European Journal of Statistics and Probability

Vol.6, No.1, pp.1-15, February 2018

Published by European Centre for Research Training and Development UK (www.eajournals.org)

COMPARISON OF FORECASTING METHODS FOR FREQUENCY OF RAINFALL IN UMUAHIA, ABIA STATE, NIGERIA

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ABSTRACT: *In this paper – A Comparison of Forecasting Methods for Frequency of Rainfall in Umuahia, Abia State, Nigeria – statistical analysis of two different forecasting techniques, Box Jenkins SARIMA and Holt-Winters Exponential Smoothing, using the data collected from the National Root Crop Research Institute, Umudike (2007-2016) was carried out with a view to determining a better forecasting method. This was achieved using four forecast error statistics–ME, MASE, MAE and RSME. Although SARIMA method has the minimum error values, a paired - sample t-test shows that there is no significant difference between the forecast values obtained from the two forecasting methods. This therefore presupposes that the Holt-Winters is equally a good forecasting method for the frequency of Rainfall in Nigeria.*

KEYWORDS: Frequency of Rainfall, Box-Jenkins SARIMA, Holt-Winters Exponential Smoothing, Forecast Error Statistics.

INTRODUCTION

Generally, agriculture in Nigeria has been receiving unprecedented attention especially with the fall in crude oil revenue in recent years. It is the most important sector of Nigeria's economy providing employment for over 70% of the labour force. In particular, Umuahia, which is the capital of Abia State and located in the south-eastern part of Nigeria with coordinates: 5º32'N7º29'E, has been known to be an agricultural hub centre since 1916. The locals are predominantly farmers and the people usually experience heavy rainfall for the better part of the year (wiki, 2017). In order to sustain the tempo and ensure that food is on the table of the average Nigerian, adequate scientific measures should always be put in place. In this regard, the effect of a good knowledge of not only the amount but also the frequency of rainfall cannot be overemphasised since over 80% of the farmers still rely on rainfall.

More so, numerous researches in the literature bothering on climatic conditions of a geographical location and the importance of their findings cannot be overstated. Most common of them are researches on rainfall, especially on the amount of rainfall (Abdulrahim et al., 2013; Janhabi & Jha, 2013; Nnaji, 2011; Sawsan, 2013). However, Akpanta et al. (2015) recently, took a unique path by researching on the frequency of rainfall in Umuahia rather than the conventional amount of rainfall. Just like them, most researchers single out a particular time series analysis method and end up concluding that that particular model is globally the best forecasting method, ignoring other numerous methods available under time series analysis. This is not always good. It is therefore to close this gap that this work sets out to juxtapose the Box-Jenkins time series modelling technique with the Holt-Winters exponential smoothing method on the updated data on the frequency of rainfall in Umuahia.

This comparison will be achieved using four forecast error statistics - Mean Error (ME), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Scale Error

(MASE) - and it is expected that the findings of this study will aid in informing the appropriate sectors, private organisations and individuals that rely on weather conditions in carrying out their functions, especially the Agricultural, Meteorological and Construction sectors in Umuahia, Abia State in particular and Nigeria in general.

REVIEW OF RELATED WORKS

There have been numerous time series analysis studies on rainfall, most especially on the amount of rainfall. In recent times, researchers are trying something new on rainfall. Recently, Akpanta et al (2015) worked on the frequency of rainfall in Umuahia, Abia State, in their findings they found out that the series contained no trend but has seasonality in it. Hence they decided to focus on the seasonal part of ARIMA also known as SARIMA.

Holt-Winters (HW) exponential smoothing has been a relevant tool for forecast especially in the business world. HW behaves in a Bayesian way, by updating its estimates in the light of new observations (information). Goodwin (2017) gives a good synopsis on Holt-Winters exponential smoothing with its extensions. Overtime the Holt-Winters method has been applied (with good success) in various sectors of life. The Holt-Winters model has been applied in the telecommunications sector by Tikunov and Nishimura (2007), the method was used in estimating future traffic in the mobile network. The extension of this model which takes into account the different seasonality was used by Taylor (2010) in forecasting electricity demand in European countries.

Oladejo and Abdullahi (2015) carried out a comparison study on exchange rate in Nigeria (Nigeria Naira versus US Dollar). But in their study they focused only on Box-Jenkins's framework. They compared Box-Jenkins's ARIMA and ARMA methods. ARIMA method was found to have the least values for all the forecast accuracy measures and was declared the most adequate model over the ARMA model.

MATERIALS AND METHODS

Dataset

The secondary data on the frequency of monthly rainfall (in days) in Umuahia, Abia State, Nigeria, for a period of a decade (2007 – 2016) was obtained from National Root Crop Research Institute, Umudike, Abia State-Nigeria. The data was divided into two sets (on the ratio of 70:30): a "training set", which will be used to build the forecast models and a "testing set or hold-out-sample" which will be compared to the forecast values. The appropriate models from each technique will be used to forecast (out-of-sample) the values of the testing set. The four error statistics will then be applied on the forecast values.

