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COLLEGE OF SCIENCE

FACULTY OF PHYSICAL AND COMPUTATIONAL SCIENCES

DEPARTMENT OF STATISTICS AND ACTUARIAL SCIENCE

TIME SERIES ANALYSIS ON PATIENT'S ATTENDANCE AT KNUST HOSPITAL

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SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF BACHELOR OF SCIENCE IN STATISTICS

September, 2022

Declaration

We hereby declare that this submission is the result of our own research work carried out in the Department of Statistics and Actuarial Science, KNUST, towards the Bachelor of Science (BSc.) degree in Statistics and that to the best of our knowledge, all references have been duly acknowledged.

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Dedication

We dedicate this project to the Almighty God and to our amazing parents in appreciation of their support, encouragement and endless contribution to our studies.

Acknowledgement

The success of this project would not have been possible the Almighty God. We are extremely grateful to our parents for their efforts and contributions to our studies. We value and appreciate our supervisor Dr. Alexander Boateng and Dr. Eric Nimako Aidoo for their efforts, encouragements, support and directions which helped us complete this research study. To all our friends who helped in one way or another, we appreciate you all.

Abstract

This research makes use of Time Series Analysis to analyse patientsâ attendance to KNUST Hospital considering three clinics of the hospital; the outpatient department, eye clinic and dental clinic and also to select the most appropriate model that will be used in forecasting monthly values of patientsâ attendance from 2022 to 2023 for the clinics of interest. A monthly basis secondary data was obtained from KNUST Hospital for the period of 2017 to 2021.

The most suitable model for the each of the clinics from the competing models are as follows; ARIMA (1 ,0, 0) (1,0 ,0) [12] was selected for Dental clinic, outpatient department was ARIMA (0 ,1, 0) (1,0 ,0) [12] and ARIMA (0 ,0, 1) (1,0 ,0) [12] for the Eye clinic all with non-zero mean, and with the least AIC value. The suitable model for each of the three clinics of the hospital was further validated by Ljung-Box test with no significant autocorrelation between the residuals at different lag times, no significant spike in the residual plots of ACF and PACF, and also the assumption of normality validated. The forecasted values recorded do not relatively vary significantly from the regular attendance rate of patients to the hospital. Findings from the study also show that patientsâ attendance in the hospital has experienced an increase and decrease linear trend from the year 2017 to 2021.

It is recommended that, management of the hospital give priority to increasing the doctor to patient ratio to reduce the waiting time in the system, increasing hospital beds and logistics to accommodate patients all of which helps maximize patient satisfaction in the healthcare system hence an incentive to patronise the hospital more.

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Chapter 1

INTRODUCTION

1.1 Background information

Forecasting is about predicting events based on certain acquired information through a systematic process or intuition. For the past years, forecasting has advanced greatly and increased in many sectors. The health sector inclusive. (Soyiri Reidpath, 2012). The concept of Health forecasting is a novel part of forecasting which concentrates on forewarning about future health events and also an important way of predicting the demand for health services and needs (Soyiri Reidpath, 2012) as well the supply of healthcare services which majorly is influenced by consumer or patient satisfaction. This aspect of forecasting is very important to the world of forecasting because it is a health system that engages and heavily informs public health planning that provides health care services to populations. There are a number of researches directed to specific health conditions and departments like the emergency department that contributed to this chapter but this particular study the focus is on attendance to 3 different departments i.e. eye, outpatients and dental of the KNUST hospital.

The KNUST Hospital has been heavily patronized by a large number of people for the high efficiency and quality of services they provide to patients within the Ashanti Region of Ghana. Though it is the university's hospital, it extends its services to the general public. So far it accommodates forty-two thousand (42,000) students and one hundred and fifty thousand (150,000) people from the neighboring communities and yet has 125 bed space capacity (University Health Service Website).

For most people, good health is one of the things to prioritize and for the past years the world has been plagued with continuous outbreak of pandemics like Ebola, corona virus that has claimed lots of lives. Reasons being that most people are reluctant to going to the hospital to check up on their health statuses mainly due to lack of resources and health care facilities especially within the African community and as a result, most of these diseases and illnesses keep on spreading and escalating despite various developments and modifications of health facilities. This certainly defies the priority that most people give to maintaining and acquiring good health.

There is still a prospective future incidents of congestions and its related issues such as inadequate infrastructure to accommodate patients, an imbalance in patient-to-healthcare provider ratio and a whole lot other issues. This is because over the years, there has been a continually corresponding increase in the students' population as well as an increase in the patronage for the services the university hospital provides. This is seen in the 2019/2020 academic year when over twenty-two thousand students were admitted into the institution (Ghana News Agency, n.d.) and this growth in population has consistently seen an upward trend. Consistently, there have been numerous complaints from students who would either have to forfeit lectures to join long queues at the students' clinic or go to lectures and never have their medical needs attended to and this is not exclusive to the general populace who would have to also sacrifice joining these long queues and their medical needs for their respective jobs. These struggles to gain medical attention then serves as a disincentive for both students and the general populace to seek medical services from the KNUST hospital.

The main goal of every health institution is **patient satisfaction**. Though there is no metric for measuring patients' satisfactory level, we believe a high patronage for the services provided in these institutions can be used as a measure for patients' satisfaction. With an increasing population and high demand for the services the hospital provides, there will be a dire need of improvement in the infrastructure, an increment in the number of medical personnel and an increase or high maintenance of hospital logistics. This project takes into consideration all these and seeks to record and analyze the monthly, quarterly and annual attendance of patients to the various departments of the KNUST hospital. The data for this project is time dependent and this is the reason time series is the appropriate method for predicting the number of patients that visit the hospital in the subsequent months. Time series has been used in many fields including insurance, healthcare, economics, finance, weather forecasting amongst many other sectors and also becomes important when identifying the fluctuations in the health attendance indicators (Anon, 2016). We believe this would be of great help in efficiently allocating and distributing resources which may include expanding these departments to continuously accommodate and satisfy the health care demands of the growing populace.

1.2 STATEMENT OF RESEARCH PROBLEM

Generally, the worldâs population is rising at an increasing rate especially in our part of the world, West Africa, which estimated to be about three hundred and eighty-one million people (381,000,000) as at 2018 (Wikipedia 2018, n.d.) and Ghana is not an exception. An increasing population would consequentially demand that there be an improvement in important sectors such as the Health sector. In KNUST, the hospital could be facing a lot of challenges in providing adequate resources and efficient services to its clients resulting from the phenomenal growth in population both internally (studentsâ population) and externally (general population) over the past decades. With regards to the internal population growth (student population) problems of congestion arising from the internal population is the inadequacy in the provision of pharmacies in campus grounds. As it stands thereâs only one pharmacy located at the extreme end of campus, Brunei Hostel that cannot cater for the needs of the large number of residential students present on the main campus and as a result, all advances for good health care acquisition are made towards the KNUST hospital. This goes on to affect the number of visitations and patients the hospital is capable of accommodating. Hence the likelihood of congestions as population growth persist.

Considerably the problem of high population and its effect in West Africa cannot substantially differ from that of Ghana. As population increases, there could be a possible depletion in the health care facilities as a result of over usage and high burden on the few health resource facilities available. Many patients as well would not be attended to as quickly as possible. Medical personnel could be stressed out, washrooms and places of convenience for patients could be choked, bed spaces availability to accommodate the increasing number of patients could be quite problematic and all these cases have higher possibilities of occurrence due to the pandemics like COVID-19. With this project, we seek to illustrate to management with enough information and data to draw attention to the impending problems and provide sustainable measures to solve these prospective problems.

1.3 OBJECTIVES

To use Time Series to analyze patients' attendance in KNUST hospital for the period 2017-2021.

1.3.1 SPECIFIC OBJECTIVES

1. To use Time Series analysis to predict patients' attendance in KNUST hospital using data obtained from the records department of the hospital from 2017-2021
2. To determine whether there is an increase or decrease in patients' attendance
3. To study the seasonal trend of outpatient, eye clinic and dental clinic attendance to KNUST hospital.

1.4 RESEARCH QUESTIONS

The overall objective of this particular research is to analyze the overall attendance of patients to the hospital and to fit time series model to the data from 2017-2021. The key guideline questions are:

1. Is there an increase or decrease in the patients' attendance?
2. Is there a seasonal trend of Patients' attendance to the hospital?
3. Are the time series patterns of patients' attendance at the KNUST hospital per month consistent for each independent year?
4. Are there any factors influencing patients' attendance in the hospital?
5. What sustainable measures can management take to minimize or solve the problems accruing from patients' attendance in the hospital?

1.5 SIGNIFICANCE OF THE STUDY

The concept of forecast is one that is very crucial and plays a pivotal role in many sectors including health institutions, businesses, industries, government works and Institutional planning because most decisions that produce efficient outcomes are highly dependent on accurate predictions. Likewise to this study, the prediction of patientsâ attendance would be beneficial to the management of the health institution of interest which is the KNUST hospital to provide the adequate infrastructure to sustain the growing population and their health status. The ever increasing patronage of the KNUST hospital requires that adequate preparations in terms of personnel, expansion of wards, further infrastructure developments and logistics are made in advance. The findings from this study would therefore help the management of University hospital to adequately prepare to accommodate the large number of prospective patients. Also the study could suggest solutions to the internal problems that the student populace face pertaining to health needs can be formulated by providing adequate health systems such as pharmacies and proper improvement in the student clinic facility such that the over reliance on the KNUST hospital is reduced hand in hand with the likelihood of congestions.

We believe this will help management make advanced plans in terms of labor and logistical requirements for better service delivery to maximize the satisfaction and meet the expectations of prospective patients.

1.6 SCOPE AND LIMITATIONS OF THE STUDY

This study majorly focuses on the operations of the Kwame Nkrumah University of Science And Technology (KNUST) Hospital. As most researches have their limitations, similarly this study is restricted by time and though quite a few reviews exist on this subject, most of the researches do not discuss the general approaches that can serve as guidelines for the development of other health forecasts rather only focus on specific health conditions and hospital departments and this makes it hard to access the relevant materials to support this study. The findings from this research may only be preserved for the Universityâs hospital and not other hospitals because of unique characteristics these other hospitals may possess. However, it may also be used as a reference material and a guide for educational institutions and companies for resolving related problems that may be challenging to the management of the of the institutions.

1.7 STRUCTURE OF THE STUDY

This study will entail five chapters.

Chapter one covers the background of the study, problem statement, objectives of the study, research questions, significance of the study, scope and limitations of the study and lastly the structure of the study. Chapter two reviews the related literature of the study on the theoretical and empirical works of the previous researches. The research methodology which looks at the methods the research will use in realizing its aimed objectives is covered in the third chapter of the study. Chapter Four focuses on data presentation, interpretations and analysis of the data from the KNUST Hospital The fifth chapter being the final chapter deals with the summary, conclusions of the research work and recommendations from the findings of the study.

Chapter 2

LITERATURE REVIEW

2.1 Health

"The health of all people is fundamental to the attainment of peace and security and is dependent on the fullest cooperation of individuals and states" remains as one of the core principles of the World Health Organization (WHO) and similarly the purpose of this chapter is to review the various research works of authors and incorporate their opinions in this project which has the improvement of health status as the focus. Hospitals usually have hard times due to the continual increase in the number of patients that visit and this in turn reduces the quality of health service given out. Potential harms and threats that these hospitals face as a result makes administrators or management willing to curb the threats (Moskop et al., 2008, 2009) and as such the best way to begin the hunt for optimal solutions is access to accurate prediction of patient attendance to facilitate strategic plans and good decision making. (Jochen Bergs et al., 2013).

The importance of human health in national development has made efficiency in the production of health services in the Health Care System a subject of intense research interests in the literature (Hollingsworth, 2003). The concept of Health plays a fundamental role in development and as it is, growth in health care costs has been attributed, at least to an honorable degree, to the inefficiency of health care institutions to maximize the patientâs satisfaction. In most researches regarding optimality test, the capital input comprises complex medical equipment, buildings, beds as well vehicles employed to facilitate health care systems and that is why it is reasonable for healthcare literatures to therefore assume that there exists a directly proportional link between quantity of capital stocks and Services (Peacock, et al., 2001). However, number of beds is the most used variable in hospital efficiency studies. The use of this variable as a proxy for

capital inputs has been accepted by researchers (Harrison , et al., 2004).
This research deals with three major departments thus the eye, dental and outpatient (OP) departments.

