YANGON UNIVERSITY OF ECONOMICS
DEPARTMENT OF STATISTICS

ANALYSIS AND FORECASTING OF ROAD TRAFFIC ACCIDENTS IN YANGON MUNICIPAL AREA (2014-2018)

BY

THIRI KO
M. Econ (Statistics)
Roll No.1

NOVEMBER, 2019

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This is certify that the thesis entitled "**ANALYSIS AND FORECASTING OF ROAD TRAFFIC ACCIDENTS IN YANGON MUNICIPAL AREA (2014-2018)"** submitted as a partial fulfillment towards the requirements of Master of Economics (Statistics) has been accepted by the Board of Examiners.

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ABSTRACT

Road accident in Myanmar is the thirteenth major cause of death after kidney disease and diarrhoea disease. The ultimate goal of this thesis is to use Poisson regression to fit a model to the secondary data which was obtained from No (2) Office of Traffic Police (Yangon) on the number of people killed and injured by road accidents in Yangon city from 2014-2018. The type of causes of accidental crash, townships with the highest rate of road accident in Yangon against time (in years) are explored in this study. The result of Poisson analysis showed that there was over dispersion in the data. Negative binomial regression analysis was therefore used to validate the Poisson regression model. It was clear that the negative binomial regression model was the best fit for the data but for the occurrence of number of people who were killed and injured given the selected townships (Hlaingtharyar, Insein, Mayangon and Mingalardon) and types of crash causes, Poisson regression model is fitter than Negative binomial regression model for that data analysis. In the long run, the number of people in both killed and injured in Yangon would be gradually decreased. Finally, the result showed that the driver fault and over speeding were the main causes of death in road traffic accidents in Yangon (Municipal Area).

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LIST OF ABBREVIATIONS

GLM	-Generalized Linear Models
RTAs	-Road Traffic Accidents
SPSS	-Statistical Packages for Social Sciences
WHO	-World Health Organization

CHAPTER I

INTRODUCTION

1.1 Rationale of the Study

Everyday a lot of people are killed by road traffic accidents all over the world. Road traffic accidents may be defines as human tragedy, associated with major health problems, negative socioeconomic growth, and poverty. Road accidents claim the largest toll of human life and it is one of the problems faced by modern societies of the world today. Worldwide, the number of people killed in road traffic accidents each year is estimated at almost 1.2 million while the number of people injured could be as high as 50 million according to the World Health Organization (WHO, 2004).

Globally, road traffic crashes are a leading cause of death among young people, and the main cause of death among aged 15-29 years (WHO, 2005). From a young age, males are more likely to be involved in road traffic crashes than females. About three quarters (73%) of all road traffic deaths occur among young males under the age of 25 years who are almost three times as likely to be killed in a road traffic crash as young females. Road traffic injuries are estimated to be the ninth leading cause of death across all aged groups globally, and are predicted to become the third leading cause of death by 2020 and the number of traffic deaths will increase up to 2.4 million in 2030.

Traffic accidents can be caused by a number of factors, including equipment malfunction as well as the actions of the driver, such as speeding or aggressive behaviors like tailgating or drinking driving or unsafe lane changes. The consequences of traffic accidents depends on variables such as the impact, number of vehicles involved and if vehicle occupants were protected by safety belts and air bags.

Road traffic injuries are a growing public health issue, affecting vulnerable groups of road users, including the poor. Not only more than half the people killed in traffic crashes are young adults aged between 15 and 44 years who are breadwinners in a family but also millions of people each year will spend long weeks in hospital after severe crashes and many will never be able to live, work or play as they used to do. Millions of others sustain injuries, with some suffering permanent disabilities.

Apart from humanitarian aspect of the problem, traffic accidents and injuries cause considerable economic losses to individuals, families, and to nations as a whole. These losses arise from the cost of treatment as well as lost productivity for those killed or disabled by their injuries, and for family members who need to take time off work or school to care for the injured. Road traffic crashes cost most countries 3% of their gross domestic product. These cost include both loss of income and the burden placed on families to care of their injured relatives. Therefore, road traffic crashes are prone to be major socio-economic problem in the world.

From an environmental perspective, gas and fluid leaks from automobile accidents can affect the environment. They emit harmful chemicals into the environment that can poison grass and neighboring plants and harm wildlife. Worldwide, nighty three percent of road accidents deaths occurred in low and middle income countries, where the majority of causalities were pedestrians, cyclists and riders of motorized two-wheelers. Although more than a quarter of all road traffic deaths occur in South-East Asia, Africa has the highest road traffic death rate 26.6 per 100,000 inhabitants. In Asia-Pacific region, one person is being killed on the road in every forty seconds (Wikipedia).

Road accidents and injuries are now growing and become serious problem in Myanmar which is ranked eightieth highest in the rate of road accidents among 193 countries of the world. In Myanmar, the numbers of deaths related to road accident have increased since 2013, and road accidents result by the Myanmar Traffic Police Force recorded 17,451 traffic accidents in 2018, resulting in 5184 fatalities and more than 26,000 injuries. Yangon recorded the most accidents with 2700 reported, followed by Mandalay (2200 traffic accidents), Ayeyarwady (2033 traffic accidents) and the rest in other states and regions. According to the Myanmar Traffic Police Force, reckless driving, speeding, substandard vehicle safety, and inclement weather are to blame for most such road accidents.

Motorcycle crashes are particularly frequent in Myanmar has the second highest death toll of road accidents in Southeast Asia, according to the Myanmar Organization for Road Safety, who quoted a WHO study. But the absolute level of fatalities is not yet as high as in other Southeast Asian countries, this is mainly because Myanmar's motorization rates are low. One-third of all injuries reported by hospitals are from traffic accidents. Each year as reported to police, more than 4800 individuals lose their lives in road traffic accidents in Myanmar and many more sustain disabling injuries. The annual cost of road accidents to Myanmar's economy is estimated at $800 million for 2013, or some 1.5% of gross domestic product (GDP).

In fifteen States and Regions, Yangon, commercial city of Myanmar, stands as highest rate of road traffic accidents in Myanmar. While Yangon Region has the highest traffic accident rate in the country, other regions also suffer traffic woes, particularly Bago, Mandalay and Sagaing. In 2018, traffic police recorded 398 deaths in Yangon Region. If the rate continues to accelerate, the death toll for 2019 is likely to exceed the total deaths recorded in 2018. Therefore, this study intends to the situation of road traffic accidents and to find out the major causes of road traffic accidents which may lead to kills and injuries in Yangon.

1.2 Objectives of the Study

The main objectives of the study are as follows:

i. To describe and interpret the situation of road traffic accidents in Yangon
ii. To investigate the model of road accidents fatality and injury in Yangon using Poisson regression and to validate the models with negative binomial regression
iii. To forecast road accidents fatality and injury in Yangon for 2019

1.3 Scope and Limitation of the Study

This study examines the condition of road traffic accidents in Yangon (Municipal Area) over the period covering from 2014 to 2018. The daily data extracted from No (2) Office of Traffic Police (Yangon) has been used as secondary data.

1.4 Method of Study

In this study, the data is combined both quantitative and categorical data for the analysis. Poisson regression and negative binomial regression are used for the analysis of the number of people who were killed and injured by road traffic accident in Yangon. Then, time series analysis is used for the forecasting in this study.

1.5 Organization of the Study

This study is organized into five chapters. Chapter I is introduction which is comprised of five sub-headings: rationale of the study, objectives of the study, scope and limitation of the study, method of study and organization of the study. Chapter II is overview of road traffic accidents which presents state of road accidents, causes of road accidents and present situations of road traffic accidents in Yangon. Chapter III discusses the theoretical concepts of not only Poisson and negative binomial regression but also time series analysis and Chapter IV presents the analysis of road traffic accidents in Yangon and Chapter V deals with findings and conclusions.

CHAPTER II

LITERATURE REVIEW

2.1 State of Road Traffic Accidents

Road Traffic Accident (RTA) is one of the varieties of transportation injuries (Road, Rail and Air). It is also a major neglected public health problem in developing countries. The road traffic mortality is only a top of the iceberg of the total losses of human and social resources from traffic crashes. Even in small injuries from road accidents, people have to spend lots of medical fee mostly from their own income and family's money. Currently, both developing and developed countries are focusing on traffic accident reduction as a first priority because millions of people die each year in traffic accidents. The annual cost of road accidents to Myanmar's economy is estimated at $800 million for 2013, or some 1.5% of gross domestic products.

According to Myanmar National Traffic Safety Council Committee, approximately 11.6 people are killed in automobile crashes each day. The World Health Organization ranks Myanmar as the second worst country in Southeast Asia for traffic related deaths. It can be understand that the road safety situation in Myanmar is very important. The absolute level of fatalities is not yet as high as in other Southeast Asian countries, but this is mainly because Myanmar's motorization rates are low. A convenient transportation system is important in Myanmar for the movement of people and goods. In Myanmar, the numbers of deaths related to road accident have increased since 2013, and road accidents result in the death of 11 people per day on average in 2015(World Health Organization (WHO), 2015).

Road traffic accident was defined as an accident which took place on the road between two or more objects, one of which must be any kind of moving vehicles (Jha et. al., 2004). Moreover, traffic accidents are a main source of death for individuals of an economically productive age (15-29 years old) (WHO, 2015) and the consecutive cost of traffic accidents places an economic burden on the family members of those involved in traffic accidents (Thwe et al., 2013).Myanmar has second highest road fatality rate in South-East Asia, and reported road traffic deaths are increasing in Myanmar. The proportion of drivers/passengers of 4-wheeled vehicles is higher in Myanmar than in Thailand, Sri Lanka, the Maldives, Indonesia and India, although

Bhutan and Bangladesh have much higher proportions (WHO, 2015).In addition, 70% of road traffic accidents in Yangon, Myanmar's former capital and largest city and economic center (population approximately 5.7 million as of 2013), were caused by buses and private cars. Public transportation accounts for 61% of all transportation in Myanmar and includes buses (49%), taxis (8%), and rail (1%), whereas private transportation is by car (8%), motorcycle (7%) and bicycle (23%) (Kojima et al., 2015).Driver distraction causes 20-50% of accidents, according to statistics from the Network of Employers for Traffic Safety (NETS) (Manjusha et al., 2014). Driving behavior is an important influence on traffic accidents, injuries and fatalities (Abojaradeh et al., 2014).

2.2 Causes of Road Traffic Accidents

A research conducted by Salim and Salimah (2005) also indicated that road accident was the ninth major cause of death in low and middle income countries and predicted that road accident was going to be the third major cause of deaths in these countries by 2020 if the trend of vehicular accident was to be allowed to continue. Developing countries bear a large share of the burden, accounting for 85 percent of annual deaths and 90.0 percent of the disability-adjusted life year. Ayeboo (2009), identified that the numerous accidents on our road networks have been linked to various causes which include over speeding, drink driving, wrong over taking, poor road network and the rickety vehicles which ply on roads.

According to the country report on Road Safety in Cambodia, road accident is caused by human factors (road users), road defects and vehicle defects. It was found in the report that road accident in Cambodia was increased by 50% in five years while the fatality rate was doubled. To reduce the rate of road accident it was suggested that Road accidents Safety Committee was set up, accident data system was established, and accident evaluation policy and driver training measures were to be put in place, Ung Chun (2007). The number of road accidents in Yangon is disturbing. Contributing factors include pedestrians crossing the roads at random and illegal parking on narrow roads that makes them more difficult to negotiate. One of the reasons for road accidents in Myanmar is because most vehicles are designed for driving on the other side of the road. About 90 percent of the cars on the country's roads are second-hand imports from Japan that have right-hand drive.

In Myanmar vehicles drive on the right and the use of right-hand drive vehicles creates a safety hazard. The quality, design and condition of Myanmar's roads are also a factor. Many roads are narrow, two-way thoroughfares and overtaking in a right-hand drive vehicle means that drivers cannot see if the road is clear when they begin the man oeuvre. This is a cause of road accidents every year. In Myanmar, there are elaborating of the common behavior of humans in accident are over speeding, overtaking, driver careless, mechanical failure and so on (Road Safety in Myanmar, 2030).

Road accidents appear to occur regularly at some flash points such as where there are sharp bends, potholes and bad sections of the highways. At such points over speeding drivers usually find it difficult to control their vehicles, which then result to fatal traffic accidents, especially at night (Atubi, 2009). Motor vehicle crashes are the leading cause of dead in adolescents and young adults (Taket 1986; Mohan and Romer 1991; Smith and Barss, 1991; Feachem et al, 1992; Atubi and Onokala 2009) and of the estimated 856,000 road deaths occurring annually worldwide, 74% are in developing countries (World Bank, 1990 and Atubi, 2000).

African and Asian countries, with relatively low vehicle densities, are experiencing substantially higher fatality rates per 10,000 vehicles than the industrialized European and North American States (Jacobs and Sayer 1983, WHO, 1984). Atubi (2010) examined the variation patterns of RTA in Lagos state using data for 32 years (1970-2001) and observed the number and type of vehicles involved in road traffic accidents.

Many researchers have studied and research related to accident study and road safety improvements for a particular place or select stretch in a different manner. Human error has been defined as an inappropriate or undesirable human decision or behavior that reduces, or has the potential of reducing, effectiveness, safety or system performance (Sanders & McCormick, 1992).

Shruthi *et al*. (2013) have conducted a retrospective observational study in the Department of Forensic Medicine and Toxicology, Kempegowda Institute of Medical Sciences, Bangalore from January 2010 to December 2012. Results of this study revealed that, out of 225 autopsied Road Traffic Accidents (RTA) victims, 55.11% victims were between 21-30 years of age, males constituted 78.22% of the total victims, and four wheeler vehicles were involved in 68.44% RTAs. Maximum RTAs occurred during the daytime, between 6 AM to 12 PM. Head injures constituted 30.22% of the total injuries, followed by injuries involving abdomen, thorax and limb. Hemorrhagic shock caused 63.11% of deaths, while head injury caused death in 30.22% of cases.

Singh *et al*. (2013) have done the study on Elucidation of risk factors in survivors of road traffic accidents in North India. This study was conducted from 1 March 2012 to 30 May 2012 at the Trauma Centre of King George's Medical University, Lucknow, India and the questions were asked from survivors of road traffic accidents using a pretested questionnaire after they received pre-medical care. At the end of the study, it was found that severe injuries are more likely to be due to over-speeding of vehicles, not using helmets and seat belts. Another study done in India by Dileep Kumar *et al*. (2013) discuss death due to fatal road traffic accidents.

Singh and Aggarwal (2010) have analyzed the fatal road traffic accidents among young children in Muzaffarnagar. In this study, descriptive statistical analysis was used and it was found that fatal road accidents are a major cause of childhood mortality up to sixteen years of age involving mainly males. Pedestrians and cyclists were the common group injured and majority of the accidents occurred during the winter season.

Heidi (2006) reported that 1.2 million people in the world lose their lives through road accidents every year. This number has rising to 1.3 million people who lose their lives globally every year and between 20 and 50 million people sustain various forms of injuries annually as a result of road accidents.

2.2.1 Drivers' Careless

Drivers are responsible for reducing the effect of personality and work related pressures on their driving; however, decreasing the influence of roadway conditions is the responsibility of road designers. Changing lanes too quickly, speeding well over the limit, and acting aggressive on the roads can lead to horrible accidents. It is important to take your time and remain calm while driving to avoid needless accidents caused by simple carelessness (Jared Staver). All of this depends on policy makers, who should make efforts to provide driver training, improve driver education and enforce traffic rules and regulations.

Driving schools should emphasize driving skills as well as driving behaviors in their training (Da Silva et al., 2014). Matthew et al. (1998) also mention that driver training should instruct trainees in coping strategies to deal safely with driving behaviors and especially with aggression.The majority of motorcyclists or their passenger do not wear helmets while plying the road thus exposing themselves and indeed other road users to road traffic accident (Odugbemi, 2010). The road traffic accidents are not just caused by human error or drivers' negligence (Sheriff, 2009).

2.2.2 Mechanical Failure

The vehicle is important when analyzing the remote causes of a traffic accident. Malfunction of any vehicle parts such as tyres, engines, braking systems, light systems can cause road traffic accidents. The reliability of the vehicle is a function of the condition of vehicle at every time.

Vehicle components and vehicle maintenance are the two main conditions which affect vehicle factors as it relates to causes of road traffic accidents (Eze, 2012). Some other tyre related causes of accidents could be due to one or a combination of overinflated tyres, underinflated tyres, thread of tyres are thoroughly worn out (Sheriff, 2009). If the brakes and tires are good and the suspension well-adjusted, the vehicle is more controllable in an emergency and thus, better equipped to avoid accidents (Odugbemi, 2010).

2.2.3 Over Speeding

Most of the fatal accidents occur due to over speeding. A vehicle moving on high speed will have greater impact during the crash and will cause more injuries. Faster vehicles are more prone to accident than the slower one and the severity of accident will be more in case of faster the severity of accident will be more in case of faster vehicles. Most of the fatal accidents occur due to over speeding. It is a natural psyche of humans to excel. If given a chance man is sure to achieve infinity in speed. But when we are sharing the road with other users we will always remain behind some or other vehicle (Jhtransport.gov.in). Increase in speed multiplies the risk of accident and severity of injury during accident.

Faster vehicles are more prone to accident than the slower one and the severity of accident will also be more in case of faster the severity of accident will also be more in case of faster vehicles. Higher the speed, greater the risk. At high speed the vehicle needs greater distance to stop i.e. braking distance. A slower vehicle comes to halt immediately while faster one takes long way to stop and also skids a long distance due to law of notion. A vehicle moving on high speed will have greater impact during the crash and hence will cause more injuries. The ability to judge the forthcoming events also gets reduced while driving at faster speed which causes error in judgment and finally a crash (jhtransport.gov.in).

In a research conducted in Delhi by Mehta (1968) and Ghosh (1992) found that most people were killed in road accidents which occurred in January but National Crime Record Bureau (2005) reported higher incidence of road accidents with much victims in May and March in India. These varying results from various researchers in different countries indicate that it will be difficult to use what prevail in one country to estimate for another country since conditions associated with road accidents may vary from country to country.

2.2.4 Alcohol Consumption

Consumption of alcohol to celebrate any occasion is common. But when mixed with driving it turns celebration into a misfortune. Alcohol reduces concentration. It decreases reaction time of a human body. Limbs take more to react to the instructions of brain. It hampers vision due to dizziness. Alcohol dampens fear and incite humans to take risks. All these factors while driving cause accidents and many times it proves fatal. For every increase of 0.05 blood alcohol concentration, the risk of accident doubles. Apart from alcohol many drugs, medicines also affect the skills and concentration necessary for driving. Consumption of alcohol to celebrate any occasion is common. Alcohol can reduce concentration and decrease reaction time of human body.

Interestingly, in a study conducted in South Delhi by Kumar et al (2008), it was found out that most fatal accidents occurred on Saturday but in a study at Nepal, the highest number of road accidents occurred on Sunday and the least number on Monday, Jha and Agrawal (2004). Coincidentally, it was found in a study at South Africa that most people died through road accidents which occurred on Saturday (20.8%) followed by Sunday with 17.1% (Injury Mortality Surveillance System, 2005).

2.3 Present Situation of Road Traffic Accidents in Yangon

In Myanmar, the number of deaths due to motor vehicle collision is more than the deaths due to murder (Traffic Rules Enforcement Supervisory Committee). As of today, road accidents in Yangon are major problem in Myanmar because the number of motor vehicles in Yangon is higher than in others. Naturally, the number of injured, deaths, and motor vehicle accident cases are highest in Yangon and Mandalay since there are quite a numbers of motor vehicles in these cities, and these cities are the most densely populated areas. Yangon is the highest road traffic accidents among fifteen States and Regions according to Traffic Rules Enforcement Supervisory Committee. The schedule of injured, deaths and motor vehicle accident cases in States and Divisions for the year 2014 to 2018 is given in Appendix Table (1).

Among fifteen States and Regions Chin State and Kayah State have the low accident cases and death. This is because the road in Chin State are hilly roads and once the vehicle overturned or fell down or land slide, all the persons involved would be dead. This was rarely cases and all the drivers in Chin State knew that facts (Saw Aye Ko Ko, 2002). The most occurrence townships in Yangon of motor vehicle collisions are Hlaingtharyar, Insein, Mayangon and Mingalardon during 2014 and 2018. This is because of smoothness and wideness of highway road, speedy drive by motorists.

2.3.1 Traffic Accidents in Yangon Municipal Area

According to the No (2) Traffic Police Yangon, eighteen years of traffic accidents in Yangon are shown in Figure (2.1).

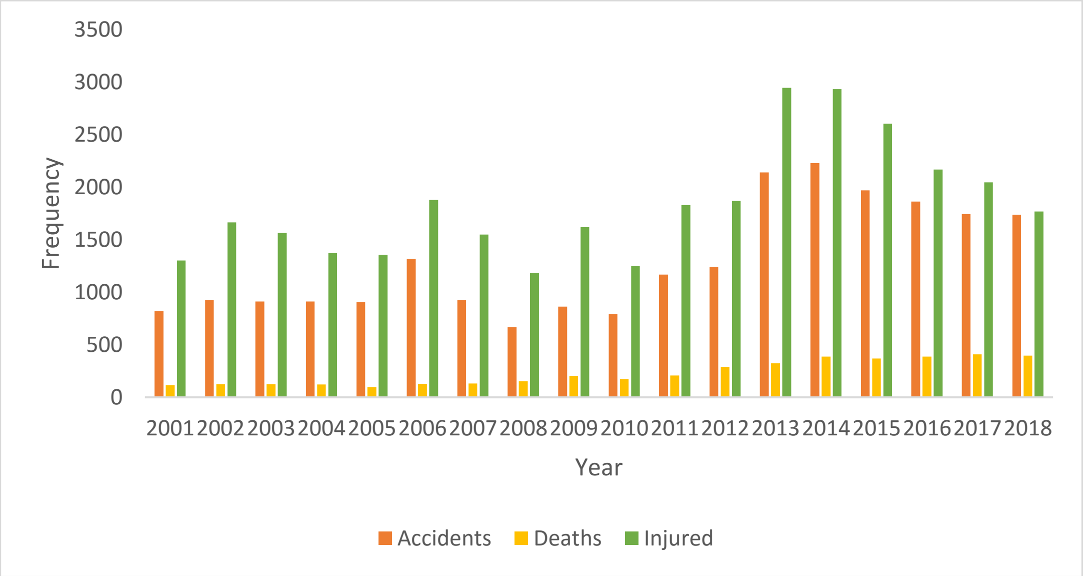


Figure (2.1): List of Road Traffic Accidents in Yangon (Municipal Area) (2001-2018)

Source: No (2) Office of Traffic Police (Yangon)

Figure (2.1) shows as, from 2001 up to 2018, the number of accidents are increasing and also the number of death and injured as well. The highest road traffic accidents happened in 2014, there were 2231traffic accidents, 387 death and 2934 injured persons. But from 2014 to 2018, it was significantly reducing the number of accidents, death and injured persons.

2.3.2 Degree of Fatality by Road Users

Categorizing degree of fatality by road users is shown in Figure (2.2).

