Modeling the Inflation Rates in Liberia SARIMA Approach

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Abstract: ***Inflation measures the relative changes in the prices of commodities and services over a period of time. It is necessary to know the pattern of inflation in the country in order to formulate better policies that will control the inflation rates. In this paper, we used Box – Jenkins methodology to build an ARIMA model for Liberia's monthly inflation rates for the period January 2006 to December 2013 with a total of Ninety Six (96) data points. The result showed that ARIMA $(0,1,0)(2,0,0)_{12}$ model was appropriate for modelling the inflation rates. ARCH-LM test and Ljung-box test performed on the residuals showed no evidence of ARCH effect and serial correlation respectively. Lastly, a 12 months forecast for the year 2013 with the model revealed that Liberia is likely to experience single digit inflation values. In glow of the forecasted result, we recommend that vigorous monetary policies and appropriate economic measure be adopted by government and some policy makers to make certain that the single digit inflation values aim is met.***

Keywords: SARIMA models, Box – Jenkins, Forecasting, Liberia, Inflation

1. Introduction

Inflation is one of the economic variables that have received much attention in Time Series Modelling. Inflation is often caused by an increase in the supply of money, usually measured by the Consumer Price Index and the Producer Price Index. Over time, as the cost of goods and services increase, the value of a dollar falls because a person won't be able to purchase as much with that dollar as he/she previously could. The annual rate of inflation has fluctuated greatly over the last half century, ranging from nearly zero inflation to 23% inflation. Inflation reflects a reduction in the purchasing power per unit of money. Policy makers will be very happy if they could know the pattern of these inflation values. Empirical research has been carried out in the area of forecasting using Seasonal Autoregressive Integrated Moving Average (SARIMA) models proposed by Box and Jenkins (1976). The forecasting advantage of SARIMA model compared to other time series models have been investigated in many studies. For instance, Aidan et al (1998) used SARIMA model to forecast Irish inflation, Junttila (2001) applied ARIMA model approach in other to forecast Finnish inflation, Pufnik and Kenova (2006) applied SARIMA model to forecast short term inflation in Croatia. Shulze and Prinz (2009) applied SARIMA model and Holt - Winters exponential Smoothing approach to forecast container transshipment in Germany, the results show that SARIMA approach yields slightly better values of modeling the container throughout than the exponential smoothing approach.

Nasiru et al (2012) used an empirical approach for modelling and forecasting inflation in Ghana. They used monthly data and modelled using Seasonal Autoregressive Integrated Moving Average (SARIMA) stochastic model. The best model that was identified for the inflation rates was ARIMA (3, 1, 3) (2, 1, 1)12. An eleven month forecast was made and it was concluded that the country is likely to experience single digit inflation for the year 2012. F.K. ODuro et al (2012) conducted a study on application to microwave transmission of Yeji-Salaga (Ghana). They applied the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to analyze the monthly data. The results showed that ARIMA $(1,1,1)(0,1,2)_{12}$ was the best fitted model. Inflation was found to be integrated of order one and follow the (6, 1, 6) order. Inflation was predicted highest for the months of March, April and May to be 8.95%, 10.07% and 10.24% respectively.

2. Methodology

Inflation has been one of the contributing factors that slow the economic growth in Liberia. In this research we analyze ninety six (96) monthly observations of inflation rate from January 2006 to December 2013. The data was obtained from the Research Department of the Central Bank of Liberia (CBL) and the Statistic department of the Liberia Institute of Statistic and Geo - Information Services (LISGIS). The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model which is the generalization of the well known Box and Jenkins ARIMA model and it was used to model the data. An ARIMA model is a combination of Autoregressive (AR) which shows that there is a relationship between present and past values, a random value and a Moving average (MA) model which shows that the present values has something to do with the past residuals. A nonseasonal ARIMA model is classified as an "ARIMA (p, d, q)" model where the first parameter p refer to the number of autoregressive lags, the second parameter d refers to the order of integration that make the data stationary and the third parameter q give the number of moving average lags (see Pankratz, 1983; Hurvich and Tsai, 1989; Hamilton, 1994; Kirchgassner and Wolters, 2007; Kleiber and Zeileis, 2008, Pfaff, 2008). Thus, the SARIMA model is sometimes called the multiplicative seasonal autoregressive integrated moving average model and it is denoted as ARIMA (p, d, q) (P, D, Q) s. This can be written in the lag form as (Halim and Bisono, 2008).

