Modelling of Emergency Vehicle Demand using Poisson Hurdle Regression Model

by

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Abstract

This research presents a Poisson Hurdle Regression Model to explore the factors influencing emergency vehicle demand. The modelling approach built on recent work on spatial modelling field that deals with an excess count of zeros in the dataset. Specifically, this research examines factors contributing to demand of emergency vehicle using geographical attributes at a 1km by 1km grid level. The spatial elements were derived from the dissemination area-level data that provides various characteristics, identifying neighborhood attributes that enabled a comprehensive hypothesis testing during model estimation stage. Moreover, this research examines the temporal characteristics of the demand and compare how different periods of the day affects emergency vehicle demand. The results of this research reveal that social-demographic characteristics, accessibility (such as distance to park, hospital, and business district) and land use measures (such as percentage share of residential and commercial land uses), can influence emergency vehicle demand. This research concludes on the impact of these variables as well as provides policy makers with meaningful deduction and insightful direction on a number of ways to improve emergency vehicle services.

List of Abbreviations and Symbols Used

Y	Count-valued Response
λ	Poisson
Pr	Probability
e	Base of the natural logarithms
µ	Rate (mean, expected count)
π	Utilization function (probability of non-zero response)
α	Dispersion parameter
AIC	Akaike information criterion
BIC	Bayesian information criterion
CBD	Central Business District
DA	Dissemination Area
ED	Emergency Department
EHS	Emergency Health Services
EMS	Emergency Medical Service
GIS	Geographic Information System
HRM	Halifax Regional Municipality
MCC	Medical Command Center

Acknowledgement

I am using this opportunity to express my gratitude to everyone who supported me throughout the course of this Thesis. Firstly, I would like to appreciate my supervisor, Dr. Ahsan Habib for providing me with the opportunity, guidance, invaluable suggestions including professional and personal advice during the course of my research. I will not have been able to complete this thesis without him. I would also like to express my sincere appreciation to Dr Mikiko Terashima for taking time out to read my reviews as well as providing me with constructive criticism on my methods. Her original research proposal got me started with this research. I would also like to acknowledge the funding from Dalhousie Transport Collaboratory (DalTRAC), support from the team, the project coordinator, Sara Campbell and the Nova Scotia provincial Emergency Medical Service (EMS) for providing the data used throughout the research. Finally, I would like to appreciate my family, most importantly, my Mum for her kind words of encouragement during the entire period of my research.

Chapter 1 – Introduction

1.1 Research Overview

The challenges presented by the increased proportion of senior citizens and pressure on emergency health services are growing. In the past few years, there has been a considerable increase in the rate of emergency vehicle use (Lowthian et al., 2011). Understanding the reasons behind this increase in demand and how it affects different population groups is essential (Reed et al. 2015). It will enable us to improve emergency health care planning, reduce operational cost as well as put in place necessary action to combat potential deterioration in emergency medical services. For example, a study in the United States has shown that up to 27% of emergency calls can be handled without the need for an emergency vehicle to respond, saving approximately $4.4 billion in health care costs annually (Weinick et al. 2010).

Furthermore, in an emergency situation, the time of delivery is very critical. Users of medical emergency vehicles expect prompt service and competent paramedic availability. Research has shown that the older groups are at risk because they are among the frequent users of emergency vehicles (Clark and FitzGerald, 1999). For instance, in Canada, a significant percentage of its population is aged 65 years or older (Anne Milan, 2011). This alone is a major concern for emergency medical services, as it does not only increase healthcare costs but also impedes access to quality health care services (Jayaprakash et al., 2009). However, with a good understanding of these studies, we can cater for emergency demand in communities or geographical regions where demand is considered trivial as well as estimate the nature of the demand for particular health needs in a region. For instance, community primary care unit can be built to support the health services in these regions, thereby preventing the need to call for an emergency ambulance service, consequently reducing the rate of emergency vehicle demand.

Moreover, research has also shown that the demand for emergency vehicles can arise as a result of different needs. A detailed literature review has provided possible explanations for these increases. For instance, two recent studies suggest that the growth in emergency vehicle use can be attributed to demographic changes, public expectation and accessibility of medical care. (Lowthian et al. 2011 and Weber et al., 2008). Also, government policies, the cost of medical insurance and provincial health management process have been considered to have an influence on demand (McCaig and Burt, 2005). In certain regions, emergency vehicle services have also been considered an attractive choice of commuting to the hospital due to ease of accessibility of service without the conventional booking of an appointment (Neelon et al. 2013, Guttman et al., 2003; Cunningham, 2006). Nonetheless, from possible primary causes such as re-occurring doctor visits, domestic accidents, automobile collisions, heart attacks and many other unexpected illnesses, to possible secondary causes such as changes in government policies, accessibility, land use measures and social-demographic, the accumulative effects of a continuous increase in the rate of emergency vehicle demand, especially for non-emergency situations, can affect overall performance of emergency medical services. Hence, the primary goal for undertaking this research is to further explore and predict the geographical variations that can influence the increase in the demand for emergency vehicles, thereby contributing to the body of knowledge within this field of study as well as provide policy makers with meaningful deduction and insightful direction on a number of ways to improve emergency vehicle services.

1.2 Research Focus:

In this research, an empirical investigation on the factors affecting emergency vehicle demand in Halifax was developed and a model of emergency vehicle demand using a Poisson regression modelling approach was generated in order to gain further insights into these patterns. The model examines the validity of different hypotheses on the spatial attributes that can affect emergency vehicle demand. The spatial attributes were derived from the census tabulations that provides various characteristics, including neighborhood attributes that enabled a comprehensive set of hypotheses testing. In practice, we expect the dataset to have excess zeros due to no calls observed from certain spatial units considered in this study. Therefore, the standard Poisson formulation which initially assumes the mean and variance of the data set to be equal is likely to produce a greater error due to larger variance in the dataset as a result of excess zero count for regions where there are no demands. Hence, the model was further developed using a Poisson hurdle model. The Poisson modelling approach build on recent work on spatial models for demand analysis with excess zero count in the dataset as developed by Neelon et al., (2013), as well as Agarwal et al. (2002), Rathbun and Fei (2006), Ver Hoef and Jansen (2007), and Gschl¨oßl and Czado (2008). Particularly, the model is similar to the one used by Neelon et al. (2013), but the two research analysis are different in various aspects. For instance, Neelon et al. (2013) explored variation in emergency department visits with emphasis on social-economic characteristics (such as users race and the ability to pay for medical insurance), obtained from the patient records. However, the model variables used in this research such as social-demographic, land use measures and accessibility were derived using neighborhood-level attributes obtained from the 2011 Canadian Census at the dissemination area level. The accessibility and land use measures were generated from GIS data obtained from DMTI using a variety of methods, for example land use mix index was derived using a methodology proposed by Bhat et al, 2013. Hence, the variation and diverseness in the variables used for study provide a very good basis for our studies.

1.3 Study Area

Nova Scotia, Canada, is the second-smallest province in Canada, with an area of approximately 55,284 square kilometres (21,300 sq mi). As of 2011, the population was 921,727 making Nova Scotia the second most-densely populated province in Canada. Approximately, 44% of Nova Scotians live in the Halifax Regional Municipality (HRM). A map of HRM is shown in Figure 1 below.

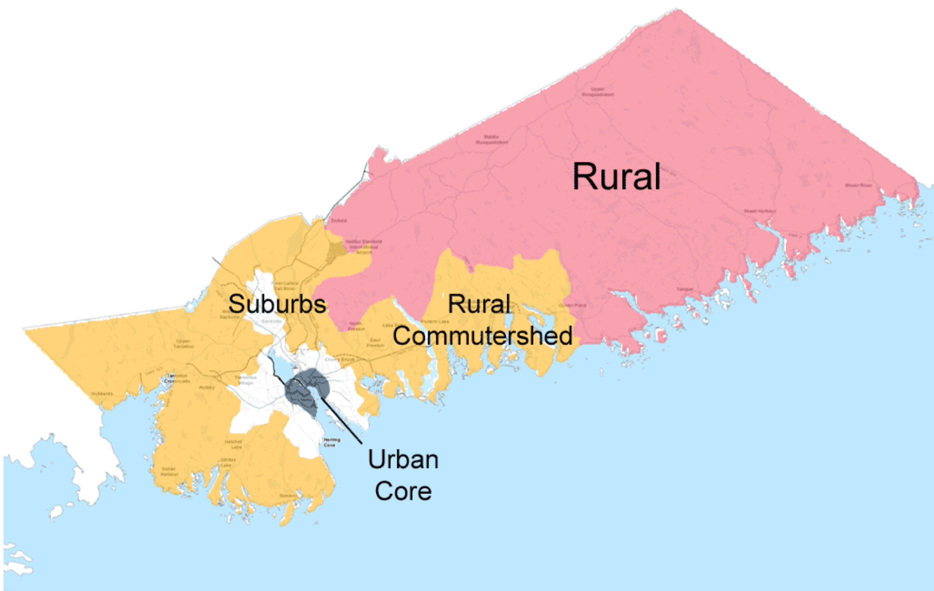

Figure 1: Map of Halifax Regional Municipality

The Province of Nova Scotia is served by a provincial health system known as Emergency Health Services (EHS) which provides dispatch of the emergency vehicle as well as medical management through a single access centralized computer system. The EHS emergency vehicle staff attend to various levels of medical care such as primary, intermediate and advanced care. The paramedic crews, consisting of at least two crew members are dispatched through communication across the entire province.

EHS Medical First Responders are often the first to reach a patient to offer some form of medical assistance. This assistance can range anywhere from a person who knows First Aid and CPR, to an individual from an organization that is certified as a Medical First Response agency. The EHS Ground

Emergency vehicle ensures an efficient and effective response to emergency vehicle calls by highly trained paramedics using available resources including Patient Transport Units, Ground Emergency vehicles, All-Terrain Vehicles, Disaster Response, and a Medical Command Center (MCC).

The Emergency Health Services receives about 120,000 – 140,000 requests for service per year, of which 50% are considered emergency and urgent while the rest are inter-facility transfers. By administrative process, the EHS requires that all paramedic responses are documented. Each response is assigned a unique identification case number and uploaded to a central server.

For the emergency vehicle demand analysis in this study, data was used from the Nova Scotia provincial Emergency Medical Service (EMS) administrative database. Records were obtained for a period of one year from January 2012 to December 2012. The dataset comprised of 24,403 cases of emergency transportation to hospitals in Halifax, representing approximately 40% of the total emergency vehicle demand during this period. This dataset includes the pickup locations (longitude and latitude), age and the gender of the service user. However, this dataset does not give detailed information such as clinical condition and socio-economic status.

1.4 Research Objectives:

This study will describe the spatial and temporal analysis of emergency vehicle demand in Halifax, Nova Scotia, Canada. It will draw upon the concepts of time-geography to identify the space-time patterns on how emergency vehicle serves the community. The focus area will identify locations where there are potential high demands for emergency vehicle services and the groups that contribute to these demands. Subsequently, using Census data from the province, a regression model will be developed to analyze variables that contribute to an increase in the demand for emergency vehicles, as well as predict and measure the effect of these variables.

In summary, the research study aims to achieve the set of objectives stated below;

i) To analyze and understand the spatial and temporal patterns of the emergency vehicle demand for Halifax, Nova Scotia, Canada.
ii) To develop a regression model that could be used to investigate the relationship between emergency vehicle demand and service users characteristics using geographical attributes at a 1km by 1km grid level.

This research study will conclude on the findings from our analysis, and how insights from the results can be used to tailor development of community-based health service needs, deployment of emergency vehicle services, future location and deployment of emergency vehicle posts including the capacity of paramedic and vehicles required per post.

1.5 Organization of this Thesis

The remainder of this thesis is organized into four additional chapters. Chapter 2 provides a detailed literature review of the research area. Chapter 3 provides an exploratory analysis of the current demand of emergency vehicle in Halifax, Nova Scotia. Chapter 4 presents the regression model structure, methodology, variables as well as the results and discussions from the analysis. Chapter 5 provides an overall conclusion from the research with policy implications and future research direction.

To conclude this chapter, it is imperative to reiterate that the study of emergency vehicle demand analysis is important. Evidence from research has shown that a demand management approach to emergency vehicle request has the potential to deliver better environmental outcomes, improved public health, build stronger communities, and make cities more prosperous (Nelson 2000). This research hopes to contribute to the ongoing development of the relationship between emergency vehicle demand, spatial association and community health needs. The next chapter will present a background knowledge that describes previous research studies, methodologies as well as a summary of the key findings within this field of studies.

Chapter 2 - Literature Review

The concept of using regression models to analyze and predict demand is not new. As far back as 1971, Aldrich et al.(1971), used a linear regression model to predict the characteristics of emergency department users. Using the count of demand as a linear function of socio-economic characteristics of the census tract within a community, a simple linear regression model was developed to find the association between users' social-economic status and their frequency of emergency department visits. Other researchers such as Andrews et al. (1975), Gibson et al. (1971), Agarwal et al. (2002), Rathbun et al. (2003) and Neelon et al. (2013) have also used this type of method to examine variations in emergency demand.

Furthermore, as seen in literature, emergency demand analysis modelling can span across different sets of objectives. There are different studies, such as predictive space–time models for Gaussian data (Wikle et al., 1998), temporal models (Dobbie and Welsh, 2001; Lee et al., 2006), and optimization models such as capacitated service and location-allocation models (Alan et. al, 1997), relocation and dispatching models (Verena, 2012) where different methods have been widely used to predict and optimized emergency vehicle services. In addition, other advanced modelling methods such as kernel warping, set covering and clustering of user groups have also promised to be an effective approach to analyzing how demand patterns are distributed as well as how we can improve delivery of emergency vehicle services (Nigel & Patel 2012).

To aid better understanding of all these methods, an outline that summarizes some of the findings from previous literature within this field of research has been developed. The summary of the literature is presented in table 1 below.

Table 1: Literature Summary of Emergency Vehicle Demand Analysis

S/N	Classification	Paper Title / Authors	Objective	Data Used	Methods	Major Findings
1	Spatial and Temporal Descriptive Analysis	The Epidemiology of Prehospital Emergency Responses for Older Adults in a Provincial EMS System Authors: - Judah Goldstein - Jan L. Jensen - Alix J. E. Carter - Andrew H. Travers - Kenneth Rockwood Canadian Journal of Emergency Medicine (CJEM) - (2015)	- To quantify the rate of EMS use by older adults in a Canadian provincial EMS system. - To compare those Transported to those not transported.	- Data from the NS provincial EMS administrative database that includes electronic Patient Care Record (ePCR) data for each patient. (2010) Study Area: Nova Scotia, Canada Observations: 63,076 records Data year: January 1 to December 31, 2010	- Described EMS use in relation to age, sex, and resources. - Conducted all statistical analyses using SPSS version 15.0 (Chicago, IL). - Baseline characteristics were reported for those ≥65 years old, as this was the focus of the analysis.	- There is increasingly high rate of EMS use with age to be consistent with other industrialized Populations. - The low-priority and non-transport calls by older adults consumed considerable resources in this provincial System and might be the areas most malleable to meet the challenges facing EMS systems.
2		Rurality as a factor in emergency vehicle use in health emergencies Authors: - Buck Reed, - Jason C Bendall Australasian Journal of Paramedicine - (2015)	- To better understand emergency vehicle use between urban and rural populations - To build a profile of the effect of rurality and other characteristics on emergency vehicle use.	- Data from emergency department (ED) records was obtained from the Hunter New England Area Health Service. Study Area: Hunter, New England, Australia. Observations: 354,909 records Data year: 1 July 2008 to 30 June 2009.	- Multivariate logistic regression was undertaken to assess the relationship between rurality and odds of transport to ED by emergency vehicle - Data analysis was undertaken using SAS 9.2.	- Rurality was a significant factor in emergency vehicle use in adults in areas outside major cities and in children in inner regional areas - Emergency vehicle utilization was substantially lower outside major cities, including in persons with high acuity conditions - Children have very low rates of emergency vehicle use and older adults had higher rates of use - People from outer regional and remote areas are 55.1% less likely overall and 27.9% less likely in

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						serious health emergencies to attend EDs by emergency vehicle compared to people living in major cities.
3		The challenges of population ageing: Accelerating demand for emergency emergency vehicle services by older patients, 1995-2015 Authors: - Judy A Lowthian - Damien J Jolle, - Andrea J Curtis - Alexander Currell, - Peter A Cameron, - Johannes Stoelwinder - John J McNeil The Medical Journal of Australia (MJA) – 2011	- To measure the growth in emergency emergency vehicle use across metropolitan Melbourne - To measure the impact of population growth and ageing on these services - To forecast demand for these services in 2015.	- Victoria's metropolitan emergency emergency vehicle transportation data - Study Area: Victoria, Melbourne, Australia Observations: 2,227 144 records Data year: 1994–95 to 2007–08	- Analysis of administrative data collected - All analyses were performed using Stata version 11 (StataCorp, College Station, Tex, USA).	- Dramatic rise in emergency transportations over the study period - Rates increased across all age groups, but more so in older patients - Acceleration is likely to have major effects on emergency vehicle services and acute hospital capacity - *Forecast models suggest that the number of transportations will increase by 46%–69% between 2007–08 and 2014–15*
4		EMS-STARS: Emergency Medical Services "Superuser" Transport Associations: An Adult Retrospective Study Authors: - M. Kennedy Hall, - Maria C. Raven, - Jane Hall, - Clement Yeh , - Elaine Allen, - Robert M. Rodriguez, - Niels L. Tangherlini ,	- Estimate the financial impact of EMS super users - Descriptive analysis of EMS super users in a large urban community	- Data for all EMS encounters with patients age ≥18 years were extracted from electronic records generated on scene by paramedics. - San Francisco Fire Department (SFFD) 2009 charge and reimbursement data Observations: 43,559 records	- Compared EMS super users to low, moderate, and high users to characterize factors contributing to EMS use. - Conducted a retrospective cross-sectional study based on 1 year of data from an urban EMS system. - EMS users were characterized by the annual number of EMS encounters: low (1), moderate (2–4),	- Super users were significantly younger than moderate EMS users, and more likely to be male. - Alcohol use was exponentially correlated with encounter frequency - The super user group created a significantly higher financial burden/person than any other group

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		- Karl A. Sporer - John F. Brown Taylor & Francis Group Journal (2015)		Data year: January 1 until December 31, 2009	high (5–14), and superusers (≥15).	
5		- Analysis of the Characteristics of Emergency Vehicle Operations in the Washington D.C. Region Authors: - Konstantina Gkritza (August, 2003)	- Enhanced understanding of the travel characteristics of emergency vehicles - Identify the travel characteristics of emergency vehicles which are of particular interest to the transportation profession. - Study the traffic flow characteristics of emergency vehicles, in terms of frequency, distribution by time of day, and average trip length. - Study the characteristics of emergency vehicles with respect to the preemption strategy deployed, in order to assess the level of frequency of preemption requests	- Emergency response log data maintained by Fairfax County Fire and Rescue Department. - Emergency vehicle preemption data collected after the deployment of signal preemption systems in Fairfax County, Virginia and in Montgomery County, Maryland. - Crash data provided for signalized intersections in U.S.1, a major arterial in Fairfax County, Virginia.	- Data were analyzed to determine Different months of the year, different days of the week and different hours of the day, as well as different time periods of the day, are compared to assess the variability in the frequency of emergency calls - An Analysis of Variance (ANOVA) Test was conducted as a parametric method to test the sample variability	- The frequency of emergency calls received by all fire stations under study is more during the daytime, between 8am to 8pm, than it is during the nighttime. - The frequency of emergency calls is higher during the PM peak period (on average, two calls per hour) than the AM peak period (on average, one call per hour) for all three stations. - The frequency of emergency calls is independent of the day of the week; in addition there does not seem to be a clear pattern in the number of emergency calls received during the weekdays and the weekends. - There is not much variability in the frequency of emergency calls according to the month of the year; in addition there does not seem to be a clear pattern in the number of emergency calls received during the wintertime and the summertime.