Methods

In this Section we will discuss in details the two forecasting methods to be considered- the commonly used Autoregressive Integrated Moving Average (ARIMA) model and the Holt-Winter exponential smoothing technique. The best model from each of the two frameworks will be used to forecast the values of the testing set as if they do not exist. ARIMA models combines Autoregressive models (AR) and Moving Average (MA) model to form a complex

ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

ARIMA model, this was suggested by Box and Jenkins (1976). Peter Winters in 1960, as a student of Holt, extended the works of C.C. Holt (1957) to account for seasonality in time series data; this is what we now know as Holt-Winters exponential smoothing method.

Sarima

In Akpanta et al (2015), it was established that the time series data on the frequency of rainfall in Umuahia, Abia State also used in this study shows only seasonal variation when plotted against time. Hence, we will consider seasonal ARIMA (SARIMA) models popularized by Box and Jenkins in 1976. SARIMA models are special case of ARIMA models, and are adequate for series that shows a periodic pattern. Many times series data are non-stationary in practice, hence, the ARIMA strategy of modelling account for this by differencing. By differencing, a non-stationary series is reduced to stationarity, and the resulting differenced series is modelled by a causal and invertible Autoregressive and Moving Average (ARMA) processes. An Autoregressive (AR) process of order p and a Moving Average process of order q are said to be causal and invertible if and only if all the roots of $\phi\ (x) = 0$ and $h(x) =\ 0$ lie outside the unit circle, respectively. This is a condition for stationarity in a series. Usually, in theory it is customary to apply successive differencing until the series appears stationary. But often than not, in practice, first or second order differencing suffices.

Definition

The series, y_t, is said to be an ARIMA (p,d,q) process of order p,d,q, for the non-seasonal terms of the series when the integer $d \geq 0$. d, indicates the number of times a series was differenced to achieve stability in its probability properties. If y_t, is the original series then let x_t represent the d-times differenced series. Similar ideas can be applied to the seasonal terms of the series to have an ARIMA (P, D, Q) process. Thus in general y_t satisfies

$$\Phi_s(B^s)\phi(B)(1-B)^d(1-B^s)^D y_t = H_s(B^s)h(B)\varepsilon_t \qquad (1)$$

For polynomials $\Phi,\ \phi,\ H, and\ h$. This model is adequate for y_t and is called the SARIMA (p, d, q) $\times$ (P, D, Q)$_s$ model *with period s*.

Where Φ and ϕ are the polynomials for the seasonal and trend part of the AR model respectively. While *H and h* are the polynomials for the seasonal and trend part of the MA model respectively. D and d are the number of times the time series was differenced to remove the seasonal and trend effects respectively, B is the back shift operator, while ε is the error term.

In a bit to search for a good fitting model on a time series data a recursive technique, technically known as Box-Jenkins technique of: (i) Model Identification (ii) Model fitting (iii) Model validation, will be applied.

Holt-Winters' Additive Method

The Holt-Winters is depicted in four equations. Each equation with its various unique functions, an equation calculating the forecast (F_t) which constitute: an equation that estimates the level (L_t), another which calculates the trend (b_t), and finally another that calculate the seasonal indices (S_t). These equations are depicted in equations (2) – (5) below;

$$F_{t+m} = (L_t + b_t m) S_{t-s+m} \quad (2)$$
$$L_t = \alpha \frac{y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (3)$$
$$b_t = \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1} \quad (4)$$
$$S_t = \gamma \frac{y_t}{L_t} + (1-\gamma) S_{t-s} \quad (5)$$
$$where\ \alpha, \beta, \gamma < 1$$

The estimation of the level (3), trend (4) and seasonality (5) above shows a unique characteristic of smoothing parameters. In estimation of these equations, there is need for initial values. However the Holt-Winters' method is easily applied through the forecast package (Hyndman and Khandakar, 2008) in the R application.

EXPERIMENTAL RESULTS AND DISCUSSIONS

R Studio version 1.0.153 was explicitly used for all analyses in this study. All statistical tests conducted were done at 5% level of significance. 70% (84 data points) of the data was used for calibrating the model; this is from January 2007 to December 2013. While 30% (36 data points) was used as the testing set, this is from January, 2014 to December, 2016.

Exploratory Data Analysis

The raw series was subjected to initial investigations to detect the presence of non-stationarity, seasonality, and trend.