$$\phi(B)\Phi(B^2)(1-B)^d(1-B^s)^D y_t = \theta(B)\Theta(B^s)\varepsilon_t$$

$$\phi(B) = (1-\phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p)$$
$$\Phi(B^s) = (1-\Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \Phi_p B^{ps})$$
$$\theta(B) = (1+\theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q)$$
$$\Theta(B^s) = (1-\Theta_1 B^s - \Theta_2 B^{2s} - \ldots - \Theta_q (B)^{Qs})$$

Where p, d and q are the order of non-seasonal AR, differencing and MA respectively and P, D and Q are the order of the seasonal AR, differencing and MA respectively. y_t represent the observable time series data at time t, ε_t represent white noise[1] error (random shock) at period t, B represent the backward shift, where $B^m y_t = y_{t-m}$ and S represent seasonal order, s=12.

Identification, estimation of parameters and diagnostic checking are the three steps that are involves in model estimation.

3. Model Identification

We determine the possible SARIMA model that best fit the data under consideration. SARIMA model is appropriate for stationary time series therefore, the data under consideration must satisfy the condition of stationarity that is the mean, and variance and autocorrelation are constant throughout. The values of p, d, q, P, D, Q are determine at this step by using the Autocorrelation function (ACF) and the Partial Autocorrelation Function (PACF). The theoretical PACF has non – zero partial autocorrelation at lags 1, 2, p and has zero partial autocorrelations at all lags for any non-seasonal ARIMA (p, d, q) process. The ACF and the PACF has spikes at lag ks and cuts off after lag ks at the seasonal level. The number of significant spikes suggests the order of the model. For seasonal MA component the ACF shows a significant spike at seasonal lags while for seasonal AR component, the PACF shows significant spikes at the seasonal lags. The values of D and d are the number of times the data was seasonally and non – seasonally differenced.

4. Estimation of Parameters

The identification process having led to the formulation of the model, we then need to obtain efficient estimates of the parameters. For the model estimate we considered the model with the minimum values of Akaike Information Criterion (AIC), modified Akaike Information Criterion (AICc) and the Normalized Bayesian Information Criterion (BIC) was consider as the best model.

4.1 Diagnostic Checking

After estimating the parameters of our chosen model, the last step is model diagnostics. At this stage we determine the adequacy of the chosen model. These checks are usually based on the residuals of the model. One assumption of the SARIMA model is that, the residuals of the model should be white noise. The ACF of the residuals is approximately zero, when the residuals are white noise. If the assumption is not fulfilled then the different model must be searched to satisfy the assumption. Several statistical tools such as Ljung - Box Q statistic, ARCH - LM test and t-test can be used to test the hypothesis of independence, constant variance and zero mean of the residuals respectively. **Ljung-Box** statistic proposed by Ljung and Box (1978) is used to check if a given observable series is linearly independent. The test usually checks if there is higher order serial correlation in the residuals of a given model. The null hypothesis of linearly independence of the series is examined by the test. ARCH-LM test of Eagle (1982) and SHAPIRO NORMALITY test can also be used to check for conditional homoscedasticity and normality among the residuals respectively.

4.2 Unit Root Test

There are several formal and informal method that can be used to determine whether the series is stationary or non stationary. For this case, we will consider the Augmented Dickey-Fuller (ADF) test which is one of the precise formal ways of testing for stationary and non stationary. The augmented Dickey-Fuller (ADF) test is a test for unit root in time series model and it is an extension of Dickey-Fuller test for large and complicated time series model. To test for unit root, we assume that:

$$\phi_p(B) = (1-B)\varphi_{p-1}(B)$$

Where $\varphi_{p-1}(B) = 1 - \varphi_1 B - \ldots - \varphi_{p-1} B^{p-1}$ has root lying outside the unit cycle. Therefore, the Augmented Dickey – Fuller test equation is giving as:

$$\Delta Y_t = \sigma Y_{t-1} + \sum_{j=1}^{p-1} \varphi_j \Delta Y_{t-j} + \theta_0 + \varepsilon_t$$

