Mauritius Research and Innovation Council

INNOVATION FOR TECHNOLOGY

# INVESTIGATING THE CAUSES OF FATAL ACCIDENTS IN MAURITIUS USING DISCRETE TIME SERIES MODEL

## Final Report

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Mauritius Research and Innovation Council

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# Road Traffic Accident Data Analysis in Mauritius using Statistical Techniques

**2019**

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# Abstract

The alarming increase in the number of road traffic accidents, in particular casualty or injury accidents, in Mauritius affirms our understanding of road traffic injuries as a major national health problem. In order to bring down these numbers effectively, it is pertinent to scientifically model the effects of the factors leading to traffic accidents on the roads of Mauritius.

The PF 178 form consists of important information on each accident across Mauritius. However, these information have not been adequately utilised so far to research on the major causes of road accidents. In this study, we first convert these information into a proper data structure and use Generalized Linear Models (GLMs) and Artificial Neural Network (ANN) approaches that can efficiently identify the significant factors underlying road traffic accidents and predict the severity of these accidents.

The inferential results illustrate that the types of road structures, the day and time effect, street lighting conditions, vehicle types and conditions and driver profiles are the potential influential factors in the causation of road traffic accidents from 2012-2017. The findings of this research would, thus, be of utmost benefit to the concerned authorities and policymakers. In this way, this would formulate and enforce the appropriate preventive measures while simultaneously strengthening the current traffic system.

**Keywords:** Road traffic accidents, GLM and ANN approaches, Estimation of effects, Predictions.

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# 1. Introduction

## 1.1 Background: The Current Status of Road Traffic accidents in Mauritius

The Global Status report on Road Safety (2018) that was launched by World Health Organization(WHO) states that the annual number of road traffic deaths have reached an approximate number of 1.35 million globally. Road traffic injuries is becoming increasingly the leading killer of people in the age group 5-29 years old. Besides, the report also highlights that road traffic accidents is now the eight leading cause of sudden deaths around the globe.

Mauritius has also seen a drastic rise in road traffic accidents during the past few years. The statistics from the digest of Road Transport and Road Accident Statistics (statsmauritius.govmu.org/) for the years 2014-2017 show the number of road traffic accidents has increased from 26,400 in 2014 to 28,476 in 2015 which is equivalent to an increase of 7.9%. For the period January to June 2016, the number of road traffic accidents recorded was 14,452 as compared to 13,635 for the corresponding period in 2015, yielding to an increase of 6.0%, among which 68 were fatal (caused death).As from 2016, road accidents have turned around 29,000 (See Table 1 below).In fact, in this current year 2019, from January to June, 61 fatal road accidents have occurred.

As per the digest of Road Transport and Road Accident Statistics (2014), road traffic accidents in Mauritius are classified into the following categories according to the severity of the accident:

- **Fatal accident** – An accident resulting in the death of one or more persons. Prior to 2002, a fatal accident was defined as an accident where deaths occurred within 7 days. As from 2002, a fatal accident is defined as an accident where deaths occurred within 30 days
- **Serious injury accident** – An injury for which a person is admitted to hospital as an "in-patient" for more than 24 hours.
- **Slight injury accident** – An injury for which a person has received medical care but has not been admitted to hospital for more than 24 hours.
- **Non-injury accident**- An accident in which no one is killed or injured but which results in damage to the vehicle/s and/or other property only.

From this classification, the road traffic accidents can be categorized broadly into: Injury (Casualty accidents) and Non-injury road traffic accidents.

*(Source: Digest of Road Transport and Road Accident Statistics 2014, Statistics Mauritius, Ministry of Finance and Economic Development, Volume 30, November 2015).*

## 1.2 Highlights on Road Traffic accidents in Mauritius

We present some figures and highlights on the trend of road traffic accidents in Mauritius, some fatal accident events and some popular measures put in place by the Ministry of Public Infrastructure and Land Transport.

**Table 1.1: Road traffic accidents and casualties, 2012-2018**

| Number | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|
| **Road Traffic Accidents** | 21,056 | 23,563 | 26,400 | 28476 | 29,277 | 29,627 | 29,075 |
| **Motor Vehicle Involved** | 40,759 | 41,888 | 51,264 | 55,827 | 57,335 | 58,178 | 56,962 |
| **Casualties: Fatal** | 156 | 136 | 137 | 139 | 144 | 157 | 143 |
| **Seriously injured** | 549 | 465 | 505 | 495 | 512 | 560 | 597 |
| **Slightly injured** | 2,948 | 3,009 | 2,950 | 3,175 | 3,206 | 3,492 | 2,978 |

*(Source: Digest of Road Transport and Road Accident Statistics 2017, Statistics Mauritius, Ministry of Finance and Economic Development, Volume 33, November 2018).*

**Table 1.2: Some fatal road accidents in Mauritius**

| Date | Fatal Road Accidents | Casualties | Reasons |
|---|---|---|---|
| 8 Sep 09 | Collision between a sugar lorry and a bus took place on the motorway entering Port-Louis | 4 people died and many injured | Sugar lorry was overtaking another vehicle |
| 13 Oct 11 | Collision between a van and a bus took place entering Curepipe | 3 people died and many injured | Van was overtaking another vehicle |
| 03 May 13 | Bus accident on the motorway in Soreze, in the region of Pailles | 10 persons died and 43 persons injured | Serious failure of the braking system |
| 15 Feb 14 | Collision between '2x4' and a private car took place at Beaux Songes | 2 people died and others were injured | Car was overtaking another vehicle |
| 23 Aug 14 | Collision of a private car with two other vehicles at Calebasses | 3 people died and others were injured | Several bottles of alcohol were found in the car |

The above tables affirm our understanding that road traffic accidents are an issue of major health concern and of economic losses as well. These events have also urged the authorities to put in place some measure that attempt to reduce road traffic accidents.
Some popular measures that have been adopted by the authorities so far are as follows:

(a). Changes made in Contravention fees: In 2015, the fines for speeding which was Rs 2000 has been replaced by a graduated scale of fines for persons convicted of exceeding speed limits, following amendments made to the Road Traffic (Amendment) Bill (No. VI of 2015). The Bill provides for the level of sanction for speeding offences to escalate, as the level of speeding above the 6 authorized speed limit increases. According Clause 21 of the Bill provides for a minimum fine of Rs1000 for exceeding the speed limit by not more than 15 km, a fine of Rs1500 for exceeding the speed limit by more than 15 km but not more than 25 km per hour and a fine of Rs2500 for driving at a speed of more than 25 km, above the authorized speed limit. (Source: The Road Traffic (Amendment) Bill (No. VI of 2015), National Assembly, Republic of Mauritius).

(b). Installation of Mobile and Fixed Speed Cameras: The operation of speed cameras around Mauritius started in June 2013 and up to date there 54 speed cameras installed around the island. However, it should be noted that all these speed cameras were switched off from 31st December 2014 to 5th September 2015, following a decision taken by the government.

(c) Others: Following amendments made to the Road Traffic (Amendment) Bill (No. VI of 2015), the penalty point system was replaced by a new sanctioning mechanism for certain specified serious driving offences, such as disqualification of a person who has been convicted of more than 5 specified serious driving offences and the cancellation of the driving license of a person who has been disqualified a second time and also in cases of disqualification or cancellation, for the Court to order road traffic offenders to follow rehabilitation courses. In addition, a two-year road safety communication strategy targeting school children who are among the most vulnerable road users is under preparation. Currently, road safety education is being provided in all primary and secondary schools to impart necessary road safety skills to the school children.
*(Source: The Road Traffic (Amendment) Bill (No. VI of 2015), National Assembly, Republic of Mauritius).*

## 1.3 International Review on the Determinants of Road Traffic Crashes

Fuller (2004) and Schulze and Kobmann (2010) found that despite mobility is important in someone's daily life, it has nevertheless causes damages and accidents. Globally, it is estimated that by 2020, road traffic accidents will be ranked among the top three burden of disease as per measured in disability adjusted life years. Worldwide, the number of people who are killed in road traffic accidents annually is estimated at approximately 1.2 million whereas the number of people injured is as high as 50 million as per the World Health Organization (WHO) 2004 report (See Agbeboh and Osarumwense, 2013). Likewise, in India, during the year 2010, there were almost 500,000 road accidents that resulted in more than 1.3 million persons losing their lives and these numbers translate to one accident death every 4 minutes (Deshpande, 2014). According to official statistics, in 2011, there were at least 3334 fatal accidents and 3740 injuries in 4114 reported accidents in Bangladesh (Nury et al., 2012). In Ghana, according to the road safety report of 2007, at least six people are victims of fatal accidents daily out of them 25% of pedestrian fatalities involve children (Coleman, 2014).

Nury et al. (2012) provide a comprehensive list of the contributing factors in the road accidents occurrences that consist of: Alcohol involvement, Ignoring toll, use narrow road, Accelerator defective, Insecure load, Attempted Suicide, Improper Turning, Avoiding Vehicle/pedestrian/cycle, Improper overtaking, Breaks defective, Obstruction on road, Cutting In, Illness of driver, Driverless vehicle, Previous traffic accident, Domestic animal, Preexisting physical disability, Defective pavement surface, Prescribed Medication, Drugs, Pedestrian error confusion, Driving without due care, Reversing Unsafely, Defective bridge, Restraint system, Drivers talking with passenger, Roadside hazard, Dangerous goods, Road construction, Defective Brake light, Road/Intersection design, Turn signal, Road Maintenance, Detective head light, Steering Failure, Driver inexperience, Sudden loss of consciousness, Driving on the wrong side of road, Suspension Defect, Engine failure, Sign obstruction, Extreme fatigue, Two Hitch failure, Failing to signal, Tires failure, Feel Asleep, Unsafe speed, Falling head light on other drivers eye, Vehicle Modification, Following- too closely, Visibility impaired, Failing to Yield Right of way, Windshield defective, Glare artificial, Wild animal, Glare sunlight Weather, Ignoring traffic control device, Oversize Vehicle, Insufficient traffic control, Others. In addition, Nury et al. (2012) set up a multiple regression model where the number of registered vehicles and the population size have a significant positive effect on the number of accidents in Bangladesh.

On the other hand, Mohanty and Gupta (2015) classified the causes of road accidents into three main headings:

a) **Personal or human behavioural factors**: Age of driver or victim, gender of victim, was he drunk while driving, etc.
b) **Road and Environmental factors**: The road geometric factors include type of junction or intersection, and the horizontal slopes and curves present on roads. On the other hand, the environmental factors include factors such as climate and environment, lighting conditions of road, time of accident (day or night), pavement conditions, etc.

c) **Vehicle/traffic factors**: These factors include speeding, density and traffic flow parameters.

Mohanty and Gupta (2015) also emphasized that the causes of road accidents may be different in urban and rural roads. Obaidat and Ramadan (2012) noted that in urban areas, average running speed, posted speed, maximum and average degree of horizontal curves, number of vertical curves, median width, type of road surface, lighting (day or night), number of vehicles per hour, number of pedestrian crossing facilities and percentage of trucks are frequent causes of road accidents. In the rural areas, Kloeden et al. (2001) concluded that increasing speed caused an exponential increase in the risk of involvement in a casualty crash. Mustakim and Fujita (2011) used a multiple non-linear regression model to conclude that accidents on rural roadway are caused by existing number of major access points without traffic light, rise in speed, increase number of annual average daily traffic and growing number of motorcycle and motorcar.

As for the road characteristics, Griebe (2003), Rengarasu et al. (2007) and Anwar et al. (2013) found out that road infrastructures such as geometry, junction and road intersection represent a major contribution of the total accidents. In some other papers, Karlaftis and Golias (2002) studied that geometric design and pavement condition are the most significant factors affecting number of accidents. Similar conclusions were made by Hills et al. (2002) in analyzing the road accident occurrences in developing countries, namely Zimbabwe, Botswana, Malawi, Tanzania, India and Nepal and concluded that curvature and gradient were significant explanatory variables in Papua New Guinea and that marked edge line in Nepal and India caused a reduction in accident rate.

As for the environmental attributes, rainfall is often cited as the weather type responsible for the maximum number of weather-related accidents (Edwards, 1999, Keay and Simmonds (2006), Qui and Nixon, 2008, Jaroszweski and McNamara, 2014). The probability of crash occurrence and increased severity is higher with rainfall, as it reduces the road surface friction (Jaroszweski and McNamara, 2014).

There are also a number of studies that have concluded the significant effect of rainfall on highway accidents (Jung at al., 2010, Amin et al, 2014). A report by Ivan et al. (2010) showed that there is a positive relationship between wet pavement friction and crash frequency.

Based on the above review, we present some cross tabulations on some of the causes identified by Mohanty and Gupta (2015), in particular, on the number of registered vehicles and number of casualty accidents by some factors.

