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STATISTICAL MODELLING OF ROAD TRAFFIC ACCIDENTS IN YANGON

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I hereby certify that content of this dissertation is wholly my own work unless otherwise referenced of acknowledged. Information from sources is referenced with original comments and ideas from the writer herself.

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ABSTRACT

Road traffic accidents constitute one of the most pressing concerns for governments worldwide. Thousands of people are fatal and injured on the roads due to accidents. This study aims to analyze and predict road traffic accidents and casualties in Yangon using data from the No. (2) Office of Traffic Police for the period from January 2013 to December 2022. Descriptive statistics show that the number of accidents increased from 2013 to 2014, but it has significantly decreased starting from 2015. The analysis of the binary logistic regression model reveals that the risk factors for traffic casualties mainly include gender, place of accident, type of vehicle, time of accident, and immediate causes of accidents. Furthermore, the best-fitting model for predicting traffic accidents was found to be ARIMAX-TFM (0, 1, 1). Similarly, ARIMAX-TFM (1, 0, 1) and ARIMAX-TFM (1, 0, 1) were the best-fitting models for traffic injury and fatality data. The forecasted number of traffic accidents and injuries is steadily decreasing, while the number of fatalities is steadily increasing for January 2023 to March 2023. Additionally, the analysis of ARIMAX-TFM confirms a significant impact of road safety measures on the reduction of the number of accidents and casualties in Yangon. To reduce road traffic accidents, traffic authorities should focus on upgrading safer driving behaviors, improving the safety features of vehicles, enforcing laws related to key risks, conducting public awareness campaigns to better understand the risks, and establishing a comprehensive strategy.

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LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
ADB	Asian Development Bank
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AMS	Accident Management System
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARIMAX	Autoregressive Integrated Moving Average with Explanatory Variable
ARIMAX-TFM	Autoregressive Integrated Moving Average with Explanatory Variables-Transfer Function
ARMA	Autoregressive Moving Average
ASEAN	Association of Southeast Asian Nations
ATM	ASEAN Transport Ministers
BAC	Blood Alcohol Concentration
BIC	Bayesian Information Criterion
CCF	Cross-Correlation Function
CDC	Centers for Disease Control and Prevention
cm	Centimeter
EVs	Electric Vehicles
FRAM	Functional Resonance Analysis Method
g/dl	Grams per Deciliter
GDP	Gross Domestic Product
GNI	Gross National Income
ICT	Information and Communication Technology
INSEE	National Institute for Statistics and Economic Studies
ISA	Intelligent Speed Adaptation
ITS	Intelligent Transportation Systems
KLTSP	Kuala Lumpur Transport Strategic Plan
km	Kilometer
km/h	Kilometer per Hour

MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLE	Maximum Likelihood Estimation
MRSAP	Myanmar Road Safety Action Plan
MSE	Mean Square Error
NRSAP	National Road Safety Action Plan
NRSC	National Road Safety Council
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
PDO	Participant Direction Option
PPP	Purchasing Power Parity
QQ	Normal Quantile-Quantile
RMSE	Root Mean Square Error
RTAs	Road Traffic Accidents
RTAD	Road Transport Administration Department
SAC	State Administrative Council
sq-km	Square Kilometer
TFM	Transfer Function Model
TMC	Traffic Management Centers
TRESC	Traffic Rules Enforcement Supervisory Committee
UN	United Nations
US	United States
USD	United States Dollar
WHO	World Health Organization
YGH	Yangon General Hospital

CHAPTER I
INTRODUCTION

Road Traffic Accidents (RTAs) are widely considered as public health issue of individual countries around the world. Recently, RTAs were the 8th leading cause of death for people of all ages, according to the World Health Organization (WHO, 2018). The Global Status Report on Road Safety 2015 by WHO predicts that RTAs will become the 7th leading cause of death by 2030. They are also the main cause of human and economic losses in both developed and developing countries. Moreover, RTAs result in physical disabilities for drivers, passengers, and pedestrians, particularly in developing countries (Zimmerman et al., 2012).

The recent economic and technological developments have led to a rapid increase in the number of vehicles used by the public. Consequently, the number of accidents and casualties has significantly risen as well (Karacasu, Ergul and Yavuz, 2013). Traffic injuries and deaths have a tremendous impact on the socio-economic development of nations. Myanmar, being a developing country, currently faces a high level of traffic accidents (World Life Expectancy, 2020).

Therefore, this study aims to analyze the current situation of road traffic accidents and casualties in Yangon, a densely populated city in Myanmar. Additionally, the study examines the impact of national road safety measures on traffic accidents and casualties, and achieves the most suitable model for forecasting the number of accidents, injuries, and fatalities in some consecutive years in the future.

1.1 Rationale of the Study

Road traffic accidents can be seen as the universal occurrences, leading to injuries and fatalities in every country worldwide, impacting the safety and well-being of individuals and communities. In recent years, it has been estimated that there are roughly 1.3 million deaths annually, averaging around 3,287 deaths per day due to road traffic accidents. Among children and young people aged 5 to 29 years, traffic fatalities are the primary cause of death globally. More than half of all road traffic deaths involve pedestrians, cyclists, and motorcyclists. These incidents predominantly occur in low-income and middle-income countries, accounting for 93% of all road traffic deaths (WHO, 2018).

Road traffic accidents are indeed caused by a variety of factors, including human errors, mechanical faults, failure to comply with regulations, and weather conditions. In many developing countries, rapid economic growth has led to significant changes in the traffic environment. As a result, there has been a substantial increase in the number of motorized two-wheelers (motorcycles) and four-wheelers (automobile vehicles) used. However, in these countries, there is often a lack of comprehensive road safety education and driving instructions available to road users.

The limited opportunity for receiving complete road safety education and driving instructions in developing countries contributes to low levels of normative awareness and underdeveloped driving skills among road users. This, in turn, leads to an increase in accidents and traffic congestion. In particular, the number of traffic accidents caused by young people has been observed to rise (Kitamura, Hayashi and Yagi, 2018).

In Myanmar, there has also been an alarming increase in traffic accidents, and its concomitant deaths, and injuries on an annual basis. Traffic injuries represent one-third of all injuries reported by hospitals over the country in 2014. Since 2008, the number of road accidents in Myanmar has been steadily rising. In 2020, the number of deaths resulting from road traffic accidents (RTAs) reached 11,004, which accounted for 3.05% of the total deaths in Myanmar. The age group most affected by road accidents is young adults aged 15 to 45. Inadequate road networks and insufficient road maintenance also contribute to the high incidence of road injuries and fatalities (WHO, 2015). Myanmar's road infrastructure is considered the second most dangerous among ASEAN countries, excluding Thailand. Moreover, Myanmar has the second-highest road fatality rate in South-East Asia regions (WHO, 2019).

Additionally, according to the 2014 Myanmar Population and Housing Census, the total population of Myanmar is 51,486,253, with over 4,407,741 registered vehicles in the country. If the rate of vehicle fleet expansion continues, it is estimated that the number of road fatalities could double by 2020 and triple by 2025, as stated by the Asian Development Bank (ADB, 2016). According to the ADB (2016) and WHO (2018), in Myanmar road accidents are usually attributed to human errors such as reckless driving, over-speeding, using defective vehicles, excessive drinking of alcohol, and the consumption of narcotics, and so on. Furthermore, factors such as rapid urbanization, poor safety standards, lack of enforcement, distracted driving, and failure to wear seatbelts or helmets are also considered significant contributors to the high number of traffic fatalities in the country.

As stated in the 2014 Myanmar Population and Housing Census, the Yangon region is indeed the most populated region in Myanmar. The Yangon Region is divided into 14 districts and encompasses a total of 45 townships. These townships are distributed as follows: 14 townships in the Eastern District, 12 townships in the Western District, 10 townships in the Southern District, and 9 townships in the Northern District. Out of these, 5 townships in the Northern District, 14 townships in the Eastern District, and 12 townships in the Western District are located within the boundaries of the Yangon municipal area. The remaining 4 townships in the Northern District and 10 townships in the Southern District are located outside the Yangon municipal area (Department of Population, 2015).

In Myanmar, the Yangon Region stands out against the highest rate of traffic accidents, and the transportation system in this region is largely dominated by cars. The number of deaths resulting from traffic accidents in the Yangon region has been increasing year by year. In Yangon, thirty-five people were dead and 197 injured in January 2017 due to road traffic accident, and this figures rose to 51 fatalities and 275 injuries in May of the same year (Oliver, 2017).

In the context of reducing road traffic accidents and casualties, the road safety plans and measures play a crucial role. Therefore, this study aims to analyze the risk factors associated with road traffic accidents and casualties while assessing the impact of road safety measures in the Yangon municipal area. To achieve this, the study will employ an appropriate time series analysis and it is expected to provide valuable insights into the effectiveness of road safety measures and its influence on reducing road traffic accidents and casualties in Yangon.

1.2 Objectives of the Study

The main objective of this study is to analyze the road traffic accidents and casualties in Yangon. This main objective is supported by the following specific objectives:

(i) To describe the status of traffic accidents and casualties in Yangon
(ii) To analyze risk factors related to traffic casualties in Yangon
(iii) To examine the impact of road safety measures on occurrence of traffic accidents and casualties in Yangon
(iv) To predict the number of traffic accidents, injuries and fatalities by using the time series model selected as the most suitable one.

1.3 Method of Study

In this study, a descriptive analysis was conducted to determine the status of traffic accidents and casualties including fatalities and injuries. Additionally, the study employed a Logistic Regression model to explore the risk factors associated with traffic casualties in Yangon. To analyze the impact of road safety measures on the occurrence of accidents, injuries, and fatalities in Yangon, several time series models such as Autoregressive Integrated Moving Average (ARIMA) model, Intervention model and Autoregressive Integrated Moving Average with explanatory variables-transfer function (ARIMAX-TFM) were employed. Intervention model and ARIMAX-TFM were used to assess the variations in the number of traffic accidents, injuries and fatalities during the period in which the safety measures were implemented. In addition, the most suitable model was chosen to predict the number of traffic accidents, injuries and fatalities occurred in Yangon.

1.4 Scope and Limitations of the Study

Yangon is not only the largest city but also the industrial and commercial center of the country. The Yangon Region comprises 14 districts with a total of 45 townships. Among these townships, 31 are located within the boundaries of the Yangon municipal area, while the remaining townships are situated outside of it. In this study, the focus is only on the townships within the Yangon municipal area. The monthly time series data of road traffic accidents as well as casualties in Yangon, covering the period from January 2013 to December 2022 are used in this study. The information which could be attributed to the risk factors such as gender, place of accident, type of vehicles, time of accident, drinking habit, immediate causes of accident, and other specific conditions including over speeding, reckless driving and pedestrian negligence were obtained from the No. (2) Office of Traffic Police in Yangon.

1.5 Organization of the Study

This study is structured into six chapters. Chapter I provides an introduction to the research, including the rationale of the study, objectives of the study, the method of study, and the scope and limitations of the study. It also outlines the organization of the study. Chapter II comprises a comprehensive literature review, encompassing various studies on road traffic accidents and casualties, risk factors, and road safety measures. Chapter III focuses on the methodology used for analyzing road traffic accidents and casualties. Then Chapter IV presents the analysis of risk factors associated with casualties in road traffic accidents occurred in Yangon. The time series analysis of road traffic accidents and casualties are discussed in Chapter V. The last chapter summarizes the findings obtained throughout the study, offers recommendations based on the results, and suggests the areas for further research.

CHAPTER II

LITERATURE REVIEW

This chapter presents a review of the available literature related to road traffic accidents and casualties as well as road safety measures. It mainly includes the definition of road traffic accidents and their consequences, previous trends of road traffic accidents and casualties, risk factors associated with road traffic accidents, and road safety measures on both global and national basis.

2.1 Defining Road Traffic Accident and its Consequences

The National Institute for Statistics and Economic Studies (INSEE, 2016) stated that: "A traffic accident refers to any accident involving at least one road vehicle, occurring a road open to public circulation, and in which at least one person is killed or injured".

The following definitions are further provided by the Department for Transport, Scottish Government in Great Britain (2010):

“Accident involves personal injury occurring on the public highway (including footways) in which at least one road vehicle or a vehicle in collision with a pedestrian is involved and which becomes known to the police within 30 days of occurrence. The vehicle need not be moving and accidents involving stationary vehicles and pedestrians or users are included”.

“Casualty is a person killed or injured in an accident. Casualties are sub-divided into killed or fatal injury, serious injury, and slight injury”.

"Killed persons’ are accident victims who die immediately or within 30 days following the accident, and ‘injured persons’ are accident victims who have suffered trauma and required medical treatment with or without hospitalization".

“Fatal injury is Human casualties who sustained injuries which caused death less than 30 days after the accident”.

“Serious injury is an injury for which a person is detained in hospital as an "in-patient", or any of the following injuries whether or not they are detained in hospital: fractures, concussion, internal injuries, crushing, burns (excluding friction burns), severe cuts and lacerations, severe general shock requiring medical treatment and injuries causing death 30 or more days after the accident”.

“Slight injury is an injury of a minor character such as a sprain (including neck whiplash injury), bruise or cut which are not judged to be severe, or slight shock requiring roadside attention. This definition includes injuries not requiring medical treatment”.

WHO refers to injuries and fatalities as “any person killed immediately or dying within 30 days as the result of an accident while recording road traffic injuries or death” (Mohan, 2006, pg.51).

According to World Report on Child Injury Prevention (WHO, 2008); "A road traffic fatality is considered to be a death occurring within 30 days of a road traffic crash" (Mackie, 2003, pg.58).

The United Nations Cost-Benefit Analysis of Transport Infrastructure Projects (2003) states: "A damage-only accident is one in which there are no causalities. A fatal accident is the death of at least one fatality. A serious accident is one in which there is at least one serious injury but no fatalities. A slight accident is one in which there is at least one slight causality but no serious injuries and no fatalities".

Injury, also known as physical trauma, is damage to the body caused by an external force. Injuries may be caused by accidents, falls, impacts, weapons, and other factors. Major trauma refers to an injury that has the potential to cause prolonged disability or death. Furthermore, the World Report on Child Injury Prevention (WHO, 2008) defines fatal or non-fatal injuries resulting from road crashes as road traffic crashes. Road Traffic Crash is defined as a collision or incident that occurs on a public road, involving at least one moving vehicle, and may or may not lead to injury. The Centers for Disease Control and Prevention (CDC) states that a non-fatal injury is a bodily harm resulting from exposure to an external force or substance or from submersion.

2.2 Global Road Traffic Accidents and Casualties

The growth of the transportation system has been, and continues to be, a key element in global economic development. Road accidents affect every nation with a result of human suffering and significant costs to communities. Moreover, Road Traffic Accidents (RTAs) are one of the leading causes of death worldwide. Every year, millions of people are injured and killed in these road traffic accidents. According to the report prepared by WHO (WHO, 2018), the death-toll from road traffic accidents has risen to 1.35 million per year, equating to nearly 3,700 people losing their lives on the world's roads every day. Additionally, countless individuals experience life-altering injuries with long-lasting effects. These losses have devastating impacts on the respective families and communities

Furthermore, WHO (2015) indicated an increase in the death rate attributed to traffic accidents in low-income countries since 2000. Pedestrians, cyclists, and motorcyclists accounted for more than half of the global deaths among vehicle-road users (WHO, 2018). According to WHO (2019), African followed by Southeast Asian countries exhibited significantly higher rates of road fatalities compared to the global average. Nearly half of the 650 daily deaths on Africa's roads involve pedestrians, cyclists, and motorcyclists. Out of which pedestrians and cyclists had been accounted for 44% of the fatalities in 2018. In contrast, in Southeast Asia and the Western Pacific regions, the highest number of deaths occur among riders of motorized two and three-wheelers, at 43% and 36%, respectively (WHO, 2018).

Moreover, motor vehicle crashes result from a variety of factors, including inadequate roadway design, hazardous conditions, failure to use safety devices such as helmets and seat belts, lack of appropriate vehicles and vehicle maintenance, unskilled or inexperienced drivers, inattention to pedestrians and cyclists, issues related to road sharing, and impairment due to alcohol, drug use, or fatigue, among others (Nantulya et al., 2010). Sometimes accidents occur due to a combination of reasons, ranging from poor visibility to unsafe road design or the lack of caution from other drivers.

Al-Ghamdi (2001) conducted an analysis of the influence of accident factors on accident severity in Riyadh. In which the accident-related data was examined using logistic regression model. A total of 560 samples were collected for serious accidents and the model utilized the including serious severity as the dependent variable along with nine explanatory variables. The study revealed that accident location and accident cause were found to be the most significantly factors associated with the severity of traffic accidents.

Cools et al. (2009) employed three modeling approaches, namely SARIMA, ARIMAX, and SARIMAX, to predict daily traffic flow. The study identified the four traffic count locations: Brussels, Gasthuisberg, Here, and Zandvoorde and the analysis involved examining the cyclicality in daily traffic data as well as identifying and comparing holiday effects across these different locations. The results indicated that the ARIMAX model was more effective in estimating the variations in daily traffic flow.

Awal (2013) investigated the risk factors involved in road accidents in Ghana using logistic regression analysis. Accident-related data were collected from the Motor Traffic and Transport Unit of Ghana Police Service, Techiman Divisional Command. A total of 494 accident data from 2007-2011 were used. In this study, the dependent variable was used as accident severity, and there were six independent variables such as gender, age, vehicle type, time of accident, and location of accident, and reasons assigned to the accident. Out of the six explanatory variables, four were statistically significant. These include gender, type of vehicle at fault, location of accident, and reasons assigned to the accident.

Katta (2013) conducted a study to identify the risk factors that influence the severity of crashes in work zones in the state of Ohio. The data for the study was collected from the Ohio Department of Traffic Safety for the year 2010. A total of 12,275 crash records, with 24 different independent variables, were used in the development of the Crash Severity Model (CSM). The study also employed various statistical methods, including the Pearson chi-square test, regression modeling, and binary logistic regression. A binomial logit model was specifically utilized to predict the severity of crashes. The results of the binary logistic regression analysis revealed that seventeen variables, divided into forty-four categories, were identified as influencing factors for crash severity which is either fatal or injury. The analysis also demonstrated that the Crash Severity Model fit the data well, with a prediction accuracy of 72.8 percent.

Avuglah, Adu-Poku and Harris (2014) examined the trends and patterns of road traffic accidents in Ghana from 1991 to 2011 using the ARIMA model. The study emphasized the importance of implementing key road safety measures to address Ghana's increasing pattern of road accidents. According to the results, the ARIMA (0, 2, 1) model was considered as the most suitable statistical tool to estimate the future road traffic accidents.

Chen and Tjandra (2014) developed the study to develop models for predicting daily total collisions. The study first analyzed trends, seasonality, and randomness using daily crash time series data before investigating potential contributors to collisions. Temporal factors such as months, weekdays, and holidays, as well as weather forecasts including daily mean temperature, amount of rainfall, and snowfall, were selected as predictive factors. The study estimated and diagnosed a seasonal autoregressive integrated moving average model with external regressors (SARIMAX), along with a series of SARIMAX models of different orders. Additionally, a generalized linear model (GLM) was developed and compared to the SARIMAX models using validation measures. The GLM model considered the significance of all parameter estimates at a 10% confidence level, and the SARIMAX $(7, 0, 0) \times (4, 0, 1)_7$ model exhibited the best performance.

Salako, Adegoke and Akanmu (2014) conducted time series analysis to model and detect the seasonality pattern of auto-crash cases in Osun. The research analyzed the data spanning six years (2006-2012) on the causes of motor vehicle. The ARIMA model was used to assess the recorded cases, and the least-squares trend indicated a quarterly decline in six causes of motor vehicle accidents. The results revealed a seasonal pattern where the fourth quarter of a year including October, November, and December had a higher prevalence of motor accidents. The study also highlighted that the Federal Road Safety Commission has performed adequately in discharging its duties.

Atubi (2015) carried out the monthly analysis of road traffic accidents in nine selected Local Government Areas of Lagos State, Nigeria. The aim of the study was to suggest preventive and corrective safety measures to reduce road traffic accidents. The investigation covered accident records from Nigeria spanning 32 years (1970-2001). Time series and averaging models were utilized to analyze road traffic accidents, including the total number of deaths, total number of injuries, and cases classified as fatal, serious, and minor in Lagos State. The researcher discovered that the months of June, July, September, October, November, and December had the highest occurrence of accidents in Nigeria. This was attributed to the rainy season, as wet road conditions adversely affected drivers' visibility. Among the rainy months, June, July, and September were identified as the peak periods for road accidents.

Mutangi (2015) identified the suitable time series model for forecasting the annual number of traffic accidents that may occur in Zimbabwe. The study utilized three categorical data such as: total reported road accident cases, persons killed in road accidents, and persons injured. The findings indicated that the ARIMA (0, 1, 0) model was the most appropriate for the estimation of potential occurrences of road traffic accident cases as well as the number of persons killed in such road traffic accidents.

Sanusi, Adebola and Adegoke (2016) conducted a study on road accidents in Nigeria categorizing the data into minor cases, serious cases, fatal cases, and total cases. The research employed the Autoregressive Moving Average (ARIMA) model to provide the reliable and valuable information for determining the rate of road accidents in Nigeria's motorways and implementing necessary preventive measures. For the minor and total cases, the ARIMA (1, 1, 1) model was obtained. The serious cases were modeled by ARIMA (1, 1, 0), while the fatal cases were modeled through the ARIMA (0, 1, 1). These models were developed using data from 1960 to 2011, and the adequacy and performance of the models were tested using data from 2012 to 2013. The models were then utilized to forecast the different cases from 2014 to 2020.

Yousefzadeh-Chalook et al. (2016) conducted an analysis using a time series model to assess the trend and forecast road traffic accident mortality. The study collected data on road traffic victims from the traffic police of Zanjan Province, Iran, covering the period from 2007 until 2013. Various time series models, including AR, MA, ARMA, ARIMA, and SARIMA, were utilized in this study. The findings revealed a decreasing trend in road traffic accident mortality over the past and some future years. Among the models tested, the SARIMA $(1, 1, 3) \times (0, 1, 0)_{12}$ was determined to be the best fitted model for the data collected, providing the most accurate predictions in this study.

Ihueze and Onwurah (2018) investigated road traffic crashes in Anambra State, Nigeria. The study employed ARIMA and ARIMAX modeling techniques to forecast the frequency of crashes in the state. In the ARIMA model, eleven contributing factors such as over speeding, tyre burst, loss of control, wrongful overtaking, brake failure, dangerous overtaking, weather condition, route violation, obstruction, dangerous driving and sign light violation were considered as explanatory variables. The study found that incorporating human, vehicle, and environmental-related factors in the time series analysis of crash datasets resulted in a more robust predictive model compared to solely using aggregated crash counts. When comparing the performance of the two models, the ARIMAX model demonstrated superior performance over the ARIMA model in this study.

Awaab, Combert and Atongdem (2019) conducted a time series analysis in relation to motorcycle registration and accidents in the Bolgatanga municipality. The study examined the relationship between issuing motorcycle licence and occurrence of accidents in Ghana. It was found that motorcycle accident cases were underreported within the municipality. The reasons for not reporting accident cases to the police included inability to identify the persons involved, belief that it was not necessary to report to the police, fear of punishment, distance from the police station, and the demand for money. Motorcycle accidents were caused by various factors, such as colliding with the back of a vehicle, hitting an animal, hitting the pavement, or being hit by another motorist. The study revealed that most victims experienced a reduction in their working abilities, and some resorted to borrowing money or selling assets to cope with the consequences of the accidents. The findings highlighted that the number of motorcycle registrations increased significantly between 2004 and 2005, followed by a steady decline until 2007. Subsequently, there was a gradual increase until 2012, followed by a sharp decline until 2014.

Eboli, Forciniti and Mazzulla (2020) conducted a study analyzing accidents and their severity, as well as the factors influencing them. The study focused on investigating the characteristics that can impact the severity of accidents in Italy, while differentiating between various accident types. The factors were examined and grouped into different categories such as road conditions, the external environment, and driver-related factors. The researchers employed logistic regression analysis to uncover significant associations between the identified factors and the severity of accidents. The findings of the study indicated noteworthy differences among the various accident types and also provided the meaningful interpretations that can be utilized to enhance safety measures and make future improvements in Italy's accident prevention strategies.

Erena and Heyi (2020) presented the prevalence of road traffic accidents and associated risk factors among drivers of three and four-wheeled vehicles in East Wollega, Western Ethiopia. From February to March 2017, a cross-sectional study design was employed, involving 400 drivers of three and four-wheeled vehicles. The bivariate and multivariate analyses were used in the study. The findings revealed that one-third of the vehicle drivers had been involved in a road traffic accident and the factors such as collisions with other vehicles and pedestrians crossing the road, talking on a mobile phone while driving, failure to wear a seat belt, type of road regularly driven on, receiving an oral warning, and penalties were found to be largely associated with road traffic accidents.

Twenefour et al. (2021) examined a time series analysis of road traffic accidents in Ghana. The study utilized monthly traffic accident data from January 1990 to December 2019, obtained from the National Road and Safety Commission in Ghana. The researchers found that the ARMA (1, 0) model provided the best fit for the estimation of the Ghana annual traffic accident data. They also discovered that the forecasted values for January 2020 to July 2020 yielded consistent results.

2.3 Regional Road Traffic Accidents and Casualties

In the South-East Asian region, road traffic injuries kill approximately 316,000 people each year. That number accounted for 25% of road traffic fatalities worldwide. The global road traffic death rate was 17.4 per 100,000 people, whereas in the South-East Asian Region, it was 17 deaths per 100,000 people. The South-East Asian Region occupied the highest proportion of global traffic deaths (WHO, 2015).

Moreover, WHO (2018) has indicated that the road fatality rate per 100,000 population in Malaysia and Thailand was about five times greater than that in Singapore. Singapore's road fatality rate of 3.6 was similar to that of the world's best-performing nations in terms of traffic, such as the Netherlands (3.4) and the United Kingdom (2.9). The following Table (2.1) provides evidence showing the status of road traffic fatalities in ASEAN countries.

Table (2.1)

Traffic Fatality Rate in ASEAN Countries

Fatalities Per 100,000 Population	**Low income ($1045 or less in per capita GNI)**	**Middle income (more than $1045 but less than $12736 in per capita GNI)**	**High income ($12736 or more in per capita GNI)**
Low (< 10)			Brunei & Singapore
Medium (10-15)		Philippines &Lao PDR	
High (> 15)	Cambodia & Myanmar	Indonesia, Malaysia, Thailand & Viet Nam	

Source: WHO (2015)

Road trauma was higher in middle-income countries and still increasing in ASEAN. Low-income countries, such as Myanmar and Cambodia, generally had lower rates of motorization and lower fatality rates. Unless strong action was taken, the economic development in these countries would be accompanied by increasing deaths and injuries on the road.

According to WHO (2018), the South-East Asia regional breakdown of deaths understated the burden of deaths among vulnerable road users in all countries except Brunei. There was also significant variation within the region, with the most profound effect observed in Thailand, where 83% of road deaths were among vulnerable road users.

Sarani et al. (2012) emphasized the development of time series models to predict road fatalities for the year 2020 in Malaysia. The research employed the ARIMA model and the Generalized Linear model (GLM) to forecast road accidents. The findings indicated that the ARIMA (0,1,1) model was deemed to be the most effective for predicting Malaysian traffic fatalities. With this ARIMA model, the expected number of fatalities was projected to reach 10,716 in 2020.

Darma (2017) conducted a study multiple regression model to select explanatory variables that exhibited significant profound effect on the number of road traffic fatalities. These variables were then used as input variables for the time series analysis. The effectiveness of a road safety measure was assessed using the State-space, ARIMA and transfer function-noise models, respectively. Forecasting of fatalities up to the year 2020 was performed using these three models as well. The findings revealed that motorcyclists were the primary victims of road traffic accidents, young adult drivers/riders aged 16-25 years accounted for the highest percentage of total fatalities, with a value of 35% and the highest rate of fatal accidents per kilometer occurs at expressways.

Haque and Haque (2018) evaluated the effect of the Road Safety System Approach on serious road casualties, specifically fatalities and serious injuries, in Brunei. The study utilized the Auto Regressive Integrated Moving Average (ARIMA) and Intervention Time Series Analysis. The findings revealed that a substantial reduction of 30% in serious road casualties was observed within the first 12 months following the implementation of the Road Safety System Approach and the introduction of reformed road safety initiatives in Brunei.

Jomnonkwao, Uttra and Ratanavaraha (2020) conducted a study on forecasting road traffic deaths in Thailand. In this study, four methods were employed: time series analysis, curve estimation, regression analysis, and path analysis. The data used in the analysis encompassed the death rate per 100,000 population, gross domestic product (GDP), the number of registered vehicles (motorcycles, cars, and trucks), and energy consumption of the transportation sector. The results indicate that the top three models, based on the mean absolute percentage error (MAPE), are as follows: multiple linear regression model 3, time-series with exponential smoothing, and path analysis, with MAPE values of 6.4%, 8.1%, and 8.4%, respectively.

Husin et al. (2021) analyzed road accident cases in Malaysia using a dataset comprising monthly accident case numbers from January 2001 to December 2019, provided by Polis Diraja Malaysia (PDRM). These studies employed Box-Jenkins and state space models, evaluating their performance through in-sample and out-sample assessments, considering metrics such as the lowest root mean square error, mean absolute percentage error, and mean absolute error. The results indicated that the basic structural state space model with trend and seasonal components was the most suitable model for forecasting road accident cases in Malaysia. The 10-year forecast from January 2020 to December 2030 revealed a consistent upward trend in monthly road accident cases in Malaysia each year. It is anticipated that the findings of this study could serve as a reference for Malaysian authorities when making recommendations aimed at enhancing road safety and reducing road traffic accidents in the country.

Yahaya et al. (2022) identified determinants of Road Traffic Collisions (RTC) in Malaysia and forecasted RTC numbers for the next ten years using an ARIMA model. They conducted a correlation test using 15 years' data on RTC, population, GDP, new drivers, and registered vehicles from JKJR and the World Bank Group. The results indicated that registered vehicles, population, and GDP were the primary RTC determinants, with motorcycle accidents causing the highest number of injuries. RTC fatalities were projected to decrease by 0.82% annually, with an expected 5588 RTA fatalities in 2029. The study highlighted the urgent need to reduce RTCs, especially after 6,284 fatalities in 2018. ARIMA (0,2, 3) was chosen as the best model for forecasting RTA fatalities in Malaysia, offering valuable insights for mitigating accidents and government intervention.

Sabenorio, Enriquez and Ramel (2023) analyzed road traffic accidents (RTAs) in Metro Manila, Philippines from 2012 to 2021. This study utilized a 10-year monthly dataset and applied an ARIMA model for a 5-year forecast. The research findings reveal that the total RTAs in Metro Manila gradually increased until the first quarter of 2020, then sharply declined, reaching its lowest point in April 2020 due to the COVID-19 lockdown. As the lockdown eased, RTAs partially rebounded, particularly those causing property damage, while injuries remained consistent. Despite the decrease in overall RTAs, injuries surged due to reckless driving behavior. The study identified ARIMA (1, 1, 12) as the best model. According to this model, the forecast suggests that total RTAs will stabilize at a halfway point in 2022 and gradually decrease over the next 4 years.

2.4 Road Traffic Accidents and Casualties in Myanmar

Myanmar is strategically located and rich in natural resources, including arable land, forests, natural gas, and freshwater and marine resources. The country boasts the largest mainland in Southeast Asia, with a total land area of 676,577 square kilometers (Florento and Corpuz, 2014). According to the ASEAN Regional Road Safety Strategy (ADB, 2016), Myanmar is classified as a low-income country in the South-East Asia Region. The International Monetary Fund estimates that Myanmar's economy ranks seventh in the ASEAN region.

ASEAN Secretariat showed that Myanmar had a road network of 151,298 km in 2012, with a paved road length of 48 km per 100 sq-km of land area. The country also had 587 km of expressways. However, by international standards, the roads in Myanmar are considered to have moderate low extent and efficiency. In 2015, Myanmar had 14.5 motor vehicles per 1000 inhabitants and 9 motor vehicles per kilometer of road (ADB, 2016).

The supervising committee of the ASEAN Secretariat for traffic rule enforcement has reported that 12 lives are lost per day on the roads in ASEAN region. Among ASEAN countries, Myanmar's road infrastructure is the most underdeveloped. Although the road network expanded to 148,690 km as of March 2012 from 90,713 km in 2004, the road density remains one of the lowest in the region. Only 39% (57,840 km) of the network is paved, while 61% (90,850 km) remains unpaved. The secondary and local road network in Myanmar is generally in poor condition and becomes unusable during the monsoon season. The main types of motorized vehicles in Myanmar include passenger cars, light trucks, heavy trucks, buses, motorcycles, two-wheelers, three-wheelers, trawlergyi, and others. As of 2015, Myanmar had over 5.38 million vehicles, with motorized two and three-wheelers comprising the majority (85%), followed by four-wheeled passenger cars (8.33%). Trucks, including light trucks and heavy trucks, accounted for 4.43%, buses for 0.47%, and other vehicles made up 1.77% (ADB, 2016).

According to ADB (2016), the rate of fatalities per 1000 vehicles remained constant between 2008 and 2014, at 9.3. However, during the same period, the motor vehicle fleet more than doubled in size, increasing from 2 million to 4.6 million. This significant growth in the number of vehicles contributed to a rise in the absolute number of fatalities per year. In 2014, the number of road-related deaths reached 4300, which is twice as many as the recorded figure in 2009. Additionally, one-third of all injuries reported by hospitals are a result of traffic accidents. If the situation remains unchanged, it is projected that fatalities will double by 2020 and reach 15,000 per year by 2025. Furthermore, the number of road injuries has also witnessed a significant increase, nearly doubling from 12,626 in 2008 to 26,375 in 2016 (ADB, 2016).

Motorcyclists and pedestrians account for the majority of annual fatalities in Myanmar. According to ADB (2016), motorcyclists (44%), three-wheel vehicle drivers (14%) and passengers comprised the majority of road traffic fatalities in 2013.

Moreover, Myanmar's Ministry of Health confirmed that motorcyclists represented the largest group, accounting for up to 47% of all injured road users in 2013. Pedestrians accounted for approximately 24.2% of all road users injured in the same year. Hospital data revealed that 31% to 36% of all injured patients admitted to Myanmar hospitals were a result of traffic crashes. In terms of fatal crash types, the major categories included head-on collisions, vehicle hitting incidents, pedestrian accidents, right-angle intersection crashes, run-off-road accidents, and rear-end collisions and these fatal crashes were mostly occurred in Yangon, Nay Pyi Taw, and Mandalay Regions (ADB, 2016).

According to the National Road Safety Council (NRSC) meeting, motorcycle accidents accounted for 49% of all traffic accidents in Myanmar in 2018, resulting in 2,376 deaths and 12,965 casualties. It was also found that not wearing safety helmets increased the risk of death or injury for motorcyclists. Similarly, failure to wear seatbelts led to 6,276 injuries and 1,214 deaths in 2018. The annual report highlighted that individuals who did not wear seatbelts were twice as likely to get injured and four times more likely to die in an accident (The Republic of the Union of Myanmar President Office, 2019).

Kyaw (2015) conducted a study on the connection between highway road accidents and human rights issues in Myanmar. The research employed purposive sampling along with semi-structured and structured questionnaires for surveying. Thematic analysis was conducted to gain a comprehensive understanding of the issue. The study delved into the reasons behind the high number of road accidents, the underlying causes of these accidents, the human rights issues arising from them, and the state's obligations to uphold fundamental human rights such as the right to life and the right to health for passengers. The study's results revealed that weaknesses in traffic policies and their implementation, as well as the state's responsibilities in protecting human rights, act as significant barriers to ensuring passenger safety. This study suggests that weaknesses in traffic policy implementation in practice, coupled with the state's obligation to safeguard human rights, continue to pose significant obstacles to passenger safety, further resulting in the neglect of individual rights within the legal framework.

Mon, Pueboobpaphan and Ratanavaraha (2016) investigated the relationship between accident occurrences and road characteristics on the Yangon-Mandalay Expressway in Myanmar. The high frequency of traffic crashes on this expressway has become a serious problem, resulting in numerous deaths, injuries, disabilities, and damage to both private and public properties. The study also examined the relationship between crash frequency and various road characteristics on the expressway. The major cause of traffic crashes on the Yangon-Mandalay Expressway was identified as over speeding. Additionally, the study further examined the impact of human behavior, road environment, and road characteristics on the occurrence of traffic crashes. To predict the number of crashes, a negative binomial regression model was used, considering variables such as average daily traffic, road geometric features, presence of bridges, and presence of village settlements along the expressway. The results indicated that accident occurrences were significantly related to average daily traffic, presence of bridges, presence of village settlements, percentage of downgrade (slope), and the combination of horizontal curve and slope on the expressway. These findings highlighted the importance of road characteristics in mitigating traffic crashes and improving road safety on the Yangon-Mandalay Expressway.

Lwin et al. (2016) analyzed the factors relating to motorcycle accidents encountered by motorcyclists, passengers, and pedestrians admitted to two hospitals in Nay Pyi Taw, Myanmar. The research findings revealed that the majority of motorcycle accident victims were male individuals under the age of 30, with an occupation of sales persons and a middle school level of education. Motorcyclists accounted for the highest proportion of road accident (57%) and 40% of these accidents were attributed to falls or motorcycles slipping. Several factors were identified as contributing to motorcycle accidents. These included driving without a license (31%), alcohol consumption (19%), high speeding (21%), over-tracking (3.5%), impaired visibility (9.4%), and mechanical issues such as broken brakes, tires, or engines (4%). In terms of accident locations, 48% of urban accidents occurred on straight roads, while 16% and 6% of rural accidents took place on rough and curved roads, respectively. The study also examined the outcomes of the accidents. Nineteen percent of the individuals were treated as outpatients, 53% were categorized as non-severe inpatients, and 18% were classified as severe inpatients. The cases resulting in fatalities were primarily attributed to head injuries (76.5%) and multiple injuries (23.5%).

Khin (2016) made an empirical analysis of traffic accidents in Myanmar, employing binary logistic regression, multinomial logistic regression, and state space models. The study yielded several noteworthy findings. In the binary logistic regression model, the coefficients for age, types of occupation, and the time period of 12-18 hours were statistically significant at the 5% level, while the time period of 0-6 hours was significant at the 1% level. However, gender did not demonstrate statistical significance in predicting traffic accidents. The multinomial logistic regression model revealed significant associations between various factors and the severity of accidents. All age groups below 60 years, possession of a learner driving license, and two types of accidents involving collisions with other vehicles and pedestrian's accidents were found to be significant predictors at the 1% level. These predictors were compared against slightly injured, severely injured, and property damage only cases. Regarding the state space models, none of them met the required assumptions for the fatality series in Myanmar from 1998 to 2014. As a result, the linear trend model was identified as the best-fitting model. These findings contribute to a better understanding of the factors associated with traffic accidents in Myanmar and emphasize the importance of considering age, occupation, time of day, and accident types in efforts to prevent and mitigate road accidents.

2.5 Road Traffic Accidents and Casualties in Yangon

Yangon, the largest city in Myanmar, served as the seat of government from 1948 to 2005. It is a significant industrial and commercial hub, acting as the main center for trade in the country. Located in lower Myanmar, Yangon sits at the convergence of the Yangon and Bago Rivers, approximately 30 km from the coast. The city falls within the wider Delta Region of the South, bordered by Bago Region to the North and East, Ayeyarwady Region to the West, and resting on the shores of the Andaman Sea to the South. Spanning a total area of 10,276.7 km2, Yangon boasts a well-developed transportation network connecting it with other regions and states. The city plays a pivotal role in foreign commerce, handling over 80% of the country's international trade. Additionally, Yangon serves as the central hub for national rail, river, road, and air transportation systems.

According to the Myanmar Population and Housing Census conducted in 2014, the total population of the Yangon Region was 7,360,703. Out of this population, there were 3,516,403 males and 3,844,300 females. The census also revealed that the population of the Yangon Region accounted for approximately 14.3% of the total population of Myanmar. In terms of transportation, the Yangon Region boasts the best infrastructure in the country. All transport to and from other parts of Myanmar, as well as international travel, passes through Yangon. The city is connected to the rest of the country through "Five highways." Additionally, Yangon serves as the central hub for national rail, river, road, and air transportation systems. Public transportation in Yangon is primarily dominated by buses, while motorcycles have been prohibited from entering the central city area, resulting in a small share of motorcycles in the transportation mix. Data from the Road Transport Administration department and the Asian Development Bank indicate that the number of vehicles in the Yangon Region increased from 174,379 in 1995 to 267,594 in 2012. Between 2012 and 2015, the vehicle fleet in the region experienced a growth of 37%. The number of cars doubled within three years, and the car ownership rate reached approximately 62 per 1000 population in 2015 (ADB, 2016).

According to Uhrig (2019), a total of 2,684 accidents were recorded within the Yangon Region in 2018, resulting in 599 deaths and 3,164 injuries. In the first four months of 2021, there were 333 car accidents reported in the Yangon Region. However, motorbikes have been banned and prohibited in 33 townships under the administration of the Yangon City Development Committee, leading to non-compliance with traffic rules by some individuals. As a result, the No.(2) Traffic Police (Yangon) has taken legal action against motorcyclists who do not adhere to the Vehicle Safety and Vehicle Management law (Maung, 2021).

Inaba and Kato (2017) conducted an analysis on the potential impacts of motorcycle demand management and its contribution to the transportation market in Yangon City (33 townships) and six adjacent townships (Thalyin, Hmawbi, Helgu, Htantabin, Twantay, and Kyauktan). The study involved surveying 8,289 households and collecting data on 24,373 trips in Yangon. Descriptive statistics and a logit model were utilized in the study. The results indicated that implementing a ban on motorcycles could lead to a reduction in traffic volume and vehicle kilometers traveled by approximately 18.0% and 26.9% in 2013, respectively. However, these reductions were projected to be only 4.5% and 6.0% by 2035. The ban was found to significantly contribute to mitigating the current urban transportation problems. It was also observed that as income levels increased, there would be a promotion of car ownership and a substitution of motorcycles, offsetting the effects of reduced motorcycle trips in the future.

Htwe (2017) studied the inpatient burden of road traffic accidents (RTAs) at Yangon General Hospital. The study analyzed electronic medical records data of RTA patients from July 2016 to June 2017, specifically focusing on a sample of 100 out of 276 patients selected through a systematic random sampling method. The results revealed that the bed occupancy rate for RTA patients was 13.62% in the neurosurgical unit, 2.64% in the orthopedic unit, and 1.34% of the total available beds in the hospital. During the study period, RTA patients accounted for 45.23% of the total admitted trauma patients at Yangon General Hospital. The average duration of hospital stay for RTA patients was 5.7 days, and 76% of them were discharged within one week. The majority of the RTA victims (78%) were male, and 83% belonged to the economically active age group. Among the patients, 78% were motorcycle drivers, and 15% were motor vehicle drivers. In terms of injuries, over half (60%) sustained injuries to the head and neck, while 11% had lower extremity injuries. The management of RTA patients predominantly involved conservative treatment, with 86% receiving oral and injection drugs. Additionally, 38% underwent dressing procedures, 23% required surgical operations, and 15% needed suturing. Based on the exchange rate of June 2017, the total clinical management cost for each RTA patient, including treatment, laboratory tests, and imaging, amounted to 82,811 Kyats, equivalent to approximately 60.8 USD incurred by the hospital.

2.6 Risk Factors of Road Traffic Accidents and Casualties

According to WHO (2009), 90% of road accidents are caused by human error. Petridou and Moustaki (2002) stated that human factors contribute to over 95% of global road fatalities. Adanu and Jones (2017) noted that drivers and their driving habits play a dominant role in causing traffic crashes. Wearing seat belts can prevent approximately 50% of fatal injuries in a traffic accident (Ma et al., 2012). Failing to wear a seat belt is particularly hazardous for drivers and contributes to more fatalities than any other unsafe driving behavior (Fernando et al., 2012). Therefore, drivers should have a good understanding of traffic rules and laws.

Drink-driving significantly increases the risk of road traffic crashes, and it also raises the likelihood of fatalities or severe injuries resulting from those crashes. Drinking and driving is often linked to engaging in other high-risk behaviors on the road. Studies have estimated that alcohol-related factors contribute to 5-35% of all reported road deaths. Driving under the influence of alcohol substantially elevates the risk of being involved in a crash and exacerbates its severity. Laws addressing drink-driving typically establish a blood alcohol concentration (BAC) limit, such as 0.05

g/dl for the general population and 0.02 g/dl for young or novice drivers (WHO, 2018).

According to the Road Safety-Alcohol report by WHO in 2004, it was found that in many high-income countries, approximately 20% of drivers who were fatally injured had a blood alcohol concentration exceeding the legal limit. In low-income countries, alcohol was found to be present in the blood of 33% to 69% of fatally injured drivers. Even drivers and motorcyclists with a blood alcohol content greater than zero face a higher risk of being involved in a crash compared to those with a blood alcohol content of zero. The risks associated with these blood alcohol levels are higher than previously believed. As a result, many countries have chosen to lower their legal blood alcohol content limits to 0.05 g/dl. Additionally, as blood alcohol levels increase, the severity of injuries sustained in a road crash also tends to increase. Inexperienced young drivers with a blood alcohol content of 0.05 g/dl have a 2.5 times higher risk of a crash compared to more experienced drivers. If the blood alcohol content limit is set at 0.10 g/dl, the risk of a crash becomes three times higher than at 0.05 g/dl, and even at 0.05 g/dl, there is still twice the risk compared to a blood alcohol content of zero.

Daisa and Peers (1997) stated that narrower streets can be affected by emergency vehicles, garbage trucks, and other large vehicles, which can reduce the visibility of drivers and make it difficult to see children playing between cars near a street. The Global Designing Cities Initiative has highlighted that narrow lanes can help reduce speeds and minimize crashes on city streets by making drivers more cautious about traffic and the presence of other road users.

In high-income countries, all vehicles are required to adhere to standard safety regulations, including the installation of seat belts, airbags, and other safety features. However, low-income countries often lack these standard safety regulations, which puts pedestrians, motorcyclists, and cyclists at a higher risk of road traffic accidents (RTAs) (WHO, 2009). Additionally, there are several faults that can be found in vehicles, which have the potential to cause serious injuries and fatalities. Some of these faults include:

(i) Defective Headlight and Taillights

Drivers rely primarily on their headlights to ensure visibility at night. It is crucial that headlights are in proper working condition during nighttime driving. If the headlights are faulty and fail to provide adequate illumination, it poses a significant danger to both the driver and other individuals on the road (The Carlson Law Firm, 2020).

(ii) Defective Tyres

Defective tires can result in the driver losing control of the vehicle. There are several factors that can contribute to defective tires, including low air pressure, overloading of vehicles, and manufacturing defects in the tires themselves (Shen et al., 2013).

(iii) Airbags Fail

When a car accident occurs and the airbags fail to deploy, drivers and passengers may experience severe injuries. Improper deployment of airbags can lead to serious injuries from the airbag propellant or even result in death (Gale, 2018).

(iv) Non-use of Motorcycle Helmets

The primary risk factor for users of motorized two-wheelers is the failure to wear motorcycle helmets. Studies have demonstrated that the absence or improper use of helmets significantly increases the risk of fatalities and injuries in road crashes involving motorized two-wheelers (WHO, 2006). Head injuries are the leading cause of death, injury, and major trauma for individuals using two- and three-wheeled motor vehicles (WHO, 2015). Wearing a motorcycle helmet can reduce the risk of death by nearly 40% and the risk of severe injury by approximately 70%. Strict enforcement of motorcycle helmet laws can improve helmet-wearing rates and thereby decrease head injuries (WHO, 2015).

(v) Non-use of Seat-Belt

According to the CDC, more than half of the individuals who were killed in car crashes were not wearing seat belts at the time of the accident. Wearing a seat belt is the most effective way to prevent death and serious injury in a crash. Seat belts have a significant impact in reducing the risk of death and serious injury. For drivers and front-seat passengers, seat belts reduce the risk of death by 45% and the risk of serious injury by 50%. The Global Health Observatory reports that wearing a seat belt reduces the risk of fatality by 40-50% for front passengers and by 25-75% for rear-seat car occupants. Seat belt laws are widespread globally, with 87% of countries implementing them. However, only 38% of low-income countries and 54% of high-income countries require seat belts to be used by both front and rear seat passengers. Twelve percent of countries have no seat belt laws at all (WHO, 2020).

According to the Global Status Report on Road Safety, wearing a seat belt can reduce the risk of death by 45-50% among drivers and front seat occupants, and reduce the risk of death and serious injuries by 25% among rear seat occupants. In 2014, seven countries made changes to their seat belt legislation to enhance road safety. Child restraints are highly effective in reducing injuries and deaths among child occupants. The use of child restraints can lead to a reduction in deaths by at least 60%. Child restraint laws typically include requirements such as placing children in a child restraint until they are at least 10 years of age or 135 cm in height, restrictions on seating children in the front seat, and reference to safety standards for child restraints. Currently, 84 countries have national child restraint laws in place. Since 2014, four countries have made amendments to their legislation regarding the use of child restraints (WHO, 2018).

2.7 Global Road Safety Measures

Various interventions and plans have been implemented by countries over the years to improve road safety. Legislation plays a crucial role in providing opportunities for researchers to contribute to road safety efforts. According to the ASEAN Regional Road Safety Strategy (ADB, 2016), a significant number of people, approximately 75,000, are killed in road crashes in ASEAN countries, and many more suffer long-term injuries. Each ASEAN country has achieved different levels of maturity in their response to road trauma. Initiatives under the Kuala Lumpur Transport Strategic Plan (KLTSP) 2016-2025 aim to reduce road fatalities by 50% in AMS (ASEAN Member States) by 2020 and by an additional 25% from 2021 to 2030. These initiatives also focus on aligning the implementation with the five pillars of the UN Decade of Action for Road Safety and intensifying regional cooperation to improve transport safety.

In 2018, the World Health Organization (WHO) published a report titled "Global Status Report on Road Safety." The report provided a comprehensive assessment of the road safety situation in 175 countries. According to the report, road traffic crashes continue to pose a significant global problem, with no significant change expected in the near future. The global rate of road traffic deaths stands at 18.2 per 100,000 population, but there is substantial variation among different regions worldwide. In Africa and South-East Asia, the rates of road traffic deaths are the highest, with 26.6 and 20.7 deaths per 100,000 population, respectively. The Eastern Mediterranean and Western Pacific regions have rates comparable to the global average, with 18 and 16.9 deaths per 100,000 population, respectively. The Americas and Europe have the lowest regional rates, with 15.6 and 9.3 deaths per 100,000 population, respectively. There is a greater challenge in reducing the number of road traffic deaths in low-income countries compared to middle- and high-income countries. On average, low-income countries have a death rate of 27.5 per 100,000 population, which is more than three times higher than the average rate of 8.3 deaths per 100,000 population in high-income countries.

According to the Global Status Report on Road Safety, implementing and enforcing legislation regarding key risk factors such as speed, drink driving, and the use of motorcycle helmets, seat-belts, and child restraints are crucial for preventing road traffic deaths. In 2014, twenty-two countries made amendments to their laws pertaining to one or more of these risk factors. Head injuries are the primary cause of death and severe trauma for users of two- and three-wheeled motor vehicles. Proper helmet use can reduce the risk of fatal injuries by 42% and the risk of head injuries by 69%. Since 2014, five countries have made changes to their existing legislation in this regard. It is worth noting that only 63 countries have specific regulations in place to restrict child passengers on motorcycles (WHO, 2018).

Exceeding the speed limit has a detrimental impact on road safety. One important measure to address this issue is the establishment of national speed limits. According to the Global Status Report on Road Safety, setting national speed limits is a crucial step in reducing speed-related accidents. It recommends that maximum urban speed limits should be set at or below 50 km/h, following best practices (WHO, 2018). In Myanmar, speed limits are determined at the national level, with a maximum speed of 100 km/h on highways. In urban areas, the maximum speed limit is set at 48 km/h, and local authorities are not permitted to set lower speed limit zones.

According to the World Bank Mission (2019), road fatalities and injuries are not only a human tragedy but also a significant threat to socioeconomic development. The World Bank, in collaboration with the Global Road Safety Facility, is actively engaged in addressing all aspects of the road safety challenge, including road design, vehicle standards, and institutional measures, to protect lives on the road. Road safety-related fatalities and injuries present a formidable obstacle to global development. In 2021, the WHO launched the Decade of Action for Road Safety 2021-2030, which sets an ambitious goal of reducing road traffic deaths and injuries by at least 50% by 2030 (WHO, 2021).

Hassouna and Pringle (2021) conducted an analysis to predict the crash fatalities in Australia. The research was divided into two parts. In the first part, road fatalities data from 2008 to 2017 were analyzed based on gender, age, and type of road users. The results were compared with global averages of road fatalities to assess the effectiveness of Australian road safety strategies. The findings revealed that male road fatalities, over-speeding, and drivers and passengers of 4-wheel vehicles had the highest fatality rates. In the second part, annual data for road fatalities in Australia spanning 53 years (1965-2008) were analyzed. The researchers employed the ARIMA model to forecast road fatalities. Among the time series models tested, the ARIMA (2, 2, 2) model yielded the lowest values for RMSE and MAPE, indicating better predictive performance. Therefore, this model was selected as the best fitted model to forecast, the number of road fatalities for the next five years (2019-2023) was forecasted.

2.8 Road Safety Laws, Targets and Measures in Myanmar

Road traffic safety encompasses various strategies and measures aimed at preventing fatalities and serious injuries among road users. In Myanmar, there is a rapid growth in motorization, leading to a significant rise in the number of accidents and casualties. This situation highlights the urgent need for comprehensive efforts to improve road safety. Immediate and substantial action, along with adequate funding, is crucial to establish effective management systems (FIA, 2017). Developing the necessary knowledge and expertise to implement essential interventions in Myanmar is imperative. This section provides an overview of diverse road safety measures, including laws, regulations, programs, and action plans aimed at enhancing road safety in the country.

2.8.1 Legislations on the Road Traffic Safety

According to the Myanmar Law Library (2015), Myanmar has implemented several road safety measures to enhance road safety within the country. These measures include the enactment of laws, rules, regulations, and safety programs that have been incorporated into road safety plans. These efforts reflect the commitment of Myanmar towards improving road safety and reducing the number of accidents and injuries on its roads.

(1) The Myanmar Motor Vehicle Act was established through three sections in 1906.

(2) In 1914, the British Government introduced the Indian Motor Vehicle Act No. 8, which became effective in Myanmar.

(3) The Myanmar Motor Vehicle Law was enacted in 1915.

(4) The Myanmar Taxi Law was passed in 1935.

(5) In 1963, the Road and Inland Water Transport Law was promulgated.

(6) The 1964 Motor Vehicle Law was established as the Revolutionary Council Law No. 17 in 1964.

(7) The existing 1989 Motor Vehicle Law was promulgated through Notification No.(1/89) of the Ministry of Transport and Communication in 1989.

(8) The Motor Vehicle Registration Procedures of 1994 were issued for the issuance of driver's licenses.

(9) The Motor Vehicle Law of 2015 was approved as Pyidaungsu Hluttaw Law No. 55 and came into effect on September 7, 2015.

(10) The Road Transport Law of 2016 was enacted as Pyidaungsu Hluttaw Law No. 7 and came into force on January 5, 2016.

(11) The Vehicle Safety and Vehicle Management Law of 2020 was promulgated as Pyidaungsu Hluttaw Law No. 6 and came into effect on May 26, 2020

2.8.2 Motor Vehicle Law

The 2015 Motor Vehicle Law (Union Parliament Law No. 55) was enforced on September 7th with approval by Pyidaungsu Hluttaw Law. The 2015 Motor Vehicle Law served as an amendment to the 1964 Motor Vehicle Law and is comprised of 14 chapters. These chapters include Title and Definition, Objective, Registration of a Motor Vehicle, Temporary Suspension and Cancellation of the

Registration of a Motor Vehicle, Issuance, Refusal, Temporary Suspension, Cancellation, and Permanent Revocation of the Driving License, the Certificate of a Spare Man, and the Training School Business License, Importation, Manufacturing, Selling, Installation, Maintenance, and Inspection of a Motor Vehicle, Powers of the Ministry, Powers of the Department, Prohibitions, Penalties, Payment for Indemnity, Maintenance of Discipline and Taking Action, Matters in the Issue of Rules, and Miscellaneous. This law prohibits over-speeding or under-speeding of a motor vehicle, driving under the influence of drugs or alcohol as described in Section 49, and mandates the use of motorcycle helmets while riding a motorcycle, as well as the fitting of driver and passenger seat belts while driving as outlined in Section 54.

2.8.3 Vehicle Safety and Motor Vehicle Management Law

The Vehicle Safety and Motor Vehicle Management Law (Union Parliament Law No. 6) were enacted on May 26th, 2020. The Vehicle Safety and Motor Vehicle Management Law (2020) consists of 15 chapters, including Title and Definition, Objective, Establishment and Duties of the National Road Council and Region or Union Area Road Safety Council, Powers and Duties of the Ministry, Powers and Duties of the Department, Registration of a Motor Vehicle, Driving and Spare Man Licenses, Business License, Appeal, Compensation Payment, Payment for Indemnity, Maintenance of Discipline and Taking Action, Setting up Fund, Receipt, Use, Maintenance and Management, Prohibitions, Penalties, and Miscellaneous. This law outlines the rules to be followed while driving as described in Section 75, the rules to be followed by motorcycle riders in Section 76, and regulations regarding speeding of a motor vehicle, speed limits, and driving under the influence of drugs or alcohol as stated in Section 77.

2.8.4 National Road Safety Action Plans

According to Zaw (2013), the Traffic Rules Enforcement Supervisory Committee (TRESC) was established with the aim of implementing road safety measures and reducing road traffic accidents in 1989. This committee was formed with the participation of various organizations and departments responsible for road safety. The organizations and departments involved as responsible bodies under the Traffic Rules Enforcement Supervisory Committee are as follows:

(1) Myanmar Police Force
(2) Road Transport Administration Department
(3) Department of Health
(4) Public Works
(5) City Development Committees
(6) Ministry of Education
(7) Ministry of Information

Furthermore, the Road Transport Administration Department (RTAD) under the Ministry of Rail Transportation plays a crucial role in ensuring road safety in the country. RTAD is primarily responsible for vehicle registration, issuing driving licenses, and implementing traffic legislation. In addition to RTAD, the National Road Safety Council (NRSC) was established in mid-2014. The NRSC consists of 25 members who are involved in promoting and implementing road safety measures. The members of the NRSC are described as follows:

(1) Ministry of Information
(2) Ministry of Natural Resources and Environmental Conservation
(3) Ministry of Education
(4) Ministry of Health and Sports
(5) Ministry of Planning and Finance
(6) Ministry of Construction
(7) The Union Attorney-General
(8) Region and Chief Minister
(9) The Mayors of Yangon, Mandalay and Nay Pyi Taw
(10) The Permanent Secretary of the Ministry of Transport and Communications
(11) The Chief of the Myanmar Police Force
(12) The Chairperson of the Lower House Transport, Communication and Construction
(13) The President of the Union of Myanmar Federation of Chambers of Commerce and Industry
(14) The President of the Myanmar Engineering
(15) The Chairperson of the All Bus Lines Control Commit

The main duties of the National Road Safety Council (NRSC) include assigning responsibilities to relevant departments and organizations to ensure the effective implementation of the tasks outlined in the Myanmar Road Safety Action

Plan (MRSAP) (2014-2020). Myanmar has developed its own National Road Safety Action Plan, which is aligned with the UN Resolution on road safety and the road safety guidelines of the Asian Development Bank (ADB). The Myanmar National Road Safety Plan sets the following targets:

(1) To reduce the annual growth rate of road crashes in order to halve the 2014 level of fatalities by 2020

(2) To reduce the fertility rate per 10,000 vehicles by 50% by 2020 from the 2013 level of 9.26

(3) To achieve a 90% motorcycle-helmet-wearing rate all over the country

(4) To achieve a 70% seat-belt-wearing rate all over the country

(5) To eliminate illegal driving

2.8.5 National Road Safety Activities

Road safety activities have played a crucial role in saving many lives by reducing the annual fatalities caused by road accidents, with the aim of halving the current death rate from 2014 to 2020. These activities include implementing a mandatory 100% usage of motorcycle helmets and seat belts nationwide, cracking down on illegal driving without a driver's license, conducting educational sessions for motorcyclists to enhance their understanding of motor vehicle laws, rules, and regulations. To ensure better enforcement, the Motor Vehicle Law has been expanded to cover all sectors related to road safety, including conducting educative talks to raise awareness about the new Motor Vehicle Law and implementing driver testing systems in line with international standards. Furthermore, various other measures have been implemented to enhance road safety, such as public campaigns, increased enforcement efforts combined with education, regulations to encourage drivers to comply with laws, rules, and regulations, collaboration with the private sector to promote road safety through activities like cartoon competitions, road safety talks, and public awareness campaigns. The new Motor Vehicle Law includes provisions mandating the use of motorcycle helmets for both riders and pillion riders, as well as requiring motorcycles to keep their lights on while driving, even during daytime.

