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SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

Investigation and Modeling of Road Traffic Accidents at Five-Legged Roundabouts in Addis Ababa City

A Thesis in Road and Transport Engineering

By Tsegay G/Micheal

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A Thesis

Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science

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A Thesis Submitted School of Graduate Studies in Partial Fulfillment of the Requirements for the Degree of Master of Science in Civil Engineering (Road and Transport Engineering)

By

Tsegay G/Micheal

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I certify that this research work titled "Investigation and Modeling of Road Traffic Accidents at Five-Legged Roundabouts in Addis Ababa City" is my own work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged / referred.

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ABSTRACT

In present time, road traffic accident is becoming among the most threatening concerns that prominently hamper the social, economic, and environmental conditions in Ethiopia and Africa at large. So far, previous crash prediction models at roundabout intersections have focused predominantly on the customary three-legged and four-legged roundabout types. This study however aimed at investigating and modeling road traffic Accidents/crashes at five-legged roundabouts in Addis Ababa City, Ethiopia. To this effect, the study collected necessary quantitative and qualitative data from both primary and secondary data sources. The data were analyzed through descriptive and inferential statistical approaches. APMs were developed using the Poisson and Negative Binomial Regression Models for the Severe-crashes (personal injuries & fatal crashes), and property damages only (non-injury) crashes, respectively. Accordingly, the study revealed that the peak hour vehicle volume entering the roundabout through the major road, ratio of diameter of the inscribed circle to diameter of the central island, and entry half road way width have positive associations with the frequency and occurrences of RTAs –particularly the PDO crashes at roundabouts. Furthermore, the study finally forwarded that reducing the entry half road width on the minor leg; constructing and maintaining bypass/detour roads; implementing advanced traffic management schemes; and decreasing the circulatory roadway width were important points that should be taken in to considerations so as to decrease crashes by decreasing the peak hour flows and optimizing the circulatory road way width to increase diameter of the central island. It has to be noted that special care should be required to consider flow parameters such as level of service and capacity situations.

Key-words: Road Traffic Accidents, Roundabouts, Poisson, Negative Binomial, Accident Predictive Models, Addis Ababa

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LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
AACRA	Addis Ababa City Roads Authority
ADT	Average Daily Traffic
AIC	*Akaike* Information Criteria
APM	Accident Prediction Model
BIC	Bayesian Information Criterion
CRWW	Circulatory Roadway Width
DCI	Diameter of Central Island
DIC	Diameter of Inscribed Circle
En-RW-MAJ	Entry half Roadway Width at Major road
En-RW-MIN	Entry half Roadway Width at Minor road
ERA	Ethiopian Roads Authority
FHWA	Federal Highway Administration
GDP	Gross Domestic Product
GLM	Generalized Linear Models
HCM	Highway Capacity Manual
LL	Log-Likelihood
LR	Log-Likelihood Ratio
MLE	Maximum Likelihood Estimates
MNL	Multinomial Logistic
MNP	Multinomial Probit
MT	Motorized Traffic
NB	Negative Binomial
NMT	Non-Motorized Traffic
PCU	Passenger Car Unit
PDO	Property Damage Only
PDO-Cr	Property Damage Only –Crashes
PHF	Peak Hour Factor
PHPV-MAJ	Peak Hour Pedestrian crossing Volume at Major road
PHPV-MIN	Peak Hour Pedestrian crossing Volume at Minor road
PHVV-MAJ	Peak Hour entry Vehicle Volume at Major road
PHVV-MIN	Peak Hour entry Vehicle Volume at Minor road
RTA	Road Traffic Accident
R-DIC-to-DCI	Ratio of Diameter of Inscribed Circle to Diameter of Central Island
Sev-Cr	Severe –Crashes
Sp-MIN	Presence of Splitter Island on Minor road
TMG	Traffic Monitoring Guide
To-PHPV	Total Peak Hour Pedestrian crossing Volume
To-PHVV	Total Peak Hour Vehicle Volume
V85-MAJ	85^{th} Percentile approach speed on Major road
V85-MIN	85^{th} Percentile approach speed on Minor road
WHO	World Health Organization
ZINB	Zero-Inflated Negative Binomial
ZIP	Zero-Inflated Poisson

CHAPTER 1 INTRODUCTION

1.1. Background information

Addis Ababa, the capital city of Ethiopia, is the largest city in the country with a population of 3,384,569; area of 540 sq.km; with rapid population growth of 2.5%; rapid urbanization rate (15% in 2005 to 24.1% in 2025); and with rapid increases in motor vehicle traffic of 25% since 2009 (*CSA*, *2007; SSATP*, *2017*).

Figure 1-1: Map Showing the Addis Ababa city Administration
(Source: Addis Ababa City Government, 2010)

The poor transport system in the city along with the fast-growing motorization and rapidly boosting economic activities during the last few decades, have exacerbated the level of road traffic accidents (RTAs). In addition, crowded roads, poor road conditions, poor road maintenance, lack of safety features in cars, and lack of police enforcements have increased exposure to potential road traffic injuries.

Contrasting to their numerous advantages in improving the traffic safety and mobility situations in the transport system, roundabouts, these days, are observed as main causes of the prevailing safety problems and gridlocked transport states observed in the city. As a result, the city's roads

Authority, along with relevant stakeholders concerning road traffic safety and management issues, has undertaken conversions of some roundabouts in to signalized-intersections.

So far, the police-recorded road traffic injury data from the Addis Ababa City Police Commission along with the day-to-day observations of grid-locked traffic movements particularly at peak-hours were the only data used for the black spot identification and conversion measures undertaken. Sometimes, low-traffic volume legs, which may cause unnecessary delays to the major streets, or the lack of clear right-of-way control for pedestrians at problematic roundabouts were assumed as additional factors for the conversion measures. Information obtained from the city's roads Authority, and Traffic Management Agency showed that traffic demands at roundabouts, which are being converted into signalized intersections, are much higher than the maximum capacities.

For the city of Addis Ababa, two clear peaks have widely been identified recently by *Haregewoin* (*2010*). That is, travel demand is reaching Morning-peak between 6:30 – 9:30 a.m. and Evening-peak between 5:30 – 7:30 p.m. and relatively drop down (low demand or off-peak) between 9:30 a.m. to 3:30 p.m. and 7:30 p.m. to 6:30 a.m.

1.2. Problem Statement

Nowadays, the exacerbating road traffic accidents in the city of Addis Ababa is posing a negative impact on the boosting economic and social activities. Though the current development and modernization of road infrastructures in the city have resulted in further expansion of new modern roads and intersections such as roundabouts, the current trends being practiced by the relevant stakeholders are not going through further insights of sustainable solutions.

The problem can well be exemplified by the recent conversions of some roundabouts into signalized intersections which is in contrary to prior studies that suggested modern roundabouts are useful solutions in reducing road traffic accidents and relieving motilities relative to other types of intersections. Though these intervention measures are apparently observed as better reliefs to the prevalent safety and mobility problems of the city's transport system, lots of works are still needed to support and analyze the current actions using strong statistical approaches. Detailed statistical analysis and investigating the correlation effects of crash-contributing factors is significant to prioritize the potential intervention measures in the construction and modification of roads and intersection.

In most prior papers, models have been developed for all intersections together with different number of legs and types of control (STOP, signalized, major/minor priority, roundabouts) which usually consider the intersection type as one of the explanatory discrete variables (*Turner* and *Nicholson, 1998*). However, separate models for different intersection types are useful in order to provide a better fit and description of the data than one model for all intersection types.

Another problem that can evidently be observed while assessing the safety aspect of roundabouts, or the transport system as a whole, is the under-reporting and poor documentation of police-recorded road crash data in the city. Indeed, the police-reported data showed only a single or the most prominent factor related to each crash occurrence, ignoring the other unobserved contributory variables to the crash.

Moreover, limited works had yet been carried out locally on crash investigation and modeling of roundabouts and rarely considered the main contributory variables in their model calibrations. Several international studies had been conducted usually on four-legged roundabouts, as they are found to be the most typical design types of modern roundabouts, and also the three-legged roundabouts (*Gross et al., 2013; Arndt* and *Troutbeck, 1998; Maycock* and *Hall 1984; Turner, 2000*). Unfortunately, what worked in studies overseas doesn't always work in the current study area context.

Further, the use of roundabouts for intersections with more than four-legs is best alternative due to the fact that applying the STOP and YIELD signs is often impractical, and signals may be less efficient due to the large number of phases required (resulting in a high proportion of lost time) (*Taekratok, 1998*). Therefore, the conventional measures of converting roundabouts in to signalized intersections, as in the contemporary trend being underway in the city, could be impractical than finding another mitigating solution.

Therefore, in order to reduce those gaps and further expand and diversify the study coverage on the safety performance and overall level of service at distinct intersection types, the present study tries to think through multi-legged roundabouts, in this case, the five-legged roundabouts residing in the city of Addis Ababa.

Research questions:

- What are the prominent geometric and traffic factors contributing to the occurrence and frequency of RTAs at five-legged roundabouts in Addis Ababa city?
- How could the basic correlations between RTAs and the underlying risk factors be explained at five-legged roundabouts in Addis Ababa City?
- What would be the practical schemes and strategic interventions that need to be considered to improve road traffic safety at five-legged roundabout intersections in Addis Ababa city?

1.3. Research objective

1.3.1. General Objective

The general objective of the study is to investigate RTAs at five-legged roundabouts (which are at-grade) with respect to their underlying risk factors, and calibrate relevant crash-predictive models in Addis Ababa city.

1.3.2. Specific Objective

- To investigate the underlying geometric and traffic factors contributing to the occurrence and frequency of RTAs at five-legged roundabouts in Addis Ababa city;
- To develop and explain the significant correlations between RTAs and prominent geometric and traffic factors by fitting APMs using standardized statistical regression methods;
- To pinpoint possible interventions for future design considerations and disseminate the analysis results to various end-users.

1.4. Scope and Limitations of the research

Though the problem seems to appear in all types of intersections, the scope of the study focused only on five-legged at-grade roundabouts that are found in Addis Ababa city. The model calibration process used crash data obtained from police divisions of the respective sub cities and from the city’s Police Commission Head Office. Due to budget and time confines, it had been difficult to study all types of intersections and even to expand the study to other regional cities. Another limitation on the data management and handling system is the absence of exact coordinate location of crashes (example: using GPS). With the absence of exact coordinates for crash locations within roundabouts, the calibration process of the derived model would be of more general. Limitations on the quality of the Police reported RTA databases as well as the availability of several non-measurable contributory factors to RTAs such as human behaviors are thought to result in less reliable APMs, particularly in developing countries.

1.5. Significance of the research

The current trends in the design and construction of road infrastructures in the country, particularly in the city of Addis Ababa appear to be passive forms of countermeasures which are of short-term relief solution measures instead of focusing on proactive actions and long-term insights. Thus, the need for diverse researches on the existing situations of the transport system is crucial so that the current and future expansion of road infrastructures cope with the requirements of the ongoing fast-growing economy of the city. Indeed, safety at roundabouts is thought as one of the present-day issue of the city's transport problems. Therefore, the significance of this study is to contribute its role in addressing and filling the gaps on safety matters prevailing at roundabouts and pose some ascents on the study of future relevant studies.

1.6. Summary

This chapter has presented the background information of the study, the objectives, scope and limitations of the study as well as the main importance of carrying out the research. The chapter has highlighted the scope of the study to think through multi-legged roundabouts, in this case, the five-legged roundabouts residing in the city. Furthermore, the objectives were explained in terms of investigating the effect of geometric and traffic flow characteristics on the frequency and occurrence of RTAs at five-legged (which are at-grade) roundabouts, and fitting relevant crash-predictive models using primary data on geometric and traffic characteristics collected from respective roundabouts and secondary data on RTA databases collected from the Addis Ababa Police. Finally, the chapter dealt with significance of the study to contribute its role in addressing and filling the gaps on safety matters prevailing at roundabouts and pose some ascents on future relevant studies. The follow up chapter will review the conceptual and theoretical models and foundations related to modeling of RTAs in a way to fit with the major objectives and questions of the study.

CHAPTER 2 LITERATURE REVIEW

2.1. Introduction

This chapter covers reviews of different approaches and practices from different researches and reports to identify gaps in the current knowledge on RTAs at road intersections particularly at modern roundabouts. Studies and practices on RTAs and the underlying causes such as traffic and geometric variables, as well as studies on statistical behaviors of various predominant APMs are discussed here to build a platform for modeling and finding tools and directions to the proposed study.

2.2. Road Traffic Crashes

2.2.1. Definition

Vehicle collisions have been described differently by various countries and organizations. For instance, the term road traffic injury has been used by the World Health Organization *(Penden, 2004)* to describe fatal or non-fatal injury incurred as a result of collision involving at least one moving vehicle. According to the *IRTAD* (*1992*) Vienna Convention, the standard international definition of road crash involves a collision of a moving vehicle on a public road in which a road user (human or animal) is injured. Similarly, the Economic Commission for Europe defined road traffic accidents (RTAs) as *accidents that occur on a way or street open to public traffic; result in one or more persons being killed or injured, and at least one moving vehicle was involved*.

The present definition of *road traffic crashes* which is interchangeably used with the term *road traffic accidents (RTAs)* is based on the prevailing definition used by the Addis Ababa Police. Accordingly, it is defined as *an accident occurring on a way or street open to public traffic resulting in bodily injury to any person or damage to property caused by, or arising out of, involves at least one moving motor vehicle on a road, and could injure the driver or passengers of a vehicle, or even other road users such as pedestrians, cyclists and motorcyclists*.

2.2.2. Facts and Figures

Nowadays, road traffic crashes have become among the most threatening concerns that can prominently hamper the economic, social, and environmental conditions of one country. The World Health Organization (*WHO, 2015*) report shows road traffic crashes kill more than 1.2

million people each year. Most of these deaths are reportedly from low and middle-income countries (see Figure 2-1) where rapid economic growth has been accompanied by increased motorization and interrelated effects of road traffic injuries. Moreover, it is estimated to cause economic losses of up to 5% of Gross Domestic Product (GDP) in low-and middle-income countries and a 3% of GDP globally (*WHO, 2015; Milligan, 2014*).

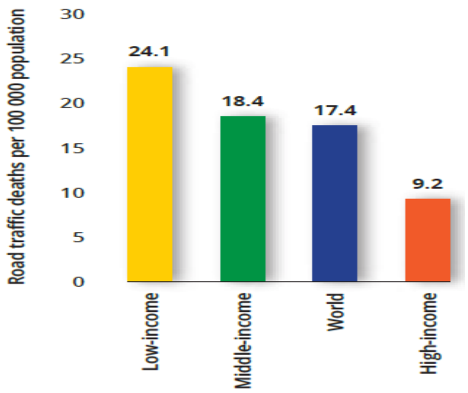


Figure 2-1: Road traffic deaths per 100 000 population, by country income status

(Source: WHO 2015)

As shown in Figure 2-2, the African region has the highest fatality rate in the world, at 26.6 per 100 000 (relative to the global rate of 17.4 per 100 000), and the least figure is accounted by the European countries with 9.3 %. Even if poorly documented, at least 20 people sustain non-fatal injuries for every road traffic fatality (*Penden 2004, WHO 2015*) which in further can have considerable economic and social impacts.

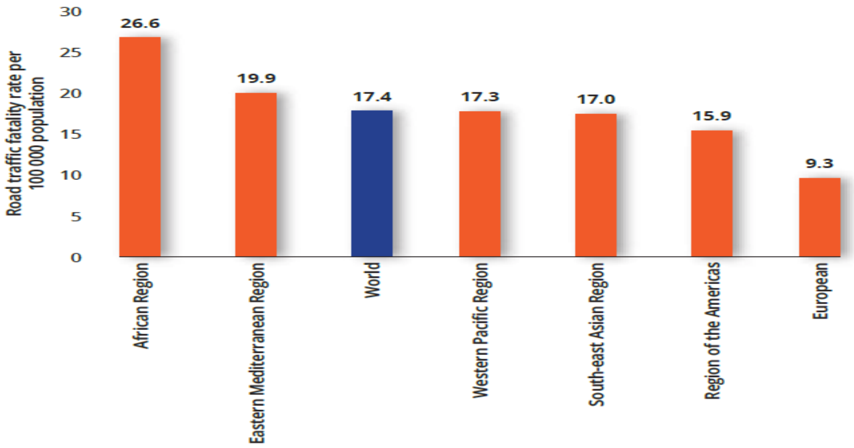


Figure 2-2: Road traffic fatality rates per 100 000 population, by WHO region

(Source: WHO, 2015)

Similarly, in Ethiopia, where there is low rate of motorization, the issue of RTA has already become critically growing experiencing a tremendous loss of life and property each year as one of the leading countries of the world with the worst accident records (*WHO, 2015*).

Consequently, global efforts such as the Decade of Action for Road Safety (2011–2020) have set goal to relieve the predominant threats on road traffic safety which calls on countries to implement the measures identified internationally to make their roads safer (*WHO, 2015*). Moreover, international attention has promised by the new Sustainable Development Goals (SDG) to halve deaths and injuries by 2020, where, so far, 126 countries have stated fatality target-settings in their national road safety strategies. However, it is indicated that, although predictable and preventable, the trend of accidents is not in a state of declining; but rather has continued to rise enormously. This has led to further increase global efforts on mitigating RTAs.

2.2.3. Types of road traffic crashes/accidents

Road traffic crashes can be categorized in to the following major classes with regard to the location of the vehicle in accident, collision type, and also the type of damage.

i. Classification due to the location of motor vehicle (*TxDOT, 2008*);

- Relative to junction:
  - At intersection accident: - within intersection limits;
  - Intersection related accident: - on an approach due to the intersection;
  - Driveway access accident: - on a driveway access; and
  - Non-intersection accident: - any accident not included in the previous types.
- Land use character:
  - Urban accident: - within city limits -more than 5,000 population;
  - Rural accident: - which cannot be classified as an urban accident.

ii. Motor vehicle accident classification (*TxDOT, 2008*)

- Non-collision accident: -any accident involving a moving motor. It can be an overturning accident, or other non-collision accident other than overturning; and
- Collision accident: - between a motor vehicle, its loads, its parts or object set in motion by the motor vehicle collides with just as pedestrians, Motor vehicle in transport, Parked motor vehicle, Railway train, Pedal cyclist, Animal, fixed object, Other object just like carts and fallen trees.

iii. Classification due to the type of damage

- The UNECE (United Nations Economic Commission for Europe) states the most common definition of traffic accident casualties as: (*UNECE 2009; ElAstal 2014*).

    - Killed casualty (fatal casualty): - any person dies during an accident or within 30 days as a result of an accident.
    - Serious casualty: - any injured person who was hospitalized for more than 24 hours
    - Slight casualty: - any injured person excluding seriously injured persons
- In the USA, the severity of traffic accident casualties is classified in to 5 categories depending on the disability to work. (*Nilsson 1997; TxDOT 2008*):
    - Fatal injury: an accident injury that result death within 30 days
    - Incapacitating Injury: serious casualty which prevents walking, driving or doing any activity he was capable of performing before the accident.
    - Non-incapacitating evident Injury: - defined as slight casualty
    - Possible Injury: slight casualty which is not a claimed in the above terms
    - No injury:
- In Addis Ababa, Ethiopia, the classification of crashes is based on severity and the type of injury; and is divided into four major types (*Beshah et al. 2010*).
    - Fatal crash or Killed: - A human casualty who dies within 30 days after an accident
    - Serious injury: - a person hospitalized for more than 24 hours due to an accident
    - Slight injury: - a person hospitalized for less than 24 hours after an accident
    - Property damage: -non-injury crashes (property damage e.g. roadside objects, vehicle etc.)

RTAs can also be categorized by collision type such as rear-end, single-vehicle run-off-the-road, right-angle, and sideswipe (*Lord et al., 2010*). In this paper, however, the researcher adopted the last approach –Classification due to the type of damage, for Addis Ababa – Ethiopia, so that the current crash analysis consistently matches with the police crash records. That is: Fatal crash or Killed, Serious injury, Slight injury, and Property damage only crashes.

2.3. Roundabouts

2.3.1. General

In 1966, a nationwide yield-at-entry rule launched the modern roundabout, also called second-generation roundabouts, revolution in the United Kingdom (UK) (*Helbing, 2012*) which gave priority-to-circulating movements unlike to the previously dominant traffic circles, also called the first-generation roundabouts, which gave priority to traffic flows entering from branches and were designed considering the weaving movements as basic goal (*Pratelli, 2006*).

The Federal Highway Administration information guide (*FHWA-RD-00-067, 2000*) characterizes modern roundabouts and identify from traffic circles that for modern roundabouts yield control is used on all entries; circulating vehicles have the right of way; pedestrian access is allowed only across the entry legs; parking is not allowed at the entries or within the circulatory roadway width; and only counter-clockwise movement of vehicles around the central island is possible. Whereas, for the traffic circles, no yield-control for the circulating traffic, require circulating traffic to yield to entering traffic at some traffic circles, pedestrians may access to the central island, parking within the circulating roadway may be allowed in some traffic circles, and in some countries left-turning vehicles to pass to the left of the central island (in clock-wise directions) may be allowed in traffic circles.

Similarly, the Addis Ababa City Roads Authority (AACRA) Geometric Design Manual (*2003*) characterizes roundabouts as a channelized one way-circulating intersections of two or more roads at which all traffic moves anticlockwise around a central island. The geometric design elements of a typical roundabout can be shown in Figure 2-3 below.

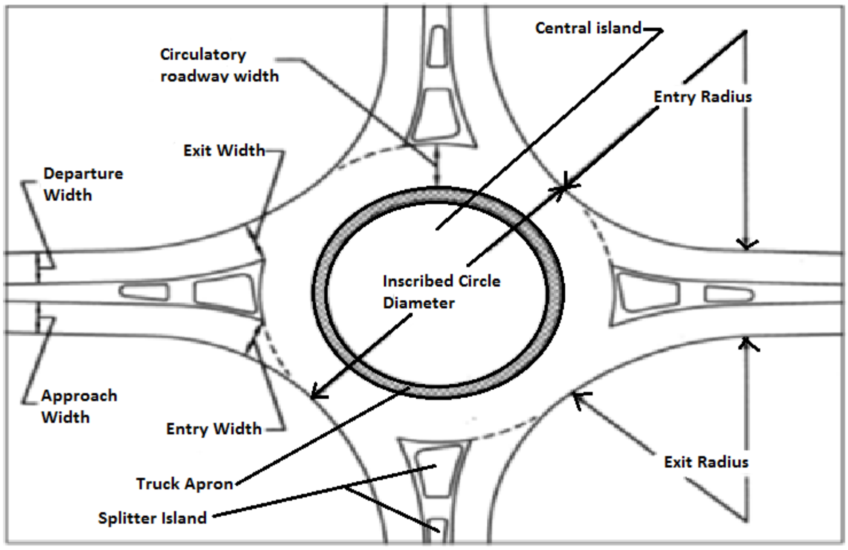


Figure 2-3: Basic Roundabout Geometrics
(source: Robinson et al., 2000)

2.3.2. Types

According to the size and the number of lanes, the FHWA classifies roundabouts generally in three basic categories: mini-roundabouts, single-lane roundabouts, and multi-lane roundabouts (*Robinson et al., 2000*).

i. Mini roundabout: - It consists
   - ✓ maximum desirable entry design speed of 15-20 (mph);
   - ✓ maximum one entry lane, inscribed circle diameter 45-90 feet;
   - ✓ fully traversable central island treatment; and
   - ✓ maximum daily volume up to 15000 vpd.

ii. Single lane roundabout: - It consists
   - ✓ maximum desirable entry design speed of 20-25 (mph);
   - ✓ maximum one entry lane;
   - ✓ inscribed circle diameter 90-180 feet;
   - ✓ raised (may have traversable apron) central island treatment; and
   - ✓ maximum daily volume up to 25000 vpd.

iii. Multiple lane roundabout: - It consists
   - ✓ maximum desirable entry design speed of 25-30 (mph);
   - ✓ greater than or equal two entry lane;
   - ✓ inscribed circle diameter 150-300 feet;
   - ✓ raised (may have traversable apron) central island treatment; and
   - ✓ maximum daily volume up to 45000 vpd.

2.3.3. Safety

Reducing many of the safety hazards of traditional intersections and nonconforming traffic circles is among the primary benefit of modern roundabouts (*pratelli, 2006; Helbing, 2012*). Compared to stop sign or signal controlled cross-roads or T-junctions, roundabouts cut the safety risk by 30% (*Jacquemart, 1998; Brilon 1988*) which is supported by another research in Netherlands dropping the risk level to 45% (*Schoon et al., 1994*). *Retting et al*. (*2003*) also showed that modern roundabouts improve vehicular and pedestrian safety issues compared to other conventional intersection types.

Meanwhile, several international studies (*Rodegerdts et al. 2007a, 2010; SETRA, 1998*) also indicated that many intersections have recently been converted into roundabouts due to the fact that roundabouts improve overall intersection safety performance and increase capacity by avoiding or changing conflict types, and reducing crash severity by causing drivers to reduce speeds. For instance, following conversions to roundabouts of 230 sites in Australia, *Rodegerdts et al*. (*2007b*) found overall reductions of 41 percent in total crashes, 45 percent in injury crashes, and a 63% reduction in fatal crashes. They have also found a reduction in injury crashes by 78% and fatal crashes by 82% studies in France. The study also realized significant reductions of 45% for all crash severities combined and 81% for all injury crashes in the US. In addition to the benefits in crash reductions noticed after conversions to roundabouts, *Montella* (*2007; 2011*) have observed lower delays, shorter queues, better management of speed and design features as well as opportunities for community enhancement features at roundabouts.

On the other hand, some road users such as pedestrians and cyclists are usually disadvantaged by the introduction of roundabouts (*Transfund, 2000*) –particularly on large roundabouts (*SETRA, 1998*). *Taekratok* (*1998*) advocated, however, that roundabouts generally improve safety for pedestrians, bicyclists, and motorists due to the lowering of speeds which in subsequent reduces the pedestrians' risk of death if hit by a motor vehicle.

2.3.4. Identification of Crash Contributory Factors at Roundabouts

Roundabouts are part of the road design system which are often favored with respect to safety and traffic operations over other intersection types. The geometric layout, operational analysis and safety evaluation, are major common requirements for roundabout design (*Kamla et al., 2016*) which implies small alterations in geometry can lead to considerable variations in the safety and/or operational performances.

Though, relatively, better safety performance is realized at roundabouts over other conventional intersection types, there are numerous road-crash occurrences observed. The contributing factors to such road-crashes at roundabouts have been identified in many different literatures. For instance, a recent study by (*Montella, 2011*), which also maintained the previous work of *Mitra et al*. (*2007*), indicated that at least one explanatory variable in the categories of traffic flow, traffic control, geometry, driver characteristics, vehicle type or features, environmental factors, and land use has a significant effect on crash occurrence. The studies finally concluded that all categories are essential in predicting the frequency and occurrence of vehicle crashes at intersections.

Tulu et al. (*2015*) have identified a number of key variables related to pedestrian safety at modern roundabouts, including pedestrian crossing volumes, traffic flows, the presence of raised medians, gradients of approach roads, presence of public transport terminals beside a roundabout, and the presence of nearby schools. The study recognized two variables as significant on explaining crash occurrences, including traffic flows and pedestrian crossing volumes. Some, but no limited, international literatures that have identified the different geometric features/parameters of roundabouts as the most/ or major determinant factors are summarized in the table below.

Table 2-1: Summary of Risk Factors at Roundabouts

[Studied by international Literatures]

Geometric features of roundabout	**Researchers or investigators**
Diameter of central island	Hels and Orozova-Bekkevold, 2007; Daniels et al. 2011; Gallelli, 2008;
Splitter islands at entries	*Gallelli, 2008;*
Diameter of inscribed circle	*Rodegerdts et al., 2010; Daniels et al. 2011; Eisenman et al., 2004; Gallelli, 2008; Kamla et al., 2016;*
Circulatory roadway width	*Hels and Orozova-Bekkevold, 2007; Rodegerdts et al., 2010; Daniels et al. 2011; Eisenman et al., 2004; ElAstal, 2014; Gallelli, 2008; Kamla et al., 2016; Brüde & Larsson, 2000*
Entry angle/deflection/radius	*SETRA ,2002; Kennedy, 2007; Rodegerdts et al., 2010; Montella, 2011;*
Deviation angle	*Šenk* and *Ambros, 2011; Ambros* and *Slabý, 2013; Montella, 2011;*
Width of entry road	*Kennedy, 2007; Rodegerdts et al., 2010; ElAstal, 2014; Kamla et al., 2016;*
Traversable apron	*Daniels et al. 2011; Šenk* and *Ambros, 2011; Ambros* and *Slabý, 2013*
Sight distances	*Arnold et al., 2013*
Pavement markings and signage	*Hourdos et al., 2012; Richfield, 2013; Montella, 2011;*
Presence of pedestrian crossings (or cycle path) on roundabout legs	*Ambros et al., 2016; Hourdos et al., 2012; Lenters et al., 2003; Nambuusi et al., 2008;*

Now, it's been clear that roundabout operation and safety performance are particularly sensitive to geometric design elements. The state-of-the-art design of roundabouts by *Bared et al.* (*1997*) specified that, generally, roundabout design in terms of vehicles, flow, speed, and sight distance have a significant impact on the safety of roundabouts. In other words, the operation and safety performance of roundabouts can significantly be affected by the geometric design and operational characteristics.

A study by *Md Diah et al.* (*2011*) showed that in large roundabouts, increased width in the circulating roadway section between the legs may result in weaving motion to occur which may not be expected to happen in smaller ones. In this way, side-to-side conflicts between circulating vehicles is expected. A French standard *SETRA (1998)* also showed that the major causes of collisions that involve entering vehicles losing control, landing on the central island, collisions at the entries, and, to a lesser extent, losses of control on the circulating roadway are high entry speeds and poor visibility in the area before the transverse YIELD line.

Moreover*, Kamla et al. (2017)* had concluded that total approach traffic, truck percentage, entry width, inscribed circle diameter, number of lanes, and presence of traffic signals were found as significant variables influencing accident occurrences at roundabouts. However, the study fails to address the interaction between parameters such as traffic flow, signalization, and element widths and diameter. *Montella et al*. (*2013*) reviewed the Australasian, European Union and United States standards and guidelines, which showed the interaction of the roundabout geometric elements is more important than their individual impacts and indicated that geometric design criteria are of fundamental importance to achieve the best performance of roundabouts in terms of both capacity and safety.

Another study by *Nambuusi et al.* (*2008*) supported that the variables –annual average daily traffic (AADT) on major and minor roads, total vehicle counts and pedestrians crossing all arms, lighting and signal timing were statistically significant. In a study by *Turner et al.* (*2006*), free speeds of vehicles travelling through the roundabouts at the limit line were found positively related to entering-circulating crashes. Also, *Rodegerdts et al*. (*2010*) had confirmed that entry radius, entry width, approach half width, inscribed circle diameter, and circulating width are positively correlated with crashes, whereas angle to the next leg has a negative impact on crashes.

On the contrary, however, recent study results by *Daneils et al*. (*2010a*) confirmed some particular geometric variables namely: inscribed circle diameter, central island diameter, road width or the number of lanes, turned out to be no meaningful predictors for the number of crash occurrences at roundabouts, in some cases maybe unanticipated. But, the study couldn't deny that those variables act as a proxy for other, influencing but unknown variables.

Generally, the researchers had suggested various crash contributing factors at roundabouts. Moreover, two variables including –traffic flows and pedestrian crossing volumes were outperforming on explaining crash frequencies and occurrences at roundabouts. On the other hand, researchers had forwarded unanticipated contradicting conclusions (gaps) on the significance or crash contribution effect of geometric variables such as the inscribed circle diameter, central island diameter, road width or the number of lanes at roundabouts. Therefore, further studies on roundabout crash characteristics appeared to be highly essential in order to provide important awareness or comprehend design decisions especially in diverse local conditions.

2.4. Available Statistical Predictive Models

Models that are developed with various statistical regression methods can be categorized as General Linear Regression Models (Simple & Multiple), and Nonlinear Regression Models (Multinomial Discrete Choice Models).

2.4.1. General Linear Regression Models (Simple & Multiple)

Nearly all real-world regression models involve multiple predictors resulting in improvements of the traditional linear regressions into multiple regression models (*Jarvis et al., 2006*). General linear models are the contemporary solutions to describe adequately the random, discrete, and non-negative events such as of unreported vehicle crashes for a given observational period (*Jovanis and Chang, 1986*). In a General linear model:

$$\mu = E(Y) = \boldsymbol{x}\beta, \boldsymbol{x} = \left[x_1, x_2, \dots, x_p\right], \tag{2-1}$$

Where the response μ or E(Y) is modeled by a linear function of explanatory variables $\boldsymbol{x}=x_1, x_2, \dots, x_p$ plus an error term. And, β is the corresponding parameter estimates of the predictor variables.

2.4.2. Nonlinear Regression Models

Unlike traditional linear regression, which is restricted to estimating linear models, nonlinear regression can estimate models with arbitrary relationships between independent and dependent variables. The class of nonlinear models in the parameters allows the mean of the dependent variable to be expressed in terms of any function $f(x_i; \theta)$, and has a general form of the model as (*Rawlings et al., 2001)*:

$$Y_i = f(x_i, \theta) + \epsilon_i, \quad (2\text{-}2)$$

Where, $f(x_i, \theta)$ is the nonlinear function relating the mean of the dependent variable, $\mathcal{E}(Y)$, to the independent variable(s), x_i is the row vector of observations on k independent variables for the ith observational unit, and θ is the vector p parameters. The usual assumptions are made on the random errors. That is, ϵ_is are assumed to be independent $N(0, \sigma^2)$ random variables.

The count and discrete choice models are the common forms of non-linear regression models available. Generally, discrete choice modelling includes: Binary Logit, Binary Probit, Multinomial Logit, Conditional Logit, Multinomial Probit, Nested Logit, Generalized Extreme Value Models, Mixed Logit, and Exploded Logit. On the other hand, count data is a statistical data type which is often termed a count variable and when treated as a random variable, the Poisson, binomial and negative binomial distributions are commonly used to represent its distribution (*Cameron & Trivedi, 2013*). Generally, nonlinear models are usually preferred since they are more realistic in some sense or because the functional form of the model allows the response to be better characterized, perhaps with fewer parameters (*Rawlings et al., 2001*).

Generalized Linear Models (GLM):

The GLM inflates the general linear model so that the dependent variable is linearly related to the factors and covariates via a specified link function which permits for the dependent variable to have a non-normal distribution. The model includes commonly used statistical models, such as linear regression for normally distributed responses, (Multinomial) logistic & probit models for (categorical) & binary data, ordered probit models for ordinal data, log-linear models for count data, complementary log-log models for interval-censored survival data, plus many other statistical models via its very general model formulation (*Cameron & Trivedi, 1998*).

The basic count data regression models (such as the Poisson, Negative Binomial, and other related models) can be treated with the GLM structure and have extensively been developed to fit accident data and traffic counts for motor vehicles only accidents (*Turner, 1995*). Their recent furtherance work (*Turner et al., 2006a*) on accident prediction had also established models on flows and non-flow contributing variables with the mean number of accidents. Indeed, a study by *Tulu* (*2015*) had confirmed the appropriateness of the GLM to establish the relationships among traffic flow, road geometry property and crashes which had been previously employed for the same task by *Maher* & *Summersgill* (*1996*).