### Table 1.3: Vehicles registered, 2008-2017

| Type of Vehicle | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Car, dual purpose and double cab.** | 155,528 | 165,036 | 175,634 | 185,357 | 197,849 | 211,586 | 225,522 | 240,289 | 255,199 | 272,213 |
| **Motor/auto cycle** | 147,988 | 152,935 | 159,329 | 165,706 | 173,508 | 180,785 | 187,851 | 193,688 | 199,399 | 205,493 |
| **Other** | 47,890 | 48,549 | 49,152 | 49,856 | 50,569 | 51,124 | 51,679 | 52,167 | 53,078 | 54,091 |
| **Total** | 351,406 | 366,520 | 384,115 | 400,919 | 421,926 | 443,495 | 465,052 | 486,144 | 507,676 | 531,797 |

### Table 1.4: Number of casualty accidents by severity of accident and weather conditions, 2016-2017

| Weather conditions | 2016 | | | | 2017 | | | |
|---|---|---|---|---|---|---|---|---|
| | Severity of accident | | | | Severity of accident | | | |
| | Fatal | Serious | Slight | Total | Fatal | Serious | Slight | Total |
| **Fine** | 126 | 393 | 2078 | **2597** | 140 | 439 | 2270 | **2849** |
| **Rainy** | 6 | 29 | 155 | **190** | 11 | 29 | 149 | **189** |
| **Foggy/misty** | 0 | 1 | 1 | **2** | 1 | 0 | 2 | **3** |
| **Other** | 0 | 0 | 0 | **0** | 0 | 0 | 0 | **0** |
| **Total** | **132** | **423** | **2234** | **2789** | **152** | **468** | **2421** | **3041** |

### Table 1.5: Number of casualty accidents by severity of accident and light conditions, 2016-2017

| Light conditions | 2016 | | | | 2017 | | | |
|---|---|---|---|---|---|---|---|---|
| | Severity of accident | | | | Severity of accident | | | |
| | Fatal | Serious | Slight | Total | Fatal | Serious | Slight | Total |
| **Daylight** | 57 | 240 | 1425 | **1722** | 72 | 267 | 1615 | **1954** |
| **Dawn/dusk** | 8 | 31 | 214 | **253** | 18 | 47 | 239 | **304** |
| **Darkness: street lights present and lit** | 51 | 116 | 452 | **619** | 46 | 112 | 429 | **587** |
| **Darkness: street lights present but unlit** | 4 | 5 | 37 | **46** | 2 | 10 | 30 | **42** |
| **Darkness: no street lighting** | 12 | 31 | 106 | **149** | 14 | 32 | 108 | **154** |
| **Not specified** | 0 | 0 | 0 | **0** | 0 | 0 | 0 | **0** |
| **Total** | **132** | **423** | **2234** | **2789** | **152** | **468** | **2421** | **3041** |

**Table 1.6: Number of casualty accidents by severity of accident and type of roads, 2016-2017**

| Type of road | 2016 | | | | | 2017 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Length of roads (kms) | Severity of accident | | | | Length of roads (kms) | Severity of accident | | | |
| | | Fatal | Serious | Slight | Total | | Fatal | Serious | Slight | Tota l |
| **Motor-way** | 100 | 12 | 27 | 149 | **188** | 100 | 21 | 24 | 147 | **192** |
| **Main road** | 1137 | 104 | 365 | 1806 | **2275** | 1192 | 113 | 410 | 1968 | **2491** |
| **Secondary road** | 756 | 13 | 25 | 246 | **284** | 833 | 14 | 27 | 269 | **310** |
| **Other road** | 509 | 3 | 6 | 33 | **42** | 561 | 4 | 7 | 37 | **48** |
| **Total** | **2502** | **132** | **423** | **2234** | **2789** | **2686** | **152** | **468** | **2421** | **3041** |

**Table 1.7: Number of casualty accidents by severity of accident and junction type, 2016-2017**

| Junction type | 2016 | | | | 2017 | | | |
|---|---|---|---|---|---|---|---|---|
| | Degree of casualties | | | | Severity of accident | | | |
| | Fatal | Serious | Slight | Total | Fatal | Serious | Slight | Total |
| **Not a Junction** | 112 | 271 | 1512 | 1895 | 134 | 267 | 1560 | 1961 |
| **Crossroads** | 6 | 55 | 230 | 291 | 8 | 91 | 302 | 401 |
| **T-Junction** | 9 | 67 | 297 | 373 | 5 | 73 | 333 | 411 |
| **Staggered-Junction** | 1 | 6 | 25 | 32 | 2 | 3 | 9 | 14 |
| **Y-Junction** | - | 2 | 21 | 23 | 0 | 3 | 21 | 24 |
| **Roundabout** | 3 | 14 | 106 | 123 | 3 | 15 | 149 | 167 |
| **Slip Road** | 1 | 4 | 28 | 33 | 0 | 9 | 26 | 35 |
| **Private Entrance** | - | 4 | 15 | 19 | 0 | 7 | 21 | 28 |
| **Total** | 132 | 423 | 2,234 | 2,789 | 152 | 468 | 2,421 | 3,041 |

As at date, in Mauritius, the papers by Agnihotri et al. (2011) and Allock and Goorah (2016) attempt to explain the relationship between road traffic accidents and alcoholic consumption, but from the reviews in Sec

## 1.4 Gaps

We note essentially that in Mauritius, there has been so far no scientific study conducted to detect the causes of road traffic accidents. Intuitively or from international reviews, it can only be guessed that some popular factors such as number of vehicles in circulation, road conditions, driving-related behaviours contribute to the occurrence of accidents.

We have access to the digests of Road Transport and Traffic Digest from the government portal for the different years which only provide us cross tabulations by some factors or conditions. However, at no point, we could deduce scientifically that these factors or conditions have contributed significantly to these accidents. Moreover, we also miss out on to what extent these factors contribute to the risk of a fatal, serious or slight accidents or non-injury accidents and hence cannot predict the severity of the accident.

## 1.5 Aims and Objectives

Thus, the aims of this project are:

(a). To identify scientifically the Potential Causes of accidents using Statistical and Computing techniques.

(b). To determine the extent the identified causes influence the risk of the accident occurrence and can also predict the severity of accident. Following the Global Safety Report (2018), much focus is to be given to how the identified causes influence the occurrence of Fatal, Serious, Slight-injury.

and the objectives are as follows:

(a). Data acquisition/cleansing: The most important is to acquire the micro road accident data on fatal, serious, slightly-injured, non-injury accidents and other features and then setting the data matrices and frames.

(b). Time Series analysis: Since the road accident data in the digest are compiled on a yearly basis, we propose to use appropriate time series models to analyze the data.

(c). Statistical Techniques: We propose to use the logistic and multinomial logistic model to obtain the potential and significant causes of road traffic accidents in Mauritius.

(d). Predicting Severity of Accidents: We use the Artificial Neural Networks and Support Vector Machine to predict the severity of accident.

## 1.6 Organization of the Project

Chapter 2 presents the research methodology and provides some details on the data acquisition, modelling and methodologies.

Chapter 3 focuses on the application of time series models to the different severity accident data.

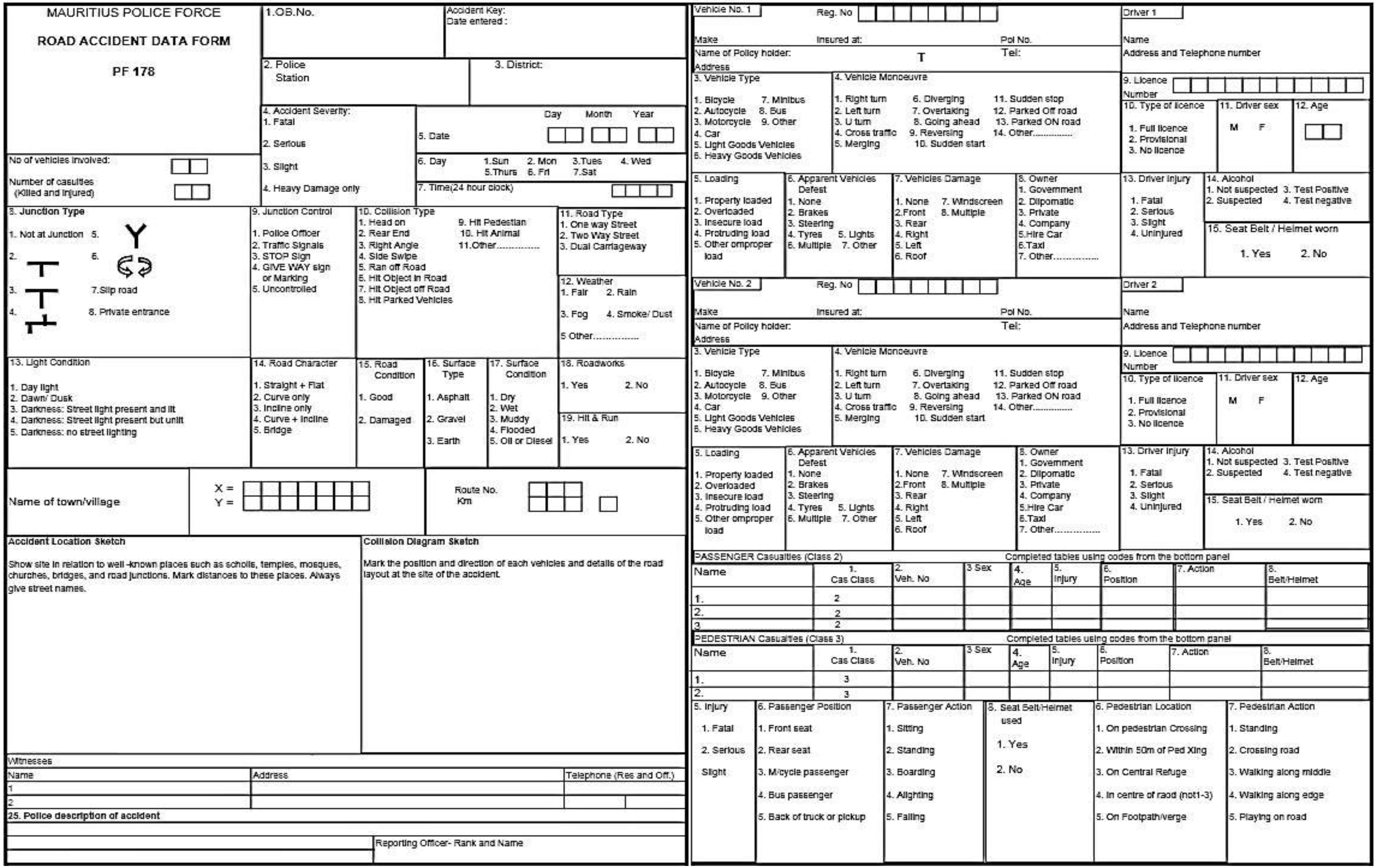
Chapter 4 is based on the application of the logistic and multinomial logistic approaches to determine the causes of injury, fatal, serious-injured and slight-injured accidents in Mauritius. This chapter also provides the pass rates for the predictive algorithms: Artificial Neural Networks and Support Vector Machine.

Chapter 5 provides the overall conclusion of this project and along with some important remarks and suggestions.

# 2. Research Methodology

## 2.1 Data Acquisition/Cleaning.

We first conducted a consultative meeting with the Ministry of Public Infrastructure and Land Transport in August 2017 to seek advice on the collection of micro data on road traffic accidents. It was discussed that all reported cases of road accident is recorded by the Police using the Police Form 178 (PF 178). This form was developed by Traffic Research Laboratory (T.R.L) of the U.K and can record about 100 details on every reported accident reported to the police. The accident data and management system is being supported by a software known as the MAAP (Micro Computer Accident Analysis Package) software for windows V.4.0. It is worth to mention here that as from 2019, the record is made using a new software called the IMAAP. The IMAAP has some additional merits as compared to the MAAP software since IMAAP records the accident on real time platform and can produce the features tables and plots immediately. However, both MAAP and IMAAP cannot detect the significant causes and not able to predict the severity of the accident. The PF 178 is illustrated below.



MAURITIUS POLICE FORCE

ROAD ACCIDENT DATA FORM

PF 178

1.OB.No.

Accident Key:
Date entered :

2. Police Station

3. District:

4. Accident Severity:
1. Fatal
2. Serious
3. Slight
4. Heavy Damage only

5. Date — Day Month Year

6. Day — 1.Sun 2. Mon 3.Tues 4. Wed 5.Thurs 6. Fri 7.Sat

7. Time(24 hour clock)

No of vehicles involved:

Number of casulties (Killed and Injured)

8. Junction Type
1. Not at Junction
2.
3.
4.
5.
6.
7.Slip road
8. Private entrance

9. Junction Control
1. Police Officer
2. Traffic Signals
3. STOP Sign
4. GIVE WAY sign or Marking
5. Uncontrolled

10. Collision Type
1. Head on
2. Rear End
3. Right Angle
4. Side Swipe
5. Ran off Road
6. Hit Object in Road
7. Hit Object off Road
8. Hit Parked Vehicles
9. Hit Pedestian
10. Hit Animal
11.Other..............

11. Road Type
1. One way Street
2. Two Way Street
3. Dual Carriageway

12. Weather
1. Fair 2. Rain
3. Fog 4. Smoke/ Dust
5 Other..............

13. Light Condition
1. Day light
2. Dawn/ Dusk
3. Darkness: Street light present and lit
4. Darkness: Street light present but unlit
5. Darkness: no street lighting

14. Road Character
1. Straight + Flat
2. Curve only
3. Incline only
4. Curve + Incline
5. Bridge

15. Road Condition
1. Good
2. Damaged

16. Surface Type
1. Asphalt
2. Gravel
3. Earth

17. Surface Condition
1. Dry
2. Wet
3. Muddy
4. Flooded
5. Oil or Diesel

18. Roadworks
1. Yes 2. No

19. Hit & Run
1. Yes 2. No

Name of town/village

X =
Y =

Route No.
Km

Accident Location Sketch

Show site in relation to well -known places such as scholls, temples, mosques, churches, bridges, and road junctions. Mark distances to these places. Always give street names.

Collision Diagram Sketch

Mark the position and direction of each vehicles and details of the road layout at the site of the accident.

Witnesses

| Name | Address | Telephone (Res and Off.) |
|---|---|---|
| 1 | | |
| 2 | | |

25. Police description of accident

Reporting Officer- Rank and Name

Vehicle No. 1 — Reg. No

Make — Insured at: — Pol No.

Name of Policy holder: — T — Tel:

Address

3. Vehicle Type
1. Bicycle 7. Minibus
2. Autocycle 8. Bus
3. Motorcycle 9. Other
4. Car
5. Light Goods Vehicles
6. Heavy Goods Vehicles

4. Vehicle Monoeuvre
1. Right turn 6. Diverging 11. Sudden stop
2. Left turn 7. Overtaking 12. Parked Off road
3. U turn 8. Going ahead 13. Parked ON road
4. Cross traffic 9. Reversing 14. Other..............
5. Merging 10. Sudden start

5. Loading
1. Property loaded
2. Overloaded
3. Insecure load
4. Protruding load
5. Other ompropor load

6. Apparent Vehicles Defect
1. None
2. Brakes
3. Steering
4. Tyres 5. Lights
6. Multiple 7. Other

7. Vehicles Damage
1. None 7. Windscreen
2.Front 8. Multiple
3. Rear
4. Right
5. Left
6. Roof

8. Owner
1. Government
2. Dilpomatic
3. Private
4. Company
5.Hire Car
6.Taxi
7. Other..............

Driver 1

Name

Address and Telephone number

9. Licence Number

10. Type of licence
1. Full licence
2. Provisional
3. No licence

11. Driver sex — M F

12. Age

13. Driver Injury
1. Fatal
2. Serious
3. Slight
4. Uninjured

14. Alcohol
1. Not suspected 3. Test Positive
2. Suspected 4. Test negative

15. Seat Belt / Helmet worn
1. Yes 2. No

Vehicle No. 2 — Reg. No

Make — Insured at: — Pol No.

