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Comparative study of Manual time series components identification with automated Break for Time Series Components (BFTSC) and Group for Time Series Components (GFTSC) in Identification in Univariate Forecasting

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Abstract:
The main objective of this study is to compare the behavior of manual time series components identification with BFTSC (break for time series components) and GFTSC (group for time series components) identification of time series components. The weaknesses of manual time series components identification were addressed by an advanced automated method which i created from the extension of BFAST (Break for Additive, Seasonal and Trend). Manual time series components identification, BFTSC and GFTSC serve the same purpose of identifications of time series components. BFTSC and GFTSC is considered better alternative than the manual method based on findings in this study in term of precision, time period of data incubation and flexible methods. BFTSC is designed to give a combined image of all the four time series components captured in a single time plot. GFTSC is designed to capture all the time series components on a different individual point time plot. BFAST only identifies trend and seasonal components while considering all other left over components as random, identification of trend and seasonal components alone is not enough to have a clear pattern of all the time series components present in the data. BFTSC and GFTSC is created to include cyclical and irregular components and this was included in the methodology. This study uses two types of data. The first empirical data was the monthly rainfall data in Ibadan Oyo State Nigeria (2007 to 2018). The second empirical data was the seasonal data which is the quarterly sales of coca cola beverages in Benin City Edo State Nigeria (1995 to 2016). These findings indicate that BFTSC and GFTSC can provide a better alternative to Manual time series components identification technique, hence BFTSC and GFTSC is recommended for future uses.

Keywords: *Manual identification, Break for Time Series Components, Group for Time Series Components, Percentage, Trend, Seasonal, Cyclical, Irregular.*

1. INTRODUCTION

The main objective of this study is to compare the behavior of manual time series components identification with BFTSC and GFTSC identification of time series components. Manual identification of time series components also known as classical time series components decomposition is the process utilized by expert and non-expert in decomposing time series components into its various components and consequently identifying each component. The common approach of identifying time series components is called the exploratory data analysis (EDA). The EDA is procedural steps that helps in careful examination of each component of time series (trend, seasonal, cyclical and irregular components).

The method BFTSC is created from BFAST to identify all the time series components and to present them in a single time plot. The method GFTSC is also created from BFAST to identify all the time series components and to present them in a different individual time plot, each components of time series has its own individual time plot based on its individual characteristics (Ajare & Ismail, 2019). BFTSC and GFTSC is an improved BFAST. BFTSC and GFTSC are produce from BFAST. BFAST (Break for Additive Seasonal and Trend) is a method used for identification of trend and seasonal components of time series data, trend breaking was first suggested by Bai and Perron (2003). Jong, Verbesselt, Schaepman and Bruin (2012) recommended an method of basic identification to spot time series component. This method was also utilized by Zewdie, Csaplovics and Inostroza (2017) as the newest time series component recognition approach which is a method that was initially described and utilized by Verbesselt et al. (2010). In this study we seek to evaluate the behavior of manual classical time series components identifications with BFTSC and GFTSC, the best method is recommended based on behavior of each method in respect to time series components identification. Though the issue of how large is large and maximum sample size accepted by BFAST is yet to be addressed (Van Leeuwen, Huete and Laing, 1999). The behaviour of the three methods was explained in this study. Two empirical data were used in validating the three techniques. The first empirical data is the monthly rainfall data from Ibadan Oyo State Nigeria (2007 to 2018), this data was lifted directly from the record of Nigeria Metrological Agency. The second data is a secondary data of yearly/quarterly sales of coca cola beverages in Benin City Edo State. This data was lifted directly from the data record of the quarterly/yearly production and sales register of Nigerian Bottling Company NBC, Plot 1084, Benin, Eyaen, Uhunwonde Auchi Road Benin City Edo State.

2. STUDY SUBJECT

2.0 MATERIAL AND METHODS

Material and methods involves the technique used and data involved. This study compare three techniques known as manual, BFTSC and GFTSC. This study also applied two types of data known as the monthly rainfall data in Ibadan Oyo State Nigeria (2007 to 2018) and yearly/ quarterly sales of coca cola beverages in Benin City Edo State Nigeria (1995 to 2016).

2.1 MANUAL TIME SERIES COMPONENTS IDENTIFICATION TECHNIQUES

A) Manual multiplicative decomposition is the method can be conducted using Microsoft excel. Microsoft excel can be used in separating time series data to its components, such as trend component, seasonal components, cyclical components and irregular components. It can also be used for further decomposed combinations such as trend (T_t), trend and seasonal (T_tS_t), trend and cyclical (T_tC_t), trend and irregular (T_tI_t), trend and irregular and cyclical components ($T_tI_tC_t$) etc through multiplicative decomposition. The seasonal components varies in respect to the primary growth in the series. Given the general time series multiplicative model of the form

$$Y_p = T_p \times S_p \times C_p \times I_p$$

B) Additive decomposition

Classical additive decomposition is the method used in separating time series data to its components, such as trend component, seasonal components, cyclical components and irregular components. It can also be used for further decomposed combinations such as trend (T_t), trend and seasonal ($T_t + S_t$), trend and cyclical ($T_t + C_t$), trend and irregular ($T_t + I_t$), trend and irregular and cyclical components ($T_t + I_t + C_t$) etc. T hrough additive decomposition. This method can also be conducted

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using Microsoft excel. The seasonal components varies in respect to the primary growth in the series. Given the general time series additive model of the form

$$Y_p = T_p + S_p + C_p + I_p$$

where (Y_p) is the observed value at time period p and (T_p) is the trend value at time period p, while (S_p) is the seasonal component value, (C_p) is the cyclical component and (I_p) is the irregular component all with time period p. Some common decomposition include the estimation of trend which is expressed as

$$T_p = Y_p - S_p - C_p - I_p$$

The estimation of trend and irregular components

$$T_p + I_p = Y_p - S_p - C_p$$

The estimation of trend and cyclical components

$$T_p + C_p = T_p = Y_p - S_p - I_p$$

The estimation of trend, cyclical and irregular components

$$T_p + C_p + I_p = Y_p - S_p$$

The estimation of trend, cyclical and irregular components

$$T_p + S_p = Y_p - C_p - I_p$$

2.2 MANUAL IDENTIFICATION OF MONTHLY RAINFALL DATA IN IBADAN OYO STATE NIGERIA (2007 TO 2018)

The monthly rainfall data of Ibadan Oyo State is lifted directly from the data record of the Nigeria metrological agency at Ibadan Nigeria. This data spanned for 144 months which streamline with the monthly sample size used for the monthly simulation of this study (Ajare & Suzilah, 2019). plot in Figure 1. 144 months large sample size was selected because from simulation study, large sample size performs better than small sample sizes (Ajare & Suzilah, 2019). Details from the plot in Figure 1 were very sketchy and not much conclusion was derived and this is due to its complicated nature of the data. Only the trend and seasonal components can be seen vividly. The second time plot in Figure 1 reveals the four components during exploratory data analysis EDA. The four components are seen in the second Figure in Figure 1 but only the trend and the seasonal components can be clearly accounted for. Hence further exploratory data analysis was conducted to separate each and every individual components of time series monthly rainfall in Ibadan Oyo State.

