MODELLING NUMBER OF ADMITTED PATIENTS IN UNIVERSITY OF ILORIN TEACHING HOSPITAL USING BOX AND JECKING METHODOLOGY

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Abstract

Did you know that hospital admissions in Nigeria have been steadily increasing in recent years? The objective of this study was to propose a suitable model for hospital patient admission in Nigeria, with the University of Ilorin Teaching Hospital, located in Ilorin, Kwara state, serving as a case study. The purpose of this model was to forecast future patient admission numbers and enable adequate planning in the Nigerian healthcare sector. Data from 1999-2015, consisting of 68 quarters, was collected from the hospital's database. As the data was time-dependent, a Time series analysis and univariate Box-Jenkins methodology were used to create an ARIMA model. The data was plotted over time and became stationary after being differ'nced once. Different time series models were evaluated and tested for the number of patient admissions. The final model chosen was an ARIMA (0, 1, 1) model, which was also used to forecast quarterly patient admission numbers for the next six years. The results showed that there was a tendency for an increase in patient admission numbers at the hospital.

Keywords:

INTRODUCTION

Accurate prediction of patient admissions is crucial for effective healthcare planning, especially in developing countries with limited resources. Nigeria, with a growing population and high disease burden, requires accurate predictions of the number of patients that will be admitted to hospitals to ensure adequate allocation of resources and provision of high-quality medical services (Ekwunife et al., 2021). This study aims to propose a suitable model for predicting patient admissions into Nigerian hospitals, using the University of Ilorin Teaching Hospital in Kwara state as a case study.

Healthcare is a major concern in Nigeria, with the country struggling to meet the health needs of its growing population. According to the World Health Organization (WHO), Nigeria has a doctor to patient ratio of 1:5,000, which is far below the recommended ratio of 1:600 (WHO, 2020). Furthermore, access to healthcare services is limited in many parts of the country, with only 3.8% of the country's Gross Domestic Product (GDP) allocated to healthcare in 2019 (World Bank, 2020). As a result, there is a need to optimize the allocation of resources in the healthcare sector to ensure that patients receive high-quality medical services.

Healthcare is an essential service that every nation provides to its citizens. It is a basic human right and an integral part of a country's development. Nigeria, like many other developing countries, faces significant challenges in providing quality healthcare services to its citizens. The country has a high burden of communicable and non-communicable diseases, including malaria, HIV/AIDS, tuberculosis, and cancer (World Health Organization [WHO], 2021). These diseases, coupled with the high population growth rate, have put immense pressure on the healthcare system in the country.

The University of Ilorin Teaching Hospital (UITH), located in Ilorin, Kwara state, is one of the tertiary hospitals in Nigeria that serves as a referral center for many other healthcare facilities in the country. The hospital provides specialized healthcare services to patients across the country and beyond. However, like other hospitals in Nigeria, the UITH faces numerous challenges in providing quality healthcare services to patients. Some of these challenges include inadequate funding, lack of equipment and supplies, insufficient skilled personnel, and poor management (Afolayan & Sholeye, 2019).

One of the critical challenges faced by hospitals in Nigeria is the lack of adequate planning and forecasting of patient admissions. The admission of patients is essential in determining the resources needed to manage the hospital effectively. Without proper planning and forecasting, hospitals may face issues such as overcrowding, inadequate staffing, and insufficient supplies and equipment, leading to poor healthcare services delivery (Oluwasola et al., 2016).

Therefore, the aim of this study is to propose a suitable model for the admission of patients into Nigeria hospitals using the University of Ilorin Teaching Hospital, Ilorin, Kwara state, as a case study. The specific objectives of this study are to:
a) show the pattern of admission of patients over some years in the past;
b) fit several models to the data;
c) propose the best model for the data; and
d) use the proposed model to forecast for the next six years.
This study is significant because it will help healthcare administrators and policymakers to plan effectively and efficiently for the admission of patients into hospitals. It will also contribute to the existing literature on healthcare planning and forecasting in Nigeria.

LITERATURE REVIEW

Hospital admissions forecasting is an essential aspect of healthcare management. Accurate forecasts of the number of patients that will be admitted to hospitals are critical for healthcare providers to effectively plan and allocate resources such as staff, equipment, and medication. Time series analysis is a statistical technique used to analyze time-dependent data and make forecasts based on historical patterns. Box and Jenkins methodology is a popular time series analysis technique that has been used in various fields, including healthcare management, to forecast hospital admissions. The review will consist of three main sections: Conceptual Review, Empirical Review, and Theoretical Review. The evidence gathered from these sections will establish the need for the current study and highlight the gaps that the study intends to fill.