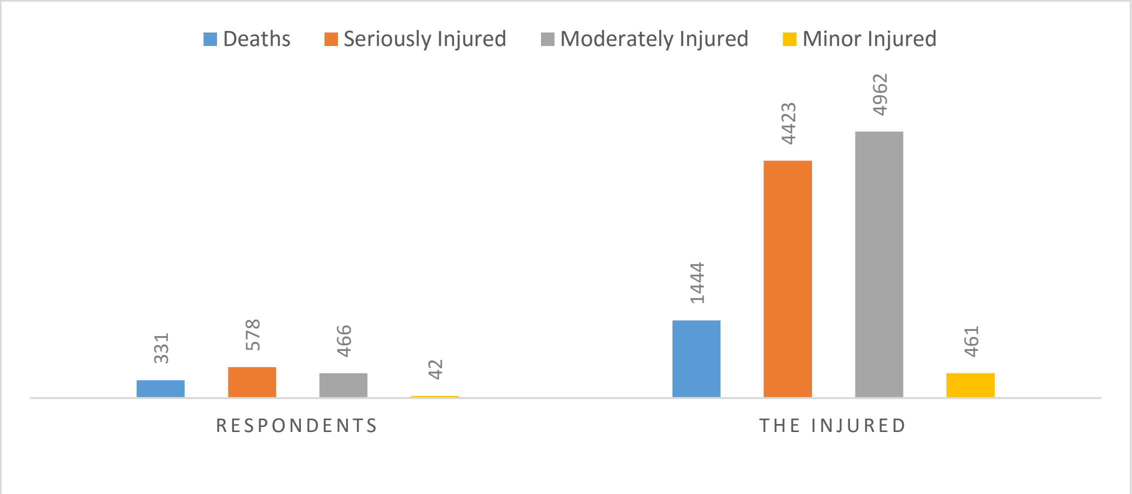


Figure (2.2): Categorizing Degree of Fatality by Road Users (2014-2018)

Source: No (2) Office of Traffic Police (Yangon)

Figure (2.2) shows the degree of fatality for two types of persons which were respondents and injured persons. The respondent was the culprit and the injured person was the victim because of the culprit. During the five year periods, 1444 injured persons and 331 respondents were killed by road accidents. 4423 injured persons and 578 respondents were seriously injured, 4962 injured persons and 466 respondents were moderately injured and 461injured persons and 42 respondents were minor injured by road traffic accidents within five year periods. Moderately injured was one of the degree of fatalities which was mostly occurred in the injured persons whenever road accidents happened during five years periods. On the other hand, one of the degree of fatalities, seriously injured, it was mostly happened in respondents.

2.3.3 Deaths Occurred by Accidents According to Date

The number of deaths involved in accidents according to date is shown in Figure (2.3).

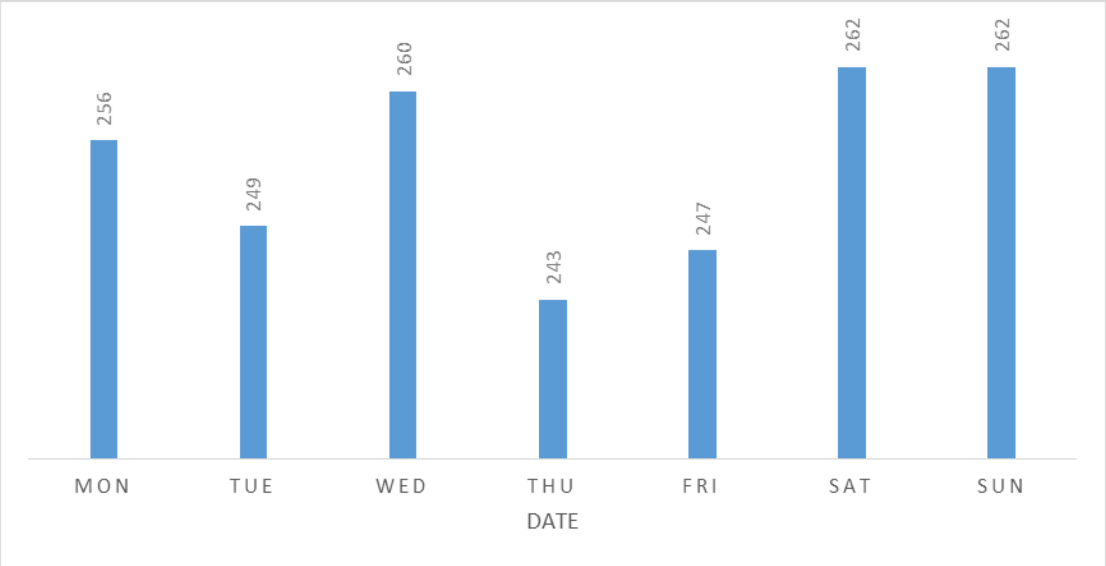


Figure (2.3): Number of People Killed by Accidents (2014-2018)

Source: No (2) Office of Traffic Police (Yangon)

From Figure (2.3), one observes that Saturday and Sunday have the same highest number of people who were killed by road accidents from 2014 to 2018 in Yangon. There were 262 people who were killed by road accidents. This was followed by Wednesday which had 260 people killed by road accidents and Thursday recorded 243 which was the least number of people who were killed in road accident within the five year period. Most fatalities occurred to weekends and among weekdays, most deaths could be seen on Wednesday and Monday.

2.3.4 Accident Types

The number of persons for each accident types is shown in Figure (2.4).

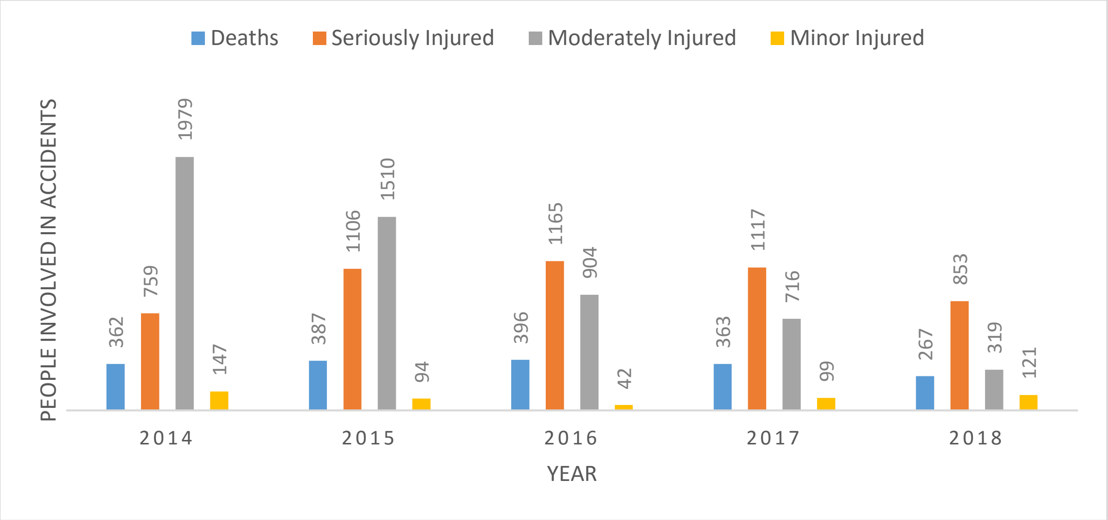


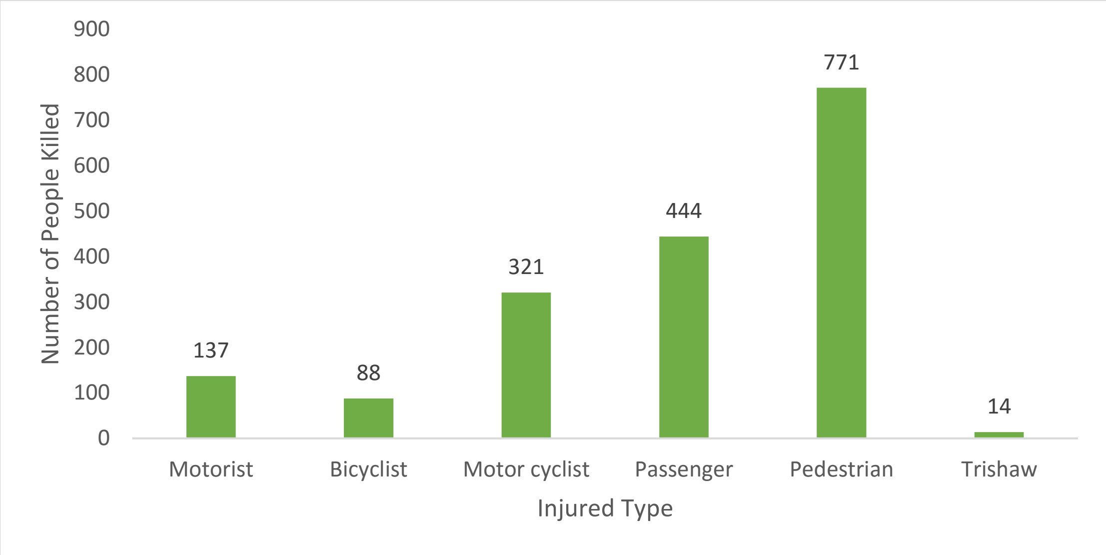
Figure (2.4): Number of Persons Killed and Injured by Road Traffic Accident during the Period of 2014-2018

Source: No (2) Office of Traffic Police (Yangon)

Figure (2.4) shows the number of persons killed and injured by each accidents types over the period from 2014 to 2018. In 2014, 362 people were dead, 759 people were seriously injured, 1979 people were moderately injured and 147 people were minor injured by road traffic accidents. It was highest year during the five year periods. The various kinds of accident types such as deaths, seriously injured, moderately injured and minor injured mostly occurred in 2014 but in 2018, it is obviously decreased.

2.3.5 Road Deaths by Injured Type

Figure (2.5) shows the number of road deaths by injured type from 2014 to 2018.



Figure(2.5): Road Deaths by Injured Type (2014-2018)

Source: No (2) Office of Traffic Police (Yangon)

In Figure (2.5), there were six types of people who were victims of road traffic accidents. They were motorist, bicyclist, motor cyclist, passenger, pedestrian and trishaw users. Among them, 771 pedestrians were recorded as the highest number of people who were killed in road accident. It seems that it is because of the pedestrians crossing the roads at random and illegal parking on narrow roads. Pedestrian who was one of the types of the injured persons mostly occurred in road traffic accidents and trishaw driver who was the lowest kinds of the injured person types in accidents.

CHAPTER III

METHODOLOGY

3.1 Generalized Linear Model

Generalized linear model (GLM) was first introduced by Nelder and Wedderburn (1972). It provided a unified framework to study various regression models, rather than a separate study for each individual regression. Generalized linear model (GLM) is an extension of the classical linear models. It includes linear regression models, analysis of variance models, Logistic regression models, Poisson regression models, Zero-inflated Poisson regression models, Negative Binomial regression models, log-linear models, as well as many other models. The above models share a number of unique properties, such as linearity and a common method for parameter estimation. A generalized linear model consists of three components:

1. A random component, specifying the conditional distribution of the response variable, Y_i, given the explanatory variables.

2. A linear function of the regression variables, called the linear predictor,

$$\eta_i = \alpha + \beta_1 X_{i1} + \cdots + \beta_\kappa X_{ik} = x_i' \beta \qquad (3.1)$$

on which the expected value μ_i of Y_i depends.

3. An invertible link function, $g\ (\mu_i) = \eta_i$

which transforms the expectation of the response to the linear predictor. The inverse of the link function is sometimes called the mean function: $g^{-1}\ (\eta_i) = \mu_i$

For traditional linear models in which the random component consists of the assumption that the response variable follows the Normal distribution, the canonical link function is the identity link. The identity link specifies that the expected mean of the response variable is identical to the linear predictor, rather than to a non-linear function of the linear predictor. The Generalized Linear Model is an extension of the Linear Model to include response variables that follow any probability distribution in the exponential family of distributions. The exponential family includes such useful distributions as the normal, binomial, multinomial, gamma, negative binomial, and others.

3.2 Poisson Distribution

The Poisson distribution (or Poisson law of small numbers) is a discrete probability distribution that expresses the probability of a number of events occurring in a fixed period of time if these events occur with a known average rate and each count occur independently of the time since the last event. The Poisson distribution can also be used for the number of events in other specified intervals such as distance, area or volume.

The Poisson regression model is a technique used to describe count data as a function of a set of predictor variables. In the last two decades it has been extensively used both in human and in veterinary epidemiological studies to investigate the incidence and mortality of chronic diseases. Also Poisson regression has been applied in the analysis of accident data for modelling traffic crashes in different parts of the world. Among its numerous applications, Poisson regression has been mainly applied to compare exposed and unexposed cohorts and to evaluate the causes of road traffic accidents.

The distribution was first introduced by Simeon-Denis Poisson (1781–1840) and published in 1838 in his probability theory. The work focused on certain random variables N that count, among other things, the number of discrete occurrences (sometimes called “arrivals”) that take place during a time-interval of given length, Poisson (1838). If the expected number of occurrences in this interval is λ, then the probability that there are exactly k occurrences (k being a non-negative integer, k = 0, 1, 2, ...) is equal to

$$f\ (k,\lambda) = \frac{\lambda^k e^{-k}}{k!} \tag{3.2}$$

where

• k is the number of occurrences of an event - the probability of which is given by the function $f(k,\lambda)$

• λ is a positive real number, equal to the expected number of occurrences that occur during the given interval.

For instance, if the events occur on average rate of 5 times per minute, and one is interested in probability for k times of events occurring in a 12 minute interval, one would use as the model a Poisson distribution with $\lambda = 12 \times 5 = 60$.

The parameter λ is not only the mean number of occurrences, (k) but also its variance

$$\sigma_k^2 = E(k^2) - (E(k))^2 = \lambda \tag{3.3}$$

Thus, the number of observed occurrences fluctuates about its mean λ with a standard deviation

$$\sigma_k = \sqrt{\lambda} \tag{3.4}$$

As a function of k, this is the discrete probability mass function. The Poisson distribution can be derived as a limiting case of the binomial distribution. The Poisson distribution can be applied to systems with a large number of possible events, each of which is rare. A classic example is the nuclear decay of atoms.The Poisson distribution is sometimes called a Poissonian, analogous to the term Gaussian for a Gauss or normal distribution.

Assumptions of Poisson distribution are:

- Observations are independent.
- Probability of occurrence in a short interval is proportional to the length of the interval.
- Probability of another occurrence in such a short interval is zero.

Poisson distribution belongs to the exponential family as defined by Nelder and Wedderburn (1972).

3.3 Poisson Regression Model

The usual regression model is based on the assumption that the random errors are normally distributed and hence the study variable is normally distributed. In case, the study variable is a dichotomous variable taking only binary values, viz., 0 and 1, then logistic regression is used where study variable follows a Bernoulli distribution. Similarly, the situations where the study variable is a count variable that represents the count of some relatively rare event. For example, the study variable can be a count of patients with some rare type of disease with one or more explanatory variables like age of variables, hemoglobin level, blood sugar etc. In another example, the study variable can be the number of defects in the car engine of a reputed car maker which again depends on one or more explanatory variables.

Assumption of normal or Bernoulli distribution for study variable will not be appropriate in such situations. The Poisson distribution describes such situations more appropriately. So we assume that the study variable y_i is a count variable and follows a Poisson distribution with parameter as $\lambda > 0$ as

$$P(Y_i = y_i) = \frac{e^{-\mu}\mu^y}{y!}, y = 0, 1, 2, \ldots \tag{3.5}$$

The mean and variance of a Poisson random variable are same and related as

$$E(y) = \lambda, Var\ (y) = \lambda \tag{3.6}$$

Based on a sample $y_1, y_2, \ldots, y_n$, we can write

$$E(y_i) = \lambda \tag{3.7}$$

and express the Poisson regression model as

$$y_i = E(y_i) + \varepsilon_i, i = 1, 2, \ldots, n \tag{3.8}$$

where ε_i are disturbance terms.

We can define a link function that relates to the mean of study variable to a linear predictor as

$$\begin{aligned} g(\lambda_i) &= \eta_i \\ &= \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k \\ &= x_i'\beta \end{aligned} \tag{3.9}$$

And

$$\begin{aligned} \lambda_i &= g^{-1}(\eta_i) \\ &= g^{-1}(x_i'\beta) \end{aligned} \tag{3.10}$$

The identity link function is

$$g(\lambda_i) = \lambda_i = x_i'\beta \tag{3.11}$$

The log-link function is

$$g(\lambda_i) = \ln(\lambda_i) = x_i'\beta \tag{3.12}$$

$$\lambda_i = g^{-1}(x_i'\beta) = exp(x_i'\beta) \tag{3.13}$$

In identity link function, the predicted values of y can be negative but in log-link function, the predicted values of y are nonnegative.

3.4 Model Specification

The primary equation of the model is

$$P(Y_i = y_i) = \frac{e^{-\lambda}\lambda^{y_i}}{y_i!},\ y_i = 0, 1, 2, \ldots \tag{3.14}$$

The most common formulation of this model is the log-linear specification as in equation

$$log\ (\lambda_i) = x_i'\ \beta \tag{3.15}$$

The expected number of events per period is given by

$$E\ (y_i\ |x_i) = \lambda_i = e^{\ x_i'}\ \beta \tag{3.16}$$

Thus:

$$\frac{dE(y_i|x_i)}{dx_i} = \beta e^{x_i'\beta} = \beta_i\lambda_i \tag{3.17}$$

The major assumption of Poisson model is

$$E\ (y_i\ |x_i) = \lambda_i = e^{x_i'}\beta = Var\ (y_i\ |x_i) \tag{3.18}$$

This assumption would be tested later on. If $Var\ (y_i\ |x_i) > E\ (y_i\ |x_i)$ then there is over-dispersion. If, $Var\ (y_i\ |x_i) < E\ (y_i\ |x_i)$ then under-dispersion has occurred.

3.5 Negative Binomial Regression Model

The negative binomial is a conjugate mixture distribution for count data. When the Poisson model assumption fails, negative binomial regression model may fit better, and address the over dispersion problem.

The major assumption of the Poisson model is:

$$E\,[y_i|x_i] = [y_i|x_i] \tag{3.19}$$

Implying that the conditional mean function equate the condition variance function. This is very restrictive. If $E\,[y_i|x_i] < Var\,[y_i|\ ]$ then it has over dispersion, and when $E[y_i|x_i] > Var[\ yi|xi\ ]$ it can say it has under dispersion. The Poisson model does not allow for over or under dispersion. Over dispersion might happen when some relevant explanatory variables are not included in the model. A richer model is obtained by using the negative binomial distribution instead of the Poisson distribution.

Instead of equation

$$P\,[Y_i = y_i] = (e^{-\lambda_i}\lambda_i^{y_i})/y_i! \tag{3.20}$$

then use

$$P\,(Y_{i=}\frac{y_i}{\beta}, x_i) = \Gamma(\theta+y_i)/\ \Gamma(\ y_i+1)\ \Gamma\ \theta\ (\lambda_i/\lambda_i+\theta)^{y_i}\,(1-(\lambda_i/\lambda_i+\theta))^{\theta} \tag{3.21}$$

This negative binomial distribution can be shown to have conditional mean λ_i and conditional variance $\lambda_i\ (1 + \eta^2\lambda_i)$ with $\eta^2 := \frac{1}{\theta}$. The parameter η^2 is not allowed to vary over the observations. As before, the conditional mean function is modeled as

$$E\,[y_i|x_i] = \lambda_i = e^{\,x_i'}\,\beta \tag{3.22}$$

The conditional variance function is then given by

$$[y_i|x_i] = e^{\,x_i'}\ \ \beta\,(1 + \eta^2 e^{\,x_i'}\,\beta) \tag{3.33}$$

Using maximum likelihood, it can estimate the regression parameter β, and also the extra parameter η. The parameter η measures the degree of over (or under)dispersion. The limit case $\eta = 0$ corresponds to the Poisson model. If $\eta>0$, the variance will exceed the mean, that is $[y_i|x_i] > E\,[y_i|x_i]$, and the distribution allows for over dispersion (Agresti, 2007).

3.6 Maximum Likelihood Estimation of Parameters

The method of maximum likelihood estimation was used to estimate the parameters of the Poisson regression model. The likelihood function is based on Poisson distribution with parameter λ and then $\beta's$ are estimated through the link function.

The likelihood function of $y_1, y_2, \ldots, y_n$

$$L(y, \lambda) = \prod_{i=1}^{n} p_i(y_i)$$

$$= \prod_{i=1}^{n} \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{y_i!}$$

$$= \frac{(\prod_{i=1}^{n} \lambda_i^{\mu_i})(\exp(-\sum_{i=1}^{n} \lambda_i))}{\prod_{i=1}^{n} y_i\,!}$$

$$lnL(y, \lambda) = \sum_{i=1}^{n} y_i\, ln(\lambda_i) - \sum_{i=1}^{n} \lambda_i - \sum_{i=1}^{n} ln(y_i)! \quad (3.34)$$

The parameter $\lambda_i$can be related to $\beta' s$ through the link function

$$\lambda_i = g^{-1}\,(x_i')\beta \quad (3.35)$$

After choosing the proper link function, the log-likelihood function can be maximized using some numerical optimization techniques for a given set of data. Let $\hat{\beta}$be the obtained maximum likelihood estimator ofβ. Then the fitted Poisson regression model is

$$\hat{y}_i = g^{-1}\,(x_i'\hat{\beta}) \quad (3.36)$$

In case of identity link,

$$\hat{y}_i = g^{-1}\,(x_i'\beta) = x_i'\beta \quad (3.37)$$

In case of log-link,

$$\hat{y}_i = g^{-1}\left(x_i'\hat{\beta}\right) = exp\left(x_i'\hat{\beta}\right) \quad (3.38)$$

3.7 Tests of Hypotheses

Likelihood ratio tests for log-linear models can easily be constructed in terms of deviances. In general, the difference in deviances between two nested models has approximately in large samples a chi-squared distribution with degrees of freedom equal to the difference in the number of parameters between the models, under the assumption that the smaller model is correct. One can also construct Wald tests, based on the fact that the maximum likelihood estimator $\hat{\beta}$ has approximately in large sample a multivariate normal distribution with mean equal to the true parameter value

β and variance-covariance matrix, $var\ (\widehat{\beta}\ ) = X'WX$ where X is the model matrix and W is the diagonal matrix of estimation weights.

3.8 Likelihood Ratio Test

A simple test on the overall fit of the model, as an analogue to the F-test in the classical regression model is a Likelihood Ratio test on the “slopes”. The maximum likelihood estimation method is used to assess the adequacy of any two or more than two nested models by using the likelihood ratio test. It compares the maximum likelihood under the alternative hypothesis with the null hypothesis. For instance, the null hypothesis can be the over dispersion parameter is equal to zero (i.e. the poisson distribution can be fit the data well) and the alternative hypothesis is that the data would be better fitted by the data well) and the alternative hypothesis is that the data would be better fitted by the negative binomial regression (i.e. the over dispersion parameter is different from zero).The likelihood ratio test is defined as:

$$\chi^2 = -2\ (L - L_0) \qquad (3.39)$$

Where L and L_0 are the log likelihood of models under the alternative and null hypotheses. This has a chi square distribution with degree of freedom equal to the difference between the degree of freedom of the model under null hypothesis and the alternative hypothesis, respectively. If this method is not appropriate for models, it can use another method such as Akaike information criteria (AIC) and Bayesian information criterion (BIC) (Jemain, et al, 2007).

3.9 Goodness of Fit Test

In order to assess the adequacy of the Poisson regression model basic descriptive statistics should analyze 1`for the event count data. If the count mean and variance are significantly different (equivalent in a Poisson distribution) then the model is likely to be over-dispersed or under-dispersed. The model analysis option gives a scale parameter (sp) as a measure of over-dispersion; this is equal to the Pearson chi-square statistic divided by the number of observations minus the number of parameters (covariates and intercept).

