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MODELLING THE SOUTH AFRICAN INFLATION RATE USING BOX-JENKINS ARIMA MODELS

Abstract:

This study investigates the performance of the South African inflation rate using Box-Jenkins ARIMA models. Several competing ARIMA specifications were identified through ACF, PACF, and EACF analyses, including ARIMA(1,1,0), ARIMA(2,1,0), ARIMA(1,1,1), and ARIMA(2,1,1). All models were estimated using the maximum likelihood method, with results indicating statistical significance and low standard errors across the board, suggesting strong model fit. The optimal model, ARIMA(1,1,1), was selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), aligning with findings by Mondal et al. (2014). Diagnostic tests, including the Ljung-Box test and residual analysis, confirmed that the ARIMA(1,1,1) model is robust and reliable for modelling inflation dynamics in South Africa. The study highlights the usefulness of ARIMA models in forecasting inflation, a crucial task for policymakers and the South African Reserve Bank in managing inflation expectations and guiding monetary policy. While the linear ARIMA model performed well, the study also recognises its limitations in capturing complex macroeconomic behaviours, suggesting future exploration of nonlinear models such as GARCH. Though the findings are specific to South Africa, the approach provides a replicable framework for other macroeconomic applications and geographical contexts.

Keywords:

Accuracy measures, ARIMA, Inflation rate, Linearity, South Africa

JEL Classification: C10, C52, E31

1. INTRODUCTION

The paper investigates the performance of Box-Jenkins ARIMA on the South African inflation rate. ARIMA was developed in 1970 and has since been widely used to forecast time series data in a range of fields (Li *et al*., 2021). ARIMA models predict relatively steady time series data with high levels of accuracy. However, it requires an essential presumption that future data values are linearly reliant on the current and past data values (Büyükşahin & Ertekin, 2019). They also assume that the residuals are white noise and require that the data be stationary when applying a linear method to it (Babu & Reddy, 2014). The ARIMA framework is characterised by three parameters of statistical significance for model reliability: (p, d, q), where $'p'$ defines the autoregressive process, $'d'$ implies difference order (Integration), and $'q'$ represents the moving average process (Alghamdi *et al*., 2019). ARIMA models can help you analyse the changing patterns of data in a certain context. Although ARIMA models are extremely adaptable in that they may represent a wide range of time series, including AR, MA, and ARMA, their fundamental disadvantage is the model's assumed linear structure (Torbat *et al*., 2018).

Time-series forecasting has historically been done in econometrics utilising ARIMA frameworks, that Box and Jenkins modified (Siami-Namini *et al*., 2018). For years, ARIMA has been the preferred method for prediction of time series. Tsoku *et al*. (2017) have indicated that when the components representing the time series fluctuate fairly fast over time, the Box-Jenkins approach is regarded as a viable prediction tool. In this ARIMA's strength relies in its capacity to model all forms of time series data, either stationary or non-stationary, which makes it a useful tool for researchers. The paper applied ARIMA to model the inflation rate of South Africa.

As a developing nation, South Africa faces a number of economic difficulties, one of which is inflation, which continues to be a major factor affecting economic stability. The general increase in prices of goods and services over time is known as inflation, and it has a substantial impact on consumer behaviour, purchasing power, and the state of the economy. In emerging countries like South Africa, where unstable inflation rates can result in economic instability, lower investment, and higher rates of poverty, inflation control is extremely important (Mandeya & Ho, 2023). For policymakers to formulate monetary policies that effectively maintain price stability and promote sustainable growth, they must be able to forecast inflation with sufficient accuracy.

Both local and international economic forces have influenced South Africa's inflation rate, which has frequently fluctuated due to things like shifts in the price of commodities globally, currency volatility, changes in fiscal policy, and, more recently, the COVID-19 pandemic's effects on the country’s economy (Asfuroğlu, 2021). These shortfalls highlight the requirement for accurate forecasting techniques in order to identify inflationary trends and offer direction for monetary policy changes. More complex statistical models, including the Box-Jenkins ARIMA approach, have become more popular for time series forecasting despite the usage of classic forecasting models because of their capacity to take trends, seasonal effects, and autocorrelations into account. The objective of the paper is to compute the Box-Jenkins ARIMA models for South African inflation rate. The results improve the knowledge of inflation dynamics, which is important for regulators and investors. To stabilize the economy and encourage sustainable growth, they can also direct the development of policy initiatives.

The remaining part of the paper is structured as follows: section 2 discusses the literature review, section 3 presents the methodology, section 4 examines the results, and section 5 gives a summary and conclusion.

2. LITERATURE REVIEW

The ARIMA approach has various advantages, including incorporating an online learning environment, neutrality from sample size and cost of storage, and the ability to execute parameter estimates online in a cost-effective and scalable manner (Kontopoulou *et al*., 2023). Another advantage is that it just takes previous data from the time series to generate a prediction and works effectively for short-term predictions (Hyndman & Athanasopoulos, 2018). The drawbacks of this approach include the bias of its progress assessment, the fact that the dependability of the chosen model may depend on the ability and expertise of the particular forecaster, and the fact that there are different variables and classes of viable models. As a result of all these constraints, selecting the final forecast model can be a tough undertaking (Spyrou *et al*., 2022).

