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DETECTING CHANGE IN A HIGHLY VOLATILE CURVE LONDON STOCK EXCHANGE (LSE) DATA USING AUTOMATED DECOMPOSITION DETECTION ALGORITHM FOR TIME SERIES.

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Abstract:
The main reason for this study is to use manual process of identification of time series components with two types of automated decomposition detection algorithm known as automated BFTSC (break for time series components) and, automated GFTSC (Group for time series components) in detecting change in a highly volatile curve London Stock Exchange (LSE) Data. Identifying the components of time series present in the data of London Stock Exchange (LSE). London Stock Exchange monthly data for 20 years (January 2001 until December 2020) was utilized in this study and obtained from Yahoo finance (yahoo-link). The London Stock Exchange (LSE) data is also available as a secondary data at the DataStream of Universiti Utara Malaysia Library. The weaknesses of BFAST were corrected by the extension of BFAST to BFTSC and GFTSC. Both were created to capture the cyclical and irregular components that was not captured by BFAST technique and it was included in the methodology of this study. BFTSC and GFTSC were designed to give a combined image of all the four time series components captured in a single time plot. Evaluation using simulation data was conducted in the past studies to verify the accuracy of both techniques of which both techniques are effective and better than BFAST because it was able to identify 100% of the data with the basic four time series components monthly. both techniques detects 99.97% of the entire components in the time series monthly data that was tested. The subsequently forecasting technique was determined. Lastly, some weakness of BFAST and GFTSC was highlighted in this paper in term of polynomial and cubic time series components identification.

Keywords: London Stock Exchange, Break for Time Series Components, Seasonal Data, Cyclical components, Irregular components.

Introduction

The main purpose for this study is to use manual process of identification of time series components, automated BFTSC (break for time series components) and automated GFTSC (Break for time series components) in identifications of the components of time series present in the empirical data of London Stock Exchange (LSE). Both BFTSC and GFTSC are considered to be more efficient in identifying all the components of time series statistics better than BFAST. BFTSC and GFTSC are improved BFAST. BFAST (Break for Additive Seasonal and Trend) is a technique used for identification of trend and seasonal components of time series observations in a remote sensing environment, trend breaking was first suggested by Bai and Perron (2003). Jong, Verbesselt, Schaepman and Bruin (2012) recommended an approach of basic swing identification to spot time series component. This approach was also used by Zewdie, Csaplovics and Inostroza (2017) as the latest time series component recognition approach which is a technique that was first described and utilized by Verbesselt et al. (2010).

The technique BFAST was for recognizing breaking points with the help of seasonal and trend decomposition using loess (STL), it facilitates the detection of trend change in a given information. The elementary standard of the BFAST technique is the splitting of time series into seasonal, trend and also remnants element by the approach for breaks detecting software in R studio core 2012 **(**Cunha**,** 2013).

Zewdie et al. (2017) opines that the technique of BFAST can predict and analyze a topographical forest movement in northwest of Ethiopia with the help of normalized difference vegetation index's branded as (NDVI). Thus, by extensively examining the period of variations of the desiccated portion of land for an enhanced perceptive of the seasonal variation path in the arid topographic area, this was done by detecting and determining factors of arid area changes using (NDIV) data to monitor the variations (Cesta, Cortellessa, Pecora, & Rasconi, 2005; Buhalau, 2016; DeVries, 2013). The technique is accessible in BFAST pack for R (R developments Core Team, 2012). Package 'bfast'which portray the main scope of BFAST. Many scholars employ the use of BFAST in identifying trend in topographical data (Porter & Zhang, 2018).

The extension of BFAST is an improved technique that identifies all-time series components. This two new techniques are known as BFTSC (Break for time series components) and GFTSC (Group for time series components). Many of the automated techniques of pattern detection are not flexible enough to be used by non experts in statistic. GFTSC and BFTSC are very flexible and easy to use by non-statistics experts, this is the first extension of BFAST in history which can produce equations together with time plots automatically.

BFTSC technique considers every vital component of time series statistics. BFAST is known to be weak in identifying and breaking random variations, also very weak in applicability to other types of empirical data (Flicek & Birney 2009). The technique considers the extension and improvement of the BFAST to BFTSC, breaks for additive, seasonal and trend to be modified to break's for time series components BFTSC.

