Impacts of Snowfall, Low Temperatures, and their Interactions on Passenger Car and Truck Traffic

A Thesis

Submitted to Faculty of Graduate Studies and Research

In Partial Fulfillment of the Requirements

For the Degree of

Doctor of Philosophy

in

Environmental Systems Engineering

University of Regina

By

Hyuk-Jae Roh

Regina, Saskatchewan

March, 2015

UNIVERSITY OF REGINA

FACULTY OF GRADUATE STUDIES AND RESEARCH

SUPERVISORY AND EXAMINING COMMITTEE

Hyuk-Jae Roh, candidate for the degree of Doctor of Philosophy in Environmental Systems Engineering**,** has presented a thesis titled, ***Impacts of Snowfall, Low Temperatures, and Their Interactions on Passenger Car and Truck Traffic,*** in an oral examination held on March 23, 2015. The following committee members have found the thesis acceptable in form and content, and that the candidate demonstrated satisfactory knowledge of the subject material.

External Examiner:	Dr. Mingyuan Chen, Concordia University
Co-Supervisor:	Dr. Satish Sharma, Environmental Systems Engineering
Co-Supervisor	*Dr. Sandeep Datla, Adjunct
Committee Member:	Dr. Yee-Chung Jin, Environmental Systems Engineering
Committee Member:	Dr. Kwei Quaye, Adjunct
Committee Member:	*Dr. Ming Zhong, Adjunct
Committee Member:	*Dr. Dianliang Deng, Department of Mathematics & Statistics
Chair of Defense:	Dr. Laurie Clune, Faculty of Nursing

*Not present at defense

Abstract

Winter weather conditions such as extremely cold temperatures, heavy snowfall, and high wind chills are common occurrences in Canada and many other countries around the world. Impacts of such adverse weather conditions on total highway traffic volume have been the subject of numerous research studies in the past. However, none of the past studies investigated thoroughly the impacts of severe cold and heavy snow fall on temporal and spatial variations of truck traffic on Canadian highways. Impacts of weather on route choice behaviour of truck and passenger car drivers have also not been addressed in the past. A detailed investigation was carried out in this study to understand and analyze traffic flow variations during severe winter weather, including development of models of cold and snowfall impacts on classified traffic volumes with detailed considerations of trucks and highway types.

On the basis of classified traffic volume data from six weigh-in-motion (WIM) sites and weather data from weather stations near the WIM sites located in the province of Alberta, the combined effect of snowfall and temperature on traffic variation for passenger cars and trucks was investigated. Statistically valid regression models with and without the interaction terms were developed to explain the relationship between the dependent variable (the daily truck/passenger car volume) and the independent variables (i.e., the historical average daily volume expected on a normal day in winter, the amount of snow fall, and the average daily temperature on that particular day). The six WIM sites were classified into three distinct groups: regional commuter routes, interregional long distance routes, and special routes. The vehicles were classified into passenger cars

and various types of trucks, including single-unit trucks, single-trailer trucks, and multi-trailer trucks.

The study results show that the total traffic, passenger car traffic, and truck traffic volumes decrease with the increase in snowfall and severity of the cold for long distance roads like Highway 2. The total traffic and the passenger car traffic decreases as well with severe weather conditions for regional commuter roads like Highway 2A. However, the truck traffic is not significantly influenced by the snowfall and severity of temperature. Interaction models show that the reduction in traffic volume due to cold temperature would intensify with a rise in amount of snowfall for both passenger cars and truck traffic on Highway 2, indicating the existence of cold and snowfall interactions. For Highway 2A, passenger cars experience higher reduction due to the combined effect of snowfall and cold; however, truck traffic is seen to increase during severe weather conditions, which could happen due to shifts of traffic from parallel low standard highways. Another significant finding of this research is that, in general, truck type distribution on commuter routes and main primary highways does not change during the winter season in Alberta. Likely causes for differential effects of severe weather conditions on passenger cars and truck traffic volumes on commuter, long distance, and other types of highways are also described in the thesis.

The traffic-weather relationships discovered in this study have numerous applications in the field of traffic monitoring and other types of operational analyses for highways, such as imputation of the missing passenger car, truck, and total traffic data during winter months, which is also described in detail in this thesis.

Acknowledgements

I sincerely wish to thank my supervisor, Dr. Satish Sharma, for his kind encouragement, invaluable guidance, and helpful insights during the course of my doctoral project, thesis writing, and reviewing up to the moment of its final completion. Also, I would like to extend my great appreciation to my co-supervisor, Dr. Sandeep Datla, for his continuous engagement and keen insights into the doctoral project.

I thank Dr. Dianliang Deng for his valuable suggestions regarding the statistical investigations. I also thank Dr. Kwei Quaye, Dr. Yee-Chung Jin, and Dr. Ming Zhong for providing constructive help in the thesis review process. I acknowledge Prasant Kumar Sahu, the Visiting Research Scholar, who willingly engaged in my thesis and contributed much clarity to the work. Many valuable suggestions of all these individuals helped me to improve the quality of the thesis.

I am grateful to Peter Kilburn, Alberta Transportation, Edmonton, for providing the study data and discussing the study results.

Financial assistance provided by the Natural Science and Engineering Research Council of Canada, Saskatchewan Government Insurance, and the Faculty of Graduate Studies and Research, University of Regina, in the form of various teaching and research assistantships and scholarships for pursuing the doctoral project are greatly appreciated.

Table of Contents

List of Tables

List of Figures

Notations and Abbreviations

AADT	:Annual Average Daily Traffic
AADTT	: Annual Average Daily Truck Traffic
ADT	:Average Daily Traffic
ADTT	:Average Daily Truck Traffic
AF	:Adjustment Factor
ARIMA	:Auto Regressive Integrated Moving Average
AT	:Alberta Transportation
ATMS	:Advanced Traffic Management Systems
AVC	:Automatic Vehicle Classifier
AVMT	:Annual Vehicle Miles Traveled
BP	:Binomial Probability
COM	:Commuter
C-SHRP	:Canadian Strategic Highway Research Program
DA	:Day
DF	:Daily Factor
DG	:Day Groups
DHV	:Design Hourly Volume
DOT	:Department Of Transportation
DVF	:Daily Volume Factor
EDVF	:Expected Daily Volume Factor

ESAL	:Equivalent Single Axle Loadings
EVF	:Expected Volume Factor
F	:Friday
FHWA	:Federal Highway Administration
GAs	Genetic Algorithms
GIS	:Geographical Information Systems
HCM	:Highway Capacity Manual
HF	:Hourly Factor
HO	:Hour
K-NN	:K-Nearest Neighborhood
LENG	:Length
LN	:Lane
LTPP	:Long Term Pavement Performance
M	:Monday to Thursday
MAPE	:Mean Absolute Percentage Error
MaxAPE	:Maximum Absolute Percentage Error
MF	:Monthly Factor
MI	:Minute
MinAPE	:Minimum Absolute Percentage Error
MO	:Month
NN	:Neural Network
PAADT	:Passenger Cars Annual Average Daily Traffic
PAVC	:Permanent Automatic Vehicle Classifiers

PCT	:Passenger Cars Traffic
PTC	:Permanent Traffic Counter
RCOM	:Regional Commuter
REC	:Recreational
RLD	:Rural Long Distance
SA	:Saturday
SDCs	:Short Duration Counters
SE	:Second
SPEE	:Speed
SPVC	:Short Period Vehicle Classification Counts
SU	:Sunday
TAADT	:Truck Average Annual Daily Traffic
TMC	:Turning Movement Count
TMG	:Traffic Monitoring Guide
TT	:Truck Traffic
VB	:Visual Basic
VKT	:Vehicle Kilometers Traveled
VPD	:Vehicles Per Day
VPH	:Vehicles Per Hour
WIM	:Weigh-In-Motion
WO	:Weather Office
WSDOT	:Washington State Department of Transportation
YE	:Year

Chapter One

Introduction

1.0 General

Traffic volume is one of the most important measures used for the safe and efficient planning, design, operation, and management of highway facilities. The Highway Capacity Manual (HCM, 2000) defines traffic volume as “the total number of vehicles that pass over a given point or section of a lane or roadway during a given time interval.” It is a well-known fact that traffic volume varies with both time and space. Temporal variations occur with respect to the hour of the day, day of the week, and month of the year. The location and type of highway causes spatial variation in traffic volumes (Sharma, 1992). Understanding such variations in traffic volumes is necessary for many transportation engineering analyses.

Highway agencies in North America and many other parts of the world commit a significant portion of their financial and human resources to traffic data monitoring programs. The most commonly used programs include the collection of traffic data using: permanent traffic counters (PTCs), which are instruments that record traffic data for the whole year on an hourly basis, and short duration counters (SDCs), which are devices that record traffic volumes several times a year for periods ranging from a few hours to several weeks. Highway agencies generally use PTCs to monitor a small number of representative road segments and SDCs to monitor the remaining road segments on a cyclic basis. The Traffic Monitoring Guide (TMG, 2001) recommends that short duration counts of 48-hour durations should be taken for all highway segments at least once every six years. Continuous counts help agencies understand the temporal (time-of-day, day-of-week, and seasonal) changes in traffic volumes on various types of highways. Short duration counts ensure geographic diversity and coverage through segment specific traffic count information on a cyclic basis.

1.1 Importance of Classified Traffic Data

Traffic flow data based on vehicle types is important for program evaluation, highway infrastructure management, safety analysis, resource allocation, traffic engineering, truck size and weight enforcement, and other applications. For many purposes, including traffic safety analysis, engineers and researchers would like to work with exposure data, which not only includes numbers of vehicles per unit time, but also subdivides these volumes by vehicle class (passenger vehicles versus trucks, heavy trucks versus light trucks, among other things).

Most highway agencies in Canada now employ permanent automatic vehicle classifiers (PAVC), and/or weigh-in-motion (WIM) systems that provide both vehicle weight and vehicle classification statistics. While automatic vehicle classification technology has advanced considerably in the past two decades, the practices of collection, analysis, and application of classification data have not progressed similarly. There is little or no evidence in the literature of a systematic application of continuously recorded vehicle classification data for developing cost-effective schedules for seasonal truck traffic counts or expanding sample 24-hour, 48-hour, or counts taken only once in a year to average annual truck volume statistics.

1.2 Vehicle Classification Systems

Most Canadian highways are built and managed under the authority of provincial, territorial, and municipal governments. There are no national standards specifying vehicle classification systems to be promoted or used in highway monitoring programs. Furthermore, the fleet characteristics vary significantly from jurisdiction to jurisdiction across the country because of differences in size and weight regulations, economic activity, physical environment, and other aspects. This has led to a wide variety of vehicle classification systems used by highway agencies and municipal authorities in their traffic monitoring programs. Such varying systems complicate efforts to develop traffic-based exposure data necessary for comparative analysis across jurisdictions. Chapter 2 of this thesis presents key aspects of the vehicle classification systems used by seven of the ten provincial highway agencies in Canada.

1.3 Weather Impact on Traffic Volume

It has long been recognized that weather conditions (in any season or climate) affect highway traffic flow in various ways (Hanbali, 1994; Hanbali and Kuemmel, 1993; Knapp and Smithson, 2000; Goodwin, 2002; Andrey et al., 2003; Keay and Simmonds, 2005). For example, the acceleration and deceleration capabilities of vehicles can be affected by icy pavement conditions. Reduced visibility can affect driving speeds, lane changing behaviour, and vehicle following patterns. Extreme weather conditions can cause drivers to change their travel patterns by, for example, taking a different route to a destination or delaying or cancelling trips. A survey by Markku and Heikki (2007) on driver behaviour during adverse weather conditions found that trip adjustments during adverse weather were often associated with driver experience, age, and gender and with the length of the trip. Travelers generally show less desire to travel during severe cold temperatures due to the increased risk associated with extreme cold in general (Bomay, 2007) and the increased necessity for precautionary measures for safe journeys (WSDOT, 2007). A break down or crash on a road or highway during extremely cold temperatures could result in prolonged exposure to the cold, causing frostbite, hypothermia or even fatalities due to lack of help or help arriving too late.

Existing literature (Andrey et al., 2003) also indicates that winter weather is associated with greater changes in traffic patterns than summer weather. This is particularly true in Canada and many parts of the United States where very severe winter weather (extremely cold temperatures, heavy snowfall, blizzards, freezing rain, and high wind chills) is often expected. Such weather conditions may compound travel disruptions, resulting in significant variations in highway traffic volumes.

A number of studies (Datla, 2009; Datla and Sharma, 2008; Datla and Sharma, 2010) were carried out at the University of Regina to examine the impacts of severe cold and snow on highway traffic volume. The total daily and hourly traffic volume data available from 350 permanent traffic counter sites and temperature, and snow fall data from 598 weather stations located in the province of Alberta were used in all these investigations. In order to study differential effects of severe weather on type of trips and location of roads, the study PTC sites were grouped into four highway types, including commuter roads, regional commuter roads, long distance rural roads, and recreational roads. Datla (2009) used regression models to relate total traffic volumes under cold and heavy snow conditions with traffic volumes under normal conditions. They categorized temperature into 7 classes: above 0^oC, 0^oC to -5^oC, -5^oC to -10^oC, -10^oC to -15^oC, -15^oC to -20^oC, -20^oC to -25^oC, and below -25^oC. Some of their study findings are listed in the following:

1. Total highway traffic volumes decrease with increases in the severity of cold temperatures. During extremely cold weather (below -25^0C), the average winter daily traffic volume could be reduced by about 30%. Weekend traffic volumes are more susceptible to cold than weekdays for all types of highways.
2. Commuter and regional commuter roads are affected least with low temperatures. The impact of cold tends to be very high for recreational roads and moderate for rural, long distance roads.
3. Snowfall causes a significant reduction in total daily traffic volumes on highways. In cases of Alberta study PTC sites that were investigated, volume reductions range between 7% and 17% for each centimetre of snowfall. Such reductions could be as high as 51% during severe snowstorms with a snowfall of 30 cm or above.

1.4 Identification of the Study Needs

Previous research has shown that traffic patterns change during severe winter weather conditions. However, most of those studies reported that average traffic volumes tend to decrease (without detailed statistical analysis) due to adverse weather conditions. The relationship between traffic variation and weather conditions has not been thoroughly investigated in previous studies. Data limitation was a major obstacle for many studies in the past. Markku and Heikki (2007) indicated that the degree of variation of highway traffic volume during adverse weather conditions depends on the type of trips (necessary trips, discretionary trips, etc.) carried by the highway segments. However, past studies have not explored the relationship between traffic variation and weather conditions by taking into account the type of trips carried by various highway segments. Except for the studies mentioned above (Datla, 2009; Datla and Sharma, 2008; Datla and Sharma, 2010), none of the past studies has considered the effect of severe cold on traffic volume variation in Canada or elsewhere. Therefore, it is desirable to carry out further research to study the temporal and spatial variations in highway traffic volumes under different cold and snowfall conditions.

A number of researchers and organizations have identified the need for further research on the impact of weather on highway traffic volumes. A few of the most relevant propositions among them are summarized below:

- Knapp and Smithson (2000) indicated that a "comprehensive knowledge of the traffic-weather relations will improve the decision making capabilities of drivers." Such knowledge would also help highway operation and maintenance decision makers by giving them knowledge of how travelers are affected by certain weather conditions and would enable them to make more efficient winter maintenance decisions.
- Smith et al. (2004) reported that transportation researchers and practitioners should have a good understanding of the impact of various weather conditions on traffic flow to provide efficient traffic operations.
- Agarwal et al. (2005) stated that "adverse weather degrades the capacities and operating speeds on roadways, resulting in congestion and productivity loss."

They also mentioned that “without a solid understanding of the mobility impacts of weather on traffic patterns, freeway operators do not have estimates of speed and capacity reductions to predict and simulate the traffic management strategies.”

- Colyar et al. (2003) pointed out that “with the advent of advanced traffic management systems (ATMS), there is an opportunity to develop traffic management strategies that seek to minimize the negative weather-related impacts on traffic operations.” Although simulation models are widely used in the evaluation of various traffic management strategies, their application in evaluating ATMS strategies under adverse weather conditions needs to be explored. Clear knowledge of the impact of weather on highway traffic is needed to develop such strategies.

As mentioned earlier, the past studies (Datla, 2009; Datla and Sharma, 2008; Datla and Sharma, 2010) carried out for Alberta highways concluded that magnitude of traffic volume variations depends on time of the day, day of the week, location, highway type and severity of the winter weather. They analyzed the variation in traffic volume reductions within the temporal and spatial context. Nevertheless, their study and other similar studies in the literature were limited to “total traffic volume” data only.

Two previous studies (Thomas et al., 1997; Sharma et al., 1998) carried out at the University of Regina used a limited database consisting of data from only eight Saskatchewan PAVC (permanent automatic vehicle classifier) sites for a period of two years and studied how to more accurately estimate truck average annual daily traffic (TAADT) from short-period vehicle classification counts (SPVC). The conclusions drawn in the two studies are relevant to this study: (1) The temporal patterns of truck traffic are considerably different than the corresponding patterns of the total traffic volume; and (2) reasonable estimates of TAADT can be obtained only when factors used to expand an SPVC come from a PAVC site that has a truck traffic pattern that is similar to the one at the SPVC site.

None of the above studies investigated the impacts of severe winter weather on temporal and spatial variations of truck traffic. Impact of weather on route choice behavior of truck and passenger car drivers have also not been addressed in the past. These findings indicated that it is worthwhile to analyze the variation of classified traffic during adverse winter weather.

The main purpose of this study is to understand and analyze traffic flow variations during severe winter weather, including development of models of cold and snowfall impacts on classified traffic volumes with detailed considerations to truck traffic and highway type. The models are developed using weigh-in-motion (WIM), and weather data from the Province of Alberta, Canada. In these models, truck and passenger car traffic variations are related to winter weather conditions by means of various techniques, such as regression analysis. The data are obtained from Alberta Transportation and Environment Canada. The study data correspond~~s~~ to more than 154 million vehicular records from six WIM sites on provincial highways in Alberta, Canada. The model parameters are estimated using CARPACKAGE from the statistical software R (RFSC, 2010). The calibrated winter weather models are applied to estimate the missing traffic volumes during winter months. The results from the winter weather regression models developed in this study confirm that they are more accurate than another commonly used non-parametric regression method known as k-Nearest Neighborhood (k-NN) method.

1.5 Objectives of the Study

The main objectives of this study are:

1. To carry out a review of relevant literature including the effect of different weather events (such as rain, snow, wind, fog, and extreme temperatures) on highway traffic flow and to present a discussion of past studies regarding the relationship between the total highway traffic volumes and the amount of snowfall and very low temperatures.
2. To provide a detailed description of study data including a huge amount of raw version of WIM data and its transformation to the final version of data containing more than 150 million of vehicular records used to carry out this study.
3. To review the vehicle classification schemes which have been used in Canada, and to find out an appropriate level of vehicle classification suitable for the present investigation.
4. To describe temporal variations of passenger cars, trucks and total daily traffic at the study WIM sites, and to show graphical patterns of truck type distribution at the investigation sites.
5. To study the temporal and spatial variations of different vehicle classes on rural highways during very cold and snowy weather conditions and to carry out statistical investigations to the relationship between the classified traffic volume and winter weather conditions.

6. To develop and discuss dummy variables regression models relating the classified winter traffic volume with amount of snow and seven categories of cold with 5 °C equal intervals by using six dummy variables in regression model, i.e., CC_1 (-5°C ~ 0°C), CC_2 (-10°C ~ -5°C), CC_3 (-15°C ~ -10°C), CC_4 (-20°C ~ -15°C), CC_5 (-25°C ~ -20°C), and CC_6 (below -25°C).
7. To develop and discuss more sophisticated traffic weather models considering both snowfall and temperature as continuous variables to understand the combined effect of snowfall and temperature variables.
8. To examine changes in traffic volume of different vehicle classes due to the simultaneous occurrence of cold temperatures and snowfall amount, i.e., to understand the variations in classified traffic volumes due to the existence of interaction between snow and temperature variables.
9. To investigate the association of truck type distribution with winter and non-winter seasons of the year using Chi-squared (χ^2) and Binomial test of statistical significance.
10. To demonstrate an example of successful application of the developed mathematical models of traffic-weather relationships for imputing missing traffic data for different vehicle classes during winter months.

1.6 Scope of the Study

To achieve the above objectives, the present study uses data from a very large traffic volume database from the province of Alberta, Canada, over a period of 5 years from 2005 to 2009. Various types of rural highways, such as commuter, regional commuter, and rural long distance, representing low to high traffic volume conditions, are included in the study. Weigh-in-motion data are also used for the purpose of studying the impact of weather conditions on classified traffic volumes. The study period is limited to the months from November to March because the province of Alberta experiences winter weather conditions during these months.

Considering the limitations of the available weather data (i.e., fog, wind speed and direction, roadway surface conditions, and hourly snowfalls, are not available), the meteorological parameters of temperature and snowfall are selected to represent winter weather conditions in the studied province. The analysis is performed based on daily average temperature in degrees Celsius and daily total snowfall in centimetres.

Weather impacts highway traffic flow in many ways; however, this study focuses on classified traffic volumes only, e.g. truck and passenger car volume. The effect of weather on traffic volumes during statutory holidays is also not included in the scope of this study.

1.7 Organization of the Thesis

The thesis is organized into nine chapters, including the present chapter, which gives an introduction to the topic along with the objectives and scope of the research.

- Chapter 2 provides a review of past studies on the relationship of highway traffic volumes and weather conditions. The limitations of past studies and the scope for the present study are also discussed in this chapter.
- Chapter 3 presents sources of traffic and weather data, the classification of highways, the spatial variation of weather conditions, the integration of weather condition data with traffic data, and information regarding the weigh-in-motion sites selected for this study.

- Chapter 4 presents a detailed investigation to the impact of different cold and snowfall conditions onto the temporal and spatial variations in highway traffic volumes at the study WIM sites for different vehicle classes.
- Chapter 5 presents the development of models to relate traffic volumes with cold categories and snowfall conditions.
- Chapter 6 presents the effect of cold and snowfall interactions on classified traffic volumes and how the effect of weather on traffic volumes varies within the winter season is also discussed in this chapter.
- Chapter 7 investigates the impact of winter weather conditions on truck type distribution at various study sites.
- Chapter 8 presents the application of the developed model to impute missing traffic data for different vehicle classes.
- Chapter 9 provides a summary of study findings and derived conclusions along with recommendations for future research.

Chapter Two

Literature Review

2.0 General

This chapter presents an introduction to related concepts and the previous research relevant to this study. First, a brief introduction to traffic volume variations is given. Then, a discussion of the effect of different weather events (such as rain, snow, wind, fog, and extreme temperatures) on highway and traffic conditions is provided. Thereafter, a review of past studies on the association of traffic volumes with weather conditions is provided. Analysis and inferences given by previous researchers on traveler behaviour during adverse weather conditions, which causes variation in highway traffic volumes, are also presented in this chapter. The limitations of the past studies and the scope for the current study are presented at the end of this chapter. Other literature reviews needed for this study are given in the relevant chapters, e.g., the literature review for missing data imputation analysis is given in Chapter 8.

2.1 Traffic Volume Variation

2.1.1 Temporal and Spatial Traffic Volume Variation

Traffic volume is defined as the number of vehicles passing a point on a highway or lane during a specified period (Garber and Hoel, 2002). Commonly, it is expressed as vehicles per day (vpd) or vehicles per hour (vph). A time series is a chronological sequence of observations on a particular variable (Bowerman and O'Connell, 1987). In this sense, traffic volume data are univariate time series because they consist of the successive observations of the number of vehicles passing a location during a specified time interval. Traffic volume varies in both spatial and temporal dimensions. Understanding of these variations is important for traffic engineers to plan, design, operate, and control highway systems to provide a reasonable level of service to the road users.

The traffic spatial variation can be found distinctively between urban and rural areas. Normally traffic in an urban area is denser than that in a rural area, and the speed of urban traffic is lower than that in the rural area. Moreover, even in the same broad category (such as rural or urban), based on their geographical locations and roles in the road networks, different roads often show distinct traffic characteristics. For example, there are large volume and speed differences between local streets, arterials, collectors, and freeways in urban areas. These differences can also be found between commuter roads and highly recreational roads in rural areas.

It is also known that traffic on a given section of a road varies from hour to hour, from day to day, from month to month, and from year to year. Yearly changes in traffic volume are usually caused by regional economic development, land-use change etc. The monthly variations of traffic volume on a highway reflect the economic and social demands for transportation, and the influence of the climatic cycles. Highways serving commuter traffic show more uniform variations, whereas recreational roads are subject to much greater variations. Average rural routes exhibit intermediate variations. The seasonal variations in traffic volume are primarily a function of the type of route and the kinds of activities present in the area it serves.

Daily variations in traffic volume are also related to the type of highway on which the observations are made. Weekend volumes are usually lower than weekday volumes for highways serving predominantly commuter travel. In comparison, peak traffic occurs on weekends on average rural routes. Recreational roads display the heaviest traffic volume on Fridays, Saturdays and Sundays.

Different types of roads have different hourly variations. The typical morning and evening peak hours are evident for commuter routes. In this case, the evening peak is somewhat more intense than the morning peak. For other road types, the hourly variation patterns vary and are less distinctive. However, for most of the road, the daily peaks tend to occur in the mid-afternoon or early evening.

The consistency of hourly variations is of great importance. The stability of peak-hour demands affects the viability of using such values in design and operational analysis of highways and other transportation facilities.

2.1.2 Traffic Volume Counts and Weigh-in-Motion Data

Traffic volume on any road segment is one of the most useful information. Highway agencies usually employ permanent traffic counters, seasonal traffic counters, short-period traffic counters and Weigh-in-Motion (WIM) technology etc. to collect the traffic volume data. Permanent traffic counters are used to monitor the traffic for 24 hours per day, 365 days per year. Seasonal traffic counters and short-period traffic counters are used to monitor the traffic for a short period ranging from a few hours to a few days (Garber and Hoel, 2002). It would be ideal to install permanent traffic counters for each and every road section. However, it is not financially feasible. Therefore, only a small number of road sections are monitored by permanent traffic counters. Seasonal traffic counters and short-period traffic counters are used to obtain sample traffic for a short period at other road sections.

WIM technology is used to collect the classified traffic volume data. Weigh-in-motion (WIM) devices are designed to capture and record axle weights and gross vehicle weights as vehicles drive over a measurement site. Unlike static scales, WIM systems are capable of measuring vehicles traveling at a reduced or normal traffic speed and do not require the vehicle to come to a stop. This makes the weighing process more efficient, and, in the case of commercial vehicles, allows for trucks under the weight limit to bypass static scales or inspection.

The data from permanent traffic counters are very important. One of the main usages of these data is to develop group expansion factors. The expansion factors are then applied to seasonal traffic counts and short-period traffic counts for estimating traffic parameters, such as AADT, design hourly volume (DHV), annual vehicle miles traveled (AVMT) for those road sections without permanent traffic counters. Out of all these parameters, AADT is the most fundamental one. Sample traffic counts are expanded to estimate AADT with hourly factors (HF), daily factors (DF), and monthly factors (MF) developed from permanent traffic count data. The detailed procedure for estimating AADT from SPTC can be found in a study done by Sharma (1983) and Sharma et al. (1998).

It is important to have enough quantity and quality of PTC data to develop expansion factors for estimation of accurate values of AADT. Therefore, highway agencies maintain ongoing continuous traffic monitoring programs to obtain the data. It is hoped that these devices could run perfectly all the time and hence provide the data needed. However, this is usually not the case. Due to the malfunctions of traffic counters, data for certain periods may not be recorded. Permanent traffic count datasets usually contain a significant number of missing values. The missing values result in the difficulties in developing expansion factors and providing accurate AADT estimates. Similar problem exists in STC and SPTC programs. Due to missing values in these datasets, accurate AADT estimates may not be provided for planned coverage.

Similarly, WIM traffic data are extremely important as it provides the classified traffic volume. In data collection, WIM systems continuously collect valuable data on truck weights, speeds, time of travel, axle configurations, and volumes. This provides the most unbiased data since most illegally operating carriers avoid weigh stations, or travel when weigh stations are closed, thereby, artificially skewing the figures to indicate a lower frequency of over weights (Mussa et al., 2006). WIM systems record all traffic information, even when weigh stations are closed. WIM data can be used to accurately predict future traffic volumes for planning of new construction, management of maintenance activities, to identify if overloading problems exist, and to evaluate the performance of pavements.

The use of WIM scales as a weight enforcement tool was first introduced in Alberta, Canada, in 1982 and has been increasing steadily since. In the United States, another WIM sorting system was installed in Oregon in 1984. By 1998, over 35 states in the United States and 4 provinces in Canada had installed WIM technology as a weight enforcement tool. In effect, WIM systems help to level the playing field for all carriers, eliminating the unfair advantage that illegally loaded carriers have. More focused enforcement means fewer delays to the trucking industry which translates directly to savings in operational costs, less deterioration to roads and more efficient enforcement operations.

2.2 Importance of Vehicle Classification and Classification Technologies

Traffic volumes vary over time and location. These variations in traffic volumes could be dramatic when volumes for specific classification of vehicles travelling in a traffic stream are analyzed separately (FHWA, 2001). In their activities related to collection of vehicle classification data, highway agencies separate the truck volumes from mixed traffic, and analyzes the variations of truck traffic by time of day, day of week, season of the year, and type of roadway (FHWA, 2001; Grush, 1998). Vehicle classification data are used for many types of transportation analyses, such as the structural design of pavements, geometric design, highway life cycle analysis and prioritization of highways.

In spite of its importance in applications, only limited amount of classification data have been collected by highway agencies and thus not much analytical work has been conducted in the past. Consequently, many characteristics of truck traffic patterns are not well explored by highway agencies involved in almost all aspects of transportation planning and engineering functions (FHWA, 2001).

To provide better understanding of how truck volumes change by classification, many highway agencies in North America have been involved in various vehicle classification monitoring programs. This atmosphere is getting expanded with the help of a rapid and widespread introduction of vehicle classification technologies. For example, Canadian Strategic Highway Research Program (C-SHRP) and Long Term Pavement Performance (LTPP) monitoring programs that are sponsored by provinces (or states) have encouraged the use of truck vehicle classification data in transportation practices.

2.2.1 Uses of Classification Data

Highway agencies are responsible for providing, maintaining, and managing transport facilities operated in their jurisdictions (Zhi et al., 1999). For these purposes, vehicle classification data are used by all levels of highway agencies, such as provincial and local transportation agencies. The need for information on truck volumes is growing as highway engineers realize the impact of truck volumes and operating characteristics on the geometric and structural design of roadways and bridges (FHWA, 2001). Representative uses of truck volume and classification information are given below:

- Pavement design;
- Pavement management;
- Scheduling the resurfacing, reconditioning, and reconstruction of highways based on projected remaining pavement life;
- Provision of design inputs relative to the current and predicted capacity of highways;
- Vehicle crash record analysis;
- Environmental impact analysis, including air quality studies;
- Assisting policy makers to address issues of highway system efficiency.

It should be noted that different levels of classifications data are used by transportation engineers depending on the purpose of analysis and the level of details of analysis.

2.2.2 Vehicle Classification Technologies

Historically, truck classification has been carried out by manually observing the traffic stream (Garber and Hoel, 2002). Manual classification count has several advantages (FHWA, 2001). By means of using visual image of vehicle, observers can classify trucks on the basis of a vehicle's body styles. In other words, they can distinguish each specific type of trucks from other truck types with a higher level of accuracy (e.g., tank trucks versus dump truck). Furthermore, manual counts can easily differentiate between a car pulling a light trailer and a tractor pulling a semi-trailer, even if the vehicles have the same number of axles and possibly even similar axle spacing characteristics (McShane and Roess, 1990). Other advantages include the lower rate of classification error and its flexibility of counting in almost all conditions.

In spite of many positive aspects of manual counting, manual classification counts are expensive and prone to errors due mainly to how the counts are performed (Garber and Hoel, 2002). For example, error rates tend to increase significantly after staffs have been working for about three consecutive hours, every two hours they should take a 10 to 15 minute break (Cambridge Systematics, 2007; Smith and Mclntyre, 2002). In addition, most observers cannot accurately count under high volume, multilane conditions. In some cases, many roads do not have places where observer can safely sit while counting traffic. For these reasons, manual classification counts could only be employed for short duration count sessions, and locations where automated vehicle classifiers (AVC) cannot be placed or where AVC will not work accurately because of variable traffic flow conditions (Cambridge Systematics, 2007).

Existing technologies for vehicle classification allows use of axle, vehicle length, and machine vision classifiers. Each of these technology solutions (axle, length, and machine vision) has their own unique sensor technologies, which can be distinguished in terms of cost, reliability, accuracy, life span, ease of set up, and type of information provided, as well as their advantages and disadvantages (Cambridge Systematics, 2007). However, it has been proven that no technology is the best under all conditions (Cambridge Systematics, 2007).

A vehicle classification technology can be selected according to the level of classification required for a specific analysis. In the operation of traffic, for most engineering tasks it is very important to separate heavy vehicles from light vehicles. That is because heavy vehicles have poor acceleration and braking characteristics and cause pavement damages. Moreover, total vehicle size (length, width, height) has major impact on geometric design which is critical for safe roadway operations. For a simple classification, conventional sensor technologies can often be used successfully. Conversely, for completing high profile vehicle classifications (i.e., the type of connection, the type of engine) classification technologies designed for that specific purpose should normally be employed (FHWA, 2001).

The 13-category classification scheme of the Federal Highway Administration (FHWA) is commonly accepted as a standard scheme by highway agencies in North America. The reason for this popularity may be simply because this classification scheme is a direct result of the compulsions on highway agencies by the limitations of vehicle sensors affordable to them (FHWA, 2001).

2.2.3 Schemes for Vehicle Classification

As discussed earlier in this chapter, vehicles can be classified into various categories on the basis of data collected using a wide variety of technologies. The vehicle classification data are comprised of detailed information on the characteristics of vehicles (i.e., vehicle speed, overall vehicle length, axle weight, axle spacing, etc.) and part of the information is used for vehicle classification using various vehicle classification schemes (or systems) (i.e., four classes, five classes, etc.,), which are chosen according to the level of details required for a specific analysis. The most commonly used information for vehicle classification is vehicle configuration information such as the number of axle and axle spacing, and vehicle length. This information is fed into an algorithm that associates the information with specified measurements for each vehicle classes.

The diversity in the purposes of vehicle classification results in various classification schemes that are used in practice by highway agencies (Cambridge Systematics, 2007). It is because provinces (or states) have different regulations on truck size, weight, and the characteristics of trucks (i.e., number and spacing of axles, overall vehicle lengths). In the U.S.A., most States need to develop their own version of basic algorithms to convert their own vehicle classes into FHWA 13-category classes for the purpose of data reporting.

Vehicle classification systems seem to vary from province to province in Canada. Some efforts have been made by Transport Canada through research project so as to produce a national vehicle classification scheme including the number of vehicle types that are in operation on highway network throughout the country (Clayton, 2000). Through this research, they focused attention on building a national vehicle classification scheme that is quite capable of providing realistic estimates of related on-road traffic exposure levels and other estimators.

Clayton (2000) indicated in his research that most Canadian highways are built and managed under the authority of provincial, territorial, and municipal government. An effort to make national standard vehicle classification scheme has never been undertaken in road traffic monitoring. Major hindrance in completing this job can be found in the fact that the fleet characteristics vary significantly from jurisdiction to jurisdiction across the country due to differences in size and weight regulations, economic activity, physical environment, and other issues. Another possible reason is that a wide variety of vehicle classification schemes are separately built and operated by highway agencies and municipal authorities.

From consideration of a wide variety of vehicle classification systems used in traffic-monitoring program across Canada, three alternatives of vehicle classification schemes that have different classification levels are proposed in the context of Canadian highway network by giving due consideration to vehicle classes included in FHWA 13-classes shown in Figure 3.2 in Chapter 3. The first alternative is a scheme that just uses two basic vehicle classes: passenger vehicles (covering FHWA classes 1-4), and trucks (covering FHWA Classes 5-13). For development of traffic-based exposure estimates (AADT-average annual daily traffic), this scheme could be feasible for all jurisdictions on major highways. The second alternative is a scheme that could be feasible for most jurisdictions and major highways: passenger vehicles (covering FHWA Classes 1-4 inclusive), single unit trucks (covering FHWA Classes 5-7 inclusive), tractor-single trailer combinations (covering FHWA Classes 8-10 inclusive), and tractor-multiple trailer combinations (covering FHWA Classes 11-13 inclusive). The third one is just to use the FHWA 13 scheme.

Based on the literature (Clayton, 2000), the general practices with regard to vehicle classification systems that are applied in 7 of the 10 provincial highway agencies in Canada are summarized in Table 2.1. In addition, the key factors of those classification schemes and the second alternative classification scheme suggested in this research (i.e., the four class scheme) are compared in Table 2.2. Clayton (2000) concluded that the four class scheme would appear feasible in fitting individual systems for many jurisdictions to facilitate national level exposure-related estimates and analysis.

2.3 Effect of Weather on Highway and Traffic Conditions

The meteorological occurrences that cause weather conditions to degrade from the ideal weather conditions are called "weather events" (Colyar et al., 2003). The conditions that represent ideal weather conditions are: dry roadway, no precipitation, good visibility (greater than 0.4 kilometres), a wind speed of less than 15 km/hr, and non-extreme temperatures. The severity of a weather event is relative to the normal conditions in a local geographical area during a specified period (i.e., some areas experience reasonable weather conditions throughout the year and others experience harsh weather conditions during certain seasons). For example, the winter weather in Canada and many parts of the United States is frequently very severe, with high wind chills, heavy snowfall, blizzards, freezing rain, and extremely cold temperatures. Such weather events (either mild or severe) cause variations in highway traffic flow.

Table 2.1 Classification System of Selected Provinces in Canada (Clayton, 2000)

Provincial Jurisdiction	Practices
British Columbia	• British Columbia uses four vehicle classes in its classification scheme • Planning to operate 12 Automatic Vehicle Classifier (AVC) under the FHWA 13 classification scheme • Vehicle classification counts are conducted visually
Alberta	• Alberta uses a vehicle classification system consisting of five classes • Information on Vehicle kilometers traveled (VKT) by five classes vehicle are estimated and distributed for all sections of primary and secondary highway based on seasonal variations, summer (May 1 to September 30) and non-summer (by subtracting VKT from year round VKT)
Saskatchewan	• Vehicle classification data is produced in two sources • the basic traffic counting program collects classification data under the FHWA 13 classification scheme • the annual/bi-annual truck surveys that use two classification scheme, one works with 16 classes expanded out from the FHWA 13 classes, the other with 10 classes
Manitoba	• Manitoba uses the FHWA 13 classification scheme • Estimates of annual average daily truck traffic (AADTT) based on percent truck estimates calculated at various AVC and WIM sites • Conducting either visual observations of truck traffic in turning movement count (TMC) or other special surveys • AADTT estimates do not distinguish between truck classes
Ontario	• Ontario used a classification scheme of 3 vehicle classes • They produce only one traffic exposure measure, Annual average daily traffic (AADT) • Truck percentage estimated are available form 8-hour manual counts • The FHWA 13 classification scheme is occasionally used at certain permanent count/enforcement locations, in some surveys conducted for specific purposes
New Brunswick	• Classification system consists of four vehicle classes defined by vehicle length: 670 cm (passenger vehicle); 670-1460 cm (straight truck); 1460-2100 cm(tractor trailer); 2100 cm or greater (truck train) • Length-based descriptive vehicle classification systems is used
Prince Edward Island	• PEI uses FHWA 13 classification scheme • AADTT is estimated based on percent truck estimates of each control section • percent truck estimates are calculated for FHWA classes 4 through 13

Table 2.2 Comparison of Existing Vehicle Classification System Used in Some Provincial Traffic Monitoring Programs with a Simplified 4-Class System (Clayton, 2000)

<table>
<tr><th>Provincial Jurisdiction</th><th>Existing Vehicle Classification System for Exposure Data</th><th>Proposed Vehicle Classification System for Exposure Data</th></tr>
<tr><td rowspan="5">British Columbia</td><td>Passenger cars</td><td rowspan="2">Passenger vehicles</td></tr>
<tr><td rowspan="2">Pick-up trucks, vans, and other non-articulated single unit trucks</td></tr>
<tr><td>Single unit trucks</td></tr>
<tr><td>Short combination trucks (articulated trucks with 1 trailers)</td><td>Tractor-single trailer combinations</td></tr>
<tr><td>Long combination trucks (articulated trucks with 2 trailers)</td><td>Tractor-multiple trailer combinations</td></tr>
<tr><td rowspan="6">Alberta</td><td>Passenger cars</td><td rowspan="3">Passenger vehicles</td></tr>
<tr><td>Recreational vehicles</td></tr>
<tr><td>Buses</td></tr>
<tr><td>Single unit trucks</td><td>Single unit trucks</td></tr>
<tr><td rowspan="2">Tractor trailer combination trucks</td><td>Tractor-single trailer combinations</td></tr>
<tr><td>Tractor-multiple trailer combinations</td></tr>
<tr><td rowspan="13">Manitoba
Saskatchewan
Prince Edward Island</td><td>Cycles (FHWA Class 1)</td><td rowspan="4">Passenger vehicles</td></tr>
<tr><td>Cars (FHWA Class 2)</td></tr>
<tr><td>2A-4T (FHWA Class 3)</td></tr>
<tr><td>Buses (FHWA Class 4)</td></tr>
<tr><td>2A-SU (FHWA Class 5)</td><td rowspan="3">Single unit trucks</td></tr>
<tr><td>3A-SU (FHWA Class 6)</td></tr>
<tr><td>4A-SU (FHWA Class 7)</td></tr>
<tr><td>4A-ST (FHWA Class 8)</td><td rowspan="3">Tractor-single trailer combinations</td></tr>
<tr><td>5A-ST (FHWA Class 9)</td></tr>
<tr><td>6A-ST (FHWA Class 10)</td></tr>
<tr><td>5A-MT (FHWA Class 11)</td><td rowspan="3">Tractor-multiple trailer combinations</td></tr>
<tr><td>6A-MT (FHWA Class 12)</td></tr>
<tr><td>Other (FHWA Class 13)</td></tr>
<tr><td rowspan="4">Ontario</td><td>Cars</td><td>Passenger vehicles</td></tr>
<tr><td>Short trucks</td><td>Single unit trucks</td></tr>
<tr><td rowspan="2">Long trucks</td><td>Tractor-single trailer combinations</td></tr>
<tr><td>Tractor-multiple trailer combinations</td></tr>
<tr><td rowspan="4">New Brunswick</td><td>Passenger vehicle</td><td>Passenger vehicles</td></tr>
<tr><td>Straight truck</td><td>Single unit trucks</td></tr>
<tr><td>Tractor trailer</td><td>Tractor-single trailer combinations</td></tr>
<tr><td>Truck train</td><td>Tractor-multiple trailer combinations</td></tr>
</table>

For example, the acceleration and deceleration capabilities of vehicles can be affected by icy pavement conditions. Reduced visibility can affect driving speeds, lane changing behaviour and vehicle following patterns.

Aversion to extreme weather conditions can cause drivers to change their travel patterns by, for example, causing them to take a different route to a destination, delay the trip, or cancel it entirely (ITT Industries, 2003). Colyar et al. (2003) stated that weather events affect traffic operations through a chain reaction: at first, the weather event causes a change in the roadway environment (for example, poor visibility and wet pavement conditions) that causes a change in traffic parameters (for example, lower speeds and volumes) and degradation in traffic flow conditions (for example, higher delays and higher crash rates).

Goodwin (2002) categorized the impact of weather events on highway traffic into 3 groups: (1) driver behaviour, (2) roadway safety, and (3) roadway mobility. During adverse weather conditions (such as snowy and icy conditions) drivers increase headway, decrease acceleration rates, and reduce speeds. Weather conditions impact safety by increasing the frequency and severity of crashes. Weather conditions also affect mobility through increased congestion and travel delays, lower traffic volumes and vehicle speeds, increased speed variations, and reduced highway capacities. On arterial routes, adverse weather reduces the effectiveness of traffic signal timing plans. Table 2.3 lists the impact of different weather conditions on highway and traffic conditions.

Table 2.3 Impact of Different Weather Conditions on Highway and Traffic Conditions (Goodwin, 2002)

Weather Events	Highway Conditions	Traffic Conditions
Rain, Snow, Sleet, Hail & Flooding	• Reduced visibility • Reduced pavement friction • Lane obstruction & submersion • Reduced vehicle stability & manoeuvrability • Increased chemical and abrasive use for snow and ice control • Infrastructure damage	• Reduced roadway capacity • Reduced speeds & increased delay • Increased speed variability • Increased accident risk • Road/bridge restrictions & closures • Loss of communications/power services • Increased maintenance & operations costs
High Winds	• Reduced visibility due to blowing snow or dust • Lane obstruction due to windblown debris & drifting snow • Reduced vehicle stability & manoeuvrability	• Increased delay • Reduced traffic speeds • Road/bridge restrictions & closures
Fog, Smog, Smoke & Glare	• Reduced visibility	• Reduced speeds & increased delay • Increased speed variability • Increased accident risk • Road/bridge restrictions & closures
Extreme Temperatures & Lightning	• Increased wild fire risk • Infrastructure damage	• Traffic control device failure • Loss of communications & power services • Increased maintenance & operations costs

2.4 Association of Traffic Volumes with Weather Conditions

Past studies on the impact of weather on highway traffic flow conditions can be broadly categorized into two groups: (1) studies focusing on the impact of weather on traffic parameters such as volume, speed, and headway and (2) studies focusing on the impact of weather events on the quality of traffic flow (e.g. operating level of service, crash rates, traffic delays, start-up delays at intersections, and traffic congestion). This thesis focuses mainly on the impact of weather on highway traffic volumes. Therefore, a review of past studies on the association of traffic volumes with weather conditions is given in this section.

Hanbali and Kuemmel (1993) studied the traffic volume reductions due to winter storm conditions on highways away from the major urban centres in the United States. Traffic volume and weather data (such as storm period, temperature, and precipitation) collected at 11 locations during the first three months of 1991 were used for their study analysis. They analyzed the average traffic reductions for various combinations of highways (classified using average daily traffic) and snowstorms and the time of day and the day of the week. They found that a reduction in traffic movement occurs due to travelers' desire to avoid travel during wet or snowy weather. The amount of reduction depended on several factors, such as the type of highway, hour, day, normal traffic volume, level of service, road-user behaviour and satisfaction, and weather conditions. The reported traffic volume reductions on weekends were 19% to 31% for light snow and 56% for heavy snow; the corresponding weekday reductions were 7% to 17% and 53%, respectively. Their study showed higher off-peak hour reductions for both weekdays and weekends.

