APPLICATION OF DECOMPOSITION TECHNIQUE ON ADMITTANCE INTO ORPHANAGE HOMES

BY

EMMANUEL, Fidel Ononuju
M.TECH/SPS/2019/10583

DEPARTMENT OF STATISTICS
FEDERAL UNIVERSITY OF TECHNOLOGY MINNA

JUNE, 2023

APPLICATION OF DECOMPOSITION TECHNIQUE ON ADMITTANCE INTO ORPHANAGE HOMES

BY

EMMANUEL, Fidel Ononuju
M.TECH/SPS/2019/10583

A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTERS OF TECHNOLOGY IN STATISTICS.

JUNE, 2023

ABSTRACT

This study applies the decomposition technique to the admission of orphans and vulnerable children (OVC) into orphanage homes. Previous studies have focused primarily on the number of OVC, estimating the number of deceased parents, and examining the socioeconomic well-being of OVC. Therefore, there is a need to examine the pattern of OVC admittance. Monthly data were collected from the register of the Niger State Orphanage Home over a twenty-year period (2000-2020). A time series decomposition analysis was conducted to determine an appropriate model, investigate the trend of OVC admission, and determine if there is a seasonal effect in the series. The results showed that the mean number of OVC admissions was 3.2022, with a standard deviation of 2.0522, indicating a considerable amount of variability in the admission data. The median value was calculated as 3.0000, indicating close alignment between the middle value in the distribution of admissions and the mean. Furthermore, the observed skewness of 0.8611 suggests a slight rightward skew in the distribution, indicating a relatively higher frequency of OVC admissions in the later periods. The findings also revealed that the pseudo-additive model was the most appropriate for the series, with the model-fitted trend equation given as $X_t = 1.23932 - 0.05375t$, indicating a decreasing linear trend. The study also identified a seasonal pattern, with the highest incidence of admission into orphanage homes occurring during the 2nd and 3rd quarters of the year.

TABLE OF CONTENTS

Contents **page**

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

1.0. INTRODUCTION

1.1. Background to the Study

A form of dormitory for a sizable cluster of children is known as an orphanage. It features a general purpose design, meaning that all children benefit equally regardless of how old they are, their sex, ability, requirement or causes of separation (Hope and Homes for Children, 2019). It is a facility for children who have no parents because their parent(s) have died or abandoned them, and they have no other close relatives who can care for them (Porta, 2018). Child abandonment is becoming more common in Nigeria (Moshood, 2020). Many such cases have been reported in traditional and social media, and it is gradually becoming a "normal" occurrence, even as child abandonment incidents spread across the country. While some of these babies are abandoned in hospitals, others are dumped in unusual locations such as public restrooms, dump sites, the bush, and drainage systems. Some of these babies are fortunate enough to be rescued by members of the public before they die (Moshood, 2020). Causes of child abandonment could be a result of protracted economic crises which leads to poverty, unwanted pregnancies, divorce which leads to single parenthood, teenage delinquency, prostitution, alcohol, and drug abuse.

A child below 18 years old who have lost either or both parents is considered an orphan according to United Nations Children's Fund (UNICEF) (DeLuca, 2019). A child who is unable or unwilling to reside with their parents for any reason is considered to be at risk. They in a sense "lost" their primary carer, like orphans. These children are easily exploited, rejected, mistreated, or whose parents merely lack the means to provide for them. Losing a caregiver exposes children to health hazards, assault, manipulation, and injustice (Mutiso & Muti, 2018).

The expression "orphans and vulnerable children" would be used interchangeably throughout this research. It was devised to cover the argument of disadvantaged children beyond orphans to other categories of children. The situation of children in the world reflects the deepening and broadening of child exclusion and transparency in Nigeria. The scarcity of data portrays a bleak picture of the deprivation, manipulation, and ill-treatment that most Nigerian children face (Ojo & Olayinka, 2019).

As of 2021, approximately 14.9 million children around the world had lost one or even both guardians. Sub-Saharan Africa is home to three-quarters of these children (11.2 million) (UNICEF, 2022b). It is reported that 95 percent of OVC get no healthcare, interpersonal, moral, economic, or academic support, and also the children confront enormous growth and well-being issues (National Population Commission-NPC/Nigeria and ICF International, 2014). A pattern of how OVC are admitted to orphanages would provide a picture of the situation of OVC and aid in mitigating the challenges they face in Nigeria.

Iwueze *et al*. (2016) state that the two primary goals of the analysis of time series are to determine the type of event depicted by the observational sequence and to make predictions (predicting future values of the time series variable). In time series, pattern recognition and model selection are crucial for predicting. As a result, these two objectives of time series analysis necessitate that the sequence of observable data sets is detected and defined (Iwueze *et al*., 2016). The concept of time series decomposition has been around for a long time and was used by seventeenth-century astronomers to calculate planetary orbits. Persons (1919) initially laid forth the underlying presumptions of undetected variables. Persons asserts that time series contains four different types of variations: a trend, cyclical motions superimposed on the trend, seasonal progression in each period, the structure of which is determined by the nature of the series; and residual variants resulting from changes influencing individual parameters or other significant events impacting multiple different factors, including military conflicts and nationwide crises (Dagum, 2010).

1.2. Statement of the Research Problem

Nigeria is one of the countries having the highest rates of OVC and is experiencing an orphaning and vulnerability crisis (Tagurum *et al.*, 2015). Official figures vary, but the Nigerian Federal Ministry of Women Affairs and Social Development (FMWASD) reported 7.5 million OVC in 2008 (FMWASD, 2009). The lack of information on OVC conditions has hindered the progress of effective policies and programmes to report the country's exact OVC needs. The plight of OVC is widely recognised in Nigeria, yet it has not garnered sufficient attention from researchers concerning the admission patterns of OVC into orphanage homes. Therefore, there is a pressing need to conduct a comprehensive study on the trends of OVC admission, aiming to establish a framework for comprehending the admission patterns in orphanage homes. On this premise, the present study focuses on the case of OVC in Niger State.

1.3. Aim and Objectives

The aim of the study is the application of decomposition models on the number of orphans and vulnerable children admitted into orphanage homes in Niger State, Nigeria. The objectives are to:

i. Formulate an appropriate model of admittance of OVC into orphanage homes.
ii. Obtain the trend of the admission of OVC in these orphanage homes

iii. Check for seasonality using the decomposition approach.

1.4. Justification of the Study

The study on the application of decomposition techniques on admittance into orphanage homes is justified for several reasons. Nigeria is currently facing a significant orphaning and vulnerability crisis, with a high number of orphaned and vulnerable children (OVC). However, there is a lack of comprehensive research on the specific patterns of admittance into orphanage homes for OVC. This study aims to bridge that research gap by focusing on the trend of OVC admittance in Niger State.

By analysing the trend of OVC admittance, the study seeks to provide valuable insights into the admission process and shed light on its associated factors. Understanding these patterns can contribute to mitigating the challenges faced by OVC and inform the development of effective policies and intervention programmes. It will also help policymakers allocate resources appropriately and design targeted strategies to address the challenges OVC faces in Niger State and Nigeria as a whole.

Additionally, the study aims to apply decomposition models to the number of OVC admitted into orphanage homes. By employing these models, the research seeks to identify trends and extract underlying components such as trends-cyclical patterns, and seasonal variations in the admittance data. This approach will provide a clearer understanding of the factors influencing admittance patterns and facilitate accurate predictions. The application of decomposition techniques adds value to the study by utilising advanced analytical methods for more comprehensive insights.

Given the importance and significance of addressing the orphaning and vulnerability crisis in Nigeria, this research is of utmost relevance. By meticulously investigating the trend and pattern of OVC admittance into orphanage homes within Niger State, the study endeavours to make a substantial scholarly contribution. The findings can contribute to the formulation of effective policies and interventions aimed at supporting OVC and enhancing their general well-being.

1.5. Scope of the Study

The scope of this study focuses specifically on the trends and patterns of OVC admittance in Niger State, Nigeria. It aims to analyse the data related to the admittance of orphaned and vulnerable children into orphanage homes within the specified geographic area. The study will utilise decomposition models to identify and interpret underlying components such as trends, cyclical patterns, and seasonal variations in the admittance data. By focusing on Niger State, the study aims to provide insights and recommendations that are contextually relevant to the specific region and contribute to the formulation of targeted policies and interventions.

1.6. Limitation of the Study

The study is limited to the data available on admittance into orphanage homes in Niger State. It relies on the accuracy and completeness of the data collected for analysis. Any discrepancies or limitations in the data quality may impact the findings and conclusions drawn from the study.

In addition, the study is focused on the patterns and trends of OVC admittance, and it may not capture the full range of factors influencing the decision-making process of admitting children into orphanage homes. Other contextual and socio-economic factors beyond the scope of this study may also play a role.

Furthermore, the research is limited to Niger State, and the findings may not be generalisable to other regions or countries. Different regions may have varying social, cultural, and administrative contexts that can influence the admittance patterns of OVC.

Lastly, the study's application of decomposition models relies on the assumptions and limitations associated with these techniques. While decomposition models can provide valuable insights, they may not capture all complexities of the admittance process, and their predictions may be subject to uncertainties.

CHAPTER TWO

2.0. LITERATURE REVIEW

2.1. Conceptual Review

2.1.1. Orphans

There are many methods to describe an orphan, reliant on whether the definition is used epidemiologically, legally, or as a social and cultural characterisation. The latter varies from person to person and from society to society. People explained this by referring to the extended family system and how it guaranteed that no children were left alone. They did not regard their children as orphans. Besides using different age groups to define orphans, there are also patterns of parental death. mother, father, or double orphan (Mutiso & Mutie, 2018).

Initially, the United Nations International Children's Fund (UNICEF) and the United Nations International Children's Fund (UNAIDS) defined children as being 15 years of age or younger, However, to comply with the treaty on the entitlement of the Child, this number was raised to 18 years of age or younger (Deacon & Stephney, 2008). Children below 18 years old who have lost one or both parents is considered an orphan by UNICEF. According to Jones (2018), there are an appraised 153 million orphans globally, with approximately 5,700 children becoming orphans each day. According to these statistics, the term "orphan" is misunderstood. Of the estimated 153 million orphans, 26 million have lost both parents (DeLuca, 2019). Accordingly, 83% of the remaining orphans have at least one parent (DeLuca, 2019). A child is considered an orphan if either their mother, father or both of their parents have passed away. A child is considered a double orphan if both of their parents have passed away. As a result, both the paternal and maternal orphans include double orphans (Rutstein, 2008).

2.1.2. Vulnerable children

Children who "have their development, safety, and well-being threatened for a variety of reasons" are considered vulnerable (Mutiso & Mutie, 2018). One of the main causes of children's increased susceptibility is a lack of affection and care, as well as proper shelter, nourishment, schooling, and supportive services Children are vulnerable in a variety of ways that are highly context-specific and depend on the environment (Mutiso & Mutie, 2018). The aforementioned definition is extremely broad and encompasses a huge amount of children for numerous reasons. Children who are unable or unwilling to live with their parents or relatives are considered vulnerable. They, like orphans, no longer have a primary guardian. They are frequently ignored, abandoned, or abused, or their parents simply have no means to properly raise them. Children who have lost their parents or guardians are at a higher risk of health problems, violence, exploitation, and discrimination (Mutiso & Mutie, 2018).

The terms orphans and vulnerable children were used interchangeably in this study. The expressions were coined to broaden the discussion of disadvantage beyond orphans to include other types of children (e.g., children of sick parents). According to Deacon and Stephney (2008), vulnerability is also socially defined, making a comprehensive definition difficult to develop. There is no need to develop a single definition of OVC as long as attempts are made to quantify the indirect impact of HIV on a child’s welfare. Indeed, they claim that "the definition of a vulnerable child is frequently determined by the availability of data and not conceptual issues" (Deacon & Stephney, 2008).

2.1.3. Orphanage home

Children in orphanages are secluded from the community, and in most cases live far away from their local area, relatives and extended family members which makes it difficult and sometimes impossible to keep close contact. Siblings are frequently disconnected, and children are separated based on age, sex, and incapacity. Aside from being a residential facility, one of the most commonly cited structures of an orphanage is its size or the number of places accessible for children in any given facility. The larger the venue, the less likely it is to deliver individualised attention to children similar to that of a family-like environment, and the more likely certain dynamics will emerge (Hope and Homes for Children, 2019).

When a child's parent or legal guardian is deceased, or in a situation where the primary caregiver is abusive to the child, the child will be admitted into the orphanage. Additionally, children may become vulnerable when there are issues such as drug abuse or mental illness present in the home that is harmful to the child's well-being, or when the parents have to leave to work in a different location where they cannot or will not bring the child with them, this will also result in the admission of the child into the orphanage.

Around 400 AD, the Romans established their first orphanage. Until the age of 18, Athenian law assisted all orphans of those who lost their parents in army duty, whereas Jewish law strongly advised caring for single mothers and orphans. Plato (Laws, 927) says, "Public guardians would be appointed to be in the care of children without parents or legal guardians." It is believed that men should fear the loneliness of orphans and the spirits of their deceased parents. A man ought to show affection to the ill-fated orphan over whom he has parental responsibility like he is looking after his biological child. “In the management of care of an orphan, he should be mindful and industrious as if it were his own property or more" (McKenna, 1911).

The United Nations Convention on the Rights of the Child (UNCRC), which was created in 1989, is the first global legal agreement that fully recognizes the civil, cultural, economic, political, and social rights of children. Leaders from throughout the world agreed that children have rights and frequently require more care and protection than adults do. Governments all around the globe have pledged to defend and uphold children's privileges, and to hold themselves responsible for carrying out this obligation to the entire international community, by consenting to take up the Convention's obligations (UNICEF, 2022a). The government could now implement a system that would maximize its ability to look after and protect orphans thanks to this statute (Mosia, 2014).