GFTSC has the advantage of producing equations of each time series components displayed together on the same time plot, this makes GFTSC to be a step further to BFTSC.

BFTSC and GFTSC are programmed into computer EZEE forecasting software as a package and can be used by anyone who wishes to be a beneficiary or need the package.

BFTSC and GFTSC are tolerant to additives models when necessary considering the structure of the system and multiplication models of the given system. 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).

BFTSC and GFTSC followed similar derivative steps like BFAST but deviated in the addition of cyclical and irregular components. BFTSC and GFTSC are both technique used in analyzing the generality of time series data by extracting the trend components and seasonal components, cyclical components and irregular components during time series decomposition. Given the general time series additive model as in equation (1.1) of the form:

$$Y_P = T_p + S_p + C_p + I_p \qquad (1.1)$$

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 (Box, Jenkins, Reinsel, & Ljung, 2015 :Maggi, 2018; Cleveland & Tiao, 1976; Caiado, 2009; Bohn, 1995; Cipra, & Romera, 1997).

BFTSC and GFTSC identifies all the of time series components relatively trend, seasonal, cyclical and irregular components to be randomized equation while GFTSC identifies all the of time series components together with addition of the equations that produces each components.

The residual component in BFAST now converted to contained cyclical and irregular component using GFTSC and BFTSC. The breakpoint which represent the change in time series caused by common noise such as natural phenomenon and human activities can be observed in both seasonal components and trend components using BFTSC technique. In BFAST only random component can be observed but in BFTSC the cyclical and irregular components is identified alongside with trend and seasonal components (Zdravevski, Lameski, Mingov, Kulakov & Gjorgjevikj, 2015).

The study highly volatile empirical data is the London Stock Exchange (LSE) which is one of the world largest financial center. The exchange was formally established around 1773 by group of stockbrokers. LSE is Europe's leading stock exchange and is owned by the London Stock Exchange Group pls (LSEG) (Rosini & Shenai, 2020).

London Stock Exchange monthly data for 20 years (January 2001 until December 2020) was utilized in this study and obtained from Yahoo finance (online link). The data was the adjusted close data which is the closing price after adjustment for all applicable splits and dividend distribution (Moradi, Jabbari. & Rounaghi, 2021). London stock exchange is measured in Great Britain Pounds (£). This data is also available in the University Utara Malaysia Library databank section (Research section RR-2568) for verification purposes.

Material and Methods

BFAST is the technique 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 randomized (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; $p_1^{\neq}$,………., $p_q^{\neq}$ then T_p can takes the form

$$T_p = \alpha_k + \beta_k \mathrm{P}$$

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

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

where k = 1… q, $p_{k-1}^{\neq} < \mathrm{p} \leq p_k^{\neq}$ and also $\omega_{k,j}$, $\sigma_{K,j}$ are the segment amplitude and *F* is the frequency (Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023; Zeileis, Kleiber, Krämer & Hornik, 2003).
To generate random components, any data that does not belong to trend nor seasonal is classified random R_p.

$$Y_P = \alpha_k + \beta_k \mathrm{P} + \sum_{j=1}^{J} \omega_{k,j} \mathrm{Sin} \frac{2\pi jt}{F} + \sigma_{K,j}) + R_p \quad (2.4)$$

$$Y_P = T_p + S_p + R_p$$

The two new technique called BFTSC and GFTSC 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 (Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023)

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 a

$$\sum_t^n \frac{Yt}{nt} \quad (2.5)$$

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

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

For a given α_0 and β_1 being the slope and intercept of the time series observations (Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023)

The cyclical components at time p is computed as

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

The new equation becomes

$$Y_P = \alpha_k + \beta_k \mathrm{P} + \sum_{j=1}^{J} \omega_{k,j} \,\mathrm{Sin}\,\frac{2\pi jt}{F} + \sum_{t}^{n} \frac{Yt}{nt} + I_p \qquad (2.8)$$

$$Y_P = T_p + S_p + C_p + I_p$$

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) (Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023).