Generally, the contemporary GLMs have been extensively employed by most safety researchers in the development of accident prediction models (APMs) under certain standard conditions where the conventional linear modeling is violated by some characteristics of traffic accident data (*Jovanis and Chang, 1986*). Nowadays, several GLM statistical software packages such as the SPSS, XLSTAT, GENMOND, SAS, and GENSTAT have been presented for the development of these models.

- **Poisson regression model**

Poisson regression models and its extensions (Zero-Inflated Poisson, Negative Binomial Regression, etc.) which are of the Generalized Linear Models (GLM) appear to be more suitable under certain standard conditions than the formerly developed conventional linear regression models (*Maycock and Hall, 1984; Jovanis and Chang, 1986*). The most common functional form of the Poisson regression model is given by:

$$\lambda_i = EXP(\beta X_i), \tag{2-3}$$

Where X_i is a vector of explanatory variables and β is a vector of estimable parameters (*AASHTO, 2010*). The model parameters can usually be estimated by the standard maximum likelihood method with the log likelihood function (*Lord et al., 2010*) which is given by:

$$LL(\beta) = \sum_1^n [-EXP(\beta X_i) + n(\beta X_i) - Ln(n!)] \tag{2-4}$$

Let Y be the random variable that represents the accident frequency at a given location/roundabout during a specific time period, and let y be a certain realization of Y. The mean of Y, denoted by Λ, is itself a random variable (*Kulmala, 1995*). For Λ = λ, Y is Poisson distributed with parameter λ: Hence, the distribution of Λ can be usually be described by a gamma probability density function as:

$$\mathrm{P(Y = y|\Lambda = \lambda) = \frac{\lambda^y e^{-\lambda}}{y!}; E(Y|\Lambda = \lambda) = \lambda; Var(Y|\Lambda = \lambda) = \lambda} \tag{2-5}$$

However, recent researchers have verified that the Poisson regression as well as its extensions are difficult to account for over-dispersion (when the conditional variance exceeds the conditional mean) and under-dispersion (when the conditional mean exceeds the conditional variance) (*Lord et al., 2010*). That is, the model underestimates the amount of dispersion in the outcome. As a result, the standard errors usually estimated by the maximum likelihood method, will be biased and the derived test statistics from the model will be erroneous that can turn out the estimation of the likelihood of accident occurrence. Though, the Poisson regression could be used with generally smaller sample sizes than linear regression (*Jovanis and Chang, 1986*), it can still be adversely affected by small sample sizes and low sample-mean values (*Lord et al., 2010).*

As the Poisson regression model is a form of the GLMs, many goodness of fit measures used for GLMs can still be used for evaluating how well the model fits the data, including the deviance, and Pearson Chi-square. If the model fits the data well, the ratio of the deviance to the degrees of freedom (df), and the ration of the Pearson Chi square to the degrees of freedom should be close to 1 (*El-Basyouny et al., 2006; Malyshkina et al., 2010*).

- **Negative Binomial (NB)/Poisson-Gamma Regression**

The negative binomial (NB) regression model relaxes the failure of the Poisson by adding a parameter that reflects unobserved heterogeneity among observations (*Cameron and Trivedi, 1998).* Let *Y* be the random variable that represents the accident frequency at a given location/roundabout during a specific time period, and let *y* be a certain realization of *Y*. The mean of *Y*, denoted by Λ, is itself a random variable (*Kulmala, 1995*). For Λ = λ, *Y* is Gamma distributed with parameter λ, and the distribution of Λ can be described by a gamma probability density function. *Hauer* (*1997*) examined many accident data sets and the empirical evidence he obtained supported the gamma assumption for the distribution of Λ. That is, if Λ is described by a gamma distribution with shape parameter κ and scale parameter κ /μ, then its density function can be given by:

$$f_{\lambda} = \frac{(\kappa/\mu)^{\kappa}\lambda^{\kappa-1}e^{-(\kappa/\mu)\lambda}}{\Gamma(\kappa)}; \mathrm{E}(\Lambda) = \mu; \mathrm{Var}(\Lambda) = \frac{\mu^2}{\kappa} \tag{2-6}$$

The distribution of Y around E(Λ) = μ is negative binomial (*Hinde and Demetrio, 1998*). Therefore, the entire probability density form can be written as:

$$P(Y=y)=\frac{\Gamma(\kappa+y)}{\Gamma(\kappa)y!}\left(\frac{\kappa}{\kappa+\mu}\right)^{\kappa}\left(\frac{\mu}{\kappa+\mu}\right)^{y};E(Y)=\mu;Var(Y)=\mu(1+\frac{\mu}{\kappa}) \qquad (2\text{-}7)$$

As shown above, the variance of the accident frequency is generally larger than its expected value reflecting the fact that crash data are generally over-dispersed. The only exception is when $\kappa \to \infty$, in which case the distribution of Λ is concentrated at a point where the NB distribution reduces to the Poisson distribution.

Nevertheless, the NB, like the Poisson, cannot handle under-dispersion as well as it can be adversely influenced by the low sample-mean and small sample size bias (*Lord et al., 2010*). As the result of the NB method is sensitive to missing values (*Lord & Mannering, 2010*), it may be unsuitable for countries that are prone to underreporting (*Tulu et al., 2015*). Generally, the traditional Poisson and NB regression models are assumed to achieve well in modelling crashes due to the theoretical persuasiveness, good statistical fitness and empirical plausibility (*Lord, et al., 2005*).

- **Zero-Inflated Count Models [Poisson (ZIP) & Negative Binomial (ZINB)]**

Previous works by *Lambert* (*1992*) has shown that slight changes in unnoticed contributory factors that can cause zero-crash state in which crashes are non-existent (or of a low enough severity so as to be unreported) and the accident state where there are potential accidents but not unavoidable (includes zeros as an outcome). The presence of such excess zero densities have not been accounted for in the classical Poisson and negative binomial models. As a result, researchers proposed and found the zero-inflated count model (both for Poisson and NB models) more favorable type of crash frequency modeling due to its flexibility and broad applicability to a variety of situations by splitting the road design parameters and variables into crash-free versus crash-prone entities that determined the occurrence and non-occurrence of crashes (*Kumara et al., 2004*).

Zero-inflated models estimate two equations, one for the count model and one for the excess zero's. The probabilities of the dual (zero- and non-zero) states are: p_i for the zero crash state, and $(1-p_i)$ for the non-zero crash state with the overall probability of crashes taken as the sum of the probabilities from each state.

For the zero state $\Pr(n_i > 0) = P_i + (1-p_i)R_i(0)$ (2-8)

For the non-zero state: $\Pr(n_i > 0) = (1-p_i)R_i(n_i)$ (2-9)

Where, $R_i(0)$ = the probability of zero crashes that occurs in the zero state; $R_i(n_i)$ = the probability of non-zero crashes in the non-zero state. The maximum likelihood estimates (MLE) can be used to estimate the parameters of both ZIP and ZINB regression models and confidence intervals are constructed by likelihood ratio tests. It is also suggested preferable in underreporting of vehicle crashes, especially those minor injury and property damage crashes. The probability of a roadway entity being in zero or non-zero state can be estimated using a logistic (logit) or probit (normal) probabilities (*Shankar et al., 1997; Lambert, 1992; Washington et al., 2003, 2010*). However, others have criticized the application of the model in highway safety. *Lord et al*. (*2007, 2010*) argued that, because the zero or safe state has a long-term mean equal to zero, the zero inflated models cannot properly reflect the crash-data generating process, and hence, biased estimates may result.

- **Conway-Maxwell Poisson Regression Models (COM-Poisson)**

The Conway-Maxwell Poisson distribution was first introduced by *Conway* and *Maxwell* (*1962*) as a generalization of the Poisson distribution that can handle both under-dispersed and over-dispersed crash data (*Lord and Mannering., 2010)* that cannot be handled by the Poisson model or the Negative Binomial model. Several common probability density functions are stemmed from Conway–Maxwell–Poisson (for example, the geometric distribution, the Bernoulli distribution, and the Poisson distribution). In practice, the estimation of these models can become very difficult as they require more parameters, a problem that has likely impeded their application to crash frequency prediction. On the other hand, the low sample-mean, and small sample size of under-dispersed crash data can influence the estimated parameters, and therefore, it has been limited in the application of crash frequency (*Lord, 2006*).

- **Gamma Probability Models**

The *gamma probability models* are found to perform well in handling *over-dispersion* and *under-dispersion* cases in the data and make use of the *Gamma probability distribution* (*Agresti, 2002*). That is, the Gamma probability distribution models are the generalized form of the negative binomial distribution models which are intended to allow for variances that are not constant or equal to the mean, but rather proportional to the square of the mean. Accordingly, suppose that for a given mean λ, the distribution of Y is Poisson with a mean λ, but the mean itself varies according to gamma distribution, $G(\varphi,\mu)$. Then, the gamma probability density function for λ is given by:

$$f(\lambda;\varphi;\mu) = \frac{(\kappa/\mu)^{\kappa}\lambda^{\kappa-1}e^{-(\kappa/\mu)\lambda}}{\Gamma(\kappa)} \qquad (2\text{-}10)$$

Where, this gamma distribution has

$$E(\lambda) = \mu, \text{ and } VAR(\lambda) = (\mu^2/\kappa)$$

The parameter $\kappa > 0$ describes the shape the density function is skewed to the right and the degree of skewness decreases as κ increases. Though, the dispersion parameter κ^{-1} is itself unknown, estimating it helps to summarize the extent of over-dispersion. The greater κ^{-1}, the greater the over-dispersion compared to the ordinary Poisson GLM. Under-dispersion exists if $\kappa > 1$, over-dispersion if $\kappa < 1$, equi-dispersion if $\kappa = 1$. When κ is unknown, ML fitting can use a Newton-Raphson routine on all the parameters simultaneously. Or, one can evaluate the profile-likelihood for various fixed κ (*Lawless, 1987*).

Theoretically, the Gamma should be the right choice when the dependent variable is real-valued on a range from 0 to 1; And if the linkage between mean and variance is suspected to be “fixed”. In other words, the ratio of the mean to the variance is a constant –no matter how large or small the mean is. As a result, when the expected value is small –near zero, the variance is small as well. Conversely, when the expected value is larger, the observed scores are less predictable in absolute terms. The relationship between mean and variance here is different than some other distributions because it is “adjustable”. In contrast, the Poisson or Negative Binomial distributions have no such modification parameter (*Johnson, 2016*).

2.4.3. Steps for Choosing the Appropriate Statistical Tests

A number of researchers pointed out that choosing appropriate statistical technique that matches the research design to suitable statistical analysis is the most important step of a modeling process (*Shankar et al, 2014; Johnson et al., 2008*). Hence, it is useful to follow a step-by-step process with the following basic questions to be answered.

- Step-1: What type of research questions are asked? Common statistical analyses include:
  - Descriptive: - such as frequency, percentiles, central tendency, standard scores;
  - Correlational/Predictive: - Correlations such as the Pearson correlation, Regression; and
  - Group-difference/Cause & effect: - t-test; One-way ANOVA; Factorial ANOVA; MANOVA.

- Step-2: What type and number of variables are required to be analyzed?
    - Independent vs dependent;
    - Number of each variable;
    - Operational definition of each variable; and
    - Normal/expected range of scores/levels of each variable.
- Step-3: What type of data are available and what characteristics does it have?
    - Nominal/Categorical; Ordinal; Interval/Ratio;
    - Normally distributed? Appropriate range of scores? Are the groups equal/balanced? Are some of the categories identical?

2.5. Model Goodness-of-Fit (GoF) Tests

Goodness-of-fit (GoF) tests are used to determine how well a data set is fitted by a specified distribution. There are several goodness-of-fit measures, where the most familiar ones include the Pearson chi-squares, deviance, likelihood ratio test, Akaike Information Criteria (AIC) and Bayesian Schwartz Information Criteria (BIC). The relevant ones with the current study will be briefly discussed in this section for claim count or frequency analysis of the GLMs with Poisson error structure and to the regression models of Negative Binomial.

- **Multi-collinearity**

Some of the explanatory variables of a model could be related to each other which might increase the standard errors of coefficients. Though, such property of explanatory variables, called multi-collinearity, does not affect the forecasting performance of a model, the resulted coefficients might be less significant as a result (*Ramanathan, 1995*).

Multi-collinearity could be identified by low values of the t-statistics, high value for correlation coefficients between variables, and the sensitivity of the estimated coefficients to specification (*Ramanathan, 1995; Montella et al., 2011*). Bivariate or pairwise correlations among explanatory variables or interdependences between explanatory variables/factors have to be checked to assess the multi-collinearity effects. Accordingly, to identify these symptoms in the models presented in this paper, there is no need to be concerned about multi-collinearity if-

- bivariate correlations among explanatory variables does not have high values (>0.5);
- there is no observation that the estimated coefficients were drastically altered when variables were added or dropped; and

- the coefficients in the estimated models are significant and had meaningful signs and magnitudes.

To avoid multi-collinearity between highly correlated variables, only the most significant variable is taken from among the highly correlated variables in a model. Hence, a bivariate correlation among predictor variables entered into the model is run and assessed statistically for multi-collinearity using two different methods: Tolerance and the variance inflation factor (VIF). For example, the total peak hour vehicle volume entering the roundabout (from all legs) was found to be highly correlated with several variables; hence, was dropped (complete details included in Appendix E: Table E- 1).

- **Pearson Chi-square (χ^2) statistic**

For an adequate model, the Pearson chi-square statistic, mentioned by *McCullagh* and *Nelder* (*1989*), has an asymptotic chi-square distribution with n – p degrees of freedom, where *n* – is the number of observations, and *p* – is the number of model parameters. The Pearson residuals are defined as:

$$r_i = \frac{[y_i - \hat{E}(Y_i)]}{\sqrt{Var(Y_i)}} \tag{2-11}$$

Then, the Pearson Chi-square (χ^2) goodness of fit statistic is equivalent to,

$$\chi^2 = \sum_{i=1}^{n} r_i^2 \tag{2-12}$$

Which would be compared to a chi-square distribution with df=n-p, where y_i is the observed number of crashes on roundabout *i*, $\hat{E}(Y_i)$ is the predicted crash frequency for roundabout *i* as obtained from the APM, and $Var(Y_i)$ is the variance of the crash frequency for roundabout *i*. Large chi-square statistics result in small *p*-values and convey evidence against the intercept-only model in favor of the current model.

- **The Deviance (D) Statistic**

The Deviance (D) refers to the distance between data and fit. It is the likelihood ratio test statistic measuring twice the difference between the maximized log-likelihoods of the studied model and the full or saturated model. For an adequate model, both Pearson chi-squares and deviance are chi-square distributed which are asymptotically close to the n – p degrees of freedom. For a Poisson distributed error structure, *McCullagh* and *Nelder* (*1989*) have shown the scaled deviance as follows:

$$D = 2\sum_{i=1}^{n} y_i \ln(\frac{y_i}{E(Y_i)}) \quad (2\text{-}13)$$

While, for a negative binomial distributed error structure, the scaled deviance is given by:

$$D = 2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{y_i}{\hat{E}(Y_i)}\right) - (y_i + \kappa)\ln(\frac{y_i+\kappa}{\hat{E}(Y_i)+\kappa})\right] \quad (2\text{-}14)$$

Then the deviance D would be compared to the asymptotically distributed chi-square close to the *n-p* degrees of freedom. Similar to the Pearson, large D values result in small *p*-values and convey evidence against the intercept-only model in favor of the current model. The full model has as many parameters as there are observations so that the model fits the data perfectly. That is, the full model, which has the maximum log-likelihood attainable under the given data, provides a baseline for evaluating the goodness of fit of an intermediate model with *p* parameters.

- **Log-Likelihood ratio (LR) test**

The likelihood ratio test is a statistical test used to test the significance of explanatory variables to use in a model or, in other words, to compare the goodness of fit of two models. The likelihood ratio (equivalently its logarithm) is based on the likelihood ratio, which expresses how many times more likely the data are under one model than the other (*Neyman et al., 1933*). When the logarithm of the likelihood ratio is used, the statistic is known as a log-likelihood ratio statistic. According to *Agresti* (*2002*), the likelihood ratio test is better, particularly if the sample size is small or the parameters are large. The likelihood ratio test statistic is twice the log of the likelihoods ratio given by:

$$LR = -2\ln\left(\frac{\text{likelihood for null model}}{\text{likelihood for alternative model}}\right) = 2[LL(\beta) - LL(0)] \quad (2\text{-}15)$$

where $LL(\beta)$ and $LL(0)$ are the model's log-likelihood under alternative (full parameters) and null (intercept only) hypotheses respectively. The probability distribution of the test statistic is approximately a chi-squared distribution with degrees of freedom equal to df_{alt}-df_{null}, respectively the number of free parameters of models alternative and null (*Lawless, 1987; Cameron and Trivedi, 1986*). Therefore, to test the null hypothesis at the significance level of α, the critical value of chi-squares distribution with significance level 2α is used, i.e., reject H_o if LR > $2\chi^2_{(1-2\alpha,1)}$. Larger values of LR lead to small *p*-values, which provide evidence against the null model in favor of the current model.

- **Over-dispersion test**

For unbiased comparison among the traditional Poisson and the negative binomial models defined by the deviance or Pearson chi-square, the log-likelihood can be estimated by initially assuming identical scale parameter, φ for both the models. Though some statisticians have used the deviance dispersion as the basis for scaling standard errors, simulation studies indicate that the Pearson dispersion better captures the excess variability (*Hilbe, 2007*), where it was consistently utilized here. A scale parameter φ =1 could first be assumed and the regression parameters can be estimated. Then, the Pearson chi-square values could be obtained to calculate the scale parameter estimates.

If the estimated scale parameter is not near the assumed value of 1, then the data may be over-dispersed (if the value is greater than 1) or under-dispersed (if the value is less than 1). It is worthwhile noting that the original log-likelihood with the assumed scale parameter is used in computing the information criteria but the revised log likelihood with an estimated scale-parameter is used in the overall model fitting test. The problem with over-dispersion is that it may cause standard errors of the estimated parameters to be underestimated in which a variable may appear to be a significant predictor, when in fact it is not.

- **Information Criteria (AIC & BIC)**

In the presence of several maximum likelihood models, one can compare the performance of alternative models using several likelihood measures among which two of the most regularly used measures are the Akaike Information Criteria (AIC) and the Bayesian Schwartz Information Criteria (BIC). Information criteria are used when comparing different models for the same data. AIC identifies the best approximating model among a class of competing models with different numbers of parameters and is defined as follows (*Akaike, 1973*).

$$\mathrm{AIC} = -2[\mathrm{LL}(\beta) - \mathrm{k}] \tag{2-16}$$

Where $L(\beta)$ is the full log-likelihood evaluated at the full set of parameter estimates, k is total of number of independent variables in the model. The smaller the value of AIC, the better the model fit. A stepwise (forward) procedure can be used to select the best model based on minimizing the AIC value. The Bayesian Information Criterion (BIC), on the other hand, is another popular method, given by the equation:

$$\mathrm{BIC} = -2\mathrm{LL}(\beta) - \mathrm{k}\log N \tag{2-17}$$

Where, LL(β) & k are described above, and *N* is the number of rating classes or observations. The smaller the test statistic BIC, the better the model is.

- **Lagrange Multiplier (LM) Test**

According to *Cameron* and *Trivedi* (*1998*), if the scale (dispersion) parameter for a given distribution is set to a fixed value or specified by the deviance or Pearson chi-square divided by the degrees of freedom, or an ancillary parameter φ for the negative binomial is set to a fixed value other than 0, the validity of the value can be established using the Lagrange Multiplier (LM) test.

That is, for a fixed φ, the LM test statistic which is a z statistic has an asymptotic standard normal distribution under the null hypothesis of equi-dispersion in a Poisson model (H_0: φ=0). Three p-values are provided. The alternative hypothesis can be one-sided over-dispersion (H_a: φ>0), under-dispersion (H_a: φ<0) or two-sided non-directional (H_a: φ≠0) with the variance function of $V(\mu)=\mu+\varphi\mu^2$. The calculation of p-values depends on the alternative. For H_a: φ>0, p -value =1− Φ (z), where Φ (·) is the cumulative probability of a standard normal distribution; for H_a: φ<0, p -value = Φ (z); and for H_a: φ≠0, p -value =2(1− Φ (|z|)).

- **Residuals & Outliers Analysis for GLMs**

When a GLM fits poorly according to an overall goodness-of-fit test, examination of residuals such as the deviance, and/or Pearson residuals highlights where the fit is poor (*Agresti*, *2002*). Residuals are essentially the difference (or error) between the observed value and the predicted value yielded from the prediction model. Residual analysis is very essential measure of model fit for meeting the linearity, normality, and homogeneity of variance assumptions of the Poisson and its derivatives. If there are values that are above an absolute value of 2.0, then there are outliers. Just like with other forms of regression, the assumptions of linearity, homoscedasticity, and normality have to be met for Poisson and negative binomial regressions. As a result, evidence of model fit is assumed when 95% of the standardized residuals which are plotted against the expected rate of outcome are between 2 and -2 (*Katz, 2011*).

- **Relative effects (elasticity) of model variables**

Once the coefficients of the parameters are estimated, the true effect of the independent variables on crash frequency can be evaluated using a process called elasticity. *Shankar et al.* (*1995*) suggested the use of elasticity to examine the true relative effects of the variables included in the models, which would measure the true relative effect of the variable on crash frequency (*Abdel-Aty et al., 2000*). Accordingly, elasticity can roughly be interpreted as the percentage change in the average frequency of crashes caused by a one-percent change in the independent variable and can be defined as,

$$E(y) = \frac{\partial \lambda}{\partial x}\frac{x}{\lambda} \tag{2-18}$$

Where λ is the mean number of crashes, x are the explanatory variables.

2.6. Black-spot Identification and Prioritization

Globally, there is no conventionally recognized definition for black-spot or what should be considered as 'dangerous' (*Geurts and Wets, 2003*). For instance, the UK customarily defines to any specific section, spot or area in a road network or entity where the number of injuries is more than a specific number (*O'Flaherty, 1997*). Whereas, the US uses weighting of accidents in a specific location depending on its severity where the weighting factor of each severity depends on the relative cost of accident types (*O'Flaherty, 1997*). In Australia and Flanders, black spot is defined as any location that have three or more injury accidents recorded in police reports in three years and the average annual daily traffic in the under consideration area. The ranking procedure uses a value of risk coefficient R_k greater than or equal to 0.8 (*Elvik, 2008*; *Geurts et.al., 2003*), where;

$$R_k = \frac{Number\ of\ Injury\ accidents\ in\ 3\ years}{0.5+7\times10^5\times AADT} \tag{2-19}$$

According to *Elvik* (*2008*), black spot in Hungary is any location with four accidents recorded in police reports in three sequential years. The researcher also reported that black spots, in Portugal, are defined based on the expected number of accident using two procedures. The first procedure defines as any location, determined by a 200-meter sliding window or less, where 5 accidents happened in one year with severity index (SI) more than 20 and can be calculated by;

$$SI = No.slight\ accidents + 10 \times No.serious\ accidents + 100 \times No.fatal\ accidents \tag{2-20}$$

The second procedure, however, relies on the anticipated number of accidents where an exclusive accident prediction model can be fitted for each class of roads depending on historical accident data, number of carriageway, carriageway width and number of lanes in each direction. On the other hand, black spots, in Germany, are defined based on the length of the identification period for one year and three years. That is, for one year of identification period, it is any location where five accidents of a similar types occurred (regardless of its severity). If three years of identification period is used, the black spot is defined as any location where five or more injury accidents have been recorded or any location where three or more serious accidents have been recorded (*Elvik, 2008*).

On the other hand, the weighted severity index method of accident ranking procedure in the Design Mobility Plan Flanders (2001), has been adopted by a number of studies focussed in developing countries such as in Ethiopia (*Yohannes & Minale, 2015; Fekadu et al., 2016; Teklu, 2016*). Accordingly, each site where in the last three years three or more accidents have occurred is considered to be a black spot when its priority value (P), calculated using the following formula, equals 15 or more. That is

$$S = (No. slight\ accidents) + (3 \times No. serious\ accidents) + (5 \times No. fatal\ accidents) \quad (2\text{-}21)$$

Though, the method lacks to assume the property damages only (PDO) crashes, it is mostly adopted in some developing countries. The level of fatal & personal injury crashes in Addis Ababa City prevalently constitute high numbers and particular attention and priorities necessary (*TPMO, 2017*), where, such reasons might reinforce the use of equation (2-21) above in the current study.

2.7. Traffic Studies

Traffic studies include both the collection and analysis of appropriate data concerning to traffic and its characteristics. The use of traffic data studies can noticeably be applied during monitoring, forecasting, calibration, validation, and evaluation of the transport system (AACRA- Geometric Design Manual, 2003). The measurements for different traffic characteristics data such as traffic volumes, spot speeds vary with the type, required precision, and intended use of the studies. According to *AACRA Geometric Design Manual* (*2003*), traffic studies related to road crashes are beneficial in identifying problems within an existing transport system to provide a basis for decisions on accident reduction measures.

2.7.1. Traffic Characteristics

2.7.1.1. Spot Speed

Spot speed studies for vehicles represent the traversed length measured between any two points of interest divided by the period of time elapsed to transverse the route. Spot speed measurements are useful in investigation of high-accident locations at which speed is suspected to be a contributing cause to the accident experience. According to *Roess et al.* (*2004*), the basic statistics that are used to describe spot speed distributions include:

Average or time mean speed: - the average speed of all vehicles passing the study location during the period of the study.

V_{85} *(85th percentile) speed:* -the speed below which 85% of the vehicles travel.

V_{50} *(Median or 50th percentile) speed:* -the speed that equally divides the distribution of spot speeds; 50% of observed speeds are higher than the median; 50% of observed speeds are lower than the median.

Pace: -a 10-mi/h increment in speeds that encompasses the highest proportion of observed speeds (as compared with any other 10-mi/h increment).

In order to take into account actual traveling speeds of vehicles, and in accordance with international standards and practices, the V_{85} speed under free flow (unimpeded traffic conditions) and the V_{50} speed are usually applied (*SETRA*, *1998*). The 85th percentile speed is used in evaluating/recommending posted speed limits based on the assumption that 85% of the drivers are traveling at a speed they spot to be safe (*Homburger et al., 1996*). The manual (such as the Stop watch) and automatic (such as the Road Detectors, and Electronic-Principle Detectors) methods of conducting spot speed studies are commonly used. The manual - stopwatch method is usually preferred due to its advantages of being used with small samples; it is quick, and inexpensive method. The 50th and 85th speed percentiles can be presented by a frequency distribution table as well as frequency and cumulative frequency distribution curves.

It is important mentioning that the speed is free speed and not that of all entering vehicles, which would depend on the traffic volumes at the time of the speed survey, where speeds would be lower in periods of high traffic flows. The average spot speed of vehicles can be obtained from a sample of measurements to estimate the true mean of the underlying spot speed distribution. Accordingly, the average spot speed measurements for vehicles are collected and analyzed for the following percentile speeds.

- *85th Percentile Speed (*V_{85}): - representing the 85th percentile free flow speed; and
- *50th Percentile Speed (*V_{50}): - representing the 50th (median) speed expressing the average speed of the traffic stream.

To calculate vehicle speed, the predetermined study length and the elapsed time it took the vehicle to move through the course (as recorded on the stopwatch data form) can be used (*Robertson, 1994*). The vehicle speed could then be calculated using the observed or elapsed time by the stop watch and the already specified study length in the formula below (*Robinson, 1994*).

$$V = 3.6\frac{\mathrm{D}}{\mathrm{T}} \tag{2-22}$$

Where,

V = spot speed (kph);

D = study length (m), and

T = elapsed time (seconds).

Though a randomly selected sample size of 50 to 100 vehicles is usually preferred for a spot speed study at each selected location (*Ewing, 1999*), a statistically significant sample size can be determined according to the procedure and equation on the NCHRP Report 398 (*Lomax et al., 1997*) and the Travel Time Data Collection Handbook (*Turner et al., 1998*). Accordingly, to ensure quality of data, the recommended minimum sample sizes (N) for different traffic environments and assumed level of confidence can be given by:

$$N \geq \frac{Z^2 * S^2}{e^2} \tag{2-23}$$

Where: -

Z = t-statistics from student t-distribution for a given confidence interval;

S = Coefficient of variance /Standard deviation/; and

e = tolerance or acceptable limit of relative error.

Note: According to *Roess et al. (2004)*, practical use is made of the knowledge that most speed distributions have standard deviations of approximately *S* = 5.0 mi/h (≈ 8kph). For most traffic engineering studies, a tolerance of e =1.0 mi/h (≈ 1.6kph) and a confidence level of 95% (Z=1.96) are quite sufficient. Hence, for the given assumptions, the minimum sample size is calculated as follows:

$$N \geq \frac{Z^2 * S^2}{e^2} = \frac{1.96^2 * 8^2}{1.6^2} \approx \underline{96}$$

The manual - stopwatch method of spot speed measurement is usually preferred due to its advantages of being used with small samples and is a quick and inexpensive method. The method considers five key steps during the process (*Smith et al., 2002*):

- Obtain appropriate study length;
- Select proper location and layout;
- Record observations on stopwatch spot speed study data form;
- Calculate vehicle speeds; and
- Generate frequency distribution table and determine speed percentiles.

To obtain the appropriate study length *Smith et al.* (*2002*) have recommended the values in the table below based on the average speed of the traffic stream.

Table 2-2: Recommended spot speed study lengths

(Source: Smith et al., 2002)

Average speed of traffic stream (Kph)	Recommended Study Lengths (m)
Below 40 kph	27
40 - 65 kph	54
Above 65 kph	80

The observer could be positioned at appropriate sight point and used reference points to aid in collecting the elapsed time it takes a vehicle to travel through a brightly colored vertical reference posts (see Figure **2-4**). To decide the average speed of traffic streams, a private test car can be used along with the traffic stream and the reading on the car's speedometer is recorded.

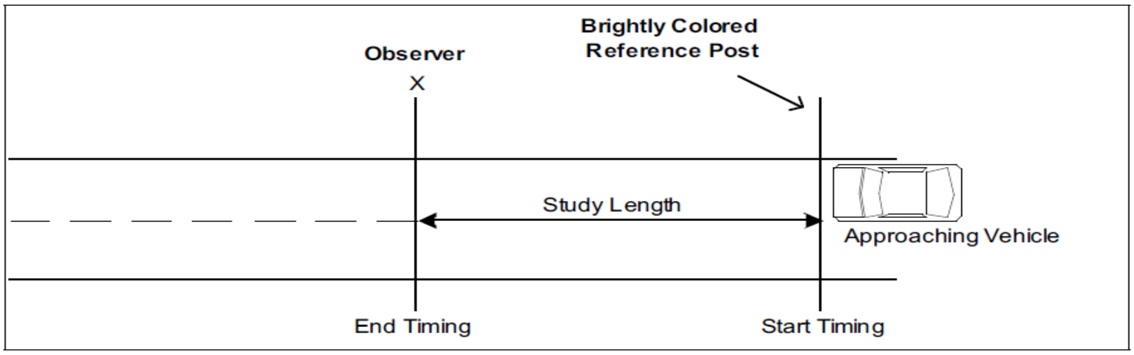


Figure 2-4: Stopwatch Spot Speed Study Layout

(Source: Smith et al., 2002)

After all the field data are collected, the frequency distribution table is completed and the required percentile speeds are computed. While computing the percentile speeds, that the exact values for the 50^{th} and 85^{th} percentiles might not be found in the cumulative percent column. To reach these exact percentages, however, an interpolation technique might be needed using percentages and speeds from the distribution table as shown below:

$$S_D = \frac{P_D - P_{min}}{P_{max} - P_{min}} \left(S_{max} - S_{min}\right) + S_{min} \tag{2-24}$$

Where S_D=speed at P_D, P_D=percentile desired, P_{max}=higher cumulative percent, P_{min}=lower cumulative percent, S_{max}=higher speed, and S_{min}=lower speed. It is worthwhile giving great care when determining periods during the collection of spot speed data such as:

- Periods of congestion;
- Periods of free-flow traffic; and
- Invalidating factors (e.g. holidays and weekends).

2.7.1.2. Traffic Volume and Flow Rate

According to the *HCM* (*2000*), both volume and flow rate are variables used to measure the traffic demand (i.e. the number of vehicles) passing a point on a lane or roadway in a specific time interval. The manual defined the relevant flow parameters as follows:

Volume: - is the total number of vehicles that pass a given point or section of a lane or roadway during a given time interval and can be expressed in terms of annual, daily, hourly, or sub-hourly periods.

Flow Rate: - is the equivalent hourly rate at which vehicles pass over a given point or section of a lane or roadway during a given interval of less than 1 hour, usually 15 min.

Average Daily Traffic (ADT): - is the total number of vehicles in a time period (more than one day and less than a year) divided by the number of days in the period.

Annual Average Daily Traffic (AADT): - is the total volume of traffic for the whole year divided by the number of days in the year.

2.7.1.3. Peak Hour Volume and Peak Hour Factor

The vehicles volume count represents the number of vehicles that pass through a particular point on a highway facility during specified time period. The single hour volume of the day that has the highest hourly volume over the 24 hours (with periods of maximum flow occurring usually during the morning and evening commuter “rush hours”) is referred to as the *peak hour* *volume* which traffic engineers for design and operational analysis usage *(Roess et al., 2004).* It is generally stated as a *directional* volume (i.e., each direction is counted separately). Accordingly, the peak flow rates and hourly produce the peak-hour-factor (PHF), which represents the ratio of total hourly volume to the peak flow rate within the hour. According to Roess, et al., (2004), planning and designing of facilities is usually made for a demand that

- **Peak Hour Vehicles Volume (PHVV)**

The vehicles flow can be categorized into *peak hour* and *off-peak hour* volumes. According to a study (*Saini, 2015*), for any traffic infrastructure design and crash study *peak hour* traffic volume is necessary. According to the *HCM* (*2000*), traffic flow rates are usually expressed in vehicles per hour, not vehicles per 15 minutes. The PHF which correlates the peak 15-minute flow rate with the full hourly volume can be computed by the following equation:

$$\mathrm{PHF} = \frac{\text{Hourly Volume}}{\text{Peak Rate of Flow Within The Hour}}$$

For 15-minute periods, the PHF can be computed as:

$$\mathrm{PHF} = \frac{V}{(4 * V_{15})} \qquad (2\text{-}25)$$

Where

V = hourly volume during the maximum-volume hour (vph); and

V_{15} = the peak 15-minute flow rate within the peak hour (veh/15 minutes).

The determination of traffic volume needs considerable adjustments to account for the presence of heavy vehicle fleet mixes or characteristics in a road network (*Rodegerdts et al., 2010*). The adjustment process may be carried out in two steps. The first step involves finding the passenger-car equivalent factors for heavy vehicles such as trucks, buses, and recreational vehicles. In this study, the types of vehicles are defined according to the breakdown adopted by ERA for traffic counts and simplified, for reporting purposes, in five classes of vehicles (with vehicle codes 1 to 5) namely: small cars, buses, medium Trucks, Heavy Trucks, and Articulated Trucks (details included in Appendix B: Table B- 1).