Hassan and Barker (1999) studied the impact of unseasonable/extreme weather on urban traffic activity within the Lothian region of Scotland. Data from thirteen locations over a period of 5 years from 1987 to 1991 were used in the analysis. The meteorological parameters considered in their study were: minimum and maximum temperatures, snow and rain fall, snow on the ground, and sunshine hours. The 10% of days with either the highest or lowest values for each meteorological variable were treated as extreme weather cases. They concluded that the traffic reductions were generally less than 5% under extreme weather, but this increased up to 10% to 15% reduction in traffic activity when snow was lying on the ground.

Knapp and Smithson (2000) did a similar analysis for the State of Iowa, United States. Their study was based on traffic and weather data from 7 sites located on interstate highways over a period of 3 years from 1995 to 1998. In their study, they included only those storm events that had recorded values (other than zero) for all of the observed weather parameters: active precipitation, air temperatures below freezing, wet pavement surfaces, pavement temperatures below freezing, and at least 4 hour durations with snowfall intensities higher than 0.51 cm/hr.

The results indicated that the impact of winter storms on traffic volume was highly varied and average reductions ranged from approximately 16% to 47% for different storm events. They also carried out a regression analysis to investigate the relationships between winter storm traffic reductions, total snowfall, the duration and intensity of snowfall, wind speed, and several other variable interactions. The results showed a statistically significant relationship between the volume reductions during winter storms, total snowfall, and the square of maximum gusting wind speed.

Maki (1999) evaluated the feasibility of implementing a coordinated traffic signal system that deals with traffic flow changes during adverse weather conditions. He defined snowstorms with three or more inches of snow as an adverse weather condition (as it results in difficult driving conditions). The study was based on five coordinated traffic signals along the 3-mile section of Highway 36 in the Minneapolis/St. Paul area. Traffic and weather data were collected during normal peak periods on January 28 and February 2, 1999. These volumes were compared with the traffic volumes during similar time periods on the days that experienced adverse weather conditions. Their study results showed that the volumes during the adverse weather conditions were 15% - 30% lower than volumes during the same time period on a normal day. He indicated that slower start-up times, slower speeds, and abnormal driver behaviour would result due to snow and icy conditions.

Perrin and Martin (2002) analyzed the traffic flow conditions at two intersections in Salt Lake Valley, Utah, during the winter seasons of the years 1999 and 2000. The main objective of their study was to evaluate the performance of a weather conditions based on signal coordination system during the days with bad weather. Their study included 30 hours of distorted traffic flow data collected during the days experiencing adverse weather conditions. For the study analysis, they classified the road weather conditions into 6 categories: dry, rain, wet and snowing, wet and slushy, wheel path slush, and snowy and sticking. By comparing the traffic flow rate during inclement weather conditions with the flow rates during normal days, they found traffic reductions of about 6% to 20% for different road weather condition categories.

Changnon (1996) studied the impact of variations in summer precipitation patterns on travel patterns in Chicago. His study was based on traffic volume data over a period of 3 years from 1996 to 1999 from the toll centres located on interstate highways in the Chicago area. The weather data to analyze the climate change and to carry out traffic weather relationships were obtained from rain gauges located within 20 kilometres of the toll centres. Using the matched-pair technique, he compared the traffic volume patterns during the days with and without rainfall. To analyze the potential effects of increased or decreased precipitation rates, the precipitation conditions were classified into normal, near normal, and below normal monthly conditions (based on the frequency and amount of rainfall). The study results showed that rain causes negligible variations in weekday traffic volumes, and the traffic volumes on rainy weekends were 9% lower than normal weekends. He pointed out that the possible reason for such a trend could be more discretionary trips during weekends.

Smith et al. (2004) studied the impact of rainfall on highway traffic flow. Their study was based on traffic and weather data during August 1999 to July 2000 from two sites located on freeway sections in the Hampton Roads region of Virginia. For the study analysis, they classified the rainfall conditions into 3 categories: none (< 0.25 mm), light rain (0.25 mm – 6.4 mm), and heavy rain (> 6.4 mm). They used a total of 12,280 15-minute speed/volume records to investigate no rain conditions, 860 records for light rain conditions, and 120 records for heavy rain conditions. Speed-flow plots were created for each station and for each rainfall category. They used the “Scheffe’s Test” to test the statistical significance of traffic volume variations due to each rainfall category. The reported reductions in maximum volumes (calculated during normal conditions) were about 4% to 10% for light rain and 25% to 30% for heavy rain.

Keay and Simmonds (2005) reported the association of rainfall and other weather variables with traffic volume on urban arterials in Melbourne, Australia. Their study was based on traffic volume data collected over 802 days (171 days in summer, 208 days in autumn, 264 days in winter and 159 days in spring) spread over a period from 1989 to 1996. The weather data (composed of rainfall, cloud amount, maximum and minimum temperatures, surface pressure, and wind speed) were obtained from the central Melbourne weather station. They designed regression models to relate daily traffic volumes with a time index, weekday/weekend, holidays, and weather variables. The reported reductions during wet days were 1.35% in the winter and 2.11 % in the spring. A maximum reduction of 3.43% was reported for a rainfall ranging from 2 mm to 5 mm in the spring. They also analyzed the percentage reductions due to rainfall in the daytime and at night for winter and spring. Their results showed traffic reductions of 1.86% in the winter and 2.16% in the spring during daytime rainfall. The reduction at night ranged from 0.87% in the winter to 2.91% in the spring. A maximum daytime reduction of 3.91% was observed for rainfall ranging from 5mm to 10mm in the winter.

Maze et al. (2006) studied the impact of adverse weather conditions on short-term traffic demand, traffic safety, and traffic flow relationships on Interstate Highway 35 in northern, rural Iowa. They showed a strong correlation between the percentage reduction in traffic volume and wind speed and visibility during snowy days. They reported traffic reductions of about 5% during rainstorms and about 20% during snowy days with good visibility and low wind speed. They further stated that traffic reductions could be as high as 80% when visibility is less than one-quarter mile and there is a high wind speed (as high as 64 kilometres per hour). Their study also showed that commercial vehicle traffic experiences little reduction during adverse weather conditions.

Several other studies (McBridge et al., 1977; Palitukof, 1981; Hall and Barrow, 1988; Andreay and Olley, 1990; Ibrahim and Hall 1994; Nixon, 1998; Shah et al., 2003; Zang et al., 2004) have also reported reductions in traffic volume levels and changes in traffic patterns during adverse weather conditions.

2.5 Traveler Behaviour during Adverse Weather Conditions

The previous section mainly discussed the impact of adverse weather conditions on traffic volumes without providing the details regarding travelers' decision-making behaviour before and during trips. In this section some studies that considered driver behaviour are reviewed.

Hanbali and Kuemmel (1993) indicated that the traveling characteristics of trip makers during adverse weather conditions depend on four factors: (1) the trip maker's willingness to travel, (2) the importance of the particular destination, (3) the difficulty of moving from the origin to the destination, and (4) other related factors. They indicated that a reduction in traffic movement occurs due to a traveler's desire to avoid travel during wet or snowy weather. Their study results further showed that a traveler's trip making decisions greatly depend severity of weather, the importance of the traveler's destination choice, and the traveler's willingness to travel.

Maki (1999) reported that the traveling characteristics of trip makers are highly dependent on the severity of weather conditions and their driving comfort in adverse weather conditions. He mentioned that the driver behaviour during adverse weather conditions varies from place to place. He pointed out that traffic volume reductions occur during adverse weather conditions due to trip adjustments such as leaving for work early, staying late before coming back, and an avoidance of unnecessary and discretionary trips.

Khattack et al. (1998) also reported that extreme and unusual weather conditions change departure times and destinations and cause significant travel mode shifts. Brodsky and Hakkert (1988) reported mode switching from either walking or public transport to private cars during wet conditions. A recent survey conducted by Markku and Heikki (2007) on driver behaviour during adverse weather conditions indicated that trip adjustments during these conditions could be associated with limited driving experience, increasing age, gender, and the length of the trip. According to their survey, discretionary trips would be underrepresented on highways during poor driving conditions due to the cancellation or postponement of trips.

2.6 Limitations of the Past Studies

Previous sections reviewed past studies on association of highway traffic volumes with weather conditions. All of those studies, except the study done by Keay and Simmonds (2005), reported average traffic volume reductions due to adverse weather conditions without detailed statistical analyses. Even though the recent study by Keay and Simmonds (2005) was statistically sound, the 159 to 264 days of data used to develop the traffic-weather relationships would not have covered different varieties of weather events. Moreover, a significant portion of their study data had imputed traffic volumes.

Data limitation was a major concern for other studies as well. For example, Hanbali and Kuemmel (1993) used traffic volume and weather data collected at 11 locations only during the first three months of the year 1991. The number of adverse weather events within that three-month period would not be enough to conclude the traffic weather relations. Even though Hassan and Barker's (1999) study was based on 5 years of data from 13 locations, their analysis included extreme weather events only.

Markku and Heikki's (2007) survey indicated that highway traffic volume variations during adverse weather conditions depend on the type of trips carried by the highway. It is known that travelers generally show less desire to travel during severe cold temperatures due to the increased risk associated with extreme cold in general (BG, 2007) and the increased necessity for precautionary measures (WSDOT, 2007) for safe journeys. A break down or a crash on highways during extremely cold temperatures could result in prolonged exposure to the cold, which can cause frostbite or hypothermia or is sometimes fatal due to a lack of help or failure of help to arrive in time.

Datla (2009) considered the type of trips variable by classifying study sites into the following road groups according to trip purpose and trip length characteristics of the driver population: (urban) commuter, regional commuter, (provincial) long distance, and recreational. This type of study site classification proved to be very effective in capturing the trip type variable in his investigation of the association of snowfall and very low temperatures with total highway traffic volumes. Nevertheless, Datla's study and other similar studies in the literature were conducted on the basis of total traffic volume data. None of the past studies investigated the impacts of severe winter weather on passenger car and truck trips separately.

Presented in the following section is a brief description of Datla's study.

2.7 Analyses of the Association of Highway Traffic with Winter Weather Conditions: A Case Study of Alberta Highways

In a previous Doctoral dissertation at the University of Regina, Datla (2009) studied the impact of cold and snow on traffic volume during winter months in Canada. He carried out a detailed investigation of total highway traffic volume variation with severity of cold, the amount of snow, and various combinations of cold and snow intensities. The study was conducted using hourly traffic data from 350 permanent traffic counter sites, and weather data from 598 weather stations located in the province of Alberta from 1995 to 2005. All the PTC sites were classified into different groups using average monthly factors (the ratio of monthly average daily traffic to annual average daily traffic). Then, the daily and hourly traffic variation patterns of highway segments belonging to each group were analyzed to identify the road types. Based on these observations and previous research by Sharma et al. (1986), the following four major road groups were identified: commuter (COM), regional commuter (RCOM), rural long distance (RLD), and recreational (REC) road groups. According to Sharma et al. (1986), the roads classified as commuter roads are predominantly used for work and business trips. Regional commuter roads serve work, business, and other regional trips. Inter-regional and long distance business trips make use of rural long distance roads. Recreational roads carry large portions of social, recreational, and other discretionary trips.

Figures 2.1 to 2.4 show typical monthly, daily, and hourly volume variations of the four highway types identified by Datla (2009).

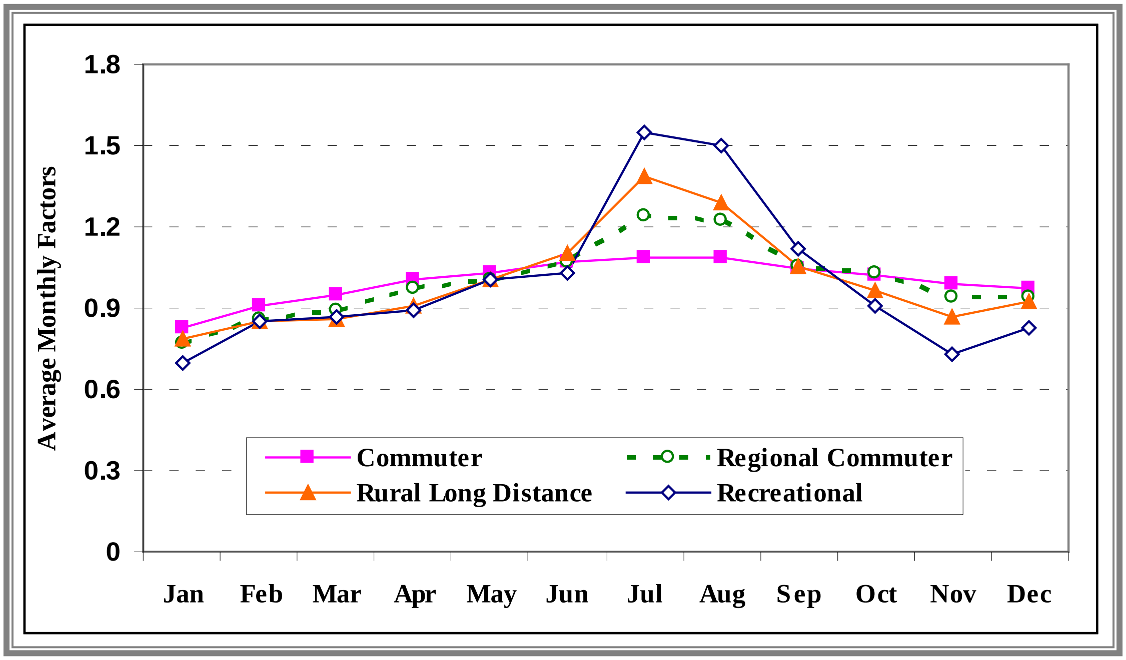


Figure 2.1 Monthly Traffic Volume Variations

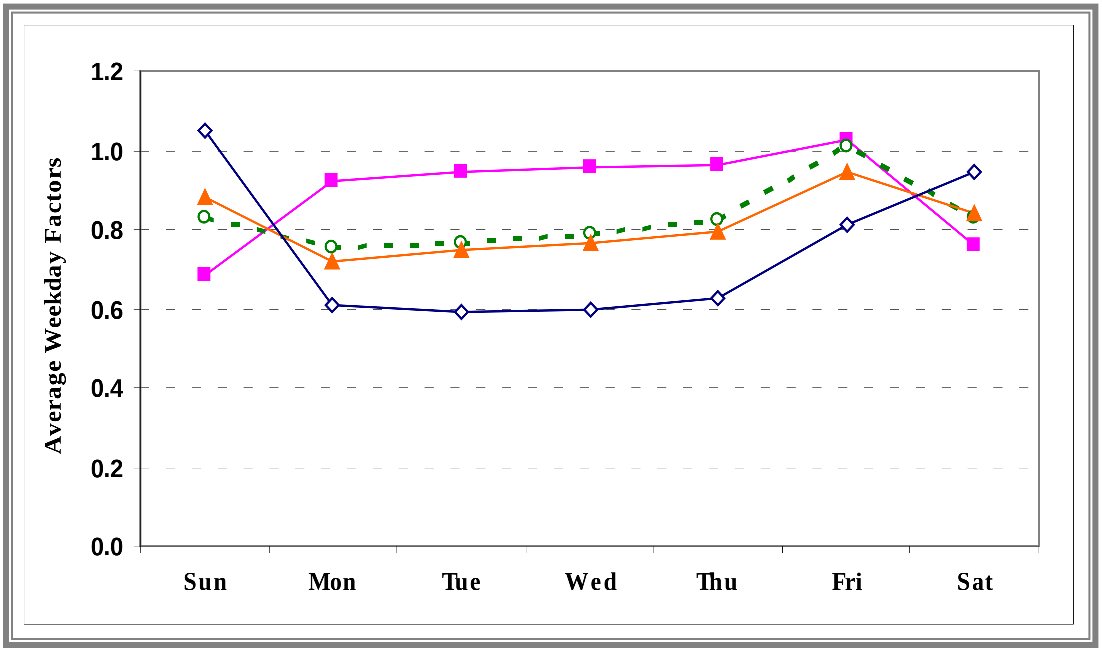


Figure 2.2 Average Winter Daily Traffic Volume Variations

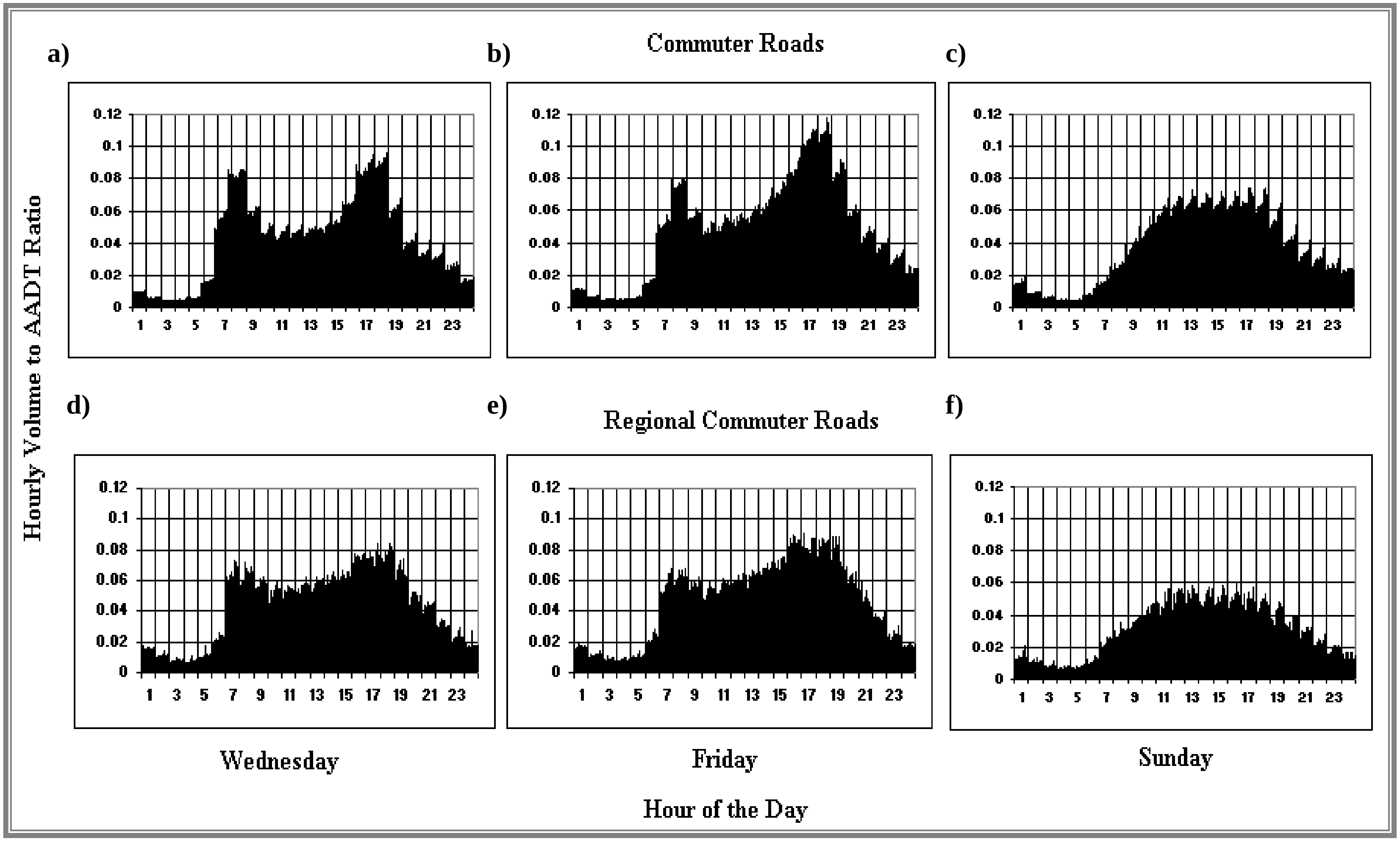


Figure 2.3 Hourly Traffic Volume Variations of Commuter and Regional Commuter Roads

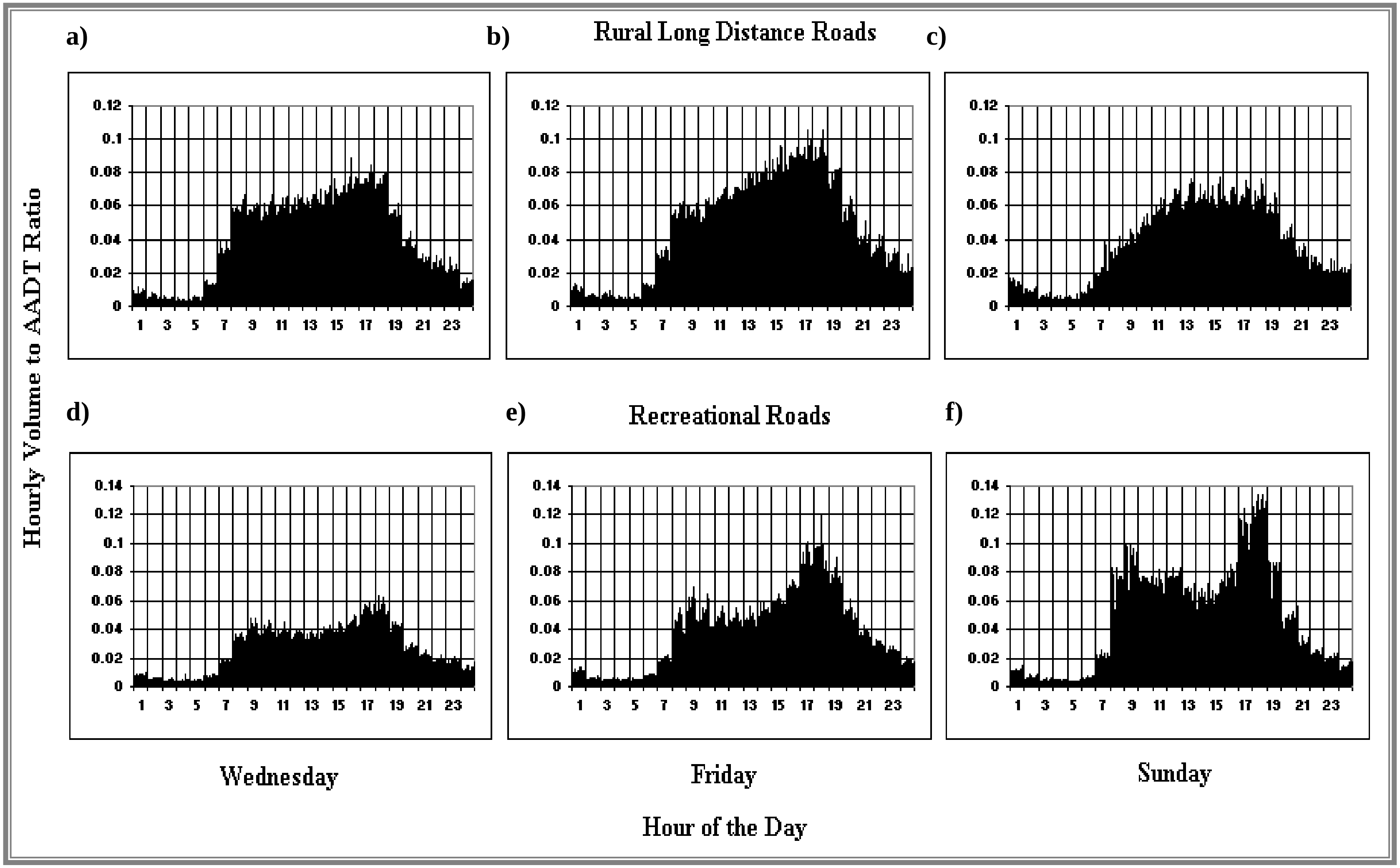


Figure 2.4 Hourly Traffic Volume Variations of Rural Long Distance and Recreational Roads

Datla (2009) developed separate daily and hourly models for four different day groups (DG), namely, Mondays-Thursdays combined, Fridays, Saturdays, and Sundays and for four different road types. The structure of the proposed model for daily traffic volume was:

$$\mathbf{V}F_{WDYCG} = B_a * EVF_{WDCG} + B_s * S_{WDYCG} + \sum_{R=1}^{R=6} B_R * C_{RWDYCG} \qquad \textbf{2.1}$$

Where: *W* represents the week number of the 13 winter weeks identified for the analysis, *D* indicates the day group (*M* for Monday to Thursday, *F* for Friday, *Sa* for Saturday, and *Su* for Sunday). *Y* represents the year (1995 to 2005), *C* is the PTC number, and *G* represents the road type to which the PTC site *C* belongs. VF_{WDYCG} is the daily Volume Factor (daily volume to AADT ratio) of a particular day group, *D,* in the week, *W,* of a year, *Y,* for the PTC site, *C,* belonging to the road type, *G.* For example: $VF_{3F96CRec}$ is the volume factor of the 3rd Friday in 1996 on the highway segment represented by a PTC site, *C,* that belongs to a recreational road type. EVF_{WDCG} (Expected Volume Factor) is the average VF_{WDYCG} calculated using all available years of data for a particular *WDCG.* For example: EVF_{3FCRec} is the average volume factor calculated from 16 years of data from 1995 to 2005 (i.e., $VF_{3F95CRec}$ to $VF_{3F05CRec}$) for the 3rd Friday on site *C*, which belongs to a recreational road type. S_{WDYCG} is the total snow on a *WDYCG* in centimetres. Both EVF_{WDCG} and S_{WDYCG} are taken as quantitative, independent variables in the model. The cold variable C_{RWDYCG} is treated as a dummy variable (Hardy, 1993) and an additional suffix, *R,* is added to this variable to represent the cold category. For the reasons mentioned earlier, temperature is categorized into 7 classes: above 0^{o}C, 0^{o}C to -5^{o}C, -5^{o}C to -10^{o}C, -10^{o}C to -15^{o}C, -15^{o}C to -20^{o}C, -20^{o}C to -25^{o}C, and below -25^{o}C.

The value of C_{RWDYCG} is 1 if the mean temperature of a *WDYCG* falls in class *R*, and it is *'0'* otherwise. For example, if the mean temperature of the day under study is -23^{o}C, it falls in class five, and the value of variable C_{5WDYCG} becomes *'1'*, while *'0'* will be assigned to the remaining classes of *R*. Any temperature above 0^{o}C is not included in the cold categorization because this category is taken as the reference class. B_{a}, B_{s}, and B_{R} are coefficients to be estimated using regression analysis. When an independent variable is continuous (such as EVF_{WDCG} and S_{WDYCG}), the distribution of the dependent variable, VF_{WDYCG}, is also continuous and the regression coefficients, B_{a} and B_{s}, indicate slope. In contrast, when an independent variable is a dummy variable (such as C_{RWDYCG}), the predicted value of VF_{WDYCG} changes by B_{R} units each time membership in the specified category, *R*, is switched on or off because a "unit" change in a dummy variable (from *'0'* to *'1'* or from *'1'* to *'0'*) indicates membership or non-membership in the designated category, *R*. Therefore, the coefficient B_{a}, in Equation 2.1 represents the deviation of VF_{WDYCG} from EVF_{WDCG}, when there is zero snow and the daily temperature falls in the reference class. Coefficient B_{s} gives the change in VF_{WDYCG} for each centimetre of change in the amount of total snowfall. B_{R} indicates the change in VF_{WDYCG} from the reference category (above 0^{o}C) to category *R*.

Some of Datla's study conclusions were:

1. The association of total highway traffic flow with cold and snow varies with day of week, hour of day, and severity of weather conditions. For the days with zero precipitation, reductions in total traffic volume due to mild and severe cold are 1% and 31%, respectively.

2. Total traffic volumes decrease with increase in the severity of cold temperatures. During extremely cold weather (below -25^{o}C), the average winter daily traffic volume could be reduced by about 30%.
3. Commuter and regional commuter roads experience the lowest variations in total volume with cold. The impact of cold is very high for recreational roads and moderate for rural long distance roads.
4. Weekend traffic volumes are more susceptible to cold than weekday numbers for all types of highways.
5. A clear reduction in daily traffic volume due to snowfall was also identified in this study. A reduction of 1% to 2% in total traffic volume for each centimeter of snowfall is observed when the mean temperature is above 0^{o}C. An additional reduction of 0.5% to 3% per centimeter of snowfall results when snowfall occurs during severe cold conditions. The reductions can be as high as 21% to 51% during snowstorms (a snowfall of 30 cm or above).

Datla (2009) used his total traffic-weather models for: (1) imputation of missing traffic data during winter months and (2) estimation of annual average daily traffic (AADT) from short-term traffic counts undertaken during winter months. The imputation efficiency of these models was superior when compared with the most efficient imputation methods used by highway agencies. He also proposed a new volume factor approach, incorporating weather conditions, to estimate AADT from short duration counts taken during winter months.

2.8 Chapter Summary

Datla (2009) and Datla and Sharma (2008) analyzed the impact of winter weather conditions on the reduction of traffic volume within temporal and spatial context. In addition, their study and other similar studies in the literature were conducted on the basis of total traffic volume data. None of the past studies has investigated the impacts of winter weather on temporal and spatial variations of truck traffic. Impact of weather on route choice behavior of truck and passenger car drivers has also not been addressed in the past. These findings suggest that it should be worthwhile to analyze the variation of classified traffic under the adverse winter weather conditions. In addition, none of the studies in the literature has presented the possibility of the increase in traffic volume on high standard highways during adverse weather conditions due to the diverted traffic from low standard highways. This study discovers and models such occurrences.

Chapter Three

Study Data

3.0 General

Vehicular traffic data is an important input for the design and maintenance of road infrastructure. Truck traffic, in particular, has been increasing significantly for the past five decades. As a result, highway planners continue to face challenges in designing and maintaining the pavement for accommodating the growth in truck traffic and their loading. With the use of weigh-in-motion (WIM) systems, the collection of traffic and weight data has become more efficient and effective. The WIM system collects vehicle axle load information, speed, lane of operation, date and time of vehicle passage, and the number and spacing of axles. In addition to the above, the average daily traffic (ADT) and the average daily truck traffic (ADTT) for a certain period of time, or the average annual daily traffic (AADT) and the average annual daily truck traffic (AADTT), can be calculated directly when a WIM system continuously counts and records all vehicles that pass through a WIM site. WIM data can also be used for forecasting two key traffic factors, i.e., the future truck volume and the corresponding axle load frequency distributions can be estimated by investigating the growth pattern of the observed truck volume and axle load frequency distributions obtained from the collected WIM data. In the context of the present study mainly two types of data set were used for study analyses:

Weigh in motion data and weather data. WIM data were obtained from the Alberta Transportation (AT). Environment Canada supplied weather data. A limited amount of PTC data from Alberta Transportation was also used in this thesis.

3.1 Weigh in Motion Traffic Data

Weigh in motion traffic data for this study were obtained from Alberta Transportation (AT), the agency responsible for provincial transportation in Alberta, Canada. There are six WIM sites operating on Alberta Transportation’s highway network. The locations of these six WIM sites are described in Table 3.1. For the ease of analysis and presentation, the WIM sites were named as shown in Table 3.1. These names were given on the basis of the adjacent city. The WIM sites were installed in July 2004 and have continuously been collecting vehicle classification and load data for programs such as Alberta's Strategic Highway Research and Long Term Pavement Performance Programs. Figure 3.1 shows location of these WIM sites along with nearby Environment Canada weather stations. The details about these WIM sites and weather stations are presented in Section 3.4.

The available WIM data spanning over a period of 5 years from 2005 to 2009 were used for this study. Table 3.2 shows the raw data format including 61 variable values for a particular vehicle. Table 3.3 shows the final version of the data format consisting of 30 variables for each vehicle chosen for the analysis. The data were extracted from the raw data and placed into the final input dataset for analysis purposes using Visual Basic (VB) program.

Table 3.1 WIM Site Location Details

Site No.	Highway	Lanes	Site name	Site description	Longitude	Latitude
1	Highway 2	4	Red Deer Hwy 2	2.6 KM N OF 2 & 42 PENHOLD	-113.81452	52.16497
2	Highway 2	4	Leduc Hwy 2	2.0 KM S OF 2 & 2A LEDUC	-113.56706	53.23707
3	Highway 2A	2	Leduc Hwy 2A	3.7 KM S OF 2 & 2A LEDUC	-113.52527	53.20646
4	Highway 3	4	Fort MacLeod Hwy 3	8.0 KM E OF FORT MACLEOD	-113.30000	49.75945
5	Highway 16	4	Edson Hwy 16	5.8 KM W OF 16 & 32 EDSON	-116.04534	53.57854
6	Highway 44	2	Villeneuve Hwy 44	3.4 KM S OF 633 & 44 VILLENEUVE	-113.81212	53.62818

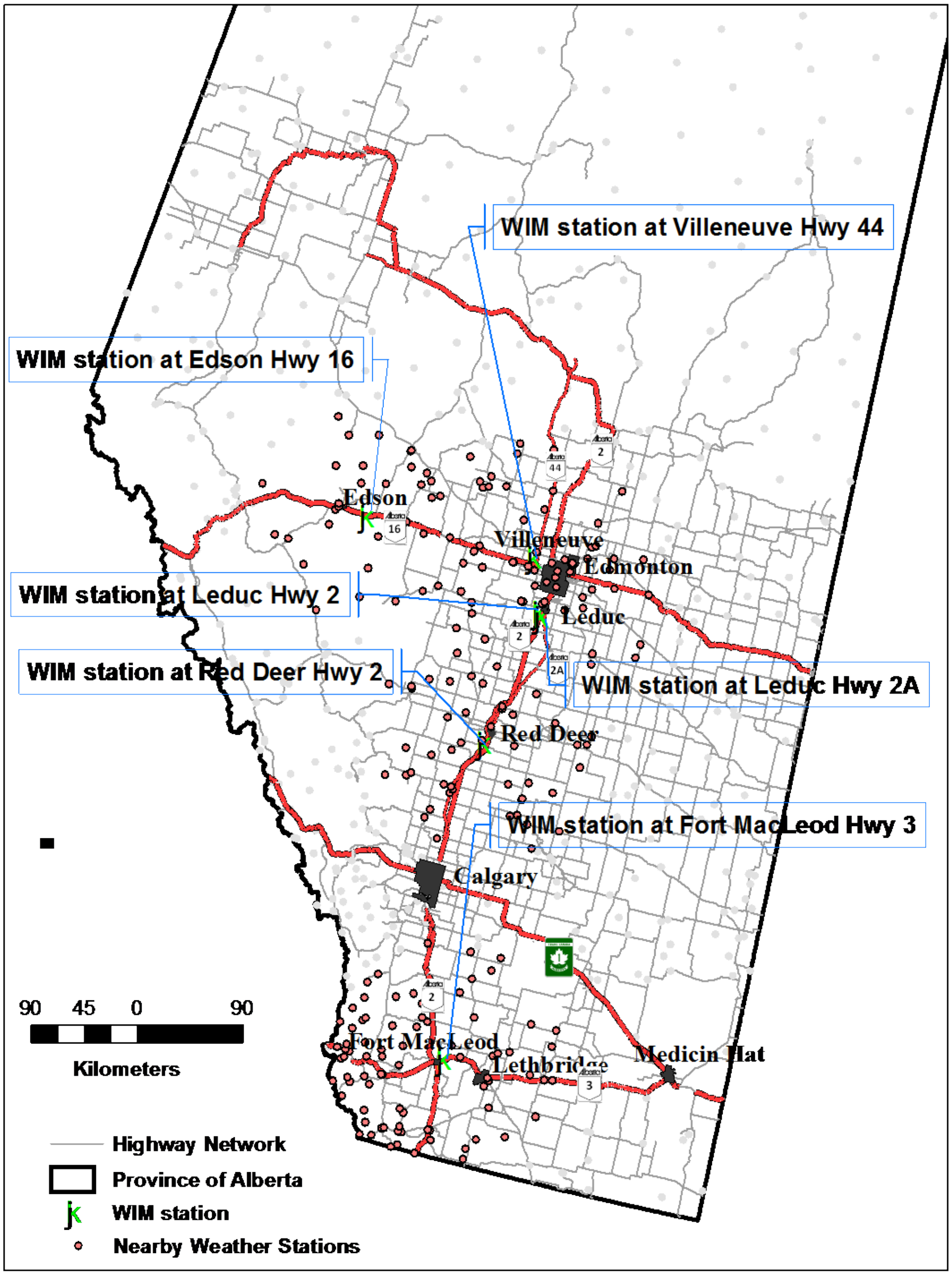


Figure 3.1 Thematic Map Showing Cities in Alberta, Study WIM site, Nearby Weather Stations, and Highway Network

Table 3.4 shows AADT values and the total number of vehicle records for all the six WIM sites from 2005 to 2009. The sum of last column over all the rows in the table contains a total of 154,133,231 (more than 154 millions) vehicular records that were finally used for the purpose of the investigation carried out in this thesis. It may also be noted that a code using VB was written to convert the 30-variable data format as shown in Table 3.3 to the vehicular records presented in Table 3.4. The 30-variable data format for 154,133,231 million vehicle records resulted in a matrix of size 154,133,231 $\times$ 30 to be processed in this study.

3.1.1 Development of Vehicle Classification Scheme 'F' for Study WIM Data

The development of an appropriate vehicle classification scheme is another important aspect of this study. Many highway agencies in North American states (or provinces) have developed their own classification schemes. Therefore, a comprehensive review of available literature on vehicle classification schemes was carried out to decide on a particular scheme to classify the vehicles for this study.

The vehicle classification system called "scheme F" (covering 13 vehicle classes) was developed in 1985 by the Maine Department of Transportation (Wyman et al., 1985) under a contract with FHWA office of Highway Planning. This classification scheme is a standard scheme adopted by many highway agencies in North America. Figure 3.2 shows the classification scheme for all those 13 different vehicle classes.

Table 3.2 Weigh in Motion Vehicular Record Data Format (scheme 1)

Field	Columns	Width	Description	Variable Used (VB)
1	1-2	2	MO (Month)	MO
2	4-5	2	DA (Day)	DA
3	7-8	2	YE (Year)	YE
4	10-11	2	HO (Hour)	HO
5	13-14	2	MI (Minute)	MI
6	16-17	2	SE (Second)	SE
7	19-20	2	A2 (NA)	A2
8	22-23	2	A1 (NA)	A1
9	25-26	2	A3 (NA)	A3
10	28-29	2	LN (Lane)	LN
11	31-34	4	VAL (NA)	VA
12	36-37	2	CA (NA)	CA
13	39-40	2	CA1 (NA)	CA1
14	42-49	8	GR81 (Config)	GR
15	51-58	8	PRVVH/ms	PR
16	60-63	4	SPEE (Speed, km/h)	SPD
17	65-70	6	LENG (Length, cm)	LEN
18	72-75	4	ESAL	ESAL
19	77-80	4	TODT (Wheelbase, cm)	TD
20	82-85	4	TWT3 (Total Weight, kg× 100)	TW
21	87-90	4	DTB1 (Front to Axle 1, cm)	D01
22	92-95	4	WT13 (Axle Weight 1, kg× 100)	W1
23	97-100	4	DT12 (Axle Spacing 12, cm)	D12
24	102-105	4	WT23 (Axle Weight 2, kg× 100)	W2
25	107-110	4	DT23 (Axle Spacing 23, cm)	D23
26	112-115	4	WT33 (Axle Weight 3, kg× 100)	W3
27	117-120	4	DT34 (Axle Spacing 34, cm)	D34
28	122-125	4	WT43 (Axle Weight 4, kg× 100)	W4
29	127-130	4	DT45 (Axle Spacing 45, cm)	D45
30	132-135	4	WT53 (Axle Weight 5, kg× 100)	W5
31	137-140	4	DT56 (Axle Spacing 56, cm)	D56
32	142-145	4	WT63 (Axle Weight 6, kg× 100)	W6
33	147-150	4	DT67 (Axle Spacing 67, cm)	D67
34	152-155	4	WT73 (Axle Weight 7, kg× 100)	W7
35	157-160	4	(Axle Spacing 78, cm)	D78
36	162-165	4	(Axle Weight 8, kg× 100)	W8
37	167-170	4	(Axle Spacing 89, cm)	D89
38	172-175	4	(Axle Weight 9, kg× 100)	W9
39	177-180	4	(Axle Spacing 910, cm)	D910
40	182-185	4	(Axle Weight 10, kg× 100)	W10
41	187-190	4	(Axle Spacing 1011, cm)	D1011
42	192-195	4	(Axle Weight 11, kg× 100)	W11
43	197-200	4	(Axle Spacing 1112, cm)	D1112
44	202-205	4	(Axle Weight 12, kg× 100)	W12
45	207-210	4	(Axle Spacing 1213, cm)	D1213
46	212-215	4	(Axle Weight 13, kg× 100)	W13
47	217-220	4	(Axle Spacing 1314, cm)	D1314
48	222-225	4	(Axle Weight 14, kg× 100)	W14
49	227-230	4	(Axle Spacing 1415, cm)	D1415
50	232-235	4	(Axle Weight 15, kg× 100)	W15
51	237-240	4	(Axle Spacing 1516, cm)	D1516
52	242-245	4	(Axle Weight 16, kg× 100)	W16
53	247-250	4	(Axle Spacing 1617, cm)	D1617
54	252-255	4	(Axle Weight 17, kg× 100)	W17
55	257-260	4	(Axle Spacing 1718, cm)	D1718
56	262-265	4	(Axle Weight 18, kg× 100)	W18
57	267-270	4	(Axle Spacing 1819, cm)	D1819
58	272-275	4	(Axle Weight 19, kg× 100)	W19
59	277-280	4	(Axle Spacing 1920, cm)	D1920
60	282-285	4	(Axle Weight 20, kg× 100)	W20
61	287-290	4	(Axle Spacing 2021, cm)	D2021

Table 3.3 Final Data Format of Vehicular Record for Analysis (scheme 2)

Field	Columns	Width	Description	Variable Used (VB)
1 (1)	1-2	2	MO (Month)	MO
2 (2)	4-5	2	DA (Day)	DA
3 (3)	7-8	2	YE (Year)	YE
4 (4)	10-11	2	HO (Hour)	HO
5 (5)	13-14	2	MI (Minute)	MI
6 (6)	16-17	2	SE (Second)	SE
10 (7)	28-29	2	LN (Lane)	LN
16 (8)	60-63	4	SPEE (Speed, km/h)	SPD
17 (9)	65-70	6	LENG (Length, cm)	LEN
18 (10)	72-75	4	ESAL	ESAL
19 (11)	77-80	4	TODT (Wheelbase, cm)	TD
20 (12)	82-85	4	TWT3 (Total Weight, kg× 100)	TW
21 (13)	87-90	4	DTB1 (Front to Axle 1, cm)	D01
22 (14)	92-95	4	WT13 (Axle Weight 1, kg× 100)	W1
23 (15)	97-100	4	DT12 (Axle Spacing 12, cm)	D12
24 (16)	102-105	4	WT23 (Axle Weight 2, kg× 100)	W2
25 (17)	107-110	4	DT23 (Axle Spacing 23, cm)	D23
26 (18)	112-115	4	WT33 (Axle Weight 3, kg× 100)	W3
27 (19)	117-120	4	DT34 (Axle Spacing 34, cm)	D34
28 (20)	122-125	4	WT43 (Axle Weight 4, kg× 100)	W4
29 (21)	127-130	4	DT45 (Axle Spacing 45, cm)	D45
30 (22)	132-135	4	WT53 (Axle Weight 5, kg× 100)	W5
31 (23)	137-140	4	DT56 (Axle Spacing 56, cm)	D56
32 (24)	142-145	4	WT63 (Axle Weight 6, kg× 100)	W6
33 (25)	147-150	4	DT67 (Axle Spacing 67, cm)	D67
34 (26)	152-155	4	WT73 (Axle Weight 7, kg× 100)	W7
35 (27)	157-160	4	(Axle Spacing 78, cm)	D78
36 (28)	162-165	4	(Axle Weight 8, kg× 100)	W8
37 (29)	167-170	4	(Axle Spacing 89, cm)	D89
38 (30)	172-175	4	(Axle Weight 9, kg× 100)	W9

Table 3.4 Summary of Vehicle Records for WIM Sites

WIM Site	Year	AADT	Number of Vehicle Records
Red Deer Hwy 2	2005	30,480	11,125,215
	2006	29,780	10,869,702
	2007	33,365	12,178,089
	2008	31,165	11,406,341
	2009	31,509	11,500,838
		Sub total	57,080,185
Leduc Hwy 2	2005	22,563	8,235,622
	2006	24,170	8,822,202
	2007	25,111	9,165,378
	2008	24,270	8,882,797
	2009	25,426	9,280,645
		Sub total	44,386,644
Leduc Hwy 2A	2005	7,195	2,626,346
	2006	7,438	2,714,938
	2007	7,843	2,862,641
	2008	7,761	2,840,488
	2009	7,569	2,762,598
		Sub total	13,807,011
Fort MacLeod Hwy 3	2005	6,601	2,409,434
	2006	7,369	2,689,743
	2007	7,466	2,725,015
	2008	6,587	2,411,010
	2009	7,124	2,600,201
		Sub total	12,835,403
Edson Hwy 16	2005	7,290	2,660,754
	2006	7,763	2,833,664
	2007	7,481	2,730,397
	2008	7,192	2,632,349
	2009	6,832	2,493,660
		Sub total	13,350,824
Villeneuve Hwy 44	2005	6,614	2,414,263
	2006	7,044	2,571,089
	2007	7,606	2,776,120
	2008	6,729	2,462,839
	2009	6,709	2,448,853
		Sub total	12,673,164
	Total Records		154,133,231

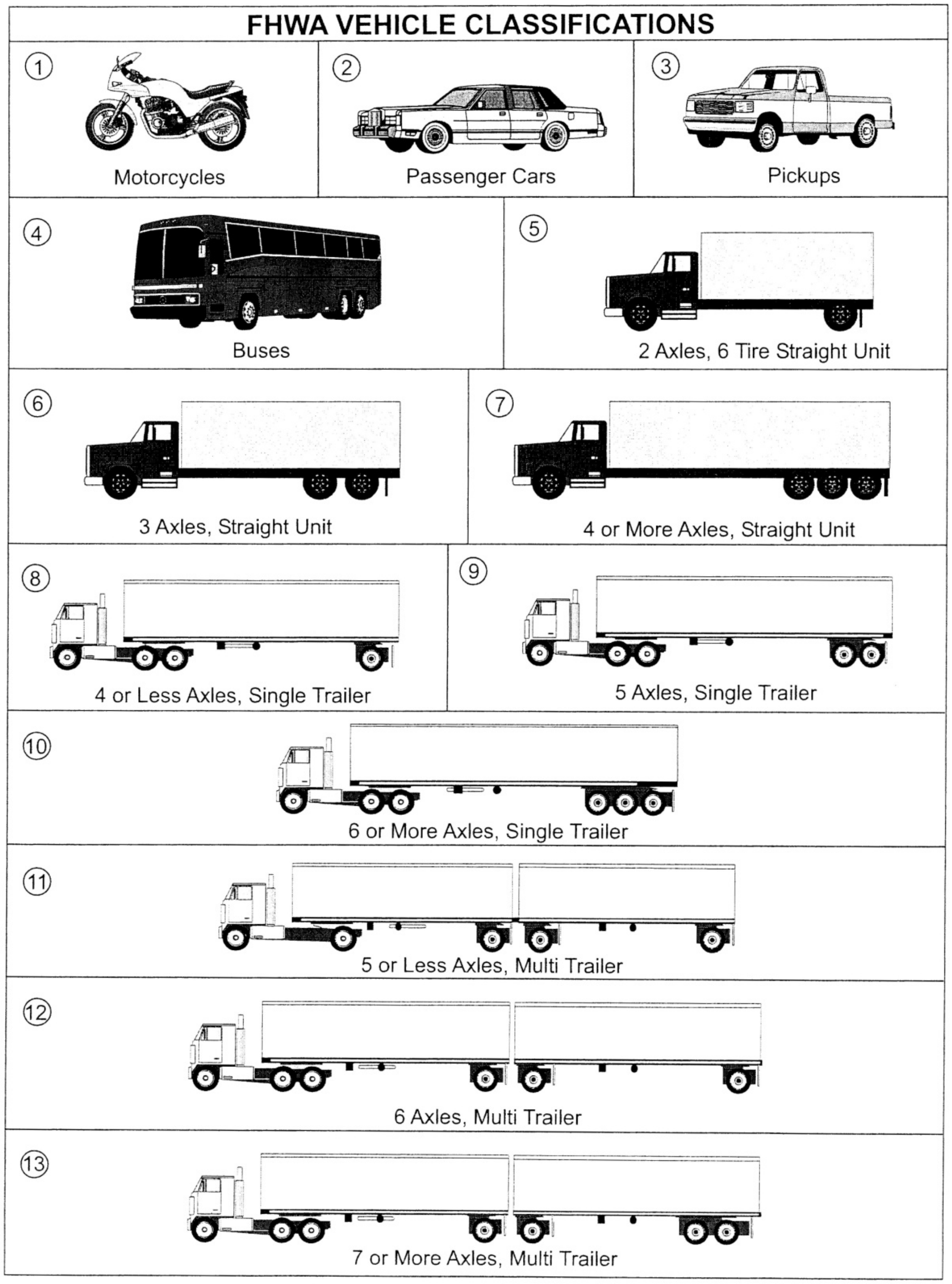


Figure 3.2 FHWA 13-Category Scheme (Anderson, 2002)

The scheme F has been used widely by many highway agencies since it was developed. It can be used to develop a variety of variations of classification schemes by researchers and practicing engineers. Therefore, the FHWA classification scheme ‘F’ was adopted in the present study to classify the vehicles which resulted in 13 vehicle classes. Figure 3.3 shows the scheme ‘F’ in a flow chart format which was used in the present study to convert the 30-variable data format (Table 3.3) into 13 vehicle classes for all the study WIM sites.