With the null hypothesis given as $H_0 : \phi = 1$ and $H_0 : \delta = 0$ against the hypothesis

4.3 Seasonal Unit Roots Test

The most common approach that is used to determine if the seasonal behavior in the data is deterministic, stochastic or stationary under the seasonal frequencies is the one of Hylleberg et al (1990). The approach was extended by Franses (1990) to be applied to monthly time series. As it is discussed in Franses (1991), the seasonal differencing operator Δ_{12} will have 12 roots on the unit circle. Seasonal frequencies in monthly data are $\pi, \frac{\pi}{2}, \frac{2\pi}{3}, \frac{\pi}{3}, \frac{5\pi}{3}, \frac{\pi}{6}$. Testing for both seasonal and non seasonal unit roots is also implied in testing for the significant of π_i. The t-test is used to test the separate $\pi's$ of the null hypothesis. It is a one sided t-test that $\pi_1 = 0$ and $\pi_2 = 0$ of the null hypothesis respectively. The two sided t-test are use in testing for the null hypothesis of $\pi_i = 0, i = 3,...,12$. The F-test is used to test for the joint null hypothesis that $\pi_2, \pi_3 and \pi_4$ are all zero and that all four $\pi's$ are jointly zero $(\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0)$.The asymptotic distribution of the test statistics under the respective null hypothesis depend on the deterministic terms in the model. There is no seasonal unit root if π_2 through π_{12} are significantly different from zero. If $\pi_1 = 0$ then the presence of non seasonal unit root 1 cannot be rejected.

5. Result and Discussion

Figure 1 and 2 below display the plots of the original data where the inflation rate is represented by R_t and the plots of the autocorrelation and partial autocorrelation functions. It can be seen that inflation exhibit volatility starting from 2007 from figure 1. The volatility in Liberia inflation series can be endorsed by so many factors including the supply of money, increase of prices on the world market such as petroleum and the poor agriculture sector of the country. The idea that Liberia is an import base economy contributed a lot to these fluctuations. Between 2008 and 2009 there exhibit a very high inflation, this was because prices of essential commodities had increased due to high importation costs and transportation costs. The main group that increases in the rate of inflation was the food and fuel groups. After 2008 single digits inflation rates were experienced all through up to 2013 at the average rate between 6.9 and 8.5 percent respectively. The vigorous macroeconomic reforms presented by the CBL were the immediate cause of the moderate rate of inflation. From figure 1 it can also be seen that the original series is non stationary. It can also be seen that the original plot of the acf dies down in a sine wave pattern which implies that there is a seasonal and non seasonal components of the series and as such the SARIMA model is required, while the pacf in figure 2 tail down at lag 1.