The variances of the coefficients can be adjusted by multiplying by sp. The goodness of fit test statistics and residuals can be adjusted by dividing by sp. Using a quasi-likelihood approach sp could be integrated with the regression, but this would assume a known fixed value for sp, which is seldom the case. A better approach to over-dispersed Poisson models is to use a parametric alternative model, the negative binomial.

Goodness of fit for a Poisson model is measured using the residual deviance instead of R^2 or the residual standard error used in linear regression. The formula for residual deviance for poisson regression is:

$$Deviance = 2\Sigma_{i=1}^{n} y_i ln \frac{y_i}{\hat{\mu}_i} - (y_i - \hat{\mu}_i) \qquad (3.40)$$

The residual deviance should be as small as possible. For poisson regression, the residual deviance, ideally, will be close to or less than the number of observations minus the number of parameters, or the residual degrees of freedom of the model. If the residual deviance is too much greater than the residual degrees of freedom, the model may not be a good fit and must be modified.

The Pearson chi-square residual is:

$$r_p = \frac{(y_i - \hat{\mu}_i)^2}{\hat{\mu}_i} \qquad (3.41)$$

For large samples the distribution of the deviance is approximately a chi-squared with n–p degrees of freedom, where n is the number of observations and p the number of parameters. Thus, the deviance can be used directly to test the goodness of fit of the model. An alternative measure of goodness of fit is Pearson's chi-squared statistic, which is defined as

The Pearson goodness of fit test statistic is:

$$\chi2 = \Sigma_{i=1}^{n} \frac{y_{i-}\mu_i}{\sqrt{\hat{\mu}_i}} \qquad (3.42)$$

The deviance residual is (Cook and Weisberg, 1982):

$$r_d = sign(y_i - \hat{\mu}_i)\sqrt{deviance(y_i, \hat{\mu}_i)} \qquad (3.43)$$

The Freeman-Tukey, variance stabilized, residual is (Freeman and Tukey, 1950):

$$r_{ft} = \sqrt{y_i} + \sqrt{y_i + 1} - \sqrt{4\hat{\mu}_i + 1} \qquad (3.44)$$

The standardized residual is:

$$r_s = \frac{y_i - \mu_i}{\sqrt{1-h_i}} \tag{3.45}$$

where h is the leverage (diagonal of the Hat matrix).

3.10 Akaike Information Criterion (AIC)

One of the most commonly used information criteria is Akaike Information Criterion (AIC). It is a way of selecting a model from a set of models. The chosen model is the one that minimizes the Kullback-Leibler distance between the model and the truth. It's based on information theory, but a heuristic way to think about it is as a criterion that seeks a model that has a good fit to the truth but few parameters. It is defined as:

$$\text{AIC} = -2\ (\ln\ (\text{likelihood})) + 2\ \text{K} \tag{3.46}$$

where likelihood is the probability of the data given a model and K is the number of free parameters in the model. AIC scores are often shown as ΔAIC scores, or difference between the best model (smallest AIC) and each model (so the best model has a ΔAIC of zero). A model with lower AIC value is preferred.

3.11 Autoregressive Process for Order p, AR (p) Process

The value of Z at time t on its own past values plus a random shock, then the following process is said to be an autoregressive process of order P, which is denoted as AR (p). It is given by

$$\dot{Z}_t = \emptyset_1 \dot{z}_{t-1} + \cdots + \emptyset_p \dot{Z}_{t-p} + a_t$$

$$\emptyset_p(B)\dot{Z}_{t-1} = a_t$$

$$\emptyset_p(B) = (1 - \emptyset_1 B - \cdots - \emptyset_p B^p)$$

The process is always invertible to be stationary, the roots of $\emptyset_p(B) = 0$ must lie outside of the unit circle. The AR process is useful in describing situations in which the present value of a time series depend on its past values plus a random shock.

3.11.1 The Second Order Autoregressive AR (2) Process

Consider the second order autogressive AR (2) process is

$$(1-\emptyset_1 B-\emptyset_2 B^2)\dot{Z}_t \;\; = a_t \tag{3.47}$$

$$\dot{Z}_t = \emptyset_1\dot{Z}_{t-1}+\emptyset_2\dot{Z}_{t-2}+a_t \tag{3.48}$$

The AR (2) process as a finite autoregressive model is always invertible. To be stationary, the roots of $(1-\emptyset_1 B-\emptyset_2 B^2)=0$ must lie outside of the unit circle. The stationarity condition of the AR (2) model can also be expressed terms of its parameter values. Let B_1 and B_2 be roots of $(1-\emptyset_1 B-\emptyset_2 B^2)=0$ (or) equivalently of $\emptyset_2 B^2+\emptyset_1 B-1=0$

$$B_1=\frac{-\emptyset_1+\sqrt{\emptyset_1^2+4\emptyset_2}}{2\emptyset_2}$$

$$B_2=\frac{-\emptyset_1-\sqrt{\emptyset_1^2+4\emptyset_2}}{2\emptyset_2}$$

$$1/_{B_1}=\frac{\emptyset_1+\sqrt{\emptyset_1^2+4\emptyset_2}}{2\emptyset_2}$$

Now,

$$1/_{B_2}=\frac{\emptyset_1-\sqrt{\emptyset_1^2+4\emptyset_2}}{2\emptyset_2}$$

$$\left|\frac{1}{B_1}.\frac{1}{B_2}\right|=|\emptyset_2|<1$$

And

$$\left|\frac{1}{B_1}.\frac{1}{B_2}\right|=|\emptyset_1|<2$$

Whether the roots are real or complex,

$$-1<\emptyset_2<1$$

$$-2<\emptyset_1<2$$

For real roots,

$$\emptyset_1^2 + 4\emptyset_2 \geq 0$$

$$-1 < \frac{1}{B_1} = \frac{\emptyset_1 - \sqrt{\emptyset_1^2 + 4\emptyset_2}}{2} \leq \frac{\emptyset_1 + \sqrt{\emptyset_1^2 + 4\emptyset_2}}{2} = \frac{1}{B_1} < 1$$

(or) equivalently,

$$\begin{cases} \emptyset_2 + \emptyset_1 < 1 \\ \emptyset_2 - \emptyset_1 < 1 \end{cases}$$

For complex roots, $\emptyset_2 < 0$ and $\emptyset_1^2 + 4\emptyset_2 < 0$. .

3.11.2 Autocorrelation Function (ACF) of the AR (2) Process

The autocovariances can be obtained by multiplying $\dot{z}_{t-k}$ on both sides of Equation (3.48) and taking in expectation,

$$E(\dot{Z}_{t-k}\dot{Z}_t) = \emptyset 2E(\dot{Z}_{t-k}\dot{Z}_{t-1}) + \emptyset_2 2E(\dot{Z}_{t-k}\dot{Z}_{t-2}) + \emptyset_1 E(\dot{Z}_{t-k}\dot{Z}a_t)$$

$$\gamma_k = \emptyset_1\gamma_{k-1} + \emptyset_2\gamma_{k-2}; k \geq 1$$

Where, $E(\dot{Z}_{t-k}\dot{Z}a_t) = 0$

By dividing γ_0, the autocorrelation function becomes

$$\rho_k = \emptyset_1\rho_{k-1} + \emptyset_2\rho_{k-2}; k \geq 1 \tag{3.49}$$

$$\rho_1 = \emptyset_1 + \emptyset_2\rho_1; k = 1 \tag{3.50}$$

$$\rho_2 = \emptyset_1\rho_1 + \emptyset_2; k = 2 \tag{3.51}$$

Where

$$\rho_0 = 1$$

Which implies,

$$\rho_1 = \frac{\emptyset_1}{1-\emptyset_2} \tag{3.52}$$

$$\rho_2 = \frac{\emptyset_1^2}{1-\emptyset_2} + \emptyset_2$$

$$\rho_2 = \frac{\emptyset_1^2+\emptyset_2-\emptyset_2^2}{1-\emptyset_2} \tag{3.53}$$

And $\rho_k$for $k \geq 3$ is calculated recursively through Equation (3.49). The pattern of the ACF is governed by the difference Equation (3.49), namely$(1-\emptyset_1 B-\emptyset_2 B^2)\rho_k = 0$. If Z_t^1 and $Z_t^2$are solution of the homogenous equation, then $b_1 Z_t^1 + b_2 Z_t^2$ is also a solution for any arbitrary constant $b_1$and b_2. Then the following as:

$$\rho_k = b_1 \left[\frac{\emptyset_1+\sqrt{\emptyset_1^2+4\emptyset_2}}{2\emptyset_2}\right]^k + b_1 \left[\frac{\emptyset_1-\sqrt{\emptyset_1^2+4\emptyset_2}}{2\emptyset_2}\right]^k \tag{3.54}$$

When the constants $\emptyset_1$ and $\emptyset_2$ can be solved using the initial conditions, it gives (3.52) and (3.53). Thus, the ACF will be an exponential decay if the roots of $(1-\emptyset_1 B-\emptyset_2 B^2)=0$are real and damped sine wave if the roots of $(1-\emptyset_1 B-\emptyset_2 B^2) = 0$ are complex. The AR (2) process is occasionally called the Yule process.

3.11.3 Partial Autocorrelation Function (PACF) of the AR (2) Process

The ACF of the AR (2) process can be expressed as the following system of equations,

$$\rho_k = \emptyset_1 \rho_{k-1} + \emptyset_2 \rho_{k-2} \tag{3.55}$$

By substituting k= 1, 2, 3, . . .

$$\emptyset_{11} = \rho_1 = \frac{\emptyset_1}{1-\emptyset_2}$$

$$\emptyset_{22} = \frac{\begin{vmatrix} 1 & \rho_1 \\ \rho_1 & \rho_2 \end{vmatrix}}{\begin{vmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{vmatrix}} = \frac{\rho_2-\rho_1^2}{1-\rho_1^2}$$

$$\emptyset_{22} = \frac{\left(\frac{\emptyset_1^2+\emptyset_2-\emptyset_2^2}{1-\emptyset_2}\right)-\left(\frac{\emptyset_1}{1-\emptyset_2}\right)^2}{1-\left(\frac{\emptyset_1}{1-\emptyset_2}\right)^2} = \frac{\emptyset_2[(1-\emptyset_2)^2-\emptyset_1^2]}{[(1-\emptyset_2)^2-\emptyset_1^2]} = \emptyset_2$$

$$\emptyset_{33} = \frac{\begin{vmatrix} 1 & \rho_1 & \rho_1 \\ \rho_1 & 1 & \rho_2 \\ \rho_2 & \rho_1 & \rho_3 \end{vmatrix}}{\begin{vmatrix} 1 & \rho_1 & \rho_2 \\ \rho_1 & 1 & \rho_1 \\ \rho_2 & \rho_1 & 1 \end{vmatrix}} = \frac{\begin{vmatrix} 1 & \rho_1 & \emptyset_1 + \emptyset_2\rho_1 \\ \rho_1 & 1 & \emptyset_1\rho_1 + \emptyset_2 \\ \rho_2 & \rho_1 & \emptyset_1\rho_2 + \emptyset_2\rho_1 \end{vmatrix}}{\begin{vmatrix} 1 & \rho_1 & \rho_2 \\ \rho_1 & 1 & \rho_1 \\ \rho_2 & \rho_1 & 1 \end{vmatrix}} = 0$$

$\emptyset_{kk} = 0\ for\ k \geq 3$Hence, the PACF of an AR (2) process cuts off after lag 2.

3.12 Moving Average Process for Order q, MA (q) Process

A time series process Z_t as a linear combination of a sequence of uncorrelated random variables, then the following process is said to be a moving average process or model of order (q) and is denoted as MA (q). It is given by,

$$\dot{Z}_t = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \tag{3.56}$$

$$\dot{Z}_t = \theta(B) a_t \tag{3.57}$$

Where

$$\theta(B) = (1 - \theta_1 B - \cdots - \theta_q B^q)$$

Because$1 + \theta_1 B + \cdots + \theta_q B^q < \infty$, a finite moving average process is always stationary. To be invertible, the roots of $\theta_q(B) = 0$ must lie outside of the unit circle.

3.12.1 The First Order Moving Average MA (1) Process

Consider the first order moving average MA (1) process

$$\dot{Z}_t = a_t - \theta_1 a_{t-1} \tag{3.58}$$

The MA (1) process is always stationary, to be invertible, the roots of $(1 - \theta_1 B) = 0$ must lie outside the unit circle. Because B=$1/\theta_1$, require that $|\theta_1| < 1$ for an invertible MA (1) process.

3.12.2 Autocovariance Function of MA (1) Process

The autocovariance generating function of an MA (1) process is

$$\gamma(B) = \sigma_a^2 \theta(B)\theta(B^{-1}) = \sigma_a^2 (1 - \theta_1 B)(1 - \theta_1 B^{-1})$$

$$\gamma_k = \begin{cases} (1+\theta_1^2)\sigma_a^2; & k=0 \\ -\theta_1\sigma_a^2; & k=1 \\ 0; & k>1 \end{cases}$$

3.12.3 Autocorrelatin Function of MA (1) Process

Dividing γ_k by γ_0 the autocorrelation generating function becomes

$$\rho_k = \begin{cases} 1; k=0 \\ \dfrac{-\theta_1}{1+\theta_1^2}; k=1 \\ 0; k>1 \end{cases}$$

Where $\rho_0 = 1$ which cuts off after lag1.

3.12.4 Partial Autocorrelation Function (PACF) of MA (1) Process

The PACF of the MA (1) process becomes,

$$\emptyset_{11} = \rho_1 = \frac{-\theta_1}{1-\theta_1^2} = \frac{-\theta_1(1-\theta_1^2)}{1-\theta_1^4}$$

$$\emptyset_{22} = \frac{-\theta_1^2}{1+2\theta_1^2+\theta_1^4} = \frac{-\theta_1^3(1-\theta_1^2)}{1-\theta_1^6}$$

$$\emptyset_{33} = \frac{\rho_1^3}{1-2\rho_1^2} = \frac{-\theta_1^3}{1+\theta_1^2+\theta_1^4+\theta_1^6} = \frac{-\theta_1^3(1-\theta_1^2)}{1-\theta_1^8}$$

In general,

$$\emptyset_{kk} = \frac{-\theta_1^2(1-\theta_1^2)}{1-\theta_1^{2(k+1)}} \quad for\ k \geq 1$$

The ACF of an MA (1) process cuts off after lag 1, the PACF of an MA (1) model tails off exponentially in one of two forms depending on the sign of θ_1.

3.13 Steps for Model Identification

Consider the general ARIMA (p, d, q) model

$$(1-\emptyset_1 B - \cdots - \emptyset_p B^p)(1-B)^d Z_t = \theta_0 + (1-\theta_1 B - \cdots - \theta_q B^q)a_t$$

Model identification refers to the methodology in identifying the required transformations such as variance stabilizing transformation and differencing transformations, the decision to include the deterministic parameters $\theta_0$when $d \geq 1$ and the proper order of p and q for the model.

The following useful steps are used to identifying a tentative model.

Step 1. Plot the time series and choose proper transformations. In any time series analysis, the first step is to plot the data. One usually get a good idea about whether the series contains a trend, seasonality, outliers, and non-stationary phenomena. This understanding often provides a basis for postulating a possible data transformation.

In time series analysis, the most commonly used transformations are variance-stabilizing transformations and differencing. Since differencing may create some negative values, one should always apply variance stabilizing transformation before taking differences. A series with non-constant variance often needs a logarithmic transformation. More generally, to stabilize the variance, one can apply Box-Cox's power transformation.

Step 2. Compute and examine the sample ACF and the sample PACF of the original series to further confirm a necessary degree of differencing. Some general rules are:

If the sample ACF decays very slowly and the sample PACF cuts off after lag 1 it indicates that differencing is needed. Try taking the first differencing$(1 - B)\dot{Z}_t$. More generally, to remove non-stationary that one may need to consider a higher order differencing $(1 - B)^d\dot{Z}_t$ for d >1. In most cases, d is 0, 1 or 2. Some authors argue that the consequences of unnecessary differencing are much less serious than those of under differencing.

Step3. Compute and examine the sample ACF and PACF of the properly transformed and differenced series to identify the order p and q, when p is the highest order in AR polynomial $(1 - \emptyset_1 B - \cdots - \emptyset_p B^p)$ and q is the highest order in MA polynomial$(1 - \theta_1 B - \cdots - \theta_q B^q)$.

Note that a strong duality exists between the AR and MA model in terms of their ACFs and PACFs. To build a reasonable ARIMA model, one need a minimum of n=50 observations and the number of sample ACF and PACF to be calculated should be about n/4, although occasionally for data of good quality one may be able to identify an adequate model with a smaller sample ACF and PACF with the theoretical patterns of know models.

Table (3.1)

Characteristics Behavior of ACF, PACF for AR, MA and ARMA Process

	Autocorrelation	**Partial Autocorrelation**
AR (p)	Infinite (damped exponentials and/ or damped sine waves) $\rho_j = \emptyset_1\rho_{j-1} + \emptyset_2\rho_{j-2} + \cdots + \emptyset_p\rho_{j-p}$	Finite Spikes at lag 1 though p, then cut off
MA (q)	Finite Spike at lag 1 though q, and then cut off.	Infinite (dominated by damped exponentials and/or damped sine waves)
ARMA (p, q)	Infinite (damped exponential and/ or damped sine wave after first q- p lags). Irregular pattern at lag 1 through q, then tails off according to $\rho_j = \emptyset_1\rho_{j-1} + \emptyset_2\rho_{j-2} + \cdots + \emptyset_p\rho_{j-p}$	Infinite (dominated by damped exponentials and/ or damped sine waves after first q- p lags). Tail off.

Step 4 Test the deterministic trend θ_0 and when d $\geq$ 0.

For nonstationary model,

$$(\emptyset_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t$$

Where the parameter θ_0 is usually omitted so that it is capable of representing series with random changes in the level slope or trend. However, the differenced series contains a deterministic trend mean, one can test for its inclusion by comparing the sample mean $\overline{W}$ of the differenced series $W_t = (1-B)^d Z_t$ with its approximates standard error $S_{\overline{w}}$

To derive $S_{\overline{w}}$

$$\lim_{n\to\infty} nVar(\bar{W}) = \sum_{j=\infty}^{\infty} \gamma_j$$

$$\sigma_{\bar{W}}^2 = \frac{r_0}{n}\sum_{j=-\infty}^{\infty} \rho_j = \frac{1}{n}\sum_{j=-\infty}^{\infty} \gamma_j = \frac{1}{n} r(1) \qquad (3.59)$$

Where, r (B) is the auto covariance generating function in $r(B) = \sum_{j=-\infty}^{\infty} \gamma_k B^k$ and

r(1) is it value at B =1. Thus, the variance and hence the standard error for $\bar{W}$ is model dependent.

Consider the ARIMA (1, d, 0) model,

$$(1 - \emptyset_1 B)(1 - B)^d Z_t = a_t$$

$$(1 - \emptyset_1 B) W_t = a_t$$

$$W_t = \frac{1}{(1 - \emptyset_1 B)} a_t$$

MA representation,

$$Z_t = \psi(B) a_t$$

$$\psi(B) = \frac{1}{(1 - \emptyset_1 B)}$$

Autocovariance generating function

$$r(B) = \sigma_a^2 \psi(B)\psi(B^{-1})$$

$$= \frac{\sigma_a^2}{(1 - \emptyset_1 B)(1 - \emptyset_1 B^{-1})}$$

When B=1, r (1) =$\frac{\sigma_a^2}{(1-\emptyset_1)^2}$,

$$\sigma_{\bar{W}}^2 = \frac{\sigma_a^2}{n} \frac{1}{(1 - \emptyset_1)^2}$$

$$= \frac{\sigma_W^2}{n} \frac{(1-\emptyset_1^2)}{(1-\emptyset_1)^2}$$

$$= \frac{\sigma_W^2}{n} \frac{(1 + \emptyset_1)}{(1 - \emptyset_1)}$$

$$\sigma_{\bar{W}}^2 = \frac{\sigma_W^2}{n}\frac{(1+\rho_1)}{(1-\rho_1)} \qquad (\because \emptyset_1 = \rho_1) \qquad (3.60)$$

The required standard error is

$$S_{\bar{W}} = \sqrt{\frac{\hat{r}_0(1+\hat{\rho}_1)}{n(1-\hat{\rho}_1)}} \qquad (3.61)$$

Expression of $S_{\bar{W}}$ for other models can be derived similarly. However, at the model identification phase, since the underlying model is unknown, most available software use the approximation.

$$S_{\bar{W}} = [\frac{\hat{r}_0}{n}(1 + 2\hat{\rho}_1 + \cdots + 2\hat{\rho}_k)]^{1/2} \qquad (3.62)$$

Where, $\hat{r}_0$ is sample variance and $\hat{\rho}_1, \hat{\rho}_2, \ldots, \hat{\rho}_k$ are the first k significance sample autocorrelation functions of $[W_t]$.

Under null hypothesis $\rho_k = 0$ for k$\geq$ 1

$$S_{\bar{W}} = \sqrt{\frac{\hat{r}_0}{n}} \qquad (3.63)$$

Alternatively, one can include θ_0 initially and discard it at the final model estimation if the preliminary estimation result is not significant.

3.14 Diagnostic Checking

Time series model building is an iterative procedure. It starts with model identification and parameter estimation. After that, to assess the model adequacy by checking whether the model assumptions are satisfied. The basic assumption is that the $\{a_t\}$ are white noise. The $a_t's$ are uncorrelated random shocks with zero mean and constant variance. For any estimated model, the residual $\hat{a}_t's$ are estimates of the unobserved white noise $a_t's$. Hence, model diagnostic checking is accomplished through a careful analysis of the residual series $\{\hat{a}_t\}$. Because this residual series is the product of parameter estimation, the model diagnostic checking is usually contained in the estimation phase of a time series package.

1. To check whether the errors are normally distributed, one can construct a histogram of the standardized residual $\frac{\hat{a}_t}{\hat{\sigma}_a}$ and compare it with the standard normal distribution using the chi square goodness of fit test.

2. To check whether the variance is constant, one can examine the plot of residuals or evaluate the effect of different λ value via Box-Cox method.

3. To check whether the residuals are white noise, one can compute the sample ACF and PACF (or) IACF of the residuals. This test uses all the residual sample ACF's to check null hypothesis.

ACF and PACF (or) IACF of the residuals. This test uses all the residual sample ACF's to check null hypothesis.

Hypothesis $H_0: \rho_1 = \rho_2 = \ldots = \rho_k = 0$

$H_1: \rho_1 \neq \rho_2 \neq \ldots \neq \rho_k \neq 0$

Test statistics: $Q = n(n+2)\sum_{K=1}^{k}(n-K)^{-1}\,\hat{\rho}_K^2$

Critical value: $K = X_{K-m}^2$

Decision Rule: $Q > K$; Reject H_0

Otherwise; Accept H_0

Where, m= the number of parameter estimated in the model.

Based on the residual results, if the model inadequate, a new model can be easily derived.

CHAPTER IV

AN ANALYSIS OF ROAD TRAFFIC ACCIDENT IN YANGON

4.1 Annual Distribution of People Killed and Injured by Road Accidents in Yangon

According to No (2) Office of Traffic Police (Yangon), there were 9548 road accidents which occurred in Yangon from 2014 to 2018 which killed 1954 people and injured 11523 people. This shows that on the average of 1920 road accidents occurred every year and 391 lives are lost and 2305 lives are damaged because of road accidents. The Table (4.1) below shows the time in years for which accidents that killed and injured people occurred. It presents the total number of people killed and injured in road accident annually from 2014 to 2018.

