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Optimal Short-Term Inflation Rate Forecasting Model in Kenya: in Depth Analysis

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ABSTRACT

Purpose: The Kenya economy experienced an increase in the price of basic commodities, increased unemployment rates and consequently reduced real wage levels due to job cuts. An accurate forecast of this unprecedented inflation rate could have cushioned the Kenyan population from its effects. Uncertainty over future inflation forecasting has caused detrimental and negative impact not only globally but also in the Kenyan economy. Combining several techniques of forecasting is an instinctual way to improve prediction performance as the limitations of one method are compensated by the strength of the other model. The general objective of the study was to develop an optimal model of forecasting short term inflation rate in Kenya. The specific objectives were to establish models of forecasting short term inflation rate using SARIMA, GARCH and hybrid SARIMA-GARCH family Models, select optimal model amongst the three models and Predict 12 months ahead inflation rate using the optimal model. Scope of the study from 2005 January to 2024 July. The study was anchored on monetary theory of inflation, Keynesian theory of inflation as well as rationale expectation theory of inflation.

Methodology: Data was sourced from KNBS and CBK. The study was guided by positivism research philosophy. Explanatory research design was used in this study. Target population was 230 monthly observations. Sample and sampling techniques used was time series. PACF, ACF Dfuller, Kpss test, Philips perron test indicated the data was stationary after 1ST differencing.

Findings: Statistic validation test results indicated SARIMA's (1,1,1)(1,1,)12 adjusted R^2 was perfectly 1 indicating all variations in squared residuals were explained by lagged residuals. P- value for lagged squared residuals were significant at (0.00). F-statistic-value was significant (0.020) suggesting overall model fit. Model stability test AR roots polynomial lied outside the unit circle. eGarch(1,1) model with lowest aic -0.534 was best in Garch Family models. Hybrid Sarima((1,1,1),(1,1,1) eGARCH(1,1) was identified. Comparison of Sarima(1,1,1)(1,1,1)12, eGARCH (1,1) and Hybrid Sarima((1,1,1),(1,1,1)12 eGARCH(1,1) using forecast accuracy revealed that hybrid model was the optimal model with lowest MAE 0.166 and RMSE 0.259. Diagnostic checks The Ljung-Box test (LL) and Q2 indicated non-significant autocorrelation p- value were greater than 05% indicating that the models residuals were white noise. The DOF/GED parameter (4.144466*, 1.101958, 6.977499) represented the degrees of freedom for the t-distribution and the coefficients where significant at 0.05% meaning the model's assumptions for normal distributions were met. The coefficients of AR Normal 0.048140, T-Student −0.031854, GED −0.02396 and MA Normal 0.055167 ,T-Student 0.059645, GED 0.051390 terms were significant at 5%.

Recommendations: The results implied that the model predicted a decrease in the Kenya's inflation rate for the next 12 months. The study recommended that inflation rate would be hovering below an average rate of 10 within the next 12 months with high volatility up to July 2025 and policy makers should use this prediction for planning in order to maintain Kenya's macroeconomic stability. Policy makers were also advised to use the hybrid model to forecast short term inflation rate 12 months ahead and in future years. The benefits of the study were added knowledge of hybridizing to researchers and to policy makers. This study therefore provided better inflation forecasts (Kenya) to be used for strategical planning for short -term effects of inflation by the government.

KEYWORDS: Inflation rate forecasting, Time series Forecasting, Sarima, Hybrid Sarima Garch family model.

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INTRODUCTION

Various factors contribute to volatility of prices. These include prices of raw materials, increased dependency of global trade, shift in the global supply chain, change in demand and supply, foreign policies and exchange rates. These many factors coupled with longer supply chain also means that retailers, exporters, investors, business community must project demand and purchase inventories a head of time. It is important therefore to have a model that reliably predicts inflation rate. Inflation is a sustained increase in the general price level of goods and services in an economy over a period of time. (Olivia Blanchard 2000) observed that when the general price level rose, each unit of currency bought fewer goods and services; consequently, inflation reflected a reduction in the purchasing power per unit of money or a loss of real value in the medium of exchange and unit of account within the economy as supported by (Paul *et al*.1973).The measure of inflation is the inflation rate, the annualized percentage change in a general price index, usually the consumer price index, over time (Mankiw and Gregory 2002).

Inflation has risen significantly in the past two years driven largely by external factors including global food prices, oil prices, and supply chain disruptions. Since domestic demand has played a more limited role given the slow recovery central banks potentially, have scope for a more gradual approach to monetary policy tightening. But the pace of tightening must be fine-tuned to changes in inflation expectations the credibility of policy frameworks and the extent of exchange rate pressures (International Monetary Fund, 2022).

Hybrid forecasting Models: Combining several techniques is an instinctual way to improve prediction performance as the limitations of one method are compensated by the strength of the other model. The hybrid model's motivation stems from the following aspects. First, determining whether a time series under investigation is created by a linear or non-linear underlying process and whether one technique is more selective than the other in out-of-sample forecasting is frequently tricky in practice (Lin *et al*., 2017).

Inflation forecasting in Kenya: The practice of forecasting inflation has generally been considered an important input in monetary policymaking (Fisher *et al*, 2002). Nothing is more important to the conduct of monetary policy than understanding and predicting inflation (Kohn, 2005).It is now well understood that expected (future) inflation is important for the design and implementation of monetary policy by central banks (Huang, 2012). In fact, inflation forecasting can be considered a comparative advantage of a central bank as it maintains information advantage about the state of the economy over the public (Huseynov *et al*, 2014).In Kenya, the second half of 2017 was characterized by general macroeconomic stability, decline in food prices, and uncertainties with regard to the prolonged election period. The Central Bank of Kenya (CBK) conducted monetary policy with the aim of keeping overall inflation within the government target range of 2.5 and 7.5% (CBK, 2017). The priority of price stability over the other policy goals seems to be politically accepted in most countries, if not appropriately mentioned in the laws governing the central bank (Gallego, 2002). Price stability remains the primary objective of monetary policy formulation and implementation (CBK, 2017).

