KSCE Journal of Civil Engineering (2016) 20(4):1514-1525
Copyright ⓒ2016 Korean Society of Civil Engineers
DOI 10.1007/s12205-015-0236-0

Transportation Engineering
pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Modeling Snow and Cold Effects for Classified Highway Traffic Volumes

Hyuk-Jae Roh*, Satish Sharma, and Prasanta K. Sahu*****

Received May 9, 2014/Accepted June 2, 2015/Published Online July 7, 2015

Abstract

This paper discusses about the effect of snowfall, temperature, and their interaction on two vehicle classes: passenger cars, and trucks on a primary highway in Alberta, Canada. The investigation is based on large data collected from the Weigh-In-Motion (WIM) site located at Leduc, on Highway 2A. The variations on traffic volume for vehicle classes are analyzed by means of a dummy-variable regression model with seven cold categories. The models are calibrated to estimate the temperature impact on daily traffic variations and, more specifically, to quantify the interaction effect of snowfall and temperature on classified traffic volume. The study results suggested distinctive patterns in traffic variations for passenger cars and trucks. The daily passenger car volume reduction is 12% when the temperature goes below -25°C and, by interaction between snow and cold, it was reduced by 36% at the temperature range -25°C ~ -20°C with 16cm snowfall. Conversely, the daily truck traffic is generally increased for all cold categories. In particular, truck traffic is not really affected by snow and cold interaction even at extreme winter weather conditions. The paper contributes to the literature by analyzing the winter weather effects on truck traffic, in particular. This study may be useful for developing efficient highway monitoring programs, and winter road maintenance programs, etc.

Keywords: *weather conditions, truck traffic, weigh-in-motion, vehicle classification, dummy-variable regression*

1. Introduction

Many highway agencies in the U.S and Canada are responsible for developing, maintaining, and managing transportation infrastructure facilities in their jurisdictions by establishing highway traffic monitoring programs (Zhi *et al*., 1999). The agencies usually maintain Permanent Traffic Counters (PTCs) on some specific highway sections to collect traffic data spatially and temporally. The data are used to generate important traffic parameters, such as Annual Average Daily Traffic (AADT) and Design Hourly Volume (DHV), etc. These parameters play a critical role in almost all levels of transportation engineering and planning functions. Although, the PTC data satisfy highway agencies' data requirement, however, at the same time, PTCs data do not provide information for vehicle classification. This issue limits the analysis to total traffic only. This issue is resolved in recent years by the use of Weigh-In-Motion (WIM) technology on highway sites in Canada. The WIM stations are installed on certain highway locations by Alberta Transportation to capture the classified vehicle data. In recent times, there have been growing interest in encouraging the use of classification data in transportation studies and it is believed that this trend is mainly due to a rapid and widespread introduction of WIM technology. However, regardless of its importance in applications, only limited amount of classification data have been collected by highway agencies and, consequently, not much analytical work has been conducted until recently. This study in its initial stage used the WIM data to classify the total traffic into two vehicle classes: passenger car and truck.

Research on highway traffic variations caused by weather conditions (i.e., rainfall, snowfall, and temperature) (Keay and Simmonds, 2005; Datla and Sharma, 2008) has been receiving significant attention in recent times in North America. Nevertheless, limited studies (Datla and Sharma, 2008 and 2010) are available which discusses about the total traffic variations due to snowfall and cold on Canadian provincial highways; whereas studies on classified traffic volume variation during sever winter conditions are next to non-existent. In the second stage of the research, the study focused to understand the winter impact in the two vehicle classes, truck in particular. Understanding truck traffic variations with time of day, day of week, season of the year and type of roadway, will not only help in developing roadway maintenance program; but also it can be applied to many types of transportation analyses, such as the structural design of pavement, geometric design, highway life cycle analysis and prioritization of highways.

To summarize, the central theme of this study is to investigate the variations of daily traffic volumes associated with weather factors (i.e., snow, temperature) with an emphasis on vehicle class (i.e., passenger cars, trucks). The analysis is based on large

*Project Engineer, City of Regina, SK, Canada, S4P 3C8 (Corresponding Author, Email: jroh@regina.ca)
**Professor, Faculty of Engineering and Applied Science, University of Regina, Regina, SK, S4S 0A2, Canada (E-mail: Satish.Sharma@uregina.ca)
***Assistant Professor, Dept. of Civil Engineering, Birla Institute of Technology, Pilani, Rajasthan 333031, India (E-mail: Email: prasantsahu222@gmail.com)

WIM data collected from Leduc site located on Highway 2A on Alberta transportation highway network. Multiple categorical linear regression models are developed to quantify the association of classified highway traffic with snowfall and temperature. The temperature is included as a dummy variable in the model. The vehicle classification procedure is carried out using computer programs developed through Visual Basic (VB). Winter weather models are developed with the help of Car package provided by statistical software R (Fox, 2008; RFSC, 2010).

2. Literature Review

Literature review in this study is divided into two parts. In the first part of the study, we reviewed literature focusing on vehicle classification. The findings from the literatures reporting vehicle classification are used to prepare data sets for analysis and modeling. In the second part of the study, we analyzed the past studies which report the weather effect on highway traffic variations. The literatures related to vehicle classification play an important role to build a systematic classification process used during the vehicle classification and, therefore, the relevant literatures on vehicle classification are referred in the following paragraph.

Literature reports about number of classification technologies used to classify trucks from the traffic stream and these technologies may be divided into three categories: axle sensor based, vehicle length based, and machine vision based technology. These categories are established according to a specific vehicle characteristic, which is the primary determinant in the classification mechanism. The classification technologies captures several information such as time, lane, speed, length, weight, axle weight, axle spacing, etc., for each vehicle passing through the WIM site. This information constitutes one vehicular record, which is usually used for vehicle classification using various vehicle classification schemes. Maine department of transportation (Maine DOT, 1985) developed a 13-category classification scheme (scheme F), which is commonly accepted as a standard scheme by many highway agencies in North America.

In an attempt to select an appropriate classification method for this study, existing literatures are reviewed (Fekpe and Clayton, 1994; Haykin, 2008; Kwigizile *et al.*, 2004; Mussa *et al.*, 2006). Among those researches, we select vehicle classification scheme presented by Mussa *et al.* (2006).In their research, they discussed about scheme F, which is based on axle spacing information between classes. They used Probabilistic Neural Network (PNN) for vehicle classification and proved that this method outperforms the performance of the existing classification scheme. We also, adopted the classification scheme F for our study and the analysis in detail is presented later in study data section. The subsequent paragraph discusses about the studies related to traffic variation with different weather conditions.

The previous studies on highway traffic vis-à-vis weather effects can be divided broadly into three categories. In the first category, few researchers studied the effect of weather on highway and traffic conditions. In their research, ITT Industries (2003), Colyar *et al.* (2003), and Goodwin (2002), reported a variety of weather conditions cause variations in highway traffic flow. For example, ITT Industries (2003) reported that extreme weather conditions compels drivers to change their travel pattern by leading them to choose a different route, delay, and even cancel the trip. Also, it is stated that reduced visibility affects driving speed, lane changing behavior, vehicle following pattern, and acceleration and deceleration capabilities, etc. A chain reaction mechanism is suggested by Colyar *et al.* (2003) to explain the impact of weather events on the traffic operation. Through this study, they explained how weather event causes a change in the roadway environment that causes a change in traffic parameters and degradation in traffic flow conditions. Goodwin (2002) explained the impact of weather events on highway traffic conditions focusing on (1) driver behavior, (2) roadway safety, and (3) roadway mobility.

