Modeling and Forecasting the Production Volume of 7up Bottling Company Nig. PLC: A SARIMA Models Approach

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ABSTRACT

Analysis of production volume of data collected from 7up Bottling Company Nig. Plc., gives us ARIMA (1, 1, 1) (1, 1, 0) [12] model which helps us in predicting the future values of production volume when KPSS uses AIC as the model selection criterion. ARIMA (0, 1, 1) (0, 1, 2) [12] was chosen for predicting when KPSS used BIC as the model selection criterion. The KPSS used both AIC and BIC as its model selection criteria, then the model which performed significantly when it comes to accuracy test, diagnostic test, and the residual plot is ARIMA (5, 0, 0) (1, 0, 0) [12]. The stationary of this model is well established; therefore this model is the best of all the models suggested by KPSS to be the best either by basing the evidence on AIC and BIC.

The estimate of the model can thereby relying upon in prospective planning and decision making as regards production decision. The main objective of this study was to forecast production volume using SARIMA model and also to determine the accuracy of the SARIMA model in forecasting production volume. In addition, ME, MSE, RMSE, MAE, MPE, and MAPE were also employed in determining the forecasting accuracy of the models. Also, Augmented Dickey Fuller test (adf), Philips Perron, and Ljung-Box test were used to validate that ARIMA (5, 0, 0) (1, 0, 0) [12] is apparently stationary and thus it can be totally relied upon in evidence based decision making and prospective planning. The Jarque-Bera test was also used to test for the normality of residuals. The ACF plots of the residuals two models were examined to see whether the residuals of the model were white noise.

SARIMA model turns to be a good model for forecasting. The best fitted SARIMA is ARIMA (5, 0, 0) (1, 0, 0) [12] for forecasting production volume of the 7up Bottling Company data for maintaining apparent accuracy in the forecast values and provide basis relying totally on its forecasting accuracy and efficiency when it comes the forecasting the future values of production and its lower error of accuracy contributed to high efficiency of the model and the reliability of its estimate.

(Keywords: Akaike' Information Criterion, AIC, Bayesian Information Criterion, BIC, white noise, Kwiatkowski-Phillips-Schmidt-Shin, KPSS, Jarque-Bera test, Augmented Dickey Fuller, ADF)

INTRODUCTION

Modeling and tracking the pattern of production is very crucial in business. In fact, many renowned economists had studied how production volume affects sales volume when it comes to keeping updated inventory and gaining public acceptance when the consumers or the wholesalers are able to buy the exact volume of product they desire. When the production volume keeps pace with the sales volume, the buyers will develop confidence in the company and this makes them to become loyalists to the company. Therefore the study is structured towards modeling and forecasting the production volume of 7up Bottling Company Nig. Plc. using Seasonal Autoregressive Integrated Moving Average Models.

Since time-series methods only require historical data, they are widely used to develop predictive models. They are simply a set of observations measured at successive points in time or over successive periods of time. Time series analyses are used to detect patterns of change in statistical information over regular interval of time. It makes the assumption that past patterns in data can be used to forecast future data points.

SARIMA Models

It is a time series $\{X_t\}$ that said to follow an autoregressive moving average (ARMA) model of order p and q denoted by ARMA (p, q) if:

$$X_t - \alpha_1 X_{t-1} - \alpha_2 X_{t-2} - \cdots \alpha_p X_{t-p} = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + \beta_q \varepsilon_{t-q} \cdots - - - \quad \textbf{(1)}$$

Where the α's and the β's are constants such that (1) is stationary and invertible and the sequence of random variables $\{\varepsilon_t\}$ is a white noise process.

We can represent Equation (1) as follows:

$$\mathrm{A(L)}X_t = \mathrm{B(L)}\varepsilon_t - - - \quad \textbf{(2)}$$

Where A (L) = 1 - α_1L - $\alpha_2 L^2$ -… - $\alpha_p L^p$ and B (L) = 1 + β_1L + $\beta_2 L^2$ +… + $\beta_q L^q$ and L is the backward shift operator defined by $L^k X_t = X_{t-k}$. It is well known that for (1) to be stationary and invertible the zeros of A (L) and B (L) must be outside the unit circle respectively. Many real life time series are nonstationary.

For such a time series, Box and Jenkins propose that differencing up to an order d could render it stationary. Suppose the stationary d^{th} order difference of Xt is denoted by $\nabla^d X_t$. Clearly ∇ = 1-L. Putting $\nabla^d X_t$ in lieu of Xt in (1) yields an autoregressive integrated moving average (ARIMA) model of order p, d and q, denoted by ARIMA(p, d, q) in {Xt}. Suppose a time series {Xt} is seasonal of periods. For such a series a SARIMA model of order (p, d, q) x (P, D, Q):

Where order (p,d,q)x(P,D,Q)s explained thus:-

p = denotes the number of autoregressive terms.

d = is an integer which denotes the number of times the series must be differenced to attain stationarity.

q = denotes the number of moving average terms.

P = denotes the number of Seasonal autoregressive terms.

D = denotes the number of Seasonal differences required to attain stationarity.

Q = denotes the number of Seasonal moving average terms.

s = denotes the seasonal period or the length of the season.

Also, Φ(L) and Θ(L) are respectively polynomials of order P and Q with coefficients such that the model is stationary and invertible respectively. Φ (L) and Θ (L) are respectively the seasonal autoregressive and moving average operators of the model.

ARIMA is the method first introduced by Box and Jenkins (1976) and until now become the most popular models for forecasting univariate time series data. This model has been originated from the Autoregressive model (AR), the Moving Average model (MA) and the combination of the AR and MA, the ARMA models. In the case where seasonal components are included in this model, then the model is called as the SARIMA model. Box-Jenkins procedure that contains three main stages to build an ARIMA model (i.e., model identification, model estimation and model checking) is usually used to fit a multiplicative model. The purpose of this research is to build model using seasonal ARIMA approach with the aim of predicting Nigeria import and export. Additionally, the present study updates the Box-Jenkins procedure particularly for Seasonal model.

The Autoregressive Integrated Moving Average Model (ARIMA)

The order of the autoregressive component is p, the order of differencing needed to achieve stationarity is d, and the order of the moving average component is q. In general the ARIMA process (1) is of the form:

$$Z_t = \sum_{k=1}^{p} \alpha_k Z_{t-k} - \sum_{k=1}^{q} \theta_k e_{t-k} + \mu + e_t \quad \textbf{(3)}$$

The Backshift and Difference Operators for ARIMA Representation

To express and understand differenced ARIMA models the concept of the backshift (lag) operator, B, and difference operator, ∇, is used, These has no mathematical meaning other than to facilitate the writing of different type of models that would otherwise be extremely difficult to express. The backshift is defined as $B^m Y_t = Y_{t-m}$.

For example $BY_t = Y_{t-1}$,

$BY_t = Y_{t-1}$ and $B^{12} Y_t = Y_{t-12}$. The difference operator takes the form $\nabla^d = (1 - B)^d$, when d differences are taken to achieve stationarity in the time series data.

Seasonal Autoregressive Models

A purely seasonal time series is the one that has only seasonal AR or MA parameters. Seasonal autoregressive models are built with parameter called seasonal autoregressive (SAR) parameters. The SAR parameters represent the autoregressive relationships that exist between time series data separated by multiples of the number of periods per season. A general AR model with P SAR parameters is given by:

$$Y_t = \sum_{i=1}^{p} \alpha_{is} Y_{t-is} \quad (4)$$

Where Y_{t-s} is of order s, Y_{t-2s} is of order 2s and Y_{t-ps}, is of order p s. A model with one SAR parameter is written as:

$$Y_t = \alpha_s Y_{t-s} + e_t \quad (5)$$

Seasonal Moving Average (SMA) models are built with SMA parameters, and the general SMA model with Q parameters is given by:

$$Y_t = \sum_{i=1}^{Q} \theta_{is} e_{t-is} + e_t \quad (6)$$

Borlando et al. (1996) used ARIMA models to forecast hourly precipitation in the time of their fall and the amounts obtained were compared with the data to measure rain. They came to the conclusion that with increasing duration of rainfall, the predictions were more accurate, and shorter duration of rainfall, rain rate difference will be more than the actual corresponding value.

Yusof and Kane (2013) analyzed the precipitation forecast using SARIMA model in Golastan province and found the seasonality measure in SARIMA to be highly useful in measuring precipitation. Deepika, Gautam, and Rajkumar (2012) have tried to study the forecasting of gold price through ARIMA model and Regression but their finding suggests that suitable model was not identified to forecast Gold price through ARIMA Model hence regression analysis was carried out in the later part of their study.

Also, Banhi et al. (2016) worked on Gold Price Forecasting Using ARIMA Model and they discovered that ARIMA (1, 1, 1) model which helps us in predicting the future values of Gold. ARIMA (1, 1, 1) was chosen from six different model parameters as it provides the best model which satisfies all the criteria of fit statistics.

Suhartono (2011), worked on the Time Series Forecasting by using Seasonal Autoregressive Integrated Moving Average: Subset, Multiplicative or Additive Model, and he eventually discovered the multiplicative SARIMA model yielded less accurate forecasted values than subset or additive models for airline data and tourist arrivals data respectively. Also, Chaido (2016) worked on modeling and forecasting the unemployment in Greece. The results of the forecast showed that the forecasted value of unemployment is close to the actual value. This result showed that model's suitability can be used to forecast unemployment in Greece for the following years, and also the lack of fit of the models were investigated through Ljung et al (1978).

Banerjee (2014) applied ARIMA model, in her research paper tagged "Forecasting of Indian Stock Market using Time-series ARIMA Model". She was able to predict the future stock indices which have a strong influence on the performance of the Indian economy. In her paper she first determined the ARIMA model then she forecasted through model validation and at the end the recurrence validation was done.