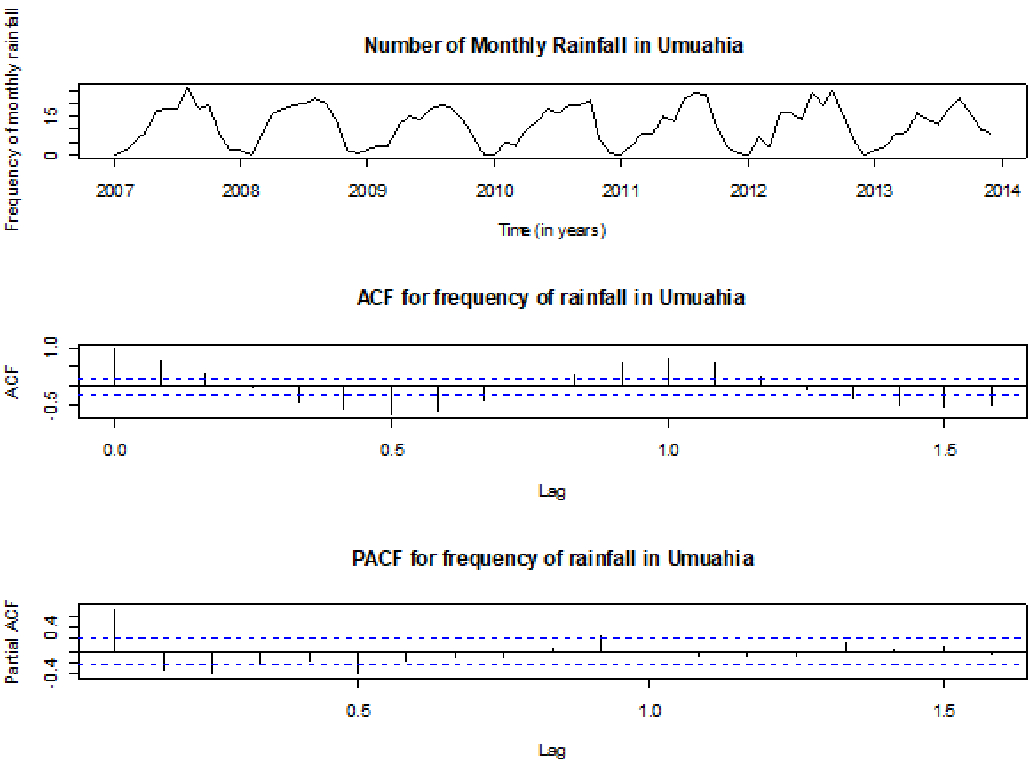


Figure 1: Time plot (Top), ACF (Centre) and PACF (Bottom) of the frequency of monthly rainfall in Umuahia from January 2007 to December 2013.

ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

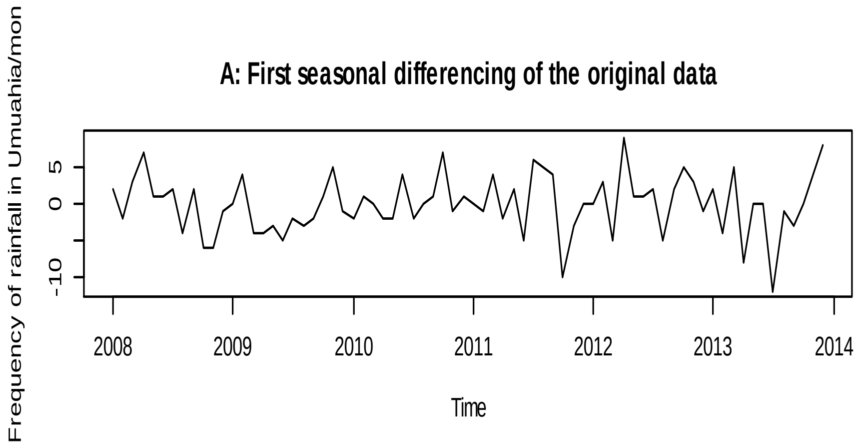
European Journal of Statistics and Probability
Vol.6, No.1, pp.1-15, February 2018
Published by European Centre for Research Training and Development UK (www.eajournals.org)

In Figure 1, the time plot (top panel) clearly indicate the presence of seasonality in the time series and it also shows that there is no trend in the time series, since the time series does not seem to change (increase or decrease) over a reasonable period of time. From the same plot we could observe that the mean is constant hence no need for any mean correction and the series does not vary with time indicating no need for data transformation. The ACF and PACF plots (centre and bottom respectively) in Figure 1 show a wave like pattern indicating the possibility of the presence of seasonality. To remove the seasonality, a seasonal differencing with lag 12 was carried out.

The Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) tests were conducted to substantiate the results obtained from the visual tests. These two tests are commonly used to test the presence of a unit root in the time series. The null hypothesis, H_0, is there is a unit root in the series (not stationary),while the alternative, H_1, is there is no unit root in the series (stationary). The presence of a unit root is a requirement for non-stationarity. With p-values of 0.01and 0.01 from an ADF and PP tests respectively, we failed to accept H_0 , and conclude that there is some evidence against H_0. Hence, the series has no unit root and can be said to be stationary, hence the mean and variance of the series are stable over time.

Sarima Analysis

SARIMA models are multiplicative combination of the trend and seasonal parts of the time series which is denoted as SARIMA (p, d, q) $\times$ (P, D, Q)$_{s}$, respectively. But from initial investigations in Section 4.1, we found that the series shows no trend hence the parameters of the trend part are all equal to zero (i.e. p = d = q = 0). Also, from Section 4.1 we found that the series shows a cyclic pattern indicating seasonality; hence we subject the series to first seasonal differencing with lag 12, so D = 1. Once the effect of seasons has been removed the next step is to determine the remaining parameters of the seasonal part, which are P and Q. This was achieved using the ACF and PACF plots presented in Figure 2.



ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

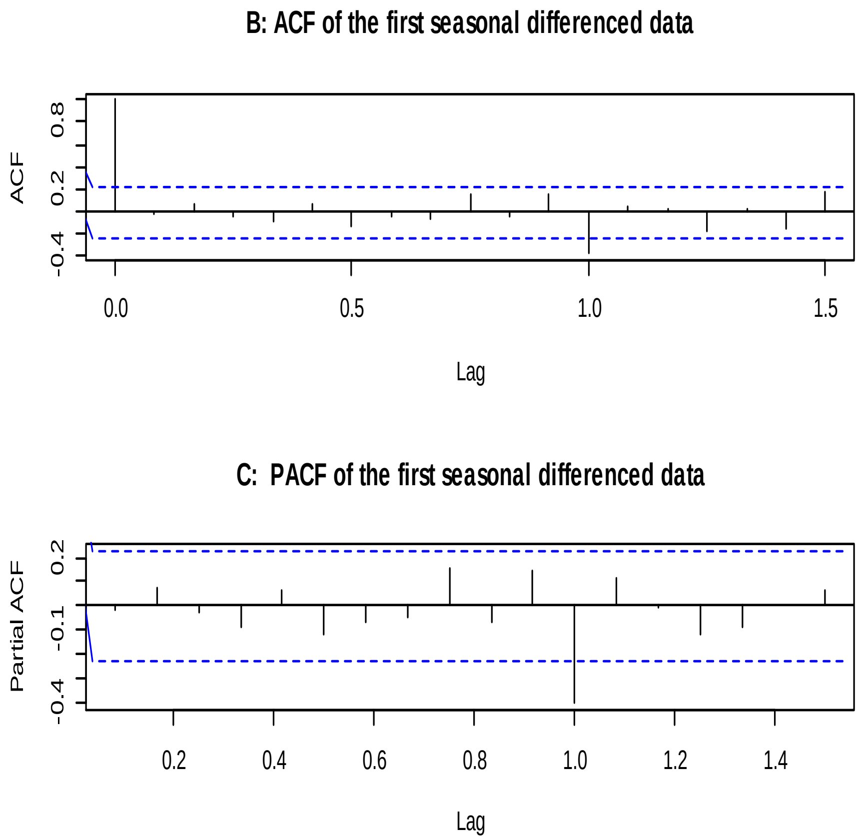


Figure 2: Time series (Plot A), ACF (Plot B) and PACF (Plot C) plots of the first seasonal differencing of the frequency of rainfall in Umuahia, Abia State (Jan. 2007-Dec. 2013).

Model Identification

From Figure 2 (plot A) it could be observe that the series is now well behaved, as the effects of seasons has been removed hence no periodic pattern is evident, and the series now fluctuates around zero. With the ACF and PACF showing clear protruding spikes at lag 1 respectively, indicating that an AR (1) and MA (1) are plausible, when combined we will have a SARIMA model of order: $(0, 0, 0) \times (1, 1, 1)_{12}$ to be the ideal prospective model. In order to apply the principle of parsimony some plausible models were selected and subjected to test using AIC and BIC as tools. The best or optimal model is that one that minimizes the value of the respective information criteria. Table 2 below show some selected plausible and competing SARIMA models, with asterisk (*) to indicate the model with the least AIC and BIC.

Table 2: Some Selected Plausible and Competing SARIMA Models

SARIMA Model	AIC	BIC
$(0, 0, 0) \times (1, 1, 0)_{12}$	391.846	396.400
$(0, 0, 0) \times (0, 1, 1)^{*}_{12}$	378.594	383.147
$(0, 0, 0) \times (1, 1, 1)_{12}$	380.123	386.953

ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

The model SARIMA (0, 0, 0) $\times$ $(0, 1, 1)_{12}$ has the least AIC and BIC as indicated in Table 2 above, so it is the best/optimal model for the time series data under Box-Jenkins structure. Hence, this model was used to conduct the out-of-sample forecast (i.e. forecasting the training set) which will be evaluated and compared with that from Holt-Winters structure.

Model Fitting

Since an optimal model has been identified, the next step is to estimate the parameters of the said model using maximum likelihood estimate method.

Table 3: Estimated Parameters for SARIMA (0, 0, 0) $\times$ $(0, 1, 1)_{12}$

	Estimate	Standard error
H_1	-1.000	0.502

The model has its estimated variance ($\hat{\sigma}^2$) and log likelihood as 7.694 and -187.3, respectively.

Model Validation

It is ideal that after a model has been fitted on a time series data for diagnostics checks to be conducted to ascertain if the model fits the data adequately. These checks are carried out on the residuals, e_t, and we expect it to behave like a WN process on the average. Visuals tests were used and then supplemented with portmanteau tests.

