ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

Statistical Modelling of *Meningococcal Meningitis* in Nigeria.

Adekanmbi DB[1]* and Olaomi JO[2].

[1]Department of Statistics, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[2]Department of Statistics, University of South-Africa (UNISA), Pretoria, South-Africa.

ABSTRACT

Meningococcal Meningitis (MM), a bacterial form of meningitis constitutes a major public health *problem* in Africa region labelled as *meningitis belt*, where the extensive North-West Nigeria lies. The present study aimed at analysing and constructing a time series model for meningococcal meningitis (MM), based on Box and Jenkins techniques, with a view of using the model as a medical surveillance tool and to forecast the pattern of incidence of the infectious disease in Nigeria. Annual epidemiological data on MM spanning the period 1990 to 2010 extracted from WHO website was subjected to Boot-Fiebes-Lisman first difference (BFL-FD) to disaggregate the data to quarterly figures in order to ensure high case-load and eradicate random fluctuation. Extensive discussion on Dickey-Fuller and Augmented Dickey-Fuller unit-root test of stationarity were provided. The results of the Dickey-Fuller (DF) test and the Augmented Dickey-Fuller (ADF) unit-root test for the null hypothesis that the series has a unit-root confirmed stationarity in mean but the disaggregated MM series was not stationary in variance. The disaggregated MM series was further subjected to Box-Cox transformation to achieve stability in variance. ARMA(1,0) was identified as a plausible model by visual inspection of the ACF and the PACF of the disaggregated MM figures, and the parameters of the model were estimated. Various diagnostic verifications conducted provide evidence of randomness of the residuals of the model and consequently the adequacy of the ARMA model. The model was used to predict the trend of the disease from 2008 to 2010, and the forecast were compared to the reported cases. The time series model for the MM series in Nigeria is of practical importance as a tool in understanding the process that builds persistence into the MM series and its trend in Nigeria overtime, which is a useful guidance for prevention and control of the disease to prevent large MM epidemics. The results of this study will also aid the health policy makers to determine periods most at risk, and consequently intensifying medical surveillance in the areas at risk in Nigeria to prevent outbreaks. Recommendations were made on intervention and preventive measures to effectively prevent future MM outbreaks.

Keywords: Quarterly disaggregated MM figures, ARMA model, Boot-Fiebes-Lisman first, difference (BFL-FD), Portmanteau lack-of-fit test, Augmented Dickey-Fuller (ADF) unit-root test, Durbin-Watson Statistic, Meningitis belt.

Corresponding author

ISSN: 0975-8585

INTRODUCTION

Meningococcal Meningitis (MM) is an inflammation of the thin protective membranes covering the brain and spinal cord known collectively as the *meninges*, [26]. Due to its proximity to the brain and spinal cord, meningitis can be life threatening, if treatment is delayed. The infection occurs most often in children, teenagers, and young adults. Some of the associated symptoms of meningitis are severe headache, a stiff and painful neck, sudden high fever, seizures, vomiting, altered consciousness, intolerance to bright light (photophobia) and intolerance to loud noises (phonophobia), [2, 26]. Viral meningitis and bacterial meningitis are the two main types of meningitis, and both can be transmitted from person-to-person through droplets of respiratory secretions and direct contact with infected persons. The two types of meningitis share the same symptoms, but the bacterial meningitis is more severe and can lead to brain damage and death if untreated. Meningitis is both infectious and contagious, and can even lead to epidemic outbreak. African countries where the magnitude of meningitis is more profound have been labelled as *meningitis belt*, [10, 12, 17, 22]. The meningitis belt of sub-Saharan Africa stretching from Senegal in the West to Ethiopia in the East has been plagued by epidemics of meningitis for more than a century, [17, 20]. Meningitis though a notifiable disease, but the exact incidence rate is not yet ascertained, [18]. It was estimated that bacterial meningitis resulted in 420,000 deaths in 2010, [19]. MM epidemics usually occur in the dry season- December to June in the meningitis belt, [21]. In Africa sub-Saharan region which is poorly served by medical care, the meningitis attack rates of 100-800 cases per 100,000 are encountered, [2]. From 1996 to 1997, the largest epidemic was recorded in the region with meningitis infected over 100,000 people and consequently led to 10,000 deaths during a three month period in the region, [14].