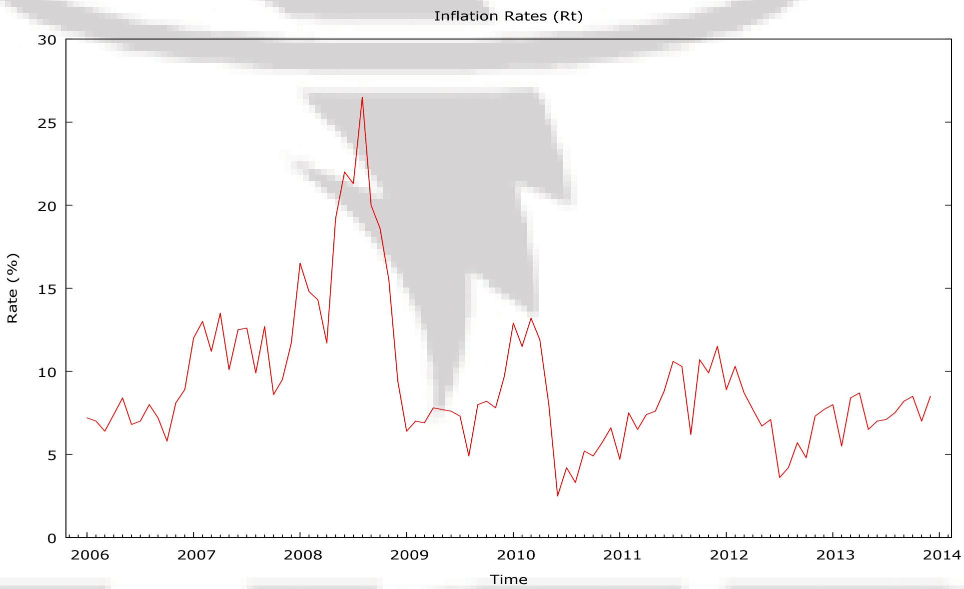


Figure 1: Monthly Inflation Rates of Liberia (2006:1-2013:12)

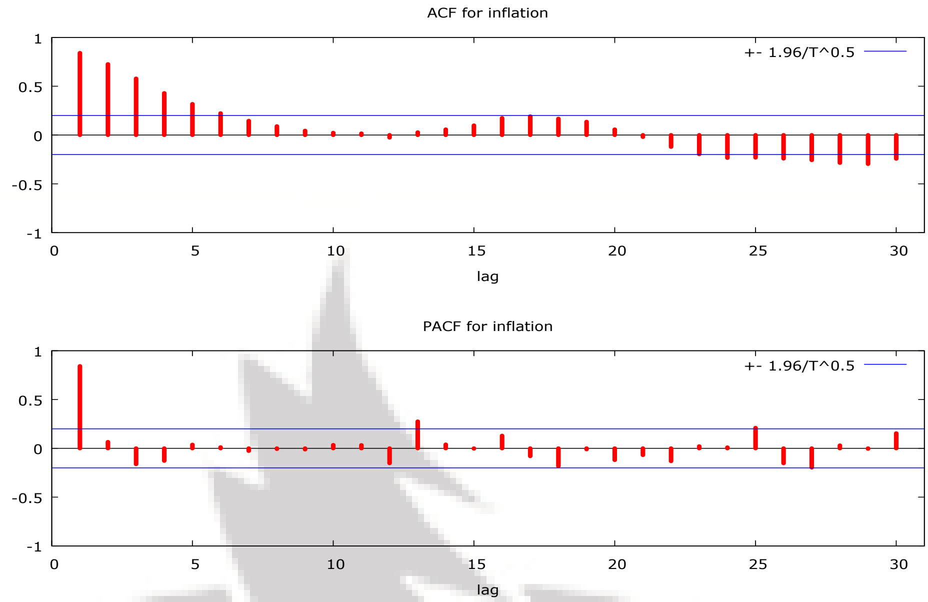


Figure 2: PACF and AFC of Liberia Monthly Inflation Rates (2006:1-2013:12)

Since SARIMA modelling requires that the series be stationary, therefore we have to test for stationarity by using the unit root test in inflation series as describe above. We apply the method of Augmented Dickey- Fuller (ADF) test in testing for stationarity. We test the null hypothesis that the inflation rate R_t is not stationary or has unit root. Table 1 present the result from the unit root test. From the result we accept the null hypothesis in which the absolute value of the 5% critical level is greater than the test statistic. Since the series is not stationary, we consider first differencing to render the series stationary and it is denoted as Y_t. We again apply the same method to check whether the series is stationary after considering the first difference. From the result of the test shown in Table 2, we can now conclude that it is stationary at a 5% significance level.

