Modelling, Simulation and Control of Signalized Intersections under Adverse Weather Conditions

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final versions, as accepted by my examiners.

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Abstract

Adverse winter weather has always been a cause of traffic congestion and road collisions. To mitigate the negative impacts of winter weather, transportation agencies have been introducing weather responsive traffic management strategies such as adaptive control of signalized intersections and variable speed limits. Currently, most traffic signal control systems are designed for normal weather conditions and are therefore suboptimal in terms of efficiency and safety for controlling traffic during winter snow events due to the changing traffic patterns and driver behavior. There is a lack of systemic guidance on weather responsive signal control from signal design manuals and guide books. Existing guidelines do not provide methodical approaches to help traffic operators determine how to deploy weather-responsive signal control strategies for a local network. Additionally, the magnitude of the benefits of implementing weather-responsive signal control strategies is largely unknown due to the lack of reliable evaluation tools. The main objectives of this thesis are therefore to develop quantitative understanding of the effects of winter weather on several key traffic parameters and to investigate the methods and potential of implementing weather-responsive signal control strategies during inclement winter weather conditions.

This thesis research consists of three main components. First, we have examined the impacts of winter weather on two key traffic parameters, namely, saturation flow rate and start-up lost time. Field data including traffic video and road weather and surface conditions were collected in the winter of 2015, from which various traffic parameters were extracted from vehicle trajectories. Extensive statistical analyses, including categorical analysis, non-linear regression, and multivariate regression, were followed to develop models for the relationship between each traffic parameter and various influencing factors such as visibility, precipitation and road surface conditions. Second, we have focused on calibrating a microscopic simulation model that can be used to simulate traffic operations under adverse winter weather conditions. A video-based approach was proposed to calibrate three important driver behavior parameters, i.e., mean desired speed, median desired acceleration rate at speed 0, and a parameter reflecting mean safe following distance. This approach is more robust and reliable than the traditional calibration

methods due to the fact that the individual parameters are estimated directly from field data in a physically consistent way as opposed to the traditional trial-and-error process. At last, we have investigated the potential benefits of implementing weather-specific signal control plans for isolated intersections as well as arterial corridors based on two case studies. For both case studies, three traffic demand scenarios, i.e., high, medium, and low, were considered. Evaluation results from both deterministic and simulation models show that implementing weather specific signal plans is most beneficial for intersections with a medium level of traffic demand. When the demand is very low or very high, such strategies has little benefit in terms of reducing traffic delay. It has also been found that the benefit of implementing weather-responsive plans is more compelling at an arterial-corridor level with signal coordination than at an isolated-intersection level.

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Table of Contents

List of Figures

List of Tables

Chapter 1 Introduction

1.1 Background

Adverse weather, including rain, snow, sleet, fog, etc., has always been a cause of traffic congestion and a threat to road safety. It has been estimated that inclement weather (snow, ice, and fog) causes delays of 544 million vehicle-hours per year in the U.S., accounting for 23% of the total non-recurrent delay on highways (Transportation Research Board, 2000). As for road safety, according to the National Highway Traffic Safety Administration (NHTSA), from 2002 to 2012, 1,311,970 crashes occurred annually in the US in adverse weather, of which 540,931 occurred on snowy days (snowing or snowy/slushy pavement).

To mitigate these negative weather impacts, transportation agencies can deploy weather-responsive traffic management (WRTM) strategies in adverse weather conditions. Such strategies can be categorized into three groups: advisory, control, and treatment strategies (Goodwin, 2003). Advisory strategies inform travelers of prevailing and predicted road weather conditions. Control strategies change the state of roadway control devices to permit or restrict traffic flow and to regulate roadway capacity. Treatment strategies focuses on keeping road clear of snow/ice and hence minimizes or eliminates weather impacts. Weather-responsive signal control is considered to be one of the most cost-effective options among the control strategies.

Traffic signals play an important role in the modern transportation system, especially in urban areas. There are more than 272,000 traffic signals in the United States, over 10% of which control intersections serving more than 60,000 vehicles daily on average (Kittelson & Associates, Inc, 2008). As for Canada, there are 3,014 and 818 signalized intersections in two major cities, Toronto[1] and Vancouver[2], respectively. Traffic signal settings are usually designed to respond to

[1] Traffic Signal Tabular, Open Data – Toronto: http://www1.toronto.ca/wps/portal/contentonly?vgnextoid=965b868b5535b210VgnVCM1000003dd60f89RCRD
[2] Traffic Signal Data Package, Open Data Catalogue, City of Vancouver: http://data.vancouver.ca/datacatalogue/trafficSignals.htm

traffic in normal weather; however, existing studies have indicated that weather conditions have a large influence on urban mobility (Goodwin, 2002). A study conducted in Salt Lake City, Utah found that saturation flow rates are up to 20% lower on signalized arterial roads in adverse weather conditions than in normal weather conditions. The average speed on slushy pavements was found to be 30% lower than the average speed on dry pavement, and start-up lost time was found to increase by 5 -10% depending on the weather condition (Perrin, Martin, & Hansen, 2001).

Therefore, signal control plans designed for normal weather may not be optimal for inclement weather due to the different traffic patterns. Adapting signal control timing to adverse weather conditions has the potential of increasing traffic efficiency and road safety at signalized intersections in inclement weather. Specific measures include, but are not limited to, increasing cycle length, changing clearance interval, and adjusting coordination plans. Advances in technology enable real-time communication between traffic control centers and controllers. In the meantime, short-term weather forecasting are becoming more accurate and reliable. Therefore, implementing weather-responsive signal plans is becoming more promising and practical than ever.

In response to the Federal Highway Administration's (FHWA) Road Management Program (RWMP) some transportation agencies have deployed and tested weather-responsive signal operations in the field. The City of Clearwater, Florida, has developed a rain-preemption signal system to accommodate increased directional travelling demand in thunderstorms (Goodwin, 2003). The City of Charlotte, North Carolina, uses a weather-related signal timing plan for a network of 149 intersections. The plan is designed to increase safety in adverse weather conditions by implementing longer cycle length to lower travel speed (Goodwin, 2003). The Utah Department of Transportation has implemented a weather-responsive signal control system along a corridor (Balke and Gopalakrishna, 2013). This system enables traffic signal operators to anticipate upcoming traffic deterioration due to the weather conditions and to deploy signal timing plans that best match the prevailing traffic.

1.2 The Research Problem

Relatively few studies have been carried out to investigate weather-responsive signal control strategies, i.e., how to modify traffic signal control plans to increase traffic efficiency and road safety under adverse weather conditions. For countries that are subject to long severe winter seasons, there is a significant need for cost-effective traffic control countermeasures to minimize the effects of inclement weather. Existing signal design manuals, such as Highway Capacity Manual (HCM), Canadian Capacity Guide (CCG), provide very limited guidance on signal operations in winter weather (Transportation Research Board, 2010; Teply et al., 2008). They simply point out that certain changes on signal control settings might help mitigate the negative impacts brought by inclement weather conditions. However, the guidelines provide no methodical approach to help traffic operators decide what weather-responsive signal control strategies to deploy and how to deploy them for a local network. Furthermore, the effectiveness of such strategies is largely unknown because of the lack of a reliable tool to evaluate such strategies. In general, the issue of deploying weather-responsive signal control strategies has not been fully addressed in literature.

Therefore, there is a need to develop a system-wide approach to develop and evaluate weather-responsive signal control strategies on the basis of certain safety and efficiency measures. Weather-responsive signal control planning is a system problem. Related tasks involve understanding driver behavior and traffic operations in various weather conditions, detecting and forecasting adverse weather events, adapting signal timing parameters to the prevailing or predicted weather conditions, and evaluating benefits of weather-responsive timing plans.

1.3 Objectives and Scope of Work

The main objective of this research is to provide guidance on the development and evaluation of weather-responsive signal control plans for the purposes of improving road safety and traffic efficiency under adverse weather con. The specific objectives are as follows:

1. To quantify weather impacts on signal-design-related traffic parameters (saturation flow rate, start-up lost time, etc.) at signalized intersections.
2. Calibrate weather-specific simulation models based on effects of adverse weather on driver behaviors and traffic operations.
3. To comprehensively investigate how signal timing parameters can be adapted to adverse-weather traffic and to reliably evaluate the performance of such weather-specific signal plans. The weather-specific signal plans are supposed to increase traffic efficiency and reduce accident risk at signalized intersections under inclement weather conditions. Plans should be evaluated in various condition (weather, traffic demand, etc.) to test the robustness of the design signal plans.

It should be noted that while the scope of this research is limited to weather-responsive signal control at urban signalized intersections, other WRTM control strategies for both freeway and highway management can be developed and evaluated using similar methodologies and techniques developed in this research.

1.4 Structure of this Document

The remainder of this thesis describes various aspects of weather-responsive signal control. The thesis is organized as follows:

- Chapter 2 describes existing literature and current research gaps on the subject.
- Chapter 3 describes the experiment design and results of a field study on quantifying weather impacts on macroscopic traffic parameters.
- Chapter 4 introduces a method for calibrating microscopic simulation models under adverse weather conditions.
- Chapter 5 explains how signal plans can be modified based on the measured weather impacts through case studies.
- Chapter 6 summarizes the research findings and proposes future research topics.

Chapter 2 Literature Review

Over the last decade, traffic management agencies have launched various strategies to mitigate the impacts of inclement weather on traffic. Among these strategies, weather responsive signal control appears to be a cost-effective option to increase traffic efficiency and road safety during inclement weather at signalized intersections. This chapter summarizes prior research on topics related to weather-responsive traffic signal control, including identification of weather impacts on urban traffic, calibration of weather sensitive traffic simulation models, detection and predication of road weather, and development of weather-specific control plans.

2.1 Weather Impacts on Traffic Operations

As inclement weather events aggravate urban traffic congestion and raise road safety concerns, many researchers and practitioners have attempted to mitigate the negative impacts. To achieve this goal, understanding the influence of adverse weather conditions on traffic flow is essential. Extensive research efforts have been undertaken on the subject.

2.1.1 Weather Impacts on Freeways

Weather affects freeway traffic flow characteristics, i.e., traffic flow-density-speed relationship. Key parameters affected by adverse weather include capacity and free-flow speed. Such parameters are normally extracted and calibrated by fitting aggregated traffic data into a traffic steam model (e.g., Van Aerde model). Summaries of research results on this subject are shown in Table 2.1.

Table 2.1 Summary of Empirical Research Results on Percent Reductions in Capacity and Free-flow Speed (Hranac et al., 2006)

	Capacity	Free-flow Speed
Low Visibility		13
Rain	4-47%	
Snow	30%	13-40%
Wind		10%

Highway Capacity Manual 2010 (HCM 2010) (Transportation Research Board, 2010), one of the most widely used traffic engineering guidance documents, provides recommended values for percent reductions in capacity in various weather conditions adapted from Agarwal et al. (2005). Recommendations are shown in Table 2.2.

Table 2.2 Recommended Values for Percent Reductions in Capacity in Adverse Weather from HCM 2010

Type of Condition	Intensity of Condition	Percent Reduction in Capacity	
		Average	Range
Rain	>0 ≤ 0.10 in./h	2.01	1.17–3.43
	>0.10 ≤ 0.25 in./h	7.24	5.67–10.10
	>0.25 in./h	14.13	10.72–17.67
Snow	>0 ≤ 0.05 in./h	4.29	3.44–5.51
	>0.05 ≤ 0.10 in./h	8.66	5.48–11.53
	>0.10 ≤ 0.50 in./h	11.04	7.45–13.35
	>0.50 in./h	22.43	19.53–27.82
Temperature	<50°F ≥ 34°F	1.07	1.06–1.08
	<34°F ≥ –4°F	1.50	1.48–1.52
	<–4°F	8.45	6.62–10.27
Wind	>10 ≤ 20 mi/h	1.07	0.73–1.41
	>20 mi/h	1.47	0.74–2.19
Visibility	<1 ≥ 0.50 mi	9.67	One site
	<0.50 ≤ 0.25 mi	11.67	One site
	<0.25 mi	10.49	One site

Apart from affecting traffic flow characteristics, weather also has impacts on traffic demand. The demand can be decreased in inclement weather conditions due to some trips being cancelled or postponed; on the other hand, there might be additional demand because some travelers who usually travel on foot or by bicycle may switch to public transit or driving on rainy or snowy days. Hanbali and Kuemmel (1993) conducted a study in Illinois, Minnesota, New York, and Wisconsin to identify traffic volume reductions due to winter storm conditions. The results of this study are

shown in Table 2.3. Ibrahim and Hall (1994) claimed that demands decrease by 10-20% in heavy rain while under light rain conditions demands do not experience significant changes. Knapp and Smithson (2000) found a range from 16-47% reduction in traffic volume in 64 winter storm events.

Table 2.3 Snowstorm Impacts on Volumes (Hanbali and Kuemmel, 1993)

Snowfall	Weekdays (Range of Volume Reduction)	Weekends (Range of Volume Reduction)
< 25 mm	7-17%	19-31%
25-75 mm	11-25%	30-41%
75-150 mm	18-34%	39-47%

Other than relating percentage of changes in traffic flow parameters to categories of weather conditions, most of the research has conducted regression analysis to examine the relationships between traffic and weather comprehensively and statistically. Common predictors include precipitation types, precipitation intensity, road surface conditions, visibility, temperature, and wind speed. One recent study of this kind was conducted by Kwon et al. (2013). The results are shown in Table 2.4. The resulted models are used to estimate capacity and free flow speed (FFS) under various weather conditions. In the first set of models, road surface condition index (RSI), a numerical indicator reflecting the slipperiness of the road surface conditions, and the logarithmic form of visibility were found to be significant to both capacity and FFS after a comprehensive multiple regression analysis. Afterwards, to exclude the influence of high correlation between snow intensity and visibility, they built a second set of models calibrated using all weather-related variables except visibility. In the second set, snowy intensity and RSI were significant.

Table 2.4 Modelling Capacity and FFS under Various Weather Conditions (Kwon et al., 2013)

Predictor	Coefficient	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1st Capacity Model: Calibrated using all variables						
(Constant)	814.27	62.25	13.08	7.46E-12	685.17	943.36
RSI	463.41	71.71	6.46	1.68E-06	314.69	612.14
Ln(Visibility)	226.51	24.69	9.17	5.67E-09	175.3	277.72
2nd Capacity Model: Calibrated using all variables except ln(visibility)						
(Constant)	1222.89	103.71	11.79	5.57E-11	1007.8	1437.98
Snow (mm/hr)	-31.97	7.37	-4.34	2.66E-04	-47.26	-16.68
RSI	619.06	108.52	5.7	9.75E-06	394	844.12
1st FFS Model: Calibrated using all variables						
(Constant)	75.33	1.77	42.6	7.10E-22	71.65	79
RSI	5.15	2.09	2.47	2.23E-02	0.81	9.49
Ln(Visibility)	5.84	0.73	8.02	7.86E-08	4.32	7.35
2nd FFS Model: Calibrated using all variables except ln(visibility)						
(Constant)	85.81	2.57	33.4	1.09E-19	80.47	91.15
Snow (mm/hr)	-0.86	0.18	-4.7	1.21E-04	-1.24	-0.48
RSI	9.54	2.7	3.53	1.98E-03	3.92	15.16

2.1.2 Weather Impacts on Urban Roads

Some studies have measured weather impacts on macroscopic traffic parameters of interrupted traffic flow at signalized intersections, commonly for the purpose of improving adverse-weather signal operations. From previous literature, the influence of adverse weather conditions on saturation flow rate, one crucial parameter to signal timing design, is summarized in Table 2.5.

Table 2.5 Summary of Research Results - Saturation Flow Rate Reduction Percentage on Arterial Roads

Road Surface Condition	Fairbanks, Alaska (Bernardi Lochumueller and Associates, Inc, 1995)	Anchorage, Alaska (Bernardi Lochumueller and Associates, Inc, 1995)	Minneapolis, Minnesota (Maki 1999)	Salt Lake City, Utah (Perrin et al 2001)	Burlington, Vermont (Sadek and Amison-Agolosu, 2004)
Dry	0	0	0	0	0
Wet	NA	NA	NA	6	2-3
Wet and Snowing	14	12	11	11	4-7
Wet and Slushy				18	7-15
Slushy in Wheel Path				18	21
Snowy and Sticking				20	16

Maki (1999) measured the impact of adverse weather events on travel speed, start-up lost time, and saturation flow rate. In his research, an adverse weather event was defined as a snowstorm causing

three or more inches of snow on the road surface. It was found that the average speed decreased from 44 mph in normal conditions to 26 mph in adverse conditions; in the meantime, start-up lost time increased from 2 seconds to 3 seconds and saturation flow rate dropped from 1800 vphpl to 1600 vphpl. However, this research did not mention the sample size of the data and measuring techniques to extract the parameters; as such, the credibility of the results was questionable. Apart from the influence on traffic flow parameters, the author also investigated the impact of adverse weather on signal operational parameters. The author claimed that signal delay per vehicle went down by a small percentage and stops per vehicle stayed the same. The author argued that the unexpected small impact was a result of decreased demand in adverse weather conditions.

Perrin et al. (2001) observed saturation flow rate, free flow speed, and start-up lost time over a range of weather severity categories at two intersections in Salk Lake City, Utah, USA. The categorized weather severity conditions are dry, wet, wet and snowing, wet and slushy, slushy in wheel paths, snowy and sticking, and snowing and packed. The researchers found that the traffic performance deteriorated over the increasing weather severities, and the largest decrease occurred when snow and slush began to accumulate on the road surface. In this case, saturation flow rate and free flow speed were found to be 20% and 30% lower than in normal weather conditions respectively, while start-up lost time was 23% higher than in normal conditions.

Sadek and Amison-Agbolosu (2004) collected field data at an intersection located in the City of Burlington, Vermont to quantify the impact of inclement weather on traffic flow parameters, i.e., saturation headways and startup lost times. The saturation headways and the startup lost times were extracted from field-collected videotapes of 956 hours in two winter seasons (2002/2003 and 2003/2004). Subsequently, they conducted descriptive statistical analysis and inferential statistical analysis to quantify the differences in both parameters under six different weather conditions. From the results, they found a range from 2% to 24% of reduction in saturation flow rate and a general increase trend in startup lost time.

Brennan Jr (2011) characterized traffic operations during winter weather conditions along with normal weather conditions. The study site was a 1.6-mile corridor of SR 37 in Noblesville, IN, USA. It was a coordinated system consisting of four intersections. High-resolution signal

controller data and Bluetooth probe vehicle travel times were available along the corridor. From this information, they compared patterns of travel time, headway, and platoon shift and dispersion in normal and winter weather conditions. They found that travel time was increased by 83 seconds in median, platoons were shifted by 15, 25, and 30 seconds at three intersections, and design speed was decreased by 7 to 11 miles per hour (mph) in snowy events.

Asamer and Van Zuylen (2011) investigated changes of saturation flow rate in inclement weather conditions. They collected video recordings at three intersections in Vienna, Austria, and then estimated saturation flow rates by training a vehicle-behavior model using data extracted from videos. They obtained values of saturation flow rate in different road surface conditions (dry, wet, and snowy) and precipitation conditions (none, light, and heavy). Their results suggested that the effect of snowfall intensity is marginal and snow-weather saturation flow rates are similar to each other at different locations despite their various saturation flow rates in normal conditions.

In summary, most of the previous research focuses on quantifying impacts of adverse weather on macroscopic traffic flow parameters (e.g., saturation flow rate, free flow speed, and start-up lost time). A general agreement exists among these studies in percentage of reduction in saturation flow rate in inclement weather conditions; however, most of these studies were conducted in the USA. As driving behavior and infrastructure characteristics vary geographically, impacts of weather need to be identified and compared with these results in other countries. Furthermore, road surface condition is considered as the only weather variable by most research studies. Relationship between traffic flow and other weather variables (e.g., visibility) can be explored.

2.2 Microscopic Simulation Model Calibration

With the increasing complexity of traffic network and traffic management systems, microscopic traffic simulation has become one of the major tools to evaluate and optimize various traffic management and control systems. Microsimulation simulation models usually contain various parameters describing traffic flow characteristics and driver behaviors, and those parameters need to be properly calibrated to replicate realistic traffic. Numerous methods have been proposed to

calibrate simulation models. Hellinga (1998) proposed a general guideline, as shown in Figure 2.1. The proposed guideline consists of three main phases:

1) Phase 1 involves tasks that should be conducted prior to the simulation modelling. Those tasks include definition of the study objectives, identification of required field data, identification of measures of performance, and specification of criteria for the calibration evaluation.
2) Phase 2 is the initial calibration of the model parameters, including network coding, link characteristics, driver behavior characteristics, and origin-destination traffic demands.
3) Phase 3 compares the simulation model results and field conditions. If the evaluation criteria are not met, refinements and modifications must be made; otherwise, the calibrated simulation model is acceptable to be used.

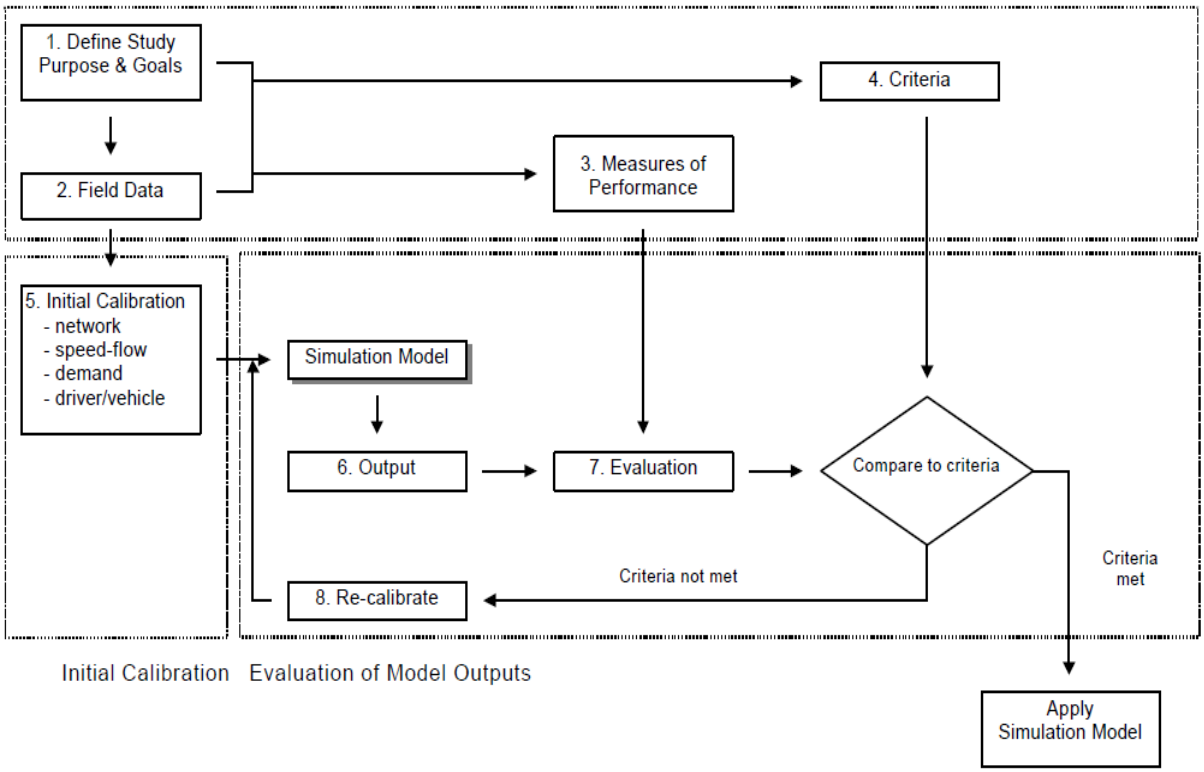

Figure 2.1 Proposed Calibration Process in Hellinga (1998)

Following this general framework, Park and Qi (2005) developed a more detailed procedure for the simulation calibration. The proposed procedure consists of five main steps: simulation model

setup, initial evaluation on default parameters, initial calibration, feasibility test, parameter calibration, and evaluation of the parameter sets. This procedure is shown in Figure 2.2. Once the first two steps are finished, initial calibration as well as feasibility test selects key parameters to be calibrated. Afterwards, those selected parameters are calibrated to match certain field-observed measures of effectiveness (MOEs). If the evaluation results show that the calibrated model is reliable, the calibration process ends; otherwise, the calibration parameters are re-selected and calibrated.