Mondal et al. (2014), in their study "*Study of effectiveness of time series modelling (ARIMA) in forecasting stock prices*", examined the effectiveness of the ARIMA model in predicting stock prices for 56 Indian companies across various industries. They collected historical data for these companies, representing seven industries with eight companies per industry, from the official NSE India website. The study utilized 23 months of training data, spanning April 2012 to February 2014, to forecast stock prices for subsequent months. The ARIMA model was chosen due to its simplicity and widespread use. The authors also analysed the influence of varying amounts of historical data on the accuracy of predictions. To parameterize and compare ARIMA models, they employed the Akaike Information Criterion (AIC). The key contributions of this research include the analysis of a substantial number of Indian stocks, the sector-wise evaluation of forecasting algorithms, and an assessment of prediction reliability based on differing lengths of historical data.

Fattah et al. (2018), in their study "*Forecasting of demand using ARIMA model",* applied the Box-Jenkins time series methodology to develop multiple ARIMA models using historical demand data. The most suitable model was identified based on four evaluation criteria: AIC, Schwarz Bayesian Criterion (SBC), maximum likelihood, and standard error. The selected model, ARIMA (1,0,1), was further validated using additional historical demand data under similar conditions. The results demonstrated that this model is effective for forecasting and estimating future demand in the food production industry, offering industrial managers reliable tools for informed decision-making.

Alghamdi *et al.* (2019) conducted a study using ARIMA-based analysis to investigate different variables that have a major impact on the degree of traffic congestion. They provided a time series framework for non-Gaussian traffic information briefs. R was used to analyse and arrange a set of data for modelling purposes. They employed the commonly used ARIMA approach to assess and forecast hourly traffic flow records in a chosen region for study in California, USA. Various ARIMA-based models are created using the ACF and PACF evaluation of traffic data series to contrast with the model provided by the "*auto.arima*" function offered by the R language, which employs drift and random walk. The algorithm's residual performs exceptionally well when forecasting future traffic conditions.

3. METHODOLOGY

The monthly inflation data of South Africa was used in the paper and obtained from the South African Reserve Bank website:https://www.resbank.co.za/en/home/what-we-do/statistics/releases/online-statistical-query. The data contains 109 observations ranging from January 2015 to January 2024. The paper applied ARIMA model to model South African inflation rate. For the entire analysis, the statistical program R-Studio and E-Views were used.

3.1. Stationarity and Unit root test

The characteristics of a stationary time series are not affected by the time at which it is observed. A stationary time series is characterised by a constant mean and variance over time, indicating that its statistical properties remain consistent throughout the series. Stationarity is a crucial strategy for performing data analysis (Cheng *et al*., 2015). The time series must be stationary or be made stationary if it is not when we intend to use a time-series analysis. Stationarity is frequently assumed in time series models, but a significant proportion of practical situations are not stationary (Box *et al*., 2015). Consequently, statisticians have found several techniques for rendering a series stationary.

A unit root test determines whether a time series parameter is stationary and has a unit root. H_0 is commonly characterised as the existence of a unit root, and H_1 is possibly stationarity, trend stationarity, or explosive root, based on the test performed (Ogbuagu & Ewubare, 2019). The equation of the unit root test is as follows:

$$Y_t = D_t + Z_t + \varepsilon_t. \tag{1}$$

where Y_t is the time series that is tested, D_t is a deterministic element, Z_t is a stochastic element and ε_t is the error term. Dickey and Fuller (1979) and Said and Dickey (1984) developed the most often computed tests for unit roots. They are referred to as DF and ADF tests. In this paper, two tests are used to check for stationarity and unit root, namely, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test.

3.1.1. Augmented Dickey-Fuller (ADF) test

The ADF test is a prominent statistical technique for detecting whether a time series is stationary or not. It is one of the most used statistical tests for assessing whether a series is constant or not (Prabhakaran, 2019). To try to get rid of the issue of autocorrelation, they modified their test by introducing more lagged dependent variables. The ADF test follows the same approach as the DF test, however, it is computed using the following model:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t. \tag{2}$$

where α is constant, β = coefficient on-time trend and p = AR lag order. The unit root test is then performed with the following hypotheses:

$H_0: \emptyset_1 = 1$ (meaning there is no stationarity).
$H_1: |\emptyset_1| < 1$ (meaning there is a stationarity).

when the value for the test statistic has been determined. The value of t-statistic (t_{DF}) is determined as follows (Arltová & Fedorová, 2016):

$$t_{DF} = \frac{\widehat{\emptyset}_1 - 1}{S_{\widehat{\emptyset}_1}}. \tag{3}$$

where $\widehat{\emptyset}_1$ is the estimated AR parameter and $S_{\widehat{\emptyset}_1}$ is the estimated standard error. The H_0 is accepted if t_{DF}> p-value, the variable being considered in this case will be non-stationary and have a unit root.

