Center for Advanced Multimodal Mobility Solutions and Education

Project ID: 2018 Project 17

MODELING THE MACROSCOPIC EFFECTS OF WINTER MAINTENANCE OPERATIONS ON TRAFFIC MOBILITY ON WASHINGTON HIGHWAYS

Final Report

by

Washington State University
Consortium Member

Chuang Chen, M.S. (ORCID ID: https://orcid.org/0000-0002-1239-1833)
Research Assistant, Department of Civil and Environmental Engineering
PO Box 642910, Pullman, WA, 99164.
Phone: 1-509-335-9578; Email: Chuang.Chen@wsu.edu

Xianming Shi, Ph.D., P.E. (ORCID ID: https://orcid.org/0000-0003-3576-8952)
Associate Professor, Department of Civil and Environmental Engineering
PO Box 642910, Pullman, WA, 99164.
Phone: 1-509-335-7088; Email: Xianming.Shi@wsu.edu

for

Center for Advanced Multimodal Mobility Solutions and Education
(CAMMSE @ UNC Charlotte)
The University of North Carolina at Charlotte
9201 University City Blvd
Charlotte, NC 28223

September 2019

ACKNOWLEDGEMENTS

This project was funded by the Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE @ UNC Charlotte), one of the Tier I University Transportation Centers that were selected in this nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT), under the FAST Act. The authors are also very grateful for all of the time and effort spent by the transportation professionals to provide the data that was critical for the successful completion of this study. Special thanks go to Mr. Joe Schmit at the Washington State Department of Transportation (WSDOT) for his efforts in collecting the historical winter maintenance related data and Mr. Ziyuan Pu at University of Washington and Michelle Akin, P.E. at Washington State University for their assistance to this study.

DISCLAIMER

Table of Contents

List of Figures

List of Tables

EXCUTIVE SUMMARY

The Washington State Department of Transportation (WSDOT) maintains a network of more than 7,000 miles of state highways, which contributes to the economic competitiveness of the State, the region, and the nation. Winter weather tends to reduce both the average traffic speed and traffic volume, whereas the implementation of winter road maintenance (WRM) operations tends to mitigate such reductions. Yet, research is currently lacking in understanding the relationship between highway mobility and WRM operations, especially when it comes to the specific road weather scenarios in the Pacific Northwest.

The objective of this project is to model the macroscopic effects of winter maintenance current practices on traffic mobility on Washington highways. In other words, the focus is placed on the aggregated outcome of winter weather and WSDOT winter maintenance practices on the parameters characteristic of traffic operations, instead of the microscopic effects or changes in individual driver behaviors. To meet this goal, the following objectives are addressed: (1) identifying appropriate WSDOT highway segments for this modeling study and collecting the relevant data related to winter maintenance practices and climatic conditions; (2) collecting sensor data at the selected WSDOT highway segments to characterize the changes in traffic patterns on winter pavements; and (3) developing a data model that correlates the traffic mobility (aggregated measures) and explanatory variables.

Through extensive coordination with WSDOT and University of Washington, a substantial amount of historical data on WRM activities, macroscopic traffic parameters, and climatic conditions was obtained by the research team. Out of this data, we identified a total of 247 complete records available which had the friction index value as well as other parameters of interest, for December 2016, over a 20-mile segment on the Interstate highway I-5. The data of interest was organized, coupled with each other based on milepost and time stamp, and readied for analyses. Out of the 247 records, a randomly selected dataset (six records) was set aside for testing the developed ANN models, whereas the rest of data was used to train the ANN models.

In this work, one ANN model (with 8-11-1 structure) was developed for the traffic volume during the current hour, *Volume(0h)* and the other (with 8-4-3-1 structure) for the average traffic speed during the current hour, *Speed(0h)*. For either of these two output factors, the following eight input factors were used for the model development and validation: *Volume(-1h), Speed(-1h), Maintenance(-1h), AirTemp, SfTemp, Accumulated Precip, Sf Status,* and *Friction Index.* From the comparisons of actual and predicted *Volume(0h)* and *Speed(0h)* values, we can validate that these two models were capable of capturing the hidden relationships between the input and output factors. As such, these two models were used to predict a hypothetical "no WRM" scenario on the 20-mile I-5 highway segment. In the absence of WRM operations, the models predicted that the hourly traffic volume and average traffic speed would drop an average value of 26.9% and 6.6% (or a median value of 17.2% and 8.1%), respectively. Another means of quantifying the mobility benefits of the WSDOT WRM operations is by the avoided travel delays. In the absence of WRM operations, the models predicted an average value of 4.7% (or a median value of 8.8%) additional time needed to go through this 20-mile highway segment during December 2016.

Chapter 1. Introduction

1.1 Problem Statement

The Federal Highway Administration (FHWA) has estimated that “over 70 percent of the nation’s roads are located in snowy regions…and nearly 70 percent of the U.S. population lives in these regions” (as shown in Figure 1.1). Improving snow and ice control operations could result in significant economic, environmental, and social benefits. These benefits include enhanced mobility, fewer crashes, fewer emergency service disruptions, reduced travel costs, better fuel economy, and sustained economic productivity (Figure 1.2). The cost of shutting down the highways in severe wintery weather conditions is not affordable. According to the American Highway Users Alliance (2014), a one-day major snowstorm can cost a state $300 to $700 million if counting both direct and indirect costs. For instance, the closure of I-90 over Snoqualmie Pass in Washington State was estimated to cost $700,000 per hour (Daily Record, 2008). In one recent study sponsored by the National Research Council (Ye et al., 2013), the quantifiable benefits of winter highway maintenance by the Minnesota Department of Transportation (DOT) was estimated at about $220 million per winter season, even without considering the risk of highway closures in the absence of winter operations.

Figure 1.1. U.S. areas affected by snow and ice (adapted from: FHWA 2017)

Nonetheless, research is currently lacking in understanding the relationship between highway mobility and winter road maintenance operations, especially when it comes to the specific road weather scenarios in the Pacific Northwest. This understanding is much needed to justify the development of cost-effective and sustainable winter maintenance programs, policies and standards, or operational strategies. Without such a quantitative understanding, it is unlikely to fully appreciate the benefits of the improved passenger and freight movements during winter weather. It is noteworthy that the Washington State Department of Transportation (WSDOT) maintains a network of more than 7,000 miles of state highways, which contributes to the economic competitiveness of the State, the region, and the nation.

Figure 1.2. Winter highway operations are vital to traffic mobility, safety, economy and society (Shi & Fu, 2018).

1.2 Objectives

The goal of this report is to model the macroscopic effects of winter maintenance current practices on traffic mobility on Washington highways. In other words, the focus is placed on the aggregated outcome of winter weather and WSDOT winter maintenance practices on the parameters characteristic of traffic operations, instead of the microscopic effects or changes in individual driver behaviors. To meet this goal, the following objectives are addressed: (1) identifying appropriate WSDOT highway segments for this modeling study and collecting the relevant data related to winter maintenance practices and climatic conditions; (2) collecting sensor data at the selected WSDOT highway segments to characterize the changes in traffic patterns on winter pavements; and (3) developing a data model that correlates the traffic mobility (aggregated measures) and explanatory variables such as indicators of weather severity and winter maintenance practices.

This scope is directly relevant to the CAMMSE theme of "*Developing data modeling and analytical tools to optimize passenger and freight movements*". The research results will allow WSDOT and other highway agencies in the region to achieve better understanding of how winter maintenance best practices affect traffic mobility. The developed models and improved understanding may inspire technologies to facilitate best practices in snow/ice control operations or countermeasures to mitigate mobility challenges related to winter weather. This research will ultimately translate to better decision-making and management practices with respect to providing reliable and safe winter highways for the traveling public.

1.3 Expected Contributions

To accomplish these objectives, several tasks have been undertaken.

Task 1. Data collection from WSDOT practitioners. The research team worked with the WSDOT stakeholders to gather data for traffic conditions and winter maintenance practices, for hundreds of WSDOT highway segments. We eventually identified a few representative highway segments with the appropriate and available data. Such data enabled the examination of how winter maintenance current practices (a combination of plowing, anti-icing, and deicing) by WSDOT impact the macroscopic measures of traffic mobility.

Task 2. Collection and analysis of WSDOT data from loop detectors. The research team collected and analyzed the historical WSDOT traffic data from loop detectors, for the highway segments of interest (from Task 1). Automatic vehicle detectors are embedded in interstates in the State of Washington. "These detectors are based on single inductive loops, from which data on traffic volumes (i.e. vehicle counts) and occupancy (i.e. proportion of time during which the loop is occupied) are available for 20 or 30 second observational periods" and this data is accessible via DriveNet: http://wsdot.uwdrive.net/WSDOT and can provided the team with valuable information on traffic patterns such as traveling speed and volumes. The team spent substantial efforts on organizing, aggregating and analyzing such data, before the data became usable for subsequent mobility data modeling. It should be clarified that this study did not examine the microscopic measures of traffic mobility, such as individual's travel choice behavior and driving behavior (e.g., time and distance headways, lane changing, and vehicle trajectory). The macroscopic measures explored include: hourly traffic volumes and average vehicle speeds on individual highway segment.

Task 3. Data modeling of winter traffic mobility on WSDOT highways. The research team combined and coupled the data collected from Task 1 and Task 2 and subsequently developed a quantitative model that describes the relationship between macroscopic measures of traffic mobility and explanatory variables such as indicators of weather severity and winter maintenance practices.

Task 4. Final report and technology transfer. This final report was written and submitted to CAMMSE UTC and a student poster will be submitted to the 2nd annual CAMMSE Symposium in Charlotte, North Carolina.

1.4 Report Overview

The remainder of this report is organized as follows: Chapter 2 presents a comprehensive review of the state-of-the-art and state-of-the-practice literature on quantifying how winter weather and winter road maintenance operations affect the macroscopic traffic parameters (i.e., mobility). Chapter 3 describes the methodology used in this exploratory study, including the procedures used to collect and process the relevant data and the approach of developing and evaluating predictive models. Finally, Chapter 4 concludes this report with a summary and a discussion of the directions for future research.

Chapter 2. Literature Review

2.1 Introduction

This chapter provides a review and synthesis of recent literature relevant to quantifying the mobility benefits of winter road maintenance (WRM) operations, with the focus on macroscopic effects (instead of microscopic effects). This aims to provide an up-to-date overview of the current understanding of this issue and help identify gaps that may exist in the current knowledge domain.

