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Identifying change and forecasting in mauritania Gross Domestic Product (GDP) using Advance automated technique

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Abstract
The main objective of this study is to use BFAST (Breaks for Additive Seasonal and Trend) to identify the components of time series present in the Mauritania Gross Domestic Product (GDP). This data is the GDP yearly data of Mauritania Gross Domestic Product (GDP). The Gross fixed capital formation (% of GDP) was provided. The (Mauritania GDP) data spanned for the period of sixty three years. The GDP of Mauritania is a secondary data obtained from the DataStream of Universiti Utara Malaysia Library. BFAST was designed to present the image of all the 3 time series components. BFAST only identifies trend and seasonal components only. Empirical data of Mauritania was employed to BFAST and subsequently the next forecast was made. The simulated and real data findings suggested that BFAST can provide a better time series components identification better than manual process and hence caution should be taken because Mauritania GDP is sliding, less it got to ruin. Improvement in Mauritania GDP is recommended.

Keywords: Mauritania, break for time series components, seasonal data, gross, cyclical, irregular components.

Introduction

This study uses BFAST (Breaks for Additive Seasonal and Trend) to identify the components of time series present in the empirical data which is the GDP yearly data of Mauritania GDP gross domestic product. BFAST (Breaks for Additive Seasonal and Trend) 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).

Real GDP growth rose to 5.3% in 2022 from 2.4% in 2021, underpinned mainly by higher extractive and agricultural production and trade. The major drivers of growth on the demand side remain household consumption and investment. Inflation rose to 9.6% in 2022 from 3.8% in 2021 due to higher global prices for imported foodstuffs and petroleum products. The Central Bank of Mauritania pursued a restrictive monetary policy in 2022 by raising its key rate 300 basis points to 8%. The banking sector increased financing to the private sector 16.4% from 2021 [39].

Higher current spending (17.0% of GDP in 2022, up from 12.0% in 2021), particularly subsidies for energy and food products, led to a budget deficit (1.2% of GDP in 2022, following a 2.2% surplus in 2021) for the first time since 2018. Tax revenue remains insufficient at 12.5% of GDP in 2022, up from 10.8% in 2021. Debt restructuring agreements with Kuwait and Saudi Arabia reduced debt to 48.4% of GDP in 2022 from 57.9% in 2018. The current account deficit widened to 13.7% of GDP in 2022 from 7.9% in 2021 due to higher prices for food imports and petroleum products. The COVID-19 pandemic had a negative impact on the social wellbeing of the population, particularly on unemployment (11.5% in 2021, up from 10.4% in 2019) and multidimensional poverty (56.9%) [39].

Real GDP is projected to grow 4.3% in 2023 and 5.9% in 2024, supported by the primary and extractive sectors and the expected benefits of gas development. Inflation is projected to rise to 10.4% in 2023 before dropping to 6.5% in 2024 with the central bank's restrictive monetary policy. The budget balance will remain in deficit (1.9% of GDP in 2023 and 1.6% in 2024), consistent with higher current and investment spending. Debt is projected to stabilize at 49% of GDP in the short term, ensuring that risk of debt distress remains moderate. The current account deficit is projected to narrow to 11.1% of GDP in 2023 and 8.5% in 2024 thanks to anticipated gas exports. Possible headwinds include security tensions in the Sahel, high prices for imported food and energy products, price volatility for exported raw materials (mainly iron), and recurrent droughts and floods, which impact food security. In addition, the efficiency of public spending and debt management needs to improve [39].

