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Long Memory Behaviour of Nigerian Telecommunication Network Flow (A Case Study MTN Network)

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Abstract: **As the demand for telecommunication services continues to grow, there is a need to understand the behavior of the telecommunication network flow to ensure optimal performance, reliability and increase the number of subscribers. This research used an Autoregressive Fractionally Integrated Moving Average (ARFIMA) model along with its different estimation procedures to investigate long memory behaviour of Nigerian telecommunication network flow from August 11, 2017, to December 31, 2022. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were employed to investigate the presence of the unit root of the series. The test results confirmed the absence of a unit root in the series. However, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test result suggested that the null hypothesis of stationarity is rejected at a 5% significance value (typical behaviour of series with a long memory). Moreover, the Autocorrelation (ACF) functions plot showed a slow decay, indicating that even very distant, the flow of the network data were still highly correlated with each other. In addition, long memory parameter $d$value for MTN internet network flow was also estimated using Geweke and Porter-Hudak (GPH), Smoothed Periodogram (Sperio), Exact Maximum Likelihood (EML) and Whittle Approximate Maximum Likelihood (WAML) method. The result found that the series exhibits some degree of long memory behaviour. However, based on the minimum AIC and BIC values ARFIMA (3, 0.2622, 3) model is suitable for the data. More so, the structural break was also investigated using the Quandt Likelihood Ratio (QLR) test. The results revealed that the series have a breakpoint in 2021. The R software package has been used for data analysis (Version: 4.1.2).**

Keywords: **Long Memory, Telecommunication, Fractionally Integrated, ARFIMA.**

1. INTRODUCTION

1.1 Background of the Study

Time series data represent sets of data points collected in a sequential manner over a specific, equal time interval. As time series presents its values sequentially over time, it is expected to present a serial correlation in time that is characteristic of dependence between the present and previous values (Ribeiro, 2003). The long memory process is known to have a high-order correlation structure, indicating that there is a significant dependency between the previous and present points. Long memory is a phenomenon one may sometimes face when analyzing time series data, where long-term dependence between two points increases the amount of distance between them (Bahar, 2017). Usually, when modelling long-term behaviour for any time series, such as those in foreign exchange, Astronomy, Hydrology, Mathematics, and Economics etc., the operation can be more accurate by relying on the ARFIMA models compared with the ARIMA models. ARFIMA can also have an important impact on the financial field (Bhardwaj and Swanson, 2006; Beran, 1994, 1995; Karia, 2016). The model was first introduced by Granjer and Joyeux (1980), as mentioned by Mostafaei and Sakhabakhsh (2012), to capture the long-memory behaviour of this time series data. The long memory feature exists if the autocorrelation function (ACF) decays more slowly than the exponential decay described by (Bahar, 2017). Structural break test when estimating the ARFIMA model is of great importance as it prevents misleading results as required to the output to be brought about and prediction confidence. For many years, many studies have been done that relate to the modeling and forecasting short memory of

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telecommunications network flow or however, very few studies are available for long memory (Kalpakis *et al.*, 2001; Yu and Zhang, 2005; Moussas *et al.*, 2005; Suarez *et al.*, 2009; Bazghandi *et al.*, 2012; Okunlola, 2013; Okunlola 2013; Wang *et al.*, 2015; Jibrin *et al.*, 2015; Siluyele, and Jere, 2016; Babayemi *et al.*, 2017; Adaramola, 2018; Oduro-Gyimah and Boateng, 2018; Adeyemo and Adeyemo, 2017; Adewumi and Adebayo, 2019; Monge and Juan, 2023). Thus, this research aimed to investigate the long memory behavior of the Nigerian telecommunication network flow, with a specific focus on the MTN network. By understanding the long memory behavior of the network flow, this study will contribute to the development of effective strategies for optimizing the performance and reliability of the Nigerian telecommunication network. with a view to achieve the following objectives (i) To examine the stationarity of the series (ii) To identify the presence of structural break (iii) To estimate long memory parameter d for the data point (iv) To determine the suitable ARFIMA model for the Nigerian Telecommunication Network