DIAGNOSTIC CHECKS ON THE RESIDUALS

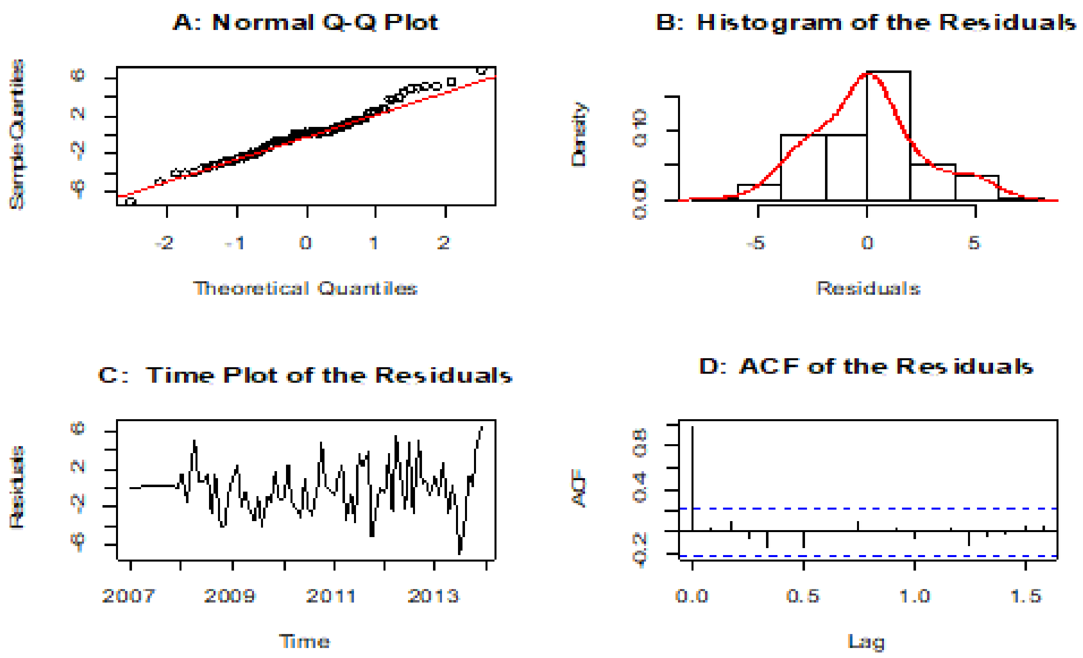


Figure 3: Adequacy checks of the fitted SARIMA (0, 0, 0) $\times$ $(0, 1, 1)_{12}$ model using its residuals.

From Figure 3, plots A and B used for checking the normality of the residuals clearly indicates that the residuals could be said to be from a normal distribution. Although, it seems that the

ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

residuals is slightly skewed to the right which may indicate that a small amount of autocorrelation still exist. But, the ACF plot (plot D) of the residuals clearly shows that none of the spikes is significant as all are contained inside the blue dash lines. Hence, we conclude that the adjacent observations are not auto – correlated. Also, the time plot (plot C) shows that the residuals fluctuates around zero indicating that the residuals has a zero mean with a constant variance. With p-values of 0.7299 and 0.2989 from a Ljung-Box-Pierce and Shapiro-Wilk tests respectively we could conclude that the residuals are not auto-correlated at 5% level of significance, in other words the residuals are normally distributed.

SARIMA Model Forecast Evaluation

The complete data is from January 2007 to December 2016. But to calibrate the model we used data from January 2007 to December 2013 (70%). Then we used the data from January 2014 to December 2016 (30%) with the assumption that they have not been observed to conduct out-of-sample forecast. The values of the out-of-sample forecast as compared to the actual (observed) values are presented in Appendix 1. The plots are presented in Figures 4 and 5 for visual inspections.