Besides, due to the presence of significant numbers and associated risks of motor-bicycles at some roundabouts in the city, the motor-bicycle counts are also included in the study. The computation of the overall adjustment factor, f_{HV}, using the suggested conversion factors given in Table 2-3 and percentages of the vehicle types in the traffic stream in question is given by:

$$f_{HV} = \frac{1}{1+(\sum_{1}^{n} P_i(E_i-1)} \quad (2\text{-}26)$$

Where,

f_{HV} = Heavy-vehicle adjustment factor;

E_i = passenger-car equivalents for vehicle type *i* in the traffic stream (Table 2-3);

P_i = proportion of vehicle type *i*, in the traffic stream;

i = vehicle type in the traffic stream (Trucks, Buses, Recreational vehicle, Motorbike, etc.); and

n = number of vehicle types available in the traffic stream.

Traffic or vehicle fleet composition represents the proportion of each type of traffic within the total traffic stream based on predetermined vehicle classification system (*TRL, 1993*). An increased proportion of heavy vehicles at intersections is assumed to reduce capacities due to their slow follow-up headways and increased size. Likewise, it is believed that the capacity situations can affect the mobility and safety performances at intersections. The conversion factors into PCU for different vehicle classes in Addis Ababa city were reviewed and recommended as shown in Table 2-3 below (*Teklu, 2016*).

Table 2-3: Recommended passenger car equivalents factors (ET) in A.A.

(Source: Teklu, 2016)

Vehicle fleet type	Passenger Car Equivalent, (E_T)
Bicycle	0.30
Motor cycles	0.40
Cars and Vans	1.00
Light Vehicle (Bus & 1-axle Truck)	2.00
Medium Trucks (2-Rear Axle Truck)	2.50
Heavy & articulated Trucks (4-Axle Truck & Large Trucks)	3.00

The volumes of Heavy Traffic should be converted into equivalent Passenger Car Units (PCUs). Then, to find the traffic demand volume in terms of Passenger Car Unit (PCU), the existing hourly demand volumes have to be converted into an equivalent flow rate under ideal conditions using the following equation:

$$V_{PCU} = \frac{V}{(PHF * f_{HV} * f_p)} \quad (2\text{-}27)$$

Where:

V_{PCU} = passenger-car equivalent unit flow rate, pcu/h;

V= hourly volume (vph);

PHF = peak-hour factor (computed by (3-2) above);

f_p = adjustment factor for presence of occasional or non-familiar users of a facility (use f_p=1, assuming zero presence of occasional or non-familiar users for this study)

f_{HV} = adjustment factor for presence of heavy vehicles (described above).

- **Peak Hour Pedestrian Volume (PHPV)**

Currently, cycling and using animal drawn carts are not popular in the city of Addis Ababa. Hence, the study particularly considers the non-motorized traffic (NMT) specific to the pedestrian flow only. The pedestrian crossing volume is the number of people per hour who cross in the vicinity of approach legs in each study roundabout (usually within 50m from the center of roundabouts). The mathematical relationship between the peak hour volume and the maximum rate of flow within the hour is defined by the peak hour factor (PHF) as follows (*Roess, et al., 2004; Miranda, et al. 2011*): For 15-minute periods, the PHF can be computed as:

$$\text{PHF} = \frac{V_{pk}}{(4*V_{15})} \tag{2-28}$$

Where:

V_{pk} = hourly volume during the maximum-volume hour (ped/h); and

V_{15} = the peak 15-minute flow rate within the peak hour (ped/15 minutes).

Then the existing hourly demand volumes V have to be converted into an equivalent flow rate under ideal conditions using the following equation:

$$\text{V}_\text{p} = \frac{\text{V}}{(\text{PHF})} \tag{2-29}$$

Where:

V_P = pedestrian flow rate, ped/h;

V= hourly volume (ped/h); and

PHF = peak-hour factor (described above).

2.7.2. Field Techniques for Traffic Counts

Traffic volume counting methods vary according to the quality, type, and vehicle classification requirements of the intended use. Generally, there are two main traffic counting methods, namely; manual counts and automatic counts.

Manual traffic count is the most common and least expensive traffic counting method which consists of assigning somebody or people to record traffic as it passes. For instance, intersection counts are usually conducted using the manual count method (*Smith et al., 2002*). However, great attention should be given to some common errors which arise with manual traffic counts such as failure to define vehicle classification, failure to observe time periods accurately, and surveyors having to count vehicles at a faster rate than they are capable (*TRL, 1993*).

For manual pedestrian volume counts, the guidance from the Traffic Monitoring Guide (TMG) (*FHWA, 2013*) suggested a minimum duration of 4 to 6 hours, and should be scheduled to coincide with the vehicles' peak hour times (typically mid-day for weekend/recreational trips and morning/evening commute times for other trips). According to the TMG, pedestrian traffic has a much stronger mid-day peak, and Manual observers' counting accuracy declines after 2 hours.

The automatic traffic count method is generally used for gathering large amounts of traffic data which are usually taken in 1-hour intervals for each 24-hour period and may extend for a week, month, or year. The exploitation of new electromagnetic spectra and wireless communication media in recent year, has allowed traffic detection to occur in a non-intrusive fashion, at locations above or to the side of the roadway. Portable counters such as Pneumatic tubes, permanent counters such as Inductive loops, Weigh-in-Motion Sensor types, Micro-millimeter wave Radar detectors, and videotape are the commonly available methods to record automatic counts (*Smith et al., 2002*).

According to the Transport Research Laboratory (*TRL, 1993*) and the Traffic Volume Count Manual in the US (*Smith et al., 2002*), the most appropriate days and times of survey as well as duration (for example whether average values or peak values are required) of survey depend on the type of count being taken, quality of data, reliability, and the intended use of the data recorded.

The duration of traffic counts varies from few minutes to several days depending on the purpose (*TRL, 1993; AACRA Traffic and Axle Load Study Manual, 2002*). Though, most manual counts are conducted for one day, shorter periods may be needed for special purposes (*TRL, 1993*). For instance, a manual traffic count at intersections can typically be used for periods of less than a day during the peak flow period with normal intervals of 5, 10, or 15 minutes (*Smith et al., 2002*) as it is found easier because the user carries out with no equipment and is the least expensive. If so, the manual recommends that manual count with 15-minute intervals could be used to obtain the traffic volume data for determination of vehicle classification, movements, pedestrian movements, or vehicle occupancy.

International study by *De Ceunynck et al*. (*2008*) advocates that the use of relatively unusual volume counts for APM, for instance a two-hour value instead of a more traditional value for one hour or for a 24-hours period, does not have an impact on the parameters because of the model form. Count periods may range from 5 minutes to 1 year (*Smith et al., 2002*) where, from international experiences, the following typical count periods can be adopted for manual traffic counts (*Robertson, 1994*) with normal intervals:

- 15 minutes or 2 hours for peak periods;
- 4 hours for morning and afternoon peaks;
- 6 hours for morning, midday, and afternoon peaks; and
- 12 hours for day-time periods.

The *AACRA Traffic and Axle Load Study Manual* (*2003*) also suggested that all traffic counting can be done on weekdays only, to minimize distortion of results due to weekend variations in flows where day shifts operate from 7:00 am in the morning (1:00 Ethiopian time) to 7:00 pm in the evening (1:00 Ethiopian time) and night shifts from 7:00 pm in the evening to 7:00 am in the morning (*AACRA Traffic and Axle Load Study Manual, 2002*).

Also, a western study in the US suggested that traffic counts during a Monday morning rush hour and a Friday evening rush hour may show exceptionally high volumes and are not normally accounted in analysis; therefore, counts are usually conducted on Tuesday, Wednesday, or Thursday (*Smith et al., 2002*).

The NMT represents pedestrians, bicycle, and animal drawn carts. Pedestrians characterize a diverse group of people with a wide range of abilities that are vulnerable road users and form a large proportion of road fatalities and injuries. Facilities are generally designed to fulfil the peak hour demand. However, there are demands within the hour that reflect a peak that may surpass the capacity and thus generate a breakdown in the system (*Roess, et al., 2004*). Pedestrian count collected using manual counts is usually required for crash prediction models. Pedestrians who are 12 years or older are customarily classified as adults and persons of grade school age or younger are classified as children (*Robertson, 1994*).

For manual counts, the guidance from the Traffic Monitoring Guide (TMG) suggested a minimum duration of 4 to 6 hours, and should be scheduled to coincide with the peak hour times (typically mid-day for weekend/recreational trips and morning/evening commute times for other trips). According to the TMG, pedestrian traffic has a much stronger mid-day peak. The time-of-day patterns for non-motorized traffic data vary by location and trip purposes, where daily peaking patterns can be seen during the weekdays for non-motorized traffic (*FHWA, 2013*). Similar to vehicle counts, many researchers employed different count periods. A study recommended pedestrian count to be carried out on Tuesday, Wednesday, or Thursday in the afternoon, and on Saturday (*Schneider, et al., 2008b*).

2.8. Summary

The chapter has reviewed important theoretical foundations and analytical models pertinent to RTAs. It begun with a brief discussion on the safety performance situations at roundabouts and, as a result, so many models have been developed to estimate and predict the traffic crash trends. The models have been explained to focus generally on (i) correlations with severities and crash types, and (ii) correlations with total crash frequencies/occurrences. The models which were concerned with severities and crash types were presented to describe the particular causes of crashes at roundabouts. The advantage of such models in making crash prediction by better reflecting the real-time situations was discussed in this chapter. Likewise, models which focused on total crash frequencies or occurrences that have been surfaced across literatures were explained to show much they are critical of modeling temporal and spatial conditions of roundabouts. The chapter further presented some important models useful of predicting RTAs, such as general linear regression and nonlinear regression models, with a particular emphasis on GLM’s Standard Poisson and Negative Binomial regression models. Last, but not least, the chapter explored existing literature gaps and contradictions of which different researches made on the significance or crash contribution effect of geometric variables such as the inscribed circle diameter, central island diameter, road way width or the number of lanes at roundabouts.

CHAPTER 3 METHODOLOGY

3.1. Introduction

This chapter deals with the methodological design and development of the study. The overall plan and approaches of the research, variables used, data collection and sampling techniques, as well as strategies used to develop crash prediction models are discussed here.

3.2. Research Design

The study design was based on the observational variables (explanatory and descriptive analysis) to model and predict the frequency and occurrences of RTAs at five-legged roundabouts. The overall methodological steps used in this paper include:

- Conducting prior literature reviews on RTAs, black spots and crash-predictive models to identify the underlying factors.
- Primary data on geometric and traffic characteristics were collected via field observational surveys.
- Secondary data on RTAs were collected from police-recorded crash data bases including their location, time, and severity levels for consecutive three years' period covering from Jan. 2014 to Dec. 2016.
- Using those data, a descriptive and inferential statistical analysis were carried out.
- Previously suggested statistical regression models were employed to calibrate APMs in order to develop particular conclusions and recommendation on alleviating the frequency and occurrences of RTAs.
- The data analysis was supported by analysis software packages, namely; SPSS 23, and Excel spreadsheets.

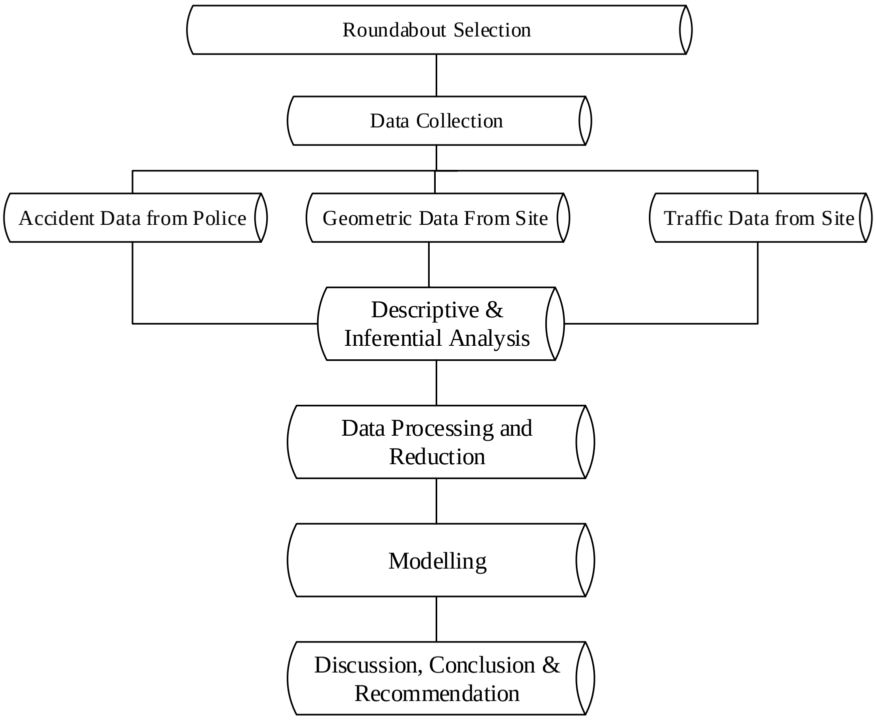


Figure 3-1: Methodological Illustration of the Study

3.3. Study Area

Current preliminary field survey data shows there are about 79 recognized (at-grade and grade-separated) roundabout intersections in the city of Addis Ababa (see Table A- 1 in Appendix A). The names were adopted from the locality or commonly used names. Roundabouts can systematically be categorized using their common variable features such as their number of lanes, number of legs, traffic conditions, crash data, geometry, environment, and pavement characteristics. In this study roundabouts with specific number of legs, though with different distances between legs, will be the focus. Field observational survey revealed that roundabouts in Addis Ababa are comprised of 15% with three legs, 65% with four legs, and 15% with five legs.

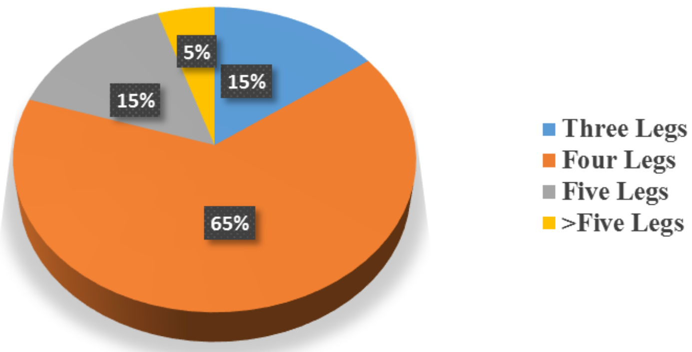


Figure 3-2: Chart Showing Types of Roundabouts in A.A by Number of Legs

(Source: Survey)

Nine roundabouts which constituted 75% of the five-legged roundabouts are at-grade. However, due to some specified reasons (see Table A- 2 in Appendix A), six roundabouts were used in the present analysis.

3.3.1. Criteria for Selection of Study Roundabouts

The following criteria were considered during the selection process of roundabouts for the analysis.

- Only at-grade roundabouts were considered in the study analysis. That is, roundabouts that are grade-separated had not been considered.
- The analysis period of this research is three years from the period of Jan. 2014 to Dec. 2016.
- Sites that had been constructed or undergone significant modifications during the study/analysis period were not considered in the study.

Accordingly, the study is limited to consider sample roundabouts listed in Table 3-1 below.

Table 3-1: List of selected five-legged at-grade roundabouts for the study analysis

No	Roundabout Name	Location (Sub city)	Leg No	Name of Approach Leg	Description
1	Tewodros' Square	Arada	1	Churchill Ave(South)	Approach from Leghar
			2	Colson St	Bete-Mengist
			3	Mahatma Gandhi St	Mahmud
			4	Curchill Ave(North)	Piasa leg
			5	Gaston Guez St	Teklehaimanot
2	Teklehaimanot	Addis Ketema	1	Gobena Aba Tigu St	Piasa
			2	Tesema Aba Kemaw St (North)	Anwar
			3	Uganda St	Abinet
			4	Tesema Aba Kemaw St (South)	Tikur Anbesa
			5	Gaston Guez St	Tewodros adebabay
3	Abinet	Arada	1	Uganda St	Teklehaymanot leg
			2	Dej.Mekonin Demisaw St (North)	Awtobus tera leg
			3	Leg from Amanuel Hospital	No official name
			4	Dej. Baltcha Abanefso St	Coca Cola
			5	Dej. Mekonin Demisaw St (South)	Lideta
4	Afincho Ber	Arada	1	Leg from Shiromeda	No official name
			2	Weatherall St (West)	Leg from Kechene Police
			3	Botswana St	Leg from Piaza
			4	Tenagnework St	Leg from Ras Mekonen dldy
			5	Weatherall St (East)	Leg from 6-kilo

5	Sumale Tera	Lideta	1	Leg to Arada Bldg	No official name
			2	Leg from Kelifa Bldg	No official name
			3	Umma Semetar St	Leg from Meta
			4	Gobena Aba Tigu St	Leg from Teklehymanot
			5	Wawel St	Leg from Cathedral School
6	6 kilo	Arada	1	King George VI St	Leg from 4-kilo
			2	Russia St	Leg from Minilik hospital
			3	Algeria St	Leg from Shiromeda
			4	Weatherall St	Leg from Afincho ber
			5	Tewodros St	Leg from Nazreth school

3.3.2. Description of Sample Roundabouts

***Tewodros* Square**

It is one of the multi-legged roundabouts in the city where it contained five approaches: namely, the *Churchill Ave* in two approaches, *Gaston Guez St*, *Colson St*, and the *Mahatma Gandhi St*. It is located at 9.03^{o}N latitude and 38.75^{o}E longitude on global map. The land use pattern around the intersection is observed constitute business areas with limited number of residential houses.

Figure 3-3: Tewodros Square

(Source: Google Earth)

***Tekle-Haimanot* Square**

It is found in *Addis Ketema* sub city which is one of the highly congested and accident prone at-grade roundabouts in the city. It is located at 9.03^{o}N latitude and 38.75^{o}E longitude and contains five approaching legs: namely, the *Tesema Ababa Kemaw St* in two approaches, *Uganda St*, *Gaston Guez St*, and the *Gobena Abab Tigu St*. While the front buildings and houses are highly populated business areas, there are some overcrowded residential houses at the back side. Also, the presence of a church in the vicinity has significant influence on the traffic movements around the intersection.

Figure 3-4: Tekle-Haimanot Square

(Source: Google Earth)

***6-Kilo* (*Yekatit-12*) Square**

It is one of the oldest roundabouts in the city which is situated in *Arada* sub city and located at 9.04^{o}N latitude and 38.76^{o}E longitude and has five approaching legs: namely, the *Russia St, Algeria St, Weatherall St, Tewodros St,* and *King George VI St*.

Figure 3-5: 6-kilo (Yekatit-12) Square

(Source: Google Earth)

***Afincho-Ber* Square**

It is one of the recently constructed/modified roundabouts situated in *Arada* sub city. It has five approaching legs; namely, the *Weatheral St* in two approaches, the *Botswana St*, the

'*TenagneWork*' St, and leg from '*Shiromeda*' (or leg from *Menen* school). *Afincho-Ber* square is located at 9.04^{o}N latitude and 38.76^{o}E longitude of the global map system.

Figure 3-6: Afincho-Ber Square

(Source: Google Earth)

***Abinet* Square**

It is one of the recently constructed/modified roundabouts found in *Lideta* sub city located at 9.04^{o}N latitude and 38.76^{o}E longitude in the global map. It has five approaching legs; namely, the *Dej. Baltcha Aba Nefso St*, *Dej. Mekonin Demisaw St* in two approaches, the *Uganda St*, and one unnamed leg or Leg-from *Amanuel Hospital*.

Figure 3-7: Abinet Square

(Source: Google Earth)

***Sumale-Tera* Square**

It is found in *Arada* sub city which is one of the highly congested roundabouts in the city, located at 9.04^{o}N latitude and 38.76^{o}E longitude in the global map. It has five approaching legs; namely, the *Umma Semetar St*, *Gobena Aba Tigu St*, *Wawel St*, as well as two unnamed streets, i.e. Leg-from-*Arada*, and Leg-from-*Kelifa bldg* as shown in the figure below.

Figure 3-8: Sumale-Tera Square

(Source: Google Earth)

3.4. Description of Variables

3.4.1. Dependent (Response) variables

The Addis Ababa Police classified RTAs based on severity and the type of injury; namely, Fatal crash or Killed, Serious injury, Slight injury, and Property damage (*Beshah et al. 2010*) where the present study also adopted similar terminologies as described below.

- *Fatal crash* or *Killed*: - A human casualty who dies within 30 days after an accident;
- *Serious injury:* - a person hospitalized for more than 24 hours due to an accident;
- *Slight injury:* - a person hospitalized for less than 24 hours after an accident; and
- *Property damage:* -non-injury crashes (e.g. roadside objects, vehicle etc.)

Accident Weightage

As previously discussed, there is no conventionally recognized accident severity weighting methods. Several researchers used various methods to prioritize and rank black spots as well as to further develop important correlational examinations. A number of studies in overseas including some developing countries adopted and extensively used accident severity weightage or Priority value (P) such that the weight given for fatal accident is 5, for serious injury is 3 and for light injury is 1 (*Geurts and Wets, 2003; Elvik, 2008; Slinn and Matthews, 200; Yohannes & Minale, 2015; Fekadu et al., 2016; Teklu, 2016*). Accordingly, the weighted crash value which was also being adopted by the present study is calculated as:

$$\mathrm{WI} = 1 * \mathrm{X} + 3 * \mathrm{Y} + 5 * \mathrm{Z} \quad (3\text{-}1)$$

Where: -

WI = Weightage/Priority Value;

X = Total Number of Light Injuries;

Y = Total Number of Serious Injuries; and

Z = Total Number of deadly injuries.

According to these studies, several countries have used the above equation to consider sites/locations as dangerous if the calculated Priority Value (P) equals 15 or more. The model calibration procedure assumed the relation given by (3-1) above in summing up the various severity levels together.

Finally, the study assumed two categories of the responses/dependent variables such at the personal injury crashes, and the property only crashes. That is,

- *Severe-Crashes (Sev-Cr):* - describes to RTAs related to personal injury crashes including fatal, serious injury, and slight injury crashes; and
- *Property Damage Only Crashes (PDO-Cr):* - describes to RTAs related to non-injury crashes.

3.4.2. Independent (Explanatory) variables

The independent variables in the current study indicate the traffic and geometric parameters.

3.4.2.1. Traffic Data

In general, the Peak Hour Vehicle entry Volumes at the major (PHVV-MAJ) and minor (PHVV-MIN) approach legs; the Total Peak Hour Vehicle Volume entering the roundabout from all legs (To-PHVV); the peak hour pedestrian crossing volumes on major (PHPV-MAJ) and minor (PHPV-MIN) legs as well as the total sum of pedestrian crossing volumes at the roundabout (To-PHPV); the 85th percentile speeds at the major (V85-MAJ) and minor (V85-MIN) approach legs were assumed as candidate explanatory variables are considered as candidate explanatory variables in the study.

3.4.2.2. Geometric Data

The geometric parameters indicate factors that are given due considerations while designing roundabouts and, hence, may influence the safety and mobility conditions. In the current study, though several, the geometric factors/variables considered in the analysis and model calibration processes are described as follows. The geometric variables are described according to the US Design Manual (*FHWA-SA-10-006*):

Entry Half-Roadway width (En-RW): - It is the half roadway(entry) width of approach leg that controls the number of side-by-side vehicles entering in to the circulatory area of a roundabout.

Diameter of Central Island (DCI): - The raised portion of a roundabout, generally circular area in the middle of a roundabout around which traffic circulates and typically includes an inside truck apron and a landscaped area. It is the maximum value in cases of non-circular islands.

Diameter of *Inscribed Circle (DIC): -* The maximum diameter of the curve defining the outside diameter edge of the circulatory roadway and one of the key roundabout design components that impact traffic operations.

Circulatory Roadway Width (CRWW): - is the roadway width around the central island of a roundabout that defines the base speed of the roundabout which is used for traffic to travel around.

Presence of Raised Splitter Island (SP) – The raised area between entering and exiting traffic at each approach leg which provides deflection for entering traffic and refuge for pedestrians to make two-stage crossings of a roundabout approach. In the current study, all the sample roundabouts have splitter islands on their major approach legs. Hence, the presence of raised splitter islands only on their minor legs had been considered.

3.5. Data collection process

Both primary and secondary data collection methods were the main tasks of the data collection process in this study.

3.5.1. Primary data collection

The primary data required in the current study included geometric and traffic parameters. The direct field survey measurement was required to collect the primary data due to its advantage of obtaining in-depth information using trained personnel. Field survey measurements on traffic conditions and geometric parameter for each study roundabout were conducted simply in an ordered counter-clockwise numbering direction (Figure 3-9).

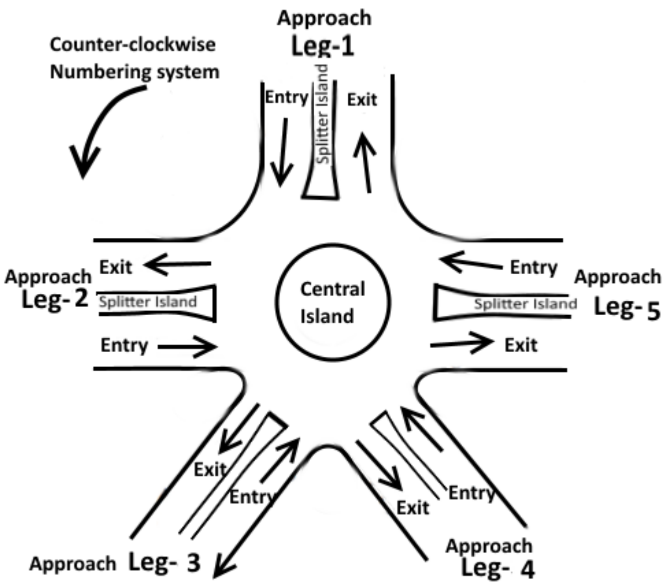


Figure 3-9: General layout of study roundabouts

3.5.1.1. Traffic Data

Field gathering of traffic data was the only reliable source and feasible way to obtain the current traffic patterns around and within the study area. The manual traffic count for traffic study was carried out during the drier months from end of April to end of May 2017. A total of ten enumerators were trained to conduct manual traffic counts for each roundabout.

The available peak hour vehicle volume on all approach legs of the study roundabouts had reasonably been collected manually for two days during the weekdays (one on Wednesdays and one on Thursdays) in order to consider the daily peak hour fluctuations. Based on previous studies and trends for peak hour durations, the volume counts for all approach legs were collected for six hours a day: two hours in the morning (7:00AM – 9:00AM), two hours at mid-day (12:00PM – 2:00PM), and two hours in the afternoon (4:00PM – 6:00PM) at 15-minute interval (complete details included in Appendix D). Besides, the three shift count considers the daily shift of directional peak hour. (i.e. peak traffic can be seen early in the morning but in the afternoon the peaks are reversed). The tally sheet format used to collect field data is given in Appendix F (Table F- 1).

Similarly, the peak hour pedestrian volume counts had been collected manually for 6-hours a day, for two days during the weekdays (one on Wednesday and one on Thursdays), conducted simultaneously with the vehicles count but with additional enumerators for each approach leg. That is, two hours in the morning (7:00 – 9:00AM), two hours at mid-day (12:00 – 2:00PM), and two hours in the afternoon (4:00 – 6:00PM) at 15-minute interval (complete details included in Appendix D). Pedestrians crossing in both directions were summed up together and those crossing the approach legs within the 50m from the center of the roundabout were accounted for. The field data collection format is given in Appendix F (Table F- 2).

Physical observation on spot speeds was carried out on the major and minor approach legs of each study roundabout using selected locations with clear observational view (without obstructions) during the measurement times. The manual - stopwatch method of spot speed measurement was preferred due to its advantages of being used with small samples and is a quick and inexpensive method. In order to conduct manual traffic counts a pre-prepared field form (Tally Sheet) as shown in Appendix F (Table F- 3) was used where the observed data could be recorded with a tick mark.

3.5.1.2. Geometric Data

Geometric data had been gathered from field survey measurements by visiting each roundabout location. The geometric data indicate factors that are given due considerations while designing roundabouts and, hence, may influence the safety and mobility conditions. In this study, though several, the geometric factors/variables considered in the analysis and model calibration processes are limited to the Diameters of the central island (DCI) and the inscribed circle (DIC), entry roadway width on major (En-RW-MAJ) and minor (En-RW-MIN) approach legs, and number of circulating lanes around the central island. The measurements of geometric variables were conducted manually using tape meter and simple observations during the field surveys.

3.5.2. Secondary data

In order to develop an APM, one should always take an average crash records of a few years (3-5) and look at long(er) term trends of the intended road infrastructure or entity (*Reuring et al., 2008*). In this study, a 3-year period (Jan. 2014 to Dec. 2016) historic crash data was collected from relevant Police divisions. A three years' cutoff time-frame was systematically preferred due to the fact that it is sufficient to characterize crash time, place, type, and reason for occurrence as well as the ratio of marginal cost of data collection to marginal benefit outweighs if collected beyond (*Cheng & Washington, 2008*). The crash data was extracted from the daily crash reports and were treated as the predicted or dependent variable in the model calibration processes.

The area of influence, for instance, driver behavior, can be influenced as far as 76 meters from intersections (or further with severe congestion and queuing) (*Ogden, 1994; TRB, 2009*). However, based on local trends of crash reports and opinions of queried police officers, the crash records were taken within 50m from the center of the intersection which was again supported by *Tulu et al*. (*2015*). On the other hand, the crash databases do not specify the precise black spot locations due to the police officers responsible for inspecting a crash lack basic training and equipment (*Tulu et al., 2013*). As a result, it was a big challenge to model crash types and understand the in depth behaviors of road traffic crashes where, instead, only the overall crash frequency/occurrences at the roundabouts had been used in the current modeling process.

3.6. Data analysis approaches

In order to answer the key questions raised in the research problem, both the qualitative and quantitative approaches are involved. The analysis of the quantitative data is used to calibrate a model using the measurements of the explanatory variables. The qualitative data includes the causes and types of crashes that happen at roundabouts.

Both descriptive and inferential statistical approaches were also used to define the analytical findings of the research. The descriptive statistics consists of the collection, organization, summarization, and presentation of data. Whereas, the inferential statistics consists of generalizing from samples to populations, performing estimations and hypothesis tests, determining relationships among variables, and making predictions. Furthermore, some important specific modeling strategies are discussed per their relevance to analyze and explain the required data of this study.

3.7. Modeling

3.7.1. Model fitting strategy

Previous international studies not only accounted for the effect of total traffic flow, but have also considered various turning movements, pedestrian flows, and even bicycle flows in some cases to model different crash outcomes. On the other hand, crashes can be categorized by collision types such as rear-end, single-vehicle run-off-the-road, right-angle, and sideswipe. However, the most common modeling approach is to consider the frequency of all crashes (*Lord et al., 2010*). This study assumed the significance of total crash modeling at five legged roundabouts.

Data on all the selected explanatory variables had been collected based on previous researches and local specific considerations so that their contribution effects in the proposed APMs are further investigated. Once the collected data had been properly edited, the proper modeling process was begun by establishing variety of diagnostics to identify:

- appropriate functional forms in which the predictor variables should be included the regression model;
- important interactions that should be included in the model scatter plots and residual plots that are useful for determining relationships and their strengths. Residual plots are helpful in deciding if a model is to be preferred statistically; and
- influential outlying observations, multi-collinearity, etc.

Accordingly, separate models were fitted for the Severe crashes (including fatalities and injuries), and Property damages only (PDO) crashes. In this case, a log linear regression models which assumes the number of crashes to follow a Poisson or a Negative Binomial distribution had been fitted and the coefficients were estimated using the maximum likelihood method.

Before the model fitting process was performed, variables were inspected for multi-collinearity effects using the bivariate correlation matrix. During the modeling stages, exposure and other significant variables which have been suggested in previous APM studies were included in the model first (*Nambuusi et al., 2008; Reurings et al. 2006*). In this study, traffic (vehicle volume) variables are treated as exposure variables since no accidents happen without exposure. In case of strong correlations between geometric variables and exposure variables, the latter were kept in the models since there are well trustworthy grounds (e.g. *Fridstrøm et al., 1995; Greibe, 2003*) to reflect them as significant crash contributing factors.

All the models were fitted using the GENLIN-procedure in SPSS 23 software package and made use of the log link function which uses the Newton-Raphson technique and the type III-test to fit the required APMs. The reason to use the type III analysis is that it won't depend on the order of effects. Compared to the Fisher Scoring Method, the Newton Raphson general-purpose iterative method which is used to determine the maximum of the likelihood function is preferred as it is fast and takes relatively few iterations for satisfactory convergence (*Agresti, 2000*). The significance of all the variables is taken at 95% confidence interval, where a variable is kept in the model if $p \leq 0.05$ and any variables that have become insignificant ($p >$ 0.05) throughout the process are omitted from the model. Finally, the preliminary model should be checked for the overall Goodness-of-fit test procedures described in the next section.

Finally, general procedural inferences had been considered to determine whether the explanatory variables have effects on the response variable and, if so, the nature and magnitude of the effects. The explanatory variables, or predictors, are the independent attributes which describe the present study focusses. And, the dependent variable is crash frequencies for the specified analysis period. Generally, total crash modeling had been employed with the relevant selected explanatory variables.

3.7.2. Selection of Model Explanatory Variables

The most relevant explanatory variables used for the intended APMs were selected based on prior works as discussed in the literature section and prevailing site specific conditions such as data availability. According to *Reurings et al.* (*2008*), besides to the usual basis for choosing explanatory variables which appears to be simply data availability, the model should include explanatory variables that:

- have been identified in prior studies as a major contributor of RTAs;
- can be measured in a valid and reliable way; and
- are not very highly correlated with other explanatory variables included in the model.

Prior study by *Nambuusi et al. (2008*) has found the variables- vehicle counts such as traffic volumes on major and minor roads, pedestrians crossing all roundabout legs as significant in APMs. Correlations between different variables can be determined by noticing the correlation matrix which is a matrix of correlation coefficients between candidate predictor variables required for modelling. A value of one in the correlation coefficients indicates a perfect positive correlation between two variables and a value of zero indicates statistical independence (see Table 4-16).

Safety researchers believe that the more explanatory variables (even variables with highly insignificant parameters) are used in a model, the better it would improve model prediction. The inclusion of explanatory variables with statistically significant model parameters results in better explanation of the variability of the crash data and, therefore, improves its fit to this data. A model that perfectly fits to the data can be achieved if the number of statistically significant variables included in the model is equal to the number of observations. Nonetheless, improvement of a model's fit to the crash data is not enough reason for retaining a variable in the model. Model generality involves the principle of parsimony, which helps avoid over fitting by explaining as much of the variability of the data using the minimum number of explanatory variables. Generally, the best-fit model is achieved by including all the available statistically significant explanatory variables.

3.7.3. Model Form

In an ideal world, the mathematical association between traffic crash and different explanatory variables is identified so as to suitably reveal the underlying effects on safety and to enable useful insights into the basic crash patterns. As discussed previously, the relationships between crash-frequencies and the underlying predictors is better explained by the GLMs. The basic APM developed using the GLMs should fulfill circumstances such as the output results have to be logical, (i.e. it must not lead to the prediction of a negative number of crashes and must ensure a prediction of zero crash occurrence for zero values of the exposure variables e.g. traffic volumes). In addition, there must exist a known link function that can transform in to a generalized linear regression model (GLM) and can result in estimating and interpreting model coefficients easily (*Sawalha et al., 2003*).

