KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

TEMPORAL MODELLING OF FIRE OUTBREAKS
CASE STUDY: ASHANTI REGION OF GHANA

By

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A Thesis submitted to the Department of Mathematics in partial fulfilment of the requirements for the award of the degree of

MASTER OF PHILOSOPHY

(ACTUARIAL SCIENCE)

NOVEMBER, 2015

Declaration

I hereby declare that this thesis is my work towards master's degree of M. Phil. Actuarial Science and that no part of it has been presented for another degree in this university or elsewhere except where the acknowledgement has been in the text:

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Dedication

This work is dedicated to my dearest family members for their educational passion which has brought me this far.

Abstract

In spite of advances in technology, occurrence of Fire Outbreaks is growing at an increasing rate all over the world but particularly in developing countries like Ghana. It is thus worrying that not much work appears to have been done in Ghana regarding the formulation of statistical and other models for predicting Fire Outbreaks. Due to this, actuarial and insurance practitioners are unable to effectively help manage the risk of Fire Outbreaks.

A Fire Outbreaks is a sudden occurrence of fire greater than would otherwise be expected at a particular time and place. Fire is a rare event often classified an 'Extremal event' and is characterized by relative rareness, huge impact, and statistical unexpectness. In this study, monthly time series data on Fire Outbreaks was obtained from Ghana's Ashanti Regional Fire Service database and was modelled using both SARIMA model and exponentially distributed survival model for monthly prediction of fire occurrences and Fire Premium calculations respectively. The results revealed that ARIMA $(4,1,1)(1,1,1)_{12}$ model was the best SARIMA model for the Fire Outbreaks. This model has the least AIC of 151.1116 and BIC of 176.9176. Diagnostic checks of this model with the LjungBox test and ARCH-LM test revealed that the model is free from higher-order serial correlation and conditional heteroscedasticity respectively. Moreover, the fire premium calculation was based on the equivalence principle of calculating insurance premium approach based more on frequencies than on severity. A more complete risk portfolio model is suggested depending on the availability of data, which would capture both severity and frequency.

Acknowledgements

I wish to express many thanks to Jehovah God Almighty who has guided and blessed me on my journey through KNUST. Furthermore express my profound gratitude to my supervisor, Dr. F. T Odurofor his professional guide, endless effort, and urge to ensuring that this work emerges as one of the standard essay in the university.

This acknowledgement would not be complete without thanking Dr. Akoto Omari Sasu, Mr. Nasiru Suleman, Mr. Abubakari Abdul Ghaniyyu and Miss Justina Brenyah Fosuhene for ensuring professional presentation of work, courage, sound advice and concern during this essay phase.

Finally I wish to express my heartfelt gratitude to my dearest parents, Mr. and Mrs. Amoah for their love and support in the completion of this work and achieving my academic goal.

Contents

Declaration . . . . **i**

Dedication . . . . **ii**

Abstract . . . . **iii**

Acknowledgement . . . . **iv**

List of Tables . . . . **viii**

List of Figures . . . . **ix**

Acronyms . . . . **x**

1 Introduction **1**

1.1 Background of the Study 1

1.2 Problem Statement 2

1.3 Justification of Study 3

1.4 The Objective of Study 4

1.5 Significance of the Study 4

1.6 Structure of the Thesis 4

2 Literature Review **5**

2.1 Introduction 5

2.2 History and Impact of Fire in Some Parts of the World 5

2.3 Fire and Forest Change 8

2.4 Overview of Fire outbreak Situation in Ghana 9

2.5 Empirical Researches on Fire 11

2.6 Generalized Linear Model 17

2.7 Review of Time Series Methods 20

2.7.1 Unit Root Tests 20

2.7.2 Overview on Time Series Methods 22

2.8 Overview of Insurance and Premium 26

2.9 Conclusion 29

3 Methodology **30**
3.1 Introduction 30
3.2 Data and Source 30
3.3 Regression Analysis 30
3.4 Trend Analysis 32
3.5 Box and Jenkins Time Series Methodology 34
3.6 Unit Root Test 34
3.6.1 Augmented Dickey-Fuller (ADF) Test 35
3.6.2 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test 37
3.7 Autoregressive Integrated Moving Average (ARIMA) Model ... 38
3.7.1 p^{th}- Order Autoregressive (AR (p)) Model 39
3.7.2 q^{th}-Order Moving Average (MA (q)) Model 39
3.7.3 Autoregressive Moving Average (ARMA) Model 40
3.7.4 Seasonal ARIMA (SARIMA) Model 40
3.8 Model Selection Criteria 41
3.9 Model Diagnostics 42
3.9.1 Ljung-Box Test 42
3.9.2 ARCH-LM Test 43
3.9.3 CUSUM Test 44
3.10 Modelling Insurance Premiums 44
3.11 Conclusion 48

4 Analysis and Discussion of Results **49**
4.1 Introduction 49
4.2 Preliminary Analysis 49
4.3 Further Analysis 53
4.3.1 Fitting the SARIMA Model 53
4.4 Modelling Insurance Premiums 60
4.5 Discussion of Results 61
4.6 Conclusion 63

5 Conclusion and Recommendations **64**
5.1 Introduction 64
5.2 Conclusion 64
5.3 Recommendations 65
References **66**
Appendix A **72**
Appendix B **77**

List of Tables

2.1 Cost of Damage for the Year 2011 12

2.2 Ashanti Region (2011) 13

4.1 Descriptive Statistics for Fire Outbreak 49

4.2 Monthly descriptive statistics for Fire Outbreak 50

4.3 Regression Parameters of the Transformed First Differenced Series 52

4.4 Monthly Effects on Fire Outbreak 53

4.5 KPSS test of Fire Outbreaks in level form 53

4.6 ADF test of Fire Outbreak in level form 54

4.7 KPSS of Seasonal Differenced Fire Outbreak 54

4.8 ADF test of seasonal differenced Fire Outbreak 54

4.9 KPSS test of Seasonal and Non-Seasonal Differenced Series 55

4.10 ADF test of seasonal and non-seasonal differenced series 55

4.11 Candidate SARIMA Models 57

4.12 Estimates of parameters for $ARIMA(4,1,1)(1,1,1)_{12}$ 58

4.13 ARCH-LM test of residuals of $ARIMA(4,1,1)(1,1,1)_{12}$ 59

4.14 Premium Calculation For Fire Policies 61

5.1 Forecast Values for ARIMA $(4,1,1)(1,1,1)_{12}$ 73

5.2 Data on Fire Outbreak in Ashanti Region of Ghana 74

List of Figures

3.1 Box and Jenkins Process 35

4.1 Time series plot of Fire Outbreak 50

4.2 Residual correlogram of the fire model 51

4.3 Time series plot of first differenced series 55

4.4 Time series plot of first differenced series 56

4.5 Diagnostic plot of $ARIMA(4,1,1)(1,1,1)_{12}$ 58

4.6 CUSUM plot of $ARIMA(4,1,1)(1,1,1)_{12}$ 59

4.7 Forecasting plot of $ARIMA(4,1,1)(1,1,1)_{12}$ 60

List of Acronyms

AIC	Akaike Information Criterion
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AR	Autoregressive
ARCH-LM	Autoregressive Conditional Heteroscedasticity Lagrange Multiplier
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criterion
CV	Coefficient of Variation
CUSUM	Cumulative Sum
df	Degrees of freedom
DF	Dickey-Fuller
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
HEGY	Hyllerberg-Engle-Granger-Yoo
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LCL	Lower Confidence Limit
MA	Moving Average
Max	Maximum
Min	Minimum
PACF	Partial Autocorrelation Function
PP	Phillip-Perron
SARIMA	Seasonal Autoregressive Integrated Moving Average
UCL	Upper Confidence Limit

MA Moving Average

Max Maximum

Min Minimum

PACF Partial Autocorrelation Function

PP	Phillip-Perron
SARIMA	Seasonal Autoregressive Integrated Moving Average
UCL	Upper Confidence Limit

CHAPTER 1

Introduction

1.1 Background of the Study

Policy makers and researchers have generally found that one major problem affecting the economy of developing countries is rampant fire occurrence and Ghana is not an exception in this respect. The current changes in ecosystem functioning and climate systems are having major impact on Fire Outbreaks conditions globally. A Fire Outbreak is a sudden occurrence of fire greater than would otherwise be expected at a particular time and place (investopedia). Through the centuries there has been such an intimate connection of fire with the cultural growth of humanity that whatever relates to the antiquity of fire is important in tracing the history of early progress and because all inventions make use of what has gone before, the stages, which lead up to the making of the first stoves, are necessary in writing of their history. Logically, of course, we may assume there was once a time when man had no fire, but very early he must have become acquainted with fire derived from natural sources, and made use of it; for no remains of man's art show him without fire as his companion. Much later in the scheme of things he invented processes for making fire artificially. Many of the legends or myths relating to the origin of fire are vivid and dramatic, and while they vary in detail there appears to be a similarity in many of the episodes that form the fire origin story in all countries of the world. Fire is a good servant but a bad master as well. Fire is a rare event and is often classified as an 'Extremal event' and is characterized by relative rareness, huge impact, and statistical unexpectness. Fire Outbreaks and disasters are caused by many factors, some of which can be blamed on humans and others beyond our control. The chief purveyors of fire outbreaks in Ghana are classified into seven main categories namely: Electrical, Domestic, Bush, Institutional, Commercial, Industrial and

Vehicular Fire Outbreaks. The name extremal event connotes an extreme case: that is the chance of occurrence is very low but the effect of which is highly severe. Fire tends to be in this category. The Fire Service of Ghana has been targeting a reduction in the number of Fire Outbreaks systematically on yearly basis and hope to achieve single digit in fire fatality rate by the year 2015 (Ghana News Agency, 2010). In order to efficiently achieve this objective, the Fire Service of Ghana needs an accurate estimate of Fire Outbreaks.In modelling the rare phenomena that lie outside the range of availably observations is a problem. Therefore it is very essential to rely on well-founded methodology and model an appropriate time series model to predict fire occurrence.

1.2 Problem Statement

The task of resolving the underlying risk of Fire Outbreaks in Ghana is still a big challenge to researchers and fire stakeholders because not much works appear to have been done in accessing the statistical model for predicting Fire Outbreaks. Due to this, actuarial and insurance practitioners are unable to effectively help manage the risk of Fire Outbreaks. However, the occurrences of Fire Outbreaks and cost of damages are of an increasing trend globally for the past decade. In Ghana, the researchers and policy makers have focused their attention on causes of Fire without paying attention to this important indicator of economic growth. Moreover, in Ghana, Fire Outbreaks did sustain a constant rise reflecting market conditions such as unexpected inflations on goods and services and statistics indicate that there has been about 1500 Fire Outbreaks recorded in Ghana for 2013 alone, and this worrying figure is expected to rise if we fail to tackle this with urgency as a national crisis (Johnson, 2013). Also, according to the late president Mills, Ghana lost GH 360,027,775.75 to Fire Outbreaks in the year 2011 (Ghana News Agency, 2011) which affected the country's economic growth.

Another Research conducted by Fire Safe Europe shows that, US in 2008, the total cost of fire was estimated at $ 362 billion, or roughly 2.5% of US GDP. Economic loss (property damage) reported or unreported, direct or indirect represents only $ 20.1 billion of this total. Net costs of insurance coverage ($ 15.2 billion), fire department costs ($ 39.7 billion), costs of fire protection in new buildings ($ 62.7 billion), other economic costs ($ 44.0 billion), monetary value of time donated by volunteer firefighters ($ 138 billion), and the estimated monetary equivalent of civilian and fire fighter deaths and injuries due to fire ($ 42.4 billion) are all larger components than property loss and these cases provide examples of extreme events. If important risk management organizations such as Ghana Fire Services cannot predict and capture the risks appropriately, their losses could be huge and therefore extremely increase behaviour of fire damages and the substantial impacts of these increments motivate us to carry out a research on modelling fire occurrence and provide insurance premium for the Fire Outbreaks.

1.3 Justification of Study

The huge impact of catastrophic events on our society is deep and long. Investigating the causes of such fire events and developing plans to protect against them should not be the only concern but also have to resolve the results of huge financial loss. For a country to not grow economically, the existence of Fire Outbreaks is a major contributing factor. This is because it causes both the individual and government to lose financially leading to a poor economic growth. The high spate of Fire Outbreaks in Ghana is said to have claimed 795 lives in total of 4577 reported cases of Fire Outbreaks recorded in the country between January December 2013. Furthermore, it was revealed that Brong-Ahafo region recorded the highest number of Fire Outbreaks with 378 fires, followed by Greater Accra region, 330, Ashanti region, 314, while Volta Region’s 46 was the lowest on record. Another study conducted by the Research, Monitoring and

Evaluation Unit of the National Fire Service revealed that the government spend GH 40,321,963 properties (**www.graphicline.com**).

1.4 The Objective of Study

Specifically, the project seeks to

To investigate the monthly effects on the Fire Outbreaks

To develop an appropriate time series model for predicting the Fire Outbreaks

To determine probabilistic actuarial models (survival model) for computing premiums with respect to Fire Outbreaks.

1.5 Significance of the Study

The findings of this study could be used by fire stakeholders such as Ghana National Fire Service to efficiently manage and perfectly prediction fire number of fire in the future to prevent unforeseen governmental losses. Also help actuarial and insurance practitioners to calculate fire premiums that will help to sustain their insurance policies. In addition, this study could provide basis for further researches on fire in the fire industries.

1.6 Structure of the Thesis

The thesis is organized into five chapters. Chapter one contains the introduction of the research work. Chapter two comprises of literature review. Chapter three outlines the methodology employed in this research while chapter four presents the analysis and discussion of results. Chapter five is devoted to conclusion and recommendations.

CHAPTER 2

Literature Review

2.1 Introduction

This chapter reviews empirical works done on Fire Outbreaks. The chapter is divided into eight main headings namely; History and Impact of Fire in Some Part of the World, Fire and Forest Change, Overview of Fire Outbreaks Situation in Ghana, empirical researches on fire, Generalized Linear Model, Review of Time Series Methods, Overview of Insurance and Premium and conclusion.

2.2 History and Impact of Fire in Some Parts of the World

Africa is mostly called 'fire continent' (Trollope and Trollope, 2004) as a result of widespread anthropogenic fire (i.e fire associated with anthropogenic land use) that yearly burn the vegetation of savannah (Mbow et al., 2000; Reid et al., 2000; Laris, 2002; Danthu et al., 2003). In the savannah of Southern Africa, where anthropogenic fire are frequent (Shcoles and Archer, 1997), the hunter gathers in the Kalahari region used savannah burning from manipulating vegetation to attract the animals they hunt (Sheuyange, 2002). Fire is a widespread process in the earth system and plays a key role in ecosystem composition and distribution (Bond and Keeley, 2005).

Also, Herakleitos famously observed that everything is change, and more specifically concluded that all things are an exchange for fire, and fire for all things. For him fire was a metaphor for dynamism. Fire changed matter. It moved: fast or slow, the world burned, and that burning accounted for Earth's ceaseless motions. By the nineteenth century, modern science had demystified fire. Energy replaced fire as a universal medium, and scientists reconceptualized flame as form of oxidation, a subset of physical chemistry. But the notion of fire as a motive power endured. Slow combustion in the form of respiration powered the living world. Fast combustion in the guise of flames transmuted landscapes. And internal combustion within mechanical chambers powered the industrial revolution (Pyne, 2014).

Furthermore most fire outbreaks are attributed to careless handle of fire by human of which some can be blame on us and other beyond our controls. Some careless behavior that can cause fire outbreaks include: Irresponsible use of fireworks; fireworks should be aimed only at the skies. Aiming fireworks to any other direction can cause a fire disaster. Falling asleep whiles you are cooking, leaving rubbish and trees near your house. Careless use of candle and other naked flames; Avoid the use of candles for illumination as much as is possible. Use candle only for your religious rituals or romantic dinners and turn them off afterwards. Pouring kerosene into the kerosene tank of your kerosene lamp lit (thus may cause explosion that can ignite a fire). Faulty electrical wiring; in order to save cost, where thicker cables ought to be used, can cause heating, which can ignite the insulation and spark off a fire disaster. Ensure that certified electrical engineers are employed to supervise your house wiring.in addition, inspect the electrical wiring of your house and ensure that it is in good condition before packing in.

