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

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Abstract
This paper discusses time series analysis 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. 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 indicate that the model for decomposition is additive.

Keywords: Buys-Ballot table, time series decomposition, choice of model, linear trend, modal structure

Introduction
One of the greatest problems in descriptive time series analysis is choice of appropriate model for decomposition of any study series. That is, when to choose any of the additive, multiplicative or mixed model is not known. It is certain that the wrong use of a model will bring unreliable estimate of the component. 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 T_t), seasonal (denoted as S_t) and the cyclical (denoted as C_t) components. The random noise (or error, irregular component) is denoted as $I_t$or e_t, 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:

$$Additive\ model: X_t = T_t + S_t + C_t + I_t \tag{1}$$

$$Multiplicative\ model: X_t = T_t \times S_t \times C_t \times I_t \tag{2}$$

$$Mixed\ model: X_t = T_t \times S_t \times C_t + I_t \tag{3}$$

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

$$Additive\ model: X_t = M_t + S_t + I_t \tag{4}$$

$$Multiplicative\ model: X_t = M_t \times S_t \times I_t \tag{5}$$

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

Where,

$$M_t \text{ is the trend} - \text{cycle component.}$$

On the most appropriate condition to use any of three models, many scholars have proposed different approaches. Chatfield [1] proposed the use of the run sequence plot (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 *and* T_j), period and seasonal average $(\bar{X}_{i.}\ and\ \bar{X}_{.j})$ period and seasonal standard deviations$(\hat{\sigma}_{i.}\ and\ \hat{\sigma}_{.j})$, as part of the Buys-Ballot table. Also included for purposes of analysis are the grand total($T_{..}$), grand mean. $(\bar{X}_{..})$.and pooled standard deviation $(\hat{\sigma}_{..})$ (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 $(\bar{X}_{i.}, i = 1,2,\ldots,m)$ and the overall mean $(\bar{X}_{..})$ to estimate the trend component. Seasonal means $(\bar{X}_{.j}, j = 1,2,\ldots,s)$ and the overall mean are use 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.

The, ultimate objective of this study is to identify the appropriate 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

2. 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]

Table 1: Buys-Ballot Table for Seasonal Time Series

Rows(period) i	Columns(season) j								
	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

2.1. Review of Buys-Ballot Procedure for Time Series Decomposition

Iwueze and Nwogu (2014) [2] 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.

2.2. Choice of Appropriate Transformation

According to Iwueze *et al* (2011) [6], transformation is a mathematical operation that changes the measurement scale of a variable. Many times series analyst assumes normality and it is well known that variance stabilization implies normality of the series. The most popular and common are the powers of transformation such as; logarithmic transformation ($\log_e X_t$), square-root transformation$\left(\sqrt{X_t}\right)$, inverse transformation$\left(\frac{1}{X_t}\right)$, inverse square-root transformation$\left(\frac{1}{\sqrt{X_t}}\right)$, square transformation $\left(X_t^2\right)$ and inverse square transformation$\left(\frac{1}{X_t^2}\right)$. Selecting the best transformation can be a difficult issue and the usual statistical technique used is to estimate both the transformation and required model for the transformed X_t at the same time, (Box and Cox, 1964). One of the statistical techniques is Bartlett transformation technique, Bartlett (1947).

2.3. 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

$$W = \frac{(N-K)\sum_{i=1}^{k} N_i(\bar{z}_i - \bar{z}_{..})^2}{(k-1)\sum_{i=1}^{k}\sum_{j=1}^{N_i}(z_{ij} - \bar{z}_i)^2} \quad (7)$$

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 $(\bar{y}_i)$. That is

$$z_{ij} = y_{ij} - \bar{y}_i \text{ or } y_{ij} - \bar{y}_i \quad (8)$$

$\bar{z}_{i.} = \frac{1}{N_i}\sum_{j=1}^{N_i} z_{ij}$ is the mean of the z_{ij} for group i (9)

$\bar{z}_{..} = \frac{1}{N}\sum_{i=1}^{k}\sum_{j=1}^{N_i} z_{ij}$ is mean of all z_{ij}. (10)