In the second category, some researches attempted to address quantitative association of traffic volumes with weather conditions. The current research also explains the traffic volume variation during winter weather in a quantitative manner. Hanbali and Kuemmel (1993) studied the traffic volume reduction on highway due to winter storm conditions and reported that traffic volume is reduced on weekends by 19% to 31% for light snow and 56% for heavy snow and on weekday by 7% to 17%, 53%, respectively using the data collected at 11 locations during the first three months of 1991 in the United States. Hassan and Barker (1999) researched on the impact of extreme weather on urban traffic activity and concluded that only less than 5% traffic reduction is occurred under extreme weather and up to 10% to 15% traffic reduction is triggered when snow is lying on the ground. This research is carried out using the data from thirteen locations over a period of 5 year from 1987 to 1991 in the Lothian region of Scotland and 10% of days of data are treated as extreme weather cases. Knapp and Smithson (2000) conducted research on the impact of winter storm on traffic volumes and found that traffic is reduced with different levels ranged approximately 16% to 47% with respect to different storm events. The data involved for the research were gained from 7 sites located on interstate highways over a period of 3 years from 1995 to 1998. In other several researches (Datla *et al.*, 2013; Maki, 1999; Roh *et al.*, 2014; Perrin and Martin, 2002; Changnon, 1996; Smith *et al.*, 2004; Keay and Simmonds, 2005; Maze *et al.*, 2006; Roh *et al.*, 2013), similar results are presented; reductions in traffic volume and changes in traffic patterns are caused by either adverse weather conditions or a variety of weather factors (i.e., rain, wind speed, visibility) combined with inclement weather.

In the third category, research focuses on the traveler behavior during adverse weather conditions. Hanbali and Kuemmel (1993) pointed that travelers' decision making behavior can be affected according to (1) the willingness to travel, (2) the importance of their destinations, (3) the difficulty of moving to destination, and also argued that a reduction in traffic movement occurs due to traveler's desire to avoid travel during adverse weather conditions. It is also indicated by the some studies (Maki, 1999; Markku and Heikki, 2007) that a reduction in traffic during adverse weather conditions are mainly resulted from the trip adjustments such as leaving for work early, and an avoidance of unnecessary and discretionary trips. Among all the past work, none of them considered the variations of truck traffic volume during adverse weather conditions.

3. The Data

The present study used two types of data: traffic data and weather data. In order to model traffic-weather relationships on the basis of vehicle classification, particularly, to separate truck traffics from traffic mix, vehicular records are procured from Alberta transportation. The vehicular records relate to the vehicles captured at one WIM site at Leduc located on Highway 2A. WIM system collects traffic data using devices installed on the road surface/roadside. There are 6 WIM sites installed in Alberta highway network. The weather data (data set includes snowfall and temperature) are obtained from Environment Canada weather information archives (Environment Canada, 2010). There are about 598 weather stations operated by Environment Canada in Alberta province.

We selected two weather stations based on the research by Datla and Sharma (2008). Their research suggested that weather conditions may be considered homogeneous within the area of 16~25 km radius around the weather station. Geographical Information Systems (GIS) base map including 598 weather stations and 6 WIM sites are developed and weather stations are located according to the level of closeness to WIM sites using Proximity analysis module provided by GIS software Arc Map 9.9 (ESRI, 2010). Weather stations: 3012205 and 3012206 are chosen corresponding to the study site (Leduc) with a radius of 16 km from the site. Through the preliminary analysis, it is found that the weather station 3012205 contains all information required for this research without any missing data. The WIM data are used in vehicle classification scheme, and is discussed in the following subsection.

Alberta experiences significant snowfall and severe cold conditions for the months from November to March. The entire investigation is limited to winter months only (November to March) during the study period: 2005 to 2009. It should be informed that three holidays are observed in the study period namely, New Year Day (1st January), Alberta Family Day (3rd Monday of February), and Christmas day (25th December). Due to their unique traffic patterns of the holiday (Liu and Sharma, 2006), the holiday and their neighboring days are excluded from the data set. Finally, the data set is formatted for regression analysis (510days).

3.1 Vehicle Classification

We used FHWA 13 category scheme F for vehicle classification in this study. The WIM data are collected by a traffic detector installed on road surface at Leduc site on highway 2A. The detector combines loop (length based counter) and piezoelectric sensor (axle based counter) technology to differentiate each vehicle class passing on the detection area (Kilburn, 2008).

Based on general mechanism of vehicle classification, we selected the information on axle spacing from the vehicular records to use as classification input. We developed VB computer codes using axle spacing algorithm for vehicle classification. The classification procedure involved with three steps. In the first step, we found that some records of the data have no information on axle spacing, which need to be separated from normal records and treated with additional attention during vehicle classification process. For this purpose, initial classification is conducted, which divided the vehicular record into two groups: Reasonable Data Records (RDR), and Unreasonable Data Records (UDR). The RDR can be used for classification purpose, whereas UDR is not appropriate for classification. It also should be noted that some years of data (i.e., 2004 and 2010) do not include traffic information for the entire year; hence, traffic data from WIM for the 5 years (i.e., 2005, 2006, 2007, 2008, and 2009) are used for further investigation. The details of data compositions are given in Table 1.

The next step for classification involved sorting the RDR and UDR into a common time base (i.e., daily basis), which is required in the current research for further analysis. Using the classification scheme F proposed by FDOT in the study of Mussa *et al.* (2006), we classified vehicles into 28 classes. The classification results are summarized in Table 2 with total number of vehicles. For example, the number 2,447,488 in the fifth column from the left of the table represents the sum of all vehicles that can be allocated into bins of 28 vehicle classes arranged on a daily basis for the year of 2005.

In the last step, we used Probabilistic Neural Network (PNN) to classify vehicles based on axle configuration patterns. Vehicle classification scheme utilized widely in transportation practices such as “scheme F” has been recognized to have weaknesses in classifying vehicle due mainly to the vagueness of demarcations used for differentiating vehicle between classes (Mussa *et al.*, 2006). In order to address this problem, the PNN concept to vehicle classification as a classification method is applied in this research. The key concept of the PNN method without any

Table 1. Data Composition for LEDUC WIM Station

Year	AADT	Total Data Records	Reasonable Data Records (RDR)	Unreasonable Data Records (UDR)
2004	N/A	1,080,833	1,018,235	62,598
2005	7,195	2,626,346	2,465,811	160,535
2006	7,438	2,714,938	2,427,930	287,008
2007	7,843	2,862,641	2,650,903	211,738
2008	7,761	2,840,488	2,683,929	156,559
2009	7,569	2,762,598	2,600,986	161,612
2010	N/A	86,652	79,570	7,082
Total	-	14,974,496	13,927,364	1,047,132

mathematical terms is presented here since the application of PNN for vehicle classification is not the main objective of this research. In this study, the input vector of vehicle characteristics (i.e., axle spacing) are involved in algebraic calculations associated with training samples given for each vehicle classes (5 training samples for each vehicle class) to provide statistical information. Based on this information, the input vector (or a record of vehicle-by-vehicle) is classified into classification bins. This practice of classification using PNN is applied to the data that remains unclassified after completing the first stage of classification. For example, the unclassified data (i.e., 18,323) for the year 2005 in Table 2 are utilized in this stage and classified into bins prepared for each of 28 vehicle classes (i.e., 17,873) leaving 450 vehicles unclassified. In the modeling process, the data remained unclassified is considered as truck traffic and UDR is distributed to each vehicle classes (i.e., passenger cars, truck) in proportion to the ratio of each vehicle classes to total daily traffic. The classification procedure is carried out by computer codes developed using Visual Basic Application (VBA) provided in MS. EXCEL.