2.8.6 Second Decade of Action for Road Safety (2021-2030)

Khin (2022) stated that during the administration of the State Administrative Council (SAC), the newly established National Road Safety Council (NRSC) was formed. The NRSC comprised four sub-committees, namely the Management Sub-Committee, Education and Inspecting Sub-Committee, Research and Health Sub-Committee, and Finance Sub-Committee. Additionally, task forces and state and regional NRSCs were established to support the implementation of the National Road Safety Action Plan (NRSAP, 2021-2030). The NRSAP is divided into eight sectors and is described as follows:

Sector (1): Management for Road Safety Institution, Measures, Human Resources and Financial Resources

Sector (2): Guidelines for Road Traffic Safety

Sector (3): Safer Vehicles

Sector (4): Safer Road and Mobility

Sector (5): Safer Road Users

Sector (6): Post – Crash Response

Sector (7): Raising Awareness, Educating and Law Enforcing for Road Safety

Sector (8): Road Accident Data Collection and Research

The targets of the Myanmar National Road Safety Action Plan (2021 – 2030) are

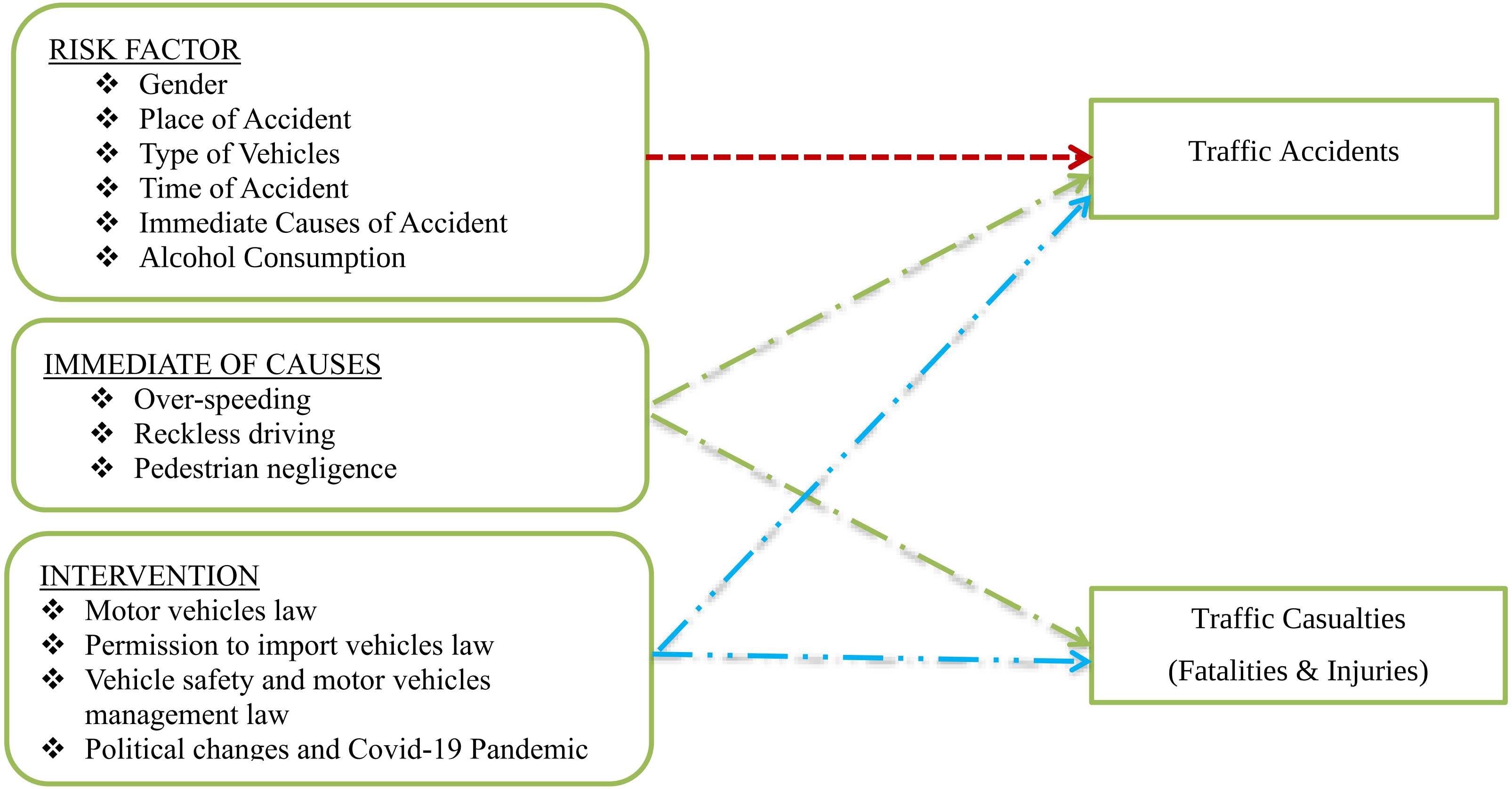
(1) 50% reduction of road fatalities by 2030 using 2020 baseline

(2) 100% use of motorcycle helmet and

(3) 100% use of seat – belt.

2.9 Conceptual Framework of Road Traffic Accidents and Casualties

Numerous authors have explored multiple risk factors in the context of traffic accidents and casualties. This study adopts a conceptual framework inspired by the works of Awal (2013), Katta (2013), and Eboli et al. (2020). The framework serves as the basis for investigating and comprehending the interplay between various factors in relation to traffic incidents. The conceptual framework built in this study depicts how the road traffic accidents and its consequences of casualties are influenced by the risk factors such as gender, place of accident, type of vehicles, time of accident and immediate causes of accident. Conceptual framework for traffic accidents and casualties are described in Figure (2.1).



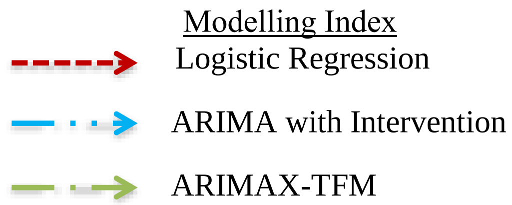


Figure (2.1)   Conceptual Framework for Traffic Accidents and Casualties

In this framework, the independent variables encompass several risk factors associated with traffic accidents, including gender (male, female), place of accident (junction, roundabout, main road, lane, on bridge), type of vehicles (private car, buses, trucks, taxi, motorcycle, other vehicles), time of accident (day, night), immediate causes of accident (human error, failure to comply with regulations, mechanical faults and weather conditions) and alcohol consumption (yes, no). The dependent variables are the number of traffic fatalities and injuries, representing the number of deaths and injuries resulting from traffic accidents.

The conceptual framework suggests that the identified risk factors can influence the occurrence and severity of traffic accidents, leading to varying levels of traffic fatalities and injuries. The studies have highlighted different impact factors contributing to traffic accidents and casualties, such as over-speeding, reckless driving, and pedestrian negligence, are employed as independent variables. Additionally, intervention variables encompass factors that can influence traffic accidents and casualties, such as motor vehicle laws, permission to import vehicle laws, motor vehicle management laws, political changes, and the Covid-19 pandemic. These intervention variables may play a role in affecting the occurrence of traffic incidents.

In summary, the presented framework utilizes figures to illustrate the relationship between the dependent variables (traffic accidents and casualties) and the risk factors, as well as the impact factors and intervention variables, which collectively contribute to a comprehensive understanding of the dynamics involved in traffic incidents.

The arrows in the framework signify the potential influence or relationship between the risk factors, impact factors and the dependent variables. The framework implies that alterations in the independent variables could affect the incidence of traffic accidents and the number of casualties. It is essential to note that this representation is simplified and tailored to the specific context and research objectives of the study.

CHAPTER III
METHODOLOGY

This chapter presents in detail the statistical methods used to analyze the number of road traffic accidents, fatalities, and injuries. It describes logistic regression and the basic concepts of time series modeling that are involved in the application of autoregressive integrated moving average (ARIMA), intervention, and autoregressive integrated moving average with explanatory variables-transfer function (ARIMAX-TFM) models in this study.

3.1 Logistic Regression

Regression methods are applied to analyze the relationship between a response variable and one or more explanatory variables. Linear regression is used to predict the mean value of the response variable. When the outcome variable is discrete and can take on two or more possible values, the logistic regression model is the most frequently used regression model for analysis (Hosmer et al., 2013). Logistic regression allows for non-linear relationships between the dependent and independent variables by applying a non-linear transformation using log transformation.

Logistic regression is used to predict a categorical (usually dichotomous) variable from a set of predictor variables. The dependent variable was dichotomous and the predictors were a mixture of continuous and categorical variables, logistic regression is employed. The logistic regression has two models; they are binary logistic regression and multinomial logistic regression. In a binary logistic regression model, the dependent variable has two levels (categorical). Outputs with more than two values are modeled by multinomial logistic regression, if the multiple categories are ordered, by ordinal logistic regression.

3.1.1 Binary Logistic Regression Model

The logistic regression is used to obtain odds ratio in the presence of more than one explanatory variable. They are analyzed the relationship between a binary dependent variable and a set of independent or explanatory variables. A binary regression model is used to understand how changes in the predictor values are associated with changes in the probability of an event occurring. The dependent variable is the probability (π_i), the resulting outcome is equal 1. Parameter obtained for the independent variables can be used to estimate odds ratio for each of the independent variables in the model. For the binary dependent variable Y, denotes its categories by 1 and 0. It used the geometric term success and failure for the two outcomes.

Odds of an event are the ratio of the probability that an event will occur to the probability that it will not occur. If the probability of an event occurring is π_i, the probability of the event not occurring is (1-π_i). Then, the expressed in terms of odds is

$$\text{Odds} = \frac{\pi_i}{1-\pi_i}$$

However, the logit transformation of the odds, or likelihood ratio that, dependent variable is 1, such that

$$\text{Logit}\ (Y) = \ln\ (\text{odds}) = \ln\left(\frac{\pi_i}{1-\pi_i}\right)$$

$$= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p\ ;\ \text{i} = 1, 2, \cdots, p \qquad (3.1)$$

where π_i = probability (Y = outcome of interest$|X_1 = x_1, X_2 = x_2, \cdots, X_p = x_p$),

x_i = the explanatory variables and

$\beta_0,\ \beta_1, \cdots, \beta_p$ = parameters of the logistic regression

The probability occurrence of interested outcome as

$$\text{E}(Y|x_i\ ) = \pi_i = \frac{e^{\beta_0+\beta_i x_i}}{1+e^{\beta_0+\beta_i x_i}}$$

where E($Y|x_i$) is viewed as a conditional mean, given the value of x_i.

3.1.2 Assumptions of Binary Logistic Regression Model

According to Field (2013), binary logistic regression is a statistical method used to analyze the relationship between a binary outcome variable (such as 0 or 1) and one or more predictor variables. In order to use binary logistic regression, several assumptions should be met;

(i) The outcome variable should be dichotomous or binary, meaning it can only take two values (e.g., yes or no, success or failure, alive or dead).

(ii) Each observation in the sample should be independent of other observations. This means that each observation should be unique and not influenced by other observations in the sample.

(iii) The relationship between the predictor variables and the logit of the outcome variable should be linear. The logit is the natural logarithm of the odds of the outcome variable being equal to 1.

(iv) The predictor variables should not be highly correlated with each other. This is because multicollinearity can make it difficult to determine the independent effect of each predictor variable on the outcome variable.

(v) A large sample size is generally required for logistic regression to provide accurate estimates of the coefficients.

(vi) The sample should not contain any extreme outliers that can have a disproportionate effect on the model.

(vii) There should be no influential observations, which are observations that can have a significant effect on the results of the model.

3.1.3 Statistical Test for Coefficients

Coefficients are tested for significance for inclusion or elimination from the model involves several different techniques. Each of the tests will be explained as follows:

Likelihood Ratio Test

The likelihood ratio test determined the ratio of the maximum value the likelihood of the data with all parameters unrestricted (L_1) over the maximum value of the likelihood when the parameters are restricted (L_0). The formula for the likelihood test statistic is:

$$\text{LR} = -2\ln\left(\frac{L_0}{L_1}\right) = -2\,[\ln(L_0) - \ln(L_1)] = -2\,[L - L_1] \qquad (3.2)$$

where $L = \ln(L_0)$ and

$L_1 = \ln(L_1)$

Wald Test

Wald test is used to determine whether a certain predictor variable x is significant or not. Wald test calculate a square of Z statistic. The Wald statistic follows a chi-square distribution. The Wald test is to find out if explanatory variables in a model are significant. Significant means that add something to the model; variables that add nothing can be deleted without affecting the model. The test can be used for a multitude of different models including those with binary variables or continuous variables. The formula for the Wald test is

$$W = \frac{\widehat{\beta}_i}{\widehat{SE}(\widehat{\beta}_i)} \tag{3.3}$$

where $\widehat{\beta}_i$ = the maximum likelihood estimate of the slope parameter and

$\widehat{SE}(\hat{\beta}_i)$ = estimate of its standard error

Hosmer-Lemeshow Test

Hosmer and Lemeshow proposed grouping based on the values of the estimated probabilities. The Hosmer-Lemeshow statistic evaluates the goodness-of-fit test. This test is used 10 groups of subjects and then compares the number actually in the each group (observed) to the number predicted by the logistic regression model (predicted). The first group contains all subjects whose estimated probability is less than or equal to 0.1, while the tenth group contains those subjects whose estimated probability is greater than 0.9. The Hosmer-Lemeshow goodness-of-fit statistic, $\hat{C}$, is obtained by calculating the Pearson chi-square statistic of observed and expected frequencies. The calculation of $\hat{C}$ is as follows:

$$\hat{C} = \sum_{k=1}^{g} \frac{(o_{ik} - n_k^{'}\bar{\pi}_k)^2}{n_k^{'}\bar{\pi}_k(1-\bar{\pi}_k)}, \quad o_{ik} = \sum_{j=1}^{c_k} Y_j \tag{3.4}$$

where o_{ik} = the sum of independent nonidentically distributed random variables

$n_k^{'}$ = the total number of subjects in the k^{th} group,

$\bar{\pi}_k$ = the average estimated probability in the k^{th} group and

$\hat{C}$ is based on the percentile-type of grouping, usually with 10 groups. These groups are referred to as the “deciles of risk”.

3.2 The Box-Jenkins Methodology

In 1970, George Box and Gwilym Jenkins was a great popularized in research on time series analysis and forecasting. While the forecasting technique they described as an Autoregressive Integrated Moving Average (ARIMA) model or the “Box- Jenkins model”. Several approaches can be used to forecast a time series such as exponential smoothing, decomposition into trend, seasonal and irregular components, regression models, and ARIMA models including Autoregressive Integrated Moving Average with Explanatory Variable (ARIMAX). These approaches can be classified into univariate and multivariate analyses.

3.2.1 Autoregressive (AR) Model

An autoregressive process of order p is given by

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t \quad (3.5)$$

where Y_t = response variable at time t

$Y_{t-1}, Y_{t-2}, \cdots, Y_{t-p}$ = response variables at time lags t-1, t-2, …, t-p, respectively,

$\phi_1, \phi_2, \cdots, \phi_p$ = coefficients to be estimated and

e_t = error term at time t.

Equation (3.5) has the appearance of a regression model with lagged values of the dependent variable in the independent variable positions. AR models are appropriate for stationary time series. In a stationary time series, the autocorrelation coefficients will often tail off to zero, whereas the partial autocorrelation coefficients will decrease to zero after the second time lag. Moreover, the sample autocorrelation functions will differ from the theoretical functions due to sampling variation. The forecasts of autoregressive models generally depend on the observed values in pervious time periods. For AR (1) model, the forecasts of the next value depend on the observations of a pervious time period. For AR (2) models, the forecasts of the next value depend on the observations for two pervious time periods, and so forth.

Autocorrelation Function of the AR (p) Process

The ACF of an AR (p) process is given by

$$\gamma_k = \phi_1 \gamma_{k-1} + \cdots + \phi_p \gamma_{k-p}, k > 0$$

$$\rho_k = \phi_1 \rho_{k-1} + \cdots + \phi_p \rho_{k-p}, k > 0$$

The ACF (ρ_K) is determined by the difference equation,

$$\phi_p(B)\rho_k = (1 - \phi_1 B - \cdots - \phi_p B^P)\rho_k = 0, \quad k > 0.$$

Now, $\phi_p(B)$ can be written as

$$\phi_p(B) = \prod_{i=1}^{m} (1 - G_i B)^{d_i}$$

where, $\sum_i^m d_i$=p and G_i^{-1} (i=1,2,...,m) are the roots of multiplicity d_i of ϕ_p (B)= 0.

Using the difference equations results, as follows,

$$\rho_k = \sum_{i=1}^{m} \sum_{j=0}^{d_i - 1} b_{ij} k^j G_i^k$$

If $d_i = 1$ for all G_i^{-1} , are all distinct and the above reduces to

$$\rho_k = \sum_{i=1}^{p} b_i G_i^k, k > 0. \tag{3.6}$$

For a stationary process, $\left| G_i^{-1} \right| > 1$ and, $\left| G_i \right| < 1$. The ACF ρ_k tails off as a mixture of exponential decays or damped sine waves depending on the roots of ϕ_p(B)= 0. Damped sine waves appear if some roots are complex.

Partial Autocorrelation Function of the AR (p) Process

The autocorrelation function of the AR (p) process is given by

$\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} + \cdots + \phi_p \rho_{k-p}$ for k >0,

it can obviously be seen that when k > p, the PACF ϕ_{kk} will vanish after lag p.

3.2.2 Moving Average (MA) Model

The mathematical representation of the qth order MA model is given by

$$Y_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q e_{t-q} \tag{3.7}$$

where Y_t = Response variable at time t

$\theta_1, \theta_2, \cdots, \theta_q$ = Coefficients to be estimated

$e_{t-1}, e_{t-2}, \cdots, e_{t-q}$ = Errors in pervious time period that are incorporated in response Y_t at the time

It can be seen from both autoregressive and moving average models that the dependent variable Y_t depends on previous values of the errors rather than on the variable itself. The Y_t forecast by MA models is based on a linear combination of a finite number of past errors. In constant, the Y_t forecast by AR models is a linear function of a finite number of past values of Y_t.

Autocorrelation Function of the MA (q) Process

The autocorrelation function of the MA (q) process is given by

$$\rho_k = \begin{cases} \frac{-\theta_k + \theta_1 \theta_{k+1} + \cdots + \theta_{q-k} \theta_q}{1 + \theta_1^2 + \cdots + \theta_q^2}, & k = 1,2,\cdots,q \\ 0, & k > q \end{cases} \tag{3.8}$$

The autocorrelation function of an MA (q) process cuts off after lag q. This important property enables us to identify whether a given time series is generated by a moving average process.

Partial Autocorrelation Function of the MA (q) Process

The Partial autocorrelation function of the MA (q) process tails off as a mixture of exponential decays on the nature of the roots of $\left(1-\theta_1 B-\cdots-\theta_q B^q\right)=0$.

3.2.3 White Noise Process

A stationary process is a sequence of independent and identically distributed random variables. Randomness or white noise (e_t) have the following characteristics:

(1) $E(e_t) = 0$

(2) $V(e_t) = E(e_t^2) = \sigma^2$

(3) $\gamma_k = Cov(e_t, e_{t+k}) = 0$ for all k≠0

3.2.4 Stationarity

A stationary process is a stochastic process in which the unconditional joint probability distribution remains unchanged when shifted in time. A time series is considered stationary when there is no systematic change in its mean (no trend), and variations in variance and strictly periodic patterns have been eliminated. Increasing the value of the time origin 'm' does not impact the joint distribution, which should be dependent on the time interval. A time series is categorized as stationary if the joint probability distribution of $Y_{t_1}, Y_2, \ldots, Y_{t_m}$ is the same as the joint distribution of $Y_{t_{1+k}}, Y_{t_{2+k}}, \ldots, Y_{t_{m+k}}$ for all $t_1, t_2, \ldots, t_m$.

For strict stationarity, a process must exhibit a probability structure that solely relies on time differences. A less stringent condition, referred to as weak stationarity, indicates that the statistical properties of the process are solely dependent on time differences. For a process $\{Y_t\}$ to be considered weakly stationary or second-order stationary, it must satisfy the following conditions:

(1) Mean: $E(Y_t) = \mu$

(2) Variance: $[E(Y_t - \mu)^2] = \sigma^2$

(3) Autocovariance: Cov (Y_t, Y_{t+k}) = $[E(Y_t - \mu)(Y_{t+k} - \mu) = \gamma_k$

3.2.5 Augmented Dickey-Fuller Test

Augmented Dickey-Fuller (ADF) test is introduced by Fuller (1976) and Dickey and Fuller (1979). According to Enders (2015), the ADF test is an extension of the Dickey-Fuller test, which removes autocorrelation from the series and then tests similar to the procedure of the Dickey-Fuller test. The ADF test is most commonly used for verifying nonstationary in the original time series. The ADF test is fundamentally a statistical significance test. The test poses the null hypothesis, the given time series data has nonstationarity, it has a unit root problem. Before run an ADF test, to find out an appropriate regression model. Three different regression equations that can be used to test for the presence of a unit root:

(i) $\Delta Y_t = \phi Y_{t-1} + e_t$ test for a unit root

(ii) $\Delta Y_t = \alpha + \phi Y_{t-1} + e_t$ test for a unit root with constant

(iii) $\Delta Y_t = \alpha + \phi Y_{t-1} + \delta t + e$ test for a unit root with the constant and deterministic trends with time

The Augmented Dickey-Fuller adds lagged differences to these models:

(i) $\Delta Y_t = \phi Y_{t-1} + \sum_{j=1}^{p-1} \varphi_j \Delta Y_{t-j} + e_t$ (3.9)

(ii) $\Delta Y_t = \alpha + \phi Y_{t-1} + \sum_{j=1}^{p-1} \varphi_j \Delta Y_{t-j} + e_t$ (3.10)

(iii) $\Delta Y_t = \alpha + \phi Y_{t-1} + \delta t + \sum_{j=1}^{p-1} \varphi_j \Delta Y_{t-j} + e_t$ (3.11)

Tests including lagged changes are called augmented Dickey-Fuller tests. The hypotheses for the test are

$H_0 : \phi = 1$ (There is unit root)

$H_1 : |\phi| < 1$ (There is no unit root)

Test statistics is

$$T = \frac{\hat{\phi} - 1}{s_{\hat{\phi}}} \tag{3.12}$$

where $\hat{\phi}$ = the least squares estimate and

$S_{\hat{\phi}}$ = the standard error estimate

In general, the p value obtained by the test should be less than the significance alpha value to reject the null hypothesis.

3.2.6 Differencing

Differencing can help stabilize the mean of a time series by removing changes in the level of a time series, and so eliminating (or reducing) trend and seasonality. Differencing is performed by subtracting the previous observation from current observation. Taking the difference between consecutive observations is called a lag-1 difference. The lag-1 difference can be adjusted to suit the specific temporal structure. For time series with a seasonal component, the lag may be expected to be the period of the seasonality. For a nonlinear trend, some temporal structure may still exist after performing a differencing operation. The process of differencing can be repeated more than once until all temporal dependence has been removed. The number of times that differencing is performed is called the difference order.

3.2.7 Variance Stabilizing Techniques

Given the inherent non-stationarity of many economic time series, it becomes essential to achieve stationarity prior to constructing any model. Non-stationary time series encompass elements such as time trends, random walks, and seasonality. If a time series is non-stationary in terms of variances, applying a logarithm or square root transformation can help stabilize the variance. The logarithmic transformation is frequently employed when the variability within the original time series increases proportionally with the series' average level. In scenarios where the original series exhibits a linear increase in standard deviation along with the mean, the logarithmic transformation emerges as an optimal approach to stabilize the variance.

A Box-Cox transformation is a way to transform non-normal dependent variables into a normal shape. Box-Cox transformation is the used of variance-stabilizing transformation technique. This transformation changes the variance of the residuals into a constant. The Box-Cox transformation is given by:

$$Y_t = \begin{cases} \frac{{Y_t}^{\lambda} - 1}{\lambda} & when\ \lambda \neq 0 \\ \ln Y_t & when\ \lambda = 0 \end{cases} \tag{3.13}$$

where $\boldsymbol{\lambda}$ is the shape parameter and a real number. The common types of Box-Cox transformation based on the value of $\boldsymbol{\lambda}$ are presented in Table (3.1).

Table (3.1)
Box-Cox Transformation Based on the Value of λ

Lambda Value (λ)	Transformed Value (y)
-1.0	$1/\ Y_t$
-0.5	$1/\sqrt{\ Y_t}$
0.0	$log_{10}\ (\ Y_t)$ or ln (Y_t)
0.5	$\sqrt{\ Y_t}$
1.0	Y_t

Source: Wei (2006)

3.2.8 Autoregressive Moving Average [ARMA (p,q)] Model

An ARMA (p , q) model is a combination of AR (p) and MA (q) models and is suitable for univariate time series modeling. The ARMA (p , q) model has the following :

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \quad (3.14)$$

The time series data must be stationary in order to apply an ARMA (p , q) model. When q=0, the model changes into a pure autoregressive model of order p. Likewise, when p= 0, the model changes into a pure moving average model of order q. The forecast of the ARMA (p, q) model are dependent upon the current and past value of the response Y as well as the current and past value of the errors.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) properties for autoregressive-moving average processes are shown in Table (3.2).

Table (3.2)

Properties of AR, MA, and ARMA Processes

Model	Autocorrelation (ACF)	Partial Autocorrelation (PACF)
AR (p)	Tails off	Cut off after order p of the process
MA (q)	Cut off after order q of the process	Tails off
ARMA(p, q)	Tails off	Tails off

Source: Wei (2006)

The orders p and q in an ARMA model are determined from the patterns of the sample ACF and PACF.

3.2.9 Autoregressive Integrated Moving Average [ARIMA (p, d, q)] Model

If an observed process time series is non-stationary in the mean, then we can difference the series.

$$\phi_p(B)Y_t = \theta_q(B)e_t \tag{3.15}$$

Then we have a model capable of describing certain types of non-stationary series. This model is also called the integrated moving average model. If Y_t is replaced by $(1-B)^d Y_t$ in the equation (3.15). The general ARIMA (p, d, q) model is

$$\phi_p(B)(1-B)^d Y_t = \theta_0 + \theta_q(B)e_t \tag{3.16}$$

where $\phi_p(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$

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

p = the number of the AR parameters in the model,

q = the number of MA parameters and

d = the degree of differencing.

The parameter θ_0 plays very different roles for d = 0 and d > 0. When d = 0, the original process is stationary, and θ_0 is related to the mean of the process. However, d $\geq$ 1 then θ_0 is called the deterministic trend term. The resulting homogeneous non-stationary model in Equation (3.16) has been referred to as the autoregressive integrated moving average model of order (p, d, q) and is denoted as the ARIMA (p, d, q) model.

The correlation and partial correlation between Y_t and Y_{t+k} is calculated as follows:

$$\rho_k = \frac{Cov(Y_t, Y_{t+k})}{\sqrt{Var(Y_t)}\sqrt{Var(Y_{t+k})}} = \frac{\gamma_k}{\gamma_0}$$

$$= \frac{Cov\left[(Y_t - \hat{Y}_t), (Y_{t+k} - \hat{Y}_{t+k})\right]}{\sqrt{Var(Y_t - \hat{Y}_t)}\sqrt{Var(Y_{t+k} - \hat{Y}_{t+k})}}$$

3.3 Model Building Strategy for ARIMA Model

The basic of Box-Jenkins approach to modeling time series consist of four stages. They are identification, estimation, diagnostic checking, and forecasting.

Step (1): Identification

The first is to determine whether the series is stationary. The unit root test is used to determine whether time series data is stationary or not. An experienced analyst, the plot of the series along with the sample ACF and sample PACF may be used to determine whether time series data is stationary or not. A time series data is non-stationary if the sample ACF decays very slowly and the sample PACF cut offs after lag 1. The model is found to be nonstationary, stationary could be achieved by differencing. The differencing method is to transform a non-stationary series to stationary series. The level of differencing to achieve stationary is denoted by d, and the non-stationary model is denoted by ARMA (p, d, q). Try taking the first difference (1-B)Y_t. More generally, to remove non-stationary that one may need to consider a higher order differencing $(1-B)^d Y_t$ for d ≥ 1. In most cases, d is 0, 1, or 2.

Once a stationary data series is attained, the next step involves computing and examine the sample ACF and sample PACF. After compute and examine the sample ACF and sample PACF of the properly transformed and differenced series to identify the orders of p and q, where p is the highest order in the autoregressive polynomial $(1-\phi B-\cdots-\phi B^p)$, and q is the highest order in the moving average polynominal $(1-\theta_1 B-\cdots-\theta_q B^q)$. Usually the needed orders of p and q are less than or equal to 3.

This step is essential in order to compare the computed autocorrelations and partial autocorrelations with the theoretical ones for various ARIMA models. Both of the sample autocorrelations and sample partial autocorrelations are compared with $\pm {}^{2}/_{\sqrt{n}}$, where n is the number of observations in the time series.

Step (2): Estimation

The next step is parameter estimation in the model. This step involves estimating the parameters of model by minimizing the sum of squared of the fitting errors. To obtain the estimate of the parameter the following methods can be used:

(i) Method of Moment

(ii) Maximum Likelihood Estimation (MLE) Method

(iii) Ordinary Least Squares (OLS) Method

The most commonly method used to estimate the parameters in the model is the maximum likelihood method.

Maximum Likelihood Method

Maximum likelihood method has two situations. These situations are approximately and exactly. The approximate situation classified two categories, such as conditional likelihood estimation and unconditional likelihood estimation.

Conditional Maximum Likelihood Estimation

For general stationary ARMA (p, q) model,

$$Y_t = \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \quad (3.17)$$

where $Y_t = Y_t - \mu$ and $\{e_t\}$ are idenpendent identically distributed (i. i. d), N $(0, \sigma_a^2)$ white noise, the joint probability density of a = $(a_1, a_2, \cdots, a_n)'$ is given by

$$\mathbf{P(a \mid \phi, \mu, \theta, \boldsymbol{\sigma_a^2}) = (2\boldsymbol{\pi\sigma_a^2})^{-n/2} exp\left[\frac{1}{2\pi\sigma_a^2}\sum_{t=1}^{n} \boldsymbol{a_t^2}\right]} \quad (3.18)$$

From Equation (3.17),

$$e_t = \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + Y_t - \phi_1 Y_{t-1} - \cdots - \phi_p Y_{t-p} \quad (3.19)$$

Let **Y** =$(\boldsymbol{Y_1}, \boldsymbol{Y_2}, \ldots, \boldsymbol{Y_n})'$ and assume that initial conditions

$\boldsymbol{Y_*} = (\boldsymbol{Y_{1-p}}, \boldsymbol{Y_{-1}}, \boldsymbol{Y_0})'$ **and** $\boldsymbol{e_*} = (\boldsymbol{e_{1-q}}, \cdots, \boldsymbol{e_{-1}}, \boldsymbol{e_0})'$

The conditional log -likelihood function is

$$\mathbf{ln}\boldsymbol{L_*}(\boldsymbol{\phi, \mu, \theta, \sigma_a^2}) = -\frac{\boldsymbol{n}}{\mathbf{2}}\,\mathbf{ln}\ \mathbf{2}\boldsymbol{\pi\sigma_a^2} - \frac{\boldsymbol{S_*(\phi,\mu,\theta)}}{\mathbf{2}\boldsymbol{\sigma_a^2}} \quad (3.20)$$

where $\boldsymbol{S_*(\phi, \mu, \theta)} = \sum_{t=1}^{n} \boldsymbol{a_t^2}(\boldsymbol{\phi,\mu,\theta} \mid \boldsymbol{Y_*, a_*}, \mathbf{Y})$ is the conditional sum of squares function. The quantities of $\hat{\phi}, \hat{\mu},$ and $\hat{\theta}$ which maximize equation are called the conditional maximum likelihood estimators.

Based on the assumptions that $\{Y_t\}$ is stationary and$\{e_t\}$ is a series of i.i.d, (0, σ_a^2). The unknown y_t by the sample mean $\bar{y}$ and unknown a_t by its expected value of 0, and also assume e_p=e_{p-1}=$\cdots$=e_{p+1-q}= 0 and calculate e_t for t > (p+1), then

$$\boldsymbol{S_*}\ (\boldsymbol{\emptyset, \mu, \theta}) = \sum_{t=p+1}^{n} \boldsymbol{a_t^2}(\boldsymbol{\phi, \mu, \theta, \sigma_a^2}) \quad (3.21)$$

The estimate $\hat{\sigma}_a^2$, of σ_a^2 can be calculated as

$$\boldsymbol{\sigma_a^2} = \frac{\mathbf{S_*}(\widehat{\boldsymbol{\emptyset}},\ \widehat{\boldsymbol{\mu}},\ \widehat{\boldsymbol{\theta}})}{\mathbf{d.f.}} \quad (3.22)$$

Unconditional Maximum Likelihood Estimation and Backcasting Method

The ARMA model can be written in either the forward form,

$$(1 - \phi_1 B - \cdots - \phi_p B^p)\, Y_t = (1 - \theta_1 B - \cdots - \theta_q B^q) e_t \quad (3.23)$$

or the backward form,

$$(1-\phi_1 F - \cdots - \phi_p F^p)\, Y_t = (1- \theta_1 F - \cdots - \theta_q F^q) e_t \qquad (3.24)$$

where $F^j Y_t = Y_{t-j}$.

The $\{e_t\}$ is also a white noise with mean zero and constant variance σ_e^2. The unconditional log likelihood function is

$$\ln \boldsymbol{L}_*(\phi, \mu, \theta, \boldsymbol{\sigma_a^2}) = -\frac{n}{2} \ln 2\pi\sigma_a^2 - \frac{S_*(\phi,\mu,\theta)}{2\sigma_a^2} \qquad (3.25)$$

where, $\mathbf{S}(\boldsymbol{\phi}, \boldsymbol{\mu}, \boldsymbol{\theta})$ is the unconditional sum of square function given by

$$\mathbf{S}(\emptyset, \boldsymbol{\mu}, \boldsymbol{\theta}) = \sum_{t=-\infty}^{n} [\boldsymbol{E}(\boldsymbol{a_t} \mid \boldsymbol{\phi}, \boldsymbol{\mu}, \boldsymbol{\theta}, \boldsymbol{Y})]^2$$

The quantitie $\widehat{\boldsymbol{\phi}}$, $\widehat{\boldsymbol{\mu}}$ and $\widehat{\boldsymbol{\theta}}$ that maximize equation are called unconditional maximum likelihood estimators. These estimator are equivalent to the unconditional least squares estimators obtained by minimizing **S (ϕ, μ,θ)** .

$$\mathbf{S}(\boldsymbol{\phi}, \boldsymbol{\mu}, \boldsymbol{\theta}) = \sum_{t=-M}^{n} [\boldsymbol{E}(\boldsymbol{a_t} \mid \boldsymbol{\phi}, \boldsymbol{\mu}, \boldsymbol{\theta}, \boldsymbol{Y})]^2$$

where M is a sufficiently large integer such that the back cast increment.

The estimate $\hat{\sigma}_a^2$ of σ_a^2 can be calculate as

$$\boldsymbol{\sigma_a^2} = \frac{\mathbf{S}(\widehat{\emptyset},\ \widehat{\mu},\ \widehat{\theta})}{\mathbf{n}}$$

Once the parameters and their standard error are known, the t values were used to check if the model generated is statistically significant or not.

Step (3): Diagnostics checking

A model should be checked for its adequacy before it is used for forecasting. An adequate model is obtained when the residuals cannot be used to improve forecasts. The residual should be random. Histogram and normal probability plots are useful to check for normality. Time sequence plots are useful to check for outliers. The following diagnostics are made:

(i) Time plot of the residuals

(ii) Plot of the residuals' ACF

(iii) Normal Quantile- Quantile (QQ) plot

The criteria used to check the model are listed as follows:

(1) The individual autocorrelations should be small and generally within $\pm 2/\sqrt{n}$ of zero.

(2) The residual autocorrelations as a group should be consistent with those produced by random errors. Checks on adequacy can be done using chi-square test based on the Ljung-Box Q test statistic.

Null Hypothesis; $H_0 : \rho_1 = \rho_2 = \cdots = \rho_k = 0$

There is no autocorrelation among random errors.

Alternative Hypothesis; H_1: At least one of the $\rho_k's$ are not equal to zero.

There is autocorrelation among random errors.

The residual autocorrelations as a group is examined using this test. The Q statistic is given by

$$Q = n(n+2)\sum_{k=1}^{m} \frac{\gamma_k^2(e)}{n-k} \tag{3.26}$$

where n = number of residuals,

k = time lag,

m = number of time lags include in the test and

γ_k(e) = sample autocorrelation function the residuals time lagged k period.

The Q statistic is approximately distributed as a chi-square random variable with m-r degree of freedom, where r is the total number of parameters estimated in the ARIMA model. If the p value associated with Q is small, the model is considered to be inadequate. Hence, a new model or a modified model needs to be developed until a satisfactory model is achieved.

Step (4): Forecasting

Forecasts are usually made using a satisfactory model or a model that has been determined to be the best model. Forecasting can be considered when compare to actual time series. The confidence interval of a forecast is needed to observe the variations that have occurred. In general, the longer the forecast lead time, the longer the prediction interval. It is important to the forecast errors in the model provides reliable forecasts. If the magnitudes of the most forecast recent errors tend to consistently larger than previous errors, the model needs to be re-evaluated. The model needs to be correlated if the recent forecast errors tend to be consistently positive or negative.

In most cases, a model having the best criteria results in unstable forecasts. For this reason, modeling is first carried out using a model with only a few parameters. The need for additional parameters will be evidence from an examination of the residual autocorrelations and partial autocorrelations. An MA parameter shall be added if the MA behavior is apparent in the residual autocorrelations and partial autocorrelations. The AR parameter will be increase if the residual autocorrelations tend to shown an AR process.

Consider the general nonstationary ARIMA (p, d, q) model with d ≠ 0. That is,

$$\phi(B)(1-B)^d Y_t = \theta(B)e_t \tag{3.27}$$

where $\phi(B) = (1-\phi_1 B - \cdots - \phi_p B^p)$ is a stationary AR operator and $\theta(B) = (1-\theta_1 B - \cdots - \theta_q B^q)$ is an invertible MA operator, respectively.

For the general ARIMA model, the model at time t+*l* in an AR representation that exists because the model is invertible. Therefore,

$$\pi(B)Y_{t+l} = e_{t+l} \tag{3.28}$$

$$Y_{t+l} = \sum_{j=1}^{\infty} \pi_j Y_{t+l-j} + e_{t+l} \tag{3.29}$$

By applying the operator

$$1+\psi_1 B + \cdots + \psi_{l-1} B^{l-1}$$

Choosing ψ weights,

$$\sum_{i=0}^{m} \pi_{m-i}\psi_i = 0, \text{ for } m = 1, 2, \ldots, l\text{-}1.$$

For a normal process, the (1-α) 100% forecast limit are

$$\hat{Y}_n(l) \pm N_{\alpha/2}\left[1+\sum_{J=0}^{L-1}\psi_J^2\right]^{\frac{1}{2}}\sigma_a$$

where, $N\alpha_{/2}$ is the standard normal deviate such that P (N > $N\alpha_{/2}$) = $\alpha/2$.

3.4 Intervention Analysis

Intervention analysis can focus on the impact of an event as its purpose or on the elimination of the impact of that event on the time series. The combination of an ARIMA model and dichotomous independent variable is called an intervention model. An intervention is an event that occurs. Sociological and legal applications of intervention models have been used to measure the impacts of new traffic laws, decriminalization, gun control laws, air pollution laws and many other interventions. Intervention functions are a subset of methods called transfer functions.

3.4.1 ARMA (p, q) Model for Intervention Analysis

In the intervention analysis, there are two types of functions. One type is step function and other type is pulse function. The step function represents an intervention occurring at time T that remains in effect thereafter. Pulse function is interventions that are temporary and will die out after time T. A step function at time T is given by:

$$S_t^{(T)} = \begin{cases} 0\,; t < T \\ 1; t \geq T \end{cases} \tag{3.30}$$

and a pulse function at T is given by:

$$P_t^{(T)} = \begin{cases} 0\,; t \neq T \\ 1; t = T \end{cases} \tag{3.31}$$

The pulse function can be produced by differencing the step function $S_t^{(T)}$.

$$P_t^{(T)} = S_t^{(T)} - S_{t-1}^{(T)} = (1\text{-}B)\, S_t^{(T)}$$

An intervention model can be represented equally with the step function or with the pulse function.

In general, an intervention model consists of two components: an intervention function and an ARIMA noise model.

Intervention model = f (I_t) + N_t

where the intervention function is designated f (I_t) and;

N_t = ARIMA (p, d, q)(P, D, Q)

$$I_t = \begin{cases} 1\,; \text{intervention occurs} \\ 0\,;\ \text{otherwise} \end{cases}$$

The several different response patterns of an intervention function are showed in Figure (3.1).

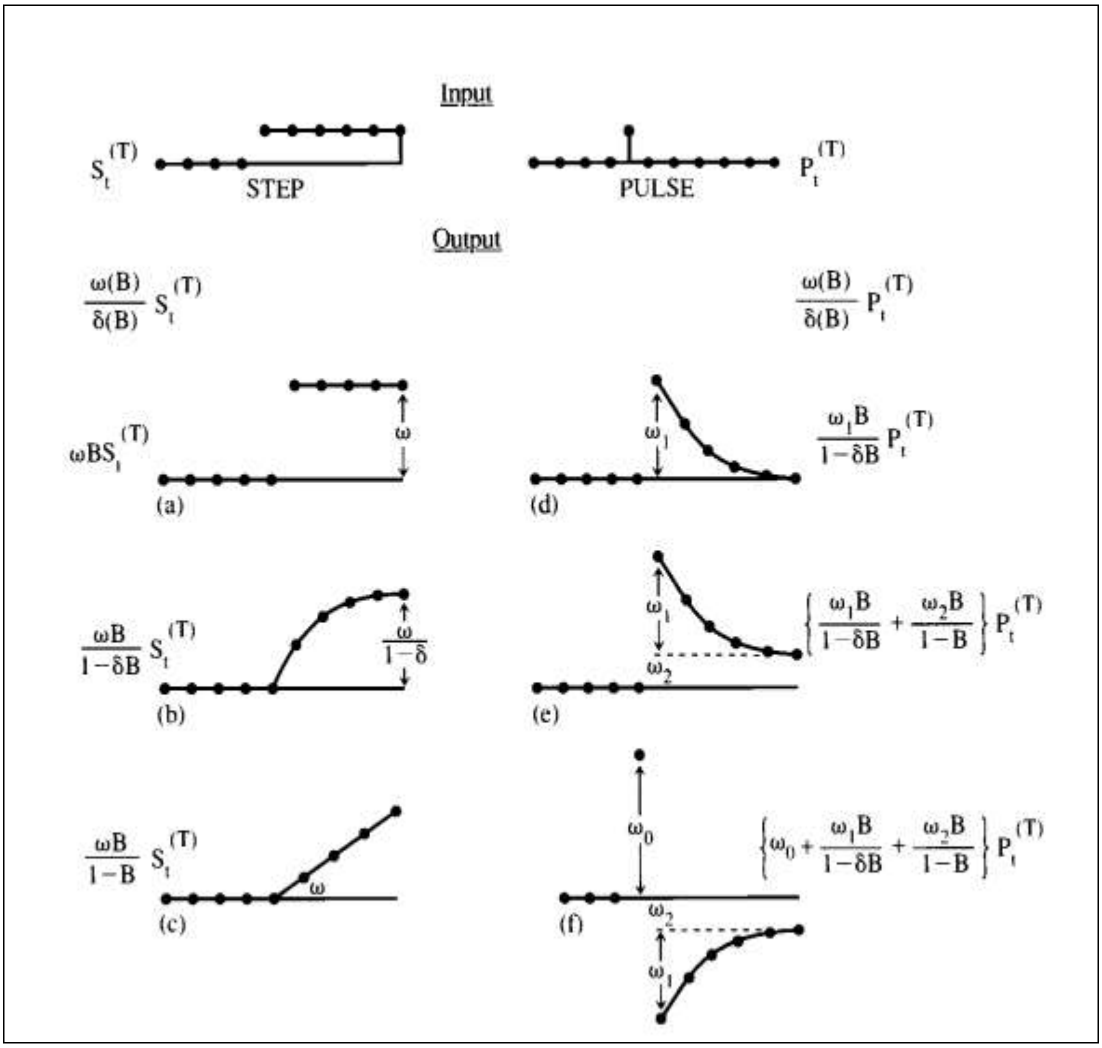


Figure (3.1) Responses to Step and Pulse Function

Source: Box et al. (2016)

Several different response patterns are possible through different choices of the transfer function. Figure 3.1 shows the responses for various simple transfer functions with both step and pulse indicators as input. In Figure 3.1(a) can be used to represent a permanent step change in level of unknown magnitude ω after time T. A gradual change with rate δ that eventually approaches the long-run change in level equal to $\frac{\omega}{1-\delta}$, is shown in Figure 3.1(b).

A sudden ‘‘pulse’’ change after time T of unknown magnitude ω_1, followed by a gradual decay of rate δ back to the original preintervention level with no permanent effect is shown in Figure 3.1(d). More complex response patterns can be obtained by various linear combinations of the simpler forms is shown in Figure 3.1(f).

3.4.2 ARIMAX- Transfer Function Model

The ARIMAX model is simply an ARIMA model with additional or input variables. It also includes other independent variables. ARIMAX model is referred to as Transfer Function Model (Wei, 2006). The ARIMAX model is similar to a multivariate regression model. The model is an integration of a regression model with an ARIMA model. The result of this model covers the advantages of both models. The regression method describes the explanatory relationship while the ARIMA method takes care of the autocorrelation in the residuals of the regression model. This model is suitable for forecasting when data is stationary or not, and multivariate with any type of data pattern.

Transfer Function Model (TFM) is assumed that the effect of the intervention model is increased from a deterministic dummy variable. The effect of the safety measures (intervention) factors which influence the level of intervention may be different from time to time. For instance, the effect of the safety seat-belt law on the number and rate of road traffic accidents is influenced by the percentage of seat-belt usage. The intervention variable can be any exogenous stochastic process. With this assumption, the transfer function-noise model is suitable to estimate the impact of the safety measures. The pattern is referred to as the transfer function-noise model (Box & Jenkins, 1976), otherwise known as the dynamic regression model (Pankratz, 1991).

Assume that X_t and Y_t are properly transformed series, they are both stationary. In a single input-output linear system are as follows:

$$Y_t = v(\mathrm{B})X_t + N_t \tag{3.32}$$

where $v(\mathrm{B}) = \sum_{j=-\infty}^{\infty} v_j B^j$. If v_j = 0 for j<0, then

$$\begin{aligned} Y_t &= v_0 X_t + v_1 X_{t-1} + v_2 X_{t-2} + \cdots \\ &= (v_o + v_1 B + v_2 B^2 + \cdots) X_t \\ &= v(\mathrm{B}) X_t \end{aligned} \tag{3.33}$$

where $v(\mathrm{B}) = \sum_{j=-\infty}^{\infty} v_j B^j$, $\sum_{j=0}^{\infty} |v_j| < \infty$ and X_t and N_t are independent.

The purposes of transfer function modeling are to identify and estimate the transfer function $v(\mathrm{B})$ and a noise model for N_t based on the available information of the input series X_t and the output series Y_t.The difficulties are that the information on X_t and Y_t is finite and the transfer function $v(\mathrm{B})$ in Equation (3.32) may contain an infinite number of coefficients.

The transfer function v(B) in the rational form

$$v(\text{B}) = \frac{\omega(B)B^i}{\delta(B)} \tag{3.34}$$

where ω(B) = $\omega_0 - \omega_1 B - \cdots - \omega_S B^S$, $\delta(B)$ = 1- $\delta_1 B - \cdots - \delta_r B^r$, and b is a delay parameter representing the actual time lag. In general, the transfer function can be written as

$$v(\text{B}) = \frac{\omega_0 - \omega_1 B - \cdots - \omega_S B^S}{1 - \delta_1 B - \cdots - \delta_r B^r} \tag{3.35}$$

The general representation of the transfer function-noise model is given by

$$Y_t \quad = \theta_0 + \sum \frac{\omega(B)B^i}{\delta(B)} I_{i,t} + \frac{(1-\theta_q B)}{(1-\emptyset_p B)(1-B)^d} e_t \tag{3.36}$$

where θ_0 = Constant mean,

$I_{i,t}$ = i^{th} input time series or a difference of the i^{th} input time series,

b = Pure time delay for the effect of the i^{th} input time series,

ω(B) = Numerator polynomial of the transfer function for the i^{th} input time series,

$\delta(B)$ = Denominator polynomial of the transfer function for the i^{th} input time series,

e_t = White noise term and

B = Backshift operator.

The estimation process and diagnostic checking are similar to ARIMA modeling the identification procedure is somewhat different. The intervention model consists of three parameters ω, δ and b, where ω is known as impact parameter which implies change due to intervention. δ is known as slope parameter which has different meaning in case of different types of intervention. In case of intervention step, if δ is near to zero, the effect of the intervention remains constant over time and if δ is near to one, the effect of intervention increases over time.

The delay parameter b usually takes value 0, 1 or 2; b=0 implies that the effect of intervention has occurred at the time of intervention, b=1 implies that the effect of intervention is felt after a delay of one period and so on. The order of b can be determined by examining the data visually and the form of the model is ascertained by comparing computed impulse response functions with theoretical impulse response functions. The impulse response functions is obtained by plotting the residual which is the absolute difference between the actual values of the post-intervention observations with the forecasted value obtained by ARIMA model which fitted on the basis of pre-intervention data. The six step model specification processes are listed as follows (Box et al., 2016 and Montgomery et al., 2015).

Step 1. Obtaining the preliminary estimates of the coefficients in v(B)

Step 2. Specifications of orders b, r and s. Figure (3.2) is shown the sample cross-correlation function (CCF) is used to the basic transfer function model structures. To determine the orders of b, r and s based on the CCF.

Step 3. Obtain the estimates of $\delta_i\ and\ \omega_i$.

Step 4. Model the noise.

Step 5. Fit the overall model.

Step 6. Check the model adequacy.

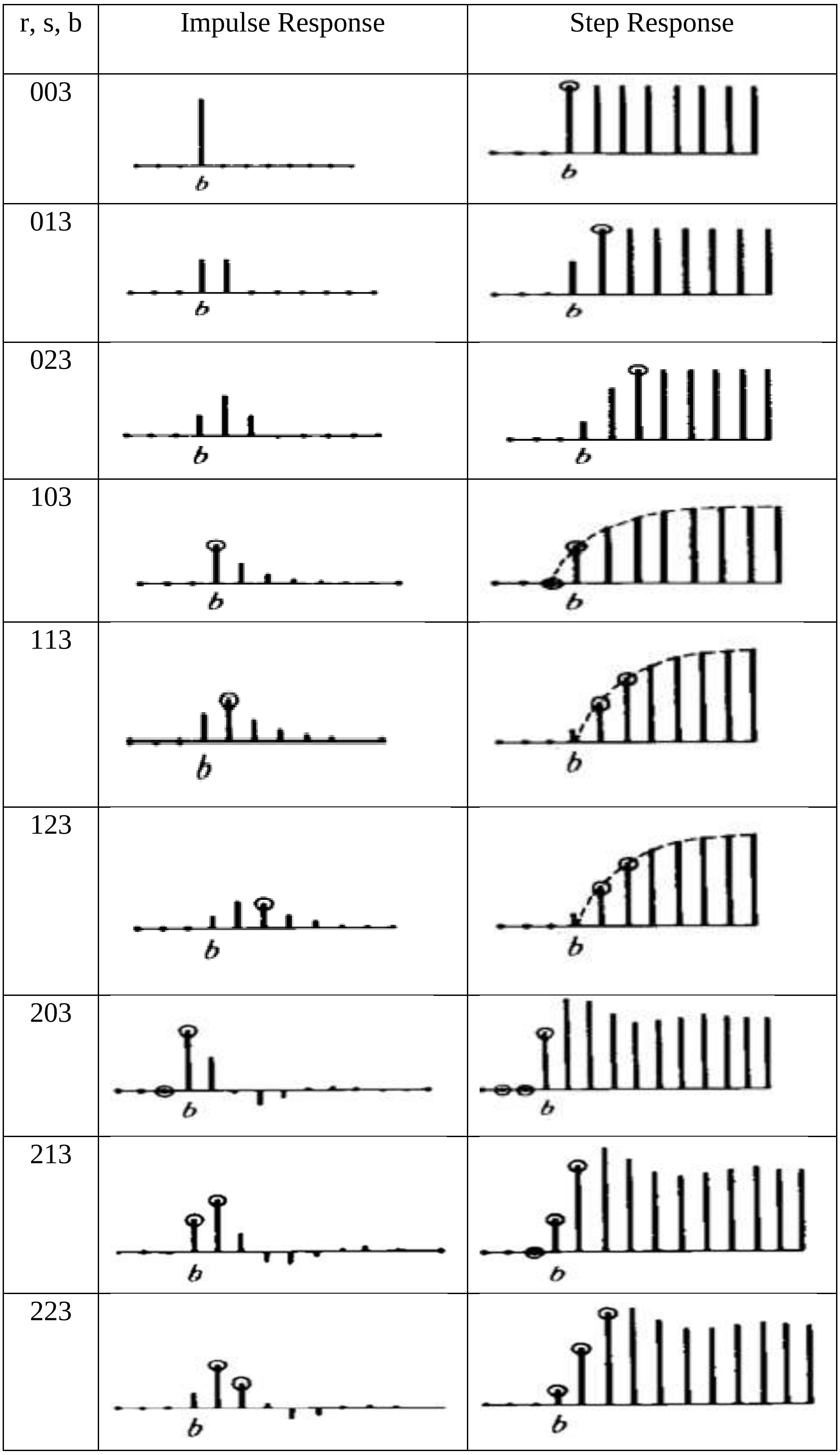


Figure (3.2) Examples of Impulse and Step Response Function

Source: Box et al. (2016)

3.4.3 Model Bulding Strategy for ARIMAX-TFM

Building an ARIMAX-TFM is a similar iterative process as building a univariate Box-Jenkins ARIMA model.

Step (1): Identification

Identification stage of transfer function involves prewhitening of both the input and output. Calculation the cross-correlation functions of the prewhitened series and identification of order b, s and r. The prewhitening process was achieved by fitting ARIMA model for each input series sufficient to reduce the residuals to white noise, then, filtered the input series with the model to get white noise series. The same ARIMA model was used to filter the output series to get white noise residual series. The prewhitening process for non-stationary series is given by

$$\phi_x(B)X_t = \theta_x(B)\alpha_t \tag{3.37}$$

where α_t is white noise with mean zero and variance σ_α^2,

$\alpha_t = \theta_x(B)^{-1}\phi_x(B)X_t$ and

$\beta_t = \theta_x(B)^{-1}\phi_x(B)Y_t$.

The cross-correlation functions between the prewhitened input series and output series were calculated at various lags, L (L= 0, $\pm1, \pm2, \cdots, \pm7$).

Step (2): Estimation

After identification of model is completed, the next step is to estimate the parameters of transfer function model. The model parameters are estimated using maximum likelihood estimation method.

$$Y_t = \frac{\omega(B)}{\delta(B)}X_{t-b} + \frac{\theta(B)}{\emptyset(B)}e_t$$

$$\delta(B)\phi(B)Y_t = \phi(B)\omega(B)X_{t-b} + \delta(B)\theta(B)e_t$$

where $\delta(B)\phi(B) = (1-\delta_1(B) - \cdots - \delta_r B^r)(1-\phi_1 B - \cdots - \phi_p B^p)$

$$\phi(B)\omega(B) = (1-\phi_1 B - \cdots - \phi_p B^p)(\omega_0 - \omega_1 B - \cdots - \omega_s B^s$$

$$\delta(B)\theta(B) = (1-\delta_1 B - \cdots - \delta_r B^r)(1-\theta_1 B - \cdots - \theta_q B^q)$$

The a_t are N (0, σ_a^2) white noise series. The conditional likelihood function is

$$L\,(\boldsymbol{\delta}, \boldsymbol{\omega}, \boldsymbol{\phi}, \boldsymbol{\theta}, \boldsymbol{\sigma_a^2} \mid \boldsymbol{b}, \boldsymbol{x}, \boldsymbol{y}, \boldsymbol{x_0}, \boldsymbol{y_0}, \boldsymbol{a_0}) = (2\pi\sigma_a^2)^{-n/2} \exp\left[-\frac{1}{2\sigma_a^2}\sum_{t=1}^{n} a_t^2\right] \tag{3.38}$$

Step (3): Diagnostic Checking

In this step, after the model has been identified and its parameters estimated, it is necessary to check the model adequacy before forecasting. In the transfer function model, the autocorrelation check of residual is performed to see whether the residual was random and cross-correlation analysis between input series that has been prewhiening with residual transfer function model. The adequacy of the model was checked using the Ljung-Box statistics.

(i) Cross-correlation check

To check the noise series a_t and the input series x_t are independent. For an adequate model, the sample CCF between $\hat{a}_t$ and α_t should no pattern and lie within their two standard errors. The following test can also be used:

$$Q_0 = \text{m(m+2)}\sum_{j=0}^{K} \frac{\gamma_{\hat{a}}^2(j)}{m-j} \tag{3.39}$$

which approximately follows a χ^2 distribution with (K+1)-M degree of freedom, where m is the number of residuals $\hat{a}_t$ and M is the number of parameters δ_i *and* ω_j estimated in the transfer function.

(ii) Autocorrelation Check

To check the noise model is adequate. For an adequate model, both the sample ACF and PACF of $\hat{a}_t$ should not show any pattern. The Q-statistic is given by

$$Q_1 = \text{m(m+2)}\sum_{j=1}^{K} \frac{\gamma_{\hat{a}}^2(j)}{m-j} \tag{3.40}$$

The Q_1 statistic approximately follows a χ^2 distribution with (K-p-q) degree of freedom depending only on the number of parameters in the noise model.

3.5 Model Selection Criteria

In time series analysis, it is crucial to identify the appropriate ARIMA model by analyzing the plot of the series and matching its sample autocorrelation and partial autocorrelation patterns. However, additional analysis is necessary to select a satisfactory model. This can be achieved by employing various model selection criteria. In this study, the following criteria are utilized to select the best model: the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error

(MSE), and Root Mean Square Error (RMSE). These criteria are computed as follows:

(i) Akaike Information Criterion (AIC)

The formula for the AIC is

$$\text{AIC} = \text{n ln } (\hat{\sigma}_a^2) + 2\text{k} \tag{3.41}$$

where $\hat{\sigma}_a^2 = \frac{Residual\ Sum\ of\ Squares}{n}$,

n = sample size and

k = the number of model parameters.

(ii) Bayesian Information Criterion (BIC)

The formula for the BIC is

$$\text{BIC} = \text{n ln } (\hat{\sigma}_a^2) + \text{k ln (n)} \tag{3.42}$$

where $\hat{\sigma}_a^2 = \frac{Residual\ Sum\ of\ Squares}{n}$,

n = sample size and

k = the number of model parameters.

In time series analysis, AIC and BIC can be used to compare different models and select the one that provides the best balance between goodness of fit and simplicity. The lower the value of AIC or BIC, the better the model is considered. Both criteria are based on various assumptions and asymptotic approximations.

(iii) The Mean Absolute Error (MAE)

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight. The mean absolute error is defined as:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |Y_t - \hat{Y}_t| \tag{3.43}$$

where $\hat{Y}_t$ = the prediction,

Y_t = the true value and

n = number of observation.

(iv) The Mean Absolute Percentage Error (MAPE)

MAPE is the mean or average of the absolute percentage errors of forecasts. Error is defined as actual or observed value minus forecasted value. The mean absolute percentage error is given by

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t} \times 100 \tag{3.44}$$

where $\hat{Y}_t$ = the prediction,

Y_t = the true value and

n = number of observation.

(v) The Mean Square Error (MSE)

MSE of an estimator measures the average of error square. It is always non-negative and values closed to zero are better. The mean square error is expressed as:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2 \tag{3.45}$$

where $\hat{Y}_t$ = the prediction,

Y_t = the true value and

n = number of observation.