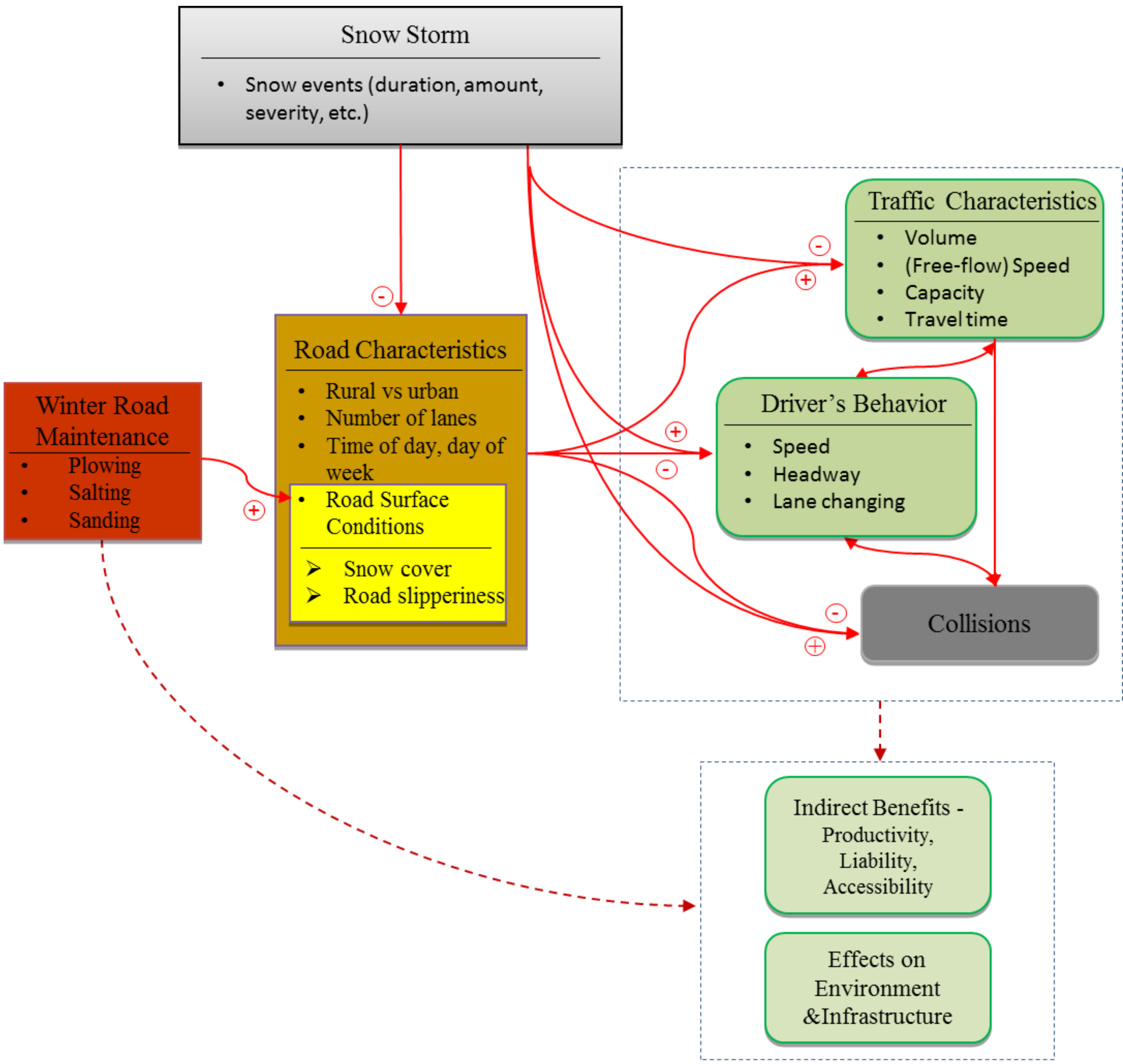

Figure 2.1: Multiple factors and interactions affecting winter mobility (Fu and Kwon, 2018)

2.2 Understanding the Macroscopic Effects of Winter Weather on Traffic

2.2.1 Background

Winter weather is known to compromise the safety, reliability, resilience, user experience and productivity of surface transportation systems. In addition to reducing the safety performance of a transportation system, snowy and icy conditions can have a significant impact on accessibility and mobility by preventing or delaying people and business to reach their desired services, activities and opportunities. Fu and Kwon (2018) developed a chart to schematically illustrate the multiple factors that affect winter mobility on roads and their interactions (see Figure 2.1). This chart considered the microscopic effects (e.g., individual traveler or driver's decisions/behaviors) as well as the macroscopic effects (aggregated outcomes such as traffic volume, speed, and capacity).

Fu and Kwon (2018) summarized the studies that investigated the effects of "winter weather on key macroscopic traffic parameters, namely, traffic volume, free-flow speed (FFS), and capacity". In the six case studies reviewed, the reductions in *traffic volume* due to winter weather ranged widely: e.g., 7-17% for light snowfall (<1", i.e., 25 mm) or 41-53% for heavy snowfall (225 mm to 275 mm), 29% (or 2.3% for each additional inch of snowfall), 2-7%, 7-51%, 13.3-22.9%, or 1.8-3.9%. There are many other factors influencing the level of reductions in traffic volumes, such as the type of roads, amount of snowfall, type of traffic (e.g., recreational vs. commuter), temperature, event duration, visibility, wind speed, road surface conditions, etc. Donaher (2014) reported that "a large drop in Road Surface Index (RSI, a friction-like measure) would cause a significant reduction in (traffic) volume on the order of 10%".

According to Fu and Kwon (2018), "winter weather conditions also affect individual drivers' driving behavior and thus the aggregated behavior of traffic as represented by the three macroscopic traffic measures - flow, speed and density". In the case studies reviewed, the reductions in *FFS* due to winter weather ranged widely: e.g., 9.5 km/h for light snowfall (and light rain) or 16.4 km/h for heavy snowfall, 18.13 km/h for snow events, 417-13.46%, 3-5% for light snowfall and 30-40% for heavy snowfall, or 5-16% for light snowfall and 5-19% for heavy snowfall. The reductions in *traffic capacity* due to winter weather also varied, e.g., 4.29-22.43%, or 12-20% for light snowfall and 5-19% for heavy snowfall. There are many other factors influencing the level of reductions in FFS and capacity, such as road geometry, climatic conditions, and WRM activities. Ghasemzadeh et al. (2018) developed speed selection models that revealed that "the odds of drivers reducing their speed 40 were 9.29 times higher in snowy weather conditions, followed by rain and fog with 1.55 and 1.29 times, respectively", relative to clear conditions.

Kwon et al. (2013) collected data for an urban freeway in Canada and their analysis suggested that the FFS and capacity reductions were 17.0% and 44.2%, respectively, given the snow precipitation rate of 5 mm/hr and RSI of 0.2 (snow covered). In contrast, the FFS and capacity reductions were only 11.0% and 24.1%, respectively, given the same snow precipitation rate but a RSI of 0.8 (bare wet).

2.3 Understanding the Macroscopic Effects of WRM Operations on Traffic

2.3.1 Background

Investing in winter transportation operations, particularly for the northern part of the U.S. is essential to optimize the passenger and freight movements and improve road user mobility and safety, which have direct benefits to the natural environment and human society. The U.S. economy is dependent on the productivity of our transportation systems, and shutting down our roads during winter conditions has significant impacts to other aspects of daily life including transport to hospitals, schools and community centers. To this end, it is desirable to use the most recent advances in the application of materials, practices, equipment and other technologies.

Highway agencies typically employ a toolbox approach to prevent or mitigate the detrimental effects of snowy/icy conditions on pavement. For instance, various tactics are used individually or sequentially in mobile operations, depending on the specific road weather conditions, materials and equipment availability, and the rules or guidelines by the agency. These tactics often include: anti-icing, deicing, mechanical removal (e.g., plowing), and sanding. Over the last two decades, there has been a transition from mostly deicing to *anti-icing* wherever possible (O'Keefe and Shi, 2005; Shi et al., 2013; Cui and Shi, 2015). Deicing aims to bread the bond between the pavement and compacted snow/ice, whereas anti-icing aims to prevent it. When conducted properly, anti-icing can reduce the amount of plowing and chemicals required (USEPA, 1999) or eliminate the need for abrasives. Anti-icing also helps to address the formation of black ice.

Numerous vehicle-based technologies, including automatic vehicle location (AVL), surface temperature sensors, on-board freezing point and ice-presence sensors, salinity sensors, visual and multi-spectral sensors and millimeter wavelength radar sensors, have been developed in recent years to facilitate more efficient and safer WRM operations (Ye et al., 2012). Among them, AVL is conceptually most integrated with other technologies. For instance, most WSDOT WRM vehicles have been equipped with AVL, such that both vehicle operators and maintenance managers can have more precise information on current roadway conditions, resulting in better winter maintenance decisions. Another increasingly popular integration tool is the maintenance decision support system (MDSS). MDSS is a software application that integrates information from a variety of sources, such as fixed road weather information systems (RWIS) and weather service forecasts, to provide recommendations for road treatment. With many mobile data collection technologies coming into the practice and integrated into an AVL platform (Ye et al., 2009a, 2009b), MDSS has been instrumental in improving WRM decisions and its benefits significantly outweighed its costs. For instance, the AVL/MDSS system developed and implemented by the Minnesota DOT provided better information for operators to optimize chemical use and service level, and for supervisors and managers to enhance scheduling, dispatch and safety (Hille and Starr, 2008). Recent advances in intelligent transportations systems (ITS) and RWIS have also made non-invasive road weather sensors viable options to estimate friction coefficient (Ewan et al., 2013).

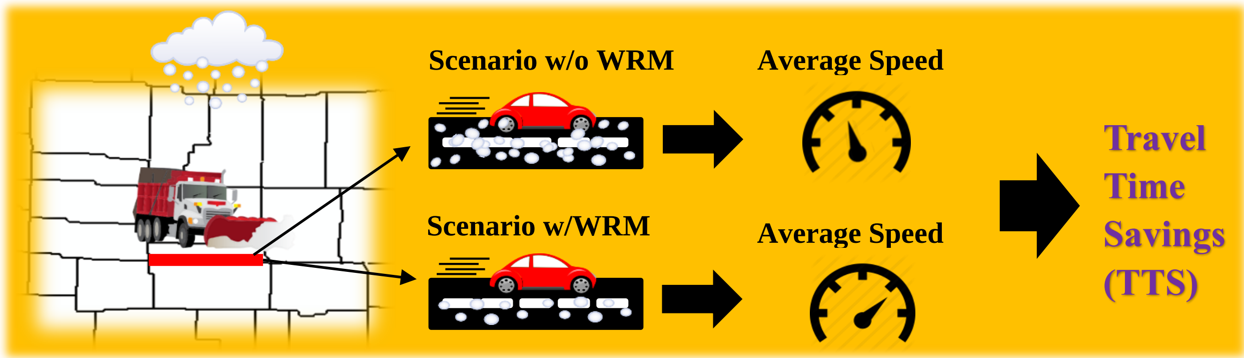

Figure 2.2: Illustration of how to calculate the TTS by WRM operations (adapted from: Fu and Kwon, 2018)

2.3.2 Quantifying the Macroscopic Mobility Benefits of WRM Operations

One major benefit item associated with highway WRM operations is improved mobility, which has been the subject of many studies (Morisugi et al., 2002; Shahdah, 2009; Shahdah and Fu, 2010). Fu and Kwon (2018) presented an approach to calculate the macroscopic mobility benefits of WRM operations over a single snowstorm event. This approach "considers all vehicles traveling on a highway as a same stream of traffic and their average speeds during a snowstorm under a given WRM scenario can be estimated". As such, the mobility benefits of WRM operations can be determined in terms of the total travel time savings (TTS), in light of the higher traffic speed due to better pavement surface condition under the scenario with WRM (see Figure 2.2). Specifically, the TTS over a particular snowstorm event can be estimated as follows (Fu and Kwon, 2018):

$$\text{TTS} = \sum_h^T Q_h \left(\frac{L}{S_{wo,h}} - \frac{L}{S_{w,h}}\right) \tag{1}$$

where,

TTS = travel time savings during a storm event, hr
T = total number of hours of a storm event, hr
L = length of the highway section, km
$S_{wo,h}$ = average traffic speed of the road section in the hth hour under the scenario without WRM, km/hr
$S_{w,h}$ = average traffic speed of the road section in the hth hour under the scenario with WRM, km/hr
Q_h = total traffic volume over the hth hour of the event

If we aim to estimate the TTS for the entire State over a winter season, then the TTS can be "calculated by summing the individual TTS across all highway sections and all winter events".