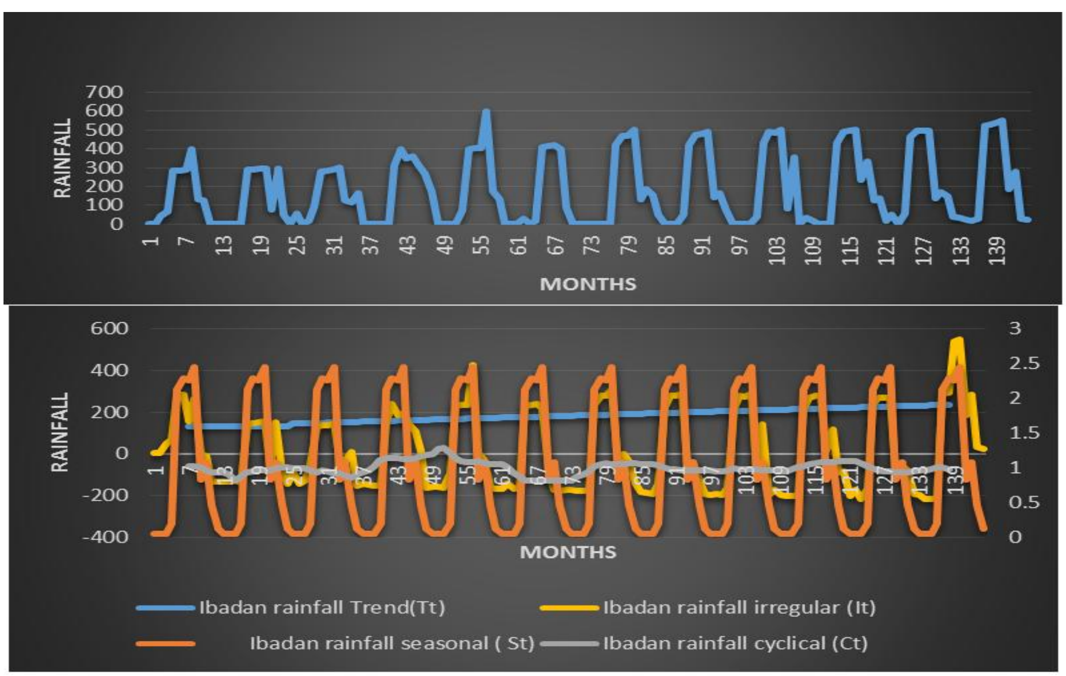

Figure 1 Manual Time plots of Monthly Rainfall in Ibadan.

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The study conducted extensive exploratory data analysis on the monthly rainfall data of Ibadan to examine critically all the time series components that exist in the data. Manual classical decomposition was utilized to decompose the Ibadan monthly rainfall into trend, seasonal, cyclical and irregular components using Microsoft excel. The decomposition reveals the existence of the four time series components being present in the monthly rainfall of Ibadan data. Figure 2 is the time plots of the four components of monthly rainfall in Ibadan. The first time plot in Figure 2 is the trend components time plot, this was extracted from the originally Ibadan rainfall data through the manual classical regression technique of extracting trend line. The second time plot in Figure 2 is the seasonal components time plot, this was extracted from the originally Ibadan rainfall data through the fitting of seasonal index to each month of the 12 seasonal months of the original Ibadan rainfall.

Th**e** third time plot in Figure 2 is the cyclical components time plot, this was extracted from the originally Ibadan rainfall data through the manual classical fraction technique of extracting cyclical movements. This was done through the division of centre moving average of Ibadan monthly rainfall with the trend components of the same data. The fourth time plot in Figure 2 is the irregular components, this was extracted from the original Ibadan rainfall data through the manual additive technique of extracting time series components. Since trend, seasonal and cyclical has being extracted, it is easy to subtract them from the original monthly Ibadan rainfall to get a left over called irregular components. Hence the four basic time series components exist in the data.

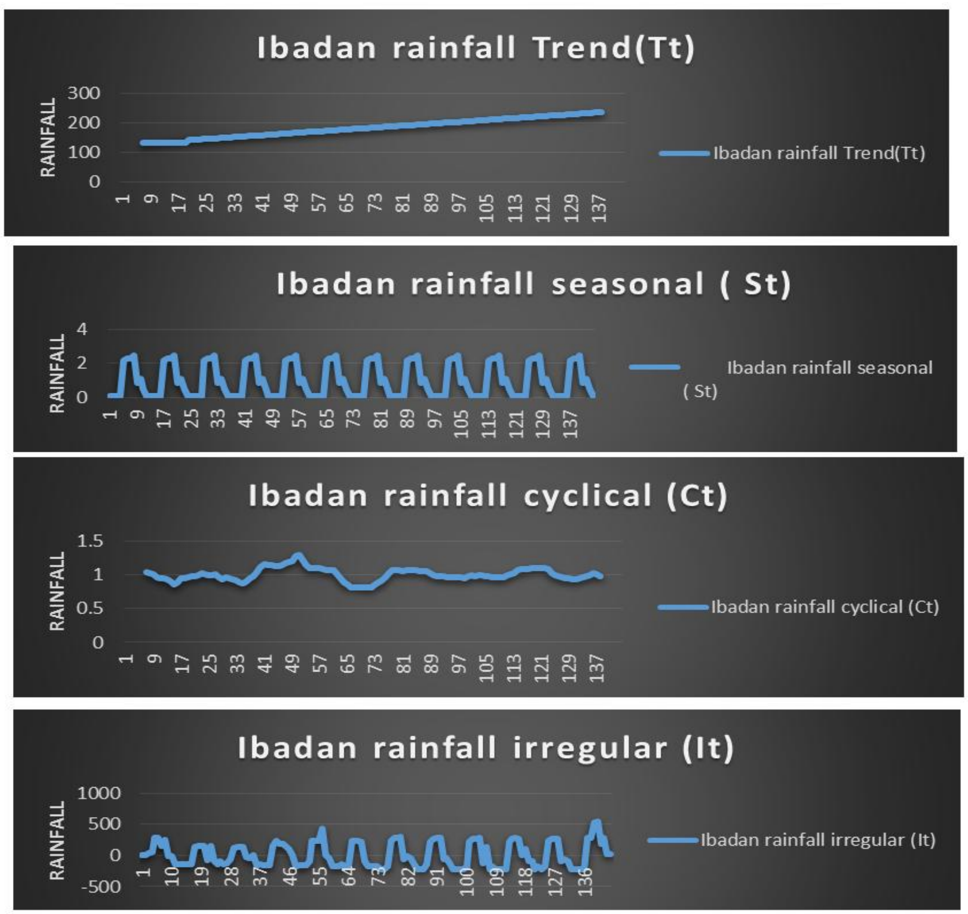

Figure 2 Manual Time plots of the Four Components of Monthly Rainfall in Ibadan.

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2.3 MANUAL IDENTIFICATION OF TIME SERIES COMPONENTS IN A QUARTERLY SALES OF COCA COLA DATA (1995 TO 2016).

The yearly quarter sales of coca cola beverages in Benin City Edo State were utilized as the second data in this study. This data was lifted directly from the data record of the quarterly/yearly production and sales register of Plot 1084, Nigerian Bottling Company NBC Benin, Eyaen, Uhunwonde Auchi road Benin City Edo State. This data spanned for 22 quarterly years which streamline with the yearly sample size used for the yearly simulation of this study. 22 years large sample size was selected because from simulation study, large sample size perform better than small sample sizes.

The first time plot in Figure 3 is the natural data of yearly sales of coca cola in Benin City before decomposition. Details from this plot are very sketchy and not much conclusion was derived and this is due to its complicated nature of the plot. Only the trend and cyclical components can be seen vividly. The second time plot in Figure 3 reveals the three components that are covered by yearly time series data during exploratory data analysis EDA. The three components are seen in the second Figure in Figure 3 but only the trend and the cyclical components can be clearly accounted for. Hence, further exploratory data analysis was conducted to separate each and every individual components of time series in yearly quarter sales of coca cola beverages in Benin City Edo.