Strength of BFTSC and GFTSC.
BFTSC and GFTSC includes the ability to clearly identify all the time series components (trend, seasonal, cyclical, irregular) automatedly and presenting them neatly in time plots that belongs to each of the components (*AJARE, & Ismail, 2019; AJARE & ADEFABI 2023; AJARE, & Ismail, 2019; AJARE, ADEFABI & ADEYEMO, 2023).*

Both BFTSC and GFTSC can be used to estimate for missing values in trend, in seasonal, in cyclical and irregular components. The fit components are very reliable in forecasting, as BFTSC and GFTSC proof and pass reliability test of 99% accurately identifying time series components in a linear data. The fit components are also very consistent, and durable to be used by non-experts in forecasting, as BFTSC and GFTSC proof and passed consistency test of 99% accurately consistently identifying time series components in a linear data (see *AJARE, & Ismail, 2019; AJARE & ADEFABI 2023; AJARE, & Ismail, 2019; AJARE, ADEFABI & ADEYEMO, 2023). BFTSC and GFTSC are both fast in generating subsequent trend, data processing, and extrapolation in an automated process. Both techniques can be employed for use in big data, panel data and can be advanced for use for multivariate data processing. Being super-hybrid of BFAST automated technique of time series decomposition, both technique can be used in remote sensing field. Both techniques (BFTSC and GFTSC) are not affected by extream values or missing values or points. Finally both techniques involves less human (expert) supervision unlike manual process that requires full attention of the expert. GFTSC had additional strength of providing and presenting equations that produces each components with their values automatically attached to the headings of each time plot (see AJARE, & Ismail, 2019; AJARE & ADEFABI 2023; AJARE, & Ismail, 2019; AJARE, ADEFABI & ADEYEMO, 2023)..*

Results
Manual Identification Approach of London Stock Exchange (LSE) Time Series Components.
The same four steps used in the manual identification approach previously was adopted for London Stock Exchange (LSE) data (see Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023). This helps in obtaining deep understanding regarding the behaviour of this data. The monthly data of London Stock Exchange (LSE) is also available with the author and can be given out to anyone who needed it based on request.
Figure 1:

Displays the time series plot of monthly LSE from January 2001 until December 2020. There was steady increment from 2001 until 2007 but dropped in 2008 due to economic crisis and slowly increased from 2009 to 2017. However, dropped once again in 2018 due to economic crisis. Then, it started to increase regularly up to 2019 but drastically dropped in 2020 due to COVID-19 pandemic (Moradi, Jabbari. & Rounaghi, 2021; Baker, Bloom, Davis, Kost, Sammon & Viratyosin, 2020). The first two dropped (in 2008 and 2018) related to economic crisis was considered as cyclical component (C1 and C2) and the third dropped (in 2020) related to COVID-19 pandemic was irregular component (I1). Figure 5.9 also shows a curve trend.

