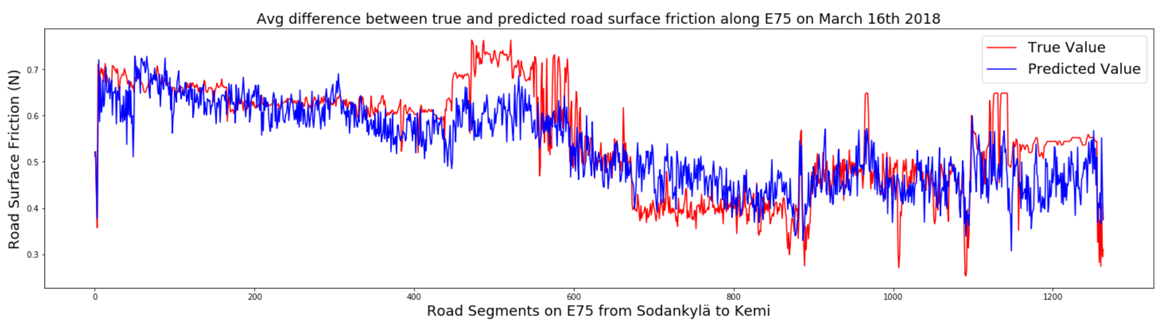


Figure 8-1. Comparison of the predictive performance of the LSTM with observed data

8.2.2. Evaluating the Influence of Number of Time-Lags on Predicting Accuracy

The number of time-lags is the temporal dimension of the input data, which could influence the prediction performance of the proposed LSTM model. Intuitively, more time-lags will convey temporal features over a longer time period, and the LSTM will learn more features from previous time periods. In order to explore the influence of the number of time-lags, the LSTM was trained by the data sets with different numbers of time-lags, from one to ten separately, for all road segments. All data samples had the same time interval (one day) between time-lags. Table 8-2 shows the average predictive performance of the proposed LSTM models that were trained by the data sets with different numbers of time-lags.

Table 8-2. Predictive performance of the LSTM with different numbers of time lags.

Time Lags	1	2	3	4	5	6	7	8	9	10
MAE (N)	0.0862	0.0836	0.0787	0.0812	0.0799	0.0800	0.0778	0.0832	0.0797	0.0824
MSE	0.0135	0.0133	0.0117	0.0126	0.0119	0.0121	0.0112	0.0128	0.0117	0.0126
MAPE (%)	17.62	17.82	16.23	16.97	16.14	16.57	15.16	16.81	15.58	16.65

Note that all three measurements (MAE, MSE, and MAPE) gradually dropped as the number of time-lags decreased from one to seven. The LSTM model performed with the most precise prediction when the number of time lags equaled seven. Once the number of time lags was greater than seven, the prediction performance became worse with a little fluctuation. The possible reason might be that the excessive time lags made the LSTM too complex, which caused some overfitting issues with the LSTM. Thus, the prediction effectiveness was influenced by the unnecessary complexity of the LSTM.

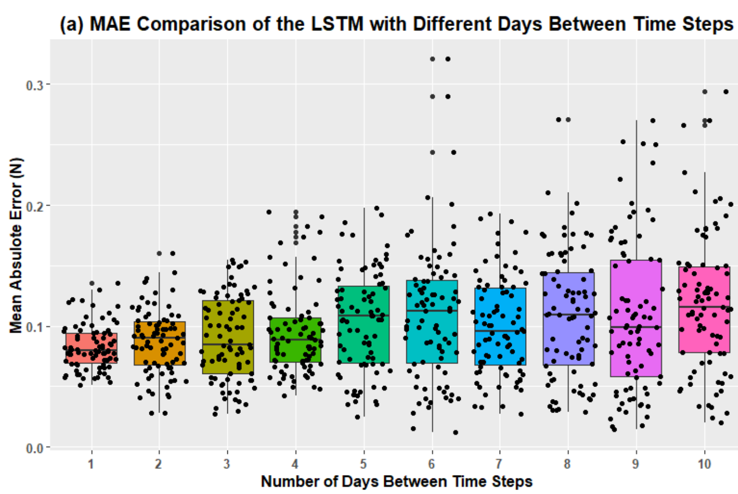
8.2.3. Evaluating the Accuracy of the Prediction after Different Days

The time interval between time-lags indicates how often a historical data point would be input into the proposed LSTM model. In this study, the frequency of road surface friction detection was once per day, so the minimum time interval between time-lags was one day. If the time interval between time-lags was set as one day, then the output would be the road surface friction after one day. Thus, if the road surface friction after l days was predicted, then the time interval between each time-lag of the input data should be set as l. By varying the time interval, the prediction time could be adjusted. Then the model could be not only dedicated to predicting the road surface friction after a fixed number of days. In order to demonstrate the road surface friction prediction accuracy after different numbers of days, the proposed LSTM was trained separately by the data sets with different time intervals between time-lags from one to ten for all road segments. Table 8-3 shows the average predictive performance of the LSTM models.

Table 8-3. Predictive performance of the LSTM with different intervals between time lags

Time Interval (Days)	1	2	3	4	5	6	7	8	9	10
MAE (N)	0.0790	0.0873	0.0903	0.0948	0.1043	0.1096	0.1000	0.1086	0.1085	0.1190
MSE	0.0127	0.0146	0.0152	0.0166	0.0195	0.0229	0.0189	0.0222	0.0220	0.0232
MAPE (%)	15.24	18.01	17.61	19.99	21.06	21.75	19.86	22.63	21.33	22.39

Obviously, as the time interval between time lags became larger, the predictive performance of the LSTM got worse for all three performance measurements. This suggested that the accuracy of road surface friction prediction would decrease with larger predicting intervals\. Note that as the predicting interval became larger, the prediction accuracy did not drop enough to make the prediction accuracy unacceptable. The road surface friction prediction of five days resulted in a MAPE of about 20 percent and relatively low MSE and MAE values. Even when the time interval between time lags was ten days, the MAPE for the proposed LSTM model was still 22.39 percent. Figure 8-2 shows the boxplots of the predictive performance of the proposed LSTM models trained with different days between time lags. They show that, while the time intervals between time-lags became larger, the variance in predictive performance got larger for all three predictive performance measurements. The 25th percentiles of the three measurements were stable as the predicting time interval got larger. The 75th percentile increased while the predicting time interval changed from one day to day days. In summary, the proposed LSTM model was found to be accurate for predicting short-term road surface friction. When the predicting time interval became larger, the prediction accuracy decreased, which was consistent with previous research results showing that the road surface weather conditions have short-term time-series features but long-term features (Brijs, et al., 2008).



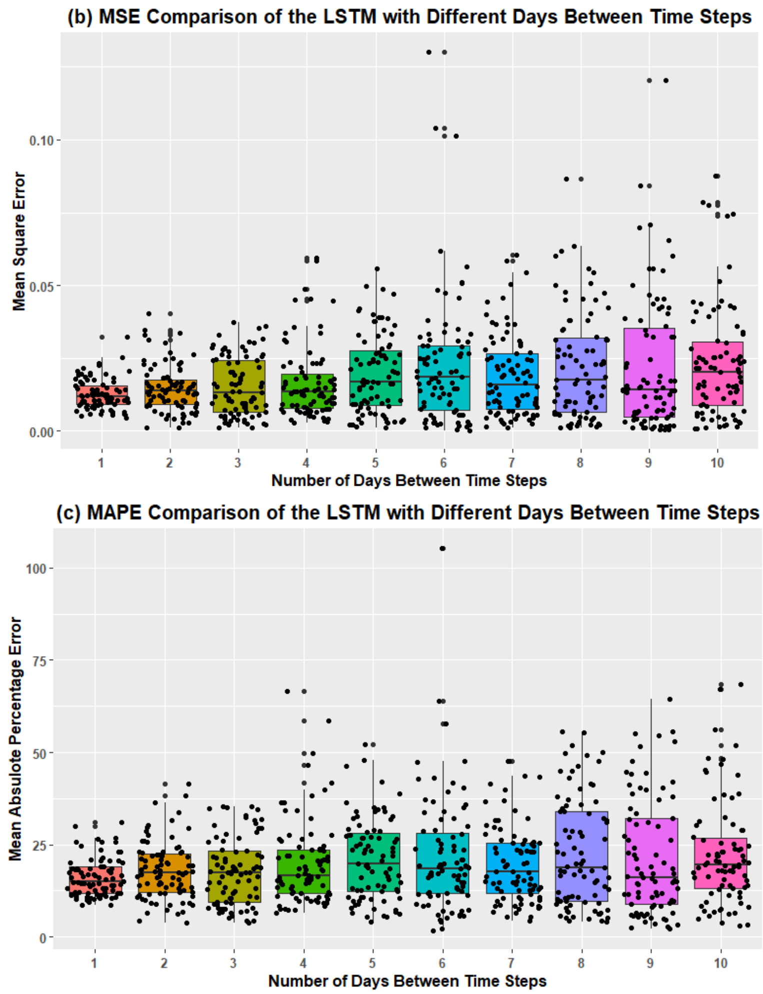


Figure 8-2. Boxplots of the predictive performance of the LSTM with different days between time lags (a) MAE comparison of the LSTM with different numbers of days between time-steps, (b) MSE comparison of the LSTM with different numbers of days between time-steps, (c) MAPE comparison of the LSTM with different numbers of days between time-steps.

8.2.4. Evaluating the Influence of Other Related Features on Predicting Accuracy

The above LSTM prediction models were trained only with friction values from past time periods. Theoretically, road surface friction is mainly determined by road surface water thickness, road surface temperature, and air temperature. Therefore, it would be meaningful to add more variables as input to the LSTM model to explore the influence of those features on prediction accuracy.

Figure 8-3 shows the scatterplot matrix of road surface water thickness, road surface friction, road surface temperature, and air temperature collected by RCM 411 sensors to display the correlations among these features. The road surface temperature and air temperature showed a strong correlation, with all the dots centralized along the diagonal line. However, road surface friction does not have a clear correlation with two temperature-related measurements. The dots spread in the plots without specific patterns. In addition, the scatter plot of road surface water thickness and road surface friction presents a U-shaped pattern. The road surface water thickness reaches a large value when the road surface friction value is relatively large or small. On the basis of the above, two additional experiments were conducted to investigate the influence of these features on predicting accuracy. The LSTM models were trained by adding road surface water thickness alone and by adding road surface water thickness and temperature. Seven time-lags and the one-day time interval between time-lags were selected for model training. The resulting prediction performance was compared with the prediction performance of the LSTM model trained with only road surface friction. A comparison of the results is shown in table 8-4.

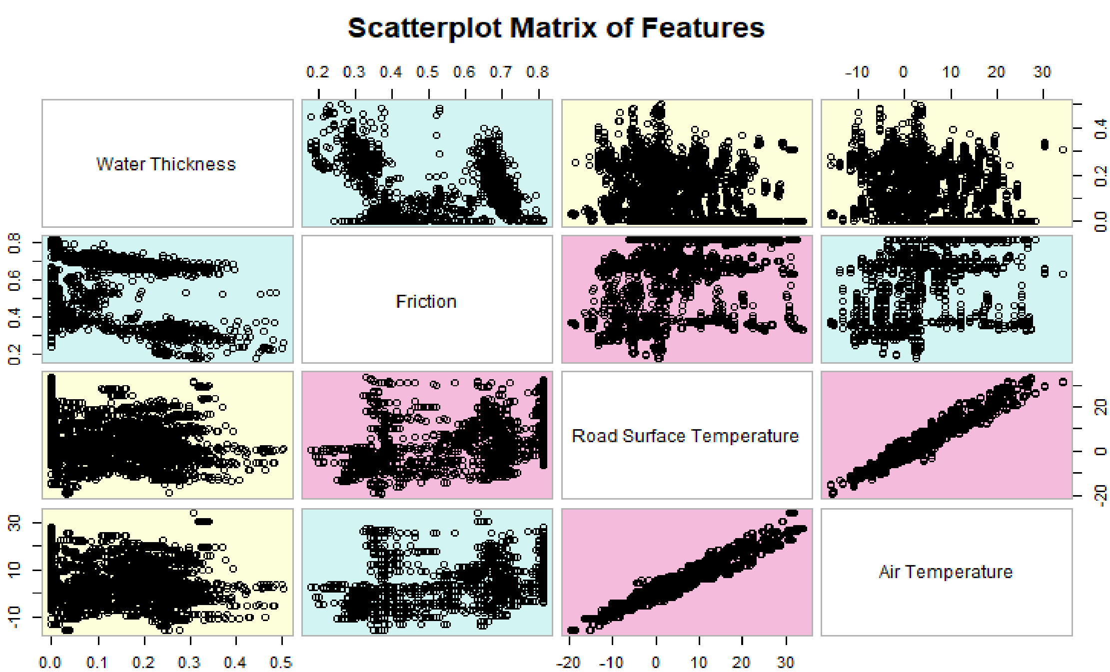


Figure 8-3. Scatter plots matrix of features

Table 8-4. Comparison of the predictive performance of the LSTM with different features

Data Input of Prediction Model	MAE (N)	MSE	MAPE (%)
Friction	0.0778	0.0112	15.16
Friction, Water Thickness	0.0742	0.0102	14.58

Friction, Water Thickness, Road Surface Temperature	0.0948	0.0159	21.97

As shown in table 8-4, the predictive performance of the LSTM was improved by adding road surface water thickness as input to the model. All three predictive performance measurements achieved lower values. This confirmed the findings of a previous study that road weather condition correlates with rainfall in the past time period (Hambly *et al.*, 2013). However, when road surface water thickness and road surface temperature were added to the prediction model, the predictive performance became worse than when only road surface friction was the input. All three performance measurements increased a lot. Given the weak correlation between road surface friction and temperature-related measurements, the possible reason could be that the additional temperature-related features made the LSTM too complicated and introduced lots of useless information to the LSTM model. The effectiveness of the useful feature could have been influenced by the excessively complex model structure, thereby reducing the model's accuracy. In a previous study, the same situation was found for short-term traffic speed prediction (Cui, et al., 2018b). In that study, the accuracy of traffic speed prediction of the proposed LSTM was not improved by adding traffic volume and traffic occupancy. In summary, the accuracy of the proposed LSTM prediction model was improved by adding road surface water thickness from the past time period as input for predicting road surface friction after one day, but accuracy was decreased by adding road surface water thickness and temperature simultaneously because of the excessively complicated model structure.