However, due to lower number of total trucks in general (ranging from 8% to 32% of total traffic volume for the Alberta WIM sites), and too many truck classes, sample data could not generate sufficient samples to carry out detailed statistical analyses by each vehicle class in this study. Therefore, the 13 vehicle classes were further aggregated into four major categories, i.e. passenger cars and 3 truck type classes, namely single unit trucks, single trailer and multi trailer units. More information on vehicle classes and truck type distribution at various study WIM sites is provided in the following chapters.

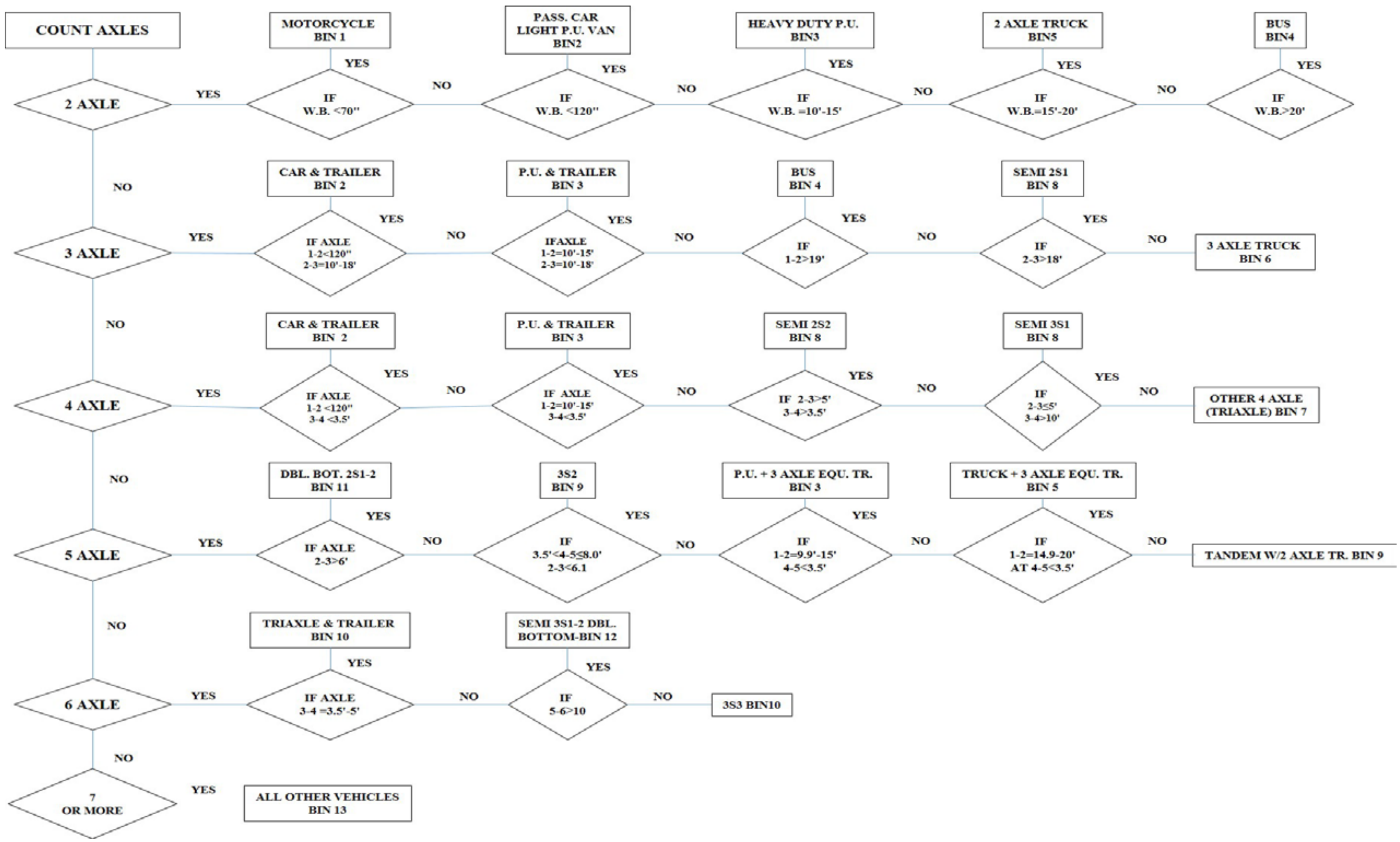


Figure 3.3 Vehicle Classification Scheme "F" Flow Chart (Wyman et al., 1985)

3.2 Weather Data

The weather data used in this study were extracted from Environment Canada's National Climate Data and Information Archive (WO, 2010). Environment Canada collects climatology data from nearly 8,000 weather stations (including many intermittent ones) across the country. Each of these weather stations provide detailed meteorological parameters such as maximum, minimum, and mean temperature (measured in degrees centigrade (°C)), total rain fall (millimetres), total snow fall (centimetres), total precipitation (millimetres) and snow on ground (centimetres) on a daily basis. Details of raw data format and measuring methods for each of these weather parameters are available on Environment Canada's website (WO, 2010). There were about 600 weather stations operated by Environment Canada in the province of Alberta between 2005 and 2009. However, six weather stations were chosen near the WIM study sites. These weather stations are shown in the Figure 3.4. The details about why the six weather sites were selected are discussed in Section 3.4.

3.3 Climatic Conditions of Alberta near Study Sites

Alberta is one of the sunniest and comparatively drier provinces in Canada. The winter weather in the province varies from severe conditions in southern Alberta to extremely severe conditions in northern Alberta. Figure 3.5 gives a general idea of the climatic conditions of Alberta. The figure shows historical average monthly climatic conditions for the City of Edmonton, which represents the central Alberta, serves as a good example of the range of weather across the province. Moreover, three of the study WIM sites, namely Leduc Highway 2, Leduc Highway 2A, and Villeneuve Highway 44 are located near the City of Edmonton.

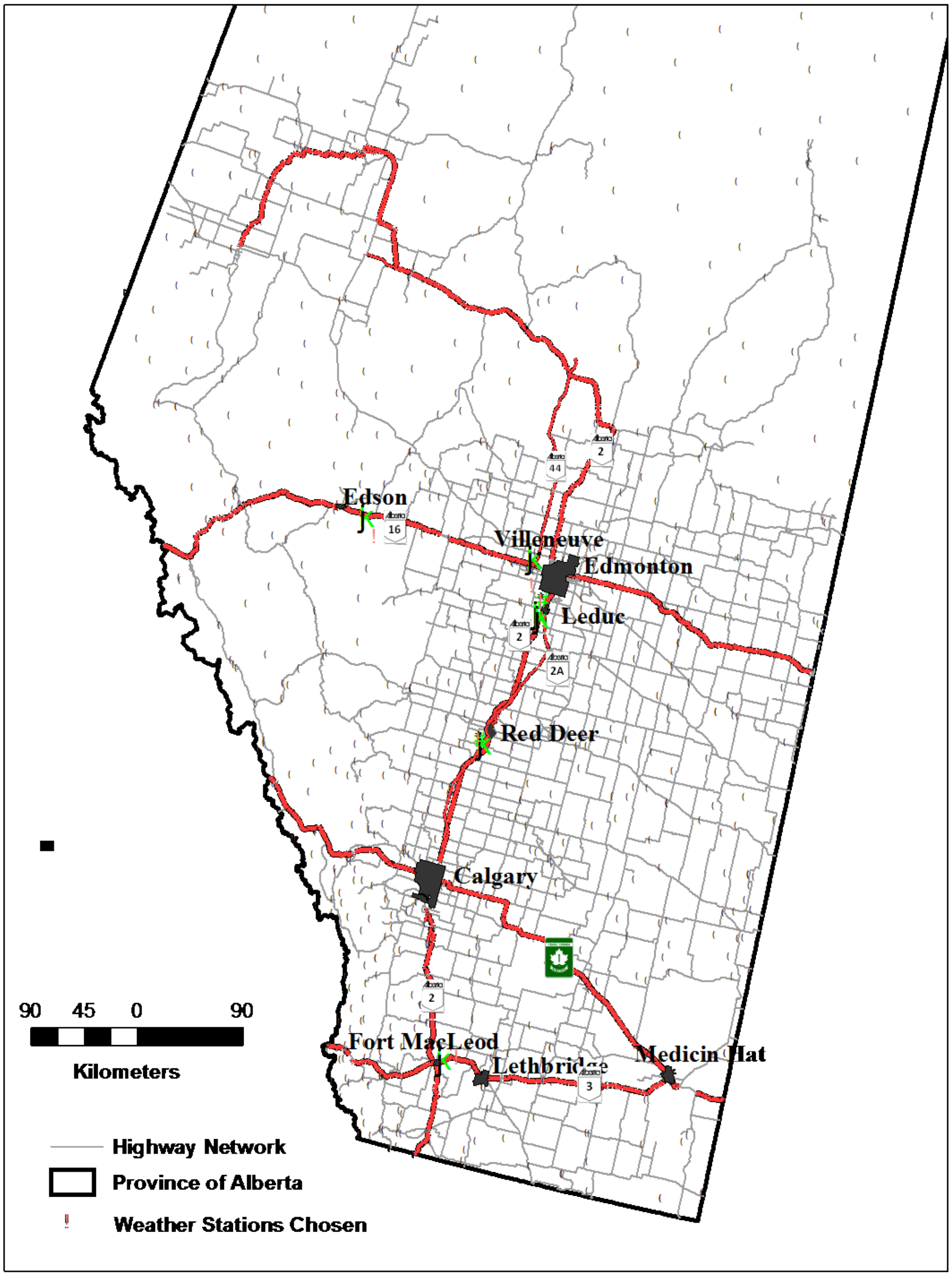


Figure 3.4 Thematic Map Showing Cities in Alberta, Weather Stations Chosen for Study WIM Sites, and Highway Network.

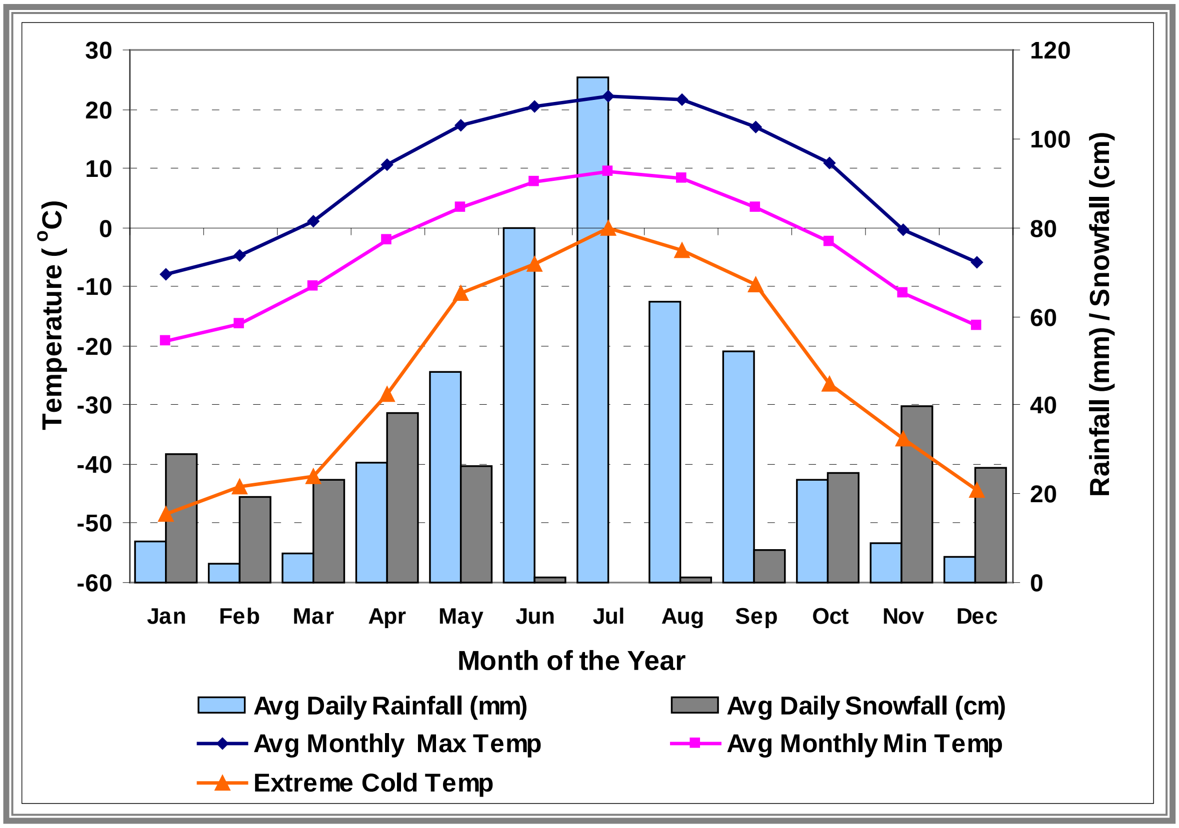


Figure 3.5 Historical Average Monthly Climatic Conditions in the City of Edmonton (Datla, 2009)

The historical average monthly minimum temperature, maximum temperature, and lowest recorded temperatures in the past 3 decades for each month are shown in Figure 3.5. The extreme daily snowfall and rainfall cases in the past 3 decades for each month are also shown using the secondary y-axis. It is clear from Figure 3.5 that the winter weather in Alberta is very severe with extremely cold temperatures and heavy snowfall. The temperatures may occasionally go below -40^{o}C, and in extreme cases, a total snowfall of 40 cm might occur in a single day.

3.4 Site Selection for Weather Stations and WIM Systems

An important task involved in this study was to identify the weather stations from which snowfall and temperature data could be used to represent weather conditions at the WIM sites. The process of selecting weather stations to represent weather conditions at a study WIM site constituted two-step algorithms. In the first step all the nearby weather stations to all WIM sites were located. However, an important issue was that how far we could go from the WIM stations to locate the weather stations assuming that the weather conditions would be considered homogeneous up to that distance. To address this issue and to understand the common practice of locating weather stations around WIM or PTC sites, a literature review was carried out and the following inference was drawn from the literature review.

Past studies by Andrey and Olley (1990), Datla (2009) and Datla and Sharma (2008, 2010) provide considerable insight into the approximate distance within which weather conditions could be considered similar. Datla (2009) carried out an investigation of temperature correlation coefficient as a function of inter-station distances for Alberta weather conditions. He found that the spatial variation of temperatures was not very large. His conclusion was that the weather stations located even at distances up to 24 km from PTC traffic count locations (WIM sites in this study) can provide accurate information about the temperature conditions at the traffic count sites. However, he also found that there was a considerable variation in snowfall conditions as a function of the distance from one location to another. The inter-station correlation coefficients for snowfall were relatively consistent only at shorter distances of up to 4 km, and much wider variations in the coefficients were noted for distances longer than 16 km.

In this study a Geographical Information Systems (GIS) base map with weather stations in Alberta, and 6 WIM sites was developed. Based on the above observations about the spatial variations in temperature and snowfall conditions in Alberta, the weather stations were identified using the proximity analysis module provided by GIS software ArcGIS 10 (2010). Table 3.5 shows the details of the weather stations in the neighborhood of the 6 WIM sites.

In the second step, the adequacy and completeness of the traffic data at the WIM sites and the weather data at the potential weather stations within the 24 km radius of the WIM sites was checked carefully. All the WIM sites had nearly 100 percent daily vehicular data available throughout the five year study period. However, considerable amount of missing weather data were found in the case of several weather stations near the study WIM sites that were identified in Table 3.5.

The adequacy of the weather data at a specific weather station was checked in terms of the number of days with missing weather data during the 1,826 days of the study period, and during 510 winter days from November to March every year between 2005 and 2009. Table 3.6 shows the missing weather data for the weather stations near the 6 WIM sites.

According to the above table, the weather stations (3025480 and 3012205) corresponding to the WIM sites of Red Deer Highway 2, Leduc Highway 2, and Leduc Highway 2A had nearly complete record of weather data. The weather stations corresponding to the other three WIM sites had many days of missing data. For this reason, these WIM sites, namely Fort MacLeod Highway 3, Edson Highway 16, and Villeneuve Highway 44 were not included in some of analyses carried out in the following chapters of this thesis. Figure 3.6 shows the location of study WIM sites and weather stations.

Table 3.5 Weather Stations nearby WIM Sites

Site No.	Site name	Site description	Weather stations (16_km)	Weather stations (16 km to 24_km)
1	Red Deer Hwy 2	2.6 KM N OF 2 & 42 PENHOLD	3025480, 3025441	3024210, 3025k22
2	Leduc Hwy 2	2.0 KM S OF 2 & 2A LEDUC	3012206, 3012205	3011138, 3011120, 3015550
3	Leduc Hwy 2A	3.7 KM S OF 2 & 2A LEDUC	3012206, 3012205	3011120, 3015550
4	Fort MacLeod Hwy 3	8.0 KM E OF FORT MACLEOD	30326QF, 3034596	
5	Edson Hwy 16	5.8 KM W OF 16 & 32 EDSON		3061360
6	Villeneuve Hwy 44	3.4 KM S OF 633 & 44 VILLENEUVE	3016083, 3017606, 3015670, 3012228	301222F, 301A001, 3012230 , 3012234, 301FFNJ, 3012208, 3012210

Table 3.6 WIM Sites and Weather Stations for Analysis

Site No.	Site name	Weather station ID	Weather station Name	Distance from WIM (Km)	Weather data Error (1,826 days)	Winter days Error (510 days)
1	Red Deer Hwy 2	3025480	Red Deer A	7.08	1days	0
2	Leduc Hwy 2	3012205	Edmonton Int'l A Alberta	8.98	0	0
3	Leduc Hwy 2A	3012205	Edmonton Int'l A Alberta	13.32	0	0
4	Fort MacLeod Hwy 3	3034596	Monarch	13.34	143 days	100 days
5	Edson Hwy 16	3061360	Carrot Creek LO	21.48	1430 days	-
6	Villeneuve Hwy 44	3012230	Edmonton Woodbend	24.19	60 days	25 days

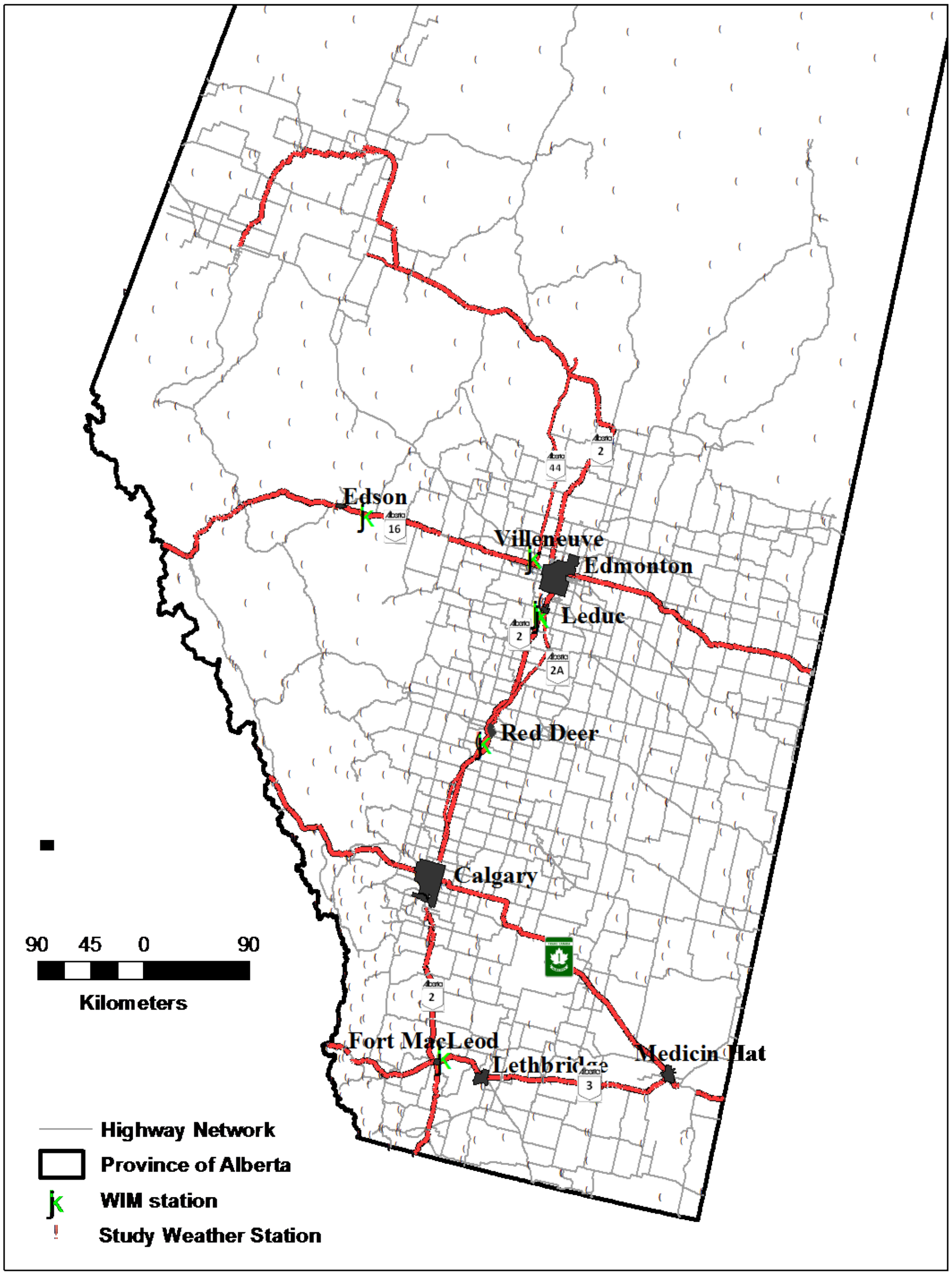


Figure 3.6 Thematic Map Showing Cities in Alberta, Study WIM site, Study Weather Station, and Highway Network

Chapter Four

Preliminary Analysis of Study Data

4. 0 General

Traffic volume on highways varies with time and space. Variation with time occurs with respect to hour, day, and month of the year. Traffic volumes also vary spatially with highway type and location. These variations need to be well comprehended for a good understanding of the nature of travel and transport demand on the roads where the WIM sites are located. It is only after examining such temporal variations that the study results can be interpreted and appropriate models of weather impacts on highway traffic volume can be developed. This chapter presents hourly, daily and monthly traffic variations for all the six WIM sites under investigation. Also included in this chapter are some descriptions of the variations in passenger car and truck traffic with temperature and snow fall.

4.1 Temporal Patterns of Total Traffic Volume and Classification of WIM Sites

The main objective of this section is to identify the road use characteristics at the WIM sites through the visual presentations of temporal variations of traffic patterns for total traffic volume of the two vehicle classes, i.e., trucks and passenger cars.

Table 4.1 provides details of various study sites in terms of AADT (annual average daily traffic), PAADT (passenger cars annual average daily traffic), TAADT (truck annual average daily traffic), and percent trucks in the traffic.

The present investigation is based on traffic data over a span of 5 years (2005-2009). The normalized traffic volumes (volume to AADT ratios) and total traffic volumes (number of vehicles) are used in the analysis. Normalized traffic volumes are called "traffic volume factors" henceforth in this thesis. The traffic volume factors have been calculated using the following Equations: 4.1 to 4.4. Highway agencies usually use these equations to estimate AADT from short-duration sample counts (Datla, 2009).

$$Estimated\ AADT = Short \quad duration\ traffic\ count \times HF \times DF \times MF \tag{4.1}$$

$$HF = \frac{average\ volume\ for\ 24\ hour\ period}{average\ volume\ for\ particular\ duration\ of\ count} \tag{4.2}$$

$$DF = \frac{average\ total\ volume\ for\ week \div 7}{average\ volume\ for\ particular\ day} \tag{4.3}$$

$$MF = \frac{total\ yearly\ volume \div 12}{total\ volume\ for\ particular\ month} \tag{4.4}$$

Where, HF, DF, and MF are hourly, daily, and monthly adjustment factors (AF), respectively developed from permanent traffic count data.

Table 4.1 Traffic Composition for Each WIM Sites

Site No.	Highway	Lanes	Site name	AADT	PAADT	TAADT	Passenger Cars (%)	Trucks (%)
1	Highway 2	4	Red Deer Hwy 2	32,252	27,276	4,976	84	16
2	Highway 2	4	Leduc Hwy 2	24,506	20,543	3,964	83	17
3	Highway 2A	2	Leduc Hwy 2A	7,562	6,969	592	92	8
4	Highway 3	4	Fort MacLeod Hwy 3	7,194	6,118	1,075	85	15
5	Highway 16	4	Edson Hwy 16	7,484	5,126	2,358	68	32
6	Highway 44	2	Villeneuve Hwy 44	6,986	4,942	2,044	73	27

Sharma et al. (1986) developed a method to classify roads according to type of road uses. Their method is based on the basic assumption that the differences in traffic flow patterns at road sites result from the different mixes of trip characteristics of road users. Hourly, daily, and monthly traffic volume factors at the study WIM sites were calculated using the study data from the five years between 2005 and 2009. The method suggested by Sharma et al. (1986) was then applied to the resulting traffic patterns (as shown in Figures 4.1 to 4.6) to classify WIM sites in to various groups according to type of road uses, as described in the following.

4.1.1 WIM Site on Regional Commuter Routes

The WIM site located on Highway 2A near Leduc was classified as a regional commuter site. Its hourly, daily and monthly patterns are shown in Figure 4.1. Morning and afternoon commuter peaks are clearly visible in the hourly patterns of this site. It is located in the Greater Edmonton Region and serves predominantly work-business trips; this group of roads also mainly serves shopping, and social recreational trips. In general, such roads have lower weekend volume factors than the weekday factors for the total traffic and experience low seasonal variation of total traffic volume.

4.1.2 WIM Sites on Interregional Long Distance Routes

Other WIM sites, namely Leduc Highway 2, Red Dear Highway 2, Edson Highway 16, and Fort McLeod Highway 3 are located on Albeta's primary highways which carry a mix of regional and provincial/interprovincial long distance trips. They are referred to as interregional long distance or simply long distance roads in this study. The morning and afternoon traffic volume peaks are not as clear on these sites as the case of regional commuter routes (refer Figures 4.2 to 4.5).

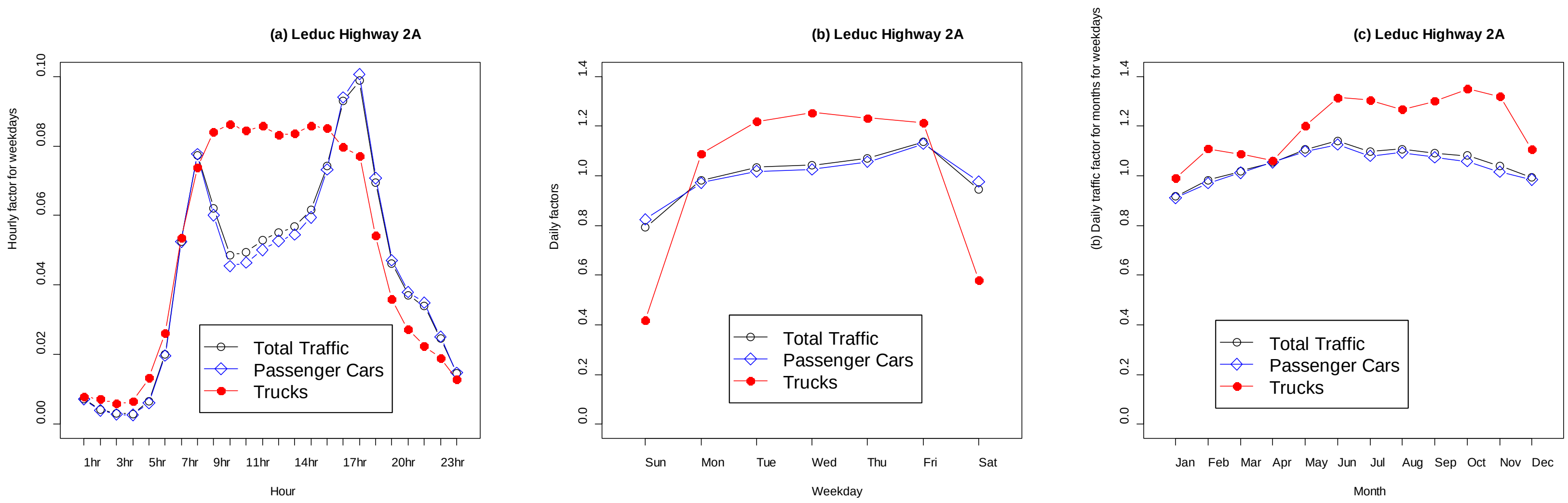


Figure 4.1 Typical Hourly, Daily, and Monthly Variations of Total, Passenger Cars and Truck Traffic for Traffic Factors for Highway 2A

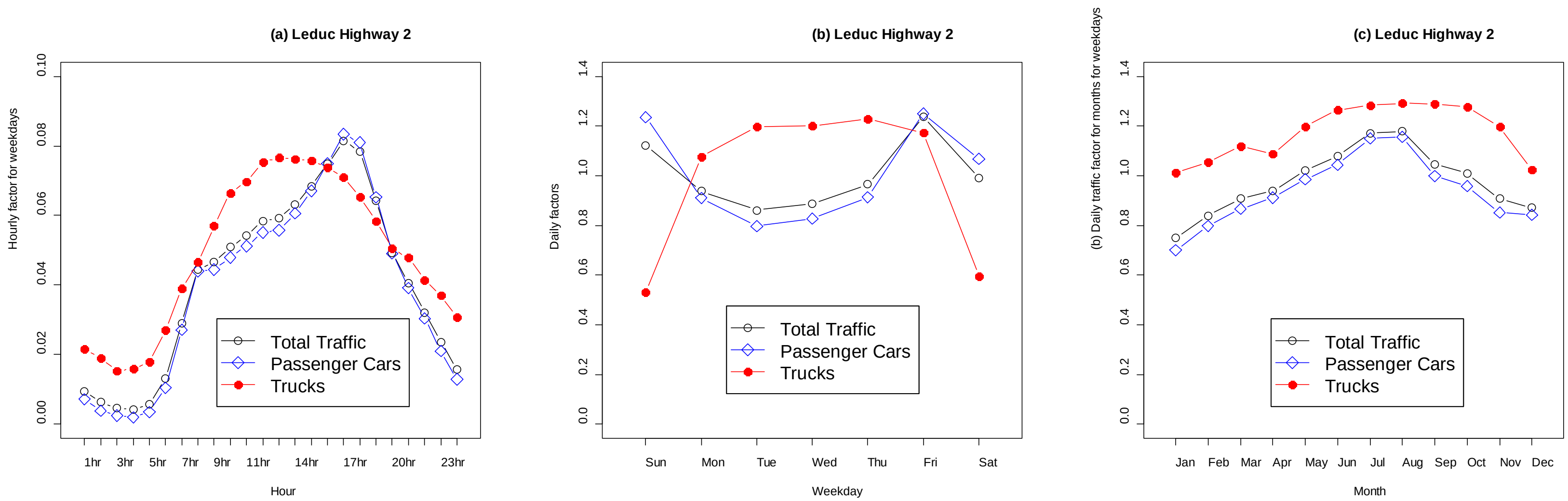


Figure 4.2 Typical Hourly, Daily, and Monthly Variations of Total, Passenger Cars and Truck Traffic for Traffic Factors for Highway 2 (Leduc)

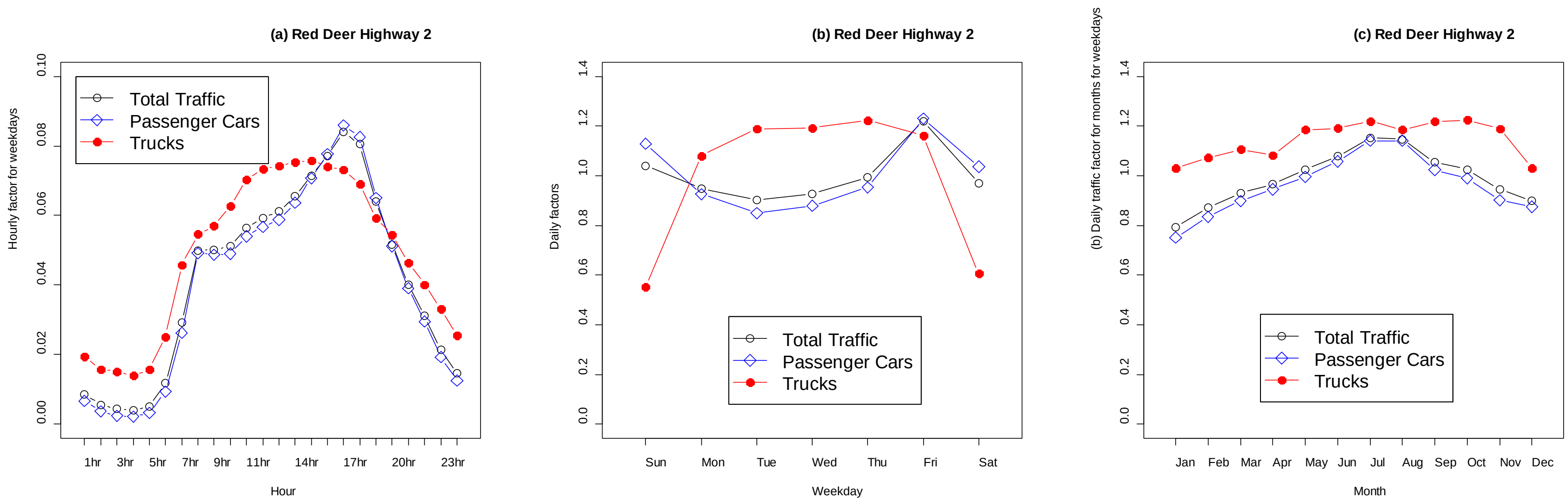


Figure 4.3 Typical Hourly, Daily, and Monthly Variations of Total, Passenger Cars and Truck Traffic for Traffic Factors for Highway 2 (Red Deer)

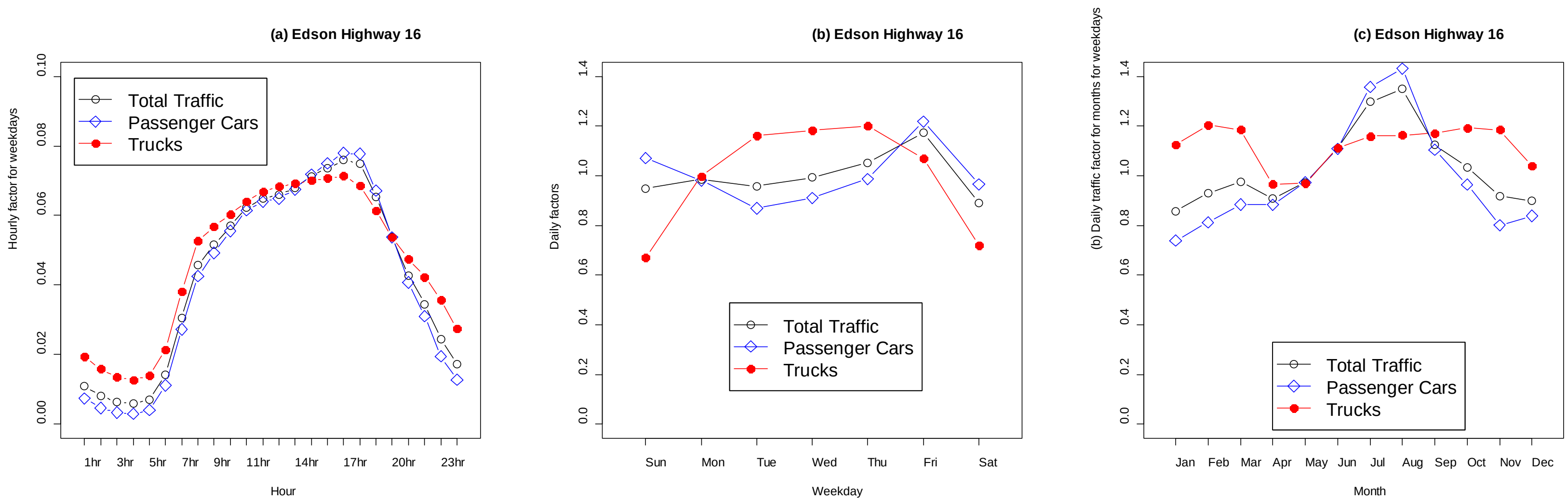


Figure 4.4 Typical Hourly, Daily, and Monthly Variations of Total, Passenger Cars and Truck Traffic for Traffic Factors for Highway 16

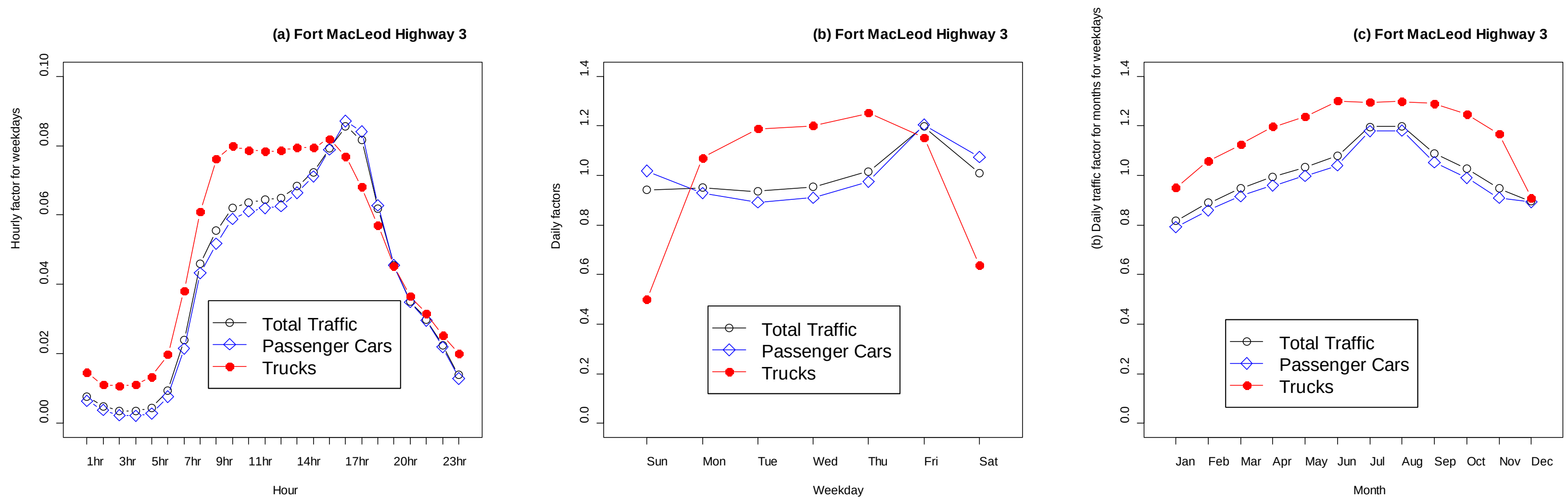


Figure 4.5 Typical hourly, daily, and monthly variations of total, passenger cars and truck traffic for traffics Factors for Highway 3

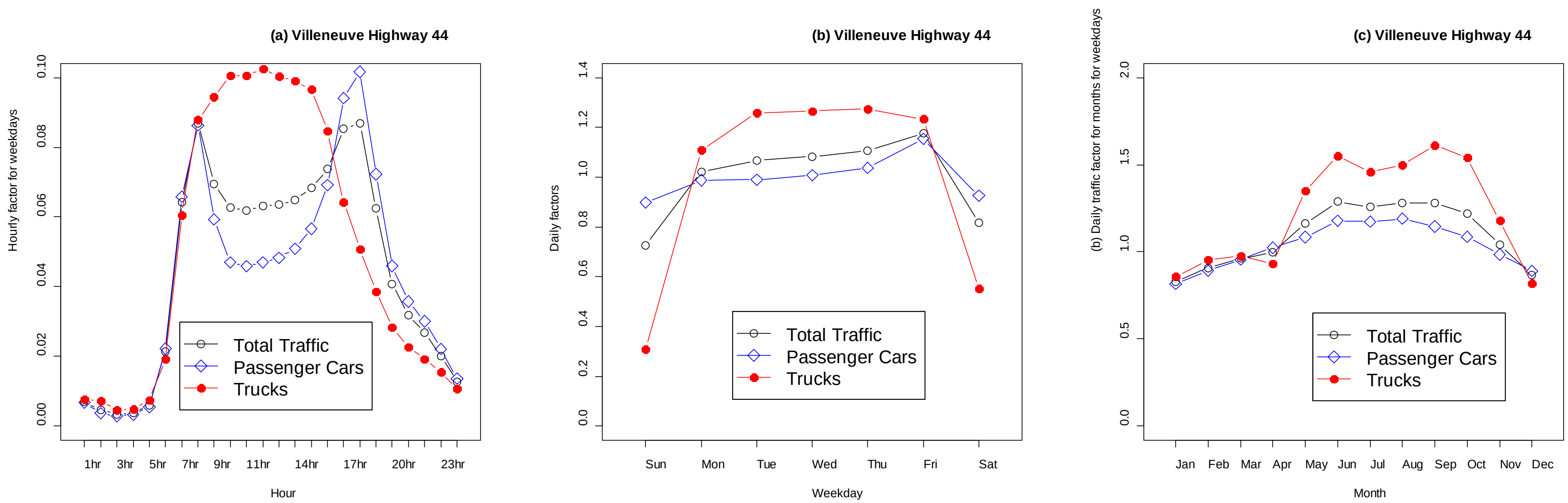


Figure 4.6 Typical Hourly, Daily, and Monthly Variations of Total, Passenger Cars and Truck Traffic for Traffic Factors for Highway 44

This is because work-business trips are not predominant road uses at these WIM sites. It may be noted that the long distance roads are located outside the major commuter shed areas. In general, such roads have higher total traffic volumes over weekend and experience higher seasonal variation than the regional commuter roads.

4.1.3 WIM Site on Special Interregional Long Distance Route

The Villeneuve WIM system located on Highway 44 was initially considered as a regional commuter site. This was because of the presence of clearly visible morning and afternoon commuter peaks in its total hourly traffic volume patterns at this site as shown in Figure 4.6. However, detailed investigations of truck traffic characteristics in Chapter 7 revealed that this highway is unlike any other study site because of the nature of trips that this facility serves in the northwest area of the Edmonton Region. It serves regional commuter traffic similar to Highway 2A site south of Leduc. Percent of truck traffic at this site is 27%, which is much higher than the highway 2A site (Table 4.1). It may be noted that Highway 44 provides a north-south linkage between Calahoo-Villeneuve aggregate operations in the Sturgeon County and the regional sand and gravel markets in the Edmonton Region (UMA, 2001). There is a very large proportion of aggregate (sand and gravel) hauling truck traffic on this highway. In addition, this road also serves as an alternate route to Highway 2 from Highway 16 (Yellowhead Highway) east of the City of Spruce Grove to north of Edmonton region. Moreover, similar to other long distance sites (on Highways 2, 3, and 16), a majority of truck traffic is composed of single- and multi-trailer trucks, which is quite different than the Highway 2A site where majority of trucks are single unit trucks.