It should be noted that different levels of classification data are

Table 2. Classification Rsults Obtained from Both FDOT* and PNN Classification Scheme

Year	AADT	PAADT**	TAADT***	Reasonable Data Records (RDR)			
				First classification		Second classification Using PNN	
				Classified	Unclassified	Classified	Unclassified
2005	7,195	6,704	491	2,447,488	18,323	17,873	450
2006	7,438	6,854	584	2,422,696	5,234	5,151	83
2007	7,843	7,210	633	2,645,326	5,577	5,467	110
2008	7,761	7,105	656	2,678,434	5,495	5,368	127
2009	7,569	6,971	598	2,597,530	3,456	3,375	81
Total				12,791,474	38,085	37,234	851

*FDOT (Florida Department of Transportation), **PAADT (Passenger Cars Annual Average Daily Traffic), ***TAADT (Truck Average Annual Daily Traffic)

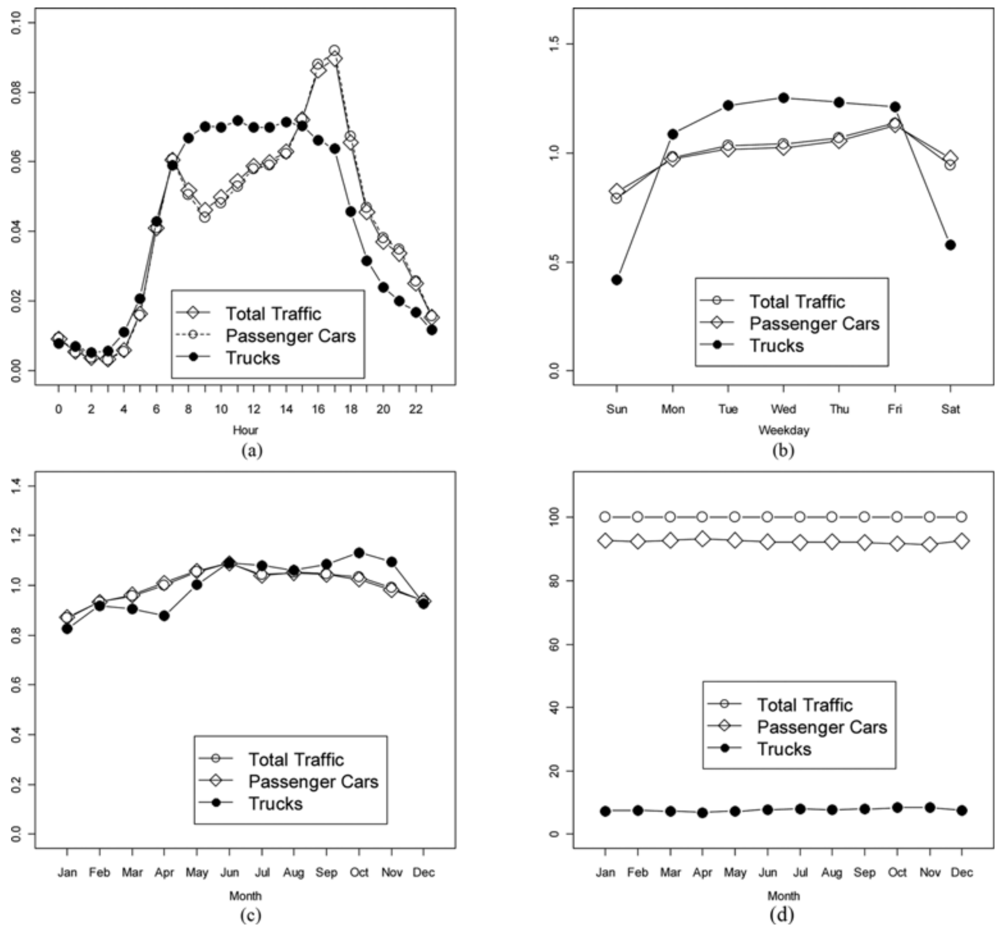

Fig. 1. Classified Traffic Volume Variation at Leduc WIM Site: (a) Hourly Average Factor, (b) Average Weekday Factors, (c) Average Monthly Factor, (d) Average Monthly Percentage Traffic

used by transportation engineers depending on the purpose and level of analysis. We used two classification levels in the context of the present research. The reason is that the truck volumes usually are very low compared to passenger cars; too many classes (e.g., passenger cars, single unit truck, and single trailer, etc.) resulted in lower sample size for analysis. Consequentially, lower samples may result in deficiency in statistical significance of results. Therefore, two vehicle classes: passenger car and truck are used for winter weather model development.

3.2 Preliminary Analysis on Study Data

3.2.1 Traffic Variation at Study Site

We analyzed the traffic patterns for passenger cars and trucks at the Leduc site using 1,826 daily traffic data. These days include 60 holidays, 305 days from fall season, 305 days from spring season, 460 days from summer season, and 756 days from winter season. Detailed observation on winter season data indicated that 413 days and 282 days experienced rain (max. 33 mm) and snow (max. 16 cm), respectively. The highest and lowest temperatures were 24ºC and -39ºC respectively during the 5 years study period.

The hourly factor (hourly traffic volume to AADT ratio) variations are shown in Fig. 1(a). The hourly passenger car factor variations show two distinct peaks: the morning peak between 7~9 AM and the evening peak between 4~7 PM. It is clear from the plots that the variation patterns are similar for the total traffic and passenger cars. Based on hourly traffic patterns, this highway can be classified as regional commuter road. The daily traffic volume factor (the ratio of daily traffic volume to passenger car AADT or truck AADT) is calculated and presented in Fig. 1(b). Fig. 1(b) shows passenger car increases during weekdays (Monday to Friday) and reaches peak on Friday. Following weekdays, passenger car count reduces on weekends (Saturday and Sunday). However, there is no significant difference in traffic variation between weekday and weekend. On the contrary, the truck traffic patterns are different for weekday and weekend. The truck volume experiences a steep increase during Sunday to Monday and decrease during Friday to Saturday. The monthly volume factor (see Fig. 1(c)) for these two vehicular classes suggested higher fluctuation in case of trucks than cars. As shown in Fig. 1(d), about 92% passenger cars and 8% trucks constitute the total traffic for a month at Leduc site. This share for the two classes remains consistent throughout the year.

3.2.2 Selection of Independent Variables

We chose snowfall and temperature as independent variables to relate with traffic volume variation for passenger cars and trucks. The scatter plot diagnostic suggested the linear association of traffic volume with the independent variables selected for model development. The probability distribution plots of average daily temperature with and without snowfall days are presented in Fig. 2. The plots shown in Figs. 2(a) and 2(b) are generally similar except a small shift is observed toward colder temperature for the probability distribution of daily average temperature corresponding to days with snowfall. The average temperature is -11ºC during the days (160 days) with snowfall and -9ºC during no snowfall days (350 days). The Pearson correlation coefficient value ranged from 0.03 to -0.18. These statistics confirms little to no correlation between snowfall and temperature. These observations supported the appropriateness for including snowfall and temperature as independent variables in modeling process.

4. The Linear Regression Model

The literature indicates that regression model structure is appropriate to quantify the association between traffic volume variations and weather factors. In fact, linear models are best suitable to represent the physical phenomena with appropriately defined dummy variables for explanatory variable categories and the interactions among them (Gourieroux *et al.*, 1984). In light of the above discussions, the proposed linear model structures are formulated for this study in Eq. (1) and Eq. (2). Eq. (1) represents the model without the snow and cold interaction effect on daily traffic volume. The

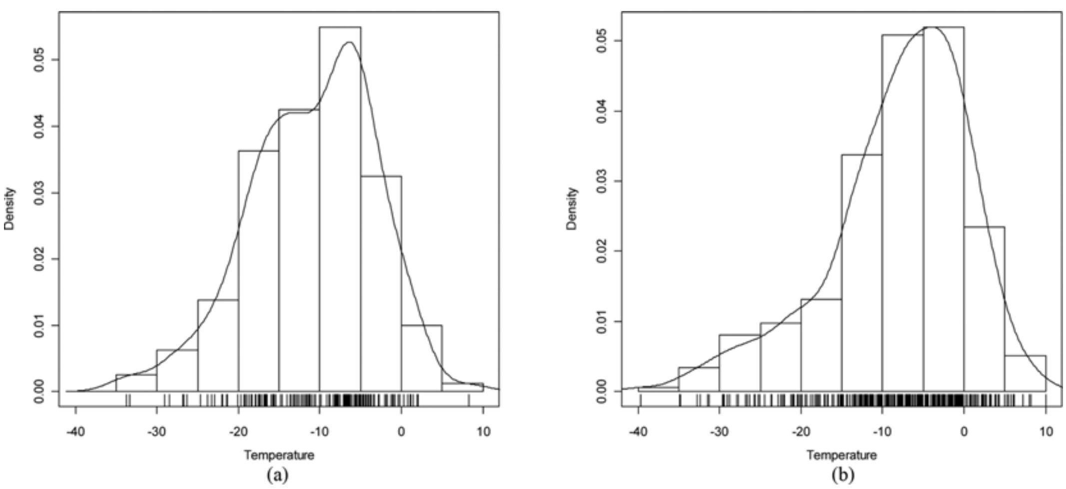

Fig. 2. Probability Distribution of Average Daily Temperature During the Days with (a) Snow, (b) No Snow

temperature represents the intensity of cold and it is included as a categorical (dummy) variable in the model specification. The temperature is assigned in 7 cold categories: Baseline (over 0ºC), CC_1 (-5ºC ~ 0ºC), CC_2 (-10ºC ~ -5ºC), CC_3 (-15ºC ~ -10ºC), CC_4 (-20ºC ~ -15ºC), CC_5 (-25ºC ~ -20ºC), CC_6 (below -25ºC) with 5ºC equal interval in model specification. The baseline category (the days having over 0ºC) is not included in model specification and assigned 0 for comparing the model with all other six cold categories.