Table (4.1)

Total Number of People Killed and Injured by Road Accidents (2014-2018)

Year	Total Number of People Killed	Total Number of People Injured
2014	387	2934
2015	371	2604
2016	388	2169
2017	410	2046
2018	398	1770

Source: No (2) Office of Traffic Police (Yangon)

From Table (4.1), it can be seen that the highest number of people killed occurred in 2017 and it followed by 2018 and 2016. The most significant feature of Table (4.1) is that the number of people who were injured by road accidents in Yangon seems to be decreasing as years go by. In 2014, there were 2934 people who were injured in road accidents, this was decreased to 2604 in 2015 and 2169 in 2016. By 2018, the number had decreased in 1770. There were sharp decreases in 2014, 2015, 2015, 2017 and 2018 with the number of who were injured in road accidents being 2934, 2604, 2169, 2046 and 1770 respectively.

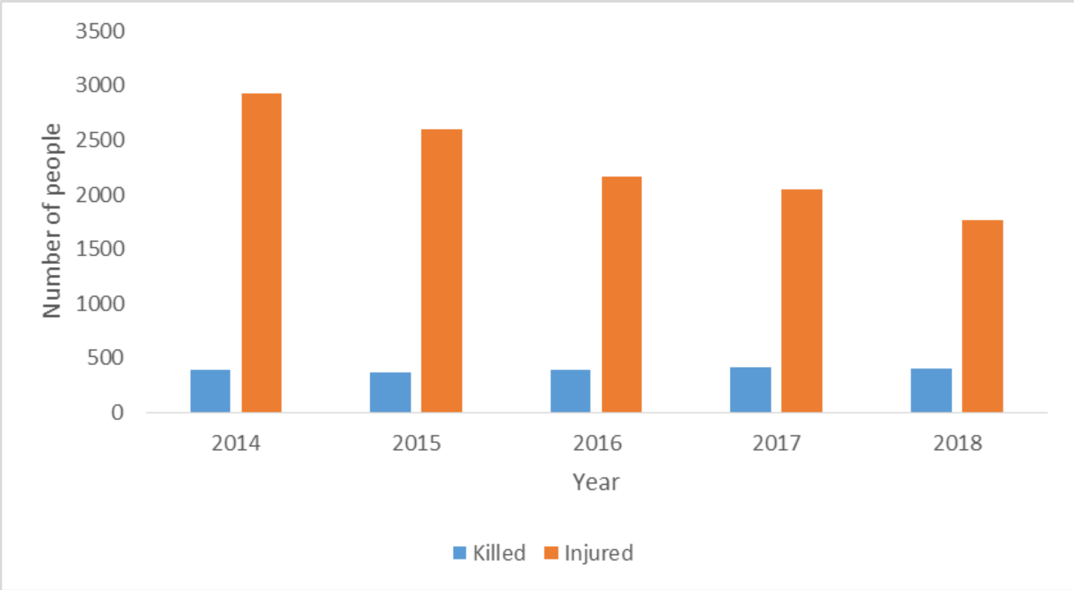


Figure (4.1): The Occurrence of Killed and Injured Persons by Road Accidents (2014-2018)

Source: No (2) Office of Traffic Police (Yangon)

From Figure (4.1), it can be seen that the number of injured people by road accidents in Yangon seems to be significantly decreasing from year to year. But the number of killed people by road accidents in Yangon is not obviously decreasing.

4.2 Type of Vehicle that Killed and Injured People in Road Accidents in Yangon

The type of vehicle involved in road accident cannot be ruled out as a contributory factor to the number of people who are killed in that accident. The type of vehicle involved in the road accident which killed and injured the people, the number of people killed and injured by the type of vehicle, the percentage number of people killed and injured and then average number of people killed and injured by type of vehicle for every year are presented in the Table (4.2) below.

Table (4.2)

Killed and Injured People by Road Accidents through Different Types of Vehicles in Yangon (2014-2018)

Vehicle type	Kill	Injury	Percentage Killed	Percentage Injured	Average Killed	Average Injured
Bicycle/Trishaw	14	29	0.7865	0.2654	2.8	5.8
Bus/Minibus	202	1735	11.3483	15.8781	40.4	347
Car	700	3736	39.3258	34.1905	140	747.2
Container	44	181	2.4719	1.6564	8.8	36.2
Cycle	327	1471	18.3708	13.4621	65.4	294.2
Pickup	95	914	5.3371	8.3646	19	182.8
Taxi	312	2559	17.5281	23.4191	62.4	511.8
Others	86	302	4.8315	2.7638	17.2	60.4

Source: No (2) Office of Traffic Police (Yangon)

From Table (4.2) above, it could be seen that Bicycle/Trishaw and Bus/Minibus killed 14 people and 202 people which constitute 1% and 11.34% of the total number of people killed and injured 29 people and 1735 people which constitute 0.27% and 15.87% of the total number of injured in the same period. The number of people who were killed and injured by car recorded the highest number of people 700 people killed representing 39.33% and 3736 people injured representing 34.19% in road accident. People who were killed and injured by bicycle/trishaw recorded the least number of people killed and injured in five year periods. In road traffic accidents, 86 people and 302 people were killed and injured by other type of vehicles such as truck, van, tawlargyi and so on which constitute 4.83% and 2.76% respectively. The average number of people killed and injured by different types of vehicles in Yangon is as shown in Figure (4.2) below.

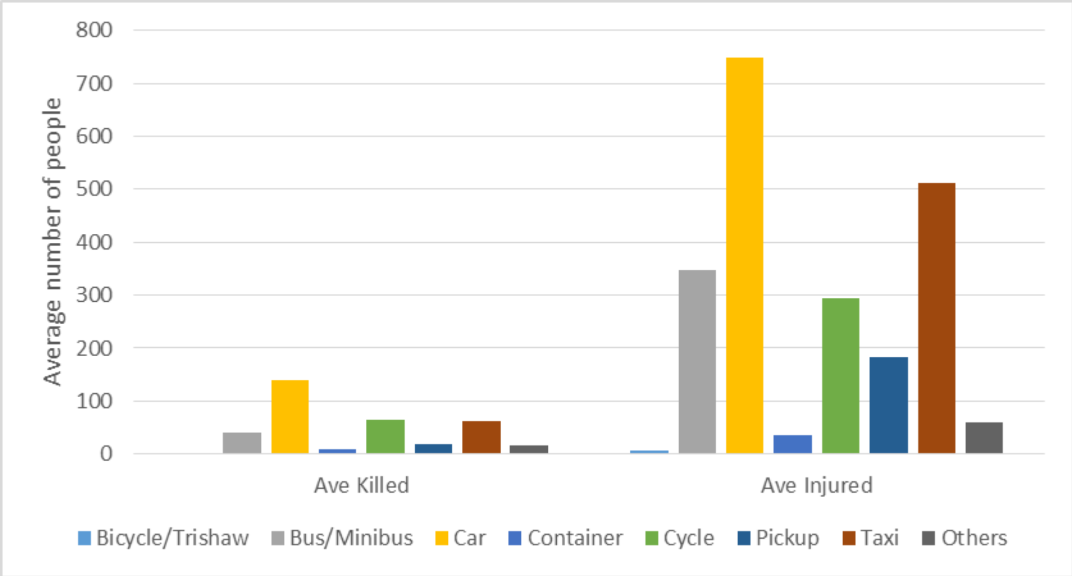


Figure (4.2): Average Number of People Killed and Injured by Different Types of Vehicles in Yangon (2014-2018)

Source: No (2) Office of Traffic Police (Yangon)

From Figure (4.2), people are injured at most by car and taxi. On the other hand, people are mostly killed by car.

4.3 People Who Were Killed and Injured in the Hours of the Day by Road Accidents in Yangon

The number of people who were killed and injured in hours of the day is presented in table from 2014-2018. It also contains the percentage number of people killed and injured in hours for the five year period and the average number of people killed and injured in hours for the five years.

Table (4.3)

Killed and Injured Persons by Crash Causes in Yangon (2014-2018)

Time	Kill	Injury	Percentage Killed	Percentage Injury	Average Killed	Average Injury
0:00-4:00	351	1583	19.7746	14.4817	70.2	316.6
4:01-8:00	237	1393	13.3521	12.7436	47.4	278.6
8:01-12:00	170	1504	9.5775	13.7590	34	300.8
12:01-16:00	186	1373	10.4789	12.5606	37.2	274.6
16:01-20:00	307	2205	17.2958	20.1719	61.4	441
20:01-24:00	524	2873	29.5211	26.2830	104.8	574.6

Source: No (2) Office of Traffic Police (Yangon)

From the Table (4.3), one observes that 20:01-24:00 has the highest number of people who were both killed and injured by road accidents from 2014 to 2018 in Yangon. There were 524 people which constitute 29.52% of the total number of killed by road accidents. It also contains 2873 people for 29.52% of the total number of injured by road accidents. It was followed by 16:01-20:00 for killed and 0:00-4:00 for injured which had 307 people involving 17.31% of those killed and 1583 people including 14.48% of injured by road accidents.8:01-12:00 recorded 170 which was the least number of people who were killed and 12:01-16:00 recorded 1373 which was the least number of people who were injured in road accident. Average number of people who were killed and injured by road accident for the hours of the day shows in Figure (4.3).

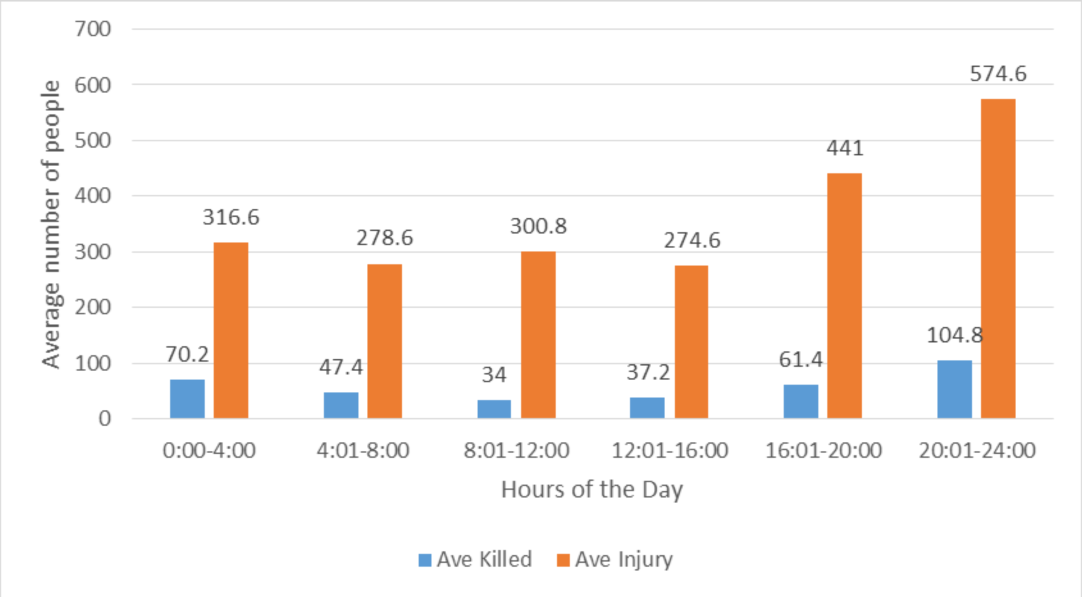


Figure (4.3): Average Number of People Killed and Injured by Road Accident for the Hours of the Day

Source: No (2) Office of Traffic Police (Yangon)

Figure (4.3) shows that during 8 pm to 12 pm, there are frequent fatal road accidents. On the other hand, fatal road accidents are mostly occurred at night.

4.4 Killed and Injured Persons by Collision Type in Yangon

The various kinds of collision which killed and injured the people, the number of people killed and injured by different type of collision, the percentage number of people killed and injured and the average number of people killed and injured by different type of collision for every year are presented in the Table (4.4).

Table (4.4)

Killed and Injured Persons by Collision Type in Yangon (2014-2018)

Collision Type	Kill	Injury	Percentage Killed	Percentage Injured	Average Killed	Average Injured
Collision with fixed object	144	917	8.0944	8.3921	28.8	183.4
Head on	271	2384	15.2333	21.8175	54.2	476.8
Out of control	416	2628	23.3839	24.0505	83.2	525.6
Pedestrian hit	516	1727	29.0051	15.8049	103.2	345.4
Rea rend	254	1586	14.2777	14.5145	50.8	317.2
Right angle	47	664	2.6419	6.0767	9.4	132.8
Sideswipe	131	1021	7.3637	9.3438	26.2	204.2

Source: No (2) Office of Traffic Police (Yangon)

From the Table (4.4), one observes that because of pedestrian hit and out of control, the highest number of people who were killed and injured by road accidents from 2014 to 2018 in Yangon. Pedestrian hit which killed 516 representing 29% of those who were killed by road accidents. Out of control was the second on the list of collision type which killed most people in accidents with 416 people who were killed for five year period. Out of control which injured 2628 people representing 24.05% of those who were injured by road accidents. The average number of people killed and injured by different type of collision in Yangon is as shown in Figure (4.4) below.

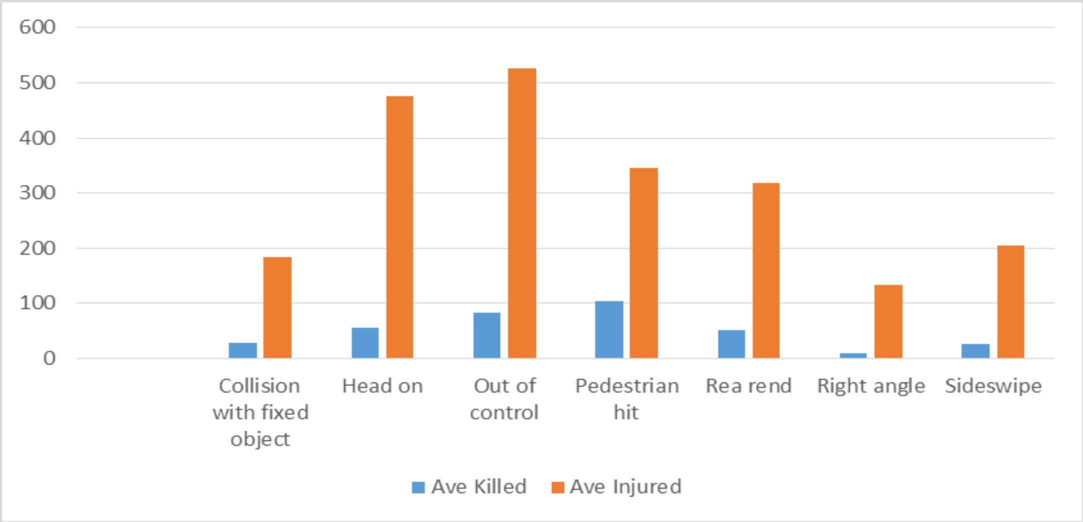


Figure (4.4): Average Number of People Killed and Injured by Collision Types in Yangon (2014-2018)

Source: No (2) Office of Traffic Police (Yangon)

Figure (4.4) shows that the types of collision such as rear end, right angle, sideswipe, pedestrian hit and etc. Among them, out of control, head on and pedestrian hit are the main types of collision when the road traffic accidents happened.

4.5 Killed and Injured Persons by Crash Causes in Yangon

Crash cause involved as a main point in road accident. Because mostly, road accident was happened by it such as driver fault, over speeding, pedestrian fault and so on. The various kinds of crash causes which killed and injured the people, the number of people killed and injured by crash cause, the percentage number of people killed and injured and the average number of people killed and injured by crash cause for every year are presented in the Table (4.5).

Table (4.5)

Killed and Injured Persons by Crash Causes in Yangon (2014-2018)

Crash Causes	Kill	Injury	Percentage Killed	Percentage Injured	Average Killed	Average Injured
Alcohol consumption	1	6	0.0562	0.0549	0.2	1.2
Driver fault	1136	8063	63.8561	73.7897	227.2	1612.6
Mechanical failure	2	9	0.1124	0.0824	0.4	1.8
Over speeding	441	2231	24.7892	20.4173	88.2	446.2
Over taking	9	106	0.5059	0.9701	1.8	21.2
Passenger fault	24	46	1.3491	0.4211	4.8	9.2
Pedestrian fault	166	466	9.3311	4.2647	33.2	93.2

Source: No (2) Office of Traffic Police (Yangon)

From Table (4.5), it could be seen that only 1 person was killed by alcohol consumption, 2 persons were killed by mechanical failure and 9 persons were killed by over taking from 2014 to 2018 which constitute 0.1%, 0.11%, 0.51% of the total number of people killed via road accident in the same period. Driver fault which killed 1136 representing 73.79% of those who were killed by road accidents. Over speeding was the second on the list of crash cause which killed most people in accidents with 441 people who were killed for five year period. This figure represents 24.79% of the total deaths through road accidents in Yangon from 2014 to 2018. 166 people were killed because of pedestrian fault which represents 9.33% of the total deaths.

For injured persons, there were 6 persons were injured by alcohol consumption, 9 persons were injured by mechanical failure, 106 persons were injured by overtaking and 46 persons were injured by passenger fault which include 0.05%, 0.08%, 1%, 0.42% of the total number of people injured by road accident in the same period. 8063 persons were injured because of driver fault and which involve 73.79% of the total injured persons. Over speeding follows as a second in the list of crash cause which consist of 2231injured persons representing 20.42% of those who were injured by road accidents. Because of pedestrian fault, 4.26% out of total 466 persons were injured. The average number of people killed and injured by crash causes in Yangon are shown in the Figure (4.5) below.

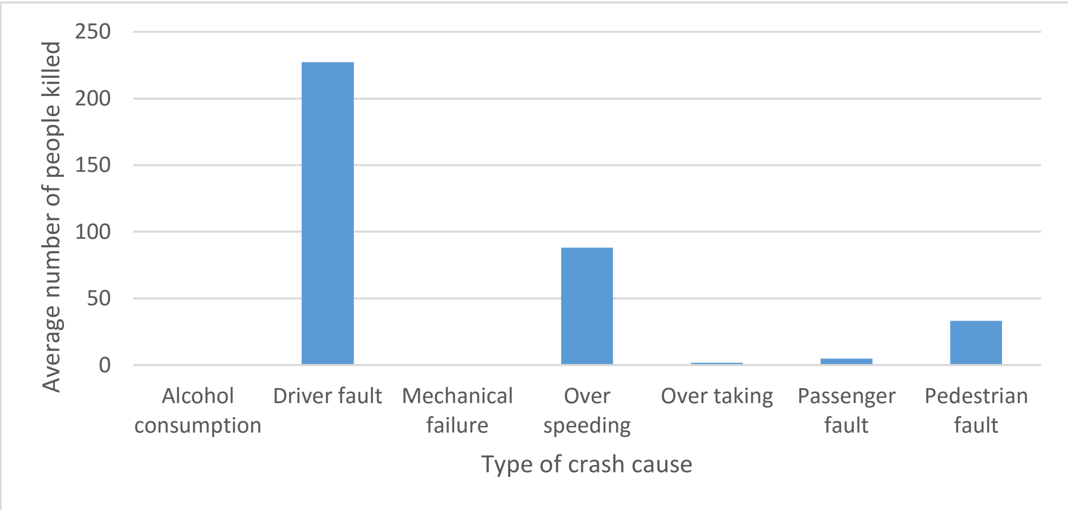


Figure (4.5): Average Number of People Killed by Different Types of Crash Cause in Yangon (2014-2018)

Source: No (2) Office of Traffic Police (Yangon)

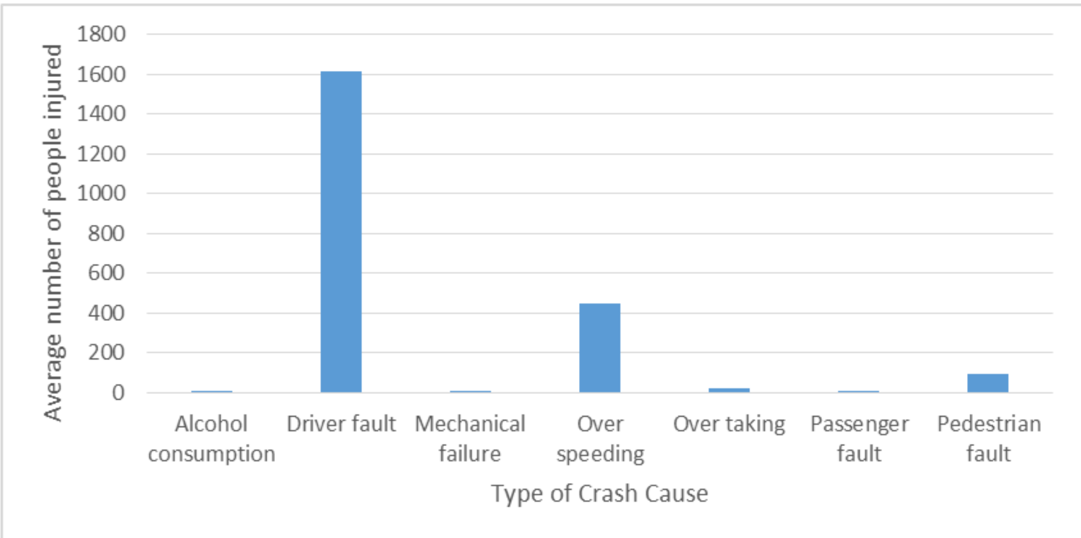


Figure (4.6): Average Number of People Injured by Different Types of Crash Cause in Yangon (2014-2018)

Source: No (2) Office of Traffic Police (Yangon)

Figure (4.5) and Figure (4.6) show clearly that driver fault, over speeding and pedestrian fault are the three major killers of road accidents in Yangon. This remind that it should held more road safety awareness campaigns in Yangon and give strict instructions.

4.6 Modeling the Number of People Killed and Injured by Road Accidents in Yangon

In order to model the number of people who are killed and injured by road accidents in Yangon, the Generalized Linear Model (glm) procedure with Poisson as the main distribution specified using the Log link function. The Negative Binomial distribution was used the error of over dispersion in the data in situations where the result of the Poisson regression model shows over dispersion. The number of people killed and injured by road accidents were regressed on crash causes are presented.

4.6.1 Crash Causes Involved in the Accident that Killed the People

The number of people killed in road accidents by different type of crash causes was modeled using poisson regression the results are presented below. Let α be the intercept for the model and β_i and β_j denote the estimates of the independent variables for i=1, 2,.., 5 and j=1, 2, …, 7 representing time in years and type of crash cause. The poission regression model is,

$$\text{Log (Killed)} = \alpha + \beta_i \text{ Year} + \beta_j \text{ Crash Cause} \quad i=1, 2,\ldots, 5 \text{ and } j=1, 2,\ldots,7$$

Table (4.6)

Parameter Estimates of Poisson Model for the Number of People Killed by Crash Cause in Road Accident in Yangon (2014-2018)

Parameter	**Estimate**	**Std. Error**	**Sig**
(Intercept)	-1.346	1.0010	0.179
Year2018	-0.291	0.0807	0.000
Year2017	0.003	0.0742	0.970
Year2016	0.089	0.0727	0.221
Year2015	0.072	0.0730	0.325
Crashcause.group7	4.865	1.0031	0.000
Crashcause.group6	3.096	1.0208	0.002
Crashcause.group5	1.951	1.0542	0.064
Crashcause.group4	5.843	1.0012	0.000
Crashcause.group3	1.028	1.2249	0.401
Crashcause.group2	6.789	1.0005	0.000

Source: SPSS Output

The Table (4.6) presents the parameter estimates of the model for the number of people who were killed by different type of crash cause in road accidents. The AIC of this model was 240.131and residual deviance of 94.954 on 20 degree of freedom following the chi-square distribution with one degree of freedom. The dispersion parameter 4.748 which is far greater than 1 was found. The assumption of equal variance to the mean in Poisson distribution has been violated since dispersion parameter is not approximately equal to 1. The parameter of the model have been over estimated and the standard errors have been under estimated which will not give a true reflection of model which could provide appropriate mean number of people who will killed by different types of crash cause in road accidents from 2014 to 2018 in Yangon. To address this error, negative binomial regression was used to modify the model for the effect of over dispersion in the data and the parameter estimates are shown in Table (4.7).