Trend of Kenya's Inflation rate: Inflation is one of the central terms in macroeconomics (Enke & Mehdiyev, 2014) as it harms the stability of the acquisition power of the national currency, affects economic growth because investment projects become riskier, distorts consuming and saving decisions, causes unequal income distribution and also results in difficulties in financial intervention (Hurtado et al, 2013). prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values (Mcnelis & Mcadam, 2004). To prevent undesirable outcomes of price instability, Kenya economy requires proper understanding of the future path of inflation to anchor expectations and ensure policy credibility.It is therefore real that uncertainty over future inflation forecasting has caused detrimental and negative impact not only globally but also in the Kenyan economy(Agingu, Jagero, Mageto, T*, et al*,2023). Inflation is also very volatile and Investors, farmers and business community have all suffered the wrath of inaccurate inflation rate forecast. Inflation rate targets in Kenya have fluctuated from the set 5.25 margins and the level of inflation rate has been higher compared with the level of inflation rate in developed and emerging economies. The general objective of the study was to develop an optimal model of forecasting short term inflation rate in Kenya over the period from January 2005 to April 2024.The specific objectives of the study was to establish model of forecasting short term inflation rate in Kenya using SARIMA Model. Hypotheses of the study Short term inflation rate forecasting in Kenya could not be achieved using SARIMA Model.

The aim of this research study was typically to estimate or infer an outcome of interest. Even for a single product or service such as a inflation rate. Precise forecasting of inflation is a significant socio-economic ramification. As a result, models that are best matched to the data are required. Developing relatively advanced models for estimating inflation rate in Kenya has recently focused on time series forecasting research. Traditional ARIMA models have been hard to beat when it comes to short term accuracy in studies such as (Barrow and Kourentzes 2018).The period covered for this study was 2005m1 to 2024m4. Hypothesis of this study was drawn from the traditional approach rationale expectation Theory. This theory was chosen because most empirical evidence seemed to support its postulations. This study borrowed the model by (Nyoni and Nathaniel,2019) used to forecast inflation rate in Nigeria from 1960 to 2016. The study modifies (Nyoni and Nathaniel,2019) model by combining the ARIMA and GARCH to form an hybrid ARIMA- GARCH family model something (Nyoni and Nathaniel, 2019) or any other research did not do in Kenya. In doing the hybridization of sarima garch model this study emulated an econometric model by (Dileep Kumar *et al*,2018) where an hybrid sarima garch family model was developed and used to forecast the price of gold in India. The study made a novel contribution to solve the problems of time series modelling i.e hybridization. This study contributed to the body of knowledge in the development of an hybrid Sarima jgrGarch model. Policy makers in Kenya should continue to engage proper economic policies in order to fight against persistent inflationary pressures in the economy. In this regard, the Central Bank of Kenya CBK is encouraged to tighten its monetary policy in order to foster macroeconomic stability in the country.

LITERATURE REVIEW

Monetary Theory of Inflation: The Quantity Theory of Money is one of the popular classical macroeconomic models that explain the relationship between the quantity of money in an economy and the level of prices of goods and services. Modern versions of the quantity theory are often associated with (Knut, 1898) and (Fisher & Brown, 1922). (Fisher and Brown 1922) states that, money was only used as a medium of exchange to settle transaction involving the demand and supply for goods and services. The quantity theory of money can be developed to a theory of price levels. Fisher, sought to provide a rigorous basis for the quantity theory by approaching it from the quantity equation i.e. MV=PT, P=MV/T. Where V - velocity of circulation, M -money supply, P – Price, and T -quantity of transactions. Assuming that V and T are roughly constant, P will vary directly with increase or decrease in the amount of M and it changes in money supply (M) that causes the prices (P) to change, not changes in price that cause the changes in supply is assumed to be constant as the economy in question is assumed to be operating at full employment.

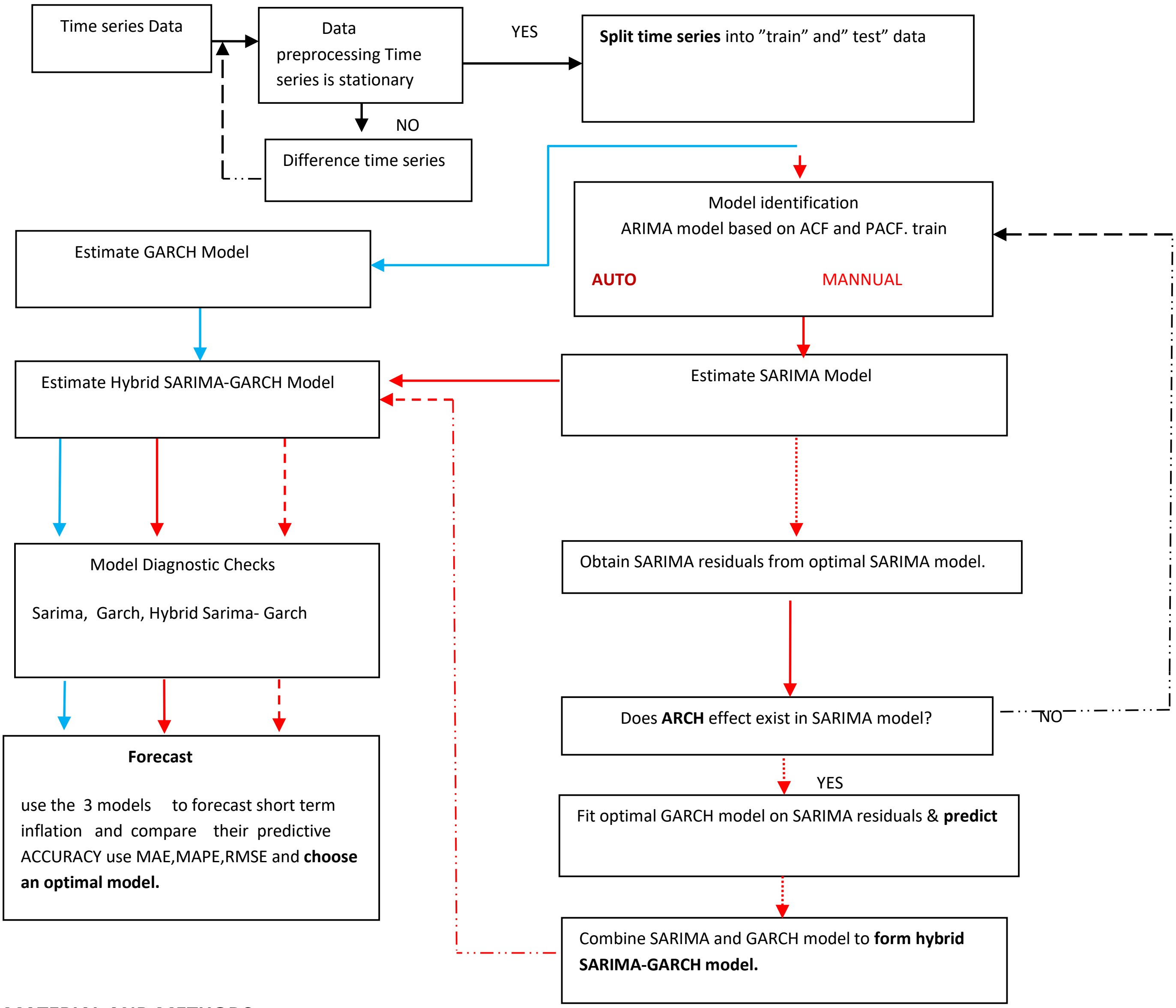
The Keynesian theory of inflation: Keynesians do not believe in the direct link between the supply of money and the price level that emerges from the classical quantity theory of money. They reject the notion that the economy is always at or near the natural level of real output so that Y in the equation of exchange can be regarded as fixed. They also reject the proposition that the velocity of circulation of money is constant. However, they do believe in an indirect link between the money supply and real output. (Phelps, 1967).