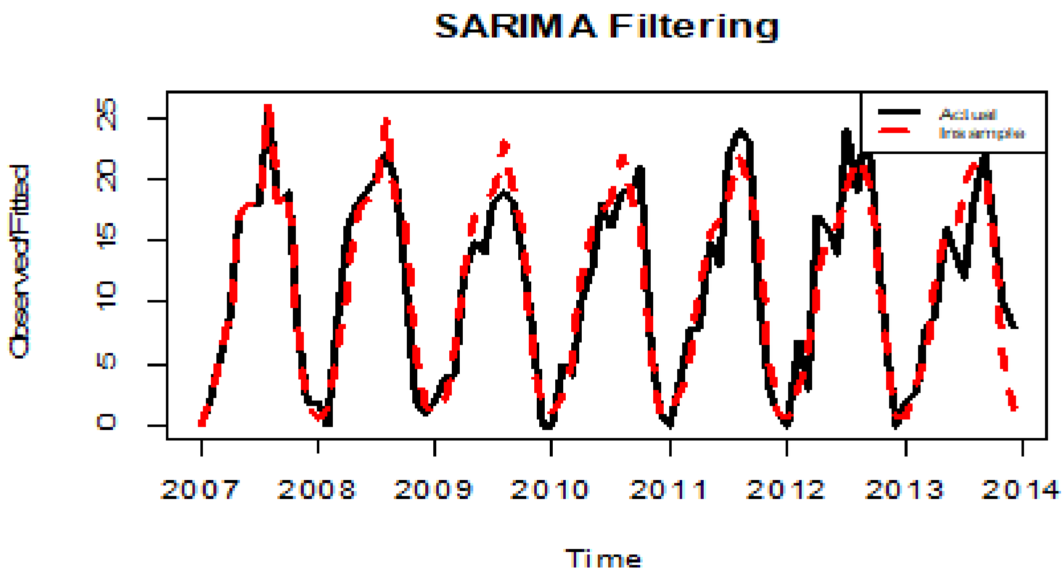


Figure 4: Plot of (in sample forecasts) actual versus fitted values from Jan. 2007 to Dec. 2013.

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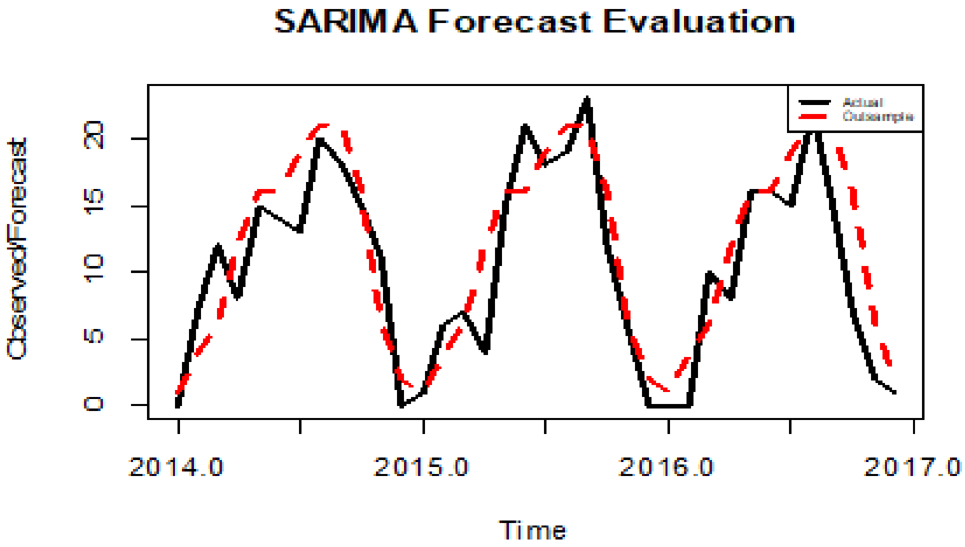

Figure 5: Plot of (out of sample forecast) hold-out-sample together with forecast values from Jan. 2014 to Dec. 2016 (36 months).

From Figures 4 and 5, we could see that the forecast values reasonably depict the pattern of the actual observations for both the in-sample and out-of-sample forecasts. Therefore, we could say that the model performed reasonable well in forecasting both the training dataset and the testing dataset (hold-out-sample).

Holt-Winters Exponential Smoothing

This Section shows the forecast results obtained from the Holt-Winters' model. The techniques of forecast used in the SARIMA method still applies here.

Fitting the Model

The Holt-Winters exponential smoothing was performed on 70% of the dataset (January 2007-December 2013). In order to make forecasts, we fitted a predictive Holt-Winters model which produced these smoothing parameters as depicted in the Table 4.

Table 4: Estimated Smoothing Parameters for Holt-Winters

Smoothing parameters	Estimated value
α	0.034
β	0.004
γ	0.378

From Table 4, α is very low and this shows that the level estimates are based on very recent observations in the series. The β value shows that the trend is slightly updated but in a very minimal way. The γ value depicts that the estimate of seasonal indices are based on observations from the distant past. The fitted model was plotted as seen in the Figure 6 and the

ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

model shows a good fit especially during most peak frequencies this encourages good forecast results.

Forecasting the Holt-Winters Model:

The coefficients of the smoothing parameters (α, β, γ) from the fitted model were used to forecast on the training set (in-sample) and the testing set (Out-of-sample). Values of these forecasts can be seen in Appendix 1. The In-sample and Out-sample forecasts were plotted against the observed values as seen in Figures 6 and 7.