Northwest Nigeria is located in the African Sahel savannah region, within the meningitis belt with high risk of MM. The first meningitis epidemic in Nigeria dated back in 1905, and has become endemic in the Northwest Nigeria. Countries in West-Africa usually experience an annual meningitis epidemic, affecting between 25,000 and 200,000 people, [12, 21]. Large outbreaks of the disease in the northern Nigeria usually occur every 10 years. Among the West-African countries in which epidemic of MM occurred in 2009, Nigeria has been the most adversely affected recording a high number of infected cases and deaths due to meningitis outbreak. In fact WHO reported that 1,100 infected persons died, while there were other 25,000 cases in Nigeria alone, [32]. In Nigeria, the harmattan period is a dry season that extends from November to May of every year with a peak between March and April when weather become hottest. Most people in the northern Nigeria believed that the intense heat usually experienced during the dry season is responsible for the outbreak of the disease. Apart from climatic factor, socio-economic and cultural factors are some of the factors that can influence meningitis outbreak. In areas largely populated by low-income earners, overcrowding is a common feature of most homes which is conducive to the transmission of the disease from person-to-person. Also most people use wood and charcoal as cooking fuel which make them vulnerable to the development and transmission of MM. Due to the symptom of stiff-neck often associated with the disease, meningitis is referred to as *Sankarau*, in the native Hausa language, meaning the disease of stiffness.

A short term protection against meningitis can be provided with antibiotics, while the long term protection could be achieved through vaccination. Short-term antibiotic prophylaxis is a method of prevention of MM which can reduce the risk of contracting the disease, but does not protect against future infections. A realistic means of combating the disease effectively is through mass vaccination of people when a certain threshold has been crossed, [3, 11, 30]. Some of the existing vaccines used in controlling the disease are meningococcal *A* conjugate vaccine, *C* conjugate vaccines, tetravalent *A, C, Y* and 135 conjugate vaccines and meningococcal poly sacchride vaccines, [33]. Childhood vaccination has been reported to reduce the rate of MM among children, [29]. Also, it has been established that polysaccharides vaccines are effective in controlling meningococcal epidemics, [11, 24]. Before the discovery of other more effective vaccines, the approach for prevention and control of MM epidemics in most African countries was based on early detection of the disease and mass vaccination of the at-risk population with bivalent A/C or trivalent A/C/W135 polysaccharide vaccines, [31]. Recently the introduction of meningococcal group A vaccine called *MenAfriVac* has shown effectiveness in combating the disease in young people, [3, 20]. Conjugate vaccine was implemented in Nigeria in 2011, specifically in five northern Nigeria states, namely: Zamfara, Gombe, Bauchi, Jigawa and Katsina. The high costs of conjugate constitute a major barrier in administering it in African countries.

ISSN: 0975-8585

It is a common practice in the epidemiological study of infectious disease to explain empirical issues with theoretical studies in order to better understand and describe the mechanisms of disease transmission and epidemics emergence, with a view of controlling their impact on human health. Time series techniques has a wide application in fields of epidemiological study of various diseases such as short term malaria, [6], tuberculosis [25], forecast of canine rabies [28], prediction of Ross River virus disease in Brisbane, [15], HIV-associated tuberculosis, [23], Viral infections diseases, [13], analysis of Syphilis, [34], analysis of gonorrhoea, [27]. Autoregressive-moving average (ARMA) is a stationary process referred to as ARMA(p,q) process. ARMA model is the combination of the AR (autoregressive) and MA (moving average) components to produce a mixed model, basically to achieve parsimony in parameterisation. An ARMA modelling approach can serve as an indicator of MM early detection strategy, based on the patterns of historical cases as a baseline to identify anomalies that may indicate the early stages of emerging epidemic, [26, 9].

Outbreaks of epidemics usually signal seasonality of such epidemics, and for MM its outbreaks usually starts in dry season. It has been established that major meningitis outbreaks in Nigeria occur every ten years, [9]. The last large MM outbreak occurred in 1996; and health workers in this field have been apprehensive of a major epidemic since 2006, [10]. The focus of this study is to develop a statistical model for MM cases, and to determine the possibility of seasonality in the disease in Nigeria. This approach should improve our understanding of trends and patterns in MM dynamics, and thereby facilitate a better epidemiological surveillance of the disease.

Description of the data employed in this study is given in section 2, while section 3 focuses on statistical theory of time series techniques, and test for stationarity. Identification of the suitable time series model for the disaggregated MM figures is presented in section 4. Estimation of the ARMA model, model adequacy and discussion on the results of the study are presented in last two sections of the study.

Data

This study is based on the secondary data on reported MM cases extracted from the WHO website. The data are the annual reported cases of MM from 1990 to 2010 in Nigeria. A rough examination of the data suggests an outbreak of the disease in 1996 with 108,568 reported cases, and the lowest number of meningitis was recorded in 2004 and 2005 with 659 and 657 respectively. Annual data can only be used to uncover pluri-annual cycles if present, but cannot detect seasonality in the incidence of a disease. It is when the data are disaggregated that patterns, trends, seasonality and other important information are uncovered. Boot-Feibes-Lisman first difference (BFL-FD) [4], method is suitable in disaggregating annual time series data into quarterly figures. This non-model based method (BFL-FD) developed by Boot *et al*, [4] is employed in this study to disaggregate the Nigeria's annual MM data to quarterly figures.