8.3. Key Functions of the System

8.3.1. Historical Data Analysis and Visualization

The system stores collected data and the historical data in the database. Once it receives a request to query historical data from the DRIVE Net, the platform calls the road data corresponding to that date from the database. In the backend, the system assigns colors according to the state for each road segment. Then the platform can show the road state with colors on the map.

8.3.2. Future Data Prediction and Visualization

On the basis of the historical collected data, the system can predict the future road surface condition and visualize it on the DRIVE Net. When there is a request to predict the road surface condition for a specified date in future, the system will call the road surface friction prediction methodology. The method is integrated into the system and uses the historical data as input. After the methodology outputs the results for prediction, the system stores the results into the database. It then shows the predicted results on the map by calling the backend of the system.

8.4. Case Study in Washington State

The following is the case study of this platform in Washington state based on the framework discussed in Section 7.1. The framework included data collection and processing, data analysis and matching, and data visualization. Data were collected on a continuous stretch of road in Washington state by the vehicle sensor. The data set needed to be preprocessed before its storage in the database. Then the framework integrated databases, algorithms, and web platforms onto the DRIVE Net platform. A new module was created on the DRIVE Net named CV4WM under Multi Module Analysis. Once a request had been made on the CV4WM panel, the framework called the methodology and the corresponding data to calculate friction on the case road. Then the results were stored in the database. The platform called the back end to show the predicted results on that road on the right map panel.

8.4.1. Data Collection

The data set RCM_WA was collected by the Road Condition Monitor (RCM) 411 sensor. The RCM 411 is an optical sensing-based, on-vehicle road surface condition sensor. It can be installed on a vehicle as in figure 8-4 and linked to cell phones by Bluetooth. RCM 411 sensors can collect road surface condition, water/ice layer thickness, and modeled friction. RCM_WA contained data from June 3, 2019, to June 14, 2019. For each road segment, 27 elements were collected, including Date, Time(-07:00), S1, S2, S3, Friction, State, Ta, S7, Tsurf, S9, S10, S11, Water, Speed, Direction, Latitude, Longitude, Height, Accuracy, Tdew, Friction2, Distance, Serial(RCM411 V 2.59 2016-09-29 - RCM Mobile v1.2.7), TaOBD, AirFlowRateOBD, and LambdaOBD. In this case, Date, Time, Friction, Latitude, and Longitude were useful for road surface prediction and visualization. The system could predict future friction from those five elements. A sample for collected data is shown in table 8-5. For the first record in this sample, the road friction at the location with the coordinate values (47.21237, -123.106) was 0.34 on June 8, 2019. The state was 5, meaning that the road surface had ice.

(a) (b)

Figure 8-4. The RCM 411 sensor

Table 2-5. A sample for source data

Date	Time	Friction	State	Latitude	Longitude	Distance
2019.06.14	11:13:40	0.34	5	47.21237	-123.106	0
2019.06.14	11:13:41	0.34	5	47.21236	-123.106	0

The locations of the data in the RCM_WA are shown in figure 8-5. The vehicle drove from near Sanderson Field to nearby Olympia every day. The total length of the road segments was 90,800 meters on average for each day.

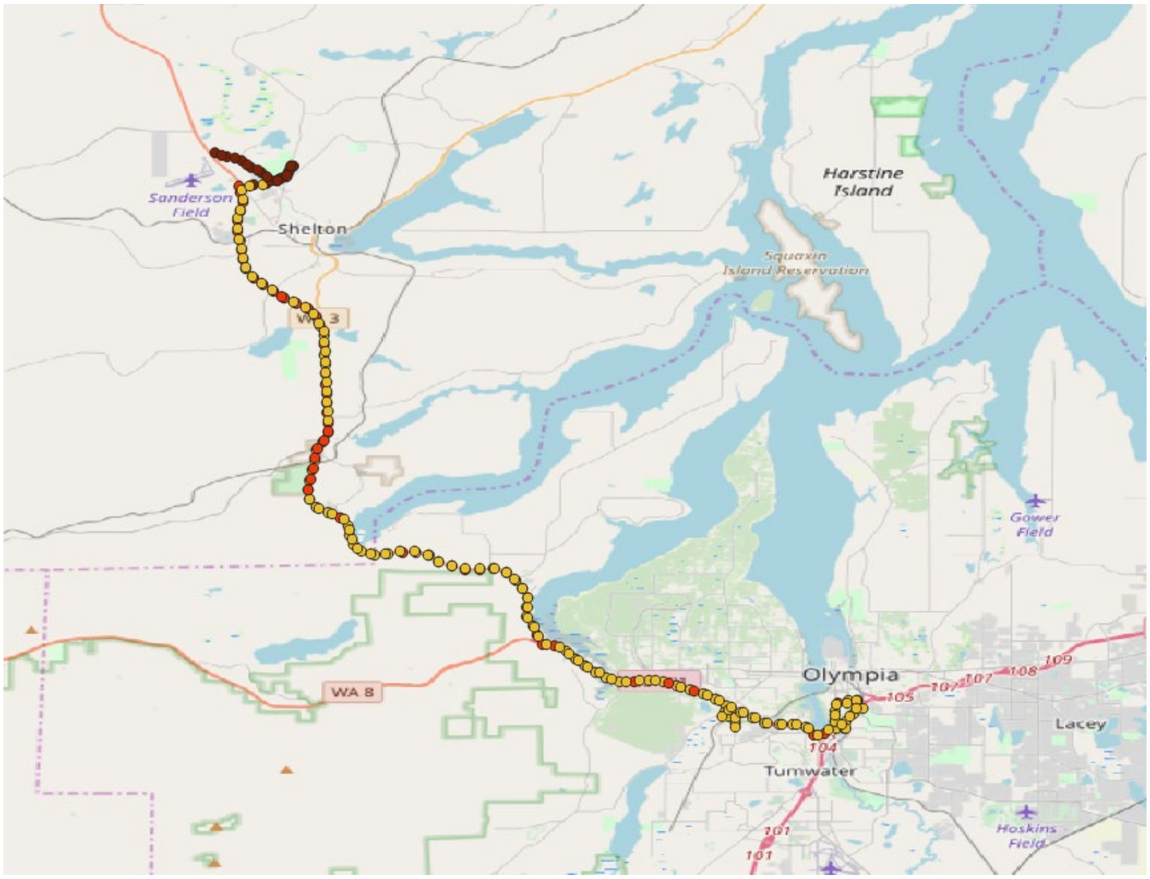


Figure 8-5. Discrete data state on the map

8.4.2. Data Analysis

The source data set is shown in table 8-6. RCM_WA covered 11 days, on June 3rd and from June 5th to 14th. Each document contained the sensing data on that day, which were the same as the file title. In each file, the data set included 27 columns, including Date, Time, Friction, State, Latitude, Longitude, Distance and so on. There were many noisy data in the each source file. For example, although the data were collected in June, there were state levels 5 and 6 caused by sensor error. State levels 5 and 6 indicated that the road had ice or snow. In addition, some documents shared the same content. An example is in table 8-7. This sample was recorded on June 14, 2019, from 11:13:40 to 12:58:09 every second. The source position was at (47.21237, -123.106). In the fourth record in this sample, the distance was 3, meaning that the vehicle had traveled for 3 miles from the source position, and the position had changed to (47.21235, -123.1061). The friction at this location was 0.33. The state was 5, indicating that the road was icy, although in fact the road in June was without ice. So data first had to be cleaned.

Only six days, from June 7, 2019, to June 12, 2019, were selected for further analysis. Then the duplicate data had to be removed. The total length of the shared road segments was 90,800 meters. The whole road was separated by 239 road segments, named from 0 to 238 in csv format. The preprocessed data were separated by 239 road segments, each saved in a file folder named from 0 to 238. Each file contained the records from June 7, 2019, to June 12, 201,9 of the same almost 380-m length road segment. An example is in table 8-8. For road segment 0, there were records from June 7, 2019, to June 12, 2019. The friction was stable (0.81), and the road state was dry (number 1). All the preprocessed data had to be stored into the SQL Server database. All data were clean and could be used as input for the methodology.

There were 35 files in the source folder. Each file included daily road data collected by sensors on the study route on June 3rd and June 5th to 14th. The acquisition time of each file was included in the middle of the file name.

Table 8-6. Source data set file folder

File name	Format
RCMF81_20190603	.csv
RCMF81_20190605	.csv
RCMF81_20190605_1	.csv
RCMF81_20190606	.csv

Table 8-7. Sample of the source data in each file

Date	Time	Friction	State	Latitude	Longitude	Distance
2019.06.4	11:13:40	0.34	5	47.21237	-123.106	0
2019.06.4	11:13:41	0.34	5	47.21236	-123.106	0
2019.06.4	11:13:42	0.33	5	47.21235	-123.1061	0
2019.06.4	11:13:43	0.33	5	47.21235	-123.1061	3
…	…	…	…	…	…	…
2019.06.4	12:58:09	0.35	6	47.23861	-123.1079	16180

Table 8-8. Processed data on road segment 0 on June 7, 2019

Date	Friction	State	Latitude	Longitude	Distance
2019.06.07	0.81	1	47.23897	-123.1084	0
2019.06.07	0.81	1	47.23899	-123.1085	0
2019.06.07	0.81	1	47.23903	-123.1087	20
…	…	…	…	…	…
2019.06.07	0.81	1	47.23625	-123.11	370
…	…	…	…	…	…
2019.06.12	0.81	1	47.23866	-123.108	0
…	…	…	…	…	…
2019.06.12	0.81	1	47.23652	-123.11	391

8.4.3. Data Visualization

Figure 8-5 shows the discrete predicted state visualization on the map. The state for each location can be seen clearly in figure 8-6. Figure 8-7 shows the final visualization on the platform. States 1 to 6 are given different colors. The platform shows the whole road state, with instructions on the left panel. The detailed state for each road segment can also be enlarged to be observed as in figure 8-8.

Figure 8-6 shows some of the detection points on the road in one day. A yellow point means that the road state was wet, and a red one means the road state was dry. This is the representation of road conditions with discrete points. Next, the system determines the road segment on map that is closest to each point and converts the discrete representation into a continuous road segment representation.

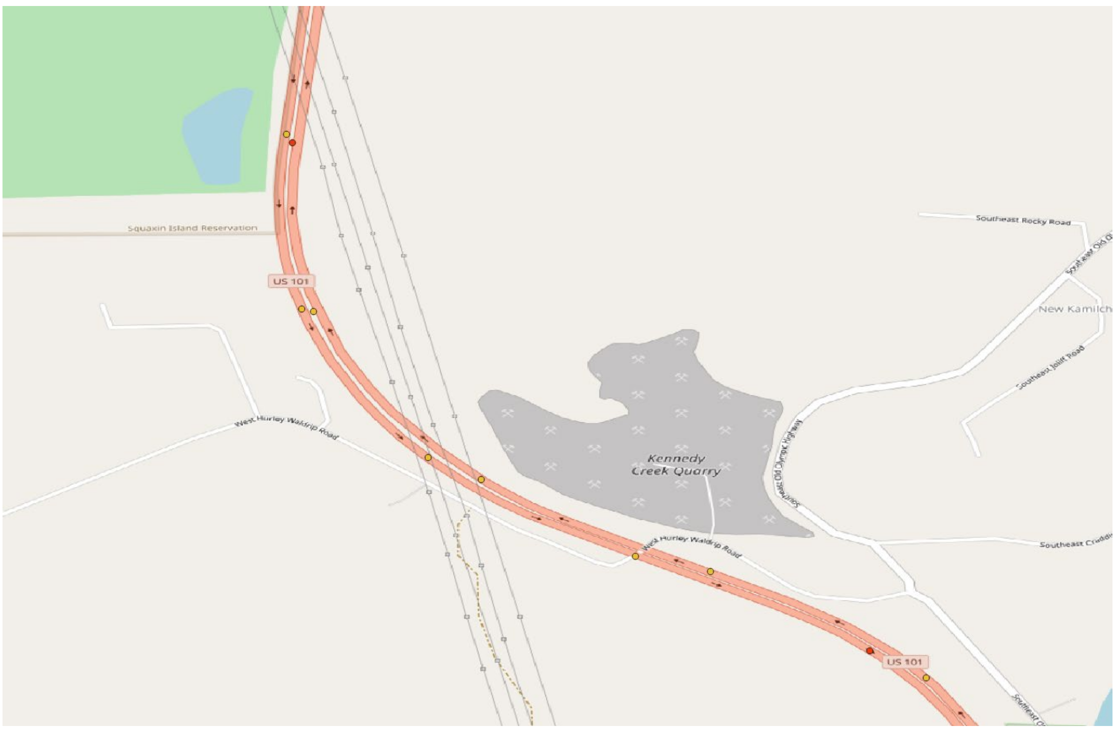


Figure 8-6. Road state for each point

On DRIVE Net, a new panel under the Multi-Model Analysis was created named CV4WM, shown in figure 8-7. This panel allows users to choose the query date. Below the date selection, there are two buttons. The second button, “Predict Washington Road Surface Condition,” was used for the case study in Washington. A legend of the road surface condition is also displayed on the map. Colors frrom dark red to dark blue indicate changes in the road state from dry to snow. On the right hand of the platform, the query result for the road state can be seen on the OpenStreetMap with colors. Because the case study in Washington took place in June, the road surface varied among dry, moist, and mostly wet.

