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TIME SERIES MODEL COMPARATIVE APPROACHES IN ANALYZING ACCIDENT AND EMERGENCY DEPARTMENTAL DEMAND IN EASTERN NIGERIA

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ABSTRACT: *The problem of the inappropriate attendances, morbidity pattern of patients in emergency condition and exhibited staff stress by some Nigerian hospitals motivated this work. The aim of the paper is to address the challenges of hospital accident and emergency departmental demand in Eastern Nigeria using statistical methods on a secondary data collected from January 2007 to December 2017. We extend a class of multivariate Vector-ARMA (VARMA) forecast models to predict the demands envisaged at Bishop Shanahan hospital's accidents and emergency department and to do a comparative study based on existing research works. In this study we compared both univariate and multivariate time series model approaches to identify the best forecasting model to be used in addressing medical services challenges in Eastern Nigeria. Multivariate Vector Autoregressive Moving Average (VARMA (p,q)) models were compared with the Box and Genkins ARMA(p,q) model and exponential smoothing model by Holt Winter to ascertain their accuracy levels in predicting Accident and Emergency Departmental Demand. The result of the work shows evidence of increasing Accident and Emergency Department for the people within the age range of 20-45 years. The multivariate VARMA (p,q) models outperformed the univariate ARMA(p,q) models and the Holt winter's model by having the smallest errors for all the error measures (MAE, RMSE, MAPE) considered in the research. In conclusion, we advise healthcare providers at Federal, State and Local Government levels in Nigeria to intensify efforts in the sensitization and campaign against hard drug and alcohol consumption among our youths, since our active workforce of the nation, age (20-45 years) are prone to emergency health related issues now and in the nearest future.*

KEYWORDS: VARMA, ARM, Holt Winter, Accident and Emergency Department.

INTRODUCTION

Accident and Emergency Departments (AEDs) in hospitals play an important role in the health care system, providing healthcare services for patients with severe illness and injury. Accident and Emergency Departments in hospital holds a highly strategic position in the field of health care, in all societies. Accident and Emergency Departments (AEDs) are serious components in health care services because it is accessible 24 hours a day, 7 days a week, mostly for all who need serious care been that it is accessible and always available to people all the time, Trezeciak and Rivers (2003).

Accident and Emergency department (AED) is one of the few institutions readily available to assist all persons. Its services are provided irrespective of religion and social-economic status of the people and without an appointment. Accident and Emergency Department (AED) congestion has been an increasingly serious health challenge for so many years now MacCabe (2001).

The inability of the Nigeria's accident and emergency departments to meet current demands is increasing among the public and health care practitioners. This increase in accident and emergency department operation has effectively saturated the capacity of AEDs medical services in many societies. The resulting phenomenon, commonly called accident and emergency department overcrowding, now impends access to emergency services for those who need them the most, Fatovich et.al (2005).

Over the last few years, accident and emergency departments demand in Nigeria have become increasingly congested due to the effects of steady demand for healthcare. AED congestion has implications for patient outcomes, as well as for the efficiency and effectiveness of AED operations as demonstrated by staff and patient satisfaction.

Accident and emergency department demand overcrowding is a clear and also, foreseeable indicator of steadily rising in demand that has exceeded available resources, MacCabe (2001). Surprisingly, this saturation of emergency healthcare services is not usually a result of excessive or inappropriate use of the AED demand by those with no emergent problems; it is a consequence of increasing numbers of patients with serious illnesses (sickness) or injuries requiring hospital and intensive care unit admission attention. AED demand congestion increases difficulty to access emergency care, causing loss of patient life sometimes due to delay in receiving healthcare attention and time sensitive treatments, and patient departure prior to the commencement of treatment which causes patient dissatisfaction, Weismann et.al (2007).

Objectives of the Research

Since the factors affecting demand for emergency healthcare in Nigeria are complex, the following are the objectives of this research:

i. To identify the demand for healthcare services by age, triage and gender;

ii. To perform a model comparison between Multivariate Vector Autoregressive Moving Average (VARMA) model, Box and Jenkin's univariate ARMA model and Exponential Smoothing model by Holt Winter to accident and emergency department's demand data from a hospital in Eastern part of Nigeria.