ARMA Models

Autoregressive moving average (ARMA) models are statistical models of the autocorrelation in a time series. Generally, time series techniques has a wide application in fields of epidemiological study of various diseases, [6, 13, 15 23, 25, 27, 28, 34]. ARMA models can be used to predict behaviour of an epidemiological series from past values. ARMA model contains autoregressive and moving average terms. The generalised form of stationary ARMA model for y_t using the B-operator, can be written as:

$$\varphi_p(B)y_t = \theta_q(B)\varepsilon_t \quad (1)$$

This is referred to as ARMA(p,q) process, and can be written explicitly as:

$$y_t = \varphi_1 y_{t-1} + ... + \varphi_p y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - .... - \theta_q\varepsilon_{t-q} \quad (2)$$

When y_t has a non-zero mean, the resulting model is:

ISSN: 0975-8585

$$y_t - \mu = \varphi_1\left(y_{t-1} - \mu\right) + ... + \varphi_p\left(y_{t-p} - \mu\right) + \varepsilon_t - \theta_1\varepsilon_{t-1} - .... - \theta_q\varepsilon_{t-q} \quad (3)$$

Let $c = \mu\left(1 - \varphi_1 - .....- \varphi_p\right)$, then (3) becomes

$$y_t = c + \varphi_1 y_{t-1} + ... + \varphi_p y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - .... - \theta_q\varepsilon_{t-q} \quad (4)$$

$\varphi_p \neq 0,\ \theta_q \neq 0$ and $B^j y_t = y_{t-j}$

Where

$\varphi_p(B)$: the p[th] order polynomial in B that captures the AR dynamics of the process. It is the autoregressive operator.

$\theta_q(B)$: the q[th] order polynomial capturing the MA dynamics. It is called moving average operator.

B: denotes the lag operator.

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - ... - \varphi_p B^p$$

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

Parameters *p* and *q* are called the autoregressive and the moving average orders respectively. Also $\{\varepsilon_t; t = 0, \pm 1, \pm 2, ...\}$ is a Gaussian white noise sequence and *c* is the intercept. A time series is ARMA(p, q) if it is stationary and satisfies either (1) or (2) or (3). An AR model is a subset of ARMA model, which expresses a time series as a linear function of its past values. Likewise the moving average (MA) model is a form of ARMA model in which the time series is regarded as a moving average of a random shock series ε_t. If q = 0, ARMA becomes the autoregressive model of order p, AR(p). Also if p = 0, ARMA becomes the moving average model of order q, MA(q). So that ARMA(1,0) is equivalent to AR(1), and ARMA(0,1) is equivalent to MA(1). The simplest ARMA model is the first-order autoregressive and first-order moving average, or ARMA(1,1) scheme, which can be written as:

$$y_t - \varphi y_{t-1} = c + \varepsilon_t - \theta\varepsilon_{t-1} \quad (5)$$

The ACF of the ARMA(1, 1) process is similar to the ACF of an AR(1) scheme after lag 1. Also its PACF behaves like that of MA(1) process after the first lag, [16]. ARMA(1,1) is stationary if $-1 < \varphi_1 < 1$, and it is invertible if $-1 < \theta_1 < 1$.

ARMA Modelling

ARMA modelling assumes the series is weakly stationary, [5]. The autocorrelation function (ACF) could be used for identification of the orders of an ARMA(p,q) process for a stationary series. The first step in ARMA modelling therefore is to ensure that the sample ACF of the series is stationary. Stationarity of a series implies that the mean and variance of a series are constant overtime and that the structure of the series depends only on the relative position in time of two observations, [16]. Linear decay of the sample ACF of such

series is a confirmation that the series is not stationary, and requires differencing. ARMA model is only appropriate for stationary series, so that it is necessary to confirm the stationarity of the series. A suitable test for stationarity is the *Augmented Dickey-fuller (ADF*) test. In order to determine the stationarity or nonstationarity of a series, the focus is on the roots of the AR polynomial $\varphi(\mathrm{B})$, so that if the modulus of any root of $\varphi(\mathrm{B}) \leq 1$, the series is nonstationary. For a series to be stationary, all roots of $\varphi(\mathrm{B})$ must lie outside the unit circle in the complex plain.

Augmented Dickey-Fuller (ADF) test of stationarity

Dickey-Fuller (DF) test which was developed by Dickey and Fuller [8] can be employed to determine whether a unit-root is present in a series. The test is conducted under the assumption that the residuals are uncorrelated. Presence of unit-root makes a series nonstationary. There are three specifications of DF test depending on whether the series exhibit a trend or not. The three specifications are:

$$\nabla y_t = \partial y_{t-1} + \varepsilon_t \tag{6}$$

Test for a uni-root.

$$\nabla y_t = a_0 + \partial y_{t-1} + \varepsilon_t \tag{7}$$

Test for a unit-root with drift.

$$\nabla y_t = a_0 + \partial y_{t-1} + \beta t + \varepsilon_t \tag{8}$$

Test for a unit-root with drift and deterministic time trend.

