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Modelling and Forecasting Inflation Rates in Kenya Using ARIMA Model

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ABSTRACT: *This research aimed to develop an ARIMA(1,0,11) model for forecasting inflation rates in Kenya. The research utilized historical inflation data from January 2005 to August 2022 to develop the model and evaluated its performance on a test set spanning from September 2022 to August 2023. The results demonstrated that the ARIMA model provided accurate forecasts, with low forecast errors in terms of MSE, RMSE, MAE, and MAPE. These forecasts have practical utility for various stakeholders, including policymakers, businesses, and financial institutions, as they can use the information to inform pricing strategies, interest rate policies, and other economic decisions. Additionally, the study highlighted the importance of data quality, continuous monitoring of economic factors, and periodic model refinement to ensure the effectiveness of inflation forecasting in a dynamic economic environment.*

KEYWORDS: modelling, forecasting, inflation rates, Kenya, Arima model

INTRODUCTION

Inflation refers to the sustained rise in the overall cost of goods and services in an economy over a certain period of time. Inflation is a crucial economic indicator that reflects the purchasing power of consumers, and central banks and policymakers rely on accurate forecasts of inflation to make informed monetary policy decisions. The inflation rate is usually expressed as an annual percentage change, and it is essential to measure inflation in order to monitor changes in the cost of living and the overall health of an economy.

In Kenya, the inflation rate has been fluctuating over the years, and this trend has prompted economists to investigate the best methods for forecasting inflation. Several studies have been conducted in recent years to Predict and estimate the rate of inflation in Kenya using different techniques, such as Seasonal Autoregressive Integrated Moving Average (SARIMA), Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and ARIMA-GARCH models.

The research of inflation forecasting is crucial in the field of economics, and several techniques have been developed to predict and estimate the rate of inflation. In Kenya, the inflation rate has been fluctuating over the years, and there is a need for accurate forecasts to support monetary policy decisions. The objective of this research is to develop a forecasting model for the inflation rate in Kenya using ARIMA. The ultimate goal is to evaluate the effectiveness of the model in forecasting inflation rates.

LIMITATIONS

The research aimed at predicting the inflation rate in Kenya has several limitations. Firstly, the research heavily relied on the availability of accurate and reliable data. Any inaccuracies or missing data points can compromise the accuracy of the forecast. Secondly, the ARIMA model used in the study was based on certain assumptions, such as the stationarity of the inflation rate data and the representativeness of the data used. If these assumptions are not met, the accuracy of the model may be impacted. Lastly, inflation rate is a dynamic phenomenon that changes over time and is influenced by various factors. As a result, the model may not be able to accurately forecast future inflation rates if the underlying factors change.

1.0 LITERATURE REVIEW

Inflation and its Impacts

Inflation, a crucial economic indicator, reflects the decrease in the purchasing power of money as prices of goods and services increase over time. Its impact is significant, directly influencing the overall economic health. Low and predictable inflation rates can foster economic growth, while high and volatile inflation rates create uncertainty, affecting savings and investments. Therefore, accurately predicting inflation is vital for policymakers and stakeholders in making informed decisions to mitigate the adverse effects and promote economic stability (Blanchard, 2017) (Fischer & Modigliani, 1978).

Kenya, like most developing countries, is vulnerable to high inflation rates due to factors such as currency devaluation, increased demand for goods and services, and supply chain disruptions. As such, forecasting inflation is crucial for policymakers, financial institutions, and other investors who wish to make informed decisions. This project aims to develop an ARIMA-ANN model for modelling and predicting inflation in Kenya. This model will integrate statistical and machine learning techniques to improve the accuracy of inflation forecasts.

Predicting inflation in Kenya is essential for several reasons. Firstly, it helps policymakers to develop effective monetary policies and make appropriate budgetary allocations. Secondly, it helps businesses and investors make informed decisions by enabling them to anticipate market trends and conditions. Finally, predicting inflation helps individuals plan their finances better by anticipating the impact of inflation on their purchasing power.

There are several models that economists and policymakers use to predict inflation. Some of these models include ANN, ARIMA, and Vector Autoregression (VAR).

