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Review Article

Time Series Modeling of Monthly Production of Eva Water in Nigerian Bottling Company, Owerri Plant

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Abstract

This paper discusses time series modeling of monthly production of Eva water in Nigerian bottling company, Owerri plant. The method adopted is Buys-Ballot procedure for time series decomposition. The ultimate objective of this study is therefore is to choose the appropriate model for decomposition of the study data. Specific objectives are to: (1) review the Buys-Ballot procedure for this series decomposition. (2) estimate the trend parameters and seasonal indices. The method is developed to, among other things, choose of appropriate model for decomposition of study data based on row, column and overall means and variances. This research is restricted to time series with linear trend that admits the additive model using registered monthly production volume of Eva water in Nigerian bottling company over a period January, 2009 to December 2023. Result indicates that variance is constant and the transformed series admits additive model. This further confirmed that the appropriate model of original series is additive. There is need that the choice of appropriate model may be affected by violation of underlying assumptions, hence, it is recommended that a study data should be evaluated for the assumptions of time series model before choosing the suitable model.

Keywords: Buys-Ballot table; Time series decomposition; Choice of model; Linear trend; Modal structure

Introduction

Identification of pattern and choice of model in time series data is critical for forecasting purposes. Two patterns that may be presented are trend and seasonality and the two competing models are the additive and multiplicative models. Hence, Iwueze and Nwogu (2014) suggested in their framework for choice of model based on row, column and overall averages and variances of the data arranged in a Buys-Ballot table the test of the hypothesis that the column variances are constant for additive model otherwise multiplicative model or mixed model. In time series, it is assumed that the data consist of observations made sequentially in time; a systematic pattern (usually a set of identifiable components) and random noise (error). The systematic pattern includes the trend (denoted as), seasonal (denoted as) and the cyclical (denoted as) components. The random noise (or error, irregular component) is denoted as or, where t stands for the particular point in time. These four classes of time series components may or may not coexist in real-life data. These components can adopt different specific functional relationship. They can be combined in an additive (additive seasonality) or a multiplicative (multiplicative seasonality) fashion and can as well take other forms such as pseudo-additive/mixed (combining the elements of both the additive and multiplicative models) model.

The Additive model, Multiplicative model and Pseudo-Additive/Mixed Model are given in Equations (1.1) -(1.3) respectively:

Additive model: $$X_t = T_t + S_t + C_t + I_t \quad (1)$$

Multiplicative model: $$X_t = T_t \times S_t \times C_t \times I_t \quad (2)$$

Mixed model: $$X_t = T_t \times S_t \times C_t + I_t \quad (3)$$

Cyclical variation which refers to the long-term oscillation or swings about the trend appears to an appreciable magnitude only in long period sets of data.

However, if short period of time is involved, the cyclical component is superimposed into the trend (Chatfield [1]). In this case Equations (1) - (3), can respectively, be written as:

Additive model: $$X_t = M_t + S_t + I_t \quad (4)$$

Multiplicative model: $$X_t = M_t \times S_t \times I_t \quad (5)$$

Mixed model: $$X_t = M_t \times S_t + I_t \quad (6)$$

Where M_t is the trend-cycle component, S_t is the seasonal component with the property $S_{(i-1)s+j} = S_j, i = 1,2,\ldots,m$ and I_t is the irregular component? For equation (4), it is convenient to make assumption that the sum of the seasonal component over a complete period is zero, ie.,

$$\sum_{j=1}^{s} S_{t+j} = 0 \quad (7)$$

Similarly, for equations (5) and (6), the convenient variant assumption is the sum of the seasonal component over a complete period is s.

$$\sum_{j=1}^{s} S_{t+j} = s \quad (8)$$

It is equally assumed that the irregular component I_t is the Gaussian $N(0,\sigma_1^2)$ white noise for equations (4) and (6), while for equation (5), I_t is the Gaussian $N(0,\sigma_2^2)$ white noise and that $Cov(I_t, I_{t+k}) = 0, \forall\, k \neq 0$.

On the most appropriate condition to use any of three models, many scholars have proposed different approaches. Chatfield [1] proposed the use of the time plot to choose between additive and multiplicative models. However, they did not provide any statistical test to justify the use. Iwueze and Nwogu [2] proposed the framework for choice of model and detection of seasonal indices in time series, showed that when the trend cycle component is linear, the seasonal indices for the multiplicative model. Therefore, choice between additive and multiplicative models reduces to test for constant variance which can be used to identify the additive model. Therefore, they suggested that any test of constant variance can be used to identify the test that admits the additive model. This is an improvement over what is in existence. However, this approach can only identify the additive model when the column variance is constant, but does not tell the analyst the alternative model when the variance is not constant.

