

# Application of Quantitative Forecasting Models in a Manufacturing Industry

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## Abstract

Time series forecasting analysis has become a major tool in different applications for the Manufacturing Company. Among the most effective approaches for analyzing time series data is ARIMA (Autoregressive Integrated Moving Average). In this study we used Box-Jenkins methodology to build ARIMA model for annual sales forecast for 7up Bottling Company Plc for the period from January 2010 to December 2015, given the available monthly sales data. After the model specification; the best model for production was ARIMA (1, 1, 1) and for utilization was ARIMA (0, 1, 1). A 12 months forecast have also been made to determine the expected amount of sales revenue in year 2016. The time plot reveals seasonal variation. It thus concludes that that there is increase in sales revenue of Company with time, hence these models can be adopted for sales, production, utilization and demand forecasting in Nigeria,

**Keywords:** ARIMA, Box-Jenkins, forecasting, production and utilization model, Time series analysis,

## 1. Introduction

Business forecasting is defined as a management tool that aims at predicting the uncertainties of business trends in order for managers to make better decisions (Hanke & Wichern, 2005). A quantitative approach to business forecasting relies heavily on statistics and the manipulation of historical data. Quantitative forecasting has been studied extensively in the last decades, and various methods on how to manipulate and interpret data have been proposed. Quantitative forecasting methods have been found to produce more accurate forecasts than judgemental, or qualitative forecasts (Pant & Starbuck, 1990). However, despite the advanced computers we have today, and the constant development of quantitative models and methods, most scholars emphasises the involvement of logic thinking and judgemental adjustment to quantitative forecasts (Pant & Starbuck, 1990; Hanke & Wichern, 2005).

There is a scarcity of resources within all firms, and companies cannot undertake all projects. Researchers studying business forecasting rarely take this fact into account, as the methods researchers construct tend to become more and more advanced, and thus more costly (Makridakis & Hibon, 2000). The risk associated to researchers not taking the boundaries of resource-reality of actual firms into consideration might be that the research becomes focused on forecasting methods that have few practical implications, as they are too expensive and too difficult to implement in actual firms. As the actual definition of business forecasting is rather practical, one might also argue that the scholarly community is moving away from the actual object the community claims to be studying.

This research exclusively deals with time series forecasting model, in particular, the Auto Regressive Integrated Moving Average (ARIMA) in describing and evaluating the trends of sales of Seven-Up Bottling Company PLC, Nigeria.

Seven-Up Bottling Company PLC was incorporated as a private company limited by shares on the 25<sup>th</sup> of June 1959 under the name 'Seven-Up Limited' after obtaining franchise to bottle and distribute 7Up beverage from Seven-Up International Inc. The Company commenced operations on 1<sup>st</sup> of October 1960 with the first bottle of 7Up coming off the production line at its Ijora Plant on the same date which coincidentally was also the date Nigeria gained independence from Britain. The company has come a long way from being a one plant business to that which currently operates 9 plants located in Aba, Abuja, Benin, Enugu, Ibadan, Ikeja, Ilorin, Kaduna and Kano. These plants support various distribution centres across the country. In a bid to widen its distribution network, the Company exports its products to the West African sub-region which products continue to enjoy increase loyalty in the market. The Company's brands: Pepsi, 7Up, Mirinda Orange, Mirinda Pinepple, Mountain Dew, Teem Bitter Lemon, Teem Tonic, Teem Soda and Aquafina. Table water are produced in conformity with International standards. In line with modern trends and market demand, the Company also package its products in PET and Can, this thus justify the choice of the case study.

## 2. Conceptual clarification

### 2.1 Background and history of Business Forecasting

When business forecasting was introduced as a subject of academic interest, the method used most widely within

the business sector was exponential smoothing methods. A practitioner, Robert G. Brown, introduced the methods in the late 50s (Lapide, 2009). These exponential smoothing methods still live on today. Later, more advanced methods taking seasonality and trend into account were brought forward in the 60's and 70's by scholars such as Holt (trend) and Winter (seasonality and trend) (Lapide, 2009).

As managers later understood that actions such as promotional activities, competitor action and product introduction would shape and create demand, these variables needed to be understood and incorporated into the forecasts. One method to incorporate explanatory variables was the ARIMA-model. Pioneers within the field of ARIMA-models were statisticians George Box and Gwilym Jenkins who 1970 created the Box-Jenkins methodology to find the best fit of a model in order to forecast (Lapide, 2009). With the introduction of computers, more advanced forecasting measures has emerged. In the latest of the M-competitions, were different forecasting methods are compared, seven (out of 24) were software-run commercially available packages (Makridakis & Hibon, 2000).