DF test removes all the structural effects (autocorrelation) in a series and then tests using hypothesis testing. For a simple AR(1) model,

$$y_t = \varphi_1 y_{t-1} + \varepsilon_t \tag{9}$$

for $t = 1,2,3,4,\ldots..$.

By subtracting the lagged value from both sides, we have

$$y_t - y_{t-1} = \varphi_1 y_{t-1} - y_{t-1} + \varepsilon_t \tag{10}$$

The test equation for a unit root can therefore be written as:

$$\nabla y_t = (\varphi_1 - 1) y_{t-1} + \varepsilon_t = \partial y_{t-1} + \varepsilon_t \tag{11}$$

where ∇ is the first difference operator.

Testing for a unit root is equivalent to testing $\partial = 0$, where $\partial = \varphi_1 - 1$. So that a unit root is present and the process $\{y_t\}$ is non-stationary if the coefficient $\varphi_1 = 1$, and it is stationary if $|\varphi_1| < 1$. The null hypothesis of DF test is $\mathrm{H}_0 : \partial = 0$ i.e there is a unit root and the series is non-stationary. The alternative hypothesis is $\mathrm{H}_1 : \partial < 0$, that is there is no unit root and the series is stationary. The test has its critical value which depends on the size of the series.

Augmented Dickey-Fuller (ADF) test is conducted by adding the lagged values of the dependent variable ∇y_t to the specifications above ((6)-(8)) to eliminate the serial correlations. ADF test is based on the equation:

$$\nabla y_t = a_0 + \partial y_{t-1} + a_1 t + \sum_{i=1}^{m} \beta_i \nabla y_{t-i} + \varepsilon_t \quad (12)$$

Where a_0 is an intercept, ε_t is a white noise, and β_i, ∂, a_1 are coefficients.

Since the MM series has been disaggregated to quarterly figures, we can set m = 4, so that there are four lagged difference variables to correct for possible serial correlation, then (12) becomes

$$\nabla y_t = a_0 + \partial y_{t-1} + a_1 t + \beta_1 \nabla y_{t-1} + \beta_2 \nabla y_{t-2} + \beta_3 \nabla y_{t-3} + \beta_4 \nabla y_{t-4} + \varepsilon_t \quad (13)$$

Having established the stationarity condition of a series, the next step is to identify a suitable model for the series, which consists of specifying the appropriate structure and order of model. Identification in time series is often based on visual inspection of the correlogram, by examining the structure and appearance of the plots of the ACF and the PACF. Identification could also be done by an automated iterative procedure, which involves fitting different possible provisional models and using a goodness-of-fit statistic to select the best model. Statistical computing software with facility for system identification can also be employed to find an appropriate ARMA model. Estimation of the parameters of ARMA model is the next step in ARMA modelling, which usually requires an iterative procedure such as maximum likelihood method. This could be accomplished with the use of appropriate computing software with little user interaction. The last stage is to subject the model to *diagnostic checking,* [1]. This involves analysing the residuals to verify that they are random, and to ensure that the estimated parameters are statistically significant. The fitting process should be guided by the principle of *parsimony,* which is based on employing the model with the fewest parameters that adequately describes the series. In the absence of inadequacy, the ARMA model is considered suitable for such series, and can be used to forecast future trend of such epidemiological series.

Model identification for the MM series

Figure 1 depicts the time series plot of the quarterly disaggregated MM serie in Nigeria from 1990 to 2010. The MM series did not show any marked seasonal pattern, suggesting a series with non-seasonal variation. There are some exceptional periods of very high number of MM cases. A decreasing trend occurs from year 2001 to year 2005, after which there is a sharp or sudden peak in the first quarter of 2005, which is an indication that a large number of MM cases were recorded in this period. Another sudden peak is noticeable in the time plot of the series around 2009, which indicate outbreak of the disease in this period. The time plot of the series does not show any upward or downward sloping pattern, suggesting that series do not show trend in mean. The MM series though stationary in mean, but a critical examination of the time plot revealed variance instability. The amplitude of vertical fluctuation is changing over some particular interval, so that the series is suspected to be heteroscedastic, and is therefore not stationary in variance. It is therefore necessary to subject the series to variance stabilising transformation referred to as Box-Cox transformation to induce stationarity in the series. The plot of $\ln(y_t)$ indicates that the fluctuations are unrelated to the level of y_t. Logarithmic transformation $[z_t = \ln(y_t)]$ appears to be appropriate for the MM series. After subjecting the series to the transformation, the series became roughly stationary in variance. In order to test for trend stationarity in the original MM series (y_t) and to assess the transformed series [$z_t = \ln(y_t)$], the two forms of the series are subjected to the *Augumented Dickey-Fuller test*. The results of the ADF tests are presented in table 1 below.