Linde [3] stated that the seasonal variation is independent of the absolute level of the time series and its amplitude is relatively close for additive model. While in a multiplicative model, the amplitude of the seasonal factor varies with level of the time series. In an additive model, the seasonal effect is the same in the same period over different years. When the seasonal effect is a proportion of the underlying trend, the multiplicative model is used. No statistical test was provided for the choice. Nwogu, et al [4] and Dozie, et al [5] established Chi-Square test based on the seasonal variances of the Buys-Ballot table. The test has been theoretically verified to be quite successful and efficient for choice between mixed and multiplicative models in time series analysis. Iwueze et al [6] summarized the Buys-Ballot procedure called the Buys-Ballot table. A Buys-Ballot table summarizes data to show seasonal variations.

Each line in the table is one period (usually a year) and each column is a season of the period/year (4 quarters, 12 months, etc). A cell (i, j), of this table contain the mean value of all observations made during the period i at the season j. To analyze the data, it is helpful to include the period and seasonal totals $(T_i \text{ and } T_j)$, period and seasonal average $\left(\bar{X}_{i.} \text{ and } \bar{X}_{.j}\right)$ period and seasonal standard deviations $\left(\hat{\sigma}_{i.} \text{ and } \hat{\sigma}_{.j}\right)$, as part of the Buys-Ballot table. Also included for purposes of analysis are the grand total $(T_{..})$, grand mean $\left(\bar{X}_{..}\right)$. .and pooled standard deviation $\left(\hat{\sigma}_{..}\right)$ (see Table 1). According to Wei [7], the arrangement of data in this manner in table is credited to Buys-Ballot; hence, the table has been called the Buys-Ballot table in the literature. Buys-Ballot is used to estimate the trend component and seasonal indices from the chosen descriptive time series model. According to Dozie [8], Buys Ballot procedure is computationally simple when compared with other descriptive methods.

The values of the estimated trend parameters and seasonal indices are easily computed in the mixed model in time series. Iwueze and Nwogu [2] proposed the Buys-Ballot estimation procedure and for the periodic means $\left(\bar{X}_{i.}, i = 1,2,\ldots,m\right)$ and the overall mean $\left(\bar{X}_{..}\right)$ to estimate the trend component. Seasonal means $\left(\bar{X}_{.j}, j = 1,2,\ldots,s\right)$ and the overall mean are used to estimate the seasonal indices. This research is restricted to time series with linear trend that admits the additive model using registered monthly production volume of Eva water in Nigerian bottling company over a period January, 2009 to December 2023. Therefore, the ultimate objective of this study is to identify the appropriate model for decomposition of the study data. The specific objectives are to: (a) review the Buys-Ballot table for seasonal time series. for in time series. (b) estimate the trend parameter and seasonal indices. This work contributes to the many existing solution of the problem of choosing the appropriate model among the three time series models

Methodology

The methods adopted in this study is the Buys-Ballot procedure developed for choice of model for decomposition of any study series, estimation of trend parameters and seasonal indices and choice of appropriate transformation based on the row, column and overall means and variances, For details of Buys-Ballot procedure for time series decomposition see Wei [8], Iwueze and Nwogu [2], Nwogu et al [4], Dozie [8], Dozie and Uwaezuoke [9], Dozie et al [5], Dozie and Ijeoma [10], Dozie and Nwanya [11], Dozie and Ihekuna [12], Dozie and Ibebuogu [13], Dozie and Ibebuogu [14], Dozie and Uwaezuoke [15], Dozie and Ihekuna [16], Dozie and Ihekuna [17], Dozie [18], Dozie and Uwaezuoke [19] and Dozie [20]. Review of Buys-Ballot Procedure for Time Series Decomposition is contained in section 2.1. Section 2.2 contains Estimation of Trend Parameters and Seasonal Indices. While section 2.3 is Test for Constant Variance (Table 1).

Table 1: Buys-Ballot Table for Seasonal Time Series.

Rows(period)	Columns(season) j								
i	1	2	…	j	…	s	$T_{i.}$	$\bar{X}_{i.}$	$\hat{\sigma}_{i.}$
1	X_1	X_2	…	X_j	…	X_s	$T_{1.}$	$\bar{X}_{1.}$	$\hat{\sigma}_{1.}$
2	X_{s+1}	X_{s+2}	…	X_{s+j}	…	X_{2s}	$T_{2.}$	$\bar{X}_{2.}$	$\hat{\sigma}_{2.}$
3	X_{2s+1}	X_{2s+2}	…	X_{2s+j}	…	X_{3s}	$T_{3.}$	$\bar{X}_{3.}$	$\hat{\sigma}_{3.}$
i	$X_{(i-1)s+1}$	$X_{(i-1)s+2}$	…	$X_{(i-1)s+j}$	…	$X_{(i-1)s+s}$	$T_{i.}$	$\bar{X}_{i.}$	$\hat{\sigma}_{i.}$
m	$X_{(m-1)s+1}$	$X_{(m-1)s+2}$	…	$X_{(m-1)s+j}$	…	X_{ms}	$T_{m.}$	$\bar{X}_{m.}$	$\hat{\sigma}_{m.}$
$T_{.j}$	$T_{.1}$	$T_{.2}$	…	$T_{.j}$	…	$T_{.s}$	$T_{..}$	-	-
$\bar{X}_{.j}$	$\bar{X}_{.1}$	$\bar{X}_{.2}$	…	$\bar{X}_{.j}$	…	$\bar{X}_{.s}$	-	$\bar{X}_{..}$	-
$\hat{\sigma}_{.j}$	$\hat{\sigma}_{.1}$	$\hat{\sigma}_{.2}$	…	$\hat{\sigma}_{.j}$	…	$\hat{\sigma}_{.s}$	-	-	$\hat{\sigma}_{..}$

Where s = number of seasons, m = number of periods and n = ms = number of observations.