## 2.2 Quantitative forecasts

The features of quantitative forecasting models vary greatly, as they have been developed for different purposes. The results are a number of techniques varying both in complexity and structure. However, a common notion is that quantitative forecasts can be applied when three conditions are met (Makridakis, et al., 1998):

1. There is information about the past
2. The information can be quantified
3. It can be assumed that the past pattern will reflect the future pattern.

Once it has been specified that the data available respond well to the three conditions above, the actual recognition of an appropriate forecasting technique can begin. This is mainly done by initially investigating the data, a task known as *Decomposition* (Hanke & Wichern, 2005)

### 2.2.1 Decomposition

Quantitative forecasting methods are based on the concept that patterns in historical data exist, and that this pattern can be used when predicting future sales (Makridakis, et al., 1998). Most of the forecasting methods break down the pattern into components, where every component is analysed separately. This breakdown of pattern is also called the *decomposition* of a pattern. Decomposition is usually divided as follows:

$$Y_t = f(T_t, S_t, E_t) \quad (1)$$

Where:

$Y_t$  = the time series value at period  $t$ ;  $S_t$  = the seasonal component at period  $t$ ;  $T_t$  = the trend-cycle component at period  $t$ ;  $E_t$  = the error component at time  $t$

The method that calculates the time series value can have an additive or a multiplicative form. The additive form is appropriate when the magnitude of the seasonal fluctuations does not vary with the level of the series. The multiplicative form is thus appropriate when seasonal fluctuations increase and decrease with the level of the series.

The additive decomposition equation has the form:  $Y_t = T_t + S_t + E_t$  (2)

While the multiplicative decomposition has the for  $Y_t = T_t \times S_t \times E_t$  (3)

### 2.2.2 Seasonally Adjusted Data

Seasonally Adjusted Data can be can easily be calculated by subtracting the seasonal component from the additive formula, or by dividing it from the multiplicative formula. Calculating the seasonal component can be done in many ways, and involves comparing seasonal data to the average value. For example, if the average value over a year is 100, while the value for January is 150, the seasonal component is 50 for an additive approach, and 1.50 for a multiplicative approach. Once the data has been seasonally adjusted, only the trend-cycle and irregular components remain. Most economic time-series are seasonally adjusted as seasonality variations are generally not of primary interest. When the seasonally adjusted component has been removed, it is easier to compare values to each other.

### 2.2.3 Trend adjusted data

Trend-cycle components can be calculated by excluding the seasonality and irregular component. There are many different methods to identify a trend-cycle but the basic idea is to eliminate the irregular component from a series (as the seasonality component has already been removed – see above) by smoothing historical data. The simplest and oldest trend-cycle analysis model is the moving average model. There are several different moving average models such as simple moving average, double moving average and weighted moving average (Makridakis, et al., 1998)

### 2.2.4 Error adjusted data

Simple moving average assumes that observations that are adjacent in time are likely to be close in value. Through a smooth trend-cycle component, simple moving average will eliminate some of the randomness that occurs (Makridakis, et al., 1998).

When using simple moving average the first thing to be decided is the order of the moving average.

Order means how many different checkpoints to use in the analysis. Common orders to use are 3 or 5. The more order of numbers included, the smoother forecast you get. The likelihood of randomness in the data will also be eliminated with a large number of orders. Simple moving average can be used for any odd order. Order is defined as  $k$ , and the trend cycle component by the use of simple moving average is computed as:

$$T_t = \frac{1}{k} \sum_{j=-m}^m Y_{t+j} \quad (4)$$

where  $m = (k - 1)/2$

$t$  is the period which trend component is estimated, and  $t$  is also the centred number. This means that in a three-order average, the third  $Y_3$  is the period that follows the period that is being measured. Every new calculation drops the oldest number and include a new number, that why that is called moving average. Because of this, it is not possible to calculate the trend-cycle in the beginning and in the end of a time series. To overcome this problem a shorter length moving average can be used in the initiating phase, which means that the first number can be estimated by using an average of  $m$ .