ISSN: 0975-8585

Table 1: Results of ADF tests

Series	ADF test statistic	p-value
y_t	-3.4655	0.0051
$z_t = \mathrm{In}(y_t)$	-2.8968	0.0174

The results of the (ADF) unit-root test conducted on the original series to test the hypothesis of non-stationarity yielded a t-statistic of value -3.47 with a p-value 0.0051, an indication that the series does not have trend in mean, and is therefore stationary. The ADF test though reject H_0 for the original MM series, the series shows evidence of heteroscedasticity, which necessitate log-transformation of the series to remove trend in variance. After subjecting the series to log- transformation, the value of the ADF test statistic is -2.90 with a p-value of 0.0174 at 5% significant level. The null hypothesis of a unit-root can therefore be rejected. Stationarity is therefore achieved both in original MM series and in the transformed MM figures. The ADF test can only detect trend nonstationarity if it is present in a series, but is not suitable in detecting variance instability in a series. In fact ADF tests have low statistical power, and often times cannot distinguish between true unit-root processes and near unit-root processes. This pitfall in using ADF test as stationarity test is often referred to as 'near observation equivalence' problem, [7].

Correlogram visual analysis method is employed in identifying an appropriate ARMA model for the MM series. This is done by using the correlogram to identify the orders *p* and *q* of an ARMA(*p,q*) generating process for the MM stationary series. Figure 2 depicts the ACF and the PACF of the disaggregated MM series. The ACF is a mixture of exponentials and damped sine waves after the first few lags, while the PACF is dominated by a mixture of exponentials and damped sine waves after the first lag, which signal a mixed process. The structure of the ACF of the MM series is typical of a first-order autoregressive process. A slow decay exhibited by the ACF of the MM series and the PACF provides a clearer picture for autoregressive processes, suggesting an AR schemes with spike at lag 1, and the rest of the values oscillate randomly about zero, within the 95% non-significance limits. Figure 3 shows the ACF and the PACF of the log-transformed MM series, and their structures further confirm an AR processes. The patterns of the correlograms of the MM series therefore gave a clear indications for first order autoregressive process, ARMA(1,0) which is equivalent to AR(1).

ARMA(1,0) can be written as:

$$(1-\varphi B)z_t = c + \varepsilon_t \tag{14}$$

$$z_t = c + \varphi z_{t-1} + \varepsilon_t \tag{15}$$

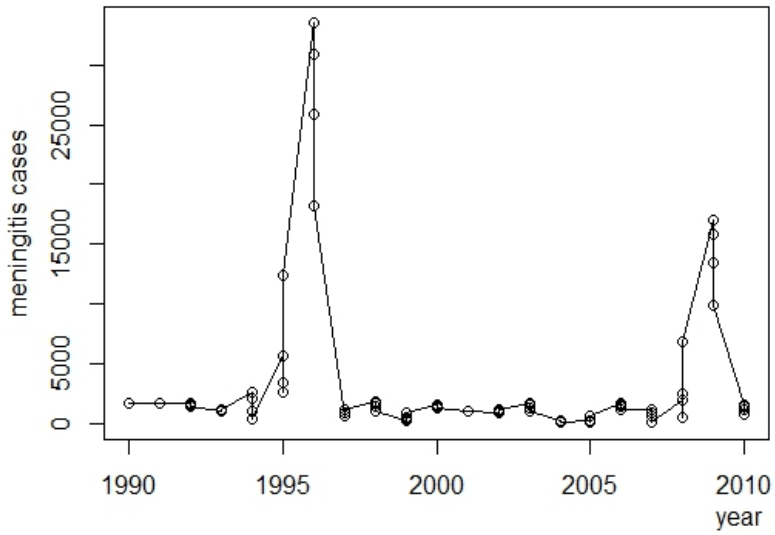

Figure 1: Time series plot of meningitis cases

ISSN: 0975-8585

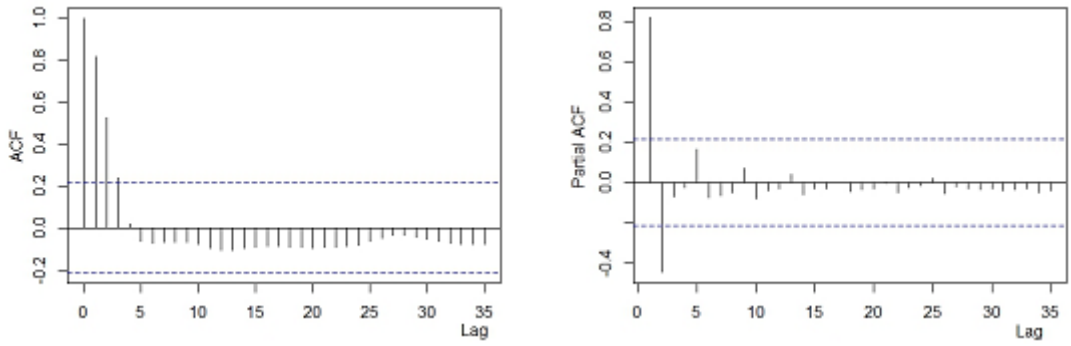

Figure 2: ACF and PACF of disaggregated MM series (y_t)