Name of Policy holder: — Tel:

Address

3. Vehicle Type
1. Bicycle 7. Minibus
2. Autocycle 8. Bus
3. Motorcycle 9. Other
4. Car
5. Light Goods Vehicles
6. Heavy Goods Vehicles

4. Vehicle Monoeuvre
1. Right turn 6. Diverging 11. Sudden stop
2. Left turn 7. Overtaking 12. Parked Off road
3. U turn 8. Going ahead 13. Parked ON road
4. Cross traffic 9. Reversing 14. Other..............
5. Merging 10. Sudden start

5. Loading
1. Property loaded
2. Overloaded
3. Insecure load
4. Protruding load
5. Other ompropor load

6. Apparent Vehicles Defect
1. None
2. Brakes
3. Steering
4. Tyres 5. Lights
6. Multiple 7. Other

7. Vehicles Damage
1. None 7. Windscreen
2.Front 8. Multiple
3. Rear
4. Right
5. Left
6. Roof

8. Owner
1. Government
2. Dilpomatic
3. Private
4. Company
5.Hire Car
6.Taxi
7. Other..............

Driver 2

Name

Address and Telephone number

9. Licence Number

10. Type of licence
1. Full licence
2. Provisional
3. No licence

11. Driver sex — M F

12. Age

13. Driver Injury
1. Fatal
2. Serious
3. Slight
4. Uninjured

14. Alcohol
1. Not suspected 3. Test Positive
2. Suspected 4. Test negative

15. Seat Belt / Helmet worn
1. Yes 2. No

PASSENGER Casualties (Class 2) — Completed tables using codes from the bottom panel

| Name | 1. Cas Class | 2. Veh. No | 3 Sex | 4. Age | 5. Injury | 6. Position | 7. Action | 8. Belt/Helmet |
|---|---|---|---|---|---|---|---|---|
| 1. | 2 | | | | | | | |
| 2. | 2 | | | | | | | |
| 3 | 2 | | | | | | | |

PEDESTRIAN Casualties (Class 3) — Completed tables using codes from the bottom panel

| Name | 1. Cas Class | 2. Veh. No | 3 Sex | 4. Age | 5. Injury | 6. Position | 7. Action | 8. Belt/Helmet |
|---|---|---|---|---|---|---|---|---|
| 1. | 3 | | | | | | | |
| 2. | 3 | | | | | | | |

5. Injury
1. Fatal
2. Serious
Slight

6. Passenger Position
1. Front seat
2. Rear seat
3. M/cycle passenger
4. Bus passenger
5. Back of truck or pickup

7. Passenger Action
1. Sitting
2. Standing
3. Boarding
4. Alighting
5. Falling

8. Seat Belt/Helmet used
1. Yes
2. No

6. Pedestrian Location
1. On pedestrian Crossing
2. Within 50m of Ped Xing
3. On Central Refuge
4. In centre of raod (not1-3)
5. On Footpath/verge

7. Pedestrian Action
1. Standing
2. Crossing road
3. Walking along middle
4. Walking along edge
5. Playing on road

Figure 2.1: PF - 178

The PF-178 records information on the Road conditions: infrastructural/environmental, on vehicle and on driver-related features. The severity of the accident is categorized as (a) fatal accident, (b) serious injury accident, (c) slight injury accident, and non-injury accident.

The Road related conditions consist of the following components:

(a) Day/Month/Time,

(b) Road Type: One-way, Motorway, Dual Carriageway,

(c) Weather: Fine, Not-fine{Rainy, Windy, Foggy, others}

(d) Light conditions: Lighting On, No-Lighting

(e) Road condition: Good/Damaged

(f) Junction

(g) Road character: Straight/Flat, Curve, Incline…

(h) Surface condition

(i) Others: Junction control, Collision type,..

The Vehicle and Driver related factors consist of:

(a). Vehicle Type

(b). Vehicle Manoeuvre

(c). Vehicle defects

(c). Number of vehicles involved

(d) Age of the drivers

(e). Gender

(f). Alcohol consumption.

(g). Others

Since these factors are categorical, a reference category is to be assumed in the analysis and interpretation.

## 2.2 Analysis

The glm (binomial) and multinom functions in R are used to analyze the accident data as follows: In both glm and multinom, the odds ratios are the output variables.

In particular, for glm(binomial), the odd ratio (OR) is represented as:

OR=Prob( Injury)/Prob(Non-injury accident)=exp( Road Related + Vehicle + Driver Related factors)

and

for multinom(logit), OR**.** is based on the different casualty accident categories:

ORFatal= Prob(Fatal)/Prob (Non-injury accident)= exp( Road Related + Vehicle + Driver Related factors)

ORSerious= Prob(Serious)/Prob (Non-injury accident)= exp( Road Related + Vehicle + Driver Related factors)

ORSlight= Prob(Slight)/Prob (Non-injury accident)= exp( Road Related + Vehicle + Driver Related factors)

The details of the glm(binomial) and multinom(logit) are described in https://www.rdocumentation.org/packages/stats/versions/3.6.1/topics/glm and https://data.princeton.edu/wws509/notes/.

From the above definition of the OR/ or OR**.**:

(a). We can measure the extent by which a concerned factor influences the odds of injury, or fatal or serious or slight accident occurrence as compared to the reference category of the factors.

(b). We can also note that an increase (decrease) in the OR/ or OR**.** implies an increase (decrease) in the probability of an injury/ or Fatal, Serious or Slight accident occurrence.

Below, we present the details of the factors and the reference categories, since these factors are of categorical variables.

| Month | Day | Road Type | Road Condition | Light Conditions |
|---|---|---|---|---|
| Jan<br>.<br>.<br>.<br>Dec(ref) | • Weekdays (ref)<br>• Friday<br>• Weekend | • One-way street (ref)<br>• Two-way street<br>• Dual carriageway | • Good (ref)<br>• Damaged | • Daylight (ref)<br>• Dawn/Dusk<br>• Darkness: Streetlight on<br>• Darkness: no streetlight |

| Weather | Surface Condition | Time interval | Time.Light |
|---|---|---|---|
| • Fine<br>• Rainy<br>• Foggy/ Misty<br>• Other<br>ref | • Dry (ref)<br>• Wet<br>• Muddy | • Morning (06:00-10:00)<br>• Off peak (10:00-14:00)(ref)<br>• Afternoon (14:00-18:00)<br>• Night (19:00-05:00) | • Dawn (05:00-06:00)<br>• Morning (06:00-10:00)<br>• Off peak (10:00-14:00) (ref)<br>• Afternoon (14:00-18:00)<br>• Dusk (18:00-19:00)<br>• Darkness (19:00-05:00) with Street light on (Night1)<br>• Darkness (19:00-05:00) with no street lighting (Night2) |

| Road Character | Gender of Driver | Vehicle Manoeuvre | Vehicle defects |
|---|---|---|---|
| • Straight (ref)<br>• Not Straight | • Male<br>• Female (ref) | • Overtaking<br>• Not Overtaking (ref) | • Any defects (brakes, steering wheels, other mechanical parts..)<br>• No defects (ref) |

| Age of driver | Vehicle Type | Junction Type |
|---|---|---|
| • 15 -24 yrs<br>• 25- 34 yrs<br>• 35 – 44 yrs<br>• 45 – 54 yrs<br>• 55 – 60 yrs<br>• ≥ 60 yrs (ref) | • Car<br>• Auto/Motorcycle<br>• Mini/Bus<br>• Other (ref) | • Not a junction<br>• T-Junction<br>• Cross-Road<br>• Staggered – Junction<br>• Y – Junction<br>• Roundabout<br>• Slip Road<br>• Private Entrance<br>ref |

## 2.3 Descriptive Plots

- The total number of road accidents for each category of Time.Light for year 2017 are illustrated below.

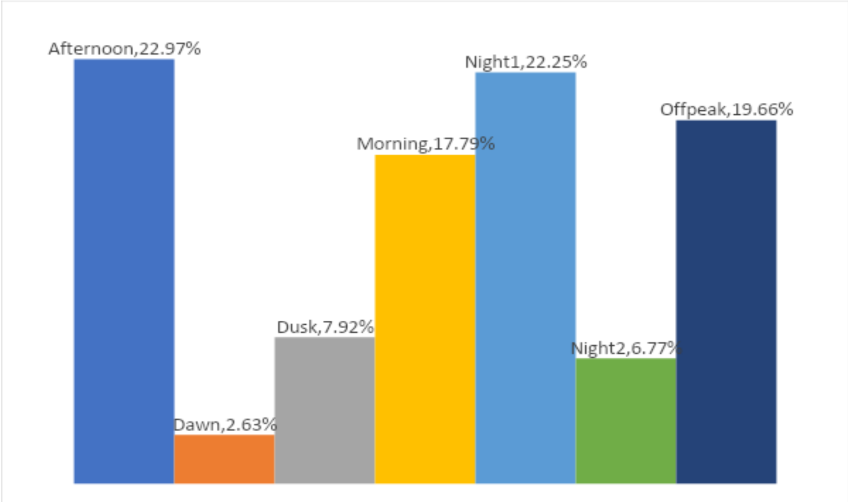



**Figure 2.2: Number of road accidents for each category of Time.Light in 2017**

The above chart indicates 22.97% of the road accidents occurred in the afternoon. Also, it is remarked that 19.66 % of total road accidents were recorded during the off-peak, that is 10:00-14:00. 29.02 % of accidents occurred at night out of which 6.77 % were on completely dark roads.

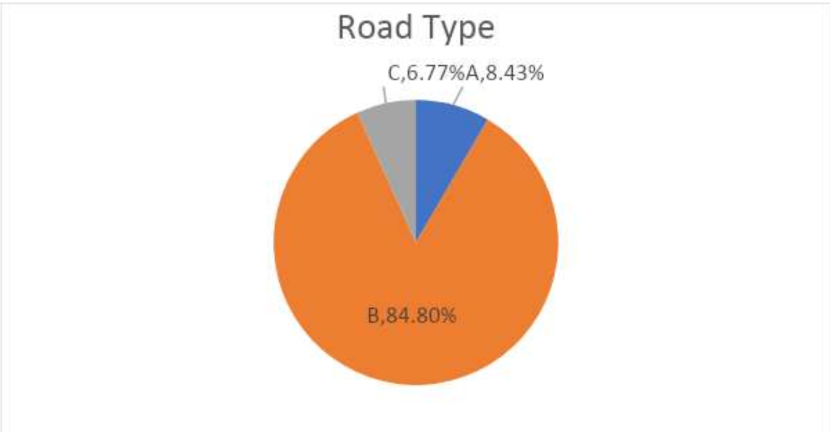



**Figure 2.3: Number of road accidents on each type of road for 2017**

The above pie chart indicates that 8.43 % ,84.8 % and 6.77 % of road accidents occurred in one-way street, two-way street and dual carriageway respectively. Thus, the two-way street is the most common road type where highest number of accidents occurred.

- Similar patterns were obtained with respect to the road accidents over the two years 2012 and 2016.

- The models developed thus get further validated and proved to be reliable in identifying the major factors as road type combined with light conditions and time interval.
- The total number of casualties for drivers under each category of vehicle type are illustrated below.

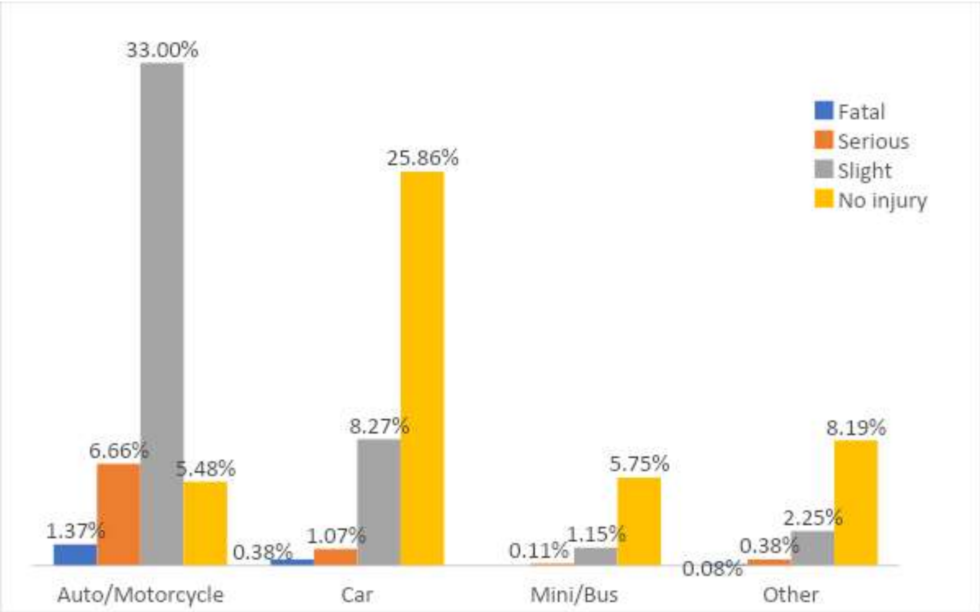



**Figure 2.4: Number of casualties for drivers of each vehicle type**

The types of vehicle associated with the high frequency of casualties of drivers are the Auto/Motorcycle (46.51 %) and Car (35.58 %). Of all casualties of drivers, 8.04 % are seriously injured auto/motorcyclist and 1.45 % are seriously injured car drivers.

- The total number of casualties for drivers under each categories of vehicle manoeuvre are illustrated below.

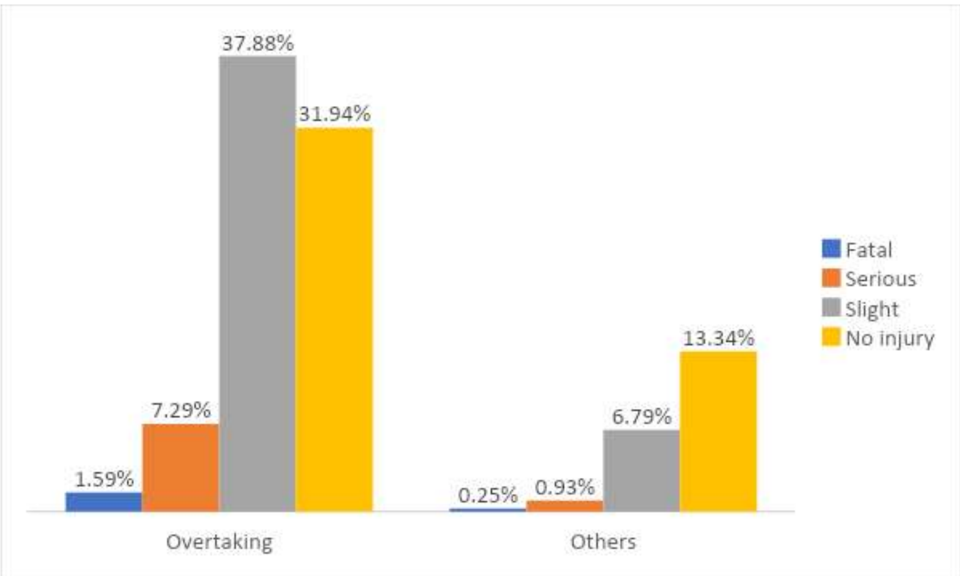



**Figure 2.5: Number of casualties for drivers under each categories of vehicle manoeuvre**

78.69 % of drivers involved in road traffic accident are seen to be overtaking, out of which 8.88 % of drivers are seriously injured due to this vehicle manoeuvre. Hence overtaking can be said to be the most common manoeuvre opted by drivers on the roads.