Table 1: Augmented Dickey-Fuller test for unit root of the Inflation Rates - R_t

	-Interpolated Dickey-Fuller-			
	Test Statistics	*1% critical value*	*5% critical value*	*10% critical value*
z(t)	-2.245	-3.532	-2.903	-2.586

Table 2: Augmented Dickey-Fuller test for unit root of the First difference Inflation Rates - Y_t

	-Interpolated Dickey-Fuller-			
	Test Statistics	1% critical value	5% critical value	10% critical value
z(t)	-4.164	-3.534	-2.904	-2.587

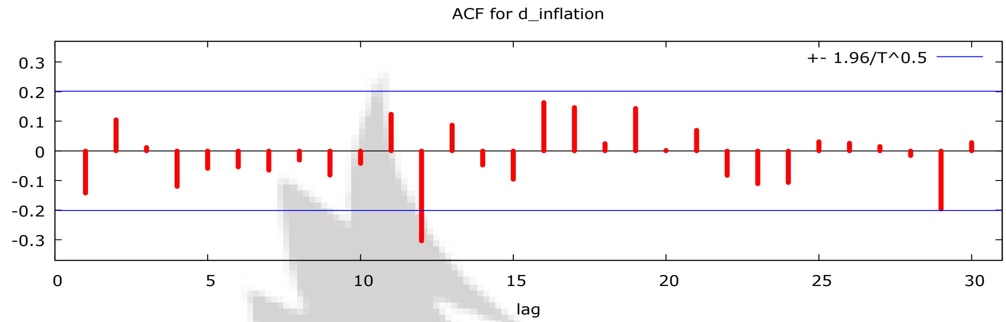
It is now necessary to test for the behavior of the seasonality in the data in which case we also need to test for seasonal unit root. The seasonal unit root will enable us to know whether the data is stationary for modelling which is one of the requirements for modelling using SARIMA model. We can now use the HEGY test stated above to test for seasonal unit root in the series. Table 3 below present the result on our data from the HEGY test, from the test results, we reject the null hypothesis of unit root at the seasonal frequency and fail to reject the presence of unit root at the non - seasonal frequency at 5% level. This implies that the contribution from these seasonal components is small of the seasonal cycle and all the frequencies are deterministic. In this regard, at seasonal level, we do not need to make differences for the data.

Table 3: HEGY Seasonal Unit Root Test for Y_t

			Constant
Auxiliary Regression	Seasonal Frequency	Critical values	Test Statistics
t-test: $\pi = 0$	0	-3.37	-0.2130
t-test: $\pi_2 = 0$	π	-1.94	-2.6723
F-test: $\pi_3 = \pi_4 = 0$	$\frac{\pi}{2}$	3.05	8.8215
F-test: $\pi_5 = \pi_6 = 0$	$\frac{2\pi}{3}$	3.05	11.1900
F-test: $\pi_7 = \pi_8 = 0$	$\frac{\pi}{3}$	3.08	6.4395
F-test: $\pi_9 = \pi_{10} = 0$	$\frac{5\pi}{3}$	3.08	13.3892
F-test: $\pi_{11} = \pi_{12} = 0$		3.09	6.3867
F-test: $\pi_1 = \pi_2,..\pi_{12} = 0$		1.88	11.7866
F-test: $\pi_2 = \pi_3,...\pi_{12} = 0$		2.30	10.3502

Note: the null hypothesis seasonal unit root is rejected at 5% significant

The next step is to determine the order of the AR and MA for seasonal and non - seasonal components following the Box and Jenkins procedure. This can be determine by using the sample ACF and PACF plots of the series as suggested by Box and Jenkins as described above. Figure 3 below display the plots of the acf and pacf of the first order differenced series and Figure 4 below displayed the plot of the first differenced series of the Monthly Inflation Rates represented as Y_t. It can clearly be seen that after the first difference the data becomes stationary and from figure 3 it can also be seen that both acf and pacf have as a seasonal lag 12 and non seasonal lag 0. In such a case to make a selection with the model that has the minimum AICc, AIC and BIC is complicated therefore our next options is to use the R software with the algorithm function auto.arima in which the best model is presented in table 4.