ARIMA Model in Forecasting

Various statistical and econometric models have been used over time in forecasting time series data. Among these, ARIMA models are one of the most popular due to their simplicity and ability to model linear relationships. ARIMA models capture patterns and structures in the historical data to make forecasts (Box & Jenkins, 1970). However, ARIMA models work on the assumption that the variables are linear and follow a specific distribution, which is often not the case in real-world situations.

ARIMA Model in Inflation Forecasting

ARIMA models are a popular approach for forecasting inflation rates in many countries. They have been widely used to study the behavior of inflation rates over time and to predict future inflation rates. Several studies have explored the use of ARIMA models to predict inflation rates in various countries, such as Sudan, Ireland, and Nigeria.

Meyler, Kenny, & Quinn, (1998) also used ARIMA models to forecast inflation rates, this time in Ireland. The authors found that the ARIMA models provided reasonable forecasts and outperformed a number of alternative forecasting methods. This result indicates that ARIMA models can be useful for predicting inflation rates in countries with low or moderate inflation rates.

Adelekan, Abiola, & Constance, (2020) applied ARIMA models to the task of forecasting Nigeria's inflation rates. The authors found that the ARIMA models provided reasonable forecasts, although the accuracy of the forecasts varied depending on the specific model used. The authors noted that the ARIMA models performed better when they were trained on longer time series of historical data.

One study by (Abdulrahman, Ahmed, & Abdellah, 2018) used ARIMA models to forecast inflation rates in Sudan. The authors found that the ARIMA model provided a good fit for the data and was able to accurately predict future inflation rates. This result suggests that ARIMA models can be useful for predicting inflation rates in countries with high inflation rates.

METHODOOGY

Research Design

The research design for this research was a quantitative research design. This is because the research seeks to collect and analyze numerical data to identify patterns and relationships between observations, and to develop a forecasting model.

Quantitative research is a method of empirical investigation that seeks to measure, quantify, and analyze data using statistical and mathematical methods. This method is suitable for research questions that require the collection and analysis of numerical data, and for questions that seek to identify patterns, relationships, or causal links between variables.

The choice of a quantitative research design was justified by the nature of the research question, which seeks to develop a forecasting model to predict inflation rates in Kenya. According to (Creswell & Creswell, 2017), forecasting models are typically developed using quantitative research methods that involve the analysis of time series data to identify the patterns and trends over time. Additionally, the use of statistical and mathematical methods such as ARIMA is also common in quantitative research designs for forecasting.

Target Population

The target population for this research was the population of Kenya as a whole. The research would seek to understand and predict changes in the inflation rate over time, which affects the cost of living and economic conditions for everyone in the country. It specifically include economists and policymakers responsible for formulating and implementing economic policies in Kenya, investors interested in making investment decisions in Kenya or in industries that are affected by inflation, business owners and managers who need to understand the impact of inflation on their operations, such as pricing decisions and production costs, researchers and academics studying macroeconomic trends and forecasting techniques, and students studying economics or related fields who are interested in learning about forecasting techniques and their applications. Essentially, anyone interested in understanding or predicting inflation in Kenya could potentially benefit from the insights provided by the modeling and prediction results of this research project.

Sampling Frame and Sampling Technique

The sampling frame for this research was the population of inflation rate data points collected by the Central Bank of Kenya from the year 2005 to 2023. Specifically, the sampling frame would consist of all monthly inflation rate data points for this time period.

As this research was using the entire population of data points, there was no need for sampling techniques. Therefore, no sampling technique was necessary or applicable for this research.

Since the research intended to analyze the entire population of inflation rate data points, the research was considered a census, rather than a sample. A census is a study in which all elements or members of a population are included, whereas a sample is a subset of a population that is selected for analysis. Therefore, in this case, the sampling frame was the entire population of data points and therefore the research was a census.

Building the model

An ARIMA model is a traditional time series model that is used to capture linear patterns and trends in time-series data. In this article, we will provide a methodology for building an ARIMA model for univariate time-series data.

Data preparation

The first step in building an ARIMA model was to prepare the data. This involved several steps, including collecting data from the relevant source, data cleaning by checking and correcting any errors or inconsistencies in the data, data splitting by splitting the data into training and testing sets. The training set was used to build the model, while the testing set was used to evaluate how the model performed.