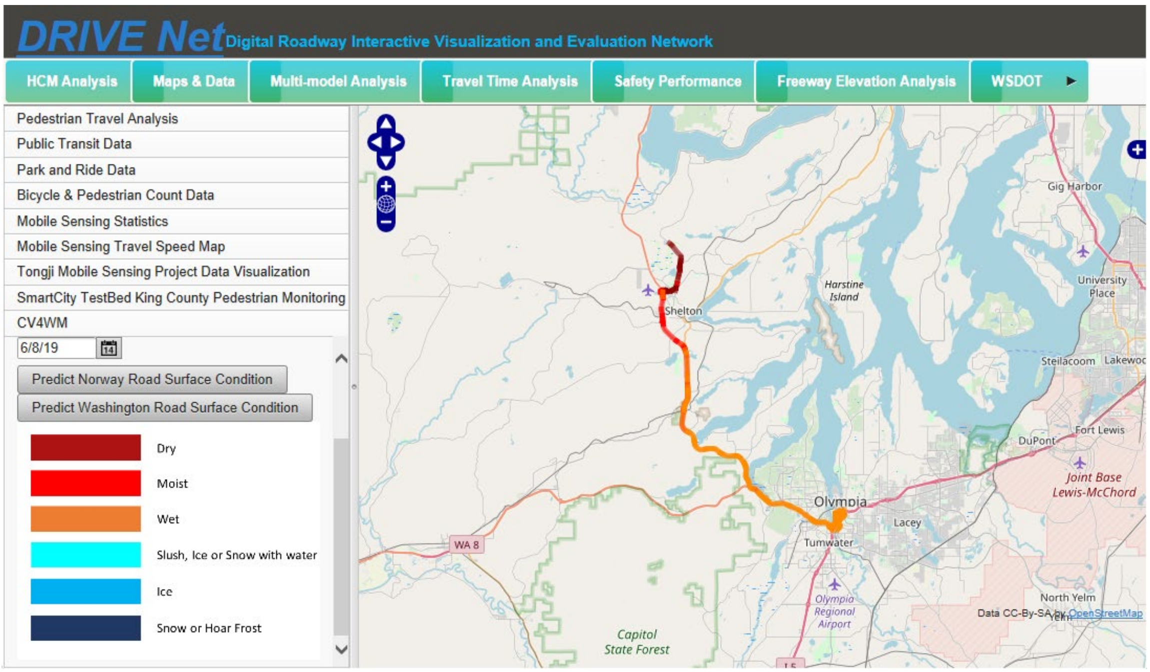


Figure 8-7. Visualization on DRIVE.NET

In figures 8-8 and 8-9, the road state can be seen more clearly. Comparing those with figures 8-6 and 8-7, the road can be shown in a sequential line by selecting the corresponding road segment according to each point. The system selects the state of the last point of a road segment as the state of the whole road segment. So the platform can show the whole road state on the map sequentially.

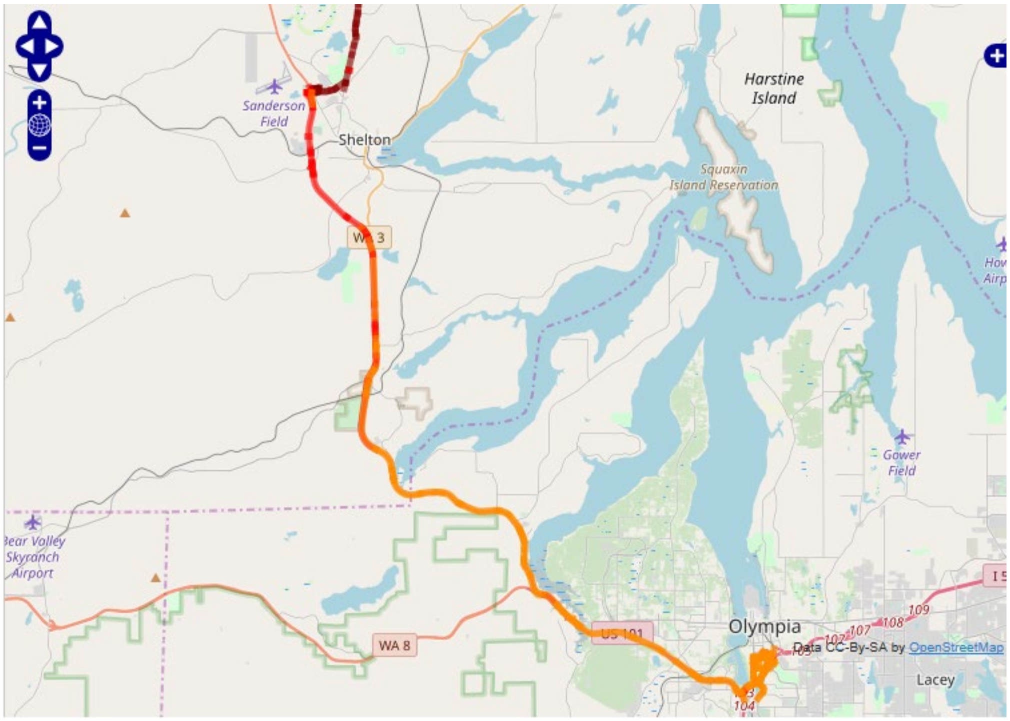


Figure 8-8. Detailed state for each road segment

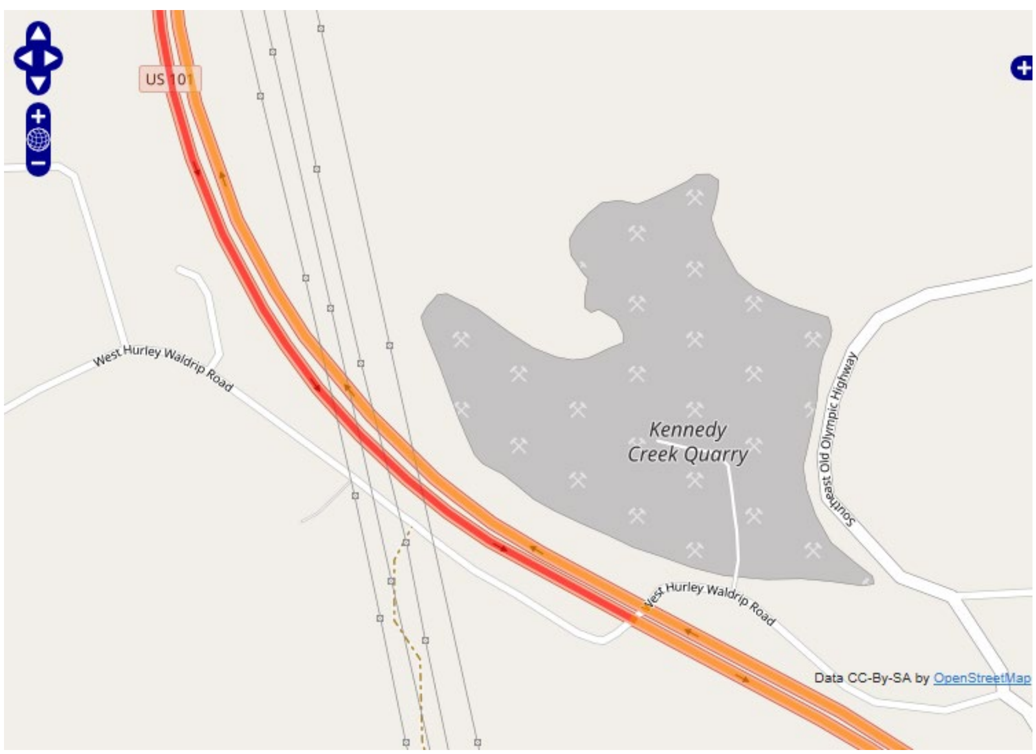


Figure 8-9. Detailed state for each road segment

9. Conclusions

This work proposed a three-layer system for road surface prediction and visualization. The proposed system includes a data collection and processing layer, a data analysis and matching layer, and a data visualization layer. The data collection layer is responsible for collecting road surface friction data and geospatial data. The data analysis and matching layer aims to predict future road surface friction and to match non-spatial data and spatial data together for visualization. The data visualization layer aims to present the predicted results and historical records on DRIVE Net based on user's requests.

To demonstrate the proposed road surface friction prediction method, several experiments were conducted to evaluate the method's predictive performance in comparison with other baseline models and to investigate the impacts of algorithm structures and other input variables. The experimental results showed that the proposed LSTM road surface friction prediction model outperformed all other baseline models in terms of the lowest values of MAE, MSE, and MAPE. The number of time-lags and the predictive time interval influenced the predictive performance of the proposed model. The LSTM prediction model achieved the most accurate prediction with seven time-lags, and the prediction accuracy dropped when the predictive time interval got larger. Road surface water thickness and road surface temperature were added to the proposed prediction model as model input. Road surface water thickness improved predictive accuracy, but road surface temperature did not.

This work also conducted a case study in Washington state to demonstrate the effectiveness of the proposed system. The findings of this study can be used to support road maintenance planning and decision making, helping to mitigate the impacts of inclement road surface conditions on traffic safety and mobility. Future research should include improving the road surface prediction algorithm in terms of accuracy and efficiency, and developing dynamic traffic control strategies based on real-time road weather conditions.

Part III: Traffic Simulations

10. Introduction: Addressing Weather Impacts on Highway Operations

Traffic congestion, both recurring and non-recurring, exerts an influence on the traffic network. It is clear from figure 10-1 that non-recurring sources of congestion account for 60 percent of traffic congestion, whereas recurring traffic sources are responsible for the remaining 40 percent. Among those, our subject of interest was how to reduce the effect of congestion during “bad weather” scenarios, leading to an improvement in the operational performance of traffic.

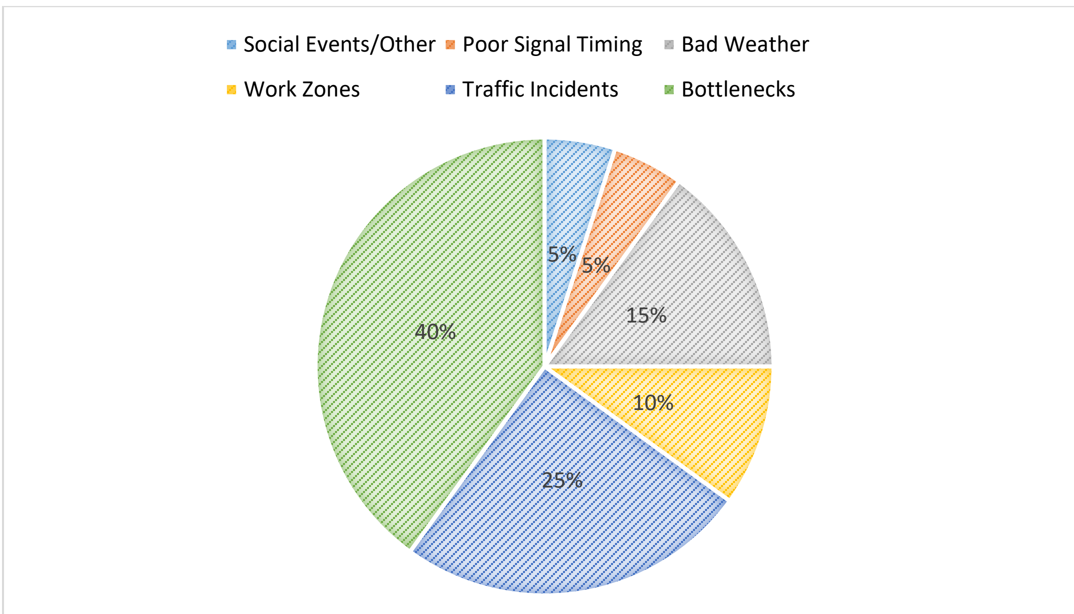


Figure 10-1. National summary for the sources of congestion
(Source: https://ops.fhwa.dot.gov/aboutus/opstory.htm)

In the past, congestion problems were solved by building new highways or adding lanes to increase roadway capacity. However, these types of practices are not encouraged as this type of solution is resource-expensive because of limited land available for right of way, increasing construction costs, and environmental impacts (Ioannou and Chien, 1993). Accordingly, different approaches are needed to improve the performance of highway sections. Limitations in the capacity of highways are attributed to disturbances and traffic flow instability that result from driver behavior. As tangible examples of new transportation modes increase every day, it is likely that future transportation will be characterized by the evolution of the cutting-edge technology of connected vehicles (CVs). Developing CV technologies will offer more safety by reducing human interaction. The USDOT anticipates that over 80 percent of non-impaired incidents could be attenuated through the implementation of CV technology (Abdulsattar *et al.*, 2019a & b). In addition, the increasing demand for the movement of people and goods could be ameliorated through the implementation of new technologies. New drivers' assistance and protection systems, in addition to vehicle communication technologies, hold promise to enhance the performance of the traffic network by providing drivers with meaningful information regarding travel conditions and other useful inputs that could help them avoid incidents and congestion locations. With these exciting prospects, leading vehicle manufacturers, with the help of technology companies, have been working on developing newer strategies to deploy CVs and coordinate with other infrastructure components. Recent endeavors to bring these concepts of CVs into the real world have included deployment through USDOT sponsored pilot programs in New York City, Tampa, Florida, and Wyoming. Because the future of connected vehicles is becoming more focused, the current transportation network must adapt to this technology in the near future.