Conceptual Review

Hospital admissions forecasting plays a vital role in healthcare management, allowing hospitals to anticipate and prepare for the future demand for services. The use of time series analysis techniques has become increasingly prevalent in this area. Researchers have recognized the importance of accurately predicting patient admission rates to optimize resource allocation, improve efficiency, and enhance patient care.

Various conceptual frameworks and models have been proposed to forecast hospital admissions. For instance, Makkawi and Alsaedi (2016) developed a predictive model using data mining techniques to forecast inpatient admissions. They emphasized the significance of accurate forecasting to assist healthcare organizations in strategic planning and resource allocation. Also, A study by Mohebbi et al. (2016) used a combination of autoregressive integrated moving average (ARIMA) models and exponential smoothing methods to forecast hospital admissions in Iran. The study found that the ARIMA model was the most accurate in forecasting hospital admissions, with an accuracy rate of 97.5%. Another study by Li et al. (2020) used a seasonal autoregressive integrated moving average (SARIMA) model to forecast the number of hospital admissions in a Chinese hospital. The study found that the SARIMA model accurately predicted the number of hospital admissions, with an average forecasting error of less than 3%.

Empirical Review

In the empirical review, several studies that have utilized the Box and Jenkins methodology for hospital admissions forecasting will be examined. Box and Jenkins methodology is a popular time series analysis technique that has been used in various fields, including healthcare management. The methodology involves three stages: model identification, parameter estimation, and model diagnostic checking. Model identification involves selecting the appropriate model that best fits the data. Parameter estimation involves estimating the model parameters using maximum likelihood estimation. Model diagnostic checking involves checking the goodness of fit of the model and identifying any residual autocorrelation. These studies have contributed to the field by applying rigorous statistical techniques to analyze and predict admission patterns.

Several studies have used Box and Jenkins methodology to forecast hospital admissions. A study by Zhang et al. (2017) used a Box-Jenkins model to forecast the number of hospital admissions in China. The study found that the Box-Jenkins model accurately predicted the number of hospital admissions, with an average forecasting error of less than 2%. Another study by Zhao et al. (2020) used a Box-Jenkins model to forecast the number of hospital admissions in a Chinese hospital. The study found that the Box-Jenkins model accurately predicted the number of hospital admissions, with an average forecasting error of less than 1%. Another notable empirical study is the work of Gupta, Patel, Patel, and Dadhich (2019), who used Box-Jenkins methodology to analyze inpatient admission data. Their study demonstrated the effectiveness of this approach in capturing the seasonal and trend components of the data and accurately forecasting future admissions. Similarly, Alshammari, Al-Masoudi, and Almasabi (2020) utilized time series models, including the Box and Jenkins approach, to forecast the number of inpatient admissions in hospitals. Their findings highlighted the importance of accurate predictions in resource planning and capacity management.

Theoretical Review

In the theoretical review, the focus is on the underlying principles and theories that support the use of time series analysis and the Box and Jenkins methodology in hospital admissions forecasting.

Time series analysis allows researchers to identify patterns, trends, and seasonality in historical data, which are crucial for making reliable forecasts.

The Box and Jenkins methodology, introduced by Box and Jenkins (1970), is a widely adopted approach for analyzing and modeling time series data. It involves a systematic process of model identification, estimation, and diagnostic testing. This methodology provides a rigorous framework for analyzing the data and selecting the best-fitting model.

Need for the Study

Despite the several studies on hospital admissions forecasting using time series analysis techniques, there is a need for further research in this area. Most of these studies have focused on hospitals in developed countries and have used data from electronic health records. There is a dearth of studies on hospital admissions forecasting in developing countries, where healthcare systems are often fragmented and data collection is often manual. Additionally, few studies have used Box and Jenkins methodology to forecast hospital admissions in Nigeria.

Gaps in Existing Literature

The existing literature on hospital admissions forecasting using time series analysis techniques has several gaps. First, there is a lack of studies on hospital admissions forecasting in developing countries, particularly in Nigeria. Second, there is a need for studies that use Box and Jenkins methodology to forecast hospital admissions in Nigeria. Third, there is a need for studies that explore the factors that influence hospital admissions in Nigeria, as this information is crucial in developing accurate forecasting models. Finally, most studies have focused on short-term forecasting, with few studies exploring long-term forecasting.