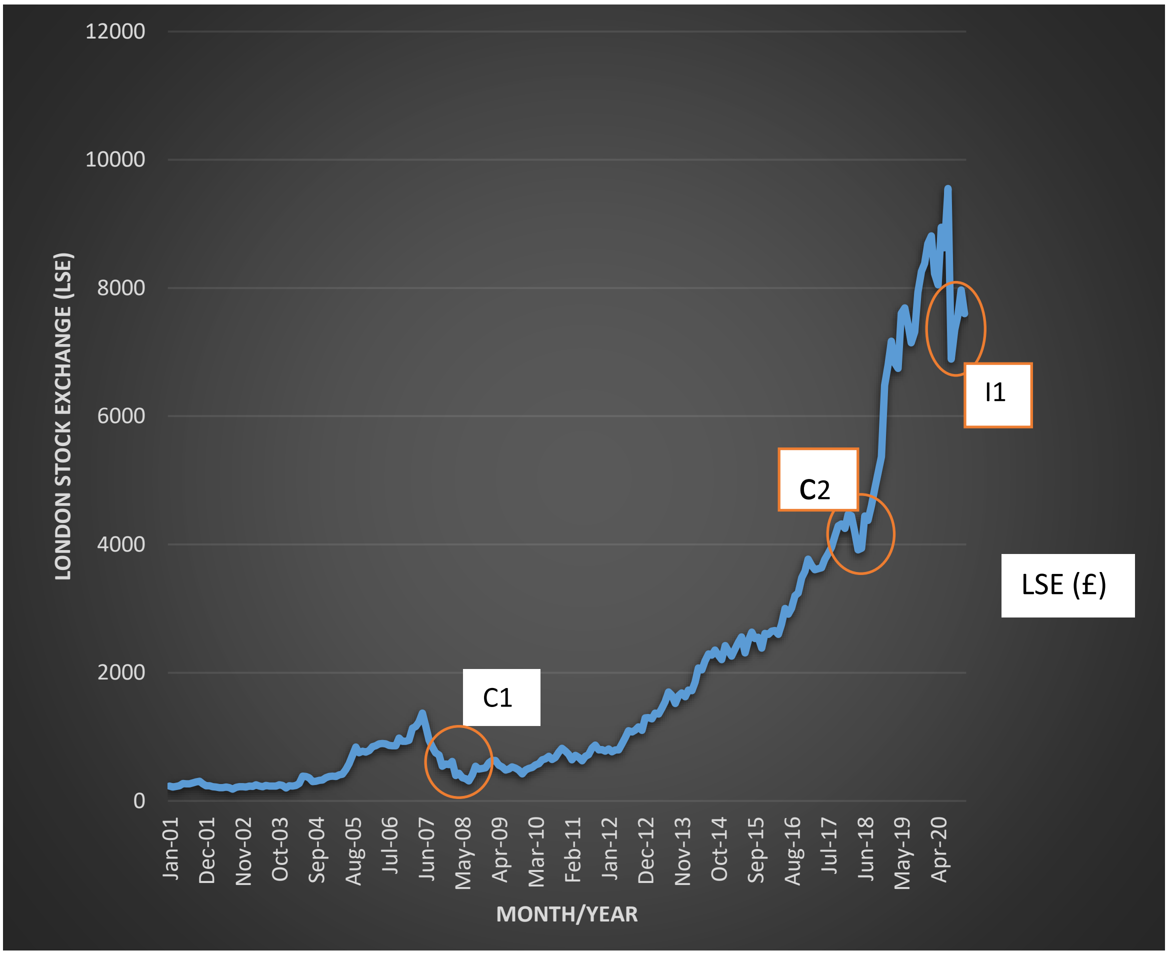

Figure 1. Time series plot of Monthly LSE

The manual time series plot in figure 1 is capable of identifying the time series components in London Stock Exchange (LSE) data but the limitation is that its required the supervision of an expert, also very slow and rigorous process, not easy to learn but more of personal judgement. Hence this study proceed to BFTSC and GFTSC which are automated in process.

Comparison of BFTSC and GFTSC with Manual Identification Approach using London Stock Exchange (LSE) data

Figure 2 show the plots produced by BFTSC for London Stock Exchange (LSE) data respectively. BFTSC managed to identify one cyclical but failed to identify curve trend and display linear trend instead, which contradict with manual approach identification as in previous studies (Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023). These indicated the limitation of BFTSC when the trend deviated from linear which reflected similar findings.

The Automate*d* BFTSC was perfectly able to identify the data which was in the observed plot, also it was able to automatically identify one cyclical but as for the trend BFTSC was weak in identification of curve trend, polynomial and highly volatile data. BFTSC converted the curve trend to a straight line trend. Hence BFTSC is weak in identification of exact trend in a very high volatile data.

Figure 2 Automated BFTSC plots of London Stock Exchange (LSE) data

Figure 2 show the plots produced by GFTSC for US Stock Market monthly data respectively. GFTSC successfully identified one cyclical but failed to identify curve trend and display linear trend instead, which contradict with manual approach identification as in previous studies (Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023). GFTSC had a special advantage as part of its features, GFTSC was able to displayed the equation of each time series components produced and attached as the heading of each plots automatically. As seen in figure 3 (Equation of observed data displayed above observed data, equation of trend displayed above trend, equation of cyclical displayed above cyclical) this is a kind of features cannot be found anywhere except by automated GFTSC. These indicated the limitation of GFTSC when the trend deviated from linear which reflected similar findings to previous studies ***(See AJARE.*** *ADEFABI & ADEYEMO, 2023).*