The primary motivation for establishing V2V communication is to improve the capacity and throughput of highways by attenuating disturbances in traffic flow (Shladover *et al*., 2008) by reducing driver-vehicle interaction. Connected vehicle technologies utilize wireless network communication systems to exchange information with surrounding vehicles and infrastructures (Malakorn and Park, 2010). CVs are considered to be a potential candidate for improving the stability of the traffic flow, travel time reliability, roadway capacity, and safety (Schakel *et al*., 2010; Abdulsattar *et al*., 2018; Abdulsattar *et al*., 2019). The exchange of information through V2V communication enables vehicles to adjust their speed and following distance on the basis of down-stream and adjacent-lane traffic. This has the potential to increase lane capacity up to double the capacity of the existing traffic network (Shladover *et al*., 2008; Milanes *et al*., 2013). Furthermore, through the utilization of the V2V communication system, vehicles can maintain short time-headways and increase lane capacity under traffic conditions that require frequent changes in speed (Van Arem *et al*., 2006; Bu *et al*., 2010). Therefore, V2V communication technology has the potential to enhance the efficiency, reliability, and operational performance of the transportation network (Talebpour *et al*., 2016). Moreover, providing real-time information to drivers is expected to improve their response times (Xu *et al*., 2002), which will positively affect existing traffic capacity (Van Arem *et al*, 2006; Bu *et al*, 2010).

Therefore, this work focused on the simulation of operational enhancements of highways through the deployment of vehicle communication technology during inclement weather. While many studies have already researched ways to mitigate congestion during adverse weather, a gap remains in the literature demonstrating how connected vehicle technologies can be applied to better manage traffic network during such events. The traffic performance benefits associated with the emergence of vehicle communication technology, and the lack of tools to evaluate those benefits, were the impetus for this project.

11. Existing Approaches to Evaluate CAV Technologies

Connected and autonomous vehicles (CAVs) will be introduced on U.S. roads in the very near future. As a medium of technological evolution, CAVs are likely to upend traditional traffic composition, usher in new operational models, and disturb the nature of traffic flow fundamentals and mobility management (Mostafizi *et al.,* 2017, Mostafizi *et al.,* 2018, Abdulsattar *et al.*, 2019a). It has been postulated that vehicle communication technology, in the form of CVs and CAVs, will influence traffic behavior, and there will be a time when human driven vehicles, CVs, and CAVs will coexist in an interconnected network of traffic. The fact that CVs and CAVs are equipped with an array of sensors that help them exchange information between vehicles and increase automated actions, making them more responsive to split-second incidents and reducing human to human interaction, establishes them as a medium for improving safety, increasing mobility, and reducing emissions. These information exchanges encompass two types: vehicle to vehicle (V2V) and vehicle to infrastructure (V2I). Vehicle communication technology involved in V2V communication represents an important step in highway automation because of its ability to improve highway performance at high market penetration rates (Vander Werf *et al.*, 2002).

Although communication technologies offer different innovative ways to improve transportation system performance, transportation agencies have not been able to evaluate and identify applications that best accommodate their requirements. The literature shows that there have not been any practical ways to determine how much advantages the transportation network would gain as a result of the deployment of CVs. In addition, available transportation planning and analysis tools are not designed to quantify the benefits associated with deployment of the emerging vehicle communication technology. In summary, these tools are not able to consolidate and simulate vehicle communication and automation features.

Because traffic congestion imposes a great amount of pressure on the environment, economy, and commuters' safety, improving the operational and traffic performance of traffic networks is of importance. Instability in traffic flow, often termed as stop-and-go conditions, is considered to be the main reason behind traffic congestion (Ploeg *et al.,* 2011). In the past, solutions to the congestion problem have been to build new highways to increase roadway capacity. However, this type of solution is often not desired for reasons that include increased construction costs, a lack of land, and environmental impacts (Ioannou and Chien, 1993). Given these factors, it is necessary to develop other effective measures to alleviate growing traffic congestion problems.

Vehicle communication technology, in the form of V2V and V2I communication, is considered to be a promising approach for solving traffic congestion problems (Zhou et al., 2012, Mostafizi et al., 2018). CVs have the potential to enhance traffic performance in terms of safety, mobility, and environmental impacts (Genders and Razavi, 2015). Moreover, V2V/V2I communications have proved their effectiveness at maintaining faster response times and thus more efficient and safer networks (Jones and Philips, 2013; Xu *et al.*, 2002). This technology promises to be an important step toward automation in highway management because of its potential to double the capacity of highways at high market penetration (MP) levels (Vander *et al.,* 2002). The primary motivation behind establishing V2V communication is that it will improve the capacity and throughput of highways, in addition to attenuating disturbances in traffic flow (Shladover *et al.,* 2015). CVs are considered to have the potential to improve stability, roadway capacity, and safety of the traffic flow (Schakel *et al.*, 2010).

CV technologies utilize wireless network communication systems to exchange information with surrounding vehicles and infrastructure (Malakorn *et al.*, 2010). The exchange of information through V2V communication enables vehicles to adjust their speed and following distance on the basis of down-stream and adjacent-lane traffic. This has the potential to double the lane capacity of the existing traffic network (Milanés *et al.*, 2014). Moreover, CVs have the ability to reduce traffic congestion at bottlenecks caused by lane-drops and to improve traffic flow (Davis 2016). Tthrough the utilization of V2V communication systems, vehicles are able to maintain short time-headways and to increase lane capacity under traffic conditions that require frequent changes in speed (Bu *et al.,* 2010). Therefore, V2V communication technology has the potential to attenuate string instability through information transfer between vehicles (Jones *et al.* 2013, Milanés *et al.,* 2014, Ploeg *et al.,* 2011, Van Arem *et al.,* 2006). In addition, Talebpour *et al.* (2016) found that CV technology has the potential to improve the efficiency and reliability of the driverless transportation network. Limitations in the capacity of highways are caused by disturbances and instability of traffic flow that result from the drivers' behaviors and lack of information (Hadiuzzaman *et al.,* 2019). Vehicle communication technology, by providing real-time information to drivers, is expected to address this situation by maintaining faster response times (Jones *et al.,* 2013). Thus, CVs have the potential to improve the traffic performance of roadway networks and increase the capacity of the highway (Bu *et al.,* 2010b, Van Arem *et al.,* 2006) because of their ability to anticipate potential incidents will result in accident-free and smooth driving under complex traffic environments (Treiber *et al.,* 2006).

To measure the impacts of the vehicle communication system on traffic performance, Milanés *et al.* (2014) designed, developed, and tested an enhanced V2V communication system for its impact on traffic performance. Results showed that there was an improvement in response time and also better string stability of traffic, demonstrating the potential to mitigate traffic disturbance and improve highway capacity and traffic flow stability. Wolshon *et al.* (2015) further tested the deployment of a CV system by using a microsimulation platform using AIMSUN. To simulate CV behavior, the time-headway between consecutive vehicles was reduced from 1.4 to 0.6 seconds. This reduction in the following time gap resulted in an increase in the lane capacity of the highway from 2,200 vphpl to 4,000 vphpl at a 100 percent MP level. Shladover *et al.* (2012) developed a microsimulation model to evaluate the impacts of V2V communication on highway capacity. The research concluded that V2V communication has the potential to increase lane capacity up to 4,000 vph at full market penetration. Arnaout and Bowling (2011) investigated the effects of V2V communication on a multi-lane freeway without introducing any traffic disturbances such as obstacles, ramps, or lane drops. The results showed that the introduction of CVs had a positive influence on traffic capacity, especially at high traffic densities. Arnaout and Bowling (2014) also assessed the impact of V2V communication technology on a four-lane freeway with an on-ramp to induce traffic disturbances. In general, the results showed the ability of CVs to improve traffic performance and reduce traffic instability.

A variety of studies have adopted empirical as well as simulation-based approaches to measure the potential impacts of variable message signs, vehicle connectivity, and other technologies that could improve network performance under different roadway scenarios. However, there has been a lack of empirical data on CVs, especially on CV market penetration levels, to establish microsimulation-based analysis as a feasible alternative for analyzing the impacts of CV market penetration levels on traffic safety performance.

Van Arem *et al.,* (2006) developed MIXIC, a traffic flow simulation model, to explore the influence of intelligent vehicles on traffic flow. The results demonstrated that an automated longitudinal control implemented in the cooperative following (CF) systems with inter-vehicular communication could exert a negative effect on traffic safety.

Paikari *et al.* (2013)used the PARAMICS microsimulation software to simulate V2V communication within a network of intelligent transportation systems (ITS) applications through a Multi-agent System Engineering (MaSE) methodology to picture CV modules as a Multi-Agent System (MAS). Two application programming interfaces (APIs) were implemented to simulate the CV systems. This study focused on the application of a DSRC-based V2V and V2I communication system to estimate traffic safety and mobility parameters. Results showed that the introduction of CVs would improve the safety and mobility of traffic conditions on the freeways of Calgary, Canada.

Later, a PARAMICS-based virtual V2V communication platform was developed to assist neighboring CVs in detecting and disseminating information about collision occurrence (Kattan *et al.*, 2010). The study showed the efficacy of inter-vehicular communication in improving the safety and travel time of the transportation network. In addition, Bu *et al.* (2010a) performed an empirical-based study in which a V2V communication system was developed to test vehicle communication impacts on traffic performance. The developed system used LIDAR technology as well as a DSRC communication system to receive information from the preceding vehicle. The new system was found to have the potential to enhance traffic safety and mobility.

Also, variable message signs (VMS) are considered to be an efficient way to convey traffic information data to drivers. This technology has the potential to be embedded in autonomous vehicles (Genders and Razavi, 2015). A simulation-based study was conducted to test the impacts of implementing two variable speed-limit control signs on highway work zones (Lin *et al.*, 2004).

Talebpour *et al.* (2016) developed a methodological framework to simulate different types of vehicles, including CAVs. The study showed that vehicle automation would help prevent shockwave formation, thereby increasing string stability and increasing the traffic throughput at certain market penetration rates under the model assumptions. Later, Tientrakool *et al.* (2011) applied a numerical analysis approach to evaluate the impact of V2V communication technology on the capacity of a highway section. The analysis involved considering the inter-vehicular distance between two consecutive vehicles. Study results showed that, at 100 percent market penetration, the CV technology had the potential to increase the capacity over 273 percent. Moreover, a two-lane cellular automaton (CA) model based on a proposed two-state, safe-speed model (TSM) was developed to investigate the impacts of CAVs in heterogeneous traffic-flow conditions (Ye *et al.* 2018). The developed model numerically simulated and analyzed the impacts of CAVs with different characteristics at different levels of market penetration. Results showed an insignificant increase in the capacity at MP level below 30 percent. However, for MP levels exceeding 30 percent, the increase in the highway capacity was highly dependent on the characteristics of the CAV. In addition, Chen *et al.* (2017) and Ghiasi *et al.* (2017) developed an analytical formulation of traffic operational capacity under mixed traffic conditions. Most of the aforementioned studies focused mainly on overall traffic performance and traffic flow stability. However, most of the studies did not quantify the impacts of the communication technology on highway capacity. Furthermore, these studies mainly focused on lane policy determination, autonomous vehicles distribution, and lane management under varying levels of traffic demand.