$$y_i = f(expected\ daliy\ volume\ factor,\ snowfall, temperature) = \beta_1 EDVF_i + \beta_2 SNOW_i + \sum_{j=1}^{6}\gamma_i CC_{ij} + \varepsilon_i \tag{1}$$

$$y_i = f(expected\ daliy\ volume\ factor, snowfall, temperature) = \beta_1 EDVF_i + \beta_2 SNOW_i + \sum_{j=1}^{6}\gamma_j CC_{ij} + \sum_{j=1}^{6}\rho_j (SNOW_i \cdot CC_{ij}) + \varepsilon_i \tag{2}$$

Where, i: refers to the i^{th} observation, β_1, β_2, $\gamma_{1\sim6}$: Estimated

Table 3. Daily Winter Traffic Model with Snowfall and Cold (without interaction)

Variables	Coefficients	Total Traffic (Model 1)
EDVF	0.953140(0.018590)***	
SNOW	-0.023224 (0.001288)***	
Baseline	0.070597 (0.019418)***	$\hat{Y}_{baseline}$ = 0.953140*EDVF-0.023224*SNOW+0.070597
CC_1	0.073338 (0.018560)***	$\hat{Y}$cc1 = 0.95s3140*EDVF-0.023224*SNOW+0.073338
CC_2	0.068258 (0.017854)***	$\hat{Y}$cc2 = 0.953140*EDVF-0.023224*SNOW+0.068258
CC_3	0.064305 (0.018540)***	$\hat{Y}$cc3 = 0.953140*EDVF-0.023224*SNOW+0.064305
CC_4	0.047415 (0.019145)**	$\hat{Y}$cc4 = 0.953140*EDVF-0.023224*SNOW+0.047415
CC_5	0.037870 (0.018753)**	$\hat{Y}$cc5 = 0.953140*EDVF–0.023224*SNOW+0.037870
CC_6	-0.037838.(0.019426)*	$\hat{Y}_{cc6}$ = 0.953140*EDVF–0.023224*SNOW–0.037838
R^2	0.9974	
F	21480***	
Change from R^2_{Naive}	0.0007	
Incremental F-statistic	22.48***	
Variables	Coefficients	Passenger Car Traffic (Model 2)
EDVF	0.936181 (0.021991)***	
SNOW	-0.025520 (0.001357)***	
Baseline	0.093456 (0.022592)***	$\hat{Y}_{baseline}$ = 0.936181*EDVF–0.025520*SNOW+0.093456
CC_1	0.092663 (0.021725)***	$\hat{Y}_{cc1}$ = 0.936181*EDVF–0.025520*SNOW+0.092663
CC_2	0.086308 (0.020974)***	$\hat{Y}_{cc2}$ = 0.936181*EDVF–0.025520*SNOW+0.086308
CC_3	0.081419 (0.021663)***	$\hat{Y}_{cc3}$ = 0.936181*EDVF–0.025520*SNOW+0.081419
CC_4	0.058777 (0.022238)***	$\hat{Y}_{cc4}$ = 0.936181*EDVF–0.025520*SNOW+0.058777
CC_5	0.052327 (0.021641)**	$\hat{Y}_{cc5}$ = 0.936181*EDVF–0.025520*SNOW+0.052327
CC_6	-0.028803(0.022436)	$\hat{Y}_{cc6}$ = 0.936181*EDVF–0.025520*SNOW-0.028803
R^2	0.9971	
F	19200***	
Change from R^2_{Naive}	0.0009	
Incremental F-statistic	25.91***	
Variables	Coefficients	Truck Traffic (Model 3)
EDVF	1.003604 (0.019506)***	
SNOW	0.003107(0.003776)	
Baseline	-0.056523 (0.027825)**	$\hat{Y}_{baseline}$ = 1.003604*EDVF+0.003107*SNOW–0.056523
CC_1	-0.013553(0.023962)	$\hat{Y}_{cc1}$ = 1.003604*EDVF+0.003107*SNOW–0.013553
CC_2	-0.005365(0.022396)	$\hat{Y}_{cc2}$ = 1.003604*EDVF+0.003107*SNOW–0.005365
CC_3	0.003082(0.024787)	$\hat{Y}_{cc3}$ = 1.003604*EDVF+0.003107*SNOW–0.003082
CC_4	0.052269.(0.028580)*	$\hat{Y}_{cc4}$ = 1.003604*EDVF+0.003107*SNOW–0.052269
CC_5	-0.000215(0.032040)	$\hat{Y}_{cc5}$ = 1.003604*EDVF+0.003107*SNOW–0.000215
CC_6	-0.006760(0.032572)	$\hat{Y}_{cc6}$ = 1.003604*EDVF+0.003107*SNOW–0.006760
R^2	0.9813	
F	2926***	
Change from R^2_{Naive}	0.0006	
Incremental F-statistic	2.68*	

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

coefficients for each independent variables, y_i: Daily traffic volumes factor for vehicle class (passenger cars, trucks), *EDVF*: Expected daily volume factor, *SNOW*: Amount of snowfall per day (cm), $CC_{i1\sim6}$: CC_{ij} = 1 if observation i falls in category j, otherwise 0, $SNOW_i \cdot CC_{i1\sim6}$: Interaction term representing partial effect of cold at a specific snowfall, $\rho_{1\sim6}$: Estimated