4.1.4 Other Observations from Traffic Patterns

The following inferences were also drawn from the patterns presented in Figures 4.1 to 4.6:

1. Truck traffic patterns are unique on different roads and are different than passenger car patterns for all the study WIM sites.
2. In most cases, the shapes of patterns for passenger cars are similar to the total traffic; this is mainly because the proportion of trucks in the traffic stream is much lower than the remaining vehicle classes.
3. Truck traffic decreases significantly (in some cases more than 50%) during the weekends as compared to weekdays.
4. The Red Deer and Edmonton WIM sites, both located on Highway 2, have similar hourly, daily and monthly traffic patterns for both the passenger cars and trucks. This indicates that the traffic conditions are very consistent along Highway 2, even though the AADT and TAADT values are significantly different at these two sites. Such an observation suggest that the similarity of traffic patterns be very helpful in developing the study models and interpretation of model results

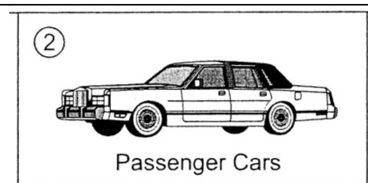
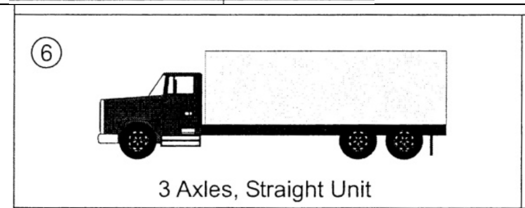
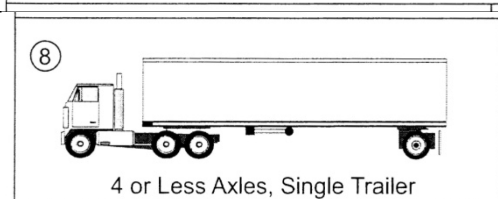
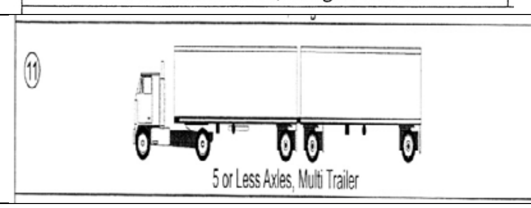
4.2 Truck Type Variations at the Study Sites

As per the road type classification system proposed by Sharma et al. (1986), and the total traffic volume patterns observed in Figures 4.1 to 4.5, five of six study WIM sites were classified in previous sections as regional commuter (on Highway 2A) or interregional long distance (on Highways 2, 3, and 16) routes. As described in Section 4.1.3, the Villeneuve WIM site on Highway 44 was recognized as a special interregional long distance route, when truck traffic characteristics were also considered in the classification. It would therefore be further interesting to classify the trucks and analyze the temporal variation among those classes. This type of analysis would also confirm the data quality before proceeding to the modeling work presented in Chapters 5 and 6.

To investigate the temporal variation of highway traffic by vehicle type, the raw data obtained from the WIM sites were classified using the FHWA classification method (Scheme ‘F’) as described in the previous chapter. This process resulted in 13 vehicle classes. However, due to lower number of total trucks in general and too many truck classes, the sample data could not generate sufficient samples to carry out detailed statistical analysis by each vehicle class. Therefore, the trucks were classified into three classes. These are: Single unit truck, Single trailer and Multi trailer units. Table 4.2 presents the details about these three classifications with corresponding figures of these classes.

To examine the variation of truck type with time, the following methodology was adopted. First, the truck traffic data were separated from the total traffic. Based on the classifications discussed above, the trucks were categorized into three types. The truck data were aggregated to daily totals, and the average daily truck volume was calculated for the 12 months of the year. Figures 4.7, 4.8 and 4.9 show the monthly average daily truck traffic variations for the study period (i.e., 2005-2009).

Table 4.2 Four Vehicle Classification Scheme

Four Classifications	FHWA-13 category scheme	Example Pictures for Four Vehicle Classification
Passenger cars	FHWA-13(1), FHWA-13(2), FHWA-13(3)	
Single Unit Truck	FHWA-13(4), FHWA-13(5). FHWA-13(6). FHWA-13(7)	
Single Trailer	FHWA-13(8), FHWA-13(9), FHWA-13(10)	
Multi Trailer	FHWA-13(11), FHWA-13(12), FHWA-13(13)	

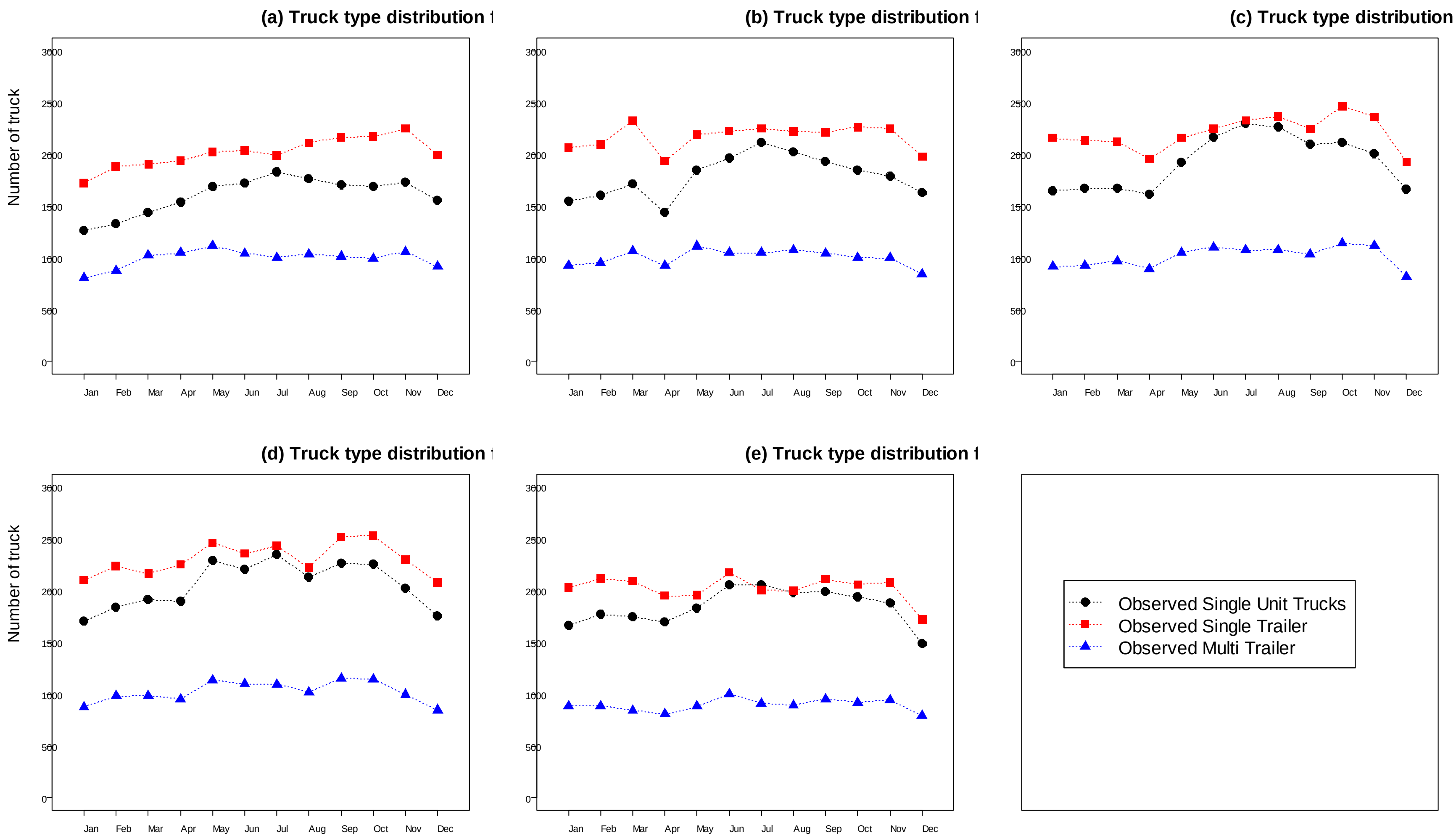


Figure 4.7 Truck Type Distributions at Red Deer Highway 2

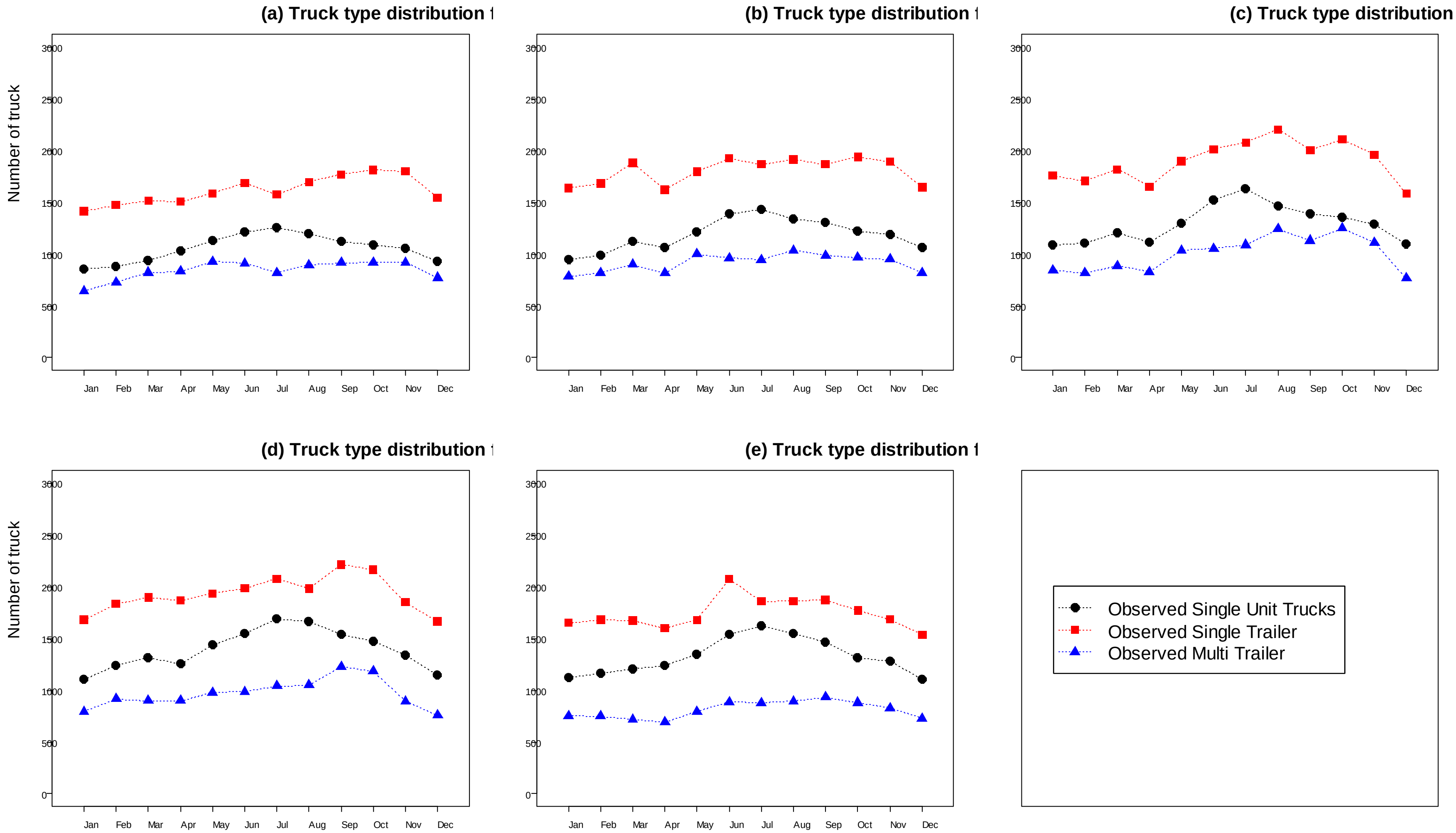


Figure 4.8 Truck Type Distributions at Leduc Highway 2

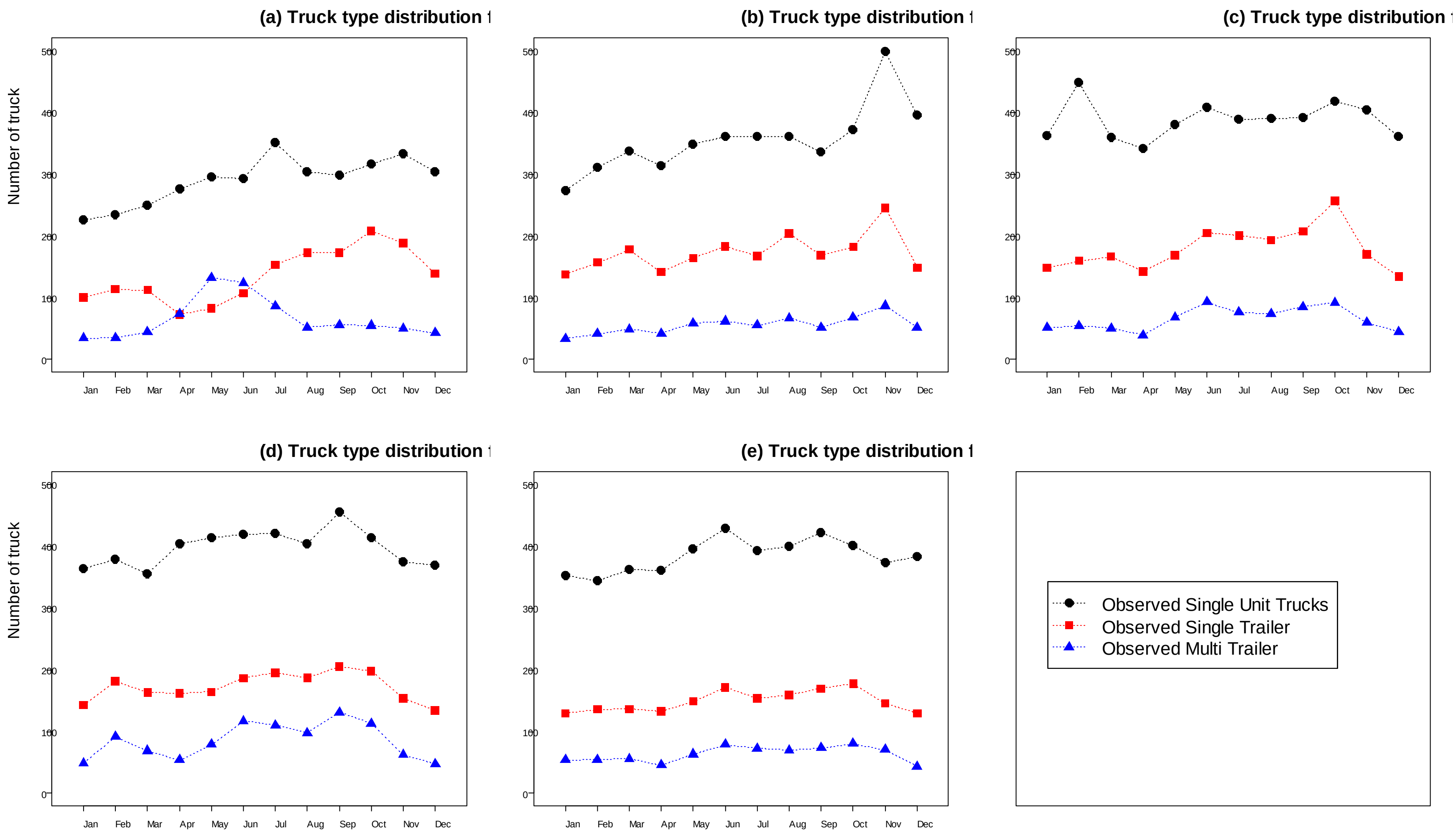


Figure 4.9 Truck Type Distributions at Leduc Highway 2A

The truck type distributions shown in Figures 4.7, 4.8 and 4.9 are limited to the three WIM sites, two on Highway 2 and one on Highway 2A. Since these three sites had complete record of traffic and weather data at the nearby weather stations, they were used in the development and testing of study models presented in Chapters 5 and 6. As mentioned in Chapter 3, the weather stations near the remaining three sites (namely Fort MacLeod Highway 3, Edson Highway 16, and Villeneuve Highway 44) had many days of missing weather data, they had to be excluded from the research investigations carried out in the following two chapters. However, a detailed presentation of truck type distribution for these three sites is presented in Chapter 7, which is to present the impact of winter weather conditions on truck type distribution.

All the plots in Figures 4.7, 4.8 and 4.9 confirm that the truck movement patterns are quite similar for all the study years. In case of both study sites on Highway 2, the proportion of single trailer truck traffic is the highest, whereas Highway 2A site experiences the maximum number of single unit trucks. Both the highways carry the lowest number of multi trailer trucks among all the three truck types.

4.3 Traffic Variations with Temperature and Snow Fall

The previous section discussed the temporal variations of passenger cars, trucks and the total traffic at the study WIM sites. However, the weather can be an important factor affecting such temporal variations. The winter weather in Canada and many parts of the United States is very severe with heavy snowfall, freezing rain, and extremely cold temperatures (sometimes going below -35^{o}C). These extreme weather conditions may cause significant changes in highway traffic volume patterns due to travel disruptions and trip adjustments that are likely to occur during such weather conditions. Therefore, the daily traffic volume factor was analysed against the variations in temperature and snow fall conditions. As an example, three weeks of data were carefully selected for the three sites when the temperature and snow fall exhibited a wide variation in both the temperature and snowfall. Figures 4.10, 4.11 and 4.12 show the daily volume factors, average daily temperatures, and daily snowfall during the selected three weeks period for the three study sites.

The weather data were obtained from weather stations 3012205 (Edmonton Int'l A Alberta), 3012205 (Edmonton Int'l A Alberta) and 3025480 (Red Deer A) for the sites on Leduc Highway 2A, Leduc Highway 2 and Red Deer Highway 2, respectively. The distances of the weather stations selected from the WIM sites are 13.32 km, 8.98 km and 7.08 km for Leduc Highway 2A, Leduc Highway 2 and Red Deer Highway 2, respectively. The distances are well within the limit as suggested by Datla and Sharma (2008) for homogeneous weather conditions from the WIM sites.

Let us consider the Highway 2A Leduc site. Here the traffic volume pattern was examined with regards to three conditions i.e. no snow, moderate or mild snow and heavy snow fall. The Friday dated November 20, 2009 reports no snow fall condition (see Figure 4.10). The corresponding truck volume factor was 1.31. Two weeks later, Friday dated on December 04, 2009 observed heavy snow fall (16 cm) and the corresponding truck volume factor decreased to 1.17. Again a week later when mild snow fall (2.5cm) was observed on Friday dated on December 11, 2009; the truck factor was 1.20. It appears that there may be a reduction in truck count due to heavy snow fall; however, the reduction is small. In no snow condition the passenger car traffic factor is 1.21 (See Figure 4.10).

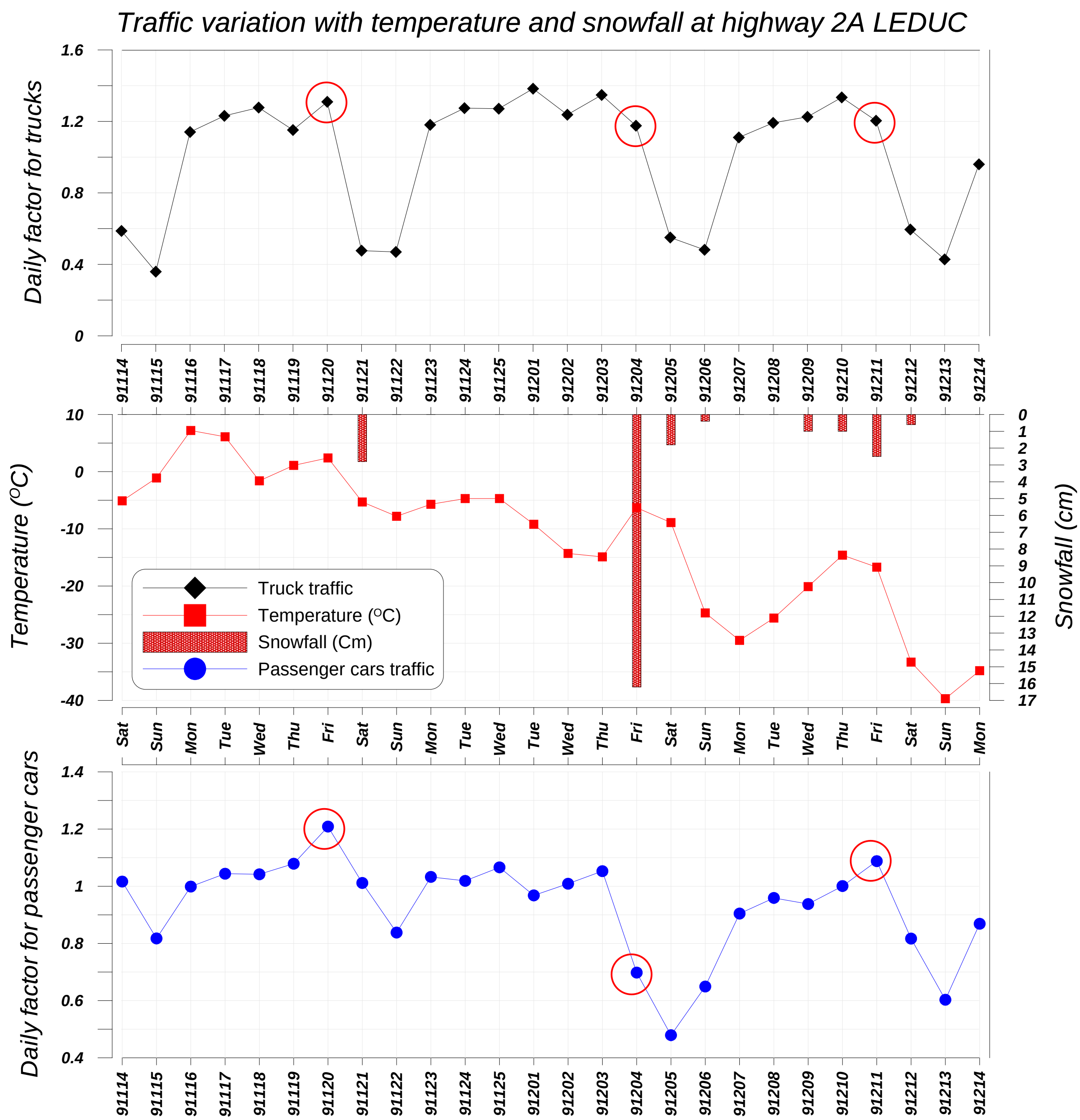


Figure 4.10 Traffic Variations with Temperature and Snowfall at Leduc Highway 2A

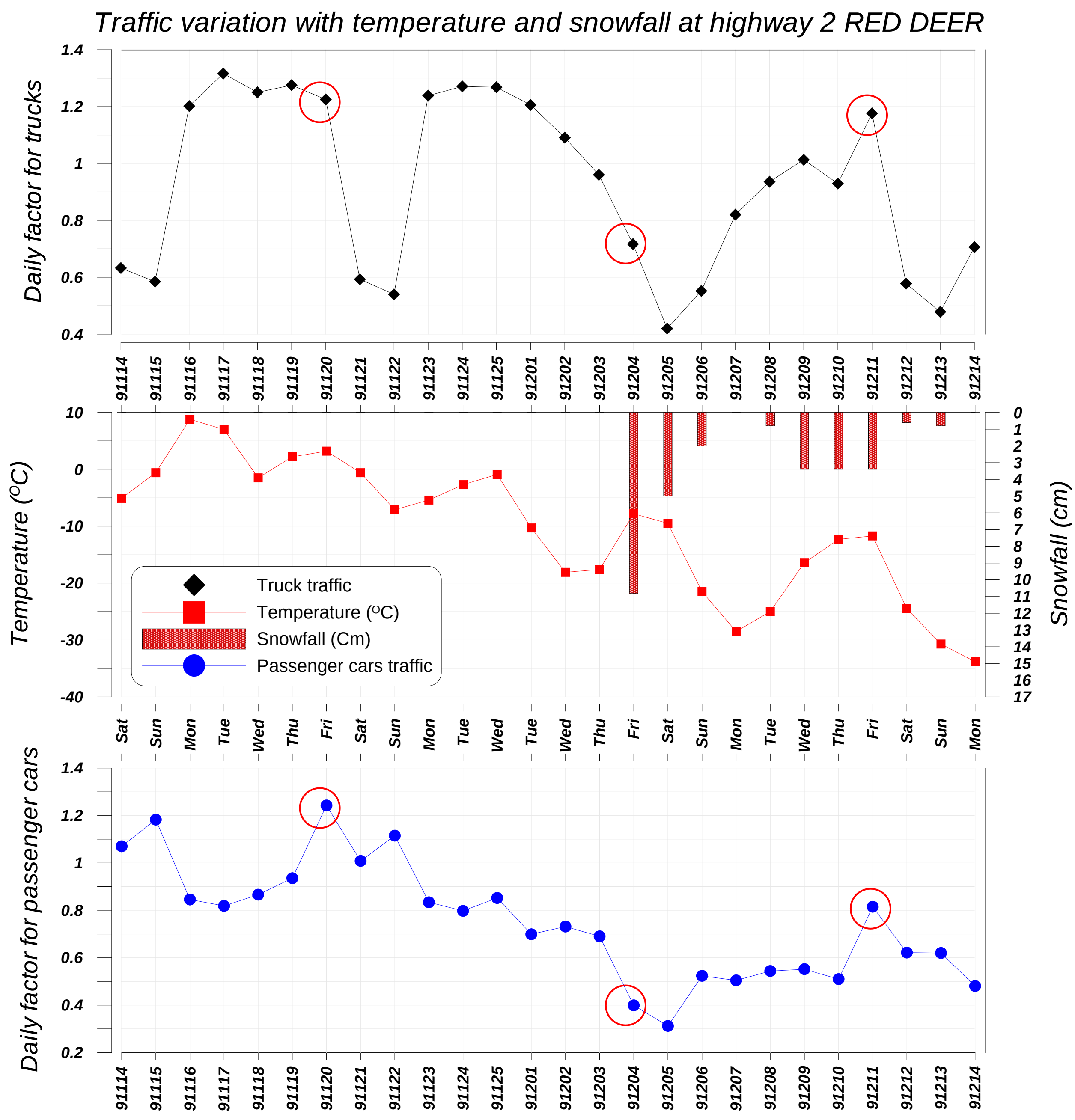


Figure 4.11 Traffic Variations with Temperature and Snowfall at Red Deer Highway 2

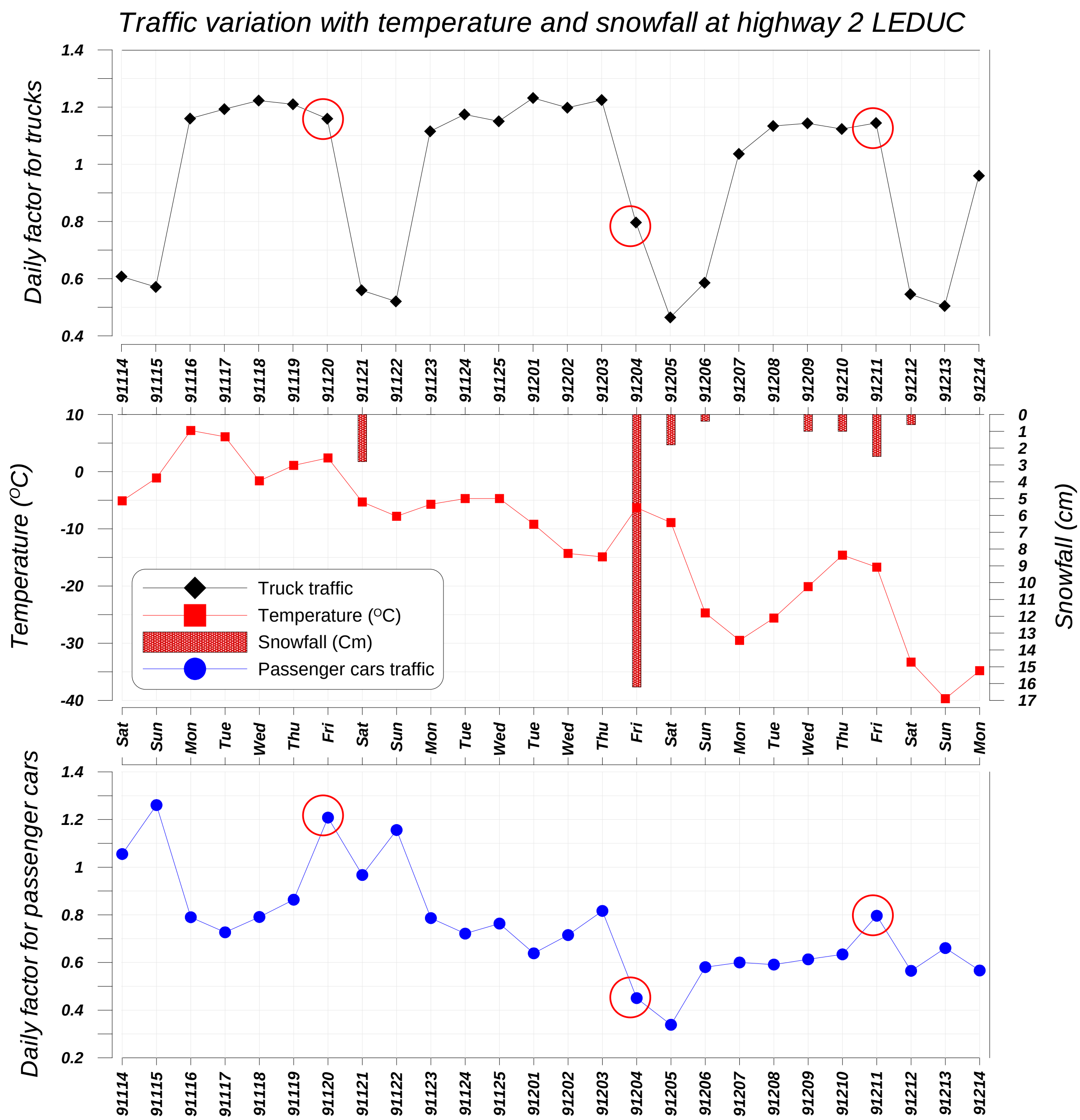


Figure 4.12 Traffic Variations with Temperature and Snowfall at Leduc Highway 2

At the mild snow condition the car volume factor is 1.09. The car volume factor reduced to 0.70 when there was a heavy snow fall. This infers the snow fall show a much more significant impact on the car volume than the truck volume at the WIM site on Highway 2A.

Similar analysis was also done for Highway 2 study sites. As shown in Figure 4.11, at the Red Deer site the truck volume factor reduces from 1.22 to 1.18 to 0.72 owing to no snow, moderate snow and heavy snow fall conditions. As far as passenger car volume factors are concerned the values are 1.24, 0.82 and 0.40 at no snow, moderate snow and heavy snow fall conditions.

As shown in Figure 4.12, at the Leduc site on Highway 2, the truck volume factors are 1.16, 1.14 and 0.80 for no snow fall, mild snow fall and heavy snow fall conditions. Similarly, the car volume factors are 1.21, 0.80 and 0.45 for the no snow fall, mild snow fall and heavy snow fall conditions.

All of above observations suggest that the passenger car volume gets severely affected by the snow fall for both highways. The truck volume does not seem to be affected as much as passenger cars at the WIM site on Highway 2A. The truck volumes in case of Highway 2 site seem to be affected more than Highway 2A. In summary, it can be concluded that the snow fall affects both the passenger car and the truck traffic. There are also indications from all the plots shown above that the traffic volume reduces as the temperature drops.

To understand the changes in traffic volumes in terms of statistical significance, several models relating traffic flows to snow fall and temperature were developed in this thesis. The developed models are discussed in detail in the following chapters.

Chapter Five

Modelling of the Impact of Snowfall and Temperature on Classified Traffic Volume using Dummy Variable Regression

5. 0 General

To quantify the relationship between traffic volumes and winter weather conditions, a detailed statistical analysis is carried out in this chapter. Regression analysis has long been recognized as a flexible and widely used technique to explain variation of quantitative dependent variable by establishing the relationships between dependent variable and a specified set of independent variables in a form of additive and linear mathematical functions (Hardy, 1993). Dummy variable regression models are developed to study the impact of temperature as a categorical variable and snowfall as a continuous variable on classified traffic volume.

The preliminary analysis included in Chapter 4 indicated that the truck volumes are usually very low as compared to passenger cars. This might result in a lack of sufficient samples to carry out detailed statistical analysis of classified truck traffic. Therefore, all the vehicle classes were aggregated into two classes (i.e., passenger cars and trucks) for the purpose of the analysis carried out in this chapter. The three vehicular traffic categories were considered in this study are total traffic, passenger car traffic and truck traffic. Because the traffic patterns for passenger cars and trucks were found to be very similar for both the WIM sites on Highway 2 (as observed in Figures 4.2 and 4.3), modeling work has been carried out for the combined Red Deer and Leduc sites on Highway 2 and Leduc Highway 2A sites. Also, as indicated in Chapter 3, the weather stations near the remaining three WIM sites on Highway 3, Highway 16 and Highway 44 had large amount of missing weather data, and hence they had to be excluded from the research investigations carried out in this chapter.

5.1 Modelling Approach

The literature indicates that a standard regression analysis is appropriate to quantify the association between highway traffic volumes and weather conditions as suggested by Keay and Simmonds (2005), Knapp and Smithson (2000), and Datla and Sharma (2008). Based on these previous experiences, regression models were developed in this study to relate traffic volume with temperature, total snowfall, and traffic volume under normal conditions without severe cold or snow conditions. Temperature variable in the models presented in this chapter was categorized into 7 categories with 5^{o}C intervals. The 5^{o}C temperature categories follow the common practice used by Environment Canada for presenting Canadian weather normals. The intention of these intervals is to reduce the analysis clutter arising from small temperature changes yet capture enough variation to provide a better understanding of the changes in traffic variations with diverse temperature ranges. As mentioned earlier, Datla (2009) successfully used these categories in his research.

5.1.1 Appropriateness of Using Temperature and Snowfall Variables

Historical weather records from the Environment Canada (WO, 2010) climate database indicate that the province of Alberta experiences severe snowfall and cold conditions from November to March. Based on this observation, the study period used in this research was selected to include the months of November to March for the period of five years (from 2005 to 2009). Since traffic patterns during long weekend statutory holidays in Alberta are very unique, special attention is needed to conduct research using data from holidays and their neighboring days (Liu and Sharma, 2006). For this reason, three holidays included in the study period (New Year's Day, Alberta Family Day (3rd Monday of February), and Christmas day were excluded from the analysis. Winter weather data (November to March) from weather stations (shown in Table 3.6) for the above stated study period were used for this analysis.

Linear Independency of Snowfall and Temperature

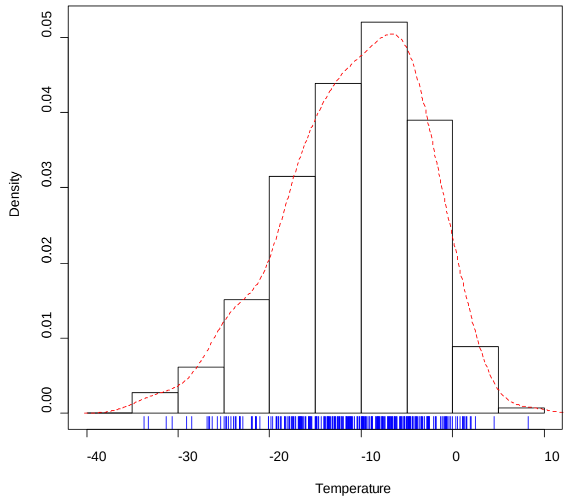
Regression analysis requires linear independence in the predictor variables. In order to check for collinear relationship between temperature and snowfall, the frequency distribution pattern of daily average temperatures during the winter seasons of the study period (2005-2009) with snowfall was compared with the distribution pattern without snowfall years.

Probability Density Plot for Temperature with and without Snowfall Conditions

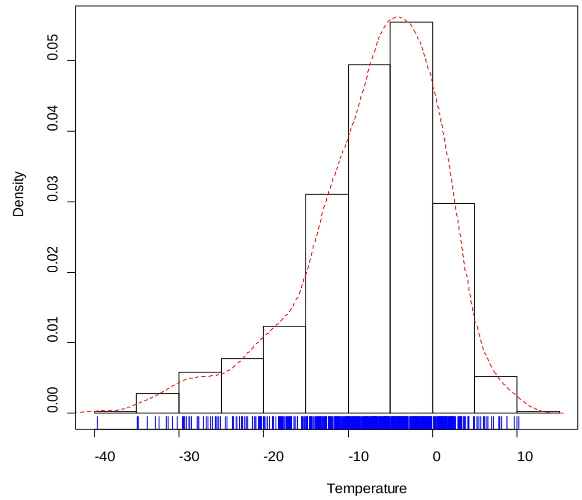
Histograms (with the estimated probability density function) of temperature for the days with snow and for the days without snow were constructed separately using the study data. Figure 5.1 shows the probability distribution patterns of average daily winter temperatures during the study years with snowfall and without snowfall.

A. Temperature Probability Density Plot for Highway 2

(a)

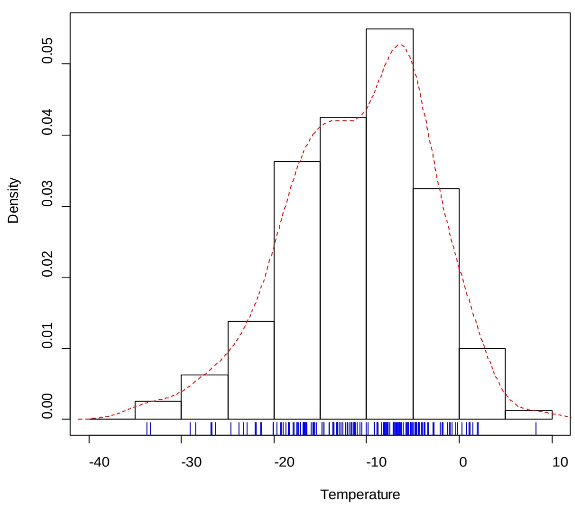


(b)



B. Temperature Probability Density Plot for Highway 2A

(a)



(b)

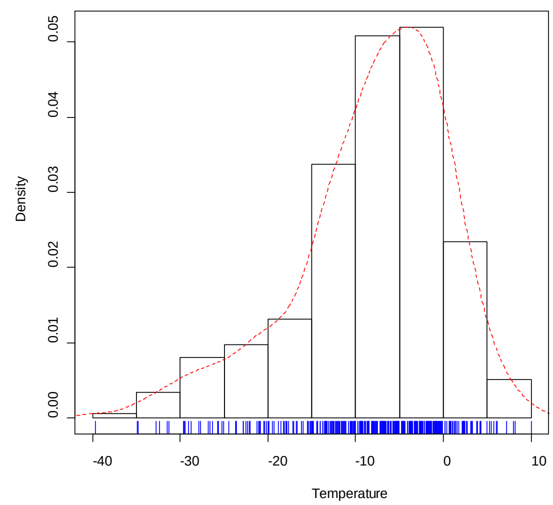


Figure 5.1 Probability Distribution Plots for Temperature for (a) with and (b) without Snowfall

Figure 5.1A shows the temperature probability distribution plot for Highway 2, and Figure 5.1B shows the distribution for Highway 2A. The shapes of the probability distribution patterns are generally similar to each other. The results indicate that average temperature is colder during the days with snowfall (-10.79 °C, 160 days during the study period) than the no snowfall days (-7.08°C, 350 days during the study periods) for Highway 2A. For Highway 2 the average temperature is -10.94 °C during snowfall days and -8.08°C during no snowfall days. These plots indicate that the distribution of winter temperatures does not change by a large extent with and without the snowfall. This means that temperature and snowfall could be treated as independent variables in the modeling process.

5.1.2 Correlation Analysis among All Independent Variables

The independent quantitative variables chosen for this study are: Expected Daily Volume Factor (EDVF) which represent normal traffic flow, snowfall and temperature. The EDVF is a factor obtained by using the following mathematical formula.

$$EDVF_{i,j,k} = \frac{\sum_{r=2005}^{r=2009} (DVF_{i,j,k})_r}{5}, \forall i, j \,\&\, k \qquad \textbf{5.1}$$

Where, i = A particular day of the week i.e. Monday – Friday, j = A particular week of the month for which all the weekday data are available i.e. Week 1 – Week 4 (5), k = A particular winter month of the year i.e. November – March, r = A counter for the years i.e. 2005 – 2009, $DVF_{i,j,k}$ = Daily volume factor for a given day in a given week for a given month in a particular year.

A correlation analysis was conducted to check multi-collinear relationship among EDVF, snowfall and temperature considering the data from the weekdays for the entire 5 years of study period. Table 5.1 shows the correlation coefficient values for the independent variables.

The correlation coefficient value for snowfall and temperature is -0.1090244, which means that little to no correlation exists between snowfall and temperature. This observation could justify the inclusion of both snow and cold as independent variables in the model. Similarly, it may be observed that the correlation coefficient values among EDVF and snowfall and EDVF and TEMP are also very low. These observations validate the inclusion of EDVF, SNOW (snowfall) and TEMP (temperature) for modeling.

5.2 Linear Relationship between Traffic Volume, Snowfall and Temperature

The traffic variation with time i.e. hourly, daily and monthly traffic patterns of trucks and passenger cars were studied in Chapters 3 and 4. It was observed that passenger car traffic increases steadily from Monday to Friday and decreases slightly during weekends. In contrast, the truck traffic is very stable during weekdays and decreases by more than 50% during weekends. It was also found that the year-to-year monthly traffic patterns at the study sites are generally similar for both the passenger cars and the trucks.

Before proceeding to modeling, the relationships among the dependent and independent variables identified for the modeling were carefully investigated with the help of scatter plots.

Table 5.1 Weekdays Correlation Matrix for EDVF, SNOW and TEMP for Total Traffic for Highway 2

Correlations	EDVF	SNOW	TEMP
EDVF	1.00000000	-0.06638809	0.2178949
SNOW	-0.06638809	1.00000000	-0.1090244
TEMP	0.2178949	-0.1090244	1.00000000

To develop the scatter plot for observed volume factors and the expected historical volume factors were calculated for each day. The observed volume factors were calculated using Equation 4.3. The historical expected volume factors were calculated using Equation 5.1.

Figures 5.2 and 5.3 show the scatter diagrams between the observed volume factors, historical volume factors, snowfall and temperature for Highway 2 and 2A respectively.

An estimated regression line is also added in the same plot to show the linear relationship between the two values. The blue circles in these plots represent weekdays and red squares represent weekends. The scatter plots between daily volume factors and expected daily volume factors show a very good cluster of sample data along the fitted regression line. This shows a strong positive linear relationship between daily volumes and historical average daily volumes. The blue circles and red squares overlap considerably in case of total traffic and car traffic plots. For trucks, the red squares are always on the lower side as compared to blue circles. This is because of significantly lower truck traffic volumes on the weekends. It is worth noting that the weekday truck traffic factors are generally clustered between the values of 0.90 to 1.30. However, the weekend daily truck factors were found to spread between 0.30 and 0.70.

The regression lines of total vehicles and car volumes versus snowfall show moderate negative linear relationship, i.e., traffic volumes decrease with increase in amount of snowfall. A positive linear relationship is observed between daily volumes and temperature, i.e., daily passenger car volumes increase with increase in daily average temperature.