Rational Expectation Theories of inflation: While rational expectations is often thought of as a school of economic thought it is better regarded as a ubiquitous modeling technique used widely throughout economics. The theory of rational expectations was first proposed by (John F. Muth, 1960) of Indiana University. He used the term to describe the many economic situations in which the outcome depends partly on what people expect to happen. The price of an agricultural commodity for example, depends on how many acres farmers plant which in turn depends on the price farmers expect to realize when they harvest and sell their crops. As another example the value of a currency and its rate of depreciation depend partly on what people expect that rate of depreciation to be.

According to (Garcia, *et al*, 2003), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models consider that the price series is not invariant (i.e. the error term: real value minus forecasted value does not have 0 mean and constant variance). The error term is now assumed to be serially correlated and can be modeled by an Autoregressive (AR) process. Thus, a Generalized Autoregressive Conditional Heteroskedasticity GARCH process can measure the implied volatility of a series due to price spikes. For example, California experienced huge price spikes during the summer of 2000 that led to the closure of the market until new rules were developed. As suggested by (Bollerslev *et al*. 1994), economic loss functions that explicitly incorporate the costs faced by volatility forecast users provided the most meaningful forecast evaluations.

In this autoregressive model, inflation rate forecasting was represented by the equation $y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} +.., y_{t-p} + \varepsilon_t$. (Zivko, I & Bosnjak, M,.2017)…………………………(2)

Conceptual Framework



MATERIAL AND METHODS

Model formulation: This study approach was dictated by philosophical context under which a researcher works. Research philosophies and theoretical paradigms about the nature of reality and the way in which reality or knowledge can be deliberated are foundations from which most researchers distinguish between advocates of quantitative and qualitative research paradigm. Area of Study was Kenyan economy that is generally characterized by high levels of inflation rate. Kenya is situated in the East African region and lies between latitudes 400^{o} North and 400^{0} South and longitudes 3400^{0} East and 4100^{0} West. It borders on the east with Somalia and the Indian Ocean, while on the north it borders Ethiopia and Sudan. On the west is Uganda and on the south is Tanzania (Marhourm and Samper, 2010). This study used explanatory research design in forecasting the time series inflation rate data. This is a research method that explains why something occurs when limited information is available. Sample and Sampling Techniques used in this study was time series from January 2005 to 2024 April. This sample was chosen because of data availability. In this study of forecasting Kenya's inflation rate in Kenya. A univariate time series regression model was used. This study borrowed (Nyoni and Nathaniel, 2018).ARIMA can be divided into three categories (Durka & Pastorekova 2012). Non-seasonal ARIMA (ARIMA), Seasonal ARIMA (SARIMA) and Multivariate ARIMA (ARIMAX). The box Jenkins methodology ARIMA models are the most general class of models for forecasting a time series, applied in cases where data showed evidence of non-stationary (Box Jenkins,1970). Non-stationary in mean was removed by transformations ie differencing while non-stationary in variance was be removed by a proper variance stabilizing transformation introduced by Box and Cox. The ARIMA (p, d, q) can be written as

$$\phi_p(B)(1-B)^d X_t = \theta_q(B)\varepsilon_t \quad \text{...(5)}$$

Where $\phi_p(B)=1-\phi_1 B-\phi_2 B^2-\ldots\theta_q B^q$ the autoregressive operator of order is $p;\theta_q(B)=1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q$ is the moving average operator of the order $q;(1-B)^d$ is the d^{th} difference; B is backward shift operator; and ε_t is the error term at time t .The orders are identified through the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the sample data. The error terms are generally assumed to be independent identically distributed random variables (i.i.d.) sampled from a normal distribution with zero mean and constant variance. (Kumar, D. et al, 2018).

Data Collection and analysis: The original data set to be consisted of measured Kenya's monthly Inflation rate over the period 1 January 2005 to July 2024. The data set was be secondary provided by Kenya national Bureau of statistics (KNBS, 2023) and Central Bank of Kenya (CBK, 2023) Kenya's Monthly Inflation rate data was calculated by using Consumer Price Index. Measures were taken to ensure that consistency in the data set was achieved across the period (Fwaga. O., Orwa. G, & Athiany, H. 2017).

Diagnostic tests and Model evaluation: In any statistical models, residuals can be calculated as a difference between the observed (actual) and predicted value. If the residuals can nearly attain white noise properties, this reasonably would indicate that the model was appropriately specified and the parameter estimates were convincingly close to the true values (Zhang, G.P. 2003). They should behave roughly like independent, identically distributed normal variables with zero mean and constant variation. Deviations from these properties can help discover a more appropriate model.