2.1.1 OUTPATIENT DEPARTMENT (OPD)

The outpatient department is the window of the hospital external services from the actual operations of the hospital (Luo, et al., 2017). The OPD is always the first point of contact at every hospital and as such, forms a gateway into the hospital premises or into the healthcare delivery system for all patients. It is the beginning for healthcare acquisition and disease prevention. A report by the Institute of Medicine (IOM) identified six fundamental aims for healthcare; safe, efficient, patient centered, equitable, effectiveness and timeliness. Of all these aims, timeliness is the least well studied and understood (Wolfe, 2001). There is a negative correlation between waiting time and patient satisfaction. IOM recommends that at least 90% of patients should receive medical care within 30 minutes of their scheduled appointment time (O"Malley, et al., 1983)
It has become prominent that healthcare institutions consider and give attention to the maintenance and planning of their OPD to reach the goal of serving patients of the healthcare industries because, patients who find trouble at this phase of the hospital are more likely to stop visiting that particular hospital and this affects healthcare systems. Therefore, reducing waiting time may lead to improvement in patient satisfaction and greater willingness to continue to receive care at the same health care facilities. (Anderson, et al., 2006) and (Al-Harajin, et al., 2019).

2.1.2 DENTAL DEPARTMENT

Dental Clinic is a place where a dentist performs dental procedures, treatments and a comprehensive oral care for patients with dental diseases. The primary responsibility of a dentist is to provide quality patient care (McDonald, et al., 2010). Oral health has an important influence on the quality of life, appearance and self-esteem of an individual hence defined as the state of being free from mouth and facial pain, oral and throat cancer, oral infections, gum or periodontal diseases, tooth loss, tooth decay and other diseases as this affect a personâs quality of life in the sense that it limits oneâs capacity to bite, chew, smile, speak and have psychosocial wellbeing (World Health Organization, 2012). Risk factors for oral diseases include poor oral hygiene, unhealthy sugar consumption and diets, tobacco and harmful alcohol use (World Health Organization, 2003). The distribution and severity of oral disease has also shown considerable variation worldwide, and within countries.

In Africa, the profile of oral diseases is also not homogeneous and though data is scarce, available evidence suggests an increasing trend (A. Abid, et al., 2015). Dental carrier cases were recorded as 98,996 out of 25,441,412 outpatient cases representing 0.4% (Ghana Health Services, 2012). Ghana has had some challenges with access to dental care including the low ratio of the number of dentists to population, targeted oral health programs focused on at risk populations and many others. Oral health has generally not been prioritized in Ghana. Unfortunately, the proportion of people obtaining oral health care is alarmingly low despite efforts at improving access including increasing number of trained dentists and clinics, and revamping the national health insurance. A study in Ghana by (Hewlett, et al., 2015) has shown that the availability of dentists and access to dental services alone does not appear to be the most important determinant of better oral health but also treatment services in maintaining and at best, place enough attention to prevent oral health complications since only a small part of the population regularly make efficient use of oral health services. (Hewlett, et al., 2022).

2.1.3 EYE CARE DEPARTMENT

Eye care is a vital aspect of managing the critically ill patient, as many of the mechanisms normally involved in protecting the eye from infection and injury (Hearne, et al., 2018). The appropriate use of eye health services is essential to reduce the burden of visual impairment worldwide (Morka Derecha, et al., 2020). One of the aims of the World Health Organizationâs (WHO) Global Action Plan 2014-2019 for Universal Eye Health was to generate evidence regarding the provision of eye health services that serve to design plans and policies to strengthen universal access to eye health (World Health Organisation, 2013) Research in low- and middle -income countries (LMICs) has identified costs, a perceived lack of need, lack of information about the location of services, transportation difficulties, and fear of adverse outcomes as factors hindering access to eye health services (Ahmad, et al., 2015).

A review of eye clinic data (2012) in Ghana showed that 50% of all eye diseases diagnosed, mainly conjunctivitis and refractive errors, could be managed at the primary level if trained eye health workers were available and appropriately equipped at this level (Ghana Health Service, 2012) and also if patients would trust the healthcare system and health staff to help them with their complicated diseases.

2.1.4 EMERGENCY DEPARTMENT

Emergency Department is one of the castigatory sectors of a health care facilities. Actions of these departments are quite vital to the hospital because they cater for exceptional issues and events such as increasing number of patients from epidemic episodes like natural disasters, accidents from different causations (Berquedich, et al., 2019, p. 15) and a reduction or delay in providing readily accessible resources to their facility may likely peak to more situations of crisis. The retrospective study performed by (Rotstein, et al., 1997) which predicted ED visits on hourly basis may be of relevance to Emergency departments that encounter continuous unpredictable problems.

(Rotstein, et al., 1997) predicted hourly Emergency Department visits in a public hospital using Statistical models (seasonal decomposition models and moving average) with over a three-year period data from the public hospital.

2.2 TIME SERIES

There are a lot of models used for forecasting and one of them is time series models which comes in different folds such as Autoregressive (AR) model , moving average(MA) model, autoregressive integrated moving average (ARIMA) model, Seasonal autoregressive integrated moving average (SARIMA) model and they are used depending on the data available. Time Series Analysis is a set of observations taken sequentially over equal time interval. The models are used for forecasting time dependent data like inflation, stock prices, Gross domestic product, and hospital attendance. The Application of time series Analysis in healthcare Systems have been successful and super-efficient in forecasting the demands (day, hour and year) in the hospital Departments, medical staff planning , length of hospital stay and this is essential because it is a means to develop key strategies to prevent overcrowding that leads to many other constraints on the healthcare center. (Banor Gyan, 2012) Used time series in modelling the ARIMA part of the time series and forecasted hospital attendance. Their research work used interview schedule as their main source of data and imported secondary data to be included. The secondary data focused on monthly outpatient unit attendance from January 2008, to December 2011, using Obuasi hospital as the case study. ARIMA (2, 1, and 0) was the best selected model based on the AIC value of 420.33. Their findings forecasted a steadied trend of OPD attendance for the forecast period and turning point at the month of January 2012. Another research titled Time series model for forecasting the number of new admission inpatients performed by (Lingling, et al., 2018) aims at exploring the application of the ARIMA-NARNN hybrid, SARIMA, NARNN models to track the trends of the new admission inpatients which provides a methodological grounds for reducing crowding. The root mean square error (RMSE) and mean absolute percentage error (MAPE) and mean absolute error (MAE) were used to compare the forecasting performance within the three models. The result shows that for the monthly data, the modelling RMSE, MAE and MAPE of SARIMA-NARNN model were less than those obtained from the single SARIMA or NARNN model but the MAE and the MAPE of modelling performance of SARIMA-NARNN model did not improve. For the daily data, all RMSE, MAE and MAPE of NARNN model were the lowest both in modelling stage and testing stage. They concluded that hybrid model does not necessarily outperform its constituentsâ performances.

With discussions about time series analysis and its application, the Energy sector is rarely mentioned but a recent study performed by (Rick Berton, 2022) showed that the consumption prediction of Energy where the data may have some features of seasonality, irregular trends, uncertainty and even sometimes missing values can be quite a difficult problem however, can be modelled by Time Series application. Unlike most studies where the forecasting methods are developed to forecast individual or small groups of time series, Rickâs and Lillianâs study deals with short term forecasting in many time series with unequal lengths. According to the study, the method of Many time series is a challenge since usually many dedicated models are needed with each of the models forecasting one time series. Time series data and application proved very important in another study by (Deb , et al., 2017) which reviews time series forecasting methods for building energy consumption. In this research, it is revealed that buildings with pre-recorded time series energy data, statistical techniques as well as machine learning techniques provide more accurate and fast results and they mention that various combinations of the hybrid model are the more efficient and effective in time series energy forecasting for building. Also, time series factors like environmental conditions, occupancy schedule, thermal properties of building resources and weather conditions are co-analyzed for the study.

2.3 FORECASTING

Time Series cannot be analyzed without a bit of detail and dissection into the concepts of forecasting. The element of uncertainty that revolves around future occurrences is not only exciting but challenging in the light that it may come with unbearable risk factors and that is the reason why States, Corporations and even regional bodies always find ways to minimize risks or in worst case scenario, mitigate the impacts of the harms that go hand in hand with the risks. The only way to combat these harms and the uncertainty levels that come with these risks is through Forecasting. Forecasting has always been at the battle front with respect to discussions and studies about Decision making and planning.

2.3.1 WHY IS THIS RELEVANT?

Forecasting in itself gives States, corporations and Bodies a peek into the future by predicting a series of likelihood of certain occurrences usually by modelling the existing records of the specific situations to create the desired outcomes. A relatable example is the easy and fast access to weather conditions like temperatures, and chances of rain within seconds and unlike past days when this was not present, people can now plan and go about their normal duties with comparatively less worry about the weather. Similarly in the study about Energy Consumption above, it can be rightly said that accurate energy forecasting models have large implications on planning systems and energy optimization of buildings and this shows how relevant and important forecasting techniques have become in our world.

This is why the highlight on forecasting in this very project is equally important because continuous diseases and discovery of new variants pose a constant threat to our healthcare systems and measures to help fight the harms are attainable with Forecasting.

2.3.2 FORECASTING TECHNIQUES

Most reviews about forecasting techniques are usually classified into quantitative and qualitative approaches. And the strengths and weaknesses of the various techniques have been ineptly reviewed by (Calantone, Benedetto, Bojanic, 1987) and (Uysal Cromption, 1985). In a study titled the forecasting of International Expo tourism using quantitative and qualitative techniques, (Choong, Song, Mjelde, 2008) inform that quantitative techniques are applied to forecasting tourism demands when the information available on past tourism can be quantified and patterns can be used to determine future demands. Two main quantitative approaches used are time series and causal or explanatory models. Time-series models use historical data patterns to generate future forecasts and in the tourism sector, ARIMA and exponential smoothing models are quite popular in terms of its application to their existing data. (Geurts Ibrahim, 1975) Compared a BoxâJenkins (ARIMA) model with a Brown exponential smoothing model in the context of Hawaiian tourism demand. Outcome showed that both models (BoxâJenkins and the exponential smoothing) performed equally well in terms of forecasting accuracy, but the exponential smoothing may be preferred because it is easier to use. Another forecasting accuracy done by (Burger, Dohnal, Kathrada, Law, 2001) indicated that the exponential smoothing time series model performs best, followed by naÃ¯ve, ARIMA and MA models after applying them in forecasting US demand for travel to Durban, South Africa.

Qualitative techniques are used for forecasting tourism demand when changes of a large and unprecedented nature are likely to occur, examples of such changes would be mega-events. Qualitative techniques include the Delphi method, which was first applied by Dalkey Norman and Olaf Helmer in the research (Dalkey Helmer, 1963). Another study by (Archer, 1987) indicates that this method is dependent on the accumulated experience of experts and assembles a panel of experts from disciplines to obtain a group consensus concerning the likely outcome of future events. This method assumes that the range of responses will decrease as convergence is achieved toward the midrange of the distribution (Kaynak Macaulay, 1984).

One example of the use of the Delphi model can be seen in (Liu, 1988) research study in which he predicted Hawaiian tourism demand for 2000 using two separate panels, local tourist receivers and overseas tourist senders Forecasts of tourism demand made by both local and outside experts were generally consistent with state projections. (Lee Kim, 1998) also used the Delphi model for predicting international tourism demand for World Cup games in Korea.

2.4 FACTORS INFLUECING PATIENT ATTENDACE TO THE HOSPITAL

2.4.1 STAFF-PATIENTSâ RELATIONSHIP

In the health sector, the relationship between nurses and patients is prime in determining the rate at which patients attend the hospital. This relationship whether positive or negative is exhibited by both parties. However, the professional is trained to deal with negative attitudes from their patients as well as restrain themselves from going beyond the rules that govern them in fulfilling their duties.