3.1.2. The Phillips-Perron (PP) Test

The PP test was developed by Phillips and Perron (1988) to test for stationarity. This is based on the DF H_0 test $\rho = 0$ in:

$$\Delta y_t = (\rho - 1)y_{t-1} + \mu_t. \tag{4}$$

where Δ is the first order integration and ρ is the autoregression. The PP test, which resembles the ADF test, deals with the problem of the method of creating data for y_t might exhibit a greater degree of autocorrelation than acknowledged in the test formula, rendering y_{t-1} intrinsic therefore denying the DF t-test. While the ADF test solves the problem by including lags of display format delta y_{t-1} as regression models in the test formula, the PP test applies a non-parametric modification to the t-test statistic. The procedure is resistant to nonspecific heteroscedasticity and autocorrelation in the test formula's disruption phase. Consider a model:

$$Y_t = \theta_0 + \emptyset Y_{t-1} + \alpha_t. \tag{5}$$

DF: $\alpha_t \sim iid$
PP: $\alpha_t \sim serial\ correlated$

The test statistics (Z) for the equation with a fixed value are stated as follows (Pesaran, 2015):

$$Z_{\emptyset} = T\left(\widehat{\emptyset}_T - 1\right) - \frac{1}{2}\frac{T^2}{S^2_{\widehat{\emptyset}}}\left(S^2_{LT} - S^2_T\right), \tag{6}$$

$$Z_T = \left[\frac{S_T}{S_{LT}}\right] t_{DF} - \frac{1}{2}\left(S^2_{LT} - S^2_T\right)\frac{1}{S_{LT}}\frac{Ts_{\widehat{\emptyset}}}{S_T}, \tag{7}$$

where $S^2_T = \frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}^2_t$, $S^2_{LT} = S^2_T + 2\sum_{j=1}^{q}(1 - \frac{j}{q+1})\hat{\gamma}_{j;T}$ and $\hat{\gamma}_{j;T} = \frac{1}{T}\sum_{t=j+1}^{T}\hat{\varepsilon}_t\,\hat{\varepsilon}_{t-j}$; t_{DF} represents the test statistic of the DF test, S^2_T is the OLS predictor of non-systematic element variance, $\hat{\gamma}_{j;T}$ represents the maximum likelihood predictor of informal factor covariance and q is an integer of lagged factors. The PP test's null and alternative hypotheses are outlined as:
H_0: The time series has a unit root and is non-stationary.
H_1: The time series has no unit root and is stationary.

If the p-value linked with the PP test is less than a predetermined significance level (typically 0.05), the null hypothesis is rejected, and the time series is considered stationary. If the p-value is higher than the significance level, the null hypothesis is not rejected, indicating that there is proof of a unit root and the time series is non-stationary.

3.2. Normality testing

In this paper, the normality in the data was tested using three types of tests namely: the Kolmogorov–Smirnov test, the Normal Q-Q plot and the histogram.

3.2.1. The Kolmogorov–Smirnov Test

The Kolmogorov-Smirnov (K-S) tests, which are based on the presumptions of specified data in the sample, are widely used for data analysis. The K-S tests for one or two samples cannot be used when the data incorporates neutrosophic observations from a complicated system or is ambiguous (Aslam, 2019). The K-S test is a strong and flexible non-parametric test that determines if a sample reflects a particular distribution, such as the normal distribution (Kini *et al*., 2023). In this paper, the K-S test for one sample is employed to determine if the data follows the normal distribution. According to Hollander *et al*. (2013), given a one-sample K-S test, the test value (D) is described as:

$$D = sup_x |F_n(x) - F(x)|. \tag{8}$$

where n is the sample, sup_x represents the highest value overall x, $F_n(x)$ is the empirical cumulative distribution function (ECDF) of the sample, and $F(x)$ is the cumulative distribution function (CDF) of the reference distribution. The K-S test follows the following hypotheses:
H_0: the data follows the normal distribution.
H_1: the data does not follow the normal distribution.

If the p-value of the K-S test is less than 0.05 level of significance, the null hypothesis is rejected, concluding that the data does not follow normal distribution.

3.2.2. The Normal Q-Q plot and the Histogram

The Q-Q plot is a handy approach to establishing normality. The dots that appear in the residual data Q-Q graph closely correspond to the straight line (45° line), suggesting that the residuals of the data possess a typical distribution. The Histogram is an amplitude graph made by plotting each cell's frequency versus the cell’s approximately once the data has been arranged into equally spaced cells (Edgar & Manz, 2017).

3.3. Estimation method

The ARIMA is a type of statistical technique that measures the significance of one dependent parameter relative to other parameters that fluctuate (Hyndman & Athanasopoulos, 2018). ARIMA models are used when data indicate a pattern of non-stationarity in terms of mean (but not variance/autocovariance), and the first differencing phase (which corresponds to the "integrated" component of the model) may be used on multiple occasions to remove the non-stationary nature of the mean function (i.e., the trend) (Pratyaksa *et al.*, 2016). The ARIMA model consists of three components namely Autoregressive (AR), Integration *(I)* and Moving Average (MA). An AR model is a description of a sort of stochastic phenomenon; therefore, it is employed to define time-dependent processes in nature, the field of economics behaviour (Box *et al*., 2015). The formula for the AR model is as follows:

$$X_t = \sum_{i=1}^{p} \emptyset_i X_{t-i} + \varepsilon_t, \tag{9}$$

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \varepsilon_{t.} \tag{10}$$

where $\emptyset_1, \emptyset_2, \ldots, \emptyset_p$ = the parameters of the AR model and ε_t = the white noise process. The term integrated *(I)* refers to the process of differencing raw data to achieve stationarity in the time series. This is achieved by replacing data values with the distinction between the current values and the previous values (Adhikari & Agrawal, 2013). Differencing is an approach for converting a time series that is not stationary into a fixed one in the mean sense yet unrelated to the variance’s non-stationary behaviour (Wang *et al*., 2019). To differentiate the data, one has to estimate the distinction between successive data points. The equation is demonstrated as:

$$Y_t' = Y_t - Y_{t-1}. \tag{11}$$

Differencing reduces fluctuations in the average level of a time series, reducing seasonal and trend variations and, as a result, levelling the time series mean (Wang *et al.*, 2019). Sometimes second-order differencing is crucial to obtain stationarity.