2.1.4. Orphans and vulnerable children in Nigeria

Children in Nigeria are more excluded and invisible, and this is reflected in the status of children around the world (Ojo & Olayinka, 2019). The meagre information that is available presents a bleak picture of the widespread abuse, exploitation, and neglect that children in Nigeria currently experience. Between 1986 and 2004, 43% of women between the ages of 20 and 24 were married or in a union before they turned 18, while 39% of youngsters between the ages of 5 and 14 worked as children. Among the appraised, 50 million children (under 18) in the country, those from disadvantaged areas, those with disabilities, from minority cultures, and children with AIDS or HIV infection are among those who encounter the most discrimination (Ibeh, 2011).

According to the Federal Ministry of Women Affairs and Social Development of Nigeria, OVC in the country is approximately 17.5 million (National Population Commission-NPC/Nigeria and ICF International, 2014). These children face enormous health and development challenges, and it is estimated that the majority of them receive no therapeutic, emotional, societal, substantial, or educational assistance (National Population Commission-NPC/Nigeria and ICF International, 2014). This burden of OVC exceeds that of war-torn countries such as Yemen, Iraq, Afghanistan, Syria, Congo, Libya, and Somalia. One out of every ten Nigerian homes is assumed to be in the care of an orphan. According to assessments, approximately 160,000 (12.3%) of the over 1.3 million children in Plateau State are orphans, with AIDS accounting for 40,000 of them (Tagurum *et al*., 2015). They are more vulnerable to illness than children from more secure circumstances. They have little or no access to health care, are malnourished and may not be opportune to attain any level of education (Tagurum *et al*., 2015).

All children should have access to safe and secure livelihoods. Evans and Murvay (2008) made the case that, in accordance with Article 19 of the African Charter on Human and People's Rights, vulnerable children should be treated with respect and dignity (ACHPR). “All people, as well as OVC, ought to be treated fairly, with regard, and entitled to the same fundamental freedoms,” according to the article. The equality and rights of OVC are guaranteed by the Nigerian constitution, but sadly, a lot of children in these conditions are neglected, live in messy environments, and are open to a variety of issues that can be harmful to both the kids and society in terms of health, education, moral development, and other areas (Ojo & Olayinka, 2019).

2.2 Time Series Analysis

A time series is a group of chronologically arranged observations made on a particular topic (target variable). Typically, the metrics are evenly spread out, for example, yearly, quarterly, monthly, weekly, and daily. The fact that organised data in a time series are time-dependent and that this reliance has its own informative effects is its most crucial feature (Dagum, 2010).

Time series analysis comprises of procedures for processing time series data to develop useful statistics and other data traits. Data from time series are always arranged chronologically. This distinguishes time series analysis from other types of statistical analysis where there is no natural organisation of the distribution (for example, describing individuals' salaries, particularly in comparison to their academic achievement, where each data can be inputted in any sequence) (Dagum, 2010).

Time series analysis has two main objectives: identifying the characteristics or properties of the event depicted by the order of the series and forecasting (forecasting future values of the time series variable). Classification of the sequence and model evaluation in time data is essential for forecasting. And hence, the objectives of time series analysis involve identifying and describing the pattern of identified time series data. The two possible patterns usually observed are trends and seasonal effects (Iwueze *et al*., 2016).

Time series analysis methods are commonly classified into three types: descriptive methods, time domain methods, and frequency domain methods. The frequency domain methods, which are model-free, are centred on spectral analysis and, more recently, wavelet analysis. A distribution-free subset of time domain methods includes autocorrelation and cross-correlation analysis. The objective of descriptive methods is to separate an identified data set into elements that reflect seasonality (structured, holidays variations), cyclical (long-term fluctuations around the trend), trend (long-term direction), and irregular (unsystematic, short-term oscillations). The descriptive method is also called the time series decomposition technique (Iwueze *et al.*, 2011).

2.2.1 Components of time series

Time series data generally consists of four elements: trend (Tt), seasonal (St), cyclical (Ct), and irregular (It).

2.2.1.1 Trend (T_t)

A trend is an extended change in time. Here, we take into account the quantity of accessible information and qualitatively characterize what is long-term. When a time series has a trend component, it signifies that it is moving over time in a smooth, stable, and consistent manner. These motions have an organized pattern, consisting of broad, continuous movements that gradually rise or decrease in a similar orientation (Ullah, 2020).

2.2.1.2 Seasonal component (S_t)

This movement in the time series data is periodic and consistent, and it is related to the season of the year. Several time series observations exhibit seasonal change throughout the year, including sales and temperature observations. Seasonal variations are simple to measure and they can be detached from data to obtain deseasonalised data with little difficulty. The term "seasonal fluctuation" refers to any recurrent change that lasts below a year. Adjustments that reoccur continuously over a defined period of time are called seasonal variations. Seasons, religious celebrations, and social customs are the primary causes of seasonal variations (Ullah, 2020).

2.2.1.3 Cyclical component (C_t)

Long-term swings or trend swings are known as cyclical variations. A cyclical component occurs when a time series exhibits variations at a fixed interval, caused by some other physical factors such as daily temperature variations.

The component that is not seasonal, but clearly cyclical, is called cyclical variation. These changes are assumed to have a more pernicious impact on sales and financial activity. The series can sometimes show alternations that have no definite period but are somewhat predictable. The period component can describe any normal variation (oscillation) in data incorporating weeks and months. Similar to a business cycle, there are four stages: (i) Rise/Prosperous; (ii) Decline; (iii) bottom/depression; and (iv) Periodic and periodic growth and deviation (Ullah, 2020).

2.2.1.4 Irregular or random component (e_t)

These are all the changes/movements that cannot be attributed to trends, seasonal patterns, or cyclical factors. The residual that remains after trend, seasonal, and cyclical variations are subtracted from a set of time series data may or may not be arbitrary. To identify residual components, various techniques for analysing this type of series are used to determine if irregular effects or residuals can be explained by probability models such as moving averages or autoregressive models. Residuals, also known as accidental or irregular oscillations, denote these sudden variations that are unpredictable (Ullah, 2020).

2.2.2 Time series decomposition

Decomposing a sequence into a collection of non-observable (latent) elements that can be connected to various kinds of temporal variations is a key objective of time series analysis. The time series decomposition method, which takes into account the chronological structure of such data, is primarily used to evaluate trends in recurring measurements taken at evenly spaced time frames along with their relationships with other trends or measures (Dozie, 2020). Issues that may arise during time series analysis or forecasting are better understood and observed when the series has been decomposed into different (Brownlee, 2017).

Astronomers in the seventeenth century used the very old concept of time series decomposition to calculate planetary orbits. First, to explicitly state the presumptions of unobserved components was Persons (1919). According to Persons, time series is made up of four different kinds of variations:

1. A secular trend or long-term inclination.
2. Cycles superimposed on the long-term trend.
3. A seasonal measure that occurs in each period.
4. Persistent variations brought on by alterations that have an effect on a single variable or by other significant occurrences like wars and national catastrophes that have an impact on many variables. Historically, the four factors (Dagum, 2010).

The goal of time series decomposition is to categorise the four available time series components. Decomposing an observed time series (X_t, t = 1, 2, …, n) into its trend (T_t), seasonal (S_t), cyclical (C_t), and irregular (I_t) components (Dozie *et al*., 2020). Decomposition methods can generally be classified as either additive or multiplicative, but they can as well take other forms, such as mixed or pseudo-additive models, which combine aspects of both types (Iwueze *et al*, 2011).

Conventional decomposition assumes that the seasonal component is constant from year to year. The m-values that form the seasonal element of the multiplicative seasonality are sometimes called "seasonal indices" (Hyndman & Athanasopoulos, 2018).

2.3 Theoretical Review

2.3.1 Constructivism

Constructivism is a theory of learning that posits that individuals actively construct meaning from their experiences and interactions with the world around them (Hudson & Ozanne, 1988). It is a theory that is founded on research into how people learn from scientific observation and study. The theory will be applied to determine whether the systems responsible for providing for the orphans and the orphans themselves give their lives in orphanages some sort of purpose.

2.3.2 Systemic

According to Guttman (1991), a system is an integrated whole made up of interconnected parts. In this study, the researcher applied the theory to learn how orphanages accommodate orphans from various systems and get them ready for successful reintegration. This theory aims to shed light on the difficulties orphans in orphanages face.

2.4 Empirical Review

Maskurul *et al* (2015) on common types of decomposition models used the logarithmic transformation to convert multiplicative models to additive. The study also used variance stabilization to ensure normally distributed data. The study also showed that the trend cycle can be estimated by smoothing the series to reduce the random variation. Maskurul *et al*., (2015) stated that the oldest and simplest method for reducing random variation is the moving average approach. However, the moving average method does not have an impact on seasonal variation and this limitation can be addressed using the decomposition method. The study also showed that decomposition models can be used to create and present seasonally adjusted values by estimating seasonal effects. The seasonally adjusted value removes the regular fluctuations that occur during specific periods of the year, allowing for a clearer analysis of underlying trends.

Nwogu *et al*., (2019) adopted the Buys-Ballot procedure to choose between mixed and multiplicative models when the trending curve is linear. The test was based on the chi-square distribution. Nwogu *et al*., (2019) presented some empirical examples that illustrated the applicability of the proposed test when the trending curve is linear.

Findings from 100 simulations showed that 97 calculated series lie outside the interval indicating that they do not admit mixed model. The study also suggested that the proposed test is capable of identifying the model correctly 98% of the time.

Mejia-Pailles *et al.,* (2020) used longitudinal demographic data of a cohort of approximately 90,000 individuals, annual incidence and prevalence of maternal, paternal, and double orphans among children and adolescents (age 20 years), and for parents of age. All-cause and cause-specific mortality were measured to estimate levels and trends in age-specific prevalence and incidence of orphans in rural KwaZulu-Natal from 2000 to 2014. The findings show that the proportion of children and adolescents (under age 20) whose parents died increased from 26% to 36% over the decade and then decreased to 32 percent after four years.

In contrast to ARIMA models, Omkar and Kumar (2017) adopted multiplicative decomposition time series methods to predict the volume of traffic that can be used in ITS. They claimed that these methods were simpler to understand and implement. The model development on a midblock section of a busy arterial road in Vellore, Tamil Nadu was done using the multiplicative decomposition technique. The data used for this purpose was the limited traffic volume data collected between 7 am and 11 am for two consecutive days. According to the study, many ITS applications can tolerate a mean absolute percentage error (MAPE) between the observed and predicted volume of 9% to 16%, as evidenced by the results.

Grassly and Timaeus (2005) investigated methods for calculating and forecasting the percentage of orphaned children due to AIDS and other causes. They adopted the epidemiologic and demographic model to calculate the ratio of maternal to paternal orphans, and by simulating the HIV status of the partners of men who die of AIDS or other causes, the effect of HIV/AIDS on child survival was taken into account. To determine the percentage of orphans whose parents were both dead, a Poisson regression model was applied to the data on orphanhood from 34 national demographic and health surveys (DHSs). The projections of the number and age distribution of orphans generated by these methods were consistent with the assessment results from Tanzania. The model can estimate the number of children in nations with generalised heterosexual HIV epidemics whose mother, father, or both parents have passed away. The results showed that the rise in orphanhood over the past decade was caused by the HIV epidemic.

In order to gather baseline data on the needs of OVC in North-Central Nigeria as a foundation for the delivery of relief services, Tagurum *et al*. (2015) used a house-to-house cross-sectional survey of OVC. Out of 825 OVC with mean ages of 9.8 4.5 years and ages ranging from 0 to 17, 59.8% were paternal orphans, and 12.1% of children had lost both parents, according to the findings. 54.9% boys and 45.1% girls made up the 151 (18.3%) children who had never attended school, and 88 (10.7%) of them were not currently enrolled. The respondents had a 1.1% HIV prevalence rate. However, 712 of them (86.4%) were HIV-uninfected. The study also demonstrated the extensive difficulties OVC in North-Central Nigeria face in areas like education, health, housing, protection, and nutrition.

A study by Okon *et al*. (2020) examined the socioeconomic well-being of orphans and vulnerable children in an orphanage in Cross River State, Nigeria, employing a descriptive study design and using a simple random sampling technique to assess survey responses. 64 participants were selected. The survey found that more of her OVCs attended school, more than average numbers of children attended school regularly, received vocational training, and few experienced many academic challenges. rice field.

The results also highlighted the need to provide her OVC at the orphanage with appropriate teaching materials to improve her educational challenges.

Iwueze *et al*. (2011) discussed the applications of Buys-Ballot techniques in data transformation, trend and seasonal fluctuations assessment, and the selection of an appropriate decomposition technique. Simulation data were generated and analysed. The results showed that the relationship between the yearly average and standard deviation can be used to transform data, that trends can be evaluated using the periodic average and seasonal elements, and that seasonal effects can be assessed by observing the pattern of the seasonal average and the series overall average.

In order to select the best decomposition model, Emmanuel *et al*. (2020) used the Buys-Ballot procedure. The ARIMA model was then fitted, allowing the series to be used for forecasting. The study's findings showed that the additive model should be used when the trend component is quadratic. The study used data on Nigeria's spot component price of oil (US dollars per barrel), i.e., when the variation does not change as the level of the trend rises or falls). Additionally, the study demonstrated that AR (2) was used for forecasting because it was determined to be suitable for the series under consideration.

2.5 Research Gap

The existing studies have provided valuable insights into the statistical analysis of orphans and vulnerable children, their increasing numbers, parental mortality, and socio-economic well-being. However, a notable gap in the literature is the lack of investigation into the admission patterns of orphans into orphanage homes and the potential existence of a seasonal pattern. By addressing this gap, this study aims to contribute to the existing body of knowledge by extending the understanding of the factors influencing the placement of orphans in orphanages. Exploring the admission patterns of orphans is crucial as it can shed light on the underlying dynamics and mechanisms that lead to their institutionalisation. Understanding whether there is a seasonal pattern in the admittance of orphans into orphanage homes can provide valuable insights into the factors that contribute to this pattern.