A research sought to look from the patientsâ perspective and help empower hospital staff through the feedback gained from the patients interviewed, by giving them the knowledge and understanding of a healthy staff-patient relationship and the impact it has on patientsâ attendance to the hospital. (Nygardh, et al., 2011) Stated that from their findings, the patients expressed trust in the healthcare staff and their competence to provide them optimal health care and were satisfied with how the staff took responsibility for their services and as a result, they believed in the decisions of the doctors and nurses with regards to the best ways to help them recover. This shows that previous experience of the professionalism of staff increased the trust, giving a faith in the future and a sense of security to the patients. A further factor in all this was the staff portraying positive attitudes by sharing and communicating their knowledge with patients.

Moreover, according to a research journal by (Kennedy Diema Konla, et al., 2021) on the Influence of nurses-patientsâ relationship on hospital attendance, the attitude of nurses towards patients is as a result of the case at hand thus whether or not they are familiar with the case). For instance, how a nurse would handle a patient with covid-19 is going to be different from a patient with an ordinary (familiar) disease like Malaria. Nurses that understand the disease process and the patientsâ specific needs and tactically attend to those needs are usually considered to have a positive attitude towards their works. When patients have good perceptions about an institutions medical staff, it serves as a higher incentive for patientsâ attendance to that hospital and also influences how quickly patients recover from sickness or injury because they are more likely to believe that the staff will adequately take care of them. This is even more pronounced in rural areas. The study was conducted at the Kwahu Government Hospital (KGH) which is located in the Kwahu South District of the Eastern Region of Ghana using a qualitative research design approach with a purposive sampling technique to interview ten participants from the various wards in the hospital on their perceptions of the nurse-patient relationship. While a few others said otherwise, the study concluded with a good number of patients attesting that nurses in the hospital had positive attitudes towards them and that improved their patronage and attendance to the healthcare facility.

2.4.2 THE LEVEL OF SATISFACTION OF OPD SERVICES

(Chakravarty Mohd, 2014) Conducted a study on Patient satisfaction with services of the outpatient department (OPD). In their study, they considered a sample size of 120 by the use of structured questionnaire.

Samples were again stratified into sub-populations of officers namely; Junior Commissioned Officers (JCOs) and Other Ranks (ORs). The result of the study was as follows: Majority of JCOs showed a higher dissatisfaction with several attributes at the OPD. Total satisfaction judgment with Outpatient Department services were rated lower by JCOs (2.56) when compared with Officers and ORs (3.10), the difference being statistically significant. The study concluded that statistically significant differences have been identified by this study against various study attributes as well as overall impression towards OPD services among the study groups, which need to be addressed by the hospital leadership to improve consumer (patients) patronage.

2.5 THE DISTANCE OF THE HEALTHCARE FACILITY

There are a lot of highly improved healthcare centers in Ghana but that is not to say that they are easily accessible to all persons. Most people are often disadvantaged by their distance away from the hospitals, especially those in the rural areas and this negatively affects their access to the improved health-care facilities. In most parts of Africa, there are unequal distributions of modern health facilities. (Julius, 2006) Used a multiple regression model to analyse factors affecting the patronage of health facilities by rural dwellers in Owo Region, Nigeriaâ. In his study, distance of the hospital away from home had a regression coefficient of 0.0293 and it was significant at 0.01 which implies that a unit change in distance will result to a corresponding 2.93% change in the patronage of the hospital. This positive relationship is as a result of the fact that, rural settlers were already familiar with the location of the hospital and also as a result of the closeness of the hospital to the dwellers of the community, so even if there is an increase in distance, there would still be a marginal (2.93%) increase in patronage however small it may be. The results could however be different if the facility were distanced from their homes. This would stem from the fact that, distance and cost are positively related such that the farther the distance, the higher the cost of access. Cost and other related factors such as inability to travel far could alter the results. (OLUJIMI, 2006).

2.5.1 INSURANCE AND ABILITY TO PAY FOR SERVICES

Being able to access health care all depends on the ability to pay for hospital bills and in some countries, the availability of health insurance for citizens. Standardised longitudinal data of NHIS coverage for the resident population (Ghana) from 2010 showed an initial increase from 33% to 41% in 2015 but had a decline to 35% in 2017 (Nsiah-Boateng E, 2018). This is an indication that more than 50% 0f Ghanaians are still not insured, hence the low patronage of health care systems.

The Kaiser commission on Medical and uninsured noted that people without insurance have lower access as compared to people who are insured and 20% of uninsured adults in 2015 avoided medical care because of cost (Foundation Kaiser Family, 2016). The access to health insurance is considered to be one of drivers of health-care inequality (Nelson Alan, 2002).

Having health insurance does not guarantee absolute insulation from health care bills because in some countries, a smaller percentage of the bills are covered by the NHIS while the higher percentage of the bill is still a burden for the insured. That is why a low income earner may face some challenges attending the hospital even though he/she may be insured.

(Borbor Sena, et al., 2019) conducted their research work by making use of seasonal ARIMA model for a 10-year time period (2008-2017) forecasting hospital attendance in the Cape Coast Teaching Hospital for both insured and uninsured patients on a monthly basis across age groups and gender. In this research, an already existing data was used in fitting the model. The Selected models were SARIMA (1,0,0) (0,1,0)12 model for insured patients (NHIS) and SARIMA (1,1,1) (2,0,1)12 model for uninsured patients (Cash and Carry system) based on their minimum AIC values of 15.66537 (insured patients) and 13.94181(uninsured patients). They concluded that there is an established significant association of hospital attendance for patients using both systems (health insurance and cash and carry) with gender and years confirmed by the Chi square tests. The number of health insurance users differ across the levels of cash and carry patients in years with hospital attendance seeking healthcare. Hence the use of using health insurance scheme to seek medical care has increased hospital attendance with time while patients using cash and carry systems (uninsured) increase attendance particularly for the age groups, 1 to 17 years. This study shows the significant difference it makes for patients to be insured so as to increase their patronage to visit healthcare systems.

2.5.2 LITERACY RATE OF INDIVIDUALS

The lens from which an individual views the need to patronize the hospital when he/she is ill largely depends on the literacy . This can be seen in most instances where people resort to self medication andother ways of treatment without necessarily knowing what the problem is and that is because they have not sought for a doctor to diagnose the cause of the illness and prescribing the right drug or treatment to them. These situations often happen due to the lack of knowledge about Health care systems and

hence they do not fully appreciate the existence of these healthcare systems.
Thus, unless a literate person forcefully sends their illetrate grandparents for probably eye care treatment at the hospital, they are most likely to use ground herbs which does not give them total relief from their eye complications.

The literacy level of most African countries is very low. Ghana happens to be graded 79% literacy which indicates about 21% illiteracy rate as at 2018 (macrotrends.net, n.d.) (OLUJIMI, 2006) in his research analysing significant factors affecting the patronage of health facilities by rural dwellers in Owo region, Nigeria by applying multiple regression stated that, educational status had a regression coefficient of 0.505 which means that a unit increase in the level of education will result to a 50% increase in hospital attendance. This analysis seems reasonable since an improvement in education will heighten their horizon on health awareness and exposure as well as broaden their knowledge on locations to access better health facilities.

Chapter 3

METHODOLOGY

3.1 DATA

The dataset being used in this research study is a secondary data from the Kwame Nkrumah University of Science and technology Hospital and it comprises of three departments; Outpatient, eye and dental departments from year 2017 to 2021. The data contains monthly records of patients attending the hospital on 24 hour basis and this will be used to ascertain future predictions of the universityâs attendance.

3.2 DEFINITION OF TIME SERIES ANALYSIS

Time series by the definition is a collection of observations made sequentially according to the time of their outcome, with equal time interval. TIME series analysis is the detailed analysis of chronological data to extract meaningful insights from historical trends and to be able to make appropriate projections about the future (Ramkumar , et al., 2022). This can help recognize the different trends present and the seasonality in the data set and then utilize the identified trends and seasonality to make fitting predictions. Hence time series analysis is broadly used in numerous applications which have chronological data such as financial analysis and the prediction of stock prices, weather prediction, health analysis and many more other significant sectors.

In Particular, time series allows one to be able to determine and track the factors that are responsible for the behavior of a certain variable from time to time. It can also be a useful tool in analyzing how a given asset, security, or economic variable changes overtime. Forecasting methods in time series are also used in fundamental and technical analysis. During investment, time series analysis can also be used to track the accumulated amount overtime. Growth in populations can also be measured using time series analysis. In planning about the future and taking the necessary steps to guard against losses and failures, it is very crucial for every firm, every government institute, and every individual and for every country to make use of data gathered overtime. Every family is also doing planning for his income expenditure. Business men and women are also interested in planning for possibilities of its financial resources and sales and for maximization of profit.

3.3 CLASSIFICATION OF TIME SERIES

If a time series can be expressed as a known function, then it is said to be a deterministic time series and when a time series is expressed as a function of a certain random variable, then it is said to be a stochastic time series

3.4 COMPONENTS OF TIME SERIES

3.4.1 TREND

Trend is the long-term movement of a time series. An increase or decrease in the values of a variable occurring over a period of several years gives it a trend. However, if the values of a variable remain statutory over several years then no trend is established in the time series. In simple terms, a trend equally means a pattern found in time series datasets. The reason for measuring trends is to study the behavior of the variable in the long run and this study is only possible when the data is devoid of all other components.

METHODS FOR MEASURING TRENDS

1. Graphic model

   This method is considered the simplest mostly because

   - it is free from mathematical calculations
   - For experienced researchers and statistician, it is time-saving due to the ease with which the trend line can be identified at a glance.

   However, the Demerits include

- It is difficult for beginners to draw the line with the eye estimation
- The method purely depends on the judgment of the statistician
- The estimate may not accurate as it is largely dependent on eye estimation
- A lot of expertise and expertise to draw the trend line.

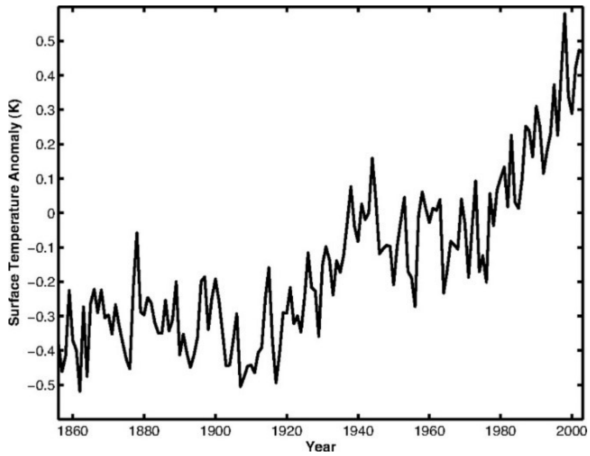


Figure 3.1

The data used in the above diagram are the annual global surface temperature anomalies analyzed by (Jones, et al., 2001) and posted at the web site of the Climate Research Unit, University of East Anglia, Norwich, U.K. (weblink), which is maintained jointly by the Climate Research Unit and the U.K. Meteorological Office Hadley Centre. The annual GSTA is the yearly averaged deviation from the 1961 – 1990 mean. The data are plotted in Fig. 3.1

2. Semi-average method

By semi-averages is meant the averages of the two halves of a series. In this method, thus, the given series is divided into two equal parts (halves) and the arithmetic mean of the values of each part (half) is calculated. The computed means are termed as semi-averages. Each semi-average is paired with the center of time period of its part. The two pairs are then plotted on a graph paper and the points are joined by a straight line to get the trend. It should be noted that if the data is for even number of years, it can be easily divided into two halves. But if it is for odd number of years, we leave the middle year of the time series and two halves constitute the periods on each side of the middle year.

MERITS

- It is simple and a flexible method of measuring trend.
- It is an objective method because any statistician applying this to a given data would get identical trend value

DEMERITS

- This method can give only linear trend of the data irrespective of whether it exists or not.
- It is an objective method because any statistician applying this to a given data would get identical trend value

3. Moving Average Method

Usually also called the moving mean method. A moving mean requires a predetermined time scale so as to carry out the mean operation. A moving average is defined as an average of fixed number of items in the time series which move through the series by dropping the top items of the previous averaged group and adding the next in each successive average. This method is an improvement over the semi average method and short-term fluctuations are eliminated by it. (Kumar Shanker, 2017))

Let (t_1, y_1), (t_2, y_2), (t_n, y_n) denote given time series $y_1, y_2, \ldots, y_n$ are the values of the variable y; corresponding to time periods $t_1, t_2, \ldots, t_n$, respectively.