#### 2.2.5 Autocorrelation

Another way to decompose a data series is to perform an autocorrelation analysis. Autocorrelation analysis allows you to investigate patterns in the data by studying the autocorrelation coefficients. The coefficient shows the *correlation* between a variable lagged a number of periods and itself. The autocorrelation can be used to answer four questions regarding patterns in a time series (Hanke & Wichern, 2005):

1. Is the data random?
2. Do the data have a trend?
3. Is the data stationary?
4. Is the data seasonal?

The autocorrelation coefficient ( $r_k$ ) is computed as:

$$r_k = \frac{\sum_{i=k+1}^n (Y_i - \text{mean}(Y)) (Y_{i-k} - \text{mean}(Y))}{\sum_{i=1}^n (Y_i - \text{mean}(Y))^2} \quad (5)$$

Where  $k$  is the lag and  $Y$  is the observed value.

If  $r_k$  is close to zero, the series can be assumed to be random. That means that for any lag  $k$  the series are not related to each other.

If  $r_k$  is significantly different from zero for the first time lags and then slowly drop towards zero as the number of lags increases, the series can be assumed to have a trend.

If  $r_k$  reappears in cycles, the series can be assumed to have a seasonal pattern. The coefficient will reoccur in a pattern as for example four or twelve lags. A seasonal lag of four means that the data-series is quarterly, while a significant value twelve means that the series is yearly.

The definition of *autocorrelation close to zero* is that the distribution of the autocorrelation coefficient is approximated as a normal distribution with a mean of zero and has an approximated standard deviation of  $1/\sqrt{n}$  (Hanke & Wichern, 2005). To calculate the critical values, Makridakis et. al. (1998) propose to use a 95% confidence interval, meaning that 95% of all samples of autocorrelations coefficients will be within  $\pm 1.96/\sqrt{n}$  for the series to be counted as *close to zero*.

#### 2.2.6 Identifying outliers

An important aspect of setting up a quantitative forecasting model is that of identifying outliers. Outliers are values outside a lower and upper limit (Typically 95% confidence interval around the mean of the data set) that depend on an external factor. In business forecasting, an outlier usually means that seasonal factors (such as the end of a budget year, or vacations) or single events (large tender orders from a big company) for a specific month/week/day affect the order intake heavily. The extreme value in order intake will not reflect normal demand, and should therefore not be considered when setting up quantitative forecasting models (Hanke & Wichern, 2005).

Consider a firm that has a price increase in December each year. The price increase makes the demand for the company's product increase by 200% in November. If the November value should be used when forecasting future demand, the forecast will be too high, as future demand will depend on a data set that doesn't reflect normal demand. Researchers have identified numerous ways of identifying outliers. Two methods are called trimming and winsorizing. When trimming data, the top and bottom values are excluded determined by a fixed value in per cent. For example, a 10 per cent trimming means that the top 5 percent and the bottom 5 percent are discarded from the data set. Winsorizing is similar to trimming, but it replaces extreme values instead of discarding them. A 10 per cent winsorization means that the data below the 5th percentile of the data is set to the 5th percentile and the values above the 95th percentile is set to the 95th percentile (Jose & Winkler, 2008).

A major factor influencing the selection of forecasting method is what pattern that can be identified within the data. Depending on characteristics such as seasonality, trend and cyclical patterns in the data series, different models are better optimized to deal with the patterns found in the data. The concept of choosing a

forecasting method is based on trial and error (Hanke & Wichern, 2005). The trial is set up by applying historical data to a forecasting model to measure how accurate the model would have forecasted. The forecasting method that produces the most accurate and the one with the least error will be used for the future (Hanke & Wichern, 2005).

### 2.3 Overview of Auto Regressive Integrated Moving Average (ARIMA)

The ARIMA procedure analyzes and forecasts equally spaced univariate time series data, transfer function data, and intervention data by using the autoregressive integrated moving-average (ARIMA) or autoregressive moving-average (ARMA) model. An ARIMA model predicts a value in a response time series as a linear combination of its own past values, past errors (also called shocks or innovations), and current and past values of other time series. The ARIMA approach was first popularized by Box and Jenkins, and ARIMA models are often referred to as Box-Jenkins models. The general transfer function model employed by the ARIMA procedure was discussed by Box and Tiao (1975). When an ARIMA model includes other time series as input variables, the model is sometimes referred to as an ARIMAX model. Pankratz (1991) refers to the ARIMAX model as dynamic regression

The ARIMA procedure provides a comprehensive set of tools for univariate time series model identification, parameter estimation, and forecasting, and it offers great flexibility in the kinds of ARIMA or ARIMAX models that can be analyzed. The ARIMA procedure supports seasonal, subset, and factored ARIMA models; intervention or interrupted time series models; multiple regression analysis with ARMA errors; and rational transfer function models of any complexity. The ARIMA class of time series models is complex and powerful, and some degree of expertise is needed to use them correctly.