Storage of fuel or other inflammable substance around the house or through the part were naked fire may pass and smoking near inflammable substances. In addition, ignorance can lead to fire outbreaks thus poor awareness of what fire is and how it can be prevented has resulted to a lot of fire occurrence; however being ignorance will also make you to ignore gadget that can save your property during a fire outbreak and also compromise with buying a fire insurance policy.

Information about fire, how to prepare for fire disaster and to prevent fire disasters can be found in many books on fire. Fire requires fuel, oxygen and heat to burn. Elimination of any of these elements will extinguish any fire no matter how intense it is. A good knowledge of fire will enable you to know the possible fire risk areas in your house.

Moreover, arson also causes fire outbreaks. Arson is a malicious burning of property of another due to riot or strike and also accident do occur sometimes. When all necessary precautions have been taken accidents can still occur. This is often beyond your control. Electrical sparks can occur; lighting and more can cause fire outbreaks. Knowing the causes of fire empowers you to prevent it (Beatthefire, 2006).

The establishment of India fire service in Bombay (1803), followed by Calcutta (1822) and Madras (1908) thus completed Advisory council under Ministry of Home Affairs recommended various aspects of uniform fire service development throughout the country. In 1997, Ministry of Home Affairs declared that a total 1754 fire stations with 5149 fire appliances and 50730 fire professionals are functioning throughout India. However, these services are limited to unban and industries areas. Furthermore studies shows that major fire incidents in India are due to the explosion in the fireworks factory and homemade fireworks followed by residential fire and others. Each year, 450 to 470 people lives are lost in India to burn injuries caused by firecrackers and ironically, majority of them are children and women. The Loss Prevention Association of India Ltd (LPA) maintain that, thousands of cases relating to burn injuries go unreported. In 2002 the LPA has advised the government to introduce a ban on sale of fireworks to children below 15 years (India Fire Service, 1997).

Also, analysis of data showed that the total number of death due to fire in 2001, 2002 and 2003 was 5787 and total property loss was estimated to Rs 1046 crore in India. The vast majority of all fire related mortality and morbidity in USA result from non-catastrophic fires which is the occurrence of fire in residential areas.

An analysis of yearly mortality data from 1978 through 1984 in USA shows that average 4897 persons died each year in residential fires.

A similar analysis of data from 1979 through 1985 indicates that smokes inhalation accounted for two-third of deaths and burns accounted for one-thirds (United State Fire Administration, 1992).

2.3 Fire and Forest Change

Stand-maintenance vs Stand-Replacement Fire: Fires change in temperature, intensity, vegetative conditions, topography, duration and size, weather conditions and attempt to suppress the fire (Wenger, 1984).

Considering these factors, fire effects on ecosystem can be viewed over continuum, ranging from small scale low intensity fires such as single lighting struck snag, to large scale high intensity fire such as those that burned a third of Yellowstone National Park in 1988.

Fire effect are mostly characterized according to the effect the fire has on the ecosystem. Stand replacement fires are also called 'catastrophic' fires ,which is characterized by moderate to high intensity fire activity that kills almost all vegetation within fire bounds. The dead vegetative substance left after the fire often creates a further fuel hazard resulting to increased fire danger in the future.

Stand fire include low to adequate intensity fire activity which commonly burn slow to the ground and mainly affect shrubs, grasses, and small trees. This type of fire typically burn off accrue vegetation debris on the ground without killing larger trees and thus reduce the danger of future fires without causing major impact on the current vegetation component of the area (Wenger, 1984).

Notwithstanding, Guyette et al. (2002) conducted a research on dynamics of anthropogenic fire regime. They noted that human interaction with fire and vegetation occurs at many levels of human population density and cultural development, from subsistence cultures to highly technological societies. The dynamics of these relations with respect to wildland fire are often challenging to understand and identify at short temporal scales. Also dendrochronological fire histories from the Missouri Ozarks, coupled with human population data, offer a quantitative means of investigative historic from 1680 to 1990 changes in the anthropogenic fire regime. Furthermore an indication of percent of sites burned and fire intervals of anthropogenic fires are conditioned by the following four limiting factors: (a) anthropogenic ignition, (b) surface fuel production, (c) fuel fragmentation, and

(d) cultural behaviour based on temporal analysis of fire scar dates over the last 3 centuries. The following conclusions were made during an ignition-dependent stage (fewer than 0.64 humans/km^2), the percent of sites burned is logarithmically related to human population ($r^2 = 0.67$). During a fuel-limited stage, where population density exceeds a threshold of 0.64 humans/km^2, the percent of sites burned is independent of population increases and is limited by fuel production. During a fuel-fragmentation stage, regional trade allows population densities to increase above 3.4 humans/km^2, and the percent of sites burned becomes inversely related to population ($r^2 = 0.18$) as decreases in fuel continuity limit the propagation of surface fires. During a culture-dependent stage, increases in the value of timber over forage greatly reduce the mean fire interval and the percent of sites burned.

2.4 Overview of Fire outbreak Situation in Ghana

The Ghana National Fire Service was established in 1963 by Act 219 with the primary objective of firefighting and extinguishment and to render humanitarian service. Subsequently, in 1997 Ghana National Fire Service Act (Act 537) was enacted to reestablish the National Fire Service with the objective of Preventing and managing undesired fires and other related matters with an expanded mandate.

There has been so many statistics on fire incidents in Ghana. Notably among them are Anaglatey (2013) reports that barely 14 days in 2013, Ghana witnessed 254 fire cases in the country. These fire cases include market fires which is a common issue that Ghanaian markets face.

Again, according late president Mills, Ghana lost GH 360, 0277,775.75 to fire outbreaks which affected the economy of the county, therefore noted that bushfire were more frequent and urged Metropolitan, Municipal and District Assemblies and Traditional authorities to enforce bye laws to protect the environment (Ghana News Agency, 2011).

Also, Dr. Albert Brown Gaizie, Chief Fire Officer of GNFS in January 2015 revealed a statistics on reduction of fire outbreak in the 2014. He compared a total of 3783 cases of fire outbreaks recorded in 2014 as against 4171 cases recorded in 2013, representing a decrease of 388 cases. Furthermore, noted that on a Regional basis, the statistics showed that there were considerable declines in most of the regions. The Ashanti Region recorded 646 in 2014 as against 836 in 2013, Brong Ahafo registered 382 in 2014 compare with 553 in 2013, while
Central Region recorded 320 cases in 2014 down from 405 in 2013. However, Greater Accra recorded the highest fire outbreaks with 857 in 2014 up from 547 reported cases in 2013. He said the service had employed several measures such as market patrol teams, where personnel are deployed to all the markets to educate the traders and ensure fire safety as well as protect lives and property. He added that the service would establish a rapid deployment force to be the first response to any unforeseen fire outbreaks since some of the incidences requires rapid response and extrication. The following recommendations were made in order to combat fire incidence in Ghana by appealing to industries to employ the

services of fire safety officers to ensure safety on their premises at all time and enumerated inadequate water hydrants, unauthorised electrical connections, and inadequate number of fire station in newly developing communities as some of the challenges facing the Service and called for government support.

Furthermore, the Ghana National Fire Service (2014) gave statistics on fire outbreaks and revealed that Accra tops the list with a total damage valued at GH 564,168,260, followed by Ashanti Region (ASHR) with GH 96,680, then Brong Ahafo Region (BAR) GH 80,621 while that of Volta Region (VR) stands at GH 60,270.

The Northern Region (NR) recorded GH 14,780 while Tema (TR) had GH 7,300. The cost of items which were salvaged was GH 7,070. Currently, there has been 300 domestic fires, 71 bush fires, and 107 commercial fires all totaling 779. The number of persons who got injured are 256 while 48 died within January and February. It is estimated that the numbers of fire for March and April would increase as the country keeps recording rampant fire outbreaks.

For the whole of 2013, the cost of damage from disasters across all the 10 regions of the country was GH 25,081,919.05. Accra recorded GH 19,940,469, BAR GH 2,476,204.00, Eastern Region GH 1,013,409.05, NR GH 44,090, TR GH 23,610, Upper East Region (UER) GH 850,411, and WR GH 733,726. Meanwhile, there was a total of 5489 fire outbreaks across the nation last year which injured 1,128 persons and caused 213 deaths.

Table 2.1 gives the statistics on fire outbreak in Ghana and Ashanti in the year 2011.

2.5 Empirical Researches on Fire

Many researches have been carried out on Fire using different theorem and mathematical models. Hence, Hansen (1999) modelled a Risk-Based Fire Research Decision to support United States Coast Guard regulators' determinations of the most appropriate fire safety areas for allocating research and development resources.

The methodology consists of risk based analysis of past shipboard fire and ex-

Table2.1:CostofDamagefortheYear2011

RegionJanFebMarAprMayJunJulAugSepOctNovDecTotal	
AR	106,000.00398505.00263685.00498520.0036974.0029590.00179055.002414717367343798874109061210372.004491699.00
BAR	143226.001700.00450630.0085429.0060.00561277.0023570.003293453410212566861651848 59.001835826.00
CR	350.000.000.001500.000.000.007200.000.007545200000.000.0036595.00
ER	0.000.000.000.000.000.000.000.000.000.000.00127800.00127800.00
GAR	0.000.000.000.000.000.000.000.000.000.000.000.000.00
NR	163300.001500.001100.000.0010600.00200.000.0010.000.0085000151801990.00278880.00
TR	11440.0032914.0040650.0034227.0015530.0016620.007025.004100.0011570.00136659650114202088 11.00
UER	2979.08540.000.000.000.000.0052000.003500.0016850.009300.0045000.0089669.08
UWR	0.000.000.000.000.000.000.000.000.000.000.000.000.00
VR	0.000.000.000.000.000.000.000.000.000.000.000.000.00
WR	0.000.00600.000.00171869.00150445.0012500.001350.00135022019.0039140.0039210438483.00
HQ	0.000.000.000.000.000.000.000.000.000.000.000.000.00
FATS	0.000.000.000.000.000.000.000.000.000.000.000.000.00
TOTAL	427295.08435159.00756665.00619676.00235033.00758132.00281350.00283365.00827459.00742437.00565541.001575651.007507763.08

Table2.2:AshantiRegion(2011)

FireOutbreak InjuryDeath	Costof Damage	Costof Salvage	Domestic IndustrialVehicularInstitutionalElectricalCommercialBushOthersTotal
	106000		291184377271
	398505		3291031910680
	263685		22363163448
	498520		2947328255
	36974		206115610159
	29590		362104410773
1	179055		2319145750
	241471		251122101253
	736734		338231157
	379887		202172881269
	410906		2751236131269
	1210372		47393610785
0	4491699		3434611835461073143769
			44.603381015.98179453815.344.5515.98213.9144.0312093635.592100

Month	Rescue No.InjuryDeath
Jan	2116026
Feb	136912
Mar	634
Apr	145
May	872
Jun	7505
Jul	2116
Aug	1721
Sept	12927
Oct	102
Nov	10188
Dec	15245
Total	15437499
%	

plosion incidents to establish historical problem areas and trends. Moreover the following results were obtained as the top five areas for possible allocation of research and development resources are: egress of passengers and crew, development of international design and approval standards for fire protection systems, hazard analysis review of fire safety regulations, development of alternative design assessment methodology, and investigation of lagging requirements for fire protection.

Furthermore Twum-Barima (2014) made a research on assessing the Awareness of Fire Insurance in the Informal Sector by considering a sample of 95 traders and found out most was found out that majority (50.52%) of the traders did not understand the concept of insurance by wrong perception about it but they were aware of the causes of fire outbreak and ranked electricity power fluctuations as the major cause. The Relevant recommendations have been made for these traders and policy makers to strategize in order to have better protection on the markets.

Next, Dare et al. (2009) modelled on Incidents of fire outbreaks during fuel truck accidents in Oyo State. They argued that accident explosions have mechanical induced activities on the road, with potential costly damages to structures and nonstructural property exposed to them, and loss of lives. The objective was to determine the various causes of accidents and rollover fire outbreaks in fuel trucks in Oyo State, Nigeria in order to properly plan to avoid costly damages to structures and non-structural property exposed to them, and loss of lives.

Using primary data collected from field and secondary data obtained from the Nigeria Police, Road Safety Commission and Fire Services Agency. The following findings were obtained: from about 358 transport accidents recorded in Nigeria between 1999 and 2002, only 33 were due to cars while the rest involved trucks and heavy-duty vehicles. The survey showed that about 32 per cent of truck drivers are below 30 years and probably immature. Also 62 per cent of fuel truck tanks manufactured are of inferior quality and may thus have been aiding fire outbreaks when there is an accident. The study also showed that about 54 per cent of tank leakages that may lead to fire outbreak are due to operators' carelessness. The research recommended that more education must be given to drivers and adequate legislation for tank manufacturers.

Again, Ignas et al. modelled on an investigation of provisions of fire safety measures in buildings in Dar es salaam. They revealed that one of the major causes of damage of constructed facilities in particular buildings in Tanzania is fire. Recently, numerous cases of fire outbreaks have caused serious damage to buildings and other properties especially in Dar es Salaam. However, the research further revealed that fire damages can be significantly reduced if appropriate fire prevention and protection measures are taken into account during the design and construction stages of buildings. In this manuscript, therefore, observations and results of investigation carried out to determine the provisions of fire safety measures in the design and construction of buildings in Dar es Salaam are presented. It has been established that in some of the buildings investigated, fire safety measures have not been adequately provided and in case of fire outbreaks serious damages are likely to occur.

In addition, Keane et al. (2013) also conducted a research on Fire Severity Mapping System for Real-Time Fire Management Applications and Long-Term Planning. Accurate, consistent, and timely fire severity maps are needed in all phases of fire management including planning, managing, and rehabilitating wildfires. The problem is that fire severity maps developed from satellite imagery are difficult to use for planning wildfire responses before a fire has actually happened and can't be used for real-time wildfire management because of the timing of the imagery delivery. The objective of the research was to blend many fire severity mapping approaches that will help meet demands from fire and other natural resource managers for accurate and rapid assessment of spatial fire severity given time, funding, and resource constraints.

Also, China fire services in 2012 modelled Fire Risk Assessment of Residential Buildings Based on Fire Statistics from China by considering incidence of fire from 1991 to 2001. From their analysis, it was noted that, the spatial, temporal and causal fire incident data for the last six years have been analysed to gain an understanding of fire characteristics and the elements affecting fire risks. It was found that the number of fires was observed to be higher during cold winter months, and fires were more frequent during the weekend. The number of fires was lower during night time, whereas the number of fire deaths between midnight and 4 a.m. was much higher than at other times of the day. Most fire incidents occurred in residential buildings. In economically developed East China, the fire situation is much more serious. Electrical failures and improperly fire use in daily life were major causes of fire incidents. Based on the statistical data from China's fire services and the China Statistical Yearbook, the risk of occupant deaths and the risk of direct property loss are calculated to express the risk level in residential buildings. It was found that the risk of occupant deaths had a declining trend over the years. Statistics is considered a useful tool for learning from the actual events, and it helps decision makers develop proactive fire protection measures to reduce fatalities and financial losses caused by fires.

In 2008, National Research Council Canada conducted a research in Fire risk evaluation and cost assessment model and presented building fire risk analysis model based on scenario clusters and its application in fire risk management of buildings. Building fire risk analysis is a process of understanding and characterizing the fire hazards, the unwanted outcomes that may result from the fire, and the probabilities of fire and unwanted outcomes occurring. Their determination was to evaluate and make a decision about the level of fire risk to determine whether to take appropriate risk management measures or not.

Therefore, building fire risk analysis serves as a basis for fire risk management. In the research, scenario clusters were constructed in the process of building fire risk analysis, and the number of deaths and directive property loss are selected as building fire risk indexes. Finally, the average fire risk of residential buildings was quantified in detail. With the types of detailed fire risk models developed here, fire risk management measures could be taken to improve the building fire safety grading and reduce fire risk levels and subsequent damage.

Also Yung and Benichou (2002) studied how design fires can be used in Fire Hazard Analysis. Many countries have introduced, or are planning to introduce in the near future, performance and aim based codes by the use of engineering analysis of fire development and occupant evacuation the performance and aim based code were considered and the level of safety provided to the occupants in a building by a particular fire safety design were assessed Central to this performance based on the approach that was used for a suitable design fires that can characterize typical fire growth in a fire compartment.