Normality and independence: The test estimates a W statistic that checks whether a random sample $x_1, x_2 \ldots\ldots\ldots x_n$ has been chosen from a normally distributed population. The smaller value of W indicates deviation from normality and critical values of the W statistic are achieved from Monte Carlo simulations (Shapiro & Wilk 1965).The hypothesis test of the normality will also be confirmed using Shapiro-Wilk test and independence is using runs test(Zhang, G.P. 2003).

$$w=\frac{(\sum_{t=2}^{n} a_i y_t)^2}{\sum_{t=1}^{n}(x_t-\bar{y})^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(22)$$

Where w is the test statistic, n the number of observations, y_t value of the ordered sample, a_i tabulated coefficients. If the test statistic W will be smaller than the critical threshold the assumption of a normal distribution has to be rejected (Zhang, G.P. 2003).

In this study w will be inflation rate time-series data points and α_i will be constants obtained from mean variance and covariance of a sample of size n from a normal distribution. The assumptions advantages and disadvantages of Shapiro Wilk test can be found in the (e-Handbook. 2022).

Graphical visualization tools (Quantile-Quantile (QQ) plot: The normality assumptions can also be checked by histograms and quantile-quantile (Q Q) plot of the residuals. The QQ plot is a visualization tool that assists in evaluating whether the rainfall time series chosen is a sample from a population of particular theoretical distribution (normal distribution in this study). It is a scatterplot produced by mapping two sets of quantiles against one another. In the present case, if the selected rainfall time-series dataset follows a perfectly normal distribution, then the points in the plot fall on a straight line (NIST/SEMATECH, 2022)

Test for Heteroscedasticity: The test for ARCH effects was proposed by (McLeod and Li, 1983). It looks at the autocorrelation function of the squares of the pre whitened data and tests whether corr (x_t^2, x_{t-j}^2) is non- Zero for some j. The autocorrelation at lag j for the squared residuals (x_t^2) is estimated by

$$\hat{\varepsilon}(j)=\frac{\sum_{j=1}^{N}(x_t^2-\hat{\sigma}^2)(x_{t-j}^2-\hat{\sigma}^2)}{\sum_{t=1}^{N}(x_t^2-\hat{\sigma}^2)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(23)$$

Where

$\hat{\sigma}^2=\sum_{t-1}^{N}\frac{x_t^2}{N}$ under the null hypothesis that x_t is an i.i.d process, (Mcleod and Li,1983) show that for fixed L: $\sqrt{N\,\varepsilon}=(\hat{\varepsilon}(1),\ldots\ldots,\hat{\varepsilon}(L))$ is a asymptotically a multivariate unit normal. Consequently, for L sufficiently large, the usual Box-

Ljung statistic will be

$$Q = N(N+2)\sum_{j=1}^{L}\frac{\hat{\varepsilon}_j^{2}}{N-j)}\text{...}(24)$$

Is asymptotically $\chi^2(L)$ under the H_0 of a linear generating mechanism for the data. Typically L is taken around 20 (Ashley and Patterson,2001)

Arch-LM Test: A methodology to test for the ARCH effect using Lagrange Multiplier test was proposed by (Engle,1982) This procedure is as follows:

Obtain the squares of residual from fitted model $\hat{\varepsilon}^2$ and regress them on the constant and q lagged values.

$$\hat{\varepsilon}^2_t = \hat{\alpha}_0 + \sum_{i=}^{q}\hat{\alpha}_i\,\hat{\alpha}^2_{t-i}\text{ ....}(25)$$

Where q is the length of the ARCH lags. The null hypothesis is that in the absence of ARCH components, there are $\alpha_i = 0$ for all i=1,2…. q. The alternative hypothesis is that, in the presence of ARCH components at least one of the estimated α_i coefficients must be significant. In a sample of T residuals under the null hypothesis of no ARCH errors, the test statistic TR^2 follows the χ^2 distribution with q degrees of freedom. If TR^2 is greater than the chi-square table value, Then the study rejects the null hypothesis and conclude there is an ARCH effect in the ARMA model. If TR^2 is smaller than the χ^2 table value, the study do not reject the null hypothesis (Hyndman, R. Athanasopoulos, C. J. 2014).

Multicollinearity Test: According to Keith (2006) multicollinearity arises when two or more independent variables that are jointly used to estimate a regression model have a strong linear relationship. However multicollinearity may not be a problem in forecasting since univariate data was used but it may be a problem in simulation. Solution to the problem of multicollinearity in this univariate study would was to possibly increase the sample size (Hyndman, R.. Athanasopoulos, C. J. 2014).The hybrid SARIMA-GARCH model is one in which the variance of the error term of the SARIMA model follows a GARCH process. The model can be written as:

$$\varphi_p(\beta)\varphi_p(\beta^S)(1-\beta)^d(1-\beta^S)^D_{y_t} = \theta_q(\beta)\Theta_Q(\beta^S)\varepsilon_t., \varepsilon_t = Z_t\sigma_t\text{......................................}(28)$$

$$\sigma_t^2 = w + \sum_{i=1}^{m}\alpha_i\varepsilon_{t-i} + \sum\beta_j\sigma^2_{t-j}\text{..}(29)$$

Where

Where y_t represents the time series $\varphi_p(\beta)(\beta^S) = (1-\varphi_1^S - \varphi_2^{\beta^{2S}} - .....\varphi^{\beta^{PS}})$. is seasonal autoregressive part. $\Theta_Q(\beta^S) = 1-\Theta_1\beta^{2S} - ...\Theta_Q\beta^{QS}$ is the seasonal moving average part. S is the seasonal period. D is the seasonal difference. (m,s) is the order of Garch process. $w, \alpha_i, and\beta_j$ are parameters of garch model. ε_t is the error term, σ_t^2 is the conditional variance of ε_t. z_t is the sequence of iid random variables with man zero and variance.

The MAPE, MAE and RMSE are used in evaluating the forecasting accuracy. The best model will be used to predict short-term inflation in Kenya.(Fwaga S., Orwa, G, & Athiany, H. 2017).

Akaike Information Criterion (AIC). The goodness of fit of a model will be assessed using $AIC = 2k - 21n(L)$ where L = the maximized value of the likelihood function for the estimated model and k = the number of free and independent parameters in the model. Bayesian Information Criteria (BIC) Akaike (1978) [22] and (1979) [23] has developed an extension of Bayesian of the minimum AIC, known as the Bayesian Information Criterion (BIC) and given by: BIC = −2 ln(maximum likelihood) + k ln(n) (3.12) Where n is the number of observations in the given stationary time series data and k is the number of parameter. In similar fashion to AIC the best model taking part in ARIMA (p,d,q) models is the one with the smallest BIC.