To enable the calculation of TTS using Equation (1), it is necessary to estimate the average traffic speed (as well as traffic volume) under the different scenarios. In light of existing studies, we can conclude that winter weather tends to reduce both the average traffic speed and traffic volume, whereas the implementation of WRM operations tends to mitigate such reductions. Shahdah and Fu (2010) employed the data from Kyte et al. (2001) and developed a model to predict the SRF as a function of precipitation intensity (PrIn) and RSC, as given in Equation (2).

$$SRF = -0.0577 + 0.0442 \times PrIn + 0.0420 \times RSC \quad (2)$$

where,

PrIn = a categorical variable representing precipitation intensity, with the values of 1, 2, 3, 4 corresponding to no precipitation, light precipitation, medium precipitation, and heavy precipitation, respectively,

RSC = a categorical variable representing road surface conditions, with the values of 1, 2, and 3 corresponding to dry, wet, and snow or ice covered pavement, respectively.

Ye et al. (2013) developed a list of speed reduction factors (SRF) for various road surface conditions (RSC), as shown in Table 2.1. They used five seasons of historical traffic speed data collected from the State of Minnesota highways. The SRF is defined as the ratio of the average traffic speed under a particular RSC to the one under the *bare pavement* condition, as given in Equation (3).

$$S_{i,\,RSC} = S_{i,\,0} * SRF_{RSC} \quad (3)$$

where,

$S_{i,\,0}$ = average traffic speed for road section i under normal weather conditions, km/hr

SRF_{RSC} = speed reduction factor under the given RSC

Table 2.1: Pavement Surface Conditions (RSC) and Associated SRF (Reproduced from Ye et al., 2013)

RSC	SRF
Chemically wet	0.96
Compacted snow	0.80
Deep slush	0.84
Dusting of snow	0.96
Icy	0.85
Lightly ice	0.94
Lightly slushy	0.90
Lightly snow covered	0.89
Slushy	0.87
Snow covered	0.84

Qiu and Nixon (2009) collected historical data for a total of 16,980 cases from the State of Iowa highways, and explored the identification of key factors that affect the macroscopic traffic parameters. One statistically significant relationship was identified between the selected climatic condition, WRM activities, and the average traffic speed, as given in Equation (4).

$$S = a + b * WindSpeed + c * RSC + d*Plow + e * Chemical \quad (4)$$

where,

s = average traffic speed under the given RSC, miles/hr

Plow = a categorical variable, 1 for plowing action and 0 for no plowing

Chemical = the measure of brine application rate, lb/lane-mile
WindSpeed, in miles/hr
a = the intercept, i.e., the average traffic speed with no wind and no WRM operations

The estimated coefficients for subgroups of Iowa highway data are presented in Table 2.2 (Qiu and Nixon, 2009). As shown, the average traffic speed decreased with the increase in wind speed (as indicated by the negative values of the coefficient b). The values of the coefficient c suggest that the average traffic speed decreased with the deteriorating RSC. The values of the coefficient d suggest that the average traffic speed is likely to increase 2 to 3 mph during the next hour if plowing occurred in the current hour. The authors pointed out that the effect of chemical application (as shown in Table 2.2) was not consistent for each subgroup, likely due to the issue of missing data in precipitation and visibility (Qiu and Nixon, 2009).

Table 2.2: Estimated coefficients for subgroups of the Iowa highway data (Qiu and Nixon, 2009)

		Primary < 1k, 55mph	Primary 1-5k, 65mph	Interstate 5-10k, 65mph	Interstate 10k+, 55mph
a		56.13	69.07	67.41	54.67
b		-0.29	-0.28	-0.19	-0.19
c	Dry	5.21	6.49	4.68	4.49
	Wet	4.22	5.23	2.72	2.58
	Snow/Ice(1)	0.00	0.00	0.00	0.00
	Chemical(2)	0.00	0.00	0.00	0.00
d	[Plowing=0]	-3.03	-1.82	-2.67	-2.83
	[Plowing=1] (3)	0.00	0.00	0.00	0.00
e		0.015	0.018	0.014	-0.016
R Square/Adjusted R2		0.658/0.629	0.442/0.416	0.566/0.515	0.430/0.402

The comparison group is (2) With Chemical, but most of the chi-square tests do not show that (1) Snow/Ice condition is statistically significant from the With Chemical condition. Thus both categories have the number of zero. The number in Dry, can be interpreted as compare the Dry surface condition to With Chemical condition,

Donaher et al. (2012) collected a substantial amount of data from highways in Ontario, Canada and developed a more complex model to predict the average traffic speed as a function of more factors that are potentially influential. The developed model is given in Equation (5).

$$S = 69.082 + 0.089 * AirTemperature - 0.078 * WindSpeed + 0.310 * Visibility - 1.258 * PrIn + 16.974 * RSI - 4.325 * \frac{v}{c} + PSL + Site \quad (5)$$

where,

S = average traffic speed under the given RSC, km/hr
PrIn = hourly precipitation rate over the event, cm
RSI = a friction-like measure indicative of the road surface condition, unitless (between 0 and 1), detailed in Usman et al. (2010).
$\frac{v}{c}$ = average volume to capacity ratio
PSL = a coefficient of posted speed limit (*PSL* = 0 when posted speed limit = 80 km/hr; 1.951 if 90 km/hr and 12.621 if 100 km/hr)

AirTemperature, in °C; *WindSpeed*, in miles/hr; *Visibility*, in km; and *Site* is a site variation indicator in binary case.

2.4 Summary

This chapter has provided a comprehensive review and synthesis of the current and historic research on quantifying the effects of winter weather on macroscopic traffic parameters and the macroscopic mobility benefits of WRM operations.

Chapter 3. Methodology

3.1 Introduction

This chapter presents a demonstration of the methodology developed to estimate the mobility benefits of winter maintenance operations. The State of Washington was selected as the case study state to estimate mobility benefits associated with WRM operations on highways. The remaining sections are organized as follows. Section 3.2 provides a description of the procedures used to collect and process the data relevant to quantification of mobility benefits by WSDOT WRM operations on highways as well as the modeling process (using artificial neural networks and the processed data). Section 3.3 concludes this chapter with a summary.

3.2 Developing Predictive Models

3.2.1 Data collection and processing

Maintenance Data

Winter maintenance information along Interstate I-5 and I-90 was obtained from a database maintained by the Washington State Department of Transportation (MSDOT). The data contained road maintenance information such as Equipment Sensor Id, Maintenance Vehicle Number, Latitude, Longitude, LogDate, Maintenance Material Composition and Rate, RoadTemp, AirTemp, State Route Number and Milepost. This information was collected every 10 to 20 second, with 10,1391 maintenance segments distributed along I-5 and I-90 highways from 01:10:49 12-01-2016 to 23:31:39 12-01-2016. The spreadsheet was representative and was used to establish the specific maintenance condition along the state route. The maintenance dataset was further cleaned, sorted and matched by action time and milepost. Ultimately, 17,982 segments were obtained for further hourly average processing and matching.

Traffic Flow Data

Traffic volume and speed data were obtained from the installed detectors loops and traffic monitoring systems in Washington State. Loop detector data collected in every 5 minutes was obtained from UWDRIVE (http://uwdrive.net/STARLab). The information contained traffic information such as speed and volume per lane per hour, speed and volume per hour for all lanes, average daily frequency of congestion. This information contained 8928 dataset at each milepost along I-5 and I-90 highways from 00:00:00 12-01-2016 to 23:55:00 12-01-2016. The data was further cleaned, sorted and matched by action time and milepost.

Surface Sensor and Weather Data

Different road surface conditions/severities and weather history data were selected based on the availability of comprehensive datasets. Surface sensor data collected every 10 minutes was first reduced to only include the winter seasons of 2016-01 to 2016-12. Those missing data were excluded. The data included Road Surface Status (Snowy, Iced, Wet, Moisture, Dry), Surface Temp, Subsurface Temp, Friction Index, Precipitation Type, Precipitation Rate, Precipitation Intensity, Accumulated Precipitation, and Chemical Factor information. The data for modeling analysis were obtained after hourly average processing and milepost matching.

3.2.2 Modeling through Artificial Neural Networks

Artificial neural networks (ANNs) have been extensively employed to address the modeling needs that could not be addressed by traditional tools. ANNs are known for their outstanding capability to model "non-linear cause-and-effect relationships inherent in complex processes" (Shi et al., 2004), because ANNs "provide non-parametric, data-driven, self-adaptive approaches to information processing". Some of the advantages of ANNs over traditional modeling methods (e.g., multi-regression) include: the ability to derive general trends even with incomplete or noisy data, the ability to capture functional relationships from examples, no need to make prior assumptions, and the ability to model highly non-linear relationships. Two disadvantages of ANNs include: the lack of an explicit model, and the risk of undertraining or overtraining the model. The type of ANNs adopted in this study was the multiplayer feed-forward neural network, of which a typical architecture is shown in Figure 3.1.

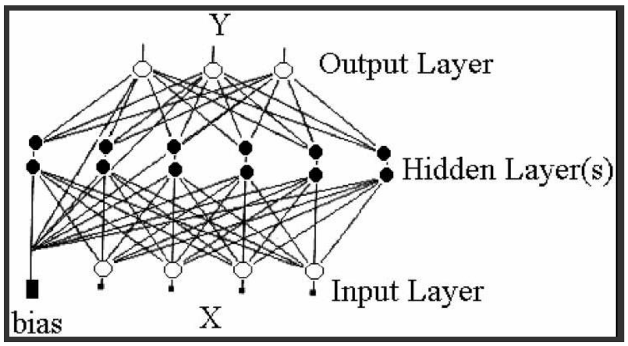

Figure 3.1: Typical Multiplayer Feed-forward Neural Network Architecture (Shi et al. 2004)

In Figure 3.1, the nodes in the input and output layers represent the independent variables and response variable(s), respectively. Depending on the complexity of the relationship(s), one or more hidden layers are included to build the ANN model. For a feed-forward network, signals are designed to "propagate from the input layer through the hidden layer(s) to the output layer, and each node in a layer is connected in the forward direction to every node in the next layer" (Shi et al., 2004). Every node simulates how an artificial neuron functions, by linearly summating the inputs (via connection weights and bias terms) and then transforming them (via a non-linear transfer function). The details of how such an ANN is trained via the error back-propagation (BP) algorithm can be found in the reference (Shi et al., 2004). In essence, the training (learning) process entails iterative adjustments of the connection weights and bias terms for each node (which initially have been randomized), with the end goal of minimizing the overall error term computed at the nodes of the output layer.