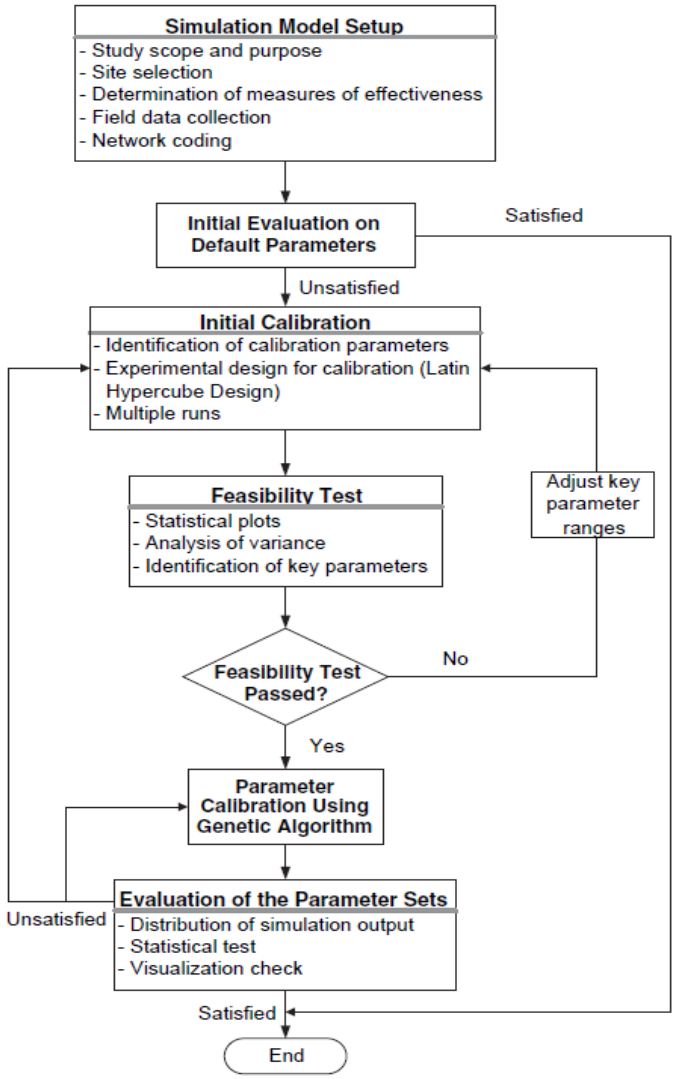

Figure 2.2 Methodology Flowchart in Park and Qi (2005)

Many following studies and practices follow this procedure; however, great efforts have been made to explore different methods to perform the parameter calibration, that is, the optimal parameter-set search. Traditionally, this step was conducted manually, based on users' experience (Hellinga, 1998). Recently, several optimization based approaches have been proposed, such as gradient search, simplex-based, and genetic algorithm (GA) aiming at automating the calibration process (Kleijnen, 1995; Ma and Abdulhai, 2002; Kim and Rilett, 2003; Dowling et al., 2004). Among those, GA is the most widely applied method due to its simplicity, computational efficiency, and ability to find a near optimal solution to a global optimization problem. However, the use of GA is not without challenges, as many practitioners view it as a "black box" solution and become skeptical of the results when multiple similar solutions arise.

In addition to the attempts to improve the parameter calibration algorithm, researchers also tried to enhance the calibration methods by allowing more extensive and thorough evaluation criteria (MOEs) used in the calibration process. The purpose of the simulation calibration is to minimize the discrepancies between model outputs and observational traffic data. Commonly used measures of the discrepancy are the root mean squared error (RMSE) and the mean absolute error (MAE), which are shown in Equation 2.1 and Equation 2.2, respectively.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {e_i}^2} \tag{2.1}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |e_i| \tag{2.2}$$

where,

e_i = samples of model errors

n = number of observations

Traditionally, RMSE or MAE of one aggregated performance, e.g., average travel time or total traffic volume, is selected as MOE. Later, methods have been developed allowing for more than one performance parameter (Duong et al., 2010). Researchers have also introduced methods that

not only evaluate the difference in measure of central tendency (i.e., mean or median) but also compare the distributions for the simulated and observed MOEs (Kim et al., 2005).

2.2.1 Microscopic Simulation Model Calibration under Adverse Weather

Only limited research has been done on microscopic traffic simulation calibration under adverse weather conditions. To evaluate weather-specific signal timing plans, Sadek and Amison-Agbolosu (2004) calibrated weather-specific models in four different simulation platforms, namely, TRANSYT-7F, SYNCHRO, CORSIM, and SIMTRAFFIC. For each simulation platform, the model parameters that were adjusted during calibration are described in Table 2.6. The adjustment on calibration parameters was mainly based on the engineering judgement to match the field measures of performance metrics. The MOEs used in the calibration were total travel time, maximum queue length, and average maximum back of the queue.

Table 2.6 Calibration Parameter Selection in Four Simulation Platforms

	CORSIM	SIMTRAFFIC	TRANYST-7F	SYNCHRO
Saturation Headway	x			
Saturation Flow Rate			X	x
Startup Lost Time	x	x	X	x
Free Flow Speed	x	x	X	x
Headway Factor		x		

Zhang et al. (2004) developed a guideline for calibrating CORSIM models to adverse weather conditions. They comprehensively identified simulation parameters in CORSIM that are potentially affected by weather events. These parameters were discussed in five categories: road geometry, traffic control and management, vehicle performance, traffic demand, and driver behavior. Then, they conducted a sensitivity analysis to assess the extent of impacts of these parameters on the quality of traffic flow with different demand levels and network complexity. Regarding model calibration, this research suggested using the most sensitive parameters identified by sensitive analysis as the calibration parameters. It was recommended to collect field data during adverse weather events as MOEs. The research also suggested an alternative calibration process involving two steps. The simulation model is first calibrated to the ideal weather conditions and,

subsequently, only the weather-related parameters in the calibrated model are adjusted on the basis of the identified weather influence from literature.

Asamer et al. (2013) proposed a method to modify simulation car-following parameters under adverse weather conditions in VISSIM. They set field measurements of saturation flow rate and start-up delay on snowy roads as MOEs and identified three categories of car-following parameters to be calibrated: desired speed, desire acceleration/deceleration, and minimum following distance. After conducting sensitivity analysis on model parameters, they used the brute-force search algorithm to conduct the parameter calibration process. Their calibration results are presented in the form of multiple combinations of values of desired speed, desired acceleration, and minimum following distance. They mentioned that the potential use of disaggregated measures, such as GPS tracking data, could narrow their solution sets.

The earlier studies share one common underlying assumption: the model parameter set is optimal in terms of the discrepancies between simulated MOEs and field observed MOEs. However, this assumption is questionable as we are often interested in the agreement in the system behavior not only at a macro level but also at a micro level. It is expected that a simulation model which is consistent with the real world behavior at a micro level is more robust and likely to capture drivers' responses to changes in system conditions (e.g., new controls and regulations). In other words, the parameter set generating the least error of some aggregated parameters may not accurately reflect local traffic conditions, especially when the selection and modification of the calibration parameters are inappropriate. This issue exacerbates the quality of winter-weather model calibration because during such weather conditions the proper parameter settings deviate from the default settings more. Thus, a more credible and reliable microsimulation model calibration method for adverse weather conditions is in demand, which include direct microscopic parameter measurements.

2.3 Detection and Prediction of Road Weather

In the context of real-world implementation of weather-responsive signal control strategies, one problem still persists: how to detect and predict adverse weather events and to trigger the special weather plan? This section summarizes current and potential practice of detecting and predicting road weather for the purpose of road weather signal control operations.

In current practices, weather-responsive signal timing plans are usually operated manually by traffic operators. Traffic operators make decisions on whether to implement weather-specific plans by assessing traffic and meteorological information. For instance, the City of Charlotte DOT utilizes weather-related signal timing plans at 149 signals (Goodwin, 2003). Operators assess traffic and weather conditions by viewing Closed Circuit Television (CCTV) video images and by receiving weather forecasts. Weather forecast information is gathered from radio and television broadcasts, weather forecasting websites, and a private weather service vendor. By combining information from these sources, operators observe severe weather events and implement a specific signal timing plan. Another example is the weather-responsive signal timing system implemented by Utah DOT along the Riverdale Road corridor (Balke and Gopalakrishna, 2013). Operators use travel speed (collected from road detectors), road weather information (collected from roadway weather information system (RWIS) stations), weather forecasts, and signal performance data (collected from a signal monitoring system) to make decisions about special signal timing implementations. The decision criteria is whether the anticipated weather event will have a significant impact on traffic operations for a substantial duration. In the case of the rain-preemption signal timing system in the City of Clearwater, Florida, an electric rain gauge is used to aid operators' decision-making (Goodwin, 2003).

Over the years, researchers and practitioners have increasingly realized the important role of data in road weather detection and forecasting. Various sensors types (e.g., environmental, imaging, mobile, and remote) have been employed to provide weather-related information. However, road weather sensors are usually owned by a variety of organizations and data formats vary across sensor types. Thus, a lack of data integration causes inefficient use of road weather data. Realizing this problem, in 2004, the Federal Highway Administration (FHWA) Road Weather Management

Program, in conjunction with the Intelligent Transportation Systems (ITS) Joint Program Office established a national, open observing system called Clarus, for promoting data sharing to support weather observations and forecasting and transportation operations. The Clarus system provides detailed roadway condition information and performs comprehensive data-quality checks. The implementation of this system enabled proactive transportation system management (Osborne et al., 2005).

In recent years, with the advances in wireless communication technologies, connected-vehicle technologies have the potential to improve the ability to detect and forecast road weather and pavement conditions based on a wealth of information communicated among vehicles, road infrastructures, and personal mobile devices.

Researchers have already initialized road weather connected vehicle applications, especially in the US. The ITS Joint Program Office has listed road weather as one key application field of connected vehicle technologies and has launched a Road Weather Dynamic Mobility Applications (DMA) Program[3]. During the last 4-year period, the program has advanced the application of connected vehicle data on winter operations support and road weather forecasts. Specific actions include (1) instrumenting and collecting data from more than six hundred vehicles; (2) collecting, quality checking, and disseminating observations from fixed and mobile platforms; and (3) applying algorithms to connected-vehicle data along with weather data to detect and forecast road weather conditions.

In 2015, Linton proposed a connected-vehicle solution for winter road surface condition monitoring (Linton, 2015). The proposed monitoring system incorporated RWIS data and a smartphone-based system to provide accurate, timely, and reliable road surface condition monitoring. The underlying models of the connected-vehicle system used machine learning techniques (artificial neural networks, random trees, and random forests). The evaluation showed the system was able to generate reliable results on road surface condition classification for local uses.

[3] http://www.its.dot.gov/road_weather/road_weather_progress.htm

Connected-vehicle technologies present a promising opportunity to detect and predict road surface conditions in details and in real-time. However, for the use of guiding weather-responsive signal control plans, there are still several topics worth researching: (1) road weather monitoring on urban streets with heavy or medium traffic; (2) a robust algorithm to translate mobile data into usable weather and road conditions; (3) reliable sources for collecting data meeting temporal and spatial needs for network signal optimization.

2.4 Development of Weather-responsive Traffic Signal Control Plans

In essence, traffic signal control plans alternatively assign right of way to movement(s) at intersections. Non-conflicting movements can be allowed to pass the intersection during the same time and be grouped into one phase. A complete sequence of phases constitutes a cycle and its duration is the cycle length. The fundamental task of designing signal timing plans is to decide how much time one phase is allocated the right of way (i.e., green indication). Figure 2.3 shows an example of a ring-and-barrier diagram, which demonstrates the phase sequence and length of a signal timing plan.

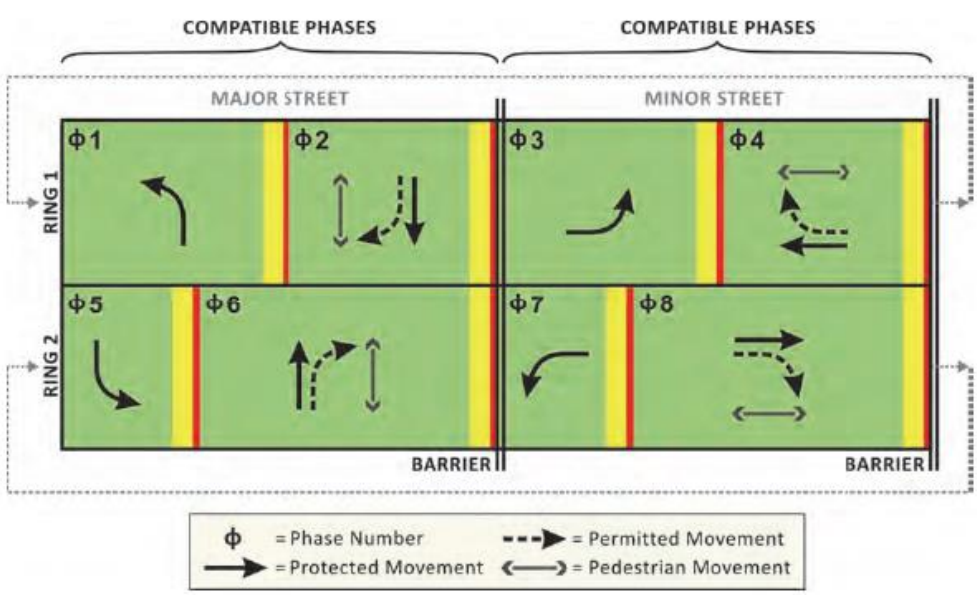

Figure 2.3 Basic Ring-and-Barrier Diagram (Urbanik, 2015)

Depending on the extent of utilizing external detector information about user demand, traffic signal control is categorized into three modes: pre-timed, actuated, and adaptive. The latter two modes are both adaptive to local traffic demand variations by using demand information from road detectors; in contrast, pre-timed controllers use no detection information to adapt operations. They use fixed signal timing plans that contain timing parameter values calculated and programmed into the controller based on historical data. One common method of designing pre-timed signal timing plans is called the Webster's method. In this method, the objective of the signal timing design is to minimize the delay and the delay is estimated by a formula developed by Webster (1958):

$$\mathrm{d} = \frac{c(1-\frac{g}{c})^2}{2[1-(\frac{g}{c})x]} + \frac{x^2}{2q(1-x)} - 0.65(\frac{c}{q^2})^{1/3} x^{2+5g/c} \tag{2.3}$$

where

d = average delay per vehicle (sec),

c = cycle length (sec),

g = effective green time (sec),

x = degree of saturation (flow to capacity ratio),

q = arrival rate (veh/sec)

Derived from Equation 2.3, the optimal cycle length is:

$$c_0 = \frac{1.5L+5}{1-\sum y_{ci}} \tag{2.4}$$

where

L = total cycle lost time (sec)

y_{ci} = the volume to saturation flow ratio of critical movement i

After the cycle length is determined, the available green time is distributed in proportion to flow ratios (y_{ci}) on the critical approaches.

Webster's method only solves signal timing designing problems for one intersection, while coordination provides potential in improving signal timing plans on an arterial or a network scale.

Coordination allows a group of signals to operate together; it synchronizes movements and promotes progression. Figure 2.4 shows an example of a time-space diagram, which is a common tool used to review coordination. The horizontal axis represents time and the vertical axis represents distance. The diagram illustrates the relationship among intersection spacing, signal timing, and vehicle movement. As for optimizing and modifying coordination plans, offset is one very important timing parameter. Offset is the time relationship between coordinated phases based on the offset reference point and a pre-defined master reference.

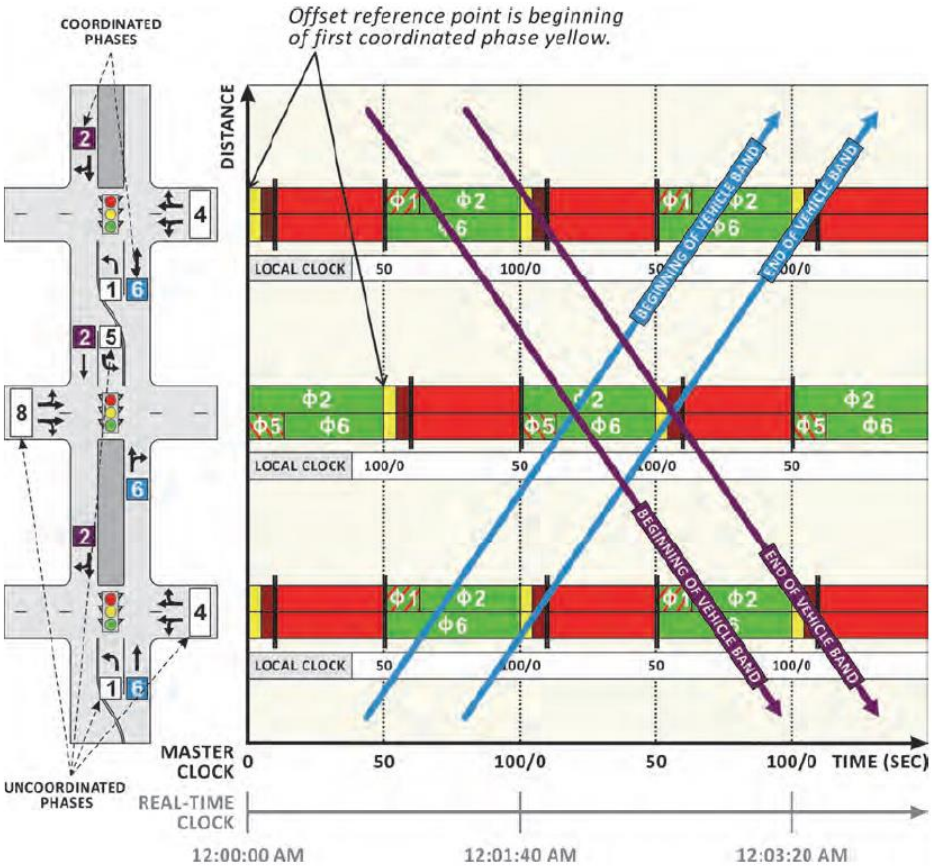

Figure 2.4 Time-Space Diagram (Urbanik, 2015)

As explained above, the methods of optimizing signal timing plans using the cycle/ split/ offset highly depend on the traffic parameter inputs, e.g., saturation flow rate, progression speed. However, these parameters change dramatically in inclement weather, making the normal-day signal plan suboptimal in inclement weather. To cope with this effect, past efforts have been

devoted to the development of weather-responsive signal control plans. These plans usually make modifications to traffic signal operations in response to changes in traffic demand and in driver behaviors under adverse winter weather events.

Maki (1999) evaluated an optimized signal plan tailored for adverse weather conditions. The plan was developed by Synchro with adjusted inputs (demand, speed, start-up lost time, and saturation flow rate). No detailed information on modified signal timing parameters was presented in the report. The evaluation stated that delay and stops per vehicle was decreased by 7.7% and 5.6% respectively. No real-world implementation was made regarding this research.

Perrin et al. (2001) suggested some modifications on traffic signal parameters at isolated intersections in adverse weather conditions. The modifications included increasing amber time by 10-15%, increasing all-red time by 1 second, decreasing the dry saturation flow rate by 20%, decreasing the average dry speed by 30%, and increasing the start-up lost time by 23%. Their suggestions were justified by the field data measurements of saturation flow, speed, and start-up lost time, and literature findings of pedestrian walking speed and deceleration rate. However, their proposed inclement weather timing plan was not evaluated.

In 2003, the Federal Highway Administration (FHWA) published a report containing 30 case studies of systems in 21 states that improve roadway operations under inclement weather conditions, of which two are signal-timing-related (Goodwin, 2003). The first one introduces a rain preemption feature developed by the traffic managers at the City of Clearwater, Florida. The frequent afternoon thunderstorms usually caused significant sudden increases in traffic exiting a tourist time. To mitigate congestion caused by the afternoon thunderstorms, the signal system computer at Clearwater issued a preemption command to traffic signals along a corridor when the rain gauge sensed a predetermined rainfall amount. The signals then executed new timing plans with longer green time for the congested approaches. The second case study was conducted by the City of Charlotte Department of Transportation (DOT), North Carolina. Weather-related signal timing plans were utilized in the central business district of the city at 149 signals to reduce traffic speeds during severe weather conditions. The occurrences of such conditions were assessed by system operators using Closed Circuit Television (CCTV) video images and weather forecast.

Both case studies claimed that the weather signal plans achieved their intended goals. However, these plans were designed for solving only one certain issue or realizing one certain function; they did not comprehensively improve signal operations in adverse weather conditions. In 2012 a new version of the report was published (Murphy et al., 2012). Nevertheless, no measure related to signal operations is mentioned in the new report.

Sadek and Amison-Agbolosu (2004) conducted a simulation study assessing potential benefits of weather-specific signal plans. Based on the reduction in saturation flow rate and free flow speed statistics in adverse weather conditions, they developed optimal signal timing plans using two simulation tools TRANSYT-7F and SYNCHRO for each weather condition (dry, wet, wet & snowy, wet & slushy, slushy in wheel paths, and snowy & sticky). They selected control/signal delay, average delay time, total travel time, average speed, total stops, and fuel consumption as performance measures. The benefits were evaluated used by both macroscopic simulation models (TRANSYT-7F and SYNCHRO) and microscopic simulation models (CORSIM and SimTraffic). Results suggested that significant operational benefits were to be expected from implementing weather-specific timing plans. In one case study, the weather-optimal plan brought a 30.8% decrease in signal delay. It was also found that the benefits varied over traffic and geometric characteristics. However, there was little discussion in their research about real-world implementation of such measures.