2. METHODOLOGY

2.1 Time Series Models

A time series $\{y_t\}$ is a collection of data points that are taken with an ordered index. The order of collection may or may not be regular and the data may or may not be continuous. A time series stochastic process ε_t is said to be a purely random process if each $\varepsilon_t$is independent from all the other observations. A time series y_t is called a white noise process denoted by ε_t, if satisfied the following conditions (i) $E\{\varepsilon_t\} = 0$ (Zero mean), (ii) $Var\{\varepsilon^2{}_t\} = \sigma^2 < \infty$ (Constant variance), (iii) Cov$\{\varepsilon_1\ \varepsilon_2\} = 0$ if $t_1 \neq t_2$ (not serially correlated in this case we write $\varepsilon_t \sim$ WN$(0, \sigma^2)$)

2.2 $MA(q)$, $AR(p)$, ARMA (p, q), ARIMA (p, d, q) and ARFIMA (p, d, q) Process

$MA(q)$ Process: A time series $\{y_t\}$ is Moving Average (MA) process of order q denoted by MA(q) and defined by $y_t = c + \theta(L)\varepsilon_t$ (2.1) where c is constant, $\theta_0 = 1$ and $\theta_1, \theta_2, \dots, \theta_q$ are fixed constant and ε_t is a white noise with mean 0 and variance σ^2. However, the exclusion of the constant c in the process y_t is called zero mean MA(q) process.	**$AR(p)$ Process:** A time series $\{y_t\}$ is an Autoregressive process of order p denoted by $AR(p)$ and defined by $\phi(L)y_t = \varepsilon_t + c$ (2.2) where c is constant, $\phi_1, \phi_2, \dots, \phi_p$ are fixed constant, ε_t is a white noise with mean 0 and variance σ^2. However, the exclusion of the constant c in the process y_t is called zero mean $AR(p)$ process.
ARMA (p, q) Process: The Autoregressive Moving Average Process of order (p, q) denoted by ARMA(p, q) and defined by $\phi(L)y_t = \theta(L)\varepsilon_t$ (2.3) where ϕ_k and θ_k are defined as for AR and MA models respectively, $\phi(L)$ and $\theta(L)$ are there lags polynomial, $\theta_0 = 1$. ARMA process is stationary if the AR component of the series is stationary and invertible, if the MA component is invertible.	**ARIMA (p, d, q) Process:** ARIMA (p, d, q) model is defined by differencing the time series data 'd' times to achieve stationarity and then applying an Autoregressive (AR) model with 'p' lags and a Moving Average (MA) model with 'q' lags to the differenced series. $ARIMA(p, d, q)$ is define by: $\nabla^d\phi(L)y_t = \theta(L)\varepsilon_t$ (2.4) However, ARM process cannot account for the slowly decaying ACF. In such cases, the ARFIMA model can be applied to account for the slow decay of the ACF.

ARFIMA (p, d, q) Process: The ARFIMA (p, d, q) process generalizes ARIMA by allowing fractional degrees of integration, accommodating time series with long memory that exhibit dependencies between 0 and 1. It is defined by differencing the series a fractional number of times (0 < d < 1). Thus, the process captured both short-term and long-term dependencies than the traditional ARIMA model. defined by: $(1 - L)^d\phi(L)y_t = \theta(L)\varepsilon_t$ (2.5)

where d denotes non-integer fractional differencing parameter, L is the lag operator, θ is the moving average parameter, ϕ is the autoregressive parameter, y_t is the time series data at time t, and $\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$ is a white noise distribution term, for all t, $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = \sigma_\varepsilon^2$ are serially uncorrelated. $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p$ and $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \dots + \theta_q L^q$. where, $\theta(L)$ and $\phi(L)$ represent $AR(P) and\ MA(q)$ Components respectively with no common roots. L is the lag operator or backward shift operation $\nabla^d = (1 - L)^d$ further expand by $\nabla^d = (1 - L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)} L^k$ where $\Gamma(.)$ denote the gamma function, ∇^d is the fractional differencing operator and the fractional differencing parameter d is escapable to have any real value.