S/N	Classification	Paper Title / Authors	Objective	Data Used	Methods	Major Findings
			and average duration of preemption. - Study the crash situation involving emergency vehicles in a major corridor of the study area, due to the fact that emergency vehicle safety is extremely important.			
6		An Assessment of Emergency Response Vehicle Pre-Deployment Using GIS Identification of High-Accident Density Locations Authors: - Bradley M. Estochen, - Tim Strauss, - Reginald r. Souleyrette Transportation Conference Proceedings - 1998	- To identify the potential benefits of emergency vehicle pre-deployment	- Research used point location data from Iowa's Accident Location Analysis System (ALAS) Study Area: Des Moines, Iowa, United States. Data year: 1990-1995	- Generate maps of high accident locations for Des Moines, Iowa - The network analysis capabilities of GIS was used to estimate the response times of strategically placed emergency vehicles; Compared to actual response times	- Changing the location of EMS services, such as through the pre-deployment of vehicles, can result in improved response times - The overall response time for the pre-dispatched vehicles was 0.4 minutes (24 seconds) lower for both the a.m. and p.m. periods - The change in facility location also resulted in an increased percentage of crashes reached within the 5-minute threshold
7		Reducing Emergency vehicle Response Times Using Geospatial–Time Analysis of Emergency vehicle Deployment Authors:	- Study aimed to determine if a deployment strategy based on geospatial–time analysis is able to reduce emergency vehicle response	- Out-of-hospital cardiac arrest patients were prospectively identified by the attending paramedics, who had to fill out a standardized cardiac arrest clinical form.	- Variation in emergency vehicle deployment according to demand, based on time of day	- A simple, relatively low-cost emergency vehicle deployment strategy was associated with significantly reduced response times for OOHCA. - Geospatial–time analysis can be a useful tool for EMS providers.

S/N	Classification	Paper Title / Authors	Objective	Data Used	Methods	Major Findings
		- Marcus Eng Hock Ong, - Tut Fu Chiam, - Faith Suan - Papia Sultana, - Han Lim, - Benjamin Sieu-Hon, - Victor Yeok Kein Ong, - Elaine Ching, - Lai Peng Tham, - Susan Yap Academic Emergency Medicine - 2010	times for out-of-hospital cardiac arrests (OOHCA) in an urban emergency medical services (EMS) system	- This was used for routine clinical purposes, and a copy was collected for the research database - Study Area: Singapore - Observations: 2,428 - Data year: From October 2001 to October 2004		
8		Demand Analysis and Tactical Deployment of Emergency vehicle Services in the National Emergency vehicle Service Mid-Western Region Author: Spatial Planning Solutions Ltd (Cork) and Active Solutions (UK)	To analyse the spatial and temporal patterns of emergency vehicle activity (emergency, urgent & patient transport) and make an assessment of emergency care demand for the National Emergency vehicle Service Mid-Western region. To explore spatial options required to produce a Tactical Deployment Plan (TDP) that will improve response times for emergency patients.	Data for the study was supplied by the emergency vehicle service of National Emergency vehicle Service Mid-Western region Data year: 1st January 2006 to 31st December 2006.	Observatory Analysis	- The ageing population of the region, especially the predicted growth of the very old (i.e. those aged 80 years +) will present new challenges regarding care for the elderly. Improvement in the quality of such care will be necessary. - Overall, the provision of equitable and sustainable healthcare services in the Mid-Western region will undoubtedly pose a number of challenges.

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9		An Analysis Of The Demand For Emergency Emergency vehicle Service In An Urban Area Authors: - Carole A. Aldrich - John C. Hisserich, - Lester B. Lave. American Journal of Public Health, Nov 1971	Demand analysis for public library	- Records of public emergency vehicle trips were collected from the files of the Los Angeles Central Receiving Hospital, - Data describing the socioeconomic characteristics of the area were derived from 1960 census records. Study area: Los Angeles, California, United States		- Low income families and non-white tend to use the public emergency vehicle system more often than others. - Areas with elderly people or children also generate many calls. - Estimates of demand are stable over time and tend to be similar across type of incident giving rise to the call.
10		Older people's use of emergency vehicle services: a population based analysis Authors: - Michele J Clark, - Gerry FitzGerald Journal of Accident & Emergency Medicine, (1999)	- To investigate the use of emergency and non-urgent emergency vehicle transport services by people aged 65 years and over	- The age and sex of patients using emergency (codes 1 and 2) and non-urgent emergency vehicle services (code 3) was extracted from the AIMS database for all requests involving emergency vehicle treatment or transport provided by QAS Study Area: Queensland, Australia - Data year: 1 July 1995 to 30 June 1996	- Descriptive analysis of data set	- People aged 65 years and over who comprise 12% of the population utilize approximately one third of the emergency and two thirds of the non-urgent emergency vehicle resources provided in Queensland. - While the absolute number of occasions of service for females for emergency services is higher than for males, when the data are stratified for age and sex, males have higher rates of emergency emergency vehicle service utilization than females across every age group, and particularly in older age groups. - As the aged are disproportionately high users of emergency vehicle services, it will become increasingly important for emergency vehicle services to plan for the projected increase in the aged population.

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11	Diagnostic and Predictive Modelling	A spatial queuing model for the emergency vehicle districting and location problem Authors: - Nikolas Geroliminis - Matthew G. Karlaftis - Alexander Skabardonis Transport Research Elsevier Journal (2009)	- Optimally locating emergency response vehicles for transportation systems with high demand	- Accident data from the California Traffic Accident Surveillance and Analysis System (TASAS) and the California Highway Patrol computer aided dispatch system (CHP/CAD) Study Area: Cali a, United States. Data year: 2004	- Examines the coverage and median problems and links them to queuing theory in order to improve the system's efficiency and reliability.	- Results from model applications indicate that the proposed approach is a useful optimization tool, particularly for cases of high demand and when the server responsible for an incident is not available
12		A Spatio-Temporal Point Process Model for Emergency vehicle Demand (May, 29, 2014) Authors: - Zhengyi Zhou - David S. Matteson - Dawn B. Woodard - Shane G. Henderson - Athanasios C. Micheas	Possibility of estimating emergency vehicle demand accurately at fine temporal and spatial resolutions	- Data from Toronto Emergency Medical Services. Study Area: Toronto, Canada. Data year: February 2007 to February 2008	- Fixed the mixture component distributions across all time periods to overcome data sparsity and accurately describe Toronto's spatial structure - Represent complex spatio-temporal dynamics through time-varying mixture weights. - Constrained the mixture weights to capture weekly seasonality, and apply a conditionally autoregressive prior on the mixture weights of each component to represent location-specific short-term serial dependence and daily seasonality. - Estimated the number of components using birth-	- The proposed model is shown to give higher statistical predictive accuracy and to reduce the error in predicting EMS operational performance by as much as two-thirds compared to a typical industry practice.

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					and-death Markov chain Monte Carlo	
13		A Spatial Poisson Hurdle Model for Exploring Geographic Variation in Emergency Department Visits Authors: - Brian Neelon, - Pulak Ghosh, - Patrick F. Loebs Journal of the Royal Statistical Society (2013)	To explore geographic variation in emergency department (ED) visits while accounting for zero inflation	Hospital admission records from the Duke decision support repository (DSR), a data warehouse cont[illegible]g demographic, diag[illegible] and treatment information on over 3.8 million patients who had been seen at Duke University Health System hospitals and clinics	- A Bernoulli component that models the probability of any ED use (i.e. at least one ED visit per year), and a truncated Poisson component that models the number of ED visits given use - Model spatial random effects via a bivariate conditionally auto-regressive prior, which introduces dependence between the components and provides spatial smoothing and sharing of information across neighboring regions	- Patients without private insurance make, on average, 4.29 times more trips to the ED per year than patients with private insurance - Analysis also indicated that Hispanic and non-Hispanic white patients tend to make similar numbers of visits annually, with Hispanics making an average of 0.51 visits per year and non-Hispanic whites making approximately 0.48 visits annually - Modest ED use is more prevalent among Hispanics, but white users tend to make more return visits. The net result is that the expected counts are similar for the two groups
14		The application of forecasting techniques to modeling emergency medical system calls in Calgary, Alberta Authors: - Nabil Channouf · - Pierre L'Ecuyer · - Armann Ingolfsson · - Athanassios Avramidis Health Care Management Science, Springer – (2007)	- To offer simple and effective models that could be used for realistic simulation of the system and for forecasting daily and hourly call volumes	- 50 months data from the Calgary EMS system Study Area: Alberta, Canada. Data year: January 1, 2000 to March 16, 2004	- Estimated models of daily volumes via two approaches: (1) autoregressive models of data obtained after eliminating trend, seasonality, and special-day effects; (2) doubly-seasonal ARIMA models with special-day effects	- The doubly-seasonal ARIMA model performed poorly when forecasting more than a week into the future

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15		Predicting Melbourne Emergency vehicle Demand Using Kernel Warping Authors - Zhengyi Zhou - David Matteson	- To predict emergency vehicle demand for any hour	- Emergency vehicle demand data from Melbourne - A sparse set of historical data that is very relevant for this prediction (labeled data) Study area: Melbourne, Australia Data year: 2011 and 2012	- A predictive spatio-temporal kernel warping method - Use a spatio-temporal kernel density estimator on the sparse set of most similar labeled data, but warp these kernels to a larger point cloud drawn from all historical observations regardless of labels in order to predict demand by the hour	- Proposed model gives significantly more accurate predictions compared to a current industry practice, an unwarped kernel density estimation, and a time-varying Gaussian mixture model.
16	Location and Covering Optimization Modelling	Solving An Emergency vehicle Location Model By Tabu Search (1997) Authors: - Frederic Semet - Michel Gendreau - Gilbert Laporte	- To address locational decisions made at the tactical level. - To develop and solve heuristically a static coverage location model.	Derived from the Island of Montreal data	Tabu search heuristic	- The tabu search algorithm provides near-optimal solutions within modest computing times.
17		An optimization approach for emergency vehicle location and the districting of the response segments on highways Authors: - Ana Paula Iannoni - Reinaldo Morabito - Cem Saydam	A method to optimize the configuration and operation of emergency medical systems on highways		Combined extensions of the hypercube model (previously developed) with hybrid genetic algorithms to optimize the configuration and operation of EMS on highways	- Study showed that the main performance measures (objectives), such as the mean user response time, imbalance of emergency vehicle workloads, and the fraction of calls not serviced within a time limit could be improved by relocating the emergency vehicle bases and simultaneously determining the district (atom) sizes of the system

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18		A multiperiod set covering location model for dynamic redeployment of emergency vehicles Authors - Hari K. Rajagopalan - Cem Saydamb - Jing Xiaoc Computers & Operations Research (Mar 2008)	To determine the minimum number of emergency vehicles and their locations for each time cluster in which significant changes in demand pattern occur while meeting coverage requirement with a predetermined reliability.		- Formulated a dynamic available coverage location (DACL) model - Incorporation of the hypercube model	The results showed that the model produces high quality solutions in reasonable computing times
19		Analysis of emergency vehicle decentralization in an urban emergency medical service using the hypercube queueing model Authors: - Renata Algisi Takeda, - João A. Widmera, - Reinaldo Morabitob Computers & Operations Research (Mar 2007)	This study analyzes the effects of decentralizing emergency vehicles and adding new emergency vehicles to the system, comparing the results to the ones of the original situation.	SAMU-192 of Campinas data	Hypercube model	- It is shown that, as a larger number of emergency vehicles are decentralized, mean response times, fractions of calls served by backups and other performance measures of the system are improved, while the emergency vehicle workloads remain approximately constant. - The total decentralization as suggested by the system operators of SAMU-192 may not produce satisfactory results.
20		Geographic-Time Distribution of Emergency vehicle Calls in Singapore: Utility of Geographic Information System in Emergency vehicle Deployment (CARE 3)+	- This study describes the geographic-time epidemiology of emergency vehicle calls in a large urban city and conducts a	- EMS system data Study Area: Singapore Data year: From 1 Jan 2006 and 31 May 2006.	- Data management was carried out using the Clintrial application software version 4.4. - All data analyses were performed using SPSS	- About twice as many emergency vehicle calls occurred during the day (0701h to 1900h) compared to night (1901h to 0700h) with the most calls on Mondays - In addition, the day cases were more clustered in the Southern

S/N	Classification	Paper Title / Authors	Objective	Data Used	Methods	Major Findings
		Authors: - Marcus EH Ong - Faith SP Ng, - Jerry Overton, - Susan Yap - Derek Andresen - David KL Yong - Swee Han Lim - V Anantharaman Academy of Medicine Singapore (March 2009)	time demand analysis		version 14.0 (SPSS Inc., Chicago, IL), - Locations of emergency vehicle calls were spot mapped using Geographic Information Systems (GIS) technology (ArcGIS9, ESRI, Redlands, California).	commercial and business areas, in contrast to at night - The general time-of-day pattern of call volumes was stable irrespective of the day of the week. - This suggests that emergency vehicle manpower should be deployed to match these peaks, rather than the current fixed manpower and shift system being used now
21		Emergency vehicle location and relocation problems with time-dependent travel times Authors: - Verena Schmid , - Karl F. Doerner European Journal of Operational Research (2010)	To maintain a certain coverage standard throughout the planning horizon	Real-world data from the city of Vienna (Austria) The locations of potential patients were derived from census data. Study area: Vienna, Austria	- Developed a metaheuristic algorithm based on VNS - Taking into account time-varying coverage areas, where we allow vehicles to be repositioned in order to maintain a certain coverage standard throughout the planning horizon	- The model in use is capable of obtaining (near-) optimal solutions - Relocating vehicles reactively can help to improve the coverage standards during the day. - On average only decreases slightly if the resulting average number of relocations is cut in half
22		Solving the dynamic emergency vehicle relocation and dispatching problem using approximate dynamic programming Verena Schmid European Journal of Operational Research (2012)	Proposed a model and solved the underlying optimization problem	Empirical tests based on real data from the city of Vienna Study area: Vienna, Austria	Approximate dynamic programming (ADP)	Results indicate that by deviating from the classical dispatching rules the average response time can be decreased from 4.60 to 4.01 minutes, which corresponds to an improvement of 12.89%

S/N	Classification	Paper Title / Authors	Objective	Data Used	Methods	Major Findings
23		Capacitated Service And Regional Constraints In Location-Allocation Modeling Authors: - Alan T. Murray - Ross A. Gerrard Location Science (1997)	Improving Location-allocation process	The Washington, DC data of Swain	- Capacitated Regionally Constrained p-Median Problem (CRCPMP) Lagrangian relaxation is utilized for solving the CRCPMP.	The Lagrangian relaxation solution procedure proved to be very efficient at solving medium-sized planning problems.
24		Covering models for two-tiered emergency medical services systems Author: Marvin B. Mandell Location Science (1998)	Improvement of the maximum covering location problem (MCLP) a		The model incorporates the two types of servers and circumstances under which a call for service is adequately served given these two types of servers. model considers the probability that demands at each node are adequately served, given the location of ALS and BLS units	The results of applying the model to a series of test problems are then considered both to provide computational experience and to illustrate how the model can be applied in policy analysis

As shown in the table 1 above, emergency vehicle demand analysis can be grouped into 3 major broad categories. 1) Spatial and temporal descriptive analysis. 2) Diagnostic and predictive modelling and 3) Location coverage and service optimization modelling. Out of these categories shown in the table, one major area that has been well studied within this field of research is the empirical data analysis of emergency vehicle demand. The descriptive and statistical analysis methods typically explore variation using numerical attributes such as age group, sex, disease type, user groups and other social economical characteristics which are already associated with the patient record. The data are aggregated and processed using a simple averaging technique represented over a spatial and temporal domain (Zhou et al. 2015), where the estimate of the space-time total demand for a region is taken to be an average of a weekly, monthly or yearly demand values for that region. Recent reviews ranging from a descriptive analysis (Goldstein et al. 2015), to statistical analysis of EMS super users (Hall et. Al 2015), and pattern analysis (Webber et al., 2011) have used this method to provide useful analysis and insights into this research area.