The estimated finance needed to reduce greenhouse gas emissions 11% by 2030 is $4.8 billion a year over 2021–30, 72.1% of which is earmarked for mitigation. But the country lacks a dedicated climate finance mechanism. The private and banking sectors have almost no presence in climate finance. Most of the $1.0 billion received over 2010–20 came from international partners. Obstacles to private sector participation include the lack of knowledge of climate change risks and opportunities, the high cost of investment related to

climate change adaptation, and the limited availability of private resources devoted to green investment. Essential actions include adopting green financial instruments such as green bond issues to increase resource mobilization, establishing a special green fund dedicated to the private sector, adopting tax incentives to encourage green private investment, and involving the private sector in strategies for climate change adaptation. Mauritania has substantial natural capital (gas, green hydrogen, iron, fishery resources, and agricultural land) valued at $24.3 billion in 2018, whose sustainable development could support climate finance and green growth. In addition, phase 1 of the Grand-Tortue/Ahmeyim gas project should provide additional room for budgetary adjustments of at least 0.5% of GDP in 2024 [39].

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 BFAST techniques would be used in analyzing time series components and forecasting in this paper.

Literature

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, 37].

EWMACD was built to focus on subtle changes, such as partial changes within pixels (Brooks, Wynne, Thomas, Blinn, Coulston, 2019). 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 [38].

Zhu, Zhang, Yang, Aljaddani, Cohen, Qiu and Zhou (2020) 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 [36].

Zewdie *et al*. (2017) argues that the technique of BFAST can predict and analyse a topographical forest movement with the help of normalized difference vegetation index's branded as (NDVI). This was done by detecting and determining factors of arid area changes using (NDIV) data to monitor the variations (9,10,11,12,13,). Many scholars employ the use of BFAST in identifying trend in topographical data [26].

The extension of BFAST is an improved technique that identifies all-time series components. This new technique is known as GFTSC (Group for time series components) [1, 2, 3, 4]. Many of the automated techniques of pattern detection are computer oriented. GFTSC is one of the first extension of BFAST in history which also focus more on computer approach strategy rather than theoretical approach strategy GFTSC 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 [21]. The technique considers the extension and improvement of the BFAST to GFTSC [2, 3, 4].

GFTSC followed similar derivative steps like BFAST but in addition of cyclical and irregular components. GFTSC is the 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:

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

For identification of Y_P, S_p, C_p, and I_p (See the paper: 7,8,9,10, 23,24,25).

GFTSC 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 component in GFTSC. In BFAST only random component can be observed but in GFTSC the cyclical and irregular components is included [29, 30, 31, 32, 33]. GFTSC is the 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 but would not be discussed in this paper (discussed in 1,2,3,4,5).

Material and Methods

BFAST (Breaks for Additive Seasonal and Trend) 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 (27, 28, 36).

From equation (1.2), BFAST takes all other components relatively to the trend and seasonal components to be randomized and the equation is expressed as:

$$Y_p = T_p + S_p + e_p \quad (1.2)$$

The residual random consists of cyclical and irregular components (17,18,19,20,22).

1. Trend Component Generation

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; $p_1,., pq$. Then T_p can take the form as follows:

$$T_p = \alpha_k + \beta_k P$$
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 is β_{k-1}, while the slope of the breaks after the change breakpoints is β_k. The intercept α_k and the slope β_k of the linear model with time period p will be used to derive the magnitude and direction of change (1,2,3,4,5).
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 = 1, 2,., J and time t:

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

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 (1,2,3).
To generate random components, any data that does not belong to trend nor seasonal is classified random R_p.

$$Y_P = \underbrace{\{\alpha_k + \beta_k P\}}_{T_p} + \underbrace{\left\{\sum_{j=1}^{J} \omega_{k,j} \operatorname{Sin}\left(\frac{2\pi jt}{F} + \sigma_{K,j}\right)\right\}}_{S_p} + \underbrace{R_p}_{R_p} \quad (1.4)$$
$$Y_P = T_p + S_p + R_p$$

The new technique called GFTSC considered splitting the random into cyclical components and irregular components which is an extension of BFAST. This was done through the inclusion of two new components.
To calculate cyclical components, center moving average is involved (14,15,16).
Derivation of cyclical code, let CMA be the center moving average of t objects, then CMA can be computed as follow

$$CMA = \sum_{t}^{n} \frac{Yt}{nt} \quad (1.5)$$
$$C_p = \frac{CMA}{\hat{CMA}} \quad (1.7)$$