The proposed study aims to fill these gaps in the literature by using Box and Jenkins methodology to forecast hospital admissions in the University of Ilorin Teaching Hospital, which is located in Kwara State, Nigeria. The study will use data collected from the hospital's manual records to develop forecasting models. Additionally, the study will explore the factors that influence hospital admissions in the hospital, including the impact of seasonal variations and disease outbreaks. Finally, the study will explore both short-term and long-term forecasting of hospital admissions.

Conclusion

In conclusion, hospital admissions forecasting is an essential aspect of healthcare management, and time series analysis techniques, including Box and Jenkins methodology, have proven to be effective in this regard. While several studies have explored hospital admissions forecasting, there is a need for further research, particularly in developing countries, such as Nigeria. The proposed study aims to fill these gaps in the literature by using Box and Jenkins methodology to forecast hospital admissions in the University of Ilorin Teaching Hospital and exploring the factors that influence hospital admissions in the hospital. The study's findings will provide valuable information for healthcare managers in the hospital and will contribute to the body of knowledge on hospital admissions forecasting.

METHODOLOGY

In this study, a retrospective time series analysis was conducted to model the pattern of patient admission in a Nigerian hospital using quarterly data from 1999 to 2015. The methodology employed for modeling and forecasting patient admissions in the University of Ilorin Teaching

Hospital involved the utilization of the Box-Jenkins methodology, a widely recognized approach for time series analysis. This section presents the model specification and the mathematical model adopted for the analysis. The data was obtained from the hospital's records and was carefully reviewed to ensure its accuracy and completeness.

The study will use the Box-Jenkins methodology to develop the time series model for hospital admissions forecasting. This methodology involves three steps: model identification, parameter estimation, and model checking (Box & Jenkins, 1970). The first step involves identifying the appropriate time series model for the data, which will be done using graphical analysis of the data and statistical tests such as the autocorrelation function (ACF) and partial autocorrelation function (PACF). The second step involves estimating the parameters of the selected model using maximum likelihood estimation. The third step involves checking the adequacy of the model using diagnostic tests such as residual analysis and the Ljung-Box test.

Model Specification

The selected model for this study was an autoregressive integrated moving average (ARIMA) model. The ARIMA model is well-suited for analyzing and forecasting time series data, as it incorporates both autoregressive (AR) and moving average (MA) components, along with differencing to handle non-stationary data.

The ARIMA(p, d, q) model is specified by three parameters:

- p: The order of the autoregressive (AR) component, which represents the number of lagged observations used to predict the current observation.
- d: The degree of differencing required to make the data stationary. It represents the number of times the data needs to be differenced to achieve stationarity.
- q: The order of the moving average (MA) component, which represents the number of lagged forecast errors used to predict the current observation.

Mathematical Model

The mathematical representation of the ARIMA(p, d, q) model can be expressed as follows:

$$Y_t = \mu + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} + e_t$$

In the above equation:

Y_t represents the time series of patient admission data.

μ represents the constant.

$\varphi_1, \varphi_2, \ldots, \varphi_p$ are the autoregressive coefficients.

$\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients.

e_t represents the error term assumed to follow a white noise process.

c is a constant term.

The ARIMA model aims to capture the patterns and relationships present in the historical patient admission data, including any seasonal, trend, and irregular components. By estimating the model parameters, it becomes possible to forecast future patient admissions based on the identified patterns and trends in the data. The mathematical model, combined with the estimation and diagnostic procedures provided by the Box-Jenkins methodology, allows for the identification of the best-fitting ARIMA model for the given patient admission data.

Both the R programming language and the Statistical Package for the Social Sciences (SPSS) were used for the analysis. The first step was to examine the time plot of the data to determine its pattern (Hyndman & Athanasopoulos, 2018). Next, autocorrelation was checked using the Durbin-Watson test, and stationarity was assessed by the Augmented Dickey Fuller (ADF) test. The data became stationary after differencing once. Once the data was determined to be stationary, the appropriate model was selected using SPSS. The best-fitting model was then used to forecast patient admission from 2016 to 2021.

The selection of the appropriate model was based on several criteria, including goodness-of-fit statistics such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model with the lowest values of AIC and BIC was selected as the best fit for the data. After selecting the best-fitting model, it was used to forecast patient admission for the next six years, from 2016 to 2021. The forecast was made based on the historical trend observed in the data, and the assumption that future patient admission would follow a similar pattern to the past.
Overall, the methodology employed in this study enabled the researchers to model the pattern of patient admission in a Nigerian hospital and to forecast future patient admission using appropriate time series analysis techniques.

RESULTS AND DISCUSSION

The methodology discussed above was applied to the series on quarterly admission of patients in university of Ilorin teaching hospital with focus of identifying the best model for the series and to forecast the number of future admissions.