The problem with this method, however, is that analysis done using this technique does not give a complete representation of the underlying variables that could influence emergency demand. In addition, a prospective study of the effect of user groups and geographical variation cannot be analyzed using available data characteristics provided by the EMS dataset, this often makes research studies difficult to reach a reasonable conclusion. To resolve some of these challenges, researchers have been able to develop regression models for analyzing emergency vehicle demand.

One of the simplest among these regression models for count data is the Poisson regression model. The Poisson model assumes that each observed count is drawn from a Poisson distribution. Typically, the Poisson model restricts the conditional variance to equal the conditional mean, a term commonly referred to as equidispersion. Correspondingly, the data are also called overdispersed if the variance exceeds the mean, and underdispersed if the variance is less than the mean. Given that the count data for spatial analysis of emergency vehicle demands are always positive and discrete, with a potential lot of zero counts in the dataset due to regions without emergency vehicle demands, the most common model employed to model emergency vehicle demand dataset is the Poisson hurdle regression model because it can address the high amount of zeros within the dataset. Generally, the Poisson hurdle model is a two-stage model that consist of a point mass at zero and a truncated Poisson distribution for the nonzero observation. Unlike the linear regression model that assumes the true values are normally distributed around an expected mean value, the Poisson assumes the mean and variance of the data set are equal. For emergency vehicle demand analysis, the Poisson distribution will describe the number of vehicle demand that occur in a given time period and also assume the mean of these demands i.e. the average number of vehicle demand per period, to be equal to its variance. In practice, count variables with excess zeros often have a variance that is greater than the mean, which is called overdispersion. This is one area that researchers have explored in great depth. Particularly, the recent development of a spatial temporal Poisson hurdle model by Neelon et al. (2013), provides one of the foundations which this research model was built upon. The model is similar to the one used by Neelon et al., 2013, but the two research methodologies are different in various aspects. For instance, Neelon et al. (2013) explored variation in emergency department visits with emphasis on social-economic characteristics (such as users race and the ability to pay for medical insurance), obtained from the patient records. However, the model variables used in this research such as social-demographic, land use measures and accessibility were derived using neighborhood-level attributes obtained from the Census at the dissemination area level. The accessibility and land use measures were generated from GIS data obtained from DMTI using a variety of methods, for example land use mix index was derived using a methodology proposed by Bhat et al, 2013. Hence, the variation and diverseness in the variables used for study provide a very good basis for our studies.

Having said that, other models have also been used within the emergency vehicle analysis domain. As shown in table 1, there are increasing numbers of research studies such as spatial queuing models (Geroliminis, et al. 2009), forecasting models (Channouf et al., 2007), space–time models for Gaussian data (Wikle et al., 1998), Kernel Warping method (Zhou et al. 2015), that have approached demand analysis using different techniques. However, the interesting conclusion about the models generally is that it provides similar results which correlate with exploratory analysis, thereby validating some of the hypotheses as well as some of the trends established from past literature.

To summarize, based on literature, the methods used to analyze the effect of emergency vehicles can vary across different sets of objectives. However, having analyzed the literature on emergency vehicle demand, one of the most common methods used to analyze emergency demand pattern is the spatial and temporal descriptive analysis that explores variation in demand using simple linear regression model. This method uses a simple averaging method over a discretized spatial and temporal domain, where the estimate of the space-time total demand for a region is taken to be an average of historical demand values for that region. Other methods such as spatial and temporal regression and location-allocation optimization models have also proven to deliver better insights. Nonetheless, the limited results within the spatial and temporal modelling using geographical attributes have prompted further research studies. Arguably, by formulating regression models using spatial and temporal characteristics with geographical variation attributes, a better analysis with different insight into factors contributing to the emergency vehicle can be established, subsequently creating new results for further research studies. Hence, the primary objective of this study is to further investigate how this neighborhood-level characteristic that can influence emergency vehicle demand, thereby contributing to the body of knowledge within this field of study.

Chapter 3 – Exploratory Analysis of Emergency Vehicle Demand in Halifax, Nova Scotia, Canada.

3.1 Overview:

In this section, we present an exploratory analysis of the emergency vehicle demand profile for Halifax, Nova Scotia, Canada. Analyzing the spatial and temporal demand patterns provides insights into some of the demographic variables that might have a significant effect on vehicle demand, this exploratory analysis, in turn, establishes the basis for model development and future demand prediction. The results of this analysis indicate areas where demand peaks are highest and how the use of emergency vehicle varies with user's location.

3.2 Data Used for Analysis

The dataset used for this research was obtained from the Nova Scotia provincial Emergency Medical Service (EMS) administrative database. All cases of emergency vehicle demands in Halifax were obtained for a period of one year from January 2012 to December 2012. The dataset comprised of 24,403 cases of emergency transportation to hospitals in Halifax, representing approximately 40% of the total emergency vehicle demand during this period. This dataset includes the pickup locations (longitude and latitude), age and the gender of the service user. However, this dataset does not give detailed information such as clinical condition and socio-economic status.

3.3 Analysis Approach

The dataset was evaluated and grouped into different segments by classifying demands based on gender and different age groups under 15 years, 15 – 24 years, 25 – 34 years, 35 – 44 years, 45 – 54 years, 55 – 64 years, 65 – 74 years, 75 – 84 years and 85 & above. Detailed analysis was performed on the group demographic based on different spatial and temporal settings such as the time of the day, day of the week, the season of the year and geographical location of emergency vehicle pickups. This was done in order to determine the age group, gender as well as geographical locations where there is a high and low level of emergency vehicle demand. Lastly, we analyzed the travel times, the time it takes for emergency vehicle to pick up patients from their respective locations and drop off patients at the hospital. This was analyzed to find out if the emergency vehicle demand characteristics, based on age groups, geographical profiles, and sex demonstrates a pattern that can help establish a justification for policy makers to generate insightful strategy decisions on a number of community planning, development and health-related issues that can be used to alleviate emergency vehicle usage.

3.4 Results and Discussions

3.4.1 Demographic Analysis

Analysis of emergency vehicle demand in Halifax measured by the number of pickups within different age groups and gender.

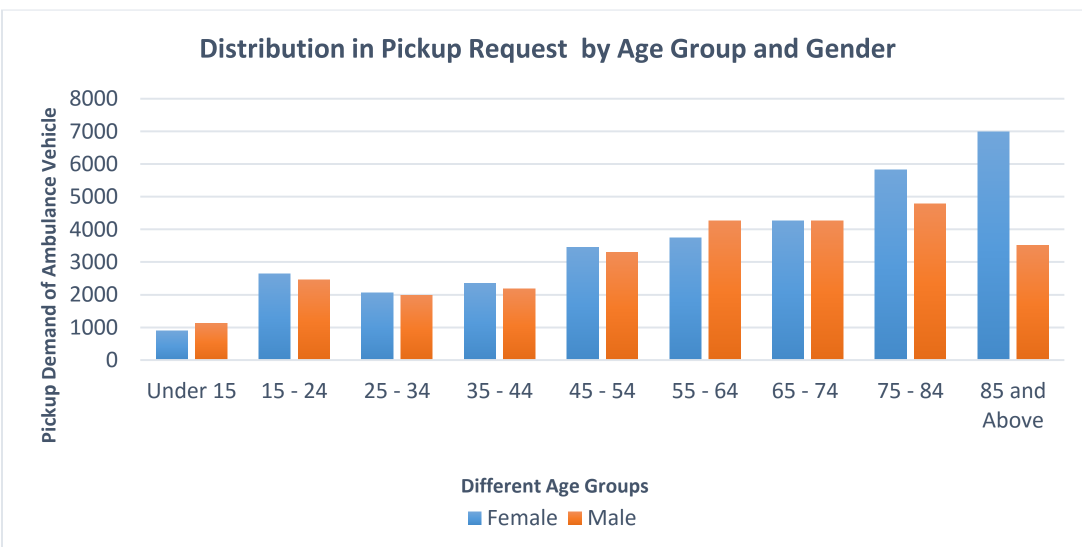

Figure 2: Distribution of emergency vehicle demand in Halifax by Age group and Gender

To understand the demand pattern within specific demographic, we examined the variation in demand by age groups and sex. A detailed analysis of specific age bracket illustrated in Figure 2 above shows how demand varies across different age groups. As it can be observed, possibly, there could be a pattern that demonstrates how demand for emergency vehicle varies with age, although, users within the age bracket 25-34 years had a relatively lower demand when compared with age group 15-24. However, the general trend reveals that emergency vehicle increases with an increase in age. This was anticipated as the general trend for emergency health care services increases as we get older due to probable complex and deterioration in health condition. Another significant observation shows a higher demand rate between the two genders. There is a significantly higher demand for EMS within the female age group 85 and above when compared to their male counterparts. This pattern is consistent with other age groups with the exception of age group 55-64 years and under 15 years. Perhaps, the higher demand within the female group, with a margin of approximately 8%, demonstrates a pattern that establishes the fact that there are more women in Halifax (see figure 3 below) and they used the emergency vehicles more frequently than their male counterparts and also maybe women tend to live longer than men in Halifax.

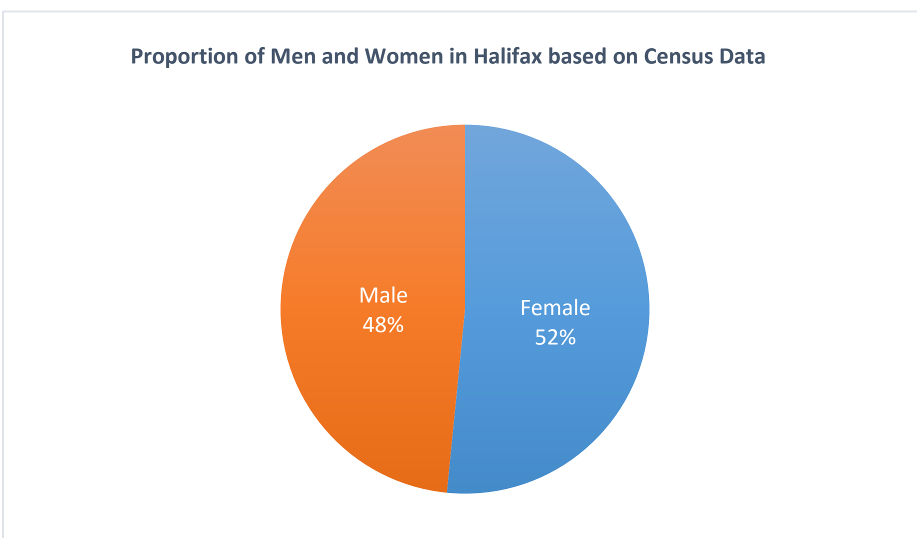

Figure 3: Proportion of Men and Women in Halifax based on Census Data

3.4.2 Temporal Analysis

Analysis of emergency vehicle demands measured by the number of pickups in the hour of the day

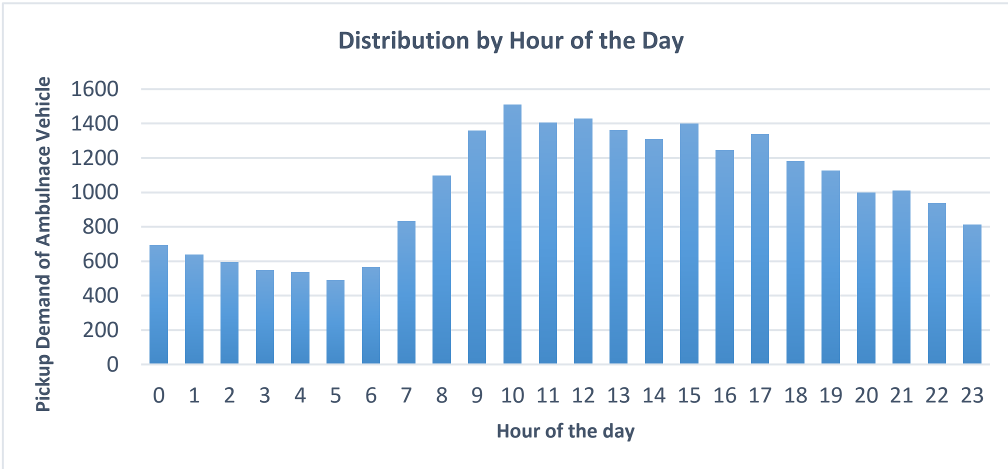

Figure 4: Distribution of emergency vehicle demand in Halifax by hour of the day

Analysis of emergency vehicle demands measured by the number of pickups in the day of the week

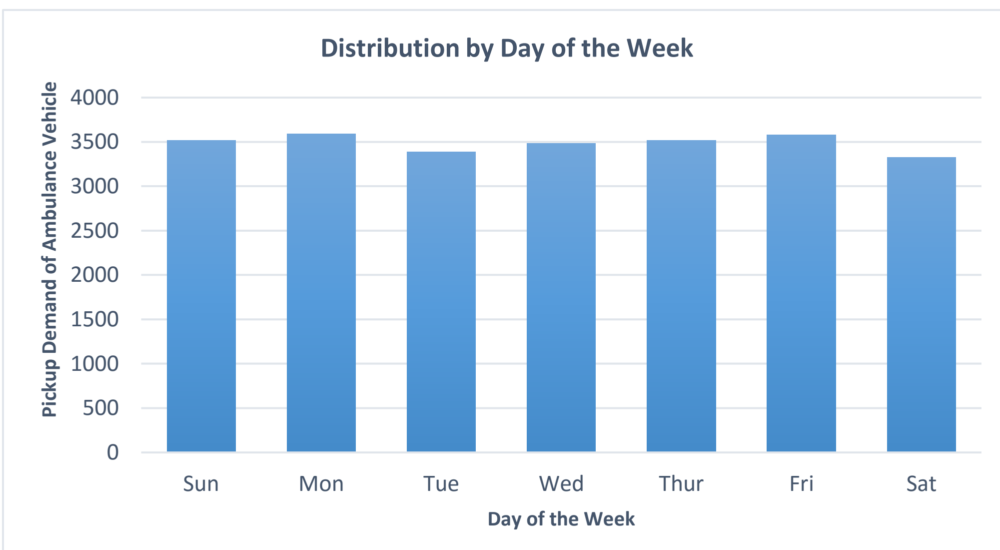

Figure 5: Distribution of emergency vehicle demand in Halifax by day of the week

The figures 4 and 5 above illustrates the vehicle demand pattern in Halifax during the hours of the day and days of the week. As it can be observed in figure 4, the demand for emergency vehicle increases gradually at the early hours of the day, reaching a peak period at 10AM after which demand begins to decline throughout the day. Interestingly, the highest peak of 10AM for emergency vehicle demand occurs at the off-peak travel demand period. This could possibly signify that the travel demand peak and emergency vehicle demand peak periods do not coincide with each other. On the other hand, the weekday demand pattern demonstrates a fairly constant request for emergency vehicle. As shown in figure 5 above, the demand varies slightly over the week, with the margin of about 8% between the highest and lowest demand for the weekday.

Analysis of emergency vehicle demands measured by the number of pickups in the Season of the year

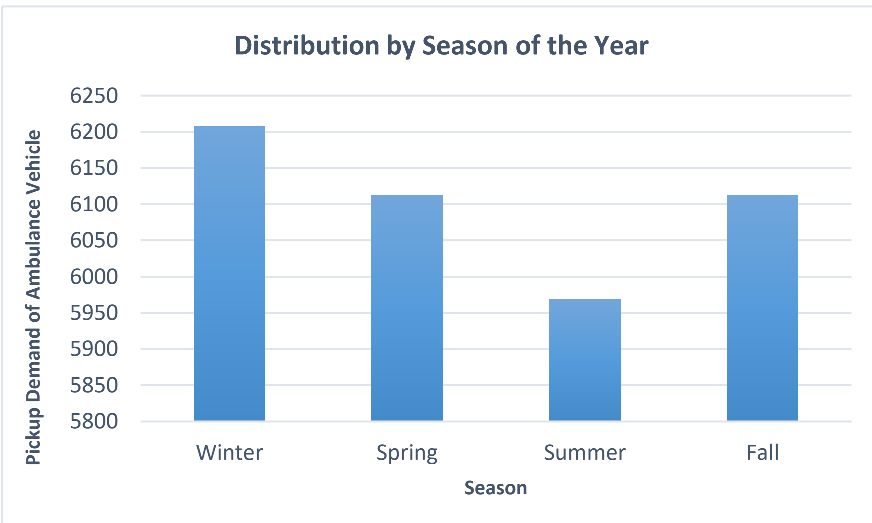

Figure 6: Distribution of emergency vehicle demand in Halifax by season of the year

The seasonal and monthly variation of emergency vehicle demonstrates a pattern similar to what we expected in an ideal situation, with emergency vehicle showing highest demand during the colder season of the year when compared with the warmer period. For instance, as shown in figure 6 and 7, emergency vehicle demand gradually increases over the course of the year, with the highest demand during the winter period and lowest during the summer period. Arguably, this means that emergency vehicle demand could have increased as a result of weather-related injuries such as falling on snow or illnesses such as influenza. Having said that, demand also varies intermittently across each month of the year. March and December show the month with a very high demand of emergency vehicle when compared with other months of the year. Overall, the pattern demonstrates an increase in demand trend.