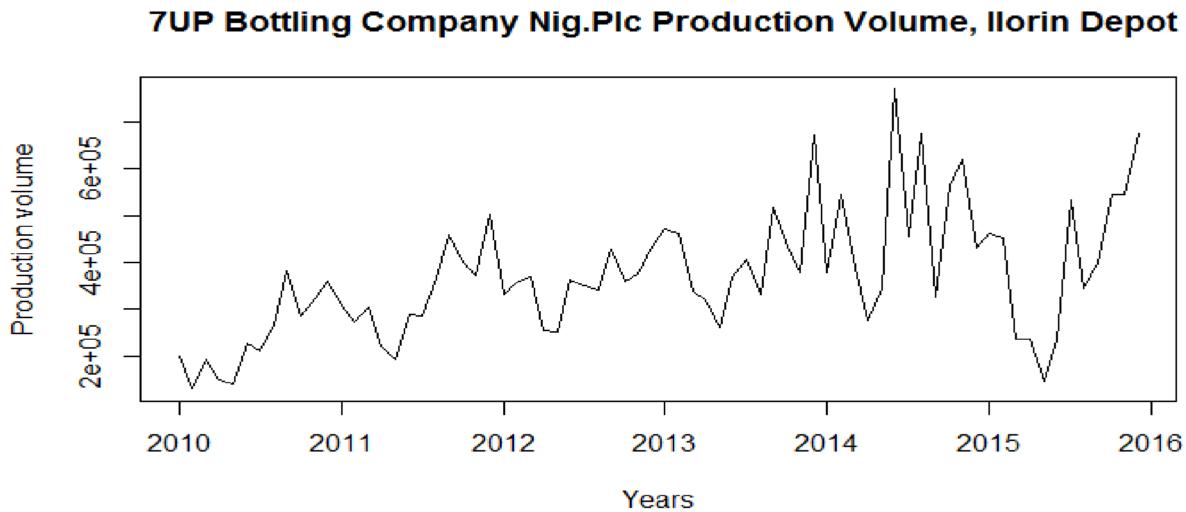

Figure 1: The Time Plot of Production Volume of 7up Bottling Company Nig. Plc, Ilorin Depot.

Table 1: Stationarity Test.

MODEL	AIC
ARIMA(2,1,2)(1,1,1)[12]	1550.908
ARIMA(1,1,0)(1,1,0)[12]	1552.072
ARIMA(0,1,1)(0,1,1)[12]	551.277
ARIMA(2,1,2)(0,1,1)[12]	1553.033
ARIMA(2,1,2)(1,1,0)[12]	1549.484
ARIMA(3,1,2)(1,1,0)[12]	1548.6
ARIMA(2,1,1)(1,1,0)[12]	1547.319
ARIMA(2,1,1)(0,1,0)[12]	1564.521
ARIMA(2,1,1)(2,1,1)[12]	1551.143
ARIMA(1,1,1)(1,1,0)[12]	1545.86
ARIMA(0,1,1)(1,1,0)[12]	1546.397

From Figure 1, we can deduce that the data is not stationary. Between 2010 and 2014, there is upward trend. Even though there is seasonality in the dataset, there is downward trend from first quarter of 2014 to second quarter of 2015. From second quarter of 2015 there is upward trend till 2016. The data maintain the seasonally significant movement with no constant variance, thus making the dataset to be non-stationary.

Before differencing the data, we need to carry out the KPSS test to experiment with the best SARIMA Model to be fitted to the data. This test bases on selecting the best SARIMA model out of all possible SARIMA model presented by KPSS. The test uses the AIC or BIC to select the model with is apparently stationary.

Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Tests when using AIC to Select Best Model

KPSS-type tests are intended to complement unit root tests, such as the Dickey–Fuller tests. By testing both the unit root hypothesis and the stationarity hypothesis, one can distinguish series that appear to be stationary, series that appear to have a unit root, and series for which the data (or the tests) are not sufficiently informative to be sure whether they are stationary or integrated.

The best model: ARIMA (1, 1, 1) (1, 1, 0) [12], as suggested by KPSS test when it used the Akaike' Information Criterion to judge the best model and selecting the model that is stationary.

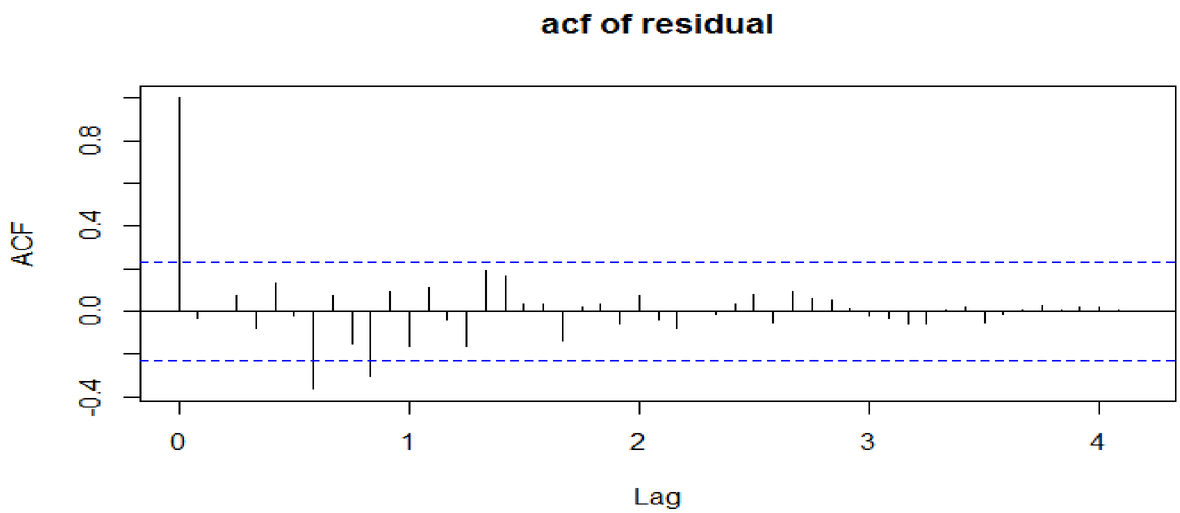

Figure 2: Plot of Autocorrelation Residual.

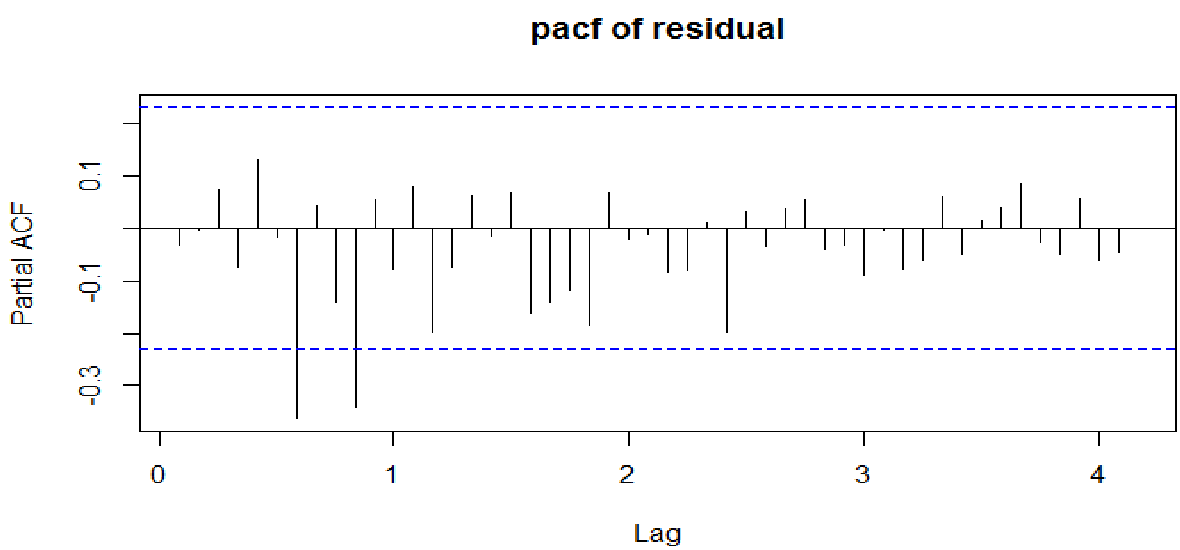

Figure 3: Plot of PACF of Residual.

From Table 1, we can therefore select model with the smallest Akaike Information Criterion (AIC), which happened to be ARIMA (1, 1, 1) (1, 1, 0) [12]. The AIC =1545.86 supported that ARIMA (1, 1, 1) (1, 1, 0) [12] is the best model because it has the smallest number of AIC as compared to other SARIMA model, when KPSS used the AIC as the mean of selecting the best model when it comes to stationarity of the model. The estimate of the selected model will have higher consistency and efficiency as compared to other models as suggested by Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

From Figure 2, we can say that the residuals are not completely white noise. This is because there are only three significant or strong spikes at different lag and everything else decay to zero. The model is partially stationary.

From Figure 3, the partial autocorrelation function says there are only two significant spikes different lag, the pronounced spike only occur at lag very close to one while the remaining decay to zero.

Parameter Estimation for ARIMA (1, 1, 1) (1, 1, 0) [12]

Table 2: The Parameter Estimates.

	ar1	ma 1	sar1	Accuracy Test
coefficient	-0.3271	-0.5294	-0..6754	AIC =1545.86
Std.error	0.1752	0.1611	0.0991	BIC = 1554.17

Table 3: Confidence Interval.

Parameter	2.5%	97.5%
ar 1	-0.670530	0.01627209
ma 1	-0.8452468	-0.21357764
sar 1	-0.8696832	-0.48112404

From Table 2, the estimate are ar(1), ma(2) and season sar(1) are statistically significant when basing the judgment on the standard error of the estimate. The sar(1) is said to be more statistically significant due to its lowest standard error as compared to other estimate.

log likelihood = **-768.93** and AIC = 1545.86 contribute to the reliability of the chosen model. The values of these parameter model adequacy checking contributed significantly to the adequacy of the model as compared to other SARIMA model. Due to its lowest AIC and BIC, this model is said to be more stationary, efficient, consistent and will have higher predictive efficiency as compared to the other models**.**

From the Table 3, the ma1 and sar1 have highest statistical significance due to its tightest confidence Interval at 2.5% and 97.5%. Since the coefficient of ma1 and sar1 at 2.5% and 97.5% respectively have the same sign, therefore, the ma1 and sar1 contributed significantly to the model adequacy, thus enhancing the predictive capability of the model.