2.3 Long Memory Process

Long memory describes the correlation structure of a series at long-range. In the time domain, it is characterized by a hyperbolically decaying auto covariance function. This slow decay of the autocorrelation function is considered to be the defining feature typical of a long memory process. y_t is called a long memory process if its autocovariance function is such that the autocorrelations are positive and decay hyperbolically to zero. The asymptotic property can be expressed as:

$$\rho_k \approx \mathrm{M}k^{2d-1} \quad ; \quad as \;\; k \to \infty \qquad (2.6)$$

when $d \in (0,\ 0.5)$ the series is stationary and said to have long memory, while if $d\ >\ 0.5$, the series is non-stationary and hence unpredictable. For $d \in (-0.5,\ 0]$, the series is described as having short memory. Stationary process has a long memory if its absolute autocorrelation function has an infinite sum. Consequently, the autocorrelation function ρ_k at lag k is defined according to:

$$\sum_{k=-n}^{n} |\rho_\mathrm{k}| = \infty \qquad (2.7)$$

where n is the number of observations. The method of estimation in this research was based on cases where $d \in (-0.5,\ 0.5)$.

2.4 Autocovariance, Autocorrelation and Partial Autocorrelation

The autocovariance of the process $\boldsymbol{y_t}$ is given by	$\boldsymbol{\gamma_k = E(y_t, y_{t-k}) = \frac{(-1)^k(-2d)!}{(k-d)!\,(-k-d)!}}$
The autocorrelation function is defined by	$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{(-d)!\,(k+d-1)!}{(d-1)!\,(k-d)!} \quad , \qquad k = 1,2,3, \ldots$ $\rho_k \approx \frac{(-d)!}{(d-1)!} k^{2d-1}$ $\rho_k \approx \mathrm{M}k^{2d-1}$
The partial autocorrelation function can be expressed as	$\varphi_k = \frac{d}{k-d}$

Properties of an ARFIMA process area bridged in the following theorem (Babayemi *et al.*, 2017). Let y_t be an ARFIMA $(\mathrm{p, d, q})$ process then: (i) y_t Is stationary and invertible if $d < 0.5$ and all the root of $\phi(L) = 0$ lie outside the unit circle (ii) y_t Is non-stationary if $d \geq 0.5$ and all the root of $\theta(L) = 0$ lie outside the unit circle (iii) If $-0.5 < d < 0.5$, the autocovariance of y_t; $\rho_k \approx Mk^{2d-1}$ as $k \to \infty$ where M is a function of d. The autocovariance function of ARFIMA process decay hyperbolically to zero as $k \to \infty$ in contrast to the faster geometric decay of a stationary ARMA process.

3. ESTIMATION PROCEDURES

This research work dealt with some well-known parametric and semiparametric methods of estimating long memory parameter d. Among the parametric estimation method used in this research work include: Exact Maximum Likelihood (EML) and Whittle Approximate Maximum Likelihood (WAML). The research implements Geweke and Porter-Hudak (GPH) and Smoothed Periodogram (Sperio) for semiparametric estimation methods. Description of these methods are as follow:

Exact Maximum Likelihood (EML): Assuming a time series y_t is stationary and invertible, such that, $-0.5 < d < 0.5$ the exact Gaussian log likelihood is defined by the objective function as:

$$\log L_E(d, \phi, \theta, \sigma^2, \mu) = -\frac{1}{2}\left[T\log(2\pi) + \log\det(\Sigma) + (Y-\mu l)'^{\Sigma^{-1}}(Y-\mu l)\right] \qquad (2.8)$$

where Σ is the variance covariance matrix of Y, such that $Y = (y_1, y_2, \ldots, y_n)'$ and $l = (1,1, \ldots ,1)'$, ϕ and the θ are the parameters $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$ and $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$ respectively and μ is the mean of Y.