Model performance or selection: The final choice of a model relied on the goodness of fit like the residual, mean square or information criteria. The main objective of this model was to forecast future values based on the current and past values so the criteria for model selection was based on forecast errors (Wei, William, W.S. 2006). If the forecast error step ahead.

$$e_t = Y_{n+1} - \hat{Y} \text{...} (30)$$

where n was the forecast which is greater or equal to the length of the series. The comparison of the forecast error helped to know how much the study should rely on the chosen prediction method based on the following statistics.

Mean percentage error (MPE) was also called bias as it measured forecast bias. This was given by the mathematical formula:

MPE = $$(\frac{l}{j}\sum_{l=1}^{j}\frac{e_l}{Y_{n+1}})\text{...}$$ ....(30)

Mean square error (MSE) MSE = $$\frac{i}{j}\sum_{l=1}^{j}e_l^2\text{.....................................}$$ ....(31)

Mean absolute error (MAE) MAE = $$\frac{l}{j}\sum_{l=1}^{j}|e_l|\text{...}$$ ....(32)

Mean absolute percentage error (MAPE) MAP E = $$(\frac{l}{j}\sum_{l=1}^{j}\left|\frac{e_l}{Y_{n+1}}\right|\text{.....................................}$$ (33)

The model with the smallest MPE, MSE, MAE and MAPE will be selected the best model for forecasting. But, (Hyndman and Koehler,2005) proposed the mean absolute scaled error become Autoregressive Models (AR):

FINDINGS

Descriptive statistics: The kurtosis values were observed to be slightly greater than 3, indicating that all of the CPI series were leptokurtic i.e data had thick tails (Humala & Rodríguez, 2013; Mallikarjuna *et al.*, 2017). The Jarque- Bera test showed that the series were not -normally distributed.

Table 4.4: Descriptive Statistics.

Obs	Mean	Max	Min	Std. Dev	Variance	Skewness	Kurtosis	Median	Jarque Bera Test
230	7.69	17.07	3.93	3.324	11.21	1.40	0.96	6.5	80.772 p-value(0.000)

Source: Researcher's Computation,2024

The variance was high 11.21 and standard deviation 3.324 referred to volatility. Therefore, the higher the standard deviation, the higher the volatility of the inflation rate. The high variance warned the existence of heteroscedastic property thus the ACF and PACF plots alone were not able to exhibit. Again, the big difference between the maximum and minimum values indicated variability of trend of the inflation rate series within the covered period. (Kazungu, E. Ndanguza, D. 2021),

Shapiro Test for Normality: The Shapiro-Wilk test was applied to the CPI dataset, resulting in a W statistic of 0.81591 and a p-value of 8.68e-16. The p-value was extremely small, which was less than the commonly used significance level of 0.05. Therefore based on the Shapiro-Wilk test, the study rejected the null hypothesis and concluded that the CPI dataset was not normally distributed. Table 4.5.2

Table 4.5.2 Shapiro-Wilk normality test

Shapiro-Wilk normality test	
W:0.815	P-value 8.68e-16

Unit root Test: Ordinarily time series data suffers from non-stationarity (Nelson & Plosser, 1982). This study tested for unit root using Augmented Dickey-Fuller test and phillip Peron test. From table4.7 and 4.7. 1 results indicated that data was non-stationary at level 1%, 5% and 10% significant levels but was stationary after first difference(M. C Kiptui, 2013).

Dfuller Test with constant				
Test Statistic	Critical values 1%	Critical values 5%	Critical values 10%	
-1.74	-3.46	-2.28	-2.57	
Dfuller Test non constant				
-1.25	-2.58	-1.95	-1.61	
Dfuller Test first difference Non Constant				
-8.67	-2.58	-1.95	-1.61	
Dfuller Test first difference Trend and Constant				
-8.65	-3.99	-3.43	-3.13	
Lags	coeff	Std Error	T test	P value
1	-0.50	0.57	-8.65	0.00
Constant	-0.03	0.75	-0.50	0.61
Trend	0.00	0.0005	0.33	0.74

Table 4.7.1 Phillip Perron Test

Pperon Test with constant				
Test Statistic	Critical values 1%	Critical values 5%	Critical values 10%	
-14.99	-28.26	-21.21	-17.93	
pperonTest non constant				
-2.78	-13.55	--7.98-	-5.568	
pperon Test first difference Non Constant				
-8.653	-3.997	-3.433	-3.133	
pperron Test first difference Trend and Constant				
-9.05	-3.99	-3.43	-0.13	
Lags	coeff	Std Error	T test	P value
1	-0.49	0.05	8.63	0.38
Constant	0.15	0.16	0.99	0.32
Trend	-0.000	0.00	0.33	0.74

Source: Researcher's computation, 2024

The plot of the first difference of the CPI confirmed that the series was stationary.4.7.2

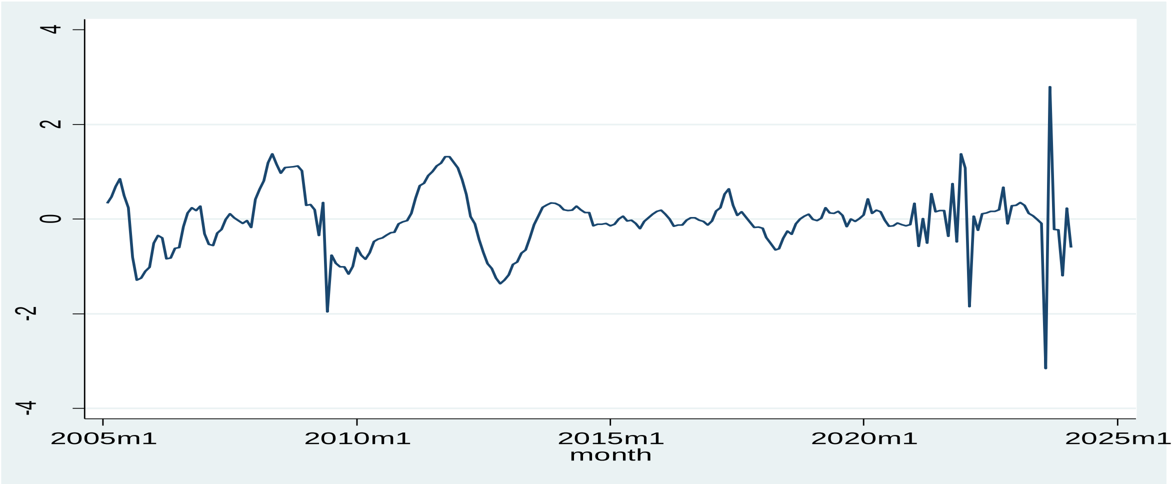


Fig 4.7.2 Plot First Difference

Plot of ACF & PACF: Autocorrelation Function (ACF) and Partial autocorrelation Functions (PACF) of CPI in addition to the inspection approach also provided extremely helpful information suggesting the series was not stationary as shown in figures 4.7.