Brennan Jr et al. (2011) utilized high-resolution signal controller data and Bluetooth probe vehicle travel time data to optimize the coordination offsets. The objective of the optimization was to minimize the delay. In their research, traffic delay was estimated by an input-output procedure calculating the area between arrival and departure curves; the offsets were optimized by a customized algorithm for a series of intersections along an arterial corridor. The algorithm preserves results from previous optimized intersections and executes a limited enumerative search on the system with one additional intersection to find the global optimum. After offset optimization, they found in their study site of a potential 23.1% reduction in total vehicle delay along the corridor. Their results are shown in Figure 2.5.

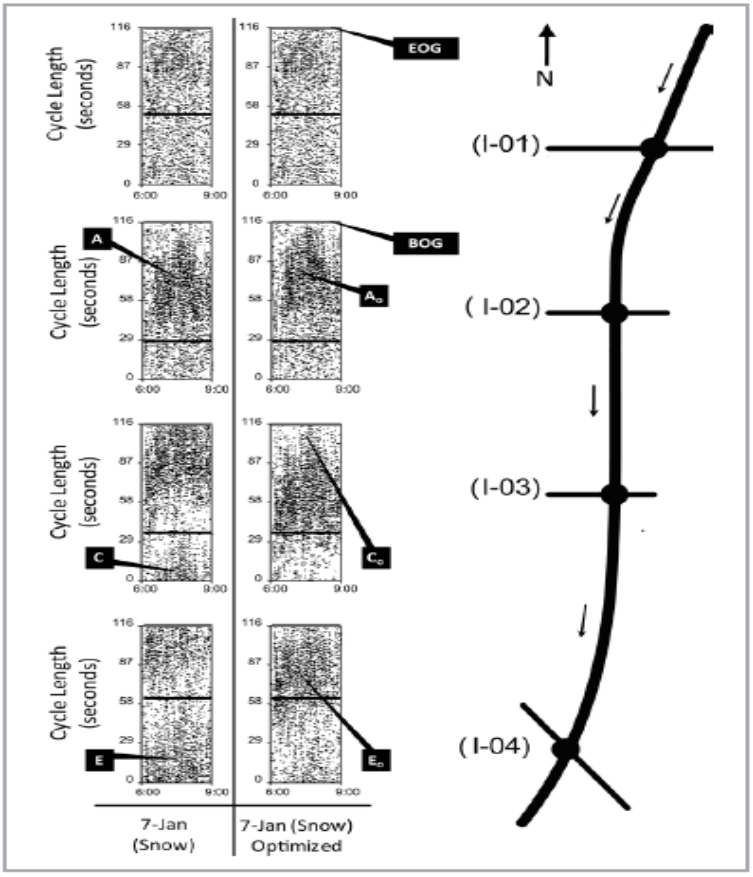

Figure 2.5 Flow Profiles for Normal Offset Times and Proposed Optimal Offsets in Brennan Jr et al. (2011)

Balke and Gopalakrishna (2013) described the implementation of a weather responsive traffic signal management system by Utah DOT. The goal of the system was to allow traffic signal operators to anticipate when weather conditions deteriorate to the point of impacting travel speeds in the study corridor and, once aware of the impending deterioration, to allow the operators to deploy traffic signal coordination timing plans that best match the prevailing travel conditions in the study corridor. The system made decisions on when to trigger weather-specific plans using travelling speed information from advanced detection systems; road weather information from RWIS stations and meteorological forecasts; and signal performance information from Utah DOT's traffic signal monitoring system. The weather-specific traffic signal timing plans consisted of three levels: one "light" snow plan and two heavy "snow" plans. The offsets were adjusted accordingly in the three plans. The evaluation of the system showed that the weather responsive timing plans reduced cumulative travel time by 4.3% and reduced the cumulative stop time by

11.2%. This research describes a real-world case study; however, the design of weather responsive signal timing plan logics is relatively simple; furthermore, only coordination-related parameters are adjusted in this practice.

The 2011 published FHWA report, Developments in Weather Responsive Traffic Management Strategies (Gopalakrishna et al., 2011), reviewed existing weather-responsive traffic signal control strategies. It listed five specific strategies during weather events. The strategies include the following: (1) redeploying signal control related detection systems; (2) changing clearance intervals (including yellow change intervals and all-red intervals); (3) modifying interval and phase durations; (4) adapting signal timing coordination plans; (5) weather-responsive ramp metering measures. The report illustrated these measures and provided examples on these measures. The report also mentioned that certain measures (e.g., modified green interval length for isolated intersections) were still in conceptual/ research stages and most of these measures lacked quantitative benefit evaluation.

In 2015 the Transportation Research Board published the second edition of the Signal Timing Manual (Urbanik, 2015). Suggestions on signal timing in weather events were given in Chapter 11 – Special Conditions. The report first summarized the impacts of weather-related operations on vehicular travel speeds, saturation flow rates, start-up lost times, and pedestrian walking speeds, and then presented some existing weather-related signal timing strategies: increase vehicular red clearance intervals, increase minimum green times, implement phase recalls, and execute weather-responsive coordination plans. The manual explained how these measures are expected to work and gave examples on the proposed measure. However, the manual did not mention how these measures could work together and to what extent of benefits these measures could achieve.

In summary, the research and practice of weather-responsive signal control strategies are still in a preliminary stage and no comprehensive guideline is given on the subject. Modifications on different parameters (e.g., cycle length, intergreen time, offset) are usually discussed separately; their combined effectiveness on improving winter traffic performance, especially the road safety aspect, has not been investigated. Also, the reliability of evaluation tools used in current research is

questionable. Thorough research on modifying signal timing plans and convincing evaluation on such plans are needed in the field of weather-responsive signal control implementation.

Chapter 3 Quantification of the Weather Impacts on Macroscopic Traffic Parameters

The first step towards developing any weather-responsive traffic management strategies is to understand how traffic behaves differently under various weather conditions. This chapter describes a field study quantifying weather impacts on two macroscopic traffic flow parameters: saturation flow rate and start-up lost time. Both parameters have a direct and important influence on signal timing design.

3.1 Data Collection

The intersection of University Avenue and Seagram Drive in the city of Waterloo was selected as the study site. This is a four-leg signalized intersection with lane configurations shown in Figure 3.1. We collected three types of data at the site: traffic video footage, road surface conditions, and local meteorological information under normal as well as adverse weather conditions.

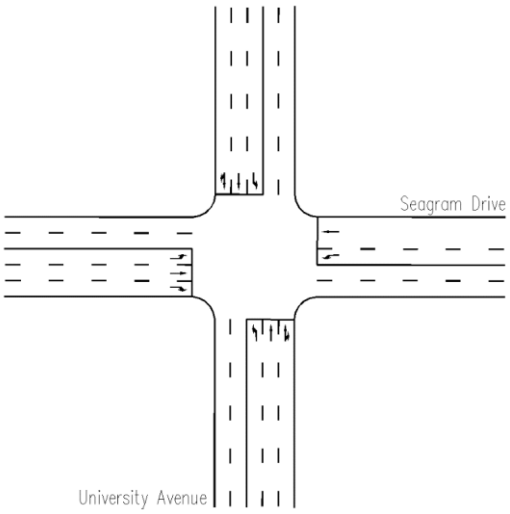

Figure 3.1 Lane Configuration of the Intersection of University Avenue and Seagram Drive

Video data was collected in the winter of 2015 using a commercial portable video data collection device called Miovision Scout, which was situated 21 feet above the road surface. The camera of the device has a wide dynamic 120° view, and the collected video has a resolution of 720 × 480 and a frame rate of 30 frames per second (fps). The intersection of interest and video location set-ups are shown in Figure 3.2. In total, we collected 16 hours of video footage from eight days (Feb 2nd, Feb 4th, Feb 9th, Feb 11th, Feb 24th, Mar 3rd, Mar 4th, and Mar 5th) covering various weather conditions.

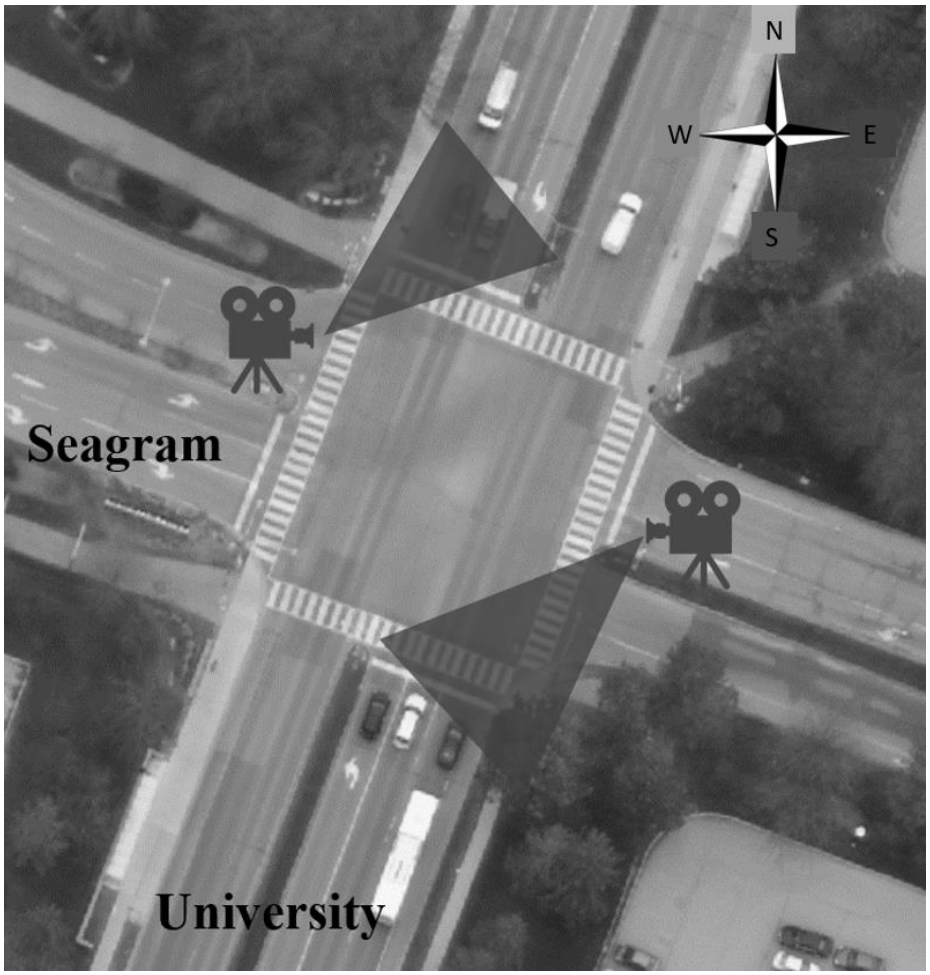

Figure 3.2 Study Site Video Camera Location Settings

During the videotaping, we continuously monitored and recorded road surface conditions. Initially, five categories of road surface conditions were defined, i.e., dry, wet, wet and slushy, slushy in the

wheel paths, and snowy and sticking. Representative screenshots of traffic video data for each road surface condition are provided in Figure 3.3.

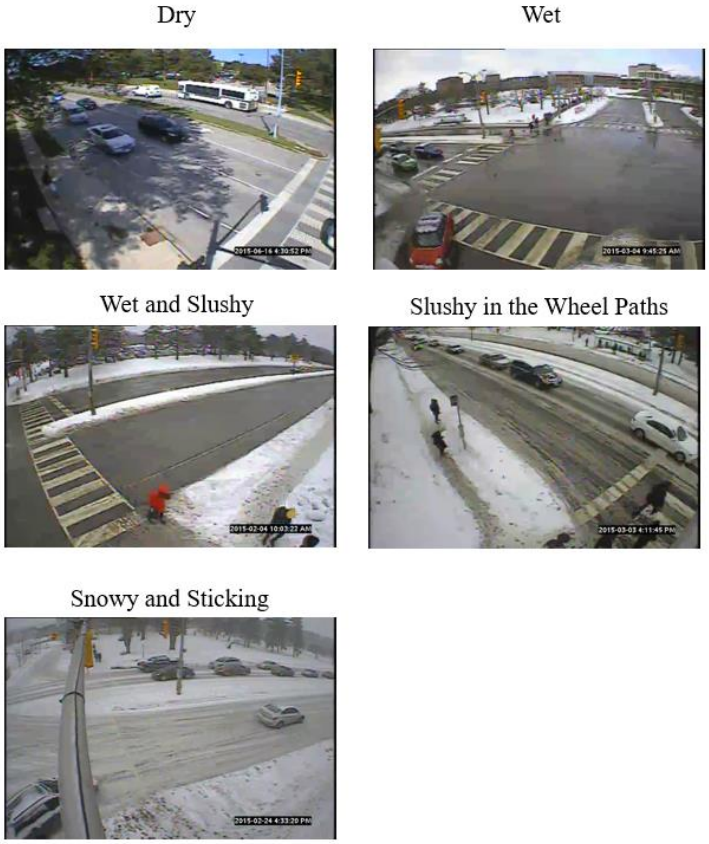

Figure 3.3 Screenshots of Traffic Video in Various Road Surface Conditions

Besides road condition data, local meteorological data was downloaded online from Environment Canada's weather web site[4]. The weather observing station representing the city of Waterloo is located at 43°27'39.000" N, 80°22'43.000" W, and the weather data is observed and recorded hourly at the station. In this research, we assume that the weather is the same at the observing station as at our study site, and that the weather is constant during every one-hour period. Common weather variables include temperature (°C), wind speed (km/h), visibility (km), and precipitation type.

[4] Environment Canada weather website: http://climate.weather.gc.ca/

3.2 Saturation Flow Rate

Saturation flow rate is an important traffic model parameter at signalized intersections. It indicates the flow rate at which vehicles could be discharged at maximum for a certain lane or approach during effective green time. The value of saturation flow rate is usually influenced by lane utilization, conflicting pedestrian and bicycle flow rate, nearby on-street parking and bus stopping rate, road geometry (including approach grade, lane number, and lane width), signal control, as well as weather conditions.

To investigate the impact of adverse weather conditions, we monitored the traffic on the four approaches over various winter events and then measured the saturation flow rates from video footage using the method described in HCM 2010 (Transportation Research Board, 2010). The first several time headways were expected to be longer than the followings time headways. From a measurement perspective, the first headway is the elapsed time, in seconds, between the initial display of the green and the rear axle of the first vehicle crossing over the stop line; the second headway is the elapsed time between the rear axles of the first and second vehicles crossing over the stop line; and subsequent headways are measured similarly. Generally, the first headway will be the longest one within the cycle, and the following headways will decrease subsequently until the headway achieves a constant value. Afterwards, the headways remain steady until when the last vehicle in the queue passes the stop line. This constant headway value is defined as saturation headway (h). Normally, the headway no longer decreases after the fourth vehicle. Hence, the saturation headway (h) is estimated as the average of headways between vehicles from the fifth vehicle in the initial queue and continuing until the last vehicle that was in the initial queue. The changes in headway values along with vehicle positions in the queue are shown in Figure 3.4. From the saturation headway, the saturation flow rate can be calculated using Equation 3.1:

$$s = \frac{3600}{h} \tag{3.1}$$

where

s = saturation flow rate (veh/h), and

h = saturation headway (sec)

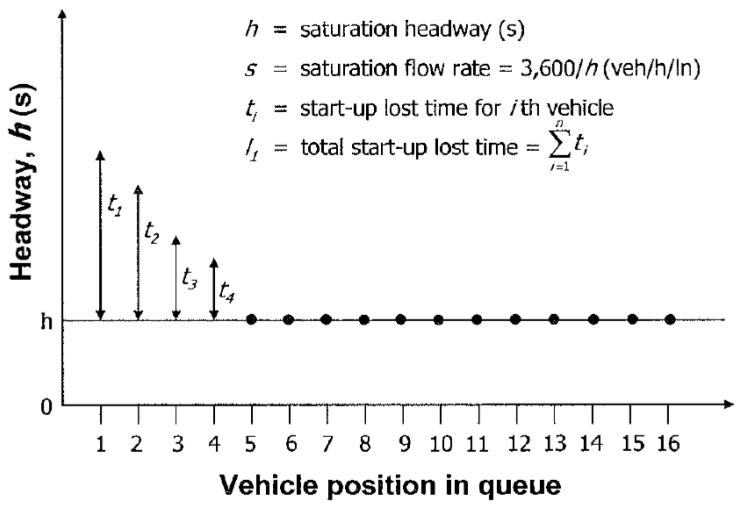

Figure 3.4 Concept Illustration of Saturation Headway and Start-up Lost Time

The specific measuring procedure of through-lane saturation flow rate used in this research is described as follows:

1) Manually record the time when each vehicle's rear axle passes the stop line from the video,
2) Calculate headways between vehicles by subtracting the time when the leading vehicle's rear axle passes the stop line from the time the vehicle's rear axle passes the line,
3) For each cycle, average the headways between vehicles after the fourth vehicle and until the last vehicle that was in the initial queue (the queue at the beginning of the green). This value is the estimated saturation headway for the cycle.

Following the guidance from HCM 2010 (Transportation Research Board, 2010), we exclude cycles with less than eight vehicles in the initial queue in order to obtain statistically reliable estimates. In total, 196 vehicles from the eight-day video footages are valid in terms of number of vehicles waiting in the initial queue. Subsequently, the relationships are examined between through-lane saturation flow rate and individual weather variables (i.e., road surface conditions, visibility). Finally, a multiple regression analysis is conducted to comprehensively grasp the relationships. The statistical analyses in this chapter were conducted using R, a language and environment for statistical computing and graphics.

3.2.1 Saturation Flow Rate by Road Surface Conditions

The observed saturation flow rates are summarized by five recorded road surface conditions defined earlier, that is, dry, wet, wet and slushy, slushy in the wheel paths, and snowy and sticking. The sample sizes (number of cycles) in each condition are 26, 57, 36, 44, and 33, respectively, which all meet the minimum requirement of 15 to calculate valid saturation flow rate (HCM 2010 requirements). Statistics of saturation headways under all road surface conditions are shown in Table 3.1 and Figure 3.5.

Table 3.1 Statistics of Saturation Flow Rates under All Road Surface Conditions

	Dry	Wet	Wet&Slushy	Slushy in Wheel Paths	Snowy&Sticking
Sample Size	26	57	36	44	33
Average (s)	1.926	1.995	2.365	2.408	2.641
Standard Deviation (s)	0.175	0.151	0.190	0.185	0.245
Maximum (s)	2.244	2.313	2.880	2.717	3.187
Minimum (s)	1.571	1.608	2.042	1.971	2.283

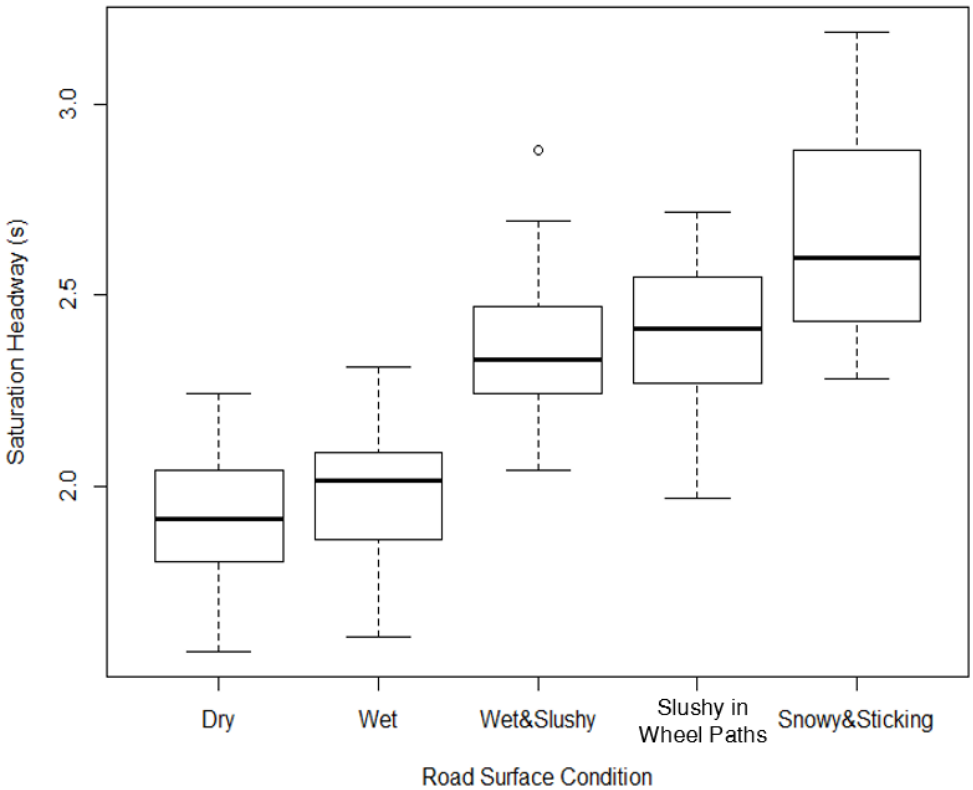

Figure 3.5 Boxplot of Saturation Headway over Road Surface Conditions

As seen in Figure 3.5, the general trend shows that the mean and standard deviation of the saturation headways increases as the road surface conditions worsen. However, there is noticeable overlapping between some of the road surface condition categories, such as between dry and wet, and between wet/slushy and slushy in wheel path. To objectively explore the relationship between saturation headway and road surface conditions, an analysis of variance (ANOVA) test was conducted. ANOVA is a commonly applied procedure used to test the difference between population means. The goal of the analysis is to determine if the differences in the sample means between the groups (road surface conditions) are due to random variation alone or, rather, due to the road surface conditions (Walpole et al., 2011).

The ANOVA test assumes that the classified populations are all independent and normally distributed with a common variance. From observations, we concluded that the assumptions held in this study. The AVONVA test results are shown in Table 3.2.

Table 3.2 ANOVA Test Results of Saturation Headways and Road Surface Conditions

	Degree of Freedom	Sum of Squares	Mean Squares	F-Value	P-Value
Road Surface Condition	4	12.989	3.247	92.67	<2e-16
Residuals	191	6.693	0.040		

Table 3.2 shows significant test results (low P-value), suggesting that a significant difference exists between at least one pair of two road surface conditions. To further explore the difference between each pair, a Tukey's range test was conducted following the ANOVA test. Tukey's range test is a single-step multiple comparison procedure and statistical test. It can be used in conjunction with an ANOVA test to find means that are significantly different from each other. Results are shown in Table 3.3.