The research gave description of what features of design fires needed and how they can help analyse fire hazards to the occupants in a building as a result of smoke movement, untenable state in the stairs, and occupant response and evacuation.

2.6 Generalized Linear Model

The generalized linear model (GLM) is a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution.

The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value Generalized linear models were formulated by John Nelder and Robert Wedderburn as a way of unifying various other statistical models, including linear regression, logistic regression and Poisson regression. They proposed an iteratively reweighted least squares method for maximum likelihood estimation of the model parameters (Wikipedia).

Regression is from the Latin root ’re’ and ’gradus’ and littrally translate ’to go back’. The general meaning to return to an earlier or more general pattern, fits well with the application to mathematics and statistics. The fire use of word is usually credited to Sir Francis Galton in 19th century to describe a biology phenomenon (Wilson, 2011).

The phenomenon was that the height of descendants of tall ancestors tends to regress down towards a normal average (this phenomenon is also known as regression towards the mean) (Mogul, 2004). For Galton, regression had only this biological meaning but his work was later extended by Udyny Yule and Karl Pearson to a more general statistical context. It is also known that the published by Legendre in 1805 and by Gauss in 1809. Legendre and Gauss both applied the method to the problem of determining from astronomical observations, orbit of bodies about the sun. Gauss published a further development on the theory of least square in 1821, including a version of the Gauss Markov Theorem.

Furthermore, Albert et al. (2013) studied the year effect on the volume of Currency in Circulation in Ghana was studied.

The New Year effect was seen in the Currency in Circulation as the first three months of Circulation. The months of January, February and 7.4309, 5.0307 and 0.2112 percent respectively. The December effect was also seen in the volume of Currency in Circulation as the month of had the highest incremental effect of (18.6046

Also, Alexander (2014) researched in Modelling Apartment Prices with the Multiple Linear Regression Model andstudied factors that were of most statistical significance for the sales prices of apartments in the Stockholm City Centre. Factors considered during his study were area, balcony, construction year, elevator, fireplace, floor number, maisonette, monthly fee, penthouse and number of rooms. On the basis of this examination, a model for predicting prices of apartments is built. In order to evaluate how the factors influence the price, his research employed was the multiple linear regression model to analyze sales statistics and the mathematical method The result of the research stated that, it is possible to construct a model, from the factors analyzed, which can predict the prices of apartments in Stockholm City Centre with an explanation degree of 91% and a two million SEK confidence interval of 95%. Furthermore, a conclusion can be drawn that the model predicts lower priced apartments more accurately. In the case-study and literature review, the result indicates support for the hypothesis that proximity to public transport is positive for the price of an apartment. However, such a variable should be regarded with caution due to the purpose of the modelling, which differs between an individual application and a social economic application.

Next, Bhattacharya and Joshi (2001) modelled the Currency in Circulation in India using regression model. They argued that the standard currency demand equation based on the theory of transactions and portfolio demand for money, and the univariate time series models used for modelling Currency in Circulation, only work well for low frequency data: their scopes are limited for high frequency series. They therefore proposed an alternative approach of modelling Currency in Circulation by incorporating day of the month effect. Their estimated equation behaved very well for the in and out of sample forecast.

Additionally, Bepari and Mollik (2009) employed a combined regression-time series model with dummy variable for months to study the monthly effect in stock returns of the Dhaka Stock Exchange (DSE).

The results of their study confirmed the existence of seasonality in stock returns but do not support the ’tax-loss-selling’ hypothesis. Instead of ’July or January effect’ they found an ’April effect’ in the DSE.

Moreover, Asante (2012) modelled on regression analysis on Fire Outbreaks in Assin North Municipality. The analysis sought to identify the five main cause of fire outbreaks (electrical, commercial, domestic, bush fire and institutional) and determine its effect on quarterly total number of Fire Outbreaks and develop implementation control and precaution system. The study was based on cases in Assin North Municipality Fire Outbreaks and covered ten years quarterly period from 2001 to 2010.

During the analytical stages of the project, it was realized that the data obtained defined the assumption of the normal distribution. From the analysis, it was concluded that, the five variables: electrical, commercial, domestic, bush fire and institutional were the best predictors of the quarterly total number of fire outbreaks and recommended that there should be intense educational on fire outbreak country wide and also urge people that call the fire service helpline to fake fire outbreaks to stop in order for Ghana Fire Service to embark on their duties professionally and efficiently.

2.7 Review of Time Series Methods

2.7.1 Unit Root Tests

Modelling time series data require the process of checking stationarity of the data. On the contrary, most time series data are found to be non-stationary. However, Fuller (1976) and Dickey and Fuller (1979) advocates tests (Dickey-Fuller (DF)) test and Augmented Dickey-Fuller (ADF) test) in which a null hypothesis is a non-stationary process with a unit root and an alternative hypothesis is a trend stationary process.

Numerous methods have been developed for testing unit root. In 1982, Nelson and Plosser used the tests developed by Dickey and Fuller to test the economic indicators of the American economy. They established a fact that almost all economic time series such as the Gross National Product have unit root.

Furthermore, Phillips and Perron (1988) weakened a strong assumption on the error term and extended the Dickey-Fuller test to a more general test (Philips-Perron (PP) test). However, the PP-test did not alter the result of Nelson and Plosser (1992), even using the same data as Nelson and Plosser (1992). In 1992, Kwiakowski et al. also made a vital contribution on unit root test . They developed a unit root test that reversed the null hypothesis and alternative hypothesis (KPSS test) and verified that only half of the economic time series had unit root using the same data set as Nelson and Plosser (1992).

Furthermore, Christiano (1992) criticised Perron's exogenous treatment of a structural change and devised a method with which structural changes with a drift term and a trend can be detected endogenously and proposed a test whose null hypothesis is a unit root process without a structural change and whose opposing hypothesis is a stationary process with a structural change.

Again, another test whose null hypothesis is a unit root process without any change in a drift term and whose alternative hypothesis is trend stationary process with a structural break was proposed by Zivot and Andrews (1992). This proposed test can detect a time point of a structural change endogenously and its asymptotic distribution is constant regardless of the time points of structural changes.

Dickey et al. (1984) following the methodology suggested by Dickey and Fuller

(1979) for the zero-frequency unit-root case, proposed the Dickey, Hasza and Fuller (DHF) test to test for seasonal unit root. The DHF test only allows for unit roots at all of the seasonal frequencies and has an alternative hypothesis which is considered rather restrictive, namely that, all the roots have the same modulus. Trying to overcome these drawbacks Hylleberg et al. (1990) propose a more general testing (HEGYs test) strategy that allows for unit roots at some (or even all) of the seasonal frequencies as well as the zero frequency. HEGY's methodology allows testing for unit roots at some seasonal frequencies without maintaining that unit roots are present at all seasonal frequencies.

Finally, Banerjee et al. (1992) proposed three kinds of unit root tests. Firstly, a recursive test that is extended on the basis of a structural stability test of Brown et al. (1975) which uses recursive residuals. Secondly, a rolling test that shifts a partial testing period successively among the whole sample period and thirdly a sequential test that conducts t-tests or Quandt likelihood ratio tests while shifting a time point of a structural change among the whole sample.

2.7.2 Overview on Time Series Methods

In the mid 1920s time series began to be treated in stochastic sense (Gottman, 1981). Yule (1927) first came out with an Autoregressive (AR) model when working on wolfer's sunspot data and in 1927 Slutzky also firstly developed a Moving Average (MA) model when studying a white-noise series. Box and Jenkins (1970) developed the Autoregressive Moving average (ARMA) model and gave a full account of the Integrated Autoregressive Moving average (ARIMA) model.

Also, a theorem to estimate the AR (p) parameters by the least squares method was proved by Mann and Wald (1943). For simplicity, Quenouille (1947) presented a test for AR (p) models and far along extended to MA models.

Furthermore, Anderson (1971) developed a procedure to estimate the order of the AR model as well as the AR parameter.

Moreover, a non-linear least squares technique procedure that resulted in developing technique of approximated likelihood solution for ARMA (p, q) models was developed by Box and Jenkins (1970). In addition, the parameter estimation for Moving Average model of order q and for Autoregressive Moving Average of order p and q models was developed by Newbold (1970). The Box-Pierce statistics was developed by Box and Pierce (1970) and modified by Ljung and Box (1978).

Again, Akaike (1974) proposed an information criterion to assist in the selection of an ARIMA model and concluded that a model with the smallest Akaike Information Criterion (AIC) is the best model to have minimum forecast mean square errors.

Also in 1978, Schwarz indicated that AIC was not consistent when probability approaches one, and proposed a Bayesian Information Criterion (BIC).

Moreover, Harvey and Phillips (1979) developed an exact likelihood procedure to estimate parameters of an ARIMA model in State-Space form. The State-Space models are also called Structural Time Series (STS) models. Many researchers have pointed out the advantages of the State-Space form over the ARIMA models (Durbin and Koopman, 2001). A time series might be characterised with trend, seasonal cycle and calendar variations, together with the effects of explanatory variables and interventions. These components can be processed separately and for different purposes for a State-Space model.

On contrary, the Box-Jenkins ARIMA model is a black-box model, which solely depends on the data without knowledge of the system structure that produces the data. The second advantage is the recursive nature of the State-Space model that obviously allows change of the system overtime, while ARIMA models are homogenous through time, based on the stationary assumption.

In 1982 Eagle came out with another important contribution in the area of time series analysis when he introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model, to model changing volatility. The non-linear term is the variance of the disturbance. An extension of the ARCH model to the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model was made by Bollerslev (1986).

Again, Weiss (1984) proposed an ARMA-ARCH model, in which an ARMA model is used to model mean behaviour and an ARCH model to model the residuals of the ARMA model. The quasi-maximum-likelihood method is used to estimate model parameters.

Furthermore, Nasiru and Sarpong (2012) modelled the pattern of reserve money growth in Ghana of which the Currency in Circulation forms an integral part of it. Box-Jenkins methodology was used in their study and an appropriate seasonal ARIMA model for the reserve money growth was identified. Their result exhibited that there was a decrease in the pattern of the reserve money from September, 2010 and a continuous surge from the middle of the year 2011 to December, 2012. They made recommendation that both government and policy holders should slow down the growth rate of the reserve money because this could lead to an increasing inflation thus high prices of commodities in the country.

In addition, Nasiru (2013) researched on Modelling of Currency in Circulation in Ghana. The Currency in Circulation was monthly data obtained from the Bank of Ghana database and modelled using both SARIMA model and Regression model with ARIMA errors. The results revealed that $ARIMA(0,1,1)(0,1,1)_{12}$ model was the best SARIMA model for the Currency in Circulation. This model has the least

AIC of -372.16, AIC_c of -371.97 and BIC of -363.53. Also, regression model with ARIMA (0, 0, 1) errors was identified as the best regression model with ARIMA errors. This model has an AIC of -417.39, AIC_c of -416.57 and BIC of -396.60. Diagnostic checks of both models with the Ljung-Box test and ARCHLM test revealed that both models are free from higher-order serial correlation and conditional heteroscedasticity respectively. A comparative analysis of the forecasting accuracy of these models with the Diebold-Mariano test revealed that there is no significant difference in the forecasting performance of the two models. The two models were therefore proposed for predicting Currency in Circulation in Ghana. However, the Currency in Circulation is volatile and subject to several unobservable developments in the economy.

Therefore continuous monitoring of the forecasting performance of these models, review of market conditions and necessary adjustments are required to make the use of these models more realistic.

Also, Cabrero et al. (2002) modelled the daily series of bank notes in circulation in the context of managing the European monetary system. Empirical models in that paper relied on two liquidity forecasting approaches; seasonal ARIMA method and Structural Time Series (STS). Cabrero et al. (2002) noted that the error in forecasting banknotes in circulation never exceeded one billion Euros in both models and they concluded that econometric models are able to explain an important part of the variation in the Currencies in Circulation.

Furthermore, Lang et al. (2008) modelled the currency outside banks in Croatia using regression analysis. They fitted two regression equations to the series. They fitted a regression model based on the first difference of the series and a regression model with the residuals having an Autoregressive Integrated Moving Average (ARIMA) structure. They compared these models with the naive model which assumes no change in the level of currency in the future, as well as the staff forecast created by the liquidity forecast division of the Croatia National Bank (Expert). Both models outperformed the naive model, due to strong seasonality of the series. Also, both statistical models slightly outperformed the Expert model in 2005. With the two models, the regression model gave the best short term forecasts up to five days ahead while the ARIMA model outperformed it at the long horizon.

Also, Dheerasinghe (2006) modelled on an impact in Currency in Circulation by forecasting the Currency in Circulation based on daily, weekly and monthly data for the period 2000 to 2005 in Sri-Lanka. Dheerasinghe (2006) captured trend and seasonal effects by regressing on trend and seasonal dummies. Cyclical dynamics were captured by allowing for Autoregressive Moving Average (ARMA) effect in the regression disturbances. The forecast produced by all the three models accurately match the shape of the monthly, weekly and daily oscillations, and capture the trend, seasonal and cyclical effects. Post sample estimation errors of the models were small and remained less than one percent in all models. All the three models clearly identified both inter-month and intra-month variations of Currency in Circulation. The forecast based on the daily and monthly models performed very well, predicting similar results and were close to realised data when used within sample.

Also, Liu (1980) studied the effect of holiday variation on the identification and estimation of ARIMA models. He suggested modifications of ARIMA models by including holiday information as deterministic input variable(s) and used the monthly highway traffic volume in Taiwan as a case study.

Another contribution to the study of Currency in Circulation was made by Simwaka (2006). He studied the determinants of Currency in Circulation in Malawi using regression analysis. He first fitted a regression model using annual data and then fitted a second model using monthly data in order to capture some seasonal factors affecting the Currency in Circulation.

The model fitted with the monthly data captured seasonal variable such as the tobacco market season and Christmas effect on Currency in Circulation. Also, the effects of ATM cards and smart card were captured in this model. Simwaka (2006) also employed the Augmented Dickey-Fuller (ADF) test to test for the stationarity of all the series before fitting the regression model. The model estimated in this study followed the standard demand for money model that includes the traditional variables such as the real interest rates, Gross Domestic Product growth, inflation and a measure of financial deepening. Instead of using the nominal value of the Currency in Circulation as the dependent variable, the Currency in Circulation per money stock ratio was used.

2.8 Overview of Insurance and Premium

The history of insurance is probably as old as the story of human. The same instinct that prompts modern businessmen today to secure themselves against disaster and loss existed in primitive men also. They most at times sought to avert the evil consequences of flood and fire and loss of life, and eager to make some sort of sacrifice in order to achieve security(Scribed, 2011).

Insurance is planned to meet the financial status of a company, individual and other entity in the case of unexpected losses. The agreement terms between an insured and the insurer create an insurance policy. In exchange for premium payments from the insured, the insurer agrees to pay the policyholder compensation upon the occurrence of a specific event (Gart, 1990).

Insurance Premium is the sum of money that the insured will be paid to the insurer in the exchange of taking the risk from the insurer. The amount of money to be charged for a certain amount of insurance coverage can be a term insurance, deferred insurance, and a whole life insurance. Insurance is a pooling of risks and based on the premise that whereas many people will pay premiums to the insurance company, probably only a few will make claims. Part of the payment of the many is used to pay compensation to the few who suffer losses (Troxel and Comick, 1983).

Conceptually, insurance is a devise whereby many individuals facing the same risk form a pool into which each individual contributes premiums, and out of which the few who actually suffer unforeseen and unexpected losses are compensated. Moreover, Fire insurance is a specialized form of insurance beyond property insurance, and is designed to cover the cost of replacement, reconstruction or repair beyond what is covered by the property insurance policy. Policies cover damage to the building itself, and may also cover damage to nearby structures, personal property and expenses associated with not being able to live in or use the property if it is damaged (Investopedia).