Using the dataset identified for the training of the ANN model, the learning process continues until "the prediction error across all samples in the training data is minimized to a reasonable range or stabilized" (Shi et al., 2004), i.e., reaching convergence.

$$f(x) = \left(1 + e^{-x}\right)^{-1} \quad (6)$$

$$NX_i = \frac{(x_i - x_{\min} + 0.1)}{(X_{\max} - X_{\min} + 0.1)} \quad (7)$$

We wrote a computer program in C language to implement the ANN model with a modified BP algorithm for training. The sigmoid function in Equation (6) was used as the nonlinear transfer function and the sum of the mean squared error (SMSE) in the output layer was used as the convergence criteria. In this work, the values of learning rate η and momentum factor α were initialized at 0.9 and 0.5, respectively, and then automatically adjusted during the training process to avoid the trap of local minima. Before the training process, all the data for input factors and output factors were normalized based on Equation (7), where X_i and NX_i are the i^{th} value of factor X before and after the normalization, and X_{min} and X_{max} are the minimum and maximum value of factor X, respectively. The training process involves the selection of the appropriate number of hidden layer nodes and the determination of the appropriate limit of allowable training error. These often require a good understanding of how the ANN model works and how complex the cause-and-relationships to be modeled are, the number of records available in the training dataset, the perceived accuracy of the modeling data, etc.

There were a total of 247 complete records available which had the friction index value as well as other parameters of interest, for December 2016, over a 20-mile segment on the Interstate highway I-5. These data were collected from three different sources for the historical records of WRM activities, macroscopic traffic parameters, and road weather conditions, respectively, before being organized, coupled with each other based on milepost and time stamp, and readied for analyses. From these records, a small fraction was randomly selected to serve as the testing dataset whereas the remainder was used to train and establish the ANN models. As shown in **Error! Reference source not found.**, data from 241 WSDOT historical records were used for the training of two ANN models, one for the traffic volume during the current hour, *Volume(0h)* and the other for the average traffic speed during the current hour, *Speed(0h)*. The testing dataset consists of six records, as shown in Table 3.2.

Table 3.1: Dataset used to train the ANN models of hourly traffic volume and average traffic speed (a)

Volume (-1h)	Speed (-1h)	Maintenance (-1h)	AirTemp	Sf Temp	Accumulated Precip	Sf Status	Friction Index	Volume (0h)	Speed (0h)
474	54.5	1	41.0	42.8	0.17	1	0.82	357	54.3
1710	62.4	0	38.0	45.3	0.02	0.98	0.8	1275	60.1
387	50.0	0	39.4	43.3	0.02	1	0.82	294	48.9
1704	61.8	0	39.4	38.8	0.14	1	0.82	1530	58.8
1530	61.6	1	38.5	37	0.09	1	0.82	702	59.7
702	60.9	1	36.6	36.5	0.06	1	0.82	360	59.1
360	62.2	1	38.2	36.3	0.03	1	0.82	240	57.3
240	51.5	1	36.3	36.9	0.02	1	0.82	228	51.9
228	54.7	1	38.7	37.6	0	1	0.82	303	51.4
303	51.8	1	39.2	38.1	0	1	0.82	474	53.1
474	52.6	1	38.1	37.9	0.01	0.98	0.81	1059	55.0
1059	55.4	1	37.4	37.4	0.03	0.96	0.73	2061	61.4
2061	60.8	1	37.0	38.5	0.04	0.98	0.8	2961	62.0
2961	62.0	1	37.8	38.8	0.05	0.96	0.79	2754	59.1
2754	51.9	1	38.1	39.4	0.06	0.98	0.81	2514	50.0
2514	58.2	1	37.3	39.4	0.06	0.98	0.8	2589	56.2
2589	53.1	1	41.1	39.9	0.07	0.96	0.78	2889	57.9
2649	45.6	0	48.0	43.5	0.07	1	0.82	3012	50.5
4023	60.9	0	43.1	41.7	0.07	1	0.82	3321	60.9
3321	59.8	1	44.5	41.4	0.07	1	0.82	2487	59.8
2487	61.6	1	43.5	40.5	0.07	1	0.82	1608	62.2
1608	65.5	1	42.4	40.5	0.07	1	0.82	1176	63.5
1176	58.2	1	40.0	38.8	0.08	1	0.82	936	57.8
936	61.1	1	39.5	38.8	0.08	1	0.82	786	60.9
786	57.9	1	39.5	38.5	0.08	1	0.82	588	57.2
588	52.4	1	40.2	37.8	0.08	1	0.82	387	53.4
387	54.6	1	39.4	37.9	0.09	0.98	0.8	363	49.2
363	48.2	1	39.5	38.1	0.09	0.98	0.81	270	48.4
270	52.6	1	37.6	37.4	0.09	0.98	0.81	363	51.1
363	50.3	1	35.2	32.7	0.11	0.96	0.69	489	47.3
489	46.9	1	34.4	36.1	0.11	0.96	0.79	981	52.7
981	59.3	1	38.4	36.3	0.09	0.98	0.81	2031	44.4
2031	60.6	1	36.9	37	0.08	1	0.82	2982	63.4
2982	58.1	1	36.4	37.6	0.07	1	0.82	2949	57.4
2949	50.0	1	38.5	40.5	0.07	1	0.82	2457	52.1
1503	57.3	0	31.0	33.4	0.04	1	0.82	1218	58.6
1218	58.7	1	34.2	33.3	0.04	1	0.82	897	60.3
897	58.7	1	32.8	32.4	0.04	1	0.82	645	58.3
645	57.6	1	31.3	31.5	0.04	1	0.82	444	58.2
444	58.0	1	33.7	30.9	0.03	1	0.82	333	50.9
333	49.8	1	30.8	30	0.03	1	0.82	282	47.8

Table 3.1: Dataset used to train the ANN models of hourly traffic volume and average traffic speed (b)

Volume (-1h)	Speed (-1h)	Maintenance (-1h)	AirTemp	Sf Temp	Accumulated Precip	Sf Status	Friction Index	Volume (0h)	Speed (0h)
282	47.3	1	30.9	30.2	0.03	1	0.82	318	49.3
318	46.2	1	30.3	29.1	0.01	1	0.82	492	48.1
492	48.4	1	32.5	28.8	0	1	0.82	1005	57.0
1005	54.8	1	30.0	28.6	0	1	0.82	2196	57.8
2196	56.2	1	30.9	28.6	0	1	0.82	3189	54.8
3189	59.0	1	28.8	28.6	0	1	0.82	2925	58.3
2925	47.9	1	37.4	31.8	0	1	0.82	2619	36.1
1260	59.6	0	30.0	32.5	0	1	0.82	924	58.2
924	58.2	1	31.7	32.5	0	1	0.82	744	57.4
744	54.1	1	30.6	31.5	0	1	0.82	441	53.8
441	55.5	1	30.7	30.6	0	1	0.82	351	51.6
258	44.2	1	32.0	30.9	0	1	0.82	321	43.5
321	46.2	1	28.2	30.7	0	1	0.82	513	46.9
513	50.0	1	28.1	29.7	0	1	0.82	966	55.7
2511	54.5	0	40.4	41.2	0	1	0.82	2595	57.4
2595	56.2	1	42.5	41.4	0	1	0.82	2727	57.3
2727	58.4	1	39.7	40.1	0	1	0.82	3087	60.1
3087	60.1	1	35.0	32.9	0.02	0.96	0.75	3045	48.4
2955	17.1	1	37.3	31.6	0.06	0.96	0.71	2604	19.9
2604	23.8	1	34.4	31.5	0.1	0.85	0.69	2559	24.6
2559	24.6	1	31.2	31.3	0.12	0.6	0.48	1770	47.3
1770	48.1	1	31.2	30.7	0.13	0.96	0.73	1005	53.6
1005	50.4	1	30.9	31.5	0.14	0.85	0.7	813	50.7
813	54.3	1	32.3	31.1	0.15	0.96	0.75	690	56.1
549	48.6	1	30.5	31.3	0.17	0.85	0.72	363	52.9
363	54.0	1	31.3	32	0.17	0.96	0.78	285	48.0
285	51.3	1	30.8	32.4	0.18	0.96	0.77	249	53.2
249	48.0	1	31.6	32.7	0.19	0.96	0.79	267	46.9
267	50.3	1	31.8	33.3	0.19	0.96	0.79	423	51.6
423	48.3	1	33.7	33.6	0.19	0.96	0.79	768	53.5
768	52.0	1	33.0	32.5	1.19	0.96	0.79	1470	51.7
2217	56.5	0	32.0	35.4	0.22	0.96	0.78	2229	55.5
2229	56.9	1	37.2	36.5	0.23	0.96	0.78	2481	56.9
2481	57.6	1	38.1	38.7	0.24	0.96	0.77	2661	58.0
2661	51.6	1	40.0	39.7	0.26	0.96	0.76	3051	52.5
3051	52.5	1	39.7	39.7	0.27	0.98	0.8	3150	53.5
348	51.9	0	34.3	34.3	0.19	0.96	0.79	579	58.9
579	60.1	1	34.5	33.4	0.19	0.98	0.8	882	61.3
882	61.5	1	35.8	34.2	0.19	0.96	0.79	1398	63.6
1398	63.6	1	37.1	35.8	0.18	0.98	0.81	2037	65.0

Table 3.1: Dataset used to train the ANN models of hourly traffic volume and average traffic speed (c)