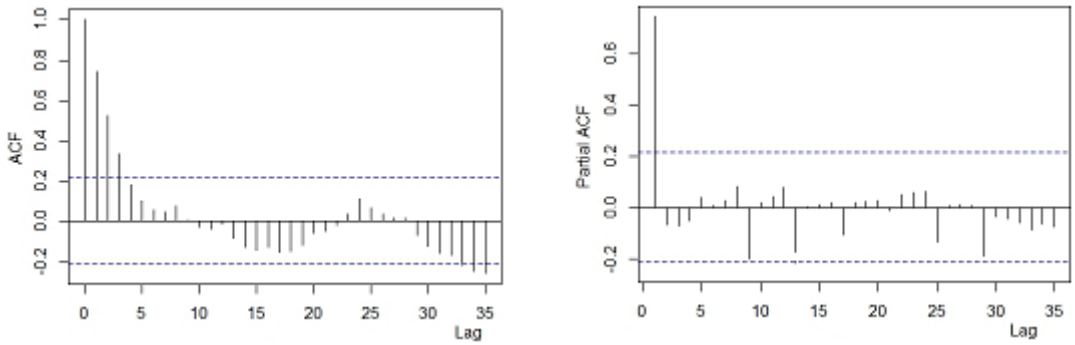

Figure 3: ACF and PACF of z_t

RESULTS

Parameter estimation for ARMA model

Table 2 contains the summary of the maximum likelihood estimates of the parameters of the ARMA model for the MM series, including the associated values of the standard errors, t-values, and the corresponding significant values. The equation of the fitted ARMA(1,0) is:

$$(1-0.738B)z_t = 7.158 + \varepsilon_t .$$

As shown in table 2, the values of the corresponding standard errors of both the constant term and the estimated *AR* parameter are low, an indication that the model fit the MM series adequately. The associated p-values of the t-test show that the estimated constant term and the *AR* parameter proved to be significantly different from zero. From table 3, the value of R^2 for the model, which is a measure of fractional variance due to persistence, is 0.553, so that more than half of the variation in the MM series is explained by the modelled persistence, and the model can therefore be considered to be practically significant.

Table 2: Summary of the ARMA (1,0) model parameters

Model	Parameter	Estimate	SE	t-value	p-value
ARMA(1,0)	Constant term	7.158	0.3080	23.279	0.000
	φ	0.738	0.0704	10.007	0.000

Table 3: Summary of the fitted ARMA (1,0) model

Model	R-squared	Normalised BIC	MSE	MAPE
$(1-0.738B)z_t = 7.158 + \varepsilon_t$	0.553	16.951	0.826	7.806

ISSN: 0975-8585

Diagnostic checks of the ARMA model for the MM series

Diagnostic verification of the model is necessary to confirm the randomness of the residuals, and to ensure that the estimated parameters are statistically significant. For an ARMA model to effectively describe persistence, the model residuals should be random, and the ACF of the residuals should be zero at all lags except lag zero. Figure 4 display autocorrelation functions (ACF) of the residuals. The autocorrelations at all lags are nearly zero, showing that there is no serial correlation in the residuals. There is therefore nothing unusual in the ACF of the residuals, since the residual serial correlations are all within $\pm 2E$, which is a desired result. A reasonable approach to evaluating the randomness of ARMA residuals is to examine the ACF as a whole, rather than the individual residual separately for high-order serial correlation. A suitable test for this purpose is called the *portmanteau lack-of-fit test*, also referred to as *Q-statistic*. The value of the Q-statistic is 10.247 with high p-value of 0.893, and is therefore non-significant at $0.05\,\alpha$-level. The Portmanteau test on the residuals therefore favours the ARMA(1,0) model as an effective model for the persistence in the MM series, and also confirms the randomness of the residuals. Durbin-Watson statistic for first-order serial correlation of adjacent residuals yielded a value of 2.010, an indication that there is no serial correlation of the residuals since the DW-statistic is around 2.