Yaohua et al. (2002) modeled on the Calculating Method of Insurance Premium of Residential Mortgage Loan and noted that residential mortgage loan insurance are developing very rapidly in current years. However, there are still some inevitable risks, how to calculate insurance rate has been a magnitude task for insurance companies. Based on discrimination between residential mortgage loan insurance and other insurances, the research analyzed an insurance structures of United States and found that insurance institute in USA can often establish its corresponding insurance structure (include insurance payment mode, number of insurance rate, disposal method when pre-payoff) according to client's specific circs (such as sum of loan, term of loan, loan to value), so the controlling of risk of regional mortgage loan insurance is become easy, the rights and interests of insurance institute can be well protected. Moreover the research present a new calculating method that can calculate insurance premium in different insurance structures by using expected return equals the expected loss, the excellence of this method was that we can calculate insurance premium in different circs if we have related parameters (such as default rate, pre-payoff rate); it's shortcoming was that these parameters are not easy to get, and so we must often change insurance premium because these parameters often change along with time.

Furthermore, Yu (2015) also modelled on Hierarchical Bayesian Modeling of Health Insurance Claims and the objective of the thesis was propose a statistical model for health insurance total claim amounts classified by age group, region of residence and time horizon of the insured population under Bayesian framework.

This model can be used to predict future total claim amounts and thus to facilitate premium determination. The future is based on the past observed information and prior beliefs about the insured population, number of claims and amount of claims. The insured population growth is modelled by a generalized exponential growth model (GEGM), which takes into account the random effects in age region and time classifications. Based on the predicted values, the premiums are estimated using four premium principles and two risk measures.

Again, Brisard (2014) modelled on Pricing of Car Insurance with Generalized Linear Models. The argument was that tarification is a difficult exercise since different explanatory variables are available and often a long history preceeds the analysis, therefore. He noted that when pricing premium the following factors must be considered; claim frequency, claim severity and Generalized linear models is very efficient to predict important ratios, like the claim frequency, claim severity and pure premium.

2.9 Conclusion

The chapter dealt with reviewing of literature that is relevant to the study. Reviewing of the literature has exposed us to the diverse techniques that researchers have employed in modelling the Fire Outbreaks. However, among the diverse techniques reviewed the Seasonal Autoregressive Integrated Moving Average model was employed in this study to model the Fire Outbreaks because they were the techniques used frequently in literature.

CHAPTER 3

Methodology

3.1 Introduction

This chapter deals with the data and statistical techniques that were employed in order to achieve the objectives of the study. The chapter is divided into eight main headings namely; data and source, regression analysis, Box and Jenkins time series methodology, unit root test, autoregressive integrated moving average model, model selection criteria, model diagnostics and modelling insurance premium.

3.2 Data and Source

In order to achieve the objectives of this study, secondary data on monthly fire outbreaks and was obtained from the Ashanti Regional Fire Station database. The data consists of monthly fire outbreaks from January, 1997 to August, 2014. The Computational Software employed to analyze the data were R, Minitab and Gretl.

3.3 Regression Analysis

The concept of regression analysis is to explain the variation in an outcome or response variable using one or more predictor variables. The end result of a regression analysis is often to generate a model that can be used to predict future values of the response variable given specified values of the predictor variables. When the model involves a single predictor variable, the model is referred to as simple linear regression model. The simple linear regression model is given by

$$Y = \beta_0 + \beta_1 X + \varepsilon \tag{3.1}$$

where Y is the response, X is the predictor variable, β_0 and β_1 are unknown parameters and ε is an error term. The model parameters, β_0 and β_1 have physical interpretation as the intercept and slope of straight line respectively. When the simple linear regression model is extended to include additional predictor variables say k predictors, then we have the multiple linear regression model. The multiple linear regression model is given by

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon \qquad (3.2)$$

The parameters β_0, β_1, β_2,⋯, β_k in this model are called the partial regression coefficients because they convey information about the effect on Y of the predictor that they multiply given that all other predictors in the model do not change. In the theoretical model, many assumptions are made about the predictor variables and the error term. This model is said to be linear because it is a linear function of the unknown parameters; β_0, β_1, β_2,⋯, β_k. In the theoretical model, many assumptions are made about the predictor variables and the error term. When these assumptions are satisfied, the estimators are unbiased and have the minimum variance property. Some of these assumptions of the regression model are;

i. ε_i is a random real variable.

ii. The mean value of ε_i in any particular period is zero.

iii. The variance of ε_i is constant in each period. iv. The

variable ε_i has a normal distribution.

v. The random term of different observations (ε_i, ε_j) are independent.

vi. The predictor variables are not perfectly linearly correlated.

Least Square Estimation method of least square may be used to estimate the regression coefficients in the multiple regression model.

Given

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \varepsilon_i$$

This can also be simplified as

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + \varepsilon_i \qquad \text{for} \qquad i = 1,2,\cdots,n$$

The least square function is

$$L = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{k} \beta_j X_{ij}\right)^2$$

Minimizing L with respect to $\beta_0, \beta_1, \beta_2, \cdots, \beta_k$. The Least Square estimate of $\beta_0, \beta_1, \beta_2, \cdots, \beta_k$ must satisfy

$$\frac{\partial L}{\partial \beta_0}(\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_k) = -2\sum_{i=1}^{n}\left(y_i - \hat{\beta}_0 - \sum_{j=1}^{k} \hat{\beta}_j X_{ij}\right)^2 = 0, \quad \text{for} \quad i = 1,2,\cdots,k$$

3.4 Trend Analysis

Many financial and economic time series data exhibit trend. It is therefore imperative to investigate what the nature of the trend is. A trend is a slow, long-run, evolution in the financial or economic variable (Dheerasinghe, 2006). Thus, the trend reflects the long-run growth or decline in the time series. The trend in a time series data may appear as a linear function of time, non-linear function of time or the trend may be characterised by a constant growth rate. If the trend in the time series is a linear function of time t, then

$$Y_t = \beta_0 + \beta_1 t + \varepsilon \quad (3.3)$$

where Y_t are the observations of the time series, t is a time dummy ($t = 1,2,\cdots,n-1,n$) and ε_t is a random error component.

Sometimes, the series may exhibit a quadratic trend or the nature of the trend may be a polynomial of higher order say k. If the trend is quadratic, then

$$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon \quad (3.4)$$

For a polynomial of order k

$$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \cdots + \beta_k t^k + \varepsilon \quad (3.5)$$

If the trend is characterised by a constant growth rate, then the equation is

$$Y_t = \beta e^{\beta_1 t} \varepsilon_t \quad (3.6)$$

In logarithmic form

$$lnY_t = ln\beta_0 + ln\beta_1 t + ln\varepsilon_t \quad (3.7)$$

If the constant growth rate is quadratic, then

$$lnY_t = ln\beta_0 + ln\beta_1 t + ln\beta_2 t^2 + ln\varepsilon_t \quad (3.8)$$

The coefficients appearing in the equations (3.3) to (3.8) above are obtained by applying the principles of Ordinary Least Squares.

3.5 Box and Jenkins Time Series Methodology

Box and Jenkins was named after the statisticians George Box and Gwilym Jenkins. Box and Jenkins Analysis refers to a systematic method of identifying, fitting, checking, and using integrated autoregressive, moving average (ARIMA) time series models. The method is appropriate for time series of medium to long length. The first stage is the identification of the appropriate ARIMA models through the study of the autocorrelation and partial autocorrelation functions. The next step is to estimates the parameters of the ARIMA model chosen. The third step is the diagnostic checking of the model. The Ljung Test, ARCH-LM Test and CUSUM Test are used for the model adequacy check. If the model is not adequate then the forecaster goes to stage one to identify an alternative model and it is tested for adequacy and if adequacy then the forecaster goes to the final stage of the process. The fourth step is where the analysis uses the model chosen to forecast and the process ends.

The Figure in 3.1 below is the diagrammatic representation of Box -Jenkins process.

3.6 Unit Root Test

A very important aspect of time series analysis is to ensure that the data is weakly stationary. A weakly stationary time series is one whose first and second moments are invariant of time. That is, the expected value of the time series does not depend on time and the autocovariance function, $cov(y_t, y_{t+k})$ for any lag k is only a function of k and not time, that is $\gamma_y(k) = cov(y_t, y_{t+k})$.

Many methods have been proposed for testing for stationarity of a time series data. These include both graphical and quantitative methods. The graphical approach includes observing the Autocorrelation function (ACF) plots. A strong and slow dying ACF will suggest deviation from stationarity. For the purpose of this study, in addition to the ACF, two quantitative techniques for testing

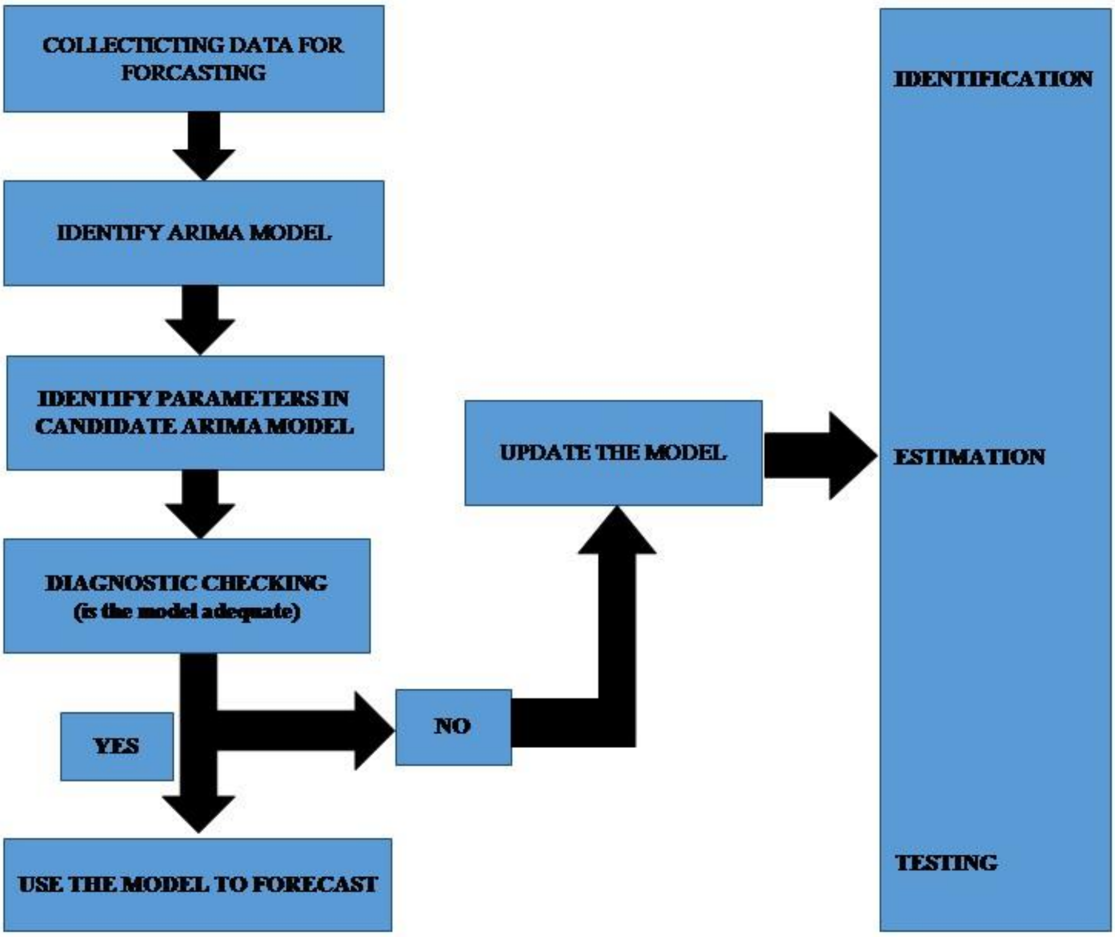

Figure 3.1: Box and Jenkins Process

for unit root were employed. These are; the Augmented Dickey-Fuller test and Kwiatkowski-Phillips-Schmidt-Shin test.

3.6.1 Augmented Dickey-Fuller (ADF) Test

The ADF test proposed by Dickey and Fuller (1979) was an improvement of the Dickey-Fuller (DF) test. The test is based on the assumption that the series follows a random walk. Consider an autoregressive process of order one, $AR(1)$, below

$$Y_t = \varphi Y_{t-1} + \varepsilon_t \tag{3.9}$$

where ε_t denotes a serially uncorrelated white noise sequence with a mean of zero and constant variance. If $\varphi = 1$, equation (3.9) becomes a random walk model without drift, which is known as a non-stationary process. The basic concept of the ADF test is to simply regress Y_t on its lagged value Y_{t-1} and find out if the estimated φ is statistically equal to one or not. Equation (3.9) can be manipulated by subtracting Y_{t-1} from both sides to obtain

$$\Delta Y_t = \delta Y_{t-1} + \varepsilon_t \qquad (3.10)$$

where $\delta = \varphi - 1$ and $\Delta Y_t = Y_t - Y_{t-1}$. In practice instead of estimation equation (3.9), we rather estimate equation (3.10) and test for the null hypothesis of $\delta = 0$ against the alternative $\delta \neq 0$. If $\delta = 0$, then $\varphi = 1$, meaning that the series have a unit root. Under the null hypothesis $\delta = 0$, the t-value of the estimated coefficient of Y_{t-1} does not have an asymptotic normal distribution (Erdogdu, 2007).

The decision to reject the null hypothesis or not is based on the DF critical values of the τ-statistic. The DF test is based on the assumption that the error terms are uncorrelated. However, the errors of the DF test usually show evidence of serial correlation. In order to overcome this problem, the ADF test includes the lags of the first difference series in the regression equation to make the error term white noise and therefore the regression equation is presented in the following form

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-1} + \varepsilon_t. \qquad (3.11)$$

To be more specific, the intercept may be included as well as time trend t, after which the model becomes

$$\Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-1} + \varepsilon_t. \qquad (3.12)$$

where α is a constant, β the coefficient on time trend series, $\sum_{i=1}^{p} \gamma_i \Delta Y_{t-1}$ is the sum of the lagged values of the dependent variable ΔY_t and p is the lag order of the autoregressive process. The parameter of interest in the ADF test is δ. For δ = 0, the series contains unit root and hence non-stationary. The choice of the starting augmentation order depends on; data periodicity, significance of y_i estimates and white noise residuals. After preliminary estimation, non-significant parameter augmentation can be dropped in order to enjoy more efficient estimates. The test statistic for the ADF test is given by

$$F_\tau = \frac{\hat{\delta}}{SE(\hat{\delta})}$$

where $SE(\hat{\delta})$ is the standard error of the least square estimate of $\hat{\delta}$. The null hypothesis is rejected if the test statistic is greater than the critical value.

3.6.2 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

This is complementary test for investigating the order of integration of a series Y_t and Y_t is to test $H_0 : Y_t \sim$ **I(0)**, thus the data generating process is stationary against the alternative $H_1 : Y_t \sim$ **I(1)** that it is non-stationary. Kwiatkowski et al. (1992) derived a test for this pair of hypotheses by assuming that there is no linear trend term therefore the point of departure is a data generating process of the form

$$Y_t = X_t + \varepsilon_t$$

where X_t is a random walk and $X_t = X_{t-1} + v_t$, $v_t \sim \text{iid}(0,\sigma_v^2)$ and ε_t is a white noise sequence. In this context, the foregoing pair of hypotheses is equivalent to the pair;

$$H_0 : \sigma_v^2 = 0$$

$$H_1 : \sigma_v^2 > 0.$$

If H_0 holds, Y_t is composed of a constant and the stationary process ε_t. Kwiatkowski et al. (1992) proposed the following test statistic

$$\text{KPSS} = \frac{1}{T^2}\sum_{t=1}^{T}\frac{S_t^2}{\hat{\sigma}_\infty^2}$$

where T is the number of observations, $S_t = \sum_{j=1}^{t}\widehat{\omega}_j$ with $\widehat{\omega}_j = Y_t - \bar{Y}$ and $\hat{\sigma}_\infty^2$ is a Hac estimator of

$$\hat{\sigma}_\infty^2 = \lim_{T\to\infty} T^{-1} Var\left(\sum_{t=1}^{T}\varepsilon_t\right)$$

That is, $\hat{\sigma}_\infty^2$ is an estimator of the long-run variance of the process ε_t. If Y_t is a stationary process, S_t is integrated of order one (**I(1)**) and the quantity in the denominator of the KPSS statistic is an estimator of its variance, which has a stochastic limit. The term in the denominator ensures that overall; the limiting distribution is free of unknown nuisance parameters. If, however, Y_t is integrated of order one (**I (1)**), the numerator will grow without bounds, causing the statistic to become large for large sample sizes. The null hypothesis of stationarity is rejected for large values of KPSS.