Time plot of number of admissions of patient

FIG 1 represents the time plot of the admission of patient into university of Ilorin teaching hospital spanning from year 1999-2015. The plot shows that there is presence of trend in the quarterly admission of patient into the hospital. However, the graph shows that there is evidence of seasonal variation. The time plot shows an upward trend from the first quarter of the year 1999 to 2ndquarter of the year 2007, a downward trend between the 3rd quarter of year 2007 to the 4th quarter of 2013 and an upward trend from 2014 to 2015. It also shows that there is a sudden downward peak in the 1st quarter of the year 2002 and the 4th quarter in year 2003 and a sudden upward peak at the 3rd quarter of year 2014

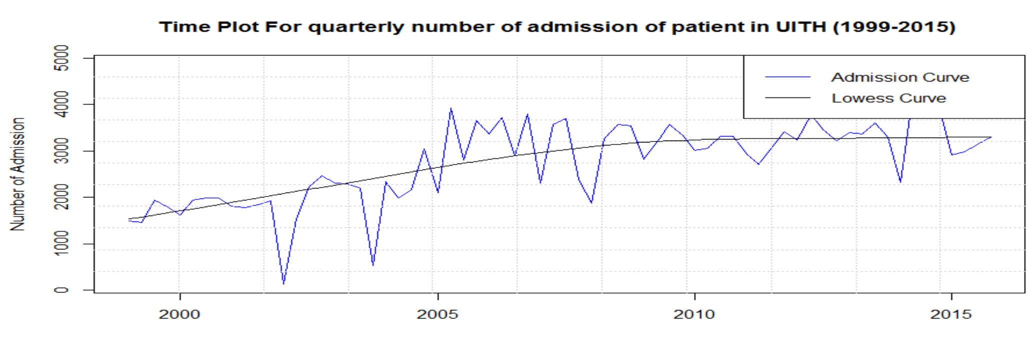

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FIG 1: Time plot of number of admissions of patient in UITH (1999-2015)

CORRELOGRAM (ACF & PACF) OF NUMBER OF ADMISSION OF PATIENT IN UITH

The FIG 2 is the correlogram (ACF and PACF) of the number of admissions of patient's log of the data series before differencing. The most striking feature of this correlogram is that the autocorrelation coefficients at various lags are high up to a lag of 12^{th} year (at lag 12 = 0.2695); these are individually statistically significantly different from zero, out of the 95% confidence bounds. This is the typical correlogram of a non-stationary time series. The autocorrelation starts at a very high value and a decline (spikes down) very slowly toward zero as the lags lengthens, showing a purely MA series. After the first four lags, the PACF drops dramatically, and most PACFs after lag 4 are statistically insignificant, showing an AR of order 3. We conclude from the result of the ACF that there is need for differencing which indicate the series is an ARIMA process.