$$Y_t^* = Y_t' - Y_{t-1}', \tag{12}$$
$$Y_t^* = (Y_t - Y_{t-1})(Y_{t-1} - Y_{t-2}), \tag{13}$$
$$Y_t^* = Y_t - Y_{t-1} - Y_{t-2}. \tag{14}$$

For order d, differencing operator can be written as:

$$\nabla^d Y_t = (1 - B)^d Y_t. \tag{15}$$

where B is the backshift operator. When analysing time series lags, the backward shift operator B is a handy notational technique. This is also known as the Lag operator. Given the time series: $X = \{X_1, X_2, \dots, X_n\}$ then the Backshift operator is given as follows:

$$BX_t = X_{t-1}. \tag{16}$$

For all $t > 1$

The above description is correspondingly written as:

$$X_t = BX_{t-1}. \tag{17}$$

For all $t \geq 1$

It can be expanded, $B^2X_t = B(BX_t) = BX_{t-1} = X_{t-2}$ and so on. As a result,

$$B^k X_t = X_{t-k}. \tag{18}$$

The MA model argues that a given value is proportionally reliant on the present as well as previous error variables. Similarly, it is believed that the error terms are completely independent and consistently spread, just like white noise (Melchior *et al*., 2021). The MA technique's primary objective, which can be achieved in numerous ways, is to track the trend evaluation of the provided time series data (Hansun, 2013). The formula for MA is as follows:

$$X_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \epsilon_t. \tag{19}$$

where $\theta_1, \dots, \theta_2, \dots, \theta_q$ = the parameters of the MA model, μ denotes the mean of the model and ϵ_t is the white noise process. The MA(q) process can be written as follows using the backshift operator:

$$X_t = \left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right)\varepsilon_t. \tag{20}$$

The MA(q) can thus be expressed more concisely as:

$$X_t = \theta(B)\varepsilon_t. \tag{21}$$

In ARIMA, every element serves as a variable with a standard notation (Adhikari & Agrawal, 2013). The ARIMA model is given as follows:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t. \tag{22}$$

where y_t = the time series value at t, p = order of AR process, q = order of MA process and d = order of difference process. If the series of $\nabla^d y_t$ fits the ARIMA (p, d, q), then the series y_t also fits the ARIMA (p, d, q) (Liu *et al.,* 2016,):

$$\nabla^d y_t = \sum_{i=1}^{q} \theta_i \epsilon_{t-1} + \sum_{i=1}^{p} \emptyset_i \nabla^d y_{t-1} + \varepsilon_t. \quad (23)$$

where p, d, and q are parameters, $\theta_i \; and \; \emptyset_i$ weights vectors.

3.4. Model Selection Criterions

The primary purpose of model selection is to compare various models and select the most suitable one to describe the framework. Model selection is important in developing an effective forecasting approach or understanding the data processing strategy (Yang *et al*., 2016). The optimal algorithm for the current paper was chosen using two criteria: the AIC and the Bayesian Information Criterion (BIC). AIC was used in eighty-four per cent of articles which employed statistical methods for multi-model inference, BIC in fourteen per cent of instances, and a few other approaches in only two per cent of situations (Aho *et al*., 2014). The two criteria are discussed in the following subsections.

The AIC developed by Akaike (1974) is a revised approach for calculating the likelihood that an algorithm will properly estimate or forecast future outcomes according to in-sample performance (Mohammed, Naugler and Far, 2015). The greatest-fitting ARIMA model is determined by selecting the optimal set of parameters that lowers the AIC. According to Vo and Slepaczuk (2022), AIC estimate is as outlined below:

$$AIC = -2\ln(\hat{L}) + 2K. \quad (24)$$

where $\hat{L} =$ likelihood function value and $K =$ the number of unknown parameters. Since $ln\hat{L}$ increases gradually when additional variables are fitted, the expression $2K$ indicates that a framework of lower ordering (small k) may be used. Whenever a sample size is low or AIC can over-fit, AIC is certainly to select models with a disproportionate number of variables.

The BIC by Stone (1979) is an additional model criterion that evaluates the trade-off between the fit of the model and complexity (Mohammed *et al.*, 2015). Algorithms with the lowest BIC are often preferred as one of a limited number of models. It is closely related to the AIC and somewhat depends on the probability function (Lin *et al*., 2017). BIC assumes the information is derived from the exponential population dispersion, $p(x|k)$ where x denotes the actual data and k denotes the sum of the number of repressors (which includes the slope). The BIC equation is expressed as:

$$BIC = -2lnL + K[\ln(n)]. \quad (25)$$

where L = the maximised value of the likelihood function and n = sample size.