Scope of the Research

This study was carried out at Bishop Shanahan's Hospital Nsukka, Enugu State; there are other private hospitals which patients also attend. The period of study spans from 2007 through 2017.

METHODOLOGY

The data for this study were collected from the Medical Record Department and Out Patient's Department (OPD) of the above-mentioned hospital. The data were collected in the following manner, gender, type of diseases suffered, age of the patient and duration of stay in the hospital. The data were presented in a tabular form for easy understanding. The data was analyzed with Microsoft Excel, SSPS and R software.

In this study, the variables considered are number of accident and emergency department demand presentation stratified according to age bracket $(0-19, 20-45, 46-65, 66 \text{ and above})$, gender (male, female) and triage category (Emergency, Urgent and $\text{Non}-\text{urgent}$). Each of these variables is time series observation taken from January 2007 to December 2017. The combinations of all the variables give the total accident and emergency departmental demand at Bishop Shanahan's hospital, Nsukka, Enugu State. For the triage category, we have emergency (requiring treatment immediately on arrival), urgent (requires treatment within thirty minutes to one hour of arrival) and non−urgent (requires treatment beyond one hour of arrival).

ARMA Model

ARMA models are for univariate time series modeling techniques, they are developed to give a general framework for forecasting observed time series data that are non-stationary. Given that y_t is an AED demand time series data that is stationary, an ARMA(p,q) model of AED demand can be expressed as follows;

$$y_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \quad 1$$

$$\phi(B) y_t = \mu + \phi(B) a_t$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$$

where $By_t = y_t - y_{t-1} \; and \; a_t \backsim N(0, \sigma^2)$

In this work, the model building procedures of Box and Jenkin's will be used, three stages are involved which are (i) Identification (ii) Estimation (iii) Diagnostic checking.

VARMA Model

VARMA modeling procedure allows several independent time series observations to be modelled together and also ascertain both cross and within correlation of the series. VARMA model is used to determine the relationships that exist between age, gender and triage category in this work. Given that y_t is a stationary k−dimensional AEDD time series data, VARMA (p,q) model can be expressed as $\boldsymbol{\phi}(B) y_t = \boldsymbol{\phi}_0 + \boldsymbol{\theta}(B) a_t$

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Where $\boldsymbol{\phi}(B) = 1_k - \sum_{i=1}^{p} \phi_i B^i$ and $\boldsymbol{\theta}(B) = 1_k - \sum_{j=1}^{q} \theta_j B^j$, ϕ_0 is a constant vector and t is the time period. For any n given time series $y_{1t}, y_{2t}, \ldots, y_{nt}$, VARMA (p,q) model can be written as

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{nt} \end{bmatrix} = \begin{bmatrix} \emptyset_{11} & \emptyset_{12} & \cdots & \emptyset_{1p} \\ \emptyset_{21} & \emptyset_{22} & \cdots & \emptyset_{2p} \\ \vdots & \vdots & \cdots & \vdots \\ \emptyset_{n1} & \emptyset_{n2} & \cdots & \emptyset_{np} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ \vdots \\ y_{nt-1} \end{bmatrix} + \begin{bmatrix} a_{1t} \\ a_{2t} \\ \vdots \\ a_{nt} \end{bmatrix} - \begin{bmatrix} \theta_{11} & \theta_{12} & \cdots & \theta_{1q} \\ \theta_{21} & \theta_{22} & \cdots & \theta_{2q} \\ \vdots & \vdots & \cdots & \vdots \\ \theta_{n1} & \theta_{n2} & \cdots & \theta_{nq} \end{bmatrix} \begin{bmatrix} a_{1t-1} \\ a_{2t-1} \\ \vdots \\ a_{nt-1} \end{bmatrix}$$

For more details about VARMA modeling see textbook by Tsay.