Table 4. Daily Winter Traffic Model with Snowfall and Cold Interactions

Variables	Coefficients	Total Traffic (Model 4)	
EDVF	0.9519379 (0.0186690)***	$\hat{Y}_{baseline}$ = 0.95194*EDVF–0.02271*SNOW+0.07171 $\hat{Y}_{cc1}$ = 0.95194*EDVF–0.01804*SNOW+0.07239 $\hat{Y}_{cc2}$ = 0.95194*EDVF–0.02294*SNOW+0.06911 $\hat{Y}_{cc3}$ = 0.95194*EDVF–0.01939*SNOW+0.06367 $\hat{Y}_{cc4}$ = 0.95194*EDVF–0.02675*SNOW+0.05374 $\hat{Y}_{cc5}$ = 0.95194*EDVF–0.03400*SNOW+0.04677 $\hat{Y}_{cc6}$ = 0.95194*EDVF–0.02365*SNOW-0.03658	
SNOW	-0.0227071 (0.0114840)**		
Baseline	0.0717118 (0.0195313)***		
CC_1	0.0723899 (0.0186349)***		
CC_2	0.0691110 (0.0179187)***		
CC_3	0.0636678 (0.0188216)***		
CC_4	0.0537359 (0.0199135)***		
CC_5	0.0467716 (0.0193160)**		
CC_6	-0.0365827.(0.0199077)*		
$SNOWCC_1$	0.0046678(0.0120947)		
$SNOWCC_2$	-0.0002346(0.0116062)		
$SNOWCC_3$	0.0033214(0.0126401)	R^2	0.9974
$SNOWCC_4$	-0.0040451(0.0118984)	F	12890***
$SNOWCC_5$	-0.0112958(0.0133574)	R^2 change from dummy-regression	0
$SNOWCC_6$	-0.0009471(0.0150307)	Incremental *F*-statistic	0
Variables	Coefficients	Passenger Car Traffic (Model 5)	
EDVF	0.934430 (0.022061)***	$\hat{Y}_{baseline}$ = 0.93443*EDVF–0.01869*SNOW+0.09425 $\hat{Y}_{cc1}$ = 0.93443*EDVF–0.02244*SNOW+0.09310 $\hat{Y}_{cc2}$ = 0.93443*EDVF–0.02456*SNOW+0.08704 $\hat{Y}_{cc3}$ = 0.93443*EDVF–0.02008*SNOW+0.08056 $\hat{Y}_{cc4}$ = 0.93443*EDVF–0.03017*SNOW+0.06726 $\hat{Y}_{cc5}$ = 0.93443*EDVF–0.03944*SNOW+0.06400 $\hat{Y}_{cc6}$ = 0.93443*EDVF–0.02745*SNOW–0.02651	
SNOW	-0.018691(0.012072)		
Baseline	0.094246 (0.022693)***		
CC_1	0.093096 (0.021787)***		
CC_2	0.087044 (0.021013)***		
CC_3	0.080555 (0.021940)***		
CC_4	0.067255 (0.023031)***		
CC_5	0.064001 (0.022165)***		
ECC_6	-0.026508(0.022895)		
$SNOWCC_1$	-0.003752(0.012714)		
$SNOWCC_2$	-0.005870(0.012200)		
$SNOWCC_3$	-0.001391(0.013287)	R^2	0.9972
$SNOWCC_4$	-0.011475(0.012507)	*F*	11560***
$SNOWCC_5$	-0.020750(0.014041)	R^2 change from dummy-regression	0.0001
$SNOWCC_6$	-0.008759(0.015798)	Incremental *F*-statistic	2.95**
Variables	Coefficients	Truck traffic (Model 6)	
EDVF	1.002006(0.019330)***	$\hat{Y}_{baseline}$ = 1.002006*EDVF–0.070871*SNOW–0.044811 $\hat{Y}_{cc1}$ = 1.002006*EDVF+0.032907*SNOW–0.024052 $\hat{Y}_{cc2}$ = 1.002006*EDVF–0.003346*SNOW+0.002103 $\hat{Y}_{cc3}$ = 1.002006*EDVF–0.014033*SNOW+0.012674 $\hat{Y}_{cc4}$ = 1.002006*EDVF+0.009918*SNOW+0.043879 $\hat{Y}_{cc5}$ = 1.002006*EDVF+0.027921*SNOW–0.016934 $\hat{Y}_{cc6}$ = 1.002006*EDVF+0.017627*SNOW–0.010489	
SNOW	-0.070871(0.033348)**		
Baseline	-0.044811(0.027839)		
CC_1	-0.024052(0.023959)		
CC_2	0.002103(0.022405)		
CC_3	0.012674(0.025519)		
CC_4	0.043879(0.030848)		
CC_5	-0.016934(0.034511)		
CC_6	-0.010489(0.033941)		
$SNOWCC_1$	0.103778(0.035117)***		
$SNOWCC_2$	0.067525(0.033704)**		
$SNOWCC_3$	0.056838(0.036698)**	R^2	0.982
$SNOWCC_4$	0.080789(0.034540)**	*F*	1798***
$SNOWCC_5$	0.098792(0.038783)	R^2 change from dummy-regression	0.0007
$SNOWCC_6$	0.088498(0.043650)**	Incremental *F*-statistic	3.2**

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

coefficient for interaction term, ε_i: Stochastic error term.

5. Validation of Statistical Robustness of Estimated Models

The proposed model structures (Eqs. (1) and (2)) are estimated through least square method for each vehicle class and summarized in Tables 3 and 4. The R^2 values for all models are over 0.98 suggesting that the model fitness is very good with the sample data. For example, the R^2 for passenger car model (Model 2) is 0.9971, indicating that over 99% of the variations in daily volume factor among the 510 days is captured by the fitted model. The overall adequacy of the model is tested by F-statistics and the results indicated that all models estimated in this research are useful for prediction by rejecting the null hypothesis (e.g., all coefficients in Eq. (1) are simultaneously zero) at 0.001significant level. Incremental F-statistic is used for Eq. (1) in order to test the appropriateness of cold as a categorical variable ($H_0:\gamma_1 = \gamma_2 = \ldots \gamma_6 = 0$). The comparison between R^2 of the dummy variable model and R^2 of naive model (model without dummy variable effect: i.e., $y_i = \beta_1 EDVF_i + \beta_2 SNOW_i + \varepsilon_i$) confirms statistical significance of dummy variable inclusion. Additionally, incremental F-statistic is also used for Eq. (2) to check the null hypothesis of no interaction effect of snowfall and cold category ($H_0:\rho_1 = \rho_2 = \ldots \rho_6 = 0$). The comparison between R^2 of interaction model (Eq. (2)) and $R^2$of model without interaction effect: (i.e., $y_i = \beta_1 EDVF_i + \beta_2 SNOW_i + \sum_{j=1}^{6}\gamma_j CC_{ij} + \varepsilon_i$) indicated the appropriateness of the inclusion of interaction term in the model specification.

The incremental F-statistic values suggested that all models except model 4 (see Table 4) are significant at 0.05 level. However, even for the model 4, other statistical tests (R^2, F-test) indicated the appropriateness of the inclusion of interaction term. The statistical significance for individual coefficients is evaluated by t-statistic, and accordingly the significance level is indicated using a symbol (*) in both Tables 3 and 4.

Figure 3(a) shows the predicted traffic volumes are closer (R^2 = 0.9974) to the actual values with the regression line between the actual and predicted traffic volumes for the model 1. Residuals plots (predicted values versus residuals) for each model were analyzed for checking the model linearity and homoscedasticity (constant variance).The standardized residuals

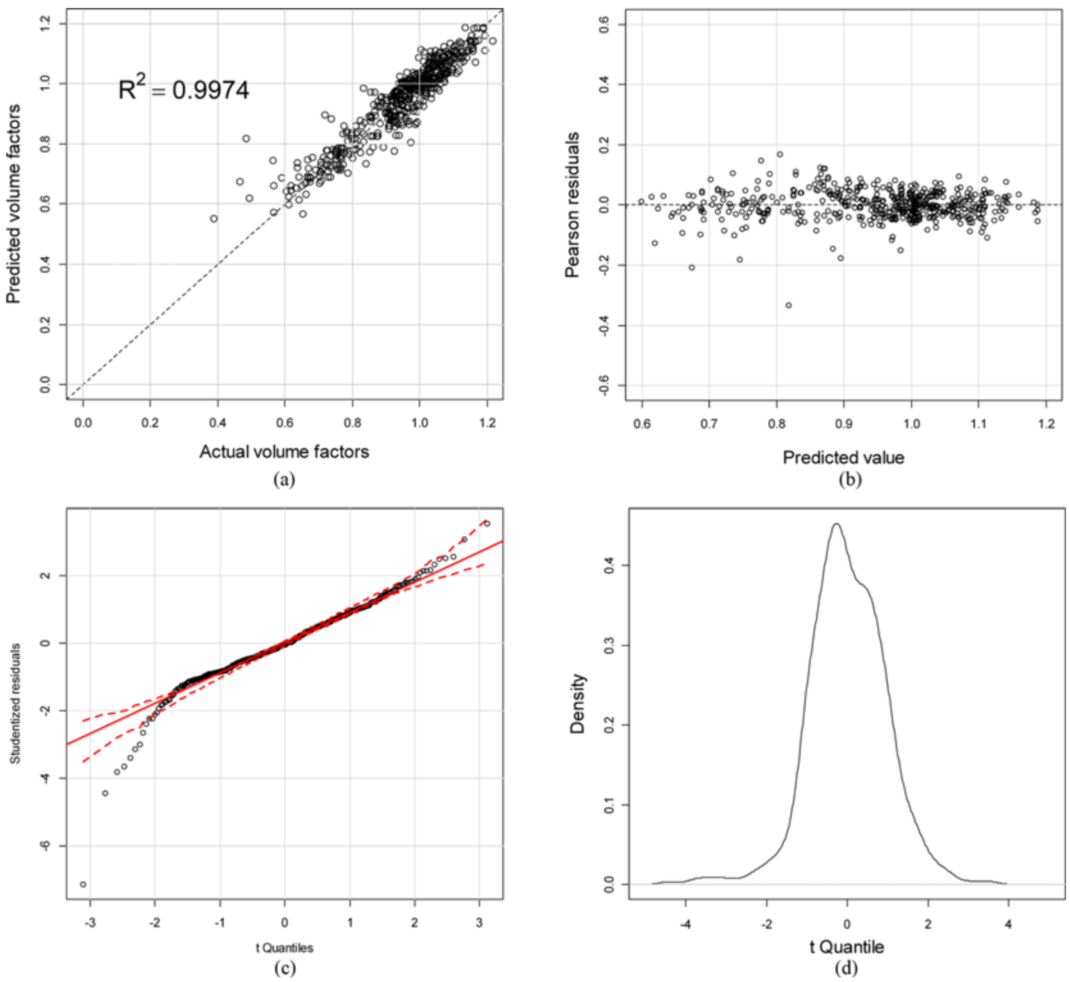

Fig. 3. Statistical Test Results to Validate the Developed Models: (a) Comparison of Actual and Predicted Traffic Voulumes, (b) Residual Scatter Plot, (c) Quantile-comparison Plot of Studentized Residuals, (d) Density estimate of Residual Distribuation