## 3. Materials and Methods

This research exclusively deals with time series forecasting model, in particular, the Auto Regressive Integrated Moving Average (ARIMA). These models were described by Box and Jenkins (Box and Jenkins, 1976) and further discussed in some other resources (Walter, 1983; Chatfield, 1996 and Montgomery, and Johnson, 1967) such as: The Box-Jenkins approach which possesses many appealing features. It allows the manager who has only data on past years' quantities, rainfall as an example, to forecast future ones without having to search for other related time series data, for example temperature. Box-Jenkins approach also allows for the use of several time series, for example temperature, to explain the behavior of another series, for example rainfall, if these other time series data are correlated with a variable of interest and if there appears to be some cause for this correlation; Box-Jenkins (ARIMA) modelling has been successfully applied in various water and environmental management applications.

The main stages in setting up a forecasting ARIMA model includes model identification, model parameters estimation and diagnostic checking for the identified model appropriateness for modeling and forecasting. Model Identification is the first step of this process. The data was examined to check for the most appropriate class of ARIMA processes through selecting the order of the consecutive and seasonal differencing required to make series stationary, as well as specifying the order of the regular and seasonal auto regressive and moving average polynomials necessary to adequately represent the time series model. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) are the most important elements of time series analysis and forecasting. The ACF measures the amount of linear dependence between observations in a time series that are separated by a lag  $k$ . The PACF plot helps to determine how many auto regressive terms are necessary to reveal one or more of the following characteristics: time lags where high correlations appear, seasonality of the series, trend either in the mean level or in the variance of the series. The general model introduced by Box and Jenkins includes autoregressive and moving average parameters as well as differencing in the formulation of the model. The three types of parameters in the model are: the autoregressive parameters ( $p$ ), the number of differencing passes ( $d$ ) and moving average parameters ( $q$ ). Box-Jenkins model are summarized as ARIMA ( $p, d, q$ ). For example, a model described as ARIMA (1,1,1) means that this contains 1 autoregressive ( $p$ ) parameter and 1 moving average ( $q$ ) parameter for the time series data after it was differenced once to attain stationary. In addition to the non-seasonal ARIMA ( $p, d, q$ ) model, introduced above, we could identify seasonal ARIMA ( $P, D, Q$ ) parameters for our data. These parameters are: Seasonal autoregressive ( $P$ ), seasonal Differencing ( $D$ ) and seasonal moving average ( $Q$ ). For example, ARIMA (1,1,1)(1,1,1) 12 describes a model that includes 1 autoregressive parameter, 1 moving average parameter, 1 seasonal autoregressive parameter and 1 seasonal moving average parameter.

These parameters were computed after the series was differenced once at lag 1 and differenced once at lag 12.

This model can be multiplied out and used for forecasting after the model parameters were estimated, as we discussed below. After choosing the most appropriate model (step 1 above) the model parameters are estimated (step 2) by using the least square method. In this step, values of the parameters are chosen to make the

Sum of the Squared Residuals (SSR) between the real data and the estimated values as small as possible. In general, nonlinear estimation method is used to estimate the above identified parameters to maximize the likelihood (probability) of the observed series given the parameter values. The methodology uses the following criteria in parameter estimation:

The estimation procedure stops when the change in all parameters estimate between iterations reaches a minimal change of 0.001. The parameters estimation procedure stops when the SSR between iterations reaches a minimal change of 0.0001

In diagnose checking step (step three), the residuals from the fitted model shall be examined against adequacy. This is usually done by correlation analysis through the residual ACF plots and the goodness-of-fit test by means of Chi-square statistics. If the residuals are correlated, then the model should be refined as in step one above. Otherwise, the autocorrelations are white noise and the model is adequate to represent our time series. After the application of the previous procedure for a given time series, a calibrated model will be developed which has enclosed the basic statistical properties of the time series into its parameters (step four). For example, the developed model, as shown in (1) above can be multiplied out and the general model is written in terms of  $X_t$ .