4. DISCUSSION OF THE RESULTS

The goals of preliminary data analysis were to describe the characteristics of the data and organise it for further analysis, characterise the essential elements of the data, and synthesise the outcomes. Table 1 summarises the preliminary test statistic results.

Table 1: Descriptive statistics test results

Data: Inflation	
Mean	608575.5
Median	558506
Standard Deviation	143214.1
Kurtosis	-1.2221

Data: Inflation	
Skewness	0.5440
Minimum	413336
Maximum	892195

Table 1 displays the descriptive statistics summary results. The Table depicts that the mean value is 608575.5 which is greater than the median of 558506. Given that the value of skewness is 0.5440, the series looks like it comprises a left tail. The results in Table 1 further revealed that the Kurtosis value is -1.2221. Since the kurtosis value is less than zero, a leptokurtic dispersion is not suggested. Skewness and kurtosis both show how unevenly distributed the data set is. The series displays significant fluctuations, as evidenced by the standard deviation of 143214.1. The plot of the original series is presented in Figure 1.

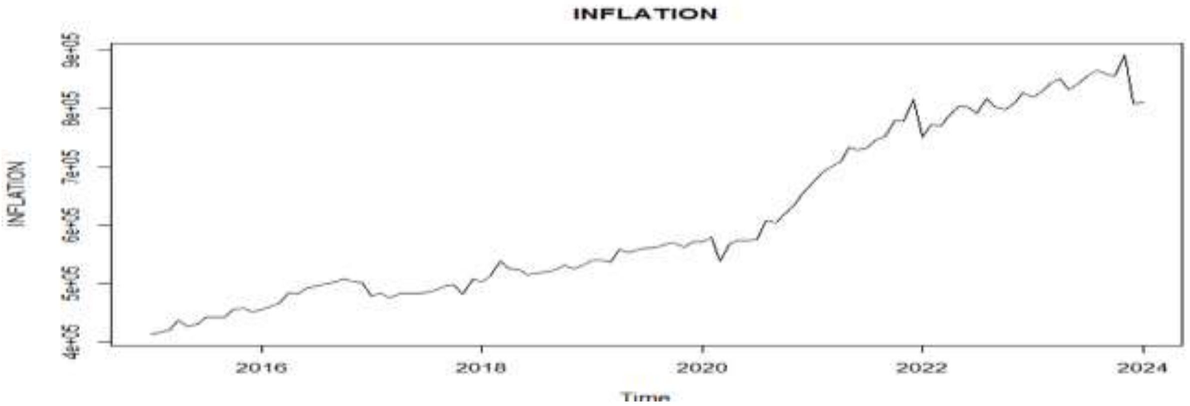

Figure 1: The original plot

The original time series graph presented in Figure 1 appears to be non-stationary due to a continuously increasing irregular fluctuation. The graph does not display any seasonal variation. The Figure shows that the mean and the variance of inflation do not remain constant over time. From inspection, the graph shows that the series is nonstationary, and the data needs to be differenced. To confirm the visual inspection, the formal test for stationarity was computed and the results are discussed in Table 2.

Table 2: The ADF and PP unit root test results

Data	**Level of test**	**ADF test statistic**	**ADF p-value**	**PP test statistic**	**PP p-vale**
Inflation	Level	-0.3362	0.9147	-0.3973	0.9047
	1st difference	-14.5867	<0.0000***	-14.3344	<0.0000***

*Note: '***', '**' and '*' denote significant standards at 0.01, 0.05, and 0.1, respectively.*

Table 2 summarises the results obtained from the ADF and PP unit root tests. The results reveal that the p-value of the ADF at level is 0.9147 which is greater than the 0.05 significance level. The results also reveal that the p-value of the PP test at level is 0.9047 which is more than the 0.05 level of significance. The results of the PP test are in support of the results obtained from the ADF test. It also shows that the ADF test statistic after first difference is -14.5867 with a p-value of <0.0000 and the PP test statistic is after first difference is -14.3344 with a p-value of <0.0000. Since the p-values of both tests after first difference are found to be lower than the significant value of 0.05 and the t-statistics of both tests are less than -2.8887 at 0.05 significance level, it can be concluded that the null hypothesis is rejected and the inflation data after the first difference is stationary and there is no unit root in the data. The Kolmogorov-Smirnov (K-S) test was employed to test for normality at level and after first difference, the results are displayed in Table 3.

Table 3: The K-S test table

The K-S test	***D***	**p-value**
Level	0.1984	0.0004***
1st difference	0.1128	0.1282

*Note: '***', '**' and '*' denote significant standards at 0.01, 0.05, and 0.1, respectively.*

Table 3 shows that the p-value of 0.0004 is less than the 0.05 level of significance at level, which means that the null hypothesis is rejected, concluding that the inflation data at the level does not follow the normal distribution. It shows that the p-value of 0.1282 is greater than the 0.05 level of significance after first difference, which means that the null hypothesis is not rejected, concluding that the inflation data after differencing follows the normal distribution. The normal Q-Q plot and histogram were also employed to test normality. The plots at level and after differencing are in Figure 2 and 3, respectively.