(vi) The Root Mean Square Error (RMSE)

RMSE is a quadratic scoring rule that also measures the average magnitude of the error. It's the square root of the average of square differences between prediction and actual observation. The root mean square error is expressed as:

$$\text{RMSE} = \sqrt{MSE} \tag{3.46}$$

where MSE = Mean Square Error

CHAPTER IV
ANAYSIS OF RISK FACTORS RELATING TO TRAFFIC CASUALTIES IN YANGON

This chapter consists of the various statistical analyses and key findings on traffic casualties in Yangon. The status of road traffic accidents and casualties were firstly analyzed by using descriptive statistics. The logistic regression was further used to analyze the risk factors which are significantly related to road traffic casualties.

4.1 Data Source

This study collected the secondary data on traffic accidents and its consequences of casualties from No.(2) Office of Traffic Police in Yangon for the period from 2013 to 2022 on the monthly basis. Based on the severity of traffic accident, the consequences of casualty were classified into fatalities and injuries. All these data were then converted from monthly basis to yearly basis.

4.2 Descriptive Statistics of Road Traffic Accidents and Casualties

The most common characteristics of road traffic accidents and casualties in Yangon are discussed through the analysis using descriptive statistics in this section.

4.2.1 Status of Traffic Accidents and Casualties

The distribution of road traffic accidents, fatalities and injuries for the period from 2013 until 2022 is presented in Table (4.1).

Table (4.1)

Yearly Traffic Accidents and Casualties in Yangon

Year	Number of Accidents	Number of Fatalities	Number of Injuries
2013	2122	342	2955
2014	2208	382	2926
2015	1956	365	2609
2016	1866	391	2176
2017	1731	403	2061
2018	1718	386	1776
2019	1432	382	1530
2020	1126	338	1218
2021	586	255	525
2022	669	310	654

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

According to Table (4.1), it was observed that the lowest number of accidents was 586 in 2021, while the highest number of accidents occurred in 2014 with a total of 2,208. In terms of fatalities, the minimum number was 255 in 2021, whereas the maximum was 403 in 2017. The lowest number of traffic injuries was 526 in 2021 however the highest number of injuries was 2,955 in 2013. It has been found that the number of injuries exceeded the number of fatalities. It can be found that each accident might involve multiple individuals getting fatal or injured. In particular, such decreases occurred in 2021 might be attributed to the significant impact of the Covid-19 pandemic in Myanmar. There were fewer vehicles and people on the roads and streets, and it is less likely to have traffic accidents at that time. It is also expected that there may be somewhat difference in the number of accidents and casualties between actual and reported cases. Particularly, minor traffic accidents and casualties might not be included in the official record of Traffic Police due to failure to report such minor cases in reality. The trend of road traffic accidents, fatalities, and injuries are presented in Figure (4.1).

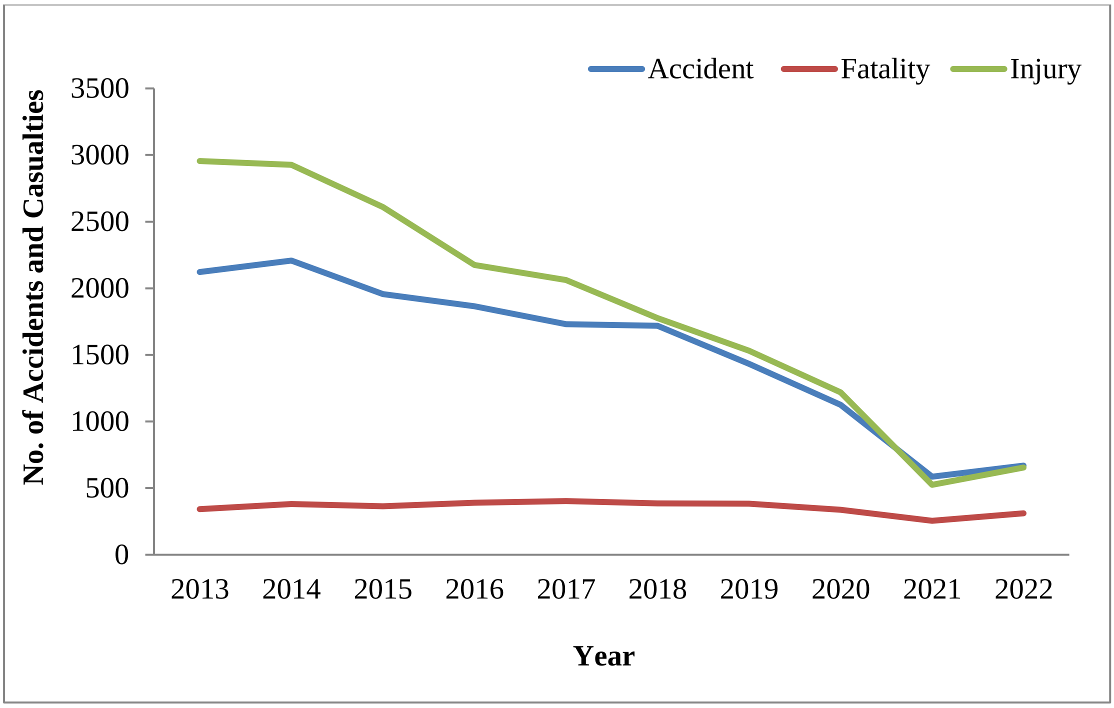


Figure (4.1) Trend of Traffic Accidents and Casualties

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

According to Figure (4.1), the number of accidents, fatalities and injuries as a downward trend during the study period from 2013 to 2021, but started to increase in 2022.

4.2.2 Traffic Casualties Status by Gender

The number of males and females who suffered from road traffic accidents causing fatalities and injuries is shown in Table (4.2) and Figure (4.2). It can be observed that there was a significant difference in the number of fatalities and injuries between males and females.

Table (4.2)

Number of Traffic Casualties by Gender

Year	Number of Fatalities		Number of Injuries	
	Male	Female	Male	Female
2013	269	73	1953	1002
2014	329	53	2003	923
2015	289	76	1737	872
2016	325	66	1527	649
2017	317	86	1414	647
2018	324	62	1248	528
2019	296	86	1021	509
2020	274	64	848	370
2021	198	57	366	159
2022	243	67	450	204

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

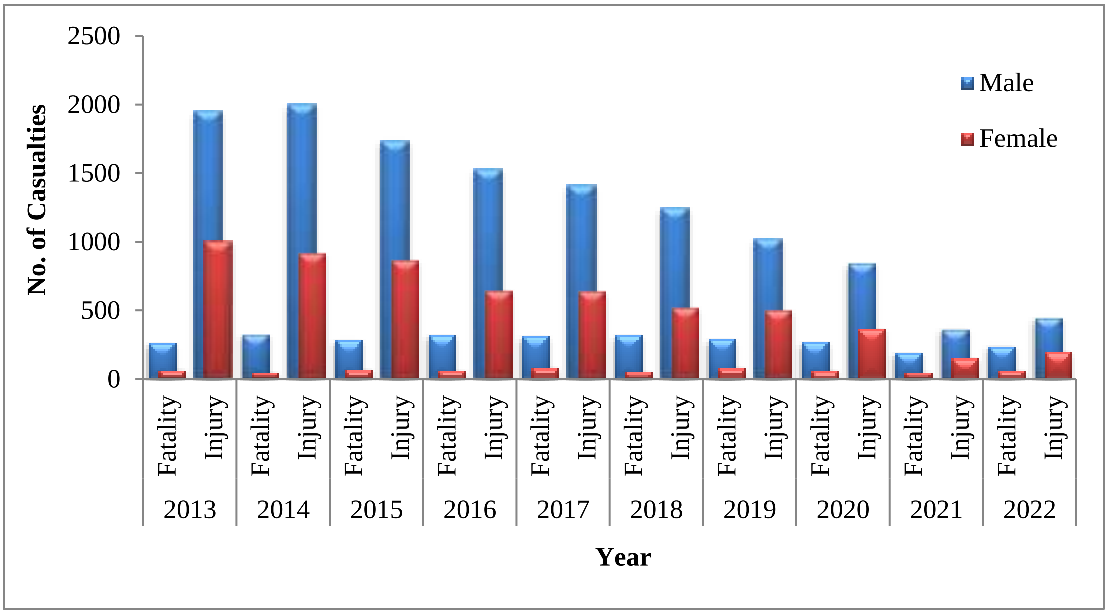


Figure (4.2) Number of Traffic Casualties by Gender

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

According to Table (4.2), it was observed that the number of fatalities and injuries caused by traffic accidents was higher for males than for females. In this study, males were likely to be less disciplined than females and more likely to drive under the influence of alcohol and drugs, resulting in higher number of injuries and fatalities in Myanmar. Additionally, a large number of males usually engage in risky working environment of driving and as a result they might be suffered from traffic accidents more than females. The number of accidents and casualties by gender was also found to be the lowest in 2021 as mentioned above.

4.2.3 Traffic Accidents and Casualties Status by Place

The place of occurrence of accident and casualties were classified into junction, roundabout, main road, lane and on bridge. Table (4.3) and Figure (4.3) provide descriptions of the place of accidents and casualties commonly recognized in Yangon.

Table (4.3)

Number of Traffic Accidents and Casualties by Place

Year	Number of Accidents					Number of Fatalities					Number of Injuries				
	Junction	Round about	Main Road	Lane	On Bridge	Junction	Round about	Main Road	Lane	On Bridge	Junction	Round about	Main Road	Lane	On Bridge
2013	347	11	1148	583	33	38	0	188	112	4	511	11	1636	773	24
2014	394	15	1387	327	85	55	2	249	60	16	563	15	1765	444	139
2015	347	7	1195	349	58	48	0	250	55	12	485	2	1533	473	116
2016	342	3	1414	48	59	40	1	330	10	10	450	0	1611	44	71
2017	366	13	1121	158	73	66	2	266	51	18	449	15	1355	155	87
2018	361	3	1135	154	65	60	0	284	33	9	385	0	1153	143	95
2019	234	3	1111	37	47	46	1	317	10	8	245	0	1189	41	55
2020	255	2	728	108	33	60	1	235	34	8	284	0	781	111	42
2021	106	2	433	22	23	42	0	197	8	8	92	0	407	14	12
2022	103	2	532	10	22	43	1	251	4	11	89	3	532	8	22

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

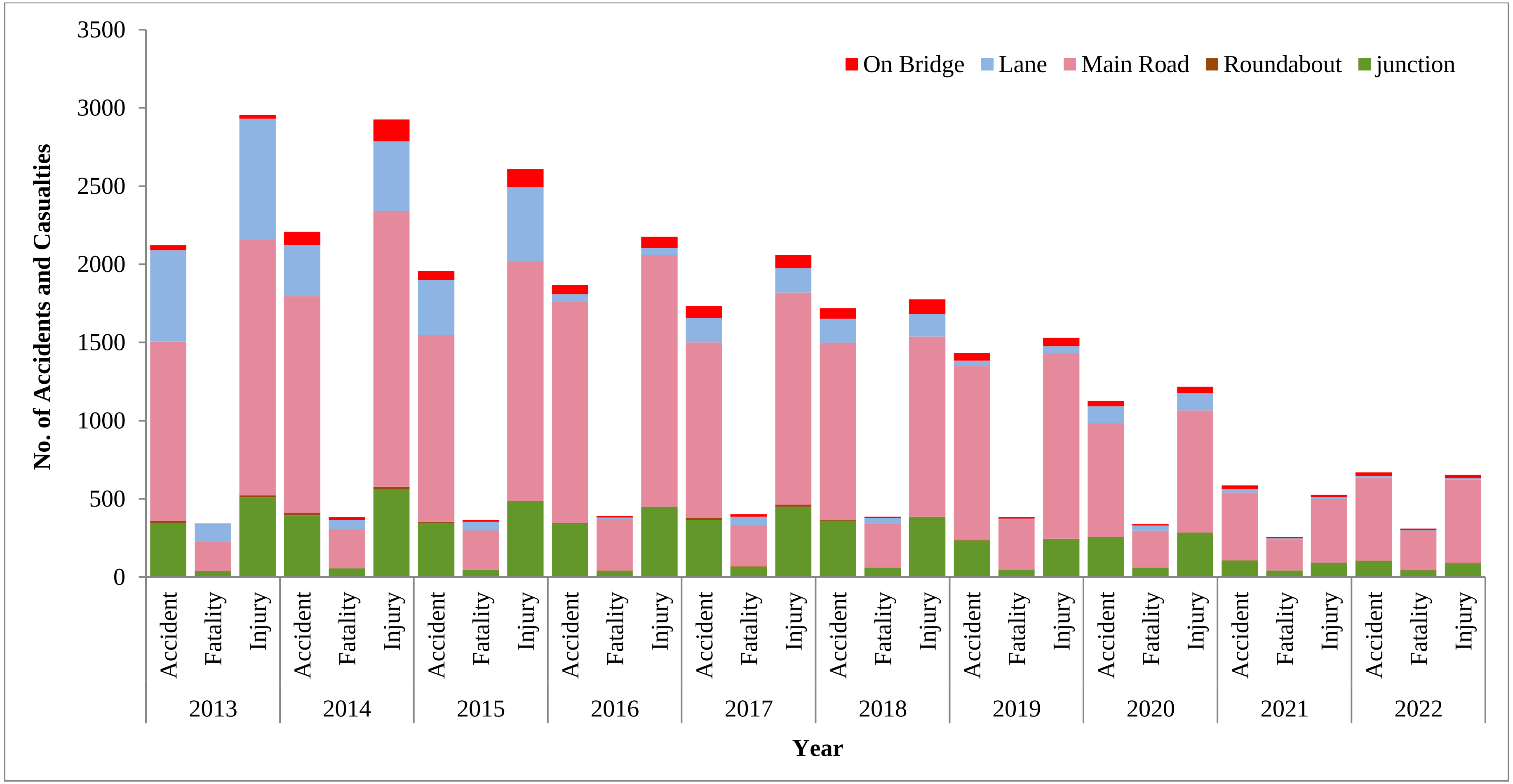


Figure (4.3) Number of Traffic Accidents and Casualties by Place

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

As shown in Figure (4.3), the majority of traffic accidents, fatalities, and injuries were occurred on main roads, followed by lanes being the second most frequent location for the occurrence of accidents and casualties. Roundabouts represented the lowest number of accidents and casualties. This situation might be influenced by several factors such as well-maintained road conditions, high-speed driving, and non-compliance with traffic regulations by road users. Interestingly, it was observed that the number of traffic accidents and casualties was at its lowest in 2021, likely influenced by the significant impact of the Covid-19 pandemic as mentioned earlier.

4.2.4 Traffic Accidents and Casualties Status by Type of Vehicles

The vehicles involved in the accidents and casualties were grouped into six categories such as private cars, buses, taxis, trucks, motorcycles, and others. The types of vehicles involved in the occurrence of accidents and casualties are presented in Table (4.4) and Figure (4.4).

Table (4.4)

Number of Traffic Accidents and Casualties by Type of Vehicles

Year	Number of Accidents						Number of Fatalities						Number of Injuries					
	Car	Bus	Taxi	Truck	Motorbike	Other	Car	Bus	Taxi	Truck	Motorbike	Other	Car	Bus	Taxi	Truck	Motorbike	Other
2013	946	310	425	89	279	73	173	62	50	19	36	2	1158	762	529	110	384	12
2014	768	275	660	126	300	79	99	60	102	37	80	4	906	613	830	175	398	4
2015	808	212	550	43	261	82	159	42	78	12	59	15	999	453	755	48	329	25
2016	893	77	599	30	200	67	209	4	120	4	50	4	923	40	940	14	245	14
2017	771	179	441	55	212	73	185	46	88	13	63	8	884	304	564	33	247	29
2018	774	146	359	67	288	84	177	40	55	10	89	15	826	148	357	76	335	34
2019	489	144	313	35	255	196	113	38	56	10	104	61	571	183	335	20	265	156
2020	474	92	215	21	239	85	131	27	58	6	100	16	538	141	206	22	257	54
2021	140	58	110	9	103	166	55	12	28	2	71	87	147	75	96	5	86	116
2022	334	82	81	70	74	28	161	40	33	30	38	8	297	89	74	89	70	35

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

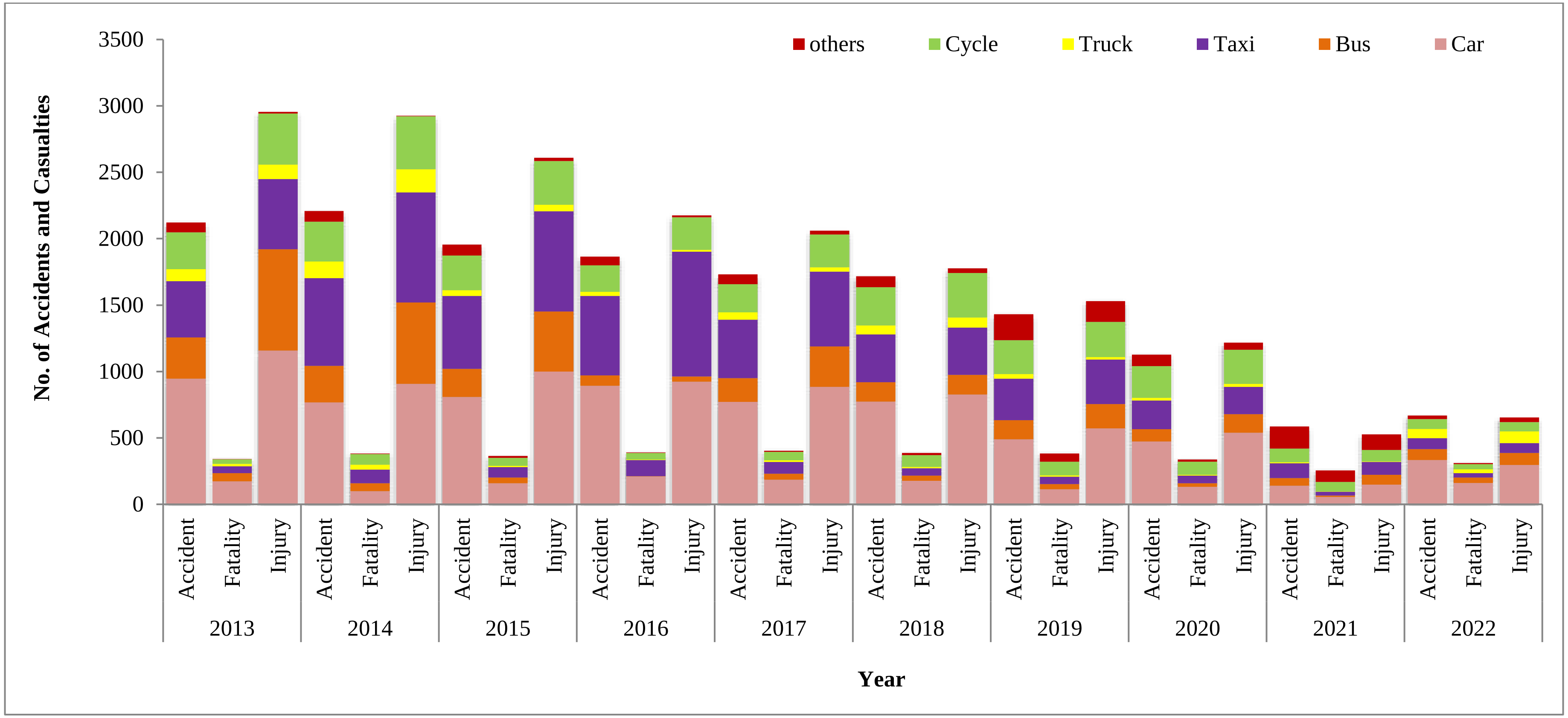


Figure (4.4) Number of Traffic Accidents and Casualties by Type of Vehicles

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

Table (4.4) highlighted that most traffic accidents, fatalities and injuries were caused by private cars, followed by buses, taxis, motorcycles, trucks, and other vehicles. When examining the number of accidents and casualties by vehicle type from 2013 to 2022, it was found that the lowest figures were recorded in 2021. As shown in Figure (4.4), the involvement of private cars in the occurrence of road traffic accidents and casualties was significantly higher than other vehicle types.

4.2.5 Accidents and Casualties Status by Time

The time of the occurrence of road traffic accidents and casualties is divided into four periods: 6:00 AM-12:00 PM, 12:00 PM-18:00 PM, 18:00 PM-24:00 AM and 24:00 AM-6:00 AM. The number of road traffic accidents and casualties occurred in day time and night time for the period from 2013 to 2022 are described in Table (4.5) and Figure (4.5).

Table (4.5)

Number of Traffic Accidents and Casualties by Time

Time	2013			2014			2015			2016			2017			2018			2019			2020			2021			2022		
	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries	Accidents	Fatalities	Injuries
6:00 AM-12:00 PM	752	65	614	743	79	592	682	51	573	549	48	449	491	71	370	409	51	305	363	57	268	282	67	189	92	39	86	134	59	150
12:00 PM-18:00 PM	839	66	680	755	54	590	739	63	586	660	57	499	629	78	471	506	62	378	522	65	396	467	53	271	162	68	126	159	58	179
18:00 PM-24:00 AM	1415	128	1137	1464	152	1147	1288	152	1000	1126	167	800	1061	157	760	1060	172	733	851	172	565	1095	169	618	286	121	289	313	145	262
24:00 AM-6:00 AM	689	83	524	784	97	597	647	99	450	642	119	427	651	97	460	552	101	360	470	88	301	348	49	140	46	27	25	63	48	63

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

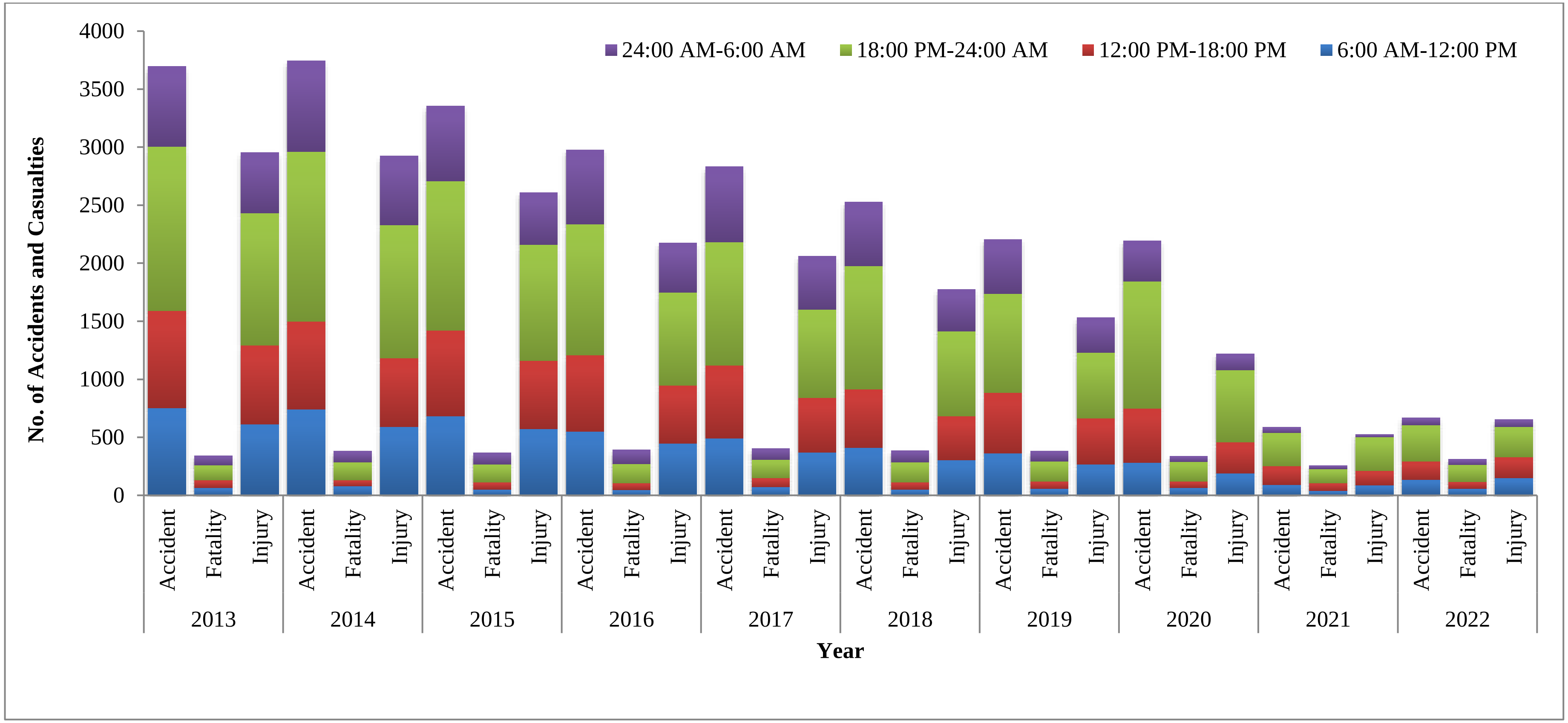


Figure (4.5) Number of Traffic Accidents and Casualties by Time

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

Based on descriptive analysis, it can be found that the highest number of accidents and casualties occurs during the night time (18:00 PM-24:00 AM), while the lowest number occurs during the morning time (6:00 AM-12:00 PM). Generally, more accidents and casualties were happened at night, and this can be influenced by factors such as being exhausted by drivers, increased alcohol consumption, and reduced visibility. Another influencing factor might be the driving speed on this particular traffic road. The data reveal that the least number of accidents and casualties occurred in 2021 for both day and night time, respectively. When examining the trends of traffic accidents and casualties over a study period, it was found that there were decreasing trends in the number of accidents and casualties since 2014, as depicted in Figure (4.5).

4.2.6 Accidents and Casualties Status by Immediate Causes

The data on various immediate causes for the occurrence of traffic accidents and casualties were collected from the No. (2) Traffic Police Office and presented in Table (4.6) and Figure (4.6).

Table (4.6)

Number of Traffic Accidents and Casualties by Immediate Causes

Year	Number of Accidents			Number of Fatalities			Number of Injuries		
	Human Error	Failure to comply with the Regulation	Mechanical Fault & Weather	Human Error	Failure to comply with the Regulation	Mechanical Fault & Weather	Human Error	Failure to comply with the Regulation	Mechanical Fault & Weather
2013	1646	462	14	232	110	0	2518	432	5
2014	1746	449	13	287	93	2	2425	451	50
2015	1660	296	0	282	83	0	2330	279	0
2016	1640	226	0	317	74	0	2010	166	0
2017	1582	148	1	333	70	0	1964	97	0
2018	1489	229	0	314	72	0	1593	183	0
2019	1278	154	0	327	55	0	1419	111	0
2020	975	151	0	289	49	0	1079	139	0
2021	478	107	1	202	53	0	462	63	0
2022	516	153	0	230	80	0	553	101	0

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

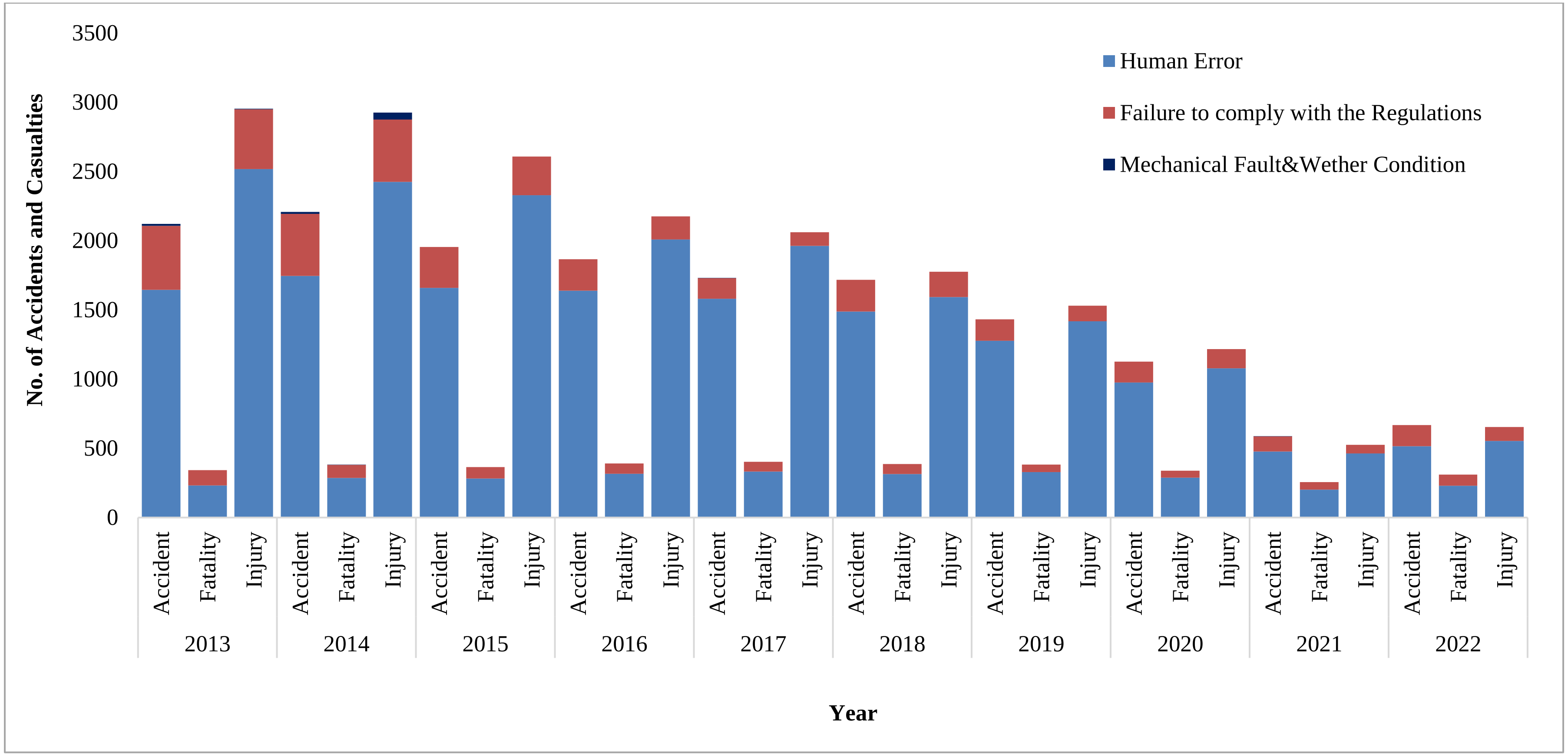


Figure (4.6) Number of Traffic Accidents and Casualties by Immediate Causes

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

According to Table (4.6), it was found that the highest number of accidents and casualties were occurred due to human error. Many traffic accidents and casualties were attributed to the failure of road users to follow traffic regulations, which was the second leading cause of such accidents and casualties. Mechanical faults and weather conditions were found to have minimal contribution to the occurrence of traffic accidents and casualties. In 2013, it was observed that only three traffic accidents in Yangon were caused by bad weather conditions, resulting in two injuries. As described in Figure (4.6), the number of traffic accidents and casualties in terms of their respective reasons show a gradual decline after the year 2014 except the number with the reason of human error.

4.2.7 Accidents and Casualties Status by Alcohol Consumption

The number of traffic accidents and casualties being occurred by alcohol consumption is presented in Table (4.7).

Table (4.7)

Number of Accidents and Casualties by Alcohol Consumption

Year	Number of Accidents		Number of Fatalities		Number of Injuries	
	Drink	No-drink	Drink	No-drink	Drink	No-drink
2013	43 (2.03%)	2079 (97.97%)	4 (1.17%)	338 (98.83%)	67 (2.27%)	2888 (97.73%)
2014	51 (2.31%)	2157 (97.69%)	4 (1.05%)	378 (98.95%)	50 (1.71%)	2876 (98.29%)
2015	23 (1.18%)	1933 (98.82%)	2 (0.55%)	363 (99.45%)	25 (0.96%)	2584 (99.04%)
2016	16 (0.86%)	1850 (99.14%)	2 (0.51%)	389 (99.49%)	12 (0.55%)	2164 (99.45%)
2017	21 (1.21%)	1710 (98.79%)	8 (1.99%)	395 (98.01%)	16 (0.78%)	2045 (99.22%)
2018	18 (1.05%)	1700 (98.95)	2 (0.52%)	384 (99.48%)	11 (0.62%)	1765 (99.38%)
2019	4 (0.28%)	1428 (99.72%)	0 (0.00%)	382 (100%)	6 (0.39%)	1524 (99.61%)
2020	8 (0.71%)	1118 (99.29%)	5 (1.48%)	333 (98.52%)	11 (0.90%)	1207 (99.10%)
2021	26 (4.44%)	560 (95.56%)	7 (2.75%)	248 (97.25)	48 (9.14%)	477 (90.86%)
2022	26 (3.89%)	643 (96.11%)	13 (4.19%)	297 (95.81%)	29 (4.43%)	625 (95.57%)

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

In terms of alcohol consumption, the highest number of occurrences of traffic accident due to alcohol consumption was found as 4.44% in 2021, followed by 3.89% in 2022, 2.31% in 2014, and 2.03% in 2013, respectively. Regarding fatalities related to alcohol consumption, the highest percentage was observed as 4.19% in 2022, followed by 2.75% in 2021, 1.99% in 2017 and 1.48% in 2020,. Regarding injuries related to alcohol consumption, the highest percentage was observed as 9.14% in 2021, followed by 4.43% in 2022, 2.27% in 2013 and 1.71% in 2014, respectively. Based on the descriptive analysis, it was found that most of the road users did not consume alcohol when facing traffic accidents. The figure depicting accidents and casualties related to alcohol consumption are shown in Figure (4.7).

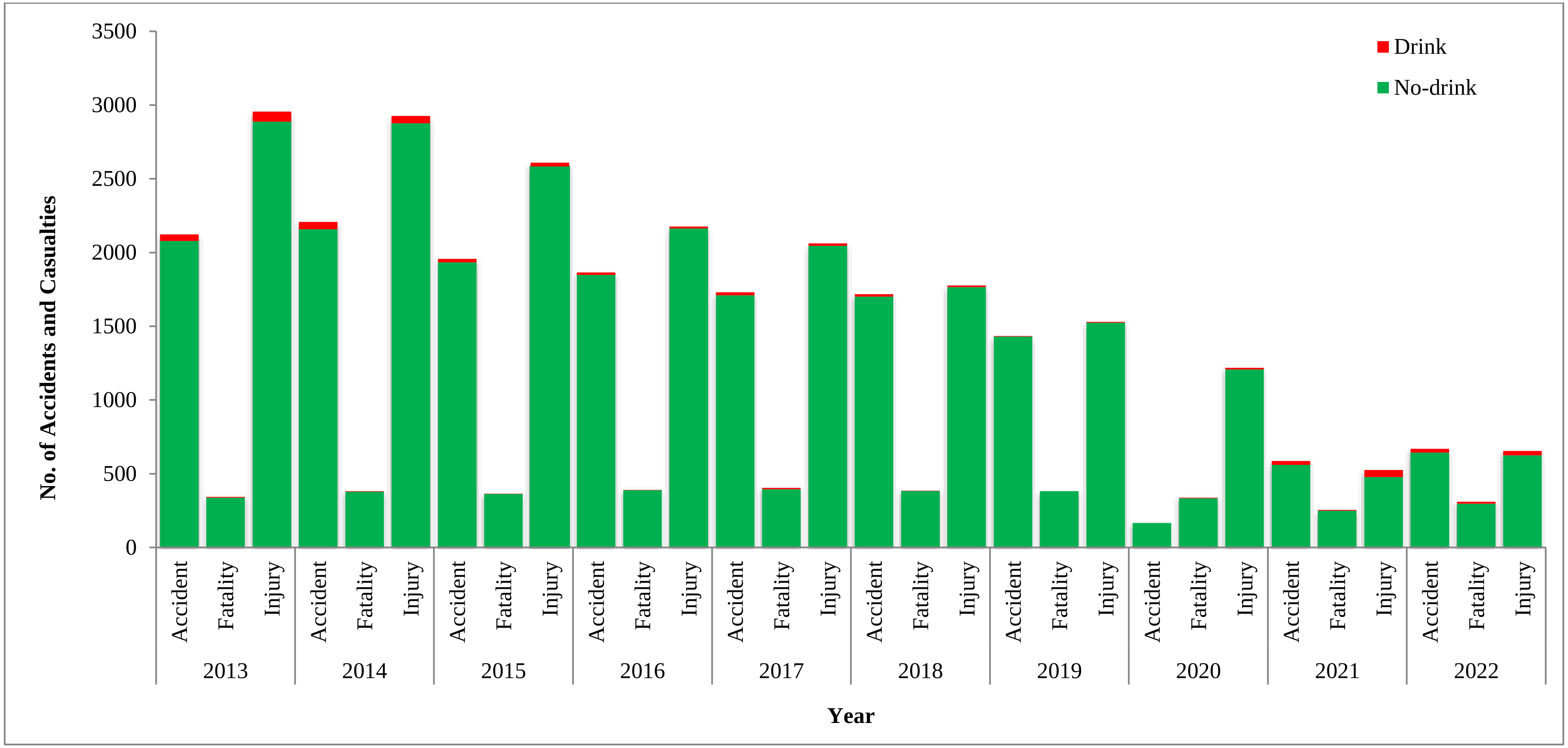


Figure (4.7) Number of Traffic Accidents and Casualties by Alcohol Consumption

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

The variables utilized to study the risk factors of traffic fatalities and injuries are described in Section (4.3), and the relationship between traffic fatalities and risk factors is illustrated in Section (4.4).

4.3 Description of Variables

After carrying out the descriptive analysis of road traffic accidents and casualties, this study intended to examine the significance of risk factors of the road traffic casualties in Yangon are through analysis works of Binary Logistic Regression.

Accordingly, the occurrence of traffic fatalities and injuries were considered as dependent variables, whereas the risk factors such as gender (male, female), place of accident (junction, roundabout, main road, lane, on bridge), type of vehicles (private car, buses, trucks, taxi, motorcycle, other vehicles), time of accident (day, night), immediate causes of accident (human error, failure to comply with regulations, mechanical faults & weather conditions) and alcohol consumption (yes, no) were considered as independent variables.

However, alcohol consumption was not statistically significant in the chi-square test, so it was excluded in Binary Logistic Regression analysis. The variable coding for traffic fatalities, and are shown in Table (4.8) and for risk factors are presented in Table (4.9).

Table (4.8)

Variable Coding for Traffic Fatalities, and Injuries

Dependent Variables

Sr. No.	Variable Type	Coding and Classifications
1	Traffic Fatalities	1 = Occurrence of traffic fatality 0 = Non-occurrence of traffic fatality
2	Traffic Injuries	1 = Occurrence of traffic injury (any person who was not killed but sustained one or more serious or slight injuries) 0 = Non-occurrence of traffic injury

Table (4.9)

Variable Coding for Risk Factors

Independent Variables

Sr. No.	Variable Type	Coding and Classifications
1.	Gender	0 = Female (Reference) 1 = Male
2.	Place of Accident	1 = Main Road (Reference) 2 = Lane 3 = Roundabout 4 = Junction 5 = On Bridge
3.	Type of Vehicles	1 = Private Car (Reference) 2 = Bus 3 = Taxi 4 = Truck 5 = Motorcycle 6 = Others
4.	Time of Accident	1= 6:00 AM-12:00 PM (Reference) 2= 12:00 PM-18:00 PM 3= 18:00 PM-24:00 AM 4 = 24:00 AM-6:00 AM
5.	Immediate Causes of Accident	1 = Mechanical Fault & Weather Conditions (Reference) 2 = Failure to comply with the Regulation 3 = Human Error

4.4 Relationship between Traffic Fatalities and Risk Factors

The chi-square test was carried out to examine the association between traffic fatalities and various risk factors. The chi-square values, degrees of freedom, and p-values were displayed in Table (4.10).

Table (4.10)

Chi-Square Analysis of Traffic Fatalities and Risk Factors

Sr. No.	Variable	Chi-Square Value	Degree of Freedom	P-value
1	Gender	218.869***	1	.000
2	Place of Accident	77.638***	4	.000
3	Type of Vehicles	284.354***	5	.000
4	Time of Accident	94.243***	3	.000
5	Immediate Causes of Accident	265.565***	2	.000

Source: Own Calculation

***denotes significant at 1% level

Table (4.10) illustrates that five risk factors, namely gender, place of accident, vehicle types, time of accident, and reasons for accident, are highly significantly associated with traffic fatalities.

The crosstabulation of gender and traffic fatality indicates that males had a higher percentage than females (refer to Appendix Table A-1). Regarding the crosstabulation of traffic fatality and place of accidents, it was found that main roads had the highest percentage of traffic fatalities compared to other places (refer to Appendix Table A-2). Based on the crosstabulation of traffic fatality and type of vehicles, private cars had a higher percentage than other vehicles (refer to Appendix Table A-3). The crosstabulation of time of accident and traffic fatalities (refer to Appendix Table A-4) shows that night time had a higher fatality rate. In terms of the crosstabulation of immediate causes of accident and traffic fatalities (refer to Appendix Table A-5), human error had a higher percentage compared to other reasons such as failure to comply with regulations, mechanical faults, and weather conditions. The analysis of traffic fatalities data using binary logistic regression is described in Section (4.5).

4.5 Binary Logistic Regression Analysis for Traffic Fatalities

The binary logistic regression analysis was conducted to identify the influencing factors on traffic fatalities in Yangon. The overall model fitting information for binary logistic regression analysis is given in Table (4.11).

Table (4.11)

Model Fitting Information for Traffic Fatalities with Risk Factors

Model Fitting Criteria	Chi-Square	df	p-value
Omnibus Tests of Model Coefficients	819.359	15	.000
Hosmer and Lemeshow	8.650	8	.373
-2Log Likelihood			18632.845
Cox and Snell R square			.037
Nagelkerke R square			.062
Overall Correct Prediction			83.8

Source: Own Calculation

The omnibus tests of model coefficients indicate that the inclusion of five independent variables results in a chi-square value of 819.359, corresponding to 15 degrees of freedom, and a p-value of 0.000. This outcome suggests that the overall model holds statistical significance in predicting the factors influencing traffic fatalities. To assess the model fit, the Hosmer and Lemeshow test is employed, evaluating the correspondence between actual and predicted values of the dependent variable. The computed Hosmer and Lemeshow test statistic produces a χ^2 value of 8.650, with an associated p-value of 0.373. This suggests that the test does not achieve statistical significance. Consequently, it can be inferred that the model demonstrates a favorable fit.

The statistic for the -2 log likelihood is 18632.845. The computed values for Cox and Snell's R^2 and Nagelkerke's R^2 are 0.037 and 0.062, respectively. These values suggest that around 3.7% and 6.2% of the variability in traffic fatalities can be explained by the linear combination of the risk factors. Overall, 83.8% of the number of fatalities is predicted correctly. The parameter estimates for the risk factors of traffic fatalities resulting from the binary logistic regression is described in Table (4.12).

Table (4.12)

Parameter Estimates for Risk Factors of Traffic Fatalities

Variable	Coefficients	S.E	Wald	df	p-value	Exp (b)	95% C.I for EXP(B)	
							Lower	Upper
Constant	-3.435***	.727	22.336	1	.000	.032		
Gender								
Female (Ref.)								
Male	0.587***	.046	159.506	1	.000	1.798	1.642	1.970
Place of Accident								
Main Road (Ref.)								
Lane	-0.446***	.054	69.474	1	.000	.640	0.576	0.711
Junction	-0.263***	.061	18.500	1	.000	.769	0.682	0.866
On Bridge	-0.270**	.109	6.084	1	.014	.764	0.616	0.946
Roundabout	-0.365	.389	.880	1	.348	.694	0.324	1.489
Type of Vehicles								
Private Car (Ref.)								
Bus	-0.210***	.065	10.440	1	.001	.810	0.713	0.921
Taxi	-0.257***	.051	25.160	1	.000	.773	0.700	0.855
Motorcycle	0.387***	.053	53.424	1	.000	1.473	1.328	1.634
Truck	0.248**	.099	6.260	1	.012	1.282	1.055	1.557
Others	0.802***	.088	82.178	1	.000	2.229	1.875	2.651
Time of Accident								
6:00 AM- 12:00 PM (Ref.)								
12:00 PM-18:00 PM	-0.154**	.063	6.000	1	.014	.857	0.757	0.970
18:00 PM-24:00 AM	0.051	.055	.879	1	.348	1.052	0.946	1.171
24:00 AM-6:00 AM	0.234***	.062	14.441	1	.000	1.264	1.120	1.426
Immediate Causes of Accident								
Mechanical Fault & Weather Condition (Ref.)								
Failure to comply with the Regulation	2.049***	.726	7.976	1	.005	7.760	1.872	32.167
Human Error	1.285*	.724	3.146	1	.076	3.615	0.874	14.954

*******denotes significant at 1% level, ******denotes significant at 5% level, *****denotes significant at 10% level

According to the results of Binary Logistic Regression analysis, it was found that males are approximately 1.798 times more likely to experience fatalities compared to females. Therefore, males have a higher likelihood of death than females when involved in accidents. In terms of the place of accidents, the junction and lane variables are statistically significant at the 1% level, while the on-bridge variable is significant at the 5% level, all with negative signs. The risk of fatalities for lane is approximately 0.36 times lower compared to the main road. The junction has a risk of fatalities approximately 0.231 times lower than the main road, while on bridges, the risk is approximately 0.236 times lower compared to the main road. On the other hand, roundabout is not statistically significant at any significant level compared to the main road. This suggests that the coefficients for roundabout regarding the risk of fatalities are not statistically different from zero when other variables are held constant. Therefore, roundabouts are less likely to result in death compared to the main road.

Type of vehicles was found to be statistically significant at the 1% and 5% levels, respectively. The coefficients for buses, taxis, motorcycles, and other vehicles (such as three-wheelers, slow vehicles, etc.) were significant at the 1% level, and the negative parameter estimates are observed for buses and taxis. It can be concluded that buses are approximately 0.19 times less likely to be involved in fatalities compared to private cars, while taxis are approximately 0.227 times less likely to be at risk of fatalities compared to private cars. On the other hand, motorcycles were approximately 1.473 times more likely to be involved in fatalities compared to private cars, and other vehicles were approximately 2.229 times more likely to be at risk of fatalities compared to private cars. These two vehicle types exhibited positive signs, indicating that they have a higher likelihood of resulting in death than private cars. The coefficient for trucks was significant at the 5% level, with a positive sign. This suggests that trucks are more likely to result in death compared to private cars.

The period of "Afternoon time" (12:00 PM – 18:00 PM) was found to hold statistical significance at the 5% level. The effect of time on traffic fatalities is negative, indicating that the likelihood of traffic fatalities during the afternoon is roughly 0.143 times less compared to the morning period (6:00 AM – 12:00 PM). The "Morning time" (24:00 AM - 6:00 AM) was found to be statistically significant at the 1% level. Morning time has a positive impact on traffic fatalities, suggesting that the likelihood of traffic fatalities during the night is approximately 1.264 times more compared to the morning period (6:00 AM – 12:00 PM). Consequently, it can be inferred that night time is more associated with a higher likelihood of fatalities compared to the daytime. On the other hand, the "Night time" (18:00 PM - 24:00 AM) does not demonstrate statistical significance at any significant level in comparison to the morning period. This implies that the coefficients for night time (18:00 PM - 24:00 AM) in relation to the risk of fatalities are not statistically distinguishable from zero when accounting for other variables. Hence, night time (18:00 PM - 24:00 AM) is relatively more likely to lead to fatalities compared to the morning period (6:00 AM - 12:00 PM).

The immediate causes of accident were found to be significant at the 1% and 10% levels, and they positively influenced traffic fatalities. Failure to comply with regulations is approximately 7.760 times more likely to result in fatalities compared to mechanical faults and weather conditions. Similarly, human error is approximately 3.615 times more likely to result in fatalities compared to mechanical faults and weather conditions. Hence, failure to comply with regulations and human error has a higher chance of resulting in death compared to mechanical faults and weather conditions. The relationship between traffic injuries and risk factors is discussed in section (4.6).

4.6 Relationship between Traffic Injuries and Risk Factors

The chi-square test was conducted to examine the association between traffic injuries and various risk factors including gender, place of accident, type of vehicle, time of accident and immediate causes of accident for the occurrence of injuries. In the data analysis of traffic injuries, the chi-square values, degrees of freedom, and p-values for the five risk factor variables were displayed in Table (4.13).

Table (4.13)

Chi-Square Analysis of Traffic Injuries and Risk Factors

Sr. No.	Variable	Chi-Square Value	Degree of Freedom	P-value
1	Gender	979.861***	1	.000
2	Place of Accident	250.598***	4	.000
3	Type of Vehicles	1239.789***	5	.000
4	Time of Accident	74.297***	3	.000
5	Immediate Causes of Accident	256.800***	2	.000

Source: Own Calculation

***denotes significant at 1% level

From Table (4.13), it is evident that all risk factors, including gender, place of accident, type of vehicles, time of accident, and immediate causes of accident are highly and significantly associated with traffic injuries.

According to the crosstabulation of gender and traffic injury, males have a higher percentage than females (see Appendix Table: B-1). In the crosstabulation of traffic injury and place of accident, it was found that the main road had the highest percentage of traffic injuries compared to other places (see Appendix Table: B-2). Based on the crosstabulation of traffic injury and type of vehicles, the percentage of private cars was higher than that of other vehicles (see Appendix Table: B-3). The results from the crosstabulation of time and traffic injuries (see Appendix Table: B-4) indicate that a higher number of injuries occurred during the night. According to the crosstabulation of immediate causes of accident and traffic injuries (see Appendix Table: B-5), it was found that the percentage of injuries caused by human error was higher than those caused by failure to comply with regulations, mechanical faults, and weather conditions. Binary logistic regression analysis for traffic injuries is discussed in Section (4.7).

4.7 Binary Logistic Regression Analysis for Traffic Injuries

The binary logistic regression analysis was conducted to identify the influencing factors on traffic injuries in Yangon. The overall model fitting information for the binary logistic regression analysis is provided in Table (4.14).

Table (4.14)

Model Fitting Information for Traffic Injuries with Risk Factors

Model Fitting Criteria	Chi-Square	Df	p-value
Omnibus Tests of Model Coefficients	3245.844	15	.000
Hosmer and Lemeshow	15.449	8	.051
-2Log Likelihood	11229.236		
Cox and Snell R square	.145		
Nagelkerke R square	.288		
Overall Correct Prediction	89.1		

Source: Own Calculation

The omnibus tests of model coefficients show that the incorporation of six independent variables yielded a chi-square value of 3245.844, corresponding to 15 degrees of freedom, and a p-value of 0.000. To assess the model's fitness, the Hosmer and Lemeshow test examines the agreement between actual and predicted values of the dependent variable. The Hosmer and Lemeshow test statistic is $\chi^2 = 15.449$, with a p-value of 0.051, indicating a lack of statistical significance. This suggests that the model exhibits a satisfactory fit. The -2 log likelihood statistic is 11229.236. The Cox and Snell's R^2 and Nagelkerke R^2 values are 0.145 and 0.288, respectively. These values indicate that approximately 14.5% and 28.8% of the variation in traffic injuries is explained by the model. Overall, 89.1% of the traffic injuries are predicted correctly. The parameter estimates for the binary logistic regression model of traffic injuries, considering the variables of gender, place of accident, type of vehicles, time of accidents, and immediate causes for accident are presented in Table (4.15).

Table (4.15)

Parameter Estimates for Risk Factors of Traffic Injuries

Variable	Coefficients	S.E	Wald	Df	p-value	Exp (b)	95% C.I for EXP(B)	
							Lower	Upper
Constant	5.383***	0.436	152.442	1	0.000	217.701		
Gender Female (Ref.) Male	-4.278***	0.260	270.230	1	0.000	0.014	0.008	0.023
Place of Accident Main Road (Ref.)								
Lane	-0.563***	0.055	104.633	1	0.000	0.569	0.511	0.634
Junction	0.935***	0.117	63.750	1	0.000	2.546	2.024	3.203
On Bridge	-0.105	0.118	0.790	1	0.374	0.900	0.714	1.135
Roundabout	-1.387***	0.355	15.227	1	0.000	0.250	0.125	0.501
Type of Vehicles Private Car (Ref.)								
Bus	-0.161**	0.078	4.293	1	0.038	0.852	0.732	0.991
Taxi	-0.141**	0.058	5.873	1	0.015	0.869	0.776	0.973
Motorcycle	3.364***	0.292	132.417	1	0.000	28.908	16.299	51.271
Truck	-0.513***	0.109	22.183	1	0.000	0.599	0.484	0.741
Others	-1.827***	0.087	445.926	1	0.000	0.161	0.136	0.191
Time of Accident 6:00 AM-12:00 PM (Ref.)								
12:00 PM-18:00 PM	-0.477***	0.081	34.879	1	0.000	0.620	0.530	0.727
18:00 PM-24:00 AM	-0.332***	0.075	19.597	1	0.000	0.718	0.620	0.831
24:00 AM-6:00 AM	-0.449***	0.082	29.868	1	0.000	0.638	0.543	0.750
Immediate Causes of Accident Mechanical Fault & Weather Condition (Ref.)								
Failure to comply with the Regulation	4.200***	0.447	88.231	1	0.000	66.684	27.760	160.185
Human Error	0.978***	0.349	7.869	1	0.005	2.659	1.343	5.267

*****denotes significant at 1% level, ****denotes significant at 5% level

Based on the results of Binary Logistic Regression, it was found that male is statistically significant at the 1% level, with a negative parameter estimate. This suggests that males are approximately 0.986 times less likely to experience injuries compared to females.

In terms of the occurrence of accident place, lane and roundabout are statistically significant at the 1% level, with negative signs. The odd ratio of lane and roundabout are 0.569 and 0.250 and this indicates that lanes are about 0.431 times less risky for injuries compared to the main road, while roundabouts are about 0.750 times less risky for injuries compared to the main road. Among these places of accident, the junction is statistically significant at 1% level when compared to main road, with a positive sign. This suggest that the junction is 2.546 more likely to get injurie compared the main road. Thus, lanes and roundabouts are considered safer options than the main road in terms of injury risk. On the other hand, the variable for accidents on bridges is not statistically significant at any significant level. This indicates that the regression coefficient for accidents on bridges is not statistically different from zero when the other variables are held constant.

The coefficients for the motorcycle, truck and other vehicles (such as three-wheelers, slow vehicles, etc.) are significant at the 1% level. The sign of the coefficient is positive for the motorcycle and negative for truck and other vehicles. This suggests that motorcycles are approximately 28.908 times more at risk of injuries compared to private cars, while truck and other vehicles are about 0.401 and 0.839 times less at risk of injuries compared to private cars. On the other hand, the coefficient for buses and taxi are significant at the 5% level. It has a negative sign, indicating that buses and taxi are approximately 0.148 and 0.131 times less at risk of injuries compared to private cars.

Afternoon time (12:00 PM – 18:00 PM), night time (18:00 PM - 24:00 AM), and morning time (24:00 AM - 6:00 AM) were all found to hold statistical significance at the 1% level, respectively. Each of these variables exhibits a negative impact on traffic injuries, suggesting that afternoon time, evening time, and early morning time are roughly 0.380, 0.282 and 0.362 times less likely to result in traffic injuries compared to the morning period (6:00 AM – 12:00 PM). On the other hand, the variable "failure to comply with regulations" and "human error" are significant at the 1% level. Both of these variables have positive coefficients, indicating that they have a positive effect on traffic injuries. Failure to comply with regulations is approximately 66.684 times more at risk of injuries compared to mechanical faults and weather conditions. Similarly, human error is about 2.659 times more at risk of injuries compared to mechanical faults and weather conditions. These results suggest that failure to comply with regulations and human error contribute to a higher likelihood of injuries compared to mechanical faults and weather conditions.

CHAPTER V

TIME SERIES ANAYSIS OF TRAFFIC ACCIDENTS AND CASUALTIES IN YANGON

This chapter consists of various statistical analyses and key findings on traffic accidents and casualties in Yangon. The study collected monthly records of road traffic accidents and casualties (fatalities and injuries) from the No. (2) Office of Traffic Police in Yangon. The impact of road safety measures was investigated using ARIMA model, Intervention model, and ARIMAX-TFM in this chapter. Moreover, this approach enables us to forecast future traffic accident and casualties, providing a proactive foundation for traffic management and accident prevention strategies.

5.1 Time Series Analysis of Road Traffic Accidents

Table (5.1) presents the compiled monthly traffic accident statistics covering the period from 2013 to 2022. The data for this table has been obtained from the Traffic Police Office No. (2) in Yangon. It provides a comprehensive overview of the accident occurrences over the years, allowing for a detailed analysis of the trends and patterns in traffic accidents in the region.

Table (5.1)

Monthly Traffic Accidents

Month/Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Jan	121	194	201	157	189	121	152	109	94	56
Feb	126	180	157	169	155	112	129	126	43	56
Mar	155	171	170	198	149	168	121	105	12	63
Apr	164	215	166	150	198	168	107	69	37	64
May	160	188	149	176	147	158	141	96	46	57
Jun	195	190	168	151	140	183	111	123	53	60
Jul	168	180	135	159	130	137	123	107	43	64
Aug	201	176	148	115	127	125	112	90	56	63
Sep	201	175	147	154	118	124	98	66	42	55
Oct	213	188	183	148	114	144	116	57	51	40
Nov	211	159	172	146	120	142	112	98	58	42
Dec	207	192	160	143	144	136	110	80	51	49

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

Based on the findings presented in Table (5.1), the number of accidents reached its peak in 2014 and gradually declined in subsequent years. However, in 2021, the number of traffic accidents was relatively lower compared to other years due to the significant impact of the Covid-19 pandemic. It is worth noting that there was a slight increase in traffic accidents in 2022. Furthermore, the highest number of traffic fatalities occurred in May 2014, totaling 215 cases, whereas the lowest number was recorded in March 2021, with only 12 cases. Figure (5.1) provides a visual representation of the monthly traffic accident trend in Yangon. The figure illustrates that the data do not exhibit any noticeable seasonal variation. The results of testing the seasonality of traffic accidents in Yangon are shown in Appendix Table C-1.

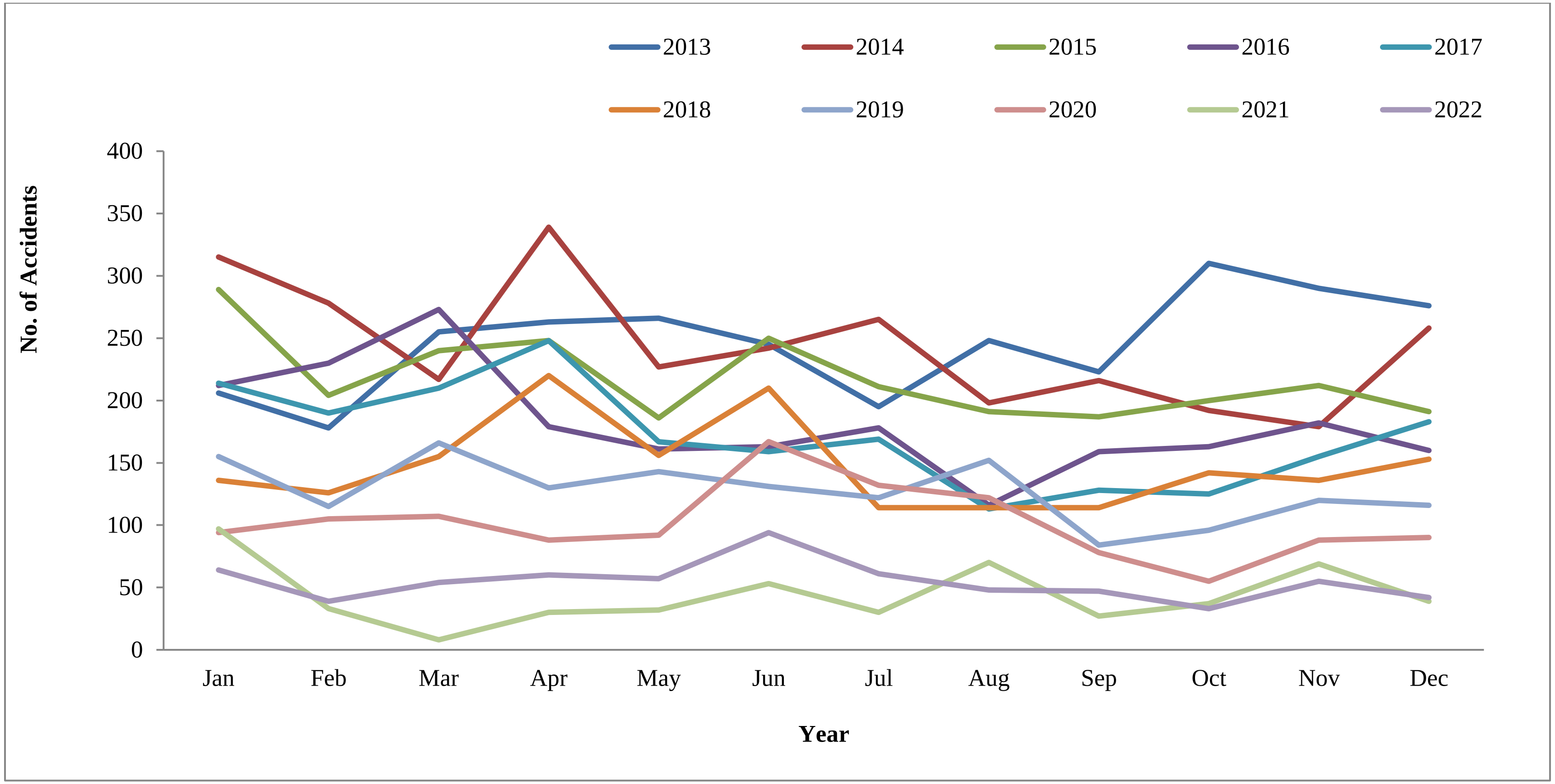


Figure (5.1) Monthly Traffic Accidents

Source: Table (5.1)

5.1.1 Statistical Test of Trend for Traffic Accidents

The series exhibits trend or not is tested as follows:

Hypotheses

Null Hypothesis: There is no trend for traffic accidents in Yangon.