Time series Model Builder (Time Series Modeler) of SPSS was used to obtain the appropriate model for the Time Series Data (Sales of Seven-Up Bottling Company PLC). The Time Series Modeler procedure estimates exponential smoothing, univariate Autoregressive Integrated Moving Average (ARIMA), and produces forecast values. The procedure automatically identifies and estimates the best-fitting ARIMA or exponential smoothing model for the series. This eliminates the need to identify an appropriate model through trial and error.

In common models for time series data can have many forms and stand for different stochastic processes. There are two commonly used linear time series models in literature, viz. Autoregressive (AR) and Moving Average (MA) models. Combining these two, the Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models have been proposed in literature. The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model generalizes ARMA and ARIMA models. For seasonal time series forecasting, a variation of ARIMA, viz. the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is used.

ARIMA model and its different variations are based on the well known Box-Jenkins principle and so these are also broadly known as the Box-Jenkins models. An ARIMA (p, q, d) model is a combination of AR(p), I(d) and MA(q) models and is suitable for univariate time series modeling. In an AR (p) model the future value of a variable is assumed to be a linear combination of p past observations and a random error mutually with a constant term.

## 4 Results and Discussion

### 4.1 Results

Since the data is a monthly production and utilization, Fig. 1, shows that there is a seasonal cycle of the series and the series is not stationary. The ACF and PACF of the original data, as shown in Fig. 3 and 4, depicts that the sales and utilization data is not stationary. In order to fit an ARIMA model, stationary data in both variance and mean are needed. Stationarity in the variance could be attained by having log transformation and differencing of the original data to attain stationary in the mean. For our data, we need to have seasonal first difference,  $d = 1$ , of the original data in order to have stationary series. After that, we need to test the ACF and PACF for the differenced series to check stationary.

#### Sequence Plot

**Table 1: Case Processing Summary**

	7-UP
Series or Sequence Length	72
Number of Missing Values in User-Missing the Plot	0
System-Missing	0

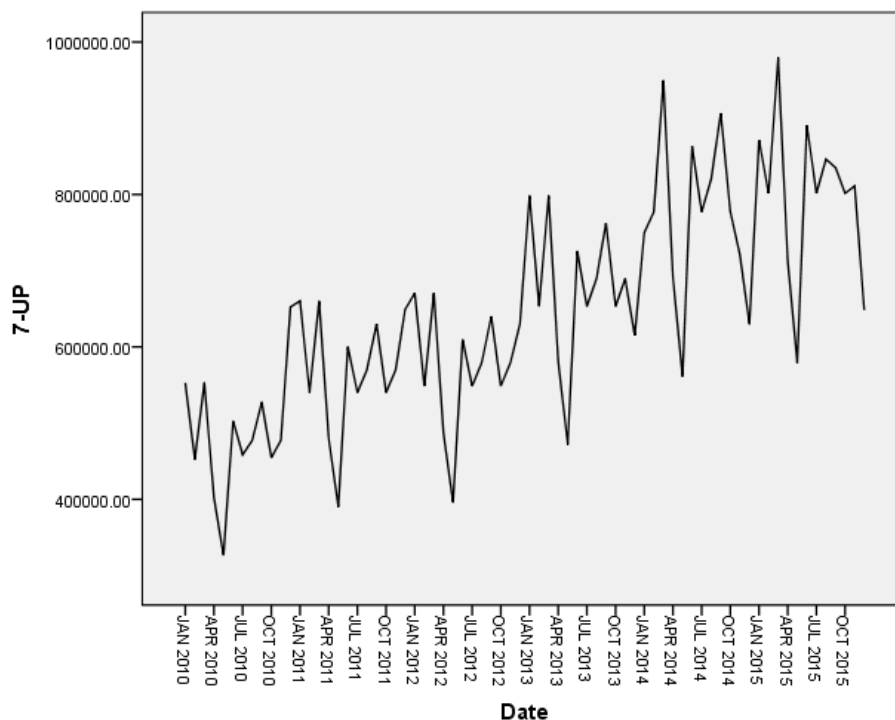


Figure 1: Time plot for sales before differencing

The plot shows the variability of the series appears to be changing with time. Therefore the mean and variance are not constant, suggesting that the series is not stationary

**Time Series Modeler**

**Table 2: Model Description**

			Model Type
Model ID	7-UP	Model_1	ARIMA(0,0,1)(0,1,0)

**Model Summary**

**Table 3: Model Fit**

Fit Statistic	Mean	SE	Minimum	Maximum
Stationary R-squared	.288	.	.288	.288
R-squared	.880	.	.880	.880
RMSE	46432.922	.	46432.922	46432.922
MAPE	5.500	.	5.500	5.500
MaxAPE	16.048	.	16.048	16.048
MAE	37819.886	.	37819.886	37819.886
MaxAE	120607.663	.	120607.663	120607.663
Normalized BIC	21.628	.	21.628	21.628