ARIMA Model Building

The next step was to build an ARIMA model. The ARIMA model consisted of three components: the autoregressive (AR) component, the integrated (I) component, and the moving average (MA) component.

The AR component was used to capture the linear relationship between the current observation and previous observations. The AR component was denoted by p and was represented by the following equation:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t$$

Where, y_t is the value of the time series at time t, c is the constant term, $\phi_1, \phi_2, \ldots, \phi_p$ are the AR coefficients, p is the order of the AR component and ϵ_t is the error term at time t.
Integrated (I) component was used to capture the non-stationarity in the data. Non-stationarity means that the statistical properties of the data change over time. The I component is denoted by d and can be represented by differencing the time series data until it becomes stationary. Mathematically, the differenced series is denoted as y', and it can be represented as:

$$y' = y_t - y_{t-1}$$

The Moving Average (MA) component was used to capture the linear relationship between the current observation and previous error terms. The MA component was denoted by q and was represented by the following equation:

$$y' = c' + \varepsilon'_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

Where $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients, $\varepsilon_{t-1}, \varepsilon_{t-2} \ldots, \varepsilon_{t-q}$ are the past forecast errors, and ε'_t is the current forecast error term at time t.

By combining the AR, I, and MA components, the general equation for the ARIMA (p, d, q) model was written as:

$$W_t = \phi_t W_{t-1} + \ldots + \phi_p W_{t-p} + c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}$$

Where $W_t = (1 - B)^d y_t$, y_t are the actual observations and ε_t is the white noise at time $t \sim WN\ (0, \sigma 2)$

The model can be shortened using the backward shift operator (B) as follows

$$\phi(B)(1 - B)^d y_t = c + \theta(B)\varepsilon_t$$

Where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ and $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_p B^p$ are the lag polynomials, $\phi i, \theta j i = 1, 2, \ldots, p, j = 1, 2, \ldots, q$ are the coefficients of AR(p) and MA(q), d represents the degree of ordinary differencing applied to make the series stationary

Model Identification

Autocorrelation (ACF) and partial autocorrelation (PACF) plots are commonly used to identify the orders of the AR and MA components in the ARIMA model. ACF and PACF assume stationarity of the underlying time series. Stationarity can be checked by performing an Augmented Dickey-Fuller (ADF) test. These plots depict the correlation between the time series observations and their lagged values. The significant spikes or decay patterns in the ACF and PACF plots can indicate the appropriate values of p and q.

AR Component (p): The PACF plot helps determine the order of the AR component. Significant spikes in the PACF plot that gradually diminish after a certain lag suggest an AR component of that order.

MA Component (q): The ACF plot helps identify the order of the MA component. Significant spikes in the ACF plot that gradually diminish after a certain lag indicate an MA component of that order.

Differencing (d) Order: The differencing order is determined by assessing the stationarity of the time series data. Stationarity implies that the statistical properties of the data, such as mean and variance, remain constant over time. If the data exhibit trends, seasonality, or non-stationarity, differencing can be applied to make the series stationary. The number of differencing required to achieve stationarity corresponds to the value of d.

No Differencing (d = 0): If the ACF and PACF plots show no significant pat- terns and the time series data appears stationary, no differencing is needed.

First Order Differencing (d = 1): If the data show a linear trend, a first-order difference ($Y_t - Y_{t-1}$) is applied to remove the trend.

Seasonal Differencing: In cases of seasonal patterns, additional seasonal differencing may be required (for example, $Y_t - Y_{t-m}$ for a seasonal lag m) in addition to the regular differencing.

Summary for ACF and PACF patterns are shown in the table below

Table 1: ACF and PACF Patterns for AR, MA, and ARMA Models

Model	AR(p)	MA(q)	ARMA (p q)
ACF Pattern	Tails off (Geometric decay)	Significant at lag q or Cuts off after lag q	Tails off (Geometric decay)
PACF Pattern	Significant at each lag q or Cuts off after lag q	Tails off (Geometric decay)	Tails off (Geometric decay)

Model Estimation

The parameters of the ARIMA model was estimated using maximum likelihood estimation (MLE).