Alternative Hypothesis: There is a positive or negative trend for traffic accidents in Yangon.

Table (5.2)

Statistical Test of Trend for Traffic Accidents

t-Test Statistic	Critical Value	Observations
-4.480	1.984	120

Source: Own Calculation

According to the values in Table (5.2), the test statistic is calculated as |-4.480| = 4.480, while the critical value is determined to be 1.984. Consequently the test statistic exceeds the critical value. Hence, it can be concluded that there is a negative trend in traffic accidents in Yangon from 2013-2022.

5.1.2 Test of Stationarity for Traffic Accidents

In this section, the Augmented Dickey-Fuller test was employed to assess the stationarity of traffic accidents in Yangon. The stationarity test results were conducted on the traffic accident series in Yangon, using monthly time series data covering the period from January 2013 to December 2022. The summarized results of this test are presented in Table (5.3).

Table (5.3)

Augmented Dickey-Fuller Test for Traffic Accidents

Before first difference				After first difference			
t-Statistic			Prob	t-Statistic			Prob
Augmented Dickey-Fuller test statistic		-1.3774	0.5916	Augmented Dickey-Fuller test statistic		-11.3906	0.0000
Test critical values:	1% level	-3.4812		Test critical values:	1% level	-3.4816	
	5% level	-2.8838			5% level	-2.8839	
	10% level	-2.5787			10% level	-2.5788	

Source: Appendix (C-2)

Hypotheses

H_0: The recorded number of traffic fatalities has a unit root (i.e., The recorded number of traffic fatalities is non-stationary).

H_1: The recorded number of traffic fatalities does not have a unit root (i.e., The recorded number of traffic fatalities is stationary).

Based on the findings in Table (5.3), the original data series is observed to be non-stationary at a 5% level of significance. However, after applying the first difference, the Augmented Dickey-Fuller (ADF) test rejects the null hypothesis of a unit root at a 5% significance level. Consequently, these processes appear to exhibit stationarity in terms of their mean level. Sections 5.2 to 5.4 present the analysis of the traffic accidents data using various models, including the ARIMA model, Intervention model, and ARIMAX-TFM model.

5.2 ARIMA Model for Traffic Accidents

In time series analysis, the most crucial steps are to identify and build a model based on the available data. ARIMA approach consists of model identification, parameter estimation and diagnostic checking.

5.2.1 Model Identification

A total of 15,414 traffic accident cases were reported in Yangon from January 2013 to December 2022. The original series depicting the traffic accidents in Yangon is illustrated in Figure (5.2).

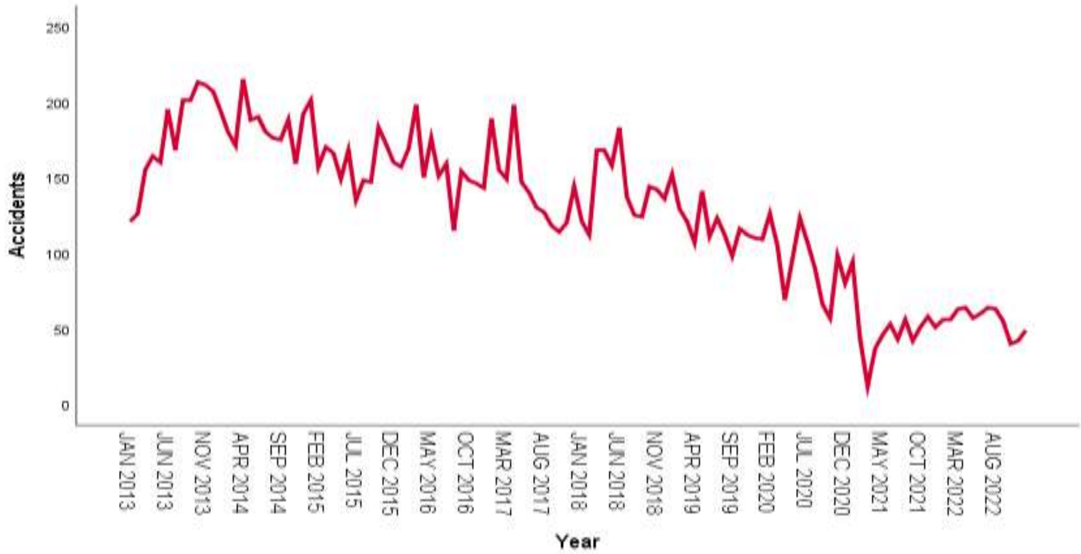


Figure (5.2) Original Series of Traffic Accidents

Regarding Figure (5.2), it is evident that the original series of traffic accidents in Yangon experienced a decline after the year 2015. This indicates a negative trend in the series, suggesting its non-stationary. To further analyze the series, the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) for traffic injuries in Yangon are illustrated in Figure (5.3).

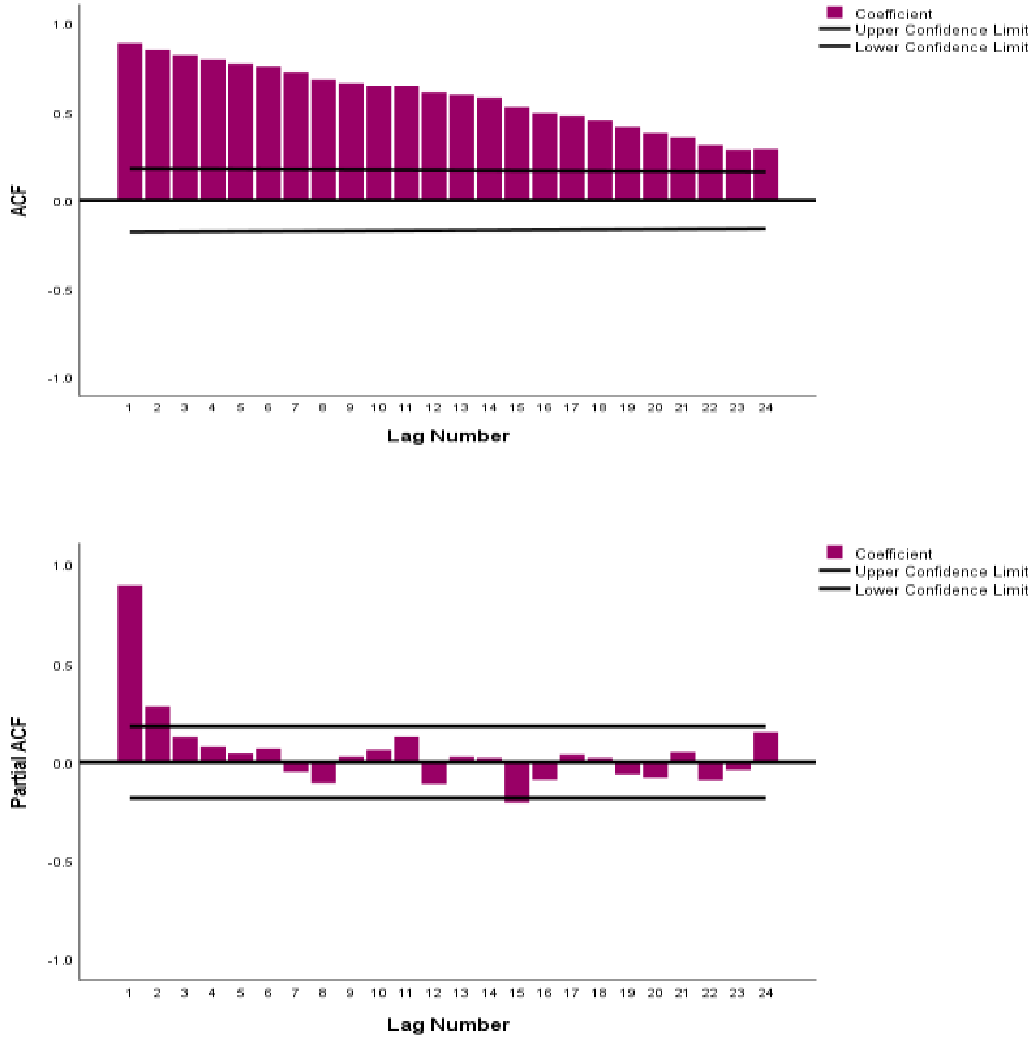


Figure (5.3) Sample Correlogram of the Original Series of Traffic Accidents

Based on Figure (5.3), it can be observed that the sample autocorrelation function (ACF) exhibits a slow decay, while the sample partial autocorrelation function (PACF) cuts off after lag 1. These patterns in the ACF and PACF indicate the presence of nonstationarity in the series. Therefore, it is necessary to apply differencing to remove the non-stationarity. The first difference series for traffic accidents in Yangon is depicted in Figure (5.4).

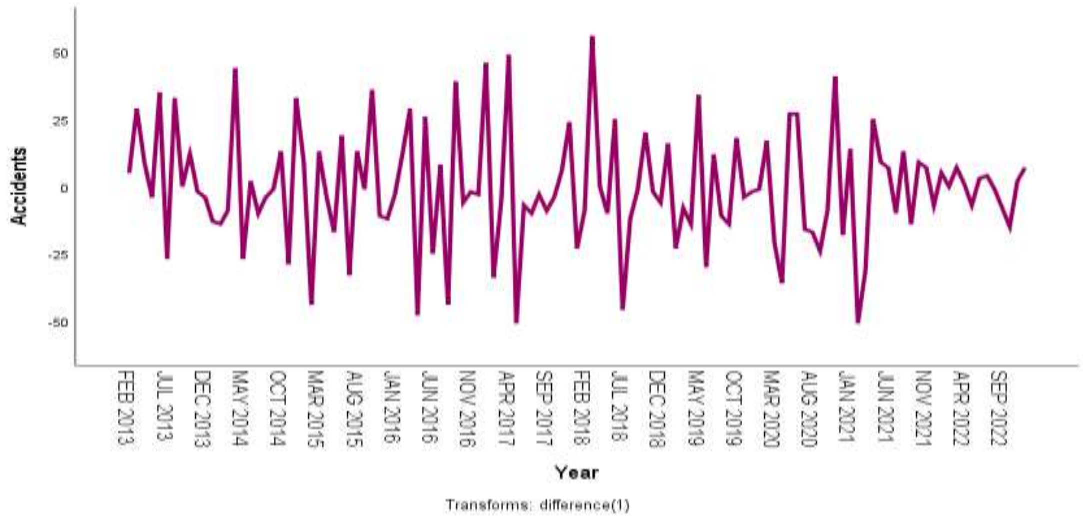


Figure (5.4) First Difference Series for Traffic Accidents

The sample ACF and sample PACF for the first differencing of traffic accidents series are presented in Figure (5.5).

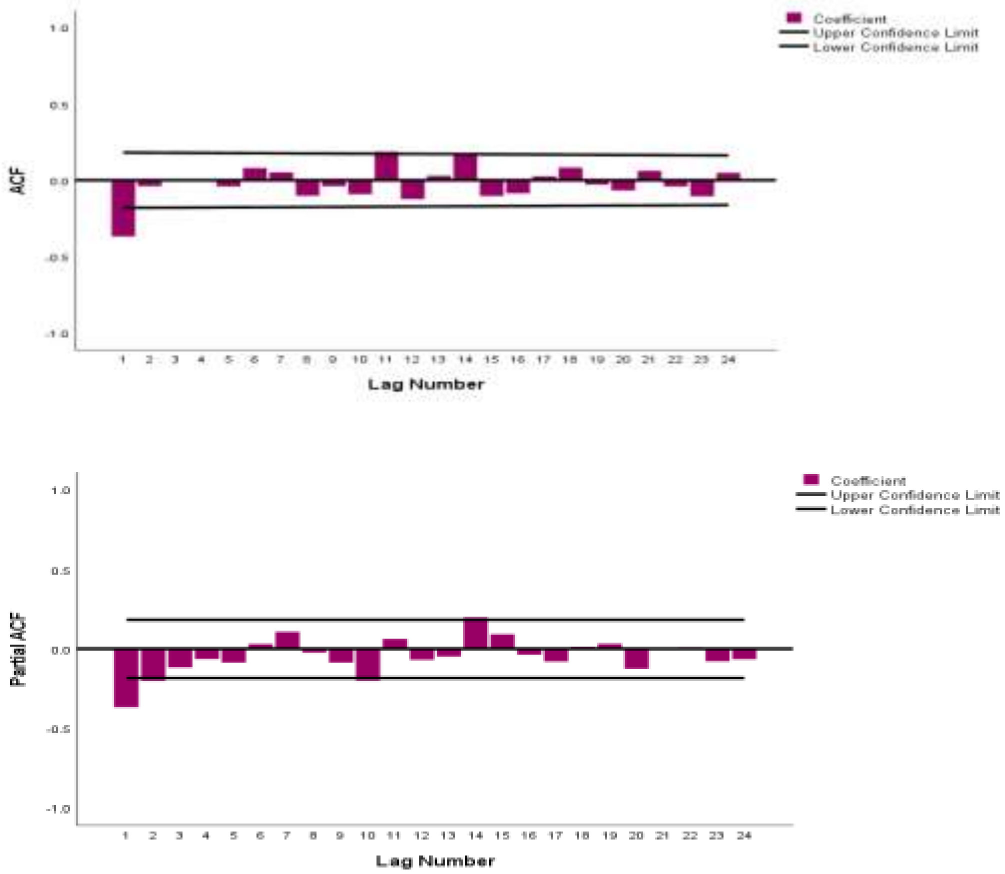


Figure (5.5) ACF and PACF of First Difference Series for Traffic Accidents

Based on Figure (5.5), it can be observed that the ACF cuts off after lag 1, and the PACF exhibits exponential decay. Therefore, the ARIMA (0, 1, 1) model is selected as the preferred tentative model for forecasting traffic accidents.

5.2.2 Parameter Estimation

The parameter estimation results show that the constant (θ_0) is not significant, but the moving average parameter (θ_1) is significant. Therefore, the estimated parameters and associated statistic for the ARIMA (0, 1, 1) model without constant (θ_0) can be found in Table (5.4).

Table (5.4)

Estimation of Parameters and their Statistics for ARIMA (0, 1, 1) Model of Traffic Accidents

Parameter	Estimate	S.E	T	Sig
θ_1	0.505***	.080	6.300	.000

Source: Own Calculation

***denotes significant at 1% level

From above Table (5.4), the estimated model is

$$(1\text{-B})\, Y_t = (1 - \theta_1 B)e_t$$

$$= (1 - 0.505\text{B})\, e_t$$

$$(0.080)$$

The fitted ARIMA (0, 1, 1) model of traffic accidents give θ_1 = 0.505 with the estimated standard error of 0.080. The test statistic t for θ_1 is statistically significant at 1% level.

5.2.3 Diagnostic Checking of ARIMA (0, 1, 1) Model for Traffic Accidents

The residual ACF and PACF for the fitted ARIMA (0, 1, 1) model are shown in Figure (5.6).

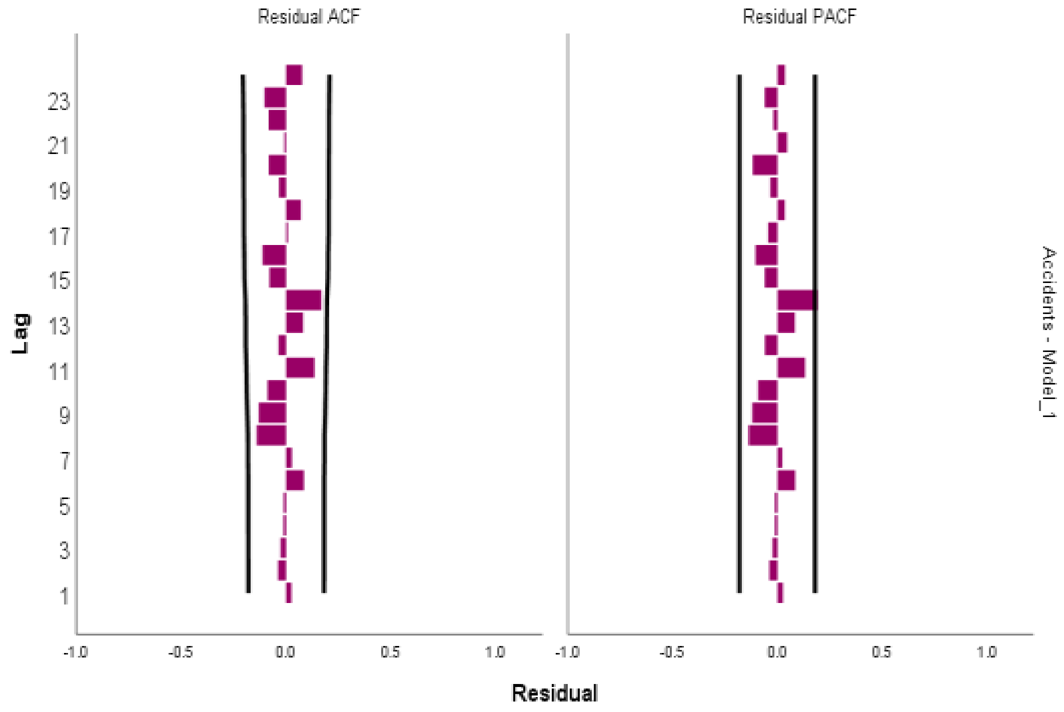


Figure (5.6) ACF PACF of Residuals for ARIMA (0, 1, 1) Model

Based on Figure (5.6), the residual values of the ACF and PACF for the traffic accidents dataset are within the bounds of two standard errors. This indicates that the residual series of the fitted ARIMA (0, 1, 1) model follows a white noise process. To further assess the autocorrelation among the residuals, the Ljung-Box (Q) test statistic was employed. Table (5.5) presents the test statistic and corresponding p-value for the residuals of the fitted ARIMA (0, 1, 1) model for traffic accidents.

Table (5.5)

Model Statistics of ARIMA (0, 1, 1) Model for Traffic Accidents

Model	**Ljung-Box Q (18)**		
	Statistic	**df**	**Sig**
ARIMA (0, 1, 1)	17.815	17	.401

Source: Own Calculation

Table (5.5) reveals that the observed value of Q is 17.815, and its associated p-value of 0.401 exceeds the significance level of 0.05. This result indicates the absence of significant autocorrelation among the residuals. Therefore, the ARIMA (0, 1, 1) model is deemed suitable for accurately fitting the data series of traffic accidents in Yangon.

5.3 Intervention Analysis of Traffic Accidents

The analyzed interventions encompassed the implementation of the Motor Vehicle Law, Permission to Import Vehicles Law, Motor Vehicle Management Law, as well as political changes and the impact of the Covid-19 pandemic on all citizens. These government policies and the pandemic have a significant impact on the time series data of traffic accidents.

5.3.1 Model Identification

Figure (5.7) displays the occurrences of traffic accidents related to the Motor Vehicles Law, Permission to Import Vehicle Law, Vehicle Safety and Motor Vehicle Management Law, as well as the influence of Political Changes and the Covid-19 pandemic for intervention analysis.

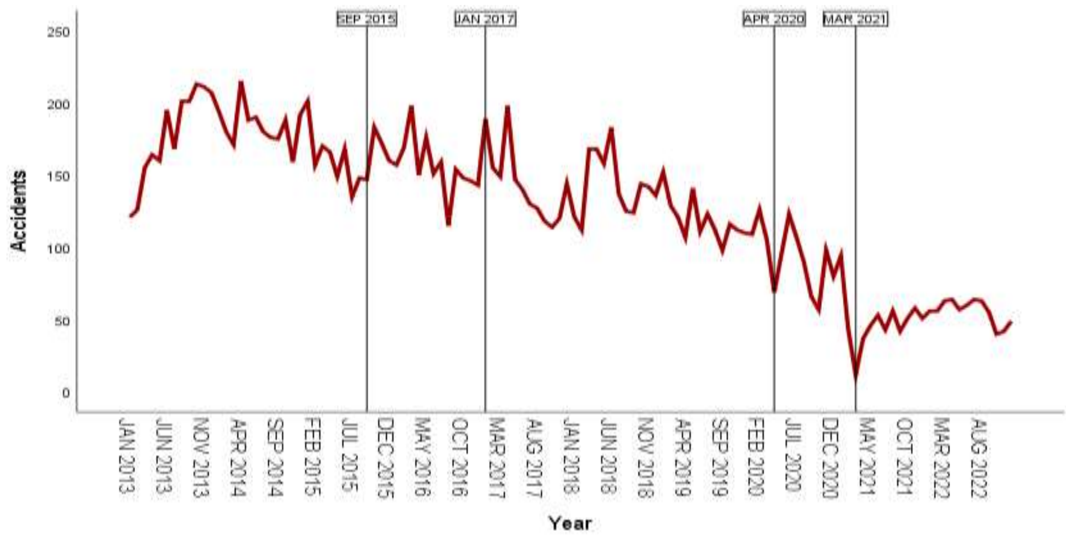


Figure (5.7) Intervention of Traffic Accidents

The stationarity test is conducted on the pre-intervention series of traffic accidents, which suggests that a transformation is necessary to achieve stationarity (refer to Appendix Table C-5).To identify an appropriate model, the sample autocorrelation function (ACF) and the sample partial autocorrelation function (PACF) are employed as primary tools. Figure (5.8) displays the ACF and PACF values of first difference pre-intervention series for traffic accidents in Yangon.

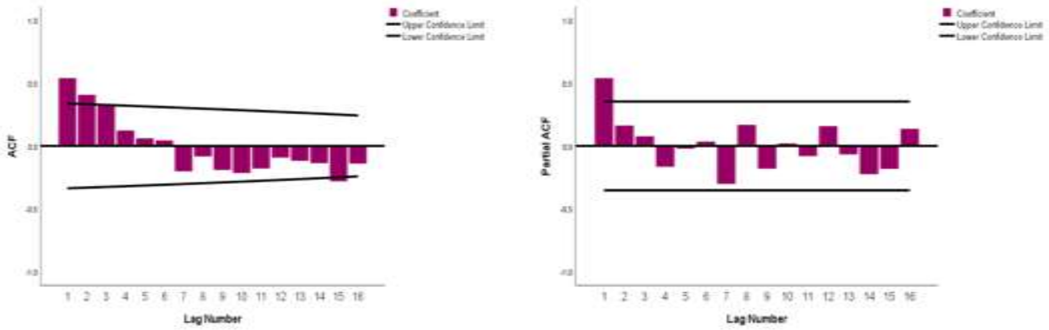


Figure (5.8) ACF and PACF of Pre-intervention Series for Traffic Accidents

The exponential decay observed in the ACF and the cuts off after lag 1 in the PACF, the ARIMA (1, 0, 0) model is found to provide a superior fit for the pre-intervention series of traffic accidents data.

5.3.2 Parameter Estimation

The intervention for the Motor Vehicle Law, political changes, and the third wave of Covid-19 occurred in September 2015, February 2017, April 2020, and March 2021, respectively. The impact of the Motor Vehicle Law represents intervention S_1, which is expected to produce a step change. Similarly, the effect of the Motor Vehicle Law is denoted as intervention P_1. The Vehicle Safety and Motor Vehicle Management Law represent intervention P_2, which is expected to produce a pulse change. The Political Changes and the Covid-19 pandemic represent intervention S_2 which is expected to cause a step change. The response functions are as follows:

$$S_1 = \begin{cases} 0 & \text{if t} < 33 \text{ (September 2015)} \\ 1 & \text{if t } \geq 33 \text{ (September 2015)} \end{cases}$$

$$P_1 = \begin{cases} 0 & \text{if t} \neq 49 \text{ (January 2017)} \\ 1 & \text{if t } = 49 \text{ (January 2017)} \end{cases}$$

$$P_2 = \begin{cases} 0 & \text{if t} \neq 88 \text{ (April 2020)} \\ 1 & \text{if t } = 88 \text{ (April 2020)} \end{cases}$$

$$S_3 = \begin{cases} 0 & \text{if t} < 99 \text{ (March 2021)} \\ 1 & \text{if t } \geq 99 \text{ (March 2021)} \end{cases}$$

As a result, the ARIMA (1, 0, 0) model with intervention is chosen as the fitted model. The estimated parameter values can be found in Table (5.6).

Table (5.6)

Estimation of Parameters and their Statistics for ARIMA (1, 0, 0) Model with Intervention

Parameters	Estimates	S.E	T	Sig
θ_0	168.178***	11.044	15.228	.000
ϕ_1	0.711***	0.073	9.756	.000
ω_1	-36.139***	12.405	-2.913	.004
ω_2	37.057***	12.454	2.976	.004
ω_3	-28.915**	12.454	-2.322	.022
ω_4	-41.297**	19.509	-2.117	.037
δ	0.336	0.502	.669	.505
ω_5	-68.371***	14.068	-4.860	.000

Source: Own Calculation

*****denotes significant at 1% level, ****denotes significant at 5% level

Based on the information provided in the above table, it is evident that the estimate of δ is not significant. Consequently, the parameter δ is excluded, and the resulting estimation outcomes are presented in Table (5.7).

Table (5.7)

Estimation of Parameters and their Statistics for ARIMA (1, 0, 0) Model with Intervention (without δ)

Parameters	Estimates	S.E	T	Sig
θ_0	167.805***	11.164	15.030	.000
ϕ_1	0.716***	0.072	9.971	.000
ω_1	-36.135***	12.515	-2.887	.005
ω_2	37.083***	12.414	2.987	.003
ω_3	-28.942**	12.414	-2.331	.022
ω_4	-33.170**	16.006	-2.072	.041
ω_5	-67.757***	14.136	-4.793	.000

Source: Own Calculation

*****denotes significant at 1% level, ****denotes significant at 5% level

From the Table (5.7), the fitted model is

$$Y_t = \theta_0 + \omega_1 S_1 + (\omega_2 + \omega_3)P_1 + \omega_4\, P_2 + \omega_5 S_2 \ + \frac{1}{(1-\phi_1 B)}\, e_t$$

$$= 167.805 - 36.135S_1 + (37.308 - 28.942)P_1 - 33.170P_2 - 67.757S_2 + \frac{1}{(1-0.716B)}\, e_t$$

The fitted ARIMAX (1, 0, 0) model of traffic accidents give ω_1= -36.135, ω_2= 37.308, ω_3= -28.942, $\omega_4 = -33.170$, $\theta_0 = 167.805$, and $\phi_1 =\ 0.716$ with the estimated standard errors of 12.515, 12.414, 12.414, 16.006, 14.136, 11.164 and 0.072, respectively. The test statistic (t) for all parameters are statistically significant at the 1% level, except for ω_3 *and* $\omega_{4,}$ which are statistically significant at the 5% level.

According to the parameter estimates presented in Table (5.32), the coefficient of the Motor Vehicle Law is statistically significant at the 1% level. The negative effect suggests that the implementation of this law is associated with a decrease in traffic accidents. After the law is implemented, there is a tendency for a reduction in the number of traffic accidents. Additionally, the coefficient of the Permission to Import Vehicle Law is statistically significant at the 1% and 5% level. The positive effect implies that the implementation of this law is associated with an increase in traffic accidents. After the law is implemented, there tends to be a higher number of traffic accidents. The difference between the two coefficients (37.308 - 28.942) indicates the net effect of the Permission to Import Vehicle Law variable on traffic accidents. The magnitude of this difference is 37.308 - 28.942 = 8.366. Since the coefficient for P_1 is positive, this implies that, on average, there is an increase of 8.366 traffic accidents for each unit increase in the Permission to Import Vehicle Law variable.

Furthermore, the coefficient of the Vehicle Safety and Motor Vehicles Management Law is statistically significant at the 5% level. The negative effect indicates that the implementation of this law is associated with a decrease in traffic accidents. After the law is implemented, there is a tendency for a reduction in the number of traffic accidents. However, the estimated coefficient of political changes and Covid-19 pandemic is statistically significant at 1% level. This suggests that the negative effects of political changes and the occurrence of the Covid-19 pandemic are indicative of the implementation of this changes being associated with a decrease in traffic accidents.

5.3.3 Diagnostic Checking

Figure (5.9) displays the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals from the ARIMAX (1, 0, 0) model with intervention.

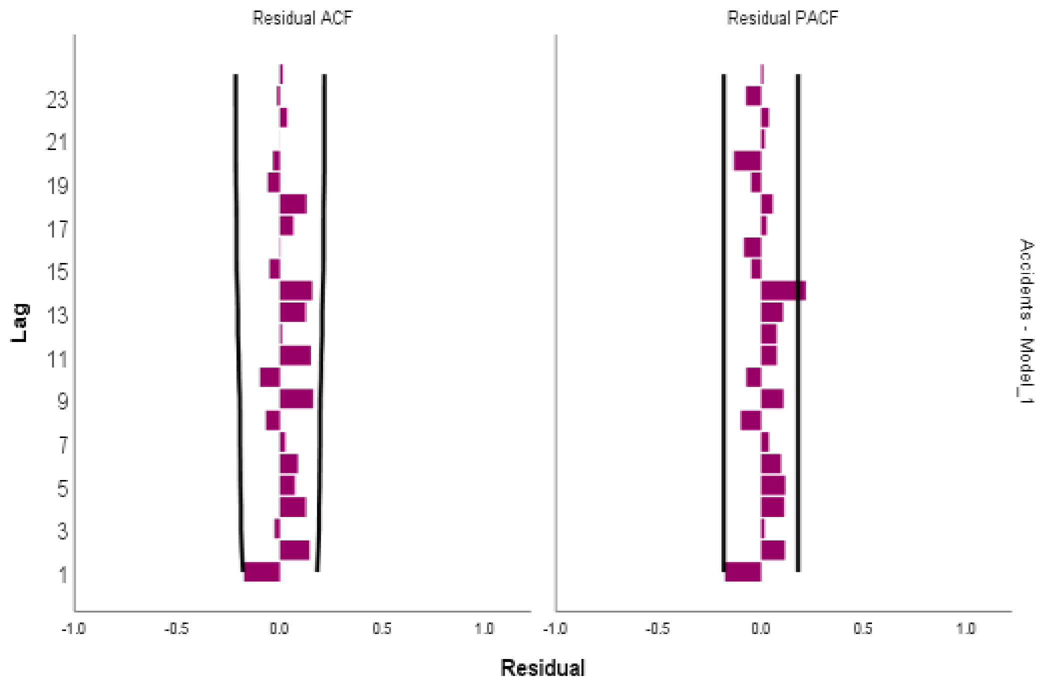


Figure (5.9) ACF and PACF of Residuals for the ARIMA (1, 0, 0) Model with Intervention

As observed in Figure (5.9), the ACF and PACF values of the residuals, resulting from the intervention, lie within the boundaries defined by two standard errors. This suggests that the residual series of the fitted ARIMA (1, 0, 0) model exhibit characteristics of a white noise process. Table (5.8) presents the Ljung-Box test statistics and corresponding p-values for the residual series of the Transfer Function - Noise Model applied to traffic accidents.

Table (5.8)

Model Statistics of ARIMA (1, 0, 0) Model with Intervention for Traffic Accidents

Model	Ljung-Box Q (18)		
	Statistic	Df	Sig
ARIMA (1, 0, 0) with Intervention	26.794	17	.061

Source: Own Calculation

Based on the information provided in the table, the observed value of Q is 26.794, and its corresponding p-value is 0.061, which is greater than the significance level of 0.05. Consequently, there is no significant evidence of autocorrelation among the residuals. This suggests that the intervention model is suitable for fitting the data series of traffic accidents in Yangon, and it can be utilized to forecast future values of traffic accidents in the area.

5.4 ARIMAX-TFM for Traffic Accidents

The ARIMAX-TFM identified a relationship between traffic accidents and three independent variables: over speeding, reckless driving, and pedestrian negligence. In this model, the dependent variable is traffic accidents, while the independent variables are over speeding, reckless driving, and pedestrian negligence.

5.4.1 Determine the ARIMA Model for Input Series

Time series plot of the traffic accidents (Y_t), over speeding ($X_{1,t}$), reckless driving ($X_{2,t}$) and pedestrian negligence ($X_{3,t}$) were described in Figure (5.10).

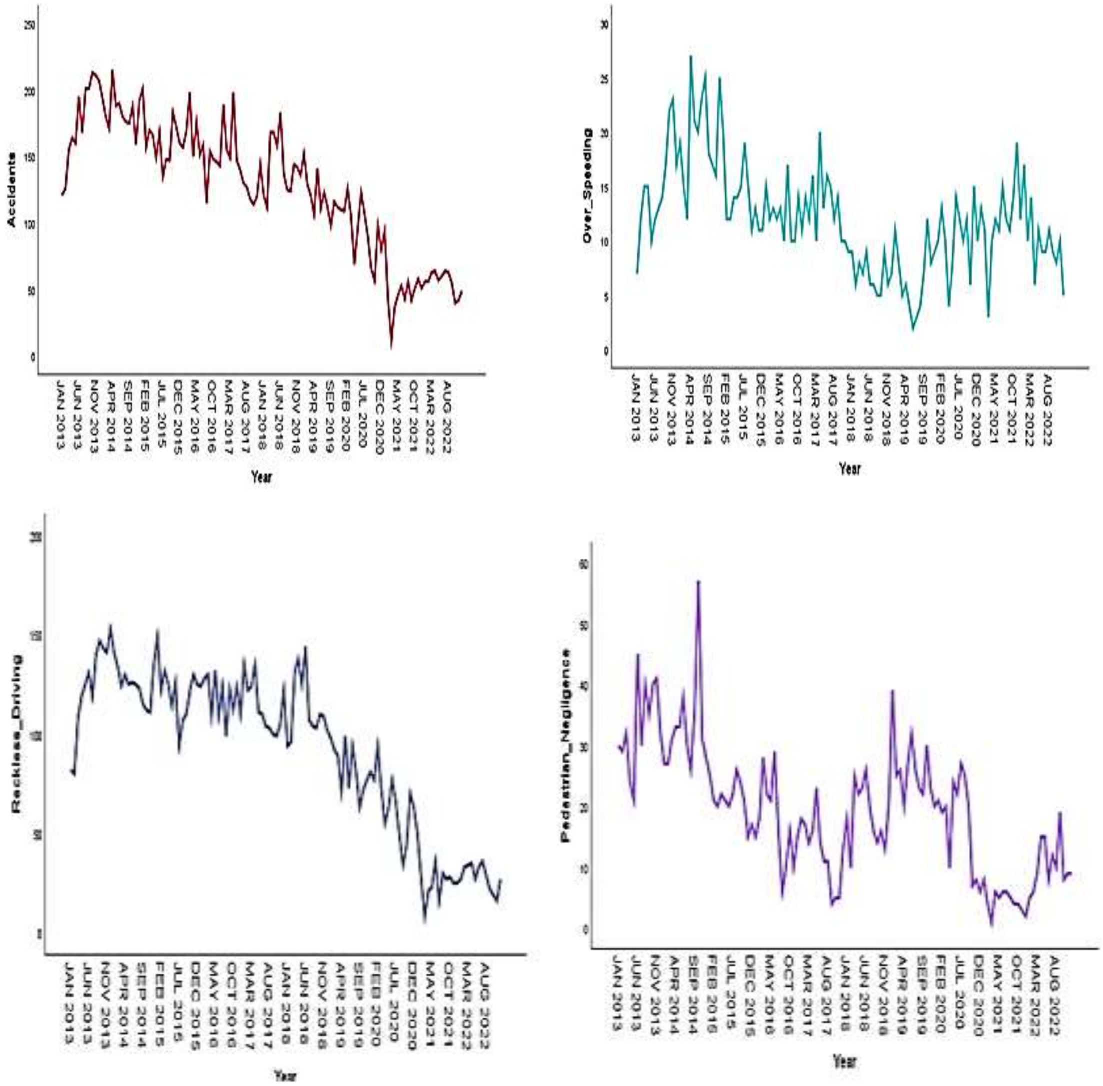
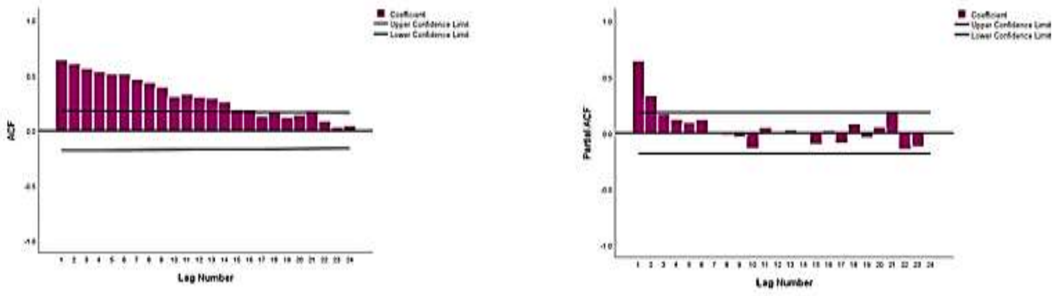


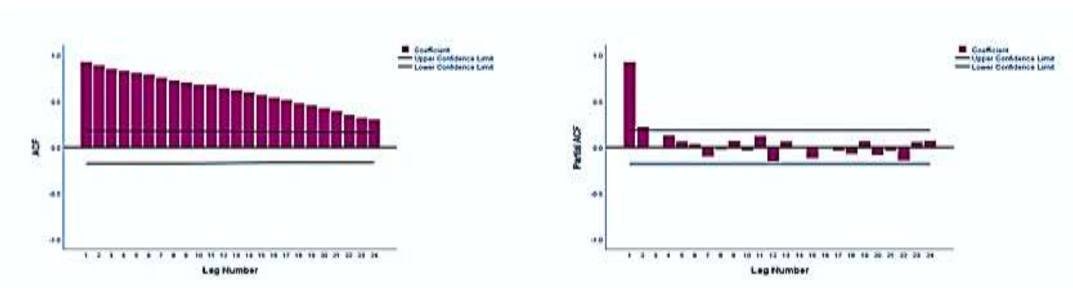
Figure (5.10) Time Series Plots of Dependent Variable (Y_t) and Independent Variables $(X_{1,t},\ X_{2,t}, X_{3,t})$

The Figure (5.10) offers an overview of the time series plots for both the output series and the input series. The stationarity or non-stationarity check specifically for the output series is described in Section (5.1.2). On the other hand, the details regarding the remaining input series (over speeding, reckless driving, and pedestrian negligence) can be found in Appendix Table (C-8). Figure (5.11) shows the corresponding sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) for these input series.

Over Speeding



Reckless Driving



Pedestrian Negligence

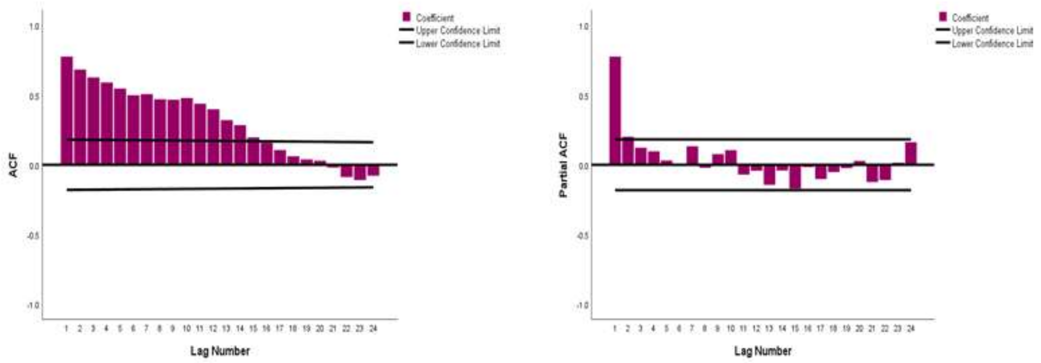


Figure (5.11) ACF and PACF Plots of the Input Series of Traffic Accidents

Based on the analysis of Figure (5.10), it is evident that the time series data for both over speeding and pedestrian negligence exhibit stationarity, which is further supported by the findings presented in Appendix Table (C-8). The observation of a slow decay in the ACF and the cuts off after lag 2 in the PACF suggests the need for autoregressive terms in the ARIMA model. The consideration of four tentative ARIMA models, ARIMA (2, 0, 0), (0, 0, 2), (1, 0, 0), and (0, 0, 1), for both the over speeding and pedestrian negligence series is appropriate based on the characteristics of the ACF and PACF. The selection of the ARIMA (2, 0, 0) model for both series due to its lowest AIC and BIC values is a well-founded decision. A lower AIC and

BIC value indicates a better fit of the model to the data and suggests that the ARIMA (2, 0, 0) model provides a superior representation of the underlying patterns in the over speeding and pedestrian negligence data.

In contrast, the reckless driving series is non-stationary (refer to Appendix Table C-7), and differencing is necessary to remove the non-stationarity. Figure (5.12) describes the first-differenced reckless driving series for traffic accidents in Yangon.

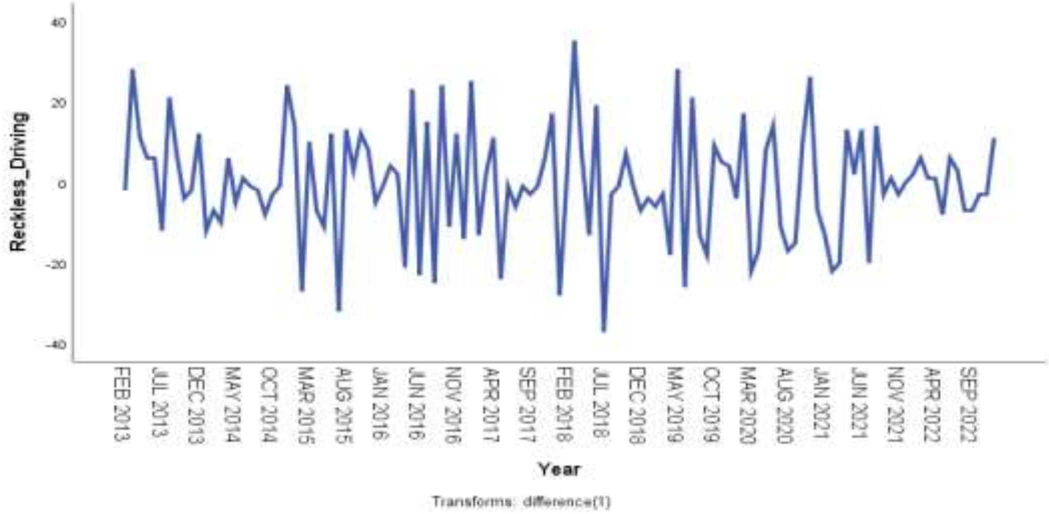


Figure (5.12) First Difference Reckless Driving Series for Traffic Accidents

Figure (5.13) displays the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) for the first differencing of the reckless driving series.

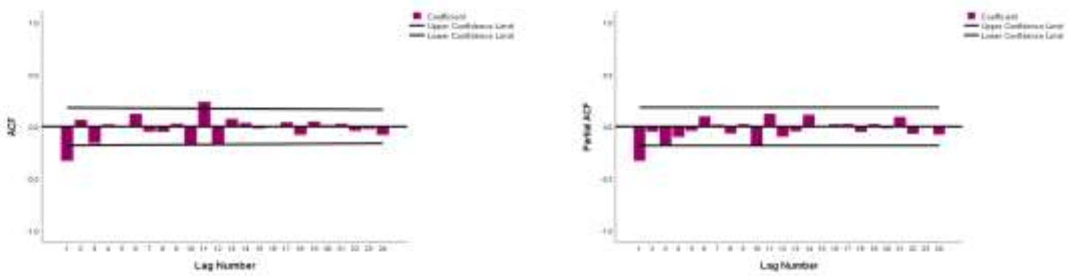


Figure (5.13) ACF and PACF of First Difference Reckless Driving Series for Traffic Accidents

Based on Figure (5.13), the ACF exhibits a spike at lag 1, and the PACF cuts off after lag 1 for the reckless driving series. Based on these observations, three tentative ARIMA models are considered: ARIMA (1, 1, 1), ARIMA (1, 1, 0), and

ARIMA (0, 1, 1), by analyzing the ACF and PACF plots. Among these three models, the ARIMA (1, 1, 1) model is not significant for one parameter. On the other hand, the other two models, ARIMA (1, 1, 0) and ARIMA (0, 1, 1), show significant parameters and have residual values that lie within the two standard error limits. This suggests that these models provide a good fit to the data and adequately capture the underlying patterns in the reckless driving series. Among the two models with significant parameters and well-behaved residuals, the ARIMA (0, 1, 1) model has the lowest values of AIC and BIC. The AIC and BIC are statistical measures used for model selection, with lower values indicating a better fit to the data. Therefore, the ARIMA (0, 1, 1) model is selected as the tentative model for the reckless driving series, as it provides a superior fit to the data compared to the ARIMA (1, 1, 0) model.

5.4.2 Parameter Estimation of ARIMA Model for Input Series

Table (5.9) presents the estimated parameters and corresponding statistic for the ARIMA (2, 0, 0), ARIMA (0, 1, 1), and ARIMA (2, 0, 0) models.

Table (5.9)

Estimation of Parameters and their Statistics for ARIMA Models for Input Series

	Model	Parameters	Estimates	S.E	t	Sig
Over Speeding	ARIMA (2, 0, 0)	θ_0	11.665***	1.328	8.785	.000
		ϕ_1	0.434***	0.088	4.947	.000
		ϕ_2	0.329***	0.088	3.730	.000
Reckless Driving	ARIMA (0, 1, 1)	θ_1	0.389***	0.085	4.568	.000
Pedestrian Negligence	ARIMA (2, 0 , 0)	θ_0	19.423***	3.312	5.864	.000
		ϕ_1	0.617***	0.090	6.836	.000
		ϕ_2	0.213**	0.091	2.349	.020

Source: Own Calculation

*****denotes significant at 1% level, ****denotes significant at 5% level

5.4.3 Diagnostic Checking for Input Series

The residuals of the reckless driving and pedestrian negligence series exhibit values within the two standard error limits, as shown in (Appendix Table: C-8). For the over speeding series, the residuals mostly fall within the two standard error limits, except for lag 21.

5.4.4 Cross Correction Function for Input Series

Cross correlation function between input series, output series and impulse response estimate. The cross correlation performed on each input and output series that has been prewhitening. Cross correlation function results are shown in Figure (5.14).

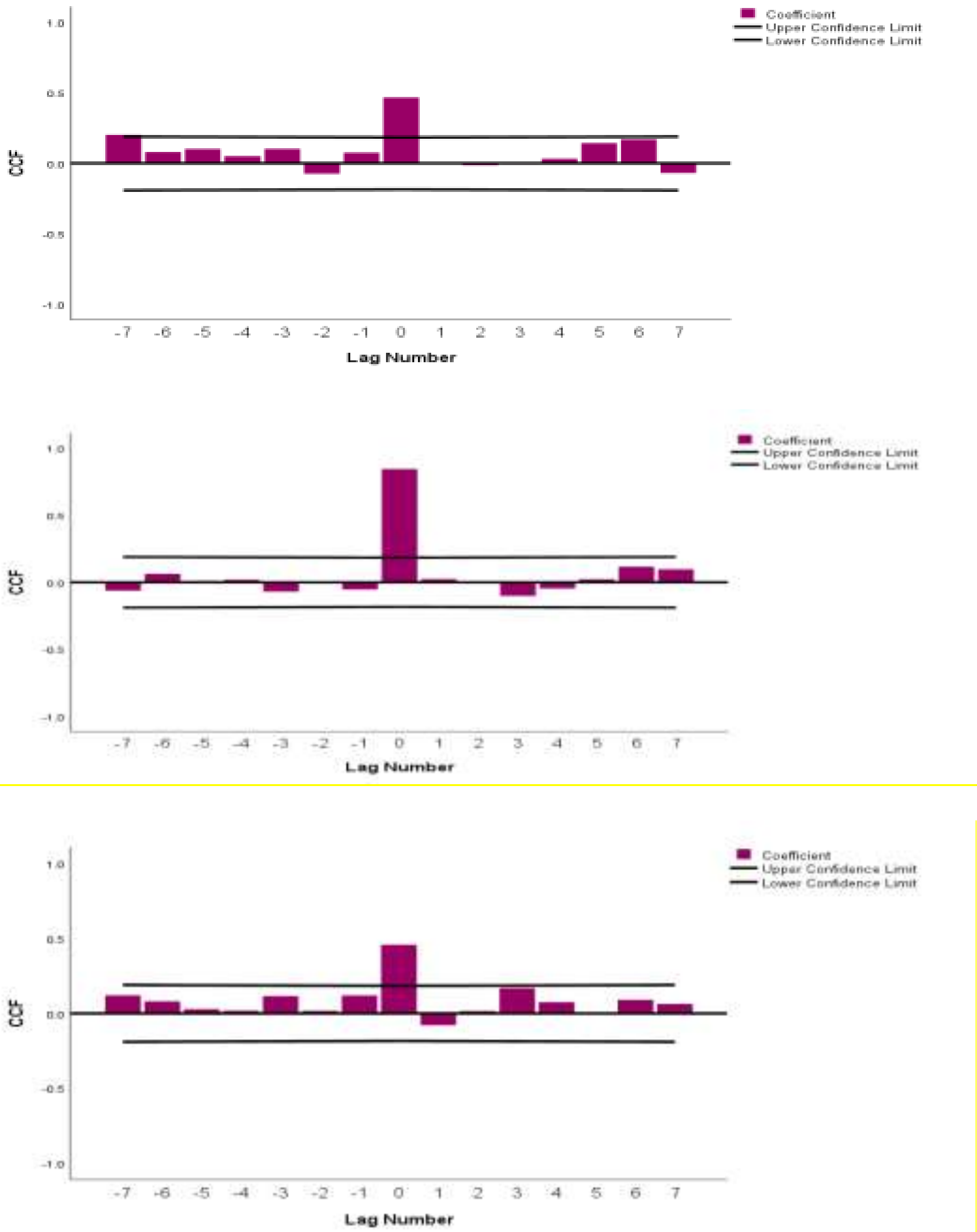


Figure (5.14) CCF Plots between Output Series and Input Series of Traffic Accidents

5.4.5 Identification of Transfer Function – Noise Model

The ARIMA model for noise series is displayed in Figure (5.15).

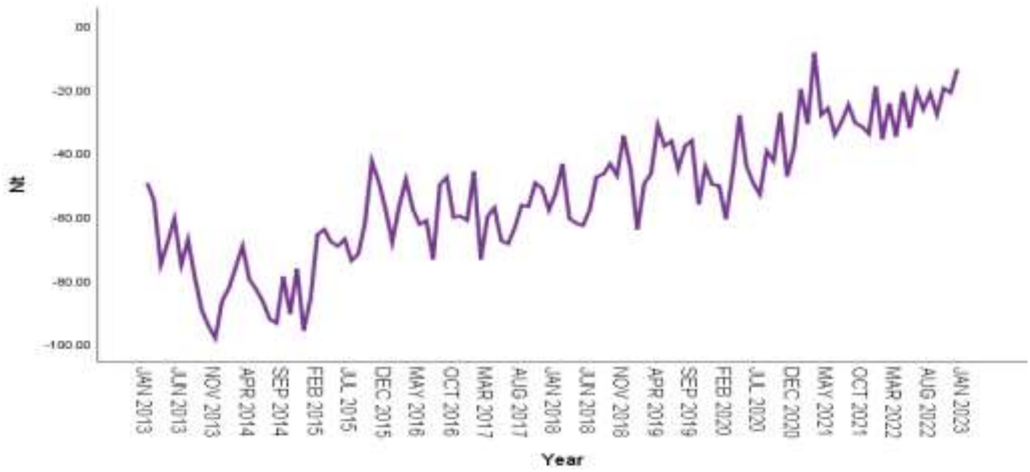


Figure (5.15) Plot of Noise Series for Traffic Accidents

Referring to Figure (5.15), it can be observed that the noise series pertaining to traffic accidents exhibits non-stationarity. As a result, the Figure (5.16) presents the first differencing applied to the sample autocorrelation function (ACF) and the sample partial autocorrelation function (PACF) of the noise series.

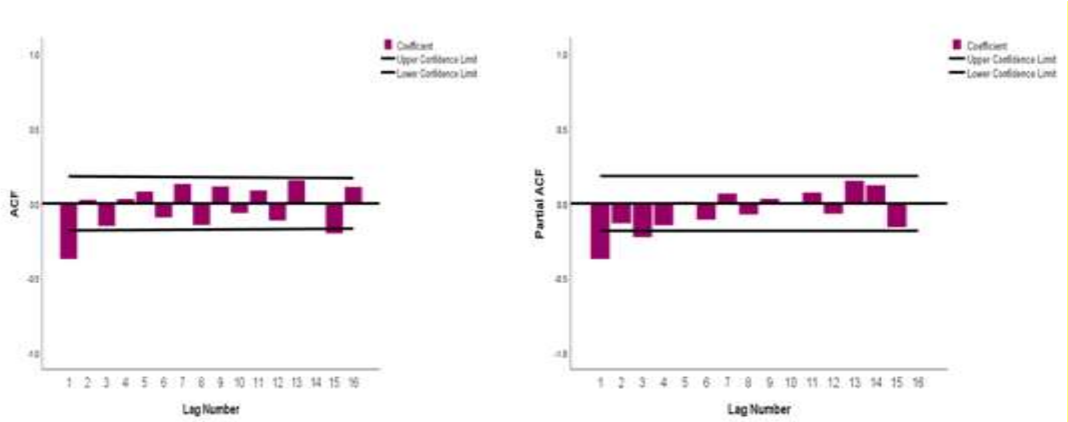


Figure (5.16) ACF and PACF of First Difference of Noise Series for Traffic Accidents

After analyzing the ACF and PACF plots, it is observed that the ACF cuts off after lag 1, and the PACF shows exponential decay for the time series data. Based on these observations, the ARIMA (0, 1, 1) model is chosen as the tentative model for further analysis and forecasting.

5.4.6 Parameter Estimation of Transfer Function – Noise Model

The analysis suggests that the ARIMA (0, 1, 1) model provides the fit for the noise series. The corresponding estimated parameters and statistic for the ARIMAX-TFM (0, 1, 1) model are provided in Table (5.10).

Table (5.10)

Estimation of Parameter and their Statistics for ARIMAX-TFM (0, 1, 1) of Traffic Accidents

Parameters	Estimates	S.E	T	Sig
ω_1	-0.415*	0.215	-1.928	0.056
ω_2	0.099***	0.036	2.733	0.007
ω_3	-0.250*	0.147	-1.706	0.091
θ_1	0.410***	0.091	4.497	0.000

Source: Own Calculation

*******denotes significant at 1% level, *****denotes significant at 10% level

From above Table (5.10), the transfer function - noise model is

$$Y_t = \omega_1 X_{1,t} + \omega_2 X_{2,t} + \omega_3 X_{3,t} + \frac{(1-\theta_1 B)}{(1-B)} e_t$$

$$= -0.415 X_{1,t} + 0.099 X_{2,t} - 0.250 X_{3,t} + \frac{(1-0.410B)}{(1-B)} e_t$$

The fitted ARIMA (0, 1, 1) model for traffic accidents gives $\theta_1 = 0.410, \omega_1 = -0.415,\ \omega_2 = 0.099,\ and\ \omega_3 = -0.250$. The test statistic (t) reveal statistical significance at the 1% level for θ_1 and ω_2, while ω_1 and ω_3 demonstrate significance at the 10% level.

5.4.7 Diagnostic Checking for Transfer Function – Noise Model

Figure (5.17) illustrates the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals obtained from fitting the ARIMAX_TFM (0, 1, 1) model.

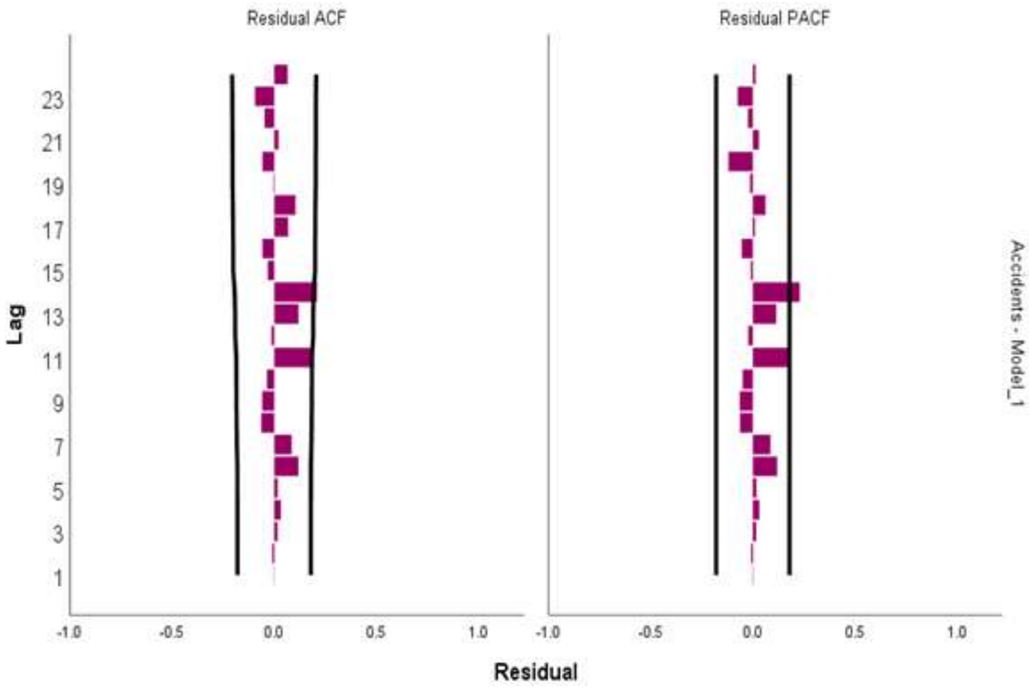


Figure (5.17) ACF and PACF of Residual Noise Series for Traffic Accidents

As depicted in Figure (5.17), the ACF and PACF of the residuals representing the transfer function-noise of traffic accidents remain within the limits of two standard errors except lag 14. This indicates that the residual series follows a white noise process, affirming the adequacy of the transfer function-noise model for future value forecasting. To further assess the autocorrelation among the residuals, the Ljung-Box (Q) test statistic was employed. Table (5.11) displays the test statistic and corresponding p-values for the residuals of the Transfer Function-Noise Model in relation to traffic accidents.

Table (5.11)

Model Statistics of ARIMAX-TFM (0, 1, 1) for Traffic Accidents

Model	**Ljung-Box Q (18)**		
	Statistic	**Df**	**Sig**
ARIMAX-TFM	19.248	17	.314

Source: Own Calculation

After examining Table (5.11), it is evident that the observed value of Q is 19.248, which is not statistically significant due to the p-value of 0.314 exceeding the significance level of 0.05. This suggests that there is no autocorrelation among the residuals. Therefore, the ARIMAX-TFM is considered appropriate for effectively modeling the data series of traffic accidents in Yangon. A comparison between the ARIMA model, Intervention model, and ARIMAX-TFM for traffic accidents was illustrated in Section (5.5).

5.5 Comparison between ARIMA Model, Intervention Model and ARIMAX- TFM for Traffic Accidents

The criteria for model comparison are different from the model identification methods. Model identification tools such as ACF, PACF, IACF, and ESACF are used only for identifying adequate models. Residuals from all adequate models are approximately white noise. The selection criterion is normally based on summary statistics from residuals computed from a fitted model or forecast errors. The comparison between ARIMA model, intervention model and ARIMAX-TFM by using AIC, BIC, MAE, MAPE and RMSE described in Table (5.12).

Table (5.12)

Comparison between ARIMA Model, Intervention Model and ARIMAX-TFM for Traffic Accidents

Model	AIC	BIC	MAE	MAPE	RMSE
ARIMA (0, 1, 1)	716.856	719.643	15.143	16.514	19.674
ARIMA (1, 0, 0) with Intervention	707.969	710.748	14.527	13.5204	19.420
ARIMAX-TFM (0, 1, 1)	419.661	422.440	3.787	3.341	5.759

Source: Own Calculation

The ARIMAX-TFM (0, 1, 1) model demonstrates the minimum AIC and BIC values compared to the alternative models. Additionally, when considering forecast errors such as MAE, MAPE, and RMSE, the ARIMAX-TFM (0, 1, 1) model yields the smallest values among the three models. As a result, the ARIMAX-TFM (0, 1, 1) model is deemed the most suitable for accurately fitting the traffic accidents in Yangon. Furthermore, this model is employed to forecast the series of traffic accidents in Yangon.