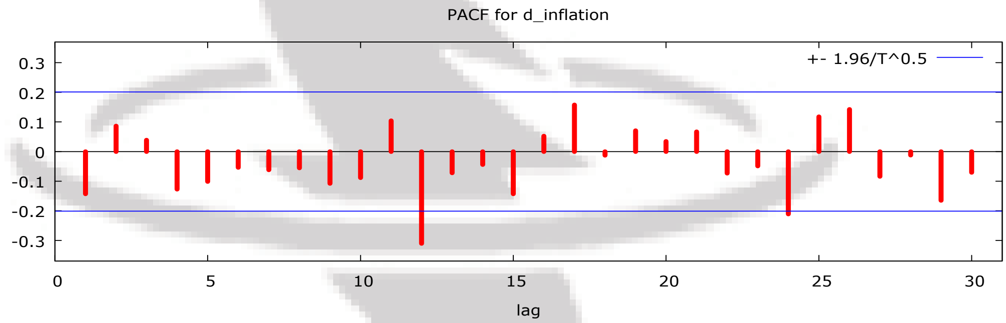


Figure 3: ACF and PACF of First Order Difference

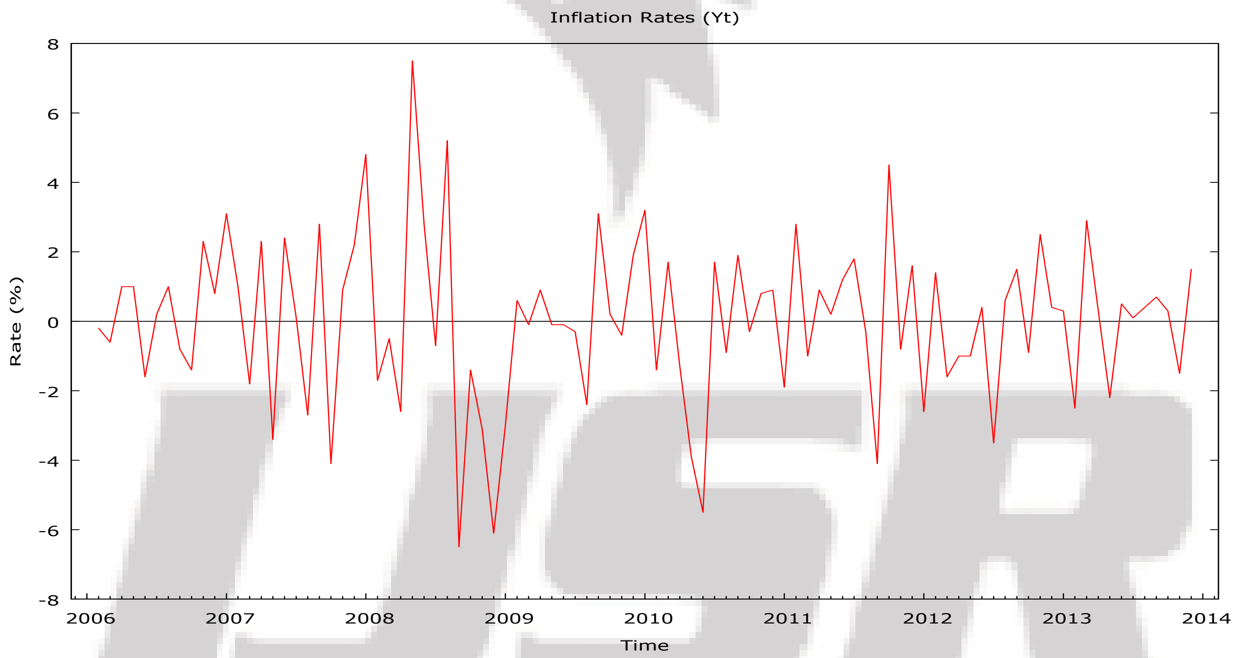


Figure 4: First order difference of the Monthly Inflation Rate Y_t

Table 4: AIC and BIC for the Suggested SARIMA

Model	AIC	AICc	BIC
ARIMA (0,1,0)(2,0,0)	420.1	420.54	430.31

Table 4, ARIMA (0,1,0)(2,0,0) could be judge as the best model that fit the data well. After the model has been identified, we then estimate the parameters. As it is shown in table 5, all the parameters are significant. We now checked the estimated model after the parameter of the model have been estimated as to whether it satisfies all the assumption of Seasonal ARIMA model which is, the residuals of the model must follow a white noise process meaning that the residual should have zero mean, constant variance and also uncorrelated. Figure 4.5 below display the autocorrelation function of the residuals of the selected SARIMA model. From the plot we can see that the autocorrelation of the residual of the model are all zero, therefore we can conclude that the residuals are uncorrelated.