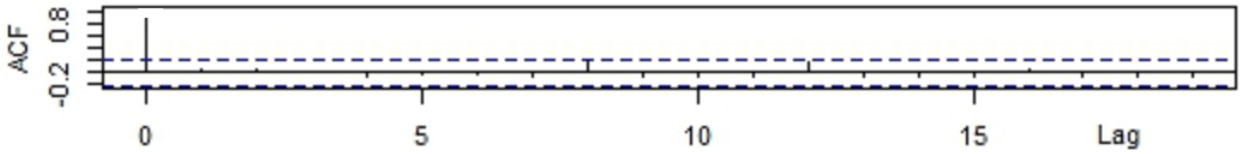

Figure 4: ACF of Residuals

DISCUSSION

MM is a potential life-threatening disease with a high mortality rate in the meningitis belt, where an extensive part of Northern Nigeria lies, hence calls for statistical investigation of the disease to determine its trend. Box and Jenkins time series techniques applied to the MM cases in Nigeria, showed that the series lack any marked seasonal fluctuations, suggesting a series with non-seasonal variation. ARMA(1,0) model was identified as a suitable model for the MM series, having subjected the series to Box-Cox transformation to induce variance stability in the series. The identified model was subjected to various diagnostic tests, and the results obtained confirmed the adequacy of the ARMA model. The ARMA model for the MM series has its usefulness in understanding the trend and pattern of MM and in determining periods of outbreaks of the epidemic for timely prevention and control measures. The model may be used to assess the quality of preventive measures to prevent epidemic outbreaks. This should aid the health policy makers to give adequate medical attention to Nigeria states most at risk in the meningitis belt, during the predicted period of possible outbreak of epidemics.

Table 4 shows the disaggregated MM figures, the log-transformed figures (z_t), and the predicted figures from 2008 to 2010 using fourth quarter of 2007 as the origin, and their prediction limits. The prediction limits which are calculated with 95% confidence intervals provide a statement of accuracy of the forecast. The values of the mean square error (MSE) and the mean absolute percentage error (MAPE) which are measures of forecast performance for the ARMA model as shown in table 2, are confirmation of the accuracy of the model in predicting future MM cases. The predicted figures can be transformed back to the original units such that $\exp(z_t) = y_t$, to obtain the actual forecast values from 2008 to 2010.

In model development for a series, the fitting process should be guided by the principle of parsimony. Principle of parsimony is based on finding the simplest representation that is consistent with the observed series. Prodigal use of parameters can force a model to perfectly fit a series, but improvement in the fit could lead to increasing complexity of model structure. The diagnostic verification shows that ARMA(1,0) model is the simplest possible model that adequately describes the MM series, and may be applied more generally to similar MM processes. A more complex time series model will not only violate the principle of parsimony but will be unnecessary since the ARMA (1,0) model proved accurate in modelling the MM series.

ISSN: 0975-8585

Table 4: Predicted and reported MM in Nigeria between 2008 to 2010

Year	Disaggregated MM figures	z_t	Lower limit	Forecast (F)	Upper limit
2008	1940.95	7.57	5.88191	7.48105	9.08019
	481.07	6.18	5.40361	7.41334	9.42307
	2438.69	7.80	5.14875	7.36180	9.57486
	6818.33	8.83	4.99983	7.32257	9.64531
2009	17028.39	9.74	4.90872	7.29270	9.67669
	15829.83	9.67	4.85120	7.26997	9.68874
	13432.72	9.51	4.81397	7.25267	9.69136
	9837.05	9.19	4.78933	7.23949	9.68966
2010	1544.3	7.34	4.77268	7.22947	9.68626
	1424.88	7.26	4.76122	7.22183	9.68245
	1186.04	7.08	4.75319	7.21602	9.67886
	827.79	6.72	4.74748	7.21160	9.67572

MM epidemics usually occur more often in the summer, the dry season in Nigeria from December to June, and an epidemic wave can last up to three years, only dying out during the intervening raining season. Seasonality of MM epidemics is well known with outbreaks, so that outbreaks of epidemic are expected to signal seasonality of such epidemic. It is therefore expected that there will be possibility of seasonal pattern, contrary to the result obtained. This is due to the fact that large MM outbreaks in Nigeria typically occur every 10 years, with the last outbreak recorded in 1996. A very large volume of data will therefore be required to determine existence of major outbreak every 10 years and consequently detecting seasonality in the disease. The MM data used in this study is from 1990 to 2010, a period of eleven years, which is the largest volume of data on the disease in Nigeria extracted from WHO website. The MM data though disaggregated into quarterly figures to detect possibility of seasonal fluctuations, it was rather difficult to identify any marked seasonal pattern of the disease. A well coordinated record keeping on MM is therefore necessary, and such data should be made readily available to researchers for scientific investigation.

MM being a contagious disease deserves serious medical surveillance; to prevent its spread. It is advisable that government should embark on preventive health care rather than curative health care by immunizing the people in the northern part of Nigeria where the disease is prevalent. Medical protection against the disease can be provided in the long term through immunization against the disease or in the short term with antibiotics, though antibiotics does not protect against future infections. A wide spread vaccination remains the only realistic means to combat meningococcal disease efficaciously. Vaccination though offers the best protection against the disease, but the recent warning on waning efficacy, non-preventive and high costs of the existing vaccines calls for a search for better meningococcal vaccines.