The moving averages of order m are defined as $((y1 + y2 + \ldots + ymm)/m)$;

$$(y2 + y3 + \ldots + ym + 1)/m;$$

Here $y_1 + y_2 + \ldots + y_m$, $y_2 + y_3 + \ldots + y_{m+1} \ldots$ are called moving totals of m.

However, the order of the moving averages may either be odd or even.

The moving averages of order 3 are

$$y1 + y2 + y3/3;\ y2 + y3 + y4/3 \ldots yn - 2 + yn - 1 + yn/3$$

MERITS

- As stated earlier, this method eliminates the short-term fluctuations.
- This method is devoid personal prejudice and bias of the estimator.
- It reduces the effect of extreme values.

DEMERITS

- Moving average method is easy to understand and easy to use because there are no mathematical complexities involved.
- The choice of the period of moving average needs a great amount of care. If an inappropriate period is selected, a true picture of the trend cannot be obtained.
- If the series given is a very large one, then the calculation of moving average is cumbersome.
- It is very much affected by extreme values

4. Curve fitting buy method of least squares

The fitted trend is termed as the best in the sense that the sum of squares of deviations of observations, from it, is minimized. The least squares curve fitting technique is to find the best fitting curve to a given set of points by minimizing the sum of the least square errors of the data points from the curve. Polynomials are one of the most commonly used types of curves. They assume that the best-fit curve

$$\therefore \quad Y = f(x) = b_0 + b_1 x + \cdots + b_k x^k = \sum_{i=0}^{k} b_i x^{k-1} \qquad (3.1)$$

Is the curve which has the minimal sum of the deviations squared (least square error) from a given set of data. To fit a polynomial order k to the data, we assume that the residuals:

$$res_i = y_i - (b_0 + b_1 x_1 + \cdots + b_k x_i^k) \tag{3.2}$$

Have normal (Gaussian) distributions with the mean $alpha = 0$ and the variance $\delta = \sigma_i^2$ where is the difference between the actual curve of the given data and the best fit curve. Then the maximum likelihood estimates for the parameters bi can be obtained by minimizing the chi-square:

$$\sum_{i=1}^{N} \frac{res_i^2}{\sigma_i^2} \tag{3.3}$$

This method of Least squares may be used either to fit linear trend or a nonlinear trend (Parabolic and Exponential trend).

FITTIG OF LINEAR TREND

Given the data (Y_t, t) for n periods, where t denotes time period such as year, month, day, etc. We have to the values of the two constants, 'a' and 'b' of the linear trend equation:

$$Y_t = a + b_t \tag{3.4}$$

Where the value of 'a' is merely the Y-intercept or the height of the line above origin. That is, when $X = 0$, $Y = a$. The other constant 'b' represents the slope of the trend line. When b is positive, the slope is upwards, and when b is negative, the slope is downward.

This line is termed as the line of best fit t because it is so fitted that the total distance of deviations of the given data from the line is minimum. The total of deviations is calculated by squaring the difference in trend value and actual value of variable. Thus, the term âLeast Squaresâ is attached to this method.

Using least square method, the normal equation for obtaining the values of a and b are:

$$\sum Y_t = na + b\sum t \tag{3.5}$$

$$\sum tY_t = a\sum t + b\sum t^2 \tag{3.6}$$

Let $X = t - A$, such that $\Sigma X = 0$, where A denotes the year of origin.

The above equations can also be written as

$$\sum Y = na + b\sum X \tag{3.7}$$

$$\sum XY = a\sum X + b\sum X^2 \tag{3.8}$$

Since $\Sigma X = 0$ i.e. deviation from actual mean is zero we can write

$$a = \frac{\sum y}{n} \tag{3.9}$$

$$b = \frac{\sum XY}{X^2} \tag{3.10}$$

MERITS

- Given the mathematical form of the trend to be fitted, the least squares method is an objective method.
- Unlike the moving average method, it is possible to compute trend values for all the periods and predict the value for a period lying outside the observed data.

DEMERITS

- As compared with the moving average method, it is cumbersome method.
- It is not flexible like the moving average method. If some observations are added, then the entire calculations are to be done once again
- It can predict or estimate values only in the immediate future or the past.

- The computation of trend values, on the basis of this method, doesnât take into account the other components of a time series and hence not reliable.
- Since the choice of a particular trend is arbitrary, the method is not, strictly, objective.
- This method cannot be used to fit growth curves, the pattern followed by the most of the economic and business time series.

3.4.2 SEASONALITY

Seasonal variations in a time series data refers to the variability of data due to seasonal influences. A cycle structure in a time series may or may not be seasonal. If it consistently repeats at the same frequency, it is seasonal, otherwise it is not seasonal and is called a cycle. Identifying seasonal components in a time series data can be subjective, it could daily, weekly, monthly, yearly or even time of the day.

METHODS FOR MEASURING SEASONAL VARIATIONS

1. Method of Simple Average

   This is the easiest and the simplest method of studying seasonal variations. This method is used when the time series variable consists of only the seasonal and random components. Taking the average of the data corresponding to the same period eliminates the effect of random component hence, the resulting averages consist only of seasonal component. Though this method may be simple, the assumption that trend and cyclical components are absent in the data makes it unrealistic.

2. Ratio to Trend Method

   This method is used when then cyclical variations are absent from the data, i.e. the time series variable Y consists of trend, seasonal and random components.

STEPS

- Obtain the trend values for each month or quarter, etc., by the method of least squares.
- Divide the original values by the corresponding trend values. This would eliminate trend values from the data
- To get figures in percentages, the quotients are multiplied by 100.

This is an objective method of measuring seasonal variations. However, it is very complicated and doesn't work if cyclical variations are present.

3. Ratio to Moving Average Method.

The ratio to moving average is the most commonly used method of measuring seasonal variations. This method assumes the presence of all the four components of a time series.

STEPS

- Compute the moving averages with period equal to the period of seasonal variations. This would eliminate the seasonal components and minimize the effect of random component. The resulting moving averages would consist of trend, cyclical and random components.
- The original values, for each quarter (or month) are divided by the respective moving average figures and the ratio is expressed as a percentage. R' and R" denote the changed random components.
- Finally, the random component Râ is eliminated by the method of simple averages

4. Method of link Relatives

This method is based on the assumption that the trend is linear and cyclical variations are of uniform pattern. The link relatives are percentages of the current period. With the computations of the link relatives and their average, the effect of cyclical and the random components is minimized. Further, the trend gets eliminated in the process of adjustment of chain relatives. This is less complicated than the ratio to moving average and the ratio to trend methods. However, this method is based upon the assumption of a linear trend which may not always hold true.

3.4.3 CYCLE

In time series analysis, cyclical nature of data sets can be identified with recurring sequence of points above and below the trend line lasting more than one year. In time series, any periodic variation may be described as a cycle. Often, however, the term is reserved for cycles generated by the autoregressive structure of the series, as opposed to seasonal variation, caused by outside influences. A disturbance to the series may affect the phase of the cycle in this sense, while a seasonal variation has always the same phase. A cyclical pattern repeats with some regularity over several years. Cyclical patterns differ from seasonal patterns in that cyclical patterns occur over multiple years, whereas seasonal patterns occur within one year.

3.4.4 IRREGULAR PATTERNS

This can be referred to as random movements or random patterns. These are variations due residual factors that accounts for deviations for the actual time series values from those expected, given the effects of the other components. An example is an irregular movements that has no pattern but caused by an unpredictable reason like earthquake. Because of their nature, it is very difficult to devise a formula for their direct computation. Like the cyclical variations, this component can also be obtained as a residue after eliminating the effects of other components.

3.5 OBJECTIVES OF TIME SERIES ANALYSIS

1. DESCRIPTION

   The first step in the analysis of a time series data is usually to plot the data to obtain simple descriptive measures of the main properties of the series such as seasonal effect and trend. Apart from trend and seasonal variation, the outlier to look for in the graph of the time series is the possible presence of turning points, where for example, an upward trend has suddenly changed to a downward trend where it is termed as fluctuations.

2. EXPLANATION

   When observations are taken on two or more variables, it may be possible to use the variation from one time series variable to explain the variation in the other time series variable. This may lead to a deeper understanding of how a given time series is generated.

3. CONTROL

   The objective of an analysis can also be to regulate or control a physical system or business outcome. For instance, an airline company may want to increase its profit by increasing the number of passengers who travel in a given period. Suppose a forecast of passengers shows a decline in travel for the said period. The airline may attempt to control this outcome by offering lower ticket prices or airline rewards, which could lead to an increase in its profit. Most instances, diagrams are such as control charts are plotted and based on the diagrams, control measures are taken. Factoring process, the aim of the analysis may be to control the process. Control procedures are of several different kinds. In statistical quality control for instance, the observations are plotted on control charts and the controller takes action as a result of studying the charts

4. PREDICTION

   Given an observed time series, one may want to predict the future values of the series. This is an important task in sales forecasting and in the analysis of economic and industrial time series. Prediction is closely related to control problems in many situations.

   For example, if one can predict that manufacturing process is going to move off target, then appropriate corrective action can be taken.

3.6 The Autoregressive (AR) Model

An autoregressive (AR) model predicts future behavior based on past behavior. It's used for forecasting when there is some correlation between values in a time series and the values that precede and succeed them. You only use past data to model the behavior, hence the name autoregressive. The process is basically a linear regression of the data in the current series against one or more past values in the same series. (Stephanie, n.d.) The AR model takes in one parameter p, which determines the number of lag operations included in the model

The AR(p) model of order p, is of the form

$$Y_t = \phi_t Y_{t-1} + \theta_p y_{t-2} + \cdots + \phi_p Y_{t-p)} + u + a_t = \Sigma \theta_k Y_{t-k} + u + e_t \tag{3.11}$$

Where is the mean of the time series and is a white noise, with non-zero mean. The order of an AR (p) process is determined by the Partial Autocorrelation Function (PACF). An AR (p) process has its PACF cutting off after lag p and the ACF decays exponentially for example the PACF of an AR (1) process cuts off after lag one (1). Autoregressive series are important because they have a natural interpretation- the next value observed is a slight perturbation of simple.

3.7 Moving Average

A moving average shows an average of data points (usually price data) for a certain number of time periods. We say it is âmovingâ because each data point is calculated using data from the previous X number of time periods (Hill). The moving average model of order q is of the form

$$Y_t = u + e_t + \theta_1 e_{t-1} + \cdots + \phi_q e_{t-q} \tag{3.12}$$

$u =$ constant mean of the time series $e_t =$ is a white noise.

3.8 ARIMA

An ARIMA model simply refers to an Auto regressive integrated Moving Average. It is composed of three functions models namely; the Autoregressive (AR), the Moving Average (MA), and a stochastic trend called an integrating (I) process. It is a form of regression analysis that focuses on predicting one dependent variable relative to other independent variables. Various parameters are assigned to each component in the ARIMA model with standard symbols. The ARIMA model uses differenced data to make the data stationary, which means there's a consistency of the data over time The standard notation is of the form ARIMA(p,d,q) where;

p: The number of lag observations included in the model

d: The degree of differencing

q: The size of the moving average window, also called the order of moving average.

These parameters (p,d,q) are usually represented by numbers to indicate the order of the various components of the ARIMA model. When two of the parameters are zeros, the model may be referred to as based on the non-zero parameter. For example an ARIMA (1, 0, 0), can be represented as AR (1), indicating the absence of MA model and the integrating factor since their corresponding parameters are zero.

ARIMA (0, 1, and 0) is I (1)

ARIMA (0, 0, and 1) is MA (1)

The general ARIMA (p, d, and q) process is of the form

$$W_t = \sum_{i=1}^{p} \phi_i W_{t-1} + \sum_{j=1}^{q} \theta_j e_{t-j} + u + e_t \quad Where \tag{3.13}$$

$$W_t = \Delta^d Y_t = (1 - B)^d Y_t \tag{3.14}$$

3.9 STATIONARITY

A stationary series has a constant mean, variance, and autocorrelation through time. The stochastic properties of the stationary process are said to be constant with respect to time. Thus, time series with trends, or with seasonality, are not stationary – the trend and seasonality will affect the value of the time series at different times.