The estimation of parameters in an ARIMA model involved finding the values of the autoregressive (AR) coefficients $(\phi_1, \phi_2, \dots, \phi_p)$ and the moving average (MA) coefficients $(\theta_1, \theta_2, \dots, \theta_q)$ through methods like Maximum Likelihood Estimation (MLE). Here are the equations for estimating these parameters:

Estimation of AR Parameters (ϕ):

The AR parameters were estimated using MLE. The likelihood function for an ARIMA(p, d, 0) model is typically based on the assumption that the residuals (ε_t) are normally distributed with mean 0 and constant variance (σ^2).

The likelihood function for an AR(p) model is:

$$L(\phi_1, \phi_2, \dots, \phi_p \mid X_1, X_2, \dots, X_T) = \frac{1}{(2\pi\sigma^2)^{T/2}} exp\left(-\frac{1}{2\sigma^2}\sum_{i=1}^{T}(X_t - \phi_1 X_{t-1} - \phi_2 X_{t-2} - \dots - \phi_p X_{t-p})^2\right)$$

To estimate the AR parameters, maximize this likelihood function with respect to $\phi_1, \phi_2, \dots, \phi_p$.

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Estimation of MA Parameters (θ):

The MA parameters are also estimated using MLE. The likelihood function for an ARIMA(0, d, q) model with MA(q) is:

$$L(\theta_1, \theta_2, \ldots, \theta_q \mid X_1, X_2, \ldots, X_T) = \frac{1}{(2\pi\sigma^2)^{T/2}} exp\left(-\frac{1}{2\sigma^2}\sum_{i=1}^{T}(X_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots - \theta_p\varepsilon_{t-q})^2\right)$$

To estimate the MA parameters, maximize this likelihood function with respect to $\theta_1, \theta_2, \ldots, \theta_q$, again using numerical optimization methods.

Estimation of σ^2 (Variance):

In addition to estimating the AR and MA parameters, estimate the variance (σ^2) of the white noise process ε_t as it appears in the likelihood functions above. The estimated σ^2 is often referred to as the residual variance and can be calculated as:

$$\hat{\sigma}^2 = \frac{1}{T}\sum_{i=1}^{T}\hat{\varepsilon}_t^2$$

Where $\hat{\varepsilon}_t$ is the estimated residual at time 't'.

Once you have estimated the AR and MA parameters along with σ^2, you have successfully fitted the ARIMA model to your inflation rate data. These parameter estimates will be used in making predictions and analyzing the model's performance.

Model Diagnosis

Model evaluation criteria such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) was used to compare the performance of different parameter combinations and select the most appropriate model.

The AIC is given by:

$$AIC = -2\,ln(L) + 2k$$

Where $ln(L)$ is the log-likelihood of the model and k is the number of parameters in the model.

The BIC is given by:

$$BIC = -2\,ln(L) + k\,ln(n)$$

Where $ln(L)$ is the log-likelihood of the model, k is the number of parameters in the model, and n is the number of observations in the data.

Model Validation and Evaluation

The next step was to evaluate the performance of the ARIMA model with, several performance metrics will be utilized. These metrics included MAE, MSE, RMSE and MAPE. These metrics provided insights into the accuracy and effectiveness of the model in forecasting the inflation rate in Kenya.

The performance metrics can be calculated using the following formulas:

Mean Absolute Error (MAE):

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|Y(t) - \hat{Y}(t)|$$

Mean Squared Error (MSE):

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(Y(t) - \hat{Y}(t))^2$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{MSE}$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{|Y(t) - \hat{Y}(t)|}{Y(t)}\right) \times 100$$

Where $Y(t)$ represented the actual inflation rate at time *t* and $\hat{Y}(t)$ represented the forecasted inflation rate at time *t*.

The model's performance was also visualized by comparing the actual and predicted values of the time series. A good model should accurately capture the trends and patterns in the data and produce accurate and reliable forecasts.