After extracting the trend, seasonal and cyclical components, the left out components is called irregular components, the new equation becomes

$$Y_P = \underbrace{\{\alpha_k + \beta_k P\}}_{T_p} + \underbrace{\{\sum_{j=1}^{J} \omega_{k,j} \operatorname{Sin}\left(\frac{2\pi jt}{F} + \sigma_{K,j}\right)\}}_{S_p} + \underbrace{\{\frac{CMA}{\hat{CMA}}\}}_{C_p} + \{\underbrace{I_p}_{I_p}\} \quad (1.8)$$
$$Y_P = T_p + S_p + C_p + I_p$$

For identification of Y_P, S_p, C_p, and I_p (See the paper: 5,6, 33).
The first stage in forecasting is to view the data and to examine all the components of time series present in that data in order to select the most appropriate forecasting technique. The Mauritania yearly GDP data components identification was carried out with the help of the new technique called BFAST. This new technique helps to have a clear image of the entire variations presents in the time series data (1,2,3,4,).

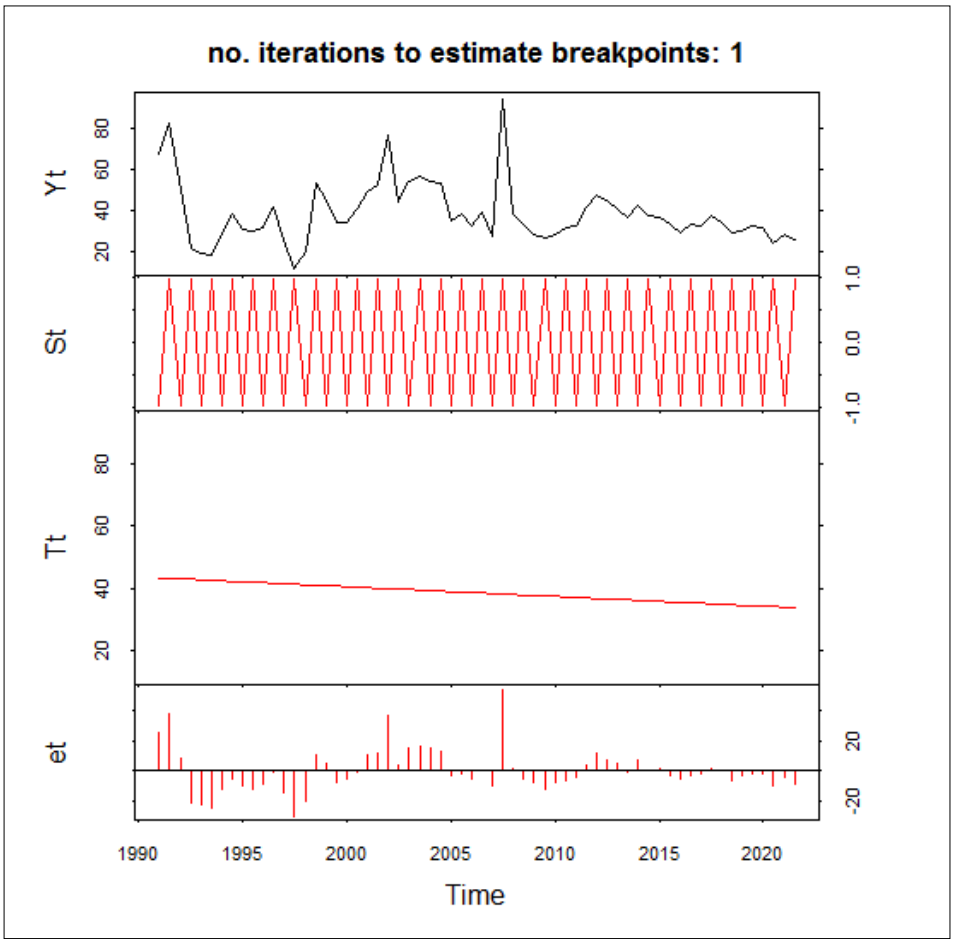

Fig 1: BFAST for Mauritania Gross Domestic Product (GDP).