From (Hyndman Athanasopoulus, 2018) , a time series with cyclic behavior (but with no trend or seasonality) is stationary. This is because the cycles are not of a fixed length, so before we observe the series we cannot be sure where the peaks and troughs of the cycles will be.

Weak Stationarity (Quora, n.d.)

In here, only the mean, correlation and covariance of the random variable are unchanging to time shift.

Strong stationarity

In a stochastic process, the probability distribution of the random variable tossed in each time instant is exactly the same along the time and that the joint probability distribution of random variables in time different time instant is invariant to time shifting.

3.10 Differencing

(Hyndman Athanasopoulus, 2018)

Differencing can help stabilize the mean of a time series by removing changes in the level of a time series, and therefore eliminating (or reducing) trend and seasonality.

- Second-order differencing

  Occasionally the differenced data will not appear to be stationary and hence necessary to difference the data a second time to obtain a stationary series:

$$y''_t = y'_t - y'_{t-1} \tag{3.15}$$

$$= (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \tag{3.16}$$

$$= y_t - 2y_{t-1} + y_{t-2} \tag{3.17}$$

In practice, it is almost never necessary to go beyond second-order differences.

SEASONAL DIFFERENCING

This is referred to as the difference in one observation and a previous observation from the same season.

$$y_t'' = y_t - y_{t-m} \tag{3.18}$$

Where $m = m =$ the number of seasons. These are also called "lag-mm differences", as we subtract the observation after a lag of mm periods.

If seasonally differenced data appear to be white noise, then an appropriate model for the original data is

$$y_t = y_{t-m} + \epsilon_t \tag{3.19}$$

- To distinguish seasonal differences from ordinary differences, we sometimes refer to ordinary differences as "first differences", meaning differences at lag 1.
- Sometimes it is necessary to take both a seasonal difference and a first difference to obtain stationary data

3.11 White Noise

- This can be defined as the sequence of uncorrelated random variables each with mean zero and a constant variance. $X_n \sim WN(0, \sigma_y^2)$
- A white noise series is stationary; it does not matter when you observe it, it should look much the same at any point in time.

3.12 SARIMA MODEL

This is the seasonal ARIMA model. In the Seasonal ARIMA model, seasonal AR and MA terms predict y_t using data values and errors at times with lags that are multiples of S (the span of the seasonality). (Hyndman Athanasopoulus, 2018)

- With monthly data ($andS = 12$), a seasonal first order autoregressive model would use y_{t-12} to predict y_t. In our research for instance, predicting patients' attendance to the KNUST hospital is based on the previous years and the monthly basis are equally on the previous year's month. (This relationship of predicting using last year's data would hold for any month of the year).

- A seasonal second order autoregressive model would use y_{t-1} and y_{t-24} to predict y_t. This means we predict using data from past 2 years. Again in our research, we use data from past years to predict patient attendance to the university hospital.

- The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is
  $ARIMA(p, d, q) \times (P, D, Q)S$,
  With p = non-seasonal AR order, d = non-seasonal differencing, q = non-seasonal MA order, P = seasonal AR order, D = seasonal differencing, Q = seasonal MA order, and S = time span of repeating seasonal pattern

3.13 Model Identification

When an appropriate differencing is obtained, competing/ or suggesting models with different orders of both AR and MA should be fitted. The order with the minimum information criteria should be selected as the suitable model or order.

Most commonly used information criteria are;

1. Akaikeâs information criterion (AIC)

- The Akaike information criterion (AIC) is an estimator of prediction error and thereby relative quality of statistical models for a given set of data. ((WIKIPEDIA, n.d.)
- When a statistical model is used to represent the process that generated the data, the representation will almost never be exact; so some information will be lost by using the model to represent the process. AIC estimates the relative amount of information lost by a given model: the less information a model loses, the higher the quality of that model.
- Let k = the number of estimated parameters in the model. L = maximum value of the likelihood function of the model.

$$AIC = 2k - 2ln(L) \tag{3.20}$$

2. Bayesian information criterion (BIC) or Schwarz Criterion

   Let k = the number of parameters, n = the number of observation

$$BIC = -2\log - likelihood + k\log n \tag{3.21}$$

3. The Hannan-Quinn information criterion (HQIC)

   Let k = the number of parameters, n = the number of observation

$$HQIC = -2\log - likelihood + 2k\log(\log n) \tag{3.22}$$

3.14 DETRENDING

- Detrending is removing a trend from a time series data. As explained earlier, the existence of trends can cause some distortions and inaccuracy in forecasting and hence the detruding process.

- To proceed with detrend, one must know the structure of the trend in order to detrend it. For instance, if you have a simple linear trend for the mean, you may calculate the least squares regression line to estimate the growth rate of the trend. Then subtract the deviations from the least squares fit line (i.e. the differences) from your data. (Glen, n.d.)

3.15 Box-Jenkins Methodology

When fitting an ARIMA model to a set of (non-seasonal) time series data, the following procedure provides a useful general approach.

- Plot the data and identify any unusual observations.
- If necessary, transform the data (using a Box-Cox transformation) to stabilize the variance.
- If the data are non-stationary, take first differences of the data until the data are stationary.
- Examine the ACF/PACF: Is an ARIMA (p, d, 0) or ARIMA (0, d, q) model appropriate? OR
- Try your chosen model(s), and use the AICc to search for a better model.
- Check the residuals from your chosen model by plotting the ACF of the residuals, and doing a portmanteau test of the residuals. If they do not look like white noise, try a modified model.
- Once the residuals look like white noise, calculate forecasts.
- There is an automated algorithm in R software, which only takes care of steps 3–5. So even if you use it, you will still need to take care of the other steps yourself.

Chapter 4

DATA ANALYSIS

4.1 Introduction

This chapter puts together the analysis and the useful information that can be obtained from the data gathered and then makes inferences based on this information in order to draw meaningful conclusions and recommendations. This analysis makes use of Box-Jenkins method of analyzing Time Series data and the software used is R studio.

4.2 Preliminary analysis

4.2.1 ANALYSIS ON DENTAL CLINIC DATA

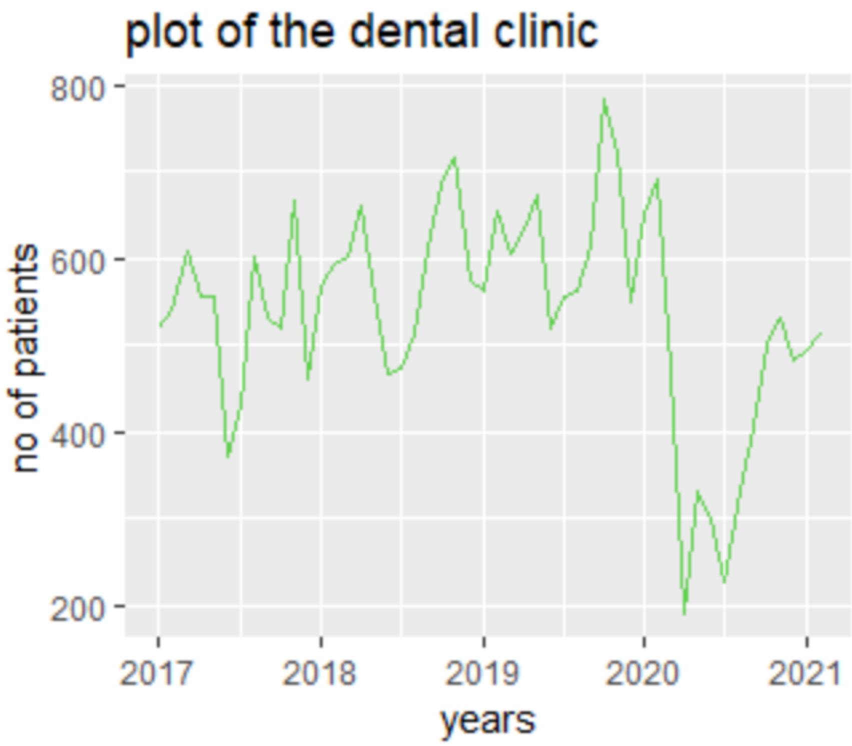


Figure 4.1: Time Series plot of monthly enrollment of the dental data

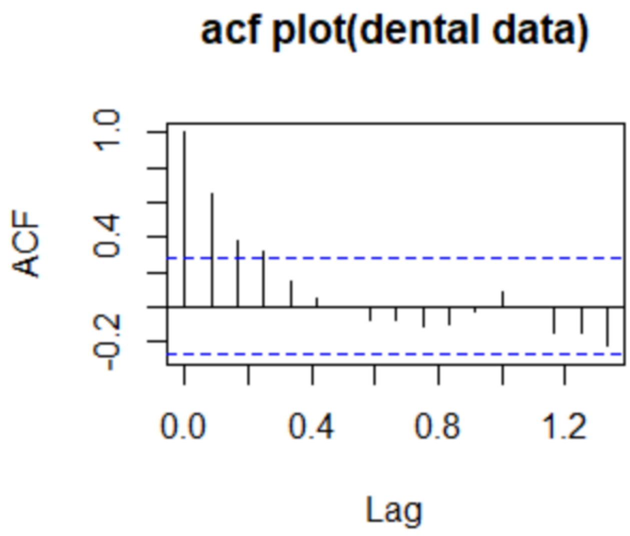
Starting from January 2017, there is increase in the number of patientsâ attendance until April 2017 where there seems to be a slight decrease till August 2017 where there seems to be an upward trend again.
Basically, the data shows both appreciation and depreciation in the number of patientsâ attendance over the years but generally, there seems to be an upward trend in the attendance to the university hospital and this can be likened to an increase in patronage in the hospitals services and hence an increase of patient satisfaction in the services.

Stationarity Test of the Series

- KPSS Test for Level Stationarity

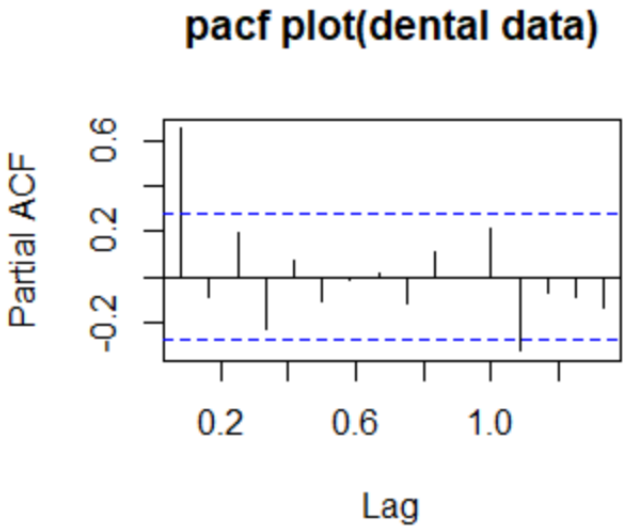
Null hypothesis: The series data is stationary.
Alternate hypothesis: The series data is not stationary.
KPSS Level = 0.25545, Truncation lag parameter = 3, p-value = 0.1
Decision: From the output of the KPSS test, the p-value obtained is 0.1 which is greater than the alpha value of 0.05 and hence we fail to reject the null hypothesis.
Conclusion: We conclude that the data is stationary therefore no differencing is required.

Figure 4.2: ACF Plot from the dental clinic data



The plotted ACF above shows significant spikes at lag 0, lag 1 and a slightly significant spike at lag3, suggesting a MA (1) model.

Figure 4.3: PACF Plot of the data from the dental clinic



The plot of the PACF above cuts off after lag 1(this shows a significant spike at lag 1) and hence depicting an AR (1) process.

MODEL SELECTION

From the table, the most suitable model is ARIMA (1, 0, 0) (1, 0, 0) [12] with non-zero mean because it is the model with the least AICC Value.