3.7 Autoregressive Integrated Moving Average (ARIMA) Model

An ARIMA model is a concatenation of Autoregressive (AR) model which shows that there is a relationship between present and past values, a random value and a Moving Average (MA) model which shows that the present value has something to do with the past shocks. It is called integrated because the stationary Autoregressive Moving Average (ARMA) model that is fitted to the differenced data has to be integrated to provide a model for a non-stationary data. A time series is said to be integrated if it has to be differenced d times to make it stationary and is denoted **I (d)**.

3.7.1 p^{th}- Order Autoregressive (AR (p)) Model

A time series variable follows an AR process if the current value depends on its past values. That is, the future of the series can be predicted using its past values. A general p^{th}- order AR model denotes as AR (p) is given as

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \dots + \varphi Y_{t-p} + \varepsilon_t \tag{3.13}$$

where ε_t is a white noise process and φ_i are constants, i = 1,2,...,p. Using the lag operator, the model can be written as

$$\Phi(L) Y_t = \varepsilon_t \tag{3.14}$$

where $\Phi(L) = 1 - \Phi_1 L - \Phi_2 L^2 - \dots - \Phi_p L^p$.

The AR (p) time series $\{Y_t\}$ is stationary if the roots of the associated polynomial $m^p - \varphi_1 m^{p-1} - \varphi_2 m^{p-2} - \dots - \varphi_p$ are less than one in absolute value.

3.7.2 q^{th}-Order Moving Average (MA (q)) Model

A time series $\{Y_t\}$ is said to follow a Moving Average process if its current values depends on its past shocks. That is the forecast values of the series depends on the past errors. Thus, a Moving Average process of order q (MA (q)) is given as

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{3.15}$$

where ε_t is white noise and θ_j are constants, j = 1,2,...,q. MA (q) process is always stationary regardless of values of the weights. In terms of the lag operator, the MA (q) process is

$$
\begin{aligned}
Y_t &= (1 - \theta_1 L - \theta_2 L^2 - \ldots - \theta_q L^q & (3.16)\\
&= \left(1 - \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t & (3.17)\\
&= \Theta(L)\varepsilon_t & (3.18)
\end{aligned}
$$

where $\Theta = (1 - \sum_{i=1}^{q} \theta_i L^i)$.

3.7.3 Autoregressive Moving Average (ARMA) Model

ARMA model is a concatenation of the AR and MA model of order p and q respectively. In general, an ARMA (p,q) model is given as

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots + \varphi Y\, t - p + \varepsilon - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \quad (3.19)$$

where φ_i and θ_j are parameters of the autoregressive and moving average components respectively, i = 1,2,··· ,p and j = 1,2,··· ,q. The stationarity of an ARMA process is related to the AR component in the model and can be checked through the roots of the associated polynomial. If all the roots are less than one in absolute value, then ARMA (p,q) is stationary.

3.7.4 Seasonal ARIMA (SARIMA) Model

The strong periodic patterns exhibited in a time series data is often referred to as seasonal behaviour in the time series and when this happens the ARIMA model becomes inefficient because it may not be able to capture the behaviour along the seasonal part of the series which result in wrong order selection for non-seasonal component. An extension of an ARIMA model is known SARIMA model which capture both seasonal and non-seasonal behaviour. The SARIMA model denoted by $ARIMA(p,d,q)(P,D,Q)_s$ can be expressed using the lag operator as (Halim and Bisono, 2008);

$$\varphi(L)\Phi(L^s)(1-L)^d(1-L^s)^D Y_t = \theta(L)\Theta(L^s)\varepsilon_t$$

$$\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - \ldots - \varphi_p L^p$$

$$\Phi(L^s) = 1 - \Phi_1 L^s - \Phi_2 L^{2s} - \ldots - \Phi_P L^{Ps}$$

$$\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \ldots - \theta_q L^q$$

$$\Theta(L^s) = 1 - \Theta_1 L^s - \Theta_2 L^{2s} - \ldots - \Theta_Q L^{Qs}$$

where

p,d,q are the orders of non-seasonal AR, differencing and MA respectively

P,D,Q are the orders of seasonal AR, differencing and MA respectively Y_t represent the time series data at period t,

s represent the seasonal order, L represent the lag operator and

ε_t represent white noise error at period t.

3.8 Model Selection Criteria

When fitting models, there is the tendency of two or more models competing and for that reason it is appropriate to use good model selection criteria to select the most adequate model. In this study, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were the measures of goodness of fit that were employed to select the most adequate model. For a given data set, several competing models may be ranked according to their AIC, or BIC values with the one having the lowest information criterion value being the best. The information criterion attempts to find the model that best explains the data with a minimum of free parameters but also includes a penalty that is an increasing function of the number of estimated parameters. This penalty discourages over fitting (Aidoo, 2010). In the general case, the AIC, and BIC are given by;

$$AIC = 2k + n\log\left(\frac{RSS}{n}\right)$$

$$BIC = \log(\sigma_e^2) + \frac{k}{n}\log(n)$$

where

k is the number of parameters in the statistical model, *RSS* is

the residual sum of squares of the estimated model,

n is the number of observations in the data,

σ_e^2 is the error variance.

3.9 Model Diagnostics

In order to use any developed model to draw any meaningful conclusion or make generalisation, it is important to diagnose the model to see whether there is concordance of the model with the real world observations. Thus, we employed the Ljung-Box, ARCH-LM and the CUSUM test in diagnosing the developed models.

3.9.1 Ljung-Box Test

One of the major problems that a researcher is likely to encounter in fitting time series models is serial correlation. That is, temporal dependency between successive values of the model residuals. In this study, the Ljung-Box test proposed by Ljung and Box (1978) was used for testing the assumption that the residuals contain no serial correlation up to any order k. The test procedure is as follows;

H_0 : There is no serial correlation up to order$k$ H_1 :

There is serial correlation up to order$k$.

The test statistic is given by;

$$Q_m = T(T+2)\sum_{k=1}^{m}(T-k)^{-1}r_k^2$$

where r_k^2 represent the residual autocorrelation at lag k, T is the number of residuals, m is the number of time lags included in the test.

When the p-value associated with Q_m is large, the model is considered adequate else the whole estimation process has to start again in order to get the most adequate model.

3.9.2 ARCH-LM Test

The issue of conditional heteroscedasticity is one of the key problems that a researcher is likely to encounter when fitting models. This happens when the variance of the residuals is not constant. To ensure that the fitted model is adequate, the assumption of constant variance must be achieved. The ARCHLM test proposed by Engle (1982) was used to test for the presence of conditional heteroscedasticity in the model residuals. The test procedure is as follows;

H_0 : There is no heteroscedasticity in the model residuals H_1

: There is heteroscedasticity in the model residuals.

The test statistic is

$$LM = nR^2$$

where n is the number of observations and R^2 is the coefficient of determination of the auxiliary residual regression.

$$e_t^2 = \beta_0 + \beta_1 e_{t-1}^2 + \beta_2 e_{t-2}^2 + \cdots + \beta_q e_{t-q}^2 + v_t$$

where e_t is the residual. The null hypothesis is rejected when the p-value is less than the level of significance and is concluded that there is heteroscedasticity.

3.9.3 CUSUM Test

Another important way to check a model is to investigate its stability overtime. The CUSUM test proposed by Brown et al. (1975) was used to test the stability of the models developed. The test statistic is given by;

$$\text{CUSUM}^{\tau} = \sum_{t=k+1}^{\tau} \frac{\hat{u}_t^{(r)}}{\hat{\sigma}_u}$$

where $\hat{u}_t^{(r)}$ are the recursive residuals and $\hat{\sigma}_u$ is the standard error of the regression fitted to all T sample points and $\tau = K + 1, \cdots, T$. If the CUSUM wanders off too far from the zero line, then there is evidence of structural instability of the underlying model. A test with a significance level of 5% is obtained by rejecting stability if $CUSUM_\tau$ crosses the lines $\pm 0.948 \left[\sqrt{T-K} + \frac{2(\tau-K)}{\sqrt{T-K}}\right]$ (Ploberger et al., 1989). This test is designed to detect a non-zero mean of the recursive residuals due to shift in the model parameters.

3.10 Modelling Insurance Premiums

Insurance is a promise of compensation for specific potential future losses in exchange for a periodic payment (Rejda, 1992). In analysis of risk of catastrophic event an insurer uses the exponential distribution with mean μ as the distribution of the time until the event occurs. However, the third objective based on equivalence principle of a semi-continuous level month benefit premium for a unit fire insurance payable immediately fire occur at time 't' where x will be the month of inception into the fire policy. The following assumptions were made for the premium calculations;

Let S_1,S_2,S_3,... be the count of sequential arrival of fire outbreaks which we assume is Poisson distributed. The count differences X_1,X_2,X_3,... correspond to inter-arrival duration and these are positive random variables defined in terms of the count arrivals by $X_1 = S_1$ and $X_i = S_1 - S_{i-1}$ for $I > 1$. These inter-arrival duration follows an exponential distribution.

Moreover, total loss (Y) by fire is given as

$$Y = S_1 + S_2 + \cdots + S_N \tag{3.20}$$

where

N is a random variable and represent frequency of fire loss and

S_k is the individual losses in the risk portfolio and represent severity.

Therefore

$$Y = N \cdot E[X/N] \tag{3.21}$$

Alternatively,

$$Y = X_1 + X_2 + \cdots + X_T$$

where

T represent frequency in the durational time and is continuously distributed,

X represent severity in the duration T.

Also,

$$Y = T \cdot E[X/T] \quad (3.22a)$$

$$E[Y] = E[T] \cdot E(E[X/T]) \quad (3.22b)$$

$$= E[T] \cdot E[X] \quad (3.22c)$$

Equation (3.22c) is indicating the product of frequency and severity,

where, by assumption,

$E[T] = \frac{1}{\mu}$ (T is exponentially distributed) and

$E[X]$ is assumed to correspond to a uniform distribution (level benefit).

Furthermore, let present value for GH 1 be denoted by V^T. Therefore the Actuarial Present Value (APV) can be expressed as

$$(APV) = E[V^T] \quad (3.23a)$$

$$= \int_0^k v^t f_T(t)dt \quad (3.23b)$$

$$= \int_0^k e^{-\delta t} \mu e^{-\mu t} dt \quad (3.23c)$$

$$= \int_0^k e^{-(\delta+\mu)t} dt \quad (3.23d)$$

Note that the model (3.23d) closely resembles temporary life insurance, where 'age x' correspond to inception month and θ is the average number of fire outbreaks in a month and μ play the role of an instant force of mortality while $\mu = \frac{1}{\theta}$ is average time until fire occurs.

Henceforth, because of the apparent resemblance, we shall use the corresponding notation of a temporary life insurance model in our fire premium calculation.

The premium calculation was based on semi-continuous insurance model because premiums are paid monthly and benefits are received immediately fire occurs, by equivalence principle, premium for semi -continuous level 12-monthly benefit for a unit temporary fire insurance payable immediately fire occurs is denoted by equivalence principle, premium for semi -continuous level 12-monthly benefit for a unit temporary fire insurance payable immediately fire occurs is denoted by;

$P(\bar{A}^1_{x:\overline{12}|})$ and is such that

$$\bar{A}^1_{x:\overline{12}|} - P(\bar{A}^1_{x:\overline{12}|})\ddot{a}_{x:\overline{12}|} = 0$$

$$\Rightarrow P(\bar{A}^1_{x:\overline{12}|}) = \frac{\bar{A}^1_{x:\overline{12}|}}{\ddot{a}_{x:\overline{12}|}} \tag{3.24}$$

where

$$\bar{A}^1_{x:\overline{12}|} = \int_x^{12+x} e^{-\delta t}\mu e^{-\mu t}\,dt \tag{3.25a}$$

$$= \mu\int_x^{12+x} e^{-(\delta+\mu)t}\,dt \tag{3.25b}$$

$$= \mu\int_x^{12+x} e^{-(\delta+\mu)t}\,dt \tag{3.25c}$$

$$\ddot{a}_{x:\overline{12}|} = \frac{1 - \bar{A}^{1}_{x:\overline{12}|}}{d} \tag{3.26}$$

$$\delta(t) = ln\left(1 + \frac{i}{12}\right) \tag{3.27}$$

$$d = \frac{i(1 + i)^{-1}}{12} \tag{3.28}$$

$\bar{A}^{1}_{x:\overline{12}|}$ indicates the actuarial present value of a 12-month term insurance policy of fire benefit of 1 payable immediately after fire occurs. $\ddot{a}_{x:\overline{12}|}$ is an annuity due per month for fire policy. $\delta(t)$ is the force of interest.

However, for these insurance policies there would be no economic incentive for the insurance policyholder to pay premium for more than 12 months, since at that moment no additional future benefit is possible.

3.11 Conclusion

The chapter dealt with the statistical techniques employed in this study. It presented the techniques in a clear, precise and concise manner.

CHAPTER 4

Analysis and Discussion of Results

4.1 Introduction

This chapter analyses, discusses and interprets the results obtained from the study. The chapter is organized into preliminary analysis, further analysis and discussion of results.

4.2 Preliminary Analysis

This section explains the descriptive statistics of the data on Fire Outbreaks in Ashanti Region of Ghana. The maximum (Max) and minimum (Min) values for the Fire Outbreaks for the entire period were 218 and 18 respectively as shown in Table 4.1. Also, the Fire Outbreaks for the entire period was positively skewed and leptokurtic in nature with the average and coefficient of variation (CV) being 54.17 outbreaks and 52.95% respectively.

Table 4.1: Descriptive Statistics for Fire Outbreak

Variable	Mean	Min	Max	CV (%)	Skewness	Kurtosis
Fire Outbreaks	54.17	18.00	218	52.95	2.03	6.37

An exploration of the Fire Outbreaks for the various months indicates that, the highest average outbreak of Fire occurred in the month of January and the least average occurred in the month of September as shown in Table 4.2. In terms of the maximum and minimum fire occurrences, January and June had the highest and lowest values respectively. The month of January has the largest variability followed by April as shown by their coefficient of variations (CV) in Table 4.2. Again, it was observed that the occurrence of fire for each month were positively and negatively skewed and leptokurtic and platykurtic in nature.

Table 4.2: Monthly descriptive statistics for Fire Outbreak

Month	Mean	Min	Max	CV (%)	Skewness	Kurtosis

January	97.6	39.00	218.00	47.89	1.15	1.13
February	92.44	53.00	150.00	30.02	0.52	-0.43
March	68.11	38.00	99.00	25.57	0.00	-0.90
April	49.28	22.00	79.00	37.25	0.35	-1.08
May	42.78	21.00	61.00	30.00	-0.01	-1.45
June	38.56	18.00	73.00	36.68	0.87	0.68
July	38.44	21.00	62.00	30.51	0.66	0.10
August	39.17	19.00	63.00	33.46	0.41	-0.74
September	37.24	19.00	57.00	30.63	1.28	-0.67
October	43.41	29.00	75.00	35.80	1.27	0.04
November	44.71	28.00	69.00	29.87	0.59	-0.75
December	56.41	25.00	85.00	29.45	0.11	-0.56

The time series plot of the fire outbreak shows that the Fire Outbreak increase and decrease exponentially as shown in Figure 4.1.