Whittle Approximate Maximum Likelihood (WAML): The WAML method is an alternative to the EML method for estimating parameter d of the ARFIMA (p, d, q) model. Whittle (1951) observed that for stationary models, the variance-covariance matrix Σ can be diagonalized by transforming the model into the frequency domain. Following the arguments of Johnstone and Silverman (1997), McCoy and Walden (1996), and Jensen (2000), the research work assumed that the asymptotic behaviour is satisfied, where σ^2 depends on other parameters of the model. Assuming Gaussian errors, the Whittle likelihood function is given by

$$L_W(d,\phi,\theta,\sigma^2) = T\left[\log(2\pi) - 1 - \log\frac{1}{T}\sum_{i=1}^{\frac{T}{2}}\frac{I(\lambda_i)}{f_y(\lambda_i)}\right] - \sum_{i=1}^{\frac{T}{2}}\log f_y(\lambda_i) \tag{2.9}$$

where $\lambda_i = \frac{2\pi i}{T}$ and the Fourier frequency, $I(\lambda_i) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} y_t e^{it\lambda}\right|^2$ is the periodogram of y_t and $f_y(\lambda)$ is the spectral density function defined by

$$f_y(\lambda) = \frac{\sigma^2}{2\pi}\left|1 - e^{i\lambda}\right|^{-2d}\frac{\left|\theta(e^{i\lambda})\right|^2}{|\phi(e^{i\lambda})|^2} = \frac{\sigma^2}{2\pi}(2sin\lambda/2)^{-2d}\frac{\left|\theta(e^{i\lambda})\right|^2}{|\phi(e^{i\lambda})|^2} \tag{2.10}$$

Geweke and Porter-Hudak (GPH): The simple spectral regression method or log periodogram regression method proposed by Geweke and Porter-Hudak (1983) is one of the most popular estimators for distinguishing long memory from short memory effects. Base on the series of length n the estimated slope coefficient of

$$\log\left(I(\lambda_i)\right) = const + d\log\left(\left\{2sin\left(\frac{\lambda_i}{2}\right)\right\}^{-2}\right) + \varepsilon \tag{2.11}$$

Is used as estimator for the fractional integrated parameter d of ARFIMA (p,d,q) model. It is denoted by GPH. where ε is the error term, $I(\lambda_i)$ is the periodogram normalized by 2π at the i^{th} Fourier frequency λ_i. $\lambda_i = i\frac{2\pi}{n}$. Only the first to the m^{th} Fourier frequency $\lambda_i; i = 1,2,\ldots,m.$, are used in the estimation. For $d < 0, GPH$ is asymptotically unbiased and normally distributed with $\frac{m(n)}{\log^2(m)} \longrightarrow \infty$ as $n \longrightarrow \infty$ (Hassler, 1993).

$$\frac{\hat{d} - d}{\mathrm{var}\left(\hat{d}\right)^{0.5}} \sim \mathrm{N}(0,1) \tag{2.12}$$

with $var\left(\hat{d}\right) = \frac{\pi^2}{6}\left[\sum_{i=1}^{m}(T_i - \bar{T})^2\right]^{-1}$ and $T_i = \log\left(\left\{2sin\left(\frac{\lambda_i}{2}\right)\right\}^{-2}\right)$. GPH proposed to use $m = \left[\sqrt{n}\right]$ for the exclusion of short memory effect, whereby $[y]$ denotes the largest integer not exceeding y.

Smoothed Periodogram (Sperio): an obvious possibility to further develop the Geweke and Porter-Hudak (1983) method of estimating long memory parameter d is to smooth the periodogram before it is used in the regression (Hassler, 1993; Peiris and Court, 1993; Reisen, 1994). In this method the truncation point in the Parzen lag windows is $m = n^\beta, 0 < \beta < 1$.

