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Novel method in determining the nature of Univariate time series in forecasting Angola Gross Domestic Product (GDP)

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Abstract
The main objective of this study is to use BFAST (Break for Additive, Season and Trend) to identify the components of time series present in the seasonal data of Gross Fixed Capital Formation know as Gross Domestic Product of Angola GDP. This data is the GDP yearly data of Angola gross domestic product (Angola GDP). The (Angola GDP) data spanned for the period of twenty years (2002 to 2022). The GDP of Angola is a secondary data obtained from the DataStream of Universiti Utara Malaysia Library. The BFAST (Break for Additive Seasonal and Trend) was utilized to identify the time series components. BFAST only identifies trend and seasonal components while considering all other components as random. Empirical data were employed to BFAST and subsequently determine the next forecasting technique after which forecast is made ahead. The real data findings suggested that BFAST can provide a better time series components identification better than manual process and hence caution should be taken serious. Angola GDP is sliding, improvement on GDP is urgently necessary or els it get to ruin. Improvement in Angola GDP is recommended.

Keywords: Angola, gross domestic product, break for time series components, forecast, control, trend change

1. Introduction

This study uses BFAST (Break for Additive Seasonal and Trend) to identify the components of time series present in the empirical data which is the GDP yearly data of Angola GDP gross domestic product. BFAST is considered to be more efficient in identifying all the components of time series statistics better than manual approach. Jong, Verbesselt, Schaepman and Bruin (2012) recommended an approach of basic swing identification to spot time series component. This approach was also used by (23) as the latest time series component recognition approach which is a technique that was first described and utilized by (33).

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 (10).

Angola is a country in Africa located in the Atlantic coast in the southern Africa, to the south of the equator and its territory is bordered by republic of Congo, Zambia to the east and republic of Namibia to the south. Angola developed its National Climate Change Strategy (2018-2030), which establishes a vision for tackling climate change in the context of its Paris Agreement commitments. In its Nationally Determined Contribution (NDC), the country committed to reducing its greenhouse gas emissions 24% by 2025 and established a Climate and Environmental Observatory to monitor emissions. Angola's NDC identifies climate finance needs of $44.1 billion for 2021-25 to spur the green growth agenda, with mitigation accounting for 99.7% and adaptation for 0.3%. Despite potential for private investment in green energy, particularly photovoltaic off-grid projects to rural communities, internal financing opportunities are limited. Unlocking the potential for climate finance requires institutional improvements in regulatory frameworks to allow private participation as independent power producers and structuring of public-private partnerships in the context of a highly subsidized electricity tariff regime.

Creating a dedicated national climate fund and strengthening public resource generation systems with green taxes can be key to promoting green growth initiatives with private participation Global inflation pressure from Russia's invasion of Ukraine1 was eased by improved terms of trade. The increased export revenue and agricultural production reduced food inflation and overall inflation from 25.8% in 2021 to an estimated 21.3% in 2022. The banking sector also improved, with more positive economic performance and lower private sector debt in 2022. Nevertheless, unemployment remains high, at 30%, and the country continues to face challenges in curbing the poverty rate (40.6% in 2019) (39).

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2. Literature Review, Analysis and Methods

The technique BFAST had much lower RMSE and was more robust against noise, Hence BFAST is recommended as one of the best trend break detection. One of the limitation of CCDC with CV is that its algorithm was made complicated, unlike CCDC, CCDC with CV did not have a straightforward relationship between RMSE number of breaks and noise. CCDC with CV was also found to be less accurate (34). Another limitation of this technique is also in terms of noise, with increased noise, the technique was less likely to detect correct results and the likelihood of detecting at least one false break remained constant. The unique pattern shown by CCDC with CV suggests that it must also detect more breaks if there is very little noise (34). EWMACD was built to focus on subtle changes, such as partial changes within pixels (34). Just like CCDC and BFAST Monitor, EWMACD also detects condition (increasing/decreasing trend) the EWMA chart, to rapidly help in identification of time series component).