MM is a contagious disease; and this call for a change in the behaviour that can lead to the transmission of the disease in order to reduce the risk of infection. It is important to educate people to follow good personal hygiene practices, especially regarding hand-washing after toilet use or handling any dirty object and covering of mouth when sneezing. Environmental health officials should be employed to educate people on personal and environmental hygiene.

REFERENCES

[1] Anderson O. Time series analysis and forecasting: Box-Jenkins approach. London: Butterworth's, 1976; 182.
[2] Attia J, Hatala R, Cook DJ, Wong JG. J American Med Assoc 1999; 282 (2): 175-81.
[3] Bishai, DM, Champion, C, Steele, ME, Thompson, L. Health Affairs (Project Hope) 2011; 30 (6): 1058-64.
[4] Boot JCG, Feibes W, and Lisman JHC. J Royal Stat Soc 1967;16(1):65-75.
[5] Box, G.E.P., and Jenkins, G.M. Time series Analysis: Forecast and Control 3rd Ed. San Francisco: Holden-Day, 1994.

[6] Briet OJ T., Vounatsou P, Gunawardena D, Galappaththy GNL and Amerasinghe PH. Malaria J 2008; 7: 15 –20.
[7] Campbell JY, and Perron P. NBER Macroecon Ann 1991; 6(1): 141-201.
[8] Dickey DA, and Fuller WA. J American Stat Assoc 1979; 74 (366): 427- 431.
[9] Greenwood B. Trans R Soc Trop Med Hyg 1999; 93(4) 341-353.
[10] Greenwood B. Trop Med Int Health 2006; 11**,** 773-780.
[11] Greenwood, BM, Hassan-King, M, Whittle HC. BMJ 1978; (1): 1317-9.
[12] Harrison LH, Trotter CL and Ramsey ME. Vaccine 2009; 27, 51-63.
[13] Helfenstein U. Stat Med 1986*;* 5: 37-47.
[14] Howard W. 1996. Wide epidemic of men fatal to 10,000 in West-Africa. The New-York Times. Retrieved 15th March, 2009.
[15] Hu WB, Nicholls N, Lindsay M, Dale P, McMichael AJ and Mackenzie JS. American J Trop Med Hyg 2004; 71: 129–137.
[16] Kendall M and Ord JK. Time series (3rd ed.). New-York : Edward Arnold, 1990.
[17] Lapeyssoinne L. Bull WHO 1963; 28, 1-114.
[18] Logan SA and Mac Mahon E. BMJ (Clinical research ed.) 2008; 336:36-40.
[19] Lozano R, Naghavi M, Foreman K, Lim S, Shibuya K, Aboyans V, Abraham J, Adair T. Lancet 2012; 380: 2095-128.
[20] Marc Larforce F, Ravenscorft N, Djingarey M, Viviani S. Vaccine 2009; 27 Suppl 2: B13-9.
[21] Medical News Today. West African meningitis epidemics driven by the wind. 2009-03-12. Retrieved 2013-09-20.
[22] Molesworth AM, Thomson MC, Connor SJ, Cresswell MP, Morse AP, Shears P. The Royal Soc Trop Med Health 2002;96:242-249.
[23] Narain JP, Raviglione MC, and Kochi A. Tubercle Lung Dis 1992; 73: 311-321.
[24] Reingold AL, Broome CV, Hightower AW. Lancet 1985; (2): 114-8.
[25] Rios M, Garcia JA, Sanchez JA, and Perez D. European J Epidemiol 2000; 16: 483-488.
[26] Saez-Llorens X and McCracken GH. Lancet 2003; 361: 2139-48.
[27] Schnell D, Zaidi A, and Reynolds G. Stat Med 1989; 8: 343-352.
[28] Scorttis M, Cattan P, and Canals M. Archivos de Medicina Veterinaria 1997; 29: 83–89.
[29] Segal S, and Pollard AJ. British Med Bull 2004; 72 (1): 65-81.
[30] World Health Orgainisation (WHO). Contorl of epidemic meningococcal disease: WHO practical guidelines. Lyon: Foundation Marcel Merieux, 1998.
[31] World Health Orgainisation (WHO). Detecting meningococcal meningitis epidemics in highly-endemic African countries. Weekly Epidemiological Record, 2000; 75: 306-9.
[32] World Health Organisation (WHO). Detecting meningococcal meningitis epidemics in highly-endemic African countries. Weekly Epidemiological Record 2003; 78: 294-6.
[33] World Health Organisation (WHO). African countries to introduce new meningitis vaccine. 2008-09-04. Retrieved 2013-09-15.
[34] Zaidi A, Schnell D, and Reynolds G. Stat Med 1989; 8: 353-362.