Forecasting

Once the model is validated and evaluated, it can be used to make forecasts. The model can be used to forecast future values of the time series, and the forecasts can be used to make informed decisions. The model is given by the equation below:

$$y_{(t)} = c + \phi_1 y_{(t-1)} + \phi_2 y_{(t-2)} + \cdots + \phi_p y_{(t-p)} + \epsilon_{(t)} + \theta_1 \epsilon_{(t-1)} + \theta_2 \epsilon_{(t-2)} + \cdots + \theta_q \epsilon_{(t-q)}$$

Where $y_{(t)}$ is the output at time t, c is the constant term, $\phi_1, \phi_2, \ldots, \phi_p$ are the AR coefficients, $\theta_1, \theta_2, \ldots, \theta_q$ are the MA coefficients and $\epsilon(t)$ is the error term at time t.

RESULTS AND DISCUSSION

Inflation data was divided into training and test set. The training set had data point of inflation rate from January 2005 to August 2022 and was used to develop the models. The test set had data point of inflation rate from September 2022 to August 2023 and was used to check the accuracy of the developed models.

Stationarity Check

One of the assumptions was that the data had to be stationary hence the need for a stationarity test. If the data was not stationary, then differencing was to be done until the data was stationary for analysis to be done.

Table 2: Augmented Dickey-Fuller Test

test	statistic	p-value
Augmented Dickey-Fuller Test	-3.53630	0.00710

An Augmented Dickey-Fuller (ADF) test was performed to assess the stationarity of the inflation time series data. The test indicated a Dickey-Fuller value of -3.53630 (p = 0.00710). The calculated p-value being below the significance level ($\alpha = 0.05$) suggested that the data was stationary.

ARIMA Model Selection

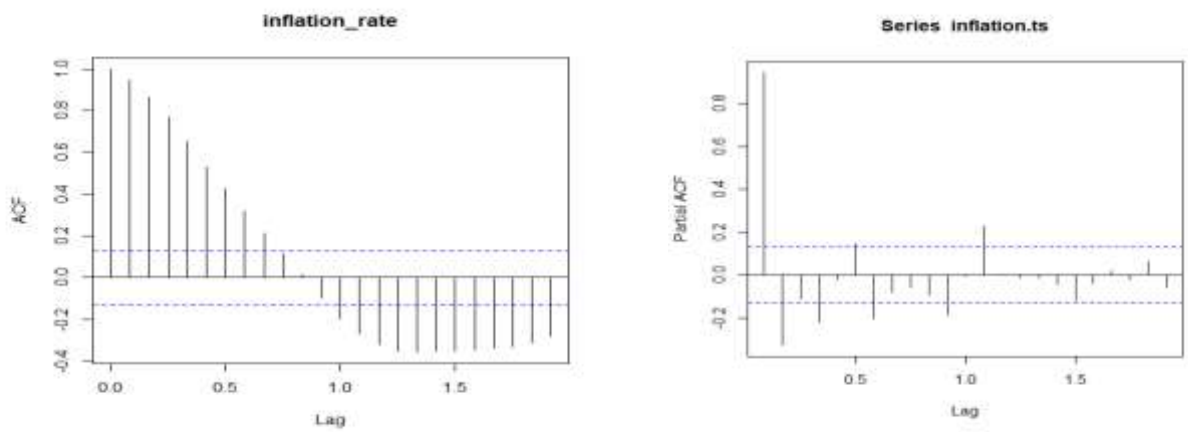

Figure 1: ACF and PACF Plots

There was a gradual decay in the ACF values and they became less significant as the lags increased. This suggested a potential non-seasonal MA(q) component. There was a significant spike at lag 1 in the PACF plot, which suggested a potential first-order AR term (p=1). Based on these observations, a consideration of an ARIMA model with the following orders: Non-seasonal AR order (p)= 1 and Non-seasonal MA order (q)= 1

The initial ARIMA model could be ARIMA(1, 0, 1), and further refinement of the model was required and testing for adequacy by fitting it to the inflation time series data and evaluating its performance using diagnostic tools like AIC and BIC criteria. Adjustment of the values of p, d, and q was needed to find the best-fitting model for the data.