Table 3.3 Tukey Test Results of Saturation Headways and Road Surface Conditions

	Difference (s)	Lower Limit (95% confidence interval)	Upper Limit (95% confidence interval)	P-value
Dry - Wet	-0.06859	-0.19059	0.05342	0.53253
Dry - Wet&Slushy	-0.43920	-0.57189	-0.30651	0.00000
Dry – Slushy in Wheel Paths	-0.47573	-0.60326	-0.34821	0.00000
Dry – Snowy &Sticking	-0.71533	-0.85052	-0.58014	0.00000
Wet - Wet&Slushy	-0.37061	-0.48037	-0.26086	0.00000
Wet – Slushy in Wheel Paths	-0.40715	-0.51060	-0.30369	0.00000
Wet - Snowy&Sticking	-0.64674	-0.75951	-0.53397	0.00000
Wet&Slushy – Slushy in Wheel Paths	-0.03653	-0.15239	0.07933	0.90811
Wet&Slushy - Snowy&Sticking	-0.27613	-0.40038	-0.15188	0.00000
Slushy in Wheel Paths - Snowy&Sticking	-0.23960	-0.35832	-0.12087	0.00000

From Table 3.3, there are two pairs with high P-values worth mentioning: dry – wet (53.25%), and wet & slushy – slushy in wheel paths (90.81%). There is no evidence supporting that the mean saturation headways on dry pavement is different from that on wet pavement; neither for the conditions of wet & slushy pavement and slushy in wheel paths. Based on the Tukey test results, a "normal" road surface condition category was created to combine "dry" and "wet", and a "slushy" category was created to combine "wet & slushy" and "slushy in wheel paths". For simplicity, the category "snowy & sticking" was renamed as "snowy".

After the re-categorization, the relationships between saturation headways and road surface conditions were re-examined. Some summaries of data analysis are shown in Table 3.4 and Figure 3.6.

Table 3.4 Statistics of Saturation Flow Rates under All Road Surface Conditions (Revised)

	Normal	Slushy	Snowy
Sample Size	83	80	33
Average (s)	1.973	2.385	2.641
Standard Deviation (s)	1.161	0.187	0.246
Maximum (s)	2.313	2.880	3.187
Minimum (s)	1.571	1.971	2.283

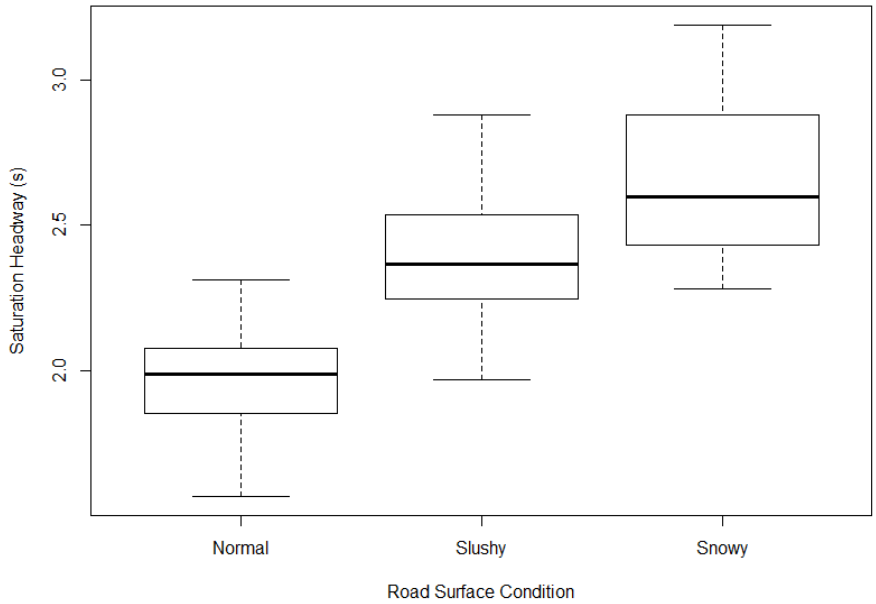

Figure 3.6 Boxplot of saturation headway over road surface conditions (revised)

As illustrated, the trend of the increasing saturation headway over weather severity still exists and the differences between groups are clearer under the new categorization. Again, an ANOVA test and Tukey test were conducted to confirm these findings. Results are shown in Table 3.5 and Table 3.6. Afterwards, the saturation flow rates for the three new road surface conditions were calculated using equation 3.1. The results were 1825 vphpl (normal pavement), 1509 vphpl (slushy pavement), and 1363 vphpl (snowy pavement).

Table 3.5 ANOVA Test Results of Saturation Headways and Road Surface Conditions (Revised)

	Degree of Freedom	Sum of Squares	Mean Squares	F-Value	P-Value
Road Surface Condition (Revised)	2	12.879	6.439	182.7	<2e-16
Residuals	193	6.804	0.035		

Table 3.6 Tukey Test Results of Saturation Headways and Road Surface Conditions (Revised)

	Difference (s)	Lower Limit (95% confidence interval)	Upper Limit (95% confidence interval)	P-value
Normal - Slushy	-0.4121912	-0.4816732	-0.3427091	<2e-16
Normal - Snowy	-0.6682278	-0.759491	-0.5769645	<2e-16
Slushy - Snowy	-0.2560366	-0.3477853	-0.1642878	<2e-16

3.2.2 Saturation Flow Rate by Visibility

Visibility in kilometers (km) is a measure of the distance at which an object or light can be clearly discerned. Atmospheric visibility can be reduced by precipitation, fog, haze, or other obstructions to visibility such as blowing snow or dust. It is expected that in low visibility saturation flow rates are lower.

From the 16-hour video footage, we collected 196 saturation flow rates in weather with visibility ranging from 0.6 km to 16.1 km. The scatterplot of the relationship is shown in Figure 3.7.

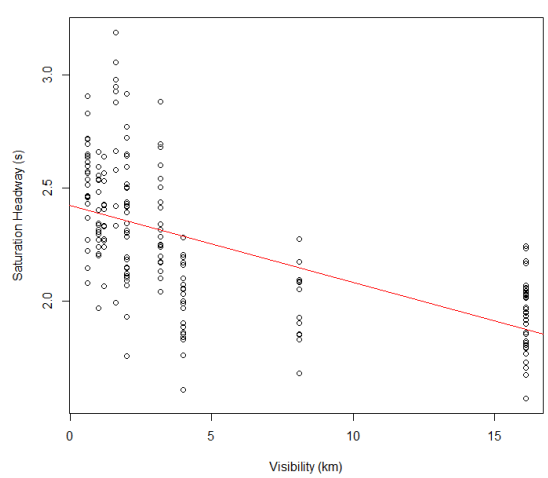

Figure 3.7 Scatterplot of Saturation Headway over Visibility

Observed from the scatterplot, saturation headway tends to increase over the decreasing visibility in adverse weather events. Subsequently, we attempted to build statistical models to explain the trend. First, a linear regression model was built based on the sample data using the least squares fitting technique. The resulting model is shown in Figure 3.7 as the straight line. Results on regression residuals and coefficients are shown in Table 3.7 and Table 3.8. The R-square value of the regression is 0.3542.

Table 3.7 Distribution of the Linear Regression Residuals

Min	1Q	Median	3Q	Max
-0.67922	-0.17016	-0.01957	0.1574	0.81773

Table 3.8 Coefficient results of the Linear Regression

	Estimate	Std. Error	t value	p value
Intercept	2.423198	0.024561	98.66	<2e-16
Visibility	-0.033912	0.003287	-10.32	<2e-16

After linear regression, exponential regression was also attempted for further study of the relationship between saturation headways and visibility. A logarithmic scale was used both on the X-axis and Y-axis to explore the exponential relationships.

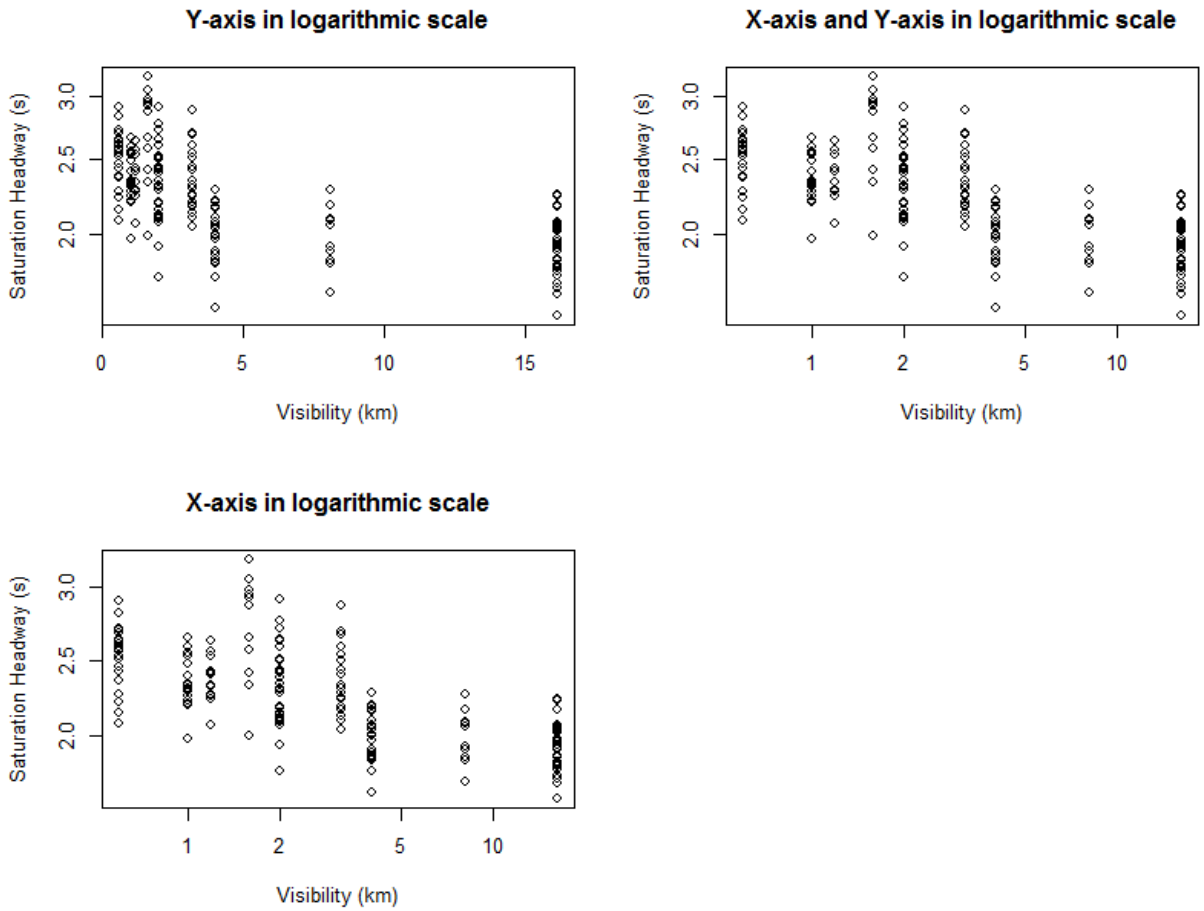

Figure 3.8 Scatterplot of Saturation Headway over Visibility in Logarithm Scale

Shown from the plots above, the scatterplot with the X-axis in logarithmic scale is the one presenting the most linear relationship. Hence, we fit a linear model to the exponential transform of visibility. The resulting exponential model is shown in Figure 3.9 as the curve and the model equation is shown as follows:

$$\mathrm{h} = -0.194\log(\mathrm{v}) + 2.453 \tag{3.2}$$

where,

h = saturation headway (s)

v = visibility (km)

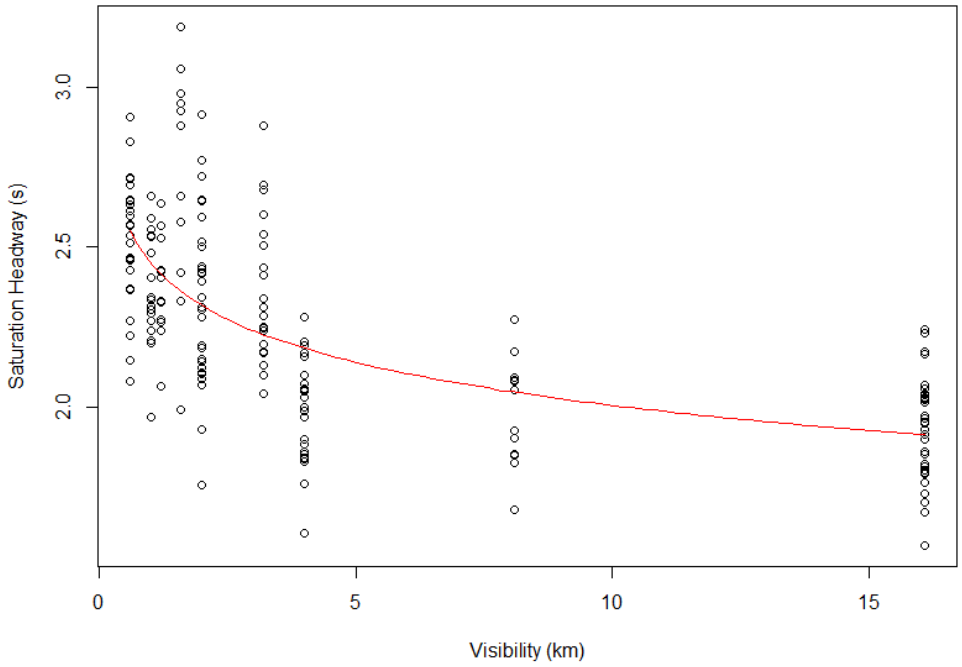

Figure 3.9 Exponential Model of Saturation Headway and Visibility

The R square for this logarithm regression model is 0.43. An improvement of 0.08 in the R square explains 8% more variance.

3.2.3 Saturation Flow Rate & Other Meteorological Variables

Meteorological variables other than visibility that we have in our database are temperature (°C), wind speed (km/h), and occurrence of weather (e.g., rain, drizzle, snow, fog). Because of the limited variability of these variables, the relationship between saturation flow rate and each of these individual variables was not examined. However, the impacts of these factors were included in the multiple regression as follows.

3.2.4 Multiple Regression Analysis

After explanatory data analysis on individual variables, multiple regression analysis was carried out to create a comprehensive and reliable predictive model. First, all the weather variables, including road surface condition, visibility, temperature, wind speed, and weather event

occurrence, were used to estimate the model. To include the influence of road surface conditions, two dummy binary variables were introduced: “Slushy” (0 if not slushy, and 1 if slushy) and “Snowy” (0 if not snowy, and 1 if snowy). Visibility was logarithmically transformed. A binary variable “Snowing” was used to represent weather event occurrence, with 1 meaning it was snowing and 0 meaning not. Table 3.9 shows the descriptive summary of these variables and Table 3.10 shows the results of the multiple regression analysis using all predictors. The overall quality of model was assessed using R square value and the statistical significance of each predictor was tested based on its P value. The R square value is 0.69. The results show that all predictors are significant at a significance level of 1% except temperature and snowing. Afterwards, a multiple regression model was built using two road surface condition dummy variables, log(Visibility), and wind speed as predictors. The results are shown in Table 3.11. In the resulting model, all predictors are statistically significant. The R square value of the model is 0.68.

Table 3.9 Descriptive Summary of Independent Variables Multiple Regression Analysis

Continuous Variable	Minimum	Maximum	Mean	Std. Dev.
Visibility	0.6	16.1	4.989	5.576
log(Visibility)	-0.511	2.779	1.028	1.074
Temperature (℃)	-13.0	22.1	-3.552	10.697
Wind Speed (km/hr)	11	39	24.38	9.521
Binary Variable	Frequency of 0	Frequency of 1	Mean	Std. Dev.
Slushy	116	80	0.408	0.493
Snowy	163	33	0.168	0.375
Snowing	48	148	0.755	0.431

Table 3.10 Results of Multiple Regression Analysis using All Predictors

	Estimate	Std. Error	t value	P value
Intercept	2.4055	0.1031	23.323	0
log(Visibility)	-0.1314	0.0317	-4.147	0
Temperature	0.0011	0.0017	0.624	0.533
Wind Speed	-0.0059	0.0017	-3.413	0
Snowing	-0.1366	0.0598	-2.286	0.023
Slushy	0.3161	0.044	7.188	0
Snowy	0.6230	0.0496	12.555	0

Table 3.11 Multiple Regression Model Result

	Estimate	Std. Error	t value	P value
Intercept	2.4055	0.1031	23.323	0
log(Visibility)	-0.1314	0.0317	-4.147	0
Wind Speed	-0.0059	0.0017	-3.413	0
Slushy	0.3161	0.044	7.188	0
Snowy	0.6230	0.0496	12.555	0

3.2.5 Model Interpretation

In this section, we created three saturation flow rate predictive models: one with road surface condition only, one with visibility only, and one multiple regression model.

The impacts of road surface conditions and visibility on saturation flow rate are evident according to the statistical analyses. The categorical road surface condition model and non-linear regression visibility model can account for some part of the saturation flow rate variability. These two models are recommended to use when local weather information is limited.

As expected, the multiple regression model has the highest predictive power. Surprisingly, the occurrence of weather events (snowing or not) is not a significant factor. This may be attributed to the fact that a high correlation exists between the occurrence of snowing and visibility as shown in Table 3.12. Also, we did not find temperature to be a significant factor, which makes intuitive sense in general. Road surface condition, visibility, and wind speed are the factors included in the final multiple regression model.

Table 3.12 Correlation Matrix of All Predictors

	Temperature	Wind Speed	Snowing	Slushy	Snowy	log(Visibility)
Temperature	1	-0.26	-0.63	-0.35	-0.26	0.70
Wind Speed	-0.26	1	0.23	0.20	0.32	-0.48
Snowing	-0.63	0.23	1	0.47	0.26	-0.84
Slushy	-0.35	0.20	0.47	1	-0.37	-0.60
Snowy	-0.26	0.32	0.26	-0.37	1	-0.25
log(Visibility)	0.70	-0.48	-0.84	-0.60	-0.25	1

3.3 Start-up Lost Time

As described earlier, the first four departure headways from the start of green in every cycle are expected to be longer than the followings. As illustrated in Figure 3.4, t_i represents the lost time for the ith vehicle in queue, and the sum of the first four lost times account for the total start-up lost time for the cycle. In the research, the individual headways were calculated as follows:

$$h_i = T_i - T_{i-1} \tag{3.3}$$

where,

h_i = the headway of i'th vehicle in the queue (sec)

T_i = time recorded when the rear axle of vehicle (i'th) passed the stop line, T_0=0 (sec)

It should be noted that the headway of the first vehicle $h_1$is composed of two parts: the elapsed time from the display of the green to the time when the first vehicle begins to move, and the time from when the first vehicle begins to move to the time when the rear axle of the first vehicle passes the stop line. The first part is called the start-up responsive time (SRT). Due to the limitation that signal control indication data is unavailable from the video footage in our research, SRT cannot be measured. Hence, we assume the value of 1.76s from literature as SRT for all vehicles (Li and Prevedouros, 2002).

The start-up lost times in various road surface conditions were examined. The data were the same as those used for analyzing saturation flow rates. Descriptive statistics and boxplots are shown as follows.

Table 3.13 Descriptive Statistics of Start-up Lost Time under All Road Surface Conditions

	Dry	Wet	Wet&Slushy	Slushy in Wheel Paths	Snowy&Sticking
Sample Size	26	57	36	44	33
Average (s)	3.320	3.129	2.864	2.648	2.777
Standard Deviation (s)	1.878	1.376	1.438	1.646	2.068
Maximum (s)	7.249	6.927	5.860	7.984	8.216
Minimum (s)	-0.173	0.393	-0.160	0.099	-1.151

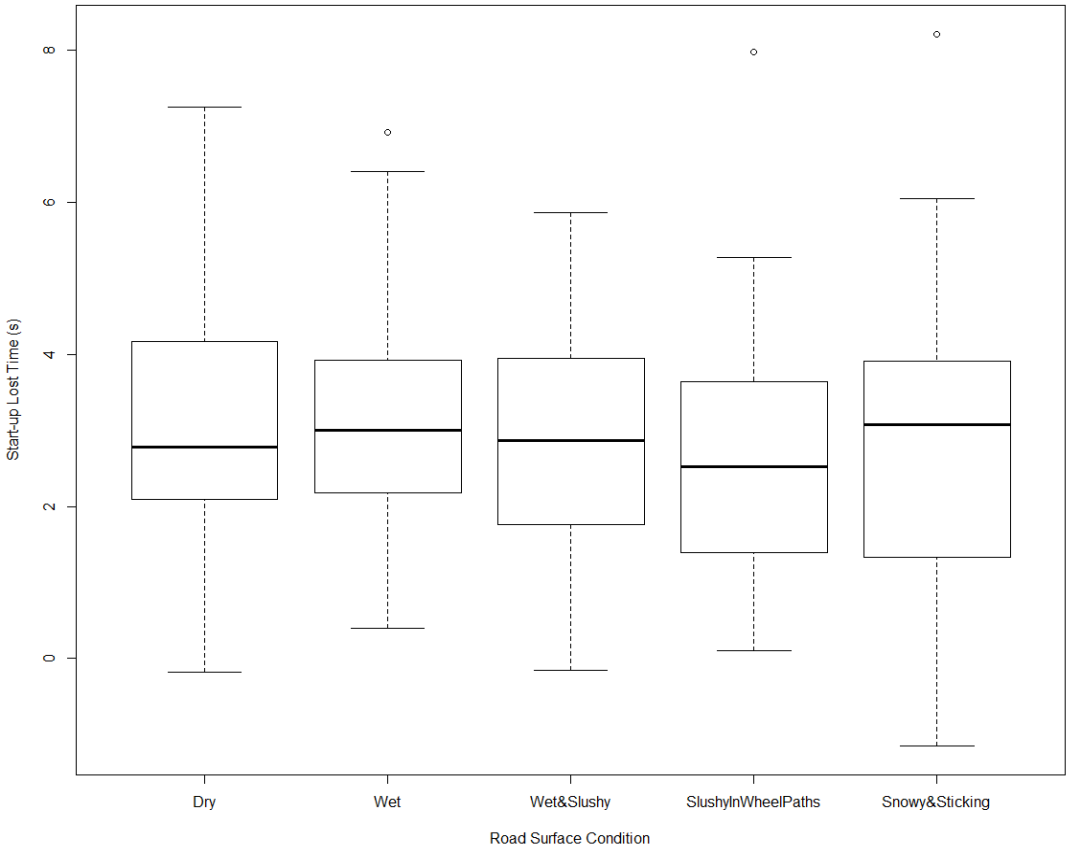

Figure 3.10 Boxplot of Start-up Lost Time over Road Surface Conditions

From the summary data shown in Table 3.13 and Figure 3.10, we found no clear pattern of how start-up lost time reacts to different road surface conditions. Also, start-up lost time does not vary largely under each road surface condition. To further explain these results, we researched the changing patterns of the first eight headways in the queue under each weather category. The mean of headways was calculated for all vehicles in the same cycle position (1st - 8th) under each weather conditions. Results are shown in Figure 3.11.