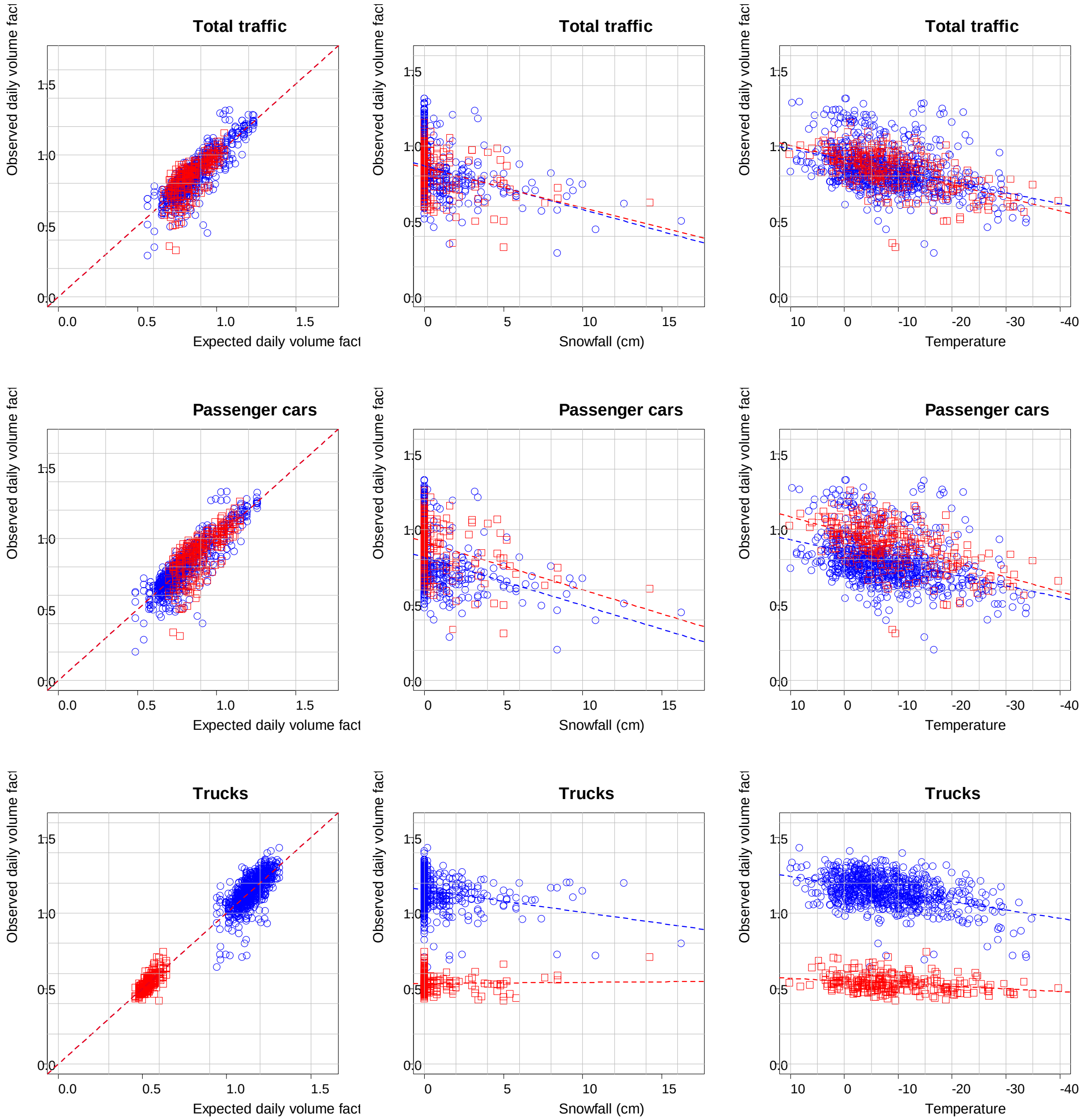


Figure 5.2 Scatter Plots for Traffic Volume Factors, Snow Fall and Temperature for Highway 2 (blue circle-weekdays, red square-weekends)

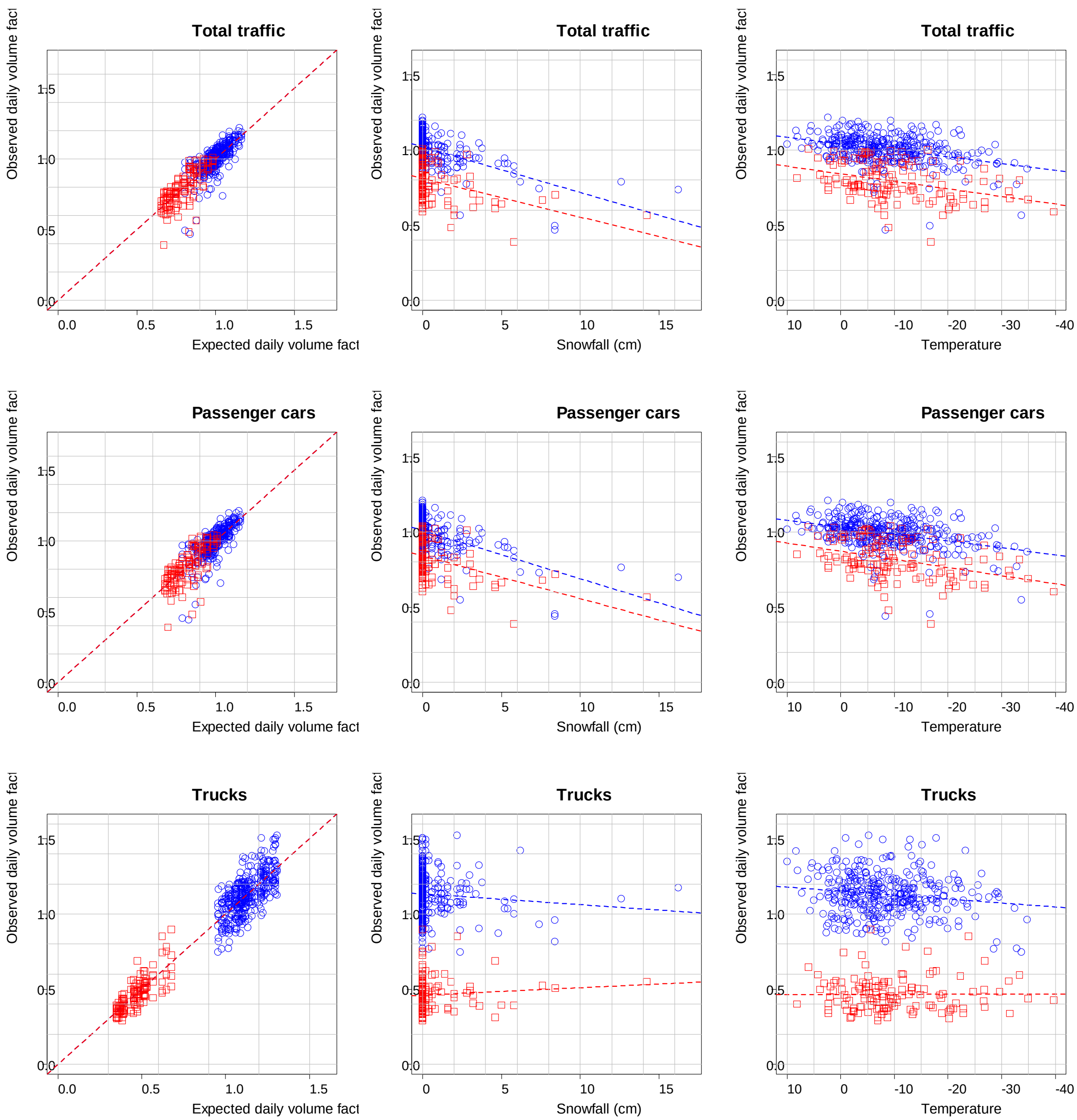


Figure 5.3 Scatter Plots for Traffic Volume Factors, Snow Fall and Temperature for Highway 2A

The slope of regression lines of both snowfall and temperature plots are very similar between weekdays and weekends for total traffic and passenger car traffic. In the case of trucks, the clusters of observed data and the fitted regression lines follow similar pattern with variation of slope as cars during weekdays. However, the regression lines for weekends are very different from weekdays for truck traffic. It is clear from the scatter plots for both the Highways 2 and 2A that the regression line has very little slope during weekends for trucks. The slope is almost zero. This may be due to the fact that truck volume is very low during weekends. Therefore, it has been decided to develop only weekday models to understand the impact of snowfall and temperature on passenger cars and trucks separately.

5.3 Dummy Variable Regression Model

Regression analysis has long been recognized as the most flexible and widely used technique to explain variation of quantitative dependent variables by establishing relationships between dependent variables and a specified set of independent variables in the form of additive and linear mathematical functions (Hardy, 1993). In this research, an attempt has been made to model the impact of weather on daily passenger cars and truck traffic volumes. For the purpose of mapping the relationships between daily traffic volume and weather factors, a dummy-variable regression model is developed with two quantitative independent variables, i.e., EDVF, SNOW, and one qualitative (or categorical) independent variable, i.e., temperature categorized at 5 ° C intervals. Although other weather factors (wind, pavement conditions, etc.,) also cause variations in daily traffic volumes, this research is limited to snow and temperature variables.

5.3.1 Regression Model Structure

The additive dummy variable regression model formulated for this research is:

$$y_i = f(expected\ daliy\ volume\ factor, snowfall, temperature)$$

$$= \beta_1 EDVF_i + \beta_2 SNOW_i + \sum_{j=1}^{6} \gamma_j CC_{ij} + \varepsilon_i \qquad \textbf{5.2}$$

Where, i: refers to the ith observation, $\beta_1, \beta_2, \gamma_{1\sim6}$: Regression coefficients estimated for the independent variables, y_i: Estimated value of daily traffic volumes factor for vehicle class (passenger cars, trucks), $EDVF$: Expected daily volume factor calculated from the historically observed data, $SNOW$: Amount of snowfall per day (cm), $CC_{i1\sim6}$: $CC_{ij} = 1$ if observation i falls in category j , otherwise 0, ε_i: Stochastic error term.

Normalized daily total volumes (ratio of traffic volume to average annual daily traffic volume, AADT), passenger car volumes (passenger car volume to passenger car AADT ratio), and truck traffic volume (truck volume to truck AADT ratio) are used instead of actual volumes to take into consideration the yearly variations in traffic volumes. The expected daily volume factor (EDVF), which is used as one of the independent variables, is calculated using the historical data for each day of the given week of a given month for all the study years and the formulation has already been discussed in the Equation 5.1.

Based on the knowledge gained from the literature (Fox, 2008; Hardy, 1993; Fox, 2011), and for the sake of easy interpretation of the dummy variable regression, the temperature (daily mean temperature, measured in ° C) has been considered as a categorical variable. In this research, temperature is categorized into 7 categories with 5 ° C equal intervals by introducing six dummy regressors, i.e., CC_1 (-5° C ~ 0° C), CC_2 (-

10° C ~ -5° C), CC_3 (-15° C ~ -10° C), CC_4 (-20° C ~ -15° C), CC_5 (-25° C ~ -20° C), and CC_6 (below -25° C). The baseline category (the days having over 0° C) is omitted in the model specifications because it is the reference category to which the other categories are compared. Table 5.2 shows the number of samples used for dummy variable regression in different temperature categories.

5.3.2 Interpretation of Coefficients

The coefficient for EDVF (β_1) represents the slope of the regression plane, which indicates a change in the estimated value of the daily volume factor (y_i), responding to a unit increase (or decrease) of the EDVF value, while the SNOW variable is kept at its mean value. Similarly, the coefficient for SNOW (β_2) indicates a change in the y_i value, responding to a unit change in snow fall, while the other independent variable, EDVF, is fixed at its mean value. The group differences (a difference of the estimated daily traffic volume factor between CC_1 and CC_2, or between CC_1 and CC_3, and so on) as the gross effect of being in CC_1 rather than CC_2 can simply be calculated by considering the algebraic difference of the coefficients of dummy variables estimated for corresponding cold categories (or levels) (i.e., $\gamma_1, \gamma_2 \; or \; \gamma_1, \gamma_3$). By conducting dummy variable regression, we are able to identify the influence of weather factors (cold) that lead to the observed differences in daily traffic volume factors between cold categories. In a more intuitive manner, the regression equation (Equation 5.2) might be described geometrically using seven parallel regression planes, which differ in their intercepts. For example, after fitting regression Equation 5.2, a regression equation fitted for cold category CC_1 becomes $\hat{Y}_{cc1} = \beta_1 EDVF_i + \beta_2 SNOW_i + \gamma_1$, and, for CC_2, it is $\hat{Y}_{cc2} = \beta_1 EDVF_i + \beta_2 SNOW_i + \gamma_2$.

Table 5.2 Temperature Category Matrix Sample Used for Modeling

Cold category	HWY 2			HWY 2A		
	All days	weekdays	weekend	All days	weekdays	weekend
Baseline	142	107	35	59	45	14
CC1	259	200	59	112	83	29
CC2	256	179	77	129	89	40
CC3	177	140	37	90	71	19
CC4	91	64	27	47	35	12
CC5	50	31	19	28	17	11
CC6	45	29	16	25	15	10
Total	1020	750	270	490	355	135

The coefficients $\gamma_1, \gamma_2, \cdots$ and γ_6 represent the intercepts of the regression planes for cold categories CC_1, CC_2,$\cdots$ and CC_6, respectively. The influence of cold categories on the dependent variable y_i can be described by taking the example of categories CC_1 and CC_2. Assuming that the two coefficients γ_1 and γ_2 are positive, and that γ_1 is greater than γ_2, then, the value of $\gamma_1 - \gamma_2$ gives the constant vertical difference between the parallel regression planes for CC_1 and CC_2, at the mean values of EDVF and the SNOW variables. The value, $\gamma_1 - \gamma_2$, in this research, can be interpreted as the increase of daily traffic factors (or daily traffic volumes) that could possibly be caused by the gross effect of being in CC_1 rather than CC_2.

5.4 Analysis of Results and Discussion

5.4.1 Calibrated Weekday Traffic Weather Models

The weekday daily model was developed separately for total traffic, passenger car traffic and truck traffic. Tables 5.3 and 5.4 show the six calibrated daily models for the two highway sites (developed using Equation 5.2) for total traffic, passenger car traffic and truck traffic, respectively. From Table 5.2, the total number of days of data for the total traffic weekday models varies from 750 days (Highway 2) to 355 days (Highway 2A).

5.4.1.1 Highway 2 Models

The values of coefficient β_1 are positive and quite high for all vehicle classes in Table 5.3, indicating that observed traffic volume factors are close to the expected traffic volume factors when there is no snowfall and the temperature falls in the reference class (above $0^{o}C$). Coefficient β_2 clearly indicates a reduction in the volume factor due to each centimeter of snowfall. The values of coefficient γ_j are different for different temperature ranges.

Table 5.3 Results of Daily Factor Model for Vehicle Class Using Dummy Variable Regression for Weekdays for Highway 2

Variables	**Total Traffic (Model 1)**	**Seven fitted regression equations for each cold categories for total traffic**	
EDVF	0.93844 (0.01673)***	$\hat{Y}_{baseline} = 0.93844 * EDVF - 0.02329 * SNOW + 0.08595$	
SNOW	-0.02329 (0.00132)***	$\hat{Y}_{cc1} = 0.93844 * EDVF - 0.02329 * SNOW + 0.08469$	
baseline	0.08595 (0.01624)***	$\hat{Y}_{cc2} = 0.93844 * EDVF - 0.02329 * SNOW + 0.07560$	
CC_1	0.08469 (0.01516)***	$\hat{Y}_{cc3} = 0.93844 * EDVF - 0.02329 * SNOW + 0.06252$	
CC_2	0.07560 (0.01465)***	$\hat{Y}_{cc4} = 0.93844 * EDVF - 0.02329 * SNOW + 0.03658$	
CC_3	0.06252 (0.01480)***	$\hat{Y}_{cc5} = 0.93844 * EDVF - 0.02329 * SNOW + 0.02345$	
CC_4	0.03658 (0.01600)*	$\hat{Y}_{cc6} = 0.93844 * EDVF - 0.02329 * SNOW - 0.06376$	
CC_5	0.02345 (0.01727)		
CC_6	-0.06376 (0.01665)***		
R^2	0.9958		
Adj. R^2	0.9957		
F	19290***	Incremental F- statistic	29.54***
Change from R^2_{Naive}	0.0012	Observations	750 days
Variables	**Passenger cars (Model 2)**	**Seven fitted regression equations for each cold categories for passenger cars**	
EDVF	0.947233 (0.015421)***	$\hat{Y}_{baseline} = 0.947233 * EDVF - 0.025049 * SNOW + 0.079942$	
SNOW	-0.025049 (0.001413) ***	$\hat{Y}_{cc1} = 0.947233 * EDVF - 0.025049 * SNOW + 0.075598$	
baseline	0.079942 (0.014544) ***	$\hat{Y}_{cc2} = 0.947233 * EDVF - 0.025049 * SNOW + 0.064781$	
CC_1	0.075598 (0.013357) ***	$\hat{Y}_{cc3} = 0.947233 * EDVF - 0.025049 * SNOW + 0.053676$	
CC_2	0.064781 (0.012797) ***	$\hat{Y}_{cc4} = 0.947233 * EDVF - 0.025049 * SNOW + 0.024312$	
CC_3	0.053676 (0.013108) ***	$\hat{Y}_{cc5} = 0.947233 * EDVF - 0.025049 * SNOW + 0.009840$	
CC_4	0.024312 (0.014585)	$\hat{Y}_{cc6} = 0.947233 * EDVF - 0.025049 * SNOW - 0.069615$	
CC_5	0.009840 (0.016270)		
CC_6	-0.069615 (0.015677) ***		
R^2	0.9945		
Adj. R^2	0.9945		
F	14940***	Incremental F- statistic	28.87***
Change from R^2_{Naive}	0.0015	Observation	750 days
Variables	**Truck Traffics (Model 3)**	**Seven fitted regression equations for each cold categories for trucks**	
EDVF	0.934490 (0.034142)***	$\hat{Y}_{baseline} = 0.934490 * EDVF - 0.013671 * SNOW + 0.083247$	
SNOW	-0.013671(0.001515) ***	$\hat{Y}_{cc1} = 0.934490 * EDVF - 0.013671 * SNOW + 0.098067$	
baseline	0.083247 (0.040875)*	$\hat{Y}_{cc2} = 0.934490 * EDVF - 0.013671 * SNOW + 0.101556$	
CC_1	0.098067 (0.039957) *	$\hat{Y}_{cc3} = 0.934490 * EDVF - 0.013671 * SNOW + 0.077407$	
CC_2	0.101556 (0.039029) **	$\hat{Y}_{cc4} = 0.934490 * EDVF - 0.013671 * SNOW + 0.068478$	
CC_3	0.077407 (0.038884)*	$\hat{Y}_{cc5} = 0.934490 * EDVF - 0.013671 * SNOW + 0.064137$	
CC_4	0.068478 (0.039455)	$\hat{Y}_{cc6} = 0.934490 * EDVF - 0.013671 * SNOW - 0.055968$	
CC_5	0.064137 (0.039482)		
CC_6	-0.055968 (0.039699)		
R^2	0.9968		
Adj. R^2	0.9968		
F	25860***	Incremental F- statistic	23.16***
Change from R^2_{Naive}	0.0007	Observation	750 days

Regression coefficients with standard errors (in parentheses)
***Coefficient is statistically significant at the 0.001 level, ** 0.01 level,* 0.05 level

Table 5.4 Results of Daily Factor Model by Vehicle Classes Using Dummy Variable Regression for Weekdays for Highway 2A

Variables	Total Traffic (Model 1)	Seven fitted regression equations for each cold categories for total traffic	
EDVF	0.885469 (0.036189)***	$\hat{Y}_{baseline} = 0.885469 * EDVF - 0.022963 * SNOW + 0.138607$ $\hat{Y}_{cc1} = 0.885469 * EDVF - 0.022963 * SNOW + 0.139473$ $\hat{Y}_{cc2} = 0.885469 * EDVF - 0.022963 * SNOW + 0.136577$ $\hat{Y}_{cc3} = 0.885469 * EDVF - 0.022963 * SNOW + 0.133561$ $\hat{Y}_{cc4} = 0.885469 * EDVF - 0.022963 * SNOW + 0.120080$ $\hat{Y}_{cc5} = 0.885469 * EDVF - 0.022963 * SNOW + 0.113728$ $\hat{Y}_{cc6} = 0.885469 * EDVF - 0.022963 * SNOW + 0.031496$	
SNOW	-0.022963(0.001456) ***		
baseline	0.138607 (0.038159) ***		
CC_1	0.139473 (0.037349) ***		
CC_2	0.136577 (0.036205) ***		
CC_3	0.133561 (0.036530) ***		
CC_4	0.120080 (0.037287) **		
CC_5	0.113728 (0.036998) **		
CC_6	0.031496 (0.036883)		
R^2	0.9979		
Adj. R^2	0.9979		
F	19650***	Incremental F- statistic	12.44***
Change from R^2_{Naive}	0.0005	Observations	375
Variables	**Passenger cars (Model 2)**	**Seven fitted regression equations for each cold categories for passenger cars**	
EDVF	0.867942(0.037071)***	$\hat{Y}_{baseline} = 0.867942 * EDVF - 0.025287 * SNOW + 0.162294$ $\hat{Y}_{cc1} = 0.867942 * EDVF - 0.025287 * SNOW + 0.158167$ $\hat{Y}_{cc2} = 0.867942 * EDVF - 0.025287 * SNOW + 0.153836$ $\hat{Y}_{cc3} = 0.867942 * EDVF - 0.025287 * SNOW + 0.150637$ $\hat{Y}_{cc4} = 0.867942 * EDVF - 0.025287 * SNOW + 0.131231$ $\hat{Y}_{cc5} = 0.867942 * EDVF - 0.025287 * SNOW + 0.129663$ $\hat{Y}_{cc6} = 0.867942 * EDVF - 0.025287 * SNOW + 0.039530$	
SNOW	-0.025287(0.001519)***		
baseline	0.162294 (0.038536)***		
CC_1	0.158167 (0.037739)***		
CC_2	0.153836 (0.036639)***		
CC_3	0.150637 (0.036966)***		
CC_4	0.131231 (0.037725)***		
CC_5	0.129663 (0.037482)***		
CC_6	0.039530 (0.037338)		
R^2	0.9977		
Adj. R^2	0.9976		
F	17600***	Incremental F- statistic	15.91***
Change from R^2_{Naive}	0.0007	Observation	375
Variables	**Truck Traffics (Model 3)**	**Seven fitted regression equations for each cold categories for trucks**	
EDVF	1.007501 (0.057602)***	$\hat{Y}_{baseline} = 1.007501 * EDVF - 0.006312 * SNOW - 0.027909$ $\hat{Y}_{cc1} = 1.007501 * EDVF - 0.006312 * SNOW - 0.008577$ $\hat{Y}_{cc2} = 1.007501 * EDVF - 0.006312 * SNOW + 0.003400$ $\hat{Y}_{cc3} = 1.007501 * EDVF - 0.006312 * SNOW + 0.002056$ $\hat{Y}_{cc4} = 1.007501 * EDVF - 0.006312 * SNOW + 0.015670$ $\hat{Y}_{cc5} = 1.007501 * EDVF - 0.006312 * SNOW + 0.018095$ $\hat{Y}_{cc6} = 1.007501 * EDVF - 0.006312 * SNOW - 0.070536$	
SNOW	-0.006312 (0.003332)		
baseline	-0.027909 (0.069444)		
CC_1	-0.008577 (0.066942)		
CC_2	0.003400 (0.065081)		
CC_3	0.002056 (0.065545)		
CC_4	0.015670 (0.067165)		
CC_5	0.018095 (0.068178)		
CC_6	-0.070536 (0.067484)		
R^2	0.9925		
Adj. R^2	0.9923		
F	5113***	Incremental F- statistic	1.31
Change from R^2_{Naive}	0.0002	Observation	355

Regression coefficients with standard errors (in parentheses)
****Coefficient is statistically significant at the 0.001 level, ** 0.01 level,* 0.05 level*

A general trend of decrease in γ_j values (from γ_1 to γ_6) were observed for all models for Highway 2. The values were highest for γ_1 in case of total traffic and passenger traffic models, indicating that the reduction in traffic volumes due to mild temperatures was low. For example, the value of γ_1 is 0.08469 for the total traffic-weather model of the Highway 2 which is a long distance road. The coefficient values for the total traffic volume systematically decreased up to -0.06376 with decrease in the temperature. Such decrease in γ_j values (from γ_1 to γ_6) indicate considerable traffic reductions because of the increase in the severity of the temperature.

The overall goodness of fit of the regression model to sample data is evaluated by the squared multiple correlation coefficient (R^2). The R^2 values for all models in Tables 5.3 and 5.4 are over 0.99, which means that all the models fit very well to the sample data.

The value of the F statistic, which is used to assess the overall adequacy of the model, is significant at the 0.001 level for all the models. The incremental values of F-statistic are also shown in Tables 5.3 and 5.4. These values are used to test the null hypothesis of "no partial effect of cold categories ($H_0\colon \gamma_1 = \gamma_2 = \cdots \gamma_6 = 0$)." By comparing the overall value of R^2 of the model including the dummy-variables (Table 5.3) with the value of R^2 of the naive model, i.e.,$y_i = \beta_1 EDVF_i + \beta_2 SNOW_i + \varepsilon_i$, it is possible to confirm statistically whether or not the inclusion of dummy variables is statistically significant. Below is an example for passenger cars in Model 2 of Table 5.3 for Highway 2:

$$F = \frac{(R^2_{dummy} - R^2_{Naive})/(k_{dummy} - k_{naive})}{(1 - R^2_{dummy})/(N - k_{dummy})}$$

$$F = \frac{(0.9945 - 0.993)/(9-2)}{(1-0.9977)/(750-9)} = 28.87$$

where, R^2_{dummy} is the value of R^2 including dummy variables for Model 2, R^2_{Naive} is the comparable measure for the naive model without dummy variables, N is the number of observations (days), k_{dummy} is the total number of independent variables including dummy variables (equal to 9), and k_{naive} is the total number of independent variables without including dummy variables (equal to 2). From the resulting value of 28.87, it can be concluded that, for passenger cars during weekdays, the inclusion of dummy variables is statistically significant at or better than 0.001 confidence level. In other words, there is a significant overall influence of cold categories on the volume of passenger cars. Similarly, the incremental F-statistics values for total traffic and truck traffic are 29.54 and 23.16 respectively. This also indicates there is significant influence of cold categories on the truck volume in case of long distance routes.

The statistical significance for individual coefficients is evaluated by the t-statistic, and the significance level is indicated using a symbol (*) in Tables 5.3 and 5.4. The Adjusted R^2 values are either same or extremely close to the R^2 values for all the cases. These observations on Adjusted R^2 values indeed confirms the evidence received from the t-test, F-test and incremental F-statistics which suggests that all the models are appropriate with the independent variables chosen for modeling. In other words this explains that the developed models are not over fitted. They are quite appropriate with the independent variables selected.

5.4.1.2 Highway 2A Models

The values of coefficient β_1, β_2, and γ_j values (from γ_1 to γ_6) for all vehicle classes for Highway 2A are given in Table 5.4. A careful examination and interpretation of these coefficients, and statistical consideration of R^2, the t-statistic and F statistic values indicate that: (1) The total traffic and the passenger car traffic are influenced significantly by all the independent variables included in the model for Highway 2A. (2) However, the truck traffic is not significantly influenced by the snowfall and severity of temperature categories, which means that the observed traffic volume factors during winter months are close to the expected traffic volume factors when there is no snowfall and the temperature falls in the reference class (above 0^{o}C).

The variations of weekday daily traffic factors estimated by the study models in Tables 5.3 and 5.4 and the observed daily traffic factors are shown in the form of a scatter plot in Figures 5.4 and 5.5. An estimated regression line is also added in the same plot to show linear relationship between the two values (see Figures 5.4 and 5.5). It is worth noting that the regression coefficient R^2 value is greater than 0.99 in case of all the classified traffic for both the highways. This also indicates the appropriateness of the models developed with the variables selected. This also explains the inclusion of cold categories in predicting the classified traffic volume.

5.5 Chapter Summary

Based on the above descriptions, the following summary points can be drawn from the results for winter weekday traffic models presented in Tables 5.3 and 5.4:

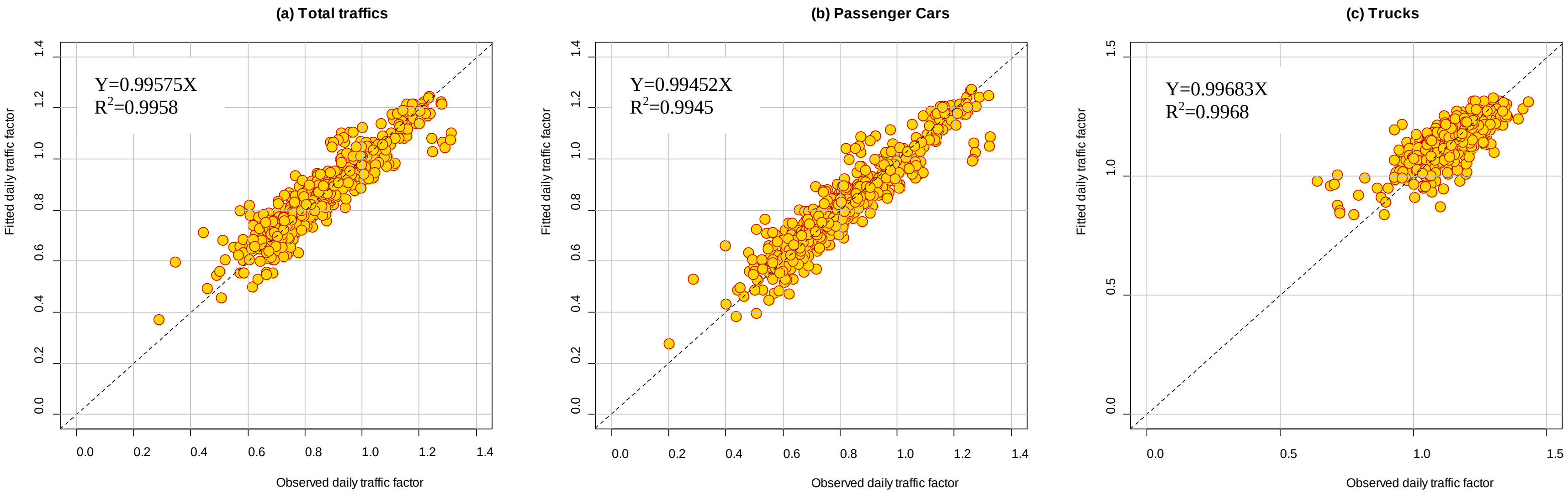


Figure 5.4 Results of Dummy Variable Regression Models of Weekdays for (a) Total Traffic, (b) Passenger Cars, and (c) Truck for Highway 2

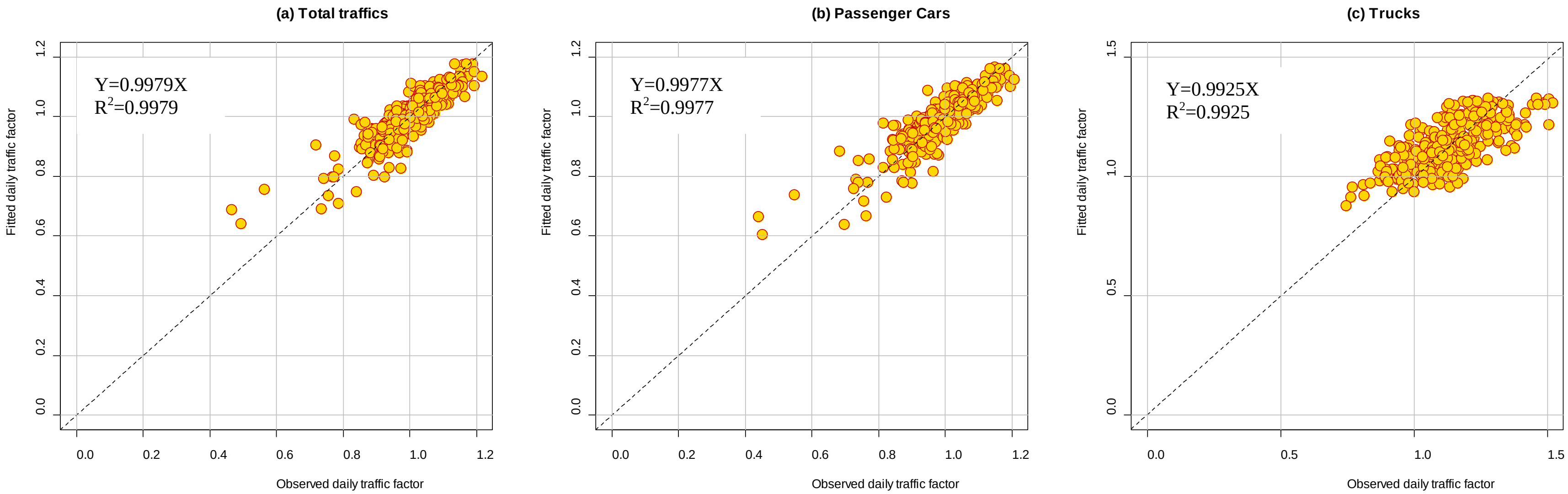


Figure 5.5 Results of Dummy Variable Regression Models of Weekdays for (a) Total Traffic, (b) Passenger Cars, and (c) Truck for Highway 2A

1. The total traffic, passenger car traffic and truck traffic volumes are influenced by all the independent variables included in the model, i.e., the expected daily volume factor EDVF, snowfall, and the cold categories in case of Highway 2.
2. There is a continuous decrease in classified traffic volume with the increase in snowfall and severity of the cold for Highway 2.
3. The total traffic and the passenger car traffic are also influenced by all the independent variables included in the model for Highway 2A. However, the truck traffic is not significantly influenced by the snowfall and severity of temperature. The probable reason could be the drivers are willing to take risk for short distance travel within the commuter shed areas in large metropolitan regions such as the Edmonton Region. The risk taking behavior is likely due to efficient winter maintenance of suburban and regional roads. It is also possible that the truck volume does decrease during severe winter conditions, but it is compensated by shifting of some additional trips from nearby roads which are not maintained as well and as quickly as Highway 2A.
4. The amount of reduction in traffic volume may be attributed to the proportion of discretionary trips in the traffic stream. The existence of more discretionary trips results in higher trip adjustments and, hence, higher traffic reductions as in the case of Highway 2. The reason of higher passenger car traffic reductions may be due to the large proportion of discretionary trips contributed from the passenger car traffic than the

truck traffic. Trucks (or commercial vehicles) are usually required to follow rigid schedules to complete their mandatory travel to keep the supply-demand in equilibrium if there is a strong commodity demand from the user end irrespective of severe weather conditions. However, commodity demand which is driven by user level of activity generally falls due to the decrease in the level of activity during the winter months. This phenomenon probably attributes to the reduction in truck traffic though less than the reduction in car traffic on both long distance highways like Highway 2 and commuter roads like Highway 2A.

Chapter Six

Investigation of the Combined Effect of Snowfall and Temperature on Classified Traffic Volume Using Interaction Model

6. 0 General

The relationships between weather and highway traffic volumes were investigated in the previous chapter, taking into account the impact of snowfall at a particular cold category, where temperature was considered as a categorical variable. A more detailed investigation is required to know whether or not the traffic volumes vary with the severity of temperature at different snowfall conditions. This chapter focuses on developing traffic weather models considering snowfall and temperature both as continuous variables to understand the combined effect of snowfall and temperature. Here, the main purpose of the analyses will be to conduct the verification of the existence or non-existence of the impact of the cold and snow interaction impacts on traffic volumes.

6. 1 Modeling Approach

The modeling approach is the same as the previous modeling procedure discussed in Chapter 5. This means regression analysis will be carried out to develop the models. The study data remains the same as before. However, the temperature is considered as a continuous variable like snowfall in this stage of the research. All the preliminary analysis were carried out as before to check the appropriateness of temperature and snowfall so as to include them as independent variables along with expected daily volume factor (EDVF) for modeling. In addition to this, a new interaction term 'SNOW*TEMP' is included in the modeling process to represent the interaction of snowfall with the severity of temperature conditions. The relationship of the traffic volumes and the independent variables are discussed in the subsequent paragraph.

Before proceeding to modeling, the relationships among the dependent and independent variables identified for the modeling were carefully examined with the help of detailed statistical analysis. To develop such plots, observed volume factors and expected volume factors were calculated for each day. The observed volume factors were calculated using Equation 4.3. The historical expected volume factors were calculated using Equation 5.1 considering the daily traffic volume for the same day in the same week and in the same month for the entire study period 2005-2009.

Figures 6.1 and 6.2 show the scatter diagrams between the observed volume factors, historical volume factors (EDVF), snowfall, temperature and the interaction term 'SNOW*TEMP' for Highway 2 and 2A respectively.

An estimated regression line is also added in the same plot to show the linear relationship between the two values. The blue circles in these plots represent weekdays and red squares represent weekends. These scatter plots were described in the previous chapter except for the variation of traffic volume with the interaction term. The regression lines of total vehicles and car volumes versus 'SNOW*TEMP' show strong negative linear relationship, i.e., total traffic volumes and car traffic volumes decrease with increase in the snowfall-temperature interaction for both the highway sites.

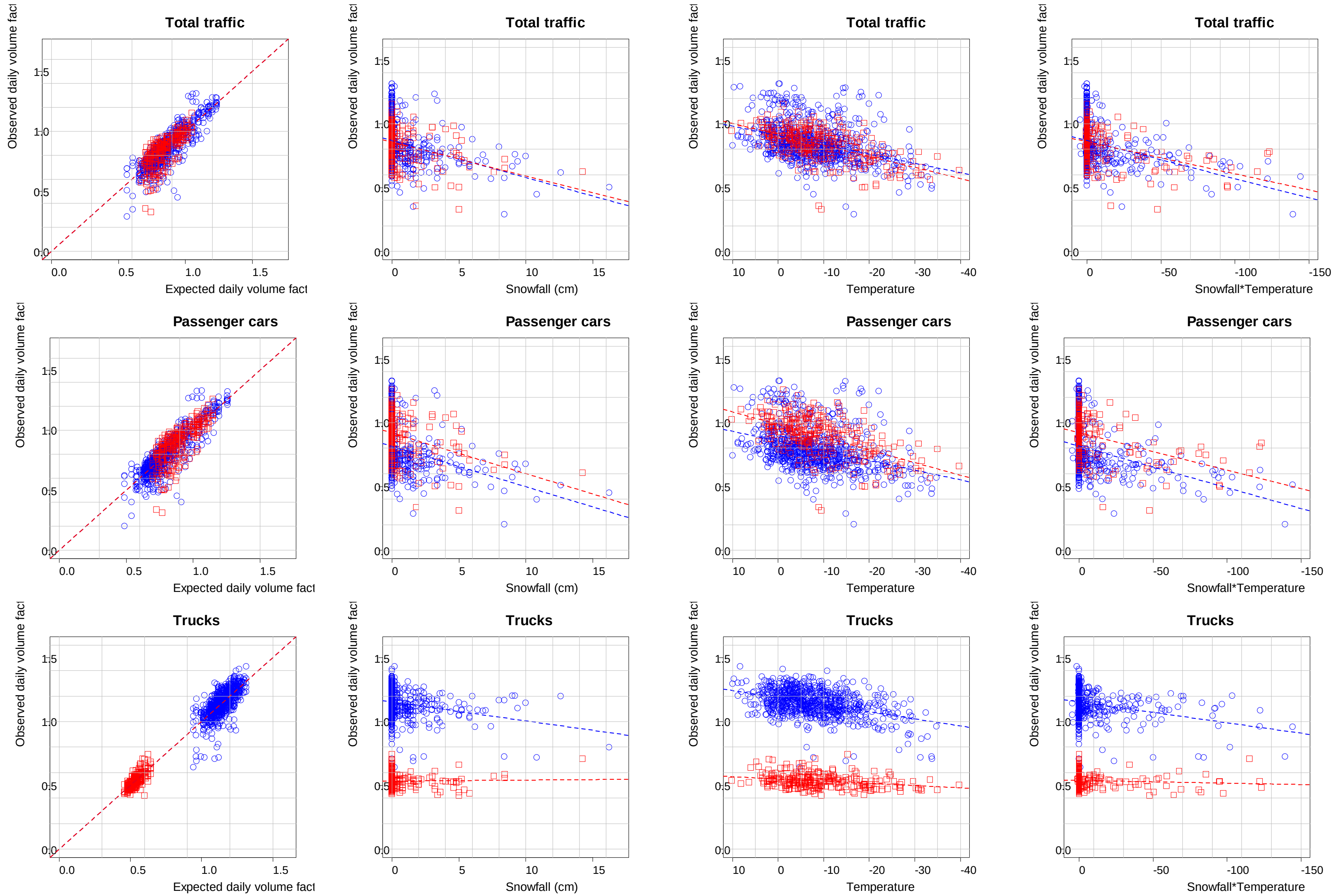


Figure 6.1 Scatter Plot between Dependent and Independent Variables for Highway 2

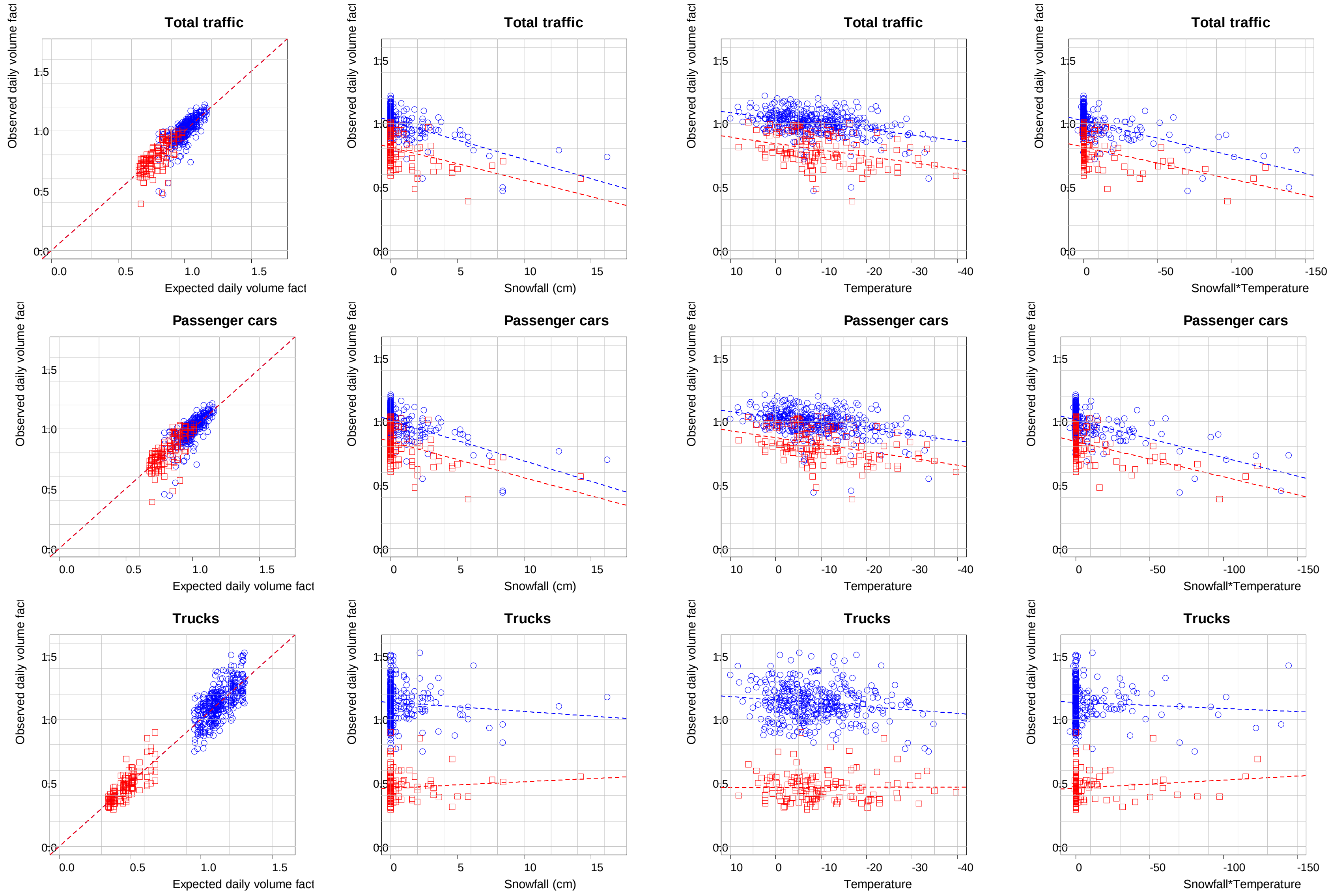


Figure 6.2 Scatter Plot between Dependent and Independent Variables for Highway 2A

The truck traffic volume during weekdays shows a moderate negative relationship with the snowfall-temperature interaction for Highway 2. However, truck traffic does not show any significant variation with the snowfall-temperature interaction either on weekday or weekend for Highway 2A. Therefore, with these observations, it was thought to develop weather interaction traffic volume models with the inclusion of the new interaction term for both the highways, considering the weekday traffic only.

6.2 Regression Models without Snow and Temperature Interaction Variables

For the purpose of mapping the relationships between daily traffic volume and weather factors, a regression model was designed with three independent variables i.e., EDVF (expected daily volume factor), SNOW, and TEMP.

6.2.1 Additive Model Structure

The additive regression model formulated for snow and temperature as continuous variables is as follows.

$$y_i = f(expected\ daliy\ volume\ factor, snowfall, temperature)$$

$$= \beta_1 EDVF_i + \beta_2 SNOW_i + \beta_3 TEMP_i + \varepsilon_i \quad \textbf{6.1}$$

Where, i: refers to the i^{th} observation, $\beta_1, \beta_2, \beta_3$: Regression coefficients estimated for the respective independent variable, y_i: Estimated value of daily traffic volumes factor for different vehicle classes (cars, trucks etc.), $EDVF$: Expected daily volume factor, $SNOW$: Amount of snowfall per day (cm), $TEMP$: Average daily temperature (^{o}C), ε_i: Stochastic error term.

Normalized daily total volumes (traffic volume to AADT ratio), passenger car volumes (passenger car volume to passenger car AADT ratio), and truck traffic volume (truck volume to truck AADT ratio) are used instead of actual volumes to take into consideration the yearly variations in traffic volumes. The normal traffic volume and weekly traffic trends are reflected by adding an expected daily volume factor (EDVF) as an independent variable in model. EDVF is calculated using historical data of the same month, week, and day. The variables SNOW and TEMP represent the weather conditions. In the last chapter, it was concluded that it would be interesting to see how the snowfall and temperature interact with each other in affecting the traffic volume. Thus, the additive model structure needs to be amended by adding snowfall and temperature interaction term. The new model structure is discussed in the subsequent section.

6.2.2 Regression Model with the Interaction of Snowfall and Temperature

The additive regression model (Equation 6.1) with EDVF, SNOW, and TEMP as independent variables would take into account the individual impact of cold and snowfall on highway traffic (i.e., the impact of temperature on traffic volumes after impact of snowfall is taken into account and the impact of each centimeter of snowfall after the effect of temperature is taken into account). A more complex model design is required to investigate whether the impact of snowfall on traffic volumes is the same at all temperature ranges or varies with the severity of temperature. Such analyses would verify the existence or non-existence of cold and snow interaction impacts on traffic volumes. Therefore the model structure shown in Equation 6.1 is modified to accommodate interactions between cold (temperature) and snow. The differential impacts of snowfall by cold or, equivalently, the differential impacts of cold by snow fall were captured in the model by including $SNOW_i * TEMP_i$ interaction terms to the earlier model design in Equation 6.1.

6.2.3 Interaction Model Structure

The interaction model used in this study takes the following form as shown in Equation 6.2 below.

$$y_i = f(expected\ daliy\ volume\ factor, snowfall, temperature)$$
$$= \beta_1 EDVF_i + \beta_2 SNOW_i + \beta_3 TEMP_i + \beta_4 SNOW_i * TEMP_i + \varepsilon_i \qquad \textbf{6.2}$$

Where, β_4 : Regression coefficients estimated for the snow-temperature interaction variable. Except interaction terms, all other terms serve the same purposes as defined in Equation 6.1.