Analysis of emergency vehicle demands measured by the number of pickups in the Month of the year

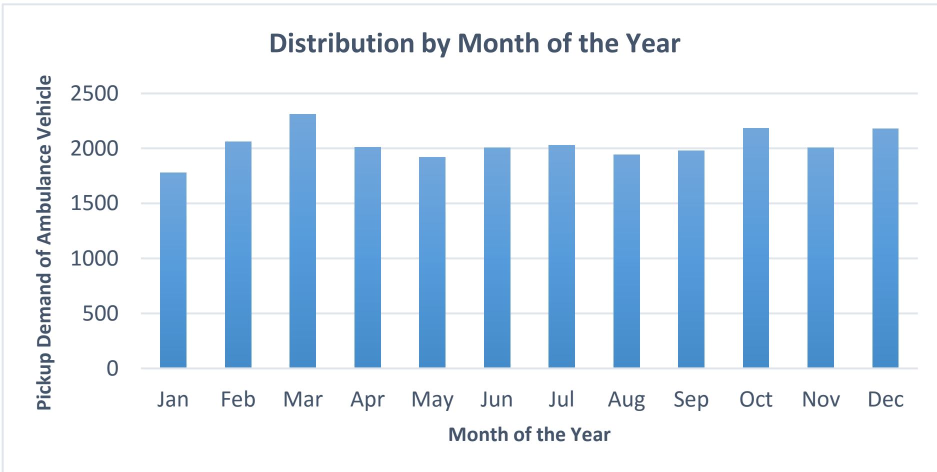

Figure 7: Distribution of emergency vehicle demand in Halifax by month of the year

3.4.3 Travel Time Analysis

As shown below in figure 8 and 9, the average travel time appears to be fairly constant throughout the course of the day. As it can be observed in figure 8, the average travel time ranges between 48 – 52 minutes. Although, a close observation into the peaks of the average travel times reveal that the AM average travel time period demonstrates similar pattern synonymous to the travel demand peak and off-peak periods. For instance, there is an increase in the average travel time for emergency vehicle during the peak times of travel demand when compared with the travel demand off peak. On the other hand, the PM average travel time period exhibit a contrasting pattern, with its lowest travel time occurring at the travel demand peak period while the highest travel time occurring at the travel demand off-peak period. In addition, as shown in figure 9, there is no clear indication that demonstrates that the average travel time is influenced by the amount of pickup request for emergency vehicle demand during a particular period.

Average travel time in minutes measured by the number of pickups by hour of the day

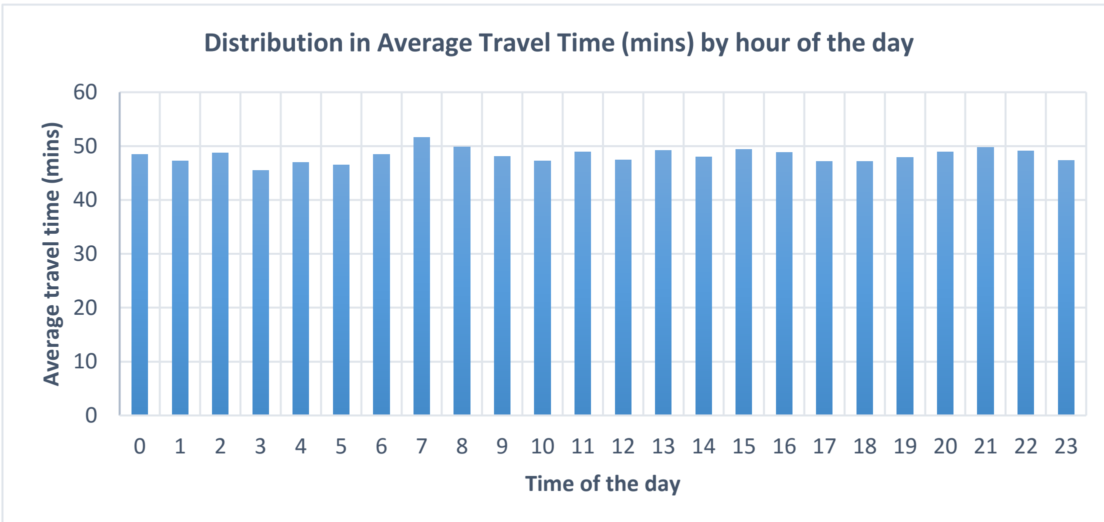

Figure 8: Average travel time distribution of emergency vehicle demand in Halifax by hour of the day

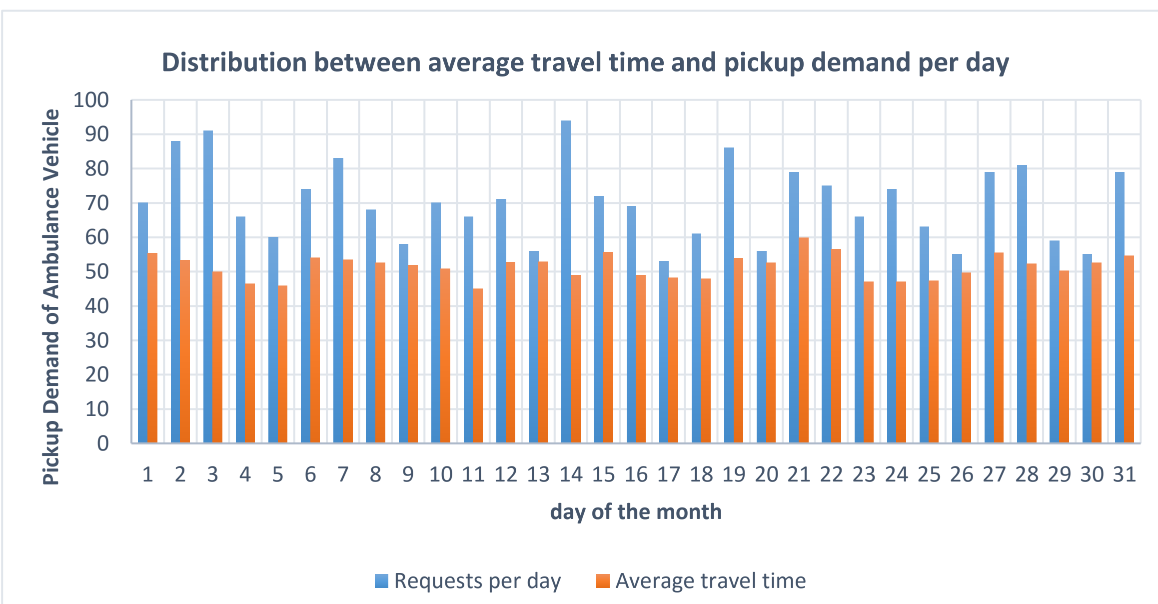

Figure 9: Average travel time and pickup demand per day for emergency vehicle in Halifax

3.4.4 Spatial Analysis

Out of all the counties in Nova Scotia, Halifax had the highest demand with a cumulative percentage of approximately 42%. This was expected considering, approximately 44% of Nova Scotians live in the Halifax Regional Municipality (HRM). Other counties also show the demand volume in proportion to the population size, which is very small with respect to the population size. A detailed analysis of emergency vehicle demand in Halifax however, demonstrates a general pattern on how emergency vehicle services varied in demand across the county. As shown in figure 10 below, demand hotspots were distributed through the entire region likely corresponding to the size of the population in general, though there could be variations based on the particular characteristics of people in the region. Demands were also very high in the downtown area of HRM when compared to the outskirts. Although, some spots outside the downtown area also have a fair amount of demand. However, it appears the majority of the emergency vehicle demand come from urban areas of Halifax.

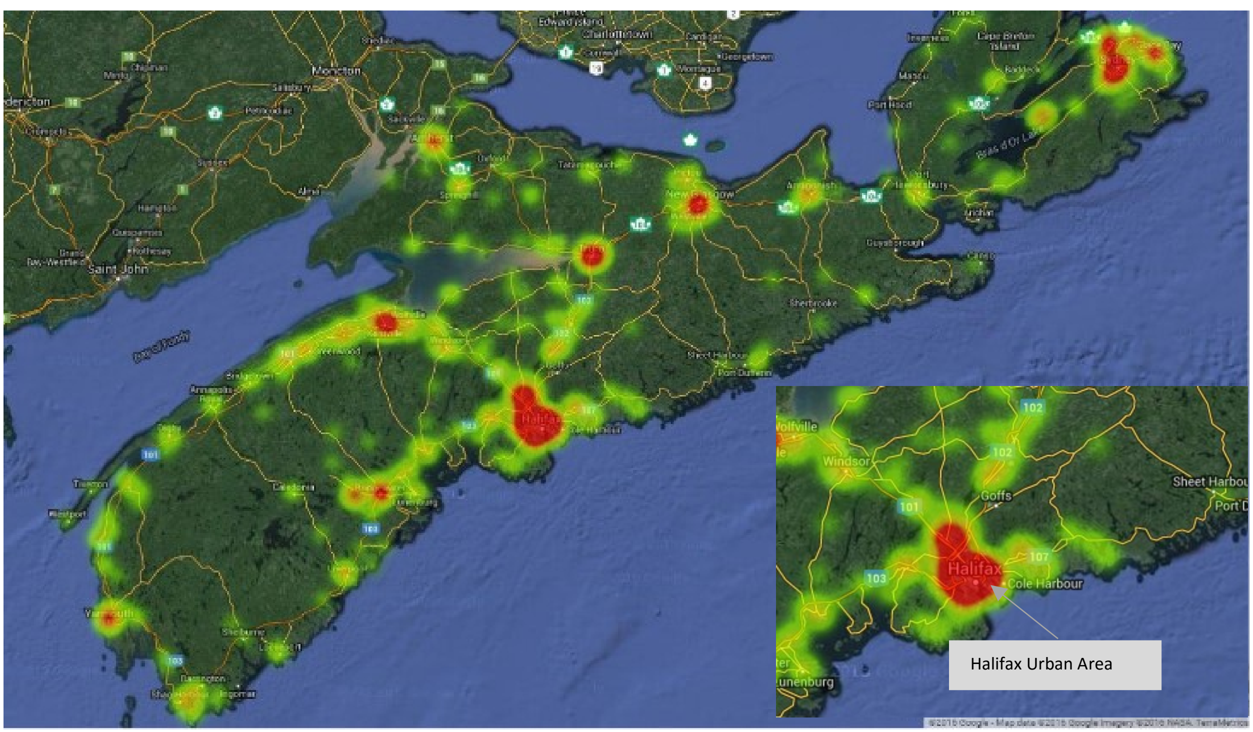

Figure 10: Spatial distribution of emergence vehicle demand in Nova Scotia

3.5 Conclusion

Our analysis shows that emergency vehicle varies considerably across different age group and gender, with older adults within the age bracket of 45 and above showing a high tendency for emergency service when compared with age bracket under 45 years. The relationship we have found between these different sets is in alignment with expectations and past literature that conclude the demand of emergency vehicles increases with age. Our findings also show a consistent relationship between demands over the hour of the day and day of the week regardless of the sub groups. A close analysis, however, shows that the season also had an influence on emergency vehicle usage, when pickup request was averaged by season, the demand appears to decline in the warmer season and increases as the season gets colder. Although this does not demonstrate a large margin as seen by variation in demand by each month of the year. Relatively, there is a higher demand within the female group with a margin of approximately 8% demonstrating a pattern that could signify that women, arguably live longer than men, and have the tendency to use the emergency vehicles more frequently. In addition, the average travel time does not have a significant effect on emergency vehicle demand pattern, with a contrasting pattern exhibited for both peaks and off-peak periods, possibly indicating that the travel demand peak and off-peak periods do not coincide with emergency vehicle demand in Halifax. Lastly, while the analysis shown above provides a representation of what emergency vehicle demand in Nova Scotia province in Canada, it is important to note it is only a reflection of a period in time. Differences in cumulative values might have been due to a onetime event or special circumstances. However, the results of our research are consistent with what have been previously established in different reports. The next section of this thesis provides a better understanding of emergency vehicle demand analysis, achieved by developing a model using service user's neighborhood-level characteristics that explore the geographic variation and associated factors that can influence demand.

Chapter 4 – Modelling of Emergency Vehicle Demand using Poisson Hurdle Regression Model.

4.1 Overview:

This chapter presents an approach to model emergency vehicle demand using Poisson Hurdle Regression Model. The modelling approach will expand on recent work on spatial models with excessive zero counts (Neelon et al., 2013). Specifically, the difference in this research method compared to most emergency demand models is that this research will examine factors contributing to an increase in demand using geographical attributes at the census 1km by 1km grid level.

Generally, geographical attributed emergency vehicle demand data are spatial and often come with a lot of zero counts (Arab, A 2015). Given that the count data are always positive and discrete, the most common technique employed to model this type of dataset is Poisson regression. The Poisson assumes the mean and variance of the data set are equal, unlike the linear regression that assumes the true values are normally distributed around an expected mean value.

For this analysis, the Poisson distribution will describe the number of emergency vehicle demand that occur in a given time period and also assumes the mean of this demand, i.e. the average number of vehicle demand per period, to be equal to its variance. In practice, we expect the emergency vehicle demand count data to have excessive zeros due to no calls observed from certain spatial units considered in this study, resulting in a variance that is greater than the mean. When this happens, the count data is set to be overdispersed and the usual Poisson model is likely to produce a greater standard error, indicating the model is not sufficiently fit and adjustment has to be made to the model. Hence, the further section of the model development is an attempt to account for the effect of overdispersion by using a Poisson hurdle regression model that can address both the abundance of zeros and the non-zero count within our dataset.

Therefore, two main objectives exist for this chapter. The first objective is to test different hypotheses in order to explore the geographic variation and associated factors such as the effect of population density, employment rate, land use mix etc. on emergency vehicle demand using a standard Poisson regression model and intuitively compare this results with the expected relationships, based on existing literature, for these geographical attributes variables. The second objective is to improve parameter estimations of the Poisson Model using the Poisson Hurdle model, compare the results and analyze how they differ in terms of estimated parameters and predictions using testing tools and criteria such as the log-likelihood, AIC and BIC. A standard formulation of hurdle model as well as vehicle demand data from the provincial Emergency Medical Service (EMS) administrative database for Nova Scotia, census and derived land use measures data from DMTI, will be used for the analysis.

4.2 Literature Review:

Regression modelling for spatiotemporal phenomena is well documented in the literature. There are different studies, such as space–time models for Gaussian data (Wikle et al., 1998), temporal models (Dobbie and Welsh, 2001; Lee et al., 2006), and spatial models (Agarwal et al., 2002; Rathbun et al. and Anderson 2003) where different methods have been developed. Particularly, within the area of interest such as emergency demand analysis, studies by Arab, A (2015), Neelon et al. (2013), and Rahim et al. (2011) have provided a different approach to analyze and improve emergency demand count data models. However, literature review suggests that one of the most common approaches used for analyzing emergency demand modelling is the linear regression predictive models. Generally, these methods collect count data, aggregate and process these data using a simple averaging technique represented over a spatial and temporal domain (Zhou et al. 2015), where the estimate of the space-time total demand for a region is taken to be an average of a weekly, monthly or yearly demand values for that region. Two recent studies by Lowthian et al. (2011) and Goldstein et al. (2015) have used this method to describe the increase in the use of EMS in relation to age, sex, and incident type. Reed & Bendall (2015) also used this method to assess the relationship between rurality and the use of transport to the emergency department using the emergency vehicle. Other research works that used this method include forecasting emergency demand (Channouf et al., 2007) and estimating future demand (Pasupathy, et al. 2013).

The limitation with this method is that analysis using this technique does not give a holistic representation of the underlying factors such as built environment and neighborhood-level characteristics, that could influence the increase in emergency vehicle demand. Nonetheless, while majority of the emergency vehicle demand modelling explore variation using statistical attributes such as age group, sex, disease type, user groups and other social economical characteristics which is already associated with the patient record, one area that is less evident in the literature is the analysis for emergency vehicle demand using geographically attributes that provides information such as population density, average income of household and different land use measures.

Similarly, improving prediction of count data variables using Poisson Hurdle model have shown significant interest in the past few years. Recently, Neelon et al. (2013) developed a spatial temporal Poisson hurdle predictive model to explore geographic variation in emergency department (ED) visits. The hurdle model which consists of two components: a Bernoulli component that models the probability of any ED use and a truncated Poisson component that models the number of ED visits provided the ED was used, presented a result which indicated that Hispanic and non-Hispanic white patients tend to make similar numbers of visits annually, with Hispanics making more visits on average when compared with non-Hispanic white. The method used in this research, in particular, shows an improvement from the work on non-spatial of two-component models by Su et al., (2009). Likewise, researchers such as Siler et al.1975, Andrews et al.1971 and others, have also used regression models with census and community features to predict emergency visits. Among these studies was a notable research done by Aldrich et al, 1971 where geographical attributes such as census tract data was used to analyze emergency department visits. Using the count of demand as a linear function of socio-economic characteristics of the census tract, the type of public service, and the availability of alternative sources of care, a simple linear regression model was developed. The model which focused on per capita demand for public emergency vehicle service demonstrates that low-income and non-white families tend to use the public emergency vehicle system more often than others. Interestingly, some of the statistical results from these analysis also correlate with the recent exploratory analysis of emergency vehicle demand done by Cunningham (2006) and Goldstein et al. (2015).