In addition to addressing the gap in the aforementioned literature, we bridged microscopic car-following behavior, represented in the utilized Intelligent Driver Model (IDM) car-following model, and macroscopic traffic flow under varying MP levels of CAVs. Most of the existing analysis and simulation tools used for transportation facility planning, operations, and evaluation, including the Highway Capacity Manual (HCM) (HCM 2010), do not incorporate the impacts of CAVs on enhancing the capacity of highways. For instance, HCM uses a static macroscopic methodology in which the parameters are sensitive to the time-headway and perception-reaction time. This research formulated an analytical capacity model to estimate the potential future impacts of CAVs under different MP levels. Furthermore, an advanced and flexible microscopic agent-based modeling and simulation (ABMS) framework able to simulate, evaluate, and quantify the impacts of CAVs on enhancing the capacity of highways in different settings was developed. The framework is able to simulate and capture the complexity and stochasticity in driver behavior. Therefore, the results obtained from this research could serve as a foundation for analysis and planning tools to incorporate the emerging CAV technologies in the future. The developed analytical and simulation frameworks are expected to serve as a foundation for transportation organizations and federal agencies to use in evaluating the future impacts of CAV technologies while developing infrastructure that accommodates this specific type of technological evolution.

In summary, the literature is replete with analyses of the impacts of CAVs on the capacity of highways. However, most of the existing analysis and simulation tools used for transportation facilities planning, operation, and evaluation, including the Highway Capacity Manual, have mainly focused on either simulation (Olia *et al.*, 2018) or analytical frameworks (Ye and Yamamoto, 2018). In addition, similar studies have not simultaneously considered microscopic traffic flow dynamics (i.e., traffic flow instabilities and lane changing behavior) that have a significant impact on the capacity performance of highways (Ghiasi *et al*, 2017) or autonomous merging and lane-changing behavior (Arnaout, 2011). Our proposed framework is an integrated approach in which all the above features are fused.

This research formulated an analytical capacity estimation model to quantify the potential future impacts of CAVs under different MP levels. This research

- addressed microscopic car-following behavior, represented in the utilized Intelligent Driver Model (IDM) car-following model and macroscopic traffic flow under varying MP levels of CAVs;
- formulated an analytical IDM-based capacity estimation model to quantify the potential future impacts of CAVs under different MP levels;
- considered the microscopic traffic flow dynamics (i.e., car-following, merging, and lane-changing behaviors) of conventional vehicles and CAVs as explained in further detail.

Therefore, the results obtained from this research could serve as a foundation for analysis and planning tools to incorporate emerging CAV technologies for better winter travel in the future. The developed analytical and simulation frameworks are expected to serve as a foundation for transportation organizations and federal agencies to use in evaluating the future impacts of CAV technologies while developing infrastructure that accommodates this specific type of technological evolution.

12. Development of a Simulation Framework for CAV

One of the major challenges in traffic flow modeling is to predict driving maneuvers and behaviors. Most lane changing and car-following models assume that a vehicle will change a lane within an available gap and will maintain a safe following distance (Arash Olia *et al.*, 2013). Moreover, for the purpose of simulating longitudinal car-following behavior, traffic flow conditions have to be defined. Traffic is considered to be at a free-flow state when there are no constraints on vehicles' longitudinal or lane-changing behavior. Once traffic density starts to influence traffic operations, such as affecting lane changing behavior or driving speeds, then traffic conditions are no longer considered to be in free flow.

12.1. CAV Agents' Communication and Behavior

For V2V and V2I communication, Dedicated Short Range Communication (DSRC) is utilized. DSRC provides a communication range of 3,000 ft in diameter, with an ability to extend the communication range through multiple transmitters (Roodell 2010). Transmission extension can be carried out with CAVs acting as transmitters. CAVs will receive information from the leading vehicle within the range of 3,000 ft. The information may include the vehicle's physical location, speed, acceleration, and deceleration of the preceding CAV. The CAV establishes communication and reacts to the information received from the preceding vehicle if it is within a 500-ft range.

Similarly, CAVs can establish V2I communication with a roadside unit. The roadside unit provides the vehicle with information related to any upcoming incident, recommended speed, and upcoming on-ramps that may require advance lane-changing. In free-flow conditions, CAVs will follow the speed limit of the roadway section provided through the V2I communication. Traffic is considered to be in free-flow conditions when there are no constraints on the vehicles' longitudinal and lane-changing behavior. However, when traffic density imposes constraints on the vehicles' maneuvering, traffic is no longer considered to be in free flow. Established V2V and V2I communications allow CAVs to maintain short following time-headway between two consecutive CAVs, as well as a very short reaction time. The reaction-time is assumed to be 0.1 second to account for communication latency. However, if the preceding vehicle is a conventional vehicle, the CAV will not be able to establish communication, and a short following time-headway cannot be maintained. Nevertheless, short reaction-times can be maintained because of the detection systems with which the CAV is equipped.

12.2. Vehicles Behavior in Heterogeneous Traffic Flow

12.2.1. Car-Following Behavior

This section describes the modeling assumptions and parameters underlying the analytical capacity formulation and the ABMS model in terms of the car-following and lane-changing behavior of CAVs and conventional vehicles for heterogeneous traffic flow.

It was necessary to develop a car-following methodology to articulate the driving behavior of CVs during inclement weather conditions. Car-following theories describe driver behavior when one vehicle follows another in a traffic stream. Car following models were first developed in the 1950s on the basis of two notions, stimulus and response; that is, each driver reacts in a particular fashion to a stimulus that leads to the event of an acceleration. A variety of studies have focused on applying car-following models to compare vehicle dynamics (e.g., velocity, acceleration) between two vehicles. In this project, car-following models were investigated in the literature. Therefore, a system of ODEs for the Intelligent Driver Model (IDM) was derived. Then we developed a framework to simulate the dynamics of the IDM for realistic driving scenarios in inclement weather. The IDM is widely used, as it can reach high desired velocities with realistic acceleration and deceleration while maintaining non-collision gaps for a platoon of vehicles.

In traffic flow theory, the IDM is considered to be a microscopic traffic flow model that can simulate freeway and urban traffic. The model was developed by Treiber, Hennecke and Helbing in 2000 using observations gained from the experimental results with other “intelligent” driver models such as Gipps’.

Let us consider two vehicles: i and *i-1*. $x_i, \dot{x}_i$ denote the position and velocity of the i-th car, respectively. l_i denotes the length of the n-th car. We define the net distance between two consecutive cars as follows:

$$S_i \coloneqq x_{i-1} - x_i - l_{i-1} \tag{10}$$

The IDM assumes the acceleration behavior to be a continuous function of the speed v_i, gap s_i, and speed differential Δv_i with the preceding vehicle (Treiber et al. 2000). Equation 11 presents the generic form of the proposed IDM model.

$$\square\, \ddot{x}_i(t) = a[1 - \left(\frac{v_i\,(t)}{V}\right)^{\delta} - \left(\frac{S(v_i\,(t),\Delta v_i(t))}{S_i}\right)^2] \tag{11}$$

where

$a_{max,i}$ = maximum comfortable acceleration;

$v_i\ (t)$ = speed of the vehicle i;

V = desired velocity;

δ = acceleration exponent;

S = actual gap between the leading vehicle $i - 1$ and the following vehicle i;

$\Delta v_i(t) = v_i(t) - v_{i-1}(t)$ is the removal rate of the vehicle *i* to its preceding vehicle i − 1;

$S\ (v_i\ (t), \Delta v_i\ (t))$ is the minimum desired gap defined by the following equation:

$$S\big(v_i\,(t), \Delta v_i(t)\big) = s_0 + \max[T v_i(t) + \frac{v_i\,(t)\Delta v_i(t)}{2\sqrt{a_{max,i} b_{max,i}}}, 0] \tag{12}$$

where s_0 is the inter-vehicular distance at standstill; *T* is the safe following time-headway; and $b_{max,\ i}$ is the desired deceleration of the vehicle *i*.

The acceleration is divided into two parts: "desired" acceleration on a free road is $[1 - \left(\frac{v_i\,(t)}{V}\right)^{\delta}]$ and braking deceleration induced by the front vehicle is $\left(\frac{S(v_i\,(t),\Delta v_i(t))}{S_i}\right)^2$. The acceleration on a free road decreases from the initial acceleration to zero when the subject car approaches the preceding car with "desired speed" $\dot{x}_o$.

Table 12-1 shows the estimated values of the IDM parameters that were found in the literature.

Table 12-1. Values of IDM parameters

IDM Parameter	Value for Human Driven Vehicle
Desired Speed, $\dot{x}_o$	120 km/h
Time Headway, *T*	1.5 s
Minimum Gap, s_0	2.0 m
Acceleration, a	0.3 m/s^2
Deceleration, *b*	3.0 m/s^2

The original IDM id model considered homogenous traffic conditions in which all vehicles were non-CAVs. It had to be modified to address a situation in which both CAVs and non CAVs co-exist in a traffic stream. For *N* number of cars, equation 11 can be written as follows:

$$\ddot{x}_1(t) = a[1 - \left(\frac{v_1\,(t)}{V}\right)^{\delta} - \left(\frac{S(v_1\,(t),\ \Delta v_1(t))}{S_1}\right)^2]$$
$$\ddot{x}_2(t) = a[1 - \left(\frac{v_2\,(t)}{V}\right)^{\delta} - \left(\frac{S(v_2\,(t),\Delta v_2(t))}{S_2}\right)^2] \tag{13}$$
$$\ddot{x}_N(t) = a[1 - \left(\frac{v_N\,(t)}{V}\right)^{\delta} - \left(\frac{S(v_N\,(t),\ \Delta v_N(t))}{S_N}\right)^2]$$

where

$$S\big(v_i\,(t), \Delta v_i(t)\big) = s_0 + \max[Tv_i(t) + \frac{v_i\,(t)\Delta v_i(t)}{2\sqrt{a_{max,i}b_{max,i}}}, 0] \tag{14}$$
$$S_i \coloneqq x_{i-1} - x_i - l_c$$

The parameters in table 12-2 needed to be calibrated to address CAVs in a heterogeneous traffic stream. The developed simulation framework provides the flexibility to set variable driving speed, reaction time, and time headway in the case of non-CAVs, in contrast to other multi-agent simulation platforms. The values for these parameters were chosen as shown in table 12-2 (Li *et al.,* 2017; Kesting *et al.,* 2010):

Table 3. Parameter values of IDM

Parameter	Value for CV Vehicle
Desired Speed, $\dot{x}_o$	120 km/h
Acceleration exponent, δ	1 m/s^2
Time Headway, T	0.6 s
Minimum Gap, s_0	2.0 m
Acceleration, a	2.8 m/s^2
Deceleration, b	1.5 m/s^2

Because the original IDM considered a homogeneous traffic condition in which all vehicles were non-CAVs, the model needed to be modified to account for heterogeneous traffic flow in which both non- CAVs and CAVs interact with each other in the traffic stream. In this study, four types of vehicle-following combinations were considered to simulate different scenarios of CAV/non-CAV heterogeneous traffic flow. (1) a non-CAV following another non-CAV, (2) a non-CAV following CAV, (3) a CAV following another non-CAV, and (4) a CAV following a CAV. Accordingly, the proposed heterogeneous IDM formulates the four-different CAV/non-CAV car-following combinations as follows (Abdulsattar *et al.* 2019b):

$$\begin{cases} \dot{v}_i(t) = a_{max,i}[1 - \left(\frac{v_i(t)}{V_i}\right)^{\delta} - \left(\frac{S_i^{R_t}(v_i(t),\Delta v_i(t))}{\Delta x_i(t) - l}\right)^2] \\ S_i^{R_t}({v_i}^{R_t}(t), \Delta {v_i}^{R_t}(t)) = s_{i,0} + \max[T_i {v_i}^{R_t}(t) + \frac{{v_i}^{R_t}(t)\Delta {v_i}^{R_t}(t)}{2\sqrt{a_{max,i} b_{max,i}}}, 0] \end{cases} \quad (15)$$

where l is the leading vehicle length, and superscript R_t refers to the reaction-time of the *ith* vehicle. Correspondingly, all the parameters $a_{max,i}$, V_i, R_t , $s_{i,0}$, T_i, and $b_{max,i}$ vary among the different types of vehicles. The aforementioned parameters were generated in the simulation framework through Monte-Carlo simulation to account for the heterogeneity in the characteristics of non-CAVs in the traffic stream. The features of heterogeneous and homogeneous traffic flow could be explained as follows: homogeneous traffic flow acts on the assumption that drivers are inclined to maintain zero acceleration, a fixed space headway, and velocity (i.e., $\Delta v_i = 0$, $\dot{v}_i = 0$) at the equilibrium state. However, in heterogeneous traffic flow, drivers tend to maintain zero acceleration as well as stable velocity while space headways vary among the vehicles (i.e., $h_a = h_i^e$), where h_i^e is the corresponding equilibrium headway of the vehicle *I* and it varies among the vehicles (Abdulsattar *et al.*, 2019b).