6.3 Result, Analysis and Discussion

The modeling process was carried out using the classified WIM data and corresponding weather records from the three study weather stations sites. Regression models were calibrated using Equation 6.2. In total, six models (2 study highway sites × 3 vehicle classes) were developed. These include separate models for passenger cars and trucks. Table 6.1 and 6.2 shows the calibrated models for weekday traffic on Highway 2 and Highway 2A, respectively, along with the statistical test results.

6.3.1 Overall Fitness and Statistical Validity of the Models

The overall goodness of fit of the regression model to the sample data is evaluated by the squared multiple correlation coefficient (R^2). The values of R^2 for all models in Tables 6.1 and 6.2 are over 0.99, which means that all the models fit well to the sample data.

Table 6.1 Calibrated Weather Interaction Models for Weekday Traffic on Highway 2 by Vehicle Class

Variables	Total Traffic	Passenger Cars	Trucks
EDVF	1.0373627***	1.0405659***	1.0211869***
SNOW	-0.0144013***	-0.0153455***	-0.0080829**
TEMP	0.0026138***	0.0026134***	0.0022545***
SNOW×TEMP	0.0007948**	0.0008879***	0.0003974
R^2	0.9953	0.994	0.9964
Adj. R^2	0.9953	0.994	0.9964
F statistic	39520***	31070***	52080***
Change from $\mathrm{R}^2_{\mathrm{Naive}}$	0.0001	0.0001	-
Incremental F- statistic	15.8723***	12.4333***	-
Number of Sample days	750	750	750

***Coefficient is statistically significant at the 0.001 level, ** 0.01 level,* 0.05 level

Table 6.2 Calibrated Weather Interaction Models for Weekday Traffic on Highway 2A by Vehicle Class

Variables	Total Traffic	Passenger cars	Trucks
EDVF	1.0266381***	1.0309509***	1.0028914***
SNOW	-0.0155569***	-0.0169710***	-0.0085150
TEMP	0.0015939***	0.0018881***	0.0001073
SNOW $\times$ TEMP	0.0006064*	0.0006976**	-0.0003994
R^2	0.9977	0.9974	0.9923
Adj. R^2	0.9976	0.9973	0.9922
F statistic	39500***	35200***	11290***
Change from R^2_{Naive}	0.0001	0.0001	-
Incremental F- statistic	16.1304***	14.2692***	-
Number of Sample days	375	375	355

***Coefficient is statistically significant at the 0.001 level, ** 0.01 level,* 0.05 level

The statistical significance for individual coefficients is evaluated by the t-statistic, and the significance level is indicated using a symbol (*) in the two tables. The value of the *F*-statistic, which is used to assess the overall adequacy of the model, is significant at the 0.001 level for all the models for both highways. The incremental values of *F*-statistic shown in Tables 6.1 and 6.2 are used to test the null hypothesis of “no effect of snowfall and temperature interaction”. These values are obtained by computing F-statistics from the model with and without the inclusion of the interaction term ‘SNOW*TEMP’. These incremental F values included in the two tables were computed from R^2_{naive} and $R^2_{snow*temp}$ using the equation given in the subsection 5.4.1.1 in Chapter 5. The incremental F-statistics results suggest that the interaction term is appropriate for the inclusion in the model**.**

The Adjusted R^2 values are either same or extremely close to the R^2 values for all the cases. These observations on Adjusted R^2 values indeed confirm the evidence received from the t-test, F-test and incremental F-statistics, which suggests that all the models are appropriate with the independent variables chosen for modeling. In other words, the developed models are not over fitted. They are quite appropriate with the independent variables selected.

The weekday daily traffic factors estimated by the study interaction models in Tables 6.1 and 6.2, and the observed daily traffic factors are shown in the form scatter plots in Figures 6.3 and 6.4 for weekday traffic on Highway 2 and Highway 2A, respectively.

An estimated regression line is also added in the same plot to show the linear relationship between the two values. It is worth noting that the regression coefficient R^2

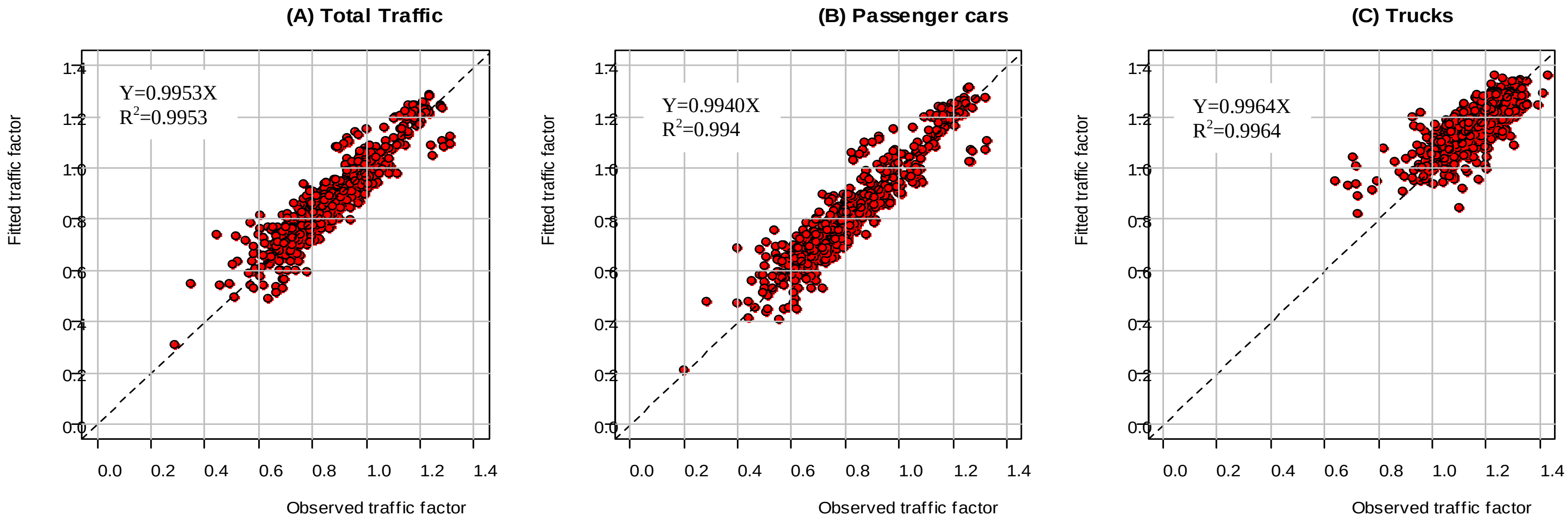


Figure 6.3 Results of Interaction Regression Models of Weekdays for (a) Total Traffic, (b) Passenger Cars, and (c) Truck for Highway 2

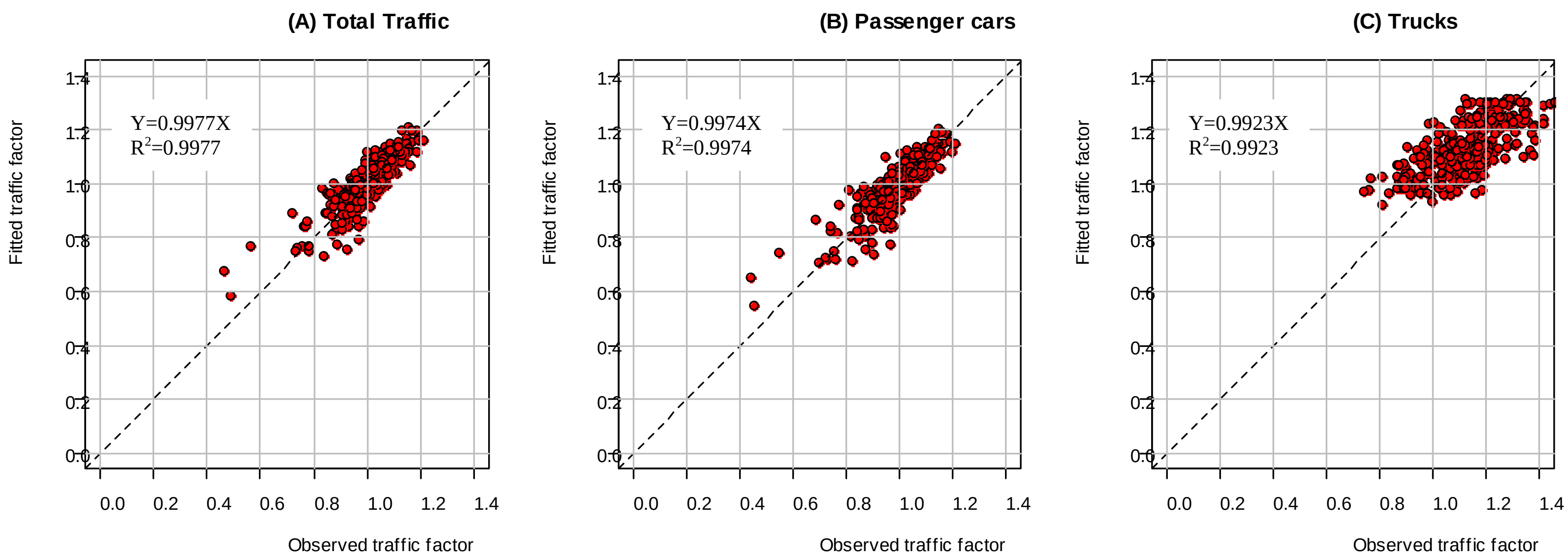


Figure 6.4 Results of Interaction Regression Models of Weekdays for (a) Total Traffic, (b) Passenger Cars, and (c) Truck for Highway 2A

value is greater than 0.99 in case of all the classified traffic for both the highways. This also indicates the appropriateness of the models developed with the variables selected.

In summary, based on these observations, it is very clear that the models fit well to the sample data and the structure of the proposed model is appropriate.

6.3.2 Further Discussion of Results

A partial effect of an independent variable on the dependent variable could be determined by varying the selected independent variable between its lower and upper boundaries (based on the study samples) and holding the other independent variables at a certain value. The partial effects of cold temperatures on daily traffic volumes are included in this section, i.e., for example, partial effect of cold temperatures on daily traffic for a specific pre-defined snowfall amount. Figures 6.5 and 6.6 show the graphs developed to study the partial impact of cold temperatures on car and truck volumes for study sites on Highway 2 and Highway 2A, respectively.

The solid lines in the charts give estimated daily traffic from the models shown in Tables 6.1 and 6.2. The dotted lines give the 95% envelope for the upper and lower thresholds of dependent variable (temperature) estimates. Each plot in Figures 6.5 and 6.6 shows the partial impact of cold temperatures on daily traffic volumes for weekday traffic for a specific combination of vehicle type, location and pre-defined amount of snowfall indicated in chart title. For example, the first row of plots in Figure 6.5 shows the change in daily volume factor of passenger cars due to winter temperatures during weekdays for the Highway 2 sites for different pre-defined amounts of snowfall. These plots are generated by fixing EDVF at its average value calculated from sample data set. It should be noted that the estimated daily volume factor at the point where the two

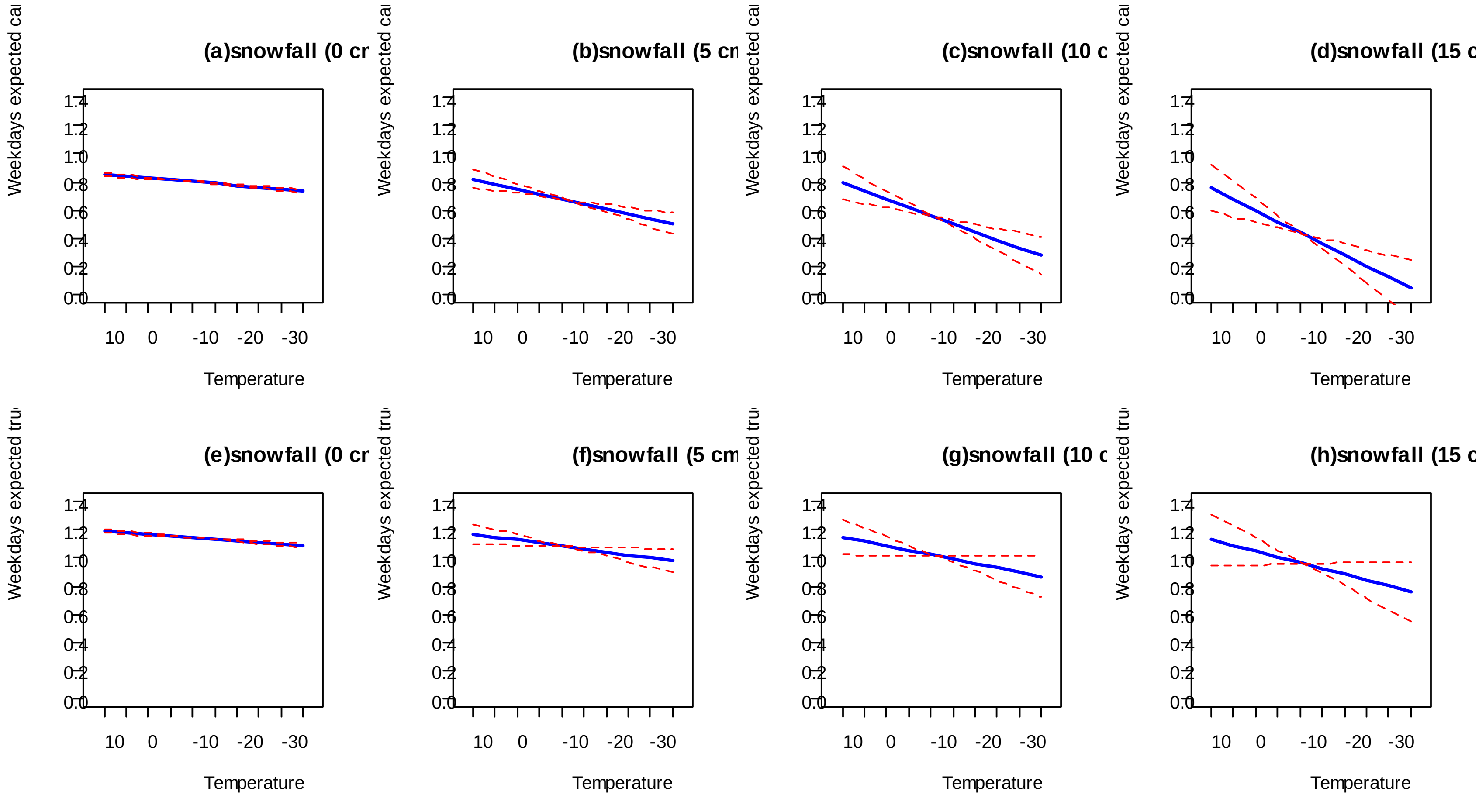


Figure 6.5 Partial Effect of Snowfall at Various Temperatures for Highway 2

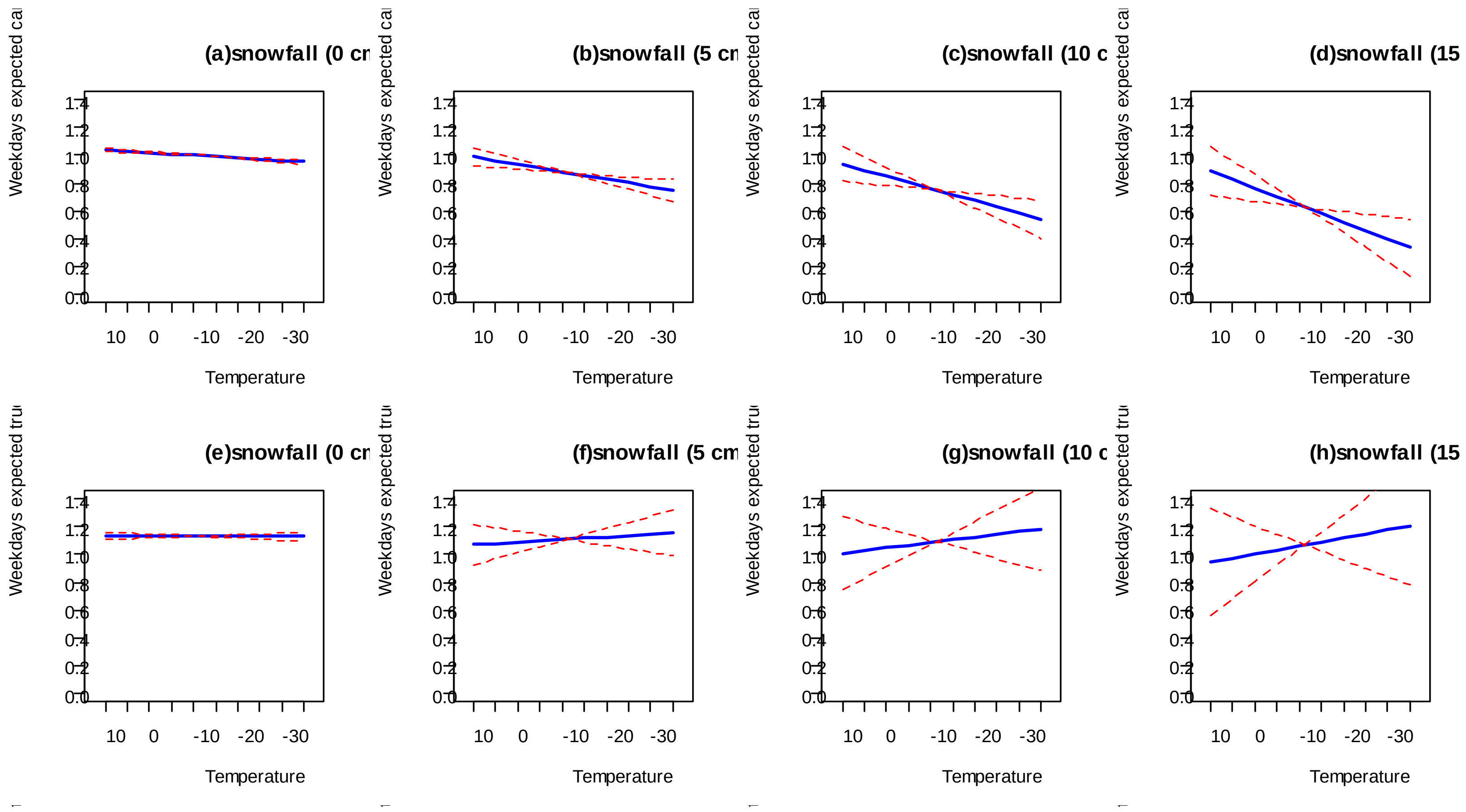


Figure 6.6 Partial Effect of Snowfall at Various Temperatures on Highway 2A

dotted lines cross each other shows the average EDVF for that particular subset of data. Also note that the crossing point generally happened at about -10^{o}C temperature which represents average and also most frequently occurring winter weather conditions in the vicinity of study sites. Comparison of the slopes of plotted lines from left to right show change in the partial impact of temperature on daily traffic with increase in amount of snowfall. Second row of plots in the two figures (see (e), (f), (g), and (h)) shows similar plots for trucks. Based on the plots presented in Figure 6.5, the following interpretations can be made for Highway 2 sites, which serve interregional and long distance trips:

- There is a clear indication that the traffic volume on a given day depends on the severity of cold and amount of snowfall.
- A reduction in passenger car and truck volumes can be expected with increase in severity of cold temperatures. The amount of decrease in traffic volume depends on severity of cold.
- When there is no snowfall the impact of cold temperature on both car and truck volumes is very marginal (see plots in Figure 6.5 (a) and (e)).
- As the amount of snowfall increases the steepness of the regression lines increases, which means that the reduction in traffic volume due to cold temperature would intensify with a rise in amount of snowfall. This clearly shows the existence of cold and snowfall interactions.
- A snowfall of 15cm or higher during severe cold conditions (-20^{o}C or lower) would result in a dramatic decrease in passenger car traffic on the road (see plots in Figure 6.5 (d)).

- With higher amounts of snowfall, passenger cars experience higher reductions due to cold and snowfall as compared to trucks (as shown in plots (d) for cars; and plots (h) for trucks).
- It should be noted that the width of the 95% envelope (shown by dashed lines) also increases from left to right indicting that the reliability of model estimate diminishes with the increase in severity of weather conditions. This could be because of smaller sample size and variability in the data.

The amount of reduction in traffic volume may be attributed to the proportion of discretionary trips in the traffic stream. The existence of more discretionary trips results in higher trip adjustments and, hence, higher traffic reductions. The reason of higher passenger car traffic reductions may be due to the large proportion of discretionary trips from the passenger car traffic than the truck traffic. Trucks (or commercial vehicles) are usually required to follow rigid schedules to complete their mandatory travel to keep the supply-demand in equilibrium if there is a strong commodity demand from the user end irrespective of severe weather conditions. However, commodity demand which is driven by user level of activity generally falls due to the decrease in the level of activity during the winter months. This phenomenon probably attributes to the reduction in truck traffic though less than the reduction as in case of car traffic on interregional long distance highways like Highway 2.

Figure 6.6 shows the partial impact of cold on car and truck traffic on Highway 2A site, which serves as a regional commuter road near the town of Leduc in the Greater Edmonton Region. Interpretation of plots is the same as in Figure 6.5. Similar to Highway 2, passenger car traffic experiences reduction in volume with increase in severity of cold and amount of snowfall. However, the regression lines seem to be less steep than those observed for Highway 2. This indicates lesser impact of cold on car traffic at Highway 2A site as compared to Highway 2. It is interesting to note that the width of the 95% envelops of volume estimates for Highway 2A site are larger as compared to the plots in Figure 6.5 for passenger car and truck traffic. This could be due to a much smaller sample size available for use in the analysis for Highway 2A site, as shown in Table 6.1. Except for these differences, all the remaining observations made earlier based on passenger car traffic-weather relation plots in Figure 6.5 are valid for Highway 2A as well.

The behavior of truck traffic on Highway 2A during adverse weather conditions is quite different from the Highway 2 site. It is very interesting to see the regression lines of truck traffic showing a reverse trend i.e., increase in truck traffic volume with increase in severity of weather conditions. Such an increase in truck traffic is, however, marginal. This is contradictory to what has been observed for truck traffic on Highway 2. Moreover, none of studies in the literature reported increase in traffic volumes during severe weather conditions. A further investigation was conducted to understand the possible reasons for such an abnormal truck traffic patterns.

After reviewing the highway network near the study site, it was found that Highway 814 runs parallel to the Highway 2A. It is possible that truck drivers may change their travel route by shifting to Highway 2A from highway 814. Next section explores and investigates such possibilities.

6.4 Traffic Shifting Analysis for Highway 2A during Winter Weather Conditions

The ideal way to understand the possibilities of diverted traffic from highway 814 to highway 2A is by conducting a roadside origin-destination and route choice survey. Conducting surveys are expensive, time consuming and requires permissions/support from police and government authorities. Considering the scope of the present study and budget limitations, it has been decided to investigate the route changing behavior of drivers using traffic volume comparisons and winter level of service guidelines of the Alberta Transportation.

The highway network near Highway 2A site was reviewed and found that Highway 814 runs parallel to the Highway 2A with 7 km distance from the study site. Highway 814 is a two lane un-divided secondary highway with 100 km/h speed limit.

Alberta Transportation has established guidelines in regards to winter highway maintenance. Regardless of the influence of precipitation, temperature, and wind, etc., the department and the contractor must ensure that the minimum level of service is maintained. The information provided in Table 6.3 illustrates the minimum acceptable levels of service for snow clearing within rural and urban locations in Alberta.

As per the Table 6.3, Highway 2A which has AADT above 7,000 falls under class B with an excellent snow clearing reaction time of less than 1 hour, in comparison, the Highway 814 with AADT of less than 5000 falls under class D with reaction time of 2 hours. Thus Highway 2A has better winter maintenance as compared to Highway 814. Also, hourly traffic data from permanent traffic counter site located on Highway 814 showed significantly lower traffic volumes during the days with severe weather

Table 6.3 Winter Level of Service Guidelines (Province of Alberta) (AT, 2011)

Class of Highway	Traffic Volume (AADT)	Maximum Reaction Time[*](hrs)	Maximum Time to Good Winter Driving Conditions[**](hrs)	Typical reaction Time (hrs)
A	15,000	2	6	1
B	7,000-15,000	4	6	1
C	5,000-7,000	4	8	2
D	2,000-5,000	4	8	2
E	1,000-2,000	6	12	3
F	500-1,000	8	12	3
G	100-500	12	18	4
H	<100	16	24	5

conditions (i.e., higher than normal traffic reductions that were seen at other similar highway segments). The finding from the “Alberta winter level service guidelines” and the significant traffic reduction on Highway 814 during severe winter conditions jointly indicate that there is high probability for traffic shifting from Highway 814 to Highway 2A.

Therefore it is very likely or true that truck drivers changed their travel route by shifting to Highway 2A because of its superior winter maintenance standard. Brief communications with local municipalities in the vicinity of the study sites also indicated the evidence of traffic shifting from Highway 814 to 2A due to poor winter maintenance of 814. Therefore, it can be concluded that there is a possibility of traffic volume increases on high standard highways during adverse weather conditions, which could happen due to shift of traffic from parallel low standard highways

6.5 Chapter Summary

The application of the interaction model used in this chapter, which takes the form as shown in Equation 6.2, confirms several findings of the dummy variable regression model (Equation 5.2) used in Chapter 5.

A number of points can be drawn from the study results presented in this chapter. Firstly, both car and truck traffic volumes on highways vary with severity of cold and amount of snowfall. The impact of cold temperature on both car and truck volumes is marginal during no snowfall days. The reduction in traffic volume due to cold temperature would intensify with a rise in amount of snowfall indicating the existence of cold and snowfall interactions. With higher amounts of snowfall, passenger cars experience higher reductions due to cold and snowfall as compared to trucks. A snowfall of 15 cm or higher during severe cold conditions (-20^{o}C or lower) would result in very few cars travelling on the road.

It is also evident from this study that passenger cars are more vulnerable to adverse weather conditions than trucks. This vulnerability to severe weather conditions could be attributed to such behavior of drivers as choosing flexible departure times, changing routes, or canceling travel entirely and being able to make trip adjustments by avoiding discretionary trips. In addition to this, car drivers may not be willing to take risk during severe winter conditions owing to technological limitations (e.g. two wheel drives) in old cars. Trucks are not as greatly affected as passenger cars by adverse weather conditions. Trucks (or commercial vehicles) are usually required to follow rigid schedules to complete their mandatory travel, and subjected to a strong demand at user side irrespective of severe weather conditions. However, since the demand usually falls which is driven by level of activity at user ends, there will be reduction in truck traffic on long distance roads like Highway 2 during adverse winter weather conditions. Interestingly, the modeling results for Highway 2A, which is a regional commuter road, reveal that higher truck traffic volumes can result during heavy snowfall (or other adverse weather conditions) in winter months. None of the studies in literature have reported such an increase in truck volumes during severe weather conditions. An attempt has been made in this chapter to explain the reason for such behavior in terms of shifting of trucks from other roads in the highway network. It can be concluded that there is a possibility of truck volume increases on high standard highways during adverse weather conditions; which could happen due to shift of traffic from parallel low standard highways.

Chapter Seven

Impact of Winter Season on Truck Type Distribution

7. 0 General

This chapter investigates truck type association with the months in a year, with a particular emphasis on the impact of winter season on truck type distribution. In the Chapters 5 and 6, the two vehicle classes, i.e. passenger cars and trucks, were investigated and models were developed to establish relationship between traffic volume, snowfall and temperature. One of the conclusions of those previous chapters was that the total daily traffic and passenger car volumes per day are significantly influenced by both the snowfall and the cold temperatures, but the truck volume is moderately affected by the amount of snowfall or winter temperatures in case of interregional long distance roads. In case of commuter roads such as Highway 2A, the trucks may not be significantly affected by the winter conditions although the passenger cars are affected by the severity of winter snowfall and temperature. Since there is a considerable lack of statistical investigations in the literature on impact of harsh winter season on the vehicle classes distribution, it was considered worthwhile to carry out a number of statistcal investigations on this subject area by classifying trucks into single-unit trucks, single-trailer, and multi-trailer units. The investigations are based on data from all the six weigh-in-motion (WIM) sites located on Highway 2, Highway 2A, Highway 3, Highway 16 and Highway 44.

7.1 Methodology

To investigate the impact of weather on highway traffic by vehicle type, the raw data obtained from all the study WIM sites were classified using the FHWA classification method, as mentioned earlier in this thesis. This process resulted in 13 vehicle classes. However, due to lower number of total trucks in general and too many truck classes sample data could not generate sufficient samples to carry out detailed statistical analysis by each vehicle class. Therefore, the 13 vehicle classes were aggregated into three major truck categories, namely single unit trucks, single-trailer, and multi-trailer units.

Historical weather records from the Environment Canada (WO, 2010) climate database indicate that the province of Alberta experiences severe snowfall and cold conditions from November to March. Based on these observations, the months of November to March, which represents severe snowfall and cold conditions, are grouped into winter months and the remaining months are grouped into non-winter months. The study period remains same as before, i.e. 2005-2009. To check the statistical significance of the association of trucks with weather, the analysis was done in two ways. First, the month to month variations of truck types were analyzed in traffic stream. Second, the season to season variations of trucks were analyzed using the winter and non-winter data from the six WIM sites. Unlike the analyses presented in Chapter 5 and 6, where impacts of daily snow fall and temperature on volumes of cars, trucks and total traffic were studied on a daily basis, the truck type distributions in this chapter are studied in terms of the average number of trucks per day in a particular month or season of the year.

To examine whether or not truck type distribution is associated with the month of the year, the following methodology was adopted. First, the truck traffic data were separated from the total traffic. Based on the classification method identified earlier the trucks were categorized into three truck types (i.e., single unit trucks, single-trailer, and multi-trailer). The truck data were first aggregated to daily totals, and the average daily truck type distribution patterns were obtained for the 12 months of the year. Combined Chi-square and Binomial statistical tests were then used to examine whether or not an association existed between truck type distribution and the month.

7.1.1 Chi-Square Test for Monthly Variation of Truck Types

The Chi-square (χ^2) test is one type of goodness-of-fit test that has been widely used in past studies (Wayne, 1990). The (χ^2) test statistic results from a comparison of expected and observed patterns. In this study, the average monthly truck type distribution patterns during the analysis period is considered as one empirical frequency distribution. The other empirical frequency distribution i.e., the expected truck type distribution patterns is calculated based on the null hypothesis of "truck type distribution is not associated with the month." If the two truck type distribution patterns are similar to each other, a close agreement is expected between the observed and expected frequencies falling into the categories, with the χ^2 values smaller than the critical value of Chi-square at $(i-1)*(j-1)$ degrees of freedom and significance level α. In this analysis 'i' denotes the number of rows i.e. the number of vehicle classes and 'j' denoted the number of columns of the number of months in a year.

In order to carry out the Chi-square statistical test, the observed truck type distribution patterns and the expected truck type distribution patterns are required. The expected truck type distribution patterns are calculated based on the null hypothesis of "truck type distribution is not associated with the month." The hypothesis can be formulated as $E_{ij} = (n_{i.}/n)n_{.j}$, where $n_{i.}$ and $n_{.j}$ are marginal grand total for row i and column$j$, and n represents a grand total in the distribution matrix.

The Chi-square test statistic (χ^2 = 241.2346, in the following example) is calculated using the following expression (Equation 7.1):

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \left[\frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}} \right] \qquad \textbf{7.1}$$

7.1.2 Binomial Probability Test for Monthly Variation of Truck Types

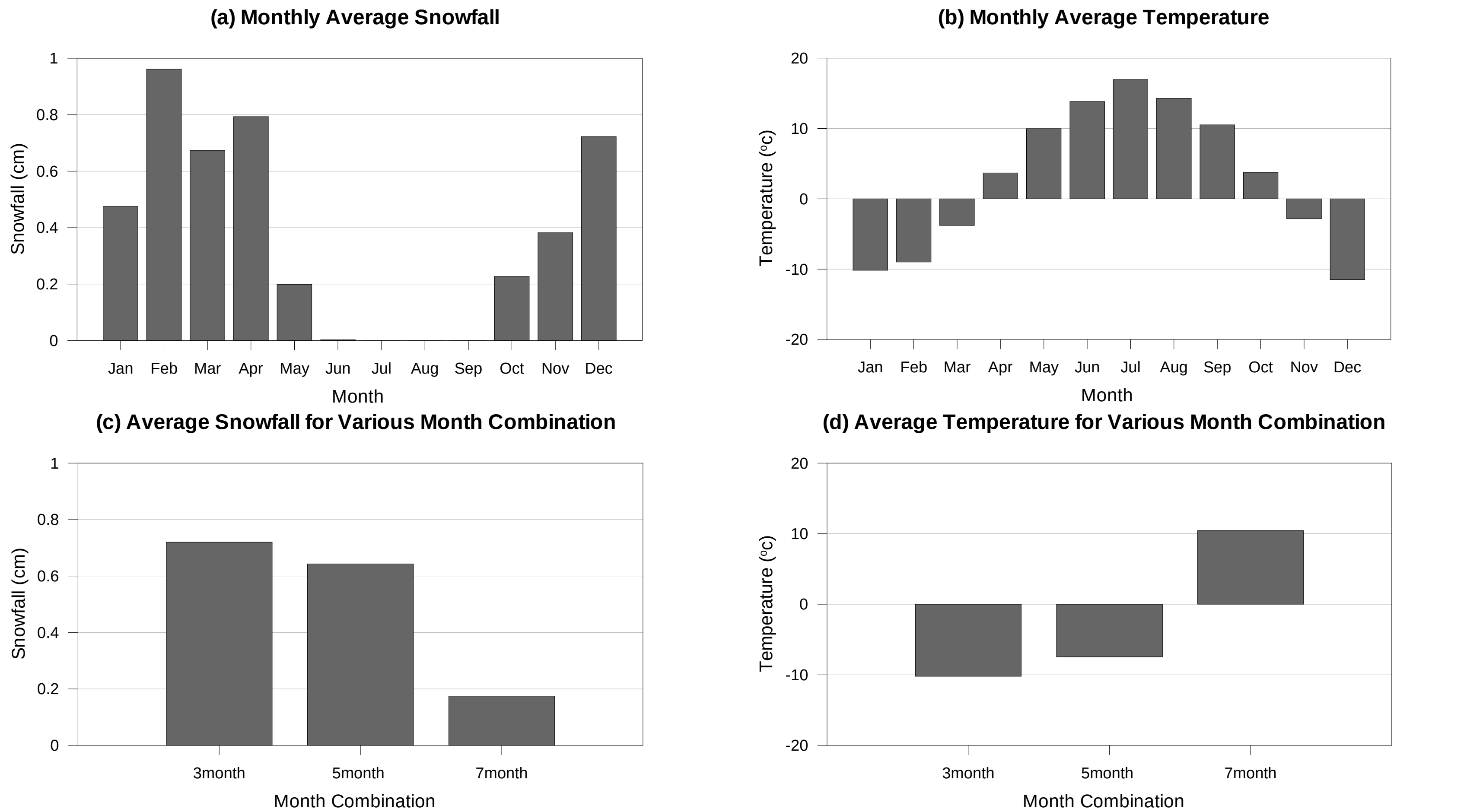
The Chi-square test only examines whether or not truck type distribution is associated with the month of the year for one individual year, so the results may not be conclusive. In order to develop adequate confidence from historical data, the Binomial Probability (BP) test is used to examine the statistical significance or repeatability of yearly Chi-square test statistic results. In this test, the yearly Chi-square test statistic results over years were considered to obey the Binomial Distribution with the success probability parameter (p) of 0.5. Therefore, with the sample size being the number of years, it could be concluded whether or not truck type distribution is associated with the month of the year at a 95% confidence level from the Binomial Probability (BP) test.

These two statistical tests i.e. chi-square test and binomial test were performed on the three truck types and the results are discussed in the following section.

7.1.3 Season to Season Variations of Types of Trucks in Traffic Stream

It has long been recognized that weather conditions (in any season or climate) affect highway traffic flow in various ways. Owing to the geographical location, the winter weather in Canada is very severe with extremely cold temperatures (below -35^0 centigrade), heavy snowfall, blizzards, freezing rain and high wind chills. Such weather conditions may result significant variation in highway traffic patterns. Therefore, it was considered worthwhile to understand the truck type distribution patterns during winter months as compared to remaining months. In order to do this, the months of the year were grouped in two different groups for statistical comparisons in this study. First, November to March (5 months) which are usual winter months were clustered in to one group, and were compared with the remaining 7 months (April to October) of the year. Second, the months of December, January and February which experience severe snowfall and cold conditions were grouped into another winter group, and the months of April to October were grouped into non-winter; the months of November and March were considered as the two transition moths and were therefore not included in the comparisons. The average daily snowfall and temperature corresponding to various months and (3-, 5-, and 7-month) combinations are shown in Figure 7.1.

The summary statistics in these figures are prepared from the weather station data near the Red Deer WIM site. The average daily truck type distribution patterns and their expected value statistics were calculated for winter and non-winter months using different month combinations as discussed above for the study sites during the years 2005 to 2009. The seasonal variation results are discussed after the monthly variations results.



December to February = 3month, November to March = 5month, April to October = 7month

Figure 7.1 Average Daily Snowfall and Temperature for Months and Various Month Combinations

7.2 Association of Truck Type Distribution with the Month

To provide a better understanding of the methodology adopted in this study, a sample analysis is presented in this section. The Leduc site on Highway 2A, and the Red Deer & Leduc WIM sites on Highway 2 were chosen to explain the methodology discussed above. The data from Red Deer and Leduc WIM sites were combined for the analysis. The following subsections illustrate and interpret the results for the truck type distribution at the Leduc site on Highway 2A.

7.2.1 Association of Truck Type Distribution on Highway 2A with the Month

The truck traffic data from the Leduc study site on Highway 2A in the year 2005 are used as an example. Table 7.1a shows the observed average daily truck type distribution patterns for each month. In order to carry out the Chi-square statistical test, the observed truck type distribution patterns and the expected truck type distribution patterns are required. The expected truck type distribution patterns are calculated based on the null hypothesis of "truck type distribution is not associated with the month." The hypothesis can be formulated as $E_{ij} = (n_{i.}/n)n_{.j}$, where $n_{i.}$ and $n_{.j}$ are marginal grand total for row i and column j, and n represents a grand total in Table 7.1a. The expected truck type distribution estimates for the sample site for the year 2005 are shown in Table 7.1b.

Based on the truck traffic patterns presented in Tables 7.1a and 7.1b, Chi-square test is conducted. The Chi-square test statistic (χ^2 = 241.2346) is calculated using Equation 7.1. From the Chi-square Distribution chart (Figure 7.2), the critical value of Chi-square test corresponding to 22 degrees of freedom and 0.05 significance level is 34.9244. The test statistic (241.2346) is greater than the critical statistic (34.9244), falling in a rejection region, therefore the null hypothesis is rejected. In other words, it is

Table 7.1 Observed and Expected Monthly Truck Type Distribution (for the year 2005 on Highway 2A)

(a)

Observed (O_{ij})	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Straight Unit	225	234	249	276	295	293	351	304	298	317	333	304
Single Trailer	101	114	112	73	83	107	153	173	173	208	188	139
Multi Trailer	34	36	44	74	133	124	86	52	56	55	50	43

(b)

Expected (E_{ij})	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Straight Unit	213	226	240	250	301	310	349	312	311	342	338	287
Single Trailer	99	106	112	117	141	144	163	146	145	160	158	134
Multi Trailer	48	51	54	56	68	70	79	71	70	77	76	65

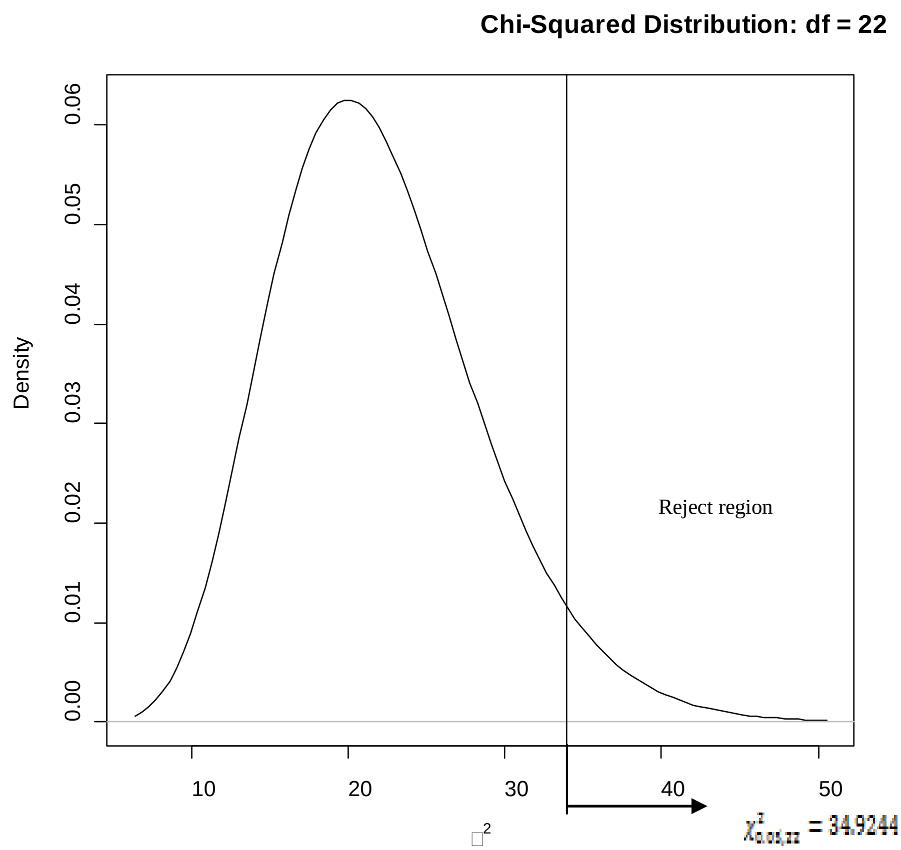


Figure 7.2 Chi-square Probability Distribution (df=22, p=0.05)

confirmed that truck type distribution is associated with the month at 0.05 significance level for the Leduc study site for the year 2005. Similar statistical analyses were done for the remaining four years of study period (2006 to 2009) and the results are summarized in Table 7.2.

Based on the Chi-square significance test results over the five years shown in Table 7.2, Binomial test was conducted to test the statistical significance of yearly Chi-square test statistic results. The Chi-square test results in Table 7.2 show that the truck type distribution depends on the month during 3 study years out of 5 years of study data. According to the table of Binomial Probability Distribution chart (Figure 7.3), for the sample size of 5 and success probability parameter (p) of 0.5, the critical value of the Binomial test is 4 to satisfy at the 95% confidence level. For the present example, there is insufficient evidence to argue that truck type distribution is associated with the month. Therefore, based on the combined Chi-square and Binomial test results, it can be concluded that the truck type distribution is not associated with the month for the Leduc site on Highway 2A during the 5 years study period of 2005 to 2009. For the illustration purposes, the observed and expected truck type distribution patterns over 5 years of study period for Leduc site are presented in Figure 7.4.