Table 3: Different ARIMA (p,d,q) fitted models

Model	AIC	BIC	log likelihood
(1,0,1)	662.61	676.04	-327.31
(1,0,5)	649.99	676.84	-316.99
(1,0,9)	647.80	688.08	-311.90
(1,0,11)	590.06	637.05	-281.03
(2,0,1)	652.71	669.49	-321.35
(3,0,1)	659.75	679.89	-323.88
(4,0,1)	652.82	676.32	-319.41
(5,0,1)	651.55	678.40	-317.77
(2,0,2)	663.78	683.92	-325.89
(3,0,2)	664.99	688.48	-325.49
(4,0,2)	636.73	663.58	-310.36
(5,0,2)	630.60	660.81	-306.30
(5,0,3)	632.23	665.79	-306.11

The presented table 3 showcases various ARIMA models, each characterized by their Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and associated log likelihood. Both AIC and BIC are essential for model selection as they strike a balance between model fit and complexity. Lower AIC and BIC values indicate more optimal models that effectively capture the data's patterns while avoiding excessive complexity.

Among the choices, the (1,0,11) ARIMA model stands out with the lowest AIC (590.06) and BIC (637.05) values. These values suggest that the (1,0,11) model offers a favorable compromise between accurately representing the data and keeping the model's complexity in check. Additionally, the model's log likelihood of -281.03 indicates the goodness of fit, measuring how well the model explains the observed data.

In summary, while considering both AIC and BIC, the (1,0,11) ARIMA model emerges as the preferable choice due to its strong performance in terms of goodness of fit and model simplicity.

Table 4: ARIMA Model

Series: training data ARIMA(1,0,11)
Coefficients:

ar1	ma1	ma2	ma3	ma4	ma5	ma6	ma7
0.5274	0.7022	0.6892	0.6537	0.6553	0.5959	0.6318	0.7225
s.e. 0.0769	0.0791	0.0849	0.0760	0.0611	0.0645	0.0746	0.0783
ma8	ma9	ma10	ma11	intercept			
0.6261	0.7797	0.6690	0.7379	7.9358			
s.e. 0.0905	0.0867	0.0677	0.0857	1.0517			

σ2 = 0.8255: log likelihood = -281.03 AIC=590.06 AICc=592.19 BIC=637.05

An ARIMA model was fitted to the training set of inflation data time series. The model was specified as ARIMA(1,0,11) with a non-zero mean.

The ARIMA equation for this model is given by:

$$y_t=0.5274y_{t-1}+\alpha_t+0.7022\alpha_{t-1}+0.6892\alpha_{t-2}+0.6537\alpha_{t-3}+0.6553\alpha_{t-4}+0.5959\alpha_{t-5}+0.6318\alpha_{t-6}+0.7225\alpha_{t-7}+0.7379\alpha_{t-8}+0.6261\alpha_{t-9}+0.7797\alpha_{t-10}+0.6690\alpha_{t-11}+7.9358$$

where y_t represents the value of the time series at time t and α_t denotes the white noise error term at time t. Standard errors for the coefficients are also provided (s.e.). The estimated variance of the error term is σ2 = 0.8255, and the log likelihood of the model is -281.03. The model selection criteria values are as follows: Akaike Information Criterion (AIC) = 590.06, Corrected AIC (AICc) = 592.19, and Bayesian Information Criterion (BIC) = 637.05.

Model Evaluation

Forecasting was done using ARIMA model. The forecasted values were then compared to the testing set which consisted of inflation rates from September 2022 to August 2023.

Table 5: Actual Data against Forecasted Data

Date	Actual	ARIMA
Sep 2022	9.18	8.682
Oct 2022	9.59	9.138
Nov 2022	9.48	9.698
Dec 2022	9.06	9.863
Jan 2023	8.98	10.377
Feb 2023	9.23	11.109
Mar 2023	9.19	10.597
Apr 2023	7.90	9.574
May 2023	8.03	9.151
Jun 2023	7.88	8.302
Jul 2023	7.28	7.760
Aug 2023	6.73	7.763

A comparison between the actual inflation rates and the forecasted inflation rates using an ARIMA(1,0,11) model. The dataset covered the period from September 2022 to August 2023. ARIMA model's forecasted values closely tracked the actual inflation rates over this period capturing the underlying patterns and trends in the data. This was shown in figure 1 below.