5.6 Forecasting Traffic Accidents

The actual values, forecast values, lower confidence limits and upper confidence limits for three periods (January 2023 to March 2023) are obtained and shown in Table (5.13) and Figure (5.18).

Table (5.13)

Forecast Values from January to March, 2023 for Traffic Accidents

Month/ Year		Jan-2023	Feb-2023	Mar-2023
Actual Values		44	50	44
Forecast Values		42	39	35
95% Limit	LCL	4	-6	-15
	UCL	80	83	84

Source: Own Calculation

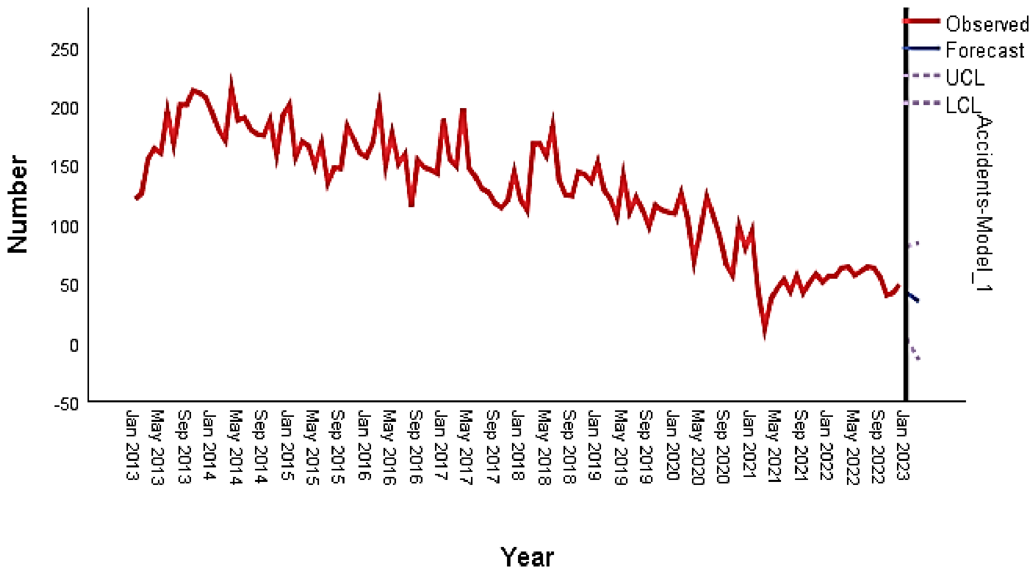


Figure (5.18) Forecast Values with 95% Confidence Limit for Traffic Accidents

The findings of this study suggest that the forecast values obtained from the ARIMAX-TFM (0, 1, 1) model are generally lower than the actual values for traffic accidents in February and March 2023. However, they generally fall within the 95% lower and upper confidence limits. The difference between the estimated value and the actual value is due to the fact that drivers and road users in the Yangon municipal area follow the established rules and regulations but not fully established ones. Notably, there is a relatively close match between the actual and forecast values for

February 2023. The upcoming section provides a detailed description of the time series analysis conducted for traffic fatalities in Yangon.

5.7 Time Series Analysis of Road Traffic Fatalities

The numbers of traffic fatalities resulting from monthly road traffic fatalities during the period from 2013 to 2022 are summarized in Table (5.14). This data was obtained from the No. (2) Office of Traffic Police in Yangon.

Table (5.14)

Monthly Traffic Fatalities

Month/ Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Jan	21	28	34	38	46	29	44	29	25	25
Feb	21	32	32	34	33	27	34	36	23	32
Mar	30	36	23	43	24	35	37	21	9	33
Apr	24	33	34	30	44	31	25	18	22	29
May	30	37	28	45	31	37	46	25	18	37
Jun	27	33	28	26	31	41	34	33	25	21
Jul	19	25	30	34	34	30	27	32	17	27
Aug	20	22	20	24	37	30	32	33	20	29
Sep	31	29	26	29	25	21	25	25	18	23
Oct	53	29	43	27	29	31	25	28	29	18
Nov	30	34	28	34	29	33	30	37	22	14
Dec	36	44	39	27	40	41	23	21	27	22

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

According to the Table (5.14), it can be observed that the traffic fatality rate reached its peak in 2017 and hit its lowest point in 2021. October 2013 witnessed the highest recorded number of traffic fatalities, with 53 deaths, whereas the lowest count was 9 in March 2021. The decline in fatalities during March 2021 can be attributed to the reduced number of vehicles and individuals on the roads and streets due to the significant prevalence of Covid-19 infections that year. The trends of monthly traffic fatalities in Yangon are illustrated in Figure (5.19). Based on the analysis of the picture, there is no apparent evidence of seasonality observed during the study period from January 2013 to December 2022. Analyzing the seasonality of traffic fatalities in Yangon is displayed in Appendix Table (C-1).

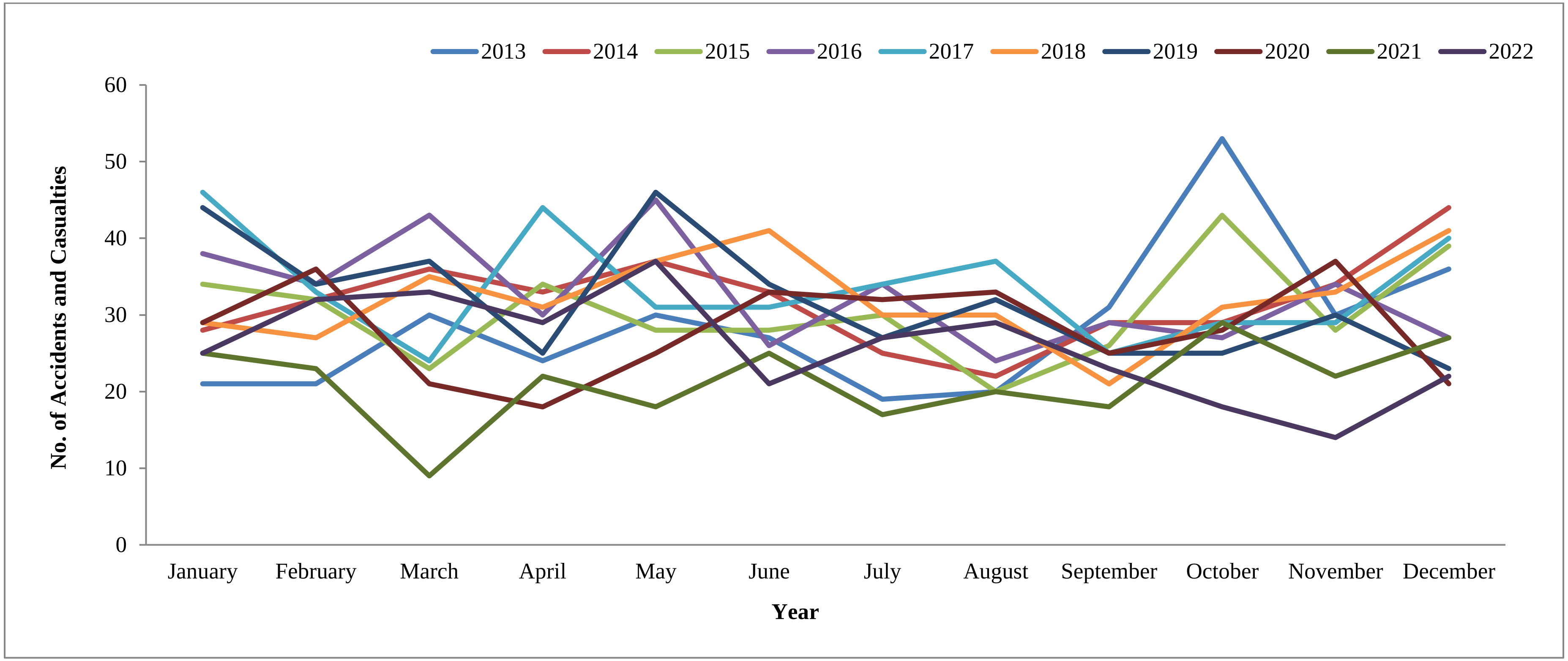


Figure (5.19) Monthly Traffic Fatalities

Source: Table (5.14)

5.7.1 Test of Trend for Traffic Fatalities

The series exhibits trend or not is tested as follows:

Hypotheses

Null Hypothesis: There is no trend for traffic fatality in Yangon.

Alternative Hypothesis: There is a positive or negative trend for traffic fatality in Yangon.

Table (5.15)

Statistical Test of Trend for Traffic Fatalities

t-Test Statistic	Critical Value	Observations
0.010	1.984	120

Source: Own Calculation

Based on the information presented in Table (5.15), the test statistic is 0.010, and the critical value is 1.984. Since the test statistic is lower than the critical value, it can be concluded that there is no significant trend observed for traffic fatalities in Yangon from 2013 to 2022.

5.7.2 Test of Stationarity for Traffic Fatalities

In this section, the Augmented Dickey-Fuller test was employed to assess stationarity. The results of the stationary test conducted on the traffic fatalities series in Yangon, utilizing monthly time series data from January 2013 to December 2022, are presented in Table (5.16).

Table (5.16)

Augmented Dickey-Fuller Test for Traffic Fatalities

		t-statistic	p-value
Augmented Dickey-Fuller test statistic		- 4.8776	0.0001
Test critical value	1% level	-3.4866	
	5% level	-2.8861	
	10% level	-2.5800	

Source: Appendix (D-1)

Hypotheses

H_0: The recorded number of traffic fatalities has a unit root (i.e., The recorded number of traffic fatalities is non-stationary).

H_1: The recorded number of traffic fatalities does not have a unit root (i.e., The recorded number of traffic fatalities is stationary).

From the Table (5.16), it can be observed that the calculated test statistic for ADF is - 4.8776, which is lower than all the critical values (-3.4866, -2.8861, and -2.5800), and the corresponding p-value is 0.0001. As a result, there is sufficient evidence to reject the null hypothesis. Therefore, it can be concluded that the traffic fatalities series exhibits stationarity. The analysis of the traffic fatalities data using the ARIMA model, Intervention model, and ARIMAX-TFM model can be found in Sections 5.8 to 5.10.

5.8 ARIMA Model for Traffic Fatalities

In time series analysis, the identification and construction of a suitable model based on the available data are crucial steps. The ARIMA approach consists of three fundamental stages: model identification, parameter estimation, and diagnostic checking.

5.8.1 Model Identification

From January 2013 to December 2022, a total of 3,554 traffic fatalities were reported in Yangon. The Figure (5.20) depicts the original series of traffic fatalities in Yangon.

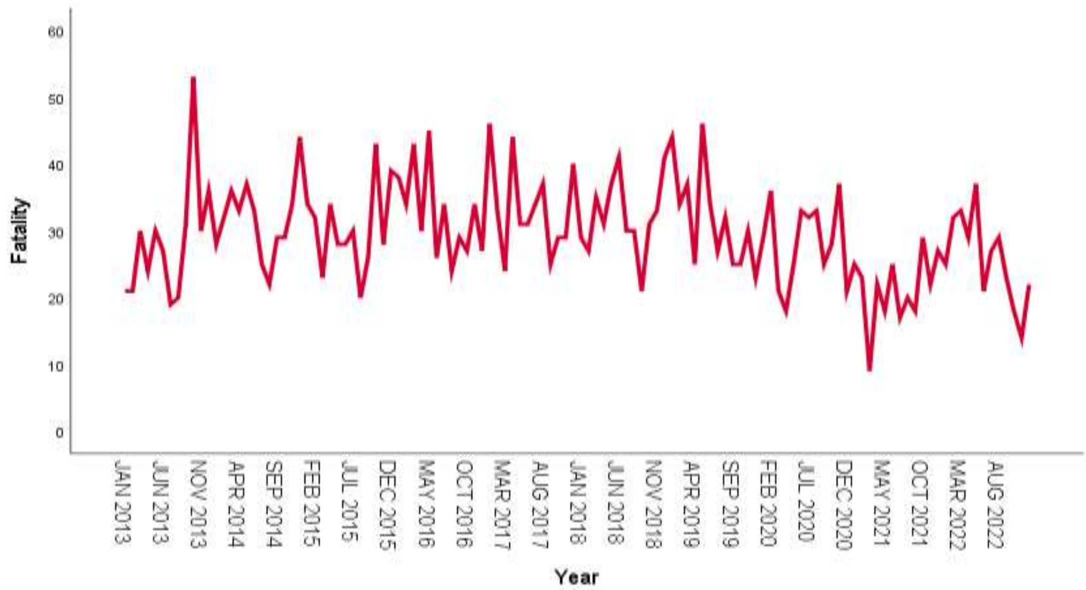
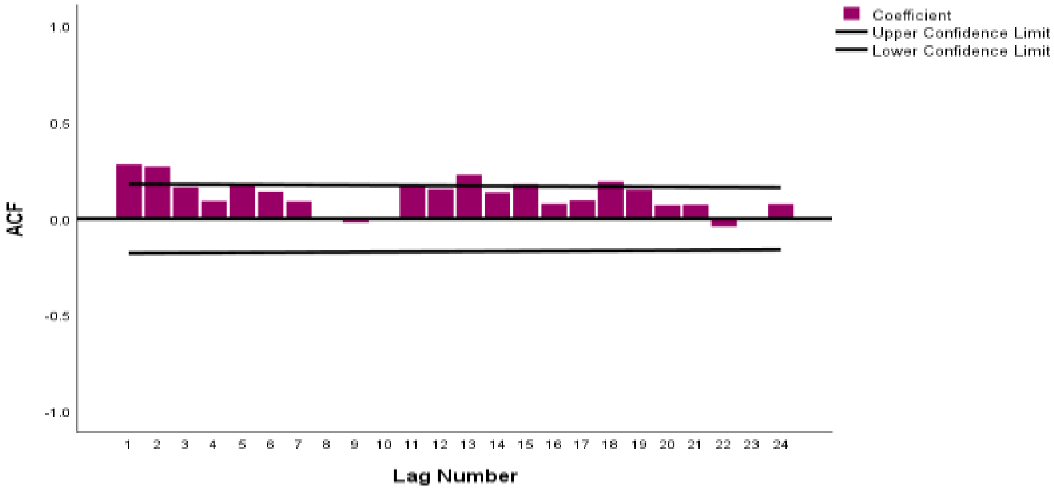


Figure (5.20) Original Series of Traffic Fatalities

Regarding Figure (5.20), the original series of traffic fatalities in Yangon displays fluctuations that are consistently around a constant mean, and the variance does not appear to change throughout the period. This plot suggests that the series is stationary. The primary method of identification is analyzing the sample autocorrelation function (ACF) and the sample partial autocorrelation function (PACF) for traffic fatalities in Yangon, as depicted in Figure (5.21).



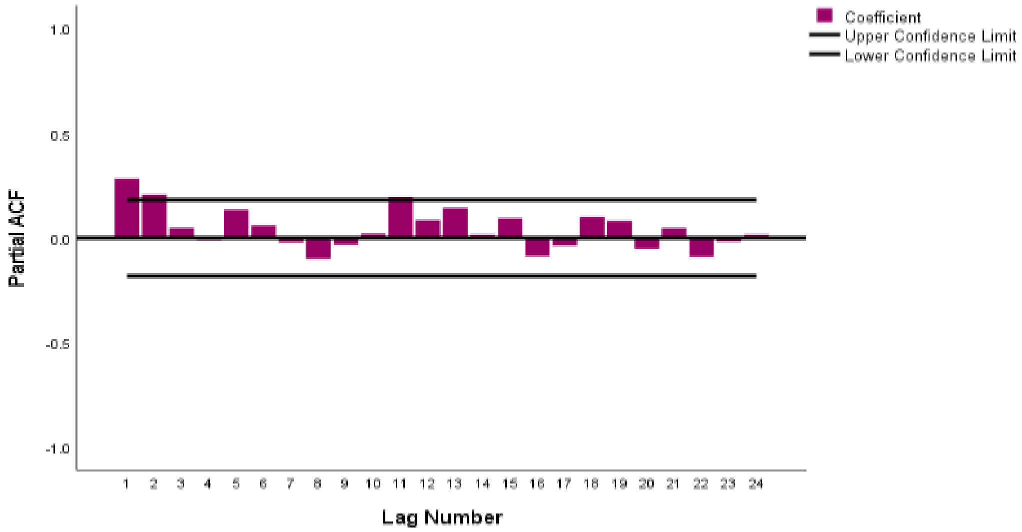


Figure (5.21) Sample Correlogram of the Original Series of Traffic Fatalities

Based on the ACF and PACF plots in Figure (5.21), it can be seen that both the ACF and PACF spikes at lag 2. Therefore, the ARIMA (0, 0, 2), (2, 0, 0), and (2, 0, 2) models are initially considered as tentative models. Among these, the ARIMA

(2, 0, 2) model shows no significance for all parameters. Consequently, the AIC and BIC values are utilized to select the fitted model. The ARIMA (2, 0, 0) model exhibits the lowest AIC and BIC values, leading to its selection as the preferred tentative model.

5.8.2 Parameter Estimation

Using the ARIMA (2, 0, 0) model, the estimated parameters with their statistics are shown in Table (5.17).

Table (5.17)

Estimated Parameters and their Statistics for ARIMA (2, 0, 0) Model of Traffic Fatalities

Parameters	Estimates	S.E	t	Sig
θ_0	29.426***	1.161	25.354	0.000
ϕ_1	0.228**	0.090	2.536	0.013
ϕ_2	0.225**	0.092	2.447	0.016

Source: Own Calculation

*******denotes significant at 1% level, ******denotes significant at 5% level

From above Table (5.17), the fitted model is

$$(1-\phi_1 B-\phi_2 B^2)Y_t=\theta_0+e_t$$

$$\underset{(0.090)}{(1-0.228\text{B}}-\underset{(0.092)}{0.225B^2)}\,Y_t=\underset{(1.161)}{29.426}+e_t$$

The fitted ARIMA (2, 0, 0) model for traffic fatality provides the following parameter estimates: $\theta_0=29.426$, ϕ_1= 0.228 and ϕ_2= 0.225. The estimated standard errors for these parameters are 1.161, 0.090, and 0.092, respectively. The test statistic t-value for θ_0, ϕ_1 *and* ϕ_2 are statistically significant at the 1% level and 5% level, respectively.

5.8.3 Diagnostic Checking

The autocorrelation function (ACF) and partial autocorrelation function (PACF) for the residuals of the fitted ARIMA (2, 0, 0) model are shown in Figure (5.22).

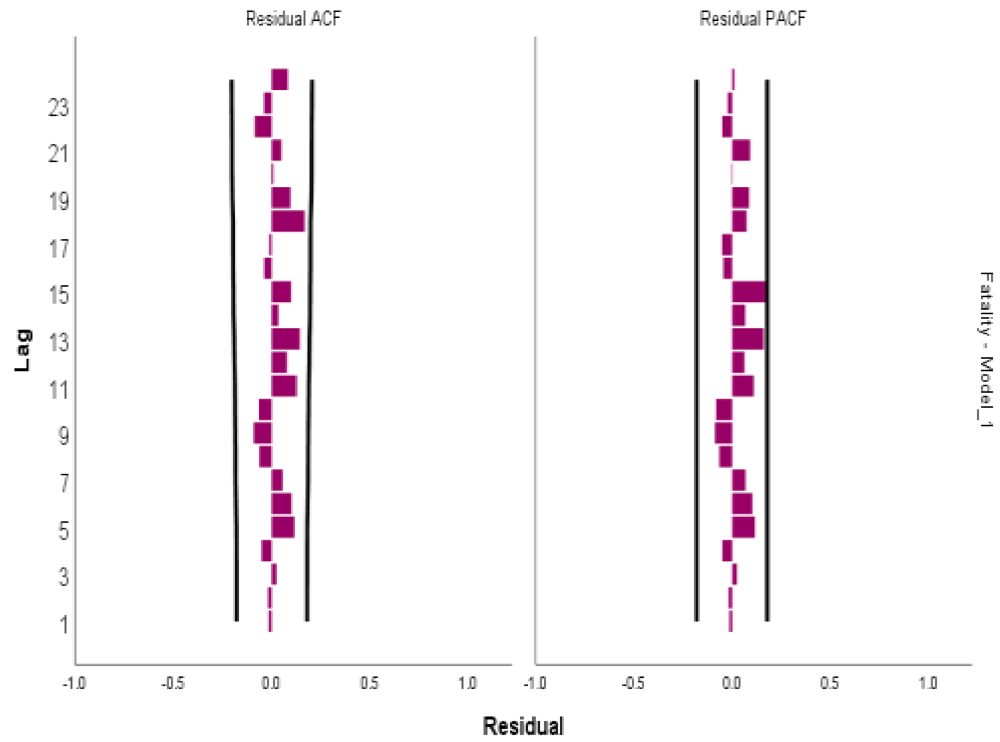


Figure (5.22) ACF and PACF of Residuals for the ARIMA (2, 0, 0) Model

According to Figure (5.22), the residual values of the autocorrelation function (ACF) and partial autocorrelation function (PACF) for traffic fatalities fall within the two standard error limits. This suggests that the residual series of the fitted ARIMA (2, 0, 0) model can be considered a white noise process. Subsequently, the autocorrelation among the residuals is checked using the Ljung-Box test statistic (Q). The test statistic, along with their corresponding p-values, for the residuals of the fitted ARIMA (2, 0, 0) model for traffic fatalities, are presented in Table (5.18).

Table (5.18)

Model Statistics for ARIMA (2, 0, 0) Model on Traffic Fatalities

Model	Ljung-Box Q (18)		
	Statistic	Df	Sig
ARIMA (2, 0, 0)	17.488	16	.355

Source: Own Calculation

As indicated in Table (5.18), the computed value of Q is 17.488, and its associated p-value is 0.355. Consequently, the observed p-value is not statistically significant, suggesting the absence of significant autocorrelation among the residuals. Therefore, the ARIMA (2, 0, 0) model is considered adequate for fitting the data series of Traffic Fatalities in Yangon.

5.9 Intervention Analysis of Traffic Fatalities

Interventions can impact the response in various ways, including abruptly transforming the level of a series, causing a delayed effect, altering the trend, or inducing more complex effects. As initially demonstrated by Box and Tiao in 1975, transfer functions can be employed to model intervention effects and ascertain whether there is evidence of a change in the series, along with its nature and magnitude. Among the methods available for evaluating the effects of an intervention or legislation, ARIMA interrupted time series analysis (also known as ARIMA intervention analysis) has been found to be the most efficient.

The interventions under examination include the Motor Vehicle Law, Permission to Import Vehicle Law, Vehicle Safety and Motor Vehicle Management Law, Myanmar's political changes, and the Covid-19 pandemic. In Myanmar, the Motor Vehicle Law was nationally enacted in September 2015, followed by the promulgation of the Permission to Import Vehicles Law in November 2016, but the law came into effect in January 2017. The Vehicle Safety and Motor Vehicle Management Law came into effect in April 2020 and remains in place to date. Myanmar's political changes began in February 2021, while the Covid-19 pandemic struck in March 2021. The impact of these government policies (interventions) is crucial in analyzing the time series data of traffic fatalities.

5.9.1 Model Identification

In Myanmar, the impact of the intervention in the Motor Vehicles Law, which was enacted in September 2015, and the promulgation of the Permission to Import Vehicles Law in January 2017, along with the enactment of the Vehicle Safety and Motor Vehicles Management Law in April 2020, and the political changes and the

Covid-19 pandemic in March 2021, affected the traffic accidents, as displayed in Figure (5.23).

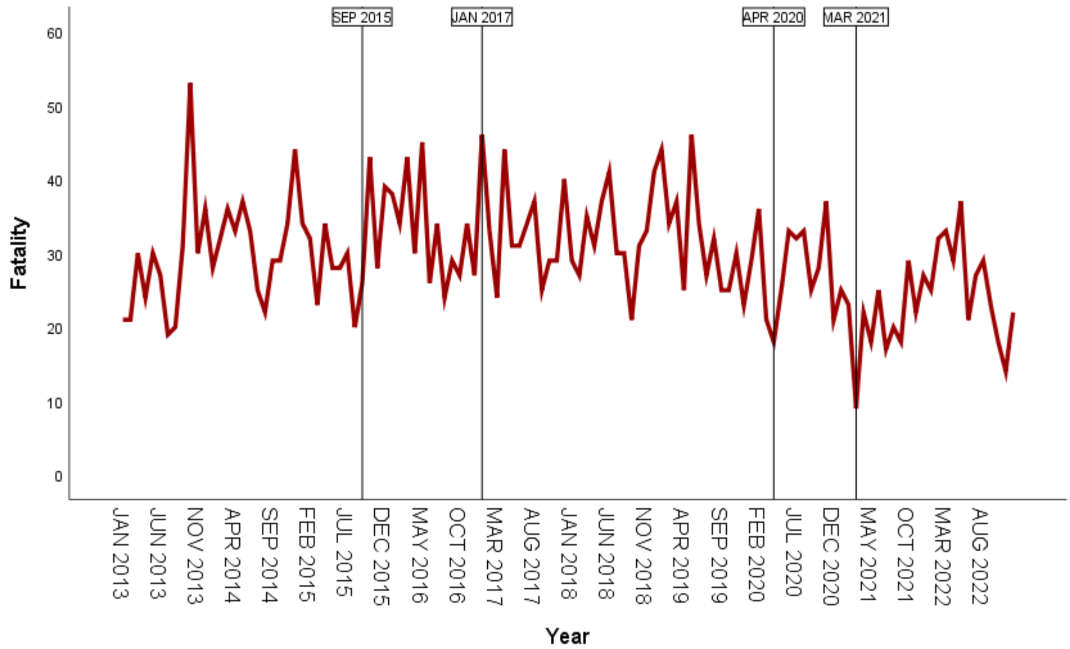
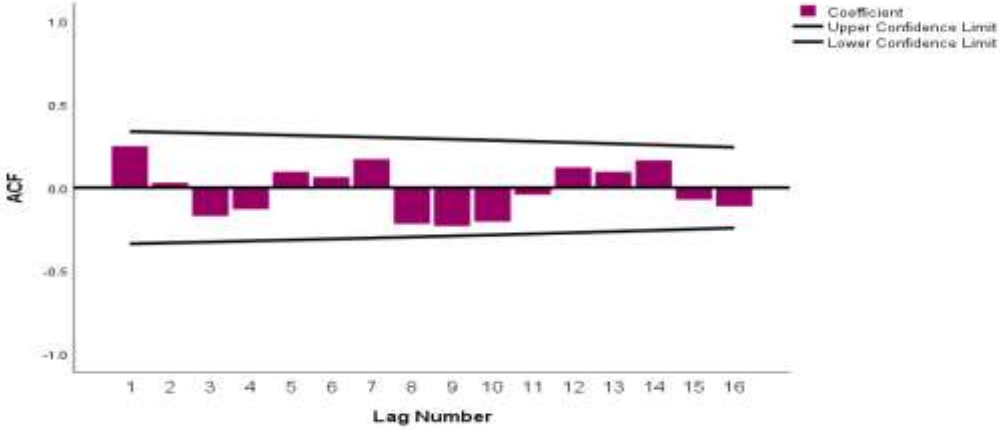


Figure (5.23) Intervention of Traffic Fatalities

The ARIMA modeling was identified using the data from the 1st data point to the 32 monthly observations before the intervention. Based on Figure (5.23), it can be seen that the data is characterized by stationarity in terms of both mean and variance. The stationarity test for the pre-intervention series of traffic fatalities is described in (Appendix D-4). Therefore, no transformation is needed to achieve stationarity. Model identification involves analyzing the sample autocorrelation function (ACF) and the sample partial autocorrelation function (PACF) for traffic fatalities in Yangon, as plotted in Figure (5.24).



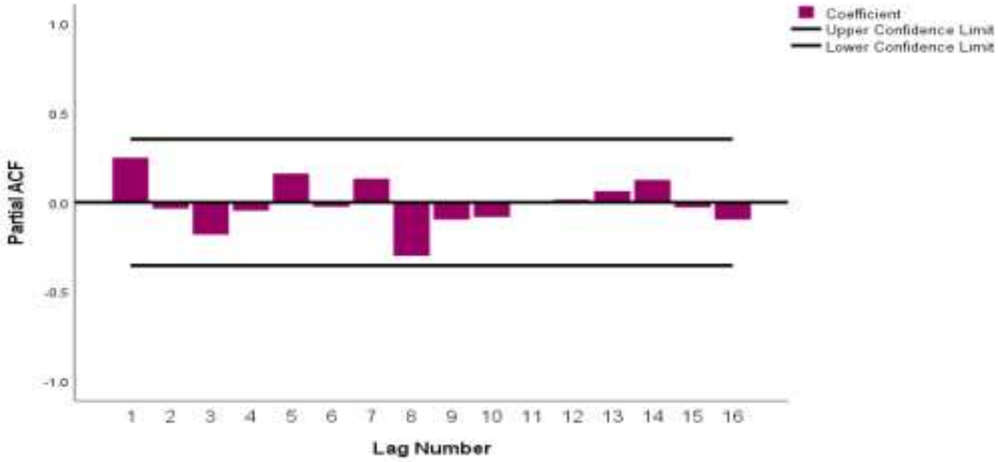


Figure (5.24) ACF and PACF of Pre-intervention Series for Traffic Fatalities

The ACF and PACF values exhibit no pattern and fall within the two-standard-error limit. As a result, the ARIMAX (0, 0, 0) model is considered a tentative model for representing traffic fatalities in Yangon.

5.9.2 Parameter Estimation

The intervention for the Motor Vehicle Law occurred in September 2015, for the Permission to Import Vehicle Law in January 2017, for the Vehicle Safety and Motor Vehicles Management Law in April 2020, and for the political changes and the Covid-19 pandemic in March 2021. The Motor vehicle Law represents an intervention S_1 which might be expected to produce a step change. The Permission to Import Vehicle Law represents an intervention, S_2. The Vehicle Safety and Motor Vehicles Management Law represent an intervention P_1, which might be expected to produce a pulse change. The political changes and the Covid-19 pandemic represent an intervention $S_{3,}$ which might be expected to produce a step change. These interventions can be represented as follows:

$$S_1 = \begin{cases} 0 & \text{if } t < 33 \text{ (September 2015)} \\ 1 & \text{if } t \geq 33 \text{ (September 2015)} \end{cases}$$

$$S_2 = \begin{cases} 0 & \text{if } t < 49 \text{ (January 2017)} \\ 1 & \text{if } t \geq 49 \text{ (January 2017)} \end{cases}$$

$$P_1 = \begin{cases} 0 & \text{if } t \neq 88 \text{ (April 2020)} \\ 1 & \text{if } t = 88 \text{ (April 2020)} \end{cases}$$

$$S_3 = \begin{cases} 0 & \text{if } t < 99 \text{ (March 2021)} \\ 1 & \text{if } t \geq 99 \text{ (March 2021)} \end{cases}$$

The estimated values of the parameters are displayed in the Table (5.19).

Table (5.19)

Estimation of Parameters and their Statistics for ARIMA (0, 0, 0) Model with Intervention

Parameter	Estimates	Std. Error	t	Sig.
θ_0	29.937***	1.218	24.578	0.000
ω_1	4.25**	2.11	2.014	0.046
ω_2	-3.427*	1.997	-1.716	0.089
ω_3	-13.078*	6.934	-1.886	0.062
δ	0.275	0.477	0.576	0.566
ω_4	-6.57***	1.812	-3.627	0.000

Source: Own Calculation

*******denotes significant at 1% level, ******denotes significant at 5% level, *****denotes significant at 10% level

From the above table, the estimate of δ is not significant, so the parameter δ is dropped, and the estimation results are described in Table (5.20).

Table (5.20)

Estimation of Parameters and their Statistics for ARIMA (0, 0, 0) Model with Intervention (without δ)

Parameter	Estimates	Std. Error	t	Sig.
θ_0	29.938***	1.215	24.637	0.000
ω_1	4.250**	2.105	2.019	0.046
ω_2	-3.534*	1.979	-1.786	0.077
ω_3	-12.653*	6.944	-1.822	0.071
ω_4	-6.463***	1.793	-3.605	0.000

Source: Own Calculation

*******denotes significant at 1% level, ******denotes significant at 5% level, *****denotes significant at 10% level

From the Table (5.20), the fitted model is

$$\mathrm{Y_t} = \theta_0 + \omega_1 \mathrm{S_1} + \omega_2 \mathrm{S_2} + \omega_3 \mathrm{P_1} + \omega_4 \mathrm{S_3} + \mathrm{e_t}$$

$$= 29.938 + 4.250\ \mathrm{S_1} - 3.534\ S_2 - 12.653\ \mathrm{P_1} - 6.463\ \mathrm{S_3}$$

The fitted ARIMAX (0, 0, 0) model with intervention of traffic fatality give $\theta_0 = 29.938$, $\omega_1 = 4.250$, $\omega_2 =$ -3.534, $\omega_3 = -12.653$, and $\omega_4 =$ -6.463 with the estimated standard errors of 1.215, 2.105, 1.979, 6.944, and 1.793, respectively. The test statistic t for θ_0 *and* ω_4 are statistically significant at 1% level, ω_2 *and* ω_3 are statistically significant at 10% level and ω_1 is 5% level respectively.

Based on the parameter estimates in Table (5.20), the estimated coefficient of the Motor Vehicle Law is statistically significant at the 5% level. The positive effect suggests that the implementation of this law is associated with an increase in traffic fatalities. After the law is implemented, there tends to be a higher number of traffic-related deaths. The estimated coefficient of the Permission to Import Vehicle Law is statistically significant at the 10% level. The negative effect indicates that the implementation of this law is associated with a decrease in traffic fatalities. After the law is implemented, there tends to be a reduction in the number of traffic-related deaths.

The estimated coefficient of the Vehicle Safety and Motor Vehicles Management Law is statistically significant at the 10% level. The negative effect suggests that the implementation of this law is associated with a decrease in traffic fatalities. After the law is implemented, there is a tendency for a reduction in the number of traffic-related deaths. The estimated coefficient of political changes and Covid-19 pandemic is statistically significant at the 1% level. The negative effect suggests that political changes and the occurrence of the Covid-19 pandemic are associated with a decrease in traffic fatalities. During political changes and the third wave of Covid-19, there tends to be a reduction in the number of traffic-related deaths.

5.9.3 Diagnostic Checking

The residuals ACF and PACF for the fitted ARIMA (0, 0, 0) model with intervention are shown in Figure (5.25).

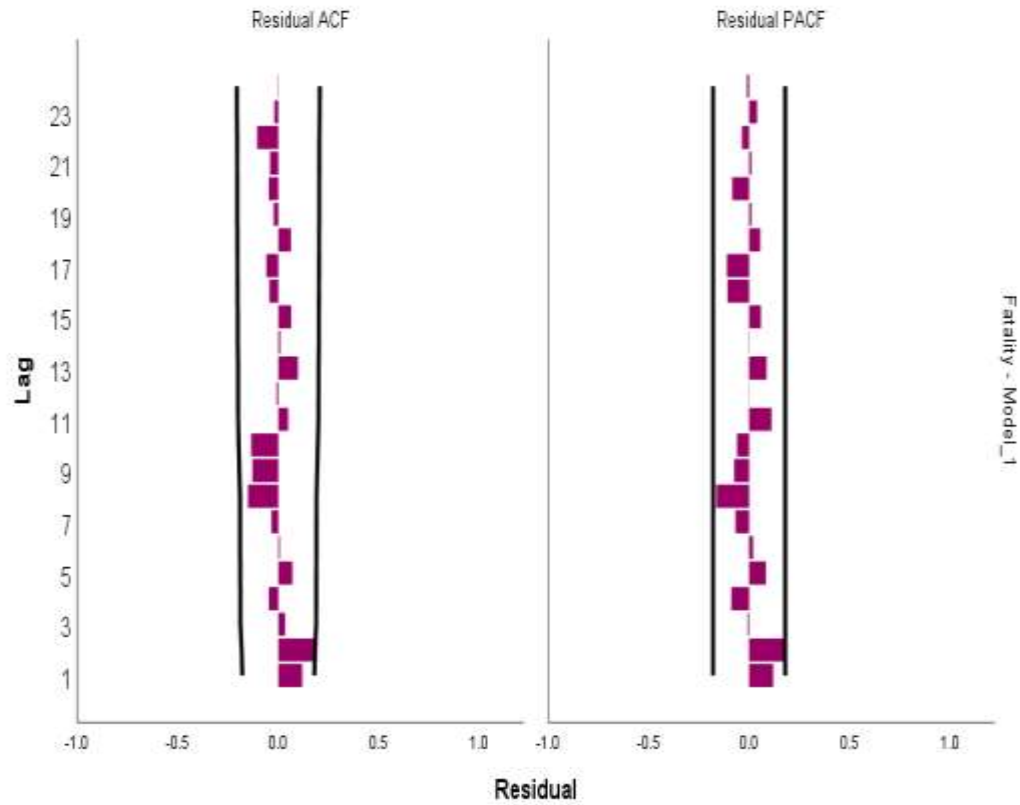


Figure (5.25) ACF and PACF of Residuals for ARIMA (0, 0, 0) model with Intervention

According to the Figure (5.25), the residual values of the ACF and PACF for the intervention of traffic fatalities fall within the two standard errors limits. Thus, the residual series of the fitted ARIMA (0, 0, 0) model with intervention are white noise process. The test statistic with the corresponding p-values of the residuals of the fitted ARIMA (0, 0, 0) Model with Intervention for traffic fatalities are shown in Table (5.21).

Table (5.21)

Model Statistics of ARIMAX (0, 0, 0) Model with Intervention for Traffic Fatalities

Model	Ljung-Box Q (18)		
	Statistic	Df	Sig
ARIMA (0,0,0) with Intervention	18.640	18	.414

Source: Own Calculation

As displayed in Table (5.21), the observed value of Q amounts to 18.640. The corresponding p-value, which is 0.414, is greater than the significance level of 0.05. This outcome implies that the observed p-value is not statistically significant, thus indicating the absence of autocorrelation among the residuals. Thus, ARIMA (0, 0, 0) model with intervention is adequate to fit the data series of traffic fatalities in Yangon and it can be used to forecast the future values of traffic fatalities in Yangon.

5.10 ARIMAX-TFM for Traffic Fatalities

In this study, we used the ARIMAX-TFM to examine the relationship between traffic fatalities and factors such as over speeding, reckless driving, and pedestrian negligence. The dependent variable in our analysis was traffic fatalities, while the independent variables were over speeding, reckless driving, and pedestrian negligence. The ARIMAX-TFM was employed to assess autocorrelations within the series and eliminate them, resulting in a white noise series. We determined the suitable orders (b, r, and s) based on the CCF plot results and then proceeded to find the noise model.

5.10.1 Identification of ARIMA Models for Input Series

The time series plots of traffic fatalities (Y_t), over speeding ($X_{1,t}$), reckless driving ($X_{2,t}$) and pedestrian negligence ($X_{3,t}$) are illustrated in Figure (5.26).

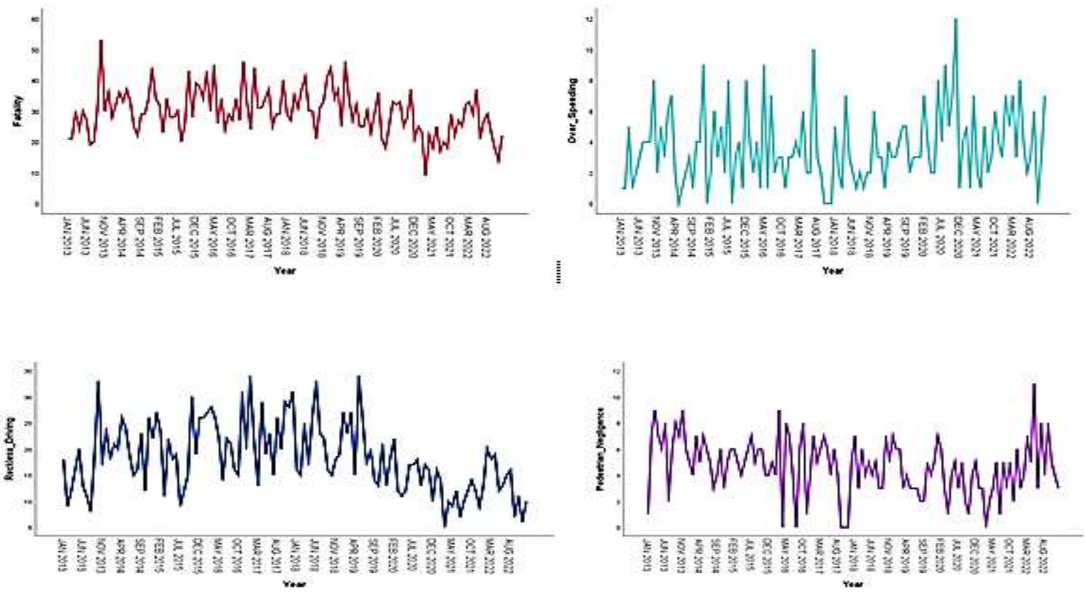
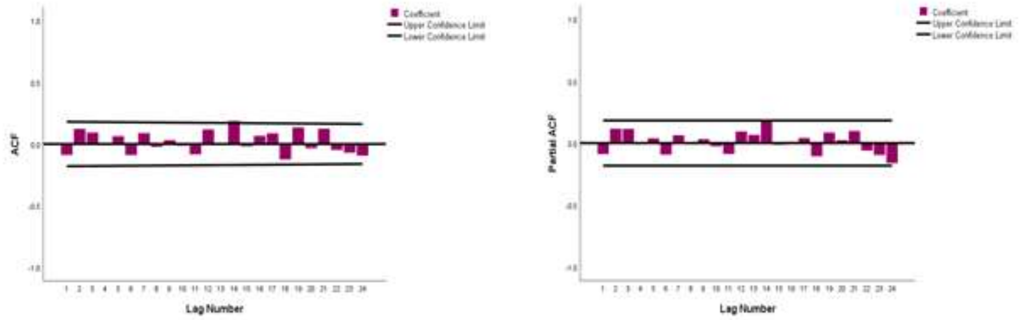


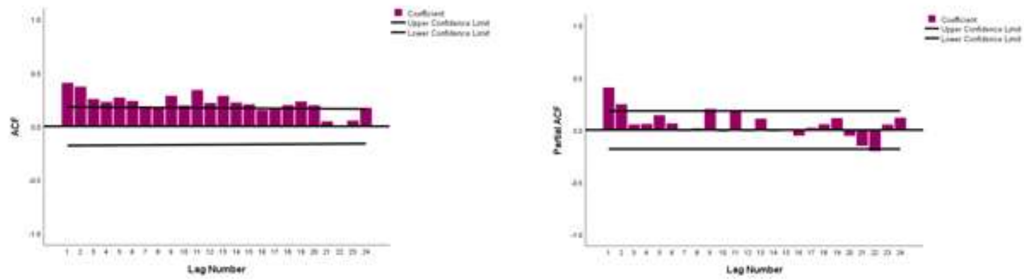
Figure (5.26) Time Series Plots of Dependent Variable (Y_t) and Independent Variables ($X_{1,t}, X_{2,t}, X_{3,t}$)

The Figure (5.26) provides information regarding the stationary or non-stationary nature of the series. Section (5.7.2) discusses the process of examining stationarity for the output series, while the analysis for the remaining input series is available in Appendix Table (D-6). The time series plots in Figure (5.26) demonstrate fluctuations around a constant mean, indicating that the input series are stationary throughout the observed period. In Figure (5.27) present the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) plots for over speeding, reckless driving, and pedestrian negligence.

Over Speeding



Reckless Driving



Pedestrian Negligence

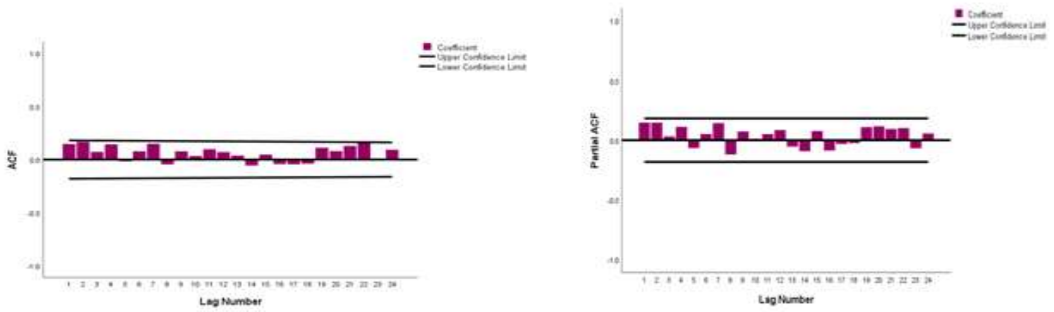


Figure (5.27) ACF and PACF Plots of the Input Series of Traffic Fatalities

After reviewing Figure (5.27), it is evident that the autocorrelation function (ACF) and partial autocorrelation function (PACF) fall within the bounds of two standard error limits for overspeeding and pedestrian negligence. Consequently, an ARIMA (0, 0, 0) model is selected as the tentative model for these two variables. In the case of reckless driving, the ACF plot displays a tails off pattern, and the PACF plot demonstrates a cutoff at lag 2. Therefore, the ARIMA (2, 0, 0) model is deemed suitable as the tentative model for modeling reckless driving.

5.10.2 Parameter Estimation for Input Series

The estimated parameter values for the fitted ARIMA (0, 0, 0), ARIMA (2, 0, 0), and ARIMA (0, 0, 0) models are presented in Table (5.22).

Table (5.22)

Estimation of Parameter and their Statistics for ARIMA Models for Input Series

Input Series	Model	Parameters	Estimates	S.E	t	Sig
Over Speeding	ARIMA (0, 0, 0)	θ_0	3.517***	0.207	16.960	.000
Reckless Driving	ARIMA (2, 0, 0)	θ_0	18.110***	1.227	14.765	.000
		$\emptyset_1$	0. 304***	0.089	3.406	.001
		$\emptyset_2$	0.264***	0.091	2.918	.004
Pedestrian Negligence	ARIMA (0, 0 , 0)	θ_0	4.667***	0.201	23.263	.000.

Source: Own Calculation

*******denotes significant at 1% level

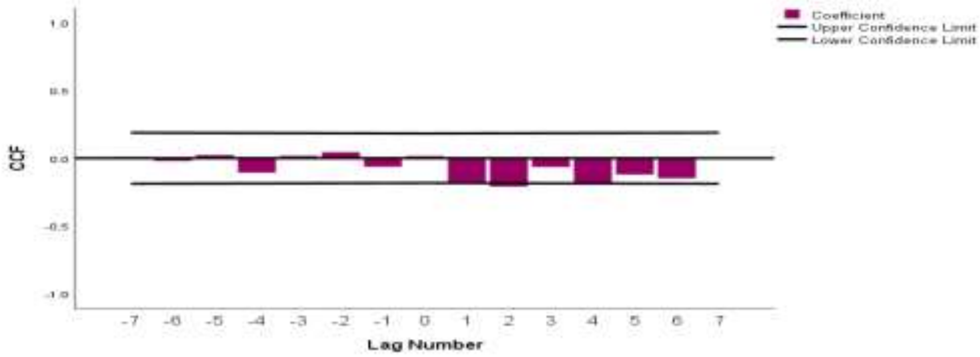
5.10.3 Diagnostic Checking for Input Series

The residual values of the ACF and PACF for the over speeding, reckless driving and pedestrian negligence are within the bounds of two standard errors, as indicated in Appendix Table (D-7).

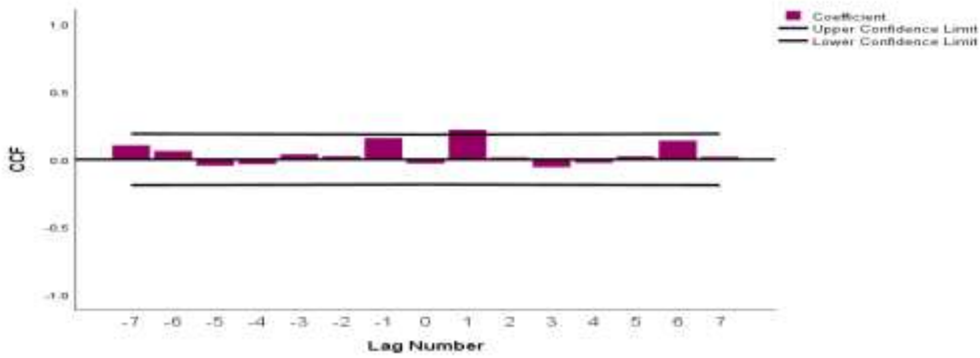
5.10.4 Cross Correction Function for Input Series

The cross-correlation function was applied between the input series, output series, and the impulse response estimate. This cross-correlation analysis was conducted on each prewhitened input and output series. The results of the cross-correlation function are depicted in Figure (5.28).

Over Speeding



Reckless Driving



Pedestrian Negligence

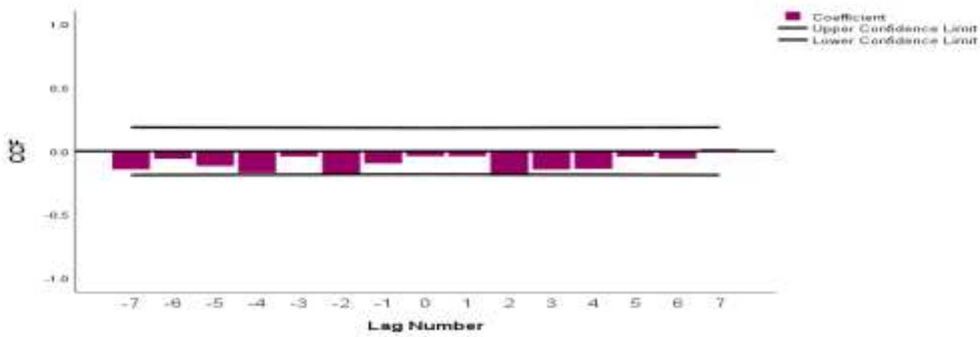


Figure (5.28) CCF Plots between Output Series and Input Series of Traffic Fatalities

5.10.5 Identification of Transfer Function – Noise Model

The ARIMA model for noise series is displayed in Figure (5.29).

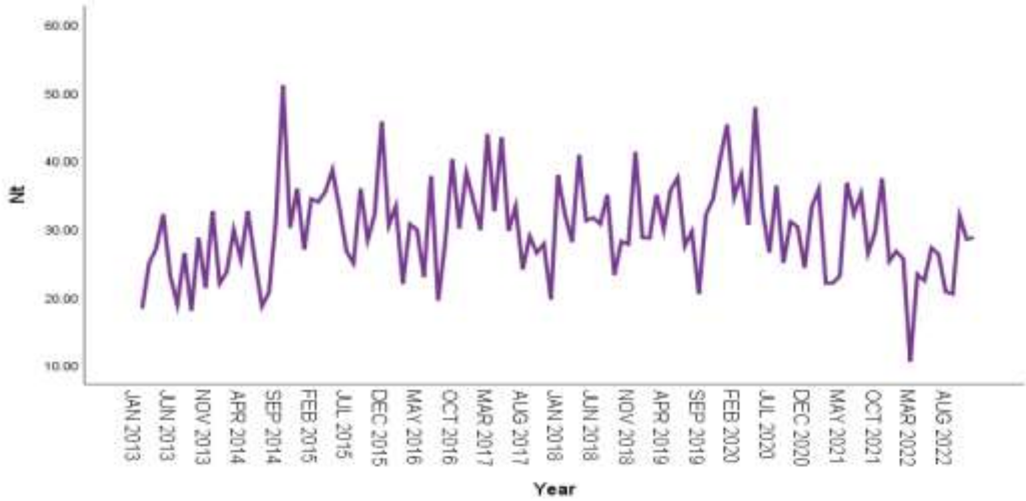


Figure (5.29) Plot of Noise Series for Traffic Fatalities

Regarding to the Figure (5.28), the noise series for traffic fatalities is stationary. The analysis of sample autocorrelation function (ACF) and the sample partial autocorrelation function (PACF) for noise series as shown in the Figure (5.30):

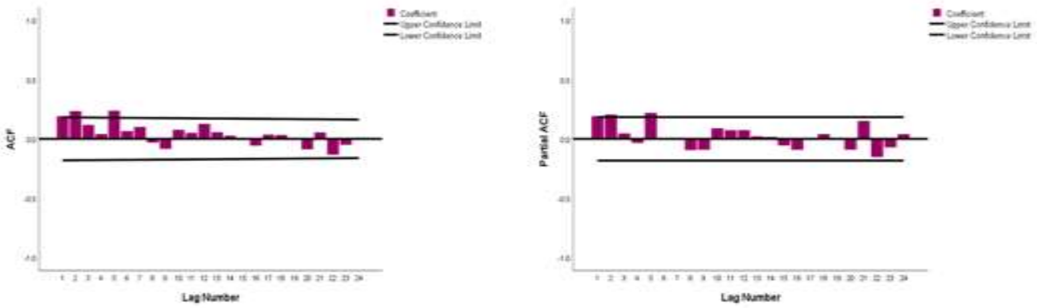


Figure (5.30) ACF and PACF of Noise Series for Traffic Fatalities

According to Figure (5.30), both the ACF and PACF plots exhibit a tails off. Utilizing the information from the ACF and PACF plots, an ARIMA (1, 0, 1) model is considered as the tentative model.

5.10.6 Parameter Estimation of Transfer Function – Noise Model

The estimated parameters and corresponding statistic for the ARIMA (1, 0, 1) model are presented in Table (5.23).

Table (5.23)

Estimation of Parameters and their Statistics for ARIMAX-TFM (1, 0, 1) Model of Traffic Fatalities

Parameters	Estimates	S.E	t	Sig
ω_1	1.342***	0.268	5.015	0.000
ω_2	1.078***	0.058	18.530	0.000
ω_3	1.051***	0.261	4.020	0.000
ϕ_1	0.385**	0.176	2.188	0.031
θ_1	0.759***	0.133	5.728	0.000

Source: Own Calculation

*****denotes significant at 1% level, ****denotes significant at 5% level

From above Table (5.23), the transfer function - noise model is

$$Y_t = \omega_1 X_{1,t} + \omega_2 X_{2,t} + \omega_3 X_{3,t} + \frac{(1-\theta_1 B)}{(1-\phi_1 B)} e_t$$

$$=1.342 X_{1,t} + 1.078 X_{2,t} + 1.051 X_{3,t} + \frac{(1-0.759B)}{(1-0.385B)} e_t$$

The ARIMAX (1, 0, 1) model fitted to the traffic fatalities data yields the following parameter estimates: $\omega_1 = 1.342$, $\omega_2 = 1.078$, $\omega_3 = 1.051$, $\phi_1 = 0.385$, and $\theta_1 = 0.759$. All test statistic (t) for these parameter values demonstrate statistical significance at the 1% level except for ϕ_1, which shows significance at the 5% level.

5.10.7 Diagnostic Checking for Transfer Function – Noise Model

The tentative overall model residual ACF and PACF for the fitted ARIMAX-TFM (1, 0, 1) model are depicted in Figure (5.31).

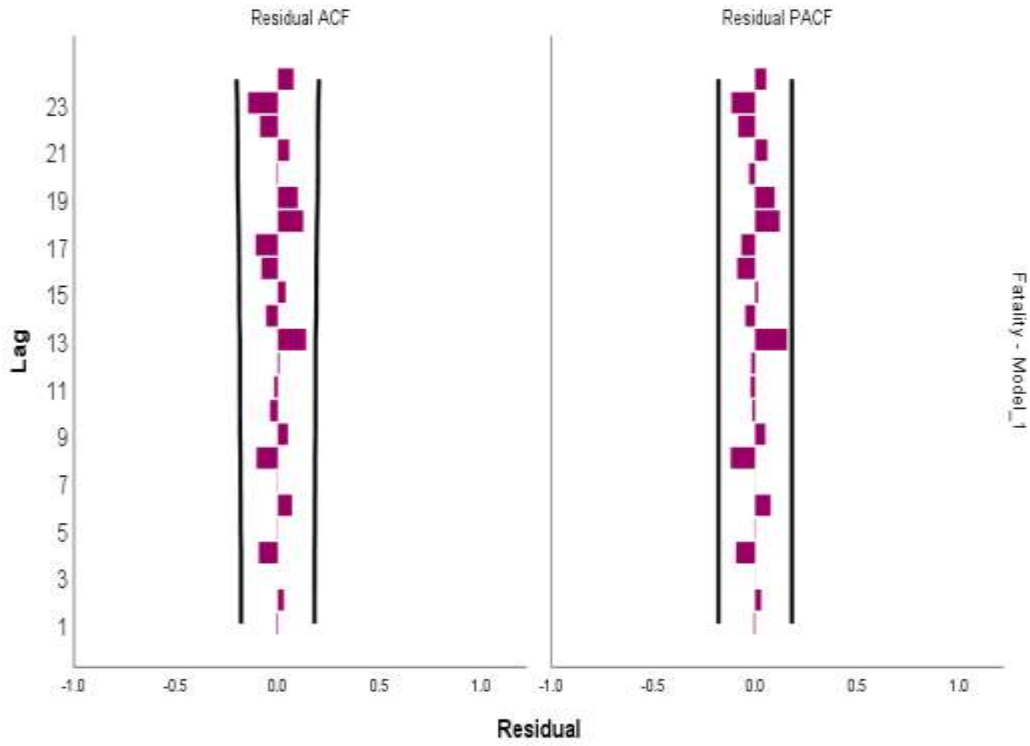


Figure (5.31) ACF and PACF of Residual Noise Series for Traffic Fatalities

Based on Figure (5.31), the residual values of the ACF and PACF for the transfer function-noise of traffic fatalities generally fall within the two standard error limits. Therefore, the residual series can be considered a white noise process, indicating that the transfer function-noise model is suitable for forecasting future values of the series. To further assess the autocorrelation among residuals, the Ljung-Box test statistics are utilized. The test statistics and corresponding p-values for the residuals of the transfer function-noise model for traffic fatalities are presented in Table (5.24).

Table (5.24)

Model Statistics of ARIMAX-TFM (1, 0, 1) Model for Traffic Fatalities

Model	Ljung-Box Q (18)		
	Statistic	df	Sig
ARIMAX_TFM	11.788	16	.758

Source: Own Calculation

According to Table (5.24), the computed value of Q is 11.788. The associated p-value, recorded as 0.758, indicates that the test results do not provide evidence of significant autocorrelation among the residuals. This indicates that the ARIMAX-TFM is suitable for fitting the data series of Traffic Fatalities in Yangon. A comparison between the ARIMA model, Intervention Model, and ARIMAX-TFM for traffic fatalities is presented in Section (5.11).

5.11 Comparison between ARIMA Model, Intervention Model and ARIMAX-TFM for Traffic Fatalities

The criteria for model comparison differ from the model identification methods. Model identification tools, such as ACF, PACF, IACF, and ESACF, are solely utilized to identify suitable models. Residuals from all appropriate models exhibit characteristics of white noise. The selection criterion is typically based on summary statistics derived from residuals computed from a fitted model or forecast errors. In Table (5.25), the comparison between the ARIMA model, intervention model, and ARIMAX-TFM model is conducted using evaluation metrics such as AIC, BIC, MAE, MAPE, and RMSE.

Table (5.25)

Comparison between ARIMA Model, Intervention Model and ARIMAX-TFM for Traffic Fatalities

Model	AIC	BIC	MAE	MAPE	RMSE
ARIMA (2, 0, 0)	469.629	472.417	5.376	20.089	6.920
ARIMA (0, 0, 0) with Intervention	454.317	457.104	5.123	19.128	6.842
ARIMAX-TFM (1, 0, 1)	203.671	208.081	1.800	6.231	2.298

Source: Own Calculation

Based on the AIC and BIC, the minimum values are occurred in ARIMAX-TFM (1, 0, 1) model. Then alternative criteria for model selection can be based on forecast errors such as MAE, MAPE and RMSE values for ARIMAX-TFM (1, 0, 1) model is the smallest among three models. Therefore, ARIMAX-TFM (1, 0, 1) model is the most suitable to fit the Traffic Fatalities in Yangon and this model is used to forecast the Traffic Fatalities series in Yangon.

5.12 Forecasting Traffic Fatalities

The actual values, forecast values, lower confidence limits and upper confidence limits for three periods (January 2023 to March 2023) are obtained and shown in Table (5.26) and Figure (5.32).