12.2.2. Lane-Changing Behavior in a Mixed Traffic Environment

Other than car-following behavior, the other major component of vehicle behavior in the traffic stream is lane-changing behavior. In order to model lane-changing behavior in a heterogeneous traffic stream, the gap-acceptance model developed by Toledo *et al.* (2003) was considered to successfully capture lane-change behaviors with integrated target lane choice. This model was developed on the basis of detailed vehicle trajectory data to simulate integrated lane-changing behavior, both mandatory and discretionary, for both CAVs and RVs. Because the model was developed on the basis of detailed vehicle trajectory data, it is considered an individual-specific latent variable, v_n, that accounts for time-invariant characteristics such as aggressiveness, level of driving skills, and vehicle speed and acceleration capabilities. However, to simulate CAVs, we considered some additional constraints to maintain traffic stability based on the desired following distance (Abdulsattar *et al.*, 2019b). Equations 16 and 17 denote the critical lead and lag gap formulas adopted for non-CAVs. Note that when values of these parameters are below the critical calculated values in the developed simulation, no lane-change maneuver will be executed.

$$G_i^{lead\,TL,cr}(t) = \exp\Big(1.353 - 2.7\,max\big[0, \Delta V_i^{lead\,TL}(t)\big] - 0.231\,min\big[0, \Delta V_i^{lead\,TL}(t)\big] - 1.27\,v_i + \in_i^{lead}\,(t)\Big) \quad (16)$$

$$G_i^{lag\,TL,cr}(t) = \exp(1.429 - 0.471\max\big[0, \Delta V_i^{lag\,TL}(t)\big] + 0.131\,v_i + \in_i^{lag}\,(t) \quad (17)$$

where $\Delta V_i^{lead\,TL}(t)$ and $\Delta V_i^{lag\,TL}(t)$ are the relative speeds of the lead and lag vehicles in the direction of change, respectively; $\in_i^{lead}\,(t)$ $N(0, 1.112^2)$; and $\in_i^{lag}\,(t)$ $N(0, 0.742^2)$. This model was used to simulate vehicles over-passing, as discretionary lane-changing behavior, and on-ramp merging, as mandatory lane-changing behavior, in the proposed highway scenarios. Because of the low reaction-time and short following time-headway of CAVs, additional logical constraints were added to the gap-acceptance model as described in Equations 18 and 19 (Abdulsattar *et al.*, 2019b).

$$G_{CAV,i}^{lead} = \max(\gamma h_{0,i}, G_i^{lead\,TL,cr}) \quad (18)$$

$$G_{CAV,i}^{lag} = \max(\gamma h_{0,i+1}, G_i^{lead\,TL,cr}) \quad (19)$$

where γh_0 is the is the critical time-headway for the i^{th} vehicle; $G_i^{lead\,TL,cr}$ is the lead gap calculated from Equation12; $\gamma h_{0,i+1}$ is the critical time-headway of the i + 1 vehicle if the vehicle is a CAV; and $G_i^{lag\,TL,cr}$ is the critical lag gap calculated from Equation 19. Given the gap acceptance behavior described in equations 18 and 19, CAVs will maintain the desired lane-changing gaps required to mitigate shock-wave propagation resulting from undesired critical gaps that can affect traffic flow and stability.

13. Results and Analysis

13.1. Simulation Framework and Setting

The developed methodology as outlined in Chapter 21 was implemented through a simulation testbed to evaluate the efficacy of CV technology during adverse weather. A hypothetical 1-km long roadway was considered, and a particular area (a 500- to 600-m offset within that stretch) was chosen to simulate inclement weather.

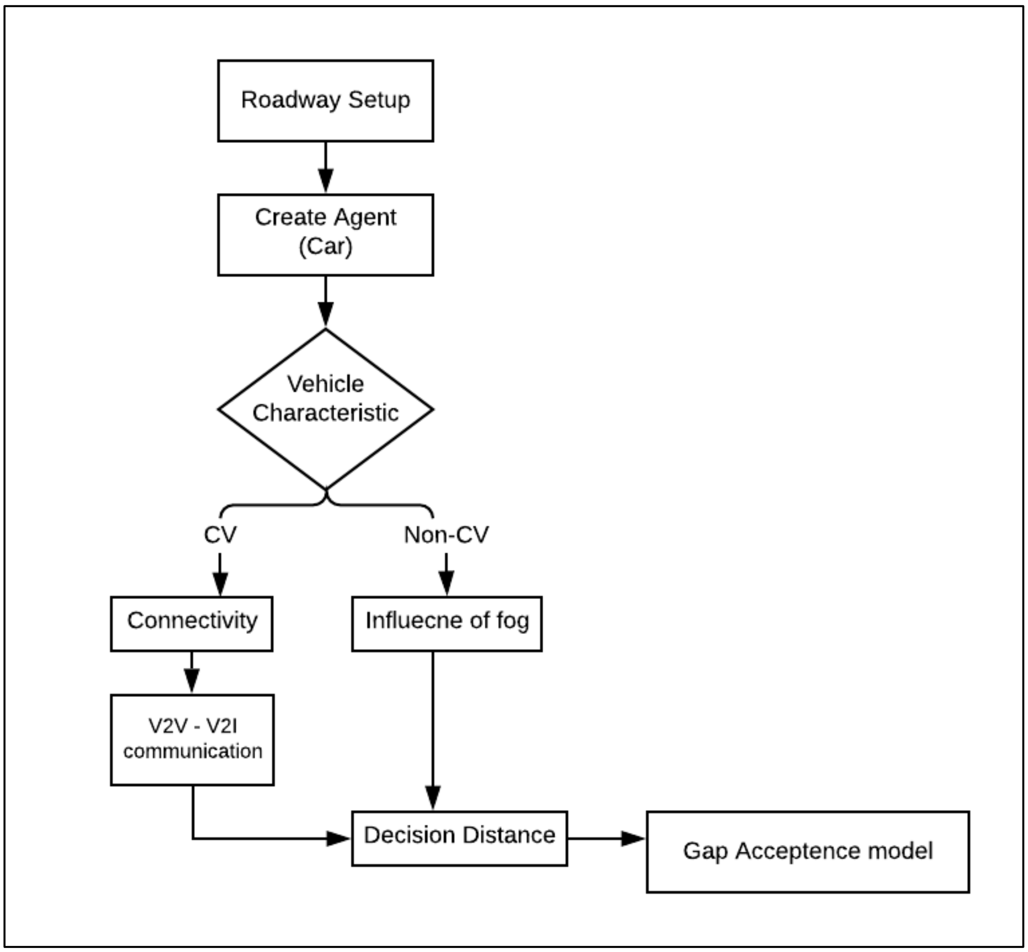


Figure 13-1. Simulation framework to characterize CAV behavior during adverse weather

In the presented scenario, a detector was placed every mile to calculate the speed, flow, and density of the passing vehicles on the roadway section. The simulation framework was divided into three phases, as described by Abdulsattar *et al*. (2018and 2020). While the first phase consisted of basic simulation and roadway configurations and settings in which the number of lanes, speed limits, and market penetration levels were defined; the second phase, consisted of non-CAV and CAV behavior models that included car-following and lane-changing behavior models, in addition to the logical constraints that simulated vehicle communication behavior. The third phase consisted of simulation execution, data acquisition, and results extraction. The simulation data were collected from 300 simulation minutes for each MP level with varying traffic flow rates to study the impacts of CAVs on the highway capacity of the hypothesized scenario. Vehicle arrival in the network followed a Poisson distribution with parameter λ = 720 veh/h. As a result, the vehicle headway followed a negative exponential distribution with μ = 5 s.

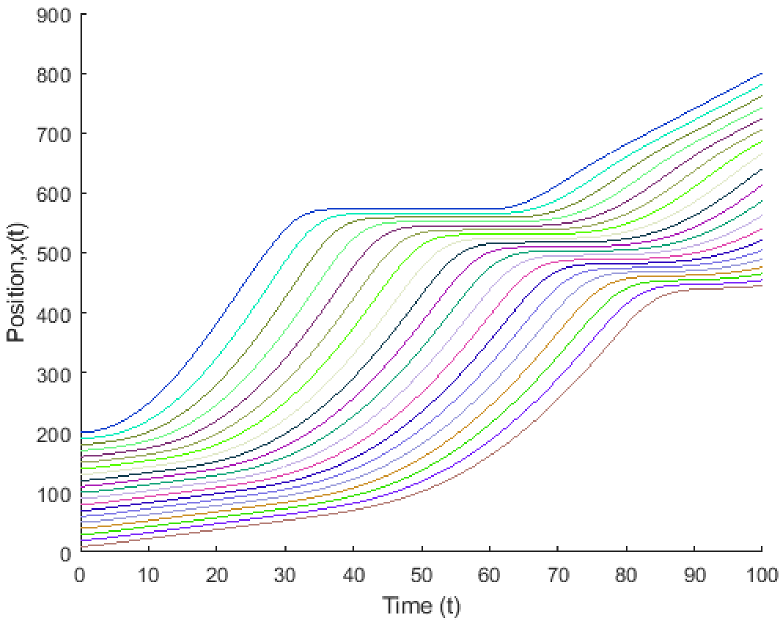
13.2. Results

Determining improvements in highway capacity performance associated with the deployment of vehicle communication technology is essential for assessing the impacts of CAVs on enhancing the traffic flow performance. This section describes an investigation of the impacts of varying MP levels on traffic during inclement weather. The numbers presented in the results are meant to provide quantitative insights into the potential benefits associated with deployment of CAVs to highway capacity, not to define threshold values that are sensitive to any possible variation in parameters and settings.

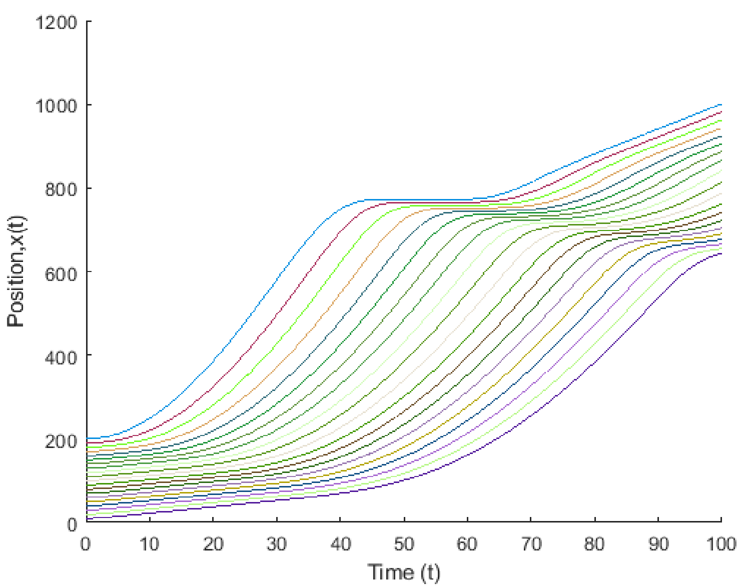
This section provides detailed descriptions of the present position and velocity profiles for different traffic situations with a mixture of human-operated vehicles (HVs) and CVs as revealed by the IDM. Figure 13-2 shows synthetic vehicle trajectories for the leader car during the developed simulation scenario. We considered the following assumptions for the simulation:

- During the initial 40 seconds, the leader car traveled with a constant velocity of 20 ft/s.
- After the next 30-second interval, the velocity of the leader vehicle was set to zero; it again moved with a 20-ft/s constant velocity.
- The position of the leader car was set at 200 ft ahead of the first follower car.
- The initial headway between other follower cars was kept at 30 ft with a 0-ft/s initial velocity.