Although, the methods used to analyze the effect of emergency vehicles can vary across different sets of objectives. However, the difference in this research method compared to most emergency demand models in literature such as Neelon et al. (2013), Agarwal et al., (2002) and Aldrich et al. (1971) is that this research examines factors contributing to emergency vehicle demand using geographical attributes at a 1km by 1km grid level, achieved by partitioning the census DA into a smaller unit (i.e. 1km by 1km grid)to realize a better reflection of the count data. Using the count of emergency vehicle demand as a linear function of built environment, neighborhood-level characteristics and derived land use measures, provides a vast amount of independent variables to formulate the prediction model. By using this geographically segregated variables with respect to the vehicle demand data, a different insight into factors contributing to the emergency vehicle increase can be established, which could help understand how emergency vehicle demand will vary and its effects over a period of time.

Hence, the goal of this study is to further explore and establish other neighborhood-level characteristic that can influence emergency vehicle demand, thereby contributing to the body of knowledge within this field of study. The Poisson Hurdle regression model that will be presented will be used to examine the validity of the different hypotheses that is believed to have an effect on the increase in the demand for emergency vehicles. The dependent variable will be the count of emergency vehicle demand in a given space (i.e. 1km by 1km grid) and independent variables will be the geographical attributes derived variables from the census and land use data received from DMTI respectively.

4.3 Data Used for Analysis:

4.3.1 Emergency Vehicle Demand:

The dataset used for this research was obtained from the Nova Scotia provincial Emergency Medical Service (EMS) administrative database. All cases of emergency vehicle demands in Halifax were obtained for a period of one year from January 2012 to December 2012. The dataset comprised of 24,403 cases of emergency transportation to hospitals in Halifax, representing approximately 40% of the total emergency vehicle demand during this period. This dataset includes the pickup locations (longitude and latitude), age and the gender of the service user. However, this dataset does not give detailed information such as clinical condition and socio-economic status.

4.3.2 Neighborhood-level Attributes:

The data of neighborhood characteristics were obtained from the 2011 Canadian Census at the Dissemination Area (DA) level. Accessibility and land use measures were generated from GIS data obtained from DMTI. The data provides us with neighborhood-level attributes such as demographic, accessibility and land use measures.

4.3.2.1 Data Preparation:

The first step in data preparation is to clean up the dataset for incomplete records such as missing locations (longitude and latitude data). Out of 24,403 recorded data of emergency vehicle demand in Halifax, 105 entries were found with incomplete information such as age, location and sex. The second step is to filter dataset for HRM from provincial records. Following the conversion, geolocations for Halifax hospitals, central business district (CBD), 1km by 1km grid shape file and the nearest parks polygon shape file were also imported to ArcGIS 10.1.

The accessibility measures such as the nearest distance from the service user's location to health service, parks and CBD were calculated using GIS function. For instance, using the nearest distance to the centroid of the park polygons, the distance between the service users to parks was established. Likewise, using the nearest distance to geolocations of hospitals and CBD, the distance between service users and the hospitals as well as the distance between service users and the CBD were established respectively. On the other hand, the land use measures such as land use for commercial, land use for residential and land use for industrial were generated from GIS data obtained from DMTI and the land use index was derived according to Bhat et al. (2013) methodology.

Similarly, in order to analyze how emergency demand varies across space, a join and intersect were performed on the polygons using ArcGIS functions and processing tools. The GIS input involved two layers, one with a 1km by 1km polygon shape file of the entire Nova Scotia Province while the other layer is the longitude and latitude points of demand cases of emergency transportation to hospitals.

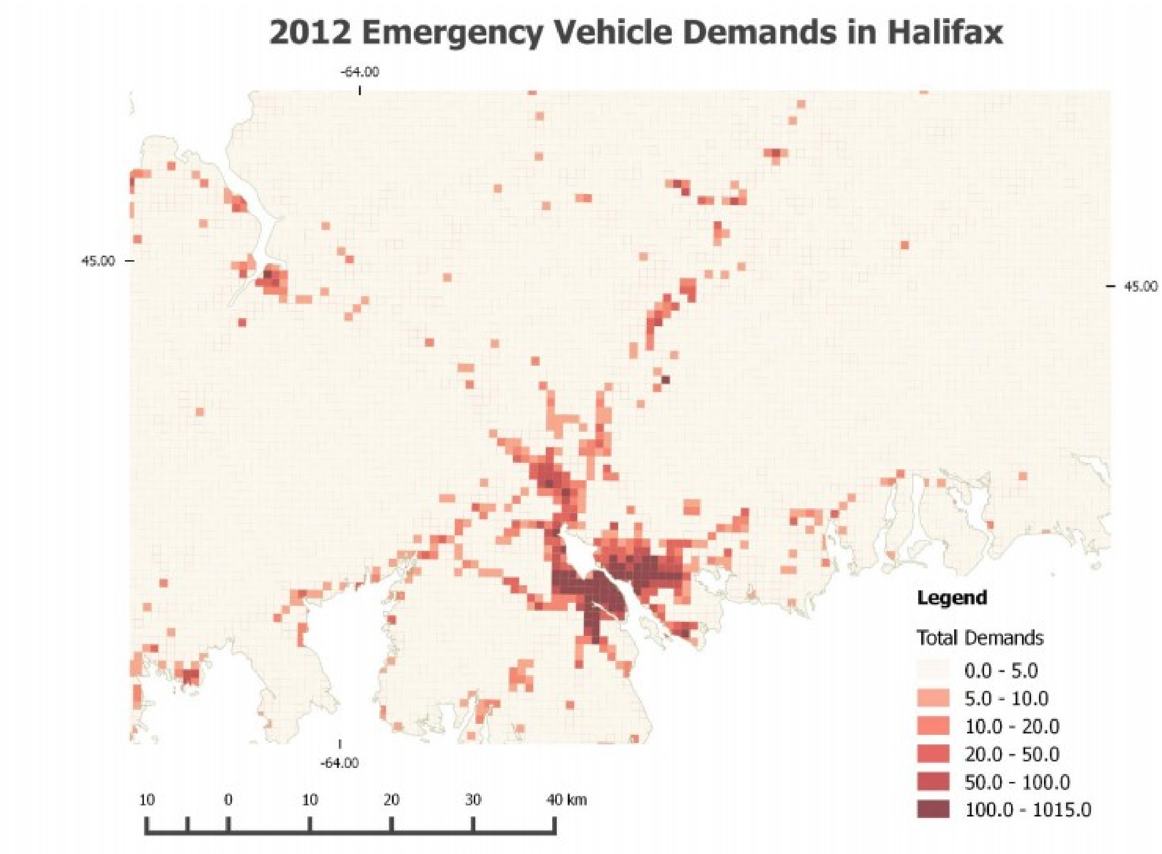

Figure 11: Locations of emergency vehicle demand for Halifax

A geo spatial join was performed to merge the attributes of the points to each 1km by 1km polygon on the shape file. Doing this enables the calculation of the count of points, as well as the attributes of patients that fall in each of the 1km by 1km polygons. As shown in figure 11 above, the sum of these points was calculated as the total demand in that particular location. Using similar approach, the 2011 census tract data for the province from statistics Canada was used to generate geographical attributes of the cells. The percentage of the DA area that falls inside of the 1km by 1km cell was calculated in order to find the weighted average of each DA within the polygon. The adjusted attributes values calculated from the proportion of DA present in the 1km by 1km on form the basis of the variables used for the econometric modelling. The data attributes of the shape file were exported and stored. Analyses and modelling were conducted using NLOGIT 9.1 econometric software.

4.3.3 Data Description:

From the analysis of the dataset, it was observed that 54% of the patients were female and the overall median age was 57 years. There were more emergency vehicle demands made during the off-peak travel demand period (9AM to 3PM and 6PM to 6AM) when compared to the travel demand peak period (6AM to 9AM and 3PM to 6PM). About 28% of all emergency vehicle usage were attributed to both AM peak and AM off-peak demand. While the peak demand was highly concentrated within regions, the off-peak demand was widely spread and almost evenly distributed across the periods. In addition, combined age group between 40 to 64 years made the highest emergency vehicle demand, while age group 75 and above had the second highest of emergency vehicle demand.

On the other hand, the geographical attributes contain a total of 9512 cells which included neighborhood-level attributes. About 59% of the cell blocks have no demand due to no calls observed from certain spatial units considered in this study. The distribution of the zeros was widely spread across the dataset. The high proportion of zeros with a right skewness of non-zero count, therefore, suggest a potential lot of zeros in the count data that can affect the standard Poisson distribution. The temporal variation also followed a similar pattern as discussed in the data count description stated earlier. The morning AM Peak had the lowest demand while the AM OFF Peak had the highest emergency vehicle demand which is followed by the evening. The PM peak and the overnight demand were relatively close with PM peak having a slightly higher proportion of demand. The modelling approach, analysis of the predictive model and parameter estimations are discussed in the subsequent sections.

4.4 Modelling Approach:

As described in section 4.1, two models, Poisson and Poisson hurdle models have been used in this research. The approach used to formulate both models is described in the following section.

4.4.1 Poisson Model

Poisson regression is one of the simplest regression models for count data and assumes that each observed count is drawn from a Poisson distribution. The Poisson model restricts the conditional variance to equal the conditional mean, a term commonly referred to as equidispersion. Correspondingly, the data are also called overdispersed if the variance exceeds the mean, and underdispersed if the variance is less than the mean. The count data for this study will follow the standard Poisson formulation such as:

$$Y \sim \text{Poisson}(\lambda), \text{then } \mathbb{E}(Y) = Var(Y) = \lambda \quad (1)$$

Where Y denote a count-valued response, $\mathbb{E}(Y)$ is the mean of Y and $Var(Y)$ is the variance of Y. Generally, the structure of the Poisson model is given by:

$$\Pr(Y - y) = \left(\frac{e^{-\mu}\mu^{y}}{y!}\right), y = 0, 1, 2 \ldots \text{n} \quad (2)$$

The parameter μ is known as the rate, the expected number of times that an event has occurred per unit of time, therefore μ can also be thought of as the mean or expected count of the distribution. If the count data are equidispersed, as the value of μ increases, the mass of the distribution shifts to the right, specifically, $\mathbb{E}(Y) = Var(Y) = \mu$. However, in practice, the count variables often have a variance that is greater than the mean due to the excess zeroes. When this occurs, the usual Poisson model likely produce a greater standard error, indicating the model is not sufficiently fit to describe the variables hence, an adjustment has to be made to the model. The further section of this model development is an attempt to account for and minimize the effect of overdispersion.

4.4.2 Poison Hurdle Model

The Poisson hurdle model is a two-stage model that consist of a point mass at zero and a truncated Poisson distribution for the nonzero observation, such that it does not distinguish between zeros from the degenerate distribution versus those from the Poisson distribution (Neelon et al. 2013). The Poisson hurdle model, therefore, can be used to handle both overdispersed and underdispersed count variables. Generally, the structure of the Poisson hurdle model is given by

$$\Pr(Y = 0) = 1 - \pi, 0 \ \leq \ \pi \ \leq 1 \tag{3}$$

$$\Pr(Y = y) = \frac{\pi p(y;\mu,\alpha)}{1 - p(0;\mu,\alpha)}, \mu > 0, \alpha > 0, y = 1, 2, \ldots, \mathrm{n} \tag{4}$$

Where Y denote a count-valued response and $\pi = \Pr(Y > 0)$ is the probability of non-zero response; the expression $p(y; \mu, \alpha)$ is a base probability distribution with a mean μ and dispersion parameter α; Hence, the expression $p(0; \mu, \alpha)$ is the base distribution evaluated at 0.

Equation (4) can also be expressed as;

$$Y \sim \left((1 - \pi) 1_{(y=0)} \ + \ \pi \frac{p(y;\mu,\alpha)}{1 - p(0;\mu,\alpha)} 1_{(y>0)} \right) \tag{5}$$

where $\pi = \Pr(Y > 0)$ is also known as the utilization function i.e. the probability of using the emergency vehicle at least once.

The following can be deduced from the model: when$(1 - \pi) = \ p(0; \mu, \alpha)$, the hurdle model will be reduced to its based distribution and when $(1 - \pi) > \ p(0; \mu, \alpha)$, the zeros are inflated relative to the base distribution and when$(1 - \pi) < \ p(0; \mu, \alpha)$, there is a zero deflation. Typically, one assumes that π is precisely between 0 and 1, so that there is a nonzero utilization probability.

4.4.3 Model Fitness Test

The models will be tested using the Log-likelihood ratio (LR), and information criteria such as AIC and BIC testing tools. The log-likelihood ratio test can easily be formulated to compare the Poisson and Hurdle model using their log-likelihood function such that;

$$LR = \text{-}2 \ (LL_{Poisson} - \ LL_{Hurdle}) \tag{6}$$

Where Log-Likelihood of Poisson $(LL_{Poisson})$ is given by;

$$LL_{Poisson} = \sum_{i=1}^{n}[-\mu + yLog(\mu) - Log(y!)] \quad (7)$$

And the Log-Likelihood of Poisson (LL_{Hurdle}) is given by;

$$LL_{Hurdle} = \sum_{i=1}^{n}\begin{bmatrix} I(Y=0)Log(\pi) \\ I(Y>0)Log(1-\pi) - \mu + yLog(\mu) - Log(1-e^{-\mu}) - Log(y!)) \end{bmatrix} \quad (8)$$

The AIC and BIC can be formulated as shown below ;

$$\text{BIC} = (-2ln(LL) + k.(ln(n) - \ln(2\pi)) \quad (9)$$

$$\text{AIC} = (2k + 2\ln(LL)) + \frac{(2k(k+1)}{(n-k-1)} \quad (10)$$

Where LL = Maximum likelihood function, n is the sample size and k is the number of free parameter to be estimated.

4.4 Results and Discussions:

The Poisson and Poisson Hurdle models tested hypotheses, including demographic characteristics, accessibility, and land-use measures, in order to understand the relationship between emergency vehicle demand and geographical variation. The table 2 below shows the parameter estimation analysis for both models. The subsequent sections discuss detailed results of the models.

4.4.1 Analysis of Poisson and Hurdle models

Model Fit Test	Poisson Model	Hurdle Model
Log-Likelihood	-83923.87	-72160.75
AIC	17.65053	15.17804
BIC	17.66708	15.19761
LR Stat	-	23526.23

Table 2: Emergency Vehicle Prediction Model Fit Values

As previously described, the Poisson hurdle models offer an alternative to Poisson models for the analysis of dataset with excessive zero counts. For this reason, the hurdle models are expected to provide a better model estimation and are often considered an ideal choice.

For this analysis, with the exception of the employment rate and the land use mix index variable, the association between the dependent and independent variables remain fairly the same for both the Poisson and Poisson Hurdle Models. With most variables from both models having a coefficient and parameter estimations that are statistically significant, with t-stats values $\geq$ 3.2 which indicates a significance level of 99.99%. From the table 2 shown above, as expected, the hurdle model suggests a better model fit with a lower AIC and BIC, when compared with the Poisson model. For instance, in the Poisson and Hurdle models, the difference in AIC and BIC values for the parameter estimation is 2.47 and 2.469 respectively. Moreover, the results of the LR test exceed the critical value for the chi-squared distribution with two degrees of freedom, which allows us to reject the Poisson model in favor of the Poisson hurdle model. In addition, as shown in Table 5 below, which presented an analysis of the model parameters, the hurdle model provided a better model relationship for the geographically segregated variables when compared with the expected outcomes from previous literature within this field of studies. Therefore, having considered the goodness-of-fit for both models as well as the parameter estimations, the ideal model selected for this research will be the Poisson Hurdle predictive model. The subsequent section will discuss in great extent the analysis of the model parameters.