Review of Buys-Ballot Procedure for Time Series Decomposition

Iwueze and Nwogu (2014) observed that the rows (periods) and column (seasons), with m and s representing the number of periods/years and seasons/columns respectively. This two-dimensional arrangement of a series is referred as the Buys-Ballot table.

Estimation of Trend Parameters and Seasonal Indices

Iwueze and Nwogu (2014) proposed the estimation of the trend parameters and seasonal indices for a linear trend and additive model as:

$$X_t = a + bt \quad (9)$$

$$\hat{b} = \frac{b'}{s} \quad (10)$$

$$\hat{a} = a' + \hat{b}\left(\frac{s-1}{2}\right) \quad (11)$$

$$\bar{S}_{.j} = \bar{X}_{.j} - \bar{X}_{..};\ j = 1,2,\ldots,12 \quad (12)$$

1.1. Levene's Test for Constant Variance

The Levene's test statistic for the null hypothesis

$H_0 : \sigma_i^2 = \sigma_j^2$

$H_1 : \sigma_i^2 \neq \sigma_j^2$ for at least one $i \neq j$ is defined as

$$W = \frac{(N-K)\sum_{i=1}^{k} N_i\left(\bar{z}_i - \bar{z}_{..}\right)^2}{(k-1)\sum_{i=1}^{k}\sum_{j=1}^{N_i}\left(z_{ij} - \bar{z}_i\right)^2} \quad (12)$$

where k is the number of different groups, N_i is the number of cases in the ith group, Y_{ij} is the value of the jth observation in the ith group.

z_{ij} may be defined as deviation of y_{ij} from the mean $(\bar{y}_i)$ or from the median $(\tilde{y}_i)$. That is

$$z_{ij} = y_{ij} - \bar{y}_i \; or \; y_{ij} - \tilde{y}_i \quad (14)$$

$$\bar{z}_{i.} = \frac{1}{N_i}\sum_{j=1}^{N_i} z_{ij} \text{ is the mean of the } z_{ij} \text{ for group } i \quad (15)$$

$$\bar{z}_{..} = \frac{1}{N}\sum_{i=1}^{k}\sum_{j=1}^{N_i} z_{ij} \text{ is mean of all } z_{ij}. \quad (16)$$

The test statistic W approximately follows the F-distribution with $k-1 \; and \; N-K$ degree of freedom. To suit the Buys-Ballot procedure, the levene's test statistic is modified with $N = ms, k = s \; N_i = m$ as;

$$W = \frac{(ms-s)}{s-1}\left[\frac{\sum_{j=1}^{s} m(\bar{z}_i - \bar{z}_{..})^2}{\sum_{j=1}^{s}\sum_{i=1}^{m}\left(z_{ij} - \bar{z}_{.j}\right)^2}\right] = \frac{s(m-1)}{s-1}\left[\frac{m\sum_{i=1}^{s}\left(\bar{z}_i - \bar{z}_{..}\right)^2}{\sum_{i=1}^{s}\sum_{j=1}^{m}\left(z_{ij} - \bar{z}_{.j}\right)^2}\right] \quad (17)$$

Empirical Example

The real-life example is based on monthly data on number of eva water production for a period of January, 2007 to December 2023 shown in appendix A. While the time plots of original and transformed series given Figure 1&2 respectively. As Figure 1&2 indicate, the time series is seasonal with no evidence of upward or downward trends. The yearly and seasonal standard deviations are both stable, suggesting that the seasonal indices may be additive. Results from Estimation of Trend Parameters and Seasonal Indices are discussed in Section 3.1. Section 3.2 presents the Choice of Appropriate Model. While Section 4 is the Concluding Remarks.