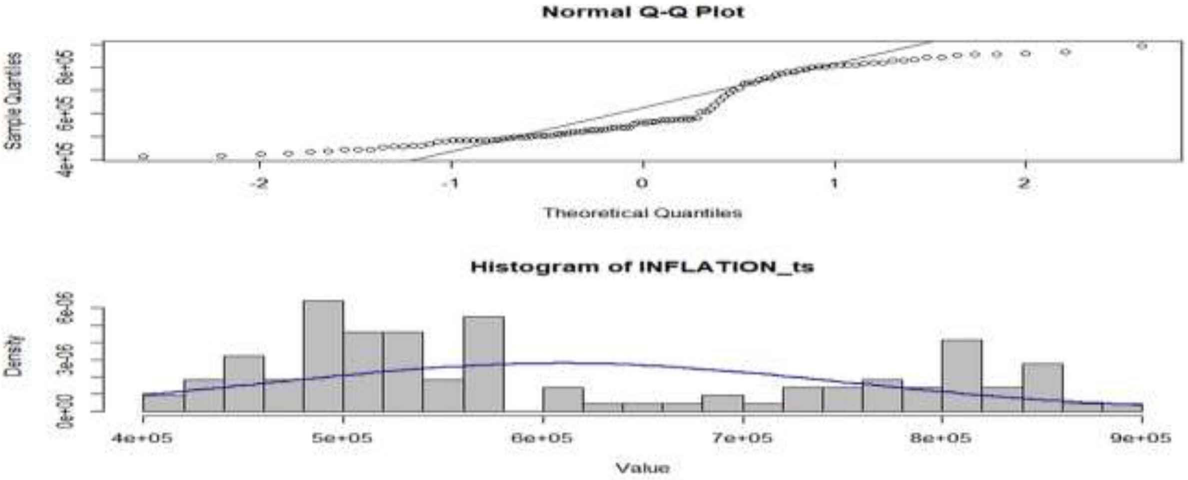

Figure 2: The normal Q-Q plot and the histogram of the original series

The normal Q-Q plot in Figure 2 shows that the inflation data does not follow normal distribution since most of the quantile points do not lie on the 45-degree line. The histogram plot above also shows that the inflation data does not follow the normal distribution since it does not display a bell shape.

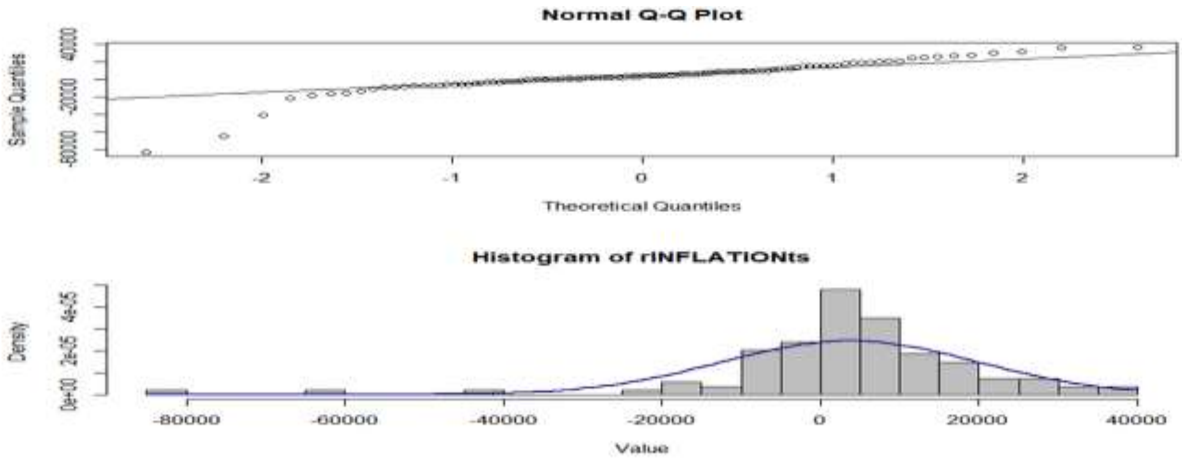

Figure 3: The normal Q-Q plot and the histogram of a differenced series

The normal Q-Q plot in Figure 3 shows that the inflation data after differencing follows a normal distribution since most of the quantile points lie on the 45-degree line. The histogram plot in Figure 3 above also shows that the inflation data after differencing follows the normal distribution since it displays a bell shape. Therefore, all three tests follow the normal distribution. Table 4 represents the EACF model estimation.

Table 4: The EACF results

AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	x	o	o	o	o	o	o	o	o	o	o	o	o	o
1	o	o	o	o	o	o	o	o	o	o	o	o	o	o
2	x	o	o	o	o	o	o	o	o	o	o	o	o	o
3	x	x	x	o	o	o	o	o	o	o	o	o	o	o
4	o	o	x	o	o	o	o	o	o	o	o	o	o	o
5	x	o	o	x	o	o	o	o	o	o	o	o	o	o
6	o	x	o	x	o	o	o	o	o	o	o	o	o	o
7	x	x	o	o	o	o	x	o	o	o	o	o	o	o

Table 4 shows that potential models are ARIMA $(1,1,0)$, ARIMA $(2,1,0)$, ARIMA $(1,1,1)$ and ARIMA $(2,1,1)$. The maximum likelihood estimation method was used to compute the parameters of the identified models, and the results are summarised in Table 5.