Hence, a mathematical form that involves the product of powers of the exposure measures multiplied by an exponential incorporating the remaining explanatory variables can be applied. For instance, commonly employed mathematical forms involve a logarithmic transformation of exposure variables allowing a nonlinear relationship between traffic flows and crashes that can limit predictions (i.e. leads to a zero expected crashes in the absence of exposure).

Transformations of exposure variables such as the major and minor road traffic flows at roundabouts have been employed by several studies (*Oh et al, 2003; Kim et al., 2006*).

The basic functional form employed by *Reurings et al.* (*2008)* and *Nambuusi et al. (2008*) have extensively been practiced nearly in all modern APMs at rural and urban intersections. Similarly, the final model structure in the present study allows the fundamental assumptions of exposure variables used. That is, the basic functional form of the present model includes exposure variables, namely: peak hour entering traffic in the major and minor approach legs as well as the total peak hour entry traffic volumes at each roundabout which is given by,

$$\lambda_i = e^{\alpha_o} * \mathrm{Q}_{T,i}^{\alpha_1} * \mathrm{Q}_{MA,i}^{\alpha_2} * \mathrm{Q}_{MI,i}^{\alpha_3} * EXP \sum \beta_j X_{ij} \tag{3-2}$$

Where,

λ_i = Estimated expected number *(*Poisson mean) of accidents at roundabout $i;$

$Q_{T,i}$ = Total Number of vehicles entering roundabout i, from all approach legs;

$Q_{MA,i}$ = Number of vehicles entering roundabout i, from the major road;

$Q_{MI,i}$ = Number of vehicles entering roundabout i, from the minor road;

X_{ij} = Vector of values of variables describing road geometry and traffic information (other than number of vehicles) in roundabout *i*;

α_0 = Intercept (estimated model parameter);

$\alpha_1, \alpha_{2,}\alpha_3$ = effect of traffic volume on the expected number of accidents (elasticity). The elasticity shows the percentage change in the expected number of accidents associated with a 1% change in traffic volume; and

β_j = Parameters to be estimated and represent the effect of risk factors, j, (road geometry and traffic information other than number of vehicles), on the expected number of accidents other than traffic volume in roundabout i.

Although model fitting can be performed without transformation, the exposure variables can be transformed to their natural logarithm to get a better fit and is a preferred practice in APM (*Reurings et al., 2008*). Therefore, for analysis purpose, all the exposure variables here were transformed to their natural logarithm. The above equation can be transformed using the log-link function as:

$$\log(\lambda_i) = \alpha_o * \alpha_1 \log Q_{T,i} * \alpha_2 \log Q_{MA,i} + \alpha_3 \log Q_{MI,i} + \sum \beta_j X_{ij} \tag{3-3}$$

The function is actually a generalized linear model (GLM) where the values of the parameters α_1, α_1, α_2, α_3 and β_i can be estimated using the employed statistical packages. Different roads meet at intersections such as roundabouts where, as a result, different accident types occur. Hence, separate models are required to assess factors associated with the different crash types and safety of various intersection types (*Nambuusi et al., 2008*). Generally, the choice of a model is based on the nature of the response and the objective of the research. Hence, this study used the general APM form given by (3-11) above to fit and calibrate the geometric and traffic data at the selected five-legged roundabout intersections to the relevant crash frequency databases.

3.7.4. Error Structure

Due to their advantages in developing of APMs as advocated by several researches, the selection of error structure in the current study focused on GLMs especially the Poisson or negative binomial density function. Whatever the probability distribution, the likelihood function is convex and can be maximized using a Newton-Raphson algorithm (*Ter Berg, 1980*). The most common functional form of the Poisson regression model is given by:

$$\lambda_i = \text{EXP}(\boldsymbol{\beta}\mathbf{X}_i), \tag{3-4}$$

Where $\mathbf{X}_i$ is a vector of explanatory variables and $\boldsymbol{\beta}$ is a vector of estimable parameters. The model parameters can usually be estimated by the standard maximum likelihood method with the log likelihood (LL) function (*Lord et al., 2010*) given by

$$LL(\beta) = \sum_1^n [-EXP(\beta X_i) + n(\beta X_i) - Ln(n!)] \tag{3-5}$$

Let Y be the random variable that represents the crash frequency at a given location/roundabout during a specific time period, and let *y* be a certain realization of *Y*. The mean of *Y*, denoted by Λ, is itself a random variable (*Kulmala, 1995*). For $\Lambda = \lambda$, *Y* is Poisson distributed with parameter λ: Hence, the distribution of Λ can usually be described by a gamma probability density function as:

$$\mathrm{P}(\mathrm{Y} = \mathrm{y}|\Lambda = \lambda) = \frac{\lambda^{\mathrm{y}} \mathrm{e}^{-\lambda}}{\mathrm{y}!}; \mathrm{E}(\mathrm{Y}|\Lambda = \lambda) = \lambda; \mathrm{Var}(\mathrm{Y}|\Lambda = \lambda) = \lambda \tag{3-6}$$

On the other hand, in case of over-dispersions in the response data the traditional Poisson model is of limited use. Hence, the negative binomial models have been introduced to relax the limitations in the previous model by handling the error terms using the Gamma-distribution. For Λ = λ, *Y* is Gamma distributed with parameter λ, and the distribution of Λ can be described by a gamma probability density function. *Hauer* (*1997*) examined many crash data sets and the empirical evidence he obtained supported the gamma assumption for the distribution of Λ. That is, if Λ is described by a gamma distribution with shape parameter κ and scale parameter κ /μ, then its density function can be given by:

$$f_\lambda = \frac{(\kappa/\mu)^\kappa \lambda^{\kappa-1} e^{-(\kappa/\mu)\lambda}}{\Gamma(\kappa)}; E(\Lambda) = \mu; Var(\Lambda) = \frac{\mu^2}{\kappa} \quad (3\text{-}7)$$

The distribution of *Y* around *E*(Λ) = μ is negative binomial (*Hinde and Demetrio, 1998; Hauer et al., 1988*). Therefore, the entire probability density form can be written as:

$$P(Y = y) = \frac{\Gamma(\kappa+y)}{\Gamma(\kappa)y!}\left(\frac{\kappa}{\kappa+\mu}\right)^\kappa \left(\frac{\mu}{\kappa+\mu}\right)^y; \; E(Y) = \mu; Var(Y) = \mu(1+\frac{\mu}{\kappa}) \quad (3\text{-}8)$$

As shown by the equations above, the variance of the crash frequency is generally larger than its expected value reflecting the fact that crash data are generally over-dispersed. The only exception is when $\kappa \rightarrow \infty$, in which case the distribution of Λ is concentrated at a point where the Negative Binomial distribution reduces to the Poisson distribution. It will be noted that a Poisson or Negative binomial model estimates the number of crashes as integers based on average number of crashes, in this case, observed for three years (Jan. 2014 – Dec. 2016). As a result, λ_i will not be the predicted number of crashes per year but per three years.

3.8. Summary

The chapter has outlined important analytical procedures appropriate to investigate and model Police reported RTAs with the underlying risk factors. It begun with describing the overall design and approaches of the study and explaining the explanatory and response variables used in the analysis. The chapter have been explained to focus on primary and secondary data collection and sampling procedures. Further, some basic modeling strategies were discussed in a manner to fit the collected data, such as selection of explanatory variables, selecting model form with appropriate error structure, as well as the fitting strategies and goodness of fit measurements. The next chapter will discuss the entire data findings and results based on this methodological foundation and the data collection and analysis approaches described earlier.

CHAPTER 4 RESULTS AND DISCUSSION

4.1. Introduction

This chapter deals with the analysis and model calibrations of the primary and secondary data which were collected from the Addis Ababa Police databases, as well as the traffic and geometric data from field observations. Evaluating the bivariate correlations among the candidate explanatory variables themselves, and with respect to the dependent variables are also explained here. The chapter also addresses the issues of selecting the most influencing explanatory variables which are required for the development of APMs. Finally, the parameter estimations for the fitted models are presented in this chapter.

4.2. Primary Data

The primary data included in the current study includes: traffic data (which include volume counts of entering vehicles, pedestrian crossing volume counts, and spot speed measurements at the minor and major approach legs), and geometric data (which include geometric design parameters).

4.2.1. Traffic Data

Motorized volume (Vehicle Count)

The peak hour entering vehicle volumes at all the sample roundabouts can be analyzed and presented in Table 4-1 below and the major and minor approach legs are identified easily as well.

Table 4-1: Peak hour entering vehicle Volume (PHVV) at selected roundabouts

S/N	Roundabout Name	Location (Sub city)	Leg No	Name of Approach Leg	Adjusted Peak Hour Entry Volume, (pcu/h)	Major Approach Leg	Minor Approach Leg	Total Peak Hour entering Vehicles Vol. (ToPHVV) (pcu/h)
1	Afincho Ber	Arada	1	Leg from Shiromeda	1233	Weatherall St (East)	Weatherall St (West)	3998
			2	Weatherall St (West)	473			
			3	Botswana St	1556			
			4	Tenagnework St	1276			
			5	Weatherall St (East)	1662			
2	Tewodros	Arada	1	Churchill Ave(South)	1599	Churchill Ave(South)	Gaston Guez St	4959
			2	Colson St	641			
			3	Mahatma Gandhi St	720			
			4	Curchill Ave(North)	1587			
			5	Gaston Guez St	562			
3	6 kilo	Arada	1	King George VI St	1096	Russia St	Tewodros St	5039
			2	Russia St	1815			
			3	Algeria St	916			
			4	Weatherall St	1266			
			5	Tewodros St	115			
4	Teklehaymanot	Addis Ketema	1	Gobena Aba Tigu St	1061	Uganda St	Gaston Guez St	5644
			2	Tesema Aba Kemaw St (North)	1084			
			3	Uganda St	1659			
			4	Tesema Aba Kemaw St (South)	1223			
			5	Gaston Guez St	646			
5	Abinet	Arada	1	Uganda St	1108	Dej. Baltcha Abanefso St	Leg from Amanuel Hospital	4746
			2	Dej. Mekonin Demisaw St (North)	1230			
			3	Leg from Amanuel Hospital	63			
			4	Dej. Baltcha Abanefso St	1323			
			5	Dej. Mekonin Demisaw St (South)	1073			
6	Sumale Tera	Lideta	1	Leg to Arada Bldg	835	Gobena Aba Tigu St	Leg from Kelifa Bldg	4015
			2	Leg from Kelifa Bldg	387			
			3	Umma Semetar St	801			
			4	Gobena Aba Tigu St	1106			
			5	Wawel St	903			

(Source: Author)

Non-Motorized volume (Pedestrian Count)

Generally, similar procedures were carried out to obtain the peak hour pedestrian volumes through all approach legs of the study roundabouts and, hence, the values can be summarized and presented as follows in Table 4-2.

Table 4-2: Summary of Peak hour pedestrian crossing volumes (PHPV)

(Source: Author)

S/N	Roundabout Name	Approach Leg	Name	Leg No.	Peak Hour Pedestrian crossing Volume PHPF (ped/h)	Total Peak Hour Pedestrian crossing Vol. (ToPHPV) (ped/h)
1	Afincho Ber	Major	Weatherall St (East)	5	189	**1003**
		Minor	Weatherall St (West)	2	238	
2	Tewodros	Major	Churchill Ave(South)	1	391	**1568**
		Minor	Gaston Guez St	5	349	
3	6 kilo	Major	Russia St	2	890	**4455**
		Minor	Tewodros St	5	1043	
4	Teklehaymanot	Major	Uganda St	3	1209	**6094**
		Minor	Gaston Guez St	5	871	
5	Abinet	Major	Dej. Baltcha Abanefso St	4	501	**3762**
		Minor	Leg from Amanuel Hospital	3	695	
6	Sumale Tera	Major	Gobena Aba Tigu St	4	625	**3331**
		Minor	Leg from Kelifa Bldg	2	854	

Vehicles Spot Speed

The observed 50th and 85th percentile speed measurements for the major and minor approach legs at the selected roundabouts are summarized and presented in Table 4-3 as follows. (Detailed illustrations of the spot speed analysis are shown in Appendix D).

Table 4-3: Summary of 50th and 85th percentile observed speeds [for major and minor Approach legs] (Source: Author)

No	Roundabout Name	Approach Leg	Name	Leg No.	Observed Speed for entering vehicles	
					50th percentile	85th percentile
1	Afincho Ber	Major	Weatherall St (East)	5	38.1	46.3
		Minor	Weatherall St (West)	2	15.5	18.5
2	Tewodros	Major	Churchill Ave(South)	1	30.5	39.1
		Minor	Gaston Guez St	5	41.1	52.2
3	6 kilo	Major	Russia St	2	23.5	29.1
		Minor	Tewodros St	5	17.8	20.4
4	Teklehaymanot	Major	Uganda St	3	34.9	41.7
		Minor	Gaston Guez St	5	29.7	33.6
5	Abinet	Major	Dej. Baltcha Abanefso St	4	26.8	34.2
		Minor	Leg from Amanuel Hospital	3	12.9	14.5
6	Sumale Tera	Major	Gobena Aba Tigu St	4	22.3	27.7
		Minor	Leg from Kelifa Bldg	2	19.4	25.1

4.2.2. Geometric Data

The field observational data for the geometric parameters are summarized in Table 4-4 (The detailed field survey data are shown in Appendix C).

Table 4-4: List of Geometric variables (independent variables)
[used in the current modeling] (Source: Author)

Geometric Variables	Description of variables	Afincho-Ber	Tewodros	Sidist-Kilo	Tekle-Haimanot	Abinet	Sumale-Tera
ENW-MAJ	Entry half-roadway width on major road (m)	14	12	6	10	10	9
ENW-MIN	Entry half-roadway width on minor road (m)	4.5	8.2	3	9	4	7
DCI	Diameter of central island (m)	30	38.2	40	76.2	71	28
DIC	Diameter of inscribed circle (m)	58	88.2	101	100.2	91	54.8
CRWW	Circulating roadway width (m)	14	25	25	12	10	14
RTC-MAJ	Presence of a right-turn channalization on Major road (Yes=1; No=0)	0	0	0	0	1	0
SPL-MAJ	Presence of Splitter island on major road? (Yes=1; No=0)	1	1	1	1	1	1
SPL-MIN	Presence of Splitter island on minor road? (Yes=1; No=0)	0	1	0	1	1	0

4.3. Secondary Data

Crash data

Table 4-5: Total crash data for the city of Addis Ababa,
[from Jul. 2014 to Jun. 2016.] (Source: A.A City Police Commission)

Calendar Year	Crash Types				Total Crashes
	Fatal	Serious Injury	Slight Injury	Property Damages	
2006 E.C	391	1,484	1,128	14,901	17,904
2007 E.C	416	1,669	1,098	17,249	20,432
2008 E.C	439	1,924	1,165	19,411	22,939
SUM	1,246	5,077	3,391	51,561	61,275
Ave./Year	415	1,692	1,130	17,187	20,425
%	2.0	8.3	5.5	84.2	100

From Table 4-5 above, it is clearly shown that during the specified three years period from Jul 2014 to Jun 2016, a total of 61,275 vehicle crashes were recorded on Addis Ababa’s roads of which 2% (1246) are reported as fatal; 8.3% (1,692) are serious injuries; 5.5% (1,130) are slight injuries; and the rest (i.e. 84.2%) are reported as property damage crashes. On average, of the 20,425 yearly reported crashes on Addis Ababa's roads, around 415 are reported as fatal crashes; and 2,822 are reported as the sum of light and serious injury crashes.

Table 4-6: Intersection crash data in A.A, from Jul. 2014 to Jun. 2016

(Source: A.A City Police Commission)

No	Road/Junction Type		Crash Types				Total Crashes	%	%
			Fatal	Serious injury	Slight injury	Property Damage			
1	Straight		525	3237	2161	32398	38321	62.5	62.5
2	Intersections	Roundabouts	212	725	441	8082	9460	15.4	36.8
3		Four-way intersection (Signalized & Unsignalized)	71	328	286	4110	4795	7.8	
4		Y-intersection	108	315	343	3254	4020	6.6	
5		T-intersection	191	402	126	2648	3367	5.5	
6		X - junction	31	41	20	814	906	1.5	
7	Others		108	29	14	255	406	0.7	0.7
Sum			1246	5077	3391	51561	61275	100	100

The police-recorded road crash data shown in Table 4-6 indicates, during the specified analysis period from Jul 2014 to Jun 2016, 36.8% of the total road crashes happened in Addis Ababa were occurred at intersections. Though roundabouts represent only a small portion of the overall transport system, the crash counts on roundabouts constituted a significant portion of the RTAs. For instance, the Addis Ababa city police commission report (as shown in Table 4-6) showed 15.4% (9,460) of the total crashes (61,275) reported in the three years' period were happened at roundabouts.

Table 4-7: Roundabout crash data records in the city of Addis Ababa

[From Jul. 2014 to Jun. 2016.] (Source: A.A city Police Commission)

Calendar Year	Crash Type				Total Crashes
	Fatal	Serious Injury	Slight Injury	Property Damages	
2006 E.C	83	159	104	2,095	2,441
2007 E.C	68	213	157	1,770	2,208
2008 E.C	61	353	180	4,217	4,811
SUM	212	725	441	8,082	9,460
%	2.2	7.7	4.7	85.4	100.0
Average/yr	71	242	147	2,694	3,153

Table 4-7 shows the crash data that were reported at roundabouts residing in the city. Accordingly, the yearly average vehicle crashes at roundabouts is about 3,153. Though, the total yearly crash figure seems to have decreased slightly in the second year, it has significantly mounted up in the third year at an alarming rate. Hence, various reduction mechanisms appear to be compulsory.

In the current study, six five-legged roundabouts were used for the analysis process and the crash data are, hence, summarized in Table 4-8 below.

Table 4-8: Crash data records and black spot ranking/identification

[From Jan. 2014 to Dec. 2016.] (Source: A.A sub cities police divisions)

No	Roundabout Name	Total Crashes (To-Cr)	Crash Types				Severe Crashes (Weighted using priority P-Value, P=x+3y+5z) (Sev-Cr)	Rank
			Fatal	Serious injury	Slight injury	Property Damage only (PDO-Cr)		
		x+y+z+p	(x)	(y)	(z)	(p)		
1	Afincho-Ber	24			4	20	20	3
2	Tewodros	111	3	4	1	103	20	3
3	Sidist-Kilo	64		3	2	59	19	5
4	Teklehaimanot	63		3	3	57	24	2
5	Abinet	30	4	3	4	19	33	1
6	Sumale-Tera	26		4	1	21	17	6
	Sum	318	7	17	15	279	133	
	Sub-Total	318	39			279	133	

Note that: Obviously, all the roundabouts have priority P values greater than 15. Hence, all of them were selected as black spots or "dangerous sites" in the current study.

During the specified analysis period (Jan. 2014 to Dec. 2016) a total of 318 crashes were happened at the six five-legged roundabouts [17.7 crashes/ (roundabout ×year)]. Of these, 39 were *Severe-Crashes (unweighted)*, causing 7 fatal crashes (see Table 4-8).

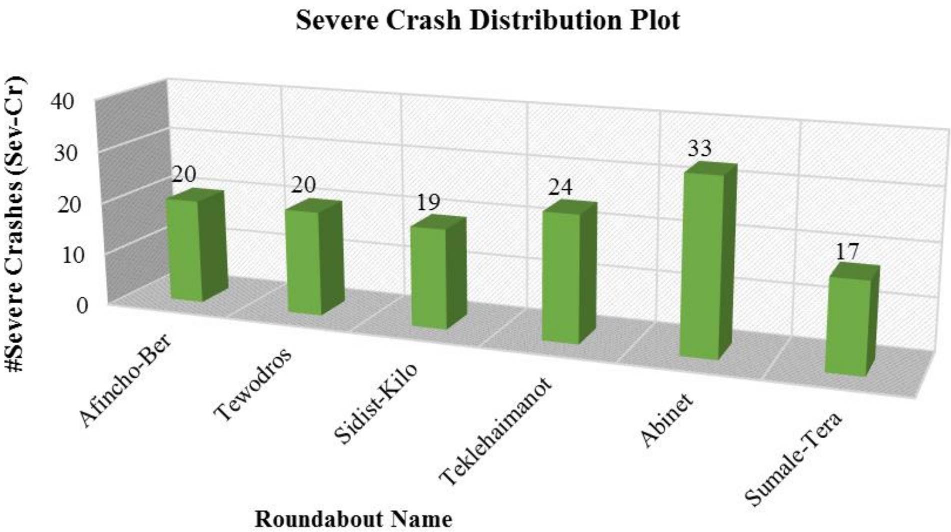


Figure 4-1: Chart showing total crashes at selected black spots (roundabouts**)**

(Source: A.A sub cities police divisions)

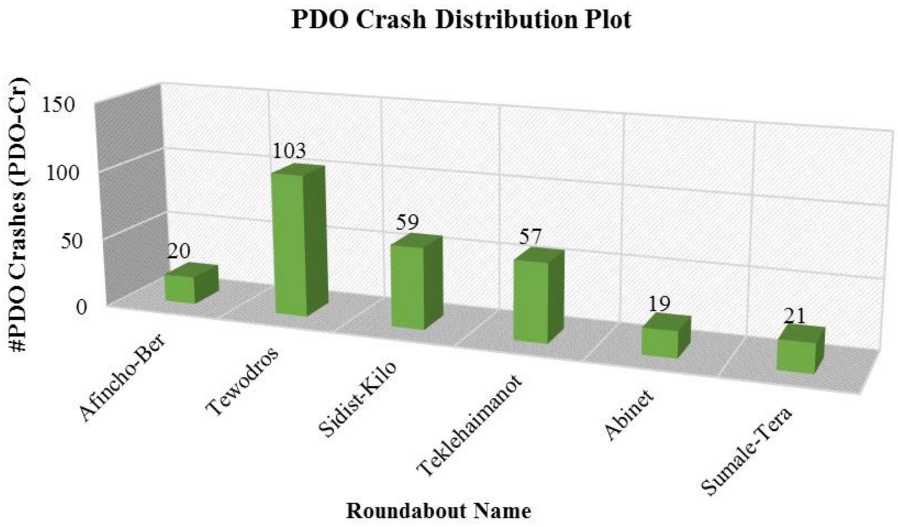


Figure 4-2: Chart showing No. of Severe Crashes at selected black spots

(Source: A.A. sub cities police divisions)

Crash Data by Time of the day

Table 4-9: Overall Traffic Crash Distribution for A.A. by Time of the Day

[From Jul 2014 -Jun 2016.] (Source: A.A. city Traffic Police Commission)

Time	Time Of the Day(24hr)	No of Crashes	%	Time	Time Of the Day(24hr)	No of Crashes	%
Day-Time	7:00-8:00	3405	5.6	Night-Time	19:00-20:00	2816	4.6
	8:00-9:00	3693	6.0		20:00-21:00	2391	3.9
	9:00-10:00	3871	6.3		21:00-22:00	1899	3.1
	10:00-11:00	3873	6.3		22:00-23:00	1467	2.4
	11:00-12:00	4073	6.6		23:00-24:00	1152	1.9
	12:00-13:00	3468	5.7		24:00-1:00	864	1.4
	13:00-14:00	3457	5.6		1:00-2:00	1019	1.7
	14:00-15:00	3749	6.1		2:00-3:00	915	1.5
	15:00-16:00	3962	6.5		3:00-4:00	863	1.4
	16:00-17:00	3629	5.9		4:00-5:00	928	1.5
	17:00-18:00	3272	5.3		5:00-6:00	1270	2.1
	18:00-19:00	3155	5.1		6:00-7:00	2142	3.5
	Sub-Total	43607	71.1		Sub-Total	17726	28.9
Note: Time counting begins at mid-night (According to police data)				GRAND-TOTAL		61333	100

The crash data analyzed by time of the day in Table 4-9 shows 71.1% of all the traffic crashes in the city of Addis Ababa were happened during the day time and 28.9% crashes were occurred at night time, where the highest figures are depicted during mid-days.

Table 4-10: Crash distribution at 5-legged roundabouts by Time of the Day

[From Jan. 2014 –Dec. 2016.] (Source: AA city Traffic Police Commission)

Time	Time Of the Day (24hr)	No of Crashes	%	Time	Time Of the Day (24hr)	No of Crashes	%
Day-Time	7:00-8:00	18	5.7	Night-Time	19:00-20:00	9	2.8
	8:00-9:00	19	6.0		20:00-21:00	4	1.3
	9:00-10:00	23	7.2		21:00-22:00	3	0.9
	10:00-11:00	19	6.0		22:00-23:00	3	0.9
	11:00-12:00	38	11.9		23:00-24:00	4	1.3
	12:00-13:00	41	12.9		24:00-1:00	2	0.6
	13:00-14:00	23	7.2		1:00-2:00	1	0.3
	14:00-15:00	15	4.7		2:00-3:00	2	0.6
	15:00-16:00	29	9.1		3:00-4:00	1	0.3
	16:00-17:00	20	6.3		4:00-5:00	2	0.6
	17:00-18:00	21	6.6		5:00-6:00	1	0.3
	18:00-19:00	12	3.8		6:00-7:00	7	2.2
	Sub-Total	278	87.4		Sub-Total	39	12.3
					Unidentified	1	0.3
					GRAND-TOTAL	318	100.0

Note: Time counting begins at mid-night (According to police data)

Similarly,

Table 4-10 shows 87.4% crashes which were happened at five-legged roundabouts were occurred during the day times especially during the mid-days. Whereas, 12.3% of crashes were occurred during the night times.

Crash data by Month of the year

Table 4-11: Crash distribution by months at 5-legged roundabouts

[From Jan 2014 -Dec 2016.] (Source: AA city Traffic Police Crash Records-unpublished)

Month Of the Year	No of crashes in 2014	%	No of crashes in 2015	%	No of crashes in 2016	%	Total crashes in 3 years (2014-2016)	%
January	7	8.1	3	3.2	8	5.8	18	5.7
February	9	10.5	6	6.4	11	8.0	26	8.2
March	9	10.5	9	9.6	14	10.1	32	10.1
April	11	12.8	3	3.2	17	12.3	31	9.7
May	8	9.3	12	12.8	11	8.0	31	9.7
June	3	3.5	12	12.8	10	7.2	25	7.9

July	6	7.0	3	3.2	9	6.5	18	5.7
August	5	5.8	7	7.4	10	7.2	22	6.9
September	4	4.7	9	9.6	9	6.5	22	6.9
October	6	7.0	6	6.4	12	8.7	24	7.5
November	6	7.0	12	12.8	11	8.0	29	9.1
December	12	14.0	12	12.8	16	11.6	40	12.6
Sub-Total	86	100.0	94	100	138	100	318	100

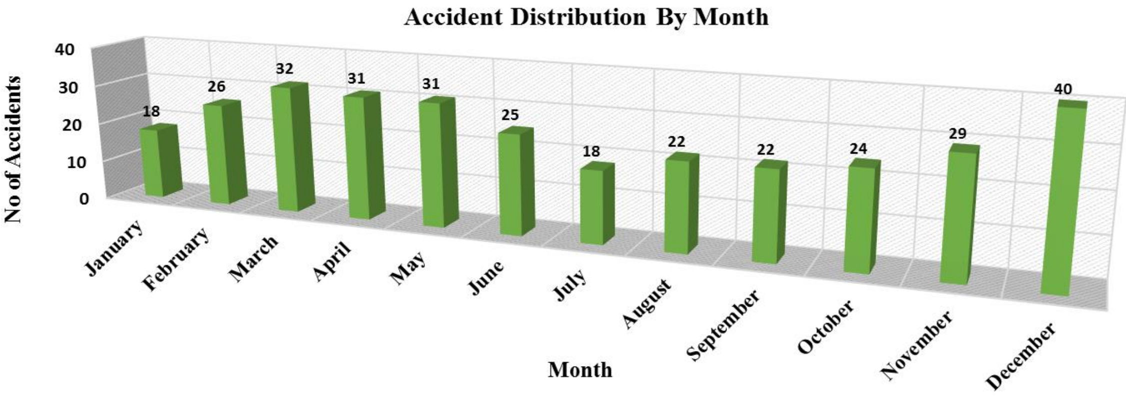


Figure 4-3: Monthly traffic crash distributions at the selected roundabouts

As it can be seen from Table 4-11 and Figure 4-3, the police recorded crashes data which is analyzed by months of the year indicated that the number of traffic crashes at roundabouts is relatively higher during the second and third quarters of the Ethiopian fiscal year (i.e. October to December, and January to March).

Vehicle movement types during the crashes

Table 4-12: Vehicle movement types during crashes at 5-legged roundabouts

(Source: AA city Traffic Police Crash Records-unpublished)

Causes	Crash Types				Total Crashs	%
	Fatal	Serious injury	Slight injury	Property damages only		
Not ceding priority		12	13	148	170	54.4
Not keeping right distance			1	44	45	14.2
Inappropriate overtaking				25	25	7.9
Steering to the right		4		18	21	6.9
Steering to the left		1		20	21	6.6
Rear driving				9	9	2.8
Off-road driving				4	4	1.3
Start from parking				4	4	1.3
Faulty steering (careless)				2	2	0.6
Fall off			1		1	0.3
Vehicle Failure				1	1	0.3

Unidentified	7			4	11	3.5
Total Sum	28	17	15	279	318	100

Note: The 'fatal' crash data found from the Addis Ababa Police Commission was not supported with the causes of the crashes (i.e. unidentified causes)

From Table 4-12, one can observe that more than half (54.4%) of the crashes that were happened at the selected five-legged roundabouts were due to entering vehicles do not cede priorities to circulating and exiting vehicles. And, 14.2% of the crashes were happened by not keeping right distance between vehicles. Inappropriate overtaking, and lane changing to the left/right had also contributed to significant portion of crash frequencies as well.

Collision types at roundabouts

Table 4-13: Reported types of collision and resulted crashes at 5-legged roundabouts

[From Jan 2014 to Dec 22016.] (Source: AA city Traffic Police)

Collision Types	**Crash Types**				**Total Crashes (no)**	**Crashes (%)**
	Fatal	**Serious injury**	**Slight injury**	**PDO**		
Vehicle –to–Vehicle				263	263	82.7
Veh –Pedestrian		12	5	2	19	6.0
Veh –Veh –Passenger		4	9		13	4.1
Veh –Stationary object				8	8	2.5
Unidentified	7				7	2.2
Veh –Veh –Stationary object				2	2	0.6
Veh –Motorbike				2	2	0.6
Motorbike –Passenger		1	1		2	0.6
Veh –Veh –Veh				1	1	0.3
Veh –Motorbike –Passenger				1	1	0.3
Sum-Total	**7**	**17**	**15**	**279**	**318**	**100.0**

Table 4-13 shows that most of the collision types that were happened at five-legged roundabouts were vehicle –to –vehicle collisions where the property damage only (PDO) crashes accounted to almost the majority (82.7%). Though very small, the vehicle –to –pedestrian collisions and injuries incurred during veh –to –veh collisions (or Veh –Veh –Passenger) accounted to slightly higher. Whereas, the other collision types have least effects on the resulted frequency of crashes at roundabout.

Vehicle types involved in the crashes

Table 4-14: Vehicle types involved during crashes at five-legged roundabouts

(Source: A.A. city Traffic Police Crash Records-unpublished)

Vehicle Type	Crash Type					
	Fatal	Serious injury	Slight injury	Property Damages	Total crash types	%
Small Car (Auto, 3-wheeled Bajajs, , …)		1	2	91	94	29.6
Light Bus (minibuses, up to 24 seats)		5	5	69	79	24.8
Medium Car (Four-Wheeled veh, Land cruisers, St. Wagon, Pickups,…)		4	2	58	64	20.1
Light Truck (Isuzu, Goods truck…)		1	6	22	29	9.1
Heavy Bus (City buses, above 35 seats, …)		2		17	19	6.0
Unidentified	7	2		7	16	5.0
Medium Truck (D. Truck, FSR, …)		2		10	12	3.8
Heavy Truck (T.Trailer, Low bed, High bed, Crane…)				2	2	0.6
Medium Bus (Higer, & above 24 seats…)				1	1	0.3
Mo-Peds (Motorbike, Bicycles,…)				1	1	0.3
Others				1	1	0.3
Sum-Total	7	17	15	279	318	100

In Table 4-14 above, it is shown that small cars, light buses, & medium cars constituted to 29.6%, 24.8%, and 20.1%, respectively, of the total vehicles involved during crashes occurred at the five-legged roundabouts which sums up to *74.5%* of the total.

Weighted accident/crash data

Finally, in order to develop specific crash predictive models, the reported crash data was systematically analyzed in to two categories, namely: Sev-Cr (which is a weighted sum of Fatal, Serious-injury, and Slight-injury crashes), and Property Damage Only Crashes. The variables are described in Table 4-15 below.

Table 4-15: descriptive summary of weighted crash data

Crash/ Accident Variables	**Description of variables**	**Roundabout**						**Total**
		Afincho -Ber	**Tewo dros**	**Sidist -Kilo**	**Tekle-Haimanot**	**Abinet**	**Sumale-Tera**	
Sev-Cr	Severe Crashes (weighted) (Fatal + Serous + slight injuries)	20	20	19	24	33	17	**133**
PDO-Cr	Property Damages Only Crashes (PDO-Cr)	20	103	59	57	19	21	**279**

4.4. Data Reductions

4.4.1. Associations among candidate explanatory variables

The collected data was properly analyzed and the candidate underlying risk factors were identified based on previously conducted literatures and local/site specific situations. Variables are reasonably evaluated in terms of their correlations with other candidate variables and in terms of their theoretical appeal (*Maher & Summersgill, 1996*) (see Table E- 2 in Appendix E). A correlation coefficient (r) measures the strength of a linear association between two variables and ranges between -1 (perfect negative correlation) to 1 (perfect positive correlation). There are several types of correlation but they are all interpreted in the same way. Pearson's correlation coefficient is the most common measure of correlation and is used when both variables are continuous (scale) (*Cohen, 1992*). *Cohen* has proposed the following guidelines for interpreting of a correlation coefficient:

Table 4-16: Guidelines for interpreting of a correlation coefficient

(Source: Cohen., L., 1992)

Correlation coefficient value	Association
-0.3 to +0.3	weak
-0.5 to -0.3 or +0.3 to +0.5	Moderate
-0.9 to -0.5 or +0.5 to +0.9	Strong
-1.0 to -0.9 or +0.9 to +1.0	Very strong

Accordingly, five explanatory variables which have least interaction effects among each other were selected and also proposed to be described and used in the model calibration processes. On the other hand, if two variables have weak association value (see Table 4-16), one with less importance is removed. Table 4-17 and Table 4-18 show the descriptive summary of the selected explanatory variables, and the Pearson correlation values among each other, respectively.