Model Diagnostic Checking

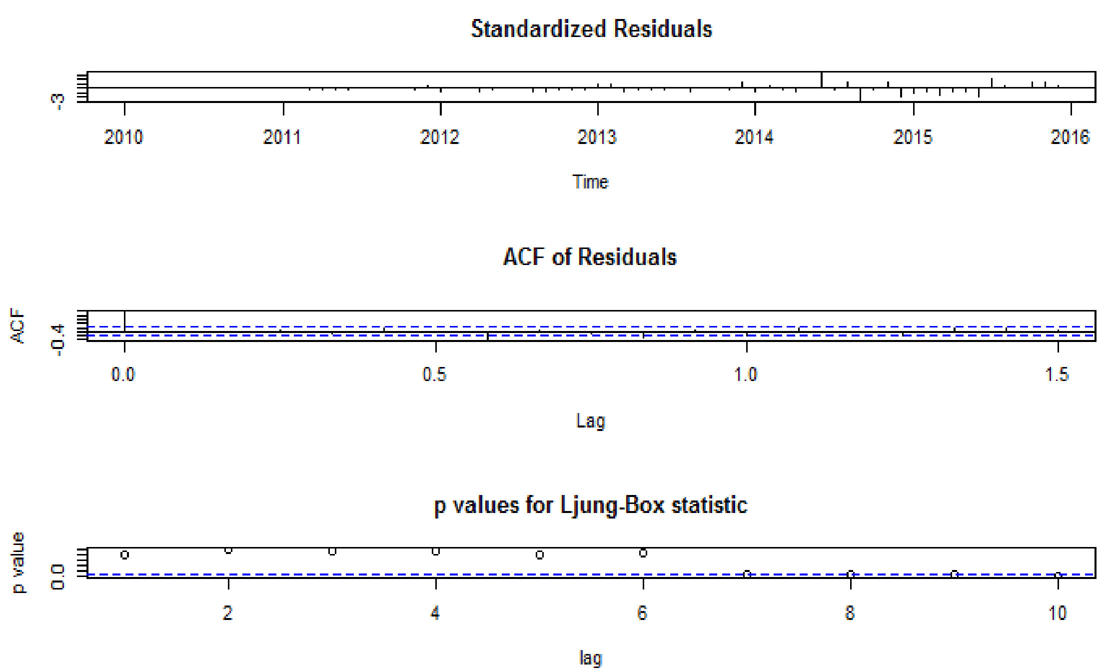

Figure 4: The Diagnostic Checking for the Model Adequacy.

Table 4: Stationary, Adequacy and Normality of Residual Test.

Model	Augmented Dickey Fuller	Jarque-Bera	Ljung-Box
ARIMA(1,1,1)(1,1,0)[12]	Adf=-1.3184,P-value=0.8528	χ^2=48.308, p-value=3.236e+11	χ^2=29.372, p-value=0.04069

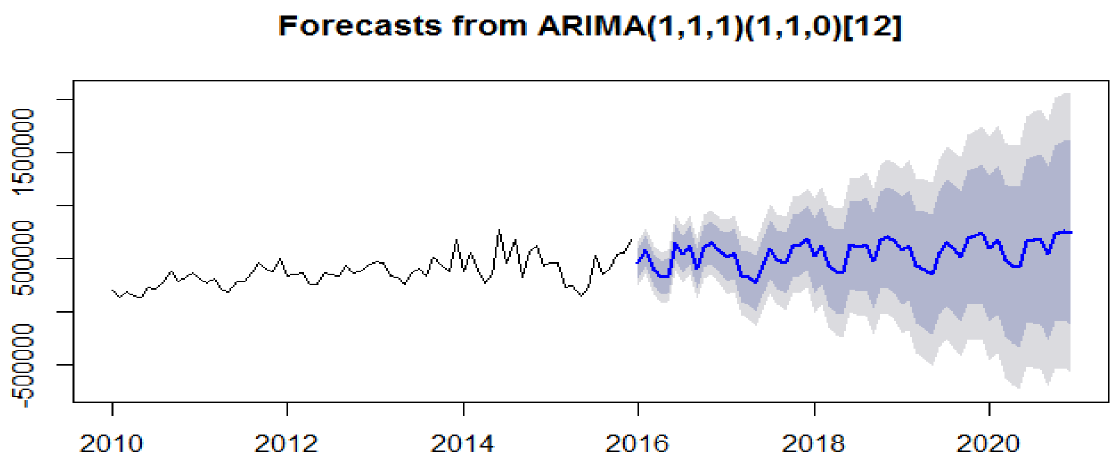

Figure 5: The Plot of Forecasts Value.

From Figure 4, we can also conclude that the residual is not completely white noise because there is presence of autocorrelation in the dataset and there are two significant spikes in the ACF plot. The points which represent the p-value of Ljung-Box test are not all above the dotted line; this shows that there is serial autocorrelation in the data, and making the residual not completely a white noise. The diagnostic graphs aren't good for the ARIMA (1, 1, 1) (1, 1, 0) [12]. The ACF has a significant spike at lag of about 0.6 and some of the Ljung-Box-Pierce p-values are below .05. We don't want them there. So, the ARIMA (1, 1, 1) (1, 1, 0) [12] isn't completely a good model.

Evidence of the Model Adequacy by Diagnosing the Residual

From the Table 4, we can use the p-value of an augmented Dickey fuller to test for the existence of apparent stationarity. We therefore deduced from the augmented Dickey Fuller test since P-value (0.8528) > α (0.05), we can therefore conclude that there is no any significant stationarity. The errors are auto-correlated and heteroscedastic.

Also the Ljung-Box test showed that the residuals or error are serially correlated, therefore there exist significant autocorrelation; P-value (0.04069) < α (0.05).

Also, since some of the p-values of the Ljung-Box test fall within the dotted line and below it, then there exist autocorrelation. The Jarque-Bera shows that the residual is not normally distributed because P-value (3.236e+11) > α (0.05).

From Figure 5, we can see the forecasted values from 2016 to 2020 with no trend and the forecasts values lie within it confidence region or interval; production volume data will have uniform behavior from 2017 to 2020. Since the result of the forecast lies within its confidence region, then we can say, the model is adequate for predicting the future production volume as compared to other SARIMA multiplicative model.

Table 5: The Stationary Test.

MODEL	BIC
ARIMA(2,1,2)(1,1,1)[12]	1565.45
ARIMA(0,1,0)(0,1,0)[12]	1613.296
ARIMA(0,1,1)(1,1,2)[12]	1559.779
ARIMA(0,1,1)(0,1,2)[12]	1556.511
ARIMA(1,1,1)(0,1,2)[12]	1558.626
ARIMA(0,1,2)(0,1,2)[12]	1558.296

Table 6: The Parameters.

parameters	ma1	sma 1	sma2	Accuracy Test
coefficients	-0.7600	-0.8524	0.5074	AIC =1548.86
Std.error	0.1185	0.1718	0.2681	BIC = 1556.51

Table 7: Confidence Interval.

parameter	2.5%	97.5%
ma 1	-0.9922054	-0.5278082
sma 1	-1.18925689	-0.5156249
sma 2	-0.0181352	1.0329215

Although the accuracy test does not totally supported the model because of its significantly higher value for MAE =58251.18 and RMSE =93509.45, the model is preferable compare to others, its autocorrelation factor is very low (ACF=-0.03050845); signifying the extent at which we can rely on the estimate of the model and its predictive capability.

The lower values of MAPE = 15.24021, MPE = -5.55828, MASE = 0.5484848 and ACF = -0.0305 validated the consistency of the model as a function of its reliability as regards the prediction of production volume from 2017 to 2020 , when compared to other SARIMA model in the series.

KPSS Test when using the BIC to Select the Appropriate Model

From the Table 5 above, we can conclude from the result of KPPS when it uses the BIC as a mean in selecting the best SARIMA model of all the SARIMA models listed above, that the seasonal ARIMA (0, 1, 1) (0, 1, 2) [12] is said to be the best model.

Parameter Estimation for ARIMA (0, 1, 1) (0, 1, 2) [12]

From Table 6, the estimate are ma(1), sma(1) and season ma(2) are statistical statistically significant when basing the judgment on the standard error of the estimate. The ma(1) is said to be more statistically significant due to its lowest standard error as compared to other estimate. log likelihood = **-770.1** and BIC = 1556.51 contributed to the reliability of the chosen model. The values of these parameter model adequacy checking contributed significantly to the adequacy of the model as compared to other SARIMA models.

Due to its lowest BIC, this model is said to be more stationary, efficient, and consistent and will have higher predictive efficiency as compared to the other models**.**

From the Table 7, the ma(1) and sma(1) have highest statistical significance due to its tightest confidence Interval at 2.5% and 97.5%. Since the coefficient of ma1 and sma(1) at 2.5% and 97.5% respectively have the same sign, therefore, the ma(1) and sma(1) contributed significantly to the model adequacy, thus enhancing the predictive capability of the model. The sma(2) does not really contribute significantly to the model accuracy.

Diagnostic Checking

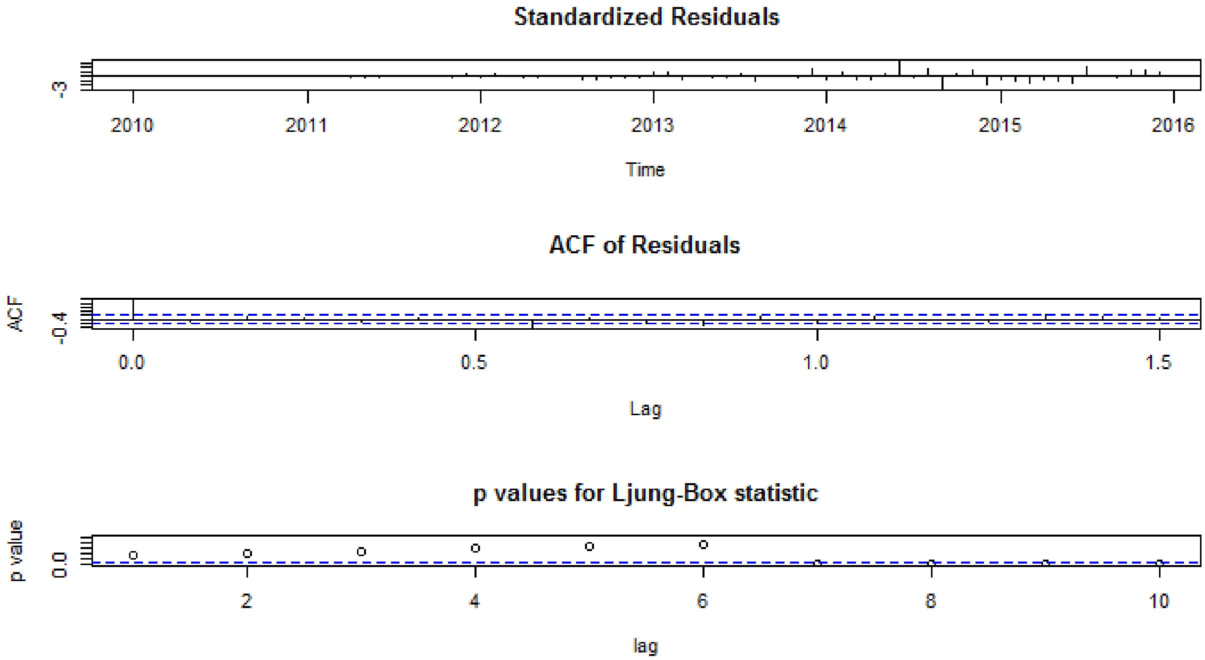

Figure 6: The Diagnostic Checking for the Model Adequacy.