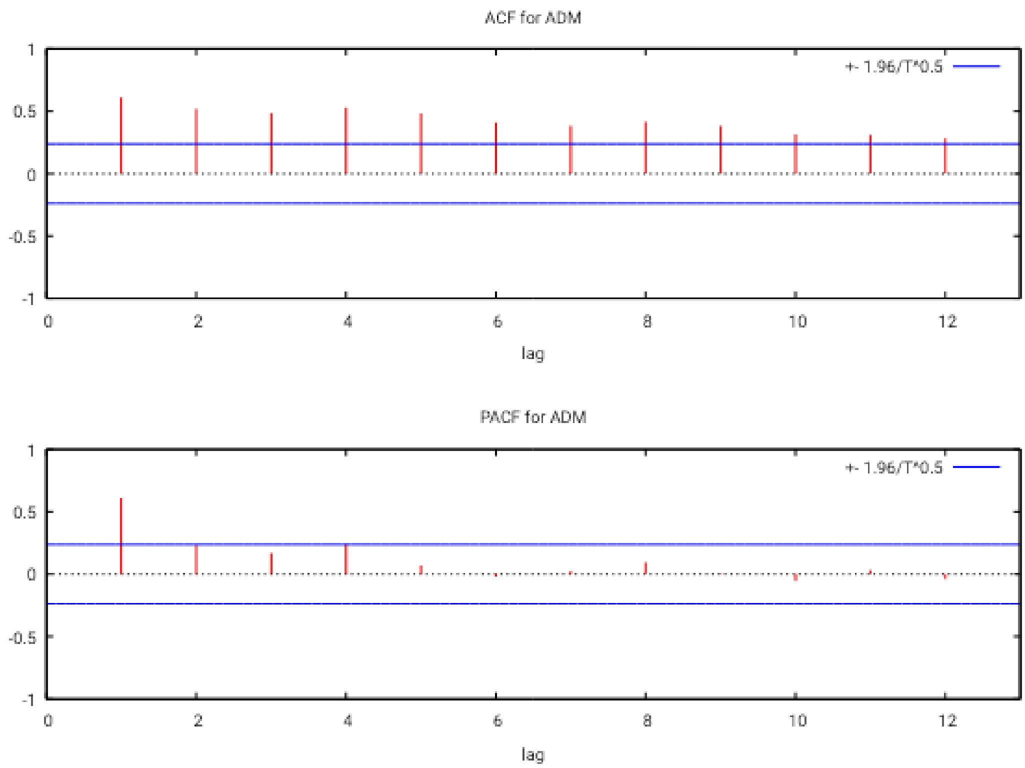

FIG 2: The ACF and PACF of quarterly number of admissions of patient in UITH

AUTOCORRELATION

Hypothesis

H_0: No autocorrelation

H_1: Autocorrelation

Level of significant: $\alpha = 0.05$

Test statistics

Durbin-Watson test

data: P ~ x

DW = 1.4984, p-value = 0.01257

alternative hypothesis: true autocorrelation is greater than 0

Decision Rule: Reject Ho if Augmented Dickey-Fuller Test statistic is less than the test critical values at 5% level of significant or if the prob. Value is less than 0.05.
Decision: Since, the Durbin-watson test statistic is less than the test critical value at 5% level of significant, I reject Ho, which means; autocorrelation is present in the data at 5% level of significant.
Conclusion: With this, we say that the data is autocorrelated at 5% level of significant

STATIONARITY TEST BY UNIT ROOT METHOD

The unit root test serves as a diagnostic tool to validate the suitability of the data for time series analysis, providing confidence in the subsequent modeling and forecasting processes. By conducting a unit root test, we can evaluate the presence or absence of a unit root in the data. If a unit root is found, it indicates that the series is non-stationary and further analysis using standard time series models may lead to unreliable results. On the other hand, if the unit root test suggests the absence of a unit root, it implies that the series is stationary or trend-stationary, making it suitable for applying time series modeling techniques.

UNIT ROOT TEST BEFORE DIFFERENCING

The Augment Dickey Fuller (ADF) test was conducted. The results of the test are given below shows that the confirming the log of the number of admission of patient is not stationary, since the tests statistics are greater than the p/critical values at some levels. Since the time series is not stationary, we have to make it stationary before we can apply the Box-Jenkins methodology. This can be done by differencing the series once.

Hypothesis

H_0: The data has a unit root

H_1: The data has no unit root

Level of significant: α = 0.05

Test statistics

Augmented Dickey-Fuller Test
data: P
Dickey-Fuller = -2.4138,
Lag order = 4, p-value =
0.4071
alternative hypothesis: stationary

Decision Rule: Reject Ho if Augmented Dickey-Fuller Test statistic is less than the test critical values at 5% level of significant or if the prob. Value is less than 0.05.

Decision: Since, the Augmented Dickey-Fuller test statistic is not less than the test critical value at 5% level of significant, I do not reject Ho, which means; the data has unit root at 5% level of significant.

Conclusion: With this, we say that the data is not stationary at 5% level of significant

DIFFERENCE ONE

FIG 3 shows the time plot of the first difference. A visual inspection of the plot shows the series has constant mean and variance. The plot however, does not show any evidence of stationary.