Table 4-17: Descriptive Summary of Selected Explanatory variables

Variables	Description of variables	Roundabout						Statistical measures				
		Afincho-Ber	Tewodros	Sidist-Kilo	Tekle-Haimanot	Abinet	Sumale-Tera	N	Min	Max	Mean	Variance
Dependent variables (Crash Data)												
Sev-Cr	Serious Crashes (Fatal, Serous & slight injuries) (3-years)	20	20	19	24	33	17	6	17	33	22.17	33.37
PDO-Cr	Property Damages Only (PDO) Crashes (3-years)	20	103	59	57	19	21	6	19	103	46.50	1113.50
Independent variables												
Traffic Variables												
Log-of-PHVV-MAJ	Logarith of Peak Hour Vehicle entry Volume on major road	7.42	7.38	7.50	7.41	7.19	7.01	6	7.01	7.50	7.32	0.034
PHPV-MAJ	Peak Hour Pedestrian Volume crossing the major road (ped/h)	189	391	890	1209	501	625	6	189.0	1209.0	633.9	134225.1
V85-MAJ	85th percentile Speed on major road (kph)	46.3	39.1	29.1	41.7	34.2	27.7	6	27.7	46.30	36.35	53.44
Geometric Variables												
En-RW-MIN	Entry half-roadway width on minor road (m)	4.5	8.2	3.0	9.0	4.0	7.0	6.0	3.0	9.0	6.0	6.0
R-DIC-to-DCI	Ratio of Diameter of inscribed circle (DIC) to Diameter of central island (DCI)	1.9	2.3	2.5	1.3	1.3	2.0	6.0	1.3	2.5	1.9	0.3

Table 4-18: Correlation matrix among selected model explanatory variables

		Logarithm of Peak Hour Vehicle Volume (PHVV) on major road	Peak Hour Pedestrian Volume crossing the major road (ped/h)	85^{th} percentile Speed on major road (kph)	Entry half-roadway width on minor road (m)	Ratio of diameter of inscribed circle (DIC) to diameter of central island (DCI)
Logarithm of Peak Hour Vehicle Volume on major road	Pearson Correlation	1	.176	.494	-.151	.321
	Sig. (2-tailed)		.739	.320	.775	.535
	N	6	6	6	6	6
Peak Hour Pedestrian Volume crossing the major road (ped/h)	Pearson Correlation	.176	1	-.262	.300	-.224
	Sig. (2-tailed)	.739		.616	.564	.670
	N	6	6	6	6	6
85^{th} percentile Speed on major road (kph)	Pearson Correlation	.494	-.262	1	.274	-.294
	Sig. (2-tailed)	.320	.616		.599	.572
	N	6	6	6	6	6
Entry half-roadway width on minor road (m)	Pearson Correlation	-.151	.300	.274	1	-.241
	Sig. (2-tailed)	.775	.564	.599		.646
	N	6	6	6	6	6
Ratio of diameter of inscribed circle (DIC) to diameter of central island (DCI)	Pearson Correlation	.321	-.224	-.294	-.241	1
	Sig. (2-tailed)	.535	.670	.572	.646	
	N	6	6	6	6	6

4.4.2. Associations of selected explanatory with dependent variables

The association effects of each selected explanatory variable on the dependent variables can be visualized by using the Pearson's correlation coefficients as well as by developing scatterplot diagrams. Both methods show similar trends or results.

Table 4-19 shows the Pearson's correlation coefficients of each explanatory variable with respect to the response/dependent variables. In this case, the dependent variables are the severe crashes (Sev-Cr) and property damages only crashes (PDO-Cr).

Table 4-19: Correlation effect of explanatory variable on the response variables

No.	Explanatory variable	Correlation	Dependent Variable	
			Severe Crashes (Sev-Cr) (Fatal, Serious & slight)	Property Damages Only Crashes (PDO-Cr)
1	Logarithm of Peak Hour entry Vehicle Volume on major leg	Pearson Correlation	-.106	.505
		Sig. (2-tailed)	.842	.306
		N	6	6
2	Peak Hour Pedestrian Volume crossing the major leg (ped/h)	Pearson Correlation	.032	.183
		Sig. (2-tailed)	.952	.729
		N	6	6
3	85th percentile Speed on major road (kph)	Pearson Correlation	.126	.112
		Sig. (2-tailed)	.812	.832
		N	6	6
4	Entry half-roadway width on minor leg (m)	Pearson Correlation	-.188	.458
		Sig. (2-tailed)	.721	.361
		N	6	6
5	Ratio of diameter of inscribed circle (DIC) to diameter of central island (DCI)	Pearson Correlation	-.751	.465
		Sig. (2-tailed)	.086	.353
		N	6	6

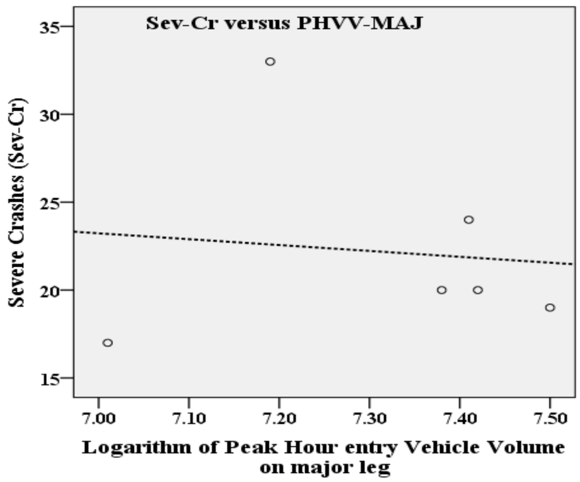
Accordingly, one can observe that the PHVV-MAJ, En-RW-MIN, and the R-DIC-to-DCI were observed to have negative associations with ‘Sev-Cr’ which implies that an increase in these variables result in decreases on the response variable – Sev-Cr. In contrast, PHPV-MAJ, and V85-MAJ have positive associations with the response variable – Sev-Cr. Likewise, the variable R-DIC-to-DCI has strong correlation with Sev-Cr compared to the other explanatory variables. Whereas, the variable PHPV-MAJ has weak association with the response variable –Sev-Cr.

In the same way, the Pearson coefficients of all the explanatory variables in

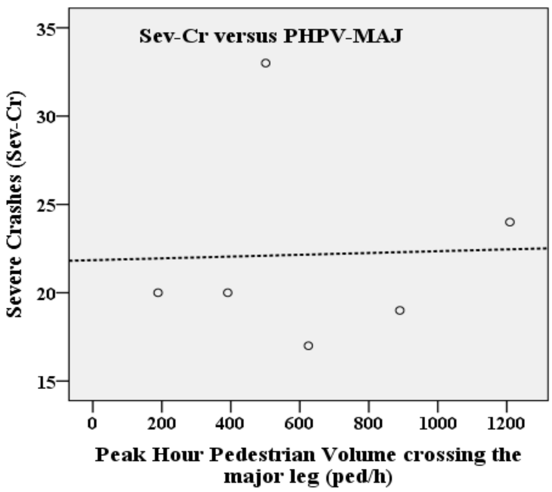
Table 4-19 are observed to have positive correlations with the response variable –PDO-Cr. This implies an increase in the value of the specified explanatory variable results in similar increases on the response variable – PDO-Cr. In this case, the exposure variable PHVV-MAJ has strong correlation with the dependent variable PDO-Cr compared to the other explanatory variables. Likewise, the variables En-RW-MIN and R-DIC-to-DCI have similarly moderate correlations with the response variable –PDO-Cr. The variables PHPV-MAJ and V85-MAJ have weak correlations with the response variable –PDO-Cr.

Scatter Plots

The effect of each explanatory variable on each response variable can carefully be evaluated and described using scatterplots. Scatterplots show possible associations or relationships that can be observed between two variables. Scatterplots are useful for interpreting statistical data by looking for trends as you go from left to right: If the data show an uphill pattern as you move from left to right, a positive relationship between the variables is indicated. If the data show a downhill pattern as you move from left to right, a negative relationship between the variables can be shown. If the data don't seem to resemble any kind of pattern, then no relationship exists between them. One pattern of special interest is a linear pattern, where the data has a general look of a line going uphill or downhill. However, just because the chart shows something is going on, it doesn't mean that a cause-and-effect relationship exists. The scatter plots of the selected explanatory variables with respect to the explanatory variable – Sev-Cr are shown in Figure 4-4 below.



(a)



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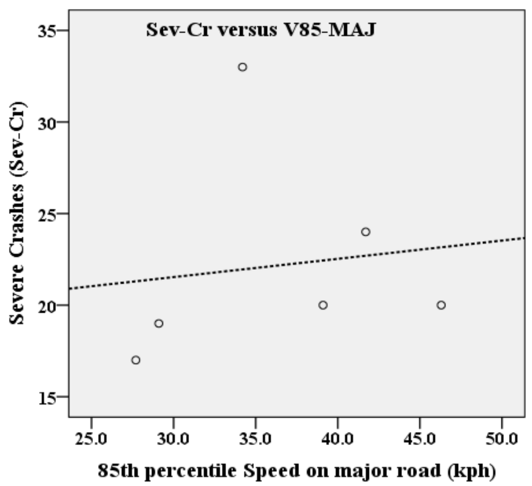

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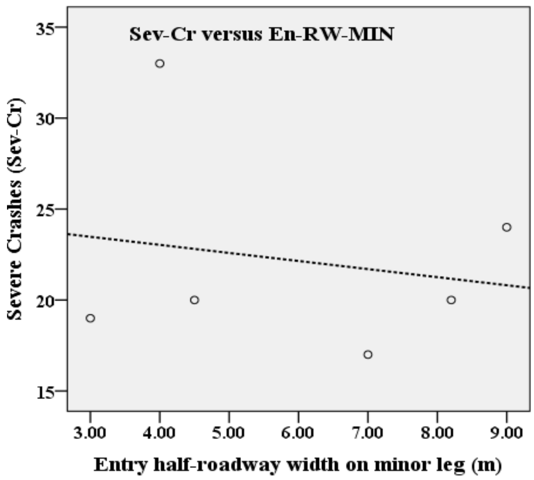
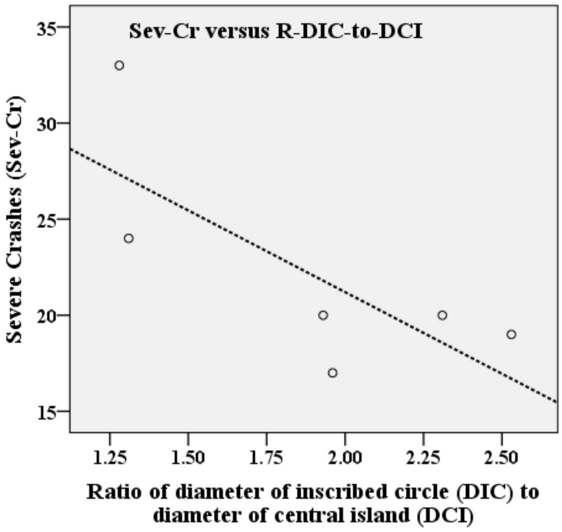


(d)

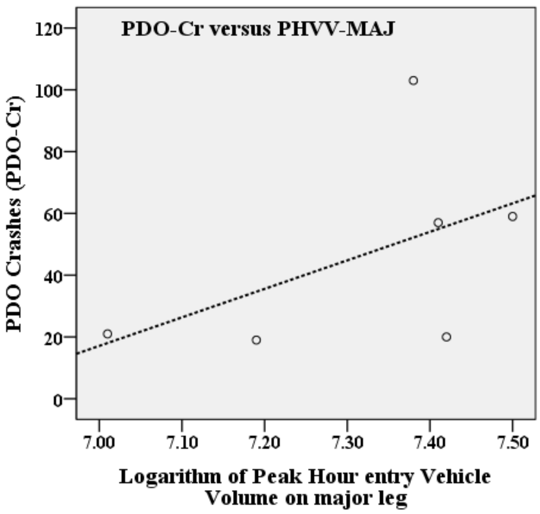


(e)

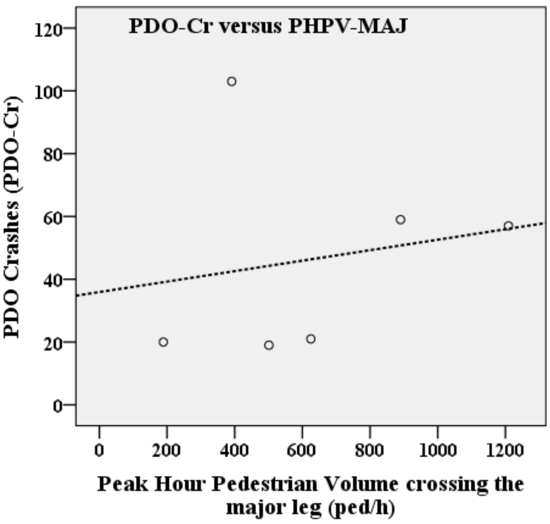
Figure 4-4: Scatterplot diagrams for each explanatory variable versus the dependent variable -Sev-Cr

Looking at Figure 4-4, it can be observed that a negative linear relationship does appear in (a), (d), and (e). Whereas, a positive linear relationship does appear in (b) and (c). That is, similar trends are depicted as the Pearson correlation described earlier.

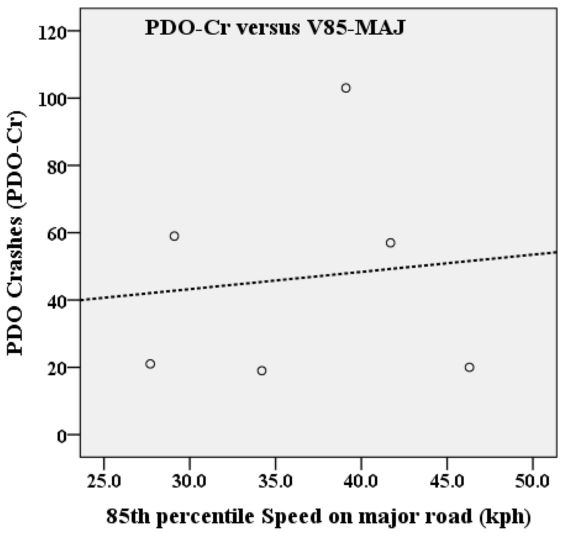
On the other hand, the scatter plots of the selected explanatory variables with respect to the response variable –PDO-Cr are also shown in Figure 4-5 below.



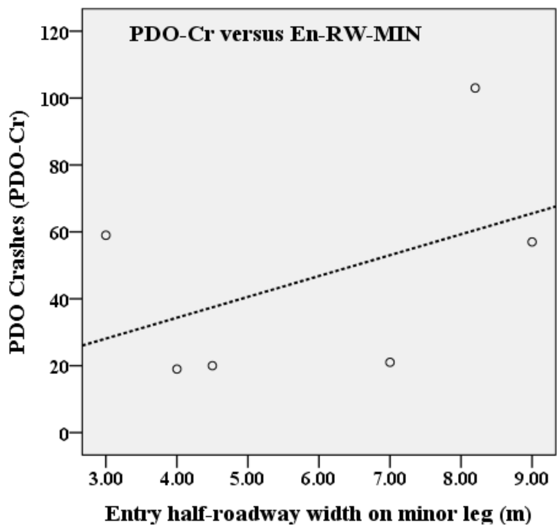
(a)



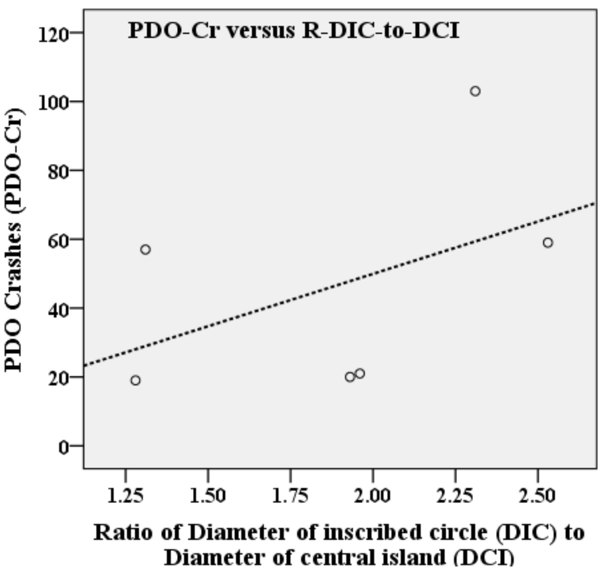
(b)



(c)



(d)



(e)

Figure 4-5: Scatterplot diagrams for each explanatory variable versus the dependent variable -PDO-Cr

Looking at Figure 4-5 above, it can be observed that positive linear relationships of the explanatory variables appear in all the scatterplots with respect to the response variable – PDO-Cr where similar trends are also depicted by the Pearson correlation described in Table 4-19. Generally, the scatter plot diagrams shown in Figure 4-4 and Figure 4-5 are observed to agree with the signs of the Pearson correlation coefficients described in Table 4-19. In other words, a positive sign in the Pearson correlation coefficients correspond to a positive (increasing) slope on the fitted-line of the scatter plots for the same variables.

4.5. Model Estimations

Two models were estimated separately here. First a model of the total predictable number of severe crashes (Sev-Cr) which includes fatal, serious & slight injuries was estimated. Moreover, another separate model was also estimated for total property only crashes (PDO-Cr). The explanatory variables evaluated in calibrating the models were obtained after being screened out for multi-collinearity effects from previous section 4.4.

As discussed previously, the selection of error structures focused on GLMs especially the Poisson or Negative Binomial density function. Accordingly, the classic Poisson regression was satisfactorily employed to estimate the parameters of the Severe crash (Sev-Cr) model, and the negative binomial error structure was fitted for the PDO crash (PDO-Cr) model allowing the observed over-dispersion effects as shown in the next sub-sections.

4.5.1. Modeling Severe-Crashes (Sev-Cr)

The estimation results for severe-crash (Sev-Cr) model were fitted with the Poisson regression model using the GENLIN procedure of the SPSS 23 software package. To begin with the analysis, the multi-collinearity test discussed in section 4.4.1 screened out to five explanatory variables or covariates that are found tolerably independent to each other. These predictor variables are described in Table 4-20 below.

Table 4-20: Description of continuous variables information used in the Models

Description		Label	N	Min.	Max.	Mean	Std. Dev.
Dependent Variable	Severe Crashes (Fatal, Serious & slight) (3-years)	Sev-Cr	6	17	33	22.17	5.776
Covariate	Peak Hour Pedestrian Volume crossing the major road (ped/h)	PHPV-MAJ	6	189	1209	634.17	366.335
	85th percentile Speed on major road (kph)	V85-MAJ	6	27.7	46.3	36.35	7.310
	Entry half-roadway width on minor road (m)	En-RW-MIN	6	3.00	9.00	5.95	2.453
	Ratio of Diameter of inscribed circle (DIC) to Diameter of central island (DCI)	R-DIC-to-DCI	6	1.28	2.53	1.89	0.510
Offset*	Logarithm of Peak Hour entry Vehicle Volume on major road	Log-PHVV-MAJ	6	7.01	7.50	7.32	0.183

*Note: *. the term 'offset' variable indicates an exposure variable where its coefficient parameter is assigned 1. In this model the variable Log-PHVV-MAJ (Logarithm of peak hour entry vehicle volume on major road) is assumed as an offset variable.*

For unbiased selection between the traditional Poisson, and the Negative Binomial models defined by the Pearson chi-square distribution, the log-likelihood can be estimated by initially assuming identical scale parameter, φ =1 for both the models. Then, the log-likelihood estimates for the alternative models could be obtained from the respective goodness of fit tables (Table 4-21 & Table 4-22).

Table 4-21: Goodness-of-fit statistics for standard Poisson regression

Goodness of Fit[a]

	Value	df	Value/df
Deviance	0.636	1	0.636
Scaled Deviance	1.004	1	
Pearson Chi-Square	0.633	1	0.633
Scaled Pearson Chi-Square	1.000	1	
Log Likelihood[b,c]	-15.077		
Adjusted Log Likelihood[d]	-23.800		
Akaike's Information Criterion (AIC)	40.154		
Finite Sample Corrected AIC (AICC)			
Bayesian Information Criterion (BIC)	39.113		
Consistent AIC (CAIC)	44.113		

Dependent Variable: Severe Crashes (Fatal, Serious & slight) (3-years)
Model: (Intercept), PHPVMAJ, V85MAJ, EnRWMIN, RDICtoDCI, offset = LogofPHVVMAJ
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.
c. The log likelihood is based on a scale parameter fixed at 1.
d. The adjusted log likelihood is based on an estimated scale parameter and is used in the model fitting omnibus test.

Table 4-22: Goodness-of-fit statistics for negative binomial regression

Goodness of Fit[a]

	Value	df	Value/df
Deviance	0.029	1	0.029
Scaled Deviance	1.006	1	
Pearson Chi-Square	0.029	1	0.029
Scaled Pearson Chi-Square	1.000	1	
Log Likelihood[b,c]	-24.598		
Adjusted Log Likelihood[d]	-839.664		
Akaike's Information Criterion (AIC)	59.196		
Finite Sample Corrected AIC (AICC)			
Bayesian Information Criterion (BIC)	58.155		
Consistent AIC (CAIC)	63.155		

Dependent Variable: Severe Crashes (Fatal, Serious & slight) (3-years)
Model: (Intercept), PHPVMAJ, V85MAJ, EnRWMIN, RDICtoDCI, offset = LogofPHVVMAJ
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.
c. The log likelihood is based on a scale parameter fixed at 1.
d. The adjusted log likelihood is based on an estimated scale parameter and is used in the model fitting omnibus test.

Accordingly, the log-likelihood reported for the standard Poisson regression is -15.077 compared to the log-likelihood reported for the negative binomial regression of -24.598. This is actually smaller than the log-likelihood for the Poisson regression, which indicates (without the need for a likelihood ratio test) that this negative binomial regression does not offer an improvement over the Poisson regression. Other than the log-likelihood, the value of AIC and BIC for the Poisson regression model is also lower than the negative binomial regression model. Hence, the standard Poisson model demonstrates a better fit than the Negative Binomial model.

Another way it could be tested for over-dispersion is to fit a negative binomial model with ancillary parameter equal to 0 and request the Lagrange multiplier test statistic using the GENLIN procedure. If the test is not significant, over-dispersion should not be a problem for this dataset (see Table 4-23 below).

Table 4-23: Test statistic for Ancillary Parameter over-dispersed Poisson Model

Lagrange Multiplier Test				
	z	Significance (by Alternative Hypothesis)		
		Parameter < 0	Parameter > 0	Non-directional
Ancillary Parameter[a]	-11.147	0.000	1.000	0.000

a. *Tests the null hypothesis that the negative binomial distribution ancillary parameter equals 0*

As shown in Table 4-23, the significance values support the null-hypothesis that the negative binomial distribution ancillary parameter equals 0 implying that no over-dispersion case in the data. Hence, the alternative test option confirmed that the standard Poisson regression model appeared to outperform the fitting for the current severe crash data. Now, by employing the selected standard Poisson regression model, we can proceed fitting the given data using the GENLIN procedure of SPSS 23 software analysis package.

```
* Generalized Linear Models.
GENLIN SevCr WITH PHPVMAJ V85MAJ EnRWMIN RDICtoDCI
  /MODEL PHPVMAJ V85MAJ EnRWMIN RDICtoDCI INTERCEPT=YES OFFSET=LogofPHVVMAJ
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=NEWTON SCALE=PEARSON COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012 ANALYSISTYPE=3(LR)
CILEVEL=95 CITYPE=PROFILE(.0001)
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION (EXPONENTIATED)
  /SAVE MEANPRED STDPEARSONRESID STDDEVIANCERESID.
```

Consequently, the analysis results of the likelihood ratio statistic and its significance level for the overall fitted model are shown in Table 4-24.

Table 4-24: Model test statistic results for Severe-Crashes (Sev-Cr) [using standard Poisson Regression Model]

Likelihood Ratio Chi-Square	df	Sig.
17.324	4	0.002

Note: The above table Compares the fitted model against the intercept-only model.

From Table 4-24 above, the likelihood-ratio chi-square test of the current model versus the null (a model without any predictors, in this case, it is the intercept only) model shows the test of the Likelihood Ratio Chi-Square value (17.324, and df=4) rejects the null hypothesis that the fitted model has explanatory power equal to that of the model with the constant term only. So, the model shows an overall good statistical fit, or the overall model is found statistically significant which outperforms the null model. As a result, Table 4-25 shows estimates of the Poisson fitted model parameters along with their standard errors, Wald chi-square values, p-values and 95% confidence intervals for the coefficients.

Table 4-25: Parameter estimates for the Sev-Cr model [Using Poisson Regression Model]

Parameter Estimates										
Parameter	β	Std. Error	95% Profile Likelihood Confidence Interval for β		Hypothesis Test			Exp (β)	95% Profile Likelihood Confidence Interval for Exp(β)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-1.8591	0.6397	-3.137	-0.626	8.4468	1	0.0037	0.1558	0.0434	0.5348
PHPV-MAJ	-0.0004	0.0002	0.002	-0.0001	2.4132	1	0.1203	0.9996	0.9991	1.0001
V85-MAJ	-0.0252	0.0126	-0.050	0.000	4.0315	1	0.0446	0.9751	0.9515	0.9995
En-RW-MIN	0.0003	0.0371	-0.073	0.073	0.0001	1	0.9940	1.0003	0.9296	1.0756
R-DIC-to-DCI	-0.6467	0.1570	-0.955	-0.338	16.9698	1	0.0000	0.5238	0.3848	0.7129
(Scale)	0.6335[a]									

Dependent Variable: Severe Crashes (Fatal, Serious & slight) (3-years)
Model: (Intercept), PHPVMAJ, V85MAJ, EnRWMIN, RDICtoDCI, offset = LogofPHVVMAJ (this is the exposure variable with coefficient =1)
a. *Computed based on the Pearson chi-square.*

The parameter estimates in Table 4-25 reviews the effect of each predictor variable on the fitted model. While direct explanation of the coefficients in such models is difficult due to the nature of the link function, the signs of the coefficients for the covariates can provide important intuitions into the effects of the predictors. As a result, the exposure variable – Log-of-PHVVMAJ and the least significant variable En-RW-MIN have both positive estimated signs (with a positive sign indicating an increase in the crash frequency as a result of increasing the predictor).

Explaining about the particular variables used in the model: besides to the exposure variable Log-of-PHVV-MAJ, the V85-MAJ and R-DIC-to-DCI were found significant (p values less than 0.05) in the prediction model. An increase in the V85-MAJ at approaching legs decreases the likely of crashes that would happen. A similar conclusion was also reached for the R-DIC-to-DCI. An increase in R-DIC-to-DCI has a negative effect on the frequency of crashes. On the other hand, minor or negligible effect of the PHPV-MAJ and the En-RW-MAJ have gone into the model. Finally, the significance of the over dispersion parameter (φ) indicates that over-dispersion should not be a problem for this dataset and the standard Poisson regression model is well preferred to the Negative Binomial model.

As normality and equal variance assumptions apply to the Poisson regression analyses, the significances of the resulting residuals were also assessed (see Figure 4-6 & Table 4-26).

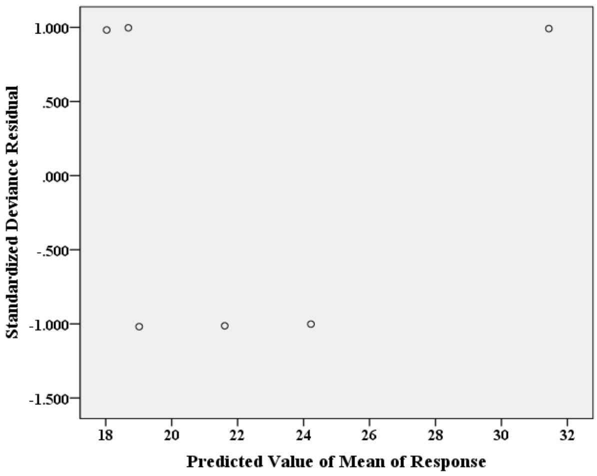


Figure 4-6: Scatterplot for standardized deviance residual by predicted value of mean of response

Table 4-26: Outlier analysis using Std-Pearson-Residual

		Frequency	%	Valid %	Cumulative %
Valid	-1.000	1	16.7	16.7	16.7
	-1.000	1	16.7	16.7	33.3
	-1.000	1	16.7	16.7	50.0
	1.000	1	16.7	16.7	66.7
	1.000	1	16.7	16.7	83.3
	1.000	1	16.7	16.7	100.0
	Total	6	100.0	100.0	

Accordingly, the resulting deviances and Pearson residuals for the data set show no significant deviations or outliers away from 0 and 95% of the residuals are under absolute value of 2.0. Therefore, the model is thought to fit the data set.

Table 4-27: Elasticity estimates for the Sev-Cr model

Variable	*Elasticity*
Logarithm of Peak Hour entry Vehicle Volume on major leg (Log-of-PHVV-MAJ) (veh/h)	1.0000
Peak Hour Pedestrian Volume crossing the major leg (PHPV-MAJ) (ped/h)	-0.0004
85^{th} percentile Speed on major road (V85-MAJ) (kph)	-0.0249
Entry half-roadway width on minor leg (m)	0.0003
Ratio of Diameter of inscribed circle to Diameter of central island (R-DIC-to-DCI)	-0.4762

To examine the relative effects of the variables included in the model, average elasticity of all the continuous variables are presented (

Table 4-27). The results indicate that the logarithm of peak hour entry vehicle volume on major leg (Log-of-PHVV-MAJ) has the greatest relative effect on the crash frequency among all the independent variables. The interaction between the diameter of inscribed circle and diameter of central island (R-DIC-to-DCI) has the next relative effect on crash frequency. This implies - for each one-unit increase on R-DIC-to-DCI, the expected count on the number of severe-crashes (Sev-Cr) decreases by 0.4762 times. Similarly, for each one-unit increase on V85-MAJ, the expected count on the number of severe-crashes (Sev-Cr) decreases by 0.0249 times. Likewise, the predictor variables PHPV-MAJ and En-RW-MIN have least or negligible counts on the number of severe-crashes each with -0.0004 and 0.0003 times, respectively. Generally, the final form of the model equation for the Poisson fitted model is given by,

$$\begin{aligned}\mathrm{Pred(SeCr)} = \ & \mathrm{PHVVMAJ} * \mathrm{EXP}[-1.8591 - 0.0004 * \mathrm{PHPVMAJ} - 0.0252 * \mathrm{V85MAJ} \\ & - 0.0003 * \mathrm{EnRWMIN} - 0.6467 * \mathrm{RDICtoDCI}]\end{aligned}$$

4.5.2. Modeling Property-Damages-Only-Crashes (PDO-Cr)

Analogous to the previous Sev-Cr model, the parameter estimation results for PDO-Cr model was analyzed using similar analysis procedures. For the selection and evaluation of model adequacy between the alternative models (standard Poisson and Negative Binomial), all the candidate predictor variables which were introduced in the previous model were also used here. However, after the better fit model was already selected, the significant ones were included in the final model. These candidate variables which were first evaluated in the model are described in Table 4-28.

Table 4-28: Description of continuous variable information used in the model

Description		Label	N	Min.	Max.	Mean	Std. Dev.
Dependent Variable	Property Damage Only Crashes (PDO-Cr)	PDO-Cr	6	19	103	46.50	33.369
Covariate	Peak Hour Pedestrian Volume crossing the major road (ped/h)	PHPV-MAJ	6	189	1209	634.17	366.335
	85th percentile Speed on major road (kph)	V85-MAJ	6	27.7	46.3	36.35	7.310
	Entry half-roadway width on minor road (m)	En-RW-MIN	6	3.00	9.00	5.95	2.453
	Ratio of Diameter of inscribed circle (DIC) to Diameter of central island (DCI)	R-DIC-to-DCI	6	1.28	2.53	1.89	0.510
Offset*	Logarithm of Peak Hour entry Vehicle Volume on major road	Log-PHVV-MAJ	6	7.01	7.50	7.32	0.183

*Note: *. the term 'offset' variable indicates an exposure variable where its coefficient parameter is assigned 1. In this model the variable Log-PHVV-MAJ (Logarithm of peak hour entry vehicle volume on major road) is assumed as an offset variable.*

Simply, one can observe that the response variable, PDO-Cr, has the variance much higher than its mean which likely mean that it is highly over-dispersed. However, it should be convinced through further statistical procedures. For over-dispersion test, fitting a negative binomial model with ancillary parameter equal to 1 and carrying out the relevant Lagrange multiplier test statistic may be required as follows.

Table 4-29: Lagrange Multiplier

(assuming ancillary parameter=1)

Lagrange Multiplier Test			
	Likelihood Chi-square	df	Sig.
Ancillary Parameter[a]	11.986	1	0.001

a. *Tests the null hypothesis that the negative binomial distribution ancillary parameter equals 1*

Assuming the ancillary parameter=1, as shown in the Table 4-29, appeared to conclude the test is strongly significant to accept the null hypothesis that the negative binomial fits the data with a dispersion parameter equal to 1. Hence, the Negative Binomial was preferred to the standard Poisson regression model to fit the PDO-Cr data.

Similar procedures as the previous model had been carried out here to select the significant predictor variables that would be included in the model. At the beginning, all the predefined five explanatory variables were included in the current model. Then, all the potential variables were evaluated for their information criteria to be included in the model. Hence, the significant predictor variables included in the final model were selected as: The Log-PHVV-MAJ, En-RW-MIN, and R-DIC-to-DCI. In other words, the other predictors appeared to be insignificant to the model and, as a result, were removed from the model. The GENLIN syntax procedure used for the analysis is given by,

```
* Generalized Linear Models.
GENLIN PDOCr WITH PHPVMAJ V85MAJ EnRWMIN RDICtoDCI
  /MODEL EnRWMIN RDICtoDCI INTERCEPT=YES OFFSET=LogofPHVVMAJ
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=NEWTON SCALE=PEARSON COVB=MODEL MAXITERATIONS=100
MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012 ANALYSISTYPE=3(LR)
CILEVEL=95 CITYPE=PROFILE(.0001)
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION (EXPONENTIATED)
LAGRANGE
  /SAVE MEANPRED STDPEARSONRESID STDDEVIANCERESID.
```

The results of the final fitted model and relevant goodness of fit measure using the likelihood ratio chi-square tests is given in Table 4-30 as follows.

Table 4-30: Model goodness of fit test statistic results for PDO-Cr

[Using Negative Binomial Regression Model]

Likelihood Ratio Chi-Square	df	Sig.
7.055	2	*0.029*

Note: Table 4-30 Compares the fitted model against the intercept-only model.

As shown in Table 4-30, the likelihood-ratio chi-square statistic was used to test the overall goodness of fit of the current model versus the null model. As a result, the test of the Likelihood Ratio Chi-Square value (7.055, and df=2) rejects the null hypothesis that the fitted model has explanatory power equal to that of the model with the constant term only. Thus, the model shows an overall good statistical fit. The parameter estimation of the Negative Binomial fitted model and relevant measures of model goodness of fit can be summarized as follows in Table 4-31.

Table 4-31: Estimated Parameters for PDO crashes (PDO-Cr) model

[Using the Negative Binomial Model]

Parameter Estimates										
Parameter	β	Std. Error	95% Profile Likelihood Confidence Interval for β		Hypothesis Test			Exp (β)	95% Profile Likelihood Confidence Interval for Exp(β)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-6.0662	0.9371	-7.833	-4.143	41.9040	1	0.0000	0.0023	0.000	0.016
En-RW-MIN	0.1734	0.0769	0.022	0.326	5.0892	1	0.0241	1.1894	1.022	1.385
R-DIC-to-DCI	0.7411	0.3608	0.020	1.446	4.2177	1	0.0400	2.0982	1.020	4.246
(Scale)	0.1844[a]									
(Negative binomial)	1[b]									

Dependent Variable: PDO Crashes (*PDO-Cr*)
Model: (Intercept), EnRWMIN, RDICtoDCI, offset = LogofPHVVMAJ (this is the exposure variable with coefficient =1)
a. Computed based on the Pearson chi-square.
b. Fixed at the displayed value.