Parameters for the SARIMA Model

$$Y_T = 91.625 + 0.6968 y_{t-1} + 0.4127 B^{12} y_t \tag{4.1}$$

MODEL	AICC
ARIMA(1,0,0)	612.0365
ARIMA(1,0,0) with non-zero mean	601.5294
ARIMA(1,0,0)(0,0,1)[12]	607.6197
ARIMA(1,0,0)(0,0,1)[12] with non-zero mean	599.234
ARIMA(1,0,0) (1,0,0)[12]	605.715
ARIMA(1,0,0) (1,0,0)[12] with non-zero mean	598.6341
ARIMA(1,0,0)(1,0,1)[12]	607.9371
ARIMA(1,0,0)(1,0,1)[12] with non-zero mean	601.1074
ARIMA(1,0,0)	613.242
ARIMA(1,0,1) with non-zero mean	602.4431

Table 4.1

MODEL	COEFFICIENT
ARIMA(1,0,0)(1,0,0)[12]	AR(1)=0.6968 SAR(1)=0.4127 Mean=514.5494

Table 4.2

MODEL DIAGNOSTICS

Ljung-Box test

Null hypothesis: The ARIMA (1, 0, 0) (1, 0, 0) [12] model is appropriate.

Alternate hypothesis: The ARIMA (1, 0, 0) (1, 0, 0) [12] model is not appropriate.

Data: Residuals from ARIMA (1, 0, 0) (1, 0, 0) [12] with non-zero mean

$Q^* = 7.7185$, degrees of freedom (df) = 7, p-value = 0.3581

Model degree of freedom (df): 3. Total lags used: 10

Decision: From the output diagram above, the p-value of 0.3581 is greater than the alpha value of 0.05 and therefore we fail to reject the null hypothesis that the ARIMA (1, 0, 0) (1, 0, 0) [12] model is appropriate.

Conclusion: We conclude that the ARIMA (1, 0, 0) (1, 0, 0) [12] model is the most suitable model for this data.

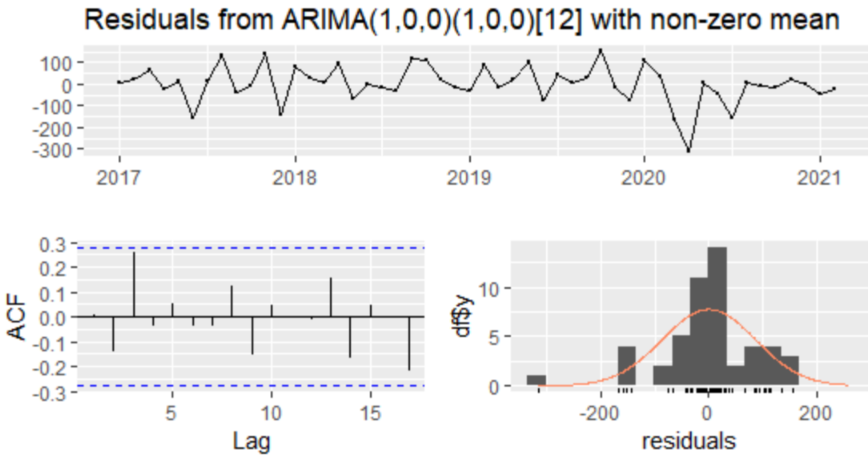


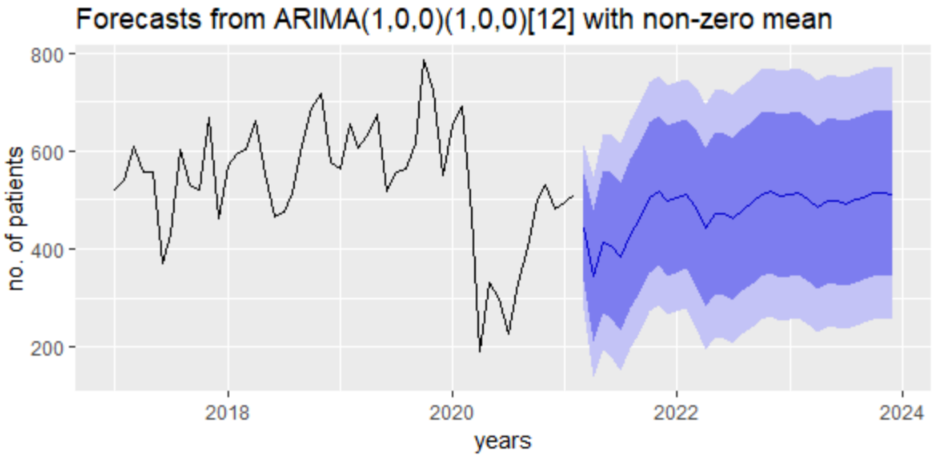
Figure 4.4

Also, the plot of the residuals of the ARIMA(1,0,0)(1,0,0)[12] model are normally distributed while the ACF plot of the residuals have insignificant spikes depicting that they are uncorrelated and hence, further conclusions that ARIMA(1,0,0)(1,0,0)[12] model is appropriate.

Table 4.3: FORECASTED VALUES FOR THE NEXT TWO YEARS

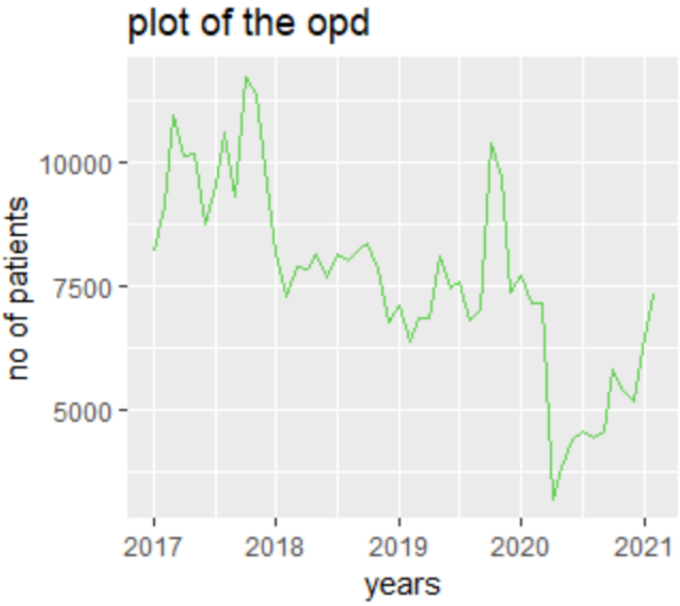
MONTHS	**2022**	**2023**
January	505	511
February	513	514
March	484	502
April	444	485
May	472	497
June	470	496
July	460	492
August	580	500
September	493	506
October	510	512
November	516	515
December	508	512

Figure 4.5: PLOT FOR THE FORECAST



4.2.2 ANALYSIS ON OUTPATIENT DEPARTMENT DATA.

Figure 4.6



- <u>KPSS Stationarity test</u>

  Null hypothesis: The series data is stationary.

  Alternate hypothesis: The series data is not stationary.

  KPSS Level = 0.91063, Truncation lag parameter = 3, p-value = 0.01

  Decision and conclusion: We reject the null hypothesis that the series is stationary since the p-value of 0.01 is less than the alpha value of 0.05 and thereby recommend that the series should be differenced in order to achieve stationarity

- Augmented Dickey-Fuller Test

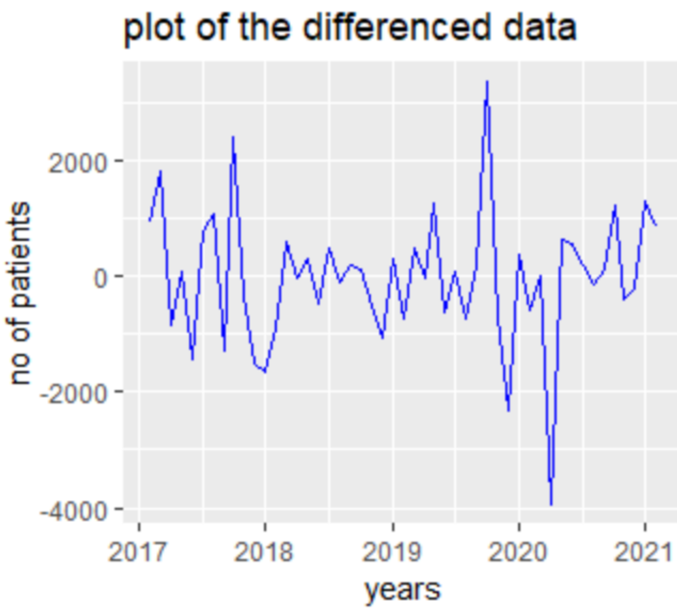
  Dickey-Fuller = -2.581, Lag order = 3, p-value = 0.3412

  Null hypothesis: The series data is not stationary.

  Alternate hypothesis: The series data is stationary.

  Decision and conclusion: We fail to reject the null hypothesis that the series is not stationary since the p-value of 0.3412 is greater than the alpha value of 0.05 and thereby recommend that the series should be differenced in order to achieve stationarity.

Figure 4.7



From the output above, it can be seen that differenced series that the series is now stationary since there is no trend in the plot.

STATIONARITY TEST FOR THE DIFFERENCED DATA

- KPSS Test for Level Stationarity

  Null hypothesis: The first difference of the series data is stationary.

Alternate hypothesis: The first difference of the series data is not stationary.

KPSS Level = 0.07053, Truncation lag parameter = 3, p-value = 0.1

Decision and conclusion: We fail to reject the null hypothesis that the first difference of the series is stationary since the p-value of 0.1 is greater than the alpha value of 0.05.

- Augmented Dickey-Fuller Test

  Null hypothesis: The first difference of the series data is not stationary.

  Alternate hypothesis: The first difference of the series data is stationary

  Dickey-Fuller = -3.7577, Lag order = 3, p-value = 0.02947

  Decision and conclusion: We reject the null hypothesis that the first difference of the series is not stationary since the p-value of 0.02947 is less than the alpha value of 0.05.

Figure 4.8

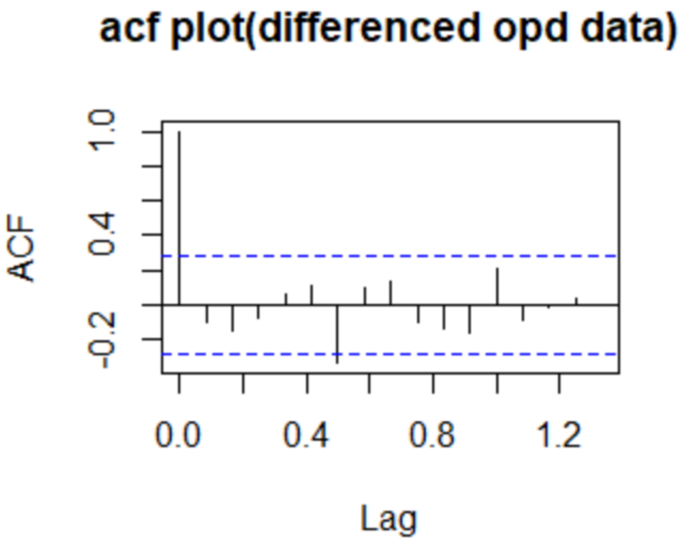
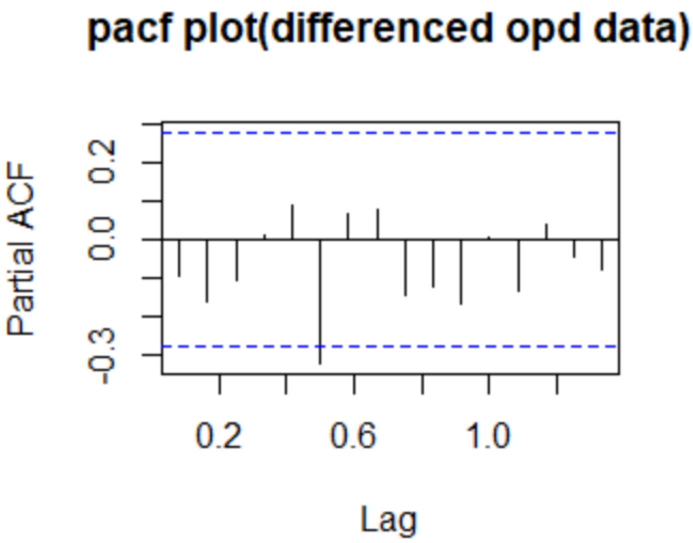


Figure 4.9



MODEL SELECTION

MODEL	AICc
ARIMA(0,1,0)	832.5
ARIMA(0,1,0) with drift	834.665
ARIMA(0,1,0)(0,0,1)[12]	832.377
ARIMA(0,1,0)(0,0,1)[12] with drift	834.64
ARIMA(0,1,0)(1,0,0)[12]	831.08
ARIMA(0,1,0)(1,0,0)[12] with drift	833.35
ARIMA(0,1,1)	834.02
ARIMA(0,1,1) with drift	836.26
ARIMA(0,1,1)(0,0,1)[12]	834.4
ARIMA(0,1,1)(0,0,1)[12] with drift	836.78
ARIMA(0,1,1)(1,0,0)[12]	833.3

Table 4.4

The most suitable model for the data is ARIMA (0, 1, 0) (1, 0, 0) [12] since itâs the model with least AICc value from the competing models generated for this data.