(34) developed a new univariate time series components identification method known as COntinuous Monitoring of Land Disturbance (COLD) using Landsat time series data. COLD can detect many time series component such as trend and seasonal. COLD can also detect land disturbance continuously as new pattern is collected and likewise provide historical land disturbance history. Evaluation of the trend detection ability and land disturbance, different kinds of data are utilized. The COLD algorithm was developed and calibrated based on all the lessons learned. The accuracy assessment shows that COLD results were accurate for detecting trend and seasonal as land disturbance with an omission error of 27% and a commission error of 28%. The limitation of COLD was inability to detect time series components accurately with large noise.

(35) argues that the technique of BFAST can predict and analyse a topographical forest movement with the help of normalized difference vegetation indexes branded as (NDVI). This was done by detecting and determining factors of arid area changes using (NDIV) data to monitor the variations (14, 19). Many scholars employ the use of BFAST in identifying trend in topographical data and can also be applied for panel and normal time series data (26).

BFAST is made available into computer R package and can be used by anyone who wishes to be a beneficiary, for better identification and diagrammatic representation of the time series data to bridge the gap of time series components identification (21). BFAST followed similar derivative steps like DBEST and other decomposition techniques. Given the general time series additive model as in equation (1.1) of the form:

$$Y_p = T_p + S_p + C_p + I_p \tag{1.1}$$

For identification of Y_p, S_p, C_p, and I_p (See the paper: 8,9,15,17 & 18).

BFAST takes all the important components relatively trend, seasonal, cyclical and irregular components to be important. The residual component in BFAST now converted to contained cyclical and irregular. In BFAST only random component can be observed but in GFTSC the cyclical and irregular components is included (36).

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 of equation 1.1 (28, 33, 37).

From equation (1.2) BFAST takes all other components relatively trend and seasonal component to be randomised (R_p) and the equation was expressed as

$$Y_p = T_p + S_p + R_p \tag{1.2}$$

The residual random consist of cyclical and irregular component (36).

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

$$T_p = \alpha_k + \beta_k p$$

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.

$$S_p = \sum_{j=1}^{J} \omega_{k,j} \operatorname{Sin}\left(\frac{2\pi jt}{F} + \sigma_{K,j}\right) \tag{1.3}$$

Where k = 1… q, $p^{\neq}_{k-1} < p \le p^{\neq}_{k}$ and also $\omega_{k,j}$, $\sigma_{K,j}$ are the segment amplitude and F is the frequency (33,38).

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

$$Y_P = \underline{\{\alpha_k + \beta_k P\}} + \underline{\left\{\sum_{j=1}^{J} \omega_{k,j} \ \text{Sin}\left(\frac{2\pi jt}{F} + \sigma_{K,j}\right)\right\}} + \underline{R_P} \quad (1.4)$$

$$Y_P = T_p + S_p + R_p$$

To calculate cyclical components, center moving average is involved (11, 12, 13).