- The total number of casualties (drivers) under each category of vehicle manoeuvre and vehicle type are illustrated below.

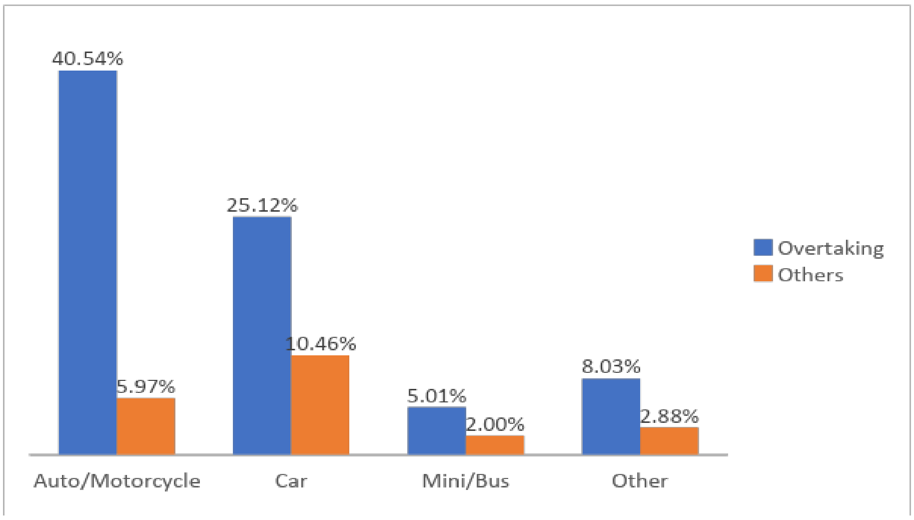



**Figure 2.6: Total number of casualties (drivers) under each category of vehicle manoeuvre and vehicle type**

From the above graph, 40.54 % of auto/motorcyclist and 25.12 % of car drivers were found to be overtaking before the accidents have occurred. Hence the most common vehicle type that overtakes is the auto/motorcycle.

## 2.4 Conclusion

This chapter provides an overview on the statistical techniques to be used to identify the potential causes of traffic accidents and tabulate the relevant variables with their respective reference categories. The next chapters will focus on these approaches and findings.

# 3. Time Series Analysis

## 3.1 Trend Analysis using Time Series Models

Data on annual road accidents from 1980 to 2016 have been analyzed using time series models. Preliminary models have been developed for total number of accidents as well as counts of fatal, serious, slight and non-injury accidents.

### 3.1.1 Total Accidents

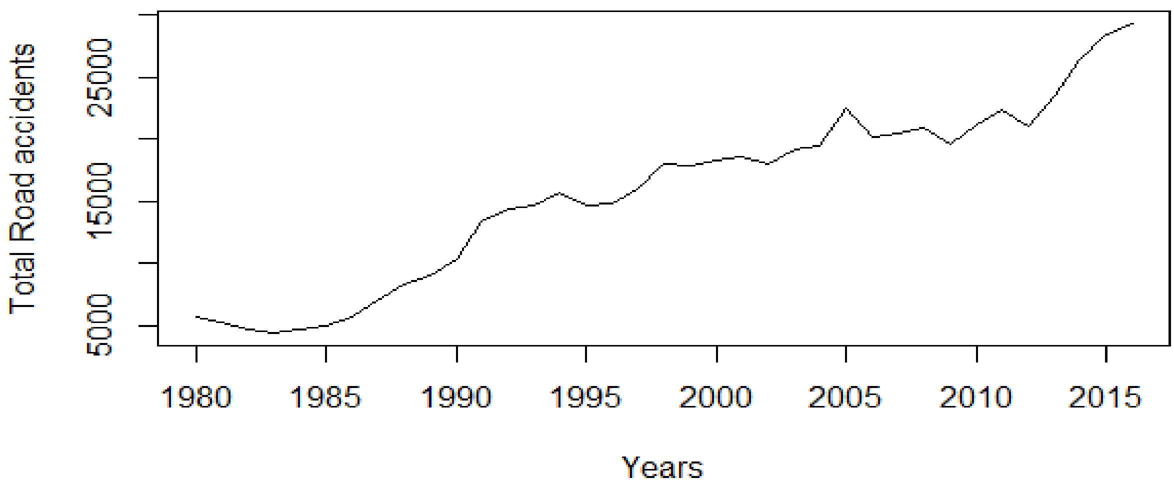



Figure 3.1: Total road accidents (1980-2016)

It is remarked that data are non-stationary, hence log values of responses is used to develop models for the period (1980 to 2014). The log series are also normal according to Jarque Bera test(p-value>0.05). Models are validated on the basis of 2-step ahead forecasts.

**ARIMA (1,1,0) without a drift**

```
Series: log10(data3)
ARIMA(1,1,0)

Coefficients:
         ar1
      0.4845
s.e.  0.1511

sigma^2 estimated as 0.001442:  log likelihood=63.35
AIC=-122.7   AICc=-122.31   BIC=-119.64

Training set error measures:
                  ME       RMSE         MAE        MPE      MAPE
MASE       ACF1
Training set 0.01067 0.03686862 0.03021747 0.2605013 0.7332917
0.869509 -0.1883245
```

**ARIMA (1,1,0) with a drift**

```
Series: log10(data3)
ARIMA(1,1,0) with drift

Coefficients:
         ar1   drift
      0.3459  0.0191
s.e.  0.1650  0.0092

sigma^2 estimated as 0.001359:  log likelihood=64.94
AIC=-123.89   AICc=-123.09   BIC=-119.31

Training set error measures:
                       ME       RMSE         MAE        MPE
MAPE      MASE
Training set 0.0007618546 0.03525086 0.02834211 0.0183769
0.6914112 0.8155457
                    ACF1
Training set -0.04907111
```

**Table 3.1: Forecasts of Total accidents**

| Year | True values | Forecasted ARIMA(1,1,0) without drift | Forecasted ARIMA(1,1,0) with drift |
|---|---|---|---|
| **2015** | 28476 | 27894.91 | 28258.46 |
| **2016** | 29277 | 28649.33 | 29773.80 |

**Table 3.2: Forecast Error Measure for Total accidents**

| | ARIMA(1,1,0) without drift | ARIMA(1,1,0) with drift |
|---|---|---|
| **MAE** | 0.009183 | 0.005319 |
| **MAPE** | 0.205868 | 0.119189 |
| **RMSE** | 0.009186 | 0.005679 |

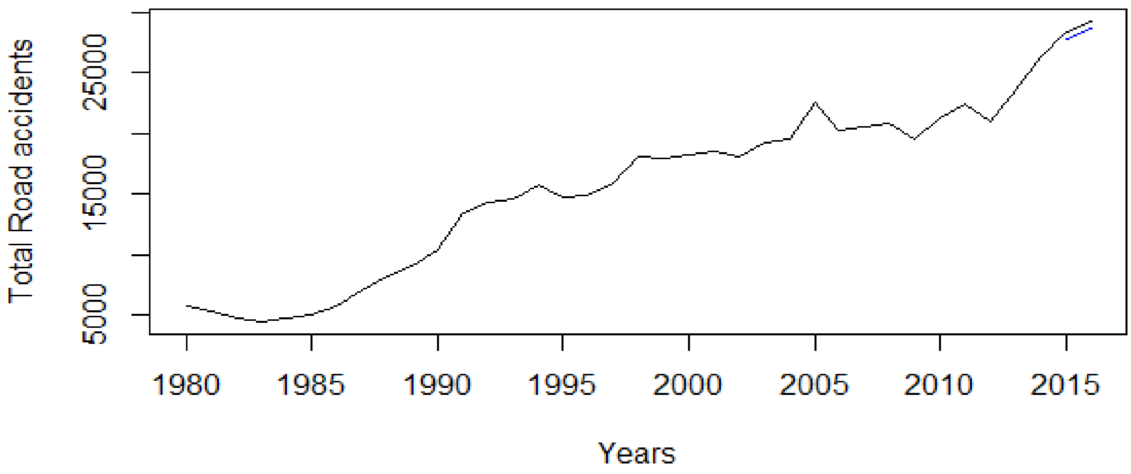



**Figure 3.2:Plot of Total accidents with forecasts of ARIMA(1,1,0) without drift**

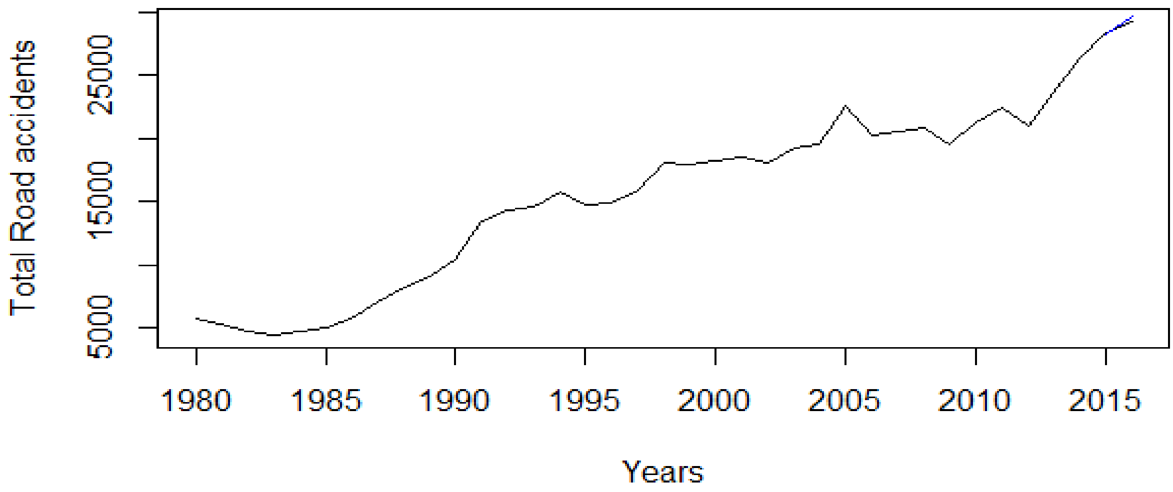



**Figure 3.3: Plot of Total accidents with forecasts of ARIMA(1,1,0) with drift**

Hence ARIMA(1,1,0) with drift is a better model for Total accidents.

### 3.1.2 Fatal accidents

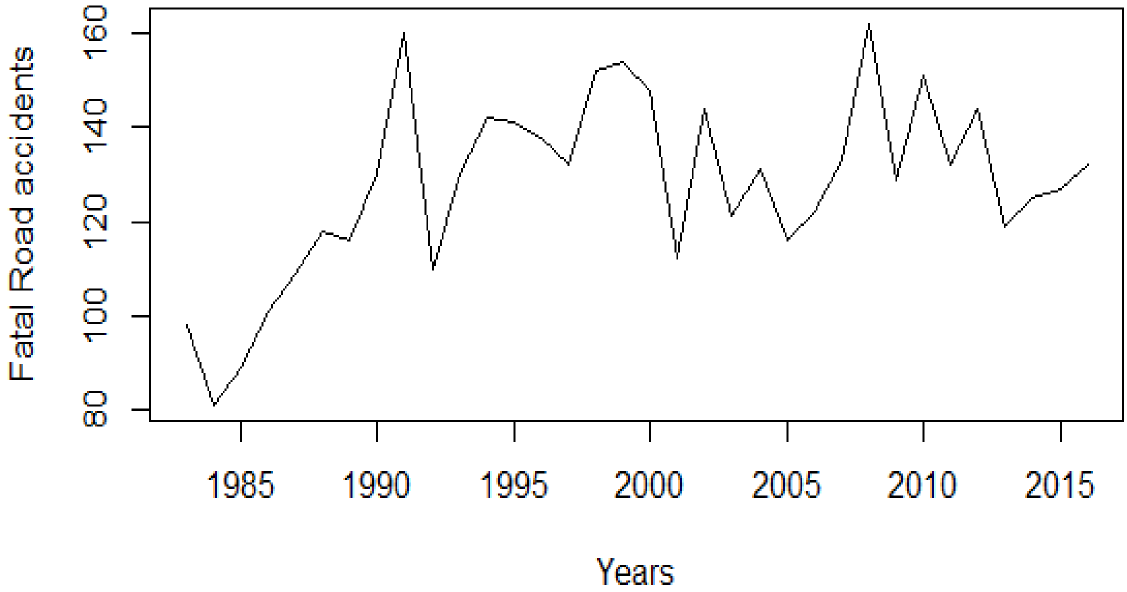



Figure 3.4: Fatal accidents (1983-2016)

Since non-stationary, the log values of responses are considered to develop models for the period (1983 to 2014) The log series are also normal according to Jarque Bera test(p-value>0.05). Models are validated on the basis of 2-step ahead forecasts.