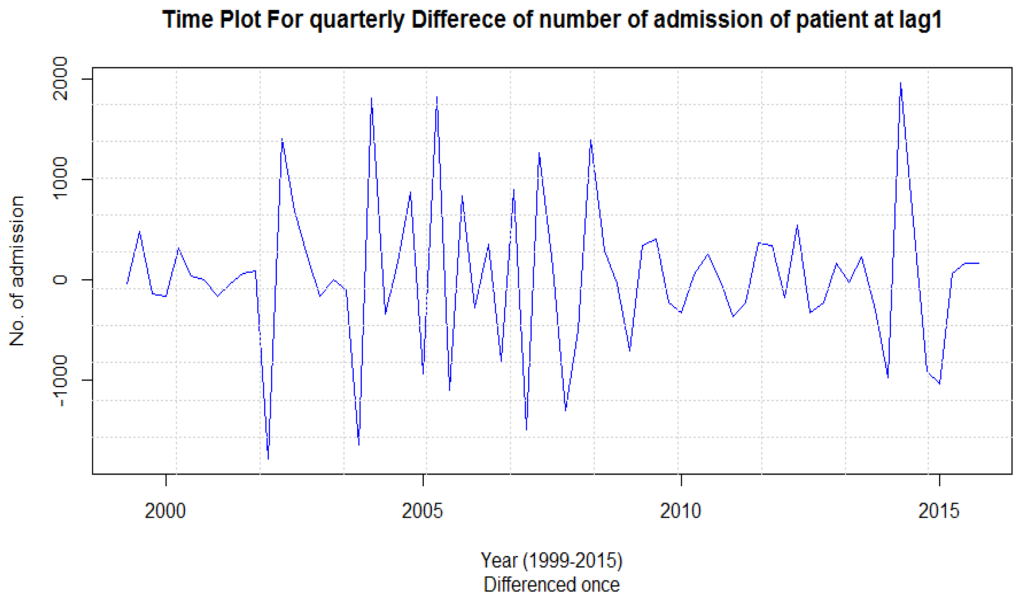

FIG 3: Time plot of first differencing of number of admissions of patient in UITH

The correlogram is shown in FIG 4: The ACFs at lag 1 seem statistically different from zero (at the 95% confidence limit, the lags are asymptotic and so can be considered approximate), but at all other lags, they are not statistically different from zero. We therefore conclude that the data series is now stationary. A formal application of the Augmented Dickey-Fuller below may show that this is indeed the case.

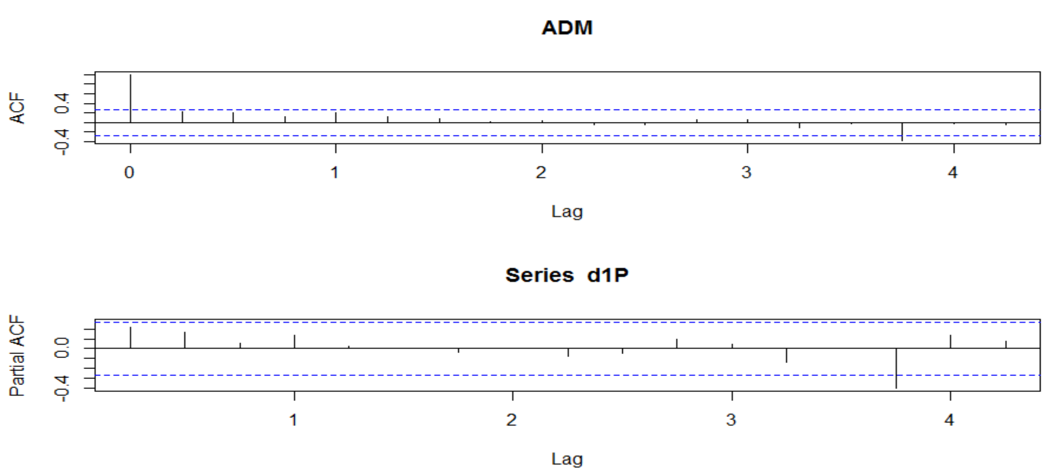

FIG 4: ACF and PACF after first differencing

UNIT ROOT AFTER FIRST DIFFERENCING

The Augment Dickey Fuller (ADF) test was conducted. The results of the test are given below which shows the entire test statistics of the ADFs are less than the critical regions, we reject the null hypothesis and therefore conclude that there is no unit root or the time series is stationary.

Hypothesis

H_0: The data has a unit root

H_1: The data has no unit root

Level of significant: $\alpha = 0.05$

Test statistics

Augmented Dickey-Fuller
Test
data: d1P
Dickey-Fuller = -5.0444,
Lag order = 4, p-value =0.01
alternative hypothesis: stationary

Decision Rule: Reject Ho if Augmented Dickey-Fuller Test statistic is less than the test critical values at 5% level of significant or if the prob. Value is less than 0.05.

Decision: Since, the Augmented Dickey-Fuller test statistic is less than the test critical value at 5% level of significant, I reject Ho, which means; the data has no unit root at 5% level of significant.

Conclusion: With this, we say that the data is stationary at 5% level of significant

SELECTION OF RIGHT MODEL FOR THE DATA

With the use of SPSS, auto-regression, moving average and auto-regression moving average model coefficient are obtained. AIC and BIC are used to get the best model among Auto-regression (AR), Moving average (MA) and Auto-regression Integrated moving average (ARIMA). The model with least AIC and BIC is the best model.