Furthermore, investigating the seasonal pattern of orphan admissions through the time series decomposition approach offers a methodological advancement. This approach allows for a detailed analysis of the temporal variations, enabling the identification of long-term trends, seasonal patterns, and other cyclic components that may be influential. By addressing this research gap and utilising a rigorous methodological framework, this study seeks to enhance the current understanding of orphanage admissions and contribute to the development of effective policies and interventions for the care and support of orphans and vulnerable children.

CHAPTER THREE

3.0. RESEARCH METHODOLOGY

3.1 Time Series Decomposition

The time series decomposition models that will be assessed are the additive, multiplicative and mixed (pseudo-additive) models. The components are represented as trend (T_t), seasonal (S_t), cyclical (C_t) and irregular (I_t).

When a brief time span is involved, the cyclical element is overlaid on the trend, and the observed time series (X_t, t = 1, 2,...,n) can be disintegrated into the trend-cycle component (M_t), seasonal component (S_t), and irregular/residual component (I_t) (Dozie *et al*., 2020).

3.1.1 Additive decomposition

According to additive decomposition, time series data is a characteristic of the sum of its components (Plummer, 2020).

$$X_t = M_t + S_t + I_t \tag{3.1}$$

Where X_t= OVC series, M_t = trend-cycle component, S_t = seasonal component, I_t = irregular/residual component.

The seasonal effect, when it occurs, is always assumed to have an *m* period, implying that it repeats after *m* periods. Where

$S_{t+m} = S_t$ for all t

Additionally, it is presumed that the seasonal components added together over a full period equal zero (Iwueze *et al*., 2011).

$$\sum_{j=1}^{m} S_{t+j} = 0 \tag{3.2}$$

3.1.2 Multiplicative decomposition

The multiplicative decomposition contends that time series data is a function of the product of its constituent parts rather than a sum (Plummer, 2020).

Here, given the time series, X_t, t ∈ Z the decomposition model is given by:

$$X_t = M_t \times S_t \times I_t \tag{3.3}$$

Where,

$S_{t+m} = S_t$ for all t

Also, it is assumed that the seasonal components add up to m throughout the course of a whole season (Dozie *et al*.,2020).

$$\sum_{j=1}^{m} S_{t+j} = m \tag{3.4}$$

3.1.3 Pseudo-additive model

Merging the components of the additive and multiplicative models results in a pseudo-additive model. According to this model, irregular and seasonal variations are independent of one another but are dependent on the level trend (Australian bureau of statistics, 2017).

Here, given the time series, $X_t, t \in Z$ the decomposition model is given by:

$$X_t = M_t \times S_t + I_t \tag{3.5}$$

Where

$S_{t+m} = S_t$ for all t

It is considered that the seasonal components add up to m throughout the course of a whole season (Dozie *et al*.,2020).

$$\sum_{j=1}^{m} S_{t+j} = m$$

3.2 Measuring the Accuracy of the Model

Traditional error metrics, like mean square error, don't offer a solid foundation for contrasting approaches. The correctness of a model can be evaluated in a variety of ways. They are the relative error, scale-free error, mean absolute error (MAE or MAD), and mean absolute percentage error (MAPE) metrics (Tirkeş *et al*., 2017). However, MAPE has numerous desirable properties which include reliability, usability and easy interpretation. In addition, it incorporates all the data into its calculation (Swanson, 2015).

3.2.1 Mean absolute percentage error (MAPE)

The MAPE is determined by dividing the absolute error for every time frame by the apparently measured data for that time frame. Then, averaging the defined percentages (Khair *et al*., 2017).

This measure will be used to select the most appropriate model. Selection will be based on the model with the least MAPE value.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{|y-\hat{y}|}{y}\right) \times 100 \qquad (3.7)$$

Where y = actual value, $\hat{y}$ = fitted value, and *n* = number of observations.

3.3 Assessment of Trend-cycle Component

The trend cycle component will be assessed by observing the plot of the de-seasonalised series which has only the seasonal component removed so that the trend can be observed more clearly (Dozie, 2020). The de-seasonalised series (D_{St}) for the additive, multiplicative and pseudo-additive models are respectively obtained from equations (3.1), (3.3) and (3.5) in the following manner:

$$D_{St} = X_t - S_t^{Adj} = M_t + I_t \tag{3.8}$$

$$D_{St} = \frac{X_t}{S_t^{Adj}} = \mathrm{T_t} \times \mathrm{C_t} \times \mathrm{I_t} \tag{3.9}$$

$$D_{St} = X_t - S_t^{Adj} = M_t \times I_t \tag{3.10}$$

Where D_{St}= de-seasonalised series X_t= OVC series, M_t = trend-cycle component, S_t = seasonal component, I_t = irregular/residual component, S_t^{Adj} = adjusted seasonal indices.

3.4 Assessment of Seasonal Component

The time plot of the complete series can be used to determine seasonality in time series (Iwueze *et al*., 2011). The de-trended series has all the seasonal components removed so that the trend can be seen more clearly. The study will also employ the Buys-Ballot table to assess seasonal effects.

According to Iwueze *et al*. (2011), the Buys-Ballot table's overall average ($\bar{X}_{..}$) and seasonal average ($\bar{X}_{.j}$), where j = 1, 2,...,s, are used to calculate the effects as a difference ($\bar{X}_{.j} - \bar{X}_{..}$), for time series that have a seasonal impact. To determine whether a seasonal effect is present, the variance between the seasonal average and the general average is employed. A line plot of the deviation that follows the same pattern of the actual seasonal indices suggests a presence of seasonal effect. The table is seen in Table 3.1.

Table 3.1 Buys-Ballot Table for Seasonal Time Series

Periods	Seasons						Total	Average
	1	2	$\cdots$	J	$\cdots$	s	$T_{i.}$	$\bar{X}_{i.}$
1	X_1	X_2	$\cdots$	X_j	$\cdots$	X_s	$T_{1.}$	$\bar{X}_{1.}$
2	X_{1+s}	X_{2+s}	$\cdots$	X_{j+s}	$\cdots$	X_{2s}	$T_{2.}$	$\bar{X}_{2.}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
M	$X_{1+(m-1)s}$		$\cdots$	$X_{j+(m-1)s}$	$\cdots$	$X_{1+(m-1)}$	$T_{m.}$	$\bar{X}_{m.}$
Total	$T_{.1}$	$T_{.2}$	$\cdots$	$T_{.j}$	$\cdots$	$T_{.s}$	$T_{..}$	
Average	$\bar{X}_{.1}$	$\bar{X}_{.2}$	$\cdots$	$\bar{X}_{.j}$	$\cdots$	$\bar{X}_{.s}$		$\bar{X}_{..}$

(Source: Iwueze *et al*., 2011)

where

$T_{i.} = \sum_{j=1}^{s} X_{j+(i-1)s}$, i = 1, 2,…, m (i^{th} periodic total)

$T_{.j} = \sum_{i=1}^{m} X_{j+(i-1)}$, j = 1, 2,…, s (j^{th} seasonal total)

m = periods

s = seasons

n = ms = number of observation

$\bar{X}_{i.} = \frac{1}{s} \sum_{j=1}^{m} X_{j+(i-1)s} = \frac{T_{i.}}{s}$, i = 1, 2,…, m (i^{th} periodic average)

$\bar{X}_{.j} = \frac{1}{s} \sum_{i=1}^{s} X_{j+(i-1)s} = \frac{T_{.j}}{m}$, j = 1, 2,…, s (j^{th} seasonal average)

$T_{..} = \sum_{i=1}^{m} T_{i.} = \sum_{j=1}^{s} T_{.j}$ (Grand total)

$\bar{X}_{..} = \frac{\sum_{i=1}^{m} T_{i.}}{m} = \frac{\sum_{j=1}^{s} T_{.j}}{s} = \frac{T_{..}}{ms}$ (Grand mean)

3.5 Data Source

The data used for study was obtained from the state orphanage home in Minna, Niger State. Monthly record on the number of children admitted into the orphanage home was collected from the admission register and was documented for the period of twenty years (2000 – 2020).

3.6 Statistical Software for Data Analysis

Minitab software will be used for the study data analysis.

CHAPTER FOUR

4.0. RESULTS AND DISCUSSIONS

4.1 Results

4.1.1 Summary statistics

Table 4.1: Summary Statistics showing the Number of Orphans and Vulnerable Children Admitted into Orphanage Homes in Niger State (2000:1 - 2020:4) (84 valid observations)

Mean	Median	Minimum	Maximum	Standard Deviation	Coefficient of variation	Skewness
3.2024	3.0000	0.0000	10.0000	2.0522	0.6408	0.8611

The data for orphans and vulnerable children (OVC) admitted from the first quarter of 2000 to the fourth quarter of 2020 are summarized in Table 4.1. The table illustrates that there were quarters over the years when OVC were not admitted into the orphanage homes, with the average number of OVC admitted each quarter being 3.2024, the largest number being 10.000, and the smallest being 0.000. which shows that there are quarters during the years where OVC was not admitted into the orphanage homes. The observation also has a skewness of 0.8611 which lies between 0.5 and 1, this shows that the observation is moderately skewed to the right. Specifically, this implies a higher frequency of lower values and a limited occurrence of larger values. In the context of the OVC admission data, this skewness characterisation signifies the presence of numerous quarters with a lower number of OVC admitted, while a small subset of quarters demonstrates a relatively higher number of admissions.

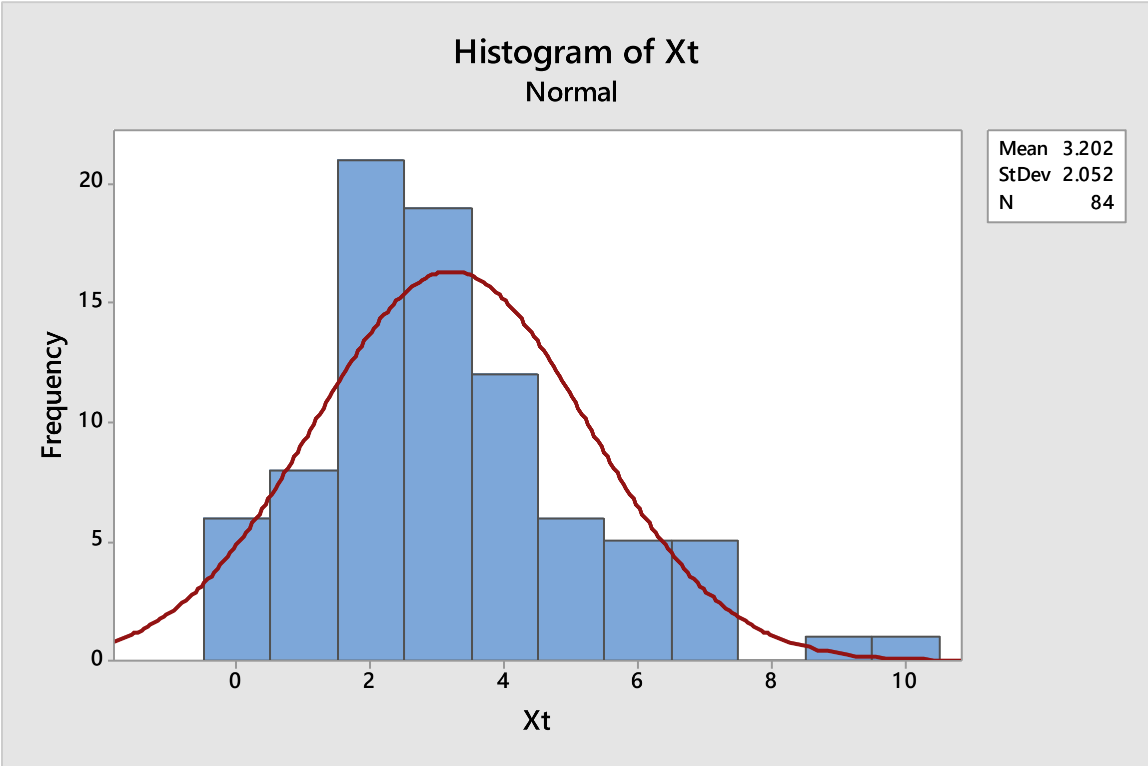

Figure 4.1. Histogram of OVC Admission

Figure 4.1 also displays the distribution's shape, which shows that the right tail is longer and the majority of the distribution is on the left, this concludes that the distribution is moderately skewed right and close to a normal distribution.