**ARIMA (0,1,1) without a drift**

```
Series: log10(dataF2)
ARIMA(0,1,1)

Coefficients:
          ma1
-0.5117
s.e.   0.1395

sigma^2 estimated as 0.003326:  log likelihood=44.81
AIC=-85.63   AICc=-85.2   BIC=-82.76

Training set error measures:
                      ME        RMSE         MAE         MPE      MAPE
MASE
Training set 0.008120533 0.05583795 0.04481081 0.3445329 2.135329
0.8226688
                    ACF1
Training set -0.09831017
```

**ARIMA (0,1,1) with a drift**

```
Series: log10(dataF2)
ARIMA(0,1,1) with drift
```

```
Coefficients:
          ma1   drift
      -0.5540  0.0047
s.e.0.1441  0.0047

sigma^2 estimated as 0.003335:  log likelihood=45.27
AIC=-84.53   AICc=-83.64   BIC=-80.23

Training set error measures:
                        ME        RMSE         MAE          MPE      MAPE
MASE
Training set -0.0005611405 0.05497352 0.04340336 -0.06683156 2.072002
0.7968298
                    ACF1
Training set -0.06148757
```

**Table 3.3: Forecasts of Fatal accidents**

| Year | True values | Forecasted ARIMA(0,1,1) without drift | Forecasted ARIMA(0,1,1) with drift |
|---|---|---|---|
| **2015** | 127 | 127.3572 | 131.1382 |
| **2016** | 132 | 127.3572 | 132.5665 |

**Table 3.4: Forecast Error Measure for Fatal accidents**

| | ARIMA(0,1,1) without drift | ARIMA(0,1,1) with drift |
|---|---|---|
| **MAE** | 0.008385 | 0.007893 |
| **MAPE** | 0.395646 | 0.374813 |
| **RMSE** | 0.01103 | 0.009934 |

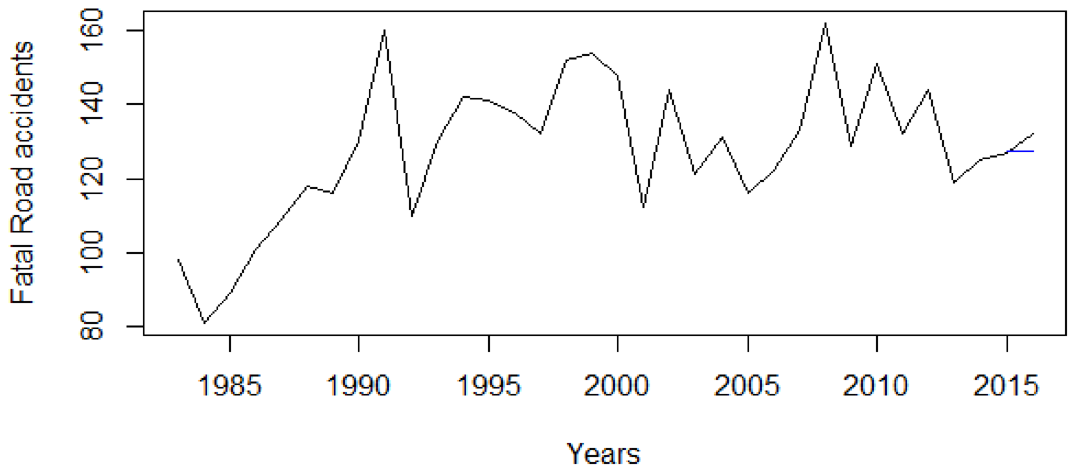



**Figure 3.5: Plot of Fatal accidents with forecasts of ARIMA(0,1,1) without drift**

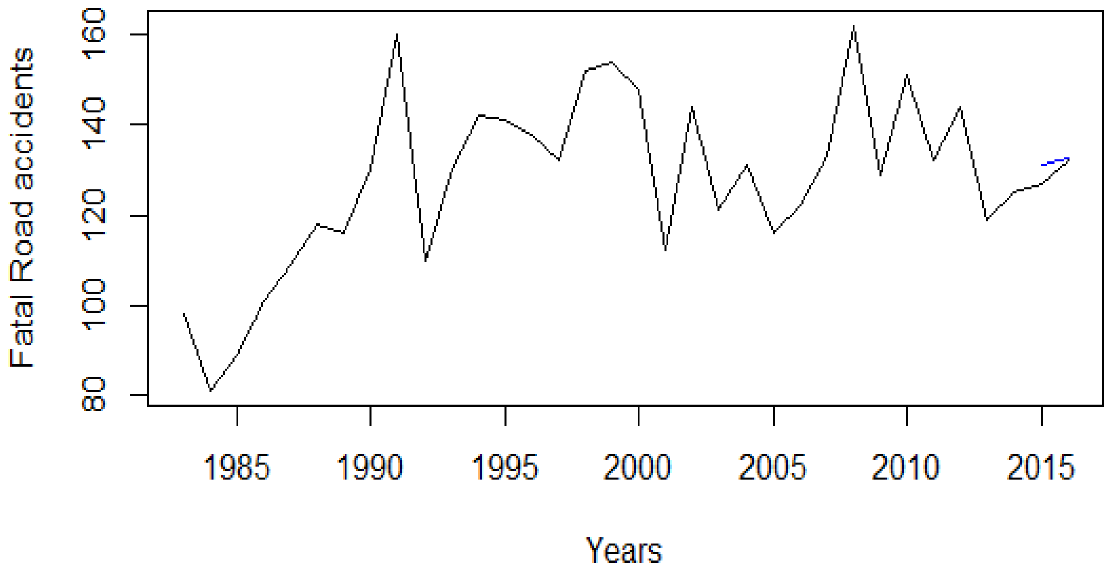



**Figure 3.6: Plot of Fatal accidents with forecasts of ARIMA(0,1,1) with drift**

### 3.1.3 Serious accidents

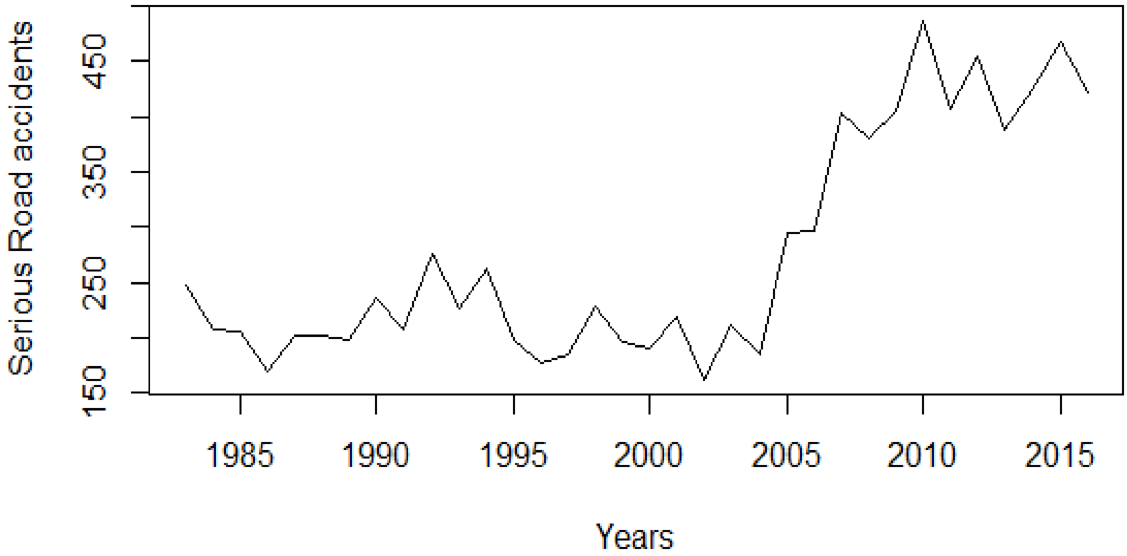



Figure 3.7: Serious accidents (1983-2016)

**ARIMA (2,1,0) without a drift**

```
Series: log(dataS2)
ARIMA(2,1,0)

Coefficients:
ar1      ar2
      -0.3244  0.3220
s.e.   0.1673  0.1681

sigma^2 estimated as 0.02526:  log likelihood=13.82
AIC=-21.64   AICc=-20.76   BIC=-17.34

Training set error measures:
                     ME       RMSE        MAE         MPE       MAPE
MASE        ACF1
Training set 0.01581967 0.1513152 0.1262977 0.2359849 2.307802
0.8127567 -0.0363527
```

**ARIMA (2,1,0) with a drift**

```
Series: log10(dataS2)
ARIMA(2,1,0) with drift
Coefficients:
          ar1      ar2   drift
      -0.3457  0.2992  0.0069
s.e.   0.1707  0.1721  0.0114
sigma^2 estimated as 0.004883:  log likelihood=39.85
AIC=-71.7   AICc=-70.16   BIC=-65.96
Training set error measures:
```

```
                              ME        RMSE           MAE            MPE       MAPE
MASE
Training set 0.0001899412 0.0653638 0.05529013 -0.04503049 2.326654
0.8192724
                         ACF1
Training set -0.0152608
```

**Table 3.5: Forecasts of Serious accidents**

| Year | True values | Forecasted ARIMA(2,1,0) without drift | Forecasted ARIMA(2,1,0) with drift |
|---|---|---|---|
| **2015** | 468 | 392.6448 | 399.8896 |
| **2016** | 423 | 414.5103 | 426.3693 |

**Table 3.6 Forecast Error Measure for Serious accidents**

| | ARIMA(2,1,0) without drift | ARIMA(2,1,0) with drift |
|---|---|---|
| **MAE** | 0.042526 | 0.035876 |
| **MAPE** | 1.595326 | 1.344612 |
| **RMSE** | 0.054272 | 0.048361 |

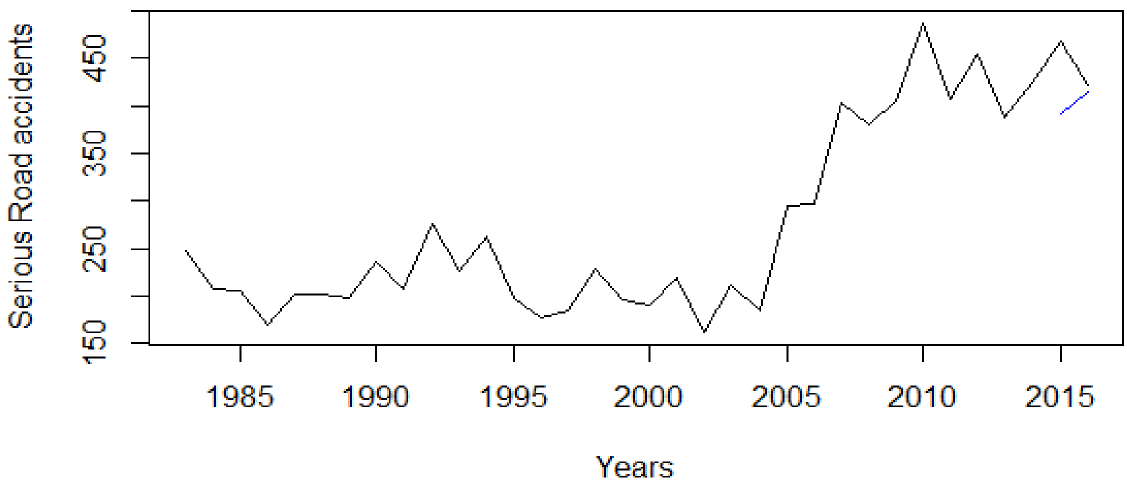



**Figure 3.8: Plot of Serious accidents with forecasts of ARIMA(2,1,0) without drift**

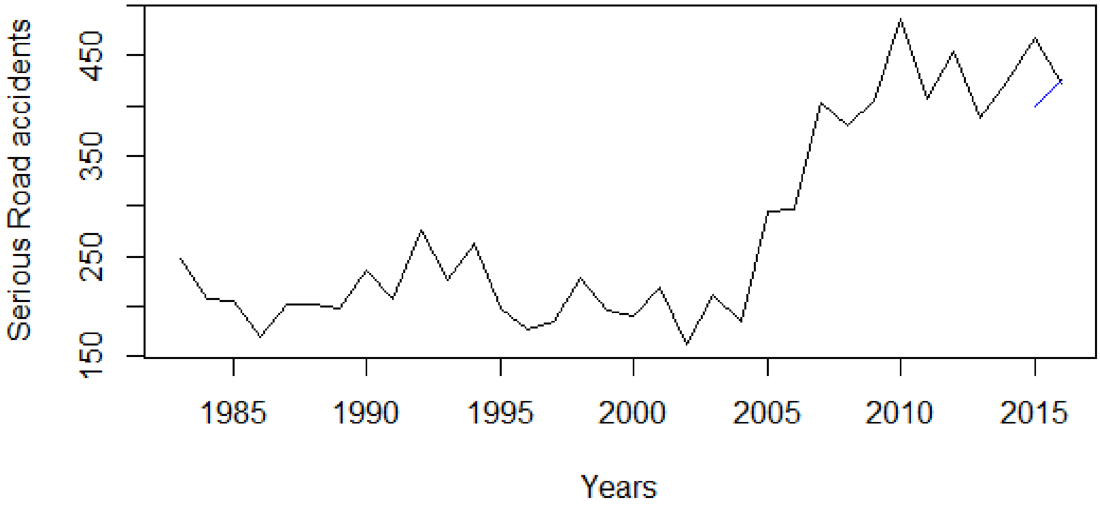



**Figure 3.9: Plot of Serious accidents with forecasts of ARIMA(2,1,0) with drift**

### 3.1.4 Slight accidents

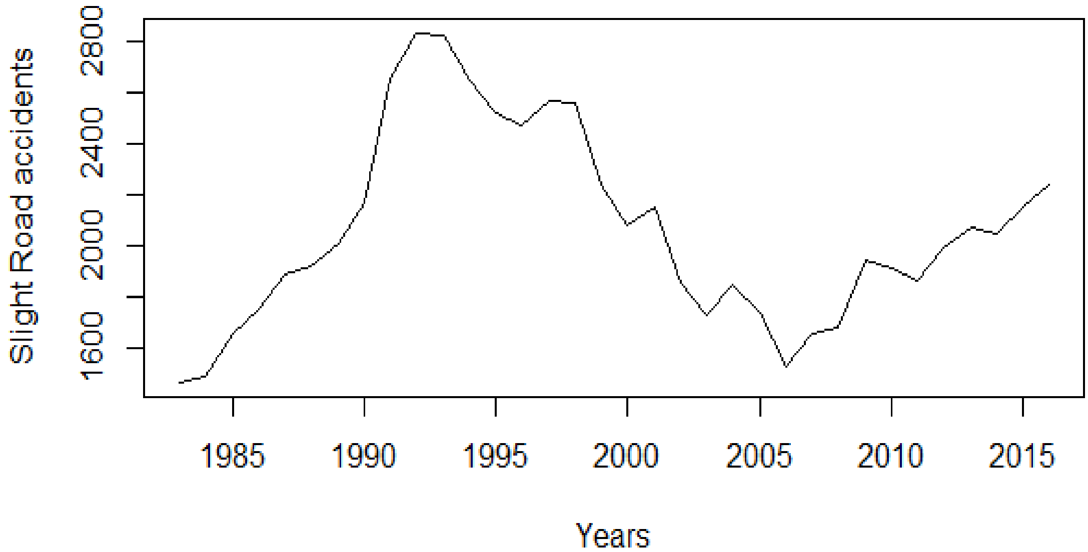



**Figure 3.10: Slight accidents (1983-2016)**

**ARIMA (2,0,0) without a drift**

```
Series: dataSl2
ARIMA(2,0,0) with non-zero mean

Coefficients:
         ar1      ar2       mean
      1.2569  -0.3799  1989.3679
s.e.  0.1582   0.1623   193.2134

sigma^2 estimated as 23881:  log likelihood=-206.17
AIC=420.33   AICc=421.81   BIC=426.19
```

```
Training set error measures:
                     ME      RMSE       MAE        MPE      MAPE       MASE
ACF1
Training set 12.88863 147.1126 111.3988 0.1392381 5.617743 0.8755993
-0.01060569
```