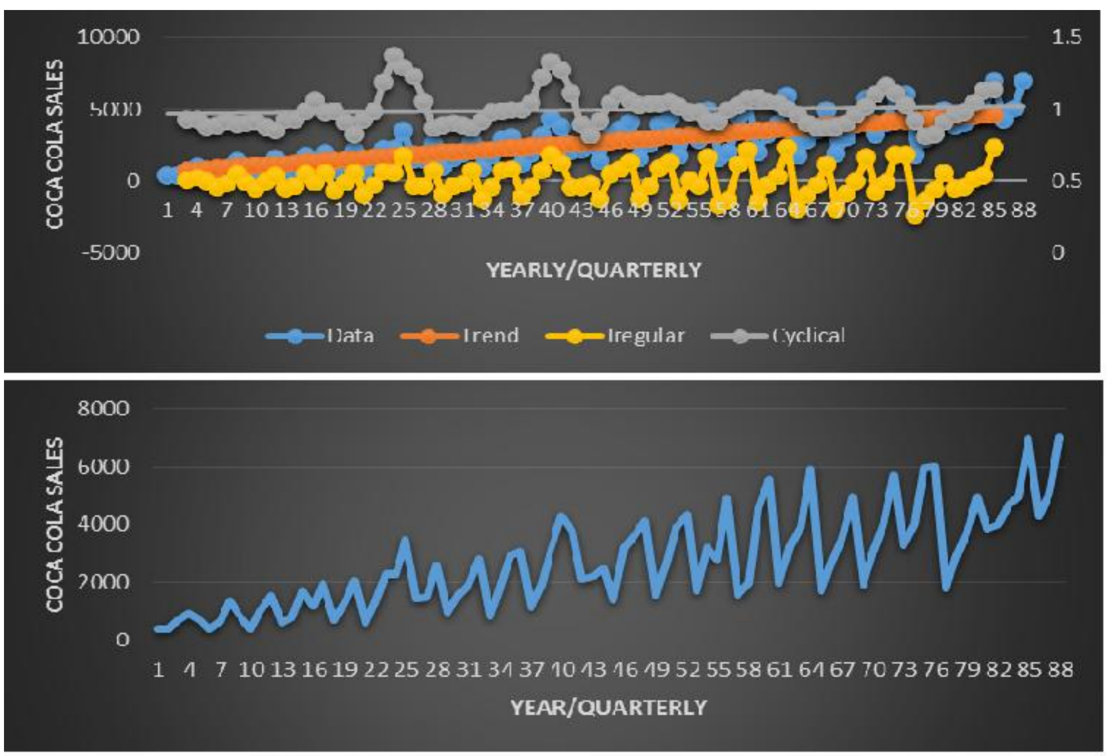

Figure 3. Manual time plots of Yearly/Quarter Sales of Coca Cola Beverages in Benin City.

The study conducted extensive exploratory data analysis on the yearly/quarter sales of coca cola beverages in Benin City Edo State to examine critically all the time series components that exist in the data. Manual decomposition was utilized to decompose the yearly/quarter sales of coca cola beverages in Benin City into trend, cyclical and irregular components using Microsoft excel. The decomposition reveals the existence of the three time series components being present in the yearly/ quarter sales of coca cola beverages in Benin City data. Figure 4 is the time plots of the three components of yearly/quarterly sales of coca cola beverages in Benin. The first time plot in Figure 4 is the trend components time plot, this was extracted from the originally yearly/quarter sales of coca cola beverages in Benin City data through the manual classical regression method of extracting trend line. The second time plot in Figure 4 is the cyclical components time plot. This was extracted from the originally yearly quarter sales of coca cola beverages in Benin City data through the manual classical fraction method of extracting cyclical movements. This was done through the division of centre moving average of yearly/ quarter sales of coca cola beverages in Benin with the trend components of the same data.

The third time plot in Figure 4 is the irregular components time plot, this was extracted from the originally yearly/quarter sales of coca cola beverages in Benin City data through the manual additive method of extracting time series components. Since trend and cyclical has being extracted, since seasonal components is also known, it is easy to subtract trend, seasonal and cyclical components data from the original yearly/quarter sales of coca cola beverages in Benin City to get a left over called irregular components. From the definition of seasonal components it is not more applicable to yearly data. Seasonal components is an identical pattern which flow over a regular period of time in a steady behaviour that can be monthly, weekly, hourly and more. Time plot 4 reveals that trend, cyclical and irregular components that exist in the data of yearly/quarterly sales of coca cola in Benin City.

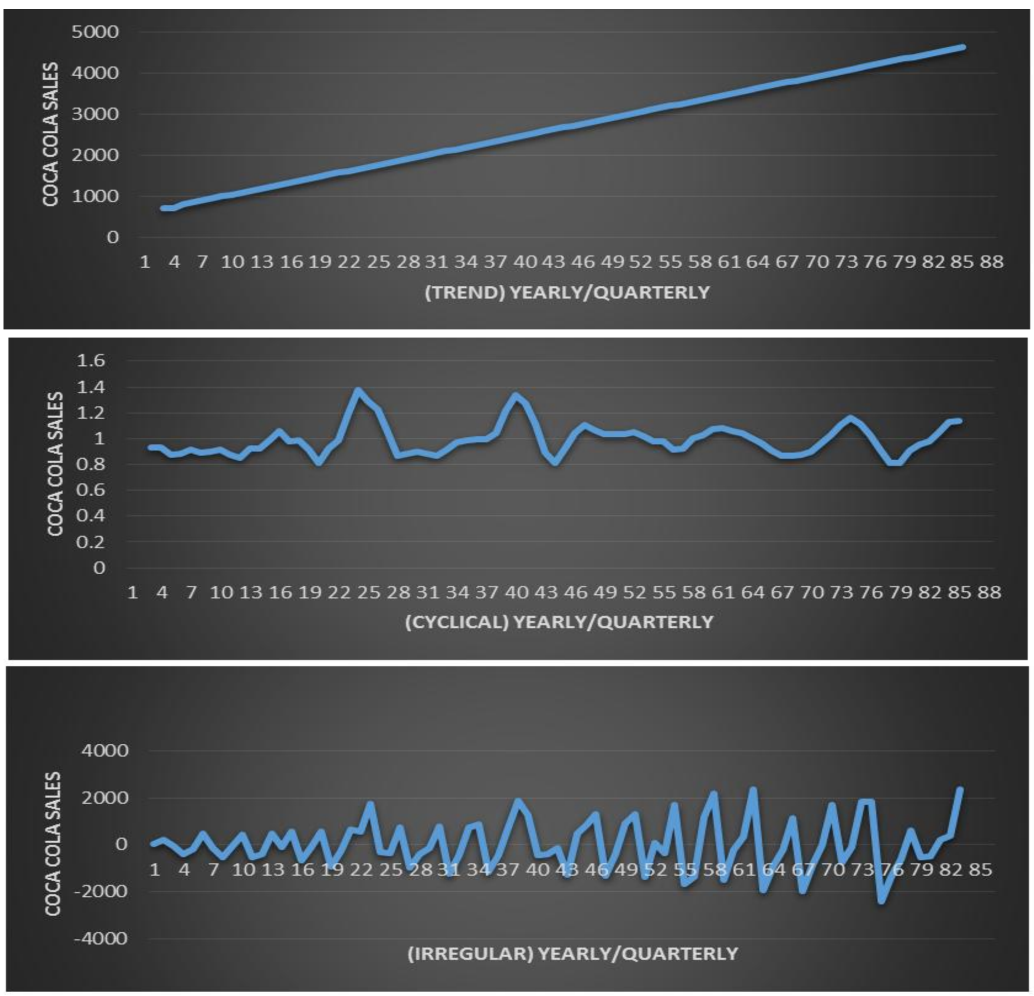

Figure 4. Manual time plots of three Components **of** Yearly/Quarter Sales of Coca Cola Beverages in Benin City Edo State**.**

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2.4. TIME SERIES COMPONENTS IDENTIFICATIONS USING BFTSC. BFTSC ARCHITECTURAL DESIGN.