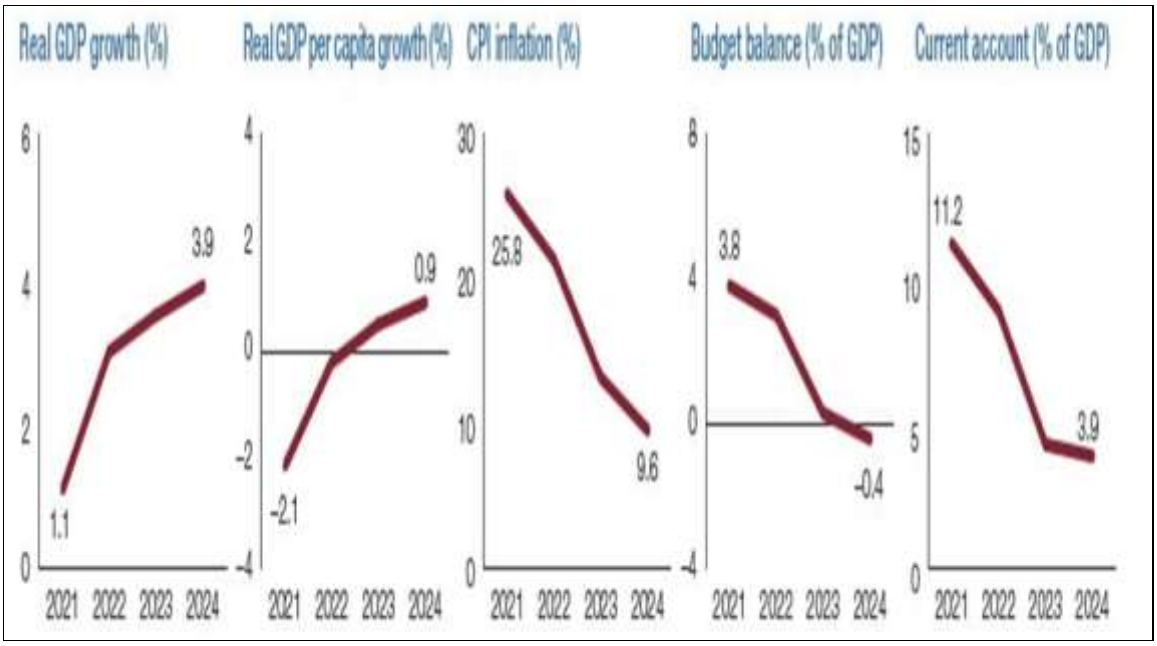
Figure 1.1 shows the growth of Angola GDP with time. Real GDP growth reached 3.0% in 2022, up from 1.1% in 2021. Income per capita growth remained negative (0.2%) in 2022 due to high population growth (3%). GDP growth was spurred by sustained high oil prices in 2022 because of Russia’s invasion of Ukraine; the average price per barrel for Angola’s crude was $100.65, above the conservative $59.00 that the 2022 national budget was based on, generating estimated additional revenue of $17.18 billion. High oil revenue further widened the fiscal surplus to 3.0% of GDP in 2022 from 1.9% in 2021. However, moderated oil exports took the current account surplus down to 8.9% of GDP in 2022 from 11.2% in 2021, while the debt-to-GDP ratio declined further, to 56.1% from 82.9% over the same period as seen in Figure 1.1.

Employing the manual time plot as seen in figure 1.2, the Angola free-hand fixed trend shows decline. Urgent steps need to be taken by Angolan government so that the country would not go into debt or get ruin in financial crisis.

The price of crude oil, influenced by Russia’s invasion of Ukraine and post-COVID-19 economic recovery, is likely to remain above the $75.00 per barrel assumed in the 2023 national budget, improving medium-term growth prospects.

GDP is projected to grow 3.5% in 2023, leading to low projected GDP per capita growth of 0.2% given high population growth.

Inflation is expected to drop further, to 13.2% in 2023 and 9.6% in 2024, as the availability of export revenue in a flexible exchange rate setting eases pressure via exchange rate pass-through. The major risk to the outlook is oil price volatility; to mitigate that risk, the 2023 national budget assumes a stable oil price. If the price of oil remains stable, a budget surplus of 0.3% of GDP is projected, with the debt-to-GDP ratio falling further, to 52.5%, and the current account staying in surplus, at 4.3% of GDP in 2023.



Source: Data are as of April 2023 and are from domestic authorities; figures for 2022 are estimates and figures for 2023 and 2024 are projections by the African Economic Outlook team.