Figure 1 reveals all the time series components hidden in the Mauritania Gross Domestic Product (GDP) data for 63 Years, the image in the figure above indicate the presence of trend, seasonal, cyclical and irregular component. Automated

ARIMA models were fitted and the best model was selected based on the ARIMA with the smallest AIC (Akaike's Information Criterion). Based on the AIC models, the ARIMA (1,2,3) is the best model to be used in fitting the Mauritania quarterly GDP. ARIMA (1,2,3) is selected and used for fitting the model.

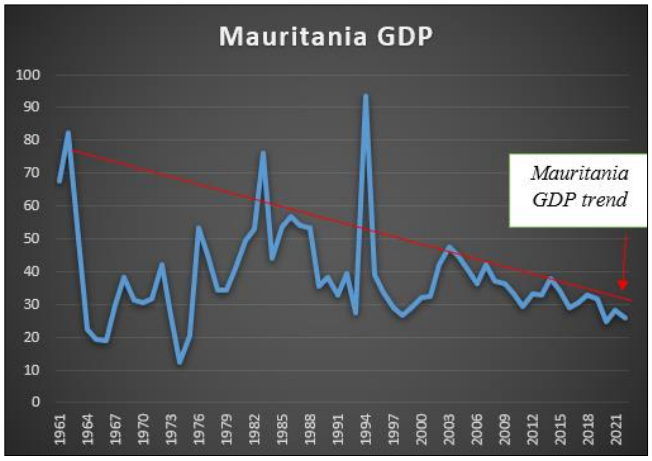

Fig 2: Manual time plot for Mauritania Gross Domestic Product (GDP).

Results

The observations from figure 1, figure 2, figure 3, all shows decline in Mauritania GDP, and this may be due to some historical evidence about economic decline. The Covid 19 also really affected Mauritania economy and almost collapse the GDP in 2020. From the prediction which is not made available in this paper reveals that Mauritania GDP would rise in 2029. Based on figure 1 and figure 2, the Mauritania GDP is sliding into bankrupt, and based on the forecast value, the GDP of Mauritania show some scientific evidence of dropping in the next five years. This reveal that for the next five years period, the Mauritania Gross Domestic Product (GDP) show evidence of decline and the fitted value did not fit well and not match intact to the original Mauritania Gross Domestic Product (GDP) data so the model can be applied for more prediction of more years GDP of Mauritania.

This should not be taken for levity but with all seriousness to make the Mauritania 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. Mauritania 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 Mauritania GDP so improvement can be establish to improve on the yearly Iceland 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 of Mauritania GDP can likewise be acquired with $1000 per year per forecast. This forecast is very good for policy making and economic development.

Discussion

The technique BFAST 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 [33].

(23 & 24) 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 [32, 33, 34].

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, 28, 29].

Based on the result in figure 1 and figure 2, there are evidence of decline in Mauritania GDP.The forecast data reveal smooth and steady decline in growth of trend in Mauritania GDP.

Hence no scientific evidence of GDP crash or ruin in the next five good years provided every other normal conditions not obstructed. Never the less this should not be taken for levity but with all seriousness to make the Colombia 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. Maritania should employ all other possible means of generating revenue (both internally and externally) for the country utilization.

BFAST (Breaks for Additive Seasonal and Trend) is the most appropriate for time series components identification.

Note: The data, BFTSC and GFTSC 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. BFAST (Breaks for Additive Seasonal and Trend) is also available free with just a single message to the author. The BFTSC and GFTSC can be acquired with $10,000 from Dr Ajare Emmanuel. The forecast in this Mauritania GDP can likewise be acquired

with $1000 per year per forecast. This forecast is very good for economic development.

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).

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.

Authors contributions

All authors contributed immensely in the aspect of technical writing.

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Ethics

This is the original manuscript; there will be no expectation of any ethical problems.

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