The architectural design of BFTSC is similar to that of BFAST. The only difference in design was the physical output of the time plot after data incubation and data processing.

BFAST is the method is structured to be used in analyzing the generality of time series data by extracting the trend and seasonal pattern during time series decomposition. Given the general time series additive model of the form:

$$Y_p = T_p + S_p + C_p + I_p \quad (2.1)$$

Where Y_p is the observed value at time period p and T_p is the trend value at time period p, while S_p is the seasonal component value, C_p is the cyclical component and I_p is the irregular component all with time period p (Maggi, 2018 ; Zhao, Li, Mu, Wen, Rayburg, & Tian, 2015).

From equation (3.1) BFAST takes all other components relatively trend and seasonal component to be randomised (R_p) and the equation was expressed as

$$Y_p = T_p + S_p + R_p \quad (2.2)$$

The residual random consist of cyclical and irregular component, the breakpoint which represents the sudden change in time series caused by uproar noise such as natural phenomenon and human activities can be spotted in both seasonal components and trend components using BFAST technique (Zdravevski, Lameski, Mingov, Kulakov & Gjorgjevikj, 2015).

To generate trend components using BFAST, we need a piecewise linear model approach. Suppose T_p is a piecewise linear model with an actual slope and intercept on q+1 segments broken with q breakpoints and P period; $p_1^{\neq}, \ldots\ldots\ldots, p_q^{\neq}$ then T_p can takes the form

$$T_p = \alpha_k + \beta_k P$$

where $p_{k-1}^{\neq} < p \leq p_k^{\neq}$

and If k = 1,…..,q then $p_0^{\neq} = 0$ and $p_{q+1}^{\neq} = n$.

The slope of the change before the breakpoints while β_{k-1} and the slope of the breaks after the change breakpoints are β_k. The intercept and the slop of the linear model α_k and β_k with time period p and it will be used to derive the magnitude and direction of change.

To generate seasonal components using BFAST, we need a simple harmonic model.

Thus, S_p can be represented by a simple harmonic model with j terms; j = 12….J and time t.

$$S_p = \sum_{j=1}^{J} \omega_{k,j} \ \text{Sin} \left(\frac{2\pi j t}{F} + \sigma_{K,j} \right) \quad (2.3)$$

where k = 1… q, $p_{k-1}^{\neq} < p \leq p_k^{\neq}$ and also $\omega_{k,j}$, $\sigma_{K,j}$ are the segment amplitude and F is the frequency (Zeileis, Kleiber, Krämer & Hornik, 2003).

To generate random components, any data that does not belong to trend nor seasonal is classified random R_p.

.

$$Y_p = \underbrace{\{\alpha_k + \beta_k P\}}_{} + \underbrace{\left\{ \sum_{j=1}^{J} \omega_{k,j} \ \text{Sin}\left(\frac{2\pi j t}{F} + \sigma_{K,j}\right) \right\}}_{} + \underbrace{R_p}_{} \quad (2.4)$$

$$Y_p = T_p + S_p + R_p$$

The new method is called BFTSC considered splitting the random into cyclical components and irregular components which is an extension of BFAST. This was done through the inclusion of cyclical components direction.

Cyclical components can be calculated through the regression cyclical movement. The regression function at the breakpoint maybe discontinuous but the model can be written in such a way that the function continues at all point including breakpoints. To calculate cyclical components, center moving average is involved (Bornhorst, Dobrescu, Fedelino, Gottschalk & Nakata, 2011).

Derivation of cyclical code, let CMA be the center moving average of t objects, then CMA can be computed as follow

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$$CMA = \sum_{t}^{n} \frac{Yt}{nt} \quad (2.5)$$

t = 1,2…………n

Yt is the observations.

n_t is the numbers of the observations

CMA is the center moving average

Let $\overset{\wedge}{CMA}$ be the regression trend line of CMA for a given time series data

The CMA regression line is represented by

$$\overset{\wedge}{CMA} = \alpha_0 + \beta_1 P \quad (2.6)$$

For a given α_0 and β_1 being the slope and intercept of the time series observations

The cyclical components at time p is computed as

$$C_p = \frac{CMA}{\overset{\wedge}{CMA}} \quad (2.7)$$

The new equation becomes

$$Y_p = \underbrace{\{ \alpha_k + \beta_k P\}} + \underbrace{\{ \textstyle\sum_{j=1}^{J} \omega_{k,j} \ \text{Sin}\left(\frac{2\pi jt}{F} + \sigma_{K,j}\right)\}} + \underbrace{\left\{ \frac{CMA}{\overset{\wedge}{CMA}} \right\}} + \{ \underbrace{I_p} \} \quad (2.8)$$

$$Y_p = T_p + S_p + C_p + I_p$$

where Y_p is the observed value at time period p and T_p is the trend value at time period p, while S_p is the seasonal component value, C_p is the cyclical component and I_p is the irregular component at period p.

I_p is the remainder variations which is not captured by trend, seasonal variations and cyclical components, every variations apart from trend, seasonal and cyclical are classified as remainder (I_p).

2.5 BFTSC STAGE OF DATA PROCESSING

The first stage of BFTSC is the iteration conducted by OLS and MOSUM to identify the breakpoints in the components and the position of the trend breaks in $p_1^{\neq} \dots p_n^{\neq}$ which are estimated from the seasonal data, $Y_p - \hat{T}_p$.

The second stage of BFTSC is to extract the trend coefficients α_k and β_k for k= 1… q using robust regression due to the breakpoints.

The third stage of BFTSC is to conduct OLS and MOSUM test to check the break points in the seasonal components, the numbers and position of the breakpoints $t_1^{\neq}$,………, $t_n^{\neq}$ are then estimated, the seasonal components are then estimated $Y_p - \hat{S}_p$.

The fourth stage is the extracting of seasonal coefficients and computations follows. The stages of iteration continue until the number and position of the breaks points are completely identified.

The fifty stage of BFTSC is to conduct OLS and MOSUM test to check the break points in the cyclical components. The numbers and position of the breakpoints $q_1^{\neq}$,………, $q_n^{\neq}$ are then estimated, the cyclical components are then estimated $Y_p - \hat{C}_p$.

The sixth stage of BFTSC is the extracting of cyclical coefficients and computations follows. The stages of iteration continue until all the number and position of the breaks points are all detected**.** The technique is designed such that it can plot all the components of the time series as individual.

The behavour of BFTSC was examined using two types of data. The process of applying empirical data to BFTSC is called evaluation of BFTSC. The first empirical data set is the monthly rainfall data in Ibadan Oyo State Nigeria (2007 to 2018), this data was lifted from the record of Nigeria Metrological Agency. The second empirical data is the quarterly/sales of coca cola beverages in Benin City Edo State Nigeria (1995 to 2016). The coca cola data was lifted directly from the data record of the quarterly/yearly production and sales of coca cola register of Plot 1084, Nigerian Bottling Company NBC Benin, Eyaen, Uhunwonde Auchi road Benin City Edo State.

The first empirical data set was plotted in Figure 5 with the help of BFTSC. The entire components of four time series components were examined (Ismail, Zakaria, & Muda 2014; Maniatis, Akhawe, Fall, Shi & Song, 2011).