The ARCH-LM test and the Ljung - Box test results are provided in Table 5. We can test for constant variance and zero mean assumptions of the residual of the selected model by using the ARCH-LM test. From the table 6, since the p-value of the ARCH-LM test is greater than 5% significant level, we fail to reject the null hypothesis of no ARCH effect (homoscedasticity) in the residuals of the selected model. Therefore, we conclude that there is a constant variance among the residuals of the selected model and the true mean of the residuals is approximately equal to zero. Also since the p-values for the Ljung-Box test exceed 5%, this indicates that there is no significant departure from white noise for the residuals. Thus, we conclude that the model can provide an adequate representation of the data since it satisfy all of the necessary assumptions.

Table 5: Estimates of Parameters for ARIMA $(0,1,0)(2,0,0)_{12}$ model

Parameters	Estimations	Standard Error	P- Values
Constant	-0.0211	0.1581	
$\overline{\phi_1}$	-0.4048	0.1099	-0.0002***
$\overline{\phi_2}$	-0.2787	0.11435	0.0148**

Table 6: Residuals Diagnostics Test for SARIMA model

P - Value		
Model	ARCH-LM test	Ljung - Box test
ARIMA $(0,1,0)(2,0,0)_{12}$	0.4618	0.7377

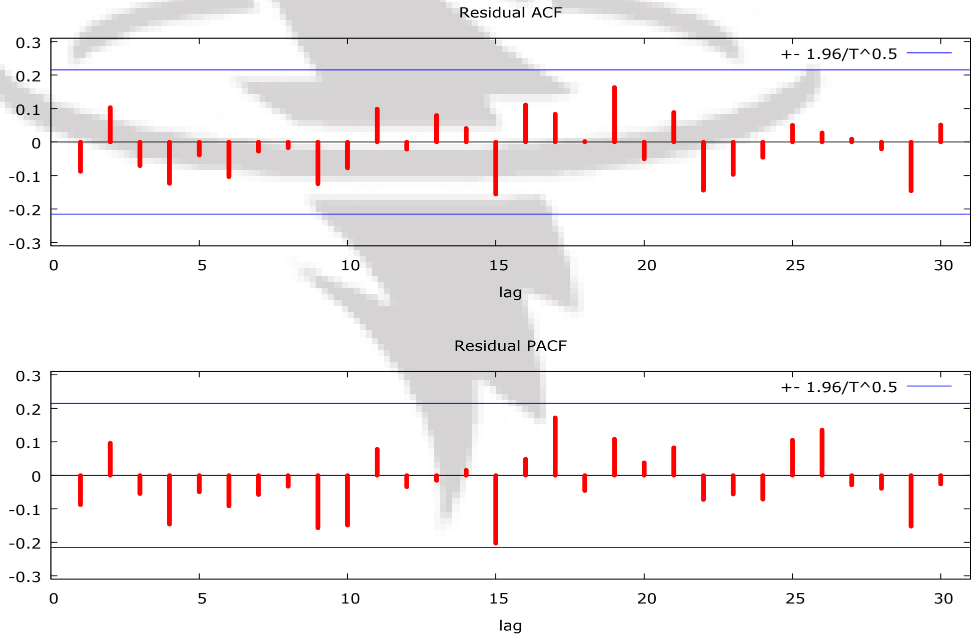


Figure 5: ACF and PACF plots of the Residuals of ARIMA $(0,1,0)(2,0,0)_{12}$

Finally, It can be seen that many research work have found that the selected model is not necessary the model that provides best forecasting. In this regards, it is advisable to perform test such as ME, RMSE, MAE, MPE etc, in testing the accuracy of the forecast. Table 7 present the model from the algorithm of Hyadman and Khandakar. The selected model from the approaches has been shown to satisfy all the model assumptions and its parameters have been estimated. We can conclude that the model is adequately and can be used to predict the inflation rates.