7.2.2 Association of Truck Type Distribution on Highway 2 with Month

The Highway 2A site case study was extended to examine whether truck type distribution is associated with a change of the month (or season). For this investigation, the same three truck types (i.e., straight unit, single-trailer, and multi-trailer) and the months are recognized as two variables and the truck traffic volumes are classified based on the classification levels for those variables. The proposed question of truck type

Table7.2 Summary of Chi-square Test Results (Month to Month Variations)

Year	χ^2	SIGNIFICANCE
2005	241.2346	Y (dependent)
2006	21.023	N (independent)
2007	62.1561	Y (dependent)
2008	67.8085	Y (dependent)
2009	17.3634	N (independent)
Number of Significant Years	3	

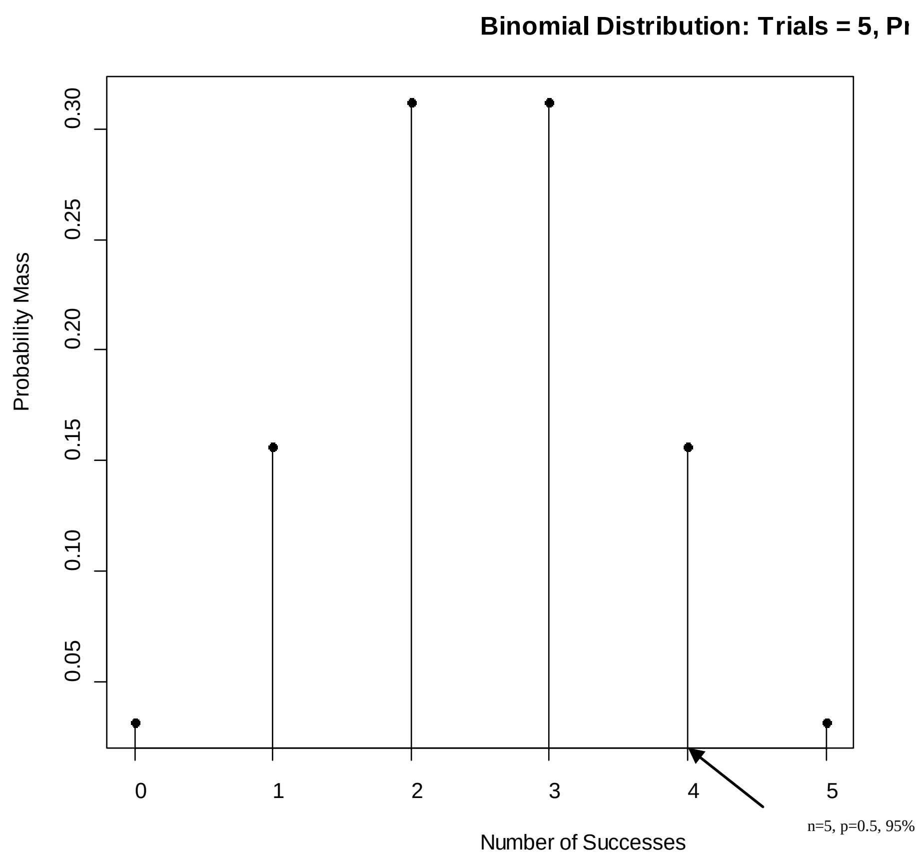


Figure 7.3 Binomial Probability Distribution (n=5, p=0.5)

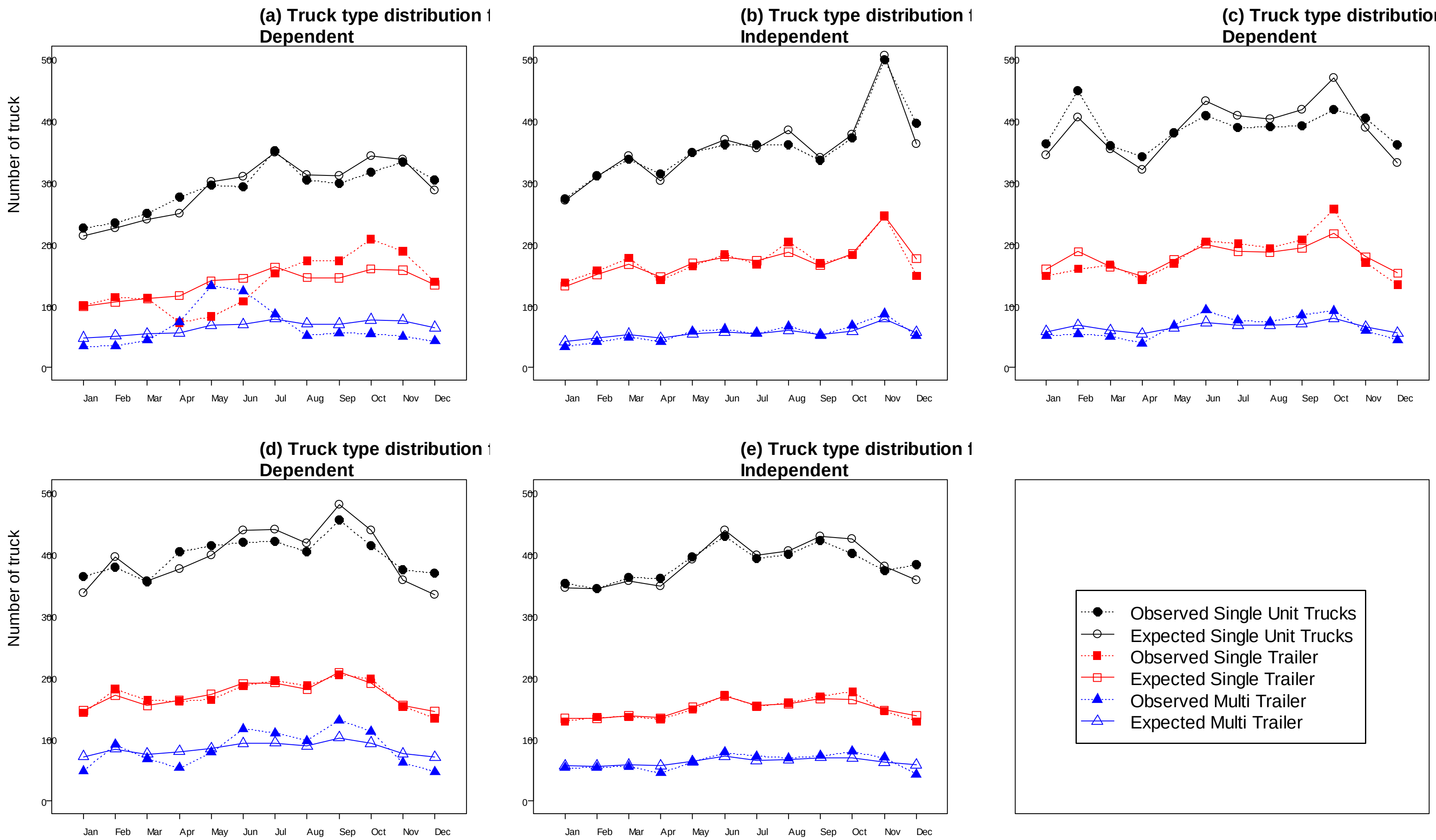


Figure 7.4 Observed and Expected Truck Type Distribution for Highway 2A Site over the 5 Years Study Period

distribution is associated with the month (or season) was verified based on combined Chi-square and Binomial statistical test. Table 7.3a shows the observed truck type distribution and Table 7.3b shows the corresponding expected truck type distribution.

The expected frequency of truck traffic in Table 7.3b is calculated based on the null hypothesis of "truck type distribution is not associated with the month (or season)." The same formula previously used for the Highway 2A site, reflecting the hypothesis as $E_{ij} = (n_{i.}/n)n_{.j}$ was used here to compute the expected number of trucks. The explanations for $n_{i.}$ and $n_{.j}$ have been given earlier in the previous section. Based on the Tables 7.3a and 7.3b, the Chi-square test was conducted to determine whether truck type distribution is associated with the month (or season). The value of Chi-square test statistic (χ^2) was calculated using the Equation 7.1 as described in the previous section. The critical value of Chi-square test corresponding to 22 degrees of freedom at 0.05 significance levels was calculated as 34.9244 (see figure 7.2) from the Chi-square distribution. Since the calculated value of Chi-square test statistic (χ^2 =77.4037) is greater than the critical statistic (34.9244), falling in a rejection region, the null hypothesis is rejected. In other words, it is confirmed that the truck type distribution is associated with the month on Highway 2 at 0.05 significance levels for the year 2005. The same Chi-square test was also applied for other four years of study data and the results are shown in Table 7.4.

It may be observed that the Chi-square values are significant for all the years. These results were analyzed for the Binomial test as before. The number of required success is 4 (see figure 7.3) from the Binomial probability test, whereas the number of success from the Chi-square results is 5. The joint analysis from the Chi-square and

Table 7.3 Observed and Expected Truck Type Distribution for the Year 2005 on Highway 2 Study Site

(a)

Observed (O_{ij})	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Straight Unit	1056	1106	1188	1287	1411	1471	1544	1484	1414	1389	1393	1243
Single Trailer	1567	1678	1712	1724	1805	1863	1782	1903	1967	1993	2026	1769
Multi Trailer	727	803	923	942	1023	977	912	966	965	959	991	845

(b)

Expected (E_{ij})	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Straight Unit	1097	1175	1252	1295	1388	1412	1388	1425	1423	1422	1445	1263
Single Trailer	1496	1602	1707	1765	1892	1924	1892	1943	1940	1938	1969	1722
Multi Trailer	757	811	864	894	958	974	958	984	982	981	997	872

Table 7.4 Summary Results of Chi-square Test of Independence for Highway 2

Year	χ^2	SIGNIFICANCE
2005	77.4037	Y (dependent)
2006	74.0026	Y (dependent)
2007	75.096	Y (dependent)
2008	59.347	Y (dependent)
2009	53.8616	Y (dependent)
Number of Significant Years	5	

Binomial Probability Test confirms the rejection of the null hypothesis. In other words, it may be interpreted as truck type distribution is associated with the month for Highway 2. The truck traffic patterns for Highway 2 are shown in Figure 7.5 for illustration purpose.

7.2.3 Results and Discussion for Highway 3, Highway 16 and Highway44

The key finding from the truck type distribution analysis for Highway 2A and Highway 2 is that the truck types are associated with months on Highway 2 whereas the association is not significant for Highway 2A. To arrive at a solid conclusion, this study was further extended to examine the truck types association with the months in a year for Highway 3, Highway 16 and Highway 44. The same methodology as discussed in Section 7.1 was employed to carry out this extended research. The results for Highway 3, Highway 16 and Highway 44 sites are summarized in Table 7.5.

From the Table 7.5, it may be observed that the numbers of years of significant association of truck type distribution with months are 4, 5 and 5 for the Highway 3, Highway 16 and Highway 44 respectively. The rejection requirement of Binomial Probability test to reject the Null-Hypothesis is 4. Since all the values are greater than or equal to 4, we may reject the null hypothesis ("Truck type distribution is not associated with months") and a conclusion can be made that the truck type distribution is associated with months for all these highways. For illustration purpose, the observed and expected truck type distributions for these three sites are shown in Figures 7.6, 7.7 and 7.8.

It is noteworthy here to examine the truck type distribution plots shown in Figures 7.4 to 7.7 for Highway 2A, Highway 2, Highway 3, and Highway 16 sites. The monthly and yearly patterns are reasonably consistent for these sites over the five year study period. However, the truck traffic patterns for Highway 44 site as shown in Figure

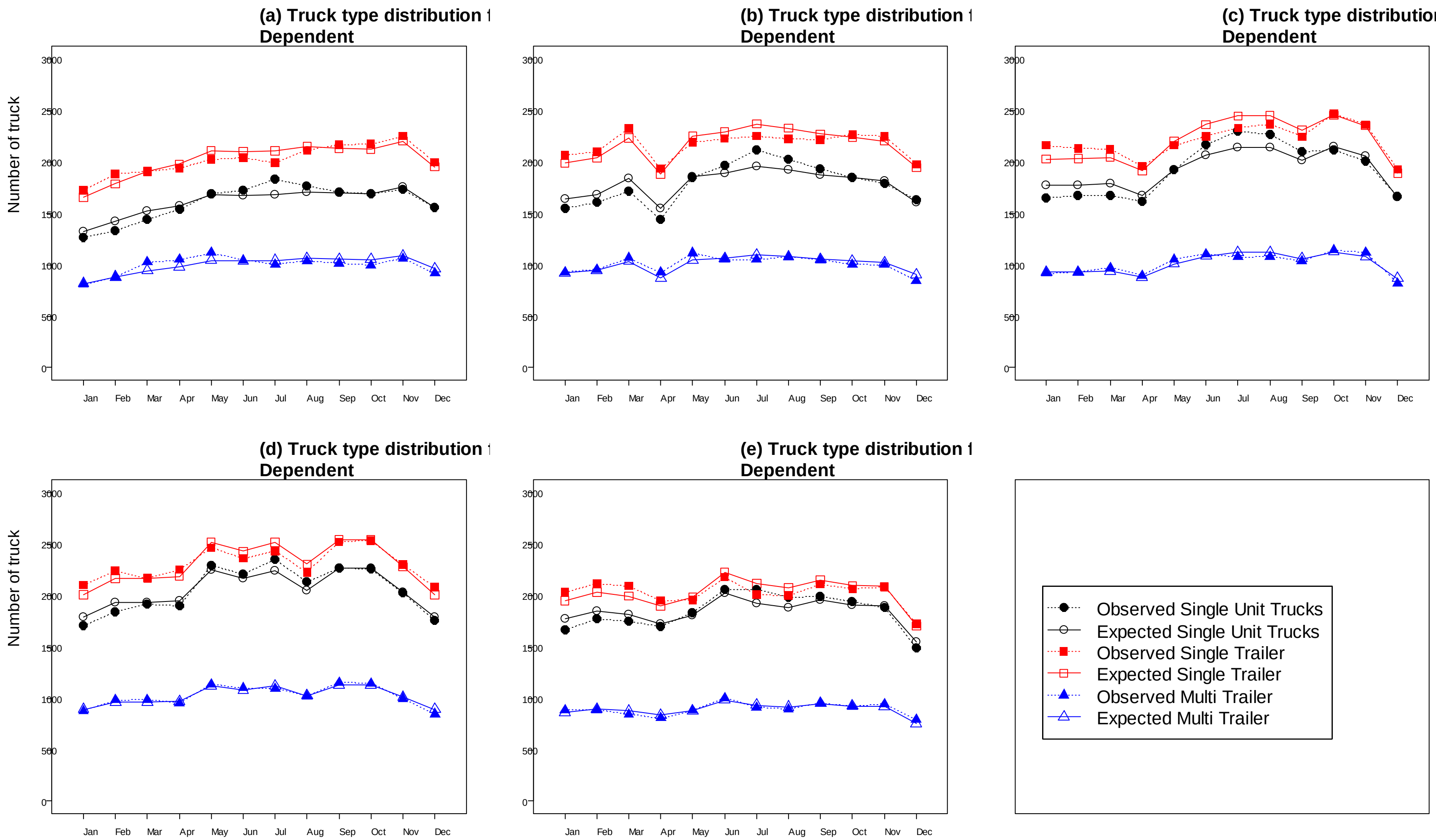


Figure 7.5 Observed and Expected Truck Type Distribution for Highway 2 Sites over the 5 Years Study Period

Table 7.5 Summaries of Results for Highway 3 and Highway 16 Sites

Highway Name	Year	χ^2	SIGNIFICANCE
Highway 3	2005	259.2112	Y (dependent)
	2006	37.4228	Y (dependent)
	2007	39.386	Y (dependent)
	2008	42.2451	Y (dependent)
	2009	26.0582	N (independent)
	Number of Significant Years	4	
Highway 16	Year	χ^2	SIGNIFICANCE
	2005	210.1799	Y (dependent)
	2006	53.2132	Y (dependent)
	2007	66.3854	Y (dependent)
	2008	42.6356	Y (dependent)
	2009	42.212	Y (dependent)
	Number of Significant Years	5	
Highway 44	Year	χ^2	SIGNIFICANCE
	2005	769.348	Y (dependent)
	2006	183.6558	Y (dependent)
	2007	448.0415	Y (dependent)
	2008	212.8397	Y (dependent)
	2009	180.0822	Y (dependent)
	Number of Significant Years	5	

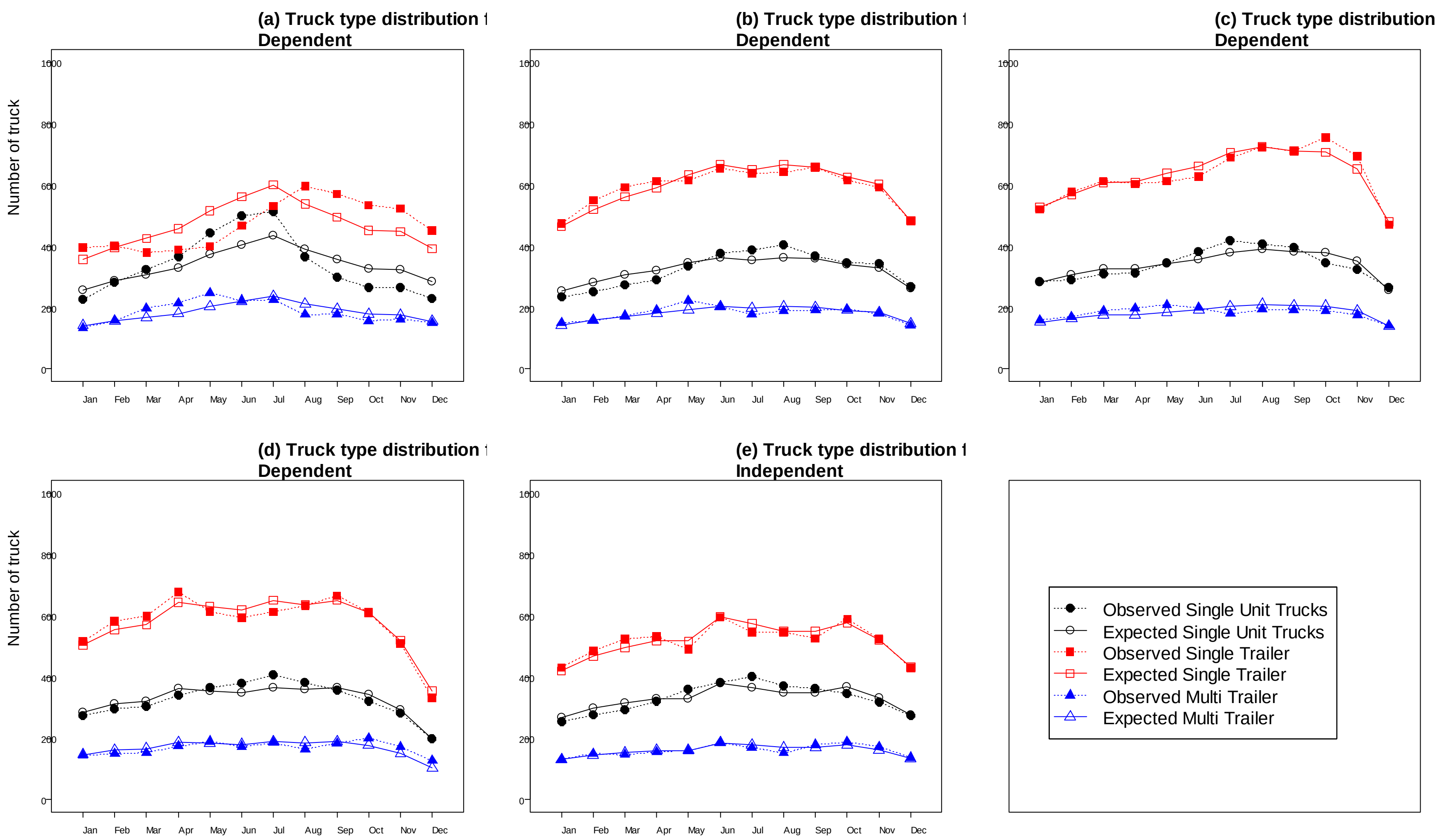


Figure 7.6 Truck Traffic Patterns for both the Observed and Expected Truck Type Distribution for Highway 3

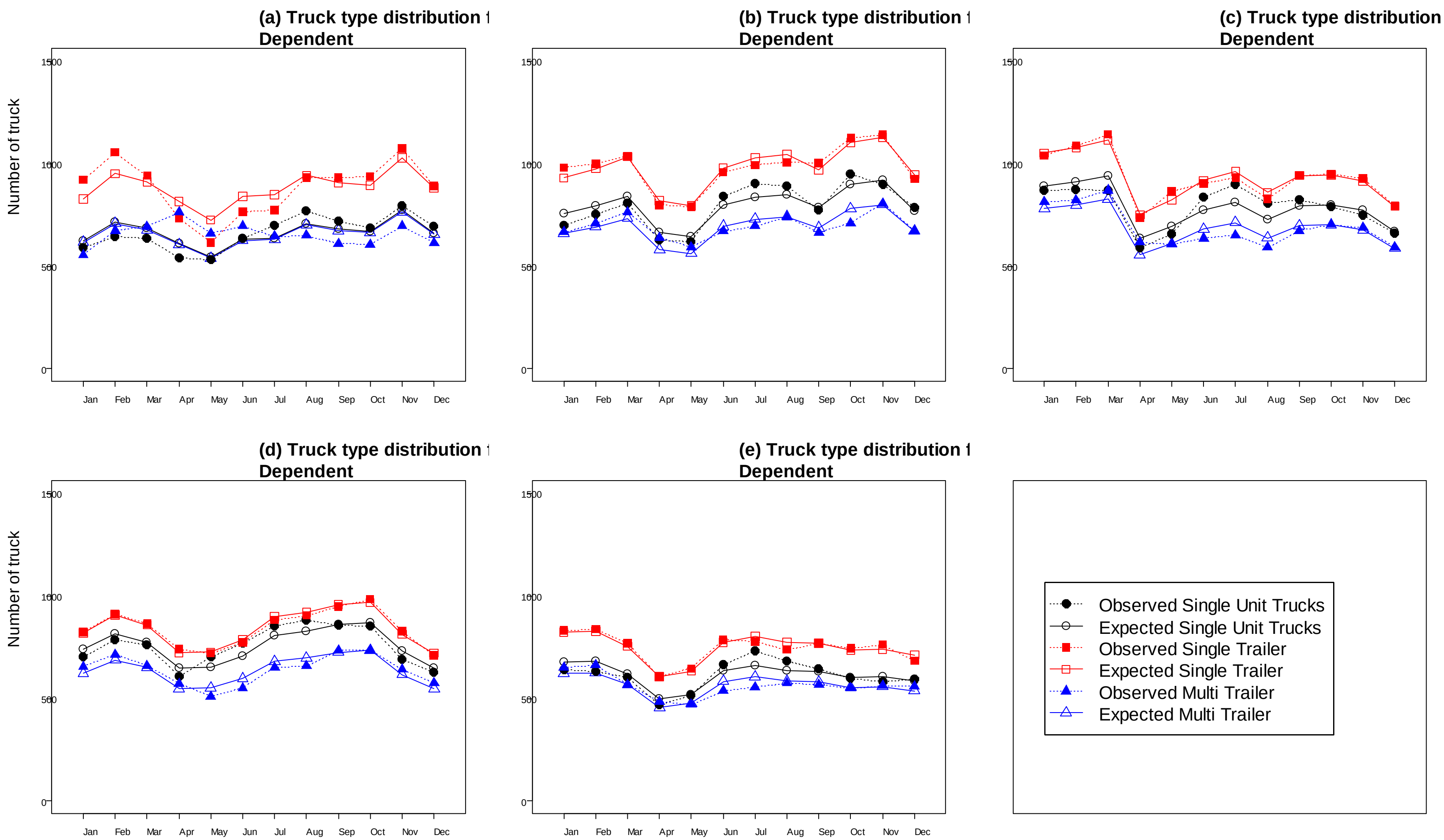


Figure 7.7 Truck Traffic Patterns for both the Observed and Expected Truck Type Distribution for Highway 16

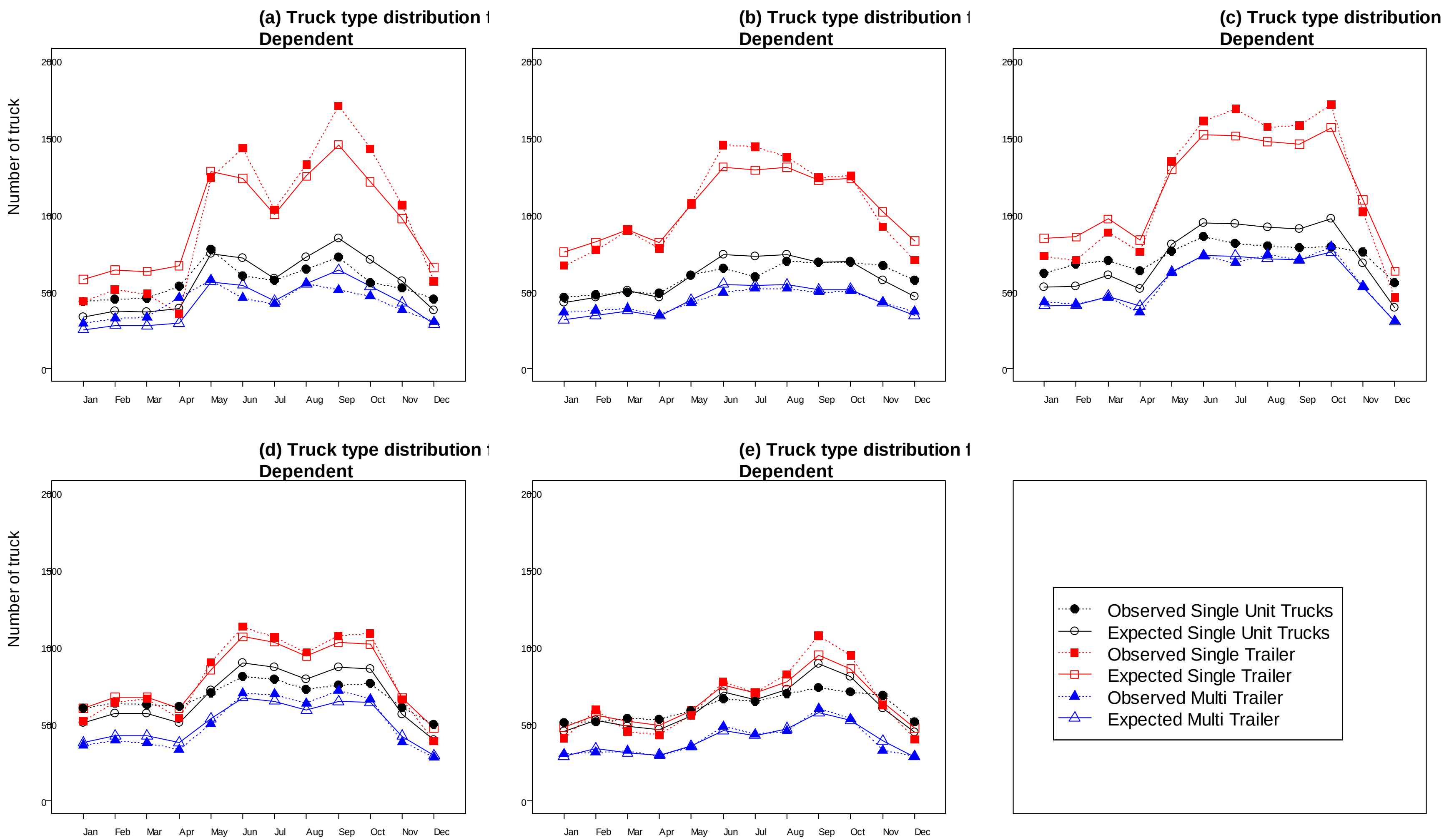


Figure 7.8 Truck Traffic Patterns for Both the Observed and Expected Truck Type Distribution for Highway 44

7.8 are quite different than the other study sites. Highway 44 provides a north-south linkage between Calahoo-Villeneuve aggregate operations in the Sturgeon County and the regional sand and gravel markets in the Edmonton Region (UMA, 2001). The truck traffic on this highway is composed of a large proportion of aggregate hauling trucks (Edmonton Journal, 2007) in the region. In Figure 7.8, the patterns for 2005, 2006 and 2007 are generally similar to each other. But because of a slowdown in the economy of Alberta, the market demand for aggregates declined in the Edmonton Region starting in 2008. As a result the truck traffic hauling aggregates decreased considerably in 2008 and 2009 (Bateman, 2010).

7.3 Results and Discussion for Winter and Non-winter Variation of Truck Type Distribution

Using the methodology explained in section 7.1, the average daily truck type distribution patterns and their expected value statistics were calculated for winter and non-winter months. Investigation were carried out by considering different combination of months as discussed in subsection 7.1.3. As an example, the observed and expected statistics for Highway 2A site for the year 2005 are shown in Table 7.6a and Table 7.6b, respectively. These statistical values were obtained by considering the November to March (5 months) as winter months.

Using Equation 7.1, the Chi-square test statistic for the Leduc site for the year 2005 was estimated as 8.37143. The critical value of Chi-square test statistic for 2 degrees of freedom at significance level (0.05) is 5.991465. Since 8.7143 > 5.991465, it could be concluded that the truck type distribution differed from season to season in 2005 for Leduc site at 95% confidence level.

Table 7.6 Observed and Expected Seasonal Truck Type Distribution (for the year 2005 at Leduc study site on Highway 2A)

(a)

Observed (O_{ij})	Winter	Non Winter
Straight Unit	269	305
Single Trailer	131	139
Multi Trailer	42	83

(b)

Expected (E_{ij})	Winter	Non Winter
Straight Unit	262	312
Single Trailer	123	147
Multi Trailer	57	68

Similar statistical analyses were done for the remaining four years and the results are summarized in Table 7.7.

Based on the 5 years of Chi-square test results shown in Table 7.7, Binomial test is conducted to test the statistical significance of yearly Chi-square test statistic results. According to the table of Binomial Probability Distribution, for the sample size of 5 and success probability parameter (p) of 0.5, the critical value of the Binomial test is 4 to satisfy the 95% confidence level. For the present example, there is insufficient evidence to argue that truck type distribution is associated with the season at 95% confidence level.

Therefore, based on the combined Chi-square and Binomial test results, it could be concluded that the truck type distribution is not associated with the season for the Leduc site during the 5 year study period of 2005 to 2009.

Similar analysis was done for the three winter-month combination i.e. December to February on Highway 2A. The results for all the remaining highway sites with the different month combinations using the methodology discussed previously were computed. The experimental Chi-square values for all the highways were compared with the critical Chi-square value at 95% confidence level. The summary of the results are tabulated in Table 7.8.

Table 7.8 shows the summary of results based on the combined tests, i.e. Chi-square test and Binomial Probability test for the all the highway sites. From the table it may be observed that, at the 95% confidence level, the truck type distribution for all highway sites, with the exception of Highway 44 site, is not associated with any combination of winter months. The truck traffic at the Highway 44 study site is associated with the winter and non-winter seasons of the year. The most likely reason for

Table 7.7 Summary of Chi-square Test Results for Highway 2A

Year	χ^2	SIGNIFICANCE
2005	8.7143	Y (dependent)
2006	0.4429	N (independent)
2007	5.4988	N (independent)
2008	3.554	N (independent)
2009	0.5195	N (independent)
Number of Significant Years	1	

Table 7.8 Summary of Results for Seasonal Truck Type Distribution on All the Study Sites

Sl. No.	Highway	Highway Class	Month Combination (Nos.)	Confidence Level	Significance
1	Highway 2A	Commuter	5**+7 and 3***+7*	95%	Independent
2	Highway 2- Red Deer	Long distance	5+7 and 3+7	95%	Independent
3	Highway 2- Leduc	Long distance	5+7 and 3+7	95%	Independent
4	Highway 2 – Combined	Long distance	5+7 and 3+7	95%	Independent
5	Highway 3	Long distance	5+7 and 3+7	95%	Independent
6	Highway 16	Long distance	5+7 and 3+7	95%	Independent
7	Highway 44	Special	5+7 and 3+7	95%	Dependent

December to February = 3***, November to March = 5**, April to October = 7* such variation is the seasonal nature of the aggregate hauling truck traffic on this highway. There is considerable slowdown in aggregate operations during the winter season because of reduction in the level of construction activities in the region. It may also be noted that the Highway 44 site has been shown as a “special highway” class in Table 7.8. This highway is unlike any other study site because of the nature of trips that this facility serves in the northwest area of the Edmonton Region. It serves regional commuter traffic similar to Highway 2A site south of Leduc. It also serves as an alternate route to Highway 2 from Highway 16 (Yellowhead Highway) east of the City of Spruce Grove to north of Edmonton region. Percent of truck traffic at this site is 32%, which is much higher than the highway 2A site (Table 4.1). Moreover, similar to other long distance sites (on Highways 2, 3, and 16), a majority of truck traffic is composed of single- and multi-trailer trucks, which is quite different than the Highway 2A site where majority of trucks are single unit trucks.

One conclusion may be made from these observations is that the truck type distribution is not affected due to severity of weather during winter for primary highway facilities which serve predominantly commuter type of roads (Highway 2A). Similarly, the severe winter months of Alberta also do not seem to have significant impact on different truck classes on a long distance highway like Highway 2, 3, or 16. On the other hand, highway facilities serving significant amount of truck traffic which is seasonal in nature are likely to be affected by seasons of the year. The study WIM site on Highway 44 is an example of such facilities. It may be noted that the results of significance can be changed if a different level of confidence is used in the analysis.

This above inference suggests that a single short-duration truck traffic count be carried out for periods ranging from a few days to several weeks on commuter and long distance roads like Highway 2A, 2, 3 and 16, irrespective of seasons of the year. On other routes serving seasonal truck traffic, two or more short duration counts in a year could be required for an accurate estimation of traffic parameters. These study findings will help traffic engineers in traffic monitoring and estimation of the highway planning and design parameters like Truck Annual Average Daily Truck Traffic (TAADT), and Design Hour Truck Volume etc. Further research on this could be able to rationalize the length and frequency of the truck counts for various road types.

7.4 Chapter Summary

The truck type distribution on study sites was tested to determine whether it is associated with various months and seasons of the year. To do this, two types of statistical tests were conducted on observed monthly and seasonal truck volumes and the expected monthly and seasonal truck volumes. These tests included the Chi-square test and Binomial probability test. From these two test results, the experimental Chi-square values for months as well as seasons were compared with the critical values at 95% confidence level. This procedure was carried out for all the six study WIM sites included in this study.

One conclusion that can be drawn from the research presented in this chapter is that the truck type distribution is associated with the months for all the highways except commuter highway site at the WIM site on Highway 2A. In other words, truck type distribution on predominantly commuter roads may not be associated with various months of the year. However, the truck type distributions on most long distance road segments like WIM sites on Highways 2, 3, 16, and 44 are associated with months of the year.

Another conclusion that could be made from the analyses presented in this chapter is that the truck type distribution is not affected due to severity of weather during winter season for primary highway facilities which serve predominantly commuter type of roads (Highway 2A). Similarly, the severe winter months in Alberta also do not seem to have significant impact on different truck classes on long distance highways like Highway 2, 3, or 16. On the other hand, highway facilities serving significant amount of truck traffic which is seasonal in nature are likely to be affected by seasons of the year. The study WIM site on Highway 44 is an example of such facilities.

The above findings have practical implications for rationalization of the length and frequency of traffic counts including classified traffic monitoring programs throughout the year. For example, a short duration traffic count can be taken even during winter season to get reasonably good estimates of truck traffic on highways like 2A, 2, 3 and 16. The knowledge about independency of truck type distribution with various seasons is likely to help in effective traffic monitoring and estimation of the highway planning and design parameters like Annual Average Daily Truck Traffic (AADTT), Average Daily Truck Traffic (ADTT) and Design Hour Truck Volume etc.

Chapter Eight

Imputation of Missing Classified Traffic Data using Winter Weather Models

8.0 General

The relationships between weather and classified traffic volumes were analysed in the previous chapters. The research investigations carried out in this study and the resulting traffic-weather models presented in this thesis have several potential applications in the field of transportation engineering. One major application among them is selected for detailed analysis and presentation here, i.e., imputation of missing traffic data during winter months. This chapter mainly focuses on the application of the developed models to impute missing classified traffic volumes i.e. total traffic, passenger car traffic and truck traffic during winter months.

The traffic volume data, such as those employed in this study, are typically collected by highway and transportation agencies using inductive loops as detectors. Because of the harsh environment in which these detectors operate, they are highly prone to malfunctioning and providing erroneous or missing data. For example, by inspecting the PTC datasets from Alberta Transportation, Minnesota Department of Transportation, and Saskatchewan Highways and Transportation, Zhong et al. (2004) found that more than half of the PTC could have missing values in datasets. The estimation of missing data has been traditionally termed as data imputation (Zhong et al., 2004).

8.1 Extent of Missing Traffic Data

The presence of missing values in the collected data due to the malfunctioning of counting devices is inevitable. For example, Figure 8.1 (Datla, 2009) shows the percentage of PTC sites with missing values for Alberta, Saskatchewan, Minnesota, and Colorado during different years. In general, 40% to 60% of the PTC sites of these agencies experienced missing values. Only traffic data without missing or erroneous parts can provide true estimates of traffic parameters. The presence of missing values in the collected data limits the accuracy of such estimates.

Several methods, ranging from simple factor approaches to advanced techniques, such as neural networks and genetic algorithms, have been used in the literature to estimate missing traffic volumes (Datla, 2009). However, none of the past studies have given much consideration to the distorted traffic composition caused by severe weather conditions, while imputing missing traffic data during winter months.

8.2 Methods in Practice for Traffic Data Imputation

Review of literature indicates that there are mainly three types of traffic data imputation methods that are used by traffic engineers and researchers. These are: heuristic methods, time series methods, and artificial intelligence methods. A brief description of each of these categories of imputation methods are described in the following paragraphs.

8.2.1 Heuristic Methods

According to Smith et al. (2003), the first category of imputation methods, namely the heuristic methods, are the most commonly used methods for solving the problems related

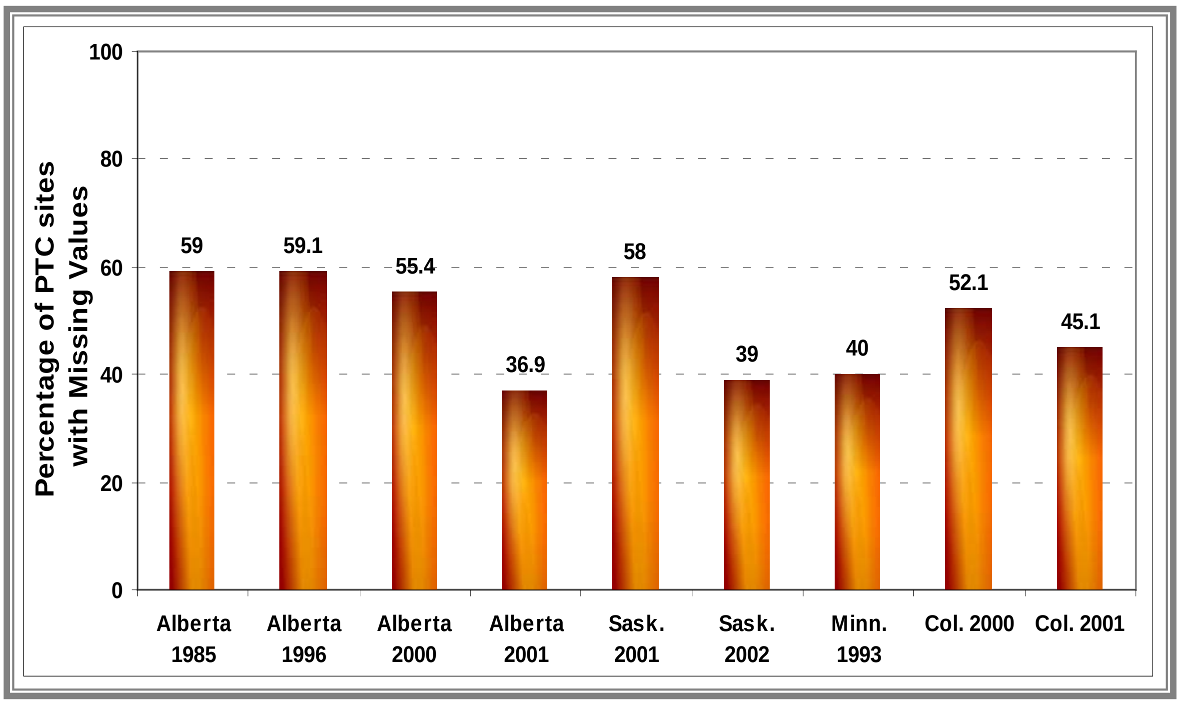


Figure 8.1 Percentages of PTC Sites with Missing Values for Alberta, Saskatchewan, Minnesota, and Colorado (Datla, 2009)

to missing traffic data. These methods are based on past records of traffic volume characteristics at the same road site or another road which is known to have similar trends of traffic in the past time periods. Hourly, daily, and monthly traffic volume factors available from the past records, as well as average, weighted average and moving average over the past days, weeks, or months can be used to replace the missing data.

Zhong et al. (2005) investigated the imputation accuracy of heuristic methods using permanent traffic counter data from the Prairie Provinces in Canada (Alberta and Saskatchewan) and found that use of the historical average values as replacements for missing data can result in very large imputation errors. They also reported that application of moving averages could result in better estimates of missing data; however, the use of moving average method may not be able to reflect accurately the sudden changes in traffic volumes due to abnormal weather conditions or sharp increases or decreases in traffic volume during holiday periods.

8.2.2 Time Series (ARIMA Family) Models

Since traffic volumes on road facilities are generally repetitive over days, weeks, months, and from year to year in most cases, transportation engineers and researchers have attempted to use time series analyses to impute missing data from traffic records. The textbooks by Brockwell and Davis (1996) and Fuller (1996) describe time series analysis models that have been used for prediction of future traffic volume based on past records of traffic data. Smith and Demetsky (1997), Williams et al. (1998), and Williams and Hoel (2003) have successfully used a time series analysis method which is known as ARIMA (autoregressive integrated moving average) model for traffic prediction during non-holiday periods.

However, other studies by Redfern et al. (1993), Kirby et al. (1997), and Williams (1999) reported poor prediction results when they applied the ARIMA model to traffic volume data set that included the summer holiday season. Very high prediction errors were reported by Zhong (2003) when he applied the ARIMA model to the data that included traffic with very high or low weekend traffic volumes as compared to the weekday traffic.

8.2.3 Artificial Intelligence Methods

Artificial intelligence techniques, such as Genetic algorithms (GAs) and neural networks (NN) have also been investigated in a number of past studies to overcome the problem of missing traffic data. Zhong et al. (2004) applied genetic algorithms and neural network models to estimate missing traffic data from Alberta PTC records. They reported low imputation errors that resulted from these models. However, their application of the artificial intelligence methods was limited only to Wednesday traffic during the months of July and August.

8.3 A Methodology for Imputing Classified Traffic Volume during Winter Weather

The previous section presented a description of the imputation methods in practice. Zhong (2003) reviewed and evaluated different methods to impute missing traffic data during summer months. These methods include simple factor approaches (Garber and Hoel, 2002), autoregressive integrated moving average (ARIMA) models (Clark, 1992; Redfern et al., 1993; Watson et al., 1993), weighted regression analysis, neural networks, genetic algorithms, and genetically designed neural networks (Zhong et al., 2005). His study concluded that genetically designed neural network approaches are superior to other methods when traffic data from summer months are being imputed. However, none of the existing imputation methods considered the variations in traffic volumes due to severe winter conditions. Therefore, the suitability of these methods to impute missing traffic data during winter months is unknown.

A nonparametric regression method namely k-Nearest Neighbour (k-NN) method, which has been used very successfully in the past for imputation of missing traffic data, was used in this study as a basis for demonstrating the imputation efficiency of the winter weather models developed in Chapter 6. The results from both the techniques are compared and it is concluded that the winter weather models result in higher level of accuracy while imputing the missing classified traffic data. The following subsection discusses the principles of the k-NN method.

8.3.1 Principles of k-NN Method for Data Imputation and k Value Determination

The k-NN method relies on memory/instance based learning for large data sets (Liu *et* al., 2008; Hardle, 1990). It matches the current input variables with similar historical records (Liu and Sharma, 2006, Davis & Nihan, 1991). In practice, traffic volume with temporal variation are defined as a state vector at time lags of,$t-1$, $t-2$, $\cdots$, etc. Because the k-NN model geometrically attempts to reconstruct a time series (Mulhern and Caprara, 1994), the inclusion of historical averages in the state vector clarifies the position of each observation along with the cyclical flow-time curve and improve forecasting accuracy (Smith et al., 2002). The state vector $x(t)$ used in this study is given in Equation. 8.1.

$$x(t) = [V(t), V(t-1), V(t-2), V_{hist}(t), V_{hist}(t+1)] \quad \textbf{8.1}$$

Where, $V(t)$, $V(t-1)$ *and* $V(t-2)$ are the traffic flows at time intervals t, $t-1$, and $t-2$, respectively. $V_{hist}(t)$ and $V_{hist}(t+1)$ are the historical average volumes at the day-of-month associated with time interval *t* and *t+1*. In cases of imputing classified traffic volumes, the historical average is calculated based on volumes that are from the same day during the same period in the past for the same vehicle class. After the state vector is defined, the k-value is found out based on Euclidean Distance, and the *k* observations with the shortest Euclidean Distances are recognized as neighbors (Liu et al., 2008). The Euclidean distance (*d (p, q)*) from historical record *p* to the current condition *q* can be written as follows:

$$d(p,q) = \sqrt{\frac{\left(V_p(t) - V_q(t)\right)^2 + \left(V_p(t-1) - V_q(t-1)\right)^2 + \left(V_p(t-2) - V_q(t-2)\right)^2}{\left(V_{hist,p}(t) - V_{hist,q}(t)\right)^2 + \left(V_{hist,p}(t+1) - V_{hist,q}(t+1)\right)^2}} \qquad \textbf{8.2}$$

In this study, 4 nearest neighbors were chosen along with their corresponding output volumes to determine the *k*-value. For example, Figure 8.2 shows the Euclidean Distances and the corresponding output volumes for the 4 nearest neighbors of one particular day.

The day is November 18, 2009 with a volume of 23,324 passenger vehicles that represents the typical traffic condition of this road site with normal winter condition. For this particular day, Figure 8.2 shows the first three neighbors' volumes are closer to the actual traffic volume. Also, the Euclidean Distances for these neighbors are relatively low. Therefore, the *k* -value is chosen as 3 in this case.

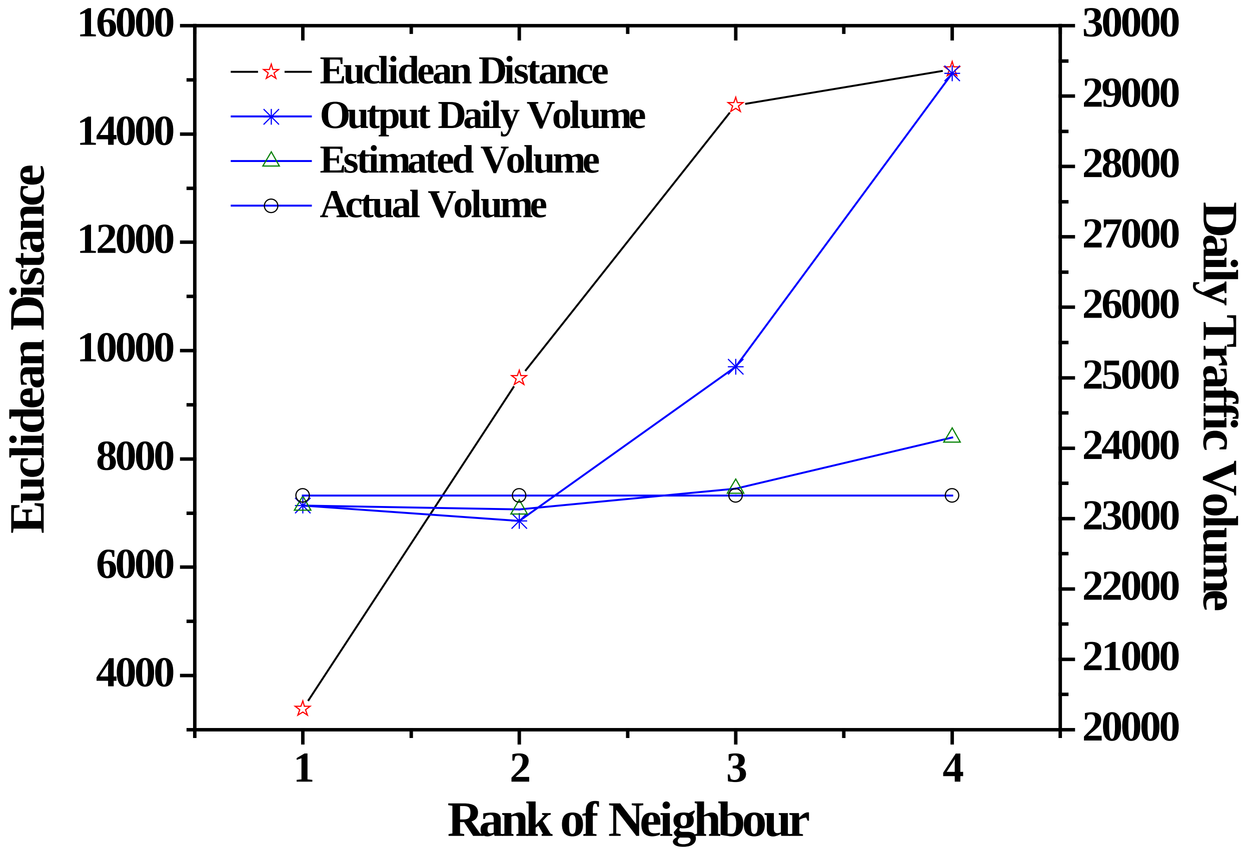


Figure 8.2 Euclidean Distance and Output Volume of the Closer 4 Neighbors

8.3.2 Application of k-NN Method and Winter Weather Model for Forecast Generation

With the determination of k=3, the k-NN method was applied to impute the daily traffic using Equation 8.3 during winter days. This subsection provides an example application of k-NN method to impute 18 days classified traffic volume by using the WIM site data located on Highway 2. The imputation period was chosen to reflect inclement weather conditions starting from the Nov 14 to Dec 14 in 2009 (Figure 8.3). The daily traffic data from the entire years of 2005, 2006, 2007 and 2008 were treated as the historical database to determine neighbors for the k-NN method.

$$y'(t) = \frac{\sum_{i=1}^{k} \frac{y_i(t)}{d_i}}{\sum_{i=1}^{k} \frac{1}{d_i}} \qquad \textbf{8.3}$$

Where, d_i is the Euclidean Distance of the i^{th} neighbor and $y(t)$ is the output volume of i^{th} neighbor. The estimated and actual values for passenger cars and trucks within the imputation period for the k-NN and the interaction model are summarized in Table 8.1 and shown graphically in Figures 8.4 and 8.5 respectively.