From Table 4-31 above, the individual parameter effects in the model is tested and checked with the presumed significance level, where a variable with a p-value less than 0.05 is assumed to contribute some evident effect to the model. The signs of the coefficients for the covariates can provide important insights into the effects of the predictors. Accordingly, the exposure variable Log-of-PHVV-MAJ, and predictors En-RW-MAJ and R-DIC-to-DCI have positive estimated signs which imply that an increase in R-DIC-to-DCI or En-RW-MAJ results in a subsequent increase on the frequency of crashes. In this case, an interaction effect between the diameter of the inscribed circle (DIC) and the diameter of central island (DCI) has been remarked. That is, When the DIC increases and at the same time the DCI decreases, the frequency of crashes also escalates. In Table 4-31, the estimated dispersion parameter computed based on the Pearson chi-square is greater than 0, which confirmed a better fit of the Negative Binomial over the standard Poisson model.

Similar to the Poisson, normality and equal variance assumptions also apply to the negative binomial regression model. So, assessment for the significances of the resulting residuals were applied here, too (see Table 4-32 & Figure 4-7).

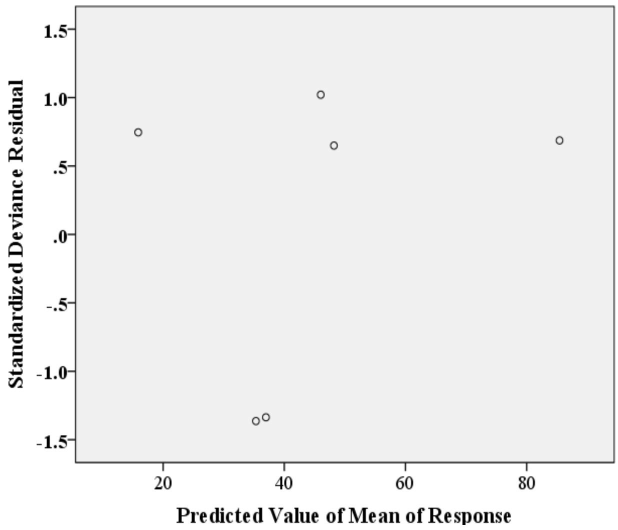


Figure 4-7: Scatterplot for standardized deviance residual Vs predicted value of Mean of Response

Table 4-32: Tests for outlier validities using Std-Pearson-Residuals

Standardized Pearson Residual

		Frequency	%	Valid %	Cumulative %
Valid	-1.142	1	16.7	16.7	16.7
	-1.120	1	16.7	16.7	33.3
	-0.689	1	16.7	16.7	50.0
	0.731	1	16.7	16.7	66.7
	0.792	1	16.7	16.7	83.3
	1.110	1	16.7	16.7	100.0
	Total	6	100.0	100.0	

Accordingly, the resulting deviances and Pearson residuals for the data set show that no significant deviations or outliers are away from 0 and 95% of the residuals are under absolute value of 2.0. Therefore, the model is thought to fit the data set.

Table 4-33: Elasticity estimates for the PDO-Crashes (PDO-Cr) model

Variable	Elasticity
Peak Hour entry Vehicle Volume on major leg (PHVV-MAJ) (veh/h)	1.0000
Entry half-roadway width on minor leg (En-RW-MIN) (m)	0.1893
Ratio of Diameter of inscribed circle to Diameter of central island (R-DIC-to-DCI)	1.0982

The relative effects of the variables included in the model can also be examined using average elasticity of the predictor variables (see Table 4-33). This implies that for each one-unit increase on En-RW-MIN, the expected count on the number of PDO-Cr also increases by 0.1893 times. Similarly, for each one-unit increase on R-DIC-to-DCI, the expected count on the number of PDO-Cr increases by 1.0982 times. Generally, the final form of the model equation for the fitted Negative Binomial regression model is given by,

$$\mathrm{Pred(PDO-Cr)} \\ = \mathrm{PHVVMAJ} * \mathrm{EXP}[-6.0662 + 0.1734(\mathrm{EnRWMIN}) + 0.7411(\mathrm{RDICtoDCI})]$$

CHAPTER 5 CONCLUSIONS AND RECCOMENDATIONS

5.1. Conclusions

The very objective of this study was to investigate the frequency and occurrence of road traffic crashes at five-legged roundabouts with respect to the underlying geometric and traffic factors, and to calibrate relevant crash-predictive models. And, the study was supported by descriptive and inferential statistics to analyze and interpret the data from primary and secondary sources. As a result, the study has come up with following concluding remarks and plausible recommendations.

Concerning the Police-reported crashes at roundabouts, the analysis results showed that significant number (about 36.8%) of vehicle crashes were happened at intersections of which roundabouts are sharing the highest –about 15.4%. Also, it is shown that the majority of the RTAs were happened during the day time –particularly at mid-days. Some traffic police officers who were asked for their opinions on the possible reasons pointed out points such as:

- High traffic movements during the day times;
- Drivers' in-obedience to give priorities to circulating traffic;
- Increased crossing pedestrians at roundabouts at day times;
- Offensive driving behaviors of some drivers especially at roundabouts etc…

It is also shown that more than half of the crashes that were happened at five-legged roundabouts were happened due to entering vehicles do not cede (give) priorities to circulating and exiting vehicles, and, significant numbers were happened by not keeping right distance between vehicles. In the study small cars, light buses, & medium cars were the most frequently involved vehicle types during the crashes at the five-legged roundabouts. In this case, driver behavior, negotiating speeds, and lane changing problems (which frequently are observed by some minibus-taxi drivers and young drivers of small cars) were among the most noticeable reasons suggested by some traffic police officers up on inquiry. The analyzed crash data for the five-legged roundabouts also indicated that vehicle –to –vehicle collisions resulting in property damage only (PDO) crashes accounted to almost the majority (82.7%) of the total crashes happened. Such results in reduced severity levels is found to agree with several previous studies (*Rodegerdts et al. 2007a, 2010; SETRA, 1998*) that at roundabouts vehicles lower their speeds in order to negotiate with the speeds of the circulating traffic.

From the bivariate correlation analysis for multi-collinearity assessment of the prominent risk factors, five explanatory variables were identified for further analysis and calibration of crash prediction models; namely, the logarithm of peak hour vehicle volume on major road (Log-of-PHVV-MAJ), peak hour pedestrian volume crossing the major road (PHPV-MAJ), 85^{th} percentile speed on major road (V85-MAJ), entry half-roadway width on minor road (En-RW-MIN), and ratio of diameter of inscribed circle to diameter of central island (R-DIC-to-DCI).

Using the collected data, two separate models –the Poisson and Negative Binomial regression models were fitted using the selected explanatory variables as predictors and the crash data as the response. As a result, for the Sev-Cr data, the standard Poisson regression model demonstrates a better fit than the Negative Binomial model. However, when the contributory effects of the explanatory variables are compared with the results of the scatter plots, some results in the scatter plots are contradicting with the results obtained from the Sev-Cr model. Some of the reasons might be due to the values are marginally very small (zero values) which could have negligible effects on the model outcomes, and also the linear correlations assumed in the scatter plots might not apply in this case, where a non-linear relation might be viable. Besides, the data which is assumed to fit the model might not be sufficient due to underreporting problems, and the small number of roundabout observations considered might be another likely reason. Hence, it is difficult to generate a reliable interpretation from the Poisson fitted Sev-Cr model.

On the other hand, for the PDO-Cr data, the NB regression model proves a better fit than the standard Poisson model. In this case, the variables Log-PHVV-MAJ, En-RW-MAJ, and R-DIC-to-DCI are found significant in the fitted model. Indeed, the NB model indicated that Log-PHVV-MAJ, En-RW-MAJ, and R-DIC-to-DCI have positive associations with the frequency of PDO-Cr at five-legged roundabouts which also agreed with the results obtained from the scatter plots and the Pearson correlations. Here, it is worth to notice that the interaction effect between the diameter of the inscribed circle (DIC) and diameter of central island (DCI). That is, when the DIC increases and at the same time the DCI decreases, the frequency of crashes also escalates up. In other words, the DIC has positive association while the DCI has negative association with PDO crashes. Equally important, the width of the circulatory road way width which has a positive effect on PDO crashes can also be deduced.

Critically, some of the major findings of this study are supported by previous works and important literatures. For instance, the logarithm of peak hour entry vehicle volume on major leg was found significant risk factor which in consonance with the AADT variable approach used in several literatures. For instance, this is also underpinned in the works of *Nambuusi et al.* (*2008*), as they are of the opinion that the variables –annual average daily traffic (AADT) on major and minor roads, total vehicle counts and pedestrians crossing all arms, lighting and signal timing were statistically significant. At times, the findings concerning the entry half roadway width on the major leg, the diameter of the inscribed circle, as well as the circulatory roadway width (as a derivative finding)–are found positively correlated with the frequency of PDO crashes which is supported by *Rodegerdts et al*. (*2010*), because they strongly concluded that entry radius, entry width, approach half width, inscribed circle diameter, and circulating width are positively correlated with crashes.

5.2. Recommendations

Concerning the possible/practical priorities of schemes and interventions that may be proposed to improve road traffic safety at roundabout intersections, particularly at five-legged roundabouts, the study forwards the following points.

- Strategies to relieve the peak hour flows such as constructing and maintaining bypass/detour roads and implementing advanced traffic management schemes (such as management of public transports) have to put in place;
- Strategies to decrease the central island diameter should be revised and consolidated in a way to reduce the circulatory roadway width at five-legged roundabouts;
- There must be some modifications and schemes to restrict the entry half road way width on the minor approach leg while giving special attention to capacity situations;
- With a hope to strengthening the overall crash data documentations, there should be improvements through introducing GPS technology and hiring skillful staffs;
- Future studies related to traffic variables should be encouraged so that reliable and quality data will be available for a better use of diverse analytical methodologies;
- Further, the researcher suggested that it would be better if future studies may complement the level of service (LOS) and capacity situations of the roundabouts.
- Finally, the study outcomes may be reinforced in future works and come up with more convincing and reliable findings by increasing the number of sample roundabouts, and by using more likely explanatory variables, as well as advancements of their measurement techniques.

REFERENCES

Abdel-Aty, M. A., & Radwan, A. E. (2000). Modeling Traffic Accident Occurrence and Involvement. Accident Analysis & Prevention, 32(5), 633-642.

AACRA. (2003). Addis Ababa City Roads Authority. Geometric Design Manual.

Agresti, A. (2002). Wiley Series in Probability and Statistics. Analysis of Ordinal Categorical Data, Second Edition, 397-405.

Akaike, H. (1973). Maximum Likelihood Identification of Gaussian Autoregressive Moving Average Models. Biometrika, 60(2), 255-265.

Akçelik, R. (2005). Capacity and Performance Analysis of Roundabout Metering Signals. In TRB National Roundabout Conference, Vail, Colorado, USA (Pp. 22-25).

Ambros, J., & Slabý, P. (2013). Comparison of Roundabout Accident Prediction Models: Challenges of Data Collection. Analysis and Interpretation. Prague, Czech Republic.

Ambros, J., et al. (2016). Central European comparative study of traffic safety on roundabouts. Transportation Research Procedia, 14, 4200-4208.

Arndt, O., & Troutbeck, R. J. (1998). Relationship Between Roundabout Geometry and Accident Rates. Transportation Research Circular, (E-C003), 28-1.

Arnold, L. et al. (2013). Identifying Factors that Determine Bicyclist and Pedestrian-Involved Collision Rates and Bicyclist and Pedestrian Demand at Multi-Lane Roundabouts.

Bared, et al. (1997). State-Of-The-Art Design of Roundabouts. Transportation Research Record: Journal of The Transportation Research Board, (1579), 1-10.

Beshah, T., & Hill, S. 2010. Mining Road Traffic Accident Data to Improve Safety: Role of Road-Related Factors on Accident Severity in Ethiopia.

Brilon, W., & Vandehey, M. (1998). Roundabouts--The State of the Art in Germany. Institute of Transportation Engineers. ITE Journal, 68(11), 48-54.

Brude, U. (2000). What Roundabout Design Provides the Highest Possible Safety? Nordic Road and Transport Research.

Bunch, D. S., & Kitamura, R. (1991). Probit Model Estimation Revisited: Trinomial Models of Household Car Ownership. University of California Transportation Center.

Caliendo, C., Guida, M., & Parisi, A. (2007). A Crash-Prediction Model for Multilane Roads. Accident Analysis & Prevention, 39(4), 657-670.

Cameron, A. & Trivedi, P. (1998), ‘Regression Analysis of Count Data, Cambridge Econometric Society Monographs, No. 30’.

Cameron, A. C.; Trivedi, P. K. (2013). Regression Analysis of Count Data Book (2nd ed.)

Cheng, W., & Washington, S. (2008). New Criteria for Evaluating Methods of Identifying Hot Spots. Transportation Research Record: Journal of The TRB, (2083), 76-85.

Cohen, L. (1992). Power Primer. Psychological Bulletin, 112(1) 155-159

Daniels, S., Brijs, T., Nuyts, E., & Wets, G. (2011). Extended Prediction Models for Crashes at Roundabouts. Safety Science, 49(2), 198-207.

Daniels, S., Brijs, T., Nuyts, E., & Wets, G. (2010a). Explaining Variation in Safety Performance of Roundabouts. Accident Analysis & Prevention, 42(2), 393-402.

De Ceunynck, T., Daniels, S., Brijs, T., Hermans, E., & Wets, G. (2011). Explanatory Models for Crashes at High-Risk Locations. In 24th International Co–Operation On Theories and Concepts in Traffic Safety Workshop (pp. 1-21).

Eisenman, et al. (2004). Operational and Safety Performance of Modern Roundabouts and Other Intersection Types. Project NYSDOT C-01- 47, 1-55

ElAstal, I. M., & Sarraj, Y. R. (2014). Modeling Road Accident Black Spots in Gaza Strip Using Artificial Neural Network (ANN). (Unpublished).

El-Basyouny, et al. (2006) Comparison of Two Negative Binomial Regression Techniques in Developing Accident Prediction Models. Transportation Research Record, 1950, 9-16.

Eluru, et al. (2008). A Mixed Generalized Ordered Response Model for Examining Pedestrian and Bicyclist Injury Severity Level in Traffic Crashes. Accident Analysis & Prevention, 40(3), 1033-1054.

Elvik R et al. (2009). The Handbook of Road Safety Measures, 2nd Ed. Bingley, UK: Emerald Group Publishing Limited.

Elvik, R. (2008). A Survey of Operational Definitions of Hazardous Road Locations in Some European Countries. Accident Analysis & Prevention, 40(6), 1830-1835.

ERA. (2002). Ethiopian Roads Authority, Geometric Design Manual, Addiss Ababa, Ethiopia.

Fekadu, et al. (2016). Identification of Road Traffic Accident Blackspot locations and its countermeasures in Oromia Region, East Wollega Zone.

FHWA, R. (2000). An Informational Guide, Publication No. FHWA-RD-00-067, US Department of Transportation, Federal Highway Administration, Washington, DC.

FHWA. (2013). Traffic Monitoring Guide. Federal Highway Administration, Washington, DC.

Fridstrom, et al. (1995). Measuring the Contribution of Randomness, Exposure, Weather, and Daylight to The Varation in Road Accident Counts. Accident Analysis and Prevention, 27(1), 1-20.

Gallelli, V., & Vaiana, R. (2008). Roundabout Intersections: Evaluation of Geometric and Behavioural Features with VISSIM. In TRB National Roundabout Conference, Kansas City, Mo.

Geurts, K., & Wets, G. (2003). Black spot analysis methods: Literature review.

WHO. (2015). Global Status Report On Road Safety.

Greene, W. (2008), 'Functional Forms for the Negative Binomial Model for Count Data', Economics Letters 99(3), 585–590

Greibe, P. (2003). Accident Prediction Models for Urban Roads. Accident Analysis & Prevention, 35(2), 273-285.

Gross, F., et al. (2013). Safety Effectiveness of Converting Signalized Intersections to Roundabouts. Accident Analysis & Prevention, 50, 234-241.

Geurts, K., & Wets, G. (2003). Black Spot Analysis Methods: Literature Review.

Haregewoin, Y. (2010). Impact of Vehicle Traffic Congestion in Addis Ababa (A Case Study of Kolfe Sub-City: Total-Ayer Tena Road).

Hauer, E., Ng, J. C., & Lovell, J. (1988). Estimation of Safety at Signalized Intersections (With Discussion and Closure) (No. 1185).

Hauer, E., et al. (1997). Two Tools for Finding What Function Links the Dependent Variable to The Explanatory Variables. Lund, Sweden.

HCM. (2000). Highway Capacity Manual. Washington, DC.

Helbing, D., et al. (Eds.). (2012). Traffic and Granular Flow'99: Social, Traffic, And Granular Dynamics. Springer Science & Business Media.

Hels, T., & Orozova-Bekkevold, I. (2007). The Effect of Roundabout Design Features On Cyclist Accident Rate. Accident Analysis & Prevention, 39(2), 300-307.

Hilbe, Joseph M. (2007). Negative Binomial Regression (Second Ed.)

Hinde, J., & Demétrio, C. G. (1998). Overdispersion: Models and Estimation. Computational Statistics & Data Analysis, 27(2), 151-170.

Hourdos, J., Richfield, V., & Shauer, M. (2012). Investigation of Pedestrian/Bicyclist Risk in Minnesota Roundabout Crossings.

Homburger, W. S., Hall, J. W., Loutzenheiser, R. C., & Reilly, W. R. (1996). Fundamentals of Traffic Engineering (No. Course Notes,).

IRTAD. Krarup Nielsen, S. (1992). General Overview of IRTAD, International Road Traffic and Accident Database. VTI Rapport, (380A PT1).

Jacquemart, G. (1998). NCHRP Synthesis of Highway Practice 264: Modern Roundabout Practice in The United States, National Cooperative Highway Research Program.

Johnson, B., & Christensen, L. (2008). Educational Research: Quantitative, Qualitative, And Mixed Approaches. Sage.

Johnson, M. T. (2016). Synthesis of Roundabout Design Optimization for Safety and Operations. In Transportation Research Board 95th Annual Meeting (No. 16-2129).

Johnson, P. E. (2016). GLM with A Gamma-Distributed Dependent Variable.

Jarvis, R. Et Al. (2006). PYCHEM: A Multivariate Analysis Package for Python. Bioinformatics, 22(20), 2565-2566.

Kamla, J., Et Al. (2016). Roundabout Accident Prediction Model: Random-Parameter Negative Binomial Approach. TRR: Journal of The TRB, (2585), 11-19.

Kamla, J., Parry, T., & Dawson, A. (2017). Application of Random Parameters Model to Estimate Truck Accidents at Roundabouts 2 (No. 17-04458).

Katz, M. H. (2011). Multivariable Analysis: A Practical Guide for Clinicians and Public Health Researchers. Cambridge University Press.)

Kennedy, J., Peirce, J., & Summersgill, I. (2005). Review of Accident Research at Roundabouts. Transportation Research Circular, 2005(E-C083), 14p-14p.

Kim, D. Et Al. (2006). Modeling Crash Types: New Insights into The Effects of Covariates On Crashes at Rural Intersections. Journal of Transportation Engineering, 132(4), 282-292.

Kim, D.G., Et Al. (2007) Modeling Crash Outcome Probabilities at Rural Intersections: Application of Hierarchical Binomial Logistic Models. Accident Analysis and Prevention, 39, 125-134.

Koppelman, F. Et Al. (1998). Alternative Nested Logit Models: Structure, Properties and Estimation. Transportation Research Part B: Methodological, 32(5), 289-298.

Koutsoyiannis, A. (1983). Theory of Econometrics: An Introductory Exposition of Econometric Methods. 2 Ed. The Macmillan Press Ltd, London.

Kulmala, R. (1995). Safety at Rural Three-And Four-Arm Junctions. Development and Application of Accident Prediction Models (Vol. 233).

Kumara, S. S. P., & Chin, H. C. (2003). Modeling Accident Occurrence at Signalized Tee Intersections with Special Emphasis On Excess Zeros. Traffic Injury Prevention, 4(1), 53-57.

Lambert, D. (1992). Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing. Technometrics, 34(1), 1-14.

Lawless, J. F. 1987. Negative Binomial and Mixed Poisson Regression. Canad. J. Statist. 15: 209-225.

Lenters, M., & Eng, P. (2003). Roundabout Planning and Design for Efficiency & Safety Case Study: In The Transportation Factor 2003. Annual Conference and Exhibition of the Transportation Association of Canada (P. 21).

Lenters, M. S. (2005). Safety Auditing Roundabouts. Transportation Research E-Circular, E-C083, 1-20.

Lomax, T. J. (1997). Quantifying Congestion (No. 398). Transportation Research Board.

Lord, D., Et Al. (2005). Poisson, Poisson-Gamma and Zero-Inflated Regression Models of Motor Vehicle Crashes: Balancing Statistical Fit and Theory. Accident Analysis & Prevention, 37(1), 35-46.

Lord, D., & Mannering, F. (2010). The Statistical Analysis of Crash-Frequency Data: A Review and Assessment of Methodological Alternatives. Transportation Research Part A: Policy and Practice, 44(5), 291-305.

Maher, M. J., & Summersgill, I. (1996). A Comprehensive Methodology for The Fitting of Predictive Account Models. Accident Analysis & Prevention, 28(3), 281-296.

Malyshkina, N. And Mannering, F. (2010) Empirical Assessment of the Impact of Highway Design Exceptions On the Frequency and Severity of Vehicle Accidents. Accident Analysis and Prevention, 42, 131-139.

Maycock, G., & Hall, R. D. (1984). Accidents at Four-Arm Roundabouts. In, PTRC Summer 591. In Annual Conference, Brighton, GB (Vol. 592).

Mbachu, Et Al. (2012). Designing A Pseudo R-Squared Goodness-Of-Fit Measure in Generalized Linear Models. Journal of Mathematics Research, 4(2), 148.

Mccullagh, P., & Nelder, J. A. (1989). Generalized Linear Models Chapman & Hall London Google Scholar.

Mcculloch, Et Al. (2000). A Bayesian Analysis of the Multinomial Probit Model with Fully Identified Parameters. Journal of Econometrics, 99(1), 173-193.

Md Diah, J., Et Al. (2011). Modeling The Relationship Between Geometric Design and Weaving Section Flow Process of Conventional Roundabouts. Journal of Transportation Engineering, 137(12), 980-986.

Milligan, Et Al. (2014). Value of A Statistical Life in Road Safety: A Benefit-Transfer Function with Risk-Analysis Guidance Based On Developing Country Data. Accident Analysis & Prevention, 71, 236-247.

Miranda, S., Et Al. (2011). Pedestrian Volume Studies: A Case Study in The City of Gothenburg.

Montella, Et Al. (2013). International Overview of Roundabout Design Practices and Insights for Improvement of the Italian Standard. Canadian Journal of Civil Engineering, 40(12), 1215-1226.

Montella, A. (2011). Identifying Crash Contributory Factors at Urban Roundabouts and Using Association Rules to Explore Their Relationships to Different Crash Types. Accident Analysis & Prevention, 43(4), 1451-1463.

Montella, A. (2007). Roundabout In-Service Safety Reviews: Safety Assessment Procedure. Transportation Research Record: Journal of The Transportation Research Board, (2019), 40-50.

Mustakim, Et Al. (2008). Blackspot Study and Accident Prediction Model Using Multiple Liner Regression. ICCIDC–I. Karachi, Pakistan.

Nambuusi, B. B., Brijs, T., & Hermans, E. (2008). A Review of Accident Prediction Models for Road Intersections (No. RA-MOW-2008-004).

O'Flaherty, C. (1997). Transport Planning and Traffic Engineering. Elsevier.

Ogden, K.W. (1994) Traffic Engineering Road Safety: A Practitioner's Guide. A Report Prepared for The Federal Office of Road Safety, Monash University, 1994.

Oh, J., Et Al. (2003). Validation of The FHWA Crash Models for Rural Intersections: Lessons Learned. Transportation Research Record. 1840: P. 41-49.

Penden, M., Scurfield, R., Sleet, D. Mohan, D. A. Hyder, A., Jarawan, E., Mathers, C. (2004). World Report On Road Traffic Injury Prevention. Geneva, WHO.

Pratelli, A. (2006). Design of Modern Roundabouts in Urban Traffic Systems. WIT Transactions On the Built Environment, 89.

Rawlings, J. O., Pantula, S. G., & Dickey, D. A. (2001). Applied Regression Analysis: A Research Tool. Springer Science & Business Media.

Retting, R. A., Et Al. (2003). A Review of Evidence-Based Traffic Engineering Measures Designed to Reduce Pedestrian-Motor Vehicle Crashes. American Journal of Public Health, 93(9), 1456-1463.

Richfield, V., & Hourdos, J. (2013). Effect of Signs and Striping On Roundabout Safety: An Observational Before/After Study. In Transportation Research Board 92nd Annual Meeting (No. 13-4568).

Robertson, H. D. (1994). Volume Studies. In Manual of Transportation Engineering Studies, Ed. H. D. Robertson, J. E. Hummer, And D. C. Nelson. Englewood Cliffs, N.J.: Prentice Hall, Inc., Pp. 6– 31.

Robinson, B. W., Et Al. (2000). Roundabouts: An Informational Guide (No. FHWA-RD-00-067,).

Rodegerdts, L., Et Al. 2007a. "Roundabouts in The United States", NCHRP REPORT-572. Transportation Research Board of the National Academies, Washington, DC.

Rodegerdts, L., Et Al (2007b). NCHRP Web-Only Document 94 – Appendixes to NCHRP Report 572: Roundabouts in The United States. TRB, Washington, DC.

Rodegerdts, L. A., Et Al. 2010. Roundabouts: An Informational Guide, NCHRP Report 672. Transportation Research Board of the National Academies, Washington, DC.

Roess, R. P., & Prassas, E. S. (2014). The Highway Capacity Manual: A Conceptual and Research History. New York: Springer.

Roess, R. P., Prassas, E. S., & Mcshane, W. R. (2004). Traffic Engineering.

Rosen Et Al. Literature Review of Pedestrian Fatality Risk as A Function of Car Impact Speed. Accident Analysis and Prevention. 2011; 43:25–33.

Rumar, K., Ed. The Role of Perceptual and Cognitive Filters in Observed Behavior. Human Behavior in Traffic Safety, Eds. L. Evans and R. Schwing. 1985, Plenum Press.

Saini, R. (June 2015). Identification and Improvement of Accident Black Spots On NH-3 District Una, Himachal Pradesh–A Case Study.

Savolainen, Et Al. (2011). The Statistical Analysis of Highway Crash-Injury Severities: A Review and Assessment of Methodological Alternatives. Accident Analysis & Prevention, 43(5), 1666-1676.

Sawalha, Z., & Sayed, T. (2003, January). Statistical Issues in Traffic Accident Modeling. In 82 Nd Annual Meeting of the Transportation Research Board.

Schoon, C., & Van Minnen, J. (1994). Safety of Roundabouts in The Netherlands. Traffic Engineering and Control, 35(3), 142-148.

Scott Long, J. (1997). Regression Models for Categorical and Limited Dependent Variables. Advanced Quantitative Techniques in The Social Sciences, 7.

Senk, P., & Ambros, J. (2011). Estimation of Accident Frequency at Newly-Built Roundabouts in The Czech Republic. Transactions On Transport Sciences, 4(4), 199.

Shankar, V., Et Al. (1995). Effect of Roadway Geometrics and Environmental Factors On Rural Freeway Accident Frequencies. Accident Analysis & Prevention, 27(3), 371-389.

Shankar, V., & Mannering, F. (1996). An Exploratory Multinomial Logit Analysis of Single-Vehicle Motorcycle Accident Severity. Journal of Safety Research, 27(3), 183-194.

Shankar, S., & Singh, R. (2014). Demystifying Statistics: How to Choose a Statistical Test? Indian Journal of Rheumatology, 9(2), 77-81.

SETRA (Service D'études Techniques des Routes Et Autoroutes). (2002). The Design of Interurban Intersections On Major Roads – At-Grade Intersections. SETRA, Bagneux, France.

SETRA–Service d'Etudes Techniques des Routes Et Autoroutes. (1998). The Design of Interurban Intersections On Major Roads: At-Grade Intersections, Bagneux Cedex.

Shadpour, E. (2014). Safety Effects of Roundabouts. MA Wilfrid Laurier University, LCERPA Commentary No, 2.

Smith, D., & Mcintyre, J. (2002). Handbook of Simplified Practice for Traffic Studies (No. Iowa DOT Project TR-455,).

SSATP. Africa Transport Policy Program. 2017 SSATP Annual Meeting. Road Safety. The Case of Addis Ababa. Https://Www.Ssatp.Org/En/Page/2017-Ssatp-Annual-Meeting. (Accessed On 30 Jun, 2017)

Taekratok, T. (1998). Modern Roundabouts for Oregon (No. OR-RD-98-17). Oregon Department of Transportation.

Teklu, B. (2016). Analysis of Impacts of Speed and Traffic Volume at Black Spot Areas: Case of Addis Ababa City (Doctoral Dissertation, Addis Ababa University).

TPMO, Feb 14, 2014. Addis Ababa City Government Transport Programs Management Office. Http://Tpmo.Gov.Et/Node/207 Accessed On Jun 30, 2017

Ter Berg P. (1980). On The Loglinear Poisson and Gamma Model. Astin Bulletin, 11, 35-40.

Train, K. E. (2009). Discrete Choice Methods with Simulation. Cambridge University Press.

Transfund, N. Z. (2000). The Ins and Out of Roundabout: A Safety Auditors' Perspective. Wellington, New Zealand.

Transport Research Board (TRB). (2009). Highway Safety Manual, First Edition. Transport Research Board, 500 Fifth St. NW, Washington, D.C.

TRL. (1993). Overseas Road Note 11- Urban Traffic Surveys, Overseas Centre, Transport Research Laboratory, Crowthorne, Berkshire, United Kingdom.

Tulu, G. S., Et Al. (2013). Why Are Pedestrian Crashes So Different in Developing Countries? A Review of Relevant Factors in Relation to Their Impact in Ethiopia.

Tulu, G. S., Et Al. (2015). Investigating Pedestrian Injury Crashes On Modern Roundabouts in Addis Ababa, Ethiopia. Transportation Research Record: Journal of The TRB, (2512), 1-10.

Tulu, G. S., Et Al. (2016). Injury Severity of Pedestrians Involved in Road Traffic Crashes in Addis Ababa, Ethiopia. Journal of Transportation Safety & Security.

Turner, S. (1996). Estimating Accidents in A Road Network.

Turner, Et Al. (1998). Intersection Accident Estimation: The Role of Intersection Location and Non-Collision Flows. Accident Analysis & Prevention, 30(4), 505-517.

Turner, S., & Roozenburg, A. (2006a). Roundabout Safety–Influence of Speed, Visibility and Design.

Turner, S., Wood, G., & Roozenburg, A. (2006b). Accident Prediction Models for Roundabouts. In Research into Practice: 22nd ARRB Conference.

Txdot. (2008), Manual On Classification of Motor Vehicle Traffic Crashes in Texas, Txdot, Texas.

UNECE. (2009). Illustrated Glossary for Transport Statistics, UNECE.

Yohannes, A. Y. W., & Minale, A. S. (2015). Identifying The Hot Spot Areas of Road Traffic Accidents. Jordan Journal of Civil Engineering, 9(3), 358-370.