Summary statistics and description of variables

Variables	Description	Mean	Standard Deviation
Demand Count	Number of emergency vehicle demand in the grid	21.6003	79.8934
Social-Demographic			
Population Density	The population density (People / km²) in the grid	358.294	1452.73
HH Average Income	Number of household average income ($ CAD)	80,740.9	30,346.9
Employment Rate (%)	Percentage of employment in a grid region	58.2968	14.2089
Population Under 15 Years	Number of population aged 15 or less in the grid	3.10529	10.8883
Population Age 16 to 39 Years	Number of population aged between 16 and 39 years	11.4162	44.0286
Population Age 40 to 64 Years	Number of population aged between 40 and 64 years	11.3457	37.4017
Population Age 65 to 75 Years	Number of population aged between 65 and 75 years	2.28158	8.64036
Population Over 75 Years	Number of population age 75 or more	1.96013	11.7724
Land-use measures			
Single Detached House	Number of Single Detached Houses	6.10457	20.4864
Apt 5 or more	Number of Apartments with 5 or more storeys	1.88082	18.3662
Apt 5 Few	Number of Apartments with 5 or less storeys	3.52731	22.8446
Apt Duplex	Number of Apartments with Duplex	0.576289	3.73888
Land Use Residential	Proportion of Land use for residential purpose	2.72258	12.6472
Land Use Commercial	Proportion of Land use for commercial purpose	0.06084	1.65322
Land Use Park	Proportion of Land use for park purpose	0.238869	1.88266
Land Use Industrial	Proportion of Land use for industrial purpose	0.108898	1.50782
Land Use Index	The Land use mix *	0.03942	0.09851
Accessibility			
Distance to CBD	Distance to the Central Business District (m)	40795.2	30261.4
Distance to Hospital	Distance to the nearest Hospital (m)	17981.7	9970.00
Distance to Park	Distance to the nearest Park (m)**	4329.72	5047.64

* The land use mix is homogenous if the value is closer to 0 and heterogeneous if the value is closer to 1
**Proportion of Distance to Park within 2KM = 47.67%

Table 3: Descriptive statistics of the variables

Summary statistics and description of temporal variables based on different time segments

Variables	Description	Mean	Standard Deviation
AM_PEAK	Number of counts for AM Peak demand in the grid	2.10765	7.81499
AM OFF_PEAK	Number of counts for OFF Peak demand in the grid	7.32328	27.0228
PM_PEAK	Number of counts for PM Peak demand in the grid	3.52986	13.3531
EVENING	Number of counts for evening demand in the grid	5.39319	19.7789
OVERNIGHT	Number of counts for overnight demand in the grid	3.24632	13.4297

Table 4: Descriptive statistics of the temporal variables based on different time segments

Analysis of Emergency Vehicle Model (Poisson and Poisson Hurdle Model)

Variables	Poisson Model			Poisson Hurdle Model		
	Coefficient	Standard error	*t-stats*	Coefficient	Standard error	*t-stats*
Constant	8.14956528	0.048725	167.256	8.3935567	0.007943	1056.733
Demographic						
Population Density	0.00021574	0.000005	41.530	0.0002111	0.000000	560.668
HH Average Income (CAD)	-0.00003921	0.000000	-54.970	-0.3610020	0.000000	-473.538
Employment Rate	0.00014811	0.000195	0.757	-0.0005152	0.000176	-29.229
Population Under 15 Years	-0.00175525	0.000229	-7.661	-0.0021606	0.000273	-79.129
Population Age 16 to 39 Years	-0.00067826	0.000588	-11.523	-0.0003834	0.000064	-59.875
Population Age 40 to 64 Years	-0.00015939	0.000111	-1.423	0.0002212	0.000141	15.680
Population Age 65 to 75 Years	0.00414220	0.000280	14.781	0.0036248	0.000041	87.534
Population Over 75 Years	0.00000203	0.000931	0.002	0.0001163	0.000131	8.846
Land use measures						
Single Detached House	-0.0055933	0.000133	-42.021	-0.0054228	0.000150	-360.643
Apt 5 or more	0.0040086	0.000913	4.386	0.0001573	0.000109	14.379
Apt 5 Few	0.0008606	0.000752	11.438	0.0005952	0.000086	69.206
Apt Duplex	0.0053623	0.000267	20.023	0.0047964	0.000360	133.120
Land Use Residential	0.0059498	0.000117	50.693	0.0052695	0.000150	349.418
Land Use Commercial	0.0049592	0.000434	11.415	0.0050075	0.000773	64.717
Land Use Park	-0.0054597	0.000488	-11.170	-0.0031739	0.000714	-44.410
Land Use Industrial	0.0060779	0.000447	13.568	0.0060783	0.000491	123.640
Land Use Index	0.1221007	0.015520	7.867	-0.0042806	0.001546	-2.767
Accessibility						
Distance to CBD	-0.0002431	0.000026	-90.441	-0.0026459	0.000002	-980.024
Distance to Hospital	0.0007073	0.000026	26.670	0.0010347	0.000002	373.780
Distance to Park	-0.0017767	0.000129	-137.309	-0.0012631	0.000019	-650.402
Distance to Park within 2KM	-1.9121892	0.045981	-41.586	-2.1911864	0.007740	-283.070
Hurdle Binary Parameters						
Constant	-		-	-2.4550654	0.138646	-17.707
Land Use Park	-		-	0.29078660	0.034136	8.518
Distance to Hospital	-		-	-0.00010004	0.000030	-32.929
Employment Rate	-		-	0.5405805	0.002153	25.097

* All p values ~ 0.000 and t-stats values ≥ 3.2 which indicates a significance level of 99.99%.

Table 5: Standard Poisson and Hurdle Model Parameter Analysis

The analysis reveals several important findings. First, the model suggests that an increase in population density will lead to an increase in emergency vehicle demand. For instance, a larger population size will tend to increase the demand for emergency vehicles. Typically, a higher population density can be associated with the urban areas. Hence, a positive correlation indicates that people living in urban areas will have more demand for emergency vehicles when compared with people living in the sub-urbans areas. As literature suggests, the increase could be most likely due to the, active social and economic activities that are present in urban environments (Reed & Bendall 2015). Furthermore, the model results also reveal some interesting similarities in terms of the relationship between the average household family income and employment rate. Both variables exhibit a negative relationship for emergency vehicle demand, with the average household family income suggesting a lower rate when compared to employment rate parameter. Arguably, a lower average income may yield a poorer lifestyle which is susceptible to chronic health conditions. Potentially, this factor, coupled with lower-level car ownership could make less privileged patients use emergency vehicles as their regular source of care even for non-urgent illness, contributing to the demand. On the other hand, for an emergency vehicles demand to increase as a result of a decrease in employment rate means a higher demand in a region is as a result of a low employment rate in that region. Arguably, some underlying factors could be that users within the region are over the working age bracket (or retired) with a possibility of the region being an elderly home health care center.

The age variables are also one of the major predictors of emergency vehicle demand. The model results suggest that younger individuals (the number of people less than 15 years of age and the number of people age 16 – 39 years in the neighborhood) exhibit a negative relationship for emergency vehicle demand while the much older workforce, the number of people age 40 years and above show higher demand for emergency vehicle. As literature suggests, demand for an emergency health care will tend to increase with age (Goldstein et al. 2015). Perhaps, a possible reason for this result could be that majority of the people living in the region of study are over the age of 40 years and are considered non-active, non-working people with a high demand for health care services. In addition, study has shown that older patients often present to emergency departments with more complex clinical conditions when compared with younger patients (Clark and FitzGerald, 1999). This pattern is also evident from the descriptive analysis of the dataset and past literature (Milan, 2011 and Goldstein et al. 2015) which concludes that over 50% of the residents within the region are over the age of 65 years.

However, a closer observation of model parameters, shows that among these older age groups, age group 40-64 demonstrates lesser rate for emergency vehicle demand when compared with age 65 years and above, potentially, this could also mean that, among the older age group, the age group under 65 years old is likely to be healthier and will demand less emergency vehicle when compared with age group above 65 years.

In terms of land use measures, the model demonstrates a negative relationship with land use index indicating demand for an emergency vehicle will decrease if the land use mix is more heterogeneous. This result correlates with some of the studies on the impact of land use mix. For instance, Bramley et al. (2009) conclude in his study that higher density neighborhoods and a mixed land use will enable better access to and increase the use of local facilities. The land use index effects can also be established with the individual components of the land use mix. For instance, the model demonstrates a positive association with land use for industrial, residential and commercial areas. This means that emergency vehicle demand will increase in the neighborhood with a higher proportion of land, collectively used for different purposes such as schools, libraries, parks, commercial places, industries as seen in the urban areas. However, among these three land use measures that positively affect emergency vehicle demand, the land use for industrial purpose exhibits the highest rate, followed by land use for commercial purpose while the land use for residential purpose exhibits the lowest impact. This means emergency vehicle demand is highly likely to come from people at work or in commercial areas when compared with people living at home. In addition, the model also suggests that suburban single detached houses show less demand when compared with inner city houses. As earlier shown in the spatial analysis in figure 11, it can be observed that a variation of demand hotspots was distributed through the entire region based on different locations. Demands were very high in the urban areas when compared to the outskirts. Although, some spots outside the downtown area also have a fair amount of demand. However, it appears the majority of the emergency vehicle demand will come from urban areas.

Lastly, the analysis reveals demand for an emergency vehicle can also be influenced by accessibility factors. The model demonstrates a negative relationship between people location and distance to the nearest parks respectively. Although, the negative relationship rate is higher when the park is closer to where people live than when compared with the overall effect for the park distance, meaning the farther the distance from the park, the more likely the demand for emergency vehicle to increase. Nonetheless, this relationship could signify that people tend to have a healthier lifestyle when they live closer to the park, meaning, people living within the region are less susceptible to health issues leading to lesser demand for emergency vehicle over time when compared with people living father away from parks that are more likely to demand more. On the other hand, the model also suggests a positive relationship between the distance from people's calling spots and the nearest hospital locations as well as a negative relationship between the distance from people's calling spots and the CBD. For instance, emergency vehicle demand will tend to increase as a result of an increase in the distance between users calling spots. The reason for this relationship cannot be fully established from analysis. Perhaps, this increase can come as a result of lack of health care centers available for an increasing number of outpatients living in the sub urban areas that require continuous transportation to the hospital on a daily or weekly basis.

Temporal Analysis of Emergency Vehicle Model (Poisson Hurdle Model Only)

Variables	Parameter Coefficients									
	AM PEAK		AM OFF PEAK		PM PEAK		EVENING		OVERNIGHT	
	Coefficient	***t-stats***	**Coefficient**	***t-stats***	**Coefficient**	***t-stats***	**Coefficient**	***t-stats***	**Coefficient**	***t-stats***
Constant	5.723537	93.254	7.45782203	354.073	6.44238302	153.632	6.76426132	213.014	6.52522260	130.754
Demographic										
Population Density	0.000159	39.454	0.202625	167.218	0.172570	71.488	0.186969	116.099	0.183753	88.921
HH Average Income (CAD)	-0.000031	-45.153	-0.254820	-114.466	-0.245930	-51.709	-0.376012	-117.146	-0.325342	-74.917
Employment Rate	-0.000275	-1.536	-0.001083	-19.580	-0.001237	-12.163	-0.000974	-13.311	0.0006727	0.688
Population Under 15 Years	-0.005164	-17.651	-0.002618	-32.416	-0.003535	-23.415	-0.001739	-14.482	-0.002934	-19.170
Population Age 16 to 39 Years	-0.000958	-1.587	-0.000116	-5.860	0.917867	2.465	-0.000720	-27.079	0.460131	1.330
Population Age 40 to 64 Years	0.000182	1.381	-0.000117	-2.709	0.001010	12.189	0.000939	15.047	0.001226	15.008
Population Age 65 to 75 Years	0.003061	7.972	0.003424	26.731	0.002248	9.924	0.001327	7.813	0.002658	12.393
Population Over 75 Years	0.001381	8.795	0.000709	14.738	-0.000223	-2.652	-0.000409	-8.787	-0.000741	-13.913
Land use measures										
Single Detached House	-0.004605	-32.781	-0.004960	-113.336	-0.005258	-59.999	-0.004953	-77.740	-0.006499	-72.628
Apt 5 or more	-0.000256	-2.406	0.821261	2.544	0.000110	1.800	0.000622	13.428	0.000357	6.384
Apt 5 Few	0.000223	2.631	0.000429	16.166	-0.329628	-0.610	0.000661	18.169	0.000860	1.834
Apt Duplex	0.004236	13.238	0.005431	54.206	0.005307	29.481	0.002931	17.423	0.000779	3.589
Land Use Residential	0.005260	39.203	0.004167	95.290	0.003421	37.938	0.004890	75.868	0.004440	57.557
Land Use Commercial	0.005953	5.662	0.004360	16.486	0.006006	11.699	0.005820	21.028	0.004423	13.477
Land Use Park	-0.000991	-1.458	-0.003537	-16.677	-0.002584	-6.196	-0.002078	-6.957	-0.000431	-1.155
Land Use Industrial	0.005275	11.099	0.006276	39.568	0.004601	15.033	0.004932	26.799	0.005207	20.383
Land Use Index	-0.152648	-9.931	-0.060100	-12.951	-0.267190	-28.838	-0.109525	-17.032	-0.287887	-33.005
Accessibility										
Distance to CBD	-0.000250	-99.492	-0.000279	-370.322	-0.000279	-168.437	-0.000328	-314.838	-0.000351	-228.152
Distance to Hospital	0.000115	45.176	0.000121	159.903	0.000126	72.385	0.000181	167.721	0.000202	125.700
Distance to Park	-0.000803	-42.296	-0.001112	-192.568	-0.000850	-76.670	-0.000912	-119.223	-0.000829	-69.859
Distance to Park within 2KM	-1.921463	-32.774	-2.336409	-115.122	-2.022091	-49.889	-1.888890	-60.998	-2.195808	-44.943
Hurdle Binary Parameters										
Constant	-2.274733	-13.516	-2.393873	-15.822	-2.319227	-14.095	-2.708938	-17.325	-2.492333	-14.914
Land Use Park	0.209776	10.554	0.302084	8.918	0.274782	9.080	0.294200	9.317	0.237153	9.828
Distance to Hospital	-0.000143	-36.821	-0.000118	-34.413	-0.000135	-35.448	-0.000118	-33.623	-0.000134	-34.854
Employment Rate	0.047259	17.829	0.050811	21.455	0.048291	18.646	0.054008	21.985	0.050258	18.977

Table 6: Hurdle Model Parameter Analysis by time segments

As shown in table 6 above, the temporal analysis of the emergency vehicle demand also exhibits a pattern that is similar to the general analysis. For instance, the variables such as Land use index, average household income and accessibility (such as distance to CBD and park) demonstrates a negative association while variables such as Population density, distance to hospital and age demonstrates a positive association. However, there seems to be variation in the proportion contributed by the coefficient of these variables within different time segments. For instance, the model suggests a higher influence for the land use index during the AM peak period when compared with the AM off-peak period for emergency vehicle demand. This signifies that the impact of land use mix on emergency vehicle demand is greater at the early hours of the day and reduces gradually over the course of the day. In addition, among these three land use measures that positively affect emergency vehicle demand, the land use for residential exhibits a higher demand during the AM peak period when compared with the PM peak period while the land use for commercial exhibits a higher demand during the PM peak period when compared with the AM peak period. This signifies that demand for an emergency vehicle will vary according to social and economy activities. For instance, the higher rate of the emergency vehicle for residential use during the AM peak period coincide with the period when users of emergency vehicles are most likely at home and the higher rate of use for commercial purpose coincide with the period when the majority of the users of emergency vehicles are most likely at work. Moreover, there is also a general trend for a lower proportion of land use for commercial during the evening and overnight period when compared with the PM peak period. A result which also suggests the demand for an emergency vehicle could be higher during the active period of economy activity when compared with the non-active period. Similarly, the demographic variables also demonstrate a different pattern for different time segments, a relationship which we anticipated for emergency vehicle demand. For instance, the model suggests a higher demand proportion for the population density coefficient during the AM off-peak than the AM peak period, as previously described in our exploratory analysis which demonstrated the demand for emergency vehicle increases gradually at the early hours of the day, reaching a peak period at 10AM after which demand begins to decline throughout the day. In addition, particularly, for the age variables, a notable difference between the variables for the different time segments exist. For instance, within the age group over 75 years old, the temporal patterns of the demand for emergency vehicle demonstrates an opposite effect as the time goes from morning to evening. Potentially, this could mean demand for an emergency vehicle only occurs during the morning period for this age group.

In conclusion, the general and the temporal analysis have shown that both the spatial and temporal Poisson Hurdle models have provided us with a stable, meaningful and useful insights and therefore suitable for the analysis of our overdispersed count data.

4.5 Conclusion

This research presents insights into the community characteristics of emergency vehicle users. Unlike other research within this field of studies, this research examined factors contributing to an increase in emergency vehicle using geographical attributes at a 1km by 1km grid level. The data from the census tract provides various characteristics and neighborhood attributes that enabled a comprehensive demand patterns analysis to be examined among users of emergency vehicle services. The dependent variable was the count of emergency vehicle demand in a given space while the independent variables were the geographical attributes derived variables from the census and land use data received from DMTI respectively. A Poisson Hurdle regression model was developed to predict some of the factors that can contribute to emergency vehicle demand. The analysis revealed that demographic, built environment and economic characteristics (such as population density employment rate and average household income), accessibility and land use measures can influence emergency vehicle demand. Particularly, the social-demographic (such as age) and land use measures (such as land use for commercial and residential purposes) demonstrates a pattern which correlates with previous studies. For instance, on the land use measures, the model suggests that higher density neighborhoods and a mixed land use will enable better access to and increase the use of local facilities such as health centers while the age factors suggest demand for an emergency health care will tend to increase with age. Also, the analysis of the models by different time segment of the day, demonstrate a similar pattern with the general model, with little exceptions such as differences in the rate of emergency vehicle demand for different land use measures as well as the age group relationships. For instance, the analysis demonstrates that effect of demand on land use for commercial will vary according to variations in the periods and locations of active social and economy activities for emergency vehicle users while the older people tend to use the emergency vehicle more at the early hours of the day when compared with the evening or overnight periods.

Lastly, this study is useful because it can provide decision makers with necessary information to accommodate for emergency vehicle demand in communities or geographical regions where demand is considered high. In addition, we can forecast the number and type of medical emergencies that a public system will be required to manage during the entire year. For instance, a community primary care unit can then be built to support the health services thereby preventing the need to call for an emergency vehicle service.

4.6 Limitations:

This research did not analyze several other factors such as weather variation, incident type and cost of emergency vehicle usage. The effect of emergency vehicle cost and incident type were not analyzed due to limited data provided. While a weather of greater extremes might cause significant seasonal variations but the data used was only for a period of one year. A prospective study of the effect of climate change would have been beyond available data. Finally, estimation of the percentage of dissemination area within a cell was highly approximated as most of the cells fell outside of the boundary. The future analysis would require improvements in approximating the percentage of grid within the boundary that affects the estimation of the independent variables attributes.

Chapter 5 – Conclusion

The challenges presented by the increased proportion of senior citizens and pressure on emergency health services are growing. Over the past two decades, the demand for emergency vehicles have increased in most industrialized nations. Research has shown that the older groups are at risk because they are among the frequent users of emergency vehicles. This thesis presented a detailed research into the factors contributing to the current increase in emergency vehicle demand in Halifax, Nova Scotia, a province in Canada where a significant percentage of its population is aged 65 years or older.

Firstly, we presented an overview of the previous literature, with a detailed outline, highlighting some of the key findings within each study areas. It established the fact that emergency vehicle demand analysis can be grouped into 3 major categories which include spatial and temporal descriptive analysis, diagnostic and predictive modelling, and location coverage and service optimization modelling. Two major areas that have received recent attention is the spatial and temporal descriptive analysis and the diagnostic and predictive modelling of emergency vehicle demand, an area which we have explored in great depth for Halifax emergency vehicle demand as seen in chapter 3 and 4 respectively.