Table 3.14 First Eight Mean Vehicle Headway under Road Surface Conditions

	1st	2nd	3rd	4th	5th	6th	7th	8th
Dry	4.51	2.54	2.10	2.08	2.00	2.08	2.16	1.78
Wet	4.19	2.49	2.31	2.12	1.96	2.01	2.07	2.00
Wet & Slushy	4.53	2.89	2.45	2.47	2.33	2.32	2.42	2.24
Slushy in Wheel Paths	4.43	2.83	2.50	2.43	2.45	2.42	2.30	2.34
Snowy & Sticking	4.77	3.23	2.63	2.72	2.74	2.74	2.53	2.46

Figure 3.11 First Eight Mean Vehicle Headway under Road Surface Conditions

Shown from the figure, the general pattern of headways complies with the ideal situation described in Figure 3.4, with first several vehicles having higher headway (especially first two). Start-up lost time measures the sum of the differences of first vehicles in saturation headway. Observed from the figure above, the differences do not vary significantly over different weather conditions. In other words, although it takes longer time for first several vehicles to leave the intersection in inclement weather, the additional time to saturation headway that each of these first vehicles takes

(t_i) is not longer. These observations explain why the start-up lost time does not show a clear changing pattern over the severity of road surface conditions.

Furthermore, other meteorological variables (e.g., visibility) also cannot account for the changes in start-up lost time.

3.4 Comparison to Results from the Literature

The results of this chapter are compared to research findings from the existing literature. Table 2.1 lists the identified weather impacts on saturation flow rate from four previous studies and this research. Since the previous studies only examine the relationship between saturation flow rate and one weather-related variable (i.e., road surface condition), the comparisons are based on the percent reduction in saturation flow rate in various road surface conditions. In the Alaska and Minnesota studies, saturation flow rates were only measured in normal (dry surface) and inclement (snow accumulations exceed 3 inches) conditions. Hence, for the comparison purposes, the inclement condition is assumed to be corresponding to the average of values from wet and snowing, wet and slushy, slushy in wheel path, and snowy and sticking.

Table 3.15 Comparison to Results of Saturation Flow Rate Reduction in Existing Literature

Road Surface Condition	Reduction in Saturation Flow Rate (%)					
	Existing Literature					This Research
	Fairbanks, Alaska (Bernardin Lochumueller and Associates, Inc, 1995)	Anchorage, Alaska (Bernardin Lochumueller and Associates, Inc, 1995)	Minneapolis, Minnesota (Maki, 1999)	Salt Lake City, Utah (Perrin et al., 2001)	Burlington, Vermont (Sadek and Amison-Agolosu, 2004)	Waterloo, Ontario
Dry	0	0	0	0	0	0
Wet	NA	NA	NA	6	2-3	3
Wet and Snowing	14	12	11	11	4-7	NA
Wet and Slushy				18	7-15	19
Slushy in Wheel Path				18	21	20
Snowy and Sticking				20	16	27

The comparison shows that the results of weather impact on saturation flow rate from our research agree to the results from existing literature closely. The only relatively large discrepancy occurs when the road surface is in snowy and sticking condition. The higher reduction in saturation flow rate may be attributed to drivers being more cautious in severe winter events in Canada.

As for the weather impact on start-up lost time, the results of this research that the influence is not significant conforms to some of the previous studies (Bernardin Lochumueller and Associates, Inc, 1995; Sadek and Amison-Agolosu, 2004). Meanwhile, some other studies claim that start-up lost time increases significantly in inclement weather conditions (Perrin et al., 2001). Such inconsistency may be resulted from different techniques applied to estimate start-up lost time and SRT.

Chapter 4 Calibration of Microscopic Traffic Simulation Parameters for Modelling Traffic under Adverse Weather Conditions

With the increasing complexity of traffic network and traffic management systems, microscopic traffic simulation has become one of the major tools to evaluate and optimize various traffic management and control systems. Microscopic traffic simulation models replicate real-world traffic network dynamics by simulating individual vehicles' movement in the network. One of the essential components of any microscopic traffic simulation model is the driver behavior models defining how drivers make decisions in terms of lane selection, car-following, speed selection, and route choice. All driver behavior models include parameters that must be appropriately calibrated before a simulation can be used. In order to model traffic operations under adverse winter conditions and develop weather-responsive traffic control strategies, it is essential to calibrate the simulation model parameters that capture how drivers adjust their driving decisions in response to adverse weather. This chapter describes a video-based approach to calibrate simulation models to three weather conditions (normal, slushy, and snowy road surface conditions). The chapter first introduces this video-based calibration approach, and then describes the step-by-step method to calibrate the simulation models of the traffic at the study site in normal, slushy, and snowy conditions.

4.1 A Video-based Calibration Procedure

The proposed procedure for calibrating microscopic simulation models consists of six main steps: field data collection, parameter selection, sensitivity analysis, microscopic parameter extraction, parameter calibration, and model validation.

4.1.1 Field Data Collection

Traffic video data are required for the proposed calibration method. The traffic video data are used to determine measures of effectiveness (MOEs) and extract certain microscopic calibration parameters. When video data are collected from the study site, several situations need to be avoided in order to facilitate automatic video data processing: 1) glare from sun; 2) frost/raindrop on camera; 3) reflection; 4) obstacle in between (Fu et al., 2015). Moreover, the field-collected video data should meet the requirements of spatial coverage, temporal coverage, and event coverage.

4.1.2 Parameter Selection

This approach mainly focuses on calibrating car-following models under various weather conditions in the VISSIM microscopic simulation environment. VISSIM uses a psycho-physical perception car-following model (Wiedemann, 1974). The basic concept of the model is that a driver decelerates when his or her perception threshold has been met, and this threshold depends on the relative speed and distance to the leading vehicle. Otherwise, the driver travels at or accelerates to his or her desired speed. The difference between drivers is taken into consideration with stochastic distribution functions of driving behavior parameters (PTV AG, 2015).

Three main categories of parameters are used in VISSIM to define car-following behaviors: desired speed, acceleration/deceleration, and safe following distance. Desired speed is defined as the speed at which a driver travels if not hindered by other vehicles or network objects, e.g., signal controls (PTV AG, 2015). Different desired speed distributions can be specified for different vehicle types. Acceleration and deceleration patterns are defined by two types of parameters, namely, maximum and desired acceleration/deceleration rates. The maximum acceleration/deceleration rate refers to the physical maximum acceleration/deceleration rate that a vehicle is able to achieve, and the desired acceleration/deceleration rate applies to all situations when maximum acceleration/deceleration rate is not required. The safe following distance parameter defines the spacing-based threshold which a driver uses to decide whether to decelerate or not. On snowy days, drivers normally drive at a slower pace to avoid skidding and keep a longer distance from the leading vehicle due to reduced acceleration/deceleration capacity; therefore,

values of these parameters for modelling traffic under adverse conditions should be different from those under normal weather conditions.

4.1.3 Sensitivity Analysis

Due to the complexity of the microscopic simulation models, the number of calibration parameters has a significant effect on the computation time. The objective of the sensitivity analysis is to identify key model parameters affecting MOEs. In a sensitivity analysis, parameters chosen from the step parameter selection are tested to assess their level of influence on MOEs. A baseline scenario is first developed using default values for all initially selected parameters. Afterwards, the values of parameters are changed one at a time, while other parameters are kept to the default values. Values of MOEs are collected for all scenarios. The trend of how the MOEs change over the varying parameter value demonstrates the intensity of the relationship between MOEs and this parameter. Based on the sensitivity analysis results, parameters with a low effect on MOEs are excluded.

4.1.4 Microscopic Parameter Extraction

Some microscopic calibration parameters can be directly measured from vehicle trajectories. In this paper, a software package called Traffic Intelligence is used to track individual vehicle trajectories from video data. The software has been applied in several other studies with its feature-based tracking technique described in Saunier and Sayed (2006). First, individual pixels' trajectories (features) are detected using the robust Kanade-Lucas-Tomasi feature tracker. Second, those features are grouped into objects, each representing a moving vehicle. The grouping of features is based on their relative distance and motion to each other. $D_{connection}$ and $D_{segmentation}$ are maximum relative distance and motion thresholds for features to be grouped as one object. These values can be adjusted by users to adapt various video filming heights, angels, and resolutions.

The implementation steps of extracting trajectories from video using Traffic Intelligence are demonstrated as follows:

1. Prepare a screenshot of the video and a high-resolution aerial map of the filming area. By matching multiple corresponding points on the screenshot and map, a homography matrix is computed to convert image coordinates into world coordinates.
2. Run feature-tracking scripts to generate feature trajectories.
3. Run feature-grouping scripts to generate object trajectories. Depending on the trajectory extraction quality (users can visually review object trajectory animations after feature-grouping), users iteratively calibrate the values of $D_{connection}$ and $D_{segmentation}$ to achieve a balance between oversegmentation and overgrouping.

After the video is processed, Traffic Intelligence outputs temporal series of individual vehicle positions in world-space coordinates. A screenshot of the Traffic Intelligence's object-reviewing interface is provided in Figure 4.1.

Figure 4.1 Traffic Intelligence Object-reviewing Interface

Vehicle speed profiles can be derived from the vehicle trajectories. They can be used to determine values of calibration parameters regarding desired speed and acceleration/deceleration. Due to the complexity of measuring front-rear distance between vehicles in video, parameters related to safe following distance are not directly measured from video data in this study. Their values are later obtained in the step parameter calibration.

4.1.5 Parameter Calibration

Since safe following distance parameters remain to be calibrated, optimization algorithms are applied to search for optimal values of these parameters to match the simulated MOEs with field measured MOEs. The choice of appropriate algorithm is influenced by the number of calibration parameters, relationship between MOEs and calibration parameters, computing time constraints, and acceptable error level.

4.1.6 Model Validation

Once model parameters are calibrated, validation is conducted to test the credibility of the model. First, simulation animations are viewed to check whether there is a significant difference with the real-world traffic. In the next step, quantitative indictors are selected to compare results from calibrated simulations and field observations. An additional dataset other than the calibration dataset should be used to validate the simulation model. If no discrepancy has been found from either animations or quantitative indicators, the model can be regarded to be valid. Otherwise, the model user needs to re-calibrate the model from parameter selection.

Furthermore, model variability needs to be considered in the process. VISSIM uses random seeds within the simulation to generate stochastic results. To acquire credible simulation results, multiple runs are necessary. The required running times are dependent on the result variability, acceptable error, and significance level.

4.2 Parameter Selection

This study applied the methodology introduced above to calibrate the simulated traffic at our study site (the intersection of University Avenue and Seagram Drive, Waterloo, Ontario) in normal, slushy, and snowy days. The simulation environment was VISSIM. As field data collection are detailed in Chapter 3, the following description of calibration process starts with parameter selection, followed by microscopic parameter extraction, parameter calibration, and simulation model validation.

4.2.1 MOE Selection

Saturation flow rate on through lanes was selected as the MOE for model calibration, as (1) it is crucial to the performance of signal timing plans and able to be measured from both field data and simulation; (2) it is an indicator of weather impact on traffic. Hence, values of saturation flow rate from Chapter 3 (normal: 1825 vphpl; slushy: 1509 vphpl; snowy: 1363 vphpl) were determined as MOE targets for three weather models.

4.2.2 Calibration Parameter

As noted previously, calibration parameters were selected from three categories: desired speed, desired acceleration/deceleration, and safe following distance.

Desired Speed: By default (on normal road surface), the driver's desired travelling speed has a uniform distribution ranging from 48 km/h to 58km/h in VISSIM. In this case study, desired speed was assumed to follow a uniform distribution, with two parameters being initially selected for calibration: the mean μ_s and range r_s of the distribution.

Desired acceleration/deceleration: Desired acceleration/deceleration values vary at different travelling speeds. In the default settings of VISSIM, the median acceleration/deceleration rate has a linear relationship with travelling speed. The intercepts, acceleration rate and deceleration rate at speed 0, i.e., a_0 and d_0, are 3.5 m/s^2 and -2.75 m/s^2 for acceleration and deceleration, respectively, by default. In the case study, these two parameters were chosen as calibration parameters.

Safe Following Distance: In VISSIM, the desired safe distance is the sum of two components, ax and bx, where ax represents the average desired standstill distance between two cars, and bx is determined by Equation 4.1:

$$bx = (bx_{add} + bx_{mult} \cdot z) \cdot \sqrt{v} \tag{4.1}$$

where bx_{add} and bx_{mult} are two VISSIM built-in parameters used for computing the desired safe distance, and z is a normally distributed variable with mean of 0.5 and standard deviation of 0.15; v represents vehicle speed (m/s). Therefore, bx is positively proportional to $\sqrt{v}$, and the coefficient follows a normal distribution with mean of $(0.5bx_{mult} + bx_{add})$ and standard deviation of $0.15bx_{mult}$. In order to separate the parameters' impact on the mean and variance, a new parameter bx_{new} is introduced as:

$$bx_{new} = bx_{add} + 0.5bx_{mult} \tag{4.2}$$

By substituting bx_{add} with bx_{new}, equation (2) is expressed as:

$$bx = [bx_{new} + (z - 0.5) \cdot bx_{mult}] \cdot \sqrt{v} \tag{4.3}$$

Thus, the coefficient distribution is centered at bx_{new} with standard deviation of $0.15bx_{mult}$. bx_{new} and bx_{mult} were then selected as preliminary calibration parameters.

4.2.3 Sensitivity Analysis

Sensitivity analysis was performed on the five parameters selected from the previous step, i.e., μ_s, r_s, a_0, d_0, bx_{new}, and bx_{mult}. The relationships between these parameters and through lane saturation flow rate were examined as shown in Figure 4.2. It can be observed that μ_s, a_0, and bx_{new} have a strong effect on the through-movement saturation flow rate, whereas the influences of r_s, d_0, and bx_{mult} were negligible. The results follow our expectations, as it is expected that deceleration behaviors have very little impact on saturation headway and typically the mean rather than the variability of these driving behaviors significantly influence saturation headway. Therefore, the former three parameters were selected as the calibration parameters.

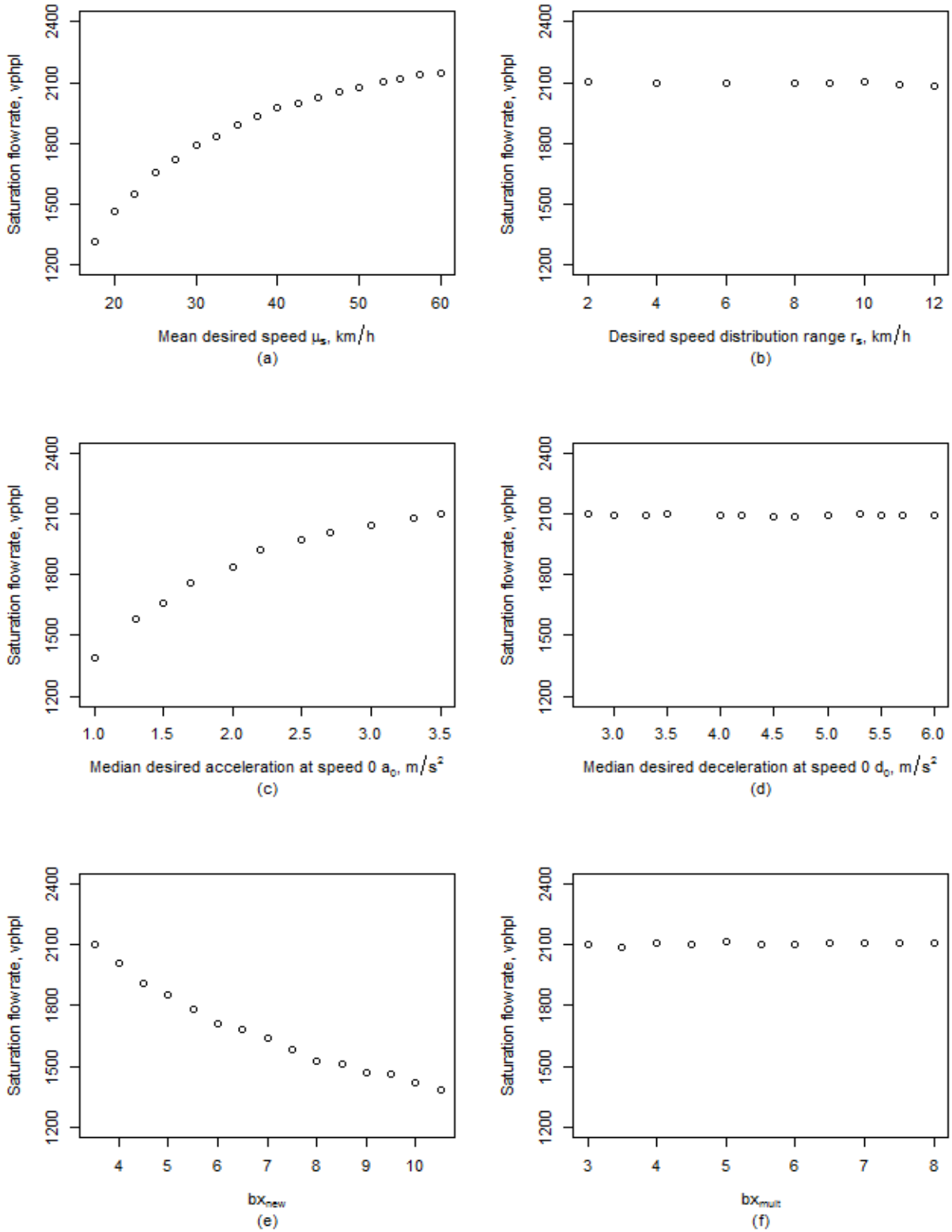

Figure 4.2 Sensitivity Analysis on: (a) μ_s, (b) r_s, (c) a_0, (d) d_0, (e) bx_{new}, and (f) bx_{mult}

4.3 Microscopic Parameter Extraction

As previously mentioned, the traffic video data from all three weather conditions were processed using the Traffic Intelligence tool to generate vehicle trajectories. In this study, 1776, 1618, and 693 through-movement vehicles from normal, slushy, and snowy weather were detected by Traffic Intelligence. Their trajectories were stored in the format of time series of positions on a planar surface. Speed and acceleration information about vehicles were obtained by a simple differentiation of position and subsequent speed over time. Thus, μ_s and a_0 were estimated according to the parameter definitions in VISSIM for all three weather conditions.

4.3.1 Mean Desired Speed (μ_s)

First vehicles were observed and identified as travelling at desired speed (not hindered by other factors) from videos. The average speed for each one of these vehicles was calculated by dividing the traversed trajectory length by its travel time. This average speed was regarded as the driver's desired speed. The sample size and mean desired speed for three weather conditions are shown in Table 4.1. This value was then used as the μ_s input in the calibration process.

4.3.2 Median Desired Acceleration Rate at Speed 0 (a_0)

Only the first vehicle departing from the stop line within each cycle was chosen to measure the desired acceleration rate. The reason was that, following vehicles may not accelerate at their desired rate due to the interference from leading vehicles. For each of these vehicles, the desired acceleration rate at speed 0 was estimated as the equivalent constant acceleration rate at which a vehicle travelled its first five meters from a stationary position. Sample size and sample median a_0 from all three weather conditions were recorded in Table 4.1. Sample a_0 values were used as the a_0 input for simulation models.

Table 4.1 Desired Speed and Desired Acceleration Rate Measurements

	Normal	Slushy	Snowy
Desired Speed Sample Size	80	77	30
μ_s (km/h)	49.0	40.7	37.6
Desired Acceleration Rate Sample Size	42	39	16
a_0 $(\mathrm{m/s^2})$	2.40	2.11	2.02

4.4 Parameter Calibration using Golden Section Search

As values of μ_s and a_0 were directly measured, bx_{new} was the only parameter remaining undetermined for each weather model. In this research, golden section search was applied to search for the optimal value of bx_{new} to minimize the difference in saturation flow rate between simulation outputs and field observations under each weather condition. Golden section search is a common technique used to find the minimum of a univariate continuous function over an interval without using derivatives (Miller, 2014). It is conducted by continuously refining the bracket which contains the optimal parameter value until the bracket is tight enough. From the sensitivity analysis, it was observed that bx_{new} has a monotonic relationship with the saturation flow rate. Thus, the optimization of bx_{new} can be resolved using the golden section search method. By setting [2, 10] as the initial bracket and 0.1 as the acceptable bracket range, the golden section search processes and results for all three weather conditions are shown in Table 4.2.

Table 4.2 Search Processes and Results of Parameter bx_{new} Calibration

Step	Normal		Slushy		Snowy	
1	2.000	10.000	2.000	10.000	2.000	10.000
2	2.000	6.944	5.056	10.000	5.056	10.000
3	2.000	5.056	5.056	8.111	5.056	8.111
4	3.167	5.056	5.056	6.944	6.223	8.111
5	3.167	4.334	5.777	6.944	6.944	8.111
6	3.613	4.334	5.777	6.498	6.944	7.666
7	3.889	4.334	5.777	6.223	7.220	7.666
8	3.889	4.164	5.947	6.223	7.390	7.666
9	3.889	4.059	5.947	6.118	7.390	7.560
10	3.954	4.059	6.012	6.118	7.455	7.560
11	3.994	4.059	6.012	6.077	7.455	7.520
Optimal Value	4.026		6.045		7.488	

4.5 Simulation Model Validation

So far all selected parameters for three models were calibrated. An initial validation on the animation of the calibrated models was performed and no obvious discrepancy was found between the simulations and field video. Then, the saturation headways from the three calibrated model was analyzed. The metric used to evaluate the models was the field-measured saturation headways from the video dataset other than the one used for calibration. The validation results are shown in Table 4.3. The saturation headways from the calibrated simulation models highly agree to the field measurements of saturation headway.

Table 4.3 Simulation Model Validation in terms of Saturation Headway (in seconds)

Road Surface Condition	Field Measurements	Results from Calibrated Model
Slushy	2.327	2.381
Snowy	2.652	2.641

Furthermore, we investigated the variability of the simulation results. Averaging saturation headway from 30 cycles from simulation models would result in an error (difference between mean field measurement and mean simulation output) of 0.025 seconds at maximum at the significance level of 0.01.This error level was acceptable.

Therefore, we concluded that the simulation model was credible and reliable. Moreover, we assume that the influence of adverse weather on car-following parameters (percentage) at this study site is applicable to other situations. In other words, in the next chapter, we use the same percentage of change on these microscopic parameters when we build simulation models to replicate traffic at other intersections in slushy or snowy conditions.