Fig 1: Time plot for trend Comparison of Angola GDP

The price of crude oil, influenced by Russia’s invasion of Ukraine and post-COVID-19 economic recovery, is likely to remain above the $75.00 per barrel assumed in the 2023 national budget, improving medium-term growth prospects (figure 1). GDP is projected to grow 3.5% in 2023, leading to low projected GDP per capita growth of 0.2% given high population growth. Inflation is expected to drop further, to 13.2% in 2023 and 9.6% in 2024, as the availability of export revenue in a flexible exchange rate setting eases pressure via exchange rate pass-through

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As seen in Figure 2, if nothing is done about Angola GDP the country would find it very difficult to maintain stable growth economy for the next few years. The plot 1.2 shows decline.

Break for Additive, Seasonal and Trend (BFAST) for Angola GDP is an automated approach to showing the total time series components in the country GDP. The trend also shows decline in economy of Angola and this can only rise if Angola government decide to improve exportation to boost internal economy.

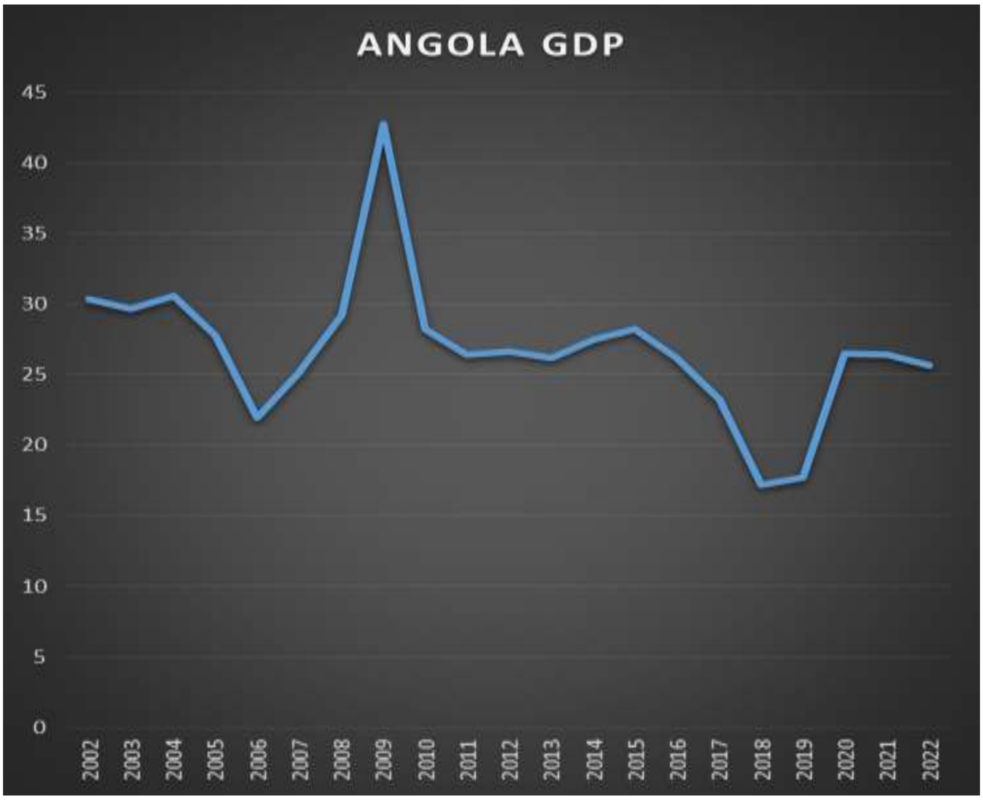

Fig 2: Manual Time Plot for Angola GDP

Break for Additive, Seasonal and Trend (BFAST)