4.1.2 Distribution of the admission of OVC into the orphanage home

The data obtained for this study showed that from the year 2000 to 2020 there were two hundred and sixty-nine (269) orphans and vulnerable children admitted into the orphanage home, where one hundred and thirty-seven (137) were male and one hundred and thirty-two (132) were female as seen in Table 4.2**.**

Table 4.2. Data Collected on the Number of OVC Admitted into Orphanage Homes

Total number of years observed	**20**
Range	2000 - 2020
Total number of OVC	269
Number of Male	137
Number of Female	132

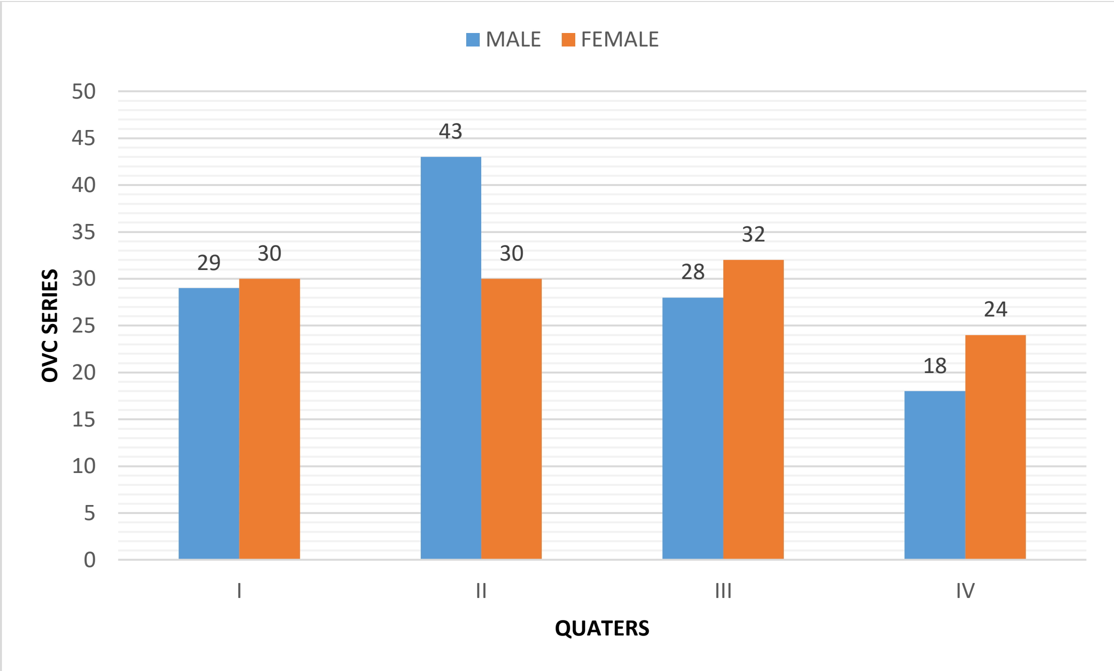

Figure 4.2. OVC Series with Respect to Gender

Figure 4.2. presents a clustered bar chart displaying the frequency of admission with respect to gender and time (quarter over the twenty years of observation), the chart shows that in each quarter, there is a number variation in the admission of the OVC into the orphanage homes, it is seen that in Quarter I, III and IV the female gender had more

admission than the male which had more admission only in Quarter II of the observed series.

4.1.3. Time Series Plot

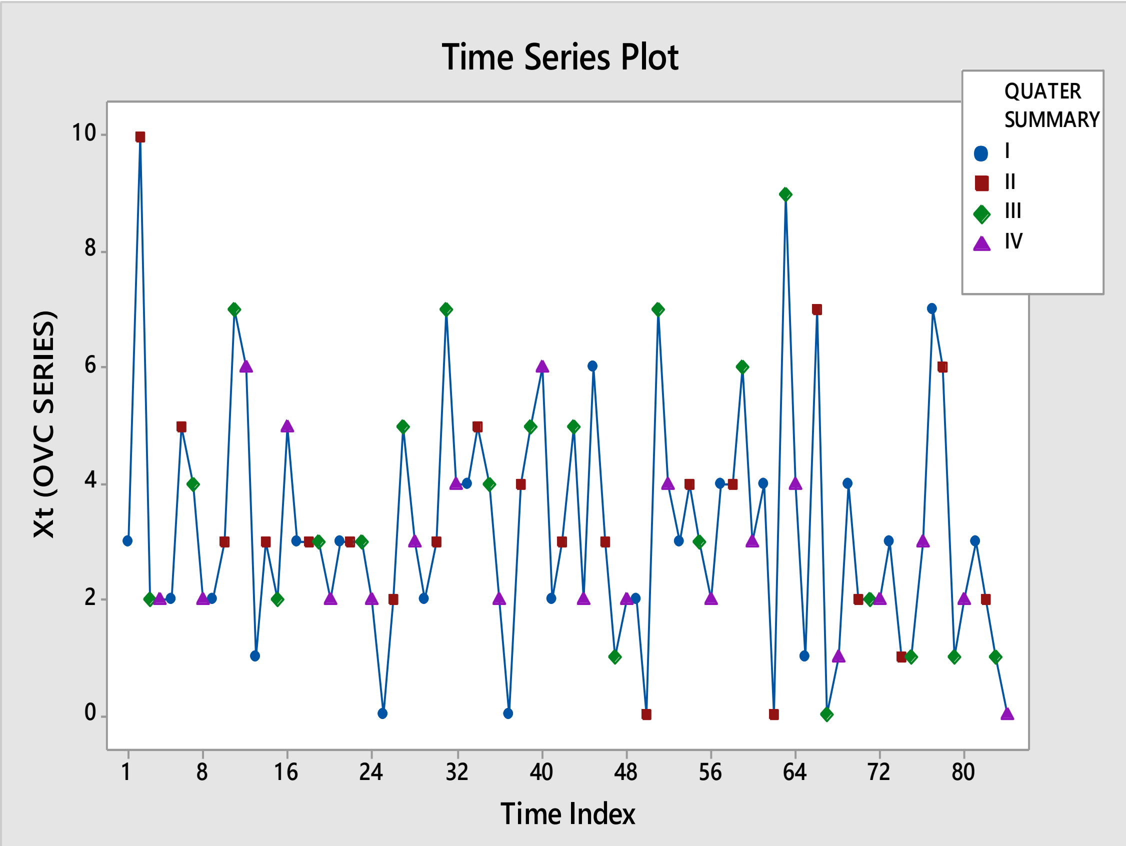

Figure 4.3: Time Series Plot Showing the Pattern of Orphans and Vulnerable Children Admitted into Orphanage Homes in Niger State, Nigeria.

Figure 4.3 shows the time plot of orphans and vulnerable children admitted into orphanage homes in Niger State. The graph shows a clear variation in the process. It was observed that in Q2:2000 of the period studied, the process has a high number of orphans admitted into orphanage homes followed by Q3:2015 which also showed a peak level of the process.

4.1.4 Time series decomposition

The OVC data were decomposed using the three techniques discussed (multiplicative, additive, and pseudo-additive). The decomposition plot for each technique depicted in

Figures 4.4, 4.5, and 4.6 displayed the value of Mean absolute percentage error (MAPE), Mean absolute deviation (MAD), and Mean squared deviation (MSD). The most suitable model was chosen using MAPE.

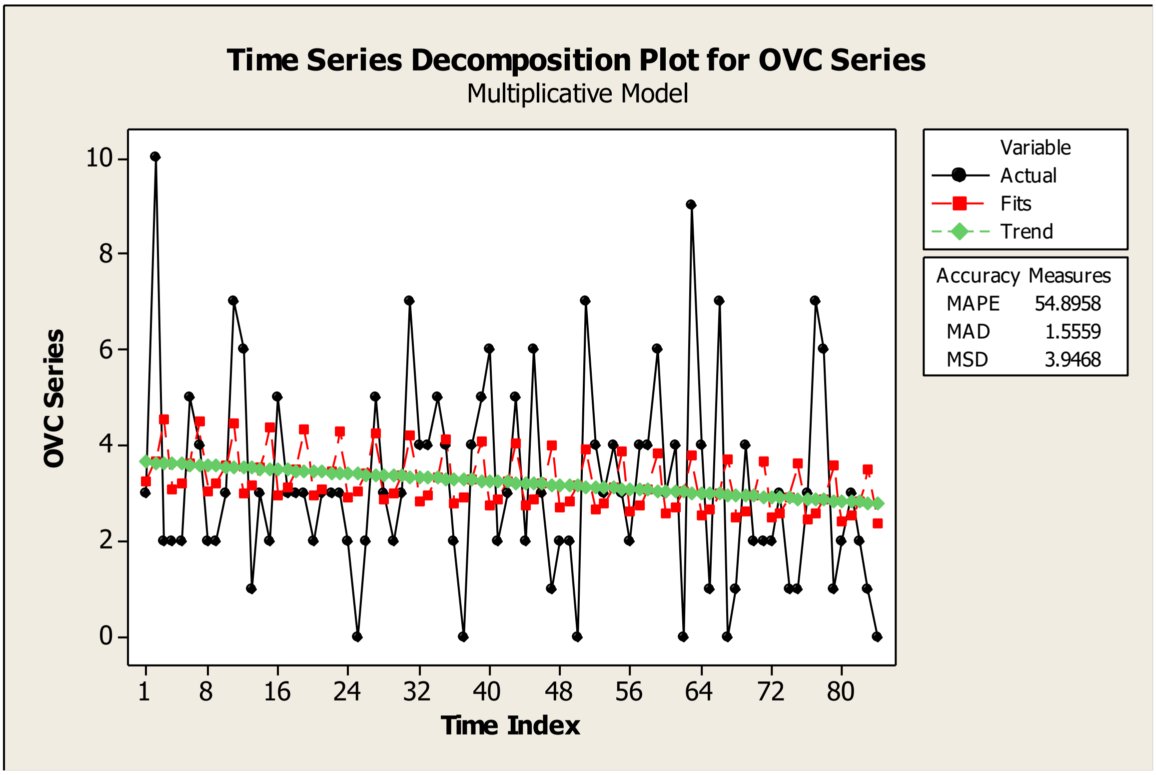

Figure 4.4. Multiplicative Decomposition Plot

Figure 4.4 shows the time series decomposition plot for the multiplicative decomposition model, which was obtained from the observed series on the number of OVC admitted into orphanage homes. From the plot (figure 4.4), the y-axis is the series on the number of OVC admitted and the x-axis is the time index which was summarised quarterly to obtain 84 valid observations. In this model, the data on OVC admitted into orphanage homes in Niger State was expressed as the product of trend, seasonal and irregular components. The model-fitted trend equation result was given as $X_t = 4.18400 - 0.01985t$ Where t is the time index of the observed series.

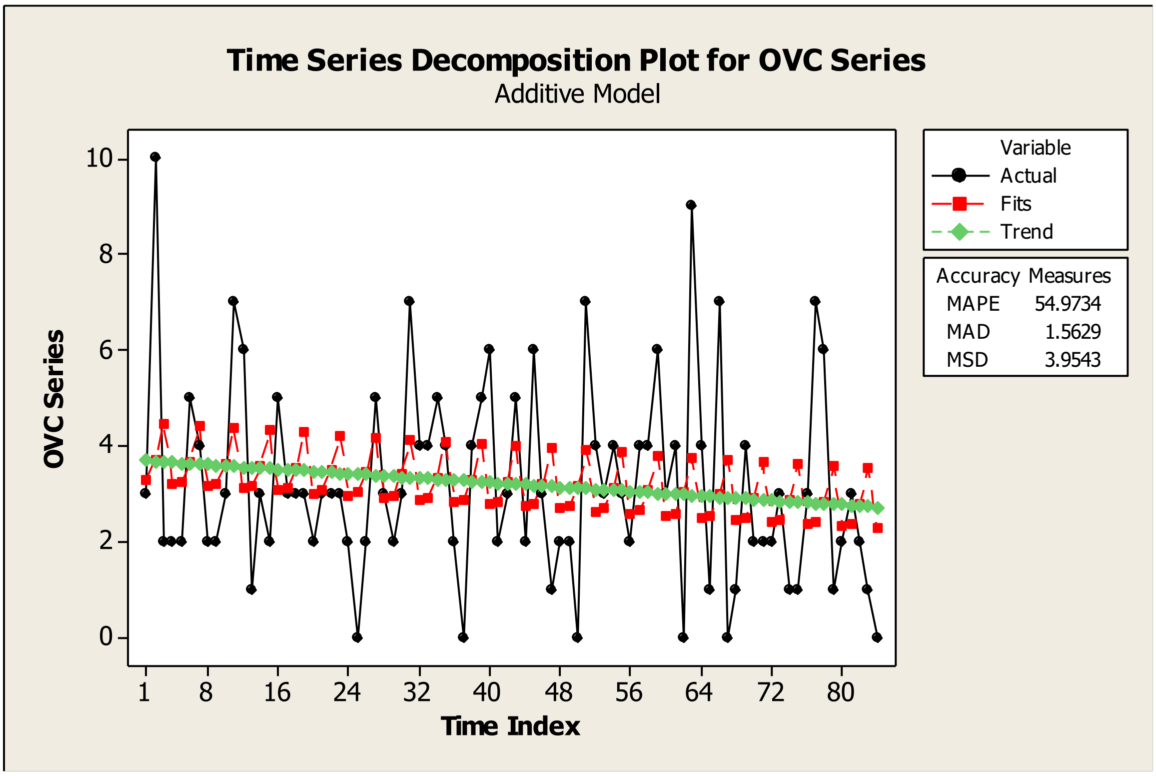

Figure 4.5. Additive Decomposition Plot

The time series decomposition plot for the additive decomposition model is shown in Figure 4.5. The data on OVC admitted into Niger State orphanage homes was described in this model as the sum of trend, seasonal, and irregular components. The model-fitted trend equation result was given as $X_t = 3.72486 - 0.01229t$. The equation represents the observed value X_t at time t, where t denotes the time period.