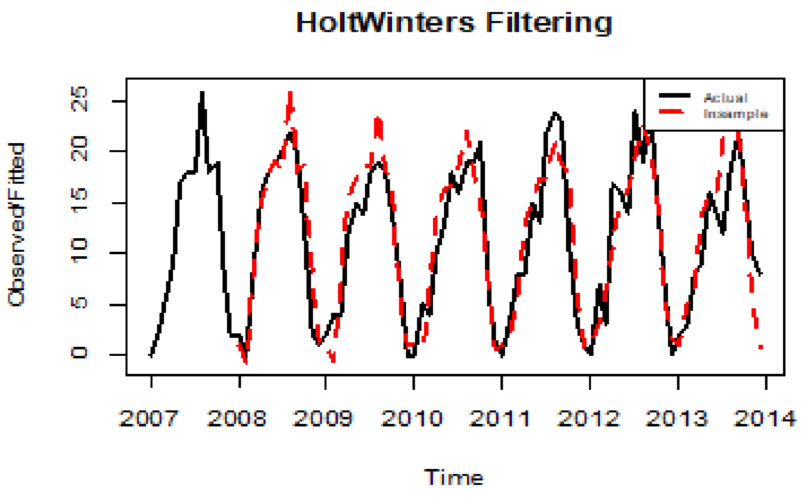

Figure 6: Plot of (in sample forecasts) observed versus fitted values from Jan. 2007 to Dec. 2013.

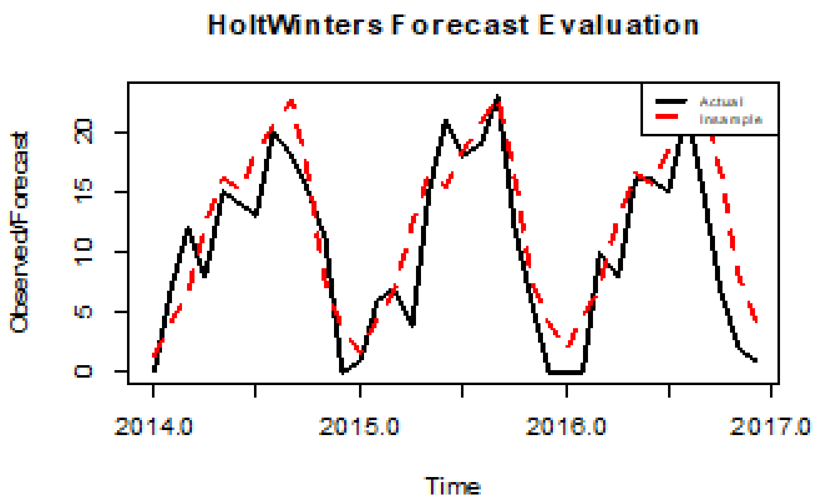

Figure 7: Plot of (out of sample forecast) hold-out-sample data together with forecast values from Jan. 2014 to Dec. 2016 (36 months).

Figure 7 shows the plot of the observed against the out- sample forecast. Figure 7 also shows that the out-of-sample forecast follow the seasonality pattern of the observed values and gives

ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

a plausible good forecast result. Values of the forecasts compared to the actual can be seen in Appendix 1.

Model Validation Test

The model is investigated whether it can be improved on by carrying out the Ljung-Box test; results of the test are seen in Table 5.

Table 5: Ljung-Box model validation test for Holt-Winters exponential model

Box-Ljung Test	
X-squared	13.379
p-value	0.861

Results obtained from the test show that the p-value (0.8605), which indicates strong evidence of no auto-correlation at lags. This suggests that Holt-Winters model provides an adequate forecast model for the frequency of rainfall which cannot be improved on.

FORECAST METHODS COMPARISON

To compare the performance of the best fitting models from the two frameworks: Box-Jenkins and Holt-Winters, we used four forecast error statistics the ME, MSE, RMSE and MAE for this comparison. This error statistics are applied on the forecasts of the training set (out-of-sample forecasts) and presented in Table 6. The general rule of thumb is the method with the lowest forecast error statistic is the best.

Table 6: Forecast error statistics of the two forecast methods

Error Statistics	Forecast Methods	
	SARIMA	Holt-Winters
ME	-0.088	-0.384
MASE	0.627	0.854
RMSE	2.568	3.329
MAE	1.917	2.608

From Table 6, it could be observed that the Seasonal Autoregressive Moving Average (SARIMA) has lower error statistics when compared to Holt Winters.

Considering the forecast values obtained from the two methods with a view to determining whether there is no significant difference, we shall conduct a test on the difference of two means of D_1 and D_2, where: D_1 is the difference between the observed values and their corresponding SARIMA forecast values and; D_2 is the difference between the observed values and their corresponding Holt-Winters forecast value. These values are show in Appendix 1.

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Test of Hypothesis

H0: $\overline{D}_1 = \overline{D}_2$

H1: $\overline{D}_1 \neq \overline{D}_2$

Table 7: Two sample t-test

$\overline{D}_1$	$\overline{D}_2$	Standard Deviation		Test statistic	Degrees of freedom	95% Confidence Interval		p-value
		D_1	D_2			Lower	Upper	
-1.194	-1.389	3.446	3.580	1.313	35	-0.106	0.495	0.198

Based on the results in Table 7, there is no significant difference between D_1 and D_2 at 5% level of significance since $p > 0.05$. Alternatively, it could equally be inferred from the 95% confidence interval (-0.106, 0.495) that there is no significant difference because the interval contains zero. This means that there is no significant difference between forecast values of frequency of rainfall obtained from SARIMA method and those from Holt-Winters.