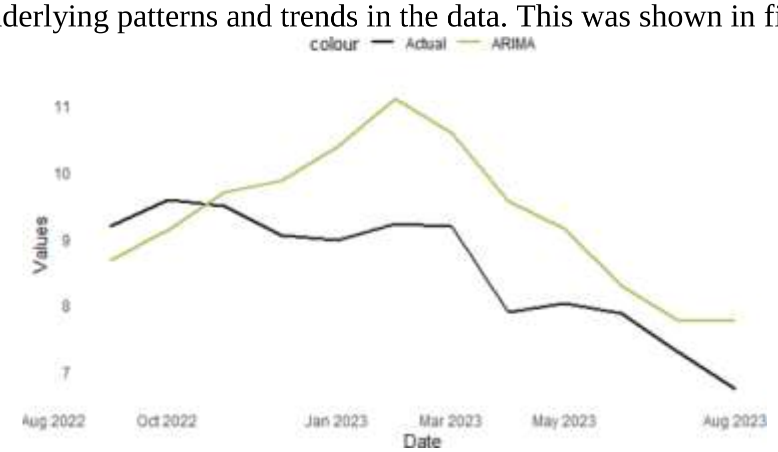

Figure 2: Actual Data verses ARIMA Forecast

Table 6: Model Evaluation

Model	MSE	RMSE	MAE	MAPE(%)
ARIMA(1,0,11)	1.178454	1.085566	0.948745	11.248809

The evaluation of the ARIMA model's performance is summarized in Table 6. The Mean Squared Error (MSE) was 1.178454, indicating the average squared difference between the actual and forecasted values. The Root Mean Squared Error (RMSE) of 1.085566 provided a measure of the standard deviation of the forecast errors, and the Mean Absolute Error (MAE) of 0.948745 represented the average absolute difference between the actual and predicted values. Additionally, the Mean Absolute Percentage Error (MAPE) of 11.248809% gave an insight into the relative accuracy of the model's predictions. This showed that the model exhibited relatively low forecast errors across multiple evaluation metrics

Forecasting

Table 7: Future Forecasted Inflation

Date	**Point Forecast**	**95% CI Lower Bound**	**95% CI Upper Bound**
Sep 2023	6.257859	4.50699243	8.008726
Oct 2023	6.131388	3.34787700	8.914899
Nov 2023	6.519684	2.86243274	10.176935
Dec 2023	7.056191	2.66875865	11.443623
Jan 2024	7.800917	2.79018237	12.811651
Feb 2024	8.187797	2.66587965	13.709715
Mar 2024	8.061394	2.06742789	14.055360
Apr 2024	8.307298	1.82672878	14.787868
May 2024	8.022959	1.05574503	14.990173
Jun 2024	7.399966	0.02351276	14.776418
Jul 2024	7.277673	-0.54650010	15.101847
Aug 2024	7.554118	-0.67450410	15.782740

The table 7 shows the model's future forecasts for inflation rates spanning from September 2023 to August 2024. The significance of this table extends to its practical utility. Stakeholders, policymakers, and economists can draw upon these forecasted inflation rates to inform a range of decisions. Businesses might adjust pricing strategies, financial institutions could refine interest rate policies, and policymakers may consider the implications for monetary and fiscal measures.

This forward-looking analysis supports informed planning and proactive responses to anticipated economic conditions.

CONCLUSION

Inflation forecasting is a critical element in economic analysis and policymaking, and this study focused on developing an ARIMA(1,0,11) model to predict inflation rates in Kenya. The results indicate that the ARIMA model performed well in capturing the underlying patterns and trends in the inflation data. The model's forecasts closely tracked the actual inflation rates, as evidenced by low forecast errors in terms of MSE, RMSE, MAE, and MAPE.

RECOMMENDATION

Continuous Monitoring: Inflation is influenced by various factors that can change over time. Policymakers and economists should continuously monitor these factors and update the model as needed to reflect changing economic conditions.

Model Refinement: While the ARIMA(1,0,11) model performed well in this study, it's important to periodically reassess the model's performance and consider alternative modeling techniques if necessary. Economic dynamics can evolve, and a different model structure may become more suitable in the future.

Policy Implications: The forecasted inflation rates can be used by policymakers to make informed decisions regarding monetary policy, interest rates, and fiscal measures. It's essential to consider the implications of forecasted inflation on the overall economy and adjust policies accordingly.

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