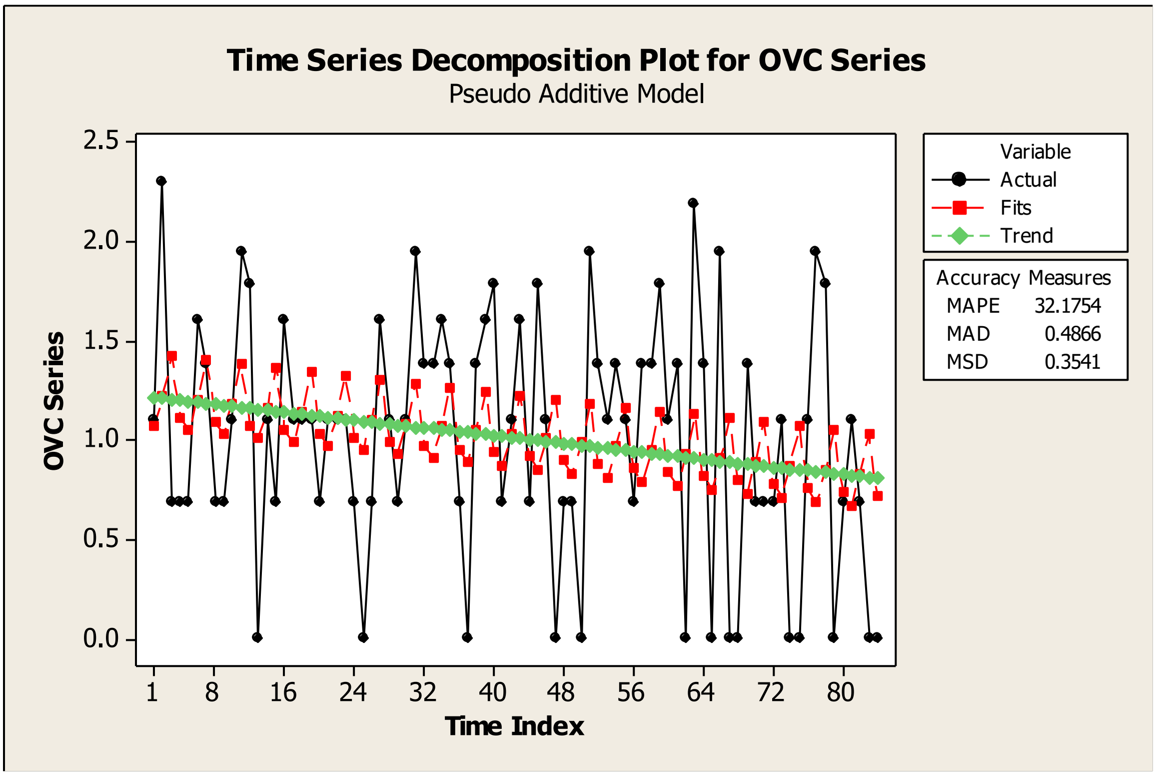

Figure 4.6. Pseudo-Additive Decomposition Plot

Figure 4.6 shows the time series decomposition plot for the pseudo-additive decomposition model. In this model, the data on OVC admitted into orphanage homes in Niger State was expressed as the product and sum of trend, seasonal and irregular components. The model-fitted trend equation result was given as $X_t = 1.23932 - 0.05375t$. The equation represents the observed value X_t at time t, where t denotes the time period.

4.1.5 Choice of decomposition model

Table 4.3: Model Comparison using Accuracy Measures

	Multiplicative model	Additive Model	Pseudo Additive Mode
MAPE	54.8958	54.9734	32.1754

Table 4.3. shows comparative analysis of model performance using the accuracy measures; Mean Absolute Percentage Error (MAPE). Since the model with the least accuracy measure is the pseudo-additive model, it shows that the most appropriate model of admittance into orphanage home is the pseudo-additive model.

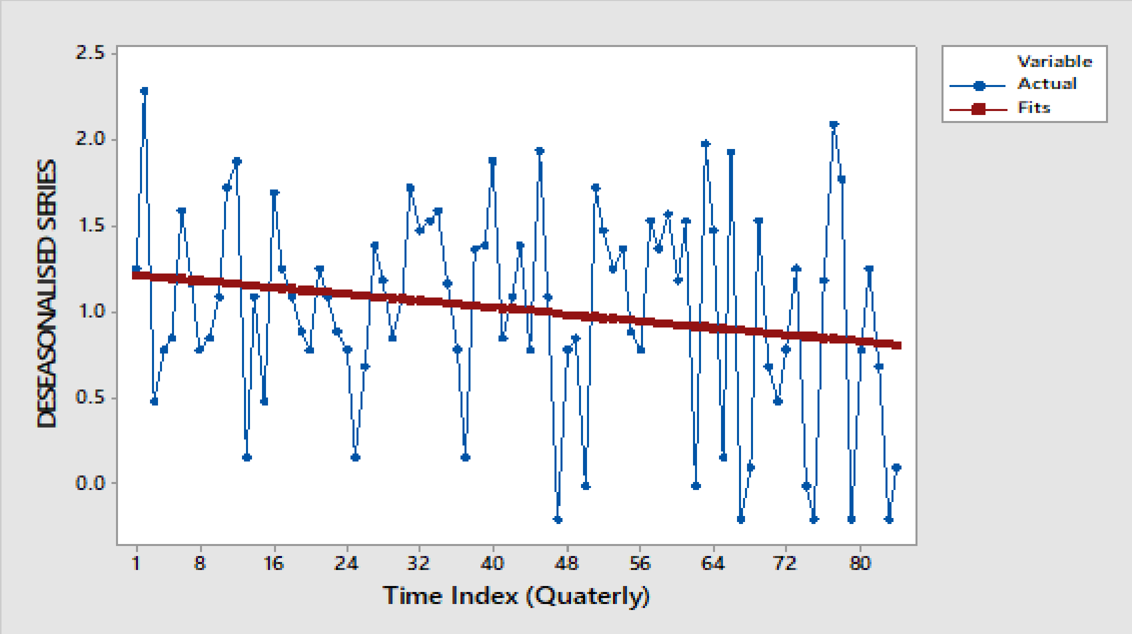

Figure 4.7. Trend Analysis Plot

Figure 4.7 shows the trend analysis of the number of orphans and vulnerable admitted into orphanage homes from the year 2000 to 2020 using the de-seasonalised series. The plot shows that the admission follows a linear downward trend. This fitted linear trend equation was given as $X_t = 1.22031 - 0.00493t$

4.1.6 Seasonal analysis

The examination of seasonality within the admission patterns of orphans and vulnerable children (OVC) into orphanage homes was conducted through two primary methods. Firstly, the detrended series facilitated a clear observation of seasonal patterns, isolating them from the overall trend. Additionally, the scrutiny of seasonal indices further enhanced the understanding of these recurring fluctuations in admission rates.

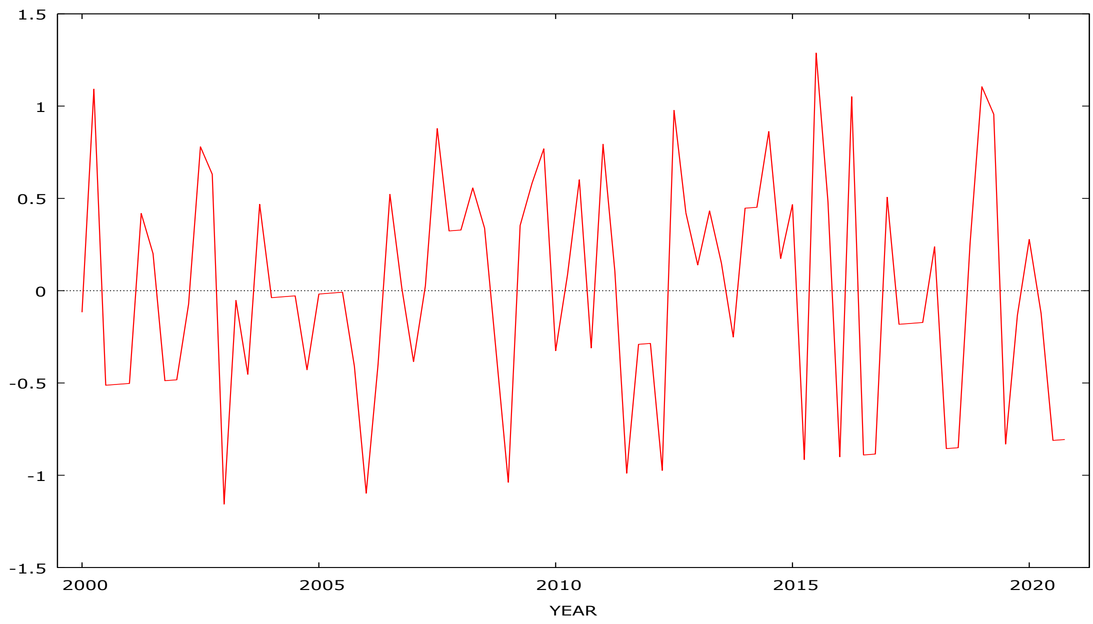

Figure 4.8. Time Plot of the Detrended Series

Figure 4.8 shows the time plot of the detrended series from the decomposed data using the pseudo-additive model. The detrended series has the trend component removed so that the seasonal and other components can be observed clearly. From the plot, it can be observed that there is seasonal variation throughout the entire series. Figure 4.9 was used to further confirm the presence of seasonality.

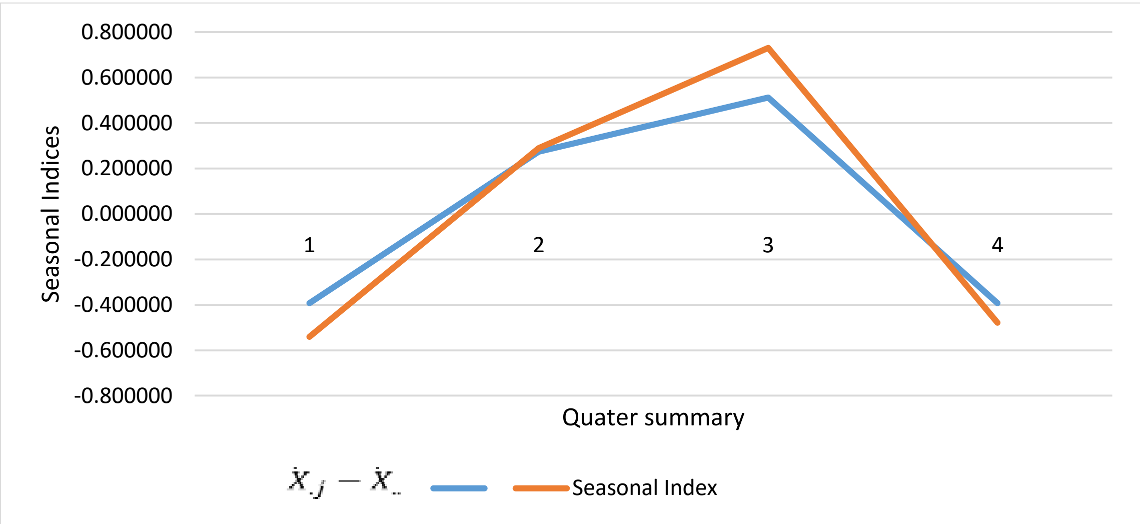

Figure 4.9. Assessment of Seasonal Effects

Figure 4.9 displays a line graph of the seasonal index and the difference between the seasonal average and the overall average $(\bar{X}_{.j} - \bar{X}_{..})$. The line plot shows the existence of seasonal effects since the pattern of deviations of the seasonal average from the overall average mimics those of the actual seasonal index. The seasonal effects are observed in quarters 3 and 2.

4.1.7 Test for randomness

In the residual analysis, the residual series would be used and the technique would be plotting the autocorrelation function to examine if it is random. For randomness, the autocorrelation coefficients are expected to lie between $\pm\frac{1.96}{\sqrt{n}}$ at a 5% level of significance. The plot of the autocorrelation function is given in Figure 4.10

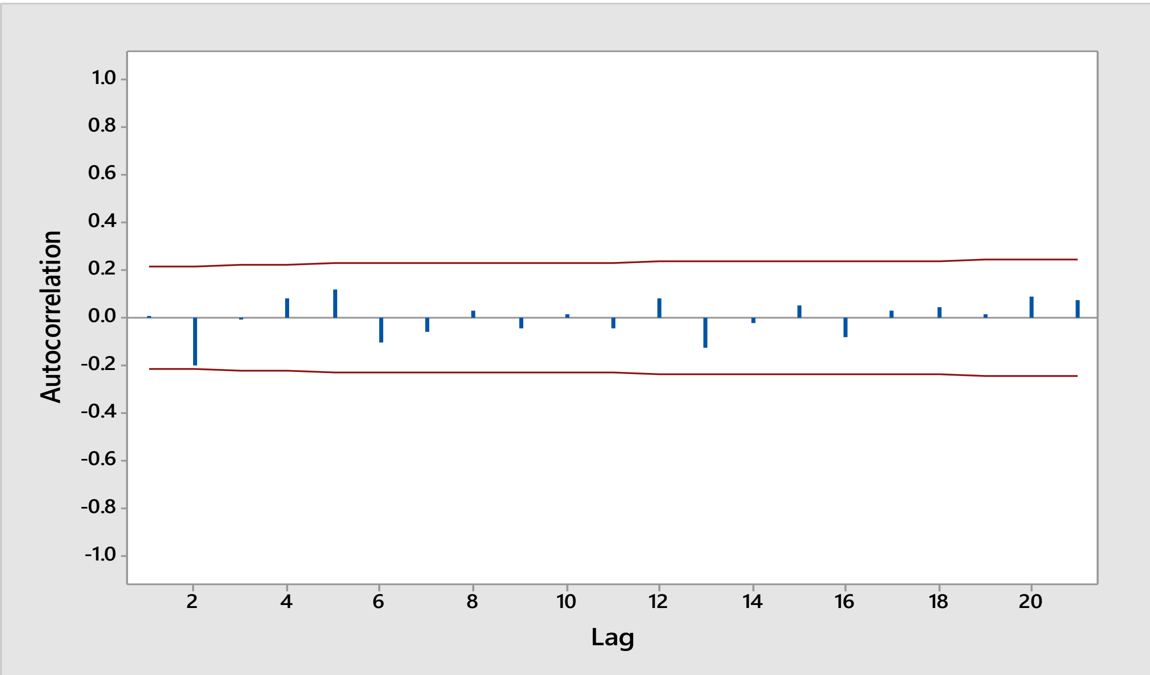

Figure 4.10: Autocorrelation Plot of the Residual Series (Irregular component)

The autocorrelation function of the residual series suggests lack of no fit since all the lags lies within the control limit. This indicates that the order of the data is random.