Table (5.26)

Forecast Values from January to March, 2023 for Traffic Fatalities

Month/ Year		**Jan-2023**	**Feb-2023**	**Mar-2023**
Actual Values		17	29	15
Forecast Values		24	26	27
95% Limit	LCL	19	21	22
	UCL	29	31	32

Source: Own Calculation

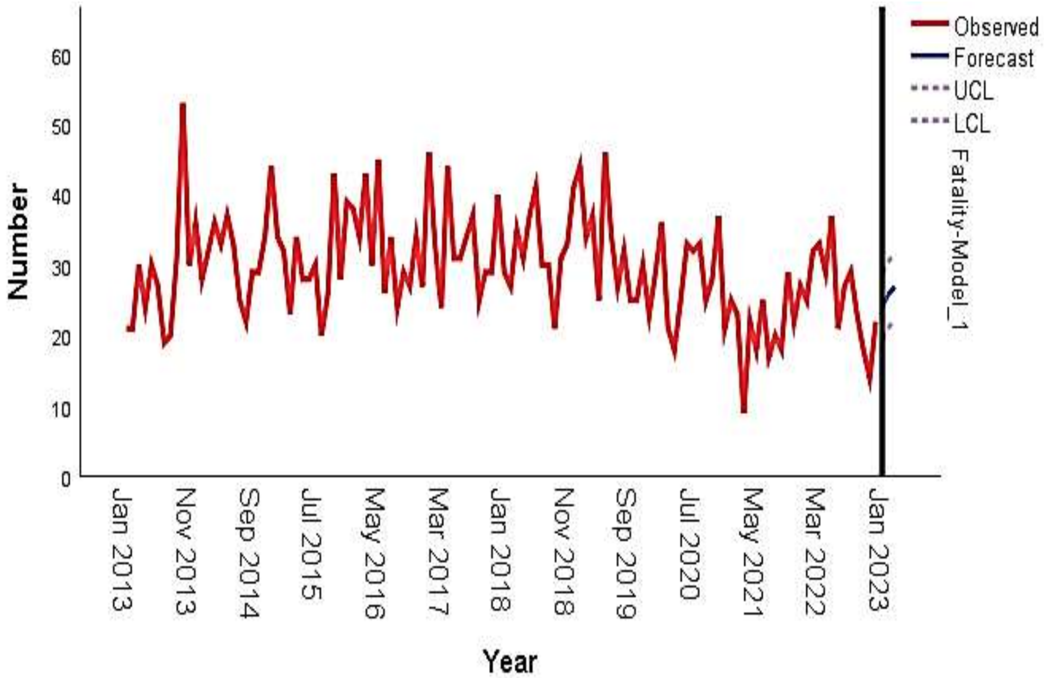


Figure (5.32) Forecast Values with 95% Confidence Limit for Traffic Fatalities

The results of this study indicate that there is a disparity between the actual values and forecast values obtained from the ARIMAX-TFM (1, 0, 1) model. Specifically, it was observed that the forecast values for January and March were not very close to the actual values. The reason behind this discrepancy is the adherence to the set traffic rules. Nevertheless, the forecast values fall within the specified confidence limits. The analysis of traffic injuries in Yangon was detailed in Section (5.13).

5.13 Time Series Analysis of Road Traffic Injuries

The numbers of traffic injuries resulting from monthly road traffic accidents during the period from 2013 to 2022 are summarized in Table (5.27). These data are obtained from No. (2) Office of Traffic Police, Yangon.

Table (5.27)

Monthly Traffic Injuries

Month / Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Jan	206	315	289	212	214	136	155	94	97	64
Feb	178	278	204	230	190	126	115	105	33	39
Mar	255	217	240	273	210	155	166	107	8	54
Apr	263	339	248	179	248	220	130	88	30	60
May	266	227	186	161	167	156	143	92	32	57
Jun	245	242	250	163	159	210	131	167	53	94
Jul	195	265	211	178	169	114	122	132	30	61
Aug	248	198	191	116	113	114	152	122	70	48
Sep	223	216	187	159	128	114	84	78	27	47
Oct	310	192	200	163	125	142	96	55	37	33
Nov	290	179	212	182	155	136	120	88	69	55
Dec	276	258	191	160	183	153	116	90	39	42

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

The trend of monthly traffic injuries in Yangon is shown in Figure (5.32). In the figure, it can be observed that the largest number of traffic injuries occurred in April 2014, while the smallest number occurred in March 2021. The decrease in traffic injuries in 2021 can be attributed to the higher incidence of COVID-19 infections during that year, resulting in fewer vehicles and people on the roads and streets. However, there was a slight increase in the number of traffic injuries in 2022. Figure (5.33) demonstrates that the data exhibits no discernible seasonal variation. The findings from the analysis of seasonal patterns in traffic injuries in Yangon are displayed in Appendix Table (C-1).

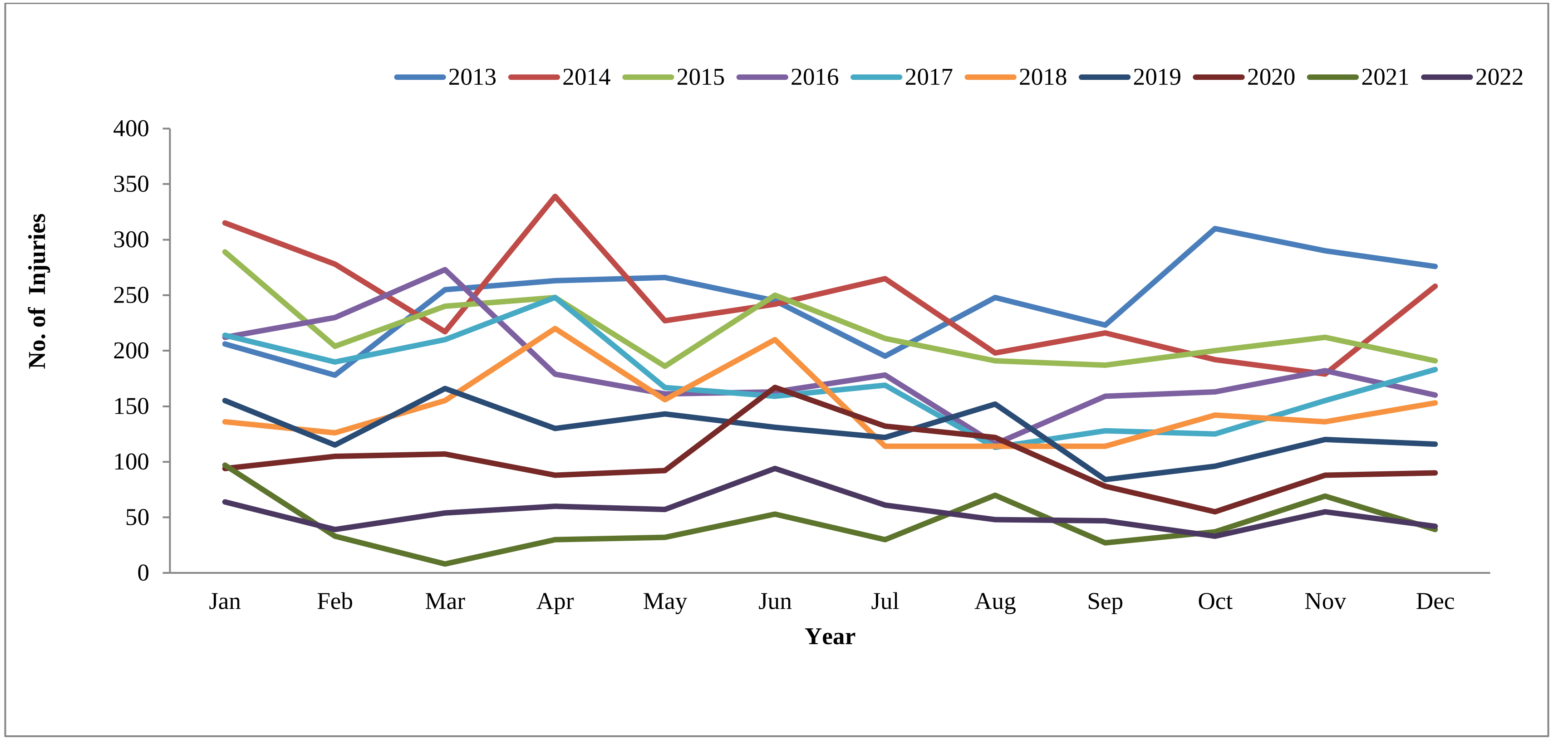


Figure (5.33) Monthly Traffic Injuries

Source: Table (5.27).

5.13.1 Test of Trend for Traffic Injuries

The series exhibits trend or not is tested as follows:

Hypotheses

Null Hypothesis: There is no trend for traffic injury in Yangon.

Alternative Hypothesis: There is a positive or negative trend for traffic injury in Yangon.

Table (5.28)

Statistical Test of Trend for Traffic Injuries

t-Test Statistic	Critical Value	Observations
- 4.999	1.984	120

Source: Own Calculation

Based on Table (5.28), the test statistic |-4.999| = 4.999, while the critical value is 1.984. As a result, the test statistic exceeds the critical value. Therefore, we conclude that there is a trend for traffic injuries in Yangon from 2013 to 2022.

5.13.2 Test of Stationarity for Traffic Injuries

In this section, the Augmented Dickey-Fuller test was utilized to test the stationarity of the traffic injuries series in Yangon. The results of the test, conducted using monthly time series data from January 2013 to December 2022 are presented in Table (5.29).

Table (5.29)

Augmented Dickey-Fuller Test for Traffic Injuries

<table>
<tr><th colspan="4">Before first difference</th><th colspan="4">After first difference</th></tr>
<tr><th colspan="3">t-Statistic</th><th>Prob</th><th colspan="3">t-Statistic</th><th>Prob</th></tr>
<tr><td colspan="2">Augmented Dickey-Fuller test statistic</td><td>-1.1998</td><td>0.6730</td><td colspan="2">Augmented Dickey-Fuller test statistic</td><td>-11.8543</td><td>0.0000</td></tr>
<tr><td rowspan="3">Test critical values:</td><td>1% level</td><td>-3.4870</td><td></td><td rowspan="3">Test critical values:</td><td>1% level</td><td>-3.4870</td><td></td></tr>
<tr><td>5% level</td><td>-2.8863</td><td></td><td>5% level</td><td>-2.8863</td><td></td></tr>
<tr><td>10% level</td><td>-2.5800</td><td></td><td>10% level</td><td>-2.5800</td><td></td></tr>
</table>

Source: Appendix (E-1)

Hypotheses

H_0: The recorded number of traffic injuries has a unit root (i.e., the recorded number of traffic injuries is non-stationary).

H_1: The recorded number of traffic injuries does not have a unit root (i.e., the recorded number of traffic injuries is stationary.

In Table (5.29), the data series is found to be non-stationarity at a 5% level of significance prior to the first difference. However, after applying the first difference, the ADF test indicates the rejection of the null hypothesis of a unit root at the 5% significance level. This suggests that the first difference of the series exhibits stationary in terms of mean level. The analysis of the traffic injuries data utilizing the ARIMA model, Intervention model, and ARIMAX-TFM model can be found in Sections 5.14 to 5.16.

5.14 ARIMA Model for Traffic Injuries

In time series analysis, the most crucial steps are to identify and build a model based on the available data. ARIMA approach consists of model identification, parameter estimation and diagnostic checking.

5.14.1 Model Identification

From January 2013 to December 2021, a total of 18,430 traffic injuries were reported in Yangon. The original series of traffic injuries in Yangon is depicted in Figure (5.34).

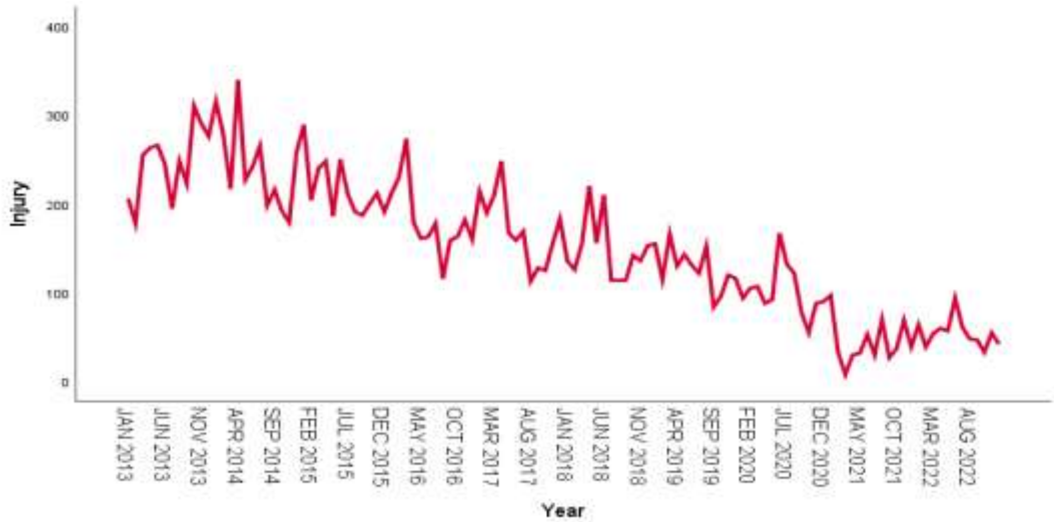


Figure (5.34) Original Series of Traffic Injuries

Regarding Figure (5.33), the original series of traffic injuries in Yangon has exhibited a decreasing trend starting from 2013. This decline points toward a negative trend within the traffic injuries series, signifying its non-stationary nature. To further analyze the series, the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) for traffic injuries in Yangon have been computed and their plots are presented in Figure (5.35).

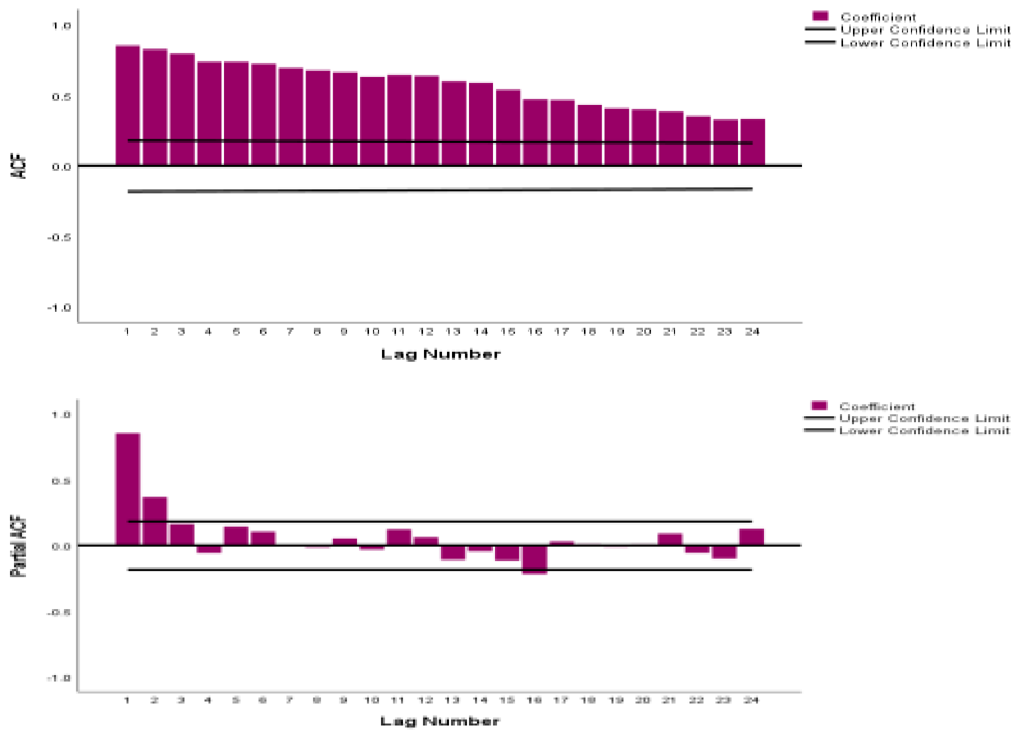


Figure (5.35) Sample Correlogram of the Original Series of Traffic Injuries

Based on Figure (5.34), it can be observed that the sample autocorrelation function (ACF) decays gradually, while the sample partial autocorrelation function (PACF) cuts off after lag 2. This confirms the non-stationary of the series, and consequently, the first difference of the series is performed to attain stationary. The first difference series for traffic injuries in Yangon is illustrated in Figure (5.36).

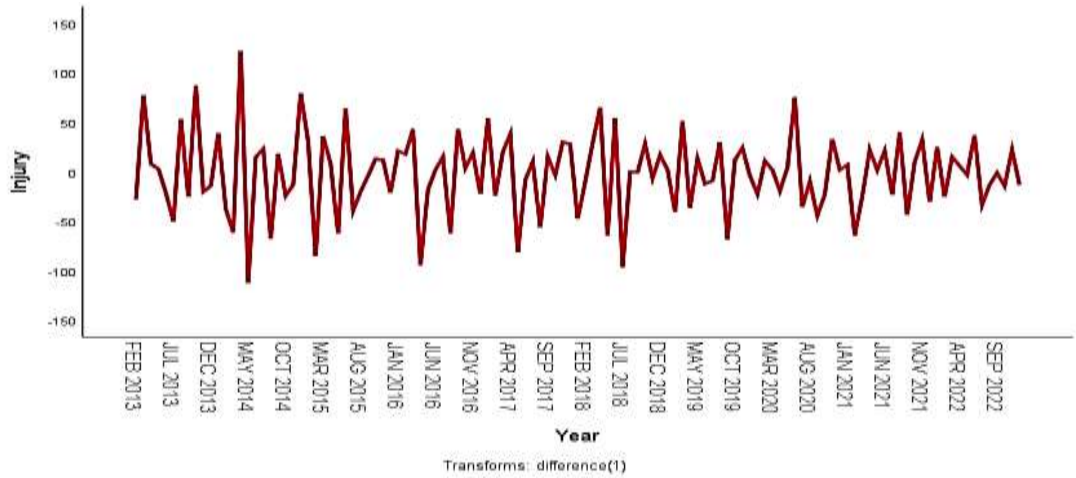


Figure (5.36) First Difference Series for Traffic Injuries

The sample ACF and sample PACF for the first difference of the traffic injuries series are illustrated in Figure (5.37).

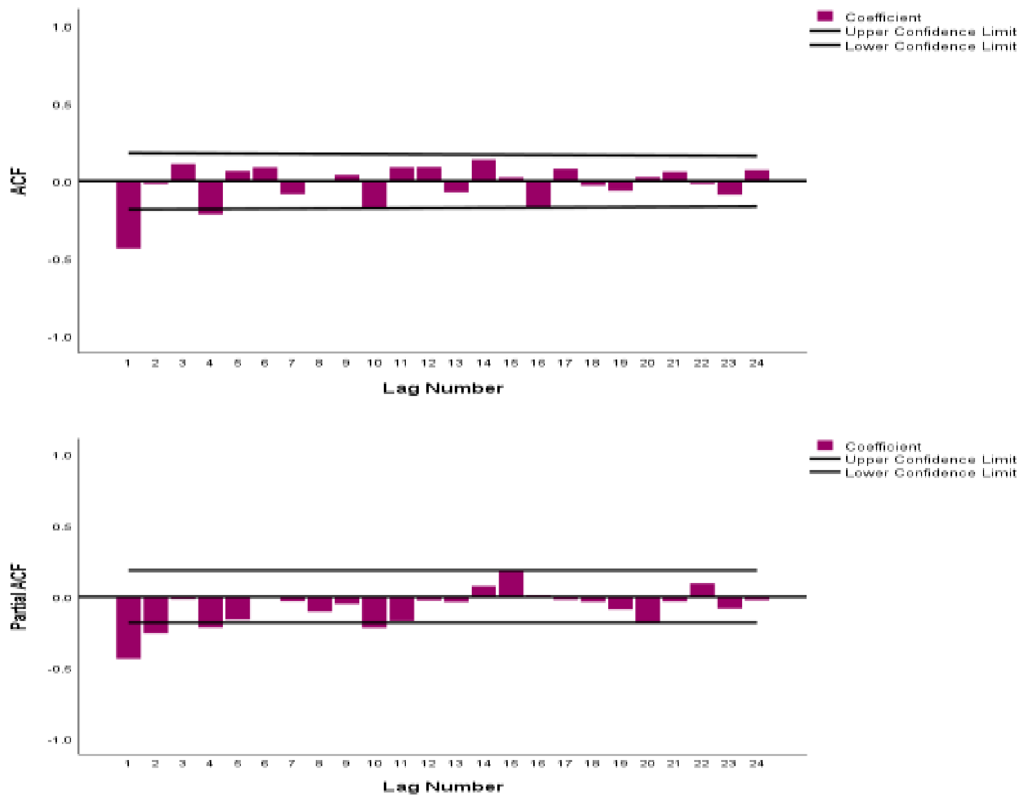


Figure (5.37) ACF and PACF of First Difference Series for Traffic Injuries

Figure (5.37) indicates that the ACF and PACF tails off. Therefore, ARIMA (1, 1, 1) is chosen as the fitted model.

5.14.2 Parameter Estimation

The estimated parameters and their respective statistic for the fitted ARIMA (1, 1, 1) model can be found in Table (5.30).

Table (5.30)

Estimation of Parameters and their Statistics for ARIMA (1, 1, 1) Model of Traffic Injuries

Parameters	Estimates	S.E	t	Sig
θ_0	-1.959***	0.127	-15.455	.000
ϕ_1	0.306***	0.094	3.247	.002
θ_1	0.993***	0.117	8.506	.000

Source: Own Calculation

*****denotes significant at 1% level

From above Table (5.30), the estimated model is

$$(1-\phi_1 B)(1-B)\,Y_t = \theta_0 + (1-\theta_1 B)e_t$$

$$(1-0.306B)\,(1-B)Y_t = -1.959 + (1-0.993B)e_t$$

(0.127) (0.094) (0.117)

The fitted ARIMA (1, 1, 1) model for traffic injury yields parameter estimates of $\theta_0 = -1.959, \phi_1 = 0.306$ and $\theta_1 = 0.993$, accompanied by estimated standard errors of 0.127, 0.094 and 0.117, respectively. The test statistic (t-values) for θ_0, ϕ_1 and θ_1 demonstrate statistical significance at the 1% level.

5.14.3 Diagnostic Checking

Figure (5.38) illustrates the residual autocorrelation function (ACF) and partial autocorrelation function (PACF) for the fitted ARIMA (1, 1, 1) model.

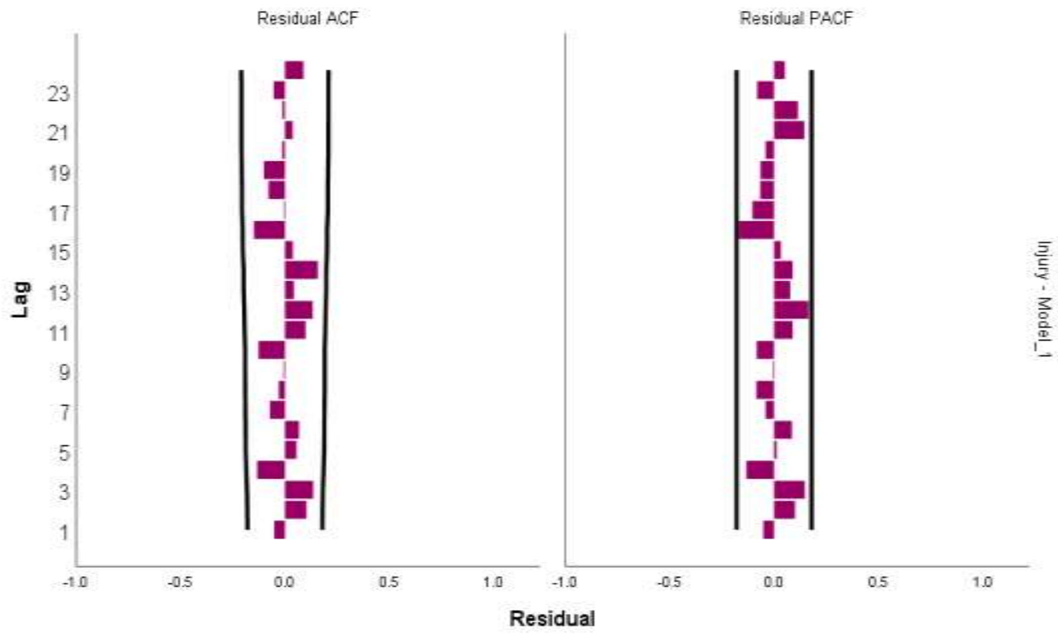


Figure (5.38) ACF and PACF of Residuals for ARIMA (1, 1, 1) Model

To assess the adequacy of the model, all the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) values of the $\hat{a}_t$ (refer to Appendix Table: E-11) lie within the confidence limits. This indicates that the residual series of the fitted ARIMA (1, 1, 1) model follows a white noise process. Subsequently, the autocorrelation among the residuals is examined using the Ljung-Box test statistic (Q). The test statistics, along with their corresponding p-values, for the residuals of the fitted ARIMA (1, 1, 1) Model in the context of traffic injuries, are presented in Table (5.31).

Table (5.31)

Model Statistics of ARIMA (1, 1, 1) Model for Traffic Injuries

Model	Ljung-Box Q (18)		
	Statistic	df	Sig
ARIMA (1, 1, 1)	21.483	16	.161

Source: Own Calculation

Based on the details in Table (5.31), the computed value of Q is 21.483. However, the associated p-value of 0.161 is not statistically significant. This outcome implies that there is no substantial evidence indicating the presence of autocorrelation among the residuals. Consequently, the ARIMA (1, 1, 1) model is considered appropriate for fitting the data series of traffic injuries in Yangon. Section 5.15 described intervention analysis of traffic injuries in Yangon.

5.15 Intervention Analysis of Traffic Injuries

The intervention under consideration includes the Motor Vehicle Law, Permission to Import Vehicles Law, Motor Vehicle Management Law, political changes, and the Covid-19 pandemic, affecting all citizens. The influence of government policies (intervention) and the pandemic is crucial in analyzing the time series data of traffic injuries.

5.15.1 Model Identification

Figure (5.39) shows the traffic injuries resulting from the Motor Vehicles Law, Permission to Import Vehicle Law, Vehicle Safety, Motor Vehicle Management Law, political changes, and the Covid-19 pandemic, which are examined for intervention analysis.

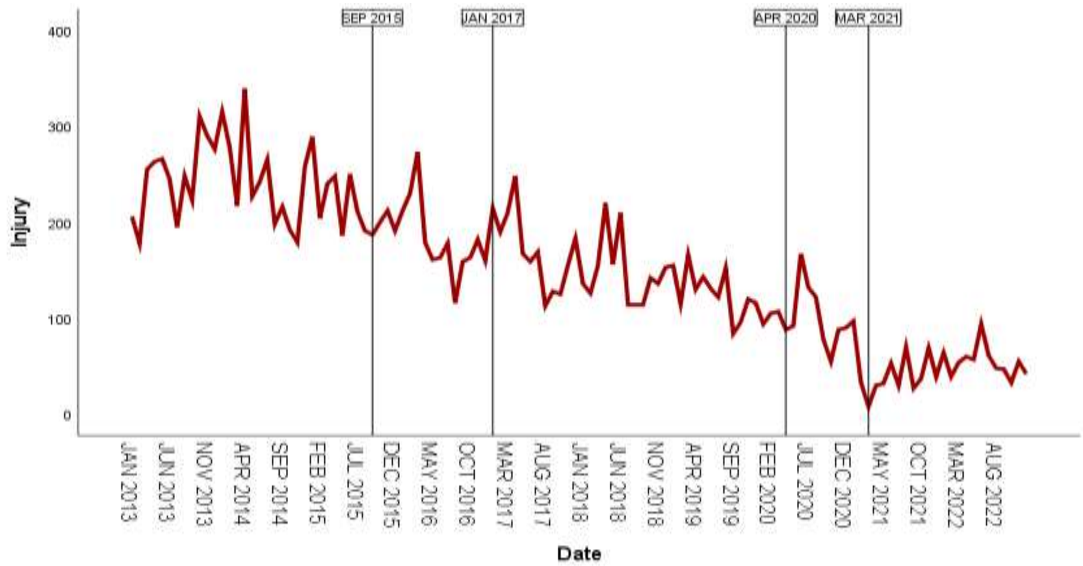


Figure (5.39) Intervention of Traffic Injuries

In Figure (5.39), the outcomes of the stationarity test for the pre-intervention series of traffic injuries are presented, and the detailed results can be referred to in (Appendix E-4). These test results confirm the stationarity of the pre-intervention series. The key tools for model identification are the analysis of the sample autocorrelation function (ACF) and the sample partial autocorrelation function

(PACF). The ACF and PACF values for traffic injuries in Yangon have been obtained and visualized in Figure (5.40).

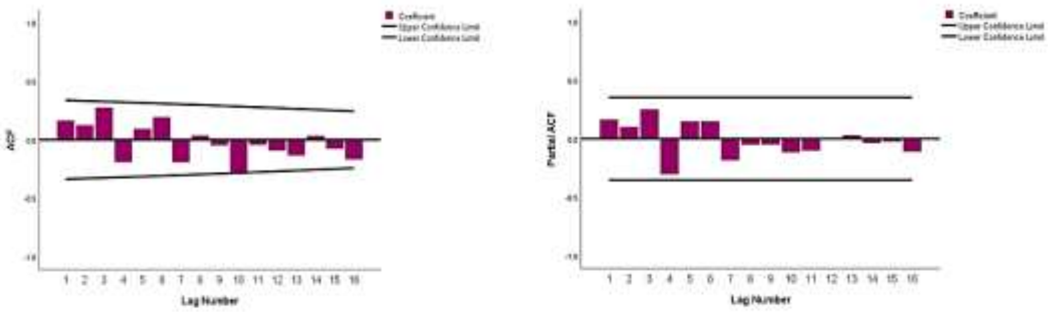


Figure (5.40) ACF and PACF of First Difference Pre-intervention Series for Traffic Injuries

The plot reveals that both the ACF and PACF values fall within the bounds of two standard error limits. As a result, the ARIMA (0, 0, 0) model is tentatively regarded as a potential model.

5.15.2 Parameter Estimation

The interventions took place at different time points: the Motor Vehicle Law intervention occurred in September 2015, the Permission to Import Vehicle Law intervention in January 2017, the Vehicle Safety and Motor Vehicles Management Law intervention in April 2020, and the political changes and the Covid-19 pandemic intervention in March 2021. The Motor Vehicle Law intervention, denoted as S_1, is anticipated to result in a step change. The intervention of the Permission to Import Vehicle Law is represented as P_1 and is anticipated to cause a pulse change. The Vehicle Safety and Motor Vehicles Management Law intervention represents P_2, expected to produce a pulse change. Lastly, the political changes and the Covid-19 pandemic intervention are denoted as S_2, which is expected to generate a step change. These interventions can be represented as follows:

$$S_1 = \begin{cases} 0 & \text{if } t < 33 \text{ (September 2015)} \\ 1 & \text{if } t \geq 33 \text{ (September 2015)} \end{cases}$$

$$P_1 = \begin{cases} 0 & \text{if } t \neq 49 \text{ (January 2017)} \\ 1 & \text{if } t = 49 \text{ (January 2017)} \end{cases}$$

$$P_2 = \begin{cases} 0 & \text{if } t \neq 88 \text{ (April 2020)} \\ 1 & \text{if } t = 88 \text{ (April 2020)} \end{cases}$$

$$S_3 = \begin{cases} 0 & \text{if } t < 99 \text{ (March 2021)} \\ 1 & \text{if } t \geq 99 \text{ (March 2021)} \end{cases}$$

The estimated values of the parameters are displayed in the Table (5.32).

Table (5.32)

Estimation of Parameters and their Statistics of ARIMA (0, 0, 0) Model with Intervention for Traffic Injuries

Parameters	Estimates	Std. Error	t	Sig.
θ_0	241.737***	6.697	36.098	.000
ω_1	-89.870***	8.865	-10.137	.000
ω_2	72.689**	31.047	2.341	.021
δ_1	0.747***	.163	4.587	.000
ω_3	-58.591***	14.409	-4.066	.000
δ_2	0.995***	.024	41.718	.000
ω_4	-51.494**	24.787	-2.077	.040

Source: Own Calculation

*******denotes significant at 1% level, ******denotes significant at 5% level

The fitted ARIMA (0, 0, 0) model with the intervention of traffic injury yields the following parameter estimates: $\theta_0 = 241.737$, $\omega_1 = -89.870$, ω_2= 72.698, $\omega_3 = -58.591$, $\omega_4 = -51.494, \delta_1 = 0.747$ and $\delta_2 = 0.995$. The estimated standard errors for these parameters are 6.697, 8.865, 31.047, 14.409, 24.787, 0.163 and 0.024, respectively. The test statistic t-values for $\theta_0, \omega_1, \delta_1,$ $\omega_3 and$ δ_2 are statistically significant at the 1% significance level. Furthermore, ω_2 and ω_4 are statistically significant at the 5% significance level.

5.15.3 Diagnostic Checking

Figure (5.40) illustrates the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals for the fitted ARIMA (0, 0, 0) model with intervention.

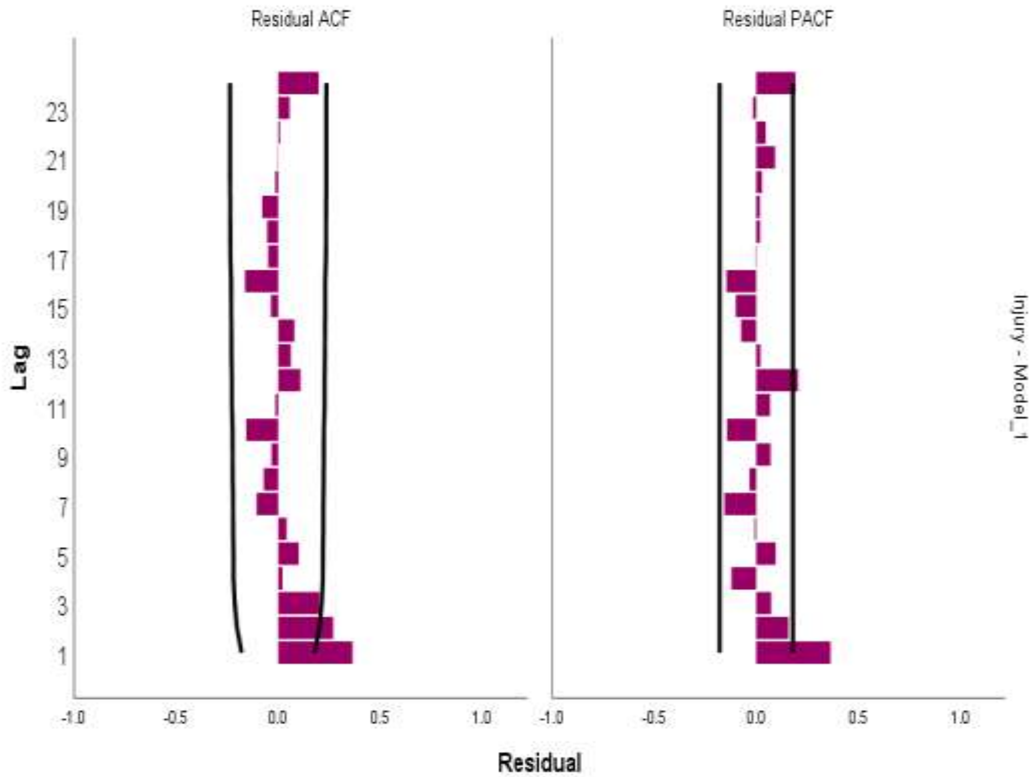


Figure (5.41) ACF and PACF of Residuals for ARIMA (0, 0, 0) model with Intervention

According to the Figure, it appears that the residuals do not exhibit characteristics of a white noise process. The characteristics of the ACF plot show exponential decay, and the PACF plot shows a cut-off after lag 1. Therefore, the ARIMA (1, 0, 0) model should be reconsidered as a tentative model and model selection was determined by evaluating the AIC and BIC values. The ARIMA (1, 0, 0) model demonstrated the lowest AIC and BIC values, indicating a superior fit for the pre-intervention series of traffic injuries.

5.15.4 Parameter Estimation

The estimated values of the parameters and their statistic for the ARIMA (1, 0, 0) model with intervention are displayed in Table (5.33).

Table (5.33)

Estimation of Parameters and their Statistics of ARIMA (1, 0, 0) Model with Intervention for Traffic Injuries

Parameters	**Estimates**	**Std. Error**	**t**	**Sig.**
θ_0	237.498***	9.856	24.096	.000
ϕ_1	0.380***	0.089	4.257	.000
ω_1	-84.283***	12.876	-6.546	.000
ω_2	63.956*	33.785	1.893	.061
δ_1	0.755***	0.232	3.256	.001
ω_3	-56.365***	19.717	-2.859	.005
δ_2	0.998***	0.029	34.355	.000
ω_4	-50.904	30.803	-1.653	.101

Source: Own Calculation

*******denotes significant at 1% level, ******denotes significant at 10% level

From Table (5.33), the fitted model is

$$Y_t = \theta_0 + \omega_1 S_1 + \frac{\omega_2}{(1-\delta_1 B)} P_1 + \frac{\omega_3}{(1-\delta_2 B)} P_2 + \omega_4 S_2 + \frac{1}{(1-\phi_1 B)} e_t$$

$$= 237.498 - 84.283 S_1 + \frac{63.956}{(1-0.755B)} P_1 - \frac{56.365}{(1-0.998B)} P_2 - 50.904 S_3 + \frac{1}{(1-0.380B)} e_t$$

The fitted ARIMA (1, 0, 0) model with the intervention of traffic injury yields the following parameter estimates: $\theta_0 = 237.498$, $\phi_1 = 0.380$, $\omega_1 = -84.283$, $\omega_2 =$ 63.956, $\omega_3 = -56.365$, $\omega_4 = -50.904, \delta_1 = 0.755$ *and* $\delta_2 = 0.998$. The estimated standard errors for these parameters are 9.856, 0.089, 12.876, 33.785, 19.717, 30.803, 0.232 and 0.029, respectively. The test statistic (t-values) for $\theta_0, \phi_1, \omega_1, \delta_1, \omega_3$ *and* δ_2 are statistically significant at the 1% significance level. Furthermore, ω_2 is statistically significant at the 10% significance level and ω_4 is not statistically significant.

Based on the parameter estimates in Table (5.33), the coefficient of the Motor Vehicle Law is statistically significant at the 1% level. The negative effect implies that the implementation of this law is associated with a decrease in traffic injuries. After the law is implemented, there is a tendency for a reduction in the number of traffic-related injuries. Furthermore, the coefficient of the Permission to Import Vehicle Law is statistically significant at the 5% level. The positive effect suggests that the implementation of this law is associated with an increase in traffic injuries.

After the law is implemented, there tends to be a higher number of traffic-related injuries.

Additionally, the coefficient of the Vehicle Safety and Motor Vehicles Management Law is statistically significant at the 1% level. The negative effect indicates that the implementation of this law is associated with a decrease in traffic injuries. After the law is implemented, there is a tendency for a reduction in the number of traffic-related injuries. However, the estimated coefficient of political changes and the Covid-19 pandemic is not statistically significant. This implies that there is no discernible effect of political changes and the occurrence of the Covid-19 pandemic.

5.15.3 Diagnostic Checking

Figure (5.42) illustrates the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals for the fitted ARIMA (1, 0, 0) model with intervention.

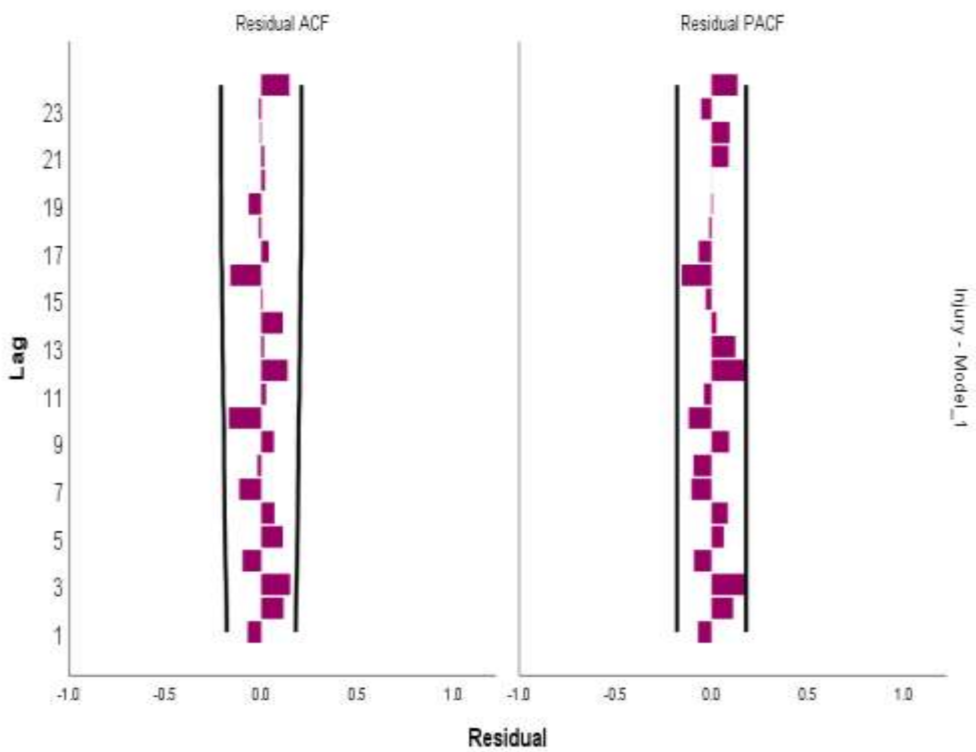


Figure (5.42) ACF and PACF of Residuals for ARIMA (1, 0, 0) model with Intervention

Based on Figure (5.41), the ACF and PACF residual values for traffic injuries are observed to lie within the boundaries defined by two standard error limits. Consequently, it can be inferred that the residuals series of the ARIMA (1, 0, 0) model with intervention can be considered a white noise process. To further assess the autocorrelation among the residuals, the Ljung-Box (Q) test statistic is employed. Table (5.34) presents the test statistics alongside their respective p-values for the Intervention Model's residuals in relation to traffic injuries.

Table (5.34)

Model Statistics of ARIMA (1, 0, 0) Model with Intervention for Traffic Injuries

Model	Ljung-Box Q (18)		
	Statistic	df	Sig
ARIMAX (1, 0, 0) with Intervention	22.712	17	.159

Source: Own Calculation

Table (5.34) displays the results, highlighting an observed Q value of 22.712. The associated p-value, recorded as 0.159, signifies that no statistically significant autocorrelation is evident among the residuals. Therefore, the intervention model is considered appropriate for accurately fitting the data series of traffic injuries in Yangon.

5.16 ARIMAX-TFM for Traffic Injuries

The ARIMAX-TFM identified a correlation between traffic injuries and factors such as over speeding, reckless driving, and pedestrian negligence. In this model, traffic injuries serve as the dependent variable, while over speeding, reckless driving, and pedestrian negligence are considered independent variables.

5.16.1 ARIMA Model for Input Series

Figure (5.43) displays a time series plot depicting the relationship between traffic injuries (Y_t), over speeding ($X_{1,t}$), reckless driving ($X_{2,t}$) and pedestrian negligence ($X_{3,t}$).

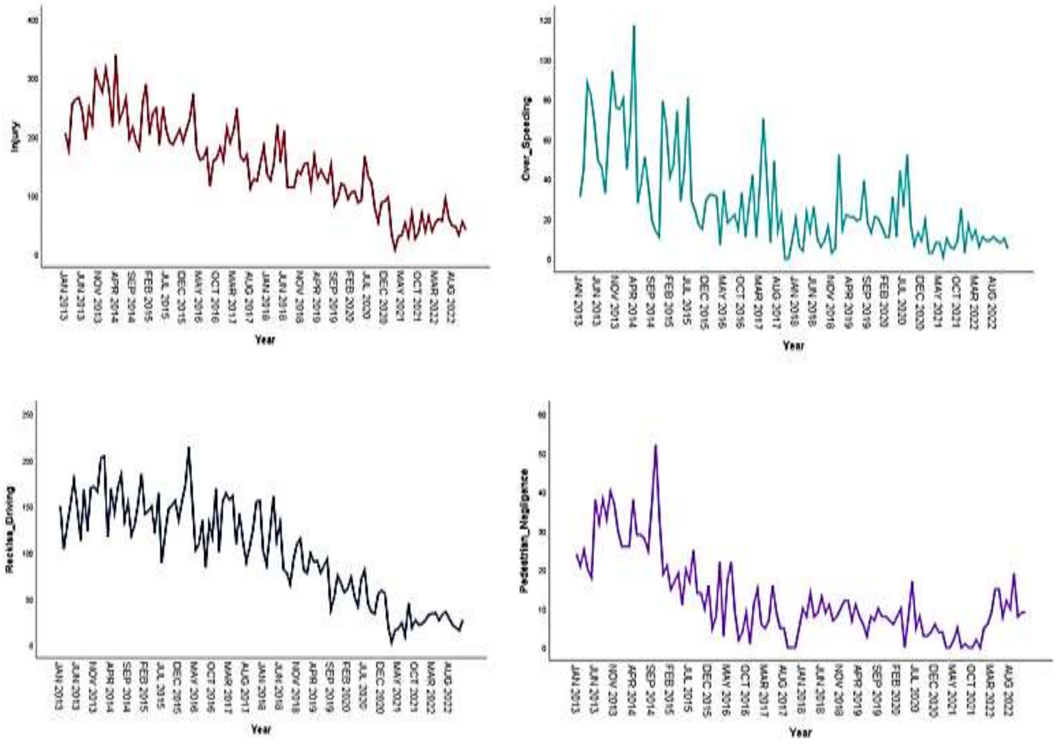
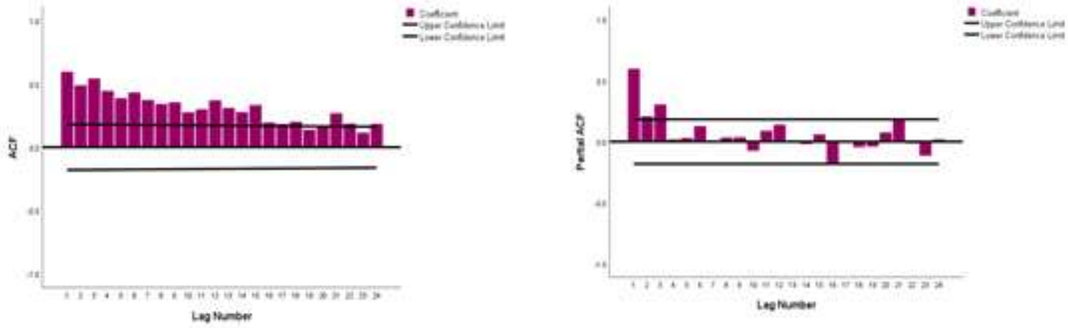


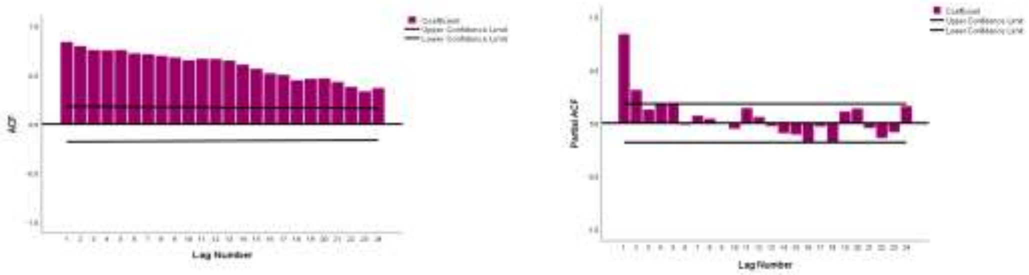
Figure (5.43) Time Series Plots of Dependent Variable (Y_t) and Independent Variables $(X_{1,t}, X_{2,t}, X_{3,t})$

According to the Figure (5.43), the process of checking stationarity is explained in Section (5.13.2) for the output series, and the corresponding information can be found in (see Appendix Table E-16) for the remaining input series. In Figure (5.43), the time series plots of the inputs series are decreasing year after year. Therefore, the inputs series have a negative trend. This shows that the non-stationary behavior of the inputs series. The plots of the sample autocorrelation function (ACF) and the sample partial autocorrelation function (PACF) of the input series for traffic injuries in Yangon as shown in the Figure (5.44):

Over Speeding



Reckless Driving



Pedestrian Negligence

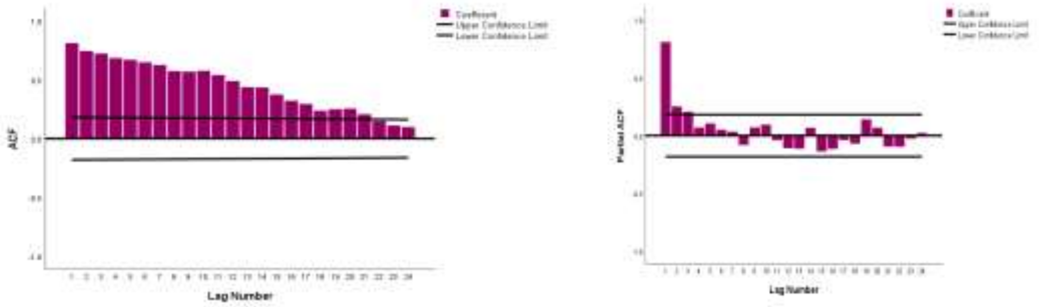


Figure (5.44) ACF and PACF Plots of the Input Series of Traffic Injuries

Based on Figure (5.44), it can be observed that these series are nonstationary, requiring differencing to remove the nonstationary in mean. Figure (5.45) illustrates the first difference input series for traffic injuries in Yangon.

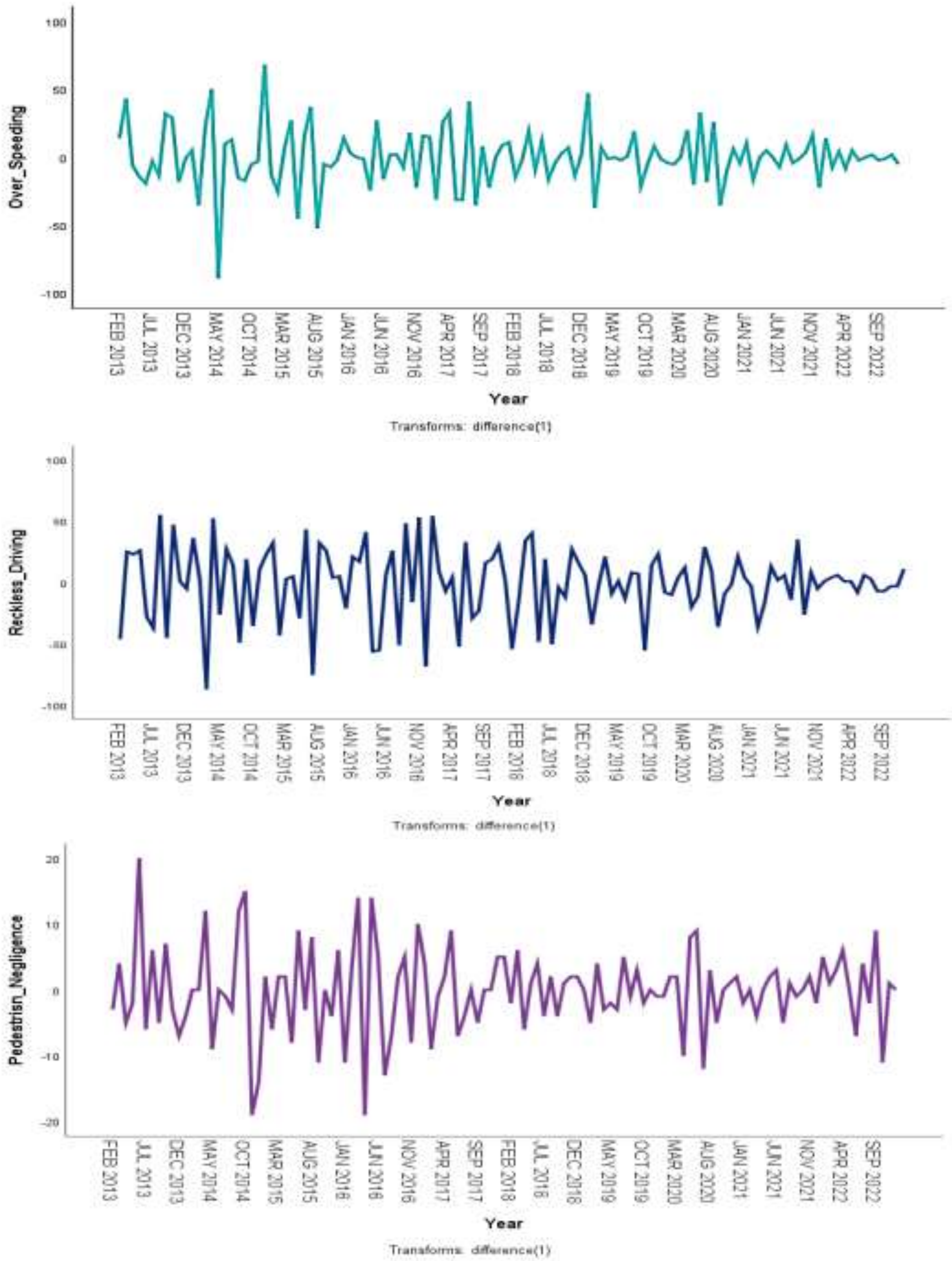
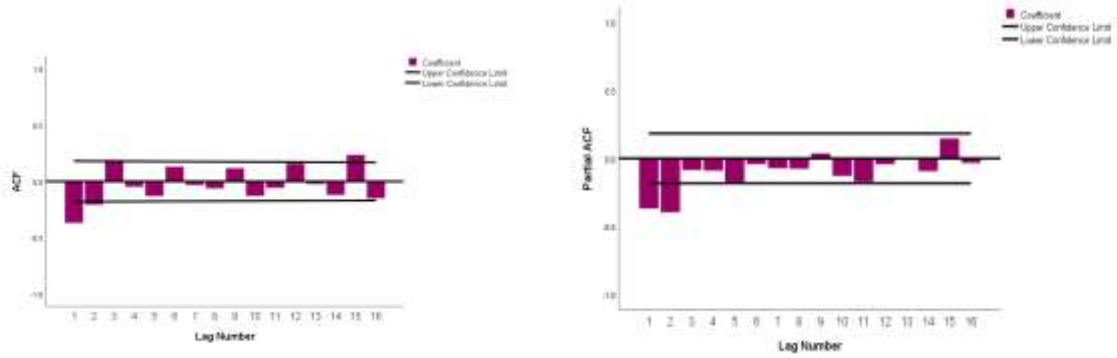


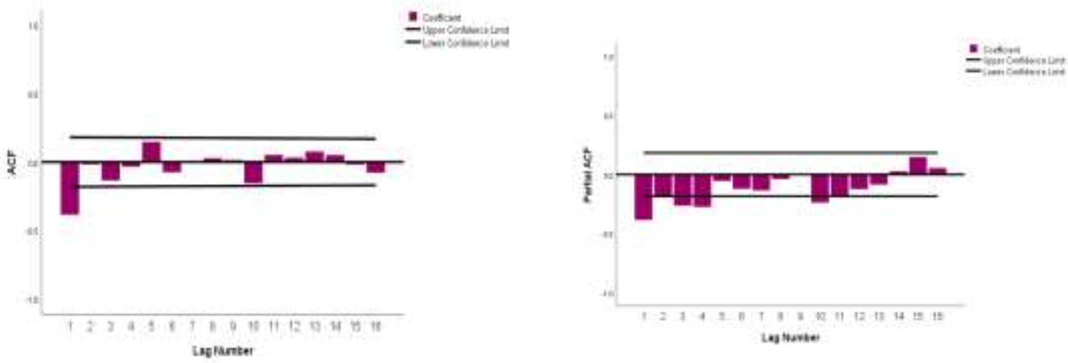
Figure (5.45) First Difference Input Series for Traffic Injuries

Figure (5.46) displays the plots of the sample ACF and sample PACF for the first differencing input series of traffic injuries.

Over Speeding



Reckless Driving



Pedestrian Negligence

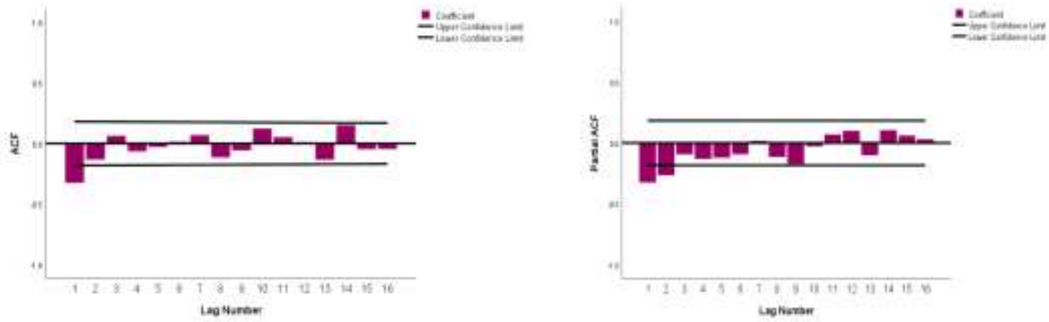


Figure (5.46) ACF and PACF of First Difference Input Series for Traffic Injuries

By analyzing the ACF plot displayed in Figure (5.46), it is observed that the ACF reaches its spike at lag 1, and the PACF plot indicates a cutoff after lag 2. Therefore, the following ARIMA models are considered as tentative models: (2, 1, 1), (1, 1, 2), (2, 1, 0), (0, 1, 2), (1, 1, 1), (1, 1, 0) and (0, 1, 1). Among them, the ARIMA

(0, 1, 2) model has the smallest AIC and BIC values. Consequently, the ARIMA (0, 1, 2) model is chosen as the tentative model for over speeding.

When examining reckless driving, the ACF indicates a cutoff after lag 1, while the PACF exhibits a tailing off pattern. As a result, three initial ARIMA models are considered: (0, 1, 1), (1, 1, 0), and (1, 1, 1). However, both ARIMA (0, 1, 1) and (1, 1, 0) models show that the residual values of ACF and PACF exceed the two standard error limits, and the Ljung-Box (Q) statistics are significant. Following a thorough analysis, the ARIMA (1, 1, 1) model is ultimately chosen as the preferred model for reckless driving. When analyzing pedestrian negligence, the ACF displays a cutoff at lag 1, while the PACF exhibits a cutoff at lag 2. As a result, several ARIMA models are considered: (2, 1, 1), (1, 1, 2), (2, 1, 0), (0, 1, 2), (1, 1, 1), (1, 1, 0) and (0, 1, 1). Among these models, the ARIMA (0, 1, 2) model demonstrates the smallest AIC and BIC values for pedestrian negligence. Consequently, the ARIMA (0, 1, 2) model is chosen as the preferred tentative model for pedestrian negligence.

5.16.2 Parameter Estimation for Input Series

Table (5.35) presents the estimated parameters and corresponding statistics for the ARIMA (0, 1, 2), ARIMA (1, 1, 1), and ARIMA (0, 1, 2) models.

Table (5.35)

Estimation of Parameters and their Statistics for ARIMA Models for Input Series

Input Series	Model	Parameters	Estimates	S.E	t	Sig
Over Speeding	ARIMA (0, 1, 2)	θ_0	-0.463**	0.177	-2.615	.010..
		θ_1	0.677***	0.092	7.371	000
		θ_2	0.224**	0.091	2.455	.016
Reckless Driving	ARIMA (1, 1, 1)	θ_0	-1.153***	0.351	-3.285	.001
		ϕ_1	0.227**	0.110	2.058	.042
		θ_1	0.887***	0.056	15.922	.000
Pedestrian Negligence	ARIMA (0, 1, 2)	θ_1	0.479***	0.091	5.250	.000
		θ_2	0.178*	0.091	1.952	.053

Source: Own Calculation

*****denotes significant at 1% level, ****denotes significant at 5% level, ***denotes significant at 10% level

5.16.3 Diagnostic Checking for Input Series

The ACF and PACF residual values for over speeding, and pedestrian negligence fall within the two standard error limits, as indicated in (Appendix Table: E-9). The analysis indicates that reckless driving falls within the two standard error limits, with the exception of lag 18 (see Appendix Table: E-9).

5.16.4 Cross Correction Function for Input Series

The calculation of the cross-correlation function involved the input series, output series, and impulse response estimate. This cross-correlation analysis was conducted on each prewhitened input and output series. The outcomes of the cross-correlation function are displayed in Figure (5.47).