Table 8: Stationary, Adequacy and Normality of Residual Test.

MODEL	Augmented Dickey Fuller	Jarque-Bera	Ljung-Box
ARIMA(1,1,1)(1,1,0)[12]	Adf=-1.3184,P-value=0.8528	χ^2=48.308, p-value=9.944e-08	χ^2=29.372, p-value=0.5461

From the Figure 6, the ACF plot of residual and standardized residual plot shows that there are no significant spikes. There is only a significant spike at lag zero and the remaining decay. This shows the presence of white noise and random walk in the process. Although, the Ljung-Box test does not really supported the total model adequacy since there is over 60% of the P-values of L Jung test above the dotted line, we can that there is no auto correlation in the data or about 60% of the autocorrelation in the data can be explained while the remaining 40% is unexplained, thereby making the residual to be over 60% white noise. Although diagnostic graphs for Ljung-Box test does not totally support ARIMA (0, 1, 1) (0, 1, 2) [12], we can rely on the evidence from ACF to say that its residual is approximately white noise. This is because it is not easy to arrive at the model which meets all the requirements or criteria for determining its apparent stationarity.

Evidence of the Model Adequacy by Diagnosing the Residual

From Table 8, we can use the p-value of an augmented Dickey fuller to test for the existence of apparent stationarity, and we can therefore conclude that there is no any significant stationarity; p-value (0.85288)> α (0.05). Also the Ljung-Box test showed that the residuals or error are serially not totally correlated, therefore there exist no significant autocorrelation; P-value (0.5461) > α (0.05). The Jarque-Bera shows that the residual is normally distributed because P-value (9.944e-08) <α (0.05).

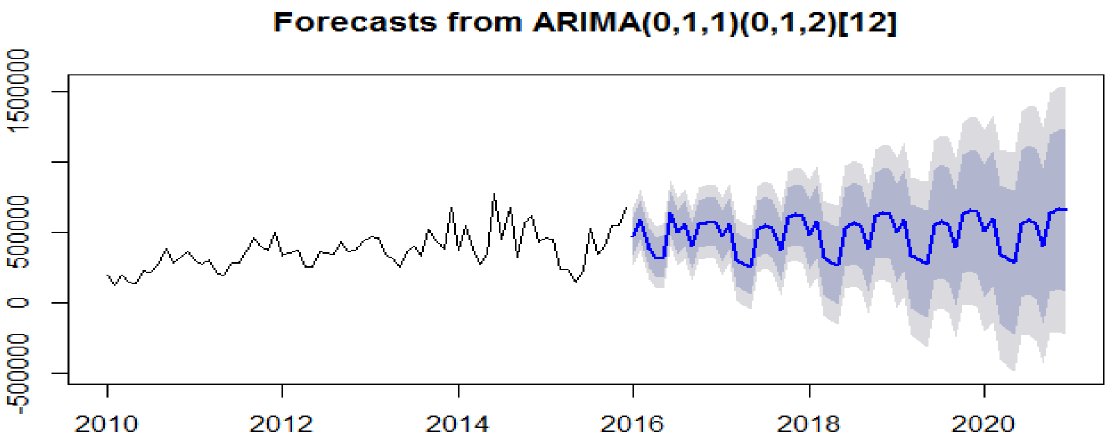

Figure 7: The Plot of Forecasts Value.

Table 9: The Stationary Test.

MODEL	AIC	BIC
ARIMA(1,0,0)(1,0,0)[12]	1587.364	1587.364
ARIMA(2,0,0)(1,0,0)[12]	1562.747	1562.747
ARIMA(2,0,0)(1,0,1)[12]	1562.728	1562.728
ARIMA(3,0,0)(1,0,0)[12]	1560.006	1560.006
ARIMA(4,0,0)(1,0,0)[12]	1555.985	1555.985
ARIMA(5,0,1)(1,0,0)[12]	1547.443	1547.443
ARIMA(5,0,0)(1,0,0)[12]	1543.24	1543.24

From the plot above, we can see the forecasted values from 2016 to 2020 with no trend and the forecasts values lie within it confidence region or interval; production volume data will have uniform behavior from 2017 to 2020. Since the result of the forecast lies within its confidence region, then we can say, the model is adequate for predicting the future trend as compared to other SARIMA multiplicative model. Although the accuracy test does not totally supported the model because of its significantly higher value for MAE =58251.18 and RMSE =91903.45, the model is preferable compare to other, its autocorrelation factor is very low (ACF=-0.1084591), signifying the extent at which we can rely on the estimate of the model and its predictive capability. The lower values of MAPE = 15.73094, MPE = -6.474791, MASE = 0.5606692 and ACF = -0.1084591 validated the consistency of the model as a function of its reliability as regards the prediction of production volume from 2017 to 2020 , when compared to other SARIMA models when using only BIC as criterion for model selection. The accuracy of this model has improved a little bit because the mean square error has reduced drastically which make the model more efficient as compared to ARIMA (1, 1, 1) (1, 1, 0) [12].

KPSS Test to Handle the Transformed Production Volume Datasets in Selecting the Most Stationary SARIMA Model

From Table 9 above, we can conclude from the result of KPPS when it uses the BIC and AIC as a mean of selecting the best SARIMA model of all the SARIMA models listed above, that the seasonal ARIMA (5, 0, 0) (1, 0, 0) [12] is said to be the best model. The selected model is apparently stationary because the AIC and BIC simultaneously supported the stationarity, adequacy, consistency and efficiency of the model. This model is better and most preferable to the other SARIMA fitted to the production volume datasets without transforming the dataset.

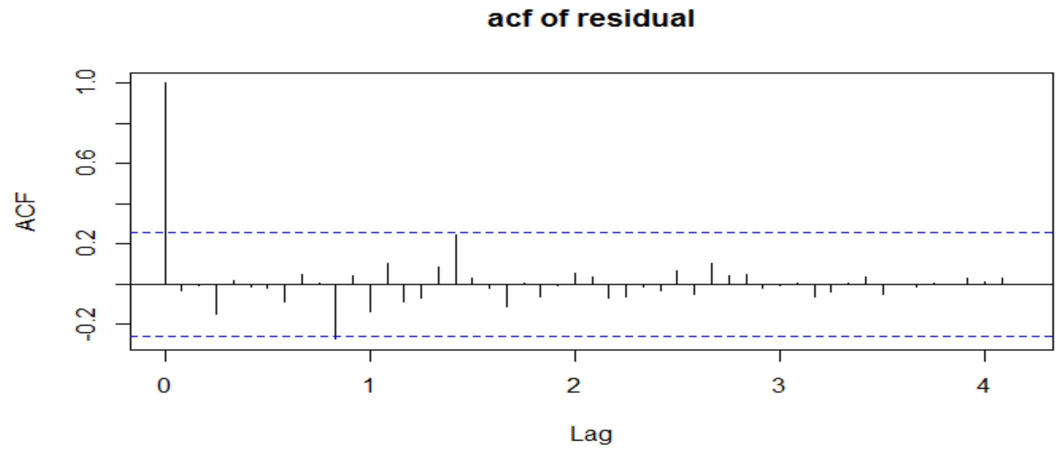

Figure 8: The ACF Plot for Residuals.

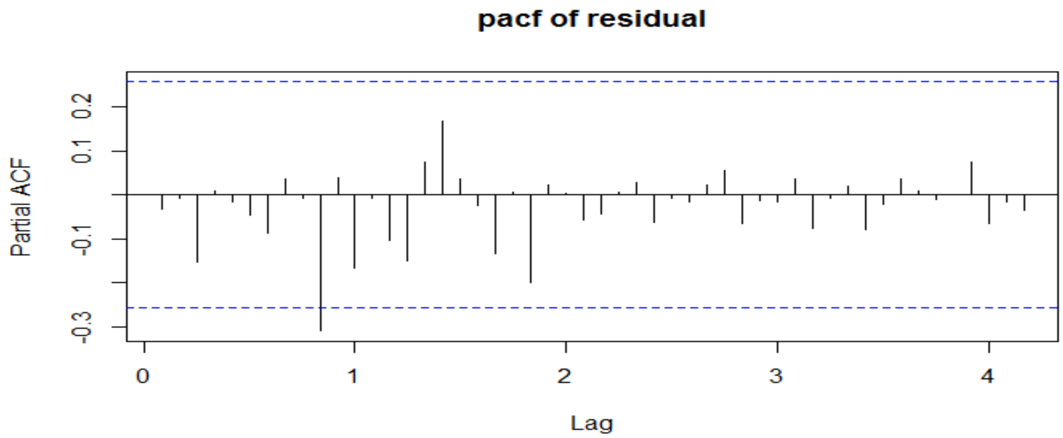

Figure 9: The PACF of Residual.

Table 10: Parameter Estimate

Parameter	ar1	ar2	ar3	ar4	ar5	sar1
coefficient	-1.6438	-1.6625	-1.33576	-1.0030	-0.5069	-0.60
Std. error	0.1123	0.2038	0.2351	0.1908	0.1099	0.1092

From Figure 8, we can say that the residuals are approximately white noise. This is because there is only one significant or strong spike at lag zero and everything else decay to zero. The model is therefore stationary. This shows that the residuals are random walk which constituting white noise, and this result to apparent stationary (which include trend stationary).

From Figure 9, the partial autocorrelation function says there is no significant spikes at any lag, the pronounced spike only occur at lag about one while the remaining decay exponential to zero.

Parameter Estimation for ARIMA (5, 0, 0) (1, 0, 0) [12]

From Table 10, the estimates are ar(1), ar(2), ar(3), ar(4), ar(5) and seasonal component sar(1) are statistical statistically significant when basing the judgment on the standard error of the estimate. The sar(1) is said to be more statistically significant due to its lowest standard error as compared to other estimate. Since all the coefficient have the same sign, we can also say that the coefficient of the model parameter are all significantly contributing to the accuracy of the model. log likelihood = **-757.01**, lower AIC and BIC contributed to the reliability of the chosen model.

Table 11: Confidence Interval.