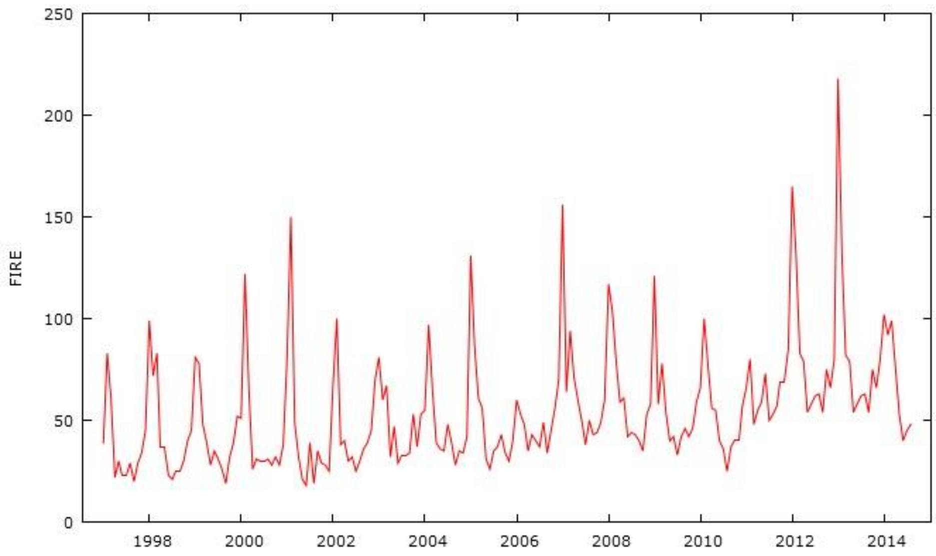

Figure 4.1: Time series plot of Fire Outbreak

The residual seasonality is obviously shown in the residual correlogram of the fire model in Figure 4.2 and the Durbin-Watson (0.813031) suggests serial correlation in errors. The following spikes 12, 24, 36 and 48 were significant at the seasonal displayed in the residual sample autocorrelation function. The residual partial autocorrelation function also showed significant spikes only at seasonal lag 12. The estimated Ljung-Box statistic of 349.027 with a *p*-value =

0.000 at lag 12 rejects the white noise null hypothesis of the residuals of the fire model.

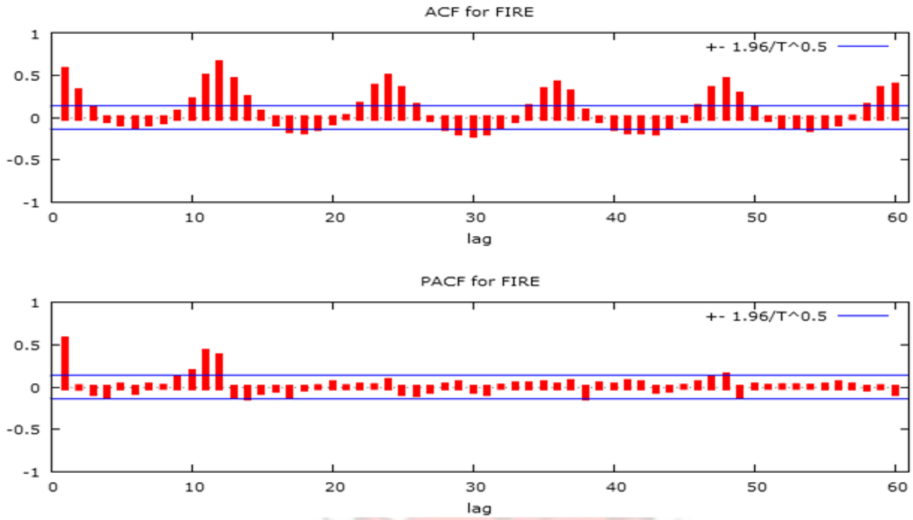

Figure 4.2: Residual correlogram of the fire model

For the purpose of analysing the monthly implication of changes of Fire Outbreak, the transformed Fire Outbreak was first differenced and regressed on the full set of periodic dummies. The intercept was not included in the model to avoid dummy variable trap. The result (Table 4.3) revealed that January, March, April, October and December had a significant monthly effects on the fire outbreaks whiles

February, May, June, July, August, September and November were insignificant. The F-statistic of 9.651750 and p-value of 0.0000 indicates that the regression model was significant and Durbin-Watson statistic of 2.911460 means that there is no serial correlation of the first order in the model residuals. Also, the LjungBox statistic of 19.7813 with a p-value of 0.0713 provides evidence that the model residuals are white noise at the lag 12.

As shown in Table 4.3, the model clearly indicates significant negative seasonality for the month of March and April and a positive significant seasonality for the month of January, October and December.

Table 4.3: Regression Parameters of the Transformed First Differenced Series

Variable	Coefficient	Standard error	T-statistic	p-value
January	0.54102	0.0737322	7.3377	0.00001*
February	0.00320	0.0716548	0.0447	0.96440
March	-0.29607	0.0716548	-4.1320	0.00005*
April	-0.35925	0.0716548	-5.0136	0.00001*
May	-0.11887	0.0716548	-1.6589	0.09871
June	-0.11947	0.0716548	-1.6672	0.09704
July	0.01537	0.0716548	0.2145	0.83039
August	0.00766	0.0716548	0.1069	0.91499
September	-0.02860	0.0737322	-0.3878	0.69855
October	0.14928	0.0737322	2.0246	0.04424*
November	0.04012	0.0737322	0.5442	0.58693
December	0.22883	0.0737322	3.1036	0.00219*

NB: * Means statistically significant at the 5% level of significance

Considering Table 4.3, their significance does not really matter because some of the estimated coefficients of the dummy variables are of an incremental month effects of each year. Hence, an approach of interpreting differential coefficients in semi-logarithmic was proposed by Halvorsen and Palmquist (1980) and the equation of the transformations of differential coefficients are to show differential effects in terms of change in percentage. The monthly effect for each is calculated with the aid of an exponential transformation and further multiplied by 100% to show percentage change as indicated in Table 4.4. The month of March, April, May, June, and September decreases the Outbreak of Fire by 25.6268, 30.1801, 11.2076, 11.2606 and 2.8191 percent respectively. Similarly, the month of January, February, July, August, October, November and December increases the Outbreak of Fire by 71.7770, 0.3207, 1.5488, 0.7688, 16.0998, 4.0939 and

25.7135 percent respectively.

Table 4.4: Monthly Effects on Fire Outbreak

Month	Coefficient	Percent effect
January	0.54102	71.7770
February	0.00320	0.3207
March	-0.29607	-25.6268

April	-0.35925	-30.1801
May	-0.11887	-11.2076
June	-0.11947	-11.2606
July	0.01537	1.5488
August	0.00766	0.7688
September	-0.02859	-2.8191
October	0.14928	16.0998
November	0.04012	4.0939
December	0.22884	25.7135

NB : Effect of January = $(e^{0.541027} - 1) \times 100\%$

4.3 Further Analysis

4.3.1 Fitting the SARIMA Model

The coefficient of skewness and kurtosis of 2.03 and 6.37 respectively in the descriptive statistics in Table 4.1 revealed that there are large swings in the data indicating non-stationarity. Furthermore, seasonality and the non-stationarity of the series can be affirmed from the oscillation of the ACF plot and a very dominant significant spike at lag 1 and 12 of the PACF plot as shown in Figure 4.2.

A unit root test was performed to prove the proper ordering of differencing filter. By the method of KPSS test, we test the null hypothesis that the original series is stationary at the non-seasonal level. From the test results as indicated in Table 4.5, since the calculated value is outside the critical region at the 5% level of significance, we reject the null hypothesis that the series is stationary.

Table 4.5: KPSS test of Fire Outbreaks in level form

Test	Test Statistic	Critical value
KPSS	1.12461	0.463

The results of ADF test are shown in Table 4.6 which confirm that there is existence of unit root under the condition where either a constant or constant with linear trend are included.

Table 4.6: ADF test of Fire Outbreak in level form

Test	**Constant**		**Constant+Trend**	
ADF	**Test Statistic**	***P*-value**	**Test Statistic**	***P*-value**
	-1.0300	0.6131	-2.10498	0.5425

The ACF plot in Figure 4.2 indicates that there is clearly evidence of seasonality in the series. Therefore, the series was transformed using logarithmic transformation in order to stabilise the variance. The transformed series was seasonal differenced and tested for stationarity. Both the KPSS and ADF test shown in Table 4.7 and Table 4.8 respectively revealed that the transformed seasonal differenced series was not stationary.

Table 4.7: KPSS of Seasonal Differenced Fire Outbreak

Test	**Test Statistic**	**Critical value**
KPSS	0.03697	0.463

Table 4.8: ADF test of seasonal differenced Fire Outbreak

Test	**Constant**		**Constant+Trend**	
ADF	**Test Statistic**	***P*-value**	**Test Statistic**	***P*-value**
	-3.8726	0.0260	-4.8635	0.0003

The transformed seasonal differenced Fire Outbreak was again non-seasonal differenced. The KPSS test of the transformed seasonal and non-seasonal differenced Fire outbreak indicates that the series is now stationary at the 5% level of significance as shown in Table 4.9.

Table 4.9: KPSS test of Seasonal and Non-Seasonal Differenced Series

Test	**Test Statistic**	**Critical value**
KPSS	0.0751	0.4630

The ADF test in Table 4.10 affirms that the transformed seasonal and nonseasonal differenced Fire Outbreak is stationary.

Table 4.10: ADF test of seasonal and non-seasonal differenced series

Test	**Constant**	**Constant+Trend**

ADF	Test Statistic	P-value	Test Statistic	P-value
	-5.5696	0.0300	-5.5619	0.0028

The stationarity of the series can also be confirmed from the time series plot of the transformed seasonal and non-seasonal differenced series. As shown in Figure 4.3, the series fluctuates about the zero line confirming stationarity in mean and variance of the series.

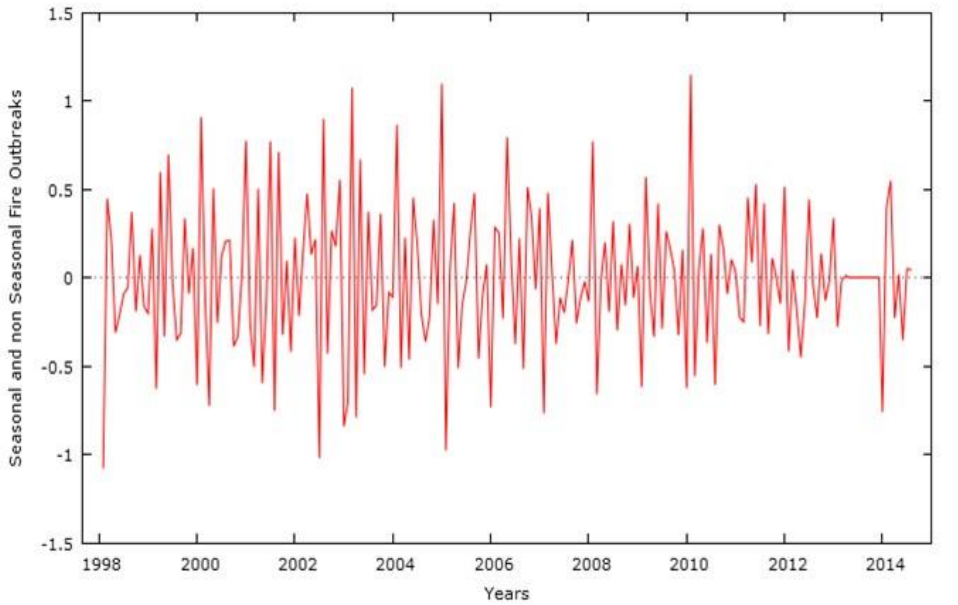

Figure 4.3: Time series plot of first differenced series

After the Fire Outbreak order of integration has been obtained, the order of the Autoregressive and Moving Average for both non-seasonal seasonal components was determined. This was obtained from the ACF and PACF plots based on the Box and Jenkins approach. From Figure 4.4, the ACF plot have significant spike at the non-seasonal lag 1 and seasonal lag 12, with significant spikes at other non-seasonal lags. The PACF plot also has significant spikes at the non-seasonal lags 1, 2, 3 and 4 seasonal lags 12 and 36. The PACF plot also has significant spike at other non-seasonal lags. We identified candidate models for the Fire Outbreak by using the lower significant lags of both the ACF and PACF and
their respective seasonal lags.

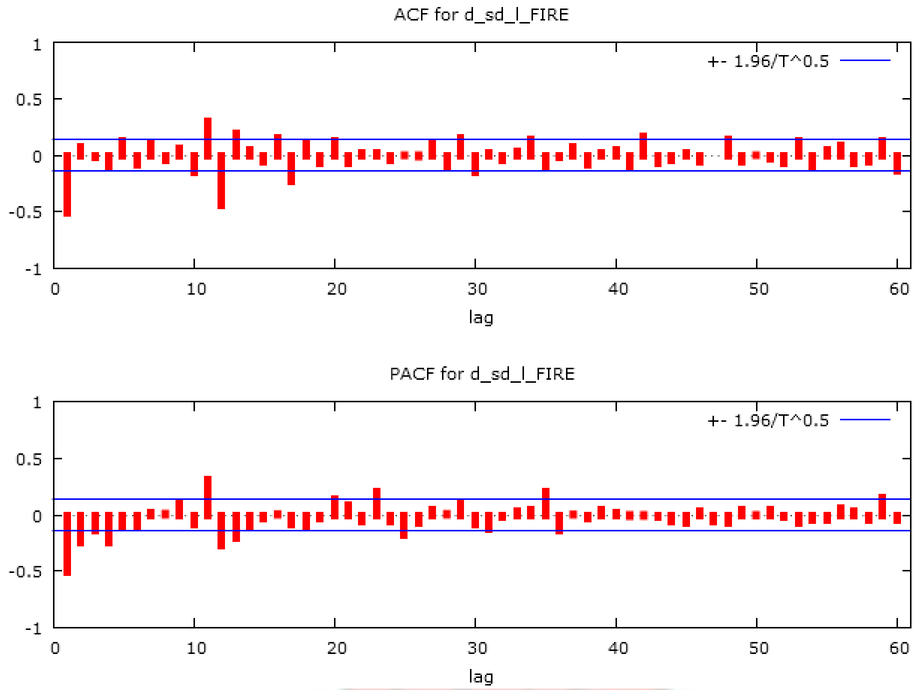

Figure 4.4: Time series plot of first differenced series

The Table 4.11 shows various candidate models identified and among these possible models presented in Table 4.11, $ARIMA(4,1,1)(1,1,1)_{12}$ was chosen as the appropriate model that fit the data well because it has the minimum values of *AIC* and *BIC* compared to other models.

Table 4.11: Candidate SARIMA Models

Model	AIC	BIC
$ARIMA(1,1,1)(1,1,1)_{12}$	176.4269	192.5566
$ARIMA(2,1,1)(1,1,1)_{12}$	166.7311	186.0855
$ARIMA(1,1,0)(1,1,0)_{12}$	399.6026	409.2798
$ARIMA(3,1,1)(1,1,1)_{12}$	164.5607	187.1409
$ARIMA(0,1,1)(0,1,1)_{12}$	260.3901	270.0673
$ARIMA(4,1,1)(1,1,1)_{12}$	151.1116 *	176.9176*
$ARIMA(0,1,1)(1,1,1)_{12}$	227.3377	240.2407
$ARIMA(1,1,0)(1,1,1)_{12}$	301.9861	314.8891

*: Means best based on the selection criteria.

The estimation of parameters of our derived model is obtained by using the method of maximum likelihood shown in Table 4.12.The $ARIMA(4,1,1)(1,1,1)_{12}$ model and can be expressed in terms of the lag operator as;

$$(1 - \varphi_1 L - \varphi_2 L^2 - \varphi_3 L^3 - \varphi_4 L^4)(1 - \Phi_1 L^s)(1 - L)(1 - L^s)\ln(Fire) = (1 - \theta_1 L)(1 - \Theta_1 L)\varepsilon_t$$

This implies

$$(1 + 0.7172L + 0.4419L^2 + 0.3441L^3 + 0.2888L^4)(1 + 0.4268L^{12})(1 - L^1)(1 - L^{12})In(Fire) = (1 + L)(1 + L)\varepsilon_t$$

The observations of the p-values of the parameters of the model for both the non-seasonal and seasonal and Autoregressive and Moving Average components are highly significant at the 5% level. The model appears to be the best model among the proposed models.

When fitting data in time series analysis, the best model selection is directly related to whether residual analysis is performed well. One important assumptions of good ARIMA model is that, the residual must follow a white noise process which implies zero mean, constant variance and uncorrelated residual. From the diagnostic plot in Figure 4.5, the standardised residuals revealed that the residTable 4.12: Estimates of parameters for $ARIMA(4,1,1)(1,1,1)_{12}$

Variable	Coefficient	Standard error	z-statistic	p-value
φ_1	-0.717208	0.0715685	-10.0213	0.0000
φ_2	-0.441989	0.0843866	-5.2377	0.0000
φ_3	-0.344114	0.0842333	-4.0852	0.0000
φ_3	-0.288846	0.0719513	-4.0145	0.0000
Φ_1	-0.426847	0.0664899	-6.4197	0.0000
θ_1	-1.000000	0.0300209	-33.3101	0.0000
Θ_1	-1.000000	0.0566841	-17.6416	0.0000

uals of the model have zero mean and constant variance. Also, the ACF of the residuals shows that the autocorrelation of the residuals are all zero which implies that they are uncorrelated. Finally, in the third panel, the Ljung-Box statistic indicates that there is no significant departure from white noise for the residuals as the p-values of the test statistic clearly exceeds the 5% significance level for almost all lag orders.