Figure 5 is the time plot of BFTSC for 12 years monthly rainfall data in Ibadan which spanned for 144 months. According to Ajare& Ismail, (2019). 144 months was choosing because during simulation study, large sample size perform better than small sample sizes. 144 months was above the medium data of 96 months that was used for evaluating BFTSC in Section 4.5. BFTSC which was able to identify 100% of the irregular components (I_t) that was present in the one hundred data. BFTSC was able to identify 100 % of the cyclical components in the one hundred data that was prepared for evaluation of BFTSC, it was able to identify t 100 % of all the entire components present in the data for large sample size. Based on the information above, this study used 144 monthly data which is above 96 months and 48 months to validate BFTSC using empirical Ibadan rainfall data.

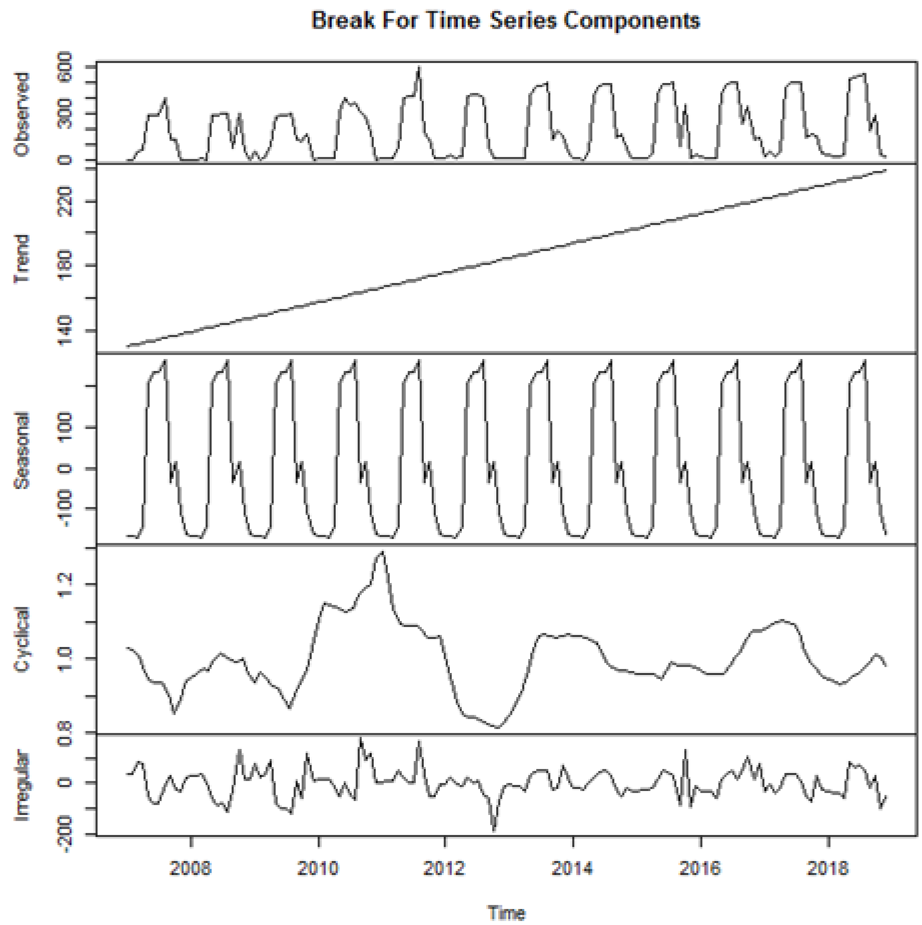

Figure 5. BFTSC of Monthly Rainfall Data in Ibadan.

The observed data in Figure 5, row 1 reveals the mixture of all the time series components (trend, seasonal, cyclical and irregular components) in its natural empirical state. It was little complicated to explain and that is why BFTSC is designed to extend to separating each components accordingly.

Figure 5, row 2. Trend components was clearly seen to be present in the time series data, the trend was not obvious in the original natural data but was obvious in the trend identification section. The trend was linear in nature and was not complicated to identify and recognized.

Seasonal components was clearly seen to be present in the time series data as observed from Figure 5, row 3. The seasonal components shows a consistent repeated pattern with equal interval and peak over the entire span of the data, this was a clear evidence that seasonal component is presents. The seasonal components was not obvious in the original natural data but was obvious in the seasonal identification section.

Figure 5, row 4. The cyclical components was clearly seen to be present in the time series data as observed from the plot. The cyclical components shows a non-consistent repeated pattern in an unequal and irregular interval and also with an irregular peak over the entire span of the data, this was a clear evidence that cyclical component is presents in the time series data. The cyclical components was not obvious in the original natural data but was obvious in the cyclical identification section with the help of BFTSC.

The last row in figure 5, row 5. The irregular components was clearly seen to be present in the time series data as observed from the plot. The irregular components shows a non-consistent and non-repeated pattern in an unequal and irregular interval and also with an irregular peak over the entire span of the data. Irregular components was most obvious in the September 2011 that means Ibadan observed flood in 2011. Around 2013 there was a very low rainfall in Ibadan. This was a clear evidence that irregular component is presents in the time series of data. The irregular components was not obvious in the original natural data but was obvious in the irregular identification section with the help of BFTSC.

The comparison of the four times series components (trend, seasonal, cyclical and irregular components) makes it easy to accept and adopt that the data is a real monthly time series data with the four common time series components.

The second data which is the yearly quarter sales of coca cola beverages in Benin City Edo was utilized as the second data in this study. This data was lifted directly from the data record of the quarterly yearly production and sales register of coca cola Company of Plot 1084, Nigerian Bottling Company NBC Benin, Eyaen, Uhunwonde Auchi Road Benin City Edo State. In Figure 6 the twenty two years data is utilized with the help of BFTSC. The same condition applied in data size selection in Ajare & Suzilah (2019) was also applied in this aspect and for subsequent uses of BFTSC and GFTSC. The entire components of time series statistic (trend components, cyclical components and irregular components) were examined (Ismail, Zakaria, & Muda 2014; Maniatis, Akhawe, Fall, Shi & Song, 2011).

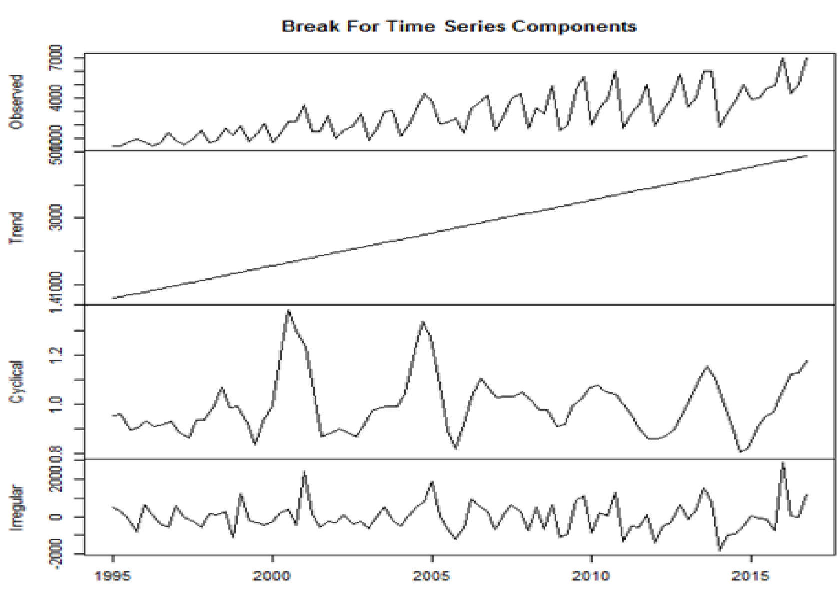

Figure 6. BFTSC of Yearly/Quarter Sales of Coca Cola

Figure 6 is the time plot of BFTSC for yearly/quarterly sales of coca cola beverages in Benin City Edo State Nigeria (1995 to 2016). The twenty two years data was choosing because it was above the small sample size of 16 years and also above the medium sample size of 16 years that was generated through simulation for evaluating yearly BFTSC Ajare & Suzilah (2019). Based on the information above, this study used twenty two years quarterly data which is the yearly/quarterly sales of coca cola beverages in Benin City Edo State Nigeria (1995 to 2016). The observed data in Figure 6, row 1 reveals the mixture of all the time series components (trend, seasonal, cyclical and irregular) which occurred in its natural empirical state. The observed data look like trend data and complicated to explain and that is why BFTSC is designed to extend to separating each components accordingly.