DISCUSSIONS

The result indicated that the model; SARIMA (0, 0, 0) $\times (0, 1, 1)_{12}$ to be the best adequate model for the series. For the Holt-Winters model 0.034, 0.004 and 0.378 were obtained for α, β *and* γ. A Ljung-Box tests showed that both models cannot be improved upon. To evaluate the forecast performance of both models, a visual test was used. A time plot of training set (in-sample) versus actual observed data and testing set (out-sample) versus hold out sample showed that both models from the two structures performed reasonably well in depicting the patterns in the data sets. To numerical compare their performance, four accuracy measures was employed this are: MA, MASE, MAE and RSME. General rule of thumb is that the one with the lowest values for the four measure is the optimal model. SARIMA model had the lowest for all the four measures, hence could be considered the optimal method.

But, a close look at Appendix 1 shows that the forecast values from both methods are very close to each other. This prompted us to investigate further in determining if the differences is significant. A paired t-test was conducted, with a p-value of 0.198 we concluded that there is no significant difference between both methods. Hence, Holt-Winters provide a promising alternative to SARIMA. This led to us suggesting that researchers should endeavour to consider at least two different methods for a data set before concluding that a particular method is unique in forecasting the data set.

ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

IMPLICATION TO RESEARCH AND PRACTICE

The norm of considering only one method under time series analysis for a data set might not be the best scientific approach to decision making. The findings of this study have some positive implication on the need to consider other robust times series methods other than the overly used Box-Jenkins method. One of such promising alternative, is the Holt-Winters method considered in this study which behaves in a Bayesian way and hence appears to be quite robust for forecasting.

CONCLUSIONS

This paper with a high degree of success has illustrated a detailed application of the two methods under consideration. From the visual inspections we could see that both selected models did a good work in forecasting both the training and most especially the testing data set. Although SARIMA has lower error statistics when compared to Holt Winters, there is no significant difference between forecast values of frequency of rainfall obtained from SARIMA method and those from Holt-Winters. Therefore, Holt Winters method could equally be seen as an interesting alternative to SARIMA approach since from the paired sample t - test of Table 7, there is no significant difference between forecast values of frequency of rainfall obtained from both.

FURTHER STUDY

In future it would be interesting to carry out more in depth study to ascertain the forecast performance of vast methods. It has been shown in literature that same model performs differently on different dataset. The datasets could be different in size or comes from different mechanism. Hence, future researches would be centred on applying same model on more than one dataset to see how well the model behaves on varying datasets. Another possible approach would be to introduce more methods such as Neural Network, Fuzzy time series method, Holt-Winters damping method and Bayesian Vector Auto-regression method and apply them on these different datasets. All these could be done using the techniques in this study as a reference/basis.

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ISSN: 2055-0154(Print), ISSN 2055-0162(Online)

European Journal of Statistics and Probability
Vol.6, No.1, pp.1-15, February 2018
Published by European Centre for Research Training and Development UK (www.eajournals.org)

Appendix 1

A: Frequency of Rainfall Testing and Forecast Data

Time	Observed (X_1)	SARIMA Forecast (X_2)	$D_1 = (X_1 - X_2)$	HW Forecast (X_3)	$D_2 = (X_1 - X_3)$
Jan 2014	0	1	-1	1	-1
Feb 2014	7	4	3	4	3
Mar 2014	12	6	6	6	6
Apr 2014	8	12	-4	12	-4
May 2014	15	16	-1	16	-1
Jun 2014	14	16	-2	15	-1
Jul 2014	13	19	-6	18	-5
Aug 2014	20	21	-1	20	0
Sep2014	18	21	-3	22	-4
Oct 2014	15	16	-1	16	-1
Nov 2014	11	6	5	7	4
Dec 2014	0	2	-2	3	-3
Jan 2015	1	1	0	1	0
Feb 2015	6	4	2	4	2
Mar 2015	7	6	1	6	1
Apr 2015	4	12	-8	12	-8
May 2015	15	16	-1	16	-1
Jun 2015	21	16	5	15	6
Jul 2015	18	19	-1	18	0
Aug 2015	19	21	-2	21	-2
Sep 2015	23	21	2	22	1
Oct 2015	12	16	-4	16	-4
Nov 2015	6	6	0	7	-1
Dec 2015	0	2	-2	4	-4
Jan 2016	0	1	-1	1	-1
Feb 2016	0	4	-4	4	-4
Mar 2016	10	6	4	7	3
Apr 2016	8	12	-4	12	-4
May 2016	16	16	0	16	0
Jun 2016	16	16	0	15	1
Jul 2016	15	19	-4	18	-3
Aug 2016	22	21	1	21	1
Sep 2016	15	21	-6	23	-8
Oct 2016	7	16	-9	16	-9
Nov 2016	2	6	-4	8	-6
Dec 2016	1	2	-1	4	-3

ISSN: 2055-0154(Print), ISSN 2055-0162(Online)