Volume (-1h)	Speed (-1h)	Maintenance (-1h)	AirTemp	Sf Temp	Accumulated Precip	Sf Status	Friction Index	Volume (0h)	Speed (0h)
2037	61.7	1	39.6	37.2	0.17	0.98	0.81	2679	63.8
477	53.4	0	37.0	37.2	0.34	0.98	0.81	1008	57.7
1008	57.7	1	38.0	38.8	0.34	0.96	0.78	2229	61.4
447	57.6	0	40.9	39.9	0.06	1	0.82	351	55.0
351	43.7	1	40.0	40.6	0.03	1	0.82	321	45.9
321	45.9	1	40.2	40.5	0.02	1	0.82	363	45.7
363	51.4	1	36.4	40.1	0.02	1	0.82	498	52.5
498	46.6	1	39.1	40.1	0.02	1	0.82	1038	48.2
1038	58.0	1	40.0	40.3	0.02	1	0.82	2262	59.8
2898	59.9	0	45.1	44.4	0.01	1	0.82	2907	59.8
471	56.3	0	34.6	35.4	0	1	0.82	372	53.8
372	47.3	1	32.9	34.7	0	1	0.82	285	50.4
285	50.7	1	32.7	34.7	0	1	0.82	339	45.7
339	49.4	1	34.1	35.8	0	0.98	0.81	513	52.3
513	51.1	1	32.8	35.2	0	0.98	0.81	1014	53.9
1014	58.6	1	36.1	35.6	0	0.98	0.81	1992	40.8
1992	62.6	1	39.3	35.8	0	1	0.81	2823	63.7
2823	57.0	1	35.3	36.3	0	1	0.81	3366	53.1
3366	63.6	1	36.6	37.2	0	1	0.81	2841	61.2
2841	55.7	1	39.0	39	0	1	0.81	2820	54.8
2775	57.4	0	39.0	41	0	1	0.81	3267	56.4
3678	62.2	0	39.0	38.8	0	1	0.81	2739	61.4
2739	61.8	1	39.7	39.4	0	1	0.81	2130	60.1
2130	61.4	1	39.2	38.8	0	1	0.81	1551	62.2
1551	58.2	1	36.3	38.7	0	1	0.81	1164	58.4
1164	60.8	1	36.9	36.3	0.01	1	0.82	903	58.6
903	63.0	1	39.0	34.2	0.02	0.96	0.78	627	63.3
627	60.6	1	37.8	33.3	0.04	0.96	0.77	408	59.6
408	54.2	1	36.5	34.2	0.05	0.98	0.8	333	57.2
333	56.0	1	33.1	34.3	0.05	0.98	0.81	297	50.0
297	50.0	1	34.6	34.2	0.05	0.98	0.81	303	50.6
303	53.3	1	35.0	34.3	0.05	1	0.82	483	53.3
483	53.1	1	35.7	34.9	0.05	1	0.82	966	56.3
966	57.0	1	37.1	35.1	0.05	1	0.82	1965	56.5
1965	59.0	1	38.0	35.1	0.05	1	0.82	2937	60.0
2937	66.1	1	35.9	36	1.05	0.98	0.81	2673	65.3
2673	61.4	1	35.9	36.9	2.05	0.98	0.81	2307	62.3
2307	57.0	1	38.0	39	3.05	1	0.82	2343	57.2
2343	57.2	1	41.0	38.8	4.05	1	0.82	2613	57.0
3114	58.6	0	34.0	39.4	5.05	1	0.82	3402	60.2
1662	61.6	0	35.6	35.6	0.04	1	0.82	1422	61.0
1422	59.7	1	35.9	36.1	0.02	0.98	0.81	1098	58.8

Table 3.1: Dataset used to train the ANN models of hourly traffic volume and average traffic speed (d)

Volume (-1h)	Speed (-1h)	Maintenance (-1h)	AirTemp	Sf Temp	Accumulated Precip	Sf Status	Friction Index	Volume (0h)	Speed (0h)
1098	58.8	1	35.4	35.2	0.01	0.98	0.81	483	60.0
483	50.8	1	36.0	34.9	0	0.98	0.81	390	46.5
390	46.5	1	33.0	33.8	0	1	0.82	336	42.2
336	53.9	1	32.8	33.6	0	1	0.82	333	48.7
333	51.3	1	32.1	32.7	0	1	0.82	459	51.3
459	52.0	1	34.9	33.3	0	1	0.82	912	57.8
912	54.7	1	32.1	32.4	0	1	0.82	1908	57.5
1908	59.6	1	31.4	33.4	0	1	0.82	2964	59.6
2964	57.2	1	34.3	32.5	0	1	0.82	2679	48.9
2679	58.5	1	33.1	33.8	0	1	0.82	2658	54.9
2988	57.6	1	40.5	39.4	0	1	0.82	3357	57.6
1347	60.4	0	26.4	26.6	0	0.98	0.81	1044	59.2
1044	62.1	1	25.9	26.2	0	0.98	0.81	693	63.7
693	63.3	1	26.1	26.2	0	0.98	0.81	522	62.8
522	57.1	1	25.1	24.6	0	0.98	0.81	396	57.7
396	60.1	1	24.2	23.9	0	0.98	0.81	339	56.5
339	50.5	1	23.8	23.7	0	0.98	0.81	360	50.1
360	54.5	1	25.7	23.4	0	0.98	0.81	603	59.9
978	59.5	1	25.3	26.4	0	0.98	0.81	1476	61.9
2121	58.7	1	29.3	29.7	0	0.98	0.81	2721	59.5
2721	63.0	1	32.4	31.1	0	1	0.82	3192	63.0
3192	57.5	1	35.5	34.2	0	1	0.82	3537	57.3
1677	66.5	0	33.4	33.6	0	0.98	0.81	1431	67.3
1431	65.6	1	31.3	32.2	0	0.98	0.81	987	65.9
987	68.6	1	32.2	29.7	0	0.98	0.81	681	64.9
681	67.9	1	28.9	29.1	0	0.98	0.81	426	65.9
426	61.9	1	29.1	29.3	0	0.98	0.81	339	61.0
339	61.1	1	30.0	28.8	0	0.98	0.81	246	59.6
246	61.7	1	53.7	29.1	0	0.98	0.81	267	60.9
267	65.7	1	29.9	28.4	0	0.98	0.81	333	65.1
333	59.3	1	28.9	28	0	0.98	0.81	552	59.7
828	64.1	1	29.4	29.3	0	0.98	0.81	1125	66.9
1125	68.6	1	31.0	30.6	0	0.98	0.81	1719	67.1
1719	66.7	1	33.0	34.3	0	0.98	0.81	2412	65.7
2412	63.2	1	42.0	38.7	0	1	0.82	2895	62.2
693	60.3	0	32.1	37.8	0	0.98	0.81	423	58.4
423	61.6	1	29.1	37.2	0.01	0.98	0.81	294	52.9
252	53.2	1	27.1	35.8	0.05	0.96	0.75	318	50.4
318	43.9	1	33.0	36.3	0.08	0.96	0.73	495	48.1
495	49.6	1	28.3	37.6	0.1	0.96	0.75	969	53.3
969	57.2	1	36.0	38.1	0.12	0.96	0.75	2031	58.0
3039	54.4	0	41.0	44.1	0.17	1	0.82	3120	54.3
714	58.3	0	44.5	45.1	0.38	0.96	0.75	504	59.0
393	52.8	0	48.0	47.1	0.35	0.96	0.79	528	50.4

Table 3.1: Dataset used to train the ANN models of hourly traffic volume and average traffic speed (e)

Volume (-1h)	Speed (-1h)	Maintenance (-1h)	AirTemp	Sf Temp	Accumulated Precip	Sf Status	Friction Index	Volume (0h)	Speed (0h)
318	52.6	1	35.8	35.1	0	1	0.82	393	50.0
393	54.3	1	34.6	35.1	0	1	0.82	594	52.6
594	47.6	1	33.9	33.4	0	1	0.82	1077	53.7
1077	55.9	1	34.4	33.8	0	1	0.82	2157	61.3
2157	59.7	1	32.0	33.1	0	1	0.82	3117	61.9
3117	64.1	1	36.5	33.1	0	1	0.82	2739	49.8
2739	60.9	1	57.7	35.4	0	1	0.82	2790	57.9
2913	56.0	1	45.5	41.5	0	1	0.82	3402	57.9
3402	54.0	1	62.6	43.7	0	1	0.82	3564	53.7
3564	59.4	1	93.9	44.2	0	1	0.82	3507	62.6
1536	64.3	0	34.9	35.8	0	1	0.82	1152	59.4
1152	59.4	1	36.8	35.4	0	1	0.82	867	58.7
867	57.0	1	36.8	35.2	0	1	0.82	525	56.2
525	56.3	1	41.0	34.5	0	1	0.82	393	53.9
393	52.6	1	49.9	34.7	0	1	0.82	366	51.9
366	50.4	1	34.3	34	0	1	0.82	426	48.7
426	49.9	1	35.6	33.6	0	1	0.82	609	51.9
609	52.3	1	35.0	33.8	0	1	0.82	1080	58.9
1080	57.6	1	36.5	34.2	0	1	0.82	2052	59.0
3471	25.4	0	41.1	38.7	0.47	0.98	0.8	3663	25.2
3663	33.2	1	39.8	37.9	0.47	0.98	0.81	3753	33.6
3327	61.2	1	41.0	38.7	0.46	1	0.82	2442	62.7
2442	64.9	1	35.5	38.5	0.44	1	0.82	2055	65.2
2055	61.5	1	37.0	37.9	0.43	1	0.82	1893	61.9
1893	65.8	1	37.3	37.4	0.42	1	0.82	1671	65.1
1671	62.4	1	38.1	37	0.41	1	0.82	1335	62.7
1335	68.7	1	37.2	35.2	0.39	1	0.82	951	66.2
951	61.2	1	35.2	34.7	0.36	1	0.82	582	60.5
582	60.5	1	36.1	34.5	0.35	1	0.82	429	57.9
429	59.9	1	33.9	35.1	0.3	1	0.82	315	58.8
315	58.8	1	34.8	34.9	0.27	1	0.81	288	57.5
288	53.5	1	34.2	34.7	0.22	1	0.81	315	56.8
315	56.8	1	33.7	34.9	0.21	1	0.81	480	58.0
480	59.9	1	37.1	35.1	0.19	1	0.81	615	62.7
615	65.9	1	37.1	35.1	0.19	1	0.81	1215	67.1
1215	60.7	1	38.5	36.1	0.18	1	0.81	1728	64.8
1728	65.3	1	39.4	37.8	0.16	1	0.81	2604	67.2

Table 3.1: Dataset used to train the ANN models of hourly traffic volume and average traffic speed (f)