An important observation can be made here by examining the plots for Friday, December 4 (91204), with a snowfall of 11 cm and the average temperature of -7^{o}C. The k-NN method results in large over estimation errors for both the passenger cars and truck traffic; whereas winter weather model imputed values are closer to actual values.

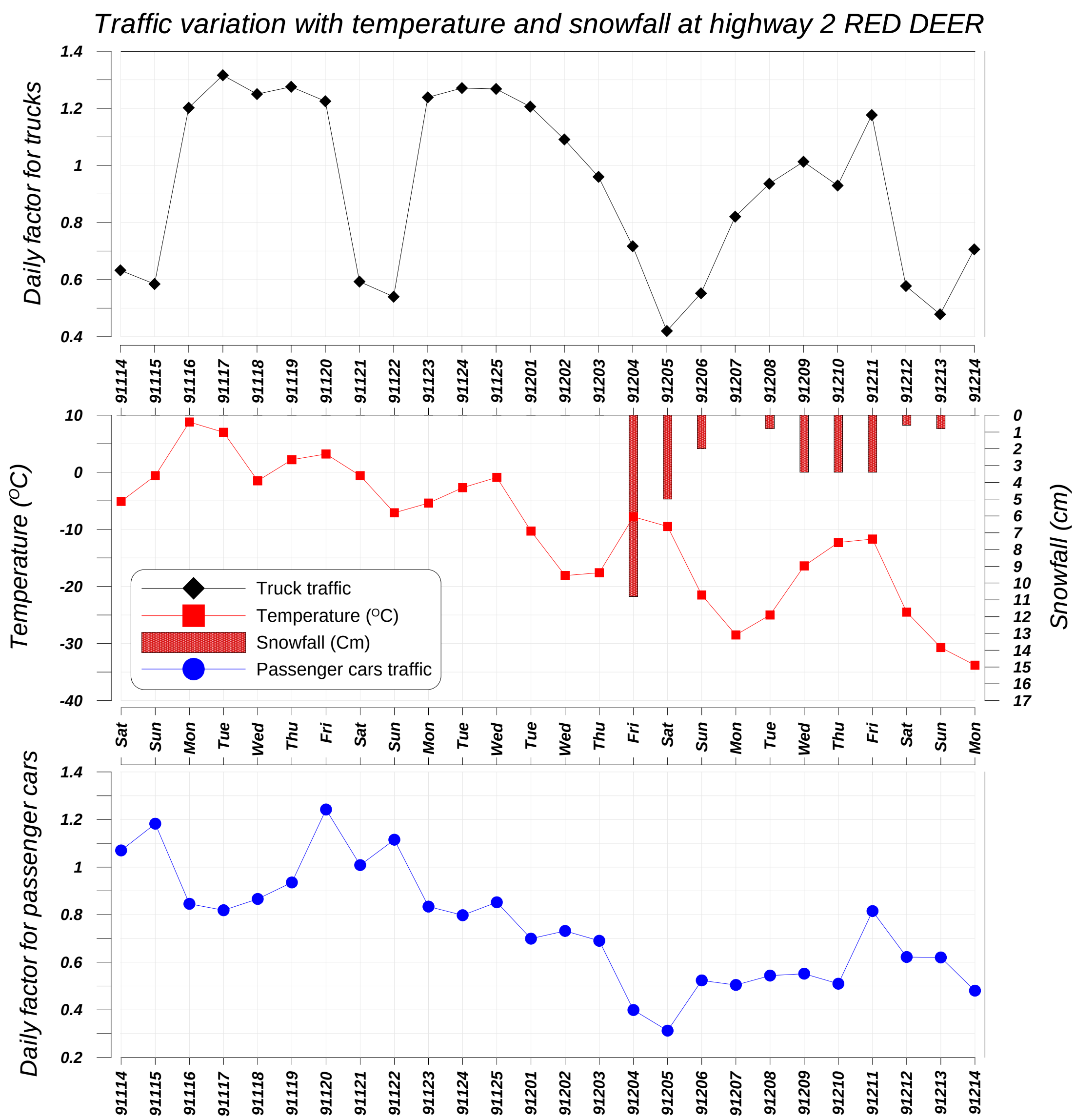


Figure 8.3 Traffic Variations for Days Assumed to be Missing in the Data Set

Table 8.1 Estimation Results for k-NN and Winter-Weather Model for Passenger Cars and Trucks

Date	Actual_TT	k-NN_TT	Interaction_TT	Actual_PCT	k-NN_PCT	Interaction_PCT
Nov-16	5,722	5,442	5,912	22,772	22,383	23,707
Nov-17	6,264	5,964	6,266	22,042	21,935	23,148
Nov-18	5,949	5,948	6,079	23,324	23,426	23,023
Nov-19	6,072	5,841	6,147	25,189	25,158	24,495
Nov-20	5,830	5,564	5,883	33,450	32,872	32,576
Nov-23	5,895	5,575	5,545	22,457	22,581	20,795
Nov-24	6,051	5,695	5,779	21,477	19,546	20,166
Nov-25	6,036	5,686	5,923	22,942	20,137	21,908
Dec-1	5,740	2,556	5,883	18,825	17,784	19,509
Dec-2	5,194	5,137	5,720	19,703	21,585	19,682
Dec-3	4,570	4,965	5,739	18,586	21,089	21,307
Dec-4	3,414	5,309	4,674	10,750	22,677	18,050
Dec-7	3,906	3,820	5,068	13,585	16,904	17,371
Dec-8	4,455	4,135	5,469	14,649	16,177	17,369
Dec-9	4,822	5,574	5,510	14,861	22,058	16,677
Dec-10	4,425	4,260	5,644	13,726	18,786	18,594
Dec-11	5,600	4,447	5,421	21,953	20,620	22,765
Dec-24	3,361	3,415	4,873	12,939	15,410	18,085

TT (Truck Traffic), PCT (Passenger Cars Traffic)

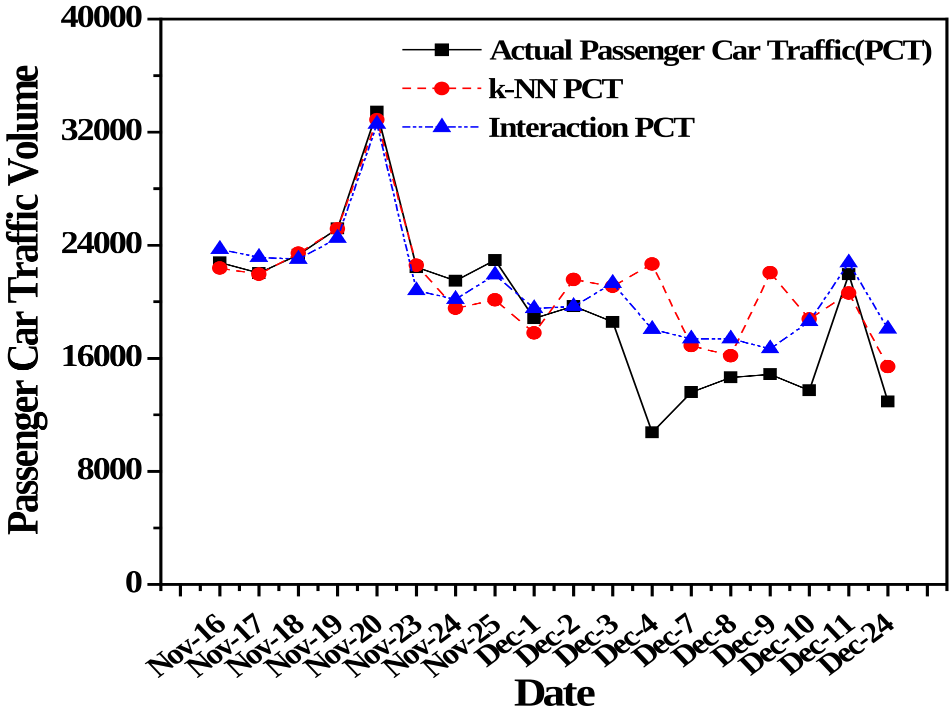


Figure 8.4 Comparison of the Actual and Estimated Volumes Using k-NN and Winter-Weather (Interaction) Model for Passenger Cars

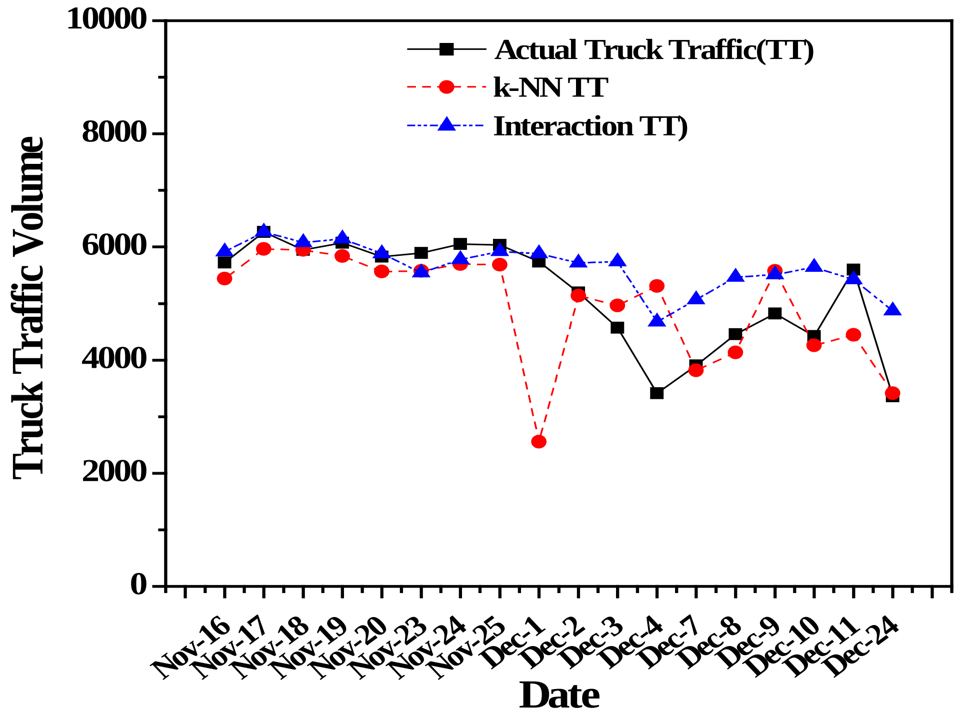


Figure 8.5 Comparison of the Actual and Estimated Volumes Using k-NN and Winter-Weather (Interaction) Model for Truck Traffic

8.3.3 Statistical Comparison of k-NN Method and Winter Weather Model Performances

The performance of the k-NN method as compared to the winter-weather model was also evaluated using a set of error measures in terms of forecasting accuracy. Usually, accuracy examines how well the model reproduces the already known data. The error measures used for this purpose are mean absolute percentage error (MAPE) which is a useful measure in order to eliminate the effect of variability observed in data sets. The formulation is as follow, Equation 8.4:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_i - F_i}{X_i} * 100\right| \qquad \textbf{8.4}$$

Where, X_i and F_i are the actual and estimated daily traffic volumes, respectively. The minimum absolute percentage error (*MinAPE*, given in Equation 8.5) and maximum absolute percentage error (*MaxAPE*, given in Equation 8.6) represent the smallest and the largest error in the results.

$$MinPE = Min\left|\frac{X_i - F_i}{X_i} * 100\right| \qquad \textbf{8.5}$$

$$MaxPE = Max\left|\frac{X_i - F_i}{X_i} * 100\right| \qquad \textbf{8.6}$$

The 50th percentile error represented by E50 in Table 8.2 means that 50% of the errors resulting from the estimation are placed below the value of E50. Similar interpretation can be made for E95. Based on estimated error measures, it is clear that winter-weather model results in better imputation results. For truck traffic volume estimation, even though MAPE for k-NN method is less than winter-weather model, the error measure of E95 for winter-weather model (i.e., 38.11) is much lower than the value for the k-NN method (55.48), meaning that more data points are estimated accurately using the winter-weather model. For passenger cars, all error measures show that winter-weather model performance is better than k-NN method. The statistical errors given in Table 8.2 are also shown in Figures 8.6 and 8.7.

8.4 Chapter Summary

This chapter focused mainly on a successful application of the traffic-weather models developed in previous chapters of this study to impute missing classified traffic volumes i.e. total traffic, passenger car traffic and truck traffic during winter months. The estimated missing traffic flow values are compared with the results from another popular imputation technique known as k-NN method, which is based on Euclidean distances. The comparison of results from both the techniques suggested that the winter weather model results be closer to the actual values.

Table 8.2 Imputation Results for k-NN and Winter-Weather Model (Interaction) for Passenger Car and Truck Traffic

Statistics	k-NN_TT	Interaction_TT	k-NN_PCT	Interaction_PCT
MAPE	11.49	13.20	17.28	14.32
MinAPE	0.02	0.03	0.12	0.11
E50	5.16	5.21	9.27	5.56
E95	55.48	38.11	57.81	43.99
MaxAPE	55.52	45.00	110.94	67.91

TT=Truck Traffic; PCT=Passenger Car Traffic

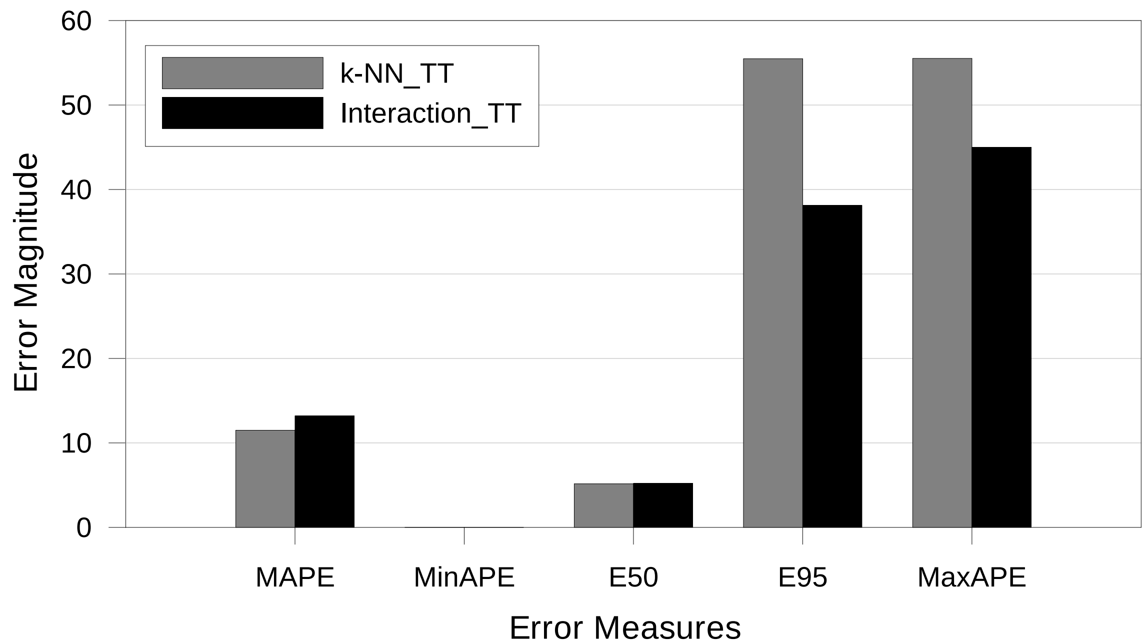


Figure 8.6 Comparison of Error Measures for k-NN Method and Winter-Weather Model for Trucks

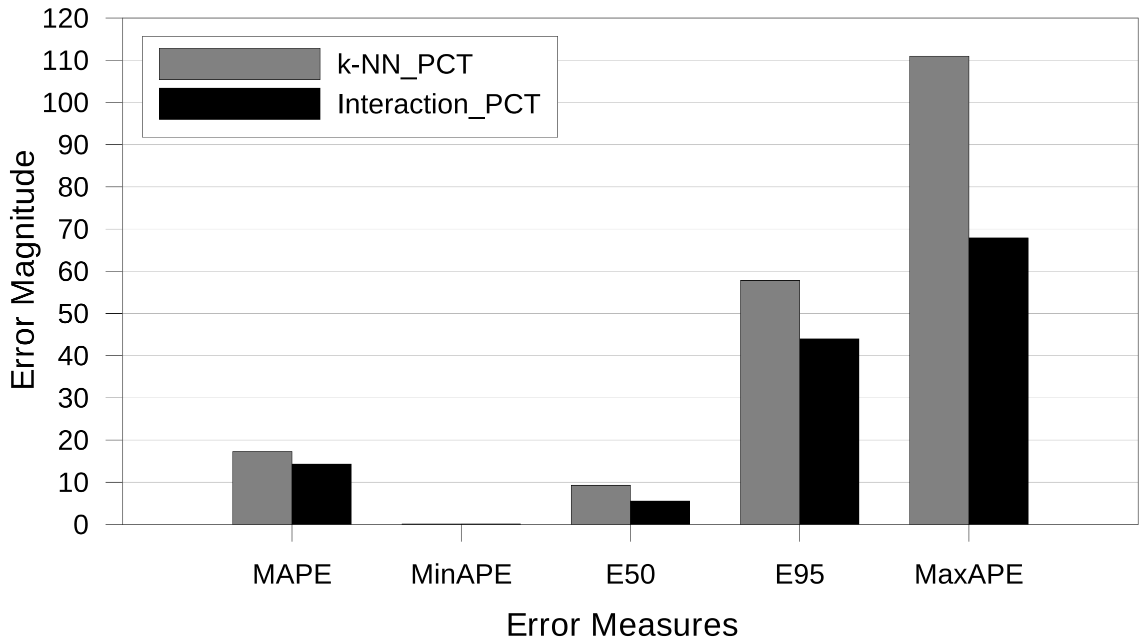


Figure 8.7 Comparison of Error Measures for k-NN Method and Winter-Weather Model for Passenger Cars

Chapter Nine

Summary, Conclusions, and Recommendations

9.1 Summary and Conclusions

The subject matter of this thesis is in the area of highway traffic monitoring. It focuses on truck traffic monitoring programs undertaken annually by all provincial highway agencies in Canada. Vehicle weight and classification statistics are collected by using permanent or portable automatic vehicle classifiers (AVC) and/or weigh-in-motion (WIM) systems. While AVC and WIM technologies have advanced considerably in the past two decades, the practices of collection, analysis, and application of classification data have not progressed similarly.

Numerous research investigations have been carried out in this study to understand and analyze traffic volume variations on primary highways during winter months in the province of Alberta. Impacts of severe cold and snowfall conditions on classified traffic volumes with detailed considerations to trucks and highway type are presented in the form of graphs, tables, and standard mathematical and computational techniques. The models are developed in this study to relate truck and passenger car traffic variations to winter weather conditions by means of various regression analysis techniques.

The traffic data for the study period of five years (2005 to 2009) were obtained from Alberta Transportation. All of the six WIM sites on Alberta highways had nearly 100 percent daily vehicular data statistics available throughout the five year study period. The study data included more than 154 million vehicular records from the six WIM sites.

The daily snowfall and average daily temperature data were obtained from Environment Canada's weather stations near the WIM sites. The weather stations within 16 km of the WIM sites of Red Deer Highway 2, Leduc Highway 2, and Leduc Highway 2A had nearly complete record of weather data. However, considerable amount of missing weather data were found for the weather stations near the other three study WIM sites. For this reason, the WIM sites, namely Fort MacLeod Highway 3, Edson Highway 16, and Villeneuve Highway 44 could not be included in building and testing of the traffic volume–weather models in this thesis. However, all the six study WIM sites traffic data was used successfully in Chapter 7 for investigation of the impact of severe winter weather season on truck type distribution.

The following is a summary of the study findings and conclusions derived from the research presented in this thesis:

1. Most of the past research on traffic monitoring has focused on total traffic volume variations with time and space. Limited research has been carried on the impact of weather on highway traffic volume. A number of past research studies focused on the impact of weather on traffic parameters such as volume, speed, and headway, while other studies focused on the impact of weather events such as snow, rain, fog, smoke, high winds, and extreme temperatures on the quality of traffic flow. However, most of

those studies reported average traffic volume reductions (without detailed statistical analysis) due to adverse weather conditions. It is indicated in the current literature that highway traffic volume variations during adverse weather conditions depend on the type of trips carried by the highway. However, past studies have not quantitatively explored the changes in traffic-weather relationships with road type or highway class.

2. A few past studies carried out at the University of Regina using highway traffic data from several provincial and state highway agencies have demonstrated that the magnitude of total traffic volume variations depends on time of the day, day of the week, location, and type of highway facility with respect to road users' considerations. A limited number of those studies investigated impacts of severe cold and snow conditions on highway traffic volume within the temporal and spatial context. Moreover, those studies and other similar studies in the literature were conducted on the basis of total traffic volume data only. None of those past studies presented the impacts of winter weather on temporal and spatial variations of truck traffic. Impact of weather on route choice behavior of truck and passenger car drivers have also not been addressed in the past.
3. A vehicle classification system called "FHWA scheme F" including 13 vehicle classes is a standard scheme adopted by many state highway agencies in the United States. This scheme has been used widely by many Canadian highway agencies in the past. It can be used to develop a variety

of variations of classification schemes by researchers and practicing engineers across highway agencies. Therefore, the FHWA classification scheme ‘F’ has been used in this study as a basis for classifying the vehicles into passenger cars and various types of trucks, such as single unit trucks, single-trailer trucks and multi-trailer trucks.

4. Based on the review of literature, the road users’ perspective can be captured by classifying roads “according to driver population and trip length characteristics.” The six study WIM sites located on Alberta’s primary highways could be classified into three distinct groups: regional commuter routes (Highway 2A site), interregional long distance routes (2 sites on Highway 2, and sites on Highway 3 and Highways 16), and special routes. The WIM site on Highway 44 has been identified as a special route, which carries a mixed type of traffic including regional commuters and long distance truck traffic as observed on Highways 2, 3, and 16. In addition, this highway site is extensively used by aggregate hauling trucks during the construction season in the Edmonton region.
5. The following inferences could be drawn from the temporal patterns of traffic volume at the study WIM sites:
   - Truck traffic patterns are noticeably different in nature from passenger car patterns for all the study WIM sites.
   - In most cases, the shapes of patterns for passenger cars are similar to the patterns of total traffic; this is mainly because the proportion of

trucks in the traffic stream is very much lower than the remaining vehicle classes.

- Truck traffic decreases significantly (in some cases more than 50%) during the weekends as compared to weekdays.
- The Red Deer and Leduc WIM sites, both located on Highway 2, have similar hourly, daily and monthly traffic patterns for both the passenger cars and trucks. This indicates that the traffic conditions are very consistent on Highway 2, even though the AADT and TAADT values are significantly different at these two sites.
- Percent trucks in the traffic stream and truck type distributions also vary from one highway to another highway site, as was found in the cases of all the study WIM sites.
- Careful examinations of truck traffic patterns also revealed that the monthly and yearly patterns of truck type distribution on commuter and long distance sites, such as Highway 2A, Highway 2, Highway 3, and Highway 16 study sites, can remain reasonably consistent over the periods of several years.

6. Both the regression models, namely the dummy variable model (Equation 5.2) and the interaction model (Equation 6.2) were found to well simulate the relationship between the dependent variable (y_i-the daily volume on a very cold and snowy day in the winter) and the independent variables (*EDVF*-the historical average daily volume expected on a normal day in winter, *SNOW*-the amount of snow fall, and *CC*-the temperature category

on that particular day). However, the interaction model was found to be more appropriate to study the interaction between the snowfall and temperature variables. This was because the classification of temperature variable in seven different categories resulted in a sample size for a particular category to be too small for tests of statistical significance.

The main conclusions that could be drawn from the development and interpretations of the two models (Figure 6.5 and Table 6.1) for the long distance sites on Highway 2 are as follows:

- There is a clear indication that the total traffic volume on a given day depends on the severity of cold and amount of snowfall.
- A reduction in passenger car and truck volumes can be expected with increase in severity of cold temperatures. The amount of decrease in traffic volume depends on severity of cold.
- When there is no snowfall the impact of cold temperature on both car and truck volumes is very marginal (see plots in Figure 6.5 (a) and (e)).
- As the amount of snowfall increases the steepness of the slope of the regression lines increases, which means that the reduction in traffic volume due to cold temperature would intensify with a rise in amount of snowfall. There is a clear evidence of the existence of cold and snowfall interactions.

- A snowfall of 15cm or higher during severe cold conditions (-20^{o}C or lower) would result in a dramatic decrease in passenger car traffic on the road (see plots in Figure 6.5 (d)).
- With higher amounts of snowfall, passenger cars experience higher reductions due to cold and snowfall as compared to trucks (as shown in plots of Figure 6.5 (d) for cars; and plots of Figure 6.5 (h) for trucks).
- From the results shown in Table 6.1, both the car and truck volumes on Highway 2 are significantly affected by snow and temperature at the 95% confidence level. The snow-temperature interaction term for the volume of cars is significant. However, the interaction term in the model for truck volume is not statistically significant.

The amount of above mentioned reduction in traffic volume may be attributed to the proportion of discretionary trips in the traffic stream. The existence of more discretionary trips results in higher trip adjustments and, hence, higher traffic reductions. The reason of higher passenger car traffic reductions may be due to the large proportion of discretionary trips contributed from the passenger car traffic than the truck traffic. Trucks (or commercial vehicles) are usually required to follow rigid schedules to complete their mandatory travel to keep the supply-demand in equilibrium if there is a strong commodity demand from the user end irrespective of severe weather conditions. However, commodity demand which is driven by user level of activity generally falls due to the decrease in the level of activity during the winter months. This phenomenon probably attributes to the reduction in truck traffic though less than the reduction as in case of car traffic on interregional long distance highways like Highway 2.

The conclusions that could be drawn from the development and interpretations of the models (Figure 6.6 and Table 6.2) for the commuter site on Highway 2A are as follows:

- Similar to Highway 2, passenger car traffic experiences reduction in volume with increase in severity of cold and amount of snowfall. But the impact of cold on car traffic at the commuter site on Highway 2A is less as compared to the long distance sites on Highway 2 site. The most likely reason for such a difference is that the regional commuter roads carry mostly non-discretionary trips, such as work and business trips, which allow lower trip adjustments resulting in less traffic reductions due to cold and snow conditions. Also, higher reductions in traffic volume on long distance roads may be due to the increased risk associated with longer journeys, which require an increased necessity for precautionary measures for safe travel in winter conditions.
- From the results shown in Table 6.2, the car volume on Highway 2A is significantly affected by both snow and temperature at the 95% confidence level; the snow-temperature interaction term for the volume of cars is also significant. There is some reduction in truck volume due to snow and temperature variables, but their impact is not

statistically significant. In addition, the interaction term in the model for truck volume is also not statistically significant.

7. Interestingly, the modeling results for Highway 2A (a regional commuter road) showed higher truck volumes during heavy snowfall. This is contradictory to observations from other similar studies in the literature. None of the studies in the past have reported such an increase in traffic volumes during severe weather conditions. A further investigation on this concluded that there is a strong possibility of traffic volume increase on high standard highways (Highway 2A) during adverse weather conditions, which could happen due to shift of traffic from parallel low standard highways (Highway 814).
8. Investigation of the impact of severe winter weather season on truck type distribution revealed that the truck type distribution is associated with the months for all the highways except commuter highway site at the WIM site on Highway 2A. In other words, truck type distribution on predominantly commuter roads may not be associated with various months of the year. However, the truck type distributions on most long distance road segments like WIM sites on Highways 2, 3, 16, and 44 are associated with months of the year.
9. Another conclusion that can be made from the analyses presented in this thesis is that the truck type distribution is not affected due to severity of weather during winter season for primary highway facilities which serve predominantly commuter type of roads (Highway 2A). Similarly, the

severe winter months in Alberta also do not seem to have significant impact on the composition of truck traffic on long distance highways like Highway 2, 3, or 16. On the other hand, highway facilities serving significant amount of truck traffic, which is seasonal in nature, are likely to be affected by seasons of the year. The study WIM site on Highway 44 is an example of such facilities.

10. Chapter 8 of this thesis focused mainly on a successful application of the interaction type (Equation 6.2) winter weather model to impute missing classified traffic volumes i.e. total traffic, passenger car traffic and truck traffic during winter months.The estimated missing traffic flow values were compared with the results from another imputation technique known as k-NN method, which is based on Euclidean distances. The comparison of results from both the techniques suggested that the winter weather model can result in significantly better estimation results as compared to the k-NN method.

9.2 Recommendations for Future Research

1. This study is based on 2005 to 2009 data from six WIM sites from the province of Alberta. More recent WIM data available from Alberta Transportation should be used to test the models developed in this study to relate truck and passenger car traffic variations to winter weather conditions by means of various regression analysis techniques.

2. It would also be desirable to conduct similar studies using WIM or AVC data that may be available from other highway jurisdictions in Canada.

3. The focus of this thesis was on the impact of snow and temperature on daily volume on truck and passenger cars. It is recommended that future research should investigate impact of winter weather conditions on speed, headway, capacity, and level of service. Such research would improve the understanding of traffic flow conditions on highways.

4. Impact of heavy snowfall and low temperature on highway traffic safety should also be investigated. It would be interesting to know if one type of road is affected more than the other types of roads.

5. The effects of snow and temperature on daily (24-hour) volumes of car, trucks and total traffic were investigated in this study. It would be desirable to expand this research to consider 24-, 48-, 72-hours and other extended duration of AVC counts to determine if the effects of daily snowfall and temperature conditions persist for longer than just one or two days.

6. The research findings of this study and the outcome of the recommended research in Point 5 above will help in optimization of frequency and duration of short-period and seasonal vehicle classification counts to estimate accurately AADT, TAADT, and vehicle composition at various locations on highway network.

7. The WIM sites in this study were classified into road uses, such as commuter and long distance facilities, according to the hierarchical grouping method proposed by Sharma et al. (1986). Since this method is based only on temporal volume patterns of total traffic and trip length distribution characteristics, it may not recognize special nature of the road in terms of truck traffic patterns and vehicle

classes. It is recommended that truck traffic information should also be used in conjunction with the hierarchical method for grouping roads.

References

Agarwal, M., Maze, T. and Souleyrette, R. (2005). Impact of Weather on Urban Freeway Traffic Flow Characteristics and Facility Capacity. Iowa State University, Center for Transportation Research and Education. Ames, IA.

Anderson, T. (2002). *TRAVEL on Saskatchewan Highways*. Regina, Saskatchewan Highways and Transportation Operational Planning and Business Support Branch.

Andrey, J., Mills, B., Leahy, M., and Suggett, J. (2003). Weather as a Chronic Hazard for Road Transportation in Canadian Cities. *Natural Hazards* 28, 319-343.

Andrey, J. and Olley, R., (1990). Relationships between weather and road safety, past and future directions. *Climatol. Bull.* 24 (3), 123–137.

ArcGIS 10. (2010). Geographic Information System (GIS), Environmental System Research Institute, Inc., Redlands, California.

AT. (2011). Alberta Transportation, www.transportation.alberta.ca/Content/docType34/Production/los_manual.pdf, Accessed Sept 20, 2011.

Bateman, A. (2010). Canada's Top Ten Aggregate Operations, Rock To Road http://www.rocktoroad.com/content/view/1118/38/, Accessed Oct 20, 2014.

BG: Bomay Group. (2007). Work in Cold, Safety Resources.

Bowerman, B.L. and O'Connell R.T. (1987). *Time Series Forecasting: Unified Concepts and Computer Implementation*. Second Edition, Duxbury Press.

Brockwell, P. J. and Davis, R. A. (1996). *Introduction to time series and Forecasting*, Springer, New York.

Brodsky, H. and Hakkert, A. (1988). Risk of a Road Accident in Rainy Weather. *Accident Analysis and Prevention*, Vol. 20, 161-176.

Cambridge Systematics (2007). *Recommended Revisions to the AASHTO Guidelines for Traffic Data Programs.* National Cooperative Highway Research Program (NCHRP), Transportation Research Board of the National Academies.

Changnon, S. A. (1996). Effects of summer precipitation on urban transportation. *Climatic Change* 32 (4), 481–494.

Clark, S.D. (1992). Application of Outlier Detection and Missing Value Replacement Techniques to Various Forms of Traffic Count Data. *ITS Working Paper 384*, University of Leeds.

Clayton, A. (2000). Feasibility of a New Vehicle Classification Systems for Canada. *North American Travel Monitoring Exibition and Conference (NATMEC)*, Madison Wisconsin.

Colyar, J. Zhang, L., and Halkias, J. (2003). Identifying and Assessing Key Weather-Related Parameters and their Impact on Traffic Operations Using Simulation, *ITE 2003 Annual Meeting*, Institute of Transportation Engineers, Washington, D.C.

Datla, S. (2009). *Development and Application of Traffic Volume - Winter Weather Relationships*, Ph.D. Thesis, University of Regina, Canada.

Datla, S. and Sharma, S. (2008). Impact of Cold and Snow on Temporal and Spatial Variations of Highway Traffic Volumes. *J. Transport Geography*. 16 (5), 358–372.

Datla, S. and Sharma, S. (2010). Variation of Impact of Cold Temperature and Snowfall and Their Interaction on Traffic Volume. *Transportation Research Records 2169*, Transportation Research Board, Washington, D.C., 107-115.

Davis, G. A. and Nihan, N. L. (1991), Nonparametric Regression and Short-Term Freeway Traffic Forecasting, *Journal of Transportation Engineering*, 117(2), 178-187.

Edmonton Journal. (2007). Moving Dirt Has Environmental Costs. http://www.canada.com/story.html?id=fcdd901f-d845-491e-92ee-7440c395f909, Accessed Oct 20, 2014.

FHWA. (2001). *Traffic Monitoring Guide.* U.S. Department of Transportation, Federal Highway Administration Office.

Fox, John. (2008). *Applied Regression Analysis and Generalized Linear Models.* SAGE, Inc., Thousand Oaks, California.

Fox, John. (2011). *An R Companion to Applied Regression.* SAGE, Inc., Thousand Oaks, California.

Fuller, W. A., (1996). *Introduction to Statistical Time Series,* 2nd Edition, Wiley, New York.

Garber, N. J. and Hoel, L. A. (2002). *Traffic and Highway Engineering*. Second Edition, Brooks/Cole Publishing Company.

Goodwin, L. C. (2002). Weather Impacts on Arterial Traffic Flow, *prepared for the Road Weather Management Program*, Federal Highway Administration, Washington, D.C.

Grush, B. (1998). *Understanding Traffic Variations by Vehicle Classifications.* New Mexico, Chaparral Systems Corporation.

Hall, F. L., and Barrow, D. (1988). Effects of Weather and the Relationship Between Flow and Occupancy on Freeways. *Transportation Research Record 1194*, National Research council, Washington, D.C., 55-63.

Hanbali, R. M. (1994). Economic Impact of Winter Road Maintenance on Road Users. *Transportation Research Record 1442,* 151-161.

Hanbali, R. M. and Kuemmel, D. A. (1993). Traffic Volume Reductions Due to Winter Storm Conditions. *Transportation Research Record: Journal of the Transportation Research Board* 1387, 159–164.

Hardle, W. (1990). *Applied Nonparametric Regression,* Cambridge, Cambridge University Press.

Hardy, M. A. (1993). *Regression with Dummy Variables*. SAGE, Inc., Newbury Park, California.

Hassan, Y. A. and Barker, J. J. (1999). The impact of unseasonable or extreme weather on traffic activity within Lothian region, Scotland. *J. Transport Geography,* 7 (3), 209–213.

HCM: Highway Capacity Manual. (2000). Transportation Research Board, National Research Council, Washington, D.C.

Ibrahim, A. T., and Hall, F. L., (1994). Effect of Adverse Weather Conditions on Speed-Flow-Occupancy Relationships. *Transportation Research Record* 1457, 184-191.

ITT Industries, Inc., (2003) Identifying and Assessing Key Weather-Related Parameters and Their Impacts on Traffic Operations Using Simulation, prepared for the U.S. DOT FHWA Office of Travel Management, 2003.

Keay, K. and Simmonds, I. (2005). The Association of Rainfall and other Weather Variables with Road Traffic Volume in Melbourne, Australia. *Accident Analysis and Prevention* 37, 109-124.

Kirby, H. R., Watson, S. M., and Dougherty, M. S. (1997). Should We Use Neural Networks or Statistical Models for Short-Term Motorway Traffic Forecasting? *International Journal of Forecasting*, 13 (1), 43-50.

Khattak, A. J., Kantor, P., and Council, F. M. (1998). Role of Adverse Weather in Key Crash Types on Limited Access Roadway – Implications for Advanced Weather System. *Transportation Research Record 1621*, Transportation Research Board, Washington, D.C., 10-19.

Knapp, K. K. and Smithson, L. D. (2000). Winter Storm Event Volume Impact Analysis Using Multiple-Source Archived Monitoring Data. *Transportation Research Record 1700*, Transportation Research Board, Washington, D.C., 10–16.

Liu, Z. and Sharma S. (2006). Statistical Investigations of Statutory Holiday Effects on Traffic Volumes, *Transportation Research Record 1945*, 40-48.

Liu, Z. B., Sharma, S., and Datla, S. (2008) Imputation of Missing Traffic Data during Holiday Periods. In: *Transportation Planning and Technology* 31 (5), 525-544.

Maki, P. J. (1999). Adverse Weather Traffic Signal Timing, P.E. *69th Annual Meeting of the ITE*, Las Vegas.

Markku, K. and Heikki, S. (2007). Effects of Weather and Weather Forecasts on Driver Behavior. *Transportation Research Part F,* Vol. 10, 288-299.

Maze, T. H., Agarwal, M., and Burchett, G. D. (2006). Whether Weather Matters to Traffic Demand, Traffic Safety, and Traffic Operations and Flow, *Transportation Research Record 1948*, 170-176.

McBride, J. C., Benlangie, M. C., Kennedy, W. J., McCornkie, F. R., Steward, R. M., Sy, C. C., and Thuet, J. H. (1977). *Economic Impacts of Highway Snow and Ice Control.* National Pool Fund Study Report FHWA-RD-77-95, Federal Highway Administration, U.S. Department of Transportation.

McShane, W. R. and Roess, R. P. (1990). *Traffic Engineering*. Englewood Cliffs, New Jersey, Prentice Hall.

Mulhern, F. J. and Caprara R. J., (1994). A Nearest Neighbor Model for Forecasting Market Response, *International Journal of Forecasting*, 10 (2), 191-207.

Mussa, R. Kwigizile, V., and Selekwa, M. (2006). Probabilistic neural networks application for vehicle classification. *Journal of Transportation Engineering*, 132 (4), 293-302.

Nixon, W. (1998) The Potential of Friction as a Tool for Winter Maintenance. Iowa Institute of Hydraulic Research Report No. 392, College of Engineering, The University of Iowa, Iowa City, Iowa, February, 1998.

Palutikof, J. P. (1981). Economic disruption caused by climatic extremes. *Climate Monitor* 10, 68-73.

Perrin, J. and Martin, P. (2002). Modifying Signal Timing during Inclement Weather, University of Utah Traffic Lab, *presented at the 2002 Institute of Transportation Engineers Annual Meeting*, ITE.

Redfern, E.J., Watson, S.M., Clark, S.D., Tight, M.R. and Payne, G.A. (1993). Modeling Outliers and Missing Values in Traffic Count Data Using the ARIMA Model, ITS Working Paper 395, Institute for Transport Studies, University of Leeds.

RFSC: R Foundation for Statistical Computing, A Language and Environment for Statistical Computing. Vienna, Austria, ISBN 3-900051-07-0, 2010.

Shah, V. P., Stern, A. D., Goodwin, L. C., and Pisano, P. (2003). “Analysis of Weather Impacts on Traffic Flow in Metropolitan Washington, D.C.,” *Presented at the Institute of Traffic Engineers International Meeting in Seattle*, Washington, August 24 – 27.

Sharma, S.C. (1983). Minimizing Cost of Manual Traffic Counts: Canadian Example. *Transportation Research Record 905*, Transportation Research Board, Washington D.C., 1-7.

Sharma, S. and Awadhesh, K. S. (1992). Reexamination of Directional Distribution of Highway Traffic, *Journal of Transportation Engineering*, ASCE, Vol. 118, pp. 323-337.

Sharma, S., Lingras, P. J., Hassan, M. U., and Murthy, N. A. S. (1986). Road Classification According to Driver Population. *Transportation Research Record 1090*, Transportation Research Board, Washington D. C., 61-69.

Sharma, S., Liu, G., and Thomas, S., (1998). Sources of Error in Estimating Truck Traffic from Automatic Vehicle Classification Data. *Journal of Transportation and Statistics*, 1 (3), 89-93.

Smith, B. L., Byrne, K. G., Copperman, R. B., Hennessy, S. M., and Goodall, N. J., (2004). An Investigation into the Impact of Rainfall on Freeway Traffic Flow, *Proceedings of the Annual Meeting of the Transportation Research Board*, Washington, D.C.

Smith, B.L and Demetsky, M.J. (1997). Traffic Flow Forecasting: Comparison of Model Approaches, *Journal of Transportation Engineering*, 123 (4), 261-266.

Smith, B.L. Scherer, W.T. and Conklin, J.H. (2003). Exploring Imputation Techniques for Missing Data in Transportation Management Systems. *Transportation Research Record 1836*, 132-142.

Smith, B., Williams, B.M., and Oswald, R.K. (2002). Comparison of Parametric and Nonparametric Models for Traffic Flow Forecasting, *Transportation Research Part C*, 10, 303-321.

Smith, D. and Mclntyre, J. (2002). *Handbook of Simplified Practice for Traffic Studies.* Ames, Iowa, Center for Transportation Research and Education lowa State University.

Thomas, S., Sharma, S., and Liu, G., (1997). Statewide Monitoring of Truck Traffic Using Automatic Vehicle Classifiers, *Institute of Transportation Engineers (ITE) Journal*, 67 (4), 28-35.

TMG. (2001). *Traffic Monitoring Guide.* U.S. Department of Transportation, Federal Highway Administration, May 2001.

UMA. (2001). *Calahoo-Villeneuve Sand and Gravel Extraction Area Structure Plan*, UMA Engineering Ltd, Edmonton, Alberta.

Watson, S. M., Clark, S. D., Redfern, E. J., and Tight, M. R. (1993). Outlier Detection and Missing Value Estimation in Time Series Traffic Count Data. *Proceedings of the Sixth World Conference on Transportation Research*, Vol. II, 1151-1162.

Wayne W. D. (1990). *Applied Nonparametric Statistics*, 2nd Edition, PWS-KENT Publishing Company.

Williams, B.L. Durvasula, P.K. and Brown, D. (1998). Urban Freeway Traffic Flow Prediction: Application of Seasonal Autoregressive Integrated Moving Average and Exponential Smoothing Models, *Transportation Research Record No. 1644,* 132-141.

Williams, B.M. (1999). Modeling and Forecasting Vehicular Traffic Flow as a Seasonal Stochastic Time Series Process, Ph.D Thesis, University of Virginia, Charlottesville, Va.

Williams, B.M. and Hoel, L.A. (2003). Modeling and Forecasting Vehicular Traffic Flow as A Seasonal ARIMA Process: Theoretical Basis and Empirical Results, *Journal of Transportation Engineering*, 129 (6), 664-672.

WO. (2010). Weather Office, Environment Canada, Gatineau, Quebec, Canada. www.climate.weatheroffice.gc.ca/climateData/canada_e.html. Accessed Oct 20, 2010.

WSDOT. (2007). Winter Driving: You're in the Driver's Seat, Be Prepared, Be Safe, Washington State Department of Transportation, USA.

Wyman, J.H., Braley, G.A., and Stephens, R.I. (1985). *Field Evaluation of FHWA Vehicle Classification Categories*. Maine Department of Transportation.

Zang, L. I., Holm, P., and Colyar, J. (2004). Identifying and Assessing Key Weather-Related Parameters and Their Impact on Traffic Operations Using Simulation, Prepared by ITT Industries, Inc. Prepared for the Office of Operations Research and Development, Federal Highway Administration, McLean, VA, Report No. FHWA-HRT-04-131, September 2004.

Zhong, M. (2003). Data Mining Applications for Updating Missing Values of Traffic Counts, Ph.D. Thesis, University of Regina, Canada.

Zhong, M. Sharma, S., and Lingras, P. (2004). Genetically Designed Models for Accurate Imputations of Missing Traffic Counts. *Transportation Research Records 1879*, 71-79.

Zhong, M., Sharma, S., Liu Z. (2005). Assessing the Robustness of Imputation Models based on Data from Different Jurisdictions: Alberta and Saskatchewan Examples. *Transportation Research Records 1917*, 116-126.

Zhi, X., Shalaby, A., Middleton, D., and Clayton, A. (1999). Evaluation of weigh-in-motion in Manitoba. *Canadian Journal of Civil Engineering*, 26, 655-666.