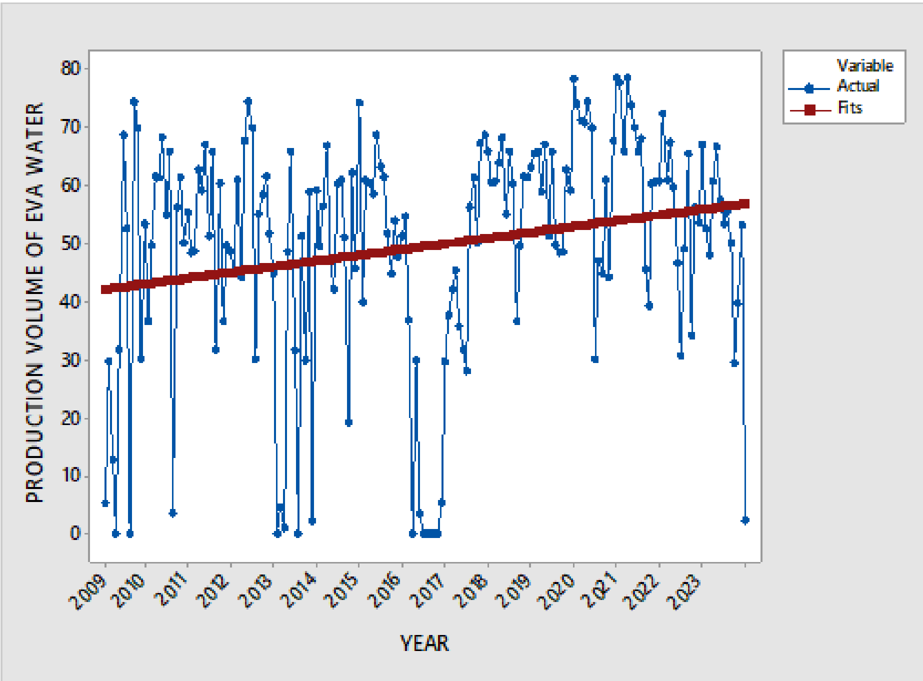

Figure 1: Time plot of original series.

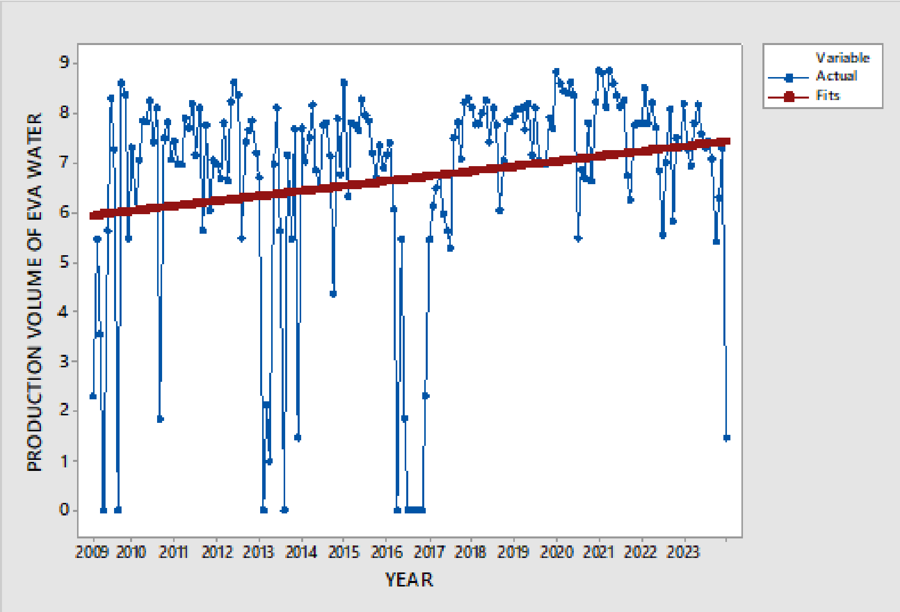

Figure 2: Time plot for Transformed Series.

Results from Estimation of Trend Parameters and Seasonal Indices

Using (10), (11) and (12), we obtain

$$\hat{b} = \frac{b^{/}}{s} = \frac{0.008}{12} = 0.001$$

$$\hat{a} = a' + \hat{b}\left(\frac{s-1}{2}\right)$$

$$\hat{a} = 5.935 + 0.001\left(\frac{12-1}{2}\right) = 5.941$$

and $\bar{S}_{.j} = \bar{X}_{.j} - \bar{X}_{..}; j = 1,2,\ldots,12$. (Table 2).

Table 2: Estimated Seasonal Indices.

J	$\bar{X}_{.j}$	$\hat{S}_{.j}$
1	6.53	-0.16
2	6.97	0.28
3	6.57	-0.12
4	7.08	0.39
5	7.12	0.43
6	6.70	0.01
7	6.43	-0.26
8	5.72	-0.97
9	6.30	-0.39
10	7.01	0.33
11	6.58	-0.11
12	7.24	0.55
$\sum_{j=1}^{12} \hat{s}_{.j}$		0.00

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Choice of Appropriate Model

To choose the appropriate model for decomposition of the study series. The first step is to check if the data admits additive model. The Levene's test is used to test the null hypothesis (H_o) that all variances are equal (it admits additive model) against the alternative (H_1) that at least one differs. The null hypothesis is rejected if the calculated test statistic $(W = 0.151)$ greater than the tabulated value$(F_{0.05,11,168} = 1.846)$ with $\alpha = 0.05$ otherwise it wouldn't be rejected.