APPENDIX A: List of Roundabouts

Table A- 1: List of Roundabouts in Addis Ababa
(Source: Author)

No.	Name	No of Legs	Grade Level	Remark
1	Abinet	5	At-Grade	
2	Abune-Petros	4	Grade-separated	
3	Abware	4	At-Grade	
4	Adisu-Gebeya	4	Grade-separated	
5	Adwa (Giorgis/Wizrol)	4	At-Grade	
6	Afincho-Ber	5	At-Grade	
7	African-Union (AU)	4	At-Grade	
8	Airport	4	At-Grade	
9	Akaki	5	Grade-separated	
10	Alem-Bank Mazorya	5	At-Grade	
11	Ararat	3	At-Grade	
12	Arat-Kilo	4	At-Grade	With elevated Ped. Crossings
13	Asra-Simint-Mazorya	4	At-Grade	Demolished->Signalized
14	Ayat	4	At-Grade	
15	Ayer-Tena	4	At-Grade	
16	Betel (Hospital)	4	At-Grade	
17	Bisrate Gebriel (Laphto Mall)	4	At-Grade	
18	BOLE/Ethio-China	4	Grade-separated	
19	CMC(Tsehay Realestate)	4	At-Grade	
20	Coca-Cola	3	At-Grade	
21	Degol	4	At-Grade	4 in; 3 out (1 is one-way)
22	Diaspora	4	At-Grade	4 in; 3 out
23	Edanamol	5	At-Grade	5 out; 4 in (1 is one-way)
24	Enqulal-Fabrica (Embilta)	4	At-Grade	
25	Ferensay	3	At-Grade	
26	Filweha	4	At-Grade	
27	General Winget	4	Grade-separated	
28	German	4	At-Grade	
29	Gofa-Gebriel	4	At-Grade	
30	Gorgorious	4	Grade-separated	
31	Goro (Sefera)	4	At-Grade	
32	Haile-Garment	4	At-Grade	
33	Haya-Hulet-Mazorya	5	Grade-separated	Modified with railway
34	Imperial	4	At-Grade	Demolished->Signalized
35	Jacros	3	At-Grade	Demolished->Signalized
36	Jan-Meda	4	At-Grade	
37	Jomo	3	At-Grade	
38	Kadisko	4	At-Grade	
39	Kaliti-Maseltegna	4	Grade-separated	
40	Karl	4	At-Grade	
41	Kebena	4	At-Grade	
42	Keranio	3	At-Grade	
43	Kidane-Mehret (Arsema Hotel)	4	At-Grade	
44	Ldeta-Court	4	Grade-separated	Modified with railway
45	Lebu/Mebrat-Hayl	4	At-Grade	Demolished->Signalized
46	Libzig (Abware)	4	At-Grade	
47	Mechanisa-Abo	3	At-Grade	
48	Medanialem-Asko	4	At-Grade	
49	Medanit-Fabrica/Tena Tabya	4	At-Grade	
50	Megenagna	5	Grade-separated	Modified with railway

51	Mexico	6	Grade-separated	
52	Michael Jomo	4	At-Grade	Demolished->Signalized
53	Michael-Bole	4	At-Grade	
54	Michael-Bole-Kelebet	4	At-Grade	Demolished->Signalized
55	Minilik	5	At-Grade	Recently modified
56	Olympia	6	Grade-separated	
57	Pastor	4	At-Grade	(1 leg is not active yet)
58	Qore-Michael	4	At-Grade	
59	Sar-Bet	4	Grade-separated	
60	Saris-Abo	4	At-Grade	
61	Sehalite-Mehret	4	At-Grade	Recently modified with LRT
62	Sheraton	3	At-Grade	
63	Sidistegna-Police-Tabya	3	At-Grade	Local
64	Sidist-Kilo	5	At-Grade	
65	Signal (Adwa)	4	At-Grade	
66	Sumale-Tera	5	At-Grade	
67	Summit-(Young Roots Acad.)	4	At-Grade	
68	Summit-Pepsi	4	At-Grade	
69	Tafo	3	At-Grade	
70	Teklehaimanot	5	At-Grade	
71	Tewodros	5	At-Grade	
72	Tilahun	2	At-Grade	Recently modified with LRT
73	Tor-hayloch	4	At-Grade	
74	Total (Sost kutr mazorya)	3	At-Grade	
75	Urael	4	Grade-separated	Recently modified with LRT
76	Varnero	4	At-Grade	
77	Wollo-Sefer	3	Grade-separated	
78	Yeka-Abado	4	At-Grade	
79	Zenebework(Alert Hospital)	4	At-Grade	

(Source: site survey)

Table A- 2: List of Five-legged Roundabouts in Addis Ababa

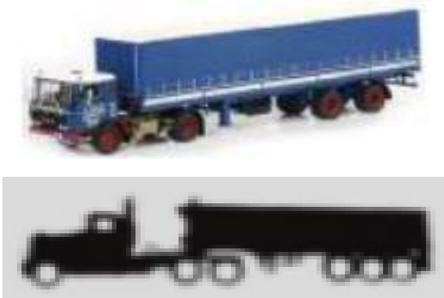
(Source: Author)

S/N	Location (Sub city)	Name of Roundabout	No of Legs	Grade	Remark
1	Lideta	Abinet	5	At-Grade	Selected
2	Arada	Afincho-Ber	5	At-Grade	Selected
3	Arada	Sidist-Kilo	5	At-Grade	Selected
4	Arada	Sumale-Tera	5	At-Grade	Selected
5	Addis Aketema	Teklehaimanot	5	At-Grade	Selected
6	Arada	Tewodros	5	At-Grade	Selected
7	Bole	Bole-Medanialem	5	At-Grade	5 out; 4 in (1 is one-way)
8	Kolfe-Keranyo	Alem-Bank Mazorya	5	At-Grade	New
9	Arada	Minilik	5	At-Grade	Recently modified
10	Yeka	Haya-Hulet-Mazorya	5	Grade separated	Modified with rail
11	Yeka	Megenagna	5	Grade separated	Modified with rail
12	Akaki-Kaliti	Akaki	5	Grade separated	Newly constructed

APPENDIX B: Vehicle Classification

Table B- 1: Vehicle Classification

(Source: ERA Pavement Design Manual, 2002)

Vehicle Code	Type of Vehicle	Description	
1	Small car	Passenger cars, minibuses (up to 24-passenger seats), taxis, pick-ups, and Land Cruisers, Land Rovers, etc	
2	Bus	Medium and large size buses above 24 passenger seats	
3	Medium Truck	Small and medium sized trucks including tankers up to 7 tons load	
4	Heavy Truck	Trucks above 7 tons load	
5	Truck Trailer	Trucks with trailer or semi-trailer and Tanker Trailers	

APPENDIX C: Geometric data Surveys

Table C- 1: Geometric data survey for 'Afincho-Ber' roundabout (Source: Author)

S.N	Parameter	Leg from Shiromeda	Weatherall St (West)	Botswana St	Tenagnework St	Weatherall St (East)
		Leg-1	Leg-2	Leg-3	Leg-4	Leg-5
1	Entry half-roadway width on major road (m)	5	4.5	8	4.5	14
2	No of Entry Lanes	1	1	2	1	3
3	Average Entry Lane Width (m)	5	4.5	4	4.5	3.5
4	Presence of Right-turn Lane (yes=1; no=0)	0	0	0	0	0
5	Presence of Splitter Island (yes=1; no=0)	0	0	0	0	1

Circulating roadway width (m)	14
Diameter of central island (m)	30
Diameter of inscribed circle (m)	58
No of circulating lanes (m)	2

Table C- 2: Geometric data survey for 'Tewodros' roundabout (Source: Author)

S.N	Parameter	Leg from Shiromeda	Weatherall St (West)	Botswana St	Tenagnework St	Weatherall St (East)
		Leg-1	Leg-2	Leg-3	Leg-4	Leg-5
1	Entry half-roadway width on major road (m)	5	4.5	8	4.5	14
2	No of Entry Lanes	1	1	2	1	3
3	Average Entry Lane Width (m)	5	4.5	4	4.5	3.5
4	Presence of Right-turn Lane (yes=1; no=0)	0	0	0	0	0
5	Presence of Splitter Island (yes=1; no=0)	0	0	0	0	1

Circulating roadway width (m)	25
Diameter of central island (m)	38.2
Diameter of inscribed circle (m)	88.2
No of circulating lanes (m)	2

Table C- 3: Geometric data survey for '6-kilo' roundabout (Source: Author)

S.N	Parameter	King George VI St	Russia St	Algeria St	Weatherall St	Tewodros St
		Leg-1	Leg-2	Leg-3	Leg-4	Leg-5
1	Entry half-roadway width on major road (m)	7	6	8	8	3
2	No of Entry Lanes	2	2	2	2	1
3	Average Entry Lane Width (m)	3.5	3	4	4	3
4	Presence of Right-turn Lane (yes=1; no=0)	0	0	0	0	0
5	Presence of Splitter Island (yes=1; no=0)	0	1	0	1	0

Circulating roadway width (m)	25
Diameter of central island (m)	40
Diameter of inscribed circle (m)	101
No of circulating lanes (m)	3

Table C- 4: Geometric data survey for 'Teklehaimanot' roundabout
(Source: Author)

S.N	Parameter	Gobena Aba Tigu St	Tesema Aba Kemaw St (North)	Uganda St	Tesema Aba Kemaw St (South)	Gaston Guez St
		Leg-1	Leg-2	Leg-3	Leg-4	Leg-5
1	Entry half-roadway width on major road (m)	9	10	10	8	9
2	No of Entry Lanes	2	2	2	2	2
3	Average Entry Lane Width (m)	4.5	5	5	4	4.5
4	Presence of Right-turn Lane (yes=1; no=0)	0	0	0	0	1
5	Presence of Splitter Island (yes=1; no=0)	1	1	1	1	1

Circulating roadway width (m)	12
Diameter of central island (m)	76.2
Diameter of inscribed circle (m)	100.2
No of circulating lanes (m)	2

(Source: Author)

Table C- 5: Geometric data survey for 'Abinet' roundabout
(Source: Author)

S.N	Parameter	Uganda St	Dej. Mekonin Demisaw St (North)	Leg from Amanuel Hospital	Dej. Baltcha Abanefso St	Dej. Mekonin Demisaw St (South)
		Leg-1	Leg-2	Leg-3	Leg-4	Leg-5
1	Entry half-roadway width on major road (m)	10	9	4	10	11
2	No of Entry Lanes	2	2	1	2	2
3	Average Entry Lane Width (m)	5	4.5	4	5	5.5
4	Presence of Right-turn Lane (yes=1; no=0)	1	0	0	1	0
5	Presence of Splitter Island (yes=1; no=0)	1	1	1	1	1

Circulating roadway width (m)	10
Diameter of central island (m)	71
Diameter of inscribed circle (m)	91
No of circulating lanes (m)	2

Table C- 6: Geometric data survey for 'Sumale-Tera' roundabout
(Source: Author)

S.N	Parameter	Leg to Arada Bldg	Leg from Kelifa Bldg	Umma Semetar St	Gobena Aba Tigu St	Wawel St
		Leg-1	Leg-2	Leg-3	Leg-4	Leg-5
1	Entry half-roadway width on major road (m)	6	7	5.5	9	5.5
2	No of Entry Lanes	1	1	1	2	1
3	Average Entry Lane Width (m)	6	7	5.5	4.5	5.5
4	Presence of Right-turn Lane (yes=1; no=0)	0	0	0	0	0
5	Presence of Splitter Island (yes=1; no=0)	0	0	0	1	0

Circulating roadway width (m)	14
Diameter of central island (m)	28
Diameter of inscribed circle (m)	54.8
No of circulating lanes (m)	1

APPENDIX D: Traffic Data Analysis

D-1. Analysis of Vehicle Counts

Table D- 1: Analysis of entering vehicle counts for 'Tewodros adebabay' [Churchill Ave -South): approach leg –1, for Day-1& 2 counts] (Source: Author)

Analysis of Vehicle Volume Counts

Location: Tewodros Square

Approach Leg: Curchill Ave(South) **Leg No:** 1

Time	Day-1 Count on 03-05-17 (Wednesday)												Day-2 Count on 04-05-17 (Thursday)												Average Hourly Vol. for Two-days Count PCU/h (V_{PCU})
	Light Vehicle		Heavy Vehicle										Light Vehicle		Heavy Vehicle										
	Motor Bike	Small Car	Bus	Medium Truck	Heavy Truck	Articulated Truck	Total 15 min Flow Rate (V_{15})	Hourly Volume (V)	PHF	f_{HV}	Adjusted 15 min flow rate (PCU/15 min)	Adjusted Demand Volume for Day-1 Count PCU/h	Motor Bike	Small Car	Bus	Medium Truck	Heavy Truck	Articulated Truck	Total 15 min Flow Rate (V_{15})	Hourly Volume (V)	PHF	f_{HV}	Adjusted 15 min flow rate (PCU/15 min)	Adjusted Demand Volume for Day-2 Count PCU/h	
	E_T=0.4	1	2	2	2.5	3							0.4	1	2	2	2.5	3							
7:00 AM - 7:15 AM	2	214	8	8	6	0	238		0.92	0.91	283		2	226	12	3	0	0	243		0.90	0.95	285		
7:15 AM - 7:30 AM	3	216	11	6	1	0	237			0.93	275		3	253	14	4	3	0	277			0.93	330		
7:30 AM - 7:45 AM	3	212	15	9	2	0	241			0.91	288		3	234	13	8	3	0	261			0.92	316		
7:45 AM - 8:00 AM	5	283	13	6	1	0	308	1024		0.95	352	**1198**	5	257	14	7	0	1	284	1065		0.93	337	**1267**	**1233**
8:00 AM - 8:15 AM	6	327	8	8	3	0	352	1138		0.95	399	**1314**	6	267	13	4	3	0	293	1115		0.94	345	**1327**	**1321**
8:15 AM - 8:30 AM	2	280	14	6	1	0	303	1204		0.94	350	**1389**	2	307	11	9	0	0	329	1167		0.95	386	**1383**	**1386**
8:30 AM - 8:45 AM	6	284	7	5	2	0	304	1267		0.96	341	**1443**	6	334	8	4	4	0	356	1262		0.96	411	**1478**	**1460**
8:45 AM - 9:00 AM	7	315	7	5	8	0	342	1301		0.95	392	**1482**	7	356	6	4	2	0	375	1353		0.98	425	**1566**	**1524**
12:00 PM - 12:15 P	2	298	9	19	3	0	331		0.98	0.91	369		2	261	11	9	1	0	284		0.95	0.93	322		
12:15 PM - 12:30 P	6	301	5	24	6	0	342			0.91	383		6	278	9	12	0	1	306			0.94	344		
12:30 PM - 12:45 P	4	300	10	28	3	0	345			0.90	392		4	251	15	9	2	0	281			0.92	323		
12:45 PM - 1:00 PM	6	302	3	23	3	0	337	1355		0.93	371	**1515**	6	263	9	8	0	0	286	1157		0.96	317	**1306**	**1411**
1:00 PM - 1:15 PM	10	259	4	11	5	1	290	1314		0.94	314	**1460**	10	222	14	10	4	0	260	1133		0.92	300	**1285**	**1373**
1:15 PM - 1:30 PM	6	262	10	24	3	0	305	1277		0.90	346	**1423**	6	233	9	9	2	2	261	1088		0.92	299	**1239**	**1331**
1:30 PM - 1:45 PM	6	251	4	17	3	1	282	1214		0.92	312	**1343**	6	241	6	10	5	1	269	1076		0.92	308	**1224**	**1283**
1:45 PM - 2:00 PM	7	251	7	15	1	0	281	1158		0.94	306	**1278**	7	236	5	11	1	0	260	1050		0.95	289	**1196**	**1237**
4:00 PM - 4:15 PM	9	215	5	29	3	0	261		0.95	0.89	311		9	306	4	12	2	0	308		0.98	0.96	329		
4:15 PM - 4:30 PM	6	292	15	21	5	1	340			0.89	404		6	293	12	13	4	1	301			0.91	338		
4:30 PM - 4:45 PM	6	292	13	25	7	0	343			0.88	410		6	304	15	14	6	0	320			0.90	362		
4:45 PM - 5:00 PM	8	308	11	18	4	0	349	1293		0.92	401	**1525**	8	314	12	15	3	0	338	1267		0.93	373	**1402**	**1464**
5:00 PM - 5:15 PM	2	315	9	17	4	2	349	1381		0.91	406	**1620**	2	329	13	13	2	0	339	1298		0.92	375	**1449**	**1534**
5:15 PM - 5:30 PM	10	346	15	12	4	0	387	1428		0.93	437	**1654**	10	337	18	17	5	1	348	1345		0.90	395	**1506**	**1580**
5:30 PM - 5:45 PM	6	348	12	11	3	0	380	1465		0.94	427	**1670**	6	299	19	15	6	0	336	1361		0.90	384	**1527**	**1599**
5:45 PM - 6:00 PM	2	302	18	8	1	0	331	1447		0.93	378	**1647**	2	317	16	12	2	2	329	1352		0.91	371	**1525**	**1586**

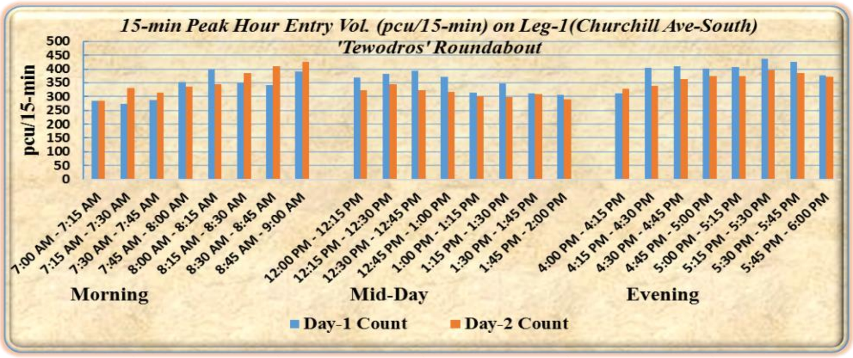


Figure D- 1: Plot showing entering vehicle counts for 'Tewodros adebabay [Churchill Ave –South: approach leg –1 for Day-1 & 2 counts] (Source: Author)

The Total entering volume of vehicles from all approach legs at 'Tewodros' roundabout can be summarized in Figure D- 2 below.

Table D- 2: Summary of average entry traffic volumes at 'Tewodros adebabay' [Average for Day-1 (03-05-17) & Day-2 (04-05-17) counts] (Source: Author)

SUMMARY OF TOTAL ENTERING TRAFFIC FLOWS (pcu/h)							
Location:	'Tewodros' Roundabout						
Time		Tewodros Roundabout					Total entering Vehicles Vol. (ToPHVV) (pcu/h)
		Leg No = 1	2	3	4	5	
		Churchill Ave(South)	Colson St	Mahatma Gandhi St	Curchill Ave(North)	Gaston Guez St	
Morning	7:00 - 8:00 AM	1233	473	498	1276	432	**3911**
	7:15 - 8:15 AM	1321	492	499	1402	474	**4187**
	7:30 - 8:30 AM	1386	539	518	1493	526	**4461**
	7:45 - 8:45 AM	1460	568	574	1528	562	**4692**
	8:00 - 9:00 AM	1524	625	601	1587	546	**4884**
Mid-Day	12:00-1:00 PM	1411	420	394	1126	459	**3810**
	12:15 - 1:15 PM	1373	422	412	1083	467	**3757**
	12:30 - 1:30 PM	1331	443	433	1062	459	**3730**
	12:45 - 1:45 PM	1283	485	413	1012	480	**3672**
	1:00 - 2:00 PM	1237	502	399	1010	453	**3602**
Evening	4:00 - 5:00 PM	1464	503	610	1287	407	**4271**
	4:15 - 5:15 PM	1534	527	605	1316	455	**4437**
	4:30 - 5:30 PM	1580	578	659	1362	505	**4683**
	4:45 - 5:45 PM	1599	622	713	1390	531	**4854**
	5:00 - 6:00 PM	1586	641	720	1457	555	**4959**

The total peak-hour entry traffic at 'Tewodros' roundabout can also be plotted as follows.

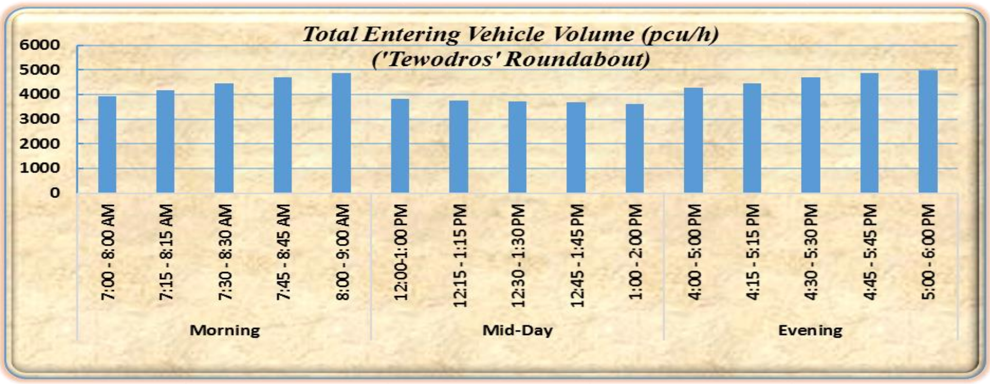


Figure D- 2: Plot of Total entry traffic through all approach legs at 'Tewodros' roundabout

The total entering peak hour vehicle flow (To-PHVV) at ‘Tewodros’ roundabout is found by taking the maximum of the total entering volumes obtained by summing up all entering volumes from all approach legs (see Table D- 2 and Figure D- 2). For example, the To-PHVV for ‘Tewodros’ roundabout is found to be 4959 pcu/h which was identified at 5:00 – 6:00PM. Similarly, the total entering hourly vehicle flows at each roundabout is shown in the following tables (see Table D- 3 through Table D- 7).

Table D- 3: Summary of average entry traffic volumes at ‘Afincho-Ber adebabay’ [Average for Day-1 (26-04-2017) & Day-2 (27-04-2017) counts] (Source: Author)

SUMMARY OF TOTAL ENTERING TRAFFIC FLOWS (pcu/h)							
	Location:	'Afincho Ber' Roundabout					
Time		Afincho-Ber Roundabout					Total entering Vehicles Vol. (ToPHVV) (pcu/h)
		Leg No = 1	2	3	4	5	
		Leg from Shiromeda	Weatherall St (West)	Botswana St	Tenagnework St	Weatherall St (East)	
Morning	7:00 - 8:00 AM	247	163	1119	175	1077	**2781**
	7:15 - 8:15 AM	320	185	1228	192	1180	**3105**
	7:30 - 8:30 AM	368	193	1328	228	1343	**3460**
	7:45 - 8:45 AM	411	207	1330	252	1471	**3670**
	8:00 - 9:00 AM	456	201	1332	262	1625	**3876**
Mid-Day	12:00-1:00 PM	321	190	1371	219	1407	**3507**
	12:15 - 1:15 PM	337	186	1424	217	1392	**3555**
	12:30 - 1:30 PM	336	174	1439	225	1387	**3561**
	12:45 - 1:45 PM	325	167	1443	224	1439	**3598**
	1:00 - 2:00 PM	304	169	1436	226	1436	**3570**
Evening	4:00 - 5:00 PM	290	158	1376	217	1383	**3423**
	4:15 - 5:15 PM	302	164	1400	242	1443	**3551**
	4:30 - 5:30 PM	320	183	1476	247	1506	**3733**
	4:45 - 5:45 PM	335	178	1514	256	1599	**3882**
	5:00 - 6:00 PM	350	170	1556	259	1662	**3998**

Table D- 4: Summary of average entry traffic volumes at ‘6-kilo adebabay’ [Average for Day-1 (10-05-17) & Day-2 (11-05-17) counts]

SUMMARY OF TOTAL ENTERING TRAFFIC FLOWS (pcu/h)							
	Location:	'6 kilo' Roundabout					
Time		6 kilo Roundabout					Total entering Vehicles Vol. (ToPHVV) (pcu/h)
		Leg No = 1	2	3	4	5	
		King George VI St	Russia St	Algeria St	Weatherall St	Tewodros St	
Morning	7:00 - 8:00 AM	872	1229	664	937	106	**3808**
	7:15 - 8:15 AM	919	1437	721	990	115	**4182**
	7:30 - 8:30 AM	912	1631	762	1041	113	**4458**
	7:45 - 8:45 AM	917	1756	792	1065	109	**4639**
	8:00 - 9:00 AM	916	1815	816	1096	112	**4755**
Mid-Day	12:00-1:00 PM	836	1511	646	1005	96	**4094**
	12:15 - 1:15 PM	822	1546	660	1010	100	**4137**
	12:30 - 1:30 PM	799	1594	687	1011	102	**4193**
	12:45 - 1:45 PM	797	1592	682	1024	97	**4192**
	1:00 - 2:00 PM	809	1613	698	1056	100	**4276**
Evening	4:00 - 5:00 PM	973	1541	814	1161	110	**4599**
	4:15 - 5:15 PM	1011	1619	841	1183	113	**4767**
	4:30 - 5:30 PM	1035	1652	867	1195	110	**4859**
	4:45 - 5:45 PM	1096	1666	891	1227	105	**4985**
	5:00 - 6:00 PM	1089	1670	916	1266	98	**5039**

Table D- 5: Summary of av. entry traffic volumes at 'Tekle-Haimanot adebabay'

[Average for Day-1 (17-05-17) & Day-2 (18-05-17) counts] (Source: Author)

SUMMARY OF TOTAL ENTERING TRAFFIC FLOWS (pcu/h)

Location: 'Tekle-Haimanot' Roundabout

Time		Tekle-Haymanot Roundabout					Total entering Vehicles Vol. (ToPHVV) (pcu/h)
		Leg No = 1	2	3	4	5	
		Gobena Aba Tigu St	Tesema Aba Kemaw St (North)	Uganda St	Tesema Aba Kemaw St (South)	Gaston Guez St	
Morning	7:00 - 8:00 AM	610	526	972	952	445	**3504**
	7:15 - 8:15 AM	720	598	1077	1027	460	**3883**
	7:30 - 8:30 AM	818	666	1202	1064	514	**4264**
	7:45 - 8:45 AM	857	777	1299	1148	566	**4647**
	8:00 - 9:00 AM	895	894	1357	1223	604	**4974**
Mid-Day	12:00-1:00 PM	715	729	1374	1028	547	**4393**
	12:15 - 1:15 PM	778	739	1359	986	559	**4421**
	12:30 - 1:30 PM	838	708	1360	955	569	**4429**
	12:45 - 1:45 PM	862	722	1369	992	542	**4487**
	1:00 - 2:00 PM	860	774	1438	1027	519	**4618**
Evening	4:00 - 5:00 PM	818	883	1526	1163	576	**4965**
	4:15 - 5:15 PM	872	908	1478	1138	575	**4971**
	4:30 - 5:30 PM	939	958	1514	1141	598	**5151**
	4:45 - 5:45 PM	1013	1043	1562	1157	621	**5395**
	5:00 - 6:00 PM	1061	1084	1659	1195	646	**5644**

Table D- 6: Summary of average entry traffic volumes at 'Abinet adebabay'

[Average for Day-1 (24-05-17) & Day-2 (25-05-17) counts] (Source: Author)

SUMMARY OF TOTAL ENTERING TRAFFIC FLOWS (pcu/h)

Location: 'Abinet' Roundabout

Time		Abinet Roundabout					Total entering Vehicles Vol. (ToPHVV) (pcu/h)
		Leg No = 1	2	3	4	5	
		Uganda St	Dej. Mekonin Demisaw St (North)	Leg from Amanuel Hospital	Dej. Baltcha Abanefso St	Dej. Mekonin Demisaw St (South)	
Morning	7:00 - 8:00 AM	639	836	39	1101	723	**3338**
	7:15 - 8:15 AM	736	914	46	1197	839	**3732**
	7:30 - 8:30 AM	821	987	52	1289	932	**4080**
	7:45 - 8:45 AM	903	1063	57	1323	969	**4315**
	8:00 - 9:00 AM	952	1112	63	1296	938	**4362**
Mid-Day	12:00-1:00 PM	834	1035	49	1099	894	**3912**
	12:15 - 1:15 PM	832	1042	53	1069	931	**3926**
	12:30 - 1:30 PM	850	1051	54	1074	926	**3954**
	12:45 - 1:45 PM	886	1020	54	1074	914	**3947**
	1:00 - 2:00 PM	932	1000	50	1111	876	**3970**
Evening	4:00 - 5:00 PM	1012	1125	46	1187	978	**4349**
	4:15 - 5:15 PM	1026	1192	47	1237	1042	**4544**
	4:30 - 5:30 PM	1060	1213	47	1280	1073	**4673**
	4:45 - 5:45 PM	1091	1230	53	1307	1065	**4746**
	5:00 - 6:00 PM	1108	1230	52	1312	1032	**4734**

Table D- 7: Summary of entry traffic volumes at ‘Sumale-Tera adebabay’

[Average for Day-1 (31-05-17) & Day-2 (01-06-17) counts] (Source: Author)

SUMMARY OF TOTAL ENTERING TRAFFIC FLOWS (pcu/h)

Location: 'Sumale-Tera' Roundabout

	Time	Sumale-Tera Roundabout					Total entering Vehicles Vol. (ToPHVV) (pcu/h)
		Leg No = 1	2	3	4	5	
		Leg to Arada Bldg	Leg from Kelifa Bldg	Umma Semetar St	Gobena Aba Tigu St	Wawel St	
Morning	7:00 - 8:00 AM	544	232	600	737	533	**2645**
	7:15 - 8:15 AM	575	248	617	735	581	**2757**
	7:30 - 8:30 AM	602	266	640	739	615	**2862**
	7:45 - 8:45 AM	614	280	653	748	645	**2940**
	8:00 - 9:00 AM	639	304	682	760	665	**3051**
Mid-Day	12:00-1:00 PM	550	366	745	788	644	**3092**
	12:15 - 1:15 PM	566	352	730	839	656	**3143**
	12:30 - 1:30 PM	571	354	722	883	754	**3284**
	12:45 - 1:45 PM	597	354	718	910	757	**3336**
	1:00 - 2:00 PM	622	353	717	935	743	**3371**
Evening	4:00 - 5:00 PM	718	337	785	997	880	**3716**
	4:15 - 5:15 PM	749	333	789	1031	883	**3786**
	4:30 - 5:30 PM	773	347	801	1070	881	**3872**
	4:45 - 5:45 PM	819	363	798	1086	894	**3959**
	5:00 - 6:00 PM	835	387	784	1106	903	**4015**

C-2. Analysis of Pedestrian Crossing Counts

For illustration purposes the *Churchill Ave* (South) approach leg of ‘Tewodros’ roundabout is assumed in Table D- 8 & Table D- 9, and it can easily be observed that the peak hour pedestrian crossing volume is 391 ped/h observed at 5:00 – 6:00PM.

Table D- 8: Analysis of pedestrian crossing volume counts for ‘Tewodros adebabay’ [Churchill Ave (South) approach leg –1, for Days-1 & 2 counts] (Source: Author)

Analysis of Pedestrian Volume Counts

Location: Tewodros Square **Leg No:** 1

Approach Leg: Churchill Ave(South)

	Time	Day-1 Count on 03-05-17 (Wednesday)								Day-2 Count on 04-05-17 (Thursday)								Average Hourly Volume (Ped/h)
		Male	Female	Children <12 yrs	Total 15 min Vol (PV_{15})	Hourly Volume (Ped/h)	PHF	Adjusted 15 min flow rate (PCU/15 min)	Adjusted hourly Volume for Day-1 Count Ped/h	Male	Female	Children <12 yrs	Total 15 min Vol (PV15)	Hourly Volume (Ped/h)	PHF	Adjusted 15 min flow rate (PCU/15 min)	Adjusted hourly Volume for Day-2 Count Ped/h	
Morning	7:00 - 7:15 AM	27	14	14	55		0.94	59		19	16	10	45		0.86	52		
	7:15 - 7:30 AM	26	21	16	63			67		22	20	18	60			70		
	7:30 - 7:45 AM	21	27	29	77			82		33	25	22	80			93		
	7:45 - 8:00 AM	40	31	20	91	286		97	**305**	27	21	22	70	255		81	**297**	**301**
	8:00 - 8:15 AM	37	39	17	93	324		99	**345**	36	19	12	67	277		78	**322**	**334**
	8:15 - 8:30 AM	36	34	15	85	346		91	**369**	53	25	11	89	306		104	**356**	**362**
	8:30 - 8:45 AM	50	20	10	80	349		85	**372**	33	24	7	64	290		74	**337**	**355**
	8:45 - 9:00 AM	39	18	9	66	324		70	**345**	48	18	10	76	296		88	**344**	**345**
Mid-Day	12:00-12:15 PM	32	19	7	58		0.89	65		35	24	7	66		0.92	72		
	12:15-12:30 PM	40	14	5	60			67		40	41	4	85			93		
	12:30-12:45 PM	33	22	8	63			71		33	35	10	78			85		
	12:45-1:00 PM	37	21	7	65	246		73	**276**	38	31	8	77	307		84	**334**	**305**
	1:00 - 1:15 PM	29	29	4	62	251		70	**281**	44	35	11	90	331		98	**360**	**321**
	1:15 - 1:30 PM	26	26	8	60	251		67	**281**	32	39	14	84	330		92	**359**	**320**
	1:30 - 1:45 PM	37	32	6	75	262		84	**294**	42	19	11	73	324		79	**353**	**324**
	1:45 - 2:00 PM	37	31	8	77	274		86	**307**	36	18	10	64	311		70	**339**	**323**
Evening	4:00 - 4:15 PM	21	32	24	77		0.95	81		44	17	22	83		0.91	91		
	4:15 - 4:30 PM	19	29	21	69			73		47	20	26	93			102		
	4:30 - 4:45 PM	22	40	21	82			87		36	32	32	100			109		
	4:45 - 5:00 PM	27	37	18	81	310		86	**327**	26	24	38	88	363		96	**398**	**363**
	5:00 - 5:15 PM	45	36	19	100	333		106	**352**	33	26	22	80	361		88	**395**	**374**
	5:15 - 5:30 PM	43	35	14	92	356		97	**376**	47	28	16	91	359		100	**393**	**385**
	5:30 - 5:45 PM	53	39	11	103	377		109	**398**	36	30	20	86	345		94	**378**	**388**
	5:45 - 6:00 PM	40	46	9	96	391		101	**413**	35	22	22	79	336		86	**368**	**391**

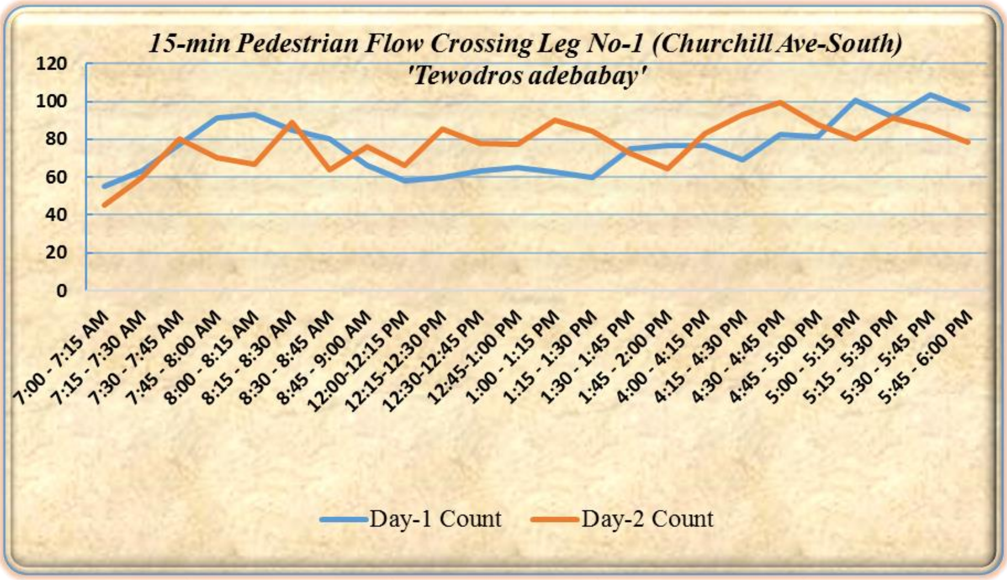


Figure D- 3: Plot of 15-min pedestrian crossing volume at 'Tewodros adebabay'
[Churchill Ave (South) approach leg –1 for Days-1 & 2 counts]

The total hourly pedestrian crossing volumes through each approach leg at 'Tewodros' roundabout can be summarized in the table below.

Table D- 9: Summary of avg. hourly ped. crossing vol. at 'Tewodros Adebabay'
[Average for Day-1 (03-05-2017) & Day-2 (04-05-2017) counts] (Source: Author)

Summary of Average Hourly Pedestrian Crossing Volume Counts (Ped/h)

Location: Tewodros' Roundabout

Time		Tewodros Roundabout					Total hourly Ped Vol (ped/h)
		Leg No = 1	2	3	4	5	
		Churchill Ave(South)	Colson St	Mahatma Gandhi St	Curchill Ave(North)	Gaston Guez St	
Morning	7:00 - 8:00 AM	301	211	236	165	267	**1179**
	7:15 - 8:15 AM	334	235	271	190	305	**1334**
	7:30 - 8:30 AM	363	246	288	205	331	**1432**
	7:45 - 8:45 AM	355	261	268	198	336	**1416**
	8:00 - 9:00 AM	345	257	237	173	337	**1348**
Mid-Day	12:00-1:00 PM	305	222	187	121	268	**1103**
	12:15 - 1:15 PM	321	235	192	116	273	**1136**
	12:30 - 1:30 PM	320	233	185	113	272	**1122**
	12:45 - 1:45 PM	324	233	187	113	282	**1138**
	1:00 - 2:00 PM	323	237	186	106	291	**1142**
Evening	4:00 - 5:00 PM	363	296	262	164	344	**1428**
	4:15 - 5:15 PM	374	292	284	176	349	**1475**
	4:30 - 5:30 PM	385	290	311	197	348	**1529**
	4:45 - 5:45 PM	388	283	336	214	342	**1562**
	5:00 - 6:00 PM	391	289	329	217	343	**1568**

The total hourly pedestrian crossing volume through each approach leg can also be plotted as follows.