4.2 Discussion

The in-depth analysis of the results, which focuses on the thorough decomposition approach, clearly demonstrated that the adoption of the pseudo-additive model was unequivocally fitting for the examined series. This validation finds strong resonance with the comprehensive studies carried out by the Australian Bureau of Statistics in 2017 and the research by Iwueze *et al*. in 2016. These studies notably underscored that the pseudo-additive model should be incorporated as the preferred approach when the time series encompasses instances of zero values. This salient observation significantly corresponds with the specific nature of the dataset collected from the state orphanage home.

The dataset's characteristics are clearly shown in Table 4.1, where it is evident that the series contains instances of a minimum value reaching 0.000. This empirical verification further reinforces the rationale behind adopting the pseudo-additive model. This model not only accommodates but effectively integrates these zero values within the framework of the analysis, thereby preventing any distortion or compromise in the overall integrity of the study.

Such choice in model selection stands as a demonstration to the robustness of the research methodology employed. It ensures that the distinctive attributes of the dataset, such as the presence of zero values, are not dismissed but rather leveraged to derive more accurate and insightful conclusions. Moreover, this selection provides a solid methodological bridge between the findings of this study and the broader body of research in the field. Consequently, it substantiates the scholarly contributions of this research in a nuanced manner, aligning with established empirical observations and fortifying the credibility of the ensuing conclusions.

The trend shows the broad direction that the time series graph appears to be moving over an extended period of time. The main feature of it is that it persists in one direction or in a predictable pattern for extended periods of time, whether it is upward (growth) or downward (decline). The graphical representation of the linear trend in Figure 4.7 distinctly portrays a noticeable downward trajectory, indicative of a discernible decline. This observation effectively underscores the prevailing trend in the admission of orphans in orphanage homes within Niger state. Specifically, it signifies a decreasing pattern over the observed period.

Such a trend, pointing unequivocally towards diminishing admissions, is indicative of the tangible impact of measures instituted to counter child abandonment rates. The proactive strategies implemented are evidently finding resonance and traction, resulting in a demonstrable reduction in the admission of orphans into orphanage homes. This interpretation reflects a positive outcome, as it aligns with the overarching goal of mitigating child abandonment instances.

This finding holds considerable significance not only from a sociological standpoint but also in terms of policy efficacy. The decreasing trend validates the effectiveness of interventions and policies aimed at curbing child abandonment. Furthermore, it reflects the dedication and collaboration of stakeholders involved in ensuring the well-being of vulnerable children.

The robustness of this observation is further emphasised by its alignment with the broader contextual understanding of child welfare measures and their impact. It reinforces the notion that collective efforts, informed by insightful data analysis such as presented in this study, can indeed yield positive societal outcomes. Thus, the decline in orphanage admissions serves as a tangible testament to the proactive endeavours undertaken to safeguard the rights and future of these vulnerable children in Niger state.

On the seasonality, the detrended series in figure 4.8 where the trend component has been removed to observe other components such as the seasonal component, showed that there is a presence of seasonality in the series. To justify the presence of seasonal effects, Iwueze *et al*., (2011) opined that the pattern of the deviation of the seasonal average from the overall average and the seasonal index can be used to assess seasonal effects in a series when the deviation $\left(\bar{X}_{.j} - \bar{X}_{..}\right)$ mimics or follows the actual seasonal index. This was the case in figure 4.9 where the pattern of the deviation $\left(\bar{X}_{.j} - \bar{X}_{..}\right)$ follows the seasonal index and hence suggest a presence of seasonality in the admission of OVC into the orphanage homes and also showed that most of the admission was carried out in the third quarter of the year (July, August and September) followed by the second quarter of the year (April, May and June). This is in agreement with the study carried out by Ibor & Jaiyeoba (2021) which indicated that high birth rates are recorded in the month of July and August. This indicates that fertility and reproductive health results are seasonally related.

Similarly, research by Osei, *et al*., (2016) showed that there is a peak in the rate of delivery in the month of May and September.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study was conducted for the purpose of applying the decomposition technique on admittance into orphanage homes. This was attained using the time series decomposition approach to formulate an appropriate model of admittance, obtain the trend of admission and check for the presence of seasonal effect. This study takes up the case of orphans and vulnerable children (OVC) in Niger State. Monthly time series data was obtained from the state orphanage home admission register and was documented for the period of twenty years (2000-2020).

To formulate the appropriate decomposition model, a comparative analysis of model performance was carried out among Additive, Multiplicative and Pseudo-Additive decomposition models and selection was based on the Mean Absolute Percentage Error (MAPE) accuracy measure. The model with the least accuracy measure was the pseudo additive model and hence the most appropriate model of admittance into orphanage homes.

Additionally, the trend analysis was carried out using the de-seasonalised series of the pseudo-additive decomposed model. The plot of the series showed that the admission of OVC follows a linear downward trend. The linear trend model was given as; $X_t = 1.22031 - 0.00492880t$. The equation represents the observed value X_t at time *t*, where *t* denotes the time period.

Finally, the series showed that there is a presence of seasonal effect on the admission of orphans. The seasonal pattern was determined using the time plot of the de-trended series and further confirmed by comparing the line plot of the seasonal index with the difference between the seasonal average and the overall average.

The study shows that the appropriate model of admittance of OVC for the series is the pseudo-additive model. The admission data contains zero values in months where OVC was not admitted which strongly agrees that the pseudo-additive model is the most appropriate model to adopt when the data contains small or zero values. The result of the trend analysis shows that the rate of admission follows a negative linear trend which indicates that the rate of child abandonment is on the decrease and the actions put in place to curb the rate of child abandonment are being adhered to. The study result also shows the presence of seasonal effects in the series. It was observed that there is a seasonal pattern in the admittance of orphans during the second and third quarters of the year.

5.2 Recommendations

Based on the analysis of the time series data, it is recommended to employ the pseudo-additive model for further analysis. This model accounts for the presence of zero values in the time series data, which was observed in the admission data collected from the state orphanage home. By adopting the pseudo-additive model, the statistical modelling of the series can be improved, leading to more accurate and reliable results. In addition, the observed downward trend in the admission of orphans in orphanage homes suggests a decline in the overall admission rates. To ensure the statistical validity of this trend, it is recommended to conduct formal hypothesis tests or statistical significance tests to assess the significance of the observed trend. This will provide more robust evidence regarding the effectiveness of actions implemented to curb child abandonment.

Furthermore, the presence of seasonality in the admission of Orphans and Vulnerable Children (OVC) into orphanage homes should be further investigated using appropriate machine-learning techniques. This will provide insights into the patterns and factors contributing to the seasonal variation in admission rates. Advanced machine learning algorithms such as recurrent neural networks (RNNs) or long short-term memory (LSTM) networks are recommended. These models have the capability to capture complex temporal dependencies and effectively handle seasonality in the data, enabling more accurate and robust predictions of OVC admission rates.

Lastly, given the association between the admission patterns of OVC and fertility/reproductive health factors, it is recommended to collaborate with experts in the field of reproductive health or demography. By partnering with professionals in related disciplines, a comprehensive understanding of the underlying causes of the observed seasonality can be achieved. This collaboration will also facilitate the development of targeted interventions and policies to address the issue effectively.

5.3 Contribution to Knowledge

The study on the application of decomposition techniques on admittance into orphanage homes in Niger State contributes significantly to knowledge in the following areas: The study presents the application of decomposition techniques, specifically the pseudo additive decomposition model, as a valuable method for analysing admittance data of orphans and vulnerable children. This approach addresses the challenge of dealing with missing and zero values in the data, providing a methodological guideline for future research in similar contexts. The findings of the study reveal a noteworthy downward linear trend in the admittance of orphans and vulnerable children. This trend suggests a decrease in child abandonment rates and indicates the effectiveness of interventions and actions implemented to address this issue. This insight contributes to the understanding of the impact of measures taken to combat child abandonment.

The study also identifies the presence of seasonal effects in the admittance of orphans, specifically during the second and third quarters of the year. This knowledge helps in identifying specific periods when admittance rates are higher, allowing for targeted resource allocation, intervention planning, and provision of support during these seasons.

REFERENCES

Australian Bureau of Statistics. (2017). Australian Bureau of Statistics website. Retrieved January 19, 2022, from Abs.gov.au website: https://www.abs.gov.au/websitedbs/D3310114.nsf/home/Time+Series+Analysis:+The+Basics

Brownlee, J. (2017). How to Decompose Time Series Data into Trend and Seasonality. Retrieved September 30, 2021, from Machine Learning Mastery website: https://machinelearningmastery.com/decompose-time-series-data-trend-seasonality/

Dagum, E.B. (2010). Time series modeling and decomposition. *Statistica*, anno LXX, 4(7), 434-457

Deacon, H., & Stephney, I. (2008). *HIV/AIDS, Stigma and Children* (1st ed.). Human Sciences Research Council. Retrieved from https://www.amazon.com/HIV-AIDS-Stigma-Children-Literature/dp/0796921881

DeLuca, H. (2019). Who is an orphan? – ONETrack international. Retrieved August 7, 2021, from ONETrack International website: https://onetrackinternational.org/who-is-an-orphan/

Dozie, K. C. N. (2020). Estimation of seasonal variances in descriptive time series analysis. *Asian Journal of Advanced Research and Reports*, 10(3), 37–47. https://doi.org/10.9734/ajarr/2020/v10i330245

Dozie, K. C. N., Nwogu, E. C., & Nwanya, J. C. (2020). Buys-Ballot Technique for the Analysis of Time Series Model. *International Journal of Scientific Research and Innovative Technology*, 7(1), 63–78.

Emmanuel, B. O., Enegesele, D., & Arimie, C. O. (2020). Additive Decomposition with Arima Model Forecasts When the Trend Component Is Quadratic. *Open Access Library Journal*, 7(7), 17–20. https://doi.org/10.4236/oalib.1106435

Evans, M., & Murray, R. (2008). *The African Charter on Human and Peoples' Rights: The system in practice 1986-2006* (2nd ed.). Cambridge: Cambridge University Press. https://doi.org/10.1017/cbo9780511493966

Federal Ministry of Women Affairs and Social Development [FMWASD]. (2009). Monitoring and Evaluation Plan for The Orphans and Vulnerable Children (OVC) Response in Nigeria. In *OVC support*. 10–12. Abuja, Nigeria: Federal Ministry of Women Affairs and Social Development. Retrieved from Federal Ministry of Women Affairs and Social Development website: https://ovcsupport.org/wp-content/uploads/Documents/Monitoring_and_Evaluation_Plan_for_The_Orphans_and_Vulnerable_Children_OVC_Response_in_Nigeria_1.pdf

Grassly, N. C., & Timæus, I. M. (2005). Methods to estimate the number of orphans as a result of AIDS and other causes in sub-saharan africa. *Journal of Acquired Immune Deficiency Syndromes*, 39(3), 365–375. https://doi.org/10.1097/01.qai.0000156393.80809.fd

Guttman, H. (1991) Systems theory, cybernetics, and epistemology. In A. S. Gurman & D. P. Kniskern (Eds.), *Handbook of family therapy*, 2, 41–62. New York: Brunner/Mazel.

Hope and Homes for Children. (2019). What is institutional care? 15 characteristics of orphanage-based systems. Retrieved August 5, 2021, from Hope and Homes for Children website: .

Hudson, L. A., & Ozanne, J. L. (1988). Alternative Ways of Seeking Knowledge in Consumer Research. *Journal of Consumer Research*, 14(4), 508–521. https://doi.org/10.1086/209132

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting : Principles and Practice* (2nd ed.). Heathmont, Vic.: Otexts. Retrieved from https://otexts.com/fpp2/

Ibeh, N. (2011). *Services available for orphans and vulnerable children in Enugu State* (Postgraduate Diploma Thesis; 12–13). University of Nigeria Nsukka.

Ibor, U. W., & Jaiyeoba, P. (2021). Seasonal Patterns of Facility-Based Deliveries in Vital Registration System: Evidence from Kogi State, North-central Nigeria. *Ghana Journal of Geography*, 13(3), 165–199.

Iwueze, I. S., Nwogu, E. C., Johnson, O., & Ajaraogu, J. C. (2011). Uses of the Buys-Ballot Table in Time Series Analysis. *Applied Mathematics*, 2(5), 633–645. https://doi.org/10.4236/am.2011.25084

Iwueze, I. S., Nwogu, E. C., Nlebedim, V. U., & Imoh, J. C. (2016). Comparison of Two Time Series Decomposition Methods: Least Squares and Buys-Ballot Methods. *Open Journal of Statistics*, 6(6), 1123–1137. https://doi.org/10.4236/ojs.2016.66091

Jones, J. (2018). *How Many Orphans Worldwide? What to Do?* Adoption.Org. Retrieved September 6, 2021, from https://adoption.org/many-orphans

Khair, U., Fahmi, H., Hakim, S. A., & Rahim, R. (2017). Forecasting Error Calculation with Mean Absolute Deviation and Mean Absolute Percentage Error. *Journal of Physics: Conference Series*, 9(7), 12–15. https://doi.org/10.1088/1742-6596/930/1/012002

Maskurul, A, Sharmin A.S., Yasin A.P., & Matiur R. (2015). Time Series Decomposition and Seasonal Adjustment. *Global Journal of Science Frontier Research*, 15(9), 11–19. Retrieved from https://journalofscience.org/index.php/GJSFR/article/view/1694

McKenna, C. (1911). Orphans and Orphanages. In the Catholic Encyclopedia. New York: Robert Appleton Company. Retrieved from New Advent: http://www.newadvent.org/cathen/11322b.html

Mejia-Pailles, G., Berrington, A., McGrath, N., & Hosegood, V. (2020). Trends in the prevalence and incidence of orphanhood in children and adolescents <20 years in rural KwaZulu-Natal South Africa, 2000-2014. *PLOS ONE*, 15(11), 5–9. https://doi.org/10.1371/journal.pone.0238563

Moshood, Y. (2020). Nigeria's growing problem of child abandonment. Retrieved January 6, 2022, from Healthwise website: https://healthwise.punchng.com/nigerias-growing-problem-of-child-abandonment/

Mosia, D.A. (2014). Perceptions of the roles and responsibilities of caregivers in children's homes (Master's dissertation). University of Pretoria.