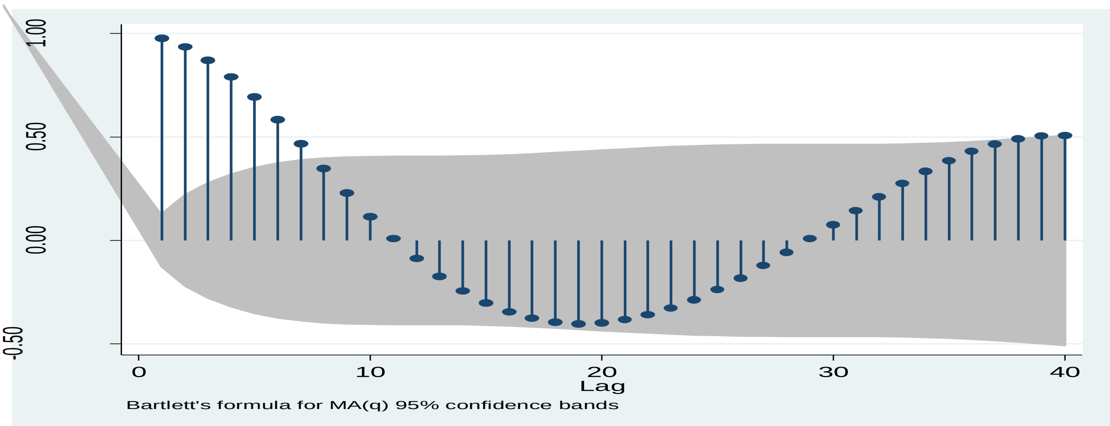


Figure 4.7.2 ACF plot of cpi data

The ACF showed a steady decline as the number of lags increases. This behavior was anticipated when a time series was likely to display random walk behavior (Selvi, 2018). To achieve stationarity in the series, the study took first differencing of the CPI and the new ACF and PACF are shown in figures 4.7.2 ACF and PACF .

The descriptive statistics displayed in Table 4.7.2 indicated values for skewness were -0.26 and kurtosis 3.23 and were within the acceptable range of normality (Demir, 2022) and therefore the study worked with the transformed data.

Table 4.7.2 Descriptive statistics after data transformation

Obs	Mean	Max	Min	Std. Dev	Variance	Skew	Kurtosis	Media
230	7.73	17.07	3.93	0.658	6.36	-0.26	3.23	-0.00

Source: Researcher's Computation,2024

The Jarque-Bera test statistic was 59.59 and the p-value was 0.825 greater than 0.05. p-value suggested that the data was normally distributed. (Jarque, Carlos M. Bera, Anil K. 1980).