Exponential Smoothing Model

The Holt-winters exponential smoothing (double exponential smoothing) is used when time series data exhibits trend. There are two smoothing procedures or equations involved in using Holt-Winters exponential smoothing for the forecasting of time series. They are; the level trend. Holt-winters exponential smoothing has two models which are the addictive and multiplicative models. We result to the use of the addictive model in this work because the variation or fluctuation in the data collected from Bishop Shanahan's hospital, Nsukka, Enugu State is relatively constant. Holt-winters exponential additive forecasting model is given by

$$\widehat{F}_t(n) = S_t + n\,T_t \tag{3}$$

for the level: $S_t = \alpha y_t + (1-\alpha)(S_{t-1} + T_{t-1})$ (4)

for the trend: $T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$ (5)

where $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$. α and β are the smoothing parameters, y_t is our accident and emergency department demand data obtained at time t, S_t is a smoothed estimate of the value of y_t at the end of period t, T_t is a smoothed estimate of average growth at the end of period t and $\widehat{F}_t(n)$ is the n step ahead value for our y_t from time t. For more insight about Holts - winters exponential smoothing see textbook by Chatfield.

Error Measures for Model Evaluation/Assessment

In this work, three popular error measures will be used in this work to assess the models in terms of their forecasting performances, they are: (i) Mean Absolute Error (MAE) (ii) Root Mean Square Error (RMSE) (iii) Mean Absolute Percentage Error (MAPE).

The mathematical expressions of these errors are given below:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |f_t - Y_t|$$

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$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(f_t - Y_t)^2}$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{Y_t - f_t}{Y_t}\right|$$

Where f_t the forecasted values at time t, Y_t is the observations taken at time t and n is the number of observations considered in the work.

3.0 Presentation and Analysis of Data

In this work, we presented the data in a tabular form and the analysis of the data was performed with the aid of Microsoft excel and R software.

Table 1: The of number of AED demand at Bishop Shanahan's hospital stratified by age for the years of the study.

Age \ Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
0-19	230	185	210	170	189	125	165	113	145	180	176
20-45	450	489	520	421	446	398	428	361	410	505	470
46-65	130	142	165	160	220	148	158	185	145	168	229
> 65	173	187	120	139	165	119	175	161	155	174	152

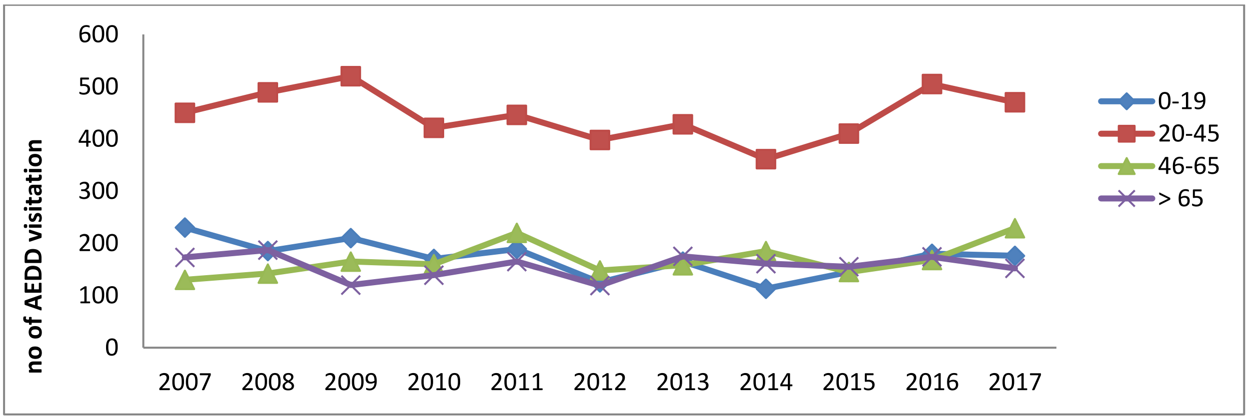

Figure 1: The plot of number of AED demand at Bishop Shanahan's hospital by age for the years of the study.

From figure 1, we can see that people within the age category of 20-45 have the highest reported cases of hospital visitation, its value ranging from 395 to 520 followed by age category of 0-19, age category of > 65years and lastly age category of 46-55 which shows an increment from year 2015 to year 2017.