4. ANALYSIS OF DATA AND RESULT

4.1 Descriptive Statistics of the Data used for the Research

Table 4.1: Descriptive statistics of the MTN internet network flow

Measure	Mean	Median	Max	Min	Std. Dev	Std. Err	Skewness	Kurtosis	Jarque-Bera	p-value
Value	9.9666	7.0908	90.245	0.05	9.3653	0.2989	3.3311	17.5938	14548	0

The result in Table 4.1 showed descriptive statistics of the MTN internet network flow. MTN Nigeria recorded an average internet flow of 9.9666 Mbps and a standard deviation of 9.3653 Mbps in the period under investigation. On October 10, 2022 and February 22, 2019 MTN observed a maximum and minimum internet flow of 90.2450 Mbps and 0.0500 Mbps respectively, due to the increase in the number of subscribers recorded. The Jarque-Bera test statistic is 14548 with a highly significant probability value of 0.000, which indicates that the distribution of network flow is not normally distributed.

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4.2 Visualization used for the Research

To identify the model of any time series data, one must make a guess as to the data generation process. In doing this, one should begin by plotting the time plot, ACF and PACF of the series.

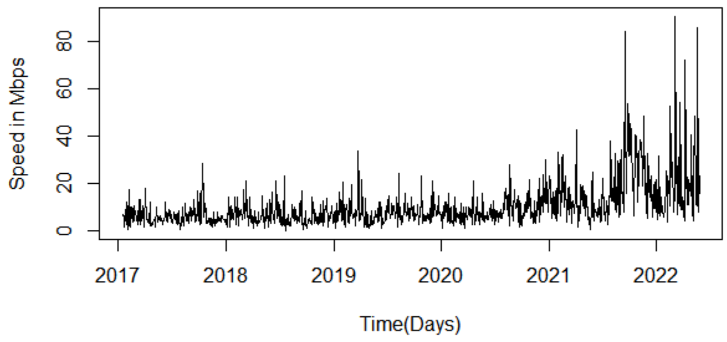

Figure 1. Time series plot for the MTN internet network flow

Figure 1 illustrated the time series plot of MTN internet flow from August 11, 2017 to December 31, 2022. Further the figure depicted a strong and thick movement of line which tended to indict highly correlated series. The fluctuation of the swing tended to be distributed around an average speed of 30 Mbps except for the last days of the period between 2021 and 2022. This indicated that as time evolved the subscribers in Nigeria tended to know the usefulness of mobile network as to improve their daily activities and jobs. The average of 30 Mbps tended to reflect the encouragement and satisfaction which can be derived from the use of mobile network to stir the affair of the economy.

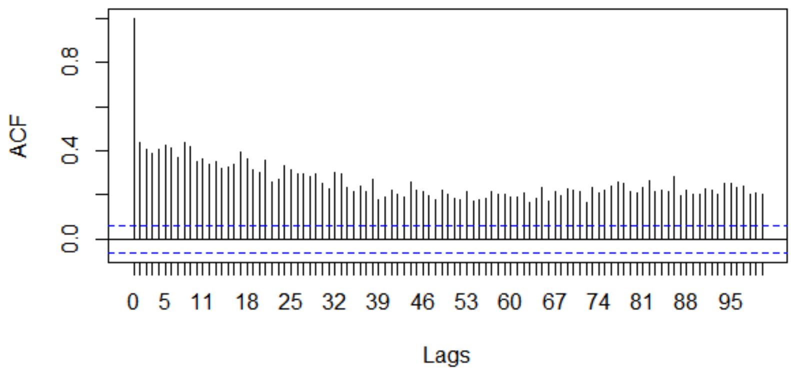

Figure 2. Plot of ACF for the MTN internet network flow

The ACF showed a slow decay, indicating the characteristics of a long memory that will later be confirmed by the long memory parameter d value. This further indicated a highly correlated data point that might likely suggest a non-stationary series. The transformation of data point is important in this procedure. Thus, the researcher investigated the unit root process of the series for identification of an unstable or long memory behaviour. The plot however, reflected the real behaviour of a long memory pattern.