Table (4.7)

Parameter Estimates of Negative Binomial Regression Model for Number of People Killed by Crash Cause in Road Accident in Yangon (2014-2018)

Parameter	Estimate	Std. Error	Sig
(Intercept)	-1.569	0.6708	0.032
Year2018	0.230	0.6783	0.580
Year2017	0.194	0.7473	0.622
Year2016	0.283	0.6947	0.469
Year2015	0.642	0.6859	0.116
Crashcause.group7	4.813	1.2159	0.000
Crashcause.group6	2.912	0.6390	0.000
Crashcause.group5	1.896	1.0429	0.014
Crashcause.group4	5.784	0.6451	0.000
Crashcause.group3	0.993	0.7313	0.263
Crashcause.group2	6.747	0.7470	0.000

Source: SPSS Output

From Table (4.7) it is observed that the parameter estimates have reduced and the standard errors have also increased. The parametric analysis for the comparison between the poisson and negative binomial regression for goodness of fit test of the model is shown in Table (4.8).

Table (4.8)

Parametric Comparison between Poisson and Negative Binomial Regression for Goodness of Fit Test

Assessment parameter	**Poisson Regression Model**	**Negative Binomial Regression Model**
Deviance	94.954	9.901
Akaike's Information Criterion (AIC)	240.131	238.294

Source: SPSS Output

It could be observed from Table (4.8) that AIC of the negative binomial regression model is 238.294 which is smaller than that of poisson regression model of AIC 240.131 and indication of better model from the negative binomial regression.

Crashcause.group1 (Alcohol consumption) and the year 2014 were picked as the base levels for comparison in the analysis of the parameter estimates in the negative binomial regression model. The intercept was found to be -1.569 which was significant at 95% level. The exception of Crashcause.group3 (Mechanical Failure) which was not significantly different from the alcohol consumption in the model, the rest of the crash causes were all significantly larger than the base level in the model at 5% alpha level for every year.Crashcause.group2 (Driver fault) was found to have parameter estimate of 6.747 more than the logarithm of the expected number of people who were killed by alcohol consumption for every year. It could also be said from Table (4.8) that the expected number of people who were killed by Crashcause.group4 (Over speeding) was $e^{5.784}$ =325.0568 times more than that of alcohol consumption for every year.

The Table (4.8) further reveals that the expected number of people who were killed by different types of crash cause for the years 2018, 2017, 2016 and 2015 were not statistically different from year 2014 for all types of crash cause in the model giving that the year 2014 is the base level. The model for the above table is presented in below.

Log(killed)=1.569+0.230Year2018+0.194Year2017+0.283Year2016+0.642Year2015 +4.813Crashcause.group7+2.912Crashcause.group6+1.896Crashcause.group5+5.784 Crashcause.group4+0.993Crashcause.group3+6.747Crashcause.group2

Where Crash cause. Group 1, 2, 3, 4, 5, 6 and 7 represent alcohol consumption, driver fault, mechanical failure, over speeding, over taking, passenger fault and pedestrian fault respectively.

4.6.2 Crash Causes Involved in the Accident that Injured the People

The number of people injured in road accidents by different type of crash causes was modeled using poisson regression the results are presented below. Let α be the intercept for the model and β_i and β_j denote the estimates of the independent variables for i=1, 2,.., 5 and j=1, 2, …, 7 representing time in years and type of crash cause. The poission regression model is,

$$\text{Log (injured)} = \alpha + \beta_i \text{ Year} + \beta_j \text{ Crash Cause} \quad i=1, 2,\dots, 5 \text{ and } j=1, 2,\dots,7$$

Table (4.9)

Parameter Estimates of Poisson Model for the Number of People Injured by Crash Cause in Road Accident in Yangon (2014-2018)

Coefficients	Estimate	Std. Error	Sig
Intercept	0.743	0.4085	0.069
Year2018	-0.797	0.0335	0.000
Year2017	-0.401	0.0264	0.000
Year2016	-0.311	0.0286	0.000
Year2015	-0.061	0.0268	0.023
Crashcause7	4.067	0.4109	0.000
Crashcause6	1.878	0.4341	0.000
Crashcause5	2.587	0.4197	0.000
Crashcause4	5.633	0.4088	0.000
Crashcause3	0.702	0.5271	0.183
Crashcause2	6.918	0.4084	0.000

Source: SPSS Output

The Table (4.9) presents the parameter estimates of the model for the number of people who were injured by different type of crash cause in road accidents. The AIC of this model was 622.348 and residual deviance of 428.399 on 20 degree of freedom following the chi-square distribution with one degree of freedom. The dispersion parameter 21.420 which is far greater than 1 was found. The assumption of equal variance to the mean in Poisson distribution has been violated since dispersion parameter is not approximately equal to 1. The parameter of the model have been over estimated and the standard errors have been under estimated which will not give a true reflection of model which could provide appropriate mean number of people who will injured by different types of crash cause in road accidents from 2014 to 2018 in Yangon. To address this error, negative binomial regression was used to modify the model for the effect of over dispersion in the data and the parameter estimates after validating the poisson regression model using negative binomial regression model are shown in Table (4.10).

Table (4.10)

Parameter Estimates of Negative Binomial Model for the Number of People Injured by Crash Cause in Road Accident in Yangon (2014-2018)

Coefficients	Estimate	Std. Error	Sig
Intercept	0.716	0.4000	0.073
Year2018	-0.807	0.3382	0.017
Year2017	-0.420	0.3295	0.203
Year2016	-0.331	0.3324	0.319
Year2015	-0.148	0.3468	0.670
Crashcause7	4.094	0.4452	0.000
Crashcause6	1.896	0.4796	0.000
Crashcause5	2.708	0.4576	0.000
Crashcause4	5.767	0.4476	0.000
Crashcause3	0.713	0.5318	0.180
Crashcause2	6.951	0.4462	0.000

Source: SPSS Output

From Table (4.10) it is observed that the parameter estimates have reduced and the standard errors have also increased. The parametric analysis for the comparison between the poisson and negative binomial regression for goodness of fit test of the model is shown in Table (4.11).

Table (4.11)

Parametric Comparison between Poisson and Negative Binomial Regression for Goodness of Fit Test

Assessment parameter	Poisson Regression Model	Negative Binomial Regression Model
Deviance	428.399	7.9
Akaike's Information Criterion (AIC)	622.348	326.029

Source: SPSS Output

It could be observed from Table (4.11) that AIC of the negative binomial regression model is 326.029 which is smaller than that of poisson regression model of AIC 622.348 and indication of better model from the negative binomial regression.

Crashcause.group1 (Alcohol consumption) and the year 2014 were picked as the base levels for comparison in the analysis of the parameter estimates in the negative binomial regression model. The intercept was found to be 0.716 which was significant at 90% level. The exception of Crashcause.group3 (Mechanical Failure) which was not significantly different from the alcohol consumption in the model, the rest of the crash causes were all significantly larger than the base level in the model at 5% alpha level for every year.Crashcause.group2 (Driver fault) was found to have parameter estimate of 6.951 more than the logarithm of the expected number of people who were injured by alcohol consumption for every year. It could also be said from Table (4.10) that the expected number of people who were injured by Crashcause.group4 (Over speeding) was $e^{5.767}$ =319.5776 times more than that of alcohol consumption for every year.

The Table (4.10) further reveals that the expected number of people who were injured by different types of vehicles for the years 2017, 2016 and 2015 were not statistically different from year 2014 for all types of crash cause in the model giving that the year 2014 is the base level. It was found 2018 had $e^{-0.807}$=0.4462 times less people injured than 2014 for all groups in Yangon. The model for the above table is presented in below.

Log(injured)=0.716-0.807Year2018-0.420Year2017-0.331Year2016-0.148Year2015+4.094Crashcause.group7+1.896Crashcause.group6+2.708Crashcause.group5+5.767Crashcause.group4+0.713Crashcause.group3+6.951Crashcause.group2

Where Crash cause. Group 1, 2, 3, 4, 5, 6 and 7 represent alcohol consumption, driver fault, mechanical failure, over speeding, over taking, passenger fault and pedestrian fault respectively.

4.7 Distribution of People Killed and Injured by Each Townships

In Yangon Division, Yangon is the capital city and the area is under Yangon City Development Committee. Htantapin, Hmawbe, Taikkyee those under northern region and Tanlyin, Kyaultan, Kayan, Thonekwa, Kokmuu, Konkyangone, Tontway, Kokogyun those under southern region which are the rest area of Yangon division apart from Yangon City Development Committee area. The Table (4.12) below shows road accidents that killed and injured people occurred in each townships under YCDC area. It presents the total number of people killed and injured in road accident during five year periods.

Table (4.12)

Kill and Injury Persons in Road Traffic Accidents in Yangon (Township)

Township	Kill	Percent Kill	Injury	Percent Injury
Alon	21	1.1851	199	1.8213
Bahan	17	0.9594	313	2.8647
Botahtaung	12	0.6772	122	1.1166
Dagon	18	1.0158	217	1.9861
Dagonseikkan	76	4.2889	368	3.3681
Dawpon	16	0.9029	243	2.2241
Eastdagon	48	2.7088	212	1.9403
Hlaing	45	2.5395	435	3.9813
Hlaingtharyar	234	13.2054	1099	10.0586

Township	Kill	Percent Kill	Injury	Percent Injury
Insein	150	8.4650	755	6.91012
Kamaryut	31	1.7494	391	3.5786
Kyauktada	4	0.2257	121	1.1075
Kyimyintine	24	1.3544	246	2.2515
Lamadaw	11	0.62077	158	1.4461
Latha	3	0.1693	66	0.6041
Mayangon	101	5.69977	992	9.0793
Mingalardon	342	19.30023	1326	12.1362
Mingalartaungnyunt	28	1.5801	218	1.9952
Notrhdagon	54	3.0474	269	2.4620
Northokkalar	100	5.433	468	4.2834
Pabaedan	5	0.28217	46	0.4210
Pazuntaung	5	0.28217	71	0.6498
Sanchaung	13	0.7336	107	0.9793
Satekan	10	0.5643	47	0.4302
Shwepyithar	75	4.2325	390	3.5694
Southdagon	91	5.1354	394	3.6061
Southokkalar	54	3.0474	251	2.2973
Tamwe	17	0.9594	155	1.4186
Tharkayta	87	4.9097	510	4.6678
Thingangyung	53	2.9910	553	5.0613
Yankin	27	1.5237	184	1.6841

Source: No (2) Office of Traffic Police (Yangon)

From the Table (4.12), it can see that the highest township of people killed and injured in Yangon is Mingalardon Township which constitutes 19.3% for kill people and 12.13% for injury people of the total number of people via road accident. The second was Hlaingtharyar Township which include 13.21% and 10.06% for kill and injury people respectively. It was followed by Insein and Mayangon townships which have 8.47% and 5.71% for kill persons and 6.91% and 9.08% for injury persons of the total number of people in road accidents. The lowest township of people deaths is Latha township and the lowest injury people is occurred in Pabaedan township which have 0.2% and 0.4% of the total number of people killed and injured in road accidents. The percentages of people who were killed and injured by road accidents in each townships shows in Figure (4.7) below.

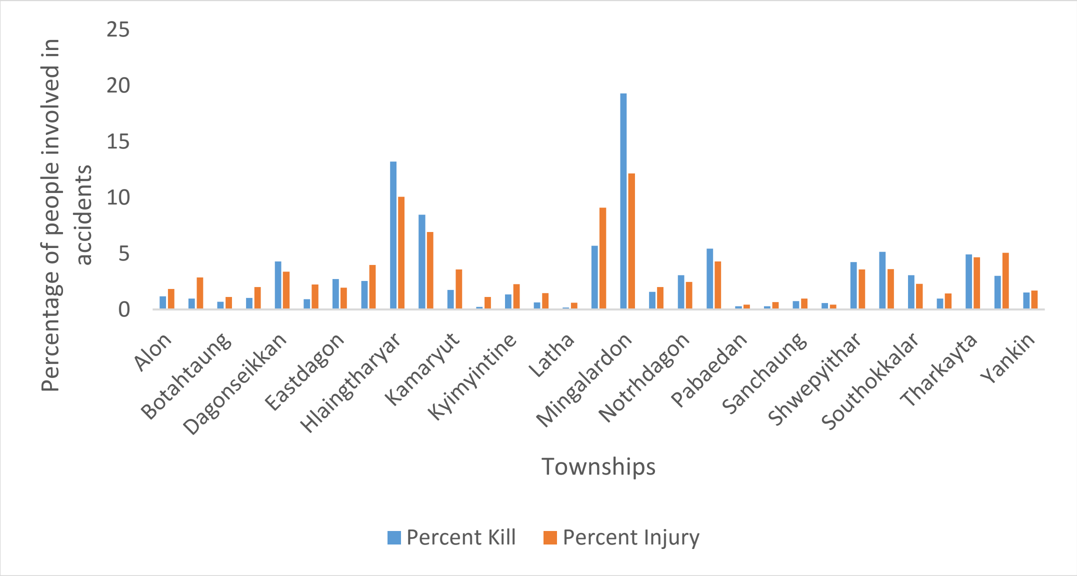


Figure (4.7): Percentages of People Killed and Injured by Each Townships

Source: No (2) Office of Traffic Police (Yangon)

In Figure (4.7), Mingalardon Township is the most highest road accidents township under the municipal area of Yangon and Hlaingtharyar, Mayangon and Insein are second, third and fourth townships.

4.7.1 Crash Causes in Which People Were Killed in Selected Four Townships

The number of people killed in road accidents by different type of crash causes was modeled using poisson regression the results are presented below. The data for selected townships and its crash causes are shown in Appendix. Selected townships involves Hlaingtharyar, Insein, Mayangon and Mingalardon and also most people were killed and injured in each townships in five year periods. Let α be the intercept for the model and β_i and β_j denote the estimates of the independent variables for i=1, 2,.., 4 and j=1, 2, …, 7 representing time in four townships and types of crash cause. The poission regression model is,

$$\text{Log (Killed)} = \alpha + \beta_i \text{ Township} + \beta_j \text{ Crash Cause} \quad i=1, 2,\dots, 4 \text{ and } j=1, 2,\dots,7$$

Table (4.13)

Parameter Estimates of Poisson Model for the Number of People Killed by Crash Cause in Road Accident in Township (2014-2018)

Parameter	Estimate	Std. Error	Sig
(Intercept)	3.307	0.1299	0.000
Township1	-0.378	0.0849	0.000
Township2	-0.826	0.0980	0.000
Township3	-1.222	0.1133	0.000
Crashcause.group1	-3.656	1.0080	0.000
Crashcause.group2	2.079	0.1306	0.000
Crashcause.group3	-3.163	0.7181	0.000
Crashcause.group4	1.204	0.1403	0.000
Crashcause.group5	-3.497	0.7177	0.000
Crashcause.group6	-2.110	0.3744	0.000

Source: SPSS Output

The Table (4.13) presents the parameter estimates of the model for the number of people who were killed by different type of crash cause in road accidents. The AIC of this model was 130.157 and residual deviance of 24.158 on 16 degree of freedom following the chi-square distribution with one degree of freedom. The dispersion parameter 1.51 which is far greater than 1 was found. The assumption of equal variance to the mean in Poisson distribution has been violated since dispersion parameter is not approximately equal to 1. The parameters of the model have been over estimated and the standard errors have been under estimated which will not give a true reflection of model which could provide appropriate mean number of people who were killed by different types of crash cause in road accidents from 2014 to 2018 in Townships. To address this error, negative binomial regression was used to modify the model for the effect of over dispersion in the data and the parameter estimates after validating the poisson regression model using negative binomial regression model are shown in Table (4.14).

Table (4.14)

Parameter Estimates of Negative Binomial Regression Model for Number of People Killed by Crash Cause in Road Accident in Townships (2014-2018)

Parameter	Estimate	Std. Error	Sig
(Intercept)	3.224	0.6255	0.000
Township1	-0.329	0.6955	0.636
Township2	-0.751	0.6761	0.267
Township3	-1.066	0.6709	0.112
Crashcause.group1	-3.728	1.3042	0.004
Crashcause.group2	2.101	0.7255	0.004
Crashcause.group3	-2.975	1.0818	0.006
Crashcause.group4	1.198	0.7281	0.100
Crashcause.group5	-3.531	1.0290	0.001
Crashcause.group6	-1.962	0.8169	0.016

Source: SPSS Output

From Table (4.14) it is observed that the parameter estimates have reduced and the standard errors have also increased. The parametric analysis for the comparison between the poisson and negative binomial regression for goodness of fit test of the model is shown in Table (4.15).

Table (4.15)

Parametric Comparison between Poisson and Negative Binomial Regression for Goodness of Fit Test

Assessment parameter	Poisson Regression Model	Negative Binomial Regression Model
Deviance	24.158	7.701
Akaike's Information Criterion (AIC)	130.057	169.167
Log Likelihood	-55.028	-74.584
Likelihood Ratio Chi-square	1733.5519(0.000)	83.546(0.000)

Source: SPSS Output

It could be observed from Table (4.15) that AIC of the negative binomial regression model is 169.167 which is larger than that of poisson regression model of AIC 130.057. The log-likelihood reported for the negative binomial regression is –74.584. This is actually smaller than the log-likelihood for the Poisson regression, which indicates that this negative binomial regression does not offer an improvement over the Poisson regression.

Crashcause.group7 (Pedestrian fault) and the Township4 (Mingalardon) were picked as the base levels for comparison in the analysis of the parameter estimates in the Poisson regression model. The intercept was found to be 3.307 which was significant at 95% level. Crashcause.group2 (Driver fault) was found to have parameter estimate of 2.079 more than the logarithm of the expected number of people who were killed by pedestrian fault for every year. It could also be said from Table (4.13) that the expected number of people who were killed by Crashcause.group1 (alcohol consumption) was $e^{-3.656}$ =0.0258 times less than that of pedestrian fault for every year. Crashcause.group6 (passenger fault) was $e^{-2.110}$ =0.1212 times less than that of pedestrian fault for every year.

The Table (4.13) further reveals that the expected number of people who were killed by different types of crash cause for Townships (Hlaingtharyar, Insein, Mayangon) were statistically different from Mingalardon for all types of crash cause in the model giving that Mingalardon is the base level. Township3 (Mayangon) was $e^{-1.222}$ = 0.2946 times less than that of Mingalardon for every year. The model for the above table is presented in below.

Log(killed)=3.307-0.378Township1-0.826Township2-1.222Township3-3.656Crashcause.group1+2.079Crashcause.group2-3.163Crashcause.group3+1.204Crashcause.group4-3.497Crashcause.group5-2.110Crashcause.group6

Where Township 1, 2, 3 and 4 represent Hlaingtharyar, Insein, Mayangon and Mingalardonr respectively and Crashcause.group 1, 2, 3, 4, 5, 6 and 7 denote alcohol consumption, driver fault, mechanical failure, over speeding, over taking, passenger fault and pedestrian fault

4.7.2 Crash Causes in Which People Were Injured in Selected Four Townships

The number of people injured in road accidents by different type of crash causes was modeled using poisson regression the results are presented below. Let α be the intercept for the model and β_i and β_j denote the estimates of the independent variables for i=1, 2,.., 4 and j=1, 2, …, 7 representing four townships and types of crash cause. The poission regression model is,

$$\text{Log (Injured)} = \alpha + \beta_i \text{ Township} + \beta_j \text{ Crash Cause} \quad i=1, 2,\ldots, 4 \text{ and } j=1, 2,\ldots,7$$

Table (4.16)

Parameter Estimates of Poisson Model for the Number of People Injured by Crash Cause in Road Accident in Township (2014-2018)

Parameter	Estimate	Std. Error	Sig
(Intercept)	3.789	0.0878	0.000
Township1	-0.188	0.0408	0.000
Township2	-0.565	0.0456	0.000
Township3	-0.293	0.042	0.000
Crashcause.group1	-3.165	0.5073	0.000
Crashcause.group2	3.091	0.0867	0.000
Crashcause.group3	-3.019	0.4553	0.000
Crashcause.group4	1.861	0.0912	0.000
Crashcause.group5	-1.150	0.1730	0.000
Crashcause.group6	-1.602	0.2071	0.000

Source: SPSS Output

The Table (4.16) presents the parameter estimates of the model for the number of people who were injured by different type of crash cause in road accidents. The AIC of this model was 199.430 and residual deviance of 53.954 on 16 degree of freedom following the chi-square distribution with one degree of freedom. The dispersion parameter 3.372 which is far greater than 1 was found. The assumption of equal variance to the mean in Poisson distribution has been violated since dispersion parameter is not approximately equal to 1. The parameters of the model have been over estimated and the standard errors have been under estimated which will not give a true reflection of model which could provide appropriate mean number of people who were killed by different types of crash cause in road accidents from 2014 to 2018 in Townships. To address this error, negative binomial regression was used to modify the model for the effect of over dispersion in the data and Table (4.17) describes the parameter estimates after validating the poisson regression model using negative binomial regression model.

Table (4.17)

Parameter Estimates of Negative Binomial Regression Model for Number of People Injured by Crash Cause in Road Accident in Townships (2014-2018)

Parameter	Estimate	Std. Error	Sig
(Intercept)	4.040	0.6699	0.000
Township1	-0.216	0.6328	0.733
Township2	-0.952	0.6206	0.125
Township3	-0.708	0.6312	0.262
Crashcause.group1	-3.108	0.9275	0.001
Crashcause.group2	3.060	0.7147	0.000
Crashcause.group3	-3.216	0.7554	0.001
Crashcause.group4	1.869	0.7523	0.009
Crashcause.group5	-1.372	1.0290	0.069
Crashcause.group6	-1.724	0.8169	0.022

Source: SPSS Output

From Table (4.17) it is observed that the parameter estimates have reduced and the standard errors have also increased. The parametric analysis for the comparison between the poisson and negative binomial regression for goodness of fit test of the model is shown in Table (4.18).

Table (4.18)

Parametric Comparison between Poisson and Negative Binomial Regression for Goodness of Fit Test

Assessment parameter	**Poisson Regression Model**	**Negative Binomial Regression Model**
Deviance	53.954	5.678
Akaike's Information Criterion (AIC)	199.430	237.768
Log Likelihood	-89.715	-108.884
Likelihood Ratio Chi-square	9382.14(0.000)	98.440(0.000)

Source: SPSS Output

It could be observed from Table (4.18) that AIC of the negative binomial regression model is 237.768 which is larger than that of poisson regression model of AIC 199.430. The log-likelihood reported for the negative binomial regression is – 108.884. This is actually smaller than the log-likelihood for the Poisson regression, which indicates that this negative binomial regression does not offer an improvement over the Poisson regression.