Figure 6, row 2. Trend components were clearly seen to be present in the time series data, the trend was not too obvious in the original natural data but was obvious in the trend identification section. The trend was linear in nature and was not complicated to identify and recognized by using BFTSC.

Figure 6, row 3. The cyclical components was clearly seen to be present in the time series data as observed from time plot. Cyclical components are cycles that repeat itself with an irregular time intervals. The cyclical components shows a non-consistent repeated pattern in an unequal and irregular time interval and also with an irregular peak over the entire span of the data. The above information was a clear evidence that cyclical component is presents in the time series data. The cyclical components was not obvious in the original natural data but was obvious in the cyclical identification section with the help of BFTSC.

The last row in Figure 6, row 4. The visibility of the irregular components was too obvious, irregular components was clearly seen to be present in the time series data. Seasonal components was not considered obvious in yearly time series data. Hence, seasonal components is not included (Ismail, Zakaria, & Muda 2014; Maniatis, Akhawe, Fall, Shi & Song, 2011).

The irregular components was common in the twenty two years quarterly sales data of coca cola beverages in Benin City Edo State Nigeria (1995 to 2016). The irregular components shows a non-consistent and non-repeated component only within the September 2011 but before that, some irregular components were noticed. This was a clear confirmation that irregular component is presents in the time series data. The irregular components was not obvious in the original natural data but was obvious in the irregular identification section with the help of BFTSC.

2.6 TIME SERIES COMPONENTS IDENTIFICATIONS USING GFTSC.

The architectural design of GFTSC is similar to that of BFTSC. The only difference in design was the physical output of the time plot after data incubation and data processing.

2.7 GFTSC STAGE OF DATA PROCESSING

The stages of GFTSC follow similar stage of the type of BFTSC. The first stage in GFTSC iteration is to conduct OLS and MOSUM to identify the breakpoints in the components and the position of the trend breaks in $p_1^{\neq} \dots p_n^{\neq}$ which are estimated from the seasonal data, $Y_p - \hat{T}_p$.

The second stage in GFTSC is to extract the trend coefficients α_k and β_k for k= 1… q using robust regression due to the breakpoints.

The third stage in GFTSC is to conduct OLS and MOSUM test to check the break points in the seasonal components, the numbers and position of the breakpoints $t_1^{\neq}$,………., $t_n^{\neq}$ are then estimated, the seasonal components are then estimated $Y_p - \hat{S}_p$.

The fourth stage in GFTSC is the extracting of seasonal coefficients and computations follows.

The fifty stage in GFTSC is to conduct OLS and MOSUM test to check the break points in the cyclical components, the numbers and position of the breakpoints $q_1^{\neq}$,………., $q_n^{\neq}$ are then estimated, the cyclical components are then estimated $Y_p - \hat{C}_p$.

The sixth stage in GFTSC is the extracting of cyclical coefficients and computations follows. The stages of iteration continue until all the number and position of

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the breaks points are detected. The technique is designed such that it can plot all the components of the time series in a different plot.

2.8 IDENTIFICATION OF TIME SERIES COMPONENTS USING GFTSC.

The validation of GFTSC is the process of applying empirical data to GFTSC. Two type of data was applied to GFTSC in this section. The first empirical data set is the monthly rainfall of data in Ibadan Oyo State Nigeria (2007 to 2018), this data was lifted from the record of Nigeria Metrological Agency. The second empirical data is the yearly/quarterly sales of coca cola beverages in Benin City Edo State Nigeria (1995 to 2016). The coca cola data was lifted directly from the data record of the quarterly/yearly production and sales of coca cola register of Plot 1084, Nigerian Bottling Company NBC Benin, Eyaen, Uhunwonde Auchi road Benin City Edo State.

The first data which is the twelve years monthly data in Ibadan is plotted in Figure 7 with the help of GFTSC. The entire components of time series statistic (trend components, seasonal components, cyclical components and seasonal components) was examined following the six steps in Chapter One (Ismail, Zakaria, & Muda 2014; Maniatis, Akhawe, Fall, Shi & Song, 2011).

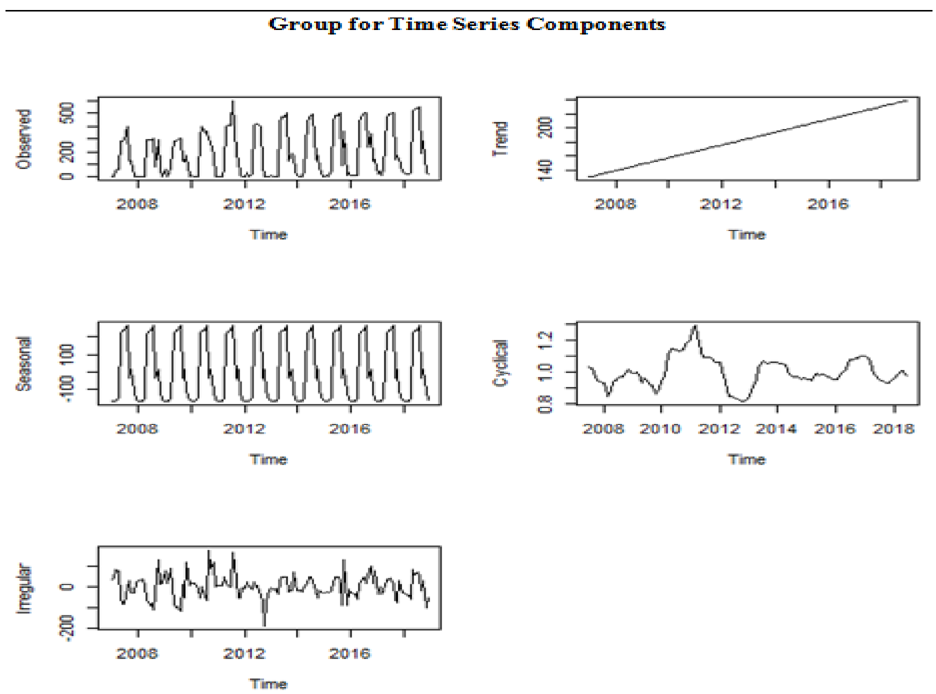

Figure 7. GFTSC of Monthly Rainfall Data in Ibadan.

Figure 7 is the time plot of GFTSC for twelve years monthly rainfall data in Ibadan which spanned for 144 months. 144 months was choosing because it streamline with the large sample size that was applied during simulation Ajare & Suzilah (2019). It was reveal that large sample size perform better than small sample sizes. When 144 monthly data of large is compared with medium sample size data of 96 months and small sample size data of 48 months. Large sample sizes outperform the small sample and the medium sample sizes. Based on the information above, this study used 144 monthly rainfall data which is above 96 months to validate GFTSC using empirical rainfall data (Ajare & Suzilah (2019)).