Volume (-1h)	Speed (-1h)	Maintenance (-1h)	AirTemp	Sf Temp	Accumulated Precip	Sf Status	Friction Index	Volume (0h)	Speed (0h)
1341	66.7	1	38.8	36.9	0	1	0.81	912	68.3
912	70.2	1	37.1	36.3	0	0.98	0.81	459	68.9
279	67.4	1	35.2	35.8	0	0.98	0.81	153	66.3
153	64.1	1	36.1	34.7	0	0.98	0.81	132	63.8
132	68.4	1	33.0	33.8	0	0.98	0.81	132	67.5
132	63.5	1	33.0	32.9	0	0.98	0.81	201	63.0
201	57.1	1	34.8	30.7	0	0.98	0.81	408	57.2
1140	68.3	0	31.0	30.9	0	0.98	0.81	1827	69.1
1827	67.7	1	35.0	33.8	0	0.98	0.81	2511	67.2
1701	63.8	0	32.2	33.3	0	0.98	0.81	1197	63.3
1197	66.5	1	32.3	32.4	0	0.98	0.81	684	66.3
684	68.5	1	33.1	31.3	0	0.98	0.81	411	66.6
411	61.8	1	34.7	30.2	0	0.98	0.81	231	61.7
174	60.4	1	30.0	32.7	0	0.98	0.81	192	61.7
192	61.2	1	31.9	31.1	0	0.98	0.81	306	56.8
306	62.9	1	31.7	30.9	0	0.98	0.81	588	64.4
588	61.3	1	26.5	31.1	0	0.98	0.81	855	63.3
855	62.3	1	30.9	32.2	0	0.98	0.81	1023	61.6
1023	60.8	1	33.4	33.3	0	0.98	0.81	1881	62.1
2718	62.8	1	39.7	38.3	0	0.98	0.81	4062	62.5
4062	52.4	1	40.0	39.7	0	0.98	0.81	4422	54.8
342	55.6	0	34.5	36.1	0.13	1	0.82	297	55.5
297	54.5	1	35.6	35.1	0.13	0.98	0.81	354	49.6
354	51.6	1	35.3	35.2	0.12	0.98	0.81	507	53.3
507	49.8	1	36.1	36	0.12	0.98	0.81	993	52.9
993	55.2	1	35.6	36.1	0.12	0.98	0.81	1932	58.6
1932	54.9	1	35.4	35.6	0.1	0.98	0.81	2829	55.9
2829	57.8	1	37.1	36.3	0.08	0.98	0.81	2472	57.5
2472	61.5	1	37.2	37.4	0.08	0.98	0.81	2619	58.9
2619	54.3	1	38.7	42.6	0.07	0.98	0.81	3267	55.2
318	55.6	0	40.8	37.8	0.05	1	0.82	369	52.3
513	51.6	1	38.8	38.7	0.05	1	0.82	912	55.0
1608	61.2	1	46.4	37.6	0.05	1	0.82	2373	58.9
3414	56.8	0	43.0	43.6	0.05	1	0.82	3954	58.0
1944	62.8	0	37.0	35.4	0	1	0.82	1623	61.5
1623	62.4	1	35.1	34.5	0	1	0.82	1293	61.6
1293	62.4	1	34.3	33.8	0	1	0.82	936	60.8

Table 3.2: Dataset used to validate the ANN models

Volume (-1h)	Speed (-1h)	Maintenance (-1h)	AirTemp	Sf Temp	Accumulated Precip	Sf Status	Friction Index	Volume (0h)	Speed (0h)
690	54.8	1	30.9	31.3	0.16	0.85	0.73	549	56.8
408	50.7	0	33.4	36	0	1	0.82	318	50.4
1650	69.0	0	37.9	37	0	1	0.81	1341	69.8
912	57.2	1	38.4	37	0.05	1	0.82	1608	60.9
3753	33.6	1	41.2	38.5	0.47	0.98	0.81	3327	53.0
3045	56.5	1	34.0	33.1	0.04	0.96	0.75	2955	55.6

In the post-processing datasets (shown in Table 3.1 and Table 3.2), the following eight input factors were used for the model development and validation:

Volume(-1h) = the traffic volume during the prior hour
Speed(-1h) = the average traffic speed during the prior hour
Maintenance(-1h) = a categorical variable, 1 if an maintenance action (plowing, anti-icing, or deicing) was taken, based on the record on the AVL-equipped snowplow; 0 if not
AirTemp = air temperature, °F
SfTemp = pavement surface temperature, °F
Accumulated Precip = accumulated precipitation, inches
Sf Status = a class of pavement surface condition, including "Dry", "Trace Moisture", "Wet", "Ice Watch", and "Snow Warning", which we converted to a numerical value of Speed Reduction Factor (SRF) of 1.0, 0.98, 0.96, 0.85, and 0.60, respectively. This conversion was necessary to enable the quantitative modeling. All SRF values except 0.60 were based on the reference (Ye et al., 2013). In the WSDOT system, "Ice Watch" corresponds to the condition of "thin or spotty film of moisture at or below freezing (32°F / 0°C)."
Friction Index = "A value from 0 to 1 representing the deceleration capabilities of vehicles while taking into account current surface conditions. Larger values indicate a higher level of friction while smaller values represent a lower level of friction" (WSDOT manual).

Similar to our case study for the Utah DOT, this project employed ANNs "as a data mining approach to abstract the useful information from existing happenstance data, in other words, to deduce reliable data from noisy data" (Strong and Shi, 2008). Once the empirical ANN models for average traffic speed and traffic volume were established and tested (using the training and testing datasets, respectively), these models were then employed to predict these macroscopic traffic parameters under a host of conditions, given that all the independent variable remain in the ranges of the data used for model development.

3.3 Summary

The objective of this chapter is to present a methodology developed to estimate the mobility benefits of winter maintenance operations, using historical traffic, WRM, and road weather data for a highway segment on I-5 in the State of Washington.

Chapter 4. Summary and Conclusions

4.1 Introduction

As a result of winter weather (e.g., snowy/icy conditions), the traffic volume on highways tends to decrease and so does the average traffic speed. To mitigate such effects, WSDOT has employed a variety of tactics (mainly anti-icing, deicing and plowing) in their highway winter maintenance operations. This study collected and processed one month of the historical data from the 2015-2016 winter season (December 2016), such that it became feasible to couple the available road weather data, WRM operations data, and traffic data on selected highway segment for model development.

The rest of this chapter is organized as follows. Section 4.2 provides a brief review of the exploration of the relationships between the factors of interest for this study. Section 4.3 presents the main results of modeling hourly traffic volume and average traffic speed by the use of ANN. Section 4.4 presents the conclusions of this Chapter, while Section 4.5 discusses the directions that should be taken in future research on this subject.

4.2 Exploring the relationships between various factors

4.2.1 Correlation between Friction Index and Surface Status

As mentioned in Section 3.2.2., we converted the values of the categorical variable *Sf Status* (various RSC classes used by WSDOT) to numerical values of Speed Reduction Factor (SRF) corresponding to the specific pavement surface condition. Using all 248 records from the I-5 highway segment, December 2016, we developed an empirical model to correlate the numerical value of *Sf Status* and the *Friction Index*. Figure 4.1 illustrates that there is a strong positive relationship between these two indicators of pavement surface condition, with a R-square as high as 0.8516. This finding is very useful because for most of the WSDOT highway segments the *Sf Status* is often reported by the Road Weather Information System (RWIS) station nearby, but there is no measurement or record of *Friction Index*. In the case of missing *Friction Index* data, Equation (8) could be used to estimate a value of *Friction Index* from the SRF associated with the *Sf Status*. The value of *Friction Index* is essential for modeling studies such as the one describe in this work.

$$Friction\ Index = 0.2366 * \exp(1.2433 * \mathrm{SRF}) \tag{8}$$

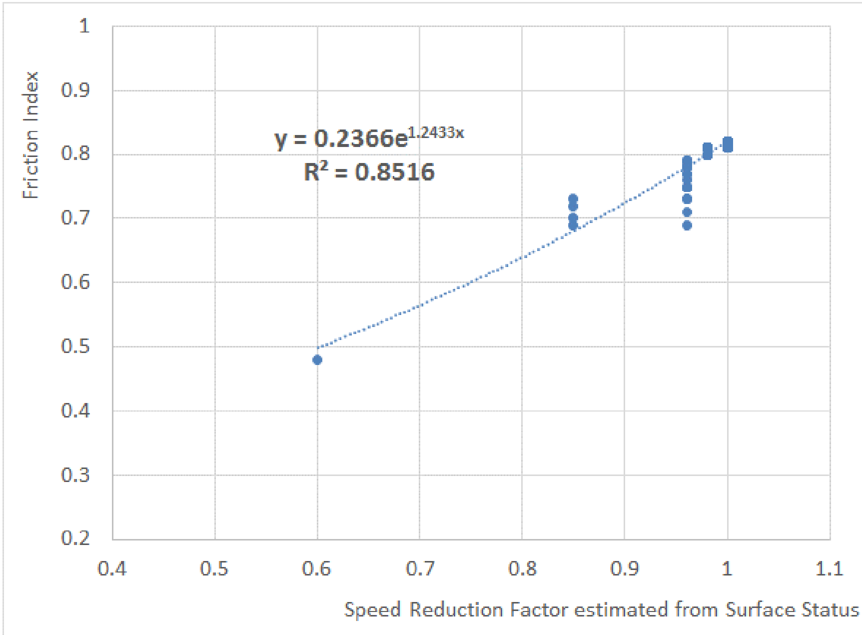

Figure 4.1: Relationship between Friction Index and Speed Reduction Factor estimated from surface status

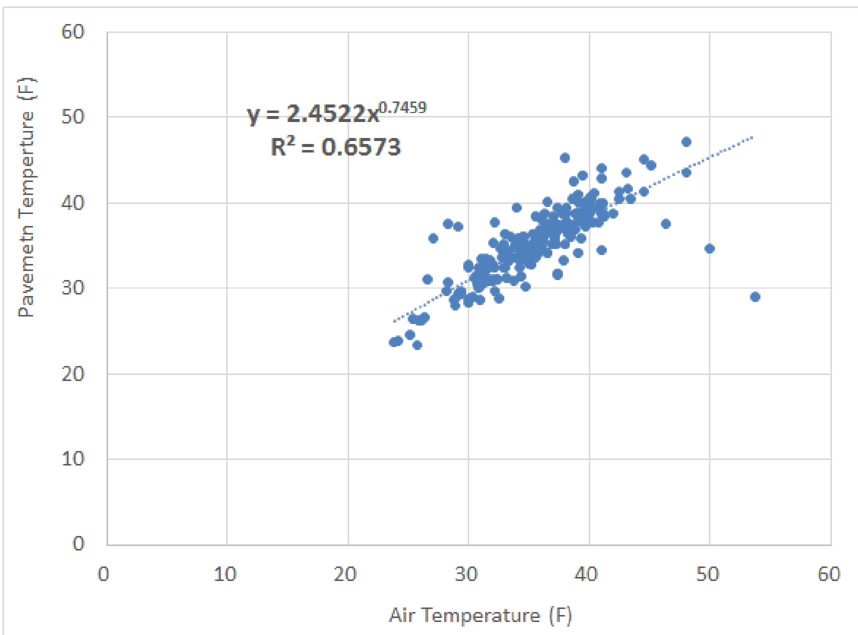

Figure 4.2: Relationship between pavement surface temperature and air temperature

4.2.2 Correlation between Friction Index and Surface Status

Using all 248 records from the I-5 highway segment, December 2016, we also developed an empirical model to correlate the *Pavement Temperature* and *Air Temperature*. Figure 4.2 illustrates that there is a relatively strong positive relationship between these two indicators of pavement surface condition, with a R-square of 0.6573. This positive correlation is intuitive as higher air temperature tends to raise the temperature of pavement surface. There are apparently some outlier data points in Figure 4.2, in which cases the pavement temperature was significantly affected by other factors (possibly wind, solar radiation, and maintenance activities). This empirical relationship is somewhat useful for the WSDOT highway segments far away from a RWIS station or any pavement surface temperature sensor. It is cautioned that this empirical equation can only be used for rough estimate of pavement temperature from air temperature, in light of the multiple factors that disrupt this correlation.