MODEL	COEFFICIENT
ARIMA(0,1,0)(1,0,0)[12]	SAR(1)=0.3354

Table 4.5

$$Y_t(1 - B) = 0.33548B^{12}y_t \tag{4.2}$$

MODEL DIAGNOSTICS

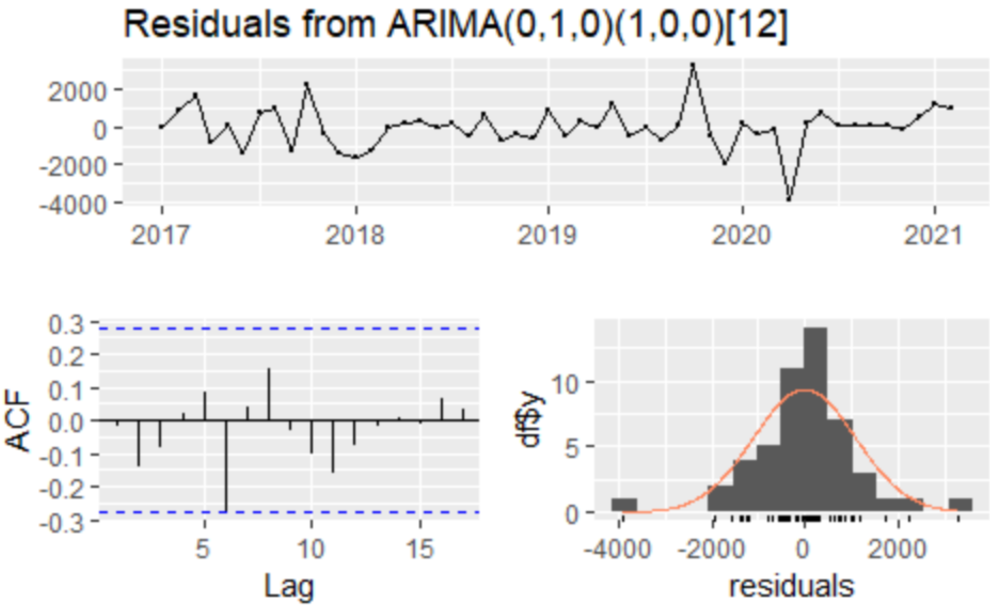


Figure 4.10

The ACF plot of the residuals clearly depicts that the errors are uncorrelated since none of the spikes are significant. Also, the errors are normally distributed from the histogram.

- Ljung-Box test

  Null hypothesis: The ARIMA (0, 1, 0) (0, 0, 1) [12] is appropriate for this data.

  Alternate hypothesis: The ARIMA (0, 1, 0) (0, 0, 1) [12] is appropriate not for this data.

  Q^* = 8.7415, df = 9, p-value = 0.4615

Model df: 1. Total lags used: 10

Decision: We fail to reject the null hypothesis since the p-value of 0.4615 is greater than the alpha value of 0.05.

Conclusion: The ARIMA (0, 1, 0) (0, 0, 1) [12] is the most suitable model for this data

Table 4.6: FORECASTED VALUES FOR THE NEXT YEAR

MONTH	**2022**
January	7075
February	7359
March	7359
April	6917
May	6989
June	7052
July	7073
August	7058
September	7071
October	7209
November	7162
December	7137

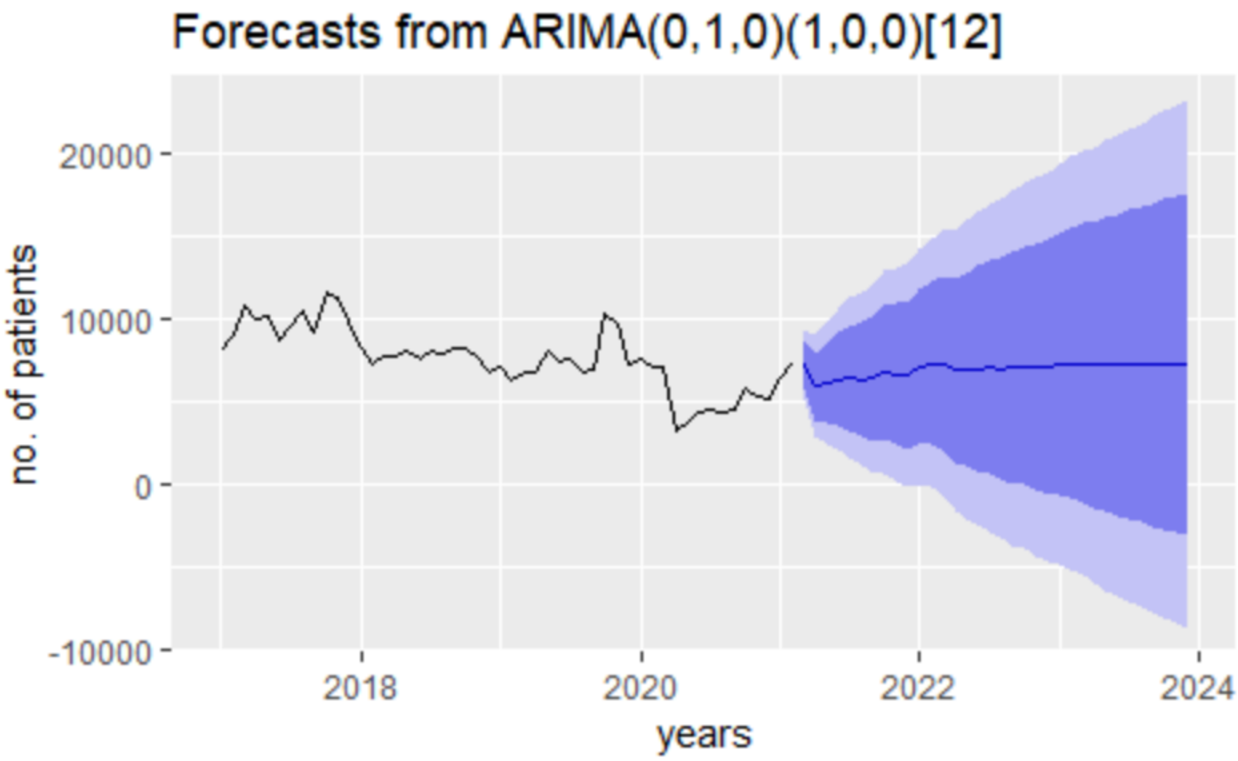


Figure 4.11

4.2.3 ANALYSIS ON EYE CLINIC DATA

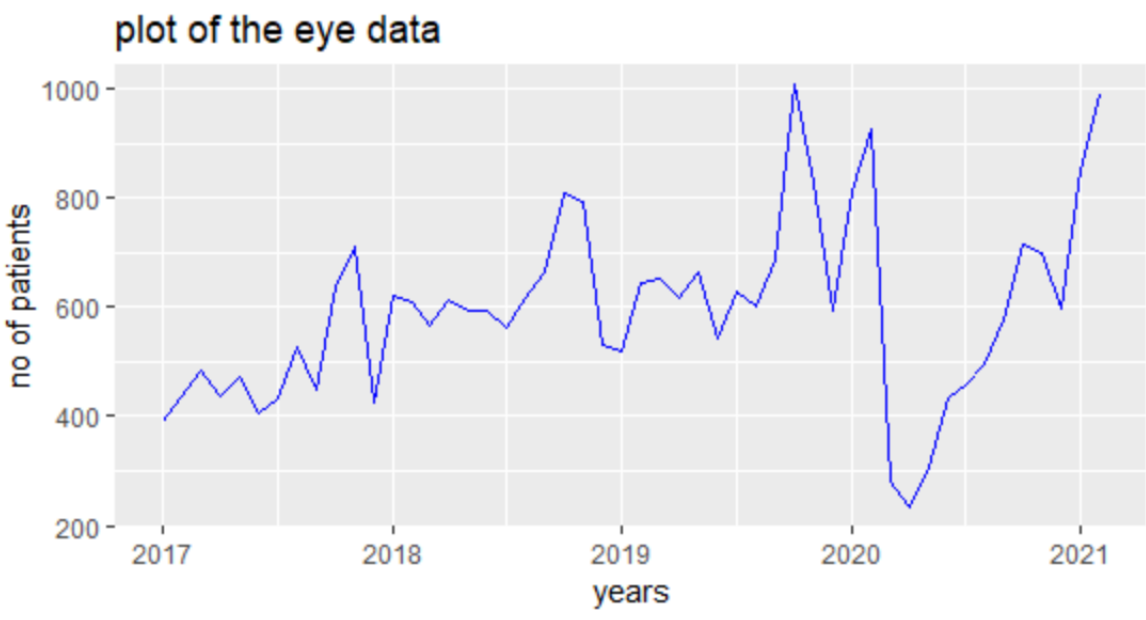


Figure 4.12

STATIONARITY TEST

- KPSS Test for Level Stationarity

  Null hypothesis: The series data is stationary.

  Alternate hypothesis: The series data is not stationary

  KPSS Level = 0.28744, Truncation lag parameter = 3, p-value = 0.1

  Decision and conclusion: We fail to reject the null hypothesis that the series is stationary since the p-value of 0.1 is greater than the alpha value of 0.05 therefore no differencing is needed.

- Phillips-Perron Unit Root Test

  Null hypothesis: The series data is not stationary.

  Alternate hypothesis: The series data is stationary

  Dickey-Fuller Z (alpha) = -22.24, Truncation lag parameter = 3, p-value =0.02558

  Decision and conclusion: We reject the null hypothesis that the series is not stationary since the p-value of 0.02558 is less than the alpha value of 0.05 and thereby recommend that no differencing is needed.

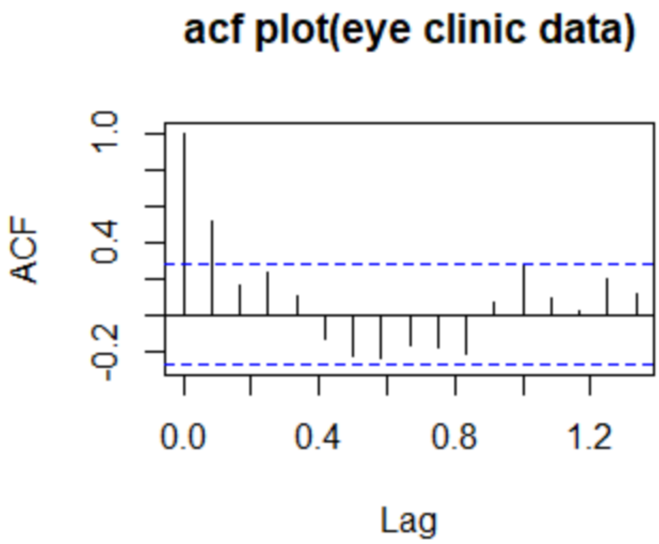


Figure 4.13

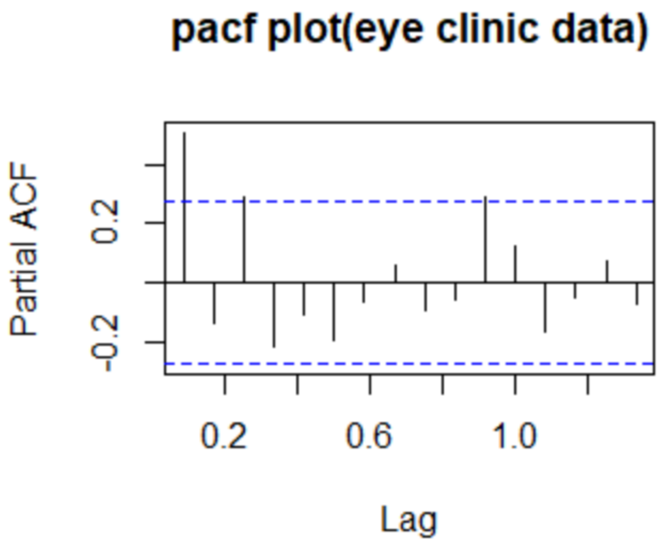


Figure 4.14

Table 4.7: MODEL SELECTION FOR THE EYE DATA

MODEL	**AICc**
ARIMA(0,0,2)	705.684
ARIMA(0,0,2) with non-zero mean	639.8122
ARIMA(0,0,4)	686.4965
ARIMA(0,0,4) with non-zero mean	641.2832
ARIMA(0,0,1)(1,0,1)[12]	637.3
ARIMA(0,0,1)(1,0,0)[12] with non-zero mean	634.9
ARIMA(1,0,0)	651.7934
ARIMA(1,0,0)(0,0,1)[12]	648.266
ARIMA(1,0,0) with non-zero mean	641.816

From the set of competing models above, the most suitable model is ARIMA (0, 0, 1) (1, 0, 0) [12] because it is the model with the least AIC and AICc values.