Crashcause.group7 (Pedestrian fault) and the Township4 (Mingalardon) were picked as the base levels for comparison in the analysis of the parameter estimates in the Poisson regression model. The intercept was found to be 3.789 which was significant at 95% level. Crashcause.group2 (Driver fault) was found to have parameter estimate of 3.091 more than the logarithm of the expected number of people who were injured by pedestrian fault for every year. It could also be said from Table (4.16) that the expected number of people who were injured by Crashcause.group1 (alcohol consumption) was $e^{-3.165}$ =0.0422 times less than that of pedestrian fault for every year. Crashcause.group6 (passenger fault) was $e^{-1.602}$ =0.2015times less than that of pedestrian fault for every year.

The Table (4.16) further reveals that the expected number of people who were injured by different types of crash cause for Townships (Hlaingtharyar, Insein, Mayangon) were statistically different from Mingalardon for all types of crash cause in the model giving that Mingalardon is the base level. Township3 (Mayangon) was

$e^{-0.565}$ = 0.5684 times less than that of Mingalardon for every year. The model for the above table is presented in below.

Log(injured)=3.789-0.188Township1-0.565Township2-0.293Township3-3.165Crashcause.group1+3.091Crashcause.group2-3.019Crashcause.group3+1.861Crashcause.group4-1.150Crashcause.group5-1.602Crashcause.group6

Where Township 1, 2, 3 and 4 represent Hlaingtharyar, Insein, Mayangon and Mingalardonr respectively and Crashcause.group 1, 2, 3, 4, 5, 6 and 7 denote alcohol consumption, driver fault, mechanical failure, over speeding, over taking, passenger fault and pedestrian fault.

4.8 Series of People Killed by Road Traffic Accidents in Yangon

The monthly data of number of people killed in Yangon cover 5 years from year 2014 to 2018. The series consist of 60 observations and it was shown in Appendix Table (2). The line graph of this series was shown in Figure (4.8). From this line graph the time series is not likely to have seasonal cycle.

Figure (4.8): Number of People Killed by Road Accident in Yangon (2014-2018) Series

Source: SPSS Output

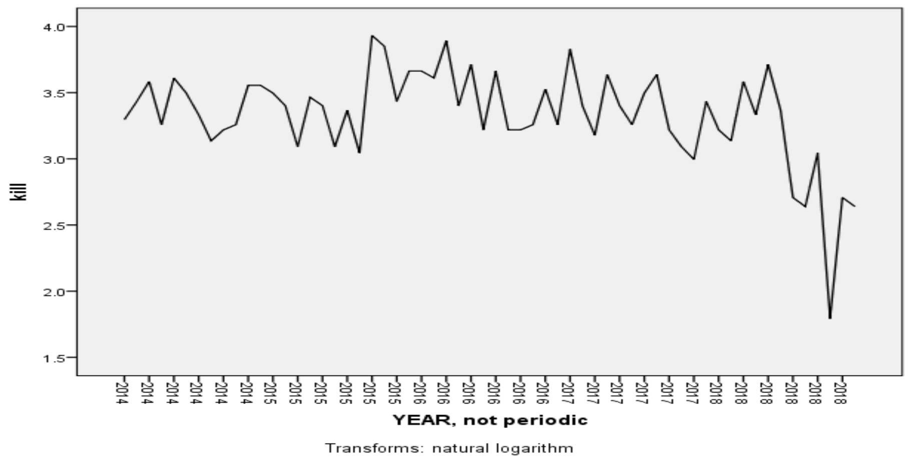


Figure (4.9): Number of People Killed by Road Traffic Accidents in Yangon (2014-2018) Series

Source: SPSS Output

The plot in Figure (4.8) indicates that the series is stationary in mean and non-stationary in the variance. Therefore, log transformation is suggested. In Figure (4.9), after using log transformation, the series shows that it is stationary in both mean and variance.

4.9 Model Identification for Number of People Killed by Road Traffic Accident in Yangon

The autocorrelation function (ACF) and the partial autocorrelation (PACF) are shown in Table (4.19).

Table (4.19)

Estimated Autocorrelation Function and Partial Autocorrelation Function of Number of People Killed in Yangon (2014-2018)

Lag	Autocorrelation	Std. Error	Partial Autocorrelation	Std. Error
1	0.414	0.126	0.414	0.129
2	0.407	0.125	0.284	0.129
3	0.251	0.124	0.017	0.129
4	0.113	0.123	-0.106	0.129
5	0.024	0.122	-0.083	0.129
6	0.010	0.120	0.023	0.129
7	-0.098	0.119	-0.090	0.129
8	0.104	0.118	0.229	0.129
9	0.081	0.117	0.088	0.129
10	0.132	0.116	0.025	0.129
11	0.110	0.115	-0.052	0.129
12	0.022	0.114	-0.137	0.129
13	0.124	0.112	0.155	0.129
14	0.018	0.111	-0.038	0.129
15	-0.21	0.110	-0.016	0.129
16	0.80	0.109	0.129	0.129

Source: SPSS Output

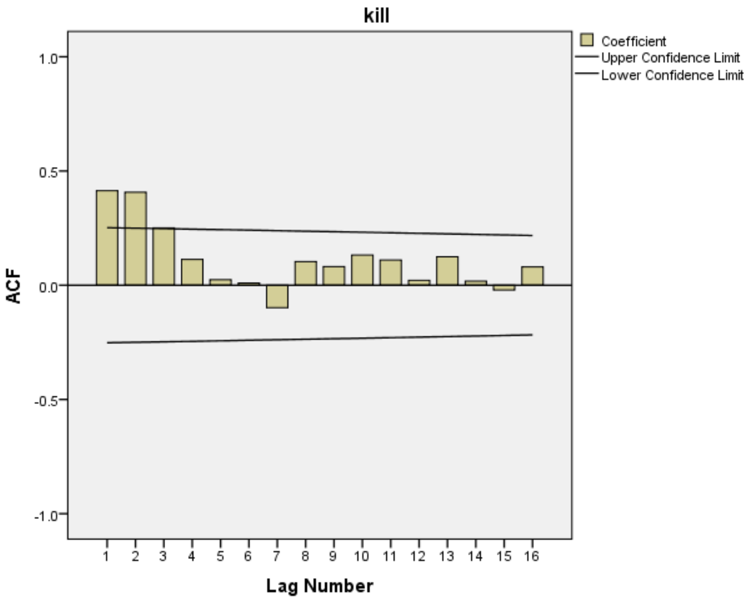


Figure (4.10): Sample Autocorrelation Function for Number of People Killed in Yangon

Source: SPSS Output

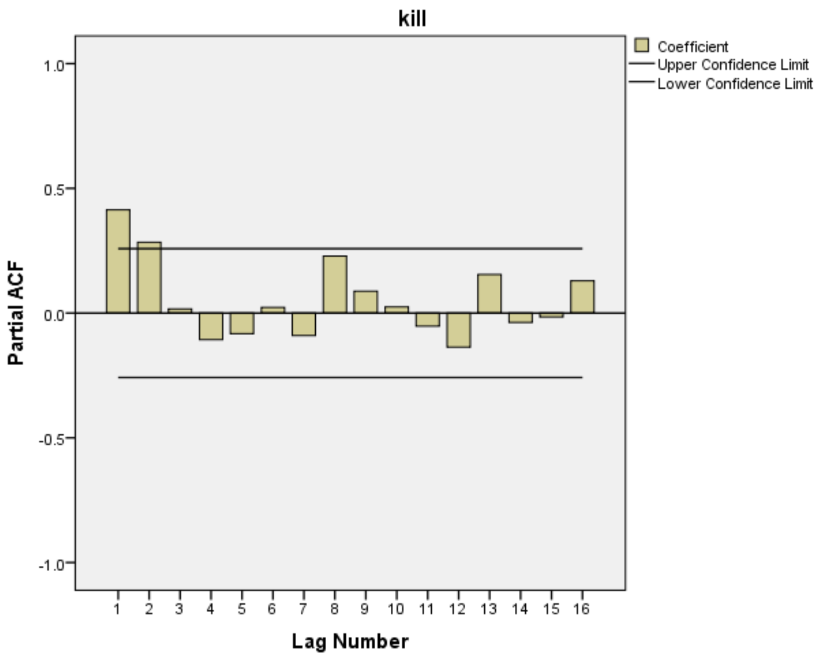


Figure (4.11): Sample Partial Autocorrelation Function for Number of People Killed in Yangon

Source: SPSS Output

Table (4.19), Figure (4.10) and (4.11) show the sample ACF and the sample PACF for the series. After log transformation, ACF tails off and PACF cut off after lag (2). So this model is assumed as AR (2).

4.10 Parameter Estimation of Number of People Killed by Road Traffic Accidents in Yangon

Using ARIMA (2,0,0) model, model statistics was shown in Table (4.20) and the estimated parameter with their statistics were shown in Table(4.21).

Table (4.20)

Model Statistics

Model	**Ljung- Box Q (18)**		
	Statistics	**Df**	**Sig**
Killed ARIMA (0,1,1)	0.268	16	0.552

Source: SPSS Output

Table (4.20) shows that Ljung- Box Q is not statistically significant for ARIMA (2, 0, 0) model.

Table (4.21)

Estimated Parameter for ARIMA (2,0,0) Model of Number of People Killed in Yangon

		Estimate	**S.E**	**t**	**Sig**
Constant		3.308	0.105	31.499	0.000
AR	Lag1	0.310	0.127	2.433	0.018
	Lag2	0.324	0.131	2.465	0.017

Source: SPSS Output

When determining whether deterministic trend is needed, P value less than alpha. So, θ_0 is significant, deterministic trend is needed. The following estimated model was obtained

$$(1 - \emptyset_1 B - \emptyset_2 B^2) LnZ_t = \theta_0 + a_t$$

$(1 - 0.310B - 0.324B^2) lnZ_t = 3.308 + a_t$

(0.127) (0.131) (0.105)

The estimated of the ARIMA(1,0,0) model of number of people killed in road traffic accident give $\emptyset_1$ =0.310 with the estimated standard error 0.127 and $\emptyset_2$=0.324 with the estimated standard error 0.13.The test statistics t for $\emptyset_1$ and $\emptyset_2$ are 2.433 and 2.465 which are statistically significant at 5% level.

4.11 Diagnostic Checking of Number of People Killed by Road Traffic Accidents in Yangon

The residual ACF and PACF are shown in Table (4.22).

Table (4.22)

Estimated Residual Autocorrelation Function and Partial Autocorrelation Function for Number of People Killed in Yangon (2014-2018)

Lag	Residual Autocorrelation	Std. Error	Residual Partial Autocorrelation	Std. Error
1	-0.036	0.129	-0.036	0.129
2	-0.012	0.129	-0.013	0.129
3	0.168	0.129	0.167	0.129
4	-0.035	0.133	-0.024	0.129
5	-0.028	0.133	-0.027	0.129
6	0.024	0.133	-0.007	0.129
7	-0.199	0.133	-0.195	0.129
8	0.095	0.138	0.097	0.129
9	0.053	0.139	0.054	0.129
10	0.084	0.139	0.163	0.129
11	0.049	0.140	0.020	0.129
12	-0.085	0.141	-0.124	0.129
13	0.133	0.141	0.105	0.129
14	-0.039	0.144	-0.095	0.129
15	-0.069	0.144	0.018	0.129
16	0.208	0.144	0.209	0.129

Source: SPSS Output

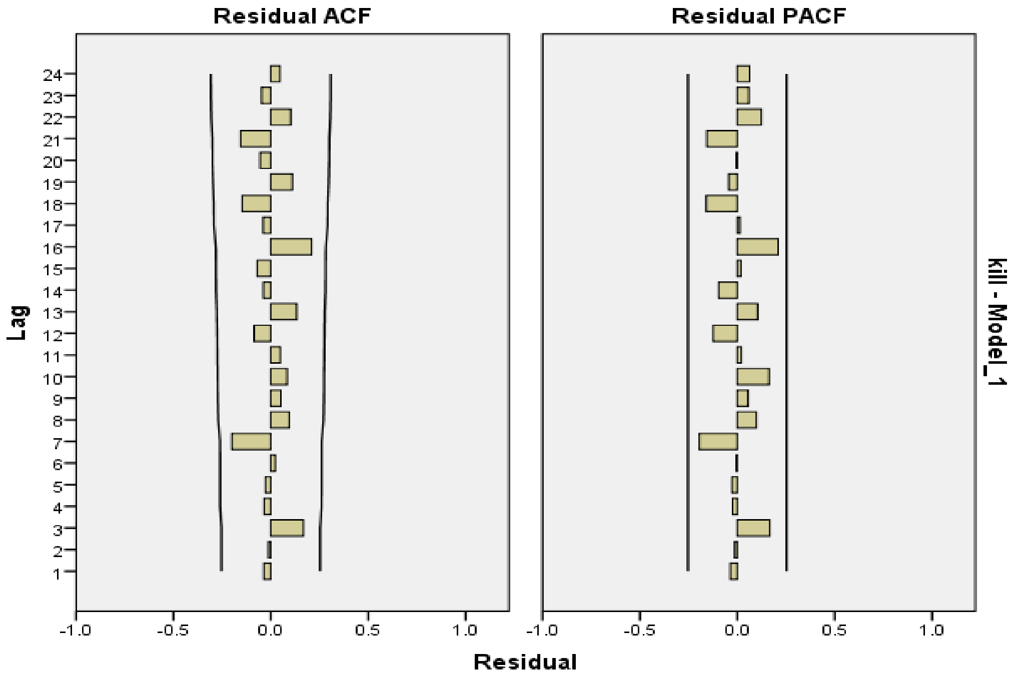


Figure (4.12): Residual Autocorrelation Function and Partial Autocorrelation Function for Number of People Killed in Yangon (2014-2018)

Source: SPSS Output

Figure (4.12) shows that estimated autocorrelation and partial autocorrelation of the two residual series are not significantly different from 0 because they all lie within the confidence band (within two standard error). Thus the residual is white noise. The model AR (2) is adequate to forecast the future values of the series.

4.12 Forecasting for Number of People Killed by Road Traffic Accidents in Yangon

The number of people who were killed by road traffic accidents in Yangon for 2019 year can be forecasted by using time series ARIMA (2, 0, 0) model. The forecasting results of killed people is described by the following Table (4.23).

Table (4.23)

The Forecast for January to December, 2019 of Number of People Killed by Road Traffic Accidents

January	19	May	26	September	28
February	20	Jun	26	October	28
March	23	July	27	November	29
April	24	August	28	December	29

Source: SPSS Output

According to Table (4.23), the highest forecasting of number of killed persons in road accidents is expected 29 persons in November and December. The lowest forecasting of number of killed persons in road accidents is expected 19 persons in January. The forecasting for the total number of killed by road traffic accidents in Yangon for year 2019 is 307 persons. The total number of people who were killed by road traffic accidents in Yangon will be expected to increase from month to month in 2019.

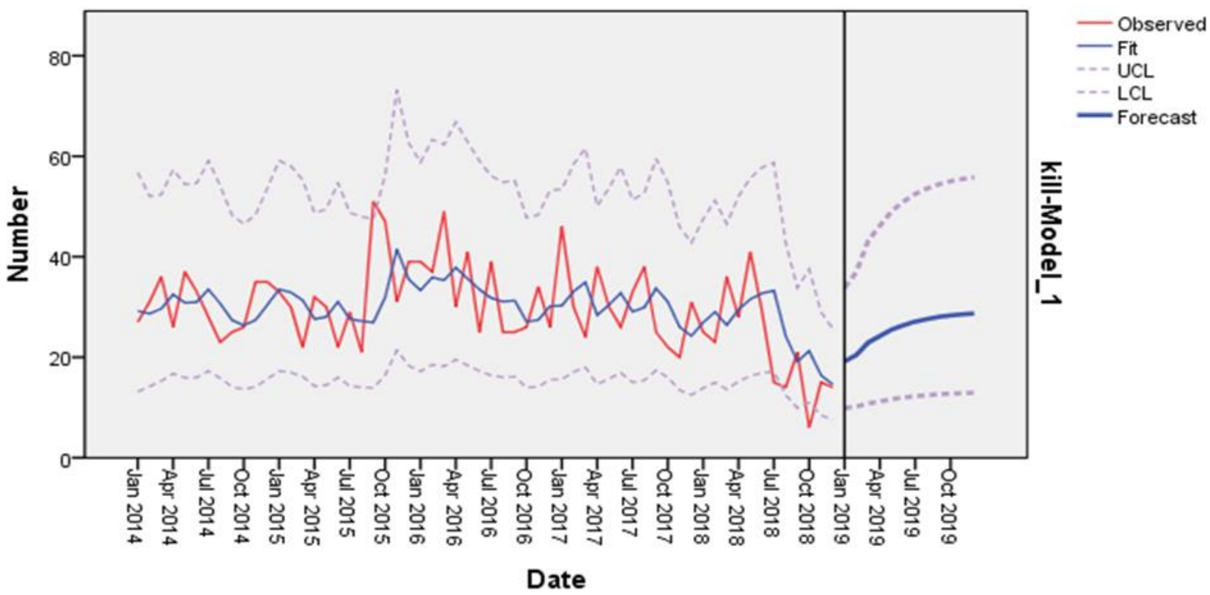


Figure (4.13): The Actual, Fitted and Forecast Values with 95% Confidence Limits for the Number of People Killed by Road Traffic Accidents

Source: SPSS Output

The actual, fitted and forecast values with 95% confidence limits for the number of people killed in road traffic accidents are shown in Figure (4.13). It shows that the number of deaths will be expected to increase the period of next year in 2019.

4.13 Series of People Injured by Road Traffic Accidents in Yangon

The monthly data of number of people killed in Yangon cover 5 years from year 2014 to 2018. The series consist of 60 observations and it was shown in Appendix Table (2). The line graph of this series was shown in Figure (4.14). From this line graph the time series is not likely to have seasonal cycle.

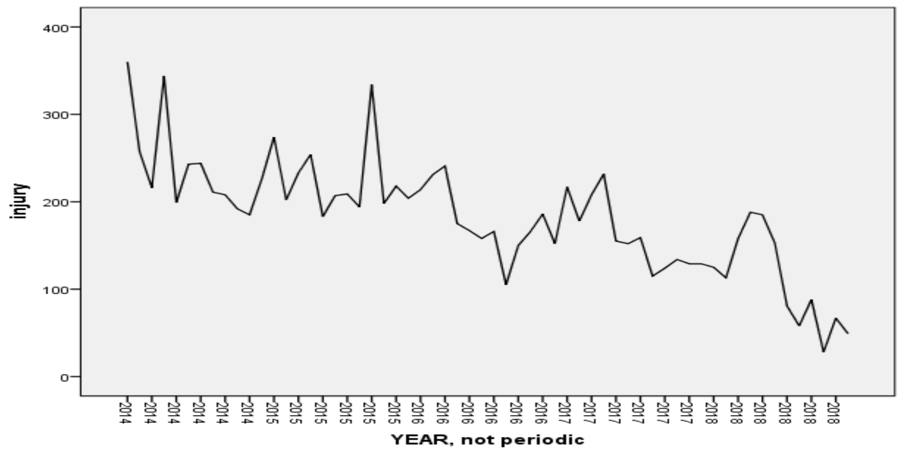


Figure (4.14): Number of People Injured by Road Accident in Yangon (2014-2018) Series

Source: SPSS Output

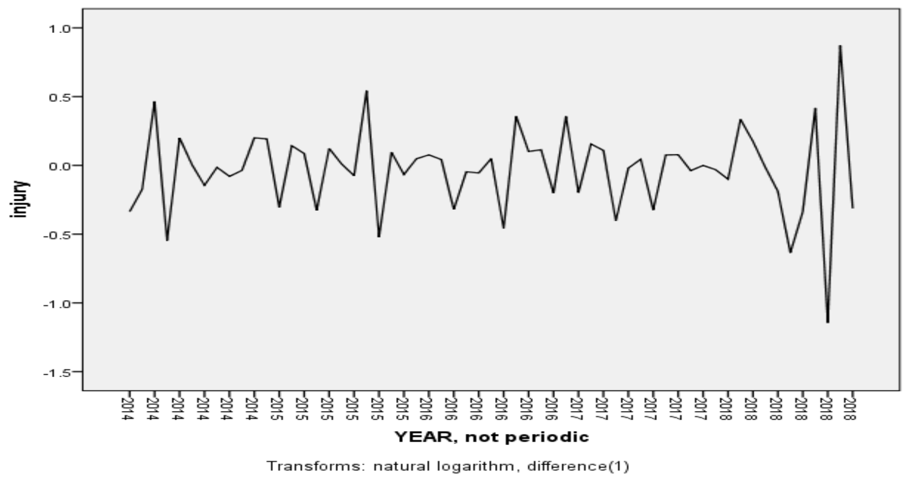


Figure (4.15): Number of People Injured by Road Traffic Accidents in Yangon (2014-2018) Series

Source: SPSS Output

The plot in Figure (4.14) indicates that the series is nonstationary in both mean and variance. So, log transform and differencing are suggested. After using log transform and differencing, the plot in Figure (4.15) indicates that the series is stationary in both mean and variance.

4.14 Model Identification for Number of People Injured by Road Traffic Accidents in Yangon

The autocorrelation function (ACF) and the partial autocorrelation (PACF) are shown in Table (4.24).