Table 5: Results of the maximum likelihood estimation method

Model	**Lags**	**Estimate**	**S-E**	**t-statistics**	**p-value**
ARIMA$(1,1,0)$	c	3686.0790	1314.0850	2.8051	0.0060***
	$\emptyset_1$	-0.3361	0.0660	-5.0925	<0.0000***
	$Difference\ (1)$				
	θ_0	-	-	-	-
ARIMA$(2,1,0)$	c	3702.7970	1309.0530	2.8286	0.0056***
	$\emptyset_1$	-0.3459	0.0785	-4.4049	<0.0000***
	$\emptyset_2$	-0.0279	0.1558	-0.1791	0.8582
	$Difference\ (1)$				
	θ_0	-	-	-	-
ARIMA$(1,1,1)$	c	3698.0440	1333.1500	2.7739	0.0066***

Model	Lags	Estimate	S-E	t-statistics	p-value
	$\emptyset_1$	-0.2868	0.4174	-0.6871	0.4935
	$Difference\ (1)$				
	θ_1	-0.0561	0.4506	-0.1245	0.9012
ARIMA$(2,1,1)$	c	3703.3090	1340.6050	2.7624	0.0068***
	$\emptyset_1$	-0.4921	3.3107	-0.1486	0.8821
	$\emptyset_2$	-0.0808	1.1125	-0.0726	0.9422
	$Difference\ (1)$				
	θ_1	0.1448	3.3115	0.0437	0.9652

*Note: '***', '**' and '*' denote significant standards at 0.01, 0.05, and 0.1, respectively.*

Table 5 summarises the results of the parameters of the competing ARIMA models. The table shows all the models are significant since most of the p-values of their parameters are less than the 0.05 level of significance. The best model was selected using AIC and BIC, they are displayed in Table 6.

Table 6: AIC and BIC model selection criteria for the ARIMA model

MODEL	AIC	BIC
ARIMA $(1,1,0)$	2413.5900	2420.9500
ARIMA $(2,1,0)$	2394.7300	2404.7730
ARIMA $(1,1,1)$	2373.9700	2384.0180
ARIMA $(2,1,1)$	2374.8400	2387.5690

Table 6 shows that the best model among the five (5) competing models is ARIMA $(1,1,1)$ based on the lowest value of AIC (2373.9700) and BIC (2384.0180). This is the same model that was suggested by ACF and PACF in Figure 4.5. The best model was used for further analysis. The residuals of the ARIMA model are tested using the LJUNG-BOX test, ACF, the histogram and the normal Q-Q plot.

Table 7: LJUNG-BOX test for ARIMA $(\mathbf{1},\mathbf{1},\mathbf{1})$ model

Statistics	χ^2 – Value	p-value
LJUNG-BOX Test	14.6900	0.7939

Table 7 reveals that the p-value (0.7939) of the LJUNG BOX test is statistically insignificant at the 0.05 level. Since the p-value is greater than the significant value of 0.05, it can be concluded that the null hypothesis is not rejected and that the residuals of ARIMA $(1,1,1)$ are normally distributed. It is also concluded that the model does not exhibit a lack of fit. The residuals of ARIMA $(1,1,1)$ were also tested using the ACF plot in Figure 4, the normal Q-Q plot and the histogram in Figure 4.

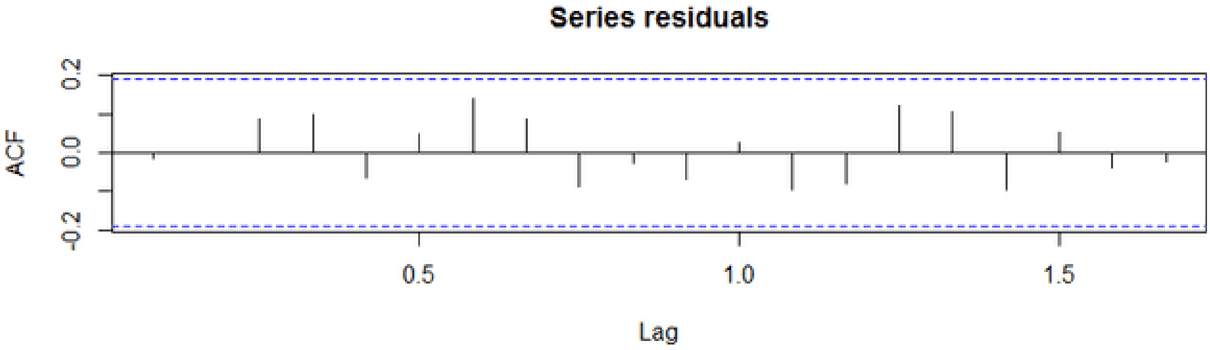

Figure 4: ACF of ARIMA $(\mathbf{1}, \mathbf{1}, \mathbf{1})$ model

The ACF plot in Figure 4 demonstrates that all the coefficients lie within the confidence interval. The ACF shows that the residuals are white noise. It displays an approximate normal distribution. This validates the residual's assumption of normality and establishes ARIMA $(1, 1, 1)$ as the best candidate model. The normal Q-Q plot and histogram were also employed to check for the residuals of ARIMA $(1, 1, 1)$.