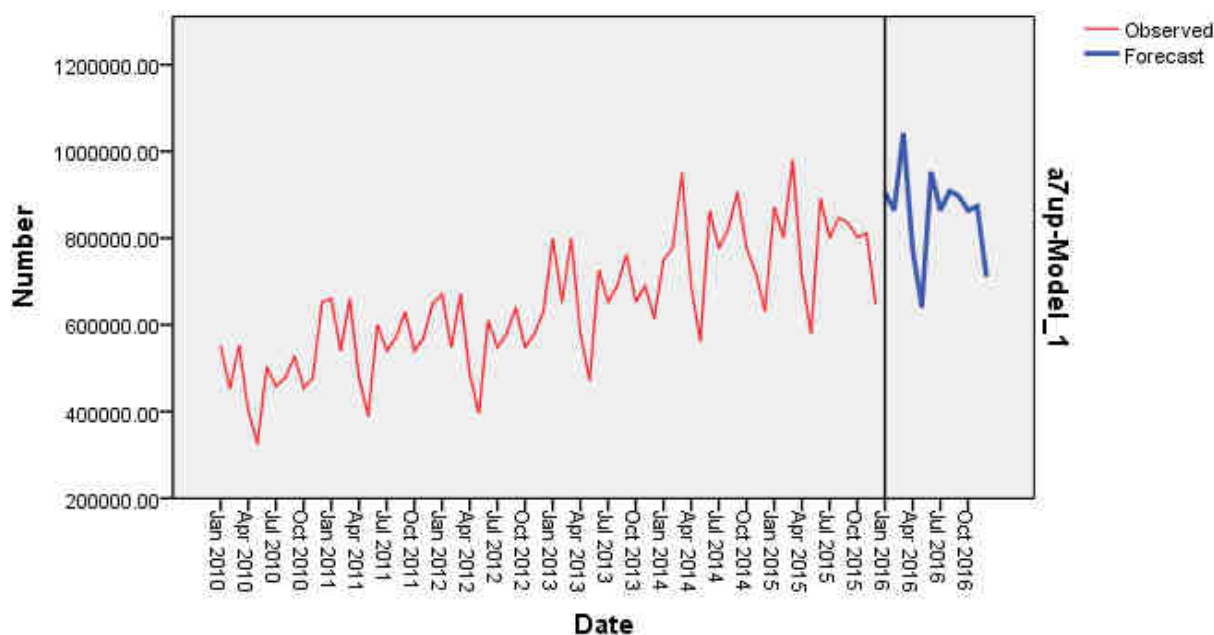
**Table 4: Model Statistics**

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
7-UP-Model_1	0	.288	23.406	17	.136	0

**Table 5: Forecast**

	Model		
	7-UP-Model_1		
	Forecast	UCL	LCL
Jan 2016	905379.07	998121.65	812636.49
Feb 2016	863950.12	970841.16	757059.07
Mar 2016	1.04E+006	1.15E+006	935209.07
Apr 2016	774875.12	881766.16	667984.07
May 2016	641263.12	748154.16	534372.07
Jun 2016	953025.12	1.06E+006	846134.07
Jul 2016	863950.12	970841.16	757059.07
Aug 2016	908488.12	1.02E+006	801597.07
Sep 2016	897440.12	1.00E+006	790549.07
Oct 2016	863950.12	970841.16	757059.07
Nov 2016	873480.12	980371.16	766589.07
Dec 2016	710818.12	817709.16	603927.07

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.



**Figure 2: Numbers Predictor ACF**

**Table 6: Model Description**

Model Name	MOD_11
Series Name	1
Transformation	None
Non-Seasonal Differencing	0
Seasonal Differencing	0
Length of Seasonal Period	12
Maximum Number of Lags	16
Process Assumed for Calculating the Standard Errors of the Autocorrelations	Independence(white noise) <sup>a</sup>
Display and Plot	All lags

Applying the model specifications from MOD\_11

a. Not applicable for calculating the standard errors of the partial autocorrelations.