Note that we expect the video-based approach to be more robust and reliable than the traditional calibration methods. This is primarily due to the fact that the individual parameters are estimated directly from field data in a physically consistent way. In contrast, traditional methods determine the values of multiple parameters through a trial-and-error process – trying out different combinations of the parameter values and find the one under which simulated traffic is most consistent with the field observation in terms of a few macro traffic measures. Unfortunately, the process is prone to unrealistic parameter calibration results and there are few ways to ensure the validity of the parameter setting under different traffic network settings.

Chapter 5 Modification of Signal Timing Plans under Adverse Weather Conditions

Chapter 3 described a field study on quantifying weather impacts on macroscopic traffic parameters. It has been found that in adverse weather conditions, saturation flow rate decreases dramatically. Moreover, the study described in Chapter 4 has revealed that drivers drive more slowly and accelerate more cautiously in adverse weather events. All these effects of weather events are essential to the performance of signal timing plans. Therefore, in this chapter, we assume that the research results from the previous two chapters can be applied to the case studies here, i.e., the identified traffic parameters and driver behaviors under various weather conditions are used as inputs for signal plan modification.

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This chapter explores how signal control systems can use road weather information to adapt their timing plans during adverse weather conditions. Based on the results from Chapter 3 and Chapter 4, special weather signal plans are developed tailored for two road surface conditions (slushy and snowy). Later, these plans are compared with the normal-weather signal plan regarding the performance in adverse weather conditions. The evaluation is conducted using both empirical methods and calibrated simulation models. The detailed procedures of developing and evaluating weather responsive plans are illustrated by the case studies.

5.1 Signal Timing of Isolated Intersections

This section demonstrates the benefits of implementing weather-specific signal control at one isolated intersection by a case study.

5.1.1 Case Description

The study site is the intersection of Columbia Street and Philip Street in the city of Waterloo, Ontario. The aerial map and lane configuration of the intersection are shown in Figure 5.1. The design speed for all approaches are 60 km/hr. We developed three demand scenarios (high, medium, low) to investigate the potential benefits of road weather signal control as shown in Figure 5.2. The normal-weather intersection volume to capacity (V/C) ratios for these three scenarios are 0.32, 0.61, and 0.94, respectively. The calculation of saturation flow rates and intersection flow ratios follows the methods in Canadian Capacity Guide (CCG) (Teply et al., 2008). Detailed calculation are described in Appendix A.

Figure 5.1 Aerial Map and Lane Configuration Diagram of the Study Site

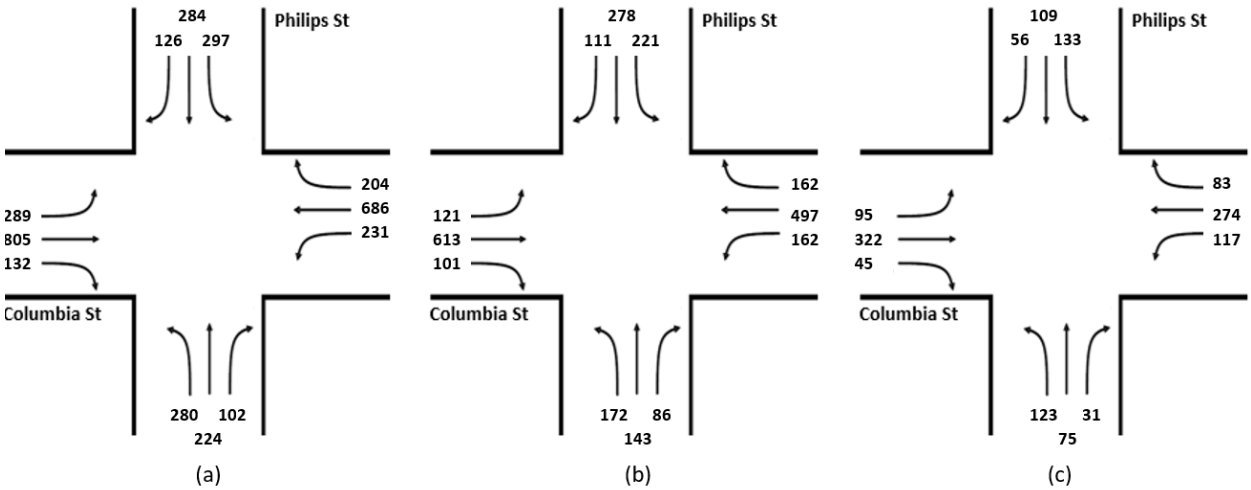

Figure 5.2 Traffic Demands for all Intersection Movements for (a) High Demand Level, (b) Medium Demand Level, and (c) Low Demand Level

5.1.2 Development of Signal Control Plans

Adverse weather can cause incorrect feedback from the detectors, e.g., snow accumulation on road surface may obscure pavement markings and consequently cause detection errors. Thus, this research only considers the application of pre-timed signal control under adverse weather conditions. For pre-timed control, signal timing variables cover cycle structure, yellow change, red clearance, cycle length, and green split. How these variables can be adapted to adverse weather conditions are discussed one-by-one in the remainder of this section. For each scenario (demand level and weather), we developed two types of weather-specific signal plans: optimal plan and safe plan. The first is designed as the most efficient plan in specific adverse weather conditions (unchanged intergreen time), and the second has longer intergreen time to ensure safety. The development of normal weather plan is also discussed in this section.

5.1.2.1 Phase Composition and Cycle Structure

For comparison purposes, all signal plans developed for various weather conditions adopt the same cycle structure with four phases (Figure 5.3):

Phase 1: protected lead left turn for eastbound and westbound approaches;

Phase 2: through movements with permitted left turn for eastbound and westbound approaches;

Phase 3: protected lead left turn for northbound and southbound approaches;

Phase 4: through movements with permitted left turn for northbound and southbound approaches.

In real-world practice, modifications on cycle structure and phase sequences can be applied in adverse weather conditions in certain cases. For example, protected left-turn phases may not be necessary for a certain intersection in normal weather; however, due to the increased cautiousness among drivers and longer green time needed to serve the opposing queue, protected left-turn phase can significantly increase mobility of left-turn movements, avoiding spillback on the left-turn lanes. Designs of this kind highly depend on local traffic conditions; there is no universal guidance that can be provided on this topic.

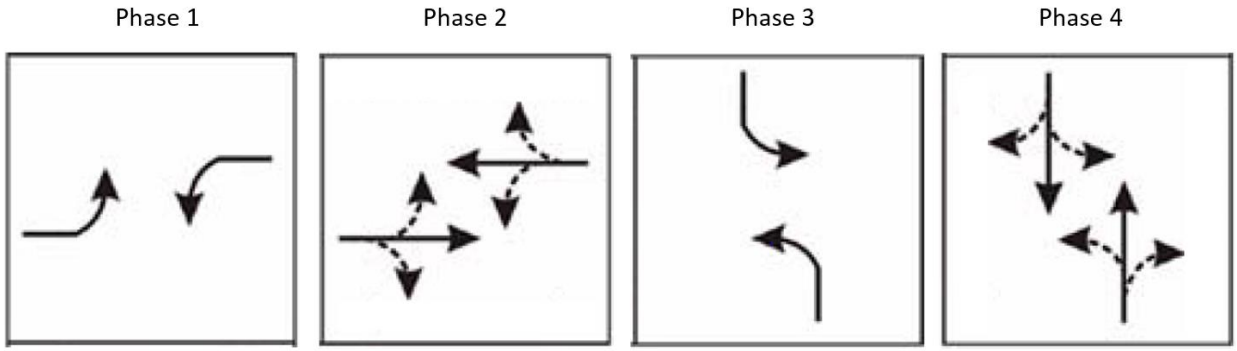

Figure 5.3 Phase Composition of a Cycle

5.1.2.2 Yellow Change

The yellow change interval is usually displayed between a green interval and a red interval to warn drivers about change in right-of-way assignment at the intersection. One common consideration for determining yellow change length is that the interval should provide sufficient time for drivers to stop the vehicle before the stop line when they feel safe to do so at the start of the yellow indication. Long yellow times may encourage violations by familiar drivers while short yellow times may create a dilemma zone or cause red-light running (Urbanik, 2015).

The Institute of Transportation Engineers (ITE) offers equation 5.1 for computing the minimum yellow change interval.

$$Y = t + \frac{1.47v}{2(a+32.2g)} \tag{5.1}$$

where

Y = yellow change interval (seconds),

t = perception-reaction time to the onset of a yellow indication (seconds),

v = approach speed (miles per hour [mph]),

a = deceleration rate in responsive to the onset of a yellow indication (ft/s^2)

g = grade, with uphill positive and downhill negative (percent grade/100)

A perception-reaction time of 1.0s and a deceleration rate of 10 ft/s^2 are widely used by practitioners in calculating the minimum yellow. Based on Equation 5.1 and the recommended values, for the normal weather signal plan, yellow change intervals are set to 3.5s.

As discussed in the previous chapter, both approach speed and deceleration rate decrease in adverse weather conditions. As seen from Equation 5.1, they have contrary effects on yellow change intervals: a lower speed allows a shorter yellow time while a lower deceleration rate requires a longer yellow time. We have measured free flow speed in different weather conditions in the previous chapter (normal: 49 km/h, slushy: 40.7 km/h, and snowy: 37.6 km/h); however, deceleration rate data in these weather conditions are unavailable to this research (the automated video processing can hardly provide reliable trajectory tracking when the speed is decreasing to values close to zero). As a result, we used values from a previous study (Garber and Hotel, 1988), which indicates that drivers' comfortable deceleration rate drops from 2.65 m/s^2 on dry surface to 1.95 m/s^2 on slippery road surface in snow events.

Using the values of approach speed and deceleration rate in adverse weather conditions, equation 5.1 suggests a 0.5 seconds increase in yellow change. This increase is adopted for safe signal plans in adverse weather conditions.

5.1.2.3 Red Clearance Interval

Red clearance interval is designed to increase road safety at signalized intersections during phase changes. By providing all-red interval between conflicting movements, the chance of right-angle collisions can be reduced. As suggested by (Urbanik, 2015), we choose 0.5 seconds as the red clearance interval for the normal plan according to the approach speed and intersection size of our study site.

In winter weather, drivers may have false predictions of the stopping distance due to the reduced pavement friction. A situation which frequently occurs is when a driver brakes when the yellow starts but then accelerates when realizing the reduced deceleration rate does not allow the vehicle to be safely stopped. This phenomenon creates the need to offer additional red clearance time in adverse weather conditions. Also, reduced speed requires longer clearance time for vehicles.

The Signal Timing Manual (2nd Edition) (Urbanik, 2015) recommends no more than 1 to 2 seconds of additional red clearance time under inclement weather. Therefore, we use 1 second as red clearance time for slushy- and snowy-safe plans considering the decreased vehicle speed.

5.1.2.4 Cycle Length and Split

In traffic signal timing field, a cycle is defined as the total time to complete one sequence of signalization for all movements at an intersection (Kittelson & Associates, Inc, 2008). One commonly used method to determine optimal pre-timed cycle length is Webster's equation (Webster, 1958):

$$\mathrm{C}_o = \frac{1.5\sum(L_i)+5}{1.0-\sum X_i} \tag{5.2}$$

where

C_o = optimal cycle length in seconds

L_i = the unusable time per cycle in seconds (sum of lost times)

X_i = degree of saturation for Phase i (critical lane groups)

Typically in practical use, cycle length ranging from $0.75C_o$ to $1.5C_o$ is regarded as optimal cycle length for isolated pre-timed intersection in terms of delay (when X_i <1). After a cycle length has been selected, the total effective green time is then allocated to phases based on the critical degree of saturation. This step is called green splits.

In this research, the cycle length optimization and green split were conducted by Synchro. Synchro is a common macroscopic analysis and optimization program, which conducts capacity analysis, develops coordinated and optimal signal control, and models actuated signals and roundabouts.

Based on intersection geometry, traffic, demand, and phase plan, Synchro determines the cycle length based on the following considerations: (1) shortest cycle length that is required to clear the critical percentile traffic; (2) optimal cycle length with the lowest performance index, which is usually shorter than the cycle length found in (1); and (3) if no cycle length is able to clear the critical percentile traffic, but a shorter cycle is able to give satisfactory v/c ratios, the shorter cycle length will be used. Table 5.1 shows the acceptable critical percentile traffic for each range of cycle lengths document in (Trafficware, Ltd., 2011). When optimizing green splits, Synchro allocates the total green time to the individual phases based on their critical flow ratios along with some other rules (Trafficware, Ltd., 2011).

The optimal cycle length and split settings for both normal and adverse weather conditions were determined by Synchro. By adjusting saturation flow rate and free flow speed to the measured values in adverse weather conditions, Synchro is able to compute the optimal cycle length and green splits for weather-specific signal plans.

Table 5.1 Acceptable Critical Percentile Traffic for Cycle Length in Synchro Settings

Cycle Length	Critical Percentile Traffic
40-60	90th
61-90	70th
91+	50th (v/c>=1)

5.1.2.5 Traffic Signal Timing Plan

Combining considerations on yellow change, red clearance interval, cycle length, and green splits, we designed optimal and safe signal plans for adverse as well as normal weather conditions at three demand levels with the aid of Synchro. The ring and barrier diagrams for these plans are shown in Figure 5.4. Note that in the diagrams, the numbers indicate the time length allocated for specific movements (including green time, yellow time, and red clearance interval). The settings of yellow time and red clearance time have been discussed earlier. For normal-weather and weather-specific optimal plans, yellow lasts 3.5 seconds and all-red lasts 0.5 seconds. For weather-specific safe plans, both yellow and all-red are 0.5 seconds longer.

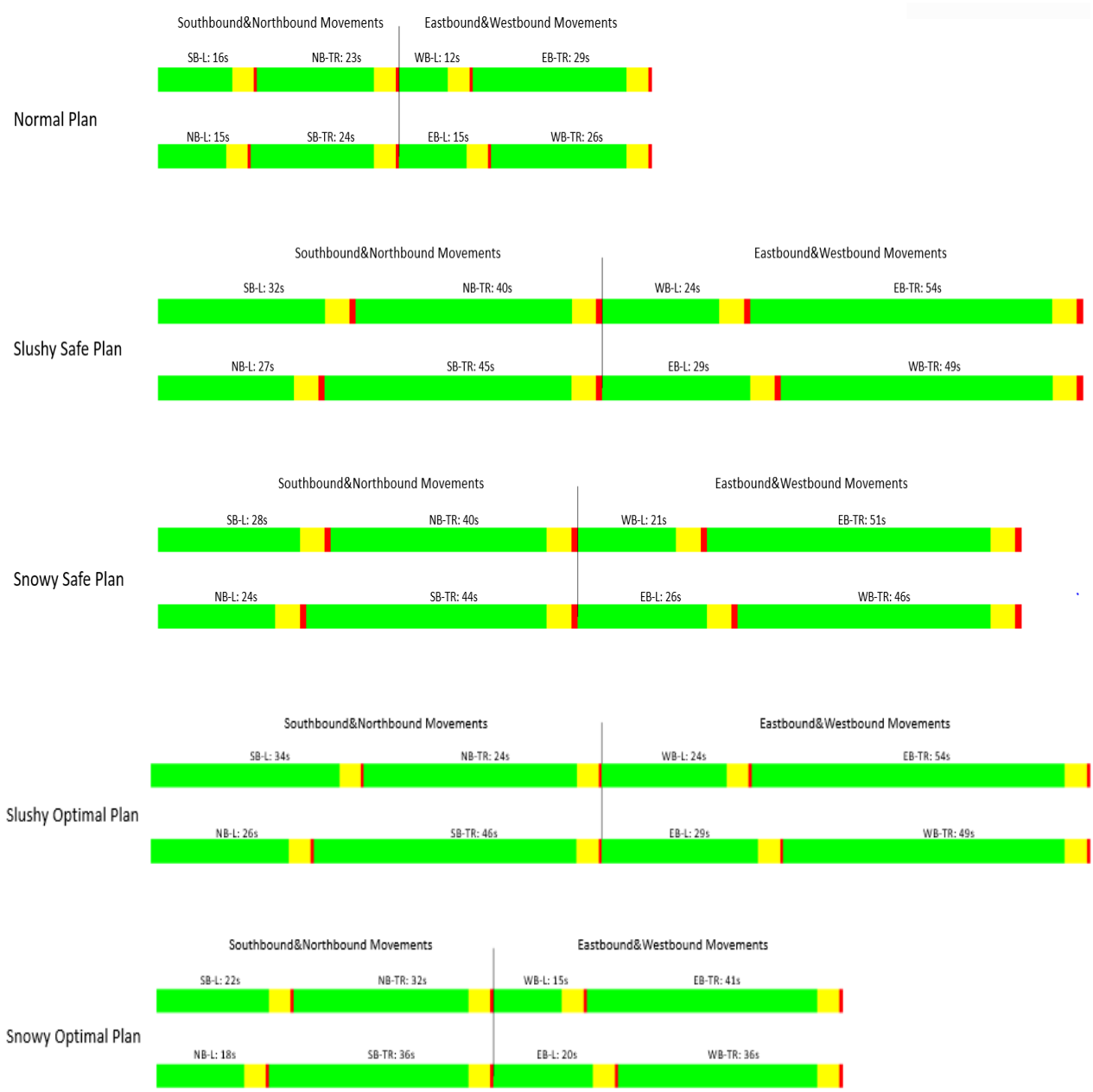

Figure 5.4 Signal Ring and Barrier Diagrams for Normal Weather Plan, Slushy Safe Plan, Snowy Safe Plan, Slushy Optimal Plan, and Snowy Optimal Plan for High-level Traffic Demand

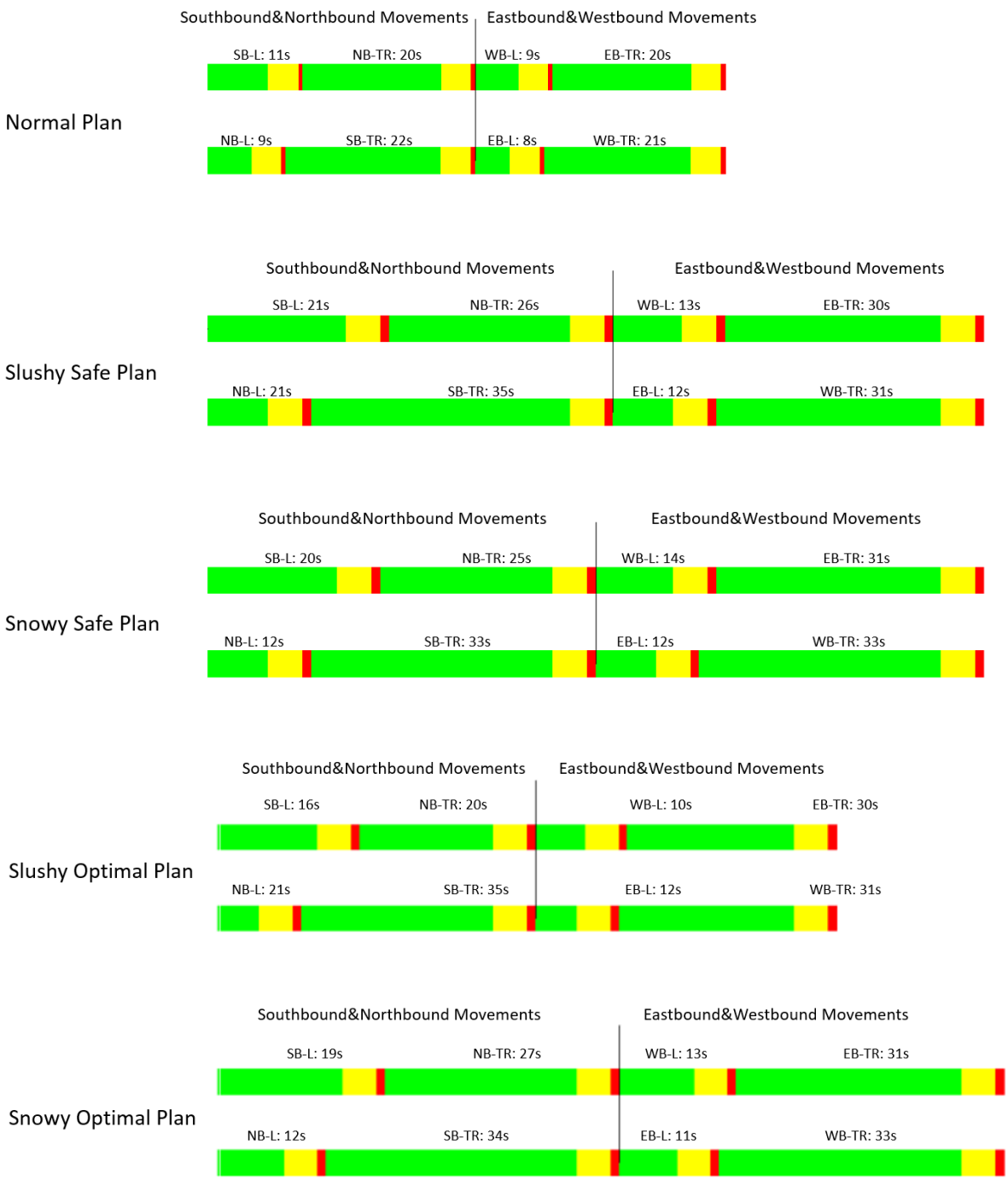

Figure 5.5 Signal Ring and Barrier Diagrams for Normal Weather Plan, Slushy Safe Plan, Snowy Safe Plan, Slushy Optimal Plan, and Snowy Optimal Plan for Medium-level Traffic Demand

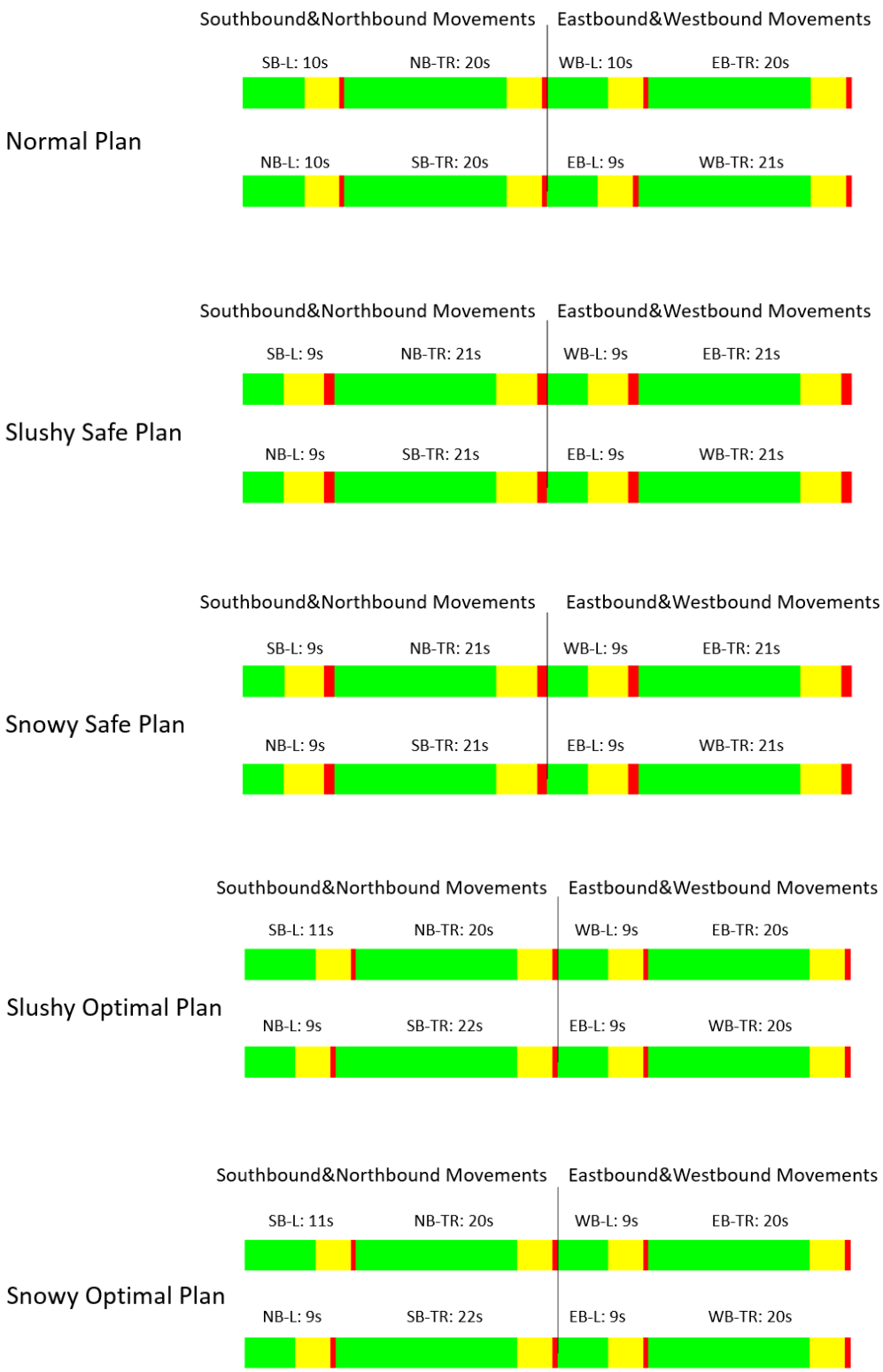

Figure 5.6 Signal Ring and Barrier Diagrams for Normal Weather Plan, Slushy Safe Plan, Snowy Safe Plan, Slushy Optimal Plan, and Snowy Optimal Plan for Low-level Traffic Demand

5.1.3 Evaluation of Weather Specific Signal Plans

We evaluated the weather specific signal plans by comparing their operational performance under adverse weather conditions to the performance of normal plans. Both Synchro and VISSIM are applied to evaluate these plans.