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

$N = ms, k = sN_i = m$ as

$$W = \frac{(ms-s)}{s-1}\left[\frac{\sum_{j=1}^{s} m(\bar{z}_i - \bar{z}_{..})^2}{\sum_{j=1}^{s}\sum_{i=1}^{m}(z_{ij} - \bar{z}_{.j})^2}\right] \quad (11)$$

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

3. 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 Figures 1 and 2. The first step is to check if the data admits additive model. The Levene's test was 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 would be rejected if the calculated Levene's test statistic, W is greater than the tabulated value with $\alpha = 0.05$ otherwise it wouldn't be rejected.

From Appendix A and Table 4

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

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

$W = 0.151$

Critical value:

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

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

$F_{0.05,11,168} = 1.846$

Decision: Since the value of the test statistic = 0.151 < the critical value = 1.846, H_o is therefore accepted.

Conclusion: The variances are equal; hence the data admits additive model.

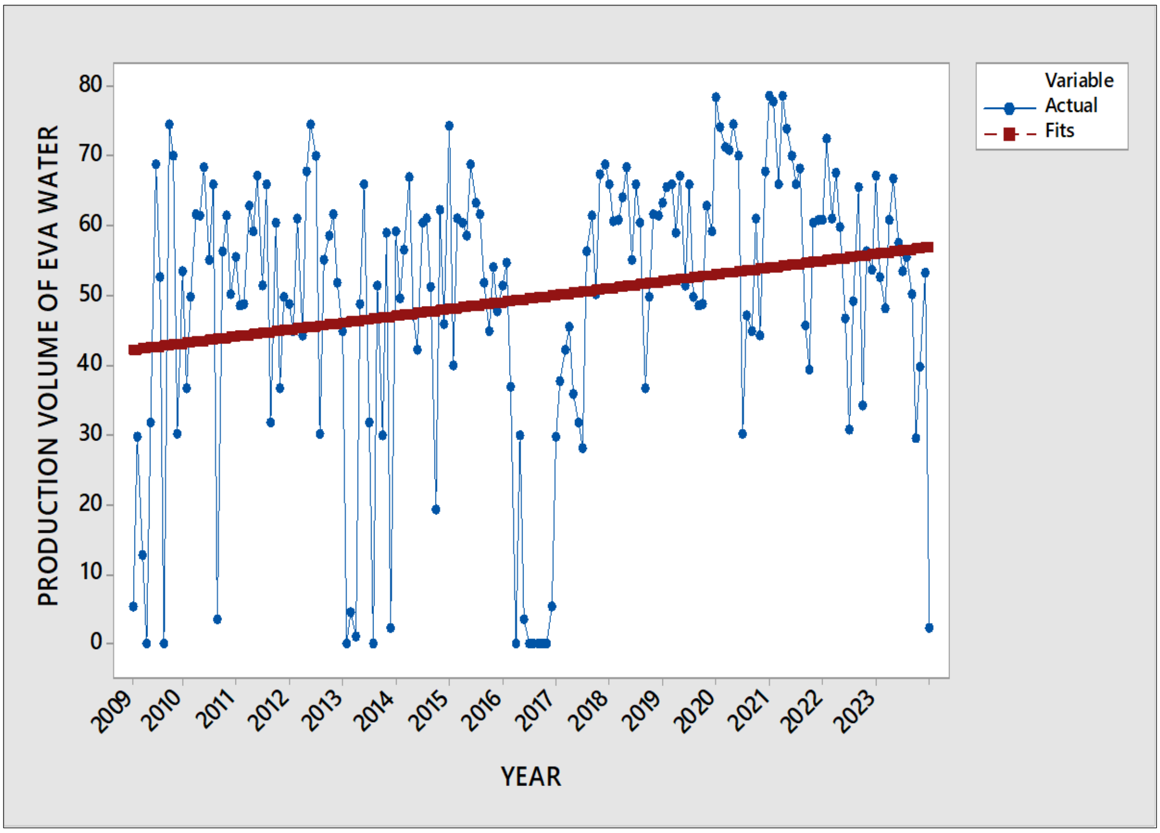

Fig 1: Time plot of original series

Table 2: The Absolute Value of the Difference between Observed Values and Seasonal Means of the Actual Data