Parameter	2.5%	97.5%
ar 1	-1.8638587	-0.5278082
ar 2	-2.0618507	-1.2631389
ar 3	-1.8184180	-0.8968213
ar 4	-1.376270	-0.6290228
ar 5	-0.7223460	-0.2915340
sar 1	-0.814128	-0.3859443

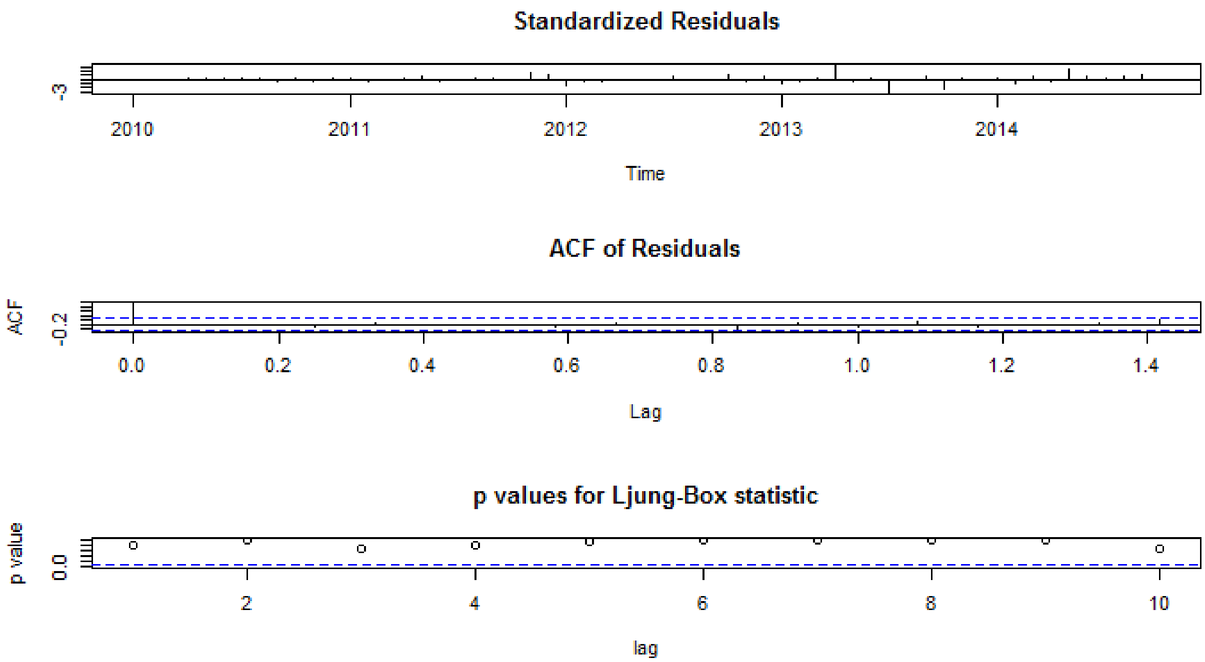

Figure 10: The Diagnostic Checking for Model Adequacy.

The values of these parameter model adequacy checking contributed significantly to the adequacy of the model as compared to other SARIMA models. Due to its lowest AIC and BIC, this model is said to be more stationary, efficient, consistent and will have higher predictive efficiency as compared to the other models.

From the Table 11 above, all the parameters have higher statistical significance due to its tightest confidence Interval at 2.5% and 97.5%. Since the coefficients of the parameters have the same signs at 2.5% and 97.5%, the they possess high statistical significance and thus can be relied upon in quantitative decision making, forecasting and prospective planning in 7up Bottling company Nigeria Plc, so that future production volume will keep pace with their sales volume. The statistical significance of the model parameter contributed significantly to the model adequacy, thus enhancing the predictive capability of the model.

Diagnostic Plot

From Figure 10, we can also conclude that the residual are white noise since there are no significant spikes in the ACF plot. The points which represent the p-value of Ljung-Box test lie above the dotted line; this shows that there is no serial autocorrelation in the data, and making the data to be random walk with white noise residual. Therefore the model is stationary, making the model to be the best model in predicting the future values for the production volume of 7up Bottling Company Nig. Plc.

Table 12: Stationary, Adequacy and Normality of Residual Test.

Model	Augmented Dickey Fuller	Jarque-Bera	Ljung-Box Test	Philip-Perron Test
ARIMA(5,0,0)(1,0,0)[12]	Adf=-1.543,P-value=0.042	χ^2=41.787, p-value=8.43e-10	χ^2=35.186, p-value=0.01	Adf(z_α)=-91.6, p=0.02

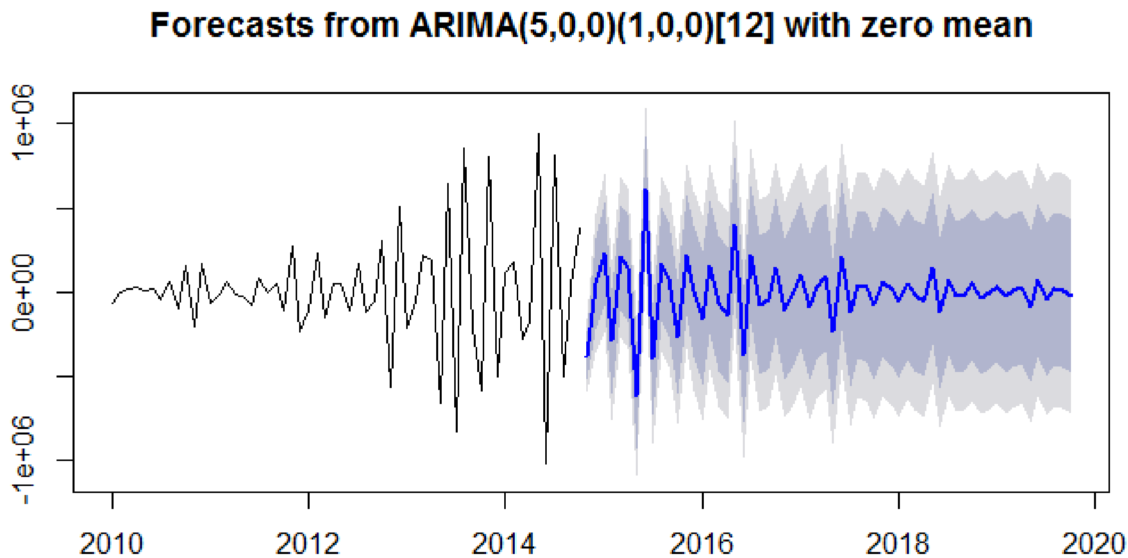

Figure 11: The Plot of Forecasts Value.

From the Table 12 above, the augmented Dickey Fuller test shows that there is no unit root, and thus there exist stationarity because (adf(-1.543 is not less than -3.41) or p-value(0.042) < α (0.05). Also the Ljung-Box test showed that the residuals or error are serially uncorrelated; P-value (0.01) <α (0.05), therefore making the model to be stationary. The Jarque-Bera shows that the residuals are totally normally distributed; P-value (8.43e-10) < α (0.05). The Philips-Perron test also confirmed that the model is stationary by cumulating on the assertion of Augmented Dickey Fuller test for the stationarity of the model. The errors are serially uncorrelated and no heteroscedasticity.

From Figure 11, we can see the forecasted values from 2016 to 2020 with no trend and no seasonality and the forecasts values lie within it confidence region or interval; the production volume data will have uniform behavior from 2017 to 2020. Since the result of the forecast lies within its confidence region, then we can say, the model is adequate for predicting the future trend as compared to other SARIMA multiplicative model.

The accuracy test totally supported the model because of its significantly lower value for MAE, RMSE, ME, the model is preferable compare to other, and its autocorrelation factor is very low, signifying the extent at which we can rely on the estimate of the model and its predictive capability.

The lower values of MAPE, MPE, MASE and ACF validating the consistency of the model as a function of its reliability as regards the prediction of production volume of 7up Bottling Company Nig. Ltd from 2017 to 2020. The accuracy test supported ARIMA (5, 0, 0) (1,0,0)[12] as the best model to predict production volume. all the test: the accuracy test, Diagnostic and the residual test or plot supported ARIMA(5,0,0)(1,0,0)[12] as the best model for forecasting the production volume of all the SARIMA models.

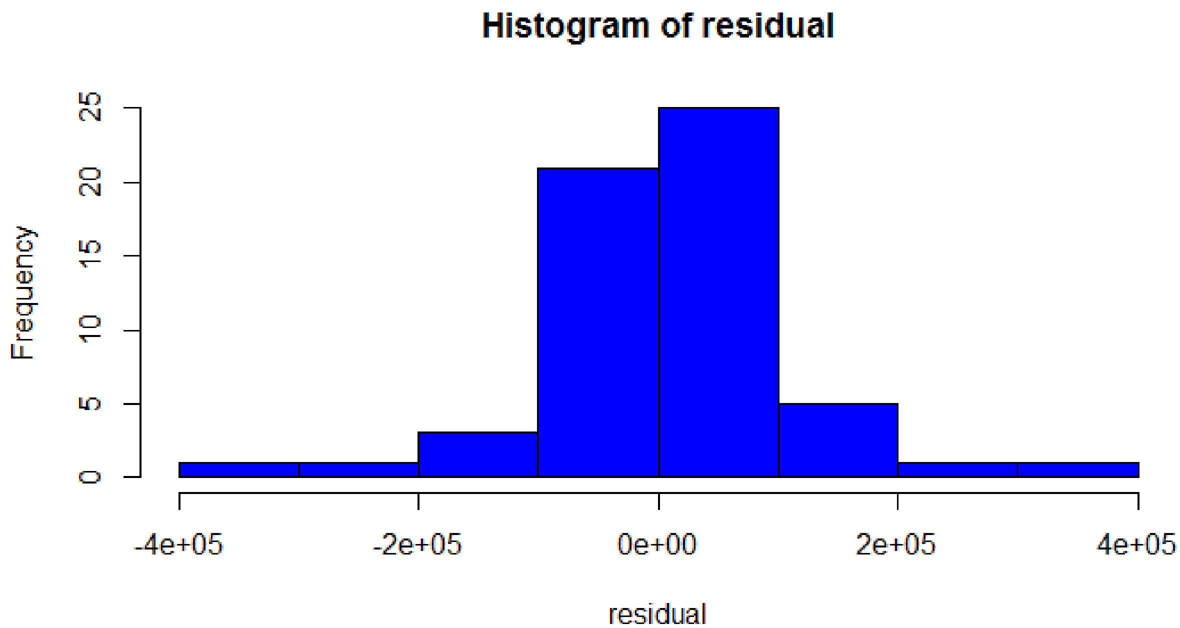

Figure 12: Normality Test of Residuals.

From Figure 12, we can deduce that residual is normally distributed as the chart above shows impression of bell-shape of normal distribution. Then, we can conclude from this graphical approach that the residuals are white noise and uncorrelated, giving evidence of the stationary model.

RESULT AND FINDINGS

It can be deduced that the ARIMA (1, 1, 1) (1, 1, 0) [12] fits production volume data reasonably well when the KPSS test only used the Akaike' information criterion to select the best model of all the model suggested by the test. Diagnosing the accuracy and predictive efficiency of the Model revealed that even though the ARIMA (1, 1, 1) (1, 1, 0) [12] is the best model when using AIC by KPSS, its predictive efficiency is so low and cannot be totally relied upon in decision making. This is because the ACF and PACF plot shows that its residual is not a white noise. Although its parameter estimate is a little bit favorable; the estimate are ar(1), ma(2) and season sar(1) are statistically significant when basing the judgment on the standard error of the estimate.