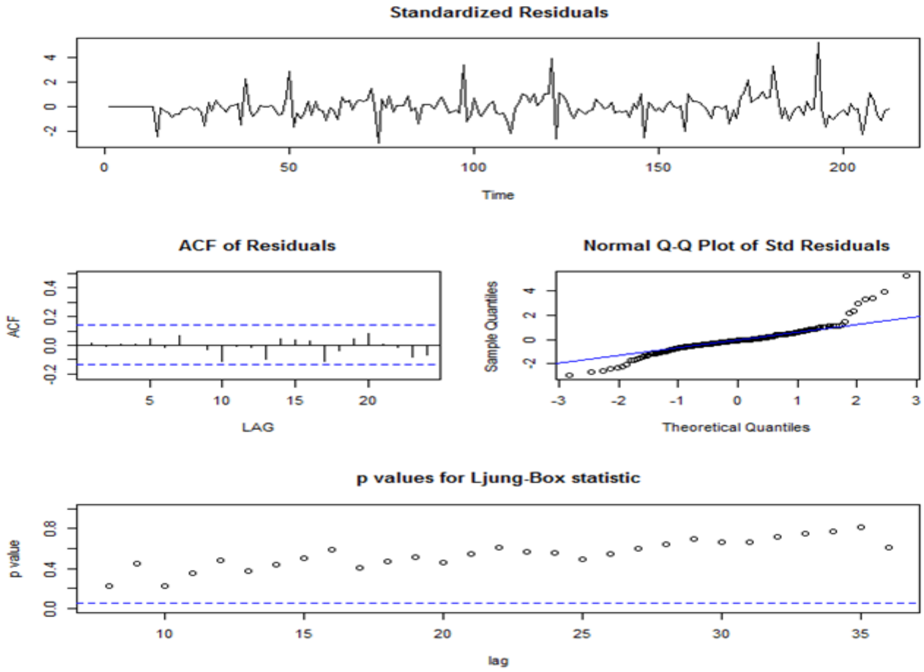

Figure 4.5: Diagnostic plot of $ARIMA(4,1,1)(1,1,1)_{12}$

To support the information depicted in Figure 4.6, the ARCH-LM test and t-test were employed to test for constant variance and zero mean assumption respectively. The ARCH-LM test result shown in Table 4.13, failed to reject the null hypothesis of no ARCH effect in the residuals of the selected model. Also, the t-test gave a test statistic of -1.3281 and a p-value of 0.1865 which is greater than the 5% significance level. Thus, we fail to reject the null hypothesis that the mean of the residuals is equal to zero. Hence, the selected model satisfies all the assumptions and it can be concluded that $ARIMA(4,1,1)(1,1,1)12$ model provides an adequate representation of the Fire Outbreak.

Table 4.13: ARCH-LM test of residuals of $ARIMA(4,1,1)(1,1,1)_{12}$

Lag	Test statistic	Df	p-value
12	6.16432	12	0.907573
24	17.5799	24	0.822901
36	28.3637	36	0.813987

df: degrees of freedom

The stability test of the model parameters was analyzed using the CUSUM test. The test observation was that, the cumulative residuals of the model fall within the 95% confidence band as shown in Figure 4.6. It can therefore be concluded that the parameters of the model are structurally stable.

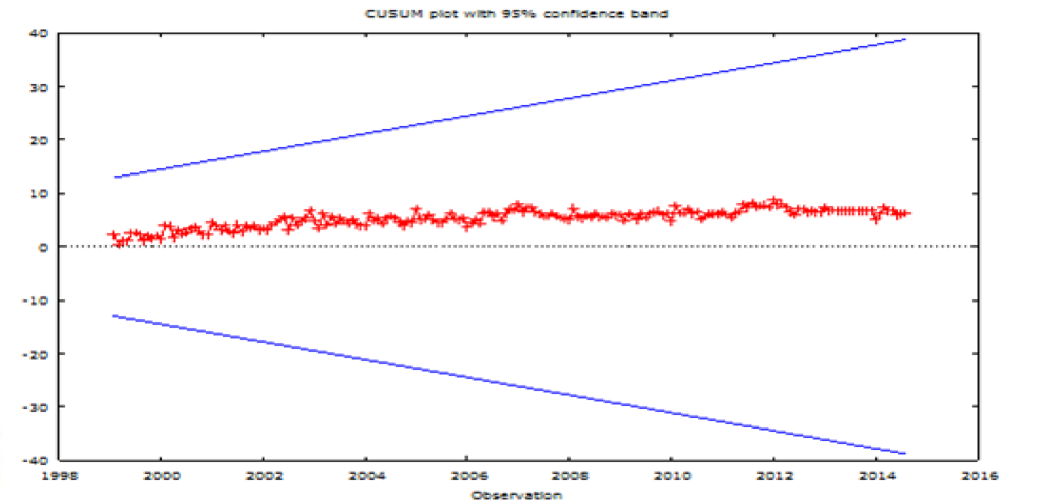

Figure 4.6: CUSUM plot of ARIMA (4, 1, 1)(1, 1, 1)$_{12}$

Figure 4.6: CUSUM plot of *ARIMA*(4,1,1)(1,1,1)$_{12}$

The graph below depict the forecast of fire outbreak from August 2014 to August 2016. From the graph there is an indication of increase and decrease pattern in fire outbreaks.

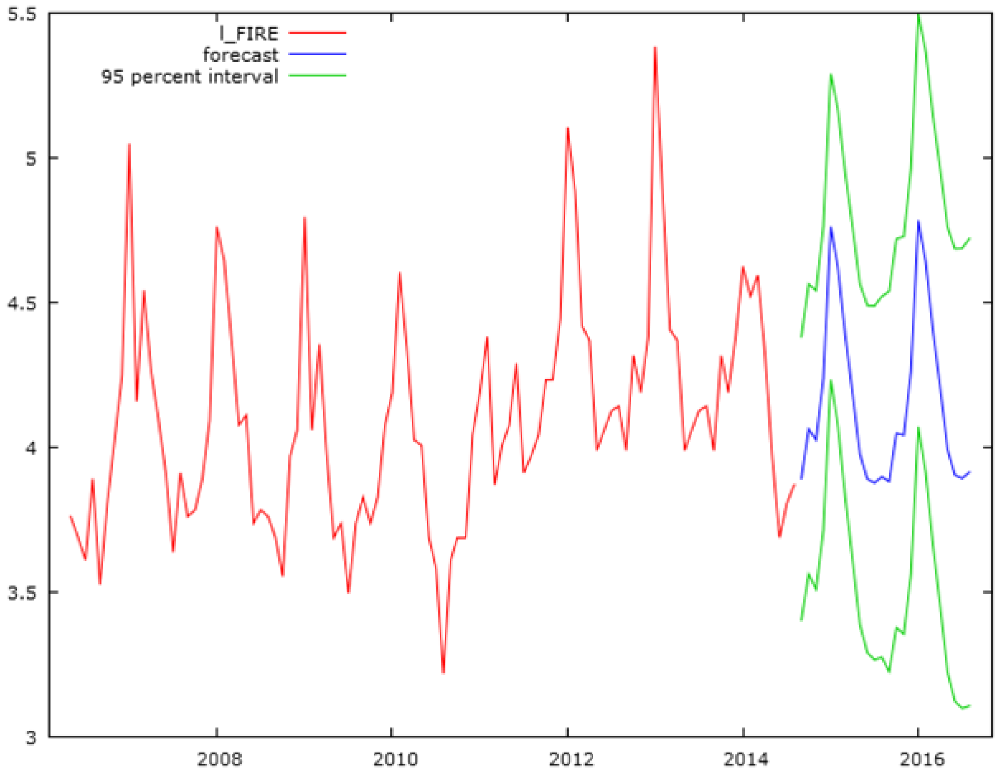

Figure 4.7: Forecasting plot of $ARIMA(4,1,1)(1,1,1)_{12}$

4.4 Modelling Insurance Premiums

Based on equivalence principle, the calculation of a fully continuous level annual benefit premium for a unit fire insurance payable immediately there is a fire is tabulated in Table 4.14.

Table 4.14: Premium Calculation For Fire Policies

Fire Categories	x	θ	d	δ	$\bar{A}^1_{x:12}$	$\ddot{a}_{x:\overline{12}}$	$P(\bar{A}^1_{x:12})$
Domestic	0	26.14623	0.016666	0.020619	0.329132	32.5364	0.010116
Industry	0	4.000000	0.016666	0.020619	0.887896	5.436927	0.163308
Vehicular	0	7.089623	0.016666	0.020619	0.747091	12.26582	0.060908
Institution	0	1.240566	0.016666	0.020619	0.975011	1.21194	0.804504
Electrical	0	2.636792	0.016666	0.020619	0.940618	2.879965	0.326607
Commercial	0	5.122642	0.016666	0.020619	0.836612	7.924148	0.105578
Bush	0	5.688679	0.016666	0.020619	0.810247	9.202823	0.088043
Other	0	0.026833	0.016666	0.020619	0.953084	2.275377	0.418869

NB: x is the Inception Time and θ: Mean Time.

4.5 Discussion of Results

The results for the study clearly indicate that the Fire Outbreak was asymmetric and more peaked in nature. This lack of symmetry can be attributed to the large swings in data set and increase in the number of occurrence of Fire in the Ashanti Region of country. The leptokurtic nature of the data set tells us about how volatile the Fire Occurrence is. Furthermore, the nature of the distribution of the data set shown that the Fire Outbreak is distributed closely around its mean value.

An investigation of the residuals of the model revealed that there was seasonality in the residuals which was obvious in the plot of the correlogram (Figure 4.2). Since there was evidence of seasonality in the residuals, the logarithmic transformed Fire Outbreak was regressed on the periodic dummies. To provide better interpretation for the coefficient of the periodic dummies, Halvorsen and Palmquist (1980) approach of interpreting differential coefficients in semilogarithmic equations was adopted and ignoring the significance of the differential coefficients, the month of January, February, July, August , October, November and December increases the Outbreak of Fire by 71.7770, 0.3207, 1.5488, 0.7688 ,16.0998, 4.0939 and 25.7135 percent respectively. The increase in the fire outbreaks in these months can be attributed to the bad weather conditions thus harmattan season.

In addition, month of January and December showed higher increment (71.7770%) and (25.7135%) respectively than other months and can be attributed to the fact that many farmer start preparing their land for next season cultivation during that period.

Again, during that period visibility become very poor (fog) resulting to fuel truck accident leading fire explosion also the reduction of electricity dam level leading electricity power fluctuation and so forth.

Relatively, the month of March, April, May, June, and September decreases the Outbreak of Fire by 25.6268, 30.1801, 11.2076, 11.2606 and 2.8191 percent respectively and this could be due to continuous rain fall during that time.

The forecasting of the number of Fire Outbreak is important to fire stakeholders and management in Ghana. The forecasting models were developed to aid in the monthly prediction of the Fire Outbreak.

The model was the $ARIMA(4,1,1)(1,1,1)_{12}$ model. The monthly forecasting model $ARIMA(4,1,1)(1,1,1)_{12}$ gives a non-seasonal autoregressive of order four (4), $AR(4)$ which indicates that the future monthly fire outbreaks correlates with its fourth months. This as a result means that an increase or decrease in fire out outbreaks in the fourth month will result in increase or decrease fire outbreaks in the future and the differencing of order one , $I(1)$ indicates the removal of linear tread in the data which makes it stationary. Also the non -moving average of order one, $MA(1)$ indicates that the future monthly fire outbreaks errors depend on error term of its preview month.

Furthermore, the seasonal autoregressive of order one, $AR(1)$, indicates that the monthly future fire outbreaks correlates with its preview one year monthly fire incidence and the seasonal moving average of order one $MA(1)$ also indicates that the forecasting values of fire outbreaks depend on it past one year errors.

The diagnostic checks on this model proved that the model was adequate for predicting the monthly number of fire outbreaks in Ashanti of Ghana. Hence, it was concluded that the model is a good for forecasting fire outbreaks. A two years forecast with this model revealed that the number of fire outbreaks will continue to increase with time.

This continues increase in the pattern of the number of fire outbreaks as evident from the forecast results could be a great danger to the economy of the country.

The results achieved for fire forecasting will help to estimate number of fire events which can be used in planning the fire activities in that region.

Also, the insurance premium calculation of level monthly benefit premium for a semi-continuous 12 month fire insurance of GH 1.00 on an inception month were determined and the premium calculation follow the trend of the frequency, thus the one with higher frequency correspond to higher premiums and vice versa.

4.6 Conclusion

This chapter dealt with the analysis and discussion of results. It presented the major findings of the study in a clear, detailed, precise and concise manner.

CHAPTER 5

Conclusion and Recommendations

5.1 Introduction

This chapter presents the conclusion and recommendations of the study. The chapter is further divided into conclusion and recommendations.

5.2 Conclusion

In this research, the monthly fire outbreaks in Ghana from January, 1997 to August, 2014 was studied and before fitting model to the fire outbreaks, the monthly characteristics of the series were explored. The research has shown that fire outbreaks are growing at alternating increasing and decreasing rates. The fire outbreaks revealed perfect evidence of various monthly effects. The wet season was seen as the months of decrease in fire outbreaks whiles the harmattan period was indicated as the period of increase in fire outbreaks. The month of January had the highest percentage increment.

The model developed for forecasting the monthly number of fire outbreaks was adequate for representing the series as evident from all the model diagnostics used. Moreover, since fire outbreaks are subject to several unobservable factors in the country and volatile, sole dependence on this forecasting model to predict the fire outbreaks for the purpose of fire management by fire stakeholders such as Ghana National Fire Service and insurance may have some errors.

Therefore continuous monitoring of the forecasting performance of this model is additionally required to make the use of these models more realistic.

Furthermore the premium calculation for the corresponding fire policies will help the insurance companies to charge reasonable premium to their policyholders.

5.3 Recommendations

Following the outcome of this research work, the following recommendations were made.

i. Much more education should be given to the public on the effect on dryseason against fire as indicated by the monthly percentage effects.

ii. Stakeholders should use statistical models such as the formulated model forthe purpose of predicting, mitigating and insuring against Fire Outbreaks.

iii. It is also recommended that further studies on the Fire premiums shouldbe carried out to consider mixed distribution to capture both high and low severity and frequency in order to cater for extreme losses of fire.

iv. Also the assumption of uniform distribution should be replaced by a different distribution to capture the actual severity and the non-homogeneous Poisson distribution could also be used capture frequency more realistically.

v. Further studies on computing fire premiums should include premium loadings to sustain the insurance policies.