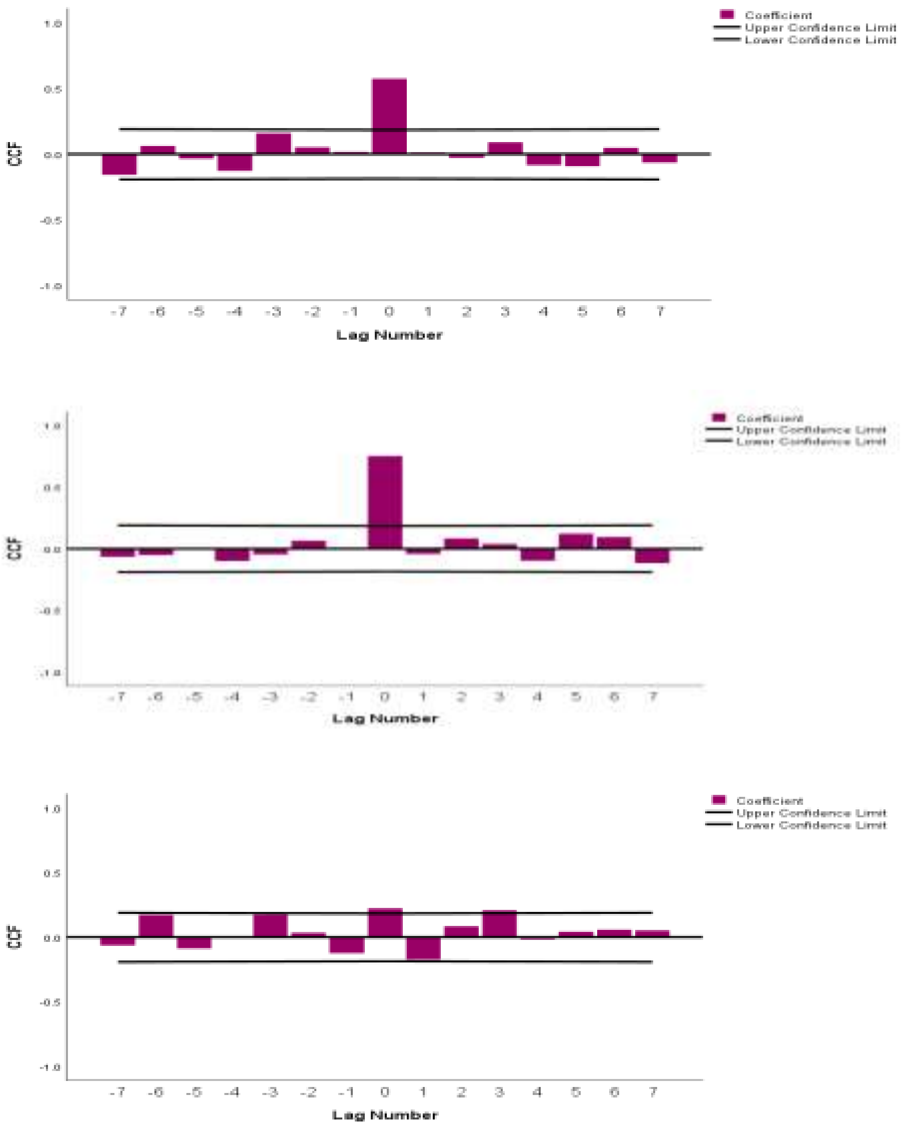


Figure (5.47) CCF Plots between Output Series and Input Series of Traffic Injuries

5.16.5 Identification of Transfer Function – Noise Model

The ARIMA model for noise series is displayed in Figure (5.48).

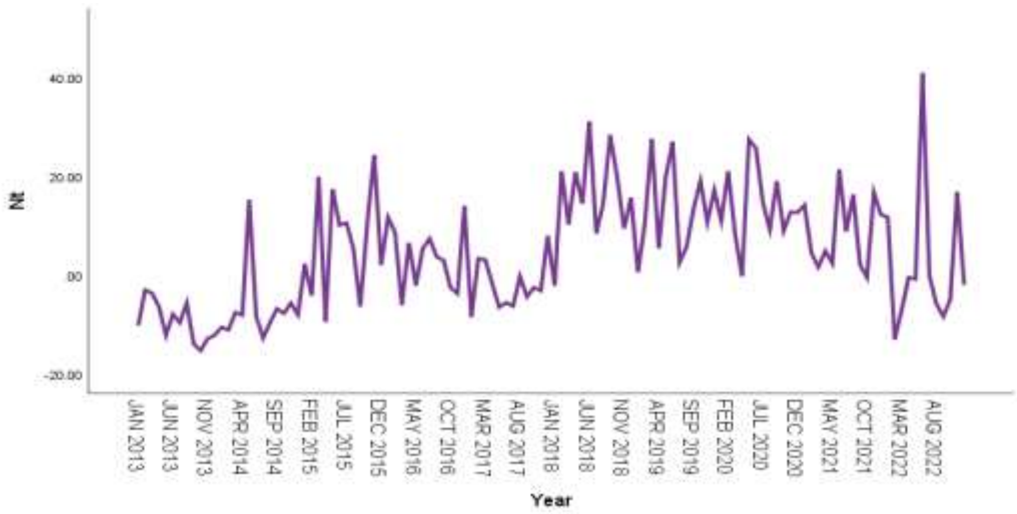


Figure (5.48) Plots of Noise Series for Traffic Injuries

In relation to Figure (5.48), it can be observed that the noise series for traffic injuries is stationarit. Figure (5.49) displays the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) for the noise series.

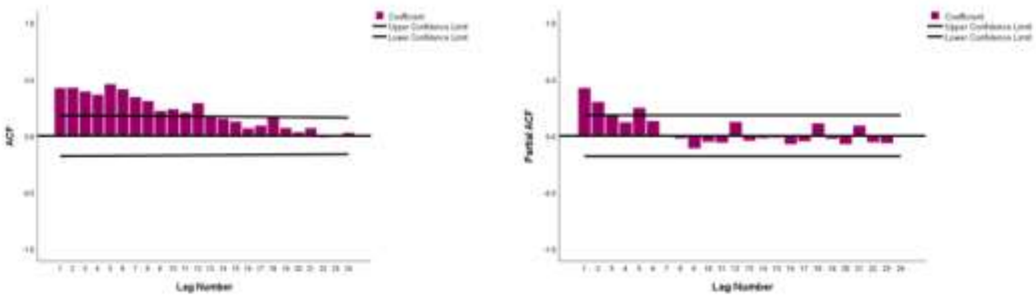


Figure (5.49) ACF and PACF of the Noise Series for Traffic Injuries

The plot of the ACF and PACF tails off. Therefore, ARIMA (1, 0, 1) model is considered as tentative model.

5.16.6 Parameter Estimation of Transfer Function – Noise Model

The estimated parameters and their corresponding statistics for the ARIMA (1, 0, 1) model are presented in Table (5.36). This table includes the coefficients for the autoregressive (AR) and moving average (MA) terms, as well as statistical measures like standard errors, t-values, and p-values.

Table (5.36)

Estimation of Parameters and their Statistics for ARIMA (1, 0, 1) Model

Parameters	Estimates	S.E	t	Sig
ω_1	1.036***	0.050	20.697	0.000
ω_2	1.013***	0.032	31.826	0.000
ω_3	1.053***	0.140	7.545	0.000
ϕ_1	0.978***	0.021	46.959	0.000
θ_1	0.786***	0.070	11.259	0.000

Source: Own Calculation

*****denotes significant at 1% level

From above Table (5.36), the transfer function - noise model is

$$Y_t = \omega_1 X_{1,t} + \omega_2 X_{2,t} + \omega_3 X_{3,t} + \frac{(1-\theta_1)}{(1-\phi_1 B)} e_t$$

$$= 1.036 X_{1,t} + 1.0137 X_{2,t} + 1{,}053 X_{3,t} + \frac{(1-0.786)}{(1-0.978B)} e_t$$

The fitted ARIMAX (1, 0, 1) model of traffic injuries gives $\phi_1 = 0.978$, $\theta_1 = 0.786$, $\omega_1 = 1.036$, $\omega_2 = 1.013$, $and\ \omega_3 = 1.053$, respectively. The test statistic t for all parameter values are statistically significant at 1% level.

5.16.7 Diagnostic Checking for Transfer Function – Noise Model

The plots of the residuals ACF and PACF for the fitted ARIMAX (1, 0, 1) model are shown in Figure (5.50).

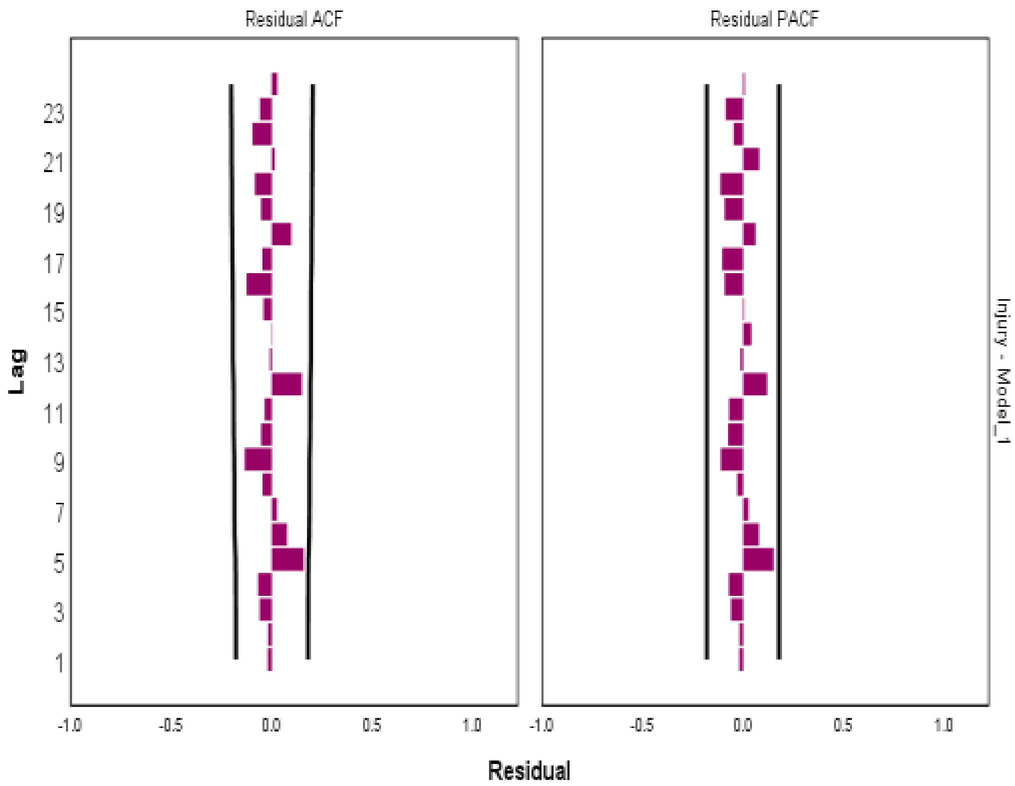


Figure (5.50) ACF and PACF of Residual Noise Series for Traffic Injuries

According to the Figure (5.50), the residual values of the ACF and PACF for the transfer function - noise of traffic injuries fall within the two standard errors limits except lag 3. Thus, the residual series is assumed to be white noise process and transfer function - noise model is adequate to forecast the future value of the series. In addition, the autocorrelation among residuals are checked by using the test statistics Ljung-Box (Q). The test statistic with the corresponding p-values of the residuals Transfer Function - Noise Model for traffic injuries are shown in Table (5.37).

Table (5.37)

Model Statistics of ARIMAX-TFM (1, 0, 1) Model for Traffic Injuries

Model	**Ljung-Box Q (18)**		
	Statistic	**Df**	**Sig**
ARIMAX	15.368	16	.498

Source: Own Calculation

As indicated in Table (5.37), the observed Q value is 15.368. The corresponding p-value of 0.4985 is not statistically significant. This outcome suggests that there is no significant autocorrelation present among the residuals. Thus, ARIMAX- TFM model is adequate to fit the data series of Traffic Injuries in Yangon. Comparison between ARIMA model, Intervention model and ARIMAX-TFM for traffic injuries are described in Section (5.17).

5.17 Comparison between ARIMA Model, Intervention Model and ARIMAX-TFM for Traffic Injuries

The criteria for model comparison are different from the model identification methods. Model identification tools such as ACF, PACF, IACF, and ESACF are used only for identifying adequate models. Residuals from all adequate models are approximately white noise. The selection criterion is normally based on summary statistics from residuals computed from a fitted model or forecast errors. The comparison between ARIMA model, intervention model and ARIMAX-TFM by using AIC, BIC, MAE, MAPE and RMSE described in Table (5.38).

Table (5.38)

Comparison between ARIMA Model, Intervention Model and ARIMAX-TFM for Traffic Injuries

Model	AIC	BIC	MAE	MAPE	RMSE
ARIMA (1, 1, 1)	852.589	862.732	26.624	28.084	33.886
ARIMAX (1, 0, 0) with Intervention	849.333	852.112	28.100	24.435	35.164
ARIMAX-TFM (1, 0, 1)	530.392	535.934	7.134	8.389	9.304

Source: Own Calculation

Based on the AIC and BIC, the minimum values are occurred in ARIMAX-TFM (1, 0, 1) model. Then alternative criteria for model selection can be based on forecast errors such as MAE, MAPE and RMSE values for ARIMAX-TFM 1, 0, 1) model are the smallest among three models. Therefore, ARIMAX-TFM (1, 0, 1) model is the most suitable to fit the Traffic Injuries in Yangon and this model is used to forecast the Traffic Injuries series in Yangon.

5.18 Forecasting Traffic Injuries

The actual values, forecast values, lower confidence limits and upper confidence limits for three periods (January 2023 to March 2023) are obtained and shown in Table (5.39) and Figure (5.51).

Table (5.39)

Forecast Values from January to March, 2023 for Traffic Injuries

Month/ Year		**Jan-2023**	**Feb-2023**	**Mar-2023**
Actual Values		35	30	55
Forecast Values		40	36	35
95% Limit	LCL	21	17	15
	UCL	60	56	55

Source: Own Calculation

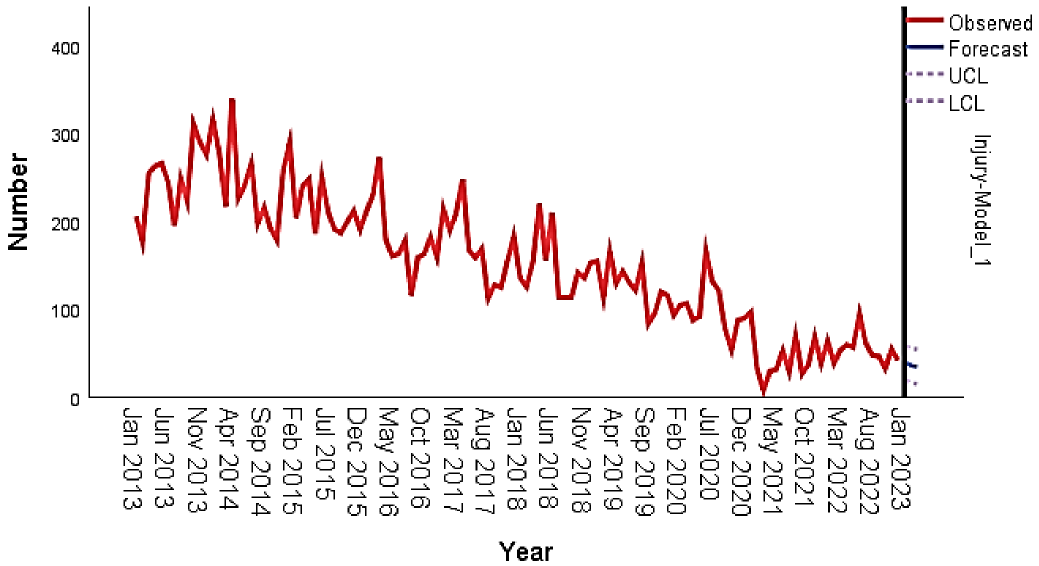


Figure (5.51) Forecast Values with 95% Confidence Limit for Traffic Injuries

Based on the results of the study, the ARIMAX-TFM (1, 0, 1) model's actual values and forecast values are not very close for March 2023. However, the forecast values still fall within the 95% lower and upper confidence limits, indicating that the model's predictions are within an acceptable range of uncertainty. Furthermore, the study found that the actual values of traffic accidents in Yangon are decreasing due to compliance with established laws. This suggests that measures implemented to enforce traffic regulations and safety laws have had a positive impact on reducing traffic accidents in the region.

CHAPTER VI
CONCLUSION

This chapter emphasizes the main findings in achieving to the objectives of this study. In addition, the recommendations and suggestions based on the statistical analysis of road traffic accidents in Yangon are made in detail. The potential further studies regarding the road traffic accidents based on the findings from this study are presented in brief.

6.1 Findings

This study analyzed and predicted the road traffic accidents and casualties in Yangon municipal area. The monthly accident data during the period from January 2013 to December 2022 were collected from No.(2) Office of Traffic Police at Yangon. The risk factors such as gender, place of accident, vehicle types, time of accident, reasons for accident and alcohol consumption were applied to examine whether these variables are related to traffic fatalities and injuries. The monthly road traffic data was also used to forecast the future road traffic accidents and casualties. First, the descriptive analysis were used to determine the pattern of traffic accidents, fatalities and injuries based on the monthly accident data for the 10-year period between 2013 and 2022 from No. (2) Office of Traffic Police at Yangon. Secondly, the significant influencing factors of the accident were explored by using logistic regression model for each of casualties. Moreover, the autoregressive integrated moving average (ARIMA), the intervention and the autoregressive integrated moving average with explanatory variables-transfer function (ARIMAX-TFM) models were used to explore the impact of road safety measures in reducing the number of accidents and casualties in Yangon. In addition, the most suitable model was chosen to predict the number of traffic accidents, and casualties occurred in Yangon for the next three months period.

The trends and patterns in annual traffic accidents were found to vary significantly, depending on the particular year. The number of accidents increased from 2013 to 2014 but it significantly decreased in 2015. Starting from decline point, the number of traffic accidents further gradually declined in the later years until 2021. It can be seen that total accidents over the study period clearly illustrated a downward trend from 2014 to 2021. This study showed that the number of fatalities by road traffic accidents peaked in 2017 and then steadily decreased to the lowest point in 2021. Therefore, the total fatality during the period (2013-2022) was an ascending trend from 2013 to 2017. However, the number of injuries caused by traffic accidents steadily declined from 2013 to 2020 but it can be seen that there was a sharp decrease in 2021 as compared to other years. In contrast, the lowest number of all cases such as traffic accidents and causalities were found in 2021. This was due to the effect of Covid-19 pandemic in Yangon.

According to the results of the descriptive analysis, males were more frequently involved in traffic accidents compared to females in Myanmar. The majorities of drivers in Myanmar were male and were also more likely to drive under the influence of alcohol than females. Additionally, men tended to be less disciplined than women in their compliance with rules and regulations. In order to study the number of traffic accidents and causalities by place, the numbers of accidents cases were the most at main road, followed by lane and junction. This case at both place of roundabout and on bridge were the fewest number. The number of traffic accidents being caused by private car was the highest as compared to other types of vehicle. The second highest number of accidents occurred due to taxi and bus, and motorcycle was also included as the third type of vehicle which was causing the traffic accidents as well. Because this study was done within the boundaries of Yangon, truck and other types of vehicles using the highway road as the main way for transportation could not be measured for the accidents in this study. As the results of accidents and causalities status by time duration, the number of accidents occurred during at night (between 18:00 PM and 24:00 PM) as compared to morning time (between 6:00 AM to 12:00 AM) duration within a day. The highest number of accidents and casualties occurred at human error. Many accidents and casualties were attributed to human error as first and failure of the regulations was constituted as the second causes. Mechanical fault and weather conditions were seen as fewer number than the former cases.

Moreover, this study analyzed the risk factors related to traffic accidents and causalities such as fatality and injury by using binary logistic regression model. Independent variables used in this model were gender, accident place, vehicle types, time of accidents, and immediate causes for accidents. As the result of logistic regression on traffic fatality data, five independent variables such as gender, accident place, vehicle type, time of accidents and immediate causes for accidents were significant. The results of analysis on binary logistic regression model highlighted that there was a significant increase in the number of traffic accidents by male than female. The traffic accidents occurring at junction, roundabout, lane and on bridge led to decrease as compared to main place. Accidents by bus and taxi were less likely to occur as compared to private car but truck and motorcycle and other types of vehicles (three-wheeler, slow vehicle, etc.) were more likely to occur as compared to private car in Yangon. According to this regression model, there was a higher likelihood of traffic fatalities occurring at night time compared to during the morning time. Additionally, it has been observed that traffic accidents and casualties mostly occurred when there was no traffic congestion. Traffic accidents caused by failure to comply with regulations and human error were more frequent than those resulting from mechanical faults and weather conditions.

By analyzing the traffic injury data using binary logistic regression, gender, accident place, vehicle types, time of accidents, and immediate causes for accidents were the significant risk factors. Male was less likely to get injury than female in the event of traffic accidents. In the traffic collision at the driving path ways such as lane, roundabout and bridge, there was less likely to be injury as compared to that at main road but that at junction was more to get injury than at main road. The traffic accident by trucks and other vehicles types (three-wheeler, slow vehicle, etc.) can be less injury than by private car but, by motorcycle, it is more likely to be injury. Being traffic accident in afternoon time and night time durations were less likely to be injury as the reference on morning time. In the point of causes of traffic accidents, people participating in the traffic accident by failure to comply with the regulation and human error were more injury compared to mechanical fault and weather condition.

During the analysis of the time series data on traffic accidents in Yangon, it was found that the ARIMA (0, 1, 1) model, the ARIMA (1, 0, 0) model with intervention, and the ARIMAX-TFM (0, 1, 1) model were all statistically significant and effectively captured the collected data. The detailed results of the ARIMAX (1, 0, 0) model with intervention indicated that the enactment of the Motor Vehicle Law (2015) and Vehicle Safety and Motor Vehicle Management Law (2020) had a negative impact, leading to a decrease in the number of traffic accidents. However, the Permission to Motor Vehicle Law (2016) had a positive impact, resulting in an increase in the number of traffic accidents. The net effect of the Permission to Import Vehicle Law variable on traffic accidents is positive; this implies that there is an increase traffic accident for each unit increase in the Permission to Import Vehicle Law variable. Political changes and the Covid-19 pandemic have had a negative impact on traffic accidents. Upon comparing model selection criteria such as MAE, MAPE, RMSE, AIC, and BIC values for the ARIMA (0, 1, 1), ARIMA (0, 1, 1) with intervention, and ARIMAX-TFM (0, 1, 1) models, it was evident that all criteria values for the ARIMAX-TFM (0, 1, 1) model were the smallest among these three models. Therefore, the ARIMAX-TFM (0, 1, 1) model is considered the most suitable for fitting the traffic accidents data and is utilized to forecast road traffic accidents for the upcoming months. As a result of the forecasting, the predicted number of road traffic accidents shows a slight decrease over the next three months from January 2023 to March 2023.

When conducting the time series analysis of traffic fatality, it was found that the ARIMA (2, 0, 0) model, the ARIMA (0, 0, 0) model with intervention and the ARIMAX-TFM (1, 0, 1) are significant and fit the data collected. The detailed results of the ARIMAX (0, 0, 0) model with intervention indicated that the enactment of the Motor Vehicle Law (2015) had a statistically significant positive impact at a 5% level. This positive impact led to an increase in the number of traffic fatalities. However, the Vehicle Safety and Motor Vehicle Management Law (2020), Permission to Motor Vehicle Law (2016), political changes, and the impact of the Covid-19 pandemic have negatively affected and resulted in a decrease in the number of traffic fatalities. After comparing model selection criteria such as MAE, MAPE, RMSE, AIC, and BIC values for the ARIMA (2, 0, 0), ARIMAX (0, 0, 0) with intervention, and ARIMAX-TFM (1, 0, 1) models, it was evident that the ARIMAX-TFM (1, 0, 1) model exhibited the smallest values across all criteria. Hence, the ARIMAX-TFM (1, 0, 1) model is considered the most suitable for fitting the traffic fatality data and is used to forecast road traffic fatalities for the upcoming months. The forecast results indicate a slight decrease in the predicted number of road traffic fatalities for the next three months from January 2023 to March 2023.

In the time series analysis of traffic injuries, significant models that fit the collected data were ARIMA (1, 1, 1), ARIMA (1, 0, 0) with intervention, and ARIMAX-TFM (1, 0, 1). The detailed results of the ARIMA (1, 0, 0) model with intervention indicated that the enactment of the Motor Vehicle Law (2015) and

Vehicle Safety and Motor Vehicle Management Law (2020) had a negative impact, leading to a decrease in the number of traffic injuries. However, the Permission to Motor Vehicle Law (2016) had a positive impact, resulting in an increase in the number of traffic injuries. Political changes and the Covid-19 pandemic showed no significant impact on traffic injuries. After comparing model selection criteria such as MAE, MAPE, RMSE, AIC, and BIC values for ARIMA (1, 1, 1), ARIMA (1, 0, 0) with intervention, and ARIMAX-TFM (1, 0, 1) models, it was evident that all criteria values for the ARIMAX-TFM (1, 0, 1) were the smallest among these three models. Therefore, the ARIMAX-TFM (1, 0, 1) is considered the most suitable for fitting the traffic injury data and is utilized to forecast road traffic injuries for the upcoming months. As a result of the forecasting, the predicted number of road traffic injuries shows a slight decrease in January and February, followed by a slight increase in March 2023.

6.2 Recommendations and Suggestions

Some recommendations and suggestions about traffic accidents are made based on the main findings. According to the findings of this study, it might be that some drivers do not usually use seatbelts which can prevent the likelihood of fatality in accidents. Also, in driving motorcycles, most people never take helmets on their heads. These are the reasons why traffic fatalities have risen in traffic collisions. Hence, the responsible government agency or department should enact the law of national seatbelt and motorcycle helmet strictly. Furthermore, people who break the traffic rules and regulations ought to be arrested in accordance with the laws due to the large number of accidents caused by those people. The importance of addressing factors such as driving behaviors, road conditions, and the use of safety measures to reduce the occurrence and severity of accidents.

To forgive human error will need upgrading the safe system approach to road safety, in which people's vulnerability to serious injuries in road traffic accidents ensure a safe transport system for all road users. In the case of reducing drink driving, random breath testing needs to be served by responsible persons for decreasing the influence of alcohol as the risk of road traffic accidents. Therefore, the warning signposts should be placed not to drink alcohol during driving on the public road. Road traffic injuries can cause the economic losses to individuals suffered by themselves, which have arisen from the cost of treatment as well as lost productivity for those killed or disable by injuries. And also, it makes their families as a whole by taking time off work to care for their recovery.

However, there are cases where individuals involved in traffic accidents resolve matters amongst themselves, leading to incidents that might go unreported in official lists of traffic accidents, fatalities, and injuries. Consequently, obtaining accurate data on actual fatalities and injuries related to traffic accidents becomes challenging. In order to address this issue, the government should actively disseminate information about traffic accidents and preventive measures, along with rules and regulations. This effort should target a wide range of individuals, including factory workers, pedestrians, students, employees from various organizations, company drivers, taxi drivers, bus drivers, and private drivers. The goal is to mitigate the occurrence of traffic accidents.

By adhering to vehicle, traffic, and road rules, substantial reductions in property damage and human casualties can be achieved. All road users, including pedestrians, share the responsibility for their own safety. Therefore, fostering public engagement becomes crucial for accident reduction, and enhancing awareness holds significant importance for everyone on the road. Ensuring drivers' and vehicles' fitness is vital for minimizing injuries and enhancing survival rates in the event of a crash.

To maintain stringent traffic regulations in Yangon, an increased number of traffic rules and awareness campaigns should be implemented. Intersection management should be reinforced with more traffic lights and roundabout installations at critical points. Additionally, incentivizing responsible behavior through rewards linked to fines collected from illegal traffic activities should be promoted. These fines could be channeled into traffic law enforcement and other national development initiatives.

To combat the rise in speeding-related collisions, drivers should be provided with clear guidelines regarding recommended average speeds within cities and townships. The rising concern of mobile phone-related distractions while driving must also be addressed. Enforcing traffic laws related to drunk driving, seat-belt usage, speed limits, helmet-wearing, and mobile phone use is essential. Neglecting enforcement of these laws undermines the anticipated reduction in accidents and casualties attributed to specific risky behaviors.

Efficient enforcement by traffic authorities should encompass promoting safer driving behaviors like seat-belt compliance, adherence to speed limits, and preventing intoxicated driving. Additionally, enhancing vehicle safety features and implementing laws targeting key risks are crucial. Public awareness campaigns should be employed to share crash-related information, enhancing the understanding of risks. A comprehensive strategy involving these aspects is essential and can be informed by this study, benefiting policy makers, planners, engineers, and the government in formulating effective prevention and safety plans. These efforts can lead to fewer accidents resulting in fatalities or injuries.

Improving road design and engineering is paramount for both safe and efficient traffic flow. Proper signage, road markings, and traffic control devices should be deployed. Pedestrian walkways and cycling lanes must be constructed to segregate vulnerable road users from motorized traffic. High-risk zones should feature traffic calming measures such as speed bumps and roundabouts. The integration of automated traffic enforcement systems, including red light cameras and speed cameras, serves to discourage violations. Extensive road safety education programs are necessary for all road users, encompassing drivers, pedestrians, and cyclists.

To promote alternative modes of transportation and reduce reliance on private vehicles, encouraging public transit, cycling, and walking is essential. Supporting electric and hybrid vehicles through infrastructure and incentives not only reduces emissions but also improves air quality. The increasing prevalence of electric vehicles and ongoing technological advancements will likely reshape the landscape of road traffic accidents and casualties. Understanding the full impact of these changes is complex, given the various benefits, risks, and challenges they bring. Safety protocols are crucial for the successful advancement of these technologies to ensure the ongoing safety of all road users.

Collaboration among government agencies, law enforcement, transport authorities, and relevant stakeholders is vital for formulating and executing comprehensive road safety strategies. Involving NGOs, community organizations, and businesses can amplify awareness and provide support for road safety initiatives. Information and Communication Technology (ICT) initiatives play a pivotal role in reducing traffic accidents by integrating advanced systems and solutions for traffic management, monitoring, and safety. Intelligent Transportation Systems (ITS), Traffic Management Centers (TMC), Connected Vehicle Technology, Intelligent

Speed Adaptation (ISA), Driver Assistance Systems, Road Weather Information Systems, Data Analytics, and Predictive Modeling, as well as Public Awareness and Education Campaigns, constitute key ICT initiatives that can contribute to a significant reduction in traffic accidents.

6.3 Further Studies

Traffic accidents can also be influenced by external factors, such as weather conditions and road infrastructure, which can be difficult to consider in this study. Besides, the road infrastructure-related factors including road users, road construction, roadway designs and installation of speed limiting devices for all vehicles are in a better position of influencing road traffic safety and reducing traffic collision. Another factor of traffic accidents for less developed countries is whether the existing roads meet technical standards for all road users that take into account for road safety. Making good quality roads with lightings and signals is not to be forgotten as the protective factors for traffic accidents. However, the data on these factors were not obtained and couldn't include in this study.

In further research, adding a more comprehensive set of traffic accident-related factors can provide the analysis to be more accurate. By accounting for the prevention measures involving enhancing post-crash care, vehicle safety, improving roads and so on, the problem of increasing traffic accidents can be examined and reduced to the optimal level in the future research. Besides, other influencing factors such as condition of brake system, the profession on driving, length of driving experience, the strength of vehicle types can be applied as the special categories in analyzing traffic fatality. However, certain risk factors, including tyre burst, broken brakes, failure to comply with traffic laws, loss of control, and other infrastructure-related factors, are not included in this study's analysis.

In this study, only the aggregated monthly count data for Yangon were used and thus generalizing the findings could not make generalization about the whole country. Therefore, additional research should be conducted to investigate whether there are variations by geographic regions. Additionally, it is suggested to conduct further research on traffic accidents using artificial neural networks, vector autoregressive models, and outlier models. By employing these distinct statistical methods, the findings can be compared and provide valuable insights into the study of traffic accidents.

REFERENCES

Adanu, E. K. & Jones, S. (2017). Effects Of Human-Centered Factors on Crash Injury Severities. *Journal of Advanced Transportation* 2017, 1-11.

ADB (2016). *Myanmar Transport Policy Note: Urban Transport*. Philippines: ASIAN Development Bank.

Al-Ghamdi, A. S. (2001). Using Logistic Regression to Estimate The Influence Of Accident Factors On Accident Servity. *Accident Analysis and Prevention,*34, 729-741.

ASEAN (2015). *Kuala Lumpur Transport Strategic Plan (2016-2025).* Jakarta: Association of Southeast Nations.

Atubi, A. O. (2015). Modelling Deaths From Road Traffic Accidents in Lagos State, Nigeria. *Aerican International Journal of Social Science,* 4(5).

Avuglah, R. K., Adu-Poku, K. A. & Harris, E. (2014). Application of ARIMA Models to Road Traffic Accident Cases in Ghana. *International Journal of Statistics and Applications*, 233-239.

Awaab, J. A., Combert, J. & Atongdem, P. (2019). Time Series Analysis of Motorcycle Registration and Accidents in the Bolgatanga Municipality. *International Journal of Applied Science and research* 2.

Awal, M. (2013). *Identification of Risk Factors Involved in Road Accidents in Ghana. A Case Study of the Techiman Municipality.* Thesis, Nkwame Nkrumah University, Faculty of Science and Technology.

Box, G. E. & Jenkins G. M. (1976). *Time Series Analysis: Forecasting and Control* (Revised ed.). USA, California: Holden-Day..

Box, G. E., Jenkins, G. M. & Reinsel, G. C. (1994). *Time Series Analysis: Forecasting and Control* (3rd ed.). New Jersey: Ntice Hall.

Box, G. E., Jenkins, G. M., Reinsel, G. C. & Ljung, G. M. (2016). *Tume Series Analysis Forecasting and Control* (5th ed.). New Jersey: John Wiley & Sons.

CDC (n.d.). Definition for WISQARS Nonfatal. Injury Prevention and Control. Retrieved from https://www.cdc.gov>injury>wisqars>non fatal-help.

Chen, Y. & Tjandra, S. (2014). Daily Collision Prediction With Sarimax And Generalized Linear Models on the Basis of Temporal and Weather Variables. *Journal of the Transportation*.

Cools, M., Moons, E. & Wets, G. (2009). Investigating the Variability in Daily Traffic Counts Through Use of Arimax and Sarimax Models. *Transport Research*, 57-66.

Darma, Y. (2017). *A Time Series Analysis of Road Traffic Fatalities in Malaysia.* Kuala Lumpur: University of Malaya.

David W. Hosmer, JR., Lemeshow S. & Sturdivant R. X. (2013). *Applied Logestic Regression* (3rd ed.). New Jersey: John Wiley & Sons.

Daisa, J. M. & Peers , J. B. (1997). Narrow Residential Streets: Do They Really Slow Down Speed? *The Institute of Transportation Enginners 67th annual Meeting, Tampa.* National Association of City Transportation Officals.

Delurgio, S. A. (1998). Forecasting Principles and Applications (1st ed.). USA, Boston: McGraw-Hill.

Department of Population. (2015). *The 2014 Myanmar Population And Housing Census.* Ministry of Immigration and Population, Myanmar.

Department for Transport (2010) Reported Road Casualties in Great Britain: 2009 Annual Report. Department for Transport, London.

Eboli, L., Forciniti, C. & Mazzulla, G. (2020). Factors Influencing Accident Severity: An Analysis by Road Accident Type. *Trasportation Research Procedia,* 47, 449-456.

Erena, M. G. & Heyi, W. D. (2020). Prevalence of Road Traffic Accident and Associated Rick Factors Among Drivers and Three And Four-Wheeler Vehicles, Western Ethiopia, 2017. *MOJ Public Health,* 9(5), 138-145.

ESCAP, U. N. (Performer). (2013). *Present situation of road safety in Myanmar.* Seoul, Republic of Korea.

Fernando, D. M. G. Vadysinghe, A. N., Sudasinghe, N., & Premasinghe, K. (2012) Use of seat Belts: Prior to the Legal Requirement. Sri Lanka Journal of Forensic Medicine, Science & Law, 2, 23- 25.

FIA. (2017). *Road Safety in Myanmar.* Paris: Suu Foundation, FIA.

Florento, H. & Corpuz, M. I. (2014). *Myanmar: The Key Link Between South Asia and Southeast Asia:* Asian Development Bank Institute.

Field, A. (2013). Discovering Statistics Using IBM SPSS Statistics (4th ed.). Sage Publications.

Gale, K. (2018). *Can You Sue If Airbags Don't Deploy?*

Haque, M. O. & Haque, T. H. (2018). Evaluating the Effects of the Road Safety System Approach in Brunei. *Transportation research part A: Policy and Practice*, 118, 594-607.

Hassouna, F. M. A. & Pringle. (2021). Analysis and Prediction of Crash Fatalities in Australia. *The Open Transportation Journal*, 15.

Hilbe, J. M. (2017). Logistic Regression Models (1st ed.). USA, New York: Chapman & Hall/ CRC

Hosmer, D. W. & Lemeshow, S. (2000). Applied Logistic Regression (2nd ed.). Canada, New Jersey: John Wiley & Sons.

Hosmer, D. W., Lemeshow, S. & Sturdivant, RX. (2013). Applied Logistic Regression (3rd ed.). Canada, New Jersey: John Wiley & Sons.

Htwe, K. K. (2017). Assessment of Inpatient Burden of Road Traffic Accidents in Yangon General Hospital. Master of Medical Science (Hospital Administration and Health Management) Thesis. University of Public Health, Yangon.

Husin, W. Z. W., Afdzal, A. S., Azmi, N. L., H. & Hamadi, S. A. T. S. (2021). Box-Jenkins and State Space Model in Forecasting Malaysia Road Accident Cases. *Journal of Physics: Conference Series*.

Ihueze, C. C. & Onwurah, U. O. (2018). Road Traffic Accidents Prediction Modelling: An Analysis of Anambra State, Nigeria. *Accident Analysis & Prevention*, 112, 21-29.

Inaba, H. & Kato, H. (2017). Impacts of Motorcycle Demand Management in Yangon, Myanmar. *Transportation Research Procedia*, 25, 4852-4868.

INSEE (2016) Definitions and Methods-Definitions Road Accidents. National Institute for Statistics and Economic Studies, France.

Jomnonkwao, S., Uttra, S., & Ratanavaraha, V. (2020). Forecasting Road Traffic Deaths in Thailand: Applications of Time-Series, Curve Estimation, Multiple Linear Regression, and Path Analysis Models. *Sustainability*, 12(1), 395, https://dai.org/10.3390/su 12010395.

Katta, V. (2013). *Development of Crash Severity Model for Predict.ing Risk Factors in Work Zones for Ohio.* Thesis. The University of Toledo.

Karacasu, M., Ergul, B. & Yavuz, A. A. (2013). Estimating the Causes of Traffic Accidents Using Logistic Regression And Discriminant Analysis. *International Journal of Injury Control and safety Promotion*, 21(4).

Khin, M. M. M. (2016). *An Empirical Analysis of the traffic Accidents in Myanmar*. Ph.D. Programme. Monywa University of Economics, Myanmar.

Khin N. N. (2022). Road Safety in Myanmar. *The 25th Meeting of the Subregional Transport Forum (STF-25)*.

Kitamura, Y., Hayashi, M. & Yagi, E. (2018). Traffic Problems in Southeast Asia Featuring the Case of Cambodia's Traffic Accidents Involving Motorcycles. *International Association of Traffic and Safety Science Research (IATSS)*, 42, 163-170.

Kyaw, M. T. (2015). Human Rights Issue on Highway Road Accidents in Myanmar. *Phnom Penh: Regional Research Initiative round-table meeting in Phnom Penh, Cambodia*.

Lwin, A. M., Win, Y. Y., Aung, T. & Lwin, T. (2016). Factors Influencing Motorcycle Accidents in Nay Pyi Taw, Myanmar. *Injury Prevention, Health System Research*.

Ma, S., Tran, N., Klyavin, V. E., Zambon, F., Hatcher, K. W. & Hyder, A. A. (2012) Seat Belt and Child Seat Use in Lipetskaya Oblast, Russia: frequencies, Attitudes, and Perceptions. Traffic Injury Prevention, 13, 76-81.

Mackie, P. J. (2003). *Cost Benefit Analysis of transport Infrastructure Projects*: United Nations Publications.

Maung, A. (2021). Global New Light of Myanmar. Retrieved May,2021, from https://www.gnlm.com.mm/12-collision-on-yangon/

Mendenhall, W. & Sincich, T. (2012). *A Second Course in Statistics: Regression Analysis* (7th ed.). United State of America: Pearson Education.

Ministry of Commerce (2017). *National Trade Situation of Myanmar in 2011-2012 Fiscal Year to 2017-2018 fiscal Year (March Monthly) (Oversea + Border)*.

Mohan, D. (2006). *Road Traffic Injury Prevention: Training Manual*: World Health Organization, Geneva.

Mon, C. T., Pueboobpaphan, R. & Ratanavaraha, V. (2016). *Examining Relationship Between Accident Occurrences and Road Characteristicson Yangon-Mandalay Expressway in Myanmar*.

Montgomery, D. C., Jennings, C. L. & Kulahci, M. (2015). *Introduction to Tume Series Analysis and Forecasting* (2nd ed.). Canada, New Jersey: John Wiley & Sons.

Mutangi, K. (2015). Time Series Analysis of Road Traffic Accidents in Zimbabwe. *International Journal of Statistics and Application*, 141-149.

Myanmar Law Library (2015). Law, Rules and Regulations, from https://myanmar-law-library.org/law-library/laws-and-regulations/laws/myanmar-laws-1988-until-now/union-solidarity-and-development-party-laws-2012-2016/myanmar

Nantulya, V. M., Sleet, D. A., Reich, M. R., Rosenberg, M., Peden, M. & Waxweiler, R. (2010). Introduction, the Global Challenge of Road Traffic Injuries. *Injury Control and Safety Promotion,* 10(1-2), 3-7.

Oliver (2017). Yangon Traffic has Killed over 500 people in 2017. Coconuts Yangon. Retrieved November, 2017, from https://coconuts.com>yangon>news>
yangon-traffic/

Pankratz, A. (1991). Forecasting with Dynamic Regression Models. Canada: John Wiley & Sons.

Petridou, E. T., & Moustaki, M. (2002). Human Factors in the Causation of Road Traffic Accident. *European Journal of Epidemiology*, 16(9), 819-26.

Sabenorio, R. F., Enriquez, M. L. & Ramel, L. M. A. (2023). Forecasting Road Traffic Accidents in Metro Manila Using ARIMA Modeling. *World Journal of Advanced Research and Reviews*, 17(03), 115–125.

Salako, R. J., Adegoke, B. O. & Akanmu, T. A. (2014). Time Series Analysis for Modelling and Detecting Seasonality Pattern of Auto-Crash Cases Recorded at Federal Road Safety Commission, OSUN Sector Command. *International Journal of Engeering and Advanced Technology Studies*, .2(4), 25-34.

Sanusi, R. A., Adebola, F. B. & Adegoke, N. A. (2016). Cases of Road Traffic Accident in Nigeria: A Time Series Approach. *Mediterranean Journal of Social Sciences*, .7(2 S-1).

Sarani, R., Mohamed Rahim, S. A., Marjin, J. & Voon, W. S. (2012). *Predicting Malaysian Road Fatalities for Year 2020.* Malaysia: Malaysian Insititute of Road Safety Research (MIROS).

Shen X., Yan Y., Li X., Xie C. & Wang L. (2013) Analysis on Tank Truck Accidents Involved in Road Hazardous Materials Transportation in China. Traffic Injury Prevention, 15, 762-768.

Shumway, R. H. & Stoffer, D. S. (2016). *Time Series Analysis and Its Applications* (3rd ed.). New York: Springer Science.

Stevens, J. P. (2009). *Applied Multivariate Statistics for the Social Sciences* (5th ed.). New York: Rutledge.

The Carlson Law Firm (2020). What are the 10 most common vehicle defects and how to spot them? Retrieved August 10, 2020, from https://www. carlsonattorneys.com>news-and-update

The Union of Myanmar President of Office. (2019). *National Road Safety Council Holds Fifth Meeting*. The Republic of the Union of Myanmar President of Office.

Twenefour, F. B.K., Ayitey, E., Kangah, J. & Brew, L. (2021). Time Series Analysis of Road Traffic Accidents in Ghana. *Asian Journal of Probability and Statistics,* 11(2), 12-20.

Uhrig, J. (2019). Road safety figures. Health in Myanmar. Retrieved January,2019, from https://hivinfo4mm.org/road-safety-figures/

UN. & ECE. (2003). *Cost Benefit Analysis of Transport Infrastructure Projects.* United Nations.

Wei, W. W. S. (2006). *Time Series Analysis, Univariate and Multivariate Method* (2nd ed.). USA, Boston: Pearson.

WHO (2004). *Alcohol-road safety*. The World Health Organization, Geneva.

WHO (2004). *World Report on Road Traffic Injury Prevention*. The World Health Organization, Geneva.

WHO (2006). *Road Traffic Injury Prevention Training Manual.* The Wrold Health Organization, Geneva.

WHO (2008). *World Report on Child Injury Prevention*. The World Health Organization, Geneva.

WHO (2009). *Global Status Report on Road Safety*. The World Health Organization, Geneva.

WHO (2009). *Road Traffic Injuries*. The World Health Organization, Geneva.

WHO (2015). *Interventions to Reduce Road Traffic Injuries: Increasing Motorcycle Helmet Use.* The World Health Organization, Geneva.

WHO (2015). *Road Safety in the South-East Region.* The Wrold Health Organization, Geneva.

WHO (2018). *Global Status Report on Road Safety.* The World Health Organization, Geneva.

WHO (2019). *Road Safety in Myanmar: Data Collection Begins on the Yangon-Mandalay Highway.* The World Health Organization, Geneva.

WHO (2020). *Road Safety: Interventions To Reduce Road Traffic Injuries.* Global Health Observatory, World Health Organization, Geneva.

WHO (2021). *Road traffic Injuries.* World Health Organization, Geneva.

World Bank (2019). *A Manual for Practitioners and Decision Makers on Implementing Safe System Infrastructure! PIARC*.

World Bank (2019). *Road Safety: An Integral Part of the World Bank's Mission.*

World Life Expectancy (2020). Road Traffic Accidents in Myanmar, from https://www.worldlifeexpectancy.com, myanmar-road-traffic-accident.

Yaffee, R. A. & McGee, M. (2000). *Introduction to Time Series Analysis and Forecasting with Applications of SAS and SPSS.* New York: Academic Press.

Yahaya, A., Rathakrishnan, B., Ramli, S. F., Maakip, I., Voo, P. & Madin, A. B., H. (2021). Road Traffic Collision: Reasons and the Future. *Hong Kong Journal Of Social Sciences*, 58, 402-407.

Yan, X. & Su, X. G. (2009). *Linear Regression Analysis.* Singapore: World Scientific Publishing.

Yousefzadeh-Chabok, S., Ranjbar-Taklimie, F., Malekpouri, R. & Razzaghi, A. (2016). A Time Series Model for Assessing the Trend and Forecasting the Road Traffic Accident Mortality. *Archives of Trauma Research,* 5(3).

Zaw, T. (2013). Present Situation of Road Safety in Myanmar. *Experts Group Meeting for Road Safety Improvement*.

Zimmerman, K., Mzige, A. A., Kibatala, P. L., Museru, L. M. & Guerrero, A. (2012) Road Traffic Injury Incidence and Crash Characteristics in Dar es Salaam: A Population Based Study. *Accident Analysis & Prevention,* 45, 204-210.

WEBSITES

Retrieved from https://www.devex.com > news> traffic-fatalities

Retrieved from https:// definitions.uslegal.com > fatal...

Retrieved from https:// safety.fhwa.dot.gov > library.

Retrieved from https://www.worldlifeexpectancy

Retrieved from https://www.myanmar.gov.mm

Retrieved from https://www.xinhuanet.com

Retrieved from https://mmbiztoday.com

Retrieved from https://www.myanmarrtad.com/?q=my/article/85

APPENDIXES

Appendix A

Table (A-1)

Traffic Fatality and Gender Crosstabulation

Crosstab

			Gender		
			Female	Male	Total
Acctype	Non-fatality	Count	5863	12567	18430
		Expected Count	5493.6	12936.4	18430.0
		% within Acctype	31.8%	68.2%	100.0%
		% within Gender	89.5%	81.4%	83.8%
		% of Total	26.7%	57.2%	83.8%
	Fatality	Count	690	2864	3554
		Expected Count	1059.4	2494.6	3554.0
		% within Acctype	19.4%	80.6%	100.0%
		% within Gender	10.5%	18.6%	16.2%
		% of Total	3.1%	13.0%	16.2%
Total		Count	6553	15431	21984
		Expected Count	6553.0	15431.0	21984.0
		% within Acctype	29.8%	70.2%	100.0%
		% within Gender	100.0%	100.0%	100.0%
		% of Total	29.8%	70.2%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	218.869[a]	1	.000		
Continuity Correction[b]	218.277	1	.000		
Likelihood Ratio	234.211	1	.000		
Fisher's Exact Test				.000	.000
N of Valid Cases	21984				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 1059.38.

b. Computed only for a 2x2 table

Table (A-2)

Traffic Fatality and Places of Accident Crosstabulation

Crosstab

			Place					Total
			Main Road	Lane	Junction	On Bridge	Roundabout	
Acctype	Non-fatality	Count	11962	3553	2206	663	46	18430
		Expected Count	12180.2	3396.1	2165.4	643.0	45.3	18430.0
		% within Acctype	64.9%	19.3%	12.0%	3.6%	0.2%	100.0%
		% within Place	82.3%	87.7%	85.4%	86.4%	85.2%	83.8%
	Fatality	Count	54.4%	16.2%	10.0%	3.0%	0.2%	83.8%
		Expected Count	2567	498	377	104	8	3554
		% within Acctype	2348.8	654.9	417.6	124.0	8.7	3554.0
		% within Place	72.2%	14.0%	10.6%	2.9%	0.2%	100.0%
Total		Count	4052	17.7%	12.3%	14.6%	13.6%	14.8%
		Expected Count	4052.0	11.7%	2.3%	1.7%	0.5%	0.0%
		% within Acctype	18.4%	14529	4051	2583	767	54
		% within Place	100.0%	14529.0	4051.0	2583.0	767.0	54.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	77.638[a]	4	.000
Likelihood Ratio	80.689	4	.000
N of Valid Cases	21984		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 8.73.

Table (A-3)

Traffic Fatality and Type of Vehicles Crosstabulation

Crosstab

			Vehicle Type						Total
			Car	Bus	Taxi	Motorcycle	Truck	Others	
Acctype	Non-fatality	Count	7249	2808	4686	2616	592	479	18430
		Expected Count	7302.8	2665.1	4488.5	2771.5	616.2	586.0	18430.0
		% within Acctype	39.3%	15.2%	25.4%	14.2%	3.2%	2.6%	100.0%
		% within Vtype	83.2%	88.3%	87.5%	79.1%	80.5%	68.5%	83.8%
	Fatality	Count	33.0%	12.8%	21.3%	11.9%	2.7%	2.2%	83.8%
		Expected Count	1462	371	668	690	143	220	3554
		% within Acctype	1408.2	513.9	865.5	534.5	118.8	113.0	3554.0
		% within Vtype	41.1%	10.4%	18.8%	19.4%	4.0%	6.2%	100.0%
Total		Count	8712	16.8%	11.7%	12.5%	20.9%	19.5%	31.5%
		Expected Count	8712.0	6.7%	1.7%	3.0%	3.1%	0.7%	1.0%
		% within Acctype	39.6%	8711	3179	5354	3306	735	699
		% within Vtype	100.0%	8711.0	3179.0	5354.0	3306.0	735.0	699.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	284.354[a]	5	.000
Likelihood Ratio	267.430	5	.000
N of Valid Cases	21984		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 113.00.

Table (A-4)

Traffic Fatality and Times of Accident Crosstabulation

Crosstab

			Time_4				
			6:00 AM-12:00 AM	12:00 AM-18:00 PM	18:00 PM-24:00 PM	24:00 PM-6:00 AM	Total
Acctype	Non-fatality	Count	3602	4180	7318	3330	18430
		Expected Count	3516.0	4021.5	7425.2	3467.4	18430.0
		% within Acctype	19.5%	22.7%	39.7%	18.1%	100.0%
		% within Time_4	85.9%	87.1%	82.6%	80.5%	83.8%
		% of Total	16.4%	19.0%	33.3%	15.1%	83.8%
	Fatality	Count	592	617	1539	806	3554
		Expected Count	678.0	775.5	1431.8	668.6	3554.0
		% within Acctype	16.7%	17.4%	43.3%	22.7%	100.0%
		% within Time_4	14.1%	12.9%	17.4%	19.5%	16.2%
		% of Total	2.7%	2.8%	7.0%	3.7%	16.2%
Total		Count	4194	4797	8857	4136	21984
		Expected Count	4194.0	4797.0	8857.0	4136.0	21984.0
		% within Acctype	19.1%	21.8%	40.3%	18.8%	100.0%
		% within Time_4	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	19.1%	21.8%	40.3%	18.8%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	94.882[a]	3	.000
Likelihood Ratio	95.875	3	.000
N of Valid Cases	21984		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 668.64.

Table (A-5)

Traffic Fatality and Immediate Causes for Accident Crosstabulation

Crosstab

			Causes			
			Mechanical Fault & Weather Condition	Failure	Human Error	Total
Acctype	Non-fatality	Count	55	2022	16353	18430
		Expected Count	47.8	2313.8	16068.4	18430.0
		% within Acctype	0.3%	11.0%	88.7%	100.0%
		% within Causes	96.5%	73.3%	85.3%	83.8%
	Fatality	Count	0.3%	9.2%	74.4%	83.8%
		Expected Count	2	738	2814	3554
		% within Acctype	9.2	446.2	3098.6	3554.0
		% within Causes	0.1%	20.8%	79.2%	100.0%
Total		Count	57	3.5%	26.7%	14.7%
		Expected Count	57.0	0.0%	3.4%	12.8%
		% within Acctype	0.3%	57	2760	19167
		% within Causes	100.0%	57.0	2760.0	19167.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	265.565[a]	2	.000
Likelihood Ratio	238.903	2	.000
Linear-by-Linear Association	217.312	1	.000
N of Valid Cases	21984		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 9.21.

Table (B-1)

Traffic Injury and Gender Crosstabulation

Crosstab

			Gender		
			Female	Male	Total
Acctype	Non-injury	Count	15	2291	2306
		Expected Count	653.7	1652.3	2306.0
		% within Acctype	0.7%	99.3%	100.0%
		% within Gender	0.3%	15.4%	11.1%
		% of Total	0.1%	11.0%	11.1%
	Injury	Count	5863	12567	18430
		Expected Count	5224.3	13205.7	18430.0
		% within Acctype	31.8%	68.2%	100.0%
		% within Gender	99.7%	84.6%	88.9%
		% of Total	28.3%	60.6%	88.9%
Total		Count	5976	5878	14858
		Expected Count	5976.0	5878.0	14858.0
		% within Acctype	27.9%	28.3%	71.7%
		% within Gender	100.0%	100.0%	100.0%
		% of Total	27.9%	28.3%	71.7%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	979.861[a]	1	.000		
Continuity Correction[b]	978.327	1	.000		
Likelihood Ratio	1490.670	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	979.813	1	.000		
N of Valid Cases	20736				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 653.68.

b. Computed only for a 2x2 table

Table (B-2)

Traffic Injury and Places of Accident Crosstabulation

Crosstab

			Accident Place					Total
			Main Road	Lane	Junction	On Bridge	Roundabout	
Acctype	Non-injury	Count	1418	686	87	101	14	2306
		Expected Count	1488.0	471.4	255.0	85.0	6.7	2306.0
		% within Acctype	61.5%	29.7%	3.8%	4.4%	0.6%	100.0%
		% within Accplace	10.6%	16.2%	3.8%	13.2%	23.3%	11.1%
		% of Total	6.8%	3.3%	0.4%	0.5%	0.1%	11.1%
	Injury	Count	11962	3553	2206	663	46	18430
		Expected Count	11892.0	3767.6	2038.0	679.0	53.3	18430.0
		% within Acctype	64.9%	19.3%	12.0%	3.6%	0.2%	100.0%
		% within Accplace	89.4%	83.8%	96.2%	86.8%	76.7%	88.9%
		% of Total	57.7%	17.1%	10.6%	3.2%	0.2%	88.9%
Total		Count	4339	13380	4239	2293	764	60
		Expected Count	4339.0	13380.0	4239.0	2293.0	764.0	60.0
		% within Acctype	20.2%	64.5%	20.4%	11.1%	3.7%	0.3%
		% within Accplace	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	20.2%	64.5%	20.4%	11.1%	3.7%	0.3%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	250.598[a]	4	.000
Likelihood Ratio	274.496	4	.000
Linear-by-Linear Association	1.302	1	.254
N of Valid Cases	20736		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 6.67.

Table (B-3)

Traffic Injury and Type of Vehicles Crosstabulation

Crosstab

			Vehicle Type						Total
			Car	Bus	Taxi	Motorcycle	Truck	Others	
Acctype	Non-injury	Count	863	290	645	12	130	366	2306
		Expected Count	902.1	344.5	592.8	292.3	80.3	94.0	2306.0
		% within Acctype	37.4%	12.6%	28.0%	0.5%	5.6%	15.9%	100.0%
		% within Vtype	10.6%	9.4%	12.1%	0.5%	18.0%	43.3%	11.1%
	Injury	Count	4.2%	1.4%	3.1%	0.1%	0.6%	1.8%	11.1%
		Expected Count	7249	2808	4686	2616	592	479	18430
		% within Acctype	7209.9	2753.5	4738.2	2335.7	641.7	751.0	18430.0
		% within Vtype	39.3%	15.2%	25.4%	14.2%	3.2%	2.6%	100.0%
Total		Count	8712	89.4%	90.6%	87.9%	99.5%	82.0%	56.7%
		Expected Count	8712.0	35.0%	13.5%	22.6%	12.6%	2.9%	2.3%
		% within Acctype	39.6%	8112	3098	5331	2628	722	845
		% within Vtype	100.0%	8112.0	3098.0	5331.0	2628.0	722.0	845.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1239.789[a]	5	.000
Likelihood Ratio	1127.636	5	.000
Linear-by-Linear Association	146.003	1	.000
N of Valid Cases	20736		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 80.29.

Table (B-4)

Traffic Injury and Times of Accident Crosstabulation

Crosstab

			Time_4				
			6:00 AM-12:00 AM	12:00 AM-18:00 PM	18:00 PM-24:00 PM	24:00 PM-6:00 AM	Total
Acctype	Non-injury	Count	308	545	912	541	2306
		Expected Count	434.8	525.5	915.1	430.6	2306.0
		% within Acctype	13.4%	23.6%	39.5%	23.5%	100.0%
		% within Time_4	7.9%	11.5%	11.1%	14.0%	11.1%
		% of Total	1.5%	2.6%	4.4%	2.6%	11.1%
	Injury	Count	3602	4180	7317	3331	18430
		Expected Count	3475.2	4199.5	7313.9	3441.4	18430.0
		% within Acctype	19.5%	22.7%	39.7%	18.1%	100.0%
		% within Time_4	92.1%	88.5%	88.9%	86.0%	88.9%
		% of Total	17.4%	20.2%	35.3%	16.1%	88.9%
Total		Count	4194	3910	4725	8229	3872
		Expected Count	4194.0	3910.0	4725.0	8229.0	3872.0
		% within Acctype	19.1%	18.9%	22.8%	39.7%	18.7%
		% within Time_4	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	19.1%	18.9%	22.8%	39.7%	18.7%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	256.800[a]	2	0.000
Likelihood Ratio	405.101	2	0.000
Linear-by-Linear Association	191.742	1	0.000
N of Valid Cases	20736		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 430.60.

Table (B-5)

Traffic Injury and Immediate Causes of Accident Crosstabulation

Crosstab

			Causes			
			Mechanical Fault & Weather Condition	Failure	Human Error	Total
Acctype	Non-injury	Count	15	13	2278	2306
		Expected Count	7.8	226.3	2071.9	2306.0
		% within Acctype	0.7%	0.6%	98.8%	100.0%
		% within Causes	21.4%	0.6%	12.2%	11.1%
	Injury	Count	0.1%	0.1%	11.0%	11.1%
		Expected Count	55	2022	16353	18430
		% within Acctype	62.2	1808.7	16559.1	18430.0
		% within Causes	0.3%	11.0%	88.7%	100.0%
Total		Count	57	78.6%	99.4%	87.8%
		Expected Count	57.0	0.3%	9.8%	78.9%
		% within Acctype	0.3%	70	2035	18631
		% within Causes	100.0%	70.0	2035.0	18631.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	74.297[a]	3	0.000
Likelihood Ratio	76.356	3	0.000
Linear-by-Linear Association	58.259	1	0.000
N of Valid Cases	20736		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.78.