**Table 7: Case Processing Summary**

		7-UP
Series Length		72
Number of Missing Values	User-Missing	0
	System-Missing	0
Number of Valid Values		72
Number of Computable First Lags		71

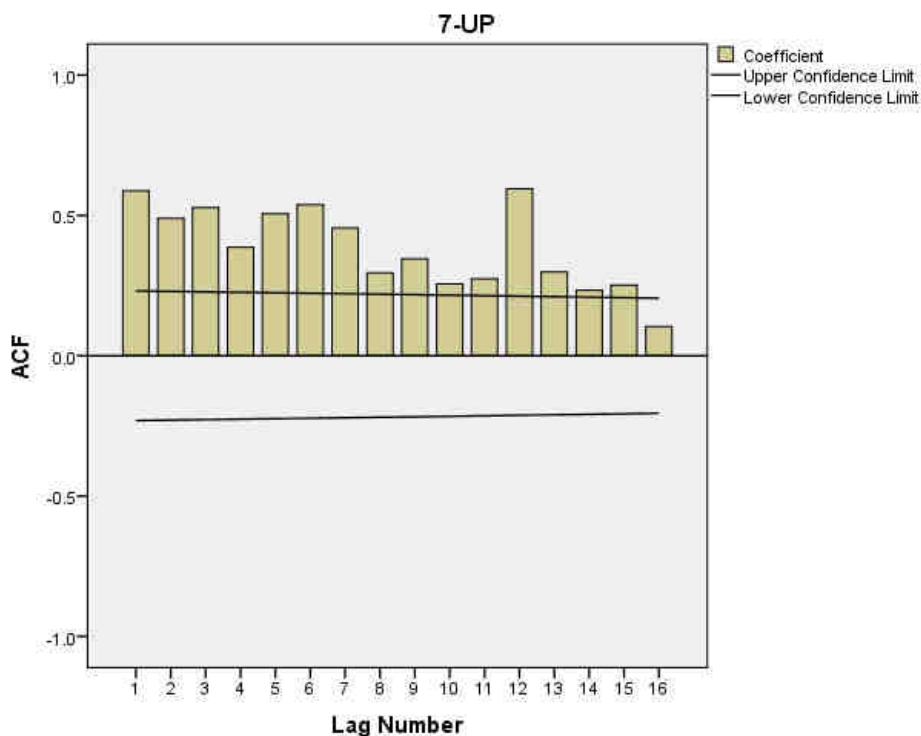
**7-UP**

**Table 8: Autocorrelation**

Series: 7-UP

Lag	Autocorrelation	Std. Error <sup>a</sup>	Box-Ljung Statistic		
			Value	df	Sig. <sup>b</sup>
1	.588	.115	25.920	1	.000
2	.490	.115	44.193	2	.000
3	.528	.114	65.695	3	.000
4	.387	.113	77.415	4	.000
5	.506	.112	97.773	5	.000
6	.538	.111	121.129	6	.000
7	.455	.110	138.130	7	.000
8	.296	.110	145.409	8	.000
9	.345	.109	155.495	9	.000
10	.256	.108	161.116	10	.000
11	.275	.107	167.702	11	.000
12	.595	.106	199.153	12	.000
13	.298	.105	207.188	13	.000
14	.234	.104	212.202	14	.000
15	.252	.103	218.126	15	.000
16	.104	.103	219.154	16	.000

- a. The underlying process assumed is independence (white noise).
- b. Based on the asymptotic chi-square approximation.