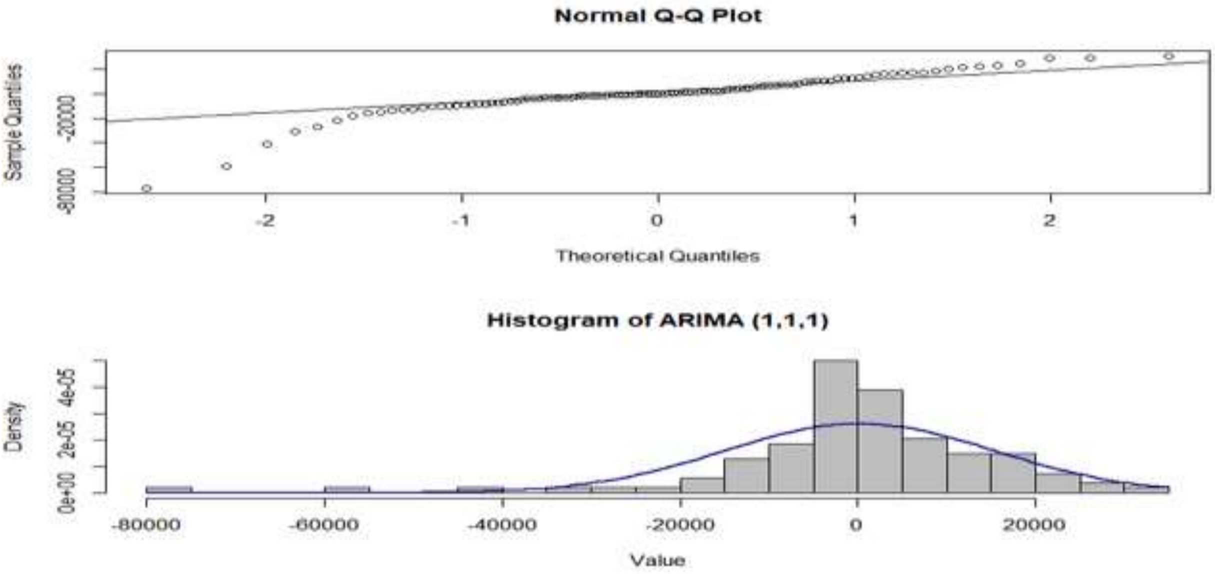

Figure 5: The normal Q-Q plot and the histogram of the ARIMA $(\mathbf{1}, \mathbf{1}, \mathbf{1})$ model

Figure 5 shows that the points on the Normal QQ graph indicate that the dataset is univariate normality because the points are aligned with the 45-degree standard line. The histogram shows a bell shape which means the residuals are normally distributed. This also demonstrates that the ARIMA $(1, 1, 1)$ model is the best model for inflation in South Africa.

5. CONCLUSION

The paper investigated the performance of the South African inflation rate using Box-Jenkins ARIMA models. The linear ARIMA models were estimated using the features of ACF, PACF and EACF. The competing ARIMA models identified by ACF and PACF is ARIMA $(1, 1, 1)$ and the competing ARIMA models identified by EACF are ARIMA $(1, 1, 0)$, ARIMA $(2, 1, 0)$, ARIMA $(1, 1, 1)$, and ARIMA $(2, 1, 1)$. Using the maximum likelihood of the parameters, the findings showed that all ARIMA models are significant. The standard error of all the competing models is low, which suggests that all these competing models are of good fit. The best fit ARIMA model was then selected using AIC and BIC model selection criteria, the results were supported by Mondal et al. (2014). It was shown that the best-fit model among competing models is ARIMA $(1, 1, 1)$ because it has the lowest values of AIC and BIC.

The findings of this study carry several important economic implications, particularly in the context of inflation modelling and forecasting in South Africa. The identification of ARIMA (1,1,1) as the best-fit model, based on AIC and BIC selection criteria, demonstrates the viability of linear time series models, specifically the Box-Jenkins methodology, in capturing the dynamics of inflation in a developing economy. This suggests that policymakers and economic analysts can rely on such models for short-term inflation forecasting, which is critical for effective monetary policy formulation and inflation targeting.

The ability of the ARIMA (1,1,1) model to pass all diagnostic checks, including the Ljung-Box test and residual analysis, further underscores its robustness and reliability. Accurate inflation forecasts can aid the South African Reserve Bank (SARB) in adjusting interest rates, managing inflation expectations, and implementing proactive policy measures to stabilise the economy.

However, the study also acknowledges the limitations of linear models when applied to complex macroeconomic data. It highlights the potential for future research to explore nonlinear modelling approaches, such as GARCH-type models, which may better account for volatility clustering and asymmetric responses in inflation behaviour. This could enhance the flexibility and accuracy of macroeconomic forecasting tools in the face of structural shifts and external shocks. Lastly, as the analysis is specific to South Africa, the results may not be generalisable to other economies with different inflation dynamics. Nonetheless, the methodological framework offers a replicable approach for similar studies in other countries or for other macroeconomic indicators, encouraging further research in this domain.

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