Table 3: The absolute value of the difference between observed values and seasonal means of the actual data $\left(Z_{ij} = \mid X_{ij} - \bar{X}_{.j} \mid\right)$.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	$T_{i.}$	$Z_{i.}$	$\sigma_{i.}$
2009	42.65	21.08	37.70	54.47	21.93	19.40	4.47	39.73	30.74	16.91	17.08	2.18	308.35	25.70	15.70
2010	11.37	1.11	11.21	6.79	14.72	5.66	17.60	36.33	12.62	8.21	2.94	0.10	128.65	10.72	9.71
2011	0.51	2.26	12.35	4.61	13.40	2.05	17.64	8.13	16.63	16.52	2.63	6.91	103.63	8.64	6.39
2012	3.19	10.00	6.05	13.09	20.87	20.72	18.16	15.20	14.72	8.50	4.63	10.62	145.73	12.14	6.00
2013	47.93	46.25	49.29	5.92	12.26	17.67	48.15	11.59	13.81	5.68	44.92	3.62	307.09	25.59	19.57
2014	1.54	5.58	16.45	7.47	11.35	10.96	12.69	11.32	24.53	9.06	1.30	18.67	130.92	10.91	6.77
2015	8.03	10.17	9.94	3.91	15.05	13.86	13.43	11.97	1.18	0.96	0.62	4.11	93.21	7.77	5.39
2016	6.57	13.97	50.29	24.62	50.13	49.27	48.15	39.73	43.66	53.08	41.79	25.73	447.01	37.25	15.65
2017	10.40	8.81	4.93	18.76	21.93	21.37	8.13	21.56	6.35	14.16	21.60	10.41	168.41	14.03	6.62
2018	12.63	9.84	13.68	13.78	1.40	16.48	12.14	3.17	6.04	8.42	14.19	7.67	119.43	9.95	4.70
2019	17.38	14.95	8.47	12.46	2.21	16.52	1.41	8.71	4.89	9.56	12.01	22.72	131.28	10.94	6.38
2020	26.00	20.41	20.41	19.93	16.46	19.28	1.22	5.01	17.15	8.84	20.49	23.01	198.20	16.52	7.53
2021	29.83	15.07	28.09	19.39	16.35	16.54	19.91	5.80	4.47	7.24	13.64	5.25	181.56	15.13	8.48
2022	24.43	10.18	17.25	5.13	6.89	18.55	0.99	25.70	9.62	3.19	6.38	11.59	139.90	11.66	8.11
2023	4.69	2.76	10.47	12.16	3.97	4.01	7.20	10.30	14.22	13.38	6.02	53.31	142.48	11.87	13.63
$T_{.j}$	247.15	192.44	296.56	222.49	228.91	252.32	231.32	254.23	220.63	183.68	210.21	205.90	2745.84		
$Z_{.j}$	16.48	12.83	19.77	14.83	15.26	16.82	15.42	16.95	14.71	12.25	14.01	13.73		15.25	
$\sigma_{.j}$	14.76	11.03	14.87	12.71	11.73	10.88	14.75	12.67	11.22	12.14	13.74	13.62			12.67

Table 4: Calculation of $m\left(Z_{.J} - Z_{..}\right)^2$.

$Z_{.J}$	$Z_{..}$	$Z_{.J} - Z_{..}$	$\left(Z_{.J} - Z_{..}\right)^2$	$m\left(Z_{.J} - Z_{..}\right)^2$
16.48	15.25	1.22188	1.49299	22.395
12.83	15.25	-2.4251	5.88131	88.22
19.77	15.25	4.51601	20.3944	305.92
14.83	15.25	-0.4222	0.17826	2.6739
15.26	15.25	0.00615	3.8E-05	0.0006
16.82	15.25	1.56668	2.45449	36.817
15.42	15.25	0.16686	0.02784	0.4176
16.95	15.25	1.69379	2.86893	43.034
14.71	15.25	-0.5461	0.29825	4.4737
12.25	15.25	-3.0095	9.05707	135.86
14.01	15.25	-1.2405	1.53889	23.083
13.73	15.25	-1.5279	2.33447	35.017
$\sum m\left(Z_{.J} - Z_{..}\right)^2$				697.9