in Fig. 3(b) are randomly scattered around the base line, providing a relatively even distribution. This means that normality and homoscedasticity assumptions are not violated. Normality of estimated residual was also tested for the residuals (Figs. 3(c) and 3(d)).

Based on four statistical test results (R^2, F-test, incremental F-test, and t-test) and the residual analysis, it may be concluded that the developed winter weather traffic regression models with or without the interaction term are appropriate to relate traffic volume with snow and cold.

5.1 Effect of Cold on Classified Traffic Volume

We tried to understand the effect of cold on traffic volume using models 2 and 3 for each vehicle class with the concept of the Percentage Changes (PCs) developed in the study conducted by Datla and Sharma (2008). Percentage change can be calculated using Eq. (3).

$$PC_{CC_1\sim CC_6} = \left(1 - \frac{N_{Baseline}}{N_{CC_1\sim CC_6}} \times \frac{\sum VF_{CC_1\sim CC_6}}{\sum VF_{Baseline}}\right) \times 100 \qquad (3)$$

Where $PC_{CC_1\sim CC_6}$ is the percentage changes in the classified traffic volume factors for each cold category (CC_1~CC_6) relative to baseline cold category (over 0ºC), $N_{Baseline}$ is the number of days that belong to baseline cold category in the sample data, $N_{CC_1\sim CC_6}$ is the number of days that belong to each cold category ($CC_1 \sim CC_6$), $\sum VF_{CC_1\sim CC_6}$ representsthe sum of predicted classified traffic volume factors for each cold category ($CC_1 \sim CC_6$), $\sum VF_{Baseline}$ representsthe sum of predicted classified traffic volume factors for baseline cold category.

The reduction in passenger car traffic volume for each cold category is presented through Fig. 4(a).The lowest and highest PCs are for CC_1 (-0.079%) and CC_6 (-12%) respectively. For the remaining categories: CC_2~CC_5, the PCs value increases as cold approaches to CC_5. The percentage change is significantly higher in case of passenger cars than trucks; passenger cars reduce at a higher rate as the weather become colder. The above observation confirms that severe weather condition causes traffic variation. On the contrary, we found increase in truck traffic (see Fig. 4(b)) as the temperature becomes colder. The maximum increase (11%) is observed in CC_4 category. The average increase in truck volume is about 6% for all the cold categories.

5.2 Interaction Effect of Snowfall and Temperature on Classified Traffic Volume

We also analyzed the partial effect of cold with varying amount of snowfall on each vehicle class through graphical analysis. It may be observed that the estimated coefficient for snowfall has same value for each model for all the cold categories reported in Table 3. However, the coefficient takes different values (see Models 4, 5 and 6) for different cold categories in Table 4, due to the inclusion of the interaction effect (or term) in model specification (see Eq. (2)). This observation indicates the effect of cold levels with the amount of snowfall and thus, the fitted

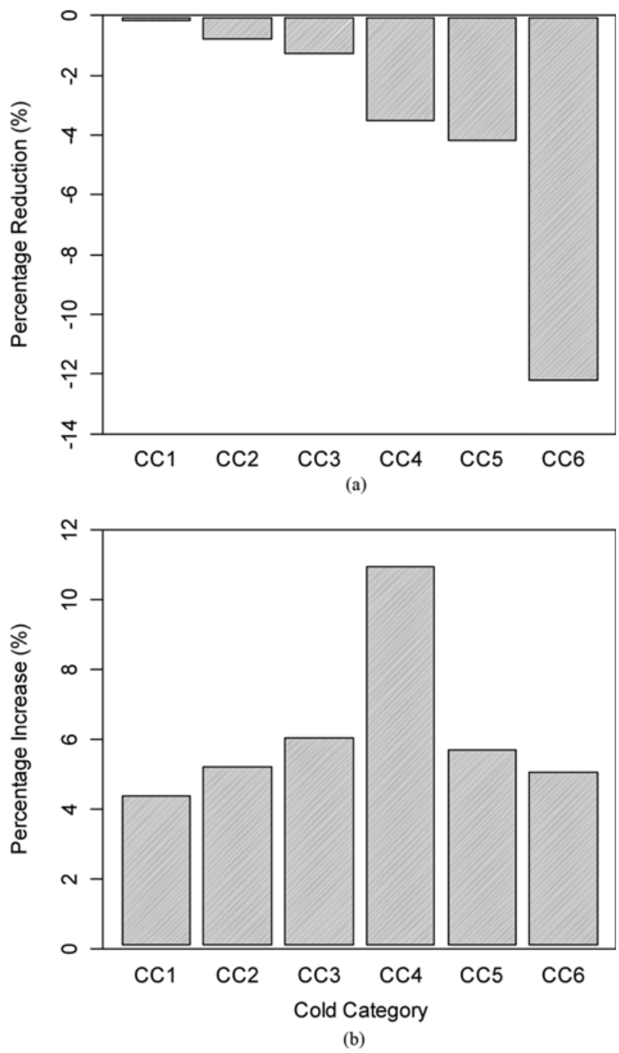

Fig. 4. Percentage Reduction for (a) Passenger Cars, Increase for (b) Trucks

model explains the differential effect of snowfall on daily traffic factor for each cold category. The partial effect of snowfall-by-cold category on the daily traffic volume is analyzed through the models 4, 5 and 6 for total, passenger car, and truck traffics (see Figs. 5(a), 5(b), and 5(c)). These plots are generated using the models reported in Table 4 by fixing EDVF to its average value (0.9471) and varying the snowfall from 0 cm to 16 cm.The comparison of plots for total traffic and passenger cars have almost same regression slope for all the cold categories. The possible reason for this is that the passenger cars share about 92% of total daily traffic volume. Nonetheless, the snow and cold interaction effects on passenger cars and trucks represented by Figs. 5(b) and 5(c) are distinct. In case of passenger cars, it is apparent that snow creates a negative effect on traffic volumes and the effect becomes significant in proportion to the amount of snowfall for every corresponding cold category. The steepest decline in passenger car due to snowfall is occurred at CC5, in the other way, the gentlest decline is detected at baseline category. The decrease in passenger car traffic volumes due to