The sar(1) is said to be more statistically significant due to its lowest standard error as compared to other estimate. log likelihood = -**768.93** and AIC = 1545.86 contribute to the reliability of the chosen model. The values of these parameter model adequacy checking contributed significantly to the adequacy of the model as compared to other SARIMA model.

Due to its lowest AIC and BIC, this model is said to be more stationary, efficient, consistent and will have higher predictive efficiency as compared to the other models**.** The Augmented Dickey Fuller test and Ljung-Box test stated that the model is not stationary and there is autocorrelation of residuals, making the residuals to deviate significantly from white noise. The Jarque-Bera test also stated that the residuals are not normally distributed. We can use the p-value of an augmented Dickey fuller to test for the existence of apparent stationarity. We therefore deduced from the augmented Dickey Fuller test since P-value (0.8528) > α (0.05), we can therefore conclude that there is no any significant stationarity. Also the Ljung-Box test showed that the residuals or error are serially correlated, therefore there exist significant autocorrelation; P-value (0.04069) < α (0.05).

Also, since some of the p-values of the Ljung-Box test fall within the dotted line and below it, then there exist autocorrelation. The Jarque-Bera shows that the residual is not normally distributed because P-value (3.236E+11) > α (0.05). Therefore the result of forecasts of this model cannot be totally relied upon because it also possess higher value of RMSE, ME and MAE which make the model not to perform significantly when it comes to accuracy test for forecasting for the future.

Also, when KPSS use only BIC to select the best model, the best fitted model is ARIMA (0, 1, 1) (0, 1, 2) [12]. The estimate are ma(1), sma(1) and season ma(2) are statistical statistically significant when basing the judgment on the standard error of the estimate. The ma(1) is said to be more statistically significant due to its lowest standard error as compared to other estimate. log likelihood = **-770.1** and BIC = 1556.51 contributed to the reliability of the chosen model. The values of these parameter model adequacy checking contributed significantly to the adequacy of the model as compared to other SARIMA models.

Due to its lowest BIC, this model is said to be stationary, efficient, and consistent and will have higher predictive efficiency as compared to the other models**.** The ma(1) and sma(1) have highest statistical significance due to its tightest confidence Interval at 2.5% and 97.5%. Since the coefficient of ma1 and sma(1) at 2.5% and 97.5% respectively have the same sign, therefore, the ma(1) and sma(1) contributed significantly to the model adequacy, thus enhancing the predictive capability of the model. The sma(2) does not really contribute significantly to the model accuracy.

The ACF and PACF plot also stated that the residual of the model is not completely white noise and random walk. About 60% of the points which represent the p-value of Ljung-Box test lie above the dotted line, then we can say about 60% of autocorrelation in the residuals are accounted for, while the remaining 40% is unexplained. This makes the residuals of this model to be approximately or roughly white noise. This contributes to the adequacy or consistency of the model and making it better than ARIMA (1, 1, 1) (1, 1, 0) [12].

From the diagnostic test, we can use the p-value of an augmented Dickey fuller to test for the existence of apparent stationarity, and we can therefore conclude that there is no any significant stationarity; p-value (0.85288)> α (0.05). Also the Ljung-Box test showed that the residuals or error are serially not totally correlated, therefore there exist no significant autocorrelation; P-value (0.5461) > α (0.05). The Jarque-Bera shows that the residual is normally distributed because P-value (9.944e-08) <α (0.05). The result of forecasts of this model has improve a little bit as compared to that of ARIMA (1, 1, 1) (1, 1, 0) [12]. We cannot still totally rely on the ARIMA (0, 1, 1) (0, 1, 2) [12] because it also possess higher value of RMSE, ME, and MAE , but its errors of forecasting have reduced significantly, which make the model not to perform significantly when it comes to accuracy for forecasting for the future.

When KPSS selected the best model based on the consensus of both AIC and BIC, it selected ARIMA (5, 0, 0) (1, 0, 0) [12] as the best model because the ACF and PACF plot validated that the residuals of the model are completely white noise. The points which represented the p-value of the Ljung-Box test fall completely above the dotted line, thus signifying that the residuals are white noise, random walk and no autocorrelation of residuals or errors. The estimates are ar(1), ar(2), ar(3), ar(4), ar(5) and seasonal component sar(1) are statistical statistically significant when basing the judgment on the standard error of the estimate. The sar(1) is said to be more statistically significant due to its lowest standard error as compared to other estimate. Since all the coefficient have the same sign, we can also say that the coefficient of the model parameter are all significantly contributing to the accuracy of the model. log likelihood = -**757.01**, lower AIC and BIC contributed to the reliability of the chosen model.

The values of these parameter model adequacy checking contributed significantly to the adequacy of the model as compared to other SARIMA models. Due to its lowest AIC and BIC, this model is said to be more stationary, efficient, consistent and will have higher predictive efficiency as compared to the other models**.** All the parameters have higher statistical significance due to its tightest confidence Interval at 2.5% and 97.5%. Since the coefficients of the parameters have the same signs at 2.5% and 97.5%, the they possess high statistical significance and thus can be relied upon in quantitative decision making, forecasting and prospective planning in 7-Up Bottling company

Nigeria Plc., so that future production volume will keep pace with their sales volume.

The statistical significance of the model parameter contributed significantly to the model adequacy, thus enhancing the predictive capability of the model. The diagnostic test shows that the augmented Dickey Fuller test shows that there is no unit root, and thus there exist stationarity because (adf(-1.543 is not less than -3.41) or p-value(0.042) < α (0.05). Also the Ljung-Box test showed that the residuals or error are serially uncorrelated; P-value (0.01) <α (0.05), therefore making the model to be stationary. The Jarque-Bera shows that the residuals are totally normally distributed; P-value (8.43e-10) < α (0.05). The Philips-Perron test also confirmed that the model is stationary by cumulating on the assertion of Augmented Dickey Fuller test for the stationarity of the model.

The histogram of residuals shows that the visual impression of the residuals are normally distributed. The forecasted values from 2016 to 2020 with no trend and no seasonality and the forecasts values lie within it confidence region or interval; the production volume data will have uniform behavior from 2017 to 2020. Since the result of the forecast lies within its confidence region, then we can say, the model is adequate for predicting the future trend as compared to other SARIMA multiplicative model.

The accuracy test totally supported the model because of its significantly lower value for MAE, RMSE, ME, the model is preferable compare to other, and its autocorrelation factor is very low, signifying the extent at which we can rely on the estimate of the model and its predictive capability. The lower values of MAPE, MPE, MASE, and ACF validate the consistency of the model as a function of its reliability as regards the prediction of production volume of 7up Bottling Company Nig. Ltd. from 2017 to 2020. The accuracy test supported ARIMA (5, 0, 0) (1, 0, 0) [12] as the best model to predict production volume. all the test: the accuracy test, Diagnostic and the residual test or plot supported ARIMA (5, 0, 0) (1, 0, 0) [12] as the best model for forecasting the production volume of all the SARIMA models.

CONCLUSION

The main objective of this study was modeling and forecasting of production volume of 7up Bottling Company Nig. Plc. using SARIMA model and also to determine the accuracy of the chosen SARIMA model using KPSS which based its decision on AIC and BIC. The model with a minimum value of these information criterions is considered as the best (Akaike, 1979; Akaike, 1974).

In addition, ME, MSE, RMSE, MAE, MPE, MAPE were also employed so as to validate the accuracy, adequacy and predictive efficiency of the model as a mean of reliability on the estimate of the model. The ACF plots of the residuals two models were examined to see whether the residuals of the model were white noise. Since SARIMA is the best model by basing the judgment on KPSS, the ARIMA (5, 0, 0) (1, 0, 0) [12] is the best model for making accurate forecasting. Also, ARIMA (1, 1, 1) (1, 1, 0) [12] and ARIMA (0, 1, 1) (0, 1, 2) [12] are also good but they did not meet all the requirements to be the best. Therefore ARIMA (5, 0, 0) (1,0,0) [12] is the best and should be used to predict the future production volume.

RECOMMENDATION

Having analyzed properly the data collected on production volume from 7up Bottling Company Nig. Plc., we therefore make the following points as suggestion:

▪ In order to make accurate forecast, the ARIMA (5, 0, 0) (1, 0, 0) [12] should be used so that the forecast values can be totally relied upon in making production decision which will affect their flavor (Pepsi, Mirinda, 7up, Teem) significantly in the area of meeting the demand of prospective buyers (wholesalers). The forecast values obtained from selected model should be used to make proactive decision towards realizing stable growth in their company and development in Nigeria. This is because production volume affects sales volume when the inventory is not balanced or when the production rate is significantly less than the rate of purchase.

▪ The management must ensure that they protect the good brand name of the company as well as their product so that they would continue to gain public acceptance and utmost recognition, even more than their major competitors. This is because ARIMA (0, 1, 1) (0, 1, 2) [12] forecasts huge production volume in the future. This shows that as the production volume increases, the sales volume also increases, this reflects that the company is in good standing to compete excellently and be at the better edge compared to their counterpart. For this reason, the management should ensure that they bring every factor that could hinder them not to achieve this target or expected production volume.

▪ The ARIMA (1, 1, 1) (1, 1, 0) [12] is also more efficient when KPSS used AIC as the means of selecting the best model. It could also be used to predict the future production when the investigator wants to base his or her judgment solely on AIC criterion. The company should not stop the giving out of incentives which has attracted the patronage of the customers which in turn lead to huge production of flavor as a result of corresponding huge sales. This also serves as one of the reasons why the company is having continuous support and acceptance of the all their products by the potential buyers.

References

1. Banerjee, D. 2014. "Forecasting of Indian Stock Market using Time-Series ARIMA Model". In: 2014 2nd International Conference on Business and Information Management (ICBIM). 131–135.

2. Banhi, G. and B. Gautam. 2016. "Gold Price Rorecasting using ARIMA Models". *Journal of Advanced Management Science*. 4(2):117-121.

3. Borlando, P., R. Montana, and R. Raze. 1996. "Forecasting Hourly Precipitation in Time of Fall using ARIMA Models". *Journal of Atmospheric Research*. 42(1):199-216.

4. Box, G.E.P. and G.M. Jenkins/ 1976. *Time Series Analysis: Forecasting and Control. 1st Edn.* Holden-Day: San Francisco, CA. ISBN: 0816211043, 575.