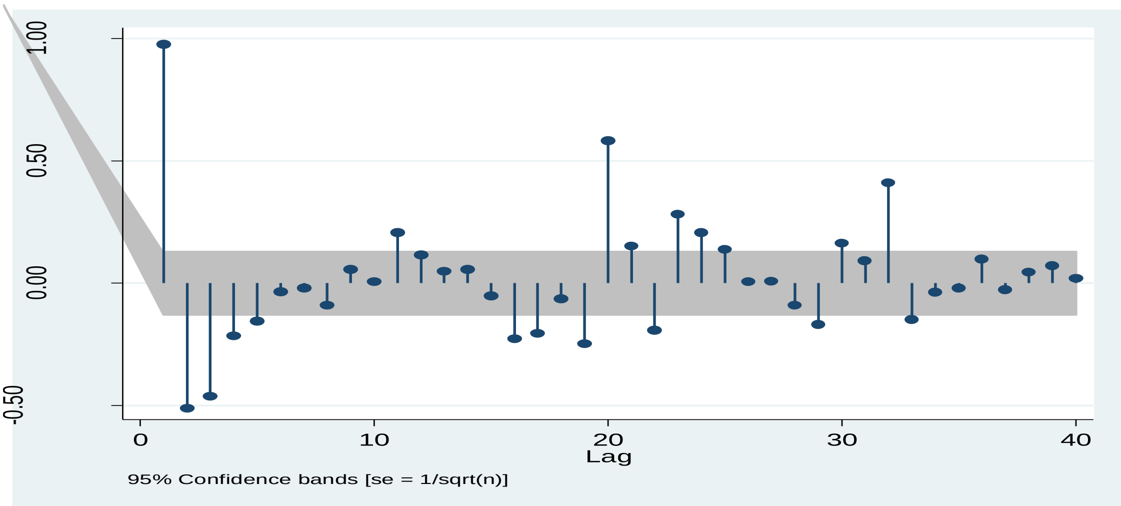


Figure 4.7.2(a) PACF plot of cpi data

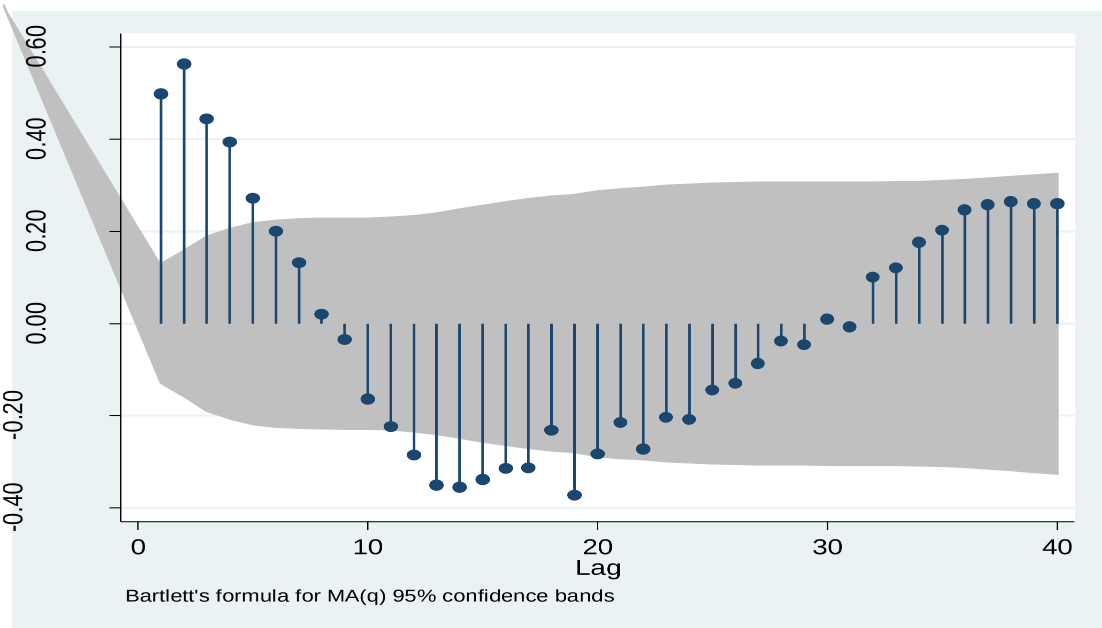


Figure 4.7.2(b) ACF plot of cpi differenced data

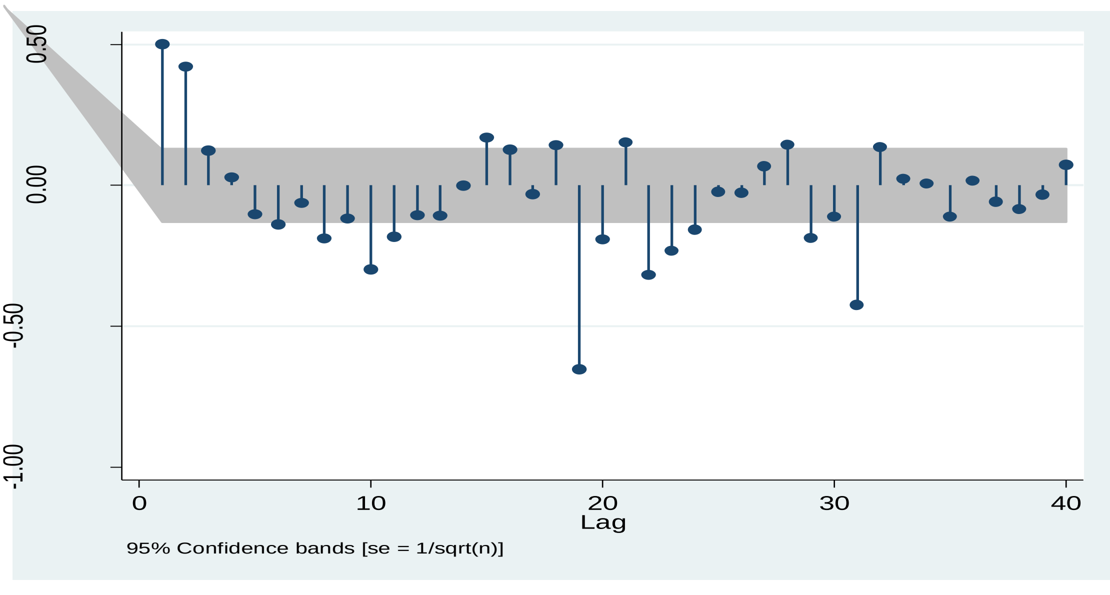


Fig 4.7.2 PACF Plot of differenced Cpi data

On inspecting Figure 4.7.2, the study noted there was strong presence of seasonal factors. This were confirmed by very high spikes around 2009,2017,2022. The ACF is shown in Figure 4.7.2(a) ACF. The study completed the data preparation process by additionally performing a first order seasonal difference and the time plot is shown in Figure4.6.1. Visual examination of Figure 4.6.1 showed that the series was stationary.

Sarima Model Estimation: The results of hybrid SARIMA (1,1,1) (1,1,1)12, eGarch (1,1) model are shown in table 4.16. The equation included AR (230) and MA (16) terms. The AR (230) term indicates that the model used 230 lagged previous months of the time series to predict the current inflation rate. The coefficients AR Normal 0.048140*, T-Student −0.031854*, GED −0.02396**, and MA Normal 0.055167* , T-Student 0.059645*, GED 0.051390* terms were significant as indicated by the asterisks in table 4.16 which meant that they were statistically significant at the 0.05% level. The results suggested that the model predicted a decrease in the Kenya's inflation rate series for the next 12 months.

The variance equation included parameters for the eGARCH(1, 1) model, with α0, α1, and β1 coefficients. The α0(1.1070661*, 1.051116*,1.015478*) parameters represented the constant term in the variance equation. The α1(0.176842*, 0.232728*,0.204613*) and the β1(0.944145*,0.958353*, 0.951375*) parameters were coefficients for the ARCH and GARCH(1,1) terms respectively. The significance of these parameters were statistically significant at 0.05% level.

The DOF/GED parameter (4.144466*, 1.101958*, 6.977499*) represented the degrees of freedom for the t-distribution and the coefficients where significant at 0.05% meaning the model's assumptions for normal distributions were met.

Model Diagnostic: The diagnostic tests provided insights into the model's performance and assumptions. The Persistence test indicated that the model's residuals were not autocorrelated at the 98% level. The results of the study suggested the model's residuals were white noise. The Ljung-Box test (LL) and Q2 test were used to check for autocorrelation in the residuals. LL test indicated non-significant autocorrelation indicating that the model's residuals were white noise. The P- values were greater than 0.05 and insignificant. The null hypothesis was not rejected and the study concluded that there was no autocorrelation, in summary the Hybrid SARIMA (1,1,1) (1,1,1)12, eGarch (1,1) model had significant AR and MA terms in the equation significant parameters in the variance equation and significant autocorrelation in the residuals which are consistent with the use of an hybrid SARIMA and GARCH family model.