Furthermore, we presented an exploratory analysis of the emergency vehicle demand profile for Halifax, using data from the Nova Scotia, Canada provincial Emergency Medical Service (EMS) administrative database within the period of January to December 2012. The analysis results revealed that emergency vehicle varies considerably across different age group and gender, with older adults within the age bracket of 40 years and above showing high tendency for emergency service when compared with the younger adults and age group under the age 15. In addition, there is a higher demand within the female group with a margin of approximately 8% demonstrating a pattern that could signify that women possibly live longer, are more than men and have the tendency to use the emergency vehicles more frequently. Furthermore, the average travel time does not have a significant effect on emergency vehicle demand pattern, with a contrasting pattern exhibited for both peaks and off-peak periods, possibly indicating that the travel demand peak and off-peak periods do not coincide with emergency vehicle demand in Halifax. Lastly, the findings also show a consistent pattern between demands over hour of the day and day of the week regardless of the sub groups. A close analysis, however, shows that the season also had an influence on emergency vehicle usage, when pickup request was averaged by season, the demand appears to decline in the warmer season and increases as the season gets colder. Arguably, this means that emergency vehicle demand could have increased as a result of weather-related injuries such as falling on snow or illnesses such as influenza.

Lastly, we presented a Poisson hurdle model that examines the validity of different emergency vehicle demand hypotheses. The modelling approach used in this chapter built on recent work on spatial models with zero data domain, a model that support both the high proportion of zero's and the right-skewness of the non-zero counts (Neelon et al., 2013). Specifically, this research examines factors contributing to demand of emergency vehicle using geographical attributes at a 1km by 1km grid level. The data from the census tract provides various characteristics and neighborhood attributes that enabled a comprehensive demand patterns analysis to be examined among users of emergency vehicle services. For each of the hypothesis, the dependent variable was the number of emergency vehicle demand in a given space modelled against other independent variables such as the geographical attributes and derived variables from the census and land use data received from DMTI respectively. The results of this analysis suggest that built environment and demographic characteristics including employment rate, average household income and land use measures, such as land used for residential, park, commercial and industrial, can influence emergency vehicle demand.

In conclusion, this study is useful because it provides an exploratory characteristics and also proposes a predictive model that can used to understand the characteristics of emergency vehicle users, which could ultimately assist decision makers to develop better health care services for the communities. For instance, by understanding the demand patterns and identifying the geographical areas with higher emergency vehicle demands, we can determine whether emergency vehicles are being used within a community because there is a lack of alternative means of transport or other factors have contributed to the high demand. Thereby, assisting policy makers to generate insightful strategy decisions on a number of community planning, development and health-related issues that can be used to alleviate emergency vehicle usage. Furthermore, insights from this research can provide health planners with necessary information to develop a location based health centers for patient requirements. These type of facilities can serve as alternative channels to providing specific medical needs thereby reducing the pressure on the use of emergency vehicles for reoccurring illnesses. Likewise, this analysis can be used to establish an alternative means of transportation such as bus, vans, carpools, etc. in order to move patient's to and from hospitals and local clinics instead of relying on emergency vehicle as the primary means of transport. These efforts can significantly reduce the need for emergency vehicles, considering most of the calls may not be a true emergency health situation.

Lastly, understanding how the time of the day and days of the week affect emergency vehicle demands can help make the necessary reservation for resources such as personnel and vehicles. More importantly, the study on how emergency vehicle demand varies with time can help determine a cost-effective method of deploying health resources to underserved communities in order to relieve access to emergency medical services; addressing neighborhoods that are not prone to emergency need. For instance, if we know that emergency vehicle demand will be higher in industrial and commercial areas during the AM off-peak periods and PM peak periods, we can strategically provide more resources to cater for these demands at the those locations during these periods, thereby reducing resource allocations for certain periods of the day as well as response travel times. Similarly, if we understand that demand for emergency vehicle is less likely to increase in a community that is more heterogeneous, policy makers can strategically make better plans for various land use measures. Making these directed efforts to address user needs will be crucial to reducing the burden placed on emergency vehicle usage, subsequently, reducing overall cost associated with servicing health care within the province.

For future work, this research could be improved by investigating a spatial-temporal demand of emergency vehicle among smaller groups of patients with specific medical diagnosis and issues. This would help understand the real causes of emergency vehicle usage among certain communities. For instance, according to Brian et al. (2013), if the increase in emergency vehicle usage is mainly due to mental health related issues, policy makers and health officials could focus on ways of improving the community behavior health services as opposed to optimizing the use of resources. In addition, improvements can be made on the predictive modelling tools and technique by introducing a model that can accommodate random effects and spatial-temporal smoothing in order to reduce bias in the spatial covariance parameters and the intercept of the Poisson component (Neelon et al., 2013, Su et al., 2009).

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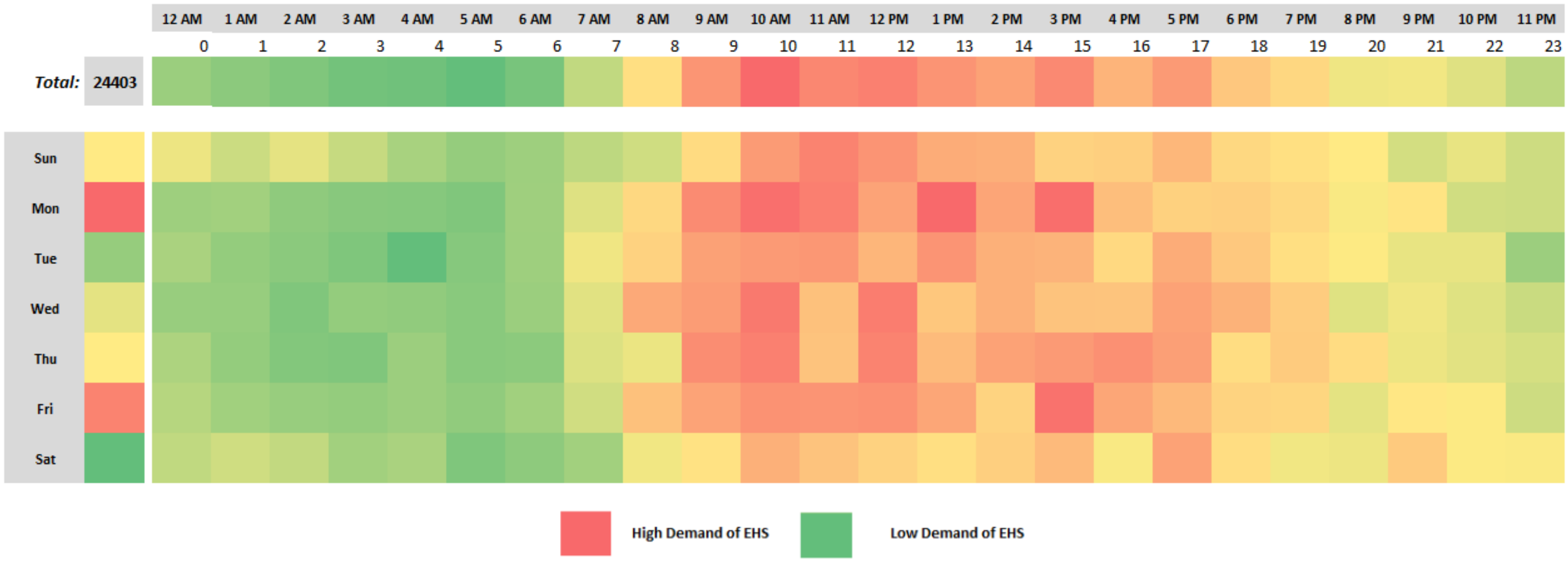
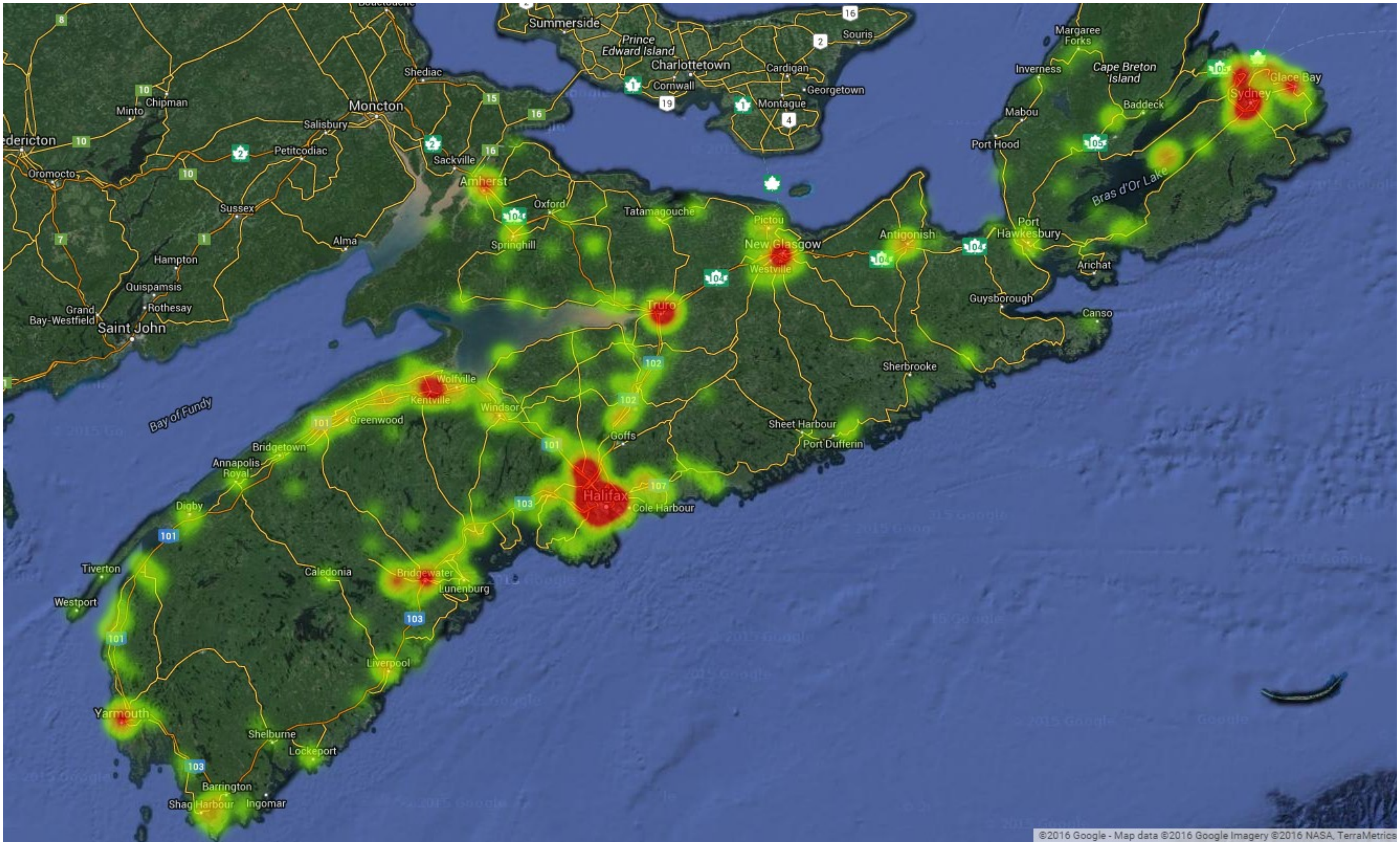
Appendix A – Distribution of emergency vehicle demand in Halifax heat map

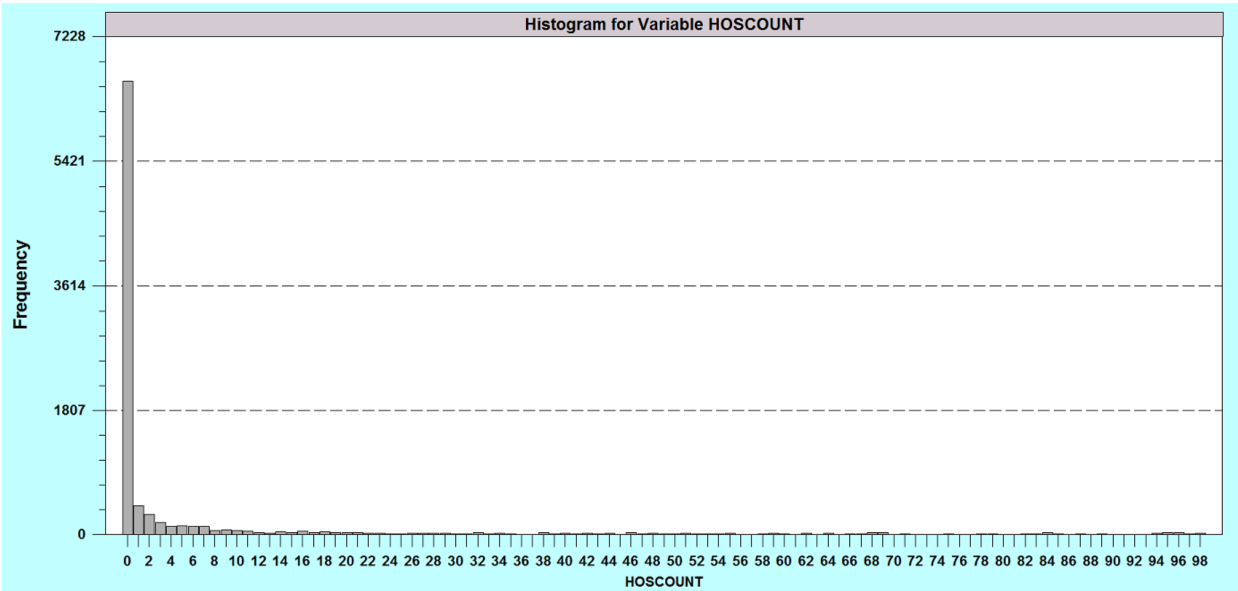


Appendix B – Distribution of emergency vehicle demand hotspot in Nova Scotia, Canada



Appendix C – A spatial-temporal analytics tool developed to examine distribution in demand

Appendix D – Histogram of Emergency vehicle demand per grid



Appendix E – Poisson Regression Model (Limdep Output)

```
+---------------------------------------------+
| Poisson Regression                          |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 17, 2016 at 06:46:23PM.|
| Dependent variable            HOSCOUNT      |
| Weighting variable                None      |
| Number of observations            9512      |
| Iterations completed                10      |
| Log likelihood function      -83923.87      |
| Number of parameters                22      |
| Info. Criterion: AIC =        17.65052      |
|   Finite Sample: AIC =        17.65053      |
| Info. Criterion: BIC =        17.66708      |
| Info. Criterion:HQIC =        17.65614      |
| Restricted log likelihood     -468479.2     |
| McFadden Pseudo R-squared      .8208589     |
| Chi squared                    769110.6     |
| Degrees of freedom                  21      |
| Prob[ChiSqd > value] =         .0000000     |
+---------------------------------------------+

+---------------------------------------------+
| Poisson Regression                          |
| Chi- squared =************  RsqP=********   |
| G  - squared =154211.00829  RsqD=   .8330   |
| Overdispersion tests: g=mu(i)  :  1.206     |
| Overdispersion tests: g=mu(i)^2:   .000     |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	8.14956528	.04872519	167.256	.0000	
POPDEN	.215743D-04	.519489D-06	41.530	.0000	358.294220
AVGINCO	-.392163D-05	.713412D-07	-54.970	.0000	80740.8935
EMPRATE	.00014811	.00019563	.757	.4490	58.2968356
UNDER15	-.00175525	.00022912	-7.661	.0000	3.10528730
WTW16N39	-.00067826	.588636D-04	-11.523	.0000	11.4161778
WTW40N64	-.00015939	.00011199	-1.423	.1546	11.3456531
WTW65N75	.00414220	.00028024	14.781	.0000	2.28157757
OVER75AB	.203310D-06	.931620D-04	.002	.9983	1.96013377
SINGDET	-.00559333	.00013311	-42.021	.0000	6.10457029
STOREY5M	.00040086	.913890D-04	4.386	.0000	1.88081615
APT5FEW	.00086069	.752498D-04	11.438	.0000	3.52730743
APTDUPX	.00536235	.00026781	20.023	.0000	.57628932
LURES	.00594988	.00011737	50.693	.0000	2.72258258
LUCOMM	.00495921	.00043446	11.415	.0000	.06084020
LUPARKS	-.00545977	.00048878	-11.170	.0000	.23886906
LUINDUS	.00607790	.00044797	13.568	.0000	.10889810
LUINDEX	.12210075	.01552078	7.867	.0000	.03942060
DISTCBD	-.00024312	.268817D-05	-90.441	.0000	40795.1515
DISTHOSP	.707317D-04	.265216D-05	26.670	.0000	17981.6744
DIST2PRK	-.00177677	.129399D-04	-137.309	.0000	4329.71617
LPARK2KM	-1.91218926	.04598191	-41.586	.0000	.47676619

Appendix F – Poisson Hurdle Regression Model (Limdep Output)