5. Chaido, D. 2016. "Forecast of SARIMA Models: An Application to Unemployment Rate in Greece". *American Journal of Applied Mathematics and Statistics*. 4(5):136-148.

6. Deepika, M.G., N. Gautam, and M. Rajkumar. 2012. "Forecasting Price and Analyzing Factors Influencing the Price of Gold Using ARIMA Model and Multiple Regression Analysis". *International Journal of Research in Management, Economics and Commerce*. 2(11): 548-563.

7. Ljung, G.M. and G.E.P. Box. 1978. "On a Measure of a Lack of Fit in Time Series Models". *Biometrika* 65(2):297–303. doi:10.1093/biomet/65.2.297CrossRefGoogle Scholar

8. Suhartono. 2011. "Time Series Forecasting by Seasonal Autoregressive Integrated Moving Average Models: Subset, Multiplicative or Additive". *Journal of Mathematics and Statistics*. 7(1): 20-27. DOI : 10.3844/jmssp.2011.20.27.

9. Yusof, F. and I.L. Kane. 2013. "Volatility Modeling of Rainfall Time Series". *Journal of Theoretical and Applied Climatology*. 113(1-2):247-258.

Appendix

AIC CASE

ARIMA(2,1,2)(1,1,1)[12]	: 1550.908
ARIMA(0,1,0)(0,1,0)[12]	: 1611.219
ARIMA(1,1,0)(1,1,0)[12]	: 1552.072
ARIMA(0,1,1)(0,1,1)[12]	: 1551.277
ARIMA(2,1,2)(0,1,1)[12]	: 1553.033
ARIMA(2,1,2)(1,1,0)[12]	: 1549.484
ARIMA(3,1,2)(1,1,0)[12]	: 1548.6
ARIMA(2,1,1)(1,1,0)[12]	: 1547.319
ARIMA(2,1,1)(0,1,0)[12]	: 1564.521
ARIMA(2,1,1)(2,1,1)[12]	: 1551.143
ARIMA(1,1,1)(1,1,0)[12]	: 1545.861
ARIMA(1,1,1)(0,1,0)[12]	: 1569.297
ARIMA(0,1,1)(1,1,0)[12]	: 1546.397

Best model: ARIMA(1,1,1)(1,1,0)[12]

```
ARIMA(2,1,2)(1,1,1)[12]                    : 1565.45
ARIMA(0,1,0)(0,1,0)[12]                    : 1613.296
ARIMA(1,1,0)(1,1,0)[12]                    : 1558.304
ARIMA(0,1,1)(0,1,1)[12]                    : 1557.51
ARIMA(0,1,1)(0,1,0)[12]                    : 1578.197
ARIMA(0,1,1)(0,1,2)[12]                    : 1556.511
ARIMA(1,1,1)(0,1,2)[12]                    : 1558.626
ARIMA(0,1,0)(0,1,2)[12]                    : Inf
ARIMA(0,1,2)(0,1,2)[12]                    : 1558.296
ARIMA(1,1,2)(0,1,2)[12]                    : 1562.365
ARIMA(0,1,1)(1,1,2)[12]                    : 1559.779

Best model: ARIMA(0,1,1)(0,1,2)[12]
```

KPSS WITH AIC AND BIC AFTER TRANSFORMING THE 7UP PRODUCTION VOLUME DATA SETS

```
ARIMA(2,0,2)(1,0,1)[12] with non-zero mean : Inf
ARIMA(0,0,0) with non-zero mean : 2047.204
ARIMA(1,0,0)(1,0,0)[12] with non-zero mean : 1980.512
ARIMA(0,0,1)(0,0,1)[12] with non-zero mean : Inf
ARIMA(0,0,0) with zero mean     : 2045.21
ARIMA(1,0,0) with non-zero mean : 1981.361
ARIMA(1,0,0)(1,0,1)[12] with non-zero mean : 1985.232
ARIMA(0,0,0)(1,0,0)[12] with non-zero mean : 2046.896
ARIMA(2,0,0)(1,0,0)[12] with non-zero mean : 1930.636
ARIMA(2,0,1)(1,0,0)[12] with non-zero mean : Inf
ARIMA(3,0,1)(1,0,0)[12] with non-zero mean : Inf
ARIMA(2,0,0)(1,0,0)[12] with zero mean     : 1928.638
ARIMA(2,0,0) with zero mean     : 1928.474
ARIMA(2,0,0)(0,0,1)[12] with zero mean     : 1929.065
ARIMA(2,0,0)(1,0,1)[12] with zero mean     : 1929.786
ARIMA(1,0,0) with zero mean     : 1979.364
ARIMA(3,0,0) with zero mean     : 1893.781
ARIMA(3,0,1) with zero mean     : Inf
ARIMA(4,0,1) with zero mean     : Inf
ARIMA(3,0,0) with non-zero mean : 1895.78
ARIMA(3,0,0)(1,0,0)[12] with zero mean     : 1892.321
ARIMA(3,0,0)(1,0,1)[12] with zero mean     : 1893.922
ARIMA(4,0,0)(1,0,0)[12] with zero mean     : 1891.31
ARIMA(4,0,1)(1,0,0)[12] with zero mean     : Inf
ARIMA(5,0,1)(1,0,0)[12] with zero mean     : Inf
ARIMA(4,0,0)(1,0,0)[12] with non-zero mean : 1893.304
ARIMA(4,0,0) with zero mean     : 1892.896
ARIMA(4,0,0)(1,0,1)[12] with zero mean     : 1892.779
ARIMA(5,0,0)(1,0,0)[12] with zero mean     : 1867.67
ARIMA(5,0,0)(1,0,0)[12] with non-zero mean : 1869.669
ARIMA(5,0,0) with zero mean     : 1869.65
ARIMA(5,0,0)(1,0,1)[12] with zero mean     : 1868.364

Best model: ARIMA(5,0,0)(1,0,0)[12] with zero mean
```

ARIMA (1, 1, 1) (1, 1, 0) [12]

```
  Point Forecast       Lo 80     Hi 80       Lo 95     Hi 95
Jan 2016        452334.7  316452.126  588217.3  244520.231  660149.2
```

Feb 2016	574749.1	437475.313	712022.9	364806.956	784691.3
Mar 2016	392488.1	243632.060	541344.2	164832.410	620143.9
Apr 2016	318798.5	163256.498	474340.4	80917.559	556679.4
May 2016	336311.6	173177.655	499445.5	86819.776	585803.4
Jun 2016	651727.7	481719.719	821735.7	391722.935	911732.4
Jul 2016	536488.1	359754.811	713221.4	266197.844	806778.4
Aug 2016	623851.4	440677.030	807025.9	343710.353	903992.5
Sep 2016	404741.7	215333.210	594150.1	115066.433	694416.9
Oct 2016	614116.8	418676.849	809556.8	315217.174	913016.5
Nov 2016	652497.2	451205.145	853789.3	344647.568	960346.8
Dec 2016	566508.9	359530.583	773487.3	249962.860	883055.0
Jan 2017	513773.1	287151.240	740395.0	167184.860	860361.4
Feb 2017	548182.2	315096.630	781267.7	191708.593	904655.8
Mar 2017	341554.0	99066.132	584041.8	-29299.178	712407.1
Apr 2017	319192.7	68698.218	569687.2	-63905.564	702291.0
May 2017	263132.0	4554.047	521710.0	-132328.865	658592.9
Jun 2017	425630.6	159318.153	691943.1	18340.857	832920.4
Jul 2017	589230.5	315368.937	863092.0	170395.408	1008065.5
Aug 2017	491241.9	210044.380	772439.4	61187.423	921296.3
Sep 2017	457349.2	168998.988	745699.5	16355.596	898342.8
Oct 2017	624028.6	328699.914	919357.4	172362.332	1075694.9
Nov 2017	636677.2	334530.810	938823.6	174584.158	1098770.3
Dec 2017	695319.4	386505.870	1004132.9	223029.864	1167608.9
Jan 2018	527857.2	175384.418	880329.9	-11203.392	1066917.8
Feb 2018	621705.4	260478.477	982932.2	69256.517	1174154.2
Mar 2018	431534.9	54287.320	808782.4	-145415.473	1008485.2
Apr 2018	374506.2	-15526.747	764539.2	-221997.726	971010.2
May 2018	368137.5	-35069.568	771344.6	-248514.514	984789.6
Jun 2018	633917.2	218207.482	1049626.9	-1855.937	1269690.3
Jul 2018	609187.9	181260.155	1037115.6	-45271.098	1263646.9
Aug 2018	636386.6	196605.867	1076167.4	-36200.009	1308973.3
Sep 2018	477397.7	26066.854	928728.5	-212853.246	1167648.6
Oct 2018	672913.9	210323.996	1135503.9	-34556.332	1380384.2
Nov 2018	702941.9	229359.556	1176524.2	-21339.781	1427223.5
Dec 2018	663900.1	179575.128	1148225.1	-76811.040	1404611.3
Jan 2019	573924.5	62048.405	1085800.7	-208922.453	1356771.5
Feb 2019	627627.3	103926.978	1151327.7	-173303.237	1428557.9
Mar 2019	426341.2	-112930.112	965612.6	-398403.118	1251085.6
Apr 2019	392727.1	-160341.655	945795.8	-453118.551	1238572.7
May 2019	352796.2	-214154.394	919746.8	-514279.917	1219872.3
Jun 2019	548819.5	-31546.174	1129185.1	-338773.180	1436412.1
Jul 2019	651288.3	57767.735	1244808.9	-256423.095	1558999.8
Aug 2019	593935.1	-12441.342	1200311.6	-333437.648	1521307.9
Sep 2019	519436.7	-99533.121	1138406.4	-427195.928	1466069.2
Oct 2019	695476.4	64165.897	1326786.9	-270029.703	1660982.5
Nov 2019	713766.3	70351.217	1357181.3	-270252.140	1697784.7
Dec 2019	740700.6	85404.699	1395996.5	-261487.995	1742889.2
Jan 2020	598390.3	-91812.854	1288593.4	-457184.313	1653964.8
Feb 2020	679207.4	-24556.186	1382971.0	-397106.118	1755520.9
Mar 2020	485428.8	-237056.384	1207914.0	-619516.949	1590374.6
Apr 2020	436000.4	-302909.244	1174910.1	-694064.393	1566065.2
May 2020	418737.6	-336813.364	1174288.5	-736777.874	1574253.0
Jun 2020	661874.5	-109774.090	1433523.2	-518260.203	1842009.3
Jul 2020	678433.3	-109043.136	1465909.8	-525907.990	1882774.6
Aug 2020	678186.8	-124786.555	1481160.2	-549854.977	1906228.6
Sep 2020	546623.2	-271559.743	1364806.0	-704679.605	1797925.9
Oct 2020	735817.4	-97295.423	1568930.3	-538318.724	2009953.6
Nov 2020	762035.2	-85745.325	1609815.8	-534533.234	2058603.7
Dec 2020	744409.1	-117789.481	1606607.6	-574209.820	2063027.9