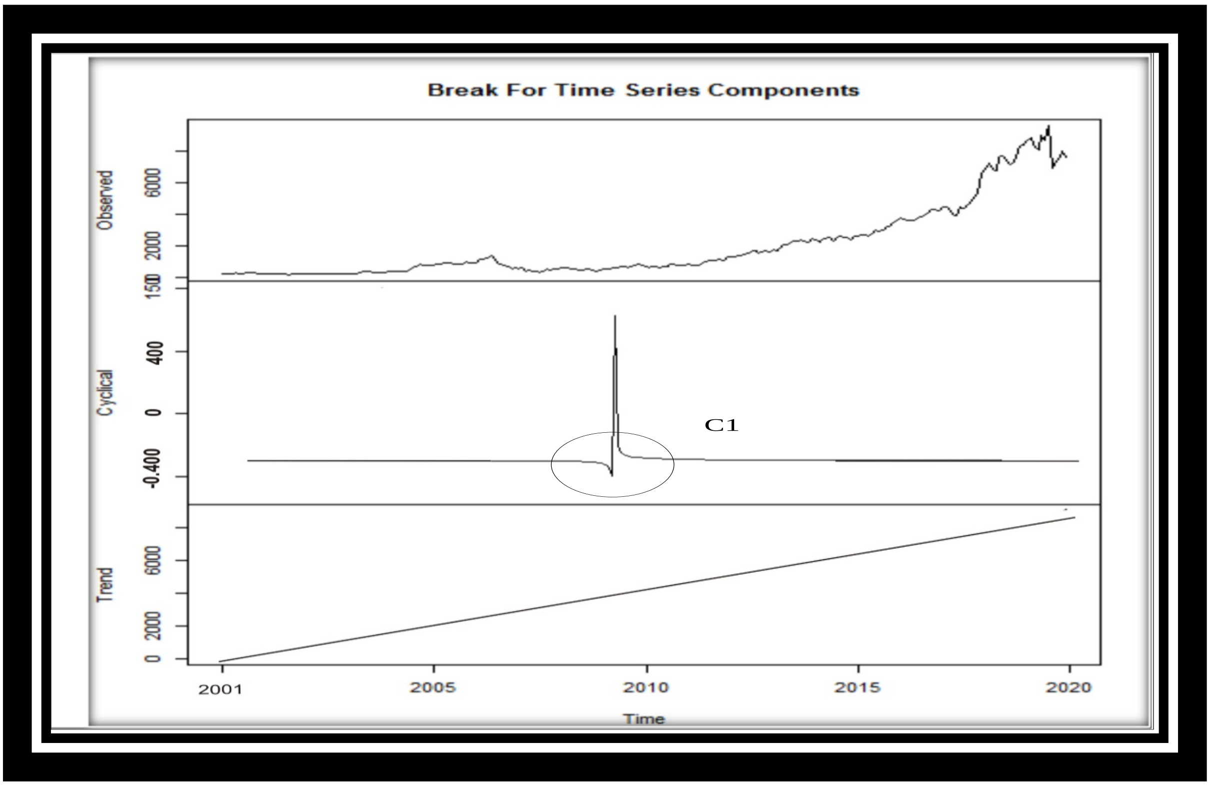

Figure 2. Automated BFTSC plots of Monthly LSE

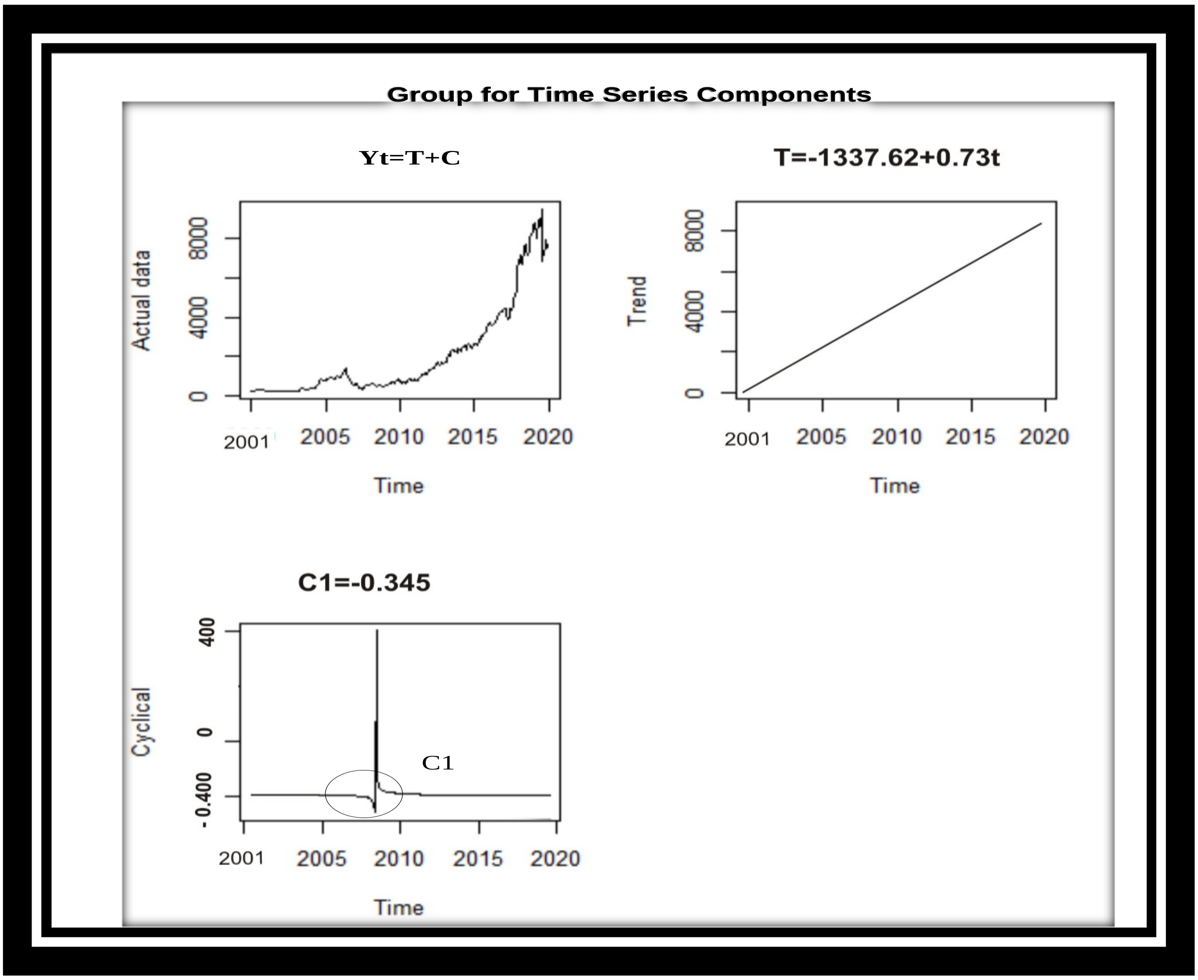

Figure 3. Automated *Figure 5.11*. GFTSC plots of Monthly LSE

Figure 2 and 3 show the plots produced by BFTSC and GFTSC for London Stock Exchange (LSE) monthly data respectively. Both BFTSC and GFTSC successfully identified one cyclical but failed to identify curve trend and display linear trend instead, which contradict with manual approach identification as in previous studies (Ajare &Suzilah 2019; Ajare, Adefabi & Adeyemo, 2023). These indicated the limitation of BFTSC and GFTSC when the trend deviated from linear which reflected similar findings with manual process of time series identifications. Both Automated Both BFTSC and GFTSC was perfectly able to identify the data which is the observed plot, also it was able to automatically identify one cyclical but as for the curve trend, both BFTSC and GFTSC was weak in identification of curve trend, polynomial and highly volatile data. Both BFTSC and GFTSC converted the curve trend to a straight line trend. Hence both BFTSC and GFTSC are weak in identification of exact trend in a very high volatile data.
The values was fitted but not displayed here, but from the fitted value and the real data of the London Stock Exchange (LSE) data, its reveal that for the next five years period the London Stock Exchange (LSE) data show no evidence of decline and the fitted value fit well and match intact to the original London Stock Exchange (LSE) data monthly data so the model can be applied for prediction of more London Stock Exchange (LSE) data. Based on the forecast model, no scientific evidence of London Stock Exchange (LSE) data crash in the period until 2028. London Stock Exchange (LSE) data appears to be in a steadily increasing state.