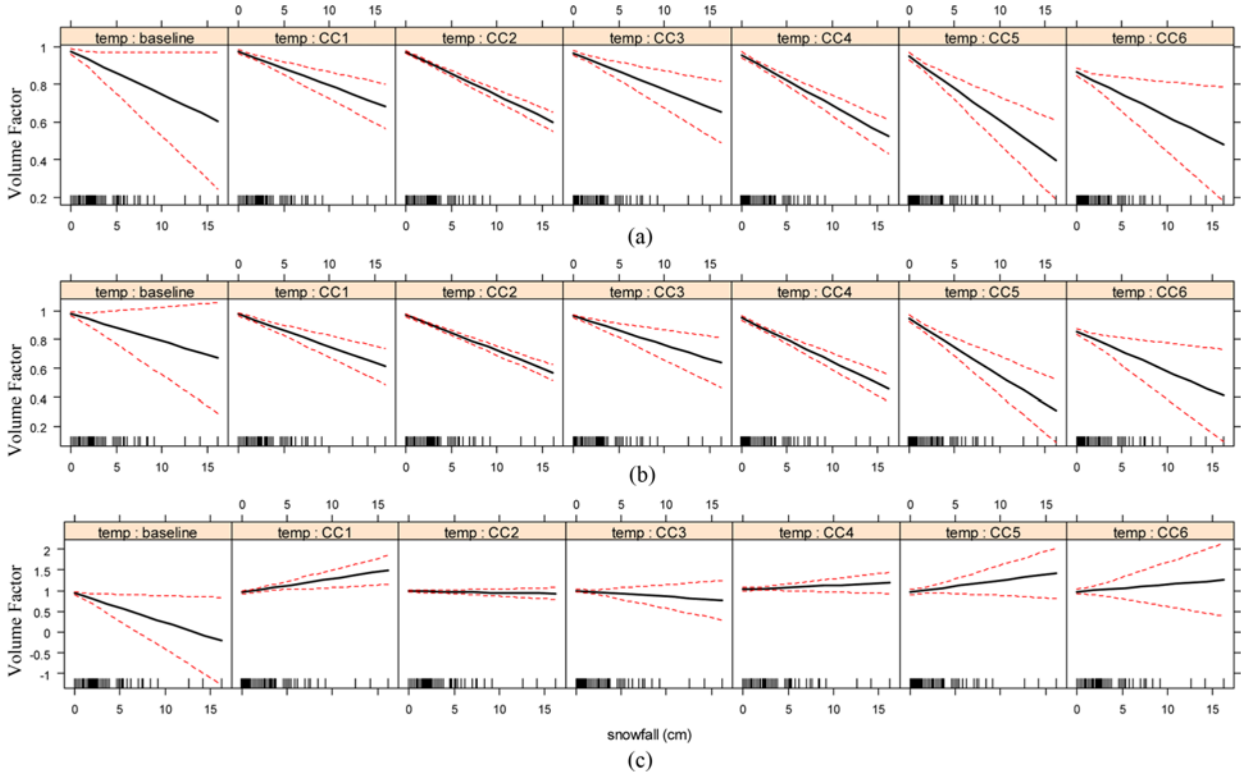

Fig. 5 Partial Effect of Snowfall-by-cold Category on Volume Factor for (a) Total, (b) Passenger Cars, and (c) Truck Traffics

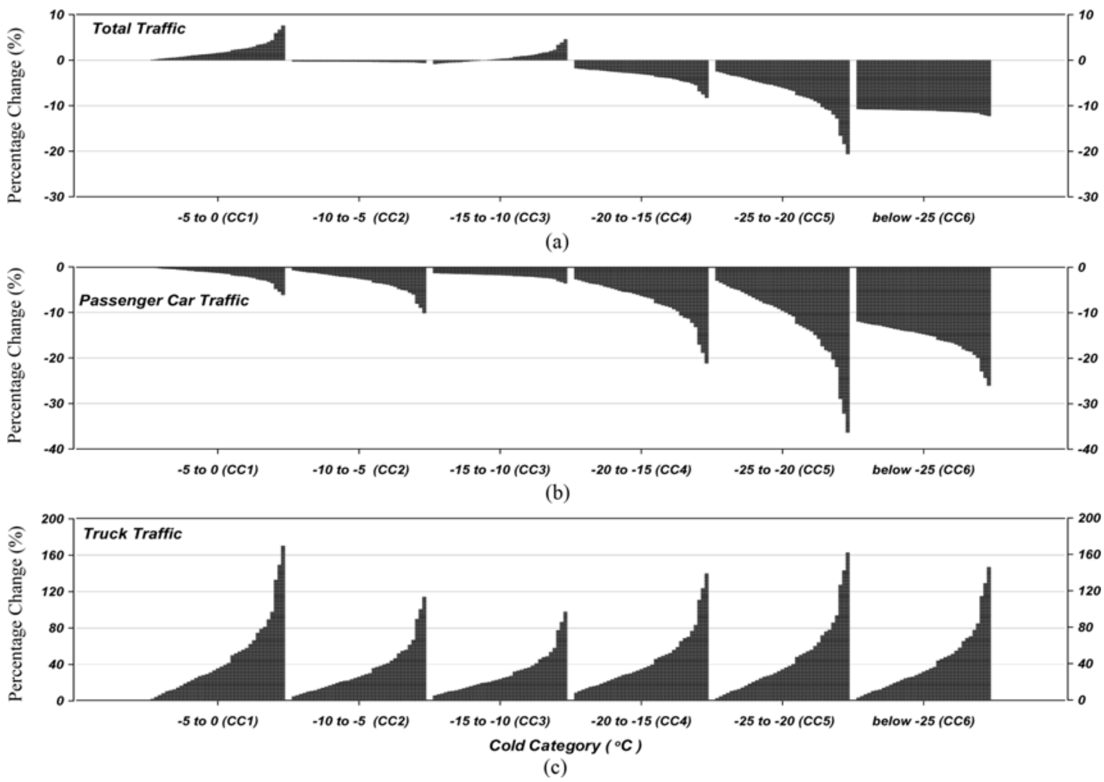

Fig. 6. Percentage Change of Traffic Corresponding to Varying Amount of Snowfall in Each Cold Category for (a) Total, (b) Passenger Cars, (c) Truck Traffics

varying snowfall ranging from 0 to 16 cm is 31% for baseline category, 34% for CC3, 68% for CC5, and 52% for CC6 respectively (Fig. 5(b)).

In case of trucks, it can be seen from Model 6 in Table 4 that snow has the largest impact on daily traffic volume factor in baseline category, and has the smallest effect in CC2. It should also be noted that, within 95% statistical envelope (shown in red dotted line in Fig. 5(c)), truck traffic are not affected as much as passenger cars, meaning that this unique traffic pattern is shown in bidirectional behavior of truck irrespective of weather. In further analysis of the interaction effect of cold and snow, in Fig. 5(c), truck volume increased with the increase in snowfall amount. The most distinct decline in truck traffic due to snowfall ranged from 0 to 16 cm is -122%in baseline category and the most significant increment is 56% for CC1. This observations suggest the change in truck traffic volumes is bidirectional in the given snowfall range. The increase for trucks at different cold categories is 16% for CC4, 30% for CC6, and 47% for CC5, respectively. The remaining categories: CC2 (-6%) and CC3 (-23%) show decrease in truck volumes in the specified snowfall range. These percentage variations (increase/decrease) compared to baseline traffic volume for the two vehicular classes are presented through Fig. 6.

6. Summary and Closing Remarks

This study primarily focuses on quantification of traffic variations associated with severe weather conditions for vehicle classes in traffic mix. For this purpose, traffic data are collected from WIM systems at Leduc site on highway 2A in the province of Alberta, Canada. These data are used to classify vehicle into two classes: passenger cars and trucks, based on the vehicle information captured through WIM technology. The classification process used FHWA scheme F and PNN vehicle classification schemes. The vehicles are classified into two classes since almost all classes (out of 28) result in very lower sample size for analysis.

Although limited studies on weather effects (snowstorm, snowfall, cold, and rain, etc.) on highway traffic volume are in existence, all of them are limited to discuss about the total traffic volume variations associated with weather conditions. Studies on classified traffic variation during winter weather condition are next to non-existent. This research investigated the cold and snow interaction effect on passenger cars and trucks separately with an emphasis on quantifying the traffic change variations under severe weather conditions. Understanding of truck variation will help in pavement performance evaluation, policy making decisions on snow clearance time for various road types, developing strategies for winter maintenance of road network, etc.

In the purpose of identifying the gross interaction effect of snow and cold on classified traffic volume, cold is used as a categorical variable in the model development process. We used categorical regression analysis, since dummy-variables represents the physical phenomenon efficiently. The two continuous variables used in this study are EDVF, and Snowfall. The cold is categorized into 7 categories considering 5°C interval for each category. The models are tested statistically through four statistical tests: R^2, *F*-test, incremental *F*-test, and *t*-test. These tests confirmed the appropriateness of the variables selected for modeling and also explained the statistical significance of the winter weather traffic models.