ARIMA (0, 1, 1) (0, 1, 2) [12]

Point Forecast		Lo 80	Hi 80	Lo 95	Hi 95
Jan 2016	470945.0	336475.72	605414.4	265291.960	676598.1
Feb 2016	587055.0	448795.87	725314.1	375605.922	798504.0
Mar 2016	386373.6	244425.88	528321.4	169283.277	603464.0
Apr 2016	319294.5	173751.52	464837.4	96705.740	541883.2
May 2016	329034.1	179982.68	478085.5	101079.622	556988.6
Jun 2016	637731.0	485251.81	790210.2	404534.190	870927.9
Jul 2016	504258.9	348427.28	660090.5	265935.004	742582.8
Aug 2016	560912.6	401799.22	720026.0	317569.667	804255.6
Sep 2016	407284.5	244955.64	569613.4	159023.932	655545.1
Oct 2016	560247.8	394765.97	725729.7	307165.169	813330.5
Nov 2016	572377.8	403801.98	740953.7	314563.303	830192.4
Dec 2016	581483.2	409869.08	753097.3	319022.052	843944.3
Jan 2017	473189.2	293557.05	652821.3	198465.552	747912.8
Feb 2017	562563.8	379165.47	745962.1	282080.268	843047.3
Mar 2017	309220.1	122131.39	496308.8	23092.616	595347.6
Apr 2017	277240.4	86532.72	467948.1	-14421.830	568902.7
May 2017	253050.2	58790.88	447309.4	-44043.769	550144.1
Jun 2017	522342.9	324595.81	720090.0	219914.828	824771.0
Jul 2017	553216.3	352041.85	754390.7	245546.533	860886.0
Aug 2017	528381.1	323836.77	732925.5	215557.528	841204.8
Sep 2017	368805.5	160945.80	576665.1	50911.540	686699.4
Oct 2017	603599.0	392476.07	814721.9	280714.352	926483.6
Nov 2017	628104.5	413768.03	842441.0	300305.153	955903.9
Dec 2017	619047.1	401544.56	836549.7	286405.653	951688.6
Jan 2018	484865.7	233988.74	735742.8	101182.470	868549.0
Feb 2018	574240.4	316742.24	831738.5	180430.966	968049.8
Mar 2018	320896.7	56943.48	584849.9	-82784.905	724578.3
Apr 2018	288917.0	18662.87	559171.2	-124401.033	702235.1
May 2018	264726.8	-11684.73	541138.2	-158008.136	687461.6
Jun 2018	534019.5	251584.87	816454.1	102073.005	965966.0
Jul 2018	564892.9	276560.90	853224.9	123927.173	1005858.6
Aug 2018	540057.7	245946.64	834168.8	90253.625	989861.8
Sep 2018	380482.1	80703.23	680260.9	-77990.096	838954.2
Oct 2018	615275.6	309934.20	920617.0	148296.241	1082254.9
Nov 2018	639781.1	328976.73	950585.5	164446.823	1115115.4
Dec 2018	630723.7	314550.72	946896.7	147178.837	1114268.6
Jan 2019	496542.3	148268.89	844815.8	-36095.936	1029180.6
Feb 2019	585917.0	228788.87	943045.0	39736.674	1132097.2
Mar 2019	332573.3	-33195.16	698341.7	-226821.279	891967.8
Apr 2019	300593.6	-73615.73	674802.9	-271710.189	872897.4
May 2019	276403.3	-106060.64	658867.3	-308524.851	861331.5
Jun 2019	545696.1	155151.88	936240.3	-51589.743	1142981.9
Jul 2019	576569.5	178108.86	975030.1	-32823.448	1185962.4
Aug 2019	551734.3	145511.56	957957.1	-69529.784	1172998.4
Sep 2019	392158.7	-21680.70	805998.0	-240754.027	1025071.3
Oct 2019	626952.2	205633.89	1048270.5	-17398.532	1271302.9
Nov 2019	651457.7	222790.97	1080124.4	-4131.493	1307046.9
Dec 2019	642400.3	206509.00	1078291.7	-24237.927	1309038.6
Jan 2020	508218.9	41412.03	975025.8	-205700.623	1222138.5
Feb 2020	597593.6	120187.92	1074999.2	-132535.358	1327722.5
Mar 2020	344249.9	-143524.24	832024.0	-401736.263	1090236.0
Apr 2020	312270.2	-185656.54	810196.9	-449243.029	1073783.4
May 2020	288079.9	-219796.50	795956.4	-488650.051	1064809.9
Jun 2020	557372.7	39737.74	1075007.6	-234281.641	1349027.0
Jul 2020	588246.1	61033.23	1115458.9	-218056.393	1394548.5
Aug 2020	563410.9	26791.11	1100030.7	-257278.266	1384100.1
Sep 2020	403835.3	-142029.46	949700.0	-430992.775	1238663.3
Oct 2020	638628.8	83673.16	1193584.4	-210102.591	1487360.1
Nov 2020	663134.3	99234.33	1227034.3	-199276.279	1525544.9
Dec 2020	654076.9	81372.27	1226781.6	-221799.263	1529953.1

ARIMA (5, 0, 0) (1, 0, 0) [12]

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Nov 2014	-380187.845	-521257.03481	-239118.65	-595934.6	-164441.1
Dec 2014	47922.008	-223504.50205	319348.52	-367189.0	463033.0
Jan 2015	230993.611	-77515.06275	539502.29	-240829.7	702816.9
Feb 2015	-292234.297	-604311.93947	19843.35	-769515.9	185047.3
Mar 2015	203961.499	-108192.12838	516115.13	-273436.3	681359.3
Apr 2015	145338.961	-168148.99935	458826.92	-334099.5	624777.4
May 2015	-618772.702	-933222.91507	-304322.49	-1099682.8	-137862.6
Jun 2015	609550.540	292020.57266	927080.51	123930.4	1095170.7
Jul 2015	-400130.523	-730473.20704	-69787.84	-905346.1	105085.0
Aug 2015	166219.939	-172644.88514	505084.76	-352029.1	684469.0
Sep 2015	83609.988	-257918.15506	425138.13	-438712.2	605932.2
Oct 2015	-267817.104	-609535.69810	73901.49	-790430.6	254796.4
Nov 2015	218188.703	-138760.64381	575138.05	-327718.2	764095.6
Dec 2015	6184.316	-385105.14815	397473.78	-592241.3	604609.9
Jan 2016	-158679.926	-558248.98481	240889.13	-769768.1	452408.2
Feb 2016	153915.772	-245669.20984	553500.75	-457196.7	765028.3
Mar 2016	-69074.389	-469940.09599	331791.32	-682145.6	543996.8
Apr 2016	-141953.130	-545372.59059	261466.33	-758930.0	475023.7
May 2016	404171.007	-86.09273	808428.11	-214086.9	1022428.9
Jun 2016	-369494.195	-775155.21755	36166.83	-989899.2	250910.8
Jul 2016	223292.637	-187937.38120	634522.65	-405629.4	852214.7
Aug 2016	-82664.221	-496770.47910	331442.04	-715985.1	550656.6
Sep 2016	-50455.130	-464904.02750	363993.77	-684300.0	583389.8
Oct 2016	142675.715	-271865.35984	557216.79	-491310.1	776661.6
Nov 2016	-105250.147	-526988.21290	316487.92	-750242.9	539742.6
Dec 2016	-24162.638	-458725.11385	410399.84	-688768.6	640443.3
Jan 2017	102255.910	-334878.36775	539390.19	-566283.3	770795.1
Feb 2017	-86558.372	-523772.81803	350656.07	-755220.2	582103.4
Mar 2017	31366.685	-406483.63029	469217.00	-638267.6	701001.0
Apr 2017	90048.614	-348593.95376	528691.18	-580797.3	760894.5
May 2017	-238331.422	-677084.15728	200421.31	-909345.8	432683.0
Jun 2017	211031.822	-228614.94050	650678.58	-461349.9	883413.5
Jul 2017	-122832.034	-564883.81028	319219.74	-798891.9	553227.8
Aug 2017	43564.203	-399520.01050	486648.42	-634074.6	721203.0
Sep 2017	29488.321	-413662.49634	472639.14	-648252.4	707229.0
Oct 2017	-80832.417	-524059.13061	362394.30	-758689.2	597024.3
Nov 2017	59032.023	-386750.89247	504814.94	-622734.1	740798.2
Dec 2017	14800.199	-435173.57728	464773.98	-673375.3	702975.7
Jan 2018	-57638.110	-508304.64862	393028.43	-746873.1	631596.9
Feb 2018	46525.338	-404215.86781	497266.54	-642823.8	735874.5
Mar 2018	-14804.438	-465811.57856	436202.70	-704560.3	674951.5
Apr 2018	-54898.547	-506161.43917	396364.34	-745045.6	635248.5
May 2018	141218.845	-310065.06972	592502.76	-548960.3	831398.0
Jun 2018	-124156.291	-575797.50639	327484.92	-814881.9	566569.3
Jul 2018	72507.589	-379971.06605	524986.24	-619498.8	764514.0
Aug 2018	-27020.335	-479812.31780	425771.65	-719505.9	665465.2
Sep 2018	-15379.554	-468181.41936	437422.31	-707880.2	677121.1
Oct 2018	46213.986	-406626.94799	499054.92	-646346.5	738774.4
Nov 2018	-34365.290	-488112.64907	419382.07	-728312.0	659581.4
Dec 2018	-8465.179	-463647.39894	446717.04	-704606.3	687676.0
Jan 2019	33377.900	-422027.12331	488782.92	-663104.0	729859.8
Feb 2019	-26935.320	-482369.91307	428499.27	-723462.4	669591.8
Mar 2019	8813.246	-446708.66032	464335.15	-687847.4	705473.9
Apr 2019	32110.914	-423488.13411	487709.96	-664667.7	728889.5
May 2019	-83588.036	-539191.37847	372015.31	-780373.2	613197.1
Jun 2019	73713.160	-382023.04668	529449.37	-623275.2	770701.5
Jul 2019	-43426.158	-499454.09403	412601.78	-740860.7	654008.4
Aug 2019	16694.300	-439437.14158	472825.74	-680898.5	714287.1
Sep 2019	8637.675	-447496.33737	464771.69	-688959.1	706234.4
Oct 2019	-27463.801	-483611.50582	428683.90	-725081.5	670153.9

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