Table 5: Calculation of $\left(Z_{ij} - Z_{j.}\right)^2$.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	$T_{i.}$
2009	1819.08	444.25	1421.59	2967.05	481.04	376.20	20.02	1578.84	944.91	285.79	291.86	4.75	10635.40
2010	129.29	1.23	125.57	46.10	216.60	31.99	309.92	1320.21	159.25	67.33	8.62	0.01	2416.12
2011	0.26	5.10	152.42	21.25	179.49	4.19	311.33	66.17	276.53	273.06	6.90	47.73	1344.43
2012	10.18	100.05	36.65	171.33	435.45	429.15	329.62	230.90	216.66	72.17	21.40	112.76	2166.31
2013	2297.35	2138.82	2429.90	35.05	150.24	312.37	2317.97	134.22	190.73	32.21	2018.17	13.11	12070.15
2014	2.37	31.17	270.47	55.81	128.88	120.03	161.15	128.04	601.75	82.00	1.70	348.62	1932.00
2015	64.49	103.48	98.72	15.28	226.42	191.99	180.49	143.17	1.39	0.91	0.38	16.88	1043.62
2016	43.16	195.09	2529.49	606.18	2513.28	2427.93	2317.97	1578.84	1906.25	2817.98	1746.74	661.96	19344.87
2017	108.17	77.57	24.34	351.96	481.04	456.85	66.17	464.63	40.31	200.37	466.39	108.40	2846.22
2018	159.50	96.88	187.03	189.87	1.95	271.46	147.49	10.08	36.47	70.82	201.24	58.85	1431.65
2019	302.04	223.58	71.67	155.23	4.90	272.78	2.00	75.78	23.91	91.30	144.14	516.26	1883.60
2020	675.97	416.68	416.40	397.18	270.84	371.87	1.48	25.05	294.10	78.23	419.68	529.52	3897.00
2021	889.79	227.19	788.82	375.95	267.24	273.44	396.59	33.59	19.99	52.35	185.94	27.58	3538.45
2022	596.79	103.69	297.42	26.31	47.51	344.25	0.99	660.25	92.56	10.15	40.65	134.36	2354.93
2023	21.99	7.60	109.54	147.85	15.74	16.05	51.91	105.99	202.23	179.15	36.19	2841.81	3736.05
$T_{.j}$	7120.43	4172.36	8960.06	5562.40	5420.63	5900.55	6615.12	6555.77	5007.04	4313.83	5590.00	5422.60	70640.79

$$\sum_{i=1}^{m}\sum_{j=1}^{s}\left(Z_{ij} - Z._{j}\right)^2 = 70640.79$$

$$W = \frac{12(15-1)}{12-1} \times \frac{697.9}{70640.79} = 0.151$$

When compared, the test statistic is less than the critical value, indicating that the model for decomposition is additive. Having confirmed that the decomposition model is additive. There is still need to transform data to meet the time series assumptions, that is, the constant variance and normality assumptions in the distribution. When the transformed data listed in 8 is subjected to test for constant variance, the test statistic $(W = 0.351)$ is less than critical value $\left(F_{0.05,11,168} = 1.846\right)$ at 5% level of significant. Hence, transformed data accepts additive model.

From Appendix B and (Table 6-8): we have $W = \frac{12(15-1)}{12-1} \times \frac{19.006}{826.21} = 0.351$

Table 6: The absolute value of the difference between observed values and seasonal means of the transformed data $\left(Z_{ij} = \mid X_{ij} - \bar{X}_{.j} \mid\right)$.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	$T_{i.}$	$Z_{i.}$	$\sigma_{i.}$
2009	4.23	1.52	3.02	7.08	1.50	1.59	0.82	5.72	2.33	1.36	1.10	0.06	30.32	2.53	2.12
2010	0.48	0.08	1.27	0.75	1.14	0.71	1.68	3.88	1.20	0.82	0.49	0.20	12.71	1.06	1.00
2011	0.43	0.00	1.34	0.61	1.06	0.46	1.68	0.10	1.46	0.96	0.47	0.27	8.86	0.74	0.55
2012	0.16	0.83	0.08	1.14	1.51	1.67	0.95	1.69	1.34	0.84	0.61	0.54	11.37	0.95	0.54
2013	6.53	4.83	5.57	0.11	0.99	1.08	6.43	1.44	0.84	0.66	5.11	0.45	34.03	2.84	2.58
2014	0.50	0.54	1.60	0.22	0.63	1.06	1.37	1.42	1.93	0.87	0.19	1.37	11.71	0.98	0.57
2015	0.21	0.84	1.19	0.56	1.16	1.25	1.42	1.47	0.40	0.34	0.33	0.07	9.25	0.77	0.51
2016	0.85	0.90	6.57	1.62	5.28	6.70	6.43	5.72	6.30	7.01	4.28	1.79	53.44	4.45	2.46
2017	0.40	0.49	0.16	1.10	1.50	1.42	1.07	2.11	0.77	1.19	1.71	0.88	12.79	1.07	0.57
2018	1.25	0.82	1.43	1.18	0.29	1.41	1.33	0.33	0.75	0.83	1.25	0.71	11.60	0.97	0.40
2019	1.55	1.14	1.10	1.10	0.04	1.41	0.61	1.24	0.67	0.90	1.11	1.60	12.49	1.04	0.44
2020	2.07	1.47	1.84	1.55	1.25	1.22	0.42	0.97	1.50	0.36	1.64	1.62	15.93	1.33	0.52
2021	2.29	1.15	2.28	1.51	1.24	1.41	1.82	1.03	0.04	0.76	1.21	0.55	15.31	1.28	0.66