Table 2: The of number of AED demand at Bishop Shanahan's hospital stratified by gender for the years of the study

Year / Gender	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Female	635	510	610	420	565	380	520	411	465	540	530
Male	348	493	405	470	515	410	430	409	390	492	497

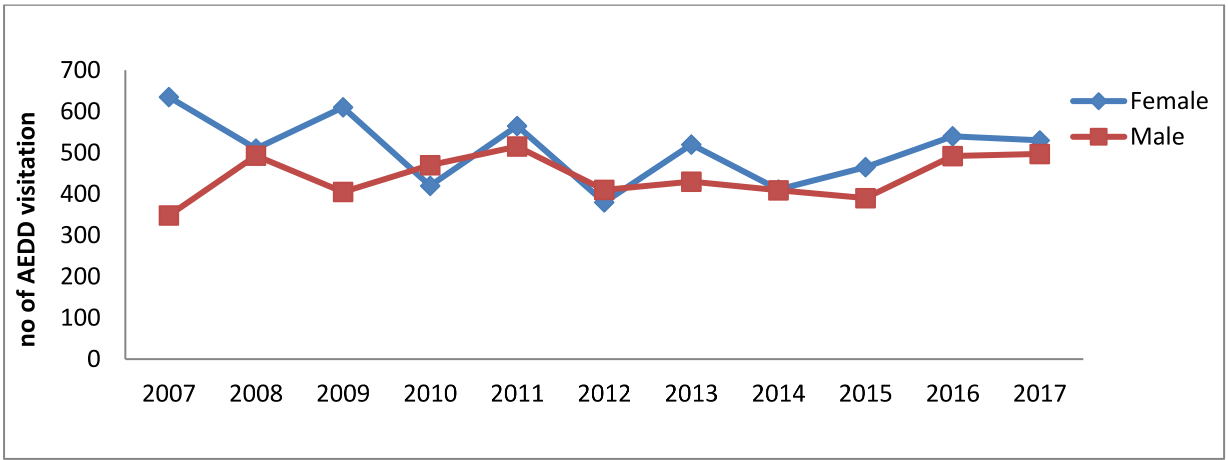

Figure 2: The plot of number of AEDD at Bishop Shanahan's hospital according to gender for the years of the study

From figure 2, it can be seen that females have the highest reported cases of hospital visitation, its values ranging from 380 to 635 followed by males that have values ranging from 348 to 515.

Table 3: The of number of AED demand at Bishop Shanahan's hospital stratified by triage for the years of the study

Year / Triage	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Emergency	323	331	284	319	255	210	278	180	255	270	277
Urgent	300	286	337	388	420	330	362	242	290	350	430
Non-urgent	360	386	400	263	345	250	310	398	310	412	320

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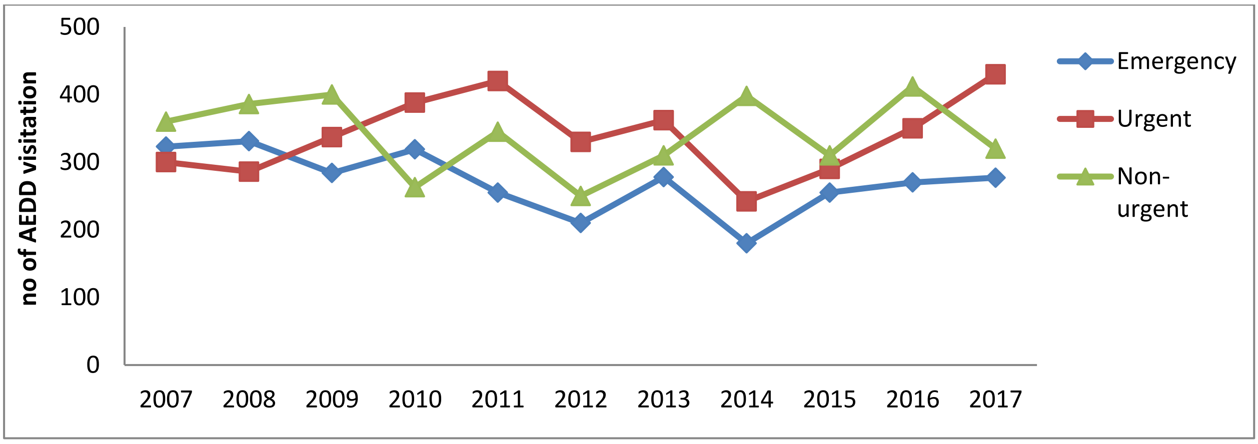

Figure 3: The plot of number of AED demand at Bishop Shanahan's hospital by age for the period of the study

From figure 3, we observed that emergency cases of AED demand were high in the following years 2010, 2014 and 2016. Urgent cases for AED demand were high in 2012 and steady rise from 2015 to 2017. Non –urgent cases were high in 2013 and 2015.