Table 1*:* Result of ARIMA model identification selection
Enrollment in local colleges, 2005

MODEL	AIC	BIC
ARIMA(0,1,1)	**1057.91**	**1062.32**
ARIMA(0,1,2)	1059.24	1065.85
ARIMA(0,1,3)	1061.22	1062.22
ARIMA(1,1,0)	1070.41	1111.44
ARIMA(1,1,1)	1059.29	1065.91
ARIMA(1,1,2)	1061.23	1070.05
ARIMA(1,1,3)	1063.06	1074.09
ARIMA(2,1,0)	1067.78	1104.32
ARIMA(2,1,1)	1061.10	1069.92
ARIMA(2,1,2)	1062.63	1066.11
ARIMA(2,1,3)	1062.98	1074.80
ARIMA(3,1,0)	1063.15	1095.26

From Table 1, we observed that the variable with the lowest AIC and BIC is ARIMA (0,1,1) which implies that the model is best fit the data

Estimation of the model gotten above:

Model

$$\mathbf{Y_t = -\theta_1 e_{t-1} + e_t}$$

$$\mathbf{Y_t = 0.7389 e_{t-1} + e_t}$$

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Call:
arima(x = P, order = c(0, 1, 1))
Coefficients:
         ma1
     -0.7389
s.e.  0.0844
sigma^2 estimated as 392512:  log likelihood = -526.95,  aic = 1057.91
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The estimates of the parameters of the model, shown above, indicates that MA (1) models are significant at the 0.05 significance level.

FORECAST

Table 2: ***Forecast Values for the Next Six Years (2016 – 2021)***

YEAR/ QUARTER	POINT FORECAST	LO 80	HI 80	LO 95	HI 95
2016 Q1	3340.64	2537.738	4143.542	2112.707	4568.572
2016 Q2	3340.64	2510.822	4170.457	2071.543	4609.736
2016 Q3	3340.64	2484.752	4196.527	2031.673	4649.607
2016 Q4	3340.64	2459.453	4221.826	1992.981	4688.298
2017 Q1	3340.64	2434.861	4246.418	1955.371	4725.909
2017 Q2	3340.64	2410.919	4270.361	1918.754	4762.525
2017 Q3	3340.64	2387.578	4293.702	1883.057	4798.222
2017 Q4	3340.64	2364.795	4316.484	1848.214	4833.065
2018 Q1	3340.64	2342.532	4338.747	1814.166	4867.114
2018 Q2	3340.64	2320.755	4360.524	1780.861	4900.419
2018 Q3	3340.64	2299.433	4381.846	1748.252	4933.027
2018 Q4	3340.64	2278.540	4402.740	1716.298	4964.982
2019 Q1	3340.64	2258.049	4423.230	1684.960	4996.319
2019 Q2	3340.64	2237.939	4443.340	1654.205	5027.075
2019 Q3	3340.64	2218.189	4463.090	1624.000	5057.279
2019 Q4	3340.64	2198.781	4482.498	1594.318	5086.961
2020 Q1	3340.64	2179.698	4501.582	1565.132	5116.147
2020 Q2	3340.64	2160.923	4520.357	1536.418	5144.861
2020 Q3	3340.64	2142.442	4538.837	1508.154	5173.125
2020 Q4	3340.64	2124.242	4557.038	1480.320	5200.960
2021 Q1	3340.64	2106.310	4574.969	1452.895	5228.384
2021 Q2	3340.64	2088.635	4592.644	1425.864	5255.416
2021 Q3	3340.64	2071.206	4610.073	1399.209	5282.071
2021 Q4	3340.64	2054.013	4627.266	1372.914	5308.365

Interpretation: Above we have the forecast table which contains the forecast of the data from 2016 – 2021 and the values of the confidence interval of each quarter in each year.