The effect of snowfall on daily volumes is clearly opposite for the two vehicle classes; passenger cars are negatively affected and the volumes are reduced in proportion to the amount of snowfall. Truck traffics, however, are found to increase as the amount of snowfall increases. The effect of cold is also clearly opposite for the two vehicle classes. The daily passenger cars traffic decrease by 12% when the temperature goes below -25°C, this decreasing pattern happened for all cold categories. Conversely, the daily truck traffics increase generally irrespective of cold category. The biggest percentage increase occurs (10.9%) in CC4.

The effect of cold with varying amount of snowfall on daily traffic volume factor is investigated with interaction dummy-variable model. Passenger cars traffic volumes decrease in all cold categories, this decreasing tendency becomes significant in proportion to the amount of snowfall. The highest reduction in daily traffics is -36% found in CC5 with the amount of snowfall of 16 cm, the smallest reduction is -0.11% in CC1 with 0cm snowfall. On the contrary, truck traffic volumes increase in all cold categories, this increasing tendency is intensified in proportion to the amount of snowfall. It is concluded that truck traffics are not affected by the effect of snow-cold interaction; conversely, show the maximum increase (170%) in volume in CC1 with snowfall amount 16 cm.

In conclusion, it is evident that passenger cars' traffics are especially vulnerable to adverse weather conditions. As pointed out in literature review, this vulnerability can be attributed to the passenger cars' traveling characteristics such as a flexibility to delay departure time, route change behavior, trip cancellation, and discretionary trip adjustment. However, the truck traffics volumes are unaffected at the Leduc site by adverse weather, and also found increasing in volume despite of the unfavorable weather conditions. This phenomenon could happen due to shift of truck traffic from parallel low standard highways. It is also worthwhile to know that 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. The research on such unique characteristic of truck traffic is currently underway and can be established with more data from some more study sites.

Acknowledgements

The authors are thankful towards the Natural Science and Engineering Research Council of Canada (NSERC). The authors are thankful to Alberta Transportation for providing the WIM data used in this study.

References

Changnon, S. A. (1996). “Effects of summer precipitation on urban transportation." *Climatic Change*, Vol. 32, No. 4, pp. 481-495, DOI 10.1007/BF00140357.

Colyar, J. and Halkias, J. (2003). "Identifying and assessing key weather-related parameters and their impact on traffic operations using simulations." *ITE Annual Meeting*, Washington, D.C., U.S.

Datla, S., Sahu P., Roh, H. J., and Sharma, S. (2013). "A comprehensive analysis of the association of highway traffic with weather conditions." *Procedia-Social and Behavioral Sciences,* Vol. 104, No. 2, pp. 497-506, DOI 10.1016/j.sbspro.2013.11.143.

Datla, S. and Sharma, S. (2008). "Impact of cold and snow on temporal and spatial variations of highway traffic volumes." *Journal of Transport Geography.* Vol. 16, No. 5, pp. 358-372, DOI: 10.1016/j.jtrangeo.2007.12.003.

Datla, S. and Sharma, S. (2010). "Variation of Impact of Cold Temperature and Snowfall and Their Interaction on Traffic Volume." *Journal of the Transportation Research Board*, No. 2169, pp. 107-115, DOI: 10.3141/2169-12.

EC (2010). Environment Canada, Weather Office, Canada. Accessed July 26, 2010. http://www.climate.weatheroffice.ec.gc.ca/climateData/canada_e.html.

ESRI (2010). *Environmental system research institute, arcgis 10 help library*, Geographic Information Sys-tem (GIS), Redlands.

Fekpe, E. S. K. and Clayton, A. M. (1994). "Vehicle classification from weigh-in-motion data: the progressive sieving algorithm." *Canadian Journal of Civil Engineering*, Vol. 21, No. 2, pp. 195-206, DOI: 10.1139/l94-023.

Goodwin, L.C. (2002). "Weather impacts on arterial traffic flow." *The Road Weather Management Program*, FHWA, US Department of Transportation, Washington D.C., USA.

Gourieroux, C., Monfort, A., and Trognon, A (1984). "Pseudo maximum likelihood methods: Applications to poisson models." *Econometrica,* Vol. 52, No. 3, pp. 701-720.

Hanbali, R. M. and Kuemmel, D. A. (1993). "Traffic volume reduction due to winter storm conditions." *Journal of the Transportation Research Board*, No. 1387, pp. 159-164.

Hassan, Y. A. and Barker, J.J. (1999). "The impact of unseasonable or extreme weather on traffic activity within Lothian region, Scotland." *Journal of Transport Geography*, Vol. 7, No. 3, pp. 209-213, DOI: 10.1016/S0966-6923(98)00047-7.

Haykin, Simon (2008). *Neural networks and learning machines*, Prentice Hall, Hamilton, Ontario, Canada.

ITT Industries, Inc. (2003). *Identifying and assessing key weather-related parameters and their impacts on traffic operations using simulation*, FHWA, US Department of Transportation, Washington D.C., USA.

John Fox (2008). *Applied regression analysis and generalized linear models,* SAGE Publications, Thousand Oaks.

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*, Vol 37, No. 1, pp. 109-124, DOI: 10.1016/j.aap.2004.07.005.

Kilburn, Peter (2008). *Alberta Infrastructure & Transportation Weigh in Motion Report,* Alberta Transportation.

Knapp, K. K. and Smithson, L. D. (2007). "Winter strom event volume impact analysis using multiple-source archived monitoring data." *Journal of the Transportation Research Board*, No. 1700, pp.10-16, DOI: 10.3141/1700-03.

Kwigizile, Valerian, Selekwa, Majura, and Mussa, Renatus (2004). "Highway vehicle classification by probabilistic neural networks." *Association for the Advancement of Artificial Intelligence (AAAI),* San Jose, California.

Liu, Z. B. and Sharma, S. (2006). "Statistical investigations of statutory holiday effects on traffic volumes." *Journal of the Transportation Research Board*, No. 1945, pp. 40-48, DOI :10.3141/1945-05.

Maki, P. J. (1999). "Adverse weather traffic signal timing." *ITE Annual Meeting*, Las Vegas, U.S.

Markku, K. and Heikki, S. (2007). "Effects of weather and weather forecasts on driver behavior." *Transportation Research Part F*, Vol. 10, No. 4, pp. 288-299, DOI: 10.1016/j.trf.2006.11.002.

Maze, T. H., Agarwal, M. and Burchett, G. D. (2007). "Whether weather matters to traffic demand, traffic safety, and traffic operations and flow." *Journal of the Transportation Research Board*, No. 1948, pp. 170-176, DOI: 10.3141/1948-19.

Mussa, Renatus, Kwigizile, Valerian and Selekwa, Majura (2006). "Probabilistic neural networks application for vehicle classification." *Journal of Transportation Engineering*, Vol. 132, No. 4, pp. 293-302, DOI: 10.1061/(ASCE)0733-947X(2006)132:4(293).

Perrin, J. and Martin, P. (2002). "Modifying signal timing during inclement weather." *ITE Annual Meeting*, University of Utah.

RFSC (2010), R Foundation for Statistical Computing, A Language and Environment for Statistical Computing, Vienna.

Roh, H. J., Datla, S., and Sharma, S. (2013). "Effect of snow, temperature and their interaction on highway truck traffic." *Journal of Transportation Technologies*, Vol. 3 No. 1, pp. 24-38, DOI: 10.4236/jtts.2013.32003.

Roh, H. J., Sharma, S., and Datla, S. (2014). "The impact of cold and snow on weekdays and weekend highway total and passenger cars traffic volumes." *The Open Transportation Journal*, Vol. 8, pp. 62-72, DOI: 10.2174/1874447801408010062.

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." *83rd Annual Meeting of the Transportation Research Board*, Washington D.C., U.S.

Wyman, J. H., Braley, G. A., and Stephens, R. I. (1985). *Field evaluation of fhwa vehicle classification categories*, FHWA, US Department of Transportation, Washington D.C., USA.

Zhi, X., Shalaby, A., Middleton, D., and Clayton, A. (1999). "Evaluation of weigh-in-motion in Manitoba." *Canadian Journal of Civil Engineering*, Vol. 26, No. 5, pp. 655-666, DOI :10.1139/l99-025.