MODEL	COEFFICIENTS
ARIMA(0,0,1)(1,0,0)[12]	MA(1)=-0.6262 SAR(1)=0.426 Mean=575.6929

Table 4.8

$$Y_t = 330.448 + 0.6262e_{t-1} + 0.426B^{12}y_{t-1} \tag{4.3}$$

MODEL DIAGNOSTICS

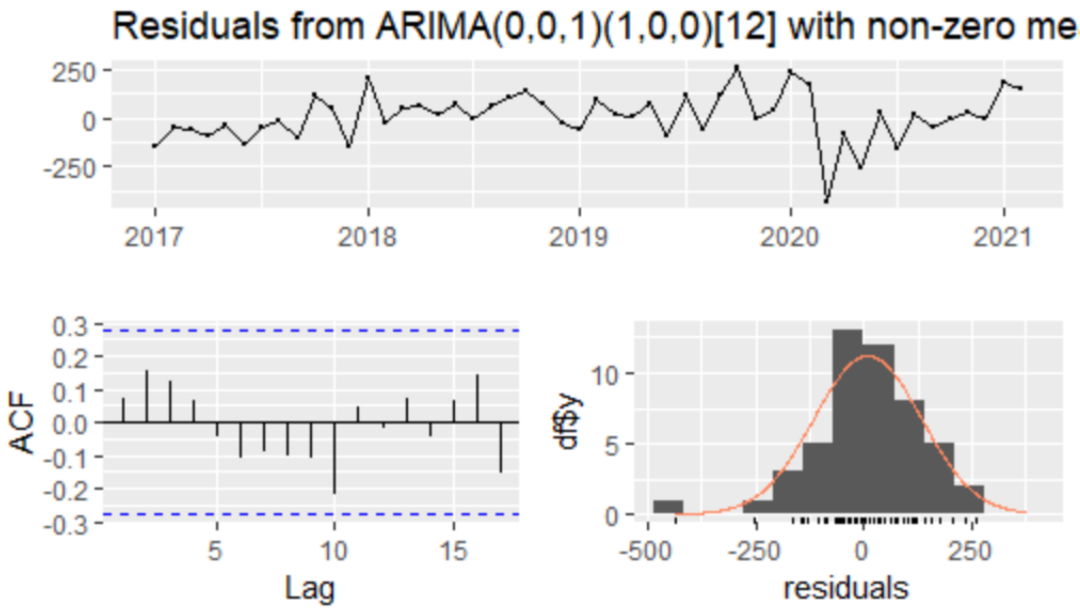


Figure 4.15

- Ljung-Box test

  Null hypothesis: The ARIMA (0, 0, 1) (1, 0, 0) [12] model is appropriate for the data.

  Alternate hypothesis: The ARIMA (0, 0, 1) (1, 0, 0) [12] model is not appropriate for the data.

  $Q^* = 8.4338$, df = 7, p-value = 0.2959

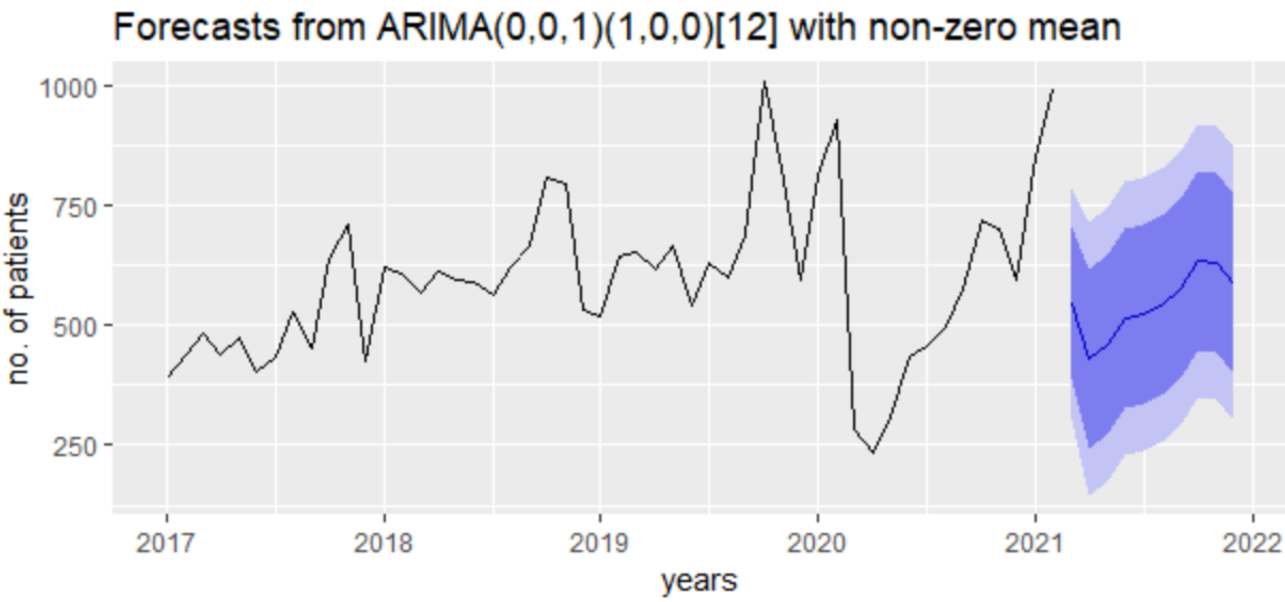
Decision and conclusion: The ARIMA (0, 0, 1) (1, 0, 0) [12] model is appropriate for this data since the p-value of 0.2959 is greater than the alpha value of 0.05.

It can also be seen from the ACF plot of the residuals that the spikes are insignificant indicating that the errors are uncorrelated while the histogram is clearly depicting that the errors are normally distributed with mean approximately zero (0).

Table 4.9: FORECASTED VALUES FOR THE NEXT YEAR

MONTH	**2022**	**2023**
January	880	828
February	938	853
March	761	775
April	716	754
May	729	760
June	752	770
July	756	771
August	764	774
September	778	781
October	804	792
November	801	790
December	782	782

Figure 4.16: PLOT OF THE FORECASTED VALUES



Chapter 5

CONCLUSION AND RECOMMENDATION

5.1 Introduction

The final chapter of this study summarizes major findings based on the specific aims of the study and recommendations are also made based on the findings. The chapter is subdivided into three sections. Section one has a summary of the study, section two presents the conclusion while section three contains the recommendation made from the analysis of the available data.

5.2 Findings

DEPARTMENT	HIGHEST VALUES	MONTH(2022)
DENTAL	580	AUGUST
OPD	7359	FEBRUARY
EYE	880	JANUARY

Table 5.1

The results obtained from the analysis of the data indicates that patient attendance to the hospital will be on its apex in January and February except for the Dental Clinic whose highest values 516 would be in November 2022 . It is observed that the hospital should expect about a total of 580 patients in the month of January 2022 at the dental clinic, 7359 in February 2022 at the OPD and a total of 880 in January 2022 at the eye clinic which would be the highest values in these departments/clinics. Comparatively, these values do not vary significantly from the regular attendance rate of patients to the hospital, hence management should direct little attention and fewer resources to the expansion of the facility since the hospital has been accommodating similar numbers over the years. The study of the data reveals that patient attendance to the hospital has an increasing and decreasing trend from the year 2017 to 2022 in the three department (clinics) of interest.

5.3 Summary

The main objective of this study was to use Time Series Analysis to analyze patientsâ attendance at KNUST Hospital using data obtained from 2017-2021 from three departments of the hospital. Box-Jenkins method was used in analyzing the Time Series data and the software used was R studio.

The residuals of the models obtained for each clinic follows the following assumptions.

- The ACF plot of the residuals should be uncorrelated.
- The residuals should follow a normal distribution with mean zero, to prevent biasness of forecasts

5.3.1 Dental Clinic

For the Dental Clinic, the data from the clinic was stationary, hence no differencing was required. The model identification process showed an ARIMA (1, 0, 0) (1, 0, 0) [12] with non-zero mean as the most suitable model because it was the model with the least AIC and AICC values. This was done by observing the behavior of the residual plots. The selected model is considered to be a statistically preferable model to predict the attendance of patients to the clinic since it does not contradict the stated assumptions.

5.3.2 Out-Patient Department

Data from the Outpatient Department was non-stationary so first differencing of the data was performed to achieve stationarity. The model identification process produced an ARIMA (0, 1, 0) (1, 0, 0) [12] and it was the most suitable model because it had the least AICC values. This was also done by observing the behavior of the residual plots. The selected model was considered to be the most appropriate to predict the attendance of patients at the out-patient department since it does not contradict the stated assumptions.

5.3.3 Eye Clinic

For the Eye Clinic, the data from the clinic was stationary hence no differencing of the data was performed. The model identification process produced the ARIMA (0, 0, 1) (1, 0, 0) model as the most suitable model since it had the least AIC and AICC values. This was also done by observing the behavior of the residual plots. The ARIMA (0, 0, 1) (1, 0, 0) model was considered to be statistically preferable to predict the patientsâ attendance at the eye clinic since its residuals do not contradict the stated assumptions.

5.4 Conclusion

5.4.1 Dental Clinic

The most suitable ARIMA model obtained is

$$Y(t) = 91.625 + 0.6968y_{t-1} + 0.4127B^{12}y_{t-1} \tag{5.1}$$

This model has been used to make predictions for each of the months in 2022. The predicted values recorded experienced an increasing and decreasing trend on average between months. Findings from the study also indicate that the number of individuals who visited the hospital had experienced an increasing and a decreasing linear trend from the year 2017 to 2021. The highest number recorded was 826 in June 2021.

5.4.2 Out-Patient department

The most suitable ARIMA model obtained

$$Y_t(1 - B) = 0.33548B^{12}y_t \tag{5.2}$$

This model has been used to make predictions for each of the months in 2022. The predicted values recorded experienced an increasing and decreasing trend on average between months. Findings from the study also indicate that the number of individuals who visit the hospital had experienced an increasing and a decreasing linear trend from the year 2017 to 2021. The highest number recorded was 11697 in October 2017.

5.4.3 Eye Clinic

The most suitable ARIMA model obtained is

$$Y_t = 330.448 + 0.6262e_{t-1} + 0.426B^{12}y_{t-1} \tag{5.3}$$

This model has been used to make predictions for each of the months in 2022. The predicted values recorded experienced an increasing and decreasing trend on average between months. Findings from the study also indicate that the number of individuals who visit the hospital had experienced an increasing and a decreasing linear trend from the year 2017 to 2021. The highest record is 1082 in July 2021.

5.5 Recommendation

Based on the findings from the study, we recommend that, management of the hospital should give less attention or priority to the expansion of the outpatient department, eye and dental clinic.
However, they should continue to increase the doctor to patient ratio as to reduce the waiting time in the system, provide more beds to accommodate patients as all these would boost patient satisfaction, incentivise people to patronize the facility more thereby increasing patient attendance to the hospital.
State authorities should support the health facility in terms of good health personnel and logistics in order to provide quality health services to patients visiting the Outpatient department, eye and dental clinic and be available to offer assistance to enable the hospital cope with general increase in patientsâ attendance over the next few years.

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