Table (C-1)

Test of Seasonality for Traffic Accidents and Casualties

Hypotheses

Null Hypothesis: There is no seasonal variation.

i.e., $\beta_1 = \beta_2 = \beta_3 = \cdots = \beta_{12}$

Alternative Hypothesis: There is seasonal variation.

i.e., at least two $\beta_j{}'s$ are not equal:

$$\beta_1 \neq \beta_2 \neq \beta_3 \neq \cdots \neq \beta_{12}$$

The test statistic used is

$$F = \frac{Mean\ square\ due\ to\ months}{Residual\ mean\ squares}$$

Data Series	F-statistic	Decision
Accidents	0.95	The monthly data of traffic accidents in Yangon do not exist seasonality.
Fatalities	1.25	The monthly data of traffic fatalities in Yangon do not exist seasonality
Injuries	0.77	The monthly data of traffic injuries in Yangon do not exist seasonality

Table (C-2)

Augmented Dickey-Fuller Test for Traffic Accidents

(Before First Difference)

Null Hypothesis: ACCIDENTS has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.377362	0.5916
Test critical values:	1% level	-3.481217	
	5% level	-2.883753	
	10% level	-2.578694	

*MacKinnon (1996) one-sided p-values.

(After First Difference)

Null Hypothesis: D(ACCIDENTS) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.39060	0.0000
Test critical values:	1% level	-3.481623	
	5% level	-2.883930	
	10% level	-2.578788	

*MacKinnon (1996) one-sided p-values.

Table (C-3)

ACF and PACF of First Difference Series for Traffic Accidents

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	ACF	-0.368	-0.039	-0.006	0.002	-0.041	0.080	0.052	-0.102	-0.039	-0.091	0.187	-0.124
	SE	0.091	0.090	0.090	0.089	0.089	0.089	0.088	0.088	0.087	0.087	0.087	0.086
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	ACF	0.030	0.168	-0.103	-0.086	0.026	0.083	-0.029	-0.067	0.061	-0.041	-0.105	0.049
	SE	0.086	0.085	0.085	0.085	0.084	0.084	0.083	0.083	0.082	0.082	0.082	0.081

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	PACF	-0.368	-0.201	-0.117	-0.065	-0.087	0.030	0.107	-0.024	-0.087	-0.200	0.062	-0.070
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	PACF	-0.049	0.199	0.092	-0.038	-0.081	0.012	0.031	-0.125	-0.003	0.008	-0.080	-0.066
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (C-4)

ACF and PACF of Residuals for ARIMA (0, 1, 1) Model

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	ACF	0.063	-0.020	-0.058	0.009	0.006	0.100	0.022	-0.138	-0.127	-0.066	0.134	0.003
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.093	0.093	0.095	0.096	0.097	0.098
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	ACF	0.126	0.113	-0.093	-0.155	-0.023	0.020	-0.054	-0.125	-0.038	-0.149	-0.118	0.074
	SE	0.098	0.100	0.101	0.102	0.103	0.104	0.104	0.104	0.105	0.105	0.107	0.108

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	PACF	0.063	-0.024	-0.055	0.016	0.002	0.098	0.011	-0.138	-0.102	-0.060	0.130	-0.029
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	PACF	0.132	0.147	-0.092	-0.152	-0.072	-0.025	-0.067	-0.131	0.051	-0.086	-0.097	0.016
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (C-5)

Augmented Dickey-Fuller Test for Pre-intervention of Traffic Accidents

Null Hypothesis: ACCIDENTS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.162257	0.0322
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Table (C-6)

ACF and PACF of Residuals for ARIMA (1, 0, 0) Model with Intervention

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	ACF	-0.174	0.143	-0.026	0.126	0.073	0.088	0.026	-0.068	0.160	-0.097	0.149	0.010
	SE	0.092	0.095	0.097	0.097	0.098	0.099	0.099	0.099	0.100	0.102	0.103	0.104
Model		13	13	14	15	16	17	18	19	20	21	22	23
Accidents-Model_1	ACF	0.125	0.156	-0.050	0.003	0.066	0.128	-0.059	-0.033	0.000	0.035	-0.014	0.014
	SE	0.104	0.106	0.108	0.108	0.108	0.108	0.109	0.110	0.110	0.110	0.110	0.110

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	-0.174	0.116	0.017	0.113	0.117	0.097	0.037	-0.099	0.109	-0.073	0.076	0.075	0.001
	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	0.107	0.218	-0.049	-0.084	0.026	0.056	-0.049	-0.133	0.017	0.037	-0.074	0.009	0.052
	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (C-7)

Augmented Dickey-Fuller Test for Over Speeding and Pedestrian Negligence

Null Hypothesis: OVER_SPEEDING has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.090089	0.0300
Test critical values:	1% level	-3.486551	
	5% level	-2.886074	
	10% level	-2.579931	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: PEDESTRIAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.768201	0.0042
Test critical values:	1% level	-3.486064	
	5% level	-2.885863	
	10% level	-2.579818	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test for Reckless Driving

(Before First Difference)

Null Hypothesis: RECKLESS_DRIVING has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.840145	0.8036
Test critical values:	1% level	-3.486551	
	5% level	-2.886074	
	10% level	-2.579931	

*MacKinnon (1996) one-sided p-values.

(After First Difference)

Null Hypothesis: D(RECKLESS_DRIVING) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.17698	0.0000
Test critical values:	1% level	-3.486551	
	5% level	-2.886074	
	10% level	-2.579931	

*MacKinnon (1996) one-sided p-values.

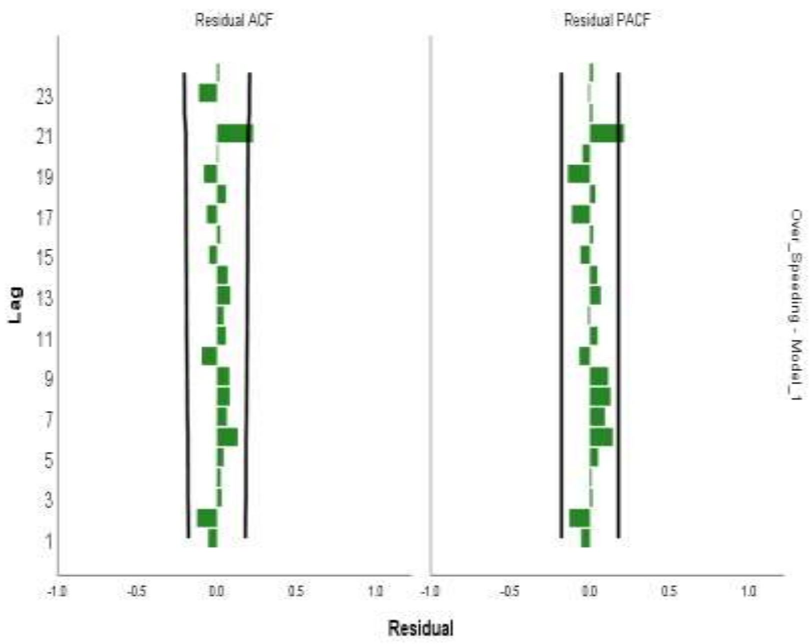
Table (C-8)

ACF and PACF of Residuals Values for Input Series

For ARIMA (2, 0, 0)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	ACF	-0.055	-0.125	0.029	0.024	0.042	0.130	0.062	0.080	0.078	-0.095	0.056	0.042
	SE	0.091	0.092	0.093	0.093	0.093	0.093	0.095	0.095	0.096	0.096	0.097	0.097
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	ACF	0.083	0.067	-0.049	0.021	-0.064	0.057	-0.081	0.008	0.227	0.001	-0.114	0.013
	SE	0.097	0.098	0.098	0.099	0.099	0.099	0.099	0.100	0.100	0.104	0.104	0.105

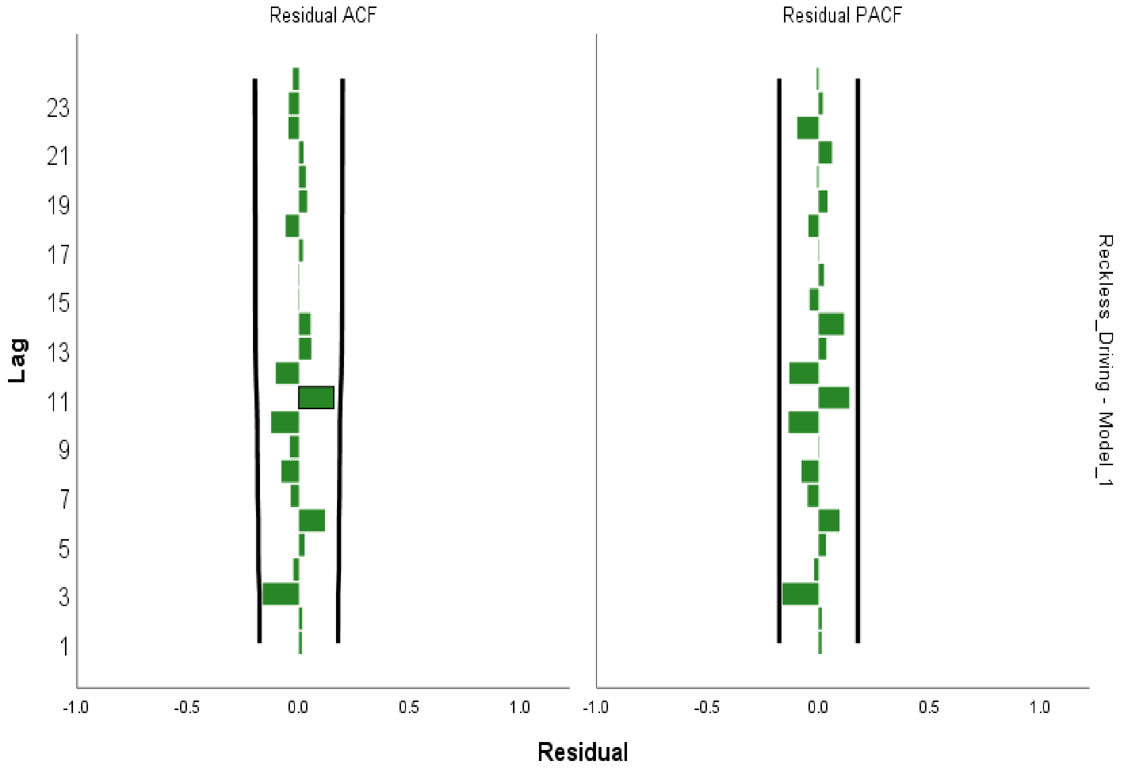
Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	PACF	-0.055	-0.129	0.015	0.010	0.051	0.143	0.094	0.130	0.114	-0.066	0.048	-0.012
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	PACF	0.067	0.046	-0.059	0.020	-0.114	0.034	-0.139	-0.047	0.214	0.016	-0.010	0.020
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091



For ARIMA (0, 1, 1)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	ACF	0.014	0.016	-0.161	-0.024	0.028	0.118	-0.036	-0.078	-0.041	-0.125	0.158	-0.103
	SE	0.091	0.091	0.091	0.093	0.093	0.093	0.094	0.094	0.095	0.095	0.096	0.098
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	ACF	0.056	0.053	-0.002	-0.002	0.019	-0.058	0.038	0.032	0.022	-0.047	-0.045	-0.027
	SE	0.099	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.100	0.101	0.101

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	PACF	0.014	0.015	-0.162	-0.020	0.034	0.095	-0.049	-0.075	-0.003	-0.135	0.140	-0.132
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	PACF	0.036	0.116	-0.041	0.025	-0.002	-0.045	0.040	-0.006	0.061	-0.096	0.019	-0.007
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091



For ARIMA (2, 0, 0)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	ACF	-0.030	-0.115	0.001	0.038	0.027	-0.072	0.109	-0.030	-0.004	0.156	0.085	0.101
	SE	0.090	0.090	0.091	0.091	0.092	0.092	0.092	0.093	0.093	0.093	0.095	0.096
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	ACF	-0.024	0.103	-0.065	0.018	-0.008	-0.055	-0.020	0.096	0.046	-0.130	-0.106	0.145
	SE	0.097	0.097	0.098	0.098	0.098	0.098	0.098	0.098	0.099	0.099	0.101	0.102

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	PACF	-0.030	-0.116	-0.007	0.025	0.029	-0.064	0.113	-0.041	0.019	0.156	0.097	0.142
	SE	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	PACF	0.142	0.029	0.121	-0.062	0.053	-0.052	-0.056	-0.070	0.076	-0.031	-0.147	-0.171
	SE	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090

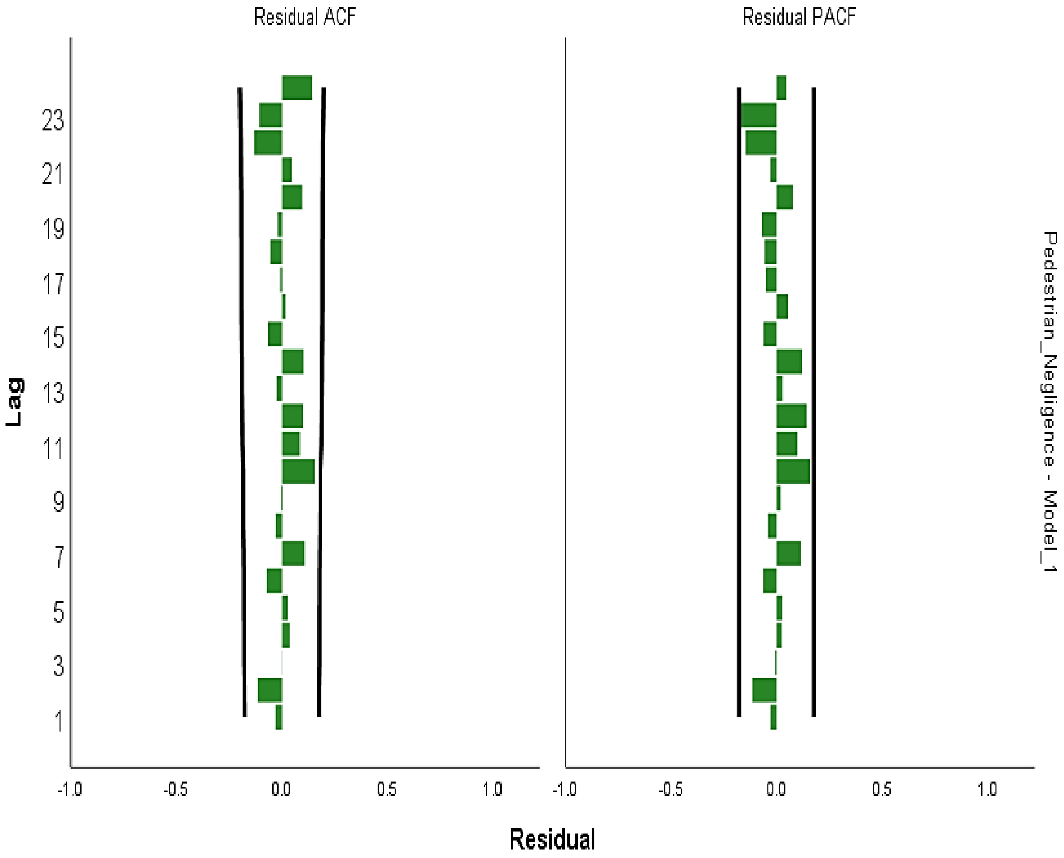


Table (C-9)
Cross Correlation between Output Series and Input Series of Traffic Accidents

For Over - Speeding

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	0.203	0.095	0.203	0.095	0.203	0.095	0.203	0.095	0.203	0.095	0.203	0.095	0.203	0.095	0.203
Std. Error[a]	0.079	0.094	0.079	0.094	0.079	0.094	0.079	0.094	0.079	0.094	0.079	0.094	0.079	0.094	0.079

For Reckless Driving

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	-0.062	0.094	-0.062	0.094	-0.062	0.094	-0.062	0.094	-0.062	0.094	-0.062	0.094	-0.062	0.094	-0.062
Std. Error[a]	0.062	0.094	0.062	0.094	0.062	0.094	0.062	0.094	0.062	0.094	0.062	0.094	0.062	0.094	0.062

For Pedestrian Negligence

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	0.12	0.095	0.12	0.095	0.12	0.095	0.12	0.095	0.12	0.095	0.12	0.095	0.12	0.095	0.12
Std. Error[a]	0.081	0.094	0.081	0.094	0.081	0.094	0.081	0.094	0.081	0.094	0.081	0.094	0.081	0.094	0.081

Table (C-10)
ACF and PACF of Noise Series for Traffic Accidents

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	ACF	-0.373	0.091	-0.373	0.091	-0.373	0.091	-0.373	0.091	-0.373	0.091	-0.373	0.091
	SE	0.024	0.090	0.024	0.090	0.024	0.090	0.024	0.090	0.024	0.090	0.024	0.090
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	ACF	0.155	0.086	0.155	0.086	0.155	0.086	0.155	0.086	0.155	0.086	0.155	0.086
	SE	-0.003	0.085	-0.003	0.085	-0.003	0.085	-0.003	0.085	-0.003	0.085	-0.003	0.085

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	PACF	-0.373	0.092	-0.373	0.092	-0.373	0.092	-0.373	0.092	-0.373	0.092	-0.373	0.092
	SE	-0.133	0.092	-0.133	0.092	-0.133	0.092	-0.133	0.092	-0.133	0.092	-0.133	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	PACF	0.152	0.092	0.152	0.092	0.152	0.092	0.152	0.092	0.152	0.092	0.152	0.092
	SE	0.121	0.092	0.121	0.092	0.121	0.092	0.121	0.092	0.121	0.092	0.121	0.092

Table (C-11)

ACF and PACF of Residuals for ARIMAX-TFM (0, 1, 1) Model

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	ACF	0.002	-0.009	0.016	0.032	0.017	0.118	0.085	-0.063	-0.059	-0.036	0.182	-0.013
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.093	0.094	0.094	0.094	0.095	0.097
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	ACF	0.120	0.209	-0.031	-0.057	0.068	0.104	-0.004	-0.057	0.021	-0.047	-0.093	0.066
	SE	0.097	0.099	0.102	0.102	0.103	0.103	0.104	0.104	0.104	0.104	0.104	0.105

Model		1	2	3	4	5	6	7	8	9	10	11	12
Accidents-Model_1	PACF	0.002	-0.009	0.016	0.032	0.017	0.119	0.086	-0.062	-0.064	-0.050	0.179	-0.022
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Accidents-Model_1	PACF	0.115	0.230	-0.010	-0.055	0.010	0.061	-0.014	-0.119	0.029	-0.023	-0.074	0.013
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (D-1)

Augmented Dickey-Fuller Test for Traffic Fatality

Null Hypothesis: FATALITY has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.081551	0.0000
Test critical values:	1% level	-3.486551	
	5% level	-2.886074	
	10% level	-2.579931	

*MacKinnon (1996) one-sided p-values.

Table (D-2)

ACF and PACF of Original Series for Traffic Fatalities

Model		1	2	3	4	5	6	7	8	9	10	11	12
Fatality-Model_1	ACF	0.284	0.271	0.162	0.092	0.182	0.14	0.09	-0.008	-0.019	0.005	0.172	0.154
	SE	0.09	0.09	0.089	0.089	0.089	0.088	0.088	0.087	0.087	0.087	0.086	0.086
Model		13	14	15	16	17	18	19	20	21	22	23	24
Fatality-Model_1	ACF	0.229	0.137	0.181	0.077	0.096	0.193	0.15	0.07	0.073	-0.041	0.004	0.076
	SE	0.085	0.085	0.085	0.084	0.084	0.083	0.083	0.083	0.082	0.082	0.081	0.081

Model		1	2	3	4	5	6	7	8	9	10	11	12
Fatality-Model_1	PACF	0.284	0.208	0.048	-0.011	0.135	0.06	-0.021	-0.1	-0.032	0.02	0.196	0.086
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Fatality-Model_1	PACF	0.144	0.016	0.095	-0.088	-0.037	0.101	0.081	-0.052	0.048	-0.09	-0.017	0.016
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091

Table (D-3)

ACF and PACF of Residuals for ARIMA (2, 0, 0) Model

Model		1	2	3	4	5	6	7	8	9	10	11	12
Fatality-Model_1	ACF	-0.015	-0.018	0.024	-0.051	0.116	0.101	0.056	-0.062	-0.091	-0.065	0.126	0.078
	SE	0.091	0.091	0.091	0.091	0.092	0.093	0.094	0.094	0.094	0.095	0.095	0.097
Model		13	14	15	16	17	18	19	20	21	22	23	24
Fatality-Model_1	ACF	0.142	0.035	0.099	-0.038	-0.012	0.166	0.096	0.009	0.050	-0.086	-0.039	0.082
	SE	0.097	0.099	0.099	0.100	0.100	0.100	0.102	0.103	0.103	0.103	0.104	0.104

Model		1	2	3	4	5	6	7	8	9	10	11	12
Fatality-Model_1	PACF	-0.015	-0.018	0.024	-0.050	0.116	0.103	0.068	-0.066	-0.088	-0.082	0.110	0.063
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Fatality-Model_1	PACF	0.160	0.066	0.168	-0.045	-0.052	0.073	0.086	-0.004	0.091	-0.051	-0.023	0.011
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091

Table (D-4)

Augmented Dickey-Fuller Test of Pre-intervention for Traffic Fatalities

Null Hypothesis: FATALITY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.633880	0.0107
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Table (D-5)

ACF and PACF of Residuals for ARIMA (0, 0, 0) Model with Intervention

Model		1	2	3	4	5	6	7	8	9	10	11	12
Fatality-Model_1	ACF	0.120	0.193	0.034	-0.047	0.070	0.007	-0.034	-0.151	-0.129	-0.135	0.049	-0.008
	SE	0.092	0.093	0.096	0.096	0.097	0.097	0.097	0.097	0.099	0.100	0.102	0.102
Model		13	14	15	16	17	18	19	20	21	22	23	24
Fatality-Model_1	ACF	0.098	0.009	0.064	-0.044	-0.060	0.063	-0.023	-0.047	-0.041	-0.105	-0.019	-0.002
	SE	0.102	0.103	0.103	0.103	0.103	0.104	0.104	0.104	0.104	0.104	0.105	0.105

Model		1	2	3	4	5	6	7	8	9	10	11	12
Fatality-Model_1	PACF	0.120	0.182	-0.007	-0.089	0.083	0.020	-0.069	-0.163	-0.074	-0.061	0.111	0.002
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Fatality-Model_1	PACF	0.087	-0.002	0.059	-0.108	-0.111	0.056	0.011	-0.084	0.011	-0.036	0.039	-0.011
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (D-6)

Augmented Dickey-Fuller Test for Over Speeding, Reckless Driving and Pedestrian Negligence

Null Hypothesis: OVER has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.78135	0.0000
Test critical values:	1% level	-3.486064	
	5% level	-2.885863	
	10% level	-2.579818	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: RECK has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.342498	0.0006
Test critical values:	1% level	-3.486551	
	5% level	-2.886074	
	10% level	-2.579931	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: PEDESTRIAN_NEGLIGANCE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.411533	0.0000
Test critical values:	1% level	-3.486064	
	5% level	-2.885863	
	10% level	-2.579818	

*MacKinnon (1996) one-sided p-values.

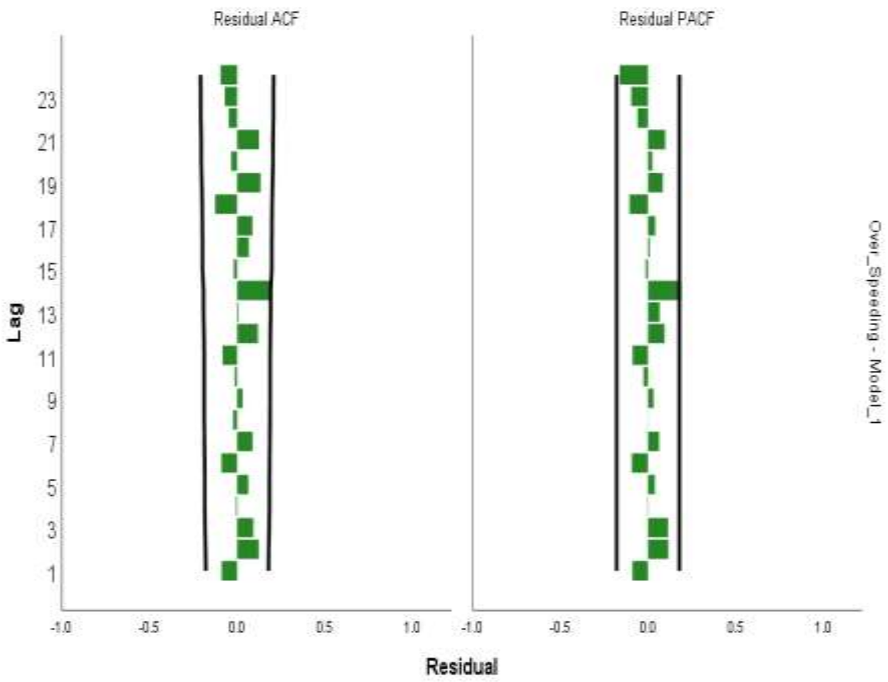
Table (D-7)

ACF and PACF of Residuals Values for Input Series

For ARIMA (0, 0, 0)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Over_Speeding-Model_1	ACF	-0.088	0.123	0.092	-0.007	0.064	-0.089	0.088	-0.023	0.031	-0.014	-0.083	0.118
	SE	0.091	0.092	0.093	0.094	0.094	0.094	0.095	0.096	0.096	0.096	0.096	0.097
Model		13	14	15	16	17	18	19	20	21	22	23	24
Over_Speeding-Model_1	ACF	0.007	0.188	-0.019	0.066	0.087	-0.125	0.134	-0.033	0.124	-0.048	-0.070	-0.094
	SE	0.098	0.098	0.101	0.101	0.101	0.102	0.103	0.104	0.105	0.106	0.106	0.106

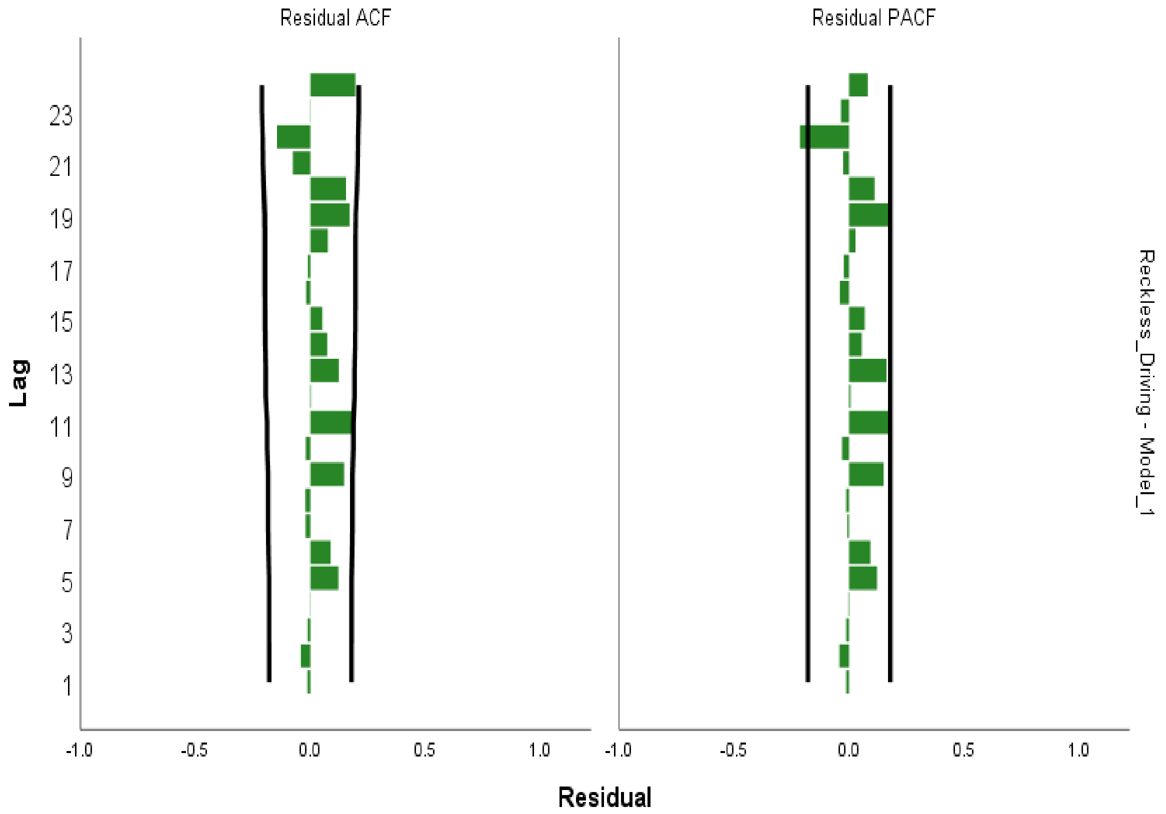
Model		1	2	3	4	5	6	7	8	9	10	11	12
Over_Speeding-Model_1	PACF	-0.088	0.116	0.115	-0.004	0.038	-0.092	0.063	0.002	0.031	-0.025	-0.088	0.094
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Over_Speeding-Model_1	PACF	0.066	0.189	-0.013	0.009	0.041	-0.105	0.085	0.024	0.098	-0.060	-0.096	-0.161
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091



For ARIMA (2, 0, 0)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Reckless_Driving-Model_1	ACF	-0.012	-0.041	-0.011	-0.001	0.123	0.089	-0.020	-0.020	0.147	-0.019	0.187	0.003
	SE	0.091	0.091	0.091	0.091	0.091	0.093	0.094	0.094	0.094	0.096	0.096	0.099
Model		13	14	15	16	17	18	19	20	21	22	23	24
Reckless_Driving-Model_1	ACF	0.124	0.074	0.053	-0.017	-0.011	0.078	0.171	0.155	-0.075	-0.144	0.002	0.196
	SE	0.099	0.100	0.100	0.101	0.101	0.101	0.101	0.103	0.105	0.106	0.107	0.107

Model		1	2	3	4	5	6	7	8	9	10	11	12
Reckless_Driving-Model_1	PACF	-0.012	-0.041	-0.012	-0.003	0.122	0.093	-0.007	-0.011	0.151	-0.031	0.183	0.006
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Reckless_Driving-Model_1	PACF	0.162	0.055	0.068	-0.040	-0.022	0.028	0.171	0.112	-0.026	-0.213	-0.036	0.082
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091



For ARIMA (0, 0, 0)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Over_Speeding-Model_1	ACF	0.147	0.166	0.073	0.144	-0.016	0.078	0.15	-0.046	0.078	0.033	0.098	0.07
	SE	0.09	0.09	0.089	0.089	0.089	0.088	0.088	0.087	0.087	0.087	0.086	0.086
Model		13	14	15	16	17	18	19	20	21	22	23	24
Over_Speeding-Model_1	ACF	0.038	-0.055	0.048	-0.042	-0.045	-0.038	0.111	0.08	0.128	0.173	0.01	0.093
	SE	0.085	0.085	0.085	0.084	0.084	0.083	0.083	0.083	0.082	0.082	0.081	0.081

Model		1	2	3	4	5	6	7	8	9	10	11	12
Over_Speeding-Model_1	PACF	0.147	0.147	0.031	0.112	-0.065	0.052	0.143	-0.12	0.073	0.011	0.051	0.085
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Over_Speeding-Model_1	PACF	-0.054	-0.092	0.077	-0.087	-0.032	-0.025	0.109	0.116	0.094	0.102	-0.068	0.056
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091

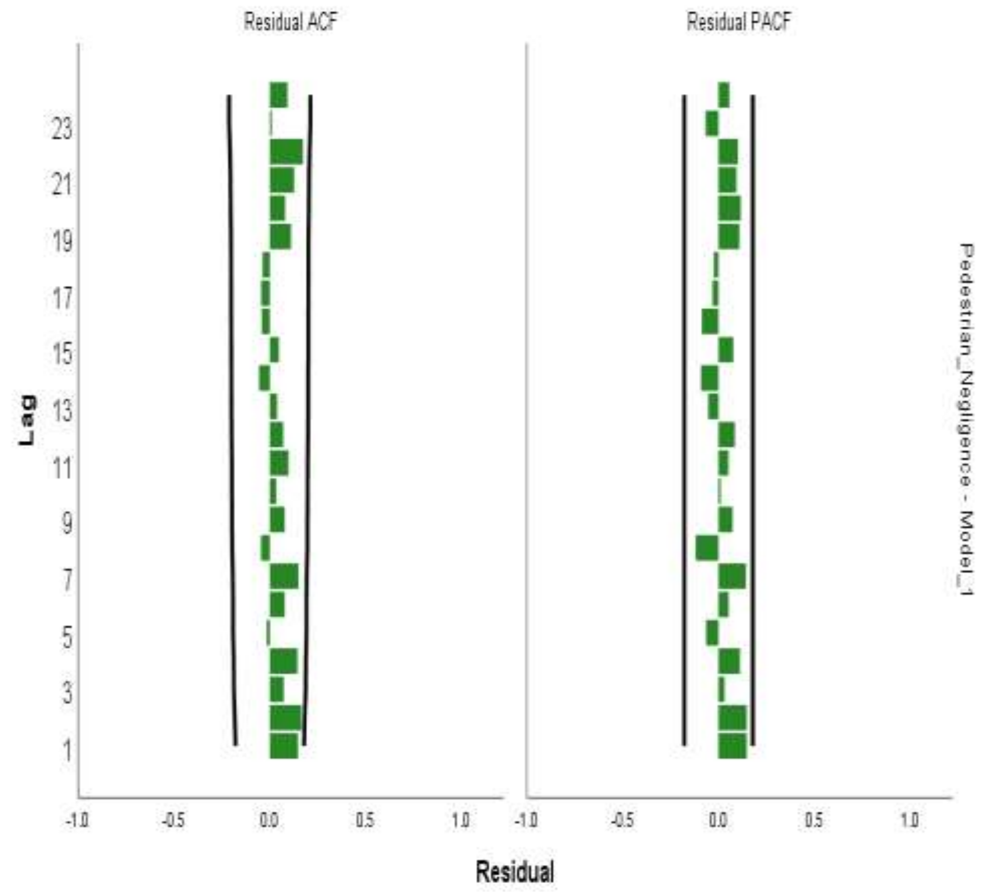


Table (D-8)

Cross Correlation between Output Series and Input Series of Traffic Fatalities

For Over Speeding

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	0.009	-0.021	0.023	-0.106	0.017	0.045	-0.063	0.016	-0.176	-0.209	-0.065	-0.189	-0.120	-0.148	0.005
Std. Error[a]	0.094	0.094	0.093	0.093	0.092	0.092	0.092	0.091	0.092	0.092	0.092	0.093	0.093	0.094	0.094

For Reckless Driving

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	0.105	0.095	0.105	0.095	0.105	0.095	0.105	0.095	0.105	0.095	0.105	0.095	0.105	0.095	0.105
Std. Error[a]	0.062	0.094	0.062	0.094	0.062	0.094	0.062	0.094	0.062	0.094	0.062	0.094	0.062	0.094	0.062

For Pedestrian Negligence

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	-0.144	0.094	-0.144	0.094	-0.144	0.094	-0.144	0.094	-0.144	0.094	-0.144	0.094	-0.144	0.094	-0.144
Std. Error[a]	-0.060	0.094	-0.060	0.094	-0.060	0.094	-0.060	0.094	-0.060	0.094	-0.060	0.094	-0.060	0.094	-0.060

Table (D-9)

ACF and PACF of Noise Series for Traffic Fatalities

Model		1	2	3	4	5	6	7	8	9	10	11	12
Pedestrian_Negligence-Model_1	ACF	-0.026	0.069	-0.048	-0.115	0.165	-0.032	0.039	-0.108	-0.162	0.053	0.018	0.120
	SE	0.092	0.092	0.092	0.092	0.094	0.096	0.096	0.096	0.097	0.099	0.100	0.100
Model		13	14	15	16	17	18	19	20	21	22	23	24
Pedestrian_Negligence-Model_1	ACF	0.038	0.007	-0.018	-0.081	0.044	0.047	0.013	-0.094	0.101	-0.134	-0.024	0.050
	SE	0.101	0.101	0.101	0.101	0.102	0.102	0.102	0.102	0.103	0.104	0.105	0.105

Model		1	2	3	4	5	6	7	8	9	10	11	12
Pedestrian_Negligence-Model_1	PACF	-0.026	0.068	-0.045	-0.123	0.170	-0.012	0.001	-0.105	-0.138	0.039	0.048	0.074
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Pedestrian_Negligence-Model_1	PACF	0.044	0.050	-0.026	-0.084	-0.008	0.045	0.014	-0.088	0.174	-0.120	-0.081	0.030
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (D-10)

ACF and PACF of Residuals for ARIMAX-TFM (1, 0, 1) Model

Model		1	2	3	4	5	6	7	8	9	10	11	12
Fatality-Model_1	ACF	0.056	0.058	0.034	-0.024	0.032	0.108	0.113	0.016	-0.010	-0.050	0.008	-0.075
	SE	0.091	0.092	0.092	0.092	0.092	0.092	0.093	0.094	0.094	0.094	0.095	0.095
Model		13	14	15	16	17	18	19	20	21	22	23	24
Fatality-Model_1	ACF	0.082	0.019	0.020	0.008	0.119	0.188	0.042	0.040	0.060	0.041	-0.002	-0.053
	SE	0.095	0.096	0.096	0.096	0.096	0.097	0.100	0.100	0.100	0.101	0.101	0.101

Model		1	2	3	4	5	6	7	8	9	10	11	12
Fatality-Model_1	PACF	0.056	0.055	0.028	-0.031	0.031	0.107	0.102	-0.009	-0.028	-0.051	0.016	-0.088
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Fatality-Model_1	PACF	0.070	0.006	0.024	0.008	0.139	0.198	0.020	-0.013	0.046	0.034	-0.042	-0.154
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091

Table (E-1)

Augmented Dickey-Fuller Test for Traffic Injury

(Before First Difference)

Null Hypothesis: INJURY has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.199830	0.6730
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

*MacKinnon (1996) one-sided p-values.

(After First Difference)

Null Hypothesis: D(INJURY) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.85432	0.0000
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

*MacKinnon (1996) one-sided p-values.

Table (E-2)

ACF and PACF of First Different Series for Traffic Injuries

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	ACF	-0.436	-0.019	0.111	-0.214	0.065	0.088	-0.085	-0.005	0.039	-0.173	0.089	0.09
	SE	0.091	0.09	0.09	0.089	0.089	0.089	0.088	0.088	0.087	0.087	0.087	0.086
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	ACF	-0.074	0.139	0.023	-0.175	0.079	-0.029	-0.064	0.026	0.059	-0.019	-0.089	0.071
	SE	0.086	0.085	0.085	0.085	0.084	0.084	0.083	0.083	0.082	0.082	0.082	0.081

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	PACF	-0.436	-0.258	-0.017	-0.218	-0.161	-0.004	-0.031	-0.105	-0.051	-0.22	-0.17	-0.026
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	PACF	-0.037	0.076	0.185	0.012	-0.021	-0.036	-0.089	-0.192	-0.033	0.095	-0.084	-0.024
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (E-3)

ACF and PACF of Residuals for ARIMA (1, 1, 1) Model

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	ACF	-0.052	0.103	0.135	-0.133	0.055	0.067	-0.073	-0.030	-0.006	-0.126	0.099	0.133
	SE	0.092	0.092	0.093	0.095	0.096	0.096	0.097	0.097	0.097	0.097	0.099	0.099
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	ACF	0.043	0.158	0.038	-0.149	-0.005	-0.079	-0.101	-0.013	0.037	-0.012	-0.054	0.089
	SE	0.101	0.101	0.103	0.103	0.105	0.105	0.106	0.106	0.106	0.106	0.106	0.107

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	PACF	-0.052	0.101	0.147	-0.133	0.013	0.086	-0.041	-0.085	-0.006	-0.084	0.089	0.165
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	PACF	0.077	0.089	0.032	-0.170	-0.104	-0.067	-0.065	-0.041	0.145	0.114	-0.081	0.052
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (E-4)

Augmented Dickey-Fuller Test of Pre-intervention for Traffic Injury

Null Hypothesis: INJURY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=7)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.473345	0.0013
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

Table (E-5)

ACF and PACF of Pre-intervention Series for Traffic Injuries

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	ACF	0.164	0.169	0.164	0.169	0.164	0.169	0.164	0.169	0.164	0.169	0.164	0.169
	SE	0.125	0.166	0.125	0.166	0.125	0.166	0.125	0.166	0.125	0.166	0.125	0.166
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	ACF	-0.135	0.132	-0.135	0.132	-0.135	0.132	-0.135	0.132	-0.135	0.132	-0.135	0.132
	SE	0.034	0.129	0.034	0.129	0.034	0.129	0.034	0.129	0.034	0.129	0.034	0.129

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	PACF	0.164	0.177	0.164	0.177	0.164	0.177	0.164	0.177	0.164	0.177	0.164	0.177
	SE	0.101	0.177	0.101	0.177	0.101	0.177	0.101	0.177	0.101	0.177	0.101	0.177
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	PACF	0.029	0.177	0.029	0.177	0.029	0.177	0.029	0.177	0.029	0.177	0.029	0.177
	SE	-0.036	0.177	-0.036	0.177	-0.036	0.177	-0.036	0.177	-0.036	0.177	-0.036	0.177

Table (E-6)

ACF and PACF of Residuals for ARIMA (1, 0, 0) Model with Intervention

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	ACF	-0.062	0.107	0.124	-0.068	0.081	0.003	-0.064	-0.054	0.049	-0.154	0.071	0.12
	SE	0.092	0.092	0.093	0.094	0.095	0.095	0.095	0.096	0.096	0.096	0.098	0.099
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	ACF	0.045	0.068	0.009	-0.124	-0.027	0.036	-0.122	0.003	0.026	-0.031	-0.023	0.179
	SE	0.1	0.1	0.101	0.101	0.102	0.102	0.102	0.103	0.103	0.103	0.103	0.103

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	PACF	-0.062	0.103	0.138	-0.065	0.045	0.009	-0.063	-0.086	0.065	-0.127	0.054	0.156
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	PACF	0.104	0.002	-0.015	-0.158	-0.094	0.043	-0.041	-0.016	0.096	0.061	-0.073	0.157
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (E-7)

Augmented Dickey-Fuller Test for Over Speeding, Reckless Driving and Pedestrian Negligence

(Before First Difference)

Null Hypothesis: OVER has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.740588	0.0703
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: RECKLESS has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.620042	0.8608
Test critical values:	1% level	-3.488063	
	5% level	-2.886732	
	10% level	-2.580281	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: PEDESTRIAN has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.069135	0.2576
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

*MacKinnon (1996) one-sided p-values.

(After First Difference)

Null Hypothesis: D(OVER) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.07316	0.0000
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(RECKLESS) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.565644	0.0000
Test critical values:	1% level	-3.488063	
	5% level	-2.886732	
	10% level	-2.580281	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(PEDESTRIAN) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.41456	0.0000
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

*MacKinnon (1996) one-sided p-values.

Table (E-8)

ACF and PACF of the First different Input Series for Traffic Injuries

For Over Speeding

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	ACF	-0.369	-0.206	0.190	-0.047	-0.130	0.131	-0.032	-0.062	0.117	-0.130	-0.057	0.159
	SE	0.091	0.090	0.090	0.089	0.089	0.089	0.088	0.088	0.087	0.087	0.087	0.086
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	ACF	-0.023	-0.120	0.236	-0.150	-0.038	0.098	-0.112	-0.092	0.230	-0.011	-0.179	0.123
	SE	0.086	0.085	0.085	0.085	0.084	0.084	0.083	0.083	0.082	0.082	0.082	0.081

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	PACF	-0.369	-0.396	-0.086	-0.090	-0.176	-0.043	-0.073	-0.077	0.037	-0.129	-0.171	-0.043
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	PACF	-0.005	-0.094	0.146	-0.033	0.018	0.008	-0.108	-0.210	-0.020	0.081	-0.039	-0.032
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

For Reckless Driving

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	ACF	-0.384	-0.017	-0.134	-0.034	0.147	-0.075	-0.003	0.029	0.016	-0.154	0.052	0.032
	SE	0.091	0.090	0.090	0.089	0.089	0.089	0.088	0.088	0.087	0.087	0.087	0.086
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	ACF	0.077	0.051	-0.018	-0.078	0.095	-0.232	0.046	0.131	0.052	-0.008	-0.259	0.081
	SE	0.086	0.085	0.085	0.085	0.084	0.084	0.083	0.083	0.082	0.082	0.082	0.081

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	PACF	-0.384	-0.193	-0.263	-0.273	-0.054	-0.120	-0.134	-0.038	0.004	-0.237	-0.180	-0.124
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	PACF	-0.084	0.027	0.148	0.055	0.210	-0.099	-0.206	-0.048	0.080	0.091	-0.127	-0.082
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

For Pedestrian Negligence

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	ACF	-0.325	-0.133	0.063	-0.065	-0.028	0.015	0.069	-0.114	-0.057	0.123	0.053	0.010
	SE	0.091	0.090	0.090	0.089	0.089	0.089	0.088	0.088	0.087	0.087	0.087	0.086
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	ACF	0.086	0.085	0.085	0.085	0.084	0.084	0.083	0.083	0.082	0.082	0.082	0.081
	SE	0.086	0.085	0.085	0.085	0.084	0.084	0.083	0.083	0.082	0.082	0.082	0.081

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	PACF	-0.325	-0.266	-0.094	-0.131	-0.121	-0.092	0.017	-0.115	-0.172	-0.028	0.070	0.100
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	PACF	-0.102	0.106	0.061	0.029	0.044	-0.173	-0.077	0.055	0.010	-0.024	-0.048	0.035
	SE	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092

Table (E-9)

Comparison of ARIMA Models for Pre-intervention Series of Traffic Injuries

Criteria	ARIMA (1, 0, 0)	ARIMA (0, 0, 1)
AIC	849.333	860.701
BIC	852.112	863.480

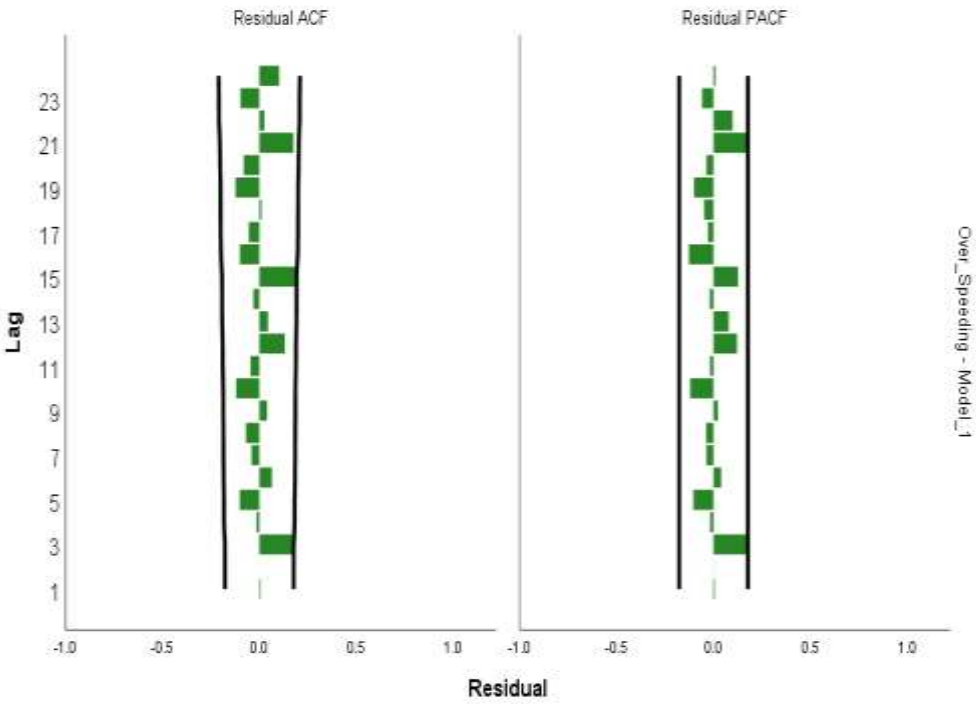
Table (E-10)

ACF and PACF of Residuals Values for Input Series

For ARIMA (0, 1, 2)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Over_Speeding-Model_1	ACF	0.006	0.000	0.170	-0.014	-0.101	0.065	-0.040	-0.070	0.040	-0.120	-0.046	0.131
	SE	0.091	0.091	0.091	0.093	0.093	0.094	0.094	0.095	0.095	0.095	0.096	0.096
Model		13	14	15	16	17	18	19	20	21	22	23	24
Over_Speeding-Model_1	ACF	0.044	-0.030	0.188	-0.100	-0.054	0.011	-0.122	-0.081	0.176	0.026	-0.098	0.103
	SE	0.098	0.098	0.098	0.101	0.102	0.102	0.102	0.103	0.104	0.106	0.106	0.107

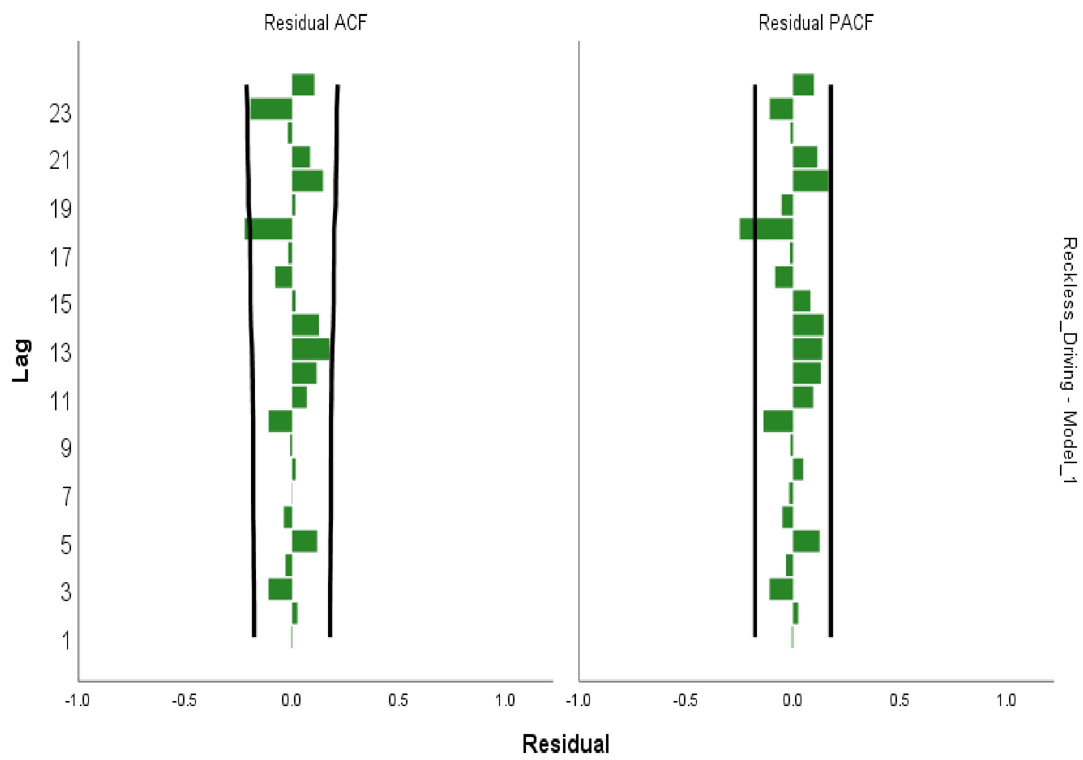
Model		1	2	3	4	5	6	7	8	9	10	11	12
Over_Speeding-Model_1	PACF	0.006	0.000	0.170	-0.017	-0.104	0.039	-0.036	-0.038	0.022	-0.121	-0.018	0.121
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Over_Speeding-Model_1	PACF	0.078	-0.019	0.126	-0.127	-0.029	-0.048	-0.100	-0.036	0.169	0.099	-0.059	0.010
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091



For ARIMA (1, 1, 1)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Reckless_Driving-Model_1	ACF	-0.004	0.025	-0.110	-0.031	0.117	-0.039	-0.002	0.017	-0.009	-0.110	0.069	0.114
	SE	0.091	0.091	0.091	0.092	0.092	0.093	0.093	0.093	0.093	0.093	0.094	0.095
Model		13	14	15	16	17	18	19	20	21	22	23	24
Reckless_Driving-Model_1	ACF	0.176	0.124	0.016	-0.079	-0.018	-0.222	0.014	0.146	0.084	-0.019	-0.196	0.104
	SE	0.096	0.098	0.100	0.100	0.100	0.100	0.104	0.104	0.106	0.106	0.106	0.109

Model		1	2	3	4	5	6	7	8	9	10	11	12
Reckless_Driving-Model_1	PACF	-0.004	0.025	-0.110	-0.033	0.124	-0.050	-0.017	0.048	-0.012	-0.137	0.094	0.131
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Reckless_Driving-Model_1	PACF	0.136	0.143	0.082	-0.083	-0.015	-0.250	-0.053	0.166	0.115	-0.011	-0.109	0.098
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091



For ARIMA (0, 1, 2)

Model		1	2	3	4	5	6	7	8	9	10	11	12
Reckless_Driving-Model_1	ACF	-0.007	0.008	0.038	-0.065	-0.044	-0.014	0.024	-0.097	-0.026	0.141	0.100	0.054
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.092	0.092	0.094	0.095
Model		13	14	15	16	17	18	19	20	21	22	23	24
Reckless_Driving-Model_1	ACF	-0.074	0.110	-0.050	-0.076	-0.014	-0.190	-0.001	0.084	0.008	-0.014	-0.048	0.015
	SE	0.095	0.096	0.097	0.097	0.097	0.097	0.100	0.100	0.101	0.101	0.101	0.101

Model		1	2	3	4	5	6	7	8	9	10	11	12
Reckless_Driving-Model_1	PACF	-0.007	0.008	0.038	-0.065	-0.045	-0.014	0.029	-0.098	-0.033	0.140	0.117	0.045
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Reckless_Driving-Model_1	PACF	-0.105	0.117	-0.015	-0.071	-0.051	-0.165	0.038	0.091	-0.042	-0.061	-0.051	0.013
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091

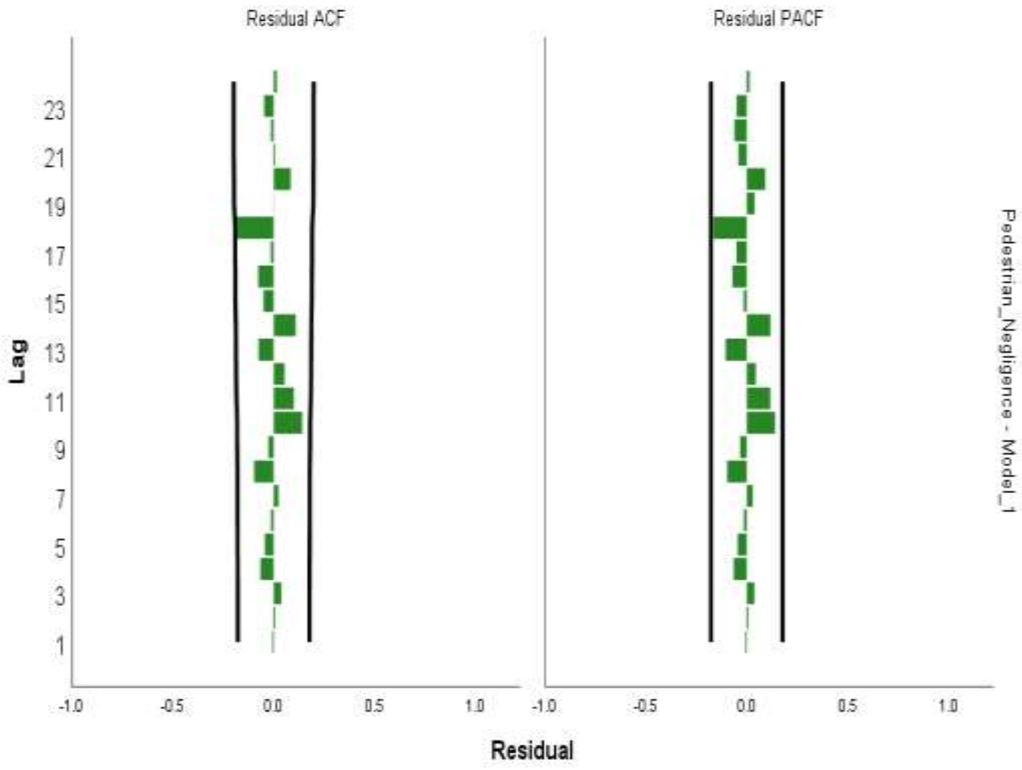


Table (E-11)

Cross Correlation between Output Series and Input Series of Traffic Injuries

For Over Speeding

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	-0.156	0.095	-0.156	0.095	-0.156	0.095	-0.156	0.095	-0.156	0.095	-0.156	0.095	-0.156	0.095	-0.156
Std. Error[a]	0.063	0.095	0.063	0.095	0.063	0.095	0.063	0.095	0.063	0.095	0.063	0.095	0.063	0.095	0.063

For Reckless Driving

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	-0.065	0.095	-0.065	0.095	-0.065	0.095	-0.065	0.095	-0.065	0.095	-0.065	0.095	-0.065	0.095	-0.065
Std. Error[a]	-0.051	0.094	-0.051	0.094	-0.051	0.094	-0.051	0.094	-0.051	0.094	-0.051	0.094	-0.051	0.094	-0.051

For Pedestrian Negligence

Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
Cross Correlation	-0.064	0.095	-0.064	0.095	-0.064	0.095	-0.064	0.095	-0.064	0.095	-0.064	0.095	-0.064	0.095	-0.064
Std. Error[a]	0.173	0.094	0.173	0.094	0.173	0.094	0.173	0.094	0.173	0.094	0.173	0.094	0.173	0.094	0.173

Table (E-12)

ACF and PACF of Noise Series for Traffic Injuries

Model		1	2	3	4	5	6	7	8	9	10	11	12
Pedestrian_Negligence-Model_1	ACF	0.424	0.090	0.424	0.090	0.424	0.090	0.424	0.090	0.424	0.090	0.424	0.090
	SE	0.425	0.090	0.425	0.090	0.425	0.090	0.425	0.090	0.425	0.090	0.425	0.090
Model		13	14	15	16	17	18	19	20	21	22	23	24
Pedestrian_Negligence-Model_1	ACF	0.180	0.085	0.180	0.085	0.180	0.085	0.180	0.085	0.180	0.085	0.180	0.085
	SE	0.153	0.085	0.153	0.085	0.153	0.085	0.153	0.085	0.153	0.085	0.153	0.085

Model		1	2	3	4	5	6	7	8	9	10	11	12
Pedestrian_Negligence-Model_1	PACF	0.424	0.091	0.424	0.091	0.424	0.091	0.424	0.091	0.424	0.091	0.424	0.091
	SE	0.300	0.091	0.300	0.091	0.300	0.091	0.300	0.091	0.300	0.091	0.300	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Pedestrian_Negligence-Model_1	PACF	-0.043	0.091	-0.043	0.091	-0.043	0.091	-0.043	0.091	-0.043	0.091	-0.043	0.091
	SE	-0.021	0.091	-0.021	0.091	-0.021	0.091	-0.021	0.091	-0.021	0.091	-0.021	0.091

Table (E-13)

ACF and PACF of Residuals for ARIMAX-TFM (1, 0, 1) Model

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	ACF	-0.019	-0.018	-0.060	-0.068	0.157	0.077	0.026	-0.045	-0.135	-0.052	-0.036	0.147
	SE	0.091	0.091	0.091	0.092	0.092	0.094	0.095	0.095	0.095	0.097	0.097	0.097
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	ACF	-0.010	0.004	-0.041	-0.125	-0.047	0.097	-0.053	-0.084	0.015	-0.096	-0.058	0.028
	SE	0.099	0.099	0.099	0.099	0.100	0.100	0.101	0.101	0.102	0.102	0.103	0.103

Model		1	2	3	4	5	6	7	8	9	10	11	12
Injury-Model_1	PACF	-0.019	-0.018	-0.061	-0.071	0.153	0.079	0.027	-0.030	-0.112	-0.075	-0.071	0.120
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Model		13	14	15	16	17	18	19	20	21	22	23	24
Injury-Model_1	PACF	-0.013	0.041	0.005	-0.093	-0.105	0.062	-0.093	-0.114	0.080	-0.047	-0.088	-0.013
	SE	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091	0.091