Table (4.24)

Estimated Autocorrelation Function and Partial Autocorrelation Function of Number of People Injured in Yangon (2014-2018)

Lag	Autocorrelation	Std. Error	Partial Autocorrelation	Std. Error
1	-0.506	0.127	-0.506	0.130
2	0.144	0.126	-0.151	0.130
3	0.091	0.125	0.135	0.130
4	-0.162	0.124	-0.045	0.130
5	-0.022	0.122	-0.203	0.130
6	0.114	0.121	0.006	0.130
7	-0.190	0.120	-0.096	0.130
8	0.096	0.119	-0.070	0.130
9	0.004	0.118	-0.014	0.130
10	-0.062	0.117	-0.026	0.130
11	-0.065	0.115	-0.206	0.130
12	0.131	0.114	-0.027	0.130
13	-0.091	0.113	0.043	0.130
14	0.197	0.112	0.230	0.130
15	-0.064	0.111	0.103	0.130
16	-0.078	0.109	-0.137	0.130

Source: SPSS Output

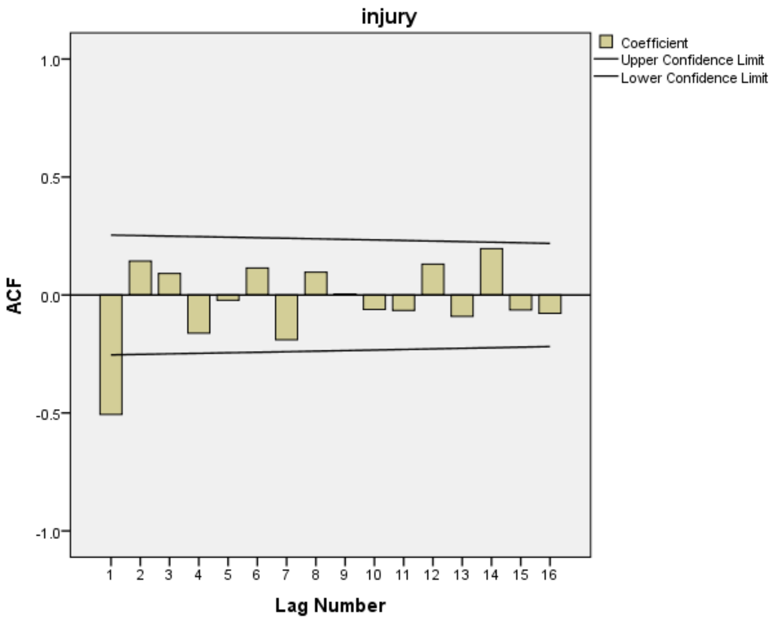


Figure (4.16): Sample Autocorrelation Function for Number of People Injured in Yangon

Source: SPSS Output

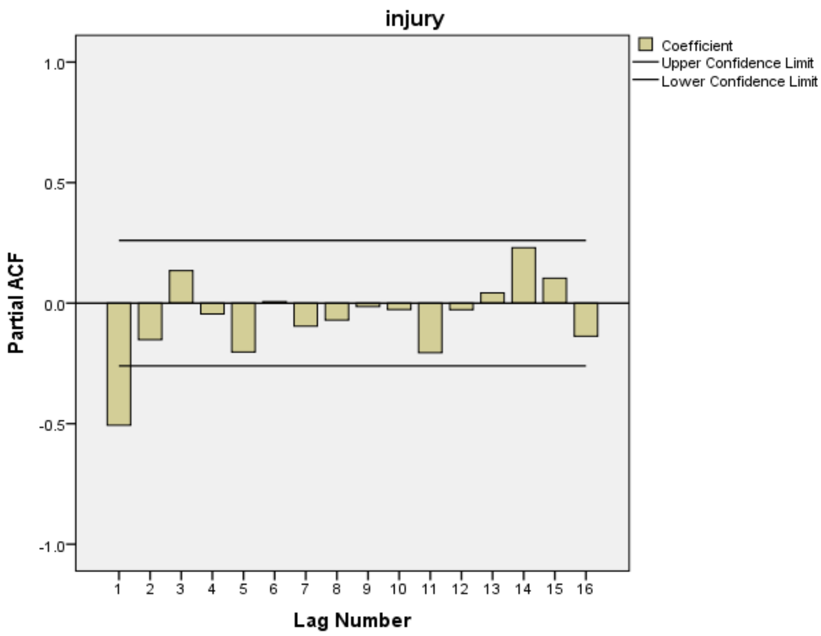


Figure (4.17): Sample Partial Autocorrelation Function for Number of People Injured in Yangon

Source: SPSS Output

Table (4.24), Figure (4.16) and (4.17) show the sample ACF and the sample PACF. After transformations, ACF and PACF cut off after lag 1. So, this model is assumed as ARIMA (1, 1, 1) model.

4.15 Parameter Estimation for ARIMA (1, 1, 1) Model

Using ARIMA (1, 1, 1) model, model statistics was shown in Table (4.25) and the estimated parameters with their statistics were shown in Table (4.26).

Table (4.25)

Model Statistics

Model	Ljung- Box Q (18)		
	Statistics	Df	Sig
Injury ARIMA (1,1,1)	15.946	16	0.457

Source: SPSS Output

Table (4.26) shows that Ljung- Box Q is not statistically significant for ARIMA (1, 1, 1) mode.

Table (4.26)

Estimated Parameter for ARIMA (1, 1, 1) Model of Number of People Injured in Yangon

		Estimate	S.E	t	Sig
Constant		-0.031	0.021	-1.470	0.147
AR	1	-0.373	0.240	-1.552	0.126
Difference		1			
MA	1	0.196	0.255	0.769	0.445

Source: SPSS Output

The following estimated model was obtained

$$(1-\phi_1 B)LnZ_t = \theta_0 + (1-\theta_1 B) + a_t$$

$$(1+0.373B)LnZ_t = -0.031 + (1-0.196B) + a_t$$

(0.021) (0.240) (0.255)

The estimated of the ARIMA (1, 1, 1) model of number of people injured in road traffic accident give $\phi_1 = -0.373$ and θ_1 =0.506 with the estimated standard error 0.240 and 0.255 respectively. The test statistics t for ϕ_1, θ_1 and constant θ_0 which are not statistically significant at 1%, 5% and 10% level.

4.16 Diagnostic Checking for ARIMA (1, 1, 1) Model

The residual ACF and PACF are shown in Table (4.27).

Table (4.27)

Estimated Residual Autocorrelation Function and Partial Autocorrelation Function for ARIMA (1, 1, 1) Model

Lag	Residual Autocorrelation	Std. Error	Residual Partial Autocorrelation	Std. Error
1	-0.002	0.130	-0.002	0.130
2	0.034	0.130	0.034	0.130
3	0.077	0.130	0.077	0.130
4	-0.209	0.131	-0.211	0.130
5	-0.108	0.137	-0.117	0.130
6	-0.001	0.138	0.010	0.130
7	-0.181	0.138	-0.148	0.130
8	0.023	0.142	-0.008	0.130
9	0.011	0.142	-0.025	0.130
10	-0.126	0.142	-0.127	0.130
11	-0.066	0.144	-0.151	0.130
12	0.126	0.144	0.108	0.130
13	0.094	0.146	0.132	0.130
14	0.236	0.147	0.189	0.130
15	-0.003	0.154	-0.092	0.130
16	-0.069	0.154	-0.102	0.130

Source: SPSS Output

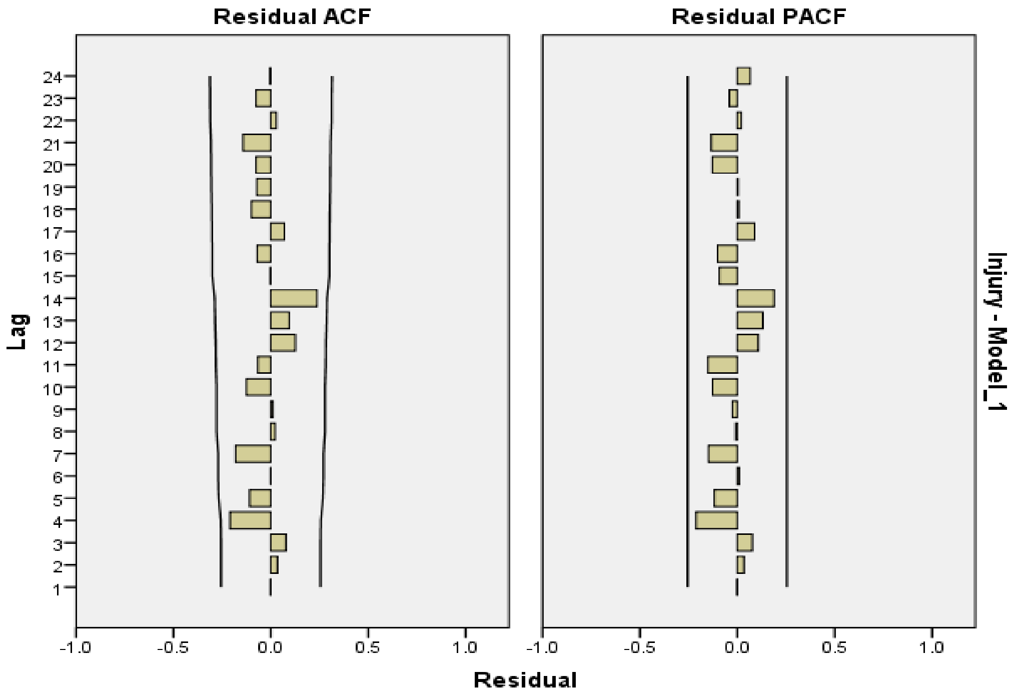


Figure (4.18): Residual Autocorrelation Function and Partial Autocorrelation Function for ARIMA (1, 1, 1) Model

Source: SPSS Output

Figure (4.18) shows that estimated autocorrelation and partial autocorrelation of the two residual series are not significantly different from 0 because they all lie within the confidence band (within two standard error). Thus the residual is white noise.

4.17 Parameter Estimation for ARIMA (0, 1, 1) Model

Although the estimated parameters for ARIMA (1, 1, 1) model are not statistically significant at all α levels, in another way, it can assume ACF cuts off after lag 1 and PACF is exponentially decay. Therefore, this model is ARIMA (0, 1, 1). Using ARIMA (0, 1, 1) model, model statistics was shown in Table (4.28) and the estimated parameters with their statistics were shown in Table (4.29).

Table (4.28)

Model Statistics

Model	**Ljung- Box Q (18)**		
	Statistics	**Df**	**Sig**
Injury ARIMA (0,1,1)	16.491	17	0.489

Source: SPSS Output

Table (4.26) shows that Ljung- Box Q is not statistically significant for ARIMA (0, 1, 1) model.

Table (4.29)

Estimated Parameter for ARIMA (0, 1, 1) Model of Number of People Injured in Yangon

		Estimate	**S.E**	**t**	**Sig**
Constant		-0.030	0.018	-1.703	0.094
Difference		1			
MA	1	0.506	0.116	4.352	0.000

Source: SPSS Output

When determining whether deterministic trend is needed, P value is less than alpha. So θ_0 is significant, deterministic trend is needed. The following estimated model was obtained

$$(1-B)LnZ_t = \theta_0 + (1-\theta_1 B) + a_t$$

$$(1-B)LnZ_t = -0.030 + (1-0.506B) + a_t$$

(0.018) (0.116)

The estimated of the ARIMA (0, 1, 1) model of number of people injured in road traffic accident giveθ_1 =0.506 with the estimated standard error 0.116. The test statistics t for $\theta_1$which is statistically significant at 5% level.

4.18 Diagnostic Checking for ARIMA (0, 1, 1) Model

The residual ACF and PACF are shown in Table (4.30).

Table (4.30)

Estimated Residual Autocorrelation Function and Partial Autocorrelation Function for Number of People Injured in Yangon (2014-2018)

Lag	Residual Autocorrelation	Std. Error	Residual Partial Autocorrelation	Std. Error
1	-0.068	0.130	-0.068	0.130
2	0.163	0.131	0.159	0.130
3	0.084	0.134	0.107	0.130
4	-0.173	0.135	-0.194	0.130
5	-0.099	0.139	-0.166	0.130
6	-0.005	0.140	0.038	0.130
7	-0.200	0.140	-0.124	0.130
8	0.011	0.145	-0.033	0.130
9	-0.025	0.145	-0.013	0.130
10	-0.092	0.145	-0.081	0.130
11	-0.051	0.146	-0.131	0.130
12	0.140	0.146	0.138	0.130
13	0.054	0.148	0.139	0.130
14	0.231	0.149	0.169	0.130
15	0.008	0.155	-0.082	0.130
16	-0.049	0.155	-0.145	0.130

Source: SPSS Output

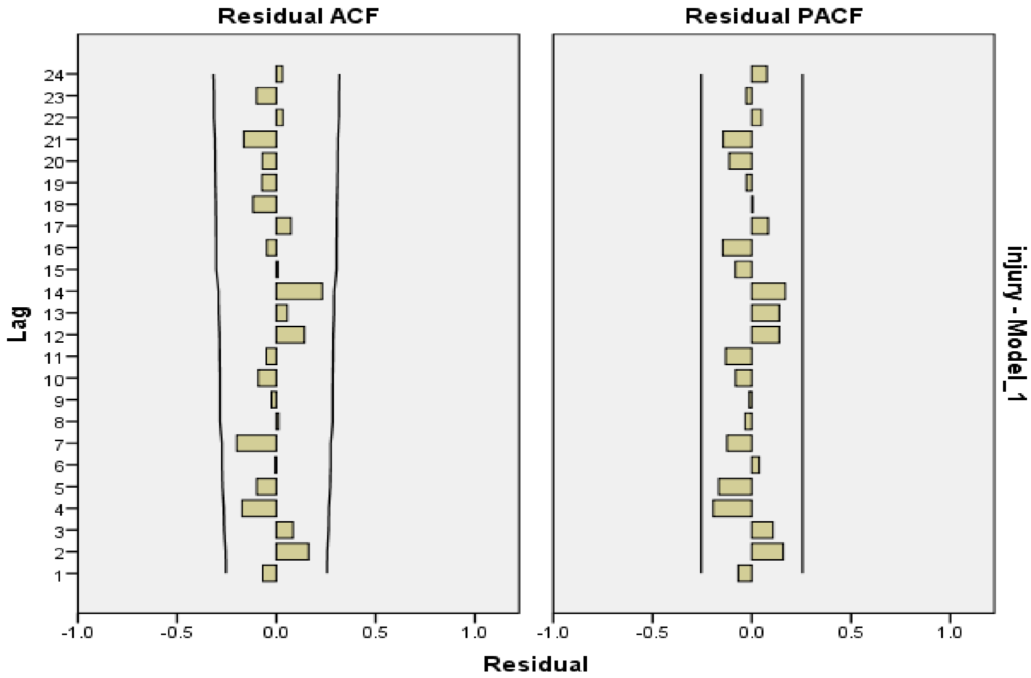


Figure (4.19): Residual Autocorrelation Function and Partial Autocorrelation Function for Number of People Injured in Yangon (2014-2018)

Source: SPSS Output

Figure (4.19) shows that estimated autocorrelation and partial autocorrelation of the two residual series are not significantly different from 0 because they all lie within the confidence band (within two standard error). Thus the residual is white noise. The model MA (1) is adequate to forecast the future values of the series.

4.19 Model Selection Criteria for Forecasting

Comparison between ARIMA (1, 1, 1) model and ARIMA (0, 1, 1) model is shown in Table (4.31).

Table (4.31)

Model Selection Criteria

Model	R-squared	MAPE	MAE	Normalized BIC
ARIMA(1, 1, 1)	0.494	21.753	33.006	7.821
ARIMA(0, 1, 1)	0.504	21.649	31.980	7.715

Source: SPSS Output

Table (4.31) shows that R squared of ARIMA (0, 1, 1) model is larger than that of ARIMA (1, 1, 1) model. And ARIMA (0, 1, 1) has smaller values of MAPE, MAE and normalized BIC than ARIMA (1, 1, 1) does. Therefore, ARIMA (0, 1, 1) model is better than ARIMA (1, 1, 1) model for forecasting.

4.20 Forecasting for Number of People Injured by Road Traffic Accidents in Yangon

The number of people who were injured by road traffic accidents in Yangon for 2019 year can be forecasted by using time series ARIMA (0, 1, 1) model. The forecasting results of injured people is described by the following Table (4.32).

Table (4.32)

The Forecast for January to December, 2019 of Number of People Injured by Road Traffic Accidents

January	57	May	51	September	48
February	52	Jun	50	October	47
March	53	July	50	November	47
April	51	August	49	December	46

Source: SPSS Output

According to Table (4.32), the highest forecasting of number of injured persons in road accidents is expected 57 persons in January. The lowest forecasting of number of injured persons in road accidents is expected 46 persons in December. The forecasting for the total number of injured by road traffic accidents in Yangon for year 2019 is 601 persons. The total number of people who were injured by road traffic accidents in Yangon will be expected to decrease from year to year.

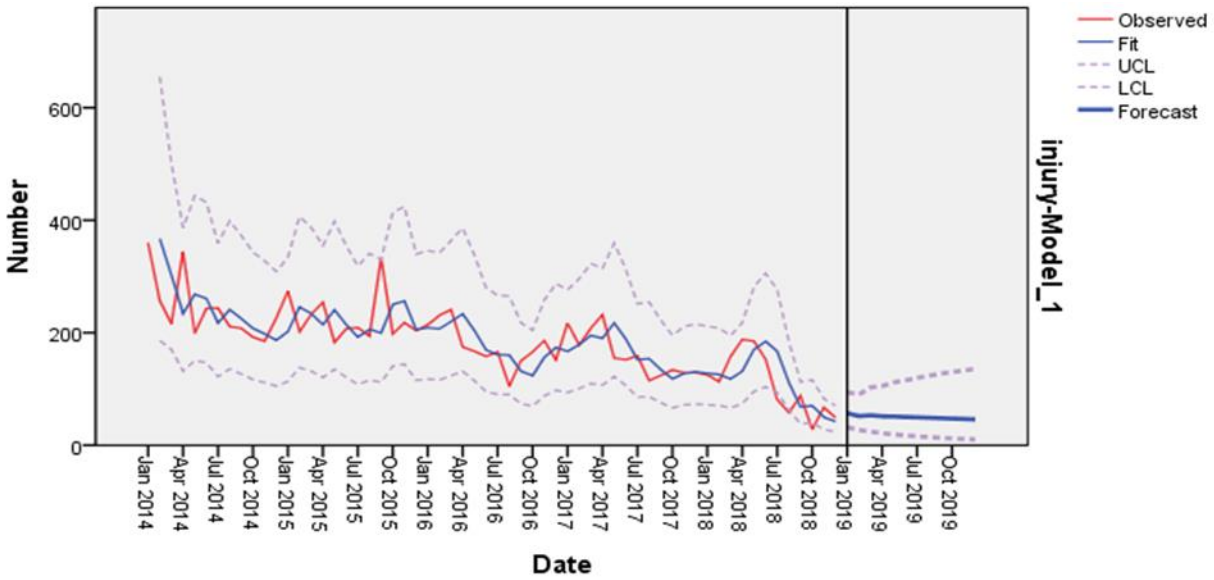


Figure (4.20): The Actual, Fitted and Forecast Values with 95% Confidence Limits for the Number of People Injured by Road Traffic Accidents

Source: SPSS Output

The actual, fitted and forecast values with 95% confidence limits for the number of people injured in road traffic accidents are shown in Figure (4.20). It shows that the number of injured people will be expected to decrease in 2019.

CHAPTER V

CONCLUSIONS

5.1 Findings

Firstly, this study aimed at modeling the number of people who were killed and injured by road accidents depending on the given time (in years) and crash causes. Secondly, it focused on modeling the number of people who were killed and injured by road accidents in selected townships (Hlaingtharyar, Insein, Mayangon and Mingalardon) and crash causes. The inferior and superior were validated using negative binomial regression model. Both poisson and negative binomial regression models were used for the analysis. Moreover, the assessment criteria of statistical goodness of fit model was also used in selecting the better model which will fit the people killed and injured in road accidents.

Based on the results, the negative binomial regression model was found to fit the data better than poisson regression model for number of people who were killed and injured by road accidents given time in years and crash causes. The poission regression model was found to fit the data better than negative binomial regression for number of people who were killed and injured by road accidents given selected townships (Hlaingtharyar, Insein, Mayangon and Mingalardon) and crash causes. In modeling the occurrence of number of people killed given time in years and crash causes, the analysis produces a reasonable AIC values, 94.954 deviance for the poisson model and a dispersion parameter of 4.748 showing an extra poisson variation or over dispersion in the data; leading to overestimated standard errors, thus inaccurate parameter estimates apparently due to a violation of one of its main assumption of the equality of mean and variance parameters. Because of over dispersion, it became a necessary tool to validate the poisson regression models using negative binomial. The deviance for the negative binomial regression model is 9.901 on 20 degree of freedom.

In the investigation of the number of people who are killed in different types of crash cause through accidents, it was identified that driver fault killed more people in road accident. This was followed by over speeding. The model also confirmed this through the parameter estimates for the various types of crash causes. It was observed from the model that driver fault was 851.5 times more than the base level for every year and over speeding was 325.1568 times more than the base level. It also reveals that the expected number of people who were killed by different types of crash causes for the years 2018, 2017, 2016 and 2015 were not statistically different from year 2014 for all types of crash cause in the model giving that the year 2014 is the base level.

In modeling the occurrence of number of people killed given selected townships (Hlaingtharyar, Insein, Mayangon and Mingalardon) and crash causes, the analysis produces a reasonable AIC values, 130.057 AIC, 24.158 deviance, -55.028 log likelihood and (1733.5519) p-value=0.000 which is significant at 1% level for the poisson model and 169.167 AIC, 7.701 deviance, -74.584 log likelihood and (83.546) p-value=0.000 which is significant at 1% level for negative binomial regression model shows that poisson regression model was found to fit the data better than the negative binomial regression model.

Based on the results, the number of people who were killed in different types of crash cause through accidents, it was recorded that driver fault killed more people in road accidents. This was followed by over speeding. The model also confirmed this through the parameter estimates for the various types of crash causes. It was found that from the model that driver fault was 8.1743 times more than the base level and over speeding was 3.3135 times more than the base level for every year, while the rest of the different types of crash causes were less than the base level. Mayangon was 0.2946 times less than that of base level (Mingalardon) for every year.

In modeling the occurrence of number of people injured given time in years and crash causes, the analysis produces a reasonable AIC values, 428.399 deviance for the poisson model and a dispersion parameter of 21.420 showing an extra poisson variation or over dispersion in the data; leading to overestimated standard errors, thus inaccurate parameter estimates apparently due to a violation of one of its main assumption of the equality of mean and variance parameters. Because of over dispersion, it became a necessary tool to validate the poisson regression models using negative binomial. The deviance for the negative binomial regression model is 7.9 on 20 degree of freedom.

The number of people who are injured in different types of crash cause through accidents, it was found that driver fault and over speeding injured more people than other facts in road accident. The model also confirmed this and the parameter estimates for the various types of crash causes. It was observed from the model that driver fault was 1044.1934 times more than base level for every year and over speeding was 319.5776 times more than the base level. It was found 2018 had 0.4462 times less people killed than 2014 in Yangon.

The occurrence of number of people injured given selected townships (Hlaingtharyar, Insein, Mayangon and Mingalardon) and crash causes, the analysis produces a reasonable AIC values, 199.430 AIC, 53.954 deviance, -89.715 log likelihood and (9382.14) p-value=0.000 which is significant at 1% level for the poisson model and 237.768 AIC, 5.678 deviance, -108.884 log likelihood and (98.440) p-value=0.000 which is significant at 1% level for negative binomial regression model shows that poisson regression model was found to fit the data better than the negative binomial regression model.

Based on the results, the number of people who were injured in different types of crash cause through accidents, it was recorded that driver fault injured more people in road accidents. This was followed by over speeding. The model also confirmed this through the parameter estimates for the various types of crash causes. It was found that from the model that driver fault was 21.9990 times more than the base level and over speeding was 6.4302 times more than the base level for every year, while the rest of the different types of crash causes were less than the base level. For injured persons, Mayangon Township was 0.5684 times less than that of Mingalardon Township for every year.

The highest forecasting of number of people killed in road accidents in Yangon is expected 29 persons in November and December and the lowest forecasting is expected 19 persons in January for 2019. And also the highest forecasting of number of people injured in road accidents in Yangon is expected 57 persons in January and the lowest forecasting is expected 46 persons in December for 2019. In the long run, the number of people in both killed and injured in Yangon would be gradually decreased. But, unexpected effects and government’s efforts on educating awareness of road traffic accident might change the number of people in both killed and injured in Yangon.

This study focused on finding the major causes of road traffic accidents which may lead to kills and injuries in Yangon. According to results, the coefficients of driver fault and over speeding were significant and also they were lager than the coefficients of other causes. The data used in this paper was social data. Therefore, this study couldn't find out how many people would be killed and injured by which crash causes in the long run. The further study would check whether the number of people killed or injured in the selected four townships would be fitted by using any other method else under generalized linear model or not.

5.2 Suggestions

In Yangon, this study found out that most people were killed and injured by driver fault and over speeding of road accidents in Yangon. The following recommendations are needed to improve traffic safety in Yangon.