The observed data in Figure 7, row 1, first plot in first column reveals the mixture of all the time series components (trend, seasonal, cyclical and irregular) in its natural empirical state. It was little complicated to explain and that is why GFTSC is designed to extend to separating each components accordingly.

Figure 7, the plot, column 2, row 1. Trend components was clearly seen to be present in the time series data. The trend was not obvious in the original natural data but was obvious in the trend identification section. The trend was linear in nature and was not complicated to be identified and recognized.

Seasonal components was clearly seen to be present in the time series data as observed from plot. Figure 7, column 1, row 2 is the plot for seasonal components. The seasonal components shows a consistent repeated components with equal interval and peak over the entire span of the data, this was a clear evidence that seasonal component is presents and dominant. The seasonal components was not obvious in the original natural data but was obvious in the seasonal identification section. Figure 7, column 2, row 2. The cyclical components was clearly seen to be present in the time series data as observed from plot. The cyclical components shows a non-consistent repeated pattern in an unequal and irregular interval and also with an irregular peak over the entire span of the data. This was a clear evidence that cyclical component is presents in the time series data. The cyclical components was not obvious in the original natural data but was obvious in the cyclical identification section with the help of GFTSC.

The last row in Figure 7, column 1, row 3. The irregular components was clearly seen to be present in the time series data as observed from plot. The irregular components shows a non-consistent and non-repeated pattern in an unequal and irregular interval and also with an irregular point at year 2010. Irregular components shows a drop in year 2013 that means Ibadan observed low rainfall in that year, in year 2011 Ibadan experience flood. This was a clear evidence that irregular component is presents in the time series data. The irregular components was not obvious in the original natural data but was obvious in the irregular identification section with the help of GFTSC.

The second data was the twenty two years/quarterly sales of coca cola beverages in Benin City Edo State.

Figure 8 is the twenty two years yearly/quarter sales of coca cola data is utilized with the help of GFTSC. The entire components of yearly time series components were observed from the time plot (trend components, cyclical components and irregular components) was examined, seasonal components is not considered obvious in yearly time series data. Hence, seasonal components is not included (Ismail, Zakaria, & Muda 2014; Maniatis, Akhawe, Fall, Shi & Song, 2011).

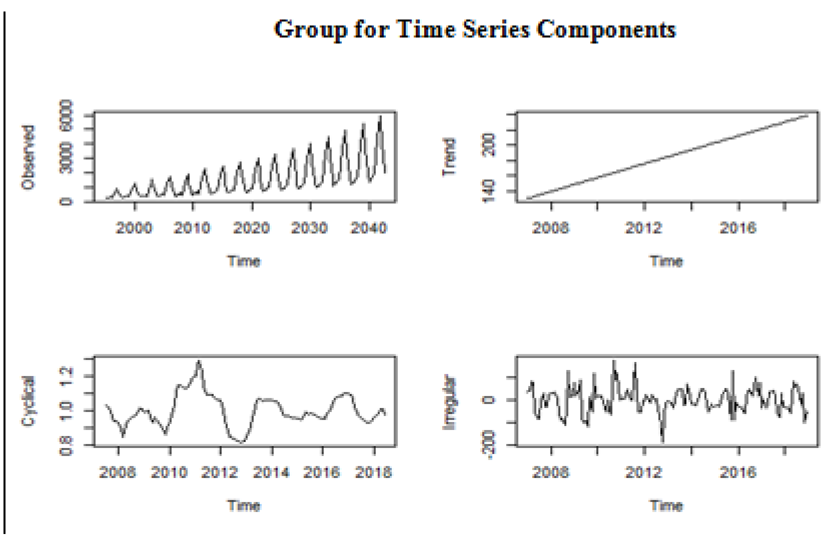

Figure 8. GFTSC of Yearly/Quarter Sales of Coca Cola

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Figure 8 is the time plot of GFTSC for twenty two years coca cola data which is the yearly/quarterly sales of coca cola beverages in Benin City which spanned for twenty two quarter years and covered eighty eight data points.

Figure 8 is the time plot of GFTSC for quarterly sales of coca cola beverages in Benin City Edo State Nigeria (1995 to 2016). The twenty two years data was choosing because it was above the small sample size of 8 years and also above the medium sample size of 16 years that was generated through simulation for evaluating yearly BFTSC (Ajare & Ismail, 2019). The observed data in Figure 8, row 1, column 1 reveals the mixture of all the time series components necessary for yearly data (trend, cyclical and irregular components) in its natural empirical state. The observed data look like trendy data and complicated to explain and that is why GFTSC is designed to extend to separating each components accordingly and this was presented automated in row 1, column 2.

Figure 8, row 1, column 2. Trend components was clearly seen to be present in the time series data, the trend was not too obvious in the original natural data but was obvious in the trend identification section. The trend was linear in nature and was not complicated to identify and recognized by using GFTSC.

Figure 8, row 2, column 1. The cyclical components was clearly seen to be present in the time series data as observed from the time plot. Cyclical components are cycles that repeat itself with an irregular time intervals. The cyclical components shows a non-consistent repeated pattern in an unequal and irregular time interval and also with an irregular peak over the entire span of the data. The above information was a clear evidence that cyclical components were presents in the time series data. The cyclical components was not obvious in the original natural data but was obvious in the cyclical identification section with the help of GFTSC.

The last row in figure 8, row 2, column 2. The irregular components was obvious, irregular components was very much seen to be present in the time series data. The irregular components was observed between the sales of coca cola in 2011 and 2012 but sales drop unexpectedly at 2013. The irregular components shows a non-consistent and non-regular repeated component. This was a clear evidence that vindicate that irregular component is presents in the time series data. The irregular components was not obvious in the original natural data but was obvious in the irregular identification section with the help of GFTSC.

The comparison of the four times series components (trend, cyclical and irregular) makes it easy to accept and adopt GFTSC for time series components identifications

3. RESULTS

The manual identifications of time series components of Ibadan monthly rainfall and yearly/quarterly sales of coca cola in Benin City Edo State are presented in Figure 1 and Figure 2 Figure 3 and Figure 4. The Ilorin monthly rainfall described indicated a steady movement trend of rainfall in Ilorin. The manual time series identification of yearly/quarterly sales of coca cola beverages in Benin City Edo State is presented. The time plots for manual identifications of caca cola sales reveal a steady growth in sales of coca cola in the specified state, hence sales of coca cola always rise in every festive period and school resumption period and remain steady in other periods.

Based on detail examining of the time series components presents in Ibadan monthly rainfall and yearly/quarterly sales of coca cola in Benin City. BFTSC was able to clearly identify the four time series components (trend, seasonal, cyclical and irregular components) presents in the Ibadan monthly rainfall and it was presented in Figure 5. BFTSC was also able to identify the three time series components (trend, cyclical and irregular components) presents in yearly/quarterly sales of coca cola in Benin City Edo State and this was presented in Figure 6. Hence BFTSC is considered as first better alternative to manual time series components identification.

Subsequently, observation from GFTSC time plot reveals that GFTSC is also effective in time series components identifications. Based on detail

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examining of the time series components presents in Ibadan monthly rainfall and yearly/quarterly sales of coca cola in Benin City. GFTSC was able to clearly identify the four time series components (trend, seasonal, cyclical and irregular components) presents in the Ibadan monthly rainfall and it was presented in Figure 7. GFTSC was also able to identify the three time series components (trend, cyclical and irregular components) presents in yearly/quarterly sales of coca cola in Benin City Edo State and this was presented in Figure 8. Hence GFTSC components is considered as the second better alternative to manual time series components identification.