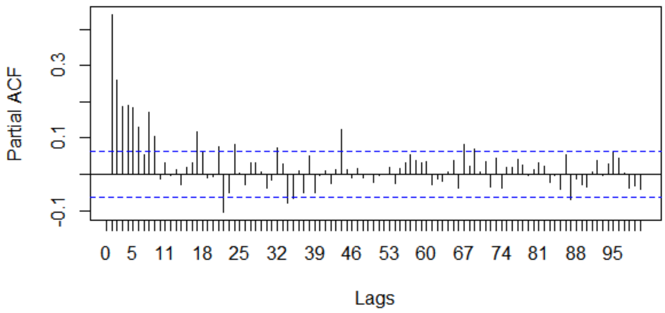

Figure 3. Plot of PACF for the MTN internet network flow

The PACF plot above depicted pattern of cut-off at lags with sinusoidal movement of pattern.

4.3 Stationarity Test/Unit Root Test

Table 4.2: Unit root test for the MTN internet network flow

Test	Value	p-value
ADF	-4.6202	0.01
PP	-975.48	0.01
KPSS	6.1263	0.01

The result in Table 4.2 presented the $p-$ values of the ADF, PP and KPSS tests. It can be seen that ADF and PP have $p-values$ of 0.01, indicated that the Nigerian telecommunication network flow for the MTN internet flow data does not contain a unit root. However, the KPSS test revealed that there is strong evidence to reject the null hypothesis of stationary of the series at 5% significance value. This signifies that the series are non-stationary.

4.4 Estimate of Long Memory Parameter d by Different Methods

Table 4.3: Long memory parameter d estimate for MTN internet network flow

Estimate	GPH	SPERIO	EML	WAML
d	0.2658	**0.2622**	0.2742	0.2852
Std. Err	0.0437	**0.0125**	0.0191	0.0250

The presence of long memory was discovered after examining ACF plots in Figure 2. The result in Table 4.3 presented the estimates of the long memory parameter d using the four different methods. The test results confirmed that the data have a long memory with estimated parameter of $-0.5 < d < 0.5$ in all the four methods. However, in order to build an ARFIMA model, the fractional difference value of $d = 0.2622$ is used for model selection. The table further indicates that there is a significant variation between the methods as far as estimating the long memory parameter d is concerned.

4.5 Selection of ARFIMA Models

Table 4.4: AIC, BIC and Loglikelihood Values of Different ARFIMA Model

Model	AIC	BIC	Log-Likelihood
ARFIMA(0, d, 0)	6795.942	6805.721	-3396
ARFIMA(1, d, 0)	6782.036	6796.704	-3388
ARFIMA(2, d, 0)	6774.591	6794.149	-3383
ARFIMA(3, d, 0)	6761.346	6785.794	-3376
ARFIMA(0, d, 1)	6770.319	6784.988	-3382
ARFIMA(0, d, 2)	6758.021	6777.579	-3375
ARFIMA(0, d, 3)	6759.221	6783.669	-3375
ARFIMA(1, d, 1)	6751.356	6770.914	-3372
ARFIMA(2, d, 1)	6753.751	6778.199	-3372
ARFIMA(3, d, 1)	6755.461	6784.799	-3372
ARFIMA(1, d, 2)	6753.707	6778.155	-3372
ARFIMA(1, d, 3)	6755.599	6784.937	-3372
ARFIMA(2, d, 2)	6751.913	6781.251	-3370
ARFIMA(2, d, 3)	6754.755	6788.982	-3370
ARFIMA(3, d, 2)	6754.718	6788.946	-3370
ARFIMA(3, d, 3)	**6740.745**	**6779.861**	**-3362**

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The result in Table 4.4 showed the AIC, BIC and loglikelihood values of different ARFIMA model for MTN internet network flow. ARFIMA $(3\ d, 3)$ model has the minimum AIC values of the model selection criteria. It is assumed in this model that the data is subject to autoregressive of order 3, fractional difference of order 0.2622 and moving average of order 3.