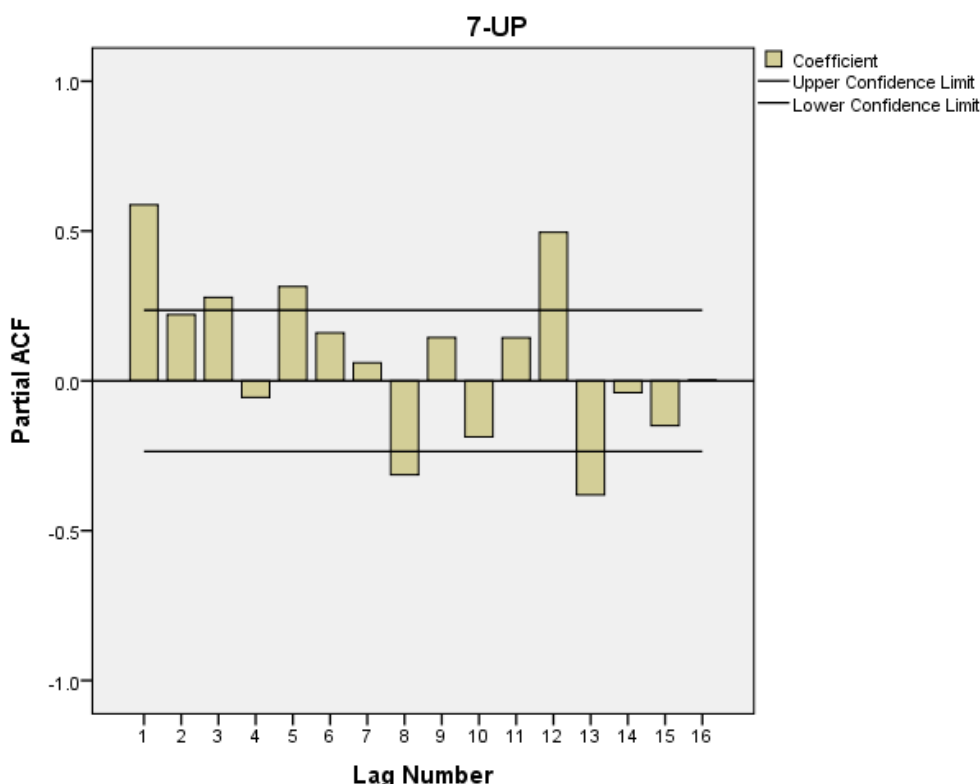
**Figure 3: ACF**



**Table 9: Partial Autocorrelations**

Series: 7-UP

Lag	Partial Autocorrelation	Std. Error
1	.588	.118
2	.221	.118
3	.279	.118
4	-.056	.118
5	.314	.118
6	.160	.118
7	.061	.118
8	-.314	.118
9	.145	.118
10	-.187	.118
11	.144	.118
12	.496	.118
13	-.380	.118
14	-.040	.118
15	-.150	.118
16	.001	.118



**Figure 4: Partial ACF**

**4.2 Discussion**

Since the time plot, autocorrelation and partial autocorrelation functions indicated seasonality in the series, the Autoregressive Integrated Moving Average (ARIMA) model is appropriate. The results are as shown in the Tables 3 to 5. The forecast values for 12 months (Jan. 2016 to Dec. 2016) were shown in Table 5. The Autocorrelation function (ACF) before differencing shows that it has no cyclical pattern but observed that the highest spike is in lag 12. While the Partial Autocorrelation function (PACF) shows that it has a cyclical pattern and cut off after lag 1 but the highest spike is in lag 1, after lag 12 everything tends to zero.

Time plot for quarterly sales as presented in figure 2, after first differencing shows the mean and variance appeared to be constant. Therefore, the series is stationary since the mean and variance are constant. ACF shows there is no correlation function after the first differencing. Therefore the series is stationary. The PACF shows that there is no correlation in the series after first difference. However the series indicate the

presence of AR and MA process models. It is clear that in both the Sales and Utilization that the pattern continues for the upcoming years 2016 and beyond and there are no indications that the quantity sold of Seven-Up products decreases with time.

## 5. Conclusion

The study aimed at predicting the amount of sales revenue that Seven-Up Bottling Company PLC would realise from January 2016 to December 2016 given the available monthly data on sales revenue from January 2010 to December 2015. This is with a view to find whether there would be an increase or decrease in sales revenue of 7Up Bottling Company's products. Time plot analysis was used in this research work to analyze the pattern of Sales revenue within the time under study. The study observed that the series have irregular pattern, after taken the first differencing the series became stationary. Nevertheless in modeling ARIMA (p, d, q) the best model is ARIMA (1, 1, 1) for production and ARIMA (0, 1, 1) for utilization. A 12 months forecast have also been made to determine the expected amount of sales revenue in year 2016. The time plot reveals seasonal variation.

ARIMA is a trendy method to analyze stationary univariate time series data. There are generally three main stages to build an ARIMA model, with model identification, model estimation and model checking, of which model classification is the most crucial stage in building ARIMA models. Thus the survey provides an insight into the various time series prediction and forecasting models with reference to ARIMA. Also a lot of real world applications conducted by the various persons were studied and it has come to prove that ARIMA is a real world toll for time series prediction, forecasting and analysis with accuracy.

From the result, the trend used to determine whether sales revenue is increasing or decreasing shows that there is increase in sales revenue of Company with time. From the forecast for sales it shows that Company's sales revenue will be increasing by each quarter Hence these models can be adopted for sales, production, utilization and demand forecasting in Nigeria.

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