Table 4: Summary of the Model Accuracy Evaluation from the Error Assessment Result.

	MAE			RMSE			MAPE		
	ARMA	VARMA	HWES	ARMA	VARMA	HWES	ARMA	VARMA	HWES
0 to 19	45.13	43.25	78.65	38.10	28.34	93.01	4.12	3.15	6.50
20 to 45	25.90	24.02	59.36	35.07	22.19	64.24	3.92	2.85	5.34
46 to 65	26.53	22.15	64.23	49.75	39.02	56.11	4.45	3.67	6.20
>65	42.16	33.57	75.11	30.12	25.18	71.21	6.52	4.23	7.20
Emergency	46.14	41.12	70.18	37.32	28.49	56.16	5.35	4.34	6.38
Urgent	29.65	36.03	42.06	41.23	29.71	58.87	4.30	2.68	5.10
Non-urgent	36.20	23.14	47.47	28.36	37.02	89.34	5.35	3.85	6.21
Male	62.43	43.18	81.23	43.08	62.17	86.36	4.12	2.55	5.14
Female	51.84	37.06	76.19	46.05	30.28	78.04	4.36	3.56	6.20

From table 4 above, it can be seen that VARMA model followed by the Box and Jenkins ARMA model outperformed the Holt Winter's exponential smoothing model by having the smallest values for all the error evaluation measures (MAE, RMSE and MAPE) considered in this work.

SUMMARY AND CONCLUSION

To summarize, from Table 4 above, it can be clearly seen that the VARMA model followed by Box and Jenkins ARMA model outperformed the Holt-winters exponential smoothing model by having the smallest error measures for model assessment/evaluation. Also, from Figure 1, people within the age category of 20 to 45 years have the highest number of reported cases of hospital visitation for the period of the study and this may be as a result of alcohol consumption and drug abuse among the youths.

In conclusion, we advise healthcare providers at Federal, State and Local Government levels in Nigeria to intensify efforts in the sensitization and campaign against hard drug and alcohol consumption among our youths, since our active workforce of the nation, age (20-45years) are prone to emergency health related issues now and in the nearest future.

REFERENCES

Box, G.E.P., Jenkins, G.N and Reinsel, G.C. (1994): Time Series Analysis, Forecasting and Control. 4th Edition, Prentice Hall, New Jersey.

Chatfield, C. (1978): The Holt-Winters forecasting procedure, Appl. Stat. 27 (3) 264–279.

Cryer, J.C. and Kung, S.C. (2010): Time Series Analysis with Application in R, Springer Text in Statistics.

Dickey, D.A. and Fuller, A.W. (1979): Distribution of the Estimators for Autoregressive Time Series with Unit Root. *Journal of the American Statistical Association, Vol. 74, Issue 366, 427-431.*

Fatovich D M, Nagree Y, Sprivulis P. (.2005): Access block causes emergency department overcrowding and ambulance diversion in Perth, Western Australia. Emerg Med. Journal. 22:351–354.

MacCabe J. B. (2001): Emergency department overcrowding: A national crisis. Academic Medicine. 76:672–674.

Trezeciak S, Rivers E P. (2003): Emergency department overcrowding in United States, and emerging threat to patient safety and public health. *Emerg Med Journal 20:402–405.*

Tsay R. (2014): Multivariate Time Series Analysis: With R and Financial Applications, first ed, John Wiley & Sons, Inc., Hoboken, New Jersey, 2014, p. 492.

Weissman J.S, Rothschild J.M, Bendavid E, Sprivulis P, Cook E.F, Evans R.S. (2007): Hospital Work load and adverse events. *MedCare Journal. 45(5):448–455.*