Table 7: Forecast Accuracy Test on the Suggested Model

Model	ME	RMSE	MAE	MPE	MAPE	MSE
ARIMA $(0,1,0)(2,0,0)_{12}$	-1.237	1.626	1.413	-18.051	20.117	2.644

We conducted both in sample and out sample forecast. Figure 5 present the in sample forecast. From figure 5, the forecast show that our model was able to ape the behavior of the actual observations although the values were not exactly the same. We carry on a 12 month out sample forecast for the year 2013. Table 8 below summarizes the out - sample forecasting results of the inflation rates from the period January 2013 to December 2013 with a 95% confidence interval.

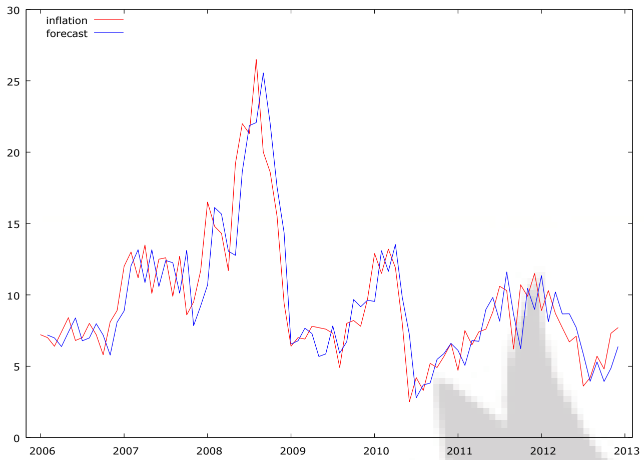


Figure 6: Plot of the In - Sample forecast for inflation data

Table 7: Twelve Month Out - Sample forecast for the year 2013

Month	Observed Values	Prediction	LCL	UCL
January	8.0	9.2	4.9	13.6
February	5.5	7.9	1.7	14.0
March	8.4	8.8	1.2	16.3
April	8.7	8.9	0.2	17.6
May	6.5	9.2	-0.5	18.9
June	7.0	8.7	-2.0	19.3
July	7.1	9.5	-2.0	21.0
August	7.5	9.3	-3.0	21.7
September	8.2	9.8	-3.2	22.9
October	8.5	8.9	-4.8	22.7
November	7.0	8.1	-6.3	22.5
December	8.5	7.4	-7.6	22.5

Comparing the observed values with the prediction value, we can see that there is an increase in pattern and decrease in pattern; as such Liberia is likely to experience single digit inflation for the year 2014. We can clearly say that ARIMA $(0,1,0)(2,0,0)_{12}$ model is adequate to be used for modelling the inflation rate in Liberia since all of its observed values fall inside the confidence interval.

6. Conclusion

In this study we model the inflation rates of Liberia using Seasonal Autoregressive Integrated Moving Average (SARIMA) model of Box and Jenkins (1976) approach. This approach was employed to analyze monthly inflation rates from January 2006 to December 2013. The entire data set was divided into two parts. Eighty four (84) observations were used to estimates the parameters of the model and an in sample forecasting while the remaining twelve (12) was used for out sample forecasting. The best model we identified for the inflation rates based on the algorithm developed by Hyadman and Khandakar in 2008 is ARIMA $(0,1,0)(2,0,0)_{12}$ with maximum log-likelihood and minimum values of AIC, AICc and BIC. ARCH-LM test and Ljung-box test performed on the residuals showed no evidence of ARCH effect and serial correlation respectively. Having satisfied all the model assumptions, ARIMA $(0,1,0)(2,0,0)_{12}$ was selected to be the best model for forecasting. A twelve month out sample forecast for the year 2013 was conducted. In general, the out-sample forecasts shows a fluctuation in inflation rates. From our out-sample forecast, we deduced that the country (Liberia) is likely to experience single digit inflation for the year 2014. In glow of the forecasted results, we recommend that vigorous monetary policies and appropriate economic measures be adopted by government and other policy makers to make certain that single digit inflation value aim is met. We recommend that future research on this topic is of great concern and it will be supportive to the admittance of the performance of the model used in this research in terms of forecasting accuracy as compare to other time series models.

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