Comparison of manual time series components identifications with BFTSC and GFTSC is a confirmation that BFTSC and GFTSC can be a better alternative to the classical manual time series components identifications. This is based on the efficiency of the two techniques in respect to time series components identification.

4. DISCUSSION

Manual time series components identification is the process utilized by expert and non expert in decomposing time series components into its various components and consequently identifying each component. The common approach of identifying time series components is called the exploratory data analysis (EDA). The EDA is procedural step that help in careful examination of each component of time series (trend, seasonal, cyclical and irregular components). The manual time series components identifications can be done by using Microsoft excel soft ware, SPSS, Sata and many more classical soft wares. The objective of manual time series components identifications is to extract out the four basic time series components (Trend, Seasonal, Cyclical and Irregular) using manual approach (Box & Jenkins, 1976). Box and Jenkins (1976) was one of the first researchers that struggle to clearly identify time series component using time plot. The first time series data obtained was plotted on a time plot using manual method and the behavior of time series data was observed. However, the limitation of this technique was the complexity, it was very complicated to differentiate the time series components using casual manual time plot and the manual technique may be extremely difficult for non-experts. In this study manual Microsoft Excel was used to extract time series components. Search for an alternative method to manual method is being carried out by carefully examining BFTSC and GFTSC which was created from BFAST.

BFAST components identification. Ewing and Malik (2013) developed DBEST (Detection Breakpoint and Estimating Segment Trend) which was modified from BFAST. DBEST take in (NDVI) normalizes difference vegetation index data. The limitation of DBEST method is that, the algorithm was built to solve the problem of topographical vegetation trend identification but cannot identify cyclical and irregular components of time series statistics. It is not flexible time series component identification technique and this is still the BFAST weakness that needs to be fully addressed. Jong, Verbesselt, Schaepman and Bruin (2012) argue and contributed to the body of knowledge by investigating the collective change identification called BFAST. The method called BFAST is used for acknowledging breaks for additive, seasonal and trend in order to classify seasonal components and also enables the identification of breaks that take place in trend within the system (Morrison et al., 2018). Verbesselt, Zeileis, Hyndman, & Verbesselt (2012). Package 'bfast'which portrays the main scope of BFAST. Many scholars employ the use of BFAST in identifying trend in topographical data (Porter & Zhang, 2018). The technique is accessible in BFAST pack for R (R developments Core Team, 2012).

Jain, Duin, and Mao (2000) describe time series component identification as a complicated issue, this lead this study to seek out for transparency regarding BFAST. Verbesselt et al. (2010) recommend a new method for broad trend detection, image classification and representative, the technique is called Break for Additive Seasonal and Trend known as BFAST. This method integrates the decomposition of time series components into the conventional elements of the

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series such as data, seasonal, trends and remnants, it was done with the help of the technique for identifying change which is embodied in the system of BFAST (Abbes & Farah, 2017; Adewoye & Chapman, 2018). Therefore, from these discussion, BFAST need to be improved to a technique that can identify the four time series components. BFTSC is recommended for efficient time series components identification for an improved forecasting.

BFTSC components identifications. Break for time series components technique BFTSC is designed to be able to process any form of time series data, it can be used by anyone who wishes to be a beneficiary or need the package that will be developed. For better identification. The diagrammatical representation of the BFTSC enable the researcher to have a broad view of all the time series components presents in a given data and presenting them on a single time plot. BFTSC is expected to be tolerant to additives models if necessary by the structure of the scheme and multiplication models if necessary by the character of the given scheme. The problem of time series components detection is a problem that should be solved in the earliest stage of time series forecasting Flicek & Birney (2009). The coding of BFTSC can be acquired through my email; ajareoloruntoba@gmail.com. The code and the Algorithm helps in understanding the details of BFTSC and its usage.

GFTSC components identifications. The technique known as group for time series components GFTSC which is the second extension of BFAST. The extension of BFAST to another technique that can consider both additives and multiplicative system, which can also group each component of time series into individual groups. This technique is known as group for time series components GFTSC. The GFTSC considers all the vital components of time series in every group and the next justifiable model to be involved. GFTSC separate each component to group A which contains elements that form trend components, group B which contains elements that form seasonal components, group C which contains elements that form cyclical components, group D which contains elements that form irregular components. The coding of GFTSC can be acquired through my email; ajareoloruntoba@gmail.com. The code and the Algorithm helps in understanding the details of BFTSC and its usage.

5. SUMMARY/CONCLUSION

This study make use of two empirical data. The first data was a secondary data of the monthly rainfall data in Ibadan Oyo State Nigeria (2007 to 2018), this data was lifted directly from the record of Nigeria Metrological Agency. The second data was the yearly/quarter sales of coca cola beverages in Benin City Edo State. This data was lifted directly from the data record of the quarterly/yearly production and sales register of Plot 1084, Nigerian Bottling Company NBC Benin, Eyaen, Uhunwonde Auchi road Benin City Edo State. The first and the second empirical data was analysed using the manual technique of time series components identification. The first data which is the monthly rainfall data contains the four time series components (trend, seasonal, cyclical and irregular components).The second data which is the years/quarterly sales of coca cola data, the three yearly time series components (trend, cyclical and irregular components) was observed in the data.

Manual time series identifications was carried out using Microsoft excel. This was used to identify the time series components in both Ibadan rainfall and coca cola sales data in Edo State.

BFTSC was the used to identify the time series components presents in the two time series data. BFTSC identify the four time series components in the first data, the monthly rainfall data contains the four time series components (trend, seasonal, cyclical and irregular components). The second data which is the years/ quarterly sales of coca cola in Benin City, BFTSC identify the three yearly time series components (trend, cyclical and irregular components) which is necessary for yearly data. Hence, BFTSC is considered as the first better alternative to manual time series components identification.

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GFTSC was also use to identify the time series components presents in the two time series data. GFTSC identify the four time series components in the first data, the monthly rainfall data contains the four time series components (trend, seasonal, cyclical and irregular components). The second data which is the years quarterly sales of coca cola in Benin City, GFTSC identify the three yearly time series components (trend, cyclical and irregular components) which is necessary for yearly data. Hence, GFTSC is considered as the second better alternative to manual time series components identification.

WEAKNESS AND FUTURE RESEARCH

The issue of how large is large and maximum sample size accepted by BFAST is yet to be addressed (Van Leeuwen, Huete and Laing, 1999). Likewise the issue of maximum sample size for Manual method of time series identification, BFTSC and GFTSC as not being fully addressed because it depends on the nature of individual research and interest.

BFTSC and GFTCS is not a forecasting technique itself but can be used to improve forecasting with 99% accuracy in time series components identification.

BFTSC and GFTSC need more beautification and to be made more attractive by adding more statistical spices in the coding.

More automated and innovated time series components identifications is a welcome development.

6. RECOMMENDATION

The contribution of this study to the scientific community is that the BFTSC and GFTSC gives good results that improve the weaknesses of the existing Manual time series components. BFSTC and GFTSC is also better than BFAST (Ajare & Suzilah, 2019). BFTSC and GFTSC time series component identification can serve as a better alternative to time series components identification and it is recommended for public utilization for forecasting. If anyone is interested in the application of GFTSC and BFTSC code, he/she can inbox me interest notification in my mail provided as (ajareoloruntoba@gmail.com) and I will send it.

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AUTHORS CONTRIBUTIONS

Ajare Emmanuel Oloruntoba: Analyzing, producing the results and writing the paper.

Suzilah bt Ismail: Supervising the contents and flow of the paper.

ETHICS

This is the original manuscript; there will be no expectation of any ethical problems after the publication. The two authors have read and approved the manuscript.

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