4.2.3 The lack of correlations between other factors

Using all 248 records from the I-5 highway segment, December 2016, we also explored the potential correlation between a set of other factors of interest. As shown in Figure 4.1, the historical data generally suggest the lack of any strong correlation between traffic volume and friction index, between average traffic speed and hourly traffic volume, between hourly traffic volume and accumulated precipitation, and between hourly traffic volume and *Friction Index*, respectively. In some of these cases, the lack of strong correlation is attributable to the presence of many other factors where were not fixed at a given level and thus disrupt the correlation between the two factors examined.

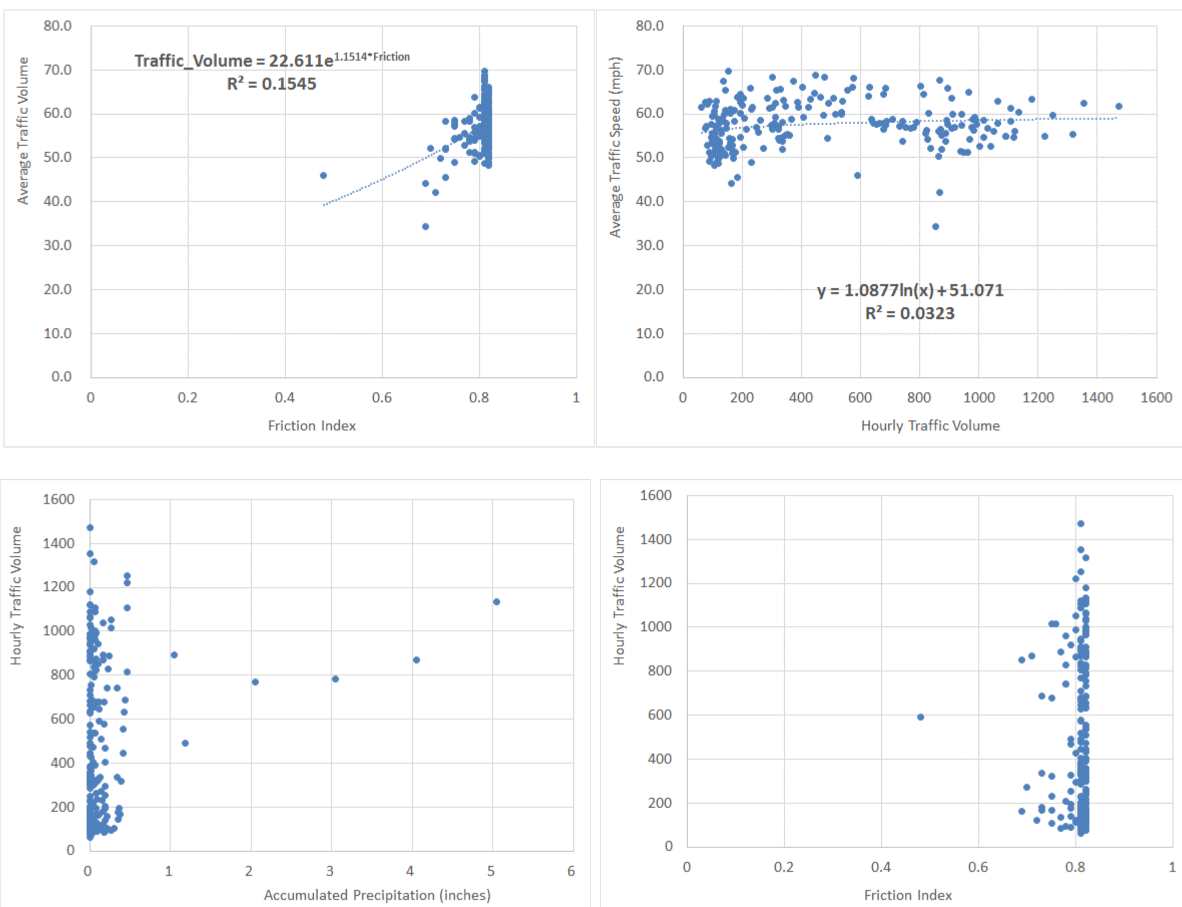

Figure 4.3: Lack of correlation between other factors of interest

4.3 Modeling through Artificial Neural Network

4.3.1 Evaluation of the trained ANN models

As discussed in Section 3.2.2, two ANN models were trained, tested, and validated to correlate the traffic volume during the current hour, *Volume(0h)* and the average traffic speed during the current hour, *Speed(0h)*, respectively, with the eight investigated factors. To develop the predictive *Volume(0h)* model, the 241 training samples in Table 3.1 were used to train an ANN with the topological structure of 8-11-1. The six samples in Table 3.2 were used for testing the validity of the trained model. The training was complete with a training SMSE of 0.083 and a testing SMSE of 0.068, respectively.

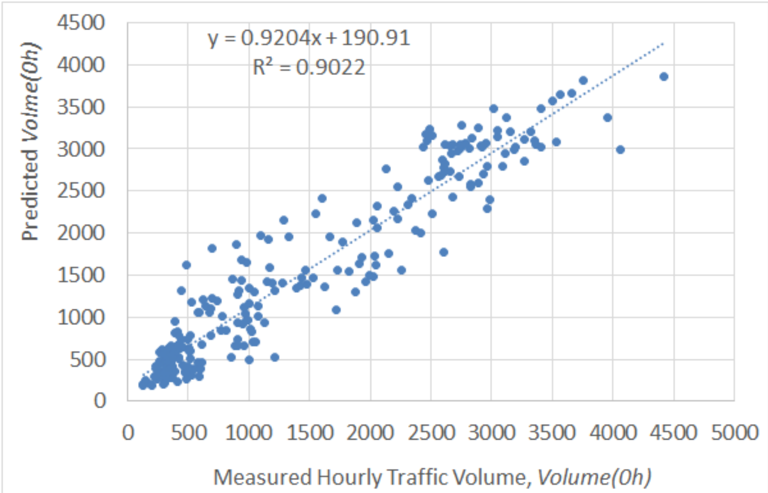

Figure 4.4: Predicted hourly traffic volume vs. actual *Volume(0h)* from the training dataset

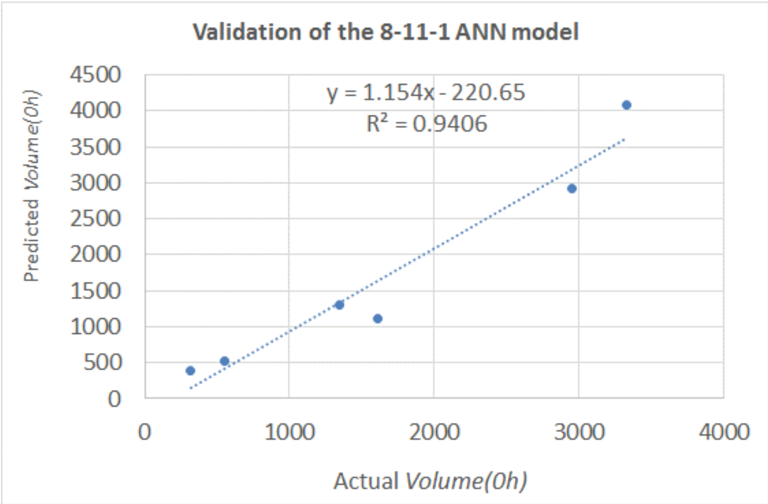

Figure 4.5: Predicted hourly traffic volume vs. actual *Volume(0h)* from the testing dataset

To develop the predictive *Speed(0h)* model, the 241 training samples in Table 3.1 were augmented by repeating once the eight samples with a *Speed(0h)* less than 45 mph. This aimed to address the poor distribution of *Speed(0h)* values in the dataset and minimize the potential bias induced by the poorly distributed data density. Subsequently, the 249 samples were used to train an ANN with the topological structure of 8-4-3-1. The six samples in Table 3.2 were used for testing the validity of the trained model. The training was complete with a training SMSE of 0.055 and a testing SMSE of 0.129, respectively.

The *Volume(0h)* value for each training data point (for the given time and mileposts) was predicted by the 8-11-1 ANN model and then compared against the actual *Volume(0h)* measured (see Figure 4.4). The testing dataset was also used to validate the trained model and the results are shown in Figure 4.5. As illustrated by the R-square values (0.9022 and 0.9406) from the training data and testing data, the model was reliable in predicting the *Volume(0h)* value from the eight input parameters, even though the relative error of prediction for the six testing samples ranged from -31.3% to 22.6%.

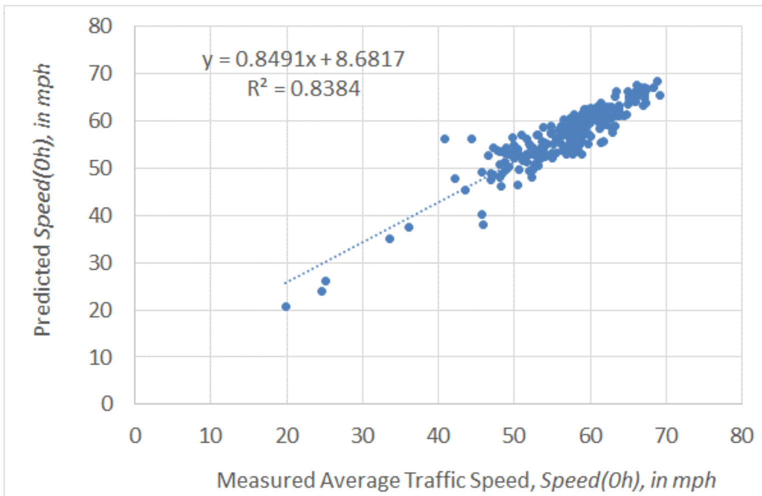

Figure 4.6: Predicted average traffic speed vs. actual *Speed(0h)* from the training dataset

The *Speed(0h)* value for each training data point (for the given time and mileposts) was predicted by the 8-4-3-1 ANN model and then compared against the actual *Speed(0h)* measured (see Figure 4.6). As illustrated by the R-square value (0.8384) from the training data, the model was mostly reliable in predicting the *Speed(0h)* value from the eight input parameters. The relative error of prediction for the six testing samples ranged from -33.6% to 3.2%. Future work may explore the addition of more data points to address the data density issue in the training dataset, which is evident in Figure 4.6. In other words, more data points with lower average traffic speed are needed to improve the usefulness of the training samples.

For both models, the relative error of individual data points can be attributed to errors in measurements (for both input and output parameters) as well as the fact that neither model considered some potentially important factors (e.g., type of traffic, hour of the day, timing of the WRM action during the hour, driver behavior, wind speed, and visibility). Nonetheless, we can conclude that the established ANN models “has relatively good ‘memory’ and the trained matrices of interconnected weights and bias reflect the hidden functional relationship very well” (Shi et al., 2004).