1. Education on road accidents should be intensified especially among the youth. Particularly for male drivers, it should provide education programs with an emphasis on increasing their vigilance of pedestrians and always using seatbelt while driving, to decrease people deaths of road traffic accidents (RTAs).
2. It should enhance traffic police law enforcement to reprimand drivers who are reckless, exhibit risk taking behavior, who are using cell phones and are not using a seat belt and should give special training courses concerning traffic laws and regulation. In particular enforcement should be stringent on weekends and 20:01-24:00 hours of the day, as there are frequent fatal RTAs occurrences during these time periods. Fitness of vehicle should be checked annually.
3. Traffic police department should put more traffic control cameras, put traffic sighs and traffic light in all the roads of the city. It also should provide basic infrastructures such as good road that accommodate many vehicles at a time and do the preventing pedestrians and cyclists from accessing motorways and preventing motor vehicles from entering pedestrian zones.
4. Improving sidewalks, towpaths, cycling lanes and safe crossing points are critical to reducing the risk of injury among road users. Especially in Yangon,

the deadlocked pavements are pocked by several uncovered openings of sewer drains, obstructed by parked cars and fully occupied by street vendors that can push pedestrians onto the perilous roads and speeding drivers could knock someone down any time and irresponsibly run away. It’s alerting that government should provide a safer environment and give strictly instructions and roughly handle the street vendors.

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APPENDIX

Appendix Table (2)

Monthly Data of Number of People Who Were Killed and Injured in Yangon (2014-2018)

Year	Month	Kill	Injury
2014	January	27	360
2014	February	31	257
2014	March	36	216
2014	April	26	344
2014	May	37	199
2014	June	33	243
2014	July	28	244
2014	August	23	211
2014	September	25	208
2014	October	26	192
2014	November	35	185
2014	December	35	226
2015	January	33	274
2015	February	30	202
2015	March	22	233
2015	April	32	254
2015	May	30	183
2015	June	22	207
2015	July	29	209
2015	August	21	194
2015	September	51	334
2015	October	47	198
2015	November	31	218
2015	December	39	204
2016	January	39	214
2016	February	37	231
2016	March	49	241
2016	April	30	175
2016	May	41	167
2016	June	25	158
2016	July	39	166
2016	August	25	105
2016	September	25	150
2016	October	26	166
2016	November	34	186
2016	December	26	152
2017	January	46	217
2017	February	30	178

2017	March	24	208
2017	April	38	232
2017	May	30	155
2017	June	26	152
2017	July	33	159
2017	August	38	115
2017	September	25	124
2017	October	22	134
2017	November	20	129
2017	December	31	129
2018	January	25	125
2018	February	23	113
2018	March	36	158
2018	April	28	188
2018	May	41	185
2018	June	29	153
2018	July	15	81
2018	August	14	58
2018	September	21	88
2018	October	6	28
2018	November	15	67
2018	December	14	49

Source: Office of Traffic Police (Yangon)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	94.954	20	4.748
Scaled Deviance	94.954	20	
Pearson Chi-Square	98.883	20	4.944
Scaled Pearson Chi-Square	98.883	20	
Log Likelihood[b]	-109.065		
Akaike's Information Criterion (AIC)	240.131		
Finite Sample Corrected AIC (AICC)	254.026		
Bayesian Information Criterion (BIC)	255.905		
Consistent AIC (CAIC)	266.905		

Dependent Variable: Kill

Model: (Intercept), Year, crashcause[a]

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
3153.754	10	.000

Dependent Variable: Kill

Model: (Intercept), Year, crashcause[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	Type III df	Type III Sig.
(Intercept)	117.337	1	.000
Year	27.614	4	.000
crashcause	1216.420	6	.000

Dependent Variable: Kill

Model: (Intercept), Year, crashcause

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-1.346	1.0010	-3.308	.616	1.809	1	.179
[Year=2018]	-.291	.0807	-.449	-.133	13.022	1	.000
[Year=2017]	.003	.0742	-.143	.148	.001	1	.970
[Year=2016]	.089	.0727	-.053	.231	1.500	1	.221
[Year=2015]	.072	.0730	-.071	.215	.970	1	.325
[Year=2014]	0[a]	.	.	.	.	.	.
[crashcause=7]	4.865	1.0031	2.899	6.831	23.527	1	.000
[crashcause=6]	3.096	1.0208	1.096	5.097	9.201	1	.002
[crashcause=5]	1.951	1.0542	-.115	4.017	3.424	1	.064
[crashcause=4]	5.843	1.0012	3.880	7.805	34.052	1	.000
[crashcause=3]	1.028	1.2249	-1.373	3.428	.704	1	.401
[crashcause=2]	6.789	1.0005	4.828	8.750	46.039	1	.000
[crashcause=1]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						

Dependent Variable: Kill

Model: (Intercept), Year, crashcause

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

Goodness of Fit[a]

	Value	df	Value/df
Deviance	9.901	20	.495
Scaled Deviance	26.473	20	
Pearson Chi-Square	7.480	20	.374
Scaled Pearson Chi-Square	20.000	20	
Log Likelihood[b,c]	-108.147		
Adjusted Log Likelihood[d]	-289.150		
Akaike's Information Criterion (AIC)	238.294		
Finite Sample Corrected AIC (AICC)	252.189		
Bayesian Information Criterion (BIC)	254.068		
Consistent AIC (CAIC)	265.068		

Dependent Variable: Kill

Model: (Intercept), Year, crashcause[a]

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
260.232	10	.000

Dependent Variable: Kill

Model: (Intercept), Year, crashcause[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	157.982	1	.000
Year	2.498	4	.645
crashcause	250.111	6	.000

Dependent Variable: Kill

Model: (Intercept), Year, crashcause

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-1.569	.7337	-3.007	-.131	4.574	1	.032
[Year=2018]	.230	.4148	-.583	1.043	.307	1	.580
[Year=2017]	.194	.3931	-.577	.965	.243	1	.622
[Year=2016]	.283	.3905	-.483	1.048	.524	1	.469
[Year=2015]	.642	.4088	-.159	1.443	2.468	1	.116
[Year=2014]	0[a]	.	.	.	.	.	.
[crashcause=7]	4.813	.7436	3.356	6.270	41.895	1	.000
[crashcause=6]	2.912	.7925	1.359	4.466	13.506	1	.000
[crashcause=5]	1.896	.7705	.386	3.406	6.054	1	.014
[crashcause=4]	5.784	.7413	4.331	7.237	60.872	1	.000
[crashcause=3]	.993	.8877	-.746	2.733	1.252	1	.263
[crashcause=2]	6.747	.7418	5.293	8.201	82.732	1	.000
[crashcause=1]	0[a]	.	.	.	.	.	.
(Scale)	.374[b]						
(Negative binomial)	1[c]						

Dependent Variable: Kill

Model: (Intercept), Year, crashcause

Goodness of Fit[a]

	Value	df	Value/df
Deviance	428.399	20	21.420
Scaled Deviance	428.399	20	
Pearson Chi-Square	464.053	20	23.203
Scaled Pearson Chi-Square	464.053	20	
Log Likelihood[b]	-300.174		
Akaike's Information Criterion (AIC)	622.348		
Finite Sample Corrected AIC (AICC)	636.243		
Bayesian Information Criterion (BIC)	638.122		
Consistent AIC (CAIC)	649.122		

Dependent Variable: injury

Model: (Intercept), Year, crashcause[a]

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
24044.063	10	.000

Dependent Variable: injury

Model: (Intercept), Year, crashcause[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	1969.155	1	.000
Year	715.225	4	.000
crashcause	8989.143	6	.000

Dependent Variable: injury

Model: (Intercept), Year, crashcause

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.743	.4085	-.057	1.544	3.311	1	.069
[Year=2018]	-.797	.0335	-.863	-.732	567.444	1	.000
[Year=2017]	-.401	.0294	-.459	-.344	186.112	1	.000
[Year=2016]	-.311	.0286	-.367	-.254	117.507	1	.000
[Year=2015]	-.061	.0268	-.113	-.008	5.154	1	.023
[Year=2014]	0[a]	.	.	.	.	.	.
[crashcause=7]	4.067	.4109	3.262	4.873	97.982	1	.000
[crashcause=6]	1.878	.4341	1.027	2.729	18.719	1	.000
[crashcause=5]	2.587	.4197	1.764	3.409	37.987	1	.000
[crashcause=4]	5.633	.4088	4.832	6.435	189.866	1	.000
[crashcause=3]	.702	.5271	-.331	1.736	1.776	1	.183
[crashcause=2]	6.918	.4084	6.118	7.719	286.906	1	.000
[crashcause=1]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						

Dependent Variable: injury

Model: (Intercept), Year, crashcause

Goodness of Fit[a]

	Value	df	Value/df
Deviance	7.900	20	.395
Scaled Deviance	7.900	20	
Pearson Chi-Square	6.163	20	.308
Scaled Pearson Chi-Square	6.163	20	
Log Likelihood[b]	-152.015		
Akaike's Information Criterion (AIC)	326.029		
Finite Sample Corrected AIC (AICC)	339.924		
Bayesian Information Criterion (BIC)	341.803		
Consistent AIC (CAIC)	352.803		

Dependent Variable: injury

Model: (Intercept), Year, crashcause[a]

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
121.689	10	.000

Dependent Variable: injury

Model: (Intercept), Year, crashcause[a]

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	303.894	1	.000
Year	1.912	4	.752
crashcause	139.659	6	.000

Dependent Variable: injury

Model: (Intercept), Year, crashcause

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.716	.7206	-.696	2.128	.987	1	.320
[Year=2018]	-.807	.6093	-2.001	.387	1.755	1	.185
[Year=2017]	-.420	.5936	-1.583	.744	.500	1	.480
[Year=2016]	-.331	.5988	-1.505	.842	.306	1	.580
[Year=2015]	-.148	.6248	-1.372	1.077	.056	1	.813
[Year=2014]	0[a]	.	.	.	.	.	.
[crashcause=7]	4.094	.8021	2.522	5.666	26.052	1	.000
[crashcause=6]	1.896	.8640	.203	3.589	4.816	1	.028
[crashcause=5]	2.708	.8244	1.092	4.323	10.787	1	.001
[crashcause=4]	5.767	.8064	4.187	7.348	51.142	1	.000
[crashcause=3]	.713	.9580	-1.164	2.591	.554	1	.457
[crashcause=2]	6.951	.8039	5.376	8.527	74.772	1	.000
[crashcause=1]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						
(Negative binomial)	1[b]						

Dependent Variable: injury

Model: (Intercept), Year, crashcause

Goodness of Fit[a]

	Value	df	Value/df
Deviance	24.158	16	1.510
Scaled Deviance	24.158	16	
Pearson Chi-Square	24.099	16	1.506
Scaled Pearson Chi-Square	24.099	16	
Log Likelihood[b]	-55.028		
Akaike's Information Criterion (AIC)	130.057		
Finite Sample Corrected AIC (AICC)	144.723		
Bayesian Information Criterion (BIC)	142.638		
Consistent AIC (CAIC)	152.638		

Dependent Variable: kill

Model: (Intercept), Township, Crashcause

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
1733.551	9	.000

Dependent Variable: kill

Model: (Intercept), Township, Crashcause

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	44.198	1	.000
Township	150.173	3	.000
Crashcause	559.835	6	.000

Dependent Variable: kill

Model: (Intercept), Township, Crashcause

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	3.307	.1299	3.052	3.561	648.324	1	.000
[Township=1]	-.378	.0849	-.545	-.212	19.843	1	.000
[Township=2]	-.826	.0980	-1.018	-.634	71.149	1	.000
[Township=3]	-1.222	.1133	-1.444	-1.000	116.350	1	.000
[Township=4]	0[a]	.	.	.	.	.	.
[Crashcause=1]	-3.656	1.0080	-5.631	-1.680	13.154	1	.000
[Crashcause=2]	2.079	.1306	1.824	2.335	253.679	1	.000
[Crashcause=3]	-3.163	.7181	-4.571	-1.756	19.406	1	.000
[Crashcause=4]	1.204	.1403	.929	1.479	73.593	1	.000
[Crashcause=5]	-3.497	.7177	-4.903	-2.090	23.732	1	.000
[Crashcause=6]	-2.110	.3744	-2.844	-1.376	31.773	1	.000
[Crashcause=7]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						

Dependent Variable: kill

Model: (Intercept), Township, Crashcause

Goodness of Fit[a]

	Value	df	Value/df
Deviance	53.954	16	3.372
Scaled Deviance	53.954	16	
Pearson Chi-Square	47.618	16	2.976
Scaled Pearson Chi-Square	47.618	16	
Log Likelihood[b]	-89.715		
Akaike's Information Criterion (AIC)	199.430		
Finite Sample Corrected AIC (AICC)	214.097		
Bayesian Information Criterion (BIC)	212.011		
Consistent AIC (CAIC)	222.011		

Dependent Variable: Injury

Model: (Intercept), Township, Crashcause

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
9382.140	9	.000

Dependent Variable: Injury

Model: (Intercept), Township, Crashcause

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	829.111	1	.000
Township	160.174	3	.000
Crashcause	3562.736	6	.000

Dependent Variable: Injury

Model: (Intercept), Township, Crashcause

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	3.789	.0878	3.617	3.961	1862.405	1	.000
[Township=1]	-.188	.0408	-.268	-.108	21.124	1	.000
[Township=2]	-.565	.0456	-.654	-.475	153.325	1	.000
[Township=3]	-.293	.0420	-.375	-.210	48.547	1	.000
[Township=4]	0[a]	.	.	.	.	.	.
[Crashcause=1]	-3.165	.5073	-4.160	-2.171	38.940	1	.000
[Crashcause=2]	3.091	.0867	2.921	3.261	1270.052	1	.000
[Crashcause=3]	-3.019	.4553	-3.911	-2.127	43.969	1	.000
[Crashcause=4]	1.861	.0912	1.683	2.040	416.728	1	.000
[Crashcause=5]	-1.150	.1730	-1.489	-.811	44.221	1	.000
[Crashcause=6]	-1.602	.2071	-2.008	-1.196	59.831	1	.000
[Crashcause=7]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						

Dependent Variable: Injury

Model: (Intercept), Township, Crashcause

Goodness of Fit[a]

	Value	df	Value/df
Deviance	5.678	16	.355
Scaled Deviance	5.678	16	
Pearson Chi-Square	4.004	16	.250
Scaled Pearson Chi-Square	4.004	16	
Log Likelihood[b]	-108.884		
Akaike's Information Criterion (AIC)	237.768		
Finite Sample Corrected AIC (AICC)	252.435		
Bayesian Information Criterion (BIC)	250.349		
Consistent AIC (CAIC)	260.349		

Dependent Variable: Injury

Model: (Intercept), Township, Crashcause

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
98.440	9	.000

Dependent Variable: Injury

Model: (Intercept), Township, Crashcause

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	169.447	1	.000
Township	2.936	3	.402
Crashcause	101.023	6	.000

Dependent Variable: Injury

Model: (Intercept), Township, Crashcause

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	4.040	.6699	2.727	5.353	36.366	1	.000
[Township=1]	-.216	.6328	-1.456	1.025	.116	1	.733
[Township=2]	-.952	.6206	-2.168	.265	2.352	1	.125
[Township=3]	-.708	.6312	-1.945	.529	1.260	1	.262
[Township=4]	0[a]	.	.	.	.	.	.
[Crashcause=1]	-3.108	.9275	-4.926	-1.290	11.229	1	.001
[Crashcause=2]	3.060	.7141	1.660	4.459	18.358	1	.000
[Crashcause=3]	-3.216	.9275	-5.034	-1.399	12.026	1	.001
[Crashcause=4]	1.869	.7147	.468	3.270	6.839	1	.009
[Crashcause=5]	-1.372	.7554	-2.852	.109	3.298	1	.069
[Crashcause=6]	-1.724	.7523	-3.198	-.249	5.251	1	.022
[Crashcause=7]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						
(Negative binomial)	1[b]						

Dependent Variable: Injury

Model: (Intercept), Township, Crashcause

Goodness of Fit[a]

	Value	df	Value/df
Deviance	7.701	16	.481
Scaled Deviance	7.701	16	
Pearson Chi-Square	6.578	16	.411
Scaled Pearson Chi-Square	6.578	16	
Log Likelihood[b]	-74.584		
Akaike's Information Criterion (AIC)	169.167		
Finite Sample Corrected AIC (AICC)	183.834		
Bayesian Information Criterion (BIC)	181.748		
Consistent AIC (CAIC)	191.748		

Dependent Variable: kill

Model: (Intercept), Township, Crashcause

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
83.546	9	.000

Dependent Variable: kill

Model: (Intercept), Township, Crashcause

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	23.609	1	.000
Township	2.878	3	.411
Crashcause	69.077	6	.000

Dependent Variable: kill

Model: (Intercept), Township, Crashcause

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	3.224	.6255	1.999	4.450	26.577	1	.000
[Township=1]	-.329	.6955	-1.693	1.034	.224	1	.636
[Township=2]	-.751	.6761	-2.076	.574	1.234	1	.267
[Township=3]	-1.066	.6709	-2.381	.249	2.526	1	.112
[Township=4]	0[a]	.	.	.	.	.	.
[Crashcause=1]	-3.728	1.3042	-6.284	-1.172	8.172	1	.004
[Crashcause=2]	2.101	.7255	.679	3.523	8.386	1	.004
[Crashcause=3]	-2.975	1.0818	-5.095	-.855	7.562	1	.006
[Crashcause=4]	1.198	.7281	-.229	2.625	2.709	1	.100
[Crashcause=5]	-3.531	1.0290	-5.548	-1.514	11.776	1	.001
[Crashcause=6]	-1.962	.8169	-3.563	-.361	5.767	1	.016
[Crashcause=7]	0[a]	.	.	.	.	.	.
(Scale)	1[b]						
(Negative binomial)	1[b]						

Dependent Variable: kill

Model: (Intercept), Township, Crashcause

..

Autocorrelations

Series: kill

Lag	Autocorrelation	Std. Error[a]	Box-Ljung Statistic		
			Value	df	Sig.[b]
1	.414	.126	10.813	1	.001
2	.407	.125	21.434	2	.000
3	.251	.124	25.552	3	.000
4	.113	.123	26.397	4	.000
5	.024	.122	26.435	5	.000
6	.010	.120	26.442	6	.000
7	-.098	.119	27.117	7	.000
8	.104	.118	27.884	8	.000
9	.081	.117	28.365	9	.001
10	.132	.116	29.668	10	.001
11	.110	.115	30.589	11	.001
12	.022	.114	30.625	12	.002
13	.124	.112	31.849	13	.003
14	.018	.111	31.875	14	.004
15	-.021	.110	31.911	15	.007
16	.080	.109	32.453	16	.009

a. The underlying process assumed is independence (white noise).

b. Based on the asymptotic chi-square approximation.

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.268	.	.268	.268	.268	.268	.268	.268	.268	.268	.268
R-squared	.172	.	.172	.172	.172	.172	.172	.172	.172	.172	.172
RMSE	8.170	.	8.170	8.170	8.170	8.170	8.170	8.170	8.170	8.170	8.170
MAPE	25.919	.	25.919	25.919	25.919	25.919	25.919	25.919	25.919	25.919	25.919
MaxAPE	254.334	.	254.334	254.334	254.334	254.334	254.334	254.334	254.334	254.334	254.334
MAE	6.420	.	6.420	6.420	6.420	6.420	6.420	6.420	6.420	6.420	6.420
MaxAE	24.085	.	24.085	24.085	24.085	24.085	24.085	24.085	24.085	24.085	24.085
Normalized BIC	4.406	.	4.406	4.406	4.406	4.406	4.406	4.406	4.406	4.406	4.406

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
kill-Model_1	0	.268	14.628	16	.552	0

Forecast

Model		Jan 2019	Feb 2019	Mar 2019	Apr 2019	May 2019	Jun 2019	Jul 2019	Aug 2019	Sep 2019	Oct 2019	Nov 2019	Dec 2019
kill-Model_1	Forecast	19	20	23	24	26	26	27	28	28	28	29	29
	UCL	34	37	43	46	49	51	53	54	54	55	55	56
	LCL	10	10	11	11	12	12	12	12	13	13	13	13

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

Autocorrelations

Series: injury

Lag	Autocorrelation	Std. Error[a]	Box-Ljung Statistic		
			Value	df	Sig.[b]
1	-.506	.127	15.898	1	.000
2	.144	.126	17.201	2	.000
3	.091	.125	17.734	3	.000
4	-.162	.124	19.453	4	.001
5	-.022	.122	19.487	5	.002
6	.114	.121	20.369	6	.002
7	-.190	.120	22.857	7	.002
8	.096	.119	23.513	8	.003
9	.004	.118	23.514	9	.005
10	-.062	.117	23.792	10	.008
11	-.065	.115	24.112	11	.012
12	.131	.114	25.427	12	.013
13	-.091	.113	26.073	13	.017
14	.197	.112	29.166	14	.010
15	-.064	.111	29.497	15	.014
16	-.078	.109	30.000	16	.018

a. The underlying process assumed is independence (white noise).

b. Based on the asymptotic chi-square approximation.

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.270	.	.270	.270	.270	.270	.270	.270	.270	.270	.270
R-squared	.494	.	.494	.494	.494	.494	.494	.494	.494	.494	.494
RMSE	45.016	.	45.016	45.016	45.016	45.016	45.016	45.016	45.016	45.016	45.016
MAPE	21.753	.	21.753	21.753	21.753	21.753	21.753	21.753	21.753	21.753	21.753
MaxAPE	157.083	.	157.083	157.083	157.083	157.083	157.083	157.083	157.083	157.083	157.083
MAE	33.006	.	33.006	33.006	33.006	33.006	33.006	33.006	33.006	33.006	33.006
MaxAE	135.246	.	135.246	135.246	135.246	135.246	135.246	135.246	135.246	135.246	135.246
Normalized BIC	7.821	.	7.821	7.821	7.821	7.821	7.821	7.821	7.821	7.821	7.821

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.260	.	.260	.260	.260	.260	.260	.260	.260	.260	.260
R-squared	.472	.	.472	.472	.472	.472	.472	.472	.472	.472	.472
RMSE	45.599	.	45.599	45.599	45.599	45.599	45.599	45.599	45.599	45.599	45.599
MAPE	22.216	.	22.216	22.216	22.216	22.216	22.216	22.216	22.216	22.216	22.216
MaxAPE	151.263	.	151.263	151.263	151.263	151.263	151.263	151.263	151.263	151.263	151.263
MAE	33.997	.	33.997	33.997	33.997	33.997	33.997	33.997	33.997	33.997	33.997
MaxAE	134.387	.	134.387	134.387	134.387	134.387	134.387	134.387	134.387	134.387	134.387
Normalized BIC	7.778	.	7.778	7.778	7.778	7.778	7.778	7.778	7.778	7.778	7.778

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
Injury-Model_1	0	.270	15.946	16	.457	0

ARIMA Model Parameters

					Estimate	SE	t	Sig.
Injury-Model_1	Injury	Natural Logarithm	Constant		-.031	.021	-1.470	.147
			AR	Lag 1	-.373	.240	-1.552	.126
			Difference		1			
			MA	Lag 1	.196	.255	.769	.445

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
injury-Model_1	0	.260	16.937	17	.459	0

Forecast

Model		Jan 2019	Feb 2019	Mar 2019	Apr 2019	May 2019	Jun 2019	Jul 2019	Aug 2019	Sep 2019	Oct 2019	Nov 2019	Dec 2019
injury-Model_1	Forecast	57	52	53	51	51	50	50	49	48	47	47	46
	UCL	94	90	103	105	112	115	120	123	127	130	133	136
	LCL	32	27	24	21	19	17	16	14	13	12	11	10

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.