$Z_{ij} = |X_{ij} - \bar{X}_{.j}|$

	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

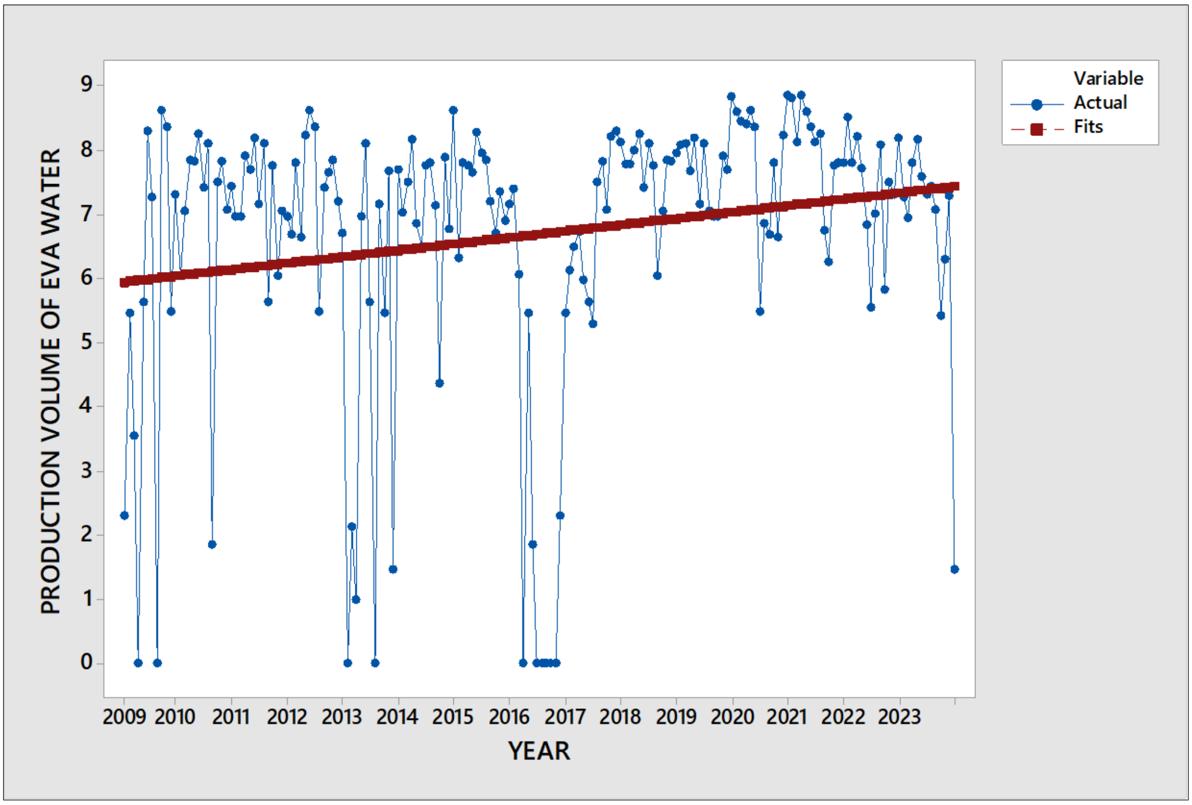

Fig 2: Time plot for Transformed Series

Table 3: Calculation of $m(Z_{.j} - Z_{..})^2$

$Z_{.j}$	$Z_{..}$	$Z_{.j} - Z_{..}$	$(Z_{.j} - Z_{..})^2$	$m(Z_{.j} - Z_{..})^2$
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
$\sum m(Z_{.j} - Z_{..})^2$				697.9

Table 4: Calculation of $(Z_{ij} - Z_{j.})^2$

	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

4. Concluding Remarks

This paper has discussed time series analysis 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. 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 indicate that the model for decomposition is additive.

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