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Appendix A

Table 5.1: Forecast Values for ARIMA $(4,1,1)(1,1,1)_{12}$

Year	Month	Forecast	LCL	UCL
2014	September	3.892519	3.403343	4.381695
2014	October	4.063589	3.563136	4.564042
2014	November	4.025636	3.50969	4.541581
2014	December	4.239689	3.715059	4.764318
2015	January	4.762162	4.233711	5.290612
2015	February	4.620319	4.075072	5.165566
2015	March	4.386936	3.827369	4.946503
2015	April	4.184895	3.610431	4.759359
2015	May	3.977023	3.388798	4.565247
2015	June	3.891001	3.291507	4.490495
2015	July	3.877329	3.26619	4.488468
2015	August	3.898621	3.276018	4.521223
2015	September	3.88257	3.225933	4.539206
2015	October	4.049236	3.377682	4.72079
2015	November	4.042108	3.355405	4.728812
2015	December	4.26286	3.562472	4.963247
2016	January	4.784716	4.072043	5.49739
2016	February	4.639297	3.91212	5.366473
2016	March	4.403726	3.662587	5.144864
2016	April	4.200748	3.445755	4.955741
2016	May	3.991638	3.223152	4.760124
2016	June	3.904607	3.12322	4.685994
2016	July	3.893268	3.099099	4.687437
2016	August	3.91479	3.108036	4.721544

LCL=Lower Confidence Limit
UCL= Upper Confidence Limit

Table 5.2: Data on Fire Outbreak in Ashanti Region of Ghana

Year	Month	No.	Year	Month	No.
1997	January	39	2006	January	49
1997	February	83	2006	February	34
1997	March	61	2006	March	45
1997	April	22	2006	April	56
1997	May	30	2006	May	70
1997	June	23	2006	June	156
1997	July	23	2006	July	64
1997	August	29	2006	August	94

1997	September	34	2006	September	71
1997	October	45	2006	October	60
1997	November	99	2006	November	50
1997	December	72	2006	December	38
1998	January	83	2007	January	50
1998	February	37	2007	February	43
1998	March	37	2007	March	44
1998	April	23	2007	April	49
1998	May	21	2007	May	34
1998	June	25	2007	June	45
1998	July	25	2007	July	56
1998	August	30	2007	August	70
1998	September	40	2007	September	156
1998	October	45	2007	October	64
1998	November	81	2007	November	94
1998	December	78	2007	December	71
1999	January	48	2008	January	60
1999	February	39	2008	February	50
1999	March	28	2008	March	38
1999	April	35	2008	April	50
1999	May	31	2008	May	43
1999	June	26	2008	June	44
1999	July	19	2008	July	49
1999	August	32	2008	August	60
1999	September	39	2008	September	117
1999	October	52	2008	October	104
1999	November	51	2008	November	79
1999	December	122	2008	December	59

No. refers to the number of fire outbreaks

Year	**Month**	**No.**	**Year**	**Month**	**No.**
2000	January	66	2009	January	61
2000	February	26	2009	February	42
2000	March	31	2009	March	44
2000	April	28	2009	April	43
2000	May	32	2009	May	40
2000	June	28	2009	June	35
2000	July	38	2009	July	53
2000	August	81	2009	August	58
2000	September	150	2009	September	121
2000	October	49	2009	October	58

2000	November	32	2009	November	78
2000	December	21	2009	December	54
2001	January	18	2010	January	40
2001	February	39	2010	February	42
2001	March	19	2010	March	33
2001	April	35	2010	April	42
2001	May	29	2010	May	46
2001	June	28	2010	June	42
2001	July	25	2010	July	46
2001	August	67	2010	August	59
2001	September	100	2010	September	66
2001	October	38	2010	October	100
2001	November	40	2010	November	77
2001	December	30	2010	December	56
2002	January	32	2011	January	55
2002	February	25	2011	February	40
2002	March	30	2011	March	36
2002	April	36	2011	April	25
2002	May	39	2011	May	37
2002	June	45	2011	June	40
2002	July	70	2011	July	40
2002	August	81	2011	August	57
2002	September	60	2011	September	66
2002	October	67	2011	October	80
2002	November	32	2011	November	48
2002	December	47	2011	December	55

No. refers to the number of fire outbreaks

Year	**Month**	**No.**	**Year**	**Month**	**No.**
2003	January	29	2012	January	59
2003	February	33	2012	February	73
2003	March	33	2012	March	50
2003	April	34	2012	April	53
2003	May	53	2012	May	57
2003	June	55	2012	June	69
2003	July	97	2012	July	69
2003	August	65	2012	August	85
2003	September	39	2012	September	165
2003	October	36	2012	October	132
2003	November	35	2012	November	83
2003	December	48	2012	December	79

2004	January	39	2013	January	54
2004	February	28	2013	February	58
2004	March	35	2013	March	62
2004	April	34	2013	April	63
2004	May	42	2013	May	54
2004	June	131	2013	June	75
2004	July	87	2013	July	66
2004	August	61	2013	August	74
2004	September	56	2013	September	102
2004	October	31	2013	October	75
2004	November	26	2013	November	66
2004	December	35	2013	December	80
2005	January	37	2014	January	102
2005	February	43	2014	February	92
2005	March	34	2014	March	99
2005	April	30	2014	April	76
2005	May	40	2014	May	53
2005	June	60	2014	June	40
2005	July	53	2014	July	45
2005	August	48	2014	August	48
2005	September	35			
2005	October	43			
2005	November	40			
2005	December	37			

No. refers to the number of fire outbreaks

Appendix B

Model 1: OLS, using observations 1997:02-2014:08 (T = 211)

Dependent variable: ld _FIRE

Coefficient	**Std. Error**	**t-ratio**	**p-value**	
0.541027	0.0737322	7.3377	<0.00001	***
0.00320213	0.0716548	0.0447	0.9644	
-0.296074	0.0716548	-4.132	0.00005	***
-0.359251	0.0716548	-5.0136	<0.00001	***
-0.118869	0.0716548	-1.6589	0.09871	*
-0.119466	0.0716548	-1.6672	0.09704	*

0.015369	0.0716548	0.2145	0.83039	
0.00765891	0.0716548	0.1069	0.91499	
-0.0285957	0.0737322	-0.3878	0.69855	
0.14928	0.0737322	2.0246	0.04424	**
0.0401232	0.0737322	0.5442	0.58693	
0.228835	0.0737322	3.1036	0.00219	***

Mean dependent var	0.000984	**S.D. dependent var**	0.372222
Sum squared resid	18.39145	**S.E. of regression**	0.304005
R-squared	0.967895	**Adjusted R-squared**	0.92954
F(12, 199)	9.65175	**P-value(F)**	1.05E-14
Log-likelihood	-41.97895	**Akaike criterion**	107.9579
Schwarz criterion	148.1802	**Hannan-Quinn**	124.2166
Rho	-0.471278	**Durbin-Watson**	2.91146

Augmented Dickey-Fuller test for FIRE including 11 lags of (1-L)FIRE (max was 12) sample size 200 unit-root null hypothesis: a = 1 test with constant model: (1-L)y = b0 + (a-1)*y(-1) + ... + e 1st-order autocorrelation coeff. for e: 0.028 lagged differences: F(11, 187) = 9.940 [0.0000] estimated value of (a - 1): -0.140007 test statistic: tau_c(1) = -1.34001 asymptotic p-value 0.6131

with constant and trend model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e 1st-order autocorrelation coeff. for e: 0.031 lagged differences: F(11, 186) = 9.197 [0.0000] estimated value of (a - 1): -0.378402 test statistic: tau_ct(1) = -2.10498 asymptotic p-value 0.5425

KPSS test for FIRE

T = 212

Lag truncation parameter = 12

Test statistic = 1.12461

	10%	5%	1%
Critical values:	0.348	0.463	0.739

KPSS test for FIRE (including trend) T = 212

Lag truncation parameter = 12

Test statistic = 0.0989846

	10%	5%	1%
Critical values:	0.120	0.148	0.217

Augmented Dickey-Fuller test for l_FIRE including 11 lags of (1-L)l_FIRE (max was 12) sample size 200

unit-root null hypothesis: a = 1 test with constant model: (1-L)y = b0 + (a-1)*y(-1) + ... + e 1st-order autocorrelation coeff. for e: 0.001 lagged differences: F(11, 187) = 11.492 [0.0000] estimated value of (a - 1): -0.0931113 test statistic: tau_c(1) = -1.19426 asymptotic p-value 0.6794

with constant and trend model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e 1st-order autocorrelation coeff. for e: 0.004 lagged differences: F(11, 186) = 10.563 [0.0000] estimated value of (a - 1): -0.363488 test statistic: tau_ct(1) = -2.17759 asymptotic p-value 0.5016

KPSS test for l_FIRE

T = 212

Lag truncation parameter = 12

Test statistic = 1.32395

	10%	5%	1%
Critical values:	0.348	0.463	0.739

KPSS test for l_FIRE (including trend) T = 212

Lag truncation parameter = 12

Test statistic = 0.0735701

	10%	5%	1%
Critical values:	0.120	0.148	0.217

Augmented Dickey-Fuller test for sd_FIRE including 11 lags of (1-L)sd_FIRE (max was 12) sample size 188 unit-root null hypothesis: a = 1 test with constant model: (1-L)y = b0 + (a-1)*y(-1) + ... + e 1st-order autocorrelation coeff. for e: 0.030 lagged differences: F(11, 175) = 4.814 [0.0000] estimated value of (a - 1): -0.888171 test statistic: tau_c(1) = -5.64443 asymptotic p-value 8.181e-007

with constant and trend model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e 1st-order autocorrelation coeff. for e: 0.030 lagged differences: F(11, 174) = 4.812 [0.0000] estimated value of (a - 1): -0.900482 test statistic: tau_ct(1) = -5.64066 asymptotic p-value 8.113e-006

KPSS test for sd_l_FIRE

T = 200

Lag truncation parameter = 12

Test statistic = 0.0369742

10% 5% 1%

Critical values: 0.348 0.463 0.739

KPSS test for sd_l_FIRE (including trend)

T = 200

Lag truncation parameter = 12

Test statistic = 0.0376102

10% 5% 1%

Critical values: 0.120 0.148 0.217

Augmented Dickey-Fuller test for d_sd_l_FIRE including 13 lags of (1-L)d_sd_l_FIRE (max was 14) sample size 185 unit-root null hypothesis: a = 1 test with constant model: (1-L)y = b0 + (a-1)*y(-1) + ... + e 1st-order autocorrelation coeff. for e: 0.001 lagged differences: F(13, 170) = 8.934 [0.0000] estimated value of (a - 1): -4.47152 test statistic: tau_c(1) = -6.18207 asymptotic p-value 4.316e-008

with constant and trend model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e 1st-order autocorrelation coeff. for e: 0.000 lagged differences: F(13, 169) = 8.904 [0.0000] estimated value of (a - 1): -4.48536 test statistic: tau_ct(1) = -6.18483 asymptotic p-value 4.037e-007

KPSS test for d_sd_l_FIRE

T = 199

Lag truncation parameter = 12

Test statistic = 0.0750892

10% 5% 1%

Critical values: 0.348 0.463 0.739

KPSS test for d_sd_l_FIRE (including trend)

T = 199

Lag truncation parameter = 12

Test statistic = 0.0594839

	10%	5%	1%
Critical values:	0.120	0.148	0.217

Test for ARCH of order 12

	coefficient	std. error	t-ratio	p-value	
alpha(0)	810.939	265.578	3.053	0.0026	***
alpha(1)	0.312597	0.0738240	4.234	3.71e-05	***
alpha(2)	-0.156879	0.0765352	-2.050	0.0419	**
alpha(3)	-0.0380928	0.0765058	-0.4979	0.6192	
alpha(4)	-0.0505903	0.0764717	-0.6616	0.5091	
alpha(5)	-0.0841647	0.0764906	-1.100	0.2727	
alpha(6)	-0.0438402	0.0770755	-0.5688	0.5702	
alpha(7)	-0.0667866	0.0770774	-0.8665	0.3874	
alpha(8)	-0.0719334	0.0903429	-0.7962	0.4270	
alpha(9)	-0.0288841	0.0922211	-0.3132	0.7545	
alpha(10)	-0.187010	0.0930761	-2.009	0.0461	**
alpha(11)	0.212887	0.0916247	2.323	0.0213	**
alpha(12)	0.253125	0.0871367	2.905	0.0042	***

Null hypothesis: no ARCH effect is present Test statistic: LM = 59.618

with p-value = P(Chi-square(12) > 59.618) = 2.64967e-008

Test for ARCH of order 24

	coefficient	std. error	t-ratio	p-value	
alpha(0)	1006.74	464.068	2.169	0.0316	**

alpha(1)	0.216919	0.0777731	2.789	0.0060 ***
alpha(2)	-0.119526	0.0791435	-1.510	0.1331
alpha(3)	-0.0327984	0.0797876	-0.4111	0.6816
alpha(4)	-0.0360151	0.0798080	-0.4513	0.6524
alpha(5)	-0.0790299	0.0796963	-0.9916	0.3230
alpha(6)	-0.0454734	0.0805812	-0.5643	0.5734
alpha(7)	0.0593084	0.0806095	-0.7357	0.4630
alpha(8)	0.0629647	0.0943839	-0.6671	0.5057
alpha(9)	-0.0267819	0.0959880	-0.2790	0.7806
alpha(10)	-0.212222	0.0966716	-2.195	0.0297 **
alpha(11)	0.0795304	0.0981753	0.8101	0.4192
alpha(12)	0.145293	0.0980641	1.482	0.1405
alpha(13)	-0.0932366	0.0985166	-0.9464	0.3455
alpha(14)	-0.0303339	0.0983231	-0.3085	0.7581
alpha(15)	-0.0868429	0.0971802	-0.8936	0.3730
alpha(16)	-0.0219194	0.0973498	-0.2252	0.8222
alpha(17)	-0.0639955	0.0972968	-0.6577	0.5117
alpha(18)	-0.0188265	0.0971096	-0.1939	0.8465
alpha(19)	-0.0293052	0.0972837	-0.3012	0.7637
alpha(20)	-0.0780540	0.0968678	-0.8058	0.4216
alpha(21)	0.00719480	0.0970110	0.07416	0.9410

alpha(22) -0.0167362 0.0971495 -0.1723 0.8635 alpha(23) 0.139944 0.0949380

1.474 0.1426 alpha(24) 0.358203 0.0915388 3.913 0.0001 ***

Null hypothesis: no ARCH effect is present Test statistic: LM = 76.9685

with p-value = P(Chi-square(24) > 76.9685) = 1.83623e-007

Test for ARCH of order 36

	coefficient	std. error	t-ratio	p-value

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alpha(0)	1054.86	613.544	1.719	0.0880 *
alpha(1)	0.249814	0.0890188	2.806	0.0058 ***
alpha(2)	-0.137247	0.0916118	-1.498	0.1366
alpha(3)	-0.0151607	0.0924822	-0.1639	0.8700
alpha(4)	-0.0170267	0.0924846	-0.1841	0.8542
alpha(5)	-0.0924963	0.0922433	-1.003	0.3179
alpha(6)	-0.0353209	0.0937327	-0.3768	0.7069
alpha(7)	-0.0577305	0.0939388	-0.6146	0.5400
alpha(8)	-0.0578504	0.111799	-0.5174	0.6057
alpha(9)	0.0123305	0.114004	0.1082	0.9140
alpha(10)	-0.233163	0.115147	-2.025	0.0450 **
alpha(11)	0.102895	0.115982	0.8872	0.3767
alpha(12)	0.152815	0.112325	1.360	0.1761
alpha(13)	-0.108477	0.109828	-0.9877	0.3252
alpha(14)	-0.0258925	0.107450	-0.2410	0.8100
alpha(15)	-0.0909741	0.107151	-0.8490	0.3975
alpha(16)	-0.00437819	0.107343	-0.04079	0.9675
alpha(17)	-0.0778539	0.106966	-0.7278	0.4681
alpha(18)	-0.0287818	0.107265	-0.2683	0.7889
alpha(19)	-0.0183035	0.107397	-0.1704	0.8649
alpha(20)	-0.0828906	0.107243	-0.7729	0.4410
alpha(21)	0.0175625	0.107412	0.1635	0.8704
alpha(22)	-0.0328345	0.107459	-0.3056	0.7604
alpha(23)	0.160596	0.107417	1.495	0.1374
alpha(24)	0.318716	0.107782	2.957	0.0037 ***
alpha(25)	-0.0218595	0.110997	-0.1969	0.8442
alpha(26)	0.0338632	0.110208	0.3073	0.7591
alpha(27)	-0.0545995	0.108752	-0.5021	0.6165
alpha(28)	-0.0381561	0.108987	-0.3501	0.7268
alpha(29)	0.0553926	0.109347	0.5066	0.6133

alpha(30)	-0.0451674	0.109256	-0.4134	0.6800
alpha(31)	0.0457762	0.112082	0.4084	0.6837
alpha(32)	-0.0970395	0.112348	-0.8637	0.3894
alpha(33)	0.0212053	0.113516	0.1868	0.8521
alpha(34)	-0.00479776	0.113615	-0.04223	0.9664
alpha(35)	-0.0719980	0.109872	0.6553	0.5135
alpha(36)	0.0351599	0.105978	0.3318	0.7406

Null hypothesis: no ARCH effect is present Test statistic: LM = 72.357

with p-value = P(Chi-square(36) > 72.357) = 0.000308527