2022	1.98	0.84	1.65	0.64	0.29	1.16	0.58	2.37	0.47	0.49	0.73	0.95	12.16	1.01	0.66
2023	0.72	0.04	1.22	1.08	0.46	0.60	1.01	1.35	0.87	0.71	0.71	5.77	14.54	1.21	1.48
$T_{.j}$	23.67	15.51	30.32	20.25	18.36	23.15	27.62	30.84	20.88	18.09	20.96	16.85	266.50		
$Z_{.j}$	1.58	1.03	2.02	1.35	1.22	1.54	1.84	2.06	1.39	1.21	1.40	1.12		1.48	
$\sigma_{.j}$	1.75	1.15	1.80	1.65	1.22	1.47	1.91	1.73	1.48	1.63	1.42	1.41			1.55

Table 7: Calculation of $m\left(Z_{.J}-Z_{..}\right)^2$.

$Z_{.J}$	$Z_{..}$	$Z_{.J}-Z_{..}$	$\left(Z_{.J}-Z_{..}\right)^2$	$m\left(Z_{.J}-Z_{..}\right)^2$
1.58	1.48	0.0972	0.00945	0.1417
1.03	1.48	-0.4464	0.19923	2.9885
2.02	1.48	0.54076	0.29242	4.3862
1.35	1.48	-0.1304	0.01699	0.2549
1.22	1.48	-0.2566	0.06583	0.9875
1.54	1.48	0.06298	0.00397	0.0595
1.84	1.48	0.36076	0.13014	1.9522
2.06	1.48	0.57542	0.33111	4.9667
1.39	1.48	-0.0888	0.00789	0.1184
1.21	1.48	-0.2745	0.07537	1.1305
1.40	1.48	-0.083	0.00689	0.1033
1.12	1.48	-0.3575	0.12778	1.9167
$\sum m\left(Z_{.J}-Z_{..}\right)^2$				19.006

Table 8: $\left(Z_{ij}-Z_{.j}\right)^2$.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	$T_{i.}$
2009	17.86	2.30	9.12	50.12	2.24	2.53	0.67	32.72	5.44	1.85	1.20	0.00	126.05
2010	0.23	0.01	1.61	0.56	1.31	0.51	2.82	15.05	1.44	0.67	0.24	0.04	24.50
2011	0.19	0.00	1.80	0.37	1.13	0.21	2.82	0.01	2.14	0.92	0.22	0.07	9.89
2012	0.03	0.70	0.01	1.30	2.29	2.79	0.90	2.86	1.80	0.70	0.38	0.29	14.04
2013	42.60	23.28	31.02	0.01	0.99	1.16	41.34	2.07	0.70	0.43	26.08	0.21	169.92
2014	0.25	0.30	2.56	0.05	0.39	1.13	1.88	2.02	3.72	0.75	0.04	1.89	14.96
2015	0.04	0.71	1.42	0.31	1.35	1.56	2.02	2.16	0.16	0.11	0.11	0.00	9.97
2016	0.73	0.80	43.16	2.62	27.84	44.88	41.34	32.72	39.66	49.16	18.30	3.19	304.41
2017	0.16	0.24	0.03	1.21	2.24	2.01	1.14	4.45	0.60	1.41	2.93	0.78	17.20
2018	1.57	0.68	2.04	1.39	0.09	1.99	1.77	0.11	0.57	0.69	1.57	0.51	12.97
2019	2.41	1.31	1.21	1.21	0.00	1.99	0.37	1.54	0.45	0.81	1.24	2.57	15.11
2020	4.30	2.17	3.39	2.40	1.57	1.49	0.18	0.94	2.26	0.13	2.70	2.64	24.16
2021	5.26	1.33	5.20	2.28	1.55	1.99	3.31	1.06	0.00	0.58	1.47	0.31	24.34
2022	3.93	0.71	2.72	0.41	0.08	1.34	0.34	5.62	0.22	0.24	0.54	0.91	17.06
2023	0.52	0.00	1.49	1.17	0.22	0.36	1.02	1.82	0.75	0.51	0.51	33.25	41.62
$T_{.j}$	80.08	34.54	106.78	65.43	43.29	65.95	101.93	105.15	59.91	58.96	57.53	46.66	826.21

Critical value:

$$F_{\alpha(k-1;N-k)}$$

$$F_{0.05,(12-1),(180-12)} = 1.846$$

Concluding Remarks

This paper has discussed time series modeling of monthly production of eva water in Nigerian bottling company, Owerri plant. The method adopted is Buys-Ballot procedure for time series decomposition. The method is developed to, among other things, choose of appropriate model for decomposition of study data bases row, column and overall means and variances. Therefore, the ultimate objective is to determine the appropriate model for decomposition of the study data. The specific objectives are to: (a) review the Buys-Ballot procedure for seasonal time series. (b) estimate trend parameters and seasonal indices. Result indicates that variance is constant and the transformed series admits additive model. This further confirmed that the appropriate model of original series is additive. There is need that the choice of appropriate model may be affected by violation of underlying assumptions, hence, it is recommended that a study data should be evaluated for the assumptions of time series model before choosing the suitable model.