4.3.2 Using the trained ANN models for predictions

As discussed in Section 4.3.1, two ANN models were trained, tested, and validated to be reasonably suitable for predicting the output parameters of unknown samples, provided that the input parameters are kept within the range of the data used to train each model. As such, this section presents a hypothetical scenario under which no WRM operations are conducted on the highway segment during the hours of interest. For this ***"no WRM" scenario***, we predicted the *Volume(0h)* and *Speed(0h)* values for each data point (for the given time and mileposts), such that the difference between the actual scenario (where WSDOT implement the best available practices and technologies for WRM) and the "no WRM" scenario can be quantified in terms of hourly traffic volume and average traffic speed.

For the "no WRM" scenario, the following assumptions were made:

1) the values for the following parameters would stay the same as the "with WRM" scenario: *Speed(-1h), AirTemp,* and *SfTemp.*
2) *Volume(-1h)* is 5% less due to the deteriorating RSC condition (in the absence of WRM operations)
3) *Maintenance(-1h)* = 0, i.e., no WRM action during the prior hour
4) *Accumulated Precip* = the highest value observed from the modeling dataset, i.e., 5.05 inches
5) *Sf Status* = the worst value observed from the modeling dataset, i.e., 0.60 corresponding to the RSC of "Snow Warning"
6) *Friction Index* = the worst value observed from the modeling dataset, i.e., 0.48

For the 247 samples over the 20-mile I-5 highway segment, the mobility benefits of WRM operations can be estimated based on the actual vs. predicted hourly traffic volume and average traffic speed summarized in Table 4.1.

Table 4.1: Summary of mobility benefits based on the ANN model predictions

	Actual (w/WRM)			Predicted (w/o WRM)		
	Volume(0h)	Speed(0h)	Travel Time (h)	Volume(0h)	Speed(0h)	Travel Time (h)
Mean	1416	57	0.36	1035	53	0.38
Standard Deviation	1096	7	0.07	695	0	0.00
Average Difference				-26.9%	-6.6%	4.7%
Median Difference				-17.2%	-8.1%	8.8%

4.4 Summary and Conclusions

Through extensive coordination with WSDOT and University of Washington, a substantial amount of historical data on WRM activities, macroscopic traffic parameters, and climatic conditions was obtained by the research team. Out of this data, we identified a total of 247 complete records available which had the friction index value as well as other parameters of interest, for December 2016, over a 20-mile segment on the Interstate highway I-5. The data of interest was organized, coupled with each other based on milepost and time stamp, and readied for analyses. Preliminary analysis revealed a strong correlation between the numerical value of *Sf Status* and the *Friction Index* and an empirical equation was developed, which could be used to fill the gaps in the missing *Friction Index* data, for modeling purposes. A relatively strong correlation between air temperature and pavement temperature was also found. Out of the 247 records, a randomly selected dataset (six records) was set aside for testing the developed ANN models, whereas the rest of data was used to train the ANN models.

In this work, one ANN model (with 8-11-1 structure) was developed for the traffic volume during the current hour, *Volume(0h)* and the other (with 8-4-3-1 structure) for the average traffic speed during the current hour, *Speed(0h)*. For either of these two output factors, the following eight input factors were used for the model development and validation: *Volume(-1h), Speed(-1h), Maintenance(-1h), AirTemp, SfTemp, Accumulated Precip, Sf Status,* and *Friction Index.* From the comparisons of actual and predicted *Volume(0h)* and *Speed(0h)* values, we can validate that these two models were capable of capturing the hidden relationships between the input and output factors. As such, these two models were used to predict a hypothetical "no WRM" scenario on the 20-mile I-5 highway segment. In the absence of WRM operations, the models predicted that the hourly traffic volume and average traffic speed would drop an average value of 26.9% and 6.6% (or a median value of 17.2% and 8.1%), respectively. Another means of quantifying the mobility benefits of the WSDOT WRM operations is by the avoided travel delays. In the absence of WRM operations, the models predicted an average value of 4.7% (or a median value of 8.8%) additional time needed to go through this 20-mile highway segment during December 2016.

4.5 Directions for Future Research

This project lays the foundation to address much needed research in the area of understanding the macroscopic effects of winter road maintenance operations on winter mobility in the State of Washington. In future research, it is desirable to develop a coherent winter mobility model that further integrates the microscopic effects (driver behavior on highways and the use of anti-icing vs. deicing tactics), such that movements of people and goods can be truly optimized by appropriate implementation of winter maintenance operations best practices and the lost capacity and increased congestion and delays due to winter weather can be minimized. Advanced technologies such as fully automated snowplows/salt spreaders and connected and automated vehicle (CAV) technologies will likely influence how winter road maintenance operations will be conducted and thus affect the winter mobility on highways.

Traffic simulations could be conducted to examine the influence of aforementioned microscopic effects and technological advances, and the ultimate goal is to develop models that integrate driver behavior and traffic mobility into a comprehensive and quantitative winter mobility model for highway segments in the Pacific Northwest.

References

1. American Highway Users Alliance, 2014. "On Heels of Polar Vortex, Several Snow Falls, American Highway Users Alliance Releases New Data Highlighting Importance and Benefits of Safe Winter Road Operations". Jan. 29, 2014, news.
2. Cui, N., Shi, X., 2015. Improved User Experience and Scientific Understanding of Anti-icing and Pre-wetting for Winter Roadway Maintenance in North America. Systematic Approaches to Environmental Sustainability in Transportation. ASCE Construction Institute. Special Publication, in press.
3. Daily record, 2008. "Snoqualmie Pass avalanche traps CWU student in car, closes I-90". Jan. 30, 2008, news.
4. Donaher, G., 2014. Impact of Winter Road Conditions on Highway Speed and Volume (Masters Thesis). University of Waterloo. Retrieved from http://hdl.handle.net/10012/8241
5. Ewan, Levi, Ahmed Al-Kaisy, and David Veneziano, 2013. "Remote sensing of weather and road surface conditions." *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2329, 8-16.
6. Federal Highway Administration, 2017. "Snow and Ice webpage", FHWA Office of Operations, Road Weather Management Program, https://ops.fhwa.dot.gov/weather/weather_events/snow_ice.htm.
7. Fu, L., Kwon, T.J., 2018. Chapter 8: Mobility effects of winter weather and road maintenance operations. In X. Shi, L. Fu (Eds.), Sustainable Winter Road Operations, Wiley-Blackwell, pp. 131-155.
8. Ghasemzadeh, A., Hammit, B. E., Ahmed, M. M., Young, R. K., 2018. "Parametric ordinal logistic regression and non-parametric decision tree approaches for assessing the impact of weather conditions on driver speed selection using naturalistic driving data." *Transportation research record*, Vol. 2672, 137-147.
9. Hille, R., Starr, R., 2008. Design and implementation of automated vehicle location and maintenance decision support system for the Minnesota Department of Transportation'. 15th World Congress on ITS, New York, November 2008.
10. Kwon, T. J., Fu, L., Jiang, C., 2013. "Effect of winter weather and road surface conditions on macroscopic traffic parameters." *Transportation research record*, Vol. 2329, 54-62.
11. Kyte, M., Khatib, Z., Shannon, P., Kitchener, F., 2001. "Effect of weather on free-flow speed." *Transportation research record*, Vol. 1776, 60-68.
12. Morisugi, H., Hayashiyama, Y., Saito, M., Sato, C., 2002. Benefit Evaluation of snow removal on Roads in Tohoku Region. Proceedings: PIARC International Winter Road Congress 2002, CD-ROM.
13. Myers, A. M., Trang, A., Crizzle, A. M. (2011). Naturalistic study of winter driving practices by older men and women: examination of weather, road conditions, trip purposes and comfort. *Canadian journal on aging*, *30*(4), 577-589

14. O'Keefe, K., Shi, X., 2005. Synthesis of Information on Anti-icing and Pre-wetting for Winter Highway Maintenance Practices in North America. Final report prepared for the Washington DOT.
15. Qiu, L., Nixon, W., 2009. Performance Measurements for Highway Winter Maintenance Operations. Final Report for the Iowa Highway Research Board, Project TR-491, Des Moines, IA.
16. Russ, A., Mitchell, G.F., Richardson, W., 2008. *Transportation Research Record*, 2055, 106-115.
17. Shahdah, U., 2009. Quantifying the Mobility Benefits of Winter Road Maintenance – A Simulation Based Approach. Master's Thesis, University of Waterloo, Ontario Canada. 177 pp.
18. Shahdah, U., Fu, L., 2010. Quantifying the mobility benefits of winter road maintenance — a simulation based analysis. Proceedings of the 89th Annual Meeting of the Transportation Research Board, Washington D.C.
19. Shi, X., Fortune, K., Smithlin, R., Akin, M., and Fay, L., 2013. "Exploring the performance and corrosivity of chloride deicer solutions: Laboratory oratory investigation and quantitative modeling." *Cold Regions Science and Technology*, Vol. 86, 36-44.
20. Shi, X., Fu, L., 2018. Chapter 1: Introduction to Sustainable Winter Road Maintenance. In X. Shi, L. Fu (Eds.), Sustainable Winter Road Operations, Wiley-Blackwell, pp. 1-6.
21. Shi, X., Schillings, P., Boyd, D., 2004. "Applying Artificial Neural Networks and Virtual Experimental Design to Quality Improvement of Two Industrial Processes." *International Journal of Production Research*, Vol.42(1): 101-108.
22. Strong, C., Shi, X., 2008. "Benefit-Cost Analysis of Weather Information for Winter Maintenance: A Case Study." *Transportation Research Record*, Vol. 2055, 119-127. DOI: 10.3141/2055-14.
23. USEPA, 1999. "Stormwater Management Fact Sheet—Minimizing Effects from Highway Deicing." Report No. EPA 832-F-99-016, Office of Water, United States Environmental Protection Agency, Washington, DC.
24. Usman, T., Fu, L., Miranda-Moreno, L. F., 2010. "Quantifying safety benefit of winter road maintenance: Accident frequency modeling." *Accident Analysis & Prevention*, *42*(6), 1878-1887.
25. Ye, Z., Strong, C.K., Shi, X., Conger, S.M., Huft, D.L., 2009a. "Benefit–cost analysis of maintenance decision support system', *Transp. Res. Record,* Vol. 2107, 95–103.
26. Ye, Z., Strong, C.K., Shi, X., Conger, S.M., 2009b. Analysis of maintenance decision support system (MDSS) benefits and costs'. Report No. SD2006-10-F, South Dakota Department of Transportation.
27. Ye, Z., Shi, X., Strong, C. K., Larson, R. E., 2012. "Vehicle-based sensor technologies for winter highway operations." *Intelligent Transport Systems, IET*, Vol. 6(3), 336-345.
28. Ye, Z., Veneziano, D., Shi, X., 2013. "Estimating Statewide Benefits of Winter Maintenance Operations." *Transportation Research Record*, Vol. 2329, 17-23.