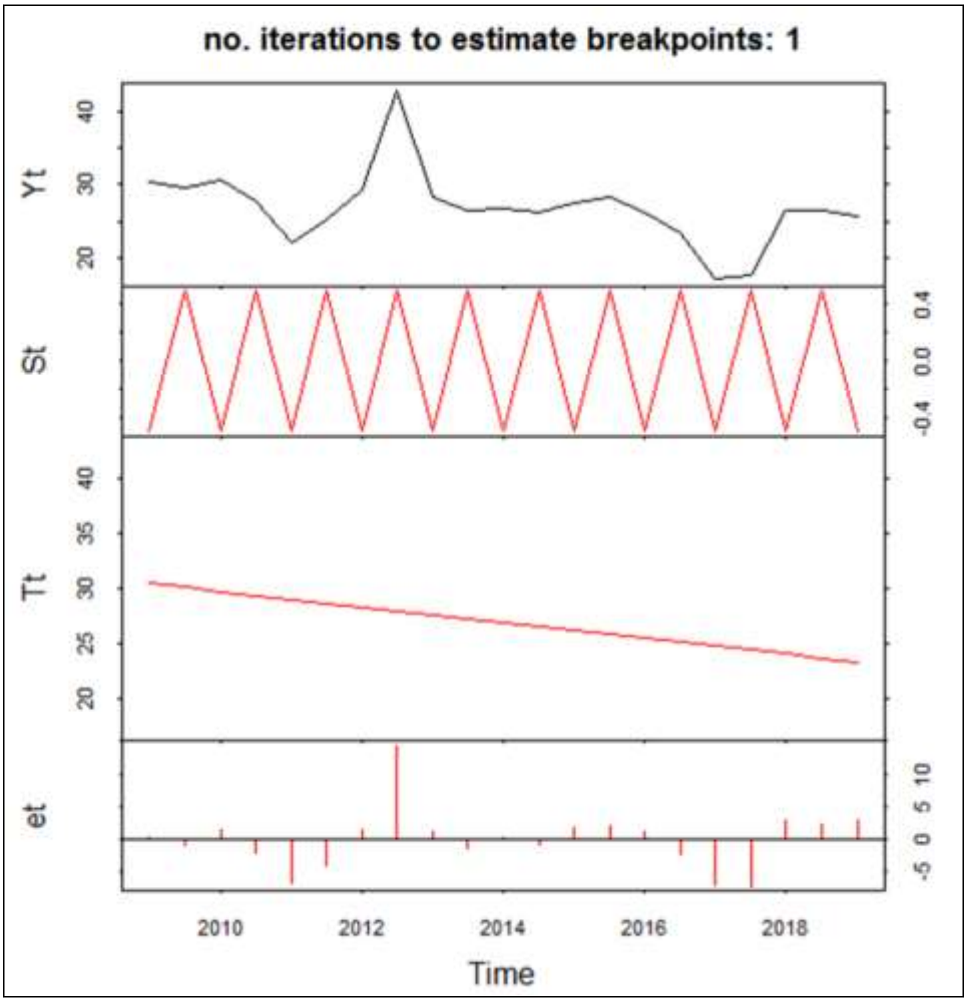

Fig 3: Break for Additive, Seasonal and Trend (BFAST) For Angola GDP

For more details about BFAST, BFTSC, GFTSC and GBEST etc. (See 1, 2, 3, 4, 5, 6)

3. Results

The observations from figure 1, figure 2, figure 3, all shows decline in Angola GDP, and this may be due to COVID-19 around 2019 to 2021. The Covid 19 really affected Angola economy and almost collapse the GDP. From the prediction which is not made available in this paper reveals that Angola GDP would rise in 2025. Based on figure 1 and figure 2, the Botswana GDP is sliding into bankrupt, and based on the forecast value, the GDP of Angola show some scientific evidence of dropping in the next five years. This reveal that for the next five years period, the Angola Gross Domestic Product (GDP) show evidence of decline and the fitted value did not fit well and not match intact to the original Angola Gross Domestic Product (GDP) data so the model can be applied for more prediction of more years GDP of Angola.

This should not be taken for levity but with all seriousness to make the Angola GDP grow beyond prediction and beyond expectation. The forecast should not stop the country from improving and investing on the country GDP so as to have blossom reserve. Angola should employ all other possible means of generating revenue (both internally and externally) for the country utilization.