Table 4.14.2(a) Forecast Comparison

MAE	0.166	1.071	1.02
RMSE	0.259	1.519	1.44

The model's assumptions were met and the residuals were normally distributed which is typical for inflation rate time series data. The study therefore used the model to forecasting inflation rate with confidence.

Forecast Validation: Predictions errors for hybrid, Sarima and eGarch(1,1) model are displayed in table 4.14.2(a). Therefore, the forecast errors results of the hybrid SARIMA (1,1,1) (1,1,1)12 eGarch (1,1) were smaller (MAE 0.166, MRSE 0.259 compared to those of Sarima and eGarch. The study therefore chose the hybrid model model as an optimal model in this study to forecast inflation rate Kenya.

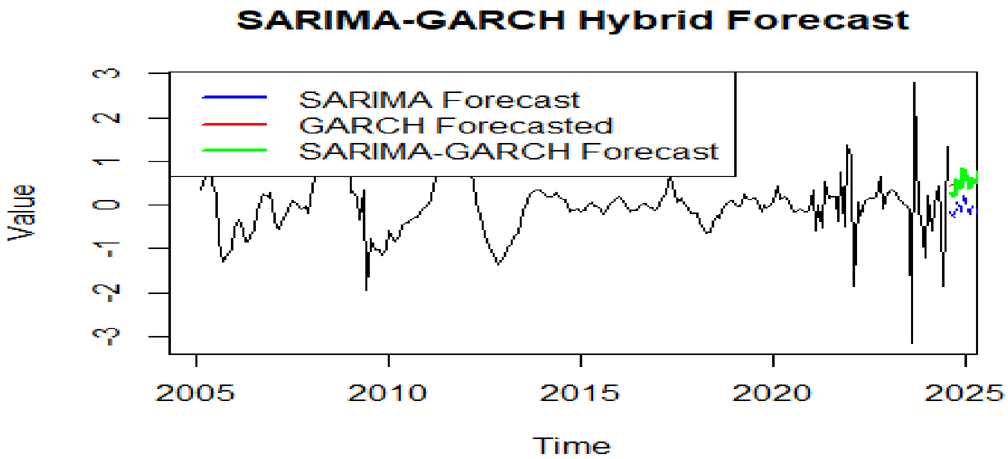
Table 4.15 Forecast Comparison

Month Year	Hybrid Sarima eGarch Model	Sarima Model (1,1,1)(1,1,1)12	eGarch(1, 1) Model
August,2024	4.4	1.7	5.1
Sept,2024	4.8	5.9	5.4
Oct,2024	5.1	3.8	5.7
Nov,2024	5.4	8.2	6.0
Dec,2024	5.7	7.2	6.2
Jan,2025	6.0	3.7	6.5
Feb,2025	6.2	6.2	6.8
March,2025	6.5	5.	7.0
April, 2025	7.0	7.8	7.3
May,2025	7.3	8.5	7.5
June,2025	7.5	5.4	5.1

July,2025	4.4	1.7	5.4
August,2025	4.8	5.9	5.7

Source: Researchers' Computation, 2024.

Forecast Trend hybrid model: The practice of forecasting inflation has typically been regarded as a vital input in monetary policymaking (Fisher JD, Liu CT, Zhou R,2002). It aids in planning and decision-making by providing awareness into the future based on the past and existing behavior of given observed values. As a result, the optimal final hybrid model was applied to 12 months ahead predictions. The forecasts results showed a decreasing trend of inflation rate from August 2024, 4.4 to October 2024 (5.1) (Table 4.14.2(b). After that, the model prediction indicates another upward trend of inflation rate from 6.0 in January 2025 to 7.5 in June 2025. The subsequent



CONCLUSIONS

Overall the study suggests that inflation rate appeared to take a decreasing trend in the next twelve months. The findings are supported by past studies, such as the study done by (Gil-Alana, Luis A), (Mudida, Robert, 2024), (Aaron O'Neill, Jul 4, 2024) whose forecasts indicated that inflation rate in Kenya is more likely to decrease in the future. The hybrid model effectively captured the temporal patterns, volatility and trends present in the inflation rate data for Kenya. This capability was crucial for informing economic decisions, policy formulation and risk assessment.

IMPLICATIONS TO KNOWLEDGE

Novel contribution or knew ideas to researchers. The study made a novel contribution to solve the problems of time series modelling i.e. hybridization. This study contributed to the body of knowledge in the development of an hybrid Sarima eGarch model for inflation forecasting which had a comparatively low MAE,RMSE when measured against independent SARIMA and GARCH model.

The low RMSE value made the hybrid Sarima eGarch model a better forecasting tool when compared to independent ARIMA and GARCH models. Hybrid model help economic planners make more accurate inflation forecasts and thus is capable of creating economic policies to maintain inflation at a stable rate. Stable inflation rate gives investors' confidence of investing in an economy thus spurring economic development (Kavila W, Roux ,2016).

Implications to Policy Makers: Policy makers should consider incorporating external economic indicators and events such as government policies, global economic conditions, and commodity prices to enhance the model's accuracy. These factors could provide additional insights into the inflation rate dynamics. (Devi, K., & Monika, *et. al*. 2021).

Theoretical Contribution: This study contributed to the existing theories by comparing hybrid model with related literature review. The proposed model tried out many innovative combination method and experimental in the inflation rate forecasting and acquired a suitable results. In particular previous studies indicated that the practical application framework of combine linear and non-linear models to build an optimal hybrid.

Knowledge Gap: This study filled the knowledge gaps to highlight the importance and significance of SARIMA, GARCH and Hybrid SARIMA- GARCH models as predictors providing the rationale for selecting an optimal hybrid model. Thus, this study's contribution and significance were in methodological and theoretical learning point of view.

Limitations and Areas for Further Study: The study suggests future studies on hybrid models in fitting the respective series. Having demonstrated that hybrid Model was the best fit for inflation rate data future studies can examine whether the hybrid models using the generalized additive ie hybrid (GAM) and SARIMA (p,d q) model can best fit the same series. In this method a researcher can fit the inflation rate data to the (GAM) model then extract its residuals. The resultant residuals would then be fitted using the SARIMA (p, q) and GAM model.(Tseng, *et al*. 2002) and (Zhang, 2003).

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