Mutiso, D., & Mutie, P. (2018). Challenges affecting orphans and vulnerable children (OVC) in Embu county. *International Journal of Sociology*, 1(1), 18–36. Retrieved January 6, 2022, from http://www.iprjb.org/

National Population Commission-NPC/Nigeria and ICF International. (2014). Nigeria Demographic and Health Survey 2013. Abuja, Nigeria: NPC/Nigeria and ICF International. Retrieved February 1, 2022 from http://dhsprogram.com/pubs/pdf/FR293/FR293

Nwogu, E. C., Iwueze, I. S., Dozie, K. C. N., & Mbachu, H. I. (2019). Choice between Mixed and Multiplicative Models in Time Series Decomposition. *International Journal of Statistics and Applications*, 9(5), 153–159. https://doi.org/10.5923/j.statistics.20190905.04

Ojo, S., & Olayinka, A. (2019). Efforts at meeting the needs of orphans and vulnerable children in vulnerable households in selected communities of Nasarawa eggon LGA of Nasarawa State (An Assessment of Centre for Women Youth and Community Action (NACWYCA-NGOs). *Journal of Humanities and Social Science*, 24(10), 39–47. IOSR. https://doi.org/10.9790/0837-2410123947

Okon, G. J., Ushie, E. M., & Otu, J. E. (2020). Socioeconomic well-being of orphans and vulnerable children in orphanages within Cross River State, Nigeria. *African Journal of Career Development*, 2(1). https://doi.org/10.4102/ajcd.v2i1.13.

Omkar, G., & Kumar, S. V. (2017). Time series decomposition model for traffic flow forecasting in urban midblock sections. *2017 International Conference on Smart Technologies for Smart Nation (SmartTechCon)*, 5(6), 5–3. https://doi.org/10.1109/smarttechcon.2017.8358465

Osei, E., Agbemefle, I., Kye-Duodu, G., & Binka, F. N. (2016). Linear trends and seasonality of births and perinatal outcomes in Upper East Region, Ghana from 2010 to 2014. *BMC Pregnancy and Childbirth*, 16(1). https://doi.org/10.1186/s12884-016-0835-x

Persons, W. M. (1919). Indices of business conditions: an index of general business conditions. *Review of Economics and Statistics*,1(1), 111-205.

Plummer, A. (2020). Different Types of Time Series Decomposition. Retrieved October 1, 2021, from Medium website: https://towardsdatascience.com/different-types-of-time-series-decomposition-396c09f92693

Porta, M. (2018). Orphanage. In *A Dictionary of Public Health*. Oxford University Press. Retrieved from https://www.oxfordreference.com/view/10.1093/acref/9780191844386.001.0001/acref-9780191844386-e-3256.

Rutstein, S. O. (2008). *Finding the Missing Maternal and Paternal Orphans*. Joint United Nations Programme on HIV/AIDS (UNAIDS). Retrieved from https://www.dhsprogram.com/pubs/pdf/OD53/OD53.pdf

Swason, D. A. (2015). On the Relationship among Values of the Same Summary Measure of Error when it is used across Multiple Characteristics at the Same Point in Time: An Examination of MALPE and MAPE. *Review of Economics & Finance*, 5(3), 1–14. Retrieved from https://escholarship.org/uc/item/1f71t3x9

Tagurum, Y. O., Chirdan, O. O., Bello, D. A., Afolaranmi, T. O., Hassan, Z. I., Iyaji, A. U., & Idoko, L. (2015). Situational analysis of Orphans and Vulnerable Children in urban and rural communities of Plateau State. *Annals of African Medicine*, 14(1), 18. https://doi.org/10.4103/1596-3519.148714

Tirkeş, G., Güray, C., & Çelebi, N. (2017). Demand forecasting: a comparison between the Holt-Winters, trend analysis and decomposition models. *Tehnicki Vjesnik - Technical Gazette*, 24 (2), 503–509. https://doi.org/10.17559/tv-20160615204011

Ullah, M. I. (2020). Components of Time Series. Retrieved October 1, 2021, from Basic Statistics and Data Analysis website: https://itfeature.com/time-series-analysis-and-forecasting/components-of-time-series

United Nations Children's Fund [UNICEF]. (2022a). Convention on the rights of the child. Retrieved January 6, 2021, from Unicef.org website: https://www.unicef.org/child-rights-convention

United Nations Children's Fund [UNICEF]. (2022b). Orphanhood. Retrieved July 13, 2022, from UNICEF DATA website: https://data.unicef.org/topic/hivaids /orphanhood/

APPENDIX

Appendix I: Decomposition Table from Multiplicative Model

Time	Xt	Trend	Seasonal	Detrend	Deseason	Predict	Error
1	3	4.16416	0.49781	0.72043	6.0264	2.07298	0.92702
2	10	4.14431	0.54986	2.41294	18.1866	2.27877	7.72123
3	2	4.12447	1.60703	0.48491	1.2445	6.62816	-4.62816
4	2	4.10462	1.33857	0.48726	1.4941	5.49434	-3.49434
5	2	4.08478	0.81317	0.48962	2.4595	3.32162	-1.32162
6	5	4.06493	1.17238	1.23003	4.2648	4.76564	0.23436
7	4	4.04509	1.14221	0.98885	3.5020	4.62035	-0.62035
8	2	4.02524	0.63313	0.49686	3.1589	2.54850	-0.54850
9	2	4.00540	1.19318	0.49933	1.6762	4.77917	-2.77917
10	3	3.98555	1.06811	0.75272	2.8087	4.25700	-1.25700
11	7	3.96571	1.17299	1.76513	5.9677	4.65173	2.34827
12	6	3.94586	0.81155	1.52058	7.3932	3.20228	2.79772
13	1	3.92602	0.49781	0.25471	2.0088	1.95443	-0.95443
14	3	3.90617	0.54986	0.76802	5.4560	2.14783	0.85217
15	2	3.88633	1.60703	0.51462	1.2445	6.24545	-4.24545
16	5	3.86648	1.33857	1.29317	3.7353	5.17557	-0.17557
17	3	3.84664	0.81317	0.77990	3.6893	3.12797	-0.12797
18	3	3.82679	1.17238	0.78395	2.5589	4.48645	-1.48645
19	3	3.80695	1.14221	0.78803	2.6265	4.34834	-1.34834
20	2	3.78710	0.63313	0.52811	3.1589	2.39773	-0.39773
21	3	3.76726	1.19318	0.79634	2.5143	4.49502	-1.49502
22	3	3.74741	1.06811	0.80055	2.8087	4.00264	-1.00264
23	3	3.72757	1.17299	0.80481	2.5576	4.37240	-1.37240
24	2	3.70772	0.81155	0.53941	2.4644	3.00901	-1.00901
25	0	3.68788	0.49781	0.00000	0.0000	1.83588	-

							1.83588
26	2	3.66803	0.54986	0.54525	3.6373	2.01689	-0.01689
27	5	3.64819	1.60703	1.37054	3.1113	5.86275	-0.86275
28	3	3.62834	1.33857	0.82682	2.2412	4.85680	-1.85680
29	2	3.60850	0.81317	0.55425	2.4595	2.93432	-0.93432
30	3	3.58865	1.17238	0.83597	2.5589	4.20726	-1.20726
31	7	3.56880	1.14221	1.96144	6.1285	4.07633	2.92367
32	4	3.54896	0.63313	1.12709	6.3178	2.24695	1.75305
33	4	3.52911	1.19318	1.13343	3.3524	4.21087	-0.21087
34	5	3.50927	1.06811	1.42480	4.6812	3.74828	1.25172
35	4	3.48942	1.17299	1.14632	3.4101	4.09306	-0.09306
36	2	3.46958	0.81155	0.57644	2.4644	2.81575	-0.81575
37	0	3.44973	0.49781	0.00000	0.0000	1.71733	-1.71733
38	4	3.42989	0.54986	1.16622	7.2746	1.88594	2.11406
39	5	3.41004	1.60703	1.46626	3.1113	5.48005	-0.48005
40	6	3.39020	1.33857	1.76981	4.4824	4.53803	1.46197
41	2	3.37035	0.81317	0.59341	2.4595	2.74067	-0.74067
42	3	3.35051	1.17238	0.89539	2.5589	3.92807	-0.92807
43	5	3.33066	1.14221	1.50120	4.3775	3.80432	1.19568
44	2	3.31082	0.63313	0.60408	3.1589	2.09618	-0.09618
45	6	3.29097	1.19318	1.82317	5.0286	3.92673	2.07327
46	3	3.27113	1.06811	0.91711	2.8087	3.49392	-0.49392
47	1	3.25128	1.17299	0.30757	0.8525	3.81372	-2.81372
48	2	3.23144	0.81155	0.61892	2.4644	2.62248	-0.62248
49	2	3.21159	0.49781	0.62274	4.0176	1.59877	0.40123
50	0	3.19175	0.54986	0.00000	0.0000	1.75500	-1.75500
51	7	3.17190	1.60703	2.20688	4.3559	5.09735	1.90265
52	4	3.15206	1.33857	1.26901	2.9883	4.21926	-0.21926

53	3	3.13221	0.81317	0.95779	3.6893	2.54702	0.45298
54	4	3.11237	1.17238	1.28520	3.4119	3.64887	0.35113
55	3	3.09252	1.14221	0.97008	2.6265	3.53231	-0.53231
56	2	3.07268	0.63313	0.65090	3.1589	1.94540	0.05460
57	4	3.05283	1.19318	1.31026	3.3524	3.64258	0.35742
58	4	3.03299	1.06811	1.31883	3.7449	3.23956	0.76044
59	6	3.01314	1.17299	1.99128	5.1151	3.53438	2.46562
60	3	2.99330	0.81155	1.00224	3.6966	2.42922	0.57078
61	4	2.97345	0.49781	1.34524	8.0351	1.48022	2.51978
62	0	2.95361	0.54986	0.00000	0.0000	1.62406	-1.62406
63	9	2.93376	1.60703	3.06773	5.6004	4.71465	4.28535
64	4	2.91392	1.33857	1.37272	2.9883	3.90049	0.09951
65	1	2.89407	0.81317	0.34553	1.2298	2.35337	-1.35337
66	7	2.87423	1.17238	2.43544	5.9708	3.36968	3.63032
67	0	2.85438	1.14221	0.00000	0.0000	3.26031	-3.26031
68	1	2.83454	0.63313	0.35279	1.5795	1.79463	-0.79463
69	4	2.81469	1.19318	1.42112	3.3524	3.35844	0.64156
70	2	2.79484	1.06811	0.71560	1.8725	2.98520	-0.98520
71	2	2.77500	1.17299	0.72072	1.7050	3.25505	-1.25505
72	2	2.75515	0.81155	0.72591	2.4644	2.23596	-0.23596
73	3	2.73531	0.49781	1.09677	6.0264	1.36167	1.63833
74	1	2.71546	0.54986	0.36826	1.8187	1.49311	-0.49311
75	1	2.69562	1.60703	0.37097	0.6223	4.33195	-3.33195
76	3	2.67577	1.33857	1.12117	2.2412	3.58172	-0.58172
77	7	2.65593	0.81317	2.63561	8.6083	2.15972	4.84028
78	6	2.63608	1.17238	2.27610	5.1178	3.09049	2.90951
79	1	2.61624	1.14221	0.38223	0.8755	2.98830	-1.98830
80	2	2.59639	0.63313	0.77030	3.1589	1.64385	

0.35615							
81	3	2.57655	1.19318	1.16435	2.5143	3.07429	-0.07429
82	2	2.55670	1.06811	0.78226	1.8725	2.73084	-0.73084
83	1	2.53686	1.17299	0.39419	0.8525	2.97571	-1.97571
84	0	2.51701	0.81155	0.00000	0.0000	2.04269	-2.04269

Appendix II: Decomposition Table from Additive Model

Time	Xt	Trend	Seasonal	Detrend	Deseason	Predict	Error
1	3	3.71257	-1.55556	-0.71257	4.5556	2.15701	0.84299
2	10	3.70028	-1.18056	6.29972	11.1806	2.51972	7.48028
3	2	3.68798	1.86111	-1.68798	0.1389	5.54909	-3.54909
4	2	3.67569	0.98611	-1.67569	1.0139	4.66180	-2.66180
5	2	3.66340	-0.59722	-1.66340	2.5972	3.06617	-1.06617
6	5	3.65110	0.52778	1.34890	4.4722	4.17888	0.82112
7	4	3.63881	0.40278	0.36119	3.5972	4.04159	-0.04159
8	2	3.62651	-1.18056	-1.62651	3.1806	2.44596	-0.44596
9	2	3.61422	0.56944	-1.61422	1.4306	4.18366	-2.18366
10	3	3.60193	0.21528	-0.60193	2.7847	3.81720	-0.81720
11	7	3.58963	0.48611	3.41037	6.5139	4.07574	2.92426
12	6	3.57734	-0.53472	2.42266	6.5347	3.04262	2.95738
13	1	3.56505	-1.55556	-2.56505	2.5556	2.00949	-1.00949
14	3	3.55275	-1.18056	-0.55275	4.1806	2.37220	0.62780
15	2	3.54046	1.86111	-1.54046	0.1389	5.40157	-3.40157
16	5	3.52816	0.98611	1.47184	4.0139	4.51428	0.48572
17	3	3.51587	-0.59722	-0.51587	3.5972	2.91865	0.08135
18	3	3.50358	0.52778	-0.50358	2.4722	4.03135	-1.03135
19	3	3.49128	0.40278	-0.49128	2.5972	3.89406	-0.89406
20	2	3.47899	-1.18056	-1.47899	3.1806	2.29843	-0.29843
21	3	3.46670	0.56944	-0.46670	2.4306	4.03614	-1.03614
22	3	3.45440	0.21528	-0.45440	2.7847	3.66968	-0.66968
23	3	3.44211	0.48611	-0.44211	2.5139	3.92822	-0.92822
24	2	3.42981	-0.53472	-1.42981	2.5347	2.89509	-0.89509
25	0	3.41752	-1.55556	-3.41752	1.5556	1.86197	-1.86197
26	2	3.40523	-1.18056	-1.40523	3.1806	2.22467	-