5.1.3.1 Synchro Evaluation

Synchro provides deterministic intersection performance evaluation based on a collection of theoretical and empirical equations from HCM 2010 (Transportation Research Board, 2010). We selected total delay and level of service (LOS) as the performance indicators. Evaluation results at intersection and approach levels are shown in Table 5.2 and Table 5.3. We found that implementing optimal plans can help reduce intersection delay when the traffic demand is at medium or high level (up to 19.3%), but when the traffic demand level is low, implementing optimal plans does not have tangible benefits in terms of traffic efficiency. With extended intergreen time, safe plans usually have higher intersection delay compared to optimal plans (5%-20%). Moreover, the percentage change in delay after implementing weather-specific plans varies over approaches.

More detailed evaluation results at lane level are presented in Appendix B.

Table 5.2 Synchro Evaluation Results of Isolated Intersection Signal Plans

Weather	Demand	Signal Plan	Intersection		EB Approach		WB Approach		NB Approach		SB Approach	
			Delay (s)	LOS	Delay (s)	LOS	Delay (s)	LOS	Delay (s)	LOS	Delay (S)	LOS
Slushy	High	Normal	115.6	F	109.1	F	134.5	F	91.5	F	117.7	F
		Optimal	114.1	F	107.2	F	123.4	F	128.1	F	99.1	F
		Safe	124.1	F	116.7	F	134.8	F	131.5	F	113.7	F
	Medium	Normal	41.2	D	55.1	E	33.5	C	29.8	C	39.8	D
		Optimal	37.3	D	44.3	D	34.4	C	36.0	D	32.4	C
		Safe	45.8	D	56.2	E	45.7	D	38.8	D	36.3	D
	Low	Normal	16.8	B	19.0	B	16.3	B	14.4	B	16.1	B
		Optimal	16.9	B	19.2	B	17.5	B	14.5	B	14.1	B
		Safe	17.8	B	19.3	B	17.8	B	15.6	B	17.1	B
Snowy	High	Normal	163.3	F	158.6	F	186.9	F	128.1	F	164.0	F
		Optimal	151.3	F	143.4	F	185.6	F	143.3	F	117.4	F
		Safe	164.2	F	162.0	F	186.8	F	156.2	F	138.8	F
	Medium	Normal	61.0	E	85.9	F	46.8	D	38.3	D	60.8	E
		Optimal	49.2	D	60.6	E	43.0	D	41.1	D	47.2	D
		Safe	57.9	E	69.9	E	46.3	D	53.6	D	60.0	E
	Low	Normal	17.9	B	20.3	C	17.3	B	15.3	B	17.2	B
		Optimal	18.0	B	20.5	C	18.8	B	15.4	B	15.0	B
		Safe	19.1	B	20.7	C	19.1	B	16.6	B	18.5	B

Table 5.3 Changes in Delay after Implementation of Weather Specific Signal Plans

Weather	Demand	Signal Plan	Intersection	EB Approach	WB Approach	NB Approach	SB Approach
			Delay (s)	Delay (s)	Delay (s)	Delay (s)	Delay (S)
Slushy	High	Optimal	-1.3%	-1.7%	-8.3%	40.0%	-15.8%
		Safe	7.4%	7.0%	0.2%	43.7%	-3.4%
	Medium	Optimal	-9.5%	-19.6%	2.7%	20.8%	-18.6%
		Safe	11.2%	2.0%	36.4%	30.2%	-8.8%
	Low	Optimal	0.6%	1.1%	7.4%	0.7%	-12.4%
		Safe	6.0%	1.6%	9.2%	8.3%	6.2%
Snowy	High	Optimal	-7.3%	-9.6%	-0.7%	11.9%	-28.4%
		Safe	0.6%	2.1%	-0.1%	21.9%	-15.4%
	Medium	Optimal	-19.3%	-29.5%	-8.1%	7.3%	-22.4%
		Safe	-5.1%	-18.6%	-1.1%	39.9%	-1.3%
	Low	Optimal	0.6%	1.0%	8.7%	0.7%	-12.8%
		Safe	6.7%	2.0%	10.4%	8.5%	7.6%

5.1.3.2 VISSIM Evaluation

VISSIM was utilized to evaluate the signal performance in inclement weather in a microscopic perspective considering random variation. The intersection of Columbia Street and Philip Street was simulated by VISSIM, as shown in Figure 5.7. The car-following model was calibrated to adverse weather conditions using the values of micro-parameters (desired speed, desired acceleration, and safe following distance) determined in Chapter 4.

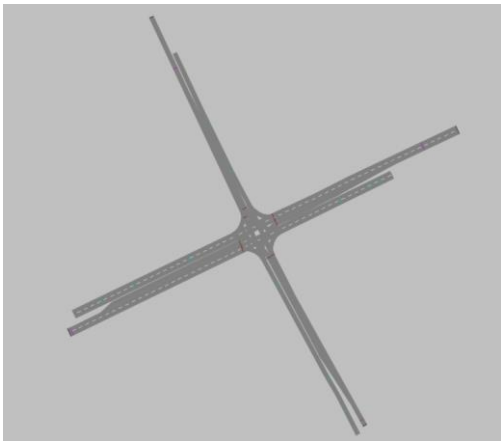

Figure 5.7 Intersection of Columbia Street and Philip Street in VISSIM

Average delays at both intersection level and movement levels were used to evaluate the signal plan performance. For each scenario to be evaluated, simulation was set to run for 6,300 simulation seconds. The first 300 seconds of the simulation were used as a warm-up period and thus were excluded from generating subsequent evaluation results. Results are presented in Table 5.4 and Table 5.5. It should be noted that a warning occurred when the high traffic demand was served by the normal and safe plans in VISSIM because the oversaturated situation. However, all demands were served using the optimal plan. This proves that the optimal plan is superior to normal and safe plans in term of efficiency. The delays for high demand scenarios are not evaluated as in oversaturated situations a significant portion of the vehicles are not able to complete their trips within the simulation period, making it challenging to compute comparable performance metrics.

The general patterns in terms of the benefits achieved by implementing weather-specific plans found in the VISSIM results agrees to those found in the Synchro results. However, the efficiency benefits are much less tangible found from the VISSIM evaluation than the benefits found from the Synchro evaluation. For example, the VISSIM results show that implementing the optimal plan at medium traffic demand on snowy road surface can only decrease the intersection delay by 6.3%, while in the Synchro evaluation, this statistics is 19.3%.

Table 5.4 VISSIM Results of Average Delay in Seconds at Intersection- and Movement-level

Weather	Demand	Signal Plan	Intersection	Eastbound			Westbound			Northbound			Southbound		
				Left	Through	Right	Left	Through	Right	Left	Through	Right	Left	Through	Right
Slushy	Medium	Normal	22.6	16.4	30.3	21.9	23.0	21.9	16.0	18.8	20.9	10.8	17.5	25.9	19.5
		Optimal	21.9	19.4	27.2	25.2	22.1	33.8	18.5	6.0	22.8	15.4	15.6	24.5	19.2
		Safe	29.1	27.2	36.8	28.5	32.9	31.8	26.9	22.3	31.6	14.8	19.2	27.1	18.6
	Low	Normal	14.7	12.6	18.4	11.0	13.5	17.0	9.3	11.6	17.8	4.9	12.0	17.2	5.5
		Optimal	14.9	13.7	18.5	12.4	14.3	18.1	10.5	11.4	17.8	4.8	11.3	15.6	5.0
		Safe	15.1	13.7	18.5	12.4	14.3	18.1	10.6	11.8	17.0	4.6	12.6	16.4	5.2
Snowy	Medium	Normal	33.3	17.7	58.0	51.2	27.6	24.1	18.4	26.2	23.4	12.3	20.0	35.3	30.9
		Optimal	31.2	29.2	37.8	32.0	30.2	31.5	14.9	41.5	30.6	27.3	21.3	30.7	23.8
		Safe	33.4	26.3	43.6	34.5	27.6	31.9	34.1	34.5	34.9	16.4	23.7	33.3	25.6
	Low	Normal	15.3	12.6	20.6	10.5	14.5	17.3	10.4	11.4	17.2	4.7	11.9	16.8	5.5
		Optimal	15.2	13.0	20.9	10.6	14.3	17.8	10.1	11.3	17.2	4.6	11.2	15.3	5.0
		Safe	15.9	13.0	20.9	10.4	14.3	17.8	10.0	12.0	19.4	4.7	13.0	18.4	7.1

Table 5.5 Changes in Delay after Implementation of Weather Specific Signal Plans in VISSIM

Weather	Demand	Signal Plan	Intersection	Eastbound			Westbound			Northbound			Southbound		
				Left	Through	Right	Left	Through	Right	Left	Through	Right	Left	Through	Right
Slushy	Medium	Optimal	-3.1%	18.3%	-10.2%	15.1%	-3.9%	54.3%	15.6%	-68.1%	9.1%	42.6%	-10.9%	-5.4%	-1.5%
		Safe	28.8%	65.9%	21.5%	30.1%	43.0%	45.2%	68.1%	18.6%	51.2%	37.0%	9.7%	4.6%	-4.6%
	Low	Optimal	1.4%	8.7%	0.5%	12.7%	5.9%	6.5%	12.9%	-1.7%	0.0%	-2.0%	-5.8%	-9.3%	-9.1%
		Safe	2.7%	8.7%	0.5%	12.7%	5.9%	6.5%	14.0%	1.7%	-4.5%	-6.1%	5.0%	-4.7%	-5.5%
Snowy	Medium	Optimal	-6.3%	65.0%	-34.8%	-37.5%	50.4%	27.0%	48.4%	15.3%	34.6%	21.1%	6.5%	-13.0%	-23.0%
		Safe	0.3%	48.6%	-24.8%	-32.6%	0.0%	32.4%	85.3%	31.7%	49.1%	33.3%	18.5%	-5.7%	-17.2%
	Low	Optimal	-0.7%	3.2%	1.5%	1.0%	-1.4%	2.9%	-2.9%	-0.9%	0.0%	-2.1%	-5.9%	-8.9%	-9.1%
		Safe	3.9%	3.2%	1.5%	-1.0%	-1.4%	2.9%	-3.8%	5.3%	12.8%	0.0%	9.2%	9.5%	29.1%

5.1.3.3 Evaluation Result Summary

The Synchro and VISSIM evaluation results show similar patterns in terms of the direction of effect of weather-specific signal control. It can be observed from the evaluation results above that the largest benefit is achieved when the optimal plan is used in snowy conditions and traffic demand is at an intermediate level. In general, the benefits of implementing weather-specific plans are larger in snowy conditions than in slushy conditions. In terms of traffic demand, it is most beneficial to implement weather-responsive strategies at medium demand. In low or high demand conditions, the efficiency improvements are relatively low. Poor weather conditions also require changing the duration of yellow change and red-clearance intervals for safe traffic operations, which would then lead to reduced efficiency or longer delays. In conclusion, weather responsive signal control is highly beneficial both for safety and efficiency and the suitable plan should be selected on the basis of weather severity and traffic.

5.2 Signal Timing of Coordinated Corridor

This section researches how signal coordination plans can be modified to ensure better traffic progression in inclement weather conditions. The development and evaluation of plans are demonstrated through a case study on an arterial corridor.

5.2.1 Case Description

The selected study site is a 1.35-kilometer arterial corridor along Columbia Street, Waterloo, Ontario, consisting four signalized intersections: Columbia St/ Philips St, Columbia St/ Albert St, Columbia St/ Hazel St, and Columbia St/ King St. An aerial map of the corridor is shown in Figure 5.8. In the later description, all these intersections will be referred to using the number indicated in Figure 5.8. The distances between these pairs of intersections are 450m (1 and 2), 350m (2 and 3), and 550m (3 and 4), respectively.

The effectiveness of weather-responsive signal control plans is investigated at two demand levels: medium and high. The specific demand information for these two situations is given in Figure 5.9

and Figure 5.10. Arterial roads with low traffic demand are usually not operated in coordination; hence, low-demand situation is not included.

Figure 5.8 Aerial Map of the Study Site: Columbia Street Corridor

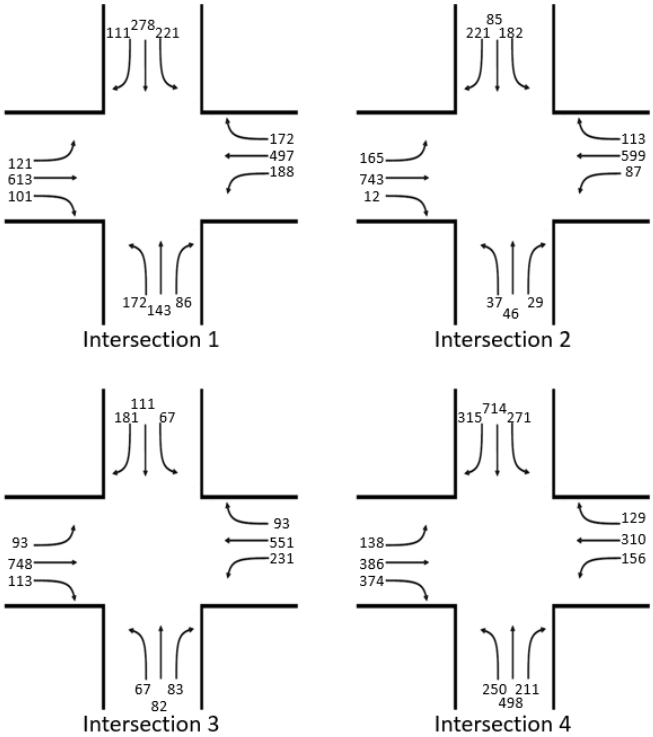

Figure 5.9 Traffic Demand for the Intersections on the Arterial Road - Medium Demand Scenario

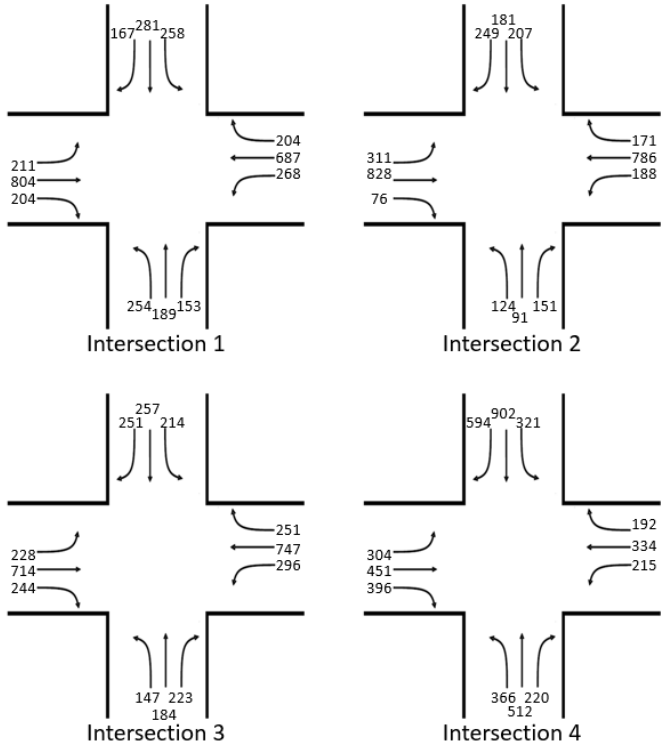

Figure 5.10 Traffic Demand for the Intersections on the Arterial Road - High Demand Scenario

5.2.2 Development of Signal Control Plans

This section describes how the normal weather plan and weather-specific plans are developed for the four intersections on the corridor. Similar to isolated intersections, specific weather plans include one optimal signal plan and one safe plan. The optimal plan aims to maximize the traffic efficiency in inclement weather without changing intergreen time, while the safe plan extends the intergreen time (increasing yellow from 3.5s to 4s, and increasing all-red from 0.5s to 1s). Synchro is used in the study to design these signal plans. The design of cycle structure, yellow change, and red clearance interval remains the same as in isolated intersection signal plan designing. The optimal design for network cycle length and offsets is describe as follows.

5.2.2.1 Network Cycle Length

For signal coordination, all the intersections within the corridor is required to keep a same cycle length (or multiple of a cycle length) to maintain a constant relationship between intersections. In

Synchro, the optimal network cycle length is determined by evaluating a group of cycle lengths within a certain pre-defined range at an incremental interval. The performance index is a function of delay and stop times. In this study, we selected 10s as the incremental interval, 60s as the minimum cycle length, and 150s as the maximum cycle length. Synchro selected the optimal network cycle lengths based on the saturation flow, speed, and intergreen time. Optimization results are shown in Table 5.6.

Table 5.6 Optimal Network Cycle Lengths for Signal Coordination Plans (in seconds)

Demand	Slushy			Snowy		
	Normal	Optimal	Safe	Normal	Optimal	Safe
High	70	100	130	70	130	150
Medium	70	80	110	70	110	130

5.2.2.2 Offsets and Splits

After the cycle length was determined, the final step was to optimize offsets. Offset is the most important parameter in arterial coordination as it defines the time relationships among the signal plans of the individual intersections. Synchro provides an offset optimization function. The function evaluates the delays by varying the offset for every 8 seconds around the cycle. Then, it varies the offset by a smaller increment (1 to 4 seconds) around the 8-second choice with the lowest delay. During the offset optimization, Synchro is also able to optimize the splits if needed. In this study, offsets and splits of all plans were designed according to these rules.

5.2.3 Evaluation of Weather Specific Signal Coordination Plans

To evaluate the weather-specific signal coordination plans, their performance was compared with the performance of the coordination plan developed for the normal weather conditions. The evaluation was conducted by Synchro and VISSIM.

5.2.3.1 Synchro Evaluation

The main purpose of the coordination plan is to ensure corridor progression. Thus, delay experienced by travelers travelling along the coordinated direction (in this study, southbound and westbound) is an important indicator to evaluate the coordination plan. Also, overall traffic

performance needs to be examined to prevent significant exacerbation on minor street movements brought by coordination.

In this study, average delay experienced by eastbound and westbound travelers was selected as the corridor progression indicator. Total network delay and average delay at each intersection were used to quantify overall traffic performance. Evaluation results are listed in Table 5.7 and Table 5.8. The results show that the efficiency benefits of implementing weather-specific plans on a coordinated corridor are significant, especially for coordinated directions. The magnitude of benefits is much larger compared to implementing weather-responsive plans on an isolated intersection. In snowy conditions, the weather-responsive plan have the potential of decreasing total delay experienced by road users by up to 20% (implementing the optimal plan at medium traffic demand on snowy road surface condition). Most benefit patterns found in the isolated intersection case apply to this coordinated corridor case as well. For example, in this coordinated corridor case, the efficiency benefit is also most compelling when the traffic demand is at medium level.