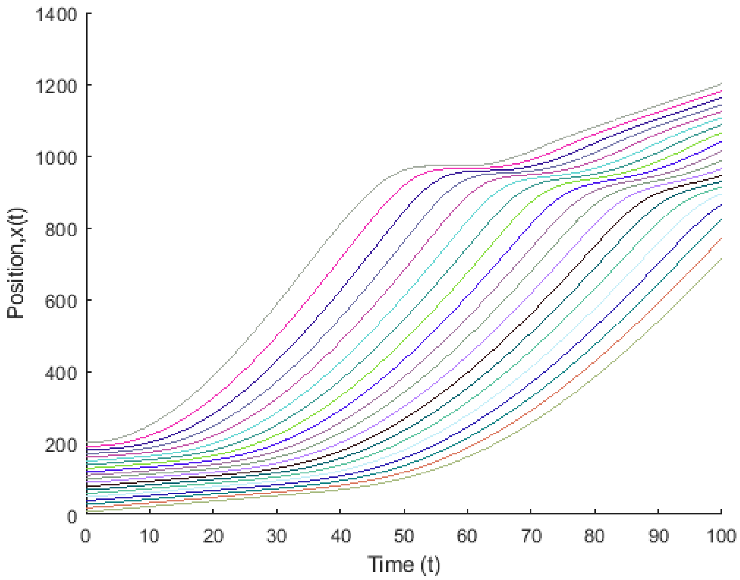
13.2.1. Trajectory Analysis



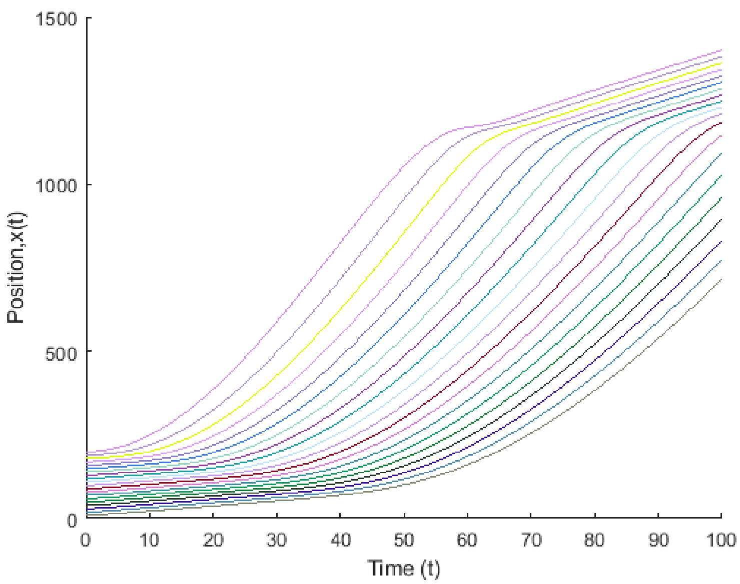
(a) 0% market penetration



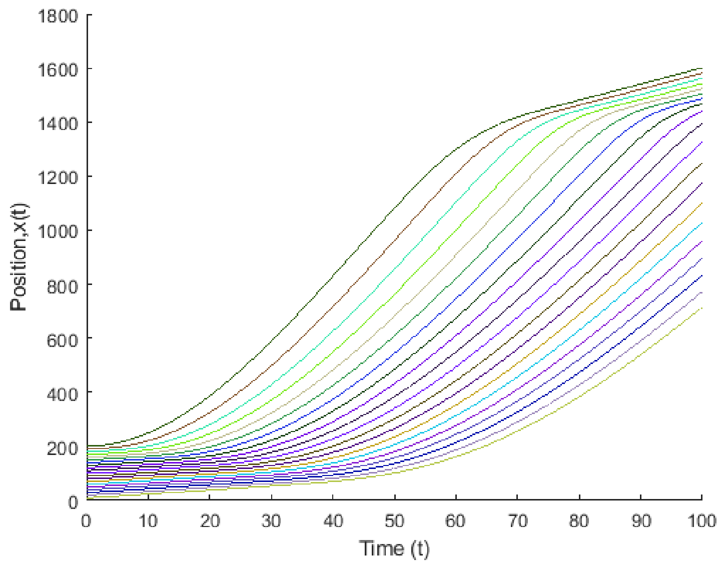
(b) 20% market penetration



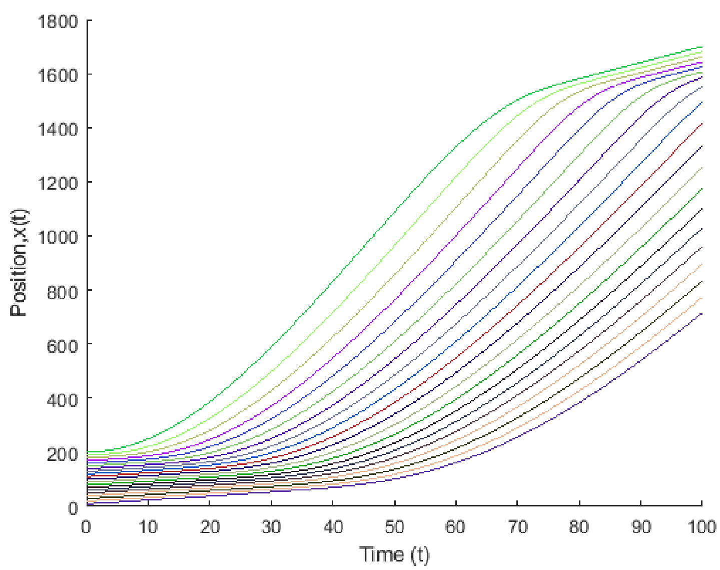
(c) 40% market penetration



(d) 60% market penetration



(e) 80% market penetration

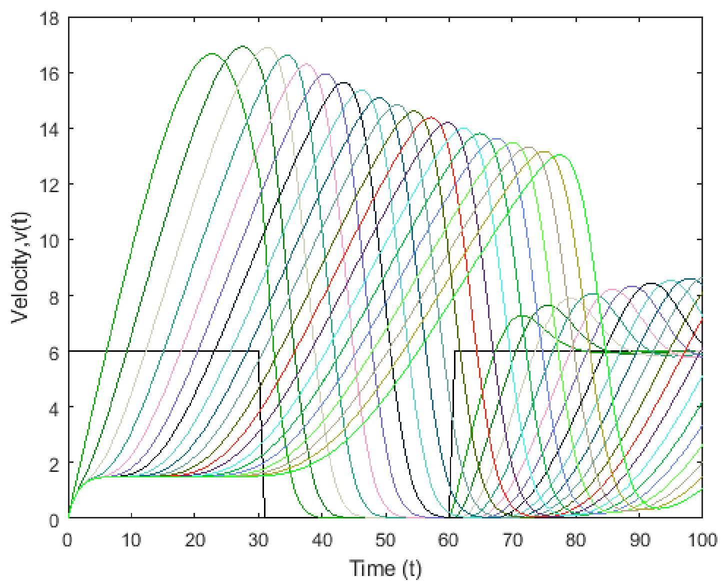


(f) 100% market penetration

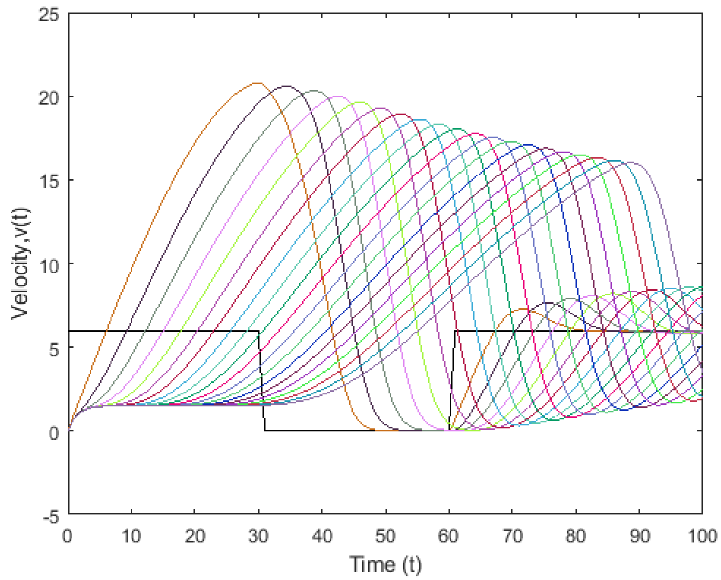
Figure 13-2. Position profile of *N* cars (a mixture of human-operated vehicles and CAVs) simulated with the IDM during inclement weather

The rajectories in figure 13-2 provide insights into how the CV technologies would facilitate less speed perturbation, leading to much smoother and safer travel. Our particular area of interest was how speed propagation would occur between 500 and 600 m, which was the area assumed to have inclement weather. With 0 percent CV market penetration, inclement weather resulted in shockwave propagation. As market penetration increased, improvement occurred in the vehicle trajectory, leading to a more stable traffic situation (figure 13-2(b)). There was less perturbation in the adverse weather zones, although the shockwave zone shifted to a later stage along the roadway (figure 13-2(d)). Speed perturbation due to the inclement weather still remained. However, as the market penetration of CVs reached 60 percent, significant improvement was observed as vehicle trajectories became smoother and perturbation decreased to a minimum.