							0.22467
27	5	3.39293	1.86111	1.60707	3.1389	5.25404	-0.25404
28	3	3.38064	0.98611	-0.38064	2.0139	4.36675	-1.36675
29	2	3.36835	-0.59722	-1.36835	2.5972	2.77112	-0.77112
30	3	3.35605	0.52778	-0.35605	2.4722	3.88383	-0.88383
31	7	3.34376	0.40278	3.65624	6.5972	3.74654	3.25346
32	4	3.33146	-1.18056	0.66854	5.1806	2.15091	1.84909
33	4	3.31917	0.56944	0.68083	3.4306	3.88862	0.11138
34	5	3.30688	0.21528	1.69312	4.7847	3.52216	1.47784
35	4	3.29458	0.48611	0.70542	3.5139	3.78069	0.21931
36	2	3.28229	-0.53472	-1.28229	2.5347	2.74757	-0.74757
37	0	3.27000	-1.55556	-3.27000	1.5556	1.71444	-1.71444
38	4	3.25770	-1.18056	0.74230	5.1806	2.07715	1.92285
39	5	3.24541	1.86111	1.75459	3.1389	5.10652	-0.10652
40	6	3.23312	0.98611	2.76688	5.0139	4.21923	1.78077
41	2	3.22082	-0.59722	-1.22082	2.5972	2.62360	-0.62360
42	3	3.20853	0.52778	-0.20853	2.4722	3.73631	-0.73631
43	5	3.19623	0.40278	1.80377	4.5972	3.59901	1.40099
44	2	3.18394	-1.18056	-1.18394	3.1806	2.00338	-0.00338
45	6	3.17165	0.56944	2.82835	5.4306	3.74109	2.25891
46	3	3.15935	0.21528	-0.15935	2.7847	3.37463	-0.37463
47	1	3.14706	0.48611	-2.14706	0.5139	3.63317	-2.63317
48	2	3.13477	-0.53472	-1.13477	2.5347	2.60004	-0.60004
49	2	3.12247	-1.55556	-1.12247	3.5556	1.56692	0.43308
50	0	3.11018	-1.18056	-3.11018	1.1806	1.92962	-1.92962
51	7	3.09788	1.86111	3.90212	5.1389	4.95900	2.04100
52	4	3.08559	0.98611	0.91441	3.0139	4.07170	-0.07170
53	3	3.07330	-0.59722	-0.07330	3.5972	2.47607	0.52393

54	4	3.06100	0.52778	0.93900	3.4722	3.58878	0.41122
55	3	3.04871	0.40278	-0.04871	2.5972	3.45149	-0.45149
56	2	3.03642	-1.18056	-1.03642	3.1806	1.85586	0.14414
57	4	3.02412	0.56944	0.97588	3.4306	3.59357	0.40643
58	4	3.01183	0.21528	0.98817	3.7847	3.22711	0.77289
59	6	2.99953	0.48611	3.00047	5.5139	3.48565	2.51435
60	3	2.98724	-0.53472	0.01276	3.5347	2.45252	0.54748
61	4	2.97495	-1.55556	1.02505	5.5556	1.41939	2.58061
62	0	2.96265	-1.18056	-2.96265	1.1806	1.78210	-1.78210
63	9	2.95036	1.86111	6.04964	7.1389	4.81147	4.18853
64	4	2.93807	0.98611	1.06193	3.0139	3.92418	0.07582
65	1	2.92577	-0.59722	-1.92577	1.5972	2.32855	-1.32855
66	7	2.91348	0.52778	4.08652	6.4722	3.44126	3.55874
67	0	2.90118	0.40278	-2.90118	-0.4028	3.30396	-3.30396
68	1	2.88889	-1.18056	-1.88889	2.1806	1.70834	-0.70834
69	4	2.87660	0.56944	1.12340	3.4306	3.44604	0.55396
70	2	2.86430	0.21528	-0.86430	1.7847	3.07958	-1.07958
71	2	2.85201	0.48611	-0.85201	1.5139	3.33812	-1.33812
72	2	2.83972	-0.53472	-0.83972	2.5347	2.30499	-0.30499
73	3	2.82742	-1.55556	0.17258	4.5556	1.27187	1.72813
74	1	2.81513	-1.18056	-1.81513	2.1806	1.63457	-0.63457
75	1	2.80284	1.86111	-1.80284	-0.8611	4.66395	-3.66395
76	3	2.79054	0.98611	0.20946	2.0139	3.77665	-0.77665
77	7	2.77825	-0.59722	4.22175	7.5972	2.18103	4.81897
78	6	2.76595	0.52778	3.23405	5.4722	3.29373	2.70627
79	1	2.75366	0.40278	-1.75366	0.5972	3.15644	-2.15644
80	2	2.74137	-1.18056	-0.74137	3.1806	1.56081	0.43919
81	3	2.72907	0.56944	0.27093	2.4306	3.29852	-

0.29852							
82	2	2.71678	0.21528	-0.71678	1.7847	2.93206	-0.93206
83	1	2.70449	0.48611	-1.70449	0.5139	3.19060	-2.19060
84	0	2.69219	-0.53472	-2.69219	0.5347	2.15747	-2.15747

Appendix III Decomposition Table from the Pseudo Additive model

Time	l_Xt	Trend	Seasonal	Detrend	Deseason	Predict	Error
1	1.09861	1.23391	-0.614388	-0.13530	1.71300	0.61952	0.47909
2	2.30259	1.22853	-0.546741	1.07405	2.84933	0.68179	1.62079
3	0.69315	1.22316	0.511833	-0.53001	0.18131	1.73499	-1.04184
4	0.69315	1.21778	0.412094	-0.52464	0.28105	1.62988	-0.93673
5	0.69315	1.21241	-0.170150	-0.51926	0.86330	1.04226	-0.34911
6	1.60944	1.20703	0.191807	0.40241	1.41763	1.39884	0.21060
7	1.38629	1.20166	0.198553	0.18464	1.18774	1.40021	-0.01392
8	0.69315	1.19628	-0.348040	-0.50313	1.04119	0.84824	-0.15509
9	0.69315	1.19091	0.194542	-0.49776	0.49860	1.38545	-0.69230
10	1.09861	1.18553	0.137558	-0.08692	0.96105	1.32309	-0.22448
11	1.94591	1.18016	0.172126	0.76575	1.77378	1.35228	0.59363
12	1.79176	1.17478	-0.139194	0.61698	1.93095	1.03559	0.75617
13	0.00000	1.16941	-0.614388	-1.16941	0.61439	0.55502	-0.55502
14	1.09861	1.16403	-0.546741	-0.06542	1.64535	0.61729	0.48132
15	0.69315	1.15865	0.511833	-0.46551	0.18131	1.67049	-0.97734
16	1.60944	1.15328	0.412094	0.45616	1.19734	1.56537	0.04406
17	1.09861	1.14790	-0.170150	-0.04929	1.26876	0.97775	0.12086
18	1.09861	1.14253	0.191807	-0.04392	0.90680	1.33434	-0.23572
19	1.09861	1.13715	0.198553	-0.03854	0.90006	1.33571	-0.23709
20	0.69315	1.13178	-0.348040	-0.43863	1.04119	0.78374	-0.09059
21	1.09861	1.12640	0.194542	-0.02779	0.90407	1.32094	-0.22233
22	1.09861	1.12103	0.137558	-0.02242	0.96105	1.25858	-0.15997
23	1.09861	1.11565	0.172126	-0.01704	0.92649	1.28778	-0.18917
24	0.69315	1.11028	-0.139194	-0.41713	0.83234	0.97108	-0.27794
25	0.00000	1.10490	-0.614388	-1.10490	0.61439	0.49051	-0.49051
26	0.69315	1.09953	-0.546741	-0.40638	1.23989	0.55278	0.14036
27	1.60944	1.09415	0.511833	0.51529	1.09760	1.60598	0.00345
28	1.09861	1.08878	0.412094	0.00984	0.68652	1.50087	-0.40226
29	0.69315	1.08340	-0.170150	-0.39025	0.86330	0.91325	-

0.22010							
30	1.09861	1.07802	0.191807	0.02059	0.90680	1.26983	-0.17122
31	1.94591	1.07265	0.198553	0.87326	1.74736	1.27120	0.67471
32	1.38629	1.06727	-0.348040	0.31902	1.73433	0.71923	0.66706
33	1.38629	1.06190	0.194542	0.32439	1.19175	1.25644	0.12985
34	1.60944	1.05652	0.137558	0.55291	1.47188	1.19408	0.41536
35	1.38629	1.05115	0.172126	0.33515	1.21417	1.22327	0.16302
36	0.69315	1.04577	-0.139194	-0.35263	0.83234	0.90658	-0.21343
37	0.00000	1.04040	-0.614388	-1.04040	0.61439	0.42601	-0.42601
38	1.38629	1.03502	-0.546741	0.35127	1.93304	0.48828	0.89801
39	1.60944	1.02965	0.511833	0.57979	1.09760	1.54148	0.06796
40	1.79176	1.02427	0.412094	0.76749	1.37967	1.43637	0.35539
41	0.69315	1.01890	-0.170150	-0.32575	0.86330	0.84875	-0.15560
42	1.09861	1.01352	0.191807	0.08509	0.90680	1.20533	-0.10672
43	1.60944	1.00815	0.198553	0.60129	1.41088	1.20670	0.40274
44	0.69315	1.00277	-0.348040	-0.30962	1.04119	0.65473	0.03842
45	1.79176	0.99740	0.194542	0.79436	1.59722	1.19194	0.59982
46	1.09861	0.99202	0.137558	0.10659	0.96105	1.12958	-0.03097
47	0.00000	0.98664	0.172126	-0.98664	-0.17213	1.15877	-1.15877
48	0.69315	0.98127	-0.139194	-0.28812	0.83234	0.84208	-0.14893
49	0.69315	0.97589	-0.614388	-0.28275	1.30754	0.36151	0.33164
50	0.00000	0.97052	-0.546741	-0.97052	0.54674	0.42378	-0.42378
51	1.94591	0.96514	0.511833	0.98077	1.43408	1.47698	0.46893
52	1.38629	0.95977	0.412094	0.42653	0.97420	1.37186	0.01443
53	1.09861	0.95439	-0.170150	0.14422	1.26876	0.78424	0.31437
54	1.38629	0.94902	0.191807	0.43728	1.19449	1.14082	0.24547
55	1.09861	0.94364	0.198553	0.15497	0.90006	1.14220	-0.04358
56	0.69315	0.93827	-0.348040	-0.24512	1.04119	0.59023	0.10292
57	1.38629	0.93289	0.194542	0.45340	1.19175	1.12743	0.25886
58	1.38629	0.92752	0.137558	0.45878	1.24874	1.06507	0.32122
59	1.79176	0.92214	0.172126	0.86962	1.61963	1.09427	

							0.69749
60	1.09861	0.91677	-0.139194	0.18185	1.23781	0.77757	0.32104
61	1.38629	0.91139	-0.614388	0.47490	2.00068	0.29700	1.08929
62	0.00000	0.90602	-0.546741	-0.90602	0.54674	0.35927	-0.35927
63	2.19723	0.90064	0.511833	1.29659	1.68539	1.41247	0.78475
64	1.38629	0.89526	0.412094	0.49103	0.97420	1.30736	0.07894
65	0.00000	0.88989	-0.170150	-0.88989	0.17015	0.71974	-0.71974
66	1.94591	0.88451	0.191807	1.06140	1.75410	1.07632	0.86959
67	0.00000	0.87914	0.198553	-0.87914	-0.19855	1.07769	-1.07769
68	0.00000	0.87376	-0.348040	-0.87376	0.34804	0.52572	-0.52572
69	1.38629	0.86839	0.194542	0.51791	1.19175	1.06293	0.32336
70	0.69315	0.86301	0.137558	-0.16987	0.55559	1.00057	-0.30742
71	0.69315	0.85764	0.172126	-0.16449	0.52102	1.02976	-0.33662
72	0.69315	0.85226	-0.139194	-0.15912	0.83234	0.71307	-0.01992
73	1.09861	0.84689	-0.614388	0.25173	1.71300	0.23250	0.86611
74	0.00000	0.84151	-0.546741	-0.84151	0.54674	0.29477	-0.29477
75	0.00000	0.83614	0.511833	-0.83614	-0.51183	1.34797	-1.34797
76	1.09861	0.83076	0.412094	0.26785	0.68652	1.24285	-0.14424
77	1.94591	0.82539	-0.170150	1.12052	2.11606	0.65524	1.29067
78	1.79176	0.82001	0.191807	0.97175	1.59995	1.01182	0.77994
79	0.00000	0.81463	0.198553	-0.81463	-0.19855	1.01319	-1.01319
80	0.69315	0.80926	-0.348040	-0.11611	1.04119	0.46122	0.23193
81	1.09861	0.80388	0.194542	0.29473	0.90407	0.99843	0.10019
82	0.69315	0.79851	0.137558	-0.10536	0.55559	0.93607	-0.24292
83	0.00000	0.79313	0.172126	-0.79313	-0.17213	0.96526	-0.96526
84	0.00000	0.78776	-0.139194	-0.78776	0.13919	0.64856	-0.64856