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APPENDIX

Appendix A: Original Data from 2009 – 2023.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
2009	52848	297298	125880	0	315956	686658	526235	0	743953	699892	299880	532783
2010	365581	497036	614981	612626	682471	549339	657538	33975	562835	612850	500060	553571
2011	484443	485479	626446	590848	669327	513192	657855	315956	602900	365581	497036	485479
2012	447383	608087	442388	675632	743953	699892	299880	549339	583774	615825	517037	448432
2013	0	45636	10003	485479	657855	315956	0	513192	298470	587561	21504	590848
2014	494736	563866	667383	469959	421751	602323	608410	510467	191333	621357	457713	741280
2015	398988	609766	602279	583774	685786	631334	615825	517037	448432	540369	476892	513547
2016	545034	368435	0	298470	33975	0	0	0	0	0	52848	297298
2017	375329	420000	453592	357098	315956	278990	562835	612850	500060	672443	686658	658667
2018	605621	606531	639658	682471	549339	657538	602900	365581	497036	614981	612626	631312
2019	653116	657648	587561	669327	513192	657855	495560	484443	485479	626446	590848	781785
2020	739334	712234	706997	743953	699892	299880	469275	447383	608087	442388	675632	784663
2021	777593	658763	783825	738593	698753	658059	680648	455304	391890	603187	607125	607125
2022	723588	609892	675368	595956	466377	307188	491424	654279	340410	562747	534475	670472
2023	526235	480501	607554	666267	575000	532783	553472	500316	294375	397031	530925	21504

Appendix B: Transformed Data from 2009-2023.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	$T_{i.}$	$Z_{i.}$	$\sigma_{i.}$
2009	2.3	5.45	3.55	0	5.62	8.29	7.25	0	8.63	8.37	5.48	7.3	62.24	5.19	3.10
2010	6.05	7.05	7.84	7.83	8.26	7.41	8.11	1.84	7.5	7.83	7.07	7.44	84.23	7.02	1.73
2011	6.96	6.97	7.91	7.69	8.18	7.16	8.11	5.62	7.76	6.05	7.05	6.97	86.43	7.20	0.79
2012	6.69	7.8	6.65	8.22	8.63	8.37	5.48	7.41	7.64	7.85	7.19	6.7	88.63	7.39	0.90
2013	0	2.14	1	6.97	8.11	5.62	0	7.16	5.46	7.67	1.47	7.69	53.29	4.44	3.25
2014	7.03	7.51	8.17	6.86	6.49	7.76	7.8	7.14	4.37	7.88	6.77	8.61	86.39	7.20	1.09
2015	6.32	7.81	7.76	7.64	8.28	7.95	7.85	7.19	6.7	7.35	6.91	7.17	88.93	7.41	0.57
2016	7.38	6.07	0	5.46	1.84	0	0	0	0	0	2.3	5.45	28.50	2.38	2.89
2017	6.13	6.48	6.73	5.98	5.62	5.28	7.5	7.83	7.07	8.2	8.29	8.12	83.23	6.94	1.06
2018	7.78	7.79	8	8.26	7.41	8.11	7.76	6.05	7.05	7.84	7.83	7.95	91.83	7.65	0.59
2019	8.08	8.11	7.67	8.18	7.16	8.11	7.04	6.96	6.97	7.91	7.69	8.84	92.72	7.73	0.59
2020	8.6	8.44	8.41	8.63	8.37	5.48	6.85	6.69	7.8	6.65	8.22	8.86	93.00	7.75	1.07
2021	8.82	8.12	8.85	8.59	8.36	8.11	8.25	6.75	6.26	7.77	7.79	7.79	95.46	7.96	0.78
2022	8.51	7.81	8.22	7.72	6.83	5.54	7.01	8.09	5.83	7.5	7.31	8.19	88.56	7.38	0.94
2023	7.25	6.93	7.79	8.16	7.58	7.3	7.44	7.07	5.43	6.3	7.29	1.47	80.01	6.67	1.78
$T_{.j}$	97.90	104.48	98.55	106.19	106.74	100.49	96.45	85.80	94.47	105.17	98.66	108.55	1203.45		
$Z_{.j}$	6.53	6.97	6.57	7.08	7.12	6.70	6.43	5.72	6.30	7.01	6.58	7.24		6.69	
$\sigma_{.j}$	2.39	1.57	2.76	2.16	1.76	2.17	2.70	2.74	2.07	2.05	2.03	1.83			2.19

Citation: Imah Isaiah*, Annastecia C Egwuekwe, Kelechukwu CN Dozie, Stephen O Ihekuna and Glory C Nwagwu, Time Series Modeling of Monthly Production of Eva Water in Nigerian Bottling Company, Owerri Plant. Annal Biostat & Biomed Appli. 7(2): 2026. ABBA.MS.ID.000658. **DOI:** 10.33552/ABBA.2026.07.000658.