```
+---------------------------------------------+
| Poisson hurdle model for counts             |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 17, 2016 at 06:46:27PM.|
| Dependent variable            HOSCOUNT      |
| Weighting variable                None      |
| Number of observations            9512      |
| Iterations completed               101      |
| Log likelihood function      -72160.75      |
| Number of parameters                26      |
| Info. Criterion: AIC =        15.17804      |
|   Finite Sample: AIC =        15.17805      |
| Info. Criterion: BIC =        15.19761      |
| Info. Criterion:HQIC =        15.18468      |
| Restricted log likelihood    -83923.87      |
| McFadden Pseudo R-squared     .1401641      |
| Chi squared                   23526.23      |
| Degrees of freedom                   1      |
| Prob[ChiSqd > value] =        .0000000      |
| LOGIT  hurdle equation                      |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
---------+Parameters of count model equation
 Constant|    8.39355673       .00794293  1056.733   .0000
 POPDEN  |    .211194D-04    .376682D-07   560.668   .0000   358.294220
 AVGINCO |   -.361002D-05    .762350D-08  -473.538   .0000   80740.8935
 EMPRATE |   -.00051520      .176265D-04   -29.229   .0000   58.2968356
 UNDER15 |   -.00216063      .273051D-04   -79.129   .0000   3.10528730
 WTW16N39|   -.00038344      .640396D-05   -59.875   .0000   11.4161778
 WTW40N64|    .00022123      .141093D-04    15.680   .0000   11.3456531
 WTW65N75|    .00362482      .414105D-04    87.534   .0000   2.28157757
 OVER75AB|    .00011632      .131485D-04     8.846   .0000   1.96013377
 SINGDET |   -.00542283      .150365D-04  -360.643   .0000   6.10457029
 STOREY5M|    .00015730      .109400D-04    14.379   .0000   1.88081615
 APT5FEW |    .00059524      .860105D-05    69.206   .0000   3.52730743
 APTDUPX |    .00479643      .360309D-04   133.120   .0000    .57628932
 LURES   |    .00526959      .150810D-04   349.418   .0000   2.72258258
 LUCOMM  |    .00500756      .773768D-04    64.717   .0000    .06084020
 LUPARKS |   -.00317391      .714684D-04   -44.410   .0000    .23886906
 LUINDUS |    .00607830      .491612D-04   123.640   .0000    .10889810
 LUINDEX |   -.00428065        .00154695    -2.767   .0057    .03942060
 DISTCBD |   -.00026459      .269988D-06  -980.024   .0000   40795.1515
 DISTHOSP|    .00010347      .276812D-06   373.780   .0000   17981.6744
 DIST2PRK|   -.00126318      .194215D-05  -650.402   .0000   4329.71617
 LPARK2KM|  -2.19118640        .00774079  -283.070   .0000    .47676619
---------+Parameters of binary hurdle equation
 Constant|  -2.45506542        .13864632   -17.707   .0000
 LUPARKS |    .29078660        .03413602     8.518   .0000      .000000
 DISTHOSP|   -.00010004      .303811D-05   -32.929   .0000      .000000
 EMPRATE |    .05405805        .00215395    25.097   .0000      .000000
```

Appendix G – Poisson Hurdle Regression Model for AM PEAK (Limdep Output)

```
+---------------------------------------------+
| Poisson hurdle model for counts             |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2016 at 06:01:25PM.|
| Dependent variable               AM_PEAK    |
| Weighting variable                  None    |
| Number of observations              9512    |
| Iterations completed                 101    |
| Log likelihood function        -12119.00    |
| Number of parameters                  26    |
| Info. Criterion: AIC =           2.55362    |
|   Finite Sample: AIC =           2.55363    |
| Info. Criterion: BIC =           2.57319    |
| Info. Criterion:HQIC =           2.56026    |
| Restricted log likelihood      -13045.15    |
| McFadden Pseudo R-squared       .0709960    |
| Chi squared                     1852.306    |
| Degrees of freedom                     1    |
| Prob[ChiSqd > value] =          .0000000    |
| LOGIT  hurdle equation                      |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
---------+Parameters of count model equation
 Constant|    5.72353723       .06137553    93.254   .0000
 POPDEN  |    .159849D-04    .405156D-06    39.454   .0000   358.294220
 AVGINCO |   -.313184D-05    .693601D-07   -45.153   .0000   80740.8935
 EMPRATE |   -.00027565       .00017945    -1.536   .1245   58.2968356
 UNDER15 |   -.00516421       .00029257   -17.651   .0000   3.10528730
 WTW16N39|   -.958816D-04    .604152D-04    -1.587   .1125   11.4161778
 WTW40N64|    .00018284       .00013244     1.381   .1674   11.3456531
 WTW65N75|    .00306191       .00038408     7.972   .0000   2.28157757
 OVER75AB|    .00138144       .00015707     8.795   .0000   1.96013377
 SINGDET |   -.00460572       .00014050   -32.781   .0000   6.10457029
 STOREY5M|   -.00025648       .00010661    -2.406   .0161   1.88081615
 APT5FEW |    .00022372      .850217D-04     2.631   .0085   3.52730743
 APTDUPX |    .00423694       .00032005    13.238   .0000    .57628932
 LURES   |    .00526051       .00013418    39.203   .0000   2.72258258
 LUCOMM  |    .00595348       .00105156     5.662   .0000    .06084020
 LUPARKS |   -.00099152       .00067986    -1.458   .1447    .23886906
 LUINDUS |    .00527595       .00047537    11.099   .0000    .10889810
 LUINDEX |   -.15264820       .01537158    -9.931   .0000    .03942060
 DISTCBD |   -.00025043      .251711D-05   -99.492   .0000   40795.1515
 DISTHOSP|    .00011525      .255121D-05    45.176   .0000   17981.6744
 DIST2PRK|   -.00080331      .189923D-04   -42.296   .0000   4329.71617
 LPARK2KM|   -1.92146322      .05862720   -32.774   .0000    .47676619
---------+Parameters of binary hurdle equation
 Constant|   -2.27473375      .16830388   -13.516   .0000
 LUPARKS |    .20977687       .01987618    10.554   .0000      .000000
 DISTHOSP|   -.00014330      .389189D-05   -36.821   .0000   17981.6744
 EMPRATE |    .04725985       .00265079    17.829   .0000   58.2968356
```

Appendix H – Poisson Hurdle Regression Model for OFF PEAK (Limdep Output)

```
+---------------------------------------------+
| Poisson hurdle model for counts             |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2016 at 06:02:07PM.|
| Dependent variable              OFF_PEAK    |
| Weighting variable                  None    |
| Number of observations              9512    |
| Iterations completed                 101    |
| Log likelihood function        -28212.11    |
| Number of parameters                  26    |
| Info. Criterion: AIC =           5.93736    |
|   Finite Sample: AIC =           5.93738    |
| Info. Criterion: BIC =           5.95694    |
| Info. Criterion:HQIC =           5.94401    |
| Restricted log likelihood      -32796.37    |
| McFadden Pseudo R-squared       .1397795    |
| Chi squared                     9168.522    |
| Degrees of freedom                     1    |
| Prob[ChiSqd > value] =          .0000000    |
| LOGIT  hurdle equation                      |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
---------+Parameters of count model equation
 Constant|    7.45782203       .02106293   354.073   .0000
 POPDEN  |    .202625D-04    .121174D-06   167.218   .0000   358.294220
 AVGINCO |   -.254820D-05    .222616D-07  -114.466   .0000   80740.8935
 EMPRATE |    -.00108331     .553285D-04   -19.580   .0000   58.2968356
 UNDER15 |    -.00261844     .807752D-04   -32.416   .0000   3.10528730
 WTW16N39|    -.00011679     .199293D-04    -5.860   .0000   11.4161778
 WTW40N64|    -.00011708     .432248D-04    -2.709   .0068   11.3456531
 WTW65N75|     .00342457       .00012811    26.731   .0000   2.28157757
 OVER75AB|     .00070964     .481494D-04    14.738   .0000   1.96013377
 SINGDET |    -.00496068     .437698D-04  -113.336   .0000   6.10457029
 STOREY5M|    .821261D-04    .322885D-04     2.544   .0110   1.88081615
 APT5FEW |     .00042933     .265574D-04    16.166   .0000   3.52730743
 APTDUPX |     .00543165       .00010020    54.206   .0000    .57628932
 LURES   |     .00416790     .437394D-04    95.290   .0000   2.72258258
 LUCOMM  |     .00436030       .00026448    16.486   .0000    .06084020
 LUPARKS |    -.00353761       .00021213   -16.677   .0000    .23886906
 LUINDUS |     .00627606       .00015861    39.568   .0000    .10889810
 LUINDEX |    -.06010005       .00464058   -12.951   .0000    .03942060
 DISTCBD |    -.00027938     .754426D-06  -370.322   .0000   40795.1515
 DISTHOSP|     .00012106     .757106D-06   159.903   .0000   17981.6744
 DIST2PRK|    -.00111208     .577501D-05  -192.568   .0000   4329.71617
 LPARK2KM|   -2.33640958       .02029509  -115.122   .0000    .47676619
---------+Parameters of binary hurdle equation
 Constant|   -2.39387323       .15129619   -15.822   .0000
 LUPARKS |     .30208437       .03387266     8.918   .0000     .000000
 DISTHOSP|    -.00011808     .343109D-05   -34.413   .0000   17981.6744
 EMPRATE |     .05081157       .00236826    21.455   .0000   58.2968356
```

Appendix I – Poisson Hurdle Regression Model for PM PEAK (Limdep Output)

```
+---------------------------------------------+
| Poisson hurdle model for counts             |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 10, 2016 at 06:02:43PM.|
| Dependent variable              PM_PEAK     |
| Weighting variable                 None     |
| Number of observations             9512     |
| Iterations completed                101     |
| Log likelihood function       -15707.49     |
| Number of parameters                 26     |
| Info. Criterion: AIC =          3.30813     |
|   Finite Sample: AIC =          3.30815     |
| Info. Criterion: BIC =          3.32771     |
| Info. Criterion:HQIC =          3.31478     |
| Restricted log likelihood     -18026.70     |
| McFadden Pseudo R-squared      .1286543     |
| Chi squared                    4638.426     |
| Degrees of freedom                    1     |
| Prob[ChiSqd > value] =         .0000000     |
| LOGIT  hurdle equation                      |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
---------+Parameters of count model equation
 Constant|    6.44238302      .04193396   153.632   .0000
 POPDEN  |    .172570D-04    .241395D-06    71.488   .0000   358.294220
 AVGINCO |   -.245930D-05    .475604D-07   -51.709   .0000   80740.8935
 EMPRATE |   -.00123741       .00010173   -12.163   .0000   58.2968356
 UNDER15 |   -.00353553       .00015100   -23.415   .0000   3.10528730
 WTW16N39|    .917867D-04    .372339D-04     2.465   .0137   11.4161778
 WTW40N64|     .00101010     .828722D-04    12.189   .0000   11.3456531
 WTW65N75|     .00224838      .00022656     9.924   .0000   2.28157757
 OVER75AB|   -.00022367      .843562D-04    -2.652   .0080   1.96013377
 SINGDET |   -.00525823      .876382D-04   -59.999   .0000   6.10457029
 STOREY5M|     .00011072     .615042D-04     1.800   .0718   1.88081615
 APT5FEW |   -.329628D-04    .540669D-04     -.610   .5421   3.52730743
 APTDUPX |     .00530720      .00018002    29.481   .0000    .57628932
 LURES   |     .00342115     .901775D-04    37.938   .0000   2.72258258
 LUCOMM  |     .00600678      .00051343    11.699   .0000    .06084020
 LUPARKS |   -.00258419       .00041706    -6.196   .0000    .23886906
 LUINDUS |     .00460146      .00030608    15.033   .0000    .10889810
 LUINDEX |   -.26719037       .00926536   -28.838   .0000    .03942060
 DISTCBD |   -.00027970      .166059D-05  -168.437   .0000   40795.1515
 DISTHOSP|     .00012651     .174780D-05    72.385   .0000   17981.6744
 DIST2PRK|   -.00085020      .110891D-04   -76.670   .0000   4329.71617
 LPARK2KM|   -2.02209135      .04053207   -49.889   .0000    .47676619
---------+Parameters of binary hurdle equation
 Constant|   -2.31922783      .16454038   -14.095   .0000
 LUPARKS |     .27478215      .03026183     9.080   .0000     .000000
 DISTHOSP|   -.00013597      .383590D-05   -35.448   .0000   17981.6744
 EMPRATE |     .04829112      .00258984    18.646   .0000   58.2968356
```

Appendix J – Poisson Hurdle Regression Model for EVENING (Limdep Output)

```
+----------------------------------------------+
| Poisson hurdle model for counts              |
| Maximum Likelihood Estimates                 |
| Model estimated: Nov 10, 2016 at 06:03:14PM.|
| Dependent variable               EVENING     |
| Weighting variable                  None     |
| Number of observations              9512     |
| Iterations completed                 101     |
| Log likelihood function        -21215.46     |
| Number of parameters                  26     |
| Info. Criterion: AIC =           4.46625     |
|   Finite Sample: AIC =           4.46626     |
| Info. Criterion: BIC =           4.48582     |
| Info. Criterion:HQIC =           4.47289     |
| Restricted log likelihood      -24823.04     |
| McFadden Pseudo R-squared       .1453316     |
| Chi squared                     7215.145     |
| Degrees of freedom                     1     |
| Prob[ChiSqd > value] =          .0000000     |
| LOGIT  hurdle equation                       |
+----------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Parameters of count model equation					
Constant	6.76426132	.03175505	213.014	.0000	
POPDEN	.186969D-04	.161042D-06	116.099	.0000	358.294220
AVGINCO	-.376012D-05	.320978D-07	-117.146	.0000	80740.8935
EMPRATE	-.00097491	.732381D-04	-13.311	.0000	58.2968356
UNDER15	-.00173906	.00012009	-14.482	.0000	3.10528730
WTW16N39	-.00072087	.266213D-04	-27.079	.0000	11.4161778
WTW40N64	.00093997	.624695D-04	15.047	.0000	11.3456531
WTW65N75	.00132704	.00016985	7.813	.0000	2.28157757
OVER75AB	-.00040933	.465814D-04	-8.787	.0000	1.96013377
SINGDET	-.00495331	.637164D-04	-77.740	.0000	6.10457029
STOREY5M	.00062208	.463278D-04	13.428	.0000	1.88081615
APT5FEW	.00066160	.364147D-04	18.169	.0000	3.52730743
APTDUPX	.00293124	.00016824	17.423	.0000	.57628932
LURES	.00489005	.644550D-04	75.868	.0000	2.72258258
LUCOMM	.00582045	.00027680	21.028	.0000	.06084020
LUPARKS	-.00207844	.00029875	-6.957	.0000	.23886906
LUINDUS	.00493209	.00018404	26.799	.0000	.10889810
LUINDEX	-.10952518	.00643066	-17.032	.0000	.03942060
DISTCBD	-.00032842	.104313D-05	-314.838	.0000	40795.1515
DISTHOSP	.00018146	.108191D-05	167.721	.0000	17981.6744
DIST2PRK	-.00091245	.765332D-05	-119.223	.0000	4329.71617
LPARK2KM	-1.88889075	.03096652	-60.998	.0000	.47676619
Parameters of binary hurdle equation					
Constant	-2.70893899	.15636232	-17.325	.0000	
LUPARKS	.29420056	.03157671	9.317	.0000	.000000
DISTHOSP	-.00011819	.351523D-05	-33.623	.0000	17981.6744
EMPRATE	.05400897	.00245662	21.985	.0000	58.2968356

Appendix K – Poisson Hurdle Regression Model for OVERNIGHT (Limdep Output)

Poisson hurdle model for counts	
Maximum Likelihood Estimates	
Model estimated: Nov 10, 2016 at 06:03:44PM.	
Dependent variable	OVERNIGH
Weighting variable	None
Number of observations	9512
Iterations completed	101
Log likelihood function	-16082.12
Number of parameters	26
Info. Criterion: AIC =	3.38690
Finite Sample: AIC =	3.38692
Info. Criterion: BIC =	3.40648
Info. Criterion:HQIC =	3.39355
Restricted log likelihood	-18063.37
McFadden Pseudo R-squared	.1096831
Chi squared	3962.493
Degrees of freedom	1
Prob[ChiSqd > value] =	.0000000
LOGIT hurdle equation	

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Parameters of count model equation					
Constant	6.52522260	.04990442	130.754	.0000	
POPDEN	.183753D-04	.206647D-06	88.921	.0000	358.294220
AVGINCO	-.325342D-05	.434270D-07	-74.917	.0000	80740.8935
EMPRATE	.672773D-04	.977509D-04	.688	.4913	58.2968356
UNDER15	-.00293491	.00015310	-19.170	.0000	3.10528730
WTW16N39	.460131D-04	.346083D-04	1.330	.1837	11.4161778
WTW40N64	.00122630	.817087D-04	15.008	.0000	11.3456531
WTW65N75	.00265814	.00021449	12.393	.0000	2.28157757
OVER75AB	-.00074164	.533040D-04	-13.913	.0000	1.96013377
SINGDET	-.00649959	.894918D-04	-72.628	.0000	6.10457029
STOREY5M	.00035730	.559721D-04	6.384	.0000	1.88081615
APT5FEW	.860216D-04	.468938D-04	1.834	.0666	3.52730743
APTDUPX	.00077945	.00021717	3.589	.0003	.57628932
LURES	.00444014	.771429D-04	57.557	.0000	2.72258258
LUCOMM	.00442301	.00032818	13.477	.0000	.06084020
LUPARKS	-.00043146	.00037361	-1.155	.2481	.23886906
LUINDUS	.00520742	.00025548	20.383	.0000	.10889810
LUINDEX	-.28788720	.00872262	-33.005	.0000	.03942060
DISTCBD	-.00035160	.154108D-05	-228.152	.0000	40795.1515
DISTHOSP	.00020207	.160757D-05	125.700	.0000	17981.6744
DIST2PRK	-.00082924	.118702D-04	-69.859	.0000	4329.71617
LPARK2KM	-2.19580852	.04885713	-44.943	.0000	.47676619
Parameters of binary hurdle equation					
Constant	-2.49233303	.16711491	-14.914	.0000	
LUPARKS	.23715305	.02413026	9.828	.0000	.000000
DISTHOSP	-.00013447	.385804D-05	-34.854	.0000	17981.6744
EMPRATE	.05025855	.00264841	18.977	.0000	58.2968356