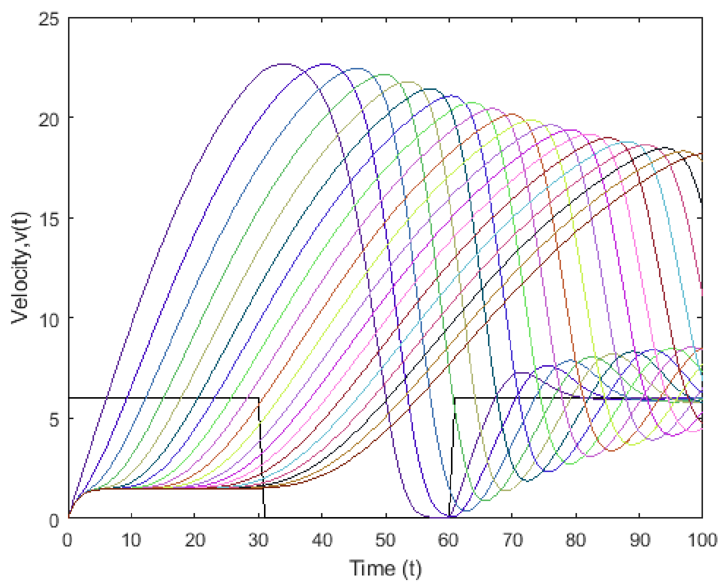
13.2.2. Velocity Profile Analysis



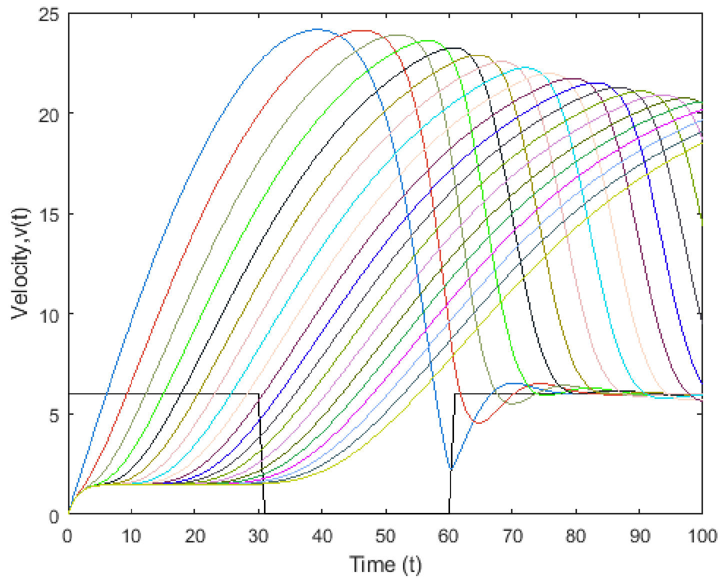
(a) 0% market penetration



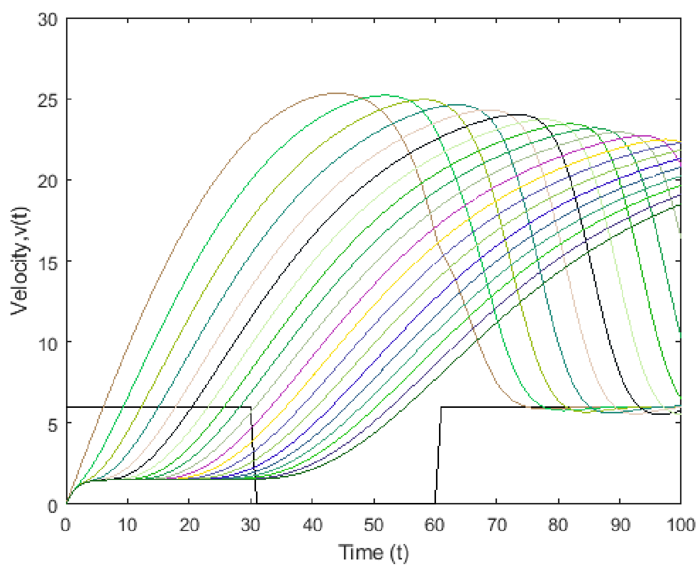
(b) 20% market penetration



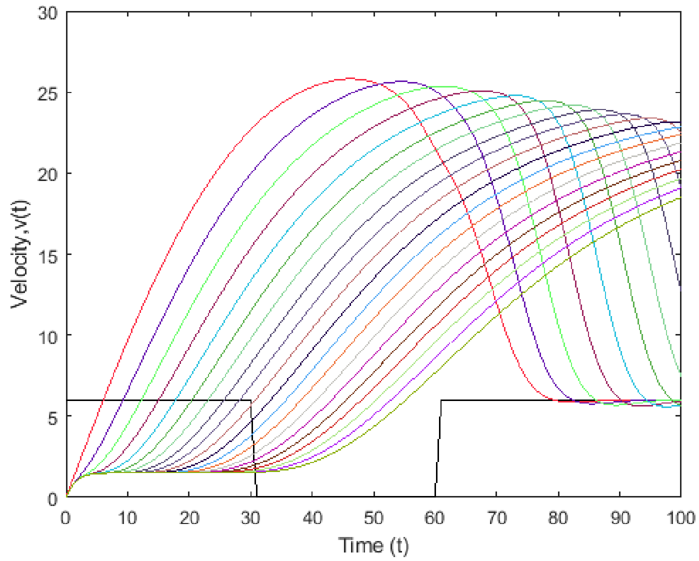
(c) 40% market penetration



(d) 60% market penetration



(e) 80% market penetration

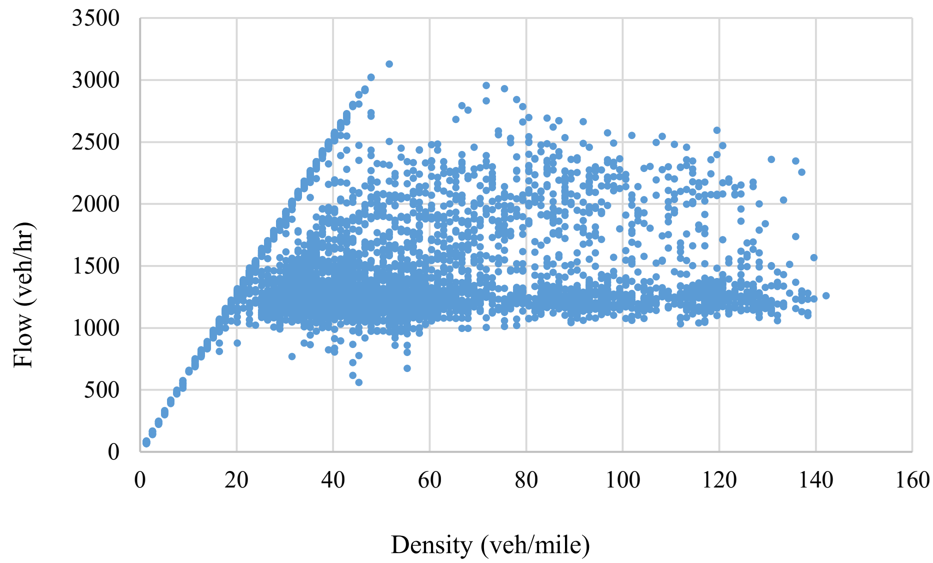


(f) 100% market penetration

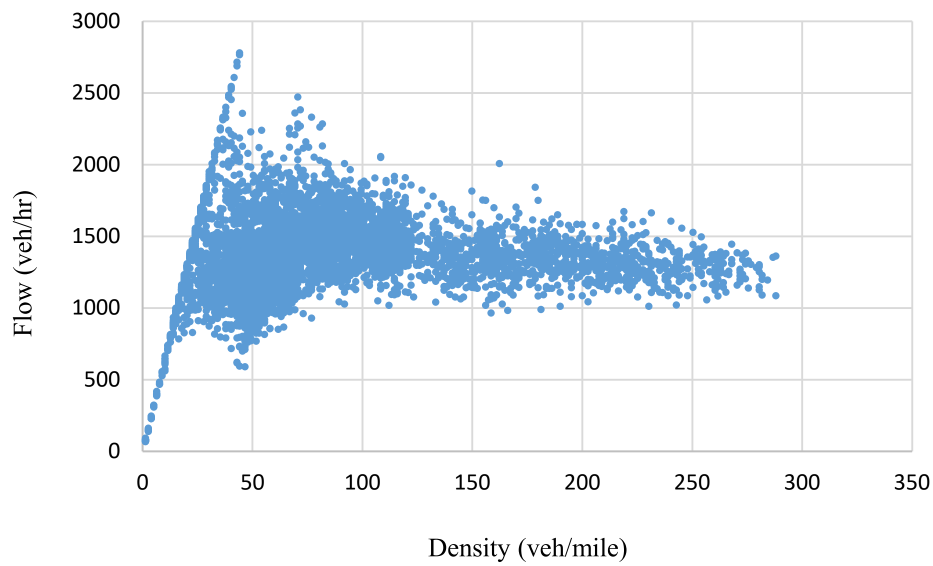
Figure 13-3. Velocity profile during adverse weather for different market penetration rates

The velocity profile based on the IDM formulation shown in figure 13-3 provides insights into how drivers interacted during the inclement weather. Results showed that for a scenario with a 0 percent MP rate, vehicles faced congestion as soon as the simulation time period reached 40 seconds. The situation improved as the MP rate increased. For example, with a 40 percent MP rate, deceleration started after 60 seconds. Significant improvement was observed when the MP rate reached 60 percent, as no vehicles did not decelerate; instead information exchange between vehicles led to more coordinated platooning, resulting in smoother traffic movement.

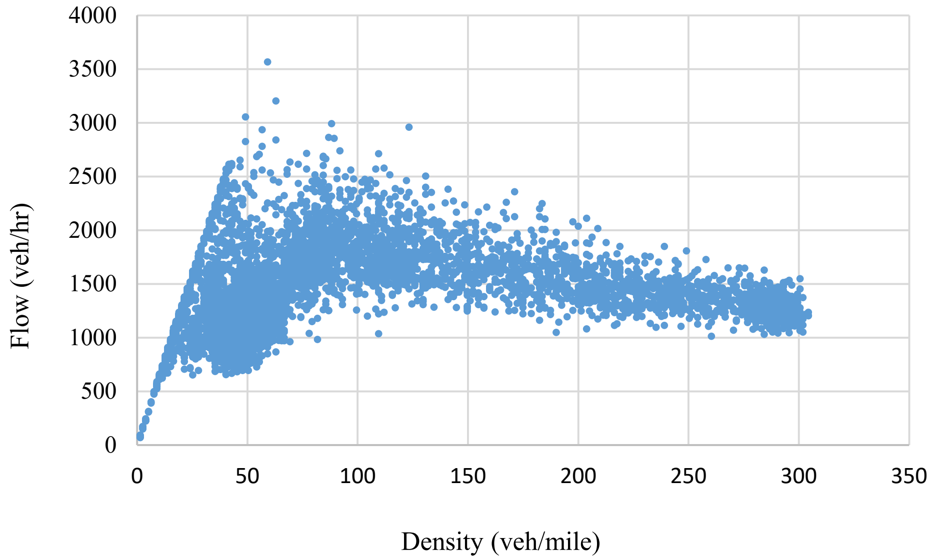
13.2.3. Fundamental Diagram Analysis



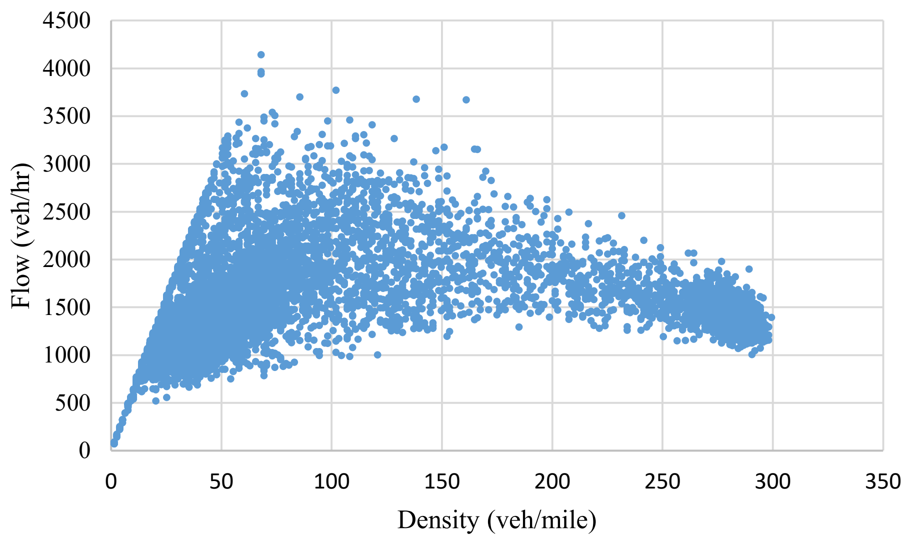
(a) 0% market penetration



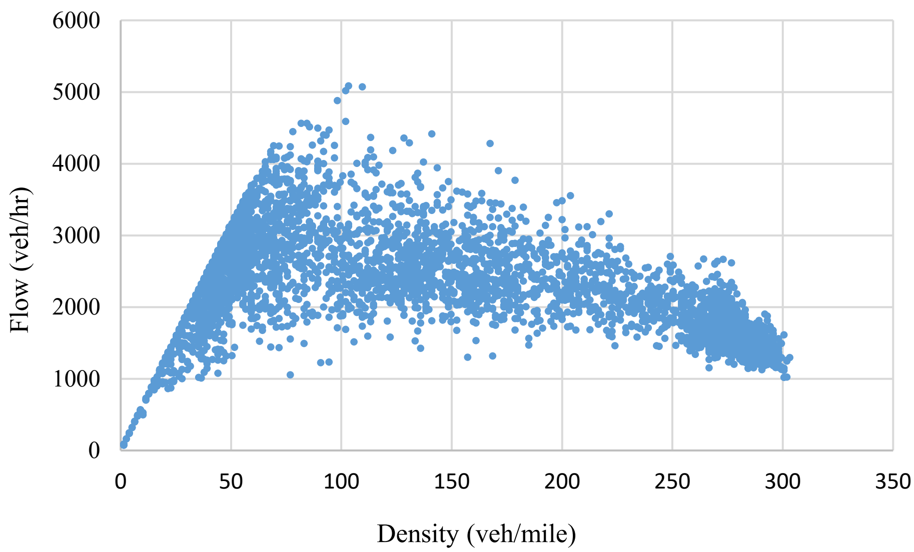
(b) 20% market penetration



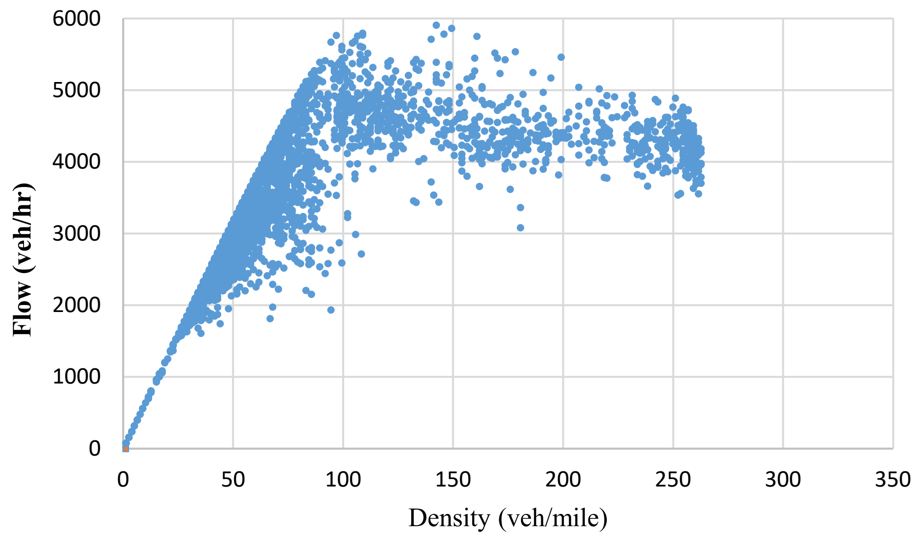
(c) 40% market penetration



(d) 60% market penetration



(e) 80% market penetration



(f) 100% market penetration

Figure 13-4. Flow- density relationship for mixtures of CVs and HVs given different market penetration rates

Figure 13-4 presents the impacts of CAVs on the flow-density relationship for MP levels ranging from 0 to 100 percent to shed light on potential changes in fundamental traffic relationships that accompany the deployment of CAVs. The simulation data presented in figure 13-4 show that the flow-density relationship persisted in its fundamental shape, regardless of the MP level. Moreover, results followed the same trend seen in the literature, in which CAV technology had no significant impact under MP levels of 40 percent. However, there is a high potential to increase the highway capacity under higher levels of market penetration. The interpretation is that the emergence of CAVs in the traffic network and their behavior did not reshape traffic flow fundamentals, but the information exchange between CAVs was essential for reducing the time-headway and reaction-time, and for inducing traffic stability, which were reflected in enhanced highway capacity.

13.2.4. Discussion of Results

The impacts of deploying CAVs during inclement weather with different levels of market penetration on fundamental traffic relationships, in terms of the flow density relationship, was investigated. For the presented scenarios, the CAVs demonstrated their potential to enhance the capacity of the highway segments. The utilization of V2V and V2I communication technology enabled the CAVs to produce a shorter following time-headway and to attenuate traffic disturbances through lower reaction-time than non-CAVs. While CAVs tended to maintain the speed limit of the roadway section, they tended to promote more stable traffic flow by implementing a fixed-time headway based on the desired distance for all CAVs. Improvement in capacity was associated with higher MP levels. Results showed that capacity did not improve below an MP level of 40 percent. These results confirm the research outcome presented by Ye and Yamamoto (2018). Because the short following time-headway was not utilized unless the following combination was CC, the benefits associated with CAVs started to surface at MP levels of greater than or equal to 60 percent. Eventually, at full MP levels, the results revealed by the developed ABMS framework showed that CAVs had the potential to increase the highway capacity on two-lane, undivided highways where no merging or over-passing was considered and on four-lane, divided highways with on-ramps where over-passing and merging maneuvers were considered in the model. The results agreed with results from similar studies, discussed in section 2, in which the V2V communication technology significantly improved the highway capacity (Tientrakool *et al*., 2011); however, none of those explored studies quantified the impacts of CAVs on the fundamental traffic relationship during inclement weather.

14. CONCLUSIONS

This project focused on the operational enhancement of highways through the deployment of vehicle communication technology during inclement weather. While a variety of studies have looked at mitigating congestion during adverse weather, a gap remains in the literature demonstrating how connected vehicle technologies can be applied to better manage traffic networks during such events. The traffic performance benefits associated with the emergence of vehicle communication technology, and the lack of tools to evaluate those benefits, were the impetus behind this project. We developed a modified IDM model to incorporate the effects of CVs into a mixed traffic scenario. The developed methodology was implemented into a simulation framework, and detailed analysis was conducted to evaluate how CVs can improve vehicle movement during adverse weather. The results showed that for high market penetration of CVs (60 percent), there was less speed perturbation along the roadway, leading to stable traffic movement.

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