Discussion

Details about development of time series components identification is as follow, Pure manual approach period. Box and Jenkins (1976) was one of the first researchers that struggle to clearly identify time series component using time plot. This first information in the form of data was plotted on a time plot using manual technique 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.
Manual approach and automation period. 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 technique is that, the algorithm was built to solve the problem of topographical vegetation trend identification and cannot identify cyclical and irregular components of time series statistics. It is not flexible time series component identification technique and this is still a problem 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 technique called BFAST is used for acknowledging breaks for additive seasonal and trend in order to justify for seasonal disorder and also enables the identification of breaks that take place in trend within the system (Morrison et al., 2018). The technique is accessible in BFAST pack for R (R developments Core Team, 2012).
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).
Jain, Duin, and Mao (2000) describe BFAST as complicated in technique, this lead this study to seek out for transparency regarding BFAST. Verbesselt et al. (2010) recommend a new technique for broad trend detection for image classification and representative, the technique is called Break for Additive Seasonal and Trend known as BFAST. This technique integrates the decomposition of time series components into the conventional elements of the 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.

Conclusion

Verbesselt, Hyndman, Newnham, and Culvenor (2010). The technique was for recognizing Breaks for Additive Seasonal and Trend (BFAST). This technique helps to recognize trend breaks enclosed by the series. The essential guide of the BFAST technique is the decomposition of time series component into seasonal, trends and miscellany elements with the technique for recognizing structural similarity and difference. Verbesselt et al. (2010) recommended that the technique of BFAST is for identifying topographical pattern and also for improvement to be applied in other related disciplines.
Jamali, Jönsson, Eklundh, Ardö, and Seaquist (2015) describe BFAST as not being capable of identifying topographical vegetation basic component perfectly, though satellite sensor image have made topographical vegetation data available for so many years but yet the detection of topographic trend and variation is not yet clearly defined. Chen (2006) suggested that, this may be due to the limited number of available trend and change detection techniques accessible, algorithm suitable in identifying and characterizing abrupt changes without sacrificing accuracy and efficiency.
Based on previous studies, BFAST is used for topographical green forest picture data at certain specific time. Introducing BFAST to time series data and how to implement BFAST on time series data which contain only one variable for each time is another form of challenge. BFAST is a technique that take in data and processed to extract each component point

of the data, it would be reasonable to use BFAST for time series components identifications (Rikus, 2018; Gorelick, 2017; Zhu, 2017).
BFAST approach give a very considerable outcome and was recommend as a modern instrument for statistics information decomposition and detections but could not separate random noise and is a customized additive decomposition method, from all indication observed so far, it reveal that BFAST need to be extended for the purpose of coping with other varieties of uses (Tolsheden, 2018; Mok et al., 2017; Maus, Câmara, Appel & Pebesma, 2017).
Based on the every result in the simulated and the empirical analysis, BFTSC and GFTSC are best and most appropriate for linear time series components identification For this reason. BFTSC and GFTSC are recommended as a good alternative to BFAST. This is because BFTSC identifies the four components of time series statistics which is one of the basic limitations of BFAST.

AJARE and Ismail, (2019) created automated Break for Time Series Components (BFTSC) and Group for Time Series Components (GFTSC) in Identification of Time Series Components in Univariate Forecasting. BFTSC is for automated identification of time series components while GFTSC is for both automated identification of time series components and automated displaying of equations that produces each components.
Based on the models values, it reveal no scientific evidence of drop and crash in London Stock Exchange (LSE) data so improvement can be establish to improve on the London Stock Exchange. The contribution of this study to the scientific community is that the BFTSC gives good results that improve the weaknesses of the existing BFAST. BFTSC forecast output is more reasonable for effective policy making.

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Note BFTSC and GFTSC is waiting for license to allow it to be incorporated into R pack. As soon as it is in R then anyone can freely use it. Contact the author for BFTSC, GFTSC and London Stock Exchange (LSE) data if you need it (ajareoloruntoba@gmail.com/**ajare_emmanuel@ahsgs.uum.edu.my**) Copies are also available at Universiti Utara Library (Section 546727 research bank 23).

Authors Contributions
Dr Ajare Emmanuel Oloruntoba: Analyzing, producing the results and writing the paper. Prof Suzilah Ismail: Superised the creation of BFTSC and GFTSC. Dr Adefabi Adekunle: works on the contents and structuring, flow of the paper. Dr Olorunpomi Temitope Olubunmi type setting and Proof reading.

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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