4.6 Parameter Estimation of ARFIMA Model

Table 4.5: Parameter Estimation for ARFIMA $(3\ 0.2622\ , 3)$ Model

Parameters	Estimate	Std. Err	z-value	p-value
AR(1)	2.638	0.000	4.696	0.000
AR(2)	-2.530	0.004	-6.036	0.000
AR(3)	0.889	0.000	6.524	0.000
MA(1)	2.641	0.002	1.123	0.000
MA(2)	-2.549	0.003	-7.645	0.000
MA(3)	0. 888	0.000	3.270	0.000

The result in Table 4.5 showed the parameters estimated by ARFIMA $(3\ 0.2622\ , 3)$. The findings showed that the parameters estimated are statistically significant.

4.7 Structural Breaks Test

Table 4.6: Quandt Likelihood Ratio (QLR) test

Test Type	Statistic	p-value
QLR test	448.33	0.000

The result in Table 4.6 revealed the test result of structural breask using the Quandt Likelihood Ratio (QLR) test. The test rejects the null hypothesis of no structural break. Further, the results pointed out that the series have a break point in the year 2021, which may be attributed to the ban on the mobile telecommunication networks in Zamfara state and some other Katsina local government areas.

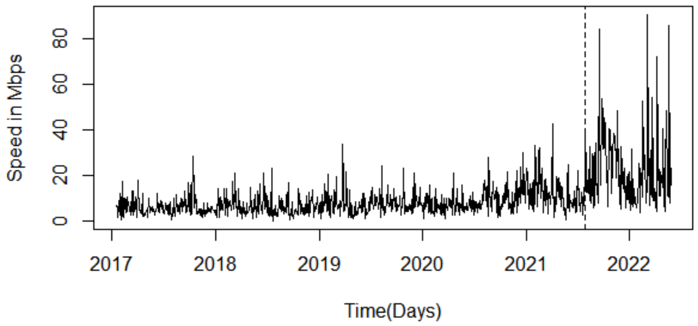

Figure 4. Time series plot for the MTN internet network flow with identified structural break

The plot above pointed out that the series has a break point or unexpected shift in the year 2021.

5. CONCLUSION

This research investigated the long-memory behaviour of Nigerian telecommunication network flow using the ARFIMA model. The descriptive statistics revealed an average internet flow of 9.9666 Mbps and a standard deviation of 9.3653 Mbps, this indicated that the flow of the network data were close to the average. The flow tended to fluctuate around 30 Mbps, except for the period between 2021 and 2022. Maximum and minimum flows of 90.2450 Mbps and 0.0500 Mbps were observed on October 10, 2022, and February 22, 2019, respectively, as a result of increased in the number of network subscribers. The Jarque-Bera test indicated significant deviations from normality (not normally distributed). ADF and PP tests confirmed the absence of a unit root in the series. However, KPSS test result suggested that the series is non-stationary. ACF plot showed a slow decay in data. Long memory parameter d for MTN internet network flow was estimated using different methods, including Geweke and Porter-Hudak (GPH), Smoothed Periodogram (Sperio), Exact Maximum

Likelihood (EML), and Whittle Approximate Maximum Likelihood (WAML). The estimation results indicated that the series exhibits some degree of long memory behaviour (i.e., the flow behaviour at one point in time can significantly affect the behaviour at a distant point in time). However, based on the minimum AIC and BIC values ARFIMA (3 0.2622 , 3) model founded to be more suitable for the data. More so, Quandt Likelihood Ratio (QLR) test result revealed that the series have a breakpoint in the year 2021.

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