BFAST is the most appropriate for time series components identification. This is because BFTSC identifies the four components of time series statistics which is one of the basic limitations of BFAST. Based on the forecast value for five years, it reveal some scientific evidence of drop and crash in Angola GDP so improvement can be establish to improve on the yearly Angola GDP. The contribution of this study to the scientific community is that the BFAST gives good results that improve the weaknesses of the existing manual approach. BFAST forecast output is more reasonable for effective policy making.

Note: The data, BFTSC and BFTSC can be made available based on request from the original author of this paper Dr. Ajare Emmanuel. The data utilized in this study is available freely if the author is contacted. The BFTSC or GFTSC can be acquired with $10,000 from Dr Ajare Emmanuel. The forecast in this Botswana GDP can likewise be acquired with $1000 per year per forecast. This forecast is very good for policy making and economic development.

4. Discussion

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. (33) Recommended that the technique of BFAST is for identifying topographical pattern and also for improvement to be applied in other related disciplines (31, 33).

(29,30) 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. (16) 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 (22, 27, 32).

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 (27,29,30).

Based on the every result BFAST is best and most appropriate for linear time series components identification for this reason. BFAST is recommended for public use. Note: This paper serve as forecasting guide and make it easier for anyone that want to forecast GDP or stock exchange or otherwise both the technique used and the forecast valuescan be acquired with little money to support the authors academic development.

5. Conclusion

Details about development of time series components identification is as follow. Pure manual approach period. (8 & 9) 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 (22) 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.

(23 & 24) 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 (24, 25). The technique is accessible in BFAST pack for R (R developments Core Team, 2012).

(33) Package 'bfast'which portrays the main scope of BFAST. Many scholars employ the use of BFAST in identifying trend in topographical data (24, 25, 26).

(24) Describe BFAST as complicated in technique, this lead this study to seek out for transparency regarding BFAST. (24) 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 (6 & 7).

Other techniques such as break for time series components and group for time series components were likewise created to capture components of time series clearly and forecast automatically (2, 3 & 4).

7. Recommendation

The basic recommendation of this paper is that Angola government need to improve on its economy, improve on local production, local processing and also increase in export or else the economy may suffer set back tremendously. Though from the forecast, the economy gradually pick up at 2026 but never the less the government should not rest and relax on the forecast but put more effort on implementing programs that would help yield better economy for Angola.

Note: The data used for this paper can be gotten freely from the authors Dr Ajare Emmanuel also the BFAST technique can be acquired from same author freely. But the forecast values can be acquired from the author likewise but not free, $1000/year forecast. If Angola government can purchase the forecast data for 10 years it would be very beneficial and advantageous for domestic GPD growth.

This paper serve as forecasting guide and it makes it easier for anyone that wants to venture into forecasting GDP or ells otherwise both the technique used and the forecast values can be acquired per-year with a little money to support the authors academic development.

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Note BFTSC and GFTSC is license to allow it to be incorporated into software pack but already in EZEE forecasting software. BFAST is already in R pack. As soon as it is in R then anyone can freely use it. Contact the author for BFAST, BFTSC, GFTSC and Angola gross domestic product data if you need it copies are also available at Universiti Utara Library (Section 546727 research bank 23).

9. Weakness and Future Research

The issue of how large is large and maximum sample size to be accepted by BFAST is yet to be addressed [28]. Likewise the issue of maximum sample size for Manual method of time series identification. BFAST are not being fully utilized addressed because it’s a new automated time series identification technique and depends on the nature of individual research and interest. More automated and innovated time series components identifications is a welcome development. Model that can predict epidemic like flood, fire outbreak, earthquake etc should be encouraged. A special technique that can forecast irregular time series component automatically is a good and welcome innovation in forecasting field.

10. Authors Contributions

Ajare Emmanuel Oloruntoba and all other co-authors listed on the introduction log: Analyzing, producing the results and writing the paper.

9. Ethics

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

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