Table 5.7 Synchro Evaluation Results of Signal Coordination Plans

Demand	Weather	Signal Plan	Network Total Dela (h)	Intersection 1			Intersection 2			Intersection 3			Intersection 4		
				Delay (s)	EB Delay (s	WB Delay (s	Delay (s)	EB Delay (s	WB Delay (s	Delay (s)	EB Delay (s	WB Delay (s	Delay (s)	EB Delay (s	WB Delay (s
Medium	Slushy	Normal	121	44.3	73.5	27.3	25.8	21.0	40.0	32.8	50.3	21.7	46.8	25.7	100.0
		Optimal	107	36.9	58.5	17.9	21.9	14.5	31.0	28.0	33.9	21.4	44.3	10.2	74.5
		Safe	122	42.7	63.4	17.7	27.2	20.7	38.2	27.8	29.1	12.6	52.0	17.4	80.9
	Snowy	Normal	173	64.0	113.2	40.5	34.6	24.5	63.1	51.2	95.3	24.3	65.7	36.5	143.0
		Optimal	138	48.8	71.9	31.7	28.5	17.8	40.1	31.0	35.8	13.8	59.6	25.0	103.2
		Safe	156	54.3	78.4	33.4	30.5	21.5	38.3	36.0	41.2	16.6	68.2	38.0	114.4
High	Slushy	Normal	449	109.9	153.4	54.3	65.4	26.9	114.7	107.7	137.5	84.7	122.1	28.4	207.8
		Optimal	424	104.0	148.6	50.5	58.6	23.1	94.1	102.9	125.2	86.1	116.4	25.1	207.5
		Safe	474	116.9	161.8	68.2	65.4	34.0	89.4	115.3	133.1	93.3	130.0	39.5	211.7
	Snowy	Normal	647	159.0	210.0	104.5	103.9	70.3	171.8	156.1	190.9	137.4	168.1	59.2	266.0
		Optimal	578	140.9	188.8	58.0	82.5	39.3	126.7	140.8	159.6	109.0	157.3	40.4	270.0
		Safe	638	152.5	211.5	73.1	91.1	30.8	140.8	158.5	181.4	136.4	173.5	64.3	273.2

Table 5.8 Changes in Delay after Implementing Weather Specific Coordination Plans in Synchro

Demand	Weather	Signal Plan	Total Delay	Intersection 1			Intersection 2			Intersection 3			Intersection 4		
				Delay	EB Delay	WB Delay	Delay	EB Delay	WB Delay	Delay	EB Delay	WB Delay	Delay	EB Delay	WB Delay
Medium	Slushy	Optimal	-11.6%	-16.7%	-20.4%	-34.4%	-15.1%	-31.0%	-22.5%	-14.6%	-32.6%	-1.4%	-5.3%	-60.3%	-25.5%
		Safe	0.8%	-3.6%	-13.7%	-35.2%	5.4%	-1.4%	-4.5%	-15.2%	-42.1%	-41.9%	11.1%	-32.3%	-19.1%
	Snowy	Optimal	-20.2%	-23.8%	-36.5%	-21.7%	-17.6%	-27.3%	-36.5%	-39.5%	-62.4%	-43.2%	-9.3%	-31.5%	-27.8%
		Safe	-9.8%	-15.2%	-30.7%	-17.5%	-11.8%	-12.2%	-39.3%	-29.7%	-56.8%	-31.7%	3.8%	4.1%	-20.0%
High	Slushy	Optimal	-5.6%	-5.4%	-3.1%	-7.0%	-10.4%	-14.1%	-18.0%	-4.5%	-8.9%	1.7%	-4.7%	-11.6%	-0.1%
		Safe	5.6%	6.4%	5.5%	25.6%	0.0%	26.4%	-22.1%	7.1%	-3.2%	10.2%	6.5%	39.1%	1.9%
	Snowy	Optimal	-10.7%	-11.4%	-10.1%	-44.5%	-20.6%	-44.1%	-26.3%	-9.8%	-16.4%	-20.7%	-6.4%	-31.8%	1.5%
		Safe	-1.4%	-4.1%	0.7%	-30.0%	-12.3%	-56.2%	-18.0%	1.5%	-5.0%	-0.7%	3.2%	8.6%	2.7%

5.2.3.2 VISSIM Evaluation

The arterial with four intersections was modelled in VISSIM as shown in Figure 5.11. Signal plans in all scenarios were evaluated based on the total delay in one hour of traffic and the average delay experienced by vehicles travelling along eastbound and westbound. The simulation period is 6, 000 simulation seconds (from 300 to 6,300). However, due the over-saturated situations, VISSIM cannot output reliable delay information for high-demand scenarios. Hence, only the aggregated results from the simulation period at medium-demand level are presented in Table 5.9 and Table 5.10. Generally, the VISSIM simulation results are consistent with the Synchro results. The benefits in terms of delay reduction are large. The modifications on network cycle length and green splits ensure a better corridor progression in adverse weather conditions, resulting up to 33% reduction in average delay along one coordinated direction. The efficiency benefits found by VISSIM (percentage change in delay ranging from -5.5% to 4.8% after implementing weather-specific plans at medium traffic demand) is still less than those found by Synchro (ranging from -11.6% to 0.8%).

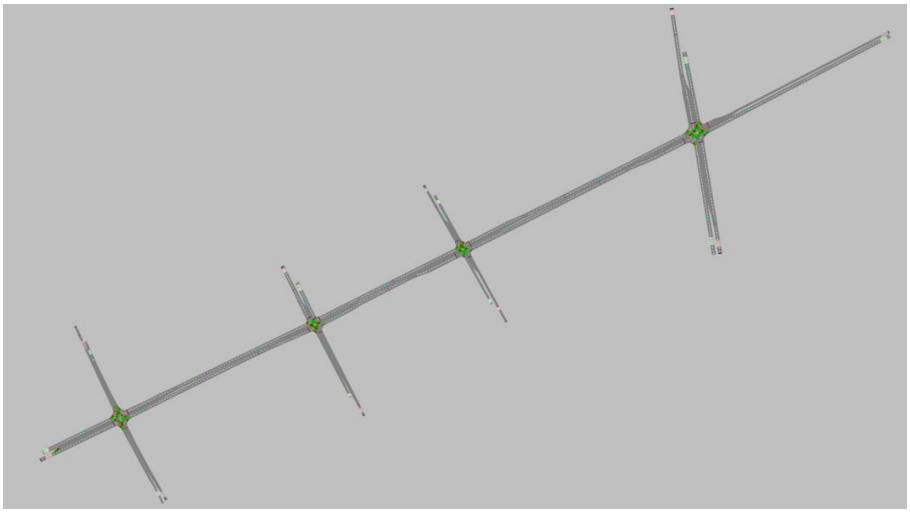

Figure 5.11 Columbia Arterial Corridor in VISSIM

Table 5.9 VISSIM Evaluation Results of Signal Coordination Plans at Medium Demand Level

Weather	Signal Plan	Total Delay (hr)	Average EB Delay (s)	Average WB Delay (s)
Slushy	Normal	69.5	99.4	113.8
	Optimal	66.4	84.9	75.8
	Safe	72.8	91.2	92.1
Snowy	Nomal	91.3	165.7	141.4
	Optimal	86.2	113.0	131.3
	Safe	90.9	162.9	141.2

Table 5.10 Changes in Delay after Implementing Weather Specific Coordination Plans at Medium Demand Level in VISSIM

Weather	Signal Plan	Total Delay	Average EB Delay	Average WB Delay
Slushy	Optimal	-4.4%	-14.6%	-33.4%
	Safe	4.8%	-8.3%	-19.1%
Snowy	Optimal	-5.5%	-31.8%	-7.2%
	Safe	-0.4%	-1.7%	-0.1%

5.2.3.3 Evaluation Result Summary

The benefits of implementing weather responsive signal plans is much more compelling at an arterial-corridor level than at an isolated-intersection level. Similar to the results from isolated intersection studies, the benefits are largest at the medium demand level and lowest at the low demand level. Also, the benefits of implementing weather specific plans are larger in snowy conditions than in slushy conditions.

Chapter 6 Conclusions and Future Research

Weather responsive signal control is a cost-effective measure to mitigate weather-related impacts on traffic operations. However, development of weather responsive traffic signal control strategies requires systematic consideration of many factors, especially effects of weather severity on driver behavior. This research approaches this problem in a three-folded manner: first, statistical methods are applied to quantify weather impact on traffic flow; second, a video-based approach is utilized to calibrate weather-specific microscopic simulation models; third, weather-specific signal control plans are developed to deal with weather impacts and are subsequently evaluated using simulation to quantify their potential under real world application settings. This chapter summarizes the major contributions and findings of the research and suggests future research areas to further the goal of developing comprehensive and practical weather-responsive signal strategies.

6.1 Contributions

This study has made the following contributions:

- The relationships between two critical traffic parameters (i.e., saturation flow rate and start-up lost time) and road weather and surface conditions in adverse weather conditions were examined using field-collected video footage. The calibrated statistical models can be used in various traffic simulations models for evaluating the effectiveness of alternative traffic management and control plans under adverse winter weather conditions.
- A video-based method was implemented to calibrate the car-following parameters required by a microscopic simulation tool (VISSIM) under adverse weather conditions. Automated video processing techniques were applied to extract myriad video-trajectories, from which vehicle speed and acceleration parameters were measured as model inputs. The approach is more robust and reliable than traditional trial-and-error calibration methods.
- Weather-specific signal plans were developed to account for the effects of both weather factors and road surface conditions (RSC). The explicit consideration of RSC in traffic

control is one of the first in the literature, providing an opportunity to evaluate the benefit of winter road maintenance program for improving traffic operations. The weather-specific plans are pre-timed signal control plans with adjusted yellow change interval, red clearance interval, cycle length, and offsets. Their performances were evaluated separately for isolated intersections and coordinated corridors using empirical equations and simulation tools.

6.2 Findings

The studies on weather impacts on traffic parameters yielded the following findings:

- Road surface conditions have a significant influence on saturation flow rate. Saturation flow rates are found to be 1825vph, 1509vph, 1363vph on normal, slushy, and snowy road surface conditions, respectively. The results from this research are consistent with those from literature.
- The relationship between saturation flow headways and visibility is close to being in a logarithmic form. A regression model was built between saturation headway and logarithmic form of visibility, with an R square of 0.43.
- Multiple regression analysis results show that road surface conditions, visibility, temperature, and wind speed have statistically significant influence on saturation flow headway. A multiple regression model was built based on these factors. The R square value of the model is 0.68.
- There is no clear relationship between start-up lost time and meteorological variables including road surface condition, visibility, temperature, wind speed, and precipitation type.
- From vehicle trajectory analysis, mean desired speed is found to be 16.9% and 23.3% lower in slushy and snowy conditions than in normal conditions. The reductions in mean desired acceleration rate are found to be 12.1% and 15.8% for slushy and snowy conditions, respectively.

Weather-responsive signal plans were found to be effective in improving traffic operations and reducing traffic delay at signalized intersections. Specifically,

- Based on the reduction in free flow speed and deceleration rate under adverse winter weather conditions, it is recommended that intergreen time be increased by 0.5-1.0 second for improved safety. This improved safety margin would however result in reduced overall efficiency. It was found that the additional intergreen time would increase the total intersection delay by 5% to 20% as compared to the weather specific plans that keep the same intergreen time as normal signal plans.
- It was found that implementing weather-responsive signal plans is most beneficial in terms of traffic efficiency for intersections with a medium level of traffic demand with an overall degree of saturation in the range of 0.4 to 0.7. It was found that up to 20% reduction in total intersection delays possible for adopting a weather-responsive signal control plan. When the demand is very low or very high, implementing such plans has little benefits in terms of reducing delay.
- The benefits of implementing weather specific plans are more obvious in snowy conditions than in slushy conditions.
- The benefits of implementing weather responsive signal plans are much more compelling at an arterial-corridor level with signal coordination than at an isolated-intersection level.

6.3 Future Research

Potential future research topics on the subject are identified as follows:

- The results of weather impact on traffic in this research are all based on video data collected at one intersection in 2015 winter (February – March). Due to the limited sample size, the relationship between traffic performance and meteorological variables needs to be further investigated. Also, there is no data available from other intersections that can be used to validate the findings. In the future, it is suggested more data should be collected with a wider temporal and spatial coverage for more robust conclusions.

- In the simulation calibration part, the method only focuses on calibrating car-following parameters. However, the work can be easily extended to calibrating car following model parameters such as those related to lane changing and route choice behaviors, which is the focus of my future research.
- This research briefly discusses the general unreliability of detectors in inclement weather. In the future, efforts can be made to quantify the weather influence on various types of detectors (e.g., inductive loop, video camera) and investigate methods to mitigate the influence, such as adjusting detector settings or altering detection zones in inclement weather.
- Once the limitations on performance of detectors in poor weather are addressed or are lessened, the combination of weather-responsive control and actuated signal control or more advanced control modes (e.g., real-time adaptive signal control) is worth being explored. Modifications on signal timing parameters, such as passage time in actuated system, may improve operation performance and safety. Adaptive systems usually have an underlying traffic model for the purpose of predicting traffic arrivals and estimating queue or delay. The model requires parametric input, such as saturation flow rate and start-up lost time. Adjusting these values under adverse weather conditions is necessary to generate reliable prediction and estimation results.

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Appendix A: Intersection Volume to Capacity (V/C) Ratio Calculation

Medium Demand Level Scenario

The overall volume-to-capacity ratio

$$\frac{\mathrm{V}}{C_{overall}} = Y \times \frac{c}{g_e}$$

where,

Y= the sum of the critical lane flow

$$\mathrm{Y} = \sum_j y_{ij} = \sum_j (q_{ij}/S_{ij})$$

where,

Y = intersection flow ratio

y_{ij} = flow ratio for the critical lane i in phase j

q_{ij} = arrival flow of critical lane I in phase j (pcu/h)

S_{ij} = saturation flow of critical lane I in phase j (pch/h)

$\sum_j =$ summation over critical lanes in phase j (one critical for each phase)

We use the field-measured saturation flow rate in normal weather of 1825 vphpl as basic saturation flow rate. In this case, there is no adjustment factors other than control factors.

Northbound Movements

Shared right and through lane:

Assume pedestrian flow $F_{Rped} = 1.0$

$S_T = S_R$

$q'_T = K_R q_R + q_T = q_{RT}$

$F_{TR} = \frac{q_R + q_T}{q'_T} = 1$

$S_{TR} = S_T$=1825

q = 86+143=229

y =229/1825=0.125

Left turn lane:

Left turn lane movement performance is calculated in two steps:

Protected in Phase 3,

Permissive in Phase 4.

(1) protected

F_L = 1

S_L = 1825

LTOI

Number of signal cycles in one hour = 3600/60 =60 cycles

Totoal LTOI = $60 \times 2 = 120$

While calculating the degree of saturation, it should be noted that the left turns on intergreen are removed from the calculations.

Capacity during Phase 3 = $1825 \times$ (5+1)/60= 183

Hence northbound left turn clearing volume = 172-120=52

y =52/1825=0.028

(2) permissive

Since all NB-L vehicles clear during Phase 1, Phase 2 y = 0

Similarly, **Southbound Movements**

Shared right and through lane: y = (111+278)/1825= 0.213

Left turn protected: y = (221-120)/1825= 0.055

Left turn permissive: y = 0

Eastbound Movements

Shared right and through lane:

$\because S_T = S_R$

$\therefore K_R = 1$

$q'_R = q_R$

$q_{RT} = (q_T + q_R)/2 = (613+101)/2=357$

y=$357/1825=0.196$

Through movement lane:

y=$357/1825=0.196$

Left turn lane:

(1) protected

LTOI=120

Capacity during Phase 1 = $1825 \times (4+1)/60 = 152$

Hence northbound left turn clearing volume = 121-120=1

y =1/1825=0.001

(2) permissive

y=0

Similarly, **Westbound Movements**

Shared right and through lane: y = (497+162)/2/1825= 0.361

Through movement lane: y=0.361

Left turn protected: y = (162-120)/1825= 0.023

Left turn permissive: y = 0

where,

F = saturation flow adjustment factor

c = cycle length

g_e = effective green time

K = movement factor

$q' =$ equivalent through flow rate

LTOI = left turns on intergreen period

Table: Summary of the Flow Ratio Calculation

Movement		Number of Lanes	Phase	LTOI	q pcu/h	S pcu/h	y	Critical y
EB	L	1	1	120	1	1825	0.001	0.023
WB	L	1	1	120	42	1825	0.023	
EB	L	1	2	0	0	1825	0.000	0.196
EB	T	1	2	0	357	1825	0.196	
EB	TR	1	2	0	257	1825	0.141	
WB	L	1	2	0	0	1825	0.000	
WB	T	1	2	0	330	1825	0.181	
WB	TR	1	2	0	330	1825	0.181	
NB	L	1	3	120	52	1825	0.028	0.055
SB	L	1	3	120	101	1825	0.055	
NB	L	1	4	0	0	1825	0.000	0.213
NB	TR	1	4	0	229	1825	0.125	
SB	L	1	4	0	0	1825	0.000	
SB	TR	1	4	0	389	1825	0.213	

Y=0.023+0.196+0.055+0.213=0.487

$$\frac{\mathrm{V}}{C_{overall}} = Y \times \frac{c}{g_e} = 0.487 \times \frac{60}{48} = 0.61$$

Appendix B: Synchro Evaluation Results of Weather-specific Plans for Isolated Intersection

Synchro Evaluation Results of Weather-specific Plans for Isolated Intersection at *High* Demand

Weather	Signal Plan	Performance	Eastbound			Westbound			Northbound		Southbound	
			Left	Through	Shared TR	Left	Through	Shared TR	Left	Shared TR	Left	Shared TR
Slushy	Normal	V/C Ratio	1.092	1.134	1.135	1.074	1.245	1.245	1.057	1.042	1.057	1.246
		Delay (s)	100.2	112.2	112.2	103.9	158.8	159.3	92	90.8	89.7	162.2
		Lane LOS	F	F	F	F	F	F	F	F	F	F
	Optimal	V/C Ratio	1.092	1.064	1.064	1.047	1.141	1.141	1.175	1.092	0.963	1.113
		Delay (s)	127.3	109.1	109.1	117.1	140.4	140.9	156.1	135	85.3	133.2
		Lane LOS	F	F	F	F	F	F	F	F	F	F
	Safe	V/C Ratio	1.13	1.085	1.085	1.091	1.167	1.167	1.175	1.061	1.053	1.168
		Delay (s)	140.7	117.1	117	131.2	151	151.5	156.3	123.8	112	155.5
		Lane LOS	F	F	F	F	F	F	F	F	F	F
Snowy	Normal	V/C Ratio	1.17	1.256	1.256	1.142	1.378	1.378	1.132	1.154	1.134	1.38
		Delay (s)	129.8	161.5	161.5	128.9	215.9	216.3	119.1	130.4	117.5	219.2
		Lane LOS	F	F	F	F	F	F	F	F	F	F
	Optimal	V/C Ratio	1.235	1.167	1.167	1.285	1.303	1.303	1.318	1.077	1.162	1.186
		Delay (s)	164.4	133.9	133.9	191.5	193.3	193.8	200.2	112.6	134.5	146.4
		Lane LOS	F	F	F	F	F	F	F	F	F	F
	Safe	V/C Ratio	1.276	1.195	1.195	1.256	1.294	1.294	1.336	1.096	1.22	1.238
		Delay (s)	193.2	155.5	155.5	188	200.1	200.6	216.7	130.9	168.8	179.4
		Lane LOS	F	F	F	F	F	F	F	F	F	F

Synchro Evaluation Results of Weather-specific Plans for Isolated Intersection at Medium Demand

Weather	Signal Plan	Performance	Eastbound			Westbound			Northbound		Southbound	
			Left	Through	Shared TR	Left	Through	Shared TR	Left	Shared TR	Left	Shared TR
Slushy	Normal	V/C Ratio	0.54	1.013	1.015	0.734	0.895	0.899	0.756	0.657	0.578	0.982
		Delay (s)	25	71.3	71.8	35.4	45.2	46.6	37.3	28.2	20.8	59.8
		Lane LOS	C	F	F	D	D	D	D	C	C	E
	Optimal	V/C Ratio	0.526	0.946	0.947	0.731	0.845	0.849	0.74	0.767	0.567	0.896
		Delay (s)	25.8	57.1	57.4	36.6	41	42	42	41.1	20.8	44.7
		Lane LOS	C	E	E	D	D	D	D	D	C	D
	Safe	V/C Ratio	0.584	0.973	0.974	0.82	0.878	0.881	0.761	0.751	0.576	0.883
		Delay (s)	34.1	70.8	71.2	52.3	52.5	53.8	49.4	46.6	25	48.8
		Lane LOS	C	E	E	D	D	D	D	D	C	D
Snowy	Normal	V/C Ratio	0.634	1.122	1.123	0.771	0.991	0.995	0.82	0.727	0.64	1.108
		Delay (s)	32	107.3	108	40.6	65.8	67.9	46.2	32.8	24.7	99.7
		Lane LOS	C	F	F	D	E	E	D	C	C	F
	Optimal	V/C Ratio	0.592	0.997	0.999	0.837	0.871	0.875	0.908	0.759	0.625	0.978
		Delay (s)	33.7	76.3	76.7	53.7	49.9	51.1	70.8	46.2	26.8	67.8
		Lane LOS	C	E	E	D	D	D	E	D	C	E
	Safe	V/C Ratio	0.624	1.036	1.037	0.839	0.903	0.906	1.033	0.831	0.71	1.048
		Delay (s)	36.6	87.8	88.4	54.4	55.4	56.9	107.4	55.7	33.5	88.9
		Lane LOS	D	F	F	D	E	E	F	E	C	F

Synchro Evaluation Results of Weather-specific Plans for Isolated Intersection at Low Demand

Weather	Signal Plan	Performance	Eastbound			Westbound			Northbound		Southbound	
			Left	Through	Shared TR	Left	Through	Shared TR	Left	Shared TR	Left	Shared TR
Slushy	Normal	V/C Ratio	0.252	0.519	0.523	0.308	0.482	0.491	0.293	0.303	0.276	0.481
		Delay (s)	15.5	23.6	23.8	15.6	21.8	22.2	15.3	19.6	14.8	22.9
		Lane LOS	B	C	C	B	C	C	B	B	B	C
	Optimal	V/C Ratio	0.264	0.519	0.523	0.328	0.512	0.522	0.277	0.303	0.264	0.419
		Delay (s)	15.8	23.6	23.8	16.6	23.4	23.9	15.6	19.6	14	19.8
		Lane LOS	B	C	C	B	C	C	B	B	B	B
	Safe	V/C Ratio	0.282	0.519	0.523	0.349	0.512	0.522	0.324	0.303	0.303	0.472
		Delay (s)	16.8	23.6	23.8	17.7	23.4	23.9	17.3	19.6	16.9	22.6
		Lane LOS	B	C	C	B	C	C	B	B	B	C
Snowy	Normal	V/C Ratio	0.269	0.574	0.579	0.332	0.534	0.544	0.311	0.336	0.289	0.522
		Delay (s)	15.9	25.7	25.9	16.3	23.5	24.1	15.8	20.3	15.2	24.3
		Lane LOS	B	C	C	B	C	C	B	C	B	C
	Optimal	V/C Ratio	0.284	0.574	0.579	0.352	0.567	0.578	0.293	0.336	0.277	0.464
		Delay (s)	16.3	25.7	25.9	17.3	25.4	26.1	16	20.3	14.3	21.1
		Lane LOS	B	C	C	B	C	C	B	C	B	C
	Safe	V/C Ratio	0.302	0.574	0.579	0.374	0.567	0.578	0.346	0.336	0.316	0.522
		Delay (s)	17.3	25.7	25.9	19	25.4	26.1	18.5	20.3	17.7	24.3
		Lane LOS	B	C	C	B	C	C	B	C	B	C