**ARIMA (2,0,0) with a drift**

```
Series: dataSl2
ARIMA(2,0,0) with drift
Coefficients:
         ar1      ar2  intercept    drift
      1.2475  -0.3651  1872.7860   6.8172
s.e.  0.1597   0.1652   365.7468  17.6991

sigma^2 estimated as 24609:  log likelihood=-206.09
AIC=422.18   AICc=424.48   BIC=429.5
Training set error measures:
                     ME     RMSE       MAE         MPE      MAPE       MASE
ACF1
Training set 10.61732 146.741 111.2028 0.04906632 5.592812 0.8740583
0.01421288
```

**Table 3.7: Forecasts of Slight accidents**

| Year | True values | Forecasted ARIMA(2,0,0) without drift | Forecasted ARIMA(2,0,0) with drift |
|---|---|---|---|
| **2015** | 2148 | 2026.148 | 2043.110 |
| **2016** | 2234 | 2015.223 | 2053.906 |

**Table 3.8: Forecast Error Measure for Slight accidents**

| | ARIMA(2,0,0) without drift | ARIMA(2,0,0) with drift |
|---|---|---|
| **MAE** | 170.3145 | 142.492 |
| **MAPE** | 7.732937 | 6.472326 |
| **RMSE** | 177.0752 | 147.3699 |

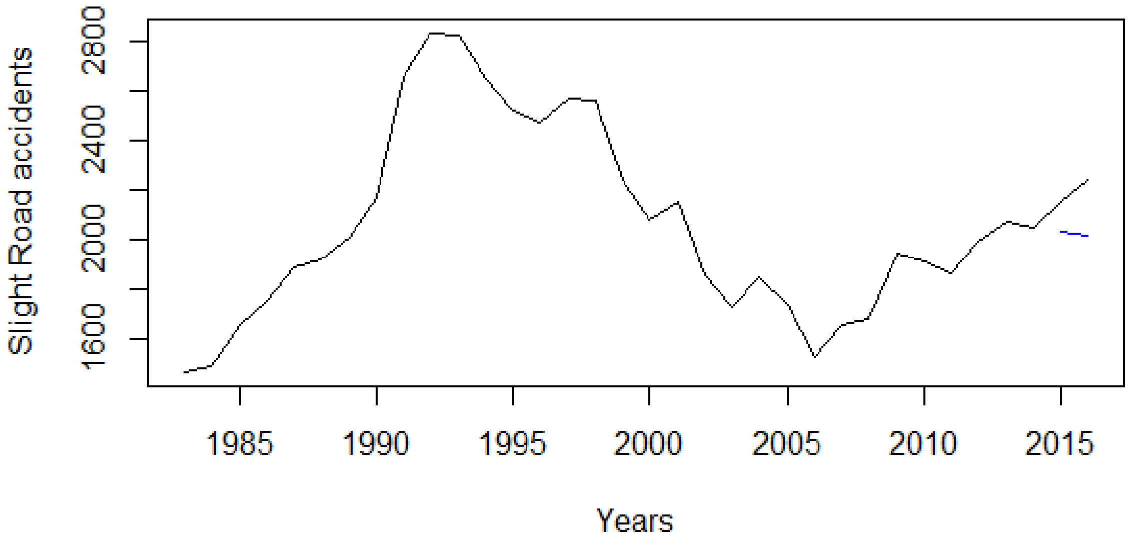



Figure 3.11: Plot of Slight accidents with forecasts of ARIMA(2,0,0) without drift

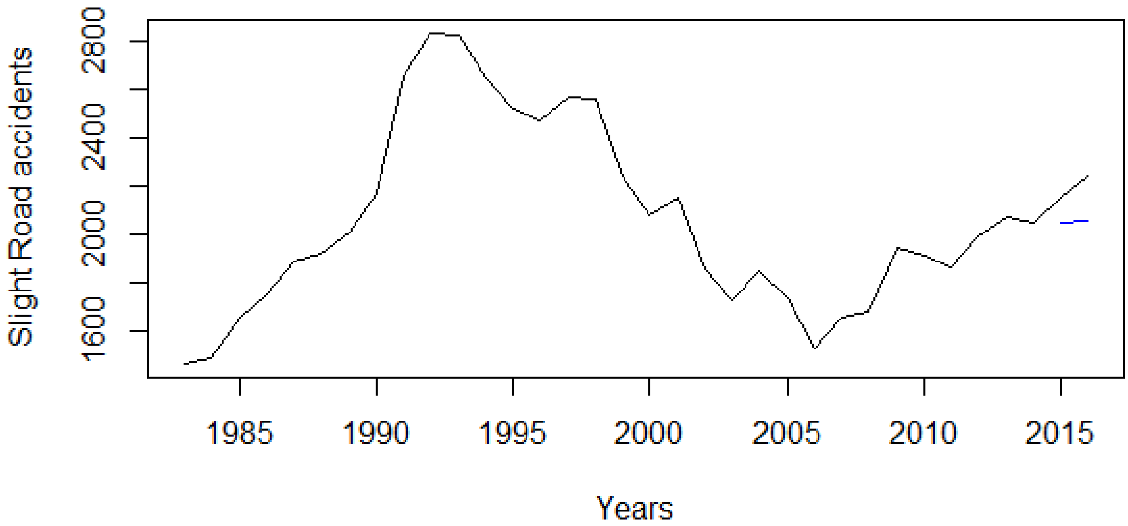



Figure 3.12: Plot of Slight accidents with forecasts of ARIMA(2,0,0) with drift

### 3.1.5 Non-injury accidents

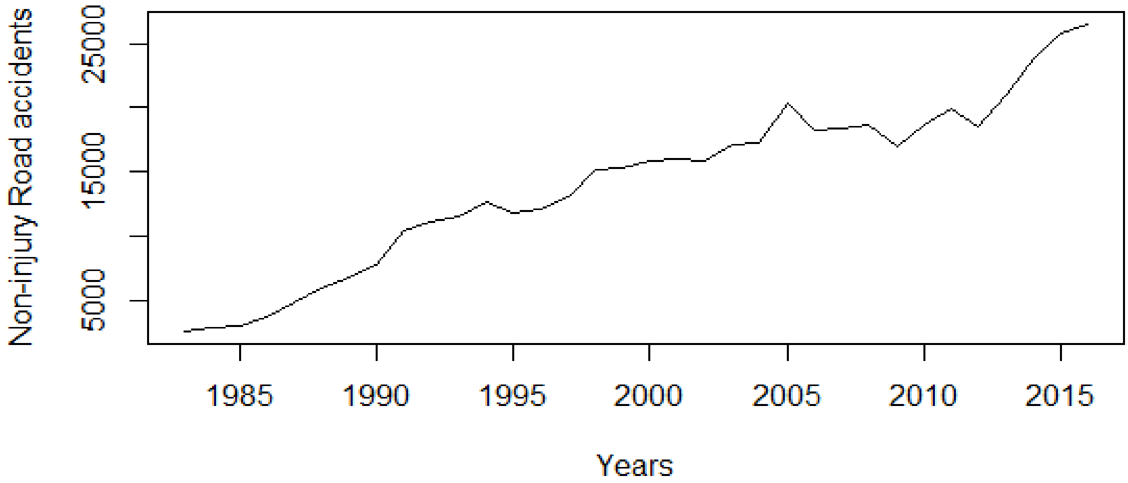



Figure 3.13: Non-injury accidents (1983-2016)

It is remarked that the data are non-stationary, hence log values of responses are considered to develop models for the period (1983 to 2014). The log series are not normal but the differenced log series are normal according to Jarque Bera test (p-value>0.05). Models are validated on the basis of 2-step ahead forecasts. No drift term is fitted as the order of difference is 2.

**ARIMA (0,2,1)**

```
Series: log10(dataN2)
ARIMA(0,2,1)

Coefficients:
ma1
      -0.7604
s.e.   0.1282

sigma^2 estimated as 0.001682:  log likelihood=53.33
AIC=-102.66   AICc=-102.21   BIC=-99.85

Training set error measures:
                      ME        RMSE         MAE         MPE      MAPE
MASE
Training set -0.00343708 0.03904732 0.03224889 -0.07902095 0.788711
0.7896197
                   ACF1
Training set -0.0241066
```

Table 3.9: Forecasts of Non-injury accidents

| Year | True values | Forecasted ARIMA(0,2,1) |
|---|---|---|
| **2015** | 25733 | 25156.90 |
| **2016** | 26488 | 26583.35 |

Table 4.0: Forecast Error Measure for Non-injury accidents

| | ARIMA(0,2,1) |
|---|---|
| **MAE** | 0.005697 |
| **MAPE** | 0.129117 |
| **RMSE** | 0.00704 |

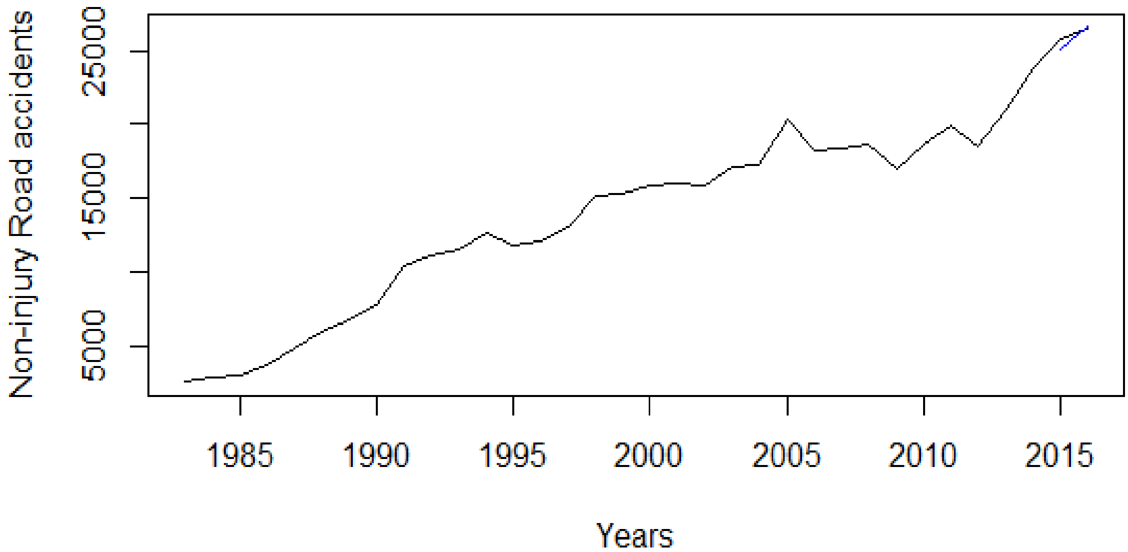



Figure 3.14: Plot of Non-injury accidents with forecasts of ARIMA(0,2,1)

## 3.2 Conclusion

This chapter presents the time series plots for the different severity of accidents. The data were tested non-stationary for all the different severity. The log transform was applied to the data followed by the differencing technique to make the data stationary. The different measures such as MAE and RMSE were computed and the forecast error measures were satisfactory. However, these time series models cannot be used to detect the causes.

# 4. Generalised Linear Models

This chapter presents two important regression techniques: Logistic and Multinomial Logistic, described in the research methodology in Sec 2 to identify the potential causes and the respective OR that would measure to what extent the identified factors influence the risk of injury, fatal, serious and slight accidents.

## 4.1. Logistic Regression

The logistic regression provides the significant factors that explain the odds of the injury accident occurrence.

From Sec 2.2,

OR=Prob( Injury)/Prob(Non-injury accident)=exp( Road Related + Vehicle + Driver Related factors)

Using Backward elimination and G-Statistics, the following factors were retained as significant for the year 2012 to 2017:

**Table 4.1: Logistic Regression Results**

| Factors | Estimate | Exp | Odds Ratio increases by |
|---|---|---|---|
| **Dawn (5hr – 6hr)** | 0.28 | 1.324 | 32.4 % |
| **Morning (6hr – 10 hr)** | 0.11 | 1.111 | 11.1 % |
| **Afternoon (14 hr – 18 hr)** | 0.22 | 1.246 | 24.6 % |
| **Dusk (18 hr – 19 hr)** | 0.18 | 1.201 | 20.1 % |
| **Darkness (Light ON) (19 hr – 5 hr)** | 0.35 | 1.425 | 42.5 % |
| **Darkness (Light OFF) (19 hr – 5hr)** | 0.40 | 1.489 | 48.9 % |
| **Friday/Weekend** | **0.36/0.33** | 1.43/1.39 | 43.1/39.1% |
| **Weather_Fine** | 0.24 | 1.271 | 27.1 % |
| **Age_15-24** | 0.17 | 1.181 | 18.1 % |
| **Age_25-34** | 0.28 | 1.325 | 32.5 % |
| **Age_35-44** | 0.25 | 1.287 | 28.7 % |

| | | | |
|---|---|---|---|
| **Age_45-54** | 0.12 | 1.133 | 13.3 % |
| **Age_55-60** | 0.10 | 1.109 | 10.9 % |
| **Junction_Not a junction** | 0.21 | 1.232 | 23.2 % |
| **Junction_Crossroad** | 0.19 | 1.215 | 21.5 % |
| **Junction_T junction** | 0.13 | 1.141 | 14.1 % |
| **Manoeuvre_Overtaking** | 0.44 | 1.555 | 55.5 % |
| **Vehicle Type_Car** | 0.25 | 1.281 | 28.1 % |
| **Vehicle Type_Auto/Motorcycle** | 0.39 | 1.472 | 47.2 % |
| **Vehicle Type_Mini/Bus** | 0.18 | 1.194 | 19.4 % |
| **Manoeuvre_Overtaking :Two-way Road** | 0.46 | 1.582 | 58.2 % |
| **Manoeuvre_Overtaking : Dual Carriage Way** | 0.26 | 1.301 | 30.1 % |
| **Vehicle Type_Car :Two-way Road** | 0.12 | 1.126 | 12.6 % |
| **Vehicle Type_Car :Dual Carriage Way Road** | 0.11 | 1.121 | 12.1 % |
| **Vehicle Type_Auto/Motorcycle: Two-way Road** | 0.11 | 1.113 | 11.3 % |
| **Vehicle Type_Auto/Motorcycle: Dual Carriage Way Road** | 0.21 | 1.231 | 23.1 % |
| **Vehicle Type_Mini/Bus : Two-way Road** | 0.09 | 1.091 | 9.1 % |
| **Vehicle Type_Mini/Bus : Dual Carriage Way Road** | 0.02 | 1.023 | 2.3 % |
| **Manoeuvre_Overtaking: Age_15-24** | 0.38 | 1.458 | 45.8 % |
| **Manoeuvre_Overtaking: Age_25-34** | 0.36 | 1.439 | 43.9 % |
| **Manoeuvre_Overtaking: Age_35-44** | 0.18 | 1.201 | 20.1 % |
| **Manoeuvre_Overtaking: Age_45-54** | 0.06 | 1.057 | 5.7 % |
| **Manoeuvre_Overtaking: Age_55-60** | 0.02 | 1.022 | 2.2 % |
| **Two-way Road: Road Character (Not Straight)** | 0.26 | 1.296 | 29.6 % |
| **Dual Carriage Way Road: Road Character (Not Straight)** | 0.15 | 1.158 | 15.8 % |
| **Vehicle defects (Yes)** | 0.36 | 1.433 | 43.3% |

| | | | |
|---|---|---|---|
| **Alcohol** | 0.48 | 1.616 | 61.6% |
| **Vehicle Type_Car : Gender_Male** | 0.18 | 1.2 | 20% |
| **Vehicle Type_Auto/Motorcycle: Gender_Male** | 0.40 | 1.498 | 49.8% |
| **Vehicle Type_Mini/Bus : Gender_ Male** | 0.08 | 1.079 | 7.9% |

## 4.2. Multinomial Logistic

### Table 4.2: Multinomial Logistic Results

| **Factors** | **Fatal** | | **Serious** | | **Slight** | |
|---|---|---|---|---|---|---|
| | **Estimate** | **Odds Ratio increases by** | **Estimate** | **Odds Ratio increases by** | **Estimate** | **Odds Ratio increases by** |
| **Dawn (5hr – 6hr)** | 0.27 | 30.4% | 0.32 | 38.4% | 0.24 | 27.4% |
| **Morning (6hr – 10 hr)** | 0.12 | 13.1% | 0.14 | 15.3% | 0.13 | 14.4% |
| **Afternoon (14 hr – 18 hr)** | 0.20 | 22.6% | 0.16 | 17.6% | 0.25 | 28.6% |
| **Dusk (18 hr – 19 hr)** | 0.19 | 20.5% | 0.21 | 23.1% | 0.19 | 21.1% |
| **Darkness (Light ON) (19 hr – 5 hr)** | 0.40 | 48.5% | 0.30 | 34.6% | 0.30 | 35.5% |
| **Darkness (Light OFF) (19 hr – 5hr)** | 0.41 | 50.9% | 0.40 | 48.5% | 0.31 | 36.9% |
| **Friday/Weekend** | 0.39 /0.32 | 47.1% /37.7% | 0.36 /0.21 | 43.3% /23.4% | 0.32 /0.42 | 37.1% /52.2% |
| **Weather_Fine** | 0.24 | 27.2% | 0.23 | 26.1% | 0.24 | 27.1% |
| **Age_15-24** | 0.17 | 18.1% | 0.17 | 18.1% | 0.17 | 18.1% |
| **Age_25-34** | 0.29 | 33.2% | 0.34 | 40.5% | 0.31 | 36.5% |
| **Age_35-44** | 0.26 | 29.7% | 0.25 | 28.2% | 0.20 | 22.7% |
| **Age_45-54** | 0.13 | 13.4% | 0.12 | 12.3% | 0.11 | 11.5% |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Age_55-60** | 0.09 | 9.9% | 0.07 | 6.9% | 0.05 | 4.9% |
| **Junction_Not a junction** | 0.18 | 19.2% | 0.23 | 25.4% | 0.21 | 23.1% |
| **Junction_Crossroad** | 0.20 | 22.5% | 0.21 | 23.1% | 0.24 | 27.5% |
| **Junction_T junction** | 0.14 | 15.6% | 0.12 | 13.2% | 0.17 | 18.1% |
| **Manoeuvre_Overtaking** | 0.46 | 58.5% | 0.42 | 52.3% | 0.36 | 43.5% |
| **Vehicle Type_Car** | 0.26 | 29.1% | 0.25 | 28.2% | 0.22 | 25.1% |
| **Vehicle Type_Auto/Motorcycle** | 0.37 | 44.2% | 0.40 | 49.5% | 0.32 | 37.2% |
| **Vehicle Type_Mini/Bus** | 0.13 | 14.4% | 0.18 | 19.3% | 0.15 | 16.4% |
| **Manoeuvre_Overtaking :Two-way Road** | 0.47 | 59.9% | 0.45 | 57.3% | 0.42 | 52.1% |
| **Manoeuvre_Overtaking : Dual Carriage Way** | 0.28 | 32.3% | 0.25 | 28.4% | 0.27 | 30.5% |
| **Vehicle Type_Car :Two-way Road** | 0.13 | 13.6% | 0.13 | 14.1% | 0.09 | 9.6% |
| **Vehicle Type_Car :Dual Carriage Way Road** | 0.11 | 11.7% | 0.17 | 18.1% | 0.15 | 16.1% |
| **Vehicle Type_Auto/Motorcycle: Two-way Road** | 0.07 | 7.3% | 0.08 | 8.3% | 0.15 | 16.1% |
| **Vehicle Type_Auto/Motorcycle: Dual Carriage Way Road** | 0.20 | 22.1% | 0.21 | 23.2% | 0.25 | 28.9% |
| **Vehicle Type_Mini/Bus : Two-way Road** | 0.07 | 7.1% | 0.09 | 9.8% | 0.06 | 6.1% |
| **Vehicle Type_Mini/Bus : Dual Carriage Way Road** | 0.03 | 2.8% | 0.04 | 4.4% | 0.03 | 3.3% |
| **Manoeuvre_Overtaking: Age_15-24** | 0.39 | 47.8% | 0.37 | 45.1% | 0.40 | 49.8% |
| **Manoeuvre_Overtaking: Age_25-34** | 0.37 | 44.9% | 0.40 | 49.9% | 0.36 | 43.7% |
| **Manoeuvre_Overtaking: Age_35-44** | 0.21 | 23.1% | 0.19 | 20.8% | 0.22 | 25.1% |
| **Manoeuvre_Overtaking: Age_45-54** | 0.05 | 4.7% | 0.05 | 5.4% | 0.09 | 9.7% |
| **Manoeuvre_Overtaking: Age_55-60** | 0.01 | 1.2% | 0.05 | 4.9% | 0.03 | 3.0% |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Two-way Road: Road Character (Not Straight)** | 0.24 | 27.6% | 0.26 | 29.5% | 0.26 | 30.0% |
| **Dual Carriage Way Road: Road Character (Not Straight)** | 0.16 | 16.8% | 0.15 | 15.9% | 0.14 | 14.8% |
| **Vehicle defects** | 0.34 | 40.4% | 0.45 | 56.8% | 0.46 | 58.4% |
| **Alcohol (Yes)** | 0.36 | 43.3% | 0.42 | 52.4% | 0.49 | 63.2% |
| **Vehicle Type_Car : Gender_Male** | 0.21 | 23.8% | 0.17 | 18.9% | 0.20 | 21.8% |
| **Vehicle Type_Auto/Motorcycle: Gender_Male** | 0.32 | 37.8% | 0.32 | 37.9% | 0.40 | 48.8% |
| **Vehicle Type_Mini/Bus : Gender_ Male** | 0.06 | 5.8% | 0.03 | 2.9% | 0.05 | 4.8% |

**NOTE:**

(a). We select the most potential factors that have increased the odds of injury,fatal, serious and slight accidents by above 25%. (See the red highlights).

(b). The most *influential* factors under both methods are:

-Darkness (19 hr-5hr) with Lighting present

-Darkness (19 hr-5hr) with Lighting Not Present

-Road Type: Two-way, Dual-Carriageway and Road Character: Not Straight

-Junction (No Junction)

-Friday/Week end effect

Driver Profiles:

-Age of the Driver (25-44 yrs old)

- Manoeuvre (Overtaking) in the Age group (25-44 yrs old)

-Alcohol

-Gender

-Vehicle Type: Motocycle and Road Type: Two-way and Dual Carriageway

-Vehicle Type: Motocycle and Gender (Male)

- Vehicle Defects

(c).We now present how some of these factors have contributed to the increase of casualty accidents in the different regions of Mauritius in 2017:

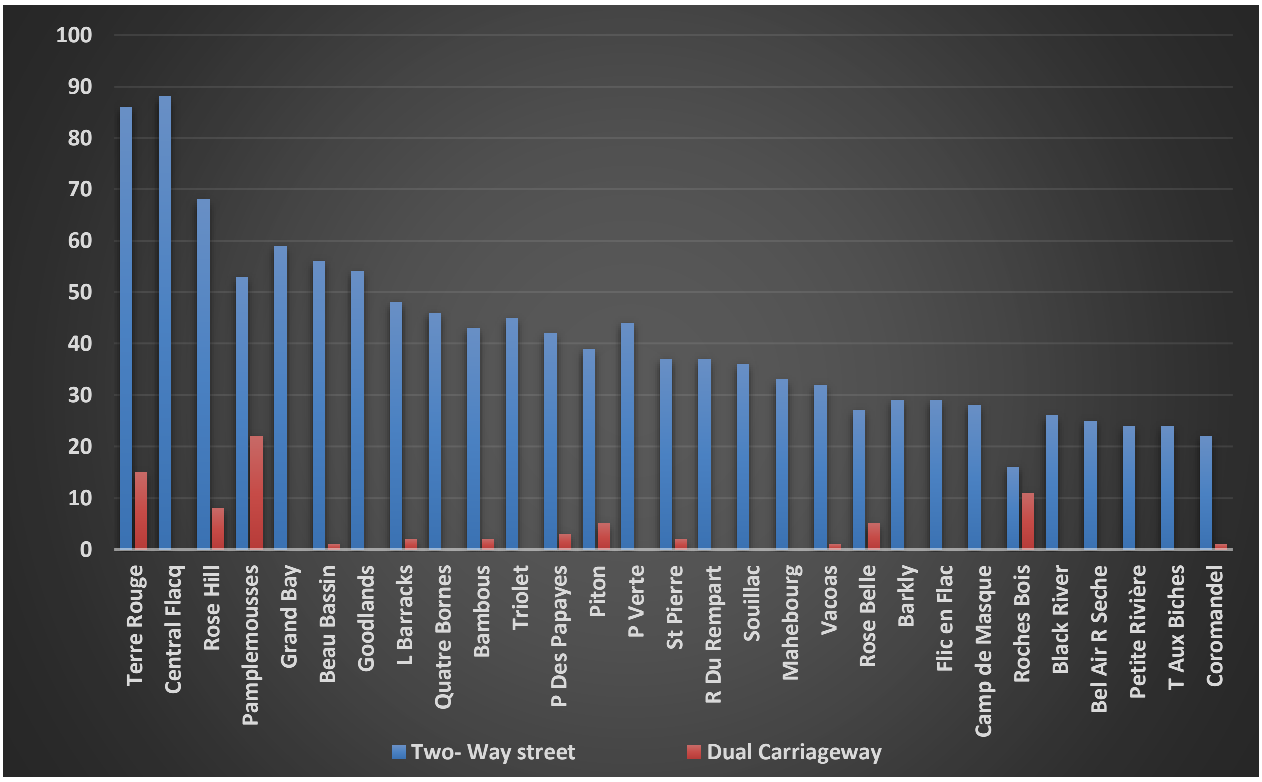



**Figure 4.1: Road Type vs Area**

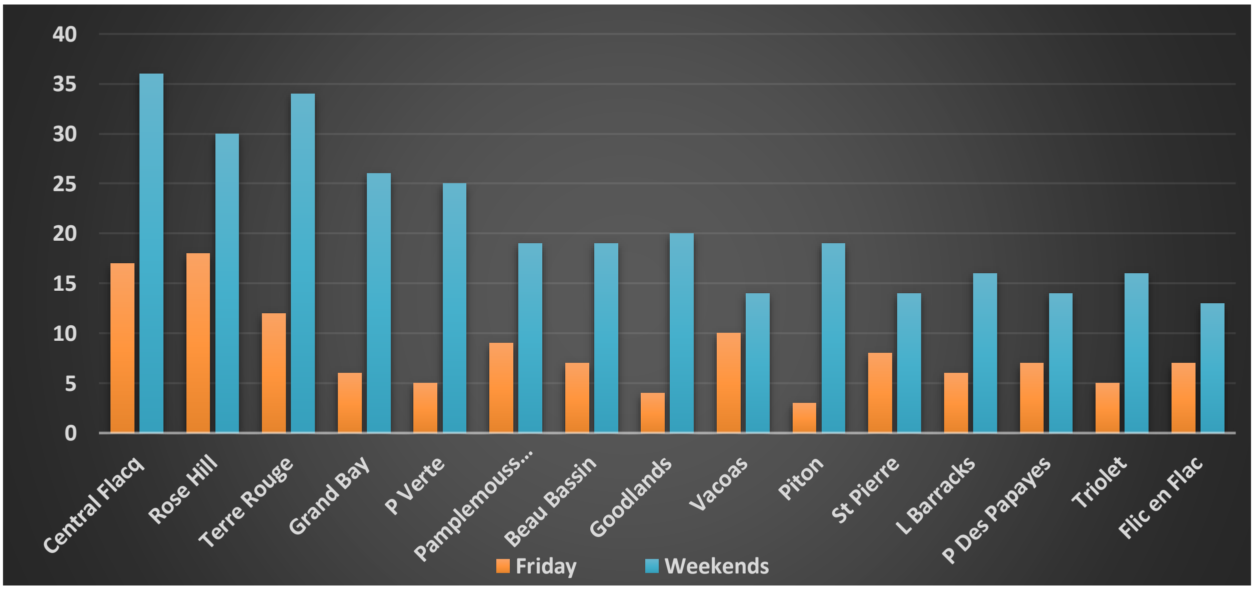



**Figure 4.2: Days vs Area**

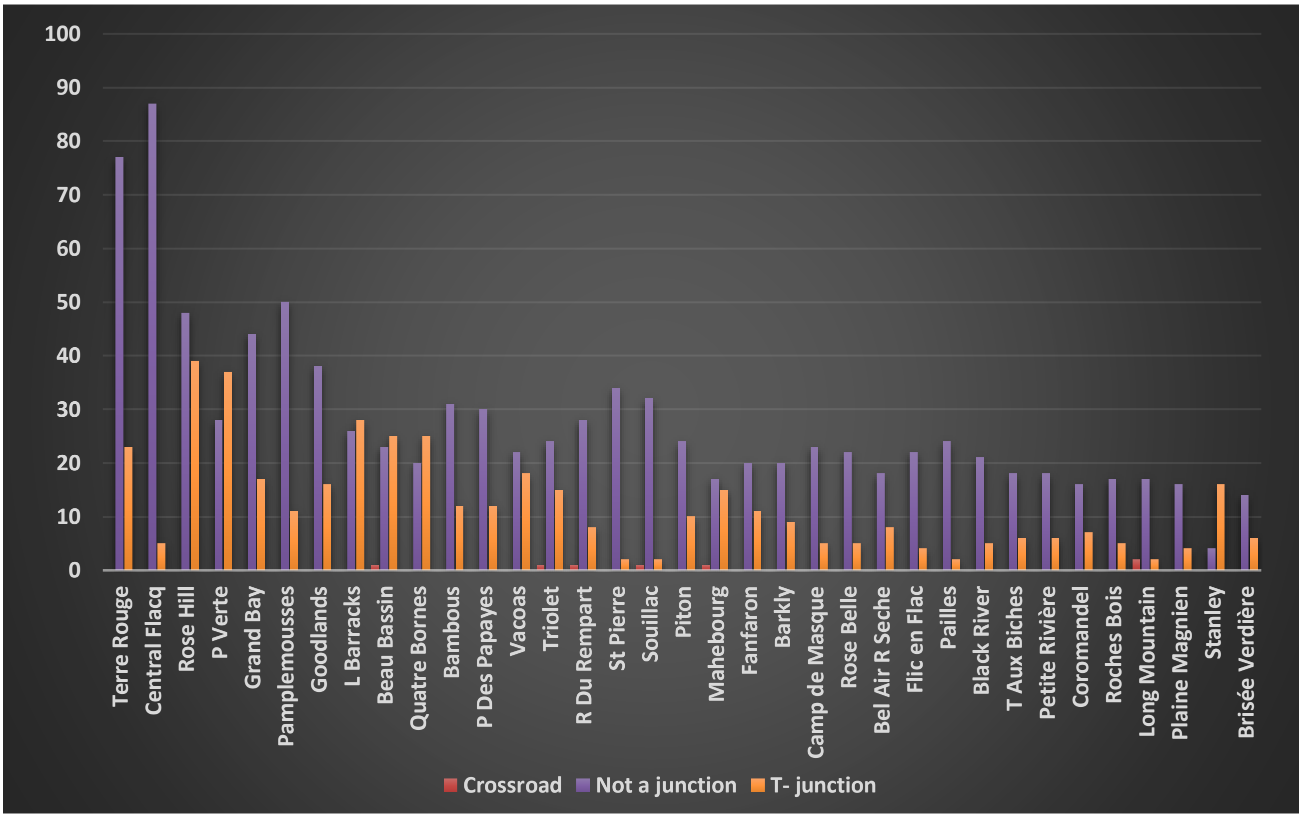



Figure 4.3:Junction vs Area

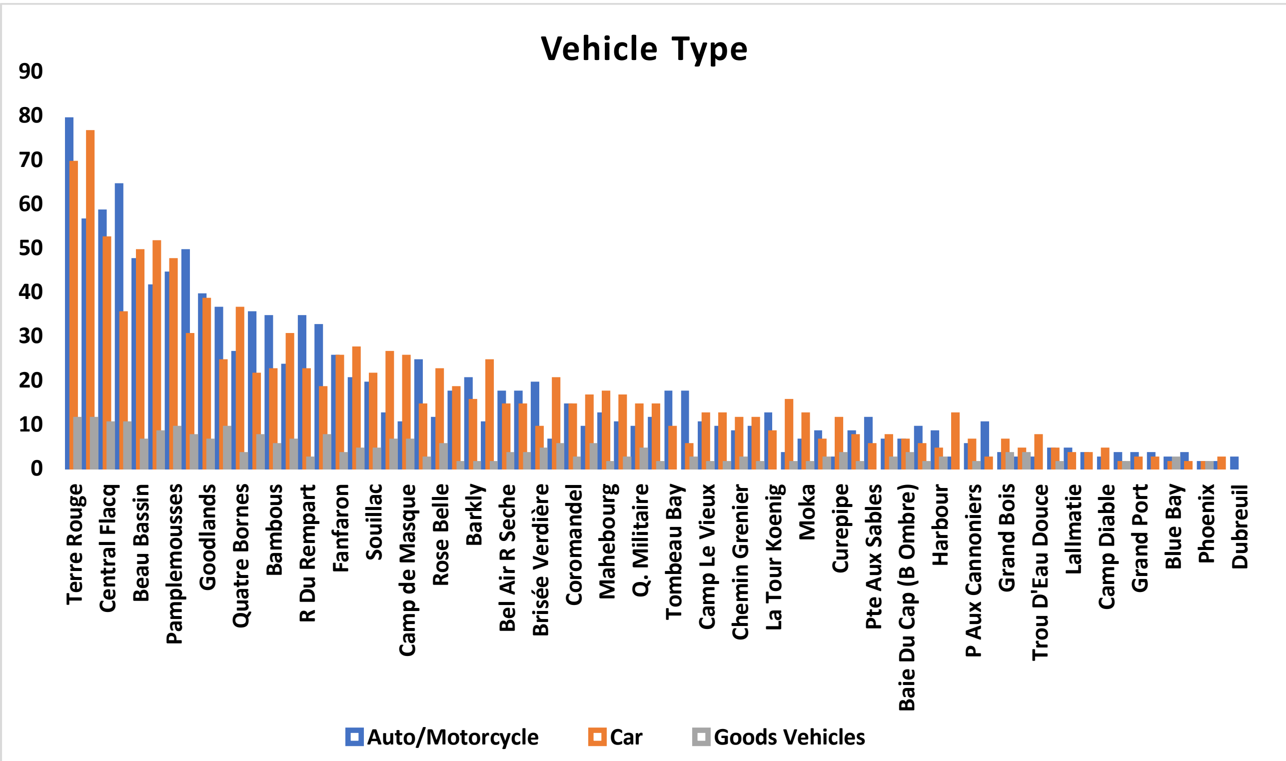



Figure 4.4: Vehicle Type vs Area

## 4.3. Artificial Neural Networks (ANN) and Support Vector Machines (SVM)

The purpose of ANN and SVM is to predict the severity of the accidents. The Artificial Neural Networks (ANNs) function similarly like a simplified model of neurons in the brain. A network of these mathematical neurons can "learn" when exposed to data. The development of further learning has made ANNs a powerful tool and highly active area of research.

Backpropagation is one of the most common ways to train an ANN. It is an example of a supervised training model, in which example answers are provided for the network to conform to. The basic idea is that we define an error function that tells us how much each of the output neurons differs from their intended value, then send this error signal backwards through the network so each weight has an idea of just how wrong they are. Mini-batch gradient descent is a variation of the gradient descent algorithm that splits the training dataset into small batches that are used to calculate model error and update model coefficients.

In this study, Artificial Neural Network (ANN) based on the feed-forward back-propagation algorithm has been used whereas SVM chooses the hyperplane so that the distance from it to the nearest data point on each side is maximized. The trained dataset: 2012-2014 and is used to predict for 2015, 2016, 2017. The two algorithms are validated by the Pass Rates which measure the number of observed and predicted pairs

**Table 4.3: Pass Rate for validation of model using ANN**

| Pass Rate (%) | | | |
|---|---|---|---|
| **Year** | **Fatal** | **Serious** | **Slight** |
| **2015** | 83.1 | 90.3 | 92.3 |
| **2016** | 89.7 | 93.1 | 94.1 |
| **2017** | 90.2 | 83.4 | 88.5 |

**Table 4.4: Pass Rate for validation of model using SVM**

| Pass Rate (%) | | | |
|---|---|---|---|
| **Year** | **Fatal** | **Serious** | **Slight** |
| **2015** | 92.1 | 95.2 | 96.1 |
| **2016** | 95.1 | 94.5 | 94.8 |
| **2017** | 95.2 | 92.3 | 92.3 |

## 4.4. Conclusion

Based on the available data from 2012-2017, this chapter uses the GLM technique to detect the causes of accidents, in particular casualty accidents, in Mauritius. The G-Statistics and deviance criteria were used as a measure to determine the significant causes of the casualty accidents. The Logit and Multinomial Logit were fitted to the data based on these identified significant causes with a residual deviance of 10.98 and 8.86 respectively and their odds or risk ratios were computed. We highlight those causes which contributed to an above 25% to the different severity accident and as such the odds ratio becomes an important indicator. From the Fig 4.1 to 4.5, we can also identify the accident prone areas stratified by the significant factors. The SVM and ANN are used to predict the severity and validate the models.

# 5. Overall Conclusion

This report identifies the potential causes of road traffic accidents, in particular the casualty accidents, in Mauritius from the period 2012-2017. The micro data was collected from the PF-178, which is an official Police form that records every details of a road accident. De-facto, the form illustrates that the number of vehicles in our street: One-way, Two-way or Dual Carriage-way is an unavoidable provoking factor that contributes to the causation of injury and non-injury accidents. Beyond this increase in the number of vehicles in circulation, there are crucially other factors that are prone to cause accidents in Mauritius.

In this study, we propose a time series analysis and a GLM approach to analyze the trend of accident data and identify the potential significant causes of the different accident severity. The time series analysis, in particular, the ARIMA model, was used to detect the trend in accident series and also to forecast the overall number of accidents: Fatal, Serious and Slight. However, this approach could not be used to identify the causes. In fact, the data was tested non-stationary and when applied the differencing technique, it was found that the time series of accident data loses the positive characteristic.

Further to AbdulHafed (2017) and Celik and Oktay (2014), we apply the binary logistic and multinomial logistic with appropriate odds ratios to identify the causes of road accidents via the PF-178 for the period 2012-2017. The causes could be subdivided into: Road Characteristics, Driver Profiles and Vehicle Characteristics. The full results are displayed in Chapter 4: Table 4.1 and 4.2. We take note of some of these significant factors that most increase the risk of the injury accident occurrence, in particular: Fatal, Serious and Slight. Among them, we note with concern the problem of: *lightning in the period 19hr-5hr, the interaction between Road Type, mainly Two-way, Dual carriageway and the road curvature, the presence of no junction and T-junction.* As regards to the Driver profiles, *the driving manoeuvre overtaking interacting with the age group (25-44 yrs old) and alcohol consumption while driving* are the notable aspects. On the other hand, the *vehicle types: Motorcycles and Cars interacting with the Gender effect, and vehicle types: Motorcycles and Cars interacting with the Road Types where they circulate* are found to be the provoking factors. We note also that *defects in Vehicles* contribute amply to the occurrence of accident.

### Remarks

From the PF-178, apart from the type and vehicle manoeuvre, it will be interesting to include information on whether the vehicle is a second hand, first hand or a repaired car and also about the latest fitness test passed by the vehicle. We understand that the information on the vehicle involved in the accident is recorded in the PF-70. Thus, we believe some fields in the PF-70 can merge with the vehicle details in PF-178.

Secondly, the PF-178 can be amended to include information about the number of street lighting poles near the accident since the study reveals that street lighting is a crucial cause of traffic accident and injuries.

Thirdly, it was noticed that the PF 178 captures information about the **road type (two-way, two way and dual carriage way)** however in the annual publications disseminated by Statistics Mauritius on road accidents, it was found that the distinction between **main road, secondary road or motorway** are used. Therefore, **the use of standard terminologies** will avoid confusion.

Fourth**, the average speed of the vehicle at the time** when the accident happened is not recorded on the PF 178. This factor is one of the most important factors to tackle because the higher the speed, the more likely a road accident happens. It was found however, that information about the average speed is sought in another form filled in by the investigation team. It will be more interesting to link the PF 178 and the other form to get a better picture of the accident and the identifiable causes of the accident.

Fifth, **the presence of traffic devices near the accident areas as well billboards displaying the maximum and minimum speed limits, speed cameras** should be captured as well. As such, the police will know whether this security technique are truly working. In case, there were billboards and CCTVs, yet an accident has occurred then it will be important to know about the remedial actions to be taken.

Sixth, **the nationality, education level as well as the driving experience (difference between length of time between license obtained and date of accident)** should be known, for instance to know whether the driver is a local or non-local will give an indication about his/her carelessness on the road. A local driver with low level of education and with a provisional license is more likely to get involve in an accident as compared to non-local and more experienced driver.

Seventh, the definition of Fatal, Serious or Slight injury accident has to be carefully reviewed. In the digest of Road accident, it is mentioned that the condition on Fatal accident is where deaths occurred **within 30 days, but about the cases where deaths occur after 30 days**. More importantly, what about those cases where the injured has had to go through amputations. We believe that for such fields, we can have the advice of a medical doctor.

Eighth, it is important to record **about the psychological and mental status** of the driver, that is whether the latter has been facing psychological or stress problems / or has visited any psychiatrist during the past few months. Questions whether the driver has been following treatment at any hospitals could be addressed as well. In this way, the mental and physical aspects of the driver could be assessed and through analysis, we can see if these factors affect carelessness on road and likelihood of accidents. In fact, it will be important if the drivers involved in a serious or fatal accident/or the passengers as well could follow a psychological treatment since it might be a traumatic experience.

Ninth, we suggest that the odds ratios in Chapter 4 can be used a key indicative measure of Fatal, Serious or Slight accident and such analytic procedure be conducted on a yearly basis so that the different stakeholders are apprised of the potential causes scientifically and from here new preventive measures can be envisaged. In this way, new factors can also emerge. The ANN and SVM approaches also can be used for prediction and be helpful in the sensitization campaign.

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