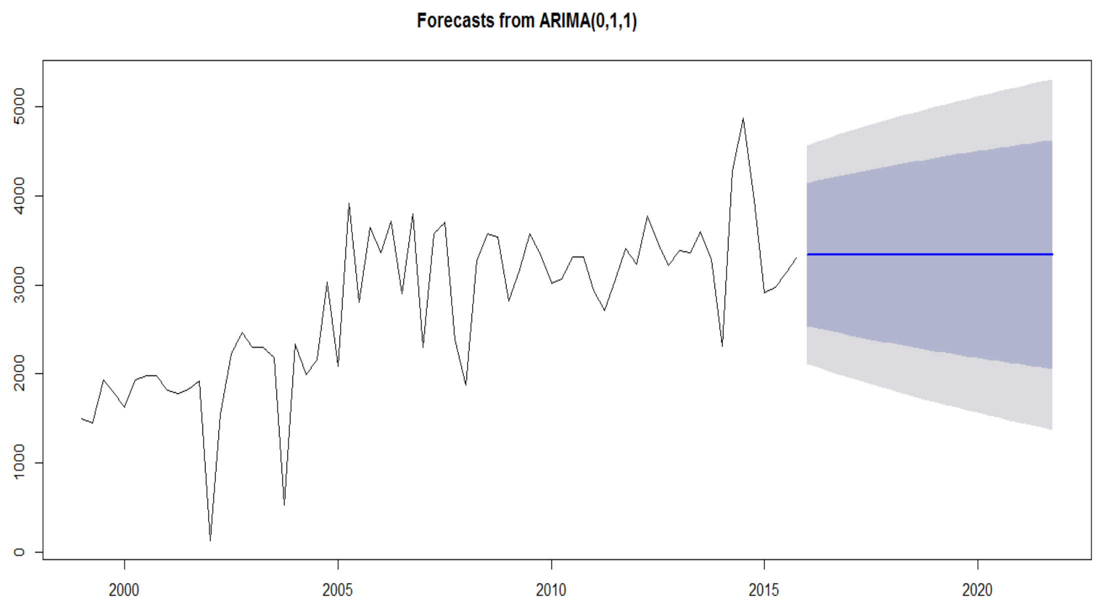

FIG 5: The Time plot that shows the original value and the forecasted value.

Interpretation: The FIG 5 shows the plot of the observed, fit and forecast of the data used for this analysis

DISCUSSION OF FINDINGS

Based on the forecast presented in this study, it was observed that the number of patient admissions in the University of Ilorin Teaching Hospital is expected to increase over the next three years. This finding is consistent with the trend observed in the past data, which showed a gradual increase in the number of patients admitted to the hospital over the years.

The hospital can use this forecast to plan for the future and prepare for the expected increase in patient admission. One way to do this is to ensure that there are enough resources, including medical personnel, hospital beds, and medical equipment, to meet the increasing demand. The hospital can also consider expanding its facilities and services to cater to the growing number of patients.

This finding is in line with previous research that has shown a consistent increase in patient admission rates over time. For example, a study by Akinloye and Adewole (2018) found that the number of patients admitted to the Obafemi Awolowo University Teaching Hospital, Nigeria, increased steadily over a ten-year period. Another study by Adejumo et al. (2017) found a similar trend in patient admission rates in a teaching hospital in Southwestern Nigeria.

The increase in patient admission rates is not unique to Nigeria but is a global trend. For example, a study by Carretta et al. (2017) in the United States found that the number of hospital admissions increased by 23.8% over a ten-year period. This highlights the need for healthcare institutions to plan for the expected increase in patient admission rates to ensure that they can continue to provide high-quality healthcare services to their patients.

In conclusion, the forecast presented in this study suggests that the number of patient admissions in the University of Ilorin Teaching Hospital is expected to increase over the next three years. The hospital can use this information to plan for the future and ensure that there are enough resources to meet the growing demand for healthcare services. This finding is consistent with previous research that has shown a steady increase in patient admission rates over time, both in Nigeria and globally.

CONCLUSION AND RECOMMENDATIONS

The main aim of any research work is to meet the requirement and to achieve the aim and objectives for which the research work is being carried out. The study was able to propose a suitable trend model for admission of patient into Nigeria hospital and also forecast the future number of admissions.

Thus, the study consists of the general introduction to the research work, talking about what is meant by admission, the levels of health care, brief view of health care in Nigeria, causes of medical admission in Nigeria hospitals, an overview of the case study-University of Ilorin Teaching Hospital, aim and objectives of the study and the description of data.

The literature review discussed about the past work that has been done on the research study by researchers. Four research work was reviewed in this study and they all concluded that the trend of admission is increasing. The methodology adopted was time series model. The best ARIMA model based on the AIC and BIC was used to get the short-term forecast of the data.

This study made the best endeavor to develop the best ARIMA model to efficiently forecasting the number of admissions of patient. After which the data was subjected to various test to choose the best model. The empirical analysis indicated that the ARIMA (0, 1, 1) model is best for forecasting the number of admissions of patient data series so far the diagnostic criteria are concerned. It now used in forecasting for three years (12 quarters). We concluded that prediction from our forecast shows a slight increase in the number of admissions of patient when it is compared to the previous records.

Based on the research, we observed that there will be slight increase in the admission of patient in the hospital in the future. Hence, there is need for the government to put more efforts and increase funding of our Teaching Hospitals, so as to meet up with future challenges in the wards of our hospitals. Individual should also be encouraged to visit the hospital whenever they are facing with any health challenge rather than engaging in self-treatment which can lead to death.

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