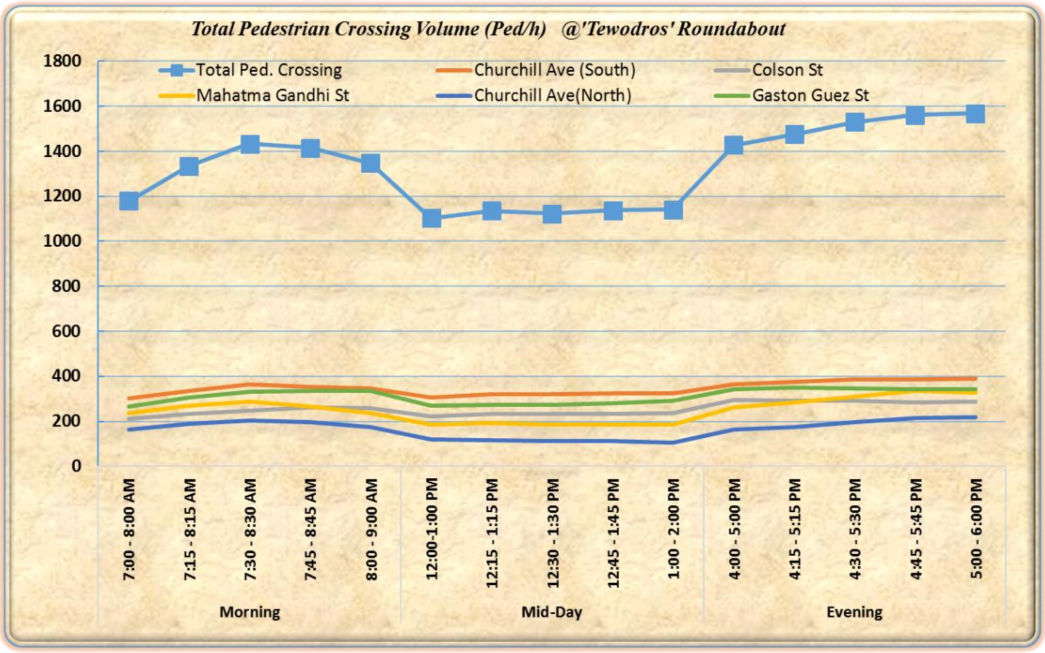


Figure D- 4: Plot of total hourly pedestrian crossing volumes at 'Tewodros adebabay'

The total peak hour pedestrian crossing volume (To-PHPV) at 'Tewodros' roundabout is found by taking the maximum of the total pedestrian crossing volumes obtained by summing up all crossing volumes at all approach legs (see Table D- 9 and Figure D- 4). For example, the To-PHPV for 'Tewodros' roundabout is found to be 1568 ped/h which was identified at 5:00 – 6:00PM. Similarly, the total entering hourly vehicle flows at each roundabout is shown in the following tables (see Table D- 10 through Table D- 14).

Table D- 10: Summary of avg. ped. crossing vol. at 'Afincho-Ber adebabay'

[Average for Day-1 (26-04-2017) & Day-2 (27-04-2017) counts] (Source: Author)

Summary of Average Hourly Pedestrian Crossing Volume Counts (Ped/h)							
Location: Afincho-Ber' Roundabout							
Time		Afincho-Ber Roundabout					Total hourly Ped Vol (ped/h)
		Leg No = 1	2	3	4	5	
		Leg from Shiromeda	Weatherall St (West)	Botswana St	Tenagnework St	Weatherall St (East)	
Morning	7:00 - 8:00 AM	189	182	153	117	121	**760**
	7:15 - 8:15 AM	214	210	156	133	140	**852**
	7:30 - 8:30 AM	229	238	159	142	159	**927**
	7:45 - 8:45 AM	222	232	160	145	175	**932**
	8:00 - 9:00 AM	197	230	169	130	166	**891**
Mid-Day	12:00-1:00 PM	145	150	182	107	112	**695**
	12:15 - 1:15 PM	140	165	170	106	111	**691**
	12:30 - 1:30 PM	137	156	166	100	107	**665**
	12:45 - 1:45 PM	137	163	162	97	104	**663**
	1:00 - 2:00 PM	130	163	157	90	100	**639**
Evening	4:00 - 5:00 PM	188	158	176	136	141	**798**
	4:15 - 5:15 PM	200	163	199	147	156	**865**
	4:30 - 5:30 PM	221	176	215	160	170	**941**
	4:45 - 5:45 PM	238	178	211	176	184	**986**
	5:00 - 6:00 PM	241	181	215	178	189	**1003**

Table D- 11: Summary of avg. ped. crossing volumes at '6-kilo adebabay'

[Average for Day-1 (10-05-17) & Day-2 (11-05-17) counts] (Source: Author)

Summary of Average Hourly Pedestrian Crossing Volume Counts (Ped/h)

Location: '6 kilo' Roundabout

	Time	6 Kilo Roundabout					Total hourly Ped Vol (ped/h)
		Leg No = 1	2	3	4	5	
		King George VI St	Russia St	Algeria St	Weatherall St	Tewodros St	
Morning	7:00 - 8:00 AM	883	697	472	862	732	**3645**
	7:15 - 8:15 AM	932	772	525	879	789	**3895**
	7:30 - 8:30 AM	935	800	547	866	783	**3930**
	7:45 - 8:45 AM	987	787	559	907	791	**4030**
	8:00 - 9:00 AM	1016	742	551	922	747	**3977**
Mid-Day	12:00-1:00 PM	904	837	432	812	769	**3753**
	12:15 - 1:15 PM	936	841	450	843	814	**3883**
	12:30 - 1:30 PM	997	841	447	908	822	**4013**
	12:45 - 1:45 PM	1008	874	442	913	858	**4094**
	1:00 - 2:00 PM	1005	870	451	912	852	**4089**
Evening	4:00 - 5:00 PM	1121	813	414	874	914	**4136**
	4:15 - 5:15 PM	1117	856	438	912	989	**4312**
	4:30 - 5:30 PM	1083	877	454	912	1030	**4354**
	4:45 - 5:45 PM	1079	888	456	930	1043	**4395**
	5:00 - 6:00 PM	1101	890	466	967	1032	**4455**

Table D- 12: Summary of avg. ped. crossing vol. at 'Tekle-Haimanot adebabay'

[Average for Day-1 (17-05-17) & Day-2 (18-05-17) counts] (Source: Author)

Summary of Average Hourly Pedestrian Crossing Volume Counts (Ped/h)

Location: 'Tekle-Haimanot' Roundabout

	Time	Tekle-Haymanot Roundabout					Total hourly Ped Vol (ped/h)
		Leg No = 1	2	3	4	5	
		Gobena Aba Tigu St	Tesema Aba Kemaw St (North)	Uganda St	Tesema Aba Kemaw St (South)	Gaston Guez St	
Morning	7:00 - 8:00 AM	1535	354	832	897	564	**4181**
	7:15 - 8:15 AM	1666	380	886	946	595	**4471**
	7:30 - 8:30 AM	1740	409	918	995	622	**4683**
	7:45 - 8:45 AM	1818	404	951	1029	648	**4850**
	8:00 - 9:00 AM	1910	421	974	1047	666	**5017**
Mid-Day	12:00-1:00 PM	1753	500	935	998	675	**4860**
	12:15 - 1:15 PM	1832	501	924	1007	694	**4957**
	12:30 - 1:30 PM	1846	533	939	1022	669	**5008**
	12:45 - 1:45 PM	1788	571	1024	1107	633	**5122**
	1:00 - 2:00 PM	1740	604	995	1108	623	**5068**
Evening	4:00 - 5:00 PM	1948	611	1134	1192	871	**5756**
	4:15 - 5:15 PM	1992	630	1138	1196	869	**5824**
	4:30 - 5:30 PM	2020	643	1157	1215	839	**5873**
	4:45 - 5:45 PM	2077	650	1199	1257	834	**6015**
	5:00 - 6:00 PM	2118	651	1209	1267	849	**6094**

Table D- 13: Summary of avg. ped. crossing vol. at 'Abinet adebabay'

[Average for Day-1 (24-05-17) & Day-2 (25-05-17) counts] (Source: Author)

Summary of Average Hourly Pedestrian Crossing Volume Counts (Ped/h)							
	Location:	Abinet' Roundabout					
		Abinet Roundabout					Total hourly Ped Vol (ped/h)
	Time	Leg No = 1	2	3	4	5	
		Uganda St	Dej. Mekonin Demisaw St (North)	Leg from Amanuel Hospital	Dej. Baltcha Abanefso St	Dej. Mekonin Demisaw St (South)	
Morning	7:00 - 8:00 AM	850	617	529	394	515	**2904**
	7:15 - 8:15 AM	961	680	576	448	593	**3257**
	7:30 - 8:30 AM	997	702	599	475	611	**3383**
	7:45 - 8:45 AM	969	722	634	501	616	**3441**
	8:00 - 9:00 AM	902	703	644	484	602	**3334**
Mid-Day	12:00-1:00 PM	848	769	628	428	588	**3260**
	12:15 - 1:15 PM	849	769	674	471	599	**3360**
	12:30 - 1:30 PM	857	739	683	483	609	**3371**
	12:45 - 1:45 PM	952	703	670	487	607	**3418**
	1:00 - 2:00 PM	957	674	657	481	583	**3350**
Evening	4:00 - 5:00 PM	972	756	643	419	713	**3501**
	4:15 - 5:15 PM	974	767	627	444	706	**3518**
	4:30 - 5:30 PM	1007	783	677	470	739	**3676**
	4:45 - 5:45 PM	1022	760	695	482	756	**3715**
	5:00 - 6:00 PM	1067	737	694	481	785	**3762**

Table D- 14: Summary of avg. ped. Crossing vol. at 'Sumale-Tera adebabay'

[Average for Day-1 (31-05-17) & Day-2 (01-06-17) counts] (Source: Author)

Summary of Average Hourly Pedestrian Crossing Volume Counts (Ped/h)							
	Location:	Sumale-Tera' Roundabout					
		Sumale-Tera Roundabout					Total hourly Ped Vol (ped/h)
	Time	Leg No = 1	2	3	4	5	
		Leg to Arada Bldg	Leg from Kelifa Bldg	Umma Semetar St	Gobena Aba Tigu St	Wawel St	
Morning	7:00 - 8:00 AM	589	726	495	557	498	**2865**
	7:15 - 8:15 AM	648	815	537	552	482	**3033**
	7:30 - 8:30 AM	668	854	550	582	505	**3158**
	7:45 - 8:45 AM	687	848	575	591	511	**3211**
	8:00 - 9:00 AM	680	796	585	593	510	**3163**
Mid-Day	12:00-1:00 PM	747	802	594	579	474	**3195**
	12:15 - 1:15 PM	753	795	640	616	528	**3331**
	12:30 - 1:30 PM	749	770	649	625	537	**3330**
	12:45 - 1:45 PM	718	806	636	612	535	**3306**
	1:00 - 2:00 PM	696	802	623	604	521	**3245**
Evening	4:00 - 5:00 PM	754	821	604	465	406	**3049**
	4:15 - 5:15 PM	765	802	593	499	441	**3100**
	4:30 - 5:30 PM	778	808	627	515	454	**3181**
	4:45 - 5:45 PM	756	820	635	541	478	**3229**
	5:00 - 6:00 PM	738	826	634	551	487	**3234**

D-3. Analysis of Spot Speed Measurements

For illustration purposes, the Spot Speed measurements at 'Tewodros' Roundabout can be computed as follows, for Major Approach Leg: Leg-1 → *Churchill Ave*(South).

Table D- 15: Frequency distribution Table for major approach leg

['Tewodros Adebabay': Churchill Ave-South] (Source: Author)

Frequency Distribution Table for Stopwatch Spot Speed Study				
Location	Tewodros adebabay'		Date	12-08-17
Approach Leg	Leg-1 (Churchill Ave-South)		Time	7:00-10:00 AM
RDWY Surface Conditi	Asphaltic Concrete		Weather	Sunny
Speed (kph)	**Frequency of Vehicles**	**Cumulative Frequency**	**Cumulative Percent (%)**	**Speed Percentile**
16.2	1	1	0.95	
16.8	0	1	0.95	
17.4	1	2	1.90	
18.0	0	2	1.90	
18.7	2	4	3.81	
19.4	1	5	4.76	
20.3	2	7	6.67	
21.1	2	9	8.57	
22.1	5	14	13.33	
23.1	4	18	17.14	
24.3	5	23	21.90	
25.6	5	28	26.67	
27.0	13	41	39.05	
28.6	6	47	44.76	
30.4	5	52	49.52	**50th**
32.4	11	63	60.00	
34.7	13	76	72.38	
37.4	10	86	81.90	**85th**
40.5	6	92	87.62	
44.2	11	103	98.10	
48.6	0	103	98.10	
54.0	2	105	100.00	
Sample size	105			

The frequency distribution table shows that the 50th percentile or median speed falls between 30.4 kph and 32.4 kph, and the 85th percentile of speed falls between 37.4 kph and 40.5 kph. The exact speeds for the 50th and 85th percentiles of speed can be interpolated as follows:

$$S_D = \frac{P_D - P_{min}}{P_{max} - P_{min}} \ (S_{max} - S_{min}) + S_{min} \qquad (5\text{-}1)$$

Therefore,

- The median speed (50th percent of observed vehicle speed): -

P_D = 50%; P_{max} = 60.00%; P_{min} = 49.52%; S_{max} = 32.4 kph; S_{min} = 30.4 kph

Then, the desired 50th percentile speed is computed as:

$$S_{50} = \frac{50\% - 30.4\%}{60.00\% - 30.4\%}(32.4kph - 30.4kph) + 30.4kph = \underline{30.5\ kph}$$

- The 85th percentile of observed speed: -

$P_D = 85\%$; $P_{max} = 87.62\ \%$; $P_{min} = 81.90\%$; $S_{max} = 40.5$ kph; $S_{min} = 37.4$ kph

Then the desired 50th percentile speed is computed as:

$$S_{85} = \frac{85\% - 81.90\%}{87.62\% - 81.90\%}(40.5kph - 37.4kph) + 37.4kph = \underline{39.1\ kph}$$

Alternatively, the desired 50th and 85th percentile speeds can be obtained from the plot of vehicles observed speed versus cumulative frequencies as shown in the following chart.

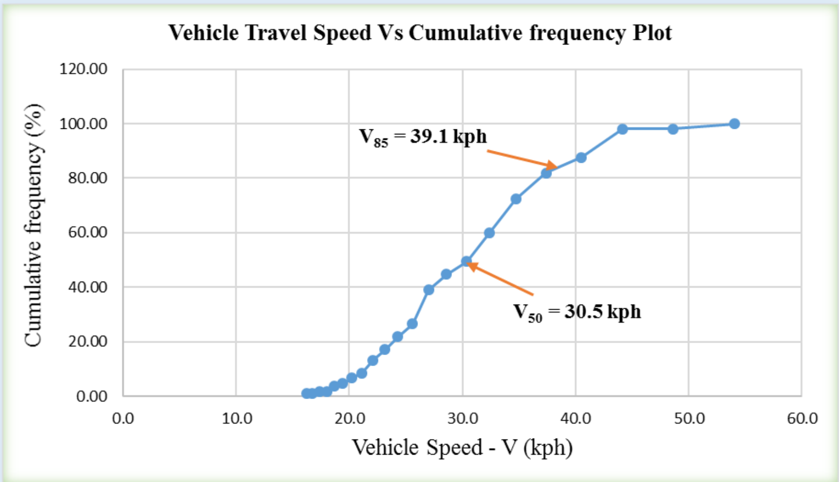


Figure D- 5: Speed Vs Cumulative Frequency Plot for Major-approach Leg

[‘Tewodros’ Roundabout: Leg-1 → Churchill Ave-South)]

Generally, the spot speed measurements for the sample roundabouts are summarized in the Table D- 16 below.

Table D- 16: Summary of spot-speed measurements (Source: Author)

S/N	Roundabout Name	Approach Leg	Name	Leg No.	Sampling Date	Sampling Time	Observed Speed for entering vehicles	
							50th percentile	85th percentile
1	Afincho Ber	Major	Weatherall St (East)	5	26-04-17	9:00-12:00AM	38.1	46.3
		Minor	Weatherall St (West)	2	26-04-17	9:00-12:00AM	15.5	18.5
2	Tewodros	Major	Churchill Ave(South)	1	03-05-17	9:00-12:00AM	30.5	39.1
		Minor	Gaston Guez St	5	03-05-17	9:00-12:00AM	41.1	52.2
3	6 kilo	Major	Russia St	2	10-05-17	9:00-12:00AM	23.5	29.1
		Minor	Tewodros St	5	10-05-17	9:00-12:00AM	17.8	20.4
4	Teklehaymanot	Major	Uganda St	3	17-05-17	9:00-12:00AM	34.9	41.7
		Minor	Gaston Guez St	5	17-05-17	9:00-12:00AM	29.7	33.6
5	Abinet	Major	Dej. Baltcha Abanefso St	4	24-05-17	9:00-12:00AM	26.8	34.2
		Minor	Leg from Amanuel Hospital	3	24-05-17	9:00-12:00AM	12.9	14.5
6	Sumale Tera	Major	Gobena Aba Tigu St	4	31-05-17	9:00-12:00AM	22.3	27.7
		Minor	Leg from Kelifa Bldg	2	31-05-17	9:00-12:00AM	19.4	25.1

APPENDIX E: Explanatory Variables

Table E- 1: Descriptive statistics of all candidate explanatory variables (Source: Author)

Variables	Description of variables	Roundabout						Statistical measures				
		Afincho-Ber	Tewodros	Sidist-Kilo	Tekle-Haimanot	Abinet	Sumale-Tera	N	Min	Max	Mean	Variance
Independent variables												
Traffic Variables												
Log-of-ToPHVV	Logarithm of Total Peak Hour Vehicle Volume entering the roundabout (all legs) (ped/h)	8.29	8.51	8.52	8.64	8.47	8.30	6	8.29	8.64	8.45	0.018
Log-of-PHVV-MAJ	Logarith of Peak Hour Vehicle entry Volume on major road	7.42	7.38	7.50	7.41	7.19	7.01	6	7.01	7.50	7.32	0.034
Log-of-PHVV-MIN	Logarithm of Peak Hour Vehicle Volume on minor road	6.16	6.33	4.75	6.47	4.14	5.96	6	4.14	6.47	5.63	0.915
To-PHPV	Total Peak Hour Pedestrian Volume crossing the roundabout (all legs) (ped/h)	1003	1568	4455	6094	3762	3331	6	1003.0	6093.5	3368.6	3520092.1
PHPV-MAJ	Peak Hour Pedestrian Volume crossing the major road (ped/h)	189	391	890	1209	501	625	6	189.0	1209.0	633.9	134225.1
PHPV-MIN	Peak Hour Pedestrian Volume crossing the minor road (ped/h)	238	349	1043	871	695	854	6	237.5	1043.0	674.8	100717.7
V85-MAJ	85th percentile Speed on major road (kph)	46.3	39.1	29.1	41.7	34.2	27.7	6	27.7	46.30	36.35	53.44
V85-MIN	85th percentile Speed on minor road (kph)	18.5	52.2	20.4	33.6	14.5	25.1	6	14.5	52.20	27.38	190.68
Geometric Variables												
En-RW-MAJ	Entry half-roadway width on major road (m)	14.0	12.0	9.0	10.0	10.0	9.0	6	9.0	14.0	10.67	3.87
En-RW-MIN	Entry half-roadway width on minor road (m)	4.5	8.2	3.0	9.0	4.0	7.0	6	3.0	9.0	5.95	6.01
DCI	Diameter of central island (m)	30.0	38.2	40.0	76.2	71.0	28.0	6	28.0	76.2	47.23	440.95
DIC	Diameter of inscribed circle (m)	58.0	88.2	101.0	100.2	91.0	54.8	6	54.8	101.0	82.20	425.46
CRWW	Circulating roadway width (m)	14.0	25.0	25.0	12.0	10.0	14.0	6	10.0	25.0	16.67	43.87
Sp-MIN	Presence of Splitter island on minor road? (Yes=1; No=0)	0	1	0	1	0	0	6	0	1	0.33	0.27
R-PHVV-MAJ-to-MIN	Ratio of major to minor approach leg peak hour entry vehicle volume	3.52	2.85	15.78	2.57	20.98	2.86	6	2.57	20.98	8.09	66.31
R-PHPV-MAJ-to-MIN	Ratio of major to minor approach leg peak hour pedestrian crossing volume	0.80	1.12	0.85	1.39	0.72	0.73	6	0.72	1.39	0.93	0.07
R-V85-MAJ-to-MIN	Ratio of major to minor approach 85^{th} percentile spot speed	2.50	0.75	1.43	1.24	2.36	1.10	6	0.75	2.50	1.56	0.50
R-EnRW-MAJ-to-MIN	Ratio of major to minor Entry/approach half-road way width	3.11	1.46	3.00	1.11	2.50	1.29	6	1.11	3.11	2.08	0.81
R-DIC-to-DCI	Ratio of Diameter of inscribed circle (DIC) to Diameter of central island (DCI)	1.93	2.31	2.53	1.31	1.28	1.96	6	1.28	2.53	1.89	0.26

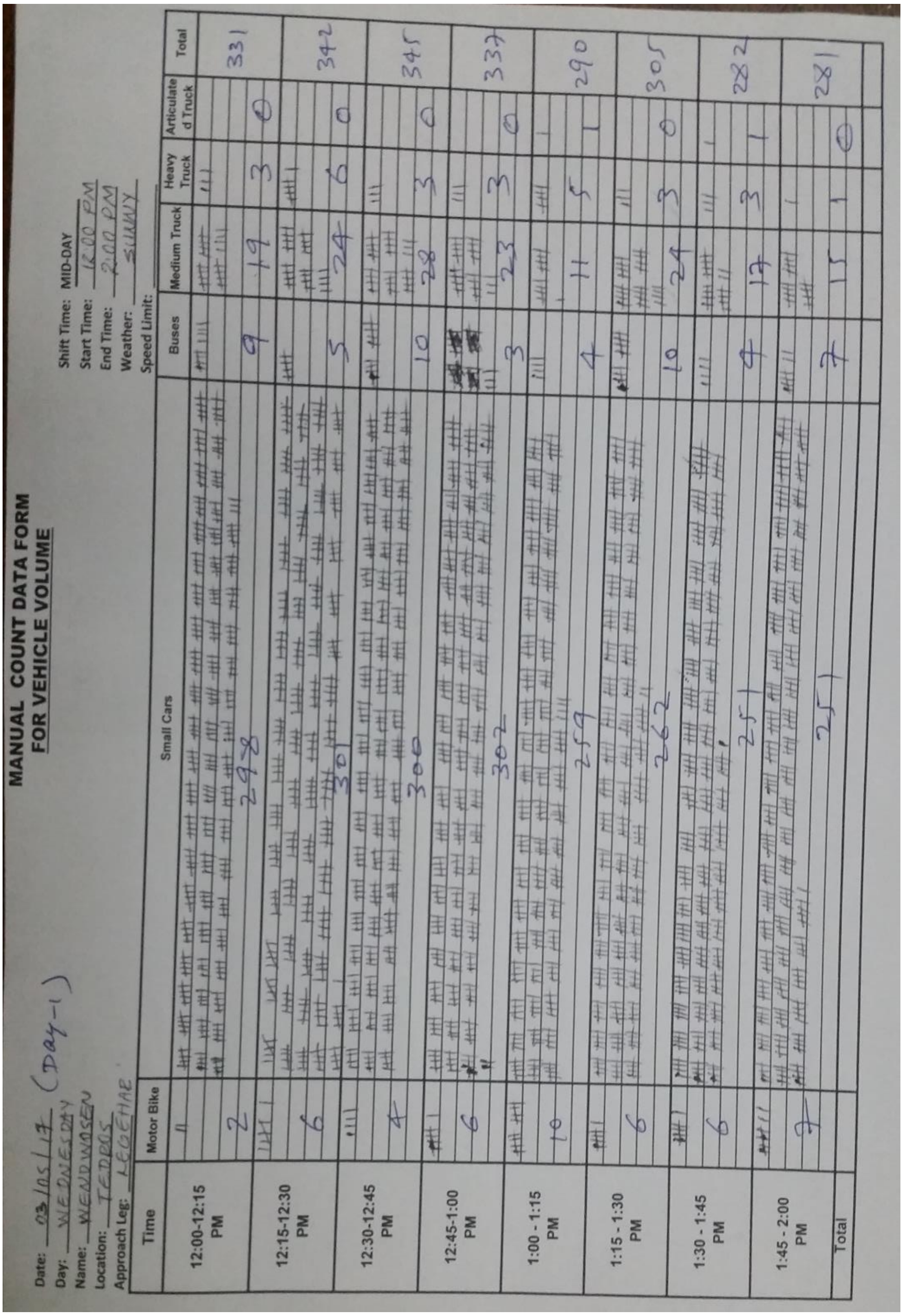
Table E- 2: Bivariate Correlation results of all candidate explanatory variables

(Source: Author)

		LogofToPHVV	LogofPHVVMAJ	LogofPHVVMIN	ToPHPV	PHPVMAJ	PHPVMIN	V85MAJ	V85MIN	EnRWMAJ	EnRWMIN	DCI	DIC	CRWW	SpMIN	RPHVVMAJtoMIN	RPHVPMAJtoMIN	RV85MAJtoMIN	REnRWMAJtoMIN	RDICtoDCI
LogofToPHVV	Pearson Correlation	1	.491	-.037	.686	.731	.402	.068	.392	-.343	.325	.739	.943**	.197	.682	.171	.769	-.381	-.318	-.199
	Sig. (2-tailed)		.322	.944	.132	.099	.430	.899	.442	.505	.530	.094	.005	.708	.136	.746	.074	.456	.539	.705
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
LogofPHVVMAJ	Pearson Correlation	.491	1	.118	.033	.176	-.129	.494	.181	.365	-.151	.100	.546	.497	.325	.008	.471	.049	.407	.321
	Sig. (2-tailed)	.322		.823	.950	.739	.807	.320	.731	.476	.775	.851	.262	.316	.530	.988	.346	.926	.423	.535
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
LogofPHVVMIN	Pearson Correlation	-.037	.118	1	-.198	.027	-.388	.527	.643	.430	.785	-.264	-.326	.070	.619	-.986**	.602	-.462	-.558	.081
	Sig. (2-tailed)	.944	.823		.707	.960	.447	.283	.169	.394	.064	.613	.528	.895	.190	.000	.206	.356	.250	.879
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
ToPHPV	Pearson Correlation	.686	.033	-.198	1	.955**	.859*	-.325	-.149	-.765	.160	.701	.622	-.240	.191	.246	.423	-.218	-.329	-.414
	Sig. (2-tailed)	.132	.950	.707		.003	.029	.529	.778	.076	.762	.120	.187	.648	.717	.638	.403	.679	.525	.415
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
PHPVMAJ	Pearson Correlation	.731	.176	.027	.955**	1	.819*	-.262	.057	-.698	.300	.564	.623	-.039	.351	.029	.585	-.417	-.413	-.224
	Sig. (2-tailed)	.099	.739	.960	.003		.046	.616	.914	.123	.564	.244	.186	.941	.496	.956	.223	.411	.416	.670
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
PHPVMIN	Pearson Correlation	.402	-.129	-.388	.859*	.819*	1	-.729	-.284	-.945**	-.113	.316	.438	-.001	-.159	.370	.037	-.288	-.163	-.040
	Sig. (2-tailed)	.430	.807	.447	.029	.046		.100	.585	.005	.832	.542	.385	.999	.764	.471	.945	.580	.757	.940
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
V85MAJ	Pearson Correlation	.068	.494	.527	-.325	-.262	-.729	1	.220	.851*	.274	.165	-.061	-.213	.429	-.429	.457	.333	.080	-.294
	Sig. (2-tailed)	.899	.320	.283	.529	.616	.100		.675	.031	.599	.755	.908	.685	.396	.396	.362	.519	.881	.572
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
V85MIN	Pearson Correlation	.392	.181	.643	-.149	.057	-.284	.220	1	.172	.774	-.071	.206	.514	.870*	-.590	.677	-.793	-.655	.275
	Sig. (2-tailed)	.442	.731	.169	.778	.914	.585	.675		.744	.071	.894	.695	.296	.024	.218	.140	.060	.158	.598
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
EnRWMAJ	Pearson Correlation	-.343	.365	.430	-.765	-.698	-.945**	.851*	.172	1	.025	-.293	-.376	.005	.131	-.390	.046	.390	.312	.060
	Sig. (2-tailed)	.505	.476	.394	.076	.123	.005	.031	.744		.963	.573	.463	.992	.804	.444	.931	.445	.547	.909
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
EnRWMIN	Pearson Correlation	.325	-.151	.785	.160	.300	-.113	.274	.774	.025	1	.186	.008	-.074	.837*	-.754	.751	-.670	-.927**	-.241
	Sig. (2-tailed)	.530	.775	.064	.762	.564	.832	.599	.071	.963		.725	.988	.889	.038	.083	.085	.145	.008	.646
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
DCI	Pearson Correlation	.739	.100	-.264	.701	.564	.316	.165	-.071	-.293	.186	1	.685	-.477	.368	.371	.475	.143	-.230	-.780
	Sig. (2-tailed)	.094	.851	.613	.120	.244	.542	.755	.894	.573	.725		.133	.338	.473	.468	.341	.787	.661	.067
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
DIC	Pearson Correlation	.943**	.546	-.326	.622	.623	.438	-.061	.206	-.376	.008	.685	1	.295	.451	.454	.535	-.221	-.037	-.079
	Sig. (2-tailed)	.005	.262	.528	.187	.186	.385	.908	.695	.463	.988	.133		.570	.370	.366	.274	.674	.944	.882
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
CRWW	Pearson Correlation	.197	.497	.070	-.240	-.039	-.001	-.213	.514	.005	-.074	-.477	.295	1	.214	-.051	.119	-.552	.121	.907*
	Sig. (2-tailed)	.708	.316	.895	.648	.941	.999	.685	.296	.992	.889	.338	.570		.683	.924	.822	.256	.820	.013
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
SpMIN	Pearson Correlation	.682	.325	.619	.191	.351	-.159	.429	.870*	.131	.837*	.368	.451	.214	1	-.512	.930**	-.621	-.684	-.116
	Sig. (2-tailed)	.136	.530	.190	.717	.496	.764	.396	.024	.804	.038	.473	.370	.683		.299	.007	.188	.134	.826
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
RPHVVMAJtoMIN	Pearson Correlation	.171	.008	-.986**	.246	.029	.370	-.429	-.590	-.390	-.754	.371	.454	-.051	-.512	1	-.481	.466	.561	-.120
	Sig. (2-tailed)	.746	.988	.000	.638	.956	.471	.396	.218	.444	.083	.468	.366	.924	.299		.334	.352	.247	.821
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
RPHVPMAJtoMIN	Pearson Correlation	.769	.471	.602	.423	.585	.037	.457	.677	.046	.751	.475	.535	.119	.930**	-.481	1	-.518	-.586	-.190
	Sig. (2-tailed)	.074	.346	.206	.403	.223	.945	.362	.140	.931	.085	.341	.274	.822	.007	.334		.292	.221	.718
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
RV85MAJtoMIN	Pearson Correlation	-.381	.049	-.462	-.218	-.417	-.288	.333	-.793	.390	-.670	.143	-.221	-.552	-.621	.466	-.518	1	.742	-.399
	Sig. (2-tailed)	.456	.926	.356	.679	.411	.580	.519	.060	.445	.145	.787	.674	.256	.188	.352	.292		.091	.434
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
REnRWMAJtoMIN	Pearson Correlation	-.318	.407	-.558	-.329	-.413	-.163	.080	-.655	.312	-.927**	-.230	-.037	.121	-.684	.561	-.586	.742	1	.271
	Sig. (2-tailed)	.539	.423	.250	.525	.416	.757	.881	.158	.547	.008	.661	.944	.820	.134	.247	.221	.091		.604
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
RDICtoDCI	Pearson Correlation	-.199	.321	.081	-.414	-.224	-.040	-.294	.275	.060	-.241	-.780	-.079	.907*	-.116	-.120	-.190	-.399	.271	1
	Sig. (2-tailed)	.705	.535	.879	.415	.670	.940	.572	.598	.909	.646	.067	.882	.013	.826	.821	.718	.434	.604	
	N	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6

APPENDIX F: Sample of Field Survey Formats

Table F- 1: Sample of field survey format for vehicle volume count



MANUAL COUNT DATA FORM FOR VEHICLE VOLUME

Date: 03/05/17 (Day-1)
Day: WEDNESDAY
Name: WENDWOSEN
Location: TEDROS
Approach Leg: LEGEHAR

Shift Time: MID-DAY
Start Time: 12:00 PM
End Time: 2:00 PM
Weather: SUNNY
Speed Limit:

Time	Motor Bike	Small Cars	Buses	Medium Truck	Heavy Truck	Articulated Truck	Total
12:00-12:15 PM	2	298	9	19	3	0	331
12:15-12:30 PM	6	301	5	24	6	0	342
12:30-12:45 PM	4	300	10	28	3	0	345
12:45-1:00 PM	6	302	3	23	3	0	337
1:00 - 1:15 PM	10	259	4	11	5	1	290
1:15 - 1:30 PM	6	262	10	24	3	0	305
1:30 - 1:45 PM	6	251	4	17	3	1	282
1:45 - 2:00 PM	7	251	7	15	1	0	281
Total							

Table F- 2: Sample field survey format for pedestrian volume count

MANUAL COUNT DATA FORM
FOR PEDESTRIAN CROSSING VOLUME

Date: 03-05-17 (day 1)
Day: Wednesday
Name: Solomon
Location: Tewodros
Approach Leg: legehar (churchil)

Shift Time: MID-DAY
Start Time: 12:00 PM
End Time: 2:00 PM
Weather: sunny

Time	Male Pedestrians	Female Pedestrians	Children <12 years age	Total
12:00-12:15 PM	36	21	8	65
12:15-12:30 PM	45	16	6	67
12:30-12:45 PM	37	25	9	71
12:45-1:00 PM	42	23	8	73
1:00 - 1:15 PM	32	33	5	70
1:15 - 1:30 PM	29	29	9	67
1:30 - 1:45 PM	41	36	7	84
1:45 - 2:00 PM	42	35	9	86
Total				

Table F- 3: Sample field survey format for spot speed measurement

MANUAL SURVEY DATA FORM
STOPWATCH SPOT-SPEED MEASUREMENTS

Date: 03-05-17
Day: Wednesday
Name: Anduale
Location: Tewodros
Approach Leg: Leghar (churchil South)

Shift Time: MORNING/~~AFTERNOON~~
Start Time: 9:00 AM
End Time: 12:00AM
Weather: Sunny

Seconds	Km/hr for 27 m.	Smaller Cars		Bus		Medium Truck		Heavy Truck		Articulated Truck		Total
		Record	No.	Record	No.	Record	No.	Record	No.	Record	No.	
1	97.2											0
1.2	81.0											0
1.4	69.4											0
1.6	60.8											0
1.8	54.0	II	2									2
2	48.6											0
2.2	44.2	~~IIII~~ III	8			I	1	II	2			11
2.4	40.5	IIII	4			II	2					6
2.6	37.4	~~IIII~~ ~~IIII~~	10									10
2.8	34.7	~~IIII~~ ~~IIII~~ II	12			I	1					13
3	32.4	~~IIII~~ III	8	II	2	I	1					11
3.2	30.4	IIII	4	I	1							5
3.4	28.6	~~IIII~~	5					I	1			6
3.6	27.0	~~IIII~~ II	7	~~IIII~~	5	I	1					13
3.8	25.6	~~IIII~~	5									5
4	24.3	III	3	II	2							5
4.2	23.1	III	3					I	1			4
4.4	22.1	II	2	III	3							5
4.6	21.1	I	1					I	1			2
4.8	20.3	II	2									2
5	19.4									I	1	1
5.2	18.7	II	2									2
5.4	18.0											0
5.6	17.4	I	1									1
5.8	16.8											0
6	16.2	I	1									1
6.2	15.7											0
6.4	15.2											0
6.6	14.7											0
6.8	14.3											0
7	13.9											0
Total			80		13		6		5		1	105